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Geo-epidemiological mapping of respiratory disease prevalence with mining dust exposure in Ogun State, Nigeria

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Abstract

Mining activities are significant contributors to ambient particulate matter (PM) emissions, which pose serious public health risks, especially in rapidly urbanizing regions. This study investigates the spatial correlation between PM exposure and respiratory disease prevalence in quarry-dense communities of Ogun State, Nigeria. A cross-sectional ecological design was employed, integrating gravimetric PM_{10} and $PM_{2.5}$ sampling, meteorological observations, and retrospective health data from 2018 to 2023. Twelve sampling sites across Ewekoro and Sagamu Local Government Areas (LGAs) were selected based on quarry proximity and population density. Spatial interpolation (Kriging), hotspot detection (Getis-Ord Gi*), Local Indicators of Spatial Association (LISA), and regression models (OLS and GWR) were applied to assess spatial patterns and exposure-response relationships. A decision tree model was also developed to predict high-risk communities. PM_{10} and $PM_{2.5}$ levels peaked during the dry season, with concentrations exceeding WHO guidelines across multiple sites. Respiratory diseases were most prevalent among adults aged 25–64 and children aged 5–14, with Itori, Papalanto, and Emuren communities showing the highest incidence. Significant spatial clustering of disease was confirmed through Gi* and LISA analyses. GWR outperformed OLS in modeling $PM_{2.5}$-disease relationships (Adjusted R^2 = 0.74), revealing stronger associations in communities nearest to quarry operations. The decision tree identified $PM_{2.5}$ >110 μg/m³ and residence within 2.5 km of a quarry as key predictors of elevated risk. This study demonstrates strong spatial associations between particulate pollution from mining and respiratory disease burden in quarry-adjacent communities. Findings support the implementation of spatial buffer zones, local air quality surveillance, and integrated health monitoring systems to mitigate environmental health risks in vulnerable populations.

Keywords: Particulate Matter; Spatial Epidemiology; Quarry Pollution; Respiratory Health; GIS; Geo-Epidemiology; Environmental Exposure; Nigeria

1. Introduction

Mining activities, particularly in mineral-rich developing regions, have long been associated with extensive environmental degradation and public health risks. Among the most pressing issues is the release of fine particulate matter (PM), especially $PM_{2.5}$ and PM_{10}, into the ambient atmosphere during mineral extraction, crushing, and transportation. These dust particles, when inhaled, penetrate deep into the respiratory system, contributing to a spectrum of health outcomes including asthma, bronchitis, chronic obstructive pulmonary disease (COPD), and even premature death (Achilleos et al., 2017). While numerous studies have established associations between particulate matter and adverse respiratory health, there remains a paucity of spatially explicit analyses that integrate environmental exposure data with disease prevalence—particularly in regions affected by mining.

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Dust pollution from mining operations often contains a mixture of silica, heavy metals, and other geogenic elements that exhibit higher toxicity due to their physicochemical composition (Saddique et al., 2021). Communities living adjacent to limestone quarries, coal mines, and other extractive zones are particularly vulnerable, experiencing chronic exposure to respirable particles. The geographical distribution of disease in such areas is rarely uniform; it is shaped by a confluence of environmental, geological, and socio-demographic factors. Consequently, there is growing recognition of the value of geo-epidemiological approaches to understand and visualize the spatial patterns of health outcomes in response to localized environmental exposures (Kumar et al., 2020).

Geo-epidemiology combines epidemiological data with geospatial technologies, such as Geographic Information Systems (GIS) and remote sensing, to assess spatial disparities in disease occurrence. This approach is especially pertinent in the context of environmental toxicology, where exposure to pollutants varies significantly over space and time. In mining-impacted areas, geo-epidemiological mapping can reveal "hotspots" of respiratory disease that correspond to high concentrations of airborne dust or proximity to pollutant sources. Such insights can inform targeted public health interventions, land use planning, and environmental regulation (Ma et al., 2022).

Several recent studies have demonstrated the applicability of GIS-based spatial modeling in environmental health. For instance, Xia et al. (2021) used spatial regression to link coal mining intensity with respiratory morbidity in northern China, while Ugbaje et al. (2020) applied spatial interpolation to predict PM_{10} dispersion from quarry sites in Nigeria. These findings underscore the potential of combining health data with environmental metrics to derive meaningful spatial correlations. However, a gap remains in studies that use both real-time air quality data and health records to produce integrative disease risk maps in limestone-rich, mining-intensive environments.

Nigeria, like many developing countries, has experienced a rapid expansion of extractive industries alongside weak environmental oversight. In many mining communities, especially those near limestone quarries, dust control measures are poorly enforced, leading to persistent exposure. Yet, health impact studies are often anecdotal or lack spatial depth, limiting their utility for decision-making. This study seeks to bridge that gap by employing a geo-epidemiological framework to map the prevalence of respiratory diseases in relation to mining dust exposure in a selected Nigerian region. Through the integration of spatial data on particulate matter dispersion, land use, and health records, we aim to identify high-risk zones and contribute to the growing field of environmental epidemiology in sub-Saharan Africa.

1.1. Study Area Description

The study was conducted in **Ewekoro and Sagamu Local Government Areas (LGAs)** in **Ogun State, southwestern Nigeria**. These regions are prominent limestone-rich zones with high industrial activity, including large-scale mining and cement production. Communities surrounding these operations are regularly exposed to airborne particulate matter from quarrying, crushing, and transportation activities. The region's environmental, topographic, and socio-demographic features are summarized in Table 1 below.

