FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 9 No. 12, December, 2025, pp 398 – 408
DOI: https://doi.org/10.33003/fjs-2025-0912-4301

ON THE MATHEMATICAL MODEL FOR THE SPREAD AND CONTROL OF MEASLES

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ABSTRACT

Measles is a highly contagious and potentially deadly disease that continues to pose a significant public health challenge, particularly in regions with suboptimal vaccination coverage. Measles remains a major threat to children, leading to severe complications and even death, despite the success of vaccination programs worldwide. This study delves into the dynamics of measles transmission and control, focusing on the development of a mathematical model. The research aims to propose a mathematical model using a system of first-order differential equations, categorizing the population into compartments representing vaccination(V), susceptible(S), exposed(E), infection(I), treatment(T) and recovery(R). The objectives include: obtaining Disease-Free Equilibrium State (DFES), performing stability analysis for DFES and the numerical simulation of the model was presented using maple software. Ultimately, the goal is to inform evidence-based strategies for measles vaccination and prevention, mitigating the disease's impact on children's health.

Keywords: Agglomerative Hierarchical Cluster, Air Pollution, Air Quality Index, Nigeria, $PM_{2.5}$

INTRODUCTION

Air pollution is a significant environmental risk to global health, associated with approximately seven million premature deaths annually (Manisalidis et al., 2020; World Health Organization, 2021; Khomenko et al., 2021). Though, fine particulate matter ($PM_{2.5}$) can penetrate deep into the lungs and enter the bloodstream, significantly contributing to the burden of cardiopulmonary morbidity and mortality (Benabed & Boulbair, 2022; Garcia et al., 2023). But, $PM_{2.5}$ pollutions is prevalent in sub-Saharan Africa; however, significant areas of the region are inadequately monitored, leading to considerable deficiencies in exposure assessment and risk estimation (Glenn et al., 2022; World Health Organization, 2022; Lawal & Muhammed, 2022).

Nigeria exemplifies this challenge distinctly. The country, with a population surpassing 200 million, confronts increasing pollution challenges due to rapid urbanization, growing industrial activities, congested transportation systems, and frequent biomass burning (Busolo & Njabira, 2022; Almsatar, 2020). National $PM_{2.5}$ levels are approximately five times higher than the WHO guideline (Ezeh et al., 2019; Wambebe & Duan, 2020). However, major cities, including Lagos, Kano, Abuja, and Port Harcourt, frequently encounter unhealthy to hazardous concentrations, especially during the dry season (Sunday, 2022). Spatial heterogeneity is evident across the country's ecological zones, influenced by industrial distribution, vehicle density, meteorological variability, and transboundary haze transport (Ogwu et al., 2024; Abulude et al., 2024). Despite the magnitude of these challenges, Nigeria's monitoring capacity is insufficient; a 2024 audit reveals that the majority of stations are either non-functional or exhibit limited reliability (Omokaro et al., 2025).

The emission landscape highlights the intricacies of exposure. Vehicular emissions are prevalent in urban environments, exacerbated by the importation of outdated and inadequately regulated vehicles (Singh et al., 2023; Oluwakoya, 2024), while, industrial sources, especially within the oil-producing corridor of the Niger Delta, significantly contribute to elevated levels of $PM_{2.5}$ and gas-phase pollutants (Meo et al., 2024; World Health Organization, 2021). But, biomass combustion and the widespread utilization of diesel and petrol generators during power outages contribute to persistent emissions in rural and peri-urban communities. Seasonal dynamics, particularly during the Harmattan period, increase $PM_{2.5}$ levels by 20–60% due to the advection of Saharan dust across the region (Léon et al., 2021).

Also, under conditions characterized by spatial diversity and limited data, it is crucial to employ analytical methods that can effectively extract robust spatial structures from sparse monitoring networks. Agglomerative Hierarchical Clustering (AHC) presents several advantages in this context. It eliminates the need for pre-defining the number of clusters, elucidates hierarchical relationships, and demonstrates effectiveness in heterogeneous pollution environments (Paparrizos et al., 2024; Mitchell & Bala, 2024). Meanwhile, research conducted in Malaysia, India, and Europe indicates that Agglomerative Hierarchical Clustering (AHC) employing Ward's method and Euclidean distance successfully categorizes regions into high, medium, and low pollution classifications, thereby enhancing the precision of regulatory and public health interventions (Rahman et al., 2022; Azizan et al., 2023). The classification has been validated with high accuracy through discriminant analysis (Azizan et al., 2023).

Despite the relevance of this approach, no nationwide AHC-based assessment of $PM_{2.5}$ spatial patterns has been conducted in Nigeria, leaving a critical evidence gap in the country's air-quality management framework. This study addresses that gap by applying hierarchical clustering to 5 years of $PM_{2.5}$ records from Nigeria's available monitoring stations. This work is guided by three research questions:

i. Can Ward's agglomerative hierarchical clustering delineate coherent $PM_{2.5}$ pollution regions across Nigeria?
ii. How do $PM_{2.5}$ levels vary temporally across these regions between 2019 and 2023?
iii. What do associate AQI values reveal about potential health risks across the identified pollution zones?

By answering these questions, the study provides the first national-scale, cluster-based characterization of $PM_{2.5}$ in Nigeria and delivers policy-relevant insights for strengthening air-quality governance in one of Africa's most polluted and data-constrained environments.

