Share Your Innovations through JACS Directory

Journal of Environmental Science and Pollution Research

Visit Journal at https://www.jacsdirectory.com/jespr

ISSN: 2455-0272

Comparative Evaluation of High-Volume Samplers and Low-Cost Sensor-Based Platforms for Air Pollutant Monitoring

Anish Ganguly[1,2,*]

[1]*Independent Researcher, 106 Portland Road Hucknall, Nottinghamshire, NG15 7SA, United Kingdom.*
[2]*Kolkata Clean Air, Kolkata – 700 071, West Bengal, India.*

ARTICLEDETAILS

Article history:
Received 16 August 2025
Revised 20 November 2025
Accepted 21 November 2025
Available online 22 December 2025

Keywords:
Particulate Matter
High Volume Sampler
Airveda
Air Pollution Monitoring
Statistical Assessment

ABSTRACT

This study presents a comparative evaluation of high-volume samplers (HVS) and low-cost Airveda sensor-based platforms for monitoring particulate matter (PM_{10} and $PM_{2.5}$) concentrations in Kolkata during the pre-monsoon period from February to May 2018. Despite identical atmospheric conditions, notable discrepancies were observed between the two methods, attributed to differences in aerosol collection efficiency, sensitivity, and calibration protocols. HVS, based on gravimetric filtration, demonstrated higher accuracy and regulatory reliability, whereas Airveda employs optical sensing, which can be affected by humidity and aerosol properties. Bland-Altman analysis indicated systematic biases and heteroscedasticity in PM_{10} and $PM_{2.5}$ measurements, with greater divergence observed at higher concentrations. Regression results for $PM_{2.5}$ suggested a fixed bias (mean difference: 19.35 $\mu g/m^3$) with minimal proportional bias. Paired t-tests revealed statistically significant differences between HVS and Airveda for both PM_{10} ($p < 0.0001$) and $PM_{2.5}$ ($p = 0.0004$), confirming systematic measurement discrepancies. The PM_{10} mean difference of 46.63 $\mu g/m^3$ highlights methodological limitations in Airveda sensors for longer-term monitoring. These findings underscore the critical need for standardized calibration, correction factor application, and validation protocols to enhance inter-instrument comparability and data reliability. Integrating diverse measurement platforms, with appropriate calibration, can strengthen air quality surveillance frameworks and inform evidence-based policy interventions for urban air pollution mitigation.

1. Introduction

Accurate measurement of airborne particulate matter (PM) is essential for understanding its distribution, sources, and health impacts, thereby informing air quality management strategies and regulatory frameworks. PM is typically categorized based on aerodynamic diameter into coarse particles (PM_{10}), fine particles ($PM_{2.5}$), and ultrafine particles ($PM_{0.1}$), each posing distinct health risks due to their size-dependent deposition patterns in the respiratory system [1]. Sampling techniques for PM are broadly classified into manual, automated, and optical methods, each with specific applications, advantages, and limitations. Manual methods, such as filter-based gravimetric analysis and diffusion tubes, are cost-effective and suitable for long-term monitoring but often lack temporal resolution [2]. Automated systems, including continuous analyzers and mobile laboratories, provide real-time data and high spatial resolution but are more expensive and require maintenance [3]. Optical methods, like Differential Optical Absorption Spectroscopy (DOAS), offer remote sensing capabilities over extended distances, facilitating large-scale assessments [4]. The selection of an appropriate sampling technique depends on the specific objectives of the study, available resources, and required data resolution. Combining different methods can enhance the robustness of air quality assessments and provide comprehensive insights into particulate pollution dynamics [1].

High volume samplers (HVS) are widely used for collecting total suspended particulates (TSP) or specific size fractions such as PM_{10} from ambient air over a 24-hour period. The sampler operates by drawing large volumes of air-typically 1.1 to 1.7 cubic meters per minute-through a pre-weighed filter medium using a high-capacity blower. Particulate matter is captured on the filter, and after the sampling period, the filter is reweighed to determine the mass concentration of the collected particles [5]. The aerodynamic size selection is often achieved using an inlet device, such as a size-selective impactor or a cyclone separator, which ensures only particles below a specified size reach the filter. High volume samplers are considered reliable and standardized methods for gravimetric PM analysis and are commonly used in regulatory and epidemiological studies [6].

Beta attenuation monitoring (BAM) is a continuous, automated technique used to measure the mass concentration of particulate matter, particularly PM_{10} and $PM_{2.5}$, in ambient air. The method is based on the attenuation of beta radiation (typically from a carbon-14 or krypton-85 source) as it passes through a particle-laden filter tape. As particulate matter is deposited onto the filter by drawing ambient air through it, the beta particles encounter greater resistance, leading to a measurable decrease in radiation intensity. This attenuation is directly proportional to the mass of the collected particles, allowing for real-time mass concentration readings [7]. BAM instruments are valued for their ability to provide high time-resolution data (e.g., hourly or sub-hourly), minimal maintenance requirements, and compatibility with regulatory standards. However, the accuracy of BAM measurements can be influenced by factors such as humidity, temperature fluctuations, and particle composition [8].

The current study aims to explore and analyze the differences in particulate matter (PM) concentrations measured using two distinct sampling techniques: the High-volume sampler (HVS) and the beta attenuation monitor (BAM). Both methods are commonly used for quantifying PM_{10} and $PM_{2.5}$ concentrations in ambient air, but they operate on different principles. The high-volume sampler collects particulate matter on a filter through which a large volume of air is drawn, and the mass of the particles is determined gravimetrically by weighing the filter before and after sampling [6]. In contrast, the beta attenuation monitor continuously measures the attenuation of beta radiation as it passes through a filter tape on which particles have accumulated, providing real-time data on PM concentrations [7]. The primary objective of this study is to assess the temporal and mass concentration differences between the two methods, taking into account factors such as measurement precision, sampling resolution, and potential biases introduced by each technique. Additionally, the study will examine the impact of environmental conditions, such as humidity and temperature, on the accuracy of both instruments, as these factors can affect the performance of the BAM while remaining less influential on the gravimetric method used in HVS. By understanding the comparative

*Corresponding Author:anishganguly70@outlook.com(Anish Ganguly)

https://doi.org/10.30799/jespr.259.25110402

performance of these sampling methods, this study will provide insights into their suitability for various monitoring applications and contribute to improving the accuracy and reliability of air quality assessments.

