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Addressing Childhood Lead Poisoning through GIS: A Proactive Approach in Scott County, Iowa

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A Proactive Approach in Scott County, Iowa

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I. Problem Statement

In June 2016, Scott County Health Department (SHCD) officially partnered with the Upper Mississippi Center (UMC) at Augustana College as part of the Sustainable Working Landscapes Initiative (SWLI). The initiative's main goal is to address childhood lead poisoning in Scott County, Iowa. While the health department has ongoing efforts to address the problem, there are still approximately 50 children testing positive for lead poisoning every year (Tibbets, 2016).

Currently, as part of the Childhood Lead Poisoning Prevention and Control Program, the health department offers case management services for children poisoned under the age of six, follow-up inspections for residences, and lead abatement regulation in residences (Scott County Health Department, 2017). Even though these provided services are necessary for creating healthy living environments, SCHD recognized that these services are more reactive, in nature, because a child has to test positive for lead poisoning before action is taken. As such, SCHD enlisted the help of UMC to transition their efforts for addressing childhood lead poisoning to a more proactive approach. The most effective route to proactively address the problem, decided upon by SCHD and UMC, was to use geographic information systems (GIS) to create a lead exposure risk map for residences in Scott County. The following report details the literature used to inform the project, methods used for creating lead exposure risk maps, and results showing the sample risk maps.

II. Introduction and Literature Review

Despite its known association with neurological damage, lead has accompanied human development for centuries (Pelc et al., 2016; Rosner & Markowitz, 2016). Only in the past 50 years have health practitioners increasingly viewed lead as a legitimate threat to human health (Rosner & Markowitz, 2016) and also discovered lead to block cell signaling during nervous system development, leading to disrupted neurological functioning (Jones, 2009). Neurological damage is most often expressed as a drop in intelligence quotient (IQ), difficulty focusing, and antisocial behavior. Dependent upon the level of exposure, lead has also been found to lead to more severe symptoms such as delayed puberty, mental retardation, the onset of seizures, and death (Heavey, 2016; Council on Environmental Health, 2016; Jones, 2009). Even though thresholds for lead exposure are still being debated, no safe level of lead exposure has been found (Jones, 2009; Miranda et al., 2002). Though lead can be removed from the body, its effects on the brain are irreversible (Heavey, 2016; Council on Environmental Health, 2016; Schnur &

John, 2015). Lead poisoning is especially dangerous due to its absence of warning symptoms, and only becomes observable after the damage is likely done (Bhullar et al., 2015; Jones 2009).

Lead was historically used to make more durable and vibrant paints but was banned in the 1970s. While lead-based paint is no longer used today, the largely immobile chemical structure of lead causes it to remain in place, posing a threat to populations who reside in places that are or have been painted with lead-based paint (Bhullar et al., 2015). Lead's detrimental mechanisms occur during neurological development, placing developing populations - specifically children - at risk for poisoning. Children unknowingly put themselves at risk for lead poisoning through their frequent contact with lead sources (lead dust, walls painted with lead-based paint, lead contaminated soil, etc.) and equally frequent hand-to-mouth contact (Rosner & Markowitz, 2016; Jones, 2009). Also appealing to children is lead's sweet taste, which exacerbates the consumption of lead via hand-to-mouth contact. Measures can be put in place to prevent contact with lead, but are often expensive (Rosner & Markowitz, 2016). Furthermore, owners of a residence are often unaware that their property is contaminated with lead, and thus do not see remediation as necessary.

The necessity for lead exposure prevention

The value in remediating a lead contaminated residence seems obvious, but it is rarely acted upon. Property owners seldom know their property is contaminated until definitive proof is offered. Unfortunately, the proof often becomes evident after a child is diagnosed with lead poisoning, essentially using children as a biological indicator for ambient lead (Rosner & Markowitz, 2016). Because even low-level lead exposure has detrimental effects on developing neurological systems, recent public health trends call of a shift from a reactive approach to a preventative approach to adequately address the issue (Miranda et al., 2011, Kim et al., 2008, Miranda et al., 2002). That is to say, measures must be taken to identify properties that are likely to be lead-contaminated rather than waiting for a child to be poisoned.

