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Quantifying Indoor Air Quality Impacts of Tijuana River Pollution across South Bay Households: A Low-Cost Sensor Network Study

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Author

Minic, Marina

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*Quantifying Indoor Air Quality Impacts of Tijuana River Pollution across South
Bay Households:
A Low-Cost Sensor Network Study*

Marina Minic
Scripps Institution of Oceanography

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Dr. Mark Merrifield
Chair of Capstone Committee

A black rectangular redaction box covering a handwritten signature.

Leila El Masri
Co-Chair of Capstone Committee

UC San Diego



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Abstract

Air pollution remains a major global health risk, and while outdoor air quality is regulated in many countries, indoor environments, where people spend most of their time, remain comparatively understudied and largely unregulated. Recent advances in low-cost sensor networks enable high-resolution monitoring of pollutants, offering new opportunities to investigate how outdoor pollution infiltrates indoor spaces. The Tijuana River (TR), a long-standing source of untreated sewage and industrial waste, has been linked to elevated outdoor air

pollution, including hydrogen sulfide and fine particulate matter (PM < 1 micron), in surrounding communities. However, the extent to which these outdoor emissions affect residential indoor air quality has not been previously quantified. This study examines the relationship between outdoor pollution and indoor air quality (IAQ) in San Diego's South Bay communities using a combination of indoor and outdoor sensor data, household surveys, and analytical techniques such as indoor-to-outdoor ratios and infiltration rates to quantify the impact Tijuana River pollution has on indoor air quality. Data was collected through a community-based citizen science initiative involving student participants and local monitoring sites. Findings indicate that proximity to the polluted river contributes not only to degraded outdoor air quality but also to measurable declines in indoor air quality, with potential implications for public health and resident well-being.

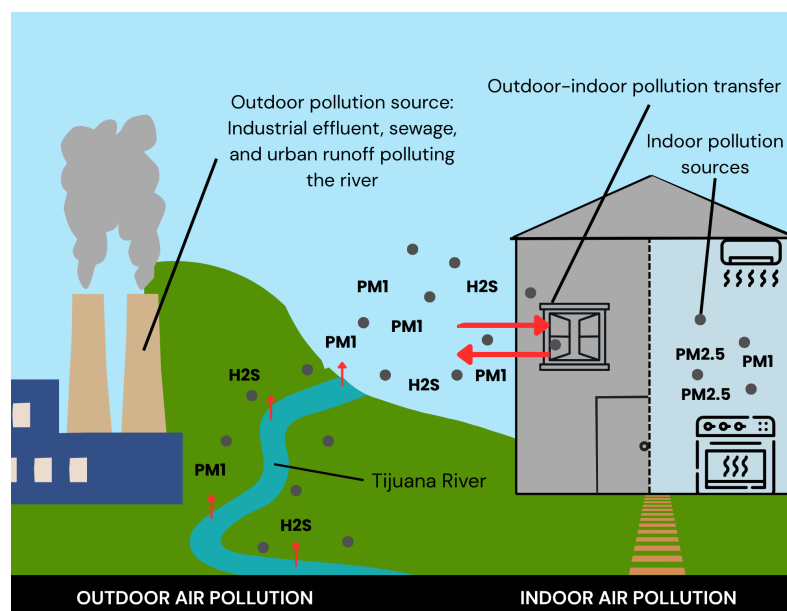


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Introduction

1.1 Pollution from the Tijuana River

One previously unexamined contributor to indoor air pollution in Southern California is the binational Tijuana River (TR). Originating in Baja California, flowing through the city of Tijuana, and crossing the U.S.–Mexico border near San Ysidro (SY), the TR transports sewage, industrial waste, and urban runoff into the Tijuana River Estuary located in Imperial Beach (IB) and empties into the Pacific Ocean (Simmons, 2022). The river has functioned as a conduit for untreated sewage and industrial waste for nearly a century and despite the construction of the South Bay International Wastewater Treatment Plant in 1997, transboundary flows have continued due to persistent infrastructure failures and capacity shortfalls on both sides of the border (Cysneiros et al., 2025; Venn and Sant, 2026). The earliest documented complaints about sewage reaching IB date the 1930s, when Tijuana's population was only 14,000 (Selgi-Harrigan, 2025; 1934; Schoenherr, 2015). The pollution crisis has persisted due to a combination of structural and political factors (Dedina, 1995; Anderson, 2018). Untreated wastewater enters the river through poorly maintained infrastructure, and transboundary flows increase during heavy precipitation, which overwhelms diversion capacity on both sides of the border (EPA 2025b). Tijuana's rapid population growth, deteriorating treatment infrastructure, and the near-complete disrepair of the South Bay International Wastewater Treatment Plant have worsened the crisis (Musegaas, 2024; Rico et al., 2025). The impact of the pollution on nearby communities is severe and ongoing. Residents of South Bay, San Diego, which encompasses both IB and SY, have reported a wide range of chronic health symptoms attributable to hydrogen sulfide (H_2S) and other airborne pollutants released from untreated wastewater (Rico et al., 2025).

Recent studies have focused on the link between pollution in the TR and outdoor air pollution in surrounding South Bay communities (Pendergraft et al., 2021; Pendergraft et al., 2023; Cooper et al., 2025; Rico et al., 2025; Cysneiros et al., 2025). The results of Pendergraft et al., (2023) and Cooper et al., (2025) identified the transfer of harmful pollutants and bacteria from the TR into the air from sea spray aerosol (SSA). H_2S has been identified as a fingerprint of TR pollution and, along with other volatile organic compounds (VOCs), serves as a precursor to secondary aerosol formation (Rico et al., 2025; Cysneiros et al., 2025). It is well characterized in the literature that H_2S can undergo atmospheric full oxidation via the OH radical to yield H_2SO_4 , and H_2SO_4 has been shown to enhance new particle formation (Seinfeld and Pandis, 2016; Lehtipalo et al., 2018; Sipila et al., 2010). TR H_2S is important to this study due to its likely status as a gas phase tracer for TR pollution events and due to its contribution to secondary aerosol formation, including PM_{10} , which can be traced to indoors (Rico et al., 2025, Cysneiros et al., 2025). While outdoor air quality impacts associated with the river have received growing attention, the extent to which these emissions influence indoor air quality in nearby communities has not been studied.

1.2 Indoor and Outdoor Air Pollution

Air pollution is a leading global public health threat, responsible for an estimated 4.2 million premature deaths worldwide annually (WHO, 2024; Liu et al., 2025; Clark et al., 2025). In addition to ambient air pollution, indoor air quality (IAQ) has emerged as a critical but comparatively understudied area of research (Siddique et al., 2023). Residents of developed countries spend approximately 90% of their time indoors, underscoring the importance of understanding how indoor environments shape overall pollution exposure (Klepeis et al., 2001; WHO, 2001; Ageel et al., 2021; Dimitroulopoulou et al., 2023). The US Environmental Protection Agency (EPA) upholds the National Ambient Air Quality Standards (NAAQS) which mandates limits on outdoor criteria pollutants but fails to regulate any indoor pollutants (EPA, 2025a). The only mandates aimed at indoor air quality in the United States are standards set by the Occupational Safety and Health Administration (OSHA) which regulate the workplaces, leaving a gap in the field for regulations regarding residential buildings (Siddique et al., 2023). While the gap between indoor and outdoor mandates persists, there is a growing global trend of countries beginning to research and develop IAQ standards to further advance the field (Siddique et al., 2023; WHO, 2010; Settimo et al., 2023; Adjei and Afriyie, 2025). In this study we utilize a similar approach to Afroz et al. (2023), in developing a low-cost sensor network (LCNs).

1.3 Low-Cost Sensor Networks

Recent advances in low-cost air quality sensors have enabled the rapid development of distributed monitoring systems globally by offering a scalable approach to continuous monitoring and generating localized data at fine spatial and temporal scales, complementing existing regulatory monitor networks (Bagkis et al., 2025; Rogulski and Badyda, 2019). LCNs are uniquely positioned to contribute to studies aimed at distinguishing indoor from outdoor pollution sources (Casado-Mansilla et al., 2025; Bagkis et al., 2025). Most buildings act as incomplete filters, letting fine particles in and leading to worsening IAQ (Rathbone et al., 2025). Source apportionment studies using paired indoor and outdoor sensors have found that outdoor infiltration can account for a vast majority of the smallest indoor particles, while indoor activities such as cooking produce the sharpest concentration spikes (Higgins et al., 2024; Rose et al., 2024). Outdoor contribution to fine indoor particles is especially evident during point source pollution events, including wildfires, dust storms, and proximity to pollution activities and/or facilities, all of which are events that have been studied utilizing LCNs (He et al., 2015, Alonso-Pérez and López-Solano, 2023; Kortoçi et al., 2022; Dev et al., 2021). Despite these contributions, important limitations temper the utility of LCN data. Sensor accuracy varies with humidity, temperature, and cross-sensitivity to other gases, and the absence of standardized validation frameworks makes cross-study comparison difficult (Silva et al., 2026). A review of 40 studies found that nearly 78% did not report calibration details, and many sensors require recalibration approximately every six months (Ródenas García et al., 2022). Standardization of

calibration protocols and performance benchmarks remains an ongoing challenge that limits the integration of LCN data into regulatory frameworks. Building off the existing QuantAQ network in the SD South Bay from Cysneiros et al. (2025), we deployed our own indoor LCN to determine infiltration rate, I/O ratio, and $PM_{2.5}/PM_{10}$ ratio (Leung, 2015; Ciuizas et al., 2015; Abt et al., 2000; Nazaroff, 2021).

This paper investigates the relationship between TR pollution and residential indoor air quality in the IB and SY communities. Indoor air quality data collected by the study is compared to outdoor pollution events tied to TR pollution. By integrating community-based monitoring with environmental analysis, this research expands the existing LCN and provides insight into how proximity to a polluted river influences indoor air quality.

Methods

2.1 Study Area

This study was conducted in the South Bay region of San Diego County, CA (Figure 1), located immediately north of the US–Mexico border, and encompassing the communities of IB and SY, a predominantly low-income, Latino population. The South Bay region sits at the intersection of three distinct outdoor PM sources. Located about 1 km to the south of the outdoor reference monitoring station used in this study (referred to as the Prather Mobile Lab, or PML), the Tijuana River corridor (Stigler-Granados et al., 2021; Cox, 2022) is a documented source of H_2S and secondary PM_{10} that reaches South Bay communities under favorable meteorological conditions (Rico et al., 2025; Cysneiros de Carvalho et al. 2025). A turbulent TR section at Saturn Boulevard ($32.559^{\circ}N$, $117.093^{\circ}W$) has been identified as the primary H_2S emission hotspot due to enhanced water-to-air transfer through hydraulic turbulence, referred to here as the Saturn Blvd. Hotspot (SBH) (Rico et al., 2025). To the west, the Pacific Ocean contributes marine aerosol through sea spray; Pendergraft et al. (2021) demonstrated that aerosols generated at the IB surf zone can travel as far as 668 m inland, and Pendergraft et al. (2023) confirmed that IB sea spray aerosol carries bacterial and chemical markers traceable to TR-contaminated coastal waters. To the east, Interstate 5 and the San Ysidro Port of Entry are established sources of traffic-related $PM_{2.5}$ and ultrafine particles from heavy-duty diesel vehicles and passenger traffic (Quintana et al., 2014; Shina and Canter, 2017).

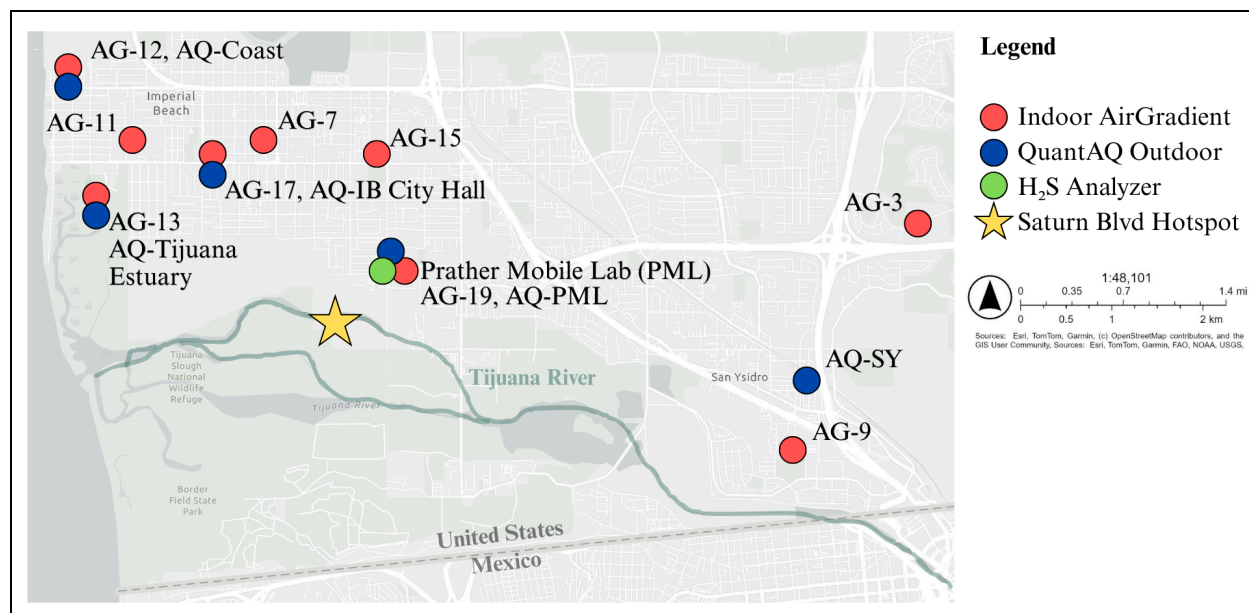


Figure 1. Map of the low-cost sensor network including Airgradient, QuantAQ, H₂S analyzer and Saturn Blvd Hotspot. There are four co-located sensor locations: AG-12 and AQ-Coast, AG-13 and AQ-TRE, AG-17 and AQ-IB City Hall, and AG-19, AQ-PML, and the H₂S Monitor at PML are co-located.

