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.

34   **Abstract**

35   The environmental justice literature demonstrates consistently that low-income and minority

36   communities are disproportionately exposed to environmental hazards. In this case study, we examined

37   cumulative multipollutant, multidomain, and multimatrix environmental exposures in Milwaukee County,

38   Wisconsin. We identified spatial hot spots in Milwaukee County both individually and through clusters

39   across a profile of environmental pollutants that span regulatory domains and matrices of exposure, as

40   well as socioeconomic indicators. The most sensitive cluster within the urban area was largely

41   characterized by low socioeconomic status (SES) and an overrepresentation of the Non-Hispanic Black

42   (NHB) population relative to the county as a whole. In this cluster, average pollutant concentrations were

43   equivalent to the 78th percentile in county-level blood lead levels, 67th percentile in county-level NO$_2$, 79th

44   percentile in county-level CO, and 78th percentile in county-level air toxics while simultaneously having

45   an average equivalent to the 62nd percentile in county-level unemployment, 70th percentile in county-level

46   population rate lacking a high school diploma, 73rd percentile in county-level poverty rate, and 28th

47   percentile in county-level median household income. The spatial patterns of pollutant exposure and SES

48   indicators suggested that these disparities were not random but were instead structured by socioeconomic

49   and racial factors. Our case study, which combines environmental pollutant exposures, sociodemographic

50   data, and clustering analysis, provides a roadmap to identify and target overburdened communities for

51   interventions that reduce environmental exposures and consequently improve public health.

52

53   **1. Introduction**

54   Previous research has established an association between health risks and exposure to various

55   anthropogenic environmental pollutants. Ambient air pollution has been consistently associated with an

56   array of adverse health impacts and is one of the leading risk factors contributing to morbidity and

57   premature mortality (Dockery et al., 1993; Bell et al., 2004; Miller et al., 2007; Apte et al., 2018). As a

58   result, the US Environmental Protection Agency (EPA) enforces national ambient air quality standards

59   (NAAQS) for six common air pollutants ("criteria air pollutants"), which are known to have adverse

60   health effects (EPA, 2023a). In addition to the criteria air pollutants, the EPA also mandates the reporting

61   of emissions of hundreds of chemicals with known cancer-causing or chronic/acute health effects (EPA,

62   2023b). Other exposure matrices are also known to have health risks. Lead exposure, which may occur

63   through air, water, paint, or soil, has been shown to adversely impact intelligence quotient scores

64   (Bellinger et al. 1992; Lanphear et al. 2005), school performance (Kordas et al. 2007; Magzamen et al.

65   2015), prosocial behavior (Wright et al. 2008; Amato et al. 2013), and cardiovascular disease

66   (Chowdhury et al. 2018; Lamas et al. 2021).

67   Current regulations are often based on single pollutant exposures, which do not consider the

68   possible synergistic effects of cumulative exposures (Mauderly and Samet, 2009; Benka-Coker et al.,

69   2020). Individuals are rarely exposed to single pollutants in isolation (e.g., Molitor et al. (2011)). Instead,

70   people and communities are commonly exposed to numerous pollutants within a regulatory domain (e.g.,

71   different criteria air pollutants such as, $PM_{2.5}$ and O_3) as well as multiple pollutants across regulatory

72   domains (for instance, criteria air pollutants and air toxics) (Benka-Coker et al., 2020). Further,

73   individuals may be exposed to environmental pollutants across multiple exposure matrices (e.g., air and

74   water). These cumulative multipollutant, multidomain, and multimatrix exposures may lead to complex

75   health responses not captured by considering single exposure to pollutants. Complicating matters,

76   interventions are rarely designed to target multidomain and multimatrix exposures.

77   Environmental epidemiology has increasingly considered exposures within the context of

78   socioeconomic status (SES) (O'Neill et al., 2003). A wealth of literature has illustrated the relationship

79   between SES and health (e.g., Adler et al. (1993); Isaacs and Schroeder (2004); Lynch et al. (2004)), as

80   well as the concept that low SES and negative environmental exposures are interrelated (Magzamen et al.,

81   2008). This association may occur because individuals living in areas of low SES may be exposed to

82   higher concentrations of environmental pollutants and/or may be more susceptible to environmental

83   pollutants (O'Neill et al., 2004). In addition to SES, numerous studies have highlighted disparities in

84   exposure to environmental pollutants across racial and ethnic lines (Morello-Frosch and Jesdale, 2006;

85   Clark et al., 2014; Jbailey et al., 2022). Furthermore, recent modeling work suggests that Black and

86   Hispanic populations in the US are exposed to a higher air pollution exposure burden relative to the

87   expected exposure originating from emissions associated with these population groups (Tessum et al.,

88   2019; Tessum et al., 2021). These racial and ethnic disparities in exposure may contribute to higher rates

89   of adverse health outcomes among communities of color (Apelberg et al., 2005; Hill et al., 2011).

90   Communities of color and low SES are exposed to higher concentrations of environmental

91   pollutants and are more susceptible to the effects of this exposure (Clark et al. 2014; Tessum et al. 2021).

