Environ Monit Assess (2023) 195:845
https://doi.org/10.1007/s10661-023-11438-9

RESEARCH

Performance-based protocol for selection of economical portable sensor for air quality measurement

Nidhi Shukla · Sunil Gulia · Prachi Goyal · Swagata Dey · Parthaa Bosu · S. K. Goyal

Received: 23 October 2022 / Accepted: 1 June 2023

Abstract An effective micro-level air quality management plan requires high-resolution monitoring of pollutants. India has already developed a vast network of air quality monitoring stations, both manual and real time, located primarily in urban areas, including megacities. The air quality monitoring network consists of conventional manual stations and real time Continuous Ambient Air Quality Monitoring Stations (CAAQMS) which comprise state-of-the-art analysers and instruments. India is currently in the early stages of developing and adopting economical portable sensor (EPS) in air quality monitoring systems. Protocols need to be established for field calibration and testing. The present research work is an attempt to develop a performance-based assessment framework for the selection of EPS for air quality monitoring. The two-stage selection protocol includes a review of the factory calibration data and a comparison of EPS data with a reference monitor, i.e. a portable calibrated monitor and a CAAQMS. Methods deployed include calculation of central tendency, dispersion around a central value, calculation of statistical parameters for data comparison, and plotting pollution rose and diurnal profile (peak and non-peak pollution measurement). Four commercially available EPS were tested blind, out of which, data from EPS 2 (S2) and EPS 3 (S3) were closer to reference stations at both locations. The selection was made by evaluating monitoring results, physical features, measurement range, and frequency along with examining capital cost. This proposed approach can be used to increase the usability of EPS in the development of micro-level air quality management strategies, other than regulatory compliance. For regulatory compliance, additional research is needed, including field calibration and evaluating EPS performance through additional variables. This proposed framework may be used as starting point, for such experiments, in order to develop confidence in the use of EPS.

Keywords Air quality monitoring protocol · Economical portable sensor (EPS) · Reference monitor · Field calibration · Collocation

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10661-023-11438-9.

N. Shukla · S. Gulia (✉) · P. Goyal · S. K. Goyal
Delhi Zonal Centre, CSIR-National Environmental Engineering Research Institute, Naraina, New Delhi 110028, India
e-mail: s_gulia@neeri.res.in

S. Dey · P. Bosu
Environmental Defense Fund, New Delhi, India

Introduction

A comprehensive air quality monitoring network is an essential component of any air quality management plan. In India, the national ambient air quality monitoring (NAMP) network has grown significantly

Published online: 15 June 2023

in the past few decades. There are about 800 manual and 376 continuous ambient air quality monitoring stations (CAAQMS) (Gulia et al., 2022). In addition, state governments have deployed manual stations. The regulators use these CAAQMS for compliance monitoring with national ambient air quality standards (NAAQS) and the status of air quality of a particular area in the form of an air quality index (AQI). Urban areas with higher population density and associated activities are responsible for high spatio-temporal variations in air pollution level which leads to the formation of hotspots (Goyal et al., 2021). It would be very tedious and highly expansive to monitor these spatial variations using CAAQMS networks (Leung, 2015). Therefore, it is essential to supplement the current CAAQMS network with economical portable sensors (EPSs). The EPS could be utilised only for air quality assessment at the micro level and monitored data to be used for air quality management aspect and evaluation of the effectiveness of implemented control actions.

In the recent past, numerous techniques for air quality monitoring, including manual, continuous, satellite, and low-cost sensors (EPSs) or can be called economical portable sensor (EPS), have been used in air quality research and management in India (Dey et al., 2020; Gulia et al., 2022). Each of these techniques comes with its own challenges, including investment and operational cost, logistics, maintenance, and expertise (Liu et al., 2021). Considering all these challenges, Indian air quality research communities are now identifying cost-effective monitoring methods, which has led to an increase in the adoption of EPS-based monitoring. The National Clean Air Programme (NCAP) of India has also identified the significance and utility of EPS for air quality (MoEF&CC, 2019). Researchers in the past have found a very high correlation between data from EPS and calibrated regulatory grade reference monitors (Gulia et al., 2020; Zheng et al., 2018).

EPS are very sensitive to environmental conditions like temperature, humidity, wind speed, and pollutant concentration (Zoest et al., 2019). Therefore, calibration is recommended at all stages of development and operation, and relying only on factory calibration is not enough for field deployment (Kureshi et al., 2022). There are numerous methods reported for the calibration of EPS under different conditions, including in-lab, with regulatory-grade instruments and modern data-driven machine-learning techniques (Spinelle et al., 2017; Zimmerman et al., 2018). EPS calibration in a laboratory is a controlled environment assessment (Levy Zamora et al., 2019). Researchers have also compared the EPS data with reference grade stations in the ambient environment (Gulia et al., 2020). In the machine learning (ML)-based calibration of EPS output, a data-driven calibration algorithm is developed which correlates the raw output of the EPS as accurately as possible to the measurements from the reference monitor (deSouza et al., 2022; Patra et al., 2021). Therefore, it is desired that every EPS-based monitoring device should be calibrated in field conditions, to accommodate environmental impacts, before its application for management practices (Gonzalez et al., 2019).

Presently, there is neither any approved indigenous EPS nor a regulation for the use of EPS-based air quality monitoring in India, a tropical climatic country. Researchers have adopted different methodologies for the evaluation of EPS performance for air quality monitoring (Chu et al., 2020; Wang et al., 2019). These studies have adopted different performance evaluation methods, which add to the ambiguity to test the accuracy of EPS for field application (Narayana et al., 2022), which has totally different environmental conditions. It is also important that sensors are very sensitive to environmental meteorological conditions which are not uniform throughout the world even within a country and vary from season to season. So, the performance evaluation approach should also be location specific considering the environmental condition.

Considering the above ambiguity in the field calibration and application of EPS in air quality management for Indian cities, the paper attempts to present a robust methodology for the selection of the EPS in air quality monitoring by assessing their performance based on (i) factory calibration (review of different sensors) and (ii) comparison with other calibrated monitors in the outdoor environment with different time resolution data. The purpose of this study is to provide a protocol for the performance assessment framework of EPS, which could increase the application of these EPS for air quality monitoring at the micro level and used for air quality management while using CAAQMS for compliance monitoring. The protocol is developed using EPS of $PM_{2.5}$ which is one of the critical pollutants in Indian cities (Singh et al., 2021) with the aim of offering affordable $PM_{2.5}$ monitors that could be used for assessment of micro-level air quality variation for hotspots in major metropolises.

Methodology

EPS has gained traction amongst researchers and regulators for monitoring and management of local air quality. Therefore, a comprehensive state-of-the-art method for using EPS for air quality monitoring and management is required for Indian conditions. This section describes the stages involved in the development of the framework for EPS performance and assessment. Initially, several EPS available in the Indian market were reviewed for techno-commercial parameters, and four were selected based on the requirements and specifications provided. Thereafter, $PM_{2.5}$ sensors having satisfactory performance based on factory calibration were considered for further comparison in field conditions in an outdoor environment.

