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Bayesian deprivation index models for explaining variation in elevated blood lead levels among children in Maryland

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ABSTRACT

Lead exposure adversely affects children's health. Exposure in the United States is highest among socioeconomically disadvantaged individuals who disproportionately live in substandard housing. We used Bayesian binomial regression models to estimate a neighborhood deprivation index and its association with elevated blood lead level (EBLL) risk using blood lead level testing data in Maryland census tracts. Our results show the probability of EBLL was spatially structured with high values in Baltimore city and low values in the District of Columbia suburbs and Baltimore suburbs. The association between the neighborhood deprivation index and EBLL risk was statistically significant after accounting for spatial dependence in probability of EBLL. The percent of houses built before 1940, African Americans, and renter occupied housing were the most important variables in the index. Bayesian models provide a flexible one-step approach to modeling risk associated with neighborhood deprivation while accounting for spatially structured and unstructured heterogeneity in risk.

1. Introduction

Environmental lead exposure has been linked to numerous adverse health effects in children, especially neurological and neurobehavioral deficits such as lower IQ, slowed growth, and anemia (Agency for Toxic Substances and Disease Registry (ATSDR) 2007; Canfield et al., 2003; Chiodo et al., 2004; Grandjean and Landrigan, 2014; Lanphear et al., 2000; Lidsky and Schneider, 2003; Mielke et al., 1997; Mielke et al., 2017; Mielke et al., 2016; Miranda et al., 2007; Nelson et al., 2015; Schnaas et al., 2000; Tellez-Rojo et al., 2006). During 2007–2010, an estimated 535,000 children aged 1–5 years in the U.S. had elevated blood lead levels (EBLLs) (Centers for Disease Control and Prevention (CDC) 2013). The U.S. Centers for Disease Control and Prevention recommends reducing future lead exposure for children with blood lead levels (BLLs) at or above 5 mcg/dL (Centers for Disease Control and Prevention (CDC) 2012; Wengrovitz and Brown, 2009). Though remediation and rehabilitation of lead contaminated areas is possible and has been demonstrated in European countries (Remediated sites and brownfields: Success stories in Europe 2015) and some U.S. cities (Staes et al., 1994; Leighton et al., 2003; Triantafyllidou et al., 2014; Schoof et al., 2016), it is unlikely that the Healthy People 2020 objective to reduce BLLs to an average of 1.6 mcg/dL will be achieved in the U.S. in the near future (Centers for Disease Control and Prevention (CDC) 2004; US Department of Health and Human Services 2012). Inadequate identification of lead hazards and limited governmental funds to sponsor remediation programs reduce efforts to prevent lead poisoning (Letter from National Safe and Healthy Housing Coalition to Members of Congress 2019; Center for American Progress 2016). While there are target maps for lead testing or lead remediation for some U.S. cities (Philadelphia Citizens for Children and Youth 2006; Maryland Department of Health and Mental Hygiene 2004; Maryland Department of Health and Mental Hygiene 2015), the cost of effective remediation, particularly in historically underserved and low-resourced areas, impacts harm reduction efforts (Lead-based Paint Hazard Reduction and Financing Task Force 1995; Sampson and Winter, 2016). Further, there is difficulty in identifying specific homes where to target lead remediation and prevention efforts because it is not feasible to obtain blood from children or direct measurements of environmental exposures in a population-based manner (Lanphear et al., 1996b; Mielke et al., 2007). Previous research suggests older housing stock and poverty are correlated

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with childhood lead exposure (Jacobs et al., 2002; Raymond et al., 2014). Therefore, targeted efforts have relied upon proxy measures for lead exposure such as the age of housing stock, interpolating environmental emissions, sampling soil and drinking water or demographic composition of neighborhoods (Lanphear et al., 1996b; Gleason et al., 2019; Lanphear et al., 1996a; Mielke et al., 2013; Moody and Grady, 2017). BLL testing practices to identify areas of potential EBLL are dubious, as BLL testing is not spatially homogeneous because testing has been focused in poor communities or among disadvantaged populations (e.g., those enrolled in Medicaid) (Wengrovitz and Brown, 2009; Maryland Department of Health and Mental Hygiene 2015). Thus, new statistical methods to enhance the predictive power of these proxy measures that incorporate the social, structural, and spatial determinants of BLLs are needed.

Recent efforts to identify areas with likely EBLL have used census data for various types of areal units (e.g., block groups, census tracts, ZIP Codes) (Aelion et al., 2013; Boutwell et al., 2016; Hanna-Attisha et al., 2016; Krieger et al., 2003). In 2016, Vox published an online interactive map of lead exposure risk across census tracts in the U.S. (Vox 2016). The Vox method calculated a score by weighting the proportion of the population living below the federal poverty level and the age of the housing stock. However, it ignored many other area-level variables that have been associated with EBLLs and may therefore have classified some areas of high risk as low risk for EBLLs (Moody and Grady, 2017; Carrel et al., 2017; Jones et al., 2010). We recently used a Poisson weighted quantile sum (WQS) regression approach to estimate a socioeconomic status (SES) index for census tracts in Minnesota and compared it with the Vox lead exposure risk score and a concentrated disadvantage index constructed with principal components analysis (PCA) to identify the best measure for explaining EBLL risk (Wheeler et al., 2019). WQS regression models are designed to accommodate correlated data when estimating an index and can perform dimension reduction (Carrico et al., 2015). WQS models estimate both the effect of an index on a health outcome and the corresponding weights for each variable included in that index, and will estimate weights that are effectively zero for variables statistically unrelated to the health outcome (Carrico et al., 2015). WQS models do not have the limitation of PCA-based indices, which are constructed based on the correlation or covariation pattern among the area-level variables without consideration of the relationship between these variables and the health outcome of interest. The PCA approach can result in indices that may include variables that are not associated with an outcome variable and therefore may also not correctly identify all areas at high risk for EBLLs. In addition, the interpretation of the PCA-based indices is more challenging than with WQS, where each SES variable has an estimated weight in the index. Our WQS index was able to explain variation in EBLLs across Minnesota and identify important SES variables for lead exposure above and beyond other SES-based approaches (Wheeler et al., 2019). Among the most important variables in the index were percent of houses built prior to 1940, percent renter occupied housing, percent unemployed, and percent African American population. These findings align with previous studies addressing the geographic distribution of lead toxicity (Gleason et al., 2019; Lanphear et al., 1996a; Moody and Grady, 2017; Lanphear et al., 2002), however, prior studies have not adjusted for spatial autocorrelation in their modeling approaches nor have they quantified the individual contributions of each SES component like the WQS method (Akkus and Ozdenerol, 2014; Griffith et al., 1998; Haley and Talbot, 2004; Hanchette, 2008; Miranda et al., 2002; Oyana and Margai, 2007).

Despite the superior performance of the WQS model approach for explaining EBLL risk with an SES index versus the Vox and PCA approaches, we did not adjust for residual confounding or spatial dependence in the outcome beyond what was explained by the SES index. Residual spatial correlation can cause biased parameter estimates for SES variables, which creates issues with the inference on relationships with the outcome (Waller and Gotway, 2004). Residual confounding that is not spatially structured, in other words is spatially random, can also create biased parameter estimates (Waller and Gotway, 2004). In addition, the WQS regression analysis did not include an approach to identify areas of significantly elevated risk. Given the limitations of existing methods for estimating SES indices, including WQS regression, our objective was to estimate an SES index while accounting for spatially structured and unstructured residual confounding using Bayesian regression models to explain variation in EBLL risk among census tracts in Maryland. In addition, we wanted to identify census tracts that had statistically elevated risk for EBLL to better geographically target public health intervention efforts. The identification of important variables in the SES index and areas of potentially elevated risk is of particular importance when blood lead testing data are unavailable.

2. Methods

2.1. Study design

We assessed the association between various potential indicators of BLL risk and risk of EBLL across 1208 census tracts in Maryland from 2005–2015 using an ecological design. We used census tract boundaries based on the 2000 U.S. Census in order to include instances of EBLL prior to 2010. We selected Maryland for this study because the statewide recommendation to perform childhood lead testing was similar to most states (Safer Chemicals Heathier Families 2017), the Maryland Department of Health has high lead surveillance reporting standards (Maryland Department of Health and Mental Hygiene 2015; Maryland Department of Health and Mental Hygiene 2017), and the data were publicly available (Maryland Open Data Portal 2018; Pell and Schneyer, 2017).

