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Special Collection:
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Key Points:

- We examine cumulative exposures to multiple pollutants and their association with socioeconomic and racial disparities in Milwaukee County
- We highlight census block groups that are most vulnerable to pollution and low socioeconomic status (SES), which can be prioritized for regulatory interventions
- People of color in Milwaukee County are not just exposed to high pollution, they are often exposed within the context of low SES

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:
J. K. Kodros,
jkkodros.research@gmail.com

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Author Contributions:
Conceptualization: John K. Kodros, Shantanu H. Jathar, Sheryl Magzamen
Data curation: John K. Kodros, Ellison Carter, Oluwatobi Oke
Formal analysis: John K. Kodros
Funding acquisition: Sheryl Magzamen
Methodology: John K. Kodros

Cumulative Exposures to Environmental and Socioeconomic Risk Factors in Milwaukee County, Wisconsin

John K. Kodros[1,2], Ellison Carter[3], Oluwatobi Oke[3,4], Ander Wilson[5], Shantanu H. Jathar[1], and Sheryl Magzamen[6,7]

[1]Department of Mechanical Engineering, Colorado State University, Fort Collins, CO, USA, [2]Now at Clarity Movement, Berkeley, CA, USA, [3]Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO, USA, [4]Now at Building Energy and Environment Division, National Institute of Standards and Technology, Gaithersburg, MD, USA, [5]Department of Statistics, Colorado State University, Fort Collins, CO, USA, [6]Department of Environmental and Radiological Health Sciences, Colorado State University, Fort Collins, CO, USA, [7]Department of Epidemiology, Colorado School of Public Health, Colorado State University, Fort Collins, CO, USA

Abstract The environmental justice literature demonstrates consistently that low-income and minority communities are disproportionately exposed to environmental hazards. In this case study, we examined cumulative multipollutant, multidomain, and multimatrix environmental exposures in Milwaukee County, Wisconsin for the year 2015. We identified spatial hot spots in Milwaukee County both individually (using local Moran's I) and through clusters (using K-means clustering) across a profile of environmental pollutants that span regulatory domains and matrices of exposure, as well as socioeconomic indicators. The cluster with the highest exposures within the urban area was largely characterized by low socioeconomic status and an overrepresentation of the Non-Hispanic Black population relative to the county as a whole. In this cluster, average pollutant concentrations were equivalent to the 78th percentile in county-level blood lead levels, 67th percentile in county-level NO_2, 79th percentile in county-level CO, and 78th percentile in county-level air toxics. Simultaneously, this cluster had an average equivalent to the 62nd percentile in county-level unemployment, 70th percentile in county-level population rate lacking a high school diploma, 73rd percentile in county-level poverty rate, and 28th percentile in county-level median household income. The spatial patterns of pollutant exposure and SES indicators suggested that these disparities were not random but were instead structured by socioeconomic and racial factors. Our case study, which combines environmental pollutant exposures, sociodemographic data, and clustering analysis, provides a roadmap to identify and target overburdened communities for interventions that reduce environmental exposures and consequently improve public health.

Plain Language Summary Our study focused on Milwaukee County, Wisconsin, where we examined how people in this region were exposed to different types of pollutants. We found that areas with the highest levels of pollution (e.g., lead, nitrogen dioxide) had a higher proportion of Black residents and residents that experienced social and economic challenges (e.g., unemployment, poverty, and low education). Our work adds to the growing evidence that patterns of pollution and economic challenges are not random, but rather, racially and socially structured. By understanding these patterns, we can develop policies that reduce pollution in these areas and improve the health for residents in these overburdened communities.

1. Introduction

Previous research has established an association between health risks and exposure to various anthropogenic environmental pollutants. Ambient air pollution has been consistently associated with an array of adverse health impacts and is one of the leading risk factors contributing to morbidity and premature mortality (Apte et al., 2018; Bell et al., 2004; Dockery et al., 1993; Miller et al., 2007). As a result, the US Environmental Protection Agency (EPA) enforces national ambient air quality standards (NAAQS) for six common air pollutants ("criteria air pollutants"), which are known to have adverse health effects (EPA, 2023a). In addition to the criteria air pollutants, the EPA also mandates the reporting of emissions of hundreds of chemicals with known cancer-causing or chronic/acute health effects (EPA, 2023b). Other exposure matrices (e.g., soil, water) are also known to have health risks. Lead exposure, which may occur through air, water, paint, or soil, has been shown to adversely impact health (Chowdhury et al., 2018; Lamas et al., 2021) and intellectual development (Amato et al., 2013;

Project administration: Ellison Carter, Shantanu H. Jathar, Sheryl Magzamen
Supervision: Shantanu H. Jathar
Validation: John K. Kodros, Ander Wilson
Visualization: John K. Kodros
Writing – original draft: John K. Kodros, Ellison Carter, Sheryl Magzamen
Writing – review & editing: John K. Kodros, Ellison Carter, Ander Wilson, Shantanu H. Jathar, Sheryl Magzamen

Bellinger et al., 1992; Kordas et al., 2007; Lanphear, 2005; Magzamen et al., 2015; Wright et al., 2008). Yet, understanding how exposures across multiple matrices jointly affect health, in tandem with potential management and mitigation strategies for multiple exposures, remains poorly understood.

