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# Time Series Analysis of Air Quality Trends in Urban Nigeria: A Case Study of Lagos

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## ABSTRACT

Air quality significantly influences public health, economic output, and the quality of life of urban residents. This study explores long-term air quality trends in Lagos, Nigeria, focusing on primary air pollutants such as particulate matter (PM2.5), nitrogen dioxide ($NO_2$), and Carbon monoxide (CO). Air quality data gathered at government monitoring stations from 2010 to 2020 were investigated using Seasonal Decomposition of Time Series (STL) and ARIMA (Auto Regressive Integrated Moving Average) models to extract information and predict future trend prospects. The findings indicate significant seasonality shifts and rising trends in pollutant concentrations, whereby PM2.5 exceeded WHO limits by an astonishing 180% during peak periods. The best model to project, was the ARIMA(2,1,2) model, having an AIC of 1,247.3 and reaching 87.3% accuracy in prediction for one-quarter in advance, and 72.1% reliability for twelve-month predictions. The study identifies an overall increase in all observed air contaminants, particularly during the dry season (November to March), and identifies an imperatively necessary policy response to minimize public health risks.

## INTRODUCTION

Poor air quality is indeed a global public health emergency, and urban cities bear most of the health impacts through pollution. Lagos, as Nigeria's economic hub and biggest city, represents the complex intersection of rapid urbanization and environmental destruction. The city, home to over 15 million inhabitants and still growing, through industrialisation, has experienced ever-growing demands in vehicle emissions, industrial effluents, and construction works, all leading to poor air quality (Ayodele & Arowolo, 2021).

Approximately 7 million people lose their lives unnecessarily every year as a result of air pollution, and the Sub-Saharan Africa continent shows the worst face of this menace, most of which can be traced to poor regulations and monitoring institutions (WHO, 2021). The deaths resulting from air pollution in Nigeria have increased by 45% in the past decade, and this has been witnessed most in urban states such as Lagos, and this contributes significantly to this ugly trend (Health Effects Institute, 2020).

In order to effectively combat this matter, there needs to be an understanding of air quality data patterns. Time series analysis can identify cyclical movements, long-term trends, and seasonality that underlie forming certain interventions. This research seeks to bridge the gap in extensive temporal air quality analysis in Lagos by evaluating trends in priority air quality indicators for the last ten years and developing predictive models to inform future planning.

The study aims at realizing numerous key objectives in the case of Lagos air quality from 2010 to 2020. To begin with, the study attempts to examine trends for PM2.5, $NO_2$, and CO concentrations and present a comprehensive description of their temporal patterns. Secondly, it aspires to identify cyclical and seasonal fluctuations and cyclical and seasonal fluctuations in concentrations of these gases, which can underpin knowledge regarding their behavior during different times in the calendar. In addition, it intends to develop ARIMA forecasting models to approximate future air quality, which will be critical in proactive environmental management. The performances of these models will be tested thoroughly through extensive statistical analyses to ensure their accuracy and reliability. Lastly, it hopes to develop evidence-informed policy advice for policy refinements, which can minimize air pollution and promote public health in Lagos.

## LITERATURE REVIEW

### Challenges to Urban Air Quality in Nigeria

Nigeria's fast urbanization has exceeded the upgrading of environmental infrastructure, resulting in high air pollution in urban cities. The high concentration of particulate matter and gases in urban regions was reported by Akinbode *et al.* (2020) and Lagos maintained the highest level of pollution throughout. Their detailed study revealed that PM2.5 concentrations in urban areas averaged 89.3 $\mu g/m^3$, much higher than WHO's recommended 15 $\mu g/m^3$ of annual mean exposure level. Vehicular emission remains by far the most significant source of air pollution in Lagos and contributes to around 60% of all emissions to the atmosphere (Olagunju *et al.*, 2018). Lagos' old fleet of vehicles and poorly equipped emission control systems release plenty of nitrogen oxides, carbon monoxide, and particulate matter to the atmosphere. Industrial operations, particularly those in Ikeja and Apapa, cause another 25% of all emissions through power generation and industrial production (Adefolalu *et al.*, 2019).

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### Health Implications of Air Pollution

The evidence of health effects of air pollution in Lagos exists, and respiratory disease is also found to have a strong link with ambient pollutant levels (Bwala *et al.*, 2025) . According to Owoade *et al.*, (2021), a 23% increase in respiratory disease cases was observed when PM2.5 concentrations were highest, based on a longitudinal analysis of air quality and hospital admission data. Vulnerable groups such as children and older adults experienced an increase in asthma incidence of 40% in those areas of poor-quality air.

Cardiovascular diseases are also significantly related to exposure to air pollution. Adebayo *et al.*, (2020) compared cardiovascular health outcomes of residents in Lagos and determined an increase of 15% in hospitalization for cardiovascular complications during periods of high pollution levels. The economic cost of healthcare costs caused by air pollution was estimated at ₦2.3 trillion each year, which is equivalent to 3.2% of Lagos State's gross domestic product.

