Identifying High-Risk ZIP Codes for Childhood Lead Exposure: A Statewide ZCTA-Level Priority List for North Carolina

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BACKGROUND Research has consistently shown that there is no safe blood lead level (BLL) for children. Despite progress in lead poisoning prevention, lead exposure remains a persistent threat to the health and neurological development of children. To identify high-risk ZIP codes for use by families and health care providers for the entire state of North Carolina, we developed a risk model using ZIP Code Tabulation Area (ZCTA)-level census data.

METHODS We obtained all available BLL testing data from the North Carolina Department of Health and Human Services for the years 2010–2015 via data use agreement. We fit a multivariable regression model with the *ZCTA-level mean of log normalized BLLs* as the dependent variable and *ZCTA-level census data for known risk factors of childhood lead exposure* as predictors. We used this model to create a priority risk categorization.

RESULTS We organized ZCTAs into 20 quantiles, or priority risk categories, that can be used in local and statewide screening programs. The first six (of 20) quantiles were identified as particularly high-risk areas for childhood lead exposure.

LIMITATIONS Because BLL testing is not universal, the BLL testing data used in this study are likely biased toward those most at risk for lead exposure.

CONCLUSION This study demonstrates the utility of ZCTA-level census data in identifying high-risk ZIP codes for childhood lead exposure, which can be used to ensure that the highest-risk children are tested in a timely manner. This approach can be replicated to address lead exposure nationally.

Since the 1970s, blood lead levels (BLLs) in children have steadily declined due to increased regulation of lead in consumer products and increased emphasis on lead poisoning prevention [1, 2]. The CDC maintained a blood lead action level of 10 micrograms per deciliter (µg/dL) for many years, despite accumulating evidence of adverse health effects even at lower levels of lead exposure. In 2012, the Centers for Disease Control and Prevention (CDC) recommended a reference value of greater than or equal to 5 µg/dL to identify children with high levels of lead in their blood, which corresponded with (National Health and Nutrition Examination Survey) NHANES data that showed 97.5% of US children aged 1–5 had BLLs below 5 µg/dL [2]. In 2021, the CDC further reduced the reference value to 3.5 µg/dL [3].

Although universal blood lead testing is encouraged for any child aged 12 to 36 months and any child aged 36 to 72 months with no record of a previous blood lead screening test, it is only required for children enrolled in Medicaid [4]. Additionally, the start of the COVID-19 pandemic disrupted routine lead screening, as evidenced by a 52% decline in testing from April 2019 to April 2020 in North Carolina [5]. The recall of LeadCare® test kits in 2021 also contributed to the decline in testing [6]. This marked reduction in testing occurred just when children were spending more time at home because of social restrictions and may have been at increased risk for lead exposure as a result [7–9].

Despite progress in lead poisoning prevention, research has consistently shown that there is no safe BLL for children [10, 11]. Behavioral and cognitive deficits are associated with lead exposure [12, 13], even at low levels. For example, studies have demonstrated that BLLs less than or equal to 5 µg/dL are associated with lower IQ [14, 15], decreased cognitive functioning [16], and neurobehavioral deficits [17]. Several studies have shown a steeper decline in IQ with increases in blood lead concentrations at lower compared to higher levels [14, 15, 18–20]. Additionally, low-level lead exposure has been linked with higher crime rates and antisocial or delinquent behaviors in adolescents. In both individual- and aggregate-level studies, lead exposure is a robust predictor of school disciplinary problems in adolescence and violent and nonviolent crime in adulthood [21–24]. Lead exposure remains a persistent threat to the health and neurological development of children.

Healthy North Carolina 2030 focuses on improving health equity and social and economic factors contributing to health outcomes [25]. North Carolina's growing Black and Brown populations are experiencing worse health outcomes [25, 26]. According to the Healthy North Carolina 2030 report, Black Americans and American Indians have the highest infant mortality rates in North Carolina and lowest life expectancies [25]. Similarly, Black and Brown children and children in lower-income communities are at greater risk of lead exposure [27, 28]. While the Healthy North Carolina 2030 initiative does not aim to reduce lead exposure and BLLs directly, it aims to improve third grade reading proficiency and severe housing problems like overcrowding, high housing costs, and lack of kitchen and/or plumbing facilities [25]. Poor housing conditions, particularly older houses in disrepair, have been linked to higher BLLs, which lead to poorer education outcomes [25, 29]. Low-level lead exposure at age 2 has been inversely associated with academic performance at age 10 [30]. Our past research shows BLLs in early childhood are negatively associated with educational achievement, particularly for educational outcomes like fourth grade reading and mathematics proficiency, as measured by performance on end of grade (EOG) standardized tests in a clear dose-response pattern [31, 32]. Additionally, early childhood lead exposure is a significant predictor of being identified with learning or behavioral disorders in educational records [33]. Both performance on EOG testing and learning and behavioral disorders have long-term implications and are correlated with socioeconomic status in adulthood [34]. Negative effects are observed with BLLs as low as 2 µg/dL.

