© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720211

Influence of Relative Humidity and Visibility on Fine Particulate Matter Concentrations in the Niger Delta: Ground Based Evidence from Edo State, Nigeria.

BLESSED C. ANYANWU[1], OBOH OSABHUOHIEN[2], RUTH I. OJOMBO[3], CHINYERE WILLIAMS[4], JEREMIAH K. OGAH[5], AUGUSTINE O. OTUM[6], CHRISTIAN O. OFOEGBU[7], MURPHY E. OBINYAN[8], BARKA WAKAWA[9], CHIJIOKE OKPARA[10], GODWIN C. OGOR-IGBOSUAH[11], ASAJU K. OLAMIDE[12], SHAGAYA H. EMMANUEL[13], MAYOWA O. BANKOLE[14], SULEIMAN A. ZAKARI[15], JIBRIL A. SALIHU[16], JABES ANYUABAGA[17], MAHMUD IBRAHIM[18].

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

Abstract- Fine particulate matter ($PM_{2.5}$) remains one of the most critical air pollutants affecting public health, atmospheric visibility, and environmental sustainability, particularly in rapidly urbanizing regions of developing countries. Despite growing concerns regarding air pollution in the Niger Delta region of Nigeria, empirical evidence on the influence of meteorological conditions on $PM_{2.5}$ variability remains limited. This study investigated the influence of relative humidity and visibility on $PM_{2.5}$ concentrations in Edo State, Nigeria, using ground based observations obtained from the Space Earth Environment Research Laboratory, Centre for Atmospheric Research, University of Benin. Weekly $PM_{2.5}$, relative humidity, temperature, and visibility data collected between January 2022 and December 2025 were analyzed using descriptive statistics, Pearson correlation, multiple linear regression, seasonal analysis of variance (ANOVA), Tukey Honestly Significant Difference (HSD) tests, time series decomposition, and Air Quality Index (AQI) assessment. Results showed that the mean $PM_{2.5}$ concentration was 23.31 ± 24.92 µg m^{-3}, exceeding the World Health Organization (WHO) annual guideline value of 5 µg m^{-3} by more than fourfold, indicating persistent particulate pollution in the study area. Correlation analysis revealed significant negative relationships between $PM_{2.5}$ and relative humidity ($r = -0.286$, $p < 0.001$) and between $PM_{2.5}$ and visibility ($r = -0.515$, $p < 0.001$), while temperature exhibited a weak positive correlation with $PM_{2.5}$ ($r = 0.208$, $p = 0.003$). Regression analysis showed that relative humidity alone explained 8.2% of the variability in $PM_{2.5}$ concentrations ($R^2 = 0.082$), whereas the combined relative humidity visibility model explained 34.9% of the observed variability ($R^2 = 0.349$). The inclusion of temperature produced only a marginal improvement in model performance ($R^2 = 0.366$), confirming the dominant influence of visibility and relative humidity on $PM_{2.5}$ dynamics in the study area. Seasonal analysis revealed significant differences in $PM_{2.5}$ concentrations across atmospheric seasons ($F(2,206) = 16.55$, $p < 0.001$; $\eta^2 = 0.138$). The dry season recorded the highest mean $PM_{2.5}$ concentration (33.86 µg m^{-3}), followed by the early wet season (18.60 µg m^{-3}) and late wet season (12.01 µg m^{-3}). Tukey HSD post-hoc analysis indicated that $PM_{2.5}$ concentrations during the dry season were significantly higher than those observed during both the early wet and late wet seasons ($p < 0.001$), whereas no significant difference existed between the two wet-season periods ($p = 0.270$). Time series decomposition further revealed recurring seasonal cycles characterized by elevated particulate concentrations during dry months and reduced concentrations during wetter periods. AQI assessment indicated that while most observations fell within the good and moderate categories, approximately 13.9% of observations were classified as unhealthy for sensitive groups or worse, indicating recurrent episodes of degraded air quality and increased health risks for sensitive populations. The study demonstrates that visibility and relative humidity are key meteorological controls of $PM_{2.5}$ variability in the humid tropical environment of the Niger Delta. The persistent exceedance of WHO guideline values highlights potential public health risks associated with long-term exposure to fine particulate matter. These findings provide a scientific basis for incorporating meteorological parameters into air quality forecasting, exposure assessment, and pollution management strategies. Strengthening monitoring networks and implementing effective emission control measures are essential for mitigating particulate pollution and improving environmental health in rapidly urbanizing cities of southern Nigeria.

Keywords:** **$PM_{2.5}$, Relative Humidity, Visibility, Air Quality Index, Seasonal Variability, Time Series Analysis, Niger Delta, Edo State, Atmospheric Pollution, Nigeria.

I. INTRODUCTION

Atmospheric visibility and relative humidity are among the most important meteorological variables governing the concentration, optical properties, and behavior of fine particulate matter ($PM_{2.5}$) in the lower atmosphere. Visibility is widely used as a practical indicator of aerosol loading, since suspended particles scatter and absorb solar radiation and thereby reduce atmospheric transparency. Numerous studies report a strong inverse relationship between $PM_{2.5}$ concentrations and visibility, such that visibility degradation closely tracks increasing aerosol burden (Fei et al., 2023). Relative humidity further shapes this relationship by promoting hygroscopic growth of aerosol particles. As particles absorb water, their size and light extinction efficiency increase, enhancing haze formation and reducing visibility even when particulate mass concentrations remain largely unchanged. Under rainfall conditions, however, high humidity can instead drive wet deposition, removing particulate matter from the atmosphere and altering both aerosol concentrations and visibility (Lin et al., 2019; Qu et al., 2015). Visibility and relative humidity are therefore increasingly recognized as important indicators and predictors of particulate pollution dynamics, particularly in humid tropical environments where high moisture availability persists throughout much of the year (Roy et al., 2022; Andrade et al., 2026). This significance sits within the broader context of air pollution as one of the most pressing environmental challenges of the twenty first century, given its wide ranging impacts on human health, ecosystem functioning, atmospheric processes, and climate regulation (Brook et al., 2010). Among atmospheric pollutants, $PM_{2.5}$ has drawn particular scientific and policy attention because of its small aerodynamic diameter (≤ 2.5 μm), prolonged atmospheric residence time, and capacity to penetrate deep into the human respiratory system (Burnett et al., 2018; Boldo et al., 2006). The World Health Organization identifies $PM_{2.5}$ as one of the most harmful air pollutants, with ambient exposure contributing to millions of premature deaths annually worldwide (WHO, 2021), while recent global burden of disease assessments confirm $PM_{2.5}$ as a leading contributor to cardiovascular disease, chronic respiratory illness, lung cancer, and premature mortality, particularly in low and middle income countries where air quality management systems remain underdeveloped (Manisalidis et al., 2020; GBD 2021 Risk Factors Collaborators, 2024). Beyond its direct link to visibility, relative humidity affects aerosol hygroscopicity, chemical transformation, atmospheric stability, and particle growth more broadly (Tai et al., 2010; Fei et al., 2023). In humid environments, aerosol water uptake can substantially alter measured $PM_{2.5}$ concentrations and sustain haze episodes even when emission rates remain relatively constant (Liu et al., 2015; Yang et al., 2023), while elevated humidity can also promote secondary particle formation through aqueous phase chemical reactions, further altering $PM_{2.5}$ concentration and composition (He et al., 2025). Because these humidity driven processes directly govern particle size and optical extinction, visibility functions as a valuable indirect proxy for aerosol loading where direct monitoring data are limited, a relationship that is especially pronounced in tropical environments, where sustained moisture availability enhances aerosol growth and optical extinction (Liu et al., 2021; Zhang et al., 2019; He et al., 2025; Seinfeld & Pandis, 2016). Understanding these combined relationships is therefore essential for improving air quality forecasting, exposure assessment, and the design of effective pollution mitigation strategies in rapidly growing tropical cities (Bai et al., 2018).

