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A U.S. Lead Exposure Hotspots Analysis

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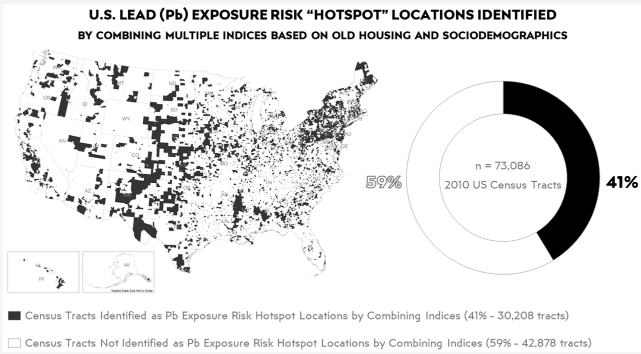
ABSTRACT: To identify U.S. lead exposure risk hotspots, we expanded upon geospatial statistical methods from a published Michigan case study. The evaluation of identified hotspots using five lead indices, based on housing age and sociodemographic data, showed moderate-to-substantial agreement with state-identified higher-risk locations from nine public health department reports (45−78%) and with hotspots of children's blood lead data from Michigan and Ohio (e.g., Cohen's kappa scores of 0.49−0.63). Applying geospatial cluster analysis and 80th−100th percentile methods to the lead indices, the number of U.S. census tracts ranged from ∼8% (intersection of indices) to ∼41% (combination of indices). Analyses of the number of children <6 years old living in those census tracts revealed the states (e.g., Illinois, Michigan, New Jersey, New York, Ohio, Pennsylvania, Massachusetts, California, Texas) and counties with highest potential lead exposure risk. Results support use of available lead indices as surrogates to identify locations in the absence of consistent, complete blood lead level (BLL) data across the United States. Ground-truthing with local knowledge, additional BLL data, and environmental data is needed to improve identification and analysis of lead exposure and BLL hotspots for interventions. While the science evolves, these screening results can inform "deeper dive" analyses for targeting lead actions.



KEYWORDS: *children's health, environmental health, metals, indices, mapping, biomonitoring*

■ INTRODUCTION

While average blood lead levels in the U.S. have declined, millions of children and adults are still exposed to various sources of lead.[1−3] Although there are known sources of lead exposure (e.g., paint in older homes, drinking water from lead pipes, soil, and consumer products),[4] it is difficult to identify communities that may have disproportionate exposures because of limitations in children's blood lead surveillance data and gaps in environmental and other exposure data.[5] There is no known level of lead exposure to be without risk,[6−8] and many communities are disproportionately impacted.[9,10]

Identifying and addressing remaining lead exposure risk hotspots are priorities in the United States. The Federal Lead Action Plan[10] and the U.S. Environmental Protection Agency (EPA) Lead Strategy (e.g., Goal 2, "Identify Communities with High Lead Exposures and Improve Their Health Outcomes")[9] highlight the need for lead mapping as part of whole-of-government efforts to address high exposure risk locations and disparities. Data mapping can inform screening and prioritization efforts to guide interventions and "deeper dive" analyses (such as enhancing children's blood lead level (BLL) surveillance data analyses and lead source apportionment analyses). These analyses can assist in efforts around primary prevention; lead-based paint mitigation; lead remediation, enforcement, education, and outreach.[11] Federal agencies are collaborating to identify geographic locations and populations at risk for lead exposure so that they can be addressed proactively. Examples include targeting HUD remediation grants, EPA environmental cleanup actions, and CDC primary prevention and enhanced blood lead testing programs for children.[5]

The EPA, U.S. Department of Housing and Urban Development (HUD), Centers for Disease Control and Prevention (CDC), and other organizations are applying geospatial statistical methods with available data (blood lead surveillance data, lead indices, and environmental data) to identify locations that are disproportionately at risk. However, there are remaining gaps and challenges such as cross-agency data collection and integration.[5] The interagency lead mapping state-of-the-science paper[5] presented a data integration roadmap to identify places for public health action:

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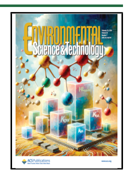

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"For national scale, one could use lead indices and evaluate identified geographic locations by available BLL data and local knowledge...While the science is evolving to compare available lead indices and models against each other and evaluate or ground-truth them against states'-measured surveillance BLL data...an analyst or decision-maker may want to use them collectively to identify high-risk locations to cast a wider net or to use their intersecting locations for a more focused list...".

This paper provides a next step in the research to identify U.S. lead exposure hotspots using existing data.

MATERIALS AND METHODS

The general approach taken for this analysis consists of the following four steps:

1. Statistically evaluated hotspots identified with lead indices against children's BLL surveillance data:
   (a) from Michigan (MI) and Ohio (OH), using the BLL data and statistical methods described in Xue et al.[12] and Stanek et al.,[13] respectively, and an expanded set of national lead indices;
   (b) from matching hotspots identified using lead indices with community hotspots identified in 9 state health department public reports (listed in Zartarian et al.[5]) and quantifying the percent; a match is defined here as a community with at least one census tract identified by the lead indices in our analyses;
2. Compared existing national indices against each other and against available BLL surveillance data using sensitivity, specificity, and Cohen's kappa score to determine which indices are the statistically strongest predictors of hotspots for the national-scale analysis;
3. Produced census tract-level maps for the United States that visualize the intersection and collective combination of hotspots based on the two methods discussed in Xue et al.,[12] top 20 (i.e., 80th−100th) percentiles and Getis-Ord Gi*[14] geospatial cluster hotspots analysis methods;
4. Conducted national-scale analyses to identify states and counties with the highest potential lead exposure risk, based on the considered indices and the number of children younger than six years old in the identified 2010 census tracts (n = 73,086 census tracts containing at least one child <6 years old in the 50 states).

