A data-driven approach for characterizing community scale air pollution exposure disparities in inland Southern California

Khanh Do[1,2], Haofei Yu[3], Jasmin Velasquez[1,2], Marilyn Grell-Brisk[2], Heather Smith[4], Cesunica E. Ivey[1,2,*]

[1]Department of Chemical and Environmental Engineering, University of California, Riverside, Riverside, CA

[2]Center for Environmental Research and Technology, Riverside, CA

[3]Department of Civil, Environmental and Construction Engineering, University of Central Florida, Orlando, FL

[4]Life Sciences Department, Riverside City College, Riverside, CA

*Corresponding Author: cesunica@ucr.edu, 1084 Columbia Avenue, Riverside CA 92507

This publication is currently under review in Journal of Aerosol Science, and a decision has not been made on its acceptance. Subsequent versions of this manuscript may have slightly different content. If accepted, the final version of this manuscript will be available via the 'Peer-reviewed Publication DOI' link on the right-hand side of this page. Please feel free to contact the corresponding author with feedback and suggestions.

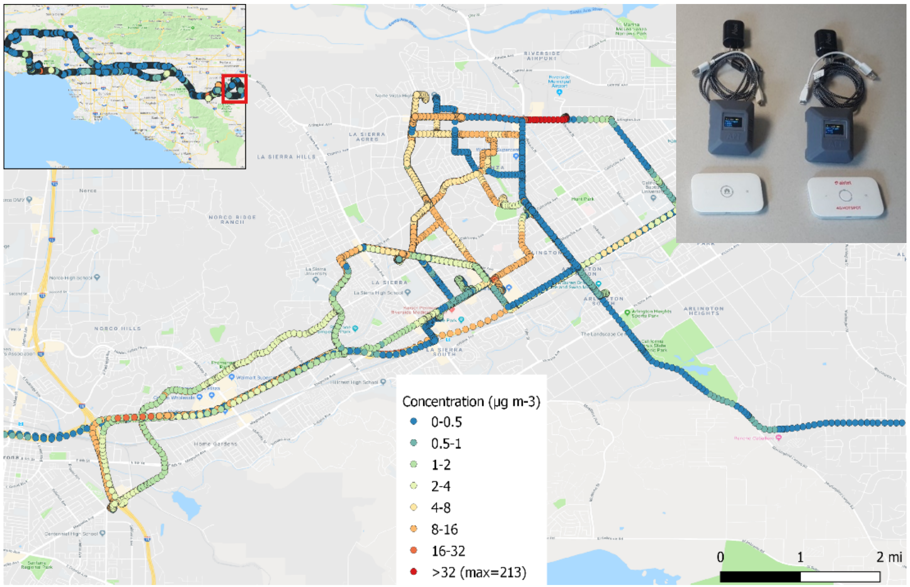
Highlights

- Wearable monitors enable high temporal resolution analysis of personal exposure
- Microenvironments were identified by GIS-based spatial clustering of measurements
- Most vulnerable community had highest observed personal-ambient ratios in the home
- High variability in personal $PM_{2.5}$ despite low variability in ambient $PM_{2.5}$

Abstract

In 2017, Assembly Bill 617 was approved in state of California, which mandated the allocation of resources for addressing air pollutant exposure disparities in underserved communities across the state. The bill stipulated the implementation of community scale monitoring and the development of local emissions reductions plans. We aimed to develop a streamlined, robust, and accessible $PM_{2.5}$ exposure assessment approach to support environmental justice analyses. We sought to characterize individual $PM_{2.5}$ exposure over multiple 24-hr periods in the inland Southern California region, which includes the underserved community of San Bernardino, CA. Personal sampling took place over five weeks in Spring of 2019, and personal $PM_{2.5}$ exposure was monitored for 18 adult participants for multiple, consecutive 24-hr periods. Exposure and location data were available at five-second resolution, and participant data recovery was 50.8% on average. A spatial clustering algorithm was used to classify data points as one of seven microenvironments. Mean and median personal-ambient $PM_{2.5}$ ratios were aggregated along SES lines for eligible datasets. GIS-based spatial clustering facilitated efficient microenvironment classification for more than 920,000 data points. Mean (median) personal-ambient ratios ranged from 0.02 (0.00) to 3.49 (0.55) for each microenvironment when aggregated along SES-lines. Aggregated ratios indicated that participants from the lowest SES community experienced higher home exposures compared to participants of all other communities over consecutive 24-hr monitoring periods, despite high participant mobility and relatively low variability in ambient $PM_{2.5}$ during the study. The methods described here highlight the robust and accessible nature of the personal sampling campaign, which was specifically designed to reduce participant fatigue and engage members of the inland Southern California community who may experience barriers when engaging with the scientific community. This approach is promising for larger-scale, community-focused, personal exposure campaigns for direct and accurate analysis of environmental justice.

Keywords: particulate matter; wearable monitors; personal exposure; environmental justice



1. Introduction

Ambient particulate matter (PM) has been widely studied, and researchers have carefully examined the impact of PM exposure on human health. Many air monitoring stations are operated in the U.S. to measure the trends and composition of ambient PM in support of the National Ambient Air Quality Standards (NAAQS). However, ambient PM concentrations may not reflect actual daily personal exposure (PE) (Koistinen et al., 2004). Further the sparseness of the monitoring network leads to low spatial resolution data and necessitates gap-filling, which affects the accuracy of PM exposure assessments that are based on ambient measurements (X. Yu et al., 2019).

