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Variability in the spatial density of vacant properties contributes to background lead (Pb) exposure in children

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ABSTRACT

Background: Heightened blood lead levels (BLL) are associated with cognitive deficiencies and adverse behavioral outcomes. Lead-contaminated house dust is the primary source of exposure in U.S. children, and evidence suggests that even background (low-level) exposure has negative consequences. Identifying sources of background exposure is of great public health significance because of the larger number of children that can be affected.

Methods: Blood lead was assessed in a bi-racial sample of children from Syracuse, NY, aged 9–11, using established biomonitoring methods. The spatial density of vacant properties was modelled from publicly available georeferenced datasets. Further, regression models were used to measure the impact of this spatial density variable on children's BLL.

Results: In a sample of 221 children, with a mean BLL of 1.06 μg/dL (SD = 0.68), results showed increases in spatial density of vacant properties predict increases in median blood-PB levels, b = 0.14 (0.06–0.21), p < .001. This association held true even after accounting for demographic covariates, and age of individual housing. Further analysis showed spatial autocorrelation of the residuals changed from a clustered pattern to a random pattern once the spatial density variable was introduced to the model.

Discussion: This study is the first to identify a background-lead exposure source using spatial density modelling. As vacant properties deteriorate, lead-contaminated dust likely disperses into the surrounding environment. High-density areas have an accumulation of lead hazards in environmental media, namely soil and dust, putting more children at risk of exposure.

1. Introduction

Lead (Pb) is the most common environmental toxicant leading to declines in neuropsychological functions (Canfield et al., 2003; Mason et al., 2014). Heightened blood leadlevels (BLL) are associated with cognitive deficiencies, increased cortisol and vascular resistance stress responses, and adverse behavioral outcomes (Dietrich et al., 2001; Gump et al., 2009, 2007; Lanphear et al., 2000; Reyes, 2015). Given these negative consequences, there have been increased efforts over the last 25 years to manage Pb exposure across the U.S. (Dixon et al., 2005; Galke et al., 2001; Smith Kormacher et al., 2012). Pb-hazard control programs in Syracuse, NY may have assisted in reducing the average BLL among children from 8.77 (μg/dL) in 1992 to 3.94 (μg/dL) in 2011 (Shao et al., 2017a). However, blood levels historically considered low (< 10 μg/dL) still impair cognitive development (Koller et al., 2004; Lanphear et al., 2005), academic performance (Canfield et al., 2003), and socio-emotional regulation (Winter and Sampson, 2017).

In a more recent cohort of Syracuse children, Gump et al. (2017) found increases in hostility and oppositional defiant behaviors, with increases in BLL, despite very low levels (M = 0.98, range 0.19–3.25). Lead control interventions have focused on mitigating identified routes of exposure, primarily from lead-based paint in older housing (Carrel et al., 2017; Pirkle et al., 1998; Saegert et al., 2003). Through Pb-contaminated dust, present within housing structures, older residential dwellings are the primary route of exposure in children, and they disproportionally affect low-income, racial minorities (Gaitens et al., 2009; Jacobs, 2011; Jacobs et al., 2002; Lanphear et al., 1998b, 1998a, 1996; Matte and Jacobs, 2000; Potash et al., 2015). In contrast,

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background routes of Pb-exposure represent sources that are harder to identify, typically because they are more difficult to measure and Pb is present at lower levels. Background exposure routes include the concentration of trace metals in street dust (Fergusson and Kim, 1991) or elevated airborne-Pb from soil resuspension (Harris and Davidson, 2005).

National figures of decreases in elevated BLL, ≥ 5 µg/dL, (Kennedy et al., 2014; Tsoi et al., 2016) obscure the fact that the spatial distribution of exposure is clustered in low-income areas. Studies have found a number of factors associated with BLL that cluster at the census-tract level including: mean age of housing, mean value of housing, median housing income, and proportion of vacant housing (Reissman et al., 2001; Sargent et al., 1997; Shao et al., 2017b; Stewart et al., 2014); more so, individual BLL have been found to be spatially auto-correlated (Berg et al., 2017; Griffith et al., 1998). In other words, measurements of BLL are correlated with each other across space, suggesting that an underlying spatial process is influencing levels of exposure (Shao et al., 2017b). This spatial process is not likely to be natural, but instead a function of the built environment (Krieger et al., 2003; Miranda et al., 2002).

In Baltimore, MD, researchers established that older housing is a significant predictor of soil-Pb and contributes to the spatial distribution pattern of Pb throughout the city's soil (Schwarz et al., 2012; Yesilonis et al., 2008). A separate study in Baltimore found that demolition, and debris removal, of older housing creates large quantities of Pb-contaminated dust, which then disperses from the demolition site (Farfel et al., 2003). Elsewhere in New Orleans, Rabito et al. (2012) concluded that the destruction of over 100,000 homes by hurricane Katrina disturbed Pb in old structures, and the ensuing dispersion created widespread exposure risk. Others have identified that Pb-contaminated dust in exterior entry areas of housing is a source of lead in street dust at the intersection of the driveway and the street curb (Clark et al., 2004), providing evidence that Pb can disperse without forceful disturbance.