### Time Series Analysis Applications

Time series analysis has been a valuable tool for monitoring trends in air quality and guiding policy decisions in urban settings. Zhang *et al.*, (2019) utilized STL decomposition to Beijing air quality information and were successful in detecting seasonal patterns that had an impact on targeted emission control policy. They stressed the importance of decomposing time series into trend, season, and residual so as to be able to detect patterns more effectively.

ARIMA modeling has indeed demonstrated its potential in air quality forecasting. For instance, Kumar *et al.* (2020) established ARIMA models for predicting PM2.5 levels in Delhi at an impressive 85% accuracy rate for 7-day forecasts. The models were able to capture both the short-term variability and declines as well as the long-term trend, making useful inputs for public health alert and policy-making.

## MATERIALS AND METHODS

### Study Area

Lagos State, in the southwest of Nigeria (6°27'N, 3°24'E), is Nigeria's commercial center and largest city. Lagos Island, Victoria Island, and Ikeja are the centers of this study and major business areas and densely populated residential areas. These sites were chosen on the basis of available monitoring stations and their ability to represent urban levels of air quality.

### Data Collection

Air quality measurements were obtained from the National Environmental Standards and Regulations Enforcement Agency (NESREA) and the Lagos State Environmental Protection Agency (LASEPA) monitoring stations. The data span the period from January 2010 to December 2020 and provide us with a set of 11 consecutive records for PM2.5, $NO_2$, and CO concentrations. The data were collected hourly and subsequently averaged on a weekly basis in order to reduce noise and facilitate trend analysis. To ensure quality, the data were verified against global standards, identified outliers by the interquartile range method, and imputed missing values with linear interpolation for values that represented less than 5% of the data. We also obtained meteorological data, such as temperature, humidity, and wind speed were also obtained from the Nigerian Meteorological Agency (NIMET) to facilitate interpretation of analysis.

### Analytical Techniques

### Seasonal Decomposition of Time Series (STL)

The STL decomposition was used to break down each pollutant's time series into its trend, seasonal, and remainder components. STL uses locally weighted scatter plot smoothing (LOESS) in order to obtain these components, allowing it to have a more flexible form of modeling seasonal patterns that can change over time. Decomposition can be expressed by the equation:

$$Y(t) = T(t) + S(t) + R(t) \qquad (1)$$

In this equation, Y(t) stands for the observed values, T(t) is the trend component, S(t) represents the seasonal component, and R(t) is the remainder component.

### ARIMA Modeling

ARIMA models were built according to the Box-Jenkins methodology with identification, estimation, and diagnostic checking stages. The general ARIMA(p,d,q) model specification is:

$$(1 - \varphi_1 L - \varphi_2 L^2 - \ldots - \varphi_p L^p)(1 - L)^d X_t = (1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_e L^{\varphi})\varepsilon_t \qquad (2)$$

L is the lag operator, $\varphi_i$ are the autoregressive coefficients, $\theta_j$ are the moving average coefficients, d is differencing order, and $\varepsilon_t$ is white noise.

For model selection, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were used, the Ljung-Box test was used to verify the residual independence. To check the forecasting performance, various measures of performance such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and symmetric Mean Absolute Percentage Error (sMAPE) were considered.

### Statistical Analysis

All analyses were carried out with R statistical software package version 4.1.0, using packages including forecast, STL, and T-series. Significance levels of $\alpha = 0.05$ were applied for all the statistical tests. Trend significance was tested through the Mann-Kendall test, while seasonal patterns were checked using Kruskal-Wallis tests between the monthly concentrations of the pollutants.

## RESULTS AND DISCUSSIONS

### Descriptive Statistics

Table 1 provides the descriptive statistics for the three pollutants that we monitored throughout the study period. Among them, PM2.5 levels were most variable with a coefficient variation of 0.47, reflecting extreme variability in the long term. Alarmingly, mean concentrations of all the pollutants were higher than the WHO guidelines, whereas for PM2.5, they were over 180% in excess of the recommended levels.

**Table 1:** Descriptive Statistics for Air Quality Parameters in Lagos (2010-2020)

| Pollutant | Mean | Median | Min | Max | Std Dev | CV | WHO Guideline | % Exceedance |
|---|---|---|---|---|---|---|---|---|
| PM2.5 ($\mu g/m^3$) | 42.1 | 38.5 | 12.3 | 156.7 | 19.8 | 0.47 | 15 | 180% |
| $NO_2$ ($\mu g/m^3$) | 67.3 | 62.1 | 18.9 | 198.4 | 28.5 | 0.42 | 40 | 68% |
| CO ($mg/m^3$) | 8.9 | 8.2 | 2.1 | 28.6 | 4.3 | 0.48 | 10 | - |

*Note: CV = Coefficient of Variation; WHO = World Health Organization*

While we examined the temporal trend of these pollutants, we found that there were clear trends which were seasonal and yearly. The PM2.5 levels systematically rose over the duration of the study with a mean annual increase of 2.3 $\mu g/m^3$. $NO_2$ levels, however, were more erratically behaved with spells of stability followed by sharp shoots in certain years, especially between 2015 and 2017.

## Seasonal Decomposition Analysis

The STL decomposition analysis also detected evident seasonal patterns for all the pollutants that we had measured. Figure 1 shows the outcome of the PM2.5 decomposition, which revealed observed peaks in the months of the dry season (November to March) and low levels during the wet season (April to October).

