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Characterization and Modeling of Indoor $PM_{2.5}$-Bound Benzo[a]Pyrene Concentration in Public Schools: A Comparative Study of Oredo and Uhunmonde Local Government Areas (L.G.As), Edo State, Nigeria

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Abstract

Indoor air quality (IAQ) has emerged as a critical concern for student health and well-being, as $PM_{2.5}$ can transport toxic compounds like benzo[a]pyrene (B[a]P), posing significant health risks to vulnerable populations such as school children. This study compares indoor air quality in public schools between Oredo (urban LGA) and Uhunmwonde (rural LGA) in Edo State, Nigeria. Forty-eight $PM_{2.5}$ samples were collected from eight sampling sites with meteorological parameters over one year. $PM_{2.5}$ mass concentrations were determined gravimetrically, and samples were analyzed for PAH compounds using gas chromatography with Mass Spectroscopy (GC-MS). Data underwent multivariate analysis to determine source contributions and develop a predictive model for B[a]P concentrations using $PM_{2.5}$ and meteorological parameters. Oredo classrooms exhibited substantially higher $PM_{2.5}$ levels (45.3–63.7 µg/m³) than Uhunmwonde (21.7–30.8 µg/m³). Similarly, total $PM_{2.5}$-bound PAH concentrations were higher in Oredo (1.27–1.47 µg/m³) than Uhunmwonde (1.14–1.19 µg/m³). High-molecular-weight (5–6-ring) PAHs dominated profiles at both locations, with Oredo showing a slightly greater proportion (3.06%) of these heavy PAHs. Principal component analysis (PCA) and diagnostic ratios indicated vehicular combustion (gasoline and diesel traffic) as the primary PAH source at both locations, with minor biomass or petroleum evaporation contributions. Estimated incremental lifetime cancer risks (ILCR) from $PM_{2.5}$-bound PAHs were higher in Oredo than Uhunmwonde (adult ILCR: 1.3×10^{-5} vs. 9.5×10^{-6} for 24h exposure). Predictive models using $PM_{2.5}$ and weather parameters achieved 91–96% accuracy, with robust regression providing the best fit. These findings highlight clear spatial differences, with Oredo schools facing substantially higher indoor $PM_{2.5}$ and PAH contamination than Uhunmwonde schools.

Keywords: $PM_{2.5}$-bound PAHs, concentrations, model indoor, LGAs

Introduction

Indoor air quality (IAQ) in schools is an increasingly critical public health concern, as children spend a significant portion of their day in classrooms where pollutant concentrations can far exceed those outdoors [1]. According to the United States Environmental Protection Agency (USEPA), indoor pollutant levels can be two to five

times higher than ambient concentrations due to limited ventilation and the continuous accumulation of contaminants [2]. Particulate matter with a diameter of 2.5 μm or less ($PM_{2.5}$) is particularly worrisome in this context as its small size allows deep lung penetration and facilitates the transport of adhered toxic species such as polycyclic aromatic hydrocarbons (PAHs) [3,4]. $PM_{2.5}$ comprises a heterogeneous mixture of fine solid and liquid particles released from combustion sources, vehicular traffic, industrial operations, and indoor dust resuspension. Owing to their small aerodynamic diameter, these particles penetrate deeply into the alveolar region of the lungs, where they trigger oxidative stress, inflammation, and other harmful biological effects [1,3]. Among PAHs, Benzo[a]pyrene (B[a]P) stands out as a potent carcinogen, mutagen, and teratogen. Long-term exposure to B[a]P-bound $PM_{2.5}$ has been linked to respiratory diseases, cardiovascular events, and elevated cancer risk in children, whose developing organ systems are especially vulnerable [5,6]. The International Agency for Research on Cancer (IARC) designates B[a]P as a Group 1 carcinogen, reflecting decisive evidence of its carcinogenicity in humans [6].

Recent epidemiological studies have demonstrated compelling evidence that children are particularly susceptible to indoor air pollutants due to their incompletely developed respiratory and immune systems. Research conducted in classroom environments has revealed alarmingly high B[a]P concentrations during heating seasons, with values reaching as high as 10.3 ng/m³, representing a severe exposure risk for school-age children. Furthermore, emerging evidence indicates that B[a]P induces neurotoxicity at doses lower than those required for carcinogenic effects, suggesting multiple pathways of harm to child health beyond cancer risk . Urban school settings have demonstrated particularly elevated PAHs concentrations, with mean levels as much as 163.87 ± 68.53 ng/m³ being recorded in classroom environments, exceeding those in suburban and residential schools [30, 31, 32, 33].

Global estimates attribute approximately 4.2 million premature deaths annually to $PM_{2.5}$ exposure, representing 7.6 % of all-cause mortality [7]. Although substantial advances have been achieved in controlling outdoor air pollutants and lowering primary particulate emissions through policy and technological innovations, indoor air quality remains comparatively underregulated and insufficiently characterized. This gap is critical, as indoor environments possess distinct pollutant sources and complex interactions shaped by human activities, architectural design, and ventilation practices. In particular, microenvironments such as schools require targeted investigation to assess pollutant origins, concentration levels, and associated exposure risks [8]. Understanding the factors that influence indoor $PM_{2.5}$ in classrooms is critical for designing effective interventions. Ventilation systems play a particularly important role in classroom air quality management; studies have demonstrated that mechanically ventilated classrooms can achieve $PM_{2.5}$ reductions of 23–48% and PM_{10} reductions of 49–57% compared to unventilated controls. Beyond mechanical interventions, building characteristics such as age, materials, and design significantly affect indoor air quality, as do occupant activities and density, which promote particle resuspension through indoor movement and infiltration of outdoor-tracked dust [34, 35]. School environments present unique source profiles. In urban areas such as Oredo Local Government Area (L.G.A.) in Benin City, which is characterized by dense vehicular traffic, industrial activities, and tightly packed buildings, both outdoor

