ENVIRONMENTAL RESEARCH LETTERS

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Indoor and ambient influences on PM2.5 exposure and well-being for a rail impacted community and implications for personal protections

Indoor and Ambient Influences on $PM_{2.5}$ Exposure and Well-being for a Rail Impacted Community and Implications for Personal Protections

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Abstract

Background

Higher air pollution concentrations can be observed near rail networks, local and highway automobile corridors, and shipyards. Communities adjacent to such sources are disproportionately exposed to air pollution from these stationary and mobile sources. One such community is West San Bernardino in California, where households are feet away from the Burlington Northern Santa Fe intermodal facility and are impacted by activities that are estimated to continuously emit air pollutants due to 24/7 operation.

Objective

This study aimed to (1) quantify the impact of personal mobility and housing characteristics on daily $PM_{2.5}$ exposures and well-being for West San Bernardino community members, and (2) develop individualized resilience plans for community collaborators to support future $PM_{2.5}$ exposure reduction.

Methods

Personal $PM_{2.5}$ exposures were measured for community collaborators for seven consecutive days during three deployment periods: October 2021, January 2022, and March 2022. Indoor and ambient $PM_{2.5}$ levels

were also continuously measured for five households over six months using PurpleAir Classic monitors. Demographic and well-being data were collected upon recruitment and after each week of engagement, respectively.

Results

Personal exposures in home microenvironments were highest near the railyard and lower farthest away from the railyard. Home exposures were 40% higher on average compared to non-home microenvironments. Household $PM_{2.5}$ had a higher-than-expected average infiltration factor of 0.55, and indoor 98th percentiles across the households far exceeded a healthy level at an average of 165 μg/m^3. Resilience plans featured summaries of personal data and recommendations for mitigating exposures.

Significance

Results suggest that surrounding land use and residential building characteristics compound to worsen air pollution exposures beyond what is expected for exposures in non-industrialized areas. Findings prompt a call for stronger regulation, not only for emissions, but also for indoor air quality and zoning standards that specifically protect disproportionately impacted communities.

1. Introduction

Fine particulate matter (PM) is the term to describe liquid or solid particles with an aerodynamic diameter less than or equal to 2.5 microns ($PM_{2.5}$). Studies have shown that exposure to high levels of $PM_{2.5}$ can adversely affect human health, causing asthma, respiratory disease, and cardiovascular disease.[1–4] Primary $PM_{2.5}$ is directly emitted from a source into the atmosphere, and sources include construction sites, smokestacks, or wildfires. $PM_{2.5}$ is also generated through complex chemical reactions in the atmosphere, known as secondary PM, which is highly correlated with urban $PM_{2.5}$.[5,6] High concentrations of $PM_{2.5}$ are found in urban areas with a high volume of anthropogenic activities.[7–9] Spatial distributions of $PM_{2.5}$ in the U.S. exhibit significant racial-ethnic disparity.[10,11] Specifically, highly polluted areas are often in low-income and non-white neighborhoods that are surrounded by industrial factories, shipping facilities, warehouses, and railyards.[12–15]

Additionally, people spend over 90% of the time indoors[16,17] and are subsequently exposed to indoor air pollutants that are generated from multiple sources. Indoor activities, such as vacuum cleaning, cooking, dusting, use of consumer products, and smoking are the primary sources of indoor $PM_{2.5}$.[18] These activities can increase indoor $PM_{2.5}$ levels by orders magnitude in a very short period of time, approximately 10 to 30 minutes.[19] An effective range hood can remove a significant amount of $PM_{2.5}$ generated during cooking activities. During high $PM_{2.5}$ episodes, air ventilation also effectively reduces indoor $PM_{2.5}$ levels by diluting with fresh outdoor air.[20,21] Further, baseline indoor $PM_{2.5}$ levels are highly influenced by the penetration of ambient $PM_{2.5}$ into the indoor environment. Although indoor air quality can be improved with proper air exchange and filtration systems, numerous studies have shown a strong relationship between indoor and ambient $PM_{2.5}$ levels.[22–26] In particular, indoor $PM_{2.5}$ concentrations are highly correlated with ambient $PM_{2.5}$ when wildfires occur.[27] Closing the windows and minimizing the air exchange rate can decrease the penetration of ambient particles during such an event. However, closing windows and using central heating or air conditioning is not always an option for lower-income households in California. According to the California Energy Commission's 2019 California Residential Appliance Saturation Study, less than 50% of households with an income less than $75,000 will have central air conditioning.[28] This implies that lower-income households rely on other methods to cool their homes, including using unfiltered cooling units or opening windows during cooler periods outside. Both approaches make indoor residential environments more susceptible to penetration of ambient air pollution for lower-income households.

This study considers personal exposures and household $PM_{2.5}$ for a lower income, disproportionately impacted community of inland Southern California, which is located near the northern and southern borders of Riverside and San Bernardino Counties, respectively. For reference, this region is historically known for its agricultural economy and more recently for freight shipping activities and a growth of warehouses, creating a significant shift in the region's economy.[14,29] The nationwide shift towards more online shopping in the United States has resulted in further expansion of freight shipping activities in the region. Roughly 45% of products imported from Asia are shipped through inland Southern California each year[30] and distributed across the United States via heavy-duty diesel trucks and railway systems. The Burlington Northern Santa Fe (BNSF) intermodal facility, which is directly adjacent to residential areas within the San Bernardino community (within 200 feet of the fence line), has long been determined as a major air pollution source and health hazard for neighboring communities.[31–34] The facility's emissions are generated from diesel trucks entering and leaving the facility, equipment to load and unload containers, and locomotives.[35]

In this study, we seek to understand intra-community variability in microenvironmental $PM_{2.5}$ exposures for a disproportionately impacted community. High-resolution microenvironmental data are scarce for such communities given the inaccessibility of consumer-grade monitors for household and personal uses.[27] We measure $PM_{2.5}$ at the individual and household levels for residents of the West San Bernardino, CA community near the BNSF intermodal facility. We utilize low-cost monitoring technology for both mobile (personal) and stationary (indoor and ambient) measurements. We characterize mobility-influenced microenvironmental exposures using spatial clustering of high-resolution geolocated $PM_{2.5}$ measurements to understand how exposure risk varies near the facility. For households with stationary monitoring, we used a mass balance approach to estimate penetration, indoor emission rate, air exchange rate, and filtration factors. We compared the findings with previous work that characterized indoor air quality in California homes using crowdsourced data. We also discuss community co-learning, subsequent advocacy activities, and how results could support rail regulation amendments.

2. Materials and Methods

2.1 Study Location

The study was conducted in the West San Bernardino community, located in the southern region of San Bernardino County, California (inland southern California), which is adjacent to the BNSF intermodal facility (Figure 1). Its climate is classified as hot-summer Mediterranean with mild winters and hot, dry summers. Prevailing winds are from the south and west, such that communities directly to the north of the facility are most exposed to its emissions. The West San Bernardino community is bounded by a highway network of U.S. Interstates 10 to the south, 210 to the north, and 215 on the east, which are always in heavy use due to the rapid expansion of freight infrastructure. The Westside San Bernardino neighborhood is a known hot spot for air pollution and high rates of cancer, which is associated with its proximity to the BNSF intermodal facility, the largest concentration of warehouses in the country, air cargo facilities, and multiple freeways.[36,37] In San Bernardino County, CalEnviroScreen 4.0 data highlights 35 census tracts in the 90-100th percentiles for ozone burden, affecting more than 100,000 people, where the majority population are Latino (Figure 1).[38] Those same tracts have average percentiles of 75.4 for $PM_{2.5}$ and 79.8 for diesel $PM_{2.5}$. See Note 1 in the Supplemental Information for more details about the BNSF intermodal facility.