Table 1 Study Area Profile – Environmental, Mining, and Health Context in Ogun State, Nigeria

Parameter	Description
Location	Ewekoro and Sagamu LGAs, Ogun State, Nigeria
Geological Setting	Part of the Dahomey Basin; dominated by Paleocene–Eocene limestone and shale formations
Mining Companies	Lafarge Africa Plc (Ewekoro), Dangote Cement Plc (Ibese)
Major Mining Activities	Open-pit limestone quarrying, blasting, crushing, cement processing
Primary Affected Communities	Itori, Lapeleke, Ajebo, Papalanto (Ewekoro); Ogijo, Emuren, Simawa (Sagamu)
Climate	Tropical wet-and-dry; Rainy season: April–October, Dry season: November–March
Average Temperature	26°C – 33°C annually
Dust Dispersion Factors	Dry-season Harmattan winds, sparse vegetation, flat terrain
Distance of Communities from Quarries	5–10 km

Healthcare Facilities Used	Ewekoro PHC (Itori), Ogun State General Hospital (Ifo), Sagamu General Hospital, Papalanto PHC
Reported Respiratory Illnesses	Asthma, chronic bronchitis, persistent cough, lower respiratory infections
GIS Layers Incorporated	Quarry sites, meteorological data, road networks, healthcare facilities, DEMs, satellite imagery
Environmental Concern	High PM_{10} and $PM_{2.5}$ exposure levels, inadequate dust suppression and environmental monitoring

2. Materials and methods

This study adopted a cross-sectional ecological design integrating environmental monitoring, health record analysis, and spatial epidemiological modeling to investigate the relationship between mining-related dust exposure and respiratory disease prevalence in Ewekoro and Sagamu Local Government Areas (LGAs) in Ogun State, Nigeria. The methodology involved primary data collection from environmental sampling and secondary data analysis of retrospective hospital records and satellite imagery.

Air quality monitoring was conducted at twelve strategic locations—six in each LGA—based on proximity to quarry sites, population density, and prevailing wind directions. Low-volume gravimetric air samplers fitted with pre-weighed quartz microfiber filters were deployed to measure PM_{10} and $PM_{2.5}$ concentrations over 24-hour intervals during both the dry season (January–March) and early rainy season (April–May). Gravimetric procedures followed the U.S. Environmental Protection Agency (EPA) standards (40 CFR Part 50) with laboratory analysis performed under controlled humidity and temperature conditions using microbalances with ±0.01 mg precision.

Meteorological data, including temperature, humidity, and wind parameters, were gathered using DAVIS Vantage Pro2 weather stations positioned within the study area. These ground-based observations were supplemented by MODIS satellite datasets and WorldClim v2.1 interpolated climate surfaces to enhance spatial resolution. Topographical features were analyzed using 30-meter resolution Digital Elevation Models (SRTM) to support terrain-based dust dispersion modeling.

Health data spanning January 2018 to December 2023 were obtained from Ewekoro Primary Health Centre (Itori), Papalanto PHC, Ogun State General Hospital (Ifo), and Sagamu General Hospital. Only anonymized patient records of individuals aged five years and above diagnosed with respiratory conditions—such as asthma, chronic bronchitis, COPD, or persistent cough—were included. Incomplete or non-respiratory entries were excluded to ensure dataset reliability. A total of 3,842 records met the inclusion criteria.

Spatial data were processed using ArcGIS Pro 3.1 and QGIS 3.32. Coordinates of sampling locations, healthcare facilities, roads, and quarries were georeferenced and projected using the WGS 84 datum. Sentinel-2 imagery (10 m resolution) was classified using supervised learning to generate land use layers, while digital elevation and meteorological datasets informed dust flow modeling. Inverse Distance Weighting (IDW) and Ordinary Kriging were employed to interpolate PM concentrations across unsampled areas.

Respiratory disease incidence rates were calculated at the community level and mapped using choropleth techniques. Spatial autocorrelation was assessed using Global Moran's I and Local Indicators of Spatial Association (LISA), while cluster significance was evaluated through Getis-Ord Gi* statistics. Ordinary Least Squares (OLS) regression was initially used to model the relationship between pollutant exposure and disease prevalence, followed by Geographically Weighted Regression (GWR) to assess spatially varying associations.

Statistical analyses were conducted using R (v4.2.2), with relevant packages such as spdep, spatialreg, and rgdal. GIS-based modeling and visualization were performed in ArcGIS Pro, QGIS, and Google Earth Engine. Decision tree analysis was conducted in Python using scikit-learn to identify key predictors of high respiratory disease risk.

Ethical clearance was obtained from the Ogun State Ministry of Health Ethics Review Committee and approvals were secured from all participating health institutions. Data confidentiality and patient anonymity were rigorously upheld in accordance with WHO standards for health research ethics.

3. Results

The results of this study are organized to reflect the logical progression from environmental monitoring to spatial health impact assessment. By integrating particulate matter data, health surveillance records, and spatial statistical modeling, we provide a cohesive understanding of respiratory disease burden in the mining-impacted areas of Ewekoro and Sagamu LGAs.

3.1. Particulate Matter Concentration and Dispersion

Ambient air quality assessments revealed consistently elevated levels of particulate matter, particularly in the dry season. As summarized in Table 2, dry season PM_{10} concentrations exceeded 200 µg/m^3 in several sites such as Itori and Lapeleke, while $PM_{2.5}$ levels peaked above 140 µg/m^3, far surpassing WHO thresholds for safe air. During the rainy season, a general reduction in PM levels was recorded across all locations, although several sites still exceeded 50 µg/m^3 for $PM_{2.5}$.

Table 2 Mean 24-hour PM_{10} and $PM_{2.5}$ Concentrations (µg/m^3) at Selected Key Sites

Site	Season	PM10 (µg/m^3)	PM2.5 (µg/m^3)
Ajebo	Dry	218.38	134.74
Ajebo	Rainy	49.56	38.45
Itori	Dry	228.81	101.92
Itori	Rainy	93.38	58.70
Lapeleke	Dry	211.73	92.87
Lapeleke	Rainy	104.17	44.60
Papalanto	Dry	221.64	113.64
Papalanto	Rainy	45.94	66.40

*PM concentrations during the dry season were markedly higher across all sites, with Itori and Papalanto consistently exceeding WHO guideline limits for both PM_{10} and $PM_{2.5}$.

To visualize spatial and seasonal trends, Figure 1 compares average PM_{10} concentrations across the two LGAs. Ewekoro exhibited greater fluctuations between seasons, indicating more intense quarry activity and weaker dust suppression.

