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Developing and Disseminating the Children’s Environmental Health Index with Web GIS

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ABSTRACT

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Environmental Health Index with Web GIS

By

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A common adage in the field of children's environmental health is "children are not small adults". Children's behavior, physiology, and dependency can increase their risk of and vulnerability to environmental exposures. Screening and web mapping tools like EPA's EJSCREEN and California's CalEnviroScreen highlight populated areas where residents may be at an increased risk of poor environmental health outcomes or environmental injustices. These tools provide valuable insight for policy makers, public health professionals, and the public. However, there are currently no screening tools that focus on spatial disparities in children's environmental health at the local level.

This project sought to address that gap by developing the Children's Environmental Health Index (CEHI), based on the framework of the World Health Organization's Urban Health Index. The CEHI is meant to be adapted to specific community concerns, and indicator selection is determined by significance to children's health as well as data availability.

This project applied the CEHI at the census tract-level in Allegheny County, Pennsylvania. Because the county is heavily industrialized, environmental health concerns focused on air quality and point-source pollution. Geospatial data was sourced from the U.S. Census Bureau, Environmental Protection Agency, PA Department of Environmental Protection, PA Department of Transportation, and Allegheny County. As expected, analysis was shaped and sometimes limited by data availability and computing resources.

The CEHI web app was designed to be user-friendly and accessible to all audiences. It includes map layers for the CEHI, each indicator, and relevant data such as schools, day cares, and parks. Users can interact with the layers and retrieve areal statistics. The web app serves as a template for organizations who wish to develop their own CEHI. Future applications of the CEHI should explore daytime exposures using school districts, as well as examine maternal and infant health outcomes from the perspective of access and environmental exposure.

Developing and Disseminating the Children's Environmental Health Index with Web GIS

by

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APPROVAL PAGE

Developing and Disseminating the Children's
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Author's Statement Page

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Allegra E. Yeley

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INTRODUCTION

Public health is, by its very nature, spatial. Infectious diseases spread based on how people interact with and move through their environments. Chronic diseases can arise based on where we live and work. Health behaviors may be driven by community composition. Physical risks cannot exist without space. In short, our health is shaped by our environment.

Children's Environmental Health

A common adage in the field of children's environmental health is "children are not small adults"[1-4]. Of the populations vulnerable to adverse health effects of environmental exposure, children are most at risk for several reasons. First, they drink more water, eat more food, and breathe more air per pound of body weight than adults. Second, they have a greater body surface area to weight ratio than adults. Third, they exhibit unique behaviors that increase their risk of exposure to ground-level toxicants. Fourth, various organ systems continue to develop in the postnatal period. Finally, they have a longer lifespan in which to develop latent disease[5,6]. In essence, their behavior increases the *rate* of environmental exposures, while their physiology increases their *vulnerability* to environmental exposures[7].

Physiology

Children's physiology primes them for increased risk of environmental exposure. Their higher surface area to weight ratio means that they lose body heat more quickly than adults, which is countered with a faster metabolic rate[7]. A high metabolism results in a greater need for oxygen, water, and food per pound of body weight. These factors expose children to larger quantities of contaminants found in breast milk, food, water, and air[8]. Children's larger surface area to weight ratio also results in more skin area per kg for increased dermal exposure and absorption[7,8].

Birth does not mark the end of critical development and growth. The systems that help the body metabolize and excrete xenobiotics are not fully mature at birth. If toxic insult occurs within that period, the substance may have a longer half-life or more potent effects[5]. For example, cytochrome P450 2E1 (CYP2E1), which is responsible for metabolizing benzene, chlorinated solvents, and other xenobiotics, does not reach full functionality until age 6-12 months[7]. As a result, infants are especially vulnerable to substances metabolized by CYP2E1[4]. Toxicokinetic and toxicodynamic disparities between adults and children are most pronounced in the first two years of life. Increased growth rates continue through puberty into mid-adolescence[9].

Organ systems function differently throughout the developmental period. Vulnerability to toxic insult also fluctuates[7]**.** The most consistently vulnerable organ systems in children are the lungs and the nervous system. They are unable to repair harm inflicted by toxicants, so environmental insults may lead to permanent damage[6]. In the brain, cell migration, synapse formation, dendritic trimming, and myelination continue throughout childhood and into early adulthood[2]. Disrupting these processes in the developing brain can have serious impacts on intellectual and neurobehavioral outcomes[7].

The immature nervous system is much more sensitive to toxicants than that of a mature adult[8]. The classic example of this sensitivity is lead (Pb) exposure. The toxic effects of Pb affect all age groups, but lead exposure is especially detrimental to children, whose nervous systems are still developing[10]. There is no safe level of lead for children, but the CDC has currently set the definition of an elevated blood lead level (BLL) at 5 μg/dL or above[11]. Nonetheless, adverse health effects have been observed at <5 μg/dL[10]. Studies indicate that children have a high rate of gastrointestinal absorption of water-soluble lead (30-50%) when compared to adults (3-10%)[10]; some forms of lead used in house paint are water-soluble. Once a child absorbs lead, approximately 75% is stored in the bones; the rest is stored in soft tissue and blood. Blood lead levels serve as an indicator of recent lead exposure (several months), while bone lead levels reflect chronic exposure[10]. Excretion is slow, which is why Pb can build up to dangerous levels and cause permanent harm. Elevated BLLs in children are associated with brain damage, lower IQ scores, poor academic performance, decrements in memory and executive function, attention deficit disorder (ADHD), mood disorders, behavioral misconduct, peripheral neuropathy, anemia, immunological disruption, decrements in auditory and motor functions, stunted growth, and delayed puberty[10,12]. Adults experience adverse effects of lead exposure as well, but symptoms often manifest in the cardiovascular and reproductive systems. There is also evidence suggestive of a relationship between elevated BLLs in adults and neurologic symptoms[12].

Like the nervous system, the lungs are not fully formed at birth and are susceptible to environmental exposures. Over the 18-20 years it takes them to mature, the lungs will grow hundreds of millions of alveoli, the small air sacs that line the lungs and enable gas exchange[13]. The lung epithelium is not fully developed in young children; its greater permeability increases risk of fine particles passing from the lungs into the blood. Children breathe 50% more air per unit of body weight than adults[14]. A toxicant at a dose that does not affect an adult lung cell may cause adverse effects in immature differentiating lung cells[8].

Children breathe 50% more air per unit of body weight than adults[14]. When this increased air intake is considered with the lungs' high cellular growth rate and increased epithelial permeability, it is easy to understand why so many environmental toxicants result in respiratory conditions. Asthma affects approximately 6.2 million children in the U.S. and is the reason for 14 million missed school days per year[15]. It is also the leading cause of pediatric hospitalization in the U.S.[16]. There are genetic factors behind childhood asthma, but there is a large body of evidence suggesting that air pollution has a causal role in pathogenesis[17-19].

There is growing interest in the relationship between exposure to air pollution and neurological effects in children. The body of research is not conclusive, but overall findings suggest a positive association between air pollution and neurological impacts[20-26]. A case-control study conducted in southwestern Pennsylvania found that the odds ratio of autism spectrum disorder (ASD) diagnosis per 2.84 $\mu g/m^3$ increase in average exposure to $PM_{2.5}$ was 1.51 ($p=0.046$)[20].

Mutagenic carcinogens are especially potent during childhood; a year of exposure for a child can have more serious consequences than a year of exposure for an adult[9]. This is reflected in the EPA's Age-Dependent Potency Adjustments Factors (ADAF), which are used in exposure assessment for mutagenic carcinogens with no chemical-specific data on early life exposure[5].

Before the ADAFs were introduced in 2008, cancer risk was calculated without adjustments to the cancer slope factor[27]. Children under age 16 are split into nine age groups with differing exposure periods. Children under 2 years have an ADAF of 10x, and children 2 to <16 years have an ADAF of 3x. In the 1 to <2 years age group, one year of exposure has an ADAF of 10x; in the 2 to <3 years age group, one year of exposure has an ADAF of 3x. The ADAF is incorporated into the calculation of Lifetime Cancer Risk[5].

$$Lifetime\ Cancer\ Risk = \Sigma(Exposure \times (Duration \div 70\ years) \times Potency\ \times ADAF),\ \text{summed across all age groups}$$

Behavior

Young children experience the world much differently from older children and adults. They explore with all five senses. Hand-to-mouth behavior, mouthing, insufficient handwashing, and playing close to the ground increase their risk of exposure to toxicants in soil, on surfaces, and vapors or gases that are heavier than air[6,7]. Hand-to-mouth and mouthing behaviors coincide with the ages when children are less mobile, short in stature, and prone to playing on the floor or ground. There is a correlation between children's blood lead levels and ingestion of lead-contaminated dust through these oral behaviors[7]. Carpets, a common surface for children to play on, harbor indoor dust and outdoor dirt[5]. These behaviors are not extraordinary – they are simply part of the developmental process. Less common, but not unusual, is the regular, intentional consumption of nonfood items – pica. A common form is soil-pica, classified by soil intake of 1,000-5,000 mg/day[27]. This behavior can significantly increase the risk of exposure to pesticides, heavy metals, and other contaminants. It is most common in children under age six[27].

Childcare facilities, schools, and after-school programs provide school-age children with opportunities for new environmental exposures. They spend a larger proportion of their time outside, increasing their potential exposure to air pollutants like particulate matter and ozone. Outdoor physical activity such as recess or sports increases both their breathing rate and their risk of exposure-related health effects[7]. Children who are still in the oral exploration stage may ingest chemicals they would not be exposed to at home. The interior of childcare and education facilities can have high levels of dangerous contaminants in the air, on surfaces, and as dust, including brominated flame retardants, asbestos, mold, lead, radon, and volatile organic compounds (VOCs) like formaldehyde[28,29].

Social Environment

Children's environmental exposures and vulnerabilities are influenced by their social environment. For the purpose of this project, the social environment is defined by dependency, socioeconomic status, and demographics.

Childhood is characterized by dependency – especially a limited ability to control the environment[6]. Infants and toddlers rely on their caregivers for everything, including their microenvironment. If a six-month-old is placed on the floor to play, they cannot move themselves or ask to be moved; they must stay there until their caregiver picks them up. Most young children can move independently throughout their home and school environments, but still depend on adults for sustenance, education, protection from hazards, medical access, and shelter. As noted above, children have little control over their exposures at childcare and education facilities. Public school students generally cannot choose what school they attend. Older children often have more autonomy (and may choose their own dangerous environmental exposures), but generally continue to rely on adult caregivers until they reach legal adulthood at age 18. A significant source of harmful exposure in the home environment is secondhand smoke, discussed in detail later[16].

Low income and minority race and ethnicity are associated with lower socioeconomic status (SES), which determines where people live, how they work, and their physical and mental wellbeing. Unfortunately, people of color have long carried the outsized burden of low SES in the U.S. Structural racism, epitomized by Jim Crow laws and federally sanctioned discriminatory mortgage lending practices ("redlining") in the 1930s, has perpetuated cycles of poverty and disinvestment in minority communities[30]. Of the racial and ethnic groups tracked by the U.S. Census Bureau, non-Hispanic Whites have had the lowest poverty rates since data collection began in the early 1970s[31].

Poverty is one of the single greatest determinants of health. It dictates access to and the quality of resources and opportunities. It forces people to make difficult decisions between life essentials like rent, food, and medical care because they can't afford everything they need. In the U.S., more children live in poverty than any other age group[7]. They are more likely to live in substandard housing and reside in areas close to industrial facilities and busy highways, increasing exposure to lead paint, mold, mildew, industrial releases, and air pollution[7]. Income is inversely related to parental smoking, making impoverished children most likely to be exposed to ETS[32]. Low-income children and their families may have difficulty accessing or affording regular medical care[7]. It may be especially challenging for low-income immigrant and migrant families to navigate the healthcare system. Data show that atopic disease and asthma frequently go undiagnosed—and therefore untreated—in urban populations of children[7].

Social programs help fill some socioeconomic gaps, but there are millions who do not qualify or do not know they qualify for aid. For example, the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides low-income pregnant, breastfeeding, and postpartum women, as well as infants and children up to age 5, with healthy food vouchers, nutrition education, screenings, and health services[33]. In 2018, the average monthly population eligible for WIC in the U.S. was 11.9 million. In that same year, the average monthly participation rate of the eligible population was only 56.9%[33]. Poor nutrition and dietary deficiencies can make children more vulnerable to adverse effects of toxic exposures; this relationship is well-documented in toxic metals like lead, mercury, and cadmium[10,34].

The influence of race and ethnicity can be difficult to separate from that of poverty, as minorities have higher rates of poverty than non-Hispanic Whites[31]. However, there is evidence that race is independently associated with hazardous environmental exposures. Mikati, et al. (2018) analyzed the distribution of particulate matter (PM) point-sources against surrounding communities' poverty and race characteristics. It found that the non-White population had a $PM_{2.5}$ pollution burden 1.28 times greater than the overall population; the non-Hispanic Black population carried a burden 1.54 times higher. The burden for people living in poverty was 1.35 times greater. The results suggest that race may be independently associated with pollution burden[35]. A spatiotemporal analysis of industrial air toxins and SES separated the population into groups by race/ethnicity (White, Black and Hispanic) and income (annual income above or below $50,000)[30]. Over the course of ten years, the two population groups with the highest levels of exposure were low-income Black and high-income Black, followed by low-income White and low-income Hispanic. Clearly, SES did not act as a protective factor for the high-income Black population[30].

GIS and Health Indexes

Geographic Information Systems (GIS) are becoming increasingly powerful – and the outputs more accessible. The combination of premade data layers and drag-and-drop design has allowed people without a GIS background to assemble public-facing web mapping applications and data dashboards[36]. These web apps have become go-to sources of information during the COVID-19 pandemic, further highlighting the value of web mapping for public health[37,38].

GIS-based web apps go far beyond tracking infectious disease. One focus area has been environmental health. The U.S. Environmental Protection Agency (EPA) has developed several apps with a focus on human-environment interaction: EnviroAtlas, Cleanups in My Community, and EJSCREEN[39]. The latter was developed with the goal of providing stakeholders and the public with easily understandable, scientifically sound data to help identify communities that may have potential environmental justice issues. EJSCREEN calculates eleven different index scores at the census block group level. Each score consists of several demographic indicators as well as a single environmental indicator. Block groups are then percentile-ranked so they can be compared to each other. The EPA emphasizes that EJSCREEN is meant to be used for screening only, and is "not designed to be the basis for agency decision-making or determinations regarding the existence or absence of EJ concerns"[40]. This caveat restricts the ways in which EJSCREEN should be interpreted, but the app's interface does not make that clear. If an average member of the public was using the app, they could easily assume that EJSCREEN is highlighting specific environmental justice areas[41].

CalEnviroScreen is produced by the California Environmental Protection Agency (Cal EPA) and focuses on state-level environmental health[42]. CalEnviroScreen aims to illustrate the impacts of environmental pollution on communities using environmental and demographic data, which are separated into percentile-ranked Pollution Burden (Exposures + Environmental Effects) and Population Characteristics (Socioeconomic Factors + Sensitive Populations). The index score for each section is available, or they can be combined to calculate the overall CalEnviroScreen Score. Like the U.S. EPA, Cal EPA developed CalEnviroScreen as part of their environmental justice efforts. However, Cal EPA's documentation indicates a higher level of confidence in their index scores, stating that the tool is "considered useful in identifying places burdened by multiple sources of pollution with populations that may be especially vulnerable"[42]. This confidence may stem from the smaller scale of a state-level analysis. California is one of the largest and most diverse states in the country, but it has the advantage of access to federal and state data. It can also focus on issues that are significant at a state, but not national, level.

National-level health indices like EPA's EJSCREEN and CDC's Social Vulnerability Index (SVI), as well as state-level efforts exemplified by California's CalEnviroScreen, are a valuable source of information for policymakers and citizens alike. The tradeoff is local specificity. Mining areas may have concerns about heavy metals, while agriculture-intensive communities may focus on levels of organophosphates. Furthermore, small-area analysis increases the likelihood of more targeted data; for example, there is no nationwide database of children's blood lead levels at geographies smaller than counties, but it may be available through a county health department or municipality[43].

Jelks, et al. (2018) conducted a community-led mapping project that demonstrates the value of locally driven hazard mapping. Long-time residents of an urban watershed in Atlanta, GA were recruited to identify the most pressing environmental hazards in their neighborhoods. They discovered that not all of the hazards they identified were documented in publicly available datasets from the EPA. The residents then led teams of university researchers around the watershed to map the hazards[44]. While the EPA databases are an essential part of mapping environmental hazards, the Atlanta study showed that they are not comprehensive. Without the input of the locals, those environmental hazards would not be on record[44].

The Children's Environmental Health Index

The Urban Health Index (UHI) was developed as a flexible framework for analyzing and visualizing health indicators at various geographic levels[45]. Its original application was focused on intra-urban health disparities, but the methodology can be adapted for other analyses. The UHI standardizes indicator values and combines them with their geometric mean. The resulting index score falls on a 0 to 1 scale.

The proposed Children's Environmental Health Index (CEHI) aims to highlight areas where children may be at an increased risk of exposure to environmental hazards and their adverse health effects. The CEHI can incorporate demographic data to highlight areas that are home to children who are statistically more likely to be vulnerable to exposures than the average child. Common vulnerabilities include race, ethnicity, poverty status, and age[46,47]. Some indicators in the CEHI are nearly universal and apply to all areas, but organizations are encouraged to supplement them with locally relevant indicators.

METHODS

CEHI Model

The Children's Environmental Health Index is predicated on the ways in which children exist in the world. Their physical environment, physiology, behavior, and social environment all determine their vulnerabilities and exposures (Figure 1).

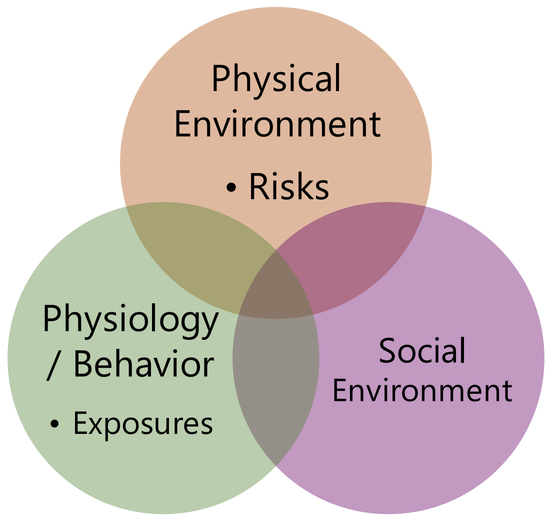


Figure 1: *Children's environmental health is shaped by their physical environment, social environment, and their physiology/behavior.*

The CEHI score is calculated using the UHI Excel workbook, which is populated with macros that calculate all scores and statistics with minimal user input. The workbook can be downloaded with the UHI Handbook[45].

Analysis Methods

All spatial analysis was performed using the Environmental Systems Research Institute (Esri) software program ArcGIS Pro 2.8 (Redlands, CA). The coordinate system was Pennsylvania State Plane South with the North American Datum of 1983. Methodology descriptions use Esri nomenclature, but the methods can be adapted for use in other GIS. The CEHI web app was built with Esri ArcGIS Online (Redlands, CA).

Geographic Scale and Unit

While they may not present the most technically sound approach to spatial analysis, census block groups and census tracts have large stores of readily available data, give audiences a frame of reference, and are politically relevant. This is why existing social and health indices are built upon Census-defined geographies[40,48]. Census tracts were selected instead of block groups because there is a greater amount of readily available data at the tract level.

Pre-Analysis Considerations

There are several classic approaches to GIS analysis of point-source environmental exposure (Figure 2). The approach of choice depends on factors like data availability, technical resources, and intended audience. The most basic method is spatial coincidence, which overlays predefined geographic units (e.g., census tracts or counties) with the hazard(s) of interest and counts how many hazards fall within each unit[49]. The count or density of hazard points is then compared to the geographic unit's demographics to identify associations between population characteristics and potential exposure. The second approach is distance-based analysis, in which buffers are generated around hazards; the populations that fall within the buffers are analyzed[49]. Finally, there is dispersion modeling, which uses advanced computer models to determine the shape and extent of a pollutant plume; the population that falls within the plume is the population of interest[50]. There are rare GIS analyses of individual sample data that use the respondent's home address and can directly tie the individual's demographics to a pollutant source[51].

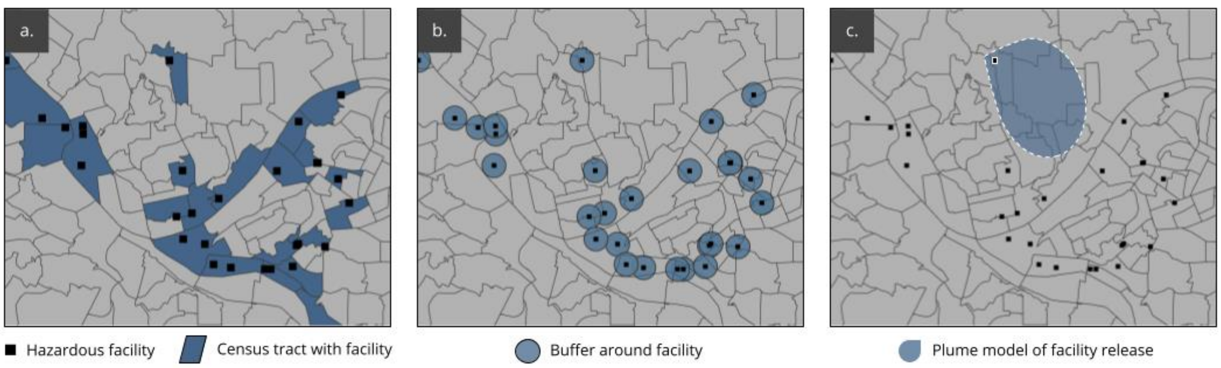


***Figure 2**: Common GIS methods for analyzing vulnerability to environmental hazards: a) spatial coincidence of hazard with geographic unit of interest, b) distance-based buffers around hazards, c) dispersion modeling of plume release*

Of the approaches, the most robust are dispersion modeling and individual sampling[49,51]. They are also the most resource-intensive, especially for organizations that do not have access to specialists and equipment. Of the remaining options, distance-based buffering is stronger than spatial coincidence. Instead of aggregating the number of facilities that fall within a census tract, it is more prudent to consider proximity to the facilities (in full acknowledgement of the limitations of a circular buffer). Pollution does not respect political boundaries.

