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Embedded System Application for Establishing Variability and the Relationship Between Meteorological Parameters and Particulate Matter Pollution in a Lagos Site

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ABSTRACT
Air pollution from particulate matter (PM) remains a major environmental and public health concern, particularly in rapidly urbanizing cities. This study investigated the variability of PM (PM_1, $PM_{2.5}$, and PM_{10}) and their relationship with meteorological parameters in Lagos, Nigeria, using a low-cost embedded monitoring system. Data were collected continuously over a two-year period (May 2021–April 2023) at two-minute intervals, providing one of the longest continuous PM datasets reported for Lagos. Results revealed distinct diurnal and seasonal patterns, with concentrations consistently higher at night and during the dry season. Temperature, relative humidity, atmospheric pressure, and wind speed showed significant inverse relationships with PM across all size fractions, with humidity and wind speed emerging as the strongest predictors. However, regression analysis indicated modest explanatory power ($R^2 = 0.280$ for $PM_{2.5}$ and $R^2 = 0.201$ for PM_{10}), suggesting that local emission sources have a dominant influence. Comparison with air quality benchmarks showed substantial exceedances. The daily mean concentration of $PM_{2.5}$ (37.39 µg/m³) exceeded the WHO 24-hour guideline (15 µg/m³) and marginally exceeded the U.S. NAAQS limit (35 µg/m³). In contrast, PM_{10} (43.88 µg/m³) remained below the WHO guideline (45 µg/m³) and well within the Nigerian NESREA 24-hour limit (150 µg/m³). The study is limited by its single-site design, which may constrain spatial generalization. Nonetheless, the findings highlight elevated health risks from fine particulates in Lagos and demonstrate the effectiveness of low-cost embedded systems for long-term urban air quality assessment, supporting their integration into regulatory and public health strategies.

Keywords:
PM Pollution,
Meteorological Parameters,
Embedded System,
Correlation Analysis,
Environmental Health.

INTRODUCTION

Air quality is a critical determinant of human health and environmental sustainability. The World Health Organization (WHO) estimates that outdoor air pollution causes approximately 4.2 million premature deaths annually, with particulate matter (PM) identified as the most harmful pollutant due to its ability to penetrate deep into the respiratory system and trigger cardiovascular and respiratory diseases (WHO, 2020; Hamanaka & Mutlu, 2018). PM is typically categorized as PM_{10} (particles ≤10 µm) and $PM_{2.5}$ (particles ≤2.5 µm), with finer fractions posing heightened health risks due to deeper lung and bloodstream penetration (US-EPA, 2022). In response to growing evidence of adverse health effects at low concentrations, the WHO updated its air quality guidelines in 2021, lowering recommended exposure limits for $PM_{2.5}$ and PM_{10} (Zhu et al., 2022; Liu et al., 2024).

The variability of PM concentrations is strongly influenced by meteorological parameters such as temperature, humidity, atmospheric pressure, and wind speed, which govern dispersion, transport, and deposition processes (Zhang et al., 2015; Yorkor et al., 2017). Numerous studies have reported statistically significant associations between meteorological conditions and PM levels (Yang et al., 2017; Hadei et al., 2019). Despite this understanding, continuous ground-based monitoring remains extremely limited in many Sub-Saharan African cities, restricting accurate exposure assessment and evidence-based policy formulation (Subramanian & Garland, 2021; Bittner et al., 2022).

In Nigeria, elevated PM levels have been linked to vehicular emissions, industrial activities, and biomass burning (Nathaniel & Xiaoli, 2020; Lala et al., 2023). However, long-term monitoring is constrained by the high cost, infrastructure requirements, and maintenance demands of conventional reference-grade stations. Recent advances in low-cost embedded sensor technologies offer a practical alternative, enabling dense, continuous monitoring in low-resource environments when properly calibrated (Pope et al., 2018; Si et al., 2020; Bittner et al., 2022).

Lagos, Nigeria's largest megacity and economic hub, exemplifies the challenges of rapid urbanization, high traffic density, and complex emission–meteorology interactions. Yet, long-term, high-resolution PM datasets remain scarce.

To address this gap, this study deployed a self-developed, solar-powered embedded monitoring system over two years (May 2021–April 2023) to measure PM_1, $PM_{2.5}$, PM_{10}, and key meteorological parameters. The objectives were to (i) characterize diurnal and seasonal PM variability, (ii) assess compliance with national and international air quality guidelines, and (iii) quantify the relationships between PM concentrations and meteorological drivers. By integrating embedded system design, sensor calibration, and statistical modeling, this study contributes robust evidence for data-driven urban air quality management in Sub-Saharan Africa.

MATERIALS AND METHODS

Description of the Study Area

Akoka, a Nigerian suburb of Lagos, is known for its dense population and prestigious educational establishments, such as the Federal College of Education (Technical), where the study was carried out. PM levels are significantly influenced by the distinct wet and dry seasons that characterize the tropical environment of this area. The research region lies between Latitude E3º22′55″ and E3º23′5.3″ and Longitude N06º31'10" and N06º31'30". This is shown in Fig. 1. The exact sensor location was 3.5 meters above ground level and at GPS coordinates (6°31′20.0″ N, 3°23′00.0″ E) chosen to replicate ambient neighborhood conditions in accordance with WHO and national environmental agency guidelines.