infiltration and indoor resuspension of dust contribute to elevated $PM_{2.5}$ concentrations [9,10]. Conversely, rural settings like Uhunmwonde L.G.A., with extensive green spaces and lower traffic density, may exhibit lower $PM_{2.5}$ mass yet variable B[a]P loadings influenced by biomass burning for cooking and heating [11,12]. Large-scale epidemiological analyses have consistently documented that air quality improves as geographic areas become more rural, with urban counties experiencing approximately 10 times unhealthier air-quality days than rural counties [36, 37]. Nationally representative data reveal that urban tracts have significantly higher $PM_{2.5}$ concentrations than rural tracts, though the gap has narrowed over time as both settings experience improving air quality. This urban-rural disparity is primarily attributed to the concentration of emission sources (vehicular traffic, industrial activities, and associated combustion processes) in densely populated urban centers [36, 37]. Meteorological factors such as temperature, humidity, and wind patterns further modulate indoor pollutant dynamics, yet their roles remain poorly quantified in both contexts. These determinants affect pollutant infiltration, indoor chemical transformations, particle resuspension, and the efficiency of ventilation. Yet, their meteorological influences are complex and remain insufficiently characterized in Nigeria, especially when contrasting urban and rural school microenvironments [1,13]. Emerging research has demonstrated the utility of predictive modeling approaches to forecast indoor pollutant concentrations using meteorological parameters. Recent studies employing linear and robust regression techniques have achieved R^2 values exceeding 0.90–0.96 for predicting PAH concentrations in indoor settings using temperature, relative humidity, pressure, wind speed, dew point, and $PM_{2.5}$ as predictors. These models offer practical, cost-effective tools for estimating indoor levels of carcinogenic PAHs without extensive chemical analyses, thereby facilitating real-time exposure assessments and informing targeted mitigation strategies. Machine learning and multivariate statistical approaches, particularly principal component analysis (PCA) combined with diagnostic ratios, have proven effective for source apportionment of PAHs in both urban and rural contexts, reliably distinguishing between vehicular emissions and biomass combustion sources [33, 38].

Health risk assessments based on incremental lifetime cancer risk (ILCR) have become the standard methodology for quantifying PAH-associated carcinogenic burden. Studies evaluating PAH exposure in various microenvironments have consistently identified ILCR values ranging from 10^{-6} to 10^{-4}, which are generally considered to represent potential or acceptable health risk levels requiring monitoring or intervention [39, 40]. Children and adults demonstrate differential sensitivities to PAH exposure, with cancer risk values for children often exceeding those for adults due to higher inhalation rates relative to body weight [41].

Existing studies in Nigeria have profiled classroom $PM^{2.5}$ levels and correlated them with ventilation and meteorological parameters, but few have quantified B[a]P specifically or compared urban versus rural exposures within the same regional framework. Limited concurrent assessments of urban and rural indoor air exposures within a single regional context hinder full understanding of spatial variability and the design of targeted interventions [14,15]. Understanding these contrasts is vital for tailoring mitigation strategies such as natural ventilation designs [16], green infrastructure interventions [10], and policy measures targeting indoor pollutant sources. Bridging these gaps is vital for context-specific

mitigation, including improved natural ventilation, green infrastructure to limit infiltration, and policies targeting biomass use in rural areas and traffic emissions in urban settings [17]. This study, therefore, aims to characterize and model indoor $PM_{2.5}$-bound B[a]P concentrations in public schools across the urban–rural gradient of Oredo and Uhunmwonde L.G.As, Edo State, Nigeria, filling a critical knowledge gap and informing evidence-based IAQ improvement in educational settings, ultimately contributing to better health outcomes for children in these communities.

Materials and Methods

Study Area

This study was conducted in two local government areas of Edo State, Nigeria – Oredo and Uhunmwonde to investigate indoor air quality parameters and assess anthropogenic impacts across urban and rural settings. Oredo Local Government Area is one of the most prominent and urbanized regions within Edo State, Nigeria. It is located in the heart of Benin City, the capital of Edo State. It lies approximately between latitudes 6º20'N and 6º30'N and longitudes 5º35'E and 5º45'E. On the other hand, Uhunmwonde local Government Area is situated in Edo State, with its headquarters in Ehor. It lies roughly between latitudes 6º30'N and 6º45'N and longitudes 5º45'E and 6º00'E. Anthropogenic activities in the study area lead to elevated air pollution levels, including $PM_{2.5}$, increasing the risk of exposure to $PM_{2.5}$-bound polycyclic aromatic hydrocarbons (PAHs), particularly B[a]P. In this study, eight schools (secondary and primary), as shown in Table 1, were selected for sampling. Fig. 1 represents the sampling locations.

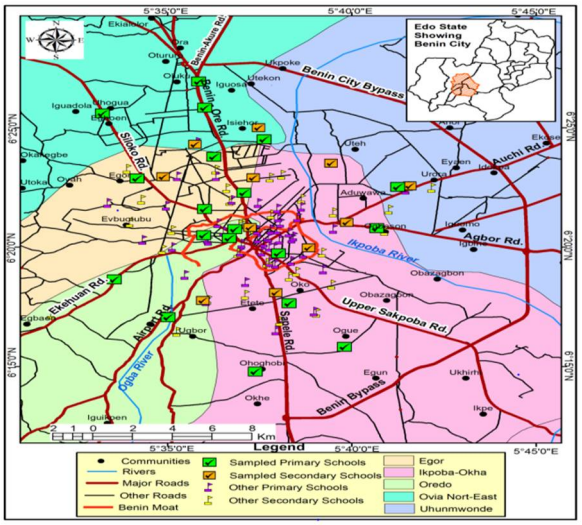


Figure 1. **Map of the sampling sites (public schools in Oredo and Uhunmwonde, Benin City).**