2. Experimental Methods

2.1 Study Area

The present study was conducted in the central part of Kolkata (22°33′ N and 88°20′ E), one of the most densely populated and industrially active metropolitan cities in eastern India. Kolkata, the capital of West Bengal, is characterized by a complex mix of anthropogenic activities including dense traffic, commercial hubs, residential areas, and small-scale industries, all of which contribute to elevated concentrations of airborne particulate matter [9,10]. The southern region of the city, which includes area such as Jadavpur, was selected for monitoring due to its high human activity levels, heavy vehicular emissions, and limited ventilation caused by narrow streets and dense infrastructure [11].

The selection of the study area was carried out through a systematic approach combining ground truth surveys, open-source geospatial datasets, and existing literature [12]. Field reconnaissance was conducted to validate the suitability of monitoring location based on factors such as land use, emission sources, accessibility, and population density. Open-source GIS platforms, particularly OpenStreetMap (OSM), were utilized to obtain detailed spatial information on road networks, industrial zones, green cover, and residential clusters, which informed the stratified selection of sampling sites [12]. Additionally, relevant peer-reviewed literature and governmental reports were reviewed to identify regions with documented air quality concerns and meteorological variability. This multi-criteria approach ensured the selection of study areas that were representative of diverse urban typologies and pollution exposure scenarios, thereby enhancing the robustness and generalizability of the findings [12]. This region has been identified in previous studies as a hotspot for poor air quality, especially with regard to PM_{10} and $PM_{2.5}$ concentrations [12]. Furthermore, meteorological conditions such as low wind speed and high humidity during certain seasons exacerbate pollutant accumulation in this area [13]. Therefore, the central part of Kolkata serves as a representative urban environment for examining spatiotemporal variations in particulate matter and assessing the potential health implications associated with long-term exposure.

2.2 Method

This study aimed to monitor the concentrations of particulate matter (PM) in central Kolkata, focusing specifically on PM_{10} and $PM_{2.5}$. To achieve this, two samplers were utilized for air quality monitoring: High-volume air sampler (APM 460) for PM_{10} and the Ecotech Model AAS 127 sampler for $PM_{2.5}$. These samplers were positioned at carefully selected monitoring sites in central Kolkata, chosen to represent areas with varying traffic density and industrial activity. The sampling duration was done for few selected days in the months of February -May with samples being collected continuously for 24 hours to capture diurnal variations in particulate matter concentrations [14,15].

The high-volume air sampler (APM 460) was used to monitor PM_{10}, which includes particulate matter with aerodynamic diameters of 10 micrometers or less. The Ecotech Model AAS 127 sampler was employed to monitor the finer $PM_{2.5}$ particles, which are of particular concern for health due to their ability to penetrate deep into the respiratory system [16]. The samplers were calibrated prior to deployment to ensure accuracy and were maintained regularly during the study to avoid discrepancies in measurements [17]. Each sampler was set up with filter media (e.g., quartz filters) to capture particulate matter from the air. Once the sampling was completed, the filters were carefully removed and transported to the laboratory for further analysis. The filters were weighed to determine the mass of collected particulate matter. PM concentrations were calculated by dividing the mass of particles collected by the volume of air sampled during the period [18]. Additionally, meteorological parameters, such as wind speed, temperature, and humidity, were recorded at each site to account for environmental factors that could influence particulate matter dispersion [19].

The concentration of the particulate matters was measured and calculated using the equation C = (A-B)/(QxT), where, C=Concentration of SPM in μg/m^3; A=Final weight of filter paper in grams; B= Initial weight of filter paper in grams; Q=Mean flow rate in m^3/min and T=time interval for which the sampling is done in hrs.

2.3 Laboratory Procedure

To ensure accurate gravimetric analysis of particulate matter, a Whatman filter paper was first folded into four quadrants and placed inside a desiccator for 24 hours to eliminate any residual moisture prior to use. On the day of sampling, the pre-conditioned filter paper was removed and weighed using a Sartorius electronic microbalance (Model: F 212-1), with the recorded mass noted as the initial weight (B). The filter was then carefully unfolded and mounted over the gasket of the APM 460BL high volume air sampler, with the protective lid secured to prevent mechanical damage. The sampler was operated for a scheduled duration of 4 hours, during which time the initial air flow rate was recorded using the U-tube manometer attached to the sampler, filled with distilled water. Throughout the sampling period, the water level in the manometer was maintained at regular intervals (every 15–20 minutes) using a syringe to ensure accurate pressure readings. Upon completion of the sampling period, the device was switched off and the final air flow rate was measured. The filter paper was then carefully removed, refolded, sealed in a zip pouch, and placed again in the desiccator for an additional 24 hours to remove absorbed moisture. After this conditioning period, the final weight (A) of the filter was measured to determine the mass of collected particulate matter by subtracting the initial weight (B) from the final weight (A).

In addition to the stationary samplers, the Airveda air quality monitor, a portable, real-time monitoring device, was deployed at the same monitoring sites. This device allowed for continuous, real-time tracking of PM_{10} and $PM_{2.5}$ concentrations. The Airveda monitor provided instant readings, which were logged throughout the study period, offering complementary data to the high-volume samplers. The advantage of the Airveda device lies in its ability to provide real-time data on air quality fluctuations, which could help capture rapid changes in pollution levels due to transient events such as traffic peaks, weather changes, or local industrial emissions [20].

Calibration of both the high-volume air sampler and the Ecotech sampler was carried out prior to deployment to ensure precision in the measurements, and regular maintenance was performed during the study to avoid any discrepancies. The Airveda monitor was calibrated and verified against the established samplers to ensure that its real-time readings were consistent with the laboratory-based measurements [21].