In sub-Saharan Africa, rapid urbanization, industrialization, population growth, and inadequate pollution control measures have contributed to rising levels of ambient air pollution (Amegah & Agyei-Mensah, 2017), yet the region remains one of the least monitored globally, leaving substantial uncertainty about pollutant distributions, temporal variability, and population exposure (Kumar et al., 2015). Nigeria exemplifies this challenge as major urban centers frequently record elevated particulate matter concentrations arising from vehicular emissions, industrial activity, biomass burning, domestic fuel combustion, waste incineration, and generator based power supply (Ana et al., 2012; Efe, 2008). Recent ground based monitoring in Abuja has reported persistent exceedances of WHO $PM_{2.5}$ guideline values, substantial seasonal variability, and significant associations between particulate matter concentrations and meteorological conditions, including periods of reduced visibility, underscoring the mounting air quality challenges confronting rapidly urbanizing Nigerian cities (Anyanwu et al., 2026). The Niger Delta, however, presents a markedly different atmospheric setting. As Nigeria's principal petroleum producing region, it is defined by intensive oil and gas activity, widespread gas flaring, rapid urban expansion, and growing industrial and transportation demand (Nwankwo & Ogagarue, 2011), with flaring emissions of black carbon, particulate matter, sulfur dioxide, nitrogen oxides, and volatile organic compounds compounding regional aerosol loading (Odiana et al., 2024; Giwa et al., 2019; Fawole et al., 2019). Whereas seasonal aerosol variability in Abuja and northern Nigeria is driven largely by harmattan dust transport under low humidity conditions, the Niger Delta is characterized by persistently high relative humidity, frequent rainfall, and intense aerosol moisture interactions layered on top of industrial, urban, and flaring emissions (Ana et al., 2012; Giwa et al., 2019; Ayanlade et al., 2019), conditions that can substantially alter aerosol growth, light extinction, pollutant dispersion, and visibility degradation. Findings from northern and central Nigeria therefore cannot be directly generalized to the south, making it essential to understand $PM_{2.5}$ meteorology interactions specific to the Niger Delta (Ede et al., 2015; Nnah & Ikwueze, 2024). Edo State occupies a strategic position within the Niger Delta and represents one of the region's fastest growing urban environments. Benin City, the state capital, has experienced rapid urban expansion, population growth, and increasing pressure from transportation, industrial, commercial, and residential activities over recent decades (Okosun & Chokor, 2021; Eghomwanre et al., 2022), with remote sensing assessments indicating substantial increases in built up areas and urban land conversion associated with the city's continued socioeconomic development (Martin, 2008). At the same time, Benin City lies within the humid tropical climatic zone of southern Nigeria, characterized by high annual rainfall, persistently elevated relative humidity, and abundant atmospheric moisture that strongly influence aerosol formation, growth, transport, and removal (Ayanlade et al., 2019). This combination of rapid urban growth and humid tropical climate makes the city an ideal natural laboratory for investigating meteorological controls on particulate matter behavior. Although previous studies have reported elevated aerosol loading and particulate pollution across southern Nigerian cities (Odu-Onikosi et al., 2022; Ibe et al., 2025), relatively few investigations have specifically examined the combined influence of relative humidity and atmospheric visibility on $PM_{2.5}$ concentrations within the Niger Delta.

More broadly, while particulate matter variability and its meteorological drivers have been extensively studied in Europe, North America, and Asia, evidence from tropical African environments remains comparatively limited (Nwokocha et al., 2019; Lin et al., 2024; Racha et al., 2026). Existing Nigerian studies, including recent work in Abuja, have focused primarily on pollutant concentration levels, source characterization, emission inventories, and short term monitoring campaigns, with relatively few examining the mechanistic relationships linking relative humidity, visibility, and $PM_{2.5}$ (Amegah & Agyei-Mensah, 2017; Ezenwa et al., 2021). Long term ground based observations capable of capturing seasonal and interannual variability also remain scarce across much of sub-Saharan Africa because of limited monitoring infrastructure and data availability (Kumar et al., 2015, 2016; Sokhi et al., 2022; Nnah & Ikwueze, 2024; Eghomwanre et al., 2022), constraining the ability of environmental managers and policymakers to assess exposure accurately, develop reliable forecasting systems, and implement evidence based mitigation strategies suited to local atmospheric conditions. Closing this gap requires continuous, location specific observations capable of characterizing both pollutant concentrations and relevant meteorological parameters. Ground based monitoring stations are particularly valuable for this purpose, offering high frequency measurements for trend detection and air quality assessment in settings where satellite derived aerosol products may be affected by cloud cover, elevated atmospheric moisture, complex surface characteristics, or limited ground validation data (Malings et al., 2020; Kim et al., 2023; Snyder et al., 2013). Continuous in situ monitoring further enables investigation of local scale pollution dynamics that satellite observations often cannot fully resolve, thereby improving exposure assessment and supporting evidence based environmental management and policy development (van Donkelaar et al., 2021; Lewis & Edwards, 2016; Martin, 2008). Against this background, the present study examines the influence of relative humidity and visibility on fine particulate matter ($PM_{2.5}$) concentrations in the Niger Delta, presenting ground based evidence from Edo State, Nigeria, using observations from the Space Earth Environment Research Laboratory, Centre for Atmospheric Research, University of Benin. Specifically, the study evaluates temporal variations in $PM_{2.5}$ concentrations, examines the relationships among $PM_{2.5}$, relative humidity, and visibility, and quantifies the extent to which these two meteorological variables jointly shape particulate pollution in a humid tropical environment. Unlike northern and central Nigerian cities, where drier conditions and harmattan dust dominate seasonal aerosol behavior, southern Nigeria experiences persistently high atmospheric moisture, frequent rainfall, and enhanced aerosol water interactions that fundamentally shape particle growth, optical properties, and removal processes. Meaning meteorological relationships identified in drier regions cannot simply be assumed to hold in the Niger Delta. By generating site specific, ground based evidence from one of Nigeria's most environmentally significant regions, this study contributes to the growing body of knowledge on aerosol meteorology interactions in Africa and offers scientific information relevant to air quality management, public health protection, and environmental policy development in the Niger Delta.

II. MATERIALS AND METHODS

2.1 Study Area

This study was conducted in Edo State, Southern Nigeria, with emphasis on Benin City, the state capital located between latitude 6°20′N and longitude 5°37′E. Benin City lies within the humid tropical rainforest zone of the Niger Delta region and experiences a bimodal rainfall regime. The major rainy season extends from April to July, followed by a short dry period commonly referred to as the August Break, while a secondary rainy season occurs between September and October. The principal dry season spans November to March. The climate is characterized by persistently high atmospheric moisture, with annual mean temperatures ranging between 24°C and 33°C and relative humidity frequently exceeding 80% throughout most of the year. These meteorological conditions promote aerosol hygroscopic growth, atmospheric light extinction, and visibility impairment. Benin City is a rapidly urbanizing metropolitan center influenced by multiple anthropogenic emission sources including vehicular traffic, domestic fuel combustion, diesel powered electricity generators, open waste burning, and industrial activities. In addition, regional atmospheric transport from oil and gas operations and gas flaring activities within the Niger Delta contributes substantially to ambient aerosol loading. The combination of high emissions and elevated humidity makes the area particularly suitable for investigating the relationship between relative humidity, visibility, and fine particulate matter concentrations.