92   Recently, several methodological approaches have been proposed to address the independent and joint

93   contribution of environmental exposures and social factors to health outcomes (Martenies et al. 2019;

94   Martenies et al. 2022a; Martenies et al. 2022b; Martenies et al. 2023). Identification of relevant social or

95   environmental factors associated with disease outcomes are an important pathway to identify effective

96   intervention and mediation strategies to improve health. Informed by earlier work (Molitor et al., 2011;

97   Lalloué et al., 2014; Shrestha et al., 2016), it is necessary to develop indicators that highlight communities

98   of high risk due to elevated cumulative exposure to environmental pollutants and/or low SES. For

99   instance, CalEnviroScreen develops an index based on percentile rankings across a set of environmental

100   and social indicators (Faust et al., 2014).

101   Comprehensive interventions that address multidomain and multimatrix exposures and adaptable

102   to varying demographic and SES contexts are scarce. In this study, we examine associations between

103   environmental exposures known to have adverse health risks and demographic and SES indicators across

104   multiple pollutants, domains, and matrices. We focus on the urban/suburban area of Milwaukee County,

105   Wisconsin. We highlight communities with cumulative exposures to elevated concentrations of

106   environmental pollutants and indicators of low SES status that can be prioritized for regulatory

107   interventions. In Section 2, we outline the environmental pollutants, SES indicators, and statistical

108   methodology used here. In Section 3, we examine geographical distributions across the profile of

109   environmental pollutants and SES indicators, and the local and global clustering of these risk factors. We

110   share our conclusions and study limitations in Section 4.

111

112   **2. Methods**

113   *2.1 Study Area*

114   Milwaukee County, Wisconsin (shown in the inset in Figure S1) includes the city of Milwaukee

115   and the suburban area outside it. Milwaukee County is the most racially diverse county in the state of

116   Wisconsin, with a Black population fraction over twice as high as the national average (US Census

117   Bureau, 2022). Milwaukee County has a history of poor environmental pollution. It was designated a

118   NAAQS maintenance area for 24-hr $PM_{2.5}$ in 2016 (Southeastern Wisconsin Regional Planning

119   Commission, 2016) and received an 'F' grade for O_3 from the American Lung Association's 2016 State

120   of the Air report (American Lung Association, 2016). In 2014, the city of Milwaukee had the highest

121   prevalence of lead poisoning in Wisconsin (which rates among the states with the highest incidence of

122   childhood lead poisoning in the US) (Wisconsin Department of Health Services, 2014).

123

124   *2.2 Environmental Pollutants*

125   We examined the cumulative exposure to blood lead levels (BLL), five of the six criteria air

126   pollutants, and inhalation toxicity-weighted summed concentrations of air toxics. These pollutants

127   spanned regulatory exposure domains and exposure matrices. We used measurements and estimates of

128   pollutants in the year 2015 (the most recent year for all data sources) at the census block group (CBG)

129   resolution (the highest resolution estimates offered for all data sources). The dataset at the individual level

130   for BLL consisted of samples collected from children who were part of the Healthy Homes and Lead

131   Poisoning Surveillance system (HHLPSS) overseen by the Wisconsin Department of Health Services,

132   Division of Public Health Services. The participants were children aged five or below, living in

133   Milwaukee County between 2015 and 2019. These data, which received ethics approval from the

134   Wisconsin Division of Public Health data governance board, encompassed information such as the child's

135   test ID, test date, test type, age at testing, gender, race, primary address, and BLL. BLL were determined

136   through venous or capillary testing methods. Some of the BLL values were reported with unknown

137   sampling methods. Therefore, to avoid duplicating samples, if a child had multiple BLL tests, the highest

138   BLL obtained from the venous test was retained since the venous test has been reported to give the most

139   reliable BLL result than the capillary method (Parson et al., 1993; Schlenker et al., 1994; Sargent and

140   Dalton, 1996; Holtrop et al., 1998; Cantor et al., 2019). When venous tests were absent, the highest value

141   from capillary tests was retained. If the testing method was unspecified, the result was still included in the

142   analysis, accounting for less than 2% of the total test data. Following data preprocessing, the BLL of

143   95,659 children in Milwaukee County were assessed, with 71,162 residing within the city of Milwaukee.

144   We aggregate measurements to the CBG resolution. We note substantial variability in measurements of

145   BLL within CBGs (Figure S2).

146   Estimates of criteria air pollutants (CO, NO_2, $PM_{2.5}$, O_3, PM_{10}, and SO_2) were taken from the

147   Center for Air, Climate and Energy Solutions (CACES) land use regression model; for details refer to

148   Kim et al. (2015). Estimates of air toxics come from the EPA's Risk-Screening Environmental Indicators

149   (RSEI) model (EPA, 2023c). RSEI aggregates data collected from the Toxic Release Inventory. We used

150   the sum of the concentrations of all chemicals in each CBG weighted by toxicity (i.e., the concentration

151   multiplied by the relative inhalation toxicity weight summed over all chemicals in the CBG). Thus, this

152   analysis was sensitive to estimates of both concentration of each chemical as well as its toxicity.

153

154   ***2.3 Demographic and Socioeconomic Data***

155   To examine the association of cumulative environmental exposure with SES and racial/ethnic

156   disparities, we downloaded data from the 5-year American Community Survey available from the US

157   Census Bureau (US Census Bureau, 2022). We used estimates of the percent of the population 16 years or

158   older within the civilian labor force that is unemployed, percent of the population older than 25 years

159   without a high school diploma, median household income, and percent of the population living below the

160   poverty line. These risk factors have been used in previous studies as measures of social vulnerability

161   (Martenies et al. 2019). To examine disparities along racial and ethnic lines, we used the percent of the

162   population in each CBG identifying as non-Hispanic White (NHW) and non-Hispanic Black (NHB). We

163   focused on these two groups due to the historical record of racial residential segregation in Wisconsin

164   between NHW and NHB populations.