Previous research has identified several factors that are commonly associated with lead being present in residences. However, there is controversy as to which factors are truly correlated with the presence of lead in a property (Akkus & Ozdenerol, 2014). The most widely acknowledged indicators of lead presence include age of building (Council on Environmental Health, 2016; Schnur & John, 2014; Kim et al., 2008; Oyana & Margai, 2007; Curtis et al., 2004; Miranda et al., 2002; Reissman, et al. 2001,), household income (Heavey, 2016; Schnur & John, 2014; Rustin, 2013; Jones, 2009; Kim et al., 2008; Oyana & Margai, 2007; Miranda et al., 2002; Reissman et al., 2001), occupant's race (Heavey, 2016; Schnur & John, 2014; Rustin, 2013; Jones, 2009; Kim et al., 2008; Oyana & Margai, 2007; Miranda et al., 2002; Reissman et al., 2001), and renter occupancy (Rustin, 2013, Reissman et al., 2001). Less supported claims have also correlated ambient lead to the number of people who live in and around the property (Pelc et al., 2016), distance between the dwelling and the ground, (Pelc et al., 2016) and the type of surrounding development (Pelc et al., 2016; Rosner & Markowitz, 2016; Jones, 2009).

It is important to stress that these factors are indicative of a property, not the individual, being contaminated with lead. For example, low-income residents are no more susceptible to lead poisoning than high-income residents as there is no physiological difference. Rather, the high cost of lead abatement has cast America's poverty stricken, often minorities, to be the primary inhabitants of lead contaminated houses (Pelc et al., 2016; Rosner & Markowitz 2016). In other words, it is the property's characteristics — not those of the resident — that create an environment conducive to lead poisoning. When these factors play upon one another, there is potential for lead-poisoning hot spots or areas of concentrated positive diagnoses.

Geographic information systems as a prevention tool

While aquatic lead exposure has recently been emphasized in the United States (i.e. Flint, Michigan), dust from lead-based paint remains the leading source of exposure for children. (Council on Environmental Health, 2016; Heavey, 2016). Lead is largely immobile due to its unique chemical structure and tends to remain in place until moved by anthropogenic force, making lead poisoning a geographically bound disease (Bhullar et al, 2015; Rustin, 2013). Given the known factors that increase the likelihood of a residence containing lead, geographic information systems (GIS), a mapping software that aids in identifying and articulating spatially relevant trends, can be used to overlay shared geographically bound characteristics and accurately assess the probability of a property containing lead (Pelc et al., 2016, Miranda et al., 2011; Reissman, 2001).

Using GIS to identify areas at risk for lead contamination is fairly common. However, the scale of the map often identifies these risks at the neighborhood or block group level. While these maps can potentially be useful, they could be more effective if used at a finer scale (Akkus & Ozdenerol, 2014; Kim et al., 2008; Miranda et al., 2002). Lead contamination risk is rarely analyzed at the tax assessor's parcel level where it is most useful (Kim et al., 2008; Miranda et al., 2002). The rarity of analysis at the tax assessor's parcel level is due to the greater time and effort needed; although, the end results will provide the most detailed scale achievable through GIS (Akkus & Ozdenerol, 2014; Kim et al., 2008; Curtis et al., 2004; Miranda et al., 2002). Previous studies conducted by Kim (2008) and Miranda (2002) found GIS risk models for lead exposure to be generalizable across widespread geographic areas. Additionally, targeted testing and remediation programs are more effective when the level of risk is found at the parcel level, than if blanket-testing methods were used (Reissman, 2001).

