https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

Spectral Analysis Approach for Assessing Accuracy of a Low-Cost Air Quality Sensor Network Data

Vijay Kumar[1], Dinushani Senarathna [1], Supraja Gurajala [2], William Olsen [3], Shantanu Sur [4], Sumona Mondal [1], and Suresh Dhaniyala *[5]

[1]Department of Mathematics, Clarkson University, Potsdam, NY, 13699, USA
[2]Department of Computer Science, State University of New York, Potsdam, NY, 13676, USA
[3]Department of Civil and Environmental Engineering, Clarkson University, Potsdam, NY, 13699, USA
[4]Department of Biology, Clarkson University, Potsdam, NY, 13699, USA
[5]Department of Mechanical and Aeronautical Engineering, Clarkson University, Potsdam, NY, 13699, USA

Correspondence: *Suresh Dhaniyala(sdhaniya@clarkson.edu)

Abstract.

Extensive monitoring of $PM_{2.5}$ is critical for understanding changes in local air quality due to policy measures. With the emergence of low-cost air quality sensor networks, high spatio-temporal measurements of air quality are now possible. However, the sensitivity, noise, and accuracy of field data from such networks are not fully understood. In this study, we use frequency analysis of a two-year data record of $PM_{2.5}$ from both the EPA and Purple Air (PA), a low-cost sensor network, to identify the contribution of individual periodic sources to local air quality in Chicago. We find that sources with time periods of 4, 8, 12, and 24 hours have significant but varying relative contributions to the data for both networks. Further analysis reveals that the 8- and 12-hour sources are traffic-related and photochemistry-driven, respectively, and that the contribution of both these sources is significantly lower in the PA data than in the EPA data. We also use a correction model that accounts for the contribution of relative humidity and temperature, and we observe that the PA temporal components can be made to match those of the EPA over the medium- and long-term but not over the short-term. Thus, standard approaches to improve the accuracy of low-cost sensor network data will not result in unbiased measurements. The strong source dependence of low-cost sensor network measurements demands exceptional care in the analysis of ambient data from these networks, particularly when used to evaluate and drive air quality policies.

1 Introduction

Air pollution is one of the world's leading risk factors for disease and premature death. An estimated 16% of total global deaths in 2015 can be attributed to diseases caused by air pollution(Landrigan et al., 2018). Of particular concern is the mass concentration of Particulate Matter (PM) smaller than 2.5 μm, i.e. $PM_{2.5}$, or fine particles. Exposure to $PM_{2.5}$ has been directly correlated to diseases such as respiratory diseases and even mortality (Li et al., 2018; Xing et al., 2016; Samoli et al., 2005; Ostro et al., 2006; Lewis et al., 2005). The high health impact of $PM_{2.5}$ is because of their ability to penetrate deep into the lungs and because their composition is often carcinogenic (Li et al., 2014). The European Study of Cohorts for Air

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

Pollution Effects (ESCAPE) shows that exposure to high $PM_{2.5}$ concentrations are linked with a risk of developing lung cancer (Raaschou-Nielsen et al., 2013). In addition to chronic diseases, exposure to $PM_{2.5}$ also impacts our response to acute diseases such as COVID-19 (Wu et al., 2020; Zhou et al., 2021; Mondal et al., 2022; Chaipitakporn et al., 2022). Accurate knowledge of $PM_{2.5}$ exposure and efforts to mitigate it are critical to protecting public health.

In the United States, the Environmental Protection Agency (EPA) monitors air quality by measuring regulated or criteria pollutants including ambient $PM_{2.5}$ concentrations using Air Quality Monitoring Stations (AQMSs). The $PM_{2.5}$ measurements are made using a range of instruments classified as federal reference methods (FRMs) or federal equivalent methods (FEMs) (Noble et al., 2001). These methods ensure consistency and accuracy in measurements, but are expensive, and difficult to operate, requiring trained personnel and significant infrastructure. The strict maintenance and calibration routines followed in these stations ensure high-quality data and comparability between different locations (Castell et al., 2017). Even in the US, with over 5000 AQMSs, the geographic coverage of these monitoring sites is inadequate. The siting of AQMS is often biased towards populated areas, disadvantaging smaller cities and underdeveloped regions (Ardon-Dryer et al., 2020). Even in populated areas, the limited number of sites do not capture the high spatial variation in $PM_{2.5}$ concentrations that are likely, resulting in an incorrect estimate of exposure and resultant health effects (Wang et al., 2015).

For accurate exposure assessment, an air quality monitoring network providing measurements at high spatio-temporal resolution is required. To address this need, researchers, communities, organizations, and individuals have been deploying low-cost air quality sensors that provide air quality data at a granular level not possible with the EPA AQMSs (Commodore et al., 2017; Woodall et al., 2017). One of these networks is composed of sensors from Purple Air (PA). The PA sensing platform incorporates a pair of Plantower PMS 5003 low-cost sensors, which use laser light scattering techniques to determine ambient aerosol concentrations. The PMS5003 reports a variety of particle concentration metrics including PM_1, $PM_{2.5}$, and PM_{10} (Sayahi et al., 2019; Ouimette et al., 2022; He et al., 2020). Using two sensors for PM measurements allows for the robustness of data collection (PurpleAir, 2020). While the low-cost sensors have the advantage of deployment ease, their accuracy and precision are variable (Kuula et al., 2017).

The various PM sensors used in low-cost monitors are all subject to biases and calibration dependencies, with some factors accounted for with moderate success (e.g. meteorology, age of sensor) and others poorly (e.g. aerosol source, composition, refractive index) (Giordano et al., 2021). The PA sensor measurements are often calibrated/corrected by co-location with a reference monitor at a regulatory site (Wallace et al., 2021; Stavroulas et al., 2020; Kelly et al., 2017). Additionally, researchers have developed correction models to account for the impact of environmental conditions on sensor performance (Barkjohn et al., 2021; Ardon-Dryer et al., 2020). The deployment of PA sensors has resulted in expanding the availability of $PM_{2.5}$ data and enabling a range of studies, including, validation of high resolution, large-scale regional modeling efforts (Bi et al., 2020) and understanding of the impact of wildfire smoke on local and regional air quality (Gupta et al., 2018).

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023


Atmospheric Measurement Techniques Discussions

Co-locating low-cost sensors with reference monitors provides a fast way for their calibration. Typically, this is done by co-locating the sensors for a period of time and then determining a scaling factor or equation based on a regression analysis. The time period for co-location is generally chosen to be around days to weeks and this allows for the calibration to be independent of data noise. The selection of the calibration time period can, however, bias the sensor data to be most sensitive to sources primarily responsible for pollutant concentration variability in that time period. Sources with shorter time periods, relative to the calibration period, are averaged out and inadequately accounted for in the calibration. Thus longer time scale events are completely lost in the calibration process.

Published studies on low-cost sensors have observed some of the above mentioned problems. The response characteristics of low-cost sensors are seen to be different from that advertised by their manufacturers, possibly because the aerosol size distributions and compositions differ with location (Kuula et al., 2020; Tryner et al., 2020). As an example, low-cost sensor data are seen to be in better agreement with reference monitors at locations with low traffic than those at high-traffic locations (Castell et al., 2017). To improve the quality of the reported data from low-cost sensor networks, we need to establish ideal field calibration principles for these units. For this, frequency based methods that have been previously used in air quality to find prominent temporal components can be used (Hies et al., 2000; Marr and Harley, 2002; Choi et al., 2008; Tchepel and Borrego, 2010). Time-series decomposition using low-pass filters can identify pollution sources that account for most of the measurement variation (Zhang et al., 2018; Bai et al., 2022). Here, using frequency-based analysis, the dependence of low-cost sensor $PM_{2.5}$ measurement accuracy on the calibration period will be established.

For this work, we chose our study area as Cook county, IL which includes the City of Chicago and a total population of nearly 10 million. Cook County is a major transportation hub lying at the crossroads of the country's rail, road, and air traffic, and an important industrial center, thus, there are a number of emission sources within the area. Despite a baseline long-term trend of improving air quality in Chicago, recent years show a worsening trend. $PM_{2.5}$ concentrations have nearly doubled since 2017, rising from 6.7 $\mu g/m^3$ in 2017 to 12.8 $\mu g/m^3$ in 2019, exceeding US EPA air quality standards (12 $\mu g/m^3$) (IQAIR, 2020). The changing air pollution levels have increased public interest in air quality monitoring, particularly using low-cost sensor networks. For the time period starting May 2018, the purple air network in Chicago and its surrounding neighborhoods have increased from a few sensors to more than 30 sensors now.