Study area

This research was carried out at two locations in Delhi, a city known for its high air pollution levels during the winter season due to unfavourable meteorology and regional air pollution from mid-Oct. to Nov. For this work, four affordable cost sensors, Sensor 1 (S1), Sensor 2 (S2), Sensor 3 (S3), and Sensor 4 (S4), were procured from four different manufacturers and tested blind. These four brands were chosen based on cost, and parameters such as concentration range, accuracy, data management practices, sensitivity, and weight. In the first stage, these sensors were deployed at the terrace of the research institute in the Naraina Industrial area (Central Delhi), wherein the data was compared with a calibrated portable reference grade instrument. In a later stage, these sensors were collocated with CAAQMS at an academic institute in Northwest Delhi. The sites are depicted in Fig. 1. In the initial stage, EPSs were collocated with Laser Aerosol Spectrometer, GRIMM (Reference Monitor 1 (RM1)) at a research institute in Naraina. These EPSs were placed on the rooftop of this institute from September 24th, 2021, to October 8th, 2021, to assess their performance with RM1 in

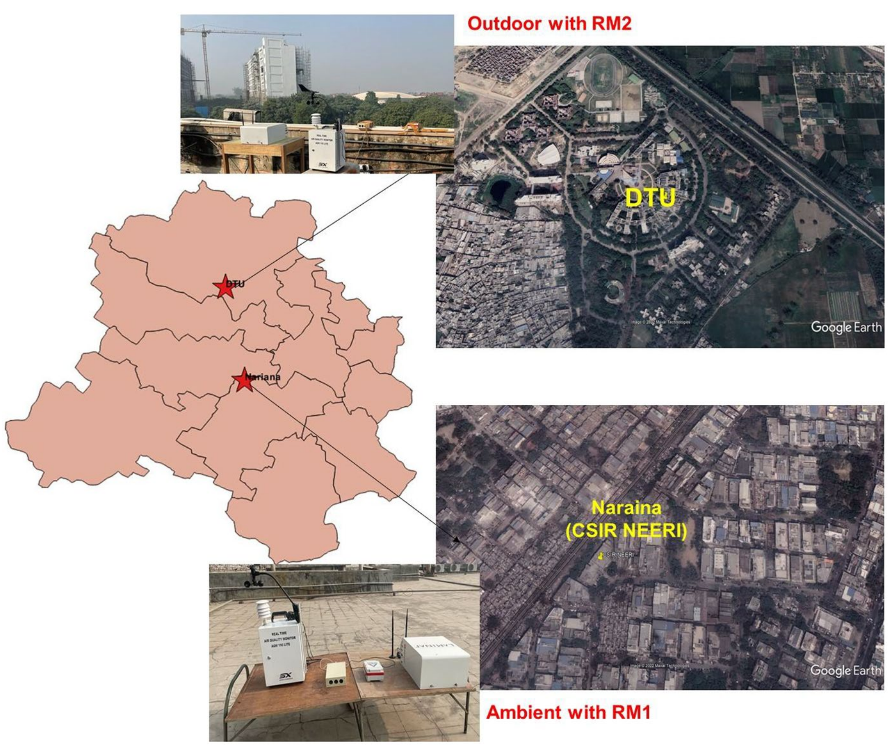


Fig. 1 Locations and photographs of sensors for co-location study; GRIMM (Reference Monitor 1 (RM1)) and CAAQMS (Reference Monitor 2 (RM2))

an ambient environment. At a later stage, these EPSs were collocated with a regulatory monitor, CAAQMS (Reference Monitor 2 (RM2)), at an academic institution. This step was planned to assess the EPS performance and inter-variability between sensors and regulatory instrument in the monitoring of $PM_{2.5}$ concentrations during a high pollution period, i.e. November 18–25, 2021. The overall air quality of Delhi as per the National Air Quality Index (https://cpcb.nic.in/National-Air-Quality-Index/) during the period of RM1 monitoring was in the Satisfactory to Moderate category ($PM_{2.5}$ concentration range 31–90), while during RM2 monitoring, it was in the range of Poor to Very Poor category ($PM_{2.5}$ concentration range 90–250). Both the selected locations have major micro-level activities causing air pollution. Therefore, any substantial variation in air quality during the monitoring period was attributed to regional emissions and changes in meteorology. Both the study period were also compared in terms of meteorological parameters and given in Table S1 in the supplementary information.

Criteria for selection of EPS

Table 1 provides the specifications of the four sensors used for the study. The selection process considered ease of use, i.e. physical size, weight, cost, accuracy and suitability of operational conditions, drift, measurement range, and frequency of measurement (Concas et al., 2021; Narayana et al., 2022). Many studies have discussed these features and their respective pros and cons. For instance, a compact instrument will always be considered better than a large and heavy instrument due to its ease of operation (Clements et al., 2017; Li et al., 2020); accuracy, which is the closeness of observed value to the value of reference measurement, so a high accuracy instrument is better (Nguyen et al., 2021); and suitability of operational conditions and requirements, i.e. a sensor with fluctuating values in high-temperature conditions may not be suitable for field monitoring during summers especially in tropical countries (Zheng et al., 2018).

The protocol adopted to assess the performance and selection of EPSs is illustrated in Fig. 2. The manufacturers are aware of the importance of the calibration of EPSs for reliable data generation. Hence, they use different techniques for the calibration of these EPSs before the sale. The performance of these EPSs may vary considerably due to external influences which necessitate the field calibration of EPSs through collocation studies and data-driven methods for improving the accuracy of these units (Concas et al., 2021). The present study has used two types of reference monitors for collocation: first, a portable reference monitor (laser aerosol spectrometer), usually employed for reliable measurement of real-time outdoor and indoor air quality (Grimm 11-R monitor) (GRIMM, 2022), and second, a continuous ambient air quality

Table 1 Comparison of different make economical portable sensor (EPS) for $PM_{2.5}$

Sr. no	Specifications	S1	S2	S3	S4
1	Principle/technology	Light scattering	Laser scattering	Laser scattering	Light scattering
2	Operative at Indian conditions (temp: 0–50 °C; RH: 10–95%)	Yes	Yes	Yes	Yes
3	Accuracy	Good	Good	High	Good
4	Sensitivity	No	No	No	No
5	Error/drift	-	-	< 3.0% change/year	-
6	Calibration requirements	Yearly	Yearly	Yearly	Yearly
7	Size including cover box	$54 \times 38 \times 22$ cm^3	$24 \times 16 \times 9$ cm^3	$14 \times 4.5 \times 19.5$ cm^3	$45 \times 30 \times 20$ cm^3
8	Weight of the device	9.6 kg	1 kg	1.5 kg	6 kg
9	Measurement range (μg/m^3)	0–1500	0–1000	1–2000	0–700
10	Measurement frequency	1 min	40 s	30 s	5 min
11	Capital cost (INR/unit)*	255,000	31,000	95,000	65,000
12	Power requirements, volts	230	230	220	220

Parameters from Sr no. 7–11 are comparable and used in the ranking of the EPSs; *cost at the time of the procurement, i.e. year 2021

