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Characterizing indoor-outdoor $PM_{2.5}$ concentrations using low-cost sensor measurements in residential homes in Dhaka, Bangladesh

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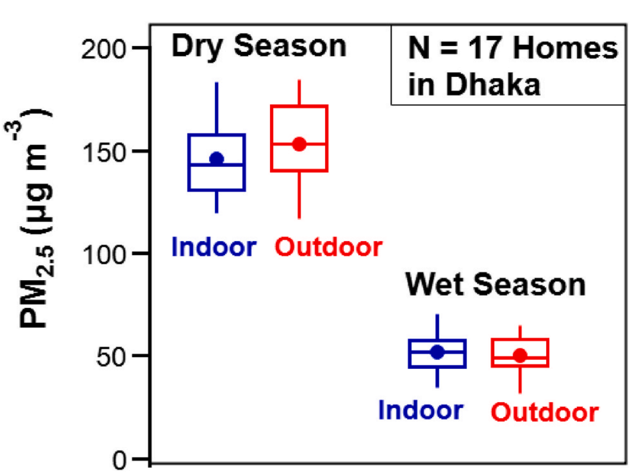
HIGHLIGHTS

- Observed indoor $PM_{2.5}$ levels were comparable to, or even exceeded, outdoor levels.
- Significant seasonal differences were observed in both indoor and outdoor $PM_{2.5}$ levels.
- Infiltration factors derived in Dhaka are generally higher than those reported in the US or Europe.
- Locally derived scientific evidence can help persuade policymakers toward a science- and data-driven approach to air quality mitigation.

GRAPHICAL ABSTRACT



ABSTRACT

We collected simultaneous indoor and outdoor $PM_{2.5}$ measurements from 17 homes in Dhaka, Bangladesh, to characterize spatio-temporal variations and identify factors influencing indoor and outdoor $PM_{2.5}$ levels. A pair of PurpleAir $PM_{2.5}$ sensors were deployed at each home, one indoors and the other outdoors, during the wet and dry seasons, and the locally calibrated data were used for analysis. Indoor and outdoor $PM_{2.5}$ levels were three times higher during the dry season (indoor 146 ± 22 μg/m³, outdoor 153 ± 23 μg/m³) than during the wet season (indoor 52 ± 12 μg/m³, outdoor 50 ± 11 μg/m³). Indoor to outdoor (I/O) ratios were close to 1 in both seasons (dry: 0.97 ± 0.14, wet: 1.05 ± 0.19). This suggests that regional background pollution levels significantly influence indoor levels observed in different households. Infiltration factors closer to 1 (dry: 0.83 ± 0.12; wet: 0.87 ± 0.14), determined through mixed-effects regression of indoor and outdoor time series data, further highlight the substantial impact of outdoor pollution on indoor levels. Data from individual households exhibited strong temporal correlation between indoor and outdoor levels in both seasons (Pearson R: 0.82 ± 0.12 during the dry season and 0.83 ± 0.14 during the wet season), whereas indoor-outdoor spatial correlations across measured households were moderate (R: 0.49 and 0.62 during dry and wet seasons, respectively). These spatial correlations and empirical

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regression modeling suggest that while the spatial variation of outdoor $PM_{2.5}$ levels significantly influences indoor levels' spatial variation, other factors such as indoor source activities and ventilation-related features play crucial roles in explaining variabilities in indoor $PM_{2.5}$ across homes. Overall, our study suggests that indoor environments in Dhaka city are nearly as polluted as outdoor settings, and this locally derived scientific evidence can be valuable for enhancing public awareness and developing mitigation measures to reduce $PM_{2.5}$ exposures in Bangladesh.

1. Introduction

Fine particulate matter ($PM_{2.5}$), consisting of airborne particles with diameters below 2.5 μm, originates from various sources and poses substantial health risks to humans(Burnett et al., 2018; Dockery et al., 1993; Pope et al., 2019). Individual daily exposures to $PM_{2.5}$ are influenced by numerous factors, including time spent in different indoor and outdoor environments, weather conditions, indoor sources, infiltration of outdoor pollution into indoor settings, and ventilation systems (Adgate et al., 2007; Hänninen et al., 2011; MacNeill et al., 2012). Regional and local outdoor pollution can significantly elevate indoor $PM_{2.5}$ levels through infiltration, while indoor sources, like cooking and cleaning, contribute to indoor and outdoor $PM_{2.5}$ levels (Adgate et al., 2007; Hänninen et al., 2011; Li et al., 2017; MacNeill et al., 2012; Massey et al., 2009).

Effective air quality management necessitates a comprehensive understanding of $PM_{2.5}$ sources, dynamics, and population exposure in both indoor and outdoor settings (Li et al., 2017; Martins and Carrilho da Graça, 2018; Sokhi et al., 2022). However, understanding $PM_{2.5}$ sources and exposure in many developing countries is largely impeded by a lack of monitoring data, particularly in South Asian countries (Abdul Jabbar et al., 2022; Gulia et al., 2015; Schwela et al., 2006). These countries are ranked as global hotspots of $PM_{2.5}$, with thousands of premature deaths annually attributed to severe outdoor and indoor elevated levels of $PM_{2.5}$ (Apte et al., 2015; Burnett et al., 2018; World Bank, 2023). Bangladesh, with its population of 170 million, is one such country where the annual mean outdoor $PM_{2.5}$ levels range from 80 to 100 μg m^{-3} (Salam et al., 2008; World Bank, 2023), which is about 15–20 times higher than the recent standard set by the World Health Organization (WHO) (World Health Organization, 2021).

Past studies in Bangladesh, employing limited ground monitoring data, satellite data, and modeling analysis, indicate significantly higher $PM_{2.5}$ concentrations across the country with distinct seasonal patterns; concentrations are 2–6 times higher in dry seasons compared to wet seasons (Begum and Hopke, 2018; Rahman et al., 2019). Seasonal sources, meteorology, and transboundary pollution play a pivotal role in determining $PM_{2.5}$ population exposure in Bangladesh (Afrin et al., 2021; Begum et al., 2011, 2013; Begum and Hopke, 2018; Rana and Khan, 2020; Salam et al., 2008; World Bank, 2023). $PM_{2.5}$ concentration gradients are observed across the country, with higher levels in the central and northwest regions and relatively lower levels in the southeast part of the country, likely influenced by strong transboundary air pollution effects from Indian states in the Indo-Gangetic Plain (IGP) region (Du et al., 2020; Islam et al., 2019; World Bank, 2023; Zaman et al., 2021).

Short-term air quality monitoring using handheld monitors has been employed in previous studies in Bangladesh to assess air pollution exposures in various micro-environments, including households in rural and urban areas (Begum et al., 2009; Gurley et al., 2013), the outdoor urban environment (Kamal et al., 2024), locations near brick kilns (Brooks et al., 2023; Haque et al., 2018), and schools (Roy et al., 2023). A study by Gurley et al. (2013) in a low-income community in Dhaka, Bangladesh, reported a substantial fraction of hours in a day with indoor $PM_{2.5}$ concentrations exceeding 100 μg/m^3. These studies provide insights into substantial variabilities in $PM_{2.5}$ exposures across micro-environments. However, they often lacked repeated sample collections, limiting their effectiveness in capturing spatio-temporal dynamics (Blanco et al., 2023; Li et al., 2019; Saha et al., 2019). Systematic repeated short-term sampling across multiple seasons at 35 locations in Dhaka city, Bangladesh, revealed a moderate intra-urban spatial gradient for $PM_{2.5}$ and a large gradient for ultrafine particle number concentration (PNC) (Saha et al., 2024).

The majority of past studies in Bangladesh focus on characterizing $PM_{2.5}$ exposures in outdoor microenvironments; thus, the scarcity of indoor air pollution monitoring data is more severe (Gautam et al., 2016; Junaid et al., 2018; Kumar et al., 2018; World Bank, 2023). However, many past studies around the world suggest that $PM_{2.5}$ concentration levels in indoor environments could also be significantly high, contingent upon indoor and outdoor sources, ventilation and building systems, geographic locations, people's behaviors, and various other factors (Adgate et al., 2007; Bi et al., 2021; Cao et al., 2012; Challoner and Gill, 2014; Korhonen et al., 2021; MacNeill et al., 2012; Massey et al., 2009). Understanding the indoor-outdoor relationship of $PM_{2.5}$ is important for developing evidence-based mitigation measures. Nonetheless, the relationship between indoor and outdoor $PM_{2.5}$ levels and their spatio-temporal variations remains largely unexplored in Bangladesh. The high capital cost of traditional air quality monitoring at higher temporal and spatial resolutions largely hinders high spatio-temporal measurements in Bangladesh.

Recent advancements in low-cost sensor technology offer a more affordable means of air quality monitoring with higher temporal and spatial resolutions, enabling continuous measurements and broader coverage across a city (Liu et al., 2020; Morawska et al., 2019). Nevertheless, proper calibration against reference monitors and careful data interpretation are essential to ensure the accuracy of low-cost sensor measurements (Giordano et al., 2021; Karagulian et al., 2019; Malings et al., 2020). Leveraging low-cost sensors presents an opportunity to address significant data gaps, particularly in exploring within-city variations in indoor and outdoor $PM_{2.5}$ exposures in Bangladesh.

To address these gaps, our study implemented locally calibrated low-cost sensors to investigate indoor and outdoor $PM_{2.5}$ exposures in various households in Dhaka, Bangladesh. We collected parallel measurements of indoor and outdoor $PM_{2.5}$ at 17 homes in Dhaka city by deploying a pair of PurpleAir low-cost $PM_{2.5}$ sensors (Barkjohn et al., 2021; Stavroulas et al., 2020) at each home, one positioned indoors and another outdoors, and collected data across multiple seasons. Analyzing this dataset, we characterized the spatial and temporal dynamics of indoor and outdoor $PM_{2.5}$ concentrations across diverse households, elucidated the interplay between indoor and outdoor $PM_{2.5}$ levels, and identified key factors influencing these relationships.