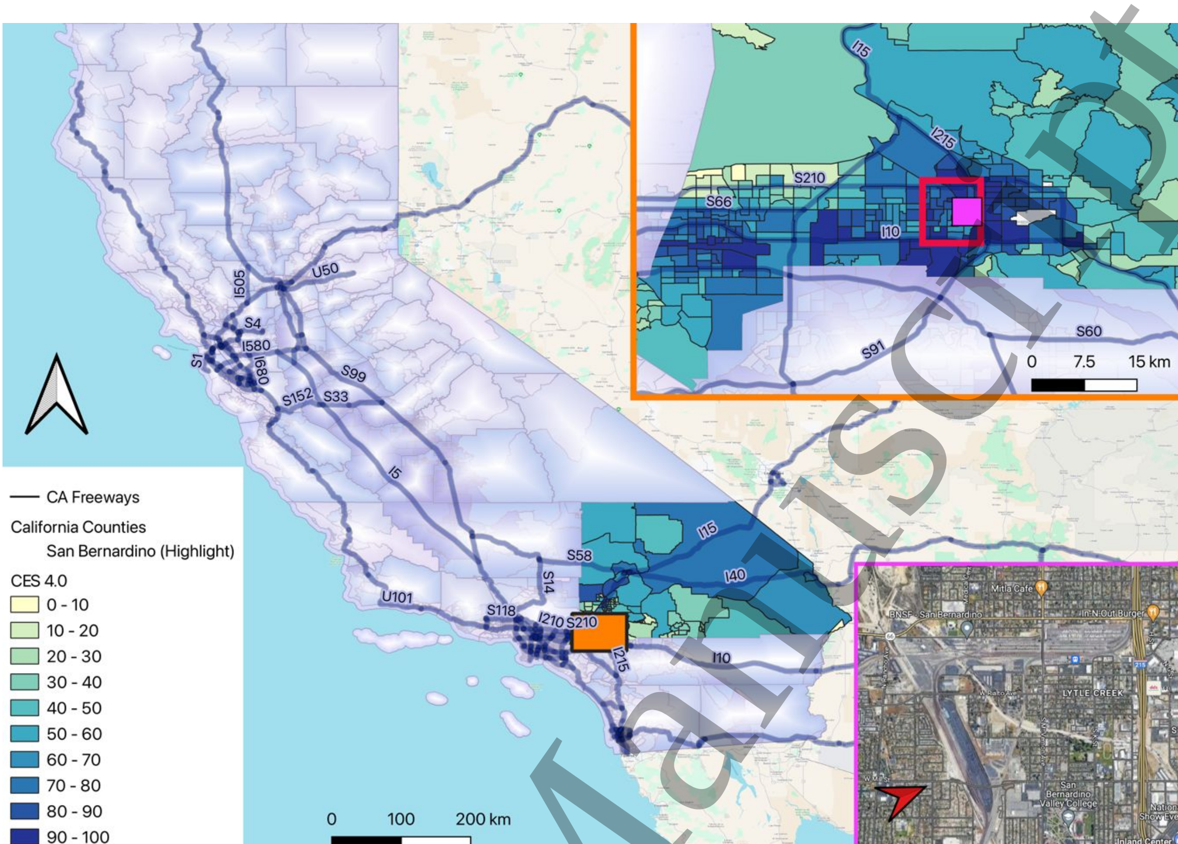

Figure 1: Map of California and the relative extent of community engagement (orange) within San Bernardino County (highlighted) with CalEnviroScreen 4.0 (CES) scores; darker colors indicating higher environmental vulnerability. The larger inset map (upper right) shows a zoomed in extent of southwest San Bernardino County and the West San Bernardino community (red), lying west of I-215 and bordered to the north and south by I-210 and I-10, respectively. The smaller inset map (lower right) shows the extent of BSNF intermodal facility, which is indicated by the magenta rectangle in the larger inset map (Map data ©2024 Google). The red arrow is the prevailing wind direction (see Figure S1 for wind rose plot).

2.2 Community Collaboration

West San Bernardino residents have a history of engaging in research and community monitoring through previous studies[31,32,37], and most recently through the California Air Resources Board Community Air Protection Program (mandated by California Assembly Bill 617).[39] Community collaborators were recruited by organizers from the Center for Community Action and Environmental Justice (Jurupa Valley, CA). Specifically, 45 community collaborators from 43 unique households were engaged in personal monitoring activities, and 5 households participated in indoor and outdoor PurpleAir monitoring. All community collaborators were invited to attend four educational sessions to gain hands-on training on operating low-cost air pollution monitors and discuss technical and logistical aspects of the community collaboration. One household participated in both the personal and household monitoring activities. All personal monitoring collaborators filled out an intake form to collect demographic and pre-existing health information (static well-being). This information included age, home rental status, annual income range, education level, occupation, vehicle ownership, smoking status (exclusion from the study if smoker), air conditioning in the home, medical history, and perception of air quality in inland southern California. Details on the intake form questions are provided in the Supplemental Information (Table S1).

2.3 Microenvironmental Exposure Analysis

Personal exposure monitoring for $PM_{2.5}$ took place over three deployment periods for three weeks at a time (October 2021, January 2022, and March 2022) (Table S2). A range of 9-14 community collaborators were engaged for seven consecutive days during each deployment week. Collaborators were asked to carry the monitor with them as they went about their daily activities, and they filled out a dynamic survey to report present-day well-being information at the end of each 7-day engagement period (dynamic well-being). Details on the dynamic survey questions are provided in the Supplemental Information (Table S3). After concluding all personal monitoring, five community collaborators provided additional context for their data in follow-up interviews at the end of the deployment period. All personal exposure participants received a one-page infographic that summarized their data and listed recommendations for exposure mitigation in high-risk microenvironments. Personal $PM_{2.5}$ exposure and GPS location was measured using wearable monitors (Applied Particle Technology (APT), San Mateo, California, USA), and measurements are made every 15 seconds.[17] The Gaussian Mixture Model (GMM) calibration description, summary of the reference comparison data, and an image of the monitor are provided in the Supplemental Information (Note 2 and Tables S4 and S5). During the colocation period, the APT sensors and FEM monitor showed good performance, where R^2 ranged from 0.63 - 0.79, mean absolute errors ranged from 2.21 - 2.59 μg/m^3, and mean biases ranged from -0.079 to 0.076 μg/m^3.

Use of the density-based spatial clustering analysis with noise (DBSCAN) method was shown to be a viable approach in the preceding pilot study.[17] DBSCAN was again used here to aggregate space-time measurements of $PM_{2.5}$ into organized clusters to quantify microenvironmental exposures. For this study, the minimum number of clustered data points was 50, and the cluster distance tolerance was 37.5 meters. Google Maps was then used to classify the microenvironment into one of seven categories: home (H), work/university (W), restaurant (R), retail (RE), leisure indoor (LI), leisure outdoor (LO), and transient (T). All microenvironment clusters are considered indoor except transient and leisure outdoor. We then identified the activity or more place-specific information based on Google Maps. Further, data points that were not clustered, but met the speed criteria, were classified as transient. Clusters are considered "unclassified" if there is not a readily identifiable activity due to unavailable GPS measurements.

2.4 PurpleAir Measurements and Data Processing

Fifteen PurpleAir Classic monitors, formerly named PA-II (Draper, Utah, USA), were deployed in the community in ten households to assess trends in $PM_{2.5}$ over seven months (July 2022 – January 2023). Specifically, five homes were selected for the installation of both indoor and ambient monitors, while the other five homes had only ambient $PM_{2.5}$ monitoring (Figure S1). Here, we focus on the indoor and ambient pairing comparison. Given the sample size and privacy protocols, locations of the five homes will not be specified, however a snapshot of the monitoring setup near the BNSF facility is provided in the Supplemental Information (Figure S1). Ambient PurpleAir monitors were installed in the back yard or front yard, and indoor monitors were installed in the living room (i.e., main room). The sensors were powered continuously by 120V outlets. The monitors provided measurements every 120 seconds for temperature (°F, converted to °C here), relative humidity (%), and $PM_{2.5}$ concentration (μg/m^3). We used 10-minute averages to compute indoor emission and decay rates. The data were averaged hourly to remove noise before computing statistical summaries. We applied a linear correction factor to the raw PurpleAir $PM_{2.5}$ measurements based on recommendations by Barkjohn et al. (Eq. 1), where $PM_{2.5}$ is the corrected concentration, PA is the average raw $PM_{2.5}$ concentration from PurpleAir channels a and b, and RH is relative humidity.[40] We used pm2.5_cf_1 as suggested by Barkjohn et al. for the study. Note that pm2.5_cf_1 refers to the method used to calculate $PM_{2.5}$ concentrations from the particle counter based on a proprietary algorithm developed by Plantower.

$$PM_{2.5} = 0.524PA - 0.0862RH + 5.75 \quad 1)$$

2.5 Indoor $PM_{2.5}$ Modeling

Simultaneously indoor and ambient $PM_{2.5}$ sampling enabled the derivation of a simple mass balance to estimate the loss rate constant, indoor emission rate constant, and penetration for the homes with paired monitors. The loss rate constant is the combination of the air exchange and filtration rate constant, which are responsible for the decay of indoor $PM_{2.5}$ concentrations. The indoor emission rate constant is the magnitude of indoor emissions, and the penetration rate constant represents the effectiveness of $PM_{2.5}$ transfer from the outside to the indoor environment. Separate models for emission events, decay events, and the baseline models were applied using PurpleAir measurements. Derivations of all model solutions are provided in Notes 3-5 in the Supplementary Information. Overall, the peaks of indoor $PM_{2.5}$ were ten times greater than the indoor average, and the slopes were steep. Typically, indoor emissions were generated in 10 to 20 minutes, and the decay lasted about 10 to 50 minutes. The red and black lines from the bottom panel in Figure 2 were used to calculate average indoor emissions and decay constants.