2.2. Data

Blood Lead Levels. Given the Centers for Disease Control and Prevention recommended age range for EBLL testing (Centers for Disease Control and Prevention (CDC) 2019), we obtained the counts and proportions of EBLL tests ($\geq$ 5mcg/dL) among children less than 72 months in age who had BLL tests performed in Maryland during 2005–2015 from Reuters (personal communication). These data were originally provided by the Maryland Department of the Environment under the Public Information Act (tracking number 2016–67,777) (Pell and Schneyer, 2017; Occupational, Industrial, and Residential Hazards: Blood Lead Reporting 2018). Our analyses are limited to one sample per child. It is important to note that lead testing was not universal in Maryland until 2016 and that children with risk factors for lead exposure (such as those living in pre-1950 housing, lower median housing values, and families living in poverty) were targeted for testing during 2005–2015. However, all blood lead tests performed in Maryland are mandatory to be reported to the Maryland Department of Health (Occupational, Industrial, and Residential Hazards: Blood Lead Reporting 2018), thus the samples included in the analysis are representative of all blood lead testing conducted throughout the state. BLL test and corresponding census data were unavailable for 12 census tracts (each has a population count of 0 persons) and these tracts were therefore excluded from the analysis, leaving 1208 census tracts with potential BLLs. A descriptive summary of the number of children tested, number of elevated tests, and the proportion of elevated tests is listed in Table 1. Notably, the range of proportion tested that had elevated blood lead levels ranged from 0.00–0.52. These

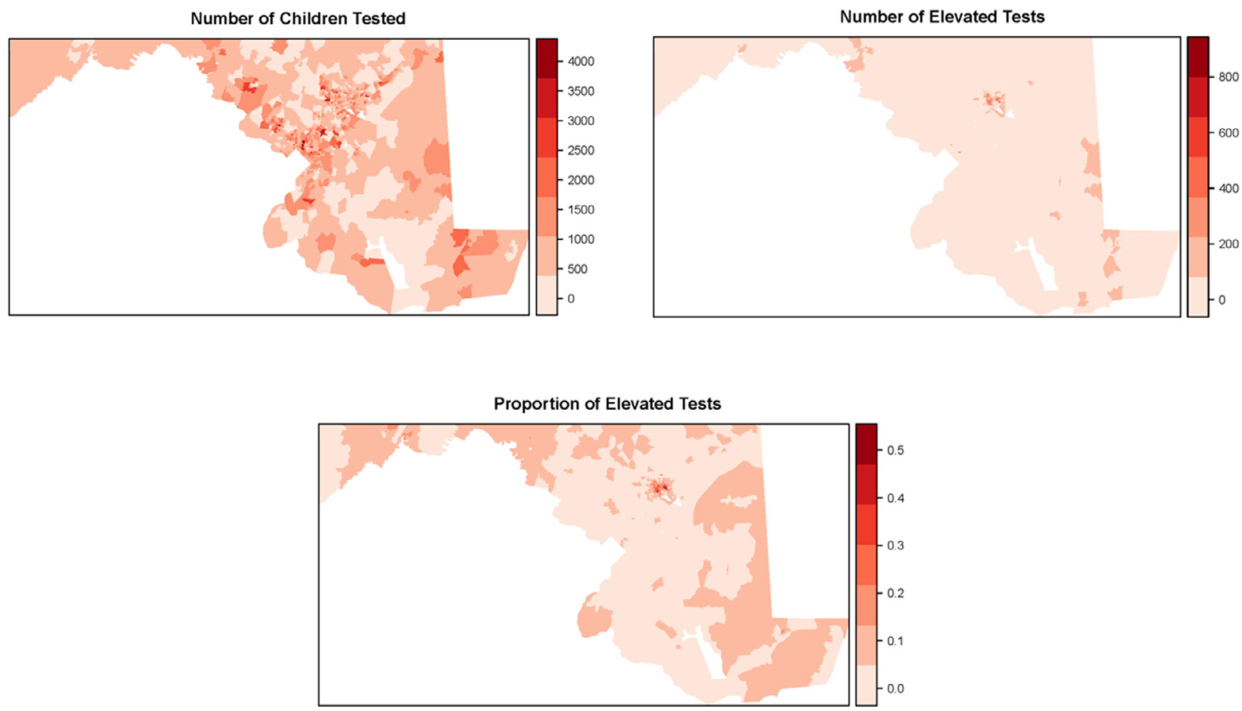

Fig. 1. Number of children tested, number of elevated tests, and the proportion of elevated tests across the census tracts in Maryland.

Table 1
Summary of the number of children tested, number of elevated tests, and the proportion of elevated tests across the census tracts in Maryland.

	Total Tested	Total Elevated	Proportion Elevated
Minimum	5	0	0.000
First Quartile	478	12	0.018
Median	745	23	0.029
Mean	871	47	0.053
Third Quartile	1112	46	0.056
Maximum	4094	881	0.519

three variables are mapped in Fig. 1 and the pattern of the number of children tested is quite different from the pattern of the proportion of the tests that are elevated. Further details regarding all aspects of data collection and reporting of lead exposure in Maryland are available elsewhere (Maryland Department of Health and Mental Hygiene 2015; Maryland Department of Health and Mental Hygiene 2017).

SES Covariates. We used the 5-year estimates from the 2005–2009 American Community Survey (ACS) to obtain SES-related variables at the census tract level when estimating the SES index (U.S. Census Bureau. American Community Survey 2017). We selected these variables based on the variables previously used in an SES index for EBLL risk, (Wheeler et al., 2019) as well as variables that have appeared to be associated with BLLs in the literature (e.g., housing age, poverty, and race/ethnicity) (Bernard and McGeehin, 2003; Cureton, 2011; Davis et al., 2016; Elreedy et al., 1999; Nriagu et al., 2006; Tyrrell et al., 2013). The SES variables are described below and listed in Table 2.

2.3. Statistical modeling

We used Bayesian regression models for the proportion of tested children that had EBLLs, assuming that the census tract EBLL count $y_i \sim Binomial(p_i,\ n_i)$ with probability p_i and number of children tested n_i. We modeled the proportion of tests that were elevated instead of the rate of elevated tests due to an unequal proportion of children tested over space. The Maryland Department of Health (MDH) has target areas for testing based on a predicted number of children that will test as elevated for blood lead, and therefore more populated areas will be more likely to have tests performed (Maryland Department of Health and Mental Hygiene 2015). We condition on the number of tests in an area and not the number of children living in an area, which avoids bias that could result from a model of the rate of elevated cases among all children living in each area. We used a logistic link between the probability and model terms. In all candidate models, we specified a deprivation index for each tract using a weighted combination $\sum_{j=1}^{C} w_j q_j$ of the quantiles $q_1, \ldots, q_C$ of the SES variables $x_1, \ldots, x_C$, where the weights $w_1, \ldots, w_C$ were given a Dirichlet prior with parameters $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_C)$. The Dirichlet prior is convenient here because it assures that the SES variable weights $w_j \in (0,\ 1)$ and $\sum_{j=1}^{C} w_j = 1$. We used quantiles of the SES variables to account for different scales of the variables, limit the effect of outliers, decorrelate the variables, and acknowledge uncertainty in the ACS covariates. Previous work has shown an improvement in accuracy with a weighted quantile sum approach over traditional ordinary regression and shrinkage methods (lasso, adaptive lasso, and elastic net) when using correlated explanatory variables (Carrico et al., 2015; Czarnota et al., 2015). The weight w_j represents the relative importance of the jth SES variable in the index.

We considered the following candidate models for modeling EBLL risk:

$$\mathrm{logit}(p_i) = \beta_0 + \beta_1\left(\sum_{j=1}^{C} w_j q_{ij}\right), \tag{1}$$

$$\mathrm{logit}(p_i) = \beta_0 + \beta_1\left(\sum_{j=1}^{C} w_j q_{ij}\right) + u_i, \tag{2}$$

$$\mathrm{logit}(p_i) = \beta_0 + \beta_1\left(\sum_{j=1}^{C} w_j q_{ij}\right) + v_i, \tag{3}$$

Table 2
ACS census tract variables used in the neighborhood deprivation index models.