2. Methods

2.1. Sampling homes

Fig. 1A shows the locations of the 17 sampled homes within Dhaka city. These selected sites represent a diverse range of land-use characteristics, including major road density, restaurant density, and population density around each location, as illustrated in Fig. 1B. Following the method of Bari et al. (2015), before initiating air pollution data collection, we conducted a questionnaire survey to gather information about indoor and outdoor characteristics of the sampled homes, with a focus on kitchen features, cooking practices, ventilation arrangements, and surrounding land use. Table S1 summarizes these indoor and outdoor features in the sampled homes.

All selected homes were apartment units, situated on floors ranging from the 1st to the 6th in different buildings. Apartments were selected as they represent the predominant residential housing option in Dhaka city (Bproperty, 2018). These homes were located within 50–500 meters of arterial roads and bus routes, with apartment sizes ranging between 850 and 3400 square feet (mean 1685 square feet). The number of windows in the apartment units varied between 3 and 11 (mean 5.4), and the number of occupants ranged from 1 to 6 (mean 4.2).

Natural ventilation served as the primary air exchange mechanism in the selected homes. Most homes had window-type air conditioning units, particularly in the bedrooms; none were equipped with central air conditioning or mechanical ventilation systems, nor did they possess air purifying units. These features reflect typical residential scenarios in Dhaka city.

None of the selected homes used solid biomass-based cook stoves. Kitchens were equipped with either gas stoves or electric stoves, and the presence of exhaust fans in the kitchen, with or without hoods, was common in all sampled homes. A subset of homes (5 out of 17) was equipped with kitchen hoods. The frequency of cooking per day varied between 1 and 3 (mean 2.1), with a daily cooking duration ranging from 1 to 4 h (mean 2.8 h), primarily involving frying and boiling. Among the 17 homes studied, 7 were inhabited by primary smokers, and 3 homes reported occasional use of mosquito coils.

2.2. Measurements of indoor and outdoor $PM_{2.5}$ in different homes

$PM_{2.5}$ data were collected in various homes across two distinct seasons: wet (June to August 2021; "summer") and dry (December 2021 to February 2022; "winter"), with approximately one week of continuous measurement at each home during each season. While 17 homes participated in the study, 2 homes did not participate in the wet season, and another two homes did not participate in the dry season, resulting in data from both seasons being available for 13 homes.

A pair of PurpleAir $PM_{2.5}$ sensors was deployed at each home, with one sensor placed indoors and another outdoors within the same apartment. This setup enabled simultaneous measurement of indoor and outdoor $PM_{2.5}$ concentration levels at each selected home, capturing dynamic variations in pollution levels inside and outside the home. The indoor sensors were positioned either in the bedroom or living room of each home at a height of approximately 5 feet from the floor, while the outdoor sensors were primarily placed on balconies at a similar height. Careful consideration was given to the placement of outdoor sensors to avoid close proximity to kitchen exhausts.

Four PurpleAir sensors (PurpleAir Classic Air Monitor, Edition: PA-II-SD) were available, enabling simultaneous measurements in two homes at a time. Each home was monitored for approximately one week per season, resulting in around 5000 2-min raw PurpleAir observations per home per season, and approximately 10,000 raw data points per home across both seasons. The overall data collection period per season was about 10–12 weeks to cover all participating homes. <Total number of household-days of paired indoor-outdoor measurements.>

PurpleAir devices use Plantower sensors to optically detect $PM_{2.5}$. Each PurpleAir unit contains two Plantower PMS5003 sensors that alternate operation every 10 s to provide 2-min averaged data (Sayahi et al., 2019). The Plantower sensors detect 90° light scattering using a laser (wavelength: 680 ± 10 nm). The effective measurement range for $PM_{2.5}$ concentration with each PMS5003 sensor is 0–500 μg/m^3, with a detection limit of 1 μg/m^3. The sensors quantify particle number concentrations across various PM fractions, with internal calibrations converting particle counts into PM mass concentrations. Each PurpleAir unit also contains sensors for temperature, relative humidity, and barometric pressure to provide basic weather data. The PurpleAir $PM_{2.5}$ sensors deployed in each home recorded data on SD cards at 2-min intervals.

2.3. Long-term continuous outdoor $PM_{2.5}$ measurements

In addition to measuring indoor and outdoor $PM_{2.5}$ at various homes, we analyzed outdoor $PM_{2.5}$ data from two continuous air monitoring stations (CAMS) in Dhaka city. The locations of these two stations are depicted in Fig. 1A. One station is operated by the Department of Environment (DoE), Bangladesh (DoE CAMS), while the other is situated inside the US Embassy Dhaka (USE CAMS). Each station employs a MetOne BAM-1020 to measure hourly $PM_{2.5}$, a real-time monitoring method compliant with the US-EPA federal equivalent method (FEM). Analyzing data from these CAMS stations allowed us to compare them with measurements from different homes, deriving co-location calibration factors for PurpleAir Sensors (section 2.4.2) and temporal adjustment factors for relatively short-term measurement at different homes (section 2.4.3).

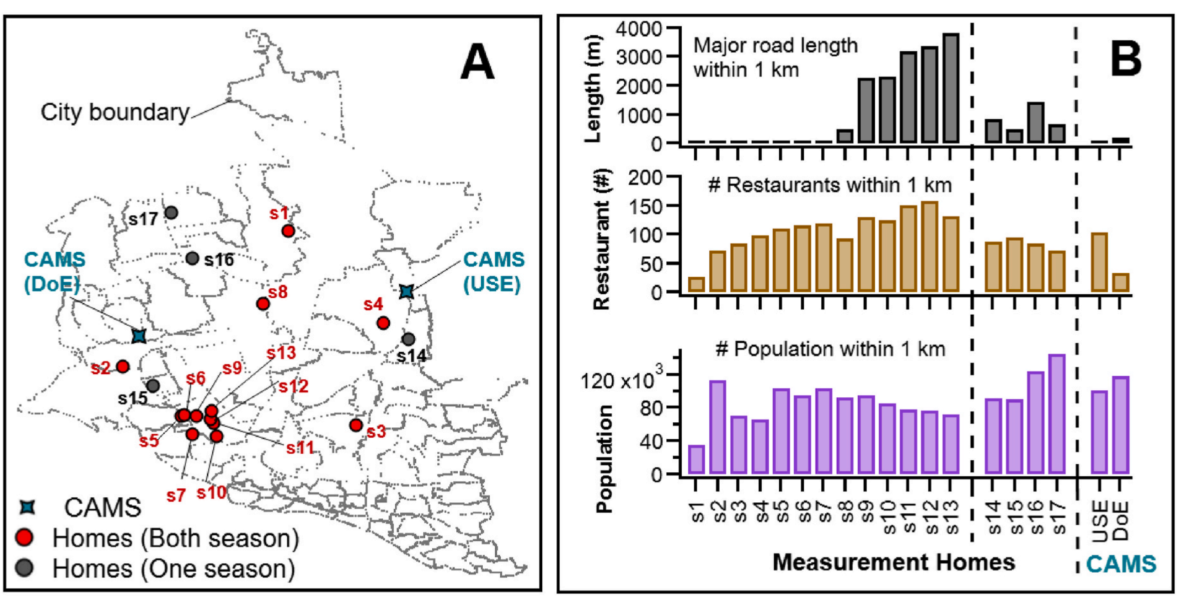

Fig. 1. Location of measurement sites and surrounding outdoor land use features. (A) The map displays the locations of selected homes for indoor and outdoor $PM_{2.5}$ measurements. Red symbols indicate locations where measurements were collected during both dry and wet seasons (S1 to S13), while black symbols represent sites where measurements from only one season were feasible (S14 to S17). Additionally, the map indicates the positions of two continuous air monitoring stations (CAMS) within Dhaka city. (B) The distribution of outdoor land use features surrounding the measurement locations, including major road (4 lanes and above) density, restaurant density, and population density within a 1 km buffer radius from each measurement site.

2.4. Data analysis and quality assurance

2.4.1. Analyzing PurpleAir $PM_{2.5}$ data

The raw PurpleAir $PM_{2.5}$ data collected at different homes underwent meticulous quality assessment, involving visual inspection of raw time series data and the exclusion of any outliers or suspicious data points. Concentration values greater than 500 μg/m^3 or less than 1 μg/m^3 are considered outliers. Each PurpleAir unit has two identical planttower sensors, and in the majority of cases, the data from both sensors showed congruence within a ±10% margin. Only a marginal less than 2% of the data deviated from this threshold and were subsequently excluded from the analysis. For data that agreed within the ±10% margin, the average of $PM_{2.5}$ measurements from both sensors were calculated at a 2-min resolution. Subsequently, hourly averages were estimated using this 2-min time resolution data.

PurpleAir unit reports two different $PM_{2.5}$ values ($PM_{2.5}$_cf_1 and $PM_{2.5}$_cf_atm) using separate internal calibration factors (Barkjohn et al., 2021; Bi et al., 2022; Stavroulas et al., 2020). While these two values were highly correlated, the absolute magnitudes of $PM_{2.5}$_cf_1 were consistently higher than $PM_{2.5}$_cf_atm. For our analysis, we used raw $PM_{2.5}$_cf_atm values and corrected them using co-location calibration factors against a reference $PM_{2.5}$ monitor.

We applied two adjustment factors to hourly average raw $PM_{2.5}$ measurements from various homes: one for co-location calibration against a reference monitor (Malings et al., 2020) (section 2.4.2) and another for temporal adjustment for short-term sampling (Eeftens et al., 2015) (section 2.4.3). Then, using these corrected hourly time series data, we investigated variability in indoor and outdoor $PM_{2.5}$ concentration levels, as well as the ratio of indoor to outdoor (I/O) concentrations across different homes, seasons, and times of day. The indoor-to-outdoor (I/O) concentration ratio is a commonly employed technique to assess the influence of outdoor pollution on indoor concentration levels (Chen and Zhao, 2011).

To examine the meteorological conditions during measurements collected in different homes, we also analyzed temperature and relative humidity data from PurpleAir sensors. A summary of the mean meteorological conditions (temperature and relative humidity) during measurements at various homes is provided in Table S2. Across all sampling homes, the mean ± standard deviation (SD) of outdoor temperature and relative humidity during the dry (winter) season were 26.3 ± 3.1 °C and 46.7 ± 6.6%, respectively, while during the wet (summer) season, they were 33.7 ± 1 °C and 57.5 ± 4.3%, respectively. Indoor temperature and relative humidity were within ±10% of outdoor conditions in both seasons.