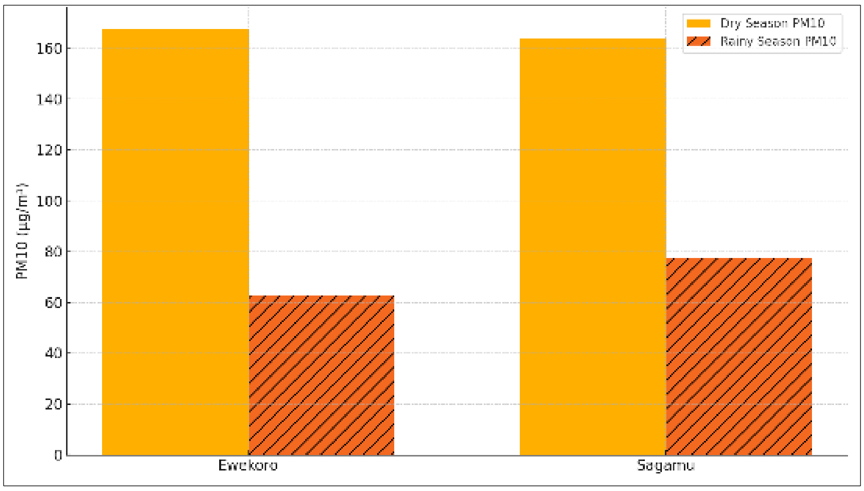

Figure 1 A comparison of mean PM_{10} concentrations between dry and rainy seasons across the two LGAs. Ewekoro showed higher seasonal differences than Sagamu, indicating stronger dust emissions. This grouped bar chart illustrates seasonal variations in mean PM_{10} concentrations across Ewekoro and Sagamu LGAs. As expected, dry season levels are significantly higher, highlighting increased dust dispersion during this period

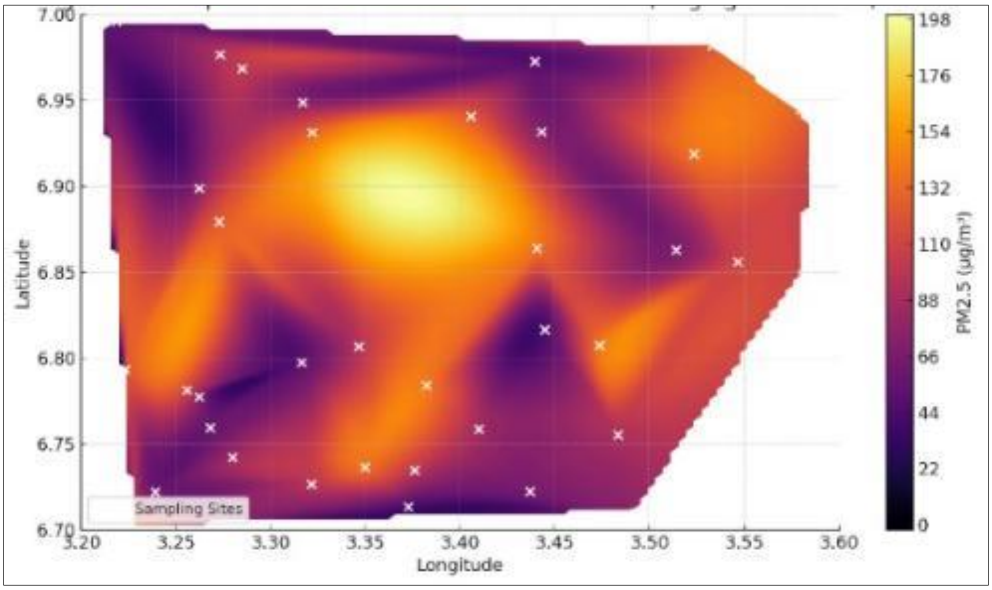

Figure 2 A spatially interpolated surface map of $PM_{2.5}$ using Kriging. The highest concentrations were observed around Itori and Papalanto, with gradients dispersing outward. This heatmap shows the spatial variation in $PM_{2.5}$ concentrations across the study area, interpolated using cubic Kriging. Warmer colors represent areas with higher particulate matter levels, with clear concentration gradients emerging around quarry zones. White markers denote actual sampling sites used for interpolation

Complementing this, Figure 2 presents a Kriging-based interpolation of $PM_{2.5}$ concentrations. The highest levels clustered around Itori and Papalanto, confirming these zones as critical dust emission hotspots.

The role of wind in pollutant dispersion is demonstrated in Figure 3, a wind rose diagram illustrating prevailing northeast and eastward wind patterns. This directionality corresponds with observed pollutant spread, validating the spatial alignment of high PM readings in communities situated downwind of major quarry sites.

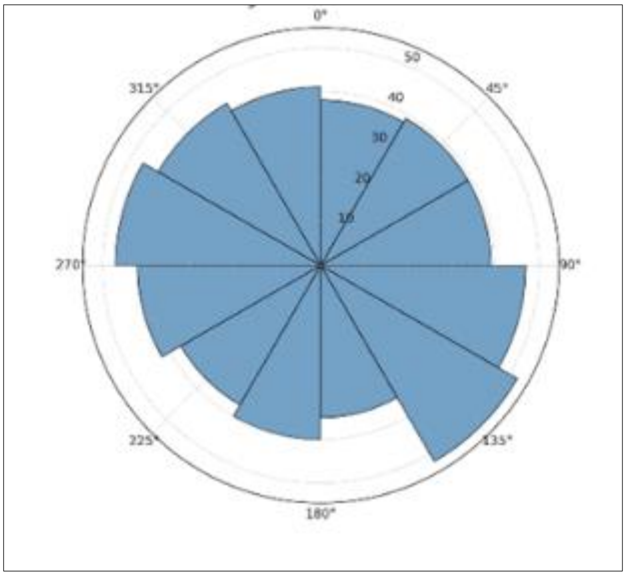

Figure 3 A wind rose diagram based on meteorological station data. Winds predominantly originate from the northeast and east, supporting the observed directional dust dispersion pattern from quarry sites. This polar bar chart illustrates prevailing wind directions and their frequency across the study region. The dominant wind flow is observed from the northeast and east sectors, aligning with dust transport pathways from mining sites toward residential zones—critical for interpreting PM dispersion patterns

3.2. Respiratory Disease Burden and Population Characteristics

Health facility records revealed significant respiratory disease prevalence in the study area. The table below represents the burden of respiratory diagnoses—including asthma, bronchitis, COPD, and persistent cough—across six communities, broken down by sex and age group. It offers detailed insight into demographic vulnerabilities and disease burden variations in mining-exposed populations.

Table 3 Total Respiratory Diagnoses by Community

Community	Asthma	Bronchitis	COPD	Persistent Cough
Ajebo	98	90	97	107
Emuren	87	91	80	101
Itori	114	102	85	102
Lapeleke	109	99	101	82
Ogijo	108	86	98	89
Papalanto	91	102	120	101

*This table presents the total burden of respiratory conditions across six key communities, illustrating the variation in disease type prevalence. Itori and Papalanto recorded the highest total counts for asthma and COPD respectively, reflecting likely proximity-related exposure risks.