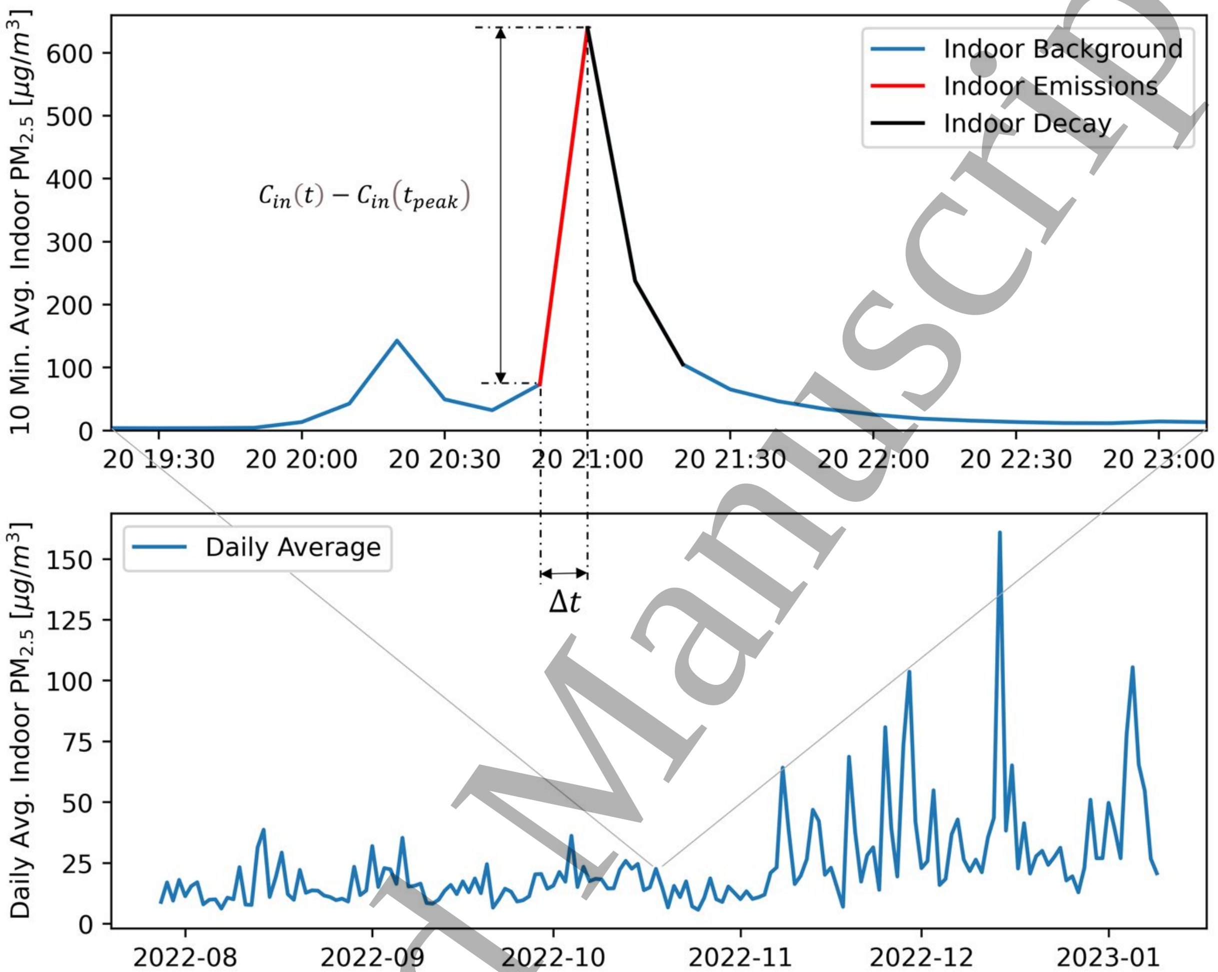

Figure 2: Sample daily average time series for one home from 2022 Aug to 2023 Jan (bottom). Zoom-in on the 10-minute average time series with x-axis labels in the format "DD HH:MM" (top); the red line is used to calculate the indoor emissions (E/V) and black line is used to calculate the decay constant (α) based on the emission and decay models, respectively (see Notes 3 and 4 in the SI).

3. Results

3.1 Personal Monitoring and Microenvironmental Exposures

DBSCAN clustering resolved a total of 573 clusters for the entire engagement period, and this total excludes data classified as transient or data within unclassified microenvironments. Taking seven days (168 hours) as the maximum possible measurement period for each collaborator's seven-day engagement period (103 unique engagement periods), there were a maximum of 17,304 possible measurement hours. Of those possible measurement hours, data were collected during 69, 80, and 67% of the possible measurement hours in October, January, and March, respectively (12,440 total hours) (Table S6). Of the data collected, only 5.1, 4.3, and 4.9% of measurements were labeled as "unclassified (U)" microenvironments. Details that follow describe $PM_{2.5}$ averages for classified microenvironment clusters: home, work/university, restaurant, retail, leisure indoor, leisure outdoor, and transient (in motion). Home microenvironments had the highest percentages of measurements collected, 86, 85, and 86% in October, January, and March, respectively.

Microenvironments were clustered and classified, and the viable (GPS available) $PM_{2.5}$ measurements were averaged for each unique engagement period and for each community collaborator (Figure 3). Larger cluster symbols indicate higher average exposures. On average, home exposures were 40% higher than non-home microenvironments, where the largest differences were seen during the October deployment – 60% higher in October, 30% higher in January, and 40% higher in March. Home average $PM_{2.5}$ was 22, 54, and 9.8 μg/m^3 for the October, January, and March deployments, respectively. Non-home average $PM_{2.5}$ was 14, 41, and 7.2 μg/m^3 for the October, January, and March deployments, respectively. Generally, microenvironmental exposures were highest near the railyard (zones 1 and 2) and lowest farther away from the railyard (zone 3), as seen in the heat map in SI Figure S2 (see Note 6 for zone description and statistics).

Upon examination of high-risk non-home/non-transient microenvironments, where high risk is considered here to be an average $PM_{2.5}$ concentration greater than the World Health Organization 24-hour air quality guideline (15 μg m^{-3})[41], Chick-fil-A, AutoZone, and a friend's home had high-risk average exposures of 69, 91, and 269 μg/m^3. It is worth noting that time spent in each location was approximately one hour or less. Other locations with similarly short-term, high-risk exposures include a dermatology center, Pinoy restaurant, shopping mall, hotel, bowling club, church, and swim complex with average concentrations of 35, 45, 46, 71, 154, 270, 1062 μg/m^3, respectively. Regarding transient or in-motion exposures, some measurements averages well-exceeded the measurement range of the sensor. It should be noted that the optimal range of measurements for Plantower 5003 sensors (within the wearable monitor) is 0-500 μg/m^3.