In this paper, hotspots refer to geographic locations with a higher prevalence of children's lead exposures, based on the percentage of higher BLLs among children and/or identification by lead exposure indices using two statistical methods: top 20 (80th−100th) percentile and Getis-Ord Gi* geospatial cluster hotspot analysis (ESRI ArcGIS Desktop v.10.8.2 and Pro 3.1 Hot Spot Analysis tool[15]). The top 20 (80th−100th) percentile method uses a direct percentile calculation conducted with traditional statistical software (i.e., Microsoft Excel). The Getis-Ord Gi* geospatial cluster hotspot analysis method uses the ArcGIS Hot Spot tool[15] which is a spatial interpolation function that calculates the Getis-Ord Gi* statistic for the exposure value of each census tract within the context of neighboring ones. To be identified as a geographic location with a higher prevalence of children's lead exposures, a given census tract will have higher BLL values and/or high lead exposure index values that are also adjacent to other census tracts with higher BLL values and/or high lead exposure index values. More detail on the application of this method can be found in Xue et al.[12]

In our analysis, "higher BLLs" (referred to previously as elevated BLLs or EBLLs) are defined as greater than or equal to CDC's previous blood lead reference value of 5 μg/dL.[16] We elected to use CDC's 2012 blood lead reference value (BLRV)[16] of 5 μg/dL for this analysis to remain consistent with the 2010 census data, MI and OH BLLs acquired through EPA's data use agreements, and the public state health department reports used in this analysis (all of which contain data predating 2020). The BLRV was updated to 3.5 μg/dL in 2021.[17]

The five lead exposure indices and models (referred to collectively as lead indices) used in this national-scale analysis are based on publicly available data on older housing (prior to 1980) and sociodemographic variables. We included the following indices: (1) the EPA EJSCREEN Lead Paint EJ Index ("EJSCREEN Index");[18] (2) Schultz et al., 2017-based BLL model ("Schultz Model") developed by the EPA Office of Research and Development (ORD);[19] (3) U.S. Department of Housing and Urban Development Deteriorated Paint Index (HUD DPI);[20] (4) the Vox U.S. Lead Risk Exposure score ("Vox");[21] and Random Forest (RF) Regression EBLL Prediction Model ("RF Model"). The first four were summarized by Zartarian et al.[5] Two versions of the new Random Forest (RF) Regression EBLL Prediction Model developed by EPA ORD[22,23] were also included: RF Model version 1 (v1) and RF Model version 2 (v2). "RF Model v1" refers to version 1 of the regression model built using Ohio 2007−2011 BLL data and the 2013 OH DH report model.[24] It includes the following five variables: percent of homes built prior to 1940, percent of homes built prior to 1950, percent of families whose income-to-poverty ratio was greater than 2, percent of population with either high school or higher education, and percent of non-Hispanic African Americans in each census tract. Demographic data originate from the American Community Survey 2013−2017 5-year summary file.[25] "RF Model v2" refers to a modified version that includes the following variables: percent of homes built prior to 1940, percent of homes built prior to 1950, and percent of families whose income-to-poverty ratio was greater than 2. Note that RF Model v2, which is a reduced form of v1, is included in a subset of tables and figures in the Results and Discussion, as it was developed after the initial analyses were conducted. Please see the Supporting Information for more details.

We used BLL data from Michigan (∼1.9 million BLL data points; 2006−2016 among children <6 years old) and Ohio (∼2.3 million BLL data points; 2005−2018 among children <6 years old) acquired through data use agreements between the state health departments and the EPA/ORD. More detail on these data can be found in Xue et al. (MI data)[12] and Stanek et al. (OH data).[13]

For steps 1 and 2, indices were compared together and with children's BLL data from MI and OH and state-identified locations in public health department reports. The identified lead exposure indices hotspots were evaluated by applying Cohen's kappa[26] agreement statistic (<0.4 = low; >0.4−0.6 = moderate; >0.6−0.8 = substantial; >0.8−0.99 = near perfect agreement) and sensitivity and specificity analyses. Note that some reports refer to these locations as "high risk communities" while others refer to them differently, e.g., "selected community". In the context of this application, sensitivity is the percentage of true positives (i.e., the rate at