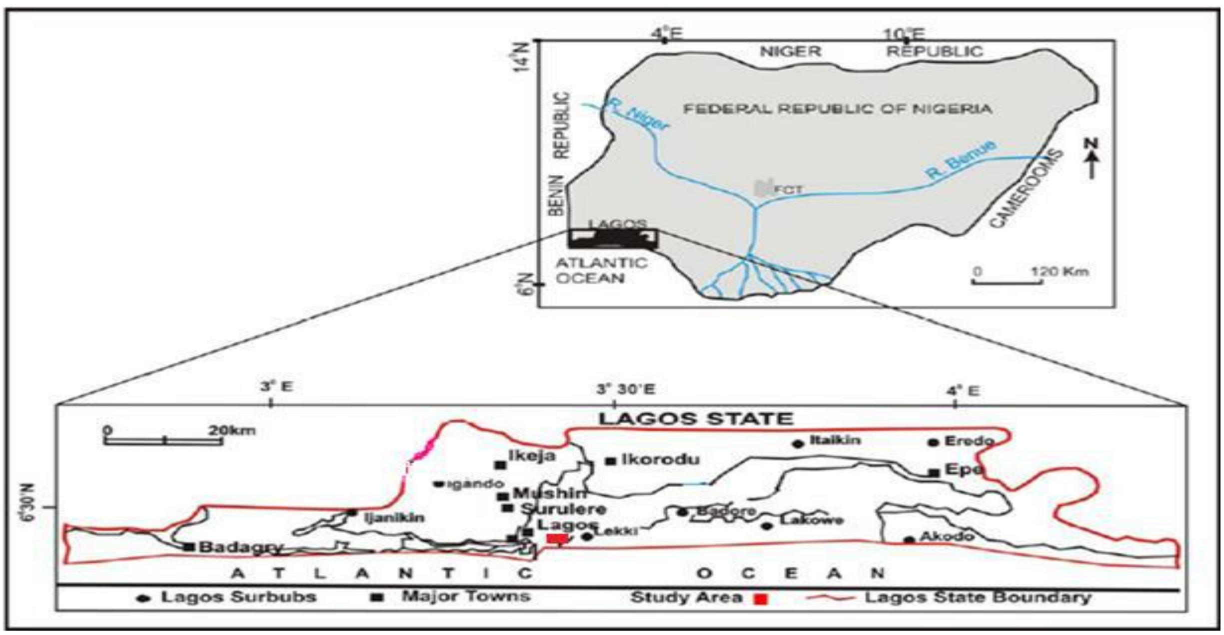

Figure 1: Map of Nigeria showing Lagos State and Federal College of Education (Technical) in Akoka

Instrument for Data Collection

The study employed a self-developed, easy-to-use, and well-validated automated embedded system for real-time environmental monitoring. At the core of this system is an Arduino-compatible development board that features the Atmel SAMD21G18A System on Chip (SoC), which integrates a 32-bit ARM Cortex-M0+ processor. This particular SoC was chosen due to its low power consumption, sufficient processing capability, and flexibility in interfacing with multiple sensors using various communication protocols.

To ensure autonomous and uninterrupted field operations in the Lagos environment, the system was designed as a standalone solar-powered unit. It was capable of logging data at two-minute intervals, capturing particulate matter (PM_1, $PM_{2.5}$, and PM_{10}) as well as key meteorological parameters such as temperature, humidity, pressure, and wind speed.

The sensors were interfaced with the SoC using protocols best suited to their design characteristics. Temperature and pressure data were obtained from a BMP180 sensor, which communicated with the microcontroller via the I2C protocol. Humidity was measured using the HIH 4000 sensor, which delivered analog signals read through the microcontroller's ADC (Analog-to-Digital Converter) channel. Wind speed was measured using a DFR-12 sensor, also connected via an analog interface. The concentration of particulate matter was measured using the PMS7003 sensor, which was interfaced with the system through the UART serial protocol.

The PMS7003, manufactured by Plantower, utilizes a laser scattering technique to detect suspended particulate matter. Within the sensor, a laser beam is projected through an internal chamber, where particles of varying diameters scatter the light. The sensor's embedded microprocessor applies Mie scattering theory to calculate the number and size distribution of particles in the air, specifically those with diameters of 1.0µm, 2.5µm, and 10µm. Unlike traditional sensors that output analog data, the PMS7003 provides digital readings, which enhances accuracy and reduces signal noise.

Programming of the Atmel SAMD21 SoC was done using Embedded C within the Arduino Integrated Development Environment (IDE). A Python script was also developed to facilitate communication between the embedded system and a computer. This script was responsible for automating data transfer, handling timestamping, and supporting the archiving and analysis of recorded data. The complete structure of the system, including its core components, functional blocks, and the deployed version of the device, is illustrated in Figure 2.