To achieve a healthier North Carolina in 2030, we must continue to reduce BLLs in the population. However, identifying children at high risk for exposure is challenging, especially in the absence of individual-level childhood blood lead data and the presence of data reporting delays and data quality issues [35].

Given the known social and economic contributors to childhood lead exposure, publicly available census data provide an opportunity to identify areas at high risk for childhood lead exposure. In previous work, we constructed geographic information system (GIS)-based childhood lead exposure models at the tax parcel level to identify children most at risk of lead exposure [36, 37]. Unfortunately, such tax parcel-level models are only possible in counties where tax assessor data include year built—roughly 50% of North Carolina's counties. Here, we adapt the Children's Environmental Health Initiative (CEHI)'s tax parcel-level lead model to the ZIP Code Tabulation Area (ZCTA) level to identify high-risk ZIP codes for childhood lead exposure across the state of North Carolina. We validate the models using blood lead testing data for 2010–2015, which were obtained from the North Carolina Department of Health and Human Services (NCDHHS).

Methods

Blood Lead Data

We obtained BLLs testing data from the Childhood Lead Poisoning Prevention Program of the NCDHHS Division of Public Health, Environmental Health Section in Raleigh, North Carolina for the years 2010–2015. The 2015 records were the latest data available to us. This modeling approach is designed to be updated as new data are made available and can be adapted to any state in the United States. The blood lead testing data include child name, birth date, test date, BLL, type of test (venous or capillary), and home address. The data were provided pursuant to a data use agreement. During the study period, all children with BLLs below the level of detection were assigned a value of 1 µg/dL. BLLs were recorded and stored in the state database as integer values.

Data Restrictions

We restricted the dataset to georeferenced records for children between age nine months and seven years and BLLs between 0 µg/dL and 300 µg/dL. For children with multiple records, we selected the record with the highest BLL.

Aggregating to ZCTAs

We aggregated log normalized BLLs at the ZCTA level and combined with ZCTA-level census data (2011–2015 American Community Survey five-year estimates) for known risk factors of childhood lead exposure. ZCTAs are generalized areal representations of United States Postal Service (USPS) ZIP code service areas [39]. The Census Bureau assigns the most frequently occurring ZIP code within a census block to the entire census block. Then, census blocks are aggregated by code to create larger areas known as ZCTAs. In most cases, ZCTA and ZIP codes are the same for an address. We opted to use ZCTA-level data instead of census tracts or block groups to easily translate results to the ZIP code level, which is more meaningful for and usable in community and health care applications. ZCTA-level census data indicate there are a total of 1,080 ZIP codes among 808 ZCTAs for the state of North Carolina. We removed ZCTAs with a total population of 0 or any missing census data, bringing the total to 1,036 ZIP codes among 775 ZCTAs.

Modeling

To fit a multivariable regression model, 2010–2014 records were used as a training data set, and 2015 records were used as a validation data set. The training data set included 775 ZCTAs, and 767 ZCTAs were included in the validation data set. The ZCTA-level mean of log normalized BLLs served as the dependent variable. We ran three models using explanatory variables commonly found in the literature [40]. The first model contained demographic risk factors of lead exposure, including % non-Hispanic Black, % Hispanic, and median household income. The second

model included the demographic risk factors and median year built, a variable to represent the environmental risk factor age of housing. The third model included the demographic risk factors and age of housing represented using two variables: % of housing units built before 1940 and % of housing units built from 1940 to 1979. Model fit information was used to assess the performance of the models.

Ranking ZCTAs

Using 2011–2015 records, we applied the vector of coefficients from the selected model to predict the expected mean of log normalized BLLs for each ZCTA. The 2011–2015 data set included 997 ZIP codes among 774 ZCTAs. We ranked the ZCTAs into 20 quantiles by predicted values and compared the distribution of elevated BLLs (eBLLs) at different quantiles to determine the appropriate priority risk categorization and identify high-risk areas for childhood lead exposure. eBLLs were defined as greater than or equal to 5 µg/dL. We also examined the distribution of eBLLs at a lower reference value of greater than or equal to 3 µg/dL. We mapped the 20 quantiles to visualize trends in childhood lead exposure at the local and state levels. All data were analyzed in SAS 9.4 [41]. All maps were created using ArcGIS Pro 2.9.3 [42].

Sensitivity Analysis

Given that there is no safe BLL for children, we performed a sensitivity analysis to determine whether the use of mean BLL in our modeling approach reliably identifies low-level lead exposure. Because all children in the BLL testing data with BLLs below the level of detection are assigned a value of 1 µg/dL, we modeled the proportion of BLLs greater than 1 µg/dL at the ZCTA level. Using 2011–2015 records, we fit a multivariate regression model where the ZCTA-level proportion of BLLs greater than 1 µg/dL served as the dependent variable, and the variables selected in the model building process served as the independent variables. We then ranked the ZCTAs into 20 quantiles by predicted values and, to compare modeling approaches, plotted the

assigned rank against the priority risk categorization of the original approach.

