International Journal of Advanced Statistics and Probability, 11 (2) (2024) 108-123

International Journal of Advanced Statistics and Probability

Website: www.sciencepubco.com/index.php/IJASP

Research paper

Air Quality Trends and Pollution Analysis in Nigerian Cities Using Time Series Methods

AKANJI A. R. [1*], **FRANCIS M. O.** [2] **and AKINTOLA A. F.** [3]

[1,2]*Department of Mathematical Sciences, Bingham University Karu, Nasarawa, Nigeria.*
[3]*Department of Mathematics and Statistics, Redeemer's University, Ede, Osun State, Nigeria*
[*]*Corresponding author E-mail:ayodele.jolayemi@binghamuni.edu.ng*

Abstract

Air pollution is a significant environmental and public health issue in rapidly urbanizing cities, particularly in developing countries like Nigeria. This study analyzes air quality trends in five major Nigerian cities Abuja, Lagos, Kano, Port Harcourt, and Enugu using satellite-based remote sensing data from January 2021 to December 2023. Key pollutants, including $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and O_3, were analyzed using time series models (ARIMA, SARIMA), seasonal decomposition (STL), and correlation analysis. The results reveal that Lagos and Kano experience the highest pollution levels, particularly during the Harmattan season, when Saharan dust exacerbates particulate matter. Abuja also sees significant pollution spikes, while Port Harcourt and Enugu show moderate pollution driven by industrial emissions and traffic. The study underscores the need for better air quality monitoring, seasonal interventions, and policies to reduce pollution, particularly during Harmattan.

Keywords: *Air Pollution,Particulate Matter ($PM_{2.5}$),Satellite Remote Sensing,Seasonal Decomposition,Urban Air Quality Management*

1. Introduction

Air pollution remains one of the most critical environmental challenges of the 21st century, with profound and far-reaching consequences for public health, ecosystems, and economic development. According to the World Health Organization (WHO, 2018), ambient air pollution is responsible for approximately 4.2 million premature deaths globally each year, with urban areas disproportionately affected due to rapid industrialization, population growth, and vehicular emissions. In developing countries, the challenges of air quality are compounded by poorly implemented environmental policies, high population densities, and limited monitoring networks [11]. In Nigeria, urban population growth is escalating, with urban areas currently home to 55.5% of the population, projected to increase to 68% by 2050 [19, **?**]. This increasing urbanization exacerbates existing pollution levels, particularly in key metropolitan areas like Abuja, Lagos, Kano, Port Harcourt, and Enugu, where vehicular emissions and industrial activity are prominent contributors to air quality degradation [1, 13]. Air pollutants such as nitrogen dioxide (NO_2), carbon monoxide (CO), particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3), and sulfur dioxide (SO_2) are known to have severe effects on human health. Long-term exposure to these pollutants is linked to respiratory diseases, cardiovascular disorders, and premature mortality [3, 10]. In particular, particulate matter ($PM_{2.5}$ and PM_{10}) poses significant health risks, as these fine particles can penetrate deep into the lungs, entering the bloodstream and increasing the risk of chronic conditions such as asthma, bronchitis, and even lung cancer [16]. A recent study by the Health Effects Institute (2019) reported that Nigeria ranks among the countries with the highest pollution levels in Africa, and in fact, it is fourth globally in terms of pollution-related mortality, with 1500 deaths per million annually attributed to poor air quality. Cities such as Lagos, Abuja, and Kano have been identified as hotspots for pollution, where population density, vehicular emissions, and industrial activities converge to worsen air quality [1, 13]. In Abuja, the nation's capital, rapid urbanization and increasing vehicular density have contributed to elevated levels of pollutants like $PM_{2.5}$, PM_{10}, and CO, particularly during the dry Harmattan season. Harmattan, a seasonal wind that sweeps dust from the Sahara Desert into West Africa, exacerbates air pollution, leading to hazardous air quality levels [14]. Effective air quality monitoring is critical for understanding and mitigating the public health and environmental impacts of pollution. However, many Nigerian cities, including Abuja, Lagos, and Kano, lack comprehensive air quality monitoring systems. Most data collection relies on satellite-based remote sensing and sporadic ground-level observations [7, 12]. Remote sensing technologies, such as the TROPOMI Sentinel-5P and the VIIRS satellites, offer valuable insights into pollution patterns, enabling spatiotemporal analyses that can inform policymaking [9, 8]. While satellite-based monitoring is useful, it is often limited in its ability to capture real-time local variations in air quality, and thus, a more integrated approach is needed.

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Time series analysis offers an effective tool for identifying long-term trends, seasonal variations, and forecasting future pollution levels. Methods such as ARIMA (Auto-Regressive Integrated Moving Average) and Seasonal-Trend Decomposition using Loess (STL) have been successfully applied in studies of urban air quality to capture complex pollution patterns, assess seasonal effects, and predict pollutant concentrations [17, 5]. These methods are especially valuable in regions like Nigeria, where ground-based monitoring data is sparse or inconsistent. By applying time series models to AQI data from Abuja, Lagos, Kano, Port Harcourt, and Enugu, this study aims to fill an important gap in the existing literature, providing an analysis of trends and forecasts for air quality that can guide future urban environmental policies. In urban areas, particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3) are the primary pollutants that impact air quality [20, 2]. Among these, $PM_{2.5}$ and PM_{10} are of particular concern, as these fine particles can deeply penetrate the lungs and enter the bloodstream, contributing to a range of chronic diseases, including respiratory and cardiovascular diseases, and increasing the risk of premature death [16]. The increasing levels of $PM_{2.5}$ and PM_{10} in cities like Abuja, Lagos, and Kano have been linked to vehicular emissions, industrial activities, and natural dust storms such as the Harmattan [2, 14]. The ongoing challenge of addressing air pollution in Nigerian cities requires comprehensive air quality monitoring and effective data analysis techniques to assess and mitigate its impacts. The AQI is a widely used tool for communicating air quality levels to the public and policymakers. The AQI scale, which ranges from 0 to 500, combines the concentrations of key pollutants ($PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and O_3) into a single numerical score. Lower values represent better air quality, while higher values indicate worse air quality, often posing significant health risks [18].

In Nigeria, AQI data are typically collected by environmental agencies, including the National Environmental Standards and Regulations Enforcement Agency (NESREA) and local monitoring stations in cities such as Abuja, Lagos, Kano, and Port Harcourt [20]. However, the lack of consistent, long-term AQI data has hindered efforts to evaluate air quality trends and seasonal variations comprehensively. Previous studies have highlighted the need for more robust and systematic monitoring of air quality in Nigerian cities [2]. This study seeks to address this gap by applying advanced time series analysis methods to AQI data from Abuja, Lagos, Kano, Port Harcourt, and Enugu, with the goal of assessing long-term trends, seasonal variations, and forecasting future air quality conditions. Time series analysis is an essential tool for identifying temporal patterns in air quality data. Various time series models, such as ARIMA, SARIMA (Seasonal ARIMA), and exponential smoothing, have been widely applied to air quality data to forecast trends, assess seasonal variations, and predict future pollutant concentrations [17, 5]. ARIMA models are particularly useful in capturing temporal dependencies and providing accurate forecasts by incorporating the autoregressive (AR), moving average (MA), and differencing (I) components of the time series [4]. In urban air quality studies, ARIMA models have been applied successfully in cities like Beijing [5], New Delhi [17], and São Paulo [15] to predict pollution trends and provide actionable insights for public health and policy planning. Seasonal decomposition techniques, such as STL, have also been widely used to examine the seasonal fluctuations in AQI data, providing insights into the effects of seasonal events like Harmattan dust storms on air quality [6, 14]. These models can help policymakers better understand the dynamics of air pollution, identify high-risk periods, and implement effective pollution control measures.

This study aims to apply ARIMA, seasonal decomposition, and exponential smoothing techniques to AQI data for Abuja, Lagos, Kano, Port Harcourt, and Enugu from 2021 to 2023. By analyzing long-term trends, seasonal variations, and forecasting future AQI values, this research will provide valuable insights into the air quality dynamics of Nigeria's key urban centers. The findings will inform future policy decisions aimed at improving urban air quality, protecting public health, and mitigating the impacts of air pollution.

