

Evaluation of a Low-Cost Sampler for Assessing
Personal Fine Particulate Matter Exposures

by

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Abstract

Fine particulate matter exposure has been consistently associated with the most adverse health effects of air pollution in both urban outdoor and indoor environments. While fixed-site monitoring networks provide an outlook of population exposures, such systems have difficulty in the assessment of personal exposures due to spatial and temporal variability. Fine particulate matter personal monitors are often expensive, cumbersome, unintuitive, or high maintenance. As such, these devices have a high barrier of entry, and are often not conducive for citizen scientists and enthusiasts. The AirBeam is a light-scattering particle counter that was chosen as an alternative experimental monitor for its low-cost, minimal form factor, and ease of use. This study evaluated the operation and monitoring accuracy of the AirBeam in producing real-time indirect fine particulate matter mass concentration estimates. Results indicate that the AirBeam displays high correlation with the pDR-1500, a more expensive light-scattering reference instrument, in both an urban outdoor and indoor environment. Both the AirBeam and pDR-1500 displayed moderate correlations with reference gravimetric filter mass analysis in an urban outdoor setting. Collocation and field experimentation in New York City provided a basis for the conversion of particle number count data into an estimated value of fine particulate matter mass concentration. These experimental personal exposure measurements provide encouraging results for the accuracy of a low-cost sampler within its concentration range.

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Introduction

Urban air quality is an ongoing global concern, as population growth has lead to increases in industrialization, road traffic, and energy use, all factors that can contribute to air pollution (Molina et al., 2004). In many of the world's cities, air pollutants have exceeded the determined concentration limits that have been advised for public health safety (Sharma, Sharma, Jain, & Kumar, 2013). Air pollution is comprised of different gaseous species and particulate matter. Gaseous species include ozone (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), carbon dioxide (CO_2), nitrogen dioxide (NO_2), and volatile organic compounds (VOC). Particulate matter is comprised of coarse particles (less than $10\mu m$ in aerodynamic diameter), fine particles (less than $2.5\mu m$), and ultrafine particles (less than $1\mu m$) (Hinds, 1999).

Fine particulate matter ($PM_{2.5}$) from combustion sources has been found to be consistently and independently associated with the most serious health effects of air pollution in both short-term exposures (days to weeks) and in long-term exposures (weeks to years) (Cohen, 2004). The World Health Organization's (WHO) 2004 Comparative Risk Assessment attributed outdoor fine particle exposure to 800,000 premature deaths worldwide each year (Cohen, 2004). An additional 1.6 million premature deaths worldwide each year have been attributed to indoor $PM_{2.5}$ exposure from biomass and coal burning (K. R. Smith, 2004). In 2010, the third leading risk factor for global disease burden estimated in disability-adjusted life years (DALYs) was household air pollution from solid fuels (Lim et al., 2012). The WHO's International Agency for Research on Cancer (IARC) classifies these airborne particulates as Group 1 carcinogens, indicating that there is sufficient evidence of carcinogenicity in humans (Loomis et al., 2013). Multiple observational studies have established an association between $PM_{2.5}$ air pollution

and cardiovascular and cardiopulmonary mortality. Several physiological mechanisms to explain such increases in cardiovascular disease (CVD) incidence have been proposed. PM_{2.5} exposure has been thought to increase the mean resting arterial blood pressure through an increase in the sympathetic tone (Brook et al., 2002). Additionally, such PM_{2.5} exposures may promote intravascular thrombosis from impaired endothelial function and increased plasma viscosity (Pekkanen et al., 2002).

In urban areas, air quality has been shown to be affected by particulate matter from road traffic (Krzyszowski, 2005). Direct tailpipe emissions, especially from diesel vehicles, are thought to be more significant contributors to mobile source PM_{2.5} concentrations than suspension of settled particulate matter (Balogh, 1994). These particles have been found to have adverse health effects on children with asthma (Spira-Cohen, Chen, Kendall, Lall, & Thurston, 2011). In New York City, roughly 69-82% of PM_{2.5} mass is attributed to transportation (Qin, Kim, & Hopke, 2006). Backward trajectory for air mass has shown that coal-fired power plants in West Virginia, Ohio, and Pennsylvania have also been found to contribute to typical high PM_{2.5} events in New York City (Qin et al., 2006). Certain elements of the built environment in urban areas, such as roadway design, building placement, and building height have been shown to contribute to differences in PM_{2.5} concentrations (Boarnet et al., 2011). Urban areas with buildings of six stories or greater on both sides of the street were found to be associated with increased PM_{2.5} concentrations (Boarnet et al., 2011). These so called “street canyons” cause PM_{2.5} to become trapped in the wakes of buildings (Pan H., 2009). In large cities, sidewalk concentrations of PM_{2.5} from adjacent high-traffic areas may comprise a significant portion of personal daily exposures (Kozawa, Fruin, & Winer, 2009). Regional fixed-site air pollution monitors are

currently not able to provide the fine spatial resolution to characterize localized PM_{2.5} impacts for regulatory purposes (McCarthy et al., 2006).

Air pollution sensors have components that can respond to a change in physical or chemical properties, and convert that change to electrical signals via transducers (White, 2012). Sensors that measure the concentration of gas phase species can be grouped into two different categories. Some commercially available sensors utilize a sensing material such as an electrochemical cell or metal oxide semiconductor, which interacts with the gas phase component (Snyder et al., 2013). Others measure the absorption of visible and infrared wavelengths of light, or absorption by chemiluminescence, the production of light from a chemical reaction. Particulate matter can be measured directly from mass concentration ($\mu\text{g}/\text{m}^3$) or indirectly from light scattering, which uses a proportionality constant that relates the scattered light to a defined aerodynamic diameter PM mass concentration (Seinfeld, 1998)

Traditional methods of PM_{2.5} exposure assessment often involve generating population exposure estimates through residence locations correlated with fixed-site monitoring (FSM) networks (Steinle, Reis, & Sabel, 2013). Due to the size and expense of these monitors, they are often sparsely deployed, often with only several stations covering large urban areas (Budde, Masri, Riedel, & Beigl, 2013). In New York City, there are 13 FSM stations covering approximately 1,200 km² ("New York State Air Quality Monitoring Center,"). In addition, the pollution exposures measured atop buildings can underestimate actual population exposures at ground-level (Restrepo et al., 2004). Such a "central site" air monitoring approach can therefore create difficulties in personal exposure assessment, as individuals can move frequently and erratically through an urban air pollution landscape that is highly spatially and temporally variable over course of any given day. In

addition, individuals spend a considerable amount of time within indoor environments, where such outdoor fixed-site monitors are unable to provide data regarding indoor air quality (Morawska et al., 2013).

An increase in monitor deployment density can provide a more accurate representation of an individual's personal exposure by accounting for the spatial and temporal variability of pollutants within an urban environment. Obtaining accurate personal exposures to air pollutants is a critical link between ambient air pollution and human health effects (Snyder et al., 2013). Increasing spatial density of monitors will result in less uncertainty from spatial interpolation of pollutant concentrations (Kumar, 2009). To supplement the relatively sparse deployment of current FSM urban monitors, several alternative approaches have been developed to provide greater geographic resolution of urban pollutant concentrations. Wireless sensor networks, low-cost static and wearable sensors, and radiometric image calibration are among the new approaches to personal exposure monitoring.

Wireless Distributed Sensor Networks (WDSN)

The OpenSense project is a system of wireless air quality sensor stations that are deployed in urban areas to assess the variations of pollutant concentrations within cities ("OpenSense," 2014). Each sensor station is equipped with an O₃, CO, NO₂, and ultrafine particle sensor. The ozone sensor is a metal oxide semiconductor gas sensor, while the CO and NO₂ sensors are electrochemical gas sensors. The current project deployment is comprised of 10 sensor stations on the tops of 10 trams in Zurich, Switzerland. The tram can power the sensor system, which monitors data in one-minute intervals creating sizable geographic monitoring coverage along the tram routes.

Researchers in the United Kingdom have experimented with a low-cost, high-density deployment of 46 static sensor nodes in Cambridge, UK (Mead et al., 2013). Each sensor node was comprised of a CO, NO, and NO₂ electrochemical sensor that monitored pollutant concentrations for 2.5 months. The results demonstrated the feasibility of a low-cost sensor node network that could produce high resolution spatial and temporal measures of pollutant concentrations for an extended period of time.

In Israel, researchers have examined the ability of static sensor nodes to identify spatial variability of pollutants at a neighborhood scale within the city of Haifa (Moltchanov et al., 2015). Sensor nodes were deployed to different microenvironments at three sites located only ~100-150m apart to distinguish variations of NO₂, O₃, and VOC. Results showed low correlations between NO₂ and VOC at different locations, which allowed for the capture of fine spatial variability of airborne pollutants at high resolution.

Intel Labs has developed a wireless sensor node approach that it hopes can deliver weather and air quality information while making revenue from advertisements (Shah, 2012). The system would comprise a population of static, low-cost sensor kits mounted on local businesses that gather real-time weather and air quality data, including CO, NO, and O₃. The sensors would then triangulate a user's position and deliver weather, air quality and advertisements to their smartphone from the nearest sensor using a personalized cloud service. Intel has previously tried a similar approach in the program Common Sense, which gathered air quality data by deploying the sensors on street sweepers in San Francisco (Shah, 2008).