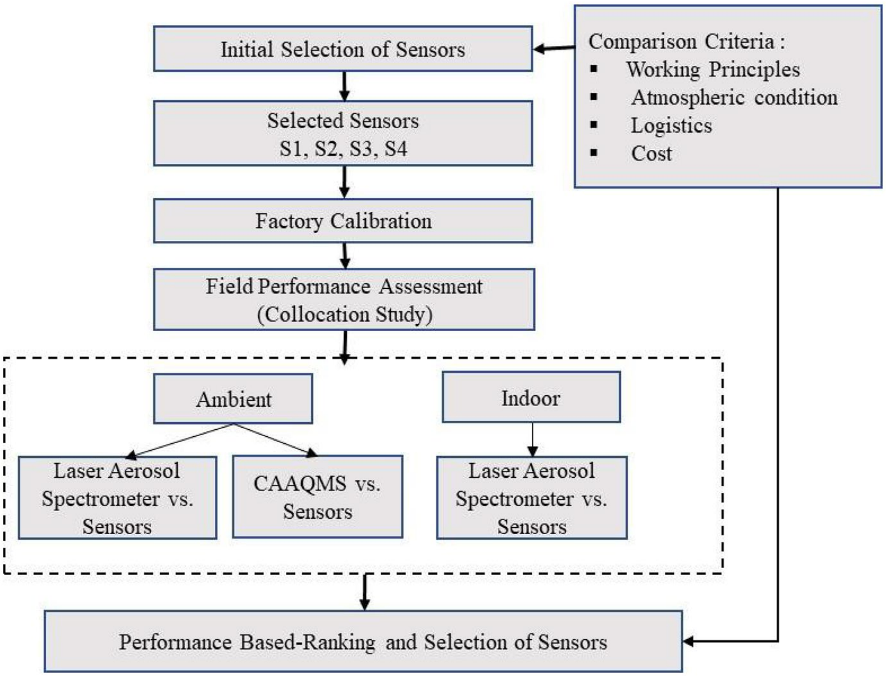


Fig. 2 Methodology adopted to assess the performance and selection of EPSs

monitors used as a regulatory monitor (CAAQMS) used by national policymakers. In these regulatory grade monitors, instruments used for PM are usually beta attenuation monitors (BAM). GRIMM is a portable aerosol spectrometer which is commonly used as a reference monitor in various studies for comparing the performance of different air quality monitoring instruments (Hegde et al., 2020; Kelly et al., 2017). It operates on the principle of light scattering at individual particles and has no border zone error, a time resolution of 6 s, and a volume flow rate of 1.2 L/m ± 3% (Gulia et al., 2020). On the other hand, BAM works on the principle of the beta ray attenuation method. Both these instruments have well-defined quality assurance and quality control protocols. The QA/QC protocol of BAM-based CAAQMS is carried out as per guidelines specified by CPCB, which requires operators to perform a weekly calibration process for simultaneous mass and flow rate checks (CPCB, 2013; Goyal et al., 2021). Mukherjee et al. (2017) also used GRIMM 11-R optical particle counter, and the Met One beta attenuation monitor (BAM) for validation of the EPS application in Cuyama Valley of California.

Results and discussion

The ease of operation along with the cost of EPSs was the first criteria used to rank the EPSs after initial selection for monitoring. Considering the manufacturers' assurances that these EPSs are well calibrated, the data collected through EPSs was not pre-processed and continuous original raw data was used for comparison with reference monitors. This "as is" comparison of raw data was important as we were selecting EPSs from commercial varieties. The EPSs' and reference grade monitor's data were statistically analysed and compared using descriptive statistics, performance measurement parameters, and assessment of pollutant loads based on wind profile and diurnal variations. These EPSs were ranked from 1 to 4, with 1 being the most suitable and 4 being the least suitable. Furthermore, these were marked with green and red colours, respectively.

Suitability based on physical features and cost

EPSs were ranked, for each parameter, but preference was given to lighter weight, compact size, higher measurement range, and time resolution.

Table 2 Ranking of EPSs based on physical features and cost.

Sr. No.	Parameters	*Criteria for Prioritization*	*S1*	*S2*	*S3*	*S4*
1	Dimension	Preference given to Compact and small size device	4	2	1	3
2	Weight of device	Low weight device can easily fit at site or a pole	4	1	2	3
3	Measurement Range	Higher range give first preference	2	3	1	4
4	Measurement Frequency	High time resolution gives first preference	3	2	1	4
5	Cost	Low cost is given first preference	4	1	3	2
Total*			**17**	**9**	**8**	**16**

*EPS having lowest total is performing more satisfactorily

Additionally, preference was given to the EPS with the lowest capital cost. Table 2 depicts the ranking of all four selected EPSs based on physical features, measurement range, frequency, and cost. The analysis indicates S3 as the most suitable EPS followed by S2, S4, and S1.

Performance based on descriptive statistics

The performance of EPSs with respect to RM1 and RM2 was evaluated by calculating statistical descriptive analysis which is considered the first screening step of performance evaluation (Bauerová et al., 2020). The mean and median describe the central tendency (central value) of the data, whereas the standard deviation values describe the dispersion (range) of the data. The pattern of measurement has been compared with a lack of symmetry or tailedness, referred to as skewness and kurtosis, respectively (Srbinovska et al., 2021). Thus, EPSs' and reference monitors' data were analysed and compared using kurtosis and skewness values. The negative values for skewness means data is skewed left (i.e. large number of data points towards the lower percentile) and while a positive skewness means the distribution is rightly skewed (Liu et al., 2020). Kurtosis provides details on the central peak height and sharpness in relation to a typical bell curve for normal distribution; the kurtosis for normally distributed data is 3 (Prieto & Cremasco, 2017).

At Location 1 (Naraina, Central Delhi)

Raw data from the EPSs and RM1 monitor was converted to 5-min averages for this analysis. Figure 3 shows the time series plot of 5-min average $PM_{2.5}$ concentration measured by all four EPSs and RM1. This showed that the overall trends of all EPSs broadly matched with that of RM1. For this, a sample size of 308 values was considered for analysis. The missing hours (only for S1) were not considered for the analysis. All four EPSs measured lower concentration (mean) compared to RM1. The recorded mean and standard deviation for $PM_{2.5}$ concentrations were 73 ± 29.8 μg/m^3 for RM1 and 38 ± 17.7 μg/m^3, 48 ± 14.2 μg/m^3, 29 ± 13.2 μg/m^3, and 30 ± 13.4 μg/m^3 for S1, S2, S3, and S4, respectively. The value of kurtosis for RM1 was found to be 0.6 while it was 7.4

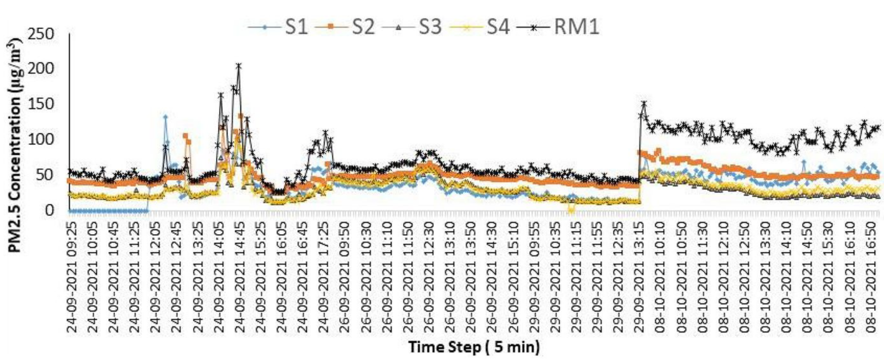


Fig. 3 Time series plot of 5-min average $PM_{2.5}$ concentration measured by four EPSs and RM1

for S1, 2.7 for S1, 3.2 for S4, and 2.6 for S3 (closest to RM1). The skewness values depict that three EPSs (S1, S3, and S4) are moderately skewed while S2 is highly right-skewed (skewness > 2). The value for the skewness of RM1 is close to S1 followed by S3, S4, and S1. Table 3 provides the EPSs' descriptive statistics with a portable reference monitor (RM1) and reference station 2 (RM2).

Location 2 (DTU, Northwest Delhi)

RM2 provides data continuously throughout the day, at a resolution of 15 min. In order to compare the data, the pollutant concentration values were converted to a 1 h average for all EPSs and RM2. Figure 4 shows the time series plot of the hourly average $PM_{2.5}$ concentration measured by all four EPSs and RM2. It is indicated that patterns of most of the EPSs matched reasonably well with RM2 except S1. The recorded mean and standard deviation for $PM_{2.5}$ concentration was 231 ± 88.2 μg/m^3 for RM2 and was 83 ± 45.0 μg/m^3, 262 ± 106.5 μg/m^3, 284 ± 154.0 μg/m^3, and 326 ± 163.8 μg/m^3 for S1, S2, S3, and S4, respectively. Based on this, the S2 and S3 EPS values are closer to RM2 instead of S1 and S4. The kurtosis is highly deviated from 3, i.e. more than 3 for S1 and less than 3 for rest. The kurtosis values of S2 and S4 are closer to RM2 values. Furthermore, S1 has higher skewness in comparison with S2, S3, and S4 and is close to RM2.