Spatial coincidence relies on geographic units like census tracts – arbitrary constructs that are invisible in the real world. They may not reflect the boundaries of a real social community or may obscure the ways in which residents of an area move and interact in space. A major waste incinerator could be located 50 feet upwind from an adjoining tract; a simple spatial coincidence analysis would assign the incinerator to its host tract, completely ignoring the exposures of nearby residents in the downwind tract. Distance-based buffering avoids this selection bias by ignoring political boundaries and focusing on the population within a specified radius of the hazard. The primary limiting factor of buffers is that they assume a toxic release will disperse in a way that affects everyone in the buffer zone equally. In reality, toxic releases are subject to the same laws of nature as everything else. The chemicals themselves have different physical properties and will behave differently. These factors affect who will be exposed and where they live. This is where dispersion (or plume) modeling comes in. Models like AERMOD and HAPEM are used in conjunction with chemical databases like ICIS to get an accurate portrait of an air toxic release, enabling local responders to identify communities at risk and develop detailed emergency response plans[52,53]. The dispersion method is still fallible, as the model's accuracy depends on the quality of the input data[52,53]. Similar modeling approaches exist for liquid spills and groundwater intrusions[54-56].

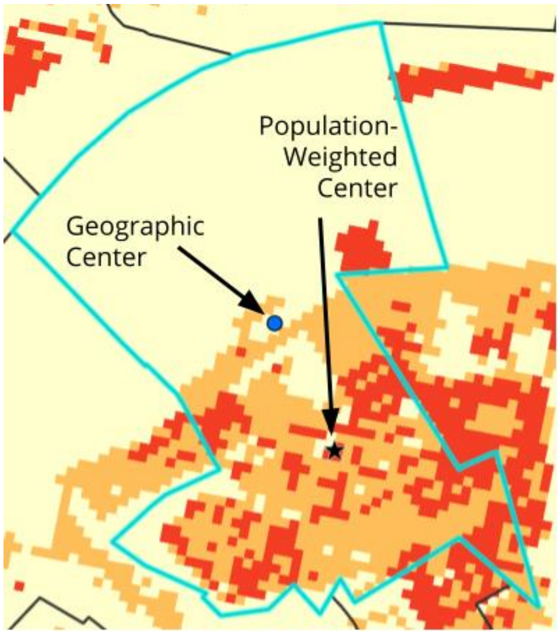


Figure 3*: The geographic vs. population-weighted center of a census tract, overlaid on dasymetric population density.*

Population exposure is the outcome of concern. But where is the population? Census tracts and block groups are developed based on population parameters, parcels, and natural boundary features like roads and rivers. They are not drawn with population *distribution* in mind. Figure 3 illustrates the difference between the geographic center of a census tract and its population-weighted center. The colored grid cells represent population density per 30m x 30m square, with red symbolizing the highest density and yellow the lowest. Weighting the calculation of geographic center by population density better reflects population distribution, and therefore exposure, within the tract. For example, the top half of our sample tract is covered by the Allegheny River. If we used the geographic center to create buffers for proximity analysis, it would not represent the population as accurately as the weighted center.

Deciding that a geographic unit is the most easily accessible way to visualize and share information does not limit analysis to spatial coincidence. There are ways to translate proximity analysis and dispersion modeling into politically defined polygons. For example, NATA 2014 makes its comprehensive data on HAPs and diesel PM available at the census tract level[52]. The RSEI toxicity-weighted concentration indicator can be converted from its original grid into census tracts using apportionment. While GIS-ready Census Bureau, NATA, and RSEI data are available nationwide, several indicators are site-specific and require geoprocessing before they can be input into the CEHI.

In acknowledgment of the varying technical skills available to organizations interested in implementing the CEHI, proximity analysis in this study was kept relatively simple. Organizations with access to GIS specialists should consider employing more complex spatial analysis methods to reflect local conditions more accurately. For example, prevailing wind speed and direction, elevation, and slope play a significant role in dispersion[57,58]. Even without access to advanced models, it is possible to incorporate these factors in geoprocessing. A potential approach for getting a more accurate idea of affected populations is to use building footprints or zoning. In

Figure 4, the left graphic shows a fan-shaped buffer based on prevailing wind direction. The right graphic is zoomed-in on that buffer and overlaid with building footprints symbolized by class. The blue buildings are Class R – residential. Footprints that are up-to-date and pass a quality control check can be suitable proxies for population exposure.

Figure 4*: An example of alternate approaches to modeling exposure area and exposed population.*

Ultimately, the methods used in this case study adhere to the concept of the "spherical cow", a term used in the physics world to signify the utility of simplifying models[59].

Methodology: Proximity

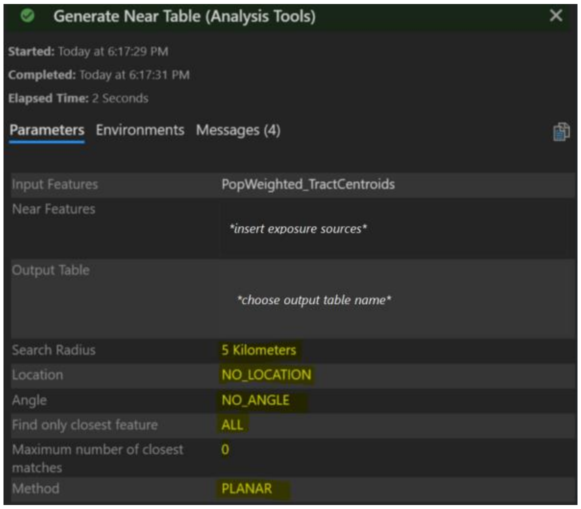
Proximity in the Allegheny County CEHI was calculated using an adapted version of the EJSCREEN methodology, outlined below[40]. The approach is a hybrid of spatial coincidence and distance-based buffering. Instead of buffering a facility, this method generates a buffer around the center of each census tract. Unlike EJSCREEN, this analysis uses population-weighted centroids instead of geographic centroids. A five-kilometer buffer extends beyond the borders of most census tracts. It strikes an acceptable balance of focusing on the census tract geography while also considering population and the potential far-reaching impacts of environmental exposures.

$$f(d_{ij}) = 1 / d_{ij}$$

This function calculates the inverse distance between a facility and the population-weighted center of a census tract, where i represents a particular facility; j represents a census tract; and d_{ij} is the distance, in kilometers, from tract j's centroid to the given location of facility i.

The general steps for the proximity analysis in ArcGIS Pro are as follows:

1. Generate 5km buffers around population-weighted census tract centroids
2. Run the Generate Near Table tool on the tract centroids, using the highlighted parameters below:



3. Small-area geographic data in the U.S. will likely be in a State Plane Coordinate System. This means that `NEAR_DIST` will be calculated in feet. In Near_Table, convert `NEAR_DIST` from feet to km: `!NEAR_DIST! * 0.0003048`
4. In Near_Table, Add Field > `Inv_Dist_km` and calculate the inverse distance as per the EPA formula: `Inv_Dist_km=1/!DIST_KM!`
5. Calculate Summary Statistics for the Near Table: `Inv_Dist_km SUM, NEAR_DIST MEAN, NEAR_DIST MIN, NEAR_DIST MAX`
6. If the output summary table has the same number of records as total census tracts, proceed to the next step. If the summary table has fewer census tracts:

   In this situation, we want to make sure that tracts that don't have a feature within 5km have the inverse distance of the nearest feature, however far that may be. To do this:

   a. Generate a second Near Table with different parameters: clear out the search radius and check the "Find only closest feature" box. Give the table the same name as the original Near_Table but append "_ALL" to the end of the table name.

   b. Calculate the inverse distance for Near_Table_ALL

   c. Join both Summary_Near_Table and Near_Table_ALL to the centroids

   d. Export to a new feature class. Fill in the inverse distance for those that don't have any features within 5km using the inverse distance calculated with Near_Table_ALL.
7. Join the summary table to the centroids using `OBJECTID` and `IN_FID`
8. Spatial Join the centroids to the census tracts

The value that will go into the CEHI calculation is `SUM_Inv_Dist_km`; the unit is facilities within one kilometer – so a tract with a score of 3.5 means that there are 3.5 facilities within a kilometer of the average person living in that tract.

The Census Bureau produces population-weighted centroids with decennial census data, so the centroids used in this analysis represent the 2010 population centers. This is not ideal but is acceptable for a case study. Future CEHI projects will have access to the 2020 population-weighted centers.

Once the data has gone through the necessary processing in ArcGIS Pro, join each of the indicators to a blank census tract feature class and then export it to a table. This ensures each census tract has the correct data appended to it before the CEHI is calculated.

Methodology: Census Data

Tabular census data includes an ID field that enables direct joins between tables and feature classes, minimizing the amount of data preparation

1. Retrieve data from https://data.census.gov/
2. Bring table into ArcGIS
3. Join to census tract feature class using the tract ID
4. Export to a new feature class
5. Perform any simple calculations needed, e.g., the percent of houses built before 1960 `(int(!Built_1950_to_1959!) + int(!Built_1940_to_1949!) + int(!Built_1939_or_earlier!)) / int(!Total!))*100.` If preferred, calculations can be done in Excel before importing the spreadsheet into ArcGIS.

Calculating the CEHI

Before calculating the CEHI, ensure that all indicators point in the same direction[45]. For example, if a high value for indicator A means worse environmental conditions, then high values for all other indicators must also signify worse conditions. It does not matter if high or low signifies a poor environment, as long as all indicators agree[45].

The first step of the CEHI calculation is indicator standardization. This adjusts for the disparate indicator metrics, which range from percentages to volumes. The indicator score (I^s) is calculated by dividing the distance of the value from the minimum, divided by the range:

$$I^s = \frac{I_i - min*(I)}{\max(I) - \min(I)}$$

where I_i is the value of the observation, $\max(I)$ is the maximum value for indicator I, and $\min^*(I)$ is the minimum value of indicator I minus a small value to avoid zeros in the numerator[60]. Ten percent of the standard deviation is the default value that is subtracted[45].

Full details on the Urban Health Index, as well as a macro-enabled Excel workbook to facilitate calculations, are available from the WHO[45].

CASE STUDY: ALLEGHENY COUNTY, PA

Allegheny County is in southwestern Pennsylvania, where the Monongahela and Allegheny Rivers converge to form the Ohio River (Figure 5). The population is 1,221,744. The median income is $61,043 and the poverty rate is 11.6%. The population is predominantly White, at almost 80%. Only 3.8% of residents do not have health insurance[61].

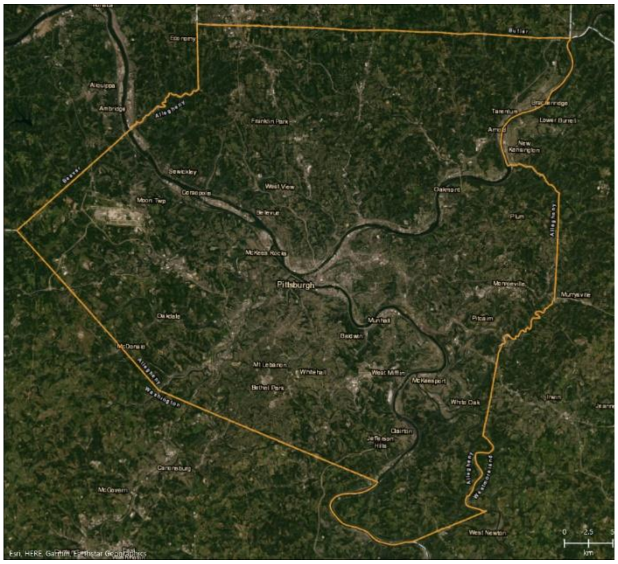


***Figure 5**: Allegheny County, PA*

The area is extraordinarily rich in natural resources, including timber, limestone, iron, coal, oil, and natural gas[62]. The county seat is the city of Pittsburgh, which began its journey towards becoming America's industrial center during the U.S. Civil War. While iron dominated the mid-19th century, steel became the driving force behind Pittsburgh and Allegheny County's growth. Southwestern Pennsylvania is home to the Pittsburgh Coal Bed, rich in low-sulfur bituminous coal – ideal for producing coke, the preferred fuel for blast furnaces[62]. The proximity of raw fuel, a confluence of navigable waterways, and the growing demand for steel from the railroad industry poised the Pittsburgh region for success. New steel production technologies and the businessman Andrew Carnegie guaranteed it[62]. In 1901, the United States Steel Corporation was incorporated by a group of notable businessmen including Andrew Carnegie, Henry Clay Frick, J.P. Morgan, and Charles Schwab[63]. By 1910, Pittsburgh was producing over 60% of steel in the U.S. and workers were flocking to the area. Boom towns anchored by factories popped up along the banks of the Monongahela River Valley (commonly called the Mon Valley). Besides the growing population, the other sign of progress was the darkening skies. During this period, Allegheny County's atmosphere was black with smoke from coke ovens, industrial facilities, and residences. On some days it was so dark that drivers needed to use their headlights to navigate[64].

In 1946, smoke reduced visibility in the downtown area one out of every four daylight hours[65]. After sustained public campaigns for cleaner air, the city of Pittsburgh enacted its first meaningful smoke control ordinance[65]. Two years later, an atmospheric inversion 20 miles south in Donora, PA engulfed residents in a thick smog. After five days, the smog dispersed. Twenty people were dead and approximately 6,000 had been sickened[65]. The Donora Smog of 1948 led to the first major epidemiological inquiry into an environmental health event in the U.S[66]. The United States Public Health Service (USPHS) conducted a wide-ranging study into the cause of the smog. They were not able to attribute the health impacts to a single toxic substance but noted that the community's location in the Mon Valley primed it for inversions. This, in combination with emissions from the American Steel and Wire plant and the Donora Zinc Works, was a recipe for disaster. Death records from 1948 to 1957 indicate that mortality from cancer and cardiovascular disease significantly increased[66]. The tragedy is often considered the impetus for the federal Clean Air Act[66]. The Donora Smog was also evidence that city centers weren't the only areas subject to serious air quality issues. As a result, officials in Allegheny County passed a county-wide smoke control ordinance in 1949[65].

Air quality in the area visibly improved after the ordinances were passed in 1946 and 1949. Nine years after the second ordinance was passed, only one out of every 65 daylight hours was impacted by heavy air pollution[65]. A decline in steel and other heavy industries began in the 1970s, and air quality continued to recover. Heavy industry and mining hold a place in the local economy, but the region is not as dependent on resource extraction and manufacturing as it once was. Education, health care, finance, and tech have become significant sectors in the economy[64].

Air quality is still at the forefront of environmental health advocacy in southwestern Pennsylvania. The Breathe Collaborative, based in Pittsburgh, is a consortium of over 50 nonprofits, citizen groups, academics, and public health professionals whose work focuses on improving area air quality through science-based evidence and community outreach[67]. The high engagement in local environmental issues lends further support to the value of a county-level health index.

Indicator Selection and Justification

Indicators were selected based on extensive review of the literature, GIS data availability, and best practices of existing environmental health indices. Because this analysis is focused on a vulnerable population, indicator selection erred on the side of caution. It is more likely that exposures have been overestimated than underestimated. Final indicators are shown in Table 1.

***Table 1**: Indicators for the Allegheny County CEHI*

Social Environment Indicators	Population density of children (<18)
	Minority children (%)
	Children in poverty (%)
	Houses built before 1960 (%)
Exposure Indicators	$PM_{2.5}$

	Ozone
	Traffic density
	SO_2 ❖
	RSEI Industrial Air Releases ❖
Environmental Risk Indicators	NATA Cancer Risk
	Hazardous waste sites
	Mining-related sites ❖

Demographics

How do you define a "child" when assessing environmental vulnerability? The legal definition is individuals under age 18. Literature on the health impacts of exposure is largely focused on preadolescent children. If you are consulting data from the U.S. Census Bureau and wish to focus on a smaller age range, you will find that age brackets are not standardized. For example, the youngest age group in the health insurance coverage data is "under 6 years", while the youngest age group in the poverty data is "under 5 years"[68]. These discrepancies make it difficult to perform simple comparative analyses. For the case study presented here, a child is a person under age 18, which reflects the lack of agency that a vast majority of children have over where they live and attend school. As with indicator selection, organizations will have to define their population of interest.

Environmental injustice is the disproportionate exposure of low-income and/or minority communities to environmental hazards such as pollution, industrial facilities, and hazardous waste sites. Many communities experiencing environmental injustice do not receive the expected protections provided by law[49]. These unresolved exposures negatively impact people's health and welfare and can promote poverty, poor health, and disenfranchisement. As discussed above, children are one of the highest-risk groups for environmental exposure and the resulting health effects.

The role of race and ethnicity in environmental injustice is well-studied. A subset of research focuses on how minority children are affected. For example, data indicate that the majority of children diagnosed with lead poisoning are a racial or ethnic minority[7]. Minority children also have the highest risk of exposure and increased susceptibility to lead toxicity: poor nutrition status characterized by deficiencies in iron and calcium, living in older, poorly maintained homes, and residing in high-traffic inner city neighborhoods still contaminated by leaded gasoline particles[49]. In Orange County, FL, analysis of pollution sources, public schools, and the residential location of 151,000 students found that Black and Hispanic children were significantly more likely than White children to both live and go to school close to a pollution source. The study's strength was that it mapped the location of each students' home and could assign a race to that point; researchers are often limited to anonymized census block- or tract-level data[46]. A California study found that minority children were three times as likely to live in an area with high traffic density than their White counterparts[69]. While proximity to a pollution source can't be assumed to be the best indicator of exposure, it may act as an indicator of the *perception* of exposure and how that perception influences an area's socioeconomic profile[70].

In Allegheny County, the relationship between poverty and race/ethnicity are painfully clear. Of the children living below the federal poverty level, 39.3% are Black, 21.3% are Hispanic or Latino, 11% are Asian, and 8.2% are non-Hispanic White[71]. This inequality reflects national trends. In the United States, 31% of Black children, 23% of Hispanic or Latino children, 10% of Asian and Pacific Islander children, and 10% of non-Hispanic White children live in families with incomes below the federal poverty level[72]. The child poverty rate in Allegheny County is approximately 15.3%. However, several municipalities in the county have child poverty rates greater than 50%[71]. This significant spatial variance warrants further investigation.

While population statistics suggest a dependent relationship between income and race/ethnicity, the spatial relationship between the two factors and environmental health risk is still debated. When controlling for one or the other, some studies have found race to be the more significant variable, while others have found income to be the most significant[35,49,51]. Settling the argument in favor of one or the other is not important for the practical application of an environmental health index like the CEHI. What matters is that race, ethnicity, and income are all associated with increased risks of exposure to environmental hazards. For this reason, poverty and minority status have been separated into two separate indicators.

Lead

Lead (Pb), a toxic heavy metal, has been used in consumer products and industrial applications for centuries. It is in our air, water, food, soil, homes, and personal belongings. The most common route of exposure is ingestion, namely of contaminated soil, indoor dust, or piped drinking water. Once absorbed, lead bioaccumulates and excretes very slowly. The elimination half-life of Pb in the bones is 10-20 years. If an individual has very high lead levels, the health effects can persist for decades, if not permanently[10]. Furthermore, lead is a striking example of how differently children and adults can be affected by a toxic substance.

Lead was a popular additive to indoor and outdoor house paint until the federal government prohibited its use in consumer settings in 1978. Of homes built before 1978, an estimated 24% built between 1960-1977, 69% built between 1940-1959, and 87% built before 1940 are likely to contain lead-based paint[73]. Even if the lead is under several coats of lead-free paint, lead dust can still be released by an act as simple as nailing something to the wall. Passive contamination is often due to cracking or flaking paint. Young children's tendency to play at floor-level, combined with their hand-to-mouth behavior—which can include chewing or sucking on accessible painted surfaces like windowsills and door edges—makes them especially at risk of paint-based lead poisoning[11].

In the early twentieth century, lead was added to gasoline to improve engine performance. In the mid-1970s, the EPA introduced a phased-in reduction of the quantity of lead in gasoline and imposed restrictions on industrial emissions. It wasn't until 1996 that the EPA banned the sale of leaded fuel for all on-road vehicles. Leaded fuel is still allowed in some aviation and off-road vehicles[74]. The ban on leaded gasoline greatly reduced the amount of lead being emitted into the air, but once it enters the environment, lead does not disappear. It is most often found in soil – especially soil close to roads, houses with exterior leaded paint, and industrial sites[11]. Edge-of-road soil has lead levels an estimated 30–2,000 µg/g above background levels, especially in areas that have been heavily trafficked for decades. Samples collected outside of homes with exterior lead-based paint have had lead levels >10,000 µg/g. Elevated lead levels have also been found in the soil surrounding elementary schools[10]. The lead can either be resuspended as PM or ingested; ingestion is the most common exposure route for children. Today, the CDC considers lead-contaminated dust and lead-based house paint to be the most dangerous sources of lead exposure for children in the U.S[11]. However, certain places in the U.S. may be primarily concerned with other sources of exposure like drinking water.

This analysis uses house age as an indicator for lead exposure because reliable nationwide data is available from the U.S. Census Bureau. Even if a child doesn't live in a home with lead paint, if they live in a community with a high proportion of older homes, there is a greater chance that they will be exposed to lead dust tracked indoors or in the soil outside. If a small area has access to more detailed data on soil concentrations, blood lead levels, lead service lines, or other suitable metrics, those may be more meaningful to the community of interest.

Hazardous Sites

The federal Resource Conservation and Recovery Act (RCRA) gives the EPA purview over the entire life cycle of hazardous and non-hazardous solid waste; state environmental agencies manage the program and report to EPA. According to the Pennsylvania Department of Environmental Protection (PADEP), hazardous waste is defined as solid waste which, "in sufficient quantities and concentrations, pose a threat to human life, human health or the environment when improperly stored, transported, treated or disposed"[75]. "Solid waste" can be solid, liquid, or a contained gas. Hazardous wastes have at least one of the four following characteristics: corrosivity, reactivity, ignitability, or toxicity. There are over 700 chemicals and over 100 industrial and manufacturing wastes officially listed as hazardous. If an unlisted substance has one of the four characteristics listed above, it is treated as a hazardous waste[76].