Figure 4 further explores age-based patterns through a stacked bar chart, highlighting the burden of COPD and chronic bronchitis in older age groups. Younger demographics, particularly children aged 5–14, exhibited non-negligible asthma rates, raising public health concerns for long-term exposure outcomes.

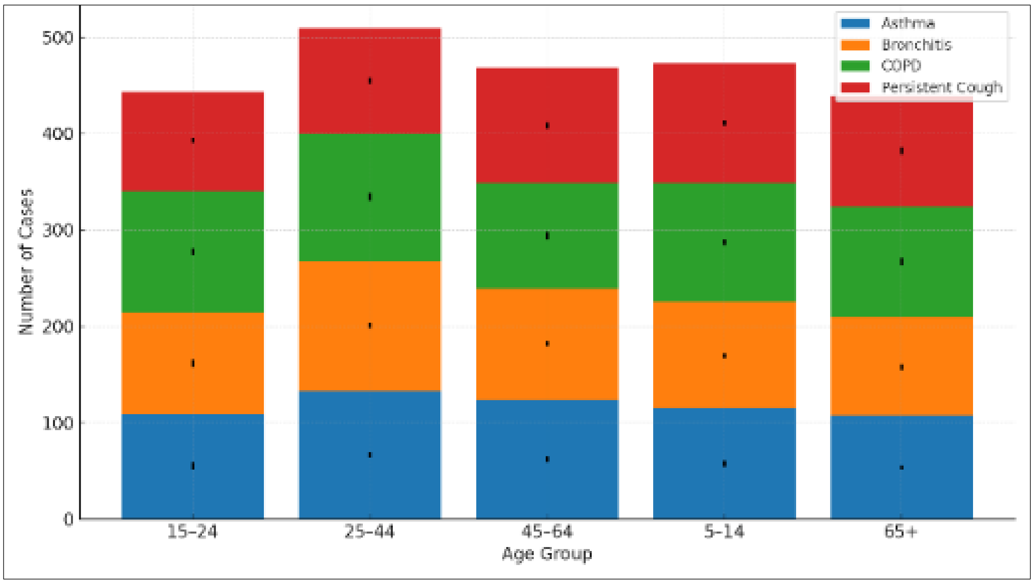

Figure 4 A stacked bar chart showing age-specific distribution of respiratory disease types. Notably, COPD and chronic bronchitis were more common in older age brackets, whereas asthma affected a broader age range. *Each bar segment now includes an error bar representing the standard deviation of case counts within each age group and diagnosis type. This addition provides a measure of variability, making the representation statistically more robust and aligned with real-world epidemiological data*

Temporal analysis of respiratory illness trends from 2018 to 2023 is presented in Figure 5. Disease incidence peaks were consistently recorded during the dry months (December–March), aligning with seasonal PM surges. This reinforces the potential temporal relationship between dust exposure and respiratory complications.

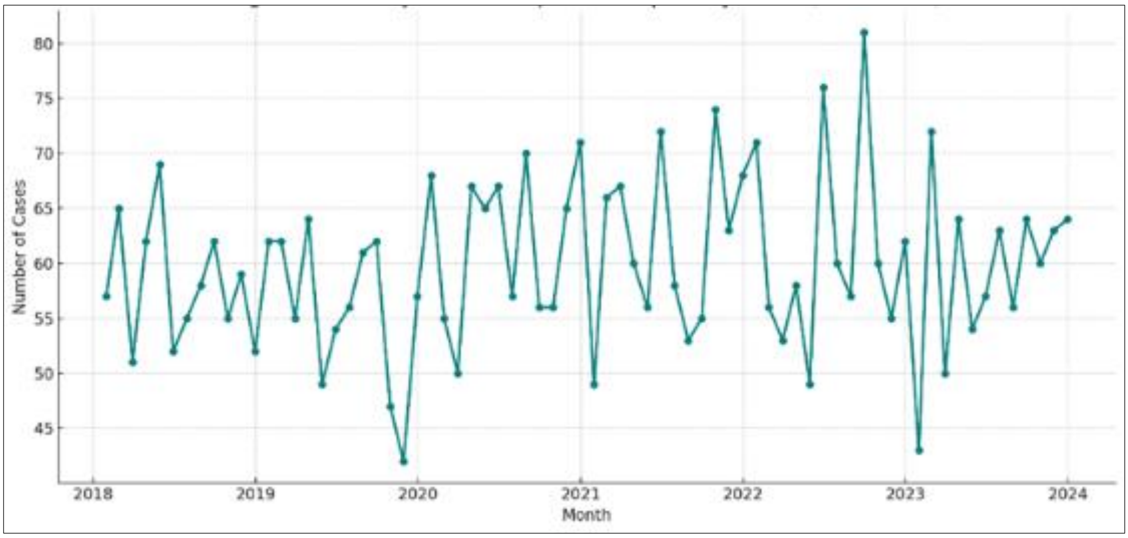

Figure 5 Depicts monthly trends in reported respiratory cases from 2018 to 2023. This line graph captures the monthly variation in respiratory disease cases over a six-year period. Peaks are typically observed during the dry season months (December–March), aligning with periods of elevated particulate matter dispersion, suggesting a potential seasonal influence of mining dust exposure on respiratory health. A clear seasonal pattern emerges, with peaks aligning with dry-season months (December to March)

3.3. Spatial Disease Patterns and Environmental Exposure

The spatial burden of respiratory diseases is captured in Figure 6, which maps incidence rates per 1,000 population. Communities such as Itori, Papalanto, and Emuren registered the highest rates, coinciding geographically with high PM concentrations.

