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Prevalence of Educational Struggle Correlates with School Districts Toxics Sites and Demographics Variables, with GIS Projections

Junu Shrestha [1], Raihan Khan [2], Shane McClintock [3], John DeGroote [4] and Catherine Zeman [2,*]

[1] University of Illinois at Springfield, jshre2@uis.edu
[2] James Madison University; khanrk@jmu.edu; zemancl@jmu.edu
[3] Clinton County Environmental Health Department; smcclintock@clintoncounty-ia.gov
[4] University of Northern Iowa; john.degroote@uni.edu
* Correspondence: zemancl@jmu.edu; Tel.: 540-568-8024

Abstract: This correlational study focused on children enrolled in individualized education plan (IEP) and contaminated sites located in each school district. Previous studies showed that various environmental factors, such as exposure to toxic substances negatively impacts human health depending on their concentration and occurrence. Therefore, the study aims to use Geographical Information System (GIS) technology and secondary data on IEP numbers of each school district, chemical occurrence in contaminated sites, and demographic data to conduct a correlational analysis. The secondary data obtained from school districts and contaminated sites from Iowa Department of Natural Resources Facility Explorer were populated in ArcMap 10.5 (a GIS software) for generating maps and data to conduct statistical analysis. The contaminants were categorized into metals, polyaromatic hydrocarbons (PAH), and solvents with weighing factors as 1, 0.5, and 0.25. A total of 1 Superfund site and 39 CERCLA sites were identified as contaminated sites for this study. The majority of contaminants were heavy metals such as lead, arsenic, mercury, and cadmium. The mean toxic score of all contaminated sites combined was 13.4 (sd 14.4). The correlational analysis between the IEP numbers from each school districts and toxic scores from the contaminated sites was positive indicting that increased toxic score increased the number of students enrolled in the IEP program ($F = 23.7$, $p < 0.0001$). The correlational analysis between toxic score and demographics indicated some interesting results. Children under the age of 10 were living in areas with high toxic score and the showed mild correlation ($p < 0.00052$). Similarly, higher number of black population resided in areas with high toxic score ($p = 0.0032$) than the white population ($p < 0.0001$). The result also indicated that children enrolled in IEP were predominantly among the black population ($p < 0.0001$). The correlational analysis between household income and poverty percentage of people residing near the contaminated area indicated that people had low average household income ($p = 0.0002$) and high poverty percentage ($p = 0.0203$) residing in areas with higher toxic score. Regarding the educational status, less number of people with post graduate degree ($p < 0.0001$) resided in areas with high toxic score and more number of people with no degree ($p < 0.0001$) resided in areas with high toxic score. Finally, the study showed the increasing trend of eligible children enrolling in free and reduced lunch programs with increasing toxic scores ($p = 0.0012$) and IEP levels ($p = 0.0416$). This study emphasize on developing multiple exposure to correlate environmental factors contributing to the negative health outcome on people.

Keywords: toxic score; individualized education plan; geographic information systems; correlation; environmental factors; multiple exposure

1. Introduction

Historically, the US has seen many environmental injustices toward indigenous populations, people of color, and the poor [1]. Environmental and social injustice towards various minoritized and "othered" groups has led to higher exposure and health consequences among them, especially children living in minoritized and/or low-income neighborhoods [1–3]. Research and advocacy beginning in the late 1980s and extending over more than 30 years and 100s of studies has established the strong association between disproportionate exposure to environmental toxins/risks and black,

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indigenous and other people of color, BIPOC, and low-income status [4], and, on going work such as this study is establishing correlations and ties between specific kinds of exposure and specific health outcomes, encouraging health sciences researchers to accomplish further and more detailed studies.

Environmental pollution gravely affects children's health due to developmental considerations, age of exposure, and the ability of childrens' bodies to detoxify exposures [5]. Children are more vulnerable to some chemicals than adults as their higher percentage of body water and higher surface-to-body ratio can mean disproportionately heavy exposure to pollutants in a given environment. And, their rapidly developing cells, tissues and organs impart a critical biological sensitivity due to growth and development [2,6]. Furthermore, infants' abilities to detoxify environmental exposures in the first year of life is not as well developed as adults or children older than one year of age [7]. Research shows that environmental pollution can have multiorgan, complex adverse effects on children's health and well-being from birth throughout childhood [8], such as adverse birth outcomes, higher mortality, neurological and behavioral abnormalities, respiratory disorder (e.g., asthma), childhood obesity, and cancers [2,8–10]. Additionally, the costs of waste generation and management seldom include the lead-on effects of health issues over time which are costly; in 2008, the annual cost of disease caused by environmental pollution was calculated to be approximately $80 billion [8].

Because of past national attention toward toxic chemical sites such as Love Canal (a neighborhood in Niagra, New York infamous for massive environmental contamination and children's health issues, including cancers) [11,12] and the Valley of the Drums (a 23 acre toxics site in Northern Kentucky where over 100,000, 55-gallon drums of toxic hazardous waste had been discarded into pits on the ground and left in barrels strewn about the site) and on-going research and social justice revelations [13,14], the US Congress established the Comprehensive Environmental Response, Compensation and Liability Act (CERCLA) in 1980, which is informally called "Superfund" and is the US law that deals with locating, classifying and responding to abandoned hazardous waste sites [14]. Superfund sites are cleaned up by the EPA (or their contractors) [15]. There are a total of 1887 superfund sites under clean-up actions in the US currently [16]. Brownfields are contaminated industrial properties which may or may not qualify as Superfund sites, the expansion, redevelopment, or reuse of which might be complicated by the presence or potential presence of hazardous pollutants, substances, or contaminants [17,18]. Although the EPA established the Brownfields and Land Revitalization Program in 1995 [17] , it does not clean up brownfield sites[19]. The responsibility of cleaning-up and managing brownfield sites is on State government entities and non-profit organizations through competitive grants.[19] There are approximately 450,000 brownfield sites in the US [17]. Brownfield locations are often public health concerns. Communities near brownfields experience safety risks, social and economic struggles, and environmental health issues [20]. Common brownfield contaminants include arsenic, asbestos, lead, petroleum hydrocarbons, polycyclic aromatic hydrocarbons (PAHs), polychlorinated biphenyls (PCBs), volatile organic compounds, cadmium, chromium, dioxin, mercury, and other pollutants [21]. These contaminants are highly harmful to human health, especially children's health and many are known carcinogens and nuerotoxins. For example, long-term arsenic exposure can lead to cancer, skin changes, and organ failure, (e.g., liver and kidney failure) [22]. Long-term asbestos exposure can cause asbestosis, and lung cancers, including mesothelioma (cancer of the plueral lining of the thoracis or abdominal cavaties) [23]. Lead exposure to children can cause anemia, reduced growth, nurological damage leading to low IQ and hyperactivity, hearing and behavior, and learning problems [24].