Meteorological parameters, including ambient temperature, relative humidity, and wind speed, were obtained from publicly available databases maintained by authorized government agencies. Specifically, data were sourced from the India Meteorological Department (IMD), which provides high-resolution, quality-controlled atmospheric observations through its urban meteorological monitoring networks. These parameters were recorded for each sampling day and location, corresponding with the particulate matter monitoring schedule, to assess the influence of atmospheric conditions on the dispersion and concentration of PM_{10} and $PM_{2.5}$ [22,23]. Temperature influences atmospheric stability, while wind speed and direction govern horizontal pollutant transport, and relative humidity affects the hygroscopic growth of particulate matter [24,25]. Integrating these parameters into the analysis enables more robust interpretation of temporal and spatial variations in PM concentrations, as well as identification of pollution episodes associated with meteorological anomalies [26].

Meteorological parameters such as temperature, relative humidity, and wind speed were cross -validated from the Central Pollution Control Board (CPCB) databases corresponding to the sampling dates and locations. To ensure the reliability of the data, validation was carried out by consulting with IMD officials regarding the protocols used for data acquisition and quality assurance. The discussions confirmed that the parameters were recorded following standardized procedures and national guidelines for meteorological data collection [22,23].

The sampling was done from February to May 2018 two days/weekly for 24 hours to access the comparison between high-volume samplers and low-cost sensor-based platforms for air pollutant monitoring between pre-monsoon season and monsoon season to determine the efficiency of both pollutants.

2.4 Statistical Assessment

As all pollutant and meteorological data utilised in this study were primary in nature, considerable emphasis was placed on their statistical assessment. Descriptive and inferential statistical techniques including correlation analysis, regression analysis, and the computation of central tendency measures such as mean, median, and mode were employed to evaluate relationships, trends, and variability within the dataset [27]. For a more in-depth evaluation, both correlation and regression analyses were employed. These statistical methods were applied to identify and quantify the relationships between pollutant levels (e.g. PM_{10}, $PM_{2.5}$) and key meteorological variables such as temperature, relative humidity, wind speed, and rainfall [27]. Correlation analysis is a statistical technique used to measure the degree of linear dependence between two continuous

https://doi.org/10.30799/jespr.259.25110402

Cite this Article as: Anish Ganguly, Comparative evaluation of high-volume samplers and low-cost sensor-based platforms for air pollutant monitoring, J. Env. Sci. Pollut. Res. 11(4) (2025) 527–532.

variables. Pearson's correlation coefficient (r) serves as a quantitative measure of this relationship, where the value of r lies within the interval -1 ≤ r ≤ 1 [24]. The correlation coefficient r indicates the strength and direction of a linear relationship between two variables, where r=1 denotes perfect positive correlation, r=−1 indicates perfect negative correlation, and r=0 signifies no linear correlation [27]. The Pearson correlation coefficient is calculated using the formula:

$$r = \frac{\sum dxdy}{\sqrt{\sum dx^2 \times \sum dy^2}}$$

where, x is the variable which represents the pollutant concentration (PM_{10}, $PM_{2.5}$) and y is the variable which represents the meteorological parameters (temperature, rainfall, humidity and atmospheric pressure)

This method enables the assessment of how closely pollutant concentrations align with variations in meteorological parameters, offering valuable insights into potential cause-effect relationships or underlying patterns [27].

To assess the agreement between the two measurement methods high volume sampler and Airveda sampler for particulate matter (PM_{10} and $PM_{2.5}$), Bland-Altman analysis was performed. This method is widely used to evaluate the agreement between two quantitative measurement techniques by plotting the differences against the averages of the two methods, allowing for identification of systematic bias and limits of agreement [28]. The mean difference (bias) and 95% limits of agreement (mean ± 1.96 SD) were calculated to determine the level of concordance between the devices. Both ordinary analysis and regression analysis were performed. In addition to the Bland-Altman analysis, a paired t-test was conducted to statistically compare the mean PM_{10} and $PM_{2.5}$ concentrations recorded by the two devices. This test assesses whether the mean difference between paired observations is significantly different from zero, under the assumption of normally distributed differences [29]. All analyses were performed using SPSS version [SPSS version 30], with significance set at $p < 0.05$. Prior to analysis, data were tested for normality using the Shapiro-Wilk test [29].

3. Results and Discussion

Monthly data from February to May 2018 were systematically collected and analysed to assess the variability and distribution of key meteorological parameters and particulate matter concentrations (PM_{10} and $PM_{2.5}$) using a combination of reference-grade and low-cost air quality monitoring instruments. The sampling campaign employed high volume samplers (HVS), specifically the APM 460 model, and the Ecotech AAS 127 ambient air quality sampler, both of which are standard reference instruments widely used in regulatory monitoring networks. Additionally, data were concurrently collected using the Airveda monitor, a compact, sensor-based device designed for real-time ambient air quality assessment. This multi-instrument approach allowed for comparative analysis of data accuracy, reliability, and spatial-temporal resolution across monitoring platforms. The instruments were deployed at designated monitoring sites representing varying land-use patterns and emission profiles. Meteorological parameters, including ambient temperature, relative humidity, wind speed, and wind direction, were recorded using co-located sensors or secondary data from the nearest meteorological stations. The integration of data from both regulatory-grade and portable monitoring devices facilitated a comprehensive evaluation of particulate pollution dynamics during the late winter to early summer transition period. Furthermore, the comparative performance assessment between Airveda and reference samplers contributed to validating the applicability of low-cost sensors in regional air quality surveillance and citizen science initiatives. The findings indicated a clear seasonal trend in the concentration levels of air pollutants in both smaplers. Specifically, the concentrations of pollutants were observed to be highest during the pre-monsoon period, with the lowest levels recorded during the monsoon season (Table 1).