Table 1. **List of schools with their respective coordinates.**

S/N	School Name	Address	Latitudes	Longitudes	Level	Ownership
1	Oba Ewuare Secondary School	Gapiona Road, Oko Central, GRA	6.296612	5.601655	Secondary	Government
2	Edo College	Murtala Muhammed Way	6.332762	5.646968	Secondary	Government
3	Emotan College	Wire Road	6.346977	5.620496	Secondary	Government
4	Ezomo Primary School	2nd Cemetery Road	6.341546	5.599672	Primary	Government
5	Ivbiore Primary School	Oghenosa Street	6.345836	5.613716	Primary	Government
6	Uvbi Primary School Girls	First East Circular Road	6.328931	5.633469	Primary	Government
7	Eyaen Secondary School	Along Old Benin Ehor Road	6.375973	5.692716	Secondary	Government
8	Eyaen Primary School	Benin Auchi Road	6.373424	5.691255	Primary	Government

Methodology

48 $PM_{2.5}$ samples were collected from the eight classrooms, Monday to Friday, during school hours (08:00–16:00) for 12 months from March 2023 to February 2024. The $PM_{2.5}$ samples were taken at 1.5–2.0 meters above the ground and placed onto 37 mm-diameter quartz filters. An Apex2IS Casella regular pump with a conical inhalable sampling (CIS) head placed centrally within classrooms was used to collect the sample for eight hours daily at a flow rate of 3.5 L per minute (LPM). Samples were collected using a standard gravimetric method. Meteorological parameters, including temperature, relative humidity, pressure, wind speed and dew point, were recorded simultaneously at 5-minute intervals onsite to determine influences on pollutant dynamics [1]. Indoor $PM_{2.5}$ samples were extracted by sonication of quartz-fiber filters in a 1:1 (v/v) acetone: dichloromethane mixture (HPLC grade; Sigma-Aldrich, USA) for 15 min, repeated three times. Combined extracts were filtered (0.22 µm), purified on a silica-gel column (7.5 cm × 1.5 cm) packed with anhydrous sodium sulphate, and eluted sequentially with 50 mL hexane and 50 mL dichloromethane.

The eluate was concentrated to 5 mL by rotary evaporation at 40 °C and further reduced to 1 mL under a gentle Nitrogen stream. Final extracts were stored in amber 2 mL auto sampler vials at 4 °C until analysis. PAH analysis was performed on an Agilent 6890 GC coupled to an Agilent 5973 MSD using an HP-5MS capillary column (30 m × 0.25 mm × 0.25 µm film). Injector and MS source temperatures were 275 °C; helium carrier flow was 1.0 mL min^{-1}. The oven program was: 100 °C (2 min); ramp 10 °C min^{-1} to 190 °C (8 min); ramp 10 °C min^{-1} to 330 °C (30 min). Injection volume was 1 µL in split mode (1.5 min split time). Instrument control, data acquisition, and peak integration were conducted with Agilent MassHunter GC/MS software (PAH 2.M method). Calibration used certified 16-PAH standards (Sigma-Aldrich, USA) over 0.02–0.64 µg mL^{-1}. All solvents and reagents were HPLC or analytical grade. Certified 16-PAH standard mixtures (naphthalene through benzo[g,h,i] perylene) were purchased from Sigma-Aldrich (USA) [12,15,18].

Multivariate and regression analyses were conducted using R software version 4.3.1. Multivariate analyses including Principal Component Analysis (PCA) with varimax rotation were conducted to identify potential PAH sources, interpreting factors based on typical emission profiles [6,12,19], and Incremental Lifetime Cancer Risk (ILCR) was calculated for infants, children, and adults exposed to indoor B[a]P concentrations, using standard exposure parameters and risk thresholds [4,6,20]. Linear and robust regression models were developed (using $PM_{2.5}$ and weather variables) to predict B[a]P concentrations. The data were incorporated into a general linear regression equation as shown in equation (1).

$$y = f\,(x_1, x_2, x_3, x_4, x_5, x_6\,) \qquad (1)$$

Where y (response) = concentration of B[a]P and f = independent variables comprising of X_1 = temperature value, X_2 = relative humidity value, X_3 = pressure value, X_4 = wind speed value, X_5 = dew point value and X_6 = $PM_{2.5}$ value.

Similarly, model performance was evaluated by mean average error (MAE), mean square error (MSE), root mean square error (RMSE), coefficient of determination (R^2) and adjusted R^2 to reflect the experimental data using the predicted and experimental datasets [21,22].

Results and Discussion

Classroom $PM_{2.5}$ Concentrations and Meteorological Parameters

The mean $PM_{2.5}$ concentrations in the classrooms collected from the eight public schools in Oredo and Uhunmwonde are shown in Tables 2 and 3. The $PM_{2.5}$ concentration in the study area ranged from 63.71±0.56 to 45.28±0.17 µg/m^3 in Oredo L.G.A. On the other hand, Uhunmwonde L.G.A $PM_{2.5}$ concentration ranged from 30.82±0.06 to 21.65±0.74 µg/m^3. Both locations exceeded the annual World Health Organization [20] and United States Environmental Protection Agency stipulated [2] limits of 5 µg/m³ and 9 µg/m³, respectively. Classroom $PM_{2.5}$ levels were markedly higher in Oredo than in Uhunmwonde by 125.7%. The difference in elevated levels may be attributed to anthropogenic activities emanating from vehicular emissions, industrial activities, and road dust resuspension, all of which release combustion byproducts such as $PM_{2.5}$ to the air [13,17]. Additionally, urban areas typically have fewer green spaces compare to rural areas, resulting in reduced natural filtration and adsorption of airborne pollutants, which contributes to elevated $PM_{2.5}$ levels [1]. Meteorological factors such as temperature (~31°C in Oredo vs. ~28°C in Uhunmwonde), relative humidity (~73% vs. ~85%), wind speed (3.79 km/h vs. 5.13 km/h), and dew point showed expected seasonal variations affecting pollutant dispersion and removal. Increased ventilation and moisture during wet months likely contributed to approximately 5% reductions in indoor $PM_{2.5}$ loads [9].