2.2 Participant Recruitment and Sampling Protocol

This pilot study was conducted through the Youth Climate Advisors program (YCA), started through the Airborne Institute at UC San Diego. YCA connects middle and high school students with hands-on scientific research opportunities and assists them in designing and carrying out their own experiments focused on targeting how pollution from the TR can impact their air quality and daily lives. The students participating in the program are predominately high school juniors and seniors residing in the South Bay area. Indoor air monitoring using the AirGradient sensors was adapted into the YCA curriculum, and participants were asked for parental consent if they were below the age of 18. All students participating received a total of \$100 in gift cards for their participation. Seven participating high school students hosted indoor air quality monitors in their homes, completed household characteristic surveys, and recorded observational data throughout the study period. In addition to the seven YCA participant households, sensors were installed in four public and institutional buildings: a high school classroom, the Tijuana River Estuary Visitors Center, and the Imperial Beach City Hall.

Indoor air sampling was conducted from April 2 through 28, 2026. Participants were trained on how to install the AirGradient in their residence and sensors were installed in the living room or kitchen of each participants' households. Each residence differed from each other in terms of ventilation, heating, and air conditioning system (HVAC), as well as type of dwelling. All sampling locations used were chosen based on their proximity to the Saturn Blvd Hotspot. Detailed information about the differences in residential buildings is available in SI Table S1.

Residential addresses are not included to protect the privacy of participants. Data on household characteristics like cooking fuel type, ventilation practices, air filtration, heating systems, and resident behaviors, collected via survey results, are used to characterize baseline indoor pollutant levels.

2.3 Monitoring network and instrumentation

2.3.1 Sensor Specifications

The AirGradient ONE Model I-9PSL (AirGradient Co. Ltd., Thailand) and the MODULAIR by QuantAQ Inc (Somerville, MA, USA) were the two low-cost sensors utilized in this study. The Air Gradient ONE measures particulate matter of 10 (PM_{10}), 2.5 ($PM_{2.5}$), 1 (PM_1) and 0.3 ($PM_{0.3}$) micrometers or less in diameter, carbon dioxide (CO_2), total volatile organic compounds (TVOCs), nitrogen oxides (NO_x), temperature, and humidity and has been utilized in other publications for low cost indoor air studies (Okkonen et al., 2025; Qian et al., 2025; Zaky et al., 2025). The AirGradient utilizes a Plantower PMS5003 optical particle sensor to detect particles ranging in diameter from 0.3 to 10 μm . Laser light scattering is transformed directly to a mass concentration based on internal calibration algorithms (Zaky et al., 2025). The sensor measures mass concentrations of particulate matter from 0 to 500 $\mu g m^{-3}$ with an accuracy of $\pm 10 \mu g m^{-3}$ below 100 $\mu g m^{-3}$, and $\pm 10\%$ of readings between 100 and 500 $\mu g m^{-3}$ according to manual specifications. To measure TVOCs and NO_x the AirGradient uses the Sensirion SGP41 TVOC/ NO_x sensor which can measure between 1-10,000 ppb for typical indoor air pollutant gases. The Sensirion uses ethanol as a proxy gas for typical VOC based indoor air events (Sensirion, 2021). The MODULAIR utilizes a similar measurement technique to the AirGradient for particles but integrates a nephelometer with single particle scattering to detect particles (QuantAQ). The QuantAQ MODULAIR monitors used in this study are the same instruments deployed by Cysneiros de Carvalho et al. (2025) in their characterization of TR contributions to regional PM_1 , providing direct methodological continuity between the two studies.

2.3.2 Sensor Network and Survey

SI Table S1 summarizes the household and building characteristics for all sensor locations. Key variables include location, cooking fuel type, ventilation practice, and mechanical filtration. AG-11 is deployed in a school classroom with central air conditioning, an air purifier, and windows that remain closed, providing a near-zero indoor source baseline and representing the most effectively filtered location in the network. AG-17 (Imperial Beach City Hall) and AG-13 (TJ River Estuary Visitors Center) are public buildings with controlled HVAC and no cooking activity; AG-13 data are available only from April 13 onward due to a delayed deployment. AG-19 is co-located with the PML and serves as an outdoor ambient reference rather than an indoor sensor.

2.3.3 Sensor Validation

AirGradient indoor PM_{2.5} concentrations are automatically corrected by the device firmware using the US EPA national correction equation for PurpleAir-class PMS5003 optical particle counters (Saladin, 2024; Barkjohn et al., 2021). No validated national correction equation exists for PM₁, which is not a federally regulated pollutant.

Optical particle counters are often impacted by fluctuations in relative humidity (RH), especially at or above RH 75%, leading to error in particle counts (Giordano, et al., 2021). Consequently, to validate the performance of the AirGradient indoors, a comparison between the AirGradient and a laboratory reference grade sizing instrument: Optical Particle Sizer (OPS) (TSI Inc.) was performed indoors at 46-50% RH (measured by the AirGradients). Combustion aerosol was generated by igniting and extinguishing a candle. Raw OPS particle number size distributions (dN/dlogDp, #/cm³) were converted to PM₁ and PM_{2.5} mass concentrations by numerical integration across the relevant size bins assuming spherical particles and bulk density of 1.0 g/cm³ (Mostafa et al., 2021; Pagels et al., 2009). Sensor-specific simple linear regression (SLR) calibration equations were derived independently for each unit (Franken et al., 2019):

$$\mathbf{PM}_{\text{calibrated}} = \beta_{\text{PM}} \cdot \mathbf{PM}_{\text{raw}} + \beta_0$$

where β_{PM} is the regression coefficient and β_0 is the y-intercept. PM₁ regression coefficients (β_{PM_1}) ranged from 0.283 to 0.563 (mean 0.43 ± 0.07 SD) and PM_{2.5} coefficients from 0.460 to 0.743 (mean 0.58 ± 0.09 SD) (SI Table S2). Additional methodology can be found in SI Table S2 shows the uncalibrated vs calibrated AirGradient PM₁ compared to OPS Reference standard.

Raw firmware PM₁ outputs are used for network-level analysis because the sensors perform consistently enough, with a mean correlation of 0.97, for relative comparisons across the network (Malings et al., 2019). The calibration derived here is not applied to the data because it was conducted under a single controlled burn event with limited temperature and humidity variation, which is not sufficient to produce reliable correction factors for deployment conditions. A redesigned calibration protocol utilizing known aerosol sizes and spanning a broader range of environmental conditions is recommended before individual sensor corrections are applied.

2.3.4 CO₂ Decay Experiments

To test the response to CO₂, the AirGradients were placed in a controlled laboratory space, with no active ventilation, save for a small rotating fan. Dry ice, filled halfway of the volume of a small 1-gallon cooler, was placed in the room. Sensors were placed approximately 2.74 meters away from the dry ice. Following the procedure outlined in Afroz et al. (2023), sensors were allowed to reach 3000 ppb CO₂ then the dry ice was removed from the room. The sensors were

monitored until the background concentration of 450 ppb CO₂ was reached again. CO₂ decay experiments are shown in SI Figure S2.

2.4 Indoor Source Detection

Indoor particulate matter concentrations in residential settings are influenced by both outdoor infiltration and indoor combustion sources, particularly cooking. Without source separation, indoor combustion events, which produce sharp, high-magnitude PM₁ spikes unrelated to outdoor air quality, would confound the outdoor-to-indoor signal that is the primary focus of this study.

A five-layer detection framework was applied to all AirGradient indoor PM₁ data at 5-minute resolution (see SI Table S3). Each layer produces a binary signal that contributes to a confidence score: Layer 1 (L1) flags periods within survey-derived cooking hours for each household (see Table 1. for sensor-specific hours); Layer 2 (L2) applies a sensor-specific absolute PM₁ spike threshold (ranging from 2.0 µg/m³, at institutional locations, to 12.0 µg/m³) and is required for any flag to be assigned; Layer 3 (L3) uses CO₂ elevation as a combustion corroborator, operating as a checkpoint for closed/mechanically ventilated buildings; Layer 4 (L4) flags periods where the PM₁₀/PM₁ ratio exceeds 2.5, indicating a coarse-mode particle shift characteristic of indoor combustion (Morawska et al., 1999); and Layer 5 (L5) flags periods where indoor PM₁ is elevated while outdoor PM₁ is below 10 µg/m³ and the indoor/outdoor ratio exceeds 2.0, indicating indoor-source decoupling from outdoor conditions (Meng et al., 2005). All periods meeting L2 and at least one additional criterion were flagged as likely cooking events and set to NaN, producing the cooking filtered dataset. Flagging rates ranged from 0.6% (AG-11) to 18.6% (AG-9); full rates and per-sensor thresholds are reported in SI Table S3. The cooking filtered dataset was used to calculate the infiltration factor estimation, statistical analyses (Mann-Whitney U tests, Spearman lag correlations), boxplots, and correlation matrices throughout this study.

2.5 TR Pollution and IAQ

2.5.1 Hydrogen Sulfide as a TR Pollution Tracer

H₂S mixing ratios were measured in parts per billion (ppb) by a UV fluorescence analyzer (H₂S Analyzer Teledyne T101; Teledyne API) co-located with MOD-00370 at 1-minute resolution. H₂S is a well-established chemical tracer for anaerobic decomposition in wastewater-impacted water bodies, and the Tijuana River corridor is documented as a significant regional H₂S source (Rico et al., 2025).

Gas phase species can contribute to new particle formation when they nucleate to form small clusters of sub-1 nm particles. H₂S mixing ratios are expected to contribute to particulate

pollution by undergoing atmospheric oxidation with the hydroxyl radical (El Masri et al., in prep). Complete oxidation of H_2S is expected to form H_2SO_4 . Sulfuric acid is known to correspond to new particle formation (NPF) events by forming stable clusters of H_2SO_4 (Seinfeld and Pandis, 2016). H_2S oxidation to sulfate aerosol is driven by photochemical reactions with hydroxyl radicals (OH), meaning elevated H_2S concentrations, which peak nocturnally under stable boundary layer conditions, are not always coincident with peak PM_{10} , but rather precede it by hours as the overnight H_2S is processed into secondary sulfate aerosol during the following morning's photochemical activity (Seinfeld and Pandis 2016). This photochemical lag explains the temporal offset between nocturnal H_2S spikes and the mid-morning outdoor PM_{10} peaks observed on High H_2S + PM_{10} event days in this study. Taken together, H_2S serves as a chemical fingerprint of active TR emissions, while outdoor PM_{10} integrates both the primary aerosol transported from the TR corridor and the accumulated secondary aerosol formed from TR gaseous precursors under photochemical and nocturnal oxidation pathways (Rico et al., 2025; Cysneiros de Carvalho et al., 2025)

2.5.2 Pollution Event Criteria

Daily H_2S and outdoor PM_{10} observations were classified into three mutually exclusive event categories: High H_2S , High H_2S + PM_{10} , and Clean reference.

H_2S event days were defined as any day on which the 1-hour rolling mean H_2S concentration at the PML exceeded 30 ppb at any point during the 24-hour period. This threshold is based on the California Ambient Air Quality Standard for H_2S of 30 ppb (1-hour average; CARB, 2024).

PM_{10} event days were defined as any day on which the 1-hour rolling mean outdoor PM_{10} concentration at the PML exceeded the top quartile at any point during the 24-hour period and where outdoor $\text{PM}_{2.5}$ concentration exceeded $9 \mu\text{g}/\text{m}^3$. There are no PM_{10} standards, which is why this dual threshold framework is being used. This framework ensures there is outdoor pollution that day (via the $\text{PM}_{2.5}$ threshold) while also selecting days with elevated outdoor PM_{10} . The $9 \mu\text{g}/\text{m}^3$ threshold aligns with the NAAQS standard for $\text{PM}_{2.5}$ (annual mean, averaged over 3 years).

The most representative dates for each pollution scenario were April 5 (High H_2S), April 8 and 24 (High H_2S + PM_{10}), and April 13 (Clean reference). Notably, under the hybrid classification framework, no days in the study period were classified as High PM_{10} only. Every day which met the High PM_{10} threshold also recorded a 1-hour H_2S maximum exceeding 30 ppb, indicating that PM_{10} elevation in the South Bay during this period was consistently co-occurring with TR gaseous emissions. Because this study uses PM_{10} to trace outdoor to indoor pollution from the TR, comparisons will largely be between clean reference days and High H_2S + PM_{10} days.

2.5.3 Atmospheric Variables

Atmospheric variables including mixing layer height (MLH), river stage, wind speed and direction, temperature, RH, and solar radiation, were compared across all event scenarios to establish the meteorological context of each event type.

MLH (m), shortwave radiation (W/m^2), and direct radiation (W/m^2) were obtained from the Open-Meteo ERA5 reanalysis archive at hourly resolution (32.5654°N , 117.0905°W) for April 2–28, 2026 and were forward filled. MLH governs the vertical volume available for pollutant dilution and ranges from 10 to 1,255 m. ERA5 MLH estimates are derived from the planetary boundary layer height diagnostic in the ECMWF model and have been validated against radiosonde observations at coastal sites by Seidel et al. (2012).

The TR river stage was identified by [Cysneiros et al. \(2025\)](#) as an important factor in increased PM_{10} levels in the IB region. Water level (stage, meters) was obtained from USGS gauge 11013101 at 15-minute resolution via bulk export through April 28, 2026. This gauge measures discharge at the US–Mexico International Boundary, directly reflecting transboundary wastewater and stormwater flow from the Tijuana watershed. River flow is a positive predictor of H_2S water-to-air transfer at the turbulent Saturn Boulevard hotspot; Rico et al. (2025) showed that H_2S levels decreased nearly 95% following a sudden reduction in transboundary wastewater flow, confirming river discharge as the dominant source control (Wallace and Ott, 2023). For meteorological parameters such as wind speed, wind direction, temperature, and relative humidity, data from the QuantAQ PML was used.

2.6 Indoor-outdoor source separation

PML was used as the PM_{10} and $\text{PM}_{2.5}$ outdoor reference in the following sections due to proximity to TR, allowing us to approximate the TR derived exposure. This section uses two size fractions to characterize different aspects of TR indoor infiltration. Indoor PM_{10} with the cooking filter applied is used for the indoor-to-outdoor (I/O) ratio analysis because it is most directly linked to TR-derived secondary aerosol at this site (Cysneiros de Carvalho et al., 2025) and provides better signal separation from coarser indoor sources (Bousiotis et al., 2023). $\text{PM}_{2.5}$ is used for infiltration factor estimation, toxicity potential, and cumulative exposure because it is the only fine particle size fraction with a validated EPA correction equation, WHO health guideline, and published decomposition methodology (Barkjohn et al., 2021; WHO, 2021; Wallace and Ott, 2023; Chen and Zhao, 2011). The transition between metrics is supported by the strong correlation between outdoor PM_{10} and $\text{PM}_{2.5}$ at the PML across the study period (Spearman $\rho = 0.977$, $p < 0.001$).