Variable Definitions[a]	Mean ± SD	Range
Household Gini index of income inequality	0.4 ± 0.06	0.2–0.7
Percent of the population that is African-American	31.1 ± 32.1	0–100
Percent female headed households with children present	13.1 ± 10.9	0–73.3
Percent of population aged ≥ 25 years with less than high school education	14.2 ± 10.5	0–79.3
Percent of households with income below federal poverty level in the past 12 months	9.8 ± 10.1	0–91.0
Percent of households receiving public assistance income in the past 12 months	2.2 ± 3.1	0–25.3
Percent of households receiving cash public assistance or food stamps/SNAP	7.0 ± 7.7	0–48.3
Percent of unemployed population aged 16 years and over	18.9 ± 8.8	0–88.8
Percent of vacant housing units	9.3 ± 9.8	0–85.7
Percent of renter occupied housing units	31.7 ± 23.5	0–100
Median household income (U.S. Dollars) in the past 12 months[b]	71,473 ± 32,941	8789–250,001
Percent of households receiving Social Security Income in the past 12 months	24.9 ± 9.9	0–80.7
Percent of housing units built in 1939 or earlier	15.0 ± 18.5	0–88.8
Percent of housing units built from 1940–1949	8.1 ± 8.9	0–53.4

[a] Estimates were obtained from the 5-year estimates of the 2005–2009 American Community Survey conducted by the U.S. Census Bureau; SNAP, Supplemental Nutritional Assistance Program.
[b] Median household income was inverted for the index analyses.

$$\text{logit}(p_i) = \beta_0 + \beta_1 \left(\sum_{j=1}^{C} w_j q_{ij} \right) + u_i + v_i, \tag{4}$$

$$\text{logit}(p_i) = \beta_0 + \beta_1 \left(\sum_{j=1}^{C} w_j q_{ij} \right) + \alpha_i u_i + (1-\alpha_i) v_i, \tag{5}$$

where β_0 is the intercept, β_1 is the effect for the index, u_i and v_i are tract level random effects, and α_i is a mixing parameter. The first model is the base index model, the second model includes unstructured tract-level random effects, the third model adds spatially structured tract-level random effects to the base model, the fourth model adds both unstructured and spatially structured tract-level random effects (convolution model), and the fifth is a convolution mixture model with a mixing parameter on the unstructured random effect and the spatially structured random effect. In model 2, the heterogeneity in EBLL risk not explained by the deprivation index is assumed to be random over space, while in model 3 it is assumed to be spatially correlated. In model 4, it can be both spatially correlated and random over space. In model 5, the mixing parameter is estimated to allow the data to inform on the nature of the heterogeneity in EBLL risk. The uncorrelated random effects model (model 2) is used as a comparison to explore the assumption of spatial dependence in the data. The choice of the convolution model (model 4) is motivated by possible spatial correlation in EBLL risk in Maryland. Model 5 is included to allow the influence of the unstructured and spatially structured random effects to fluctuate through the addition of the mixing parameter. The models are not adjusted for child age because the exact age of tested children is not reported in the publically available data.

The assumption of spatial correlation in tract effects was implemented through an intrinsic conditional autoregressive (ICAR) prior (Waller and Gotway, 2004), where each random effect has the conditional distribution given by $v_i|v_{-i} \sim Normal(\bar{v}_l, 1/\tau_v\delta_i)$ with $\bar{v}_l = \sum_{j\,\text{in}\,\omega_i} v_j/\delta_i$, where δ_i represents the number of neighbors in set ω_i and precision $\tau_v = 1/\sigma_v^2$ and $\sigma_v \sim Uniform(0,\ 100)$. We defined spatial structure using binary neighborhood weighting and queen contiguity. The prior for the unstructured random effects was $u_i \sim Normal(0, \tau_u)$ with precision $\tau_u = 1/\sigma_u^2$ and $\sigma_u \sim Uniform(0,\ 100)$. The mixing parameter α_i followed a $Beta(1,\ 1)$ prior. The intercept followed an improper uniform distribution $\alpha \sim dflat()$, while the index regression coefficient had a vague normal prior $\beta_1 \sim Normal(0, \tau_1)$ with precision $\tau_1 = 1/\sigma_1^2$ and $\sigma_1 \sim Uniform(0,\ 100)$.

We used $C = 14$ variables in the SES index, which are listed in Table 2. The variables were defined to reflect a hypothesized positive association of the index with EBLL risk. Of the ACS variables, 13 had a positive association with EBLL counts in univariate analyses. Median household income was the only variable that was negatively associated with EBLL counts. We inverted this variable by using the formula $max(x) - x_i$, where x_i is the value of the variable, and used this inverted form in the deprivation index.

We used Markov chain Monte Carlo (MCMC) to estimate the model parameters with a total of 30,000 iterations from two chains and a thinning parameter of one, where the first 5000 iterations were used for burn-in. We assessed convergence of the MCMC algorithm for parameters of interest using the Gelman-Rubin statistic. A parameter was considered to have converged if its Gelman-Rubin statistic was less than 1.2 (Lunn et al., 2000). Among the five candidate models, the one with the lowest deviance information criterion (DIC) was chosen as the best model (Lunn et al., 2000). The 95% credible interval for the odds ratio was used to determine statistical significance of the deprivation index; it was deemed statistically significant if the interval did not contain the value of 1. We fit the Bayesian models using WinBUGS1.4.1 (Lunn et al., 2000) and completed all other analyses in the R computing environment (R: A language and environment for statistical computing 2018).

We identified census tracts as being significantly elevated for EBLL risk using posterior estimates of exceedance probabilities (Richardson et al., 2004), defined as $\hat{q}_i^c = \sum_{g=m+1}^{m+G} \frac{I(p_i^{(g)} > c)}{G}$, where m represents the burn-in (5000 iterations) and G represents the number of posterior samples after the burn-in (30,000 iterations). The overall mean probability $c = 0.053$ was used as a threshold value for p_i. Counties with an exceedance probability ($\hat{q}_i^c$) greater than 0.99 were deemed to have highly significant elevated risk of EBLL.

3. Results

The declining DIC values show that there was a steady improvement in goodness-of-fit going from model 1 to model 5 (Table 3). There was a dramatic increase in the goodness-of-fit of models 2–5 when adding tract-level random effects to the base deprivation index model (model 1). Even though the effective number of parameters increased substantially from the base model according to the pD statistic, the decrease in deviance much exceeded the increase in model complexity, resulting in improved fit. The addition of spatial random effects (model 3) lead to a better fit than independent random effects (model 2). Hence, the unexplained risk in EBLL after estimating the deprivation index was more spatially structured than spatially random. Adding independent random effects to the model with spatially correlated random effects (model 4) resulted in a small decrease in DIC from 8054 to 8050. Adding

Table 3
Deviance information criterion (DIC) and effective number of parameter (pD) values for candidate Bayesian binomial regression models and posterior mean odds ratio (OR) and 95% credible intervals for the neighborhood deprivation index.

Model	Description	DIC	pD	Index OR	2.50%	97.50%
1	Base index	22,850.10	12.06	3.86	3.80	3.91
2	Independent random effects	8163.23	983.68	2.82	2.67	3.00
3	Spatial random effects	8053.58	834.34	1.58	1.47	1.66
4	Convolution	8050.44	848.97	1.60	1.52	1.70
5	Convolution mixture	7790.40	594.61	1.80	1.69	1.92

a mixing parameter to the convolution model (model 5) resulted in a large decrease in DIC from 8050 to 7790, revealing that the flexibility in modeling residual confounding provided by the convolution mixture model was beneficial. Hence, the most complex model had the best goodness-of-fit and was the most useful for explaining variation in EBLL risk.

In all models, there was a significant positive association between the deprivation index and EBLL risk according to the odds ratios (ORs) and 95% credible intervals (Table 3). In the base model, there was a nearly 4-fold increase in EBLL risk with each one-unit increase in the deprivation index. The odds ratio decreased from the base index model when adding tract-level random effects (models 2–5), but decreased more when adding spatial random effects (model 3), suggesting that the spatially correlated random effects explained a portion of the effect of the spatially structured deprivation index. Yet even after accounting for spatially structured and unstructured residual confounding, in the best fitting model (model 5) there was an 80% increase in EBLL risk with each unit increase in the index, revealing a strong positive association between neighborhood disadvantage and EBLL risk.

Given the DIC findings, we focus on the mixture convolution model (model 5) for the remainder of the results. The estimated weights for the variables in the deprivation index (Table 4) for the best fitting model (model 5) show that three of the 14 variables received weights greater than the equal-weight threshold of 0.071 (1/14). These most highly weighted variables in decreasing importance were percent of housing units built in 1939 or earlier (weight = 0.395), percent of the population that is African-American (weight = 0.154), and median household income in the past 12 months (weight = 0.105). The three variables with the smallest weight (<0.02) were percent of renter occupied housing units, the Gini index of income inequality, and percent of houses built in the 1940s, suggesting that these variables contributed little to explaining variation in EBLL risk.