Mobile Laboratories

To supplement fixed-site monitors, mobile laboratories have been used for obtaining air quality data for specific purposes. These mobile sites can be used to collect

road-site monitoring data to assess traffic management plans, which requires capturing pollutant concentrations that are highly spatially and temporally variable. Mobile laboratories were used to conduct in situ monitoring of on-road air pollutants before, during, and after the 2008 Olympic Games in Beijing (Wang, 2009). In addition, this platform has been used to evaluate pollutant concentrations in a highway-adjacent urban environment during variations in traffic and meteorological conditions (Padró-Martínez, 2012).

Location tracking with fixed site exposure monitoring

In Berkeley, California, researchers sought to measure individual exposures of Nitrogen Oxides (NO_x) in space-time by utilizing existing FSM monitors with individual location tracking from smart phones (Su, Jerrett, Meng, Pickett, & Ritz, 2015). Personal exposures were then estimated from the location tracking by superimposing the annual mean NO_x pollutant concentration surface with a Land Use Regression modeling technique. This strategy found that an individual's cumulative exposure could vary significantly from exposures estimated at the home location alone. The researchers concluded that integrating smart phones for momentary location tracking in conjunction with FSM monitoring, could make the personal exposure assessment of large populations (>1000 people) for weeks to months feasible.

Mobile Sensing

The concept of Mobile Sensing involves utilizing an optical technique to measure air visibility from smartphone camera photographs (Poduri, 2012). Photos are taken within the mobile application, which tags the photo for its specific location, orientation, and time. The photo is then uploaded to a server to determine visibility through radiometric image calibration and comparison of the image intensity to a model of sky luminance. Using the

focal length and orientation of the camera, an estimation of the turbidity of the image can then be calculated from a predetermined visibility estimation algorithm. Since smartphone cameras often do not allow for optical zooming, images from a phone have a fixed focal length, which allows for a one-time calibration. Common radiometric calibration techniques require taking a series of images at varying exposures to estimate the inverse response function, however this approach is not feasible in most smartphones, as they do not allow for manual manipulation of exposure settings. Instead, an alternative technique was used that could utilize a single image (S. Lin, 2004). This Mobile Sensing approach has displayed promising initial results, however the technique was limited to landscape images taken in cloudless skies that displayed haze that did not have a layered appearance within the image.

Low-Cost Light Scattering Monitors

Low-cost, wearable light-scattering PM_{2.5} particle counters provide new opportunities for both personal exposure monitoring and a “crowd sourced” high-density network of personal monitors uploading data to a single geographic overlay. With the advent of ad-hoc short wave radio connections such as Bluetooth, cellular geo-tagging and mobile data, a next-generation wearable PM_{2.5} monitor and mobile smartphone together can now perform tasks that previously required multiple high-cost devices. After being “paired” in an ad-hoc connection with a capable mobile phone, the monitor can relay real-time measurements that are then geo-tagged by the mobile phone and subsequently uploaded via mobile data to a geographic server overlay. Previous generation PM_{2.5} light-scattering systems have required data to be manually uploaded to a computer via a universal serial bus (USB) port where time-stamped data would be saved in a .CSV spreadsheet file. A separate GPS unit would then be run in tandem with the monitoring

device to create geographically marked timestamp data that could be manually matched back to the air monitor's time-stamped data.

The automation of this process, coupled with the low-cost of this next-generation light scattering PM_{2.5} particle counter can supplement fixed-site monitoring, provide personalized monitoring data for exposure assessment researchers, and help build on the concept of citizen science (Tweddle, 2012). Crowd funded projects such as the AirBeam (<http://goo.gl/70kTkL>), the AirQualityEgg (<http://goo.gl/mPJoD7>), the TZOA Enviro-Tracker (<http://goo.gl/y9fnJa>), and the Air.Air! (<http://goo.gl/r3ZVVW>) are now seeking to empower citizen scientists to monitor and collect air pollution data by providing a commercially available, easy to use, and low-cost wearable device. These wearable monitors have the potential to be used in large quantities and in conjunction with physiological monitors, such as wearable heart-rate monitors. For many personal exposure-monitoring objectives including those related to citizen science, wearable monitor performance may not need to meet the same critical accuracy requirements as reference instruments or fixed-site monitors (Snyder et al., 2013). Instead, as Snyder et al. (2013) describe, the aim is to assess how these sensors and monitors perform and see if they can achieve known degrees of precision. However, if the personal air monitoring data are to be combined with regulatory data, their measurements must be characterized and related to standard methods (e.g., gravimetric filter samples for PM_{2.5}), but this has not yet been accomplished for most low-cost personal samplers, to date.

Study Objectives

The objective of this study was the evaluation of a next-generation PM_{2.5} light-scattering particle counter in terms of accuracy for short-term exposure measurements of

PM_{2.5} mass, in real world and controlled scenarios. Collocation experimentation was performed with PM_{2.5} light-scattering particle counters to validate the performance against reference light-scattering aerosol monitors and Teflon gravimetric filters, both with PM_{2.5} particle cut-points. Urban outdoor stationary experiments were first conducted in New York, NY to determine particle counter accuracy. Indoor controlled experiments were then conducted to determine the particle count sensor saturation point and the accuracy of the monitor at the upper threshold of its capacity. Lastly, data collected in the validation experiments were used to develop a calibration to convert particle number counts (PNCs) in hundred particles per cubic foot (hpcf) from the AirBeam (HabitatMap) light-scattering particle counter into calculated PM2.5 mass ($\mu\text{g}/\text{m}^3$). This conversion method can be integrated into the light-scattering particle counter at the software level to allow for real-time PM_{2.5} mass data outputs from the particle count.

Materials and Methods

Sampling Instruments and Setup

In this research, the AirBeam (HabitatMap) was employed as a personal wearable light scattering particle counter during the study experimentations. The device emits an IR light beam inside a measurement chamber, where incoming particles interact with the emitted light, scattering the light in proportion to the particle number concentration. This allows the device to quantify particle number count per unit volume, which can then be indirectly converted into PM_{2.5} mass concentration after applying an assumed particle distribution, or using a field calibration, as conducted here. The AirBeam can log time stamped particle number counts with geographic tagged metadata into a paired Bluetooth Android mobile phone, where data can then be uploaded to a geographic server overlay or manually exported into a .CSV spreadsheet via the Aircasting app (<http://goo.gl/zguLX3>) available in the Google Play Store. The monitor's measurement size range includes all particle sizes, although the scattering of light varies with particle size, with the maximum scattering in roughly the 0.5 to 1.0 μm range diameter. The sampler weighs approximately 0.23kg, and costs roughly \$200 per unit (Table 1).

The AirBeam contains an Arduino Leonardo single microcontroller board encased in a 3D printed enclosure. The Leonardo has 20 digital input/output pins, which allow for the connection of the light-scattering sensor, a small inflow push fan, and the Bluetooth adapter. The microcontroller board is powered through a micro USB input and has a rechargeable battery that is estimated to last up to 12 hours per charge. For stationary monitor experiments, the AirBeam was powered through the micro USB input with an external power supply. In addition, the micro USB input can be connected to a computer

running the Arduino software package (<http://goo.gl/khylxx>), allowing the device's settings to be reprogrammed. The default-monitoring interval of the board was set to 1-second, but this was reprogrammed to 1-minute intervals in the Arduino software package to match the intervals of the other reference instruments, and to damp random noise in the AirBeam outputs. Monitoring runs were started and stopped via the Aircasting app, which provided real-time particle count data, temperature (°F), relative humidity (RH%), and noise (dB). Multiple AirBeam monitors were simultaneously paired to a single Android mobile phone with simultaneous readouts during the experimentation.

A Personal Data- RAM model 1500, or pDR-1500 (Thermo Scientific Inc., USA) was used with a $2.5\mu\text{m}$ cut-point inlet as a portable light scattering reference instrument. The monitor's measurement size range is $0.1\text{--}10\ \mu\text{m}$, with a concentration range from $1\ \mu\text{g}/\text{m}^3$ to $4 \times 10^5\ \mu\text{g}/\text{m}^3$ (Steinle et al., 2015). The device weighs 1.2 kg and costs roughly \$5500 with the $2.5\ \mu\text{m}$ and $10\ \mu\text{m}$ cut-point inlets. The humidity correction factor of the device was turned off for experimentation, as the day-to-day relative humidity during monitoring never rose above 60%. Data were recorded in 1-minute intervals for monitoring to match the intervals of the other instruments. The pDR-1500 was connected via an S-video input plug to an auxiliary Arduino microcontroller board with a Bluetooth adapter, powered by a separate external battery pack. The pDR-1500 was then paired via Bluetooth with the Aircasting app along with the AirBeam for the purpose of logging monitoring runs with matching timestamps for both instruments.

