DEPARTMENT OF ENVIRONMENTAL PROTECTION
Environmental Justice Office

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TITLE:	Pennsylvania Environmental Justice Mapping and Screening Tool (PennEnviroScreen) Methodology Documentation 2023
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AUTHORITY:	Air Pollution Control Act (35 P.S. §§ 4001, et seq.); Solid Waste Management Act (35 P.S. §§ 6018.101, et seq.); Clean Streams Law (35 P.S. §§ 691.1, et seq.); Storage Tank and Spill Prevent Act (35 P.S. §§ 6021.101, et seq.); Hazardous Sites Cleanup Act (35 §§ 6020.101, et seq.); Safe Drinking Water Act (35 P.S. §§ 721.1, et seq.); Municipal Waste Planning, Recycling and Waste Reduction Act (53 P.S. §§ 4000.1, et seq.); Infectious and Chemotherapeutic Waste Law (35 P.S. §§ 6019.1, et seq.); Surface Mining Conservation and Reclamation Act (52 P.S. §§ 1396.1, et seq.); Noncoal Surface Mining Conservation and Reclamation Act (52 P.S. §§ 3301, et seq.); Bituminous Mine Subsidence and Land Conservation Act (52 P.S. §§ 1406.1, et seq.); Oil and Gas Act (58 Pa.C.S. §§ 2301–3504.); Coal Refuse Disposal Act (52 P.S. §§ 30.52, et seq.); Pennsylvania Sewage Facilities Act (35 P.S. §§ 750.1, et seq.); Dam Safety and Encroachments Act (32 P.S. §§ 679.101, et seq.); Radiation Protection Act (35 P.S. §§ 7110.101, et seq.); Low-Level Radioactive Waste Disposal Act (35 P.S. §§ 7130.101, et seq.); and Radon Certification Act (63 P.S. §§ 20001, et seq.); Commonwealth of Pennsylvania Executive Order 2021-07; 40 C.F.R Part 7; Title VI of the Civil Rights Act of 1964 (42 United States Code §§ 2000d to 2000d-7).
POLICY:	It is the Department of Environmental Protection's (Department or DEP) policy to ensure environmental justice (EJ) in the administration of DEP's policies and programs. The Pennsylvania Environmental Justice Mapping and Screening Tool (PennEnviroScreen) supports the Department's implementation of that policy.
PURPOSE:	The purpose of the Pennsylvania Environmental Justice Mapping and Screening Tool (PennEnviroScreen) Methodology Documentation is to explain rationale behind the PennEnviroScreen tool used to implement the Environmental Justice Policy (EJ Policy) (015-0501-002).
APPLICABILITY:	This document refers to the methodology behind the Pennsylvania Environmental Justice Mapping and Screening Tool (PennEnviroScreen).
DISCLAIMER:	The policies and procedures outlined in this guidance are intended to supplement existing requirements. Nothing in the policies or procedures shall affect regulatory requirements.

The policies and procedures herein are not an adjudication or a regulation. DEP does not intend to give this guidance that weight or deference. This document establishes the framework, within which DEP will exercise its administrative discretion in the future. DEP reserves the discretion to deviate from this policy statement if circumstances warrant.

PAGE LENGTH: 113 pages

Commonwealth of Pennsylvania

Pennsylvania Environmental Justice Mapping and Screening Tool (PennEnviroScreen) Methodology Documentation 2023

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INTRODUCTION

This document explains the methodology behind the Pennsylvania Environmental Justice Mapping and Screening Tool (PennEnviroScreen) available online at https://gis.dep.pa.gov/PennEnviroScreen/. The PennEnviroScreen tool and methodology was created by the Pennsylvania Department of Environmental Protection (DEP) to shape the implementation of an Environmental Justice Policy (EJ Policy) (015-0501-002).