Figure 1: Description of study area.

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DOI: https://doi.org/10.64388/IREV10I1-1720211

https://www.unocha.org/publications/map/nigeria/nigeria-reference-map-edo-state-24-december-2018

2.2 Data Acquisition

Ground based air quality and meteorological data were obtained from the Space Earth Environment Research Laboratory, Centre for Atmospheric Research, University of Benin, Nigeria. The station is equipped with a PurpleAir PA-II SD monitoring system (Firmware Version 7.02) for continuous atmospheric measurements. The dataset comprised weekly averaged $PM_{2.5}$ concentrations together with corresponding measurements of ambient temperature (°C), relative humidity (%), and horizontal visibility (km) collected between January 2022 and December 2025. The four year monitoring period was selected to capture seasonal variability, inter annual fluctuations, and long term atmospheric conditions representative of the study area. To ensure consistency, all air quality and meteorological variables were obtained from the same monitoring location.

2.3 Data Quality Control

Quality assurance procedures were implemented prior to statistical analysis. Missing observations, duplicate records, and anomalous values resulting from sensor malfunction or transmission errors were identified through visual inspection and statistical screening. Outliers were assessed using the interquartile range (IQR) method and verified against corresponding meteorological conditions before removal. Data validation procedures followed standard atmospheric monitoring protocols recommended for environmental data analysis. The final dataset consisted of validated weekly observations of $PM_{2.5}$ ($\mu g\ m^{-3}$), Relative Humidity (%), Temperature (°C) and Visibility (km)

Tables 1, 2, 3 and 4 summarize weekly averages for 2022 to 2025. The values used in subsequent statistical analysis correspond exactly to these tables, ensuring consistency in all computations.

Table 1: Weekly mean of variables for year 2022.

Year (2022)	$PM_{2.5}$ ($\mu g\ m^{-3}$)	Temp. (°C)	R. Humidity (%)	Visual Range (Km)
Jan	75.23	31.80	43.00	15.54
Feb	36.73	33.25	53.50	25.78
March	21.55	32.75	57.50	37.20
April	11.40	31.25	60.25	58.55
May	14.04	30.60	62.20	48.58
June	12.82	29.25	64.75	54.60
July	12.18	28.20	67.00	60.12
Aug	11.12	28.25	66.25	65.50
Sep	5.78	28.75	69.75	99.35
Oct	10.50	30.20	66.00	65.92
Nov	16.63	33.00	58.00	45.80
Dec	24.77	32.75	56.75	36.00

Table 2: Weekly mean of variables for year 2023.

Year (2023)	$PM_{2.5}$ ($\mu g\ m^{-3}$)	Temp. (°C)	R. Humidity (%)	Visual Range (Km)
Jan	36.19	32.80	57.20	27.70
Feb	47.37	33.00	56.00	29.95
March	13.05	31.50	64.00	53.70
April	9.06	32.00	65.20	67.88
May	8.94	32.00	66.50	64.25
June	12.23	29.52	72.75	57.48
July	10.61	29.80	74.80	63.02
Aug	10.07	29.50	75.00	58.23
Sep	5.77	30.25	78.75	86.00
Oct	8.82	31.40	74.80	68.28
Nov	11.30	32.00	75.00	54.65
Dec	42.24	31.80	59.40	19.52

Table 3: Weekly mean of variables for year 2024.

Year (2024)	$PM_{2.5}$ ($\mu g\ m^{-3}$)	Temp. (°C)	R. Humidity (%)	Visual Range (Km)
Jan	63.40	33.00	59.75	13.35
Feb	59.50	33.00	63.25	18.68

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DOI: https://doi.org/10.64388/IREV10I1-1720211

March	21.97	32.80	75.40	25.70
April	14.69	32.00	77.50	32.43
May	18.87	31.75	81.00	27.43
June	21.93	30.20	89.60	26.20
July	28.14	30.75	75.25	21.90
Aug	18.05	30.00	61.75	29.80
Sep	13.97	29.80	73.00	33.58
Oct	18.94	30.75	82.25	26.90
Nov	29.49	32.25	71.25	20.70
Dec	44.99	32.60	59.60	15.42

Table 4: Weekly mean of variables for year 2025.

Year (2025)	$PM_{2.5}$ (µg m^{-3})	Temp. (°C)	R. Humidity (%)	Visual Range (Km)
Jan	46.05	3.00	69.50	15.40
Feb	29.82	33.00	78.25	21.30
March	20.90	32.40	84.80	25.84
April	16.47	32.25	87.00	29.08
May	14.07	31.50	87.25	32.33
June	16.20	30.40	92.80	29.00
July	82.80	28.75	99.75	24.80
Aug	15.98	29.00	100.00	30.72
Sep	10.24	29.50	100.00	41.48
Oct	14.53	30.75	99.50	33.98
Nov	15.00	32.40	96.60	34.80
Dec	16.15	32.50	97.50	34.38

2.4 Statistical Analysis

All statistical analyses were performed using Python Version 3.11 with the Pandas, NumPy, SciPy, Statsmodels, and Matplotlib libraries. Microsoft Excel was used for preliminary data organization and verification.

2.4.1 Descriptive Statistics

Descriptive statistics including mean, median, standard deviation, minimum, maximum, coefficient of variation, and quartile distributions were calculated to summarize temporal characteristics of $PM_{2.5}$, relative humidity, temperature, and visibility. Time series plots were generated to evaluate temporal trends and seasonal fluctuations in $PM_{2.5}$ concentrations over the study period, while box plots were used to compare the distribution, central tendency, variability, and occurrence of extreme values across seasons and years.

2.4.2 Correlation Analysis

Pearson Product Moment Correlation analysis was conducted to evaluate the strength and direction of relationships between $PM_{2.5}$ concentrations and meteorological variables. Prior to correlation analysis, data normality was assessed using the Shapiro Wilk test.

2.4.3 Multiple Linear Regression Analysis

Multiple linear regression analysis was employed to quantify the influence of relative humidity and visibility on $PM_{2.5}$ concentrations. Because the primary objective of the study was to examine the extent to which atmospheric moisture conditions and visibility impairment explain variations in fine particulate matter concentrations, a hierarchical modeling approach was adopted.

(a) Model 1: Relative Humidity as a Predictor of $PM_{2.5}$

The first model evaluated the independent influence of relative humidity on $PM_{2.5}$ concentrations:

$$PM_{2.5} = \beta_0 + \beta_1 (RH) + \varepsilon$$

Where: $PM_{2.5}$ = fine particulate matter concentration (µg m^{-3}), RH = relative humidity (%), β_0 = regression intercept, β_1 = regression coefficient, ε = random error term. This model was used to determine the extent to which atmospheric moisture alone contributes to observed variability in $PM_{2.5}$ concentrations.

(b) Model 2: Relative Humidity and Visibility Model

The second model incorporated visibility as an additional explanatory variable:

$$PM_{2.5} = \beta_0 + \beta_1 (RH) + \beta_2 (Vis) + \varepsilon$$

Where: Vis = horizontal visibility (km).

This model represents the principal analytical framework of the study because it directly evaluates the combined influence of relative humidity and visibility on particulate matter concentrations.

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DOI: https://doi.org/10.64388/IREV10I1-1720211

Changes in the coefficient of determination (R^2) between Models 1 and 2 were used to assess the additional explanatory power provided by visibility.