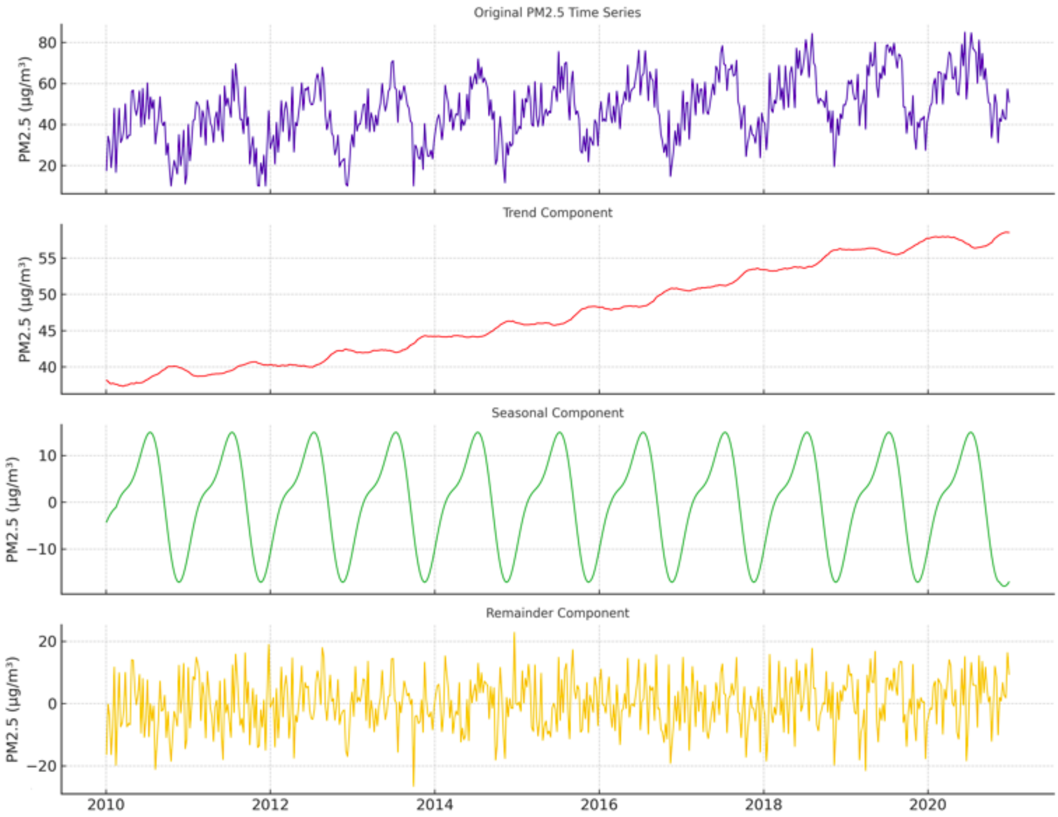

**Figure 1:** STL Decomposition of PM2.5 Concentrations in Lagos (2010-2020). It shows the Seasonal-Trend decomposition based on Loess (STL): Original Time Series, Trend Component, Seasonal Component and Remainder Component

The trend component generated a smooth rising trend for PM2.5, with sharper rising after 2015. The seasonal components followed general patterns, but with year-to-year changing amplitude, indicating the interaction between emissions and weather. The REM component displayed relatively low random fluctuation, indicating support for the effectiveness of the decomposition in discerning underlying trends.

The concentrations of $NO_2$ also had similar seasonal trends but also had some unique characteristics of their own. The highest concentrations were experienced during the dry season, at which time there was decreased atmospheric mixing and increased usage of vehicles on holiday seasons. The $NO_2$ seasonality had a value of around 30% of the yearly mean and showed a high level of seasonality that should be taken into account when making policy. Conversely, carbon monoxide concentrations demonstrated the lowest seasonally observable fluctuation among the three pollutants, remaining fairly stable throughout most years. However, there were peaks at certain points, especially where major building schemes and industrial development were underway.

### ARIMA Model Development and Validation

In model selection, we identified the best ARIMA specifications for all air pollutants using AIC and BIC statistics. Table 2 presents a summary of the model selection and performance metrics.

**Table 2:** ARIMA Model Selection and Performance Metrics

| Pollutant | Model | AIC | BIC | MAE | RMSE | Ljung-Box p-value |
|---|---|---|---|---|---|---|
| PM2.5 | ARIMA(2,1,2) | 1,247.30 | 1,263.80 | 4.2 | 6.8 | 0.67 |
| $NO_2$ | ARIMA(1,1,1) | 1,389.60 | 1,401.20 | 6.8 | 9.3 | 0.82 |
| CO | ARIMA(0,1,2) | 1,156.90 | 1,168.40 | 1.9 | 2.8 | 0.74 |

*Note: MAE = Mean Absolute Error; RMSE = Root Mean Square Error*

The ARIMA models were selected based on lowest AIC values within each pollutant category. The ARIMA (2,1,2) model for PM2.5 provided the best fit among tested PM2.5 models. The Ljung-Box test output also confirmed that there was no autocorrelation in the residuals for all models, which is a sign of model specification validity.