Table 1 The average and median concentration of pollutants and meteorological parameters in pre-Monsoon period (February 2018- May 2018)

Statistical parameters	Wind-speed (mph)	Humidity %	Mean Temp (°C)	High Volume Samplers (HVS)		Airveda Sampler (Airveda)	
				PM_{10} (µg/m³)	$PM_{2.5}$ (µg/m³)	PM_{10} (µg/m³)	$PM_{2.5}$ (µg/m³)
Avg	13.73	69.42	28.08	102.74	51.71	58.88	32.54
Median	13.5	70.87	29.44	106	50	52.5	31.5

Table 2 Pearson Correlation assessment between the Particulate matters (PM) collected in high volume samplers (HVS) and Airveda Sampler and with the meteorological parameters.

	High Volume Sampler		Airveda Sampler (Airveda)	
Parameters	PM_{10} (µg/m³)	$PM_{2.5}$ (µg/m³)	PM_{10} (µg/m³)	$PM_{2.5}$ (µg/m³)
Windspeed (mph)	-0.71	-0.69	-0.699	-0.69
Humidity %	-0.63	-0.56	-0.45	-0.39
Mean Temperature(°C)	-0.74	-0.82	-0.58	-0.61

3.1 Correlation Between Wind Speed and PM Concentrations

The analysis revealed a negative correlation between wind speed and PM concentrations across both samplers in pre-Monsoon period, suggesting that as wind speed increases, particulate matter concentrations tend to decrease (Table 2).

These findings suggest a consistent trend where higher wind speeds likely contribute to improved dispersion of particulate matter, thereby reducing its concentration at the sampling location. This is consistent with the general atmospheric dynamics where increased wind speed aids in the dilution and transportation of airborne pollutants [30,24]. However, the strength of the correlation is somewhat weaker than expected, which may be attributed to local variations in pollution sources, the complex interaction of meteorological conditions, and differences in the spatial distribution of pollution.

3.2 Correlation Between Humidity and PM Concentrations

The analysis revealed negative correlations between humidity and both PM_{10} and $PM_{2.5}$ concentrations, indicating an inverse relationship where higher humidity levels were generally associated with lower concentrations of particulate matter.

These negative correlations suggest that, as humidity levels increase, the concentration of particulate matter tends to decrease. The inverse relationship may be attributed to several atmospheric mechanisms. Increased humidity can promote the wet scavenging of airborne particulate matter, a process where water droplets collide with and remove particles from the air. Additionally, higher humidity can increase the size of particles through hygroscopic growth**,** which can lead to more particles being removed from the atmosphere through gravitational settling [30,24].

3.3 Correlation Between Temperature and PM Concentrations

The analysis of the correlations revealed a negative correlation between temperature and PM concentrations, which suggests that as temperature increases, particulate matter concentrations tend to decrease. This trend can be explained by several atmospheric processes, primarily related to thermal dispersion and increased atmospheric stability during warmer periods. Higher temperatures can enhance the vertical mixing of the atmosphere, allowing pollutants to disperse more effectively and resulting in a reduction of ground-level particulate concentrations [30,24].

3.4 Comparison Between High Volume Sampler (HVS) and Airveda in Pre-Monsoon Season

Although both instruments show similar correlations, the HVS displayed slightly stronger negative correlations (r = -0.71 for PM_{10} and r = -0.69 for $PM_{2.5}$) compared to the Airveda (r = -0.699 for PM_{10} and r = -0.69 for $PM_{2.5}$). The HVS is a standard, high-accuracy method used for regulatory air quality monitoring, which may contribute to its more robust correlation with wind speed, as it typically captures more representative concentrations over longer sampling periods. The Airveda, being a low-cost, portable sensor, might show slightly weaker correlations due to inherent limitations in precision, temporal resolution, or potential calibration differences [31,32]. Despite this, the similarity in the correlation results between both samplers indicates that the Airveda could be a reliable tool for monitoring PM concentrations, particularly in settings where high volume samplers are not feasible.

The negative correlation between humidity and PM concentrations is observed in both the HVS and Airveda data, the strength of the correlation is stronger for the HVS. Specifically, the correlation for PM_{10} (r = -0.63) and $PM_{2.5}$ (r = -0.56) from HVS was more pronounced compared to the Airveda monitor, which showed weaker correlations (r = -0.45 for PM_{10} and r = -0.39 for $PM_{2.5}$). This difference may be due to the higher precision and accuracy of the HVS, which is a reference-grade instrument designed for regulatory air quality monitoring. The Airveda, being a low-cost, portable sensor, could have inherent limitations in temporal resolution, calibration, or sensor sensitivity, which might affect the strength of the observed correlation [31,32].

https://doi.org/10.30799/jespr.259.25110402

Cite this Article as: Anish Ganguly, Comparative evaluation of high-volume samplers and low-cost sensor-based platforms for air pollutant monitoring, J. Env. Sci. Pollut. Res. 11(4) (2025) 527–532.

The HVS exhibited stronger negative correlations between temperature and PM concentrations compared to the Airveda. For PM_{10}, the correlation for the HVS was -0.74, while for Airveda, it was -0.58. Similarly, the correlation for $PM_{2.5}$ was -0.82 for the HVS and -0.61 for the Airveda. The stronger correlations observed with the HVS can be attributed to its greater accuracy and precision as a reference-grade instrument, which provides more reliable and robust data, especially over longer sampling durations and more consistent calibration. On the other hand, the Airveda, being a portable and low-cost sensor, may have inherent limitations in terms of calibration, sensitivity, and temporal resolution, which could slightly weaken the observed correlation with temperature [31,32].

