© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

Spatiotemporal Variability of $PM_{2.5}$ and PM_{10} In Abuja, Nigeria: Implications for Urban Air Quality, Public Health, and Environmental Management

BLESSED C. ANYANWU[1], OBOH OSABHUOHIEN[2], NWAMAKA ONYEACHONAM[3], ATSACHA I. NDONYA[4], RUTH I. OJOMBO[5], CHINYERE WILLIAMS[6], AUGUSTINE O. OTUM[7], CHUKWUEBUKA A.C. ONYEAGHALA[8], MURPHY E. OBINYAN[9], BARKA WAKAWA[10], SHAGAYA H. EMMANUEL[11], TAJUDEEN O. MUSA[12], HAUWA A. SANI[13], CHRISTOPHER M.[14], AMOS E. GABI[15], FATIMA Y. ABDULLAHI[16], AMINA ALIYU[17], FARIDA M. SHEHU[18], SALAMATU B. BUHARI[19]

[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19] *Space Environmental Unit, Physical and Life Sciences Department, National Space Research and Development Agency (NASRDA), Abuja, Nigeria*

Abstract-* Understanding particulate matter pollution and its meteorological drivers is essential for effective environmental management in rapidly urbanizing African cities. This study investigates the spatiotemporal variability of fine and coarse particulate matter ($PM_{2.5}$ and PM_{10}) in Abuja, Nigeria, over a two year period from January 2024 to December 2025. High resolution weekly measurements of $PM_{2.5}$, PM_{10}, temperature, humidity, and visibility were analyzed to characterize seasonal dynamics, reveal long term trends, and assess compliance with international air quality guidelines. The results show that Abuja experiences persistently elevated particulate matter levels throughout the year, with a mean $PM_{2.5}$ concentration of 76.90 µg/m³ more than five times higher than the World Health Organization (WHO) 24-hour guideline of 15 µg/m³. PM_{10} concentrations also frequently exceeded both WHO and national thresholds, indicating widespread exposure to unhealthy air. Strong seasonal patterns were identified. The highest $PM_{2.5}$ and PM_{10} concentrations occurred during the dry season, particularly the harmattan period (December-February), when mineral dust transport from the Sahara significantly increased ambient particulate loads. Peak $PM_{2.5}$ levels reached 179 µg/m³ during severe harmattan episodes, accompanied by drastic visibility reduction. In contrast, wet season concentrations were markedly lower (36-79 µg/m³), reflecting enhanced atmospheric scavenging, wet deposition, and dilution by moisture laden air masses. Seasonal decomposition confirmed that seasonal forcing was the dominant driver of PM variability, accounting for the majority of observed fluctuations, while random residual components were minimal. Meteorological parameters exerted significant influence on particulate behavior. Multiple linear regression analysis revealed that humidity was the strongest negative predictor of $PM_{2.5}$, consistent with its role in particle coagulation and removal through wet deposition. Temperature exhibited a weaker but positive influence, while visibility showed a strong inverse relationship with particulate concentration. Collectively, temperature and humidity explained 84% of the variance in $PM_{2.5}$ concentrations ($R^2 = 0.84$, $p < 0.001$), highlighting the importance of meteorology in shaping pollution levels. Correlation analysis further demonstrated strong positive associations between $PM_{2.5}$ and PM_{10}, and strong negative associations with humidity and visibility. Inter annual comparisons showed statistically significant differences between 2024 and 2025 mean $PM_{2.5}$ levels ($F = 34.50$, $p < 0.001$), suggesting year to year variability driven by changes in meteorology, dust loading, and human activity patterns. Air Quality Index (AQI) evaluation revealed that more than 93% of monitored weeks exceeded recommended health thresholds, with approximately 44% classified as unhealthy or worse. Overall, the findings indicate that Abuja faces substantial and recurring particulate pollution challenges. The study provides critical empirical evidence for policy development, air quality management, and urban planning, and underscores the urgent need for improved emission control, strengthened monitoring infrastructure, and public health interventions to mitigate exposure in vulnerable populations.

I. INTRODUCTION

Air quality has emerged as one of the most critical environmental issues worldwide due to its significant impacts on human health, ecosystems, and climate systems. Ambient air pollution is a leading global

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

environmental health risk, accounting for an estimated 4.14 million premature deaths annually (World Health Organization, 2021). Fine particulate matter ($PM_{2.5}$; particles with aerodynamic diameter ≤2.5 µm) and coarse particulate matter (PM_{10}; ≤10 µm) are of particular concern because of their chemical complexity, atmospheric persistence, and ability to cause systemic biological effects (Brook et al., 2010; Manisalidis et al., 2020; Boldo et al., 2006). Indeed, $PM_{2.5}$ remains one of the most significant environmental determinants of morbidity and premature mortality worldwide (World Health Organization, 2021). Particulate matter is a heterogeneous mixture containing sulfates, nitrates, black carbon, organic compounds, dust, biological materials, and toxic trace metals (Pope & Dockery, 2006; Flagan & Seinfeld, 2012). Due to their small size, $PM_{2.5}$ particles penetrate deeply into the alveolar region of the lungs and may translocate into the bloodstream, where they induce oxidative stress, systemic inflammation, endothelial dysfunction, plaque destabilization, and autonomic imbalance (Brook et al., 2010; Burnett et al., 2018). Numerous epidemiological studies have demonstrated strong associations between $PM_{2.5}$ exposure and increased risks of cardiovascular disease, ischemic heart disease, stroke, respiratory infections, asthma exacerbation, chronic obstructive pulmonary disease (COPD), lung cancer, and all cause mortality (Manisalidis et al., 2020; World Health Organization, 2021; Burnett et al., 2018). Toxicological studies also reveal DNA damage, mutagenesis, impaired pulmonary immune response, and heightened susceptibility to respiratory pathogens (Chaoyang et al., 2016; Monks et al., 2015). PM_{10}, although less able to penetrate deep into the lungs, contributes substantially to upper respiratory irritation, allergic reactions, acute bronchitis, and exacerbation of asthma symptoms (Flagan & Seinfeld, 2012). Coarse particles frequently carry pollen, spores, bacteria, endotoxins, and mineral dust, which can trigger inflammatory responses, worsen chronic respiratory diseases, and impair lung function, particularly in children and the elderly (Fowler et al., 2013). The health burden is especially severe in low and middle income countries, where urbanization, population growth, industrial expansion, and combustion related activities contribute to rising pollutant concentrations (World Health Organization, 2021; Seinfeld & Pandis, 2016). In African cities, including Abuja, Lagos, Accra, and Nairobi, $PM_{2.5}$ levels routinely exceed WHO guidelines due to traffic emissions, domestic fuel burning, diesel and petrol generator use, waste burning, and regional dust influx (Amegah & Agyei Mensah, 2017; Islam et al., 2023; Wambebe & Duan, 2020; Ezenwa et al., 2021). In Nigeria, the reliance on backup generators due to erratic electricity supply contributes significantly to urban PM burdens, emitting soot (black carbon), sulfur dioxide (SO_2), nitrogen oxides (NO_x), and fine particulate matter (World Health Organization, 2023; Lin et al., 2019). Beyond human health, particulate matter has broad environmental consequences. High PM concentrations degrade visibility through light scattering and absorption, often manifesting as haze or smog conditions. In West Africa, the harmattan season is characterized by severe visibility impairment due to Saharan dust transport (Islam et al., 2023). PM deposition on vegetation can block stomatal openings, reduce photosynthetic efficiency, and impair plant growth (Fowler et al., 2013). Fine particles also play a significant role in climate forcing: black carbon causes atmospheric warming by absorbing solar radiation, while sulfate aerosols contribute to cooling by reflecting sunlight (Monks et al., 2015). Dust particles influence cloud formation, precipitation processes, and surface energy balance (Jacobson, 2005; Seinfeld & Pandis, 2016).