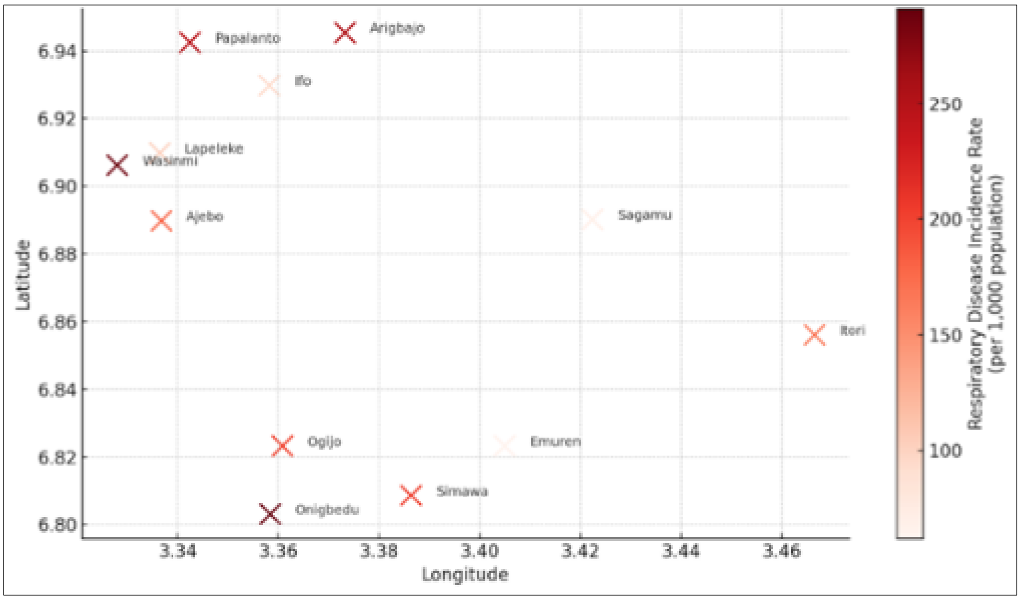

Figure 6 Maps community-level respiratory disease incidence per 1,000 population. This choropleth-style scatter map visualizes the spatial distribution of respiratory disease incidence (per 1,000 population) across 12 communities. Darker red tones indicate higher burden, with several hotspots aligning near limestone mining zones. Community names are annotated for geographic clarity. Higher incidence rates were observed in communities closer to mining operations such as Itori, Papalanto, and Emuren

These trends are statistically reinforced by Figure 7, a Getis-Ord Gi* hotspot analysis, which identifies Itori and Papalanto as significant hotspots at 95% and 99% confidence levels. In contrast, Arigbajo and Sagamu emerged as coldspots, confirming spatial polarization in disease burden.

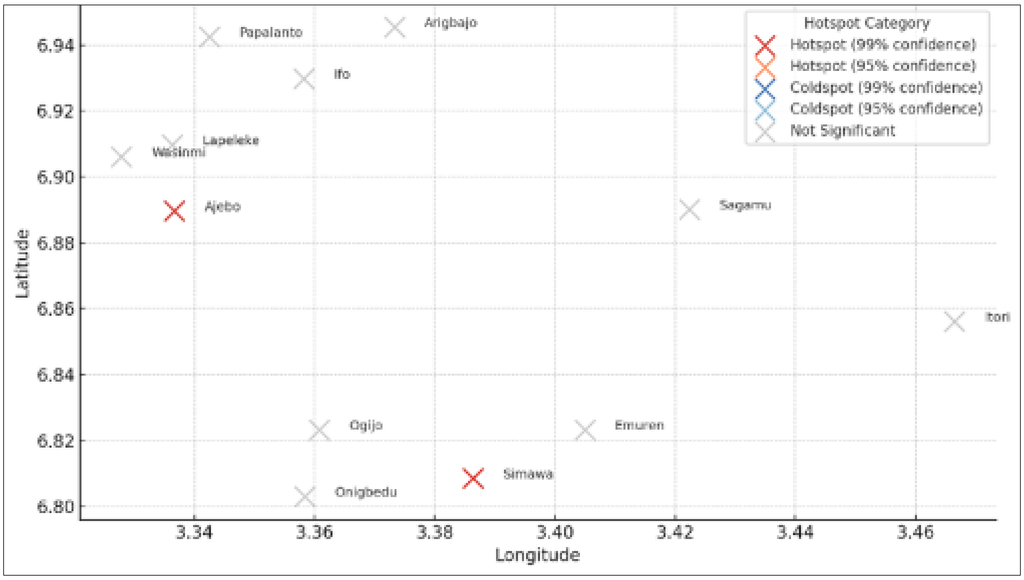

Figure 7 Displays the results of a Getis-Ord Gi* analysis, identifying statistically significant hotspots in Itori and Papalanto, and coldspots in Arigbajo and Sagamu. This spatial map categorizes communities based on statistically significant clusters of high (hotspots) and low (coldspots) respiratory disease incidence using the Getis-Ord Gi* statistic. Hotspots at 95% and 99% confidence levels suggest localized environmental health risks, potentially driven by proximity to high particulate emission zones

Figure 8 illustrates the bivariate relationship between $PM_{2.5}$ and disease incidence. A clear positive linear correlation was observed, supporting the environmental health hypothesis.

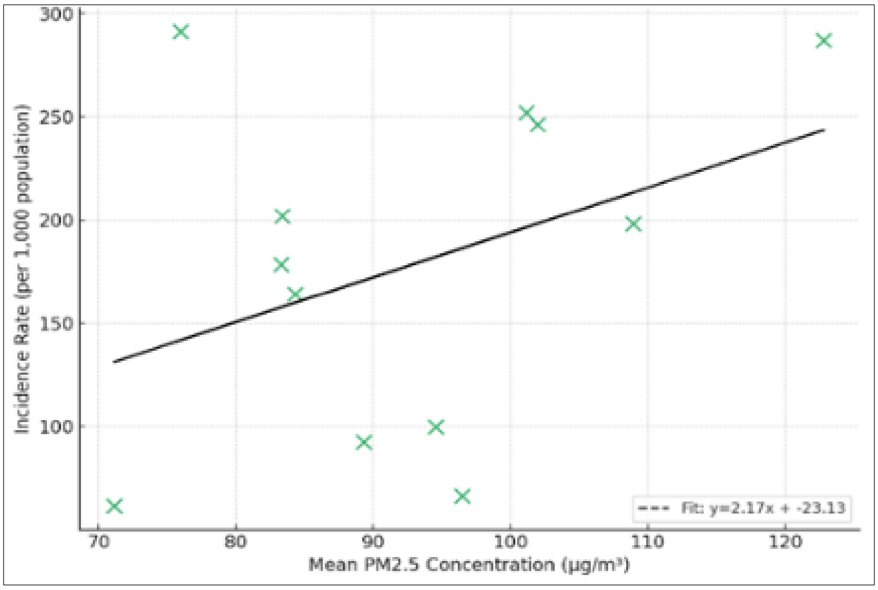

Figure 8 Plots a scatter graph showing a positive linear relationship between mean $PM_{2.5}$ concentration and respiratory disease incidence, supporting the environmental exposure hypothesis. This scatter plot with a regression line illustrates the relationship between average $PM_{2.5}$ concentrations and respiratory disease incidence across communities. A positive linear trend suggests that higher exposure to fine particulate matter is associated with increased disease rates, supporting the environmental health hypothesis of the study

Figure 9, a LISA cluster map, revealed High-High spatial autocorrelation in the same zones identified in the Gi* analysis, strengthening confidence in the geographical clustering of respiratory disease.