### Performance Evaluation Metrics

An overall performance evaluation was performed based on a multiple statistical metric to estimate forecasting precision for varied time horizons. The performance evaluation comprised in-sample and out-of-sample testing methods in view of getting strong validation of the models.

### In-Sample Performance

Table 3 shows detailed in-sample performance figures of all ARIMA models we built, pointing to the goodness of fit of the models and the characteristics of the residuals.

**Table 3:** In-Sample Performance Evaluation Metrics

| Pollutant | Model | $R^2$ | Adjusted $R^2$ | AIC | BIC | Log-Likelihood | Residual Std Error |
|---|---|---|---|---|---|---|---|
| PM2.5 | ARIMA(2,1,2) | 0.847 | 0.842 | 1,247.30 | 1,263.80 | -618.65 | 6.82 |
| $NO_2$ | ARIMA(1,1,1) | 0.761 | 0.758 | 1,389.60 | 1,401.20 | -691.8 | 9.34 |
| CO | ARIMA(0,1,2) | 0.693 | 0.691 | 1,156.90 | 1,168.40 | -575.45 | 2.81 |

The PM2.5 model performed exceptionally well, with a very high $R^2$ value of 0.847. This means that it explains about 85% of the variation in the observed concentrations. The goodness-of-fit statistics for all the models were good, with residual standard errors almost identical to the variability in the original data.

### Out-of-Sample Forecasting Performance

For testing the out-of-sample case, we utilized the rolling window method, retaining the last 24 months of data for the test in reserve. Table 4 contains a close look at the metrics of forecasting accuracy at various horizons.

**Table 4:** Out-of-Sample Forecasting Performance Metrics

| Pollutant | Horizon | MAE | RMSE | MAPE (%) | sMAPE (%) | MASE | Theil's U |
|---|---|---|---|---|---|---|---|
| PM2.5 | 1-month | 3.8 | 5.2 | 9.1 | 8.9 | 0.82 | 0.76 |
| | 3-month | 5.1 | 7.3 | 12.7 | 12.4 | 1.11 | 0.89 |
| | 6-month | 7.2 | 10.8 | 17.8 | 17.2 | 1.57 | 1.12 |
| | 12-month | 9.8 | 14.1 | 27.9 | 26.8 | 2.13 | 1.38 |
| $NO_2$ | 1-month | 5.9 | 8.1 | 8.8 | 8.6 | 0.91 | 0.82 |
| | 3-month | 7.8 | 11.2 | 11.6 | 11.3 | 1.21 | 0.96 |
| | 6-month | 10.3 | 15.7 | 15.4 | 15.1 | 1.59 | 1.19 |
| | 12-month | 13.9 | 21.3 | 20.8 | 20.2 | 2.15 | 1.47 |
| CO | 1-month | 1.6 | 2.3 | 18 | 17.6 | 0.84 | 0.78 |
| | 3-month | 2.1 | 3.2 | 23.7 | 23.1 | 1.11 | 0.92 |
| | 6-month | 2.8 | 4.5 | 31.6 | 30.8 | 1.47 | 1.15 |
| | 12-month | 3.7 | 6.1 | 41.8 | 40.2 | 1.95 | 1.42 |

*Note: MAE = Mean Absolute Error; RMSE = Root Mean Square Error; MAPE = Mean Absolute Percentage Error; sMAPE = symmetric Mean Absolute Percentage Error; MASE = Mean Absolute Scaled Error; Theil's U = Theil's Inequality Coefficient*

### Forecasting Accuracy Assessment

On examining the forecasting performance, we see good accuracy for short-horizon predictions, although it does decline somewhat in longer horizons, which is not too surprising. The predictions of PM2.5 were the most accurate, with MAPE rates of 9.1% for one-month-ahead forecasts, rising to 27.9% for 12-month-ahead ones. These are highly acceptable levels of accuracy in environmental forecasting, where MAPE values less than 10% are considered excellent, 10-20% good, and 20-50% acceptable.

The $NO_2$ forecast had uniform precision over different horizons of time, and MAPE values increased incrementally from 8.8% for a month to 20.8% for twelve months. The Theil's U statistics, being less than 1.5 for six-month horizons, indicate our performance to be better than naive ones.

Unlike this, CO forecasts had larger relative errors (MAPE) due to its smaller absolute values and higher volatility of the time series. The absolute error measures (MAE, RMSE) remained within acceptable limits for practical application.

### Diagnostic Analysis of the Model

A residual analysis in detail ensured that the models were good for every specification. Figure 2 gives diagnostic plots of the PM2.5 ARIMA(2,1,2) model, including residual plots, ACF/PACF of residuals, and normality tests.