People spend most of their time indoors (approximately 85-90%) and are most frequently exposed to indoor pollutants(Long et al., 2001). Home and workplace are the two most dominant indoor microenvironments. Indoor PM originates from cooking, smoking, cleaning products, vacuuming, and dusting; while in offices, PM is emitted from printing, mechanical grinding, consumer products, and dusting. The Environmental Protection Agency (EPA) carried out the particulate total exposure assessment methodology (PTEAM) study on 178 non-smoking randomly selected homes in Riverside, CA. The study showed that indoor $PM_{2.5}$ (PM with an aerodynamic diameter less than or equal to 2.5 μm) levels were slightly lower than outdoor levels during the day. However, at night the differences were significant (Clayton et al., 1993; Özkaynak et al., 1996; Thomas et al., 1993). Although ambient $PM_{2.5}$ penetrates into indoor environments, individual behaviors and living conditions are found to be the most important factors that affect indoor concentrations of PM (Kulmala et al., 1999; Long et al., 2001; Wallace, 1996).

Further, human mobility must also be taken into account for accurate exposure assessment. Yu et al. compared call detail record and home-based methods to estimate biases in exposure methods. The study showed that the home-based method both over- and under-estimates air pollutant exposure levels (H. Yu et al., 2018). In addition, many studies have used outputs from chemical transport models to verify the misclassification when using central monitor concentrations (CMC) to represent the exposure near the monitoring sites. Hu et al. showed that the population weighted concentrations of primary $PM_{2.5}$ of the model differ from the CMC values by -40 to +60%. The misclassification could be significant when assuming the same representative distance across central monitoring sites for multiple pollutants in a large-scale, spatial and temporal epidemiology studies (Hu et al., 2019).

Advancements in low-cost environmental sensing technologies have enabled the development of small, portable, and relatively precise PM sensors for personal exposure assessment. In a recent study by Quinn et al., filter-based, wearable, automated microenvironmental aerosol samplers (AMAS) were used to conduct a personal exposure study with 37 high school students from 25 high schools in Fresno, CA (Quinn et al., 2018). The wearable AMAS enabled the measurement of black carbon and oxidative potential in targeted microenvironments, but the measurements were coarsely-resolved in time. Further, low-cost optical PM sensors have very high sampling frequencies, and low-cost sensing measurements are moderately accurate (Feenstra et al., 2019). The Plantower PMS (v. 1003/3003) is a commonly used optical sensor, and has a correlation coefficient of 0.88 with the federal reference method (FRM), which reflects the viability of the sensor for exposure measurements (Kelly et al., 2017). Combined with Internet of Things (IoT) technology, the Plantower PMS can be further integrated to deliver more functionalities to end users. Data collected from a low-cost sensing device or IoT network can be uploaded to the cloud and made available in near-real-time to users. Despite of all the conveniences of low-cost sensing, there are still room for improvements of PM sensor accuracy. Sensors require consistent calibration, and the measurements may require additional post-processing (Zheng et al., 2018).

In this paper, we detail a pilot-scale personal exposure campaign using wearable $PM_{2.5}$ sensors with real-time, remote monitoring capability. Our study engaged residents of five inland Southern California cities and captured spatial and temporal variability of $PM_{2.5}$ exposures over multiple, consecutive 24-hour periods. The main objective of this pilot study was to develop and implement a high-resolution monitoring and analysis framework for characterizing $PM_{2.5}$ exposure variability for individuals from different cities of residence and subsequently different socioeconomic status (SES) neighborhoods. As Southern California historically has high ambient $PM_{2.5}$ levels, we sought to understand which microenvironments posed the greatest exposure risk in the region. Our study elucidates the behavior-dependent patterns of $PM_{2.5}$ exposure in a high-traffic, industrialized region of Southern California.

2. Materials and Methods

2.1 Study Area

Our personal exposure study was conducted in inland Southern California, better known as the Inland Empire, covering an area of approximately 200 square miles (Figure S1). More specifically, the study area includes the cities of Moreno Valley (2018 U.S. Census population of 209,050), Redlands (71,596), Riverside (330,063), San Bernardino (215,941), and Yucaipa (53,682), CA (Table S1). In 2018, median household income estimates were $63,572, $72,523, $65,313, $43,136, and $63,657; and poverty rates were 19.9%, 13.6%, 15.6%, 28.4%, and 12.3%, respectively (U.S. Census Bureau). The major routes that service these cities include interstate routes 10, 15, and 215, and U.S. highways 60, 66, 91, and 210. The major air pollution sources in inland Southern California are on-road traffic, off-road mobile sources (e.g., railyard equipment), industrial point sources (e.g., cement manufacturing and power generating facilities), and smaller point sources (e.g., auto body shops, residential combustion, and restaurants). In recent years, the logistics industry has expanded in the region, prompting the construction of large warehouses that rely on heavy-duty vehicles for goods transport.

The recently implemented California Assembly Bill 617 was designed partially to address disproportionate impacts of air pollution in environmental justice communities, and San Bernardino was selected as a Phase 1 community in 2018 (Garcia, 2017). Previous studies have highlighted health disparities in the San Bernardino community due to its proximity to a large railyard (Spencer-Hwang et al., 2015, 2016). Through our study, we sought to understand personal exposure patterns as they relate to the unique environmental and socioeconomic characteristics of inland Southern California.

2.2 Sampling Campaign

For the sampling campaign, we recruited 18 adult participants (18 years and older; 61% males; 55% Latinx) with varied occupations (50% identified as college students). All sampling activities and interactions with participants were pre-approved by the University of California, Riverside Institutional Review Board (protocol number: *HS 18-206*). The overall campaign took place over a five-week period from 03-10-2019 to 04-14-2019. Each week on Sunday, we distributed a PM monitoring pack to four participants, except for the first week which had two participants (Figure 1). Participants kept the packs for a duration of seven days, allowing the assessment of inter- and intra-day exposure variability for each individual.

Figure 1. (Left) Wearable particulate matter monitors from Applied Particle Technology (St. Louis, MO). Data were transmitted via Wi-Fi hotspots and were accessible online in real-time. (Right) PM sampling pack used in the personal exposure study. The monitors were clipped outside of the pack, and the Wi-Fi and GPS data loggers were housed inside of the pack.