In this study, we used $PM_{2.5}$ data from EPA sites and PA sensors located in Cook County, IL to understand differences in their data as a function of sensor location and time. Using spectral theory, we extract temporal signatures of the EPA and PA data and analyze their differences as a function of time period to determine the effectiveness and limitations of the current approach to correct low-cost sensor data to match EPA data. The results of this analysis will help us understand biases in the data from low-cost sensors such as PA networks and provide guidance in devising new approaches to foe;d calibrate data from these sensors.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

2 Materials and Methods

2.1 Data Collection and Pre-processing

Cook County, IL, has 14 EPA air quality monitoring sites, providing data on criteria pollutants, including ambient $PM_{2.5}$ concentrations (EPA, 2021). Hourly $PM_{2.5}$ measurements from EPA are available at 7 out of 14 monitoring sites in Cook County, IL. The PA network in Cook County consists of more than 30 PA low-cost sensors, that currently provide $PM_{2.5}$ data (PA, 2021). Our analysis was conducted using data from a time period of October 2019 to September 2021. For this time period, hourly $PM_{2.5}$ data was only available at 10 out of 30 PA sensors. Further, after eliminating sites with more than 20% missing data, our analysis could only use data from 5 EPA sites and 9 PA sensors, as shown in (Figure 1) and in (Table S1)

It was observed that PA data included some outliers with very large $PM_{2.5}$ concentrations, which are likely erroneous data. To eliminate these outliers from our analysis, we chose a data range of [0,70] ug/m^3 as valid data (Ardon-Dryer et al., 2020). In (Figure 1a) the sampling locations of EPA and PA are plotted on the map with the population density around the sampling locations in (Figure 1b). The population density in census blocks, as defined by US Census Bureau (Bureau, 2021), was calculated using ArcgisPro 2.8. From a cursory analysis of the siting of sensors, it is clear that the PA sensors are located in urban areas where population densities on average are higher than what they are at the EPA sites except few sensors i.e P1, P5, and P8.

2.2 Standard Correction Model

It has been established that low-cost sensors are sensitive to meteorological parameters, especially relative humidity (Barkjohn et al., 2021; Ardon-Dryer et al., 2020). The PA measurements are based on light scattering, with factory calibration to report $PM_{2.5}$ values. As the composition and size distribution of particles in Chicago is likely different from that used in the sensor calibration, the reported values will need some correction. Additionally, while temperature and relative humidity also impact particle physical and optical properties that govern PA measurements, they do not affect EPA measurements due to thermal conditioning of particles in FRM and FEM instruments prior to measurements (Zheng et al., 2018; Kelly et al., 2017; Magi et al., 2020). Recently a US-wide correction model for PA sensors that takes into account the contribution of ambient conditions on sensor performance was introduced (Barkjohn et al., 2021). The model was built using data from 53 PA sensors, with data spanning the time period of September 2017 to January 2020, at 39 distinct sites spread throughout 16 states. From an evaluation of several models using temperature and relative humidity, they suggested a final model only considering the effect of relative humidity (RH) on PA sensor data. This model, herewith called the standard correction model, is:

$$PM_{2.5}\ \text{Std\_Corr} = 0.524\ \text{PA}_{cf\_1}\ PM_{2.5} - 0.0862\ \text{RH} + 5.75, \tag{1}$$

where, cf_1 is the higher correction factor, and RH is the relative humidity in percent.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023


Atmospheric Measurement Techniques Discussions

In our study, the corrections made to the PA data used the relative humidity (RH) (and temperature for the local correction model introduced later in the manuscript) reported by the 9 PA sensors themselves. Using the EPA data from sites in the vicinity of each of the sensors, the standard correction model was used to correct all sensors in our Cook County area.

2.3 Monitoring Data Summary

This study uses 2 years of $PM_{2.5}$ data from 5 EPA sites and 9 PA sensors from October 2019 to October 2021. Sample time series trend in $PM_{2.5}$ from a set of EPA and PA sites (EPA site E2 and PA sensor P6) that are in close vicinity (within 2 km) to each other is shown in (Figure 2a). The gap in the total time series of $PM_{2.5}$ data around April 2020 in E2 and September-October, 2021 in P6 is due to missing observations in the time series in (Figure 2a). The major causes for missing air pollutant data in reference monitor includes monitor malfunctions and errors, power outages, computer system crashes, pollutant levels lower than detection limits, and filter changes (Imtiaz and Shah, 2008; Hirabayashi and Kroll, 2017). For low-cost sensors, approximately 40 % of the data generated is missing, most likely because of extreme weather events, battery failure, and disruption in internet accessibility at sensors location (Kim et al., 2021; Rivera-Muñoz et al., 2021).

The data from both networks show high temporal variations along with some seasonal trends over longer timescales. A direct comparison of the two data sets (Figure 2b) for the combination of E2 and P6 sites shows that on average the raw PA data overestimates the EPA data by 50%, consistent with previous findings. use of the standard correction results in a decrease in the reported PA values. The resultant best-fit linear model suggests that the corrected data slightly underestimates the actual $PM_{2.5}$.

The overall distribution of $PM_{2.5}$ data at each of the EPA and PA sites over the entire time period of our analysis is shown in (Figure 3,Table S2). The median values of $PM_{2.5}$ reported by the PA sites are always higher and more variable than that from EPA sites in the region. The median $PM_{2.5}$ values from the average from the 5 EPA sites in the region is 8.4 μg m^{-3} while the PA data reports a median value of 10 ug/m^3. With the standard correction it is seen that the variability is reduced and the median is 6.9 ug/m^3, 20% lower than the EPA value.

While the accuracy of the correction model can be improved with some local tuning, it is clear the model did not improve the quality of fit. This suggests that the correction model does not account for all of the causes of discrepancy between the two data sets. In particular, a regression based model will not be able to account for the sensitivity of the sensors to particle compositions and hence to different emission sources. A preliminary validation of model dependence on composition can be obtained from the evaluation of model performance for the prediction of $PM_{2.5}$ concentrations during weekdays and weekends. The differing strengths of some emission sources between weekdays and weekends are expected to result in slightly different aerosol populations during these two time periods. Here, we separated the data as weekday and weekend and applied the correction model to get corrected PA data for each of the data sets. A two-sample t-test between the EPA and corrected PA data (Figure 4) shows a statistically-significant difference between the two data sets (p-value < 0.05) on weekdays but not on weekends, providing some initial validation that the correction model does not account equally for the contribution of all sources.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

To better understand the causes of model under-performance and to determine the primary drivers for this discrepancy, a frequency-based analysis is helpful. Such an analysis can help extract the contribution of any periodic emission sources that might exist and establish if the standard correction model provides a bias-free correction for all of these components.

3 Spectral Analysis

In meteorology and air quality studies, spectral analysis has been used to extract and examine different temporal components in the obtained data (Hies et al., 2000; Marr and Harley, 2002; Choi et al., 2008; Tchepel and Borrego, 2010). Here, we are using spectral analysis to determine the effectiveness of the correction model to bring PA data close to EPA data over the entire range of emission sources that contribute to Cook County's $PM_{2.5}$ population.

To ensure the time-series datasets used in this spectral analysis are not affected by deviations from stationarity, we use the augmented Dickey-Fuller (ADF) test method (Wang et al., 2021; Lian and Ma, 2013).

The discrete Fourier transform, $X(k)$, of hourly time series X_t, can be calculated using the Fast Fourier transform (FFT) algorithm. The spectral density for a finite time series can then be calculated as the squared magnitude of $X(k)$:

$$\Phi(v_k) = |X(k)|^2 = \left| \frac{1}{\sqrt{N}} \sum_{t=0}^{N-1} X_t e^{-2\pi i v_k t} \right|^2 \tag{2}$$

where $k = 0, 1, ..., (N-1)$. N is the number of observations and $v_k = \frac{k}{N}$.

For a measurement resolution of 1 hour, a wave with a period of 2 hours or more is required (Nyquist theorem). For spectral analysis using FFT, successive equal length sequences are required without any missing observations (Dilmaghani, 2007). Here we replace the missing data points from the EPA and PA data sets using the ARIMA model with Kalman filter (Hadeed et al., 2020; Afrifa-Yamoah et al., 2020; Wijesekara and Liyanage, 2020; Saputra et al., 2021). The power spectral density of each EPA and PA hourly time series of $PM_{2.5}$ data was then calculated using the stats package in R.