2.6.1 Indoor to Outdoor Ratio (I/O)

The indoor-to-outdoor (I/O) ratio is a widely used metric in indoor air quality research for quantifying the relationship between indoor and outdoor pollutant concentrations and distinguishing between pollutants that originate indoors versus those that infiltrate from outside (Dockery and Spengler, 1981; Chen and Zhao, 2011). As much as 30%–75% of indoor $PM_{2.5}$ pollution is due to the outdoor environment (Dockery & Spengler, 1981; Jenkins et al., 1992). The I/O PM_1 ratio was computed for each indoor sensor as the ratio of filtered indoor PM_1 to simultaneous outdoor PM_1 at PML. PML was used as the outdoor reference due to its proximity to the Saturn Blvd hotspot. I/O ratios were computed at 5-minute resolution and aggregated to study-period means and event-type means.

An I/O ratio of 1.0 indicates that indoor and outdoor concentrations are equal, with no net reduction or amplification by the building envelope. A review of 77 studies covering more than 4,000 homes found that the average I/O ratio for $PM_{2.5}$ is approximately 1.0, with significant variability explained by building characteristics and ventilation behavior (Chen and Zhao, 2011). Values below 1.0 indicate building filtration or restricted air exchange; values above 1.0 indicate a net indoor source contribution where indoor activity generates more PM than the building removes (Hagan and Kroll, 2020; Rosenberg, 2012).

2.6.2 PM_1 Source Decomposition, and TR-Attributable Indoor Exposure

To isolate how much indoor PM_1 came from outdoor pollution, total indoor $PM_{2.5}$ was decomposed into three components following Wallace and Ott (2023):

$$C_{total} = C_{background} + C_{outdoor} + C_{indoor}$$

$C_{background}$ is the indoor baseline, estimated using the two clean reference days within the study period (April 13 and April 25). This component represents dust and other permanent indoor sources and was subtracted as a constant for each sensor. $C_{outdoor}$ is the calculated outdoor-attributable component, taken as the fraction of outdoor pollution that penetrates indoors at each 5-minute window. It is calculated as:

$$C_{outdoor} = F \times C_{PML}$$

where F is the sensor-specific infiltration factor (the fraction of outdoor $PM_{2.5}$ that gets inside) and C_{PML} is the observed outdoor $PM_{2.5}$ at the QuantAQ PML. C_{indoor} represents indoor pollution sources like cooking, candles, cleaning, and other episodic indoor sources. It is computed as $C_{total} - C_{background} - C_{outdoor}$ (with any negative values set to zero).

The infiltration factor F was estimated separately for each sensor by ordinary least squares regression of $(C_{\text{indoor}} - C_{\text{background}})$ on C_{PML} during periods when outdoor $\text{PM}_{2.5}$ exceeded $5 \mu\text{g}/\text{m}^3$ and no cooking activity was detected. These windows represent times when the indoor sensor is responding primarily to outdoor infiltration, so the slope of the regression, how steeply indoor $\text{PM}_{2.5}$ rises as outdoor $\text{PM}_{2.5}$ rises, measures what fraction of outdoor $\text{PM}_{2.5}$ gets inside. A steep slope means a leaky building; a flat slope means a well-sealed or filtered one. Regression plots for all sensors are provided in SI Figure S3. Wallace and Ott (2023) define a Forbidden Zone, which is an upper boundary where no observations should appear below if F is constant and is applicable to all data points. Forbidden Zone diagnostics revealed substantial violation rates (27–89%) consistent with variable ventilation behavior, indicating that F represents a characteristic infiltration rate under active ventilation conditions rather than a time-invariant constant (Wallace and Ott, 2023).

C_{outdoor} is used for toxicity potential and cumulative exposure calculations as it better quantifies the TR-specific outdoor contribution to indoor $\text{PM}_{2.5}$ at each 5-minute window. All other analyses, correlation matrices, boxplots, and statistical tests, use the cooking-filtered indoor PM_1 dataset.

2.6.3 Toxicity Potential

To express the TR-attributable indoor pollution burden in terms that are meaningful for human health, a toxicity potential (T_p) metric was calculated for each sensor. T_p is a dimensionless health risk index that expresses indoor $\text{PM}_{2.5}$ concentration as a fraction of a recognized health-based guideline threshold (Zaman et al., 2021; Ayodele et al., 2016; Chamseddine et al., 2019). In this study, T_p represents the fraction of the WHO 24-hour $\text{PM}_{2.5}$ guideline ($15 \mu\text{g}/\text{m}^3$) attributable to TR outdoor infiltration on a given event day (WHO, 2021). To enable fair comparison across event categories with unequal day counts (Clean: $n = 3$, High H_2S : $n = 15$, High $\text{H}_2\text{S} + \text{PM}_1$: $n = 8$), T_p was first averaged within each event day and then averaged across days within each category, giving a per-day T_p that is independent of the number of days in each category. T_p was calculated as:

$$T_p = (F \times C_{\text{PML}})/15$$

where F is the sensor-specific infiltration factor and outdoor $\text{PM}_{2.5}$ is the simultaneous measurement at PML (Shah et al., 2021). The numerator is the estimated TR-attributable indoor $\text{PM}_{2.5}$ at each 5-minute window, the same C_{outdoor} calculation described in Section 2.4.2, applied to $\text{PM}_{2.5}$ rather than PM_1 . Dividing by $15 \mu\text{g}/\text{m}^3$ scales the result to the WHO guideline, which recommends that 24-hour average exposures should not exceed $15 \mu\text{g}/\text{m}^3$ more than 3–4 days per year. A T_p of 1.0 means TR derived pollution alone is responsible for indoor $\text{PM}_{2.5}$ reaching the guideline threshold, and a T_p of 0.1 means TR derived pollution is responsible for 10% of it.

2.6.4 Cumulative Exposure

Cumulative TR-attributable indoor PM_{2.5} exposure (E) was calculated by summing the TR-attributable PM_{2.5} concentration at each time interval across the full study period:

$$E = \Sigma(F \times C_{PML} \times \Delta t)$$

where $\Delta t = 0.083$ hours (5-minute interval expressed in hours), summed across all observations in the study period, and following the infiltration decomposition of Chen and Zhao (2011) and Wallace and Ott (2023). WHO guideline-days, the number of days at continuous guideline-level exposure that would produce the same cumulative dose, were computed as $E / (15 \mu\text{g m}^{-3} \times 24 \text{ h})$. The result is expressed in $\mu\text{g/m}^3 \cdot \text{h}$, the total mass concentration of TR-derived PM_{2.5} a resident would have inhaled if they were home continuously. An occupancy-weighted version was also calculated to reflect that Americans spend approximately 69% of their time specifically in their home environment (Klepeis et al., 2001).

Results and Discussion

3.1. Atmospheric Drivers of Poor IAQ in South Bay

The transport and accumulation of TR-derived H₂S and PM₁ in South Bay communities are governed by a complex set of meteorological variables acting across different timescales. PM concentrations, temperature, relative humidity, wind speed, wind direction, MLH, precipitation, river stage, and solar irradiance, are relevant to the TR pollution system and are showcased in SI Figure S4 (Lunderberg et al., 2023; Dawson et al., 2007; Miao et al., 2018; Liu et al., 2022). The figure also includes H₂S mixing ratios and outdoor PM₁ concentrations at the PML which exhibited distinct temporal variability over the study period, consistent with photochemical oxidation of H₂S and other co-emitted gas-phase species (Seinfeld and Pandis, 2016). High H₂S+PM₁ days, as described in section 2.5.2 make up 8 days within the study period, with all but three days in the study exhibiting H₂S > 30 ppb sustained hourly mean. The two clean reference days (April 13 and 25) are clearly distinguishable by their near-zero H₂S and low PM₁. SI Figure S4 displays the different atmospheric variables and meteorological parameters on clean reference versus H₂S+PM₁ days. Clean reference days had higher MLH levels (April 13: 600 m, April 25: 822.5 m) compared to H₂S+PM₁ days, which averaged 295 m, consistent with the nocturnal boundary layer dynamics documented by Rico et al. (2025), who identified stable, low-MLH nights coupled with sustained elevated temperatures as the primary meteorological driver of extreme H₂S accumulation at this site. TR pollution following low river flow, showed a river stage of 0.18 m on April 25 compared to the average H₂S+PM₁ day levels of 0.34 m. April 13 had a river flow of 0.44 m, which is higher than the H₂S+PM₁ average, suggesting there may be other factors contributing to the low PM₁ concentration on the clean reference day. One potential

explanation may be the above average wind speed (3.26 m/s on April 13 compared to 2.40 m/s on H₂S+PM₁ days), which can contribute to pollution dispersal (IQAir, 2022). Wind direction can also determine how pollution is transported to residential communities; with southerly winds transporting TR pollution toward IB. The outdoor PM₁ levels on days with northerly wind versus southerly wind are statistically significantly different as confirmed by independent t-test, which found the mean outdoor PM₁ at the PML on northerly wind days to be statistically lower (5.288 $\mu\text{g m}^{-3}$) compared to southerly wind days (8.092 $\mu\text{g m}^{-3}$) (T-statistic: -4.637, P-value: 6.973e-06) (Issakhov et al., 2024; Hu et al., 2022; Danek et al., 2022).

Among the meteorological variables examined, outdoor PM₁ at the PML showed the strongest Spearman rank correlations with short wave radiation, RH, and wind direction ($\rho = 0.388, 0.229, 0.224$, respectively), whereas outdoor H₂S measured at the PML most greatly correlates with; MLH, shortwave radiation, and river stage ($\rho = -0.570, -0.553, 0.339$, respectively) (SI Table S5) (Danek et al., 2022).

3.2. Indoor Air Quality Across the Sensor Network

Indoor to Outdoor Signal Across All Sampling Locations

Heatmaps were used to visualize the pollution gradient at locations moving farther from the Saturn Boulevard Hotspot. Figure 2 shows how outdoor PM₁ corresponds to indoor PM₁ at different locations in the South Bay region. PM₁ concentration is low across sensors on identified clean days including April 13 and April 22, in comparison to days like April 5, 8, 9, 10, 14, 18, and 24 which see strong PM₁ signals across sensors. Indoor sensors AG-9 and AG-3 exhibit PM₁ patterns independent of TR pollution. The deviation of these sensors from the outdoor PM₁ measured at PML may be attributed to San Ysidro specific traffic, given its proximity to I-5, I-805, and State Route 54 (SR-54) and the San Ysidro Port of Entry, due to higher correlation values between AG-9 and AG-3 with QuantAQ SY (0.53, 0.60) (Quintana et al., 2014; Dumbauld, 2011). There are likely other indoor events happening, as the PM₁ events at the AG monitors are much higher than what is occurring at QuantAQ SY. We cannot distinguish between how SY pollution impacts IAQ at those sites from TR pollution, and for that reason do not conduct further analysis on the indoor SY locations. There are still important public health implications for these locations, as they are experiencing very high daily indoor PM₁ pollution.

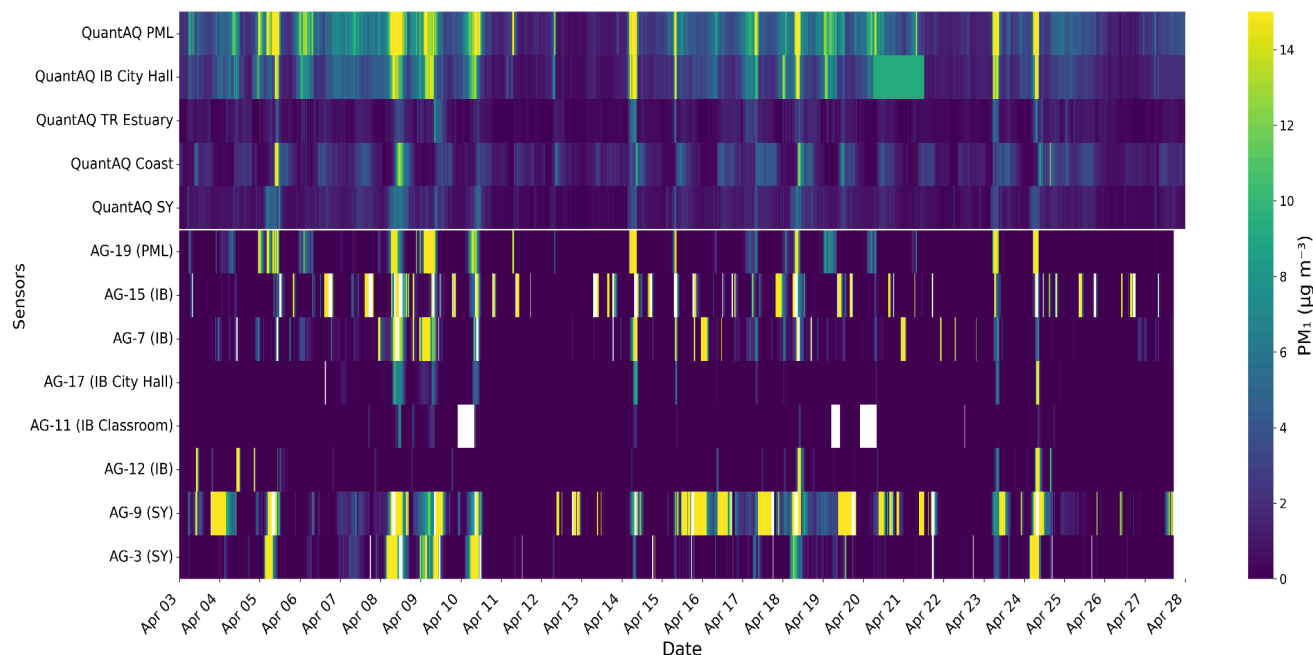


Figure 2. Diurnal PM_{10} heatmaps at all South Bay sensor locations April 3-28. Color intensity represents PM_{10} concentration ($\mu\text{g m}^{-3}$) at 5-minute resolution across the full 24-hour local day. Yellow coloring indicates a higher PM_{10} concentration and blue represents a lower concentration. The five outdoor reference rows above the white dividing line show raw outdoor PM_{10} measured directly by the QuantAQ monitors. Indoor sensor rows below the dividing line show filtered indoor PM_{10} , with high-confidence cooking events removed. White gaps indicate windows flagged by the cooking detection algorithm. Sensors are ordered from top to bottom by increasing distance from the Saturn Boulevard hotspot. Color scale is fixed at 0–15 $\mu\text{g m}^{-3}$ across all panels.

