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Performance Evaluation and Calibration of Low-Cost PurpleAir $PM_{2.5}$ Sensors in South Asian Conditions: Dhaka, Bangladesh

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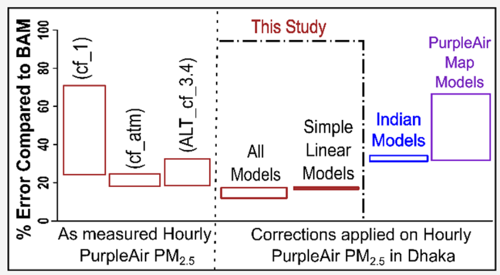
ABSTRACT: In this study, we assessed the performance of PurpleAir $PM_{2.5}$ sensors and developed calibration models in Dhaka, Bangladesh—one of the global hotspots most severely affected by extreme air pollution. We collocated an array of PurpleAir (PA-II-SD) sensors alongside a beta attenuation monitor (BAM: MetOne BAM-1020) across the dry and wet seasons. Specifically, we collocated 10 sensors during the wet season and 20 sensors during the dry season, collecting one month of colocation data per season, covering a wide range of pollution levels and meteorological conditions. Quality-assured hourly concentrations from different PurpleAir units have shown good consistency, with pairwise R^2 values generally exceeding 0.95. We developed empirical correction models by testing 29 multiple linear regression (MLR) forms and Random Forest models. Results showed that for hourly average $PM_{2.5}$ concentrations measured by PurpleAir, a simple linear correction model achieved an accuracy (nRMSE) within 17−18% of hourly BAM measurements. More complex MLR models incorporating several meteorological variables and interaction terms improved accuracy (nRMSE) slightly, to ∼15%. Random Forest models slightly outperformed all MLR models, at 12−14% (nRMSE) accuracy relative to BAM. Our findings highlight that existing correction models—particularly those developed for U.S. cities and used in the PurpleAir map—are inadequate for Bangladeshi conditions. Uncorrected PurpleAir cf_atm $PM_{2.5}$ data yielded accuracy within 25% of BAM measurements. Further research is needed to assess sensor performance in rural and suburban environments and to evaluate long-term performance under diverse climatological and source conditions in Bangladesh and South Asia.



KEYWORDS: *low-cost sensors, co-location calibration, $PM_{2.5}$, South Asia*

1. INTRODUCTION

Atmospheric particulate matter (PM) with an aerodynamic diameter smaller than 2.5 μm ($PM_{2.5}$) is a significant contributor to global morbidity and mortality.[1−3] $PM_{2.5}$ penetrates the respiratory system, where it deposits in the lungs and disrupts microRNA activity, leading to alveolar epithelial cell injury and exacerbating local lung tissue damage.[4,5] Depending on its composition, $PM_{2.5}$ exposure is also linked to cardiovascular diseases, kidney diseases, and psychological disorders.[6,7] These health effects can result from both long-term and short-term exposure, highlighting the critical need for public health interventions and policy implementations based on high-resolution spatiotemporal monitoring of $PM_{2.5}$ exposure. Although traditional reference methods, such as the US EPA designated Federal Equivalent Method (FEM) and the Federal Reference Method (FRM), provide accurate and reliable $PM_{2.5}$ monitoring, their high installation costs (a MetOne BAM costs US$20,000 and a GRIMM EDM 180 $PM_{2.5}$ costs US$25,000; most of the low-cost sensors (LCS) costs approximately US$250 to US$400) and stringent maintenance and calibration requirements hinder the development of a dense network of these monitors.[8,9]

Recent advancements in sensor technology and data science have led to the increased use of LCS in particulate matter exposure research, particularly in community air monitoring.[8] Among the various low-cost optical $PM_{2.5}$ sensors available on the market, PurpleAir is widely used, particularly in the U.S. and many other parts of the world, likely due to its public platform and data-sharing convenience. Like most low-cost $PM_{2.5}$ sensors, PurpleAir sensors employ the light scattering principle, which limits their ability to measure particles smaller than a certain threshold, typically 0.3 μm.[10−12] During factory calibration, these sensors are adjusted to align with reference $PM_{2.5}$ mass measurements for a calibration "smoke", partially correcting the underreporting of small particles by optical PM sensors.[13] Studies have also reported that PurpleAir sensors often misclassify larger particles (failing to accurately sort

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particles >0.8 μm into the correct bin), leading to an underestimation of $PM_{2.5}$ during extreme mass concentration and dusty conditions.[14−16]

Additionally, light-scattering PM sensors are sensitive to particle composition and environmental conditions, making them susceptible to variations based on geographical location, climate, and PM sources.[17,18] This sensitivity arises because the light-scattering properties of PM change according to its physical and chemical characteristics.[19] For example, as ambient humidity increases, particles grow due to hygroscopicity, enhancing their light-scattering coefficient and consequently increasing the mass recorded by optical sensors per unit concentration.[20−22] To mitigate these potential inaccuracies, researchers typically evaluate and calibrate these sensors against FRM or FEM measurements, particularly under varying climatic conditions, diverse PM sources, concentration levels, and compositions that match the intended operational environment.[10,23,24]

South Asia is a global hotspot for $PM_{2.5}$ pollution, with levels 10 to 30 times higher than the limits recommended by the World Health Organization (WHO).[25] Despite this, $PM_{2.5}$ monitoring coverage in the region remains very sparse. Low-cost sensors offer a promising solution for expanding air quality monitoring in data-poor regions. Bangladesh—a country of 170 million people—is a prime example, as it lacks extensive monitoring infrastructure. Bangladesh consistently ranks among the top five countries with the worst air quality, with its capital, Dhaka (20 million people), frequently listed among the most polluted cities in the world.[25] However, the use of low-cost sensors in Bangladesh remains limited, and a systematic evaluation of their performance is lacking.

Numerous studies have evaluated the performance of low-cost $PM_{2.5}$ sensors under a wide range of laboratory and field conditions and have proposed correction models to adjust raw measurements.[23,24,26−31] However, the majority of these studies originate from North America, where aerosol loading conditions are relatively low compared to the Global South. In regions like South Asia—such as Bangladesh—$PM_{2.5}$ levels, sources, and climatological conditions differ significantly. Recently, a few studies in China and India have assessed low-cost sensor performance and developed correction models that differ from those used in North America.[32−36]

The $PM_{2.5}$ source profile in Bangladesh is notably different from that of low-pollution Western countries such as the United States and those in the European Union. In addition to conventional air pollution sources like transportation and industrial emissions, Bangladesh experiences significant contributions from solid fuel combustion in informal sectors—such as brick kilns, household cooking, and informal solid waste burning. Although quantitative source apportionment studies in Bangladesh are limited, existing research reported that brick kilns alone contribute approximately 25−35% of the total $PM_{2.5}$ mass. Biomass burning accounts for around 40.2% of the $PM_{2.5}$ burden. Vehicular emissions and fossil fuel combustion contribute an additional 20−25%, followed by road and soil dust (∼15%), with other minor sources accounting for around 8%.[37−39] In contrast, $PM_{2.5}$ in Western countries such as the U.S. and EU predominantly originates from vehicular sources (∼25−30%) and secondary aerosols (30−50%) formed from industrial and vehicular emission precursors.[40−42]

$PM_{2.5}$ levels in Bangladesh exhibit significant seasonal variation, with concentrations 3−5 times higher during the dry season compared to the wet season. This variation is largely driven by meteorological conditions and transboundary pollution. During the dry season, elevated $PM_{2.5}$ levels are attributed to increased seasonal emissions (e.g., brick kilns), seasonal changes in boundary layer height, and substantial transboundary inflow from the Indo-Gangetic Plain (IGP) regions of India. In contrast, the wet (monsoon) season brings heavy rainfall and favorable wind patterns from the Bay of Bengal, which help reduce ambient $PM_{2.5}$ concentrations. Given the distinct source profiles, climatological conditions, and pollution levels in South Asian countries like Bangladesh, further research is essential to assess sensor performance and develop calibration models for low-cost $PM_{2.5}$ sensors under local environmental conditions.

To address gaps in the performance evaluation and calibration of low-cost $PM_{2.5}$ sensors under the pollution and climatological conditions of Bangladesh, we assessed the performance of PurpleAir $PM_{2.5}$ sensors in Dhaka, Bangladesh—a global $PM_{2.5}$ hotspot—across a wide range of pollution levels and meteorological conditions. We collected collocation data by deploying a large array of PurpleAir sensors across dry and wet seasons (wet season: 10 sensors, dry season: 20 sensors) and compared their measurements against a collocated $PM_{2.5}$ beta attenuation monitor (MetOne BAM-1020. The collocation data set was analyzed to develop calibration models.