With no amount of BLL considered inconsequential, low-level background exposure is of great public health significance due to the larger number of children that can be affected (Betts, 2012; Canfield et al., 2003; Gump et al., 2017, 2011; Lanphear et al., 2018, 2000; Winter and Sampson, 2017). Existing research has determined that older housing and vacant structures increase the risk of Pb exposure; however, some key limitations exist in the literature (Akkus and Ozdenerol, 2014). Vacant structures have only been studied at aggregated measures of various census-designated areas and these large spatial scales limit our ability to determine in what way this risk factor increases the likelihood of exposure. Models of dispersion have measured Pb levels at the immediate boundaries of a structure, i.e. the driveway or property fence, and have not considered dispersion from structures in the surrounding area. Furthermore, GIS-based exposure research has overlooked low-BLL as an outcome, and has rarely accounted for individual characteristics of children (Akkus and Ozdenerol, 2014). The present study aims to address these limitations.

Herein, we describe methodology for modelling background exposure to environmental Pb utilizing the spatial density of older vacant properties. This density measure is a continuous spatial variable with peaks and valleys, where high values (peaks) represent areas where high number of vacant properties exist close together. We know that at a minimum, Pb can disperse from a built structure to the street curb. It is unlikely that dispersion stops there, thus, we hypothesize that increases in spatial density of vacant properties predicts increases of BLL in children.

2. Methods

Participants were drawn from the Environmental Exposures and Child Health Outcomes (EECHO) study in Upstate New York (Gump et al., 2017; Lefferts et al., 2017). The EECHO research project's focus is on environmental toxicant exposures and cardiovascular risk indices in children The study recruited 295 participants during 2013–2017 and had a ZIP-code selection criteria to target low- to middle-income neighborhoods in Syracuse, NY and surrounding areas. Similar numbers of male (54%) and female (46%), and African American (58%) and White (42%) children participated in the study. At the time of the present analysis, BLL data were available for 270 children. Data were excluded for one participant who had very high BLL, 14.72 µg/dL, a value + 12 SD from the mean. Re-testing of the blood-sample confirmed this value was not a measurement error and likely represents an outlier with acute high-level exposure.

Data were also excluded for 35 participants who resided outside Syracuse city limits. From those who resided within the city limits, an additional 13 were excluded because age of housing was not available from records. These 13 cases did not differ from the sample in terms of socioeconomic status (SES) (t (13.2) = -0.96, p = 0.35), BLL (t (15.7) = 0.28, p = 0.78), body mass index (BMI) (t (13.3) = -0.85, p = 0.41), age (t (13.6) = 0.26, p = 0.79), or race (X^2 (1) = 0.01, p = 0.92). The data for this paper were from the remaining 221 children recruited into the study. Since the scope of this study was limited to the city boundaries of Syracuse, we did not make comparisons between the sample and the 35 cases residing outside the city. Geographic distribution of our sample is shown in Supplemental Fig. 1.

EECHO study participants arrived at the research laboratory in Syracuse University on Saturday mornings. During this visit, children signed an assent form while parents signed a separate guardian consent form, both approved by the Institutional Review Board at Syracuse University. Participants were paired with a trained research assistant to measure their height and weight, and provide electronic surveys administered on iPads through Qualtrics Survey Software (Qualtrics, Provo, UT). Children were also part of an extensive blood draw protocol to measure metals and metabolic panels. A certified phlebotomist drew 5-mL venous blood into a plastic lavender-top (EDTA) tube, certified by the analyzing laboratory for measurement of blood-Pb concentrations. Blood specimens were immediately placed on ice. Within 2 h of the blood draw, samples were transferred into 5-mL cryovials (certified by the analyzing laboratory) and frozen at − 80 °C pending shipment to the trace elements section of the Laboratory for Inorganic and Nuclear Chemistry at the New York State Department of Health's Wadsworth Center, Albany, NY.

2.1. Measures

2.1.1. Blood lead levels

Whole blood was analyzed for Pb using a well-established biomonitoring method optimized for a Thermo XSeries2 Inductively Coupled Plasma-Mass Spectrometer (ICP-MS), which was used throughout the EECHO study (Thermo Fisher Scientific, MA). A complete description of the biomonitoring method has been described elsewhere (Palmer et al., 2006). The ICP-MS instrument was calibrated using a matrix-matched (blood) protocol, with calibration standards traceable to the National Institute of Standards and Technology (NIST, Gaithersburg, MD). Method detection limits were calculated during the study using the IUPAC recommendations for lead in a blood matrix: 0.07 µg/dL. Internal quality control (IQC) materials (four levels) covering the range of exposures expected in the US population were analyzed at the beginning, end and throughout each analytical run. All IQC samples were prepared in-house from whole blood obtained from lead-dosed animals, and supplemented with inorganic salts of mercury (Hg), and methylmercury chloride. Typical repeatability, or between-run imprecision, was 2.6% for lead. Method accuracy was assessed throughout the study by analyzing NIST Standard Reference Material (SRM) 955c – Toxic Metals in Caprine Blood. Method performance was monitored through successful participation in six external quality assessment schemes for trace elements that included these Pb in whole blood. The analysis was repeated for any elevated value: lead > 5 µg/dL.