(c) Model 3: Meteorological Control Model

A third model was developed by introducing temperature as a control variable:

$$PM_{2.5} = \beta_0 + \beta_1 (RH) + \beta_2 (Vis) + \beta_3 (Temp) + \varepsilon$$

Where: Temp = ambient temperature (°C).

This model was used to determine whether the relationships between $PM_{2.5}$, relative humidity, and visibility remained significant after accounting for thermal atmospheric conditions. Model performance was evaluated using the coefficient of determination (R^2), adjusted R^2, root mean square error (RMSE), and F-statistics. Statistical significance of regression coefficients was assessed at the 95% confidence level ($p < 0.05$). To ensure model reliability, residual diagnostics were performed to verify normality, homoscedasticity, and independence of errors. Multicollinearity among explanatory variables was assessed using the variance inflation factor (VIF), with values greater than 5 indicating potential multicollinearity concerns.

2.4 Air Quality Assessment

Observed $PM_{2.5}$ concentrations were evaluated against the World Health Organization (WHO) Air Quality Guidelines (WHO, 2021) to assess compliance with recommended exposure limits. For public health interpretation, $PM_{2.5}$ concentrations were further converted to the United States environmental protection agency (U.S. EPA) air quality index (AQI) using the standard breakpoint interpolation equation:

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

Where: (I_p) is the AQI value, (C_p) is the observed $PM_{2.5}$ concentration, (BP_{high}) and (BP_{low}) represent concentration breakpoints, (I_{high}) and (I_{low}) represent corresponding AQI breakpoints. AQI values were classified into the EPA categories of Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous. Weekly AQI estimates were aggregated into monthly means to examine seasonal patterns. Observed concentrations were also benchmarked against the WHO 2021 Global Air Quality Guidelines of 15 µg/m³ for 24 hour $PM_{2.5}$ and 5 µg/m³ for annual mean.

2.5 Seasonal Analysis

To investigate seasonal variability, weekly observations were grouped into climatological seasons and compared using one way analysis of variance (ANOVA). Where significant differences were detected, Tukey's honestly significant difference (HSD) test was applied for pairwise comparisons.

2.6 Trend and Time Series Analysis

Temporal variations in $PM_{2.5}$ concentrations were evaluated using additive seasonal decomposition techniques. The $PM_{2.5}$ time series was decomposed into trend, seasonal, and residual components to identify long term patterns and recurring seasonal signals. A 12 week moving average was additionally applied to smooth short term fluctuations and highlight persistent pollution episodes associated with meteorological conditions.

III. RESULTS

3.1 Descriptive Characteristics of $PM_{2.5}$ and Meteorological Variables

A total of 209 weekly observations collected between January 2022 and December 2025 were analyzed. Descriptive statistics for $PM_{2.5}$ concentration, relative humidity, temperature, and visibility are presented in Table 5.

Table 5: Descriptive statistics of variables from (2022-2025).

Variables	Mean Value	Standard Deviation	Minimum	Maximum	First Quartile	Third Quartile

$PM_{2.5}$ (µg m⁻³)	23.31	24.92	3.74	247.22	11.29	23.99
Humidity (%)	73.06	14.95	36.00	100.00	63	82
Temperature (°C)	31.23	1.60	28.00	35.00	30	33
Visibility (Km)	39.68	20.80	6.50	120.80	24.7	53.8

The average $PM_{2.5}$ concentration (23.31 µg m^{-3}) exceeded the WHO annual guideline value of 5 µg m^{-3} by more than fourfold, indicating persistent particulate pollution throughout the study period. Considerable variability was observed, with concentrations ranging from 3.74 to 247.22 µg m^{-3}. Relative humidity remained consistently high, averaging 73.06%, reflecting the humid tropical climate of the Niger Delta region.

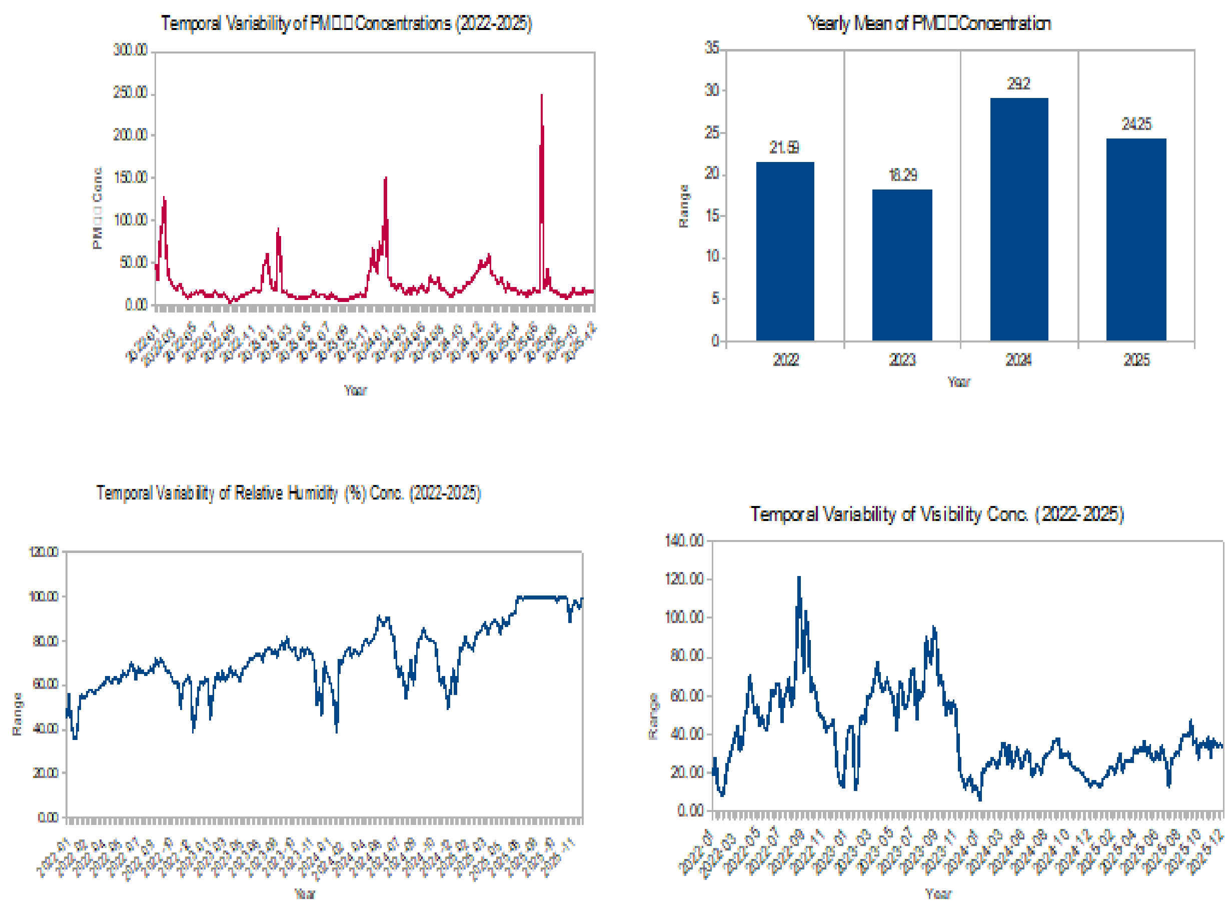

Figure 2: Weekly/Monthly Time Series of $PM_{2.5}$, RH and Visib. Conc. (2022-2025)

Figure 2 illustrates the temporal variation in $PM_{2.5}$ concentrations between 2022 and 2025. Pronounced fluctuations were observed throughout the study period, with elevated concentrations occurring predominantly during the dry season and lower concentrations during wet season months. Several

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DOI: https://doi.org/10.64388/IREV10I1-1720211

pollution episodes exceeding 100 µg m^{-3} were recorded, indicating periods of severe particulate pollution

3.2 Correlation between $PM_{2.5}$, Relative Humidity, Visibility, and Temperature

Pearson correlation analysis revealed statistically significant relationships between $PM_{2.5}$ concentrations and the examined meteorological variables.