Pregnant women's exposure to lead is an example of intergenerational impact. It can lead to serious developmental anomalies in their fetuses and infants [24]. Therefore, it is important to examine the potential exposure patterns and health effects on children living near brownfield sites, particularly sites where known neurotoxins are present. This correlational analysis examines the strength of the association between known brownfield sites as geolocated in school districts and the number of Individual Educational Plans, IEPs in those districts.The purpose of the study was to correlate the potential for exposure to brownfield contaminants in the school district with children's developmental health, using IEPs as a proxy for their learning challenges. IEPs are developed when children struggle to keep pace in school with their peers and need additional, tailored services to make good progress. The study also correlates demographic variables such as race, educational attainment, and the need to rely on reduced cost/low-cost lunch programs with toxic scores from the school district brownfield sites to examine the patterns of these relationships. To the authors' knowledge, no such study has ever been conducted in Black Hawk County, Iowa (IA). The paper will describe the methods used to locate Brownfield sites, identify toxins, and develop an algorithm to "rate" the dangers at the sites, identify geospatial data, and correlate both statistically and geospatially this data. The conclusions will discuss the strengths and weaknesses of the work and suggest additional work as well as the need for this work to be done at the county regional health department level as a means of monitoring populations for possible impacts and mitigating possible future impacts of exposure.

2. Materials and Methods

2.1. Locating contaminated sites

Brownfield sites were identified using the Iowa Department of Natural Resource's (IDNR) "*Facility Explorer*" website. This publicly available website lists all contaminated sites and contaminants present, including soil and water samples that were tested to quantify any possible level of contamination (Figure 1). Thus, study sites were identified, along with the number and type of contaminants present at each site and the number of years the site had been under management. After site identification, the latitude and longitude of each site were obtained from a IDNR Facility Explorer website [25] The sites were selected based on criteria of being a superfund site, brownfield site, CERCLA pre-remedial site, CERCLA remedial site, a site registered as Iowa Chapter 133/Chapter 137 program, or a RCRA site. This allowed researchers to identify a total of 40 Sites, with 35 being used for analysis due to five of the sites having incomplete information regarding contaminants.

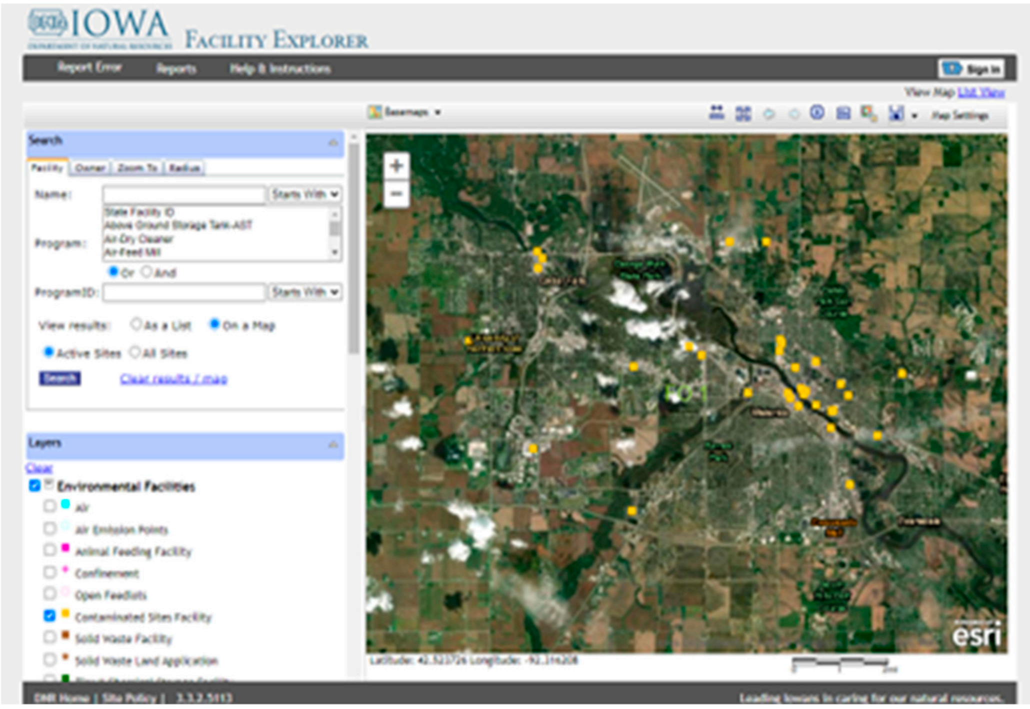

Figure 1. Contaminated Sites as listed in Iowa DNR Facility Explorer Website.

2.2. Demographics Data Collection and Sources of IEP Data

The data on demographics such as age, education, race/ethnicity, income, and poverty percentage was taken from the United States Census Bureau 2015 census data. The study also

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included data on the counts by school of Individualized Education Plans (IEP) obtained from Cedar Falls and Waterloo Community School District Area Education Agency, AEA Offices in the Spring of 2017. AEA offices declined to provide demographics beyond the number of IEPs per school demarcated by grade. Private schools in the districts were contacted but declined to participate in the study. Data on students enrolled in free or reduced-cost lunch programs in each school district was obtained from the Iowa Department of Education, 2016–2017 database.

2.3. GIS Data Collection Sources: Toxics Sites, School District Polygons, Housing Characteristics

Toxics sites needed to be precisely geospatially located, data identifying the geospatial boundaries of schools districts was needed, and age of housing data was sought (an important indicator of possible lead exposure within the home). These data would be used both statistically and geospatially to correlate with number of IEPs in the respective school districts. The coordinate of each contaminated site was fixed by using a GPS device. The polygon (a shape file recognized by ArcGIS associated with a data spreadsheet for unique data points contained within that shape file) feature classes of the Waterloo and Cedar Falls school districts were obtained from the "locate my school" website (https://www.locatemyschool.com/map/waterloo). It is an interactive web-based mapping format that shows school district boundary map.

2.4. Embedding Contaminated Sites with School District

A polygon feature class was created for each contaminated site by carefully aligning the boundary with google maps. The geoprocessing tool intersect was used to embed contaminated sites with school districts. In some cases, one school district consisted of multiple contaminated sites. Therefore, the toxic score of multiple contaminated sites was added together for one school district.