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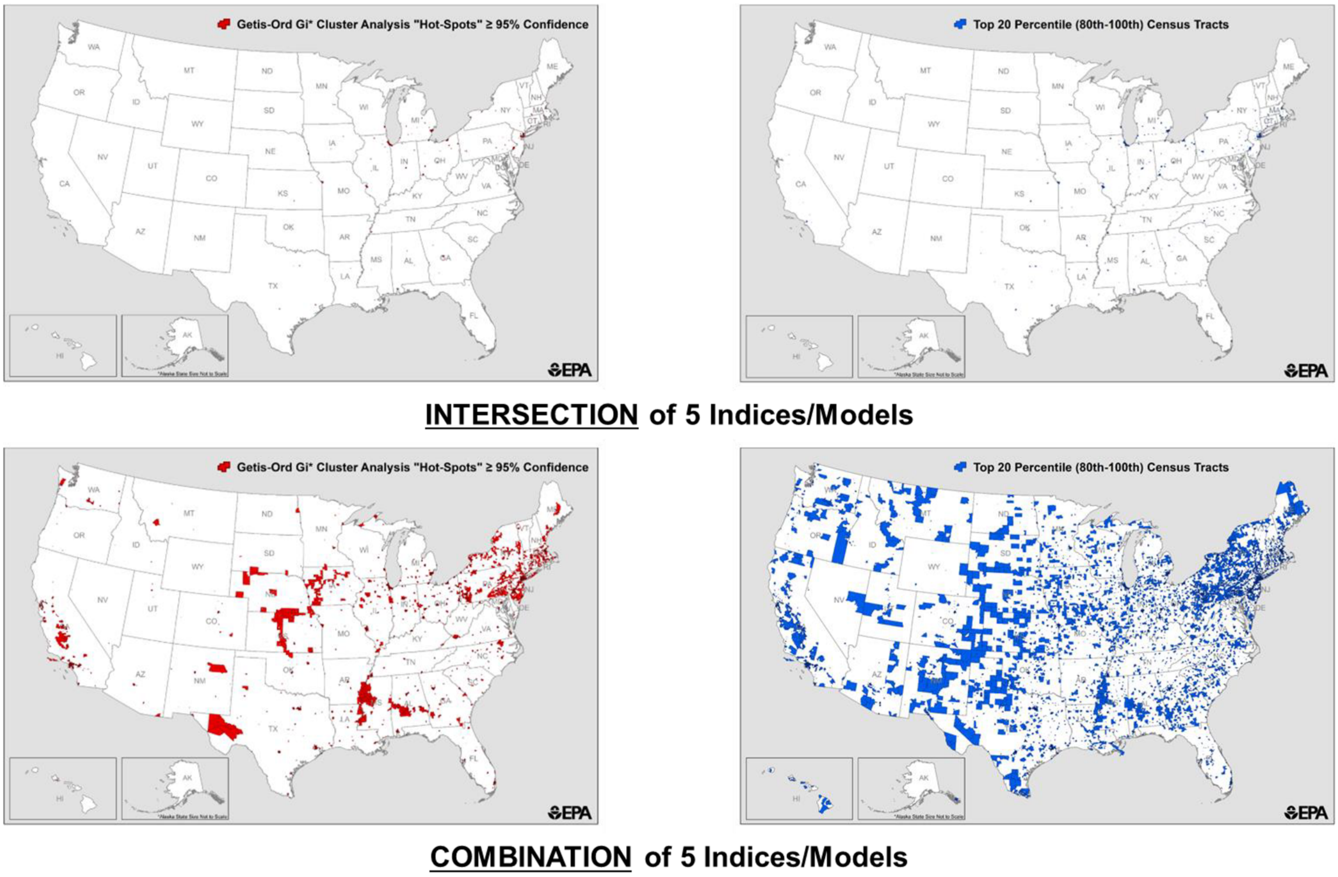

Figure 1. National analyses of the highest potential lead (Pb) exposure risk locations identified using 5 available indices and models with the Getis-Ord Gi* geospatial cluster and top 20 percentile (80th−100th) methods.

which a model or index correctly predicts a hotspot for BLLs) and specificity is the percentage of true negatives (i.e., the rate at which a model or index correctly predicts a nonhotspot for BLLs).

To compare hotspots identified by the lead indices with "high risk locations" identified by state health departments based on their BLL surveillance data, we assessed the summary of available data and reports listed in Zartarian et al. figure B (left panel) and table D.[5] Note that 9 of 32 public reports identified hotspots at the community/city/town level; the rest reported them at other geographic scales (i.e., state, county, parish, health jurisdiction, zip code). The 9 states used for evaluation were: Connecticut (city/town), Maine (city/town), Massachusetts (city/town, census tracts), Michigan (city/town), New Hampshire (city/town, census tracts), New Jersey (municipality), Ohio (city/town, county), Pennsylvania (municipality), and Rhode Island (city). As Table D in Zartarian et al.[5] shows, states used different criteria, geographic scales, time periods, and blood lead reference values for identifying higher risk locations.

After comparing and evaluating the indices using the statistical methods (i.e., top 20th percentile and Getis-Ord Gi* geospatial clustering) described in Xue et al.,[12] the intersection and collective combinations were mapped with ESRI ArcGIS Desktop version 10.8.2. This data intersection and combination was executed in ArcGIS by performing spatial data joining using census tract geographic identification numbers (GEOIDs).

We summarized the results into tables by U.S. states and counties, ranking them by total number of children <6 years old (per 2010 Census[27]) in identified census tracts based on the lead exposure indices results. Corresponding county and state ranking tables are displayed by index or model identification (1 = identified as a lead exposure risk hotspot by index or model; 0 = not identified by index or model as a lead exposure risk hotspot; Total = total number of indices and models that identified the respective location). For Tables S1−S8 identifying states and counties with the highest potential lead exposure risk (as defined by total number of children <6 years old identified by the indices based on housing age and sociodemographics), we featured the Schultz Model, Vox, and RF Model v1 based on the evaluation results. Our intent of identifying states and counties is to inform further tailored analyses for lead mitigation efforts.

■ RESULTS AND DISCUSSION

National-Scale Lead Exposure Hotspot Maps Based on 5 Indices and Models. Figure 1 shows national analyses of high lead exposure locations with five available indices/models, using the Getis-Ord Gi* geospatial cluster method and the top 20 percentile (80th−100th) method. The top panels show the intersection of the five indices, and the bottom shows the combination. Figures S-1 and S-2 show the individual hotspot maps for the five indices using the two statistical methods. The maps look different due to the nuances in underlying science and data as discussed in Zartarian et al.,[5] i.e., national-scale lead indices constructed with different