To visualize the difference between clean and $\text{H}_2\text{S}+\text{PM}_{10}$ days, Figure 3 compares heatmaps from April 8, 13, and 24 which represent the top two $\text{H}_2\text{S}+\text{PM}_{10}$ days, and a clean reference day.

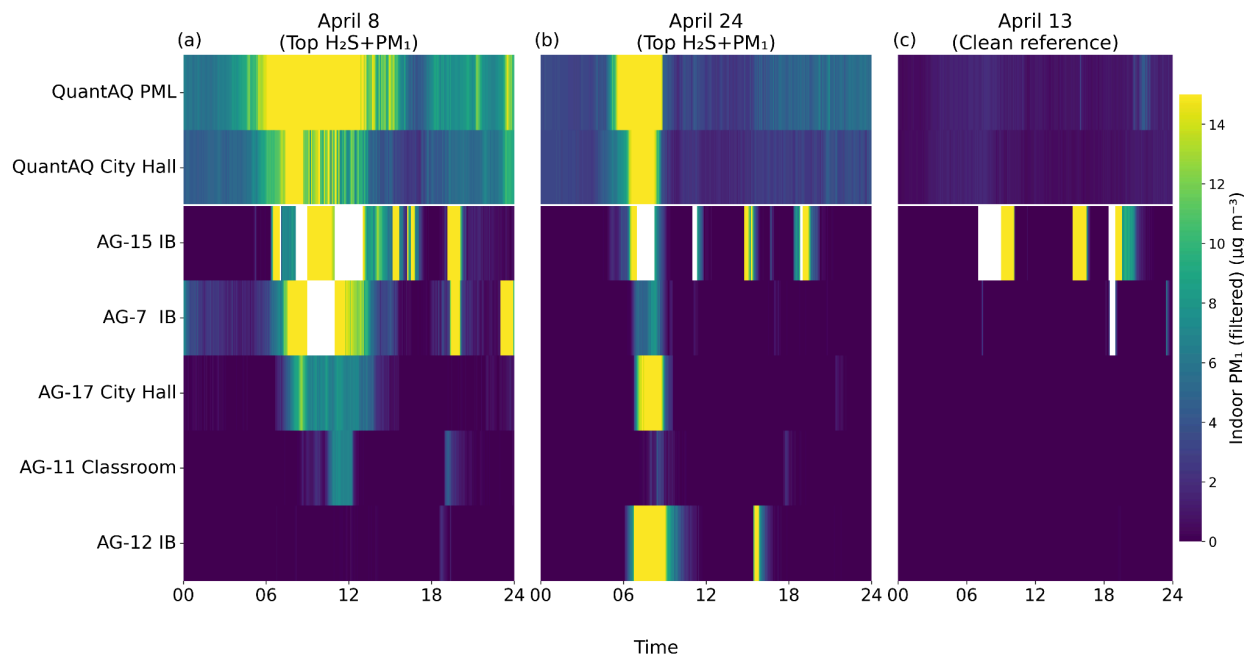


Figure 3. Diurnal PM_{10} heatmaps at all South Bay sensor locations across three contrasting outdoor pollution days: (a) April 8 (Top $\text{H}_2\text{S} + \text{PM}_{10}$), (b) April 13 (clean reference), and (c) April 24 (Top $\text{H}_2\text{S} + \text{PM}_{10}$). Color intensity represents PM_{10} concentration ($\mu\text{g m}^{-3}$) at 5-minute resolution across the full 24-hour local day. The two outdoor reference rows above the white dividing line (QuantAQ PML and QuantAQ City Hall) show raw outdoor PM_{10} measured directly by the QuantAQ MODULAIR monitors. Indoor sensor rows below the dividing line show filtered indoor PM_{10} , with high-confidence cooking events removed. White gaps indicate windows flagged by the cooking detection algorithm. Sensors are ordered from top to bottom by increasing distance from the Saturn Boulevard hotspot. Color scale is fixed at 0–15 $\mu\text{g m}^{-3}$ across all panels.

Outdoor PM_{10} at QuantAQ PML is elevated throughout the entire day, peaking (yellow, $>14 \mu\text{g/m}^3$) between 06:00 and 14:00 (Figure 3a). QuantAQ City Hall shows a similar but slightly muted and delayed pattern, reflecting the spatial gradient between the Saturn Boulevard hotspot and the City Hall location. AG-15 (IB) and AG-7 (IB) both show clear indoor responses peaking around 10:00–14:00, though with larger white cooking gaps. The persistence of elevated indoor PM_{10} across most of the daytime period, rather than a single brief spike, distinguishes April 8 as a sustained outdoor event rather than an episodic one. AG-11 and AG-12 remain near-zero throughout, with AG-11 showing a signal around midday.

April 24 the QuantAQ sensors record PM_{10} levels near zero from midnight through approximately 05:00 local time at the PML and 06:00 local time at IB City Hall, which then rises sharply to peak (yellow, $>14 \mu\text{g/m}^3$) until 09:00, before rapidly declining (Figure 3b). This midmorning outdoor peak may reflect photochemical processing of overnight H_2S and other gas-phase emissions into secondary aerosols under increasing solar radiation (Cysneiros et al., 2025; Sbail et al., 2021; Xu et al., 2023; Malecha and Nizkorodov, 2016). AG-15 and AG-17 show moderate responses. AG-17 (City Hall) and AG-11 (Classroom) remain near-zero throughout, confirming institutional building protection. White gaps at AG-15 and AG-7 around 10:00–11:00 are cooking-flagged windows, coinciding with the outdoor peak.

The outdoor PM₁ at QuantAQ PML and City Hall are near-zero throughout the entire day (Figure 3c). All indoor sensors also read near-zero with only two exceptions: AG-15 and AG-9 show brief yellow flashes throughout the day that are likely residual cooking activity or other indoor sources that passed through the moderate cooking filter. Their presence on the clean reference day confirms they are indoor-source events unrelated to TR pollution.

The outdoor-to-indoor coupling is strongest on April 8 with every AirGradient sensor responding to elevated outdoor PM₁, and April 13 exhibits the weakest indoor responses where outdoor PM₁ provides no driving force.

Diurnal Variability of Indoor PM₁ Classified by Event Type

Analysis of indoor PM₁ by event type and separated by day and night shows that H₂S + PM₁ days produce significantly elevated indoor concentrations across most sensor households during daytime hours, with slightly muted elevation during nighttime hours. Figure 4 displays the distribution of daily maximum indoor PM₁ across the sensor network, separated by event type and time of day. Sensors are in order of distance from the PML. Daily maximum PM₁ captures peak exposure events within each day, the highest 5-minute concentration a resident would have experienced, rather than sustained average exposure, making it a relevant metric for understanding acute indoor PM₁ burden.

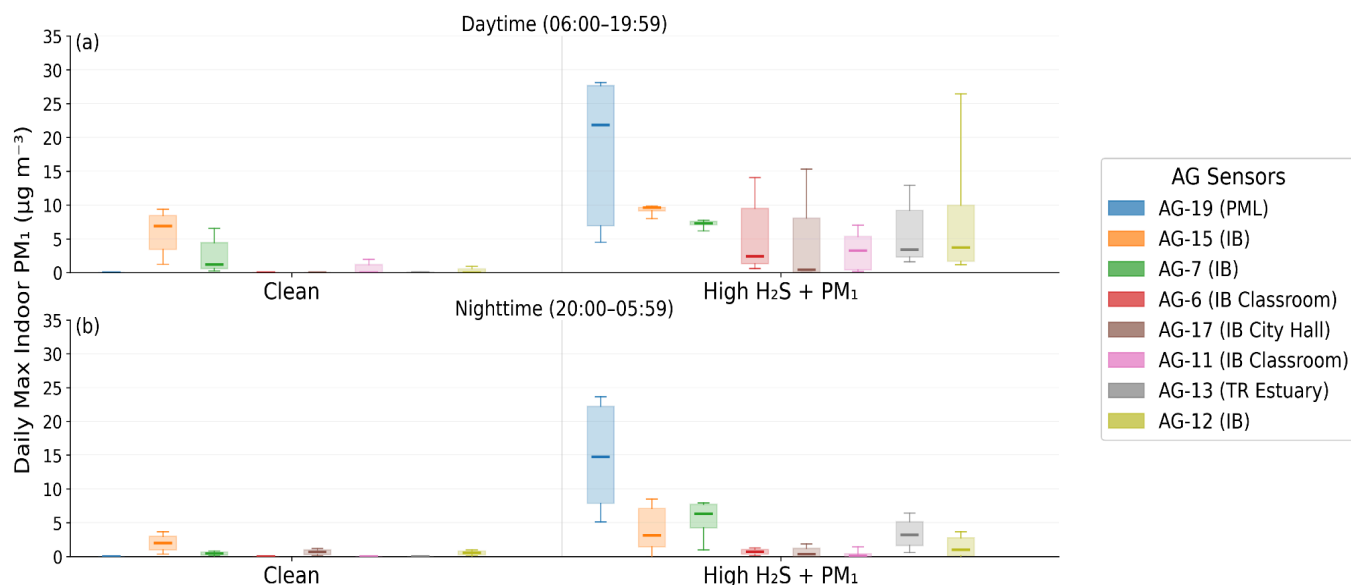


Figure 4. Indoor PM₁ average daily maximum by pollution event type and time of day across the South Bay sensor network, April 3–28, 2026. Each box represents one sensor's indoor PM₁ average daily maximum within the given event type and time-of-day period; sensors are ordered left to right by increasing distance from the Saturn Boulevard hotspot within each event group. Box spans the interquartile range (IQR, 25th–75th percentile); horizontal line shows the median; whiskers extend to the 9th and 91st percentiles. All values are from the filtered indoor PM₁ dataset, with high-confidence cooking events removed. Event classification uses boundaries: Clean = no threshold met; High H₂S + PM₁ = max hourly H₂S ≥ 30 ppb, 1-hour rolling PM₁ ≥ study-period top quartile, and daily mean

$PM_{2.5} \geq 9 \mu g m^{-3}$. Panel (a): daytime observations (06:00–19:59 PDT); Panel (b): nighttime observations (20:00–05:59 PDT).

On clean reference days, daily maximum indoor PM_1 remained near zero at every sensor, confirming that in the absence of outdoor TR pollution, indoor PM_1 stays low regardless of building type (Figure 4a). On High $H_2S + PM_1$ event days the contrast is significant. AG-19, located inside the PML about 1 km from the Saturn Boulevard hotspot, shows a median daytime peak exceeding $20 \mu g m^{-3}$, illustrating the acute exposure burden experienced by anyone in direct proximity to the emission source. Among residential IB sensors, AG-15 and AG-7 show the highest peak responses, with median daytime maximums around $8\text{--}10 \mu g m^{-3}$ on event days, while the institutional sensors AG-11 and AG-17 remain substantially lower, consistent with their building filtration characteristics. AG-12 shows a notably wide distribution on event days, reflecting potential coastal influence and its variable window behavior.

Despite TR H_2S emissions being predominantly nocturnal, nighttime daily maximum PM_1 is generally lower than daytime at most sensors, even on High $H_2S + PM_1$ event days (Figure 4b). AG-19 shows a median nighttime peak around $15 \mu g m^{-3}$, lower than its daytime peak, and residential sensors AG-7 and AG-15 show median nighttime peaks of approximately $6 \mu g m^{-3}$. This daytime-nighttime asymmetry is consistent with the photochemical secondary aerosol formation that drives daytime PM_1 peaks and requires solar radiation. On High H_2S -only nights, H_2S is present but outdoor PM_1 has not yet accumulated to event-day levels, so indoor PM_1 remains low regardless of building permeability.

Across both panels, the pattern is consistent: High $H_2S + PM_1$ event days produce substantially elevated indoor PM_1 peaks at every sensor compared to clean reference conditions, with the magnitude of the peak determined primarily by building permeability and proximity to the source.

Paired t-test results confirm that indoor PM_1 on High $H_2S + PM_1$ event days is significantly higher than on clean reference days at every sensor in the network (all $p < 0.001$; SI Table S6). Mean indoor PM_1 on High $H_2S + PM_1$ days relative to clean reference conditions increase most dramatically at AG-3 (0.021 to $3.98 \mu g m^{-3}$), AG-7 (0.039 to $4.75 \mu g m^{-3}$), and AG-9 (4.26 to $14.0 \mu g m^{-3}$). Even institutionally filtered sensors show statistically significant elevations with AG-11 increasing from 0.017 to $0.192 \mu g m^{-3}$ ($p < 0.001$) (SI Table S6). These results suggest that IAQ for community members living near the TR is likely adversely impacted by days with higher fine PM_1 concentrations outdoors.

Indoor-Outdoor Signal

Indoor PM_1 response to outdoor conditions shows enhanced PM_1 across the LCN on $H_2S + PM_1$ days. Figure 5 compares indoor PM_1 to the outdoor PML PM_1 levels at three different sensor locations on three different days. April 8 and 24, which represent the two highest PM_1 days at the

PML, are plotted alongside April 13, the clean baseline day. Figures 5a, 5d, and 5g show results for AG-7 on each selected day; Figures 5b, 5e, and 5h show results for AG-11; and Figures 5c, 5f, and 5i show results for AG-17.