Results

A summary of the three models considered in the model building process is presented in Table 1. The results of all models were consistent with our previous findings obtained from models that were fit using data at the tax parcel unit level [36, 37]. The % non-Hispanic Black, % housing units built before 1940, and % housing units built from 1940 to 1979 are positively correlated with the mean of log normalized BLLs at the ZCTA level. The % Hispanic, median household income, and median year built are inversely associated. A comparison of model fit information shows a decrease in root mean square error (RMSE) and an increase in adjusted R^2 with the addition of the variable median year built to represent housing age. Model fit criteria improve further when median year built is replaced with % housing units built before 1940 and % housing units built from 1940–1970, resulting in the selection of model 3. There were 774 ZCTAs included in this analysis.

The mean of the log normalized BLLs was estimated for each ZCTA using the vector of coefficients from model 3. ZCTAs were then ranked into 20 quantiles based on the predicted values. The first quantile consists of ZCTAs with estimated BLLs in the top 5%; the second quantile represents the second highest, and so on. The 20th quantile consists of ZCTAs with estimated BLLs in the bottom 5%. Individual blood lead screening records for 2011–2015 were organized into 20 quantiles based on the rank assigned to each ZCTA and stratified by dichotomous variables for elevated blood lead levels (eBLLs) greater than or equal to 3 µg/dL and greater than or equal to 5 µg/dL (Table 2). By examining the distribution of eBLLs, we provide an example of how the model can be used to identify high-risk ZIP codes for screening in North Carolina.

Between 2011 and 2015, 479,906 children aged 7 years or younger across 997 ZIP codes and 774 ZCTAs were screened for lead in North Carolina. Of the children screened, 3.37%

TABLE 1.
Results of Multivariable Regression for Mean of Log Normalized BLL (in µg/dL)

–	Model 1	–	Model 2	–	Model 3	–
Independent variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	0.68	<.0001	6.61	<.0001	0.58	<.0001
% non-Hispanic Black	1.09×10^{-3}	<.0001	9.46×10^{-4}	.0004	8.50×10^{-4}	.0012
% Hispanic	-5.99×10^{-3}	<.0001	-5.38×10^{-3}	<.0001	-5.06×10^{-3}	<.0001
Median household income	-3.92×10^{-6}	<.0001	-3.23×10^{-6}	<.0001	-3.26×10^{-6}	<.0001
Median year built	–	–	-3.00×10^{-3}	<.0001	–	–
% homes built before 1940	–	–	–	–	4.16×10^{-3}	<.0001
% homes built 1940-1979	–	–	–	–	1.09×10^{-3}	.0061
Adjusted R^2	0.26	–	0.29	–	0.31	–
AIC	-2334	–	-2367	–	-2392	–
Root mean square error	0.1340	–	0.1312	–	0.1289	–

TABLE 2.
Distribution of eBLLs in North Carolina by 20-quantiles

Quantile	No. ZCTAs	No. ZIP codes	No. BLL tests	No. (%) BLL tests ≥ 5 µg/dL	No. (%) BLL tests ≥ 3 µg/dL
1 (Top 5%)	38	52	10889	792 (7.27)	2651 (24.35)
2	39	50	12629	625 (4.95)	2442 (19.34)
3	39	53	15917	865 (5.43)	3436 (21.59)
4	38	43	12375	597 (4.82)	2597 (20.99)
5	39	51	21216	944 (4.45)	3603 (16.98)
6	39	49	20169	895 (4.44)	3863 (19.15)
7	39	49	20264	714 (3.52)	3241 (15.99)
8	38	51	22899	892 (3.90)	3815 (16.66)
9	39	47	22761	893 (3.92)	3601 (15.82)
10	39	49	21278	784 (3.68)	2905 (13.65)
11	39	55	25982	955 (3.68)	4043 (15.56)
12	38	45	17968	687 (3.82)	2698 (15.02)
13	39	43	16002	509 (3.18)	2170 (13.56)
14	39	54	36203	1090 (3.01)	4674 (12.91)
15	39	56	38427	1093 (2.84)	4564 (11.88)
16	38	48	31959	902 (2.82)	3893 (12.18)
17	39	52	39249	912 (2.32)	4166 (10.61)
18	39	50	33027	776 (2.35)	3470 (10.51)
19	39	54	36299	708 (1.95)	3351 (9.23)
20 (Bottom 5%)	38	46	24393	534 (2.19)	2080 (8.53)
Total	774	997	479906	16167 (3.37)	67263 (14.02)

had eBLLs at or above 5 µg/dL and 14.02% had eBLLs at or above 3 µg/dL. Using a reference value of greater than or equal to 5 µg/dL, the prevalence of eBLLs appears to be higher among ZIP codes in the top 12 20-quantiles, whereas prevalence rates in the remaining quantiles are lower than the statewide rate. Using a reference value of greater than or equal to 3 µg/dL, eBLLs also appear to be higher among ZIP codes in the top 12 20-quantiles, with the exception of the 10th quantile.