Current regulations are often based on single pollutant exposures, which do not consider the possible synergistic effects of cumulative exposures (Benka-Coker et al., 2020; Mauderly & Samet, 2009). Individuals are rarely exposed to single pollutants in isolation (e.g., Molitor et al. (2011)). Instead, people and communities are commonly exposed to numerous pollutants within a regulatory domain (e.g., different criteria air pollutants such as, $PM_{2.5}$ and O_3) as well as multiple pollutants across regulatory domains (for instance, criteria air pollutants and air toxics) (Benka-Coker et al., 2020). Here, we use the term multipollutant to describe multiple chemical compounds within one pollutant class (e.g., a multipollutant air pollution study may include $PM_{2.5}$, O_3, NO_2, etc). We further consider multiple pollutants across more than one environmental matrix (e.g., air, soil) to reflect a multimatrix approach. Lastly, we define a multidomain approach, as described in Benka-Coker et al. (2019), as "an approach that considers the joint effect of multiple classes of environmental agents along the theme of the "total environment" paradigm, which takes into consideration a more comprehensive range of concurrent exposures experienced by a population."

In addition to environmental exposures, environmental epidemiology has increasingly considered exposures within the context of socioeconomic status (SES) (Ferguson et al., 2020; O'Neill et al., 2003). A wealth of literature has illustrated the relationship between SES and health (e.g., Adler et al., 1993; Isaacs and Schroeder, 2004; Lynch et al., 2004), as well as the concept that low SES and negative environmental exposures are interrelated (Hajat et al., 2021; Magzamen et al., 2008). This association may occur because individuals living in areas of low SES may be exposed to higher concentrations of environmental pollutants and/or may be more susceptible to environmental pollutants (O'Neill et al., 2003). In addition to SES, numerous studies have highlighted disparities in exposure to environmental pollutants across racial and ethnic lines (Clark et al., 2014; Jbailey et al., 2022; Morello-Frosch & Jesdale, 2006); recent modeling work suggests that Black and Hispanic populations in the US are exposed to a higher air pollution exposure burden relative to the expected exposure originating from emissions associated with these population groups (Tessum et al., 2019, 2021). Communities of color and low SES are exposed to higher concentrations of environmental pollutants and may be more susceptible to the effects of this exposure (Clark et al., 2014; Tessum et al., 2021), as evidenced by the higher rates of adverse health outcomes among communities of color (Apelberg et al., 2005; Hill et al., 2011).

Recently, several methodological approaches have been proposed to address the independent and joint contribution of environmental exposures and social factors to health outcomes (Martenies, Hoskovec, et al., 2022; Martenies, Zhang, et al., 2022; Martenies et al., 2023). Identification of relevant social or environmental factors associated with disease outcomes are an important pathway to identify effective intervention and mediation strategies to improve health. Informed by earlier work (Lalloué et al., 2013; Molitor et al., 2011; Shrestha et al., 2016), it is necessary to develop indicators that highlight communities of high risk due to elevated cumulative exposure to environmental pollutants and/or low SES. For instance, CalEnviroScreen develops an index based on percentile rankings across a set of environmental and social indicators (Faust et al., 2014). While the single index score approach for tools like CalEnviroScreen might be useful for categorizing health impacts, this method does not necessarily improve the understanding of the spatial patterns of clusters of contaminants within a community.

Cumulative multipollutant, multimatrix, and multidomain exposures may lead to complex health responses not captured by considering single exposure to pollutants. Complicating matters, interventions are rarely designed to target multidomain and multimatrix exposures. We have employed a multidomain approach in prior studies (e.g., Benka-Coker et al. (2019)) to investigate joint effects of ambient air pollutants and agricultural pesticides, two exposures that are not often examined together, but may occur together in high levels in agricultural communities. We extend our framework to Milwaukee, an urban community with multiple environmental and chemical exposures that adversely impact health. In this study, we examine associations between environmental exposures known to have adverse health risks and demographic and SES indicators across multiple pollutants, domains, and matrices. We focus on the urban/suburban area of Milwaukee County, Wisconsin due to the multiple adverse environmental exposures that co-occur in the area, including lead exposure, air pollution exposure, housing quality and housing insecurity, as well as sociodemographic factors that are associated with poor health outcomes, including poverty. We highlight communities with cumulative exposures to elevated concentrations of environmental pollutants and indicators of low SES status that can be prioritized for regulatory interventions.

2. Methods

2.1. Study Area

Milwaukee County, Wisconsin (shown in the inset in Figure S1 in Supporting Information S1) includes the densely populated city of Milwaukee and the suburban area outside it (Figure S2 in Supporting Information S1). Milwaukee County is the most racially diverse county in the state of Wisconsin, with a Black population fraction (38.6%) over twice as high as the national average (14%) (US Census Bureau, 2023). Milwaukee County has a history of poor environmental pollution. It was designated a NAAQS maintenance area for 24-hr $PM_{2.5}$ in 2016 (Southeastern Wisconsin Regional Planning Commission, 2016) and received an "F" grade for O_3 from the American Lung Association's 2016 State of the Air report (American Lung Association, 2016). In 2014, the city of Milwaukee had the highest prevalence of lead poisoning in Wisconsin, which rates among the states with the highest incidence of childhood lead poisoning in the US (Wisconsin Department of Health Services, 2014).

2.2. Environmental Pollutants

We examined the cumulative exposure to blood lead levels (BLL), five of the six criteria air pollutants, and inhalation toxicity-weighted summed concentrations of air toxics. These pollutants spanned regulatory exposure domains and exposure matrices. We used measurements and estimates of pollutants in the year 2015 (the most recent year for all data sources) at the census block group (CBG) resolution (the highest resolution estimates offered for all data sources).