A 5 – 15 L/min programmable personal-sized pump (Leland Legacy®) was used to draw air through a conventional PM_{2.5} impaction filter mass sampler. Teflon filters were chosen as the filter media because they are non-hygroscopic and chemically inert (Jantunen, Hanninen, Koistinen, & Hashim, 2002). The filters were first allowed to

equilibrate in NYU School of Medicine's temperature and temperature controlled filter weighing room for a minimum of 24 hours before pre and post mass collection experiments. The weighing room mean temperature, relative humidity and pressure were 20.47 °C, 40.06% and 743.2 mmHg respectively. The filters were weighed after initial equilibration to determine the initial (pre) weight of the filter. A flow calibrated Leyland pump was then set to 10L/min with the 2.5µm cut point inlet and Teflon filter attached. The Leyland pump was calibrated for the desired flow rate by connecting it to a Dry Cal Defender 530 (BIOS, Butler, NJ) calibrating instrument to adjust the flow rate to 10L/min for the 10L pump. The CalCheck flow calibrator controlled for temperature and pressure during flow rate calibration. The filter collected particulate matter via impaction for a fixed sampling period, and was also subjected to gravimetric mass analysis at the NYU filter

Specification	Personal Data- RAM model 1500 (pDR-1500)	AirBeam	Android Mobile Smartphone	10L/min Personal-sized Pump
Device				
Manufacturer	Thermo Scientific Inc.	HabitatMap	Kyocera	Leland Legacy
Unit Quantity	1	5	1	1
Measurement Method	Light-scattering	Light-scattering	N/A	Particle mass impaction
Particle Size	PM _{2.5} and smaller (with cut-point inlet)	All particles	N/A	PM _{2.5} and smaller (with cut-point inlet)
Averaging Interval Time	60 seconds	60 seconds	N/A	N/A
Reported Units	Microgram per cubic meter (µg/m ³)	Hundreds of particles per cubic foot (hpcf)	N/A	Microgram per cubic meter (µg/m ³)
Device Weight	1.2kg	0.23kg	0.12kg	1kg
Device Cost Per Unit (USD)	\$5500	\$200	\$50	

Table 1. Collocation experimentation device specifications

weighing room post-mass collection (after the second 24-hour equilibration period). The NYU School of Medicine's filter weighing room meets EPA guidelines for filter conditioning, storage, temperature (20.47 °C), relative humidity (40.06%) and gravimetric measurement of PM_{2.5} and PM₁₀ filters (EPA, 1997). Using the equation [W₂ - W₁(mg) x 1000(µg)]/[Time(min) x Flow(L/min x 10⁻³)], the average mass concentration in (µg/m³) was determined by using the filter mass before monitoring, after monitoring, sampling volume, and total run time.

Urban Outdoor Monitoring

Collocation stationary outdoor monitoring experiments were conducted from June to August 2014 at New York University's campus on Broadway and West 3rd St. in New York, NY. The instruments used were: 2 AirBeam light-scattering particle counters; 1 Android mobile smartphone; 1 pDR-1500 light-scattering/mass concentration monitor with 2.5µm cut-point inlet; and, 1 Leland air sampling pump and gravimetric filter with 2.5µm cut-point inlet. All instruments were powered with external power adapters throughout monitoring. All real-time instruments had monitoring intervals set to 1-minute readings. Monitoring runs were conducted in 12-hour segments in order to allow sufficient time for enough sample collection on the filter for gravimetric determination of PM_{2.5} mass. One minute average mass concentration and particle count data from the light-scattering instruments were then averaged over the run time length for direct comparison to the impaction pump Teflon filters. AirBeam-2 served as a reference for AirBeam-1 in validating the accuracy of the average particle count data collected. The monitoring runs were spread out and repeated for multiple days in June, July, and August 2014. The

experimental procedure for the collocation stationary outdoor monitoring experiments consisted of the following steps:

1. The Leyland pump was first calibrated to 10L/min before each sampling period using the Dry Cal Defender 530 calibrator instrument;
2. The AirBeam particle counters were paired via Bluetooth to the Aircasting app and the geographic metadata log was turned off (to prevent app crashes from stationary logging);
3. The pDR-1500 was connected via S-video port to the auxiliary Arduino micro-controller board, and was then paired via Bluetooth to the Aircasting app;
4. The pDR-1500 filter compartment was cleaned with an alcohol swab before replacing the glass filter;
5. The pDR-1500 was zeroed by adding a circular loop of tubing that ran from the exhaust to the input while running the zeroing function on the pDR-1500 onboard display;
6. The 2.5 μm cut-point inlet on the impaction pump was cleaned with an alcohol swab;
7. A pre-weighted Teflon filter was then added into the 2.5 μm cut-point inlet attachment;
8. Monitoring instruments were turned on and the time was recorded at the start and stop of the run;
9. A second flow calibration of the 10L pump was conducted after sample collection for each sampling event;
10. Repeat steps 1 through 9

Data were uploaded from the Android mobile phone to a computer via Bluetooth where it was saved as a .CSV spreadsheet file. Teflon filters were sealed until they were brought to the filter weighing room for 24-hour equilibration and weighing. Monitoring data were then organized in Microsoft Excel according to instrument type and averaged across the monitoring run time period. Data was then graphed using both GraphPad Prism Version 6.0 (GraphPad Software, Inc.) and Microsoft Excel (Microsoft, Inc.).

Indoor Monitoring

Controlled indoor monitoring experiments were also conducted to determine the point of saturation of the AirBeam particle count, and to evaluate the accuracy of the device at its upper threshold range against the pDR-1500. Instruments used in these experiments were: 5 AirBeam monitors; 1 Android mobile phone; and, 1 pDR-1500 monitor with 2.5 μ m cut-point inlet. All instruments were collocated, set to 1-minute data intervals, and powered by external power supply for the duration of the monitoring runs.

Indoor stovetop cooking experiments were then performed by cooking meat in a stovetop pan for an allotted amount of time, then allowing the room to gradually dissipate of smoke. This experiment was performed to evaluate the rapid increase of PM_{2.5} of the instruments from the initial smoke followed by a gradual decrease in PM_{2.5} concentration as the smoke dispersed and eventually cleared the room. Smoke dispersal happened slowly, as PM_{2.5} concentrations still remained moderately above average several hours after cooking had concluded. Due to the very poor kitchen ventilation of many older New York City apartments, such cooking experiments can create very high PM_{2.5} concentrations that can linger potentially for hours after the cooking has taken place. These experiments differed from the outdoor urban experiments due to the compositional differences of the

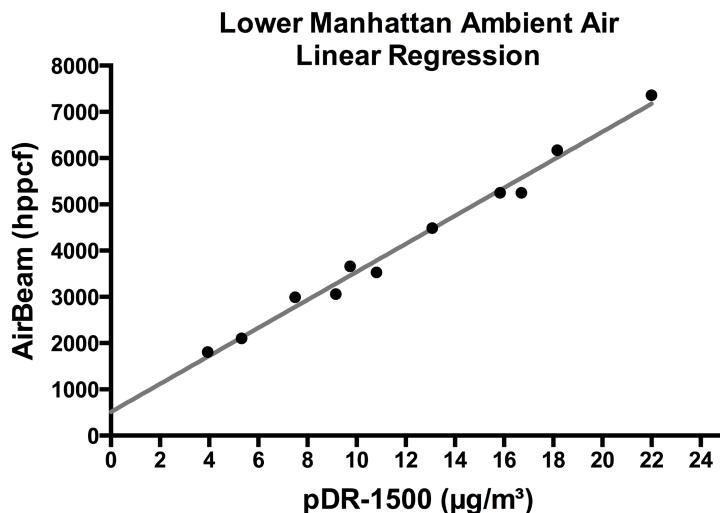
measured aerosols. Particulate matter generated from stovetop cooking is comprised of high concentrations of organic particulates, while the composition of outdoor New York City particulate matter is rich in elemental carbon soot and sulfates.

The experimental procedure of this indoor experiment was the same as that for the urban outdoor experiments, with the absence of the impaction pump and gravimetric filters. Since the filters were not used for these experiments, monitoring data were not averaged across the run time, but kept and analyzed in time stamped 1-minute readings.

Results

Urban Outdoor Exposure Concentrations

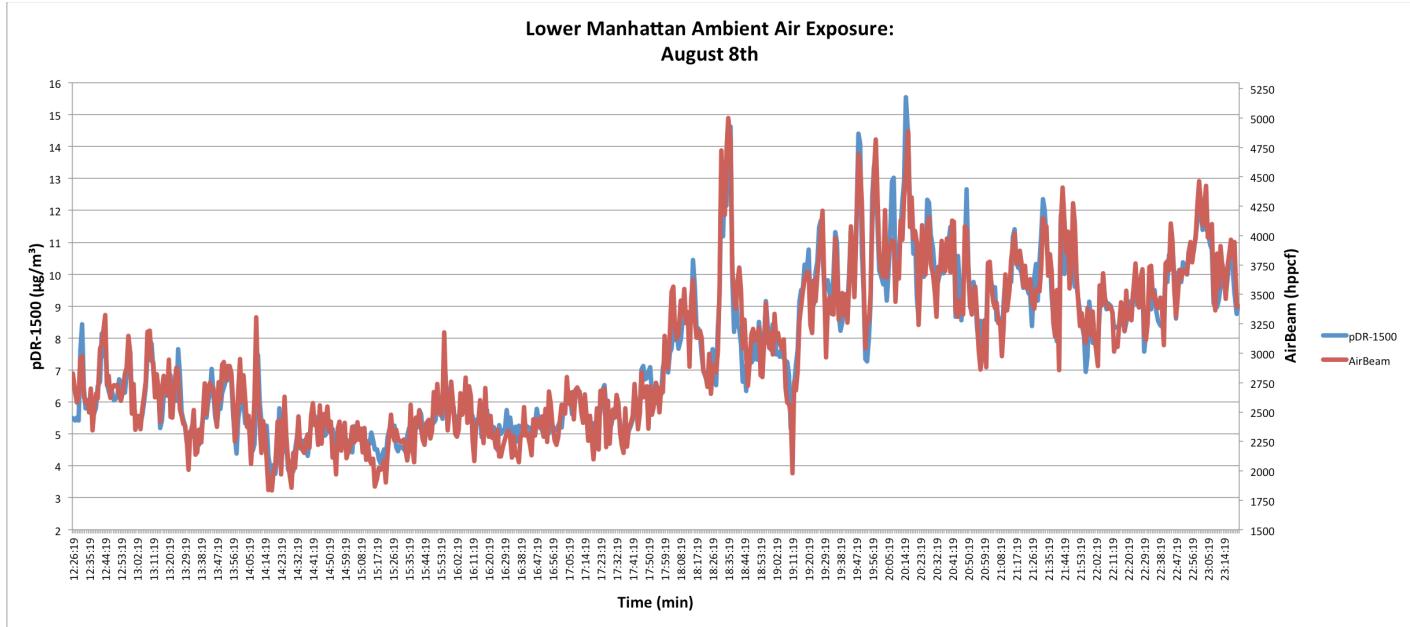
Figure 1 illustrates the relationship between the light-scattering pDR-1500 and AirBeam monitors in stationary conditions in a highly urban outdoor environment. Monitoring data from each instrument was averaged across the 12-hour monitoring time, creating single data points to show the day-to-day variability between instruments. Figure 1 shows this correlation between light-scattering instruments for 11 day-averages. The monitoring data suggest a highly significant linear relationship ($p < 0.0001$) between the two continuous sampling instruments, with a strong correlation, and excellent fit to the linear model ($R^2 = 0.9873$). Figure 1A and 1B show the 1-minute interval data on August 8th and 9th, 2014 of each instrument prior to averaging across the 12-hour monitoring time. This graph allows for a visual representation of the noise created from the strong temporal variability of PM_{2.5} in an urban environment throughout the day. Figure 1A and 1B show strong correlations between instruments at 1-minute intervals despite the strong ambient PM_{2.5} fluctuations throughout the day.