3.1 Spectral Analysis: Results and Discussion

We determined the power spectral density (PSD) of $PM_{2.5}$ data for three data sets - EPA, PA, and corrected PA data - for all of the locations available. Then, the average PSDs for each of the data sets were determined by averaging the individual PSDs of the different locations in each network. By averaging over the different locations, the PSDs in (Figure 5) represent the power spectrum of air quality over the entire Cook County area. The PSD shows that for both networks (EPA and PA), power is higher in long time periods than in short-time periods. Thus, the predominant variation in $PM_{2.5}$ data reported by both networks over the studied duration is driven by their long-term trend. The PA data is seen to have lower power compared to the EPA at smaller time periods. Applying the US-wide EPA correction model (Equation (1)) to the PA data brings the PA PSD closer to the EPA over the entire range of frequencies.

At smaller time periods, both networks show distinct peaks at 4, 8, 12, and 24 hours, as seen in (Figure 6). These peaks likely represent the contribution of periodic aerosol sources, such as traffic and photochemistry, and diurnal weather patterns to the local air quality. For ease of direct comparison, we removed the baseline trend in each of the datasets. The peaks in the

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023


Atmospheric Measurement Techniques Discussions

EPA data are higher than the PA standard corrected data for all 4 times. The PSD peaks at the 4 specific time periods were then obtained for each of the 5 different EPA sites and 9 different PA sites. The distribution of peak heights at the different time periods (Figure 7a) show that the EPA data peaks are consistently higher than the PA corrected data for all 4 time periods (4, 8, 12, and 24 hours) and higher than the PA raw data for all time periods except 12 hours. The ratio of the PSD peaks in the PA data to the EPA is shown in (Figure 7b). The correction is seen to result in reducing the relative value of the PA peaks at all time periods, and the reduction is inconsistent.

Assuming that the 8-hour peak corresponds to traffic sources, our analysis suggests that the corrected PA data has a traffic contribution of around 17% of that in the EPA data. This finding is consistent with general observations in previous studies that low-cost sensor measurements more closely match reference monitors at locations with low traffic than at high-traffic locations (Castell et al., 2017). The other interesting finding is that the 12 peak is highly over-represented in the raw data and while the correction decreases its contribution, it is relatively a higher contribution to the PA data than the 8 hour source. We speculate that the 12 hour peak represents the contribution of secondary aerosol formed due to photochemistry, and possible diurnal changes in winds (Jia et al., 2017; Hollaway et al., 2019; Tchepel and Borrego, 2010). The mean sizes of particles formed due to photochemistry are likely larger than the traffic aerosol, resulting in their relatively higher efficiency of detection in low-cost PM sensors (He et al., 2020). The over-correction of the 12 hour peak that results in its significant suppression, suggests that these particles are likely less hygroscopic than the average particles. The 24 hour peak likely represents harmonics of the 8 hour and 12 hour signals, and hence represents a combination of both sources.

To confirm that the 8 hour peak is traffic and the 12 hour peak is likely to be driven by photochemistry, we analyzed changes in these peaks for weekend/weekday and winter/summer. The EPA weekday data was considered as Monday 12am to Friday 11:59 pm and weekends as Saturday 12 am to Sunday 11:59 pm. The Winter data was generated as Dec/Jan/Feb and Summer as Jun/Jul/Aug. The PSD peaks for the two time periods were then calculated and relative changes are shown in (Figure 8). The weekend 8-hour PSD peak is seen to be nearly only 60% lower than on weekdays, consistent with changes in traffic patterns expected between the two time periods (Blanchard et al., 2008) and confirming that this peak is indeed traffic related. Seasonally, the 8-hour peak does not change significantly, again largely consistent with the expectation that traffic patterns are not overly dependent on seasons. The 12-hour peak also changes weekends vs weekdays but has a greater change seasonally than that observed with the 8-hour peak. The seasonal change points to the likely contribution of photochemistry to the 12 hour peak, but the slight change of this peak between weekends and weekdays also points to contribution from other sources, including possible traffic.

4 Local Correction Model

Some of the imperfections of the correction model could be attributed to the fact that the model was based on data from a wide range of locations with different emission characteristics and meteorology. Consequently, it could be hypothesized that a local correction model tuned to local conditions will result in a better correction of PA data. Additionally, as the standard correction model is built based on daily data, it could also be hypothesized that the sub-24 hour components may not be well accounted

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023


Atmospheric Measurement Techniques Discussions

for. To determine if the sub-24 hour components in the PA data could be better matched with EPA data, we built an hourly local correction model using the same approach used in building the standard correction model (Barkjohn et al., 2021) using PA data from different selected locations and data from the closest EPA site. A stepwise forward selection algorithm was used to build multiple linear regression (MLR) models. A 10-fold cross-validation technique was employed by repeating the process a total of 5 times. This method of cross-validation involves dividing the data into 10 equally sized folds, and training the model on 9 of the folds while using the remaining fold as a hold-out test set. This process is repeated 10 times, with each fold serving as the test set once. By repeating the process 5 times, the robustness of the developed model is increased by training and testing it on different subsets of the data.

The obtained equation for the local correction model is:

$$PM_{2.5}\ \text{Loc\_Corr} = 0.44\ \text{PA}_{\ cf\_1}\ PM_{2.5} - 0.026\ \text{RH} + 0.023\ \text{temperature} + 19.76 \tag{3}$$

where PA_{cf_1} represents the PA data with the higher correction factor cf_1 reported at a specific sensor, and RH and temperature are obtained from the PA network.

After obtaining the model, its performance was evaluated using several metrics: R^2, root mean square error (RMSE), and mean absolute error (MAE) (see supplementary material for details about these metrics). The model performances of the standard correction and local correction models are summarized in (Table S3). The effectiveness of the local correction model in improving the accuracy of the PA data and addressing the problem of under-accounting of high frequency sources such as traffic must be ascertained.

5 Time Series Decomposition

For a full model evaluation, its performance will be determined for three time period components: less than 12 hours (short-term), 12 hours to a month (medium-term), and more than a month (long-term). The short-term component represents the changes in $PM_{2.5}$ data due to high frequency sources such as traffic and short-term weather events. The medium-term component accounts for variations within time periods between 12 hours and a month. The long-term component primarily captures low frequency emissions such as those related to seasonal changes in weather and meteorology, and changes in emission rates over time. (Rao and Zurbenko, 1994; Rao et al., 1997; Wise and Comrie, 2005).

To separate the time series data into the 3 components of short-term, medium-term, and long-term time periods, we use the Kolmogorov–Zurbenko (KZ) filter technique (Rao and Zurbenko, 1994), as was done in several recent $PM_{2.5}$ studies(Bai et al., 2022; Fang et al., 2022; Zhang et al., 2018; Sá et al., 2015). The KZ filter is a low-pass filter produced through repeated iterations of moving average with parameters moving window (m), and iterations (p) also known as $KZ_{m,p}$:

$$Y_t = \frac{1}{m}\sum_{j=-k}^{k} X_{t+j} \tag{4}$$

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023


Atmospheric Measurement Techniques Discussions

where Y_t is a filtered time sequence; X_t is the input time series; k is the number of values included on each side of the targeted value, $m = 2k + 1$ is window length; t is the time index, and j is the time point of sliding.

The output of the first pass then becomes the input for the next pass. Adjusting the window length and the number of iterations makes it possible to control the filtering of different scales of motion (Eskridge et al., 1997; Milanchus et al., 1998). To filter a period of fewer than N days, the following criterion is applied to determine the filter's effective width (Wise and Comrie, 2005):

$$m \times p^{1/2} \leq \mathrm{N} \tag{5}$$

Also, the filter can be used to remove frequencies below a desired cutoff frequency w_0 (Rao et al., 1997):

$$w_0 \approx \frac{\sqrt{6}}{\pi} \sqrt{\frac{1-(1/2)^{1/2p}}{m^2-(1/2)^{1/2p}}} \tag{6}$$

The cutoff period can be obtained by $\frac{1}{w_0}$. For our study, we have used the following equations to get long-term, medium-term, and short-term components of the time series of $PM_{2.5}$ data as defined by (Hogrefe et al., 2000; Kang et al., 2008)

The long-term $PM_{2.5}$ ($PM_{2.5,B}$) component is obtained as:

$$PM_{2.5,B}(t) = KZ_{900,5}PM_{2.5}(t) \tag{7}$$

The medium-term $PM_{2.5}$ ($PM_{2.5,M}$) component is obtained as:

$$PM_{2.5,M}(t) = KZ_{3,3}PM_{2.5}(t) - KZ_{13,5}PM_{2.5}(t) \tag{8}$$

The short-term $PM_{2.5}$ ($PM_{2.5,S}$) component is obtained as:

$$PM_{2.5,S}(t) = PM_{2.5}(t) - KZ_{3,3}PM_{2.5}(t) \tag{9}$$

5.1 Time Series Decomposition: Results and Discussion

We separated the time series of $PM_{2.5}$ data from EPA, PA, and standard and local corrected PA data (Equations (7) to (9)) into the three time periods of long-term, medium-term, and short-term in (Figure 9). A comparison of the long-term component signals shows that the two-year trends of the PA raw data is different from that of the EPA data (Figure 9a). The correction models both lower the mean of the PA data. The standard correction is, however, seen to over-correct for mean, and does not capture the signal density accurately. Using the local model results in largely replicating the long-term $PM_{2.5}$ distribution, except at the lowest values. This might suggest that long-term changes might be driven by more than humidity, and including the effect of temperature on sensor performance could be important. In addition to air properties, long-term changes may also be driven by drift in sensor performance, which could be captured with a local model but not a standard model. In the medium-term, the standard correction model shifts the mean $PM_{2.5}$ values higher, contrary to the change in the long-term component, to