MATERIALS AND METHODS

Study Area

Figure 1 shows Nigeria map which spans 923,768 km² in West Africa, between latitudes 4°N and 14°N and longitudes 3°E and 14°E (Adeleye et al., 2021), with a tropical climate with wet and dry seasons. The rainy season is April to October, while the dry season is November to March. Sufiyan et al. (2020) reported that the Harmattan wind blows dusty Sahara Desert air during the dry season, affecting air quality. Nigeria is divided into six geopolitical regions, South South, South West, South East, North Central, North West, and North East, each characterized by unique economic activities, varying population densities, and specific sources of pollution (Elechi et al., 2023).

Figure 1: Map of Nigeria Showing the Locations. Britannica, Inc. (2025)

Air Quality Monitoring Stations

This study utilized data gathered from 15 air quality monitoring stations that are strategically located throughout Nigeria's six geopolitical zones, as shown in Table 1. The selection of stations was determined by factors such as geographical representation and classification into urban, industrial, and suburban categories. The stations include seven (7) urban stations positioned in central urban areas characterized by significant traffic volume, five (5) suburban stations located in residential neighborhoods characterized by moderate development, and three (3) industrial stations located in proximity to oil refineries, manufacturing plants, and industrial zones. The coordinates of the stations varied between 4.82°N and 12.00°N latitude, as well as 3.35°E and 13.08°E longitude, providing extensive spatial coverage.

Table 1: Air Quality Monitoring Stations in Nigeria

Station Code	Station Name	State	Zone	Location Type	Coordinates
NIG01	Lagos-Ikeja	Lagos	Southwest	Urban	6.5977°N, 3.3464°E
NIG02	Lagos-Lekki	Lagos	Southwest	Suburban	6.4437°N, 3.4700°E
NIG03	Abuja-Municipal	FCT Abuja	North Central	Urban	9.0574°N, 7.4898°E
NIG04	Abuja-Asokoro	FCT Abuja	North Central	Suburban	9.0365°N, 7.5339°E
NIG05	Kano-City	Kano	Northwest	Urban	12.0022°N, 8.5920°E
NIG06	Kano-Industrial	Kano	Northwest	Industrial	11.9716°N, 8.5378°E
NIG07	Port Harcourt-Trans Amadi	Rivers	South South	Industrial	4.8156°N, 7.0498°E
NIG08	Port Harcourt-Rumuola	Rivers	South South	Urban	4.8891°N, 7.0229°E
NIG09	Benin City-Central	Edo	South South	Urban	6.3381°N, 5.6157°E
NIG10	Benin City-Airport Road	Edo	South South	Suburban	6.3176°N, 5.6347°E
NIG11	Enugu-Coal Camp	Enugu	Southeast	Suburban	6.4398°N, 7.4951°E
NIG12	Ibadan-Bodija	Oyo	Southwest	Urban	7.3876°N, 3.9093°E

Station Code	Station Name	State	Zone	Location Type	Coordinates
NIG13	Warri-Effurun	Delta	South South	Urban	5.5378°N, 5.7821°E
NIG14	Maiduguri-GRA	Borno	Northeast	Urban	11.8469°N, 13.0820°E
NIG15	Calabar-Marian	Cross River	South South	Suburban	4.9517°N, 8.3417°E

$PM_{2.5}$ Measurement and Data Collection

$PM_{2.5}$ concentrations were measured through a network of stations equipped with Tapered Element Oscillating Microbalance (TEOM 1405/1400a) and Beta Attenuation Monitors (BAM-1020), both recognized as Federal Equivalent Methods by the U.S. EPA (Magi et al., 2020; Jin et al., 2019). TEOM units were primarily utilized at southern and coastal locations, equipped with humidity control modules to reduce high-moisture interference. In contrast, BAM monitors were positioned at northern and inland stations to ensure stable performance in drier environments (Jin et al., 2019).

Hourly measurements were compiled into 24-hour averages from 1 January 2019 to 31 December 2023, yielding 1,826 daily observations per station (total n = 27,390). Outlier detection utilized the interquartile range (IQR) method for the daily series of each station. Among the flagged values, 147 observations (0.54% of the dataset) were initially identified as potential outliers; 112 were confirmed as instrument or power-related anomalies and subsequently removed, while 35 were retained following cross-validation with calibration and meteorological logs. Data gaps, representing less than 5% of total observations, were addressed through linear interpolation. However, longer periods of missing data were omitted from further analyses.

Agglomerative Hierarchical Cluster Analysis

Agglomerative Hierarchical Clustering (AHC) was employed to identify spatial groupings of stations based on similarities in $PM_{2.5}$ levels (Azizan et al., 2023; Rahman et al., 2022). This was conducted to ascertain the spatial distribution of the stations. Maldonado-Salguero et al. (2022) indicate that the method commenced with each station operating as an individual cluster. Subsequently, an iterative process was employed to merge the clusters. Ward's linkage was selected due to its ability to minimize variation within clusters, resulting in compact groups that are distinctly separated from each other (El-Araby et al., 2023). Metrics, including median, percentiles, and variability measures, provide various insights into air quality. However, long-term mean $PM_{2.5}$ is preferred for clustering due to its representation of chronic exposure, which is the main contributor to cardiovascular and respiratory risks, and its compliance with WHO and U.S. EPA standards (Zhou et al., 2025; Roy et al., 2025; Jalali et al., 2021). The mean, unlike medians or short-term variability, mitigates the impact of episodic extremes and offers a stable, comparable metric across stations, thereby serving as an optimal tool for detecting enduring spatial patterns within Nigeria's $PM_{2.5}$ network as illustrated in Eq. 1.

$$\Delta S = \frac{p_i q_j}{p_i + q_j} \|q_i - q_j\|^2 \quad [1]$$

where p_i and p_j are the number of observations in clusters i and j, and q_i and q_j are the cluster centroids.