We used the chi-square test for independence to show a statistically significant association between priority risk category and prevalence of eBLLs (p-value less than .0001). Cell chi-square values show that most of this association is due to the first six quantiles (1–6), where the number of

SUPPLEMENTAL TABLE 1
Cell Chi-Square Values for Chi-Square Test Using 5 µg/dL Reference Value

*This appendix is available in its entirety in the online edition of the NCMJ.*

observed eBLLs is greater than expected, and the last four quantiles (17–20), where the number of observed eBLLs is less than expected (Supplemental Table 1). Conversely, the contribution of risk categories 7–16 to the total chi-square statistic is relatively small. We also observed a similar trend when using 3 µg/dL as the reference for eBLLs, although differences between expected and observed eBLLs are greater and span additional risk categories (Supplemental Table 2).

SUPPLEMENTAL TABLE 2
Cell Chi-Square Values for Chi-Square Test Using 3µg/dL Reference Value

This appendix is available in its entirety in the online edition of the NCMJ.

Results of the sensitivity analysis show the rank assigned to each ZCTA using the proportion of BLLs greater than 1 µg/dL as the dependent variable is comparable to the priority risk categorization of the original approach (Supplemental Figure 1). When plotting the risk rank of

SUPPLEMENTAL FIGURE 1
Comparison of Modeling Approaches for ZCTA-Level Risk Index

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the original approach versus risk rank of the new modeling approach, the points are mostly along the 45-degree line. Where there are differences in priority risk categorization, it is typically by a difference of one risk rank.

Discussion

This analysis builds on our parcel-level model for childhood lead exposure risk. Whereas the parcel-level model

Predicted Mean of Log Normalized BLLs: (a) Unclassed; (b) 20-quantiles; (c) Lead (Pb) Priority Risk Categories
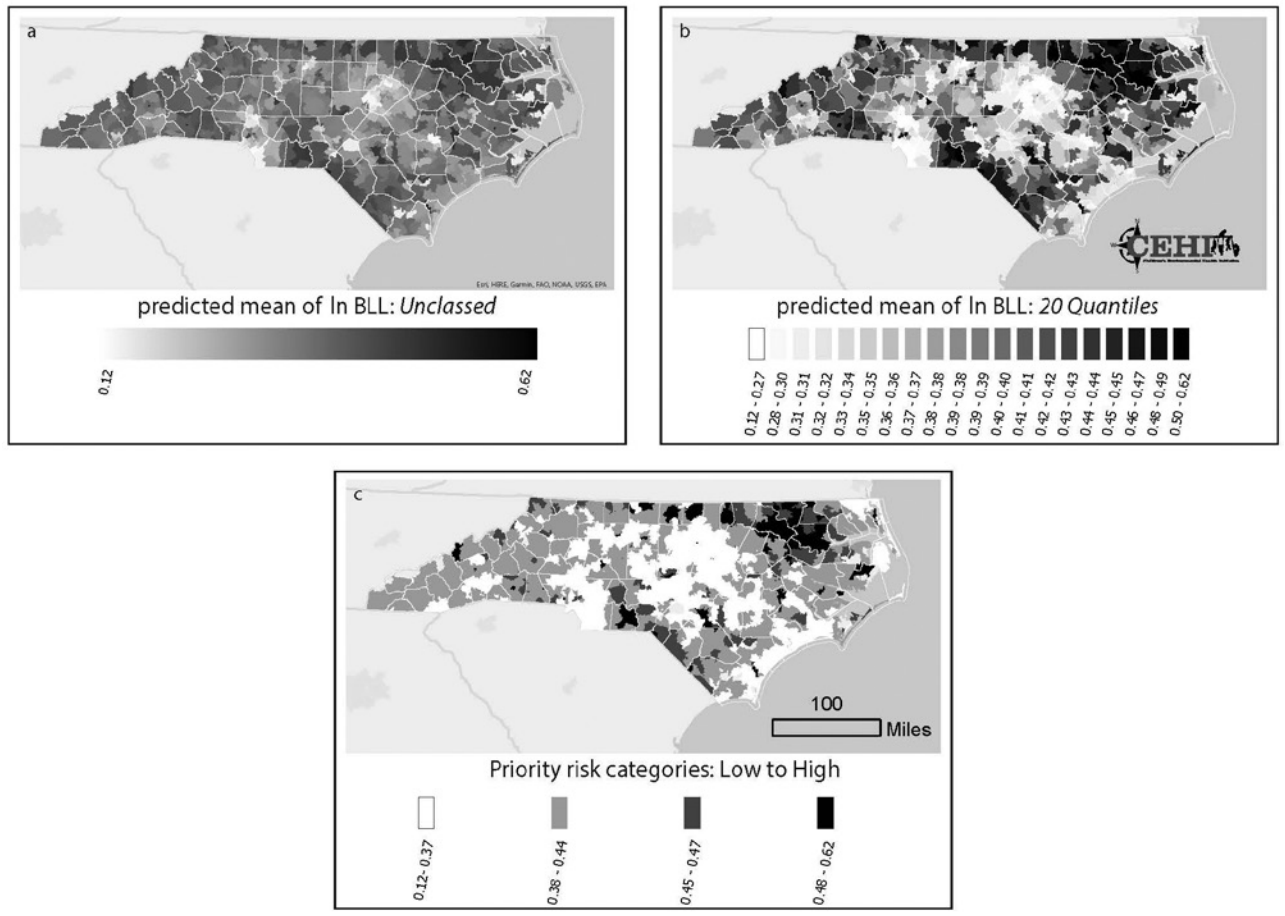
was constructed for select counties in North Carolina (six counties in the initial analysis [36] and 18 in Kim and colleagues' 2008 analysis [37]), the ZCTA-level model was built using data for 775 of the 808 ZCTAs in North Carolina, covering a larger geographic area.