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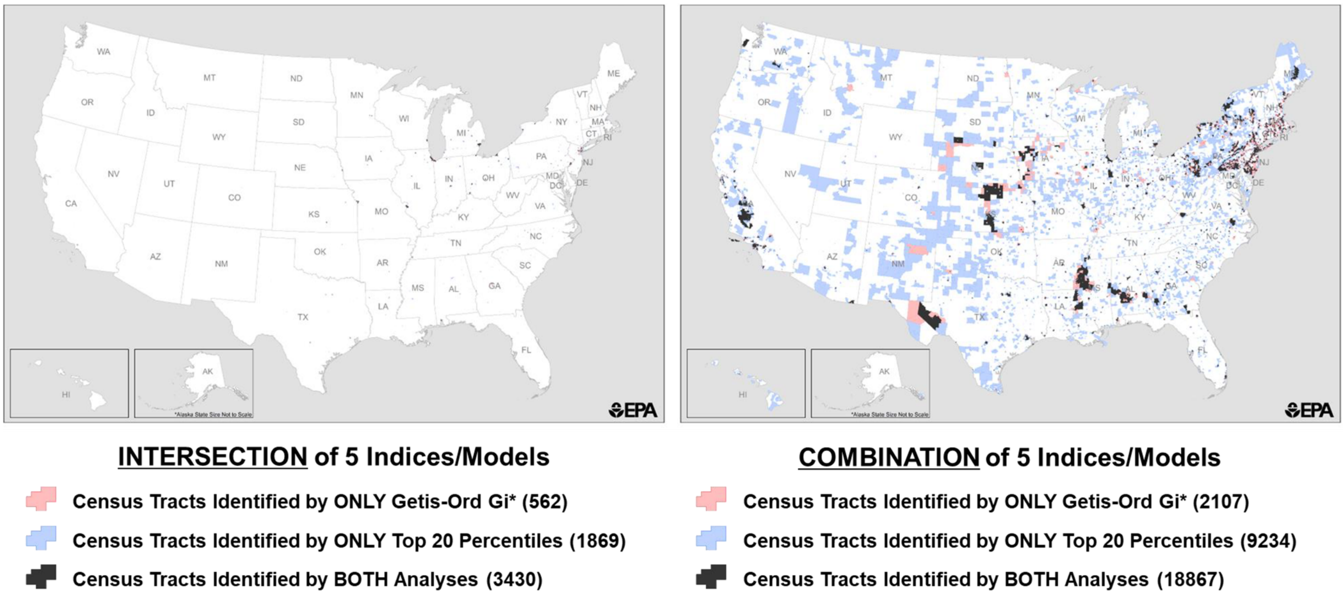

Figure 2. National scale convergence analyses of the highest potential lead (Pb) exposure risk locations identified using 5 available indices and models with the Getis-Ord Gi* geospatial cluster and top 20 percentile (80th−100th) methods.

Table 1. States with the Highest Potential Lead (Pb) Exposure Risk as Defined by Total Number of Children (<6 years old) Living in 2010 Census Tracts Identified by Each Respective Pb Exposure Index and Model Using the Getis-Ord Gi* Geospatial Cluster Method

state	EJSCREEN Index	Schultz Model	HUD Index	Random Forest Model v1	Vox	total[a]
Illinois	1	1	1	1	1	5
Michigan	1	1	1	1	1	5
New Jersey	1	1	1	1	1	5
New York	1	1	1	1	1	5
Ohio	1	1	1	1	1	5
Pennsylvania	1	1	1	1	1	5
Massachusetts	0	1	1	1	1	4
California	1	1	0	1	1	4
Indiana	0	0	1	1	1	3
Texas	1	1	1	0	1	4
Connecticut	0	0	1	0	0	1
Florida	1	1	0	0	0	2
Maryland	1	0	0	0	0	1
Wisconsin	0	0	0	1	0	1

[a]Total = total number of indices and/or models that identified the respective location. 1 = identified by index or model. 0 = not identified by index or model.

methods, variables, and geographic scales. For example, different years of housing age (% pre-1940 vs pre-1960 vs pre-1980 homes) or different sociodemographic variables (e.g., % people of color vs % non-Hispanic African American) can produce different looking maps with differences in hotspots identified, depending on the location and population.

Figure 2 shows the intersection and combination of the two statistical methods on the same maps, along with the number of U.S. census tracts identified. Considering the intersection of the five indices, the number of census tracts is 562 (0.8%) based on Getis-Ord Gi* identified only, 1869 (2.6%) based on top 20 percentiles identified only, and 3430 (4.7%) identified by both analyses (for a total of ∼8%). Considering the combination of the five indices, there is much more coverage over the entire United States, with the number of census tracts as 2107 (2.9%) based on Getis-Ord Gi* identified only, 9234 (12.6%) based on top 20 percentiles identified only, and 18 867 (25.8%) identified by both analyses (for a total of ∼41%).

States and Counties with the Most Children Living in Hotspot Census Tracts Based on Lead Exposure Indices. Utilizing five indices and the two geospatial statistical methods (Getis-Ord Gi* and top 20 percentiles), states and counties with the most children <6 years old residing in hotspot census tracts include:

- IL, MI, NJ, NY, OH, PA (identified by 5 indices); MA, CA, TX (identified by 4 indices) (Getis-Ord Gi* geospatial cluster method) as shown in Table 1 along with other results (i.e., states identified by 1, 2, or 3 indices);
- IL, MI, NJ, NY, OH, PA, TX (identified by 5 indices); CA (identified by 4 indices) (top 20, 80th−100th, percentile method) as shown in Table S-1 along with other results (i.e., states identified by 1, 2, or 3 indices);