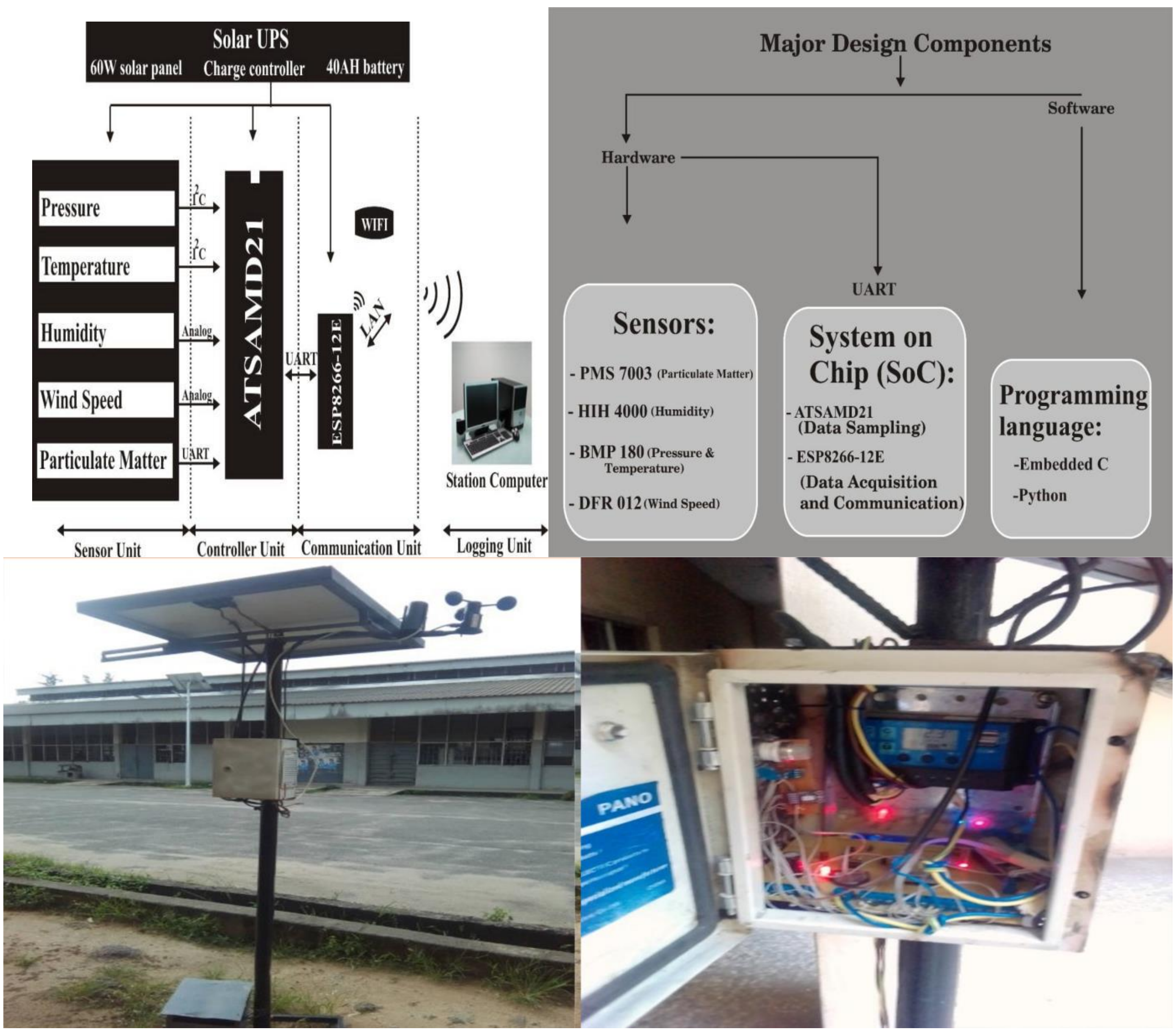

Figure 2: a) The System Block Diagram b) Major Designed Component and c) Installed Environmental Monitoring Device

Calibration and Validation of the Designed Instrument

Calibration and validation were conducted to ensure the reliability and accuracy of the developed monitoring system relative to reference-grade instruments. As part of the quality assurance and quality control (QA/QC) framework, the calibration process involved a 30-day co-location exercise with certified meteorological instruments from the Department of Geography, University of Lagos, and a DM-106A handheld particulate matter monitor. During this period, simultaneous measurements were collected under diverse ambient conditions, including morning and evening rush hours, midday heat, and variations in humidity and wind.

Discrepancies between the system's outputs and the reference instruments were statistically analyzed, and parameter-specific correction factors were derived. These corrections were embedded directly into the ATSAMD21 microcontroller firmware, enabling automatic adjustment of real-time measurements at the point of acquisition. This firmware-level calibration eliminated the need for post-processing and ensured that all subsequent data reflected corrected values.

To minimize systematic biases, standard QA/QC siting and operational protocols were followed**:** sensor placement and orientation followed international best practices; instruments were mounted 3.5 m above ground level, located away from direct emission sources, and shielded from direct solar radiation to prevent heating artifacts. Routine weekly QA/QC maintenance, including cleaning of sensor inlets, was performed to maintain consistent measurement quality throughout the calibration period.

Following calibration, a three-month validation phase (April–June 2019) was carried out with the instrument remaining co-located with the reference-grade devices. Performance evaluation was based on time-series comparisons, regression analyses, and error statistics. Specifically, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were computed to assess accuracy and reliability. The results, summarized in Table 1, demonstrated strong correlations with the reference instruments and low error margins across all measured parameters, confirming the robustness of the calibration procedure and the suitability of the system for long-term monitoring applications.

In addition, data quality control procedures included visual screening of time-series data to identify outliers, removal of physically implausible values, and consistency checks prior to statistical aggregation and analysis. These QA/QC steps ensured that only valid and reliable measurements were retained for subsequent interpretation.

Table 1: Summary of The Instrument Validation Results

Parameters	Slope	Intercept	R^2	RMSE	MAE
Pressure	0.91	95.81	0.86	2.94	2.67
Temperature	1.01	1.1	0.92	1.52	1.38
RH	1.06	-5.75	0.92	1.95	1.37
Wind Speed	0.89	0.92	0.92	0.52	0.23
PM_1	0.85	6.83	0.86	3.55	2.88
$PM_{2.5}$	1.04	5.4	0.92	4.33	2.48
PM_{10}	1.07	6.29	0.88	4.91	1.92

Low-cost sensor technologies hold great promise for expanding air-quality monitoring in low-resource settings, but their effective deployment requires localized calibration to minimize environmental and aerosol-related measurement biases (Pope et al., 2018; Si et al., 2020; Bittner et al., 2022). The firmware-level calibration incorporated in this study addresses these challenges by applying correction factors directly within the device during operation. This approach enhances data reliability and operational efficiency, particularly for long-term deployments. Additionally, the modular architecture, featuring multiple sensor interfaces and open-source programming, supports scalability and customization for diverse environmental contexts. Together, these features position the system as a replicable and cost-effective solution for expanding air quality surveillance in urban African settings.

