

## Using low-cost sensors for source attribution and health assessment: An air quality study in Brownsville, Texas

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### ABSTRACT

Air quality monitoring remains a challenge in areas lacking or having sparse federal monitoring infrastructure, posing significant barriers to public health research. This study demonstrates the usage of low-cost sensors in addressing gaps in air quality monitoring, source attribution, and health risk assessment in a Brownsville, TX neighborhood impacted by emissions from a barite and celestite mineral processing unit. PM<sub>2.5</sub> concentrations were measured using PurpleAir sensors deployed across three residential locations, with the site nearest to the processing unit recording a 24-h averaged PM<sub>2.5</sub> concentration of 25.12 µg/m<sup>3</sup>—approximately 2.79 times higher than the nearest Texas Commission of Environmental Quality (TCEQ) CAMS (Continuous Ambient Monitoring Station) site. Indoor air quality was also evaluated in two of the residential units to characterize the influence of outdoor pollution on indoor microenvironment. The local wind data was used to conduct source attribution, and the results suggested that the mineral processing entity located south of the neighborhood was the likely source of particulate pollution in this middle-income neighborhood. A health risk assessment for PM<sub>2.5</sub> exposure was conducted, and the results indicate a hazard quotient level below unity, suggesting low-risk non-carcinogenic effects on the community. This study underscores the pivotal role of low-cost sensors in generating localized air quality data, and their potential to support ameliorative evidence-based interventions.

### 1. Introduction

Clean air is essential for a healthy environment and human well-being. A plethora of research has demonstrated that air pollution has a detrimental impact not only on the environment but also on human health. Acid rain, and ozone depletion (Manosalidis et al., 2020; Department of Environmental Protection, 2017) are some of the environmental consequences of air pollution. Globally, 8.1 million deaths are attributed to air pollution, making it the second leading cause of death only after high blood pressure (Health Effects Institute, 2024). Fine inhalable particles, referred to as PM<sub>2.5</sub>, with aerodynamic diameters of 2.5 µm or smaller, are a significant threat to human health. Long-term or chronic exposures to PM<sub>2.5</sub> were found to increase the risk of health endpoints including asthma (Jacquemin et al., 2023; Kkreis et al., 2017; Ni et al., 2024; Pierangeli et al., 2020; Zhang et al., 2022), cardiovascular problems (Jia et al., 2023; Lim et al., 2021; Zou et al., 2022; Hamanaka and Mutlu, 2018) and mortality (Li et al., 2018; Maji

et al., 2018; Zhao et al., 2018). Short-term or acute exposure to elevated levels can also cause health problems ranging from irritation of the eye, skin, nose, and throat (Balali-Mood et al., 2016; Manosalidis et al., 2020; Shetty et al., 2023) to severe conditions including chronic obstructive pulmonary disease (COPD) (Manosalidis et al., 2020) and nasal infections such as nasopharyngitis (Zhang et al., 2019).

In the United States of America, the Clean Air Act and its subsequent amendments thereof have resulted in a 64.9 % reduction in particulate air pollution since 1970, increasing the average American's life expectancy by 1.4 years (Air Quality Life Index, 2023; Greenstone et al., 2025). However, the disparities in particulate air pollution exposure are known to exist. Re-suspension of settled particles such as road dust, construction activities, and industrial dust are potential sources of urban ambient PM<sub>2.5</sub> Anastasopoulos et al. (2022); Shapero et al. (2023); Mikati et al. (2018) analyzed nationwide disparities in PM<sub>2.5</sub> exposure by linking PM-emitting facilities from the 2011 National Emissions Inventory to nearby residential populations, calculating emission burdens

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by race, ethnicity, and poverty, and evaluating disparities at various levels. The study found significant nationwide disparities in PM<sub>2.5</sub> exposure, with the black population and the population in poverty facing 1.54 and 1.35 higher burdens, respectively than the overall population, consistent across geographic scales. Tessum et al. (2021) concluded that industrial activities, light-duty gasoline vehicles, construction, and heavy-duty diesel vehicles are among the largest sources of disparity, varying between source type and location.

The local and regional attainment of the National Ambient Air Quality Standard (NAAQS) is assessed by utilizing data from the State and Local Air Monitoring Stations (SLAMS) network (Kelp et al., 2022). However, almost two-thirds of U.S. counties lack an ambient air quality monitoring station (American Lung Association, 2024; Holloway et al., 2021). Numerous studies have also concluded that the distribution of monitoring stations is uneven and disproportionately placed (Wang et al., 2024; Kelp et al., 2022; Haskell-Craig et al., 2024). The regulatory monitoring network may also obscure pollution hotspots by not incorporating community-based air monitoring, which could reveal polluted microenvironments where communities are exposed to harmful levels of air pollution (Bradbury and Cross, 2023). Recent methodologies involving satellite-based monitoring and ground-based low-cost sensors have proved to be instrumental in understanding the air quality in regions with no or low regulatory monitoring (Malings et al., 2020). Low-cost sensors, however, come with their challenges, including sensor drift and shorter lifespans (Wang et al., 2023). They are also affected by various meteorological parameters, such as relative humidity and temperature (Zou et al., 2021; Jayaratne et al., 2018), as well as wind, barometric pressure, and particle composition (Wang et al., 2023). However, these can be addressed by calibrating measurements using collocated data (Gupta et al., 2022; Aix et al., 2023; Raheja et al., 2023).

PM<sub>2.5</sub> pollution sources, like industrial facilities, are often found in low-income neighborhoods, leading to higher air pollution in these areas (Jbaily et al., 2022; Tessum et al., 2021; Rentschler and Leonova, 2023). However, the lack of regulatory or community monitoring at such locations may inhibit our ability to accurately characterize pollution issues at the neighborhood level. This study focuses on a middle-income neighborhood of Brownsville, South Texas, and employs low-cost

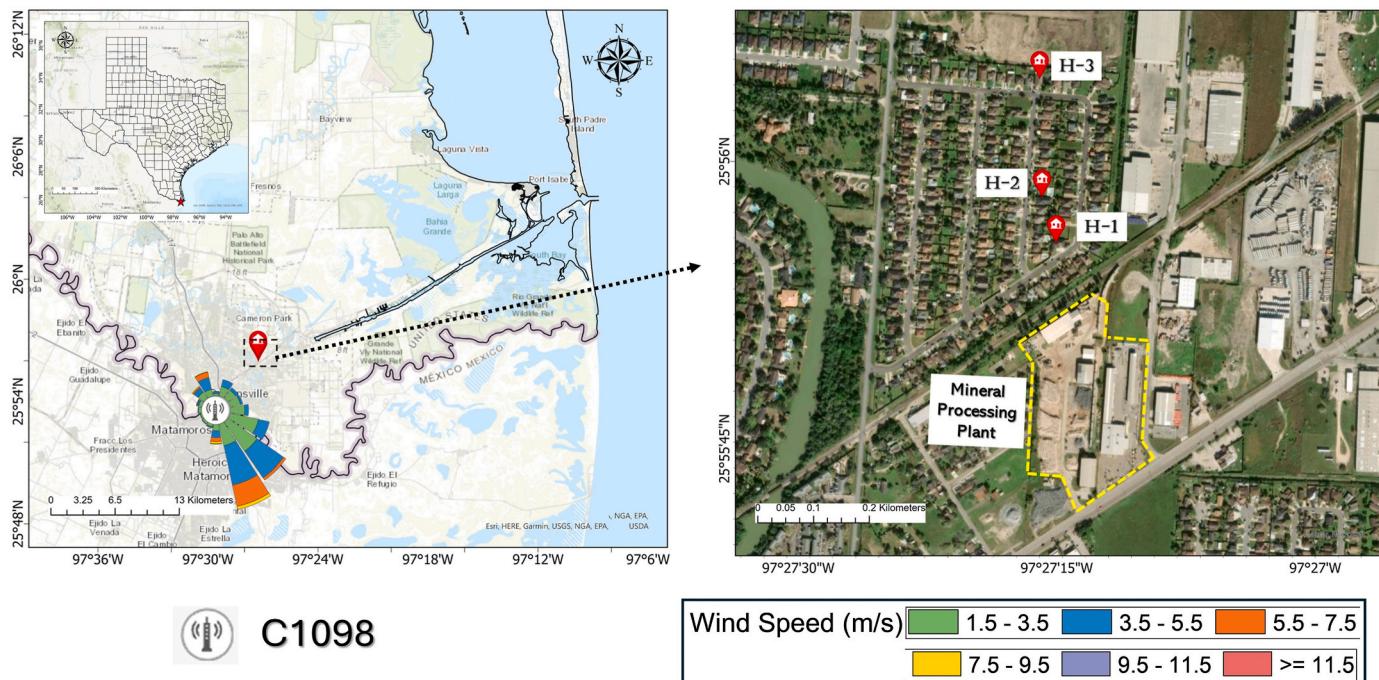
sensors along with community involvement to gather air quality data. Brownsville is a city located on the U.S.-Mexico border region adjacent to the Gulf of America (Fig. 1). Of the total estimated population of 190,158 as of 2023, 94 % are of Hispanic/Latino origin, making it the fourth-highest percentage of any U.S. city outside of Puerto Rico (U.S. Census Bureau, 2023).