2.1.2. Georeferenced data

Parcel data were obtained from the City of Syracuse's open data website (http://data.syrgov.net). A polygon shapefile of all city parcels was downloaded and all parcels with a designated *vacant building*[1] were extracted. Afterwards, the coordinates for each polygon centroid of a vacant building's parcel were calculated and projected to NAD83/UTM Zone 18 N for use as point data. The point data file consisted of 1828 vacant parcels in the City of Syracuse. Thirty-three vacant parcels were excluded from analysis for having a built year of 1979 or later. Lead-based paints were banned in 1978, thus, any structure built afterwards, has a low probability of containing lead hazards. The resulting shapefile consisted of 1795 points for analysis, of which 33 points (1.8%) had no information regarding year built but were kept for analysis due to the vast majority of structures being older than 1978. Parcel data used was the most up to date as of August 2017.

2.1.3. Spatial density

The spatial density of vacant properties was calculated using the Kernel Density tool in the Spatial Analyst toolbox of ArcGIS 10.4 (Esri, Redlands, CA). This tool calculates the density of point features at a set distance, or bandwidth, using a quartic kernel function based on Silverman's formula for density estimation (Silverman, 1986). The tool creates a kernel surface map, assigning a value of 1 at each points' location and then smoothly decreasing to zero at the set bandwidth. An output raster surface is created in which the values from all the kernel surfaces, layered on top of each other, are added to calculate the density at each raster cell. To assign vacant density values to each research participant with measured BLL, street home addresses were geocoded using the NYS GIS Program Office's Street and Address Composite locator (http://gis.ny.gov), with a NAD83/UTM Zone 18 N projection. Geocoded addresses were then plotted on top of each density raster, and the corresponding value was extracted. Geocoding quality of address points is shown in Supplemental Table 1.

2.1.4. Bandwidth selection

The bandwidth is an important estimate in any kernel density analysis. In the spatial case, however, there is no clear methodology for how to choose a bandwidth. The bandwidth defines the radius at which a window is created, centered at each point, and calculates the density within. Smaller bandwidths lead to spikier surfaces, with less dispersion from point sources. Larger bandwidths lead to smoother surfaces, with more dispersion from point sources. It is acceptable to use several 'reasonable' values and then choose one that is plausible based on the process being studied (Bivand et al., 2008; Gatrell and Bailey, 1996). In this case, kernel density was calculated at different bandwidths, from 90 to 240 m in 30 m increments, with each creating a different raster surface of vacant property densities. Given that there is no prior reference for this, we began with 90 m because a radius of that size provides a large enough window to include 2–3 properties around the point of interest. Each bandwidth was tested individually as a predictor in regression models, and model quality was examined using Aikake's information criteria (AIC) (Burnham and Anderson, 2004). We aimed to find a bandwidth at which the density variable became non-significant and/or quality did not improve. All bandwidths, however, were significant predictors of BLL, and with each increase in bandwidth, there was a decrease in AIC, which indicates an improvement in model quality. AIC minimization is a widely used method in analysis utilizing a spatial variable that requires a bandwidth selection (Oshan and Fotheringham, 2017; Shao et al., 2017b; Webber and Stone, 2017; Xie et al., 2015). Ultimately, a bandwidth of 240 m was chosen to present as results because it had the most explanatory power (Supplemental Table 2).

2.1.5. Period built

Geocoded home addresses from research participants were plotted on top of the shapefile containing all the city parcels and information was merged from each parcel spatially intersected by an address point. Year built information for the children's individual residence was categorized into four groups (pre-1940, 1940–1959, 1960–1977, and 1978–2017). These categorizations have a clear association with blood-Pb (Fig. 1) and are based on previous research showing that, prior to 1978, each period backwards in time has a higher prevalence of homes containing lead-based paint (www.epa.gov/lead/protect-your-family-exposures-lead; Jacobs et al., 2002).

2.1.6. Covariates

To avoid over-fitting our model with too many confounders (Babyak, 2004), we selected a limited number of known confounding variables consisting of race, age, BMI, and SES, based on previous research. Racial differences have been documented in lead exposure (Lanphear et al., 1996; Winter and Sampson, 2017), as well as SES, health outcomes, and neighborhood environments (Diez-Roux et al., 2010; Rognerud and Zahl, 2006; Yang et al., 2017). Age has been identified as a significant risk factor for exposure (Jones et al., 2009; Keller et al., 2017), with younger children being at higher risk. BMI has also been found to have a significant, inversed association with BLL (Cassidy-Bushrow et al., 2016; Scinicariello et al., 2013). BMI was calculated from height and weight measurements and then converted to a percentile rank on the CDC BMI-for-age growth chart. To measure SES, annual household income, on a 1–10 scale, was divided by the square root of the number of household members (Rognerud and Zahl, 2006). This adjusted income, education level and occupation data were collected, using categorizations outlined in Hollingshead (Hollingshead, 1975), for both parents when available and given equivalent weights by using z-scores. Subsequently, an SES score was calculated by averaging across these 3 measures. For some parents who refused to provide information on all three variables, most notably *occupation*, SES was calculated from the average of the other two domains. There is a great deal of variability in the operationalization of SES in the literature. This approach of combining multiple indicators of SES (education, income, occupation, and family size) to properly capture the broad nature of this construct has been utilized before (Gump et al., 2017; Lefferts et al., 2017).