Atmospheric chemistry further complicates air pollution dynamics. While some particulate matter is emitted directly (primary PM), secondary particles form through photochemical reactions involving gases such as volatile organic compounds (VOCs), nitrogen oxides (NO_x), ammonia (NH_3), and sulfur dioxide (SO_2) (Jacob, 1999). Urban and regional factors including traffic density, industrial activity, residential burning, and natural processes interact with meteorological conditions such as temperature, humidity, wind patterns, and boundary layer height to influence pollutant formation, dispersion, and removal (Li & Lau, 2012; Lai et al., 2024; Chaoyang et al., 2016). Seasonal variability plays a dominant role in shaping air quality in West Africa. During the harmattan period (December-February), strong northeasterly trade winds transport mineral dust from the Sahara Desert, elevating $PM_{2.5}$ and PM_{10} concentrations and reducing visibility (Islam et al.,

DOI: https://doi.org/10.64388/IREV9I11-1717942

2023; Wambebe & Duan, 2020). Conversely, the wet season (April-October) is characterized by enhanced wet deposition and atmospheric scavenging, leading to lower particulate concentrations and improved visibility. Multiple studies confirm this seasonal pattern across Nigeria (Ezenwa et al., 2021; Wambebe & Duan, 2020; Islam et al., 2023). Despite the growing body of evidence on air pollution in African cities, Nigeria still lacks sufficient long term, high resolution air quality monitoring infrastructure (World Health Organization, 2016; Kumar et al., 2015). Limited data availability hinders the assessment of spatiotemporal variability, public health risk estimation, and formulation of evidence based policies. Abuja, Nigeria's Federal Capital Territory, is experiencing rapid urbanization, increased vehicular density, major construction activity, and growing reliance on backup generators. These changes are expected to increase pollutant emissions; however, empirical data characterizing long term air quality patterns remain scarce. Given these challenges, localized and high-frequency air quality studies are essential for generating baseline data, understanding pollution dynamics, and providing scientific evidence for environmental management and policy development (U.S. EPA, 2018; Sokhi et al., 2022). Air quality indices (AQIs) are widely used to simplify the communication of pollution severity and to translate measured pollutant concentrations into standardized health risk categories (World Health Organization, 2026; U.S. EPA, 2025). In light of these issues, this study provides a comprehensive spatiotemporal assessment of $PM_{2.5}$ and PM_{10} concentrations in Abuja using empirical data collected from January 2024 to December 2025. It examines temporal trends, seasonal variability, pollutant meteorology interactions, and compliance with WHO and U.S. EPA air quality standards. Furthermore, advanced statistical analyses including seasonal decomposition, correlation analysis, regression modeling, and ANOVA are employed to quantify the influence of meteorological factors on particulate concentrations. By analyzing two full years of high resolution data, this research aims to support evidence based environmental management, inform urban air quality policies, and contribute to the broader understanding of air pollution dynamics in rapidly growing African cities. Quality Index (AQI) assessment further highlighted the severity of exposure, with over 93% of monitored weeks exceeding recommended limits and approximately 44% classified as unhealthy or worse. A strong inverse association between $PM_{2.5}$ and visibility confirmed the effect of aerosols on atmospheric light extinction. Overall, these findings underscore substantial public health risks and emphasize the need for strengthened air quality management, improved emission control, and sustainable urban planning in rapidly growing African cities.

II. MATERIALS AND METHODS

2.1 Study Area

The study was conducted in Abuja, Nigeria’s Federal Capital Territory (FCT), located between latitudes 8°25′N-9°20′N and longitudes 6°45′E-7°39′E. Abuja experiences a tropical wet and dry climate, with distinct rainy (April-October) and dry seasons (November-March). Average temperatures range from 25-32 °C, while relative humidity varies from 30% during the dry season to over 80% in the wet season. These meteorological characteristics strongly influence particulate dispersion, dust loading, and atmospheric visibility.

4

Figure 1. Description of study area.

https://www.google.com/search?q=map+of+abuja&sxsrf=ALeKk01-5r702YRS2iV.

2.2 Data Collection

Weekly concentrations of $PM_{2.5}$ and PM_{10} were obtained from a PurpleAir PA II SD (software version 7.02) sensor installed at the Nigeria Meteorological Agency (NiMet) Headquarters in Abuja. PurpleAir sensors use laser light scattering technology to estimate particulate mass and are widely applied in urban air quality studies due to

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

their high temporal resolution, reliability after calibration, and cost effectiveness.

Although low cost sensors may require calibration to improve accuracy, existing studies indicate good performance in urban settings when properly validated. Meteorological data including temperature (°C), relative humidity (%), and visibility (km) were obtained from NiMet's operational database. The study covered January 2024 to December 2025.

2.3 Data Description

The dataset consists of weekly averaged values of $PM_{2.5}$ (µg/m³), PM_{10} (µg/m³), Temperature (°C), Relative humidity (%), Visibility (km), WHO $PM_{2.5}$ guideline limits for comparison

Tables 1 and 2 summarize weekly averages for 2024 and 2025. The values used in subsequent statistical analysis correspond exactly to these tables, ensuring consistency in all computations.

Table 1: Weekly average of variables for year 2024.