The modeled EBLL probabilities from the convolution mixture model are mapped in Fig. 2. The mean probability of 0.053 is used as a reference in the color ramp; blues are below average risk and reds are above average risk. The pattern shows that the largest EBLL probabilities are in the Baltimore area, where there is a spatial cluster of above average risk. In this cluster, there are tracts having an EBLL probability exceeding 0.5 (maximum = 0.52), which is approximately 10 times the average for Maryland. Conversely, some of the smallest probabilities are located in the metropolitan areas outside Washington, DC, including Montgomery County, MD which is among the wealthiest counties in the U.S. Areas of above average risk also tend to occur in the more rural census tracts in southeastern and northwestern Maryland (Morello, 2013). The estimated deprivation index in Fig. 3 shows that the largest values of the index are also in Baltimore, as well as in southeastern and northwestern Maryland. In contrast, areas of Montgomery County have the lowest deprivation index values. It is clear that there is spatial agreement between the deprivation index and the probability of EBLL. Generally, higher deprivation index scores occur where there are higher EBLL probabilities.

Table 4
Posterior mean weights and 95% credible intervals for variables in the neighborhood deprivation index.

Variable[a]	Mean	2.50%	97.50%
Household Gini index of income inequality	0.018	0.001	0.052
Percent of the population that is African-American	0.154	0.083	0.224
Percent female headed households with children present	0.025	0.002	0.083
Percent of population aged ≥ 25 years with less than high school education	0.047	0.003	0.136
Percent of households with income below federal poverty level in the past 12 months	0.021	0.002	0.068
Percent of households receiving public assistance income	0.029	0.002	0.085
Percent of households receiving cash public assistance or food stamps/SNAP	0.028	0.002	0.064
Percent of unemployed population aged 16 years and over	0.052	0.008	0.106
Percent of vacant housing units	0.047	0.006	0.096
Percent of renter occupied housing units	0.013	0.001	0.039
Inverse median household income in the past 12 months[b]	0.105	0.028	0.191
Percent of households receiving Social Security Income in past 12 months	0.050	0.002	0.098
Percent of housing units built in 1939 or earlier	0.395	0.332	0.461
Percent of housing units built from 1940–1949	0.016	0.001	0.051

[a] Estimates were obtained from the 5-year estimates of the 2005–2009 American Community Survey conducted by the U.S. Census Bureau; SNAP, Supplemental Nutritional Assistance Program.
[b] Median household income was inverted for the index analyses.

The estimated spatial random effects (Fig. 4) and exchangeable random effects (Fig. 5) show the adjustments to the tract probability of EBLL beyond what the deprivation index explains. The reference value in these maps is 0. The spatial random effects show a cluster of elevated values in Baltimore, and generally elevated values in northwestern and southeastern Maryland. There is a cluster of lowered values in Montgomery County and Prince George's County. As expected, there is no clear pattern in the independent random effects that represent spatially unstructured residual confounding. The convolution mixing parameter main and inset maps (Fig. 6) show where more weight is given to the spatial random effects than the independent random effects. The reference for these maps is 0.5 for equal weight of the random effects. Areas shaded in red are where more weight is given to the spatial random effect than the independent random effect. The largest weights are generally found in the Baltimore metropolitan area. This is reasonable given the strong clustering of elevated values of the EBLL probabilities in this geographic area (Fig. 2). The exceedance probabilities (Fig. 7)

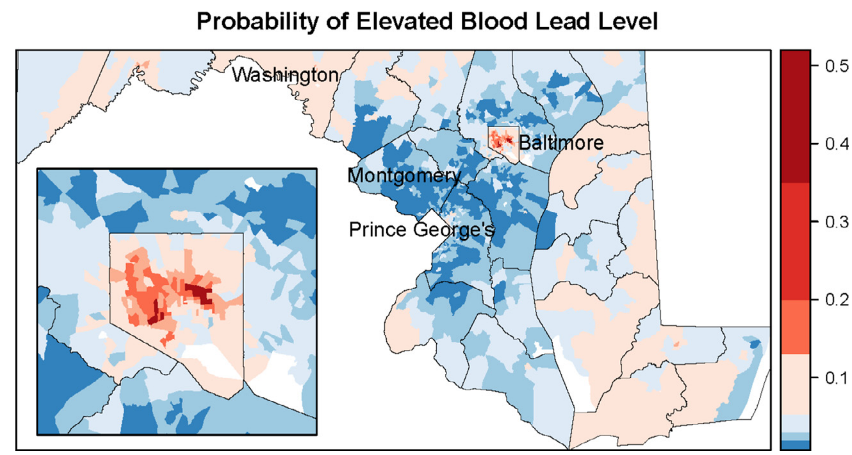

Fig. 2. Estimated probability of elevated blood lead level in census tracts in Maryland with county lines drawn for reference. The inset map is focused on Baltimore. Montgomery County, Prince George's County, Washington County, and Baltimore are labeled.

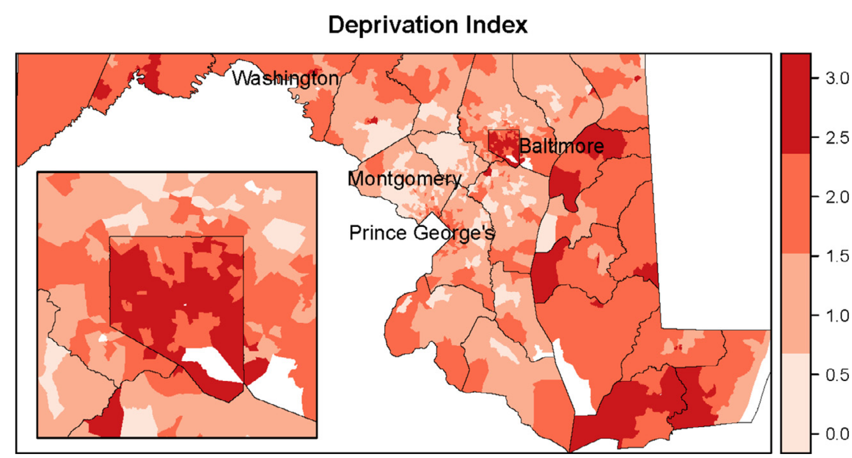

Fig. 3. Estimated neighborhood deprivation index for elevated blood lead levels in census tracts in Maryland with county lines drawn for reference. The inset map is focused on Baltimore. Montgomery County, Prince George's County, Washington County, and Baltimore are labeled.

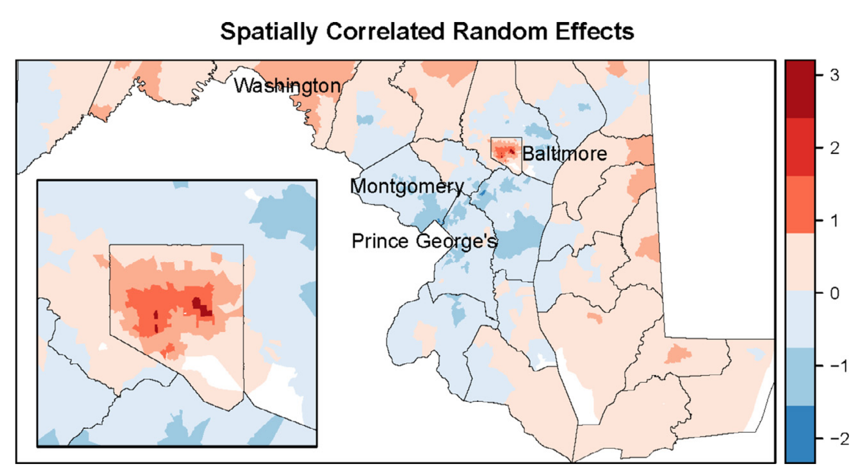

Fig. 4. Estimated spatial random effects (v) for elevated blood lead levels in census tracts in Maryland with county lines drawn for reference. The inset map is focused on Baltimore. Montgomery County, Prince George's County, Washington County, and Baltimore are labeled.

reveal several tracts of highly significantly elevated risk of EBLL. There is a large cluster in Baltimore city. There is also a large cluster of tracts located in northwestern Maryland in Washington County that includes the city of Hagerstown. There are also several tracts of elevated risk along the eastern border of Maryland.