2.4.2. Co-location calibration of PurpleAir $PM_{2.5}$ sensors

To develop calibration factors under local meteorological and pollution conditions for the PurpleAir sensors used in this study, we conducted co-location calibration experiments of all sensors used for home samplings against the BAM at the DoE CAMS station. Colocation experiments were conducted over two seasons, wet (April–May 2022) and dry (November 2022), with approximately a month-long data collection period in each season.

The collocation dataset was used to derive correction factors through regression analysis (Barkjohn et al., 2021; Malings et al., 2020). Collocated measurements from various sensors exhibited strong consistency, with Pearson correlation coefficients (R) ranging from 0.99 to 1 across sensor batches (Fig. S1). Therefore, regression models were developed by combining data from all sensors, although separate calibration models were derived for each season. Details regarding colocation data collection, linear regression fittings, derived coefficients, and model performances are illustrated in Fig. S1. Linear regression models produced R^2 values of 0.87 in the dry season and 0.83 in the wet season, with corresponding normalized root mean square errors (nRMSE) of 14% and 17%, respectively, for the dry and wet seasons.

In addition to the simple linear regression model, we explored multiple linear regression models (Malings et al., 2020) that included temperature, relative humidity, dew points, and various interaction terms of these meteorological variables (Table S3). However, these models did not significantly enhance model performance, resulting in a reduction of nRMSE by less than 1%. Therefore, for the purpose of applying correction, we applied the season-specific simple linear regression model (corrected $PM_{2.5}$ = slope × PurpleAir Measured $PM_{2.5}$ + intercept) to adjust hourly time series data collected in different homes. The same factor was employed to correct both indoor and outdoor data.

2.4.3. Adjustment for temporal variability

As simultaneous measurement at all homes was not feasible due to the limited number of available sensors, we adopted a rotating approach, conducting one week of data collection at each home over a 10–12 week campaign in a season. This posed a challenge for direct comparison of variability in measured concentrations across different homes. The observed variability could arise from spatial differences in measured concentrations in different homes as well as week-to-week temporal fluctuations of city background $PM_{2.5}$ levels. Week-to-week temporal variations of city background $PM_{2.5}$ levels are expected to be nearly uniform across the city since they are largely dictated by meteorological phenomena (such as atmospheric inversion and long-range transported pollution), which affect all sites across the city similarly. Our analysis of data from two CAMS sites within Dhaka city supports this, where we found that the ratio of weekly mean to long-term seasonal mean at each site follows almost a similar trend (Fig. S2).

To account for temporal variations, we applied a temporal adjustment factor to the measurement from each home based on long-term continuous measurements at a reference site (i.e., CAMS site in the US Embassy, Dhaka). There are two commonly used methods for temporal adjustment used in past studies: the difference method (Klompmaker et al., 2015) and the ratio method (Eeftens et al., 2015). Both methods rely on adjusting the spatially and temporally distributed measurements with data collected at the central reference site. We adopted the ratio method for our analysis. Following the method of Eeftens et al. (2015), we calculated temporally corrected concentrations for site i by multiplying the uncorrected concentration at site i in period t by the ratio between the long-term concentration measured at the reference site (over 10–12 weeks, encompassing the data collection period at all homes in a season), and the concentration measured at that same reference site during period t (typically 1 week at each season); $C_{i,t,corr} = (C_{ref,\ long\text{-}term}/C_{ref,\ t}) \times C_{i,t,un\_corr}$.

An example of the derivation of such temporal correction factors is provided in Fig. S3. We derived correction factors as a function of the hour of the day by comparing the long-term average diurnal profile to the short-term average diurnal profile at the CAMS location. We estimated such factors for the measurement period at each different home and each season. Then, we applied these factors to measured concentrations from each home as a function of the hour so that if we used the corrected hourly time series to estimate mean concentrations at each home, the resulting mean concentration should give a quasi-long-term mean concentration.

Both BAM collocation correction factors and temporal adjustment factors were derived based on outdoor concentrations. When we applied these correction factors to correct data from different homes, we used the same factors for both indoor and outdoor measurements. We do not anticipate substantial bias from applying the same correction factors to both indoor and outdoor sensors. This is because indoor $PM_{2.5}$ levels are largely influenced by outdoor levels, as suggested by the high correlation and similarity in diurnal and seasonal patterns observed in measured indoor and outdoor $PM_{2.5}$ from different homes, as discussed in detail in the results sections. Moreover, in the absence of indoor-specific correction factors, which were not feasible for both BAM collocation and derivation of temporal adjustment factors, applying outdoor-derived factors allows us to correct the data using the best available correction factors, thereby improving the quantitative assessment of the absolute value of $PM_{2.5}$ concentrations. For relative assessment, such as the comparison of indoor/outdoor (I/O) ratio of $PM_{2.5}$ in different homes, these correction factors do not make any difference.

2.5. Analyzing relationships between indoor and outdoor $PM_{2.5}$ levels

2.5.1. Temporal relationship

Utilizing corrected hourly time series data from each home, we investigated the temporal relationship between indoor and outdoor $PM_{2.5}$ levels measured in different homes and seasons using the Pearson correlation coefficients. Furthermore, we applied a statistical regression technique called mixed-effects regression (Harrison et al., 2018) to quantify the infiltration factor of outdoor pollution indoors.

The mixed-effects regression analysis, as employed in previous indoor-outdoor air pollution studies (Bi et al., 2021; Chen and Zhao, 2011; Lunderberg et al., 2023; Wallace et al., 2022), involves fitting timeseries of indoor and outdoor concentrations to a linear regression equation ($y = mx + c$; where y represents indoor concentration, x denotes outdoor concentrations, m indicates the slope, and c indicates the intercept). However, unlike simple linear regression, mixed-effects regression allows for variation in both the slope and intercept of the regression relationship. This analysis is conducted separately for each home and each season. Regression is carried out using the 'lmer' function of the 'lme4' package in the R programming language.

The coefficients obtained from mixed-effect regression analysis can provide valuable insights. In prior studies (Bi et al., 2021; Chen and Zhao, 2011; Lunderberg et al., 2023; Wallace et al., 2022), the slope is typically interpreted as the infiltration factor of outdoor pollution (the proportion of outdoor pollution infiltrated indoors), while the intercept signifies the contribution of indoor sources to indoor $PM_{2.5}$ levels.

In our analysis, we allowed both the slope and intercept of the regression to vary based on the time of day. This approach aimed to capture real-world dynamics, where indoor-generated levels fluctuate with indoor activities such as cooking and cleaning. Similarly, the infiltration of outdoor pollution may vary throughout the day due to changes in ventilation settings (typically, windows remain open during the daytime and closed at night), fluctuations in outdoor concentration levels due to meteorological factors (such as changes in mixing height), and variations in local outdoor source strength (such as traffic during rush hours).

2.5.2. Spatial relationship

Using mean $PM_{2.5}$ concentrations from each measured home, we examined the spatial relationship between indoor and outdoor $PM_{2.5}$ levels measured across diverse homes using the Pearson correlation coefficient. To explore the factors influencing spatial variability, we conducted univariate and multivariate regression analyses with indoor and outdoor $PM_{2.5}$ levels and various indoor and outdoor physical features at measurement locations. Various physical features used in regression analysis were collected during a baseline questionnaire survey at the selected homes (Table S1). These include apartment size, number of windows, cooking habits, and kitchen features (cooking duration, presence of exhaust fan, kitchen hood), as well as other indoor sources such as the use of mosquito coils and presence of smokers in the apartment. The analysis is conducted using season-specific mean $PM_{2.5}$ values as well as the overall mean $PM_{2.5}$ from both seasons.

The goal of the multiple linear regression analysis was to identify important features and develop a model that explains the spatial variability for indoor $PM_{2.5}$. This model development process resembled that of empirical land-use regression models (Hoek et al., 2011; Saha et al., 2019), where measured concentrations and land-use covariates are regressed to establish a statistical relationship. We used various indoor features (Table S1) and mean outdoor $PM_{2.5}$ from measured homes as potential covariates.

For the multiple linear regression analysis, the selection of predictor variables among the available list of potential covariates followed a supervised stepwise regression approach (Eeftens et al., 2012; Saha et al., 2019). In this process, the model selects variables one at a time based on the adjusted R-squared (coefficient of determination) of univariate linear regressions, starting with the variable that provides the highest adjusted R-squared. The variable selection process continues until a newly added variable would improve the overall model adjusted R-squared by more than 1%. Variables with p-values (predictor significance) exceeding 0.1 were removed from the selected set. We employed a leave-one-out cross-validation approach to assess the model's performance on unseen data. Model performance was evaluated using adjusted R-squared and root mean square error (RMSE) for both model development and cross-validation. The model development was implemented in the R programming language.

3. Results and discussion

3.1. Measured indoor and outdoor $PM_{2.5}$ levels

Table 1 presents the mean indoor and outdoor $PM_{2.5}$ concentrations and indoor-to-outdoor (I/O) ratios from individual homes, while Fig. 2 illustrates measurement variability. Data are shown separately for dry and wet seasons. In the dry season, across all sampled homes, the overall mean ± SD of indoor $PM_{2.5}$ was 146 ± 22 μg/m^3, outdoor 153 ± 23 μg/m^3, and the I/O ratio 0.97 ± 0.14. In the wet season, indoor levels were 52 ± 12 μg/m^3, outdoor 50 ± 11 μg/m^3, and the I/O ratio 1.05 ± 0.19. Both indoor and outdoor levels were approximately three times higher during dry seasons compared to the wet season, while the I/O ratios remained similar. Mean $PM_{2.5}$ levels from two outdoor CAMS measurements were 162 μg/m^3 and 50 μg/m^3 during the dry and wet seasons, respectively, also showing about a threefold seasonal difference.

Large seasonal differences were consistently observed in all measurement locations, including indoor and outdoor levels of sampled homes and outdoor CAMS locations. This indicates that the large seasonal differences are due to variations in regional background pollution levels between seasons. While there are variations between indoor and outdoor levels within specific homes and between homes during a particular season, these differences are relatively smaller (vary between 10 and 30%) compared to differences between seasons, which are approximately a factor of three.