2.2.1. Lead

The data set at the individual level for BLL consisted of samples collected from children who were part of the Healthy Homes and Lead Poisoning Surveillance system (HHLPSS) overseen by the Wisconsin Department of Health Services, Division of Public Health Services (WDHS, 2023). The participants were children aged five or below, living in Milwaukee County between 2015 and 2019. These data, which received ethics approval from the Wisconsin Division of Public Health data governance board, encompassed information such as the child's test ID, test date, test type, age at testing, gender, race, primary address, and BLL. More details on BLL surveillance in Wisconsin can be found in Christensen et al. (2019). Following data preprocessing, the BLL of 95,659 children in Milwaukee County were assessed, with 71,162 residing within the city of Milwaukee; we aggregated BLL measurements to the CBG resolution.

2.2.2. Criteria Pollutants

Estimates of criteria air pollutants (CO, NO_2, $PM_{2.5}$, O_3, PM_{10}, and SO_2) were taken from the Center for Air, Climate and Energy Solutions (CACES) land use regression model; for details refer to Kim et al. (2020). This model does not include an estimate for airborne lead, which, as a result, is excluded from this analysis (although, the present study does include estimates of BLL).

2.2.3. Air Toxics

Estimates of air toxics come from the EPA's Risk-Screening Environmental Indicators (RSEI) model (EPA, 2023b). RSEI aggregates point-source data collected from the Toxic Release Inventory (EPA, 2023c). We used the sum of the concentrations of all chemicals in each CBG weighted by toxicity (i.e., the concentration multiplied by the relative inhalation toxicity weight summed over all chemicals in the CBG). Thus, this analysis was sensitive to estimates of both concentration of each chemical as well as its toxicity.

2.3. Demographic and Socioeconomic Data

To examine the association of cumulative environmental exposure with SES and racial/ethnic disparities, we downloaded data from the 5-year American Community Survey (years 2015–2019) available from the US Census Bureau (US Census Bureau, 2023). We used estimates of the percent of the population 16 years or older within the civilian labor force that is unemployed, percent of the population older than 25 years without a high school diploma, median household income, and percent of the population living below the poverty line. These risk factors have been used in previous studies as measures of social vulnerability. To examine disparities along racial and ethnic lines, we used the percent of the population in each CBG identifying as non-Hispanic White (NHW) and non-Hispanic Black (NHB). We focused on these two groups due to the historical record of racial residential segregation in Wisconsin between NHW and NHB populations (Paulson et al., 2016).

2.4. Statistical Analysis

To investigate the degree of spatial structure in the data set, we calculated measures of global and local spatial autocorrelation for the environmental pollutants and SES indicators. We reported Moran's I as our metric for global spatial autocorrelation (Moran, 1948). Moran's I was normalized to range from −1 to +1 with values closer to +1 indicating a greater degree of positive spatial autocorrelation. Further, we calculated Local Indicators of Spatial Association using Local Moran's I to identify statistically significant hot and cold spots across environmental pollutants and SES indicators (Anselin, 1995). This measure of local spatial autocorrelation identifies geographic clusters with high (low) values beyond what we would expect by random chance. Statistical significance was assessed at the 95th percentile confidence interval. Both local and global spatial autocorrelation were calculated using queen-adjacent spatial weights matrices. Spatial statistics were calculated in Python using the PySAL package (Rey & Anselin, 2010). We quantified inequality through the Gini index, which we calculated for each environmental pollutant and SES indicator. The Gini index ranges from 0 to 1 with higher values indicating a greater degree of inequality. This index, borrowed from economic studies (Gini, 1936), has also been used frequently in previous studies investigating disparities in environmental pollutants (e.g., Levy et al., 2006).

To identify clusters of vulnerable populations across a profile of environmental pollutants and SES indicators, we used K-means clustering. As input features, we used standardized values for all environmental pollutants and SES indicators with all features weighted equally. We did not include demographic or geographic data as inputs to the clustering algorithm to explore the degree to which spatial and demographic factors are associated with the predicted clusters. The number of predicted clusters was to some degree subjective. We chose three clusters as this number demonstrated consistent environmental social profiles across the clusters. In addition, the three predicted clusters occupied a roughly spatially homogeneous region.

3. Results

3.1. Geographic Distribution of Environmental Pollutants and Socioeconomic Indicators

Annual (year 2015) mean concentrations of BLL, criteria air pollutants, and air toxics exhibited substantial spatial structure across Milwaukee, County; though, the spatial patterns differed by pollutant (Figure 1 and Table 1); we note substantial variability in measurements of BLL within CBGs (Figure 3). The highest concentrations of BLL, CO, NO_2, $PM_{2.5}$, and air toxics occurred within the city of Milwaukee (Figure 1), while O_3 and PM_{10} had slightly lower concentrations in this area relative to other parts of the county. For SO_2, the highest concentrations were found both inside and outside the Milwaukee city limits. Pollutants generally exhibited weak (less than 0.4) paired correlations with the exception of CO and NO_2 (0.72), CO, and O_3 (−0.65), and NO_2 and $PM_{2.5}$ (0.64) (Figure S4 in Supporting Information S1).