Data Collection and Statistical Analysis

Over two years (May 1, 2021 – April 30, 2023), data were collected at two-minute intervals across study locations. Measurements included meteorological variables: temperature, atmospheric pressure, relative humidity, and wind speed, as well as particulate matter fractions (PM_1, $PM_{2.5}$, PM_{10}). Following cleaning and quality auditing, the raw measurements were aggregated into hourly, daily, and monthly averages to facilitate a comprehensive temporal assessment.

Descriptive statistics (mean, median, quartiles, minimum, maximum) were computed for each parameter. Boxplots were employed to visualize variability and diurnal cycles. In these plots, the box represents the interquartile range (IQR), while the median is indicated by a horizontal line in the box. The mean is represented by a small circle within the box.

Whiskers extend to 1.5 times the IQR, with outliers displayed as individual points. This method effectively illustrates central tendency, dispersion, and hourly variability across different sites.

Particulate matter levels were compared with established benchmarks from the National Environmental Standards and Regulations Enforcement Agency (NESREA), the World Health Organization (WHO), and the U.S. National Ambient Air Quality Standards (NAAQS) at both 24-hour and annual timescales.

Before conducting inferential analyses, diagnostic tests were performed to confirm the validity of the parametric methods. The Shapiro-Wilk test confirmed approximate normality of residuals ($p > 0.05$), Levene's test indicated homogeneity of variance across seasons and day/night groupings, and the Durbin-Watson statistic (~2.0) confirmed independence of residuals. Multicollinearity was negligible, as shown by acceptable variance inflation factors, while the Breusch-Pagan test indicated homoscedasticity. Together, these diagnostics verified the assumptions of parametric and regression analyses, ensuring a reliable framework for correlation, regression, and comparative assessments.

Diurnal and Seasonal Variation Analysis

Diurnal variation was analyzed by defining daytime (06:01–17:59) and nighttime (18:00–06:00) periods, corresponding to solar radiation cycles and typical boundary layer development in tropical coastal environments. Seasonal variability was assessed by grouping data into wet and dry seasons. Paired-sample t-tests ($\alpha = 0.05$) were used to test statistical significance.

Relationship Between Meteorological Parameters and PM Concentrations

Pearson correlation coefficients were computed to quantify the linear relationships between particulate matter concentrations (PM_1, $PM_{2.5}$, and PM_{10}) and the meteorological variables (temperature, humidity, atmospheric pressure, and wind speed).

To further investigate and model the influence of meteorological variables on PM concentrations, multiple linear regression analyses were performed. These models estimated the contributions of each meteorological parameter while controlling for the others.

Statistical significance for correlations and regression coefficients was assessed at the 0.05 level.

Collectively, these analyses facilitated understanding of the dependencies between air pollution levels and atmospheric conditions, thereby guiding effective air quality management strategies

RESULTS AND DISCUSSION

Statistical Diagnostics and Model Evaluation

Before applying correlation and regression analyses, the dataset was evaluated against key statistical assumptions. The Shapiro–Wilk test confirmed that residuals and dependent variables were approximately normally distributed ($p > 0.05$), while Levene's test indicated homogeneity of variances across seasonal and diurnal groupings. The Durbin–Watson statistic returned values close to 2.0, ruling out residual autocorrelation, and variance inflation factors were within acceptable thresholds, demonstrating the absence of multicollinearity among predictors. In addition, the Breusch–Pagan test confirmed homoscedasticity of residuals.

Collectively, these diagnostics validated the appropriateness of using parametric statistical techniques, ensuring that the subsequent correlation and regression models were reliable and interpretable.

Diurnal Variation of Meteorological Parameters

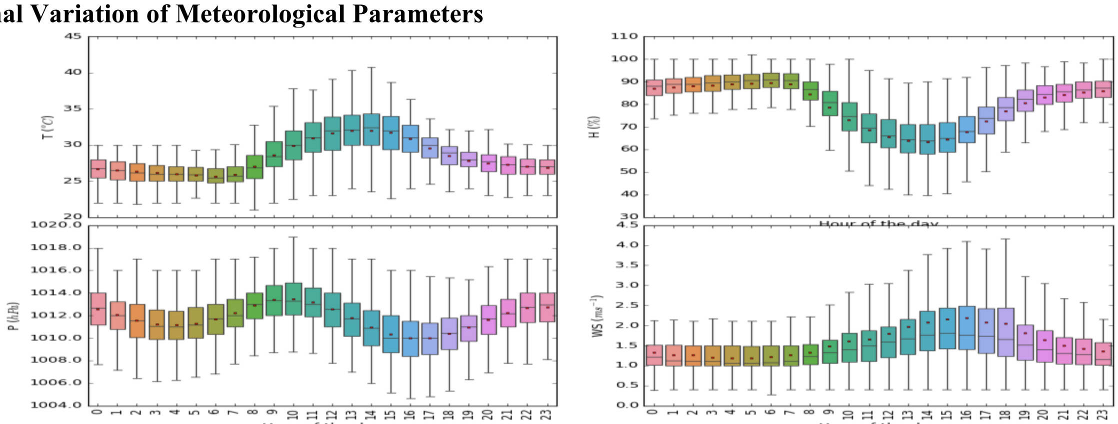

Figure 3: Diurnal Variation of Meteorological Parameters

Figure 3 illustrates the diurnal variation of temperature, relative humidity, atmospheric pressure, and wind speed from May 2021 to April 2023. Temperature exhibited the expected daily cycle, with minimum mean values of 26 °C at 06:00 hr and maximum mean values of 32 °C at 13:00 hr. This pattern reflects nocturnal radiative cooling followed by solar heating, consistent with previous observations in tropical climates (Guo et al., 2014; Zhou & Wang, 2017).