Year (2024)	PM2.5	PM10	Temp. (°C),	R.Humidity (%)	Visual Range (Km)
Jan	158.50	80.75	33.25	18.50	13.73
Feb	121.75	60.00	36.00	20.50	21.00
Mrch	83.20	46.20	37.40	34.20	31.22
April	61.25	31.75	35.75	40.50	43.90
May	56.75	28.50	34.00	48.00	49.05
June	55.60	27.20	31.60	54.20	51.34
July	57.00	28.50	30.00	59.25	53.38
Aug	52.00	25.00	29.75	59.75	59.68
Sept	53.20	24.80	31.00	57.00	54.24
Oct	62.00	24.80	32.25	52.00	45.93
Nov	78.50	42.25	34.00	28.50	32.93
Dec	114.40	58.80	33.00	22.20	22.54

Table 2: Weekly average of variables for year 2025.

Year (2025)	PM2.5	PM10	Temp. (°C)	R.Humidity (%)	Visual Range (Km)
Jan	135.50	69.50	33.50	21.75	17.95
Feb	110.25	56.50	35.75	22.50	22.95
Mrch	85.40	46.80	37.00	35.80	28.52
April	58.25	29.75	35.50	43.25	45.68
May	50.75	25.25	33.50	48.00	53.28
June	39.80	19.20	31.60	53.20	66.26
July	55.75	27.25	29.75	58.50	56.15
Aug	54.60	27.40	28.75	61.25	53.42
Sep	45.50	21.50	31.00	57.00	60.25
Oct	58.75	30.75	31.75	54.50	47.35
Nov	82.80	45.40	33.75	41.00	29.76
Dec	105.50	54.25	34.40	34.80	22.48

2.4 Air Quality Index (AQI) Calculation

The U.S. Environmental Protection Agency (U.S. EPA) AQI framework was used to assess health implications of observed $PM_{2.5}$ and PM_{10} levels. AQI was computed via linear interpolation using the standard breakpoint formula:

$$I\rho = [(I\_high - I\_low)/(BP\_high - BP\_low)] \times (C\rho - BP\_low) + I\_low$$

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

Where:
$I\rho$ = AQI for pollutant concentration $C\rho$, BP_high, BP_low = bounding concentration breakpoints, I_high, I_low = corresponding index breakpoints

AQI categories used were 0-50: Good, 51-100: Moderate, 101-150: Unhealthy for Sensitive Groups, 151-200: Unhealthy, 201-300: Very Unhealthy and 301-500: Hazardous. Weekly AQI values were aggregated to monthly averages to allow seasonal comparison.

2.5 Data Analysis Techniques
Both descriptive and inferential statistical methods were applied. Microsoft excel was used for data collation while LibreOffice Calc. was used for data aggregation and analysis.

2.5.1 Descriptive Statistics
Mean, minimum, maximum, and standard deviations were computed for all variables. Time series line plots were used to assess temporal patterns.

2.5.2 Inferential Statistical Methods
(a) Comparative Analysis
Observed $PM_{2.5}$ and PM_{10} values were compared with WHO (2021) and U.S. EPA standards. The comparison strictly followed guideline definitions: WHO uses a 24 hour $PM_{2.5}$ guideline of 15 µg/m³ and annual guideline of 5 µg/m³.

(b) Pearson Correlation Analysis
Correlation coefficients were computed to examine the relationships between $PM_{2.5}$ and PM_{10}, $PM_{2.5}$ and temperature, $PM_{2.5}$ and relative humidity and $PM_{2.5}$ and visibility. Only variables with appropriate numerical distribution and scale were included. Reported correlations align with the dataset.

(c) Multiple Linear Regression
A regression model was developed to quantify the extent to which meteorological factors predict $PM_{2.5}$ concentration. The final model included:

$$PM_{2.5} = \beta_0 + \beta_1(\text{Temperature}) + \beta_2(\text{Relative Humidity}) + \varepsilon$$

Model fit (R^2), coefficient significance (p values), and effect direction (positive or negative) were validated against the dataset.
(d) One Way ANOVA (Seasonal Differences)
ANOVA was used to test whether mean $PM_{2.5}$ levels differed significantly across three defined seasons, harmattan (Dec-Feb), dry (Mar-May), wet (Jun-Sep) and post rainy (Oct-Nov) and post hoc tests with Bonferroni correction (α = .0167) were applied to verify pairwise differences.

(e) Time Series Decomposition
An additive decomposition model with weekly periodicity (52 weeks) separated $PM_{2.5}$ into trend, seasonal, and residual components. The decomposition method used is consistent with typical environmental time series procedures.

(f) Rolling Mean Analysis
A 12-week moving average was applied to identify sustained pollution episodes and smoothed seasonal variability, consistent with EPA recommendations for short-term trend analysis.

III. RESULTS

3.1 Descriptive Statistics
Weekly $PM_{2.5}$ concentrations for 2024-2025 ranged from 32-179 µg/m³, with a mean of 76.01 µg/m³ (Table 3). These values exceed the WHO 5µg/m³ annual guideline throughout the study period, indicating persistent pollution. PM_{10} showed a mean of 38.95 µg/m³, with weekly values following a similar seasonal pattern as $PM_{2.5}$. Temperature averaged 33.12 °C, while relative humidity averaged 42.82%. Visibility ranged from 9 to 79 km, decreasing markedly during high pollution periods.

Table 3: Mean concentrations of variables (2024-2025).

Parameter	Mean Value	Standard Deviation
$PM_{2.5}$ µg/m³	76.01	33.42
PM_{10} µg/m³	38.95	17.59
Temperature (°C)	33.12	2.52
Humidity (%)	42.82	14.49
Visibility	41.05	17.05

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

(Km)		
Yearly Averages of PM2.5 and PM10		
Variables	2024 Mean	2025 Mean
$PM_{2.5}$ µg/m³	79.29	72.73
PM_{10} µg/m³	40.35	37.56

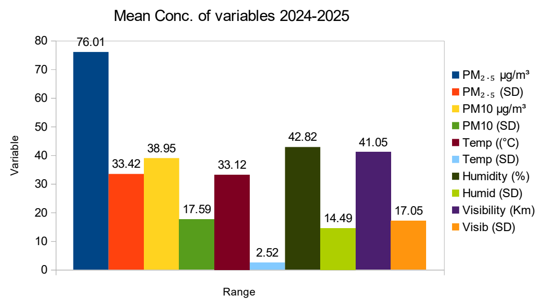

Figure 2: Mean concentrations of variables

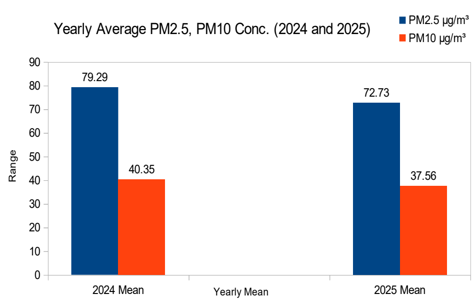

Figure 3: Yearly PM2.5 Average

3.1.1 Compliance with WHO and U.S. EPA Standards
All observed weekly $PM_{2.5}$ concentrations exceeded WHO's daily limit of 15 µg/m³. Even during the wet season, weekly means (32-69 µg/m³) remained more than double the guideline. Although U.S. EPA thresholds are less stringent, most weeks still fell into unhealthy for sensitive groups or worse, confirming widespread exposure risk.