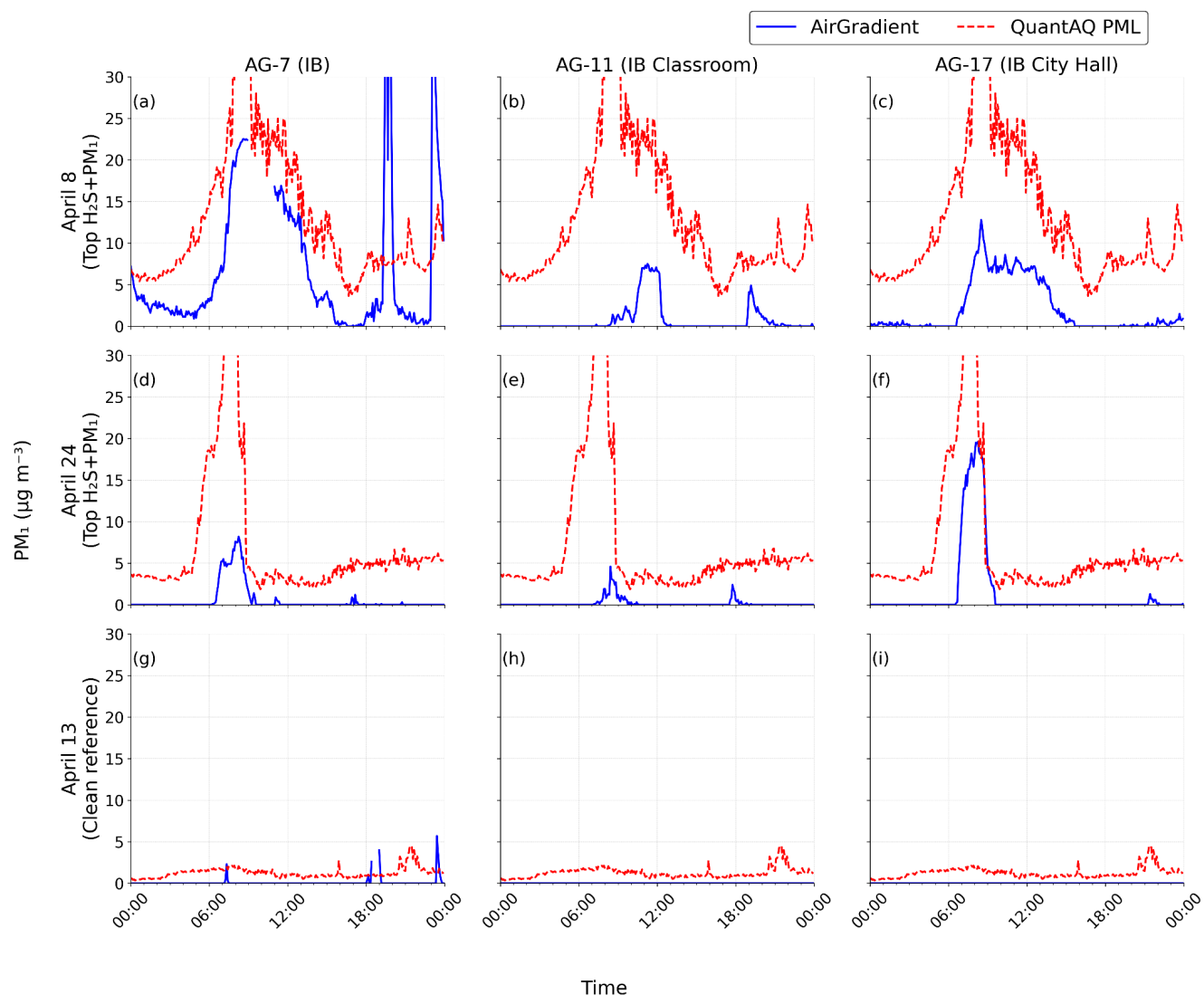


Figure 5. Indoor PM_{10} at three South Bay sensor locations across three contrasting outdoor pollution days. April 8 (High H_2S+PM_{10} , top row), April 13 (clean reference, middle row), and April 24 (High H_2S+PM_{10} , bottom row). Blue lines show indoor PM_{10} at each AirGradient sensor (PM_{10} data filtered, with high-confidence cooking events removed); red dashed lines show simultaneous outdoor PM_{10} at the QuantAQ PML. Columns correspond to three sensors spanning different building types and South Bay communities: AG-7 (residential, always-open windows, Imperial Beach); AG-11 (classroom, HVAC + filtration, Imperial Beach); AG-17 (City Hall, sometimes-open windows, Imperial Beach). Gaps in indoor time series indicate windows removed by the cooking detection algorithm.

The highest mean PM₁ levels of the study period occur on April 8, with all three indoor sensors responding with elevated indoor PM₁ levels (Figure 5a-c). AG-7, a house located in IB which almost always has windows opened and no central AC, most closely follows the outdoor PM₁ signal. AG-7's PM₁ peaks at around 16 µg/m³ at 10:00, which corresponds to the large outdoor PM₁ peak that occurs at the same time. There are other smaller peaks throughout the day that are most likely cooking events or other indoor pollution events that made it past the cooking filter, especially the peak occurring at 18:00, which occurs during the typical cooking hours for this sensor (see SI Table S3). AG-11 and AG-17 are both institutional buildings with more insulation (although AG-17 has more frequent window usage) and show a reduced response to outdoor PM₁ when compared to AG-7. The tie between mechanical ventilation, closed windows, and air purification to lower outdoor to indoor pollution transport is corroborated by Adjei et al. (2025).

Indoor sensors show reduced PM₁ concentrations in response to outdoor PM₁ on April 24th compared to April 8. Both are high H₂S+PM₁ days, with lower overall concentrations on April 24 (Figure 5d-f). The reduced PM₁ concentrations are likely a result of increased MLH (511 m) on April 24 compared to April 8 (227 m). April 24 has a short spike in outdoor PM₁ from 5-9am, which in turn led to correspondingly short spikes in indoor PM₁.

Low outdoor PM₁ levels occur at the PML on April 13, with correspondingly low indoor PM₁ levels at AG-7, AG-11, and AG-17 (Figure 5g-i). April 13 is a clean reference day, and the lack of indoor PM₁ response on this day corroborates the idea that indoor PM₁ is impacted by outdoor PM₁ levels (Bousiotis et al., 2023; Afroz et al., 2023). AG-7 shows mild (2-6 µg/m³) PM₁ peaks around 7:00, 18:00, 19:00, and 23:00, which correspond to a small morning elevation and two smaller peaks around 16:00 and 21:00.

Collectively, Figures 5 demonstrates that outdoor-to-indoor PM₁ transport in South Bay is both significant and strongly influenced by building characteristics. Across all three sensors and both event days, indoor PM₁ responded systematically to outdoor forcing, rising on High H₂S + PM₁ days and remaining near zero on the clean reference day, confirming that TR-derived outdoor PM₁ is the primary driver of indoor PM₁ variability at these locations rather than indoor generation. The magnitude of the indoor response, however, differed across sensors exposed to identical outdoor conditions, with AG-7 reaching indoor peaks exceeding 15 µg/m³ on April 8 while AG-11 remained below 8 µg/m³ throughout the same day. The contrast between April 8 and April 24 further demonstrates that indoor response scales with outdoor event intensity and boundary layer conditions, a more spatially confined outdoor PM₁ spike under higher MLH on April 24 produced correspondingly attenuated and shorter-duration indoor responses relative to the sustained daytime peak on April 8. The clean reference day, April 13, establishes that in the absence of outdoor TR forcing, indoor PM₁ at all three sensors remains near background regardless of building ventilation characteristics, confirming that the indoor elevations observed on event days are attributable to outdoor infiltration rather than indoor sources

Correlation between Indoor and Outdoor PM₁ at all Sensors

Spearman correlation analysis reveals a strong positive relationship between the QuantAQ PML, and indoor sensors located in IB. Z score normalization of the data matrix across all indoor and outdoor sensors allows for cross comparisons. Weak correlations between Tijuana Estuary Visitors Center and the Coast QuantAQ indicate a decoupling from the TR derived pollution with PM₁ from indoor air sensors, except for the coastal indoor sensor (AG-12). The PML and IB City Hall are located closest to the Saturn Blvd hotspot (about 1 km and 4 km respectively), while the Coast and Estuary sensors are positioned closer to the Pacific Ocean (as shown in Fig. 1).

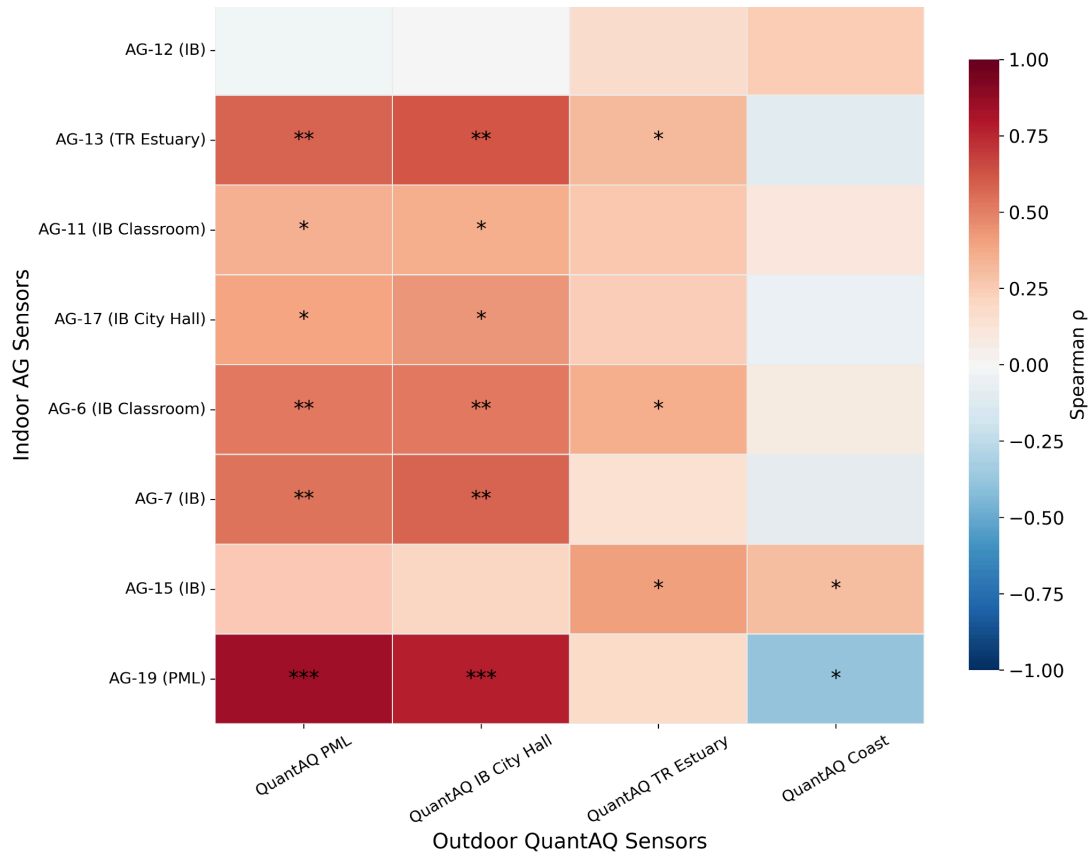


Figure 6. Full-period Spearman rank correlation matrix between indoor AG PM₁ and outdoor QuantAQ PM₁ across the South Bay sensor network on High H₂S+PM₁ days. Rows show indoor AirGradient sensors ordered from top to bottom by increasing distance from the Saturn Boulevard hotspot; columns show outdoor QuantAQ sensors spanning the South Bay network. Correlations are computed at 5-minute resolution across the full study period using filtered PM₁ data. Star annotations indicate effect size: *** $\rho \geq 0.70$ (strong); ** $\rho \geq 0.50$ (moderate); * $\rho \geq 0.30$ (weak); blank < 0.30 .

AG-19, the AirGradient sensor located inside the PML, shows the highest indoor-outdoor correlation in the matrix ($\rho \approx 0.85\text{--}0.90$), consistent with its near-direct exposure to outdoor air through the trailer envelope, effectively the most permeable 'building' in the network. Although AG-19 co-located with the QuantAQ PML, it is also representative of homes located with the

same, if not closer proximity to the hotspot. Both institutionally filtered sensors in Figure 5 show weak correlations with most outdoor references ($\rho < 0.30$), confirming that mechanical filtration and sealed building envelopes substantially decouple indoor PM_{10} from outdoor conditions across the full study period. AG-7, AG-6, and AG-13 all show moderate correlation with outdoor PML PM_{10} levels, while AG-15 does not show any correlation. This could be because AG-15 has strong indoor pollution sources and a noisy signal, likely contributing to hiding a potential correlation that may exist between AG-15 and outdoor PM_{10} at the PML.

The QuantAQ Coast sensor in Figure 5 shows a notably different pattern from the other outdoor references with correlations with indoor sensors being weaker and more variable, and with some negative values appearing for AG-12. There are likely different dynamics at the coast, impacting both indoor and outdoor PM_{10} patterns and levels. These dynamics could consist of closer proximity to onshore and offshore winds, greater distance from the hotspot, and diluted pollution at the Pacific Ocean.

The spatial gradient across the five outdoor columns, strongest at PML and IB City Hall, moderate at TR Estuary, weakest at Coast, confirms that the TR hotspot at Saturn Boulevard is the dominant driver of PM_{10} variability across the network and that its influence attenuates somewhat spatially with distance from the emission source.

3.3 Indoor-outdoor source separation

This section uses the indoor/outdoor ratio (I/O), infiltration factor (F), and a toxicity potential metric (T_p) to identify households with the most outdoor sourced PM exposure, the ratio of indoor to outdoor PM, and the health burden of indoor PM concentrations. I/O ratios by event type and sensor are reported in SI Table S8; the sensor ordering mirrors the infiltration factor results below.

$PM_{2.5}$ infiltration factors ranged from $F = 0.067$ at AG-11 to $F = 0.817$ at AG-19, with residential sensors AG-7 ($F = 0.225$), AG-15 ($F = 0.268$), and AG-12 ($F = 0.106$) intermediate (SI Table S8). These values indicate that for every $1 \mu\text{g}/\text{m}^3$ increase in outdoor TR-derived $PM_{2.5}$, approximately $0.07\text{--}0.81 \mu\text{g}/\text{m}^3$ enters the most permeable residential buildings, consistent with the range of infiltration factors ($0.3\text{--}0.82$) reported across US residences (Chen and Zhao, 2011). Here, the range calculated in this study extends lower because institutional buildings are used as sampling locations in addition to residences. AG-11's near-zero infiltration factor ($F = 0.018$) reflects a sealed building envelope and air purifier usage, corroborated by participant survey results. Although AG-19 is located in a mobile lab, for this section it can be considered a poorly insulated residence, as it is located in a residential area and can represent homes that are as close, if not closer, to the Saturn Blvd hotspot that lack an HVAC system or air purifiers. According to US Census data, 4,597 people live in census tract 101.09, the tract where the hotspot is located (United States Census Bureau). For residents living near the TR without an adequate filtration or

purification system, they are likely experiencing higher levels of outdoor to indoor pollution transport.