This region engages in extensive cross-border international trade with Mexico under the trilateral North American Free Trade Agreement (NAFTA) enacted in 1994 (Mendez et al., 2022). With this border city having accessible transportation options (Dietrich, 2023), the growth of industrial activity in the recent past has been exponential which has resulted in environmental pollution. Biomass burning, heavy traffic-related diesel emissions, industrial boilers, and dust from unpaved roads and construction sites are major sources of particulate emissions in this region (Karnae and John, 2019; Pinakana et al., 2023). Dust emissions from paved roads in this area is also projected to rise from 2018 to 2032 due to increased vehicle miles traveled (U.S. EPA, 2024a). Air quality data collected by regulatory monitors from 2019 to 2021 indicates that Cameron County, where Brownsville is located, does not meet the newly proposed annual PM<sub>2.5</sub> standard of 9.0 µg/m<sup>3</sup> (U.S. EPA, 2024b). This research study aims to quantify the particulate pollution, its sources, and the health impacts on the local community. This endeavor also exemplifies the usage of low-cost sensor data in identifying spatial and temporal trends of air pollutants along with baseline source attribution.

## 2. Materials and methods

### 2.1. Study area and sampling

The study was conducted in the community neighborhood of block group number 480610131022, the city of Brownsville, TX. This community is located at coordinates 25.933° N and 97.455° W, covering an area of 0.169 square kilometers (Fig. 1). The prevailing wind directions are mainly south and southeast. The community is bordered by warehouse operations to the east, barren land to the north, a barite and celestite specialty mineral processing entity to the south, and limited



**Fig. 1.** Map showing the location of Brownsville, Texas, situated adjacent to the Rio Grande River, which also serves as the international border with Mexico. The city is near the Gulf of America. The wind patterns in the region are shown via a wind rose for the study period.

greenery to the west. Residents had voiced ongoing concerns about air pollution in the community as well (Clark, 2024a, 2024b; Rosales, 2025).

$\text{PM}_{2.5}$  data is publicly available from a regulatory TCEQ (Texas Commission on Environmental Quality) Continuous Ambient Monitoring Station (CAMS) site in the city of Brownsville. TCEQ CAMS – 1098, also referred to as C1098 is one of the four CAMS sites in this region that monitors  $\text{PM}_{2.5}$ . However, located at 25.9009° N and –97.50779° W, it is 6 km away from the neighborhood. Hence, as shown in Fig. 1, PurpleAir  $\text{PM}_{2.5}$  sensors by Purple Air L.L.C., Draper, UT, U.S. A., were deployed in three different houses, House-1, House-2, and House-3 across the neighborhood, referred to as H1, H2, and H3 respectively. PurpleAir (PA)  $\text{PM}_{2.5}$  sensors use dual Laser Particle Counters (PMS-5003) to measure concentrations of  $\text{PM}_{2.5}$  and have been used in multiple community-based air pollution studies across the world (Raheja et al., 2022; Lu et al., 2022). The outdoor data was collected for a period of 133 days, i.e., from December 23, 2023, to May 03, 2024. Data collection for  $\text{PM}_{2.5}$  in indoor environments was also done simultaneously at H1 from February 10–24, 2024, and H3 from February 25–March 6, 2024, for a period of 14 days each.

## 2.2. Calibration of DustTrak

Using  $\text{PM}_{2.5}$  data from low-cost sensor units in collocation with a Federal Equivalent Method (FEM) or Federal Reference Method (FRM) monitor is a common method to improve measurement accuracy. This data is typically used to correct both the bias of low-cost sensors and address the effects of meteorological parameters such as T and RH (deSouza et al., 2022). In the absence of FEM or FRM, multiple studies have used reference instruments such as TSI DustTrak II 8533 (deSouza et al., 2023; Huang et al., 2022) and TSI DustTrak Aerosol Monitor 8530 (Zheng et al., 2024). In this research study, obtaining the requisite permission to conduct the collocation activities with the regulatory-grade instrument at the local TCEQ CAMS site was nearly impossible. Therefore, a collocation activity was performed by deploying the PA sensors used in the study with the research-grade instrument DustTrak™ DRX Aerosol Monitor 8534 (TSI Inc., Shoreview, MN, USA). However, literature has reported that the DustTrak measurements are not identical to mass-based measurements, as the instrument uses an aerosol scattering method. Javed and Guo (2021) concluded that the TSI DustTrak DRX aerosol monitor overestimated  $\text{PM}_{2.5}$  measurements by a factor of ~2, compared to those obtained using a filter-based gravimetric technique. Both et al. (2013) compared DustTrak  $\text{PM}_{2.5}$  measurements with E-BAM Beta Attenuation Mass Monitor (MetOne, Grants Pass, OR) readings, finding a strong correlation ( $R^2 = 0.96$ ) but applying a correction factor of 2.77 for accurate readings.  $\text{PM}_{2.5}$  levels recorded by the TSI DustTrak were approximately 2.2 times higher than those measured with a Met One E-BAM (Cheng et al., 2008). To correct the data reported by the reference grade instrument, the following equation was used based on the results from the study by Jaffe et al. (2014). This equation was developed using a Reduced Major Axis (RMA) Regression method after comparing measurements of DustTrak to those of Tapered Element Oscillating Microbalance (TEOM). It was chosen because of its consistency with earlier findings by Jamriska et al. (2004), which reported a nearly identical relationship with a slope value of 0.45 and an intercept value of 4.882. The equation used in this study is as below:

$$\text{Corrected PM}_{2.5} = \text{DustTrak PM}_{2.5} (\mu\text{g/m}^3) \times 0.4193 + 4.414$$

## 2.3. Correction of PurpleAir $\text{PM}_{2.5}$ values

PurpleAir sensors are being used worldwide to measure hyper-local  $\text{PM}_{2.5}$  values. Utilizing two optical particle sensors of Plantower PMS5003 referred to as Channel A and B, these sensors provide 2-min-

average data sampled at alternating 10-s intervals. Although these sensors are very useful in understanding particle pollution trends at a very high spatial and temporal resolution, data quality remains a major challenge. Changes in temperature (T) or relative humidity (RH) could affect the performance of the PA-II units Bi et al. (2020); deSouza et al., 2022; Barkjohn et al. (2021) developed an empirical U.S.-wide correction factor for  $\text{PM}_{2.5}$ , which is used widely in addition to all PA measurements in the AirNow Fire and Smoke Map. However, Jaffe et al. (2023) studied the accuracy of a  $\text{PM}_{2.5}$  correction factor and found it provided reasonable results for urban winter pollution and smoke events but underestimated concentrations by 5–6 times during dust events.