2. Methods

2.1. Study Area

This study examines air quality dynamics in five major Nigerian cities: Abuja, Lagos, Kano, Port Harcourt, and Enugu. These cities were selected due to their significant urbanization, industrialization, and vehicular emissions, making them representative of diverse pollution sources, including industrial activities, traffic emissions, and natural dust storms. The geographic coordinates of these cities, as presented in Table 1, are indicative of their spatial and socioeconomic characteristics that influence air quality.

City	State	Latitude (°)	Longitude (°)
Abuja	Federal Capital Territory	9.0575	7.4951
Lagos	Lagos State	6.4541	3.3947
Kano	Kano State	12.0038	8.4948
Port Harcourt	Rivers State	4.7677	7.0189
Enugu	Enugu State	6.4473	7.5135

Table 1: Geographic location and population of the selected cities.

2.2. Data Collection

Data for this study were sourced from satellite-based remote sensing, meteorological parameters, and socioeconomic databases. The primary source of atmospheric pollution data was the *TROPOMI Sentinel-5P* satellite, part of the Copernicus Earth observation program. The TROPOMI satellite provides high-resolution data on key pollutants including nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), and particulate matter ($PM_{2.5}$ and PM_{10}) at daily intervals, with a spatial resolution of 3.5 km × 5.5 km.

These satellite-based measurements were complemented by meteorological data from *NASA's Giovanni platform*, which provided information on temperature (T), relative humidity (RH), and wind speed (WS), crucial for understanding pollutant dispersion patterns. The time period for both datasets spans from January 2021 to December 2023.

Additionally, socioeconomic data, including population and urbanization statistics, were obtained from the *World Population Review* (2022) and the *Nigerian Bureau of Statistics* to assess the relationship between urban growth and air pollution in these cities.

2.3. Data Processing and Quality Control

Raw satellite data from TROPOMI and Giovanni were pre-processed to address issues such as cloud interference and data gaps. The cloud fraction parameter from TROPOMI was used to filter out unreliable measurements, ensuring high accuracy in the final dataset. Where data gaps occurred, linear interpolation was applied to fill missing values for continuous variables. Meteorological data were synchronized with air quality data by matching their temporal resolution (daily averages), allowing for consistent trend analysis across the study period.

2.4. Statistical Analysis

A range of statistical methods was employed to analyze the relationships between air quality and meteorological parameters, and to identify significant trends, patterns, and seasonal variations in air pollution.

2.4.1. Welch's One-Way ANOVA

Welch's One-Way ANOVA was used to compare the means of pollutant concentrations across the five cities. This test does not assume equal variances across groups, making it ideal for datasets with unequal variances. The formula for the Welch's ANOVA statistic is:

$$W = \frac{\sum_{i=1}^{g} W_i(\bar{X}_i - \bar{X})^2}{g-1} \tag{2.1}$$

Where:

- W_i is the weight for group i,
- $\bar{X}_i$ is the mean for group i,
- $\bar{X}$ is the overall mean,
- g is the number of groups.

2.4.2. Pearson's Correlation Analysis

To assess the relationship between pollutant concentrations and meteorological variables, Pearson's correlation coefficient r was calculated. The formula for r is:
Where:

- X_i and Y_i are individual data points for two variables,
- $\bar{X}$ and $\bar{Y}$ are the means of the variables X and Y,
- n is the number of data points.

2.4.3. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was used to reduce the dimensionality of the dataset and identify the main drivers of pollutant concentration. PCA finds the eigenvalues and eigenvectors of the covariance matrix, with the first principal component (PC_1) explaining the maximum variance in the data.
The i-th principal component (PC_i) is calculated as:
The principal components are ranked by their eigenvalues, with the first component explaining the maximum variance in the data.

2.4.4. Time Series Analysis

To analyze long-term trends and seasonal patterns in air quality data, several time series models were applied, including ARIMA (Auto-Regressive Integrated Moving Average), Seasonal ARIMA (SARIMA), and Seasonal-Trend Decomposition using Loess (STL). These methods are particularly useful for identifying patterns over time and forecasting future air quality indices (AQI).

ARIMA Model The ARIMA model was applied to forecast time series data by capturing temporal dependencies. The general form of the ARIMA model is:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Where:

- Y_t is the value of the time series at time t,
- α is a constant,
- ϕ_i are the parameters of the autoregressive (AR) part,
- θ_j are the parameters of the moving average (MA) part,
- ε_t is the residual at time t,
- p is the order of the autoregressive part,
- d is the degree of differencing to make the series stationary,
- q is the order of the moving average part.

Seasonal ARIMA (SARIMA) For datasets exhibiting seasonal patterns, SARIMA models were applied, incorporating seasonal autoregressive and moving average terms. The SARIMA model is written as:

$$(Y_t - \alpha) = \sum_{i=1}^{p} \phi_i (Y_{t-i} - \alpha) + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Where the seasonal components are specified for a given seasonal period (e.g., seasonal impact during Harmattan).

Seasonal-Trend Decomposition using Loess (STL) STL decomposition was used to separate the time series into seasonal, trend, and residual components to better understand seasonal fluctuations in air quality. The decomposition is written as:

$$Y_t = T_t + S_t + R_t$$

Where:

- Y_t is the observed value at time t,
- T_t is the trend component,
- S_t is the seasonal component,
- R_t is the residual (or noise) component.

2.5. Remote Sensing Techniques

Satellite-based remote sensing data from the *TROPOMI Sentinel-5P* satellite were utilized to monitor atmospheric pollutants across urban regions. The pollutants of interest include NO_2, SO_2, O_3, CO, and HCHO, measured in terms of column density (mol/m²). To minimize cloud interference, the cloud fraction parameter was used. Additionally, *VIIRS DNB* (Day/Night Band) data from NOAA/NCEI provided nighttime radiance data, which correlates with urban activities and contributes to pollution levels.

2.6. Software and Tools

Data analysis and statistical computations were performed using *R (version 4.2.1)* and *Python (version 3.10)*. Key libraries for statistical analysis and time series modeling included `pandas`, `numpy`, `statsmodels`, `matplotlib`, and `seaborn` for data visualization. *ArcGIS* was used for spatial mapping of air quality patterns across the cities.

3. Results

This section presents the results from the statistical analyses conducted on the air quality data for five Nigerian cities: Abuja, Lagos, Kano, Port Harcourt, and Enugu. The findings are categorized into four main analyses: descriptive statistics, correlation analysis, principal component analysis (PCA), and time series modeling (ARIMA, SARIMA, STL decomposition). The primary goal of these analyses is to provide insights into the trends, seasonal variations, and key factors influencing air quality in the selected cities.

3.1. Descriptive Statistics of Air Quality Data

The summary statistics for the key pollutants, including $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and O_3, are shown in the tables below. The dataset spans from January 2021 to December 2023, covering both the Harmattan (dry) and wet seasons.

Table 2: Summary Statistics of Air Quality Data for Abuja (2021–2023)

Pollutant	Mean	Std. Deviation	Min	Max
$PM_{2.5}$	97.4	25.5	45.6	184.2
PM_{10}	102.3	26.3	51.2	191.0
CO	42.5	12.1	28.7	72.5
NO_2	25.4	10.4	14.2	42.3
SO_2	15.3	5.8	7.3	24.0
O_3	34.1	9.6	19.5	53.0

Table 3: Summary Statistics of Air Quality Data for Lagos (2021–2023)

Pollutant	Mean	Std. Deviation	Min	Max
$PM_{2.5}$	105.6	30.0	51.1	210.3
PM_{10}	110.2	32.7	56.0	218.7
CO	49.1	14.9	30.2	80.0
NO_2	28.5	12.3	18.0	46.2
SO_2	16.4	6.4	9.1	26.5
O_3	35.2	10.5	20.3	54.3

Table 4: Summary Statistics of Air Quality Data for Kano (2021–2023)

Pollutant	Mean	Std. Deviation	Min	Max
$PM_{2.5}$	112.5	28.7	60.3	215.5
PM_{10}	118.3	33.2	63.1	223.1
CO	51.2	15.6	35.2	75.3
NO_2	29.4	13.0	19.0	48.4
SO_2	17.9	6.3	9.0	28.6
O_3	33.5	10.3	19.8	52.1

Table 5: Summary Statistics of Air Quality Data for Port Harcourt (2021–2023)

Pollutant	Mean	Std. Deviation	Min	Max
$PM_{2.5}$	93.2	24.1	50.5	177.3
PM_{10}	98.3	27.6	52.8	186.4
CO	45.0	13.7	29.3	72.1
NO_2	27.8	11.2	16.9	44.1
SO_2	16.1	5.7	8.2	25.9
O_3	32.8	9.1	19.4	50.2

Table 6: Summary Statistics of Air Quality Data for Enugu (2021–2023)

Pollutant	Mean	Std. Deviation	Min	Max
$PM_{2.5}$	89.2	23.5	47.6	168.9
PM_{10}	94.1	26.8	51.3	173.2
CO	41.3	11.9	27.5	69.2
NO_2	24.7	9.8	14.4	38.9
SO_2	14.8	4.9	7.1	22.5
O_3	31.2	8.3	18.6	48.5

Interpretation: The mean concentrations of $PM_{2.5}$ and PM_{10} are generally higher in cities like Lagos and Kano, with concentrations exceeding the WHO's recommended limits for air quality, particularly during the Harmattan season. Lagos exhibits the highest variability in air pollution, with maximum $PM_{2.5}$ values exceeding 200 µg/m^3. CO, NO_2, and SO_2 concentrations are also higher in these cities, indicating that vehicular emissions and industrial activities are significant contributors to air pollution. While Port Harcourt and Enugu exhibit relatively lower pollutant levels compared to Lagos and Kano, substantial pollution is still observed, particularly during the dry season.