To express the TR-attributable indoor $\text{PM}_{2.5}$ burden in health-relevant terms, we calculated a toxicity potential (T_p) metric for each sensor, defined as the fraction of the WHO 24-hour $\text{PM}_{2.5}$ guideline ($15 \mu\text{g}/\text{m}^3$) attributable to TR outdoor infiltration on a given event day (Abulude et al., 2022). The WHO 24-hour guideline recommends that average exposures should not exceed $15 \mu\text{g}/\text{m}^3$ more than 3–4 days per year, a threshold set at the lowest level for which there is evidence of adverse health effects. A T_p of 1.0 means TR pollution alone consumes the entire daily WHO $\text{PM}_{2.5}$ exposure budget; a T_p of 0.25 means TR pollution is responsible for 25% of that budget before accounting for cooking, cleaning, or other indoor sources. For context, T_p values above 1.0 have been reported in high-pollution indoor environments in developing countries, Abulude et al. (2022) reported a $\text{PM}_{2.5}$ T_p of 2.74 in a commercial setting in Nigeria where concentrations substantially exceeded WHO limits, and Zaman et al. (2021) reported a T_p of in a hospital in Dhaka of greater than 10. These cases come from locations with ambient $\text{PM}_{2.5}$ levels much higher than those measured in this study. For our region of study, the sub-1.0 values found in this study reflect that TR infiltration contributes meaningfully to indoor $\text{PM}_{2.5}$ exposure without alone driving concentrations above the guideline threshold, though total indoor $\text{PM}_{2.5}$ including cooking and other indoor sources was not separately quantified in this analysis.

Figure 7 displays TR-attributable T_p at each sensor across three categories, the entire study period, clean reference days, and High $\text{H}_2\text{S} + \text{PM}_1$ event days, with sensors ordered by increasing distance from the Saturn Boulevard hotspot. Horizontal bars indicate ± 1 standard deviation across days within each category, reflecting day-to-day variability in outdoor $\text{PM}_{2.5}$ forcing within each event class.

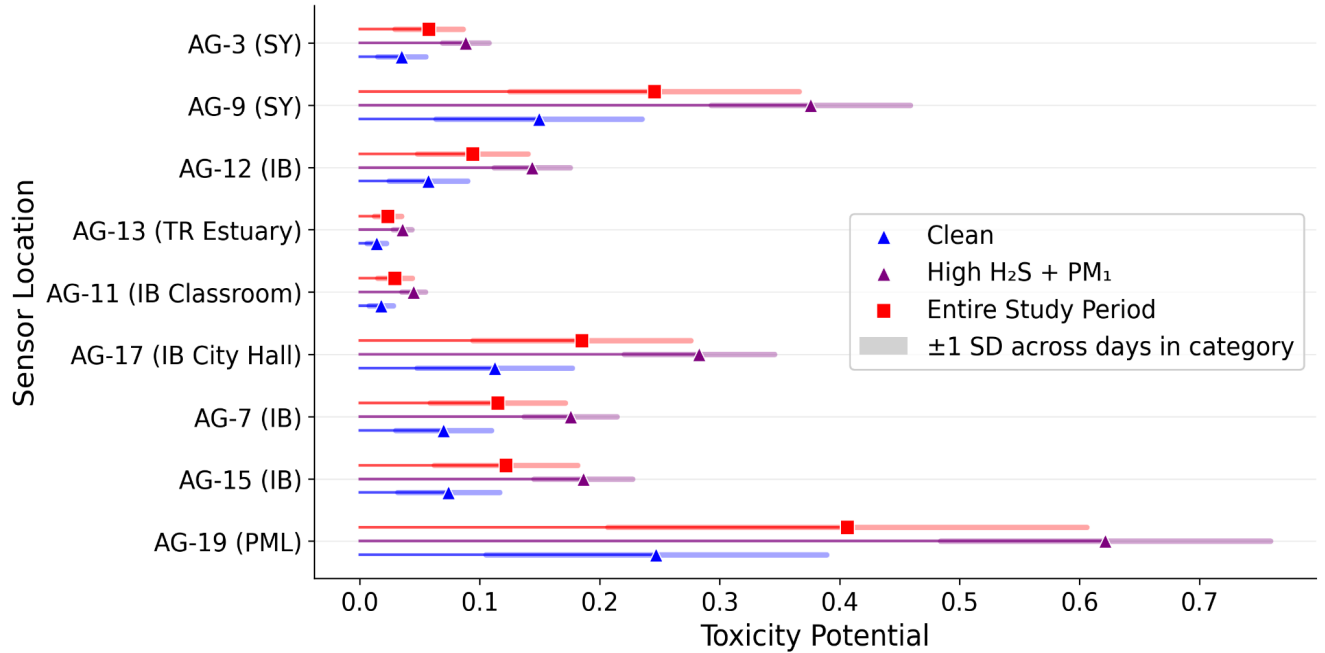


Figure 7. Daily mean TR-attributable toxicity potential (T_p) by outdoor pollution event type across the South Bay sensor network, April 3–28, 2026. Points show the mean of daily T_p values within each event category; horizontal bars show ± 1 standard deviation across days within each category. To enable a fair cross-category comparison, T_p is first averaged per event day before averaging across days, removing the confound of unequal category day counts (Clean: $n = 2$ days, High H₂S: $n = 15$ days, High H₂S + PM₁: $n = 8$ days). Sensors are ordered top to bottom by increasing distance from the Saturn Boulevard hotspot (1.3–4.3 miles). $T_p = \text{mean daily } C_{\text{tr_pm25}} / 15 \mu\text{g m}^{-3}$, where $C_{\text{tr_pm25}} = F_{\text{pm25}} \times C_{\text{PML_PM}_{2.5}}$.

TR-attributable T_p increased consistently across all sensors on High H₂S + PM₁ days relative to clean reference conditions, approximately doubling at every sensor in the network. The consistent doubling confirms that the event classification is capturing a physically meaningful and reproducible gradient in outdoor pollution intensity rather than sensor-specific noise.

On High H₂S + PM₁ days, mean daily T_p ranged from 0.051 at the filtered institutional classroom (AG-11) to 0.395 at AG-9, with AG-19, the mobile laboratory trailer co-located at the outdoor reference, reaching 0.622, serving as a near-direct-outdoor upper bound. These values indicate that TR pollution was responsible for between 5% and 62% of the WHO daily PM_{2.5} exposure budget at different sensor locations before accounting for cooking, baseline indoor PM_{2.5}, or other indoor sources. The wide range across sensors, nearly an 8-fold difference between AG-11 and AG-9 on identical outdoor days, confirms that building characteristics, and proximity to the hotspot are primary determinants of TR-attributable indoor exposure burden.

The standard deviation bars reveal substantial day-to-day variability within the High H₂S + PM₁ category, particularly at AG-9 and AG-19, reinforces that the reported T_p values represent averages across a heterogeneous set of event days rather than a single fixed exposure level, and

that on the most intense event days, such as April 8, individual-day T_p values at the most permeable sensors likely approach or exceed the study-period means reported here.

To capture the total $PM_{2.5}$ exposure burden over the full study period at each indoor sensor, we calculate cumulative WHO guideline-days, a metric that expresses how many full days of continuous exposure at exactly the WHO 24-hour $PM_{2.5}$ threshold ($15 \mu\text{g}/\text{m}^3$) would occur if the T_p of each day in the study period were summed. Unlike a simple exceedance count, this metric accumulates exposure continuously, a day at half the threshold counts as 0.5 guideline-days, meaning sub-threshold days still contribute to the cumulative burden. This approach extends the established practice of counting guideline exceedance days as a measure of health burden, the Born in Bradford cohort study similarly compared indoor $PM_{2.5}$ concentrations against the WHO 24-hour threshold across 309 UK homes, finding that exposure burdens were not equally distributed across social determinants of health, to a continuous cumulative metric that captures partial-day exposures and sub-threshold events rather than simple threshold crossings (NHS). Unlike toxicity potential, which describes the fraction of the WHO daily guideline consumed on a typical event day, WHO guideline-days integrate both the intensity of TR pollution on event days and the frequency with which those events occurred across the entire study period. The WHO recommends that 24-hour average $PM_{2.5}$ should not exceed $15 \mu\text{g}/\text{m}^3$ more than 3–4 days per year, making the guideline-day a natural unit for expressing cumulative exposure relative to a recognized health standard (WHO, 2021).

Over the full 26-day study period, cumulative TR-attributable indoor $PM_{2.5}$ exposure ranged from 0.814 WHO guideline-days at the filtered institutional classroom (AG-11) to 10.57 guideline-days at AG-19, the mobile laboratory trailer co-located at the outdoor reference and serving as a near-direct-outdoor upper bound. Among residential and institutional building sensors, AG-9 accumulated the highest burden at 6.71 guideline-days, while AG-7 (2.91 guideline-days) and AG-17 (2.97 guideline-days) each accumulated nearly three full days at the WHO threshold from TR infiltration alone over a single month, before any contribution from cooking, traffic, or other indoor sources is considered. To contextualize this: the WHO guideline permits no more than 3–4 exceedance days per year, yet TR infiltration alone delivered the equivalent of nearly three guideline-threshold-days of $PM_{2.5}$ exposure at AG-7 and AG-17 in just 26 days. In a community where TR pollution exceeded the H_2S threshold on 23 of 26 study days, this cumulative framing reveals an exposure burden that any single-day metric alone would substantially understate.

Taken together, these results establish that the Tijuana River is a measurable and quantifiable indoor air quality threat to South Bay households, not merely an outdoor odor nuisance. Across the Imperial Beach sensor network, indoor PM_1 on High H_2S + PM_1 event days was significantly elevated above clean reference conditions at every sensor (all $p < 0.001$), with mean increases ranging from $0.18 \mu\text{g}/\text{m}^3$ at the filtered classroom (AG-11) to $4.75 \mu\text{g}/\text{m}^3$ at the most permeable open-window residence (AG-7). The $PM_{2.5}$ -based toxicity potential and WHO guideline-days

metrics provide a regulatory anchor for interpreting the health significance of these PM_{10} observations: TR-attributable T_p approximately doubled on High $H_2S + PM_{10}$ days relative to clean conditions at every sensor, and at AG-7, TR infiltration consumed the equivalent of 2.91 full days at the WHO $PM_{2.5}$ threshold over a single month. These findings underscore a broader and underappreciated principle: water pollution does not stay in the water. Through the volatilization of gas phase species photochemical conversion to secondary aerosol and subsequent infiltration into the indoor environments where people spend most of their time, a wastewater discharge event in the Tijuana River can become an indoor air quality event in an Imperial Beach home. The results of this study indicate living near a polluted watershed not only impacts outdoor air quality, but can have significant impacts on IAQ, which may have lasting effects on resident health and well-being.

3.4 Climate Change Implications

The findings of this study take on added urgency in the context of climate change, which is projected to intensify both the frequency and impact of transboundary pollution events. Climate change is projected to worsen regional air quality more broadly through increased wildfire smoke, dust events, and more frequent atmospheric stagnation, periods of suppressed vertical mixing and light winds that trap surface-level pollutants, compounding existing pollution burdens in already-disadvantaged communities (Jacob and Winner, 2009; Climate Central, 2022). The same shallow boundary layer conditions that drive nocturnal H_2S accumulation at the Saturn Boulevard hotspot are projected to become more frequent under future climate scenarios (Zhao et al., 2020; Rico et al., 2025), suggesting that TR pollution events in South Bay may increase in both frequency and duration. The South Bay communities studied here, predominantly low-income and Latino, face compounded environmental justice burdens: pre-existing air quality challenges from traffic and industrial sources, climate-driven intensification of TR pollution, and limited financial capacity to implement building-level protective measures such as HVAC upgrades or air purifiers. AG-11 demonstrates that filtration is effective, but access to filtered indoor environments is not equitably distributed across the network, the households with the highest infiltration factors (AG-7, AG-15) are private residences where occupants bear individual responsibility for protection that could instead be addressed through policy.

3.5 Policy recommendations

These findings point to concrete policy interventions and research priorities that could meaningfully reduce TR-attributable indoor PM exposure across South Bay communities.

Standards

Current regulatory frameworks focus exclusively on outdoor ambient concentrations and provide no guidance or recourse for residents experiencing outdoor-driven indoor PM exceedances. Indoor air quality standards must be developed for residential settings, particularly in communities adjacent to known industrial or environmental pollution sources, and for renters, who often cannot make the material changes to a living space that may be required to successfully block outdoor air pollution. PM₁ health guidelines must also be developed to complement existing PM_{2.5} standards. The predominantly sub-micron nature of TR-derived secondary aerosol means PM_{2.5} standards may underweight the health-relevant fraction at sites like South Bay. Finally, regulatory recognition of water-to-air pollution transport as a distinct exposure pathway must occur and must be distinct from direct wastewater discharge standards. This has implications for other communities residing near polluting bodies of water, which may be unexpected or unknown indoor pollution sources.

Monitoring

Real-time H₂S and outdoor PM₁ monitoring must be expanded to enable community notification and early warning systems, leveraging the low-cost sensor infrastructure already deployed in this study to alert residents when conditions require indoor infiltration.

Public Programs

Building envelope improvements and air filtration in affordable and low-income housing in communities adjacent to environmental pollution sources should be implemented and modeled on existing weatherization assistance program.