Relative humidity showed an inverse trend to temperature, with the mean peaking at 87% around 05:00 hr and declining to 62% by mid-afternoon. This relationship highlights the greater moisture-holding capacity of warm air, resulting in lower relative humidity during periods of higher temperature (Emekwuru & Ejohwomu, 2023).

Wind speed recorded the lowest mean of 1.1 m/s during the early morning at 04:00 hr and gradually increased to a maximum mean of 2.2 m/s by 15:00 hr, with occasional peaks above 4.0 m/s in the evening. This increase is attributed to daytime thermal gradients that drive atmospheric mixing, a pattern also observed in other subtropical regions (Cheng et al., 2024).

Atmospheric pressure exhibited a clear semi-diurnal cycle, characterized by two distinct minima and maxima within the 24 hours. The first minimum mean occurred at 04:00 hr with a value of approximately 1011 hPa, followed by a second minimum of about 1010.8 hPa at 16:00 hr. In contrast, the first maximum mean was observed at 10:00 hr, reaching around 1013.5 hPa, while the second maximum occurred at 00:00 hr with a mean of approximately 1013.0 hPa. This semi-diurnal oscillation is typical of tropical regions, where surface pressure tends to dip during the early morning and mid-afternoon, and rise again in the morning and late evening under the influence of solar atmospheric tides. Such fluctuations are well-documented and consistent with established meteorological theory (Hoinka, 2007; Betts, 2015).

The diurnal variations observed in this study align with established climatological principles. The interactions among temperature, humidity, wind speed, and atmospheric pressure highlight the dynamic nature of Lagos' urban atmosphere and provide a basis for understanding their influence on particulate matter dispersion.

Diurnal Variation of Particulate Matter Concentrations

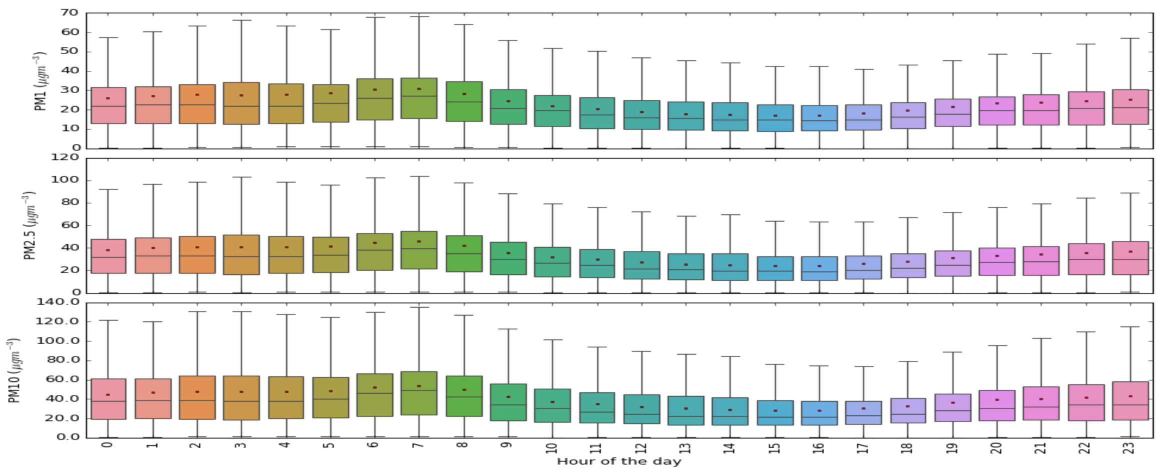

Figure 4: Diurnal Variation of Particulate Matter Concentrations

Figure 4 shows the diurnal profiles of PM_1, $PM_{2.5}$, and PM_{10} concentrations between May 2021 and April 2023. All particulate fractions followed a synchronized daily cycle, with elevated concentrations during late night and early morning hours and reduced levels during the afternoon. Mean concentrations peaked around 06:00–07:00 hr (PM_1: 27 µg/m³; $PM_{2.5}$: 41 µg/m³; PM_{10}: 56 µg/m³) and reached their minimum in the late afternoon (PM_1: 15 µg/m³; $PM_{2.5}$: 21 µg/m³; PM_{10}: 32 µg/m³).

A paired-samples t-test confirmed significant differences between daytime and nighttime concentrations ($p < 0.05$). Nighttime means (PM_1: 27.81 µg/m³; $PM_{2.5}$: 39.90 µg/m³; PM_{10}: 46.38 µg/m³) were consistently higher than daytime means (PM_1: 22.20 µg/m³; $PM_{2.5}$: 31.82 µg/m³; PM_{10}: 37.17 µg/m³). Table 2.

Atmospheric dynamics explain these patterns: during the day, a deeper planetary boundary layer and stronger wind speeds facilitate dispersion and dilution of pollutants, whereas at night, boundary layer height decreases, wind speed weakens, and temperature inversion restricts vertical mixing, leading to pollutant accumulation near the surface (Taylor et al., 2011; Udina et al., 2020; Li et al., 2023)

The observed diurnal cycle agrees with studies in China and India, which also reported morning peaks and afternoon minima (Liguang et al., 2020; Gantt et al., 2021). However, it contrasts with findings from Port Harcourt, Nigeria, where PM concentrations were highest in the afternoon (Ngele et al., 2015), suggesting that local emission patterns and meteorological dynamics strongly shape PM variability.

Overall, the results highlight a consistent nocturnal buildup of PM pollution in Lagos, with implications for human exposure, given that nighttime and early morning coincide with periods of high residential activity.