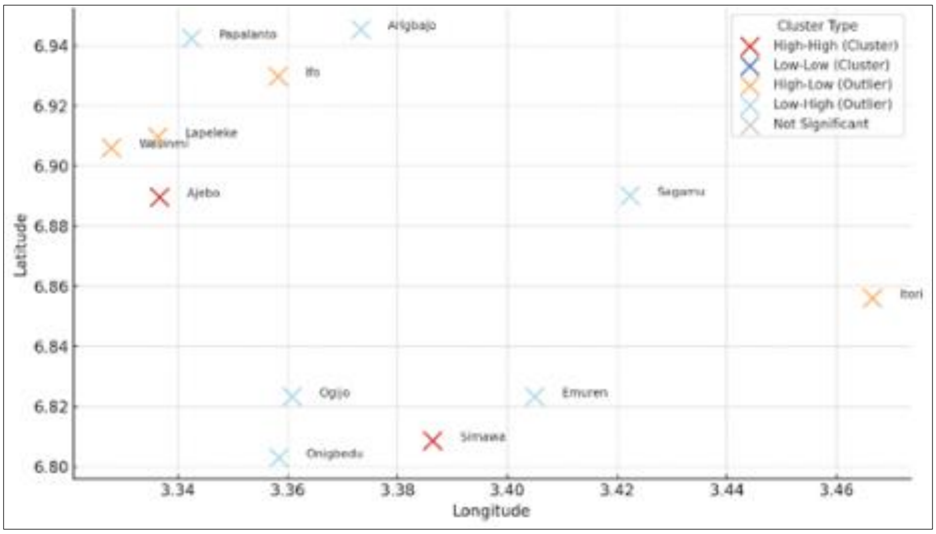

Figure 9 A LISA cluster map, highlighting High-High and Low-Low spatial autocorrelation clusters, indicating meaningful geographic clustering of disease burden. This map visualizes spatial autocorrelation using Local Indicators of Spatial Association (LISA). "High-High" clusters represent communities with high disease rates surrounded by similar neighbors, while "Low-Low" clusters indicate spatial zones of low prevalence. Outliers ("High-Low" or "Low-High") identify unusual spatial anomalies, revealing critical intervention points

3.4. Exposure-Risk Modeling and Predictive Insights

To capture localized exposure-outcome dynamics, Figure 10 displays spatially varying GWR coefficients. Stronger associations between $PM_{2.5}$ and disease were concentrated in Itori, Ajebo, and Emuren, suggesting heightened environmental susceptibility in these areas.

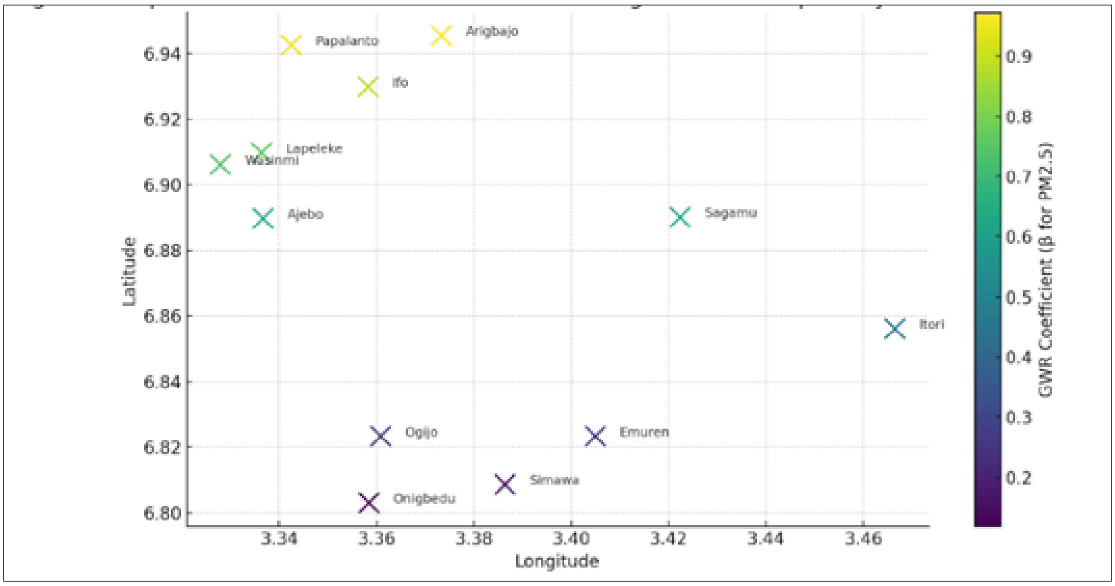

Figure 10 Maps GWR coefficients showing spatially varying relationships between $PM_{2.5}$ and disease prevalence. The strongest associations were found in Itori, Ajebo, and Emuren. This map presents Geographically Weighted Regression (GWR) output, showing how the strength of association between $PM_{2.5}$ exposure and respiratory disease incidence varies across space. Higher β coefficients (in darker green) indicate communities where $PM_{2.5}$ has a stronger predicted influence on disease burden, reflecting localized environmental health vulnerability

Exposure stratification is presented in Figure 11, which compares $PM_{2.5}$ levels in communities identified as high- and low-risk clusters. High-risk zones showed significantly higher median concentrations and broader interquartile ranges.