Distance Metric

Euclidean distance was employed as illustrated in Eq. 2 (Balaji et al., 2022) as the dissimilarity measure, calculated as:

$$E_{ij}^2 = \sum_{k=1}^{n} (d_{ik} - d_{jk})^2 \quad [2]$$

In this context, E^2_{ij} refers to the squared Euclidean distance between stations i and j, while d_{ik} denotes the mean $PM_{2.5}$ concentrations at station i. Additionally, n represents the number of variables, which in this instance is n = 1, indicating the mean $PM_{2.5}$. (Fu et al., 2020). The linkage distance was standardized using the formula (E_{link}/E_{max}) × 100, with E_{link} representing the distance at which clusters converge and E_{max} indicating the maximum distance within the dataset. This normalization enhances the understanding of the y-axis in the dendrogram used in the results analysis. The AHC analysis utilized the SciPy library in Python. The process included determining the average $PM_{2.5}$ concentrations for each station from 2019 to 2023. Calculating the Euclidean distances among all stations and utilizing Ward's linkage algorithm to create a dendrogram visualization and determine the optimal height for cutting the dendrogram to yield three distinct clusters. Assigning cluster labels of HPR, MPR, and LPR according to the average $PM_{2.5}$ values was also implemented.

Air Quality Index

The Air Quality Index (AQI) was determined utilizing the updated breakpoints for $PM_{2.5}$ as provided by US EPA $PM_{2.5}$ AQI (2024) and Horn & Dasgupta (2024), as seen in Table 2. AQI value formula is stated as stated in Eq. 3 (Pyae, 2021),

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}}(C_p - BP_{Lo}) + I_{Lo} \quad [3]$$

where:

I_p = AQI value for pollutant p ($PM_{2.5}$), C_p = Truncated concentration of $PM_{2.5}$ (to 1 decimal place), BP_{Hi} = Concentration breakpoint ≥ C_p, BP_{Lo} = Concentration breakpoint ≤ C_p, I_{Hi} = AQI value corresponding to BP_{Hi}, I_{Lo} = AQI value corresponding to BP_{Lo}

Table 2: US EPA $PM_{2.5}$ AQI Range (2024)

AQI Category	AQI Range	$PM_{2.5}$ Range (µg/m³)	Health Implications
Good	0-50	0.0-9.0	Air quality is satisfactory
Moderate	51-100	9.1-35.4	Acceptable quality
Unhealthy for Sensitive Groups	101-150	35.5-55.4	Sensitive groups may experience effects
Unhealthy	151-200	55.5-125.4	Everyone may experience health effects
Very Unhealthy	201-300	125.5-225.4	Health alert conditions
Hazardous	301+	225.5+	Emergency conditions

Data visualization analyses and visualizations were conducted using Python (version 3.13.5). The workflow including data preprocessing, normalization, clustering and performance assessment and evaluation using libraries such as scikit-learn, pandas, NumPy, and matplotlib. Descriptive statistics such as mean, median, standard deviation, skewness, and kurtosis. Positive skewness values suggest right-tailed distributions typical of pollution events (Rahman et al., 2022). Temporal trends were examined through the aggregation of monthly and annual data.

RESULTS AND DISCUSSION

Spatial Distribution of $PM_{2.5}$ Concentrations

Over a five-year period, $PM_{2.5}$ concentrations at 15 Nigerian monitoring stations ranged from 33.7 to 67.2 µg m⁻³, exceeding the WHO annual recommendation of 5 µg m⁻³ by factors of 6.7 to 13.4, as shown in table 3. Concentrations were highest in industrialized urban centers, including Kano-Industrial (67.2 µg m⁻³), Port Harcourt-Trans Amadi (59.9 µg m⁻³), and Kano-City (57.8 µg m⁻³), which are emission hotspots in Nigeria's manufacturing and petroleum refining areas. Lower but significantly increased values were seen at semi-rural sites such as Calabar Marian (33.7 µg m⁻³), Enugu Coal Camp (35.9 µg m⁻³), and Abuja Asokoro (38.4 µg m⁻³). Positive skewness (1.07–1.91) and leptokurtic distributions (kurtosis: 2.42–8.99) indicated rare high-pollution episodes over baseline concentrations. Warri-Effurun had the highest skewness at 1.91, reflecting Nigeria's oil and gas sector's interrupted industrial emissions. Distributional features show that long-term averaging in air quality management is insufficient and suggest that policy frameworks should account for episodic pollution spikes. Nigeria's exceedance of WHO guidance, compared to sub-Saharan African baselines where many cities report similar or elevated $PM_{2.5}$ levels, highlights regional air quality issues caused by rapid industrialization, insufficient emissions control, and biomass burning.