Considering the above results, it can be inferred that the overall performance of S2 and S3 was observed to be closer to the reference monitors, as compared to EPS 1 and 4. It was also observed that EPSs show variable performance under different environmental conditions, i.e. Locations 1 and 2. Due to this variability, it is important to look into other aspects such as performance under seasonal and geographic variations. Additionally, the $PM_{2.5}$ concentration data monitored by ESPs and reference monitors were compared visually by plotting frequency histogram and box plots for both locations and provided as

Table 3 Descriptive statistics of outdoor $PM_{2.5}$ concentration measured by EPSs and reference monitor at Location 1 and Location 2

Sr. no	Parameter	Location 1					Location 2				
		S1	*S2*	*S3*	*S4*	*RM1*	*S1*	*S2*	*S3*	*S4*	*RM2*
1	Sample size (nos.)	*308*	*308*	*308*	*308*	*308*	192	192	192	192	192
2	Missing hours (nos.)	*30*	*0*	*0*	*1*	*0*	*2*	*2*	*26*	*0*	*6*
3	Actual sample size (nos.)	278	308	308	307	308	190	190	166	192	186
4	Mean (μg/m^3)	38	48	29	31	73	83	262	284	326	231
5	Median (μg/m^3)	37	46	26	28	60	71	247	236	284	228
6	Standard deviation (μg/m^3)	18	14	13	13	30	45.0	106	154	164	88
7	Kurtosis	3	7	3	3	0.6	5.4	−0.7	0.4	−0.3	−1.1
8	Skewness	1.0	2.1	1.3	1.3	0.9	1.9	0.3	0.9	0.7	0.01
9	Minimum (μg/m^3)	12	23	11	13	26	25.0	69.8	63	72	61
10	Maximum (μg/m^3)	132	132	99	98	204	293	516	793	797	417

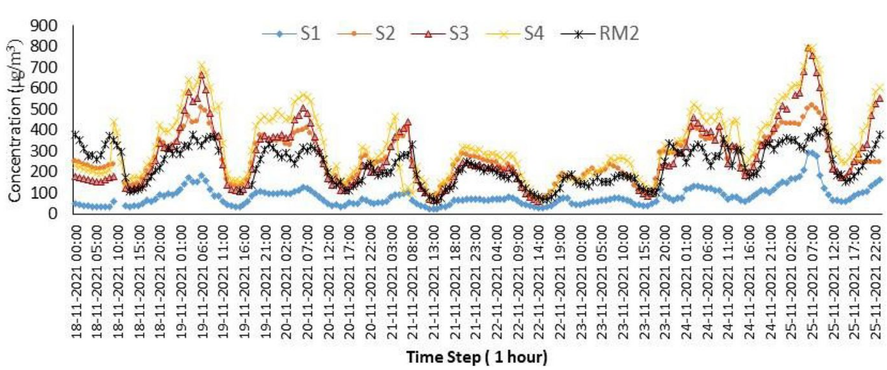


Fig. 4 Time series plot of 1 h average $PM_{2.5}$ concentration measured by four EPSs and RM2

part of supplementary information (SI) as Fig.S1 and Fig. S2 for Location 1 and Location 2, respectively. The plot clearly shows that the distribution patterns of monitored data by S2 are matching with patterns of reference monitors at both locations.

Performance based on linear regression analysis

The linear regression method ($y \sim x$) was used to model the relationship between EPSs and reference instruments for both sites. The coefficient of determination ($0 \leq r^2 \leq 1$) was used to evaluate the performance of a EPS with respect to the reference monitor. The linear regression method has already been used in various studies for EPS performance and assessment (Bittner et al., 2022). Figures 5 and 6 depict the association between the EPS' monitored data and reference monitors wherein the high and low represents the concentration of $PM_{2.5}$, respectively. The same data has been considered in the descriptive statistics. At Location 1, the r^2 values varied between 0.28 and 0.64 and were highest for S1, followed by S2, S4, and S3; however, the mean concentration of RM1 was close to S2 and S3, although it seems all the EPSs underestimated the mean value. The r^2 values varied between 0.45 and 0.69 with the highest values for S2, at Location 2. However, past studies have reported that the values for r^2 are not enough to conclude on the performance assessment of EPSs (Giordano et al., 2021; Karagulian et al., 2019).

Evaluation based on performance evaluation matrices

In order to corroborate the findings of descriptive statistics and coefficient values, other statistical parameters were also calculated for an overall ranking of the

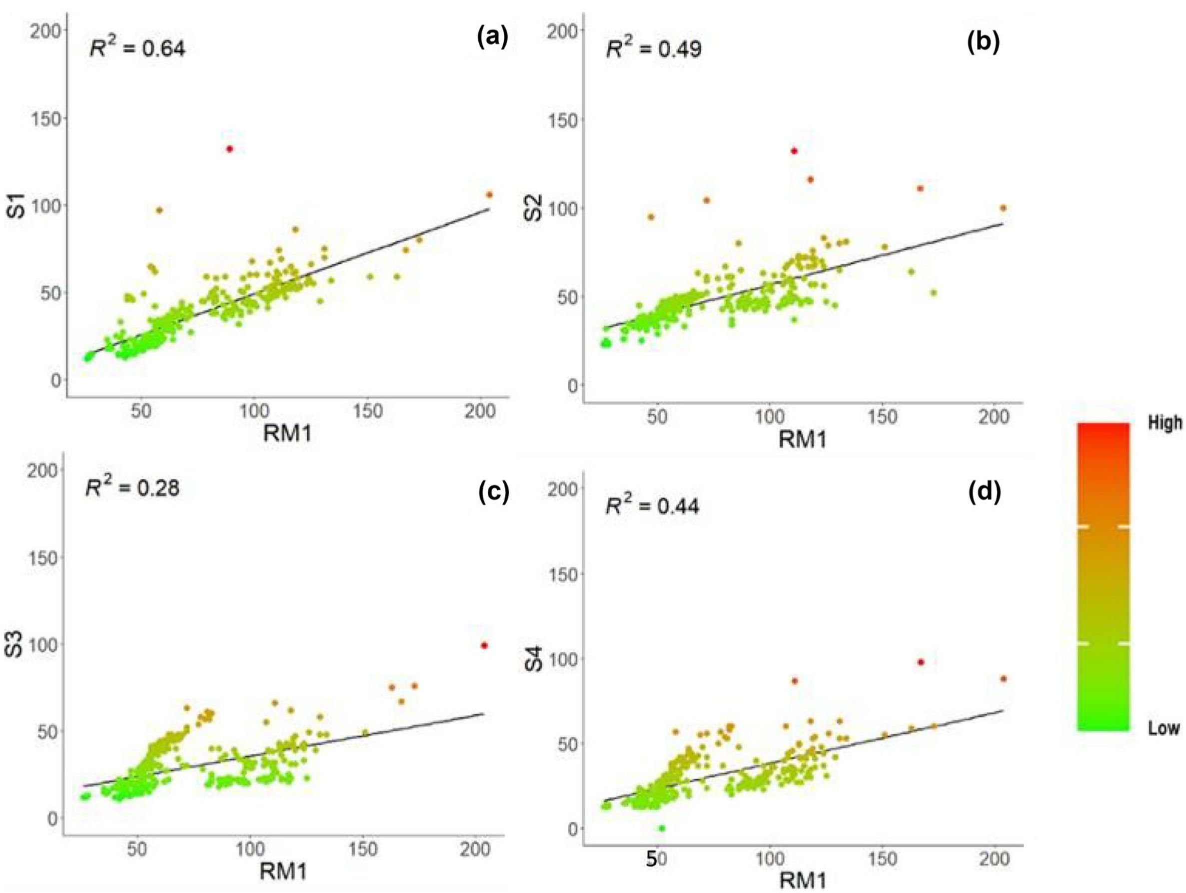


Fig. 5 Regression plot For EPSs with RM1 for $PM_{2.5}$ concentration (μg/m.^{3}) at Location 1 (**a** S1 vs RM1; **b** S2 vs RM1; **c** S3 vs RM1; **d** S4 vs RM1) (high and low means maximum and minimum $PM_{2.5}$ concentration)