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023


Atmospheric Measurement Techniques Discussions

reasonably match EPA data as demonstrated by the density plot (Figure 9b). The performance of the local correction model is seen to match the standard correction model, suggesting that over this medium term, relative humidity is probably the primary driver of aerosol changes. In the short-term, the density plot shows that both the standard and local correction models fail to capture the $PM_{2.5}$ distribution accurately. In fact, the use of the correction models then to dampen any contribution of short-term sources to the total signal and increase the difference between the EPA and PA data sets (Figure 9c). This suggests that the primary driver of short-term fluctuations are particles that are poorly sensed by the PA network and regression-based correction models cannot capture their contribution.

6 Conclusions

The use of low-cost sensors for air quality monitoring is becoming more widespread and their use has resulted in a better understanding of air quality at a hyper-local level. Several studies have shown that data from low-cost sensors such as from the purple air (PA) network are less accurate than the gold standard EPA data. Other studies have reported that using correction models, PA data can become comparable to EPA data in accuracy (Mei et al., 2020; Ardon-Dryer et al., 2020; Barkjohn et al., 2021). Understanding the quality of the data reported by low-cost air sensor networks is critical to determining the extent and limitations of the use of this data in policy-making and health studies.

Here, using long-term $PM_{2.5}$ measurements from EPA and PA networks in the Cook County, IL area, we evaluated the accuracy of the reported raw data and recommended correction models. Our initial analysis showed that the corrected PA data was, on average, under-predicting $PM_{2.5}$ in the study area. To determine the cause of discrepancy between the PA and EPA datasets, we used a spectral analysis approach to identify the presence of periodic sources in both data sets and then determined their relative response to these sources. Our analysis clearly demonstrates for the first time that the PA network's very different sensitivity to different sources. The use of the standard correction model results in significant under-presentation of high frequency sources, particularly traffic. Also, the standard correction model over corrects for some sources, such as the 12 hour time period source that we identified in this study.

Using a local correction model based on temperature and relative humidity, we show that the long-term and medium trends in PA data can be matched with EPA data. In the short-term, both the local and standard correction models perform poorly. The use of these models actually results in suppression of the contribution of high frequency sources. Our study clearly demonstrates that, while regression-based correction models maybe seem to improve the accuracy of low-cost sensor network performance by accounting for the contribution of meteorology, they do not uniformly improve the network response to all emission sources. Thus, care must be taken in using their data in studies where a diversity of emission sources maybe present and their relative strengths are varying over time or space. Advances in sensing technologies and improvements in correction models are critical for expanding our use of data from these emerging low-cost sensor networks.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

Data availability. The datasets used for this study are available at and can be accessed through the following github repository. `https://github.com/vijaykumar18/Airquality-Spectral-Analysis.`

For the entire workflow (reading and organizing data, descriptive analysis, and data analyses) we used the R software (R: A Language and Environment for Statistical Computing) (version 4.2.0), along with the following libraries in our coding: readxl, dplyr, tidyr, ggplot2, car, qqplotr, kza, stats, relaimpo, caret, glmnet,sample, recipes.

Competing interests. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgements. Vijay Kumar acknowledges the support from US-Pakistan Knowledge Corridor PhD Scholarship Program under Higher Education Commission, Pakistan.

Author contributions. VK: Writing original draft, conceptualization, methodology, editing, investigation, analysis, DS: Data curation, visualization, SG: Conceptualization, validation, editing, SS: Supervision, conceptualization, methodology, validation, editing, SM: Supervision, conceptualization, methodology, validation, editing, SD: Writing, review draft, conceptualization, methodology, formal analysis, project administration, All authors contributed to the article and approved the submitted version.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

References

Afrifa-Yamoah, E., Mueller, U. A., Taylor, S., and Fisher, A.: Missing data imputation of high-resolution temporal climate time series data, Meteorological Applications, 27, e1873, 2020.

Ardon-Dryer, K., Dryer, Y., Williams, J. N., and Moghimi, N.: Measurements of PM 2.5 with PurpleAir under atmospheric conditions, Atmospheric Measurement Techniques, 13, 5441–5458, 2020.

Bai, H., Gao, W., Zhang, Y., and Wang, L.: Assessment of health benefit of PM2. 5 reduction during COVID-19 lockdown in China and separating contributions from anthropogenic emissions and meteorology, Journal of Environmental Sciences, 115, 422–431, 2022.

Barkjohn, K. K., Gantt, B., and Clements, A. L.: Development and application of a United States-wide correction for PM 2.5 data collected with the PurpleAir sensor, Atmospheric Measurement Techniques, 14, 4617–4637, 2021.

Bi, J., Wildani, A., Chang, H. H., and Liu, Y.: Incorporating low-cost sensor measurements into high-resolution PM2. 5 modeling at a large spatial scale, Environmental Science & Technology, 54, 2152–2162, 2020.

Blanchard, C. L., Tanenbaum, S., and Lawson, D. R.: Differences between weekday and weekend air pollutant levels in Atlanta; Baltimore; Chicago; Dallas–Fort Worth; Denver; Houston; New York; Phoenix; Washington, DC; and surrounding areas, Journal of the Air & Waste Management Association, 58, 1598–1615, 2008.

Bureau, U. C.: US Census Bureau: Public Database, https://www.census.gov/geo/maps-data/data/tallies/tractblock.html, 2021.

Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., and Bartonova, A.: Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates?, Environment international, 99, 293–302, 2017.

Chaipitakporn, C., Athavale, P., Kumar, V., Sathiyakumar, T., Budisic, M., Sur, S., and Mondal, S.: COVID-19 in the United States during pre-vaccination period: Shifting impact of sociodemographic factors and air pollution, Frontiers in Epidemiology, 2, 48, https://doi.org/10.3389/fepid.2022.927189, 2022.

Choi, Y.-S., Ho, C.-H., Chen, D., Noh, Y.-H., and Song, C.-K.: Spectral analysis of weekly variation in PM10 mass concentration and meteorological conditions over China, Atmospheric Environment, 42, 655–666, 2008.

Commodore, A., Wilson, S., Muhammad, O., Svendsen, E., and Pearce, J.: Community-based participatory research for the study of air pollution: A review of motivations, approaches, and outcomes, Environmental monitoring and assessment, 189, 1–30, 2017.

Dilmaghani, S.: Spectral analysis of air quality data, University of Southern California, 2007.

EPA: US Environmental Protection Agency (EPA):Publically available air quality data API, https://aqs.epa.gov/aqsweb/documents/data_api.html, 2021.

Eskridge, R. E., Ku, J. Y., Rao, S. T., Porter, P. S., and Zurbenko, I. G.: Separating different scales of motion in time series of meteorological variables, Bulletin of the American Meteorological Society, 78, 1473–1484, 1997.

ESRI: Esri. "Navigation" [basemap]. Scale Not Given. "World Navigation Map"., http://www.arcgis.com/home/item.html?id=30e5fe3149c34df1ba922e6f5bbf808f, 2021.

Fang, C., Qiu, J., Li, J., and Wang, J.: Analysis of the meteorological impact on PM2.5 pollution in Changchun based on KZ filter and WRF-CMAQ, Atmospheric Environment, 271, 118 924, https://doi.org/https://doi.org/10.1016/j.atmosenv.2021.118924, 2022.

Giordano, M. R., Malings, C., Pandis, S. N., Presto, A. A., McNeill, V., Westervelt, D. M., Beekmann, M., and Subramanian, R.: From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors, Journal of Aerosol Science, 158, 105 833, 2021.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Gupta, P., Doraiswamy, P., Levy, R., Pikelnaya, O., Maibach, J., Feenstra, B., Polidori, A., Kiros, F., and Mills, K.: Impact of California fires on local and regional air quality: the role of a low-cost sensor network and satellite observations, GeoHealth, 2, 172–181, 2018.