References

- Abt, E., Suh, H. H., Catalano, P., & Koutrakis, P. (2000). Relative contribution of outdoor and indoor particle sources to indoor concentrations. *Environmental Science & Technology*, 34(17), 3579–3587. <https://doi.org/10.1021/es990348y>
- Abulude, F. O., Arifalo, K. M., Adamu, A., Kenni, A. M., Akinnusotu, A., Oluwagbayide, S. D., & Acha, S. (2022). Indoor air quality (PM_{2.5} and PM₁₀) and toxicity potential at a commercial environment in Akure, Nigeria. *Environmental Sciences Proceedings*, 24(1), 8. <https://doi.org/10.3390/environsciproc2022024008>
- Adjei, F. A., & Afriyie, A. (2025). Air pollution as a global health risk: Emerging evidence, interventions and policy insights. *World Journal of Advanced Research and Reviews*, 27(1), 1925–1940. <https://doi.org/10.30574/wjarr.2025.27.1.2716>
- Afroz, R., Guo, X., Cheng, C.-W., Delorme, A., Duruisseau-Kuntz, R., & Zhao, R. (2023). Investigation of indoor air quality in university residences using low-cost sensors. *Environmental Science: Atmospheres*, 3(2), 347–362. <https://doi.org/10.1039/d2ea00149g>
- Ageel, H. K., Harrad, S., & Abdallah, M. A.-E. (2021). Occurrence, human exposure, and risk of microplastics in the indoor environment. *Environmental Science: Processes & Impacts*, 24(1), 17–31. <https://doi.org/10.1039/d1em00301a>
- Alonso-Pérez, S., & López-Solano, J. (2023). Long-term analysis of aerosol concentrations using a low-cost sensor: Monitoring African dust outbreaks in a suburban environment in the Canary Islands. *Sensors*, 23(18), 7768. <https://doi.org/10.3390/s23187768>
- Anderson, E. (2018, March 2). *Feds facing lawsuit over cross-border sewage spills in San Diego*. KPBS Public Media. <https://www.kpbs.org/news/2018/mar/02/federal-government-faces-lawsuit-over-cross-border/>
- Ayodele, C. O., Fakinle, B. S., Jimoda, L. A., & Sonibare, J. A. (2016). Investigation on the ambient air quality in a hospital environment. *Cogent Environmental Science*, 2(1), 1215281. <https://doi.org/10.1080/23311843.2016.1215281>
- Bagkis, E., Hassani, A., Schneider, P., DeSouza, P., Shetty, S., Kassandros, T., Salamalikis, V., Castell, N., Karatzas, K., Ahlawat, A., & Khan, J. (2025). Evolving trends in application of low-cost air quality sensor networks: Challenges and future directions. *Npj Climate and Atmospheric Science*, 8(1). <https://doi.org/10.1038/s41612-025-01216-4>
- Barkjohn, K. K., Gantt, B., & Clements, A. L. (2021). Development and application of a United States-wide correction for PM_{2.5} data collected with the PurpleAir sensor. *Atmospheric Measurement Techniques*, 14(6), 4617–4637. <https://doi.org/10.5194/amt-14-4617-2021>
- Bousiotis, D., Alconcel, L.-N., Harrison, R. M., Beddows, D. C., & Pope, F. (2023). Monitoring and apportioning sources of outdoor and indoor air quality using low-cost particulate matter sensors. *Environment International*, 174. <https://doi.org/10.5194/egusphere-egu23-1011>

- CARB. (2024, July 16). *Ambient air quality standards pollutant averaging time California Standards I*. CARB.
https://ww2.arb.ca.gov/sites/default/files/2024-08/AAQS%20Table_ADA_FINAL_07222024.pdf
- Casado-Mansilla, D., Pujante, A., Illueca Fernández, E., Udina, S., Castell, N., Serrano, N., & López-de-Ipiña, D. (2025). Perspective chapter: A protocol for the use of low-cost air pollution sensors in citizen science to foster evidence-based policy making. *Environmental Sciences*. <https://doi.org/10.5772/intechopen.1009024>
- Chen, C., & Zhao, B. (2011). Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. *Atmospheric Environment*, 45(2), 275–288. <https://doi.org/10.1016/j.atmosenv.2010.09.048>
- Clark, S. N., Anenberg, S. C., & Brauer, M. (2025). Global burden of disease from environmental factors. *Annual Review of Public Health*, 46(1), 233–251.
<https://doi.org/10.1146/annurev-publhealth-071823-105338>
- Chamseddine, A., Alameddine, I., Hatzopoulou, M., & El-Fadel, M. (2019). Seasonal variation of air quality in hospitals with indoor–outdoor correlations. *Building and Environment*, 148, 689–700. <https://doi.org/10.1016/j.buildenv.2018.11.034>
- Ciuzas, D., Prasauskas, T., Krugly, E., Sidaraviciute, R., Jurelionis, A., Seduikyte, L., Kauneliene, V., Wierzbicka, A., & Martuzevicius, D. (2015). Characterization of indoor aerosol temporal variations for the real-time management of Indoor Air Quality. *Atmospheric Environment*, 118, 107–117. <https://doi.org/10.1016/j.atmosenv.2015.07.044>
- Climate Central. (2022). *Summer air: Hot, stagnant, polluted*.
<https://www.climatecentral.org/climate-matters/stagnant-air>
- Cooper, A., Cancelada, L., Torres, R. R., Belcher, K., Small, M., Belda-Ferre, P., Morris, C., Mitts, B., Dinasquet, J., Knight, R., Slade, J. H., & Prather, K. A. (2025). Identifying wastewater chemicals in coastal aerosols. *Science Advances*, 11(22).
<https://doi.org/10.1126/sciadv.ads9476>
- Crilley, L. R., Singh, A., Kramer, L. J., Shaw, M. D., Alam, M. S., Apte, J. S., Bloss, W. J., Hildebrandt Ruiz, L., Fu, P., Fu, W., Gani, S., Gatari, M., Ilyinskaya, E., Lewis, A. C., Ng'ang'a, D., Sun, Y., Whitty, R. C., Yue, S., Young, S., & Pope, F. D. (2020). Effect of aerosol composition on the performance of low-cost optical particle counter correction factors. *Atmospheric Measurement Techniques*, 13(3), 1181–1193.
<https://doi.org/10.5194/amt-13-1181-2020>
- Cysneiros de Carvalho, K., Barsanti, K. C., Hamlin, J. D., Prather, K. A., & Porter, W. C. (2025). Contaminated Tijuana River contributes to regional particulate matter (PM) levels highlighting overlooked water–air transfer of gaseous PM precursors. *Environmental Science & Technology*, 59(51), 27903–27917.
<https://doi.org/10.1021/acs.est.5c08369>

- Danek, T., Weglinska, E., & Zareba, M. (2022). The influence of meteorological factors and terrain on air pollution concentration and migration: A geostatistical case study from Krakow, Poland. *Scientific Reports*, 12(1). <https://doi.org/10.1038/s41598-022-15160-3>
- Dawson, J. P., Adams, P. J., & Pandis, S. N. (2007). Sensitivity of PM_{2.5} to climate in the eastern us: A modeling case study. *Atmospheric Chemistry and Physics*, 7(16), 4295–4309. <https://doi.org/10.5194/acp-7-4295-2007>
- Dimitroulopoulou, S., Dudzińska, M. R., Gunnarsen, L., Hägerhed, L., Maula, H., Singh, R., Toyinbo, O., & Haverinen-Shaughnessy, U. (2023). Indoor air quality guidelines from across the World: An appraisal considering energy saving, health, productivity, and comfort. *Environment International*, 178, 108127. <https://doi.org/10.1016/j.envint.2023.108127>
- Dedina, S. (1995). The political ecology of transboundary development: Land use, flood control and politics in the Tijuana River Valley. *Journal of Borderlands Studies*, 10(1), 89–110. <https://doi.org/10.1080/08865655.1995.9695467>
- Dev, S., Barnes, D., Kadir, A., Betha, R., & Aggarwal, S. (2021). Outdoor and indoor concentrations of size-resolved particulate matter during a wildfire episode in Interior Alaska and the impact of ventilation. *Air Quality, Atmosphere & Health*, 15(1), 149–158. <https://doi.org/10.1007/s11869-021-01094-8>
- Dockery, D. W., & Spengler, J. D. (1981). Indoor-outdoor relationships of respirable sulfates and particles. *Atmospheric Environment* (1967), 15(3), 335–343. [https://doi.org/10.1016/0004-6981\(81\)90036-6](https://doi.org/10.1016/0004-6981(81)90036-6)
- Dumbauld, J. J. (2011). *Traffic related air pollution in the community of San Ysidro, California, in relation to northbound delays at the u.s.-mexico border* (dissertation). *Traffic related air pollution in the community of San Ysidro, California, in relation to northbound delays at the U.S.-México Border*. San Diego State University, San Diego, Calif.
- Environmental Protection Agency. (2025, November 4). *NAAQS Table*. EPA. <https://www.epa.gov/criteria-air-pollutants/naaqs-table>
- Environmental Protection Agency. (2025, December 5). *USMCA Tijuana River Watershed*. EPA. <https://www.epa.gov/sustainable-water-infrastructure/usmca-tijuana-river-watershed>
- Franken, R., Maggos, T., Stamatelopoulou, A., Loh, M., Kuijpers, E., Bartzis, J., Steinle, S., Cherrie, J. W., & Pronk, A. (2019). Comparison of methods for converting Dylos particle number concentrations to PM_{2.5} mass concentrations. *Indoor Air*, 29(3), 450–459. <https://doi.org/10.1111/ina.12546>
- Giordano, M. R., Malings, C., Pandis, S. N., Presto, A. A., McNeill, V. F., Westervelt, D. M., Beekmann, M., & Subramanian, R. (2021). From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost Particulate Matter Mass Sensors. *Journal of Aerosol Science*, 158, 105833. <https://doi.org/10.1016/j.jaerosci.2021.105833>
- Hagan, D. H., & Kroll, J. H. (2020). Assessing the accuracy of low-cost optical particle sensors using a physics-based approach. *EGU*. <https://doi.org/10.5194/amt-2020-188>

- He, J., Huang, C.-H., Yuan, N., Austin, E., Seto, E., & Novosselov, I. (2022). Network of low-cost air quality sensors for monitoring indoor, outdoor, and personal PM_{2.5} exposure in Seattle during the 2020 wildfire season. *Atmospheric Environment*, 285, 119244. <https://doi.org/10.1016/j.atmosenv.2022.119244>
- Higgins, C., Kumar, P., & Morawska, L. (2024). Indoor air quality monitoring and source apportionment using low-cost sensors. *Environmental Research Communications*, 6(1), 012001. <https://doi.org/10.1088/2515-7620/ad1cad>
- Hu, H., Chen, Q., Qian, Q., Zhou, X., Chen, Y., & Cai, Y. (2022). Field investigation for ambient wind speed and direction effects exposure of cyclists to PM_{2.5} and PM₁₀ in urban street environments. *Building and Environment*, 223, 109483. <https://doi.org/10.1016/j.buildenv.2022.109483>
- IQAir. (2022, August 18). *How wind and weather affect air pollution*. IQAir. <https://www.iqair.com/newsroom/wind-weather-air-pollution>
- Issakhov, A., & Abylkassymova, A. (2024). Assessment of the dispersion of pollutants from automobile exhaust, taking into account relative humidity, pavement temperature, wind direction and speed, which varies depending on the time of day. *International Communications in Heat and Mass Transfer*, 159, 108140. <https://doi.org/10.1016/j.icheatmasstransfer.2024.108140>
- Jacob, D. J., & Winner, D. A. (2009). Effect of climate change on air quality. *Atmospheric Environment*, 43(1), 51–63. <https://doi.org/10.1016/j.atmosenv.2008.09.051>
- Jaffe, D. A., Miller, C., Thompson, K., Finley, B., Nelson, M., Ouimette, J., & Andrews, E. (2023). 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*, 16(5), 1311–1322. <https://doi.org/10.5194/amt-16-1311-2023>
- Jenkins, P. L., Phillips, T. J., Mulberg, E. J., & Hui, S. P. (1992). Activity patterns of Californians: Use of and proximity to indoor pollutant sources. *Atmospheric Environment. Part A. General Topics*, 26(12), 2141–2148. [https://doi.org/10.1016/0960-1686\(92\)90402-7](https://doi.org/10.1016/0960-1686(92)90402-7)
- Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P., Tsang, A. M., Switzer, P., Behar, J. V., Hern, S. C., & Engelmann, W. H. (2001). The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants. *Journal of Exposure Science & Environmental Epidemiology*, 11(3), 231–252. <https://doi.org/10.1038/sj.jea.7500165>
- Kortoçi, P., Motlagh, N. H., Zaidan, M. A., Fung, P. L., Varjonen, S., Rebeiro-Hargrave, A., Niemi, J. V., Nurmi, P., Hussein, T., Petäjä, T., Kulmala, M., & Tarkoma, S. (2022). Air pollution exposure monitoring using portable low-cost air quality sensors. *Smart Health*, 23, 100241. <https://doi.org/10.1016/j.smhl.2021.100241>
- Lehtipalo, K., Yan, C., Dada, L., Bianchi, F., Xiao, M., Wagner, R., Stolzenburg, D., Ahonen, L. R., Amorim, A., Baccarini, A., Bauer, P. S., Baumgartner, B., Bergen, A., Bernhammer, A.-K., Breitenlechner, M., Brilke, S., Buchholz, A., Mazon, S. B., Chen, D... Worsnop,