In Bangladesh, substantial seasonal differences in $PM_{2.5}$ levels are influenced by seasonal meteorology, transboundary pollution influx, and seasonal sources (Afrin et al., 2021; Begum et al., 2011; World Bank, 2023; Zaman et al., 2021). During the dry season, factors contributing to higher concentrations include long-range transported pollution from neighboring countries, particularly driven by predominant winds from the Indian Indo-Gangetic Plain (IGP) states; seasonal sources such as solid biomass burning in brick kilns, construction activities; and meteorological phenomena like reduced atmospheric mixing, less rainfall. On the other hand, heavy rainfall during the monsoon, along with a relatively lesser impact from long-range transport, driven by predominant winds from the Bay of Bengal, are likely important factors contributing to observed lower $PM_{2.5}$ levels in the wet season.

Despite notable seasonal variations in $PM_{2.5}$ concentrations, the I/O ratios of $PM_{2.5}$ from each season were similar and closer to 1. This suggests that regional background air pollution levels have a large influence on indoor pollution levels in different households. While there were home-to-home variations of measured I/O ratios, on average, these variations were relatively small and remained within ±15% of 1 in both seasons. This underscores that, regardless of seasons, the indoor environment of residential homes in Dhaka city is nearly as polluted as outdoor settings, with pollution levels in many homes surpassing outdoor levels. Our observed $PM_{2.5}$ I/O ratios of closer to 1 are consistent with findings from several past studies in India, China, and other regions (Cao et al., 2012; Chen and Zhao, 2011; Deng et al., 2017; Jones et al.,

Table 1
Summary of indoor and outdoor $PM_{2.5}$ concentrations measured in individual homes during dry and wet seasons.

Site ID	Dry (Winter) Season[a]						Wet (Summer) Season[a]					
	Mean Indoor $PM_{2.5}$ (μg m^{-3})	Mean Outdoor $PM_{2.5}$ (μg m^{-3})	Ratio of Indoor to Outdoor $PM_{2.5}$	Person R of Indoor -Outdoor $PM_{2.5}$	Slope of indoor-outdoor regression	Intercept of indoor-outdoor regression	Mean Indoor $PM_{2.5}$ (μg m^{-3})	Mean Outdoor $PM_{2.5}$ (μg m^{-3})	Ratio of Indoor to Outdoor $PM_{2.5}$	Person R of Indoor -Outdoor $PM_{2.5}$	Slope of indoor-outdoor regression	Intercept of indoor-outdoor regression
S1	153	138	1.11	0.88	0.96	21.1	55	46	1.19	0.95	0.97	4.9
S2	189	174	1.09	0.69	0.75	59.6	38	30	1.26	0.76	0.95	9.7
S3	103	108	0.96	0.90	0.87	8.8	52	45	1.15	0.99	0.96	3.9
S4	159	146	1.09	0.65	0.79	42.6	69	63	1.1	0.92	0.95	8.6
S5	147	153	0.96	0.93	0.93	3.7	45	60	0.74	0.71	0.60	11.1
S6	181	183	0.99	0.62	0.86	24.6	56	49	1.15	0.68	0.92	8
S7	158	141	1.12	0.89	0.94	23.3	55	49	1.13	0.98	0.98	2.2
S8	126	140	0.91	0.94	0.89	2.5	47	56	0.84	0.98	0.81	1.1
S9	142	155	0.91	0.71	0.77	21.9	35	54	0.64	0.54	0.53	7.1
S10	139	162	0.86	0.90	0.75	21.9	45	42	1.05	0.99	0.97	3.4
S11	157	169	0.93	0.63	0.76	24.3	74	60	1.24	0.81	0.90	23
S12	132	184	0.72	0.93	0.61	19.6	51	45	1.13	0.74	0.94	3.6
S13	129	186	0.69	0.92	0.64	9.9	33	32	1.03	0.9	0.94	3.6
S14	–	–	–	–	–	–	59	69	0.88	0.68	0.74	8.0
S15	–	–	–	–	–	–	69	53	1.28	0.87	0.85	16.8
S16	143	140	1.03	0.88	0.98	2.5	–	–	–	–	–	–
S17	128	120	1.11	0.85	0.96	12.5	–	–	–	–	–	–
Outdoor CAMS												
USE	161	–	–	–	–	–	49	–	–	–	–	–
DoE	163	–	–	–	–	–	52	–	–	–	–	–
Mean ± Standard Deviation (SD) of all sampled homes (S1 – S17)[b]												
Mean ±SD	**146 ± 22**	**153 ± 23**	**0.97 ± 0.14**	**0.82 ± 0.12**	**0.83 ± 0.12**	**19.9 ± 15.4**	**52 ± 12**	**50 ± 11**	**1.05 ± 0.19**	**0.83 ± 0.14**	**0.87 ± 0.14**	**7.7 ± 5.9**

[a] Uncertainty in $PM_{2.5}$ measurements by low-cost sensors: Local co-location calibration of the low-cost sensors used in this study with a BAM over two seasons showed a normalized RMSE (measure of relative uncertainty) of 14% (dry season) and 17% (wet season) for hourly average measurements (see SI Fig. S1 for details).

[b] There were data from 15 sites for the seasonal comparison. All 15 sites were used to calculate the aggregate seasonal mean and standard deviation, as shown in the bottom row of Table 1. Table S6 in the SI presents a similar seasonal comparison of indoor and outdoor $PM_{2.5}$ concentrations for homes with data available from both seasons. The conclusions remain mostly unchanged.

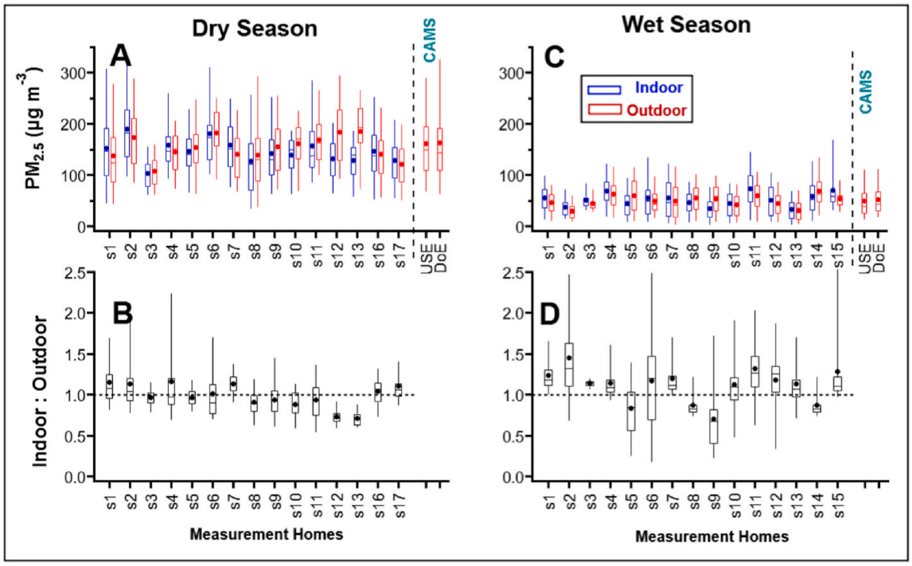

Fig. 2. Measured indoor and outdoor $PM_{2.5}$ concentration levels and indoor-to-outdoor (I/O) ratios in individual homes during dry and wet seasons. (A) Box-whisker plot showing the distribution of hourly average indoor and outdoor concentrations measured at each home during the dry season. Data from outdoor CAMS stations for the period of measurements collected from different homes are shown. (B) I/O ratios at each home during the dry season. (C) and (D) are similar to panel (A) and (B) respectively, showing the measurement data from the wet season. For the box-whisker plot, boxes indicate the interquartile range, whiskers represent the 5th-95th percentile range, horizontal lines within the boxes indicate the median, and circles represent the mean. The horizontal dashed line in panels B and D serves as a visual guide.

2000; Lv et al., 2017; Massey et al., 2009).

3.2. Diurnal variations of indoor and outdoor $PM_{2.5}$

Fig. 3 shows the daily fluctuations in indoor and outdoor $PM_{2.5}$ levels, along with their corresponding indoor-to-outdoor (I/O) ratios, in the dry and wet seasons. Both indoor and outdoor $PM_{2.5}$ levels showed significant variability throughout the day, with more pronounced fluctuations during the dry season compared to the wet season.

Outdoor $PM_{2.5}$ levels were relatively higher during nighttime and

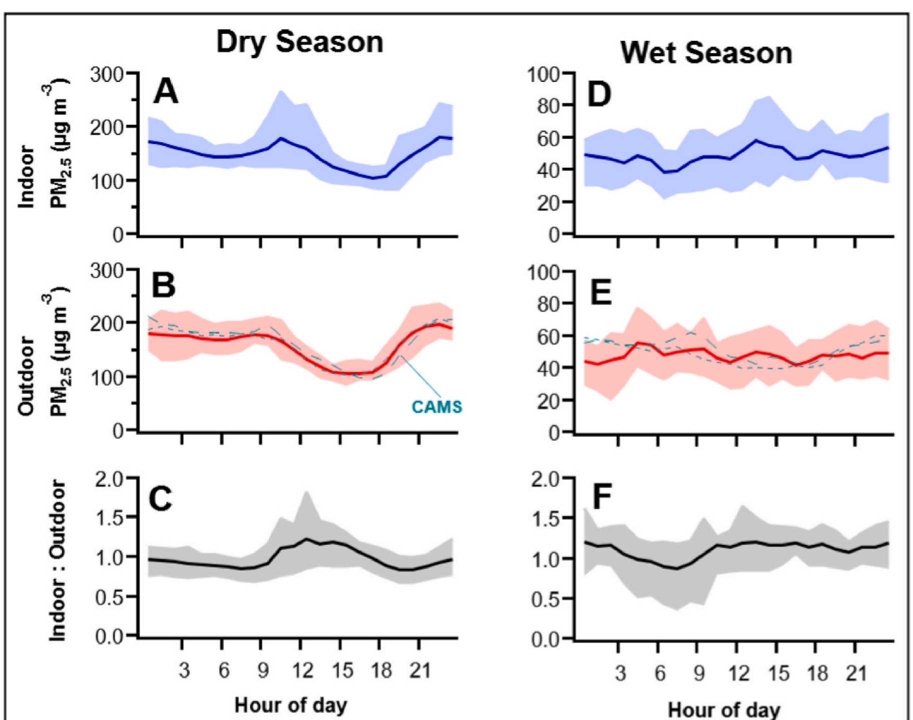

Fig. 3. Diurnal variation of indoor and outdoor $PM_{2.5}$ concentration levels and indoor-to-outdoor (I/O) ratios during dry and wet seasons. (A) Diurnal variation of indoor $PM_{2.5}$ levels during the dry season. The line represents the mean diurnal profile across all sampled homes, while the shaded region indicates the range of average diurnal profiles from individual homes. (B) Similar to panel A, showing the diurnal variation of outdoor $PM_{2.5}$ concentrations during the dry season. Diurnal profiles from two outdoor CAMS locations are also shown. (C) Similar to panel A, showing the diurnal variations of indoor-to-outdoor (I/O) ratios during the dry season. Panels (D), (E), and (F) are similar to (A), (B), and (C), respectively, showing measurements from wet seasons.

early morning hours, and lower during the afternoon. When comparing the average diurnal profiles across all measurement locations, outdoor $PM_{2.5}$ levels were 15–25% higher than average during nighttime and early morning in the dry season, and 10–15% higher-than-average during the wet season. Levels were 30–35% and 10–15% lower-than-average in the afternoon during the dry season and wet season, respectively.