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Table 2. Counties with the Highest Potential Lead (Pb) Exposure Risk as Defined by Total Number of Children (<6 years old) Living in Census 2010 Tracts Identified by Each Respective Pb Exposure Index and Model Using the Getis-Ord Gi* Geospatial Cluster Method

state	county	EJSCREEN Index	Schultz Model	HUD Index	Random Forest Model v1	Vox	total[a]
Illinois	Cook County	1	1	1	1	1	5
Michigan	Wayne County	1	1	1	1	1	5
New York	Bronx County	1	1	1	1	1	5
New York	Kings County	1	1	1	1	1	5
New York	New York County	1	1	1	1	1	5
New York	Queens County	1	1	1	1	1	5
Pennsylvania	Philadelphia County	1	1	1	1	1	5
New Jersey	Essex County	0	1	1	1	1	4
California	Los Angeles County	1	1	0	1	1	4
Maryland	Baltimore City	0	1	0	1	1	3
Massachusetts	Suffolk County	0	0	1	1	1	3
Ohio	Cuyahoga County	0	1	0	1	1	3
Pennsylvania	Allegheny County	0	0	1	1	1	3
Texas	Harris County	1	1	1	0	1	4
Wisconsin	Milwaukee County	0	1	1	1	1	4
Arizona	Maricopa County	1	1	0	0	1	3
California	Alameda County	1	0	0	1	1	3
Florida	Miami-Dade County	1	1	0	0	1	3
Indiana	Marion County	0	1	1	0	0	2
New Jersey	Hudson County	0	0	1	1	0	2
New York	Erie County	0	0	1	1	0	2
Connecticut	New Haven County	0	0	1	0	0	1
Massachusetts	Middlesex County	0	0	1	0	1	2
New York	Westchester County	0	0	1	0	0	1
Ohio	Hamilton County	0	1	0	1	0	2
Rhode Island	Providence County	0	0	0	1	0	1
Tennessee	Shelby County	0	1	0	0	0	1
Texas	Dallas County	1	1	0	0	0	2
California	Fresno County	1	0	0	0	0	1
California	Kern County	1	0	0	0	0	1
California	Orange County	1	0	0	0	0	1
California	Riverside County	1	0	0	0	0	1
California	San Bernardino County	1	0	0	0	0	1
California	San Diego County	1	0	0	0	0	1
California	San Francisco County	0	0	0	0	1	1
District of Columbia	District of Columbia	0	1	0	0	0	1
Missouri	St. Louis city	0	0	0	1	0	1
New Jersey	Middlesex County	0	0	1	0	0	1
New York	Suffolk County	0	0	1	0	0	1
Texas	Bexar County	1	0	0	0	0	1

[a]Total = total number of indices and/or models that identified the respective location. 1 = identified by index or model. 0 = not identified by index or model.

- Cook County, IL, Wayne County, MI, Bronx, Kings, New York, Queens counties, NY, Philadelphia County, PA (identified by 5 indices); Essex County, NJ, Los Angeles County, CA, Harris County, TX, Milwaukee County, WI (identified by 4 indices); others shown in Table 2 (Getis-Ord Gi* geospatial cluster method);
- Cook County, IL, Wayne County, MI, Bronx, Kings, Queens counties, NY, Philadelphia County, PA, Los Angeles County, CA, Harris County, TX, Milwaukee County, WI (identified by 5 indices); Essex County, NJ, New York County, NY, Dallas County, TX (identified by 4 indices); others shown in Table S-2 (top 20, 80th–100th, percentile method).

Details of states and counties identified based on the number of children in lead indices hotspot census tracts are shown in Tables S-3, S-4, and S-5 and S-6, S-7, and S-8, respectively. Of the three featured indices (RF Model v1, Schultz Model, and Vox), the Vox score yielded the highest number of children living in identified lead exposure risk hotspots in New York state (627 045; Table S-4) and in Los Angeles County (279 113) (Table S-7).

Evaluation of Lead Indices and Hotspots Identified. Statistical evaluation of hotspots identified using five lead indices showed good agreement with OH and MI BLL data hotspots. Comparing the indices vs BLLs, Cohen's kappa scores demonstrate moderate to substantial statistical agreement (0.49–0.63) between hotspots (Table 3). Generally, the RF Model v1 and v2 had the strongest agreement results (0.63 and 0.54/0.52 for MI and OH, respectively). Tables S-9 and S-10 further illustrate strong statistical agreement with sensitivity

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Table 3. Statistical Agreement Analyses (Cohen's Kappa) of the Highest Potential Lead (Pb) Exposure Risk Hotspots Identified: Michigan and Ohio Blood Lead Levels (BLLs) vs Pb Exposure Indices and Models[a]

	Michigan BLLs			Ohio BLLs		
	N	Getis-Ord Gi*	top 20 percentiles	*N*	Getis-Ord Gi*	top 20 percentiles
		kappa			kappa	
EJSCREEN Index	2401	0.56	0.53	2850	0.59	0.50
HUD DPI	2401	0.50	0.43	2850	0.49	0.42
Random Forest Model version 1	2401	0.63	0.52	2850	0.54	0.51
Schultz Model	2401	0.49	0.49	2850	0.46	0.51
Vox	2401	0.50	0.55	2850	0.44	0.51
Random Forest Model version 2	2401	0.63	0.52	2850	0.52	0.51

[a]Cohen's kappa agreement statistic: <0.4 low; >0.4−0.6 moderate; >0.6−0.8 substantial; >0.8−0.99 near perfect agreement.

and specificity analyses: sensitivity of 91−96% for three of the indices (RF Model v1, Schultz Model, and Vox − Getis-Ord Gi*); specificity of 78−94% for all indices (top 20 percentiles and Getis-Ord Gi*). Compared against each other, the lead indices demonstrate low to near-perfect statistical agreement (e.g., kappa scores of 0.37−0.87 as shown in Table S-11).