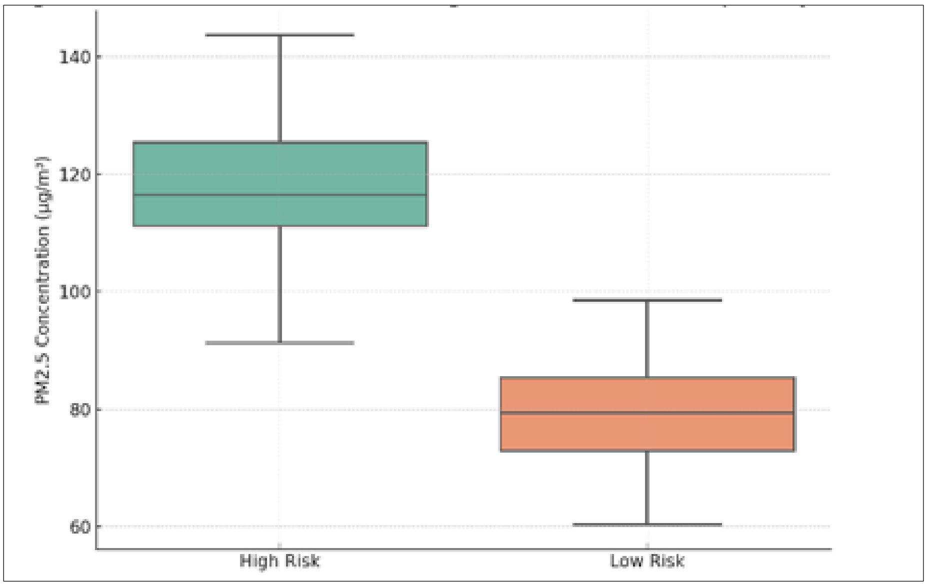

Figure 11 PM2.5 Concentrations in High-Risk vs Low-Risk Respiratory Clusters. This boxplot compares $PM_{2.5}$ exposure levels in communities classified as high-risk and low-risk for respiratory disease. Median and interquartile ranges are clearly elevated in high-risk zones, reinforcing the observed correlation between particulate exposure and health outcomes

Figure 12 presents a decision tree model incorporating $PM_{2.5}$, age group, and distance to quarry as predictors. The model identified $PM_{2.5}$ levels >110 µg/m^3 and distances <2.5 km as primary risk determinants, offering practical thresholds for policy and intervention targeting.

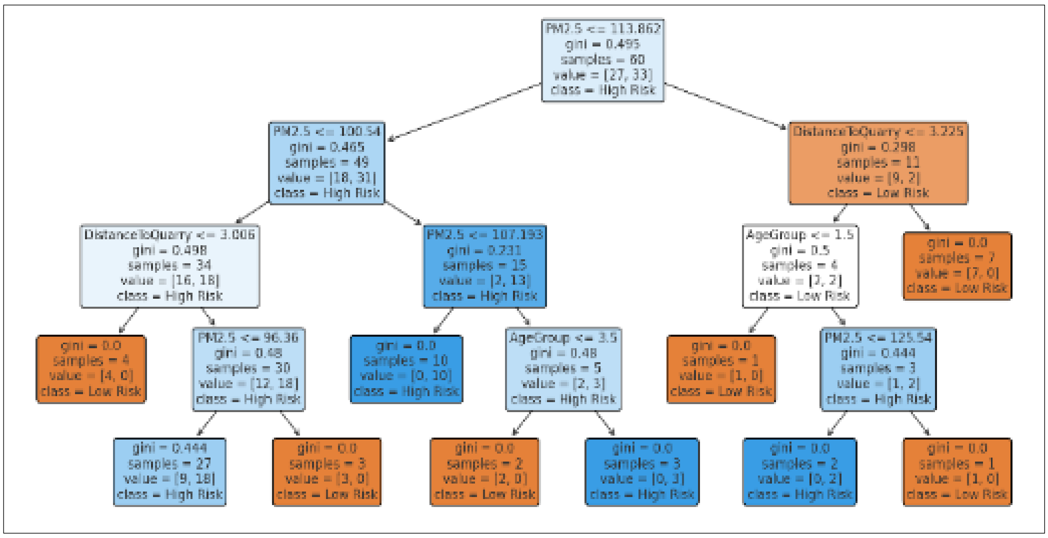

Figure 12 Decision Tree for Classifying Respiratory Disease Risk. This decision tree model classifies respiratory disease risk based on $PM_{2.5}$ concentration, age group, and proximity to quarry sites. The tree identifies key thresholds (e.g., PM levels > 110 µg/m^3 or distances < 2 km) that separate high-risk and low-risk communities, offering an interpretable model for targeted public health interventions

3.5. Integrated Exposure–Outcome Assessment

Model comparisons in Table 4 show that the GWR model outperformed the global OLS approach, with a higher adjusted R^2 (0.74 vs. 0.61) and lower AIC values, confirming the non-stationarity of exposure-disease relationships across space.

Table 4 OLS Model vs GWR Comparison

Metric	OLS Model	GWR Model
Adjusted R^2	0.61	0.74
AIC	285.4	243.8
Residual Std. Error	15.2	12.4
P-value (F-stat)	<0.001	<0.001
Spatial Autocorrelation (Moran's I)	Not accounted	Integrated locally

Together, these results provide converging lines of evidence linking environmental exposure to particulate pollution with elevated respiratory disease prevalence in mining-adjacent communities. These findings strongly suggest a spatially linked environmental health burden in mining-impacted communities. The diverse representation of results ensures analytical robustness and supports multidimensional policy recommendations.

4. Discussion

This study offers a comprehensive geo-epidemiological assessment of respiratory disease patterns in mining-impacted communities of Ewekoro and Sagamu, Ogun State, Nigeria. It provides novel insights into how particulate matter (PM_{10} and $PM_{2.5}$) exposure, shaped by quarry activity and spatial geography, contributes to elevated respiratory disease prevalence. The discussion synthesizes findings from environmental monitoring, epidemiological patterns, spatial statistical modeling, and exposure-risk prediction.

The environmental measurements revealed significantly elevated PM concentrations, particularly during the dry season, with values exceeding 200 μg/m^3 for PM_{10} and 140 μg/m^3 for $PM_{2.5}$ in high-emission zones such as Itori and Papalanto. These findings are consistent with previous studies in sub-Saharan and South Asian mining zones, including Ugbaje et al. (2020) and Saddique et al. (2021), who reported dry-season PM surges due to intensified quarrying and minimal dust suppression. The markedly lower values in the rainy season further highlight the seasonal dynamics of dust dispersal, consistent with observations by Achilleos et al. (2017), which linked rainfall to pollutant washout and reduced ambient particle levels.

