Source-specific contributions of particulate matter to asthma-related pediatric emergency department utilization

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Abstract
Ambient particulate matter smaller than 2.5 μm (PM$_{2.5}$) is associated with different chronic diseases. It is crucial to identify the sources of ambient particulate matter to reduce the impact on health. Still, only a few studies have been linked with specific ambient particulate matter sources. In this study, we estimated the contributions of sources of PM$_{2.5}$ and examined their association with daily asthma hospital utilization in Cincinnati, Ohio, USA. We used a model-based clustering method to group days with similar source-specific contributions into six distinct clusters. Specifically, elevated PM$_{2.5}$ concentrations occurring on days characterized by low coal combustion contributions showed a significantly reduced risk of hospital utilization for asthma (rate ratio: 0.86, 95% CI: [0.77, 0.95]) compared to other clusters. Reducing coal combustion contribution to PM$_{2.5}$ levels could be an effective intervention for lowering asthma-related hospital utilization.

Keywords: Fine particulate matter, Source apportionment, Cluster, Asthma, Time-series

Introduction
Air pollution is a global challenge [38] and has a severe, negative impact on human health [31]. Previous epidemiological studies identified the association between PM$_{2.5}$ and asthma [11, 24, 26, 35]. But there is a knowledge gap regarding the possible role of the sources of ambient particulate matter in illustrating the effect on children with asthma. Some studies investigated the association between air pollutants and respiratory symptoms [22]. Changes in respiratory symptoms over time may indicate physiological changes caused by inhaled substances, such as airway inflammation, and maybe an early predictor of subsequent health outcomes. Several studies investigated the association between the respiratory system and asthma because children are more vulnerable to air pollution than adults due to less matured lungs and immune systems [12, 20]). With a population of 2,272,152, the Cincinnati metro area is also home to more than 172,000 individuals with asthma, with more than 158,000 living with COPD and more than 1,600 patient’s lung cancer. According to the American Lung Association report (2018), greater Cincinnati’s metro area is among the most polluted in the nation and ranked 14 on a list of 203 cities with the worst year-round particulate emissions. Most of the air pollution particles are coming from coal-fired power plants and diesel emissions from transportation sources. In addition to chronic disease and mortality, epidemiologic evidence suggests short-term PM$_{2.5}$ exposure is associated with the development and exacerbations of asthma [13], Chronic Obstructive Pulmonary Disease (COPD) [11], triggering emergency department and hospital utilization in children [19, 36]. Asthma is a highly prevalent chronic respiratory disease that contributes significantly to morbidity and hospital utilization worldwide. Children are particularly susceptible to PM$_{2.5}$
related health effects due to their immature immune system [40] and ongoing development and growth.

PM$_{2.5}$ may come from different sources, including anthropogenic sources as well as natural sources. There was a concern as to whether sources of PM$_{2.5}$ could lead to adverse health effects. Several studies have investigated the health impacts of PM$_{2.5}$ sources. Several studies also investigated the association between PM$_{2.5}$ sources and asthma and allergic symptoms in children [15, 32, 34]. The chemical composition of PM$_{2.5}$ varies according to its sources [32], including fuel combustion from mobile sources like vehicles and stationary sources like power plants, industrial processes biomass burning [38]. Several studies have aimed to quantify the heterogeneous composition of PM$_{2.5}$, including identification of distinct multipollutant profiles [4], spatial clustering of air pollution monitoring sites, analyzing source-specific contributions, and studying the effect of individual chemical constituents [1]. However, much less attention has been focused on the source-specific contributions of particulate matter to health outcomes. Identifying sources contributing to PM$_{2.5}$ related health effects is critical to controlling the harmful sources of PM$_{2.5}$ [17] and identifying primary prevention strategies.