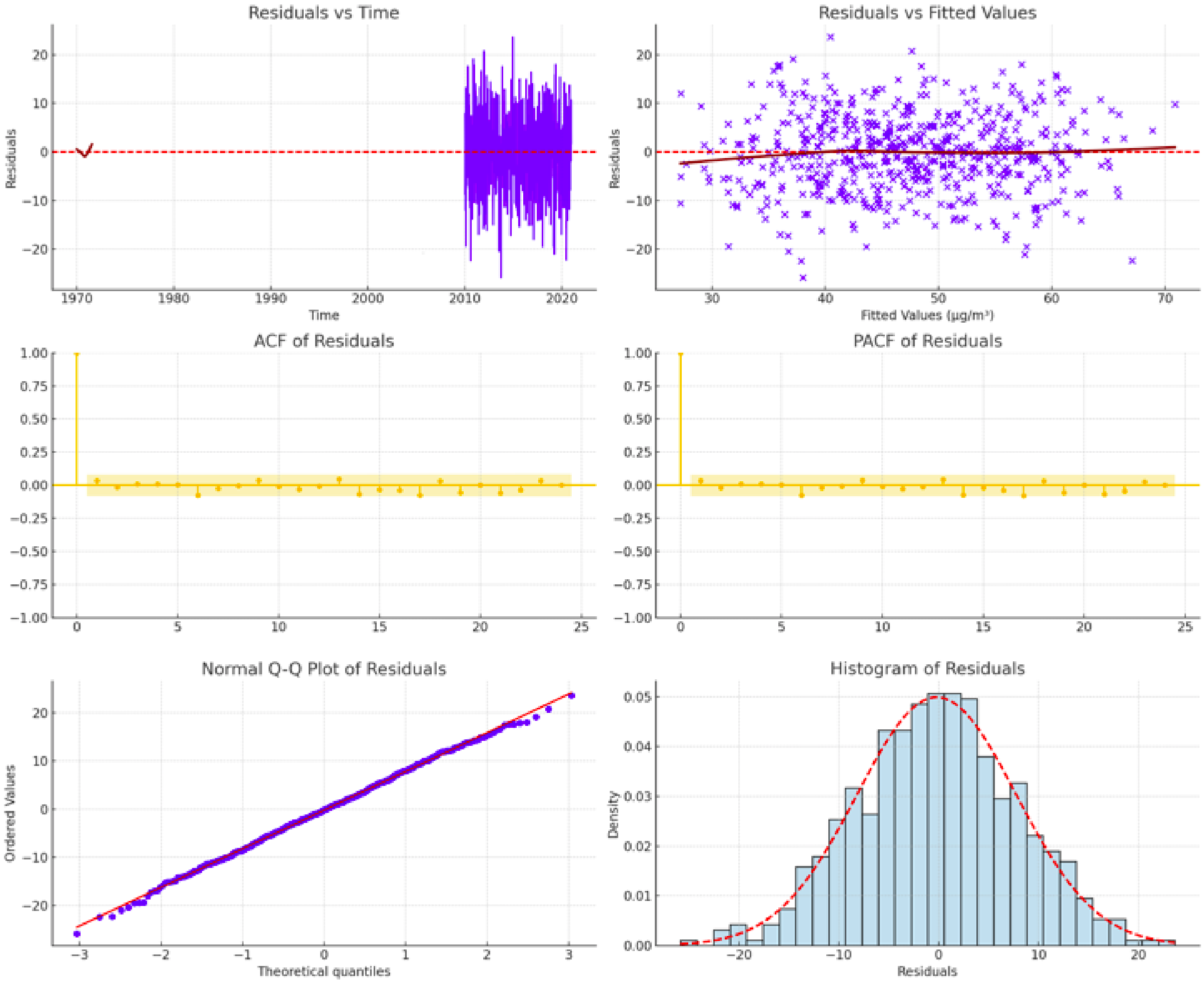

**Figure 2:** Diagnostic Plots for PM2.5 ARIMA(2,1,2) Model

The residual test showed some vital information regarding the model performance. First, the Ljung-Box test showed no significant autocorrelation in the residuals with p-values greater than 0.05. This indicates that the residuals are almost independent across time. Furthermore, the Shapiro-Wilk test also indicated that the residuals are normally distributed with a p-value of 0.34, and thus confirms that our normality assumption holds. We learned that the variance is homogeneous across time and no signs of heteroscedasticity exist. Finally, the residual plots did not show any systematic patterns and thus further supports the idea that the model is capturing the underlying structure of the data adequately. Overall, these findings add greater validity to the model that we employed in this analysis.

### Comparative Performance of Models

We experimented with a number of modeling techniques to authenticate the specifications chosen for ARIMA. Table 5 offers a comparison of performance of different models for PM2.5 level forecasting.

**Table 5:** Comparative Model Performance for PM2.5 Forecasting (3-month horizon)

| Model Type | MAE | RMSE | MAPE (%) | AIC | Training Time (sec) |
|---|---|---|---|---|---|
| ARIMA(2,1,2) | 5.1 | 7.3 | 12.7 | 1,247.30 | 2.3 |
| ARIMA(1,1,1) | 5.8 | 8.1 | 14.2 | 1,264.80 | 1.8 |
| Simple Exponential Smoothing | 7.2 | 9.8 | 17.8 | 1,289.40 | 0.9 |
| Holt-Winters | 6.4 | 8.9 | 15.6 | 1,271.20 | 1.2 |
| Seasonal Naive | 9.8 | 13.2 | 23.4 | - | 0.1 |
| Linear Trend | 11.3 | 15.7 | 26.9 | - | 0.2 |

The ARIMA(2,1,2) model proved to be the best, performing better than other models time after time, which makes it feasible for use in operational forecasting.