Table 2. **Monthly, Seasonal and Annual Mean $PM_{2.5}$ Concentrations and Measured Meteorological Parameters in Oredo LGA.**

Period	Temperature (°C)	Relative Humidity (%)	Pressure (mmHg)	Wind speed (Km/h)	Dew point (%)	$PM_{2.5}$ conc. (µg/m^3)	Season
Nov	30.93±0.81	71.16±0.96	1006.49±0.80	3.89±0.99	25.09±0.19	53.19±0.89	Dry
Dec	31.86±0.45	69.82±0.16	1007.65±0.86	3.54±0.75	24.09±0.59	59.06±0.01	
Jan	31.99±0.43	69.00±0.47	1007.92±0.76	4.06±0.58	22.87±0.34	63.71±0.56	
Feb	31.87±0.55	75.73±0.96	1008.19±0.75	3.92±0.68	26.18±0.27	60.67±0.36	
Mar	31.92±0.49	69.42±0.11	1007.49±0.57	3.57±0.18	24.11±0.42	58.52±0.71	
Apr	30.28±0.09	74.33±0.15	1007.43±0.91	3.24±0.95	23.91±0.21	52.47±0.27	Wet
May	30.47±0.90	75.58±0.43	1008.46±0.88	4.37±0.52	25.79±0.27	48.13±0.82	
Jun	31.62±0.37	70.62±0.24	1006.85±0.31	3.84±0.37	25.42±0.01	59.59±0.18	
Jul	29.70±0.84	77.74±0.23	1006.47±0.70	4.21±0.32	26.26±0.34	45.28±0.17	
Aug	30.87±0.11	75.32±0.71	1007.31±0.36	3.84±0.87	25.10±0.12	57.64±0.06	
Sep	30.48±0.27	77.73±0.27	1008.81±0.02	3.79±0.74	24.49±0.34	50.73±0.05	
Oct	30.20±0.09	72.91±0.26	1008.06±0.63	3.62±0.87	25.89±0.59	49.94±0.26	
Dry season	31.14±0.23	72.56±0.47	1007.47±0.43	3.67±0.74	24.44±0.19	56.50±0.32	
Wet season	30.89±0.12	73.84±0.52	1007.71±0.45	3.90±0.32	24.64±0.74	53.33±0.13	
Annual mean	31.02±0.18	73.20±0.50	1007.59±0.44	3.79±0.53	23.54±0.47	54.92±0.23	

Table 3. **Monthly, Seasonal and Annual Mean $PM_{2.5}$ Concentrations and Measured Meteorological Parameters in Uhunmwonde LGA.**

Period	Temperature (°C)	Relative Humidity (%)	Pressure (mmHg)	Wind speed (Km/h)	Dew point (%)	$PM_{2.5}$ conc. ($\mu g/m^3$)	Season
Nov	26.27±0.43	85.97±0.90	1006.87±0.54	5.60±0.42	27.36±0.67	26.00±0.71	Dry
Dec	29.53±0.74	85.53±0.65	1006.95±0.53	5.70±0.41	27.69±0.05	26.73±0.06	
Jan	30.18±0.62	89.97±0.27	1009.25±0.47	4.85±0.28	25.86±0.47	30.82±0.08	
Feb	29.23±0.74	89.96±0.60	1008.00±0.09	5.17±0.32	26.70±0.42	28.29±0.35	
Mar	28.31±0.29	88.60±0.60	1008.98±0.12	5.12±0.17	26.70±0.30	22.93±0.14	
Apr	26.36±0.33	86.60±0.27	1007.00±0.09	5.61±0.32	26.39±0.65	22.36±0.32	Wet
May	28.80±0.43	79.53±0.75	1004.54±0.54	4.90±0.42	26.52±0.01	21.67±0.21	
Jun	29.44±0.48	81.35±0.62	1005.71±0.17	4.23±0.27	27.76±0.41	26.93±0.28	
Jul	25.88±0.33	78.22±0.15	1007.20±0.51	4.83±0.43	27.97±0.51	21.65±0.74	
Aug	28.57±0.40	85.46±0.41	1006.95±0.22	5.70±0.58	26.08±0.29	24.74±0.31	
Sep	27.52±0.27	89.25±0.11	1004.63±0.79	5.23±0.18	26.62±0.38	21.94±0.29	
Oct	29.07±0.74	84.41±0.65	1007.63±0.53	4.61±0.23	27.53±0.74	21.86±0.09	
Dry season	28.70±1.41	84.98±1.51	1008.01±0.88	5.29±0.80	26.86±0.96	26.95±0.67	
Wet season	27.49±1.49	86.36±1.48	1006.24±1.43	5.02±1.22	26.98±1.49	23.02±0.77	
Annual mean	27.76±2.90	85.54±0.34	1006.88±2.31	5.13±2.02	26.94±2.45	24.36±1.44	

WHO Threshold - 15$\mu g/m^3$ (daily) and 5$\mu g/m^3$ (annual) – (WHO, 2021)

U.S. EPA (NAAQS) Threshold - 35$\mu g/m^3$ (daily) and 9$\mu g/m^3$ (annual) – (USEPA, 2024)

PAHs concentration in classrooms

The mean concentrations of the individual PAH compounds in the classroom air collected from the different schools in both locations are shown in Table 4. The sum of 16 PAHs ranged from 1.27–1.47 µg/m³ in Oredo schools, and 1.14–1.19 µg/m³ in Uhunmwonde. The comparative evaluation within the two locations shows distinct variations in both concentration and carcinogenic potential. The mean concentration of ∑PAHs in Oredo was approximately 17.74% folds than that of Uhunmwonde, indicating a relatively greater PAH burden in Oredo [6,12]. The proportion of carcinogenic PAHs (CANPAHs) relative to total PAHs was similar across both locations, with a marginal increase of 0.54% in Oredo, suggesting comparable contributions of high molecular weight PAHs in both areas [23]. However, the percentage contribution of benzo[a]pyrene, a potent carcinogenic marker, within the CANPAHs pool was significantly elevated in Oredo by 17.73% compared to Uhunmwonde. This indicates that a potentially higher health risk associated with PAH exposure in Oredo is associated with increased respiratory ailments, developmental issues, and elevated cancer risk [15,24], which may be attributed to differences in anthropogenic activities, emission sources, or local environmental conditions.