2. METHODS

2.1. PurpleAir Sensors and Its Collocation with BAM.

To assess the performance of PurpleAir sensors and develop calibration models under Bangladesh-specific conditions, we collocated an array of PurpleAir sensors with a BAM. These collocation measurements were conducted at a continuous air monitoring station (CAMS) in Darussalam, Dhaka, which is operated by the Department of Environment (DoE), Bangladesh. At the CAMS, DoE measures hourly $PM_{2.5}$ concentrations using a MetOne BAM 1020, which is an EPA-approved FEM $PM_{2.5}$ instrument equipped with a Very Sharp Cut Cyclone (VSCC) separator, maintaining a flow rate of 16.7 L min^{-1}.[43] Since the sampler inlet of the reference FEM monitor (BAM) is heated to reduce moisture deposition in the pipeline, BAM's particulate matter estimates are not expected to be strongly influenced by the effects of relative humidity (RH) on the mass concentration.[44]

To capture variations in pollution levels, seasonality, and differences across individual sensors, we collected data over two seasons. During the wet season, 10 PurpleAir sensors (labeled "PA 1" through "PA 10" in the results section) were deployed at the CAMS site, collecting data from April 5 to May 5, 2022. During the dry season, in addition to these 10 sensors, another 10 sensors (labeled "PA A" through "PA J") were deployed from November 1 to November 30, 2022. Specifically, first we collocated a batch of 10 sensors for one month during the wet season, then deployed them across various field locations in Bangladesh, including rural and suburban areas, for 5 months. Afterward, we brought them back for another month of collocation during the dry season, adding 10 more sensors for the dry-season colocation. Following the dry season collocation, all sensors were redeployed to different field locations across Bangladesh. The primary focus of this paper is to utilize the collocation data set from two seasons to evaluate sensor performance and develop calibration models. We did not discuss the field deployment data set in this paper, as there was no collocated reference monitor during those deployments, and the key focus of this study is performance evaluation.

In our experiments, we utilized the PurpleAir (PA) PA-II-SD model (PurpleAir LLC, Draper, UT, USA), which incorporates a pair of PMS5003 laser optical particle counter (OPC) sensors (Plantower Ltd., Beijing, China), along with a BME 280 sensor for temperature, relative humidity, and barometric pressure (Bosch Sensortec GmbH, Reutlingen, Germany). Each PurpleAir contains two Plantower PMS5003 sensors that alternate operation every 10 s to provide 2 min averaged data. The Plantower sensors detect 90° light scattering using a laser (wavelength: 680 ± 10 nm).[45] 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 PMS5003 sensors can operate in temperatures ranging from -40 to 60 °C and relative humidity from 0% to 100%.[46] PMS5003 counts particles in different bins of aerodynamic diameters (<0.3 μm (PM_1), < 0.5 μm $PM_{2.5}$, and <1 μm, < 2.5 μm and <10 μm) and reports the mass concentration of particles in μg m^{-3} by applying two proprietary algorithms (cf_1 and cf_atm). We further employed a published algorithm, ALT_cf_3.4, also available in purple air map, for conversion to mass concentration from particle counts in each bin size (bin size categories: 0.3−0.5 μm, 0.5−1 μm, and 1−2.5 μm): ALT_cf_3.4 $PM_{2.5} = 3.4 \times (0.00030418 \times N_{0.3-0.5} + 0.0018512 \times N_{0.5-1.0} + 0.02069706 \times N_{1.0-2.5})$.[44,47]

2.2. Quality Assurance and Averaging of Raw Data. Each PurpleAir unit contains two identical PMS5003 sensors (typically referred to as Channel A and Channel B). Under the typical configuration of PurpleAir, each PMS5003 sensor reports $PM_{2.5}$ concentrations at 2 min intervals. We refer to these measurements as raw PurpleAir data (2 min time-resolution data from each PMS5003 sensor). A critical step in quality assurance is assessing the consistency between raw data from the two PMS5003 sensors within a PurpleAir unit. Since the two independent PMS5003 sensors (A & B) operate under identical conditions within the same unit, any significant discrepancy in their measurements may indicate internal errors. Therefore, for each data point, we evaluated the precision between the two channels by measuring the percentage absolute difference relative to the mean of their paired observations. If the precision was less than 20%, or if the absolute difference between the raw measurements from both channels was within 5 μg/m^3, we classified the data as consistent and averaged the readings from the two PMS5003 sensors.[31,44] If the raw data did not meet these criteria, we flagged them as inconsistent (outlier) data and excluded them from further analysis.

Figure S1 presents a comparison of raw 2 min measurements from Channels A and B. For most PurpleAir units, more than 90% of raw observations met these quality assurance (QA) criteria. However, in some cases, we observed significant inconsistencies between the two channels in specific PurpleAir units (e.g., wet season: PA_9; dry season: PA_2, PA_6, and PA_10). In such cases, if more than 50% of a sensor's data was classified as outliers, we excluded that sensor from our analysis, for example, PA_9 in the wet season and PA_2, PA_6, and PA_10 in the dry season (Figure S1). More faulty sensors in the later dry period may result from sensor aging or sporadic electrical malfunctions. Among the accepted sensors, about 6% and 8% of the 2 min raw data were respectively filtered out of the wet and dry seasons for not conforming to the quality assurance. This increased number of outliers in the dry season might be because of PurpleAir's limitation of sorting larger particles and dealing with high levels of $PM_{2.5}$ during the dry period. Literature suggests the aging effect of an LCS unit can be significant, and therefore, repeated evaluation of the LCS would be crucial for ensuring data reliability.[24]

To compare with the collocated BAM-measured $PM_{2.5}$, which has an hourly time resolution, we computed hourly averages of PurpleAir $PM_{2.5}$. This was done using 2 min resolution data, averaged from channels A and B, that passed the quality assurance criteria as discussed above. Hourly averages were calculated for each sensor only if at least 75% of the data for that hour (i.e., 23 or more 2 min measurements per hour) were available. We applied the same quality assurance and data averaging steps to $PM_{2.5}$ measurements from both the internal mass conversion algorithms (cf_1, cf_atm) and the alternative algorithm (ALT_cf_3.4). The number of valid data points generated by each algorithm across all sensors, in comparison with BAM measurements, is reported in Figures S6 and S7.

Among the different data columns (cf_1, cf_atm, ALT_cf_3.4.), data retention was the highest for the cf_atm. While the number of valid data points in cf_1 was slightly different from cf_atm, the largest discrepancy was observed in ALT_cf_3.4. In particular, PA_04 during the dry season retained a negligible number of data points compared to other data columns.

Typically, cf_1 and ALT_cf_3.4 report higher $PM_{2.5}$ mass concentrations than cf_atm, but the magnitude of this variation depends on ambient $PM_{2.5}$ levels (see Figure S3). Our analysis indicates that the ratio of cf_1 to cf_atm $PM_{2.5}$ varies linearly when ambient $PM_{2.5}$ levels are between 25−80 μg/m^3. Above 80 μg/m^3, the ratio stabilizes at approximately 1.5 (Figure S3).

Using quality-assured hourly average PurpleAir data, we computed various statistical metrics to assess the consistency between measurements from different PurpleAir units, as well as their agreement with hourly collocated BAM $PM_{2.5}$ data (Figures 1, S2, and Table 1). The metrics include the coefficient of determination (R^2), Mean Bias Error (MBE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Normalized Mean Bias Error (nMBE) and Normal-

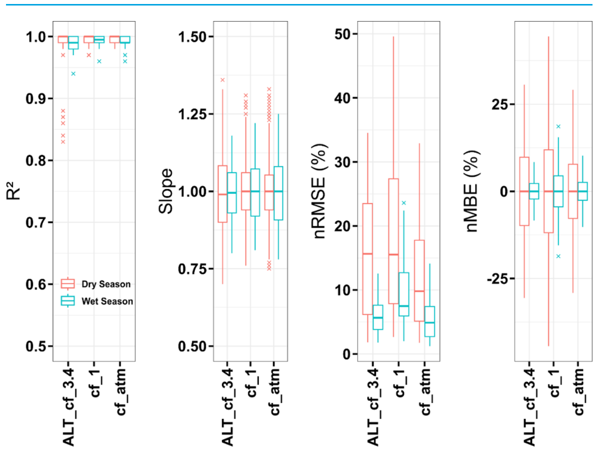

Figure 1. Consistency among collocated PurpleAir sensors. Pairwise metrics (R^2, slope, nRMSE, nMBE) for the array of PurpleAir sensors during wet and dry seasons.