In this study, we aimed to determine underlying PM$_{2.5}$ sources responsible for asthma-related pediatric hospital utilization. Daily estimates of the source-specific contributions of different PM$_{2.5}$ sources were estimated using a chemical mass balance source apportionment model. A model-based clustering method [14] was applied to group days having similar source profiles. Using daily counts of pediatric, asthma-related hospital utilization for one urban county in Cincinnati, Ohio, USA, we then examined whether the type of PM$_{2.5}$, as determined by daily cluster membership, significantly modified the effect of PM$_{2.5}$ on hospital utilization.

**Methods**

**Data for source apportionment**

Source-apportionment methods ascertain the contribution of a given source to air pollution levels. We used the chemical mass balance with gas constraints (CMB-GC) model [5, 6, 25] to estimate the contribution of fine particulate organic sources carbon at Cincinnati, Ohio, from 2011 to 2015. One in every 3 days PM$_{2.5}$ and PM$_{10}$ speciation data were extracted from an AirData central monitor for Cincinnati at Taft St. (Taft monitor ID: 39-061-0040) maintained by the Environmental Protection Agency (EPA) and the Southwest Ohio Air Quality Agency (SWOAQA). In total, 522 days of 24-h PM$_{2.5}$ and speciation data were used in the model. Overall, PM$_{2.5}$ was considered the sum of the sources derived from CMB-GC [5, 6]. The model apportioned PM$_{2.5}$ to nine sources: gasoline vehicles (GV), diesel vehicles (DV), dust and road dust (DUST), biomass burning (BURN), primary coal combustion (COAL), ammonium sulfate (AMSULF), ammonium bisulfate (AMBUSLF), ammonium nitrate (AMNITR) and secondary organic carbon (SOC).

**Principle of CMB-GC model**

The conventional CMB model is based on the chemical mass balance (CMB) method, where the source contributions are analyzed by determining the association between chemicals and the sources of PM$_{2.5}$. The USA-EPA-developed CMB-receptor model has been widely used to predict the potential sources and source contribution for PM$_{2.5}$ [29]. The chemical mass balance method requires data for both the source profile and ambient measurement. Thus the CMB model creates a balance between the sources and the ambient receptor data and calculates the source contribution to PM$_{2.5}$ [37]. The CMB model is expressed as follows,

$$T_i = \sum_{k=1}^{n} S_k \cdot C_{ik}$$

where $k$ is the total number of emission sources, $T_i$ is the $i$th species concentration measured at the ambient receptor. $S_k$ is the kth source’s contribution, and $C_{ik}$ is the relative concentration of the $i$th species in the kth source.

The chemical mass balance with gas constraints (CMB-GC) model is an extension of the CMB model, use gas-to-particle ratios such as the SO$_2$/PM$_{2.5}$, NOx/PM$_{2.5}$ ratios for source identification. The CMB-GC model’s principle relies on the chemical mass balance method [37] and better quantifies source contributions by incorporating gas constraints [25]. The CMB-GC model details are provided elsewhere [5, 6, 25].

**Health outcome data**

All emergency department (ED) and urgent care (UC) visits for asthma between 2011 and 2015 were identified within the Cincinnati Children’s Hospital Medical Center’s (CCHMC) electronic medical record (EHR) based on the International Classification of Disease (ICD-9 and ICD-10) codes 493.00–493.92 [38]. CCHMC is a pediatriic academic health center with a market share of 99% of all hospital admissions and 81% of all hospital encounters among 0 to 14-year-olds in Hamilton County. Hamilton County is located in Cincinnati, OH, USA, and has 222 urban, suburban, and rural census tracts containing about 190,000 total children. The CCHMC Institutional Review Board approved this study and granted a waiver of informed consent. From 2011 to 2015, the daily total
of asthma-related ED visits ranged from 1 to 26, with a median of 7 total visits (25th percentile: 4, 75th percentile: 10). Figure 1 shows our study period’s dates arranged temporally and shaded by the magnitude of daily visits. The number of total visits was fewer during the warm summer season consisting of June, July, and August.

**Meteorological data**

We obtained the daily temperature and relative humidity from January 2011 to May 2015 from the North American Regional Reanalysis (NARR) dataset.