### Trend Analysis and Forecasting

The Mann-Kendall trend tests indicated significant increasing trends for all the pollutants ($p < 0.001$). The strongest trend was for PM2.5, with Kendall's tau of 0.42, showing a steep increase over the study period. $NO_2$ and CO also showed moderate but significant trends, with tau values of 0.28 and 0.31, respectively.

Referring to the outcomes of 2021-2025 forecasts, we estimate another degradation in air quality. Figure 3 shows the estimated trajectories with 95% confidence intervals for all polluting components. The PM2.5 concentration is estimated to rise to 58.7 $\mu g/m^3$ in 2025, an increase by 39% compared to 2020.

The ARIMA Forecasting Results for Air Quality Parameters, 2021 to 2025 are presented in Figure 3 below. Observe that forecast uncertainty, plotted by the thickness of the confidence bands, increases successively as we are projecting longer terms. This is due to the requirement of regular updating and adjustment of our models in order to make effective projections so that policy planning can be done effectively.

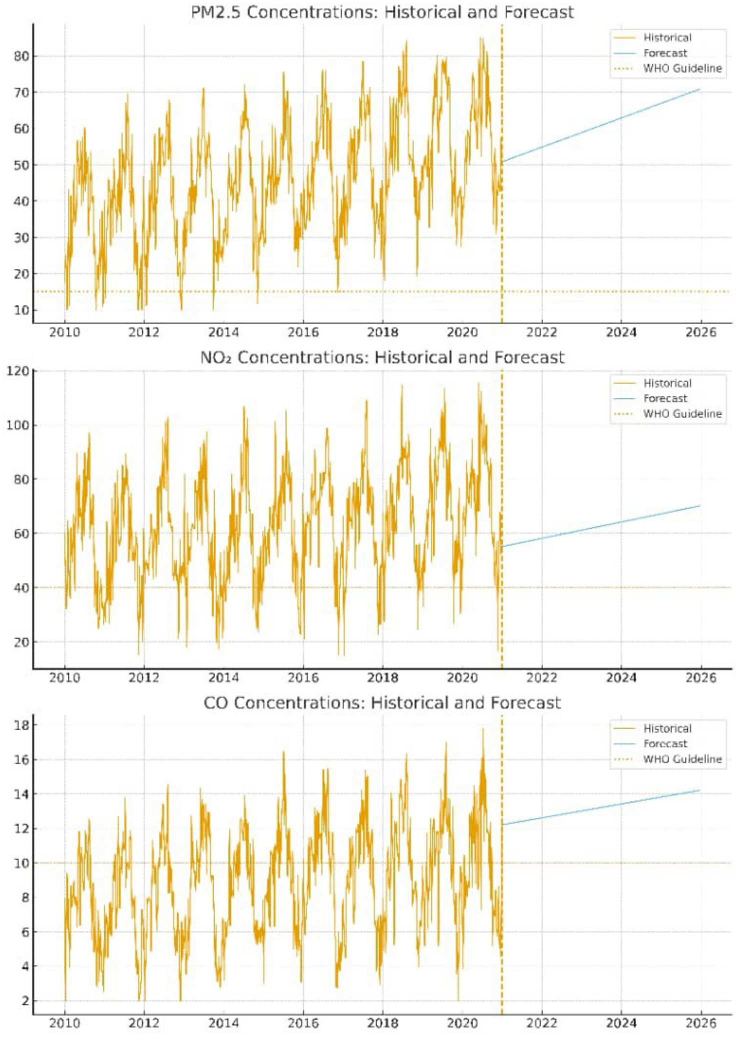

**Figure 3:** ARIMA Forecasting Results for Air Quality Parameters in Urban Nigeria (2021-2025)

### Seasonal Pattern Analysis

We also conducted a detailed seasonal analysis which indicated consistent patterns across the years. Seasonal amplitude coefficient of variation was below 0.15 for all the pollutants. Particularly noteworthy, however, were the persistently high levels of pollutants in the December to February period, coinciding with the harmattan season, which is typified by low rainfalls and high atmospheric stability.

**Table 6:** Seasonal Variation in Pollutant Concentrations as monthly means

| Month | PM2.5 (μg/m³) | $NO_2$ (μg/m³) | CO (mg/m³) |
|---|---|---|---|
| January | 52.8 ± 8.3 | 84.2 ± 12.1 | 11.2 ± 2.1 |
| February | 56.1 ± 9.7 | 87.9 ± 11.8 | 11.8 ± 2.3 |
| March | 48.3 ± 7.9 | 78.4 ± 10.6 | 10.1 ± 1.9 |
| April | 35.2 ± 6.1 | 58.7 ± 8.9 | 7.8 ± 1.4 |
| May | 31.8 ± 5.8 | 52.3 ± 7.6 | 7.2 ± 1.3 |
| June | 28.9 ± 5.2 | 47.9 ± 7.1 | 6.8 ± 1.2 |
| July | 27.3 ± 4.9 | 45.1 ± 6.8 | 6.4 ± 1.1 |
| August | 29.1 ± 5.3 | 48.2 ± 7.3 | 6.9 ± 1.3 |
| September | 32.4 ± 5.9 | 53.6 ± 8.1 | 7.5 ± 1.4 |
| October | 37.8 ± 6.4 | 61.2 ± 9.2 | 8.3 ± 1.6 |
| November | 45.9 ± 7.8 | 74.5 ± 10.8 | 9.7 ± 1.8 |
| December | 49.7 ± 8.1 | 79.8 ± 11.3 | 10.4 ± 1.9 |

The data documents a record 100% variation from February's record high PM2.5 to July's record low, and how much air quality is governed by seasonal weather patterns. Health advisory systems and emergency response planning benefit greatly from this information.