These diurnal variations are primarily influenced by meteorological conditions, particularly the diurnal variation of the atmospheric mixing layer (Saha et al., 2024; Sarwar et al., 2023). The height of the atmospheric boundary layer tends to increase during midday and decrease at night, resulting in lower $PM_{2.5}$ concentrations during midday and higher concentrations during nighttime and early morning hours (Sarwar et al., 2023). Consistent variation patterns observed across different homes throughout the city and outdoor CAMS locations also suggest the significant influence of meteorological and atmospheric phenomena on outdoor diurnal profiles.

In contrast to outdoor profiles, indoor diurnal profiles from both seasons showed midday peaks, indicating a likely association with indoor cooking activities. During the dry season, a midday peak occurred around 10–11 a.m., with concentrations 20–25% higher than-average. In the wet season, a midday peak was observed around 1–2 pm, with concentrations 15–20% higher-than-average. Late morning and midday are the primary cooking periods in most homes in Bangladesh (Akteruzzaman et al., 2023). Lower indoor $PM_{2.5}$ concentrations were observed in the evening (5–6 pm) during the dry season and early morning (6–7 am) during the wet season when cooking is less likely to occur.

The diurnal profiles of I/O ratios showed elevated values during midday (12 p.m.–2 p.m.), similar to the indoor $PM_{2.5}$ profiles, likely indicating the influence of cooking. Midday peak levels were 22% and 19% higher-than- average during the dry and wet seasons, respectively. Conversely, lower I/O ratios were observed in the evening (7–8 pm) during the dry season (18% below the average) and in the morning (6–7 am) during the wet season (16% below the average). These variations in I/O profiles are influenced by fluctuations in indoor source activities, outdoor concentration levels, indoor-outdoor air exchange rates, etc. Thus, the observed profile reflects the influence of a combination of indoor sources, meteorological conditions, and other factors.

3.3. Temporal relationship and infiltration factors

We observed strong temporal correlations between indoor and outdoor $PM_{2.5}$ levels across both the dry and wet seasons. During the dry season, Pearson correlation coefficients (R) between hourly time series of indoor and outdoor $PM_{2.5}$ levels measured in individual homes ranged from 0.62 to 0.94, with a mean ± SD of 0.82 ± 0.12. Similarly, in the wet season, correlations varied from 0.54 to 0.99, with a mean ± SD of 0.83 ± 0.14 (Table 1). The consistently positive and strong temporal correlation levels further demonstrate the substantial influence of outdoor $PM_{2.5}$ levels and meteorological factors on variations in indoor levels.

The derived infiltration factors, represented by slopes from mixed effect regression of indoor and outdoor $PM_{2.5}$ time series data, also underscore the significant impact of outdoor pollution on indoor environments. During the dry season, infiltration factors varied between 0.61 and 0.98 (mean ± SD: 0.83 ± 0.12), while during the wet season, they ranged from 0.53 to 0.98 (mean ± SD: 0.87 ± 0.14). On average, infiltration factors were slightly higher during the wet seasons compared to the dry seasons. This difference may be attributed to variations in the ventilation conditions of buildings between seasons. For instance, during the wet season, which coincides with summer in Bangladesh, individuals are more likely to keep their windows open for enhanced ventilation, thus facilitating greater infiltration of outdoor pollutants into indoor spaces.

The infiltration factors derived from this study tend to be at the upper end of the distribution reported in the literature (Bi et al., 2021; Chen and Zhao, 2011; Hänninen et al., 2004, 2011; Krebs et al., 2021; Lunderberg et al., 2023; Wallace et al., 2022; Zahed et al., 2022). Infiltration factors observed in our study are generally higher than those reported in studies from the US and Europe (Chen and Zhao, 2011; Lunderberg et al., 2023; MacNeill et al., 2012). Compared to Europe and many locations in the USA—which typically have colder climates, mechanical ventilation, and more insulated building structures—the relatively warmer climate in Bangladesh leads to less insulated buildings, increased reliance on natural ventilation, and, consequently, greater infiltration of outdoor pollutants into indoor spaces.

The regression intercepts, interpreted as the mean indoor generated source contribution, varied significantly between homes and seasons (dry season: 19.9 ± 15.4 μg/m3, wet season: 7.7 ± 5.9 μg/m3) (Table 1). Seasonal variations in indoor sources, meteorological influence, and other factors likely contribute to these differences. Derived factors indicate that approximately 15–20% of the overall indoor $PM_{2.5}$ levels come from indoor generated sources, with the remaining 80–85% contributed by outdoor infiltrations.

While the regression approach employed here is a well-established method in the literature (Bi et al., 2022; Chen and Zhao, 2011; Lunderberg et al., 2023; Wallace et al., 2022), it's important to acknowledge potential challenges in accurately isolating contributions of outdoor infiltration and indoor generated sources through statistical analysis. However, near unity I/O ratios, consistent seasonal influence on both indoor and outdoor locations, and strong correlations between indoor and outdoor levels all support the significant influence of outdoor levels on indoor $PM_{2.5}$ levels in Dhaka residences. Therefore, putting these context all together, the derived coefficients from regressions, indicating high outdoor contributions (80–85%) and relatively small contributions (15–20%) from indoor generated sources, are physically plausible.

3.4. Factors influencing the spatial variability of indoor concentrations

The Pearson's R between mean indoor and outdoor concentrations across different homes were 0.49 during the dry season, 0.62 during the wet season, and 0.41 across both seasons. Notably, these correlations are lower than the temporal correlations observed within individual homes: 0.82 ± 0.12 during the dry season and 0.83 ± 0.14 during the wet season. The moderate spatial correlation suggests that while the among-household variation of outdoor $PM_{2.5}$ levels significantly influences indoor levels' spatial variation, other factors, such as indoor source activities and ventilation-related features, likely play crucial roles in explaining variabilities in indoor $PM_{2.5}$ levels across homes.

Univariate correlation analysis between indoor $PM_{2.5}$ levels and various physical features in sampled homes revealed negative correlations with apartment size (R = - 0.33) and the presence of a kitchen hood (R = - 0.48), while positive correlations were observed with the presence of a smoker (R = 0.33) and the use of mosquito coils (R = 0.17) in the apartment (Table S4). We also compared mean indoor $PM_{2.5}$ concentrations between homes with smokers or mosquito coil users and those without (see Table S7). Overall, mean indoor $PM_{2.5}$ concentrations are 5–10% higher in homes with smokers compared to those without and approximately 20% higher in homes using mosquito coils during the wet season (the predominant mosquito season in Bangladesh). However, these differences are not statistically significant ($p > 0.1$).

Stepwise multiple regression identified outdoor $PM_{2.5}$, the presence of a kitchen hood in the apartment, and the number of windows as key predictors, collectively explaining 50–70% of the spatial variability in indoor $PM_{2.5}$ measured in different households. The multiple linear regression model incorporating these covariates had a fit R^2 of 0.78, an RMSE of 7.6 μg/m^3, and a CV R^2 of 0.52, with an RMSE of 9.6 μg/m^3 for overall mean concentrations across both seasons (Table 2 and Fig. S4). Season-specific models revealed similar predictor variables; however, their model performances were relatively lower (wet season: fit R^2: 0.64, CV R^2: 0.45; dry season: fit R^2: 0.56, CV R^2: 0.40) (Table S5).

Table 2
Multiple linear regression model for predicting spatial variabilities in indoor $PM_{2.5}$ levels across sampled homes.

Model	Model parameters	Coefficients			Model performance			
		Estimate	Std. Error	p-value	Development		Cross validation	
					R^2	RMSE (μg m^{-3})	R^2	RMSE (μg m^{-3})
Indoor $PM_{2.5}$ concentration (μg m^{-3})	Intercept	43.8	21.17	0.068	0.78	7.6	0.52	9.6
	Outdoor $PM_{2.5}$	0.92	0.22	0.0022				
	Kitchen hood in apt	−26.1	5.27	0.0008				
	No of windows in apt	−5.0	1.44	0.0068				

The selected predictor variables through stepwise regression and the signs of their coefficients were physically interpretable. For instance, the presence of a kitchen hood and an increasing number of windows exhibited negative coefficients, suggesting their potential to decrease indoor $PM_{2.5}$ levels. In contrast, outdoor $PM_{2.5}$ showed a positive coefficient, indicating that higher outdoor levels are linked with elevated indoor levels. The negative association between the increasing number of windows and indoor $PM_{2.5}$ levels has also been reported in a past study in a low-income community in Dhaka (Gurley et al., 2013).