165

166   ***2.4 Statistical Analysis***

167   To investigate the degree of spatial structure in the dataset, we calculated measures of global and

168   local spatial autocorrelation. We reported Moran's I as our metric for global spatial autocorrelation

169 (Moran, 1948). Moran's I was normalized to range from -1 to +1 with values closer to +1 indicating a

170 greater degree of positive spatial autocorrelation. Further, we calculated Local Indicators of Spatial

171 Association using Local Moran's I to identify statistically significant hot and cold spots across

172 environmental pollutants and SES indicators (Anselin, 1995). This measure of local spatial

173 autocorrelation identifies geographic clusters with high (low) values beyond what we would expect by

174 random chance. Statistical significance was assessed at the 95th percentile confidence interval. Both local

175 and global spatial autocorrelation were calculated using queen-adjacent spatial weights matrices. Spatial

176 statistics were done in Python using the PySAL package (Rey and Anselin, 2010). We quantified

177 inequality in environmental pollutants and SES indicators using the Gini index. The Gini index ranges

178 from 0 to 1 with higher values indicating a greater degree of inequality. This index, borrowed from

179 economic studies (Gini, 1936), has also been used frequently in previous studies investigating disparities

180 in environmental pollutants (e.g., Levy et al., 2006).

181   To identify clusters of vulnerable populations across a profile of environmental pollutants and

182 SES indicators, we used K-means clustering. As input features, we used standardized values for all

183 environmental pollutants and SES indicators with all features weighted equally. We did not include

184 demographic or geographic data as inputs to the clustering algorithm to explore the degree to which

185 spatial and demographic factors are associated with the predicted clusters. The number of predicted

186 clusters was to some degree subjective. We chose three clusters as this number demonstrated consistent

187 environmental social profiles across the clusters. In addition, the three predicted clusters occupied a

188 roughly spatially homogeneous region.

189

190 **3. Results**

191 ***3.1 Geographic Distribution of Environmental Pollutants and Socioeconomic Indicators***

192   Annual (year 2015) mean concentrations of BLL, criteria air pollutants, and air toxics exhibited

193 substantial spatial structure across Milwaukee, County; though, the spatial patterns differed by pollutant

194 (Figure 1 and Table 1). The highest concentrations of BLL, CO, NO_2, $PM_{2.5}$, and air toxics occurred

195 within the city of Milwaukee (Figure 1), while O_3 and PM_{10} had slightly lower concentrations in this area

196 relative to other parts of the county. For SO_2, the highest concentrations were found both inside and

197 outside the Milwaukee city limits. Pollutants generally exhibited weak (less than 0.4) paired correlations

198 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).

199   All pollutants exhibited a high degree of spatial structure (evidenced by Moran's I measure of

200 global spatial autocorrelation) across Milwaukee County, as expected based on known differences in

201 emissions across an urban area (Table 1). Children residing in the census tract in the metropolitan area of

202 the city of Milwaukee, particularly in older housing stock with a median housing age of 94 years

203 (interquartile range = 48 years), exhibited elevated BLLs. These aged residences may contain lead-based

204 paints in multiple layers of painted surfaces, despite the absence of lead in the topmost paint layer.

205 Additionally, a significant majority of these residential homes, approximately 90% are equipped with lead

206 service lines, which are major sources of childhood lead poisoning. Mixing ratios of NO_2 exhibited the

207 highest degree of spatial structure, with elevated concentrations along major roadways. While on-road

208 sources mostly emit NO, some of this NO is rapidly converted to NO_2. Emissions of CO are also likely

209 associated with traffic and urban sources. In contrast, $PM_{2.5}$ was spatially heterogeneous, which includes a

210 mixture of primary (e.g., elemental carbon) and secondary (e.g., ammonium nitrate, ammonium sulfate)

211 species. Annually-averaged measurements from the EPA's Chemical Speciation Network in Milwaukee

212 reported a normalized $PM_{2.5}$ mass composition of organic carbon (37%, by mass), nitrate (26%), sulfate

213 (18%), and ammonium (11%) ions, and elemental carbon (8%). PM_{10} and SO_2 could have been higher in

214 some pockets outside the city due to the presence of specific emissions sources. O_3 is a regional pollutant

215 formed from photochemical reactions and, hence, exhibited less variability across the county. The spatial

216 pattern of toxicity-weighted concentrations of air toxics was strongly dependent on the location of the

217 point sources (e.g., factories).

218 In addition to deleterious environmental exposure, the city of Milwaukee remains one of the most

219 segregated areas in the United States (Johnston 2022). An analysis of 2000 census data for cities over 1

220 million residents indicated that Milwaukee was the most segregated city in the United States, where Black

221 residents are concentrated in the central city (Frey 2018). Further, according to analyses conducted by the

222 Center for Economic Development at University of Wisconsin-Milwaukee, Milwaukee's Black

223 community faces myriad social challenges: median Black household income in Milwaukee is 42% that of

224 a NHW household, the largest racial disparity in the country. Additionally, Milwaukee has the second-

225 lowest Black homeownership rate among the nation's largest metropolitan areas at approximately 27.2

226 percent (Levine 2020). Over 72% of Black schoolchildren in Milwaukee attend hypersegregated schools,

227 the highest rate in the country, and significantly higher than the percentage 30 years ago (Levine 2020).