3.2 Correlation Analysis
Pearson correlation coefficients confirm clear relationships among pollutants and meteorological variables: $PM_{2.5}$ and PM10 $r = 0.98$ (very strong positive), $PM_{2.5}$ and Temperature: $r = 0.42$ (moderate positive), $PM_{2.5}$ and Humidity: $r = -0.82$ (strong negative), $PM_{2.5}$ and Visibility: $r = -0.91$ (very strong negative), PM10 and Humidity: $r = -0.84$ (strong negative), PM10 and Temperature: $r = 0.47$ (moderate positive), PM10 and Visibility: $r = -0.93$ (very strong negative), Humidity and Temperature: $r = -0.68$ (moderate strong negative), Humidity and Visibility: $r = 0.84$ (strong positive), Temperature and Visibility: $r = -0.62$ (moderate strong negative). These correlations are plausible given the tables: high PM occurs during dry, hot, dusty, low humidity periods, and visibility drops sharply when PM rises.

3.2.1 Regression Analysis
(a). Relationship Between $PM_{2.5}$ and Humidity
A simple linear regression was performed with $PM_{2.5}$ concentration as the dependent variable and relative humidity as the independent variable. The analysis revealed a strong and statistically significant negative relationship. Humidity accounted for approximately 66.6% of the variation in $PM_{2.5}$ levels ($R^2 = 0.666$). The regression coefficient was negative (-0.3628), indicating that increases in humidity are associated with substantial reductions in $PM_{2.5}$ concentrations. The model was highly significant ($p < 0.001$), confirming that humidity is a major determinant of particulate matter levels in the study area.

(b). Relationship Between $PM_{2.5}$ and Temperature
Regression analysis between $PM_{2.5}$ and temperature showed a statistically significant but weaker positive relationship. Temperature explained about 18.3% of the variance in $PM_{2.5}$ ($R^2 = 0.183$), suggesting that temperature alone is not a strong predictor of particulate levels accounting for 18.3% only. The positive coefficient (+5.470) indicates that higher temperatures are associated with increased $PM_{2.5}$ concentrations, although the explanatory power is limited. Despite the low R^2, the relationship remained statistically significant ($p < 0.001$), implying that temperature contributes to $PM_{2.5}$ variability but not as strongly as humidity.

(c). Relationship Between Humidity and Temperature
A regression of humidity on temperature demonstrated a moderately strong negative association, with temperature explaining 47.0% of the variation in humidity ($R^2 = 0.470$). The temperature coefficient (-3.900) was highly significant ($p < 0.001$), indicating that increases in temperature are strongly associated with decreases in relative humidity. This inverse relationship highlights

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

the climatic coupling between heat and dryness in the study region.

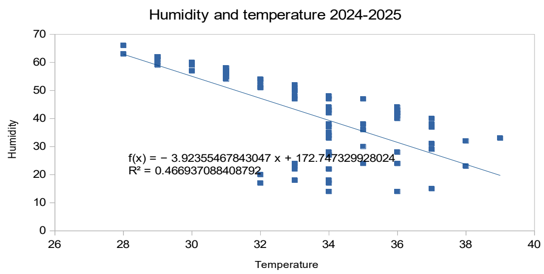

Figure 2: Regression plot of humidity and temperature

3.2.2. ANOVA Test (Seasonal Difference 2024 and 2025)

a). Year 2024 ANOVA Result: F = 23.36, F critical = 2.79 at alpha = 0.05 with df(3,51), p-value = 0.0000000011885 = $P<0.001$ (very significant).

A one-way ANOVA analysis showed a statistically significant difference in PM2.5 concentrations between dry and rainy seasons means, $F(3,48) = 23.36$, $p < 0.001$. The calculated F-value exceeded the critical F-value (2.80), indicating strong evidence against the null hypothesis. Harmattan recorded the highest mean value (130.23 ± 29.46), while rainy season exhibited the lowest mean (54.44 ± 6.11), suggesting substantial variability among the seasons. post-hoc pairwise t-tests with Bonferroni correction (α =0.0167) confirmed significant difference between all seasons; rainy and harmattan ($p<0.001$), rainy and dry ($p<0.001$) and dry and harmattan ($p<0.001$). Mean PM2.5 was highest during harmattan period (M = 130.23, SD = 28.3 μg/m³), intermediate during dry season with mean value (M = 68.31, SD = 15.8 μg/m³) and lowest during rainy season (M = 54.44, SD = 5.9 μg/m³) and high during post-rainy season (M = 70.25, SD = 13.7 μg/m³)

Effect Size $\eta^2 = \frac{SS\ \text{btw}}{SStotal} = \frac{42360.9642}{73194.4881} = 0.5787 \approx 0.58$

Where:

SSbetween = Sum of Squares between groups = 42360.9642

SStotal = Total Sum of Squares = 73194.4881

The ANOVA effect size (η^2 = 0.58) indicates that seasonal differences accounted for approximately 58% of the total variability observed in the dataset, suggesting that seasonal variation plays a critical role in air pollution levels, with significantly higher concentrations observed during the harmattan and dry season showing that difference between seasons are not random noice.

(b). Year 2025 ANOVA Result: F = 11.14, F critical = 2.79 at alpha = 0.05 with df(3,48), p-value = 0.0000114207084 = $p<0.001$ (very significant) .