The hotspots identified with the five considered lead indices match well with community hotspots identified in the available state health department reports (Tables 4 and 5). For the U.S., the results were 45% (EJSCREEN Index), 62% (Schultz Model), 78% (HUD DPI), 58% (RF Model v1), 72% (Vox), and 61% (RF Model v2). For OH and MI, the results were 74% (EJSCREEN Index), 95% (Schultz Model), 89% (HUD DPI), 89% (RF Model v1), 100% (Vox), and 95% (RF Model v2). Since the convergence analyses of RF Model v1, Schultz Model, and Vox show better statistical agreement with each other (Cohen's kappa of ∼0.7) than with EJSCREEN Index and HUD DPI (kappa ranged from 0.47 to 0.59 with the Getis-Ord Gi* method) for the national scale analysis (Table S-11), we focused on these three indices for identifying states and counties with the highest potential lead exposure risk (as mentioned in Materials and Methods).

DISCUSSION

Strengths. This paper presents an innovative, state-of-the-science geospatial data analysis and screening approach to help identify and address U.S. lead exposure hotspot locations. Current limitations and gaps in environmental, sociodemographic, and blood lead data make it challenging to develop a single U.S. blood lead map or blood lead prediction model accounting for all sources of lead exposure. Thus, our methodology is to utilize a convergence and collective set of currently available information, considering uncertainties and different data sets and approaches. The results are displayed visually with U.S. hotspot map figures showing the intersection and combination of five available lead indices and corresponding tables with locations they identified. The accompanying statistical analyses in the tables presented show the strength of the indices used and verification of locations they identified.

Our results support the use of available lead indices in the absence of consistent, complete BLL surveillance data across the United States. This analysis utilizes peer-reviewed, published lead exposure hotspot analysis methods in EPA's Michigan lead analysis paper[12] and builds off an interagency (EPA/HUD/CDC) lead mapping state-of-the-science paper.[5] Statistical evaluation of the available lead indices was conducted in multiple ways: with MI and OH children's BLL surveillance data and locations identified from 9 state health department reports.

We used census tract level analyses to identify, on a national scale, the states and counties with the highest potential lead exposure risk based on the number of children living in lead exposure hotspots. These results can inform further tailored analyses for lead mitigation efforts. For example, these screening analysis results could include identifying the most disproportionately impacted communities that might be eligible for federal or state lead mitigation programs; determining where resources should be focused to reduce lead-based paint exposures, replace lead service lines, and address lead-contaminated soils and other sources; assessing additional data needs and priority locations for collecting more environmental and biomonitoring data to identify lead exposure hotspots and their drivers. The analysis presented in this paper to advance the science for identifying high lead exposure locations supports U.S. efforts including the Federal Lead Action Plan,[10] EPA Lead Strategy,[9] Biden-Harris Lead Pipe and Paint Action Plan,[28] and Biden-Harris "Get the Lead Out" Partnership.[29]

This science can guide other lead hotspot identification and verification efforts and inform lead reduction actions through collaborations with state and local health departments.[30] Not only are these national-scale maps and results informative to help target U.S. efforts, but the approaches of this paper could also inform lead discussions and efforts in other countries. For example, a report to G7 ministers[31] on the outcomes of the November 2022 workshop entitled, "Lead as a Major Threat for Human Health and the Environment: An Integrated Approach Strengthening Cooperation toward Solutions," discussed options for future work to reduce sources of lead and minimize lead exposure in low- and middle-income countries (LMICs) that included: "helping LMICs conduct initial diagnostic assessments about the prevalence of lead poisoning and identification and ranking of sources of lead exposure." In the U.S. and other countries, while data collection and hotspot mapping science evolves to help pinpoint the highest risk locations, short-term national and community actions can be informed by existing best practices and toolkits (e.g., EPA's Local Lead Action Plan Guide;[32] United Nations Environment Programme, Toolkit for establishing laws to eliminate lead paint[33]).

Limitations. There are a number of limitations of this analysis and opportunities to enhance data and methods to identify lead exposure risk hotspots. The lead indices used in this analysis include 2010 census data, geographic identifiers, and boundaries. The 2020 census data, geographic identifiers, and boundaries cannot be fully incorporated at this time due to incomplete census data or index incompatibility. As mentioned in the Materials and Methods, this analysis uses 5 μg/dL rather than the current CDC blood lead reference value of 3.5 μg/dL to be consistent with the underlying data in the lead indices and the data used to evaluate them (public reports and BLL data from MI and OH). Although this may be considered a limitation of the analysis, Xue et al.[12] found that, when comparing MI census tract hotspots using 5 μg/dL vs

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Table 4. State-Identified Locations in 9 Public Health Department Reports (Based on Blood Lead Levels ≥5 μg/dL) Across the United States That Were Also Identified by the Getis-Ord Gi* Analysis of Lead Exposure Indices and Models[a]