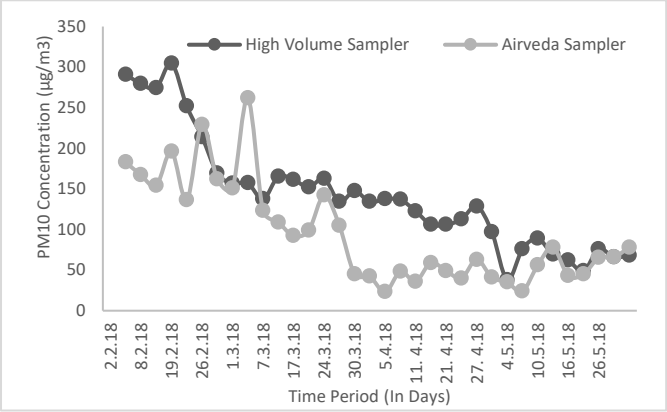

Fig. 1 PM_{10} Concentrations (µg/m³) trends between high volume sampler (APM460) and Airveda sampler in pre monsoon period (February 2018-May 2018)

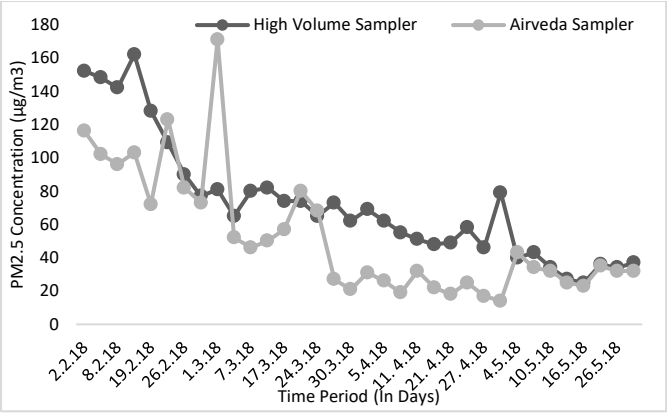

Fig. 2 $PM_{2.5}$ Concentrations (µg/m³) trends between high volume sampler (Ecotech Model AAS 127 sampler) and Airveda sampler in pre monsoon period (February 2018-May 2018)

The discrepancy observed in PM_{10} and $PM_{2.5}$ concentration measurements between high volume samplers and Airveda samplers, despite identical atmospheric conditions (Figs. 1 and 2) likely arises from variations in instrument sensitivity, aerosol collection efficiency, and calibration methodologies. High volume samplers operate using gravimetric filtration, where air is drawn through a filter at high flow rates, accumulating particulates that are later weighed to determine PM_{10} mass concentration, a method known for high accuracy and regulatory compliance [2]. In contrast, Airveda Samplers employ optical sensors that estimate PM_{10} and $PM_{2.5}$ concentrations by detecting light scattering from suspended particulates, a technique susceptible to variations in humidity and particle refractive index, potentially leading to underestimation in high-pollution environments [20]. The differences in particle deposition mechanisms and flow dynamics between the instruments may also influence measurement outcomes, as filter-based systems tend to capture a broader range of particulate sizes compared to optical sensors, which are more sensitive to real-time fluctuations but can be affected by calibration drift [6]. Standardized inter-instrument calibration procedures, including side-by-side collocation studies and correction factor applications, are essential to harmonize data discrepancies and ensure comparability across air quality monitoring networks [32].

The presence of a systematic difference suggests that one sampler consistently reports higher or lower PM_{10} or $PM_{2.5}$ concentrations than the other [32]. The range within which most differences fall provides insight into the measurement consistency and the reliability of inter-device comparison [33]. If the differences vary with PM_{10} or $PM_{2.5}$ concentration levels, it may indicate increasing measurement divergence at higher PM_{10} or $PM_{2.5}$ values due to calibration discrepancies or sensitivity [6].

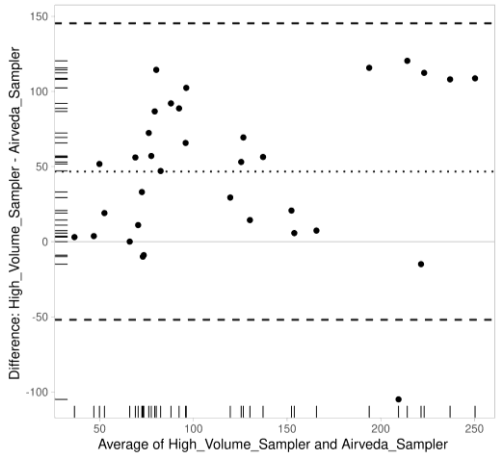

Fig. 3 Bland Altman Plot for assessing the agreement for PM_{10} between high volume sampler (HVS) and Airveda sampler

Table 3 Bland Altman Plot for assessing the agreement for PM10 between high volume samplers (HVS) and Airveda sampler with the Shapiro-Wilk test for normality of the distribution of the y-variable returns a p-value of 5.38e-02.

Parameter	Value	95%CI lower limit	95%CI upper limit
difference	46.63	28.8	64.45
upper Limit of Agreement	145.29	114.8	175.77
lower Limit of Agreement	-52.03	-82.51	-21.55
Difference between LoA	197.32		
intercept	29.75	-8.76	68.26
slope	0.14	-0.15	0.43
widest possible LoA	258.28		

The Bland-Altman plot for PM_{10} concentration measurements during the pre-monsoon period provides a statistical assessment of agreement between high volume samplers and Airveda samplers, highlighting systematic biases and variability between these two measurement methods (Fig. 3). The x-axis represents the mean PM_{10} concentration from both samplers, while the y-axis displays the difference between their measurements, allowing for a visual evaluation of bias consistency and dispersion across varying pollution levels (Fig. 3). The plot suggests a mean bias, indicating that one sampler consistently records higher PM_{10} values compared to the other, potentially due to differences in calibration methodologies, sensor precision, or aerosol capture efficiency [32]. Additionally, the presence of heteroscedasticity implies that measurement divergence increases with higher PM_{10} concentrations, suggesting instrumental sensitivity limitations or environmental influences affecting particle detection accuracy [6]. The limits of agreement provide a statistical threshold within which most differences fall, ensuring comparability for air quality surveillance and regulatory compliance[34]. These findings underscore the necessity of calibration standardization, inter-sampler validation, and correction factor applications to minimize discrepancies and enhance air pollution monitoring reliability [6]. The systematic bias observed in PM_{10} measurements emphasizes the importance of integrating diverse measurement techniques within environmental monitoring frameworks to improve data accuracy and support evidence-based policy interventions aimed at mitigating urban particulate pollution. Standardized calibration procedures are essential to reduce discrepancies and ensure reliable PM_{10} air quality monitoring (Fig. 3). Moreover, the interpretation of Table 3 proves that Airveda is falling to accurately monitor PM_{10} for a longer timeline.