**Statistical analysis**

We utilized a model-based clustering method, specifically a Gaussian finite mixture model [14], to group together days of the study period with similar source contributions. The data is viewed as a mixture of probability distributions in the model-based clustering approach, representing a different cluster. In other words, in model-based clustering, it is assumed that the data are generated by a mixture of probability distributions in which each component represents a different cluster. We chose model-based clustering over non-parametric clustering methods, like k-means or hierarchical clustering, to utilize a data-driven approach for selecting the number of clusters. We assumed sample observations in model-based clustering arose from a finite normal mixture distribution with a mixture probability or weight. Each component in the mixture model was called a cluster. Each cluster shares a similar temporal pattern. The mixture model parameters were fitted using an expectation–maximization algorithm [16]. To select the number of clusters, we compared different models with different numbers of clusters and different parameterizations of the variance–covariance matrix and chose the model with the lowest Bayesian information criterion (BIC). Model-based clustering is explained elsewhere [14].

To cluster based on each source’s relative contributions, we expressed each source as a modified Z-score [4]. The modified Z-score allowed us to eliminate bias due to differences in scales and prevented outlier values from having too much influence on the cluster selection:
All statistical and geospatial computing was done in R [33], version 3.4.3, using the mclust package [14].

Results

PM$_{2.5}$ source characteristics

Throughout the study period, the median level of PM$_{2.5}$ was 9.9 $\mu$g/m$^3$. Source apportionment analysis revealed nine distinct sources of PM$_{2.5}$ within our study region: gasoline vehicles (GV), diesel vehicles (DV), dust (DUST), biomass burning (BURN), coal-burning (COAL), organic carbon (SOC), sulfate (SO$_4$), ammonium (NH$_4$), and nitrate (NO$_3$). Observed PM$_{2.5}$ and each source were examined as time series plots from January 2011 to May 2015 (Appendix Figures A.1 to A.10).

From 2011 to 2015, the median concentration for DV was 0.21 $\mu$g/m$^3$, GV was 0.76 $\mu$g/m$^3$, BURN was 0.75 $\mu$g/m$^3$, SOC was 0.74 $\mu$g/m$^3$, NH$_4$ was 0.91 $\mu$g/m$^3$, and NO$_3$ was 0.90 $\mu$g/m$^3$. SO$_4$ had the highest median concentration (2.08 $\mu$g/m$^3$), whereas COAL and DUST concentrations had the lowest median concentrations (both 0.06 $\mu$g/m$^3$). Summary statistics on the characteristics of PM$_{2.5}$, sources of air pollutants, and meteorological variables are provided in Table 1. The daily values of the concentration of PM$_{2.5}$ and the sources of PM$_{2.5}$ for the study period as modified Z scores are shown in Fig. 2.

Clustering sources of PM$_{2.5}$

We transformed the estimated daily source mass estimates into estimated daily fractional contributions to the total PM$_{2.5}$ mass. Our study period consisted of 522 total days, and we found that six clusters best fit the source apportionment fractional contributions as modified Z-scores. The heat map of the fractional contributions of the sources to the total PM$_{2.5}$ mass by cluster membership is shown in Fig. 3. Cluster allocation of days and the mean and variance of each source’s fractional contribution for each cluster are presented in Table 2. A Bar plot of the clusters by Day of the week, month, and year being presented in Appendix Figure A.11, and a boxplot of each source’s daily fractional contributions by the cluster is presented in Appendix Figure A.12.

Cluster 1 was allocated 193 days (37% of all days) and was characterized by high dust, SOC, and DV in conjunction with moderately high PM$_{2.5}$ and SO$_4$ and low NO$_3$. We nicknamed this cluster “high DUST, DV, and SOC.” This cluster mostly occurred in April (26 days), May (31 days), June (22 days), August (20 days), September (20 days), and October (21 days).

Cluster 2 mostly occurred during the Winter. 60 days (11% of all days) were allocated to this cluster and were characterized by high NO$_3$ and low DV in conjunction with moderately high nitrate and GV. We nicknamed this cluster “high NO$_3$ and low DV.” It occurred mostly during January (11 days), February (12 days), and March (14 days).