state health department community hotspot[b]	EJSCREEN Index	Schultz Model	HUD Index	Random Forest Model v1	Vox	community index-model identification count
Akron, OH	1	1	1	1	1	5
Atlantic City, NJ	1	1	1	1	1	5
Bridgeport, CT	1	1	1	1	1	5
Brockton, MA	1	1	1	1	1	5
Canton, OH	1	1	1	1	1	5
Central Falls, RI	1	1	1	1	1	5
Cincinnati, OH	1	1	1	1	1	5
Cleveland, OH	1	1	1	1	1	5
Columbus, OH	1	1	1	1	1	5
Dayton, OH	1	1	1	1	1	5
Detroit, MI	1	1	1	1	1	5
East Cleveland, OH	1	1	1	1	1	5
East Orange, NJ	1	1	1	1	1	5
Flint, MI	1	1	1	1	1	5
Hamtramck, MI	1	1	1	1	1	5
Harrisburg, PA	1	1	1	1	1	5
Hartford, CT	1	1	1	1	1	5
Highland Park, MI	1	1	1	1	1	5
Irvington, NJ	1	1	1	1	1	5
Lancaster, PA	1	1	1	1	1	5
Meriden, CT	1	1	1	1	1	5
Muskegon, MI	1	1	1	1	1	5
New Haven, CT	1	1	1	1	1	5
Paterson, NJ	1	1	1	1	1	5
Plainfield, NJ	1	1	1	1	1	5
Reading, PA	1	1	1	1	1	5
Toledo, OH	1	1	1	1	1	5
Trenton, NJ	1	1	1	1	1	5
Waterbury, CT	1	1	1	1	1	5
York, PA	1	1	1	1	1	5
Youngstown, OH	1	1	1	1	1	5
Jackson, MI	0	1	1	1	1	4
Lewiston, ME	0	1	1	1	1	4
New Bedford, MA	0	1	1	1	1	4
Portland, ME	0	1	1	1	1	4
Providence, RI	0	1	1	1	1	4
Scranton, PA	0	1	1	1	1	4
Springfield, OH	0	1	1	1	1	4
Woonsocket, RI	0	1	1	1	1	4
Grand Rapids, MI	0	1	1	1	1	4
Bangor, ME	0	1	1	0	1	3
Adams, MA	0	0	1	0	1	2
Auburn, ME	0	0	1	0	1	2
Gloucester, MA	0	0	1	0	1	2
Newark, NJ	0	1	1	0	0	2
Newport, RI	0	0	1	0	1	2
North Adams, MA	0	0	1	0	1	2
Total	31	43	54	40	50	
Percent[c]	45	62	78	58	72	

[a]1 = identified by index or model; 0 = not identified by index or model. [b]State health department reports and their respective community hotspots are sourced from Table D in Zartarian, V.; Poulakos, A.; Garrison, V. H.; Spalt, N.; Tornero-Velez, R.; Xue, J.; Egan, K.; Courtney, J. Lead Data Mapping to Prioritize US Locations for Whole-of-Government Exposure Prevention Efforts: State of the Science, Federal Collaborations, and Remaining Challenges. *Am. J. Public Health*. 2022, *112* (S7), S658−S669. DOI: 10.2105/AJPH.2022.307051 (ref 5). [c]Percent refers to the percentage of community hotspots identified by each respective index or model. Percentages were calculated by taking the values in the "Total" row and dividing them by 69 (i.e., the total number of state health department community hotspots in the aforementioned 9 public health department reports). 57 community hotspots were identified by at least one index/model. 47 of the 69 are shown in the table as these are the communities identified by two or more indices/models (this was also done due to table formatting and spacing limitations).

Table 5. State-Identified Locations in Michigan and Ohio Public Health Department Reports (Based on Blood Lead Levels ≥5 μg/dL) That Were Also Identified by the Getis-Ord Gi* Analysis of Lead Exposure Indices and Models[a]

	Pb exposure indices and models					
state health dept. community hotspot[b]	EJSCREEN Index	Schultz Model	HUD Index	Random Forest Model v1	Vox	community index-model identification count
Akron, OH	1	1	1	1	1	5
Canton, OH	1	1	1	1	1	5
Cincinnati, OH	1	1	1	1	1	5
Cleveland, OH	1	1	1	1	1	5
Columbus, OH	1	1	1	1	1	5
Dayton, OH	1	1	1	1	1	5
Detroit, MI	1	1	1	1	1	5
East Cleveland, OH	1	1	1	1	1	5
Flint, MI	1	1	1	1	1	5
Hamtramck, MI	1	1	1	1	1	5
Highland Park, MI	1	1	1	1	1	5
Muskegon, MI	1	1	1	1	1	5
Toledo, OH	1	1	1	1	1	5
Youngstown, OH	1	1	1	1	1	5
Jackson, MI	0	1	1	1	1	4
Springfield, OH	0	1	1	1	1	4
Grand Rapids, MI	0	1	1	1	1	4
Lansing, MI	0	1	0	0	1	2
Adrian, MI	0	0	0	0	1	1
Total	14	18	17	17	19	
Percent[c]	74	95	89	89	100	

[a]1 = identified by index or model; 0 = not identified by index or model. [b]State health department reports and their respective community hotspots are sourced from Table D in Zartarian, V.; Poulakos, A.; Garrison, V. H.; Spalt, N.; Tornero-Velez, R.; Xue, J.; Egan, K.; Courtney, J. Lead Data Mapping to Prioritize US Locations for Whole-of-Government Exposure Prevention Efforts: State of the Science, Federal Collaborations, and Remaining Challenges. *Am. J. Public Health.* 2022, *112* (S7), S658−S669. DOI: 10.2105/AJPH.2022.307051 (ref 5). [c]Percent refers to the percentage of community hotspots identified by each respective index or model. Percentages were calculated by taking the values in the "Total" row and dividing them by 19 (i.e., the total number of MI and OH state health department community hotspots).

3.5 μg/dL, a Cohen's kappa value of ∼0.94 was calculated, demonstrating near perfect statistical agreement. Furthermore, the use of 3.5 μg/dL as a blood lead reference value has yet to be adopted by all state health departments, which presently limits and complicates its use in a national scale analysis.

This research focuses on children because of available blood lead data, but reducing lead exposure is also important for adults.[1] We note that some researchers have questioned the interpretability of agreement statistics such as Cohen's kappa.[34,35] Only nine state health department reports identified community-level locations; this, along with most of them not reporting at the census tract level, limited the extent to which we could evaluate the indices across the country. Ideally, more blood lead data would be available for ground-truthing of index-identified hotspots.