2.5. Calculating Toxic Score

Each contaminated site was evaluated for three classes of chemicals: Heavy Metals, Polyaromatic Hydrocarbons (PAH), and Solvents. These chemical classes were chosen for their known neurotoxic effects. The toxic score, TS of the individual brownfield sites was determined by weighting each of the contaminants present in each site on a scale of 0–1 and summing them. Based on the level of neurotoxicity as supported by previous toxicological studies, the weighting factor used (WF) was: Heavy Metals-1, PAH-0.5, and Solvents–0.25. Thus:

$$TS = (Xhm1\ (x1 + x2...) + Ypah0.5\ (y1 + y2...) + Zslv0.25*(z1 + z2...)) \quad (1)$$

where: TS = toxics score and hm = heavy metal; pah = polyaromatic hydrocarbon; slv = solvent

If the contaminated sites had multiple chemicals, the weighting factor was added to get one toxic score. For example, if the site had contaminants such as Arsenic, Lead, Dibenzo pyrene, and Toluene, then the Toxic Score of that contaminated site for characterizing its neurotoxic weighting is 1 + 1+0.5 + 0.25= 2.75.

Python script was used to automate the task of generating the toxic score weighting of each contaminated site based on the above algorithm and the identified contaminants at the site. The chemicals were reclassified based on the weighting factor (Table 1).

2.6. GIS Tools and Data Analysis

The GIS tools used during the research were mapping overlay tools such as intersect, buffer, and union. We also used a python script [26] for repetitive analysis to add the toxic score in each school district. The table analysis and management tools were used to join the existing excel sheets [27] and geocoding for mapping techniques. After using GIS overlay tools, the final attribute table was imported, and data analysis using JMP software [28].

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Table 1. List of chemicals with Weighting Factors Found in Black Hawk County Brownfields Data.

Metals (WF = 1),	PAH (WF = 0.5)	Solvents (WF = 0.25)
Antimony, Arsenic, Barium, Beryllium, Cadmium, Chromium, Cobalt, Copper, Lead, Mercury, Nickel, Selenium	(124-Trimethylbenzene), (135-Trimethylbenzene), Acenaphthylene, Benzene, Benzo(a)anthracene, Benzo(a)pyrene, Benzo(b)fluoranthene, Benzo(ghi)perylene, Benzo(k)fluoranthene, Chrysene, Cumene, Dibenzo(ah)anthracene, Diesel, Ethylbenzene, Fluoranthene, Fluorene, Gasoline, Indenol(123cd) pyrene, Phenanthrene, Polychlorinated Biphenyls, TEH-D, TEH-WO, Xylene, n-Propyl benzene, Arochlor1260	(111trichlorothane) anthracene, 2butanone, Acetone, Bromomethane, Methylene chloride, TCE, TPH, Tetrachloroethylene, Trichloroethene, cis12-dichloroethylene, Toluene

3. Results

3.1. School Based Demographics, IEP Data and Associated Contaminated Sites

There was a total of 26 schools at all levels in the sample from which IEP data was derived. Sixty-five percent of the schools ($n = 7$) were located in Waterloo School Districts while 35% of the schools ($n = 9$) were located in the Cedar Falls associated school districts. The majority of the sample consisted of elementary schools, (17, 0.65)then middle schools (6, 0.23) followed by high schools (3, 0.12). The number of toxics sites per school district was impacted by the school type (elementary, middle or high school) as districts enlarge with higher grades. The mean number of toxic sites within the school district ranged from 0 for three Waterloo and two Cedar Falls districts, to a high of 15 in one Waterloo, High School District. The mean number of sites per school District was 3.6 (sd 3.58). The algorithmically derived toxic score ranged from 0 to 65.25 (the high number associated with the Waterloo High School District with 15 toxics sites within the district). The mean toxics score was 13.4 (sd 14.4). The numbers of IEPs range from a low of 41 to a high of 247 with a mean of 85.3 (sd 49.8).

Percentage of minority students ranged from a low of 4.9% to a high of 79.5%. Percentage of multi-racial students ranged from a low of 3.1% to a high of 13.6 percent. Table ? indicates the percentage of youth receiving and eligible for free or reduced cost lunch as a proxy for food scarcity and socioeconomic status indicating a low of 12% eligability in one Cedar Falls elementary school district and a high of 95% eligability in one Waterloo elementary school district. These two percentages of eligibility and students actually receiving free/reduced lunch, are in agreement 57.7 percent of the time. See Table 2 for a coded listing of schools and these data points.The authors have coded the original school names to protect their identity and to reduce stigma.

Table 2. Key Demographics of School Sample and Related Toxics Score.

School (coded)	City	School Type	# Sites (in district)	Toxics Score	IEP #	% Minority	% Multi-race	% *Taking* Free or Reduced Lunch	% *Eligible* free or reduced lunch
W1	W	E	5	19.75	58	79	9	88	95
W2	W	E	4	10	81	38	11	67	72
W3	W	E	1	5.5	93	61	9	85	90
W4	W	E	2	8.25	66	65	13	89	91
W5	W	E	0	0	48	18	8	44	44
W6	W	E	1	2	92	37	10	54	66
W7	W	E	3	8	103	67	11	85	90
W8	W	E	0	0	57	39	5	59	59
W9	W	E	4	25	41	55	14	89	89
W10	W	E	2	7	56	18	10	46	49
W11	W	E	0	0	73	11	10	61	61
CF1	CF	E	2	3	50	12	7	27	27

CF2	CF	E	1	6.5	83	11	5	10	12
CF3	CF	E	0	0	41	9	6	23	24
CF4	CF	E	3	8.75	65	13	3	22	22
CF5	CF	E	3	13.75	50	5	6	36	38
CF6	CF	E	0	0	45	13	3	15	15
CF7	CF	M	6	22.5	79	12	5	22	22
CF8	CF	M	3	9.5	77	12	5	20	20
W12	W	M	4	23	74	23	6	63	63
W13	W	M	10	30.5	99	55	9	86	86
W14	W	M	6	17	102	73	8	91	91
W15	W	M	3	9	87	25	5	50	50
W16	W	HS	7	23.25	229	47	6	62	62
W17	W	HS	15	65.25	247	37	5	55	55
CF9	CF	HS	9	32	122	13	4	19	19

School coded to protect student anonymity; City= W= Waterloo, CF= Cedar Falls; E = elementary, m = middle school, hs = high school; #Sites = number of toxic sites in school district associated with that school; Toxics score = algorithm derived ranking of neurotoxins present at toxics sites; IEP# = Number of Individual Educational Programs at the school; % Free or Reduced Lunch = Percentage of students actually receiving free/reduced lunch.

