Validation of In-field Calibration for Low-Cost Sensors Measuring Ambient Particulate Matter in Kolkata, India

Siddharth Nobell[1], Arnab Majumdar[1], Shovon Mukherjee[1], Sukumar Chakraborty[1], Sanjoy Chatterjee[1], Soumitra Bose[1], Anindita Dutta[2,3], Sandhya Sethuraman[3], Daniel M. Westervelt[4], Shairik Sengupta[5], Rakhi Basu[6,7], V. Faye McNeill[3,8]*

[1] Enviome Research, Kolkata 700091, INDIA
[2] Department of Medicine, University of Chicago, Chicago, IL USA
[3] Department of Chemical Engineering, Columbia University, New York, New York 10027, USA
[4] Lamont-Doherty Earth Observatory, Columbia University, Palisades, New York, USA
[5] Indian Institute of Science, Bangalore 560012, INDIA
[6] The World Bank Group, Washington, D.C., USA
[7] Conveh, Irvine, California, USA
[8] Department of Earth and Environmental Sciences, Columbia University, New York, New York 10027, USA

* Corresponding author. +1 212-854-2869 vfm2103@columbia.edu

Abstract

Low-cost sensors (LCS) provide opportunities for neighborhood-level air pollution data collection, yet significant knowledge gaps remain regarding the accurate application and interpretation of LCS. In this study, we present an in-field calibration of a network of 20 low-cost ambient particulate matter sensors (LCS) in greater Kolkata, India, operating between October 2018-April 2019. In order to understand LCS performance in relation to local reference-grade $PM_{2.5}$ monitors (RGMs), three of these LCS were co-located with RGMs operated by the West Bengal Pollution Control Board at Rabindra Bharati University (RBU), Victoria Memorial (VICTORIA), and Padmapukur (Howrah, PDM). Data from the co-locations were used to calibrate the LCS network using random forest regression and multiple linear regression approaches. Measured relative humidity and temperature were significant model features. Agreement between the LCS and RGM for 24-h averaged $PM_{2.5}$ measurements was strongest at RBU, with an uncalibrated root mean squared error (RMSE) of 27.1 μg m^{-3}, followed by PDM (32.6 μg m^{-3}) and VICTORIA (50.7 μg m^{-3}). Multiple linear regression was used to derive calibration models. Cross-calibration between co-located LCS-RGM pairs was tested. The LCS data after cross-calibration correctly identified days as being in or out of attainment with the 24h National Ambient Air Quality Standard of 60 μg m^{-3} 91% of the time. The corrected data accurately identifies days with an India scale Air Quality Index of "poor" or worse 94% of the time. This suggests that LCS can be a useful supplement to RGM networks for air quality management. Diurnal trends and a high level of correlation across the hybrid LCS-RGM network suggest regional and secondary sources of $PM_{2.5}$ are important in Kolkata.

Keywords: Air Pollution, Air Quality, Atmospheric Aerosols, $PM_{2.5}$, Urban Aerosols

1 INTRODUCTION

Ambient air pollution is a major environmental health issue. Atmospheric fine particulate matter, or $PM_{2.5}$ (particles with aerodynamic diameters less than 2.5 micrometers), is one of the leading causes of premature mortality and morbidity worldwide (Cohen et al., 2017). $PM_{2.5}$ exposure causes an estimated 1.56-year decrease in life expectancy in South Asia, more than in any other region (Apte et al., 2018). Although the World Health Organization has set guideline values for $PM_{2.5}$ at 5 μg m^{-3} annual mean and 15 μg m^{-3} 24-hour mean, pollutant levels remain many-fold higher than this value in most places, particularly in low- and middle-income countries (LMICs) (WHO, 2021). Continuous measurements of $PM_{2.5}$ are needed in order to establish baseline conditions, quantify the local negative impacts of pollution, identify pollution sources, plan policies to comply with set air quality goals, and track air quality improvements (McNeill, 2019; World Bank, 2017). While the density of ground-based reference-grade $PM_{2.5}$ monitors across India has increased since 2016 under the National Air Quality Monitoring Programme (CPCB, 2022; Sethuraman et al., 2021; McNeill and Nunes, 2017), data are not yet available at high spatial resolution. Low-cost sensors (LCS) provide opportunities for neighborhood-level data collection, enabling the identification of air pollution "hotspots" and the quantification of local health impacts (Pinder et al., 2019). LCS are lower-fidelity sensors that generally operate on optical principles for $PM_{2.5}$ detection and require less power and maintenance than reference-grade monitors (RGMs).

Although the use of LCS for air pollution monitoring and air pollution research has proliferated in the past decade, significant knowledge gaps and caveats remain regarding the accurate application and interpretation of LCS (Malings et al., 2020; Giordano et al, 2021; Hagler et al., 2018). LCS that measure ambient $PM_{2.5}$ often underperform under the environmental conditions typical of air pollution events in India (high humidity, high pollution loadings, light-absorbing particles) (Di Antonio, et al., 2018; Jayaratne et al., 2018). Sensor performance may also degrade

in harsh environments (Amegah, 2018). The impact of environmental conditions and particle characteristics such as size, shape, and composition on different LCS technology remains a knowledge gap.

In-field calibration of LCS sensors has emerged as a solution for improving the accuracy of data from LCS networks (Malings et al., 2020; Giordano et al, 2021). Including RGMs in an air quality network provides a reference for LCS calibration. By co-locating LCS and RGMs, a calibration for the LCS network may be developed. Several studies have focused on local calibrations of LCS distributed in the U.S. (Malings et al., 2020; Zimmerman et al., 2018) and African cities (McFarlane et al, 2021a,b; Raheja et al., 2022) with machine learning approaches, but to date this approach has had limited application in urban environments in India (Gupta et al., 2022).

In this manuscript, we describe a sensor network deployed by Enviome Research in collaboration with The World Bank between October 2018 and January 2019 in central Kolkata, India, which collected data until summer 2019. The network consisted of twenty low cost $PM_{2.5}$ sensors (Clarity, Inc.), and included three co-locations with reference grade $PM_{2.5}$ monitors under the operation of the West Bengal Pollution Control Board (WBPCB). The design of this network allowed for the analysis of the performance of these light-scattering based LCS in the Indian urban environment. Using the network, we were able to establish a baseline assessment of local air quality along two major transportation corridors targeted for transition to electric vehicle public transportation (World Bank, 2020) (Fig. 1). The multiple co-locations also enabled a robust test of the principle of field calibration by allowing calibration and cross-check across co-location pairs.

