Available online at www.worldscientificnews.com

World Scientific News

An International Scientific Journal

WSN 204 (2025) 311-327 EISSN 2392-2192

Temporal Analysis and Prediction of Air Quality Index for Atmospheric Pollutants in Port Harcourt, Rivers State

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ABSTRACT

Over the last few decades, air pollution has become a major environmental concern. Its impact on public health, safety, and our ecosystems has been quite alarming. It's crucial for government officials to anticipate air pollution levels to help safeguard our climate and protect the environment, enabling them to develop effective strategies for pollution prevention. This study aims to examine the trends and patterns of significant air pollutants in Port Harcourt of Nigeria, which is situated in Niger Delta region, investigate seasonal variations and their connections to weather conditions and human activities, and create and validate forecasting models to predict future air quality indices. The study dived deep into the air quality by employing time series analysis techniques to reveal the patterns of air pollutants over time. The study spans from January 2010 to December 2023, providing a thorough 14-year time series for analysis. By using methods like autoregressive integrated moving average (ARIMA), Prophet, Seasonal ARIMA (SARIMA), and exponential smoothing models, the research uncovers key seasonal trends and patterns in pollutant levels from 2010 to 2023. To assess the models, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Theil's U statistic, and the Ljung-Box test for residual autocorrelation were implemented. The particulate matter ($PM_{2.5}$) received particular attention in the study because it poses the greatest health risk among measured pollutants, showed the most alarming increasing trend, significantly exceeded WHO guidelines, and demonstrated predictable patterns that enable effective prediction and intervention strategies in the industrially active Port Harcourt city. The SARIMA model showed the best predictive performance for most pollutants, effectively accounting for both seasonal variations and long-term trends.

(Received 15 April 2025; Accepted 24 May 2025; Date of Publication 18 June 2025)

The SARIMA model proved to be the most accurate for predicting $PM_{2.5}$ with an RMSE of 5.2, MAPE of 7.4%, and Theil's U of 0.13. The results indicate that SARIMA can be effectively used in Port Harcourt city to evaluate air pollution levels and mitigate harmful health impacts. The agencies responsible for monitoring air quality could leverage this model to assess pollution levels in the near future and establish a system to identify the highest pollution spikes.

Keywords: Time series analysis, ARIMA, Air quality forecasting, Port Harcourt, Niger Delta, Air pollution, Environmental monitoring.

INTRODUCTION

Air pollution is a major environmental and public health issue in the rapidly growing urban areas of Nigeria, especially in industrial hotspots like Port Harcourt in the Niger Delta. Since oil was discovered in significant amounts at Oloibiri in 1956, this region has become the heart of Nigeria's petroleum industry, contributing over 90% of the country's foreign exchange earnings (Osuji & Nwoye, 2007).

Port Harcourt city plays a crucial role in the oil and gas sector, and with the rise in urbanization, industrial activities, and vehicle emissions, it's facing some serious air quality challenges (Yakubu, 2018; Ede & Edokpa, 2020). To tackle these issues effectively, we need to accurately analyze and predict air quality over time, which is vital for understanding pollution trends, implementing control measures, and safeguarding public health. Port Harcourt is particularly fascinating to study because of its mix of industrial activities, weather patterns, and geographical features. The city has two main seasons—a rainy season from April to October and a dry season from November to March—which greatly affect how pollutants spread and concentrate in the air (Nwankwo et al., 2020). Moreover, this economic growth has come at a significant environmental cost. Activities related to oil exploration and production, such as gas flaring, oil spills, and refinery operations, emit large amounts of air pollutants, which create a complicated air quality situation that demands advanced analytical methods. These pollutants include particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen oxides (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and volatile organic compounds (VOCs). However, in this study, the $PM_{2.5}$ received particular attention because it poses the greatest health risk among measured pollutants, showed the most alarming increasing trend, significantly exceeded WHO guidelines, and demonstrated predictable patterns that enable effective prediction and intervention strategies in the industrially active Port Harcourt city Unfortunately, these industrial efforts, combined with rapid urban growth, increasing population, and emissions from transportation, have created a complicated air pollution problem in the area (Ede & Edokpa, 2017). Osuji and Avwiri (2005) found that communities near oil production sites had higher levels of air pollutants, while Nnaji et al. (2016) pointed out how gas flaring worsens air quality in the region. The decline in air quality has been associated with a range of negative impacts, such as respiratory issues, heart diseases, and environmental harm (Ana, 2011).

According WHO, (2012) the air quality in Nigeria is considered very dangerous to the ecosystem. And as at October 2023, Nigeria has extremely high $PM_{2.5}$ levels, often exceeding $50\mu g/m^3$in urban areas. In contrast, the WHO recommends that annual $PM_{2.5}$ concentrations should not exceed $5\mu g/m^3$. This indicates that many regions in Nigeria significantly surpass the WHO guidelines, posing serious public health risks. More recently, Edokpa and Ikelegbe (2019) discovered links between industrial operations and the presence of key pollutants like PM_{10}, SO_2, and NO_2.

Giwa et al. (2019) estimates that Nigeria flares around 7.4 billion cubic meters of gas per year, with the bulk happening in the Niger Delta. This technique emits significant amounts of CO_2, CH_4, NO_2, SO_2, and particulate matter into the environment. Uyigue and Agho (2007) discovered significant geographical connections between gas flaring locations and higher pollutant concentrations in the surrounding areas, which is the main cause of high incidence of premature mortality and morbidity. Beyond industrial sources, traffic emissions, biomass burning, and dust from unpaved roads also contribute considerably to the region's air pollution (Obinna et al., 2018). The combined effect of these many pollution sources generates complicated air quality concerns that differ geographically and temporally over the Port Harcourt city.