Though PennEnviroScreen provides data that can be used by other agencies, nonprofits, academic institution, and community groups, the primary purpose is to assist DEP staff in implementing the EJ Policy. DEP staff need to be quickly aware of where the EJ Policy should primarily be focused as in annual work which includes the processing thousands of permit applications, conducting thousands of inspections, overseeing hundreds of grant applications, negotiating enforcement actions, and more. PennEnviroScreen provides an initial analysis as to whether the EJ Policy should apply in particular cases, but is only a screening tool that may require further research or analysis. This screening tool can help provide a snapshot of disproportionate impacts impacting a community, which can help shape more detailed data analysis and community interaction which may be needed after this initial screening.

DEP intends to update the data source information used in PennEnviroScreen on an annual basis. This will allow for up to date data to be considered when making decisions, but it should be noted that not all data may be the most currently available as a variety of data sources may be updated at various points throughout the year while DEP will only make one update per year. In order to be used by DEP in implementation of the EJ Policy, PennEnviroScreen updates need to be systematic in their timing, as DEP will need to choose a moment in time for PennEnviroScreen data to follow permits or grants that may span a period of years. This also means that it is necessary to track older PennEnviroScreen data in order to match with the appropriate projects.

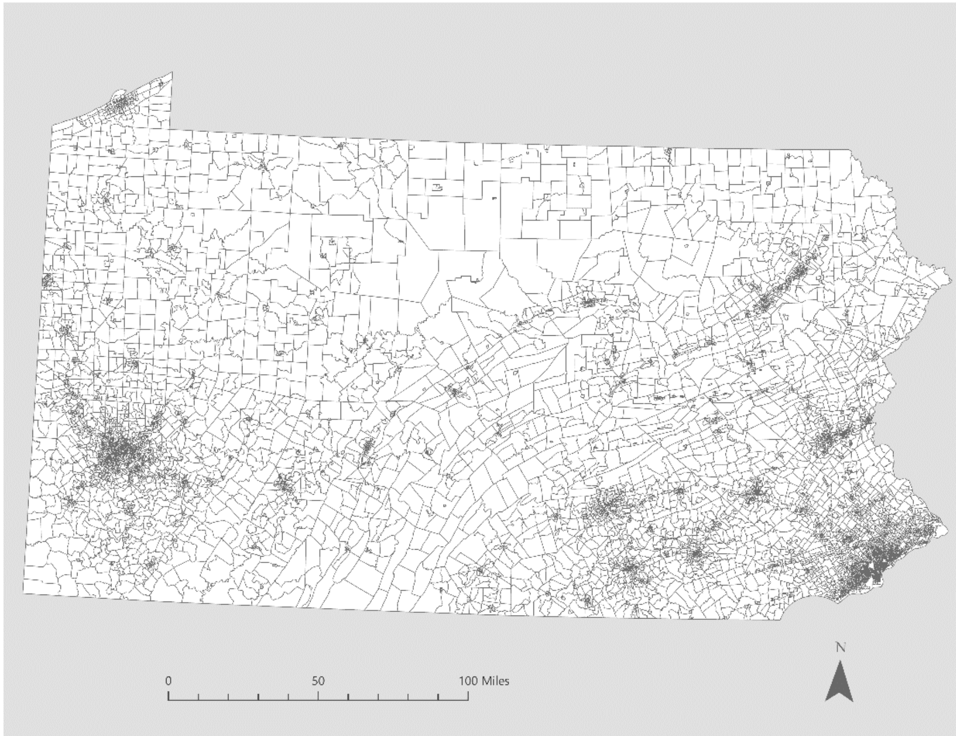
In order to provide easier access to those outside the Commonwealth to these data sources, this PennEnviroScreen methodology documentation cites the primary data sources in detail and calculated data will be available on the Pennsylvania Department of Environmental Protection Open Data Portal. This can allow community groups, nonprofit organizations, academic institutions, and others to be able to use PennEnviroScreen data as a baseline for further research and analysis.

METHODOLOGY AND RATIONALE

In the development of the PennEnviroScreen tool, the methodologies used in other EJ screening tools created by federal and state agencies were systematically evaluated. While the Environmental Protection Agency (EPA) does have a national-level EJ screening tool called EJScreen, it is limited in its ability to provide a holistic score, presenting a set of indices each containing a single exposure in combination with a single demographic index composed of census race and poverty measurements. The lack of a national-level EJ index that combines all environmental exposures with demographic and health characteristics has led to several states developing their own EJ screening tools. Tools that were explicitly defined as EJ tools were evaluated, for example those that were created to identify EJ communities and/or intended to comply with or respond to a federal or state EJ policy. An evaluation of these tools revealed that environmental and population characteristics were essential in determining EJ areas. Environmental indicators included exposures in the categories of climate, land, water, and air quality, while population indicators included socioeconomic characteristics, community health, and other population characteristics.