Hadeed, S. J., O'Rourke, M. K., Burgess, J. L., Harris, R. B., and Canales, R. A.: Imputation methods for addressing missing data in short-term monitoring of air pollutants, Science of The Total Environment, 730, 139 140, 2020.

He, M., Kuerbanjiang, N., and Dhaniyala, S.: Performance characteristics of the low-cost Plantower PMS optical sensor, Aerosol Science and Technology, 54, 232–241, 2020.

Hies, T., Treffeisen, R., Sebald, L., and Reimer, E.: Spectral analysis of air pollutants. Part 1: elemental carbon time series, Atmospheric Environment, 34, 3495–3502, 2000.

Hirabayashi, S. and Kroll, C. N.: Single imputation method of missing air quality data for i-tree eco analyses in the conterminous united states, Retrieved January, 1, 2021, 2017.

Hogrefe, C., Rao, S. T., Zurbenko, I. G., and Porter, P. S.: Interpreting the information in ozone observations and model predictions relevant to regulatory policies in the eastern United States, Bulletin of the American Meteorological Society, 81, 2083–2106, 2000.

Hollaway, M., Wild, O., Yang, T., Sun, Y., Xu, W., Xie, C., Whalley, L., Slater, E., Heard, D., and Liu, D.: Photochemical impacts of haze pollution in an urban environment, Atmospheric Chemistry and Physics, 19, 9699–9714, 2019.

Imtiaz, S. A. and Shah, S. L.: Treatment of missing values in process data analysis, The Canadian Journal of Chemical Engineering, 86, 838–858, 2008.

IQAIR: Air quality in Chicago.: Public Database, https://www.iqair.com/us/usa/illinois/chicago, 2020.

Jia, M., Zhao, T., Cheng, X., Gong, S., Zhang, X., Tang, L., Liu, D., Wu, X., Wang, L., and Chen, Y.: Inverse relations of PM2. 5 and O3 in air compound pollution between cold and hot seasons over an urban area of east China, Atmosphere, 8, 59, 2017.

Kang, D., Mathur, R., Rao, S. T., and Yu, S.: Bias adjustment techniques for improving ozone air quality forecasts, Journal of Geophysical Research: Atmospheres, 113, 2008.

Kelly, K., Whitaker, J., Petty, A., Widmer, C., Dybwad, A., Sleeth, D., Martin, R., and Butterfield, A.: Ambient and laboratory evaluation of a low-cost particulate matter sensor, Environmental pollution, 221, 491–500, 2017.

Kim, T., Kim, J., Yang, W., Lee, H., and Choo, J.: Missing Value Imputation of Time-Series Air-Quality Data via Deep Neural Networks, International Journal of Environmental Research and Public Health, 18, 12 213, 2021.

Kuula, J., Mäkelä, T., Hillamo, R., and Timonen, H.: Response characterization of an inexpensive aerosol sensor, Sensors, 17, 2915, 2017.

Kuula, J., Mäkelä, T., Aurela, M., Teinilä, K., Varjonen, S., González, Ó., and Timonen, H.: Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors, Atmospheric Measurement Techniques, 13, 2413–2423, 2020.

Landrigan, P. J., Fuller, R., Acosta, N. J., Adeyi, O., Arnold, R., Baldé, A. B., Bertollini, R., Bose-O'Reilly, S., Boufford, J. I., Breysse, P. N., et al.: The Lancet Commission on pollution and health, The lancet, 391, 462–512, 2018.

Lewis, T. C., Robins, T. G., Dvonch, J. T., Keeler, G. J., Yip, F. Y., Mentz, G. B., Lin, X., Parker, E. A., Israel, B. A., Gonzalez, L., et al.: Air pollution–associated changes in lung function among asthmatic children in Detroit, Environmental Health Perspectives, 113, 1068–1075, 2005.

Li, L., Losser, T., Yorke, C., and Piltner, R.: Fast inverse distance weighting-based spatiotemporal interpolation: a web-based application of interpolating daily fine particulate matter PM2. 5 in the contiguous US using parallel programming and kd tree, International journal of environmental research and public health, 11, 9101–9141, 2014.

Li, T., Hu, R., Chen, Z., Li, Q., Huang, S., Zhu, Z., and Zhou, L.-F.: Fine particulate matter (PM2. 5): The culprit for chronic lung diseases in China, Chronic diseases and translational medicine, 4, 176–186, 2018.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Lian, L. and Ma, H.: FDI and economic growth in western region of China and dynamic mechanism: Based on time-series data from 1986 to 2010, International Business Research, 6, 180, 2013.

Magi, B. I., Cupini, C., Francis, J., Green, M., and Hauser, C.: Evaluation of PM2. 5 measured in an urban setting using a low-cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor, Aerosol Science and Technology, 54, 147–159, 2020.

Marr, L. C. and Harley, R. A.: Spectral analysis of weekday–weekend differences in ambient ozone, nitrogen oxide, and non-methane hydrocarbon time series in California, Atmospheric Environment, 36, 2327–2335, 2002.

Mei, H., Han, P., Wang, Y., Zeng, N., Liu, D., Cai, Q., Deng, Z., Wang, Y., Pan, Y., and Tang, X.: Field evaluation of low-cost particulate matter sensors in Beijing, Sensors, 20, 4381, 2020.

Milanchus, M. L., Rao, S. T., and Zurbenko, I. G.: Evaluating the effectiveness of ozone management efforts in the presence of meteorological variability, Journal of the Air & Waste Management Association, 48, 201–215, 1998.

Mondal, S., Chaipitakporn, C., Kumar, V., Wangler, B., Gurajala, S., Dhaniyala, S., and Sur, S.: COVID-19 in New York state: Effects of demographics and air quality on infection and fatality, Science of The Total Environment, 807, 150 536, 2022.

Noble, C. A., Vanderpool, R. W., Peters, T. M., McElroy, F. F., Gemmill, D. B., and Wiener, R. W.: Federal reference and equivalent methods for measuring fine particulate matter, Aerosol science & technology, 34, 457–464, 2001.

Ostro, B., Broadwin, R., Green, S., Feng, W.-Y., and Lipsett, M.: Fine particulate air pollution and mortality in nine California counties: results from CALFINE, Environmental health perspectives, 114, 29–33, 2006.

Ouimette, J. R., Malm, W. C., Schichtel, B. A., Sheridan, P. J., Andrews, E., Ogren, J. A., and Arnott, W. P.: Evaluating the PurpleAir monitor as an aerosol light scattering instrument, Atmospheric Measurement Techniques, 15, 655–676, 2022.

PA: Purple Air: Public Database of sensors installed in entire world, https://map.purpleair.com/1/mAQI/a10/p604800/cC0#11.44/41.8363/-87.6973, 2021.

PurpleAir: PurpleAir.: PublicLab, https://publiclab.org/wiki/purpleair, 2020.

Raaschou-Nielsen, O., Andersen, Z. J., Beelen, R., Samoli, E., Stafoggia, M., Weinmayr, G., Hoffmann, B., Fischer, P., Nieuwenhuijsen, M. J., Brunekreef, B., et al.: Air pollution and lung cancer incidence in 17 European cohorts: prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE), The lancet oncology, 14, 813–822, 2013.

Rao, S., Zurbenko, I., Neagu, R., Porter, P., Ku, J., and Henry, R.: Space and time scales in ambient ozone data, Bulletin of the American Meteorological Society, 78, 2153–2166, 1997.

Rao, S. T. and Zurbenko, I. G.: Detecting and tracking changes in ozone air quality, Air & waste, 44, 1089–1092, 1994.

Rivera-Muñoz, L. M., Gallego-Villada, J. D., Giraldo-Forero, A. F., and Martinez-Vargas, J. D.: Missing data estimation in a low-cost sensor network for measuring air quality: A case study in Aburrá Valley, Water, Air, & Soil Pollution, 232, 1–15, 2021.

Sá, E., Tchepel, O., Carvalho, A., and Borrego, C.: Meteorological driven changes on air quality over Portugal: a KZ filter application, Atmospheric Pollution Research, 6, 979–989, 2015.

Samoli, E., Analitis, A., Touloumi, G., Schwartz, J., Anderson, H. R., Sunyer, J., Bisanti, L., Zmirou, D., Vonk, J. M., Pekkanen, J., et al.: Estimating the exposure–response relationships between particulate matter and mortality within the APHEA multicity project, Environmental health perspectives, 113, 88–95, 2005.

Saputra, M., Hadi, A., Riski, A., and Anggraeni, D.: Handling Missing Values and Unusual Observations in Statistical Downscaling Using Kalman Filter, in: Journal of Physics: Conference Series, vol. 1863, p. 012035, IOP Publishing, 2021.