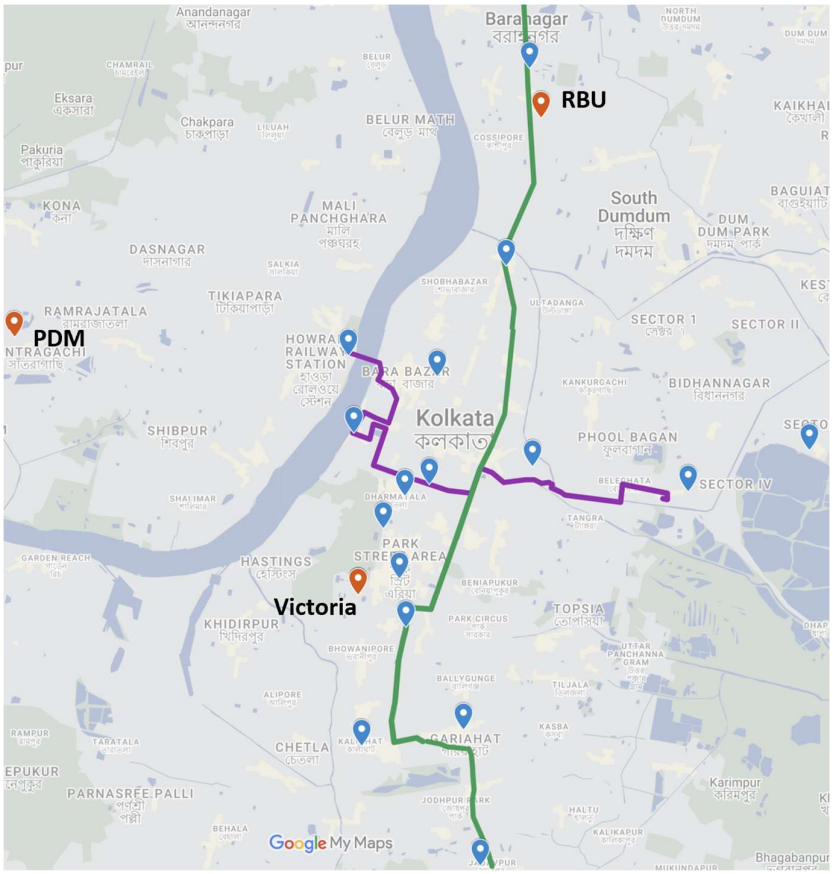

Figure 1. Sensor placement. Markers indicate the locations of Clarity Monitors. Red markers indicate Clarity Monitors co-located with WBPCB reference grade $PM_{2.5}$ monitors. S12 (purple) and S9 (green) bus routes are indicated. See text for details. Background map © Google, 2023

2. NETWORK DESCRIPTION AND METHODOLOGY

In this section, we describe the sensors, the network design, and the analysis approach. Twenty Clarity Node S air quality monitors were deployed in Kolkata and Howrah, India starting in Fall 2018 (Fig. 1). Table 1 provides a complete list of sensor locations. The sensor network was designed to characterize baseline air pollution levels along the two busiest bus corridors in central Kolkata, and to compare LCS performance to RGMs in three areas of the city. The bus corridors studied were route S9 (Belgharia to Jadavpur) and S12 (Newtown to Howrah), which span across the city from far North to South, and far East to West. Clarity Node S devices were placed at 2-3 km intervals along these routes. Five more Clarity Node S devices were placed near existing $PM_{2.5}$

Table 1. Sensor Network Details.

Code	Area	Lat (N), Lon (E)	Note
Victoria Memorial (VICTORIA)	Central, S9 Route	22.543529, 88.345144	Installed Nov 30, 2018 WBPCB Co-location
Esplanade	Central, S12 Route	22.560900, 88.354100	Installed Oct 9, 2018
Marble Palace	Central	22.58206, 88.360217	Installed Oct 30, 2018
Camac Street	Central	22.546349,88.353041	Installed Oct 30, 2018
Park Street Crossing	Central, S12 Route	22.555199, 88.349983	Installed Oct 30, 2018
Wellington	Central, S12 Route	22.562954, 88.358787	Installed Oct 30, 2018
Beleghata	East, S12 Route	22.561763, 88.408248	Installed Oct 30, 2018
SDF Building	East, S12 Route	22.569032, 88.431324	Installed Oct 6, 2018
Sealdah Sales Tax	East, S12 Route	22.566107, 88.378469	Installed Oct 7, 2018
Padmapukur (PDM)	Howrah	22.58898, 88.279613	Installed Nov 30, 2018 WBPCB Co-location
Howrah Bus Depot	Howrah, S12 Route	22.585611, 88.343274	Installed Oct 9, 2018
Ghusuri	Howrah	22.611539, 88.347443	Installed Oct 26, 2018
Rabindra Bharati University (RBU)	North	22.627875, 88.3804	Installed Jan 1, 2019 WBPCB Co-location
Belgharia Police Station	North, S9 Route	22.658795, 88.376852	Installed Oct 30, 2018
Shyambazar	North, S9 Route	22.601706, 88.373702	Installed Oct 30, 2018
Baranagar Police Station	North, S9 Route	22.636537, 88.378087	Installed Oct 30, 2018
Elgin & Lansdowne	South, S9 Route	22.537756, 88.354285	Installed Oct 30, 2018
Gariahat	South, S9 Route	22.519741, 88.365247	Installed Oct 26, 2018
Jadavpur (8B bus stand)	South, S9 Route	22.495761, 88.368469	Installed Oct 7, 2018
Rashbehari Crossing	South, S9 Route	22.516881, 88.345842	Installed Oct 30, 2018
Millenium Park	West, S12 Route	22.571949, 88.344400	Installed Oct 30, 2018

RGMs (WBPCB and U.S. Diplomatic Post). Out of the five devices, three were placed in sufficiently close proximity to the RGMs (i.e., on the enclosures housing the RGMs) to be considered co-located for calibration purposes. These three were PDM: Padmapukur, RBU:

Rabindra Bharati University, and VICTORIA: Victoria Memorial. Sensors were installed 12-18 feet from the ground. Each Clarity Movement Node S monitor consisted of a Plantower PMS 6003 dual laser light scattering PM sensor, an NO_2 electrochemical cell sensor (110-508, SPEC Sensors), and a Bosche BME280 sensor to estimate pressure, relative humidity (RH), and temperature (T) inside the sensor housing. The Node S reported measurements of $PM_{2.5}$, PM_{10}, NO_2, RH, and T at a default frequency of 15 minutes and uploaded the data via cellular signal to the Clarity cloud system. Data were processed, including data cleaning, by Clarity prior to data storage in the Clarity Cloud. No additional cleaning of Clarity data was performed in this study; data were used as received from the Clarity Dashboard. The present analysis focuses on the $PM_{2.5}$ data. The Clarity sensors were co-located as a group in a controlled environment in Kolkata (SDF building) and checked for consistent performance prior to deployment.

WBPCB $PM_{2.5}$ monitors (RGMs) are Beta Attenuation Monitors (MP101M, Envea Global). These instruments were housed in enclosures roughly 4.2 m × 3.5 m × 2.5 m high (WBPCB, 2018). Co-located LCS were installed on poles extending 3-4 feet from the roof of these enclosures. The RGMs collected sample data every fifteen minutes and uploaded the data to the online data collection and reporting web portal as hourly average. WBPCB instruments are certified on a 24-hour basis. WBPCB performed data cleaning prior to storage, but we also screened for values of 0 and 999 $\mu g\ m^{-3}$ from the WBPCB datasets (<1% of data points). These values were discarded before averaging and further analysis.