4. Discussion

This study estimated the effect of a neighborhood deprivation index while accounting for spatial dependence and residual confounding using Bayesian regression models to explain variation in EBLL risk among children in Maryland census tracts. In the best

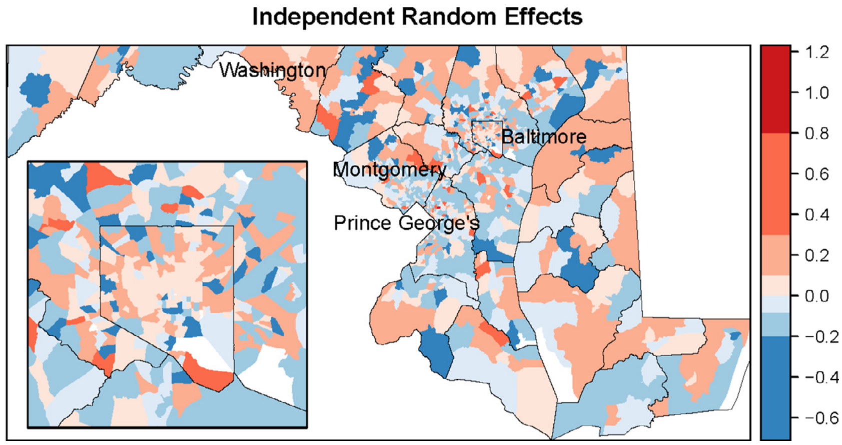

Fig. 5. Estimated independent random effects (u) for elevated blood lead levels in census tracts in Maryland with county lines drawn for reference. The inset map is focused on Baltimore. Montgomery County, Prince George's County, Washington County, and Baltimore are labeled.

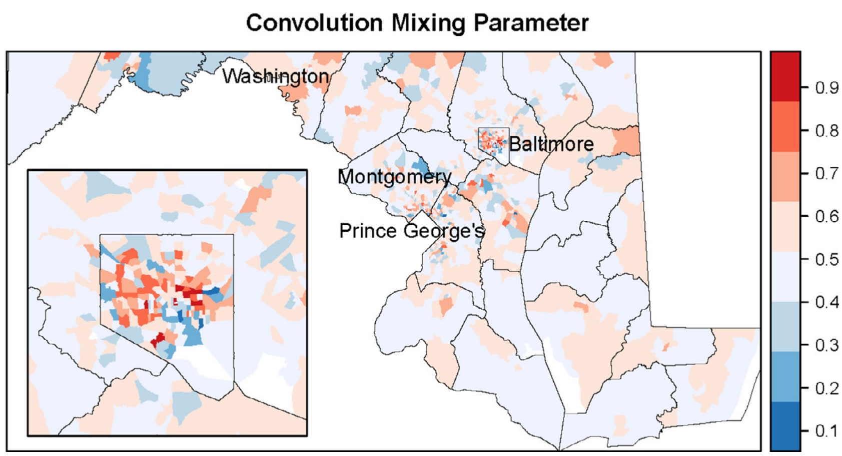

Fig. 6. Estimated convolution mixture parameter for elevated blood lead levels in census tracts in Maryland with county lines drawn for reference. The inset map is focused on Baltimore. Montgomery County, Prince George's County, Washington County, and Baltimore are labeled.

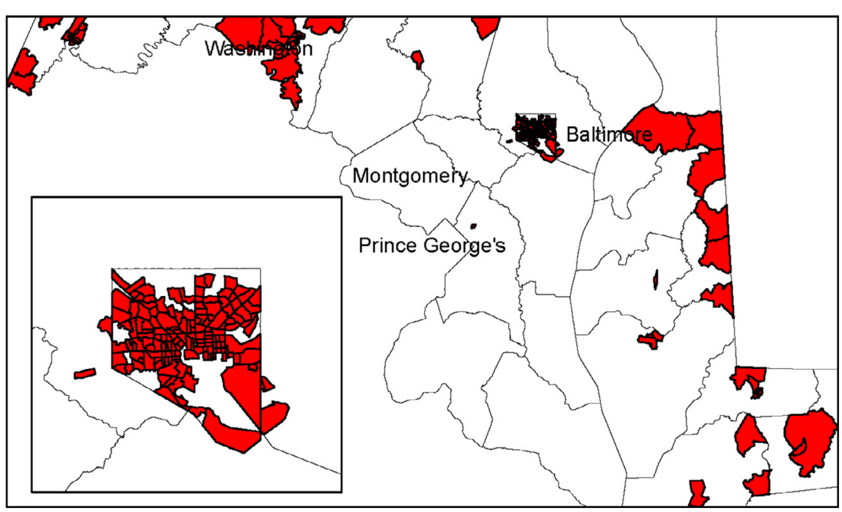

Fig. 7. Census tracts at significant risk for elevated blood lead levels according to exceedance probabilities in Maryland with county lines drawn for reference. The inset map is focused on Baltimore. Montgomery County, Prince George's County, Washington County, and Baltimore are labeled.

fitting model, the most important SES variables were percent of homes built before 1940, percent of African American population, and inverse median household income. In our previous WQS analysis of EBLLs among Minnesota census tracts, percent of homes built before 1940 and percent African American population were two of the most important variables but median household income received no weight (Wheeler et al., 2019). In the current study and the Minnesota study, percent of homes built before 1940 was the most important variable. Previous research also has found that age of housing stock and poverty are correlated with lead exposure among children (Jacobs et al., 2002; Raymond et al., 2014). Taken together, there is strong evidence that areas with a high percentage of homes built before 1940 and a larger African American population, and to a lesser extent areas of low income or high poverty, should be targeted for lead intervention efforts. These findings have implications for state and local public health agencies as they consider targeted testing and risk reduction activities and/or messaging.

This study illustrates the utility of Bayesian hierarchical modeling for estimating a neighborhood deprivation index to explain variation in EBLL risk. It is beneficial to estimate the index weights from the data through the Bayesian modeling approach instead of assigning *a priori* weights to potential risk factors such as with the Vox score or summed z-score index approaches, whose measures are not likely to capture the complexity of SES across all geographic areas. Contrary to the common equal weighting assumption in the summed z-score approach, we found strong deviations in weighting of the SES variables in our estimated deprivation index. Also, the Bayesian approach eliminates the need to split the data into training and testing datasets as done in WQS regression; thus, all data are used to evaluate the association of the deprivation index with the health outcome. Moreover, the Bayesian framework flexibly allows a model specification that includes residual confounding that is either spatially structured or unstructured, or a mixture of both. For Maryland EBLL risk, adding spatially structured random effects led to improvements in model fit, showing that there was significant unexplained risk not accounted for by the estimated deprivation index. However, even in the most complex mixture model of spatially structured and unstructured random effects, the deprivation index was significantly associated with EBLL risk.

One benefit of the Bayesian modeling approach is the ability to easily identify areas of significantly elevated risk using exceedance probabilities. We identified many census tracts of significantly elevated EBLL risk in northern and southeastern Maryland, including a large cluster that includes the city of Hagerstown and a large cluster in Baltimore city (Fig. 7). The tracts in the Baltimore cluster have very high EBLL risk and consistently have the largest deprivation index values. This is not unexpected as the residential segregation index for Baltimore City suggests extremely high segregation and segregation is related to economic deprivation and health outcomes (Robert Wood Johnson Foundation 2018; Williams and Collins, 2001). This indicates that structural disparities, above and beyond economics, are linked to environmental hazards and poor health outcomes at the census tract level (Sampson and Winter, 2016). The percent of minority population is lower in Washington County but many of tracts in the cluster have deprivation index values in the upper half of the distribution. The spatial random effects are elevated in both of these cluster areas suggesting that there are other factors in addition to the deprivation index contributing to elevated EBLL risk. In addition to lead paint and lead-contaminated household dust that children can ingest, lead exposure can be high given leaching from old pipes, faucets, etc. into drinking water; soil and water contamination from historic and/or current industrial sites (e.g., smelting sites and mining) (Agency for Toxic Substances and Disease Registry (ATSDR) 2017; Dewalt et al., 2015; President's Task Force on Environmental Health Risks and Safety Risks to Children 2019; Scott and Nguyen, 2011; U.S. Environmental Protection Agency (EPA) 2019). Also, inner city soil and areas along heavily traveled interstate highways may still have high lead levels from accumulation prior to the total ban on leaded gasoline in 1995 (Agency for Toxic Substances and Disease Registry (ATSDR) 2017; Scott and Nguyen, 2011; Brinkmann, 1994). Moreover, remediation efforts may be uneven over space given that the expense of comprehensive abatement can be greater than the fair market value of older housing stock in more disadvantaged neighborhoods. However, it is estimated that lead abatement and control yields $17-$221 return on investment for each dollar spent, which would equate to a net savings of $181–$269 billion in the U.S (Gould, 2009).