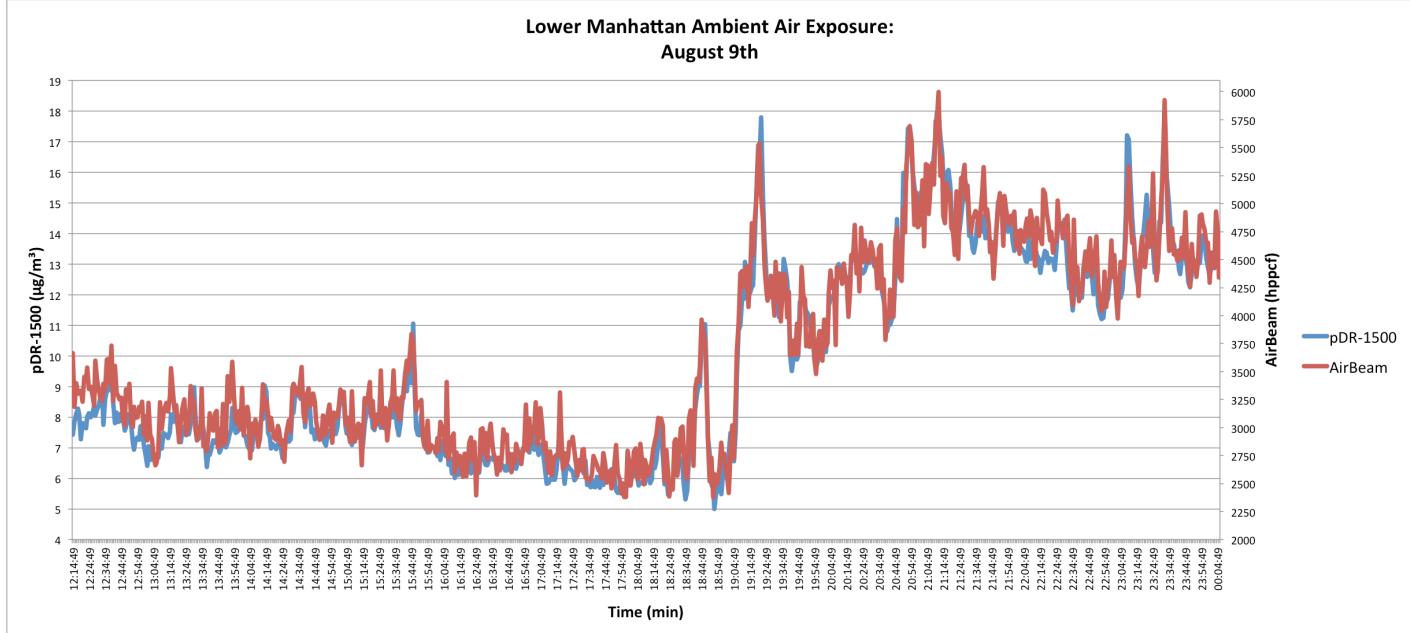
pDR-1500 vs. AirBeam	
Pearson r	
r	0.9936
95% confidence interval	0.9748 to 0.9984
R squared	0.9873
P value	
P (two-tailed)	< 0.0001
P value summary	****
Significant? (alpha = 0.05)	Yes
Number of XY Pairs	11

AirBeam	
Equation	$Y = 302.8 \times X + 512.1$

Results, Figure 1. 12-hour averaged AirBeam and pDR-1500 light-scattering monitor data comparison in urban outdoor conditions



Results, Figure 1A. 1-minute interval data between AirBeam and pDR-1500 light-scattering monitors on August 8th 2014



Results, Figure 1B. 1-minute interval data between AirBeam and pDR-1500 light-scattering monitors on August 9th 2014

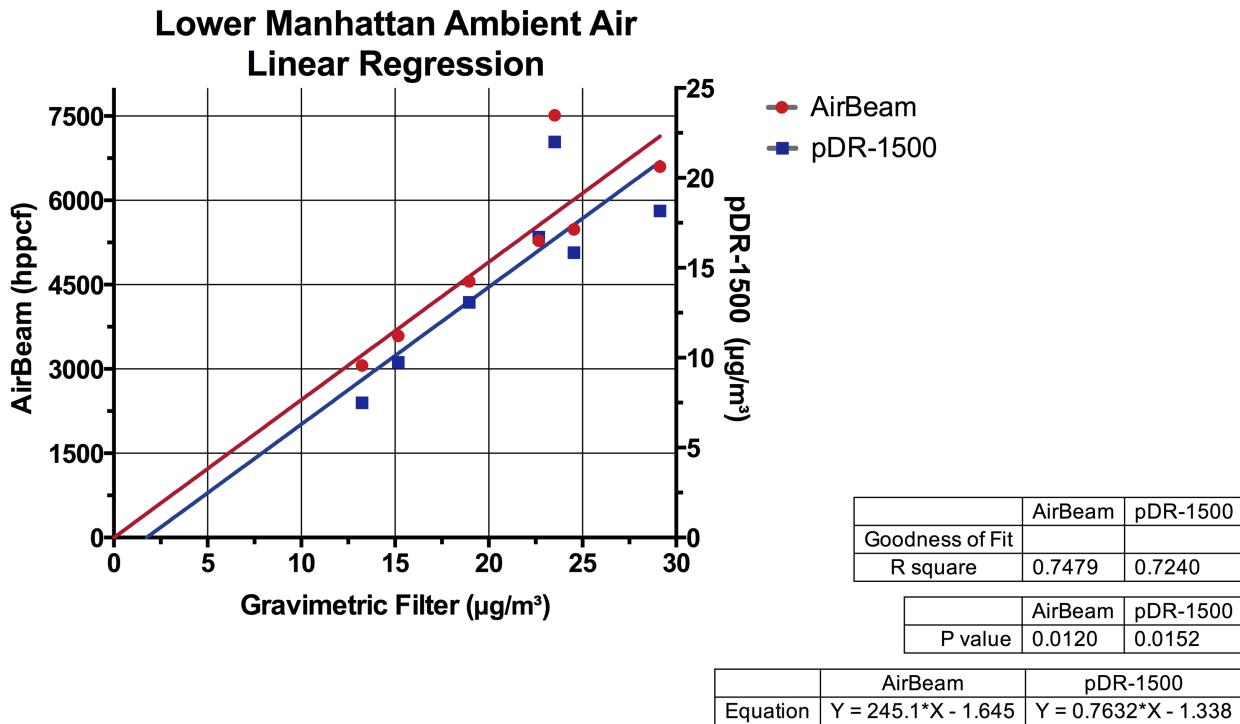
Date	PM _{2.5} Gravimetric Filter Avg. ($\mu\text{g}/\text{m}^3$)	pDR-1500 Avg. ($\mu\text{g}/\text{m}^3$)	AirBeam Avg. (hpcf)	Converted AirBeam Avg.* ($\mu\text{g}/\text{m}^3$)	Gravimetric Filter / pDR-1500 Ratio	Gravimetric Filter / AirBeam Ratio
July 3, 2014	29.133	18.162	6597.694	19.301	1.357	1.509
July 31, 2014	22.667	16.700	5279.969	15.114	1.069	1.500
August 1, 2014	23.521	22.000	7514.000	22.239	1.179	1.058
August 6, 2014	24.544	15.840	5482.676	15.750	1.550	1.558
August 7, 2014	18.961	13.073	4557.741	12.883	1.450	1.472
August 8, 2014	13.242	7.493	3063.321	8.556	1.767	1.548
August 9, 2014	15.169	9.738	3586.641	10.015	1.558	1.515
Cumulative Average:	21.034	14.715	5154.577	14.837	1.419	1.451