In addition, Port Harcourt in the Niger Delta region of Nigeria serves as a significant example of these challenges, as it is home to extensive petroleum extraction activities that have adversely affected environmental quality for decades. Even though air quality is crucial for public health and environmental sustainability, there has been a lack of thorough time series analysis and forecasting of air pollutants in Port Harcourt city. Earlier studies have concentrated on point measurements or short-term evaluations, failing to identify long-term trends or develop predictive models (Yakubu, 2018; Nwankwo et al., 2020). This gap in research makes it difficult to plan effectively for environmental issues and public health initiatives. The aim of this article is to model air pollution in Port Harcourt city, with four main objectives: examining the trends and patterns of major air pollutants in the Port Harcourt over time; exploring seasonal changes and how they relate to weather conditions and human activities, create and validate forecasting models to predict future air quality indices (AQI), and offer evidence-based recommendations for managing air quality and implementing policies. Time series analysis has become a popular tool for studying air quality data around the world. For instance, Zhang et al. (2018) used ARIMA models to predict $PM_{2.5}$ levels in Beijing, achieving impressive accuracy rates of over 85%. Likewise, Cadelis et al. (2014) applied seasonal decomposition methods to uncover trends in respiratory disease admissions tied to air pollution in Guadeloupe.

In Africa, Awe et al. (2019) showcased how exponential smoothing models can be effectively used for air quality forecasting in Lagos, Nigeria. Again, in Nigeria, Balogun and Garba (2021) utilized random forest algorithms to predict air quality in urban areas, although their research didn't specifically cover the Port Harcourt. Despite increased interest in Nigeria's air quality issues, considerable research gaps persist. Most present research offer brief assessments rather than long-term assessments of pollution patterns. Extensive time series investigations of air pollution in Port Harcourt city are very rare, limiting our knowledge of temporal trends and forecasting capabilities. By delivering a thorough analysis of air pollution trends using time series methods, this research will enhance our understanding of the environmental challenges facing Port Harcourt city and aids in crafting sustainable solutions.

Study Area

Port Harcourt, located at 4°49′27″N 7°2′1″E, serves as the capital of Rivers State and stands out as a key industrial hub in Nigeria's Niger Delta. Home to around 1.8 million people, this vibrant city is packed with a variety of petroleum-related industries, including two refineries, a petrochemical plant, and a natural gas liquefaction facility, along with several manufacturing sectors (National Population Commission, 2020). The area enjoys a tropical monsoon climate, boasting an average annual rainfall of 2,400 mm and temperatures that typically range from 25°C to 32°C (Nigerian Meteorological Agency, 2021).

Data Monitoring

Monitoring stations run by the Nigerian National Environmental Standards and Regulations Enforcement Agency (NESREA) and the State Environmental Protection Agencies provided hourly concentration data for six important air pollutants: Particulate Matter (PM_{10}), Fine Particulate Matter ($PM_{2.5}$), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), carbon monoxide (CO) and volatile organic compounds (VOCs). The pollutants' concentrations are compared to the WHO Guidelines that are summarized in Table 1.

Table 1. WHO guidelines for air pollution.

Pollutant	Annual Mean	24-hour Mean	8-hour Mean
PM_{10}	15	45	-
$PM_{2.5}$	5	15	-
NO_2	10	25	-
SO_2	-	40	-
CO	-	7000	10000

The study covers a period from January 2010 to December 2023, giving a comprehensive 14-year time series for analysis. The air quality data were gathered from the Rivers State Environmental Protection Agency (RSEPA) monitoring stations distributed across Port Harcourt. This dataset includes daily measurements of six key air pollutants: Particulate Matter (PM_{10} and $PM_{2.5}$), Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Carbon Monoxide (CO) and Volatile Organic Compounds (VOCs). Meteorological data were also collected—like temperature, humidity, rainfall, and wind speed/direction—from the Nigerian Meteorological Agency (NIMET) to understand how these factors influence pollution patterns.

Methodology

To ensure quality and consistency, the raw data underwent a number of preprocessing steps; Missing values were imputed using linear interpolation for gaps shorter than three consecutive days and applied multiple imputations by chained equations (MICE) for longer gaps; outliers were detected and addressed using the modified Z-score method, and the daily Air Quality Index (AQI) were calculated based on the US EPA methodology.

Statistical Model

In Time Series Analysis, the following methods were used: trend analysis – pollutant concentrations were assessed using the Mann-Kendall test to identify monotonic trends, Sen's slope estimator to measure the magnitude of these trends, Pettitt's test to spot any potential change points in the time series. Seasonal Pattern Analysis – seasonal patterns were examined through seasonal decomposition of time series (STL decomposition), seasonal subseries plots, and spectral analysis using fast Fourier transforms. Correlation Analysis – a close look at the relationships between various pollutants and their potential predictors using a few different methods were taken: Cross-correlation functions, Granger causality tests, Dynamic conditional correlation models. Forecasting Models - three different classes of forecasting models were developed and compared; ARIMA and SARIMA Models - Autoregressive Integrated Moving Average (ARIMA) models were formulated as ARIMA(p,d,q), where p stands for the autoregressive order, d is the degree of differencing, q represents the moving average order.

For seasonal patterns, SARIMA models were specified as SARIMA(p,d,q)(P,D,Q)s, adding in: P, D, Q for the seasonal components, s to indicate the seasonal period (12 for monthly data). To choose the best model, we relied on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Exponential Smoothing Methods - three variations of exponential smoothing were implemented; simple exponential smoothing for series that don't show trend or seasonality, Holt's linear method for data that has trends, and Holt-Winters' method for series that include both trend and seasonal components.