Calibration analysis was performed using the scikit-learn package in Python (Müller and Guido, 2017). Basic features of the datasets included $PM_{2.5}$ measured by RGM and Clarity Monitor, as well as T and RH measured by the Clarity Monitor. Regression was performed for individual co-located Clarity-RGM pairs using Clarity $PM_{2.5}$, T, and RH as explanatory variables. The 24-hr averaged datasets consisted of 188 (i.e., 24-hr averages for 188 days) and 194 points for RBU and

PDM, respectively. A 75:25 train:test split implemented via random distribution was used. The generalizability of the calibration was tested by cross-calibrating between Clarity-RGM pairs (i.e., train dataset from co-location pair 1, test data from co-location Clarity Monitor 2, compared result to the location 2 RGM). Additional details are available in the Results section.

The algorithms tested for calibration were multiple linear regression and Random Forest regression. Random Forest regression is attractive for this application because it is powerful while making it possible to avoid overfitting. Multiple linear regression, if it provides enough accuracy, is valuable in that it produces an analytical expression for the calibration as follows, simplifying calibration of the wider network (Malings et al., 2020; McFarlane et al., 2021a):

$$PM_{2.5,\,corrected} = \beta_0 + \beta_1 \times \text{Clarity } PM_{2.5} + \beta_2 \times T\ (°C) + \beta_3 \times RH\ (\%) \quad (1)$$

Where the β_i are fitting parameters. The default settings in `scikit_learn` were applied for `linear_model.LinearRegression()` (Müller and Guido, 2017). For `RandomForestRegressor()`, we used 100 estimators, a maximum tree depth of 10, 10 minimum samples required to be a leaf node, and a fixed random state of 5.

The raw data and the regression results were evaluated based on their agreement with the WBPCB reference data, as measured by the coefficients of determination (r^2) and the root mean squared error (RMSE), and the normalized RMSE (NRMSE). RMSE is calculated according to:

$$\sqrt{\frac{\sum_{i=0}^{n}(x_i - \widehat{x_i})^2}{N}} \quad (2)$$

where x_i is the series of observed values, $\widehat{x_i}$ is the expected value, and N is the number points in the series. NRMSE, a unitless metric, is calculated by normalizing the RMSE with the range of the variable, i.e.

$$NRMSE = \frac{RMSE}{x_{high} - x_{low}} \quad (3)$$

The corrected data were also evaluated for their accuracy in diagnosing a day as in or out of attainment with the Indian 24h National Ambient Air Quality Standard (NAAQS) of 60 μg m^{-3}, or placing the day in the correct Indian Air Quality Index (AQI) category.

Spatial variability in the data was analyzed by calculating the Pearson correlation coefficient, *r*, between datasets obtained at different sites. For datasets A and B,

$$r_{AB} = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{A_i - \mu_A}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right) \quad (4)$$

where *N* is the size of each dataset, μ_j is the mean, and σ_j is the standard deviation.

3. RESULTS

Data collection spanned the post-monsoon season 2018 (October-November), winter 2018/2019 (December-February), and spring/summer 2019 (March-July). Sensor installation took place between November 2018-January 2019 (Table 1). Comparisons between the WBPCB RGM data and the uncorrected Clarity data at the three co-location sites are shown in Fig. 2. We used 24-hour averaged data since this is the basis upon which the RGM was certified. Typical of Plantower-based instruments, the Clarity sensors showed qualitative agreement with the RGMs, with some high bias for higher $PM_{2.5}$ loadings (>100 μg m^{-3}). Agreement between the LCS and RGM was strongest at RBU, with an uncalibrated RMSE of 27.1 μg m^{-3} (NRMSE = 0.070), followed by PDM (RMSE = 32.6 μg m^{-3}, NRMSE = 0.086) and VICTORIA (RMSE = 50.7 μg m^{-3}, NRMSE = 0.122). The RBU site is located inside the university campus, away from traffic and other sources (167 m away from the nearest major roadway). PDM is in a primarily residential area near a pond, 15 m from a minor roadway, 167 m from a major roadway, and 373 m from the Mumbai-Kolkata

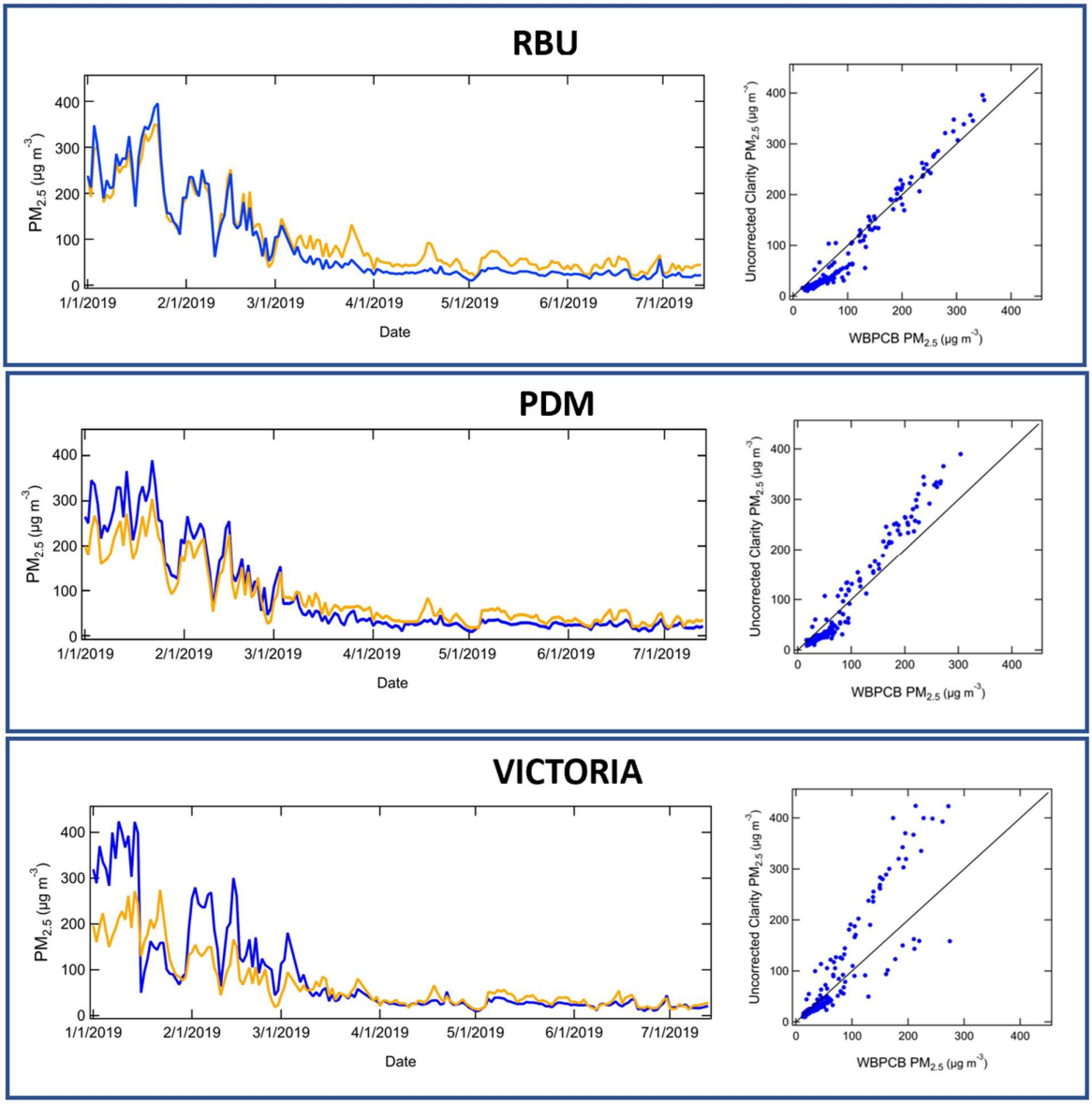

Figure 2. 24-hr averaged $PM_{2.5}$ data from WBPCB RGMs (orange) and uncorrected Clarity Monitor data (as received from Clarity Cloud) (blue) for the RBU, PDM, and VICTORIA co-locations during the study period. 1:1 lines are shown on the right hand panels as a guide to the eye. Refer to Table 2 and Table 3 for performance metrics.