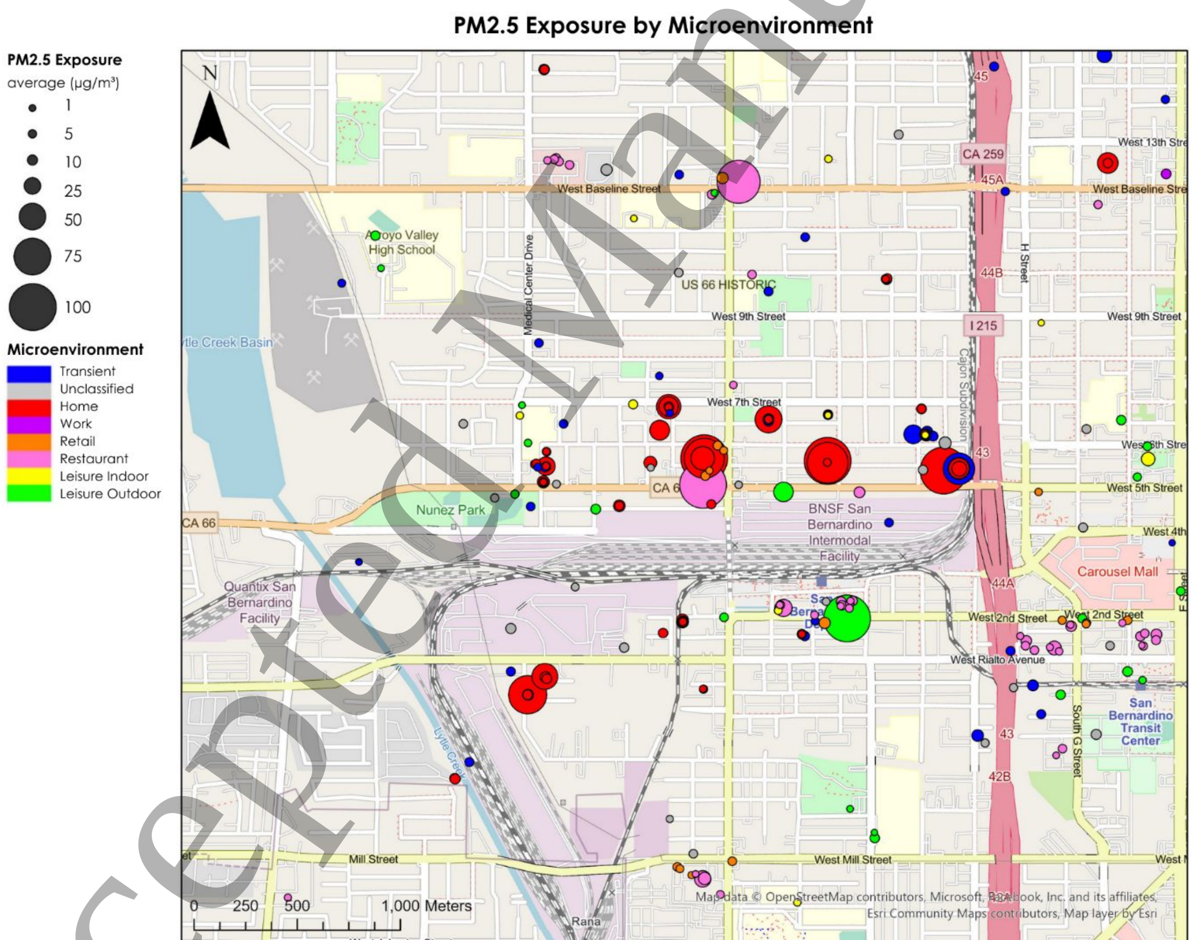

Figure 3: Personal $PM_{2.5}$ clusters with quantified averages and classified microenvironments. One cluster marker represents one participant's data in one deployment period that is geolocated to a physical location, and all participant data are represented by the clusters presented.

3.2 Indoor and Ambient PurpleAir Analysis

We present the analysis of indoor $PM_{2.5}$ for the five homes where indoor and ambient pairs of PurpleAir were installed. Based on an evaluation indoor and ambient temperature, house 3 does not have air conditioning unit, as its indoor temperature was approximately greater than the ambient temperature during summertime (Figure S3). The histograms in Figure S4 show the ratio of indoor and ambient $PM_{2.5}$ (I/O ratio); indoor and outdoor histograms and time series are also provided for reference (Figures S5 and S6). The peaks of the I/O histogram distributions are centered around the value of one. For homes 3 and 5 (no listed cooling system, Table 1), the mode for I/O ratio (most frequent occurrence) occurs when the indoor $PM_{2.5}$ is nearly the same as ambient $PM_{2.5}$.

Our findings also suggest that elevated ambient $PM_{2.5}$ levels directly influence indoor air quality in West San Bernardino homes (Table S7), which is further evidenced by the seasonal statistics (Tables S7-S8). During the summer months, outdoor PurpleAir readings across five houses showed similar means ranging from 13.1 μg m^{-3} to 14.0 μg m^{-3} (Table S8), indicating high precision for corrected ambient measurements in the West San Bernardino area. Under normal conditions, indoor $PM_{2.5}$ levels are lower than ambient levels, as indicated by the 50^{th} percentile values shown in Table S8. During these periods, we anticipated that there would be no indoor activities, such as cooking, vacuuming, or other household tasks, which could contribute to an increase in indoor $PM_{2.5}$ levels. The indoor 98^{th} percentile $PM_{2.5}$ concentrations are considerably higher than ambient levels for all five houses. The ratios between indoor and outdoor concentrations range from 1.3 to 5.0, indicating significant indoor emissions during these periods.

Seasonal variations between summer (Jul – Sep 2022) and fall (Oct 2022– Jan 2023) are provided in the Supplemental Information (Tables S8 and S9). Summer temperatures were high, with an average of 28 °C and exceeding 38 °C around 5% of the time. During high-temperature periods, median (50^{th} percentile) indoor $PM_{2.5}$ levels were notably less than ambient levels for homes with cooling systems (houses 2 & 4), compared to homes without cooling systems that had median indoor $PM_{2.5}$ near ambient levels (Table S8). This indicated that filtration systems from air conditioning units effectively reduced concentrations. The average temperature was 16 °C in the fall/winter, allowing open-window ventilation to regulate indoor environments and potentially increasing air exchange rate and penetration (Table S9).

Estimated indoor emissions: All five homes had an indoor 98th percentile that exceeded a recently proposed 1-hour indoor standard based on World Health Organization air quality guidelines (15 μg m^{-3}).[41] High 98th percentiles resulted from high indoor emissions and poor ventilation, which can be explained by the average decay constants (Homes 1 and 5 in Table 1). Houses with low decay constant suffered from prolonged periods of high $PM_{2.5}$ episodes after indoor emission events (Homes 2, 3, and 4 in Table 1). An indoor emission event is defined as when indoor $PM_{2.5}$ levels are significantly higher than ambient $PM_{2.5}$ levels. The frequencies of indoor emissions were also estimated for the homes, considering the instances where indoor $PM_{2.5}$ concentrations peaked at levels five times higher than the average indoor $PM_{2.5}$ concentrations. Indoor emission rates per m^3 were estimated to be a minimum of 1098 $\mu g * h^{-1} * m^{-3}$ and a maximum of 1796 $\mu g * h^{-1} * m^{-3}$ for houses 2 and 4, respectively.

Table 1. Summary of calculated average decay constants, average indoor emissions per m^3, infiltration factors, home type, and heating and cooling information for all five participant houses. Indoor peaks account for values greater than five times the indoor average $PM_{2.5}$.

	House 1	House 2	House 3	House 4	House 5
Indoor 98th Percentile ($\mu g/m^3$)	64	134	276	260	91
Exceed Ambient $PM_{2.5}$ %	32	26	36	30	40
Indoor Emission Peaks (frequency, f)	491	753	767	999	400
Infiltration ($F_{in} = C_{in}/C_{out}$)	0.30	0.46	0.75	0.53	0.71
Avg Decay Constant, α (hr^{-1})	4.8	2.0	2.6	3.0	4.9
Avg Indoor Emissions, E/V ($mg * hr^{-1} * m^{-3}$)	1.7	1.1	1.6	1.8	1.5
Home Type^	mobile	single family	single family	single family	single family
Cooling System^	none	wall	none	central	none
Heating System^	other	wall	wall	furnace	wall

^Information from Zillow.com and Redfin.com

Estimated decay and infiltration constants: The average decay constants, average indoor emissions per m^3, and infiltration factors for all five homes were calculated based on the mass balance and the set assumptions discussed in Note 3 in the Supplemental Information. Indoor activities, air exchange rates, and filtration rates were highly variable, resulting in different infiltration values across the study period. The average infiltration values for each house also represent family habits during the community engagement period. Infiltration value ranges from zero to one, where zero represents no penetration, and one indicates the indoor $PM_{2.5}$ and ambient $PM_{2.5}$ levels are equal. In our study, the lowest infiltration value is 0.30 and the highest is 0.75 for houses 1 and 3, respectively, implying the vulnerability of indoor environments to the changes in ambient conditions (Table 1).

Baseline indoor $PM_{2.5}$ model: To evaluate the calculated infiltration and decay constant, we reconstructed indoor $PM_{2.5}$ concentrations using the mass balance. Here, we did not consider emissions in the baseline model. Therefore, the model is only a function of decay constant, penetration, and ambient $PM_{2.5,}$ as described in Note 5 in the Supplemental Information. The model gave good predictions and captured the trend of occurrences (Figure 4). Although the model successfully reconstructed the distribution of indoor $PM_{2.5}$ for homes 3, 4, and 5, it did not capture the peak for house 1 and 2 and high concentrations in homes 1 and 5. The errors were caused by minor indoor emission events, which were not accounted for as long as the indoor $PM_{2.5}$ was still less than ambient $PM_{2.5}$. Minor emissions are difficult to trace with the time series without additional activity information from home occupants. Uncertainties in participants' habits, such as opening the windows, turning on the fume hood, and using air conditioning, largely contributed to the model's errors.