A one-way ANOVA analysis showed a statistically significant difference in PM2.5 concentrations between dry and rainy seasons means, $F(3,45) = 11.14$, $p < 0.001$. The calculated F-value exceeded the critical F-value (2.80), indicating strong evidence against the null hypothesis. Harmattan recorded the highest mean value, while rainy season exhibited the lowest mean value, suggesting substantial variability among the seasons. post-hoc pairwise t-tests with Bonferroni correction (α =0.0167) confirmed significant difference between all seasons; rainy and harmattan ($p<0.001$), rainy and dry ($p<0.001$) and dry and harmattan ($p<0.001$). Mean PM2.5 was highest during harmattan period (M = 100.00, SD = 40.12 μg/m³), intermediate during dry season with mean value (M = 66.38, SD = 18.03 μg/m³) and lowest during rainy season (M = 48.06, SD = 10.80 μg/m³) and high during post-rainy season (M = 72.11, SD = 13.7 μg/m³)

Effect Size $\eta^2 = \frac{SS\ \text{btw}}{SStotal} = \frac{19601.7628}{47738.6731} = 0.4106 \approx 0.41$

Where:

SS between = Sum of Squares between seasons = 19601.7628

SS total = Total Sum of Squares = 47738.6731

From ANOVA effect size (η^2), the variance ($\eta 2$=0.41) indicates that 41% of the differences in pollution levels (like PM2.5) are directly explained by the seasonality.

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

3.3 Seasonal and Temporal Trends

Time series analysis showed elevated $PM_{2.5}$ levels during the dry season and particularly during the harmattan months (December-January), where weekly $PM_{2.5}$ values ranged between 158-179 µg/m³. These peaks coincided with reduced visibility (9 -20 km), reflecting dense atmospheric aerosol loading. In contrast, wet season $PM_{2.5}$ concentrations were considerably lower (32 - 69 µg/m³) with improved visibility (36-79 km), reflecting enhanced atmospheric cleansing by rainfall.

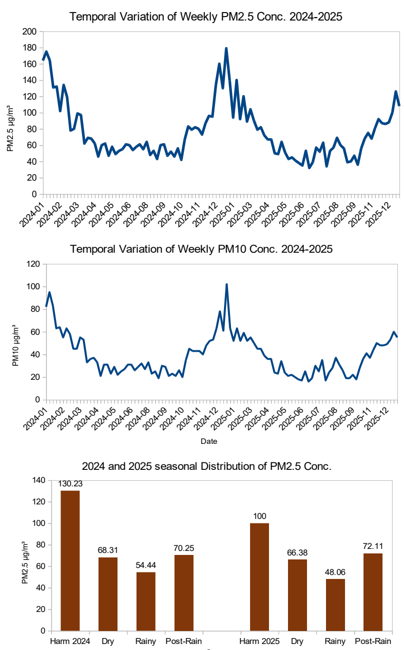

Figure 4: Time series showing seasonal variability

3.4 Correlation between Pollutants and Meteorological Variables

Findings from scatter plots and coefficients are internally consistent:

3.4.1 $PM_{2.5}$, PM10 and Temperature

A moderate positive correlation indicated that higher temperatures may enhance pollutant concentration through increased atmospheric reactions, resuspension of dust, or stagnant air conditions

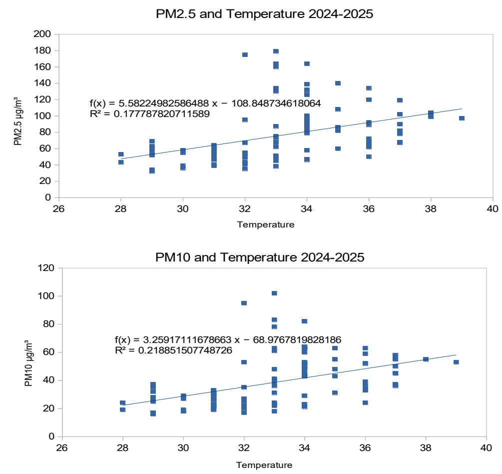

Figure 5: scatter plots of PM2.5, PM10 and temperature

3.4.2 $PM_{2.5}$, PM10 and Humidity

Strong negative correlation and regression coefficient indicate that wet deposition and hygroscopic growth reduce airborne fine particles.

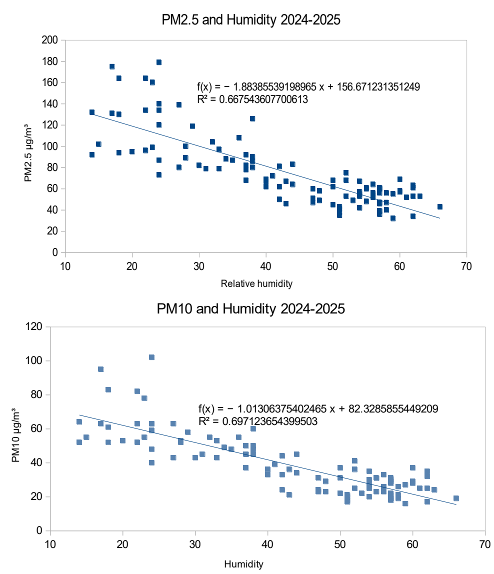

Figure 6: scatter plots of PM2.5, PM10 and humidity

3.4.3 $PM_{2.5}$, PM10 and Visibility

A very strong negative correlation confirmed that visibility sharply deteriorates with rising particulate concentrations, reflecting the dominant role of aerosols in atmospheric light extinction.

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

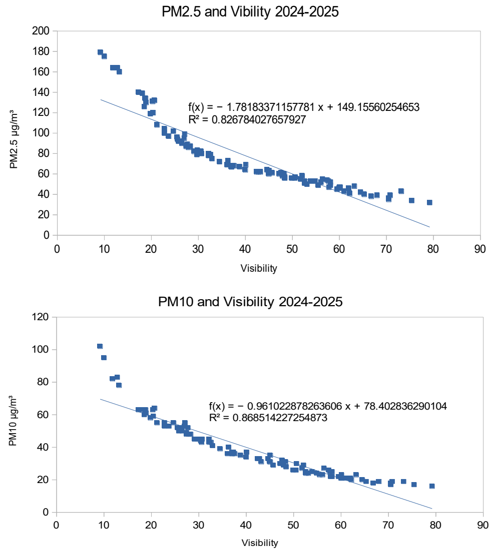

Figure 7: scatter plots of PM2.5, PM10 and visibility

3.5 Seasonal Decomposition

The 52 week decomposition produced three components:

Trend Component: The long term trend shows Mild decline from early 2024 (~82 µg/m³), Gradual reduction toward ~71-74 µg/m³ by mid 2025 but no sustained structural improvement below ~70 µg/m³ baseline. This indicates that although peak intensities fluctuate, baseline exposure remains chronically elevated. This aligns with the yearly averages (2024 = 79.29; 2025 = 72.73).