All pollutants exhibited a high degree of spatial structure (evidenced by Moran's I measure of global spatial autocorrelation) across Milwaukee County (Table 1). This spatial structure is expected based on known differences in risk factors (such as housing age which has been shown to influence BLL levels) and emissions (such as on-road sources for NO_2 and regional sources and chemistry for O_3) across an urban area. In addition to the queen-adjacent spatial weights matrix, we conducted a sensitivity analysis of local spatial autocorrelation and rook-adjacent (Figure S5 in Supporting Information S1) and bishop-adjacent (Figure S6 in Supporting Information S1) spatial weights matrices and found the results and overall conclusions to be similar. To quantify the degree of spatial inequality in environmental pollutants, we calculated the Gini coefficient for each pollutant for Milwaukee County (Table 1). A value of the Gini coefficient of 0 indicates perfect equality with increasing values indicating a higher degree of inequality (with a maximum of 1). We calculated the Gini coefficient based on the distribution of annual means in the CBGs for each pollutant. BLL and air toxics had by far the highest degree of inequality across the county, 0.2 and 0.3, respectively. The criteria air pollutants generally had low Gini coefficients, ranging from 0.006 to 0.09. O3 had the lowest measure of inequality (0.006) consistent with the low spatial variability in concentration across the county.

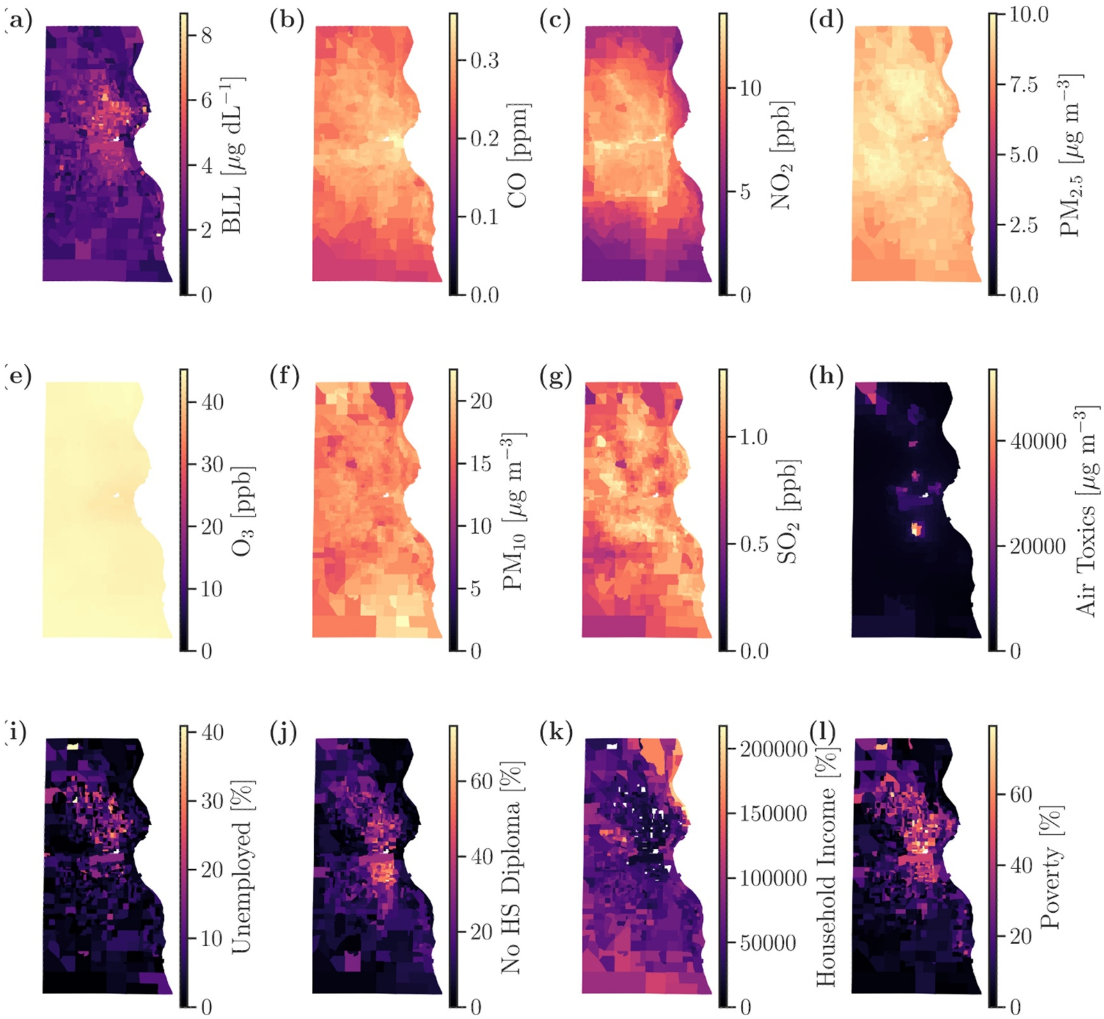

Figure 1. Annual mean year 2015 values in Milwaukee County, Wisconsin of (a) blood lead levels, (b) CO, (c) NO_2, (d) $PM_{2.5}$, (e) O_3, (f) PM_{10}, (g) SO_2, (h) air toxics as well as socioeconomic factors (i) unemployment rate, (j) percent of the population without a high school diploma, (k) median household income, (l) percent of the population below the poverty line.

Similar to the environmental pollutants, the SES indicators also exhibited a high degree of spatial structure where indicators of low SES were concentrated in the center of the city of Milwaukee (Table 1 and Figure 1). These indicators were moderately correlated with the absolute value of the paired correlations ranging from 0.34 to 0.67 (Figure S6 in Supporting Information S1). The Gini coefficient was high for all indicators considered here, ranging from 0.3 to 0.5, indicating a high degree of spatial inequality across Milwaukee County.