The Bland-Altman plot for $PM_{2.5}$ concentrations visually evaluates the agreement between high volume samplers and Airveda samplers, with the x-axis representing the mean $PM_{2.5}$ concentration for both methods and the y-axis showing the difference between their measurements. The observed systematic bias suggests that one sampler consistently measures higher $PM_{2.5}$ concentrations compared to the other, potentially due to differences in filter-based gravimetric sampling versus optical sensor-based detection [32]. The limits of agreement define the acceptable range within which most differences fall, offering insight into measurement variability and instrument comparability [33]. The plot reveals heteroscedasticity, where measurement discrepancies increase at higher $PM_{2.5}$ concentrations, indicating that sensor precision, calibration drift, or aerosol composition variations may influence measurement accuracy [32]. These findings emphasize the need for standardized calibration procedures, correction factor applications, and cross-instrument validation to ensure reliable $PM_{2.5}$ monitoring within air quality surveillance frameworks [32]. Calibration standardization is crucial to improve inter-sampler agreement and enhance the accuracy of $PM_{2.5}$

https://doi.org/10.30799/jespr.259.25110402

monitoring. As the Shapiro-Wilk test for normality yields a p-value <0.05, an ordinary analysis became unsuitable and regression analysis was taken into consideration.

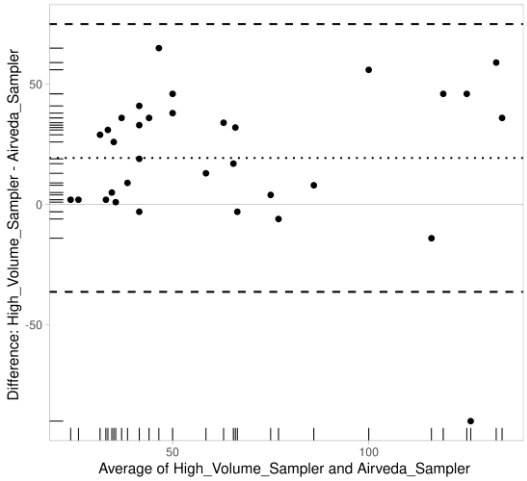

Fig. 4 Bland Altman Plot for assessing the agreement for $PM_{2.5}$ between high volume sampler (HVS) sampler and Airveda sampler

Table 4 Bland Altman plot for assessing the agreement for $PM_{2.5}$ between high volume samplers (HVS) and Airveda sampler with the Shapiro-Wilk test for normality of the distribution of the y-variable returns a p-value of The Shapiro-Wilk test for normality of the distribution of the y-variable returns a p-value of $8.58x10^{-4}$

	Parameter	Value	95%CI lower limit	95%CI upper limit
1	difference	19.35	9.3	29.41
2	upper Limit of Agreement	74.99	57.8	92.18
3	lower Limit of Agreement	-36.28	-53.47	-19.09
4	Difference between LoA	111.27		
5	intercept	20.49	-0.68	41.66
6	slope	-0.02	-0.32	0.28
7	widest possible LoA	145.65		

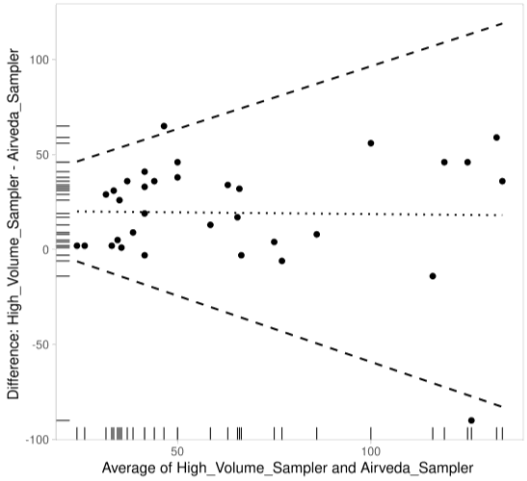

Fig. 5 Regression analysis for Bland Altman plot for assessing the agreement for $PM_{2.5}$ between high volume samplers (HVS) and Airveda sampler

Table 5 Bland Altman plot for assessing the agreement for $PM_{2.5}$ between high volume samplers (HVS) and Airveda sampler with the Shapiro-Wilk test for normality of the distribution of the y-variable returns a p-value of The Shapiro-Wilk test for normality of the distribution of the y-variable returns a p-value of 8.58e-04.

	Parameter	Value	95%CI lower limit	95%CI upper limit
1	Difference	19.35	9.3	29.41
2	Intercept	20.49	-0.68	41.66
3	Slope	-0.02	-0.32	0.28

The Bland-Altman regression analysis for $PM_{2.5}$ concentration measurements assesses agreement between high volume samplers and Airveda samplers by quantifying systematic bias and proportional trends (Table 5, Figs. 4 and 5). The mean difference of 19.35 $\mu g/m^3$, with a confidence interval ranging from 9.3 to 29.41 $\mu g/m^3$, suggests a moderate discrepancy between the two methods, indicating potential measurement inconsistencies attributed to sensor sensitivity or calibration differences. The intercept value of 20.49 $\mu g/m^3$, with wide confidence limits (-0.68 to 41.66 $\mu g/m^3$), implies variability in the initial bias, potentially influenced by ambient conditions or aerosol composition variability [6]. The observed slope of -0.02, with a confidence interval spanning -0.32 to 0.28, suggests a negligible proportional bias, indicating that measurement differences remain fairly constant across $PM_{2.5}$ concentrations rather than scaling with pollution levels [33](Table 5). This finding supports the hypothesis that while systematic bias exists, the relative discrepancy between the two samplers does not increase at higher $PM_{2.5}$ concentrations (Table 5). Standardized calibration procedures and correction factor applications are essential to reconcile these differences and enhance measurement comparability in air quality surveillance frameworks [6].

The regression analysis confirms a fixed bias in $PM_{2.5}$ measurements but minimal proportional bias, underscoring the need for calibration standardization to improve inter-sampler agreement (Tables 4 and 5).