We tracked participant locations with GPS data loggers. Participants were required to carry the packs during the day, and packs were placed in their bedroom or living spaces at night. After the seven-day deployment, the packs were returned to our research facility. We retrieved and removed the GPS data from the data loggers before the next deployment for privacy. One participant's GPS data were missing, so this dataset was removed, and subsequent analyses were carried out for 17 datasets. The participant breakdown by city was the following: two from Moreno Valley, two from Redlands, five from Riverside, six from San Bernardino, and two from Yucaipa. We recognize the uncertainty introduced by the sample size and city breakdown. However, our pilot study generated useful insights that will be leveraged during our larger phase two sampling campaign.

2.3 Monitoring Equipment

Each monitoring pack (total = 4) included a battery-powered PM monitor, a GlobalSat-DG-500 (New Taipei City, Taiwan) GPS module, a Huawei Wi-Fi hotspot, Elitech temperature log, and necessary accessories. The PM monitors are developed by Applied Particle Technology (APT, St. Louis, Missouri, USA) and utilize the Plantower PMS optical sensor (Figure 1). The monitors are commercially available, and our research team was not directly involved with monitor development. The dimensions of the PM monitors are 2 in. x 1 in. x 2.25 in. (L x W x H). The APT monitor provided four PM_1, $PM_{2.5}$, and PM_{10} measurements per minute, but we only analyzed

$PM_{2.5}$ measurements due to the extensive literature and relevance of $PM_{2.5}$ exposure and health, and due to the availability of suitable reference measurements for monitor evaluation. The APT monitors also provide measurements of relative humidity and temperature, and the data are uploaded in real-time via the mobile hotspot to the vendor-hosted web interface. The size, simplicity, mobility, and accessibility of the APT device was ideal for community engagement. The sampling rate of the PM monitor was once every 15 seconds, totaling a maximum of approximately 40,320 possible measurements at the end of the seven-day sampling period, plus or minus a few hours of measurements depending on the scheduled pick-up and drop-off times.

2.4 Data Processing

Although a uniform usage protocol was established for the study, datasets had varying degrees of availability due to the operating habits of the participants. We assigned all missing PM measurements as "-9999", then PM data were synced with the GPS data by their dates and timestamps. Since the GPS data logger's sampling rate was once every five seconds, we performed a linear interpolation on the PM data from 15 to five second intervals to obtain the highest resolution for our datasets. The resulting combined datasets provide the date, time of day, $PM_{2.5}$ concentrations, relative humidity, temperature, and the corresponding latitude and longitude. As a note, the GPS position was intermittently measured at times because the data logger stopped recording if the no movement was detected after 30 seconds. To account for the idling periods, we assigned the previous latitude and longitude to the missing timestamp if the distance between the two intervals was less than 20 meters (Figure S2). When the distance was greater than 20 meters and less than or equal 50 meters, we performed linear interpolation between the two points. A distance greater than 50 meters was assigned "NaN" and considered an invalid data point due to uncertainty in participant mobility during the idle period. The five-second syncing lends a maximum of approximately 120,960 possible data points for each participant.

2.5 Co-location and Adjustments

We co-located the personal PM monitors at the Mira Loma Van Buren (MLVB, AQS ID: 060658005) air monitoring site to evaluate the hourly performance of the monitors. We housed the wearable monitors in a home-built enclosure and positioned the enclosure near the site's federal equivalent method (FEM) $PM_{2.5}$ samplers. The enclosure was built using steel mesh panels to maximize the air flow over the monitors. The monitors were kept on-site for two weeks, and we continuously monitored the activities of each sensor through the web server to ensure that each device was operating optimally. At the end of the co-location period, we obtained $PM_{2.5}$ reference data for the performance analysis. For our study, we used polynomial fitting to adjust the raw data to the FEM reference data. Our measurements were determined to be uninfluenced by relative humidity and temperature, hence the polynomial fittings were solely based on two parameters: reference measurements and raw measurements (Note S1). The fitting method is well described in a paper by Zheng et al. (Zheng et al., 2018). We also explored one other approach to adjust the raw data, for which we utilized using machine learning with random forest regression (RFR) to construct a pattern-based relationship between the reference and raw data. See Note S2 for further discussion of the calibration model testing.

2.6 Data Analysis

We classified microenvironments of all data points based on the GPS measurements. We used the density-based spatial clustering of applications with noise (DBSCAN) algorithm in the QGIS (https://www.qgis.org/) open source GIS platform, and DBSCAN clusters points based on a two-dimensional implementation.(QGIS Development Team, 2019) We then defined each spatial cluster by mandating a minimum size of 120 $PM_{2.5}$/GPS measurements within a maximum distance of 0.0005 degrees (~55 meters). The clusters were manually evaluated and assigned a microenvironment class and activity by overlaying the clusters onto Google Maps. Microenvironment classes included home (H), work (or university, W), restaurant (R), retail (RE), leisure indoor (LI), leisure outdoor (LO), and transient (T); and microenvironment was classified and assigned to the cluster based on the proximity of the cluster center to labels available in Google Maps. The “transient” classification indicates that the speed measurement was greater than 10 kilometers per hour, regardless of prior cluster classification. The “unclassified” classification was given to non-clustered, non-transient data points. We make no assumptions about participant mobility within the microenvironment.

2.7 Ambient $PM_{2.5}$ Contour Fields

We constructed a $PM_{2.5}$ contour mesh over Southern California to compare the personal exposure of $PM_{2.5}$ to ambient $PM_{2.5}$. Participant mobility varied, and measurement locations were up to 100 miles away from the main study location. The input data for the ambient $PM_{2.5}$ spatial fields were accessed from the regulatory monitoring network of the South Coast Air Quality Management District. To construct hourly contour fields, we performed cubic interpolation on hourly $PM_{2.5}$ measurements from 18 monitoring stations. Participant coordinates were paired to the corresponding contour location, resulting in corresponding ambient and personal $PM_{2.5}$ data points for all participants.