Highway. VICTORIA is in a centrally located green zone near a pond, near a minor roadway, and 200-230 m from two major roadways, so, humidity and local source effects are possible. PDM and VICTORIA showed higher average RH than the rest of the network. Only the RBU and PDM

datasets were used for calibration analysis due to the lower Clarity-RGM agreement and higher variability in the Clarity data at VICTORIA.

In order to investigate the sensitivity of the sensor performance to environmental factors, we analyzed the Clarity:RGM agreement after splitting the dataset based on RH and/or $PM_{2.5}$ levels (Table 2). This analysis was done using hourly averaged data in order to capture diurnal variations in RH. Performance of Plantower-based sensors has been reported to degrade for RH > 75% (Jayaratne et al., 2018). We split the RBU, PDM, and VICTORIA datasets into RH >75% and RH<75% groups. The results varied by co-location site, with VICTORIA showing significant degradation in sensor performance for RH>75%. PDM also showed worse Clarity:RGM agreement for RH >75%, although the difference was not as great as observed at VICTORIA. No significant RH effect was observed at RBU.

Table 2. Uncorrected Clarity node:RGM agreement for the three co-location sites. Shown are root mean squared error (RMSE (μg m^{-3})) and normalized RMSE (NRMSE, unitless, in parentheses), on 24 hr or hourly averaging basis, and for the full dataset, or segregated based on relative humidity level or fine particle mass loading.

Location	**$RMSE_{24}$**	**$RMSE_{hourly}$**	**$RMSE_{hourly}$ RH>75%**	**$RMSE_{hourly}$ RH<75%**	**$RMSE_{hourly}$ $PM_{2.5}$>100 μg m^{-3}**	**$RMSE_{hourly}$ $PM_{2.5}$<100 μg m^{-3}**
RBU	27.1 (0.070)	44.7 (0.091)	40.0 (0.081)	46.8 (0.136)	70.0 (0.142)	31.5 (0.350)
PDM	32.6 (0.086)	55.0 (0.112)	68.1 (0.139)	39.2 (0.116)	101 (0.207)	24.1 (0.268)
VICTORIA	50.7 (0.123)	74.9 (0.181)	100 (0.242)	44.2 (0.147)	155 (0.375)	18.4 (0.204)

Splitting the dataset on $PM_{2.5}$ = 100 μg m^{-3} showed significantly better Clarity:RGM agreement for lower $PM_{2.5}$ loadings, and worse sensor performance for higher loadings, for all three co-location sites (Table 2). Deterioration of sensor performance for high $PM_{2.5}$ loadings >100 μg m^{-3} is consistent with studies of low-cost optical particle counter performance in Delhi (Crilley, et al.

2020) and Plantower PMS3003 sensors in Kanpur (Zheng, et al. 2018). Seasonal variation in $PM_{2.5}$ in Kolkata is strong enough that splitting the data at $PM_{2.5}$ = 100 μg m^{-3} is effectively similar to segregating the data by seasons, since loadings are generally <100 μg m^{-3} outside the post-monsoon and winter seasons (Fig. 2). There are many other reasons to characterize sensor performance with the changing seasons, including varying meteorological conditions, varying sources, and possible degradation of sensor performance with time. However, because of the timing of the sensor deployment in this study (deployment beginning in post-monsoon, when $PM_{2.5}$ is high, and ending in summer, when $PM_{2.5}$ is lower), it is difficult to distinguish the effects of these influences on the sensor performance from the strong effect of $PM_{2.5}$ loading.

Random Forest (RF) and Multiple Linear Regression (MLR) analyses were performed on the 24-hr averaged RBU and PDM datasets, because the WBPCB monitors are certified on a 24 hour basis. Factors tested were $PM_{2.5}$, T, and RH (Table 3). $PM_{2.5}$ was the most significant explanatory variable in the RF regression, followed by RH and T, consistent with the results of the data segregation analysis (Table 2). The RF and MLR approaches yielded similar satisfactory agreement with the reference data for both co-location sites, with $R^2 > 0.9$ in each case. Since MLR yields an analytical expression for the calibration model, which is straightforward to apply to the rest of the sensor network, MLR was used in the remainder of the study.

Malings et al. (2020) used a piecewise MLR approach for Pittsburgh, USA data, splitting the data at $PM_{2.5}$ = 20 μg m^{-3}. We tested this approach, splitting the data at $PM_{2.5}$ = 100 μg m^{-3}. Using 24-hr averaged data the segregated datasets were not large enough for the calibration analysis (N<50 for $PM_{2.5}$>100 μg m^{-3}) so hourly averaged data were used. An alternative calibration was developed using the hourly averaged PDM co-location data ($PM_{2.5,corr}$ = 111 + 0.596*$PM_{2.5,\ Clarity}$ - 0.861*T - 0.801*RH, RMSE = 27.8 μg m^{-3}, NRMSE = 0.0732 μg m^{-3}). The piecewise calibration model showed improved performance for $PM_{2.5}$<100 μg m^{-3} (RMSE = 16.5 μg m^{-3}, NRMSE =

Table 3. Calibration results for RBU and PDM co-located Clarity Monitor/WBPCB pairs on a 24 hr average basis. RMSE: root mean squared error. RF: random forest regression. MLR: Multiple linear regression. $PM_{2.5}$ is in units of μg m^{-3}, temperature is in degrees Celsius and relative humidity is in percent.

Location	***Uncorrected Clarity-WBPCB***	***RF***	***MLR***
RBU	RMSE: 27.1 μg m^{-3} NRMSE: 0.070 R^2 = 0.870	RMSE: 13.3 μg m^{-3} NRMSE: 0.035 R^2 = 0.962 *Feature importance* $PM_{2.5}$: 0.989 T: 0.00447 RH: 0.00642	RMSE: 15.3 μg m^{-3} NRMSE: 0.040 R^2 = 0.950 *Calibration model* $PM_{2.5,\ corr}$ = 54.1+0.838*$PM_{2.5,\ Clarity}$ +0.182*T-0.491*RH
PDM	RMSE: 32.6 μg m^{-3} NRMSE: 0.086 R^2 = 0.876	RMSE: 15.2 μg m^{-3} NRMSE: 0.040 R^2 = 0.936 *Feature importance* $PM_{2.5}$: 0.987 T: 0.00599 RH: 0.00676	RMSE: 10.2 μg m^{-3} NRMSE: 0.027 R^2 = 0.971 *Calibration model* $PM_{2.5,\ corr}$ = 0.928+0.770*$PM_{2.5,\ Clarity}$ +2.19*T-0.710*RH

0.165) but performance was worse for $PM_{2.5}$>100 μg m^{-3} (RMSE = 44.5 μg m^{-3}, NRMSE = 0.091), and both models underperformed compared to the MLR model developed with the full 24-hr averaged PDM dataset (Table 3). Therefore, we opted not to use piecewise calibration.