Table 6: Pearson correlation coefficients between $PM_{2.5}$ and meteorological parameters.

Variables	Correlation Coefficient (r)	p-value
Humidity (%)	-0.286	<0.001
Visibility (Km)	-0.515	<0.001
Temperature (°C)	0.208	0.003

$PM_{2.5}$ exhibited a weak to moderate negative correlation with relative humidity ($r = -0.286$, $p < 0.001$), indicating that particulate concentrations generally declined with increasing atmospheric moisture. A stronger negative relationship was observed between $PM_{2.5}$ and visibility ($r = -0.515$, $p < 0.001$), suggesting that periods of elevated particulate loading were associated with reduced atmospheric clarity. Temperature showed a weak positive relationship with $PM_{2.5}$ ($r = 0.208$, $p = 0.003$).

3.3 Multiple Linear Regression Analysis

(a) Influence of Relative Humidity on $PM_{2.5}$ Concentrations

Model 1 examined the independent influence of relative humidity on $PM_{2.5}$ concentrations.

[PM_(2.5) = 58.11- 0.476 (RH)]

The model explained 8.2% of the observed variability in $PM_{2.5}$ concentrations ($R^2 = 0.082$). The regression coefficient indicated that a 1% increase in relative humidity was associated with an average decrease of approximately 0.48 µg m^{-3} in $PM_{2.5}$ concentration. Although statistically significant, the relatively low explanatory power suggests that additional atmospheric factors contribute to $PM_{2.5}$ variability in the study area.

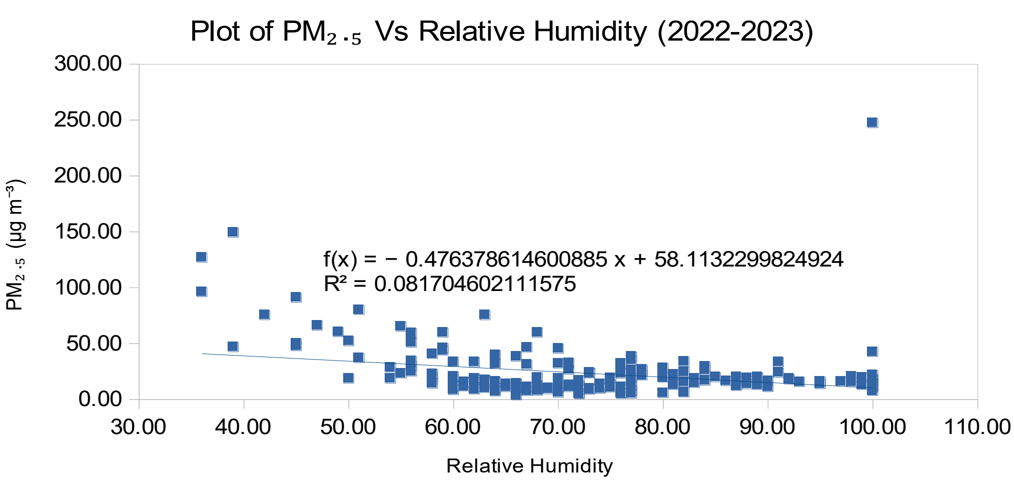

Figure 3: scatter plots of PM2.5 and humidity

(b) Combined Influence of Relative Humidity and Visibility on $PM_{2.5}$

Model 2 incorporated visibility alongside relative humidity.

[PM_(2.5) = 83.14 - 0.483 (RH) - 0.619 (Vis)]

The model explained 34.9% of the total variation in $PM_{2.5}$ concentrations ($R^2 = 0.349$; Adjusted $R^2 = 0.343$). Compared with model 1, inclusion of visibility increased the explanatory power by approximately 27 percentage points. Visibility emerged as the stronger predictor, with each 1 km

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DOI: https://doi.org/10.64388/IREV10I1-1720211

increase in visibility corresponding to a decrease of approximately 0.62 µg m⁻³ in $PM_{2.5}$ concentration.

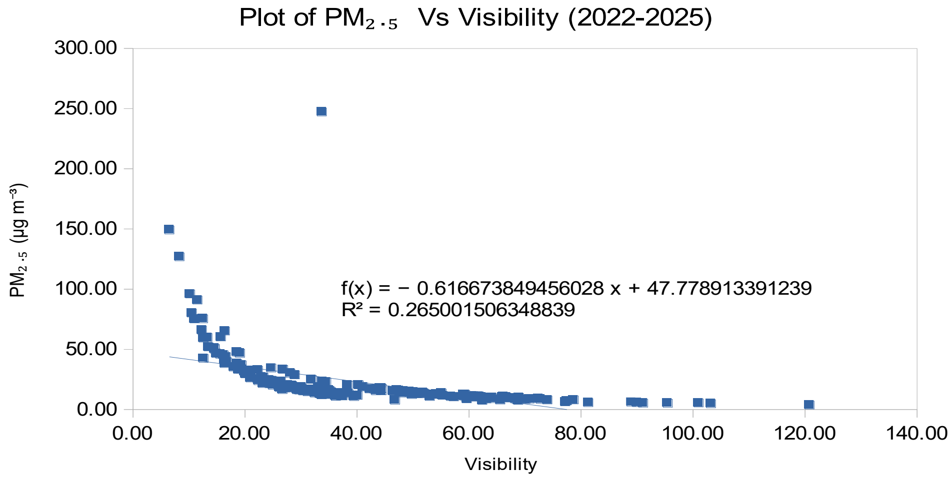

Figure 4: scatter plots of PM2.5 and Visibility

(c) Meteorological Control Model
A third model included temperature as a control variable.

[PM_(2.5) = 166.69 - 0.559 (RH) - 0.703 (Vis) - 2.391 (Temp)]

This model explained 36.6% of $PM_{2.5}$ variability ($R^2 = 0.366$; Adjusted $R^2 = 0.356$).

The modest increase in explanatory power relative to model 2 indicates that temperature contributed only marginally to model performance. Relative humidity and visibility remained the dominant predictors of $PM_{2.5}$ concentrations.

3.4 Air Quality Index (AQI) Assessment
AQI classifications followed the EPA six category scales: Good (0-50), Moderate (51-100), Unhealthy for Sensitive Groups (101-150), Unhealthy (151-200), Very Unhealthy (201-300), and Hazardous (301-500).