There are hazardous waste generators, transporters, and storage/treatment/recycling/disposal facilities. Generators are classified by the quantity of hazardous waste they produce in a calendar month: a Very Small Quantity Generator (VSQG) produces ≤100kg of non-acute hazardous waste, a Small Quantity Generator (SQG) produces ≤1kg of acute hazardous waste or greater than 100 but less than 1,000kg of non-acute hazardous waste, and a Large Quantity Generator (LQG) produces more than 1,000kg of non-acute hazardous waste or has >1kg of acute hazardous waste onsite[77]. Transporters use roads, railways, and waterways to move the waste from generators to facilities where it will be recycled, stored, treated, or disposed. When possible, hazardous waste is recycled. Waste that cannot be recycled is sent to Treatment Storage and Disposal Facilities (TSDFs). TSDFs are used for temporary storage, final treatment, or permanent disposal of hazardous waste. The volume of waste and processes used at recycling facilities and TSDFs carry a high risk of hazardous waste spills or other contamination events. Improper storage and handling can pollute drinking water, soil, and air[76].

The Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), often called Superfund, is invoked when hazardous waste is grossly mismanaged and poses a threat to human and environmental health. Landfills, mines, and industrial facilities comprise the majority of Superfund sites[78]. Of the tens of thousands of Superfund sites across the country, 1,870 are on the National Priorities List. Of these, only 438 have been deleted (remediated). Three of the 19 Superfund sites in Allegheny County are actively listed on the NPL[79].

Children cannot decide where they will live. They depend on their caregivers for life's necessities, including shelter. Unfortunately, that shelter may be located close to a hazardous waste facility. The hazardous waste management/solvent recovery industry is one of the largest emitters of carcinogens and developmental and reproductive toxicants. Landfills and waste incinerators are significant sources of lead, mercury, PCBs, dioxins/furans, and other heavy metals[80]. Adults may not be aware that they live in an area that puts their child at risk of toxic exposures – or they may not have the resources to move away or pay for abatement measures[6]. The health impacts of living close to hazardous waste sites have been examined for decades. Studies of children residing near Love Canal, the first Superfund site in the country, found elevated rates of health problems ranging from seizures to stunted height in comparison to control populations[81,82]. Numerous studies have shown that children who live close to hazardous waste incinerators have measurable quantities of heavy metals in their hair, blood, and tissues[83,84]. Data from a cohort study in Greece indicated that residential proximity to a major landfill was associated with lower neurodevelopmental scores in children, attributed to heavy metal exposure. The same study found that incinerators increase exposures to plasticizers like BPA and phthalates[83]. Children residing near hazardous waste generators and TSDFs have also experienced high rates of respiratory illness, speech and hearing impairments, sleep disorders, diminished academic performance, and neurological disorders[6,78,85,86].

Mining

The Allegheny County of today exists because of its rich bituminous coal deposits. Coal demand has slowed down, but mines and processing facilities still operate.

Coal has been mined in Allegheny County for over 300 years[63]. The area is riddled with Abandoned Mine Lands (AMLs), areas where coal was mined before the passage of the federal Surface Mining Control and Reclamation Act of 1977 (SMCRA). Prior to 1977, coal operations did not have to take measures to prevent the environmental and health impacts of mining. Furthermore, reclamation was not a required part of a mine's life cycle. Vast swaths of land and waterbodies have been affected by the lack of regulation. Water is polluted by heavy metal leaching and acid mine drainage from underground mines, surface mines, and refuse piles. Open mine shafts, subsidence events, and unstable highwalls can lead to physical injury or death. Underground coal mine fires and burning refuse piles release particulate matter and toxic gases[87].

The Abandoned Mine Lands Program was established to rectify the serious threats AMLs pose to public health and safety. In Pennsylvania, the AML Program is administered by the Bureau of Abandoned Mine Reclamation under the purview of the federal Office of Surface Mining. There are over 15,000 yet-to-be reclaimed mine hazards in Pennsylvania[88]. Children playing in or near AMLs are at increased risk of physical injury and exposure to toxic chemicals via ingestion, inhalation, and dermal contact.

Since the passage of the SMCRA in 1977, coal mining operations have been regulated with a focus on public health, safety, and environmental protection. These are referred to as “modern mines” in comparison to AMLs[87]. However, the advent of new technologies and a deeper understanding of the far-reaching effects of coal mining have led to changes in the rules and regulations over the past 40 years. For example, Pennsylvania has long been concerned with polluting postmining discharge, especially acid mine drainage (AMD). The state began requiring permit applicants to prove their operation would not result in hazardous postmining discharge in the mid-1970s. Seventeen percent of the coal mines permitted between 1977 and 1983 later developed AMD, while only 2% of coal mines issued permits between 1987 and 1996 resulted in AMD[89]. Furthermore, acid drainage and heavy metal leaching are not restricted to mines; coal storage, coal refuse piles, and sedimentation and impound basins for coal ash can also contaminate soil and water. Coal dust is another significant contaminant. The reduction in AMD between the 1970s and 1990s reflects improvements in water science. Nevertheless, post-1977 mines also pose a threat to public and environmental health and should be included in the CEHI.

Air Quality

Air pollution has both acute and chronic health effects that affect people across the demographic spectrum. There is a vast body of research concerned with children’s respiratory health. In the past century, advances in technology and scientific understanding have vastly improved air quality in many regions of the United States. By the middle of the 20th century, most large U.S. cities were commonly engulfed in smog; in some cases, the air quality was so poor that it led to illness and fatalities[90]. It became increasingly apparent that air pollution was harming human and environmental health, which in turn led to lost worker productivity, reduced agricultural yields, and additional economic impacts. In response to these events and pressure from the burgeoning environmental movement, the U.S. Congress and passed the Clean Air Act (CAA) and established the Environmental Protection Agency (EPA) in 197. Further revisions were made in 1977 and 1990[90]. Under the CAA, the EPA established primary and secondary national ambient air quality standards (NAAQS) for “criteria air pollutants” (CAPs), designated as such because they are widespread and pose a threat to health and the environment[91]. As seen in Figure 6, there are six criteria air pollutants: particulate matter ($PM_{2.5}$ and PM_{10}), ground-level ozone (O_3), lead (Pb), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2)[91]. Primary standards aim to protect human health, while

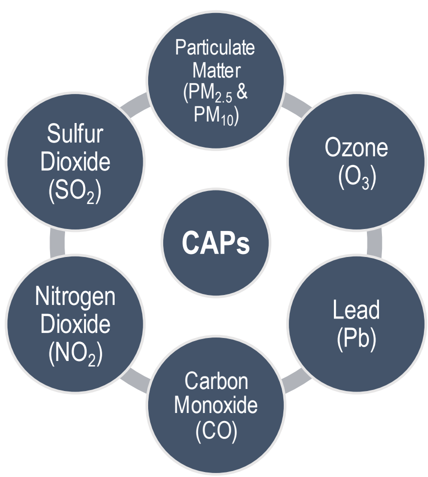


Figure 6*: EPA Criteria Air Pollutants*

secondary standards are set to protect public welfare from adverse side effects of CAPs such as property damage and loss of crops and livestock. Major sources of anthropogenic CAPs include on- and off-road transportation, industrial facilities, power plants, and machinery[92].

$PM_{2.5}$

Particulate matter is the term for small, suspended particles of solids and liquids in the atmosphere. The particles consist of organic materials, chemicals, acids, metals, and liquid droplets. Primary PM is the immediate result of an emission process, like smoke from a fire. Secondary PM can form when emitted gases like SO_2, NO_x, and VOCs condense into particulates[93]. There are natural and anthropogenic sources of PM, and the composition of the PM depends upon its source(s). Particles smaller than 2.5µm are called $PM_{2.5}$. The most common sources of $PM_{2.5}$ are combustion of fossil fuels (vehicles, industrial facilities, power plants, etc.) and other high-heat processes (smelting, coking, etc.). They can stay suspended in the atmosphere for days to weeks and travel 10 to 100 km. $PM_{2.5}$ can be removed from the atmosphere via diffusion to surfaces, dry deposition, and rain[94]. These particles are fine enough to enter the alveoli in the lungs and, in some instances, can enter the bloodstream and cause systemic health effects[93].

Short-term exposure to $PM_{2.5}$ has a variety of health effects: respiratory (exacerbation of asthma, chronic obstructive pulmonary disease (COPD), and combined respiratory diseases); cardiovascular (ED visits and hospital admissions for heart failure and ischemic heart disease, cardiovascular-related mortality); and nonaccidental mortality. There is less robust evidence suggesting potential causality between short-term exposure and effects on the metabolic, nervous, and reproductive systems[94].

Evidence indicates that long-term $PM_{2.5}$ exposure has wide-ranging adverse effects: respiratory (decreased lung development, asthma development and prevalence in children); cardiovascular (cardiovascular mortality); nervous system (cognitive decline, dementia, changes in brain morphology); cancer (lung); and nonaccidental mortality. Further studies provide insufficient but suggestive evidence indicating potential causality between long-term $PM_{2.5}$ exposure and impacts on the metabolic and reproductive systems[94].

The EPA's 2019 *Integrated Science Assessment (ISA) for Particulate Matter* concludes there is adequate evidence "children are at increased risk for $PM_{2.5}$-related health effects" compared to the general population. This is especially supported by numerous studies indicating associations between long-term $PM_{2.5}$ exposure and decreased lung function growth, reduced lung function, and increased incidence of asthma development in children[94].

Ozone

Ozone (O_3) can be categorized into two types based on its location in the atmosphere. Stratospheric ozone occurs in the upper atmosphere and is responsible for protecting us from solar radiation; this is often referred to as the "ozone layer"[95]. Tropospheric, or ground-level ozone, is the type of concern. It is a secondary pollutant that forms in the air when sunlight reacts with nitrogen oxides (NO_x) and VOCs[96]. The majority of NO_x and VOC emissions in urban environments and industrial areas come from passenger vehicles, trucks, industrial facilities, and power plants. Unfortunately, ozone-forming chemicals can travel long distances and impact areas many miles downwind of emitters. Because ozone formation requires sunlight, day-to-day levels are typically lowest in the morning; seasonal levels are typically highest in the summer. In Pennsylvania, "ozone season" is April 1 through September 30, peaking from June to August[95].

The health effects of ground-level ozone exposure are well-documented. Short-term exposure to O_3 is associated with cough, wheezing, chest pain, inflammation, and reduced lung function. Exacerbation of asthma, bronchitis, and emphysema have been observed at ambient concentrations of ground-level ozone. Chronic exposure can lead to lung damage and may be a causal factor in the development of asthma in children[92].

Ambient levels of ozone have been associated with increased asthma symptoms, visits to the emergency department, and hospital admissions[97-101]. More pronounced effects have been observed in younger age groups (0-6 years; 1-4 and 5-12 years), but there is debate regarding the validity of asthma diagnoses in children younger than 4-5 years of age[97,101]. Age stratification aside, there is ample evidence supporting a causal relationship between ozone exposure and exacerbation of asthma and respiratory symptoms in children.

Sulfur Dioxide

Sulfur dioxide (SO_2) is a gas that is mostly emitted by high-heat industrial processes and electricity generation via coal or sulfur-containing oil[102]. It is also naturally emitted by fires and volcanoes. Because it is the most common sulfur oxide in the atmosphere and has the most evidence of human health effects, SO_2 is used as the indicator species to set the NAAQS for all SO_x. Sulfur dioxide is a primary and secondary pollutant. Its primary form is the result of combustion, while the secondary form is atmospheric oxidation of sulfides[103]. The resulting sulfates are a component of $PM_{2.5}$[104].

Exposure to SO_2 causes respiratory effects. The relationship is especially apparent with short-term exposure, with many studies showing a positive association between short-term SO_2 exposures and asthma-driven ED visits and hospital admissions. The association is strongest in people with asthma, children, and older adults. Observable symptoms include wheezing, shortness of breath, and chest tightness[92]. A number of these studies controlled for co-pollutant confounding and saw little difference in the association. Evidence supporting a relationship between long-term SO_2 exposure and respiratory effects is not as strong as that for short-term exposure, but results are suggestive of a causal relationship. Several studies indicate long-term exposure may lead to asthma development in children, but they did not control for co-pollutant confounding. Besides respiratory health, there is evidence suggestive of a causal relationship between short-term SO_2 exposure and nonaccidental mortality. Further study is required to clarify the relationship[103].

The EPA's 2017 *Integrated Science Assessment (ISA) for Sulfur Oxides – Health Criteria* concludes that evidence is "suggestive of increased risk in children compared to adults". The determination is based upon evidence from SO_2 studies and toxicological data. Study results trend in support of increased risk, but there are enough studies finding the null hypothesis that the EPA cannot definitively state that children are at increased risk of effects from SO_2 exposure compared to adults[103].

Air Toxics

In 1990, amendments to the Clean Air Act required the EPA to expand its oversight to almost 190 chemicals classified as "hazardous air pollutants" (HAPs), also called air toxics. This list comprises chemicals known or suspected to have adverse effects on human health, carcinogenic or otherwise. They can be directly inhaled, but also enter our drinking water, soil, and food chain through deposition. Ultimately, the population can be exposed to HAPs via inhalation, ingestion, and dermal absorption. Examples of HAPs include benzene, mercury, and polychlorinated biphenyls (PCBs)[90]. In addition to establishing the general list of HAPs, the amended Clean Air Act directed the EPA to identify urban air toxics[105]. Unlike CAPs, HAPs do not have standards for ambient air concentration; they are required to meet industry-specific performance levels and maximum achievable control technology (MACT)[106].

Air toxics will be considered in several ways for the Allegheny County CEHI. First, the EPA's Risk-Screening Environmental Indicators (RSEI) will provide estimates of the air concentration of all industrial emissions listed on the Toxics Release Inventory (TRI). The TRI is an EPA database of facilities that handle at least one of over 700 chemicals that have been deemed toxic to human and environmental health. To qualify for TRI, a facility must meet three criteria: be federally owned/operated *or* in a TRI-reportable industry sector; have at least 10 full-time or equivalent employees; and handle a TRI-listed chemical in quantities above a specific threshold. TRI keeps annual facility-level records of the amounts of chemicals released on-site into the environment as well as quantities transferred off-site[107]. The RSEI consider the quantity of TRI chemical released, environmental modeling, chemical toxicity, exposure route and extent, and the affected population. The goal of the RSEI is to analyze the potential human health impact of chronic exposure to chemical releases from TRI-regulated industrial facilities.

The second metric for air toxics is cancer risk from EPA's 2014 National Air Toxics Assessment (NATA), which models the health effects of exposure to HAPs and diesel PM. The data originates as point stationary sources, nonpoint sources, mobile sources, and fires from the National Emissions Inventory (NEI), with supplementation from the TRI and other data sources as needed. It then goes through dispersion and complex exposure modeling. The latter uses the population at the census tract level, splitting it into six age groups: 0–1, 2–4, 5–15, 16–17, 18–64, and ≥65 years of age. The focus on the young population indicates that age is an important variable in the exposure model[52]. As children have a longer latency period in which to develop cancer, the spatial variation in cancer risk is a valuable input for the CEHI.

Traffic-Related Air Pollution

Wherever there are motor vehicles, there is traffic-related air pollution (TRAP). Fossil fuel combustion in engines emits pollutants like NO_x, ultrafine particles (UFP; PM with a diameter <0.1µm), CO, CO_2, polycyclic aromatic hydrocarbons (PAHs), benzene, formaldehyde, and metals. Many primary pollutants are converted into secondary pollutants by photochemical reactions in the atmosphere. The composition of the emissions depends on the vehicle type, age, fuel, fluids, and maintenance status[108]. For example, a heavy-duty diesel truck and a gasoline-powered sedan will emit many of the same pollutants, but in different proportions. Diesel fuel produces more PM, while gasoline produces more VOCs like benzene[109]. Asthma, wheeze, cardiopulmonary diseases, low birth weight, and some cancers have been associated with increased exposure to traffic pollution[108].

Concern about the health effects of TRAP on children has inspired numerous studies. One of the largest is the longitudinal Children's Health Study at the University of Southern California (CHS), which has recruited thousands of schoolchildren living in southern California since 1992. The goal of the CHS was to learn about the relationship between ambient air pollution in communities and its effect on children's respiratory health. Researchers recorded clinical respiratory data and levels of O_3, NO_2, PM_{10}, $PM_{2.5}$, and acid vapor. A 2017 review of TRAP and lung function in children found that early-life and pre-adolescent TRAP exposure negatively affected lung function. They were not able to identify conclusive evidence of health effects in subsets of the population, including gender, sensitization, and asthma status[110]. A large-scale study of where children lived, traffic density, SES, and race in California found that low-income minority children were more likely to live in traffic-dense block groups than their White or higher-income counterparts[69].

There is ample evidence that roadway proximity is strongly associated with exposure to traffic emissions. Variations in fleet composition, wind conditions, geography, local weather, time of day, and noise barriers all influence TRAP measurements. The WHO's Health Effects Institute Panel determined that the area 300–500m from a highway or arterial road had the highest concentration of TRAP[108]. Karner, et al. conducted a meta-analysis of over 40 near-roadway air pollution studies and calculated how high above the background concentrations individual TRAPs were at the edge of the road, and the approximate distance from the road at which TRAPs reached average background concentrations[111]. A selection of their results is provided in Table 2.

***Table 2**: Excerpted summary of background normalized data. Karner, et al., 2010*

Pollutant	Approximate multiplier above background concentration at edge-of-road	Approximate distance required to reach background concentration (m)
Benzene	2.1	280
NO	3.3	565
NO_2	2.9	380
NO_x	1.8	570
PM_{10}	1.3	176

Proximity to or density of traffic is a popular metric for determining population exposure to TRAP and its principal components. Based on the WHO and Karner studies, the buffer distance used to measure traffic density for the CEHI was set at 500 meters.

Air Pollution in Allegheny County

Due to children's susceptibility and the area's industrial past and present, the Allegheny County CEHI is heavily focused upon air pollution. The Allegheny County Health Department (ACHD) Air Quality Program focuses on the following pollutants: ozone, particulate matter, carbon monoxide, lead, nitrogen dioxide, sulfur dioxide, hydrogen sulfide (H_2S), benzo(a)pyrene (B(a)P), and over 30 HAPs. ACHD maintains 13 air monitoring sites around the county, four of which are located at public schools. Discussions of poor air quality readings often refer to measurements from Liberty, which consistently has high measurements of PM2.5, PM10, SO2, and benzene. It is located at South Allegheny High School, approximately 3 km downwind of the U.S. Steel (USS) Clairton Coke Works[71].

As of June 2021, the EPA Green Book notes that Allegheny County, in whole or in part, is in nonattainment of several criteria air pollutant standards. Details are provided in Table 3.

Table 3*: Allegheny County NAAQS Nonattainment, 2021*[112]

Pollutant	NAAQS	Location
$PM_{2.5}$ (1997)	15.0 µg/m^3 (annual mean, averaged over 3 years)	Liberty-Clairton, PA
$PM_{2.5}$ (2006)	15.0 µg/m^3 (annual mean, averaged over 3 years)	Liberty-Clairton, PA
$PM_{2.5}$ (2012)	12.0 µg/m^3 (annual mean, averaged over 3 years)	County-wide
SO_2 (2010)	75 ppb (99th percentile of 1-hour daily maximum concentrations, averaged over 3 years)	Allegheny, PA
8-Hour O_3 (2008)	70 ppb (annual fourth-highest daily max 8-hour concentration, averaged over 3 years)	Pittsburgh-Beaver Valley, PA

A recent study examined the prevalence and control of asthma among 5- to 17-year-olds (n=1,202) who lived near sources of air pollution in Allegheny County, PA. The sources included steel works, coke works, a coal-fired power plant, and a major interstate junction. Pollutants examined included NO_x, $PM_{2.5}$, and individual components of $PM_{2.5}$ (black carbon, potassium, sulfur, chromium, iron, silicon, and zinc). Over 70% of children were exposed to $PM_{2.5}$ levels above the WHO-determined threshold of 10 ug/m3; the overall rate in the U.S. is 3.1%. $PM_{2.5}$, NO_x, sulfur, and zinc were significantly associated with the odds of asthma diagnosis. $PM_{2.5}$, black carbon, and silicon were significantly associated with uncontrolled asthma. Within the study population, the prevalence of asthma was 22.5% and the rate of uncontrolled asthma was 59.3%. Prevalence was higher in African American students as well as students with public health insurance, which was used as a proxy for socioeconomic status[15].