Table 3: Descriptive Statistics of $PM_{2.5}$ (µg/m³) by Station from 2019 to 2023

Station Code	Station Name	State	Region Type	Min	Q1	Median	Q3	Max	Mean	SD	Skewness	Kurtosis
NIG06	Kano-Industrial	Kano	HPR	24.08	49.74	61.78	81.76	241.32	67.20	23.84	1.39	4.12
NIG07	PortHarcourt-TransAmadi	Rivers	HPR	20.41	45.08	55.47	73.35	197.61	59.97	20.08	1.18	3.25
NIG05	Kano-City	Kano	HPR	18.64	43.02	53.70	69.90	228.97	57.81	19.79	1.42	5.57
NIG09	BeninCity-Central	Edo	MPR	19.89	39.76	48.88	64.17	180.72	52.58	16.98	1.17	3.93
NIG01	Lagos-Ikeja	Lagos	MPR	14.94	37.82	46.58	60.89	181.85	50.57	17.86	1.58	5.56
NIG13	Warri-Effurun	Delta	MPR	16.64	37.21	45.98	59.46	189.00	49.60	17.61	1.91	8.99
NIG08	PortHarcourt-Rumuola	Rivers	MPR	16.89	36.39	44.82	58.43	158.67	48.22	15.75	1.07	2.42
NIG03	Abuja-Municipal	FCT Abuja	MPR	13.67	34.01	41.94	55.66	182.41	46.01	16.75	1.76	7.03
NIG12	Ibadan-Bodija	Oyo	MPR	14.94	34.30	42.43	55.64	166.46	45.63	15.41	1.33	4.82
NIG10	BeninCity-AirportRoad	Edo	MPR	12.45	32.35	39.86	52.49	137.64	43.25	14.86	1.21	2.86
NIG14	Maiduguri-GRA	Borno	MPR	16.06	31.86	39.64	51.46	176.69	42.53	14.62	1.51	6.23
NIG02	Lagos-Lekki	Lagos	MPR	14.18	31.46	38.41	51.00	142.06	41.85	14.26	1.34	4.34
NIG04	Abuja-Asokoro	FCTA buja	LPR	13.62	29.12	35.37	46.70	122.27	38.40	12.85	1.18	2.67
NIG11	Enugu-Coal Camp	Enugu	LPR	13.99	26.96	33.33	43.37	130.81	35.93	12.02	1.26	4.10
NIG15	Calabar-Marian	Cross River	LPR	11.69	25.16	31.13	40.79	103.96	33.74	11.46	1.22	3.08

Agglomerative Hierarchical Clustering

Ward's hierarchical clustering categorized 15 Nigerian monitoring stations into three distinct clusters: High Pollution Region (HPR), Medium Pollution Region (MPR), and Low Pollution Region (LPR), according to patterns of $PM_{2.5}$ concentrations. This method aligns with hierarchical agglomerative clustering used in African air quality networks, successfully identifying geographically relevant pollution zones characterized by unique health exposure profiles (Izah et al., 2024). The dendrogram in figure 2 indicated optimal cluster separation at normalized linkage distances similar to established thresholds in comparable studies. The concentration of HPR clusters in industrialized centers such as Kano and Port Harcourt facilitates targeted public health interventions for populations facing increased $PM_{2.5}$-related cardiorespiratory issues. Additionally, MPR and LPR classifications aid in the implementation of differentiated monitoring and policy protocols. The cluster-based framework converts spatially diverse pollution data into practical epidemiological insights that conform to risk-stratified air quality management standards.

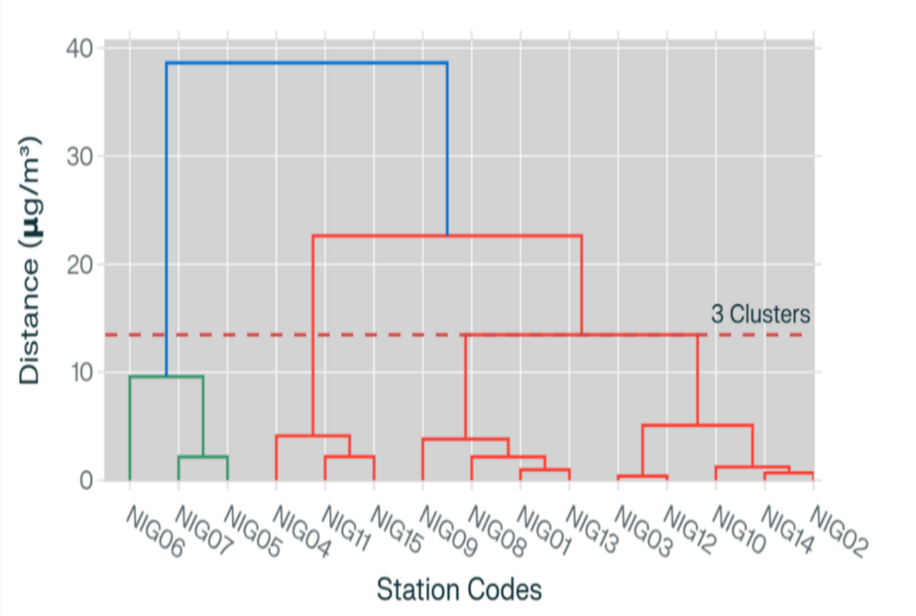

Figure 2: *A dendrogram Illustrating the Hierarchical Clustering of 15 $PM_{2.5}$ Monitoring Stations in Nigeria, Employing Ward's Method Alongside Euclidean Distance for the Years 2019 to 2023. The Red Dashed Line Signifies the Ideal cut-off for Three Distinct Clusters. HPR (High Pollution Regions), MPR (Medium Pollution Regions), and LPR (Low Pollution Regions)*

High Pollution Regions (HPR)