*Calibration equation is detailed in Figure 4

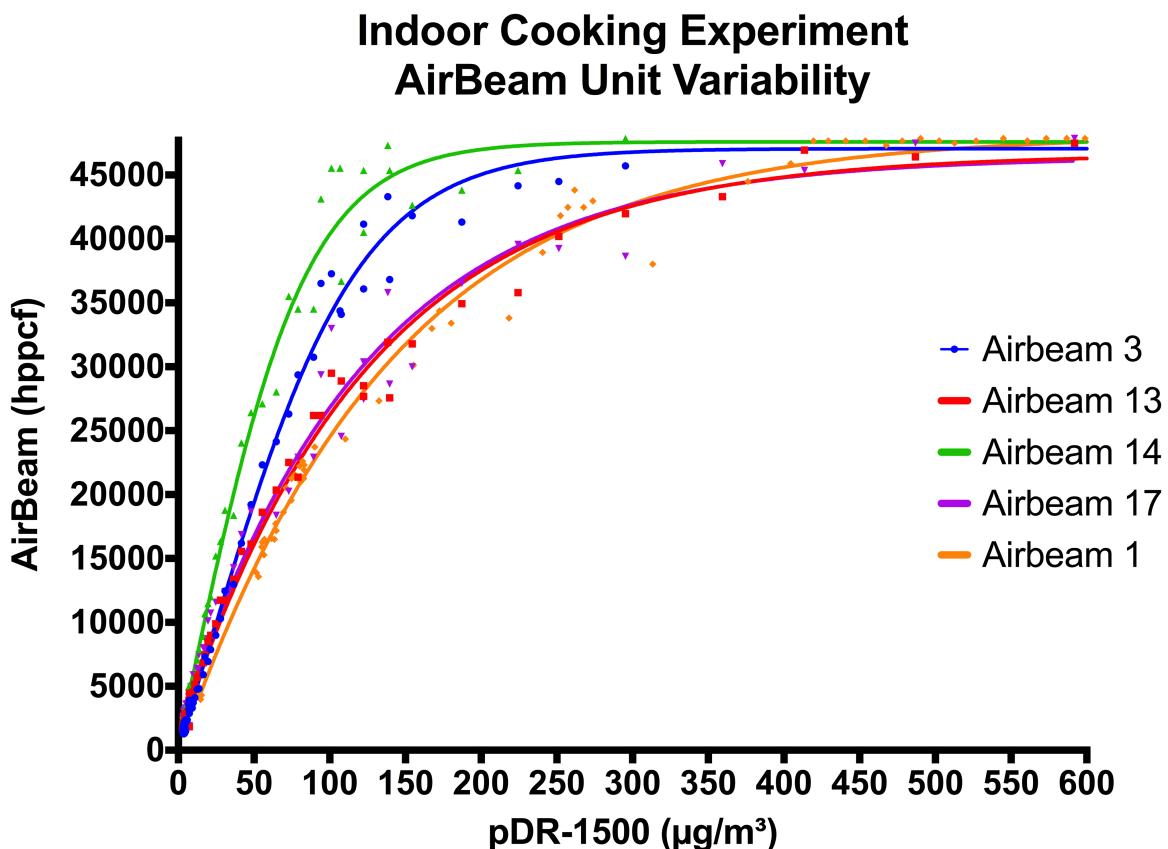
Results, Table 2. 12-hour averaged AirBeam, pDR-1500, and Gravimetric Filter Data

Table 2 summarizes the 12-hour averaged data of the gravimetric filters, pDR-1500, and AirBeam. The cumulative average of gravimetric filters was found to be 21.0 $\mu\text{g}/\text{m}^3$, 14.7 $\mu\text{g}/\text{m}^3$ for the pDR-1500, and 5154.6 hppcf for the AirBeam. The ratio between the gravimetric filters and pDR-1500 was obtained by dividing each gravimetric filter value by the corresponding pDR-1500 value and taking the cumulative average. The ratio between the gravimetric filters and the AirBeam was obtained by using the same method. The converted AirBeam values were obtained by using the calibration equation (Figure 4) to convert AirBeam (hpcf) values into ($\mu\text{g}/\text{m}^3$). The averaged ratios were found to be 1.419 between the gravimetric filters and the pDR-1500 and 1.451 between the gravimetric filters and the AirBeam.

Figure 2 shows the relationship between both light-scattering monitors and the collocated Teflon gravimetric filter mass concentration. Each data point represents the 12-hour averaged mass concentration, or particle count data point, plotted against the 12-hour average gravimetric mass concentration. Figure 2 demonstrates a strong and significant correlation between both the pDR-1500 ($R^2 = 0.7240$) and AirBeam ($R^2 = 0.7479$) with the



Results, Figure 2. 12-hour averaged AirBeam and pDR-1500 light-scattering monitor data comparison against gravimetric filter analysis in urban outdoor conditions



Results, Figure 3. 1-minute interval AirBeam and pDR-1500 light-scattering monitor data comparison in indoor conditions with stovetop smoke

gravimetric filters across 7 days. In addition, both the pDR-1500 ($p < 0.0152$) and AirBeam ($p < 0.0120$) displayed a significant linear relationship when plotted against the gravimetric filter data.

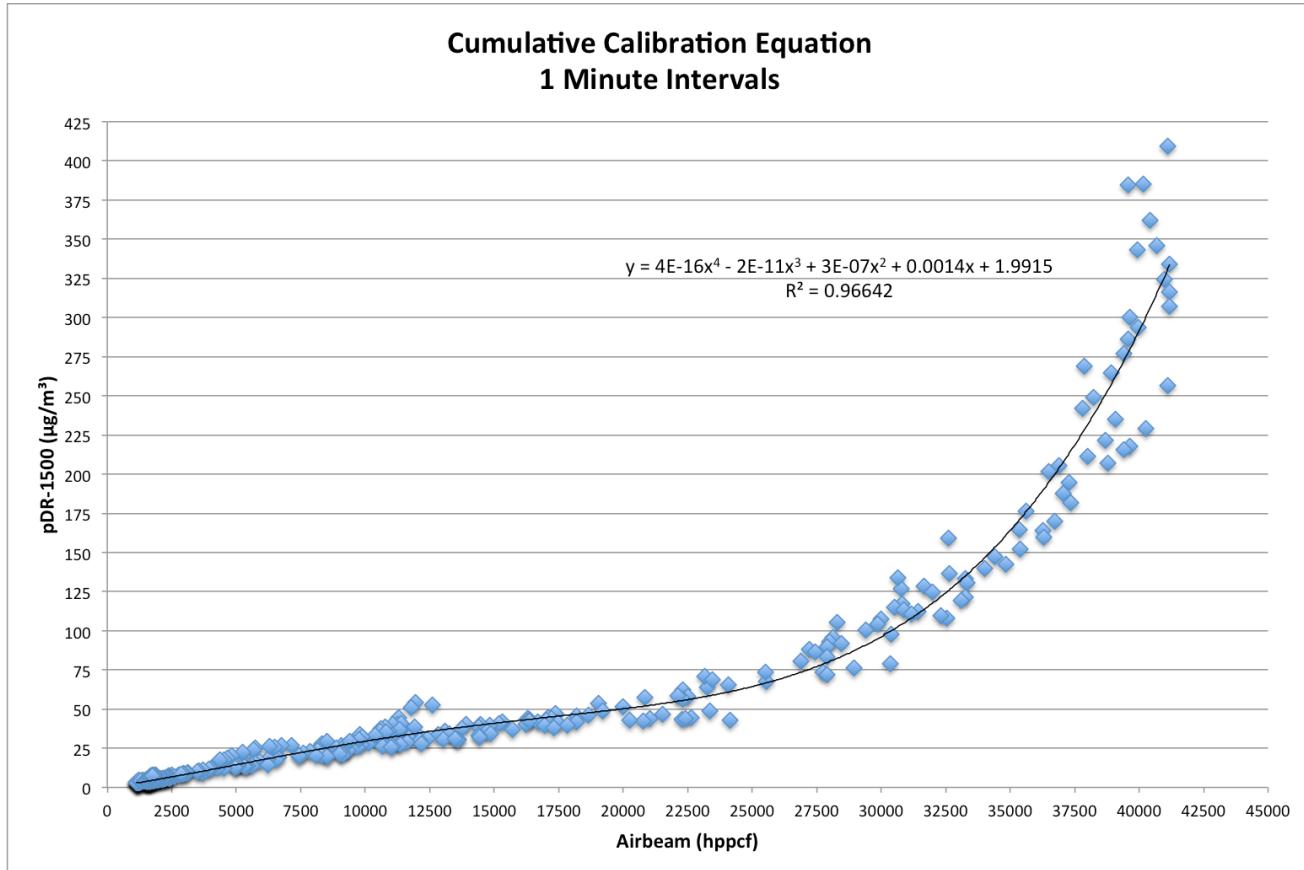
Indoor Exposure Concentrations

Figure 3 illustrates the results of the indoor cooking experiment with regard to both the AirBeam sensor saturation point and the variability of sensor data across multiple AirBeam monitors at upper threshold PM_{2.5} concentrations. As seen in Figure 3, the 5 AirBeam monitors reached a sensor saturation point between approximately 45,000 and 47,000 hppcf, where the respective AirBeam curves each approach the asymptote. This sensor saturation point corresponds to between 300 and 400 $\mu\text{g}/\text{m}^3$ in PM_{2.5} mass concentration, which is an order of magnitude above usual outdoor ambient levels in the Developed world. Figure 3 shows an increasingly nonlinear relationship between the pDR-1500 and AirBeam above 50 $\mu\text{g}/\text{m}^3$ wherein the curves becomes sigmoidal. In addition, AirBeam units displayed increasing deviation from one another above 50 $\mu\text{g}/\text{m}^3$.