We also examined the potential confounding of several other variables that were not included in the final model. We examined the effect of residential lead plumbing. Data was only available for 173 participants, and modelled with the other covariates. Lead plumbing was not associated with BLL and therefore excluded from further analysis. The City of Syracuse treats water with orthophosphate, which coats pipes and prevents lead from seeping into the water. We also considered the influence of distance to highway, from place of residence, but there was no association with BLL. Historically, lead exposure from vehicle emissions was a function of leaded gasoline. EPA regulations of gasoline's lead-content have dramatically reduced lead levels air pollution (www.epa.gov/air-trends/lead-trends; Koller et al., 2004). Additionally, we examined nutrition as a possible confounder. Nutrition quality was measured using the Healthy Eating Index (HEI) (Guenther et al., 2014). HEI scores (n = 199), however, were not associated with BLL in a covariate model or in bivariate analysis. Because some BLL samples were collected as far back as 2013, we assessed sensitivity by modelling samples collected during 2017 only (n = 26) – our final model held true even with the truncated sample size. We also considered the condition of vacant structures in a regression model by

[1] City of Syracuse Code of Ordinance Sec. 27–10 defines a vacant building as: *A building or portion of a building which meets one or more of the following criteria – Unoccupied and unsecured; Unoccupied and secured by other than normal means; Unoccupied and unsafe, or unfit, as determined by the division; Unoccupied and in violation of federal, state, or local laws, ordinances and/or regulations; and/or unoccupied and one (1) or more violations of this chapter or the New York State Union Fire Prevention and Building Code exists on the building, parcel, or property.*

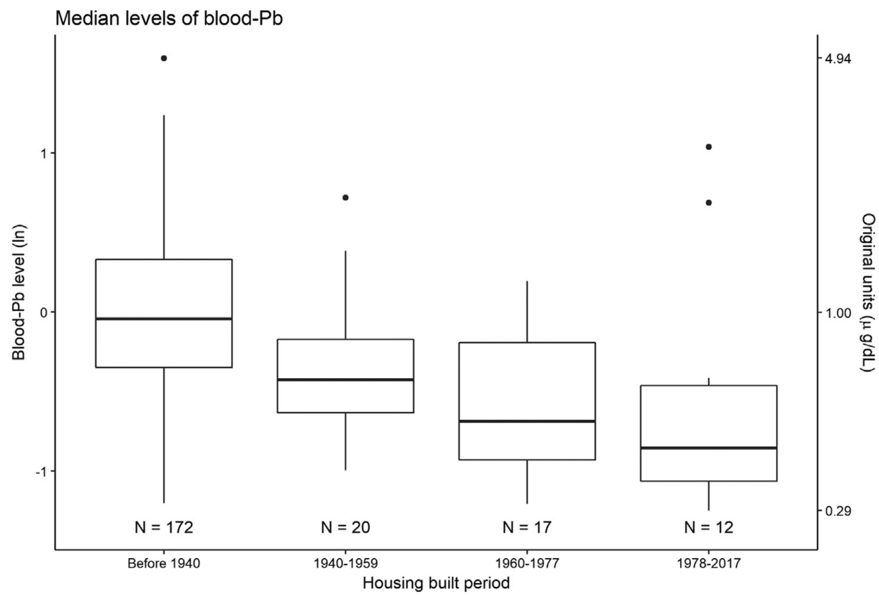

Fig. 1. Relationship between age of housing and BLL among children (N = 221) in Syracuse, NY. Outcome shown in log-transformed and original units or measurement.

Table 1
Sample characteristics.

Characteristic	N	Mean or %	SD	Min.	Max.
Male	115	52%			
African American	141	64%			
Age (in years)	221	10.49	0.94	8.99	12.00
BMI score[a]	221	69.06	29.91	0.00	99.85
BLL (ug/dL)	221	1.066	0.68	0.28	4.94
Family SES score[b]	218	− 0.060	0.800	− 1.58	2.07
Parental income[c]	219			1.00	10.00
No income/homemaker	14	6.4%			
Under $5 K	27	12.3%			
$5 K - $20 K	60	27.3%			
$20 K - $45 K	66	30.2%			
$45 K - $65 K	10	4.6%			
$65 K or greater	42	19.2%			
Occupation[d]	192			1.00	9.00
Not applicable/unknown	81	38%			
Unskilled or semi-skilled (levels 1–3)	47	21.8%			
Skilled (levels 4–6)	58	26.9%			
Managerial (levels 7–9)	28	13.3%			
Parental education[e]	219			1.00	8.00
Less than HS	40	18.2%			
High School	64	29.2%			
Some college/college graduate	84	38.4%			
Some grad/graduate degree	31	14.2%			
Housing period					
Pre-1940	172	77.8%			
1940–1959	20	9.1%			
1960–1977	17	7.7%			
1978–2017	12	5.4%			