3. Results

3.1 Personal and Ambient Data Overview

Calibration of PM monitors using the polynomial fittings resulted in good agreement between the adjusted personal measurements and reference $PM_{2.5}$ measurements. The mean bias for the four monitors ranged from -0.11 to 0.61, slopes ranged from 0.99 to 1.10, intercepts ranged from 0.012 to 0.75, and R^2 ranged from 0.41-0.45 (Note S2).

For interpolated personal measurements, we define data recovery as the percentage of five-second data points available out of the total possible data points for each participant's sampling period (range: 0.5 – 95.6%). Mean data recovery was 50.8%, corresponding to 54,120 valid data points per participant; and median data recovery was 51.8%, corresponding to 53,921valid data points per participant (Table S2). In comparison to prior studies our approach was successful in collecting an exceptionally large amount of data, where valid personal data points from all 17 participants totaled 920,045 (Bekö et al., 2015; Li et al., 2017; Minet et al., 2018; Piedrahita et al., 2017; Quinn et al., 2018; Thomas et al., 1993).

Personal $PM_{2.5}$ measurements were compared to corresponding ambient $PM_{2.5}$ measurement, and ambient data were extracted from contours of hourly measurements from regulatory monitoring stations (Figure S3). Median ambient $PM_{2.5}$ concentrations for each sampling week ranged from 4.4 to 10.2 µg m^{-3}, and maximum concentrations ranged from 22.3 to 28.2 µg m^{-3} (Figure 2). Ambient $PM_{2.5}$ concentrations are lowest in the spring season in southern California.

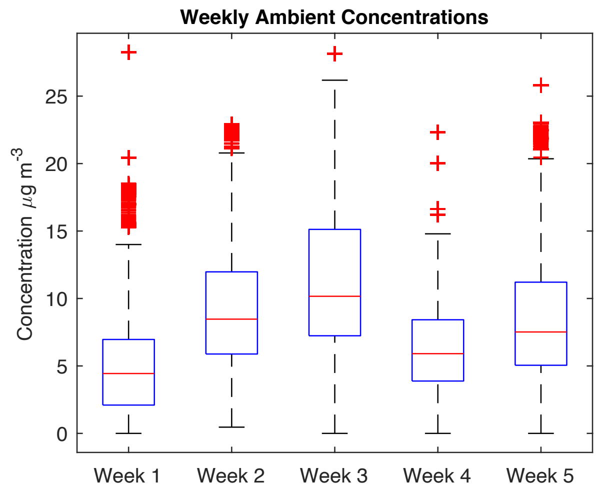


Figure 2. Distributions of ambient $PM_{2.5}$ concentrations (µg m^{-3}) corresponding to participant locations during each week of the study. Median concentrations were 4.4, 8.5, 10.2, 5.9, and 7.5, for weeks 1-5, respectively.

3.2 Exposure and Activity

Time series of individual personal exposure measurements identify acute $PM_{2.5}$ exposure episodes (less than one hour, > 35 µg m^{-3}), and acute exposures were highly variable for all participants. We highlight time series of consecutive, 24-hour personal measurements at 5-seconds resolution along with the corresponding ambient hourly measurement for four participants. Maximum acute exposures ranged from approximately 70 (Redlands) to 2500 (Moreno Valley) µg m^{-3}, further justifying the need for individual level analysis of exposure risk (Figure 3). Participant 2 (San Bernardino) experienced the highest exposures in the home microenvironment in the late afternoons and early evening, as well as in an indoor residential microenvironment that was not classified as home. Participant 5 (Redlands) experienced all acute episodes in the work/university microenvironment, and the residential location university housing. Participant 5 exposures were not as severe as the other highlighted exposures.

Participant 13 (Moreno Valley) experienced frequent, extreme exposures with consistently high measurements greater than 500 µg m^{-3} in the home and leisure indoor microenvironments. High measurements were observed in short intervals in the restaurant microenvironments, specifically a popular burger and coffee chain. High measurements were also infrequently observed in the transient and work microenvironments. Based on the short duration (< 10 minutes) of the extreme exposures and the occurrence in the majority of microenvironments, it is suspected that the participant is a smoker. Participant 15 (Riverside) experienced exposures greater than 100 µg m^{-3} in the home microenvironment, and consistently elevated $PM_{2.5}$ was observed during time spent in a restaurant microenvironment (range 20–50 µg m^{-3}). Time series for all participants can be found in Note S3 in the Supplementary Material.