Table 1. Comparison of Raw (As-Measured Hourly Concentrations) PurpleAir $PM_{2.5}$ with BAM Data

season	PA $PM_{2.5}$	no of valid data pairs[a]	no of possible data pairs	R^2	MBE (μg m^{-3})	MAE (μg m^{-3})	RMSE (μg m^{-3})	mean BAM $PM_{2.5}$ (μg m^{-3})	nRMSE (%)
wet season	cf_atm	5683	6012	0.84	7.72	8.42	12.89	52.64	24.5
	cf_1	5638		0.84	−7.16	9.53	12.75		24.2
	ALT_cf_3.4	5500		0.84	14.23	14.25	16.99		32.3
dry season	cf_atm	9219	9435	0.91	−9.16	17.46	23.51	129.6	18.1
	cf_1	9154		0.91	−79.59	79.66	91.85		70.9
	ALT_cf_3.4	8789		0.90	−7.24	17.19	24.12		18.6
season combined	cf_atm	11,017	11,562	0.93	2.57	11.73	17.89	87.6	20.4
	cf_1	10,907		0.93	−37.70	38.98	58.00		66.2
	ALT_cf_3.4	10,496		0.93	7.57	14.57	19.80		22.6

[a]Total valid data points across selected sensors: wet season— 9 sensors; dry season- 17 sensors; season combined- 9 from wet and 10 from dry season.

ized Root Mean Square Error (nRMSE). The equations used to compute these metrics are provided in Table S1.

We applied similar quality assurance and data averaging steps to meteorological parameters measured by the PurpleAir sensors (temperature, relative humidity, and dew point). Table S2 shows a comparison of the meteorological parameters measured by PurpleAir with those of the reference instrument at the CAMS site. Figure S4 shows the diurnal variation of ambient RH and temperature during the wet and dry season data collection period.

2.3. Developing Co-Location Calibration Models.

2.3.1. Model Covariates and Forms. Using hourly average BAM and PurpleAir measured $PM_{2.5}$ concentrations, we developed correction models using each of cf_atm, cf_1 and ALT_cf_3.4 data columns. We incorporated meteorological variables available in PurpleAir as covariates, including temperature (T), relative humidity (RH), and dew point (DP), along with multiple interaction terms among covariates. We also considered a nonlinear relative humidity term (NL_RH), $RH^2/(100 - RH)$, to address the deliquescence of PM in the estimation of $PM_{2.5}$ by optical sensors.[48] We evaluated a wide range of model forms (see Table S3) with varying levels of complexity, including 29 multiple linear regression (MLR) models and 7 random forest (RF) models.

We developed models using data from individual sensors (sensor-specific models, referred to as "individual") as well as a cumulative approach, where data from all sensors were combined (i.e., data from all sensors were fitted combinedly against reference BAM data; referred to as "cumulative" fit approach). Additionally, we divided the data set by season to develop season-specific models and also created combined models using data from both seasons. This resulted in three seasonal cases (dry, wet, and combined), with both individual and cumulative fits for each case.

Random forest (RF) models were trained with increasing complexity of meteorological variables (Table S3). Optimal parameter selection was prioritized, and the parameters of the models were tuned using a grid search. The number of variables used to construct trees, were tuned between 1 and total number of covariates in the model form. The choice of the number of trees was based on stabilized error reduction, with error reduction checked against an increasing number of trees up to 500 (Figure S5) and 300 trees found to stabilize the error reasonably. In RF models the tree complexity control parameters are critical, as improper use can introduce bias. Minimum observations per terminal node were used to control tree complexity and were tuned between 3 to 13. Additionally, the split rule of trees was tuned between "Variance" and "Extra Trees." "Extra Trees" found to model RF consistently better than the "Variance."

2.3.2. Model Performance. Model performance was evaluated using various statistical metrics, including RMSE, nRMSE, MBE, nMBE, and R^2 (Table S1). To assess the models' performance on unseen data, we employed a leave-one-week-out cross-validation approach. We collected about one month of collocation data from each season. For cross-validation, we divided the data into five folds (each fold contains 6 days ~ 1 week of data). The model was trained on data from four folds and tested on the holdout fold. This process was repeated iteratively for each fold. Cross-validation performance was assessed by comparing the predicted concentrations for the holdout fold with reference BAM measurements from that week. We used this weekly holdout cross-validation approach because it better represents a realistic field deployment scenario compared to conventional random 10-fold cross-validation.[24,49] Cross-validation performance was also assessed in terms of nRMSE and R^2. Similar to MLR models, cross-validation exercises were also performed for the random forest models using the leave-one-week-out cross-validation method discussed above.

3. RESULTS AND DISCUSSION

3.1. Consistency between the Array of Collocated PurpleAir Sensors.

Figure 1 shows the pairwise comparisons of different metrics (R^2, nRMSE, nMBE, Slope) used to assess the observed consistency between PurpleAir units collocated during two seasons. These metrics were estimated using hourly averaged QA-ed data from each sensor. Data from different collocated sensors generally showed a strong correlation with each other (pairwise R^2 typically exceeding 0.95) for both cf_1 and cf_atm. However, in several instances, correlation with the ALT_cf_3.4 data column was lower than 0.9. These outliers in R^2 results from the sensor PA_04, which retained only 10% of observations in the ALT_cf_3.4 data column; nonetheless, in pairwise comparison, PA_04 has an R^2 exceeding 0.8.

Some seasonal differences were observed in these metrics. For instance, pairwise R^2 values were relatively higher during the dry season, along with a broader distribution of nRMSE and nMBE metrics. However, the mean and median bias (nMBE) remained around 0% for each data column in both seasons, though the interquartile range (IQR) was larger in the dry season. The IQR of error metrics (nRMSE and nMBE) was highest for cf_1 and ALT_cf_3.4 compared to cf_atm in

Table 2. Comparison of Model Performance across Different Model Forms, Seasons (Wet, Dry, and Combined), and PurpleAir $PM_{2.5}$ Data (cf_1, cf_atm, and ALT cf_3.4)

		nRMSE (%)								
		wet season			dry season			season combined		
model ID[a]	model name	(cf_atm)	(cf_1)	(ALT cf_3.4)	(cf_atm)	(cf_1)	(ALT cf_3.4)	(cf_atm)	(cf_1)	(ALT cf_3.4)
	raw	24.5	24.2	32.3	18.1	70.9	18.6	20.4	66.2	22.6
M1	MF[b]	17.4	17.3	16.69	16.8	16.8	17.41	20	21.39	21.97
M2*	linear	16.4*	16.6*	16.66	16.8*	16.8*	17.39	19.43	19.51	19.86
M19	+PA x RH	15.9	16.0	15.99	16.6	16.6	17.23	19.33	19.35	19.65
M20*	+PA x NL_RH[c]	15.8	15.9	16.15	16.5	16.5	17.25	19.31	19.34	19.66
M21	+PA x T	16.0	16.1	16.62	16.6	16.5	17.38	19.22	19.24	19.66
M22	+PA x DP	16.4	16.6	15.96	16.7	16.7	17.17	18.94	18.84	19.32
M23	+PA x RH x DP	15.8	15.8	15.8	16.5	16.5	17.18	18.84	18.68	19.18
M24	+PA x NL_RH x DP	15.7	15.8	15.79	16.5	16.5	17.17	18.86	18.71	19.21
M25	+PA x RH x T	15.6	15.8	15.69	16.5	16.5	17.17	18.84	18.68	19.17
M26	+PA x NL_RH x T	15.6	15.7	15.93	16.5	16.5	16.82	18.82	18.64	19.14
M27	+PA x DP x T	15.8	15.9	15.51	16.1	16.1	16.64	18.75	18.52	19.03
M28	+PA x RH x DP x T	15.4	15.6	15.44	16.0	16.0	16.6	18.73	18.48	18.98
M29*	+PA xNL_RHxDPxT	15.5	15.6	11.8	16.0	16.0	14.6	18.74	18.48	18.97
M30*	RF(PA)	15.35	15.35	15.05	16.62	16.52	17.76	19.42	19.32	20.3
M31*	RF(PA, RH)	14.05	14.18	13.97	15.69	15.57	16.98	18.43	18.41	19.34
M32	RF(PA, NL_RH)	14.08	14.13	13.97	15.7	15.51	17.02	18.45	18.48	19.44
M33*	RF(PA, T, RH)	12.1	12.28	11.95	13.68	13.66	14.81	16.69	16.46	17.33
M34	RF(PA,T, NL_RH)	12.14	12.34	11.95	13.68	13.69	14.82	16.52	16.47	17.43
M35	RF(PA,T,DP,RH)	12.05	12.16	11.88	13.59	13.44	14.68	16.22	16.32	17.03
M36	RF(PA,T,DP,NL_RH)	12.18	12.39	11.86	13.46	13.46	14.59	16.38	16.25	17.03

[a]The full list of the model forms (M1 to M36) is shown in the Table S3, while this table shows only a subset of model forms that have the lowest nRMSE in each complexity level and an improvement of ΔnRMSE > 0.5% from the selected model of the immediate lower complexity level. [b]MF stands for multiplication factor. [c]NL-RH is the nonlinear relative humidity term; NL-RH = $RH^2/(100 - RH)$.