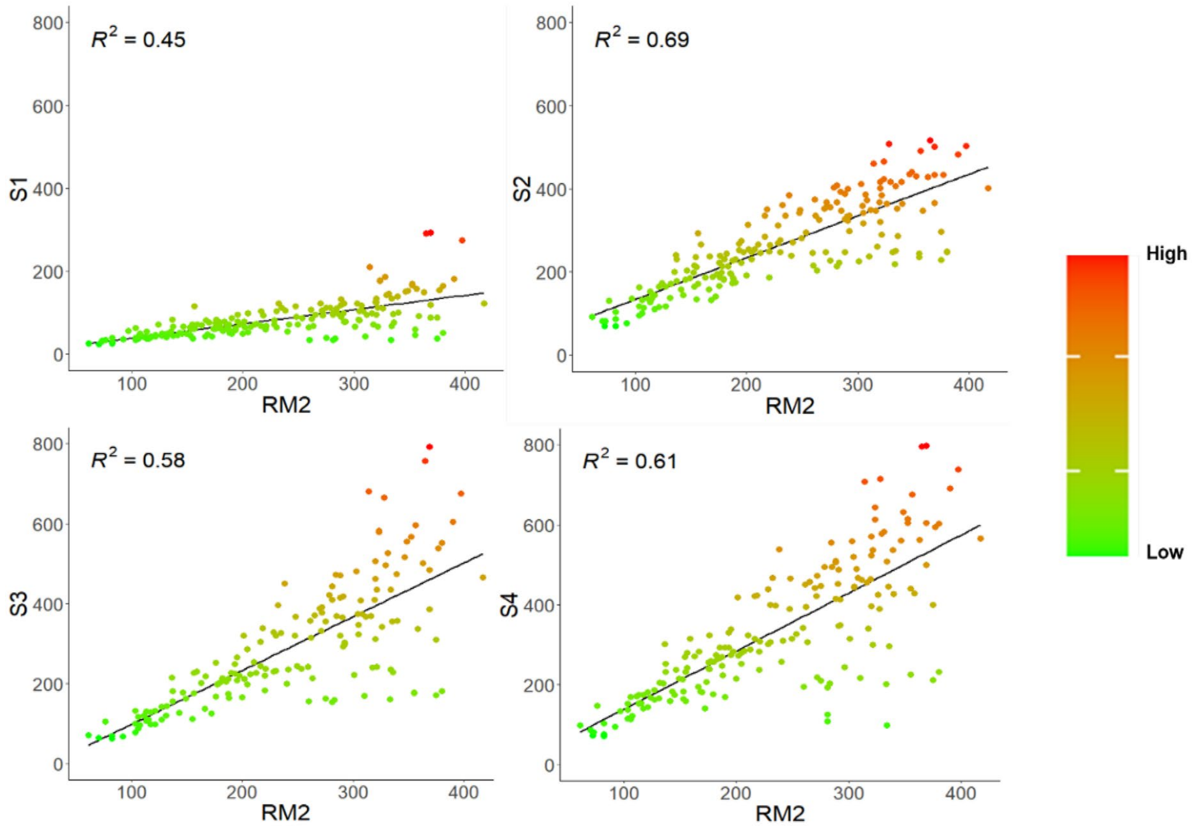


Fig. 6 Regression plot for EPSs with RM2 for $PM_{2.5}$ concentration (μg/m.[3]) at Location 2 (high and low means maximum and minimum $PM_{2.5}$ concentration)

performance of EPSs. These statistical descriptors are root mean square error (RMSE), normalise mean bias (NMB), normalise mean error (NME), fractional bias (FB), and mean absolute error (MAE), tabulated in Table 4. These are some of the most frequently used predictive performance metrics for the assessment of model performance (Chambliss et al., 2020; Simon et al., 2012). These parameters measured bias and error statistics metrics between two data sets, which measure the EPS's tendency to over- or under-measure as well as calculate the magnitude of the difference between values observed with the reference

Table 4 Statistical metric for assessment of EPS performance

Parameter	Range	Outdoor environment							
		EPSs vs RM1				EPSs vs. RM2			
		S1	S2	S3	S4	S1	S2	S3	S4
RMSE	0 to + ∞	299	**34**	51	73	190	**140**	282	160
NMB	− 1 to + ∞	0.79	**− 0.34**	− 0.54	− 0.6	− 0.19	0.017	**0.016**	0.08
NME	0 to + ∞	5.002	**1.03**	1.72	1.79	0.301	**0.14**	0.35	0.23
FB	+ 2 to − 2	− 0.44	**− 0.37**	− 0.84	− 0.81	− 0.59	**0.05**	0.14	0.15
FE	0 to 2	0.81	**0.38**	0.84	0.82	0.6	**0.16**	0.28	0.25
MAE	0 to + ∞	128	**26**	44	46	111	**54**	129	86

The bold value indicates higher performance for the respective parameter in comparison with other sensors monitor and EPS. The higher r^2 for the regression model presents the precision of the performance of the EPS with respect to the reference instrument (Badura et al., 2019). The statistical parameters like MSE, RMSE, and MAE indicate performance based on the EPS's average measurement (Giordano et al., 2021). High variability of RMSE was also observed in the case of all the EPSs both with RM1 and RM2. If the NMB is zero, then the EPS is assumed to be unbiased with respect to the reference monitor while negative or positive NMB implicates under or over estimation by the EPSs respectively. As per the assessment of the aforementioned performance parameters in Table 4, in the case outdoor environment at both Locations 1 and 2, S2 performed well, followed by S3 (close to S2) and S4.

Performance evaluation with respect to wind profile (pollutionrose analysis)

The EPSs' performance with respect to wind speed and direction was studied and compared by plotting the data in the form of pollutionrose. Pollutionrose is primarily used as a tool for source characterisation which provides information on the potential source influences at the receptor site. Pollutionrose plots of EPSs and reference monitors (RM1 and RM2) were developed for outdoor environments only and shown in Fig. 7.

The pollutionrose plot for $PM_{2.5}$ concentration in RM1 indicates that higher concentrations were mainly from the south-west and south-east of the air quality station wherein values for EPS 2 and 3 were observed to be similar with RM1. The pollution roses indicate that significant $PM_{2.5}$ sources for the monitoring site would be located in the south during the monitoring period. Similarly, in the case of RM2, the higher concentration was mainly from the south-west and south-east, and S2 and S3 were found to be similar to RM2.

Performance based on diurnal profile at Location 2

The hourly $PM_{2.5}$ concentration of RM2 ranged from 61 to 471 μg/m^3 whereas it ranged between 25–293, 70–516, 63–793, and 72–797 μg/m^3 for S1, S2, S3, and S4 respectively. The diurnal variation of EPSs and RM2 was assessed as depicted in Fig. 8. Based on the qualitative observation, the diurnal patterns of RM2 data broadly matched with S2 followed by S3, S4, and S1 which means the minimum difference between hourly patterns of RM2 and S2 in comparison of S3, S4, and S1. Although the recorded observations vary widely, the collocated EPSs presented an accurate variation of recorded values in terms of day and night profiles. As expected, it showed two peaks in the morning (07:00–10:00 am) and evening (06:00–08:00 pm). It was due to peak traffic hours during this period and lower mixing height during this time interval, in contrast with low traffic and high mixing height after 12:00 to 05:00 pm (Song et al., 2022).