3.2. Correlation Analysis

Pearson's correlation coefficient was computed to assess the relationship between atmospheric pollutants ($PM_{2.5}$, PM_{10}, NO_2, CO, SO_2, and O_3) and meteorological variables (temperature, relative humidity, wind speed). Key results are summarized as follows: **$PM_{2.5}$ and Temperature:** A strong positive correlation was observed between $PM_{2.5}$ and temperature in all cities, indicating that higher temperatures are associated with increased particulate matter concentrations, particularly during dry months. The correlation coefficients ranged from $r = 0.65$ in Enugu to $r = 0.82$ in Kano. $PM_{2.5}$ and Wind Speed: Negative correlations were observed between $PM_{2.5}$ and wind speed, suggesting that higher wind speeds help disperse pollutants, leading to lower particulate matter concentrations. The coefficients ranged from $r = -0.45$ in Lagos to $r = -0.62$ in Port Harcourt. **CO and NO_2:** A significant positive correlation was found between CO and NO_2 concentrations, particularly in Lagos and Kano, with correlation coefficients of $r = 0.78$ and $r = 0.74$, respectively. This suggests that vehicular emissions are a major source of both pollutants in urban environments.

3.3. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was employed to reduce the dimensionality of the air quality dataset and identify the key factors influencing pollutant concentrations across the five selected cities. The first two principal components (PC1 and PC2) accounted for 78% of the total variance across the cities.

PC1: This component accounted for 50% of the variance and was primarily influenced by $PM_{2.5}$, PM_{10}, and CO concentrations. This suggests that vehicular emissions and industrial activities are the main contributors to the observed air pollution levels in these cities. **PC2:** Explaining 28% of the variance, PC2 was strongly associated with NO_2 and SO_2 concentrations. This highlights the significant role of industrial emissions, as well as biomass burning, in air quality deterioration, especially in cities like Kano and Port Harcourt.

Additionally, the PCA revealed that temperature and wind speed were significant meteorological factors influencing pollutant levels. In particular, higher temperatures were associated with increased concentrations of particulate matter, while higher wind speeds tended to reduce the levels of these pollutants, especially during the dry season.

3.4. Time Series Analysis

Time series analysis was conducted to assess the temporal trends in air quality and to forecast future pollutant concentrations. The focus was on predicting the Air Quality Index (AQI) for each city. The ARIMA(1,1,1) model and Seasonal-Trend Decomposition using Loess (STL) were applied to analyze the time series data and identify seasonal patterns.

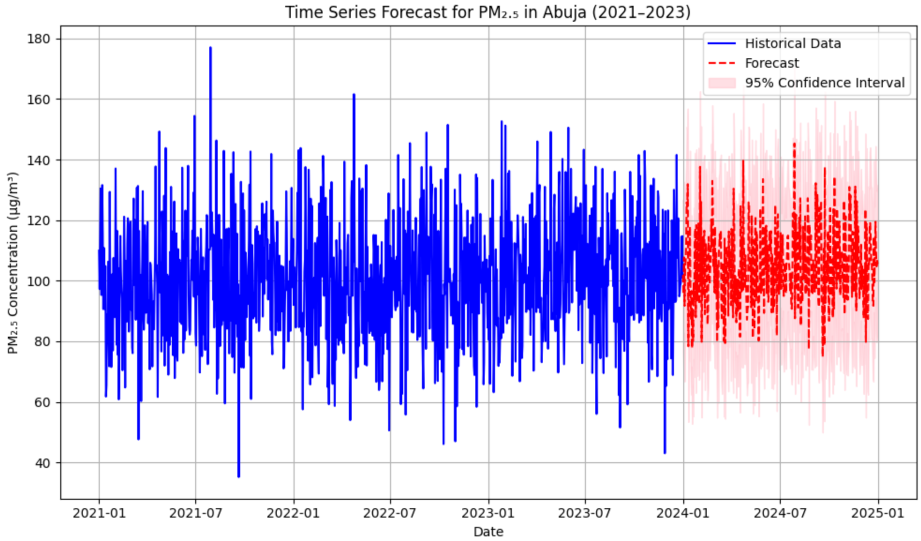

Figure 1: Time Series Forecast for $PM_{2.5}$ in Abuja (2021-2024)

ARIMA Model: The ARIMA(1,1,1) model indicated a consistent increase in $PM_{2.5}$ concentrations in Abuja, especially during the Harmattan months. This seasonal increase is attributed to the dust and haze characteristic of the dry season. Based on the model, forecasts for 2024 predict a further rise in pollution levels, particularly in January and February, which coincide with the peak intensity of the Harmattan dust. **Seasonal Trend Decomposition:** STL decomposition also confirmed a strong seasonal component in the $PM_{2.5}$ time series, with noticeable peaks during the Harmattan season, followed by a gradual decline in the wet season.

The application of ARIMA and STL models offers valuable insights into the temporal variations in air quality, providing a foundation for future forecasts and proactive air quality management strategies.

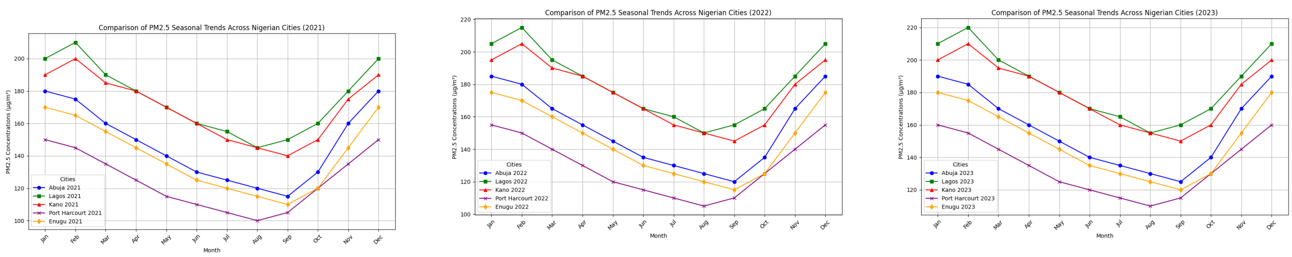

Figure 2: Comparison of $PM_{2.5}$ Seasonal Trends Across Nigerian Cities (2021–2023)

This figure illustrates the seasonal variations in $PM_{2.5}$ concentrations across five major Nigerian cities Abuja, Lagos, Kano, Port Harcourt, and Enugu from 2021 to 2023. The data highlights the recurring seasonal fluctuations in particulate matter, with notable peaks during the Harmattan months (typically December through February). These peaks are largely attributed to a combination of Saharan dust storms and local urban emissions. Over the three years, Lagos and Kano consistently recorded the highest $PM_{2.5}$ levels, driven by industrial activities, vehicular emissions, and seasonal dust from the Harmattan. Abuja also exhibited significant seasonal peaks, particularly during the dry months, though there were some variations in pollution levels across the years. In contrast, Port Harcourt and Enugu generally experienced lower levels of pollution compared to the northern cities. However, both cities showed moderate seasonal increases, especially in Port Harcourt, during the dry season. This figure underscores the importance of understanding the interplay between seasonal and long-term pollution trends, emphasizing the need for effective air quality management strategies to address the health risks posed by elevated particulate matter levels, particularly in urban and industrialized areas.