In order to test the robustness of applying the calibrations developed at a single Clarity/RGM co-location site to another distant site (11.3 km apart) in the network, the following cross-calibration test was performed using the calibrations developed using the 24-hr averaged co-location data: the MLR calibration developed for the RBU site (Table 3) was applied to the PDM dataset, and the output was compared to the PDM WBPCB reference data. Likewise, the MLR calibration developed for PDM was applied to RBU and compared to the RBU WBPCB reference data. When the PDM MLR calibration was applied to the RBU dataset, agreement for the corrected data with the RBU WBPCB reference data improved (RMSE = 20.1 μg m^{-3}) compared to the raw Clarity data (RMSE = 27.1 μg m^{-3}), but not as much as when the locally developed calibration was applied (RMSE = 15.3 μg m^{-3}). Similar results were observed when the RBU MLR model was

applied to the PDM dataset: RMSE was equal to 24.2 μg m^{-3}, improved compared to the raw Clarity data (RMSE = 32.6 μg m^{-3}), but not as much as when the locally developed MLR calibration was applied (RMSE = 10.2 μg m^{-3}). The cross-calibration corrected Clarity Monitor data for PDM and RBU accurately diagnosed days as being in or out of attainment with the 24-hour mean Indian NAAQS of 60 μg m^{-3}, as compared to the WBPCB reference monitor data, 91% of the time. The corrected data identified days with an India scale AQI of "poor" or worse ($PM_{2.5}$ > 90 μg m^{-3}) in agreement with the reference grade monitors 94% of the time.

Once the calibration method was established, the 24 hr average based MLR model derived from the PDM dataset (Table 3) was applied to the entire sensor network to derive a corrected dataset. Average corrected $PM_{2.5}$ values for the months of November 2018, January 2019, and April 2019, as representative of the post-monsoon, winter, and spring/summer, are shown for each Clarity Monitor in Table 4. Where data are not shown, no data are available for that month for that sensor. Note that co-location data are not available for November 2018 and therefore the calibration was not developed using data from that time period, however we expect the calibration model performance for November to be similar to that for January since it is in the higher $PM_{2.5}$ loading period. Averages for the 6 geographic zones and network-wide averages are also shown. Consistent with regional trends for the Indo-Gangetic Plain (Guttikunda and Gurjar, 2012; Bhowmik, et al. 2021), pollution is highest in January, when citywide average $PM_{2.5}$ is 205 ± 27 μg m^{-3}, followed by November, with an average value of 153 ± 21 μg m^{-3}. These values exceeded the NAAQS and fell in the "Very Poor" category of the Indian AQI. $PM_{2.5}$ levels are significantly lower in April, with an average of 47 ± 8 μg m^{-3}. $PM_{2.5}$ levels were highest at Howrah Bus Depot and lowest at Camac Street (U.S. Consulate area). Among the zones, Howrah had the highest average $PM_{2.5}$ levels, although data were somewhat limited for that zone. There were only 3 sensors in the Howrah zone. Ghusuri had limited data due to loss of the sensor after November 2018, and PDM was not

Table 4. Monthly average corrected Clarity $PM_{2.5}$ data (μg m^{-3}) and standard deviation for November 2018, January 2019, and April 2019, months representing the post-monsoon, winter, and summer seasons in Kolkata. Data shown for each site, geographic zonal averages, and citywide average.

Code	Area	Nov 2018	Jan 2019	April 2019
Victoria Memorial	Central		189	41
Esplanade	Central	196	203	32
Marble Palace	Central	140	196	46
Camac Street	Central	130	166	41
Park Street Crossing	Central	142	192	42
Wellington	Central	150	216	51
Beleghata	East	149	201	52
SDF Building	East	126	162	33
Sealdah Sales Tax	East	176	257	58
Padmapukur (PDM)	Howrah		247	48
Howrah Bus Depot	Howrah	193	261	57
Ghusuri	Howrah	126		
Rabindra Bharati University (RBU)	North		204	48
Belgharia Police Station	North	162	203	57
Shyambazar	North	159	216	57
Baranagar Police Station	North	159		
Elgin & Lansdowne	South	141	188	48
Gariahat	South	141	183	45
Jadavpur (8B bus stand)	South	147	198	52
Rashbehari Crossing	South	162	225	
Millenium Park	West	153	207	48
Howrah zone		160	254	52
North zone		146	184	47
West zone		141	188	48
East zone		126	204	43
South zone		173	221	45
Central zone		146	196	46
AVERAGE		**153 ± 21**	**205 ± 27**	**47±8**

288 installed until WBPCB approval for the co-location, which was obtained in January 2019.

289 In order to investigate diurnal patterns in $PM_{2.5}$ across the network, the calibration developed
290 using the hourly averaged PDM co-location data ($PM_{2.5,corr}$ = 111 + 0.596*$PM_{2.5,\ Clarity}$ - 0.861*T -
291 0.801*RH, RMSE = 27.8 μg m^{-3}, NRMSE = 0.0732 μg m^{-3}) was applied to hourly average data for
292 the network, as shown in Figure 3. The diurnal trend varied seasonally. Generally, in November
293 and January, maximum $PM_{2.5}$ was observed in the late night hours (midnight-1 AM), with an
294 additional minor peak in the morning (7-10 AM), while in April, $PM_{2.5}$ varied more smoothly
295 throughout the day, with a maximum in the afternoon (1-4 PM). This post-monsoon/wintertime
296 diurnal pattern was consistent with what had been observed earlier for other large cities in the Indo-
297 Gangetic plain (Guttikunda and Gurjar, 2012; Gani et al. 2020). The nocturnal maximum in $PM_{2.5}$
298 could be attributed to low boundary layer height at night during post-monsoon and winter seasons.
299 Nighttime emissions such as residential burning for heating or cooking may also contribute. The
300 April pattern of an afternoon maximum with relatively little influence from morning and evening
301 traffic suggests regional non-traffic sources and/or secondary aerosol formation. We note this trend
302 observed in the corrected Clarity data, while unusual for cities in the IGP, is corroborated by the
303 WBPCB RGM data. Gani et al. (2020) reported that secondary components of PM_1, consisting of
304 oxygenated organic aerosol, ammonium, nitrate, and sulfate, show a similar diurnal profile, with a
305 single peak in the afternoon, in Delhi during all seasons.