APPLICATION

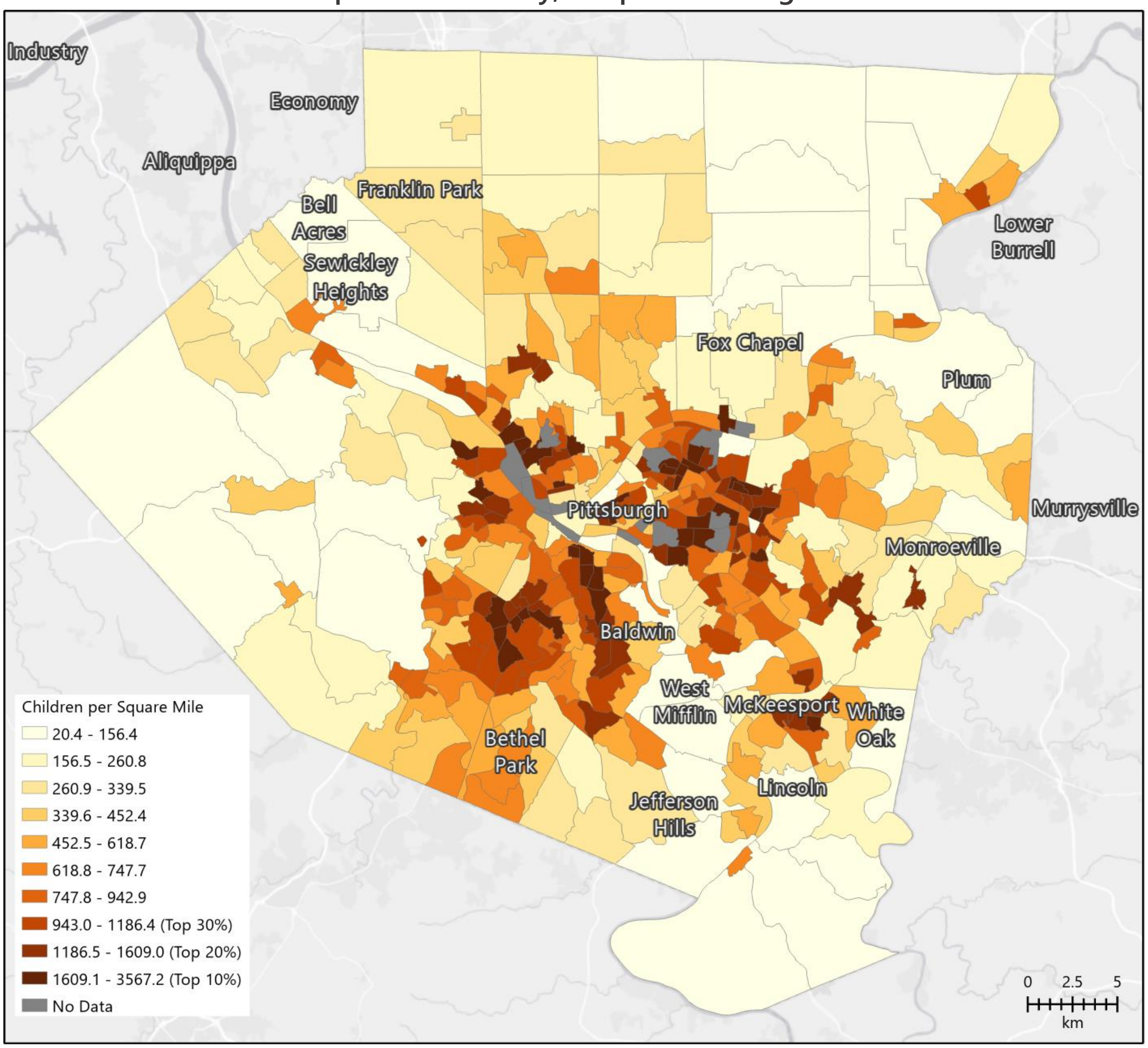
Indicator Profiles

❖ = Specific for Allegheny County

CHILD POPULATION DENSITY

Indicator	Children (age 0-17) per square mile, by census tract
Data Source	U.S. Census Bureau 2015-2019 American Community Survey 5-Year Estimates, Table B01001 "Sex By Age"
Method	The only preparation required for this layer was calculating `Pop_U18/SQ_MI`.

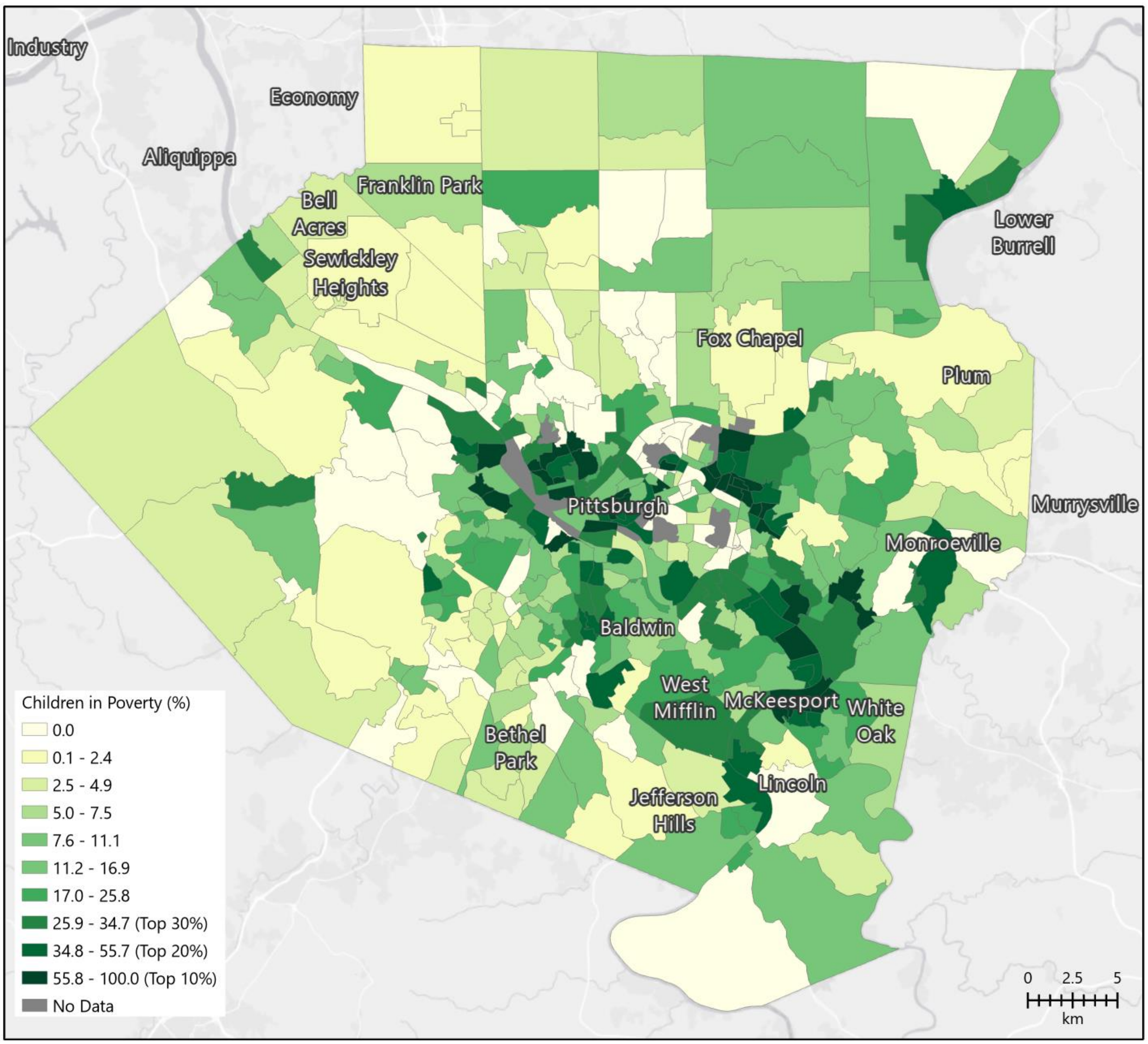
Population Density, People Under Age 18



POVERTY STATUS

Indicator	The percent of children under age 18 who live below the federal poverty level
Data Source	U.S. Census Bureau 2015-2019 American Community Survey 5-Year Estimates, Table S1701 "Poverty Status In The Past 12 Months" Poverty status is determined for the entire population except for institutionalized people, people in military group quarters, people in college dormitories, and unrelated individuals under 15 years old (foster children).
Method	This data required no pre-CEHI manipulation.

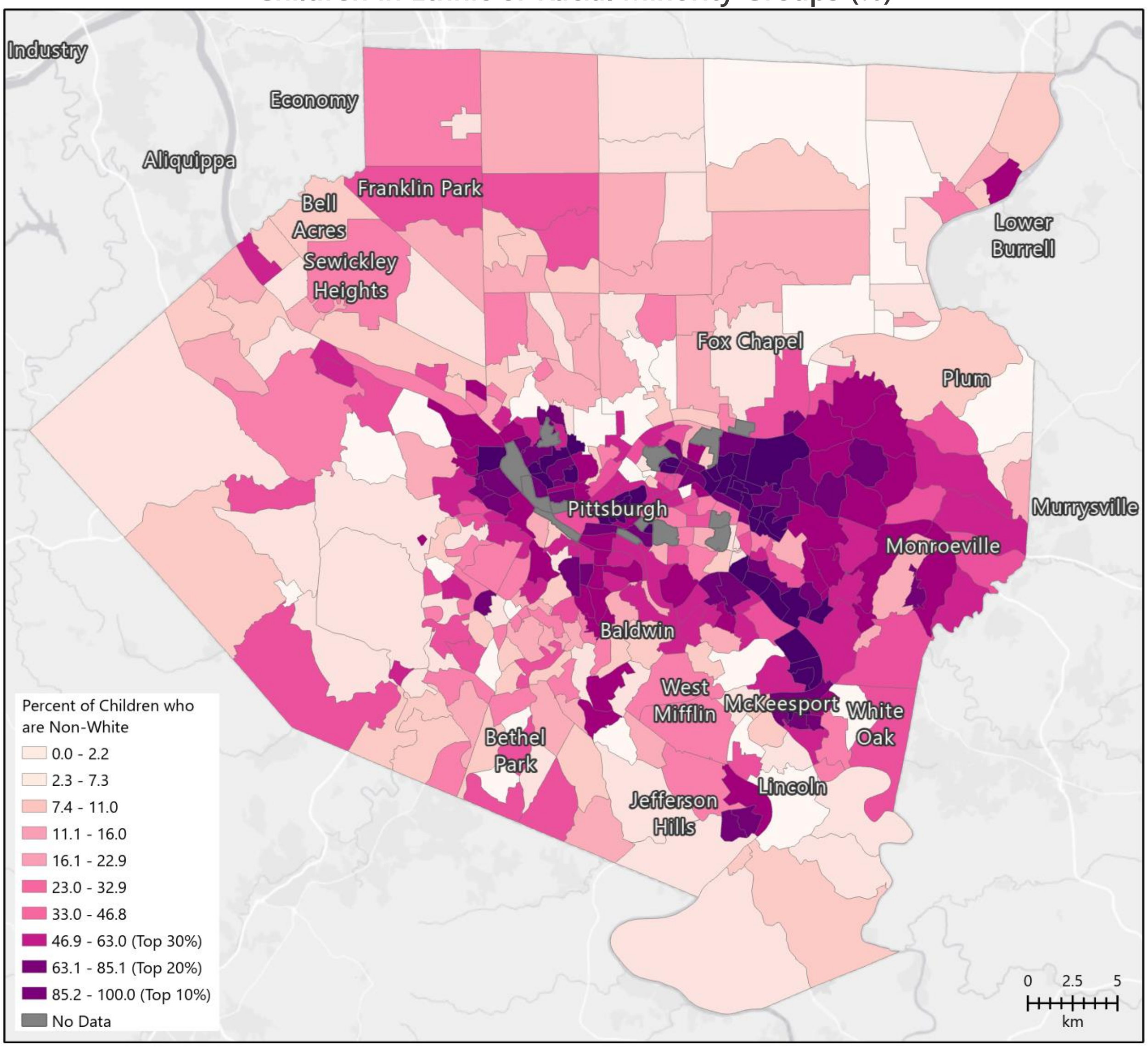
Percent of Children Living Below the Federal Poverty Level (%)



MINORITY STATUS

Indicator	Percent of children (population under age 18) who are not categorized as "White Alone"
Data Source	U.S. Census Bureau 2015-2019 American Community Survey 5-Year Estimates, Table B01001A "Sex By Age (White Alone)"
Method	Data preparation entailed calculating the proportion of non-Hispanic White children and subtracting the value from 1 to produce the minority population proportion.

Children in Ethnic or Racial Minority Groups (%)

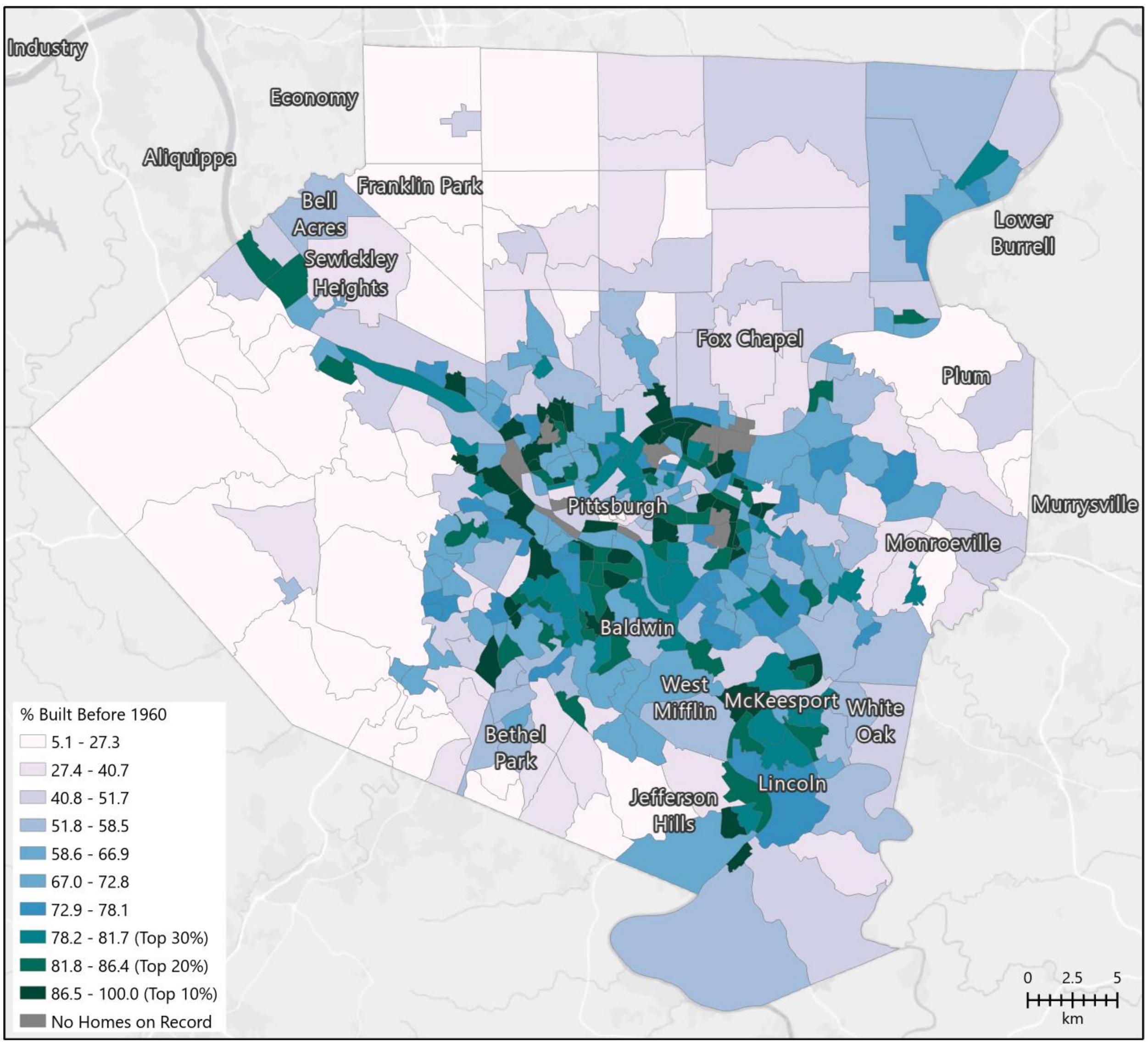


LEAD-BASED PAINT

In Allegheny County, 61.5% of homes were built before 1960. As of 2018, the ACHD requires a blood lead level test for infants aged 9-12 months, and a second test at 24 months. The county provides free screening to under- or uninsured children. In 2019, 1.8% of children tested in Allegheny County had blood lead levels (BLLs) above 5µg/dL[113].

Indicator	Percent of homes built before 1960
Data Source	U.S. Census Bureau's American Community Survey 2015-2019 Five-Year Estimates, Table DP04 "Selected Housing Characteristics"
Method	Data preparation entailed calculating the % of homes built before 1960.

Percent of Houses Built Before 1960

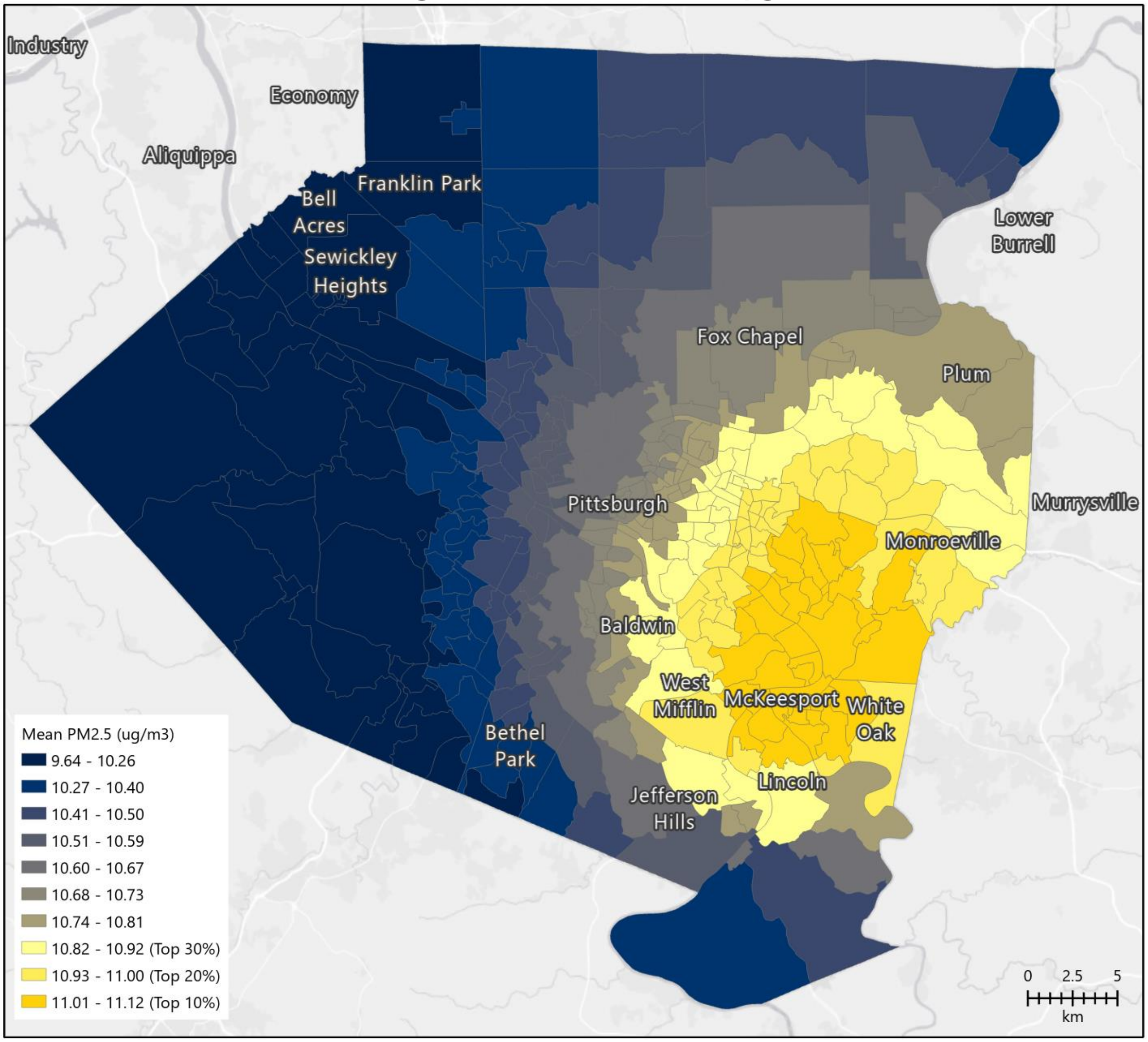


$PM_{2.5}$

The American Lung Association's annual "State of the Air" report examines levels of ozone, short-term $PM_{2.5}$, and long-term $PM_{2.5}$ over a three-year period for counties and metro areas, and then issues report cards for each. Allegheny County received a failing grade for all three metrics, and the Pittsburgh-New Castle-Weirton metro area was ranked 9th out of 199 metro areas in the nation for worst annual $PM_{2.5}$. The recorded levels of O_3 and $PM_{2.5}$ in the region have improved, but the risk of exposure is still higher than most places in the U.S[114].

Indicator	Annual Average $PM_{2.5}$ concentration in micrograms per cubic meter (µg/m^3)
NAAQS	12.0 µg/m^3 (annual mean, averaged over 3 years)
Data Source	U.S. EPA EJSCREEN 2020; $PM_{2.5}$ concentrations are based on monitoring and modeling estimates from 2017[115].
Method	The $PM_{2.5}$ data required no pre-CEHI manipulation.