Model Evaluation and Performance Metrics

The dataset was divided into training (2010-2020) and testing (2021-2023) periods. Assessing the model's performance is the aim of the evaluation. A number of metrics were employed to validate the models, starting by concentrating on the calculation of the most popular RMSE because it is accurate and readable.

$$RMSE = \sqrt{\frac{1}{n}\sum_{ii=1}^{n}(\hat{y}_i - y_i)^2}$$

Secondly, a precise metric that characterizes the measurement's accuracy is the Mean Absolute Percentage Error (MAPE). The relative precision of two or more measurements is determined by MAPE.

$$MAPE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{\sum_{i-1}^{n} y_i} \times 100$$

Thirdly, the Theil's U statistic is a relative accuracy measure that compares the forecasted results of forecasting with minimal historical data. And measures the quality of the forecast.

$$\text{Theil's U statistic} = \frac{\sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(y_i)^2\right)} + \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(\hat{y}_i)^2}}$$

Finally, Ljung-Box test for checking residual autocorrelation was applied to assess whether residuals from a time series model exhibit autocorrelation by examining the accumulated sample autocorrelations at multiple lags.

Results and Discussion

After filtering the data, the daily averages were calculated along with some descriptive statistics for the values recorded at the monitoring station. We recommend using numerical values for data aggregation, like calculating daily or monthly averages was recommended. In this case, the focus was on computing the daily average values. Once the pollution data was processed, R software was utilized for the analysis. The observations spans from January 2010 to December 2023 in Port Harcourt. Figures 1 and 2 showcase some graphical representations of our findings.

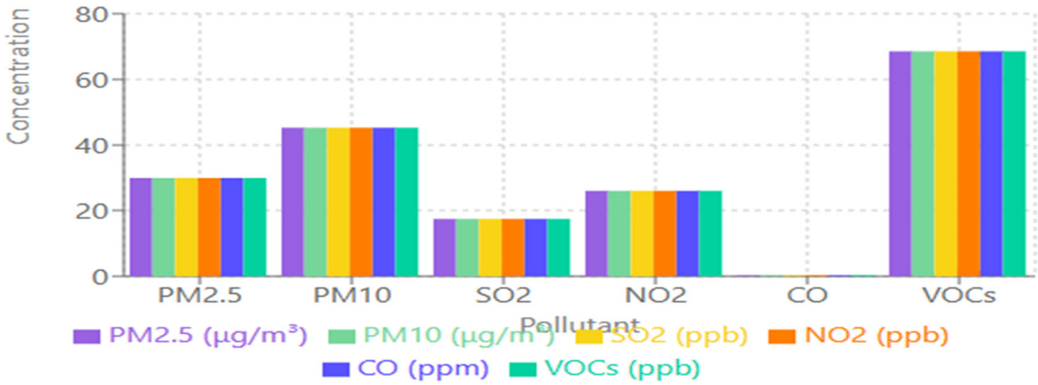

Figure 1. Statistical Summary for all pollutants.

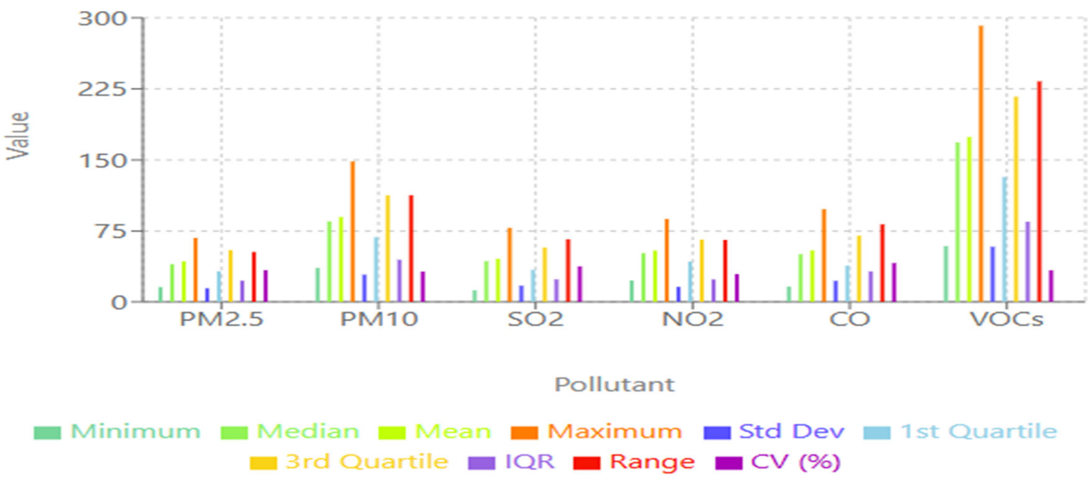

Figure 2. Q1(25%), Q3(75%), Mean, Median, Minimum, Maximum, Standard Deviation for the pollutants in Niger Delta.

Temporal Patterns of Air Pollutants

The air quality in Port Harcourt paints a complex picture of pollution dynamics, revealed through a detailed analysis over time. By looking at 14 years of air quality data that were processed and analyzed, this study uncovers subtle patterns in how pollutants behave across different timescales.

Long-term Trends

After examining a 14-year time series, as shown in Table 2, a long-term trend analysis using the Mann-Kendali, particulate matter ($PM_{2.5}$ and PM_{10}) shows highly significant increase, likely due to industrial emissions, gas flaring, and vehicular exhaust.

The most notable increase was where the Sen's slope was 1.8 μg/m³/year ($p < 0.001$). SO_2 and NO_2 showed significant increases, associated with petroleum processing and combustion activities. VOCs showed strong upward trend, linked to petroleum operation and industrial processes. Interestingly, CO levels have been on a slight decline everywhere, which might indicate that vehicle emission controls are getting better.