The BOSCH BME280 sensor in PurpleAir measures temperature and relative humidity, providing values that are highly correlated with ambient conditions but are typically 2.7–5.3 °C warmer and 9.7%–24.3% drier, as its placement inside the polyvinyl chloride (PVC) cap contributes to these differences (Barkjohn et al., 2022). These values are used in calibration models or equations. Prior studies have used linear regression, multivariate regression, and machine learning algorithms including random forest (RF), artificial neural network (ANN), extreme gradient boosting (XGBoost), Super Learner (SL), support vector regression (SVR), light gradient boosting machine (LightGBM) (Zimmerman et al., 2018; Giordano et al., 2021; Gupta et al., 2022; Wang et al., 2023; Shah et al., 2024).

## 2.4. Data cleaning and calibration

The verification of data quality from each sensor is essential before proceeding with data analysis to obtain accurate and reliable results. Gupta et al. (2022) concluded in their study that there can be significant differences between channel A and channel B of the same PurpleAir sensor. To ensure data quality and reliability for the exposure calculations, data cleaning criteria were followed for our dataset. All PA sensor readings exceeding 1000  $\mu\text{g/m}^3$ , either from the A or B channel, were excluded as the maximum range of PurpleAir is 1000  $\mu\text{g/m}^3$ . Negative temperature values recorded in degrees Fahrenheit were removed, too, as they are likely erroneous. Data points with absolute differences exceeding 50 % between the channels were removed.

In this study, we utilized a neural network-based calibration model. Different predictor variables used were T, RH, and raw  $\text{PM}_{2.5}$  measurements acquired from the low-cost PA sensors. The 1-h average values from PA sensors paired with the corrected DustTrak™ DRX values were used to train the calibration model. Multiple studies, including Yaqoob et al. (2024), Si et al. (2020); Chen et al. (2018), have concluded that Neural Networks perform better than other calibration methods. Unlike linear regression methods, they capture the non-linear relationship; however, the overall computation load in terms of memory and time is higher (Mahajan & Kumar, 2020). Hence, for better data accuracy, we have utilized a neural network. It consisted of a single hidden layer with a linear transfer function.

## 2.5. Source attribution

Understanding the sources of ambient particulate pollution is crucial, and source apportionment studies are gaining traction as an effective method to pinpoint their origins. Positive Matrix Factorization (PMF) is one of the most used methods to identify ambient sources of  $\text{PM}_{2.5}$  (Ho et al., 2018; Anwar et al., 2024; Dutton et al., 2010; Srivastava et al., 2021; Lee et al., 2023). Receptor models, such as chemical mass balance (Yao et al., 2024; Tian et al., 2023; Tefera et al., 2021) and Unmix (Song et al., 2006; Lewis et al., 2003; Hu et al., 2006) have also been widely used. Other models for source apportionment include the Conditional Probability Function (CPF) (Kim et al., 2003; Seyed et al., 2024) and Nonparametric Wind Regression (NWR) (Henry et al., 2009; Du and Turner, 2015), which use local wind data, as well as the Potential Source Contribution Function (PSCF) (Ashbaugh et al., 1985; Kim et al., 2016), which incorporates back trajectories. With the increase in use of

low-cost sensors for air quality monitoring, different methods including Principal Component Analysis (PCA), Non-negative Matrix Factorization (NMF), Machine Learning (ML), Simplified Quantified Trajectory Bias Analysis (SQTBA), and Chemical Mass Balance (CMB) were studied to be used for sources identification and apportionment (Bousiotis et al., 2025).

While source apportionment quantifies the relative contributions of various emission source types, this study primarily used CPR and NWR models to conduct source attribution. Unlike source apportionment, source attribution focuses on identifying the geographical or directional origin of source. Hodoli et al. (2023) also used data collected from low-cost sensors to understand sources of PM through bivariate plots and cluster analysis.

The CPF model is summarized as below respectively:

$$\text{CPF} = \frac{m_{\theta j}}{n_{\theta j}}$$

$m_{\theta j}$  represents the number of samples within the wind sector  $\theta$  and wind speed interval  $j$  that have mixing ratios greater than a specified concentration.  $n_{\theta j}$  refers to the total number of samples observed in the same wind direction and speed interval.

The NWR model implements the Non-parametric Wind Regression approach of Henry et al. (2009), with a slightly different method using Gaussian kernels for both wind direction and speed. CPF values, polar plots, and NWR plots were visualized using hourly wind direction and speed data using the OpenAir package in R (Carslaw and Ropkins, 2012). Origin Pro (Origin Lab Corporation, Northampton, MA, USA; Version, 2024) was used to plot all the graphs.

## 2.6. Human health risk assessment

Health risk analysis systematically evaluates the relationship between environmental pollutants and their effects on human health (Abdulaziz et al., 2022). Hazard Quotient (HQ) is a widely used metric to understand the non-carcinogenic risk caused by PM exposure (Chalvatzaki et al., 2023; Rostami et al., 2019; Yunesian et al., 2019). A HQ value of  $\leq 1$  indicates a low-risk non-carcinogenic effect of the pollutant, while a value  $> 1$  indicates a high-risk effect on the exposed population. It was calculated using the following equation:

$$\text{HQ} = \text{ADD/RfD}$$

$$\text{ADD } (\mu\text{g kg}^{-1} \text{ d}^{-1}) = (\text{C}_{\text{total}} \times \text{IR} \times \text{ED} \times \text{EF}) / (\text{BW} \times \text{AT})$$

$$\text{RfD} = (\text{RfC} \times \text{IR}) / \text{BW}$$

where ADD is the average daily dose, and RfD is the reference dose of the pollutant,  $\text{C}_{\text{total}} (\mu\text{g m}^{-3} \text{ d}^{-1})$  = concentration of pollutant, IR ( $\text{m}^3 \text{ d}^{-1}$ ) = inhalation rate, ED (year) = exposure duration, EF ( $\text{d year}^{-1}$ ) = exposure frequency, BW (kg) = body weight, AT (d) = average timing and RfC is the reference concentration ( $\mu\text{g m}^{-3}$ ). The ED value was set for 1 year, AT value at 365 days, EF value at 365 days again since the sampling places were residential areas, and RfC value used was the 24-hr U.S. EPA National Ambient Air Quality Standards (NAAQS) for PM<sub>2.5</sub>, i.e., 35  $\mu\text{g/m}^3$ .

## 3. Results and discussion

### 3.1. Calibration of raw PM<sub>2.5</sub> values

The data from low-cost sensors was cleaned and corrected using the methodology explained in Section 2.3, employing a one-hidden layer neural network with a linear transfer function. The accuracy of the trained model was tested utilizing the data from the research-grade monitor DustTrak™ DRX Aerosol Monitor 8534, which was installed in the indoor environments at two of the study residences along with the PA sensor for a period of two weeks each. Performance metrics such as mean absolute error (MAE), root mean squared error (RMSE), along

with  $R^2$ , as shown in the equations below, are usually reported (Giordano et al., 2021).

$$\text{MAE} = \frac{\sum_{i=1}^n |c_{\text{estimated},i} - c_{\text{true},i}|}{n}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (c_{\text{estimate},i} - c_{\text{true},i})^2}{n}}$$

As shown in Fig. 2a, the RMSE improved from 8.53 to 7.06, while MAE decreased from 5.34 to 3.82, indicating an improvement in the corresponding values. The higher PM<sub>2.5</sub> values in the indoor environment are probably due to indoor events like cooking, dusting, vacuum cleaning, or secondhand smoke (Pinakana et al., 2024). Overall, the combined metrics highlight the model's accuracy and reliability in calibrating the outdoor PM<sub>2.5</sub> concentrations at the residences to evaluate the residents' exposure levels. Fig. 2b shows the time series of data from the reference monitor along with both raw and corrected low-cost sensor data in the indoor environment.