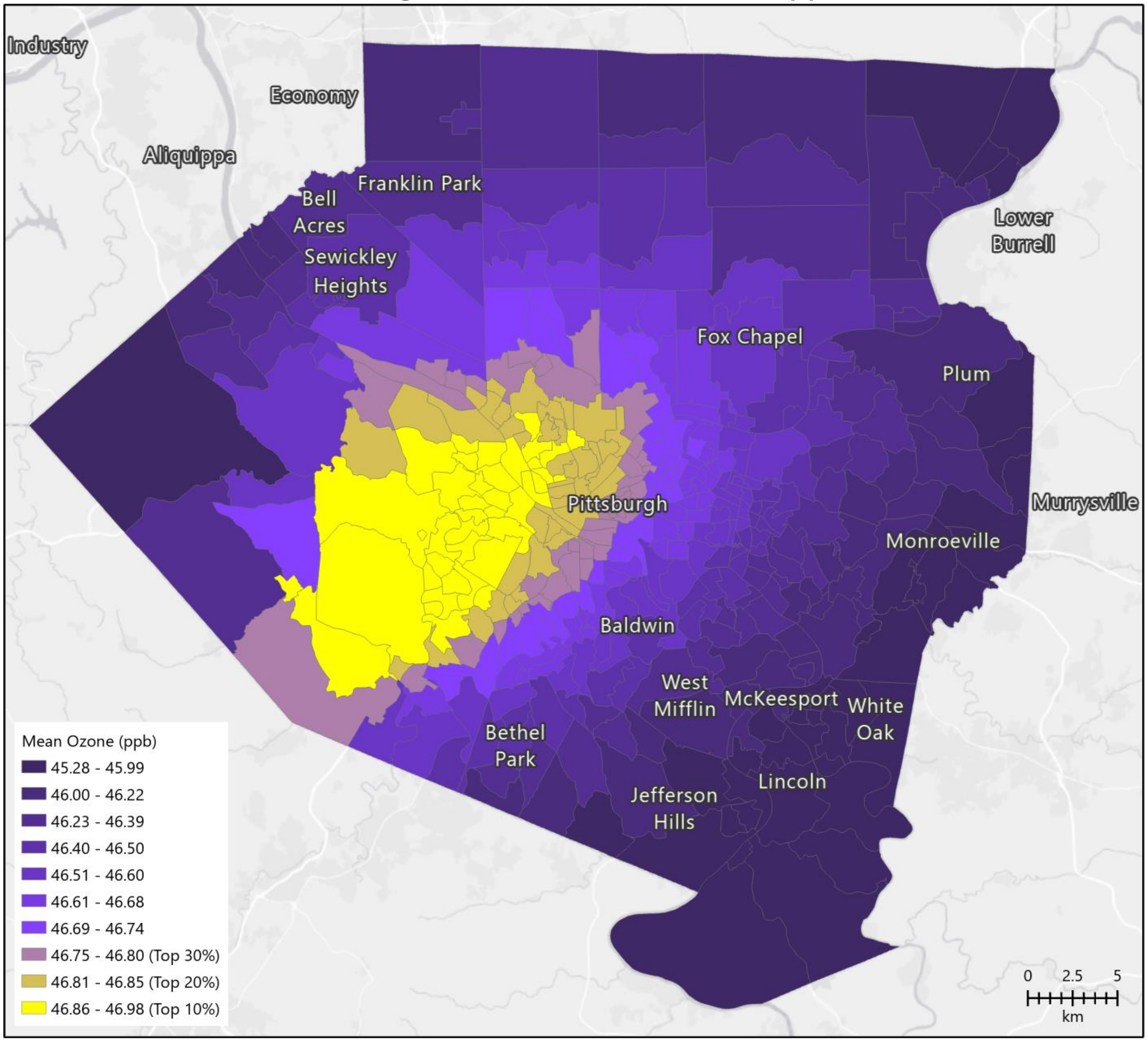
Annual Average $PM_{2.5}$ Concentration ($\mu g/m^3$), 2017



OZONE

Indicator	The May–September average of daily-maximum 8-hour-average ozone concentrations, in parts per billion (ppb).
NAAQS	0.070 ppm (annual fourth-highest daily max 8-hour concentration averaged over 3 years)
Data Source	U.S. EPA EJSCREEN 2020; O_3 concentrations are based on monitoring and modeling estimates from 2017[115].
Method	The Ozone data required no pre-CEHI manipulation.

8-hour Average Concentrations of Ozone (ppb), 2017



TOXIC AIR RELEASES ❖

Indicator	Toxicity-weighted concentration* of all TRI air releases, µg/m^3, 2017-2019 **Concentration of chemical multiplied by its inhalation toxicity weight (reference concentration (RfC) or inhalation unit risk (IUR)), summed over all chemicals impacting each 810mx810m cell.*
Data Source	U.S. EPA's Risk-Screening Environmental Indicators for 2017-2019 Aggregated Geographic Microdata

Method

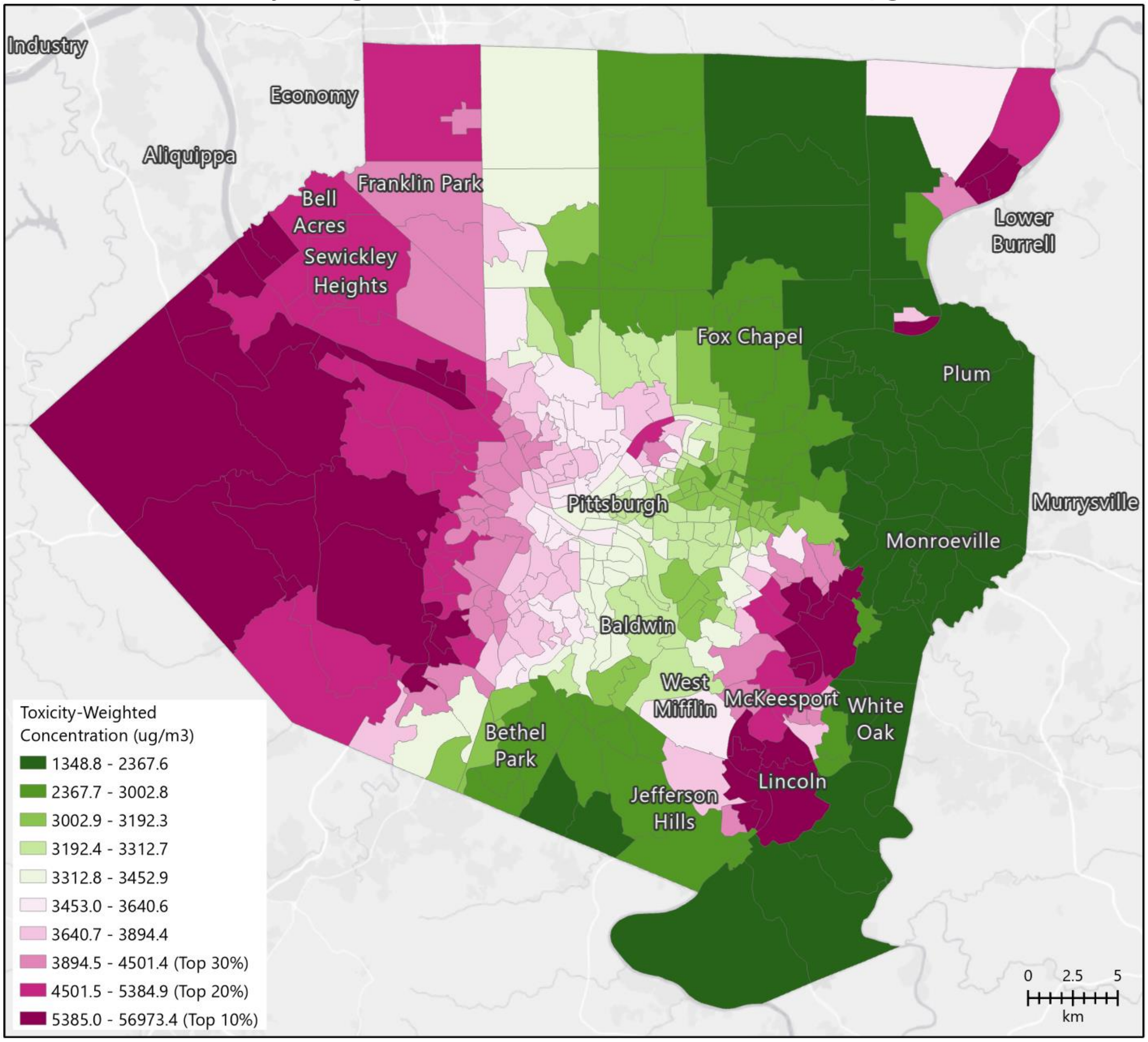
RSEI results are derived from TRI-reporting industrial point-sources. Air releases are classified as "stack" (point-source) or "fugitive" (areal). Chemical concentrations in the air are modeled up to 49km away from each facility. They are modeled using a steady-state Gaussian plume model that estimates chemical concentrations downwind of the source. When available, the model incorporates facility-specific details like stack height, diameter, and exit-gas velocity. Meteorologic data is a key component of the model[53].

The RSEI geographic microdata (RSEI-GM) enables mapping of TRI air releases, including concentrations, toxicity-weighted concentrations, and RSEI Scores. The data is stored in an 810m x 810m grid that covers the U.S.

The RSEI-GM were translated from grids to census tracts in ArcGIS Pro using polygon apportionment. Once the grid has been converted to census tracts, the most viable metric is the TWC ($\mu g/m^3$) of all TRI chemicals in the air. The toxicity-weighted concentration (TWC) reflects the industrial air toxics burden in an area, irrespective of population. While population size and density are important, they are accounted for in other indicators.

The most notable limitation for Allegheny County is that the model assumes flat terrain[53]. As previously discussed, the area's geography contributes to the severity of its air pollution.

Toxicity-Weighted Concentration of TRI Emissions (µg/m^3)

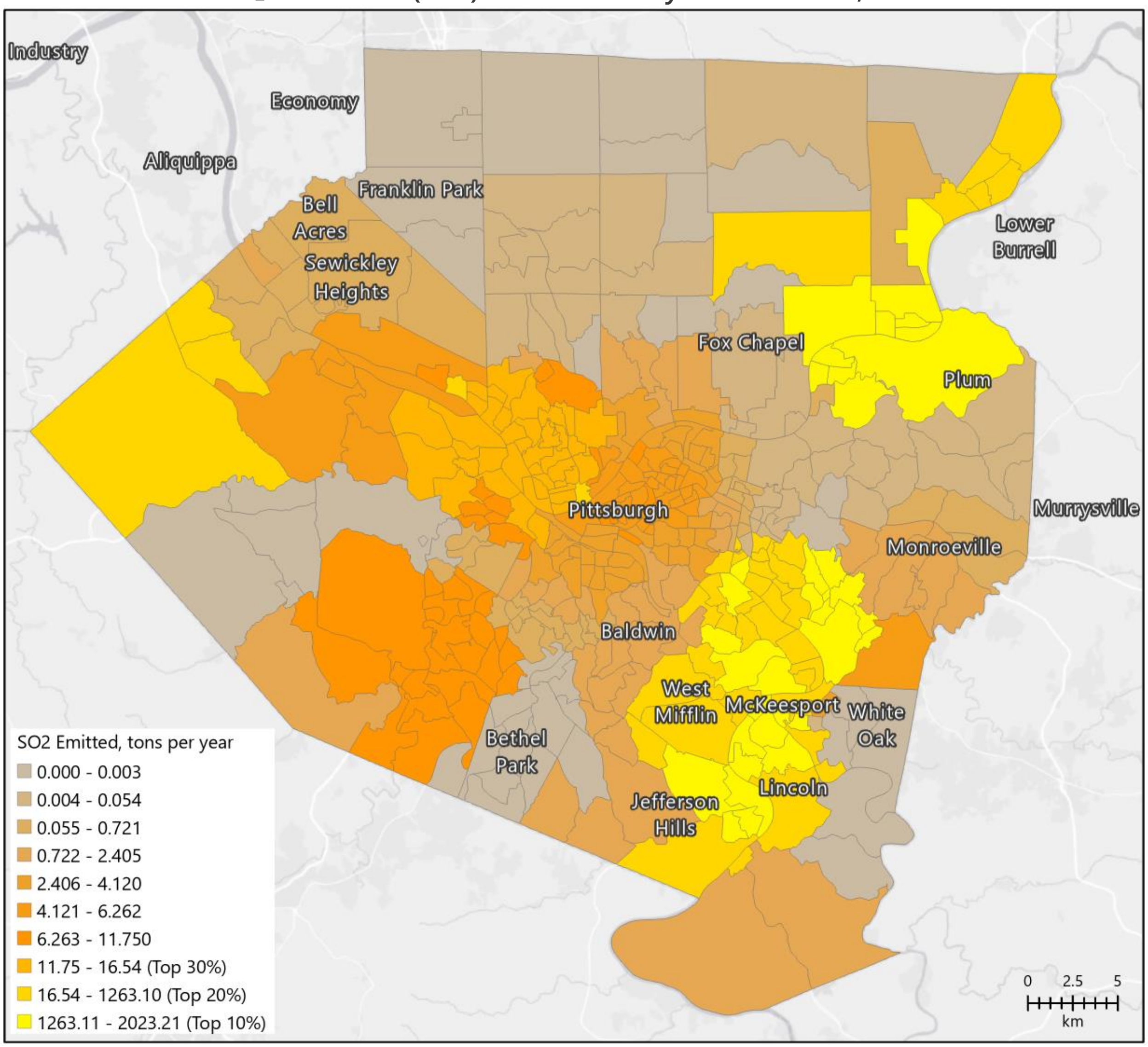


SULFUR DIOXIDE ❖

Indicator	Tons of SO_2 emitted within a 5-mile radius of a tract's population center, 2017
NAAQS	75 ppb (99th percentile of 1-hour daily maximum concentrations, averaged over 3 years)
Data Source	Point-source facilities from the 2017 National Emissions Inventory (NEI), U.S. EPA Office of Air Quality Planning and Standards (OAQPS). The NEI is assembled from several data sources, with priority given to

	state/local/tribal emissions data. Gaps are filled in by EPA data sources like the Toxic Release Inventory.
Method	Five-kilometer buffers were generated around the population-weighted centroid of each census tract. The buffer distance was selected based on observations of point-source SO_2 dispersion and concentrations[103]. All point-sources that fell within a buffer were summarized, yielding the total tons of SO_2 emitted within a 5-mile radius of the population center of the tract.

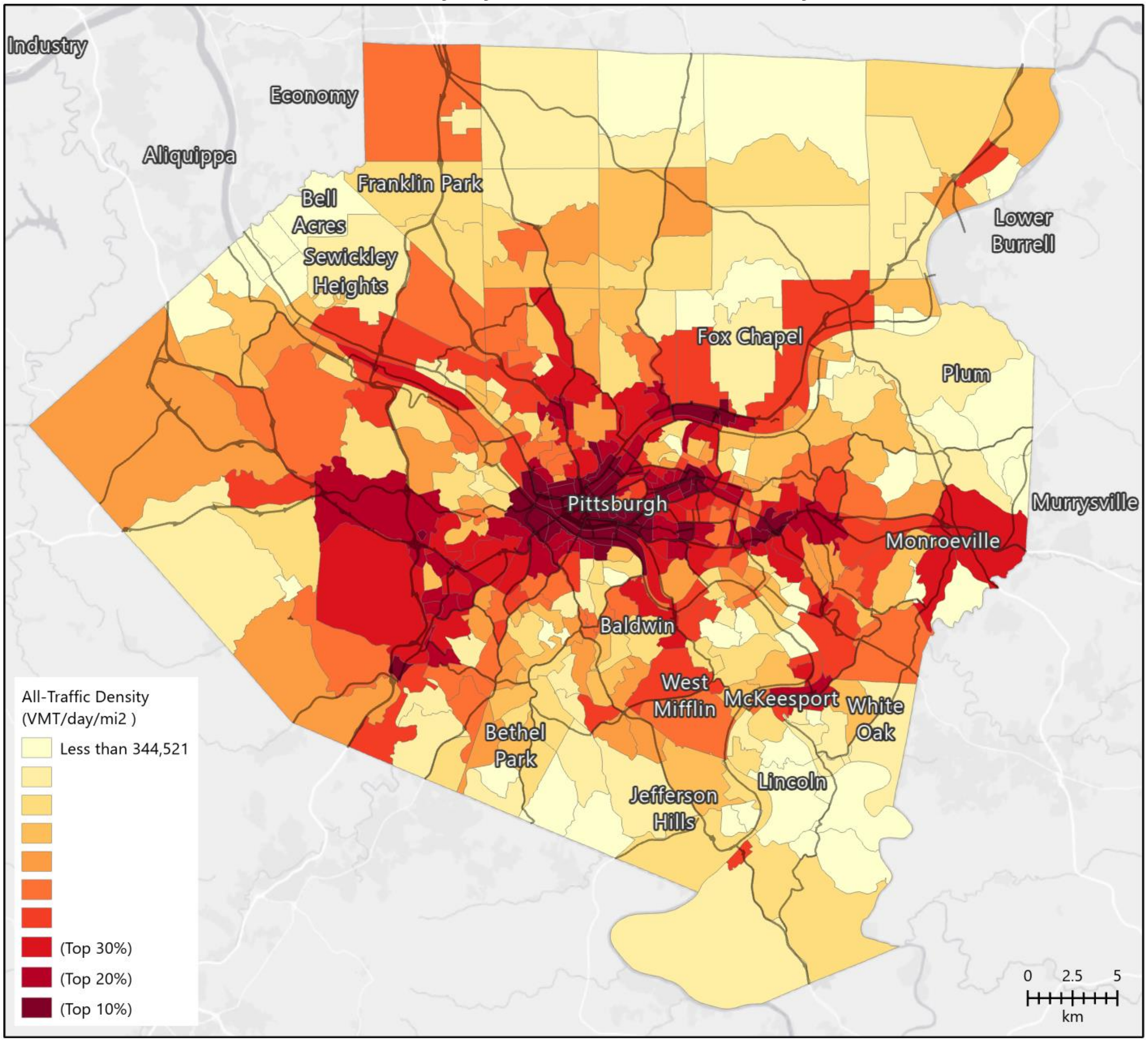
SO_2 Emissions (TPY) within 5km by Census Tract, 2017



TRAFFIC-RELATED AIR POLLUTION

Indicator	Census tract traffic density: vehicle miles traveled per day per square mile (VMT/day/mi^2)
Data Source	Pennsylvania Department of Transportation (PennDOT)
Method	Results from Karner, et al. and the WHO provided justification for a 500-meter buffer around census tracts to account for the edge-of-road dispersion of TRAP[108,111]. Traffic density was calculated using methods discussed by Liu, et al.[116]: $$\text{Traffic Density (TD)} = \sum(L \times AADT) / A_B$$ Where L is the summed length of roads within the tract, AADT is the summed annual average daily traffic for those roads, and A_B is the area of the buffered tract. TD is expressed as vehicle miles traveled per day per square mile (VMT/day/mi^2). Traffic density within the buffered census tract was selected as the traffic-related metric because it is straightforward and easy to calculate. It does not consider population or its distribution.

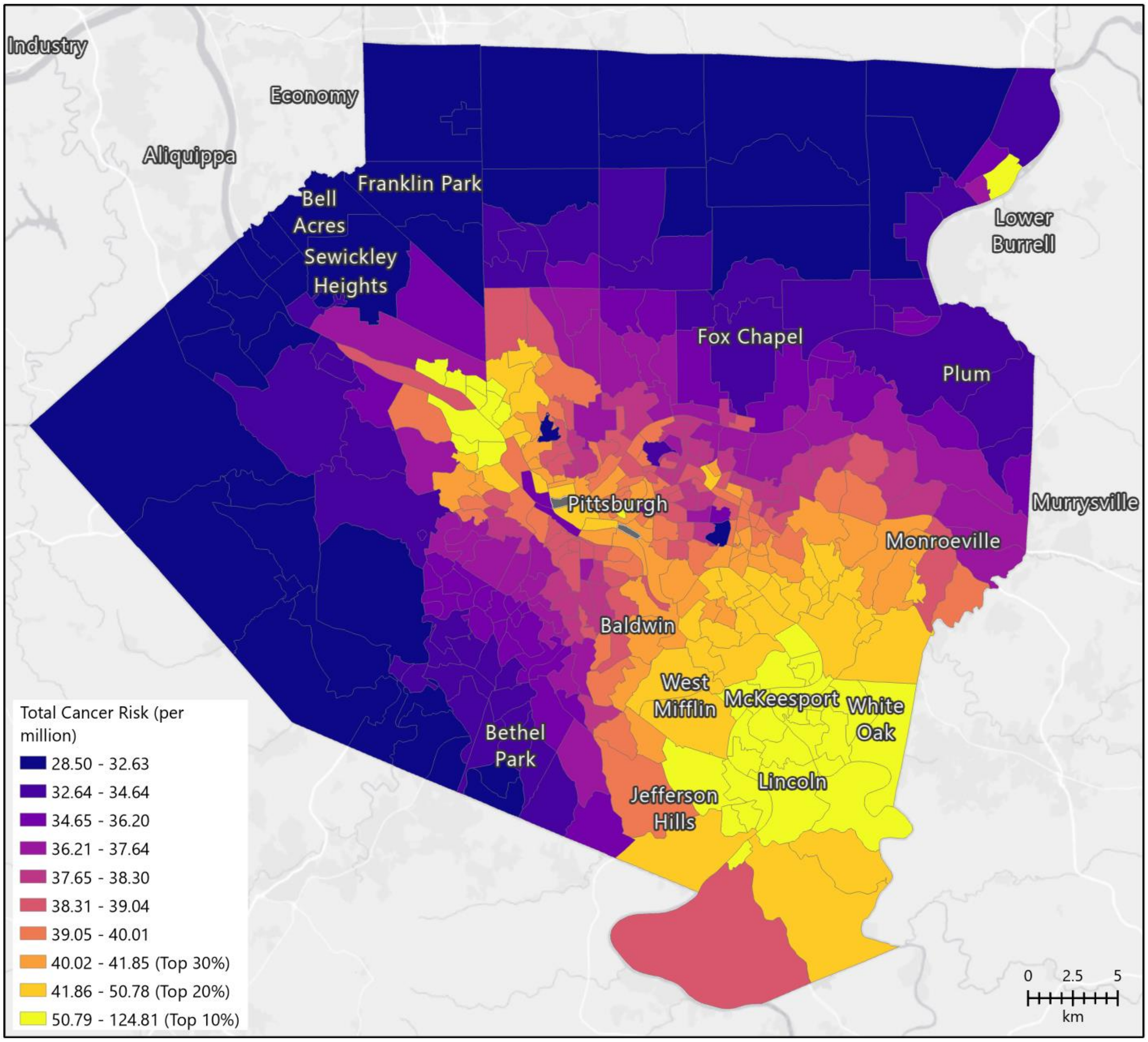
Traffic Density by Census Tract (VMT/day/mi^2)



NATA CANCER RISK

Indicator	Lifetime cancer risk on an "in a million" basis due to outdoor air toxics
Data Source	U.S. EPA's 2014 National Air Toxics Assessment (NATA)
Method	The NATA data required no pre-CEHI manipulation. Details on the modeling used to determine NATA values can be found in the 2014 NATA Technical Documentation[52].