306 We further investigated the spatial variability in $PM_{2.5}$ by calculating the Pearson correlation
307 coefficient (r) between the datasets shown in Figure 3 (RBU, Howrah Depot, Beleghata, Camac
308 Street, and Jadavpur) for November, January, and April. The results are shown in Figure 4. $PM_{2.5}$
309 is highly linearly correlated among these sites for all seasons. This high level of correlation among
310 these sites with differing local sources underscores the importance of regional and secondary
311 sources of aerosol in Kolkata and Howrah. Although still highly correlated ($r \geq 0.79$) Howrah

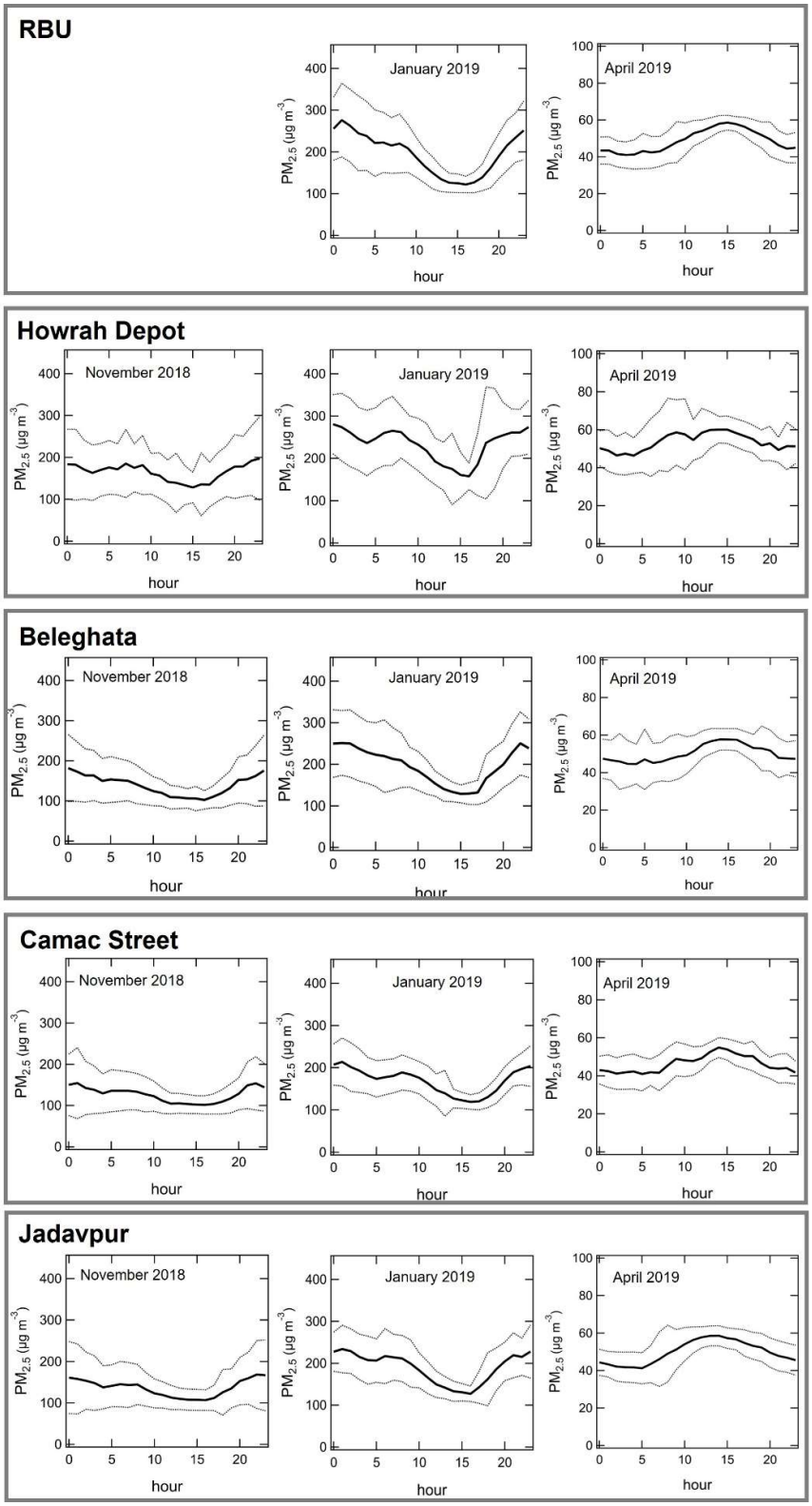

Figure 3. Hourly average corrected Clarity $PM_{2.5}$ data for representative locations, for months representing the post-monsoon, winter, and summer seasons in Kolkata. Thin grey lines represent +/- one standard deviation.

NOVEMBER 2018

	Howrah	Camac St.	Beleghata	RBU	PDM
Jadavpur	0.92	0.96	0.96		
PDM					
RBU					
Beleghata	0.89	0.96			
Camac St.	0.90				

JANUARY 2019

	Howrah	Camac St.	Beleghata	RBU	PDM
Jadavpur	0.96	0.97	0.98	0.96	0.92
PDM	0.83	0.96	0.95	0.98	
RBU	0.87	0.97	0.98		
Beleghata	0.92	0.95			
Camac St.	0.88				

APRIL 2019

	Howrah	Camac St.	Beleghata	RBU	PDM
Jadavpur	0.90	0.94	0.92	0.96	0.95
PDM	0.81	0.95	0.98	0.99	
RBU	0.83	0.95	0.98		
Beleghata	0.79	0.92			
Camac St.	0.88				

Figure 4. Correlation between hourly average corrected $PM_{2.5}$ measurements at different representative locations in the Clarity network, for months representing the post=monsoon, winter, and summer seasons in Kolkata.

Depot showed lower correlation with the other sites, consistent with strong local sources. Correlation was slightly weaker in April as compared to November and January. The high degree of correlation of PDM with the other sites lend additional confidence in the choice to calibrate the network using the calibration developed based on the PDM co-location data.

4. DISCUSSION AND IMPLICATIONS

Air quality is a major public health issue in Kolkata. Previously published studies have shown that chronic exposure to ambient air pollution in Kolkata adversely affects pulmonary and cardiovascular health of its residents (Lahiri et al., 2000; Roy et al., 2001; Dutta et al., 2013). It is important to be empowered with low cost tools and knowledge to assess local air pollution and the associated health risks to advocate relevant policy measures in addressing environmental pollution issues affecting local communities. Hence, we undertook this study to understand and validate the performance of LCS in Kolkata, which could then be used to supplement existing RGM networks for better air quality management.

During the study period, which covered the post-monsoon, winter, and spring/summer seasons of 2018-2019, $PM_{2.5}$ levels exceeded the NAAQS 45% of the time (and nearly 100% of the time during the post-monsoon and winter months). This observation is consistent with other analyses of $PM_{2.5}$ in the IGP region (see, e.g., Zheng et al. 2018, Gani et al. 2020, and Gupta et al. 2022). The highest average $PM_{2.5}$ values in the network were observed at Howrah Bus Depot, suggesting that idling buses may be a significant local source of $PM_{2.5}$ that could be reduced with the introduction of electric buses. The diurnal trends and high correlation among sites in different zones suggest that regional and secondary sources are also very important. Winds are mostly north-westerly during post-monsoon and winter seasons (October-February), bringing airmasses from the Indo-Gangetic Plain, transporting regional haze as well as pollution from regional thermal power plants, mining and steel industries. Based on Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT) analysis, Mallik et al. (2014) showed that, during April, prevailing winds in Kolkata generally come from the south (Bay of Bengal and coastal India) and transport occurs near surface level. A future multi-season investigation involving aerosol composition and gas measurements would provide necessary insight into the sources of $PM_{2.5}$ in Kolkata.