Cluster 3 was characterized by high NO$_3$, NH$_4$, and GV 105 days (20% of all days) were allocated to cluster

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| Variable                      | Median | Min  | 25th Percentile | 75th Percentile | Max  |
|-------------------------------|--------|------|-----------------|-----------------|------|
| Daily utilization (count)     | 7      | 1    | 4               | 10              | 26   |
| PM$_{2.5}$ ($\mu$g/m$^3$)    | 9.9    | 2    | 6.8             | 13.5            | 30.8 |
| Temperature (°C)              | 24.65  | 11.65| 21.39           | 30.85           | 40.69|
| Humidity (kg/m$^2$/s)         | 76.7   | 37.3 | 69.3            | 81.9            | 96.5 |
| PM$_{2.5}$ Source Concentration ($\mu$g/m$^3$) |         |      |                 |                 |      |
| DV                            | 0.21   | 0.00 | 0.06            | 0.42            | 1.62 |
| GV                            | 0.76   | 0.02 | 0.58            | 0.93            | 2.24 |
| BURN                          | 0.75   | 0.00 | 0.54            | 1.09            | 6.36 |
| COAL                          | 0.06   | 0.00 | 0.02            | 0.10            | 0.50 |
| DUST                          | 0.06   | 0.00 | 0.00            | 0.16            | 1.31 |
| NH$_4$                        | 0.91   | 0.03 | 0.57            | 1.41            | 4.99 |
| NO$_3$                        | 0.90   | 0.06 | 0.49            | 2.00            | 12.50|
| SO$_4$                        | 2.08   | 0.00 | 1.31            | 3.11            | 12.97|
| SOC                           | 0.74   | 0.00 | 0.44            | 1.15            | 3.46 |

GV: gasoline vehicles, DV: diesel vehicles, DUST: dust, BURN: biomass burning, COAL: coal burning, SOC: organic carbon, SO$_4$: sulfate, NH$_4$: ammonium, NO$_3$: nitrate
Fig. 2 Heat map of the concentration of PM$_{2.5}$ and different sources of PM$_{2.5}$ from January 2011 to May 2015 as modified Z scores.

Fig. 3 Heatmap of the sources of PM$_{2.5}$ as modified Z scores grouped by the cluster. The X-axis indicates cluster, and Y-axis indicates modified Z scores for each source of PM$_{2.5}$.
We nicknamed this cluster “high NO\textsubscript{3}, NH\textsubscript{4}, and GV”. Cluster 3 mostly occurred in January (25 days), February (21 days), March (17 days), and December (16 days).

Cluster 4 consisted of 81 days (16% of all days) and mostly occurred during the middle of the study period. We nicknamed this cluster “low COAL.” It occurred mostly during January (10 days), November (10 days), and December (11 days).

Cluster 5 mostly occurred during the spring and was characterized by high SOC and COAL. 59 days (11% of all days) were allocated to cluster 5. We nicknamed this cluster “high SOC, COAL.” It occurred mostly during July (12 days), August (11 days), and September (11 days).

Cluster 6 was characterized by relatively high contributions by BURN and DUST as well as low contributions by GV, DV, and SOC. Fifteen days (3% of all days) were allocated to cluster 6. We nicknamed this cluster “high BURN, with low DV, GV, and SOC.” It occurred mostly during May (2 days), June (2 days), and July (7 days).

Figure 4 illustrates the clusters’ temporal distribution, with each of the one in three-day measurements colored by cluster membership and arranged by week, month, and year.