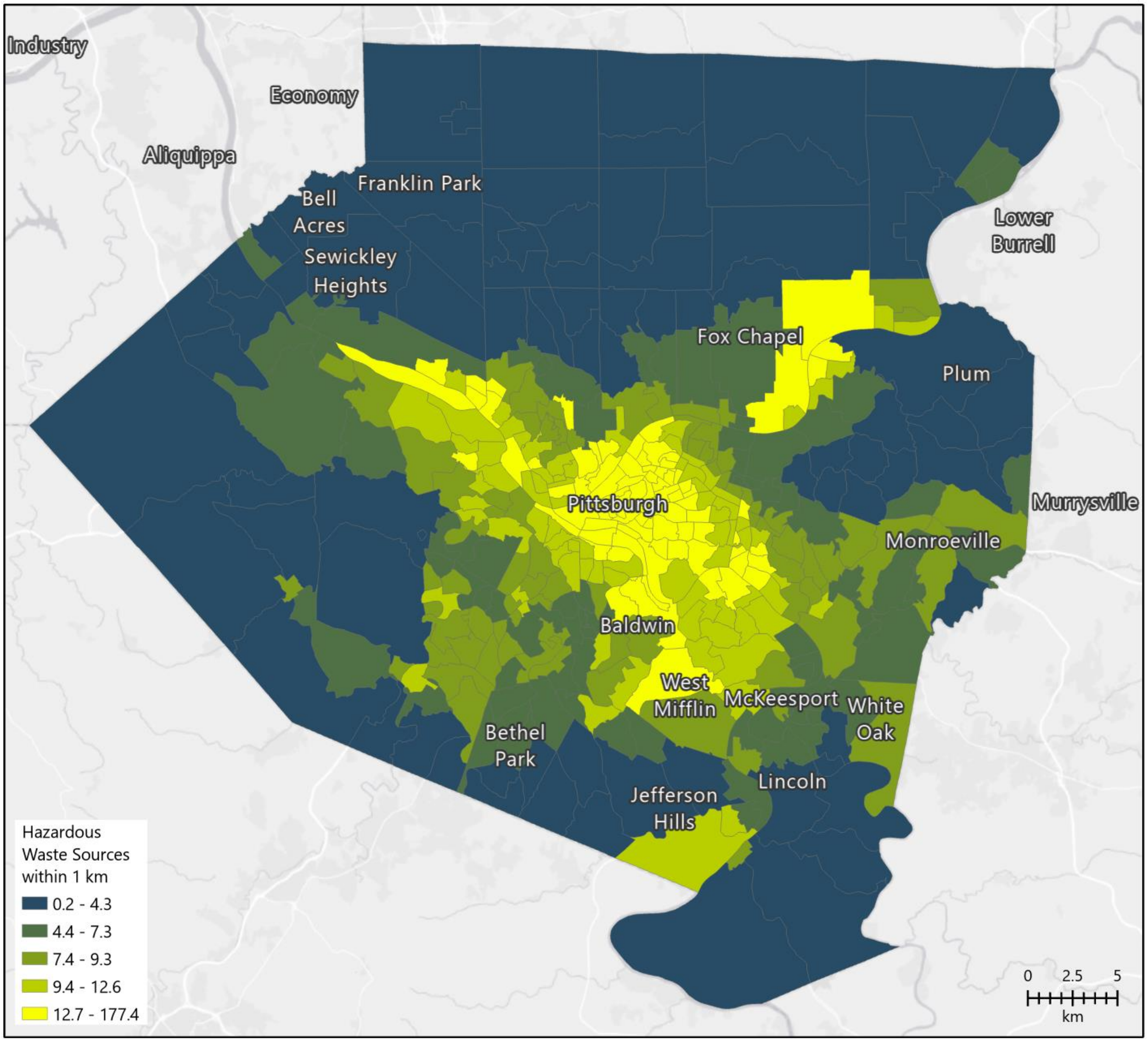
Lifetime Cancer Risk (in a million) due to Air Toxics, 2014



HAZARDOUS WASTE

Indicator	Number of hazardous waste sources within 1 km of the average tract resident
Data Source	PA Department of Environmental Protection: Captive Hazardous Waste Operation (`SUB_FACI_2 <> 'HAZARDOUS GENERATOR CAPTIVE'`) U.S. EPA: Superfund sites, RCRA LQG, RCRA TSD, Leaking USTs
Method	This employed the general Proximity methods outlined earlier.

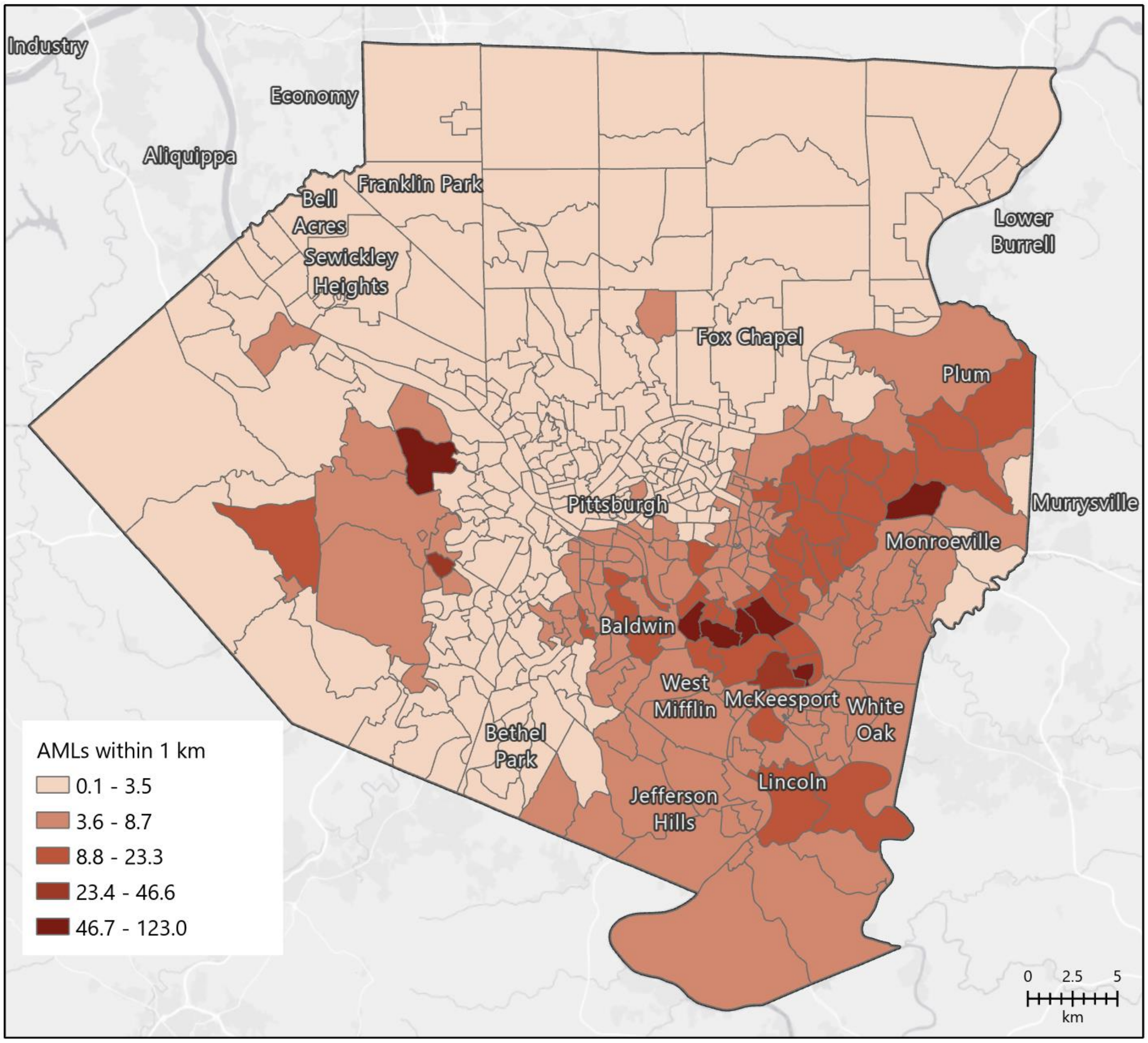
Number of Hazardous Waste Sources within 1 km of the Average Tract Resident



ABANDONED MINE LANDS ❖

Indicator	Number of AMLs within 1 km of the average tract resident
Data Source	PA Department of Environmental Protection, Abandoned Mine Lands polygons
Method	This employed the general Proximity methods outlined earlier.

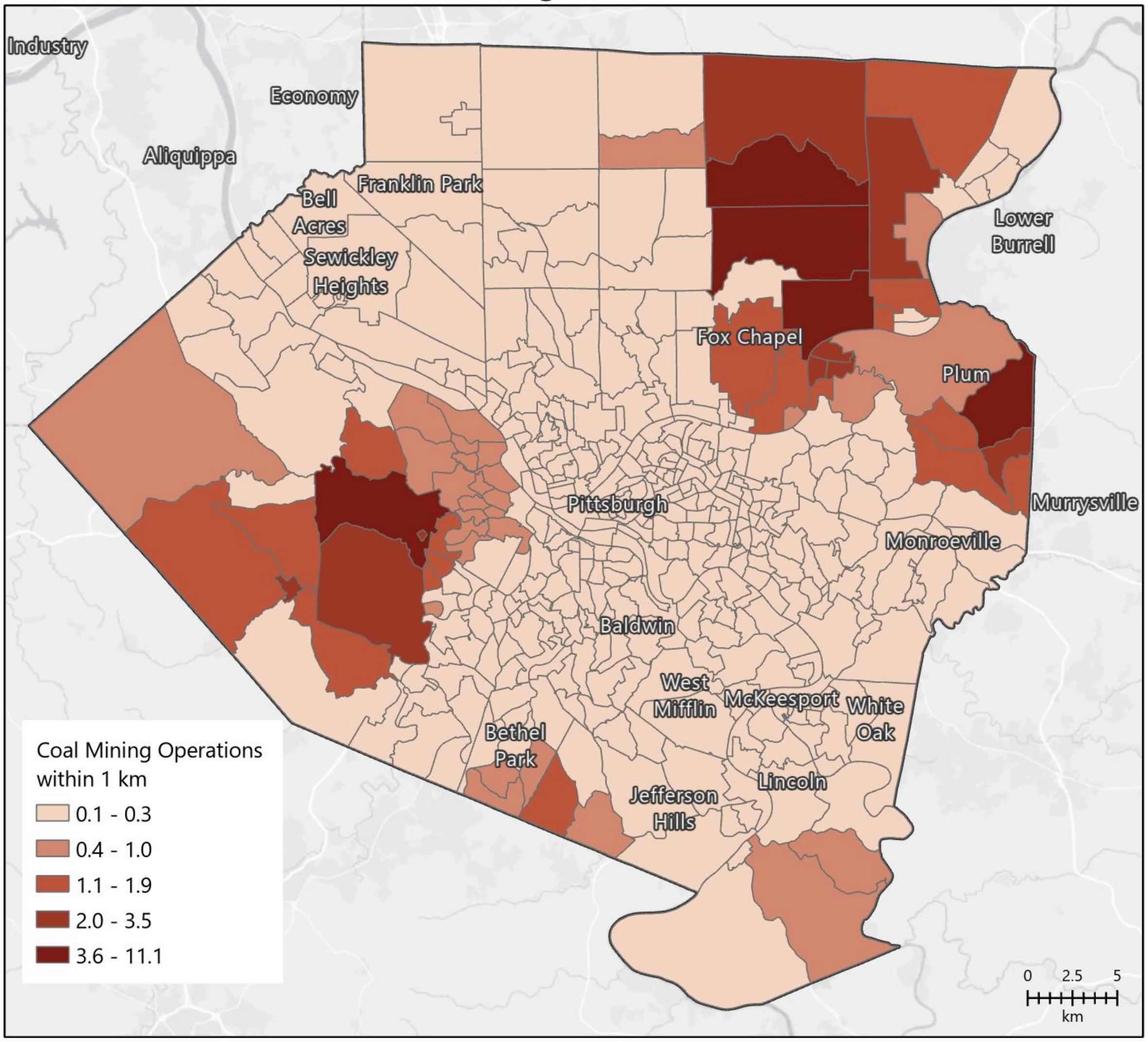
Number of Abandoned Mine Lands within 1 km
of the Average Tract Resident



COAL MINING OPERATIONS ❖

Indicator	Number of coal mining operations within 1 km of the average tract resident
Data Source	PA Department of Environmental Protection, Coal Mining Operations points
Method	This employed the general Proximity methods outlined earlier.

Number of Coal Mining Operations within 1 km of the Average Tract Resident



The Allegheny County CEHI

Of the 402 census tracts in Allegheny County, 394 had the population data needed to calculate CEHI scores with all 13 indicators. A summary of CEHI statistics is provided in Table 4.

***Table 4**: Summary of CEHI scores and disparities*

CEHI Summary Statistics			CEHI Disparities and Inequalities	
Mean	0.079		**Selected Proportion (Extreme Areas)**	0.200
Standard Deviation	0.035		**10th percentile**	0.036
Minimum	0.017		**90th percentile**	0.127
10th Percentile	0.036		**Mean CEHI for bottom extreme group**	0.030
Median	0.077		**Mean CEHI for top extreme group**	0.148
90th percentile	0.127			
Maximum	0.217			

In Figure 7, blue areas are the least adversely affected by the CEHI indicators. Red areas bear the highest burden.

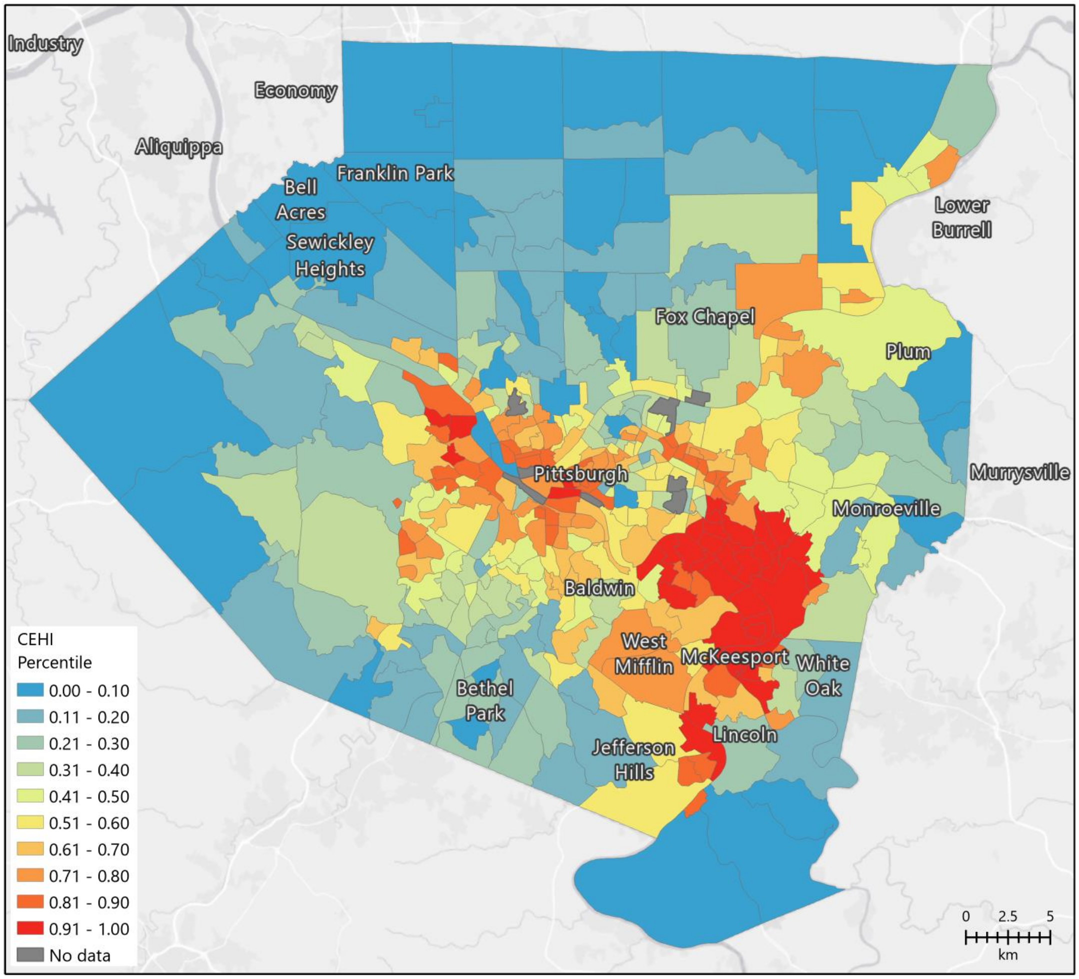


Figure 7*: The Allegheny County CEHI*

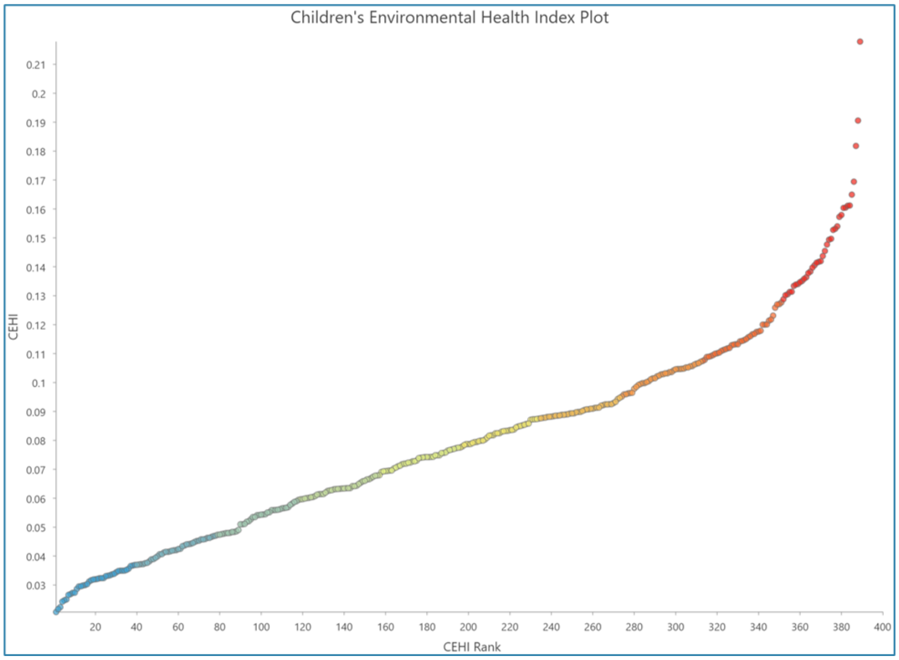


Figure 8*: Distribution of CEHI for 394 census tracts in Allegheny County.*

Figure 8 plots census tract CEHI ranks against values. The health disparities ratio is 4.896, indicating a high disparity between the top 10% (blue) and bottom 10% (red) of census tracts. The Disparity Slope, which is the slope of the middle 80% of the data, reflects the heterogeneity of the grouping. The Disparity Slope in Allegheny County is 0.081. The Health Disparities Difference is 0.118.

Variations on the CEHI

After the full 13-indicator CEHI was calculated, several variations were explored. The variations and their indicators are shown in Table 5.

Table 5*: CEHI Variations and Indicators*

	Full CEHI	**No Social Vulnerability**	**No Population**	**No Local Variables**	**Local Variables Only**	**Local Variables + SV**
Hazardous Waste	X	X	X	X		
Coal Mining	X	X	X		X	X
AMLs	X	X	X		X	X
SO_2 Emissions	X	X	X		X	X
Minority Children	X			X		X
Child Pop. Density	X	X		X	X	X
Pre-1960 Homes	X	X		X		
Children in Poverty	X			X		X
Traffic Density	X	X	X	X		

RSEI Industrial Emissions	X	X	X		X	X
Mean $PM_{2.5}$	X	X	X	X		
Mean Ozone	X	X	X	X		
Air Toxics Cancer Risk	X	X	X	X		

CEHI: Without Social Vulnerability Indicators

The second calculation of the CEHI omitted minority status and poverty status for a total of 11 indicators. Child population density and homes built before 1960 were included, so the number of census tracts was still limited to 394. A summary of CEHI statistics without social vulnerability indicators is provided in Table 6. A map of the results is shown in Figure 9.

Table 6*: Summary of CEHI scores and disparities without social vulnerability indicators*

CEHI Summary Statistics			CEHI Disparities and Inequalities	
Mean	0.072		**Selected Proportion (Extreme Areas)**	0.200
Standard Deviation	0.027		**10th percentile**	0.038
Minimum	0.017		**90th percentile**	0.112
10th Percentile	0.038		**Mean CEHI for bottom extreme group**	0.030
Median	0.072		**Mean CEHI for top extreme group**	0.125
90th percentile	0.112			
Maximum	0.181			

The Health Disparities Ratio decreased to 4.195. The Health Disparities Difference was 0.095, and the slope was 0.057.