3.2. Local Hot and Cold Spots for Environmental Pollutants and SES Indicators

We identified statistically significant geographic hot and cold spots of individual environmental pollutants and SES indicators. BLL, CO, NO_2, and $PM_{2.5}$ showed a similar geographic distribution, with a hot spot (a region of elevated values) in the center of the county (and roughly the center of the city of Milwaukee) and cold spots (low values) around the northern and southern parts of the county (Figure 2). BLL in the elevated clusters were 49% higher than the county average, indicating an important area of elevated exposure and associated health risk to this pollutant. In contrast, the average concentrations of CO, NO_2, and $PM_{2.5}$ in the elevated clusters were only moderately higher than the county average: 8%, 15%, and 6%, respectively. Air toxics, which displayed the greatest variability across the state (Table 1), were 165% higher in the elevated cluster on average than in the county average. There were 503 CBGs identified as a hot spot for at least one of BLL, CO, NO_2, $PM_{2.5}$, and air toxics (Figure S7 in Supporting Information S1). While the hot spots for BLL, CO, NO_2, $PM_{2.5}$, and air toxics had

Table 1
Summary Statistics (Annual Mean, Standard Deviation As Well As the 5th, 25th, 50th, 75th, and 95th Percentile) in 2015, Global Spatial Autocorrelation (Moran's I), and Gini Index for Blood Lead Levels, Criteria Air Pollutants, Air Toxins, and Socioeconomic Indicators Across Milwaukee County, Wisconsin

Pollutant	Mean	SD	5th	25th	50th	75th	95th	Moran's I	Gini
BLL [µg dL]	2.99	1.18	1.54	2.13	2.73	3.66	5.17	0.51	0.21
CO [ppm]	0.29	0.02	0.25	0.28	0.29	0.31	0.32	0.85	0.04
NO_2 [ppb]	10.1	1.74	6.53	9.13	10.7	11.3	11.9	0.93	0.09
$PM_{2.5}$ [µg m^{-3}]	9.17	0.48	8.28	8.88	9.25	9.53	9.83	0.82	0.03
O_3 [ppb]	44.1	0.46	43.2	43.8	44.1	44.4	44.7	0.96	0.01
PM_{10} [µg m^{-3}]	17.2	1.32	15.2	16.3	17.1	17.9	19.4	0.61	0.04
SO_2 [ppb]	1.01	0.12	0.8	0.93	1.02	1.10	1.20	0.70	0.07
Air Toxics [µg m^{-3}]	4,070	3,760	1,970	2,400	3,080	4,550	7,890	0.56	0.32
Unemployed [%]	6.29	6.61	0.00	1.65	4.35	8.51	20.29	0.26	0.53
No HS diploma [%]	17.1	13.9	1.42	6.59	13.6	23.6	48.2	0.69	0.44
Household Income [USD]	55,000	30,000	20,000	35,000	50,000	68,000	109,000	0.61	0.28
Poverty [%]	20.3	17.1	1.27	6.19	15.3	32.0	51.9	0.55	0.46