### 3.2. Temporal trends of particulate pollution levels

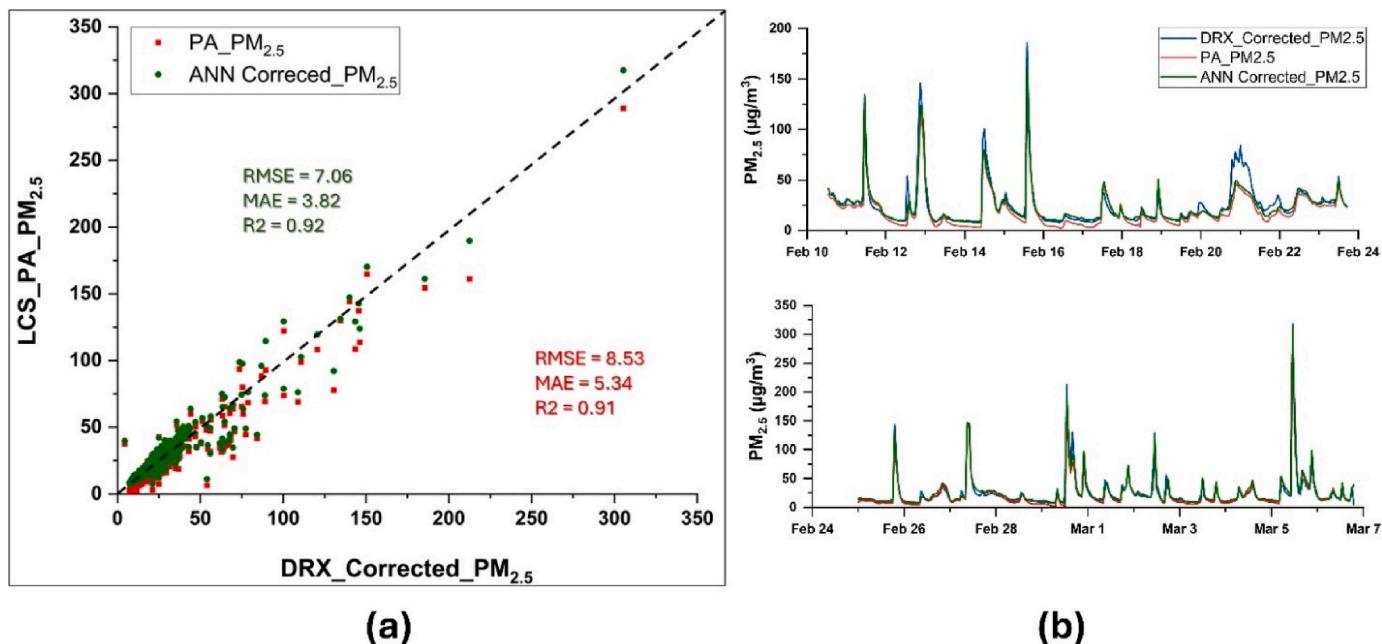
#### 3.2.1. 1-Hour averaged concentrations

The descriptive statistics of 1-h averaged PM<sub>2.5</sub> concentrations observed at the residences are shown in Table 1. The sensor at H1 malfunctioned midway during the study resulting in the data completion percentage of only 54 %. However, this data was included in the final analysis because of the value it adds to understanding the spatial and temporal trends in the neighborhood. Also, H1 was located nearest to the specialty mineral processing unit. A clear variation was observed between the data recorded at three residences and the TCEQ CAMS site. The mean PM<sub>2.5</sub> observed at H1, H2, and H3 is 24.85 + 15.81  $\mu\text{g/m}^3$ , 25.34 + 15.21  $\mu\text{g/m}^3$  and 25 + 15.43  $\mu\text{g/m}^3$  respectively, while the mean value at C 1098 was 9.17 ± 8.36  $\mu\text{g/m}^3$ . As observed in the trends in the mean observations, the maximum value at H1 was recorded as high as 163.9  $\mu\text{g/m}^3$  on February 20, 2024, while the maximum value recorded at H2 and H3 was 129.29  $\mu\text{g/m}^3$ , and 101.04  $\mu\text{g/m}^3$  respectively. Fig. 3 also shows the time series of the recorded data. Box plot analysis, as shown in Fig. 4, also signifies the variability of PM<sub>2.5</sub> concentrations from H1, H2, and H3 compared to C1098.

#### 3.2.2. 24-Hour average concentrations

24-h average concentration values were calculated to compare the particulate pollution with the federal air quality standards. The descriptive statistics, as noted in Table 2, detail the differences in mean values at different locations in the study. The mean PM<sub>2.5</sub> value recorded at H1 was 24.92 ± 11.06  $\mu\text{g/m}^3$  and values ranging from 11.03  $\mu\text{g/m}^3$  to 54.64  $\mu\text{g/m}^3$ . The concentrations at H2 were slightly higher than that of H1, with a mean of 25.12 + 11.22  $\mu\text{g/m}^3$  and a range between 8.70 and 54.37  $\mu\text{g/m}^3$ . H3 exhibited similar concentrations as the other two sampling locations, with a mean value of 25.09 ± 12.50  $\mu\text{g/m}^3$  and values ranging between 9.68 and 62.47  $\mu\text{g/m}^3$ . C1098, located farther away from the neighborhood, stands out for its significantly lower mean of 9.13 ± 6.24  $\mu\text{g/m}^3$  and a tight range from 1.41 to 29.83  $\mu\text{g/m}^3$ .

PM<sub>2.5</sub> concentrations from three sampling points along with the CAMS site, i.e., C1098, over a period of December 22, 2023, to April 22, 2024 is shown in Fig. 5. The black dotted line in the time series plot represents the 24-hr U.S. EPA NAAQS for PM<sub>2.5</sub>, i.e., 35  $\mu\text{g/m}^3$ . The number of days each sampling location in the neighborhood crosses the NAAQS was 12 days for H1, 25 days for H2, and 29 days for H3. This, along with the maximum values of all three locations, H1, H2, and H3, standing at 54.64, 54.37, and 62.47  $\mu\text{g/m}^3$ , indicates that the neighborhood was significantly impacted by particle pollution. And all the sampled locations in the neighborhood were comparatively more



**Fig. 2.** (a) Scatter plot showcasing the comparison of raw and ANN-corrected low-cost sensor data with reference monitor. (b) Time series of data from the reference monitor, along with both the raw and corrected low-cost sensor data.