Table 7: .Distribution of $PM_{2.5}$ Air Quality Index (AQI) Categories in Edo State, Nigeria (2022-2025)

AQI Category	$PM_{2.5}$ Range (µg m⁻³)	Frequency (n)	Percentage (%)
Good	0.0 - 12.0	57	27.3
Moderate	12.1 - 35.4	123	58.9
Unhealthy for Sensitive Groups (USG)	35.5 - 55.4	15	7.2
Unhealthy	55.5 - 150.4	13	6.2
Very Unhealthy	150.5 - 250.4	1	0.5
Hazardous	≥ 250.5	0	0.0
Total	-	209	100.0

AQI classification revealed that the majority of $PM_{2.5}$ observations fell within the moderate category (58.9%), followed by the good category (27.3%). Approximately 13.9% of observations were classified as unhealthy for sensitive groups, unhealthy, or very unhealthy, indicating recurring episodes of degraded air quality and elevated health risks. Only one observation (0.5%) reached the very unhealthy category, while no observations were classified as hazardous. These findings suggest that although air quality was generally within the good to moderate range, periodic pollution episodes occurred that may adversely affect sensitive populations, including children, the elderly, and individuals with pre existing respiratory or cardiovascular conditions

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DOI: https://doi.org/10.64388/IREV10I1-1720211

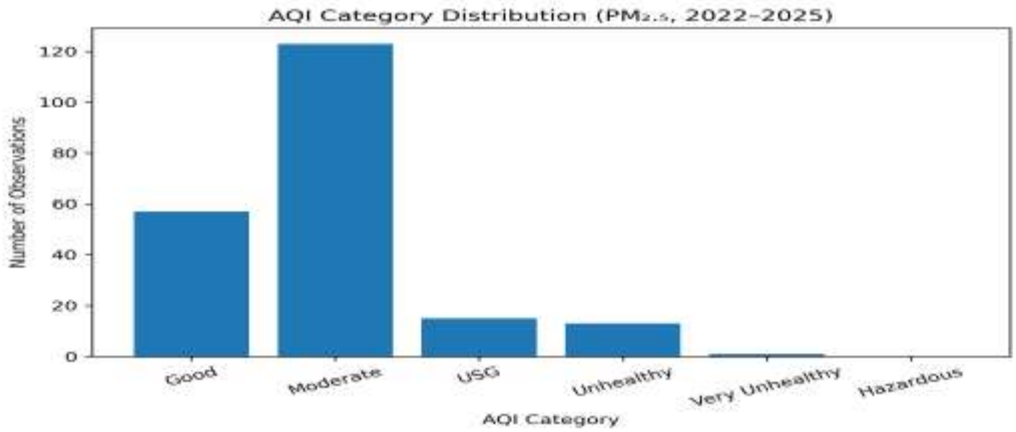

Figure 5: Distribution of $PM_{2.5}$ Air Quality Index (AQI) categories.

3.5 Seasonal Variability of $PM_{2.5}$ Concentrations

Table 8: Seasonal Mean $PM_{2.5}$ Concentrations in Edo State, Nigeria (2022-2025)

Season	Mean $PM_{2.5}$ (µg m^{-3})
Dry Season (Nov-Mar)	33.86
Early Wet Season (Apr-Jul)	18.60
Late Wet Season (Aug-Oct)	12.01

This illustrates the seasonal distribution of $PM_{2.5}$ concentrations in Edo State between 2022 and 2025, demonstrating the strong influence of seasonal atmospheric conditions on particulate pollution levels. The dry season recorded the highest median $PM_{2.5}$ concentration nearly three times greater than that observed during the late wet season alongside the widest interquartile range, indicating both elevated particulate pollution and greater variability during this period. Several high value outliers were also observed during the dry season, suggesting episodic pollution events associated with unfavorable dispersion conditions and increased particulate accumulation. In contrast, the late wet season recorded the lowest median concentration and a narrower distribution, reflecting the influence of rainfall induced atmospheric cleansing processes.

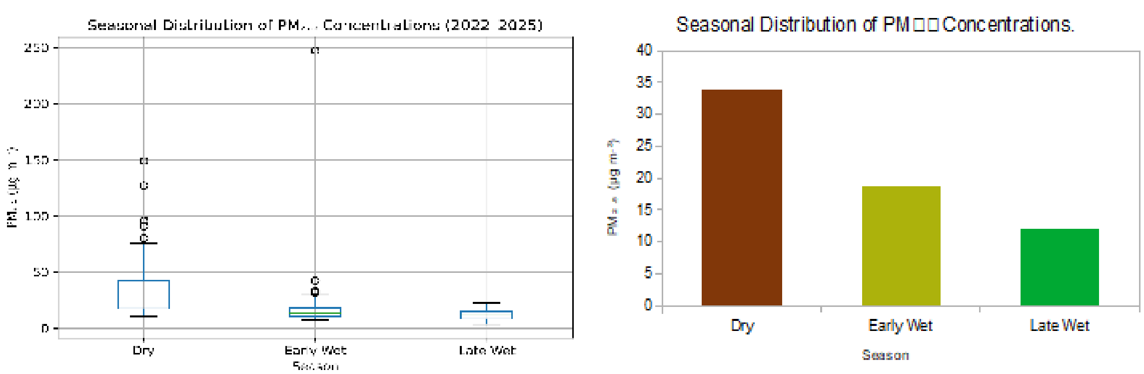

Figure 6: Seasonal distribution of $PM_{2.5}$ concentrations.

Boxplots show the distribution of weekly $PM_{2.5}$ concentrations grouped into dry (November-March), early wet (April-July), and late wet (August-October) seasons. The central line represents the median, the box indicates the interquartile range (IQR), whiskers represent data variability outside the upper and lower quartiles, and individual points denote outliers

Table 9: One-Way ANOVA for Seasonal Variations in $PM_{2.5}$ Concentrations

Source of Variation	Sum of Squares (SS)	Df	Mean Square (MS)	F-value	p-value
Between Seasons	17,884.27	2	8,942.13	16.55	<0.001
Within Seasons (Error)	111,279.85	206	540.19		
Total	129,164.11	208			

The one way ANOVA revealed a statistically significant difference in mean $PM_{2.5}$ concentrations among the three climatological seasons ($F(2,206) = 16.55$, $p < 0.001$), indicating that seasonal atmospheric conditions exert a significant influence on particulate matter concentrations in Benin City. The magnitude of the seasonal effect was assessed using eta-squared (η^2). The analysis yielded an η^2 value of 0.138, indicating that approximately 13.8% of the total variance in $PM_{2.5}$ concentrations was attributable to seasonal differences. According to conventional benchmarks for effect size interpretation, this represents a moderate effect, suggesting that seasonality is an important determinant of $PM_{2.5}$ variability in the study area.

Table 10: Seasonal Mean $PM_{2.5}$ Concentrations and Tukey HSD Grouping

Season	N	Mean $PM_{2.5}$ ($\mu g\ m^{-3}$)	Group
Dry Season (Nov-Mar)	87	33.86	a
Early Wet Season (Apr-Jul)	70	18.60	b
Late Wet Season (Aug-Oct)	52	12.01	b

Means sharing the same letter are not significantly different at $p < 0.05$.

The Tukey HSD grouping revealed that the dry season constituted a distinct statistical category (Group a), while the early and late wet seasons were classified within the same statistical group (Group b). This finding indicates that seasonal variations in $PM_{2.5}$ concentrations are primarily driven by the transition between dry and wet atmospheric conditions. The lack of significant differences between the two wet season periods suggests that rainfall induced scavenging and elevated atmospheric moisture exert similar controls on particulate matter concentrations throughout the wet season

Table 11: Tukey Honestly Significant Difference (HSD) Pairwise Comparisons

Comparison	Mean Difference ($\mu g\ m^{-3}$)	Lower CI	Upper CI	p-value	Significant
Dry Season - Early Wet Season	15.26	24.07	6.45	<0.001	Yes
Dry Season - Late Wet Season	21.85	31.47	12.24	<0.001	Yes
Early Wet Season - Late Wet Season	6.59	16.64	3.45	0.270	No

Post hoc Tukey HSD analysis showed that $PM_{2.5}$ concentrations during the dry season were significantly higher than those recorded during both the early wet season (mean difference = 15.26 $\mu g\ m^{-3}$, $p < 0.001$) and the late wet season (mean difference = 21.85 $\mu g\ m^{-3}$, $p < 0.001$). However, no statistically significant difference was observed between the early wet and late wet seasons ($p = 0.270$).