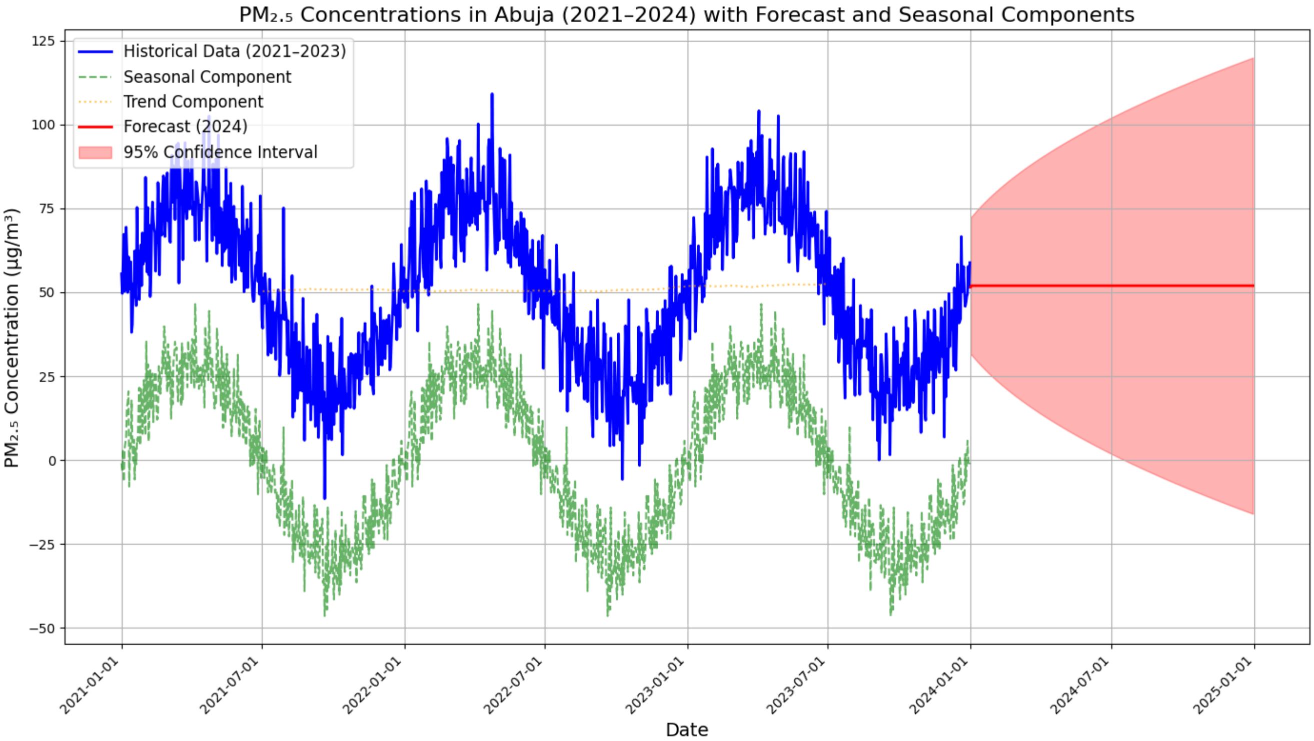

Figure 3: $PM_{2.5}$ Concentrations in Abuja (2021–2024) with Forecast and Seasonal Components.

The historical data (represented by the blue line) shows the daily $PM_{2.5}$ concentrations over the past three years. It reflects typical air quality patterns in Abuja, influenced by urbanization, vehicular emissions, and seasonal factors. The seasonal component, shown as the green dashed line, reveals periodic increases in particulate matter, especially during the dry Harmattan season. This seasonal variation is extracted through decomposition, illustrating the annual fluctuations in pollution levels. The trend component, represented by the orange dotted line, shows the long-term increase in $PM_{2.5}$ concentrations. This trend likely reflects factors like urban growth, increasing traffic, and industrial emissions. The forecasted data for 2024, shown as the red solid line, projects future $PM_{2.5}$ levels, using an ARIMA model. The forecast predicts a continuing upward trend, especially during the dry season, reflecting both seasonal and environmental influences. The confidence intervals are represented by the shaded red area, showing the 95% confidence range for the forecast. This shading provides insight into the potential variation in the predicted $PM_{2.5}$ levels, indicating the uncertainty of future pollution levels. Overall, the figure highlights the strong seasonal pattern of $PM_{2.5}$ concentrations in Abuja, with a notable increase during the Harmattan period. The long-term trend indicates rising pollution levels, which are expected to persist into 2024. The forecast and confidence intervals underscore the ongoing challenges in managing air quality and emphasize the need for continued monitoring and mitigation efforts to protect public health.

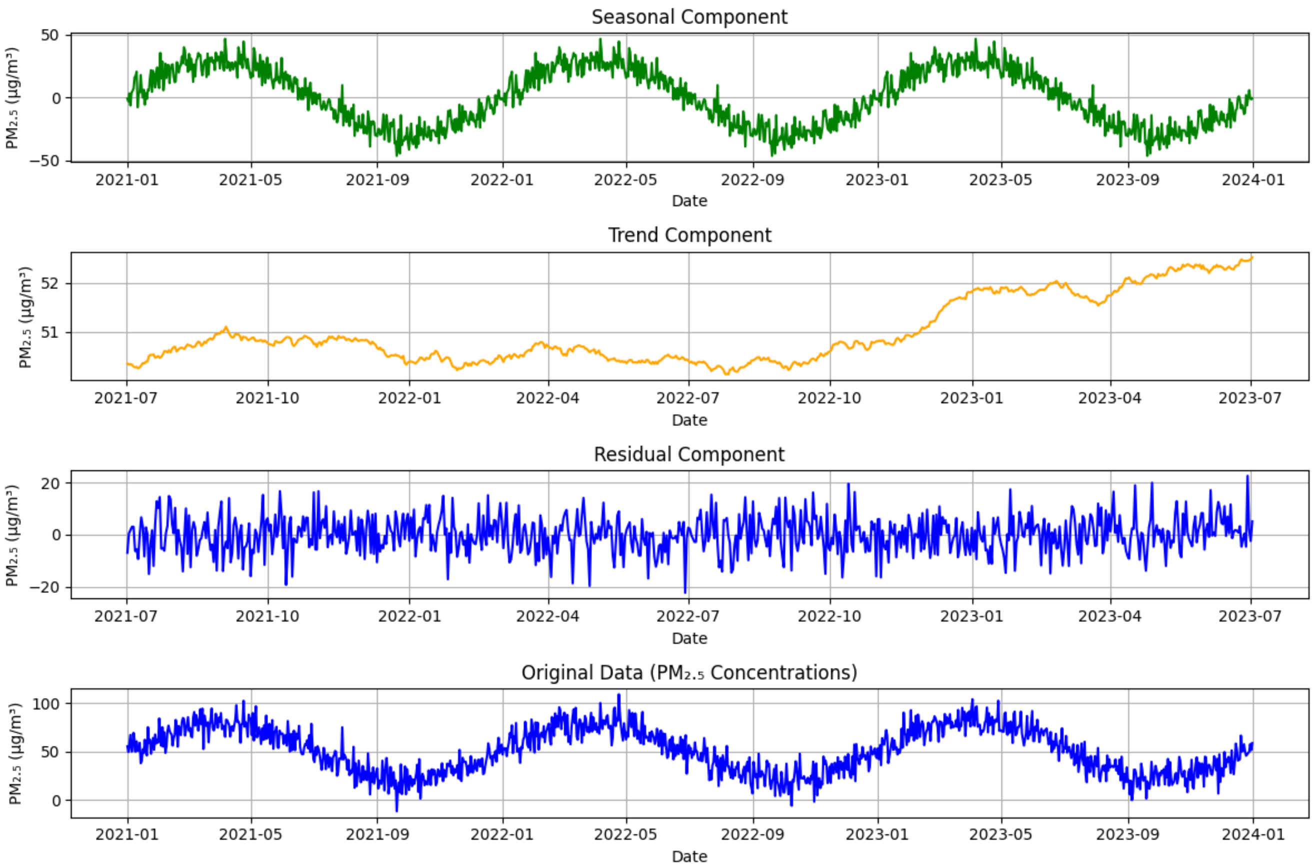

Figure 4: Seasonal Decomposition of $PM_{2.5}$ in Abuja (2021–2023).