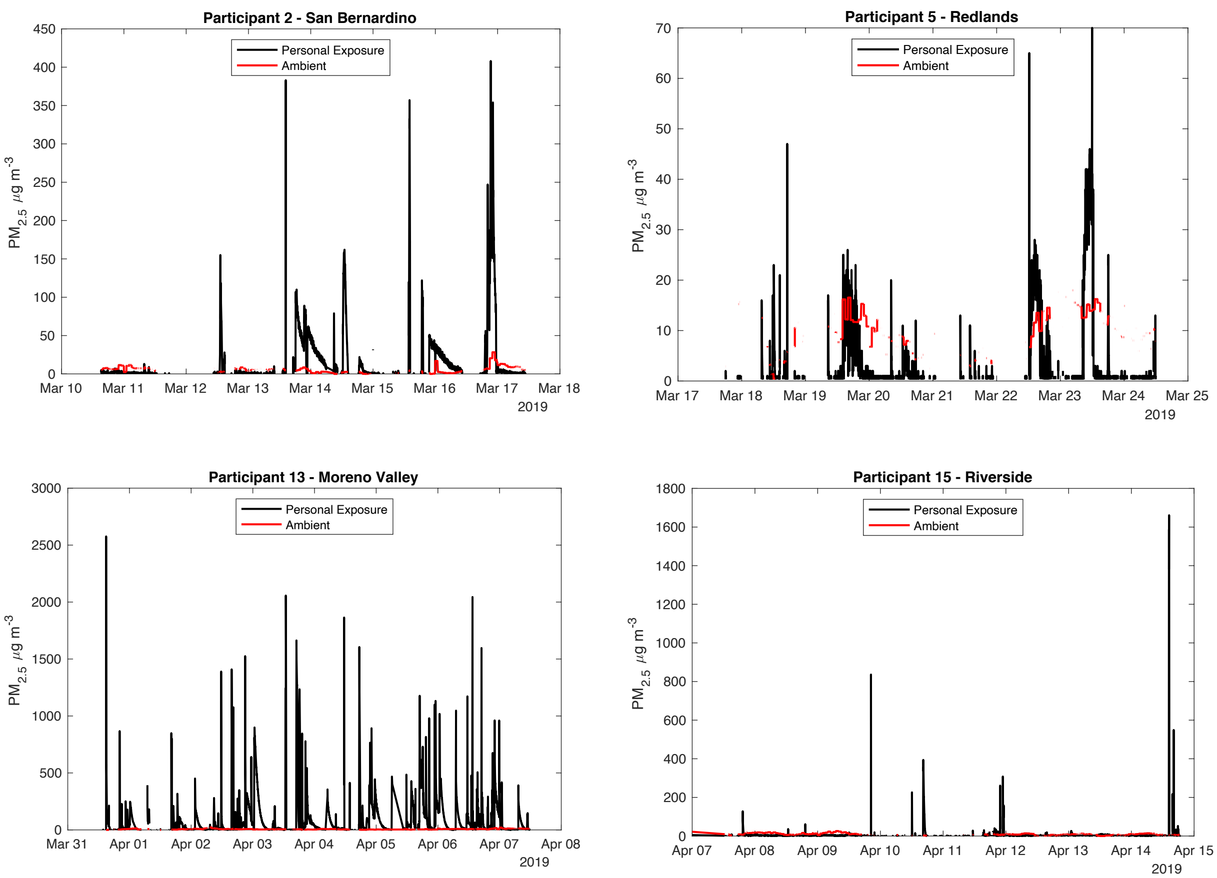


Figure 3. Sample time series of 5-second personal (black) and hourly ambient (red) monitoring data for four participants from San Bernardino (*top-left*), Redlands (*top-right*), Moreno Valley (*bottom-left*), and Riverside (*bottom-right*).

3.3 Inter-City Comparative Analysis

Personal and ambient $PM_{2.5}$ data were aggregated for cities with two or more participants with 50% or greater data recovery, which was the criteria for inclusion in the inter-city analysis (Table 1). Results from those participants were then stratified along SES lines: Redlands/Riverside (N = 5, high SES) and San Bernardino (N = 4, low SES); there were no datasets from Moreno Valley and Yucaipa that met the aggregation criteria. Average data recovery for these participants was 73% (Redlands/Riverside) and 72% (San Bernardino). Aggregated median ambient concentrations were consistently higher than median personal concentrations, and the highest median personal concentrations were observed in home microenvironment for both SES groups. San Bernardino personal medians in the home microenvironment were higher despite having slightly lower ambient medians than Redlands/Riverside. Short-term personal exposures were higher than 20 µg m^{-3} in work, university, restaurant, retail, leisure indoor, and transient microenvironments for aggregated datasets (Figure 4).

Table 1. Summary of the total number of valid data points, average data recovery, and median personal (ambient) $PM_{2.5}$ concentrations (µg m^{-3}) for Redlands and Riverside (N = 5), and San Bernardino (N = 4) participants with data recovery greater than 50%.

City	**Redlands and Riverside**	**San Bernardino**
Number of Data Points (Average Data Recovery)	387,781 (73%)	302,305 (72%)
Home	1.67 (8.66)	5.33 (7.69)
Work or University	0.00 (8.91)	0.00 (3.85)
Restaurant	1.00 (9.36)	0.00 (4.50)
Retail	1.00 (8.64)	0.00 (7.48)
Leisure Indoor	0.00 (11.3)	2.00 (6.52)
Leisure Outdoor	0.00 (6.17)	0.00 (1.68)
Transient	1.00 (7.49)	0.00 (9.79)
Unclassified	1.00 (6.22)	0.00 (5.20)