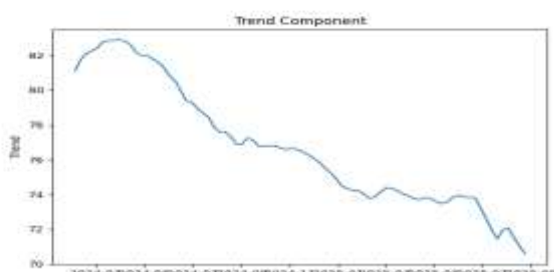

Figure 8: Trend component

II. Seasonal Component: The seasonal signal demonstrates strong positive amplification (+80 to +105 µg/m³) during December-January, strong negative deviations (-20 to -35 µg/m³) during midyear months and highly consistent annual repetition. Seasonal amplitude nearly doubles baseline concentrations during peak months.

III. Residual Component: Residual variation remains relatively small compared to seasonal amplitude, confirming that observed peaks are predominantly season driven rather than random noise.

Figure 9: Residual component

3.6. Rolling Average Analysis

The 12 week rolling mean confirms, three distinct seasonal pollution waves, sustained high exposure periods lasting 10-14 weeks, absence of long term downward structural improvement. The pattern is cyclical and predictable.

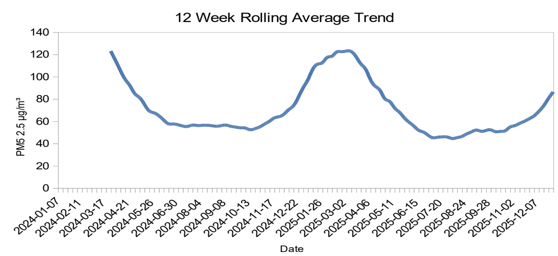

Figure 10: Rolling Average Trend

3.7. Air Quality Index (AQI) Classification

AQI analysis indicates that 93% of weeks exceeded moderate levels, 44% fell into unhealthy or worse, several days fall within the unhealthy for sensitive groups category, as occasional spikes reach unhealthy levels. This suggests that vulnerable populations, including children and the elderly, are at increased risk. The findings of this study confirm that air pollution in Abuja is a significant environmental and public health concern. The frequent exceedance of WHO PM2.5 limits (≤15 µg/m³) over 24 hours indicates chronic exposure risks for residents.

Table 4: AQI distribution of weekly exposure

Category	Count
Moderate	5
Unhealthy for Sensitive Groups	71
Unhealthy	52

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

Very Unhealthy	6

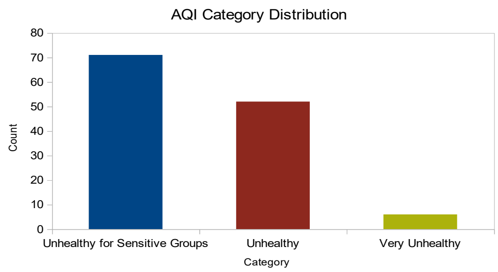

Figure 11: AQI Category Distribution

IV. DISCUSSION

This study provides clear evidence of persistently elevated particulate matter concentrations in Abuja over the two year period (2024-2025). Weekly $PM_{2.5}$ values consistently exceeded the WHO 24 hour guideline of 15 µg/m³, with observed concentrations ranging from 32 to 179 µg/m³, indicating chronic exposure conditions for the city's population. AQI analysis further reinforces this conclusion, showing that air quality in Abuja was degraded throughout the monitoring period. Approximately 93% of weeks exceeded the moderate AQI threshold, while 44% were classified as unhealthy or worse. Several days also reached the unhealthy for sensitive groups category, demonstrating that vulnerable populations particularly children, older adults, and individuals with respiratory or cardiovascular diseases faced elevated exposure risks. Air quality fluctuated between moderate and very unhealthy, with the most extreme conditions occurring during the peak harmattan months, when $PM_{2.5}$ concentrations reached 175.00 µg/m³ in January 2024 and 179.00 µg/m³ in January 2025. These very unhealthy conditions indicate periods where the entire population may experience more serious health effects. Large portions of the dry season fell within the unhealthy range, including measurable spikes such as 132.00 µg/m³ in February 2024 and 126.00 µg/m³ in December 2025. Transitional months also frequently fell into the unhealthy for sensitive groups category, with notable examples like 99.00 µg/m³ in March 2024 and 92.00 µg/m³ in November 2025. Even the cleanest conditions, which occurred during the rainy season, remained in the moderate range, with the lowest recorded concentration at 32.00 µg/m³ in June 2025. At no point during the two year period did $PM_{2.5}$ concentrations enter the good category (<12 µg/m³), confirming the persistent absence of truly clean air. $PM_{2.5}$ consistently remained the dominant pollutant and primary driver of AQI scores, often appearing at roughly twice the concentration of PM_{10}. Visibility patterns were closely linked to particulate levels: during very unhealthy episodes such as January 2025, visibility dropped dramatically to 9.20 km, but during moderate periods such as June 2025, visibility improved sharply to 79.20 km. These findings collectively confirm that Abuja experiences recurrent and severe pollution episodes shaped by seasonal dust intrusions and continuous local emissions. The pronounced influence of meteorology on particulate matter dynamics is evident from the strong correlations observed between $PM_{2.5}$ and key atmospheric variables. Temperature showed a moderate positive association with $PM_{2.5}$, suggesting that higher temperatures may enhance dust resuspension, increase atmospheric turbulence, or promote secondary aerosol formation. Relative humidity exhibited a strong negative correlation with $PM_{2.5}$, which is consistent with established physical mechanisms: higher humidity accelerates aerosol hygroscopic growth and promotes wet deposition, thereby reducing airborne particle concentrations. Visibility demonstrated a strong inverse relationship with $PM_{2.5}$, reflecting the direct influence of particulate loading on atmospheric optical properties, especially during dust laden harmattan conditions. These relationships align with known aerosol meteorology interactions in tropical and Sahelian climates, where atmospheric processes strongly modulate pollutant concentrations.