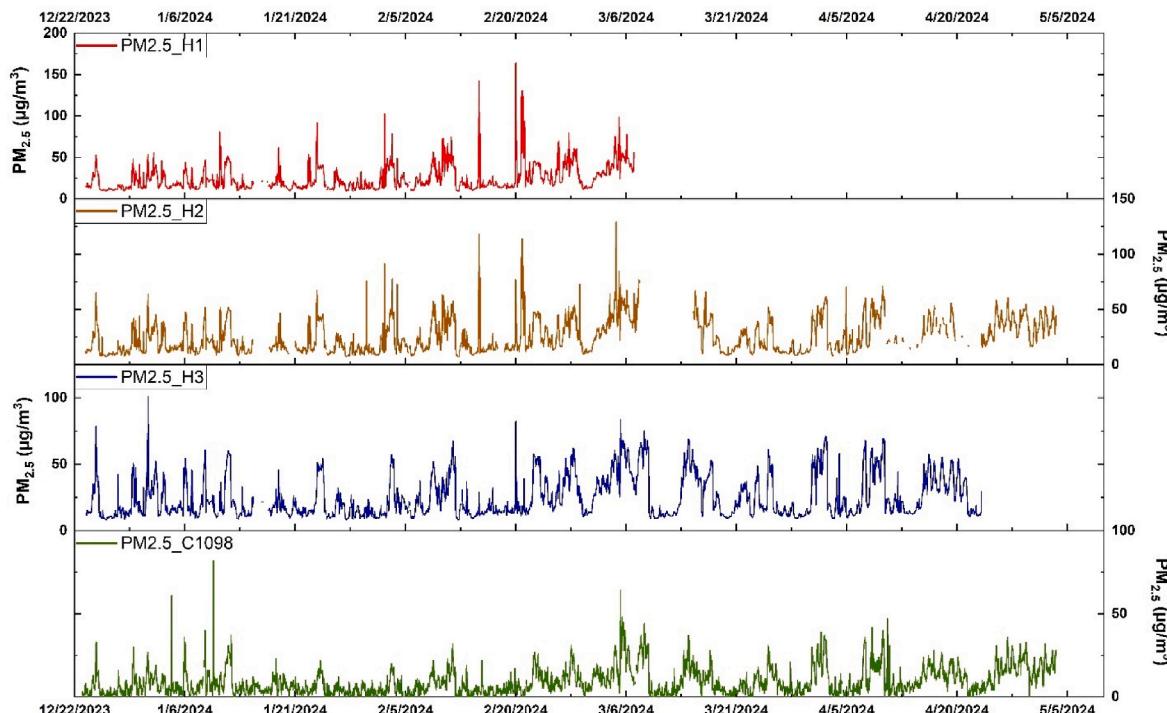
**Table 1**  
Descriptive statistics of 1-h averaged PM<sub>2.5</sub> concentrations ( $\mu\text{g}/\text{m}^3$ ).

	Mean + SD	Minimum	Maximum	Median	% of data completion
H1	24.85 ± 15.81	9.54	163.9	19.27	54.47
H2	25.34 ± 15.21	7.19	129.29	20.04	84.28
H3	25 ± 15.43	8.14	101.04	18.44	89.87
C1098	9.17 ± 8.36	1	82	7	99.65

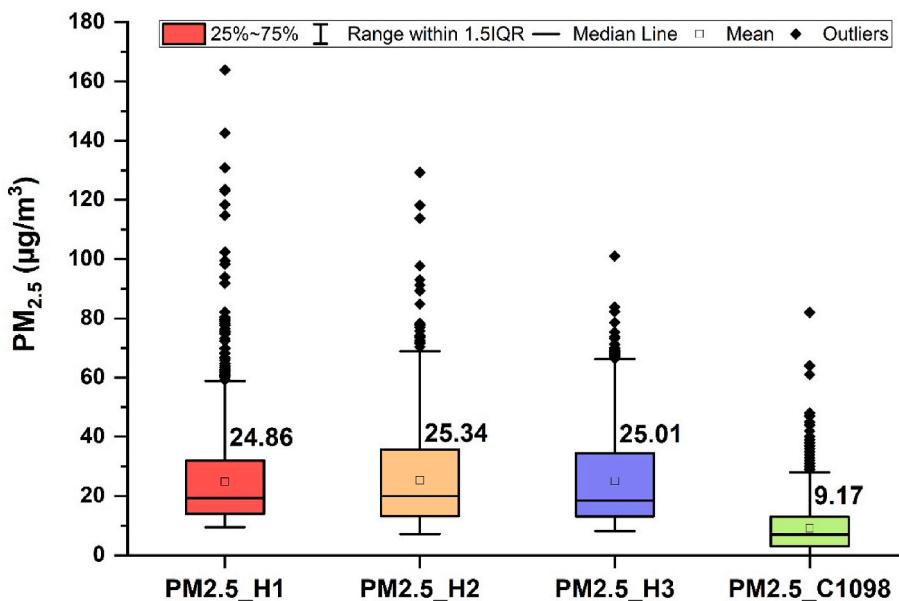
impacted than the nearest CAMS station recording the ambient PM<sub>2.5</sub> concentrations. Fig. 6 shows the boxplots also signifying the variability of 24-h average PM<sub>2.5</sub> concentrations from H1, H2, and H3 to C1098.

### 3.3. Comparison of outdoor – Indoor concentrations

To understand the impact of outdoor particulate pollution on indoor levels, purple air sensors were deployed in indoor environments for two of the three sampling sites. The sensors were deployed for a period of 13 and 11 days at H1 and H3 sites, respectively. The descriptive statistics of



**Fig. 3.** Time series of 1-h averaged PM<sub>2.5</sub> values at the sampling sites and nearest federal monitoring site C1098.



**Fig. 4.** Box plots of 1-h averaged  $\text{PM}_{2.5}$  values at the sampling sites along with the nearest federal monitoring site C1098.

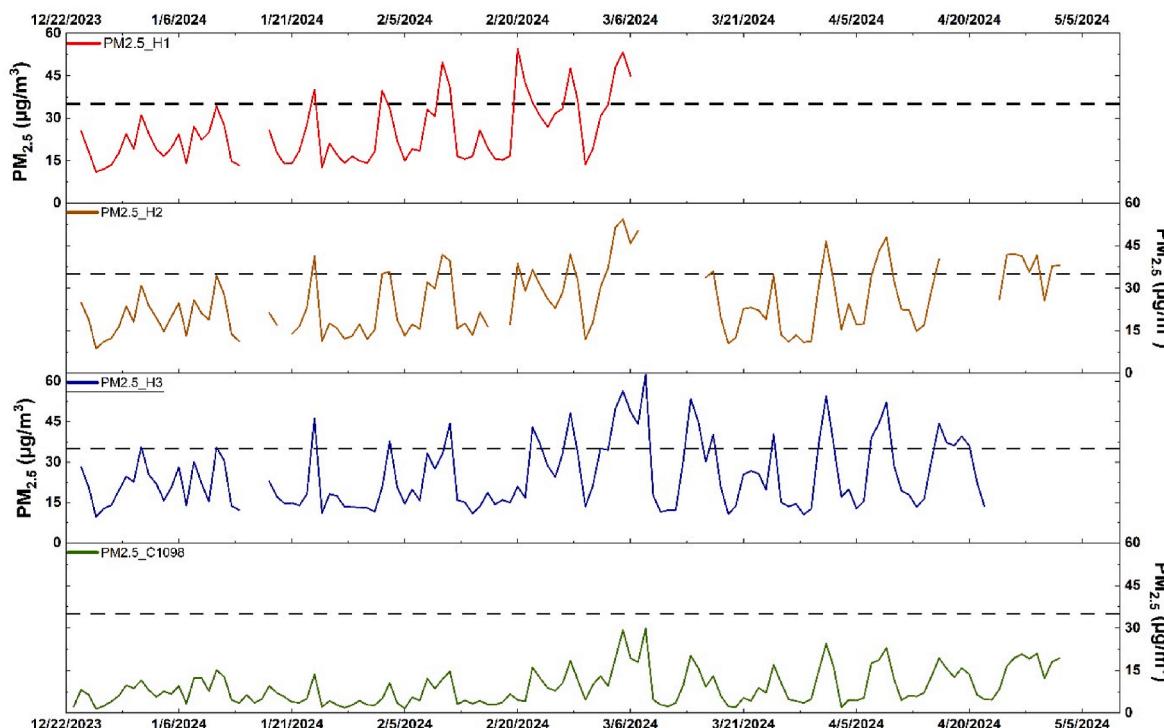
**Table 2**

Descriptive statistics of 24-h averaged  $\text{PM}_{2.5}$  concentrations ( $\mu\text{g}/\text{m}^3$ ).

