Characterizing Indoor-Outdoor PM$_{2.5}$ Concentrations Using Low-Cost Sensor Measurements in Residential Homes in Dhaka, Bangladesh

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Abstract

We collected paired measurements of indoor and outdoor PM$_{2.5}$ concentrations at 17 homes in Dhaka, Bangladesh, to quantify indoor-outdoor levels, their spatio-temporal variations, and influencing factors. A pair of PurpleAir PM$_{2.5}$ sensors were deployed at each home, one indoors and the other outdoors, during the wet (June to August 2021) and dry (December 2021 to February 2022) seasons, and the locally calibrated (against a beta attenuation monitor) and quality-assured 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. Higher infiltration factors (dry: 0.83 ± 0.12; wet: 0.87 ± 0.14), determined through mixed effect regression of parallel indoor and outdoor timeseries 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 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.

Graphical Abstract
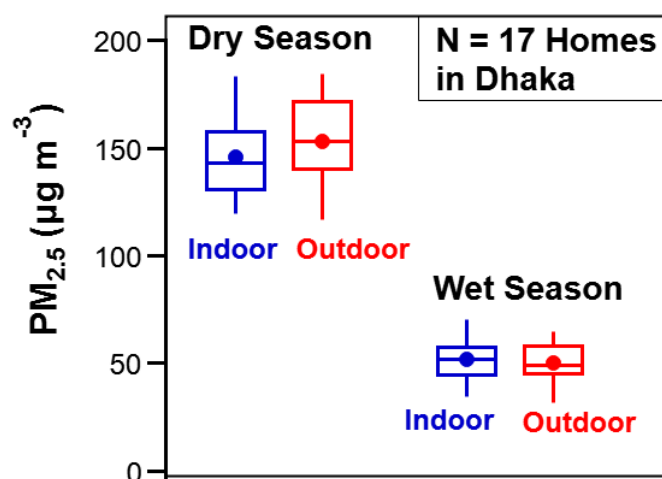
Highlights
- Simultaneous measurements of indoor and outdoor $PM_{2.5}$ concentrations were collected at 17 homes in Dhaka, covering wet and dry seasons.
- Both indoor and outdoor $PM_{2.5}$ levels showed substantial and similar seasonal differences.
- Indoor to outdoor $PM_{2.5}$ ratios were close to 1 in both seasons.
- High infiltration factors highlight the substantial impact of outdoor pollution on indoor $PM_{2.5}$ levels.

1. Introduction

Fine particulate matter (PM$_{2.5}$), consisting of airborne particles with diameters below 2.5 micrometers, originates from various sources and poses substantial health risks to humans[1–3]. 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[4–6]. 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[4–8].

Effective air quality management necessitates a comprehensive understanding of PM$_{2.5}$ sources, dynamics, and population exposure in both indoor and outdoor settings[8–10]. 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[11–13]. 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$_{2.5}$[3,14,15]. 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} [14,16,17], which is about 15-20 times higher than the recent standard set by the World Health Organization (WHO).

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[18,19]. Seasonal sources, meteorology, and transboundary pollution play a pivotal role in determining PM$_{2.5}$ population exposure in Bangladesh[14,17,18,20–23]. 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[14,24–26].

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[27,28], the outdoor urban environment[29], locations near brick kilns[30,31], and schools[32]. A study by Gurley et al.[28] 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/m³. 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[33–35]. 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)[36].

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[14,37–39]. 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[4,5,7,40–43]. 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[44,45]. Nevertheless, proper calibration against reference monitors and careful data interpretation are essential to ensure the accuracy of low-cost sensor measurements[46–48]. 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[49,50] at each home, one positioned indoors and another outdoors, and collected data across multiple