Many of the Clarity Monitor sites in the network were near or on roadways or bus stands, whereas the co-location sites, particularly RBU, were selected by WBPCB to be farther from roads for security reasons and to characterize the urban background pollution. With the exception of Howrah Depot, the difference in average $PM_{2.5}$ levels for the roadside vs. urban background sites in each geographic zone is not consistently distinguishable within the error, even when filtering for expected high traffic times (i.e., weekdays, 9-11 AM). However, some differences can be discerned in the diurnal variation, e.g. the afternoon peak time during summer (Fig. 3). Sites located closer to pollution sources, such as Howrah Depot, also showed greater day to day variability in measured $PM_{2.5}$.

We have demonstrated the potential utility for a field-calibrated LCS network with neighborhood-level spatial resolution to support air quality management efforts in Kolkata. This study contributes to the growing body of work showing the promise of LCS in the South Asian context (Zheng et al., 2018; Hagan et al., 2019; Crilley et al., 2020; Gupta et al., 2022; Kushawaha et al., 2022). This study was the first deployment of Clarity devices in the Indian subcontinent. Some practical limitations of application of the Clarity devices in Kolkata included issues with charging and network connectivity, which resulted in data loss, the cost per unit, and the data subscription charge. Supplementing the existing reference grade monitoring network with these devices revealed spatiotemporal trends and insight into sources, which were not available with the RGM network alone. Reasonable agreement between Clarity Monitors and WBPCB reference grade monitors was obtained with in-field calibration, as tested by cross-calibration with two co-located sensor/RGM pairs: the calibrated network accurately diagnosed days as being in or out of attainment with the 24-hour mean Indian NAAQS of 60 $\mu g\ m^{-3}$ with 91% accuracy, and correctly assigned days to a category of the India scale Air Quality Index of "poor" or worse ($PM_{2.5} > 90\ \mu g\ m^{-3}$) with 94% accuracy.

ACKNOWLEDGEMENTS

Enviome Research acknowledges the World Bank for funding the deployment of the Clarity Monitor network. AD, DMW, and VFM acknowledge the Columbia University Earth Institute for support of this work under the Clean Air Toolbox for Cities initiative. DMW acknowledges NSF OISE grant 2020677. We are grateful to the West Bengal Pollution Control Board for sharing data, permitting sensor co-locations at monitoring sites, and helpful discussions. The authors are also grateful to Sarbani Palit, Celeste McFarlane, Shahzad Gani, and Sean Wihera for helpful discussions. Corrected Clarity monitor data will be made publicly available on PANGAEA (www.pangaea.de) after acceptance. Regulatory instrument data from the West Bengal Pollution Control Board are available through the CPCB Central Control Room for Air Quality Management data dashboard (https://app.cpcbccr.com).

REFERENCES

Amegah, A.K. (2018). Proliferation of low-cost sensors. What prospects for air pollution epidemiologic research in Sub-Saharan Africa? *Environ. Pollut.* 241 1132-1137. https://doi.org/10.1016/j.envpol.2018.06.044

Apte. J.S., Brauer, M., Cohen, A.J., Ezzati, M., Pope III, C.A. (2018). Ambient $PM_{2.5}$ Reduces Global and Regional Life Expectancy. *Environ. Sci. Technol. Lett.* 5, 546-551. https://doi.org/10.1021/acs.estlett.8b00360

Bhowmik, H.S., Naresh, S., Bhattu, D., Rastogi, N., Prevot, A.S.H., Tripathi, S.N. (2021). Temporal and spatial variability of carbonaceous species (EC; OC; WSOC and SOA) in PM2.5 aerosol over five sites of Indo-Gangetic Plain. *Atmos. Pollut. Res.* 12(1) 375-390. https://doi.org/10.1016/j.apr.2020.09.019

Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Feigin, V. ,Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska ,L., Pope, C.A., Shin, H., Straif, K., Shaddick, G., Thomas, M., van Dingenen, R., van Donkelaar, A., Vos, T., Murray, C.J.L., Forouzanfar, M.H. T. (2017) Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *Lancet* 389, 10082, 1907-1918. https://doi.org/10.1016/S0140-6736(17)30505-6

CPCB Central Control Room for Air Quality Management - All India https://app.cpcbccr.com (Accessed February 2022).

Crilley, L.R., Singh, A., Kramer, L.J., Shaw, M.D., Alam, M.S., Apte, J.S., Bloss, W.J., Ruiz, L.H., Fu, P., Fu, W., Gani, S., Gatari, M., Ilyinskaya, E., Lewis, A.C., Ng'ang'a, D., Sun, Y., Whitty, R.C.W., Yue, S., Young, S., Pope, F.D. (2020) Effect of aerosol composition

413 on the performance of low-cost optical particle counter correction factors. *Atmos. Meas.*
414 *Tech.,* 13, 1181–1193. https:\\doi.org\10.5194/amt-13-1181-2020
415 Di Antonio, A., Popoola, O.A.M., Ouyang, B., Saffell, J., Jones, R.L. (2018) Developing a
416 Relative Humidity Correction for Low-Cost Sensors Measuring Ambient Particulate
417 Matter. *Sensors* 18(9), 2790 https://doi.org/10.3390/s18092790
418 Dutta, A. and Ray, M.R. (2013) Increased cardiovascular risk due to systemic inflammatory
419 changes and enhanced oxidative stress in urban Indian women. *Air Qual. Atmos. Health*
420 6(2), 501- 508. https://doi.org/10.1007/s11869-012-0189-0
421 Gani, S., Bhandari, S., Patel, K., Seraj, S., Soni, P., Arub, Z., Habib, G., Ruiz, L.H., Apte, J.S.
422 (2020) Particle number concentrations and size distribution in a polluted megacity: the
423 Delhi Aerosol Supersite study. *Atmos. Chem. Phys.* 20, 8533-8549.
424 https://doi.org/10.5194/acp-20-8533-2020
425 Giordano, M.R., Malings, C., Pandis, S.N., Presto, A.A., McNeill, V.F., Westervelt, D.M.,
426 Beekmann, M., Subramanian, R. (2021) From Low-cost Sensors to High-Quality Data: A
427 Summary of Challenges and Best Practices for Effectively Calibrating Low-Cost
428 Particulate Matter Mass Sensors. *J. Aerosol Sci.* 158, 105833
429 https://doi.org/10.1016/j.jaerosci.2021.105833
430 Gupta, P., Doraiswamy, P., Reddy, J., Balyan, P., Dey, S., Chartier, R., Khan, A., Riter, K.,
431 Feenstra, B., Levy, R.C., Tran, N.N.M., Pikelnaya, O., Selvaraj, K., Ganguly, T.,
432 Ganesan, K. (2022) Low-Cost Air Quality Sensor Evaluation and Calibration in
433 Contrasting Aerosol Environments *Atmos. Meas. Tech. Discuss.* [preprint],
434 https://doi.org/10.5194/amt-2022-140