Conclusion

Given lead's detrimental impacts on the neurological system and the continuing evidence that there is no safe level of exposure for children, there is a need for public health programs to proactively address the issue of childhood lead poisoning. One emerging research trend is to use geographic information systems (GIS) as a tool to locate residential properties that are potential sources of lead exposure. This trend allows for public health programs to move from a reactive approach to a preventative approach since the source will be targeted and not the child. Overall, conducting a spatial analysis with GIS to identify potential lead sources appears to be more effective at preventing lead poisoning than simply testing and treating children.

III. Methods

The methods used for this project are largely based on the approach by Miranda (2002) in the article *Mapping for Prevention: GIS models for directing childhood lead prevention programs.* What set the Miranda (2002) study apart was the scale at which the GIS analysis was conducted. This studied created lead exposure risk maps at the tax assessor's parcel level, which allows for fine-scale detail (Akkus & Ozdenerol, 2014; Kim et al., 2008; Curtis et al., 2004; Miranda et al., 2002). The risk factors and the relative weight of each risk factor were based on the most widely acknowledged predictors of lead exposure discovered in literature. The decided upon risk factors included age of building (Council on Environmental Health, 2016; Schnur & John, 2014; Kim et al., 2008; Oyana & Margai, 2007; Curtis et al., 2004; Miranda et al., 2002; Reissman, et al. 2001,), household income (Heavey, 2016; Schnur & John, 2014; Rustin, 2013; Jones, 2009; Kim et al., 2008; Oyana & Margai, 2007; Miranda et al., 2002; Reissman et al., 2001), African-American populations (Heavey, 2016; Schnur & John, 2014; Rustin, 2013; Jones, 2009; Kim et al., 2008; Oyana & Margai, 2007; Miranda et al., 2002; Reissman et al., 2001), and renter occupancy (Rustin, 2013, Reissman et al., 2001). The graphic following depicts the four risk factors inputted into geographic information systems (Figure 1).

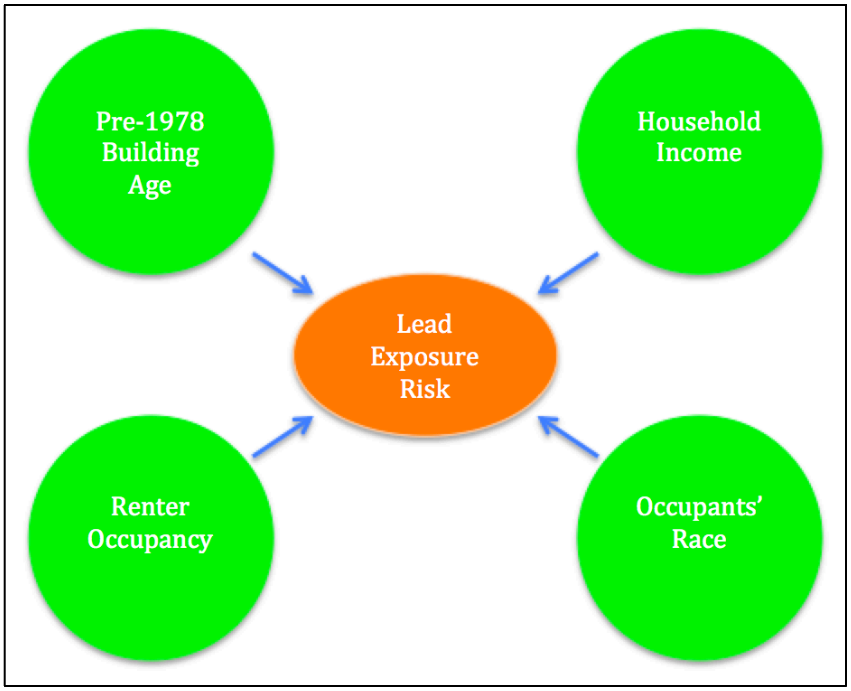

Figure 1: Graphic showing risk factors that are predictive of lead exposure.