Table 2. Mann-Kendall Trend test Results for Major Pollutants (2010-2023).

Pollutant	Trend Direction	Statistical Significance	Sen's Slope (unit/year)
$PM_{2.5}$	Increasing	*** ($p < 0.001$)	1.8 μg/m³/year
PM_{10}	Increasing	*** ($p < 0.001$)	2.4 μg/m³/year
SO_2	Increasing	** ($p < 0.01$)	0.7 ppb/year
NO_2	Increasing	* ($p < 0.05$)	0.5 ppb/year
CO	Decreasing	* ($p < 0.05$)	-0.2 ppm/year
VOCs	Increasing	*** ($p < 0.001$)	1.2 ppb/year

Seasonal Patterns

When the time series were broken down, clear seasonal trends were noticed for most pollutants. Figure 3 offers a visual breakdown of the seasonal changes in $PM_{2.5}$ levels in Port Harcourt, showcasing the various components of its fluctuations. This breakdown reveals the trend, seasonal patterns, and residual elements that define how pollutants have behaved from 2010 to 2023. $PM_{2.5}$ levels peaked during the dry/harmattan season (from November to February), that is +20-25 μg/m³ above trend, which aligns with increased Saharan dust and biomass burning. While during the rainy season, $PM_{2.5}$ levels is low (May to August), that is -20 μg/m³ below trend. SO_2 and NO_2 didn't show as much seasonality but had higher concentrations during times of heightened industrial activity. VOCs displayed more complex seasonal behaviors, with peaks occurring during both the dry season and periods of increased petroleum processing. Additionally, the study's insights into seasonal patterns are particularly noteworthy. These findings are essential for grasping the air quality dynamics in the region, shedding light on the complex interactions between atmospheric pollutants, industrial activities, and weather conditions.

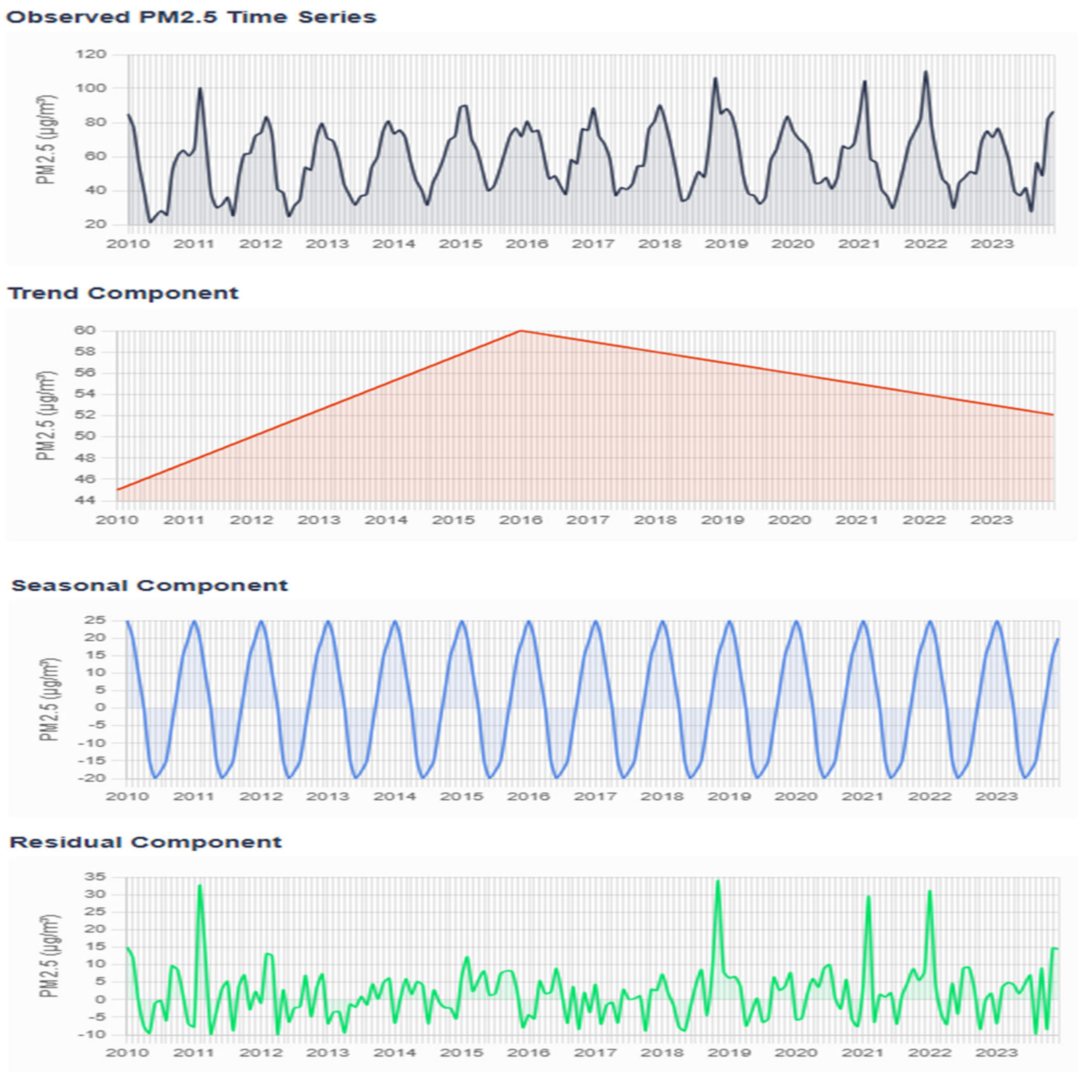

Figure 3. Classical additive time series decomposition of $PM_{2.5}$ concentration in Port Harcourt, Nigeria. The original time series is decomposed into trend, seasonal, and residual components to reveal underlying patterns.