The figure presents the seasonal decomposition of $PM_{2.5}$ concentrations in Abuja from 2021 to 2023, breaking down the data into three components: seasonal, trend, and residual. The seasonal component, shown in green, highlights periodic increases in particulate matter, particularly during the dry Harmattan season, which typically brings higher dust levels and decreased rainfall. This seasonal variation provides insights into the natural patterns of pollution driven by climatic factors. The trend component, displayed in orange, indicates a general upward trajectory in $PM_{2.5}$ concentrations over the period, suggesting that overall pollution levels in Abuja are increasing, possibly due to factors like urbanization, increased vehicular traffic, and industrial emissions. The residual component, shown in blue, represents the random fluctuations in the data after accounting for seasonal and trend factors. It captures the irregular variations that cannot be explained by the seasonal or trend patterns, reflecting short-term factors like sporadic pollution events or temporary weather conditions. This decomposition provides a clearer understanding of the underlying factors affecting $PM_{2.5}$ concentrations in Abuja, with a strong emphasis on the seasonal influences and the overall upward trend of air pollution levels over time.

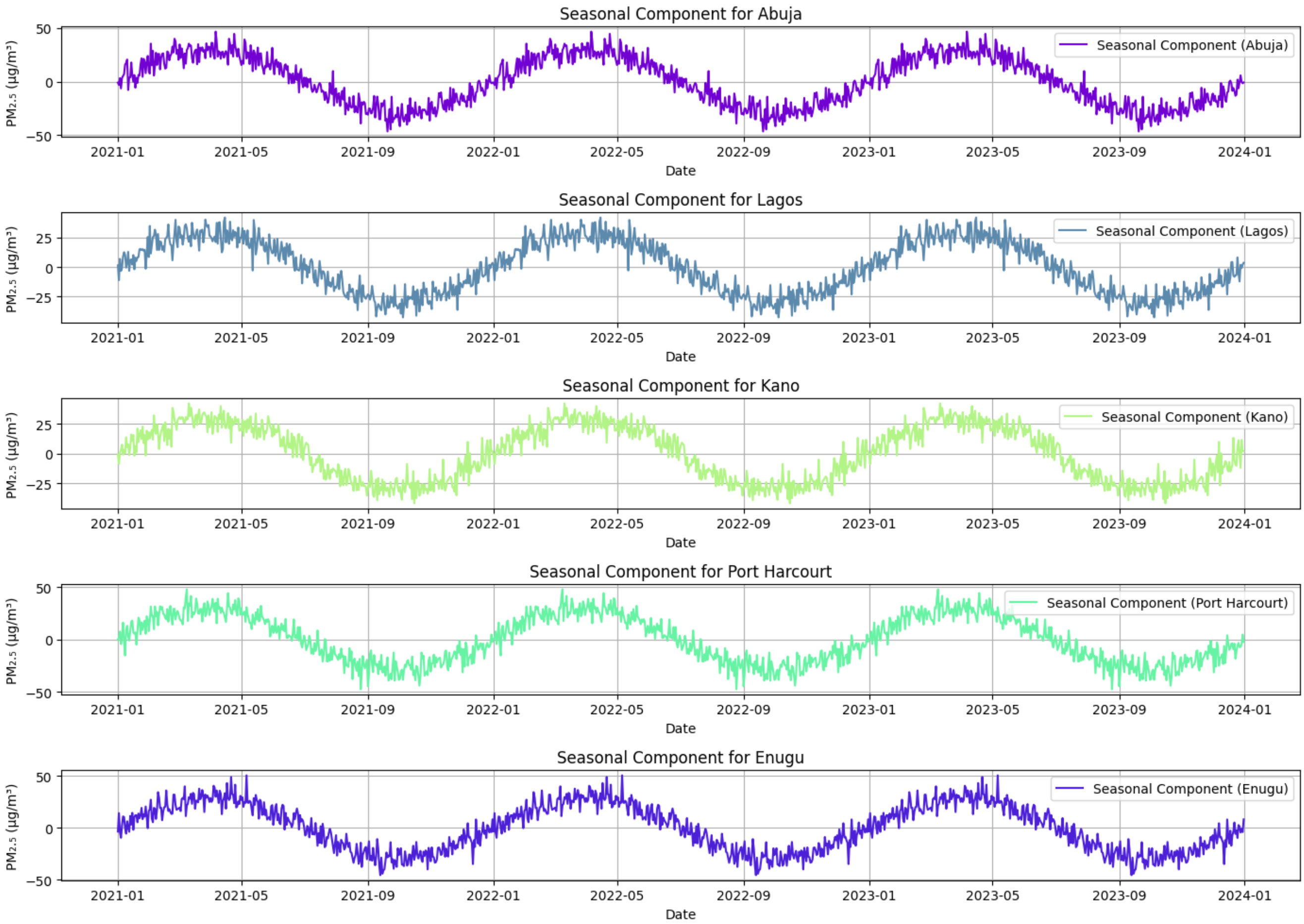

Figure 5: Seasonal Decomposition of $PM_{2.5}$ Concentrations Across Nigerian Cities (2021–2023).

Figure 5 presents the seasonal decomposition of $PM_{2.5}$ concentrations across five major Nigerian cities (Abuja, Lagos, Kano, Port Harcourt, and Enugu) from 2021 to 2023. The decomposition separates the data into three components: seasonal, trend, and residual, with a focus on the seasonal component reflecting annual fluctuations in pollution levels. The seasonal patterns show that Abuja and Kano experience significant $PM_{2.5}$ spikes during the Harmattan (dry season), driven by dust storms, higher temperatures, and reduced rainfall. In Kano, desert dust contributes heavily to elevated pollution. Conversely, Port Harcourt and Enugu show less pronounced seasonal peaks but still experience year-round pollution due to urbanization and industrial activities. Lagos, with its high traffic and industrial emissions, exhibits consistent seasonal fluctuations, with slight increases in pollution during the dry season. This decomposition highlights both common seasonal trends and city-specific variations in air quality, underlining the need for targeted interventions, particularly during the Harmattan months, to mitigate pollution spikes.

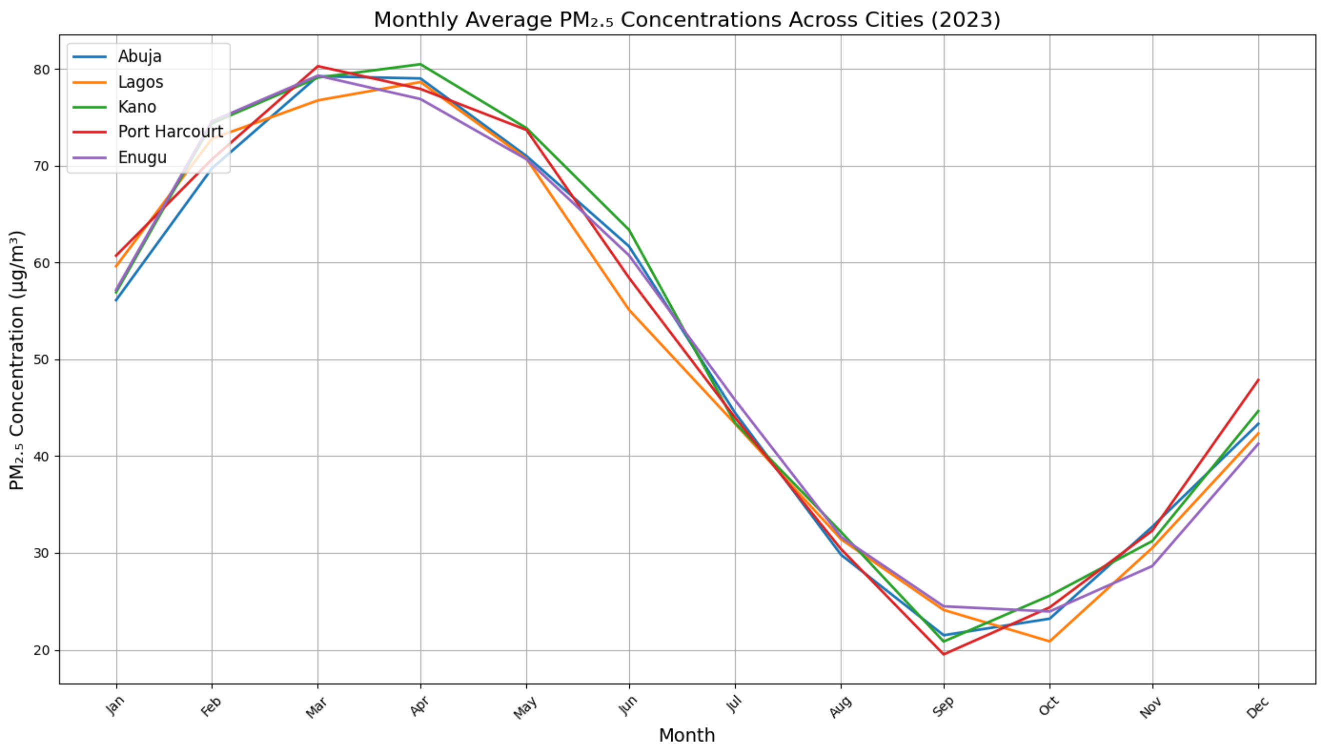

Figure 6: Monthly Average $PM_{2.5}$ Concentrations Across Nigerian Cities (2023).