Table 4. **Total Concentration of the Priority Sixteen PAHs obtained from Oredo and Uhunmwonde LGAs.**

PAH Components	No of Rings	Oredo		Uhunmwonde	
		Dry	Wet	Dry	Wet
Naphthylene	2	0.051±0.009	0.049±0.009	0.051±0.013	0.051±0.009
Acenaphthylene	3	0.062±0.002	0.055±0.008	0.052±0.004	0.052±0.007
Acenaphthene	3	0.054±0.005	0.052±0.008	0.052±0.002	0.052±0.010
Flourene	3	0.061±0.011	0.055±0.005	0.051±0.005	0.051±0.003
Phenanthrene	3	0.066±0.008	0.063±0.007	0.057±0.007	0.057±0.002
Anthracene	3	0.077±0.009	0.065±0.002	0.065±0.009	0.065±0.007
Fluoranthene	4	0.055±0.007	0.063±0.005	0.059±0.012	0.059±0.005
Pyrene	4	0.064±0.005	0.060±0.009	0.048±0.011	0.048±0.008
Benzo[a]anthracene	4	0.071±0.008	0.060±0.007	0.059±0.009	0.059±0.009
Chrysene	4	0.067±0.005	0.062±0.005	0.058±0.008	0.058±0.002
Benzo[b]fluoranthene	5	0.066±0.005	0.058±0.011	0.054±0.007	0.054±0.009
Benzo[k]fluoranthene	5	0.084±0.009	0.054±0.002	0.055±0.009	0.055±0.007
Benzo[a]pyrene	5	0.091±0.007	0.069±0.008	0.056±0.005	0.055±0.005
Dibenzo [a,h] anthracene	5	0.096±0.015	0.080±0.009	0.080±0.015	0.080±0.012
Indeno [1,2,3 –cd] pyrene	6	0.299±0.012	0.162±0.010	0.154±0.007	0.154±0.007
Benzo [g,h,i] perylene	6	0.306±0.008	0.265±0.006	0.238±0.005	0.238±0.007
∑PAH (µg/m^3)		1.470±0.063	1.272±0.056	1.189±0.064	1.140±0.055
% CANPAHs of ∑PAH		45.85	43.55	43.39	45.53
%BaP of CANPAHs		13.50	12.66	10.85	11.37

Possible Sources of Classroom PAHs

Principal Component Analysis (PCA) is an exploratory method used to identify potential sources of particulate PAHs by simplifying complex data sets [25].

In this study, three factors were identified using varimax with Kaiser Normalization from the PCA loadings. The three factors collectively explain 96.81% of the total variance in $PM_{2.5}$-bound PAHs. Factors 1, 2, and 3 accounted for 63.99, 21.51, and 11.31% of the total variance, respectively. These factors were mainly anthropogenic sources such as vehicular emissions (gasoline/ diesel), re-entrained soil factor, and urban biomass burning. The component plots in rotated space presented in Fig. 2a & 2b are in good agreement with the PCA.

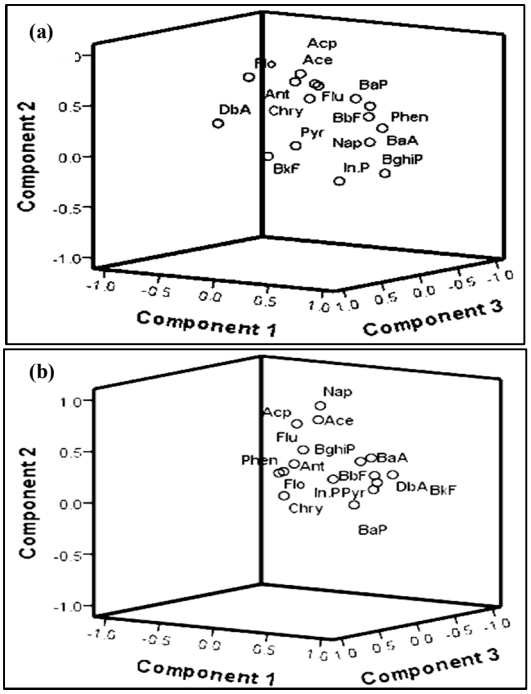


Figure 2a & b. **Component Plot in Rotated Space for Dry and Wet Seasons in Oredo L.G.A.**

Similarly, three factors were extracted from the PCA loadings in Uhunmwonde L.G.A. Together, these factors accounted for 95.97% of the total variance in $PM_{2.5}$-bound PAHs, with Factor 1, Factor 2, and Factor 3 explaining 63.30%, 18.23%, and 14.44% of the total variance, respectively. These factors were primarily linked to anthropogenic sources, including gasoline and diesel emissions from moving vehicles, fuel / oil leakage, and rural wild/forest fire (biomass burning). The component plots in rotated space (Fig. 2a and 2b) display strong agreement with the PCA results.