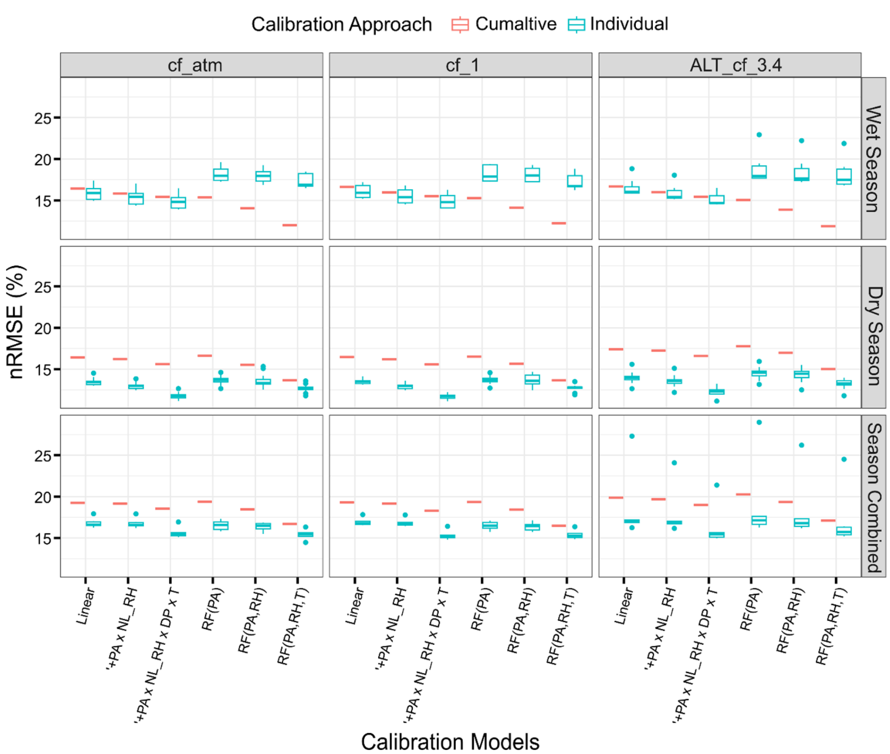

Figure 2. Comparison of model performance across different model forms using two fitting approaches (Cumulative − All Sensors Together vs Individual Sensor). A similar comparison based on adjusted R^2 is presented in Figure S8.

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both seasons. Except for ALT_cf_3.4 in the dry season, the slope metric had a median value of 1 for all sensors.

These observed seasonal differences in consistency metrics could arise from variations in aerosol loading during collocations as well as meteorological conditions. The dry-season collocation period had $PM_{2.5}$ levels approximately 2.5 times higher than those in the wet season (a typical seasonal pattern in $PM_{2.5}$ levels in Bangladesh) (Table 1). Some high concentration points could influence the observed higher R^2 values during the dry season and may also contribute to a broader distribution of error metrics (nMBE, nRMSE). Additionally, meteorological conditions (see Figure S4; relative humidity in the dry season generally ranged between 20−80%, whereas during the wet season it was between 40−80%) could further contribute to some of the seasonal differences in sensor performance observed in Figure 1.

3.2. Comparison of As-Measured PurpleAir $PM_{2.5}$ with BAM. Figures S6 and S7 present scatter plots of as-measured hourly PurpleAir $PM_{2.5}$ versus BAM $PM_{2.5}$ from individual sensors during the wet and dry seasons, respectively. The R^2 values between PurpleAir and BAM $PM_{2.5}$ ranged from 0.83 to 0.86 in the wet season and 0.93 to 0.96 in the dry season, except for PA_04 with ALT_cf_3.4, where R^2 = 0.846.

The comparison between hourly BAM and as-measured hourly PurpleAir $PM_{2.5}$ for each season and the combined data set is presented in Table 1. For both cf_1 and cf_atm $PM_{2.5}$, the normalized RMSE (nRMSE) was about 24.5% in the wet season. However, ALT_cf_3.4 $PM_{2.5}$ had the highest error during the wet season, with an nRMSE of 32.3%. In the dry season, cf_atm $PM_{2.5}$ and ALT_cf_3.4 $PM_{2.5}$ had an nRMSE of approximately 18.5%, while cf_1 $PM_{2.5}$ had a much higher nRMSE of 70.9%.

Our analysis of the ratio of cf_1 to cf_atm $PM_{2.5}$ as a function of reference (BAM) $PM_{2.5}$ provides insights into the large differences in nRMSE observed between cf_1 and cf_atm $PM_{2.5}$ during the dry season. At lower ambient concentrations, the two data columns (cf_1 and cf_atm) are nearly identical, but at higher concentration levels, the differences become substantial (Figure S3). The observed differences at higher concentrations may be related to the concentration-dependent correction algorithm in cf_atm, as described by Barkjohn et al.,[24] where an internal correction is applied at elevated concentration levels.

Overall, cf_atm $PM_{2.5}$, as reported by PurpleAir, aligns more closely with BAM-measured ambient $PM_{2.5}$ levels. Our analysis indicates that as-measured PurpleAir cf_atm $PM_{2.5}$ achieves accuracy within 20−25% of BAM-measured levels. However, the error can be significantly higher when using cf_1, particularly during high-concentration periods. Additionally, ALT_cf_3.4 $PM_{2.5}$—with its transparent mass conversion algorithm—may be a viable option for high-concentration dry season conditions. However, some studies report that cf_1-based models can outperform cf_atm-based models.[9,15,24]

3.3. Correction Models. Table 2 provides a summary of model performance across different model forms, seasons (wet, dry, and combined), and data types (cf_1, cf_atm, and ALT cf_3.4). Given the significant variations in seasonal concentration levels, performance in Table 2 is presented in terms of nRMSE, as it effectively visualizes the models' relative performance across different seasons. The results in Table 2 are based on the cumulative fit approach, while Figure 2 compares model performance between the cumulative and individual fit approaches. The overall strong consistency between different sensor measurements (as shown in Figure 1) supports the development of a single model that combines data from different sensors. This generalized model is not only easier to apply but also simplifies communication. In contrast, fitting separate models for individual sensors generates a large of models, which can make their application cumbersome. However, in our analysis, we applied both the individual and cumulative approaches to ensure a more comprehensive and informed decision-making process.

The results in Table 2 and Figure 2 indicate that a simple linear model without any meteorological variables has an nRMSE of around 17%, in both seasons. The MLR model forms incorporating various meteorological variables improve performance marginally, with nRMSE reductions between 1% and 2%. This trend is consistent across both seasons and for different PurpleAir $PM_{2.5}$ data columns (cf_1, cf_atm, and ALT cf_3.4).

Among the MLR models with different meteorological variables, relative humidity (RH) exerts the most influence, aligning with previous research findings.[15,21,24,50,51] Model forms with additive terms of meteorological variables (M3-M13) and additive interaction term between meteorological variables (M14-M18) show negligible error reductions from the "Linear" model (ΔnRMSE < 0.2%). Among the Model forms with two factor interaction term between PA $PM_{2.5}$ (PA) and meteorological variable (M23−27), RH and NL_RH improves model accuracy significantly from linear model only in wet season. Model forms with three PA and meteorological variables (M19-M22) does not improve model accuracy (ΔnRMSE < 0.5%) significantly from "+PM × (nonlinear RH)" and "+PM × RH,". Lastly, Among models with four-factor interaction terms, only for Alt_cf_3.4 data column, Model "+PA xNL_RHxDPxT" achieve significant error reductions (ΔnRMSE > 2%) from "+PM × RH,".

Random Forest model seems to outperform all tested MLR model forms. The nRMSE for Random Forest models incorporating PurpleAir and several meteorological variables (e.g., RF(PA), RF (PA, RH), RF(PA, T, RH)) ranges from 12% to 15.3%, outperforming all MLR model forms, where nRMSE values range from 15.5 to 17%. This suggests that Random Forest is a superior correction model compared to MLR models. However, Random Forest models have limited transferability and interpolation or extrapolation beyond the training data range.[52] Furthermore, they are inherently less interpretable compared to MLR.