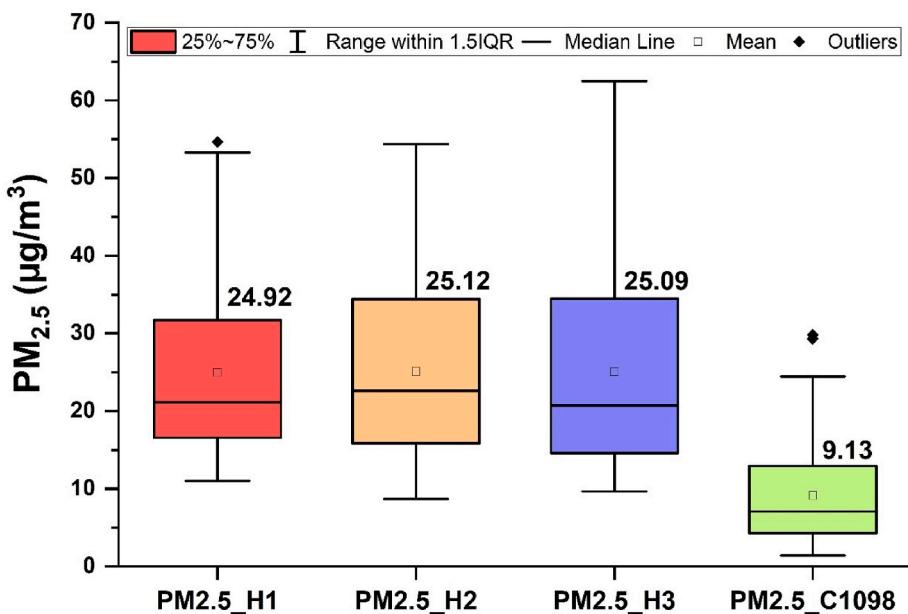
	Mean + SD	Minimum	Maximum	Median	% of data completion
H1	$24.92 \pm 11.06$	11.03	54.64	21.14	53.79
H2	$25.12 \pm 11.22$	8.70	54.37	22.64	83.33
H3	$25.09 \pm 12.50$	9.68	62.47	20.73	89.39
C1098	$9.13 \pm 6.24$	1.42	29.83	7.08	100.00

the hourly-averaged  $\text{PM}_{2.5}$  collected indoors are presented in [Table 3](#). At H1, the mean indoor  $\text{PM}_{2.5}$  concentration was  $25.36 \mu\text{g}/\text{m}^3$ , while at H3, the mean indoor  $\text{PM}_{2.5}$  concentration was as high as  $24.32 \mu\text{g}/\text{m}^3$ . The maximum indoor  $\text{PM}_{2.5}$  concentration at H1 reached  $137.29 \mu\text{g}/\text{m}^3$ , whereas the maximum value at H3 reached  $172.97 \mu\text{g}/\text{m}^3$ , which is higher than that of H1. [Fig. 7](#) presents a stacked time-series graph illustrating hourly averaged  $\text{PM}_{2.5}$  concentrations ( $\mu\text{g}/\text{m}^3$ ) over two different periods and sample sites. The upper graph visualizes data from site H1 (February 10–24, 2024), and the lower graph visualizes H3 (February 25–March 6, 2024), where black and red stacks indicate outdoor and indoor levels, respectively.

The indoor  $\text{PM}_{2.5}$  levels at H1 exhibited greater variability, with



**Fig. 5.** Time series of 24-hr averaged  $\text{PM}_{2.5}$  values at the sampling sites and nearest federal monitoring site C1098.



**Fig. 6.** Box plots of 24-h averaged PM<sub>2.5</sub> values at the sampling sites along with the nearest federal monitoring site C1098.

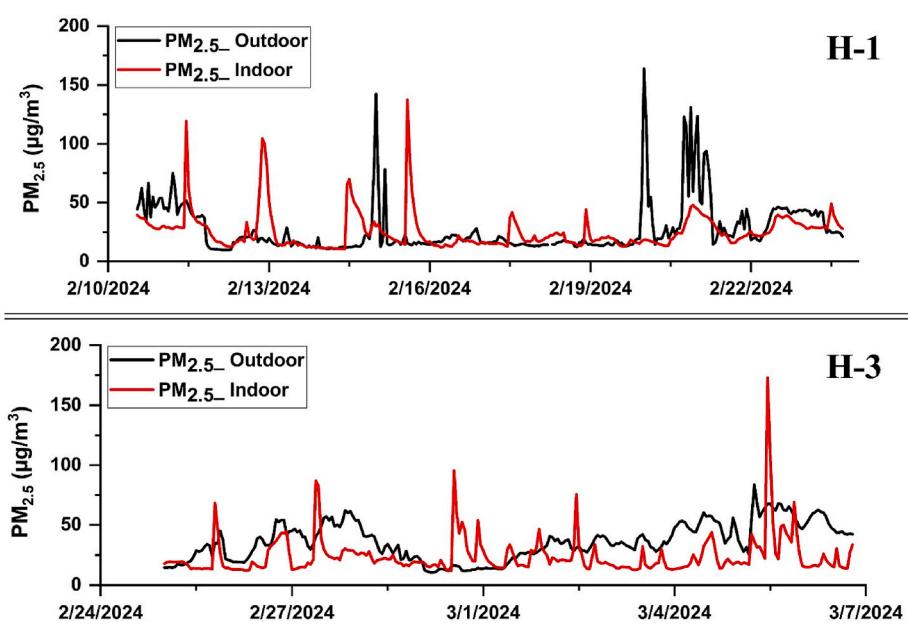
**Table 3**  
Descriptive statistics of 24-h averaged indoor PM<sub>2.5</sub> concentrations (µg/m<sup>3</sup>).

S.No.	Mean ± SD	Minimum	Maximum	Median	% of data completion
H1_Indoor	25.36 ± 10.63	15.79	137.29	20.30	99.68 %
H3_Indoor	24.32 ± 16.57	12.07	172.97	19.20	100.00 %

hourly-averaged concentrations surpassing 100 µg/m<sup>3</sup> for several hours. Indoor concentrations also constantly exceeded outdoor concentrations at H1. At H3, the outdoor concentrations remained significantly higher than indoor levels, with periodic peaks reaching up to 172 µg/m<sup>3</sup>. Indoor concentrations showed greater fluctuations when compared to

outdoor concentrations. A probable reason for the periodic fluctuation of indoor concentrations can be the impact of cooking, as the sensor was deployed close to the kitchen at H3, unlike H1, where the sensor was deployed close to the living room. Multiple studies recorded the impact of cooking on the indoor PM<sub>2.5</sub> levels (Chowdhury et al., 2022; Sun et al., 2017; Pinakana et al., 2024). H1 and H3 exhibited significantly higher indoor PM<sub>2.5</sub> concentration levels than outdoor ones.

The I/O ratio, which is based on multiple factors including outdoor levels, spatial differences, and indoor activities, is used to evaluate indoor and outdoor air pollutant relationships (Hasheminassab et al., 2014; Deng et al., 2016; Guo et al., 2010). A value of more than 1.2 indicates higher indoor concentrations than outdoor, likely from indoor sources. Meanwhile, a value between 0.8 and 1.2 indicates that the indoor concentrations are similar to outdoor levels. A higher outdoor influence is indicated by an I/O ratio of less than 0.8 (Deng et al., 2016).



**Fig. 7.** Stacked time-series of 1-h averaged PM<sub>2.5</sub> values (µg/m<sup>3</sup>) for sites H1 and H3.

I/O ratios were calculated in this study for the sampling period at two sampling sites, providing more insights into the infiltration of outdoor pollutants into the indoor environments. At H1, the I/O ratio fluctuates throughout the day, with mean I/O values exceeding 1.2 from 11:00 a.m. to 5:00 p.m., suggesting indoor sources contribute to higher indoor concentrations. The peak mean I/O of 1.92 at 2:00 p.m. indicates strong indoor emissions, possibly from cooking, cleaning, or human activities. Early morning values (12:00 a.m.–6:00 a.m.) mostly range between 0.9 and 1.1, suggesting minimal outdoor influence during nighttime hours. The highest I/O ratio of 1.09 at 1:00 p.m. and 0.99 at 11:00 a.m. suggests limited indoor emissions at H3. Fig. 8 provides the hourly box plots of I/O ratios at H1 and H3. The ratios increased towards midday, peaking in the afternoon (1:00 p.m. to 2:00 p.m.), suggesting a significant impact of indoor activities such as cooking on indoor concentrations. This analysis of I/O ratios indicates that outdoor pollutants had a lesser effect on indoor environments during the study period.