In addition to indicator information, other methods and materials were evaluated for each publicly available EJ screening tool. To inform the screening framework and scoring metrics used in Pennsylvania, the risk assessment framework, data sources, data quality, overarching purpose, presentation (interactive or static display), and geographic resolution, such as boundaries defined by ZIP code, census tracts, census blocks, or municipalities, were examined. Agencies with publicly accessible EJ tools generally rely on environmental and demographic characteristics, utilizing a risk-scoring framework that incorporates the formula: *Risk = Threat × Vulnerability* (Brody, 2020[i]). This formula, with varying degrees of complexity, has gained widespread adoption and acceptance by EJ screening tools developed by both federal and state agencies. The California EJ Screening Tool, known as CalEnviroScreen 4.0 (CalEPA, 2021[ii]), which employs a weighted index, has served as a model framework in the development of the approach utilized for the DEP EJ screening tool.

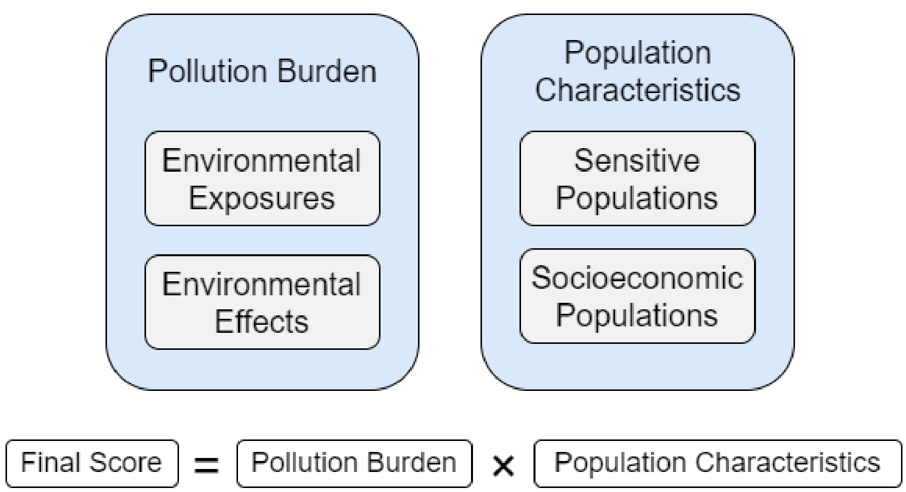
The PennEnviroScreen model uses a census block group geographic resolution, provided by the US Census Bureau. [iii] https://tigerweb.geo.census.gov/arcgis/rest/services/TIGERweb/tigerWMS_Census2010/MapServer/16 The 2010 census block groups for this analysis were used instead of the newer 2020 block groups, because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, and data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. As defined by the Census Bureau, block groups are subdivisions of census tracts and generally contain between 600 and 3,000 people. Census block groups are the smallest available geographic units for which the Census Bureau publishes sample data and were chosen for this analysis because many of the data sets used in the PennEnviroScreen model are published at the block group level. For certain data that are only available at lower resolutions such as census tracts or counties, the lower resolution indicator values can be assigned to the block groups that fit within those block groups or counties. For more information on different census geometries, see the US Census Bureau's Understanding Geographic Identifiers https://www.census.gov/programs-surveys/geography/guidance/geo-identifiers.html page.[iv] County boundaries[v] https://data-pennshare.opendata.arcgis.com/datasets/pennsylvania-county-boundaries/explore and the Pennsylvania state boundary[vi]https://data-pennshare.opendata.arcgis.com/datasets/pennsylvania-state-boundary-1/about were used for the purpose of calculating certain indicators.