Our analysis is different from and adds to the findings of the 2015 report Maryland Targeting Plan for Areas at Risk for Childhood Lead Poisoning from the MDH (Maryland Department of Health and Mental Hygiene 2015). The MDH report used 2005–2009 data while we used 2005–2015 data. We also used a smaller spatial unit of analysis, the census tract instead of ZIP Code. In addition, our methods are different from what MDH used to determine "at-risk" areas, which are based on a predicted number of children that will test as elevated for blood lead. These "at-risk" areas are not true measures of risk or probability of disease. Our Bayesian hierarchical models estimate disease risk and are based on the number of tests performed and the proportion of elevated cases in each census tract. We also account for spatial dependence in EBLL risk and determine which SES variables among a large set are associated with risk. Because of the differences in data and methods, our results highlight smaller areas of significant elevated risk compared with the larger MDH "at-risk" areas. For example, we find much smaller areas in northwest and eastern Maryland compared with the MDH "at-risk" areas. This means our results enable more precise spatial targeting for interventions. We also do not identify any tracts as being significantly elevated in risk in Montgomery County or in Prince George's County bordering Washington, DC. These are highly populated areas that show up as "at-risk" areas in the MDH map (see page A-2 of MDH report) (Maryland Department of Health and Mental Hygiene 2015).

Study findings should be considered in the context of its limitations. First, we used an ecological model because individual-level covariate data were unavailable. However, the ecological approach allowed us to identify areas of elevated EBLL risk. Second, Maryland did not mandate BLL testing for children until 2016; thus, areas thought to be at high-risk may have had a higher proportion of all children tested. However, our Bayesian hierarchical models are based on the number of tests done and the proportion of elevated cases in each area and not the number of children living in each area. Therefore, our EBLL risk estimates are less biased than EBLL rates using these data. Third, our deprivation index results may not generalize to other geographic units such as ZIP Codes or counties and to all states beyond Maryland.

In conclusion, the Bayesian deprivation index model approach accounting for spatially structured residual confounding better explains variation in rates of EBLL at the census tract level than a standard WQS regression. Further, the Bayesian modeling approach is better for identifying census tracts for targeted intervention to reduce lead exposure among children. More efficient allocation of resources for prevention of EBLLs can be attained through advocacy to target clusters of neighborhoods with significantly elevated risk.

References

Aelion, C.M., Davis, H.T., Lawson, A.B., Cai, B., McDermott, S., 2013. Associations between soil lead concentrations and populations by race/ethnicity and income-to-poverty ratio in urban and rural areas. Environ. Geochem. Health 35 (1), 1–12.

Agency for Toxic Substances and Disease Registry (ATSDR), 2007. Toxicological Profile for Lead. U.S. Department of Health and Human Services, Public Health Services, Atlanta, GA. Available at https://www.atsdr.cdc.gov/toxprofiles/TP.asp?id=96&tid=22#bookmark16. Accessed 1 September 2018.

Agency for Toxic Substances and Disease Registry (ATSDR), 2017. Lead Toxicity. Where is it Found?. U.S. Department of Health and Human Services, Public Health Services, Atlanta, GA. Available at https://www.atsdr.cdc.gov/csem/csem.asp?csem=34&po=5. Accessed 11 March 2019.

Akkus, C., Ozdenerol, E., 2014. Exploring childhood lead exposure through GIS: a review of the recent literature. Int. J. Environ. Res. Public Health 11 (6), 6314–6334.

Bernard, S.M., McGeehin, M.A., 2003. Prevalence of blood lead levels >or= 5 micro g/dL among US children 1 to 5 years of age and socioeconomic and demographic factors associated with blood of lead levels 5 to 10 micro g/dL, Third