Figure 2 compares model performance between the individual and cumulative fitting approaches for a subset of model forms that demonstrated relatively better performance in the analysis presented in Table 2. Specifically, models that showed an improvement of ΔnRMSE > 0.5% compared to the next lower complexity level were selected. The analysis in Figure 2 indicates that fitting data from individual sensors can enhance performance, particularly in the dry season. However, the nRMSE differences between models based on individual sensors and those based on cumulative data within a season remain within 2%. This suggests that a model based on cumulative data from all sensors in a given season can be reasonably used, especially considering its ease of application for correcting data in actual field deployments for monitoring purposes. Nonetheless, our analysis suggests that season-specific models may be more appropriate in the context of Bangladesh. Models based on combined data from both seasons exhibit higher nRMSE values—approximately 20%

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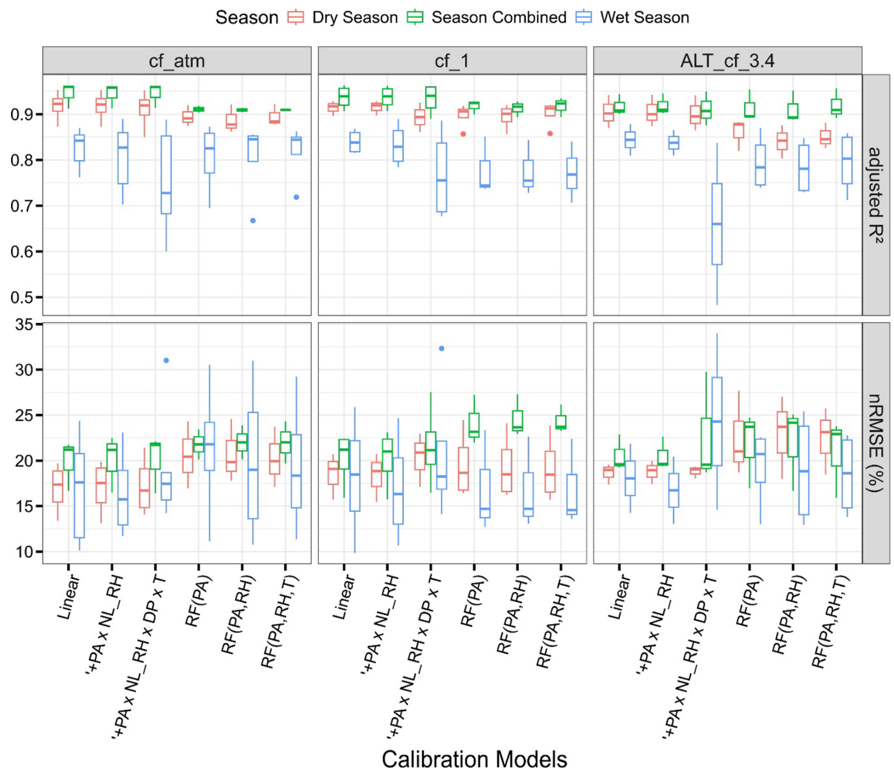

Figure 3. Cross-validation performance of selected model forms (as shown in Figure 2). The box plot illustrates the variation in performance metrics across different weekly withheld folds (Top: adjusted R^2; Bottom: nRMSE).

(Figure 2)—which is comparable to the nRMSE value for uncorrected (as-measured) PurpleAir $PM_{2.5}$ measurements, particularly for cf_atm (see as-measured nRMSE reported in Table 1). Similar to Figures 2 and S8 presents a comparison of model performance, in terms of adjusted R^2, across different model forms and seasons. Model performance based on the adjusted R^2 metric aligns with conclusions drawn from nRMSE.

The pattern of nRMSE variations with increasing complexity in MLR models for individual sensors is similar to that of cumulative models. However, for individual sensors, the nRMSE for the simple RF (PA) model is higher than the simple linear model, and as the RF model complexity increases, nRMSE decreases marginally. Random Forest performs poorly in individual sensors, probably because of fitting to noise (specific to each sensor), which is more likely to be prominent in limited individual sensor data.

The performance metrics (adjusted R^2, nRMSE) for models based on different data columns (e.g., cf_1, cf_atm) appear similar. However, model coefficients vary depending on the choice of data columns due to differences in their absolute values. Tables S4–S9 present the model coefficients for different MLR models in season-specific cumulative models. Coefficients are provided for models using cf_atm (Table S4: Wet Season; Table S7: Dry Season), cf_1 (Table S5: Wet Season; Table S8: Dry Season), and ALT_cf_3.4 (Table S6: Wet Season; Table S9: Dry Season) PurpleAir data.

3.4. Cross-Validation of Model Performance. Figure 3 shows the cross-validation (CV) model performance for selected model forms at different levels of complexity to evaluate their performance on unseen data. A comparison between the original fit (Figure 2) and cross-validation (Figure 3) across different model forms and data sets (dry, wet, and combined) indicates that while nRMSE in the original fits generally remained between 15–20% for most models, CV nRMSE varied between 10–30%. This variability is expected, as performance metrics typically fluctuate more for unseen data compared to fitted models.

While CV performance remained within a few percentage points of the original fit for most model forms—indicating minimal systematic overfitting—there are exceptions. For example, CV performance for Model 29 (+PA x NL_RHxDPxT) showed substantially different R^2 and nRMSE values, particularly for ALT_cf_3.4 in the wet season. This suggests potential overfitting in the original model for these specific instances.

3.5. Recommended Correction Model. Based on our evaluation of the performances of many MLR model forms in season-specific and combined season model, we found that a simple linear correction model (corrected $PM_{2.5}$ = slope × PurpleAir $PM_{2.5}$ + intercept) provides accuracy within 16–17% compared to BAM measurements, for hourly average data. A complex MLR model formed with several meteorological variables and interaction terms can reduce the error further, but not more than 1–2%. Given the simplicity of uses, we recommend simple correction models. Figure 4 shows a comparison of corrected PurpleAir $PM_{2.5}$ values from season-specific linear correction models derived using the cumulative fit approach. The figure demonstrates that the corrected $PM_{2.5}$ values using simple linear models show a reasonable accuracy relative to BAM measurements.

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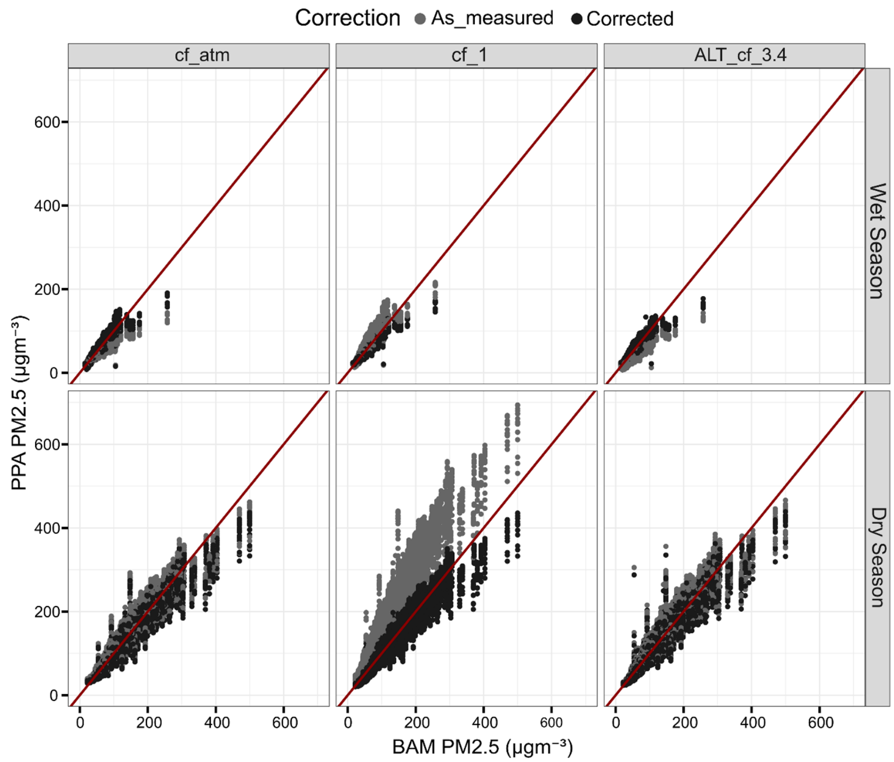

Figure 4. Scatter plots comparing as-measured PurpleAir $PM_{2.5}$ with BAM $PM_{2.5}$ across all sensor data. The figure also includes comparisons between BAM $PM_{2.5}$ and corrected PurpleAir $PM_{2.5}$ from season-specific linear correction models derived using the cumulative fit approach. Solid read line is 1:1 line.

Table 3. Recommended Correction Models from This Study and Comparison with Other Studies

			on study location	on Dhaka test data	
study	location	equation	nRMSE	nRMSE	MBE (μg m^{-3})
this study (dry season)	Dhaka, Bangladesh	$PM_{2.5}$ = 0.63 × PA (cf_1) − 1.63	18.01%	18.01%	9.97
		$PM_{2.5}$ = 0.95 × PA (cf_atm) − 2.24	18.01%	18.01%	9.96
this study (wet season)		$PM_{2.5}$ = 0.77 × PA (cf_1) + 6.56	17%	17%	0.63
		$PM_{2.5}$ = 1.40 × PA (cf_atm) - 10.15	16.8%	16.8%	0.49
this study (combined both seasons)		$PM_{2.5}$ = 0.61× PA (cf_1) + 12.39	18.98	18.98	2.27
		$PM_{2.5}$ = 0.95 × PA (cf_atm) + 7.05	18.95%	18.95%	2.13
Campmier et al.[15]	Delhi, India	$PM_{2.5}$ = 0.546 × PA (cf_1) − 0.936 × RH + 50.3	31.7%	31.94%	18.29
	Hamirpur, India	$PM_{2.5}$ = 0.496 × PA (cf_1) − 0.296 × RH + 22.0	21.3%	34.19%	21.14
	Bengaluru, India	$PM_{2.5}$ = 0.515 × PA (cf_1) − 0.139 × RH + 14.1	19.5%	31.3%	18.98
US EPA[24]	US-wide	$PM_{2.5}$ = 0.524 × PA (cf_1) − 0.0862 × RH + 5.75	36%[a]	34.64%	23.63
LRAPA[54]	Springfield, Oregon, US	$PM_{2.5}$ = 0.5 × PA (cf_atm) − 0.66		66.44%	47.64
AQ & U[45]	Salt Lake City, Utah, US	$PM_{2.5}$ = 0.778 × PA (cf_atm) + 2.65	37.4%	33.41%	20.97
woodsmoke[9]	Indoor woodsmoke, New South Wales, Australia	$PM_{2.5}$ = 0.55 × PA (cf_1) + 0.53		31.75%	21.43

[a]Normalized by median.