228 To quantify the degree of spatial inequality in environmental pollutants, we calculated the Gini

229 coefficient for each pollutant for Milwaukee County. A value of the Gini coefficient of 0 indicates perfect

230 equality with increasing values indicating a higher degree of inequality (with a maximum of 1). We

231 calculated the Gini coefficient based on the distribution of annual means in the CBGs for each pollutant.

232 BLL and air toxics had by far the highest degree of inequality across the county, 0.2 and 0.3, respectively.

233 The criteria air pollutants generally had low Gini coefficients, ranging from 0.006-0.09. O_3 had the lowest

234 measure of inequality (0.006) consistent with the low spatial variability in concentration across the

235 county.

236   Similar to the environmental pollutants, the SES indicators also exhibited a high degree of spatial

237 structure where indications of low SES were concentrated in the center of the city of Milwaukee (Table 1

238 and Figure 1). These indicators were moderately correlated (with the absolute value of the paired

239 correlations ranging from 0.34-0.67) (Figure S4). The Gini coefficient was high for all indicators

240 considered here, ranging from 0.3 to 0.5, indicating a high degree of spatial inequality across Milwaukee

241 County.

242

243 *3.2 Local Hot and Cold Spots for Environmental Pollutants and SES Indicators*

244   We identified statistically significant geographic hot and cold spots of individual environmental

245 pollutants and SES indicators. BLL, CO, NO_2, and $PM_{2.5}$ showed a similar geographic distribution, with a

246 hot spot (a region of elevated values) in the center of the county (and roughly the center of the city of

247 Milwaukee) and cold spots (low values) around the northern and southern parts of the county (Figure 2).

248 BLL in the elevated clusters were 49% higher than the county average, indicating an important area of

249 elevated exposure and associated health risk to this pollutant. In contrast, the average concentrations of

250 CO, NO_2, and $PM_{2.5}$ in the elevated clusters were only moderately higher than the county average: 8%,

251 15%, and 6%, respectively. Air toxics, which displayed the greatest variability across the state (Table 1),

252 were 165% higher in the elevated cluster on average than in the county average. There were 503 CBGs

253 identified as a hotspot for at least one of BLL, CO, NO_2, $PM_{2.5}$, and air toxics (Figure S5). While the hot

254 spots for BLL, CO, NO_2, $PM_{2.5}$, and air toxics had roughly similar patterns, only eight CBGs,

255 representing less than 1% of the county population, were considered a statistically significant hot spot for

256 all these pollutants. While central Milwakuee clearly showed a risk of cumulative exposure across

257 environmental pollutants, the individual hot and cold spots were not necessarily overlapping when

258 considering all pollutants.

259   The pattern of hot and cold spots for O_3, PM_{10}, and SO_2 was notably different than for the other

260 environmental pollutants (Figure 2). O_3 displayed the opposite pattern, with a cluster of low

261 concentrations in the center of the county, likely due to titration by urban NO emissions. The variability

262 of O_3 across the county was much lower than for the other pollutants considered here (Table 1). In

263 contrast, PM_{10} and SO_2 did not show a homogenous area in central Milwaukee of either high or low

264 concentrations. This was likely caused by the spatial pattern of emissions for these pollutants. PM_{10} is

265 commonly associated with resuspension of mineral dust and may be linked to natural emissions or

266 agriculture while SO_2 is linked to the use of coal and petroleum at electric utilities and industrial facilities.

267   Similarly, the SES indicators showed regions of low SES in central Milwaukee; though, the

268 spatial patterns of these hot spots weres varied. The clusters indicating low SES (the hot spots for

269   unemployment, lower education, and poverty and the cold spot for median household income) were on

270   average 110 -160% higher than the county average (and 48% lower for the median household income).

271   There was a clear difference in the demographics across CBGs in clusters with elevated values

272   compared to lower values of environmental pollutants. In the local clusters with elevated values for BLL,

273   CO, NO_2, $PM_{2.5}$, and air toxics the NHB population proportion ranged from 34-62% (the 66th-74th

274   percentile in the county), while the NHW population proportion in these same CBGs ranged from 11%-

275   42% (23rd-44th percentile across the county). Conversely, in clusters of low values for these pollutants the

276   NHB population percent ranged from 9%-14% while the NHW population ranged from 71%-75%.

277

278   *3.3 Clustering Across the Profile of Environmental Pollutants and SES Indicators*

279   To identify the most vulnerable residential areas, we performed K-means clustering across the

280   profile of environmental pollutants and SES indicators. While geographic information was not included in

281   the clustering algorithm, we selected 3 clusters of roughly homogeneous spatial extent. The selection of

282   the number of clusters was subjective to some degree. We chose this number of clusters as it provided

283   insight into geographic areas of elevated values across the profile of environmental pollutants and

284   consistent low SES indicators. We show alternate choices of the number of clusters in Figure S6.

285   The three clusters chosen showed consistent environmental and social profiles. The first cluster

286   was located in the center of the county and was characterized by the highest BLL (the average was

287   equivalent to the 78th percentile in county-level BLL), NO_2 (67th percentile), CO (79th percentile), and air

288   toxics (78th percentile) across the three clusters considered here (Table 2 and Figure 3). The third cluster,

289   located in the northern/southern parts of the county, had the lowest concentrations of these pollutants

290   (ranging from the 13th-28th percentile across the pollutants). $PM_{2.5}$ (46th percentile in county-level

291   concentrations) and SO_2 (48th percentile) also showed elevated concentrations in the first cluster;

292   however, their concentrations were on average higher in the second cluster, which was geographically

293   sandwiched between the first and third clusters. Still, concentrations of $PM_{2.5}$ and SO_2 were clearly

294   elevated in the first and second clusters relative to the third cluster. O_3 showed a different trend with the

295   lowest concentration in the first cluster and highest in the third cluster. This was consistent with the

296   moderate anticorrelation of O_3 with NO_2.