National Health and Nutrition Examination Survey, 1988–1994. Pediatrics 112 (6 Pt 1), 1308–1313.
Boutwell, B.B., Nelson, E.J., Emo, B., et al., 2016. The intersection of aggregate-level lead exposure and crime. Environ. Res. 148, 79–85.
Brinkmann, R., 1994. Lead pollution in soils adjacent to homes in Tampa, florida. Environ. Geochem. Health 16 (2), 59–64.
Canfield, R.L., Henderson Jr., C.R., Cory-Slechta, D.A., Cox, C., Jusko, T.A., Lanphear, B.P., 2003. Intellectual impairment in children with blood lead concentrations below 10 microg per deciliter. N Engl. J. Med 348 (16), 1517–1526.
Carrel, M., Zahrieh, D., Young, S.G., et al., 2017. High prevalence of elevated blood lead levels in both rural and urban iowa newborns: spatial patterns and area-level covariates. PLoS ONE 12 (5), e0177930.
Carrico, C., Gennings, C., Wheeler, D.C., Factor-Litvak, P., 2015. Characterization of weighted Quantile sum regression for highly correlated data in a risk analysis setting. J. Agr. Biol. Envir. St. 20 (1), 100–120.
Center for American Progress. Creating safe and healthy living environments for low-income families. 2016. Accessed 17 May 2019. Available at: https://cdn.americanprogress.org/wp-content/uploads/2016/07/14065816/SafeAndHealthyHomes-report.pdf.
Centers for Disease Control and Prevention (CDC). Preventing lead exposure in young children: A housing-based approach to primary prevention of lead poisioning. Atlanta, GA. 2004. Available at: https://www.cdc.gov/nceh/lead/publications/primarypreventiondocument.pdf. Accessed 1 September 2018.
Centers for Disease Control and Prevention (CDC), 2012. Response to the advisory committee on childhood lead poisoning prevention report, low level lead exposure harms children: a renewed call for primary prevention. MMWR Morb. Mortal. Wkly. Rep. 61 (20), 383.
Centers for Disease Control and Prevention (CDC), 2013. Blood lead levels in children aged 1-5 years - United States, 1999–2010. MMWR Morb. Mortal. Wkly Rep 62 (13), 245–248.
Centers for Disease Control and Prevention (CDC). Childhood lead poisoning data, statistics, and surveillance. 2019; https://www.cdc.gov/nceh/lead/data/index.htm. Accessed 11 March 2019.
Chiodo, L.M., Jacobson, S.W., Jacobson, J.L., 2004. Neurodevelopmental effects of postnatal lead exposure at very low levels. Neurotox. Teratol 26 (3), 359–371.
Cureton, S., 2011. Environmental victims: environmental injustice issues that threaten the health of children living in poverty. Rev. Environ. Health 26 (3), 141–147.
Czarnota, J., Gennings, C., Wheeler, D.C., 2015. Assessment of weighted quantile sum regression for modeling chemical mixtures and cancer risk. Cancer Inf. 14 (Suppl 2), 159–171.
Davis, H.T., Aelion, C.M., Liu, J., et al., 2016. Potential sources and racial disparities in the residential distribution of soil arsenic and lead among pregnant women. Sci. Total Environ 551-552, 622–630.
Dewalt, F.G., Cox, D.C., O'Haver, R., et al., 2015. Prevalence of lead hazards and soil arsenic in U.S. housing. J. Environ. Health 78 (5), 22–29 quiz 52.
Elreedy, S., Krieger, N., Ryan, P.B., Sparrow, D., Weiss, S.T., Hu, H., 1999. Relations between individual and neighborhood-based measures of socioeconomic position and bone lead concentrations among community-exposed men: the normative aging study. Am. J. Epidemiol 150 (2), 129–141.
Gleason, J.A., Nanavaty, J.V., Fagliano, J.A., 2019. Drinking water lead and socioeconomic factors as predictors of blood lead levels in new Jersey's children between two time periods. Environ. Res 169, 409–416.
Gould, E., 2009. Childhood lead poisoning: conservative estimates of the social and economic benefits of lead hazard control. Environ. Health Perspect. 117 (7), 1162–1167.
Grandjean, P., Landrigan, P.J., 2014. Neurobehavioural effects of developmental toxicity. Lancet Neurol 13 (3), 330–338.
Griffith, D.A., Doyle, P.G., Wheeler, D.C., Johnson, D.L., 1998. A tale of two swaths: urban childhood blood-lead levels across Syracuse, New York. Ann. Assoc. Am. Geogr 88 (4), 640–665.
Haley, V.B., Talbot, T.O., 2004. Geographic analysis of blood lead levels in New York state children born 1994–1997. Environ Health Perspect. 112 (15), 1577–1582.
Hanchette, C.L., 2008. The political ecology of lead poisoning in eastern north carolina. Health Place 14 (2), 209–216.
Hanna-Attisha, M., LaChance, J., Sadler, R.C., Champney Schnepp, A., 2016. Elevated blood lead levels in children associated with the flint drinking water Crisis: a spatial analysis of risk and public health response. Am J Public Health 106 (2), 283–290.
Jacobs, D.E., Clickner, R.P., Zhou, J.Y., et al., 2002. The prevalence of lead-based paint hazards in U.S. housing. Environ Health Perspect 110 (10), A599–A606.
Jones, E.A., Wright, J.M., Rice, G., et al., 2010. Metal exposures in an inner-city neonatal population. Environ Int 36 (7), 649–654.
Krieger, N., Chen, J.T., Waterman, P.D., Soobader, M.J., Subramanian, S.V., Carson, R., 2003. Choosing area based socioeconomic measures to monitor social inequalities in low birth weight and childhood lead poisoning: the public health disparities geocoding project (US). J. Epidemiol. Commun. Health 57 (3), 186–199.
Lanphear, B.P., Dietrich, K., Auinger, P., Cox, C., 2000. Cognitive deficits associated with blood lead concentrations <10 microg/dL in US children and adolescents. Publ. Health Rep 115 (6), 521–529.
Lanphear, B.P., Hornung, R., Ho, M., Howard, C.R., Eberly, S., Knauf, K., 2002. Environmental lead exposure during early childhood. J. Pediatr. 140 (1), 40–47.
Lanphear, B.P., Weitzman, M., Eberly, S., 1996a. Racial differences in urban children's environmental exposures to lead. Am. J. Pub. Health 86 (10), 1460–1463.
Lanphear, B.P., Weitzman, M., Winter, N.L., et al., 1996b. Lead-contaminated house dust and urban children's blood lead levels. Am. J. Pub. Health 86 (10), 1416–1421.
Lead-based Paint Hazard Reduction and Financing Task Force, 1995. Putting the pieces together: Controlling lead hazards in the nation's housing. University of Michigan Library, Washington, DC.
Leighton, J., Klitzman, S., Sedlar, S., Matte, T., Cohen, N.L., 2003. The effect of lead-based paint hazard remediation on blood lead levels of lead poisoned children in New York city. Environ Res 92 (3), 182–190.
Letter from National Safe and Healthy Housing Coalition to Members of Congress, 2019, Accessed 17 May 2019. Available at: https://www.apha.org/~/media/files/pdf/advocacy/letters/2016/160317_nshhc_fy17_lead_letter.ashx.
Lidsky, T.I., Schneider, J.S., 2003. Lead neurotoxicity in children: basic mechanisms and clinical correlates. Brain 126 (Pt 1), 5–19.
Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. WinBUGS - A Bayesian modelling framework: concepts, structure, and extensibility. Stat Comput 10 (4), 325–337.
Maryland Department of Health and Mental Hygiene. Targeting plan for areas at risk for childhood lead poisoning. 2004. Available at: https://phpa.health.maryland.gov/OEHFP/EH/Pages/LeadTesting.aspx. Accessed 11 March 2019.
Maryland Department of Health and Mental Hygiene. Targeting plan for areas at risk for childhood lead poisoning. 2015. Available at: https://phpa.health.maryland.gov/IDEHASharedDocuments/MD%202015%20Lead%20Targeting%20Plan.pdf. Accessed 11 March 2019.
Maryland Department of Health and Mental Hygiene. Lead screening of children in Medicaid. 2017. Available at: https://mmcp.health.maryland.gov/Documents/JCRs/2016/leadJCRfinal11-16.pdf. Accessed 13 March 2019.
Maryland Open Data Portal. Crownsville, MD. Available at: https://data.maryland.gov/. Accessed 3 November, 2018.
Mielke, H.W., Dugas, D., Mielke Jr., P.W., Smith, K.S., Gonzales, C.R., 1997. Associations between soil lead and childhood blood lead in urban New Orleans and rural Lafourche Parish of Louisiana. Environ Health Perspect 105 (9), 950–954.
Mielke, H.W., Gonzales, C.R., Powell, E.T., 2017. Soil lead and children's blood lead disparities in Pre- and Post-Hurricane Katrina New Orleans (USA). Int J Environ Res Public Health 14 (4).
Mielke, H.W., Gonzales, C.R., Powell, E.T., Mielke, P.W., 2013. Environmental and health disparities in residential communities of New Orleans: the need for soil lead intervention to advance primary prevention. Environ Int 51, 73–81.
Mielke, H.W., Gonzales, C.R., Powell, E.T., Mielke Jr., P.W., 2016. Spatiotemporal dynamic transformations of soil lead and children's blood lead ten years after hurricane Katrina: new grounds for primary prevention. Environ Int 94, 567–575.
Mielke, H.W., Powell, E.T., Gonzales, C.R., Mielke Jr., P.W., 2007. Potential lead on play surfaces: evaluation of the "PLOPS" sampler as a new tool for primary lead prevention. Environ Res 103 (2), 154–159.
Miranda, M.L., Dolinoy, D.C., Overstreet, M.A., 2002. Mapping for prevention: GIS models for directing childhood lead poisoning prevention programs. Environ Health Perspect 110 (9), 947–953.
Miranda, M.L., Kim, D., Galeano, M.A., Paul, C.J., Hull, A.P., Morgan, S.P., 2007. The relationship between early childhood blood lead levels and performance on end-of-grade tests. Environ Health Perspect 115 (8), 1242–1247.
Moody, H., Grady, S.C., 2017. Lead emissions and population vulnerability in the Detroit (Michigan, USA) metropolitan Area, 2006-2013: a spatial and temporal analysis. Int. J. Environ. Res. Pub. Health 14 (12).
Morello, C., 2013. The D.C. suburbs dominate the list of wealthiest U.S. counties. Washington Post.
Nelson, E.J., Shacham, E., Boutwell, B.B., et al., 2015. Childhood lead exposure and sexually transmitted infections: new evidence. Environ Res 143 (Pt A), 131–137.
Nriagu, J., Burt, B., Linder, A., Ismail, A., Sohn, W., 2006. Lead levels in blood and saliva in a low-income population of Detroit, Michigan. Int. J. Hyg. Environ Health 209 (2), 109–121.
Occupational, Industrial, and Residential Hazards: Blood Lead Reporting. Maryland Department of the Environment. Available at: http://www.mde.state.md.us/programs/LAND/LeadPoisoningPrevention/Documents/www.mde.state.md.us/assets/document/LeadCoordination/BloodLeadReporting26.02.01.pdf. Accessed 3 November, 2018.
Oyana, T.J., Margai, F.M., 2007. Geographic analysis of health risks of pediatric lead exposure: a golden opportunity to promote healthy neighborhoods. Arch. Environ Occup. Health 62 (2), 93–104.
Pell M.B., Schneyer J. Reuters finds 3,810 U.S., areas with lead poisoning double Flint's. 2017; https://www.reuters.com/article/us-usa-lead-map/reuters-finds-3810-u-s-areas-with-lead-poisoning-double-flints-idUSKBN1DE1H2. Accessed 1 July 2018.
Philadelphia Citizens for Children and Youth. Getting the Lead Out: The Philadelphia Story, 2006. Available at: https://www.pccy.org/wp-content/uploads/2016/02/Get-The-Lead-Out.pdf. Accessed 11 March 2019.
President's Task Force on Environmental Health Risks and Safety Risks to Children. Key Federal Programs to Reduce Childhood Lead Exposure and Eliminate Associated Health Impacts. Available at: https://ptfceh.niehs.nih.gov/features/assets/files/key_federal_programs_to_reduce_childhood_lead_exposures_and_eliminate_associated_health_impactspresidents_508.pdf. Accessed 11 March, 2019.
R: A language and environment for statistical computing [computer program]. Vienna, Austria: R Foundation for Statistical Computing; 2018.

Raymond, J., Wheeler, W., Brown, M.J., 2014. Centers for disease C, Prevention. Lead screening and prevalence of blood lead levels in children aged 1-2 years–Child blood lead surveillance System, united States, 2002-2010 and national health and nutrition examination Survey, United States, 1999-2010. MMWR Suppl 63 (2), 36–42.