Data Collection and Description

To obtain data on the above risk factors, data sources including tax assessors' parcel data, U.S. Census Bureau (5-year American Community Survey), and childhood blood lead level (BLL) data were used. A description of the data and its purpose is as follows.

Tax Assessor data offers a variety information on individual tax parcel units that include property value, property description, and age of structure. Scott County, IA presents a unique circumstance because there are separate assessor offices for the county and Davenport, IA, the largest city in the county. For both datasets, GIS shapefiles representing individual tax parcel units were presented by parcel points and parcel polygons. All data was converted to parcel polygons for better representation of the data. Due to the separate tax assessor datasets, joining the data into one layer was necessary for further analysis. Two sets of information were necessary for the analysis: residential property and age of structure.

U.S. Census Bureau data is obtained different geographical scales depending on the data being expressed. Racial/Ethnicity data is available at the block group which is the most detailed scale provided by the census. For median household income and owner/renter occupancy, the data is provided at the block group level, which is a combination of census blocks.

Childhood blood lead level (BLL) data from 1995 to 2014 was obtained through a confidentiality agreement with Scott County Health Department that is mandated by Iowa Code 761--4.1(22). The data contained an address point and tested blood lead levels starting at levels >/= 10 ug/uL. Since the BLL data provided the address of the child's residence at the time they tested positive, giving the data a spatial component was possible. Geocoding allows addresses to be assigned values of longitude and latitude creating specific map coordinates (Curtis, et al. 2004). After the BLL data was geocoded, the attributes were joined to individual tax parcels based on the property's address, which resulted in each blood lead level being identifiable in the individual tax parcel attribute table.

Spatial Analysis

To conduct a spatial analysis, the tax assessors' parcel, U.S. Census Bureau, and childhood BLL data was combined into one spatial overlay. The tax assessors' parcel data was used as a target layer, so the combined risk factors were displayed at a fine-scale. Since all data sources share a similar geographic component, a combination at the parcel level was possible. The U.S. Census Bureau data, existing at a much more generalized scale, became attached to individual residential properties through a spatial join.

The next step involved categorizing each individual risk factor in an effort to later create a weighting system that helped establish priority areas. The basic method for categorizing the risk factors was based on Housing and Urban Development (HUD) household income cut-offs for federal funding, county averages, and literature-based housing age lead predictability. Outlined below are the categories used for each risk factor in the spatial analysis.

- Age of building (Spatial scale: Parcel level (target layer)
    1. Pre-1955
    2. 1956-1978
- Household income (Spatial scale: Census block group level)
    1. < $34,400 (HUD income cut-off for grant assistance)
    2. $34,400-68,800
    3. > $68,800 (Twice the cut-off)
- Renter occupancy (Spatial scale: Census block group level)

    1. < 31.3% (county average)
    2. 31.3% - 62.6%
    3. > 62.6% (twice the county average)
- African-American populations (Spatial scale: Census block level)
    1. < 7.2% (county average)
    2. 7.2% - 14.4%
    3. > 14.4% (twice the county average)

After the risk factors were categorized, they received weights based on their predictive power of lead exposure. Age of building received the strongest weight followed by household income and then renter occupancy and African-American populations. The weights were necessary to organize different risk factor categories into priority levels that could be mapped spatially. Overall, the risk factor categories were condensed into four separate priority levels, which were verified by childhood blood lead levels and are displayed spatially.

IV. Results

The spatial analysis resulted in maps displaying priority areas for lead exposure risk in Scott County, Iowa. These maps only display residential parcels built before 1978 and contain four priority levels. On the maps (following page), the warmer color tones (i.e. red & orange) represent a higher priority while the cooler color tones (i.e. yellow & green) represent a lower priority. However, it should be noted that all parcels displayed are at risk for lead contamination given their construction before 1978. The four priority levels help illustrate the risk factors of lead exposure. The following two maps display the resulting priority levels and their spatial relation. The first map shows Davenport, Iowa and Bettendorf, Iowa (Figure 1) while the second map shows a large scale displaying Davenport city wards 3, 4, & 5 (Figure 2).