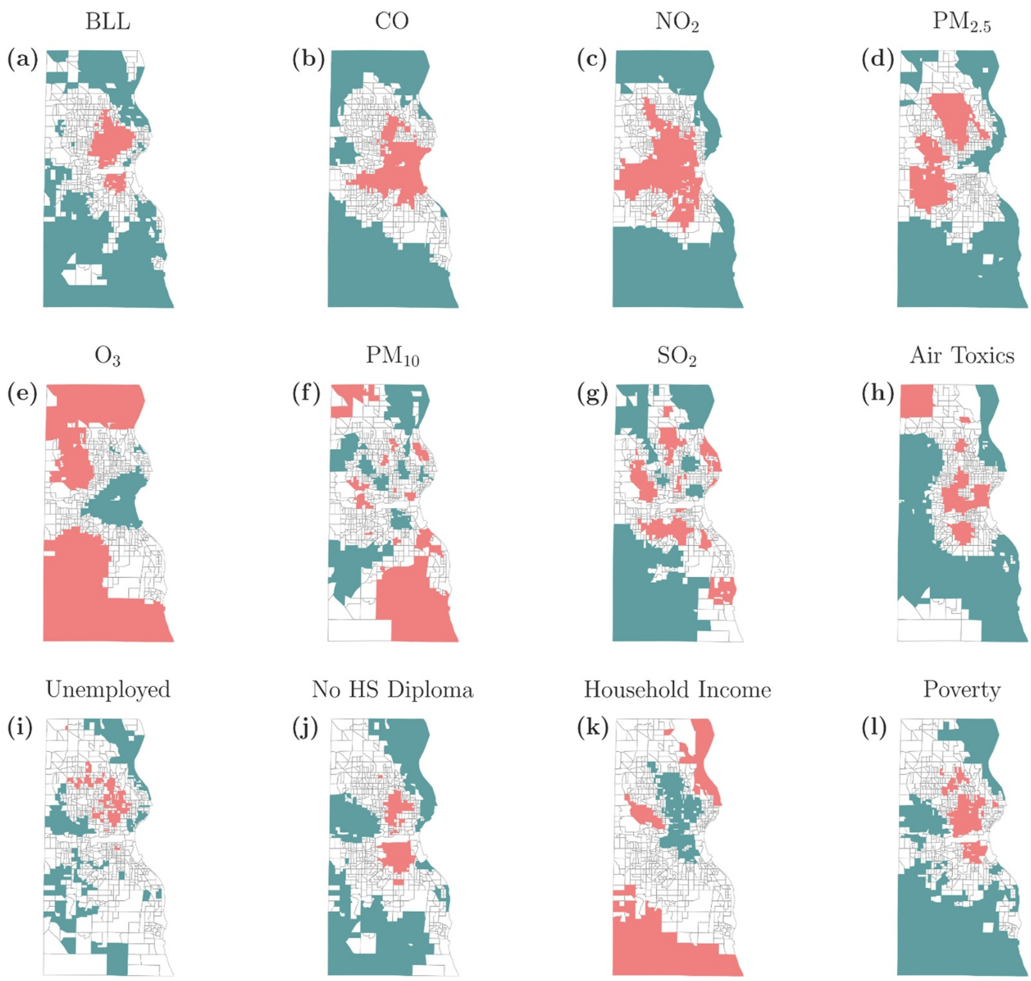

Figure 2. Statistically significant local clusters of high values (red) and low values (blue) for (a) blood lead levels, (b) CO, (c) NO_2, (d) $PM_{2.5}$, (e) O_3, (f) PM_{10}, (g) SO_2, (h) air toxics, (i) unemployment rate, (j) percent of the population without a high school diploma, (k) median household income, (l) percent of the population below the poverty line in Milwaukee County.

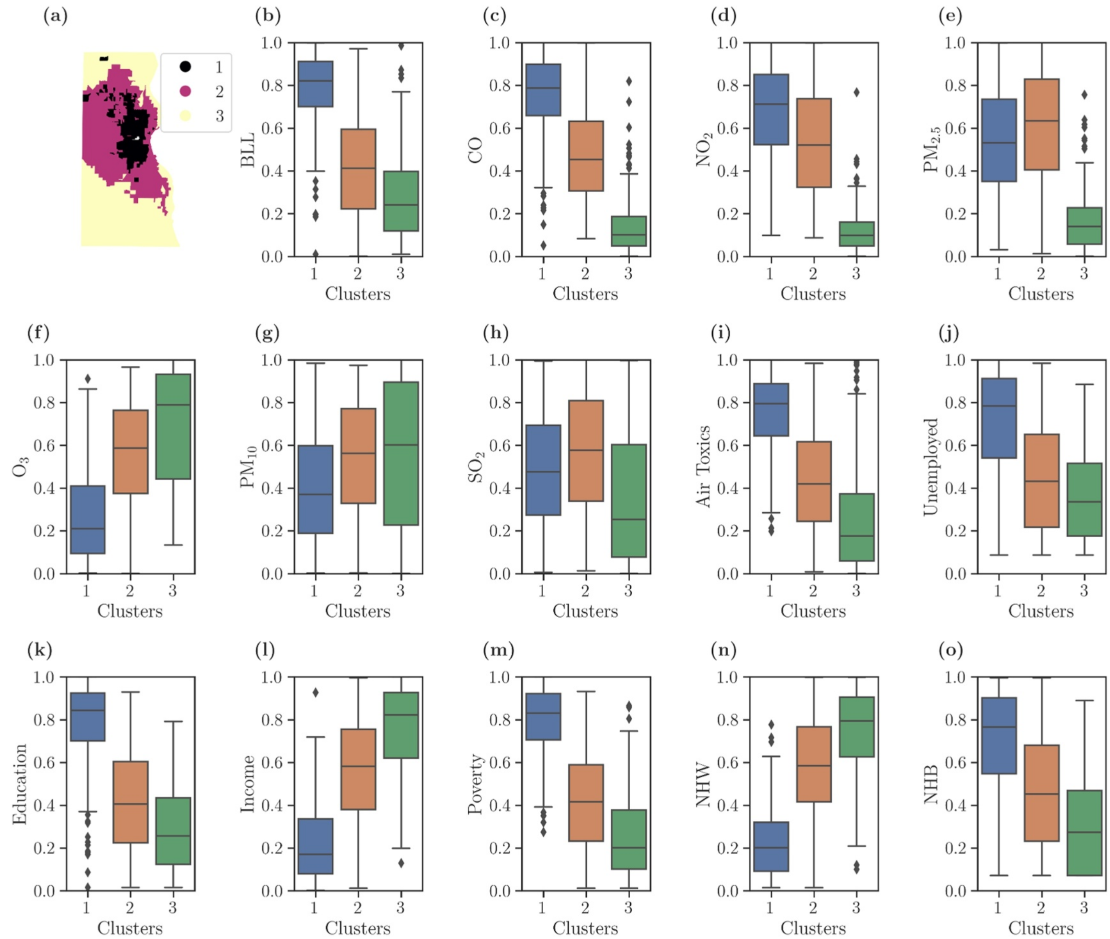

Figure 3. (a) Geographic distribution of K-means cluster predictions and distribution of annual mean values (expressed as a percentile ranking) across the three predicted clusters for (b) blood lead levels, (c) CO, (d) NO_2, (e) $PM_{2.5}$, (f) O_3, (g) PM_{10}, (h) SO_2, (i) air toxics, (j) percent unemployed, (k) percent without a high school diploma, (l) median household income, (m) percent below the federal poverty line, (n) percent of the population identifying as non-Hispanic White, (o) percent of the population identifying as non-Hispanic Black. Environmental pollutants (b–i), SES indicators (j–m), and population racial groups (n–o) are expressed as percentile rankings.

roughly similar patterns, only eight CBGs, representing less than 1% of the county population, were considered a statistically significant hotspot for all these pollutants. While central Milwaukee clearly showed a risk of cumulative exposure across environmental pollutants, the individual hot and cold spots were not necessarily overlapping when considering all pollutants.