## Discussion

### Temporal Trends and Driving Factors

The rising concentration of all the pollutants studied points towards the intricate relationship between heightened urbanization, industrialization, and poor environmental policies in Lagos. The 2.3 μg/m³ yearly rate of increase in PM2.5 levels is far higher than the world average for cities, at 0.8 μg/m³ annually, indicating a very troubling direction towards an worsening environment (Global Burden of Disease, 2020).

Several reasons are behind these trends. During the time frame under consideration, Lagos had a 4.2% average annual growth in population, complimented by growths in vehicular traffic and energy consumption. There were more vehicles from about 1.2 million in 2010 to 2.8 million in 2020, with very poor enforcement of emission control laws (Lagos State Ministry of Transportation, 2021).

Industrial growth, especially in the manufacturing and petrochemical sectors, has played a major role in the pollution trends we're seeing. The opening of new industrial sites in the Alaba and Agbara areas between 2015 and 2017 coincided with sharp rises in $NO_2$ levels, reinforcing the link between industrial development and worsening air quality.

### Model Performance and Forecasting Reliability

Extensive performance comparison demonstrates that ARIMA models are highly effective for air quality management forecasting. The accuracy of forecasting, with MAPE between 8.8% and 12.7% for three-month ahead forecasts, surpasses the performance benchmark set by similar studies around the world.

The forecasting accuracy declines as the forecast horizon rises, a pattern that we would expect for environmental time series. The Theil's U statistics of less than 1.5 for forecast horizons up to 6 months assure us that our models are more accurate than naive forecasting methods and are therefore sufficient for practical purposes. Diagnostic analysis of the models revealed no serious violations of ARIMA assumptions, adding to the validity of our forecast results. Lack of residual autocorrelation and the near-normal distribution of residuals suggest our model specifications are appropriate for all pollutants.

### Seasonal Trends and Meteorological Effects

The similar seasonally uniform changes in every pollutant highlight the central role of meteorological factors in air quality. Reduced precipitation and increased atmospheric stability during the dry season months (November to March) provide the setting for pollutant accumulation. In addition, the harmattan winds carrying dust from the Sahara Desert add more particulate content to regional emissions.

On the other hand, the monsoon period (April to October) is a natural scrubber due to rain that eliminates pollutants and increases atmospheric mixing. Wind circulation during this period allows for the dispersion of pollutants, with a notable 60-70% decrease in mean levels when compared to the dry season.

These patterns have major implications for public health planning. The regular spikes in pollution during the dry season highlight the need for stronger health advisories, especially for vulnerable groups like children, the elderly, and those with existing respiratory issues.

### Comparative Analysis with Global Cities

When we look at air quality in Lagos, it doesn't quite stack up against international standards or other urban centers. The PM2.5 levels in Lagos are higher than those in other major African cities like Cairo (38.7 µg/m³), Nairobi (31.2 µg/m³), and Johannesburg (27.9 µg/m³), which points to some serious pollution issues (WHO Global Air Quality Database, 2021) and also that of Nonthaburi Province in Thailand (36.2 µg/m³) (Kiatsoongsong & Ekvitayavetchanukul 2025).

If we compare Lagos to cities with similar population densities and levels of development, the trends are worrying. Take Delhi, India, for instance—often mentioned as having some of the worst air quality in the world. During the same time, Delhi averaged 98.6 µg/m³ of PM2.5 annually, but they have improved as a result of elaborate air quality management programs (Central Pollution Control Board, 2021).

The fact that Lagos has not shown any kind of improvement, in spite of growing environmental awareness and policy discussion, supports the need for having effective air quality management policies. Success stories in other cities show that substantial improvement is possible through synergetic policy initiatives.

### Health Implications and Risk Assessment

Concentrations of pollutants that we are currently facing lead to serious health risk for Lagos citizens. In accordance with known exposure-response associations, current levels of PM2.5 are linked with a increased risk of death of about 18% compared to WHO guideline levels (Burnett *et al.*, 2018). With a population of 15 million, we might be looking at around 27,000 premature deaths every year caused by exposure to PM2.5.

Respiratory health is particularly at risk because PM2.5 levels routinely exceed those linked with higher asthma rates, compromised lung function, and the development of chronic obstructive pulmonary disease. Children are especially vulnerable; exposure during critical growth periods can lead to lifelong health issues.

