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

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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 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

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 those residents also 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.

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. We identified spatial hot spots in Milwaukee County both individually and through clusters across a profile of environmental pollutants that span regulatory domains and matrices of exposure, as well as socioeconomic indicators. The most sensitive cluster within the urban area was largely characterized by low socioeconomic status (SES) and an overrepresentation of the Non-Hispanic Black (NHB) 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 while simultaneously having 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.

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 (Dockery et al., 1993; Bell et al., 2004; Miller et al., 2007; Apte et al., 2018). 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 are also known to have health risks. Lead exposure, which may occur through air, water, paint, or soil, has been shown to adversely impact intelligence quotient scores (Bellinger et al. 1992; Lanphear et al. 2005), school performance (Kordas et al. 2007; Magzamen et al. 2015), prosocial behavior (Wright et al. 2008; Amato et al. 2013), and cardiovascular disease (Chowdhury et al. 2018; Lamas et al. 2021).

Current regulations are often based on single pollutant exposures, which do not consider the possible synergistic effects of cumulative exposures (Mauderly and Samet, 2009; Benka-Coker et al., 2020). 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). Further, individuals may be exposed to environmental pollutants across multiple exposure matrices (e.g., air and water). These cumulative multipollutant, multidomain, and multimatrix 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.

Environmental epidemiology has increasingly considered exposures within the context of socioeconomic status (SES) (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 (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., 2004). In addition to SES, numerous studies have highlighted disparities in exposure to environmental pollutants across racial and ethnic lines (Morello-Frosch and Jesdale, 2006; Clark et al., 2014; Jbailey et al., 2022). Furthermore, 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; Tessum et al., 2021). These racial and ethnic disparities in exposure may contribute to higher rates of adverse health outcomes among communities of color (Apelberg et al., 2005; Hill et al., 2011).

Communities of color and low SES are exposed to higher concentrations of environmental pollutants and are more susceptible to the effects of this exposure (Clark et al. 2014; Tessum et al. 2021). Recently, several methodological approaches have been proposed to address the independent and joint contribution of environmental exposures and social factors to health outcomes (Martenies et al. 2019; Martenies et al. 2022a; Martenies et al. 2022b; 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 (Molitor et al., 2011; Lalloué et al., 2014; 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).

Comprehensive interventions that address multidomain and multimatrix exposures and adaptable to varying demographic and SES contexts are scarce. 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. 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. In Section 2, we outline the environmental pollutants, SES indicators, and statistical methodology used here. In Section 3, we examine geographical distributions across the profile of environmental pollutants and SES indicators, and the local and global clustering of these risk factors. We share our conclusions and study limitations in Section 4.

2. Methods

2.1 Study Area

Milwaukee County, Wisconsin (shown in the inset in Figure S1) includes the city of Milwaukee and the suburban area outside it. Milwaukee County is the most racially diverse county in the state of Wisconsin, with a Black population fraction over twice as high as the national average (US Census Bureau, 2022). 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). The dataset 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. 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. BLL were determined through venous or capillary testing methods. Some of the BLL values were reported with unknown sampling methods. Therefore, to avoid duplicating samples, if a child had multiple BLL tests, the highest BLL obtained from the venous test was retained since the venous test has been reported to give the most reliable BLL result than the capillary method (Parson et al., 1993; Schlenker et al., 1994; Sargent and Dalton, 1996; Holtrop et al., 1998; Cantor et al., 2019). When venous tests were absent, the highest value from capillary tests was retained. If the testing method was unspecified, the result was still included in the analysis, accounting for less than 2% of the total test data. Following data preprocessing, the BLL of 95,659 children in Milwaukee County were assessed, with 71,162 residing within the city of Milwaukee. We aggregate measurements to the CBG resolution. We note substantial variability in measurements of BLL within CBGs (Figure S2).

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. (2015). Estimates of air toxics come from the EPA's Risk-Screening Environmental Indicators (RSEI) model (EPA, 2023c). RSEI aggregates data collected from the Toxic Release Inventory. 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 available from the US Census Bureau (US Census Bureau, 2022). 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 (Martenies et al. 2019). 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.

2.4 Statistical Analysis

To investigate the degree of spatial structure in the dataset, we calculated measures of global and local spatial autocorrelation. 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 done in Python using the PySAL package (Rey and Anselin, 2010). We quantified inequality in environmental pollutants and SES indicators using the Gini index. 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). 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).