Ranking for suitable EPSs for air quality assessment

A comparative analysis of each EPS's performance was conducted to obtain the best-performing EPS during the observation period and at the specified study location. Table 5 provides the overall ranking of EPSs based on the statistical results and physical features, measurement range and frequency along with cost. The EPSs were ranked from 1st to 4th based on the difference between obtained and ideal values for all the parameters. All the ranks and scores are summarised to deduce the final ranking for their suitability at Locations 1 and 2. The ranking as described in Table 2 is added at both locations to get the final ranking. Therefore, the final ranking of EPSs based on physical features, cost, and statistical analysis S2 performed better over other EPSs. Considering the findings from both locations, it is inferred that S2 and S3 are the most preferable EPSs suitable for air quality assessment. Ideally, EPS whose monitored data is close to reference monitor data with reasonable cost and is easily deployable at study sites should be considered for air quality assessment.

Conclusion

Robust monitoring is the key to any effective air quality management plan. These now need to be augmented with new generation cost-effective monitoring technologies like EPS. Considering the purpose of this study, where it aims to introduce the EPS for air quality monitoring at the micro level (hotspots), there is a need to develop such performance assessment protocols to increase the reliability of the EPS

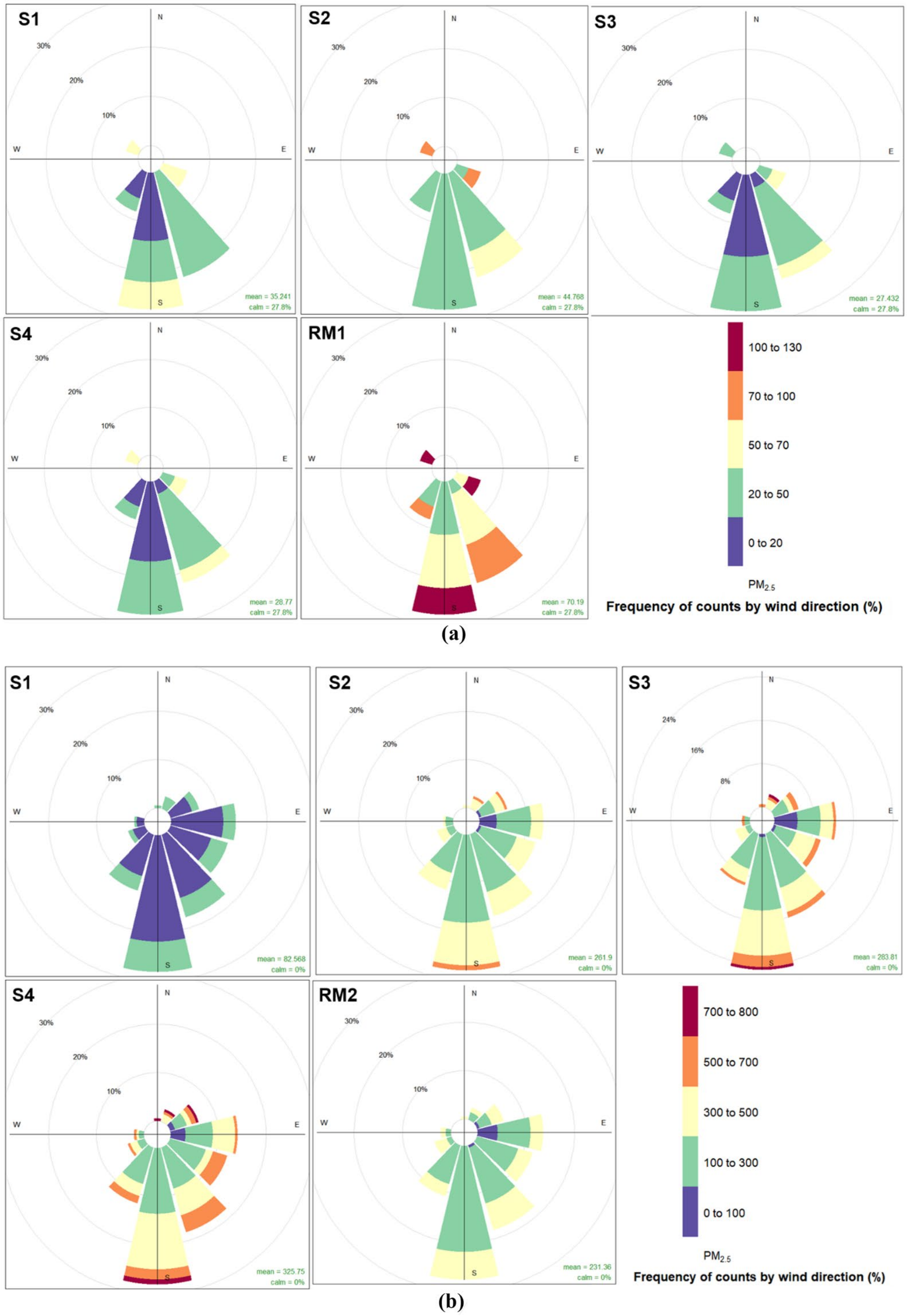
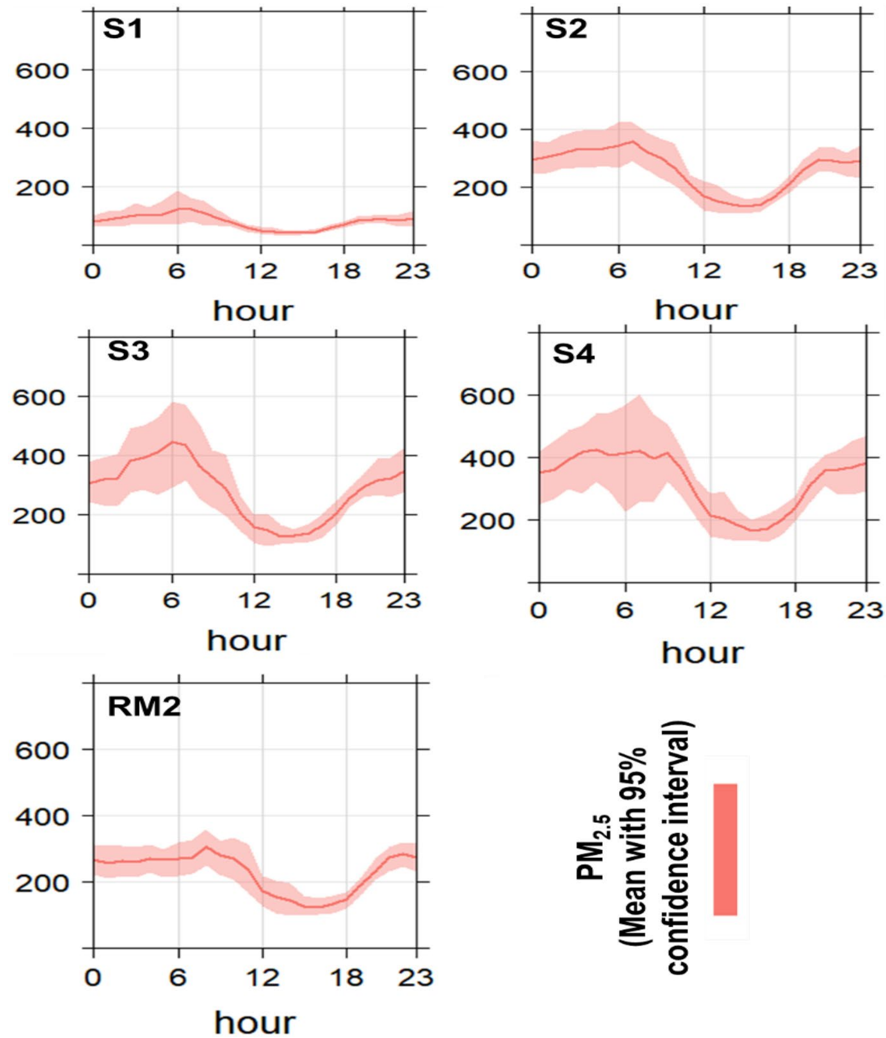


Fig. 7 Pollution plot for EPSs for RM1 (**a**) and RM2 (**b**) with EPSs

Fig. 8 Diurnal variation of EPSs and real time monitor (RM2)



for air quality management. This needs consistent research towards better technology, laboratory, and field-based pilot studies in different work environments, i.e. indoor and outdoor micro-environments, and consideration of seasonal variations and other similar themes.