Figure 1a shows a map of the predicted mean of log normalized BLLs we generated for each ZCTA. Using this information alone, it can be difficult to determine which areas to prioritize. While Figure 1a highlights a few high-risk areas, the majority of ZCTAs in the state appear to be at moderate risk for childhood lead exposure. The use of priority risk categories provides more clarity and highlights additional areas of potential concern. Maps of the different display structures show how the model allows for flexibility and adaptation to different screening programs (Figures 1b and 1c). While the larger groupings help to visualize statewide trends in childhood lead exposure risk, smaller groupings may provide more detailed and useful information to local health departments and allow communities to use resources more efficiently.

In our consultations with the North Carolina Childhood Lead Poisoning Prevention Program, we recommended designating at least the first six quantiles as high-risk areas for childhood lead poisoning, consisting of 298 ZIP codes.

However, policymakers should use whatever input process they deem most appropriate to set the cutoff. Any child in the high-risk ZIP codes should be tested for lead. For children in the remaining ZIP codes, health care providers should employ the CDC lead screening questionnaire to determine whether lead testing is needed. This will help to identify more children with low-level lead exposure, including BLLs greater than or equal to 3 µg/dL. The 20-quantiles can be consolidated into whichever larger risk categories are most helpful to health departments, pediatric practices, or community groups.

Limitations

In theory, all children whose parents responded "yes" or "don't know" to any of the three questions on the CDC's Clinical Lead Risk Assessment Questionnaire should have been tested for lead, but it is difficult to ascertain true practice at the time [38, 43]. Because BLL screening is not universal and only mandatory for children enrolled in Medicaid, the BLL screening records used in this study may not be representative of all at-risk children, creating potential for selection bias. This makes it more likely that we will recommend ZIP codes with high numbers of Medicaid-enrolled

children as universal high-risk ZIP codes, potentially missing other high-risk ZIP codes and children.

Additionally, the adjusted R2 value of the selected model indicates that our model explains only 31% of the variance in BLLs at the ZCTA level. By scaling our model to the ZCTA level, we lost information available at the tax parcel unit level. Yet, the number of counties with available tax assessor data limits our ability to create a parcel-level model for the entire state. Still, all explanatory variables in the model are statistically significant and have the expected sign. Furthermore, this value is comparable to the R2 values of other models that use aggregated individual-level data [44, 45]. Despite these limitations, this analysis shows the usefulness of ZCTA-level information, particularly when individual or tax parcel unit-level data are not available.

Conclusions

The BLLs of children exposed to lead tend to increase during ages 0–2 years and peak at ages 18–24 months [46]. Children enrolled in Medicaid are at high risk for lead exposure because they are more likely to live in older, poorly maintained homes that are more likely to contain lead paint [47]. Children enrolled in Medicaid are required to receive blood lead tests at ages 12 months and 24 months or once if aged 24–72 months with no record of a previous blood lead test [4]. For children not enrolled in Medicaid, the CDC recommends focusing efforts on high-risk neighborhoods and children [48]. Clinicians can use the priority risk categorization presented here to flag high-risk ZIP codes in the medical record that trigger an assessment. The recommended vaccination schedule from birth through age 6 provides several opportunities for blood lead testing in a clinical setting [49]. In addition to well-child visits, health care providers can also conduct blood lead tests at sick-child visits [43].

The findings of this study demonstrate the utility of ZCTA-level census data in identifying high-risk ZIP codes for childhood lead exposure. Results of the ZCTA-level model are consistent with our previous findings at the tax parcel level but cover a wider geographic area. We identified six (of 20) quantiles, corresponding to 232 ZCTAs and 298 ZIP codes, as high-risk areas for childhood lead exposure. The model can be used at the state level to determine high-risk ZIP codes for universal testing. It can also be used by local health departments to tailor screening and testing strategies at the county level and can be used by clinicians to inform screening at well- and sick-child visits. Leveraging the availability of ZCTA-level census data, this approach can be replicated nationwide to achieve Healthy People 2030 objectives. NCMJ