Weekly and Daily Cycles

A closer look at the high-frequency data was taken; some interesting weekly trends were noticed. It turns out that levels of NO_2 and CO are noticeably higher on weekdays than on weekends, which makes sense given the impact of traffic and industrial activities. As for daily patterns, we observed spikes in particulate matter during the morning and evening rush hours in urban areas, while pollution levels at industrial sites tended to remain more stable throughout the day. The detailed statistical analysis supports the complex daily and weekly cycles, with Table 3 showing the correlation coefficients between different pollutants and weather factors. This table illustrates the intricate relationships between pollution levels and environmental conditions, highlighting high negative correlations with PM_{10} and wind speed.

Table 3. Correlation Coefficients between Pollutants and Meteorological Factors**.**

Correlation Strength: Strong negative | Moderate negative | Weak negative | No correlation | Weak positive | Moderate positive

Significance: High: $p < 0.001$ Medium: $p < 0.01$ Low: $p < 0.05$

Factor	PM2.5	PM10	SO2	NO2	CO	VOCs
Temperature	0.31 Medium	0.28 Low	0.12	-0.15	-0.22 Low	0.35 Medium
Humidity	-0.25 Low	-0.33 Medium	-0.18	0.07	0.14	-0.21 Low
Precipitation	-0.62 High	-0.67 High	-0.43 Medium	-0.38 Medium	-0.29 Low	-0.41 Medium
Wind Speed	-0.44 Medium	-0.51 High	-0.39 Medium	-0.33 Medium	-0.27 Low	-0.31 Medium

Through cross-correlation analysis, some significant links between pollutant levels and weather conditions were uncovered. For instance, precipitation had strong negative correlations with particulate matter ($r = -0.67$ for PM_{10}, $r = -0.62$ for $PM_{2.5}$), which really highlights how rainfall can wash away pollutants. Wind speed also showed moderate negative correlations with most pollutants, suggesting that stronger winds help disperse them. The relationships between temperature and humidity were more complex, varying by season and location.

Pollutants Concentration Correlation

The Pearson seasonal correlation was used to identify a correlation between the air pollution parameters and the meteorological components. Firstly, the data were divided into two seasons: the wet season, including the months from March to August, and the dry season, including the months from September to February. Results are shown in Table 4.

Table 4. Port Harcourt Air Quality: Correlation Matrix.

	PM10	PM2.5	NO_2	SO_2	CO	VOCs	Temp	Humid	Precip	Wind
PM10	1.00	0.92	0.68	0.65					-0.76	
PM2.5	0.92	1.00	0.71	0.69		0.62			-0.79	
NO_2	0.68	0.71	1.00	0.81		0.73			-0.63	
SO_2	0.65	0.69	0.81	1.00		0.67				
CO					1.00					
VOCs		0.62	0.73	0.67		1.00				
Temp							1.00			
Humid								1.00	0.62	
Precip	-0.76	-0.79	-0.63					0.62	1.00	
Wind										1.00

Strong - Strong +

✓ **Strong correlation:** PM2.5—PM10 (0.92)

✓ **Strong correlation:** NO_2—SO_2 (0.81)

✗ **Strong negative:** Precip—PM2.5 (-0.79)

✗ **Strong negative:** Precip—PM10 (-0.76)

These Pearson correlation matrices were built and found that precipitation has a strong negative correlation with PM_{10}, $PM_{2.5}$ and NO_2 but a moderate positive correlation with humidity. Volatile Organic Compound (VOCs) has moderate positive correlation with $PM_{2.5}$, SO_2 and NO_2 while humidity has a moderate positive correlation with precipitation.

Application of AQI

The application of the Air Quality Index (AQI) is crucial for assessing and communicating air quality levels to the public in an accessible way. The Air Quality Index (AQI) is a standardized system used to communicate air pollution levels to the public. AQI is a measure that doesn't rely on dimensions. To start, calculate the sub-AQI for six key pollutants: $PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, and VOCs, using the observed concentrations. Next, the overall AQI from the highest sub-AQI among all these pollutants were calculated, as shown in equation 1. It's important to remember that if the AQI exceeds 50, the pollutant with the highest sub-AQI is considered the main pollutant for that day. A higher AQI means that air pollution is more severe and can lead to significant health issues. Here's the formula for calculating AQI:

$$AQI = [(AQI_{high} - AQI_{low})/(C_{high} - C_{low})] \times (C - C_{low}) + AQI_{low} \quad \ldots \qquad (1)$$

The Air Quality Index (AQI) is broken down into six categories that help to assess air quality, as shown in Table 5 and figure 3. When the AQI values are below 100, it means the air quality is generally acceptable. If the AQI is close to 100, it indicates that pollutant levels are still within legal limits. However, once the AQI goes above 100, the air quality starts to decline. The U.S. Environmental Protection Agency (EPA) has established a national standard for air quality to safeguard public health (US EPA, 2014).