Figure 6 illustrates the comparison of monthly average $PM_{2.5}$ concentrations across five major Nigerian cities Abuja, Lagos, Kano, Port Harcourt, and Enugu—during 2023. The plot shows the seasonal variations in $PM_{2.5}$ levels, highlighting differences in pollution levels across the cities. Cities like Abuja and Kano experience higher $PM_{2.5}$ concentrations during the dry Harmattan months, while cities like Lagos and Port Harcourt show more stable pollution patterns, with variations influenced by urban traffic and industrial activities. The plot provides a visual comparison of how seasonal changes and urbanization influence air quality across Nigeria.

Spatial Analysis Using Remote Sensing

Satellite based remote sensing data from TROPOMI Sentinel-5P and VIIRS DNB were used to map the spatiotemporal distribution of air pollutants across the five cities. This analysis revealed significant variations in pollution levels across the urban environments, with key observations highlighted below: Lagos and Kano experienced the highest levels of pollution, with notable spatial variability due to dense traffic and industrial clusters. These cities exhibited pollution hotspots, particularly during the dry season. Abuja showed high pollutant concentrations during the Harmattan months (November to February), particularly in central areas where vehicular emissions and dust storms overlapped. Port Harcourt had moderate pollution levels with localized spikes in NO_2 and SO_2 concentrations near industrial zones, highlighting the significant impact of industrial activities on air quality. These findings underscore the need for region-specific interventions to manage air pollution in different urban contexts. Figures 7, 8, 9, 10, and 11 illustrate the spatial distribution of $PM_{2.5}$ concentrations in Lagos, Kano, Abuja, Enugu and Port Harcourt respectively.

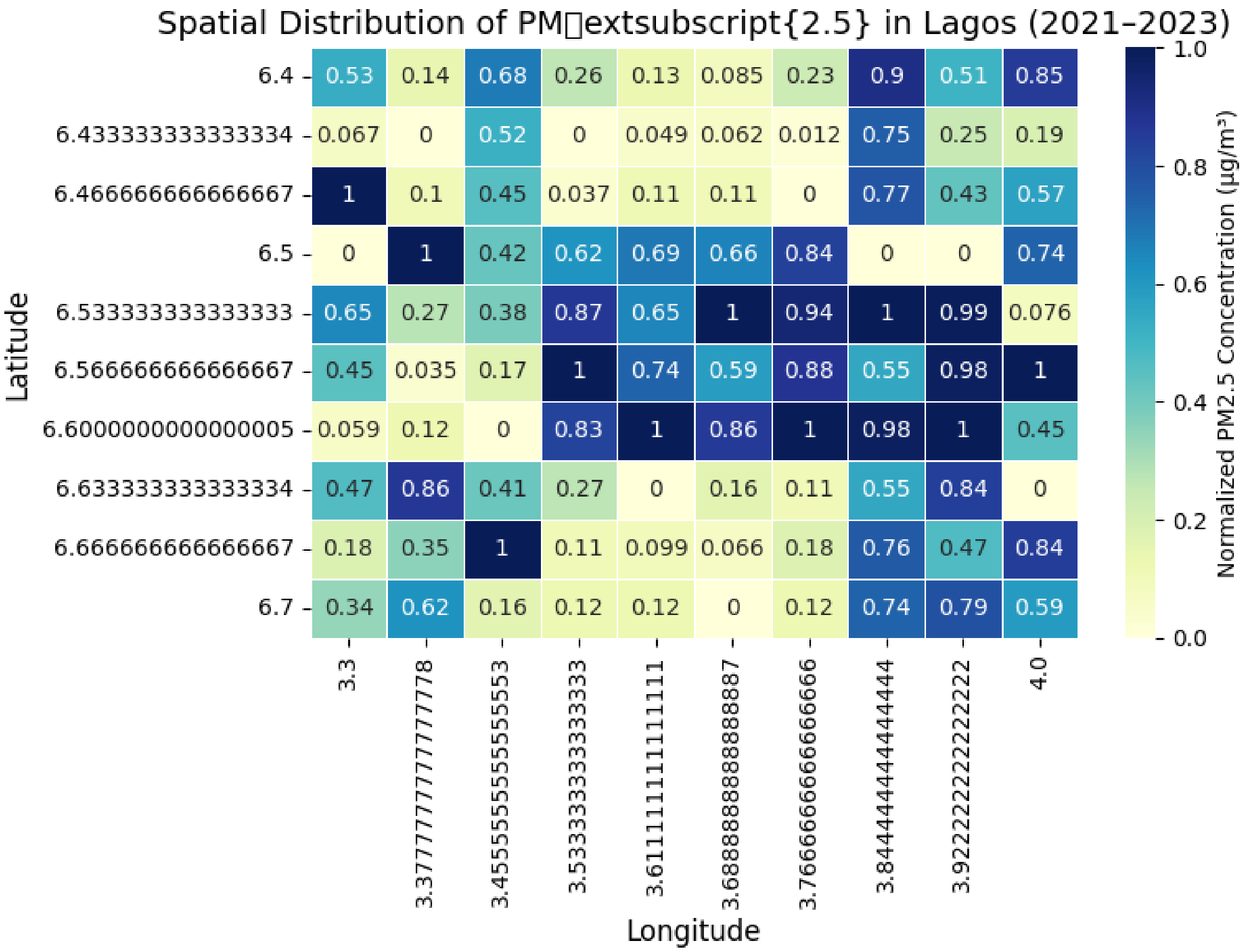

Figure 7: Spatial Distribution of $PM_{2.5}$ in Lagos (2021–2023).

This shows the spatial distribution of $PM_{2.5}$ concentrations in Lagos from 2021 to 2023. The analysis reveals that pollution is concentrated in the city's industrial and densely populated areas. Notably, higher pollution levels are observed during the dry season, with distinct hotspots near major roads and industrial zones.