The indices utilized are moderate to substantial predictors of higher BLLs and do not include environmental data and sources that could likely improve the identification of lead exposure hotspots (e.g., prevalence of lead service lines; drinking water and soil lead concentration data in residences, schools, and daycare centers; other data discussed in Zartarian et al.[5]). We emphasize that, because the indices and models used in this paper are based on publicly available housing age and sociodemographic data, the lead exposure risk hotspots identified in this national-scale analysis are most relevant to old housing-related sources of lead (e.g., lead-based paint, residential soil and dust, and lead in drinking water in old homes with lead pipes). Identification of high-risk locations and their underlying sources may change as environmental data, and ideally also food and consumer products data, are incorporated into the indices and finer scales are considered. Understanding which lead sources and pathways are contributing the most to BLLs within lead exposure hotspots identified is important for prioritizing exposure reduction actions and resources. However, source apportionment can vary by location and scenarios,[36,37] and quantification is challenging without an integrated database of multimedia environmental lead and BLL data.[5]

Table 1 results, based on Pb indices constructed with old housing and sociodemographic data from the census, may potentially be skewed toward states with higher population densities because of significantly more old housing stock (i.e., in northeastern and north-central U.S. in comparison to the south and other parts of the U.S). Rural counties may appear less than urban areas in this analysis because of smaller populations and potentially lower quantity of census data from those counties used in the indices. Prior research with Michigan data showed that the HUD DPI, EJSCREEN Index, and Schultz Model predominantly identify urban hot spots, particularly with the geospatial cluster analysis (Xue et al.[12]). This U.S. analysis paper and the ones it builds upon focus on potential lead exposure risk from old housing-related sources, based on population level (census tract, county, and state results) not at the individual or household levels.

As a screening approach to identify locations with an increased potential of high lead exposure or higher BLLs, this national-scale analysis cannot identify sources at particular addresses or risk at an individual level. Our methodology focuses on the census tract scale for reasons discussed in Xue et al..[12] To target resources for local-scale source and risk mitigation, further investigation of hotspots identified should be conducted to identify individuals who may have been exposed.[30] More verification or "ground-truthing" of lead hotspots is needed using more blood lead surveillance data, as it becomes available, and information from local partners with on-the-ground knowledge of their communities.[30] We also note that counties with high population densities were identified by most or all of the indices used, which may raise the question of whether population density alone may be sufficient in determining high lead exposure risk. As described in the U.S. EPA Integrated Science Assessment for Lead,[4] old housing—a key environmental variable included in all lead exposure indices considered in this paper—is a widely known and acknowledged indicator of potential lead exposures. This reinforces its use over simple population-based metrics. Furthermore, lead exposure risk has been observed to disproportionately impact specific communities.[9,10] From a social and environmental justice perspective, population density data alone cannot account for this.

Research Needs. More research is needed to understand the differences in high potential lead exposure risk locations identified and the choice of the most appropriate index or indices for different geographic locations. In addition, while some indices statistically agree more with higher BLL hotspots for MI and OH (as shown in Table 3), the requisite BLL data to be able to preferentially select one over another are not available across the entire U.S. Thus, our national approach is to intersect or combine indices (as shown in Figure 2) to narrow or broaden the set of locations for lead-related efforts, depending on the intended purpose and available resources.

Future research can also include enhancing and expanding the current lead indices to address the various limitations as more data become available. Research is underway to enhance the Random Forest Model by incorporating environmental data in EPA/OECA's POST (EPA Office of Enforcement and Compliance Assurance Pb Occurrence and Source Tool described in Zartarian et al.[5]). For example, analyses have been conducted to determine the relative impact of lead service line (LSL) prevalence vs old housing in two cities where LSL data are available[22] and to geospatially analyze linkages between commercial sources of lead and childhood BLLs.[38] CDC is currently developing a web-based Lead Exposure Risk Index (LERI) that will incorporate multiple demographic, geographic, and environmental risk factors at the census tract level. This tool is intended for use by health agencies and providers to identify high-risk areas where children should be tested for lead and to target lead-reduction interventions.[39] In the next two years, HUD plans to geocode the historic database of HUD grants' production of lead-safe housing units and update the Deteriorated Paint Index in 2024 after the 2023 American Housing Survey, Healthy Homes supplement is fielded.

Due to the current data limitations discussed in Zartarian et al.,[5] development of lead indices as surrogates in the absence of complete and accurate population-level BLL surveillance data requires a whole-of-government approach. EPA, HUD, and CDC continue to collaborate and evolve the research and address data gaps. Various groups are working to collect more representative BLL surveillance data and detailed environmental lead sources and measurement data that could help evaluate and improve future indices.[30] Collaborative interagency case studies applying the EPA Lead Strategy Goal 2 "blueprint"[9,30] to identify and prioritize potential places for action are further developing and applying these methods to determine drivers of lead exposure hotspots. While science in this area evolves, these U.S. screening results identifying states, counties, and census tracts with potential high lead exposure risk can inform further efforts to target lead actions (such as those described in Breysse et al.[11] and Zartarian et al.[5]) for public health protection.

The overarching public health questions this research is addressing to help prioritize actions are as follows: Where are exposure risk hotspots and what sources are driving them? The lead-focused methodologies in this paper and previous research it expands upon, using available blood lead surveillance data and surrogate exposure indices, could potentially be applied to other chemicals (and countries) depending on available data.

■ ASSOCIATED CONTENT

Data Availability Statement

Data from this paper are available in EPA's Environmental Dataset Gateway at https://doi.org/10.23719/1529907.

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.3c07881.

Additional maps and analyses of high lead exposure risk locations based on available lead indices and blood lead data (PDF)

Detailed background information and method details on Random Forest Model v1 and v2; table showing variables used; figure showing model validation and performance (PDF)

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Notes

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