3.2. Contaminated sites

A total of 1 Superfund site and 39 CERCLA sites were identified as contaminated sites for this study (Figure 2). Among this list, 35 contaminated sites were included, five were eliminated from the study due to a lack of data on lists of contaminants. The figure below shows the contaminated sites in the red polygon. The date of first testing of the contaminated sites ranged from 1989 to 2013 with a median date for all sites tested of 2003, 14 years before the IEP data was compiled. The IEP data was drawn from AEA datapoints available in the Spring of 2017. Figure 3 is a density plot of time of first testing over the time period sites were discovered. As can be seen, the majority of all sites (darkest concentrations) were known and tested before 2010.

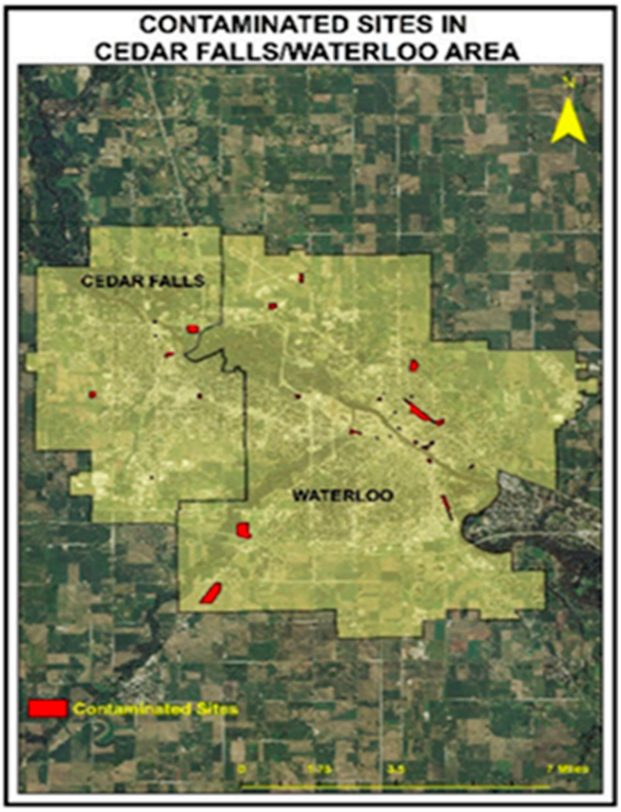

Figure 2. List of Contaminated Sites.

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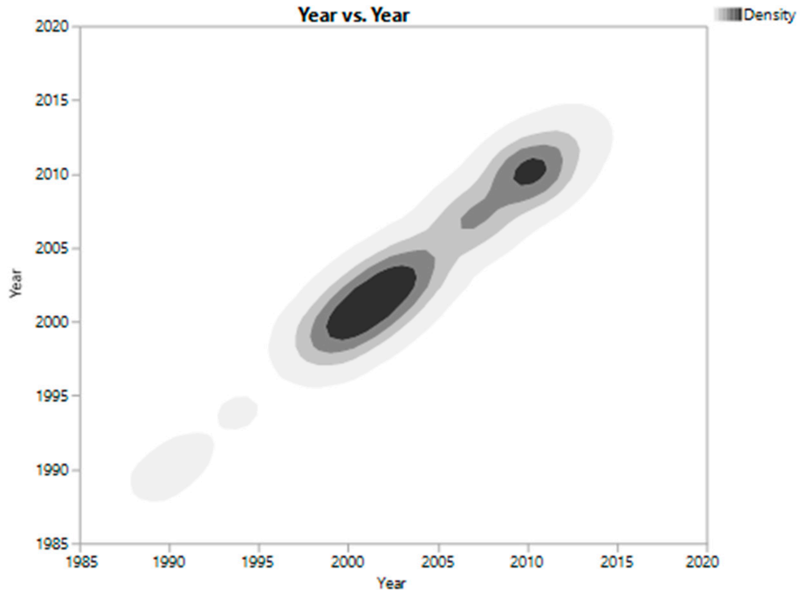


Figure 3. Year of First Testing vs. Density of Time of Sites.

Also, a qualitative analysis using a word cloud indicated that heavy metals were frequently reported in these contaminated sites, such as Lead, Arsenic, Mercury, and Chromium. Figure 4 below shows the constellation of contaminants in the study area.

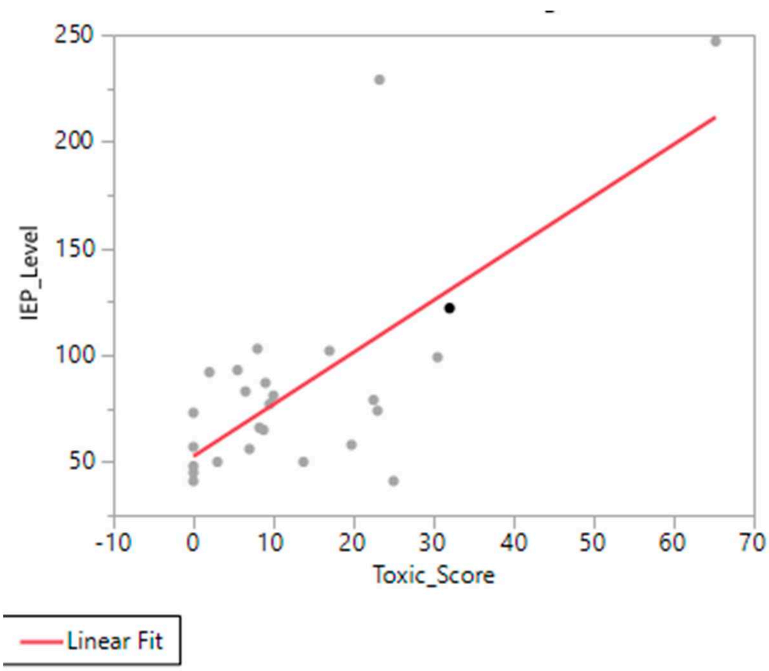
Figure 4. Constellation of Contaminants.

3.3. Toxic Scores and IEP Statistical Analysis

Statistical analysis and GIS tools were both used to explore correlations between the toxic score for the smallest unit of geographical measurement (elementary districts, which are included in the larger middle and high school districts) and IEP data across all school sites. The statistical analyses will be presented first followed by GIS projections.

School locations, school district polygons, and the correlational relationship between toxic scores and IEPs by school were explored. Bivariate analysis between the total toxic score and total IEP level was calculated based on the smallest unit of physical proximity, elementary school district. Groupings of middle school and high school districts are drawn from the existing elementary groups.