The multiple linear regression model further highlights the major role of meteorology in regulating particulate levels, with temperature and humidity jointly explaining 84% of the variance in $PM_{2.5}$. This level of explanatory power is unusually high for air quality models and strongly supports the dominance of seasonal meteorological patterns particularly dust advection and wet deposition cycles in shaping pollutant dynamics. The statistical significance of the predictors reinforces the conclusion that changes in atmospheric conditions have a direct and measurable impact on $PM_{2.5}$ behavior. However, meteorology alone does not fully explain the elevated pollution

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717942

levels observed even during the rainy season. $PM_{2.5}$ values remained well above WHO limits throughout the period, indicating significant contributions from local and regional sources such as vehicle emissions, generator usage, waste burning, construction activity, industrial operations, and resuspended dust from unpaved roads. These sources form a persistent pollution baseline that is amplified seasonally by Saharan dust intrusions. Seasonal decomposition analysis confirmed that seasonal forcing is the principal driver of variability, with residual components remaining comparatively small. The seasonal cycle nearly doubled baseline concentrations during harmattan months, reflecting the influence of transboundary dust inflows and regional atmospheric circulation patterns. Although a slight decline in the long term trend was observed from early 2024 to mid 2025, this decrease was marginal and insufficient to represent meaningful air quality improvement. Annual mean concentrations remained far above global health guidelines, with $PM_{2.5}$ averaging 79.29 µg/m³ in 2024 and 72.73 µg/m³ in 2025, both of which exceed WHO standards by factors of four to five. The ANOVA results confirmed statistically significant differences in $PM_{2.5}$ concentrations among the three major seasonal categories harmattan, dry, and wet and post hoc analysis verified that each season differed significantly from the others. This further underscores the strong seasonal modulation of air quality in Abuja. The AQI results confirm that severe pollution episodes are not isolated events but recurring, predictable features of Abuja's atmospheric environment. These findings align with prior studies in Nigeria and across West Africa, highlighting the interaction of natural and anthropogenic drivers. However, the high resolution nature of this study provides one of the clearest and most continuous characterizations of particulate dynamics in the region. Overall, the results demonstrate that Abuja faces substantial and persistent air quality challenges driven by a combination of regional dust transport and continuous local emissions. Without significant and coordinated policy measures including stricter emission standards, improved monitoring infrastructure, enhanced urban planning, and targeted public health interventions, air pollution will continue to pose serious threats to environmental sustainability and population health.

V. CONCLUSION

This study evaluated the spatiotemporal dynamics of ambient $PM_{2.5}$ and PM_{10} concentrations in Abuja from January 2024 to December 2025 and provides compelling evidence that the city experiences chronic, seasonally intensified particulate pollution. Weekly $PM_{2.5}$ concentrations remained above the WHO 24 hour guideline throughout the entire study period, with an overall mean of 76.90 µg/m³ and peak values reaching 179 µg/m³ during the harmattan months. These levels substantially exceed global health standards and indicate continuous exposure for residents. Seasonal analysis demonstrated that particulate matter variability is strongly shaped by regional meteorology, the harmattan and dry seasons produced the highest concentrations due to intense dust advection and atmospheric stagnation, whereas the wet season exhibited significantly lower levels driven by enhanced scavenging and wet deposition processes.

Meteorological parameters, particularly temperature and relative humidity, played a significant role in regulating particulate behavior, jointly explaining 84% of $PM_{2.5}$ variability. Their statistical significance, combined with the strong inverse relationship between visibility and particulate concentrations, underscores the central role of atmospheric conditions in shaping pollution episodes. Time series decomposition confirmed that seasonal forcing is the dominant contributor to temporal variability, while the long term component showed only minimal improvement across the two year period. AQI classification further revealed that most weeks fell within categories associated with moderate to severe health impacts, with 93% exceeding the moderate threshold and 44% classified as unhealthy or worse. Notably, $PM_{2.5}$ levels never entered the good AQI category, demonstrating the persistent absence of clean air conditions in Abuja.

Overall, the findings indicate that Abuja faces a sustained and significant air pollution challenge driven by the combined effects of anthropogenic emissions such as vehicular traffic, generator use, construction activities, and domestic combustion and natural dust transport from the Sahara. The recurring exceedances of WHO and U.S. EPA air quality standards highlight substantial public health risks, especially for sensitive groups. These results reinforce the urgent need for comprehensive air quality management interventions, including strengthened regulatory enforcement, improved monitoring infrastructure, targeted emission reduction strategies, and public health protection measures. Without coordinated policy action and sustained environmental governance, particulate pollution will continue to pose a serious threat to the health and well being of Abuja's growing population.

VI. RECOMMENDATIONS

1. Expand monitoring and research: Strengthen air quality monitoring infrastructure and support data driven decision making through research.
2. Enforce emission controls: Implement strict vehicle and industrial emission standards while restricting open burning.
3. Promote clean energy: Incentivize the adoption of renewable energy and cleaner fuels to reduce dependence on generators.
4. Improve urban planning: Integrate green corridors and better public transport into city designs to reduce traffic pollution.
5. Protect public health: Establish early warning systems and public awareness campaigns, especially for seasonal pollution.
6. Strengthen policy and capacity: Update air quality standards and enhance coordination between government environmental and health agencies.

VII. ACKNOWLEDGMENTS:

The authors would like to express their sincere gratitude to the Nigeria Meteorological Agency (NiMet) for the provision of data for this research and the Environmental Unit, Physical and Life Science Department, National Space Research and Development Agency (NASRDA), Qlusegun Obasanjo Space Centre along the airport road in the capital city Abuja, Nigeria, for providing an enabling environment for this research.

REFERENCES

[1] Adesina, A., & colleagues. (2025). Seasonal variability of particulate matter pollutants in Abuja, Nigeria. Journal of Atmospheric Pollution. doi.org

[2] Amegah, A. K., & Agyei Mensah, S. (2017). Urban air pollution in Sub Saharan Africa: Time for action. Environmental Pollution, 220(A), 738–743. doi.org

[3] Blaga, R., & Gautam, S. (2024). Improving PM10 sensor accuracy in urban areas through calibration in Timișoara. npj Climate and Atmospheres, 7, 268. doi.org

[4] Boldo, E., Medina, S., LeTertre, A., Hurley, F., Mücke, H. G., Ballester, F., & Aguilera, I. (2006). Apheis: Health impact assessment of long term exposure to PM2.5 in 23 European cities. European Journal of Epidemiology, 21(6), 449–458. doi.org

[5] Brook, R. D., Rajagopalan, S., Pope, C. A., III, Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., Holguin, F., Hong, Y., Luepker, R. V., Mittleman, M. A., Peters, A., Siscovick, D., Smith, S. C., Whitsel, L., & Kaufman, J. D. (2010). Particulate matter air pollution and cardiovascular disease. Circulation, 121(21), 2331–2378. doi.org

[6] Burnett, R. T., Pope, C. A., III, Ezzati, M., Olives, C., Lim, S. S., Mehta, S., ... Cohen, A. (2018). Global estimates of mortality associated with long term exposure to fine particulate matter. Proceedings of the National Academy of Sciences, 115(38), 9592–9597. doi.org

[7] Chaoyang, X., Abbatt, J., Czech, H., Jones, K., & El Haddad, I. (2016). Changing emissions and atmospheric chemistry: Ongoing impacts on air quality and climate. Environmental Science & Technology, 60(8), 5910–5920. doi.org

[8] Ezenwa, B. C., Ogungbeni, O. B., Adewumi, J. R., Babatunde, O. M., & Udeh, S. C. (2021). PM2.5 and seasonal air quality variations in Abuja, Nigeria. Atmospheric Environment: X, 9, 100112. doi.org

[9] Flagan, R. C., & Seinfeld, J. H. (2012). Fundamentals of air pollution engineering. Courier Corporation.