Sayahi, T., Kaufman, D., Becnel, T., Kaur, K., Butterfield, A., Collingwood, S., Zhang, Y., Gaillardon, P.-E., and Kelly, K.: Development of a calibration chamber to evaluate the performance of low-cost particulate matter sensors, Environmental Pollution, 255, 113 131, 2019.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

Stavroulas, I., Grivas, G., Michalopoulos, P., Liakakou, E., Bougiatioti, A., Kalkavouras, P., Fameli, K. M., Hatzianastassiou, N., Mihalopoulos, N., and Gerasopoulos, E.: Field Evaluation of Low-Cost PM Sensors (Purple Air PA-II) Under Variable Urban Air Quality Conditions, in Greece, Atmosphere, 11, 926, 2020.

Tchepel, O. and Borrego, C.: Frequency analysis of air quality time series for traffic related pollutants, Journal of Environmental Monitoring, 12, 544–550, 2010.

Tryner, J., Mehaffy, J., Miller-Lionberg, D., and Volckens, J.: Effects of aerosol type and simulated aging on performance of low-cost PM sensors, Journal of Aerosol Science, 150, 105 654, 2020.

Wallace, L., Bi, J., Ott, W. R., Sarnat, J., and Liu, Y.: Calibration of low-cost PurpleAir outdoor monitors using an improved method of calculating PM2. 5, Atmospheric Environment, 256, 118 432, 2021.

Wang, X., Wang, L., Liu, Y., Hu, S., Liu, X., and Dong, Z.: A data-driven air quality assessment method based on unsupervised machine learning and median statistical analysis: The case of China, Journal of Cleaner Production, 328, 129 531, https://doi.org/https://doi.org/10.1016/j.jclepro.2021.129531, 2021.

Wang, Y., Li, J., Jing, H., Zhang, Q., Jiang, J., and Biswas, P.: Laboratory evaluation and calibration of three low-cost particle sensors for particulate matter measurement, Aerosol Science and Technology, 49, 1063–1077, 2015.

Wijesekara, W. and Liyanage, L.: Comparison of imputation methods for missing values in air pollution data: Case study on sydney air quality index, in: Future of Information and Communication Conference, pp. 257–269, Springer, 2020.

Wise, E. K. and Comrie, A. C.: Meteorologically adjusted urban air quality trends in the Southwestern United States, Atmospheric Environment, 39, 2969–2980, 2005.

Woodall, G. M., Hoover, M. D., Williams, R., Benedict, K., Harper, M., Soo, J.-C., Jarabek, A. M., Stewart, M. J., Brown, J. S., Hulla, J. E., et al.: Interpreting mobile and handheld air sensor readings in relation to air quality standards and health effect reference values: Tackling the challenges, Atmosphere, 8, 182, 2017.

Wu, X., Nethery, R. C., Sabath, M. B., Braun, D., and Dominici, F.: Exposure to air pollution and COVID-19 mortality in the United States: A nationwide cross-sectional study, 2020.

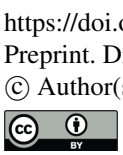
Xing, Y.-F., Xu, Y.-H., Shi, M.-H., and Lian, Y.-X.: The impact of PM2. 5 on the human respiratory system, Journal of thoracic disease, 8, E69, 2016.

Zhang, Z., Kim, S.-J., and Ma, Z.: Significant decrease of PM2. 5 in Beijing based on long-term records and Kolmogorov-Zurbenko filter approach, 2018.

Zheng, T., Bergin, M. H., Johnson, K. K., Tripathi, S. N., Shirodkar, S., Landis, M. S., Sutaria, R., and Carlson, D. E.: Field evaluation of low-cost particulate matter sensors in high-and low-concentration environments, Atmospheric Measurement Techniques, 11, 4823–4846, 2018.

Zhou, X., Josey, K., Kamareddine, L., Caine, M. C., Liu, T., Mickley, L. J., Cooper, M., and Dominici, F.: Excess of COVID-19 cases and deaths due to fine particulate matter exposure during the 2020 wildfires in the United States, Science Advances, 7, eabi8789, 2021.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023



Atmospheric Measurement Techniques Discussions

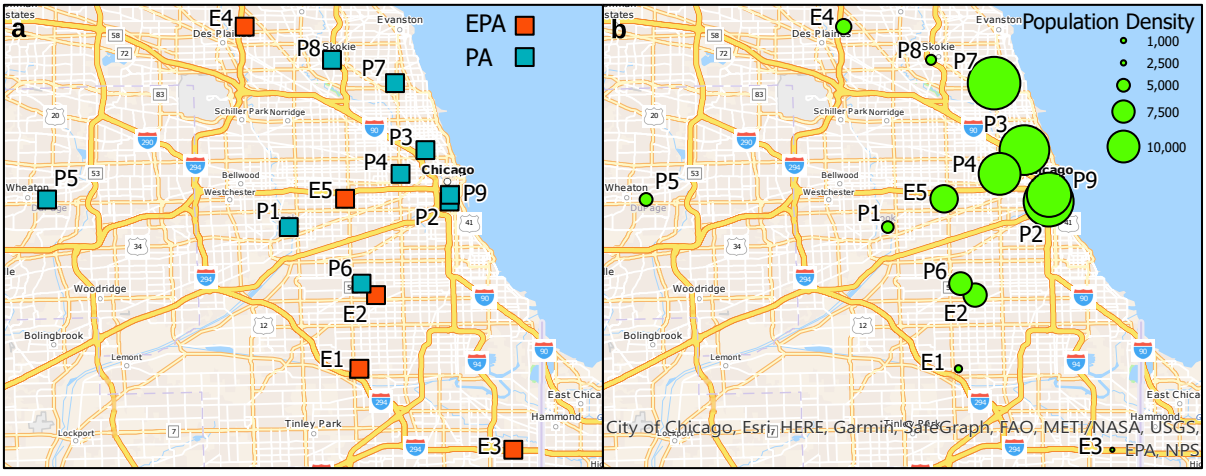


Figure 1. (a) EPA and PA sampling locations (b) Population density in the block defined by US Census Bureau in Cook County, IL. Basemap used from ESRI (ESRI, 2021)

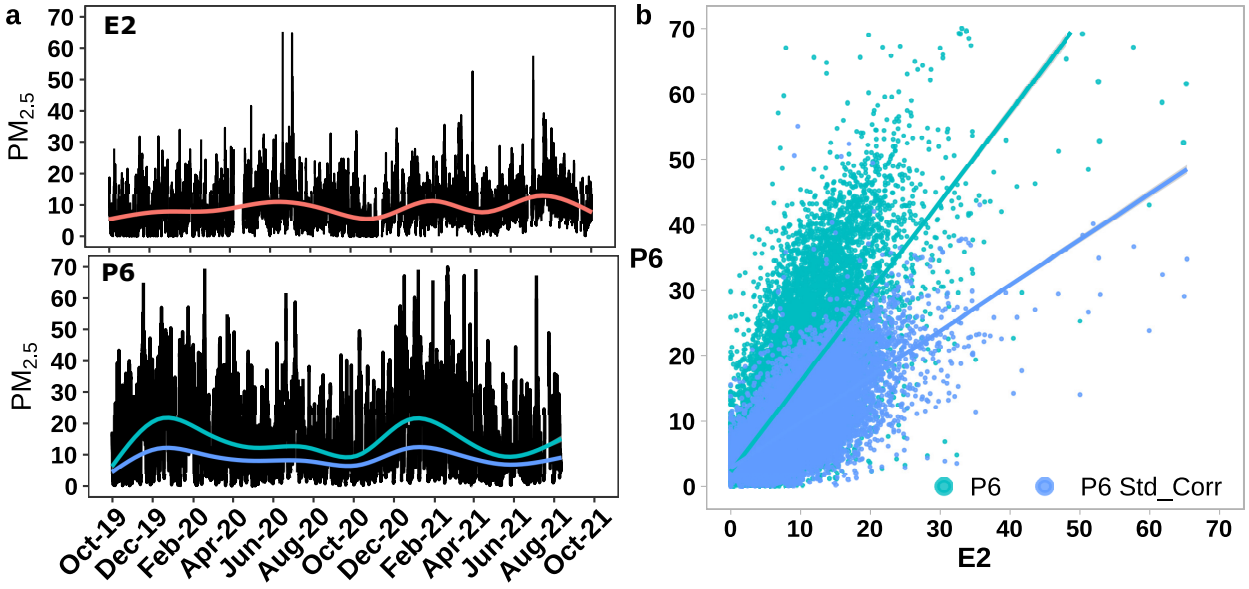


Figure 2. (a) Hourly $PM_{2.5}$ measurements from EPA site E2 and PA sensor P6, and (b) hourly $PM_{2.5}$ measurements from EPA site E2 vs PA sensor P6 raw and P6 corrected.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