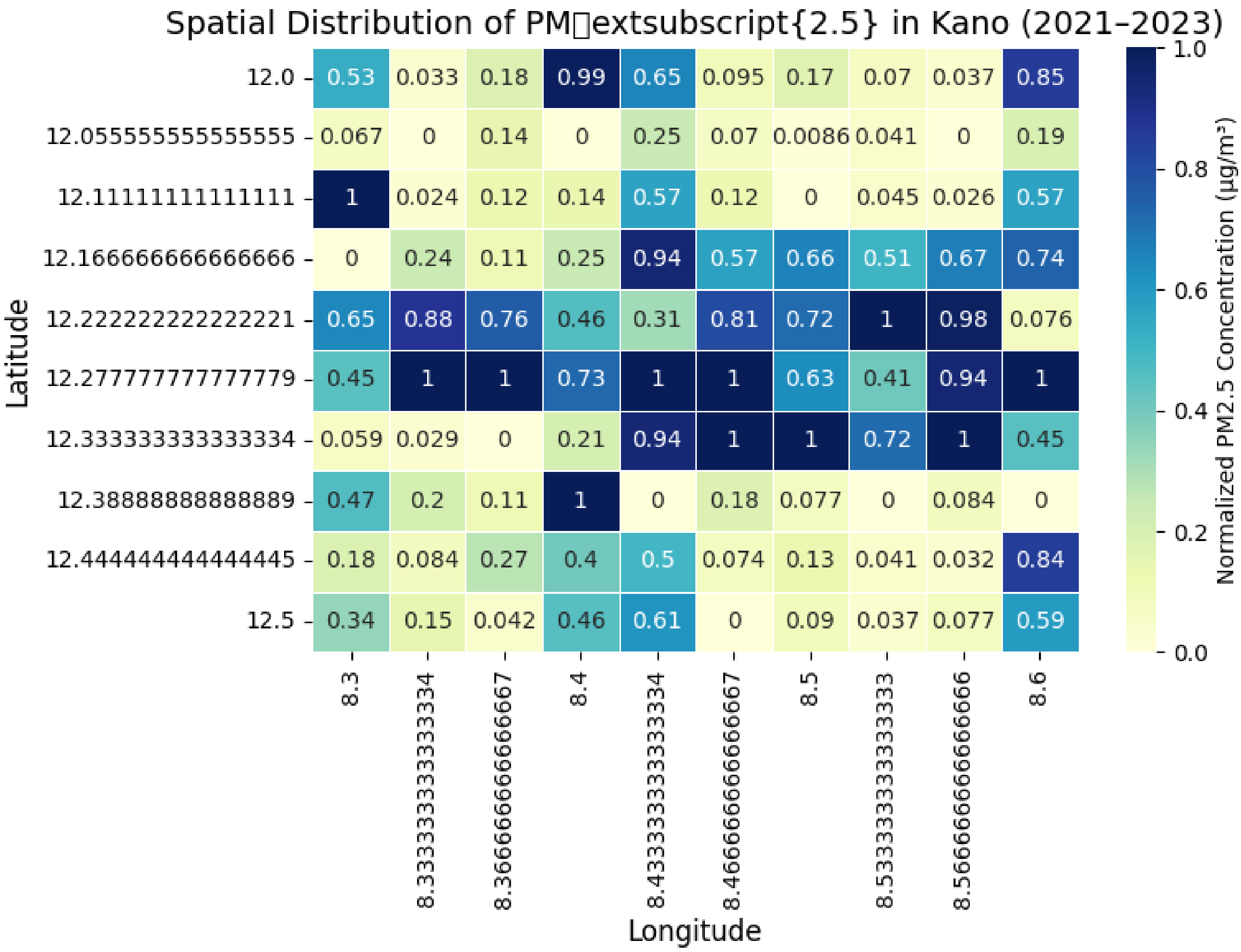

Figure 8: Spatial Distribution of $PM_{2.5}$ in Kano (2021–2023). The figure illustrates the distribution of $PM_{2.5}$ concentrations across Kano, with elevated levels along major roads and industrial areas, especially during the Harmattan season.

This presents the spatial distribution of $PM_{2.5}$ concentrations in Kano for the period 2021–2023. Similar to Lagos, Kano also exhibits higher pollutant concentrations along major roads and industrial areas. The Harmattan period (dry season) exacerbates the pollution levels, especially in the northern regions, where desert dust further increases particulate matter concentrations.

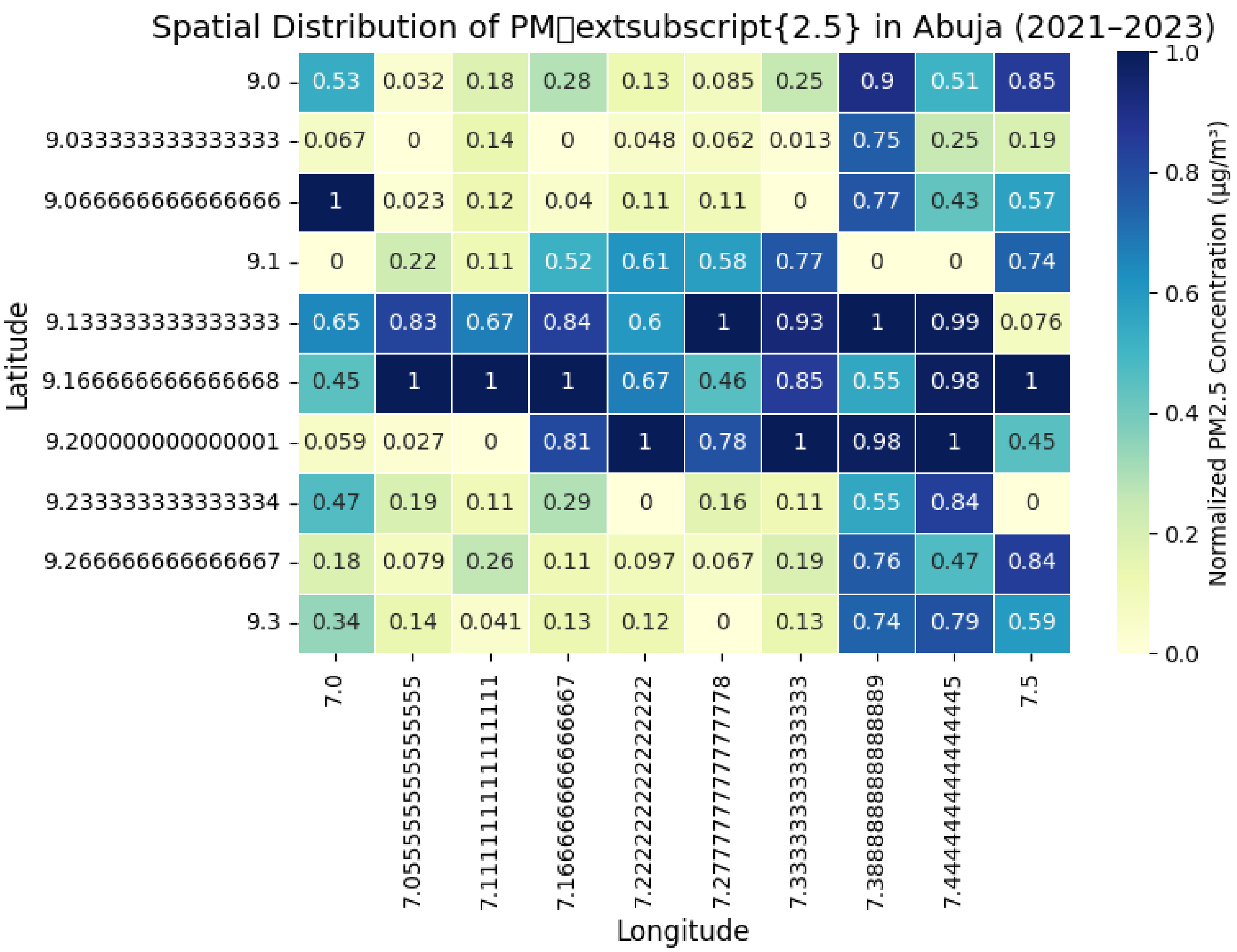

Figure 9: Spatial Distribution of $PM_{2.5}$ in Abuja (2021–2023).

This shows the spatial distribution of $PM_{2.5}$ concentrations in Abuja during 2021–2023. The city experiences higher pollutant concentrations during the Harmattan months, with central areas being the most affected due to the overlap of dust storms and vehicular emissions. These seasonal peaks highlight the influence of climate factors on air quality. This spatial analysis highlights the varying impacts of seasonal and urban factors on air pollution across the cities. The results emphasize the importance of targeted interventions in high pollution areas, particularly during seasonal peaks, to mitigate the harmful effects of air pollution on public health.