Calibration Equation

Figure 4 shows the 4th order polynomial calibration equation ($y = 4E-16x^4 - 2E-11x^3 + 3E-07x^2 + 0.0014x + 1.9915$) used to convert AirBeam particle count (hppcf) units into mass concentration ($\mu\text{g}/\text{m}^3$) units. Using cumulative 1-minute interval data in both the urban outdoor environment and the indoor cooking experiment, the nonlinear plot was fitted with a 4th order polynomial curve to determine the unit conversion. Figure 4 displays a regression line that strongly approximates the real monitoring data points ($R^2 = 0.96642$). This conversion equation can be utilized at the software level to allow for real-time mass concentration ($\mu\text{g}/\text{m}^3$) unit output from the AirBeam monitor. In addition,

multiple conversion equations can be developed, tailored for specific environments to allow for more accurate output readings.



Results, Figure 4. Calibration equation to convert PNCs in hundred particles per cubic foot (hpcf) to estimated ($\mu\text{g}/\text{m}^3$) PM_{2.5} mass concentration

Discussion

This study evaluates the accuracy of a next-generation light-scattering PM_{2.5} monitor for assessing personal fine particulate matter exposures. This generation of light scattering monitor differs from past iterations in the low-cost, geo-tagged metadata, and aggregated geographic overlay of monitoring data. Monitor comparisons were performed between the AirBeam and the pDR-1500, an indirect light-scattering monitor. Previous experimentation has found that the pDR-1500 shows strong correlations with EPA reference instruments (Met One BAM 1020 PM_{2.5}, MageeSci AE22) in Developed world field tests (Allen, 2012). Both light-scattering monitors were then subject to comparison against Teflon gravimetric samples collected on filters. Gravimetric filter analysis provides a highly accurate output of average PM_{2.5} mass concentration that can be used as a primary method reference for calibrating light-scattering monitors.

Outdoor urban monitoring between the two light-scattering monitors clearly illustrates the strong accuracy of the AirBeam against the pDR-1500 at urban ambient conditions (1 - 25 $\mu\text{g}/\text{m}^3$). The monitors displayed some inconsistencies at 1-minute intervals (Fig. 1A,1B) due to the high PM_{2.5} noise created from strong temporal variability of the urban environment. This variability did not persist with the 12-hour averaged data, as this data displayed a linear relationship between the pDR-1500 at urban ambient PM_{2.5} concentrations for each of the 11 days that monitoring runs were recorded. The Figure 1 correlation coefficient ($R = 0.9936$) and coefficient of determination ($R^2 = 0.9873$) support this strong linear relationship in New York City urban ambient conditions of the AirBeam against the pDR-1500 in terms of accuracy. These results support previous findings that found a correlation coefficient range of $R=0.87-0.90$ between the AirBeam monitor and the pDR-1500 in an ambient outdoor microenvironment (Dye, 2014).

The addition of the Teflon gravimetric filter in the outdoor monitoring experiments provided a primary method measurement of PM_{2.5} mass to compare with the indirectly estimated measurements obtained from the light-scattering monitors. While a linear regression line represents the relationship between light-scattering monitors data well, Figure 2 illustrates an increase in the scatter about the line of best fit between the gravimetric filter analysis and each of the light scattering monitors. This is reflected by the decreased (but still significant) coefficient of determination values in the pDR-1500 ($R^2 = 0.7240$) and AirBeam ($R^2 = 0.7479$) against the gravimetric filter mass.

The gravimetric filter mass obtained was, however, found to be consistently higher than the estimated mass reported by the pDR-1500, by an averaged ratio of 1.41 ± 0.09 (Table 2). This may be attributed to the pDR-1500 manufacturer calibration to Arizona road dust, which may not accurately reflect the PM_{2.5} compositions seen in the ambient air of New York City (which is likely higher in carbon soot, and lower in wind-blown dust, as a percentage of mass). Despite this environmental calibration discrepancy, both light scattering instruments still displayed a linear relationship, with moderate variability, to the gravimetric filter mass concentration data. This provides encouraging evidence to support the accuracy of these light-scattering monitors in providing indirect PM_{2.5} mass concentration estimates in ambient conditions.

The indoor cooking experiment served as a stress test of the AirBeam monitor to determine both the sensor saturation point and how the monitor performed at PM_{2.5} concentrations considerably above ambient levels. By utilizing 5 simultaneous collocated AirBeam monitors (Fig. 3), the particle count variability between monitors was observed in an indoor smokeless environment followed by the accumulation and dissipation of smoke from stovetop cooking with poor ventilation. While particle count variability

remained negligible at ambient PM_{2.5} concentrations under 30µg/m³ ($R^2 = 0.98 - 0.99$), discrepancies between certain monitors gradually increased until reaching the sensor saturation point at 300 - 400µg/m³, when the monitor concentration curves approached the asymptote (Fig. 3). This variability was most pronounced in AirBeam-3 and AirBeam-14, while AirBeam-1, AirBeam-13, and AirBeam-17 displayed minimal particle count variability with increasing PM_{2.5} concentrations. This variability may suggest that there is manufacturing quality variability resulting in differences at high concentration levels. Previous high concentration collocation experiments of light-scattering monitors have displayed inter-monitor variability. A pDR-1500 collocation test in a smoke and soot chamber of 6 new monitors found up to ±10% variability between monitors (Allen, 2012).

The 300 - 400µg/m³ sensor saturation point of the AirBeam marks a considerable shortfall in comparison to the pDR-1500 light-scattering monitor. The manufacturer specifications of the pDR-1500 show the maximum concentration measurement range reaching 400mg/m³ ("pDR-1500 Aerosol Monitor: Full Specifications,"), approximately 10³µg/m³ higher than that of the AirBeam. The concentration measurement range of the AirBeam is therefore most suited to the Developed world, but not for the Developing world, where levels can frequently exceed 100 µg/m³. Outdoor ambient PM_{2.5} concentrations are less likely to exceed the sensor detection limit, unless in some heavily polluted traffic or smoking environments. Use in indoor environments with biomass burning or occupational PM_{2.5} exposures are likely to far exceed the sensor detection limit of the AirBeam monitor.

AirBeam and pDR-1500 1-minute interval monitoring data from both the outdoor urban experiments and indoor cooking experiments were aggregated in (Fig. 4) to produce a single curve that encompassed the concentration measurement range of the AirBeam

from roughly 1 - 325 ($\mu\text{g}/\text{m}^3$). Using known AirBeam (hppcf) X-values, the unknown mass concentration ($\mu\text{g}/\text{m}^3$) Y-values were then approximated through the 4th order polynomial equation that followed the best-fit curve. This equation can be programmed into the Arduino micro-controller board to generate real-time estimated mass concentration ($\mu\text{g}/\text{m}^3$) output values from observed particle count (hppcf) data. While only a single conversion equation was generated here to perform this conversion, a more accurate approach may involve generating multiple equations for multiple specific outdoor microenvironments. These equations could each be programmed into the Arduino's code, with the ability to allow the user to select their specific microenvironment prior to monitoring. Indeed, a recent production batch of these AirBeams sold on KickStarter actually incorporated the calibration curve from this Thesis into its design.

Previous evaluations of the AirBeam particle counter by others have determined that the sensor has a precision ranging from 4.0% to 4.8% in comparison to the pDR-1500 precision of 6.0% (Dye, 2014). The AirBeam monitor was assessed for correlation coefficients against the pDR-1500 in the following microenvironments: indoor candle smoke ($R=0.89-0.93$), indoor vacuuming ($R=0.89-0.94$), outdoor ambient conditions ($R=0.87-0.90$), and outdoor wildfire smoke conditions ($R=0.80-0.95$) (Dye, 2014). Results determined that the AirBeam performed well in PM_{2.5} concentrations less than 300 $\mu\text{g}/\text{m}^3$ and very well in PM2.5 concentrations under 100 $\mu\text{g}/\text{m}^3$.

Ferro, Kopperud, & Hildemann collocated real-time particle counters and integrated filter samples in both an outdoor and indoor microenvironment for five days in Redwood City, CA (2004). The particle counter and filter used in the experimentation was the Met-One Model 237B particle counter (Grants Pass, OR, USA) and TF-1000 Polytetrafluoroethylene (PTFE) Membrane 47mm, 2.5 μg filters (Gelman). Results showed

that indoor PM_{2.5} and outdoor PM_{2.5} ratios of measured filter concentrations to the estimated concentrations from the real-time particle counter were found to be 1.8 and 1.2 respectively. The authors attributed these discrepancies to the particle density being greater or less than 2.5g/cm³ and the low efficiency of indoor particles at scattering light (Whitby, 1979).

Brauer, Hirtle, Hall, & Yip performed a similar series of collocation experiments in both laboratory and field settings between a light-scattering particle counter and gravimetric filters (1999). The particle counter and filter used in the experimentation was the APC-1000 (Bioteest Diagnostics) and 37mm, 2.5µg Teflon filters (Gelman). The particle counter recorded monitoring data at four different size ranges: $\geq 0.3 - < 0.5 \mu\text{m}$, $\geq 0.5 - < 1.0 \mu\text{m}$, $\geq 1.0 - < 5.0 \mu\text{m}$ and $\geq 5.0 \mu\text{m}$. Results showed that particle counts in the 0.3-0.5µm and 0.5-1.0µm ranges were poorly correlated with PM_{2.5} mass concentrations ($N=17$, $R^2=0.39$ and 0.36, respectively). Similarly, particle counts in the 1.0-5.0µm and $> 5.0 \mu\text{m}$ size ranges had correlations of $R^2=0.20$ and 0.002 respectively. The authors attributed the discrepancies between the concentrations from measured particle mass and estimated particle counts to be from differences in particle density within the different size ranges and between the different microenvironments. Attempts to estimate particle mass concentrations from the particle count data resulted in even lower correlations between the two instruments.