3.6 Trend and Time Series Analysis

The trend and time series analysis presents the temporal evolution of $PM_{2.5}$ concentrations between 2022 and 2025 together with the 12 week moving

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DOI: https://doi.org/10.64388/IREV10I1-1720211

average. Considerable short term fluctuations were observed throughout the study period, reflecting variations in meteorological conditions and emission patterns. The moving average smoothed these short term variations and revealed persistent pollution episodes characterized by sustained increases in $PM_{2.5}$ concentrations. Elevated particulate levels were generally associated with dry season periods, while lower concentrations were observed during wetter months, suggesting the influence of atmospheric scavenging and enhanced dispersion processes

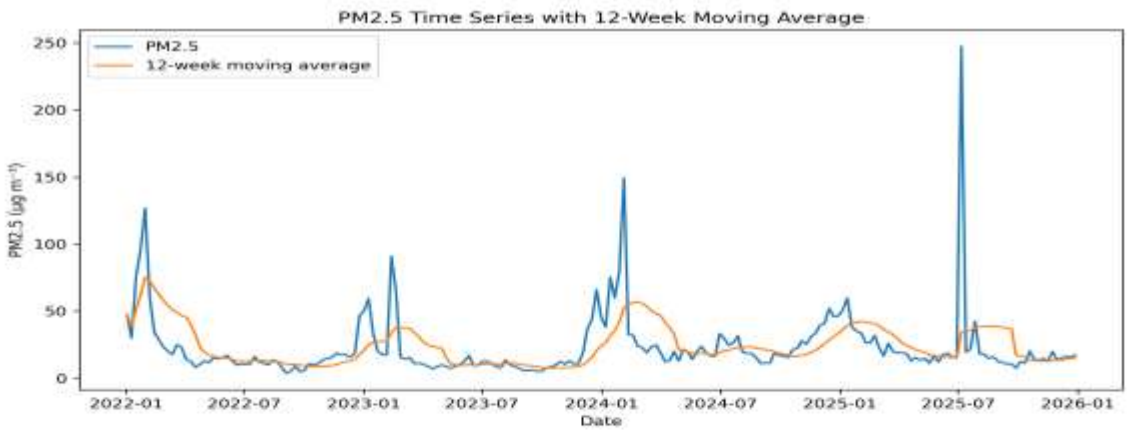

Figure 7: Weekly $PM_{2.5}$ Concentrations and 12-Week Moving Average (2022–2025)

3.6.1 Seasonal Decomposition of $PM_{2.5}$ Concentrations

Figure 5 below shows the additive decomposition of the $PM_{2.5}$ time series into trend, seasonal, and residual components. The trend component reveals the underlying long term variation in particulate matter concentrations after removing seasonal effects and random fluctuations. The seasonal component indicates recurring annual patterns in $PM_{2.5}$ concentrations, with systematic increases during the dry season and reductions during wetter periods. The residual component represents unexplained variability that may be attributable to episodic pollution events, local emission sources, or short-term meteorological disturbances not captured by the seasonal pattern

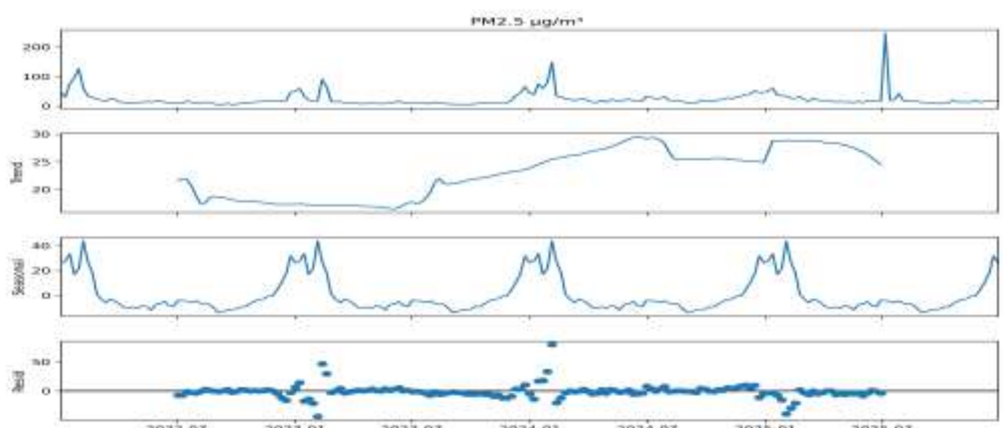

Figure 8: Seasonal Decomposition of $PM_{2.5}$ Concentrations

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IV. DISCUSSION

This study examined the influence of relative humidity and visibility on $PM_{2.5}$ concentrations in Benin City, Edo State, using four years (2022-2025) of continuous ground based observations. The findings revealed persistent particulate matter pollution, with a mean $PM_{2.5}$ concentration of 23.31 µg m^{-3}, exceeding the World Health Organization (WHO) annual guideline value of 5 µg m^{-3} by more than fourfold. These elevated concentrations indicate sustained exposure of the urban population to fine particulate pollution and reflect the combined influence of vehicular emissions, fossil fuel combustion, electricity generator use, biomass burning, industrial activities, and regional atmospheric transport associated with oil and gas operations within the Niger Delta. The observed inverse relationship between $PM_{2.5}$ concentrations and relative humidity ($r = -0.286$, $p < 0.001$) suggests that atmospheric moisture plays an important role in regulating particulate pollution in the humid tropical environment of southern Nigeria. While studies conducted in several Asian megacities have reported positive associations between particulate matter and relative humidity due to hygroscopic aerosol growth, the present findings indicate a different atmospheric response. In Benin City, elevated relative humidity is typically associated with increased cloud formation, rainfall occurrence, and enhanced wet deposition processes, all of which facilitate the removal of suspended particles from the atmosphere. Consequently, periods characterized by higher atmospheric moisture tend to exhibit lower $PM_{2.5}$ concentrations owing to more efficient atmospheric cleansing. Among all meteorological variables examined, visibility emerged as the strongest predictor of $PM_{2.5}$ variability. The moderate negative correlation between $PM_{2.5}$ and visibility ($r = -0.515$, $p < 0.001$) demonstrates that increasing particulate concentrations substantially impair atmospheric transparency through enhanced light scattering and absorption. This finding is consistent with previous studies conducted in tropical and subtropical regions, where aerosol loading has been identified as a major determinant of visibility degradation. The strong statistical relationship observed in this study suggests that visibility measurements may provide a useful surrogate indicator of particulate pollution in locations where continuous PM monitoring infrastructure remains limited. The regression analysis further highlighted the importance of meteorological controls on $PM_{2.5}$ concentrations. Relative humidity alone accounted for 8.2% of the observed variability in $PM_{2.5}$ concentrations, indicating that moisture related removal processes exert a measurable but limited influence on particulate levels. However, the addition of visibility substantially improved model performance, increasing the explanatory power of the model to 34.9%. The inclusion of temperature resulted in only a marginal improvement in prediction accuracy, confirming that visibility and relative humidity are the dominant meteorological determinants of $PM_{2.5}$ concentrations in the study area. These results emphasize the close interaction between aerosol loading, atmospheric moisture, and optical conditions in humid tropical environments. Seasonal analyses demonstrated pronounced temporal variability in particulate matter concentrations. $PM_{2.5}$ concentrations were significantly higher during the dry season than during either wet season period, as confirmed by both ANOVA and Tukey HSD analyses. The dry season recorded the highest particulate levels, whereas the late wet season exhibited the lowest concentrations. This seasonal pattern can be attributed to reduced precipitation, weaker atmospheric scavenging, increased atmospheric stability, and greater accumulation of locally emitted pollutants during dry months. In contrast, enhanced rainfall during the wet season promotes efficient washout and rainout processes that remove particulate matter from the atmosphere. The absence of a statistically significant difference between the early and late wet seasons suggests that both periods experience comparable atmospheric removal efficiencies despite differences in rainfall distribution and intensity. The time series and seasonal decomposition analyses further confirmed the dominant role of seasonality in controlling $PM_{2.5}$ dynamics in Edo State. The decomposition results revealed a clear recurring seasonal signal characterized by elevated concentrations during dry months and lower concentrations during wetter periods. The 12 week moving average analysis identified persistent pollution episodes extending beyond individual weeks, indicating that meteorological conditions exert sustained influences on air quality. These findings corroborate the seasonal statistical analyses and highlight the importance of atmospheric processes in shaping particulate matter variability across the study period. The AQI assessment revealed that although a substantial proportion of observations fell within the good and moderate categories, recurrent episodes of unhealthy for sensitive groups and unhealthy conditions occurred throughout the study period. Such episodes may pose considerable health risks to vulnerable populations, including children, older adults, and individuals with preexisting respiratory or cardiovascular diseases. The frequent exceedance of WHO guideline values underscores the need for enhanced air quality management and public health interventions within the rapidly urbanizing environment of Benin City. Overall, the study demonstrates that visibility and relative humidity are critical meteorological determinants of $PM_{2.5}$ variability in Benin City and the wider Niger Delta region. The findings provide empirical evidence supporting the integration of meteorological information into air quality forecasting systems and pollution mitigation strategies. Strengthening monitoring infrastructure, controlling urban emission sources, and incorporating visibility-based indicators into environmental management frameworks may contribute significantly to improving air quality and protecting public health in southern Nigeria.