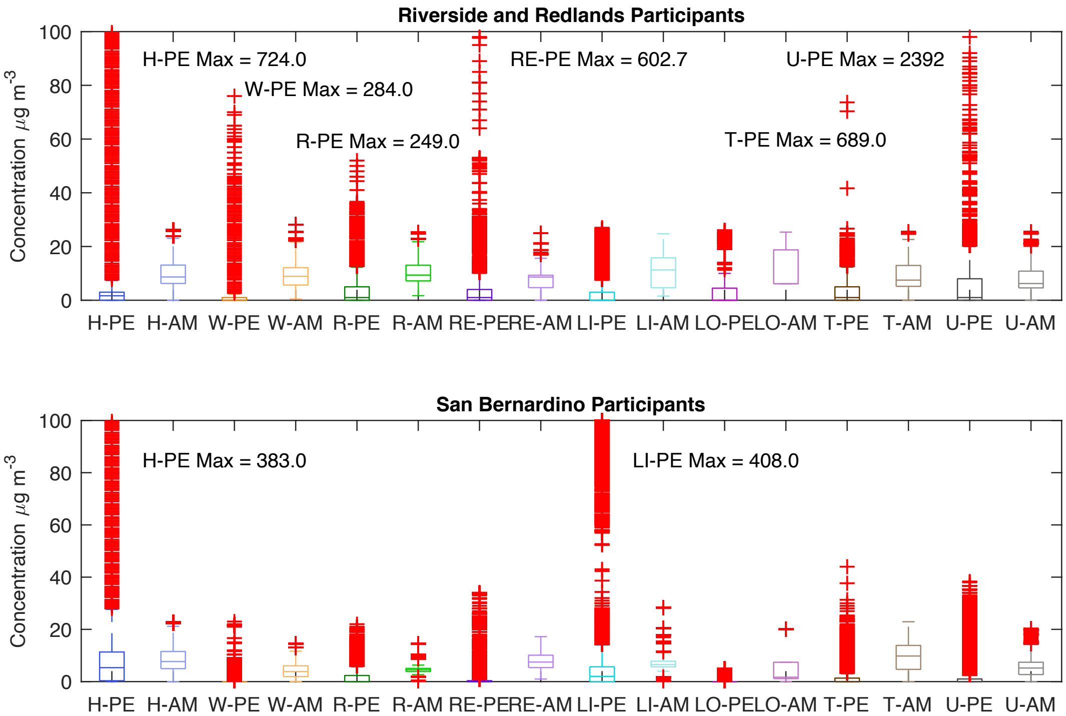


Figure 4. Distributions of personal and ambient $PM_{2.5}$ measurements for Redlands and Riverside (N = 5), and San Bernardino (N = 4) participants with data recovery greater than 50%. The labels indicate the microenvironment classifications: home (H), work (or university, W), restaurant (R), retail (RE), leisure indoor (LI), leisure outdoor (LO), transient (T), and unclassified (U). Personal exposure measurements are labeled "-PE," and ambient data are labeled as "-AM."

For SES-aggregated datasets, mean personal-ambient (P-A) ratios for each microenvironment ranged from 0.02 to 3.49, and median ratios ranged from 0.00 to 0.55 (Table 2). Higher mean ratios compared to median ratios reflect the influence of the outliers in the personal measurements. Ratios less than one indicate that personal environments had lower $PM_{2.5}$ levels than those derived from ambient data. For classified microenvironment clusters, the highest mean P-A ratios were observed in the retail 1.45 (0.60, Redlands/Riverside) and home (3.49, San Bernardino) microenvironments (Table 2). Redlands/Riverside had ratios greater than one for transient (1.17) and unclassified data points (2.81), while the mean home ratio was 0.76. San Bernardino retail ratio was 2.47. The highest median P-A ratios were observed in the home microenvironments for both Redlands/Riverside (0.16) and San Bernardino (0.55) for classified clusters. Wilcoxon rank sum tests indicated significant ($p < 0.05$) differences between non-outlier personal-ambient data pairs for all microenvironments and for every participant with the exception of the leisure indoor and restaurant microenvironments for Participants 5 and 8, respectively. Outlier personal data and corresponding ambient data were excluded from the Wilcoxon tests. Mean and median ratios for all participants can be found Tables S4 and S5 in the Supplementary Material.

Table 2. Mean (median) personal-ambient ratios by city of residence for Redlands and Riverside (N = 5) and San Bernardino (N = 4) participants with data recovery greater than 50%. Bold indicates higher personal $PM_{2.5}$ concentrations than the corresponding ambient concentrations.

City	Redlands and Riverside	San Bernardino
Home	0.76 (0.16)	**3.49** (0.55)
Work or University	0.30 (0.00)	0.06 (0.00)
Restaurant	0.35 (0.12)	0.48 (0.22)
Retail	1.45 (0.15)	0.09 (0.00)
Leisure Indoor	0.28 (0.00)	**2.47** (0.29)
Leisure Outdoor	0.22 (0.00)	0.02 (0.00)
Transient	**1.17** (0.08)	0.14 (0.00)
Unclassified	**2.81** (0.21)	0.23 (0.00)

4. Discussion

The majority of data points were classified as home for the highlighted participants (mean: 65%, median: 69%) (Table S2). This is slightly higher, but consistent with previous personal exposure studies (Bekö et al., 2015; Hsu et al., 2020; Quinn et al., 2018). Data points were classified in these microenvironments at an average of 31% (median: 16%) of the time, therefore non-home exposures may be significant in the long-term (Table S2). Transient $PM_{2.5}$ measurements were within range of a previous personal exposure study conducted in California (Ham et al., 2017). Microenvironment distributions of personal and ambient measurements can be found in Note S4 in the Supplementary Material.

Calculations of time spent in each microenvironment are impacted by data recovery, and charging protocols were best adhered to in the home environments near a convenient supply of electricity. There were compliance issues during sampling that affected data recovery, which is common in human subjects research (Chenail, 2011; Mehra, 2001). Monitor mobility and real-time data transfer of PM monitors enabled the high-resolution personal sampling of our study. However, data collection was impeded when component batteries drained, although a charging schedule was provided but not always adhered to. At times the hardware stalled, or data transfer was limited by availability of Wi-Fi signal. Participant accidents with the monitors, while rare, also interrupted sampling; minor damages to the protective casings were mended before redeployment.

Our monitoring approach intuitively identifies participants that may be actively or passively exposed to cigarette or vaping smoke, as very high personal measurements (> 100 μg m^{-3}) are classified as outliers in a five-second resolution dataset (Figure 4) (Götschi et al., 2002; Koistinen et al., 2004; Salmon et al., 2018; Slezakova et al., 2009). Suspected smoking events occur at relatively shorter time scales throughout the day and are easily identified in the time series and boxplots of personal measurements. Consequently, median P-A ratios derived from high temporal resolution data are useful for evaluating non-smoking related $PM_{2.5}$ exposures when smoking status is undisclosed. Therefore, when comparing the bulk (non-outliers) of personal and ambient measurements for Redlands/Riverside microenvironments, personal $PM_{2.5}$ measurements are much less than ambient $PM_{2.5}$. Conversely, the San Bernardino median home microenvironment exposure was most similar to the corresponding median ambient exposure (Table 1).

Considering the relatively small number of participants in the study, definitive generalizations cannot be made regarding influences of residential location. However, the large amount of measurements analyzed here provides a preliminary, yet robust, investigation of exposure disparities. San Bernardino (highest poverty rates, lowest median household income) participants with greater than 50% data recovery experienced higher home exposures compared with participants from other cities. Redlands/Riverside (second/third lowest poverty rate, highest/second-highest household incomes) participants overall had lower home personal exposures and experienced higher personal exposures outside of the home. Since most time was spent in the home microenvironment for the majority of participants, San Bernardino participants were more likely to be exposed to higher $PM_{2.5}$ concentrations, even when taking into account the high degree of mobility of participants which is reflected in the diversity of classified microenvironments.