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References
1. Dignam T, Kaufmann RB, LeStourgeon L, Brown MJ. Control of lead sources in the United States, 1970-2017: Public health progress and current challenges to eliminating lead exposure. *J Public Health Manag Pract.* 2019;25(Suppl 1, Lead Poisoning Prevention):S13–S22. doi: 10.1097/PHH.0000000000000889
2. Childhood lead poisoning prevention timeline of highlights. Centers for Disease Control and Prevention. Updated October 25, 2022. https://www.cdc.gov/nceh/lead/about/timeline.html
3. Childhood lead poisoning prevention: CDC updates BLRV. Centers for Disease Control and Prevention. Updated December 16, 2022. https://www.cdc.gov/nceh/lead/news/cdc-updates-blood-lead-reference-value.html
4. Lead screening. Centers for Medicare & Medicaid Services. https://www.medicaid.gov/medicaid/benefits/early-and-periodic-screening-diagnostic-and-treatment/lead-screening/index.html
5. Barnes G. Testing for lead in children declines in NC during pandemic. *North Carolina Health News.* September 21, 2020. https://www.northcarolinahealthnews.org/2020/09/21/testing-for-lead-in-children-declines-in-nc-during-pandemic/
6. Recall of LeadCare® blood lead tests due to risk of falsely low results. Centers for Disease Control and Prevention. Updated July 6, 2021. https://emergency.cdc.gov/han/2021/han00445.asp
7. Loza AJ, Doolittle BR. The effect of COVID-19 pandemic restrictions on lead screening in a primary care clinic. *J Pediatr Health Care.* 2022;36(1):64–70. doi: 10.1016/j.pedhc.2021.03.004
8. Courtney JG, Chuke SO, Dyke K, et al. Decreases in young children who received blood lead level testing during COVID-19 — 34 jurisdictions, January–May 2020. *MMWR Morb Mortal Wkly Rep.* 2021;70(5):155–161. doi: 10.15585/mmwr.mm7005a2
9. Anthes E. More childhood lead poisoning is a side effect of Covid lockdowns. *New York Times.* March 12, 2021. https://www.nytimes.com/2021/03/11/health/virus-lead-poisoning-children.html
10. Rossi E. Low level environmental lead exposure – a continuing challenge. *Clin Biochem Rev.* 2008;29(2):63–70. PMID: 18787644
11. Agency for Toxic Substances and Disease Registry (ATSDR). *Toxicological Profile for Lead.* U.S. Department of Health and Human Services, Public Health Service; 2020. https://wwwn.cdc.gov/TSP/ToxProfiles/ToxProfiles.aspx?id=96&tid=22
12. Canfield RL, Jusko TA, Kordas K. Environmental lead exposure and children's cognitive function. *Riv Ital Pediatr.* 2005;31(6):293–300. PMID: 26660292
13. Koller K, Brown T, Spurgeon A, Levy L. Recent developments in low-level lead exposure and intellectual impairment in children. *Environ Health Perspect.* 2004;112(9):987–994. doi: 10.1289/ehp.6941
14. Canfield RL, Henderson CR, Cory-Slechta DA, Cox C, Jusko TA, Lanphear BP. Intellectual impairment in children with blood

lead concentrations below 10 microg per deciliter. *N Engl J Med.* 2003;348(16):1517–1526. doi: 10.1056/NEJMoa022848

15. Jusko TA, Henderson CR, Lanphear BP, Cory-Slechta DA, Parsons PJ, Canfield RL. Blood lead concentrations < 10 microg/dL and child intelligence at 6 years of age. *Environ Health Perspect.* 2008;116(2):243–248. doi: 10.1289/ehp.10424

16. Lanphear BP, Dietrich K, Auinger P, Cox C. Cognitive deficits associated with blood lead concentrations <10 microg/dL in US children and adolescents. *Public Health Rep.* 2000;115(6):521–529. doi: 10.1093/phr/115.6.521

17. Chiodo LM, Jacobson SW, Jacobson JL. Neurodevelopmental effects of postnatal lead exposure at very low levels. *Neurotoxicol Teratol.* 2004;26(3):359–371. doi: 10.1016/j.ntt.2004.01.010

18. Schwartz J. Low-level lead exposure and children's IQ: A meta-analysis and search for a threshold. *Environ Res.* 1994;65(1):42–55. doi: 10.1006/enrs.1994.1020

19. Bellinger DC, Needleman HL. Intellectual impairment and blood lead levels. *N Engl J Med.* 2003;349(5):500–502; author reply 500–502. doi: 10.1056/NEJM200307313490515

20. Lanphear BP, Hornung R, Khoury J, et al. Low-level environmental lead exposure and children's intellectual function: An international pooled analysis. *Environ Health Perspect.* 2005;113(7):894–899. doi: 10.1289/ehp.7688

21. Billings SB, Schnepel KT. Life after lead: Effects of early interventions for children exposed to lead. *American Economic Journal: Applied Economics.* 2018;10(3):315–344. doi: 10.1257/app.20160056

22. Aizer A, Currie JM. Lead and juvenile delinquency : New evidence from linked birth, school and juvenile detention records. The Review of Economics and Statistics. 2019;101(4):575–587. doi: 10.1162/rest_a_00814