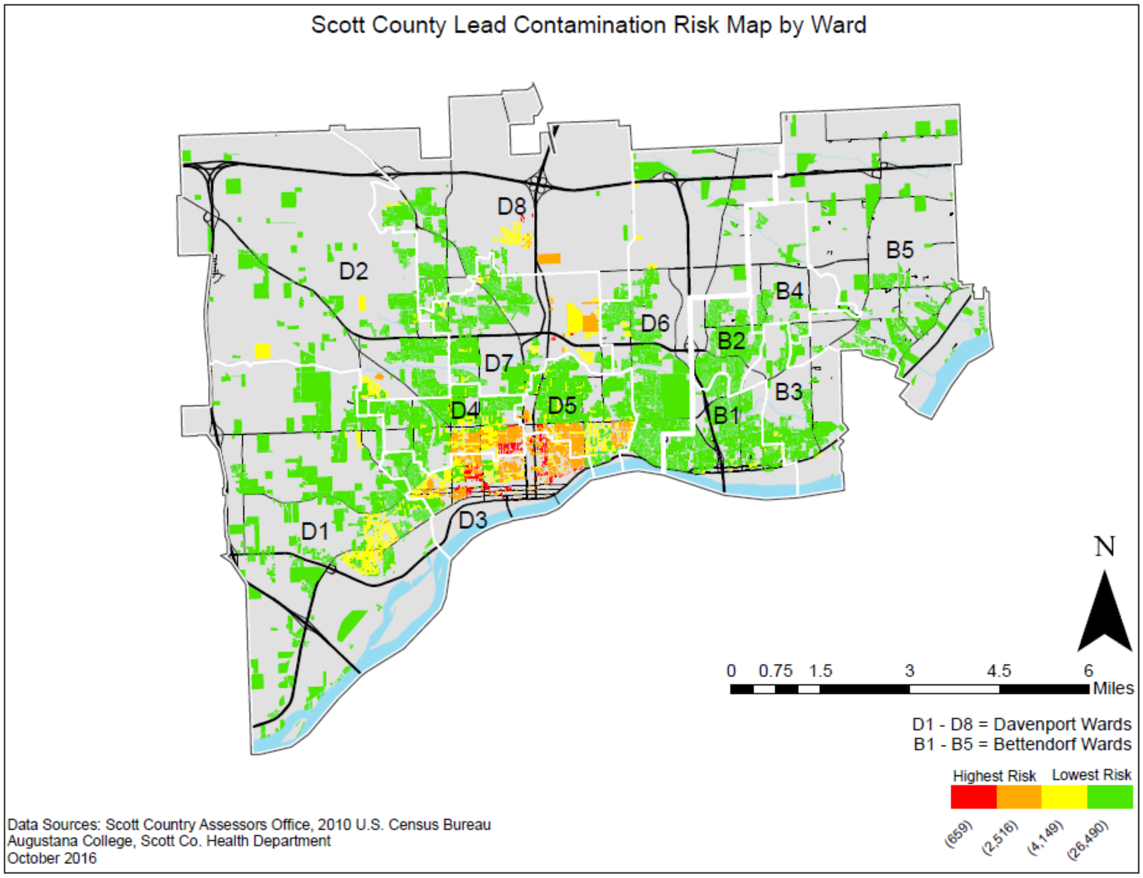

Figure 2: Residential properties mapped into risk priorities in Davenport and Bettendorf, Iowa.