Remediated sites and brownfields: Success stories in Europe. A report of the European Information and Observation Network's National Reference Centres for Soil. 2015. Accessed 5/17/19. Available at: http://publications.jrc.ec.europa.eu/repository/bitstream/JRC98077/lbna27530enn.pdf.

Richardson, S., Thomson, A., Best, N., Elliott, P., 2004. Interpreting posterior relative risk estimates in disease-mapping studies. Environ Health Perspect 112 (9), 1016–1025.

Robert Wood Johnson Foundation. Residential segregation - black/white. 2018; http://www.countyhealthrankings.org/app/maryland/2018/measure/factors/141/data. Accessed November 3, 2018.

Safer Chemicals Heathier Families. Children at risk: Gaps in state lead screening policies. 2017; http://saferchemicals.org/children-at-risk/state-lead-screening-policies/. Accessed 1 April 2018.

Sampson, R., Winter, A., 2016. The racial ecology of lead poisoning: toxic inequality in Chicago neighborhoods, 1995-2013. Du Bois Rev. Social Sci. Res. Race 13 (2), 261–283.

Schnaas, L., Rothenberg, S.J., Perroni, E., Martinez, S., Hernandez, C., Hernandez, R.M., 2000. Temporal pattern in the effect of postnatal blood lead level on intellectual development of young children. Neurotoxicol Teratol 22 (6), 805–810.

Schoof, R.A., Johnson, D.L., Handziuk, E.R., et al., 2016. Assessment of blood lead level declines in an area of historical mining with a holistic remediation and abatement program. Environ Res. 150, 582–591.

Scott, L.L., Nguyen, L.M., 2011. Geographic region of residence and blood lead levels in US children: results of the national health and nutrition examination survey. Int. Arch. Occup. Environ Health 84 (5), 513–522.

Staes, C., Matte, T., Copley, C.G., Flanders, D., Binder, S., 1994. Retrospective study of the impact of lead-based paint hazard remediation on children's blood lead levels in St. Louis, missouri. Am. J. Epidemiol. 139 (10), 1016–1026.

Tellez-Rojo, M.M., Bellinger, D.C., Arroyo-Quiroz, C., et al., 2006. Longitudinal associations between blood lead concentrations lower than 10 microg/dL and neurobehavioral development in environmentally exposed children in Mexico City. Pediatrics 118 (2), e323–e330.

Triantafyllidou, S., Le, T., Gallagher, D., Edwards, M., 2014. Reduced risk estimations after remediation of lead (Pb) in drinking water at two US school districts. Sci Total Environ 466-467, 1011–1021.

Tyrrell, J., Melzer, D., Henley, W., Galloway, T.S., Osborne, N.J., 2013. Associations between socioeconomic status and environmental toxicant concentrations in adults in the USA: NHANES 2001-2010. Environ Int 59, 328–335.

U.S. Census Bureau. American Community Survey. 2017. Available at: https://www.census.gov/programs-surveys/acs/. Accessed September 1, 2018.

U.S. Environmental Protection Agency (EPA). Lead at superfund sites. Available at: https://www.epa.gov/superfund/lead-superfund-sites. Accessed March 11, 2019.

US Department of Health and Human Services. Healthy people 2020: topics and objectives index. Washington, DC. 2012. Available at: http://www.healthypeople.gov/2020/topicsobjectives2020. Accessed 1 September 2018.

Vox. The risk of lead poisoning isn't just in Flint. So we mapped the risk in every neighborhood in America. 2016; https://www.vox.com/a/lead-exposure-risk-map. Accessed 1 April 2018.

Waller, L.A., Gotway, C.A., 2004. Applied Spatial Statistics For Public Health Data. John Wiley & Sons, Hoboken, N.J.

Wengrovitz, A.M., Brown, M.J., 2009. Advisory committee on childhood lead poisoning DoE, emergency health services NCfEH, centers for disease C, Prevention. Recommendations for blood lead screening of Medicaid-eligible children aged 1-5 years: an updated approach to targeting a group at high risk. MMWR Recomm Rep 58 (RR–9), 1–11.

Wheeler, D.C., Jones, R.M., Schootman, M., Nelson, E.J., 2019. Explaining variation in elevated blood lead levels among children in minnesota using neighborhood socioeconomic variables. Sci. Total Environ 650 (Pt 1), 970–977.

Williams, D.R., Collins, C., 2001. Racial residential segregation: a fundamental cause of racial disparities in health. Pub. Health Rep. 116 (5), 404–416.

Update

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Erratum regarding missing Declaration of Competing Interest statements in previously published articles

Declaration of Competing Interest statements were not included in the published version of the following articles that appeared in previous issues of Spatial and Spatio-temporal Epidemiology

The appropriate Declaration/Competing Interest statements, provided by the Authors, are included below.

1. Assessing the spatial heterogeneity in black-white differences in optimal cardiovascular health and the impact of individual- and neighborhood-level risk factors: The Multi-Ethnic Study of Atherosclerosis (MESA) (Spatial and Spatio-temporal Epidemiology, 2020; 33C) https://doi.org/10.1016/j.sste.2020.100332 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
2. Deep learning for supervised classification of spatial epidemics (Spatial and Spatio-temporal Epidemiology, 2018; 29C) https://doi.org/10.1016/j.sste.2018.08.002 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
3. Multivariate spatiotemporal modeling of drug- and alcohol-poisoning deaths in New York City, 2009-2014 (Spatial and Spatio-temporal Epidemiology, 2019; 32C) https://doi.org/10.1016/j.sste.2019.100306 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
4. Mapping rates of inpatient hospitalizations related to mental disorders in the state of Missouri: A conditional autoregressive model with zip code-level data (Spatial and Spatio-temporal Epidemiology, 2018; 28C) https://doi.org/10.1016/j.sste.2018.11.003 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
5. Bayesian Hierarchical Spatial Models: Implementing the Besag York Mollié Model in Stan (Spatial and Spatio-temporal Epidemiology, 2019; 31C) https://doi.org/10.1016/j.sste.2019.100301 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
6. Mapping ruralâ€“urban disparities in late-stage cancer with high-resolution rurality index and GWR (Spatial and Spatio-temporal Epidemiology, 2018; 26C) https://doi.org/10.1016/j.sste.2018.04.001 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
7. Using spatiotemporal models to generate synthetic data for public use (Spatial and Spatio-temporal Epidemiology, 2018; 27C) https://doi.org/10.1016/j.sste.2018.08.004 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
8. Assessment of Spatial Mobility Among Young Men who have Sex with Men within and across High HIV Prevalence Neighborhoods in New York City: The P18 Neighborhood Study (Spatial and Spatio-temporal Epidemiology, 2020; 35C) https://doi.org/10.1016/j.sste.2020.100356 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
9. Spatio-Temporal Analysis of Differences in Campylobacteriosis Incidence between Urban and Rural Areas in the Southern District Health Board, New Zealand (Spatial and Spatio-temporal Epidemiology, 2019; 31C) https://doi.org/10.1016/j.sste.2019.100304 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
10. Model-based small area estimation at two scales using Moran's spatial filtering (Spatial and Spatio-temporal Epidemiology, 2019; 31C) https://doi.org/10.1016/j.sste.2019.100303 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
11. Bayesian deprivation index models for explaining variation in elevated blood lead levels among children in Maryland (Spatial and Spatio-temporal Epidemiology, 2019; 30C) https://doi.org/10.1016/j.sste.2019.100286 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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12. Application of kernel smoothing to estimate the spatio-temporal variation in risk of STEC O157 in England (Spatial and Spatio-temporal Epidemiology, 2019; 32C) https://doi.org/10.1016/j.sste.2019.100305 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
13. Exploring socio-demographic-and geographical-variations in prevalence of diabetes and hypertension in Bangladesh: Bayesian spatial analysis of national health survey data (Spatial and Spatio-temporal Epidemiology, 2019; 29C) https://doi.org/10.1016/j.sste.2019.03.003 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
14. Cost-efficient case-control cluster sampling designs for population-based epidemiological studies (Spatial and Spatio-temporal Epidemiology, 2018; 26C) https://doi.org/10.1016/j.sste.2018.05.002 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
15. Longitudinal impacts of two causal drivers of alcohol demand on outlet concentrations within community settings: Population size and income effects (Spatial and Spatio-temporal Epidemiology, 2018; 27C) https://doi.org/10.1016/j.sste.2018.07.003 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.