All pollutants exhibited a high degree of spatial structure (evidenced by Moran's I measure of global spatial autocorrelation) across Milwaukee County, as expected based on known differences in emissions across an urban area (Table 1). Children residing in the census tract in the metropolitan area of the city of Milwaukee, particularly in older housing stock with a median housing age of 94 years (interquartile range = 48 years), exhibited elevated BLLs. These aged residences may contain lead-based paints in multiple layers of painted surfaces, despite the absence of lead in the topmost paint layer. Additionally, a significant majority of these residential homes, approximately 90% are equipped with lead service lines, which are major sources of childhood lead poisoning. Mixing ratios of NO_2 exhibited the highest degree of spatial structure, with elevated concentrations along major roadways. While on-road sources mostly emit NO, some of this NO is rapidly converted to NO_2. Emissions of CO are also likely associated with traffic and urban sources. In contrast, $PM_{2.5}$ was spatially heterogeneous, which includes a mixture of primary (e.g., elemental carbon) and secondary (e.g., ammonium nitrate, ammonium sulfate) species. Annually-averaged measurements from the EPA's Chemical Speciation Network in Milwaukee reported a normalized $PM_{2.5}$ mass composition of organic carbon (37%, by mass), nitrate (26%), sulfate (18%), and ammonium (11%) ions, and elemental carbon (8%). PM_{10} and SO_2 could have been higher in some pockets outside the city due to the presence of specific emissions sources. O_3 is a regional pollutant formed from photochemical reactions and, hence, exhibited less variability across the county. The spatial pattern of toxicity-weighted concentrations of air toxics was strongly dependent on the location of the point sources (e.g., factories).

In addition to deleterious environmental exposure, the city of Milwaukee remains one of the most segregated areas in the United States (Johnston 2022). An analysis of 2000 census data for cities over 1 million residents indicated that Milwaukee was the most segregated city in the United States, where Black residents are concentrated in the central city (Frey 2018). Further, according to analyses conducted by the Center for Economic Development at University of Wisconsin-Milwaukee, Milwaukee's Black community faces myriad social challenges: median Black household income in Milwaukee is 42% that of a NHW household, the largest racial disparity in the country. Additionally, Milwaukee has the second-lowest Black homeownership rate among the nation's largest metropolitan areas at approximately 27.2 percent (Levine 2020). Over 72% of Black schoolchildren in Milwaukee attend hypersegregated schools, the highest rate in the country, and significantly higher than the percentage 30 years ago (Levine 2020).

To quantify the degree of spatial inequality in environmental pollutants, we calculated the Gini coefficient for each pollutant for Milwaukee County. 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 0.006-0.09. O_3 had the lowest measure of inequality (0.006) consistent with the low spatial variability in concentration across the county.

Similar to the environmental pollutants, the SES indicators also exhibited a high degree of spatial structure where indications 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 0.34-0.67) (Figure S4). 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 hotspot for at least one of BLL, CO, NO_2, $PM_{2.5}$, and air toxics (Figure S5). While the hot spots for BLL, CO, NO_2, $PM_{2.5}$, and air toxics had roughly similar patterns, only eight CBGs, representing less than 1% of the county population, were considered a statistically significant hot spot for all these pollutants. While central Milwakuee 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, likely due to titration by urban NO emissions. 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. This was 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.

Similarly, the SES indicators showed regions of low SES in central Milwaukee; though, the spatial patterns of these hot spots weres 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 34-62% (the 66^{th}-74^{th} percentile in the county), while the NHW population proportion in these same CBGs ranged from 11%-42% (23^{rd}-44^{th} percentile across the county). Conversely, in clusters of low values for these pollutants the NHB population percent ranged from 9%-14% while the NHW population ranged from 71%-75%.

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. The selection of the number of clusters was subjective to some degree. 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. We show alternate choices of the number of clusters in Figure S6.

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 78^{th} percentile in county-level BLL), NO_2 (67^{th} percentile), CO (79^{th} percentile), and air toxics (78^{th} 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 13^{th}-28^{th} percentile across the pollutants). $PM_{2.5}$ (46^{th} percentile in county-level concentrations) and SO_2 (48^{th} 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 62^{nd} percentile across the county), highest rate of people without a high school degree (70^{th} percentile), lowest median household income (28^{th} percentile), and highest rate of poverty (73^{rd} 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.

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 et al., 2023; Nardone et al., 2021). 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, i.e., 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 EJ Screen; https://www.epa.gov/ejscreen) and state (e.g., CalEnviroScreen; https://oehha.ca.gov/calenviroscreen) 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.

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. Finally, 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. 2015). 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.

The study described has several notable strengths as well. First, the study took 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 hotspots 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 datasets.

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.