In Table 3, we provide correction equations from simple linear models for different PurpleAir $PM_{2.5}$ data columns (e.g., cf_1, cf_atm, ALT_cf_3.4) and seasons (dry, wet, combined of two seasons). The season-specific models demonstrated relatively better performance metrics in our analysis. The nRMSE of the combined model is 20%, which is comparable to the as-measured PurpleAir cf_atm $PM_{2.5}$. However, when using uncorrected (as-measured) PurpleAir cf_1 $PM_{2.5}$, the error can be substantially higher, particularly during periods of elevated ambient $PM_{2.5}$ levels. Therefore, if using as-measured data, we recommend using cf_atm $PM_{2.5}$ from PurpleAir. At daily resolution (24-h average), the nRMSE of as-measured cf_atm $PM_{2.5}$ is 16.3% in the wet season and 16.5% in the dry season. For cf_1 and ALT_cf_3.4, the nRMSE is 26.5% and 27.5%, respectively, in the wet season, and 61.9% and 20.1%, respectively, in the dry season.

Several past studies have recommended models that incorporate meteorological variables, particularly RH.[15,24,53]

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Consistent with previous literature, our study also found that RH is the most important meteorological variable among those included in our model (T, RH, DP). Model with interaction term of RH and PA $PM_{2.5}$ (e.g., model form M20 in Table 2) reduces error, particularly during the wet season. However, including RH as an additive term (e.g., model form M3 in Table S10) resulted in only minimal performance improvement. These observations were consistent across season-specific models (dry and wet seasons) as well as models based on the combined data set from both seasons.

3.5.1. Comparison with Existing Correction Models. Several studies in the literature provided recommended models for different regions.[15,24,30,53] In the absence of locally available data, one can think about using available models from literature. As a sensitivity analysis, we applied those models to correct our PurpleAir data and estimated error by comparing those corrected concentrations with BAM $PM_{2.5}$, results are shown in Table 3. In the case of using models from literature, we used average concentrations from both seasons.

Our estimates indicate that in the case of using models based on measurements in different Indian cities, Bengaluru, Delhi, and Hamirpur, the nRMSE were between 30 and 35%, much worse than the as-measured PurpleAir cf_atm $PM_{2.5}$. The errors are even much higher, in the case of using models based on US and Australian cities. For example, a model based on US -wide data (also known as the US EPA model) yielded an nRMSE of 34.64% for the measurements in Dhaka. That result indicates that models developed in other locations, specifically in based on data from US cities, are not well transferable to Bangladesh. Our analysis suggests it is important to use locally developed models to correct the data from Bangladesh. In the case of not using any locally available models, it is better to use as-measured PurpleAir cf_atm $PM_{2.5}$. In the absence of locally available models, if someone uses the models from other geographical locations, the error could be even higher than the accuracy of uncorrected data.

Calibration models from our study as well as other relevant studies in different parts of the world, as listed some of those in Table 3 are empirically derived based on colocation data or comparing LCS data from nearby regulatory monitoring stations. Our analysis indicates that locally derived calibration models perform better than those developed in other regions, which is expected.

Aerosol levels, sources, composition, and meteorological conditions all can influence the performance of low-cost sensors. Therefore, it is not surprising that models developed in American and European cities may not be well transferable to the conditions of Bangladesh. A fully mechanistic explanation is beyond the scope of this paper, as detailed aerosol composition data for Bangladesh are limited. However, based on the literature, variations in PM levels, composition, size distribution, and meteorological conditions likely impact the direct transferability of calibration models developed in the US, Europe, and other regions in Bangladesh and vice versa.

$PM_{2.5}$ levels in Bangladesh are substantially higher than in many parts of the world, especially compared to the US, European cities. Further, $PM_{2.5}$ levels in Bangladesh exhibit strong seasonality, driven by meteorological conditions and seasonal sources. Differences in $PM_{2.5}$ concentrations, sources, and composition likely affect model performance across seasons, making season-specific models more accurate than a combined model- as we observed in Figures 2 and 3. For instance, $PM_{2.5}$ levels in the dry season are 2−3 times higher than in the wet season, a seasonal pattern distinct from many Western countries. Additionally, seasonal sources, such as biomass burning in brick kilns during the dry season, significantly alter aerosol composition.[38,55]

Meteorological conditions, particularly relative humidity (RH), could explain some seasonal variations in models. When RH exceeds a threshold known as deliquescence relative humidity (DRH), certain inorganic particles absorb water, increasing in size and mass. This threshold varies based on chemical composition, typically ranging from 60% to 68% RH, while efflorescence RH (ERH) averages between 30% and 35% RH.[56]

In the wet season during our data collection, diurnal RH rarely falls below 35%, typically ranging between 40% and 84%; we observed model performance somewhat improves when RH or NL_RH is included as a variable. In contrast, during the dry season, RH varies between 23% and 81%, spanning both DRH and ERH, complicating the relationship between humidity and hygroscopic growth. As a result, including RH or NL_RH in dry-season models did not improve performance substantially.

3.6. Limitations and Implications. In this study, we deployed an array of low-cost PurpleAir sensors across multiple seasons, compared their performance against a collocated BAM, and developed colocation calibration models under Bangladesh-specific conditions. Our research provides valuable insights into the performance and correction models of low-cost sensors in South Asian environments, particularly in Bangladesh. We found that locally developed, season-specific correction models are necessary for achieving reasonable accuracy when correcting PurpleAir data. Our analysis recommends simple correction models that achieve accuracy within 16−17% compared to BAM-measured $PM_{2.5}$ at an hourly time resolution. Our findings indicate that correction models from the literature, particularly those developed for US cities, are unsuitable for correcting PurpleAir data measured in Bangladesh. In the absence of locally available correction models, applying models from other geographical locations results in more error than using uncorrected (as-measured) concentrations.

While it is reasonable to expect that a model developed at a specific location in Bangladesh may be more applicable or transferable to other locations within the country compared to models developed outside Bangladesh, this assumption requires verification. Our correction models were developed based on measurements from a single urban location in Dhaka, Bangladesh. Further research is needed to determine whether these models and the observed sensor performance vary in rural and suburban settings. Currently, all continuous reference monitoring stations in Bangladesh are located in urban areas, limiting our ability to evaluate sensor performance in nonurban environments. Future research should address this gap.

Although we collected colocation data across wet (summer) and dry (winter) seasons in Bangladesh, data collection was limited to approximately one month per season. There was a 5 month gap between the two colocation campaigns, during which the sensors were deployed in various field locations across Bangladesh, including rural, urban, and suburban areas. No significant and systematic changes in sensor performance were observed during this period (Figure S2). Future studies should assess the long-term performance of these sensors under Bangladesh's climatological and source conditions.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsestair.5c00105.

Equations for statistical metrics; various model forms considered in developing correction models; coefficients from multiple MLR models fitted using different forms of PurpleAir $PM_{2.5}$ (cf_atm, cf_1, ALT_cf_3.4) during the wet and dry seasons; variation of PurpleAir-measured cf_1 to cf_atm $PM_{2.5}$ ratios as a function of ambient $PM_{2.5}$; comparison of uncorrected PurpleAir $PM_{2.5}$ measurements (cf_atm, cf_1, ALT_cf_3.4) with BAM-measured $PM_{2.5}$ during the wet and dry seasons; relationship between the number of trees and error levels in Random Forest model development; additional details on model performance evaluation; comparison of meteorological parameters measured by PurpleAir with those from the reference instrument; and variation in meteorological parameters during sensor collocation (PDF)

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Notes

The authors declare no competing financial interest.

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■ REFERENCES

(1) Apte, J. S.; Marshall, J. D.; Cohen, A. J.; Brauer, M. Addressing Global Mortality from Ambient PM2. 5. *Environ. Sci. Technol.* **2015**, *49* (13), 8057−8066.

(2) Bu, X.; Xie, Z.; Liu, J.; Wei, L.; Wang, X.; Chen, M.; Ren, H. Global PM2. 5-Attributable Health Burden from 1990 to 2017: Estimates from the Global Burden of Disease Study 2017. *Environ. Res.* **2021**, *197*, No. 111123.

(3) Wang, Y.; Xiao, S.; Zhang, Y.; Chang, H.; Martin, R. V.; Van Donkelaar, A.; Gaskins, A.; Liu, Y.; Liu, P.; Shi, L. Long-Term Exposure to PM2.5 Major Components and Mortality in the Southeastern United States. *Environ. Int.* **2022**, *158*, No. 106969.