#### 3.4. Source attribution

Wind speed and direction significantly influence aerosol concentration and background levels of air pollutants. Lynam et al. (2017), Rana et al. (2016); Tshering Nidup et al., 2017 used pollution roses to identify the probable direction of pollutant sources. Fig. 9 depicts the pollution roses, representing the relationship between PM<sub>2.5</sub> and wind direction, individually at the three houses (H1, H2, and H3). Each rose provides insights into the relationship between PM<sub>2.5</sub> levels, wind direction, and wind speed, helping to identify potential pollution sources and assess spatial variability in air quality. At H1, PM<sub>2.5</sub> concentrations show a strong directional pattern, with elevated levels predominantly associated with winds from the south and southeast. Levels at H2 also exhibit a diffused distribution of PM<sub>2.5</sub> concentrations. However, moderate to high levels are observed when winds originate from the south and southeast. Overall, southeasterly winds contributed to particulate pollution throughout the sampling period at all three sampling points.

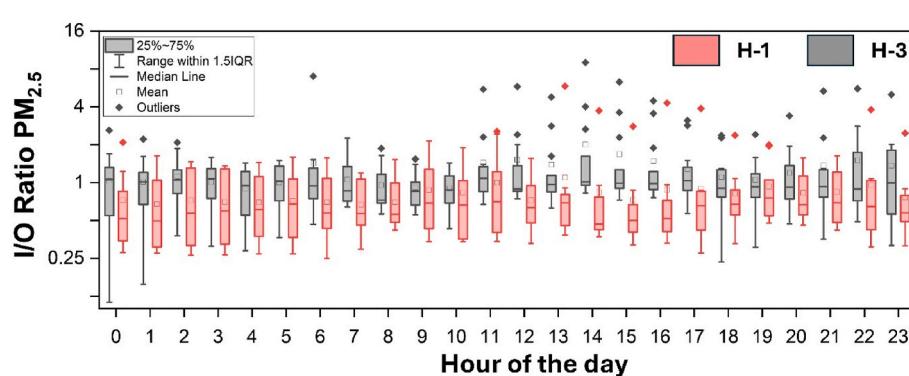
Basic polar plots of PM<sub>2.5</sub> concentrations were performed for each of the three monitoring locations, suggesting a similar spatial distribution of PM<sub>2.5</sub> concentrations across the sites as shown in Fig. 10. Notably, higher concentrations of PM<sub>2.5</sub> were predominantly found in the southern directions. Specifically, at monitoring site H1, the majority of elevated PM<sub>2.5</sub> levels occurred during periods of lower wind speed, measured at 4 m/s. This suggests the closer proximity of the pollution source to the H1 site, with lower wind speeds impacting the PM<sub>2.5</sub> levels at the residence. At sites H2 and H3, higher wind speeds ranging from 6 m/s to 8 m/s were causing increased PM<sub>2.5</sub> levels across the houses. This indicates that windier conditions contribute to particle pollution at H2 and H3, creating a different concentration dynamic compared to H1.

The Conditional Probability Function (CPF) effectively identifies the source direction of emissions impacting the receptor site and has been used in multiple studies (Angyal et al., 2021; Yadav et al., 2019). To

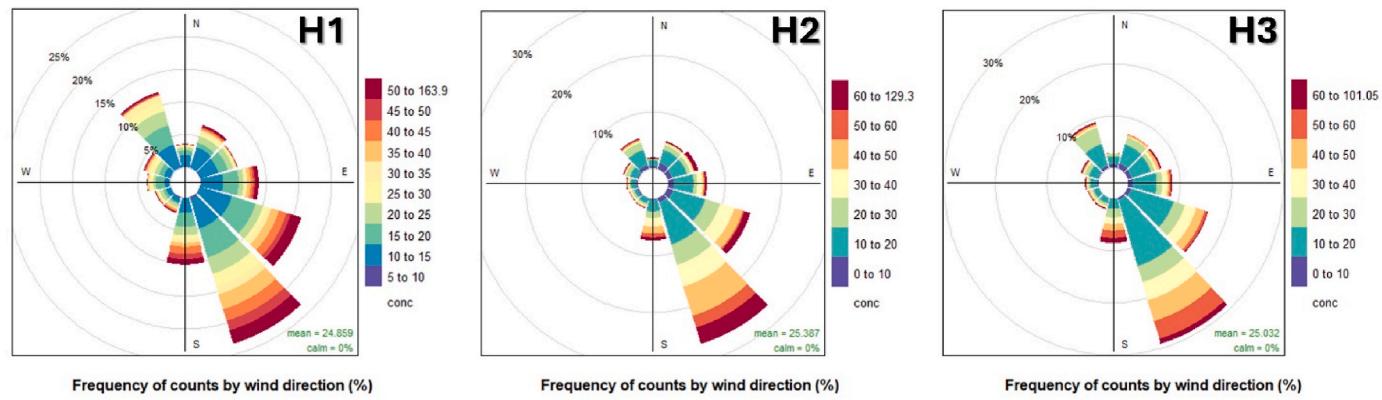
further analyze the relationship, CPF plots for PM<sub>2.5</sub> concentrations at the 75th percentile were plotted as shown in Fig. 11, providing insights into the dominant sources influencing air quality at three houses (H1, H2, and H3). For H1, elevated PM<sub>2.5</sub> probabilities are predominantly observed toward the south at moderate wind speeds (~4 m/s), indicating a potential localized source in this direction. At H2, the CPF plot reveals a strong probability of high PM<sub>2.5</sub> concentrations from the south-southeast, especially at higher wind speeds, suggesting the influence of a farther source than for H1. For H3, the CPF plot highlights significant contributions from the southeast, with elevated probabilities spanning a range of moderate to high wind speeds, pointing toward a mix of nearby and distant sources impacting the air quality at this location. The southern and southeastern winds consistently raise PM<sub>2.5</sub> levels across the three houses but with differences in proximity to the source.

Non-Parametric Wind Regression (NWR) plot is a source-to-receptor model that uses nonparametric kernel smoothing to allocate average pollutant concentrations Pandey and Negi (2022); Yu et al. (2004); Donnelly et al. (2011); Gu et al. (2020) are some of the studies that employed this method successfully to study the relationship between pollutants and their sources. Fig. S1 presents the results of NWR analysis conducted on 1-h measurements of PM<sub>2.5</sub> concentrations recorded at all three sampling locations. The plot for H1 suggests that locally sourced PM<sub>2.5</sub> was present, as indicated by low wind speed from the directions of the southern side. Higher concentrations of PM<sub>2.5</sub> were recorded with winds from the southeast, ranging from 1 m/s to 10 m/s. At H2 and H3, the concentration source direction was primarily from the south. Unlike H1, which was impacted by lower wind speed, H2 and H3 were mainly impacted by higher wind speeds ranging from 6 m/s to 8 m/s. These results suggest that H1 experienced elevated PM<sub>2.5</sub> levels when compared to H2 and H3. The CPF and NWR analysis also indicates that PM<sub>2.5</sub> levels are influenced by meteorological factors such as wind speed. H1 was affected by lower wind speeds, while H2 and H3 were influenced by higher wind speeds predominantly coming from the southern direction, indicating that H1 is closer to the source than H2 and H3.