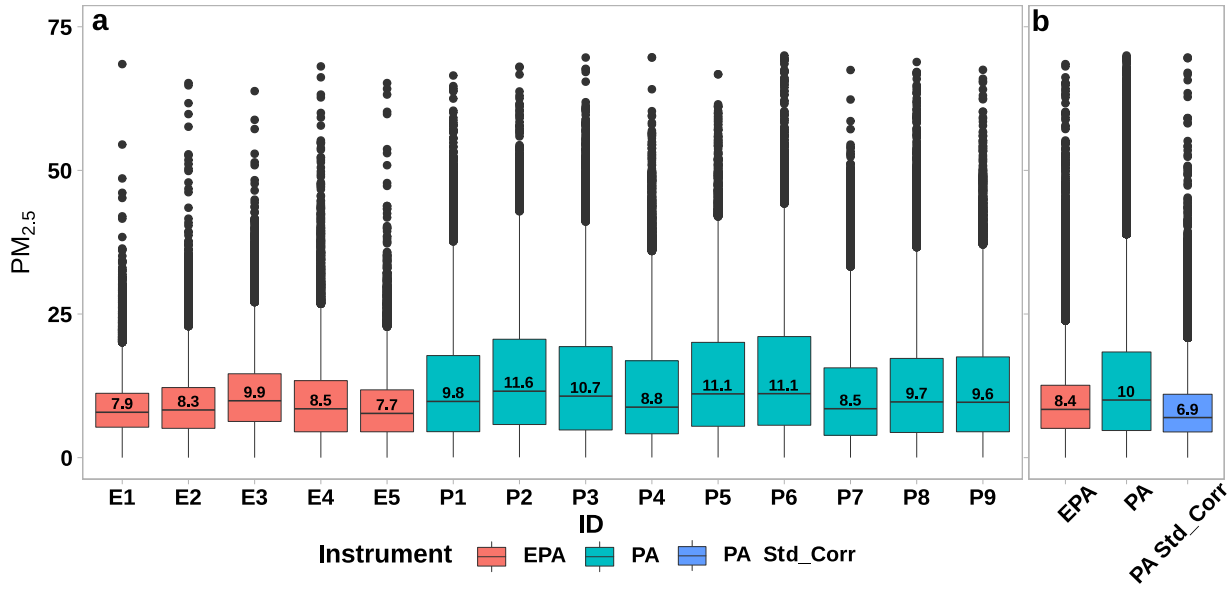


Figure 3. (a) Hourly $PM_{2.5}$ measurements from each EPA site and PA sensor located in Cook County, IL (b) all EPA, PA, and PA corrected data together. The box plots represent the overall distribution with quartiles (25th percentile Q_1, median 50th percentile Q_2, and 75th percentile Q_3) values of $PM_{2.5}$ data. The values in black dots over Q_3 are outliers.

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

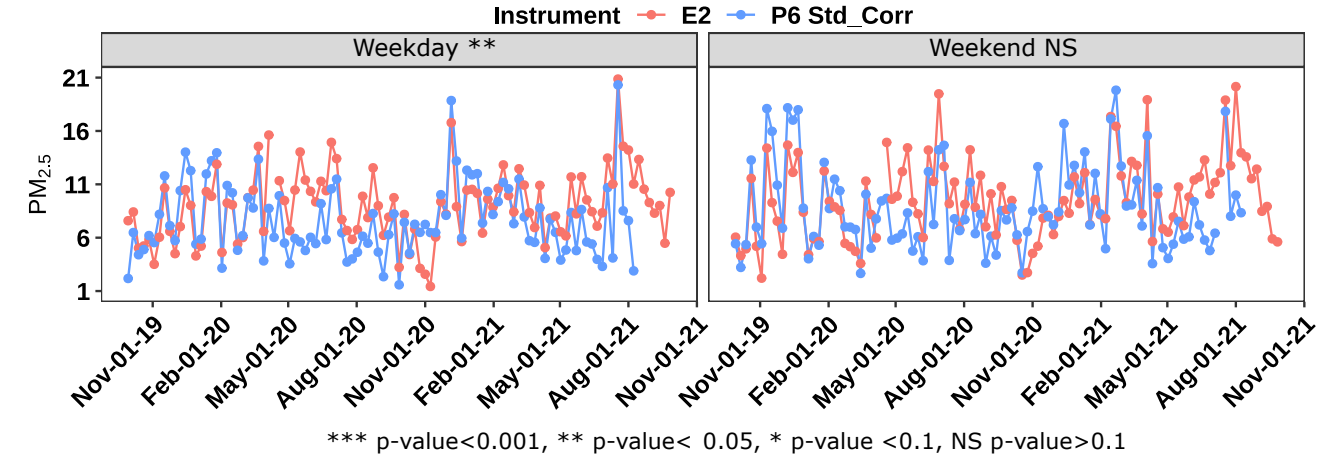


Figure 4. Corrected PA sensor $PM_{2.5}$ measurements during weekdays and weekends compared with nearby EPA sites E2, P6. The t-test statistics are provided to determine if there is a statistically significant difference between the two data sets (EPA & PA).

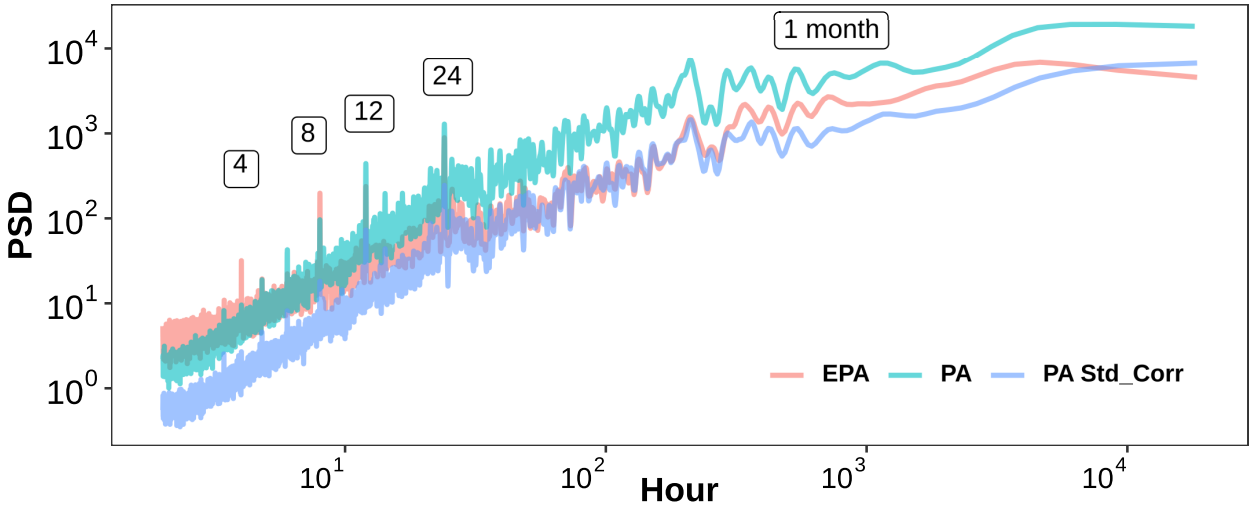


Figure 5. Mean PSD of $PM_{2.5}$ data from all EPA sites, all PA sensors, and PA standard corrected data

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

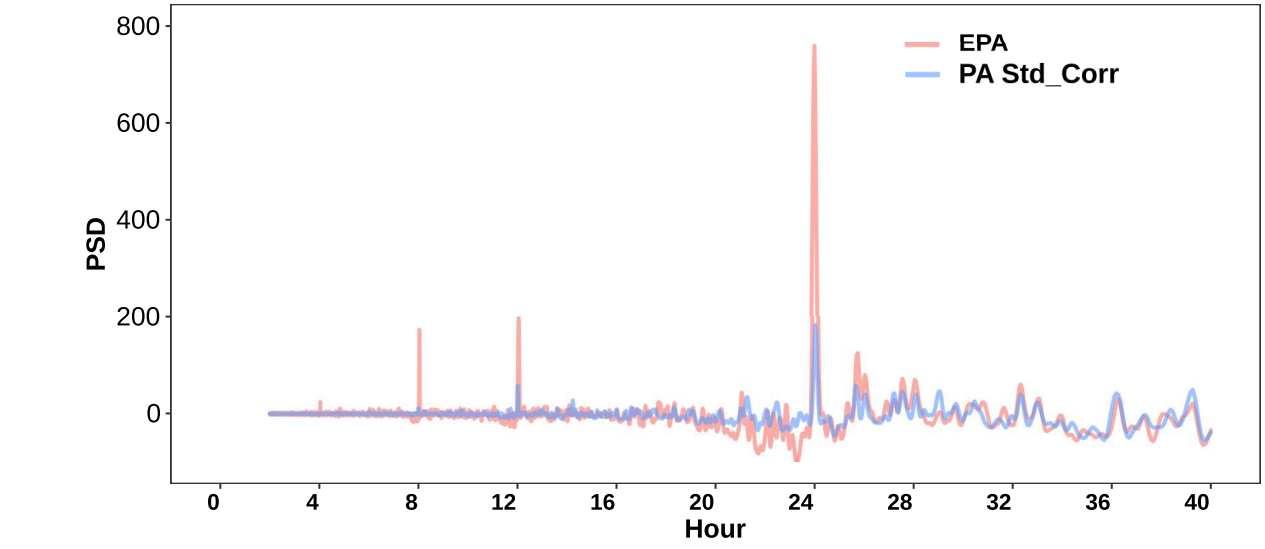


Figure 6. Mean PSD of $PM_{2.5}$ data from all EPA sites, all PA sensors, and PA standard corrected data at 4 hours to 24 hours peaks of both networks after removing their baselines.