Ward's clustering analysis in table 4 revealed three distinct $PM_{2.5}$ exposure zones, each carrying important implications for health policy. The High Pollution Region (HPR), which encompasses 20% of monitoring stations, includes Kano-Industrial and Port Harcourt-Trans Amadi, both recognized as industrial hotspots. The mean $PM_{2.5}$ concentrations in this area is 61.66 ± 21.69 μg m⁻³, exceeding Nigeria's national standard of 25 μg m⁻³ by a factor of 2.5 and surpassing WHO guidelines by a factor of 12.3 (World Health Organization, 2021). The concentration range recorded in Port Harcourt (32.3–184.0 μg m⁻³) reflects the episodic gas flaring and refinery emissions characteristic of the Niger Delta region. The Medium Pollution Region (MPR), encompassing nine significant urban centers and representing 60% of monitoring stations, exhibited an average particulate matter concentration of 46.69 ± 16.45 μg m⁻³. The current level is 8 -10 times above the recommendations established by the World Health Organization, with vehicular emissions accounting for approximately 32% of the $PM_{2.5}$ burden. The Low Pollution Region (LPR; 20% of stations) exhibited a mean concentration of 36.02 ± 12.27 μg m⁻³, exceeding the WHO annual guidelines by 7.2 times and surpassing WHO Interim Target-4 (35 μg m⁻³) (World Health Organization, 2021). This suggests that even the least polluted monitoring areas in Nigeria pose significant public health risks. This three-tier stratification identifies geographically distinct populations, necessitating proportionally scaled intervention strategies. Emission source controls are implemented in high pollution risk (HPR) industrial zones, while vehicle emission standards and traffic management are applied in moderate pollution risk (MPR) urban centers. Additionally, baseline monitoring continues in low pollution risk (LPR) areas.

Table 4: Summary Statistics by Region Type (2019-2023)

Region Type	NStations	Mean $PM_{2.5}$ (μg/m³)	SD (μg/m³)	Min (μg/m³)	Max (μg/m³)	Median (μg/m³)	Q1 (μg/m³)	Q3 (μg/m³)
HPR	3	61.66	21.69	18.64	241.32	56.86	45.78	74.63
MPR	9	46.69	16.45	12.45	189.00	43.21	34.76	56.39
LPR	3	36.02	12.27	11.69	130.81	33.41	26.96	43.36

Spatial Pattern Analysis

The spatial distribution map in Figure 3 illustrates clear geographical clustering patterns. Northern Nigeria, particularly Kano State, has been recognized as a notable pollution hotspot, with urban and industrial stations classified as high pollution risk (HPR). The identified pattern reflects the characteristics of the area's semi-arid climate, which promotes dust resuspension, alongside vigorous commercial activities and a lack of vegetation to facilitate pollutant deposition.

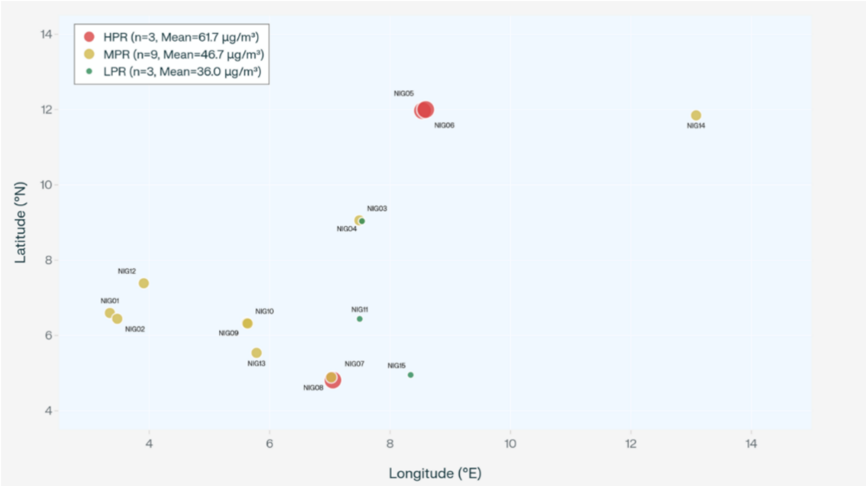

Figure 3: *Analysis of the Spatial Distribution of $PM_{2.5}$ Monitoring Stations Throughout Nigeria Categorized by Pollution Levels. Red Circles Indicate Areas with High Levels of Pollution, Orange Circles Denote Regions with Medium Pollution Levels, and Green Circles Signify Areas with Low Pollution Levels. The Size of the Circle Indicates the Level of Pollution*

The Niger Delta region, encompassing Rivers, Delta, and Edo states, exhibits varied patterns, featuring industrial stations in HPR and urban stations in MPR. This distribution highlights the significant impact of oil and gas operations on pollution levels in this region (Ukpong et al., 2019). Port Harcourt has been noted for its exceptionally high $PM_{2.5}$ concentrations in sub-Saharan Africa, with measurements sometimes surpassing 500 µg m^{-3} during severe pollution events. Although Lagos is recognized as the largest metropolis in West Africa, its coastal position and the influence of prevailing winds contribute to a degree of natural dispersion of pollutants. Traffic congestion contributes to significant $PM_{2.5}$ emissions from vehicular exhaust.