3

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

Figure 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 Figure 1B. Before initiating air pollution data collection, we conducted a questionnaire survey to gather information about indoor features in the sampled homes, focusing on kitchen features, cooking practices, and ventilation arrangements. Table S1 summarizes these indoor features in the sampling 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. These homes were located within 50-500 meters of arterial roads and bus routes, with apartment sizes ranging between 850-3400 square feet (mean 1685 square feet). The number of windows in the apartment units varied between 3-11 (mean 5.4), and the number of occupants ranged from 1-6 (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 1-3 (mean 2.1), with a daily cooking duration ranging from 1-4 hours (mean 2.8 hours), 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.
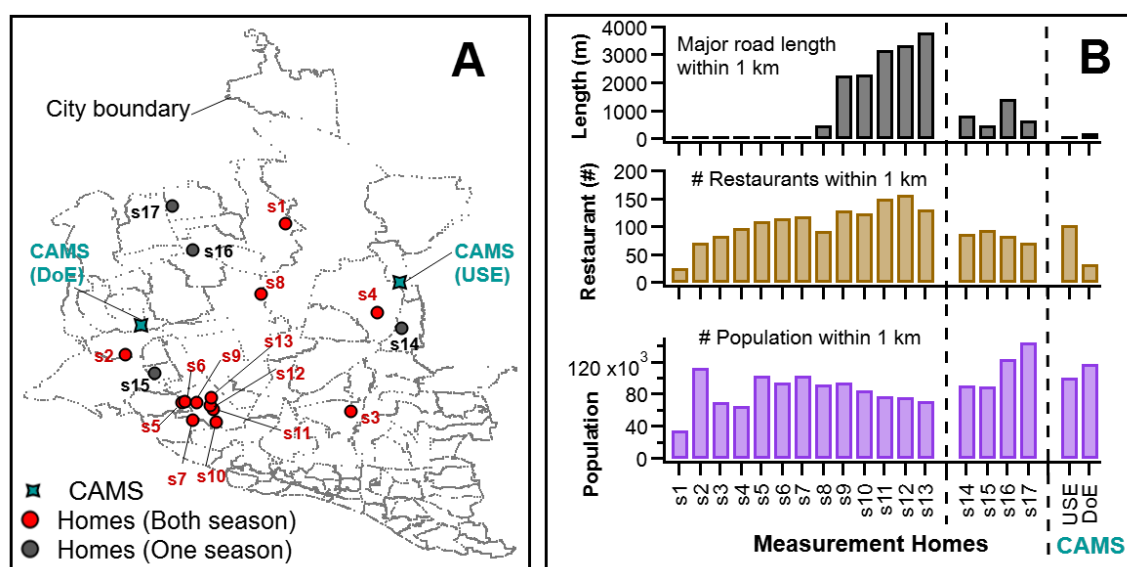

Figure 1: Location of measurement sites and surrounding outdoor land use features. (A) The map displays the locations of selected homes for indoor and outdoor PM$_{2.5}$ measurements. Red symbols indicate locations where measurements were collected during both dry and wet seasons (S1 to S13), while black 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,

4

restaurant density, and population density within a 1 km buffer radius from each measurement site.

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 (Purple Air, Classic Air Monitor, Edition: PA-II-SD) were available, allowing for simultaneous measurements in two homes at a time. Each home was monitored for approximately one week during a particular season, resulting in an overall data collection period of about 10-12 weeks per season to cover all participating homes. < Total number of household-days of paired indoor-outdoor measurement.>

PurpleAir uses Plantower sensors to optically detect PM$_{2.5}$[51]. Each PurpleAir is equipped with two identical particulate sensors, alongside temperature and relative humidity sensors. The sensors quantify number concentrations of various PM fractions, with internal calibrations converting particle counts into PM mass concentrations. The PurpleAir PM$_{2.5}$ sensors deployed at each home recorded data at two-minute intervals, storing it on SD cards.

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 Figure 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).

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. Each PurpleAir unit has two identical planttower sensors, and in the majority of cases, the data from both sensors showed congruence within a $\pm 10\%$ 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 $\pm 10\%$ margin, the average of PM$_{2.5}$ measurements from both sensors were calculated at a 2-minute resolution. Subsequently, hourly averages were estimated using this 2-minute 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[49,50,52]. 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.

5

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[47] (section 2.4.2) and another for temporal adjustment for short-term sampling[53] (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[54].

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[47,49]. Collocated measurements from various sensors exhibited strong consistency, with Pearson correlation coefficients (R) ranging from 0.99 to 1 across sensor batches (Figure 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 Figure 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[47] 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 (Figure 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[55] and the ratio method[53]. 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.[53], we calculated temporally corrected concentrations for site i by

6

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); $C_{i,t,corr} = (C_{ref, long-term} / C_{ref, t}) \times C_{i,t,un\_corr}$.

An example of the derivation of such temporal correction factors is provided in Figure 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[56] to quantify the infiltration factor of outdoor pollution indoors.

The mixed-effects regression analysis, as employed in previous indoor-outdoor air pollution studies[40,54,57,58], 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 [40,54,57,58], 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

7

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[34,59], 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[34,60]. 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 PM2.5 Levels

Table 1 presents the mean indoor and outdoor $PM_{2.5}$ concentrations and indoor-to-outdoor (I/O) ratios from individual homes, while Figure 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/m³, outdoor 153 ± 23 µg/m³, and the I/O ratio 0.97 ± 0.14. In the wet season, indoor levels were 52 ± 12 µg/m³, outdoor 50 ± 11 µg/m³, 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/m³ and 50 µg/m³ 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 10-30%) 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[14,20,22,24]. 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

8

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[7,43,54,61–63].