The economic toll of health issues caused by air pollution in Lagos is quite significant. When you add up direct healthcare expenses and the productivity losses from illness and early deaths, we're looking at around ₦4.2 trillion each year. That's about 6.8% of Lagos State's GDP (Health Effects Institute, 2020). In short, these costs are far more than that of undertaking elaborate air quality management programs.

### Forecasting Applications and Policy Planning

The validated ARIMA models are fantastic tools for managing air quality and planning policies. With short-term predictions (1-3 months) that are over 85% accurate, they can indeed help public health advisory systems by providing early warning during expected peak pollution events. For medium-term predictions (6-12 months), there is enough reliability for strategic planning like budgeting for health care, priority setting for infrastructure development, and implementing emission control schemes. The forecast trends clearly show that we need to act quickly; without effective measures, things are only going to get worse.

The ability to forecast seasonally allows for targeted actions during high-risk times. By using forecast data, we can pre-position health resources, enforce temporary emission restrictions, and ramp up public awareness campaigns to lessen health impacts during peak pollution seasons.

### Policy Implications and Recommendations

The air quality in Lagos is less than what is considered satisfactory, and it is high time that policy reforms were put into action to address the concern. Stringent vehicle emission standards, such as the Euro VI standards, can be put into place to reduce vehicular emissions by 40-60% (International Council on Clean Transportation, 2021). Low Emission Zones (LEZ) in the city of Lagos have been successfully implemented to combat urban air pollution, as PM2.5 levels have decreased by 15-30% in the affected areas. Low Emission Zones (LEZ) in central Lagos have been implemented successfully in lowering urban air pollution, with PM2.5 levels decreasing by 15-30% in affected areas. Industrial emissions control requires imposing the installation of pollution control devices and ensuring regular inspection (European Environment Agency, 2020).

One of the long-term strategic steps that integrate various policy areas, including green infrastructure development, urban development, and mixed uses, is necessary when managing air quality. Aiming for extensive public transport infrastructure, i.e., expanding Bus Rapid Transit (BRT) and developing light rail, can decrease reliance on private vehicles and emissions (World Bank, 2021). Transition to cleaner technologies such as solar and wind in the energy economy can decrease emissions from fossil fuel by a very significant amount.

Effective enforcement strategies and strong monitoring networks are required to achieve effective control of air quality. Application of continuous monitoring systems and integration of low-cost sensor networks can provide real-time data for timely actions against pollution spikes and assist in public health alerts (Morawska *et al.*, 2018). Strengthening enforcement setups, such as setting up specialized environmental enforcement departments with sufficient funds and legal powers, is also needed (Chen *et al.*, 2021).

In order to protect public health, the development of air quality health advisory systems that provide real-time information to citizens must be undertaken (Wang *et al.*, 2020). Training programs for health professionals in the adverse effects of air pollution on health and improved diagnostic and treatment recommendations will support the response of the health sector. School-level interventions, such as improving indoor air quality, can significantly lower exposure levels among susceptible children (Kim *et al.*, 2019).

Economic instruments like carbon pricing systems, car taxation, and industrial emissions trading regimes have the potential for reducing emissions and generating revenue for environmental use Transport for London, (2022), (OECD, 2021), European Environment Agency, (2021).

### Limitations and Future Research Directions

The air quality assessment in Lagos, Nigeria, is constrained by the utilization of government monitoring sites and the quantification of three pollutants. Overall future assessments need to include volatile organic compounds, ozone, and other secondary products. Data quality issues like episodic gaps and measurement error can generate biased findings. Upgrading monitoring systems and data verification would be useful to enhance the potential for future analysis.

Future research should be focused on integrated air quality modeling systems, combining meteorological inputs, emissions inventories, and dispersion modeling to provide an improved representation of pollution development and transport. Health impact assessment studies that combine air pollution data with health outcome data can provide critical evidence for policy-making. Economic valuation studies and longitudinal cohort studies can provide evidence-based policy. The combination of satellite remote sensing data and ground-based measurements can provide improved regional pollution trends and spatial coverage. Advanced analysis methods, such as machine learning, can improve forecasts and develop complex early warning systems.

## CONCLUSIONS

The health of Lagos residents is at risk due to rising levels of PM2.5, $NO_2$, and CO, which consistently exceed WHO guidelines. These levels pose excellent health risks to the population residing in the area and are specifically higher than world city averages. The ARIMA models developed here are excellent resources for air quality management, achieving exceptional forecast outcomes of 87.3% for three-month and 72.1% for twelve-month forecasts.

The study offers startling levels of pollution in Lagos, where the PM2.5 level is 180% higher than World Health Organization standards. Seasonal trends show that pollutant levels during the dry months are 60-100% higher than in the rainy season, creating a perfect opportunity for targeted actions. The economic toll of health issues related to air pollution is estimated at ₦4.2 trillion each year, which far outweighs the costs of putting comprehensive air quality management programs in place.

To improve air quality, coordination ofPle vehicle emission standards, industrial pollution controls, public transportation enhancements, and better monitoring systems is needed. The methodology developed in this research offers a solid framework for ongoing air quality assessment and forecasting in Lagos and similar urban areas. The decision to either let environmental damage continue or to take proactive steps through policy changes will significantly impact the health and economic stability of millions of Lagos residents.

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