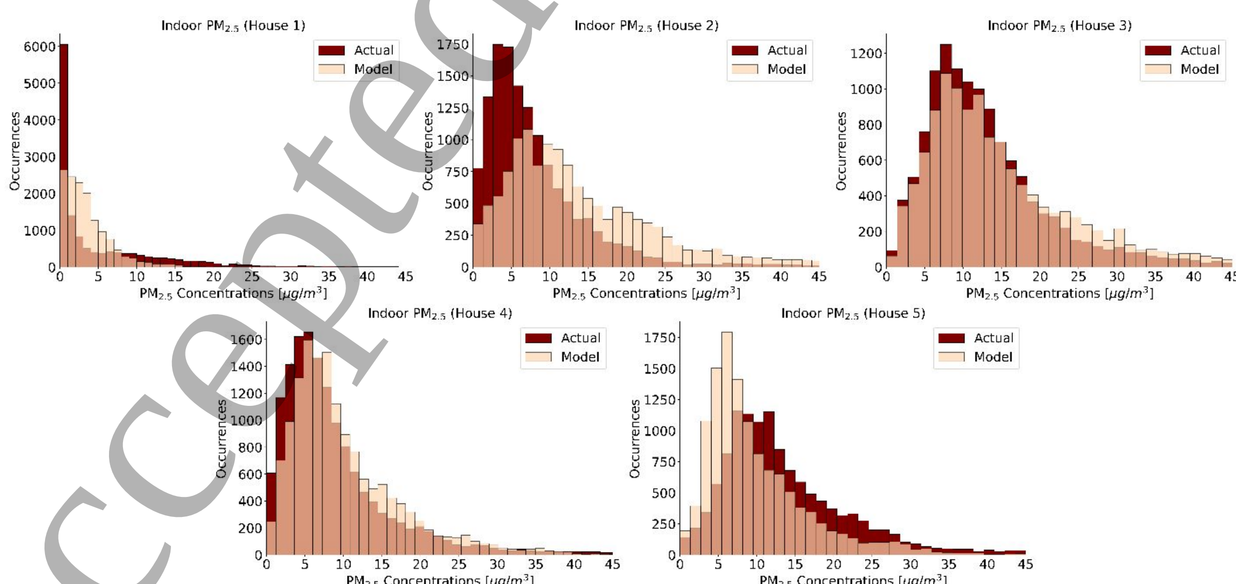

Figure 4: Actual indoor $PM_{2.5}$ (maroon) and model $PM_{2.5}$ (peach) baseline concentrations based on 10-minute averaged data. The distribution only shows the data when indoor $PM_{2.5}$ levels were less than ambient $PM_{2.5}$ levels.

98th percentile regression model: Intuitively, indoor $PM_{2.5}$ levels are managed by the frequency, f, and the decay constant, $(\alpha = a + k)$, where α is the decay constant, a is the air exchange rate, and k is the filtration constant. We performed linear regression with the two dependent variables to predict the indoor 98th percentiles, for which $Indoor\ 98^{th}\ \%ile = c_1\alpha + c_2 f + c_3$, where $c_1$and c_2 are the coefficients for decay constant $(\alpha = a + k)$ and frequency, respectively, and c_3 is the bias. The values for c_1, c_2, and c_3 are listed in Eq. 2, and the R^2 for the regression model is 0.7. The scatter plot for the prediction and actual indoor 98th percentile is provided in the Supplemental Information (Figure S7). The regression model shows that the indoor 98th percentile has a negative correlation with the decay constant and a positive correlation with indoor emission frequency.

$$Indoor\ 98^{th}\ \%ile = -6.0\alpha + 0.31f -$$

In Eq. 2, the decay constant and frequency account for the $PM_{2.5}$ peaks, which are identified when indoor $PM_{2.5}$ is greater than five times the indoor average. Interestingly, the computed average indoor emission rates (E/V) had relatively little impact on the modeled indoor 98th percentile, for which house 1 with the highest average emission rate still had the lowest indoor 98th percentile $PM_{2.5}$.

3.3 Community Well-being

Here we focus on self-reported dynamic well-being at the end of each seven-day deployment period, and rankings included excellent, good, fair, and poor. Distributions of cluster averaged $PM_{2.5}$ were grouped based on these dynamic well-being rankings for each deployment period (Figure 5). Outliers (indicated by red crosses) for good, fair, and poor were higher than those for excellent for each deployment period. Although not reported in January, the 75th percentile for poor rankings exceeded that of the other rankings for the October and March periods. Median $PM_{2.5}$ associated with fair scores was lower than the median $PM_{2.5}$ for good scores for the October and January periods. In a Wilcoxon rank sum test, the statistical difference in the $PM_{2.5}$ cluster averages for good vs. fair for all months was significant (p = 0.02).

The higher income levels (>$20,000) experienced higher outlier $PM_{2.5}$ compared to the lowest income group. In Wilcoxon rank sum tests, the statistical difference in the $PM_{2.5}$ cluster averages for $0 – $20,000 vs. all other income ranges for all months was significant ($p < 0.0001$). Also, 25th percentile, median, and 75th percentile cluster averages were highest for the $0 – $20,000 income group when considered across all months.

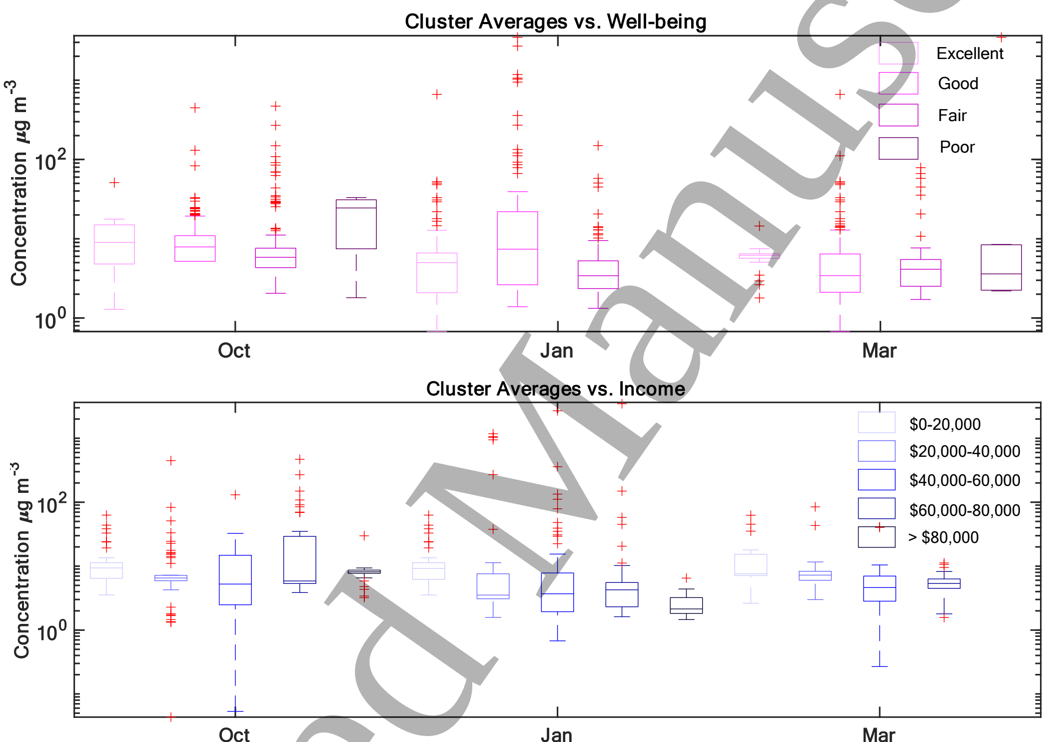

Figure 5: *Top*: Cluster $PM_{2.5}$ averages corresponding to self-reported, dynamic well-being. There were no poor rankings in January. *Bottom*: Cluster $PM_{2.5}$ averages corresponding to self-reported income. There were no data points associated with household income >$80,000 in March.

3.4 Community Co-learning and Personal Protection

The research team engaged with community collaborators on four occasions for group co-learning sessions. In summer of 2021, a virtual interest meeting was held to discuss the objectives, motivation, and timeline of the study, and to provide an overview of the CARB Community Air Protection Program. A second in-person meeting was held before monitoring began to discuss study logistics and schedule participation. Two additional community meetings were held in-person during and after personal monitoring concluded to discuss preliminary findings, as well as other concerns surrounding air, water, and soil pollution in and around San Bernardino. Each meeting provided an opportunity to receive community feedback on study logistics and purpose, and prioritizing this intimate exchange of critical information reduced communication barriers and logistical challenges. In-person meetings were held at the local community center to reduce accessibility challenges for community collaborators.

A critical goal of the community collaboration was the dissemination of individualized resilience plans, which were one-page text and graphical summaries of the personalized monitoring data and the team's subsequent recommendations for reducing personal $PM_{2.5}$ exposure (Figure S8). Generalized tips were provided across all exposure resilience plans that addressed air pollution basics, respective health impacts, and relevant indoor and outdoor pollution sources. High-risk microenvironments were relayed to community collaborators, along with daily average exposures throughout each engagement week. Tailored recommendations were based on microenvironment(s) with highest exposures. Recommendations included, but were not limited to:

- Use an air filter to clean indoor air
- Wear a fitted mask (N-95) to reduce your pollution exposure
- Avoid outdoor activity when the air quality is poor
- Reduce open flames/smoke from potential sources indoors
- Open windows if there is an open flame, and turn on the exhaust fan when cooking
- Breathe through your nose to filter out larger particles
- Check local air pollution and daily Air Quality Index

Five follow-up interviews were conducted to better understand community collaborator concerns and feedback regarding their tailored resilience plans. Collaborators also provided additional context for the personal exposure data collected, including the identification of indoor pollution generating activities and the frequency of those activities. In the weeks that followed, collaborators were able to reference their resilience plans during community advocacy meetings, providing quantitative evidence that reflected their individual lived experiences around air pollution exposure. The resilience plans featuring data driven $PM_{2.5}$ exposures and the community microenvironmental exposure maps have also been used by community members most recently in regional, state, and federal efforts to reform rail emissions policy.