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						Wet (Summer) Season					
	Mean Indoor $PM_{2.5}$ ($\mu g\ m^{-3}$)	Mean Outdoor $PM_{2.5}$ ($\mu g\ m^{-3}$)	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 $PM_{2.5}$ ($\mu g\ m^{-3}$)	Mean Outdoor $PM_{2.5}$ ($\mu g\ m^{-3}$)	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)												
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

9

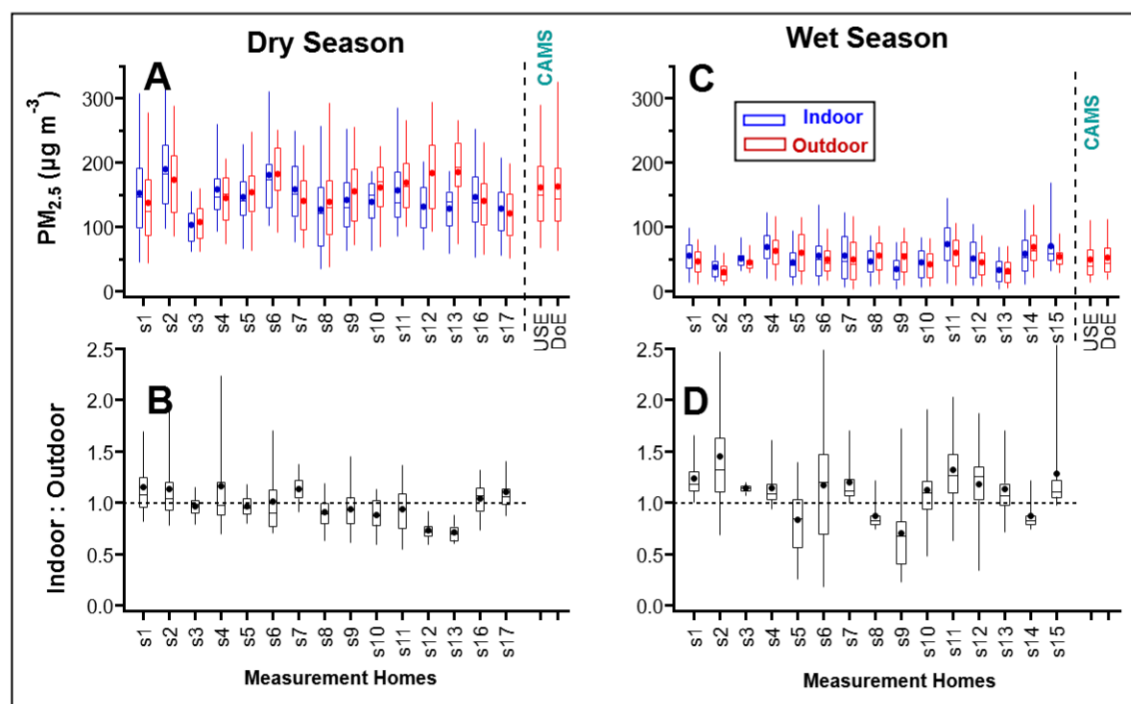**Figure 2:** Measured indoor and outdoor PM$_{2.5}$ concentration levels and indoor-to-outdoor (I/O) ratios in individual homes during dry and wet seasons. (A) Box-whisker plot showing the distribution of hourly average indoor and outdoor concentrations measured at each home during the dry season. Data 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.