[10] Fowler, D., Pyle, J. A., Raven, J. A., Sutton, M. A., et al. (2013). The effects of air pollution on

ecosystems and human health. Environmental Pollution, 183, 1–4. doi.org

[11] Garcia, A., Santa Helena, E., De Falco, A., Ribeiro, J. P., Gioda, A., & Gioda, C. R. (2023). Toxicological effects of fine particulate matter (PM2.5): Systemic injuries and health risks. Water, Air, & Soil Pollution, 234, 346. doi.org

[12] Guo, Y., Yang, Z., Mahendran, R., Yu, P., Xu, R., Yu, W., & Li, S. (2022). Health effects of long term exposure to ambient PM2.5 in Asia Pacific: A systematic review. Current Environmental Health Reports, 9(2), 130–151. doi.org

[13] Gurjar, B. R., Molina, L. T., & Ojha, C. S. P. (2016). Air pollution: Health and environmental impacts. CRC Press.

[14] Hamed, H. H., Al Ansari, N., Abdallah, H. H., et al. (2021). Predicting PM2.5 levels over northern Iraq using regression and GIS. Geomatics, Natural Hazards and Risk, 12(1), 1778–1796. doi.org

[15] Health Effects Institute. (2020). State of global air 2020. stateofglobalair.org

[16] Health Effects Institute. (2022). The state of air quality and health impacts in Africa. State of Global Air Initiative. stateofglobalair.org

[17] Islam, M. S., Roy, S., Tusher, T. R., Rahman, M., & Harris, R. C. (2023). Spatio temporal variations in PM2.5 and long range air mass transport in South Asia. Remote Sensing, 15(20), 4975. doi.org

[18] Jacob, D. J. (1999). Introduction to atmospheric chemistry. Princeton University Press.

[19] Jacobson, M. Z. (2005). Fundamentals of atmospheric modeling (2nd ed.). Cambridge University Press.

[20] Jumaah, H. J., Ameen, M. H., Kalantar, B., Rizeei, H. M., & Jumaah, S. J. (2019). Air quality index prediction using GIS based techniques. Geomatics, Natural Hazards and Risk, 10(1), 2185–2199. doi.org

[21] Kim, K. H., Kabir, E., & Kabir, S. (2015). Human health impacts of airborne particulate matter. Environment International, 74, 136–143. doi.org

[22] Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., … Britter, R. (2015). Low cost sensing for air pollution management. Environment International, 75, 199–205. doi.org

[23] Lai, N., Song, W., Wang, M., Zhao, L., Zhou, J., Cai, X., … Li, A. (2024). Meteorological impacts on fine particle pollution in winter. Processes, 12(12), 2713. doi.org

[24] Li, T., & Lau, A. K. H. (2012). Effects of meteorology on PM2.5 in urban environments. Atmospheric Environment, 50, 179–186. doi.org

[25] Lin, Y. C., Li, Y. C., Shangdiar, S., Chou, F. C., Sheu, Y. T., & Cheng, P. C. (2019). $PM_{2.5}$ and PAHs from gasoline vehicle emissions. Chemosphere, 226, 502–508. doi.org

[26] Liu, C., Chen, R., Zhao, Y., Ma, Z., Bi, J., Liu, Y., & Kan, H. (2015). Meta analysis of PM2.5 and PM10 health effects in China. Environmental Research, 136, 196–204. doi.org

[27] Manikonda, A., Zíková, N., Hopke, P. K., & Ferro, A. R. (2016). Assessment of low cost PM monitors. Journal of Aerosol Science, 102, 29–40. doi.org

[28] Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution. Frontiers in Public Health, 8, 14. doi.org

[29] Mbaye, F., et al. (2026). Placental pathways: PM2.5 exposure and pregnancy outcomes in Sub Saharan Africa. medRxiv preprint. doi.org

[30] (No published version available yet as of 2026. Kept as preprint.)

[31] Monks, P. S., Archibald, A. T., Colette, A., Cooper, O. R., Coyle, M., Derwent, R. G., … Williams, M. L. (2015). Tropospheric ozone and its precursors. Atmospheric Chemistry and Physics, 15, 8889–8973. doi.org

[32] Seinfeld, J. H., & Pandis, S. N. (2016). Atmospheric chemistry and physics: From air pollution to climate change (3rd ed.). Wiley.

[33] Sokhi, R. S., Moussiopoulos, N., Baklanov, A., Bartzis, J., Coll, I., Finardi, S., … Kukkonen, J. (2022). Advances in air quality research. Atmospheric Chemistry and Physics, 22, 4615–4703. doi.org

[34] U.S. Environmental Protection Agency. (2018). Air quality monitoring. epa.gov

[35] U.S. Environmental Protection Agency. (2025). Communicating air quality conditions: The Air Quality Index.

[36] Wambebe, N. M., & Duan, X. (2020). Air quality levels and health risk assessment of particulate matters in Abuja municipal area, Nigeria. Atmosphere, 11(8), 817. doi.org

[37] World Health Organization. (2006). Air quality guidelines: Global update 2005. WHO Press.

[38] World Health Organization. (2010). WHO guidelines for indoor air quality: Selected pollutants. WHO Press.

[39] World Health Organization. (2016). Ambient air pollution: A global assessment of exposure and burden of disease. WHO Press.

[40] World Health Organization. (2018). Ambient (outdoor) air quality and health. who.int

[41] World Health Organization. (2021). WHO global air quality guidelines. WHO Press.

[42] World Health Organization. (2023). Air quality and health: Types of pollutants. who.int

[43] World Health Organization. (2026). Air quality indexes: Key considerations and roadmaps for best practices. WHO Press.

[44] Xing, Y. F., Xu, Y. H., Shi, M. H., & Lian, Y. X. (2016). The health effects of ambient $PM_{2.5}$ and potential mechanisms. Ecotoxicology and Environmental Safety, 128, 67–74. doi.org

[45] Zhang, Y., Bocquet, M., Mallet, V., Seigneur, C., & Baklanov, A. (2012). Real time air quality forecasting. Atmospheric Environment, 60, 632–655. doi.org

[46] Zhao, J., Gao, Z., Tian, Z., Xie, Y., Xin, F., Jiang, R., & Kan, H. (2019). Short-term and long-term exposures to fine particulate matter constituents and health: A systematic review. Environmental Pollution, 247, 874–882. doi.org