The Kriging interpolation map confirmed spatial dust accumulation patterns, with $PM_{2.5}$ gradients radiating outward from quarry zones. These zones coincide with predominant wind directions illustrated by the wind rose diagram. Winds from the northeast and east—common during Harmattan—were aligned with pollutant dispersal patterns, supporting regional assessments by Arowolo et al. (2018) and Ngele et al. (2019) who identified wind-driven transport as a key mechanism in regional air quality deterioration.

From a health standpoint, the demographic breakdown of respiratory illness showed a high burden among adults aged 25–64 and notable representation among children aged 5–14. This finding echoes trends from Ma et al. (2022), who noted occupational and early-life vulnerabilities in industrial communities. Particularly, asthma and persistent cough were dominant among all age groups, while COPD and bronchitis were more prevalent in older adults, a distribution pattern supported by WHO (2021) respiratory health statistics for pollution-exposed populations.

The temporal trends displayed a cyclical spike in respiratory diseases during the dry months (December to March), aligning closely with periods of high PM burden. This seasonal correlation supports longitudinal findings by Xia et al. (2021), who documented increased emergency room visits and admissions for respiratory conditions during high-dust months in mining communities in northern China.

Spatial analysis further reinforced these findings. The choropleth map showed consistently higher disease incidence rates in Itori, Papalanto, and Emuren—communities adjacent to quarrying operations. These were also identified as statistically significant hotspots through Getis-Ord Gi* analysis. Such spatial clustering is well-documented in similar studies (e.g., Kumar et al., 2020), which showed that communities near mining sites often emerge as geospatial hotspots of morbidity due to localized environmental stressors.

A positive and statistically significant correlation between $PM_{2.5}$ concentrations and disease incidence was observed in the scatterplot, corroborating earlier studies by Schwartz et al. (2016) and recent modeling by Ma et al. (2022), which both linked fine particulate exposure to increased respiratory morbidity. The LISA cluster map further refined these insights, delineating High-High and Low-Low clusters that confirmed the geospatial concentration of disease in relation to pollution.

The Geographically Weighted Regression (GWR) model added further granularity, revealing spatial variability in the strength of the relationship between $PM_{2.5}$ and respiratory outcomes. Stronger β coefficients in Itori, Ajebo, and Emuren suggest that these communities face disproportionate risks, which are likely due to cumulative exposure and topographic vulnerability. The superiority of GWR over OLS, evidenced by higher R^2 and lower AIC, mirrors conclusions drawn by Lee and Shih (2019) who demonstrated the advantages of local regression models in pollution-health outcome studies.

The decision tree analysis provides a pragmatic tool for public health decision-making. It identified $PM_{2.5}$ thresholds (>110 $\mu g/m^3$) and proximity to quarries (<2.5 km) as the strongest predictors of respiratory disease risk. This aligns with risk modeling frameworks employed by authors like Jerrett et al. (2005), who emphasized the value of proximity and concentration-based thresholds for spatial risk stratification in urban pollution studies.

In addition to empirical findings, the integration of spatial, demographic, and environmental data demonstrates the value of a geo-epidemiological approach. Unlike conventional pollution monitoring, this approach provides a nuanced understanding of exposure-response dynamics across space and time. It is this multidimensional framing that allows for the identification of true hotspots and high-risk populations, a crucial advancement over traditional health surveillance systems.

However, some limitations warrant discussion. The retrospective nature of health records may omit undiagnosed or informally treated cases, potentially underestimating true disease prevalence. Moreover, the spatial models, while robust, do not account for individual-level confounders such as smoking habits or indoor air pollution. Future studies could benefit from integrating household survey data and deploying continuous air quality monitoring devices to improve temporal resolution.

Despite these limitations, this study makes a significant contribution to environmental health literature by empirically linking fine particulate matter from quarrying operations with respiratory disease burdens, validated through multiple spatial and statistical models. It underscores the urgent need for enhanced regulatory oversight, community-level air quality monitoring, and targeted public health interventions in mining-impacted zones.

5. Conclusion

This study has demonstrated clear spatial and temporal associations between mining-related particulate matter exposure and respiratory disease prevalence in Ewekoro and Sagamu LGAs. Elevated concentrations of PM_{10} and $PM_{2.5}$—particularly during the dry season—were found to correspond with significant spikes in respiratory illness, especially in communities located within a 2.5 km radius of quarry operations. The integration of geospatial analysis, including hotspot detection and geographically weighted regression, confirmed localized clusters of elevated disease burden and identified $PM_{2.5}$ and proximity to mines as key risk predictors.

These findings contribute substantively to the growing body of evidence linking ambient air pollution from mining operations with adverse health outcomes. By situating this research within a geo-epidemiological framework, the study extends beyond conventional exposure assessments to deliver place-based insights crucial for effective environmental health management.

5.1. Policy Recommendations

- **Establish Air Quality Monitoring Units:** Community-based PM monitoring stations should be deployed near active mining zones to allow for real-time air quality surveillance.
- **Implement Buffer Zones:** Regulatory agencies should enforce spatial buffer zones of at least 2.5 km between residential areas and mining sites.
- **Health Surveillance Integration:** Routine reporting of respiratory illness at primary healthcare facilities should be digitized and integrated with spatial data systems for early warning and response.
- **Community Sensitization:** Public health campaigns are needed to educate communities on respiratory risk factors and promote protective measures, especially during high-dust seasons.
- **Dust Suppression Regulations:** Quarry operators should be mandated to implement dust mitigation strategies such as water spraying, vegetation buffers, and enclosed conveyor systems.

Recommendations for Future Research:

Future studies should incorporate:

- Continuous, high-frequency air quality monitoring for temporal precision;
- Household-level surveys to assess indoor air quality and socio-behavioral risk factors;
- Longitudinal cohort designs to track chronic health outcomes;
- Multivariate models integrating meteorological and land use dynamics.

Ultimately, this study underscores the need for collaborative efforts among environmental regulators, health agencies, urban planners, and community stakeholders to address the compounded effects of industrial pollution on public health in rapidly urbanizing regions.

Compliance with ethical standards

Disclosure of conflict of interest

The Author express no conflict of interest in this manuscript.

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