23. Boutwell BB, Nelson EJ, Emo B, et al. The intersection of aggregate-level lead exposure and crime. *Environ Res.* 2016;148:79–85. doi: 10.1016/j.envres.2016.03.023

24. Boutwell BB, Nelson EJ, Qian Z, et al. Aggregate-level lead exposure, gun violence, homicide, and rape. *PLoS One.* 2017;12(11):e0187953. doi: 10.1371/journal.pone.0187953

25. North Carolina Institute of Medicine. Healthy North Carolina 2030: A path toward health. Morrisville, NC: North Carolina Institute of Medicine; 2020. https://nciom.org/wp-content/uploads/2020/01/HNC-REPORT-FINAL-Spread2.pdf

26. NC Department of Health and Human Services. Racial and ethnic health disparities in North Carolina: North Carolina health equity report 2018. Raleigh, NC: NC Department of Health and Human Services, Office of Minority Health and Health Disparities; 2018. https://schs.dph.ncdhhs.gov/SCHS/pdf/MinorityHealthReport_Web_2018.pdf

27. Teye SO, Yanosky JD, Cuffee Y, et al. Exploring persistent racial/ethnic disparities in lead exposure among American children aged 1-5 years: Results from NHANES 1999-2016. *Int Arch Occup Environ Health.* 2021;94(4):723–730. doi: 10.1007/s00420-020-01616-4

28. Brown RW, Longoria T. Multiple risk factors for lead poisoning in Hispanic sub-Populations: A review. *J Immigr Minor Health.* 2010;12(5):715–725. doi: 10.1007/s10903-009-9245-8

29. Raymond J, Wheeler W, Brown MJ; Centers for Disease Control and 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.* 2014;63(2):36–42. PMID: 25208256

30. Bellinger DC, Stiles KM, Needleman HL. Low-level lead exposure, intelligence and academic achievement: A long-term follow-up study. *Pediatrics.* 1992;90(6):855–861. PMID: 1437425

31. Miranda ML, Kim D, Galeano MA, Paul CJ, Hull AP, Morgan SP. The relationship between early childhood blood lead levels and performance on end-of-grade tests. *Environ Health Perspect.* 2007;115(8):1242–1247. doi: 10.1289/ehp.9994

32. Miranda ML, Kim D, Reiter J, Overstreet Galeano MA, Maxson P. Environmental contributors to the achievement gap. *Neurotoxicology.* 2009;30(6):1019–1024. doi: 10.1016/j.neuro.2009.07.012

33. Miranda ML, Maxson P, Kim D. Early childhood lead exposure and exceptionality designations for students. *Int J Child Health Hum Dev.* 2010;3(1):77–84. PMID: 21533004

34. Reuben A, Caspi A, Belsky DW, et al. Association of childhood blood lead levels with cognitive function and socioeconomic status at age 38 years and with IQ change and socioeconomic mobility between childhood and adulthood. *JAMA.* 2017;317(12):1244–1251. doi: 10.1001/jama.2017.1712

35. Angelon-Gaetz K, Chelminski AN. Running the numbers: Trends in lead poisoning prevention data for children aged < 6 years in North Carolina. *N C Med J.* 2018;79(5):339–342. doi: 10.18043/ncm.79.5.339

36. Miranda ML, Dolinoy DC, Overstreet MA. Mapping for prevention: GIS models for directing childhood lead poisoning prevention programs. *Environ Health Perspect.* 2002;110(9):947–953. doi: 10.1289/ehp.02110947

37. Kim D, Galeano MA, Hull A, Miranda ML. A framework for widespread replication of a highly spatially resolved childhood lead exposure risk model. *Environ Health Perspect.* 2008;116(12):1735–1739. doi: 10.1289/ehp.11540

38. Centers for Disease Control and Prevention. Screening young children for lead poisoning: Guidance for state and local public health officials. November, 1997. www.cdc.gov/nceh/lead/docs/cdc_13364_1997.pdf

39. ZIP Code Tabulation Areas (ZCTAs). Washington, DC: United States Census Bureau. www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html#:~:text=USPS%20ZIP%20Codes%20are%20not,of%20the%20U.S.%20Postal%20Service

40. Lanphear BP, Dietrich KN, Berger O. Prevention of lead toxicity in US children. *Ambul Pediatr.* 2003;3(1):27–36. doi: 10.1367/1539-4409(2003)003<0027:poltiu>2.0.co;2

41. SAS. 9.4 ed. Cary, NC: SAS Institute Inc.; 2013.

42. Esri Inc. ArcGIS Pro (Version 2.9.3). Redlands, CA: Esri. 2021. www.esri.com/en-us/arcgis/products/arcgis-pro/overview

43. Lead toxicity clinical assessment - exposure history. Agency for Toxic Substances and Disease Registry. 2019. Updated May 24, 2023. www.atsdr.cdc.gov/csem/leadtoxicity/clinical_assessment.html

44. Schultz BD, Morara M, Buxton BE, Weintraub M. Predicting bloodlead levels among U.S. children at the census tract level. *Environmental Justice.* 2017;10(5). doi: https://doi.org/10.1089/env.2017.0005