The present study is an effort towards the development of a protocol for the selection of EPS-based monitors for air quality assessment, based on physical attributes, measurement range, cost, accuracy, and robustness in measurement. Data from each EPS and reference grade monitor were compared statistically by computing central tendency, dispersion measures, and bias measurement parameters and by plotting diurnal profiles (peak and non-peak pollution measurement). Subsequently, the EPS were ranked on the basis of performance for different statistical assessments. Based on the above performance data, each EPS was ranked.

The proposed methodology can be followed for the selection of an EPS-based monitor to measure pollution levels and track air pollution. Furthermore, future research should focus on field testing and calibration and sensitivity analysis of EPS in different pollution loads and climatic conditions before accepting them for regulatory and compliance monitoring. This approach is a useful starting point for future research studies like seasonal variations in air pollution level, long-term annual average, variance evaluation in polluted and non-polluted environments, and so on. The EPS have the potential to capture micro-level variations in air

Table 5 Ranking and selection of EPSs for based on performance assessment

Parameters	Location 1				Location 2			
	S1	*S2*	*S3*	*S4*	*S1*	*S2*	*S3*	*S4*
a. Central Tendency								
Mean	2	1	4	3	3	1	2	4
Median	2	1	4	3	4	1	2	3
b. Dispersion of data								
Standard Deviation	1	2	4	3	3	1	2	4
Kurtosis	2	4	1	3	4	1	2	3
Skewness	1	4	2	3	4	1	3	2
Minimum	3	1	4	2	4	2	1	3
Maximum	1	2	3	4	4	1	2	3
c. Other Statistical Parameters for Comparative Analysis								
R^2	1	2	4	3	4	1	3	2
RMSE	4	1	2	3	3	1	4	2
NMB	4	1	2	3	4	2	1	3
NME	4	1	2	3	4	1	3	2
FB	2	1	4	3	4	1	2	3
MAE	4	1	2	3	2	1	4	2
Pollution Rose	2	1	3	4	4	1	2	3
Diurnal Profile	-	-	-	-	4	1	2	3
d. Physical Parameters and Cost basis*								
Dimension	4	2	1	3	4	2	1	3
Weight of device	4	1	2	3	4	1	2	3
Measurement Range	2	3	1	4	2	3	1	4
Measurement Frequency	3	2	1	4	3	2	1	4
Cost	4	1	3	2	4	1	3	2
Total Score	**50**	**32**	**49**	**59**	**76**	**27**	**45**	**61**

ranking as per Table 2 is considered for both locations

pollution at an affordable cost, which are otherwise difficult to capture with ambient air quality stations. Due to their smaller size, these may be deployed for field studies to aid authorities in the identification of hotspots or priority problematic locations in a time-bound and efficient manner.

Acknowledgements Authors are acknowledging the Central Pollution Control Board for using air quality data of their station (available online in public domain) located at the Delhi Technological University (DTU) campus. The authors are also thankful to Dr Rajeev Mishra and his students at DTU for their logistical support during the monitoring period.

Author contribution Nidhi Shukla: writing—original draft, monitoring, and data analysis, Sunil Gulia: conceptualization, methodology, editing of the draft version, supervision. Prachi Goyal: critical review and corrections. Swagata Dey: critical review and monitoring support. Parthaa Bosu: review and supervision. S.K. Goyal: critical review, visualisation, and supervision.

Funding The present research work is part of the CSIR NEERI's ongoing project, financially supported by the Environment Defense Fund, NY, USA. The members of EDF are also the authors of this manuscript.

Data availability The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Conflict of interest The authors declare no competing interests.

References

Badura, M., Batog, P., Drzeniecka-Osiadacz, A., & Modzel, P. (2019). Regression methods in the calibration of low-cost sensors for ambient particulate matter measurements. *SN Applied Sciences, 1*(6), 1–11. https://doi.org/10.1007/s42452-019-0630-1

Bauerová, P., Šindelářová, A., Rychlík, Š., Novák, Z., & Keder, J. (2020). Low-cost air quality sensors: One-year field comparative measurement of different gas sensors and particle counters with reference monitors at Tušimice Observatory. *Atmosphere 11.5*(2020), 492. https://doi.org/10.3390/atmos11050492

Bittner, A. S., Cross, E. S., Hagan, D. H., Malings, C., Lipsky, E., & Grieshop, A. P. (2022). Performance characterization of low-cost air quality sensors for off-grid deployment in rural Malawi. *Atmospheric Measurement Techniques, 15*(11), 3353–3376. https://doi.org/10.5194/amt-15-3353-2022

Chambliss, S. E., Preble, C. V., Caubel, J. J., Cados, T., Messier, K. P., Alvarez, R. A., et al. (2020). Comparison of mobile and fixed-site black carbon measurements for high-resolution urban pollution mapping. *Environmental Science and Technology, 54*(13), 7848–7857. https://doi.org/10.1021/acs.est.0c01409

Chu, H. J., Ali, M. Z., & He, Y. C. (2020). Spatial calibration and PM2.5 mapping of low-cost air quality sensors. *Scientific Reports, 10*(1), 1–11. https://doi.org/10.1038/s41598-020-79064-w

Clements, A. L., Griswold, W. G., Abhijit, R. S., Johnston, J. E., Herting, M. M., Thorson, J., et al. (2017). Low-cost air quality monitoring tools: From research to practice (a workshop summary). *Sensors (switzerland), 17*(11), 1–20. https://doi.org/10.3390/s17112478

Concas, F., Lagerspetz, E., Varjonen, S., & Liu, X. (2021). Low-cost outdoor air quality monitoring and sensor calibration: A survey and critical analysis, (May). https://doi.org/10.1145/3446005

CPCB. (2013). Guidelines for real time sampling & analyses. *National Ambient Air Quality Series:NAAQMS/36/2012–13. Vol - II*. Central Pollution Control Board, Ministry of Environment, Forest and Climate Change. http://www.cpcb.nic.in

deSouza, P., Kahn, R., Stockman, T., Obermann, W., Crawford, B., Wang, A., et al. (2022). Calibrating networks of low-cost air quality sensors. *Atmospheric Measurement Techniques Discussions*, *2022*(March), 1–34. https://amt.copernicus.org/preprints/amt-2022-65/. Accessed 4 June 2022.

Dey, S., Purohit, B., Balyan, P., Dixit, K., Bali, K., Kumar, A., & Shukla, V. K. (2020). A satellite-based high-resolution (1-km) ambient PM2. 5 database for India over two decades (2000–2019): Applications for air quality management. *Remote Sensing, 12*(23), 3872. https://doi.org/10.3390/rs12233872

Giordano, M. R., Malings, C., Pandis, S. N., Presto, A. A., McNeill, V. F., Westervelt, D. M., et al. (2021). From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors. *Journal of Aerosol Science, 158*(January), 105833. https://doi.org/10.1016/j.jaerosci.2021.105833

Gonzalez, A., Boies, A., Swason, J., & Kittelson, D. (2019). Field calibration of low-cost air pollution sensors. *Atmospheric Measurement Techniques Discussions, 2050*(August), 1–17.