Note.
[a] Raw BMI converted to CDC growth chart percentile scores.
[b] Three measures of social status were converted to z-scores and combined to yield a score.
[c] Income based on a 1–10 scale, some categories combined for presentation only, scale was subsequently adjusted by number of people in household.
[d] Occupation based on Hollingshead's scale of occupational prestige, some categories combined for presentation only, 1–3 (unskilled and semi-skilled), 4–6 (small business owner, clerical, semi-professional), 7–9 (manager, business owner, higher executive).
[e] Education based on 1–8 scale, some categories combined for presentation only, a score of five on education scale corresponds to “some college”. Education was averaged across parents.

modelling a weighted kernel density. Weighted kernel density was estimated by using city assigned conditions (1 = Best to 5 = Worst) for 1560 vacant structures, but did not improve our model and was excluded from further analysis.

2.2. Analysis

Because BLLs were not normally distributed, this variable was log transformed. This transformation resulted in a normal distribution of the values: likewise, kernel density values were normalized to z-scores. These transformations allow us to better understand how changes in z-score affect log-changes in BLL values. Three participants who did not have an SES score due to parental missing data, were assigned the mean SES score of this sample. To account for confounding, we used successive linear regression models. First, we modelled the covariates in Model 1 as predictors of BLL. Second, age of housing was introduced in Model 2, and finally the spatial density variable was introduced in Model 3. Age of housing was included in the regression models as a *Period Built* ordinal scale; this variable, along with SES and limiting our study area to the city limits, allows us to control for variation in indoor dust-lead exposure (Lanphear et al., 1998a; Sargent et al., 1997). Regression models were conducted using R version 3.4.1 (R Core Team 2016, Vienna, Austria) in RStudio 1.0.153 (RStudio Team 2016, Boston, MA.).

Spatial autocorrelation of the residuals was tested using ArcGIS' Global Moran's*I* tool. Moran's*I*can be viewed as a spatially weighted form of Pearson's correlation, in which a value of zero represents a random spatial pattern of the attribute, whereas positive values indicate neighbors tend to be similar when close together and negative values indicates the opposite (Waller and Gotway, 2004). The attribute tested was the Studentized residuals of the regression models, which are a scaled version of the true errors and have a constant variance of one. An incremental spatial autocorrelation analysis of the covariate-only residuals showed 1188 m to be the peak distance for autocorrelation. We further tested Moran's*I*on the residuals for all the models, with a zone-of-indifference relationship and a threshold of 1188 m (Euclidean Distance). Zone of indifference (ZOI) allows us to use a set distance for analysis but does not impose sharp boundaries on the attributes. All neighbors within 1188 m (fixed-distance method), of any one point, have the same weight of influence, but the influence of neighbors right past the set threshold is still considered, and starts decreasing with

Table 2
Regression coefficients (with 95% confidence intervals), r-squared change, and AIC values are shown for all models (n = 221).

Predictor	b	b 95% CI	β	β 95% CI	sr^2	sr^2 95% CI	r	Fit	Difference
Model 1 (Intercept)	1.37**	(0.57, 2.18)							
Age	− 0.10**	(−0.18, −0.03)	− 0.17	(−0.30, −0.04)	.03	(−.01, .07)	− .22**		
Race	− 0.05	(−0.21, 0.11)	− 0.04	(−0.17, 0.10)	.00	(−.01, .01)	− .09		
BMI	− 0.00**	(−0.01, −0.00)	− 0.25	(−0.38, −0.13)	.06	(.00, .12)	− .27**		
SES	− 0.13**	(−0.22, −0.03)	− 0.18	(−0.31, −0.05)	.03	(−.01, .07)	− .18**		
								R^2 = .142**	
								95% CI(.06,.22)	
								AIC = 357.24	
Model 2 (Intercept)	1.86**	(1.10, 2.62)							
Age	− 0.11**	(−0.19, −0.04)	− 0.19	(−0.31, −0.07)	.03	(−.01, .07)	− .22**		
Race	− 0.13	(−0.28, 0.02)	− 0.11	(−0.24, 0.02)	.01	(−.01, .03)	− .09		
BMI	− 0.00**	(−0.01, −0.00)	− 0.20	(−0.32, −0.08)	.04	(−.01, .08)	− .27**		
SES	− 0.11*	(−0.20, −0.02)	− 0.15	(−0.27, −0.03)	.02	(−.01, .05)	− .18**		
Period built	− 0.24**	(−0.32, −0.16)	− 0.36	(−0.48, −0.24)	.12	(.05, .20)	− .36**		
								R^2 = .262**	ΔR^2 = .12**
								95% CI(.15,.34)	95% CI(.05, .20)
								AIC = 325.77	
Model 3 (Intercept)	1.55**	(0.79, 2.31)							
Age	− 0.0*	(−0.16, −0.02)	− 0.15	(−0.27, −0.04)	.02	(−.01, .05)	− .22**		
Race	− 0.10	(−0.25, 0.05)	− 0.08	(−0.21, 0.04)	.01	(−.01, .02)	− .09		
BMI	− 0.00**	(−0.01, −0.00)	− 0.20	(−0.31, −0.08)	.04	(−.01, .08)	− .27**		
SES	− 0.04	(−0.13, 0.05)	− 0.06	(−0.19, 0.08)	.00	(−.01, .01)	− .18**		
Period built	− 0.20**	(−0.28, −0.12)	− 0.30	(−0.42, −0.18)	.08	(.02, .14)	− .36**		
Spatial density	0.14**	(0.06, 0.21)	0.24	(0.11, 0.37)	.04	(−.00, .09)	.38**		
								R^2 = .306**	ΔR^2 = .04**
								95% CI(.19,.38)	95% CI(−.00, .09)
								AIC = 314.49	