4. Discussion

4.1 Microenvironmental Analysis and Uncertainties

Personal $PM_{2.5}$ was highest in winter (January), which correlates with the peak $PM_{2.5}$ period in inland Southern California. Higher relative humidity and lower temperatures during winter promote aerosol formation through heterogenous chemistry and condensation.[42,43] It is well-known that relative humidity may influence low-cost sensor readings[44–46], and therefore the reference-based adjustments were carried out for personal measurements, improving overall correlations of hourly averages. As such, the personal exposure results presented in this study are precise across all wearable sensors. We also temper interpretation of measurements greater than 500 μg m^{-3} given the effective range (0-500 μg m^{-3}) of the PMS5003 sensor within the wearable monitor.[47,48] Also, there is a challenge in extrapolation by the GMM for correcting APT $PM_{2.5}$ data beyond the co-location data. Further details on the GMM extrapolation are provided in Tables S10-S13.

Given that approximately 70% of all possible measurements were collected, there is the possibility of missing personal exposures. Community collaborators reported intermittent loss of connectivity and battery power, which explains the uncaptured measurements. Further, the visual classification of microenvironments could possibly be influenced by human error in Google Maps interpretation. However, the microenvironment classification results are of high confidence due to the majority of measurements being made in home microenvironments, where collaborators spent most of their time and had ready access to electricity to charge the monitors. We find that the lower-cost, wearable sensor choice promoted more inclusive community collaboration given the fewer technological knowledge barriers, as well as its ability to resolve high-resolution, mobility-influenced exposure disparities.[17]

While most microenvironments were recorded within several blocks of the BNSF intermodal facility, there was still a pattern of higher median exposures for lower household incomes, suggesting that additional exposure prevention interventions should be directed towards the lower income community members within the impacted area. Further, although home microenvironments posed the greatest chronic risk for higher $PM_{2.5}$ exposures, elective time spent in non-home microenvironments also posed high exposure risks. Such non-home locations may be good candidates for continuous monitoring to protect sensitive populations (e.g., children and people with asthma).

4.2 Indoor Analysis and Uncertainties

Throughout this paper, raw PurpleAir $PM_{2.5}$ data have been corrected using the Barkjohn et al., correction method for outdoor and indoor sensors.[40] However, one limitation has emerged. First, the Barkjohn et al. correction was evaluated using outdoor $PM_{2.5}$, which may differ in constituents and sources from indoor $PM_{2.5}$. While some indoor $PM_{2.5}$ originates from the outdoor through penetration, indoor $PM_{2.5}$ levels during high episodes are often generated by indoor activities such as cooking, cleaning, or consuming personal products.[17,49] These differences in $PM_{2.5}$ components can lead to deviations in PurpleAir readings that the Barkjohn et al. correction does not address. We also acknowledge that the correction may not be optimal for low-concentration environments due to the high limit of detection of PurpleAir.

The infiltration values of this study are significantly higher than those in the previous studies that rely on crowdsourced data or a test house. Stephens et al. used a mass balance, and the calculated penetration was 0.34 for a test house (UTest House, Austin, Texas, USA).[19] Liang et al. used a similar approach and utilized the PurpleAir sensor network in California that monitored more than 1400 buildings to assess the impact of wildfire smoke on indoor air quality, and the derived average infiltration factor was 0.45.[27] The average infiltration factor in this study across the five homes is 0.55, which is relatively higher compared to previous studies, indicating a more significant impact of ambient air quality on the indoor environments of this rail-impacted community. The infiltration factor strongly depends on home designs; homes with tight seals and air conditioning filters tend to have lower infiltration factors. Additionally, homeowner habits, such as opening windows for ventilation, can influence this factor. The houses in this study are relatively old, and some of them do not have central air conditioning, necessitating the opening of windows to increase air exchange during cooler summer nights. These conditions contribute to the higher infiltration factor observed in this study compared to the crowdsourced data and the test house. I/O ratio distribution modes were approximately 0.62 using crowdsourced information compared to modes near one in this study.[27] The I/O ratios from crowdsourced data generally reflect a higher socioeconomic status population with high accessibility to indoor air quality monitoring. Further, population-based studies will likely not reflect the lived experiences of disproportionately impacted communities that have more limited access to indoor monitoring equipment. Compounding this limitation is the historical pattern of racial-ethnic minority groups being most affected by poor ambient air quality.[10,11,50]

The 98th percentile regression model implies 98th percentile concentrations are linearly correlated with the air exchange rate, filtration, and indoor emission frequency. Indoor $PM_{2.5}$ concentrations can be regulated by increasing ventilation during indoor emission events or minimizing the air exchange rate when outdoor $PM_{2.5}$ concentrations are high (during daytime peaks in fall/winter). We strongly recommend that impacted homes near the BNSF facility have adequate air filter to minimize penetration and indoor levels. We also recommend that open access fenceline monitoring data for the BNSF facility be made available for $PM_{2.5}$, its species, criteria pollutants, and select hazardous pollutants given the current study's findings and the historical environmental health challenges for downwind areas. We suggest that PurpleAir sensors be permanently installed in impacted homes near the BNSF facility (or any large industrial source) to continuously monitor home indoor air quality and provide real-time feedback for mitigating indoor pollution. For instance, occupants should increase filtration and ventilation during indoor emission events when ambient $PM_{2.5}$ levels are low. We also support efforts to standardize indoor air quality.[41]

The uncertainties of estimated constants arose from the assumption that there were no emissions at the peaks (inflection points) and no penetration when indoor $PM_{2.5}$ levels were high. Infiltration uncertainty is derived from omitting minor indoor emissions from consideration, causing a slight overestimation of infiltration factors. Despite these uncertainties, our analysis of household infiltration is critical for the protection of disproportionately impacted communities due to the influence of proximate outdoor sources on indoor $PM_{2.5}$.[39,51]

During the deployment periods, the indoor 98th percentile for PurpleAir sensors ranged from 64 µg m^{-3} to 260 µg m^{-3}, with the maximum $PM_{2.5}$ concentrations well above 1000 µg m^{-3}. According to Barkjohn et al., when the $PM_{2.5}$ levels exceed 400 µg m^{-3}, the bias of these low-cost sensors and the reference monitoring network becomes nonlinear.[52] However, it is impractical to reproduce extremely high particle concentration levels during ambient co-location. Applying linear correction (Equation 1) for extreme high $PM_{2.5}$ levels would not overcome this nonlinearity. Additionally, the infiltration factor is influenced by particle size and the conditions of the house. Very small and very large particles have the lowest penetration. Particles with a diameter ranging from 0.08 µm to 0.5 µm have the highest infiltration factors[16].

APT and PurpleAir use laser particle counters from Plantower Technology, both experiencing the same limitations of low-cost sensors. These sensors are directly affected by particle diameters, the constituents of $PM_{2.5}$, and meteorological conditions. PurpleAir tends to underestimate the $PM_{2.5}$ concentrations for particles with small diameters (0.3 µm – 0.5µm) but overestimate for larger diameters (0.5 µm – 1.5 µm).[53] The measurements vary with different $PM_{2.5}$ components. For instance, PurpleAir overestimates $PM_{2.5}$ concentrations in smoky conditions, and they underestimate concentrations during dust events, leading to exposure underestimation in communities with high dust contributions.[54]

4.3 Recommendations for Future Studies

In future studies, the team will provide additional information to community collaborators on how to rank dynamic health status as there wasn't clarity on the category definitions. This may have led to the unexpected trends in good and fair well-being rankings. In ongoing work, the team seeks to understand the drivers of public action toward personal $PM_{2.5}$ exposure protections. Overall, the greatest strength of the study is the creation of resilience plans for community collaborators, supporting community data sovereignty and making efforts towards exposure reduction. This step is oftentimes missing in air pollution studies that seek to address the environmental injustices faced by historically impacted communities. Future efforts will mirror this study, where community collaborations will be centered in data collection and subsequent solution building. We add a disclaimer regarding the generalizability of the well-being findings given the sample size and unique community characteristics, but the methods employed here are transferrable to other case studies of near-source community impacts. Findings support ongoing efforts to reduce direct and indirect emissions from industrial sources that are near disparately impacted communities.

Acknowledgments

First and foremost, we thank community collaborators of West San Bernardino for the collective execution of this work. We thank student volunteers from University of California, Riverside and Riverside City College for their participation in community engagement activities, including community outreach, equipment deployments, and surveying efforts. We thank Janet Bernabe and the Center for Community Action and Environmental Justice (CCAEJ) for providing and coordinating the PurpleAir installation. We also thank Ms. Jean Kayano of the People's Collective for Environmental Justice for her initial conceptualization, planning, and fundraising for the project. This paper was prepared as a result of work sponsored and paid for, in whole or in part, by the California Air Resources Board (CARB). The opinions, findings, conclusions, and recommendations are those of the authors and do not necessarily represent the views of CARB.