The figure below shows an increase in IEP numbers with an increased toxic score with a clear linear line between those parameters by bivariate fit, Analysis of Variance. The mean-variance of the number of students enrolled in the IEP program is approximately 24 (23.7027) times greater, with an increased toxic score. The *p*-value was <0.0001 showing a significant correlation (Figure 5, Table 3).



IEP Level = 52.56294 + 2.4359472*Toxic_Score

Figure 5. Correlation between Toxic Score and IEP numbers.

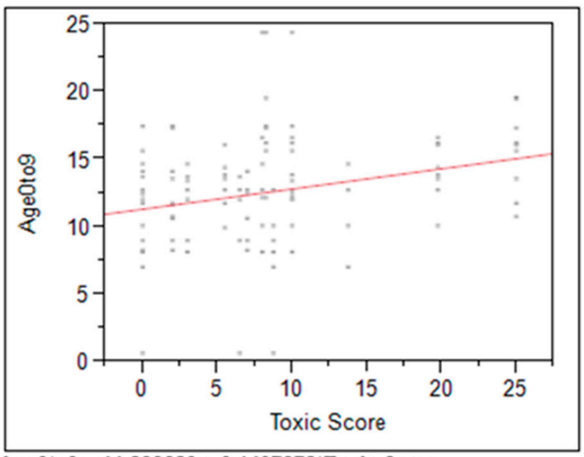
Table 3. IEP number by Toxic Score and Total Sites, *n*= 26.

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	30838.389	30838.4	23.7027
Error	24	31225.149	1301.0	**Prob > F**
C. Total	25	62063.538		<0.0001*

3.4. Demographics of Race and Poverty Proxy

3.4.1. Age by Toxic Score

Population demographic data (2015 US Census) of children under nine years of age was correlated with the toxic scores by the smallest unit of district demarcation (elementary). The result showed a mild correlation, indicating that a correlation with children under the age of 10 living in areas with a high toxic score (Figure 6, Table 4).

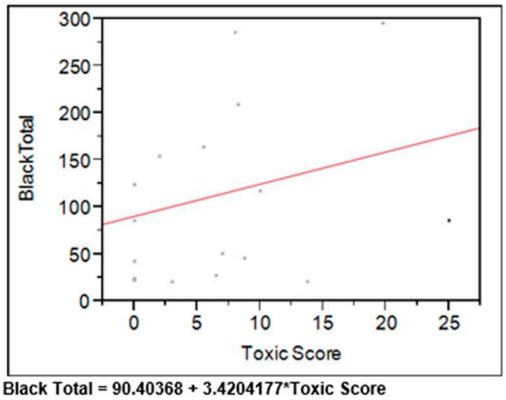


Age0to9 = 11.288629 + 0.1497272*Toxic Score

Figure 6. Correlation between Toxic Score and Age (0 to 9) (*p*= 0.00052).

3.4.2. White vs. Black Population by Toxic Score and IEP

The study also found a correlation between the black and white populations by toxic score. The study found fewer white people residing in an area with a higher toxic score (inverse relationship downward sloping mean fit), but the scenario differs for the black population. The analysis showed a higher number of the black population residing in areas having a high toxic score. Both correlations were statistically significant (Figure 7, Table 4).



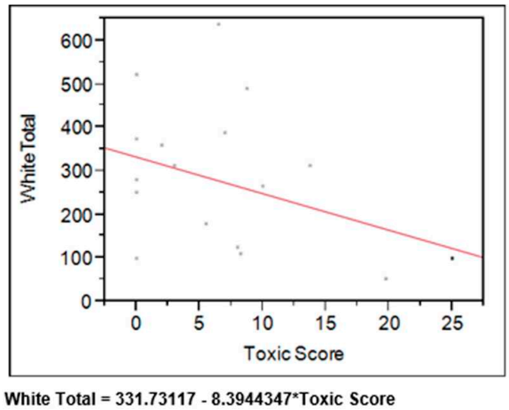


Figure 7. Correlation between Black (Left, $p = 0.0032$) and White (Right, $p \leq 0.0001$) Population and Toxic Score.

Similarly, the children enrolled in IEP programs were predominantly among the black population (Figure 8, Table 4), but there was no significant correlation found with the white racial/ethnic group.

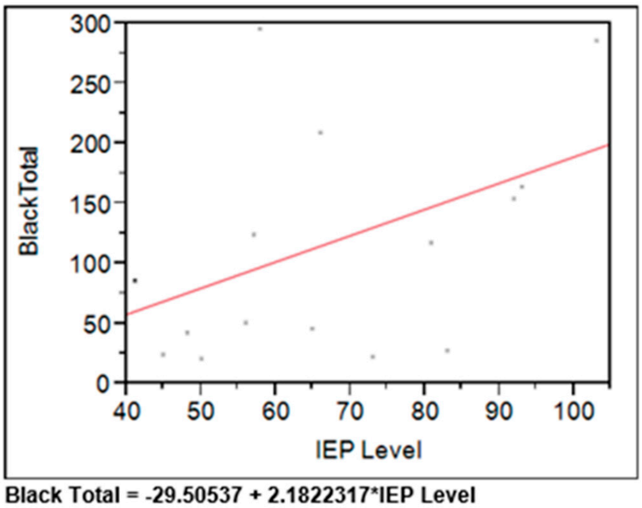


Figure 8. Correlation between Black Population and IEP Level, ($p \leq 0.0001$).

3.4.3. Household Income and Poverty Percentage by Toxic Score

The bivariate fit between the socioeconomic status indicators of household income and poverty percentage presented a significant correlation, indicating that people with lower household income and the highest poverty percentage resided in areas with higher toxic scores. The median household income for the area was $48,007, but the majority of low-income households were found to be in areas with a toxic score of more than 20 (Figure 9, Table 4).