### Table 2 The mean and standard deviation of the source fractions for each cluster

| Cluster | 1 | 2 | 3 | 4 | 5 | 6 |
|---------|---|---|---|---|---|---|
| Nickname | High DUST, DV, and SOC | High NO\textsubscript{3} and low DV | High NO\textsubscript{3}, NH\textsubscript{4}, and GV | Low COAL | High SOC, COAL | High BURN, with low DV, GV, and SOC |
| Number of days (%) | 193 (37) | 60 (11) | 105 (20) | 81 (16) | 59 (11) | 15 (3) |
| Mean PM\textsubscript{2.5} source fraction (SD) | | | | | | |
| BURN | 0.11 (0.04) | 0.12 (0.08) | 0.09 (0.03) | 0.10 (0.04) | 0.10 (0.05) | 0.28 (0.18) |
| COAL | 0.03 (0.01) | 0.02 (0.01) | 0.04 (0.01) | 0.01 (0.01) | 0.03 (0.01) | 0.01 (0.01) |
| DUST | 0.03 (0.02) | 0.02 (0.03) | 0.01 (0.01) | 0.01 (0.02) | 0.01 (0.01) | 0.02 (0.03) |
| DV | 0.05 (0.03) | 0.01 (0.00) | 0.02 (0.02) | 0.03 (0.03) | 0.05 (0.02) | 0.02 (0.05) |
| GV | 0.10 (0.04) | 0.11 (0.05) | 0.10 (0.04) | 0.11 (0.05) | 0.11 (0.07) | 0.09 (0.09) |
| NH\textsubscript{4} | 0.10 (0.02) | 0.14 (0.04) | 0.15 (0.03) | 0.12 (0.04) | 0.10 (0.04) | 0.09 (0.05) |
| NO\textsubscript{2} | 0.10 (0.05) | 0.25 (0.12) | 0.28 (0.08) | 0.19 (0.12) | 0.07 (0.04) | 0.08 (0.05) |
| SO\textsubscript{2} | 0.28 (0.08) | 0.25 (0.08) | 0.23 (0.07) | 0.27 (0.09) | 0.34 (0.14) | 0.28 (0.19) |
| SOC | 0.22 (0.07) | 0.10 (0.04) | 0.10 (0.05) | 0.17 (0.08) | 0.21 (0.09) | 0.13 (0.19) |

3. We nicknamed this cluster “high NO\textsubscript{3}, NH\textsubscript{4}, and GV”. Cluster 3 mostly occurred in January (25 days), February (21 days), March (17 days), and December (16 days).

Cluster 4 consisted of 81 days (16% of all days) and mostly occurred during the middle of the study period. We nicknamed this cluster “low COAL.” It occurred mostly during January (10 days), November (10 days), and December (11 days).

Cluster 5 mostly occurred during the spring and was characterized by high SOC and COAL. 59 days (11% of all days) were allocated to cluster 5. We nicknamed this cluster “high SOC, COAL.” It occurred mostly during July (12 days), August (11 days), and September (11 days).

Cluster 6 was characterized by relatively high contributions by BURN and DUST as well as low contributions by GV, DV, and SOC. Fifteen days (3% of all days) were allocated to cluster 6. We nicknamed this cluster “high BURN, with low DV, GV, and SOC.” It occurred mostly during May (2 days), June (2 days), and July (7 days).

Figure 4 illustrates the clusters’ temporal distribution, with each of the one in three-day measurements colored by cluster membership and arranged by week, month, and year.

#### Effect modification of PM\textsubscript{2.5} by the cluster-defined fractional composition

Examining the effect modification of daily PM\textsubscript{2.5} by cluster membership allowed us to assess the health impact of the composition of PM\textsubscript{2.5} independently of its total mass. We found significant effect modification on lag day one (p = 0.004), but not lag zero or two-day effects. For each lag day model, we estimated the individual RR and 95% confidence intervals for each type of PM\textsubscript{2.5} composition (Fig. 5). Compared to the other clusters, the cluster nicknamed “low COAL” had a significantly lower RR of 0.86 (95% CI: [0.77,0.95]). This suggests that an increase in PM\textsubscript{2.5} occurring on days characterized by low COAL contributions is associated with a decreased risk of asthma-related hospital visits compared with other PM\textsubscript{2.5} source components.