297   Similarly, the first cluster showed a consistent social profile of low SES indicators. This cluster

298   had the highest rate of unemployment (an average rate equivalent to the 62nd percentile across the county),

299   highest rate of people without a high school degree (70th percentile), lowest median household income

300   (28th percentile), and highest rate of poverty (73rd percentile) relative to the other two clusters (Table 2

301   and Figure 3). Demographic data were not included in fitting the clustering algorithm; however, applying

302   the predicted labels to this data clearly showed a pattern across racial and ethnic lines (Table 2 and Figure

303   3). The first cluster, characterized by elevated BLL, NO_2, CO, air toxics, $PM_{2.5}$ and SO_2, had the lowest

304   population fraction of NHW (30th percentile in the county) and the highest population fraction of NHB

305   (63rd percentile). Of the total NHB population in Milwaukee County, a plurality resided in the first cluster

306   (46%) compared to 43% in the second cluster and 11% in the third cluster. On the other hand, only 8% of

307   the NHW resided in the first cluster.

308   The CBGs that made up the first cluster experience elevated multipollutant, multidomain, and

309   multimatrix exposures to environmental pollutants. Moreover, this cluster was characterized by low SES

310   with an overrepresentation of the NHB population (relative to the rest of the county). The environmental

311   and social profile of this area indicated the most vulnerable population to exposure to environmental

312   pollutants.

313

314   **4. Discussion**

315   Across the United States, environmental justice communities, in both urban and rural areas,

316   contend with multiple environmental pollutants from multiple domains. Residential segregation due to

317   discriminatory mortgage lending practices (Home Owners Loan Corporation or "redlining") have resulted

318   in historically minoritized communities residing in close proximity to industrial sources of pollution,

319   traffic related air pollution from roadways, and lack of beneficial resources for health, such as green

320   spaces (Kowalski et al., 2023; Nardone et al., 2021). Yet, within reason, environmental regulatory

321   strategies in the United States have been developed to focus on interventions within the same regulatory

322   domain (e.g., air, water). As a result, they are not intentionally designed to address the cumulative and

323   synergistic effects of exposure to multiple pollutants nor the systemic nature of exposure disparities.

324   Tools that leverage existing data resources for the identification of localized spatial clusters of high

325   cumulative exposures lead to better identification of at-risk communities where investments could be

326   made to address multiple systemic disparities at once through place-based, multi-pronged interventions.

327   Here, we applied a novel approach to identify vulnerable populations where regulatory interventions

328   across multiple domains could be braided to reduce exposure to a wider range of environmental pollutants

329   than would be achieved by a single regulatory domain. The first cluster, characterized by high pollutant

330   concentrations, low SES, and high representation of NHB residents represents an exemplar output of this

331   approach to cluster analysis, i.e., a high-risk population in need of interventions across multiple regulatory

332   domains. If implemented with data resources like existing and emerging federal (e.g., EPA EJ Screen;

333   https://www.epa.gov/ejscreen) and state (e.g., CalEnviroScreen; https://oehha.ca.gov/calenviroscreen)

334   environmental screening and mapping tools, the approach presented here may also be useful in other

335   settings where the spatial structure of environmental exposures, socioeconomic factors, and racial/ethnic

336   demographics overlaps. Furthermore, this example may be also the most useful for urban areas where

337 there is a legacy of lead pollution as well as air pollution from anthropogenic (e.g., transportation, oil and

338 gas) sources.

339   We note several limitations in this analysis. First, we weighted all environmental pollutants

340 equally in this analysis; however, the health risks due to exposure to each in isolation are likely unequal.

341 Moreover, we note that the association between exposure and health risk also varies by health outcome

342 being considered (e.g., hospital admissions for asthma compared to stroke). Second, application of this

343 approach to other cities may not result in clear spatial designations. In our analysis, predicted clusters

344 tended to be spatially homogeneous, reflecting the underlying distributions of the environmental

345 pollutants and SES indicators. Third, when determining local individual clusters, the hot and cold spots

346 were determined relatively and may not necessarily indicate high or low values in a broader context.

347 Finally, we note that the modeled criteria air pollutants from the CACES land use regression model were

348 developed and aggregated at the national level (Kim et al. 2015). Quantitative comparisons of this model

349 at high spatial resolution are limited by lack of high-spatial resolution monitoring data, which highlights a

350 need for enhanced monitoring of multiple pollutants.