The paired t-test results indicate a highly significant difference between PM_{10} measurements from the high volume sampler and Airveda sampler, with a two-tailed p-value of less than 0.0001, confirming statistical significance at conventional thresholds [34]. The mean difference of 46.63 $\mu g/m^3$ suggests systematic bias, likely attributable to methodological discrepancies between gravimetric filtration in high volume samplers and optical sensing in Airveda samplers [3].

The confidence interval, ranging from 29.06 to 64.19 $\mu g/m^3$, further supports the consistency of the bias across sampling events, emphasizing the need for calibration adjustments to improve measurement comparability [7]. A t-statistic of 5.40 and a degree of freedom of 33 indicate a strong effect size, reinforcing the substantial difference between the two measurement methods. The observed variability in standard deviations, 70.76 $\mu g/m^3$ for high volume sampler versus 62.60 $\mu g/m^3$ for Airveda Sampler, highlights inherent differences in particle detection sensitivity and aerosol collection efficiency, potentially influenced by environmental factors such as humidity, temperature, and pollutant composition [32]. These findings underscore the importance of standardized calibration techniques, correction factor applications, and instrument validation to ensure accurate PM10 monitoring in air quality surveillance systems.

The paired t-test results for $PM_{2.5}$ concentration measurements between the high-volume sampler and Airveda sampler indicate a statistically significant difference, with a two-tailed p-value of 0.0004, confirming strong evidence against the null hypothesis. The mean difference of 19.35 $\mu g/m^3$ suggests a systematic bias, indicating that the high-volume sampler consistently records higher $PM_{2.5}$ concentrations than the Airveda sampler, potentially due to methodological discrepancies in aerosol collection and sensor sensitivity [3]. The 95% confidence interval, ranging from 9.45 to 29.26 $\mu g/m^3$, provides a reliable range within which the true mean difference is expected to fall, reinforcing the observed bias. The t-statistic of 3.9756 with a degree of freedom of 33 highlights the strength of the effect, suggesting a substantial deviation between measurement methods, while the standard error of difference of 4.868 reflects the variability in individual paired observations [33].

The standard deviations of 36.87 $\mu g/m^3$ for the high-volume sampler and 37.44 $\mu g/m^3$ for the Airveda sampler indicate similar dispersion patterns, though differences in mean values suggest calibration inconsistencies or sensor limitations that may affect comparability [33]. These findings underscore the need for standardized calibration procedures, correction factor applications, and validation protocols to ensure consistency in $PM_{2.5}$ monitoring within air quality surveillance frameworks, thereby improving measurement reliability and enabling informed policy decisions for air pollution management. The statistical significance of the paired t-test confirms systematic bias in $PM_{2.5}$ measurements, necessitating calibration adjustments to improve agreement between sampling methods [32].

4. Conclusion

The analysis of $PM_{2.5}$ and PM_{10} concentration measurements across various statistical methods, including Bland-Altman plots, regression analysis, and paired t-tests, highlights significant discrepancies between high volume samplers and Airveda samplers, suggesting systematic bias due to methodological differences in aerosol collection and sensor sensitivity. The observed mean differences indicate that gravimetric filtration in high volume samplers consistently measures higher particulate concentrations than optical sensing methods employed in Airveda samplers, a trend confirmed by the statistical significance of the paired t-tests and regression models. While proportional bias remains minimal, the fixed bias underscores the necessity of standardized calibration adjustments and correction factor applications to enhance comparability in air quality surveillance. Moreover, the correlation analysis with meteorological variables suggests that both instruments

https://doi.org/10.30799/jespr.259.25110402

respond similarly to environmental influences, though high volume samplers display slightly stronger negative correlations with wind speed, reinforcing their robustness in long-term monitoring.

The potential for Airveda samplers to replace high volume samplers (HVS) in PM_{10} and $PM_{2.5}$ air quality monitoring depends on their measurement accuracy, reliability, and consistency under varying environmental conditions. The paired t-test and Bland-Altman analyses indicate a systematic bias, with Airveda consistently underestimating PM concentrations compared to HVS, likely due to differences in sensor technology and aerosol collection efficiency. Gravimetric filtration in HVS provides highly accurate particulate mass measurements, whereas Airveda employs optical sensing, which can be affected by humidity, aerosol composition, and calibration drift. The regression analysis suggests minimal proportional bias but confirms a fixed bias, indicating that Airveda samplers require calibration adjustments to align with HVS measurements. Correlation assessments with meteorological variables demonstrate that while Airveda responds similarly to environmental fluctuations, its sensitivity and long-term reliability are lower than HVS. While Airveda offers advantages such as portability and cost-effectiveness, its measurement discrepancies necessitate validation and Airveda cannot directly replace HVS without rigorous calibration adjustments and methodological improvements to enhance measurement accuracy and reliability.

Acknowledgment

The author gratefully acknowledges the invaluable guidance and support provided by the dissertation supervisors at Kolkata Clean Air, India during the course of this research. Their mentorship and critical feedback were instrumental in shaping the study.

Disclosure Statement

The author declares that there are no competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