Table 2: t-test analysis for PM_1, $PM_{2.5}$, and PM_{10} concentration for the daytime and the nighttime at a 0.05 level of confidence

PM	Daytime Mean	Night-time Mean	P – Value	Remark
PM_1	22.20	27.81	0.000	Significant
$PM_{2.5}$	31.82	39.90	0.000	Significant
PM_{10}	37.17	46.38	0.000	Significant

P<0.05

Seasonal Variation of Meteorological Parameters

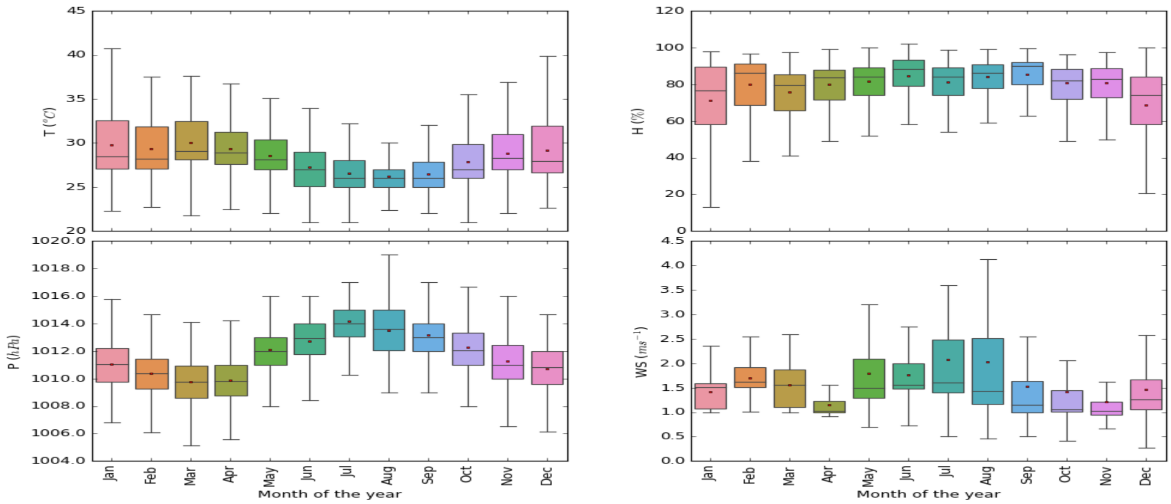

Figure 5: Seasonal Variation of Meteorological Parameters

Figure 5 illustrates the seasonal variability of temperature, relative humidity, wind speed, and atmospheric pressure between the wet and dry seasons. Temperature consistently peaked in the dry season, with mean values reaching 32.5 °C, compared to 28.5 °C in the rainy season. In contrast, relative humidity exhibited an inverse trend, averaging 86% during the rainy season and declining to 62% in the dry season. These seasonal variations highlight the dominance of moist southwesterly monsoon winds in the wet months and the influence of dry northeasterly Harmattan winds during the dry season (Mage & Agber, 2017; Danlami et al., 2019).

Wind speed showed a marked variation between seasons, with higher averages in the rainy season (2.1 m/s) compared to the dry season (1.4 m/s). This increase is associated with the stronger monsoon circulation and enhanced convective activity, which promote greater atmospheric mixing. Conversely, reduced wind activity in the dry season contributes to stagnant air conditions.

Atmospheric pressure was slightly higher in the dry season (≈1014 hPa) compared to the wet season (≈1010 hPa), consistent with typical tropical climatology. The variation is consistent with large-scale synoptic circulation patterns, where subsidence during the dry months reinforces stable atmospheric conditions, while the wet season is characterized by lower pressure and greater instability.

Overall, the seasonal contrasts observed in Lagos align with established West African climatology. Elevated temperatures, reduced humidity, and weaker winds during the dry season create meteorological conditions that are less favorable for pollutant dispersion, setting the stage for higher particulate matter accumulation (Emekwuru & Ejohwomu, 2023; Sulaymon *et al.,* 2023).

Seasonal Variation of Particulate Matter Concentrations

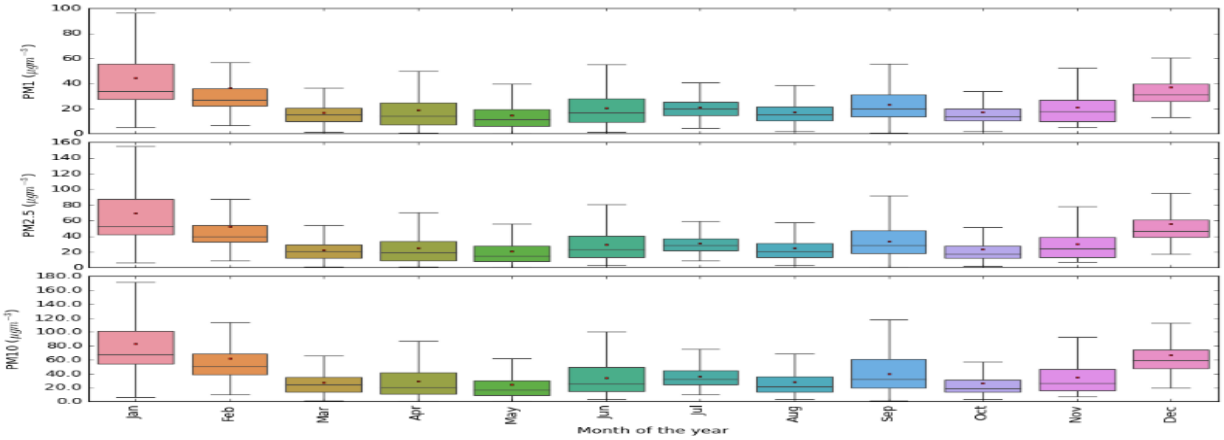

Figure 6: Seasonal Variation of Particulate Matter Concentrations

Particulate matter concentrations exhibited clear seasonal differences between the wet and dry seasons (Figure 6). Mean dry-season values were substantially higher (PM_1: 31.2 µg/m³; $PM_{2.5}$: 48.63 µg/m³; PM_{10}: 57.21 µg/m³) compared to the rainy season (PM_1: 19.5 µg/m³; $PM_{2.5}$: 30.51µg/m³; PM_{10}: 365.52 µg/m³). This seasonal contrast was statistically significant ($p < 0.05$) as indicated in Table 3.