351   The study described has several notable strengths as well. First, the study took comprehensive

352 approach by considering multiple environmental pollutants across different domains and matrices. This

353 approach was more reflective of real-world conditions where individuals are exposed to a mix of

354 pollutants rather than a single pollutant. This study went beyond just examining multipollutant exposures

355 by also considering SES and racial disparities. This allowed for a more nuanced understanding of

356 environmental health risks and how they intersected with social and ethno-racial factors. Another strength

357 of this study was the use of spatial analysis techniques, such as Moran's I and Local Indicators of Spatial

358 Association, which provided a detailed understanding of the geographic distribution of environmental

359 pollutants and SES indicators. This helped identify hotspots of exposure and vulnerability. Further, the

360 application of K-means clustering to identify vulnerable populations across a profile of environmental

361 pollutants and SES indicators was a novel approach. This can help prioritize areas for intervention and

362 policy action. The use of the Gini coefficient to quantify spatial inequality in environmental pollutant

363 exposures and SES indicators was a significant strength. Another strength was the use of multiple data

364 sources in a localized context. The study's focus on Milwaukee County, Wisconsin, allowed for a detailed

365 examination of environmental, socioeconomic, and racial disparities in a specific geographic context.

366 This can provide valuable insights for local policymakers and stakeholders. Lastly, the study integrated

367 data from multiple sources, including measurements and estimates of pollutants, demographic and

368 socioeconomic data from the US Census Bureau, and data from the Healthy Homes and Lead Poisoning

369 Surveillance system. This allowed for a more comprehensive analysis of environmental exposures and

370 their social determinants using publicly available datasets.

11

371   In conclusion, this study provided valuable insights into the spatial distribution of environmental

372   pollutant exposure and its association with SES and racial disparities in Milwaukee County. The findings

373   underscore the need for comprehensive interventions that address multipollutant, multidomain, and

374   multimatrix exposures, particularly in communities with low SES and high minority populations. Future

375   research should focus on understanding the health impacts of cumulative exposure to multiple pollutants

376   and developing effective strategies to reduce these exposures and mitigate their health effects.

377

378   **5. Data Availability**

379   No new data were generated as part of this work. The BLL data were collected as part of the

380   Healthy Homes and Lead Poisoning Surveillance system (HHLPSS) overseen by the Wisconsin

381   Department of Health Services. Household BLL data may be made available after careful consultation

382   with all co-authors, partners, and stakeholders. The criteria air pollutant data were downloaded from

383   https://www.caces.us/data, the air toxics data were downloaded from https://www.epa.gov/rsei, and

384   socioeconomic and demographic data were downloaded from https://data.census.gov/cedsci/.

385

386   **6. Supporting Information**

387   Additional information about the study area, demographic distribution, pairwise correlations, and

388   sensitivity to clustering assumptions.

389

390   **7. Author Contributions**

391   JK, SHJ, and SM designed the study. OO and EC provided the blood lead level data. JK analyzed

392   and visualized the data. JK, EC, and SM wrote the paper with contributions from all co-authors.

393

394   **8. Acknowledgements**

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513

514 *Table 1. Summary statistics (annual mean, standard deviation as well as the 5th, 25th, 50th, 75th, and 95th*
515 *percentile) in 2015 and global spatial autocorrelation (Moran's I) for blood lead levels, criteria air*
516 *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

517

518   *Table 2. The average percentile ranking for blood lead levels, criteria air pollutants, air toxins,*
519   *demographic indicators, and socioeconomic indicators across the three predicted clusters.*

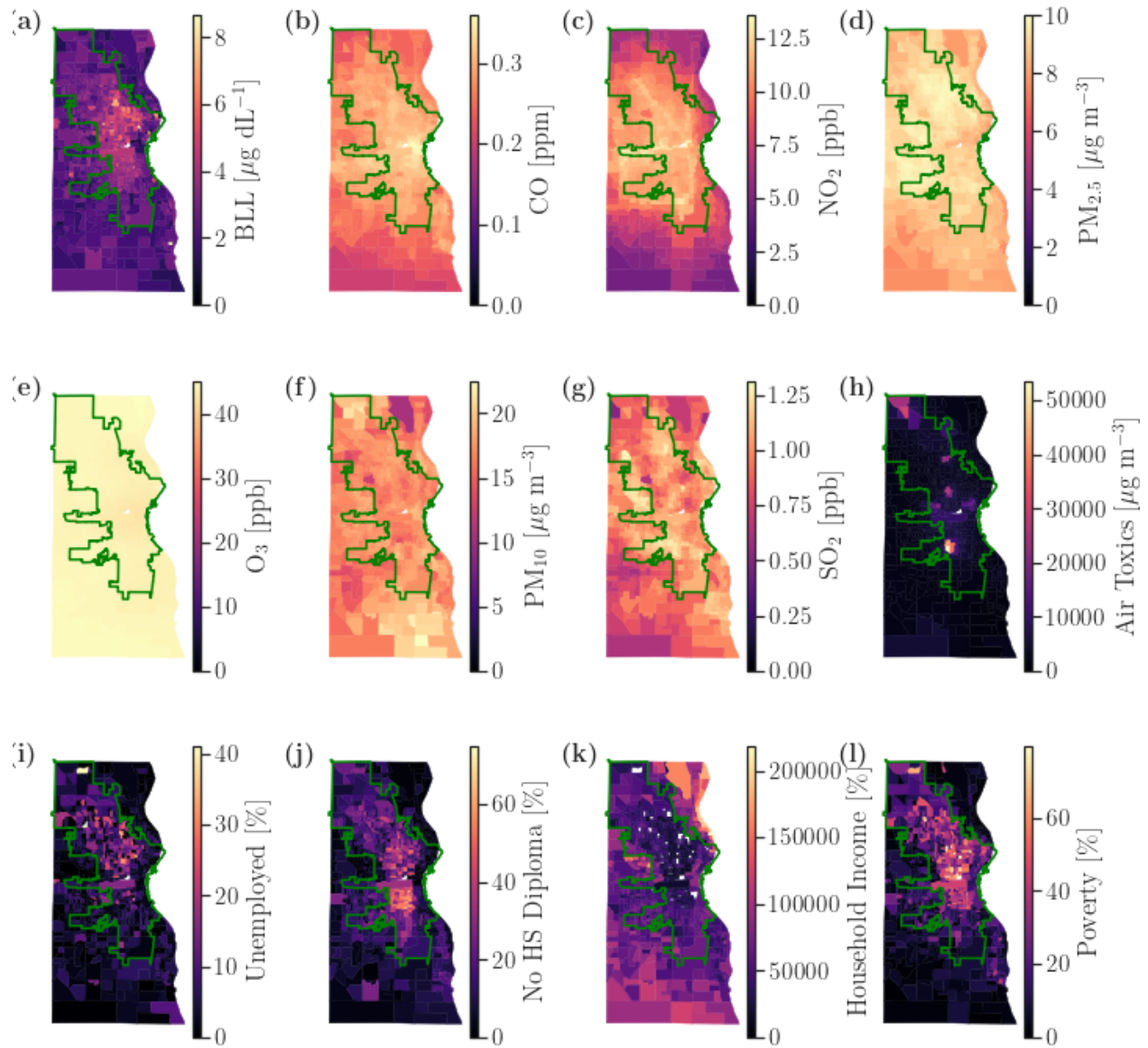| Variable	Cluster 1	Cluster 2	Cluster 3
BLL	0.78	0.42	0.28
CO	0.79	0.47	0.17
NO_2	0.67	0.56	0.13
$PM_{2.5}$	0.46	0.67	0.17
O_3	0.21	0.59	0.69
PM_{10}	0.37	0.56	0.54
SO_2	0.48	0.58	0.35
Air toxics	0.78	0.43	0.27
% NHW	0.30	0.53	0.72
% NHB	0.63	0.50	0.33
% Unemployed	0.62	0.48	0.38
No high school diploma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