This evaluation of the AirBeam monitor had several limitations. Outdoor urban collocation experiments were performed at a single fixed location. The use of one urban microenvironment may have limited monitoring to a relatively homogenous composition of particle compositions and associated particle densities. The discrepancies between filter mass concentrations and particle count data may be attributed to this specific

microenvironment. Additional fixed monitoring at multiple microenvironments can allow for different calibrations between instruments across multiple environmental conditions.

Twelve hour monitoring runs were conducted to allow sufficient time for a calculable mass to be obtained on the filter from particle impaction. Particle impaction in ambient conditions produced only minimal variations in mass concentration after 12 hours, however this amount of time was sufficient to detect variations in mass concentration.

Initial software limitations in the AirBeam restricted logging to 12-hour continuous monitoring runs, however later software updates fixed this restriction. To maintain consistency, all outdoor urban monitoring runs were kept to the same 12-hour run time.

AirBeam raw particle count data outputs displayed inter-instrument variability at high PM_{2.5} concentrations, which presented difficulties in accurately assessing the saturation point of the sensor. Future studies should examine the inter-instrument variability at a fixed aerosol concentration within a chamber to determine where the point of deviation is significant, relative to the uncertainty of measurement. Based on this study, and a previous evaluation of the AirBeam in wildfire conditions (Dye, 2014), a saturation point range of the AirBeam was estimated. This value was determined when the concentration curve of the monitor had approached its asymptote, and was estimated to be between 300 - 400 µg/m³ (Fig. 3). Lastly, the calibration equation (Fig. 4) is problematic because of the non-constant variance between the data points with varying concentration level. Generating enough high concentration data points to maintain constant variance was not logically feasible in this study. Calibrating multiple conversion equations for specific microenvironments should be attempted in the future to allow for more widely representative calibrations to gravimetric mass.

The ease of use and price-point of such an aerosol monitor provides a considerably lower barrier of entry for citizen scientists performing monitoring of personal PM_{2.5} exposures as compared with other monitors. While other portable light scattering monitors such as the pDR-1500 or the smaller variant pDR-1000 may be advertised as “wearable,” they still remain considerably more cumbersome compared with the smaller AirBeam (Table 1). For the purposes of urban outdoor mobile monitoring, a small form-factor plays an important role in the instrument’s convenience and accessibility. Outsourcing the AirBeam’s data logging and geo-tagging to a paired Android smartphone serves two significant purposes. First, it lowers the monitor unit price by utilizing existing geographic location tools and mobile data upload capabilities already present in the mobile smartphone to which is paired. Second, it provides a negligible weight addition to the monitoring unit, since individuals using the unit frequently already carry smartphones with them throughout the day. The ownership of a smartphone is one potential barrier of entry to consider, as the Nielsen 2013 U.S. Digital Consumer Report found that 65% of all Americans owned a smartphone in 2013 (Nielsen, 2013). Android is thought to control 78% of the smartphone market, according to a Q4 2013 report from research firm IDC (“Smartphone OS Market Share, Q3 2014,” 2014). In 2013, Google announced that Android activations have surpassed 1 billion devices worldwide, indicating high worldwide accessibility (Pichai, 2013).

To create a “crowd sourced” high-density network of personal monitors, logged monitoring data from each individual monitor must be uploaded to a single geographic overlay. Individuals can first “map” the PM_{2.5} concentrations within their neighborhoods or on their daily commute. When individual data from multiple users is then aggregated, a network of PM_{2.5} concentrations is created across a larger geographic area. When users

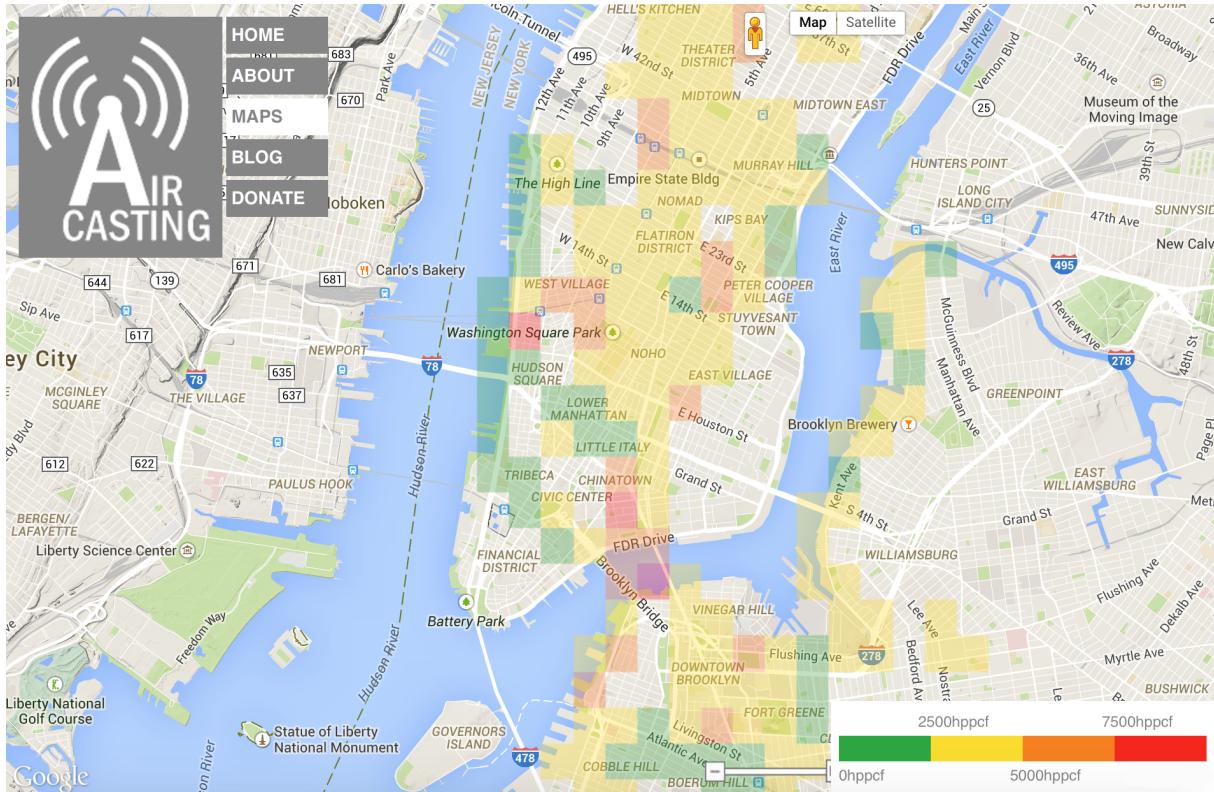


Figure 5. Aggregated AirBeam particle count data from multiple users across multiple points in time in New York City

record PM_{2.5} concentrations over the same geographic area at different points in time, the concentration average is taken for that unit area. Figure 5 illustrates the aggregated data from multiple users across multiple points in time in New York City. The level of map magnification determines which monitoring data is averaged, as a highly magnified map only averages data from a smaller unit area. Individuals can filter monitoring data to display only the cumulative averages from their monitor, or the specific monitoring data from a given monitoring run. Figure 6 shows the PM_{2.5} concentration at a specific point in time with the overlaid geographic location at which the monitoring sample was taken. This aggregation of monitoring data to a single geographic overlay marks a paradigm shift in how users log personal aerosol monitoring data. For citizen scientists and enthusiasts,

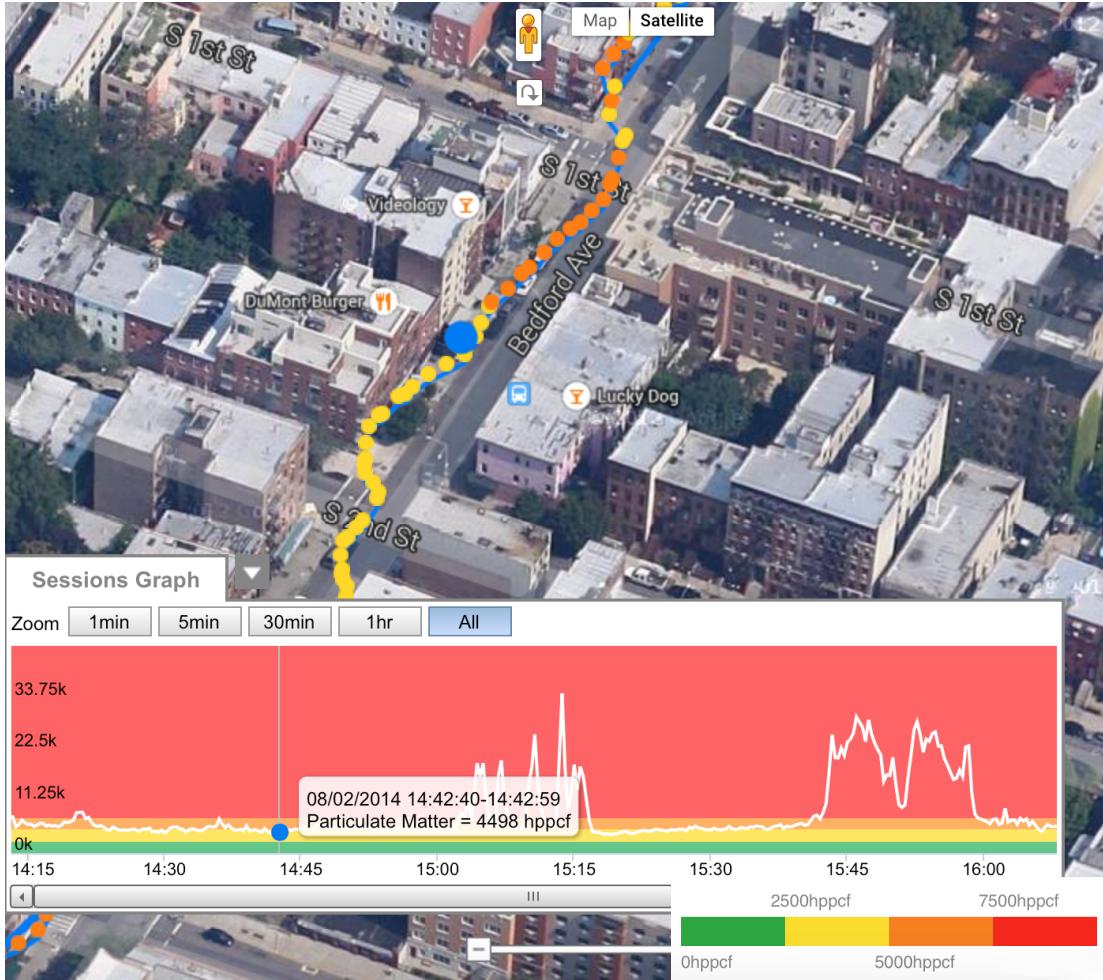


Figure 6. AirBeam particle count monitoring data at a specific point in time with the overlaid geographic location

users are not required to organize monitoring data in spreadsheets for interpretation and are no longer limited to accessing only their own data findings.