435 Guttikunda, S.K. and Gurjar, B.R. (2012) Role of meteorology in seasonality of air pollution in
436 megacity Delhi, India. *Environ. Monit. Assess.* 184, 3199-3211
437 https://doi.org/10.1007/s10661-011-2182-8
438 Hagan, D.H., Gani, S., Bhandari, S., Patel, K., Habib, G., Apte, J.S., Ruiz, L.H., Kroll, J.H. (2019)
439 Inferring Aerosol Sources from Low-Cost AIr Quality Sensor Measurements: A Case Study
440 in Delhi, India. *Environ. Sci. Technol. Lett.* 6 (8) 467-472. 10.1021/acs.estlett.9b00393
441 Hagler, G.S.W., Williams, R., Papapostolou, V., Polidori, A. (2018) Air Quality Sensors and
442 Data Adjustment Algorithms: When Is It No Longer a Measurement? *Environ. Sci.*
443 *Technol.* 52, 10, 5530–5531. https://doi.org/10.1021/acs.est.8b01826
444 Jayaratne, R., Liu, X., Thai, P., Dunbabin, M., Morawska, L. (2018) The influence of humidity
445 on the performance of a low-cost air particle mass sensor and the effect of atmospheric
446 fog. *Atmos. Meas. Tech.*, 11, 4883–4890. https://doi.org/10.5194/amt-11-4883-2018
447 Kushawaha, M., Sreekanth, V., Upadhya, A.R., Agrawal, P., Apte, J.S., Marshall, J.D. (2022) Bias
448 in PM2.5 measurements using collocated reference-grade and optical instruments. *Environ.*
449 *Monit. Assess.* 194:610. https://doi.org/10.1007/s10661-022-10293-4
450 Lahiri, T.; Roy, S.; Ganguly, S.; Ray, M.R.; Lahiri, P. (2000) Air pollution in Calcutta elicits
451 adverse pulmonary reaction in children. *Ind. J. Med. Res.* 112, 21–26.
452 Malings, C.; Tanzer, R.; Hauryliuk, A.; Saha, P. K.; Robinson, A. L.; Presto, A. A.; Subramanian,
453 R. (2020) Fine particle mass monitoring with low-cost sensors: Corrections and long-term
454 performance evaluation. *Aerosol Sci. Technol.*, 54:2, 160-174,
455 https://doi.org/10.1080/02786826.2019.1623863
456 Mallik, C., Ghosh, D., Ghosh, D., Sarkar, U., Lal, S., Venkataramani, S. (2014) Variability of
457 SO_2, CO, and light hydrocarbons over a megacity in Eastern India: effects of emissions

and transport. *Environ. Sci. Pollut. Res.* 21, 8692–8706. https://doi.org/10.1007/s11356-014-2795-x

McFarlane, C., Isevulambire, P.K., Lumbuenamo ,R.S., Dhammapala, R., Jin, X., McNeill, V.F., Malings, C., Subramanian, R., Westervelt, D.M. (2021a) First ambient measurements of $PM_{2.5}$ in Kinshasa, Democratic Republic of Congo and Brazzaville, Republic of Congo using field-calibrated low cost sensors, *Aerosol Air Qual. Res.* 21 (7) 200619. https://doi.org/10.4209/aaqr.200619

McFarlane,C., Raheja, G., Malings C., Appoh, E.K.E., Hughes A.F., Westervelt, D.M. (2021b) Application of Gaussian Mixture Regression for the Correction of Low Cost $PM_{2.5}$ Monitoring Data in Accra, Ghana *ACS Earth Space Chem.* 5 (9) 2268-2279. https://doi.org/10.1021/acsearthspacechem.1c00217

McNeill, V.F. (2019) Addressing the Global Air Pollution Crisis: Chemistry's Role. *Trends Chem*. 1 (1), 5-8. https://doi.org/10.1016/J.TRECHM.2019.01.005

McNeill, V.F. and Nunes, J.F. (2017) "India's Air Pollution Crisis: By the Numbers," *Huffpost India*, October 26, 2017 https://www.huffpost.com/archive/in/entry/indias-air-pollution-crisis-by-the-numbers_in_5c12c6c3e4b0d73db4b48126

Müller, A. and Guido, S. (2017) *Introduction to Machine Learning with Python: A Guide for Data Scientists*. O'Reilly.

Pinder. R.W., Klopp, J.M., Kleiman, G., Hagler, G.S.W., Awe, Y., Terry, S. (2019) Opportunities and challenges for filling the air quality data gap in low- and middle-income countries. *Atmos. Environ.* 215, 116794. https://doi.org/10.1016/j.atmosenv.2019.06.032

Raheja, G., Sabi, K., Sonla, H., Gbedjangni, E.K., McFarlane, C.M., Hodoli C.G.,Westervelt, D.M. (2022) A Network of Field-Calibrated Low-Cost Sensor Measurements of $PM_{2.5}$ in

Lomé, Togo. *ACS Earth Space Chem.* 6(4) 1011-1021. https://doi.org/10.1021/acsearthspacechem.1c00391

Roy S, Ray MR, Basu C, Lahiri P, Lahiri T. (2001) Abundance of siderophages in sputum: indicator of an adverse lung reaction to air pollution. *Acta Cytol.* Nov-Dec; 45 (6), 958-964. https://doi.org/10.1159/000328371

Sethuraman S., Das Y., McNeill, V.F. (2021) "INDIA'S AIR POLLUTION BY THE NUMBERS: 2019–2020 ANALYSIS" *Medium*, October 8, 2021 https://aqtoolbox.medium.com/indias-air-pollution-by-the-numbers-2019-2020-analysis-7d1082316305

WBPCB (2018) CAAQM Technical Specifications https://www.wbpcb.gov.in/writereaddata/files/Bid_CAAQMTechnicalBid2018_5.pdf

World Bank (2021) ESMAP IMPACT report "INDIA: TRANSITION TO ELECTRIC VEHICLES PUTS KOLKATA ON THE ROAD TO CLEAN TRANSPORT" https://documents1.worldbank.org/curated/en/479341609914443074/pdf/India-Transition-to-Electric-Vehicles-Puts-Kolkata-on-the-Road-to-Clean-Transport.pdf

WHO, 2021. Ambient (outdoor) air pollution. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (Accessed on December 19, 2022)

Zheng, T., Bergin, M.H., Johnson, K.K., Tripathi, S.N., Shirodkar, S., Landis, M.S., Sutaria, R. Carlson, D.E. (2018) Field evaluation of low-cost particulate matter sensors in high- and low-concentration environments *Atmos. Meas. Tech.*, 11, 4823–4846. https://doi.org/10.5194/amt-11-4823-2018

Zimmerman, N., Presto, A.A., Kumar, S.P.N., Gu, J. Hauryliuk, A., Robinson, E.S., Robinson, A.S., Subramanian, R. (2018) A Machine Learning Calibration Model Using Random

Forests to Improve Sensor Performance for Lower-Cost Air Quality Monitoring. *Atmos. Meas. Tech.* 11, 291-313. https://doi.org/10.5194/amt-11-291-2018