5. Data Availability

No new data were generated as part of this work. The BLL data were collected as part of the Healthy Homes and Lead Poisoning Surveillance system (HHLPSS) overseen by the Wisconsin Department of Health Services. Household BLL data may be made available after careful consultation with all co-authors, partners, and stakeholders. The criteria air pollutant data were downloaded from https://www.caces.us/data, the air toxics data were downloaded from https://www.epa.gov/rsei, and socioeconomic and demographic data were downloaded from https://data.census.gov/cedsci/.

6. Supporting Information

Additional information about the study area, demographic distribution, pairwise correlations, and sensitivity to clustering assumptions.

7. Author Contributions

JK, SHJ, and SM designed the study. OO and EC provided the blood lead level data. JK analyzed and visualized the data. JK, EC, and SM wrote the paper with contributions from all co-authors.

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Table 1. Summary statistics (annual mean, standard deviation as well as the 5th, 25th, 50th, 75th, and 95th percentile) in 2015 and global spatial autocorrelation (Moran's I) 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}]	4070	3760	1970	2400	3080	4550	7890	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

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

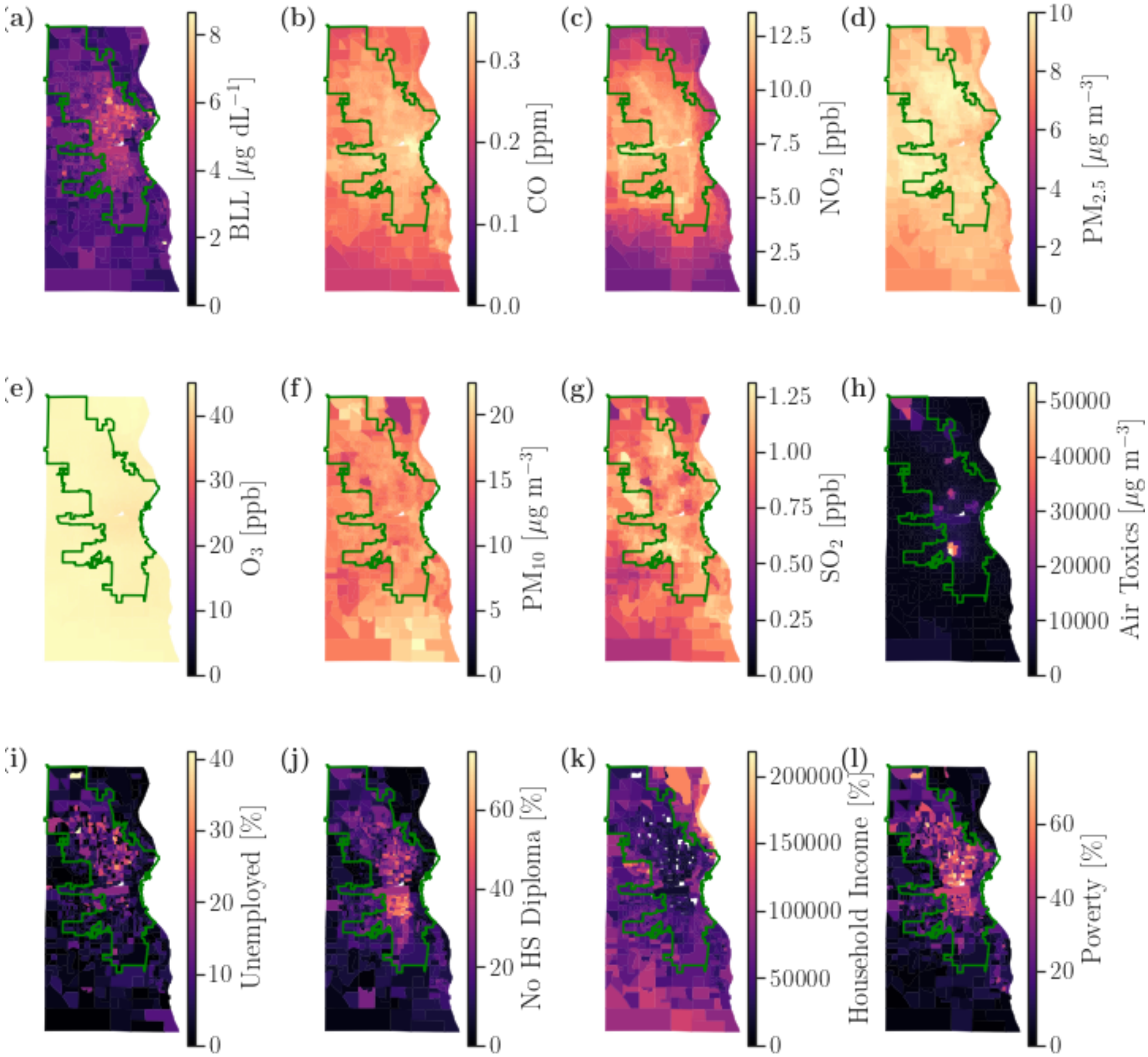

Figure 1. Annual mean year 2015 values in Milwaukee County, Wisconsin of (a) blood lead levels, (b) CO, (c) NO_2, (d) $PM_{2.5}$, (e) O_3, (f) PM_{10}, (g) SO_2, (h) air toxics as well as socioeconomic factors (i) unemployment rate, (j) percent of the population without a high school diploma, (k) median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