(4) Ling, S. H.; van Eeden, S. F. Particulate Matter Air Pollution Exposure: Role in the Development and Exacerbation of Chronic Obstructive Pulmonary Disease. *Int. J. Chron. Obstruct. Pulmon. Dis.* **2009**, 233−243.

(5) Liu, G.; Li, Y.; Zhou, J.; Xu, J.; Yang, B. PM2. 5 Deregulated microRNA and Inflammatory Microenvironment in Lung Injury. *Environ. Toxicol. Pharmacol.* **2022**, *91*, No. 103832.

(6) Lubczyńska, M. J.; Sunyer, J.; Tiemeier, H.; Porta, D.; Kasper-Sonnenberg, M.; Jaddoe, V. W. V.; Basagaña, X.; Dalmau-Bueno, A.; Forastiere, F.; Wittsiepe, J.; Hoffmann, B.; Nieuwenhuijsen, M.; Hoek, G.; De Hoogh, K.; Brunekreef, B.; Guxens, M. Exposure to Elemental Composition of Outdoor PM 2.5 at Birth and Cognitive and Psychomotor Function in Childhood in Four European Birth Cohorts. *Environ. Int.* **2017**, *109*, 170−180.

(7) Shi, L.; Zhu, Q.; Wang, Y.; Hao, H.; Zhang, H.; Schwartz, J.; Amini, H.; van Donkelaar, A.; Martin, R. V.; Steenland, K.; Sarnat, J. A.; Caudle, W. M.; Ma, T.; Li, H.; Chang, H. H.; Liu, J. Z.; Wingo, T.; Mao, X.; Russell, A. G.; Weber, R. J.; Liu, P. Incident Dementia and Long-Term Exposure to Constituents of Fine Particle Air Pollution: A National Cohort Study in the United States. *Proc. Natl. Acad. Sci. U. S. A.* **2023**, *120* (1), No. e2211282119.

(8) Giordano, M. R.; Malings, C.; Pandis, S. N.; Presto, A. A.; McNeill, V. F.; Westervelt, D. M.; Beekmann, M.; Subramanian, R. 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.* **2021**, *158*, No. 105833.

(9) Robinson, D. L. Accurate, Low Cost PM2.5 Measurements Demonstrate the Large Spatial Variation in Wood Smoke Pollution in Regional Australia and Improve Modeling and Estimates of Health Costs. *Atmosphere* **2020**, *11* (8), 856.

(10) Kelly, K. E.; Whitaker, J.; Petty, A.; Widmer, C.; Dybwad, A.; Sleeth, D.; Martin, R.; Butterfield, A. Ambient and Laboratory Evaluation of a Low-Cost Particulate Matter Sensor. *Environ. Pollut.* **2017**, *221*, 491−500.

(11) Rai, A. C.; Kumar, P.; Pilla, F.; Skouloudis, A. N.; Di Sabatino, S.; Ratti, C.; Yasar, A.; Rickerby, D. End-User Perspective of Low-Cost Sensors for Outdoor Air Pollution Monitoring. *Sci. Total Environ.* **2017**, *607*, 691−705.

(12) Koehler, K. A.; Peters, T. M. New Methods for Personal Exposure Monitoring for Airborne Particles. *Curr. Environ. Health Rep.* **2015**, *2*, 399−411.

(13) Liu, D.; Zhang, Q.; Jiang, J.; Chen, D.-R. Performance Calibration of Low-Cost and Portable Particular Matter (PM) Sensors. *J. Aerosol Sci.* **2017**, *112*, 1−10.

(14) Kuula, J.; Mäkelä, T.; Aurela, M.; Teinilä, K.; Varjonen, S.; González, Ó.; Timonen, H. Laboratory Evaluation of Particle-Size Selectivity of Optical Low-Cost Particulate Matter Sensors. *Atmospheric Meas. Technol.* **2020**, *13* (5), 2413−2423.

(15) Campmier, M. J.; Gingrich, J.; Singh, S.; Baig, N.; Gani, S.; Upadhya, A.; Agrawal, P.; Kushwaha, M.; Mishra, H. R.; Pillarisetti, A.; Vakacherla, S.; Pathak, R. K.; Apte, J. S. Seasonally Optimized Calibrations Improve Low-Cost Sensor Performance: Long-Term