Goyal, P., Gulia, S., & Goyal, S. K. (2021). Identification of air pollution hotspots in urban areas - An innovative approach using monitored concentrations data. *Science of the Total Environment, 798*, 149143. https://doi.org/10.1016/j.scitotenv.2021.149143

GRIMM. (2022). 11-D. https://www.grimm-aerosol.com/products-en/environmental-dust-monitoring/handheld-pm-monitor/11-d/. Accessed 10 June 2022

Gulia, S., Prasad, P., Goyal, S. K., & Kumar, R. (2020). Sensor-based wireless air quality monitoring network (SWAQMN) - A smart tool for urban air quality management. *Atmospheric Pollution Research, 11*(9), 1588–1597. https://doi.org/10.1016/j.apr.2020.06.016

Gulia, S., Shukla, N., Padhi, L., Bosu, P., Goyal, S. K., & Kumar, R. (2022). Evolution of air pollution management policies and related research in India. *Environmental Challenges*, *6*(July 2021), 100431. https://doi.org/10.1016/j.envc.2021.100431.

Hegde, S., Min, K. T., Moore, J., Lundrigan, P., Patwari, N., Collingwood, S., et al. (2020). Indoor household particulate matter measurements using a network of low-cost sensors. *Aerosol and Air Quality Research, 20*(2), 381–394. https://doi.org/10.4209/aaqr.2019.01.0046

Karagulian, F., Barbiere, M., Kotsev, A., Spinelle, L., Gerboles, M., & Lagler, F., et al. (2019). Review of the performance of low-cost sensors for air quality monitoring. *Atmosphere*, *10*(9). https://doi.org/10.3390/atmos10090506.

Kelly, K. E., Whitaker, J., Petty, A., Widmer, C., Dybwad, A., Sleeth, D., et al. (2017). Ambient and laboratory evaluation of a low-cost particulate matter sensor. *Environmental Pollution, 221*, 491–500. https://doi.org/10.1016/j.envpol.2016.12.039

Kureshi, R. R., Mishra, B. K., Thakker, D., John, R., Walker, A., Simpson, S., et al. (2022). Data-driven techniques for low-cost sensor selection and calibration for the use case of air quality monitoring. *Sensors*, *22*(3). https://doi.org/10.3390/s22031093.

Leung, D. Y. C. (2015). Outdoor-indoor air pollution in urban environment: Challenges and opportunity. *Frontiers in Environmental Science*, *2*(JAN), 1–7. https://doi.org/10.3389/fenvs.2014.00069.

Levy Zamora, M., Xiong, F., Gentner, D., Kerkez, B., Kohrman-Glaser, J., & Koehler, K. (2019). Field and laboratory evaluations of the low-cost plantower particulate matter sensor. *Environmental Science and Technology, 53*(2), 838–849. https://doi.org/10.1021/acs.est.8b05174

Li, J., Mattewal, S. K., Patel, S., & Biswas, P. (2020). Evaluation of nine low-cost-sensor-based particulate matter monitors. *Aerosol and Air Quality Research, 20*(2), 254–270. https://doi.org/10.4209/aaqr.2018.12.0485

Liu, X., Jayaratne, R., Thai, P., Kuhn, T., Zing, I., Christensen, B., et al. (2020). Low-cost sensors as an alternative for long-term air quality monitoring. *Environmental*

Research, 185(March), 109438. https://doi.org/10.1016/j.envres.2020.109438

Liu, B., Tan, X., Jin, Y., Yu, W., & Li, C. (2021). Application of RR-XGBoost combined model in data calibration of micro air quality detector. *Scientific Reports, 11*(1), 1–14. https://doi.org/10.1038/s41598-021-95027-1

MoEF&CC. (2019). *National Clean Air Programme (NCAP)*. Central Pollution Control Board. Ministry of Environmental Forests and Climate Change, The Government of India.

Mukherjee, A., Stanton, L. G., Graham, A. R., & Roberts, P. T. (2017). Assessing the utility of low-cost particulate matter sensors over a 12-week period in the Cuyama valley of California. *Sensors, 17*(8), 1805.

Narayana, M. V., Jalihal, D., & Nagendra, S. M. S. (2022). Establishing a sustainable low-cost air quality monitoring setup: A survey of the state-of-the-art. *Sensors, 22*(1), 1–39. https://doi.org/10.3390/s22010394

Nguyen, N. H., Nguyen, H. X., Le, T. T. B., & Vu, C. D. (2021). Evaluating low-cost commercially available sensors for air quality monitoring and application of sensor calibration methods for improving accuracy. *Open Journal of Air Pollution, 10*(01), 1–17. https://doi.org/10.4236/ojap.2021.101001

Patra, S. S., Ramsisaria, R., Du, R., Wu, T., & Boor, B. E. (2021). A machine learning field calibration method for improving the performance of low-cost particle sensors. *Building and Environment, 190*, 19–25. https://doi.org/10.1016/j.buildenv.2020.107457

Prieto, W. H., & Cremasco, M. A. (2017). Application of probability density functions in modelling annual data of atmospheric NOx temporal concentration. *Chemical Engineering Transactions, 57*, 487–492. https://doi.org/10.3303/CET1757082

Simon, H., Baker, K. R., & Phillips, S. (2012). Compilation and interpretation of photochemical model performance statistics published between 2006 and 2012. *Atmospheric Environment, 61*, 124–139. https://doi.org/10.1016/j.atmosenv.2012.07.012

Singh, V., Singh, S., & Biswal, A. (2021). Exceedances and trends of particulate matter (PM2. 5) in five Indian megacities. *Science of the Total Environment, 750*, 141461. https://doi.org/10.1016/j.scitotenv.2020.141461

Song, J., Saathoff, H., Gao, L., Gebhardt, R., Jiang, F., Vallon, M., et al. (2022). Variations of PM2.5 sources in the context of meteorology and seasonality at an urban street canyon in Southwest Germany. *Atmospheric Environment, 282*(April), 119147. https://doi.org/10.1016/j.atmosenv.2022.119147

Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., & Bonavitacola, F. (2017). Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. *Sensors and Actuators, b: Chemical, 238*, 706–715. https://doi.org/10.1016/j.snb.2016.07.036

Srbinovska, M., Andova, V., Mateska, A. K., & Krstevska, M. C. (2021). The effect of small green walls on reduction of particulate matter concentration in open areas. *Journal of Cleaner Production, 279*, 123306. https://doi.org/10.1016/j.jclepro.2020.123306

Wang, Y., Du, Y., Wang, J., & Li, T. (2019). Calibration of a low-cost PM2.5 monitor using a random forest model. *Environment International*, *133*(October), 105161. https://doi.org/10.1016/j.envint.2019.105161.

Zheng, T., Bergin, M. H., Johnson, K. K., Tripathi, S. N., Shirodkar, S., Landis, M. S., et al. (2018). Field evaluation of low-cost particulate matter sensors in high-and low-concentration environments. *Atmospheric Measurement Techniques, 11*(8), 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., et al. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. *Atmospheric Measurement Techniques, 11*(1), 291–313. https://doi.org/10.5194/amt-11-291-2018

Zoest, V. V., Osei, F. B., Stein, A., & Hoek, G. (2019). Calibration of low-cost NO_2 sensors in an urban air quality network. *Atmospheric Environment, 210*(2), 66–75. https://doi.org/10.1016/j.atmosenv.2019.04.048