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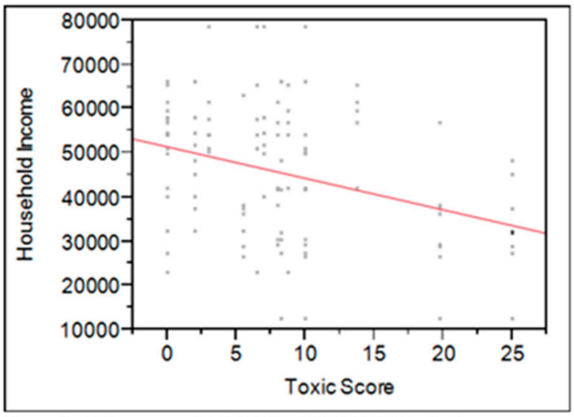
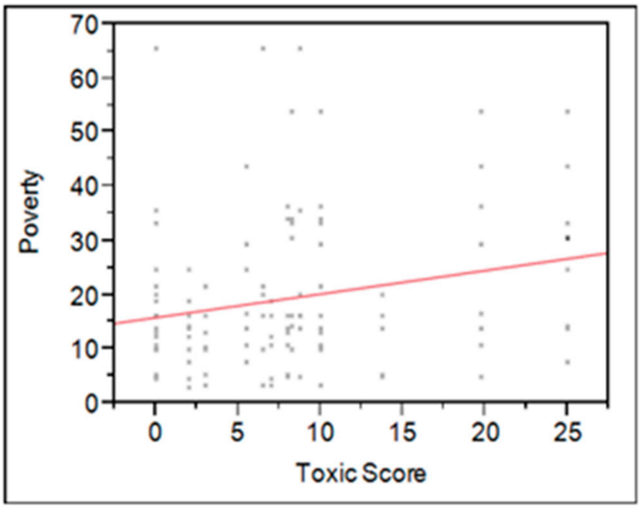


Household Income = 51422.499 - 712.99957*Toxic Score

Figure 9. Bivariate fit of Household Income and Toxic Score, ($p = 0.0002$).

A similar strong correlation was seen between poverty percentage and toxic score. The areas with high poverty percentages also had a high toxic score, indicating that people living in poverty resided in areas with higher toxic scores (Figure 10, Table 4).



Poverty = 15.837309 + 0.4339314*Toxic Score

Figure 10. Bivariate fit of poverty percentage and Toxic Score, ($p = 0.0203$).

3.4.4. Education and Toxic Score

A bivariate fit between education level and the toxic score showed a significant correlation between the two variables. Four categories of education level were available: No Degree, High School, Some College Degree, Bachelor, and Postgraduate. The analysis showed that people with a higher level of education tend to live in areas with lower toxic scores (Figure 11, Table 4).

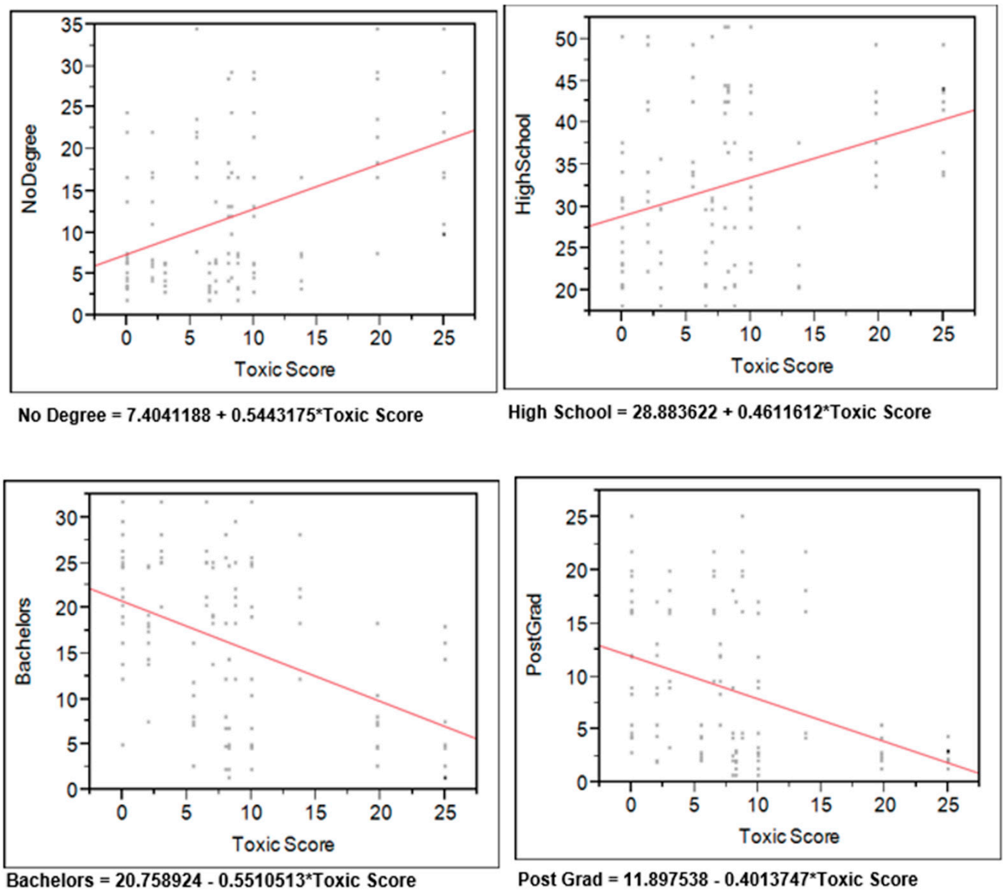


Figure 11. Correlation between various education levels and Toxic Score, (p-value range, <0.0001–0.0002).

3.4.5. Free and Reduced Lunch Enrollment by Toxic Score and IEP Level

A bivariate fit with students eligible to enroll in free or reduced lunch program significantly correlated with the Toxic Score and IEP Level. Figure 12 below shows the increasing trend of eligible children enrolling in free and reduced lunch programs with increasing toxic scores and IEP levels. Table 4 also shows the significance level of the correlation between these parameters.

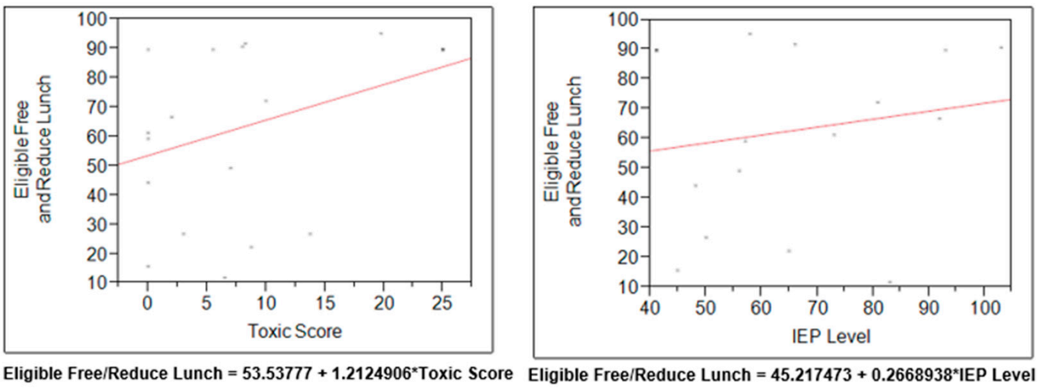


Figure 12. Correlation between children eligible to enroll in free or reduced lunch program by toxic score (left, $p = 0.0012$) and IEP (right, $p = 0.0416$).