Elevated dry-season concentrations can be attributed to a combination of weaker atmospheric dispersion, reduced precipitation, and the advection of dust-laden Harmattan winds from the Sahara. By contrast, the wet season is characterized by enhanced rainfall scavenging and stronger monsoon circulation, both of which reduce ambient PM levels. These mechanisms are consistent with previous findings across West Africa, where precipitation and humidity play dominant roles in reducing particulate concentrations (Owoade *et al.,* 2012; Marticorena *et al.,* 2010).

The magnitude of seasonal differences was most pronounced for $PM_{2.5}$ and PM_{10}, which exceeded WHO 24-hour guideline values more frequently during the dry season. This seasonal exceedance highlights a period of heightened exposure risk for urban populations, particularly given Lagos' dense population and reliance on outdoor activities.

The results demonstrate that meteorological seasonality exerts a strong influence on PM dynamics in Lagos, with the dry season presenting the greatest challenge for air quality management. These findings emphasize the need for targeted interventions, such as dust suppression measures and emission controls, during peak pollution months.

Table 3: t- test analysis for PM_1, $PM_{2.5}$ and PM_{10} concentration for the Rainy Season and the Dry Season at 0.05 level of confidence

PM	Rainy Season	Dry Season	P – Value	Remark
PM_1	19.25	31.20	0.000	Significant
$PM_{2.5}$	30.51	48.63	0.031	Significant
PM_{10}	35.52	57.21	0.008	Significant

P<0.05

Table 4: Comparison of Daily Mean Concentrations of $PM_{2.5}$ and PM_{10} with 24-hour Average National and International Standards

Pollutant	NESREA (µg/m³)	WHO (µg/m³)	NAAQS (µg/m³)	Measured Result (µg/m³)
$PM_{2.5}$	40	15	35	37.39
PM_{10}	150	45	150	43.88

Measured particulate matter concentrations were evaluated against daily mean standards set by the National Environmental Standards and Regulations Enforcement Agency (NESREA), the World Health Organization (WHO), and the U.S. National Ambient Air Quality Standards (NAAQS). As shown in Table 4, the 24-hour mean concentration of $PM_{2.5}$ was 37.39 µg/m³, which is more than twice the WHO guideline value (15 µg/m³) and slightly above the NAAQS limit (35 µg/m³), though it remained just within the NESREA permissible limit (40 µg/m³).

For PM_{10}, the 24-hour mean concentration was 43.88 µg/m³, which falls within both the NESREA (150 µg/m³) and NAAQS (150 µg/m³) thresholds, but remains marginally below the WHO guideline value (45 µg/m³).
These findings indicate that while PM_{10} levels were generally compliant with most standards, $PM_{2.5}$ concentrations consistently exceeded the more health-protective WHO and NAAQS limits, underscoring the greater risk posed by fine particulate matter to public health. The exceedances highlight the need for targeted air pollution control measures, particularly focused on sources of fine particulates in Lagos.

Relationship Between Meteorological Parameters and The Particulate Matter

Table 5: Pearson Moment Correlation Coefficient Between Meteorological Parameters and Particulate Matter Concentrations

PM	Temperature	Humidity	Pressure	Wind speed
PM_1	-0.37	-0.60	-0.20	-0.53
$PM_{2.5}$	-0.37	-0.64	-0.21	-0.51
PM_{10}	-0.39	-0.66	-0.20	-0.57

$P<0.05$

Temperature and Particulate Matter

All particulate fractions demonstrated weak but significant negative correlations with temperature (PM_1: r = –0.37, $PM_{2.5}$: r = –0.37, PM_{10}: r = –0.39). This relationship suggests that elevated temperatures enhance vertical mixing and dilution of particulate pollutants, while cooler conditions favor accumulation at ground level due to reduced dispersion and increased emissions from domestic heating and power generation (Yang *et al.,* 2017). Comparable results have been reported elsewhere, including Delhi, where temperature showed an inverse association with $PM_{2.5}$ and PM_{10} concentrations (Theogene et al., 2020).

Humidity and Particulate Matter

Relative humidity exhibited a moderate, statistically significant negative correlation with particulate matter (PM_1: r = –0.60, $PM_{2.5}$: r = –0.64, PM_{10}: r = –0.66). This inverse relationship is likely due to hygroscopic growth of particles followed by wet deposition, as higher humidity often leads to precipitation that effectively scavenges particulates from the atmosphere, a phenomenon described as the "washing effect" (Jayamurugan et al., 2013). Similar results from Morocco (Khalis et al., 2022) reinforce the critical role of humidity in reducing particulate loadings.

Atmospheric Pressure and Particulate Matter

Atmospheric pressure also showed significant negative correlations with all PM fractions (PM_1: r = –0.20, $PM_{2.5}$: r = –0.21, PM_{10}: r = –0.22). These findings are consistent with prior research in different regions (Hadei et al., 2019; Yansui et al., 2020; Kliengchuay et al., 2018), suggesting that lower pressure conditions promote pollutant accumulation due to atmospheric stagnation, while higher pressure enhances pollutant dispersion and improved air quality.