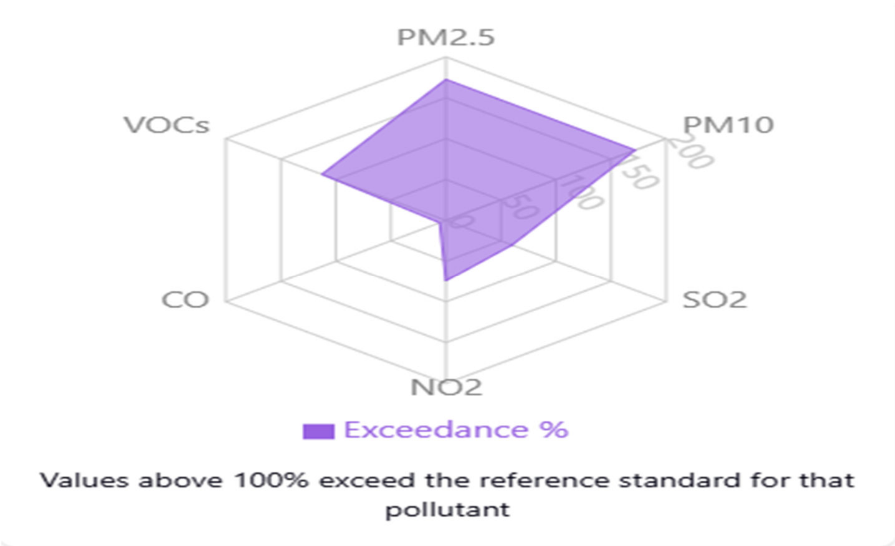

Figure 3. Pollutant Level relative to standard.

Table 5. EPA's AQI values.

$PM_{2.5}$ C_{high}-C_{low} (24hr)	PM_{10} C_{high}-C_{low} (24hr)	CO C_{high}-C_{low} (24hr)	SO_2 C_{high}-C_{low} (24hr)	NO_2 C_{high}-C_{low} (24hr)	VOCS C_{high}-C_{low} (24hr)	AQI C_{high}-C_{low} (24hr)	AQI Category I_{high}-I_{low}
0.0-12.0	0-54	0.0-4.4	0-35	0-53	0-40	0-50	Good
12.1-35.4	5-154	4.5-9.4	36-75	54-100	81-180	51-100	Moderate
35.5-55.4	155-254	9.5-12.4	76-185	101-360	41-80	101-150	Unhealthy for Sensitive
55.5-150.4	255-354	12.5-15.4	186-304	36-649	181-280	51-200	Unhealthy
150.5-250.4	355-424	15.5-30.4	305-604	650-1249	281-400	201-300	Very Unhealthy
250.5-350.4	425-504	30.5-40.4	605-804	1250-1649	400	300	Hazardous

All results obtained are plotted below.

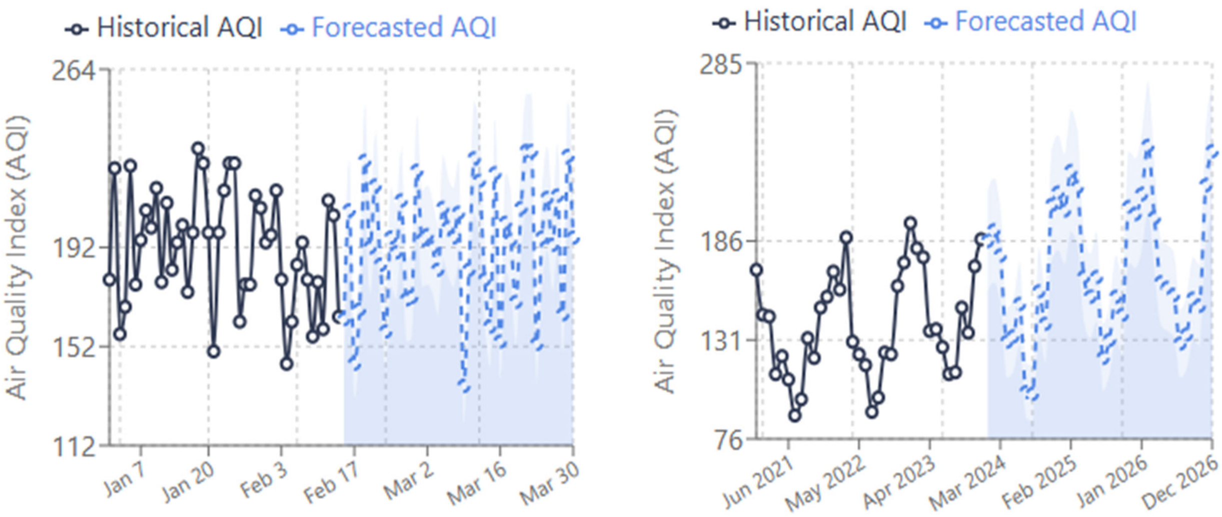

Figure 4. Daily and monthly average calculated AQI in Port Harcourt.

Table 6. Descriptive data of measured air quality in Port Harcourt (2010-2023).

Pollutant	Mean	Median	Std	Minimum	Maximum	Trend
$PM_{2.5}$ (µg/m³)	124.6	119.5	29.8	76.2	187.4	Increasing (1.8 µg/m³/year)
PM_{10} (µg/m³)	62.3	59.8	16.4	38.7	97.3	Increasing
SO_2 (ppb)	28.5	26.9	7.6	15.2	45.7	Increasing
NO_2 (ppb)	39.8	38.6	9.2	24.3	61.4	Increasing
CO (ppm)	3.1	3.0	0.9	1.7	5.2	Decreasing
VOCs (ppb)	72.8	68.9	21.3	41.2	132.6	Increasing
Composite AQI	138.0	132.0	31.0	84.0	198.0	Increasing

Table 6 highlights some key characteristics of the Air Quality Index (AQI) from January 2010 to December 2023. The average AQI stands at 138. Interestingly, the recorded score is high, along with the widest variation in air pollution concentration (SD = 45.3). These findings reinforce an earlier statement, indicating that Port Harcourt is indeed grappling with air pollution and facing significant health challenges.