9,740 Census Block Groups in Pennsylvania

Model Development

The PennEnviroScreen model consists of four indicator components (each containing several indicators), grouped into two broad categories: The Pollution Burden category contains the Environmental Exposures and Environmental Effects components, and the Population Characteristics category contains the Sensitive Populations and Socioeconomic Populations components. The Final Score is calculated by multiplying Pollution Burden by Population characteristics; detailed model methods are outlined below.



Component	Description
Environmental Exposure	Measurable magnitude of exposure levels of (or proxies for) pollution that people are exposed by direct contact through the environment. (e.g. pollutants released into air, water, soil).
Environmental Effects	Adverse environmental conditions caused by pollution (or risks thereof) that is proximity based. Examples of adverse environmental conditions include: • Living in an environmentally degraded community can lead to stress, which may affect human health. • Threats to ecology and community environment (e.g. presence of sites/facilities can lead to communities being unsafe/undesirable). • Limit people's ability to use ecological resources (e.g. eating fish, swimming in rivers). • Largely measured by proximity to certain sites/facilities.
Sensitive Population	Population health characteristics (e.g. Cancer, asthma) that result in increased vulnerability to environmental threats that may be caused by or amplify their adverse effects.
Socioeconomic Factors	Population level demographic characteristics associated with disproportionate impacts from pollution which may reduce the community's ability to mitigate the adverse effects of environmental threats. (e.g. race, poverty, unemployment, low educational attainment).

Prior to all model calculations, one block group (GEOID 420499900000) is located entirely within Lake Erie and was excluded from this analysis. All model calculations were performed in the *NAD1983 UTM Zone 18N* projected coordinate system and are displayed as such in this document. For display in the PennEnviroScreen interactive web viewer, results were projected to the *WGS 1984 Web Mercator Auxiliary Sphere* projection.

The model consists of these steps, corresponding to the six steps in the Methodology diagram below:

1. Values were calculated for each indicator (detailed methodology for each indicator is provided below in the indicators section). For each indicator, each block group was assigned a percentile based on its position in the statewide distribution of indicator values. Block groups in which the phenomenon relevant to a given indicator was not present were assigned a percentile score of zero and were thereby excluded from the percentile calculation. As a result, the non-zero percentile range for a given indicator represents only the block groups in which the indicator phenomenon was present.

   Additionally, there are several conditions that can result in a null (non-existent) percentile value. For population-related indicators calculated using American Community Survey (ACS) data, zero-population areas were given a null percentile value. Also, because the ACS is tabulated using samples of the population, it contains uncertainty that is reflected in the margin of error that the ACS provides for each block group. Block groups containing a high degree of uncertainty for a given indicator were excluded from analysis for that indicator and assigned a null percentile. See the Indicators section for details regarding a particular indicator.

It is important to be cautious when interpreting these indicators. They are calculated based on percentiles, which means that each block group's value is compared to the rest of the block groups in the state. This also means that some block groups will always be assigned high percentile values, even if they meet acceptable regulatory standards for any indicator. As a result, there will always be areas of the state that are portrayed as being in the top 20%, regardless of improvements.

$$P = \frac{v_i}{v_{all}} \times 100$$

P = Percentile score
vi = number of block groups with indicator values less than or equal to this block group’s indicator value
vall = total number of block groups

2. The four component scores (Environmental Exposures, Environmental Effects, Sensitive Populations, Socioeconomic Populations) were calculated by averaging the percentile values of all indicators within those components.

$$C = \frac{\sum c}{\mathrm{n}}$$

Component score
Σc = Sum of all indicator percentiles within component
n = Number of indicators within component

3. The Pollution Burden score was calculated by taking the weighted average of the Environmental Exposures and Environmental Effects components, with Environmental Effects receiving a weight of 0.5 relative to Environmental Exposures. The reason for the half weight of Environmental Effects is that not every resident may come into contact with the phenomena related to these indicators. The Population Characteristics score was calculated by taking the average of the Sensitive Populations and Socioeconomic Populations component scores.