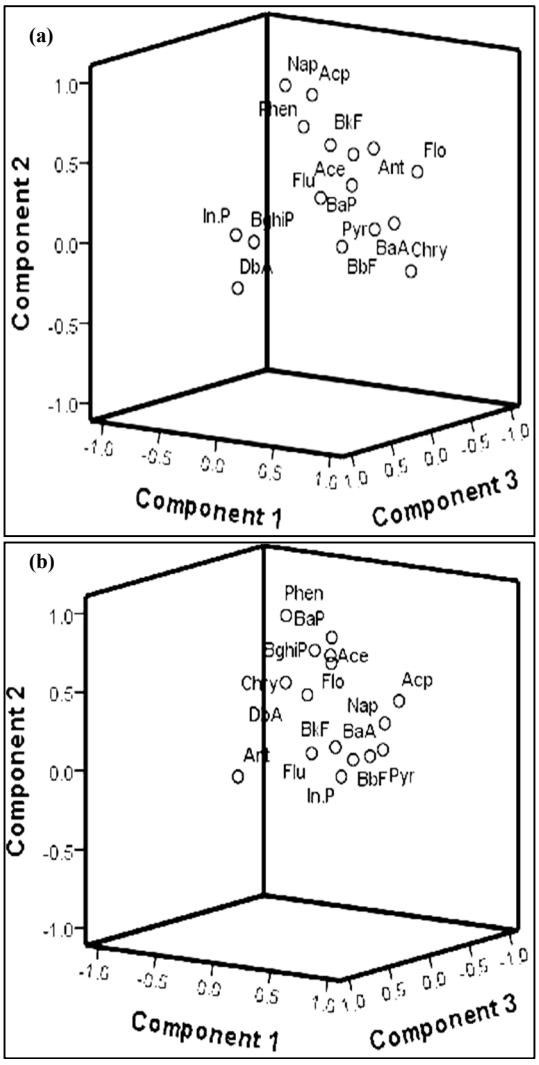


Figure 3a&b. **Component Plot in Rotated Space for Dry and Wet Seasons in Uhunmwonde L.G.A.**

Both locations show high total variance explained by the three extracted factors, suggesting that the major sources of $PM_{2.5}$-bound PAHs are well captured. However, Oredo has a slightly higher explained variance of 0.84%, indicating a more dominant or distinguishable set of sources. The differing factor structures validate the importance of site-specific source apportionment [26]. Also, an evaluation of polycyclic aromatic hydrocarbon (PAH) sources in Benin City, Nigeria, reveals distinct spatial patterns between the urban center of Oredo and the rural locality of Uhunmwonde as shown in Table 5. Each ratio is used to distinguish possible sources from their chemical composition. In Oredo, elevated diagnostic ratios such as BaA/Chry (>0.35) and ∑ComPAH/∑PAH (<1.0) indicated a predominance of vehicular emissions and petroleum-derived pollutants, characteristic of dense urban traffic and industrial activities. In contrast, Uhunmwonde exhibited higher Flu/Pyr ratios (>0.5) alongside lower mobile-source indicators, suggesting a greater influence of biomass combustion, likely from domestic fuel sources such as firewood or charcoal [27]. While both locations displayed signatures of mixed combustion sources, the divergent environmental and socioeconomic contexts produced distinct contamination profiles. Oredo is more strongly influenced by mobile and fossil fuel-related emissions, whereas Uhunmwonde reflects primarily stationary, biomass-based combustion. These results align well with existing literature highlighting traffic and biomass burning as major contributors to indoor and ambient PAHs in both urban and rural African contexts [11,25]. The findings also underscore the importance of targeted mitigation strategies: strengthening traffic emission regulations in urban areas and promoting the adoption of cleaner domestic energy sources in rural communities [25].

Table 5. **PAHs Diagnostic Ratios in Oredo and Uhunmwonde L.G.As.**

DRs	Oredo		Uhunmwonde	
	Dry	Wet	Dry	Wet
Ant/Phen	0.51±0.01	0.51±0.05	0.51±0.07	0.51±0.01
Flou/Pyr	0.51±0.04	0.56±0.01	0.49±0.04	0.54±0.05
Pyr/BaP	0.87±0.05	0.90±0.09	0.73±0.05	0.90±0.04
BaP/Chry	0.52±0.05	0.49±0.05	0.54±0.05	0.50±0.09
BaP/BghiP	0.27±0.02	0.23±0.02	0.33±0.09	0.20±0.07
InP/BghiP	0.67±0.02	0.62±0.04	0.76±0.02	0.56±0.04
BaA/Chry	0.51±0.03	0.49±0.05	0.49±0.07	0.50±0.02
∑PAHlmw/∑PAHhmw	0.27±0.01	0.36±0.0	0.38±0.05	0.33±0.05
∑ComPAH/∑PAH	0.82±0.02	0.73±0.05	0.72±0.05	0.75±0.05

Table 6. **Incremental Lifetime Cancer Risk (ILCR) for 8hrs/24hrs Time Weight Average (TWA) Exposure in Oredo and Uhunmwonde L.G.As.**

Location/Period	Incremental Lifetime Cancer Risk (ILCR) for 8hrs/24hrs-TWA exposure					
	Dry season			Wet season		
	Infants	Children	Adults	Infants	Children	Adults
Oredo (8hrs)	7.67E-07	1.93E-06	4.42E-06	5.88E-07	1.49E-06	3.40E-06
Uhumnwonde (8hrs)	5.49E-07	1.39E-06	3.18E-06	5.13E-07	1.28E-06	2.96E-06
Oredo (24hrs)	2.30E-06	5.79E-06	1.33E-05	1.76E-06	4.47E-06	1.02E-05
Uhumnwonde (24hrs)	1.65E-06	4.17E-06	9.54E-06	1.54E-06	3.84E-06	8.88E-06

Health Risk Assessment of Classroom $PM_{2.5}$-Bound PAH Compounds

The incremental lifetime cancer risk (ILCR) values presented in Table 6 revealed critical insights into the spatial, temporal, and demographic variations in carcinogenic risk associated with indoor $PM_{2.5}$-bound PAHs exposure in the two locations.. Estimated ILCR values from PAH exposure were higher in Oredo than Uhunmwonde for all age groups. For example, adult ILCR from 24h exposure was 1.3×10^{-5} in Oredo against 9.5×10^{-6} in Uhunmwonde. Children's risk was particularly notable given their higher inhalation rate relative to body weight, underscoring the pressing need to mitigate pollutant sources in school environments, aligning with the environmental health concerns highlighted by Lewis *et al.* [8]. Both locations exceeded the 10^{-6} risk threshold [6,20], but Oredo was far larger by 38.84%. With the elevated pollutant levels observed, urban schoolchildren face greater carcinogenic risk from indoor PAHs [28,29,30].

Model Development of Classroom $PM_{2.5}$-Bound PAH Compounds

Two different models – Linear Regression and Robust Regression Models were employed using R software version 4.3.1 in the two locations. The developed models are in equation 2.