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Table 4. Correlation between Demographics and Toxic Score and IEP Level.

Demographics	RSq	Mean of Response	F Ratio	*p*-value
Age (0 to 9) and Toxic Score	0.064	12.48	8.10	0.0052
White Population and Toxic Score	0.13	264.66	18.32	<0.0001
Black Population and Toxic Score	0.07	117.73	9.03	0.0032
Black Population and IEP Level	0.24	117.73	37.70	<0.0001
Household Income and Toxic Score	0.11	45725.99	14.96	0.0002
Poverty and Toxic Score	0.045	19.30	5.53	0.0203
No Degree and Toxic Score	0.19	11.75	28.29	<0.0001
High School and Toxic Score	0.109	32.56	14.33	0.0002
Bachelor and Toxic Score	0.19	16.35	28.52	<0.0001
Postgraduate and Toxic Score	0.15	8.69	21.64	<0.0001
Eligible Free or Reduced Program and Toxic Score	0.08	63.22	11.068	0.0012
Eligible Free or Reduced Program and IEP Level	0.03	63.22	4.24	0.0416

3.5. GIS Visuals on IEP, Toxic Score, and Demographics based on school districts

3.5.1. Toxic Score and IEP level with Poverty Percentage

The GIS mapping included three layers of datasets. The first layer is the census data on poverty percentage. The second and third layers show the IEP level and toxic scores in each school district. This data was replicated for elementary, middle and high school districts. The GIS tool called intersect was used to extract the census tract data for each elementary, middle, and high school district in the study area. The visual GIS overlay map showed interesting patterns of toxic scores and IEP data on the poverty percentage. The darker color pattern shows high toxic score, IEP level, and poverty percentages (Figure 13). The figure below shows high toxic scores and IEP levels concentrated in the cencus tract having high poverty percentage. The result was significant by a bivariate fit analysis between toxic score and poverty percentage (see previous data, Table 4).

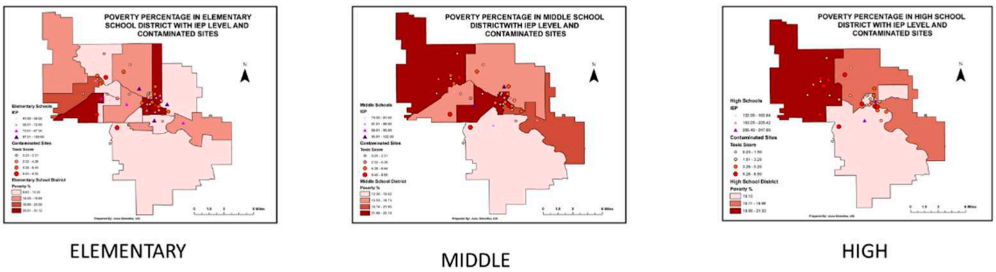

Figure 13. GIS visualization of Poverty Percentage with Toxic Score and IEP Level in each Census Tract by Elementary, Middle and High School District (p = 3.4.2. IEP and Toxic Score with Black Population.

Similar to the previous figure, the GIS mapping included three layers of datasets and utilized an intersect GIS tool to extract data for the elementary, middle and high school mapping . The first layer in this mapping is the census data on black population percentage. The second and third layers show the IEP level and toxic scores in each school district. The GIS visual mapping showed that darker areas with high population percentages had high concentrations of toxic score and IEP level (Figure 14). The bivariate analysis also showed statistically significant relationship among IEP level and toxic score with black population percentage (Table 4).

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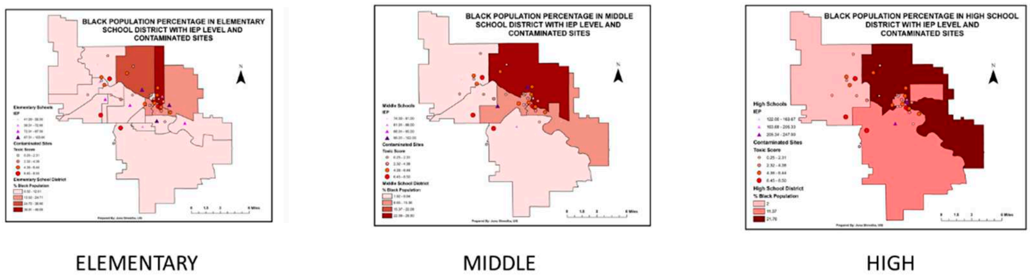

Figure 14. GIS visualization of Black Population Percentage with Toxic Score and IEP Level in each Census Tract and Elementary, Middle and High School District, (p = 0.0032 and <0.0001).

3.5.3. IEP and Toxic Score with Free/Reduced Lunch in Elementary School District

Again, with the assistance of an Intersect GIS tool extracting data for the elementary, middle and high school sites, this map shows the visual graphics in three layers: percentage of students enrolled in free or reduced lunch program (shown in darker polygon), toxic score (shown in circle), and IEP level (shown in triangle). The map in Figure 15 showed an interesting pattern of high toxic score and IEP level concentrated in school districts where highest percentage of kids are enrolled in free or reduced lunch program.

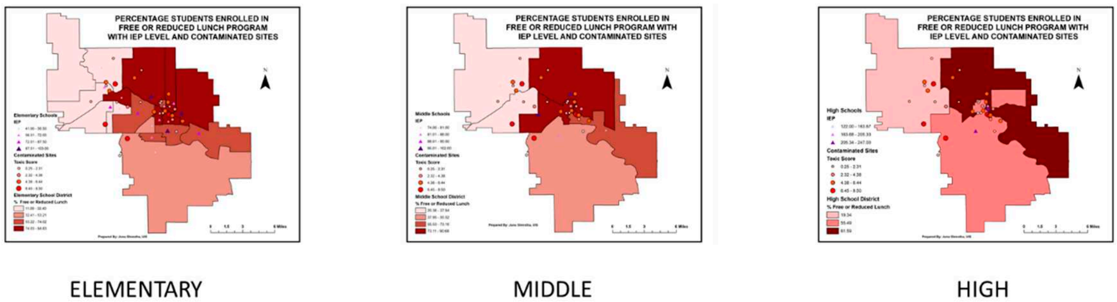

Figure 15. GIS visualization of Student Enrolled in Free/Reduced Lunch Program with Toxic Score and IEP Level in each elementary school district, (p = 0.0416).