The pattern of hot and cold spots for O_3, PM_{10}, and SO_2 was notably different than for the other environmental pollutants (Figure 2). O_3 displayed the opposite pattern, with a cluster of low concentrations in the center of the county. The variability of O_3 across the county was much lower than for the other pollutants considered here (Table 1). In contrast, PM_{10} and SO_2 did not show a homogenous area in central Milwaukee of either high or low concentrations. Similarly, the SES indicators showed regions of low SES in central Milwaukee; although, the spatial patterns of these hot spots were varied. The clusters indicating low SES (the hot spots for unemployment, lower education, and poverty and the cold spot for median household income) were on average 110%–160% higher than the county average (and 48% lower for the median household income).

There was a clear difference in the demographics across CBGs in clusters with elevated values compared to lower values of environmental pollutants. In the local clusters with elevated values for BLL, CO, NO_2, $PM_{2.5}$, and air toxics the NHB population proportion ranged from 34% to 62% (the 66th–74th percentile in the county), while the NHW population proportion in these same CBGs ranged from 11% to 42% (23rd–44th percentile across the county). Conversely, in clusters of low values for these pollutants the NHB population percent ranged from 9% to 14% while the NHW population ranged from 71% to 75%.

Table 2
The Average Percentile Ranking for Blood Lead Levels, Criteria Air Pollutants, Air Toxins, Demographic Indicators, and Socioeconomic Indicators Across the Three Predicted Clusters

Variable	Cluster 1	Cluster 2	Cluster 3
BLL	0.78	0.42	0.28
CO	0.79	0.47	0.17
NO_2	0.67	0.56	0.13
$PM_{2.5}$	0.46	0.67	0.17
O_3	0.21	0.59	0.69
PM_{10}	0.37	0.56	0.54
SO_2	0.48	0.58	0.35
Air toxics	0.78	0.43	0.27
% NHW	0.30	0.53	0.72
% NHB	0.63	0.50	0.33
% Unemployed	0.62	0.48	0.38
No high school diploma	0.70	0.46	0.32
Median Income	0.28	0.54	0.71
% Below Poverty	0.73	0.45	0.30

3.3. Clustering Across the Profile of Environmental Pollutants and SES Indicators

To identify the most vulnerable residential areas, we performed K-means clustering across the profile of environmental pollutants and SES indicators. While geographic information was not included in the clustering algorithm, we selected 3 clusters of roughly homogeneous spatial extent. We chose this number of clusters as it provided insight into geographic areas of elevated values across the profile of environmental pollutants and consistent low SES indicators.

The three clusters chosen showed consistent environmental and social profiles. The first cluster was located in the center of the county and was characterized by the highest BLL (the average was equivalent to the 78th percentile in county-level BLL), NO_2 (67th percentile), CO (79th percentile), and air toxics (78th percentile) across the three clusters considered here (Table 2 and Figure 3). The third cluster, located in the northern/southern parts of the county, had the lowest concentrations of these pollutants (ranging from the 13th–28th percentile across the pollutants). $PM_{2.5}$ (46th percentile in county-level concentrations) and SO_2 (48th percentile) also showed elevated concentrations in the first cluster; however, their concentrations were on average higher in the second cluster, which was geographically sandwiched between the first and third clusters. Still, concentrations of $PM_{2.5}$ and SO_2 were clearly elevated in the first and second clusters relative to the third cluster. O_3 showed a different trend with the lowest concentration in the first cluster and highest in the third cluster. This was consistent with the moderate anticorrelation of O_3 with NO_2.

Similarly, the first cluster showed a consistent social profile of low SES indicators. This cluster had the highest rate of unemployment (an average rate equivalent to the 62nd percentile across the county), highest rate of people without a high school degree (70th percentile), lowest median household income (28th percentile), and highest rate of poverty (73rd percentile) relative to the other two clusters (Table 2 and Figure 3). Demographic data were not included in fitting the clustering algorithm; however, applying the predicted labels to this data clearly showed a pattern across racial and ethnic lines (Table 2 and Figure 3). The first cluster, characterized by elevated BLL, NO_2, CO, air toxics, $PM_{2.5}$ and SO_2, had the lowest population fraction of NHW (30th percentile in the county) and the highest population fraction of NHB (63rd percentile). Of the total NHB population in Milwaukee County, a plurality resided in the first cluster (46%) compared to 43% in the second cluster and 11% in the third cluster. On the other hand, only 8% of the NHW resided in the first cluster.

The CBGs that made up the first cluster experience elevated multipollutant, multidomain, and multimatrix exposures to environmental pollutants. Moreover, this cluster was characterized by low SES with an overrepresentation of the NHB population (relative to the rest of the county). The environmental and social profile of this area indicated the most vulnerable population to exposure to environmental pollutants.

The selection of the number of clusters was subjective to some degree. We show alternate choices of the number of clusters in Figure S8 in Supporting Information S1. A choice of two clusters results in a cluster in the center of the county, characterized by high pollutant concentrations and low SES indicators (Figure S9 in Supporting Information S1). The primary difference between a choice of two and three clusters is shown in the profiles for NO_2 and $PM_{2.5}$ concentrations, where in the case of three clusters there is a cluster with notably lower NO_2 and $PM_{2.5}$ pollution while with only two clusters these pollutant profiles are overlapping.