45. Distler S, Saikawa E. A new screening index to better target low-level lead exposure in Atlanta, Georgia. *Sci Rep.* 2020;10(1):18087. doi: 10.1038/s41598-020-75000-0

46. Wengrovitz AM, Brown MJ; Advisory Committee on Childhood Lead Poisoning Division of Environmental and Emergency Health Services; National Center for Environmental Health; Centers for Disease Control and 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.* 2009;58(RR-9):1–11. PMID: 19661858

47. Advisory Committee on Childhood Lead Poisoning Prevention. Recommendations for blood lead screening of young children enrolled in medicaid: Targeting a group at high risk. *MMWR Recomm Rep.* 2000;49(RR-14):1–13. PMID: 11147551

48. Testing children for lead poisoning. Centers for Disease Control and Prevention. Updated January 20, 2023. https://www.cdc.gov/nceh/lead/prevention/testing-children-for-lead-poisoning.htm#:~:text=A%20healthcare%20provider%20will%20test,has%20lead%20in%20their%20blood

49. Recommended Vaccinations for Infants and Children. Atlanta, GA: Centers for Disease Control and Prevention; 2023. https://www.cdc.gov/vaccines/schedules/easy-to-read/child-easyread.html

SUPPLEMENTAL TABLE 1.
Cell Chi-Square Values for Chi-Square Test Using 5 µg/dL Reference Value

Observed No. BLL tests
Expected No. BLL tests
Cell Chi-Square

Risk Category	No. BLL tests < 5 µg/dL	No. BLL tests ≥ 5 µg/dL	Total No. BLL tests
	–	–	–
1	10097 10522 17.18	792 366.83 492.8	10889
2	12004 12204 3.2632	625 425.44 93.603	12629
3	15052 15381 7.0285	865 536.21 201.61	15917
4	11778 11958 2.7129	597 416.89 77.816	12375
5	20272 20501 2.5642	944 714.72 73.551	21216
6	19274 19490 2.3839	895 679.45 68.381	20169
7	19550 19581 0.0502	714 682.65 1.4397	20264
8	22007 22128 0.65712	89 771.42 18.848	22899
9	21868 21994 0.7245	893 766.77 20.781	22761
10	20494 20561 0.2196	784 716.81 6.298	21278
11	25027 25107 0.2531	955 875.28 7.2613	25982
12	17281 17363 0.3844	687 605.3 11.026	17968
13	15493 15463 0.0585	509 539.07 1.6777	16002
14	35113 34983 0.4801	1090 1219.6 13.772	36203
15	37334 37132 1.0937	1093 1294.5 31.372	38427
16	31057 30882 0.9875	902 1076.6 28.325	31959
17	38337 37927 4.4369	912 1322.2 127.27	39249
18	32251 31914 3.5503	776 1112.6 101.84	33027
19	35591 35076 7.5566	708 1222.8 216.75	36299
20	23859 23571 3.5127	534 821.75 100.76	24393
Total	**463739**	**16167**	**479906**

X^2 (19, N = 479,906) = 5730.3, P <.0001

SUPPLEMENTAL TABLE 2.
Cell Chi-Square Values for Chi-Square Test Using 3 µg/dL Reference Value

Observed No. BLL tests
Expected No. BLL tests
Cell Chi-Square

Risk Category	No. BLL tests < 3 µg/dL	No. BLL tests ≥ 3 µg/dL	Total No. BLL tests
1	8238 9362.8 135.13	2651 1526.2 828.99	10889
2	10187 10859 41.578	2442 1770.1 255.07	12629
3	12481 13686 106.11	3436 2230.9 650.97	15917
4	9778 10641 69.918	2597 1734.5 428.93	12375
5	17613 18242 21.715	3603 2973.6 133.22	21216
6	16306 17342 61.906	3863 2826.9 379.78	20169
7	17023 17424 9.2207	3241 2840.2 56.567	20264
8	19084 19690 18.621	3815 3209.5 114.24	22899
9	19160 19571 8.6249	3601 3190.2 52.912	22761
10	18373 18296 0.3266	2905 2982.3 2.0034	21278
11	21939 22340 7.212	4043 3641.6 44.244	25982
12	15270 15450 2.0885	2698 2518.4 12.812	17968
13	13832 13759 0.3854	2170 2242.8 2.3643	16002
14	31529 31129 5.1442	4674 5074.2 31.558	36203
15	33863 33041 20.444	4564 5385.9 125.42	38427
16	28066 27480 12.511	3893 4479.3 76.749	31959
17	35083 33748 52.817	4166 5501.1 324.02	39249
18	29557 28398 47.304	3470 4629 290.2	33027
19	32948 31211 96.627	3351 5087.6 592.78	36299
20	22313 20974 85.469	2080 3418.9 524.33	24393
Total	463739	16167	479906

X^2 (19, N = 479,906) = 5730.3, P <.0001

SUPPLEMENTAL FIGURE 1.
Comparison of Modeling Approaches for ZCTA-Level Risk Index