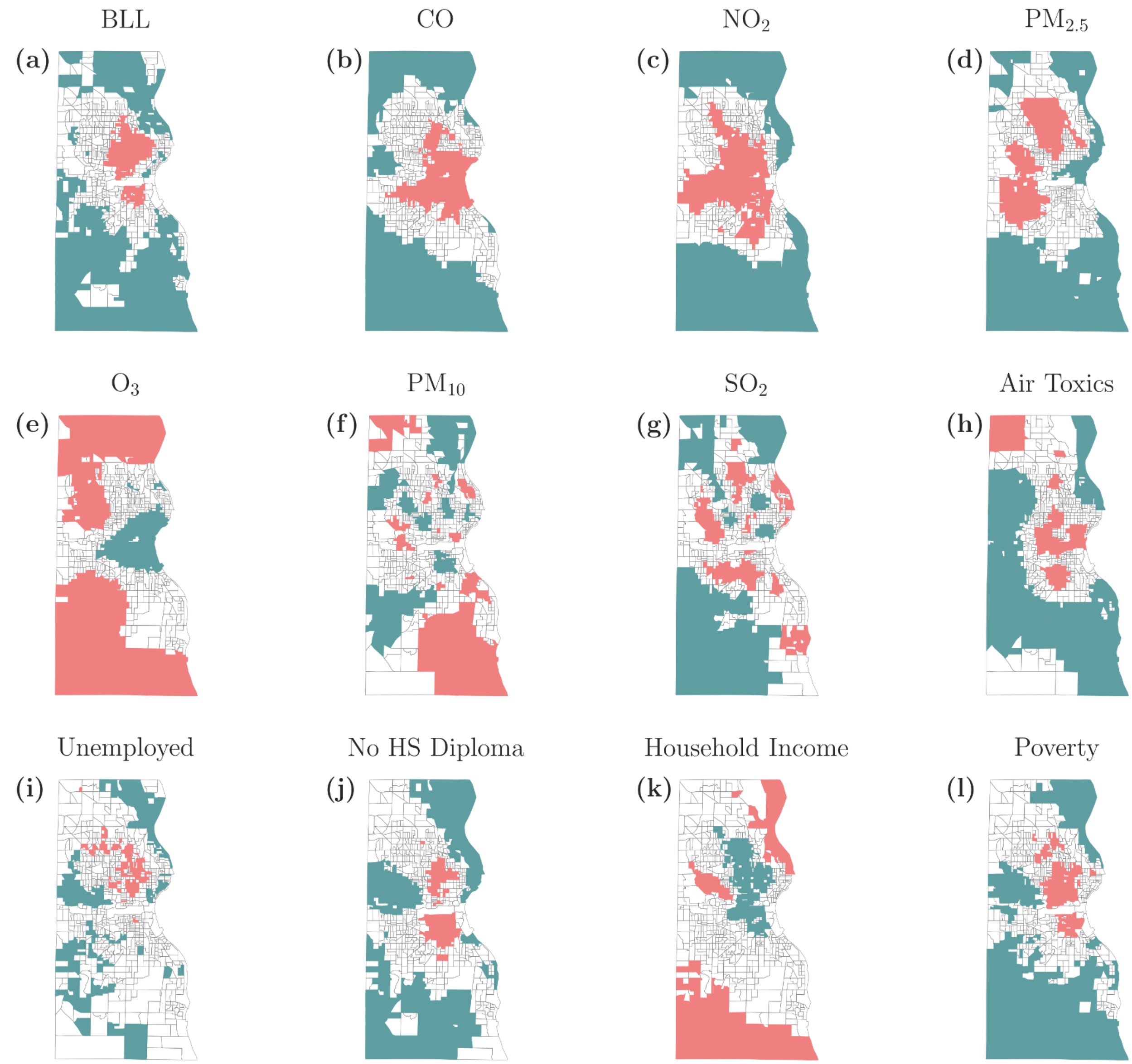

Figure 2. Statistically significant local clusters of high values (red) and low values (blue) for (a) blood lead levels, (b) CO, (c) NO_2, (d) $PM_{2.5}$, (e) O_3, (f) PM_{10}, (g) SO_2, (h) air toxics, (i) unemployment rate, (j) percent of the population without a high school diploma, (k) median household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