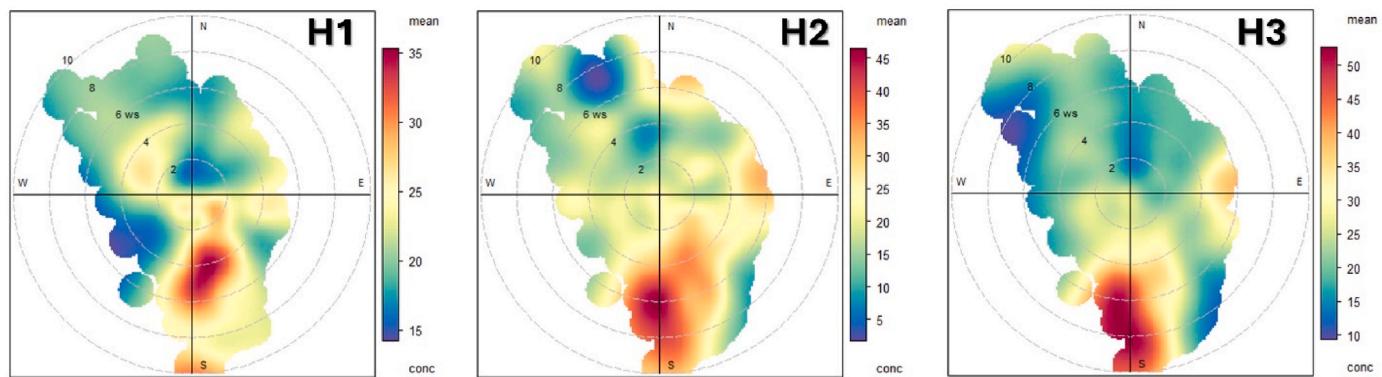
Our results support the findings of TCEQ, which found that the source of this particulate pollution is a mineral processing entity located to the south of the neighborhood. The laboratory report by TCEQ (TCEQ, 2023), concluded that X-ray and Energy Dispersive Spectroscopy (EDS) analysis of the field and reference samples detected strontium, barium, and sulfur—elements consistent with Barite and Celestite that were processed at this entity. According to the report, these elements were absent in background samples. The mineral processing entity is a regular processor of Barite and Celestite. Samples collected from the neighborhood properties contained elements matching those found in the regulated entity, indicating no alternative source of dust in the region. The processing entity was permitted to stockpile up to 69,000 square feet of raw material at the site; however, an approximate double amount of



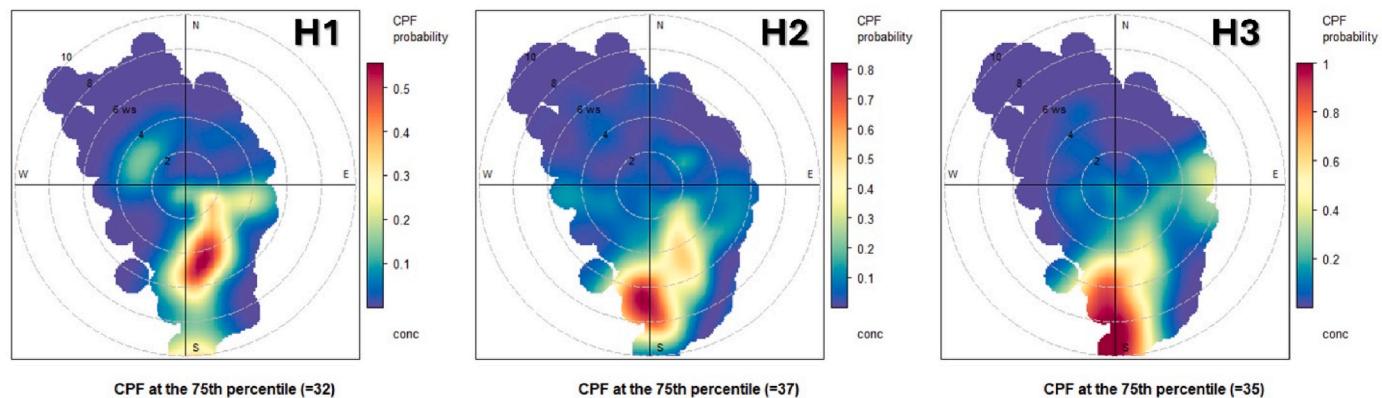
**Fig. 8.** Box plots of indoor-to-outdoor (I/O) ratios in different hours of the day at sites H1 and H3.



**Fig. 9.** Pollution roses illustrating the relationship between PM<sub>2.5</sub> concentrations and wind direction at houses H1, H2, and H3.



**Fig. 10.** Polar plots of PM<sub>2.5</sub> concentrations at sites H1, H2, and H3.



**Fig. 11.** CPF plots for PM<sub>2.5</sub> concentrations at the 75th percentile, showing dominant sources at houses H1, H2, and H3.

146,740 square feet of material was found at the site (Taylor, 2024) further impacting the local air quality during high wind events.

Numerous studies have been conducted worldwide to understand the impact of mining on local air quality (Ambastha and Haritash, 2021; Boente et al., 2023; Raysoni et al., 2022; Santacatalina et al., 2010). However, simple measures such as covering the material with tarpaulin and water sprinkling can have a decreased negative impact on the local neighborhoods (Roychowdhury et al., 2022; Ambastha and Haritash, 2021). Vegetation restoration or development of green belts around the processing area was also found to have a decreased negative impact on the local communities (Yu and Zahidi, 2023; Naik et al., 2006).

### 3.5. Health risk assessment – Hazard quotient

The Hazard Quotient values for PM<sub>2.5</sub> exposure at H1, H2 and H3 were 0.71, 0.72 and 0.71 respectively. All three of them were below the safe threshold of 1, indicating low-risk non-carcinogenic effects from exposure to the pollutant. HQ value for the sampling site of TCEQ was 0.25. This indicates a clear difference in increased health risk for the community living near the industrial facility, when compared to those living far away from it. Although HQ values at the three residences near the industrial vicinity remained below unity, studies have recorded that long-term exposures to even concentrations considered “safe” can lead to health complications such as cardiovascular effects (Alexeff et al., 2023) and increased mortality (Di et al., 2017).

#### 4. Conclusions

This case study highlights the importance of low-cost sensors in assessing local air quality, baseline source attribution, and health risk assessment studies, particularly in regions with limited federal monitoring. Using data from PurpleAir sensors deployed at three houses, we quantified PM<sub>2.5</sub> in a middle-income neighborhood impacted by emissions from a mineral specialty processing unit. The highest 24-averaged PM<sub>2.5</sub> of  $25.12 \pm 11.22 \mu\text{g}/\text{m}^3$  was recorded at H2. This value is approximately 2.79-fold more than the PM<sub>2.5</sub> concentration recorded at the nearest CAMS site, i.e., CAMS 1098. Indoor particulate pollution levels were also measured using low-cost sensors. However, calculating the I/O ratio provided insights into the lower impact of outdoor pollution on indoor environments. The source attribution was conducted utilizing polar plots, conditional probability function, and nonparametric wind regression. This analysis helped in understanding the probable source of pollution, i.e., a mineral processing entity. The data collected also aided in conducting initial screening techniques such as hazard quotient calculations for health risk assessments. In conclusion, this study demonstrates the utility of low-cost sensors in generating localized, high-resolution air quality data. It highlights their value in identifying pollution sources and evaluating health risks in regions with limited federal or state monitoring of the said pollutants.

#### CRediT authorship contribution statement

**Sai Deepak Pinakana:** Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **Kabir Bahadur Shah:** Methodology, Investigation, Data curation. **Daniel Jaffe:** Writing – review & editing, Validation, Methodology, Investigation, Conceptualization. **Juan L. Gonzalez:** Writing – review & editing, Resources, Funding acquisition. **Owen Temby:** Writing – review & editing, Resources. **Gabriel Ibarra-Mejia:** Writing – review & editing, Validation, Conceptualization. **Amit U. Raysoni:** Writing – review & editing, Supervision, Project administration, Conceptualization.

#### Ethics statements

This study contains no human subjects, human data or tissue, or animals.

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#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.aeaoa.2025.100405>.

<https://doi.org/10.1016/j.aeaoa.2025.100405>

#### Data availability

Data will be made available on request.

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