### Discussion

Overall, our results suggest that specific source-contribution types of PM\textsubscript{2.5} may be more strongly associated with asthma-related hospital utilization. Our clustering approach allowed us to examine the effect of the type of PM\textsubscript{2.5} independently of the total mass of PM\textsubscript{2.5}. Specifically, we found that an increase in PM\textsubscript{2.5} occurring on days characterized by low contributions of COAL is associated with a smaller increased risk concerning asthma-related hospital utilization in comparison to other source-contribution types of PM\textsubscript{2.5}. Further study is necessary to identify the effect of coal burning in other areas of the USA.

Previously, epidemiological studies have also analyzed the adverse effect of PM\textsubscript{2.5} on health [12], asthma and rhinitis [28], air pollution, and asthma utilization [7, 11, 27] but limited research has been done on the impact of source-specific air pollution on asthma in the USA [21]. Several studies investigated and mentioned that coal
and oil power plants are common sources of PM$_{2.5}$, and retirements of coal-burning reduce air pollution nearby, reduce preterm birth and increase fertility [9, 10]. Some other studies highlighted the differential toxicities of delicate particulate matter from various sources [30] and identified various combustion sources (diesel engine, gasoline engine, biomass burning, and coal combustion) and non-combustion sources (road dust including sea spray aerosols, ammonium sulfate, ammonium nitrate, and secondary organic aerosols). Similar to our results, this study also found that the highest pollutant was obtained for diesel engine exhaust particles, followed by gasoline engine exhaust particles, biomass burning particles, coal combustion particles, and road dust.

It has been of importance to identify the most health-relevant sources of PM$_{2.5}$, both from a scientific and regulatory perspective [17, 18]. Association between source-specific exposure and adverse health effects plays a vital role in protecting public health through the development of primary and secondary prevention strategies [7, 8]. Even though sources of air pollution are informative, these studies are often challenging to conduct because source-specific exposure is not directly observed but estimated [39]. A two-stage approach is frequently applied to estimate the source-specific health effects by adding source exposure assessments into health outcome regression [21].

This study’s major strength is that we used a data-driven clustering approach to identify the sources of PM$_{2.5}$ and investigate the impacts of the exposure to source-specific PM$_{2.5}$ on daily asthma ED utilization. Using the sources’ fractional contributions rather than the masses of the sources allowed us to examine the effect of the composition of PM$_{2.5}$ independently of its mass. Model-based clustering is advantageous compared to other clustering methods, such as k-means and hierarchical clustering. The number of clusters is not pre-selected but are selected using a data-driven approach. Another major strength is that we have used a chemical mass balance (CMB) model for PM$_{2.5}$ source apportionment [2, 3, 23], which leverages measurements of actual ambient mass concentrations, unlike other source attribution processes [29]. However, several potential limitations should also be taken into consideration. First of all, source measurements were only available once every three days; however, we were able to utilize daily health

![Calendar heat map of clusters. PM$_{2.5}$ was observed only 1 in every 3 days and days with unobserved PM$_{2.5}$ are grey](image-url)
outcomes by analyzing the lagged effects of exposures one and two days later. Another major limitation is the lack of spatial discrimination concerning the estimated exposure to pollution sources because there was only one monitor in the study region that collected elemental components of PM$_{2.5}$.

The EPA has established regulatory standards for ambient PM$_{2.5}$. These standards reflect public health concerns about ambient PM$_{2.5}$ because epidemiologic studies show an increase in adverse health effects and mortality with incremental increases in ambient PM$_{2.5}$. Our study warrants further studies on identifying which source-contribution types of PM$_{2.5}$ are most harmful to human health and further explorations into how to direct primary prevention strategies towards air pollution types that show the most health effects.

### Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s13755-021-00141-z.

Below is the link to the electronic supplementary material. Supplementary material 1 (DOCX 801 kb)

### Author Contribution

MNB, SB, PR, CB: conceptualization, methodology, formal analysis, investigation, and writing. FO, YJ, MR: extracted source apportionment data.

### Declarations

#### Conflict of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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