The experimental formulations for the Linear and Robust Regression Models for both locations are as follows:

$$B[a]P_{Oredo\ or\ Uhunmwonde} = \beta_0 + \beta_1 Temp + \beta_2 RH + \beta_3 Pre + \beta_4 WS + \beta_5 DP + \beta_6 PM_{2.5} + \epsilon \quad (2)$$

Where $B[a]P_{Oredo\ or\ Uhunmwonde}$= concentration of B[a]P in both locations which represents the response while 0 = Intercept, Temp = temperature value, RH= relative humidity value, Pre = pressure value, WS = wind speed value, DP = dew point value, PM $_{2.5}$ = PM $_{2.5}$ value and ϵ = error value respectively as the independent variables.

At both locations, the regression coefficients represent the influence of each independent variable on the response. According to equation 2, positive coefficients (e.g., $PM_{2.5}$, temperature) indicate that an increase in these variables leads to elevated B[a]P levels, while negative coefficients (e.g., relative humidity, dew point) imply that an increase in these variables results in lower B[a]P levels [21].

The predicted linear regression model for Oredo and Uhunmwonde is presented in equations 4 - 5.

$$BaP_{Oredo} = 0.00396 + 0.000337Temp + (-0.00009)RH + 0.0000702Pre + (-0.00348)WS + (-0.00386)DP + 0.00055PM_{2.5} \quad (4)$$

$$BaP_{Oredo} = 0.00396 + 0.00337Temp - 0.00009RH + 0.0000702Pre - 0.00348WS - 0.00386DP + 0.00055PM_{2.5} \quad (5)$$

The predicted robust regression model for Oredo is stated by equations 6 - 7 as follows:

$$BaP_{Oredo} = 0.0001 + 0.00048Temp + (-0.00050)RH + 0.00091Pre + (-0.0013)WS + (-0.000068)DP + 0.0030PM_{2.5} \quad (6)$$

$$BaP_{Oredo} = 0.0001 + 0.00048Temp - 0.00050RH + 0.00091Pre - 0.0013WS - 0.000068DP + 0.00030PM_{2.5} \quad (7)$$

The predicted linear regression model for Uhunmwonde is presented in equations 8-9.

$$B[a]P_{Uhunmwonde} = 0.00363 + 0.00371Temp + (-0.00099)RH + (-0.00077)Pre + 0.00384WS + (-0.00424)DP + 0.00061PM_{2.5} \quad (8)$$

$$B[a]P_{Uhunmwonde} = 0.00363 + 0.0037Temp - 0.00099RH - 0.00077Pre + 0.00384WS - 0.00384DP + 0.00061PM_{2.5} \quad (9)$$

The predicted robust regression model for Uhumnwonde is stated by equations 10 -11 as follows:

$$B[a]P_{Uhunmwonde} = 0.000669 + 0.00245Temp + (-0.00046)RH + 0.00102Pre + 0.00165WS + (-0.00074)DP + 0.00036PM_{2.5} \quad (10)$$

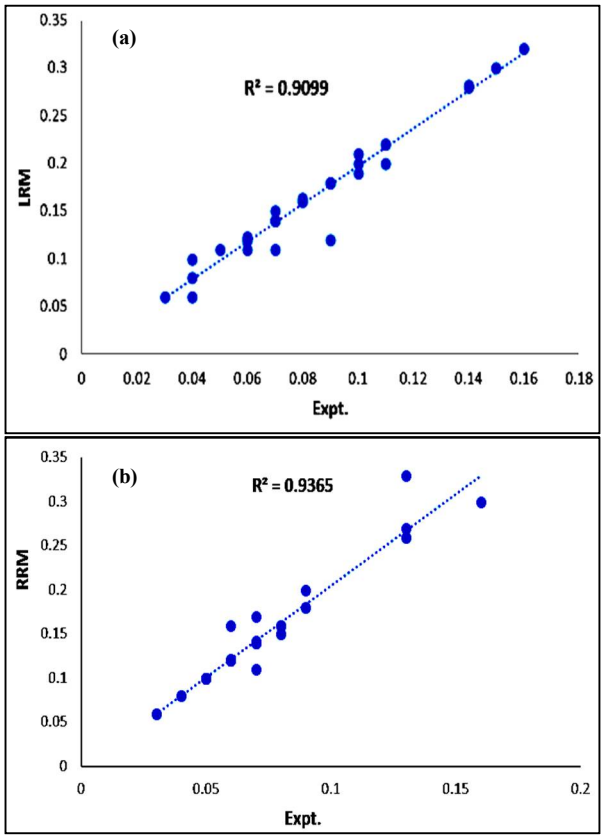
$$B[a]P_{Uhunmwonde} = 0.000669 + 0.00245Temp - 0.00046RH + 0.00102Pre + 0.00165WS - 0.00074DP + 0.00036PM_{2.5} \quad (11)$$

Table 7 evaluates the overall performance metrics for LRM and RRM using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2, and adjusted R^2. Model performance is slightly better in the Uhunmwonde by 2.13%, suggesting more stable and predictable B[a]P concentration patterns. Oredo shows more variability, likely due to diverse urban pollution sources. RRM proves more effective across both sites, especially in handling urban data complexity [22].