Our analysis suggests that indoor exposure levels in Dhaka homes can be predicted using outdoor $PM_{2.5}$ and indoor activity-related covariates. Implementing the model in unmeasured areas will necessitate estimates of outdoor $PM_{2.5}$ levels and other covariates. Outdoor $PM_{2.5}$ levels can potentially be estimated via a land-use regression model (Eeftens et al., 2012; Hoek et al., 2011; Saha et al., 2019). Univariate regression analysis between measured outdoor $PM_{2.5}$ and land-use covariates such as restaurant density (R = 0.47), major road density (R = 0.46), and population density (R = 0.28) within a 1 km buffer radius shows good associations (Table S4), suggesting the potential for developing a land-use regression model for outdoor $PM_{2.5}$ in Dhaka city using readily available covariates.

3.5. Implications, limitations, future directions

In this study, we conducted simultaneous measurements of indoor and outdoor $PM_{2.5}$ levels across 17 homes in Dhaka city, Bangladesh. Significant variations in both indoor and outdoor $PM_{2.5}$ levels were observed between seasons, primarily driven by regional pollution levels. Our findings indicate that indoor $PM_{2.5}$ levels were similar to outdoor levels, with I/O ratios close to 1 across diverse locations and seasons.

Contrary to the prevalent perception among the general population in Bangladesh that air pollution primarily exists outdoors, our data indicate that indoor environments in Dhaka city are nearly as polluted as outdoor settings. Our study provides locally derived scientific evidence to enhance public awareness and develop mitigation measures for reducing $PM_{2.5}$ exposures in Bangladesh. Educating the public and policymakers with scientific evidence is the very first step for implementing evidence-based air pollution interventions.

Our measurements reveal high indoor $PM_{2.5}$ levels in Dhaka city, akin to outdoor levels, influenced by both outdoor pollution and indoor sources. This underscores the need for comprehensive and multi-pronged measures to reduce indoor $PM_{2.5}$ exposures in Bangladesh. Implementing simple and affordable modification should serve as initial steps. For instance, our analysis highlights the importance of kitchen hoods and ventilation in buildings in explaining the spatial variability of indoor $PM_{2.5}$ across different homes. Awareness and mitigation measures should be promoted to enhance such practices, including the use of kitchen hoods, ensuring proper ventilation during and after cooking, and closing windows during periods of high outdoor pollution levels. Numerous studies have demonstrated the effectiveness of indoor air filters in reducing indoor pollution levels (González-Martín et al., 2021; Liao et al., 2019). However, given affordability challenges in Bangladesh, locally based low-cost air filter technology will be essential. The use of personal protective equipment (PPE), such as high-efficiency particulate air masks, is a viable option for reducing personal $PM_{2.5}$ exposure levels in both indoor and outdoor settings.

Regional pollution levels play a significant role in indoor pollution in Bangladesh, highlighting the need for substantial efforts to reduce regional pollution levels. This requires a holistic and long-term clean air program, currently absent in Bangladesh, which should address pollution from local sources, secondary particulate pollution, and long-range transported pollution and coordination with neighboring countries (World Bank, 2023).

While our study provides valuable insights, it has limitations, and further research is needed to strengthen our findings. Future efforts should aim to expand measurement locations and conduct long-term (year-long) continuous measurements to better understand indoor and outdoor pollution dynamics. Careful use of low-cost sensors can play a critical role in such research. For example, a low-cost sensor network comprising continuous measurements of indoor and outdoor levels over several years at 20–30 locations across the city could provide a valuable dataset to comprehensively understand indoor and outdoor pollution dynamics.

Our measurements use low-cost sensors, which have inherent uncertainties. Although we performed a local calibration of the low-cost sensors, achieving an agreement within 14–17% of a beta attenuation monitor (BAM) at a site in Dhaka, the co-location calibration was based on ambient outdoor measurements. Consequently, we applied the same calibration factors to both indoor and outdoor measurements, as indoor co-location calibration was not feasible. Future studies should investigate potential differences in sensor performance between indoor and outdoor settings and assess the long-term performance of sensors through year-long co-location data collection in environments like Dhaka, where pollution levels are high, and atmospheric conditions are very humid.

Furthermore, our study installed a single sensor in each study home, either in the bedroom or living room. There may be substantial variations in pollutant levels across different micro-environments within a home (Vardoulakis et al., 2020), such as between the living room and bedroom or rooms near versus away from the kitchen. Examining this within-home micro-environmental variability was beyond the scope of our work but should be explored in future studies with a systematic study design.

Although our modeling analysis shows promise in predicting spatial variability in indoor $PM_{2.5}$ levels using outdoor $PM_{2.5}$ and indoor physical features as predictor covariates, the statistical model developed based on a limited number of locations may limit the generalizability of any statistical relationships established. Therefore, future endeavors should consider incorporating more locations and additional covariates as potential input predictor variables to strengthen the robustness of relationships. Furthermore, future research should consider size- and chemically-specific $PM_{2.5}$ measurements, VOCs, and air toxics for comprehensive air pollution characterization in diverse rural and urban locations. The combination of comprehensive measurements and modeling analysis can inform evidence-based mitigation measures and strategies tailored to specific environments.

CRediT authorship contribution statement

Provat K. Saha: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Ahsan Habib:** Writing – review & editing, Data curation. **Dipika R. Prapti:** Writing – review & editing, Formal analysis. **Talha Jubair:** Writing – review & editing, Formal analysis. **Abu U. Zarrah:** Writing – review & editing, Formal analysis. **Chowdhury A. Hossain:** Writing – review & editing, Formal analysis. **Sheikh M. Rahman:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Abdus Salam:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Md Aynul Bari:** Writing – review & editing, Resources, Methodology, Investigation, Conceptualization. **Julian D. Marshall:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

All authors declare they have no actual or potential competing financial interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2024.120945.

Data availability

Data will be made available on request.

References

Abdul Jabbar, S., Tul Qadar, L., Ghafoor, S., Rasheed, L., Sarfraz, Z., Sarfraz, A., Sarfraz, M., Felix, M., Cherrez-Ojeda, I., 2022. Air quality, pollution and sustainability trends in South asia: a population-based study. Int. J. Environ. Res. Publ. Health 19, 7534. https://doi.org/10.3390/ijerph19127534.

Adgate, J.L., Mongin, S.J., Pratt, G.C., Zhang, J., Field, M.P., Ramachandran, G., Sexton, K., 2007. Relationships between personal, indoor, and outdoor exposures to trace elements in PM2.5. Sci. Total Environ. 386, 21–32. https://doi.org/10.1016/j.scitotenv.2007.07.007.

Afrin, S., Islam, M.M., Ahmed, T., 2021. A meteorology based particulate matter prediction model for megacity Dhaka. Aerosol Air Qual. Res. 21, 200371. https://doi.org/10.4209/aaqr.2020.07.0371.

Akteruzzaman, Md, Rahman, MdA., Rabbi, F.M., Asharof, S., Rofi, M.M., Hasan, MdK., Muktadir Islam, MdA., Khan, M.A.R., Rahman, M.M., Rahaman, MdH., 2023. The impacts of cooking and indoor air quality assessment in the southwestern region of Bangladesh. Heliyon 9, e12852. https://doi.org/10.1016/j.heliyon.2023.e12852.

Apte, J.S., Marshall, J.D., Cohen, A.J., Brauer, M., 2015. Addressing global mortality from ambient PM2.5. Environ. Sci. Technol. 49, 8057–8066. https://doi.org/10.1021/acs.est.5b01236.

Bari, MdA., Kindzierski, W.B., Wheeler, A.J., Héroux, M.-È., Wallace, L.A., 2015. Source apportionment of indoor and outdoor volatile organic compounds at homes in Edmonton, Canada. Build. Environ. 90, 114–124. https://doi.org/10.1016/j.buildenv.2015.03.023.

Barkjohn, K.K., Gantt, B., Clements, A.L., 2021. Development and application of a United States-wide correction for $PM_{2.5}$ data collected with the PurpleAir sensor. Atmos. Meas. Tech. 14, 4617–4637. https://doi.org/10.5194/amt-14-4617-2021.

Begum, B.A., Biswas, S.K., Hopke, P.K., 2011. Key issues in controlling air pollutants in Dhaka, Bangladesh. Atmos. Environ. 45, 7705–7713. https://doi.org/10.1016/j.atmosenv.2010.10.022.

Begum, B.A., Hopke, P.K., 2018. Ambient air quality in Dhaka Bangladesh over two decades: impacts of policy on air quality. Aerosol Air Qual. Res. 18, 1910–1920. https://doi.org/10.4209/aaqr.2017.11.0465.

Begum, B.A., Hopke, P.K., Markwitz, A., 2013. Air pollution by fine particulate matter in Bangladesh. Atmos. Pollut. Res. 4, 75–86. https://doi.org/10.5094/APR.2013.008.

Begum, B.A., Paul, S.K., Dildar Hossain, M., Biswas, S.K., Hopke, P.K., 2009. Indoor air pollution from particulate matter emissions in different households in rural areas of Bangladesh. Build. Environ. 44, 898–903. https://doi.org/10.1016/j.buildenv.2008.06.005.

Bi, J., Carmona, N., Blanco, M.N., Gassett, A.J., Seto, E., Szpiro, A.A., Larson, T.V., Sampson, P.D., Kaufman, J.D., Sheppard, L., 2022. Publicly available low-cost sensor measurements for PM2.5 exposure modeling: guidance for monitor deployment and data selection. Environ. Int. 158, 106897. https://doi.org/10.1016/j.envint.2021.106897.

Bi, J., Wallace, L.A., Sarnat, J.A., Liu, Y., 2021. Characterizing outdoor infiltration and indoor contribution of PM2.5 with citizen-based low-cost monitoring data. Environ. Pollut. 276, 116763. https://doi.org/10.1016/j.envpol.2021.116763.

Blanco, M.N., Doubleday, A., Austin, E., Marshall, J.D., Seto, E., Larson, T.V., Sheppard, L., 2023. Design and evaluation of short-term monitoring campaigns for long-term air pollution exposure assessment. J. Expo. Sci. Environ. Epidemiol. 33, 465–473. https://doi.org/10.1038/s41370-022-00470-5.

Bproperty, 2018. Housing Trends in Popular Areas of Dhaka -. Blog Homes Trends Tips Life Bproperty. URL. https://www.bproperty.com/blog/housing-trends-dhaka-people-apartments/, 11.11.24.