Note. * indicates $p < .05$; ** indicates $p < .01$. A significant *b*-weight indicates the *b*eta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights; *beta* indicates the standardized regression weights; sr^2 represents the semi-partial correlation squared; ***r*** represents the zero-order correlation.

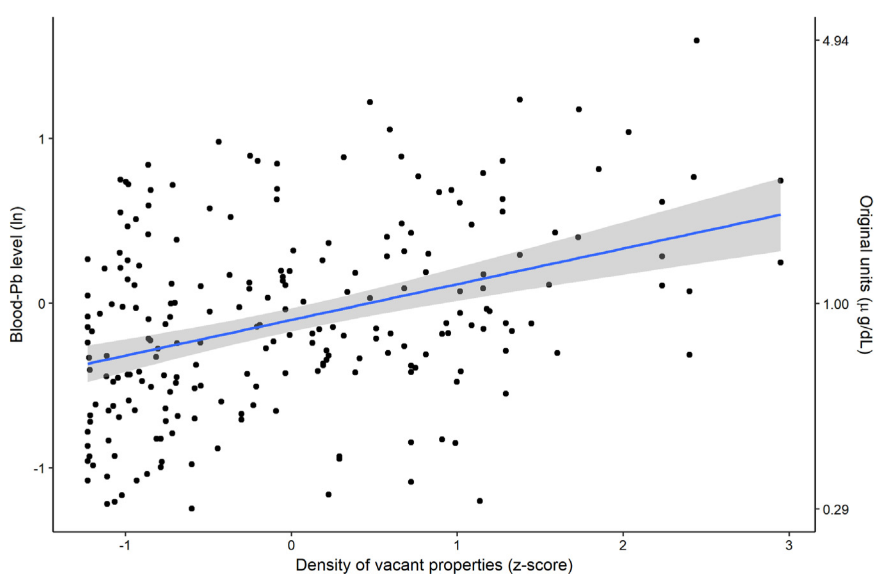

Fig. 2. Relationship between BLL and increases in the spatial density of vacant properties around point of residence of children (N = 221) in Syracuse, NY. Outcome shown in log-transformed and original units of measurement.

distance (inverse-distance method).

3. Results

Our sample consisted of 221 children with a mean age of 10.5 (SD = 0.94), 64% self-identified as African American, and 52% were male. The sample was low-middle income, 7% of parents reported having no income, 40% of families had an annual income of $20,000 or less, and 30% reported making between $20,000 and $45,000. The large majority of families lived in houses built before 1940, and BLL ranged from 0.29 µg/dL to 4.94 µg/dL, with a mean of 1.07 (SD = 0.67). All sample characteristics are shown in Table 1.

3.1. Linear regression models

All covariates, except for race, were significant predictors of BLL in our sample. Before accounting for the effect of the spatial density variable, age, BMI, and socio-economic status (SES) were all inversely associated with BLL (p = 0.0086, p < 0.0001, and p = 0.0083, respectively). In a successive model, age of housing also had a significant association with BLL (p = 0.0004). More notably, we found a positive, significant relationship between BLL and the spatial density of vacant

Table 3
Moran's I summary (spatial autocorrelation) of Studentized residuals.

Model	N	Moran's I	Z score	p-value	Pattern
Model 1	221	0.03	2.19	0.03	Clustered
Model 2	221	0.022	1.68	0.09	Clustered
Model 3	221	0.018	1.45	0.14	Random

Note. Index summaries were calculated with a distance threshold of 1188 m and a zone of
indifference spatial relationship. Zone of indifference allows for a set distance band without
imposing sharp boundaries on neighbor relationships. Clustered patterns indicate residual values are similar when close to each other but does not specify whether they are under-predicting or over-predicting the model.

properties ($p = 0.0003$), even after accounting for individual housing age. Interestingly, the effect of SES remained the same with the introduction of housing age, but became a non-significant predictor after accounting for spatial density. All regression coefficients are shown in Table 2. Given the log function of the outcome measure, each unit increase in the spatial density of vacant properties is associated with a 15% increase in the median BLL (see Fig. 2). That is, median levels of blood-Pb increase by as much as 15% as distance decreases from point of residence to spatial density peaks of vacant housing.