Temporal Annual Trends in $PM_{2.5}$ Concentrations

The five-year trend analysis in Figure 4 and Table 5 reveals distinct temporal patterns with important implications for public health concerning the three pollution clusters. The High Pollution Region (HPR) and Moderate Pollution Region (MPR) peaked in 2019, saw a notable decrease in 2020 owing to reduced industrial and vehicular activity during the COVID-19 lockdown, and reverted to near-baseline levels by 2023, underscoring the transient character of emission reductions in the absence of structural policy reforms. The Low Pollution Region (LPR) displayed relative stability alongside increasing variability, suggesting localized emissions linked to urban expansion, traffic growth, and industrial activities. The results demonstrate that even areas in Nigeria with lower pollution levels are affected by human activities, highlighting the need for continuous emission control strategies. The implementation of stricter vehicular standards, industrial monitoring, and strategic land-use planning is essential to mitigate long-term health risks associated with chronic $PM_{2.5}$ exposure.

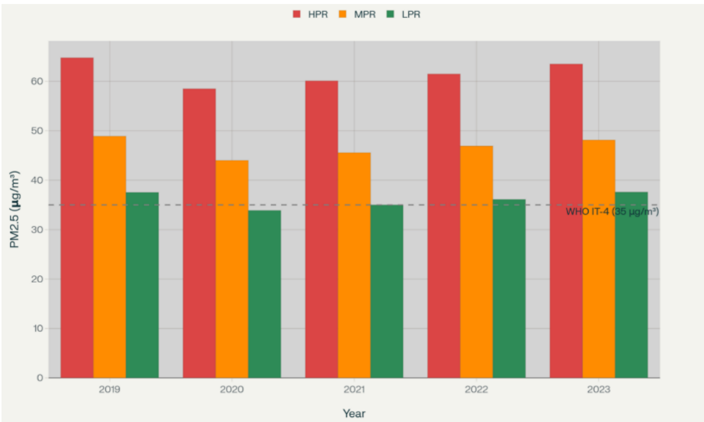

Figure 4: *Analysis of Temporal Annual Trends in $PM_{2.5}$ Concentrations Throughout Nigeria from 2019 to 2023. The Upper Panel Illustrates Monthly Fluctuations Characterized by Seasonal Trends, Whereas the Lower Panel Presents Yearly Averages Categorized by Region Type. Dashed Lines Represent the Interim Targets Set by the WHO*

Table 5: Annual $PM_{2.5}$ and AQI Extremes by Region Type

Region Type	Year	Mean $PM_{2.5}$ (µg/m³)	Max $PM_{2.5}$ (µg/m³)	Mean AQI	Max AQI	Max AQI Status
HPR	2019	64.76	197.70	148.84	273	Very Unhealthy
HPR	2020	58.47	241.32	141.92	312	Hazardous
HPR	2021	60.09	197.61	144.33	272	Very Unhealthy
HPR	2022	61.47	195.73	146.04	271	Very Unhealthy
HPR	2023	63.51	211.13	148.76	286	Very Unhealthy
LPR	2019	37.54	100.92	106.76	183	Unhealthy
LPR	2020	33.88	106.60	99.24	187	Unhealthy
LPR	2021	34.99	96.83	101.64	180	Unhealthy
LPR	2022	36.11	113.90	103.73	192	Unhealthy
LPR	2023	37.60	130.81	106.54	206	Very Unhealthy
MPR	2019	48.90	186.90	127.21	262	Very Unhealthy
MPR	2020	44.01	166.46	118.92	242	Very Unhealthy
MPR	2021	45.56	165.75	121.54	241	Very Unhealthy
MPR	2022	46.89	181.85	123.80	257	Very Unhealthy
MPR	2023	48.12	189.00	125.95	264	Very Unhealthy

Monthly and Seasonal Patterns

Figure 5 presents the monthly and seasonal fluctuations of $PM_{2.5}$ concentrations across various regions. In the dry season (November–March), concentrations significantly increased, reaching their peak between December and February, coinciding with the Harmattan period. Dry-season levels were, on average, 35–58% higher than those observed during the rainy season (April–October). Mean monthly $PM_{2.5}$ concentrations in the High Pollution Region (HPR) varied from 45 µg m⁻³ during July–August to 85 µg m⁻³ in January–February. In contrast, the Moderate Pollution Region (MPR) and Low Pollution Region (LPR) exhibited ranges of 35–62 µg m⁻³ and 28–48 µg m⁻³, respectively. The results align with findings from West African studies (e.g., Evans et al., 2022), which attribute 20–60% seasonal increases in $PM_{2.5}$ to dust intrusion and meteorological conditions during Harmattan, thereby reaffirming the significant seasonal impact on air quality dynamics in Nigeria.

Peak Concentrations and Timing

The Kano industrial station reported the highest $PM_{2.5}$ concentration of 197.70 µg m⁻³ on March 12, 2019. Figure 5 and Table 6 show all locations experienced high amounts in September and October. September had an average daily HPR high of 142 µg m⁻³, with several days exceeding 150 µg. The MPR peaked at 186.90 µg m⁻³ in Warri-Effurun on October 31, 2019, due to biomass burning. Additionally, the LPR peaked at 100.92 µg m⁻³ in Abuja-Asokoro on October 10, 2019.