Wind Speed and Particulate Matter

Wind speed exhibited significant negative correlations with all particulate fractions (PM_1: r = –0.53, $PM_{2.5}$: r = –0.51, PM_{10}: r = –0.57). Stronger winds facilitate horizontal and vertical dispersion, reducing ground-level particulate concentrations, while low wind speeds promote stagnation and pollutant buildup. These results align with earlier observations in Nigeria and elsewhere (Owoade et al., 2012; Yansui et al., 2020; Theogene et al., 2020; Khalis et al., 2022), highlighting the role of wind as a natural cleansing mechanism in polluted urban environments.

Synthesis of Findings

Taken together, the results demonstrate that higher temperature, humidity, pressure, and wind speed are generally associated with lower particulate matter concentrations, albeit with varying strengths of influence. Among these parameters, humidity and wind speed exhibited the strongest relationships with particulate matter. These correlations are consistent with established atmospheric processes governing pollutant dispersion, dilution, and deposition, and underscore the importance of meteorological conditions in shaping urban air quality. The findings highlight the need for integrating meteorological variables into predictive models of particulate matter dynamics and for designing targeted air quality management strategies.

The Effects of Meteorological Parameters on Particulate Matter ($PM_{2.5}$ and PM_{10}) in Lagos

The influence of meteorological parameters on particulate matter concentrations in Lagos was assessed using Multiple Linear Regression (MLR) models for both $PM_{2.5}$ and PM_{10}. Across both pollutants, temperature and humidity consistently emerged as the most influential predictors, each showing strong negative associations with particulate levels. This

suggests that higher temperatures and humidity enhance atmospheric mixing and particle dispersion, thereby reducing pollution concentrations.
Atmospheric pressure also exhibited negative coefficients in both models, though its effect was comparatively weaker. Wind speed similarly showed a negative influence, indicating that increased air movement contributed to the dispersion of particles, albeit modestly. The explanatory power of the regression models was relatively low, with R^2 values of 0.280 for $PM_{2.5}$ and 0.201 for PM_{10}, indicating that meteorological parameters alone account for only a fraction of particulate variability in Lagos. The regression equations are expressed as:

$$PM_{2.5} = 32.660 - 6.615T - 1.909H - 0.062P - 0.635WS \quad (1)$$

$$PM_{10} = 42.590 - 6.784T - 1.175H - 2.039P - 0.712WS \quad (2)$$

In summary, the Lagos models demonstrate that increases in temperature and humidity are the most effective meteorological drivers of reduced particulate matter concentrations. Pressure and wind speed play secondary roles, while wind direction exerts no meaningful influence. The modest R^2 values further suggest that non-meteorological factors, such as traffic emissions, industrial activity, and other urban sources, are likely key contributors to air quality outcomes in Lagos.

Study Limitations and Future Directions

The study's two-year dataset and methodological rigor offer robust insights into the variability and relationships between meteorological parameters and particulate matter concentrations. However, several limitations warrant consideration. Potential calibration drifts or sensor inaccuracies may persist despite the extensive validation efforts, potentially influencing measurement accuracy over time. Additionally, unmeasured factors such as temporal variability in local emission sources, chemical transformations of pollutants, and other meteorological variables, including wind direction, solar radiation, and precipitation intensity, were not incorporated into the current analysis.
A key limitation is the spatial scope of the study, which was confined to a single monitoring site. While this site was carefully selected to reflect ambient neighborhood conditions, the spatial heterogeneity characteristic of urban environments may not be fully captured, limiting the generalizability of the findings across broader regions. Future research should prioritize multi-site deployments across diverse urban and peri-urban zones to account for spatial variability in emissions, meteorology, and land use. Such an approach would enhance the robustness of calibration models, improve predictive accuracy, and support more comprehensive air quality management strategies.
Expanding sensor networks and incorporating a wider array of atmospheric variables, alongside advanced modeling techniques, will be critical to improving the precision of air quality predictions and informing more effective interventions.

CONCLUSION

The present study monitored variations in meteorological parameters, temperature, humidity, pressure, and wind speed, and their relationship with particulate matter concentrations (PM_1, $PM_{2.5}$, and PM_{10}) on both diurnal and seasonal scales. It was found that PM concentrations exhibited seasonal dependence, with statistically significant differences observed between daytime and nighttime levels, as well as between dry and rainy seasons. In many instances, PM concentrations exceeded both the 24-hour and annual averages established by national (NESREA) and international standards (WHO and NAAQS). All meteorological parameters were significantly correlated with PM concentrations, with correlation strengths ranging from weak to moderate. Specifically, correlations with temperature were –0.37, –0.37, and –0.39 for PM_1, $PM_{2.5}$, and PM_{10}, respectively; with humidity, they were –0.60, –0.64, and –0.66; with pressure, –0.20, –0.22, and –0.22; and with wind speed, –0.53, –0.51, and –0.57. Regression analysis indicated that temperature, humidity, atmospheric pressure, and wind speed collectively influence PM concentrations, though the strength of these relationships was modest (R^2 = 0.280 for $PM_{2.5}$ and R^2 = 0.201 for PM_{10}). These findings highlight the importance of considering additional environmental and anthropogenic factors when modeling air quality dynamics. Future research should explore other meteorological variables such as wind direction, precipitation, solar radiation, and rainfall to provide a more comprehensive understanding of this complex topic.
The findings of this study have direct relevance for urban air quality management in Nigeria. The consistent exceedance of WHO and national PM guidelines underscores the urgent need for regulatory interventions targeting emission sources, particularly during high-risk periods such as the dry season and nighttime hours. The demonstrated effectiveness of low-cost embedded systems for continuous monitoring offers a scalable solution for expanding Nigeria's air quality surveillance network. Policymakers should consider integrating such technologies into national environmental strategies, enabling real-time data collection, public health alerts, and evidence-based decision-making. By aligning technological innovation with regulatory frameworks, Nigeria can take meaningful steps toward mitigating

pollution-related health risks and achieving cleaner urban air.

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