5. Conclusions

Our pilot study highlights the variability in community-scale exposure in a socioeconomically diverse air basin that is heavily burdened by air pollution. A novel spatial clustering approach was applied to classify the microenvironments of more than 900,000 high temporal resolution personal exposure data points. Results from the study indicate that participants from the lowest socioeconomic status community experienced overall higher personal exposures over consecutive 24-hr monitoring periods, despite high participant mobility and low variability in ambient $PM_{2.5}$ during the study. Our inclusive monitoring protocol minimizes participant fatigue and is well-suited for real-time, long-term characterization of $PM_{2.5}$ exposure disparities in underserved communities. $PM_{2.5}$ serves as a useful surrogate species for many other air pollutants that may influence disproportionate exposures. The application of our streamlined, data-driven methods in a larger-scale exposure study will further elucidate personal exposure disparities along racial and socioeconomic lines.

Data Availability

In accordance with the University of California, Riverside Institutional Review Board, personal data may only be distributed in an aggregated form to preserve participant privacy. All aggregated and anonymized data are summarized in the Supplementary Material.

Vitae

Khanh Do	Ph.D. Candidate in the Chemical and Environmental Engineering graduate program at UC Riverside.	
Haofei Yu	Assistant Professor of Civil, Environmental and Construction Engineering, specializing in air quality modeling, air pollution sensor development, and health impacts studies.	

Jasmin Velasquez	Undergraduate research assistant in the Chemical and Environmental Engineering Department at UC Riverside.	
Marilyn Grell-Brisk	Assistant research scientist of environmental sociology at the Center for Environmental Research and Technology, specializing in macro-comparative quantitative research methods.	
Heather Smith	Director of Life Sciences at Riverside City College, specializing in environmental toxicology.	N/A
Cesunica E. Ivey	Assistant Professor of Chemical and Environmental Engineering, specializing in air quality modeling, exposure monitoring, and environmental justice.	

Acknowledgements

We acknowledge Aaron Garcia, Saray Rodriguez, Hector Soto, Priscilla Villegas, and David Wilson for their assistance with the field data collection. We thank Chela Larios of Center for Community Action and Environmental Justice and Yassi Kavezade of Sierra Club for their help with recruiting participants. We thank Jiaxi Fang and Tandeep Chadha of Applied Particle Technology for their technical assistance, and Brandon Feenstra and Nelson Marquez for facilitating co-location at the Mira Loma Van Buren air monitoring site.

Funding

This work was supported by the Alfred P. Sloan Foundation and Social Science Research Council.

References

Bekö, G., Kjeldsen, B. U., Olsen, Y., Schipperijn, J., Wierzbicka, A., Karottki, D. G., Toftum, J., Loft, S., & Clausen, G. (2015). Contribution of various microenvironments to the daily personal exposure to ultrafine particles: Personal monitoring coupled with GPS tracking. *Atmospheric Environment*, *110*, 122–129. https://doi.org/10.1016/j.atmosenv.2015.03.053

Chenail, R. J. (2011). Interviewing the investigator: Strategies for addressing instrumentation and researcher bias concerns in qualitative research. *Qualitative Report*, *16*(1), 255–262.

Clayton, C. A., Perritt, R. L., Pellizzari, E. D., Thomas, K. W., Whitmore, R. W., Wallace, L. A., Ozkaynak, H., & Spengler, J. D. (1993). Particle Total Exposure Assessment Methodology (PTEAM) study: Distributions of aerosol and elemental concentrations in personal, indoor, and outdoor air samples in a southern California community. *Journal of Exposure Analysis and Environmental Epidemiology*, *3*(2), 227–250.

Feenstra, B., Papapostolou, V., Hasheminassab, S., Zhang, H., Boghossian, B. Der, Cocker, D., & Polidori, A. (2019). Performance evaluation of twelve low-cost PM2.5 sensors at an ambient air monitoring site. *Atmospheric Environment*, *216*, 116946. https://doi.org/10.1016/j.atmosenv.2019.116946

Garcia, C. (2017). *Assembly Bill No. 617*. California State Assembly.

Götschi, T., Oglesby, L., Mathys, P., Monn, C., Manalis, N., Koistinen, K., Jantunen, M., Hänninen, O., Polanska, L., & Künzli, N. (2002). Comparison of Black Smoke and PM 2.5 Levels in Indoor and Outdoor Environments of Four European Cities. *Environmental Science & Technology*, *36*(6), 1191–1197. https://doi.org/10.1021/es010079n

Ham, W., Vijayan, A., Schulte, N., & Herner, J. D. (2017). Commuter exposure to PM2.5, BC, and UFP in six common transport microenvironments in Sacramento, California. *Atmospheric Environment*, *167*, 335–345. https://doi.org/10.1016/j.atmosenv.2017.08.024

Hsu, W.-T., Chen, J.-L., Candice Lung, S.-C., & Chen, Y.-C. (2020). PM2.5 exposure of various microenvironments in a community: Characteristics and applications. *Environmental Pollution*, *263*, 114522. https://doi.org/10.1016/j.envpol.2020.114522

Hu, J., Ostro, B., Zhang, H., Ying, Q., & Kleeman, M. J. (2019). Using Chemical Transport Model Predictions To Improve Exposure Assessment of PM 2.5 Constituents. *Environmental Science & Technology Letters*, *6*(8), 456–461. https://doi.org/10.1021/acs.estlett.9b00396

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

Koistinen, K. J., Edwards, R. D., Mathys, P., Ruuskanen, J., Künzli, N., & Jantunen, M. J. (2004). Sources of fine particulate matter in personal exposures and residential indoor, residential outdoor and workplace microenvironments in the Helsinki phase of the EXPOLIS study. *Scandinavian Journal of Work, Environment and Health*, *20*, 36–46.