Brooks, N., Biswas, D., Hossin, R., Yu, A., Saha, Shampa, Saha, Senjuti, Saha, S.K., Luby, S.P., 2023. Health consequences of small-scale industrial pollution: evidence from the brick sector in Bangladesh. World Dev. 170, 106318. https://doi.org/10.1016/j.worlddev.2023.106318.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C.A., Apte, J.S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S.S., Kan, H., Walker, K.D., Thurston, G.D., Hayes, R.B., Lim, C.C., Turner, M.C., Jerrett, M., Krewski, D., Gapstur, S.M., Diver, W.R., Ostro, B., Goldberg, D., Crouse, D.L., Martin, R.V., Peters, P., Pinault, L., Tjepkema, M., Donkelaar, A. van, Villeneuve, P.J., Miller, A.B., Yin, P., Zhou, M., Wang, L., Janssen, N.A.H., Marra, M., Atkinson, R.W., Tsang, H., Thach, T.Q., Cannon, J.B., Allen, R.T., Hart, J.E., Laden, F., Cesaroni, G., Forastiere, F., Weinmayr, G., Jaensch, A., Nagel, G., Concin, H., Spadaro, J.V., 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. Proc. Natl. Acad. Sci. USA 115, 9592–9597. https://doi.org/10.1073/pnas.1803222115.

Cao, J.J., Huang, H., Lee, S.C., Chow, J.C., Zou, C.W., Ho, K.F., Watson, J.G., 2012. Indoor/outdoor relationships for organic and elemental carbon in PM2.5 at residential homes in guangzhou, China. Aerosol Air Qual. Res. 12, 902–910. https://doi.org/10.4209/aaqr.2012.02.0026.

Challoner, A., Gill, L., 2014. Indoor/outdoor air pollution relationships in ten commercial buildings: PM2.5 and NO2. Build. Environ. 80, 159–173. https://doi.org/10.1016/j.buildenv.2014.05.032.

Chen, C., Zhao, B., 2011. Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. Atmos. Environ. 45, 275–288. https://doi.org/10.1016/j.atmosenv.2010.09.048.

Deng, G., Li, Z., Wang, Zhichao, Gao, J., Xu, Z., Li, J., Wang, Zhiyong, 2017. Indoor/outdoor relationship of PM2.5 concentration in typical buildings with and without air cleaning in Beijing. Indoor Built Environ. 26, 60–68. https://doi.org/10.1177/1420326X15604349.

Dockery, D.W., Pope, C.A., Xu, X., Spengler, J.D., Ware, J.H., Fay, M.E., Ferris, B.G., Speizer, F.E., 1993. An association between air pollution and mortality in six U.S. Cities. N. Engl. J. Med. 329, 1753–1759. https://doi.org/10.1056/NEJM199312093292401.

Du, X., Jin, X., Zucker, N., Kennedy, R., Urpelainen, J., 2020. Transboundary air pollution from coal-fired power generation. J. Environ. Manag. 270, 110862. https://doi.org/10.1016/j.jenvman.2020.110862.

Eeftens, M., Beelen, R., de Hoogh, K., Bellander, T., Cesaroni, G., Cirach, M., Declercq, C., Dėdelė, A., Dons, E., de Nazelle, A., Dimakopoulou, K., Eriksen, K., Falq, G., Fischer, P., Galassi, C., Gražulevičienė, R., Heinrich, J., Hoffmann, B., Jerrett, M., Keidel, D., Korek, M., Lanki, T., Lindley, S., Madsen, C., Mölter, A., Nádor, G., Nieuwenhuijsen, M., Nonnemacher, M., Pedeli, X., Raaschou-Nielsen, O., Patelarou, E., Quass, U., Ranzi, A., Schindler, C., Stempfelet, M., Stephanou, E., Sugiri, D., Tsai, M.-Y., Yli-Tuomi, T., Varró, M.J., Vienneau, D., Klot, S. von, Wolf, K., Brunekreef, B., Hoek, G., 2012. Development of land use regression models for PM2.5, PM2.5 absorbance, PM10 and PMcoarse in 20 European study areas; results of the ESCAPE project. Environ. Sci. Technol. 46, 11195–11205. https://doi.org/10.1021/es301948k.

Eeftens, M., Phuleria, H.C., Meier, R., Aguilera, I., Corradi, E., Davey, M., Ducret-Stich, R., Fierz, M., Gehrig, R., Ineichen, A., Keidel, D., Probst-Hensch, N., Ragettli, M.S., Schindler, C., Künzli, N., Tsai, M.-Y., 2015. Spatial and temporal variability of ultrafine particles, NO2, PM2.5, PM2.5 absorbance, PM10 and PMcoarse in Swiss study areas. Atmos. Environ. 111, 60–70. https://doi.org/10.1016/j.atmosenv.2015.03.031.

Gautam, S., Yadav, A., Tsai, C.-J., Kumar, P., 2016. A review on recent progress in observations, sources, classification and regulations of PM2.5 in Asian environments. Environ. Sci. Pollut. Res. 23, 21165–21175. https://doi.org/10.1007/s11356-016-7515-2.

Giordano, M.R., Malings, C., Pandis, S.N., Presto, A.A., McNeill, V.F., Westervelt, D.M., Beekmann, M., Subramanian, R., 2021. From low-cost sensors to high-quality data: a summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors. J. Aerosol Sci. 158, 105833. https://doi.org/10.1016/j.jaerosci.2021.105833.

González-Martín, J., Kraakman, N.J.R., Pérez, C., Lebrero, R., Muñoz, R., 2021. A state–of–the-art review on indoor air pollution and strategies for indoor air pollution control. Chemosphere 262, 128376. https://doi.org/10.1016/j.chemosphere.2020.128376.

Gulia, S., Shiva Nagendra, S.M., Khare, M., Khanna, I., 2015. Urban air quality management-A review. Atmos. Pollut. Res. 6, 286–304. https://doi.org/10.5094/APR.2015.033.

Gurley, E.S., Salje, H., Homaira, N., Ram, P.K., Haque, R., Petri, W.A., Bresee, J., Moss, W.J., Luby, S.P., Breysse, P., Azziz-Baumgartner, E., 2013. Seasonal concentrations and determinants of indoor particulate matter in a low-income community in Dhaka, Bangladesh. Environ. Res. 121, 11–16. https://doi.org/10.1016/j.envres.2012.10.004.

Hänninen, O., Hoek, G., Mallone, S., Chellini, E., Katsouyanni, K., Gariazzo, C., Cattani, G., Marconi, A., Molnár, P., Bellander, T., Jantunen, M., 2011. Seasonal patterns of outdoor PM infiltration into indoor environments: review and meta-analysis of available studies from different climatological zones in Europe. Air Qual. Atmosp. Health 4, 221–233. https://doi.org/10.1007/s11869-010-0076-5.

Hänninen, O.O., Lebret, E., Ilacqua, V., Katsouyanni, K., Künzli, N., Srám, R.J., Jantunen, M., 2004. Infiltration of ambient PM2.5 and levels of indoor generated non-ETS PM2.5 in residences of four European cities. Atmos. Environ. 38, 6411–6423. https://doi.org/10.1016/j.atmosenv.2004.07.015.

Haque, M.I., Nahar, K., Kabir, M.H., Salam, A., 2018. Particulate black carbon and gaseous emission from brick kilns in Greater Dhaka region, Bangladesh. Air Qual. Atmosp. Health 11, 925–935. https://doi.org/10.1007/s11869-018-0596-y.

Harrison, X.A., Donaldson, L., Correa-Cano, M.E., Evans, J., Fisher, D.N., Goodwin, C.E. D., Robinson, B.S., Hodgson, D.J., Inger, R., 2018. A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ 6, e4794. https://doi.org/10.7717/peerj.4794.

Hoek, G., Beelen, R., Kos, G., Dijkema, M., Zee, S.C. van der, Fischer, P.H., Brunekreef, B., 2011. Land use regression model for ultrafine particles in amsterdam. Environ. Sci. Technol. 45, 622–628. https://doi.org/10.1021/es1023042.

Islam, MdN., Ali, MdA., Islam, MdM., 2019. Spatiotemporal investigations of aerosol optical properties over Bangladesh for the period 2002–2016. Earth Syst. Environ. 3, 563–573. https://doi.org/10.1007/s41748-019-00120-1.

Jones, N.C., Thornton, C.A., Mark, D., Harrison, R.M., 2000. Indoor/outdoor relationships of particulate matter in domestic homes with roadside, urban and rural locations. Atmos. Environ. 34, 2603–2612. https://doi.org/10.1016/S1352-2310(99)00489-6.

Junaid, M., Syed, J.H., Abbasi, N.A., Hashmi, M.Z., Malik, R.N., Pei, D.-S., 2018. Status of indoor air pollution (IAP) through particulate matter (PM) emissions and associated health concerns in South Asia. Chemosphere 191, 651–663. https://doi.org/10.1016/j.chemosphere.2017.10.097.

Kamal, A.T.M.M., Islam, MdS., Zaman, S.U., Miah, MdJ., Ahmed, T., Hoque, S., Salam, A., 2024. Quantification and source apportionment of atmospheric trace gases over Dhaka, Bangladesh. J. Atmos. Chem. 81, 4. https://doi.org/10.1007/s10874-024-09457-y.

Karagulian, F., Barbiere, M., Kotsev, A., Spinelle, L., Gerboles, M., Lagler, F., Redon, N., Crunaire, S., Borowiak, A., 2019. Review of the performance of low-cost sensors for air quality monitoring. Atmosphere 10, 506. https://doi.org/10.3390/atmos10090506.

Klompmaker, J.O., Montagne, D.R., Meliefste, K., Hoek, G., Brunekreef, B., 2015. Spatial variation of ultrafine particles and black carbon in two cities: results from a short-term measurement campaign. Sci. Total Environ. 508, 266–275. https://doi.org/10.1016/j.scitotenv.2014.11.088.