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522
523 *Figure 1. Annual mean year 2015 values in Milwaukee County, Wisconsin of (a) blood lead levels, (b)*
524 *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)*
525 *unemployment rate, (j) percent of the population without a high school diploma, (k) median household*
526 *income, (l) percent of the population below the poverty line. The green polygon shows the municipal*
527 *boundary of the city of Milwaukee, Wisconsin.*
528

BLL   CO   NO$_2$ PM$_{2.5}$

(a)   (b)   (c)   (d)

O$_3$ PM$_{10}$ SO$_2$ Air Toxics

(e)   (f)   (g)   (h)

Unemployed   No HS Diploma   Household Income   Poverty
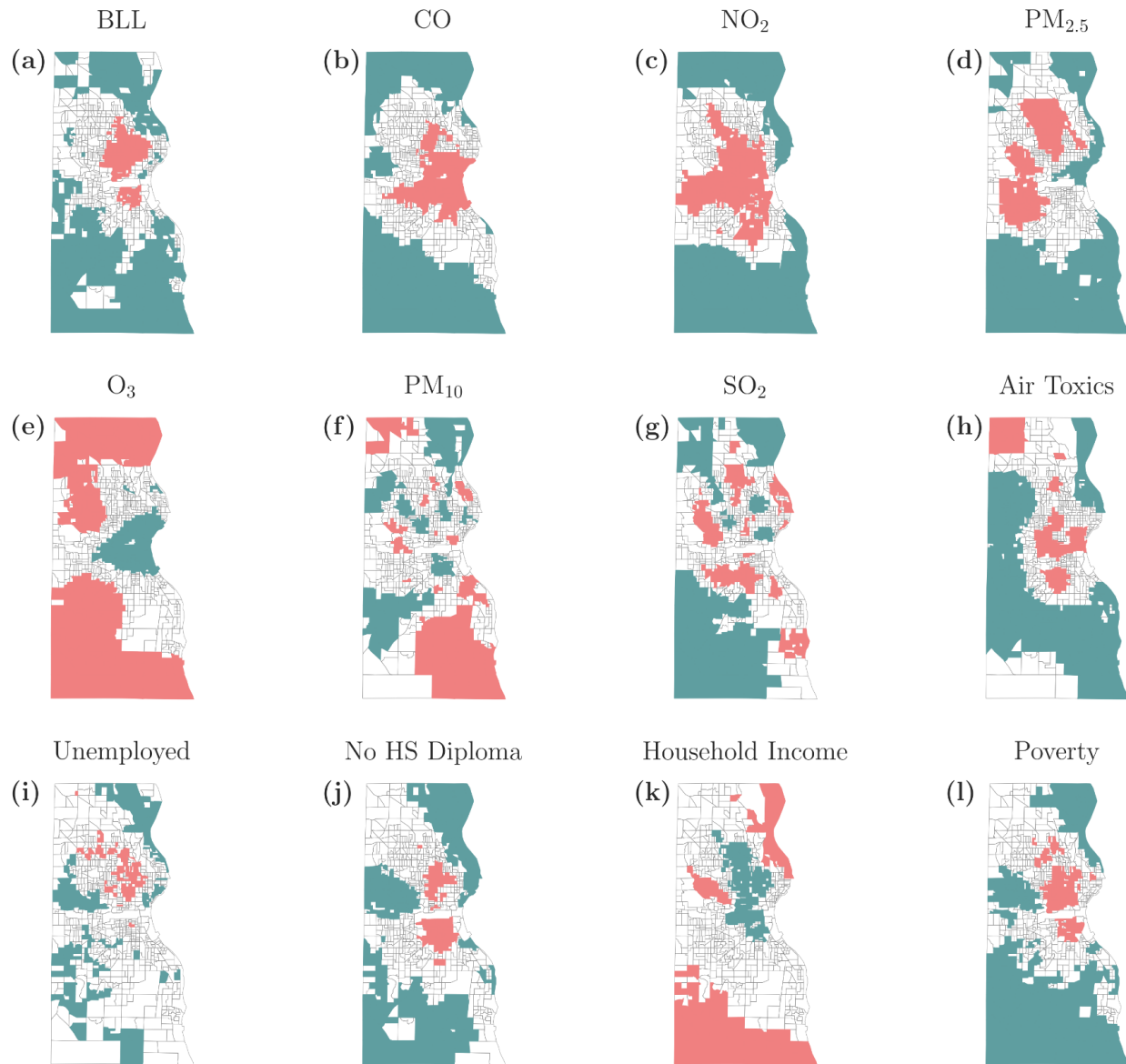
(i)   (j)   (k)   (l)