- D. R. (2018). Multicomponent new particle formation from sulfuric acid, ammonia, and biogenic vapors. *Science Advances*, 4(12). <https://doi.org/10.1126/sciadv.aau5363>
- Leung, D. Y. (2015). Outdoor-indoor air pollution in urban environment: Challenges and opportunity. *Frontiers in Environmental Science*, 2. <https://doi.org/10.3389/fenvs.2014.00069>
- Liu, B., Ma, X., Ma, Y., Li, H., Jin, S., Fan, R., & Gong, W. (2022). The relationship between atmospheric boundary layer and temperature inversion layer and their aerosol capture capabilities. *Atmospheric Research*, 271, 106121. <https://doi.org/10.1016/j.atmosres.2022.106121>
- Liu, Q., Li, D., Xu, Z., Wang, Y., & Liu, J. (2025). Disparities in global disease burden attributed to ambient particulate matter pollution and household air pollution from solid fuels. *Ecotoxicology and Environmental Safety*, 291, 117908. <https://doi.org/10.1016/j.ecoenv.2025.117908>
- Lunderberg, D. M., Liang, Y., Singer, B. C., Apte, J. S., Nazaroff, W. W., & Goldstein, A. H. (2023). Assessing residential PM_{2.5} concentrations and infiltration factors with high spatiotemporal resolution using crowdsourced sensors. *Proceedings of the National Academy of Sciences*, 120(50). <https://doi.org/10.1073/pnas.2308832120>
- Malecha, K. T., & Nizkorodov, S. A. (2016). Photodegradation of secondary organic aerosol particles as a source of small, oxygenated volatile organic compounds. *Environmental Science & Technology*, 50(18), 9990–9997. <https://doi.org/10.1021/acs.est.6b02313>
- Malings, C., Tanzer, R., Haurlyuk, A., Saha, P. K., Robinson, A. L., Presto, A. A., & Subramanian, R. (2019). Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation. *Aerosol Science and Technology*, 54(2), 160–174. <https://doi.org/10.1080/02786826.2019.1623863>
- Masic, A., Bibic, D., Pikula, B., Blazevic, A., Huremovic, J., & Zero, S. (2020). Evaluation of optical particulate matter sensors under realistic conditions of strong and mild urban pollution. *Atmospheric Measurement Techniques*, 13(12), 6427–6443. <https://doi.org/10.5194/amt-13-6427-2020>
- Meng, Q. Y., Turpin, B. J., Korn, L., Weisel, C. P., Morandi, M., Colome, S., Zhang, J., Stock, T., Spektor, D., Winer, A., Zhang, L., Lee, J. H., Giovanetti, R., Cui, W., Kwon, J., Alimokhtari, S., Shendell, D., Jones, J., Farrar, C., & Maberti, S. (2004). Influence of ambient (outdoor) sources on residential indoor and personal PM_{2.5} concentrations: Analyses of riopa data. *Journal of Exposure Science & Environmental Epidemiology*, 15(1), 17–28. <https://doi.org/10.1038/sj.jea.7500378>
- Miao, Y., Liu, S., Guo, J., Huang, S., Yan, Y., & Lou, M. (2018). Unraveling the relationships between boundary layer height and PM_{2.5} pollution in China based on four-year radiosonde measurements. *Environmental Pollution*, 243, 1186–1195. <https://doi.org/10.1016/j.envpol.2018.09.070>

- Morawska, L., Thomas, S., Jamriska, M., & Johnson, G. (1999). The Modality of Particle Size Distributions of Environmental Aerosols. *Atmospheric Environment*, 33(27), 4401–4411. [https://doi.org/10.1016/s1352-2310\(99\)00217-4](https://doi.org/10.1016/s1352-2310(99)00217-4)
- Mostafa, M. Y., Khalaf, H. N., & Zhukovsky, M. (2021). Attachment rate characteristics of different wide used aerosol sources in indoor air. *Journal of Environmental Health Science and Engineering*, 19(1), 867–879. <https://doi.org/10.1007/s40201-021-00653-6>
- Musegaas, P. (2024, November 1). *Understanding the Tijuana River sewage crisis – an overview of causes and consequences*. San Diego Coastkeeper. <https://www.sdcoastkeeper.org/blog/tijuana-river-sewage-crisis-causes-consequences/>
- Nazaroff, W. W. (2021). Residential air-change rates: A critical review. *Indoor Air*, 31(2), 282–313. <https://doi.org/10.1111/ina.12785>
- NHS. (n.d.). Born in Bradford. <https://borninbradford.nhs.uk/>
- Okkonen, L., Elsayed, M., Silvonen, V., Taylor, J., Salo, L., Rönkkö, T., & Viitanen, A.-K. (2025). Utilization of low-cost sensor technology in indoor air quality monitoring. *Tampereen Yliopisto*.
- Pagels, J., Wierzbicka, A., Nilsson, E., Isaxon, C., Dahl, A., Gudmundsson, A., Swietlicki, E., & Bohgard, M. (2009). Chemical composition and mass emission factors of candle smoke particles. *Journal of Aerosol Science*, 40(3), 193–208. <https://doi.org/10.1016/j.jaerosci.2008.10.005>
- Pendergraft, M. A., Grimes, D. J., Giddings, S. N., Feddersen, F., Beall, C. M., Lee, C., Santander, M. V., & Prather, K. A. (2021). Airborne transmission pathway for coastal water pollution. *PeerJ*, 9. <https://doi.org/10.7717/peerj.11358>
- Pendergraft, M. A., Belda-Ferre, P., Petras, D., Morris, C. K., Mitts, B. A., Aron, A. T., Bryant, M., Schwartz, T., Ackermann, G., Humphrey, G., Kaandorp, E., Dorrestein, P. C., Knight, R., & Prather, K. A. (2023). Bacterial and chemical evidence of coastal water pollution from the Tijuana River in sea spray aerosol. *Environmental Science & Technology*, 57(10), 4071–4081. <https://doi.org/10.1021/acs.est.2c02312>
- Petition for sewer projet circulated. (1934, January 19). *The Chula Vista Star's San Ysidro Weekly News*, pp. 7–7.
- Qian, J., Wynn, T., Liu, B., Shan, Y., Bartington, S. E., Pope, F. D., Dai, Y., & Shi, Z. (2025). Enhancing accuracy of indoor air quality sensors via Automated Machine Learning Calibration. *Atmospheric Measurement Techniques*, 19(2), 603–615. <https://doi.org/10.5194/amt-19-603-2026>
- QuantAQ. (n.d.). *Welcome to the quantaq docs!:* *Quantaq Docs*. QuantAQ. <https://docs.quant-aq.com/>
- Quintana, P. J. E., Dumbauld, J. J., Garnica, L., Chowdhury, M. Z., Velascosoltero, J., Mota-Raigoza, A., Flores, D., Rodríguez, E., Panagon, N., Gamble, J., Irby, T., Tran, C., Elder, J., Galaviz, V. E., Hoffman, L., Zavala, M., & Molina, L. T. (2014). Traffic-related air pollution in the community of San Ysidro, CA, in relation to northbound vehicle wait

- times at the US–Mexico Border Port of Entry. *Atmospheric Environment*, 88, 353–361.
<https://doi.org/10.1016/j.atmosenv.2014.01.009>
- Rathbone, C. J., Bousiotis, D., Rose, O. G., & Pope, F. D. (2025). Using low-cost sensors to assess common air pollution sources across multiple residences. *Scientific Reports*, 15(1).
<https://doi.org/10.1038/s41598-025-85985-1>
- Rico, B., Barsanti, K., Porter, W., Stigler Granados, P., & Prather, K. (2025). Heavily polluted Tijuana River drives regional air quality crisis. *Science*, 389(6763).
<https://doi.org/10.26434/chemrxiv-2024-mjgbr>
- Ródenas García, M., Spinazzé, A., Branco, P. T. B. S., Borghi, F., Villena, G., Cattaneo, A., Di Gilio, A., Mihucz, V. G., Gómez Álvarez, E., Lopes, S. I., Bergmans, B., Orłowski, C., Karatzas, K., Marques, G., Saffell, J., & Sousa, S. I. V. (2022). Review of low-cost sensors for indoor air quality: Features and Applications. *Applied Spectroscopy Reviews*, 57(9–10), 747–779. <https://doi.org/10.1080/05704928.2022.2085734>
- Rogulski, M., & Badyda, A. (2019). Current trends in network based air quality monitoring systems. *IOP Conference Series: Earth and Environmental Science*, 214, 012085.
<https://doi.org/10.1088/1755-1315/214/1/012085>
- Rose, O. G., Bousiotis, D., Rathbone, C., & Pope, F. D. (2024). Investigating indoor air pollution sources and student’s exposure within school classrooms: Using a low-cost sensor and source apportionment approach. *Indoor Air*, 2024(1).
<https://doi.org/10.1155/2024/5544298>
- Rosenberg, P. D., Dean, A. R., Williams, P. I., Dorsey, J. R., Minikin, A., Pickering, M. A., & Petzold, A. (2012). Particle sizing calibration with refractive index correction for light scattering optical particle counters and impacts upon PCASP and CDP data collected during the Fennec campaign. *Atmospheric Measurement Techniques*, 5(5), 1147–1163.
<https://doi.org/10.5194/amt-5-1147-2012>
- Saladin, S. (2024, September 18). *Does the EPA correction algorithm for Wildfire Smoke PM2.5 developed for PurpleAir work for airgradient monitors?*. AirGradient.
<https://www.airgradient.com/blog/epa-correction-and-airgradient/>
- Sbai, S. E., Li, C., Boreave, A., Charbonnel, N., Perrier, S., Vernoux, P., Bentayeb, F., George, C., & Gil, S. (2021). Atmospheric photochemistry and secondary aerosol formation of urban air in Lyon, France. *Journal of Environmental Sciences*, 99, 311–323.
<https://doi.org/10.1016/j.jes.2020.06.037>
- Schoenherr, S. (2015, February 27). *Tijuana River Valley*. Tijuana River Valley - south bay historical society. <http://sunnycv.com/history/exhibits/trv.html>
- Seidel, D. J., Zhang, Y., Beljaars, A., Golaz, J.-C., Jacobson, A. R., & Medeiros, B. (2012). Climatology of the planetary boundary layer over the continental United States and Europe. *Journal of Geophysical Research: Atmospheres*, 117, D17106.
<https://doi.org/10.1029/2012JD018143>
- Seinfeld, J. H., & Pandis, S. N. (2016). *Atmospheric chemistry and physics: From air pollution to climate change* (3rd ed.). Wiley.

- Selgi-Harrigan, A. (2025, May 16). *Sewage pollution history reaches back to the 1930s*. imperialbeachnewsca.com.
https://www.imperialbeachnewsca.com/news/article_c9133f9e-ef7e-4960-b37a-23e0c6444c47.html
- Sensirion. (n.d.). *Datasheet SGP41 Air Quality Sensor for VOC and NOx Measurements*. Sensirion.
https://sensirion.com/media/documents/5FE8673C/61E96F50/Sensirion_Gas_Sensors_Datasheet_SGP41.pdf
- Settimo, G., Yu, Y., Gola, M., Buffoli, M., & Capolongo, S. (2023). Challenges in IAQ for indoor spaces: A comparison of the reference guideline values of indoor air pollutants from the governments and international institutions. *Atmosphere*, 14(4), 633.
<https://doi.org/10.3390/atmos14040633>
- Shah, K. B., Kim, D., Pinakana, S. D., Hobosyan, M., Montes, A., & Raysoni, A. U. (2024). Evaluating indoor air quality in residential environments: A study of PM2.5 and CO2 Dynamics using low-cost sensors. *Environments*, 11(11), 237.
<https://doi.org/10.3390/environments11110237>
- Shina, D. N., & Canter, A. (2017). (tech.). *Annual Air Quality Monitoring Network Plan 2016*. SDAPCD. Retrieved from
<https://www.sdapcd.org/content/dam/sdapcd/documents/monitoring/2016-Network-Report.pdf>
- Siddique, A., Al-Shamlan, M. Y., Al-Romaihi, H. E., & Khwaja, H. A. (2023). Beyond the outdoors: Indoor air quality guidelines and standards – challenges, inequalities, and the path forward. *Reviews on Environmental Health*, 40(1), 21–35.
<https://doi.org/10.1515/reveh-2023-0150>
- Silva, G., Duarte, J., Baptista, J. S., & Rufo, J. C. (2026). Low-cost sensors for indoor air quality monitoring: A systematic review of accuracy, applications, and limitations. *Journal of the Air & Waste Management Association*, 76(5), 315–341.
<https://doi.org/10.1080/10962247.2026.2624795>
- Simmons, A. (2022). Tijuana River Valley pollution: How the Environmental Protection Agency expects to end a ninety-year environmental and public health crisis. *Villanova Environmental Law Journal*, 33(1), 113–142.
- Sipilä, M., Berndt, T., Petäjä, T., Brus, D., Vanhanen, J., Stratmann, F., Patokoski, J., Mauldin, R. L., Hyvärinen, A.-P., Lihavainen, H., & Kulmala, M. (2010). The role of sulfuric acid in atmospheric nucleation. *Science*, 327(5970), 1243–1246.
<https://doi.org/10.1126/science.1180315>
- United States Census Bureau. (n.d.). United States Census Bureau.
https://data.census.gov/profile/Census_Tract_101.09;_San_Diego_County;_California?g=1400000US06073010109
- Venn, M. A., & Sant, K. E. (2026). Transboundary Environmental Challenges: The Tijuana River Crisis. essay.

- Wallace, L., & Ott, W. (2023). Long-term indoor-outdoor PM_{2.5} measurements using PurpleAir sensors: An improved method of calculating indoor-generated and outdoor-infiltrated contributions to potential indoor exposure. *Sensors*, 23(3), 1160. <https://doi.org/10.3390/s23031160>
- World Health Organization. Regional Office for Europe (2010). WHO guidelines for indoor air quality: selected pollutants. World Health Organization. Regional Office for Europe. <https://iris.who.int/handle/10665/260127>
- World Health Organization. (2021). *WHO global air quality guidelines: Particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. World Health Organization. <https://www.who.int/publications/i/item/9789240034228>
- World Health Organization. (2024, October 24). *Ambient (outdoor) air pollution*. World Health Organization. [https://www.who.int/news-room/fact-sheets/detail/ambient-\(outdoor\)-air-quality-and-health#:~:text=Overview,in%20cardiovascular%20illness%20and%20death](https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health#:~:text=Overview,in%20cardiovascular%20illness%20and%20death)
- Xu, K., Liu, Y., Li, C., Zhang, C., Liu, X., Li, Q., Xiong, M., Zhang, Y., Yin, S., & Ding, Y. (2023). Enhanced Secondary Organic Aerosol Formation during dust episodes by photochemical reactions in the winter in Wuhan. *Journal of Environmental Sciences*, 133, 70–82. <https://doi.org/10.1016/j.jes.2022.04.018>
- Zaky, N., Li, T., & Stopps, H. (2025). Validating the performance of low-cost IAQ sensors through co-location. *Journal of Building Physics*, 49(6), 829–851. <https://doi.org/10.1177/17442591251367436>
- Zaman, S. U., Yesmin, M., Pavel, Md. R., Jeba, F., & Salam, A. (2021). Indoor air quality indicators and toxicity potential at the hospitals' environment in Dhaka, Bangladesh. *Environmental Science and Pollution Research*, 28(28), 37727–37740. <https://doi.org/10.1007/s11356-021-13162-8>
- Zhao, Z., Di, P., Chen, S., Avise, J., Kaduwela, A., & DaMassa, J. (2020). Assessment of climate change impact over California using dynamical downscaling with a bias correction technique: Method validation and analyses of summertime results. *Climate Dynamics*, 54(7–8), 3705–3728. <https://doi.org/10.1007/s00382-020-05200-x>