3.2 Diurnal Variations of Indoor and Outdoor PM$_{2.5}$

Figure 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 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[36,64]. 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[64]. 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 am, 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[65]. 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 pm – 2 pm), 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.
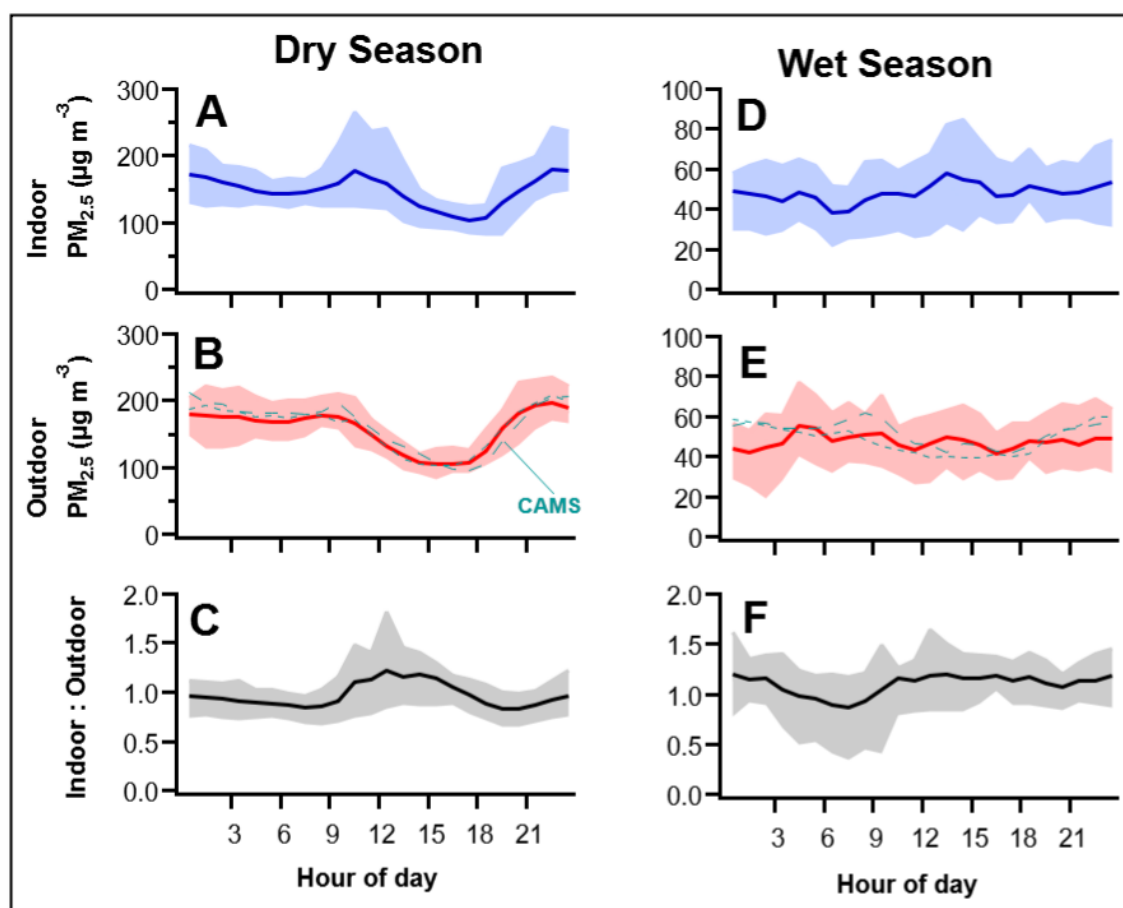

Figure 3: Diurnal variation of indoor and outdoor PM$_{2.5}$ concentration levels and indoor-to-outdoor (I/O) ratios during dry and wet seasons. (A) Diurnal variation of indoor PM$_{2.5}$ levels during the dry season. The line represents the mean diurnal profile across all sampled homes, while the shaded 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.

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 to 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 situated towards the upper end of the distribution reported in the literature[6,40,54,57,58,66–68]. A review paper[54] encompassing 21 studies from the USA and Europe reported a range of infiltration factors between 0.3 and 0.82. Additionally, a recent study[58], utilizing data from crowdsourced sensors from around 4000 residences across the US, indicated average infiltration factors ranging from 0.2 to 0.4, with higher values observed during summer/fall and lower values during winter.

Climate conditions exert a significant influence on building structures, ventilation, and human behaviors, all of which impact the infiltration of outdoor pollution into indoor environments[5,54]. Compared to Europe and many locations in the USA that have predominantly colder climate conditions, mechanical ventilation and more insulated building structures The relatively warmer climate in Bangladesh fosters less insulated building conditions, increased reliance on natural ventilation, and thus facilitates 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[52,54,57,58], 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 Spatial Relationship and Factors Affecting Spatial Variability

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). This provides insights into important factors affecting spatial variability in indoor $PM_{2.5}$ levels across homes.

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

12

R^2 of 0.78, an RMSE of 7.6 µg/m³, and a CV R^2 of 0.52, with an RMSE of 9.6 µg/m³ for overall mean concentrations across both seasons (Figure 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).

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.[28]

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 ($\mu g\ m^{-3}$)	R^2	RMSE ($\mu g\ m^{-3}$)
Indoor $PM_{2.5}$ concentration ($\mu g\ m^{-3}$)	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				

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[34,59,60], although its development is beyond this paper's scope. 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 and Future Directions
In this study, we conducted simultaneous measurements of indoor and outdoor $PM_{2.5}$ levels across 17 homes in Dhaka city, Bangladesh, covering both dry and wet seasons. 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[69,70]. However, given affordability challenges in Bangladesh, locally based low-cost air filter technology will be essential.

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[14].

While our study provides valuable insights, it has limitations, and further research is needed to enhance our findings. Future efforts should focus on expanding measurement locations and conducting long-term (year-long) continuous measurements to better understand indoor and outdoor pollution dynamics. 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.

Acknowledgments

Supplemental Information: Supplementary Information are available online.

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15

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