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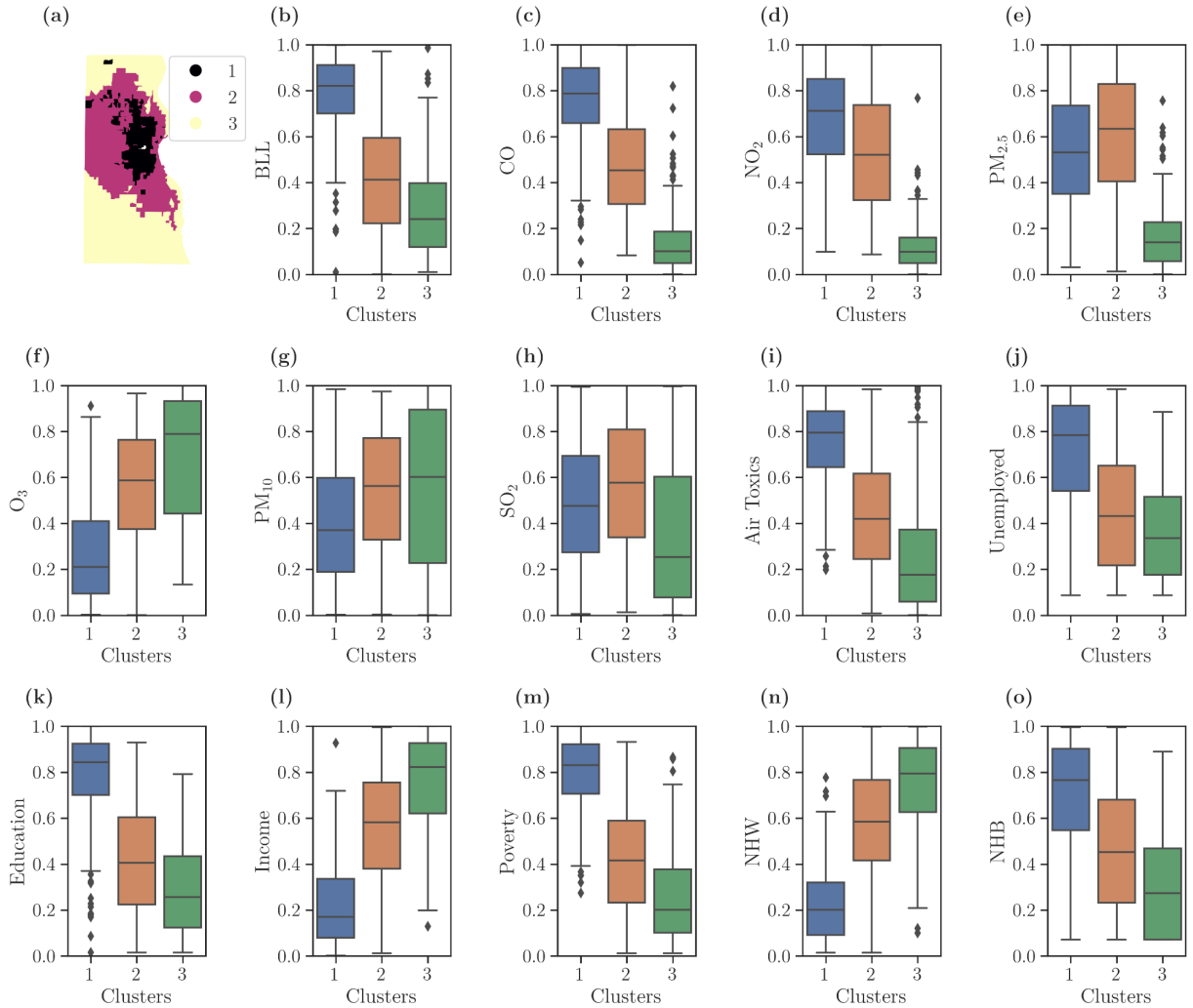
Figure 3. (a) Geographic distribution of K-means cluster predictions and distribution of annual mean values (expressed as a percentile ranking) across the three predicted clusters for (b) blood lead levels, (c) CO, (d) NO_2, (e) $PM_{2.5}$, (f) O_3, (g) PM_{10}, (h) SO_2, (i) air toxics, (j) percent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