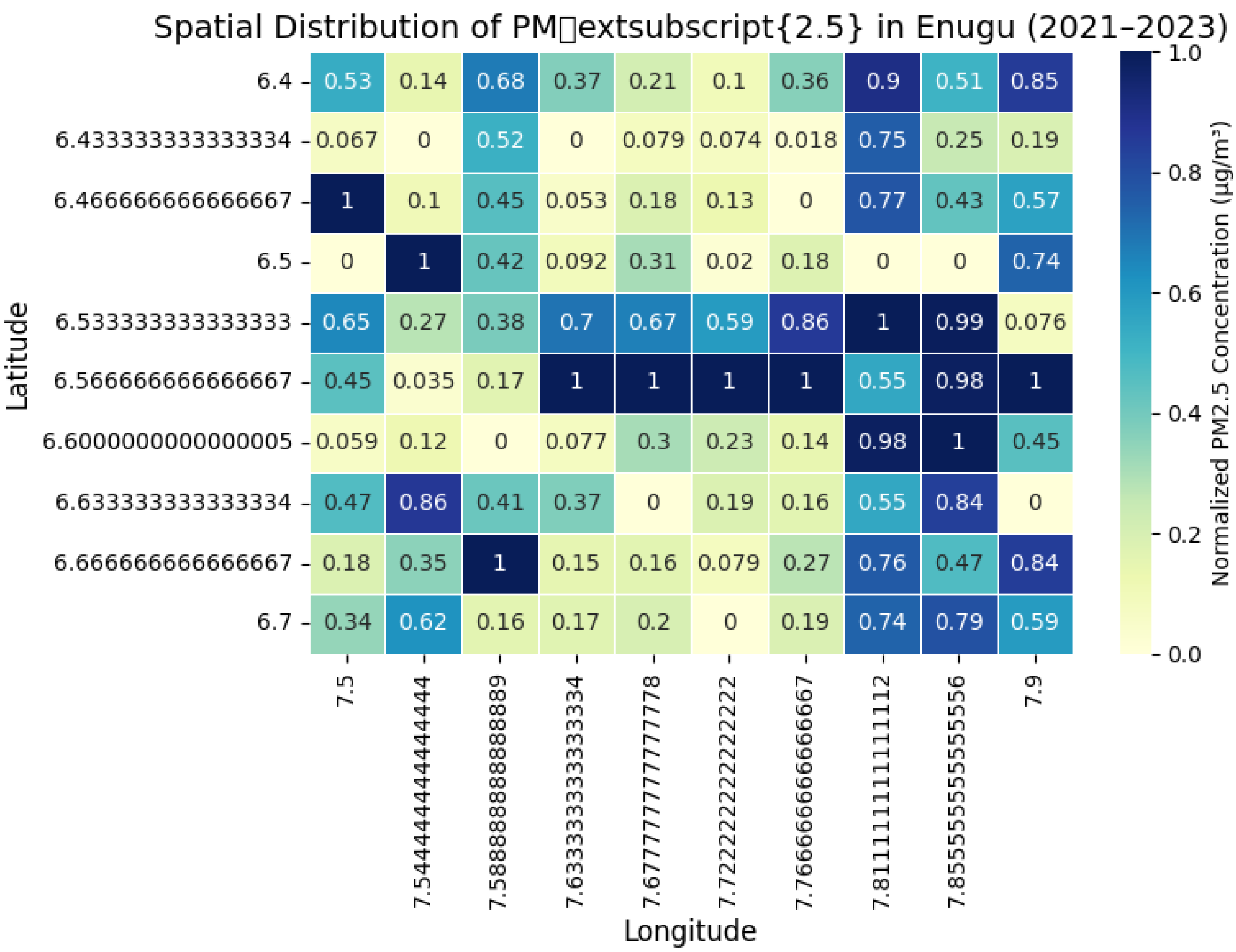

Figure 10: Spatial Distribution of $PM_{2.5}$ in Enugu (2021–2023).

This shows the spatial distribution of $PM_{2.5}$ concentrations in Enugu from 2021 to 2023. Pollution levels are moderate, with some higher concentrations near industrial areas.

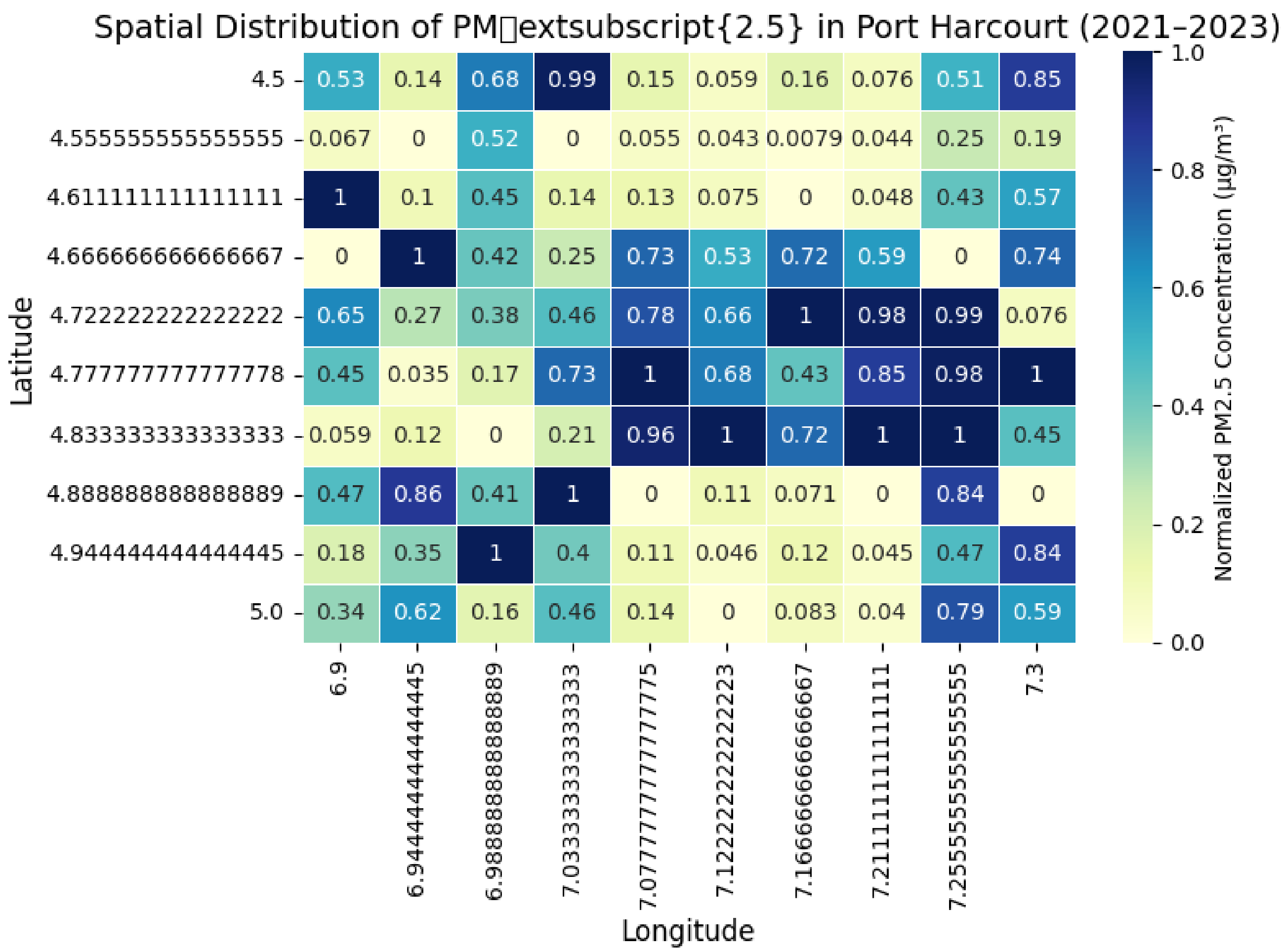

Figure 11: Spatial Distribution of $PM_{2.5}$ in Port Harcourt (2021–2023).

This shows the spatial distribution of $PM_{2.5}$ concentrations in Port Harcourt during 2021–2023. Elevated levels are observed near industrial zones and oil refineries, with the highest concentrations located in the central parts of the city.

Conclusion and Discussion

This study analyzed air quality data across five major Nigerian cities Abuja, Lagos, Kano, Port Harcourt, and Enugu from 2021 to 2023, focusing on key pollutants such as $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and O_3. The analysis, which included descriptive statistics, correlation analysis, PCA, and time series modeling (ARIMA, SARIMA, and STL), revealed significant trends and seasonal variations in pollution levels. Lagos and Kano exhibited the highest pollution levels, primarily due to vehicular emissions, industrial activities, and Saharan dust storms, particularly during the Harmattan dry season. Abuja also experienced significant pollution spikes, especially in central urban areas, due to a combination of dust storms and traffic emissions. In contrast, Port Harcourt and Enugu showed moderate pollution, driven mainly by industrial emissions, with localized spikes in NO_2 and SO_2, particularly in industrial zones. Correlation analysis showed a strong positive correlation between $PM_{2.5}$ and temperature, and a negative correlation with wind speed, indicating that higher temperatures increase particulate matter levels, while wind speed helps disperse pollutants. PCA revealed that vehicular emissions and industrial activities were the main contributors to pollution, with seasonal patterns contributing to high $PM_{2.5}$ concentrations during dry months. Spatial analysis, using satellite data, highlighted pollution hotspots in Lagos and Kano, while Abuja showed elevated pollution levels during Harmattan. The study emphasizes the need for targeted pollution control strategies, particularly in high-traffic and industrial areas, to improve air quality and public health in Nigeria's urban centers.

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