4. Discussion

Across the United States, environmental justice communities, in both urban and rural areas, contend with multiple environmental pollutants from multiple domains. Residential segregation due to discriminatory mortgage lending practices (Home Owners Loan Corporation or "redlining") have resulted in historically minoritized communities residing in close proximity to industrial sources of pollution, traffic related air pollution from roadways, and lack of beneficial resources for health, such as green spaces (Kowalski & Conway, 2023; Nardone et al., 2024). Yet, within reason, environmental regulatory strategies in the United States have been developed to focus on interventions within the same regulatory domain (e.g., air, water). As a result, they are not intentionally designed to address the cumulative and synergistic effects of exposure to multiple pollutants nor the systemic nature of exposure disparities. Tools that leverage existing data resources for the identification of localized spatial clusters of high cumulative exposures lead to better identification of at-risk communities where investments could be made to address multiple systemic disparities at once through place-based, multi-pronged interventions. Here, we applied a novel approach to identify vulnerable populations where regulatory interventions across multiple domains could be braided to reduce exposure to a wider range of environmental pollutants than would be achieved by a single regulatory domain. The first cluster, characterized by high pollutant concentrations, low SES, and high representation of NHB residents represents an exemplar output of this approach to cluster analysis, that is, a high-risk population in need of interventions across multiple regulatory domains. If implemented with data resources like existing and emerging federal (e.g., EPA EJScreen (2024)) and state (e.g., California OEHHA (2024)) environmental screening and mapping tools, the approach presented here may also be useful in other settings where the spatial structure of environmental exposures, socioeconomic factors, and racial/ethnic demographics overlaps. Furthermore, this example may be also the most useful for urban areas where there is a legacy of lead pollution as well as air pollution from anthropogenic (e.g., transportation, oil and gas) sources.

Several features of air pollution chemistry and source apportionment help contextualize our findings. For example, low O_3 concentrations in the center of the county (higher areas for $PM_{2.5}$ and NO_2) are likely due to titration by urban NO emissions. In contrast, PM_{10} and SO_2 did not show a homogenous area in central Milwaukee for either high or low concentrations, likely caused by the spatial pattern of emissions for these pollutants. PM_{10} is commonly associated with resuspension of mineral dust and may be linked to natural emissions or agriculture while SO_2 is linked to the use of coal and petroleum at electric utilities and industrial facilities.

We note several limitations in this analysis. First, we weighted all environmental pollutants equally in this analysis; however, the health risks due to exposure to each in isolation are likely unequal. Moreover, we note that the association between exposure and health risk also varies by health outcome being considered (e.g., hospital admissions for asthma compared to stroke). Second, application of this approach to other cities may not result in clear spatial designations. In our analysis, predicted clusters tended to be spatially homogeneous, reflecting the underlying distributions of the environmental pollutants and SES indicators. Third, when determining local individual clusters, the hot and cold spots were determined relatively and may not necessarily indicate high or low values in a broader context. Fourth, we note that the modeled criteria air pollutants from the CACES land use regression model were developed and aggregated at the national level (Kim et al., 2020). Quantitative comparisons of this model at high spatial resolution are limited by lack of high-spatial resolution monitoring data, which highlights a need for enhanced monitoring of multiple pollutants. Finally, the time period used in this study reflects the availability of data. Recent trends in environmental pollutants, demographics, and SES indicators may continue to evolve. This work demonstrates a methodology that can continue to be applied as data sources are updated.

The study described has several notable strengths as well. First, the study undertook a comprehensive approach by considering multiple environmental pollutants across different domains and matrices. This approach was more reflective of real-world conditions where individuals are exposed to a mix of pollutants rather than a single pollutant. This study went beyond just examining multipollutant exposures by also considering SES and racial disparities. This allowed for a more nuanced understanding of environmental health risks and how they intersected with social and ethno-racial factors. Another strength of this study was the use of spatial analysis techniques, such as Moran's I and Local Indicators of Spatial Association, which provided a detailed understanding of the geographic distribution of environmental pollutants and SES indicators. This helped identify hot spots of exposure and vulnerability. Further, the application of K-means clustering to identify vulnerable populations across a profile of environmental pollutants and SES indicators was a novel approach. This can help prioritize areas for intervention and policy action. The use of the Gini coefficient to quantify spatial inequality in environmental pollutant exposures and SES indicators was a significant strength. Another strength was the use of multiple data sources in a localized context. The study's focus on Milwaukee County, Wisconsin, allowed for a detailed examination of environmental, socioeconomic, and racial disparities in a specific geographic context. This can provide valuable insights for local policymakers and stakeholders. Lastly, the study integrated data from multiple sources, including measurements and estimates of pollutants, demographic and socioeconomic data from the US Census Bureau, and data from the Healthy Homes and Lead Poisoning Surveillance system. This allowed for a more comprehensive analysis of environmental exposures and their social determinants using publicly available data sets.

In conclusion, this study provided valuable insights into the spatial distribution of environmental pollutant exposure and its association with SES and racial disparities in Milwaukee County. The findings underscore the need for comprehensive interventions that address multipollutant, multidomain, and multimatrix exposures, particularly in communities with low SES and high minority populations. Future research should focus on understanding the health impacts of cumulative exposure to multiple pollutants and developing effective strategies to reduce these exposures and mitigate their health effects.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

No new data were generated as part of this work. BLL data supporting this research are available through the Wisconsin Department of Health Services' Healthy Homes and Lead Poisoning Surveillance system (HHLPSS) (WDHS, 2023). The data are not currently accessible to the public or research community without prior approval from the HHLPSS. Researchers interested in gaining access to the data would be advised to contact the HHLPSS for further information and approval procedures. We believe that sharing this data with qualified researchers under appropriate safeguards would have significant value for future research in environmental and public health. We are open to providing any additional information or clarification you may need regarding the data or its availability. The criteria air pollutant data were downloaded from CACES (2023), the air toxics data were downloaded from EPA (2023b), and socioeconomic and demographic data were downloaded from US Census Bureau (2023).

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