With the announcement of the Apple Watch in 2014, wearable technology was thrust into the mainstream media spotlight and heralded as the future of mobile technology. The watch, which monitors an individual's heart rate, calories burned, and daily activity joined a growing list of new wearable gadgets that monitor personal health indicators (Apple, 2014). As Apple CEO Tim Cook explained upon its introduction, "Apple Watch gives us the ability to motivate people to be more active and more healthy." IDC Health Insights estimates that by 2018, 70% of healthcare institutions worldwide will have

invested in mobile health technology in the form of mobile apps, wearable monitoring, or virtual care ("Worldwide Wearable Computing Device 2014–2018 Forecast and Analysis," 2014). This new mentality of personal health monitoring has fueled a new emerging market for intuitive and aesthetically pleasing wearable health monitors.

Wired Magazine's Bill Wasik wrote of wearable technology sensors, "Data will not help you if you can't see it when you need it" (Wasik, 2013). Data must be delivered to the user in an intuitive and accessible fashion to promote ease of use. As wearable physiology sensors such as the Apple Watch may allow individuals to become informed and educated about their bodies, wearable air pollution sensors may provide an opportunity for individuals to become more informed and educated with the air quality in which they live. This form of education and engagement can then allow individuals to become more involved with air quality policy issues and community-based strategies to reduce air

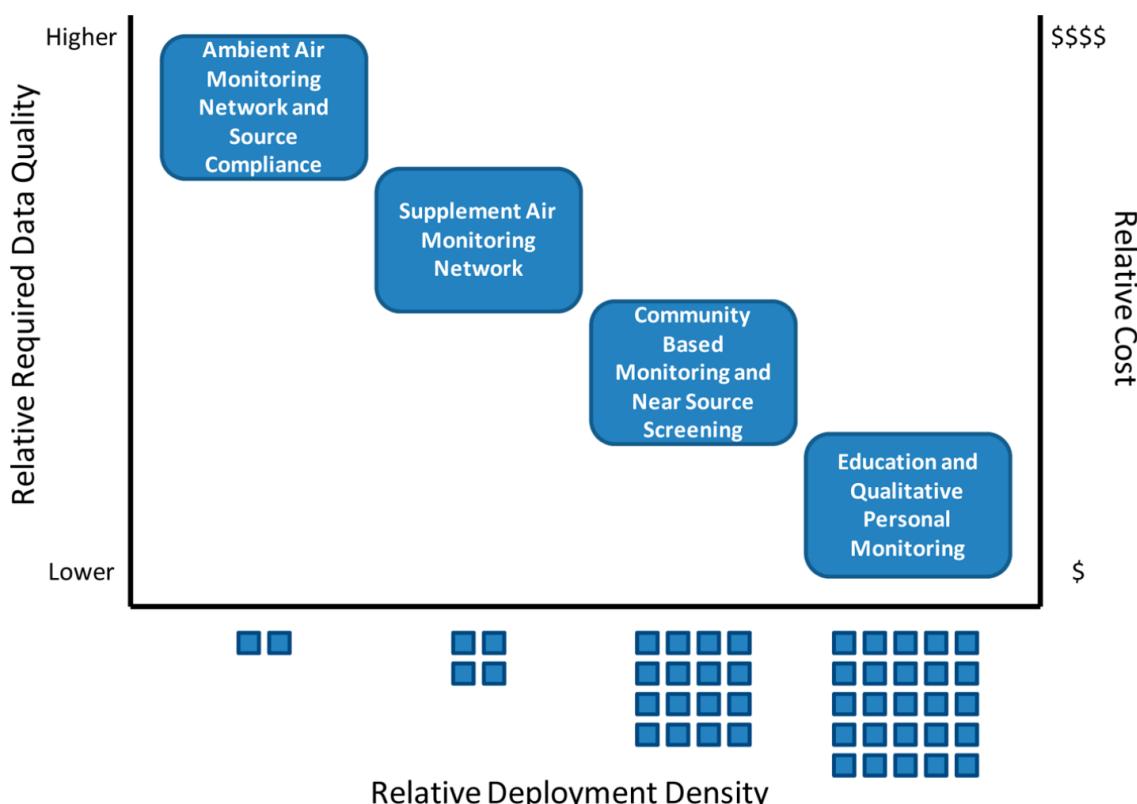


Figure 7. Aerosol monitor relative data requirements, deployment density, and cost by application (Snyder et al., 2013)

pollution exposures (Snyder et al., 2013). Whether it's personal health or environmental information, providing intuitive and easily accessible personal monitoring data allows for the individual to take personal ownership of their body and their environment. As seen in Figure 7, such wearable environmental health sensors can be deployed at the highest density with the lowest cost to provide public education and engagement of air quality. While stationary ambient air FSM networks are able to provide the highest quality data at a highest cost, such monitors are most relevant for policy and research purposes. Low-cost, high-density personal monitoring may then fill the gap at the community and individual level for air quality education and engagement.

In 2004, the International Telecommunications Union (ITU) found that mobile phone use in continent of Africa had eclipsed the use of wired landlines ("ITU 2013 Facts and Figures,"). The ability of developing countries to leapfrog legacy technology can have far reaching economic, educational, health, and environmental consequences. The cellular infrastructure in the Developing world may provide a new means to conduct epidemiological data monitoring and surveillance of healthcare and environmental endpoints at a large scale. Mobile phone data analytics has previously been used in sub-Saharan Africa to generate malaria risk maps from human mobility data (Buckee, Wesolowski, Eagle, Hansen, & Snow, 2013). In the aftermath of the 2010 Haiti earthquake and cholera outbreak, trends of populations movements were rapidly generated from the geographic positions of cell phones in an effort to aid disaster relief (Bengtsson, Lu, Thorson, Garfield, & von Schreeb, 2011).

These location tracking and mobile data capabilities provided by the cellular infrastructure in the Developing world can be utilized in the same way with the AirBeam. The low-cost, battery operation, location tracking, and automation of the device make it a

promising candidate for personal exposure epidemiology research in the Developing world. Expanding the personal exposure monitoring capabilities in the Developing world in both outdoor and indoor environments is critical. Due to the disproportionate burden of disease from outdoor and indoor pollutants seen in newly industrialized cities, the need for comprehensive air pollution monitoring in these urban zones is clear. The AirBeam can be a first step towards developing a cost effective strategy to generate personal exposure assessments in the Developing world however, it's current hardware is not without limitations. In many developing cities, daily ambient PM_{2.5} concentrations can exceed the sensor saturation point of the device. In addition, indoor exposure concentrations generated from biomass or coal burning would likely far exceed the sensor saturation point. Future iterations of the device may be developed to address this key hardware limitation however, the current monitoring platform and Web back-end offer a glimpse into the future potential of personal monitoring within the Developing world.

Conclusion

To successfully create a high-density personal monitoring sensor that can serve both citizen scientists in community education as well as researchers in supplementing FSM monitoring systems, several criteria need to be met (Budde et al., 2013). First, the monitor must be compact such that it is both wearable and embeddable into a ubiquitous technology such as mobile phones. Second, the sensor must be inexpensive to allow for a low barrier of entry to citizen scientists, and to allow for large quantities to be used in epidemiological research studies. Third, the device must be usable such that it does not require frequent maintenance, filter changes, or difficult calibrations. Fourth, the monitor must be able to provide real-time, geo-tagged monitoring data that can be easily aggregated between multiple devices. Fifth, the monitor must be accurate, allowing for meaningful monitoring data to be obtained.

This study evaluated the operation and monitoring accuracy of the AirBeam, a wearable light-scattering aerosol sensor, for conducting personal fine particulate matter exposures. The monitor displayed strong correlations in PM_{2.5} concentration against the more expensive reference pDR-1500 light-scattering sensor up to 300 – 400 $\mu\text{g}/\text{m}^3$ in both urban outdoor and indoor conditions. Both light-scattering sensors displayed similar moderate correlation against the reference gravimetric filter mass analysis in an urban outdoor setting. Within the observed outdoor PM_{2.5} concentration range in New York City, the AirBeam monitor displayed excellent accuracy against the more the expensive light-scattering unit, and similar associations with a gravimetric filter pump and filter reference approach. These are validating results in the development of a low-cost, accurate, and wearable sampler for the utilization of assessing personal fine particulate matter exposures.

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