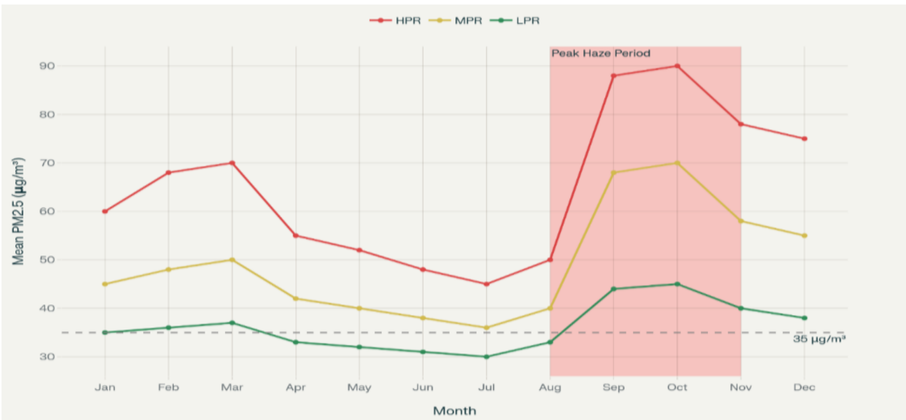

Figure 5: *Analysis of Monthly $PM_{2.5}$ Concentrations Throughout the 2019 Haze Episode in Three Distinct Pollution Regions. The Shaded Area (September-October) Represents the Peak Haze Period, Pollution from Local Emissions, Resulted in the Highest Recorded Concentrations*

The observed values significantly surpassed the WHO's 24-hour guideline of 15 µg m⁻³, as well as the Nigerian national standard of 50 µg m⁻³ (Air Quality Life Index, 2025; WHO, 2021).

Table 6: 2019 Haze Maximum Recorded Values by Region

Region Type	Date	Station Code	$PM_{2.5}$ Max(µg/m³)	AQI Max	Health Status	N Stations	Mean Annual $PM_{2.5}$(µg/m³)
HPR	2019-03-12	NIG06	197.70	273	Very Unhealthy	3	64.76
MPR	2019-10-31	NIG13	186.90	262	Very Unhealthy	9	48.90
LPR	2019-10-10	NIG04	100.92	183	Unhealthy	3	37.54

Air Quality Index During Haze Episode

In Figure 6, the mean AQI for HPR was recorded at 148.84, with a peak maximum of 273, categorizing it as Very Unhealthy during the period. The distribution of AQI categories revealed that Good (0-50) is 0%, Moderate (51-100) is 6.12%, Unhealthy for Sensitive Groups (101-150) is 36.26%, Unhealthy (151-200) is 55.62%, Very Unhealthy (201-300) is 2.01%, and Hazardous (301+) is 0%.

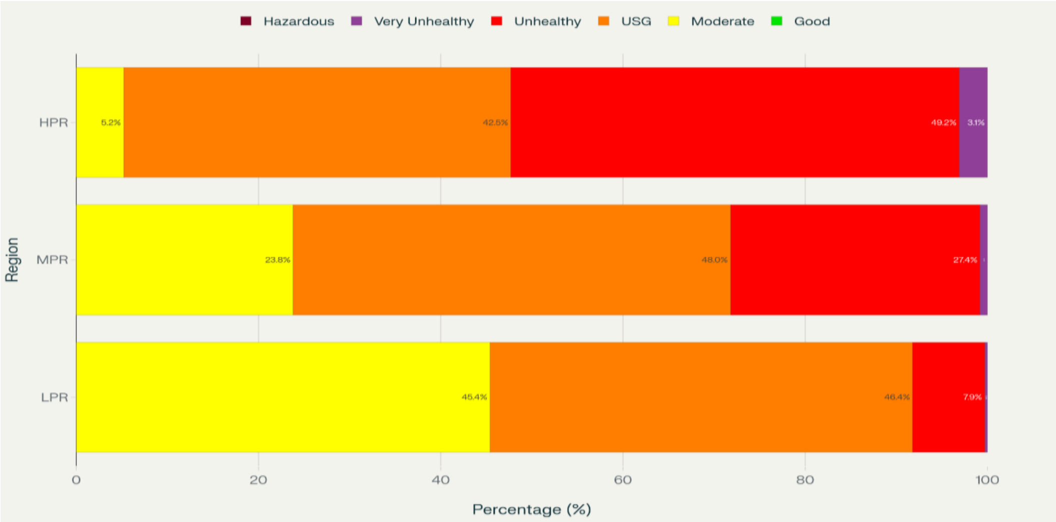

Figure 6: *Analysis of the Distribution of Air Quality Index Categories Across Various Pollution Regions, Highlighting the Percentage of days within Each Health Category from 2019 to 2023. HPR Encountered Adverse Conditions on 52% of days, Whereas LPR also Faced Subpar Air Quality on more than Half of the Days. Throughout the Study Period, no Region Attained Good Air Quality at any Point*

MPR showed a mean AQI of 127.21, peaking at 262, which is Very Unhealthy. Moderate, 24.84%. Unhealthy for Sensitive Groups, 41.67%. Unhealthy, 33.27%. Very Unhealthy, 0.21%. LPR's mean AQI was 106.76, with a maximum of 183, which is unhealthy. Moderate, 51.69%. Unhealthy for Sensitive Groups, 38.36%. Unhealthy, 9.95%. Every region shows Unhealthy levels during September and October, while HPR and MPR reached Very Unhealthy levels that required public health warnings.

AQI Distribution

Nigeria's five-year dataset showed sustained poor air quality in Figure 7. HPR's mean AQI was 146.4, indicating an unhealthy threshold for sensitive groups. The data shows that 94.8% of days had an AQI over 100 and 52.3% over 150, making them unhealthy. 3.1% of days had an AQI over 200, which is Very Unhealthy.