Field Evaluation of PurpleAir Sensors in Urban and Rural India. *Atmospheric Meas. Technol.* **2023**, *16* (19), 4357−4374.
(16) Ouimette, J. R.; Malm, W. C.; Schichtel, B. A.; Sheridan, P. J.; Andrews, E.; Ogren, J. A.; Arnott, W. P. Evaluating the PurpleAir Monitor as an Aerosol Light Scattering Instrument. *Atmospheric Meas. Technol.* **2022**, *15* (3), 655−676.
(17) Burkart, J.; Steiner, G.; Reischl, G.; Moshammer, H.; Neuberger, M.; Hitzenberger, R. Characterizing the Performance of Two Optical Particle Counters (Grimm OPC1. 108 and OPC1. 109) under Urban Aerosol Conditions. *J. Aerosol Sci.* **2010**, *41* (10), 953−962.
(18) Levy Zamora, M.; Xiong, F.; Gentner, D.; Kerkez, B.; Kohrman-Glaser, J.; Koehler, K. Field and Laboratory Evaluations of the Low-Cost Plantower Particulate Matter Sensor. *Environ. Sci. Technol.* **2019**, *53* (2), 838−849.
(19) Tryner, J.; Quinn, C.; Windom, B. C.; Volckens, J. Design and Evaluation of a Portable PM 2.5 Monitor Featuring a Low-Cost Sensor in Line with an Active Filter Sampler. *Environ. Sci. Process. Impacts* **2019**, *21* (8), 1403−1415.
(20) Cabada, J. C.; Khlystov, A.; Wittig, A. E.; Pilinis, C.; Pandis, S. N. Light Scattering by Fine Particles during the Pittsburgh Air Quality Study: Measurements and Modeling. *J. Geophys. Res.: Atmos.* **2004**, *109* (D16). DOI: 10.1029/2003JD004155
(21) Jayaratne, R.; Liu, X.; Thai, P.; Dunbabin, M.; Morawska, L. The Influence of Humidity on the Performance of a Low-Cost Air Particle Mass Sensor and the Effect of Atmospheric Fog. *Atmospheric Meas. Technol.* **2018**, *11* (8), 4883−4890.
(22) Zikova, N.; Hopke, P. K.; Ferro, A. R. Evaluation of New Low-Cost Particle Monitors for PM2. 5 Concentrations Measurements. *J. Aerosol Sci.* **2017**, *105*, 24−34.
(23) Morawska, L.; Thai, P. K.; Liu, X.; Asumadu-Sakyi, A.; Ayoko, G.; Bartonova, A.; Bedini, A.; Chai, F.; Christensen, B.; Dunbabin, M.; et al. Applications of Low-Cost Sensing Technologies for Air Quality Monitoring and Exposure Assessment: How Far Have They Gone? *Environ. Int.* **2018**, *116*, 286−299.
(24) Barkjohn, K. K.; Gantt, B.; Clements, A. L. Development and Application of a United States-Wide Correction for PM2.5 Data Collected with the PurpleAir Sensor. Atmospheric. *Meas. Technol.* **2021**, *14* (6), 4617−4637.
(25) IQAir *IQAir World Air Quality Report*; IQAir, 2024. https://www.iqair.com/us/newsroom/waqr-2024-pr (accessed Mar 13, 2025).
(26) Awokola, B. I.; Okello, G.; Mortimer, K. J.; Jewell, C. P.; Erhart, A.; Semple, S. Measuring Air Quality for Advocacy in Africa (MA3): Feasibility and Practicality of Longitudinal Ambient PM2. 5 Measurement Using Low-Cost Sensors. *Int. J. Environ. Res. Public. Health* **2020**, *17* (19), 7243.
(27) Ardon-Dryer, K.; Dryer, Y.; Williams, J. N.; Moghimi, N. Measurements of PM 2.5 with PurpleAir under Atmospheric Conditions. Atmospheric. *Meas. Technol.* **2020**, *13* (10), 5441−5458.
(28) Kosmopoulos, G.; Salamalikis, V.; Wilbert, S.; Zarzalejo, L. F.; Hanrieder, N.; Karatzas, S.; Kazantzidis, A. Investigating the Sensitivity of Low-Cost Sensors in Measuring Particle Number Concentrations across Diverse Atmospheric Conditions in Greece and Spain. *Sensors* **2023**, *23* (14), No. 6541.
(29) Magi, B. I.; Cupini, C.; Francis, J.; Green, M.; Hauser, C. Evaluation of PM2. 5 Measured in an Urban Setting Using a Low-Cost Optical Particle Counter and a Federal Equivalent Method Beta Attenuation Monitor. *Aerosol Sci. Technol.* **2020**, *54* (2), 147−159.
(30) Stavroulas, I.; Grivas, G.; Michalopoulos, P.; Liakakou, E.; Bougiatioti, A.; Kalkavouras, P.; Fameli, K.; Hatzianastassiou, N.; Mihalopoulos, N.; Gerasopoulos, E. Field Evaluation of Low-Cost PM Sensors (Purple Air PA-II) Under Variable Urban Air Quality Conditions, in Greece. *Atmosphere* **2020**, *11* (9), No. 926.
(31) Tryner, J.; L'Orange, C.; Mehaffy, J.; Miller-Lionberg, D.; Hofstetter, J. C.; Wilson, A.; Volckens, J. Laboratory Evaluation of Low-Cost PurpleAir PM Monitors and in-Field Correction Using Co-Located Portable Filter Samplers. *Atmos. Environ.* **2020**, *220*, No. 117067.
(32) Bai, L.; Huang, L.; Wang, Z.; Ying, Q.; Zheng, J.; Shi, X.; Hu, J. Long-Term Field Evaluation of Low-Cost Particulate Matter Sensors in Nanjing. *Aerosol Air Qual. Res.* **2020**, *20* (2), 242−253.
(33) Jha, S. K.; Kumar, M.; Arora, V.; Tripathi, S. N.; Motghare, V. M.; Shingare, A. A.; Rajput, K. A.; Kamble, S. Domain Adaptation-Based Deep Calibration of Low-Cost $PM_{2.5}$ Sensors. *IEEE Sens. J.* **2021**, *21* (22), 25941−25949.
(34) Kulkarni, P.; Puttaswamy, N.; Prabhu, V.; Agrawal, P.; Upadhya, A. R.; Rao, S.; Sutaria, R.; Mor, S.; Dey, S.; Khaiwal, R.; et al. Inter-versus Intracity Variations in the Performance and Calibration of Low-Cost PM2. 5 Sensors: A Multicity Assessment in India. *ACS Earth Space Chem.* **2022**, *6* (12), 3007−3016.
(35) Malyan, V.; Kumar, V.; Sahu, M. Significance of Sources and Size Distribution on Calibration of Low-Cost Particle Sensors: Evidence from a Field Sampling Campaign. *J. Aerosol Sci.* **2023**, *168*, No. 106114.
(36) Puttaswamy, N.; Sreekanth, V.; Pillarisetti, A.; Upadhya, A. R.; Saidam, S.; Veerappan, B.; Mukhopadhyay, K.; Sambandam, S.; Sutaria, R.; Balakrishnan, K. Indoor and Ambient Air Pollution in Chennai, India during COVID-19 Lockdown: An Affordable Sensors Study. *Aerosol Air Qual. Res.* **2022**, *22* (1), No. 210170.
(37) Begum, B.; Nasiruddin, Md.; Randal, S.; Sivertsen, B.; Hopke, P. Identification and Apportionment of Sources from Air Particulate Matter at Urban Environments in Bangladesh. *Br. J. Appl. Sci. Technol.* **2014**, *4* (27), 3930−3955.
(38) Begum, B. A.; Hopke, P. K. Identification of Sources from Chemical Characterization of Fine Particulate Matter and Assessment of Ambient Air Quality in Dhaka. *Bangladesh. Aerosol Air Qual. Res.* **2019**, *19* (1), 118−128.
(39) Rahman, M. M.; Begum, B. A.; Hopke, P. K.; Nahar, K.; Thurston, G. D. Assessing the PM2.5 Impact of Biomass Combustion in Megacity Dhaka, Bangladesh. *Environ. Pollut.* **2020**, *264*, No. 114798.
(40) US EPA *Integrated Science Assessment (ISA) for Particulate Matter (Final Report, Dec 2019)*; US EPA. https://assessments.epa.gov/isa/document/&deid%3D347534 (accessed Aug 02, 2025).
(41) McDuffie, E. E.; Martin, R. V.; Spadaro, J. V.; Burnett, R.; Smith, S. J.; O'Rourke, P.; Hammer, M. S.; van Donkelaar, A.; Bindle, L.; Shah, V.; Jaeglé, L.; Luo, G.; Yu, F.; Adeniran, J. A.; Lin, J.; Brauer, M. Source Sector and Fuel Contributions to Ambient PM2.5 and Attributable Mortality across Multiple Spatial Scales. *Nat. Commun.* **2021**, *12* (1), 3594.
(42) *Sources and emissions of air pollutants in Europe*; European Environment Agency. https://www.eea.europa.eu/publications/air-quality-in-europe-2021/sources-and-emissions-of-air (accessed Aug 02, 2025).
(43) US EPA *Air Monitoring Methods - Criteria Pollutants*. https://www.epa.gov/amtic/air-monitoring-methods-criteria-pollutants (accessed Aug 02, 2025).
(44) Wallace, L.; Bi, J.; Ott, W. R.; Sarnat, J.; Liu, Y. Calibration of Low-Cost PurpleAir Outdoor Monitors Using an Improved Method of Calculating PM2. 5. *Atmos. Environ.* **2021**, *256*, No. 118432.
(45) Sayahi, T.; Butterfield, A.; Kelly, K. E. Long-Term Field Evaluation of the Plantower PMS Low-Cost Particulate Matter Sensors. *Environ. Pollut.* **2019**, *245*, 932−940.
(46) Yong, Z.; Haoxin, Z. *Digital Universal Particle Concentration Sensor Pms5003 Series Data Manual*; Plantower: Beijing, China, **2016**.
(47) Wallace, L.; Zhao, T.; Klepeis, N. E. Calibration of PurpleAir PA-I and PA-II Monitors Using Daily Mean PM2.5 Concentrations Measured in California, Washington, and Oregon from 2017 to 2021. *Sensors* **2022**, *22* (13), No. 4741.
(48) Zhang, X.; Turpin, B. J.; McMurry, P. H.; Hering, S. V.; Stolzenburg, M. R. Mie Theory Evaluation of Species Contributions to 1990 Wintertime Visibility Reduction in the Grand Canyon. *Air Waste* **1994**, *44* (2), 153−162.
(49) Cerqueira, V.; Torgo, L.; Mozetič, I. Evaluating Time Series Forecasting Models: An Empirical Study on Performance Estimation Methods. *Mach. Learn.* **2020**, *109* (11), 1997−2028.

(50) Malings, C.; Tanzer, R.; Hauryliuk, A.; Saha, P. K.; Robinson, A. L.; Presto, A. A.; Subramanian, R. Fine Particle Mass Monitoring with Low-Cost Sensors: Corrections and Long-Term Performance Evaluation. *Aerosol Sci. Technol.* **2020**, *54* (2), 160−174.
(51) Han, J.; Liu, X.; Chen, D.; Jiang, M. Influence of Relative Humidity on Real-Time Measurements of Particulate Matter Concentration via Light Scattering. *J. Aerosol Sci.* **2020**, *139*, No. 105462.
(52) Raheja, G.; Nimo, J.; Appoh, E. K.-E.; Essien, B.; Sunu, M.; Nyante, J.; Amegah, M.; Quansah, R.; Arku, R. E.; Penn, S. L.; Giordano, M. R.; Zheng, Z.; Jack, D.; Chillrud, S.; Amegah, K.; Subramanian, R.; Pinder, R.; Appah-Sampong, E.; Tetteh, E. N.; Borketey, M. A.; Hughes, A. F.; Westervelt, D. M. Low-Cost Sensor Performance Intercomparison, Correction Factor Development, and 2+ Years of Ambient PM2.5 Monitoring in Accra, Ghana. *Environ. Sci. Technol.* **2023**, *57* (29), 10708−10720.
(53) Zusman, M.; Schumacher, C. S.; Gassett, A. J.; Spalt, E. W.; Austin, E.; Larson, T. V.; Carvlin, G.; Seto, E.; Kaufman, J. D.; Sheppard, L. Calibration of Low-Cost Particulate Matter Sensors: Model Development for a Multi-City Epidemiological Study. *Environ. Int.* **2020**, *134*, No. 105329.
(54) Knudsen, T. *Air Quality Monitor*; Lane Regional Air Protection Agency. https://www.lrapa-or.gov/air-quality-protection/current-aqi/air-quality-monitor/ (accessed Mar 11, 2025).
(55) Rana, M.; Khan, M. H. Trend Characteristics of Atmospheric Particulate Matters in Major Urban Areas of Bangladesh. *Asian J. Atmospheric Environ.* **2020**, *14* (1), 47−61.
(56) Jose, C.; Singh, A.; Kalkura, K. N.; Jose, G. V.; Srivastava, S.; Ammini, R. K.; Yadav, S.; Ravikrishna, R.; Andreae, M. O.; Martin, S. T.; Liu, P.; Gunthe, S. S. Complex Hygroscopic Behavior of Ambient Aerosol Particles Revealed by a Piezoelectric Technique. *ACS Earth Space Chem.* **2024**, *8*, 983.

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ACS EST Air 2025, 2, 1904−1915