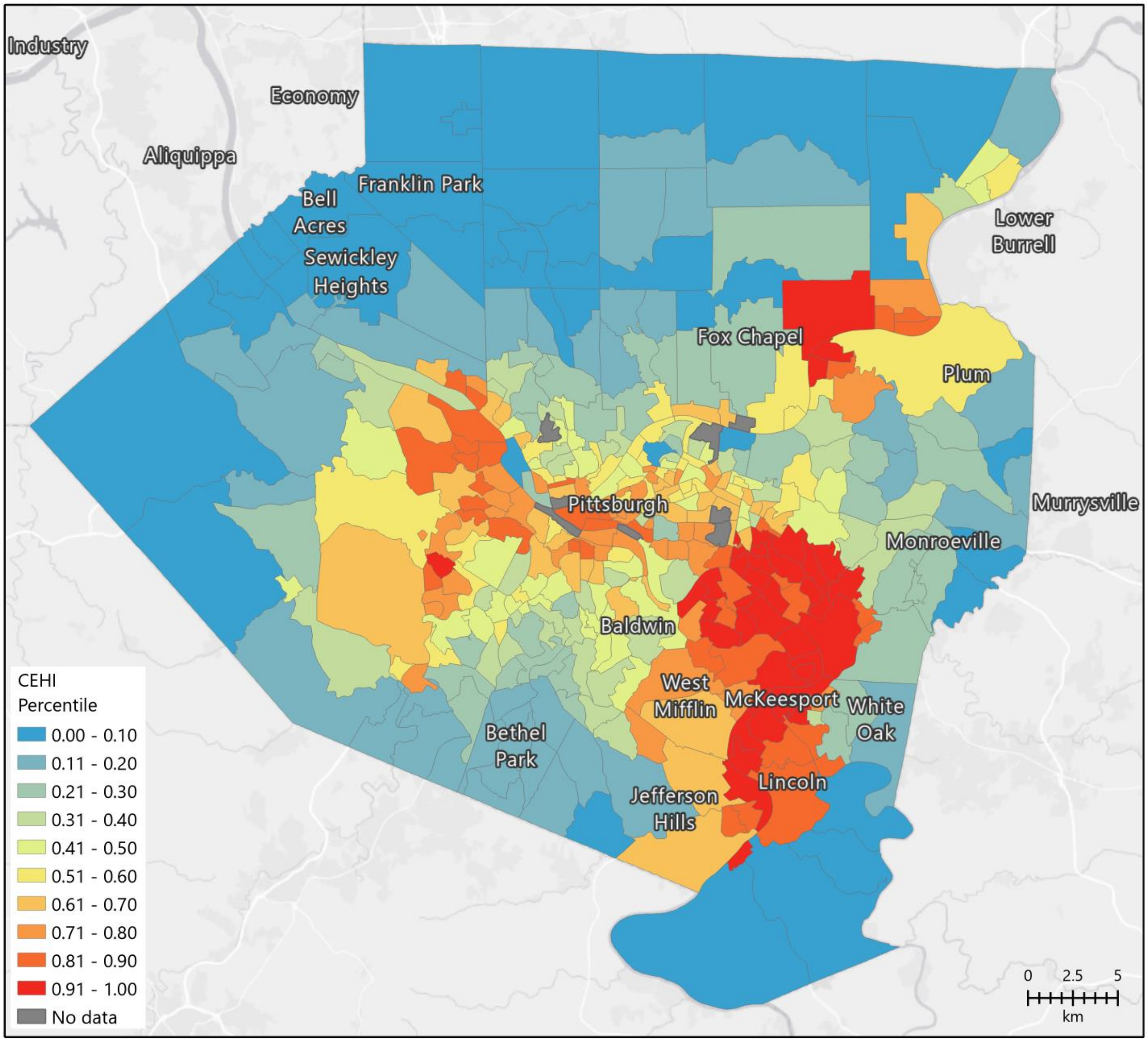


***Figure 9**: The Allegheny County CEHI without social vulnerability indicators*

CEHI: Without Population Indicators

The third calculation omitted the population indicators sourced from the Census Bureau: minority status, poverty status, and child population density, for a total of 10 indicators. The percent of houses built before 1960 was changed from <null> to zero in the eight tracts with no population so it could be included. This expanded the analysis to all 402 census tracts. A summary of CEHI statistics without population indicators is provided in Table 7. A map of the results is shown in Figure 10.

***Table 7**: Summary of CEHI scores and disparities without population indicators*

CEHI Summary Statistics			CEHI Disparities and Inequalities	
Mean	0.066		**Selected Proportion (Extreme Areas)**	0.200

Standard Deviation	0.026	**10th percentile**	0.035
Minimum	0.017	**90th percentile**	0.106
10th Percentile	0.035	**Mean CEHI for bottom extreme group**	0.028
Median	0.064	**Mean CEHI for top extreme group**	0.121
90th percentile	0.106		
Maximum	0.166		

The Health Disparities Ratio decreased to 4.245. The Health Disparities Difference was 0.092, and the slope was 0.057.

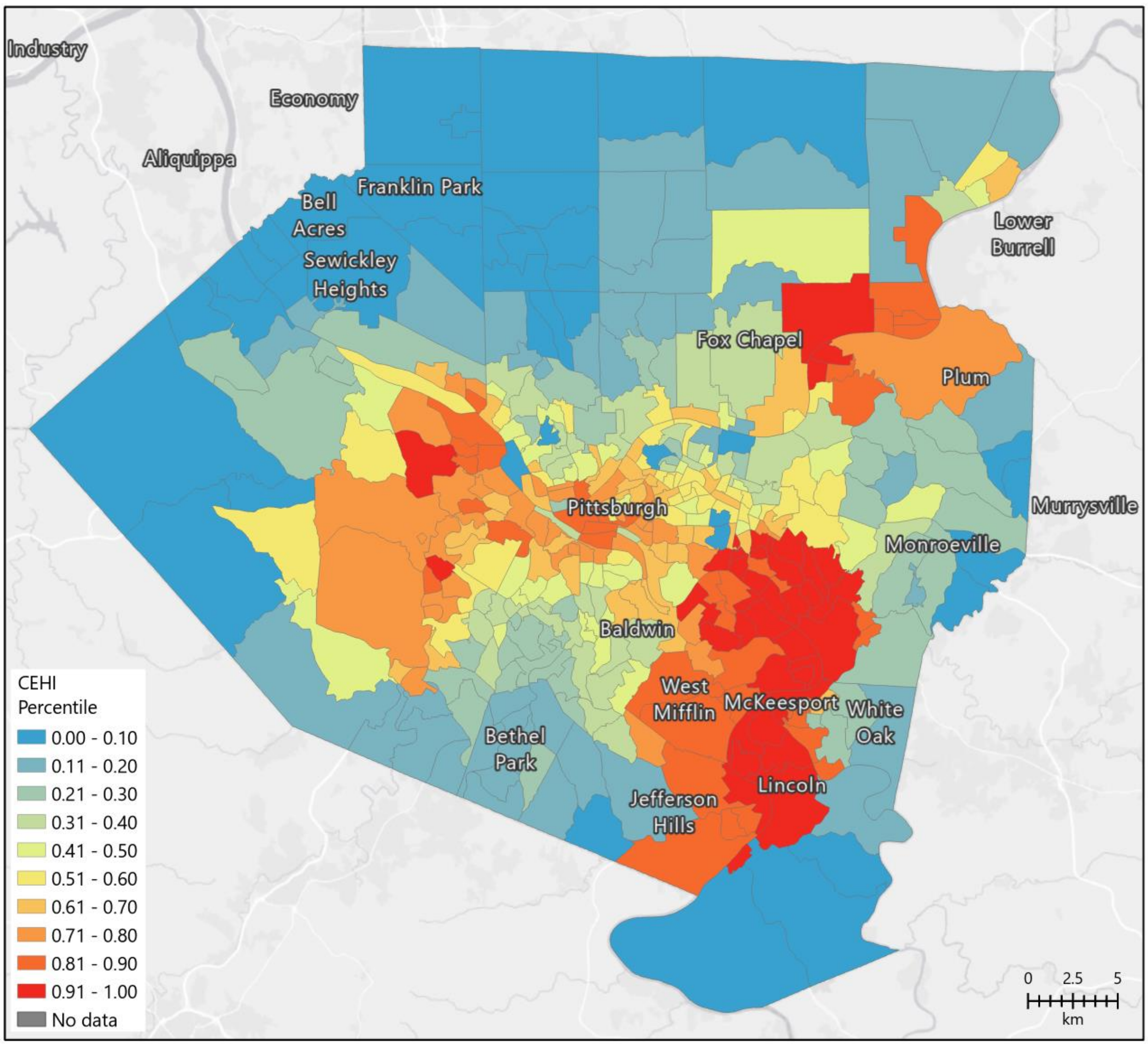


Figure 10: *The Allegheny County CEHI without population indicators*

CEHI: Without Local Indicators

The fourth calculation omitted the indicators chosen to reflect Allegheny County: coal mine proximity, AML proximity, SO_2 emissions, and RSEI industrial emissions. 394 of 402 tracts were included. A summary of CEHI statistics without local indicators is provided in Table 8. A map of the results is shown in Figure 11.

***Table 8**: Summary of CEHI scores and disparities without local indicators*

CEHI Summary Statistics			CEHI Disparities and Inequalities	
Mean	0.167		**Selected Proportion (Extreme Areas)**	0.200
Standard Deviation	0.082		**10th percentile**	0.065
Minimum	0.022		**90th percentile**	0.283
10th Percentile	0.065		**Mean CEHI for bottom extreme group**	0.049
Median	0.156		**Mean CEHI for top extreme group**	0.319
90th percentile	0.283			
Maximum	0.435			

The Health Disparities Ratio increased to 6.56. The Health Disparities Difference was 0.270, and the slope was 0.205.

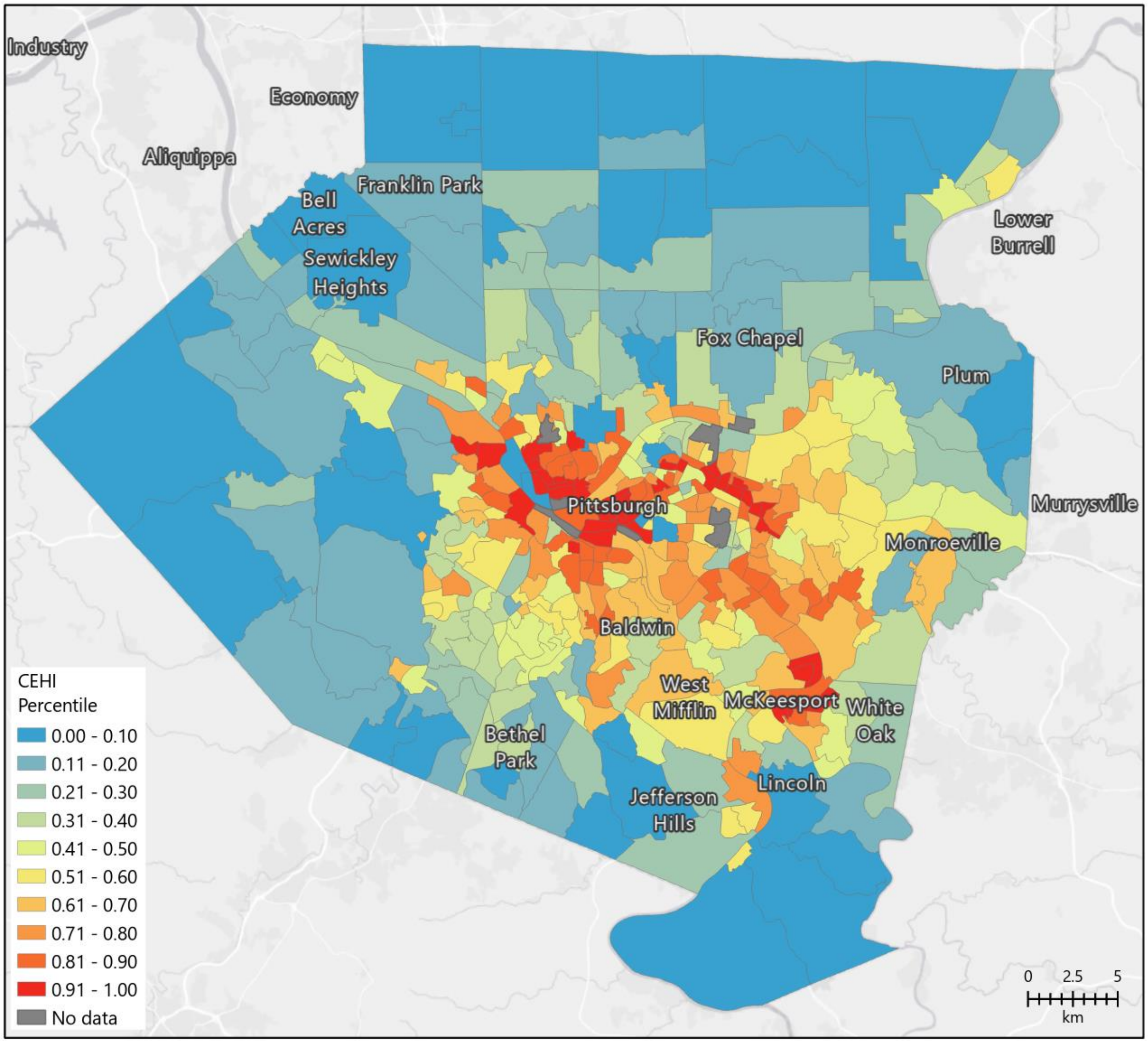


Figure 11*: The Allegheny County CEHI without local indicators*

CEHI: Local Indicators Only

The fifth calculation only included the child population density as well as the indicators chosen to reflect Allegheny County: coal mine proximity, AML proximity, SO_2 emissions, and RSEI industrial emissions. Omitting the more general indicators will highlight areas that are uniquely impacted by local environmental health concerns. 394 of 402 tracts were included. A summary of CEHI statistics with local indicators only is provided in Table 9. A map of the results is shown in Figure 12.

Table 9*: Summary of CEHI scores and disparities with local indicators only*

CEHI Summary Statistics			CEHI Disparities and Inequalities	
Mean	0.028		**Selected Proportion (Extreme Areas)**	0.200

Standard Deviation	0.020	**10th percentile**	0.011
Minimum	0.005	**90th percentile**	0.062
10th Percentile	0.011	**Mean CEHI for bottom extreme group**	0.009
Median	0.021	**Mean CEHI for top extreme group**	0.076
90th percentile	0.062		
Maximum	0.133		

The Health Disparities Ratio increased to 8.233. The Health Disparities Difference was 0.067, and the slope was 0.034.

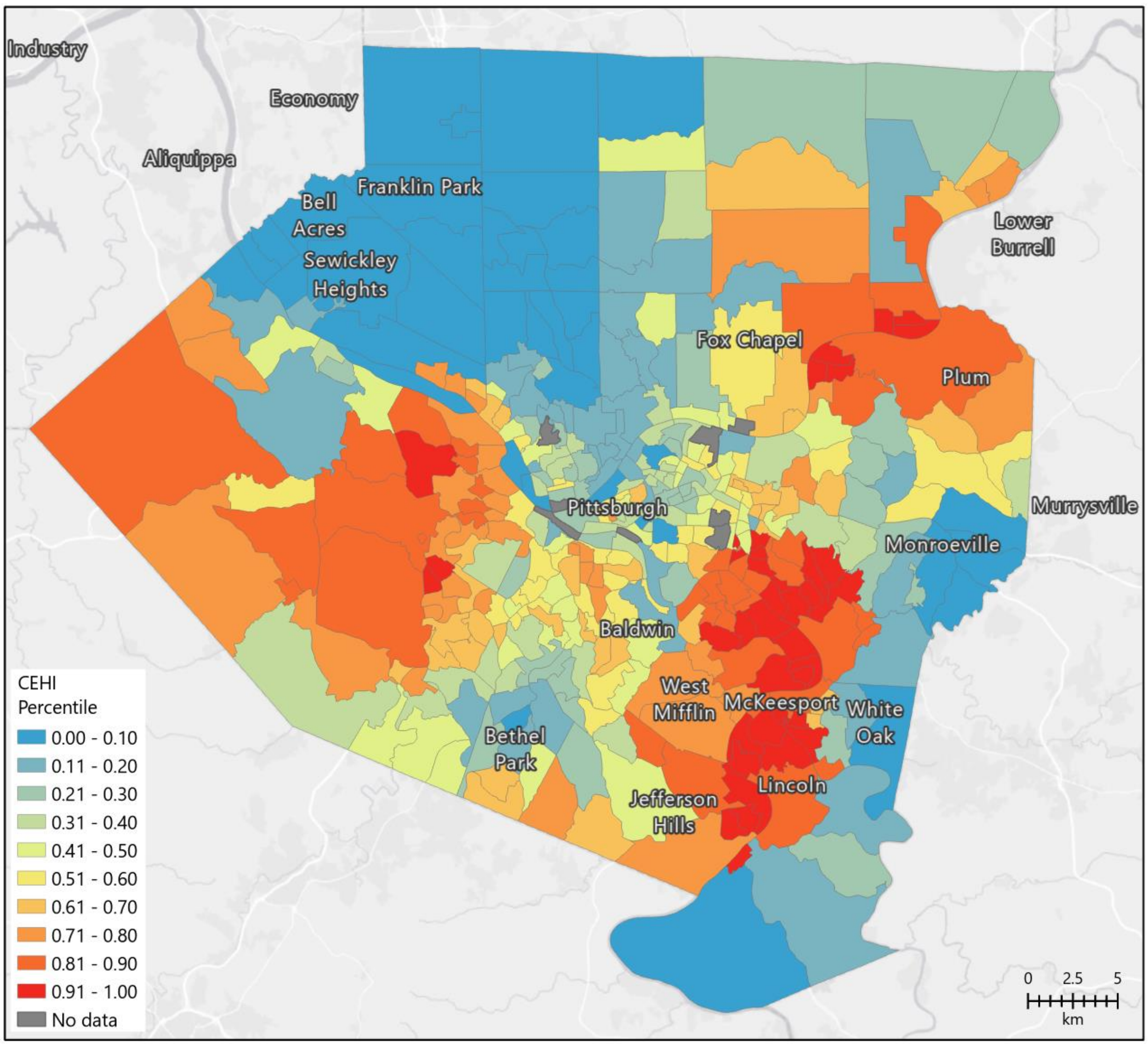


Figure 12: *The Allegheny County CEHI with local indicators only*

CEHI: Local Indicators and Social Vulnerability

The sixth variation included the local indicators, child population density, minority children, and children in poverty for a total of seven indicators. 394 of 402 tracts were included. A summary of CEHI statistics without local indicators and social vulnerability is provided in Table 10. A map of the results is shown in Figure 13.

***Table 10**: Summary of CEHI scores and disparities with local and social vulnerability indicators*

CEHI Summary Statistics			CEHI Disparities and Inequalities	
Mean	0.045		**Selected Proportion (Extreme Areas)**	0.200
Standard Deviation	0.031		**10th percentile**	0.016
Minimum	0.005		**90th percentile**	0.089
10th Percentile	0.016		**Mean CEHI for bottom extreme group**	0.011
Median	0.037		**Mean CEHI for top extreme group**	0.118
90th percentile	0.089			
Maximum	0.205			

The Health Disparities Ratio increased to 10.331. The Health Disparities Difference was 0.107, and the slope was 0.056.

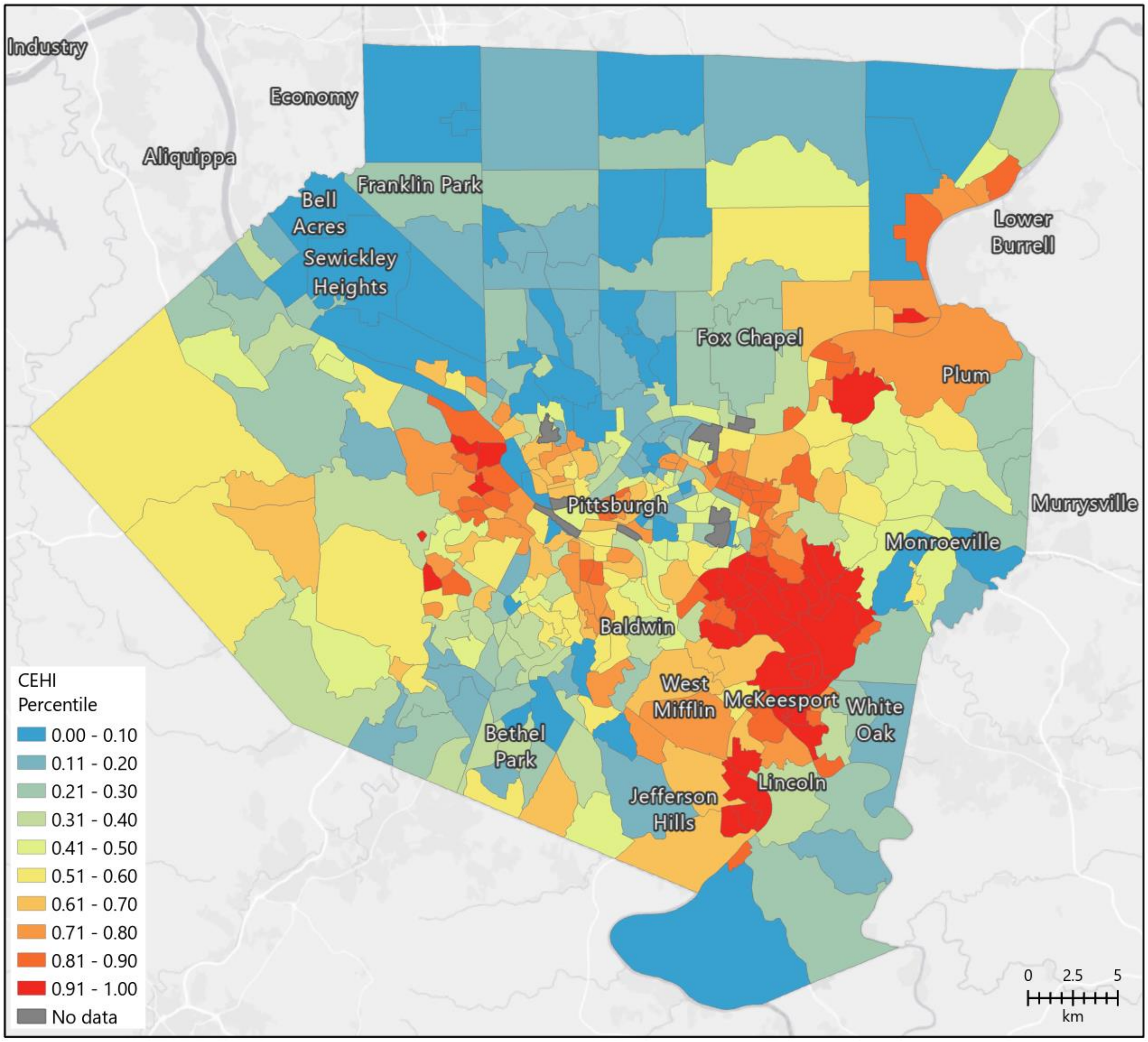


Figure 13*: The Allegheny County CEHI with local and social vulnerability indicators*

Web App Development

The CEHI is meant to be shared. Advances in online mapping software have made it easier than ever to translate findings to browser-based GIS web applications. The industry leader is Esri, which produces ArcGIS Online (AGOL). The AGOL web platform is integrated with their desktop applications ArcMap and ArcGIS Pro. This integration allows users to upload maps and layers to AGOL from their desktop, as well as access their web layers and thousands of others, many of which are released by reputable, verifiable sources[36].

A drawback of ArcMap and ArcGIS Pro is the considerable cost, computing power, and specialization required to use them to their full extent. Reduced-cost licenses are available for nonprofit organizations, small governments, and schools[117-119]. Free ArcGIS Online accounts are available to those who wish to create web applications using premade layers or GIS data from open-source software like QGIS. Free accounts do not have the full capabilities of the paid version, but users can still upload data, access verified premade layers, and create basic web applications.