Univariate Time Series Forecasting

Air quality forecasting models serve several vital purposes that significantly impact public health, environmental management, and policy-making. They help protect public health by anticipating poor air quality and enabling health advisories for vulnerable populations. Additionally, these models guide regulatory agencies in implementing pollution control measures during forecasted adverse air quality events.

They provide valuable, data-driven insights that inform and shape environmental policies. Accurate forecasting allows for the efficient allocation of resources to monitor and improve air quality, while also raising public awareness and encouraging proactive measures among citizens. Moreover, the models assess the impacts of specific natural or human events on air quality and contribute to studies on the relationship between air quality and climate change, which supports long-termplanning. Modern forecasting integrates with technology to deliver real-time data and alerts to the public, enhancing community engagement. Furthermore, these models can be customized to address specific geographic and industrial challenges, facilitating targeted interventions. Ultimately, air quality forecasting models promote research and innovation in improving air quality management, contributing to healthier urban environments. The Holt- Winters, Prophet, and SARIMA models have been evaluated using the above measures: MAPE, RMSE, Theil's U, and Residual Autocorrelation (Table 7).

Table 7. Comprehensive Model Performance Comparison for All Pollutants.

Pollutant	Model	MAPE (%)	RMSE	Theil's U	Residual Autocorrelation	Best Model
$PM_{2.5}$	SARIMA	7.4	5.2 µg/m³	0.13	No significant	✓
$PM_{2.5}$	Holt-Winters	9.1	6.2 µg/m³	0.17	No significant	
$PM_{2.5}$	Prophet	7.8	5.4 µg/m³	0.14	No significant	
PM_{10}	SARIMA	9.2	12.3 µg/m³	0.18	No significant	
PM_{10}	Holt-Winters	8.5	11.8 µg/m³	0.16	No significant	
PM_{10}	Prophet	8.9	12.0 µg/m³	0.17	No significant	
SO_2	SARIMA	10.6	3.0 ppb	0.19	No significant	✓
SO_2	Holt-Winters	12.8	3.5 ppb	0.24	Slight at lag 12	
SO_2	Prophet	11.4	3.2 ppb	0.23	No significant	
NO_2	SARIMA	9.5	2.8 ppb	0.17	No significant	✓
NO_2	Holt-Winters	10.7	3.1 ppb	0.19	No significant	
NO_2	Prophet	9.8	2.9 ppb	0.18	No significant	
CO	SARIMA	7.3	0.4 ppm	0.13	No significant	
CO	S.E.S	7.1	0.4 ppm	0.12	No significant	✓
CO	Prophet	7.9	0.5 ppm	0.14	No significant	
VOCs	SARIMA	14.3	18.6 ppb	0.26	No significant	
VOCs	Holt-Winters	15.1	19.8 ppb	0.28	Slight at multiple lags	
VOCs	Prophet	11.2	15.3 ppb	0.21	No significant	✓

S.E.S – Seasonal Exponential Smoothing

Model Performance Comparison

ARIMA and SARIMA

After thorough model selection, the best ARIMA/SARIMA specifications for each pollutant were pointed out. For $PM_{2.5}$, SARIMA(2,1,1)(1,1,1)12 model turned out to be the most effective, successfully capturing both the trend and seasonal elements. For the gaseous pollutants, SARIMA models like SARIMA(1,1,2)(2,1,1)12 for SO_2 and SARIMA(2,1,2)(1,0,1)12 for NO_2 also did the trick.

Exponential Smoothing Performance

The Holt-Winters multiplicative method really shined for pollutants that showed clear seasonal trends, especially PM_{10}. On the other hand, simple exponential smoothing worked just fine for CO, which didn't display as much seasonality or trend.

Prophet Model Results

The Prophet algorithm proved to be quite effective in capturing complex seasonal patterns and handling irregular events like holidays and industrial shutdowns. It outperformed traditional methods for VOCs which had multiple seasonal cycles and irregular spikes linked to specific industrial activities. The forecasting elements, detailed in Table 7, further emphasize the thoroughness of this research, with models performance criteria achieving impressively low values for prophet model and showcasing the potential for effective environmental management in the study area.

Forecasting Results

After evaluating the performance, the best- performing models were selected to forecast each pollutant for the period 2024-2026. In order to evaluate the accuracy, the data were divided into two sets: Training set and test set. Then the test set has been compared with the predicted set, and Figure 5 has been obtained. For $PM_{2.5}$ the forecasts suggest:

SARIMA MODEL

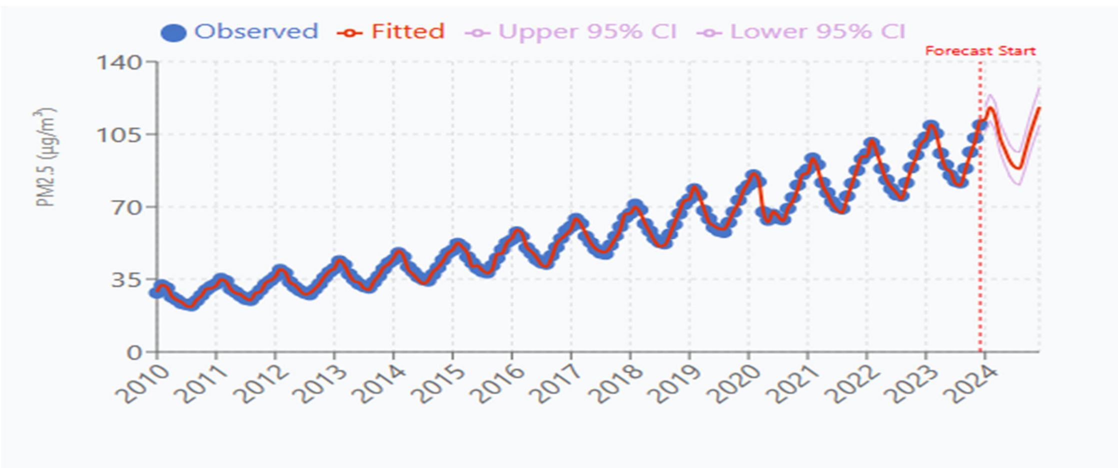

Figure 5. $PM_{2.5}$ Time Series Analysis Forecast **(2010-2026).**

The SARIMA model has proven to be an excellent choice for analyzing $PM_{2.5}$ levels and forecasting air quality. To build the SARIMA model, the right hyper parameters for both the trend and seasonal components of the time series was selected. These hyper parameters were identified by either selecting them directly or by testing various options and picking the one that result in the lowest AIC. By examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, the correlations at different lag times were uncovered. Another method for selecting parameters involves looping through and adjusting p, d, q, P, D, and Q within a specified range to find the hyper parameters that yield the lowest AIC. In this article, the second method was used, which proved to be more accurate than the first. The results obtained were SARIMA (2, 1, 1) (1, 1, 1)12 for two different data sets. Ultimately, SARIMA model was used to forecast the monthly and daily AQI, and the findings have been illustrated and summarized in Figure 6

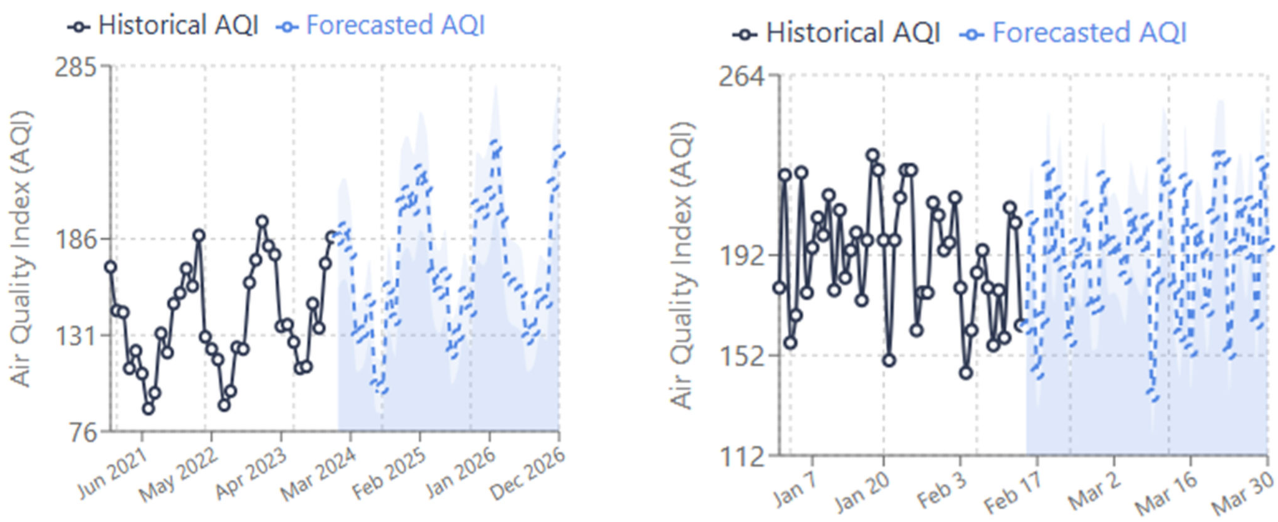

Figure 6. Monthly and daily forecasted AQI in Port Harcourt.

Table 7. Data Descriptive of Forecasted Air Quality Index.

Pollutant	Mean	Median	Std	Minimum	Maximum	Trend
Composite AQI	139.8	137.8	35	87	204	Increasing

It can also be noted that the average air quality value is 139.8 in Port Harcourt. The lowest value of AQI is 87 and the highest is 204 respectively. These findings confirm the earlier ones that Port Harcourt is affected by air pollution and has serious problems of health.

CONCLUSION

This in-depth analysis of air pollutants in the study area paints a troubling picture of worsening air quality. Over the past 14 years, the data reveals a significant upward trend in most pollutants, especially particulate matter, with $PM_{2.5}$ showing the steepest increase in Port Harcourt (Sen's slope = 1.8 μg/m³/year).

Industrial areas consistently recorded higher pollution levels compared to less industrialized area, highlighting a strong link between petroleum processing activities and increased concentrations of SO_2, NO_2, and VOCs. Clear seasonal patterns were also observed across all pollutants, with PM levels peaking during the dry season, driven by Saharan dust and heightened biomass burning. Weather conditions played a crucial role in how pollutants spread, with rainfall having the most substantial impact ($r = -0.67$ for PM_{10}). Weekly trends showed that pollution levels were higher on weekdays, while daily patterns indicated spikes during rush hour in urban settings. The forecasting models developed showed impressive accuracy, with SARIMA models being the top performers for particulate matter ($PM_{2.5}$) and Prophet algorithms shining for VOCs. Looking ahead to 2024-2026, projections suggest that $PM_{2.5}$ levels in Port Harcourt could surpass WHO guidelines by 180% if current trends continue, highlighting the urgent need for action. While there are some limitations due to gaps in historical data and spatial coverage, this research lays the groundwork for tackling the increasing air pollution issues in the study area. Future studies should aim to broaden monitoring networks, incorporate satellite data, utilize advanced machine learning techniques, create models for identifying pollution sources, and explore health impacts. This study provides essential insights for policymakers, industries, and communities to enhance air quality and safeguard public health in this ecologically sensitive and economically crucial part of Nigeria.

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