3.2. Spatial autocorrelation

The spatial density variable of vacant properties removed spatial autocorrelation from our final model. Spatial autocorrelation (SA) of the residuals violates the assumption in regression models of independent observations and indicates that an underlying spatial process is responsible for some of the unexplained variance in the outcome. SA results are shown in Table 3.

4. Discussion

Results show that the spatial density patterns of vacant properties are a salient determinant of background Pb exposure among Syracuse residents. Our results hold true after accounting for known factors associated with exposure, and even explain the spatial variation observed in children's BLL. The methodological approach presented in this paper addresses some important limitations in the current literature of GIS-based exposure research; namely, the lack of research on low-level exposure, the use of aggregated measurements of risk factors, and not accounting for individual characteristics of children (Akkus and Ozdenerol, 2014). This novel methodology identifies the spatial density pattern of vacant properties as having more explanatory power than demographic variables when predicting low-BLL. In fact, socio-economic status (SES) becomes a non-significant predictor after accounting for vacant property density, suggesting that low-SES does not serve as a risk factor beyond what type of neighborhood one can afford to live in. This presents a more concrete explanation for differences in exposure, than simply living in poverty.

Vacant structures are frequently neglected with deteriorating interior and exterior paint. Given we only measured structures built pre-1978, paints are presumably Pb-based. It is not implausible that as these properties deteriorate, Pb-contaminated dust disperses into the surrounding environment. Because increases in spatial density values are a function of increases in the number of vacant properties within a small area, they serve as indicators of increasing levels of accumulated Pb in the surrounding environmental media, namely street dust and soil. Given the age range of our sample, the most likely pathway of exposure is simply through being outdoors engaged in activities around these vacant structures. Additionally, many children walk or bike to school. Children residing in areas with multiple vacant properties close together are at the highest risk of exposure given that lead-dust will disperse, and accumulate, from multiple structures. Furthermore, lead can be tracked indoors from the surrounding environment. This is relevant given the low car ownership in most impoverished neighborhoods.

In Syracuse, there are over 1800 vacant properties. Eighty-five percent of them were built before 1940. These properties are densely located in identified areas of elevated BLL (Griffith et al., 1998), elevated soil-Pb concentrations (Shao et al., 2017b), concentrated poverty, and low rates of homeownership, that are demarcated by the two interstate highways that split the city (Larsen et al., 2017) (see Fig. 3). The establishment of the New York Land Bank Act of 2011 aimed to empower communities to address vacant properties and revitalize neighborhoods. However, The Greater Syracuse Land Bank, which has sold 500 properties as of December 2017, was defunded $1.5 million by the City Common Council; similarly, New York State funding is not committed past 2018. More strikingly, the Syracuse Lead Program, the city's abatement and primary intervention entity, was dismantled after renewal of federal funding was not approved. With two major programs lacking funding, we can expect Pb hazards associated with vacant properties to persist as the city's housing stock continues to age and deteriorate. This complex social problem creates chronic, insidious exposure in particularly vulnerable low-income populations that cannot afford to relocate to better neighborhoods (Diez-Roux et al., 2010; Lanphear et al., 2018).

4.1. Limitations

The parcel dataset obtained did not contain information on how long a property had been left vacant. It is likely that the longer a property lies vacant, the greater amount of Pb that is disturbed; however, we were unable to test for this in the presented analysis. Additionally, we were unable to measure levels of soil-Pb or indoor dust-Pb of participants' dwellings that could have provided a direct test of this pathway. The lack of knowledge on when the properties became vacant, how long a family had resided at their current address, and whether primary intervention abatement was performed, makes it difficult to establish a causal link with BLL. It is possible that exposure occurred elsewhere or before these properties became vacant. Nonetheless, we expect the vacancy status of these properties has remained relatively constant over the past few years. A news report in 2010 noted 1600 vacant properties (Dowty, 2010) in Syracuse; a number that increased to 1854 by 2013 (Knauss, 2013). It is not unlikely that the majority of vacant properties have remained vacant for the past several years (Weaver, 2015). Since BLL have been found to be auto-correlated over time (Shao et al., 2017a), any changes in vacant property status or intervention utilization is introducing random error, thereby, the effect found in this study could be underestimated (Armstrong, 1998).

5. Conclusion

Despite its limitations, the present study is the first to identify this pathway of background Pb exposure. Given that this model accounted for spatial autocorrelation suggests that the spatial density pattern of vacant structures may be the underlying spatial process that previous studies have found, but not identified (Haley and Talbot, 2004). This model allows for discerning practical strategies to address Pb-hazards in any city, and can help prevent misspecification of exposure models in future research. Because this hazard is an ongoing concern associated with adverse behavioral, cognitive, and physiological outcomes (Gump et al., 2017, 2009, 2007; Lanphear et al., 2018, 2005), future studies are needed to explicitly measure, simultaneously, indoor residential exposure and the contribution of vacant properties to environmental Pb. The present study adds to this body of knowledge and can help inform our efforts towards mitigating exposure.