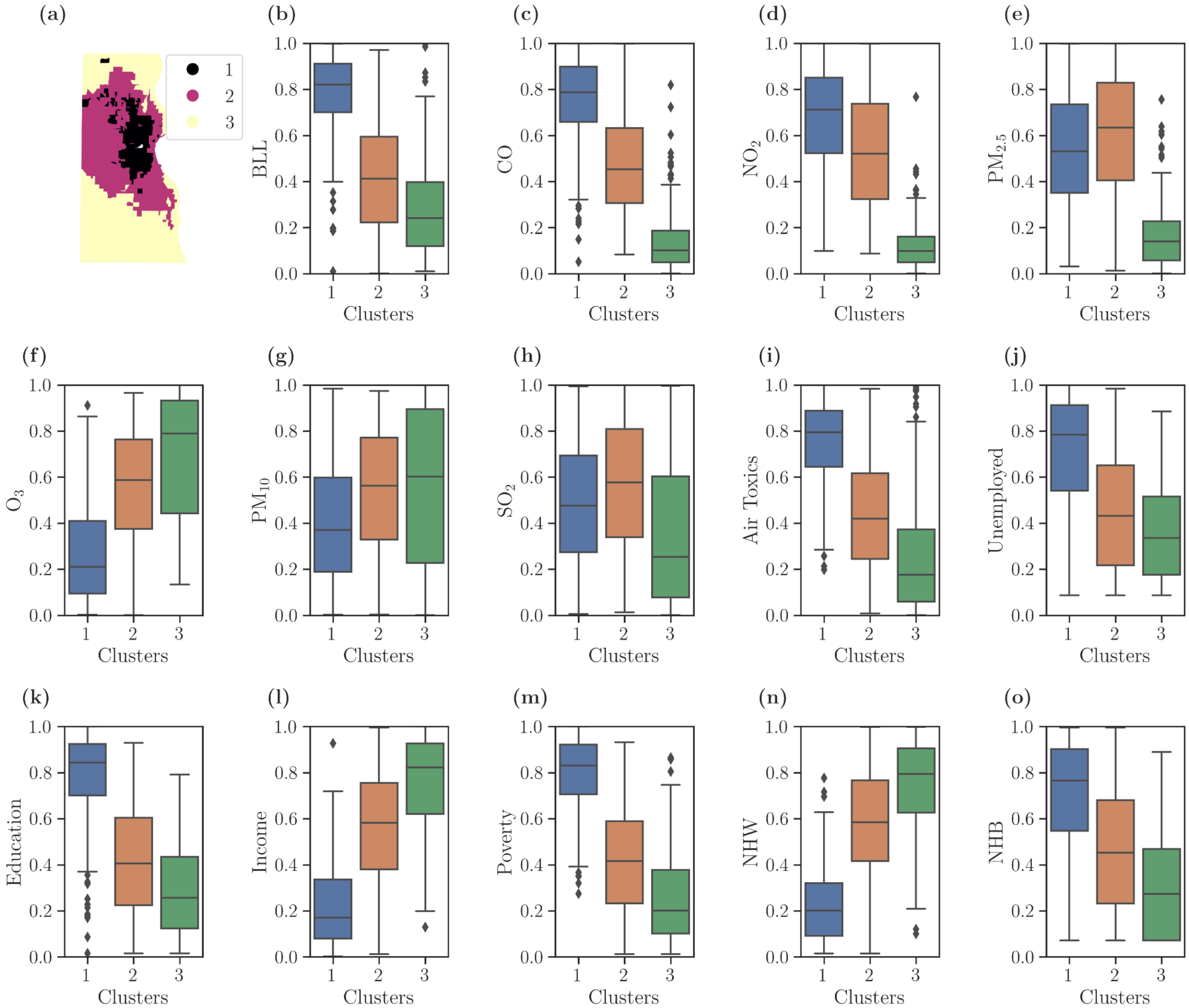

Figure 3. (a) Geographic distribution of K-means cluster predictions and distribution of annual mean values (expressed as a percentile ranking) across the three predicted clusters for (b) blood lead levels, (c) CO, (d) NO_2, (e) $PM_{2.5}$, (f) O_3, (g) PM_{10}, (h) SO_2, (i) air toxics, (j) percent 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.