Funding Details

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] B.V.S. Chauhan, K. Corada, C. Young, K.L. Smallbone, K.P. Wyche, Review on sampling methods and health impacts of fine ($PM_{2.5}$) and ultrafine ($PM_{0.1}$) particles, Atmosphere 15(5) (2024) 572.
[2] X. Yang, L. Jiang, W. Zhao, Q. Xiong, W. Zhao, X. Yan, Comparison of ground-based $PM_{2.5}$ and PM_{10} concentrations in China, India, and the U.S., Int. J. Environ. Res. Public Health 15(7) (2018) 1382.
[3] X. Wang, S. Gronstal, B. Lopez, H. Jung, L.-W.A. Chen, G. Wu, S.S.H. Ho, J.C. Chow, J.G. Watson, Q. Yao, S. Yoon, Evidence of non-tailpipe emission contributions to PM2.5 and PM10 near southern California highways, Environ. Pollut. 317 (2023) 120691.
[4] J. Chapman, V.K. Truong, A. Elbourne, S. Gangadoo, S. Cheeseman, P. Rajapaksha, K. Latham, R.J. Crawford, D. Cozzolino, Combining chemometrics and sensors: Toward new applications in monitoring and environmental analysis, Chem. Rev. 120(13) (2020) 6048–6069.
[5] P.M. SPM, Sampling of ambient air for total suspended particulate matter (SPM) and PM_{10} using high volume sampler, Center for Environmental Research Information, Office of Research and Development, 1999.
[6] R.A. Eldred, T.A. Cahill, R.G. Flocchini, Composition of $PM_{2.5}$ and PM_{10} aerosols in the IMPROVE network, J. Air Waste Manag. Assoc. 47(2) (1997) 194–203.
[7] A. Chung, D.P. Chang, M.J. Kleeman, K.D. Perry, T.A. Cahill, D. Dutcher, E.M. McDougall, K. Stroud, Comparison of real-time instruments used to monitor airborne particulate matter, J. Air Waste Manag. Assoc. 51(1) (2001) 109–120.
[8] T.Y. Yu, Characterization of ambient PM2.5 concentrations, Atmos. Environ. 44(24) (2010) 2902–2912.
[9] B.R. Gurjar, K. Ravindra, A.S. Nagpure, Air pollution trends over Indian megacities and their local-to-global implications, Atmos. Environ. 142 (2016) 475–495.
[10] R. Das, B. Khezri, B. Srivastava, S. Datta, P.K. Sikdar, R.D. Webster, X. Wang, Trace element composition of $PM_{2.5}$ and PM_{10} from Kolkata, Atmos. Pollut. Res. 6(5) (2015) 742–750.
[11] N. Halder, M. Kumar, A. Deepak, D. Kumar, N. Yasmin, S. Ullah, S.G. Al-Ghamdi, Spatiotemporal assessment of urban thermal discomfort in Kolkata, India, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 02 (2025) 02072.
[12] M.Z. Chowdhury, Characterization of fine particle air pollution in the Indian subcontinent, Georgia Institute of Technology, USA, 2004.
[13] K. Karar, A.K. Gupta, A. Kumar, A.K. Biswas, S. Devotta, Statistical interpretation of weekday/weekend differences of ambient particulate matter in Kolkata, Indoor Built Environ. 15(3) (2006) 235–245.
[14] Central Pollution Control Board (CPCB), Air quality monitoring, emission inventory and source apportionment study for Indian cities, CPCB, India, 2010.
[15] A. Lawrence, N. Fatima, Urban air pollution and its assessment in Lucknow City, Sci. Total Environ. 488 (2014) 447–455.
[16] World Health Organization, Health effects of particulate matter: policy implications, WHO Regional Office for Europe, Geneva, 2013.
[17] D. Massey, A. Kulshrestha, J. Masih, A.B. Taneja, Seasonal trends of PM_{10}, $PM_{5.0}$, $PM_{2.5}$ and $PM_{1.0}$ in residential homes, Build. Environ. 47 (2012) 223–231.
[18] N.S. Muruganandam, U. Arumugam, Dynamic ensemble multivariate time series forecasting model for $PM_{2.5}$, Comput. Syst. Sci. Eng. 44(2) (2023) 979-989.
[19] B.R. Gurjar, A. Jain, A. Sharma, A. Agarwal, P. Gupta, A.S. Nagpure, J. Lelieveld, Human health risks in megacities due to air pollution, Atmos. Environ. 44(36) (2010) 4606–4613.
[20] A. Parmar, S. Sara, A.K. Dwivedi, C.R. Reddy, I. Patwardhan, S.D. Bijjam, S. Chaudhari, K.S. Rajan, K. Vemuri, Development of an end-to-end low-cost IoT system for PM monitoring, Frontiers in the Internet of Things 3 (2024) 1332322.
[21] S.K. Sahu, G. Beig, N.S. Parkhi, Emissions inventory of anthropogenic $PM_{2.5}$ and PM10 in Delhi, Atmospheric Environment 45(34) (2011) 6180–6190.
[22] A.K. Jaswal, N.M. Narkhede, S. Rachel, Atmospheric data collection and database management in IMD, Proc. Indian Natl. Sci. Acad. 80 (2014) 697–704.
[23] S.I. Laskar, India Meteorological Department, Government of India, 2016.
[24] J.H. Seinfeld, S.N. Pandis, Atmospheric chemistry and physics: from air pollution to climate change, John Wiley & Sons, USA, 2016.
[25] D.J. Jacob, Introduction to atmospheric chemistry, Princeton University Press, USA, 1999.
[26] X. Li, Y. Ma, Y. Wang, N. Liu, Y. Hong, Temporal and spatial analyses of PM_{10} and $PM_{2.5}$ in northeast China, Atmos. Res. 198 (2017) 185–193.
[27] H. Mulholland, C.R. Jones, Fundamentals of statistics, Springer, 2013.
[28] J.M. Bland, D.G. Altman, Statistical methods for assessing agreement between two clinical measurement methods, The Lancet 327(8476) (1986) 307–310.
[29] A. Field, Discovering statistics using IBM SPSS statistics, Sage Publications, UK, 2024.
[30] R.R. Draxler, HYSPLIT model access via NOAA ARL READY website, NOAA Air Resources Laboratory, 2003.
[31] C.G. Hodoli, Investigating the applicability of low-cost sensors for air quality monitoring networks, Ghana case study, Ghana.
[32] S. Brienza, A. Galli, G. Anastasi, P. Bruschi, A low-cost sensing system for cooperative air quality monitoring, Sensors 15(6) (2015) 12242–12259.
[33] P. Liehr, Y.L. Dedo, S. Torres, J.C. Meininger, Assessing agreement between clinical measurement methods, Heart & Lung 24(3) (1995) 240–245.

https://doi.org/10.30799/jespr.259.25110402

Cite this Article as: Anish Ganguly, Comparative evaluation of high-volume samplers and low-cost sensor-based platforms for air pollutant monitoring, J. Env. Sci. Pollut. Res. 11(4) (2025) 527–532.