4. Discussion

The contaminated sites in this study were examined for their neurotoxic compounds. The majority of toxic materials at the sites were comprised of heavy metals such as lead, arsenic, barium, chromium, and mercury. The sites also contained polyaromatic hydrocarbons such as benzopyrene and dibenzo anthracene. Brownfield sites are mostly contaminated with chemicals such as lead, petroleum, asbestos, polyaromatic hydrocarbons, other metals, and arsenic [29]. Most of these substances have both acute and chronic neurotoxic effects.

The Individualized Education Plan (IEP) is a program that ensures a child with identified learning challenges and disability attending elementary and secondary educational institutions receive specialized instruction and related services. A child can enroll in IEP based on their present level of educational performance [30].

Long-term exposure to lead in children has been linked to learning disability due to critical enzyme disruption and damage in the central nervous system (CNS), leading to reduced cognitive and neurobehavioral development[31–33]. Numerous studies report an association between chronic arsenicosis and neuro-cognitive disorders, including encephalopathy, among children [34]. Exposure to mercury in early childhood was found to be associated with lower IQ [33]. Research also shows that prenatal exposure of mothers in mercury can also lead to neuro-cognitive developmental delay and abnormality among children [35,36]. Although the effects of chromium on children's cognitive abilities require more rigorous study, a recent study noted that prenatal exposure to chromium toxicity could reduce fetal growth, which could lead to lower IQ and increased IEP scores in children [37].

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Medical doctor Rupa Marya and health sociologist Raj Patel describe the delicate balance between the neuronal structures of the central nervous system, CNS, and the supporting glial cells (about 50% overall of the CNS) that maintain that system [38]. They describe how these cells work together to support cognition and learning as a system, each being conceptualized in their work as an orchestra that must develop as a fully functional system in order to provide an individual with the full experience of consciousness and the ability to learn, grow and assimilate information. They note that, "when neurological systems are working well, you're able to engage in fluent conversation, to read, to name and recall, to ponder and imagine and explore and analyze [38]." And, they note that in the larger system of environmental, social, and racial inequities, the opportunity and likelihood of developing a exquisitely balanced and optimally functioning CNS are challenged and comprimised. Is it not likely that this imperiled opportunity leads to further missed opportunities and milestones. That this legacy of exposure and compromise has lead-on cascade effects that put young, developing minds at risk? When does compromised learning translate into missed educational opportunities that lead to missed economic opportunities? When could those challenges lead to acting out as a juvenile leading to police involvement which disproportionately occurs in minority and low-income communities? In a sample of juveniles in detention in Connecticut, researchers found that learning disabilities in 1,337 detained juveniles ranged from 13–40% using two different instruments (Wide Range Achievement Test and a computerized educational screener) with an average of 24.9% for the total sample, much higher than the average population [39].

It should be remembered that correlational (ecological) studies are complicated by the fact that data sets are correlated at a group level. The nature of such studies precludes the association of individual exposure with individual outcomes. This kind of study suggests hypotheses that need to be further tested and proven and is not *definitive* proof of a particular exposure's impact on health outcomes. However, it is a strong correlational analysis, and it points to the need for further cohort or case-control studies that can establish both the timeline of exposure and outcome and the strength of that individual association. It rightly asks us to question and further explore the physical, environmental, social, and equity structures of our communities that may be creating and perpetuating inequities.

5. Conclusions

This study found that youth experiencing behavior and learning difficulties enrolled in Individualized Education Plans within their respective school districts were more likely to live in areas with higher toxic scores, as determined by the number of CERCLIS listed sites in those school districts and the number and types of neurotoxic substances reported to be present at those sites (Figure 5, Table 2). Also, families with lower incomes lived in school district areas with higher toxic scores (Figure 9). When all these variables were visualized using GPS/GIS applications, the areas with a higher poverty percentage along with higher toxic scores illustrated a preponderance of youth enrolled in IEPs in their school districts (Figure 13). In a study that looked at three separate states on students from low-income families and special education, the authors found that students from low-income backgrounds in all three states were disproportionately placed in special education and more than twice as likely to be put in substantially separate classrooms, compared to their non-low-income peers [40].

The positive correlation between racial ethnic minority populations (African American, Native American, Hispanic, etc.) with toxic scores and IEP indicated that racial ethnic minority youth living in school districts with high toxic scores were more likely to be enrolled in IEP plans. The representation of students of color in special education is a concern, especially those coming from low-income families. Black students, for example, are twice as likely to be labeled as emotionally disturbed and three times as likely to be identified with intellectual disabilities compared to their White peers. Also, one in four black boys with disabilities is suspended each year, compared to only one in ten white boys with disabilities [41]. Further, Native American students receive special education services 53% more than Anglo students and receive services for developmental delay 189% more than Anglo students [42]. Special education researchers point to the multiple factors that may be influencing these outcome disparities in the need for special education services, including poverty, teacher perception, and sociohistorical context [43]. This study makes a strong case that environmental factors and exposures be considered also. And, it indicates the need to develop sophisticated multiple-exposure models and studies that can correlate individual exposures with individual outcomes. It is only by truly understanding the fundamentals of inequity in the environment and exposure that the full understanding of and elimination of environmental inequity can be achieved.

Author Contributions: Dr. Junu Shrestha - Dr. Shrestha collected the demographic data, GIS base maps, and categorized all chemicals based on their weighing factors. Dr. Shrestha also analyzed the data with help from Dr. Zeman and wrote the manuscript. Dr. Shrestha also created all the GIS maps and generated data based on GIS analysis. Dr. Raihan Khan – Dr. Khan contributed by updating several sections of the manuscrtipts (introduction, discussion), included reference and in-text citations, and formatted the manuscript. Mr. Shane McClintock – Mr. McClintock identified and gathered the information on the CERCLIS listed sites including the substances present used to calculate toxic scores in the school districts in this study. Mr. John DeGroote – Mr. DeGroote helped Dr. Shrestha with the GIS data generation and provided data on free school lunch program. Dr. Catherine Zeman – Dr. Zeman conceptualized of the research and provided graduate funding support and research guidance for Mr. Shane Mclintock and Dr. Junu Shrestha during their graduate study work and work on this paper. Dr. Zeman also aquired the IEP data, suggested the approach for calculating the toxics scores, (exposure algorithym) provided background bibliographic works and provided supportive data analysis and final edits, contributtions to this paper.

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Informed Consent Statement: This is a correlational study with preexisting data.

Data Availability Statement: Data request should be directed to the primary and senior author of this text.

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