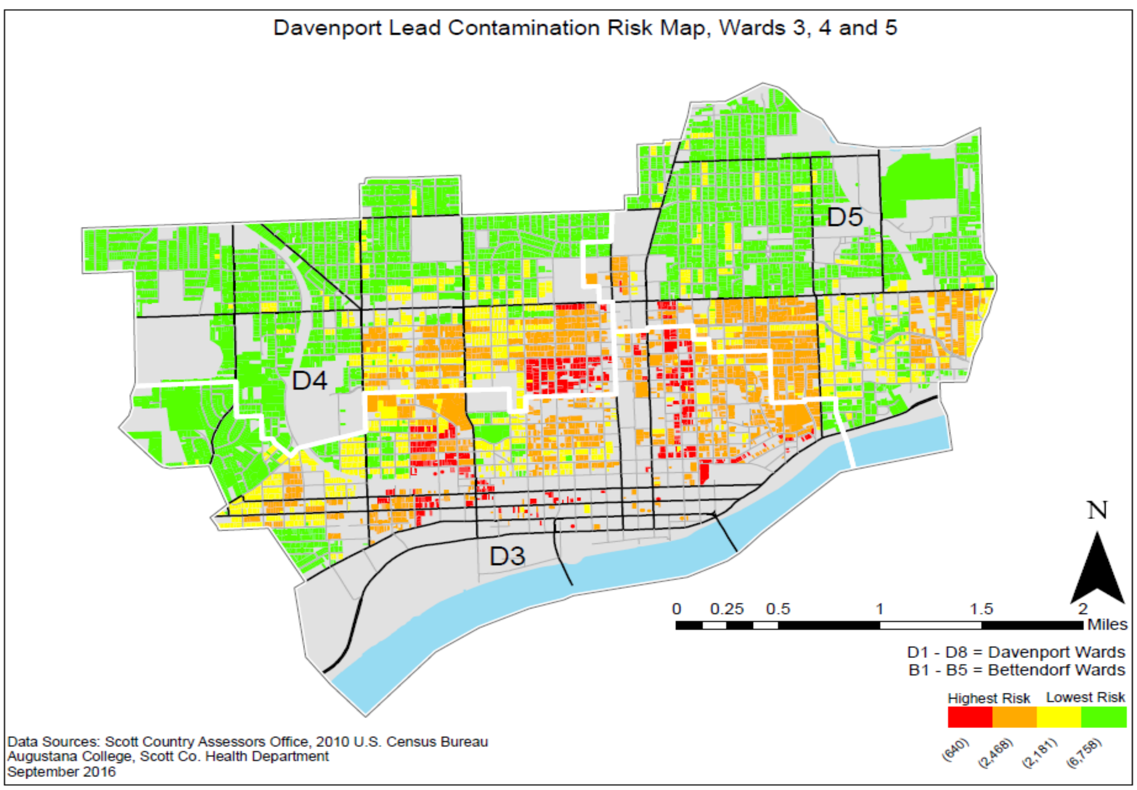

Figure 3: Example of the detailed scale acquired by mapping at the parcel level. Shown are Davenport city wards 3, 4, & 5.

Since the previous maps only show pre-1978 parcels, there are 33, 797 geographic units on the first map (Figure 2). Out of these 33, 797 parcels, there are 659 in the first priority level, 2,516 parcels in the second priority level, 4,149 parcels in the third priority level, and 26,490 parcels in the fourth priority level. The table below shows the priority levels and the corresponding number of parcels in each level.

Table 1: Priority levels with corresponding number of parcels.

Priority Level	Number Of Parcels
1 (Higher)	659
2	2,516
3	4,149
4 (Lower)	26,490

V. Conclusion

Overall, a lead exposure risk map provides Scott County public health officials with concrete evidence on the scope of the problem and an understanding of the spatiality of risk in the county. Prioritizing parcels is necessary due to the limited funding and resources to remediate a large number of residences at once. The higher priority parcels are most likely to contain lead, which means a child living there is at greater risk for lead exposure than a child living at a lower priority level. Directing funds and targeted prevention programs at higher priority parcels will hopefully be the most impactful way to remediate residences and inform the public of potential lead hazards. While the maps presented in this report will need constant updating and attention due to potential remediation, new childhood blood lead level tests, updated census data, etc., they act as a starting point for future projects and efforts.

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