$$PB = \frac{\mathrm{EXP}_{avg} + (\mathrm{EE}_{avg} \times 0.5)}{1.5}$$

PB = Pollution Burden score
EXP = Environmental Exposures component score (average of all Environmental Exposures indicators)
EE = Environmental Effects component score (average of all Environmental Effects indicators)

$$\mathrm{PC} = \frac{\mathrm{SOC}_{avg} + \mathrm{SP}_{avg}}{2}$$

PC = Population Characteristics score
SOC = Socioeconomic Populations component score (average of all Socioeconomic Populations indicators)
SP = Sensitive Populations component score (average of all Sensitive Populations indicators)

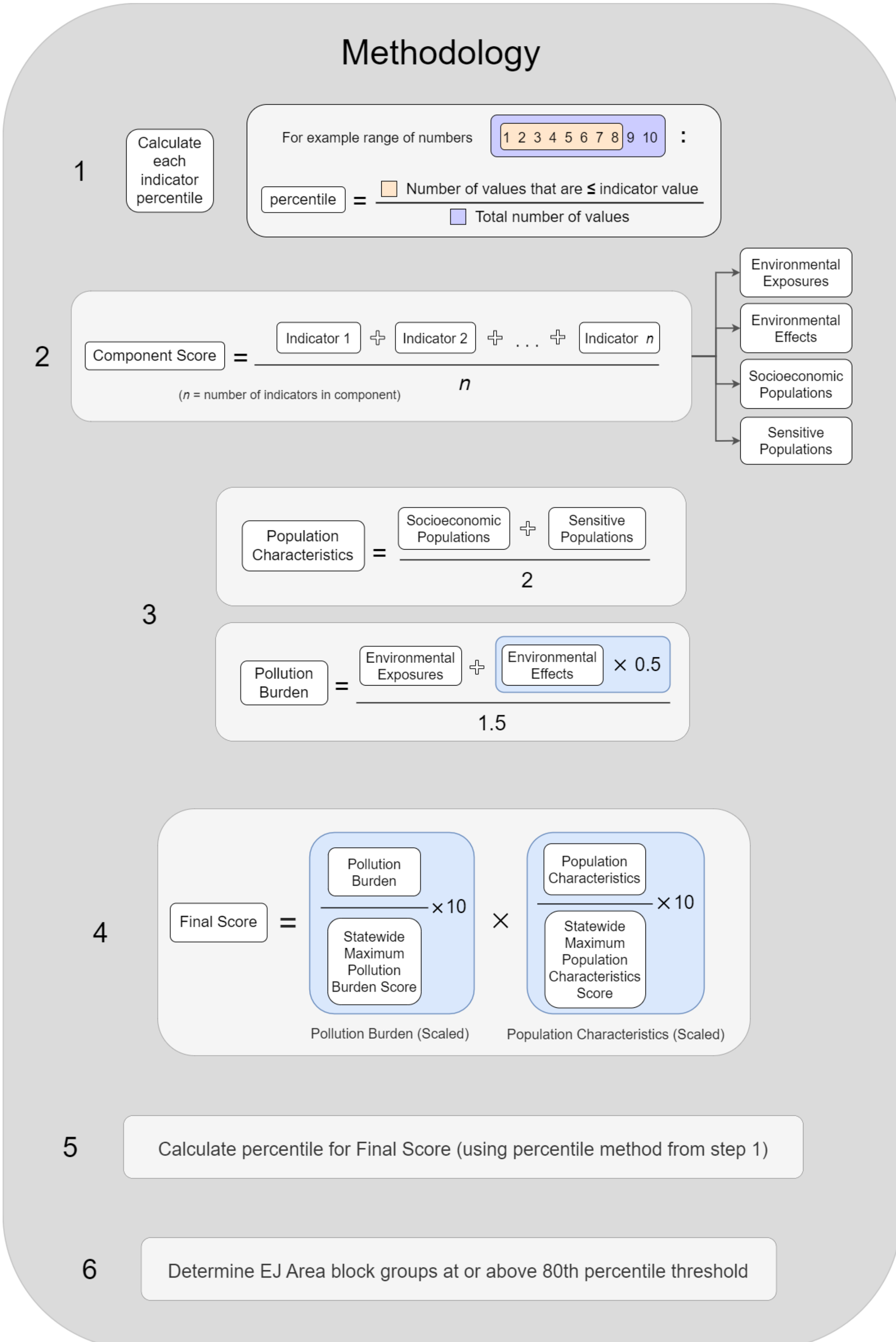
4. The final score was calculated by first scaling the Pollution Burden and Population Characteristics scores between 1 and 10 by dividing the score by the maximum block group score in Pennsylvania, then multiplying this value by 10; the scaled Pollution Burden and Population Characteristics scores were then multiplied together to produce the final score.