Conflict of Interest

Authors declare no conflicts of interest.

Ethics Statement

This study was conducted in accordance with University of California, Riverside IRB protocol HS 18-206. The research was conducted in accordance with the principles embodied in the Declaration of Helsinki and in accordance with local statutory requirements. All adult participants gave written informed consent to participate in the study.

Data Availability

The data cannot be made publicly available upon publication because they contain sensitive personal information. The data that support the findings of this study are available upon reasonable request from the authors.

References

(1) Deng, Q.; Deng, L.; Miao, Y.; Guo, X.; Li, Y. Particle Deposition in the Human Lung: Health Implications of Particulate Matter from Different Sources. *Environmental Research* **2019**. https://doi.org/10.1016/j.envres.2018.11.014.

(2) Brown, J. H.; Cook, K. M.; Ney, F. G.; Hatch, T. Influence of Particle Size upon the Retention of Particulate Matter in the Human Lung. *American Journal of Public Health and the Nations Health* **1950**. https://doi.org/10.2105/ajph.40.4.450.

(3) Maté, T.; Guaita, R.; Pichiule, M.; Linares, C.; Díaz, J. Short-Term Effect of Fine Particulate Matter (PM2.5) on Daily Mortality Due to Diseases of the Circulatory System in Madrid (Spain). *Science of the Total Environment* **2010**. https://doi.org/10.1016/j.scitotenv.2010.07.083.

(4) Wang, C.; Feng, L.; Chen, K. The Impact of Ambient Particulate Matter on Hospital Outpatient Visits for Respiratory and Circulatory System Disease in an Urban Chinese Population. *Science of the Total Environment* **2019**. https://doi.org/10.1016/j.scitotenv.2019.02.256.

(5) Zawacki, M.; Baker, K. R.; Phillips, S.; Davidson, K.; Wolfe, P. Mobile Source Contributions to Ambient Ozone and Particulate Matter in 2025. *Atmospheric Environment* **2018**. https://doi.org/10.1016/j.atmosenv.2018.04.057.

(6) Zhang, R.; Wang, G.; Guo, S.; Zamora, M. L.; Ying, Q.; Lin, Y.; Wang, W.; Hu, M.; Wang, Y. Formation of Urban Fine Particulate Matter. *Chem. Rev.* **2015**, *115* (10), 3803–3855. https://doi.org/10.1021/acs.chemrev.5b00067.

(7) Hasheminassab, S.; Daher, N.; Saffari, A.; Wang, D.; Ostro, B. D.; Sioutas, C. Spatial and Temporal Variability of Sources of Ambient Fine Particulate Matter (PM2.5) in California. *Atmos. Chem. Phys.* **2014**, *14* (22), 12085–12097. https://doi.org/10.5194/acp-14-12085-2014.

(8) Gildemeister, A. E.; Hopke, P. K.; Kim, E. Sources of Fine Urban Particulate Matter in Detroit, MI. *Chemosphere* **2007**, *69* (7), 1064–1074. https://doi.org/10.1016/j.chemosphere.2007.04.027.

(9) Fruin, S.; Urman, R.; Lurmann, F.; McConnell, R.; Gauderman, J.; Rappaport, E.; Franklin, M.; Gilliland, F. D.; Shafer, M.; Gorski, P.; Avol, E. Spatial Variation in Particulate Matter Components over a Large Urban Area. *Atmospheric Environment* **2014**, *83*, 211–219. https://doi.org/10.1016/j.atmosenv.2013.10.063.

(10) Ivey, C. Land Use Predicts Pandemic Disparities. *Nature* **2020**, *588* (7837), 220–220. https://doi.org/10.1038/d41586-020-03480-1.

(11) Wang, Y.; Apte, J. S.; Hill, J. D.; Ivey, C. E.; Patterson, R. F.; Robinson, A. L.; Tessum, C. W.; Marshall, J. D. Location-Specific Strategies for Eliminating US National Racial-Ethnic PM2.5 Exposure Inequality. *Proceedings of the National Academy of Sciences* **2022**, *119* (44), e2205548119. https://doi.org/10.1073/pnas.2205548119.

(12) Allen, N. Exploring the Inland Empire: Life, Work, and Injustice in Southern California's Retail Fortress. *New Labor Forum* **2010**, *19* (2), 37–43. https://doi.org/10.4179/NLF.192.0000006.

(13) Bluffstone, R. A.; Ouderkirk, B. Wearhouses, Trucks, and PM2.5: Human Health and Logistics Industry Growth in the Eastern Inland Empire. *Contemporary Economic Policy* **2007**, *25* (1), 79–91. https://doi.org/10.1111/j.1465-7287.2006.00017.x.

(14) deSouza, P. N.; Ballare, S.; Niemeier, D. A. The Environmental and Traffic Impacts of Warehouses in Southern California. *Journal of Transport Geography* **2022**, *104*, 103440. https://doi.org/10.1016/j.jtrangeo.2022.103440.

(15) Houston, D.; Wu, J.; Ong, P.; Winer, A. Structural Disparities of Urban Traffic in Southern California: Implications for Vehicle-Related Air Pollution Exposure in Minority and High-Poverty Neighborhoods. *Journal of Urban Affairs* **2004**, *26* (5), 565–592. https://doi.org/10.1111/j.0735-2166.2004.00215.x.

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

(17) Do, K.; Yu, H.; Velasquez, J.; Grell-Brisk, M.; Smith, H.; Ivey, C. E. A Data-Driven Approach for Characterizing Community Scale Air Pollution Exposure Disparities in Inland Southern California. *Journal of Aerosol Science* **2021**, *152*, 105704. https://doi.org/10.1016/j.jaerosci.2020.105704.

(18) Mattila, J. M.; Arata, C.; Wang, C.; Katz, E. F.; Abeleira, A.; Zhou, Y.; Zhou, S.; Goldstein, A. H.; Abbatt, J. P. D.; DeCarlo, P. F.; Farmer, D. K. Dark Chemistry during Bleach Cleaning Enhances Oxidation of Organics and Secondary Organic Aerosol Production Indoors. *Environ. Sci. Technol. Lett.* **2020**, *7* (11), 795–801. https://doi.org/10.1021/acs.estlett.0c00573.

(19) Stephens, B.; Siegel, J. A. Penetration of Ambient Submicron Particles into Single-Family Residences and Associations with Building Characteristics: **Particle Penetration and Building Characteristics**. *Indoor Air* **2012**, *22* (6), 501–513. https://doi.org/10.1111/j.1600-0668.2012.00779.x.

(20) Xiang, J.; Hao, J.; Austin, E.; Shirai, J.; Seto, E. Residential Cooking-Related PM2.5: Spatial-Temporal Variations under Various Intervention Scenarios. *Building and Environment* **2021**, *201*, 108002. https://doi.org/10.1016/j.buildenv.2021.108002.

(21) Kang, K.; Kim, H.; Kim, D. D.; Lee, Y. G.; Kim, T. Characteristics of Cooking-Generated PM10 and PM2.5 in Residential Buildings with Different Cooking and Ventilation Types. *Science of The Total Environment* **2019**, *668*, 56–66. https://doi.org/10.1016/j.scitotenv.2019.02.316.

(22) Mousavi, A.; Wu, J. Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. *Environ. Sci. Technol.* **2021**, *55* (9), 5648–5656. https://doi.org/10.1021/acs.est.0c06937.

(23) Leung, D. Y. C. Outdoor-Indoor Air Pollution in Urban Environment: Challenges and Opportunity. *Front. Environ. Sci.* **2015**, *2*. https://doi.org/10.3389/fenvs.2014.00069.

(24) Poupard, O.; Blondeau, P.; Iordache, V.; Allard, F. Statistical Analysis of Parameters Influencing the Relationship between Outdoor and Indoor Air Quality in Schools. *Atmospheric Environment* **2005**, *39* (11), 2071–2080. https://doi.org/10.1016/j.atmosenv.2004.12.016.

(25) Lee, H. S.; Kang, B.-W.; Cheong, J.-P.; Lee, S.-K. Relationships between Indoor and Outdoor Air Quality during the Summer Season in Korea. *Atmospheric Environment* **1997**, *31* (11), 1689–1693. https://doi.org/10.1016/S1352-2310(96)00275-0.

(26) Freijer, J. I.; Bloemen, H. J. Th. Modeling Relationships between Indoor and Outdoor Air Quality. *Journal of the Air & Waste Management Association* **2000**, *50* (2), 292–300. https://doi.org/10.1080/10473289.2000.10464007.

(27) Liang, Y.; Sengupta, D.; Campmier, M. J.; Lunderberg, D. M.; Apte, J. S.; Goldstein, A. H. Wildfire Smoke Impacts on Indoor Air Quality Assessed Using Crowdsourced Data in California. *Proceedings of the National Academy of Sciences* **2021**, *118* (36), e2106478118. https://doi.org/10.1073/pnas.2106478118.