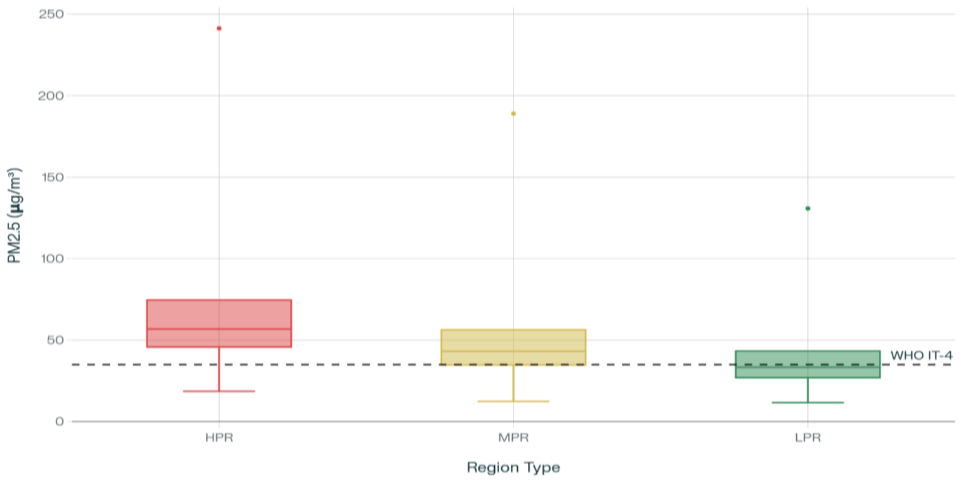

Figure 7: *Comparative Boxplots Illustrating the Distributions of $PM_{2.5}$ Concentrations (Left) and Air Quality Index Values (Right) Across the Three Pollution Regions from 2019 to 2023. Reference Lines Denote Established Guidelines and Air Quality Index Thresholds.*

The MPR showed a mean AQI of 123.7, an unhealthy level for sensitive groups. The data showed that 76.2% of days had an AQI above 100, 28.4% above 150, and 0.8% above 200. The LPR had an unhealthy for sensitive groups mean AQI of 103.6. The data shows that 54.6% of days had an AQI above 100, 8.2% above 150, and 0.3% above 200. In Nigeria's least polluted areas, air quality standards were surpassed on more than half of the observed days. These conditions pose ongoing health risks for children, the elderly, and individuals with respiratory or cardiovascular issues (US EPA, 2024).

Health Impact Assessment in Global Context

Nigerian residents face an increasing health burden across pollution zones, as classified by the US EPA AQI. Residents of HPR encounter "unhealthy" air quality conditions (AQI 151–200), which are associated with increased risks of respiratory dysfunction and cardiovascular stress in the general population. In contrast, MPR residents experience "unhealthy for sensitive groups" conditions (AQI 101–150), impacting 30% of exposed children and adults who exhibit moderate or greater lung function impairment during moderate exertion. LPR regions surpass an AQI of 100 in 55% of measurements, resulting in all exposure zones exceeding internationally accepted safety thresholds. Examining these levels in relation to regional and global datasets highlights the seriousness of Nigeria's pollution issue. Nigerian HPR concentrations (61.66 $\mu g\ m^{-3}$) surpass those of significant West African counterparts Accra, Ghana (49.5 $\mu g\ m^{-3}$) and Lomé, Togo (23.5 $\mu g\ m^{-3}$)—and are comparable to Delhi, India (92.7 $\mu g\ m^{-3}$). In contrast, Nigerian LPR (36.02 $\mu g\ m^{-3}$) is similar to levels in Beijing, China (32.6 $\mu g\ m^{-3}$) and Bangkok, Thailand (21.7 $\mu g\ m^{-3}$), suggesting that even Nigeria's least-polluted stations exceed urban baselines in developed nations (US urban average: 7–12 $\mu g\ m^{-3}$). This gradient illustrates that Nigeria's air quality crisis is pervasive throughout its monitored regions, indicating the need for immediate structural emission interventions instead of sporadic policy measures.

CONCLUSION

In this study, a comprehensive nationwide and regionally comparative classification of $PM_{2.5}$ pollution in Nigeria was explored, utilizing agglomerative hierarchical clustering (AHC) with Ward's linkage. This study examined five years of continuous observations (2019–2023) from 15 monitoring stations, categorizing the data into three distinct zones: High Pollution Region (HPR), Medium Pollution Region (MPR), and Low Pollution Region (LPR). These zones collectively illustrate the diverse industrial, urban, and climatic characteristics of Nigeria. The findings reveal a distinct pollution gradient, defined by HPR zones (e.g., Kano and Port Harcourt) predominantly impacted by industrial and combustion-related emissions, MPR zones influenced by considerable urbanization and vehicular activity, and LPR zones exhibiting comparatively lower, yet still notable, particulate concentrations pertinent to health. This hierarchical classification offers a comprehensive spatial overview of air quality in Nigeria, transcending analyses centered on individual monitoring stations and enhancing the understanding of spatial variations in pollutant exposure.

The approach attempts to demonstrates robustness. However, limitations remain due to inconsistent station coverage and reliance on a single clustering algorithm. To overcome these limitations, integrating satellite-derived $PM_{2.5}$ data is crucial for enhancing spatial completeness, alongside the adoption of hybrid machine learning or source apportionment models to improve clustering accuracy. Targeted mitigation strategies are essential from a policy standpoint, encompassing the regulation of industrial emissions and enforcement of fuel standards in HPR zones, improved urban transport management in MPR zones, and proactive land-use and agricultural controls in LPR zones. Future research should build upon this framework by incorporating meteorological and chemical composition data to strengthen the link between emission sources and observed pollution patterns, thus supporting evidence-based air quality management and public health protection in Nigeria.

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