The Allegheny County CEHI web app contains the layers outlined in Table 11. Ideally, the CEHI would be presented as a package containing links to a web map containing nationally available web layers that can be used in the app, imported into ArcGIS Pro, and downloaded as shapefiles for those using non-Esri software. To reduce barriers to app creation, a template of the app would also be available. Users will only have to add their own customizations.

Table 11*: Layers included in CEHI web application. Those in blue could be provided as out-of-the-box layers that are available nationwide.*

CEHI Index	NEI emitters, symbolized by SO_2
A layer for each indicator	EPA NAAQS nonattainment areas
Layers with basic demographics	PADEP hazardous waste sites
Roads with annual average daily traffic (AADT)	Leaking underground storage tanks
Schools & daycares	Mines
School districts	AMLs
Parks	Superfund sites
Airports	EPA Facility Registry Service (updated weekly)
Railroads	Air Quality Index (updated daily)
Public transit	Impaired waterways

The CEHI web app is a source of information – not opinion. Data should be presented clearly, without bias or commentary. The language should be easy to understand. Pop-ups within the map should be well-formatted and any graphs should be simple to interpret. An “About” button or splash page can provide the user with basic information on how to navigate the app, as well as link to the organization’s website and/or a user guide. These steps take time and effort, but they are essential to the web app’s success. **Figure 14** illustrates these concepts.

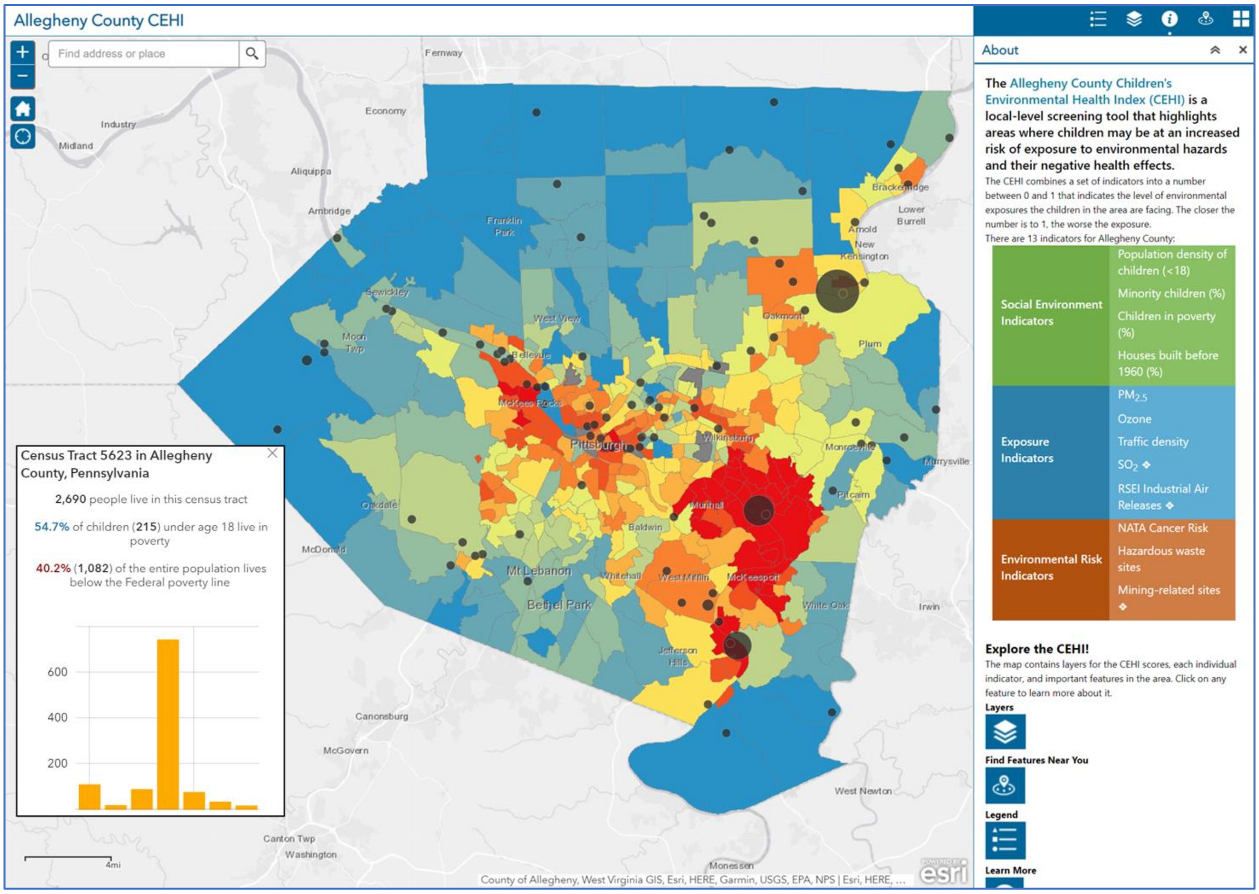


__Figure 14__: Basic user interface of the CEHI web app

Interactivity goes beyond clicking on features to see attribute information. Users can query the data and gain deeper perspective of local relationships. For example, a resident of the area can search their home address and find out if there are any Superfund sites within 3 miles of their house.

The app was designed with considerations of user experience,

RESULTS

Observations

The six variations of the Allegheny County CEHI illustrate the ways in which the various indicators influence the outcome. Spatial autocorrelation was assessed with Global Moran's I. All six CEHIs had statistically significant clustering ($p=0.000$); the weakest clustering was observed in CEHI D (no local indicators), while the strongest clustering was observed in CEHI C (no population indicators).

A visualization of the six CEHIs (Figure 15) shows clear differences. The most striking difference is seen between CEHI D and CEHI E – no local indicators versus only local indicators. The only indicator they have in common is child population density. CEHI E is limited to the indicators chosen specifically for Allegheny County (coal mine proximity, AML proximity, industrial air emissions, and SO_2 emissions). CEHI D contains the indicators that could be applied to most communities – all except the four in CEHI E. A side-by-side comparison of D and E suggests that the downtown Pittsburgh area is not heavily impacted by the environmental hazards specific to Allegheny County. Conversely, the areas most affected by local environmental exposures are outside the city center and extend to the periphery of the county. Taken separately, neither D nor E adequately capture the full spectrum of the environmental health threats that local children face.

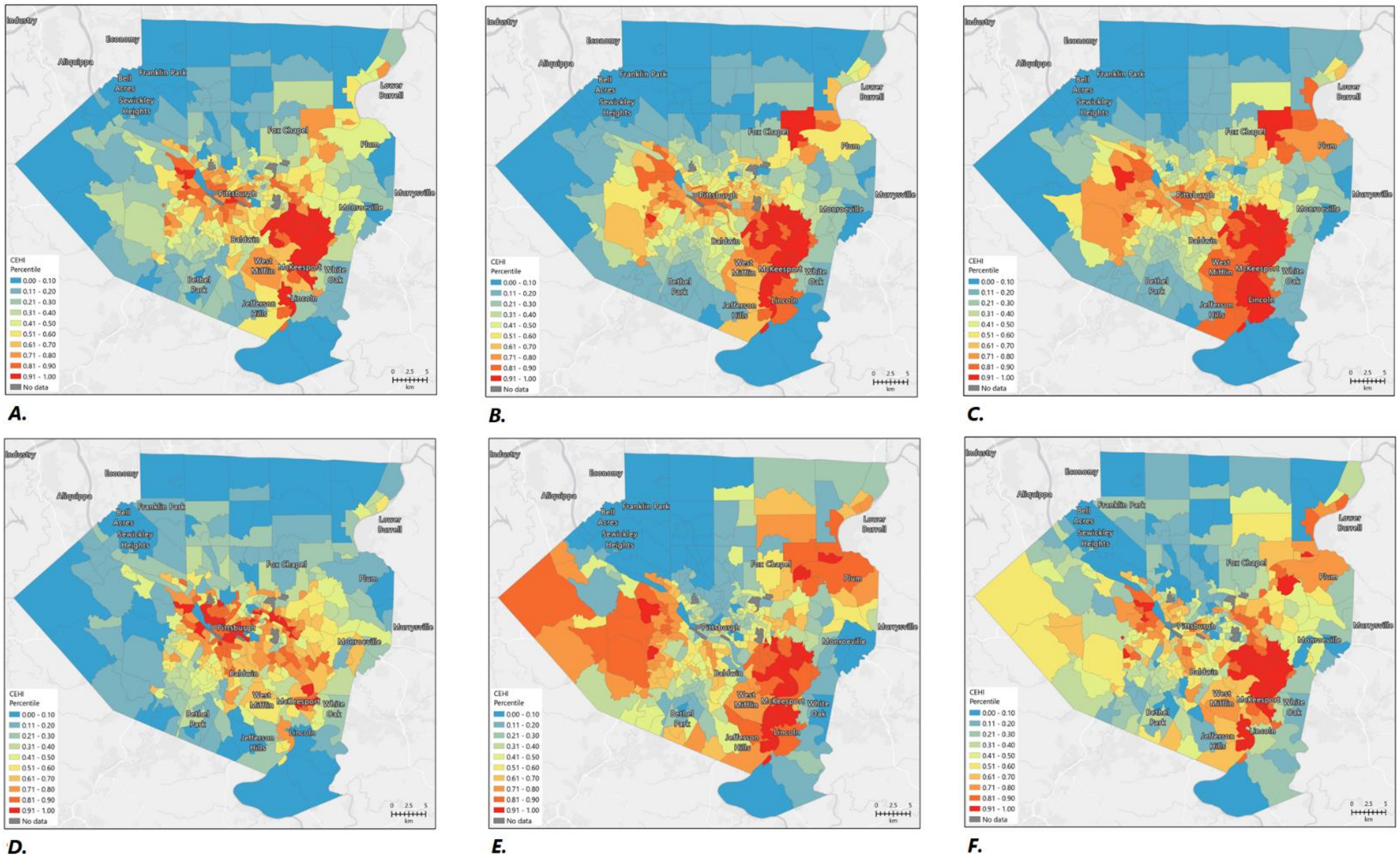


Figure 15*: Six versions of the CEHI and their Moran's Index scores (range -1.0 to +1.0): A. Full (I= 0.653), B. Without social vulnerability (I= 0.697), C. Without population (I= 0.706), D. Without local indicators (I= 0.603), E. With local indicators only (I=0.676), F. Local and social vulnerability indicators (I= 0.621)*

The area that consistently displays the highest index score – and therefore the worst environmental health conditions for children – is southeast of Pittsburgh in the Mon Valley. Nineteen of the twenty census tracts at the bottom of the CEHI rankings are in that area. A 2019 investigation by the Pittsburgh Post-Gazette found seven municipalities in Allegheny County where half of children live in poverty[120]. North Braddock, Rankin, Duquesne, McKeesport, and Clairton are directly on the Monongahela River; Mount Oliver and Wilmerding are less than 2 miles away. Six of the seven contain census tracts in the bottom 10% of CEHI scores. Four of the top ten TRI emitters in the county are located in these communities: U.S. Steel Clairton Coke Works, Thermal Transfer Corp., Holtec Manufacturing, and U.S. Steel Edgar Thomson Plant. Clairton Coke Works is the largest coke manufacturing facility in the U.S[121]. The facility is one of the most consistent violators of emissions standards in the county: between 2009 and 2016, U.S. Steel paid over $3.9 million to the ACHD as penalties for emissions violations[122]. ACHD issued a further $3.5 million in fines between 2018 and Q1 2020[123]. Between February 2020 and March 2021, the ACHD recorded 32 exceedances of the county air quality standard for H_2S at the Clairton Coke Works[124]. The Clairton area is the only portion of the county that is in nonattainment for SO_2 NAAQS[112]. U.S. Steel's Edgar Thomson Plant, Clairton Coke Works, and Irvin Plant are all located in the Mon Valley.

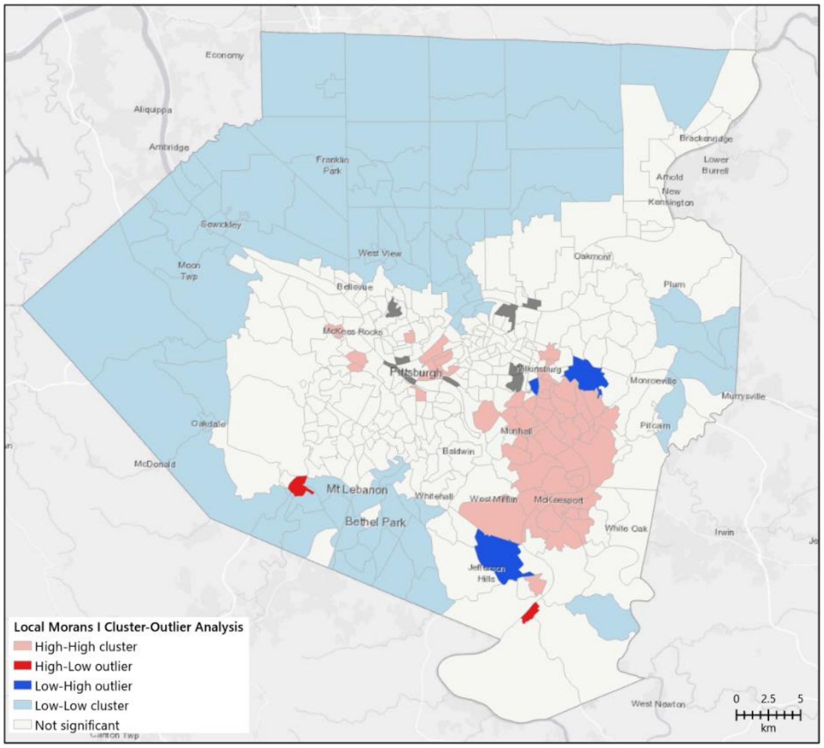


Figure 16*: Anselin Local Moran's I Cluster-Outlier Analysis for the full CEHI*

The Anselin Local Moran's I cluster-outlier analysis in Figure 16 visualizes the statistical significance (p=0.005) of this trend using the 13 original indicators. High-High clusters are high values surrounded by other high values, while Low-Low clusters are low values surrounded by other low values. High-Low and Low-High classifications are applied to census tracts that are spatial outliers. The large High-High cluster in the Mon Valley and surrounding areas indicates that children in the region may be at a statistically significant disadvantage concerning environmental health exposures compared to children in other parts of the county. The area should be prioritized for public health surveillance and interventions.

DISCUSSION

Adapting the CEHI for Other Small Areas

The Allegheny County case study showed us that local indicators are key to building an environmental health index that accurately reflects environmental disparities in a community. If the CEHI had limited the indicators to those that could be applied on a more universal scale, the result would have missed the significant exposures from Allegheny County's local industries.

Only at small-scale geographies can we adapt an index score to a specific community's concerns. Every community is different, and every local iteration of the CEHI should reflect that. While the local indicators in Allegheny County were focused on industrial byproducts, an agricultural community may wish to focus on pesticide drift and drinking water contamination from livestock. One must also recognize that hazards come in different forms. For example, the public health crisis in Flint, Michigan was the result of lead leaching into drinking water[125]. Meanwhile, soil is the source of lead exposures at the USS Lead smelter Superfund site in East Chicago, Indiana[126]. These two communities may choose different indicators of lead exposure to best reflect the most dominant exposure routes and environmental media in their area. When considering the population, indicator selection should reflect the people most at risk in the area. While the Allegheny County CEHI defined poverty as living below the federal poverty line, another project may benefit from a different cutoff point. Furthermore, a community with significant exposures to developmental toxicants like lead may wish to concentrate on a smaller age group than all children under age 18. CEHIs in Flint and East Chicago would likely consider focusing on children under age six.

The groups most likely to implement the CEHI are those with ties to the community of interest and enough resources to put it into action. These include county or municipal governments, universities, and large community organizations.

The anticipated audience for the CEHI includes members of local government, businesses, residents, and community organizations. The audience depends on the intended use of the CEHI. It could be limited to a restricted tool used by public health professionals, environmental scientists, and private stakeholders to identify areas that require further investigation. It may be leveraged as a public communication tool to keep the community informed. In an ideal situation, it would be used for both.

Strengths & Limitations

The Allegheny County CEHI illustrates the value of small-scale indices that incorporate local factors. As opposed to more generalized environmental health indices that cover large geographic areas and focus on the entire population, the CEHI targets a specific vulnerable population – children. The CEHI is also customizable; only at small-scale geographies can we adapt an index score to a specific community's concerns. An additional benefit is that the analysis behind the indicators can be as simple or as complex as the developers wish. There are numerous out-of-the-box layers that do not require any manipulation. The cost of software is not a barrier. It is possible to calculate the CEHI using a proprietary software like ArcGIS, or use a free open-source program like QGIS.

The CEHI is not without limitations:

- Indicator selection is partially determined by data availability.
- Software may have a steep learning curve.
- All geographic data should not be assumed accurate. Point locations and important attributes should be verified through a QA process.
- Hazardous facilities often report to multiple state and federal programs. Overlap between GIS data layers is likely and could lead to exaggerated density of facilities.
- Conversely, a single program inventory may not contain all relevant facilities. For example, the TRI does not contain all facilities that produce, use, store, or dispose of hazardous substances[107].
- Data is from different years, ranging from 2014 to 2021. All demographic indicators had a common source to ensure consistent population measures. This cannot be guaranteed for other data.
- Correlations among indicators were not assessed.
- Indicators were selected without community input.

These limitations should be addressed in a full-scale implementation of the CEHI.

Conclusions and Future Uses

As evidenced by the Allegheny County case study, constructing an environmental health index focused on children's health can yield compelling results that reflect the ways in which social environments, environmental exposures, and physiological vulnerabilities interact. As opposed to more generalized environmental health indices that cover large geographic areas and focus on the entire population, the CEHI is tailored to one of our most vulnerable populations: children.

The indicator selection process should be driven by public health professionals, subject matter experts, and diverse stakeholders who live or work in the local area. The lead organization should meet with and gather insight from the community at the outset. Academic institutions with relevant research may be willing to share data or lessons learned. Schools and parents may consent to data collection[15]. If the Allegheny County Health Department piloted the CEHI, they would be able to consult with large non-governmental organizations like the Breathe Collaborative as well as advocacy groups and local universities.

The CEHI does not have to be limited to census-defined geographies or the entire child population. An alternative analysis would use school districts instead of census tracts or block groups. Children both live and go to school in their district, so district-level analysis can provide a more complete portrait of a child's exposome. For example, exposure to high levels of vehicle emissions could be assessed using the proximity of schools and daycares to major roads. School administrators can use the School District CEHI to expand their understanding of their student body and provide programs and services accordingly. This approach to the CEHI would only be viable in areas with high population density and numerous municipalities; otherwise, a school district may be an entire county.

Prenatal exposures are a significant subset of children's environmental health[2]. In order to identify areas of increased exposure to reproductive and developmental toxicants, as well as other determinants of infant health, an adapted CEHI could focus on teratogenic exposures, low birth weights, maternal and infant mortality, and access to obstetric care. In this instance, the base population for the CEHI would be women within a predetermined reproductive age range.

The Children's Environmental Health Index is defined by two things: place and population. It is designed to reflect the ways in which local environmental exposures impact the local child population. It is flexible enough to accommodate a wide variety of environmental concerns and, in turn, a wide variety of communities. A comprehensive user guide, data package, and web app template will reduce the barriers to deployment. To build a diverse set of examples and gather additional evidence, future CEHI pilot projects should explore communities whose predominant sources of exposure differ from those observed in Allegheny County.

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Appendix A. Additional Indicators of Interest

What follows are brief outlines of additional indicators that were considered but not used in the Allegheny County CEHI.

Additional Indicators

Elevation

Areal topography and elevation can significantly influence the concentration and persistence of air pollution[53]. As noted earlier, Allegheny County's Mon Valley has experienced inversions that lasted for days and exposed the population to dangerous levels of pollutants.

Endocrine-Disrupting Chemicals

There is increasing concern around exposure to hormone-disrupting chemicals like polychlorinated biphenyls (PCBs), dioxins, and dichloro-diphenyl-trichloroethane (DDT), which have been linked to issues with reproduction, immune function, neurodevelopment, and growth[7].

Greenspace

Low-income children have less access to green space than their higher-income counterparts. The play areas that are available to them are consistently rated as more hazardous than those in higher-income neighborhoods[32]. The health benefits of urban green spaces are well-documented. Urban residents with access to public green spaces have better physical and mental health outcomes[127]. These benefits are due in part to factors including reduced air pollution and noise, increased opportunities for physical activity, higher rates of social interaction, and the soothing effects of being in an aesthetically pleasing environment[128].

Exposure to Environmental Tobacco Smoke

A child's inability to control their environment is the source of one of the most significant threats to their health: environmental tobacco smoke (ETS), often referred to as secondhand smoke. Many places in the U.S. have banned smoking in public places, making the home the greatest source of ETS[16]. Nonsmokers living with smokers are exposed to enough ETS to have measurable levels of cotinine, a biomarker of ETS exposure, in their bodily fluids. There is a significant association between pediatric asthma development and parental smoking[19]. Children who already have asthma will experience exacerbated symptoms. In addition to respiratory effects, secondhand smoke is a risk factor for sudden infant death syndrome and is classified as a carcinogen[16].

There is no federal-level data on parental smoking for small-area geographies or secondhand smoke. Allegheny County has a census-tract level dataset of adult smoking rates, but it was developed from a model that did not use any data collected specifically for Allegheny County.

Diesel Particulate Matter

Diesel engine exhaust consists of gases and particles. The particulate matter is primarily composed of organic carbon materials, polycyclic aromatic hydrocarbons (PAHs), and trace metals. The gaseous portion contains CO_2, CO, NO_x, So_x, benzene, formaldehyde, acrolein, and hydrocarbons (including PAHs). Diesel emissions are approximately 200 times above the EPA's one-in-a-million cancer risk threshold. The International Agency for Research on Cancer (IARC) has classified diesel engine exhaust as carcinogenic for humans: it is a cause of lung cancer and is positively associated with bladder cancer [93].