Korhonen, A., Relvas, H., Miranda, A.I., Ferreira, J., Lopes, D., Rafael, S., Almeida, S.M., Faria, T., Martins, V., Canha, N., Diapouli, E., Eleftheriadis, K., Chalvatzaki, E., Lazaridis, M., Lehtomäki, H., Rumrich, I., Hänninen, O., 2021. Analysis of spatial factors, time-activity and infiltration on outdoor generated PM2.5 exposures of school children in five European cities. Sci. Total Environ. 785, 147111. https://doi.org/10.1016/j.scitotenv.2021.147111.

Krebs, B., Burney, J., Zivin, J.G., Neidell, M., 2021. Using crowd-sourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter. Environ. Sci. Technol. 55, 6107–6115. https://doi.org/10.1021/acs.est.0c08469.

Kumar, P., Patton, A.P., Durant, J.L., Frey, H.C., 2018. A review of factors impacting exposure to PM2.5, ultrafine particles and black carbon in Asian transport microenvironments. Atmos. Environ. 187, 301–316. https://doi.org/10.1016/j.atmosenv.2018.05.046.

Li, H.Z., Gu, P., Ye, Q., Zimmerman, N., Robinson, E.S., Subramanian, R., Apte, J.S., Robinson, A.L., Presto, A.A., 2019. Spatially dense air pollutant sampling: implications of spatial variability on the representativeness of stationary air pollutant monitors. Atmos. Environ. X 2, 100012. https://doi.org/10.1016/j.aeaoa.2019.100012.

Li, Z., Wen, Q., Zhang, R., 2017. Sources, health effects and control strategies of indoor fine particulate matter (PM2.5): a review. Sci. Total Environ. 586, 610–622. https://doi.org/10.1016/j.scitotenv.2017.02.029.

Liao, J., Ye, W., Pillarisetti, A., Clasen, T.F., 2019. Modeling the impact of an indoor air filter on air pollution exposure reduction and associated mortality in urban Delhi household. Int. J. Environ. Res. Publ. Health 16, 1391. https://doi.org/10.3390/ijerph16081391.

Liu, X., Jayaratne, R., Thai, P., Kuhn, T., Zing, I., Christensen, B., Lamont, R., Dunbabin, M., Zhu, S., Gao, J., Wainwright, D., Neale, D., Kan, R., Kirkwood, J., Morawska, L., 2020. Low-cost sensors as an alternative for long-term air quality monitoring. Environ. Res. 185, 109438. https://doi.org/10.1016/j.envres.2020.109438.

Lunderberg, D.M., Liang, Y., Singer, B.C., Apte, J.S., Nazaroff, W.W., Goldstein, A.H., 2023. Assessing residential PM2.5 concentrations and infiltration factors with high spatiotemporal resolution using crowdsourced sensors. Proc. Natl. Acad. Sci. USA 120, e2308832120. https://doi.org/10.1073/pnas.2308832120.

Lv, Y., Wang, H., Wei, S., Zhang, L., Zhao, Q., 2017. The correlation between indoor and outdoor particulate matter of different building types in daqing, China. In: Procedia Eng., 10th International Symposium on Heating, Ventilation and Air Conditioning, vol. 205. ISHVAC2017, Jinan, China, pp. 360–367. https://doi.org/10.1016/j.proeng.2017.10.002, 19-22 October 2017.

MacNeill, M., Wallace, L., Kearney, J., Allen, R.W., Van Ryswyk, K., Judek, S., Xu, X., Wheeler, A., 2012. Factors influencing variability in the infiltration of PM2.5 mass and its components. Atmos. Environ. 61, 518–532. https://doi.org/10.1016/j.atmosenv.2012.07.005.

Malings, C., Tanzer, R., Hauryliuk, A., Saha, P.K., Robinson, A.L., Presto, A.A., Subramanian, R., 2020. Fine particle mass monitoring with low-cost sensors: corrections and long-term performance evaluation. Aerosol Sci. Technol. 54, 160–174. https://doi.org/10.1080/02786826.2019.1623863.

Martins, N.R., Carrilho da Graça, G., 2018. Impact of PM2.5 in indoor urban environments: a review. Sustain. Cities Soc. 42, 259–275. https://doi.org/10.1016/j.scs.2018.07.011.

Massey, D., Masih, J., Kulshrestha, A., Habil, M., Taneja, A., 2009. Indoor/outdoor relationship of fine particles less than 2.5 μm (PM2.5) in residential homes locations in central Indian region. Build. Environ. 44, 2037–2045. https://doi.org/10.1016/j.buildenv.2009.02.010.

Morawska, L., Wierzbicka, A., Buonanno, G., Cyrys, J., Schnelle-Kreis, J., Kowalski, M., Riediker, M., Birmili, W., Querol, X., Cassee, F., Yildirim, A., Elder, A., Yu, I.J., Ovrevik, J., Hougaard, K., Loft, S., Schmid, O., Stöger, T., Peters, A., Lucht, S., 2019. Ambient Ultrafine Particles: Evidence for Policy Makers. A Report Prepared by the 'Thinking outside the Box' Team.

Pope, C.A., Coleman, N., Pond, Z.A., Burnett, R.T., 2019. Fine particulate air pollution and human mortality: 25+ years of cohort studies. Environ. Res. 108924. https://doi.org/10.1016/j.envres.2019.108924.

Rahman, M.M., Mahamud, S., Thurston, G.D., 2019. Recent spatial gradients and time trends in Dhaka, Bangladesh, air pollution and their human health implications. J. Air Waste Manag. Assoc. 69, 478–501. https://doi.org/10.1080/10962247.2018.1548388.

Rana, M., Khan, M.H., 2020. Trend characteristics of atmospheric particulate matters in major urban areas of Bangladesh. Asian J. Atmosp. Environ. 14, 47–61. https://doi.org/10.5572/ajae.2020.14.1.047.

Roy, S., Zaman, S.U., Joy, K.S., Jeba, F., Kumar, P., Salam, A., 2023. Impact of fine particulate matter and toxic gases on the health of school children in Dhaka, Bangladesh. Environ. Res. Commun. 5, 025004. https://doi.org/10.1088/2515-7620/acb90d.

Saha, P.K., Li, H.Z., Apte, J.S., Robinson, A.L., Presto, A.A., 2019. Urban ultrafine particle exposure assessment with land-use regression: influence of sampling strategy. Environ. Sci. Technol. 53, 7326–7336. https://doi.org/10.1021/acs.est.9b02086.

Saha, P.K., Shovon, T.M., Rahman, S.M., Marshall, J.D., Robinson, A.L., Presto, A.A., 2024. Contrasting intra-urban variability of ultrafine particle number and fine particle mass concentrations in Dhaka, Bangladesh, and Pittsburgh, USA. Atmos. Environ. 327, 120497. https://doi.org/10.1016/j.atmosenv.2024.120497.

Salam, A., Hossain, T., Siddique, M.N.A., Alam, A.M.S., 2008. Characteristics of atmospheric trace gases, particulate matter, and heavy metal pollution in Dhaka, Bangladesh. Air Qual. Atmosp. Health 1, 101. https://doi.org/10.1007/s11869-008-0017-8.

Sarwar, G., Hogrefe, C., Henderson, B.H., Foley, K., Mathur, R., Murphy, B., Ahmed, S., 2023. Characterizing variations in ambient PM2.5 concentrations at the U.S. Embassy in Dhaka, Bangladesh using observations and the CMAQ modeling system. Atmos. Environ. 296, 119587. https://doi.org/10.1016/j.atmosenv.2023.119587.

Sayahi, T., Butterfield, A., Kelly, K.E., 2019. Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. Environ. Pollut. 245, 932–940. https://doi.org/10.1016/j.envpol.2018.11.065.

Schwela, D., Haq, G., Huizenga, C., Han, W.-J., Fabian, H., Ajero, M., 2006. Urban Air Pollution in Asian Cities: Status, Challenges and Management. Routledge, London. https://doi.org/10.4324/9781849773676.

Sokhi, R.S., Moussiopoulos, N., Baklanov, A., Bartzis, J., Coll, I., Finardi, S., Friedrich, R., Geels, C., Grönholm, T., Halenka, T., Ketzel, M., Maragkidou, A., Matthias, V., Moldanova, J., Ntziachristos, L., Schäfer, K., Suppan, P., Tsegas, G., Carmichael, G., Franco, V., Hanna, S., Jalkanen, J.-P., Velders, G.J.M., Kukkonen, J., 2022. Advances in air quality research – current and emerging challenges. Atmos. Chem. Phys. 22, 4615–4703. https://doi.org/10.5194/acp-22-4615-2022.

Stavroulas, I., Grivas, G., Michalopoulos, P., Liakakou, E., Bougiatioti, A., Kalkavouras, P., Fameli, K.M., Hatzianastassiou, N., Mihalopoulos, N., Gerasopoulos, E., 2020. Field evaluation of low-cost PM sensors (purple air PA-II) under variable urban air quality conditions, in Greece. Atmosphere 11, 926. https://doi.org/10.3390/atmos11090926.

Vardoulakis, S., Giagloglou, E., Steinle, S., Davis, A., Sleeuwenhoek, A., Galea, K.S., Dixon, K., Crawford, J.O., 2020. Indoor exposure to selected air pollutants in the home environment: a systematic review. Int. J. Environ. Res. Publ. Health 17, 8972. https://doi.org/10.3390/ijerph17238972.

Wallace, L.A., Zhao, T., Klepeis, N.E., 2022. Indoor contribution to PM2.5 exposure using all PurpleAir sites in Washington, Oregon, and California. Indoor Air 32, e13105. https://doi.org/10.1111/ina.13105.

World Bank, 2023. Striving for Clean Air: Air Pollution and Public Health in South Asia.

World Health Organization, 2021. WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide.

Zahed, F., Pardakhti, A., Motlagh, M.S., Mohammad Kari, B., Tavakoli, A., 2022. Infiltration of outdoor PM2.5 and influencing factors. Air Qual. Atmosp. Health 15, 2215–2230. https://doi.org/10.1007/s11869-022-01246-4.

Zaman, S.U., Pavel, MdR.S., Joy, K.S., Jeba, F., Islam, MdS., Paul, S., Bari, MdA., Salam, A., 2021. Spatial and temporal variation of aerosol optical depths over six major cities in Bangladesh. Atmos. Res. 262, 105803. https://doi.org/10.1016/j.atmosres.2021.105803.