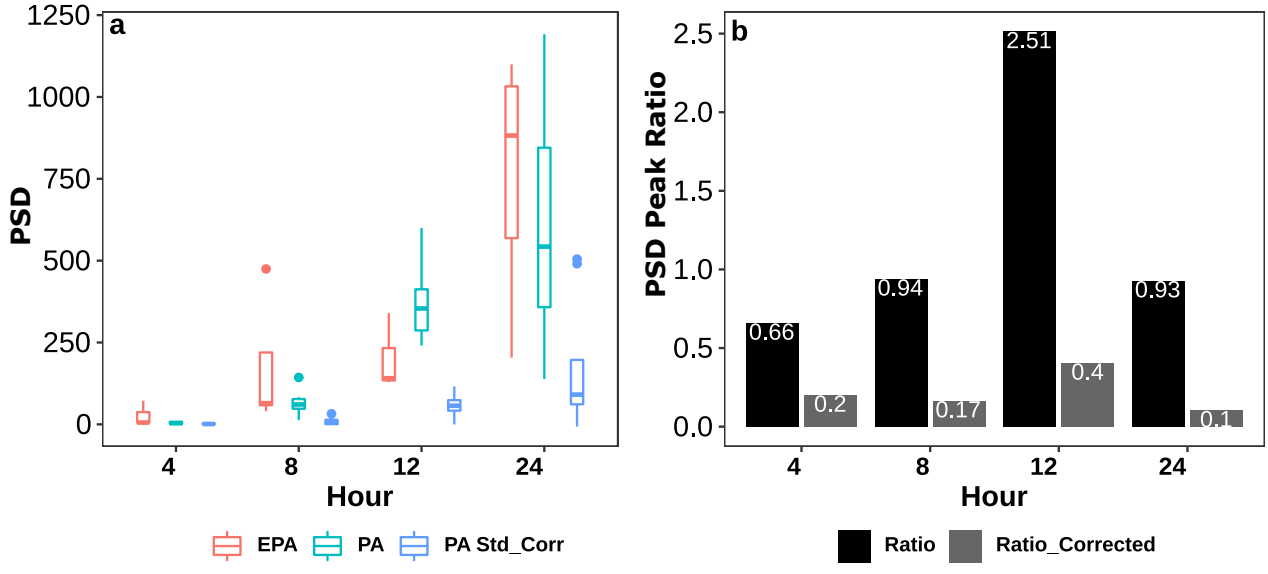


Figure 7. (a) Distribution of $PM_{2.5}$ PSD peaks at 4, 8, 12, and 24 hours for all EPA sites and PA locations, before and after correction (b) Ratio of PA to EPA PSD peaks for both raw data (labeled "Ratio") and corrected data (labeled "Ratio_corrected")

https://doi.org/10.5194/amt-2023-62
Preprint. Discussion started: 25 April 2023

Atmospheric Measurement Techniques Discussions

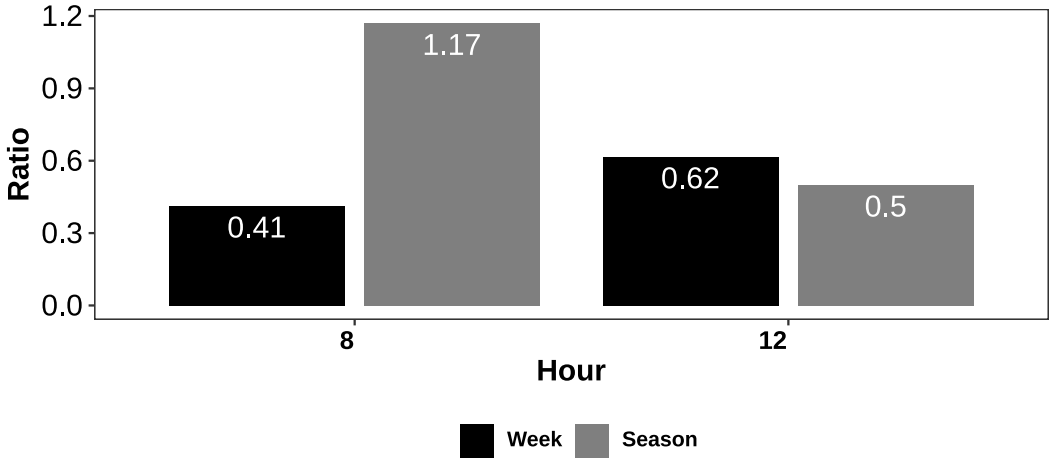


Figure 8. Ratio of EPA PSD peaks at 8 hours and 12 hours for the weekend to weekday (labeled "week") and winter to summer (labeled "season").

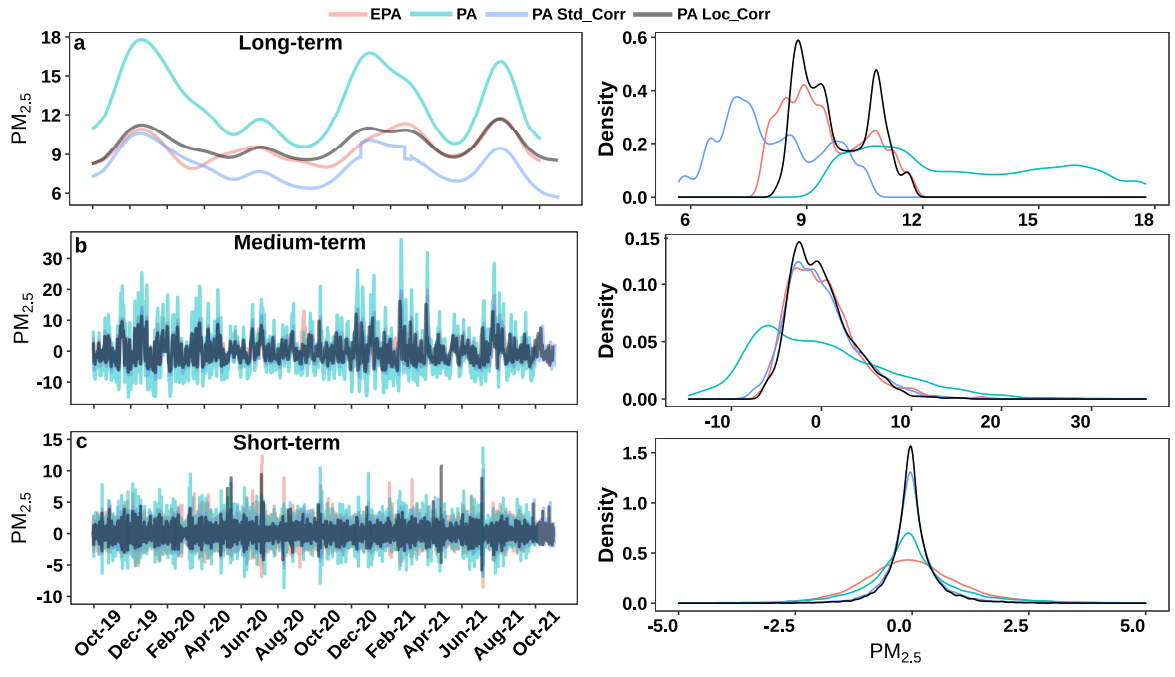


Figure 9. Time series and density plot of EPA data, PA data, corrected PA data using standard correction model, and corrected PA data using local correction model for (a) long-term component, (b) medium-term component, and (c) short-term component.