(28) Palmgren, C.; Ramirez, B.; Goldberg, M.; Williamson, C. *2019 California Residential Appliance Saturation Study*; CEC-200-2021-005-PO; California Energy Commission: Oakland, California, 2021; p 50. https://www.energy.ca.gov/sites/default/files/2021-08/CEC-200-2021-005-PO.pdf.

(29) Allen, N. Exploring the Inland Empire: Life, Work, and Injustice in Southern California's Retail Fortress. *New Labor Forum* **2010**, *19* (2), 37–43. https://doi.org/10.4179/NLF.192.0000006.

(30) Patterson, T. C. *From Acorns to Warehouses*, 0 ed.; Routledge, 2016. https://doi.org/10.4324/9781315428215.

(31) Spencer-Hwang, R.; Montgomery, S.; Dougherty, M.; Valladares, J.; Rangel, S.; Gleason, P.; Soret, S. Experiences of a Rail Yard Community: Life Is Hard. (Cover Story). *Journal of Environmental Health* **2014**.

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

(33) Spencer-Hwang, R.; Soret, S.; Valladares, J.; Torres, X.; Pasco-Rubio, M.; Dougherty, M.; Kim, W.; Montgomery, S. Strategic Partnerships for Change in an Environmental Justice Community:

The ENRRICH Study. *Progress in Community Health Partnerships: Research, Education, and Action* **2016**. https://doi.org/10.1353/cpr.2016.0062.
(34) Spencer-Hwang, R.; Pasco-Rubio, M.; Soret, S.; Ghamsary, M.; Sinclair, R.; Alhusseini, N.; Montgomery, S. Association of Major California Freight Railyards with Asthma-Related Pediatric Emergency Department Hospital Visits. *Preventive Medicine Reports* **2019**, *13*, 73–79. https://doi.org/10.1016/j.pmedr.2018.11.001.
(35) South Coast Air Quality Management District. *Determine That Community Emissions Reduction Plan for Wilmington, Carson, West Long Beach Community Is Exempt from CEQA and Adopt Community Emissions Reduction Plan Per Assembly Bill 617*. AQMD Governing Board. aqmd.gov/docs/default-source/Agendas/Governing-Board/2019/2019-sep6-025c.pdf.
(36) Torres, I.; Victoria, A.; Klooster, D. *Warehousees, Pollution, and Social Disparities: An Analytical View of the Logistics Industry's Impacts on Environmental Justice Communities across Southern California*; People's Collective for Environmental Justice, 2021; p 27. https://earthjustice.org/wp-content/uploads/warehouse_research_report_4.15.2021.pdf.
(37) California Air Resources Board. *Health Risk Assessment for the BNSF Railway San Bernardino Railyard*; 2008. https://ww2.arb.ca.gov/our-work/programs/community-air-protection-program/communities/san-bernardino-muscoy (accessed 2023-08-14).
(38) August, L. *CalEnviroScreen 4.0*. OEHHA. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40 (accessed 2023-11-27).
(39) Garcia, C. *Assembly Bill No. 617*; California State Assembly, 2017.
(40) Barkjohn, K. K.; Gantt, B.; Clements, A. L. Development and Application of a United States-Wide Correction for PM2.5 Data Collected with the PurpleAir Sensor. *Atmospheric Measurement Techniques* **2021**, *14* (6), 4617–4637. https://doi.org/10.5194/amt-14-4617-2021.
(41) Morawska, L.; Allen, J.; Bahnfleth, W.; Bennett, B.; Bluyssen, P. M.; Boerstra, A.; Buonanno, G.; Cao, J.; Dancer, S. J.; Floto, A.; Franchimon, F.; Greenhalgh, T.; Haworth, C.; Hogeling, J.; Isaxon, C.; Jimenez, J. L.; Kennedy, A.; Kumar, P.; Kurnitski, J.; Li, Y.; Loomans, M.; Marks, G.; Marr, L. C.; Mazzarella, L.; Melikov, A. K.; Miller, S. L.; Milton, D. K.; Monty, J.; Nielsen, P. V.; Noakes, C.; Peccia, J.; Prather, K. A.; Querol, X.; Salthammer, T.; Sekhar, C.; Seppänen, O.; Tanabe, S.; Tang, J. W.; Tellier, R.; Tham, K. W.; Wargocki, P.; Wierzbicka, A.; Yao, M. Mandating Indoor Air Quality for Public Buildings. *Science* **2024**, *383* (6690), 1418–1420. https://doi.org/10.1126/science.adl0677.
(42) Gao, Z.; Ivey, C. E.; Blanchard, C. L.; Do, K.; Lee, S.-M.; Russell, A. G. Emissions, Meteorological and Climate Impacts on PM2.5 Levels in Southern California Using a Generalized Additive Model: Historic Trends and Future Estimates. *Chemosphere* **2023**, *325*, 138385. https://doi.org/10.1016/j.chemosphere.2023.138385.
(43) Quevedo, D.; Gao, Z.; Do, K.; Bahreini, R.; Collins, D.; Ivey, C. E. Multidecadal Analysis of Meteorological and Emissions Regimes for PM2.5 Across California. *ACS ES&T Air, in press.* **2023**. https://doi.org/10.1021/acsestair.3c00019.
(44) Hasan, M. H.; Yu, H.; Ivey, C.; Pillarisetti, A.; Yuan, Z.; Do, K.; Li, Y. Unexpected Performance Improvements of Nitrogen Dioxide and Ozone Sensors by Including Carbon Monoxide Sensor Signal. *ACS Omega* **2023**, *8* (6), 5917–5924. https://doi.org/10.1021/acsomega.2c07734.
(45) Tryner, J.; Good, N.; Wilson, A.; Clark, M. L.; Peel, J. L.; Volckens, J. Variation in Gravimetric Correction Factors for Nephelometer-Derived Estimates of Personal Exposure to PM2.5. *Environmental Pollution* **2019**, *250*, 251–261. https://doi.org/10.1016/j.envpol.2019.03.121.
(46) Tryner, J.; Mehaffy, J.; Miller-Lionberg, D.; Volckens, J. Effects of Aerosol Type and Simulated Aging on Performance of Low-Cost PM Sensors. *Journal of Aerosol Science* **2020**, *150*, 105654. https://doi.org/10.1016/j.jaerosci.2020.105654.
(47) Sayahi, T.; Butterfield, A.; Kelly, K. E. Long-Term Field Evaluation of the Plantower PMS Low-Cost Particulate Matter Sensors. *Environmental Pollution* **2019**, *245*, 932–940. https://doi.org/10.1016/j.envpol.2018.11.065.

(48) *Plantower PMS5003 Manual*. https://www.aqmd.gov/docs/default-source/aq-spec/resources-page/plantower-pms5003-manual_v2-3.pdf (accessed 2023-11-27).

(49) US EPA. *Sources of Indoor Particulate Matter (PM)*. https://www.epa.gov/indoor-air-quality-iaq/sources-indoor-particulate-matter-pm (accessed 2024-04-13).

(50) Patterson, R. F.; Harley, R. A. Effects of Freeway Rerouting and Boulevard Replacement on Air Pollution Exposure and Neighborhood Attributes. *IJERPH* **2019**, *16* (21), 4072. https://doi.org/10.3390/ijerph16214072.

(51) National Academies of Sciences, Engineering; Medicine; Engineering, N. A. of. Chapter 2: Outdoor Sources of Indoor Particulate Matter. In *Indoor Exposure to Fine Particulate Matter and Practical Mitigation Approaches: Proceedings of a Workshop*; Butler, D. A., Alper, J., Eds.; The National Academies Press: Washington, DC, 2022. https://doi.org/10.17226/26331.

(52) Barkjohn, K. K.; Holder, A. L.; Frederick, S. G.; Clements, A. L. Correction and Accuracy of PurpleAir PM2.5 Measurements for Extreme Wildfire Smoke. *Sensors* **2022**, *22* (24), 9669. https://doi.org/10.3390/s22249669.

(53) Park, S.; Lee, S.; Yeo, M.; Rim, D. Field and Laboratory Evaluation of PurpleAir Low-Cost Aerosol Sensors in Monitoring Indoor Airborne Particles. *Building and Environment* **2023**, *234*, 110127. https://doi.org/10.1016/j.buildenv.2023.110127.

(54) Jaffe, D. A.; Miller, C.; Thompson, K.; Finley, B.; Nelson, M.; Ouimette, J.; Andrews, E. An Evaluation of the U.S. EPA's Correction Equation for PurpleAir Sensor Data in Smoke, Dust, and Wintertime Urban Pollution Events. *Atmospheric Measurement Techniques* **2023**, *16* (5), 1311–1322. https://doi.org/10.5194/amt-16-1311-2023.