Kulmala, M., Asmi, A., & Pirjola, L. (1999). Indoor air aerosol model: The effect of outdoor air, filtration and ventilation on indoor concentrations. *Atmospheric Environment*, *33*(14), 2133–2144. https://doi.org/10.1016/S1352-2310(99)00070-9

Li, Z., Che, W., Frey, H. C., Lau, A. K. H., & Lin, C. (2017). Characterization of PM 2.5 exposure concentration in transport microenvironments using portable monitors. *Environmental Pollution*, *228*, 433–442. https://doi.org/10.1016/j.envpol.2017.05.039

Long, C. M., Suh, H. H., Catalano, P. J., & Koutrakis, P. (2001). Using Time- and Size-Resolved Particulate Data To Quantify Indoor Penetration and Deposition Behavior. *Environmental Science & Technology*, *35*(10), 2089–2099. https://doi.org/10.1021/es001477d

Mehra, B. (2001). Bias in Qualitative Research: Voices from an Online Classroom. *The Qualitative Report*, *7*(1), 1–19.

Minet, L., Liu, R., Valois, M.-F., Xu, J., Weichenthal, S., & Hatzopoulou, M. (2018). Development and Comparison of Air Pollution Exposure Surfaces Derived from On-Road Mobile Monitoring and Short-Term Stationary Sidewalk Measurements. *Environmental Science & Technology*, *52*(6), 3512–3519. https://doi.org/10.1021/acs.est.7b05059

Özkaynak, H., Xue, J., Spengler, J., Wallace, L., Pellizzari, E., & Jenkins, P. (1996). Personal exposure to airborne particles and metals: Results from the particle team study in Riverside, California. *Journal of Exposure Analysis and Environmental Epidemiology*, *6*(1), 57–78.

Piedrahita, R., Kanyomse, E., Coffey, E., Xie, M., Hagar, Y., Alirigia, R., Agyei, F., Wiedinmyer, C., Dickinson, K. L., Oduro, A., & Hannigan, M. (2017). Exposures to and origins of carbonaceous PM2.5 in a cookstove intervention in Northern Ghana. *Science of The Total Environment*, *576*, 178–192. https://doi.org/10.1016/j.scitotenv.2016.10.069

QGIS Development Team. (2019). *QGIS User Guide—Release 3.4*.

Quinn, C., Miller-Lionberg, D. D., Klunder, K. J., Kwon, J., Noth, E. M., Mehaffy, J., Leith, D., Magzamen, S., Hammond, S. K., Henry, C. S., & Volckens, J. (2018). Personal Exposure to PM 2.5 Black Carbon and Aerosol Oxidative Potential using an Automated Microenvironmental Aerosol Sampler (AMAS). *Environmental Science & Technology*, *52*(19), 11267–11275. https://doi.org/10.1021/acs.est.8b02992

Salmon, M., Milà, C., Bhogadi, S., Addanki, S., Madhira, P., Muddepaka, N., Mora, A., Sanchez, M., Kinra, S., Sreekanth, V., Doherty, A., Marshall, J. D., & Tonne, C. (2018). Wearable camera-derived microenvironments in relation to personal exposure to PM2.5. *Environment International*, *117*, 300–307. https://doi.org/10.1016/j.envint.2018.05.021

Slezakova, K., Castro, D., Pereira, M. C., Morais, S., Delerue-Matos, C., & Alvim-Ferraz, M. C. (2009). Influence of tobacco smoke on carcinogenic PAH composition in indoor PM10 and PM2.5. *Atmospheric Environment*, *43*(40), 6376–6382. https://doi.org/10.1016/j.atmosenv.2009.09.015

Spencer-Hwang, R., Soret, S., Knutsen, S., Shavlik, D., Ghamsary, M., Beeson, W. L., Kim, W., & Montgomery, S. (2015). Respiratory Health Risks for Children Living Near a Major Railyard. *Journal of Community Health*, *40*(5), 1015–1023. https://doi.org/10.1007/s10900-015-0026-0

Spencer-Hwang, R., Soret, S., Valladares, J., Torres, X., Pasco-Rubio, M., Dougherty, M., Kim, W., & Montgomery, S. (2016). Strategic Partnerships for Change in an Environmental Justice Community: The ENRRICH Study. *Progress in Community Health Partnerships: Research, Education, and Action*, *10*(4), 541–550. https://doi.org/10.1353/cpr.2016.0062

Thomas, K. W., Pellizzari, E. D., Clayton, C. A., Whitaker, D. A., Shores, R. C., Spengler, J., Ozkaynak, H., Froehlich, S. E., & Wallace, L. A. (1993). Particle Total Exposure Assessment Methodology (PTEAM) 1990 study: Method performance and data quality for personal, indoor, and outdoor monitoring. *Journal of Exposure Analysis and Environmental Epidemiology*, *3*(2), 203–226.

Wallace, L. (1996). Indoor Particles: A Review. *Journal of the Air & Waste Management Association*, *46*(2), 98–126. https://doi.org/10.1080/10473289.1996.10467451

Yu, H., Russell, A., Mulholland, J., & Huang, Z. (2018). Using cell phone location to assess misclassification errors in air pollution exposure estimation. *Environmental Pollution*, *233*, 261–266. https://doi.org/10.1016/j.envpol.2017.10.077

Yu, X., Stuart, A. L., Liu, Y., Ivey, C. E., Russell, A. G., Kan, H., Henneman, L. R. F., Sarnat, S. E., Hasan, S., Sadmani, A., Yang, X., & Yu, H. (2019). On the accuracy and potential of Google Maps location history data to characterize individual mobility for air pollution health studies. *Environmental Pollution*, *252*, 924–930. https://doi.org/10.1016/j.envpol.2019.05.081

Zheng, T., Bergin, M. H., Johnson, K. K., Tripathi, S. N., Shirodkar, S., Landis, M. S., Sutaria, R., & Carlson, D. E. (2018). Field evaluation of low-cost particulate matter sensors in high- and low-concentration environments. *Atmospheric Measurement Techniques*, *11*(8), 4823–4846. https://doi.org/10.5194/amt-11-4823-2018