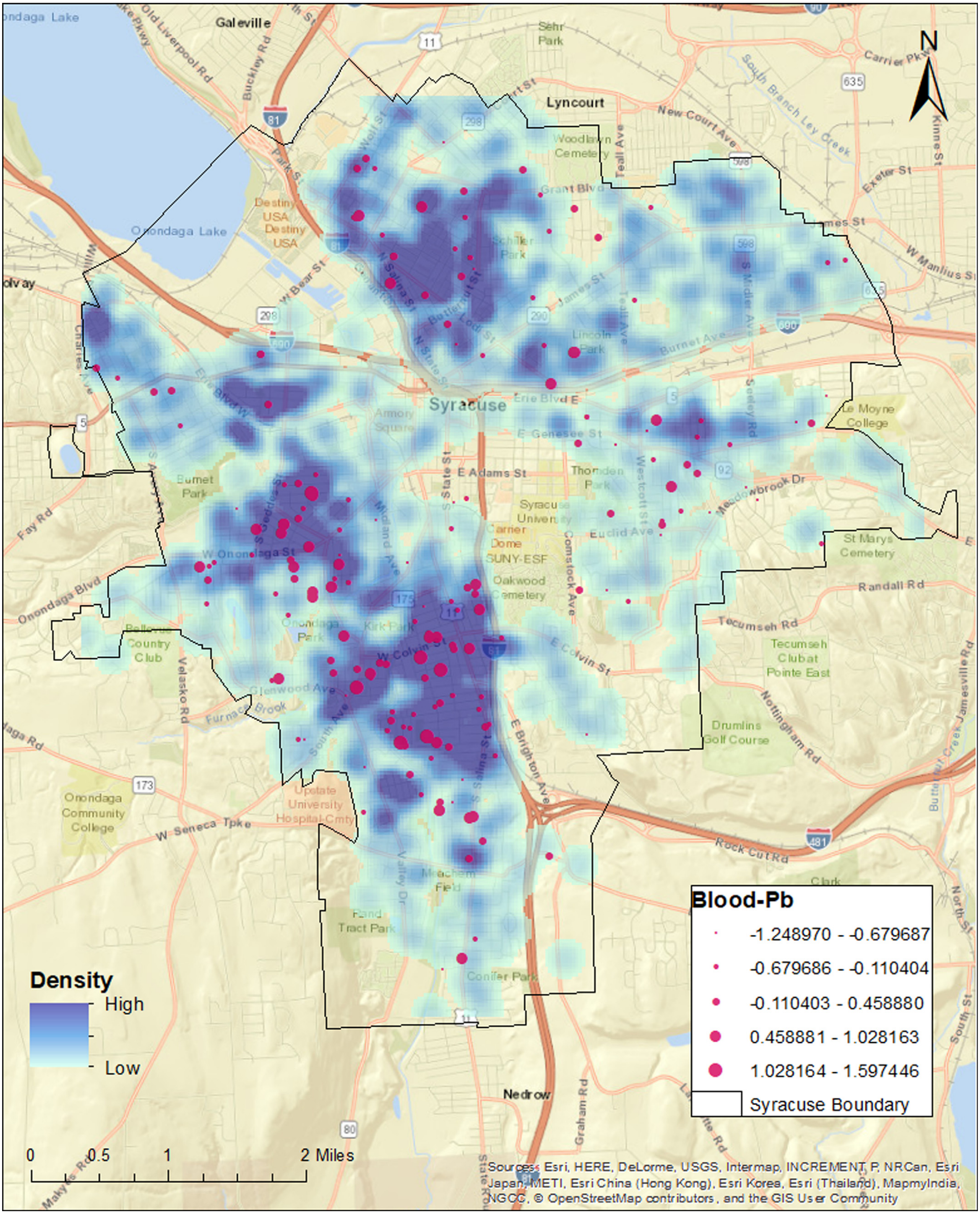

Fig. 3. Map of Syracuse, NY showing log-transformed BLL of children (N = 221) at their point of residence in relation to the spatial density of vacant properties throughout the city.

CRediT authorship contribution statement

Ivan E. Castro: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **David A. Larsen:** Conceptualization, Methodology, Formal analysis, Supervision, Validation, Writing - review & editing. **Bryce Hruska:** Project Administration, Supervision, Validation, Writing - review & editing. **Patrick J. Parsons:** Formal analysis. **Christopher D. Palmer:** Formal analysis. **Brooks B. Gump:** Funding acquisition, Supervision, Validation, Writing - review & editing.

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Data and materials availability

Geospatial data used in this study is publicly available from the City of Syracuse's Open Data website. Other materials, such as data and statistical code, can be requested from the authors; nonetheless, in order to maintain the confidentiality of our participants, we may refrain from sharing individual home addresses.

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Competing financial interests

The authors declare they have no actual or potential competing financial interests.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envres.2018.12.069

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