V. CONCLUSION

This study evaluated the influence of relative humidity and visibility on $PM_{2.5}$ concentrations in Edo State, Nigeria, using weekly ground based observations collected between 2022 and 2025. The results revealed persistent particulate pollution, with a mean $PM_{2.5}$ concentration of 23.31 $\mu g\ m^{-3}$, exceeding the World Health Organization (WHO) annual guideline value by more than fourfold. These findings indicate sustained exposure to elevated particulate matter concentrations and highlight the need for improved air quality management within the study area. Both relative humidity and visibility exhibited significant inverse relationships with $PM_{2.5}$ concentrations, although visibility emerged as the strongest meteorological predictor ($r = -0.515$, $p < 0.001$). Regression analysis demonstrated that relative humidity alone explained only a modest proportion of $PM_{2.5}$ variability, whereas the combined relative humidity visibility model accounted for 34.9% of the observed variation in particulate concentrations. The inclusion of temperature provided only a marginal improvement in model performance, confirming the dominant influence of visibility and atmospheric moisture on $PM_{2.5}$ dynamics in the humid tropical environment of southern Nigeria. Seasonal analyses revealed significant differences in $PM_{2.5}$ concentrations across atmospheric seasons, with the dry season recording substantially higher particulate levels than both wet season periods. The absence of significant differences between the early and late wet seasons suggests that seasonal changes in particulate pollution are primarily driven by the transition between dry and wet atmospheric regimes rather than variations within the wet season itself. Time series decomposition further confirmed the presence of recurring seasonal cycles and persistent pollution episodes linked to prevailing meteorological conditions. Overall, the study demonstrates that visibility and relative humidity are critical determinants of $PM_{2.5}$ variability in Edo State and may serve as valuable indicators for air quality forecasting in regions with limited monitoring infrastructure. The findings contribute to the growing body of evidence on particulate pollution in the Niger Delta and provide a scientific basis for integrating meteorological parameters into air quality assessment and management frameworks. Strengthening emission control measures, expanding ground based monitoring networks, and incorporating meteorological information into environmental planning and public health strategies are recommended to reduce particulate pollution and improve air quality in rapidly urbanizing cities of southern Nigeria.

VI. RECOMMENDATIONS

6.1 Air Quality Monitoring and Data Management

The findings demonstrate the need for strengthening air quality monitoring infrastructure across Edo State and the wider Niger Delta region. Additional ground based monitoring stations should be established to provide continuous measurements of particulate matter and meteorological parameters. Integrating visibility and relative humidity observations into routine monitoring programs could improve pollution forecasting and early warning systems, particularly in locations where direct $PM_{2.5}$ measurements are unavailable.

6.2 Emission Control Strategies
Environmental regulatory agencies should implement stricter control measures targeting major sources of particulate emissions, including vehicular exhaust, open waste burning, diesel and petrol generators, biomass combustion, and industrial activities. Particular attention should be given to reducing emissions during the dry season when particulate matter concentrations are significantly elevated and atmospheric dispersion conditions are less favorable.

6.3 Public Health Protection
Public awareness programs should be developed to inform residents about the health risks associated with prolonged exposure to elevated $PM_{2.5}$ concentrations. During periods of poor air quality, especially when visibility is substantially reduced, vulnerable groups such as children, older adults, pregnant women, and individuals with respiratory or cardiovascular diseases should be advised to limit outdoor activities.

6.4 Integration of Meteorological Parameters into Forecasting Systems
Given that visibility emerged as the strongest meteorological predictor of $PM_{2.5}$ concentrations, environmental agencies should incorporate visibility and relative humidity measurements into operational air quality forecasting models. Such integration would enhance the prediction of pollution episodes and support timely public health advisories in data limited regions.

6.5 Policy and Environmental Management
Government agencies should strengthen the enforcement of existing environmental regulations aimed at controlling particulate emissions. Urban planning strategies should promote cleaner transportation systems, improved waste management practices, and increased adoption of renewable energy technologies to reduce dependence on fossil fuel powered generators.

6.6 Future Research
Future studies should:

i. Investigate the influence of additional meteorological variables such as wind speed, atmospheric pressure, and boundary layer height on $PM_{2.5}$ variability, since the present study focused primarily on seasonal rainfall driven patterns.

ii. Conduct source apportionment analyses to distinguish contributions from traffic emissions, biomass burning, industrial activities, and regional transport, as the current study characterized seasonal concentration trends without identifying specific emission sources.

iii. Examine the chemical composition of $PM_{2.5}$ to better understand the toxicity and associated health implications of particulate pollution in the Niger Delta, building on the concentration-based assessment presented here.

iv. Employ satellite observations and atmospheric dispersion models to complement ground-based measurements, thereby improving regional scale assessments beyond the single state focus of this study.

v. Model atmospheric dispersion and stagnation conditions during the dry season to better characterize the episodic high value outliers identified in this study.

vi. Explore the long term impacts of climate variability and land use change on particulate matter concentrations and visibility conditions, extending the 2022-2025 observation window used here.

VII. ACKNOWLEDGMENTS:

The authors would like to express their sincere gratitude to the Space Earth Environment Research Laboratory, Center for Atmospheric Research, University of Benin Campus, Benin City, for the provision of data for this research and the Space

Environmental Unit, Physical and Life Science Department, National Space Research and Development Agency (NASRDA), Olusegun Obasanjo Space Centre along the airport road in the capital city Abuja, Nigeria, for providing an enabling environment for this research.

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