Table 7. **Model Selection Evaluation for Oredo and Uhunmwonde L.G.As.**

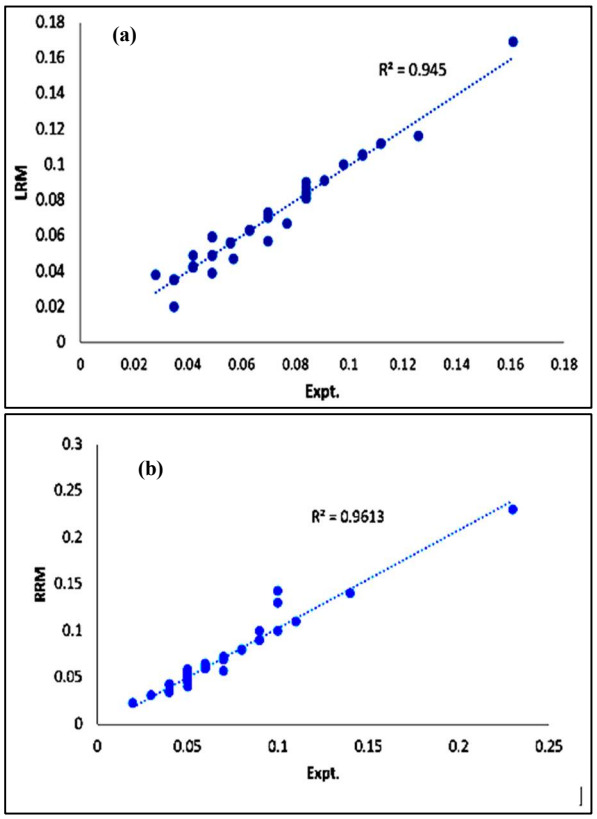
Model/Location	MAE	MSE	RMSE	R^2	Adj. R^2
LRM (Oredo)	0.0055	0.00046	0.0257	0.91	0.83
RRM (Oredo)	0.0047	0.000046	0.00678	0.94	0.86
LRM (Uhunmwonde)	0.017	0.00016	0.04	0.95	0.87
RRM (Uhunmwonde)	0.01	0.000096	0.031	0.96	0.88

Fig. 4 a & b represent line plots showing experimental vs predicted data for B[a]P in concentrations with LRM and RRM, respectively. The R^2 values for both models are 0.91 and 0.94, which indicates a strong correlation between the experimental and predicted data for B[a]P concentrations in both models. The higher R^2 value of 0.94 for RRM suggests that RRM provides a better fit for predicting B[a]P concentrations in the study area.



Figures 4a & 4b. **Line Plots indicating Experimental vs Predicted data for B[a]P in concentrations with LRM and RRM in Oredo L.G.A**

Similarly, Fig. 5a and 5b display line plots showing experimental and predicted B[a]P concentrations using the LRM and RRM models, respectively. Both models show strong correlations, with R^2 values of 0.95 for LRM and 0.96 for RRM. The slightly higher R^2 value for RRM (0.96) indicates a better fit and greater accuracy in predicting B[a]P concentrations within the study area.



Figures 5a & 5b. **Line Plots indicating Experimental vs Predicted data for B[a]P in concentrations with LRM and RRM in Uhunmwonde L.G.A**

The robust regression worked well in both locations, where pollutant data are more variable and influenced by outliers [22], offering a practical tool to estimate indoor PAHs from routine data. The similar model performance in urban and rural contexts suggests that calibration can accommodate background differences, allowing decision-makers to forecast classroom B[a]P levels regionally. Such models also enable practical, cost-effective estimations of indoor

carcinogenic PAHs, facilitating real-time exposure assessments without requiring extensive chemical analyses [10,16].

Indirect Impacts of the Study

This study delivers important indirect benefits by raising public awareness of indoor carcinogenic exposures in classrooms, particularly B[a]P, thereby prompting schools, parents, and communities to adopt practical interventions such as improved natural ventilation [8,16]. The consistent exceedance of WHO and USEPA air quality guidelines provides a strong evidence base for revising national indoor air quality standards tailored to educational environments [2,20]. Methodologically, the study advances a replicable framework that integrates $PM_{2.5}$ gravimetric sampling, PAH analysis, meteorological monitoring, and predictive modeling, offering a tool for harmonized assessments in low-resource contexts and global comparative research [6,12,26]. The clear urban–rural disparities also underscore the value of green infrastructure, such as tree planting and green roofs in reducing indoor pollutant infiltration [9,10]. By bridging environmental chemistry, epidemiology, building science, and data analytics, the study fosters interdisciplinary collaboration and innovation, including climate-responsive ventilation designs and continuous IAQ monitoring systems [24].

Despite its strengths, the study carries indirect drawbacks that merit caution. Communicating high indoor carcinogen levels without context could cause unnecessary alarm and demands for costly interventions beyond the reach of many schools [8,27]. Overemphasis on urban schools risks neglecting rural contexts where biomass combustion remains a major pollution source [11,12], while adopting stringent high-income country IAQ standards may impose unaffordable retrofit requirements, deepening inequalities [17]. Furthermore, over-reliance on predictive modeling though highly accurate could shift focus away from essential emission control strategies, and uncalibrated application of local models to other climates or buildings may lead to misleading exposure estimates [13,19].

This study advances indoor air quality research by providing robust evidence, methodological innovation, and policy-relevant insights for healthier school environments. Nonetheless, careful interpretation is required to prevent undue alarm, ensure equitable resource distribution, and integrate pollution control strategies.

Conclusion

This study demonstrates that indoor $PM_{2.5}$ and PAH concentrations in Nigerian schools exceed WHO and USEPA guidelines, with urban (Oredo) classrooms bearing significantly higher burdens than rural (Uhunmwonde) ones, largely due to traffic-related emissions. High-molecular-weight PAHs, particularly B[a]P, were more prevalent in urban schools, resulting in greater estimated carcinogenic risks. The predictive models developed highlight the value of integrating meteorological data with $PM_{2.5}$ measurements as a practical tool for estimating indoor pollutant levels. These findings underscore the urgent need for targeted interventions such as improved ventilation, urban green infrastructure, and continuous monitoring, while also raising equity concerns given the disproportionate exposure urban schoolchildren face. At the same time, they underscore the importance of balancing public awareness with feasible policy responses to avoid undue alarm or unsustainable demands. Overall, the study offers critical insights to guide context-

sensitive and equitable strategies for improving air quality in school environments.

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Conflicts of Interest

The authors have no actual or potential conflict of interest, including any financial, personal or other relationships with other people or organizations within three years of beginning the submitted work that could inappropriately influence, or be perceived to influence, their work.

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