$$F = \left(\frac{PB}{PB_{max}} \times 10\right) \times \left(\frac{PC}{PC_{max}} \times 10\right)$$

F = Final Score
PB = Highest block group Pollution Burden score in state
PC = Highest block group Population Characteristics score in state

5. A final score percentile was calculated for each block group based on that block group's position within the statewide distribution of values (using the percentile method from step 1). The gradient of percentile values shows the range of EJ vulnerability throughout the state.

6. Each block group was determined to be an Environmental Justice Area (EJ Area) as defined by the EJ Policy if its final score percentile was greater than or equal to a threshold of the 80^{th} percentile.


Methodology
1
Calculate each indicator percentile
For example range of numbers 1 2 3 4 5 6 7 8 9 10 :
percentile = Number of values that are ≤ indicator value / Total number of values
2
Component Score = Indicator 1 + Indicator 2 + . . . + Indicator n / n
(n = number of indicators in component)
Environmental Exposures
Environmental Effects
Socioeconomic Populations
Sensitive Populations
3
Population Characteristics = Socioeconomic Populations + Sensitive Populations / 2
Pollution Burden = Environmental Exposures + Environmental Effects × 0.5 / 1.5
4
Final Score = Pollution Burden / Statewide Maximum Pollution Burden Score × 10 × Population Characteristics / Statewide Maximum Population Characteristics Score × 10
Pollution Burden (Scaled)
Population Characteristics (Scaled)
5
Calculate percentile for Final Score (using percentile method from step 1)
6
Determine EJ Area block groups at or above 80th percentile threshold

INDICATORS

This section describes the environmental and demographic data used in the PennEnviroScreen model. Indicators were selected by considering the type and quality of information based on the following inclusion process:

1. Identify potential indicators representing widespread concerns about environmental justice based on stakeholder/community input and review of other state-level environmental justice screening tools.

2. Inclusion of an indicator should be supported by evidence from scientific literature.

3. Data for an indicator must either be available at the census block group level or translatable to this resolution.

4. Indicators should be available across the entire Commonwealth of Pennsylvania.

5. Data should be regularly updated.

Pollution Burden: Environmental Exposures
Ozone
Fine Particulate Matter of 2.5 micrometers or less in diameter
Diesel Particulate Matter
Toxic Air Emissions
Toxic Water Emissions
Pesticides
Traffic Density
Compressor Stations
Children’s Lead Risk
Pollution Burden: Environmental Effects
Oil Gas Locations (Conventional wells)
Oil Gas Locations (Unconventional wells)
Proximity to Railroads
Land Remediation
Hazardous Waste and Storage Sites
Municipal Waste Sites
Coal Mining
Impaired lakes and streams
Abandoned Mining Concerns
Flood Risk
Population Characteristics: Sensitive Populations
Asthma
No Health Insurance
Cancer
Disability
Heart Disease

Population Characteristics: Socioeconomic Population
Low Educational Attainment
Linguistic Isolation
Housing-Burdened Low -Income Households
Poverty
Unemployment
Race
Age over 64
Age under 5

Indicator Information

Each indicator description includes these sections as applicable:

Rationale – Outlines the reasoning and evidence for using this indicator.

Data Source – Specifies the original input data and associated details.

Data	Temporal Resolution	Agency	Source
Description of data set	Length of time represented by data set as available for download. “Continuous" indicates that only one continuously updated data set is available, instead of separate updates representing specific lengths of time.	Agency providing data	Link to data

Methods – The calculation process by which the PennEnviroScreen model processes the input data into an indicator value and percentile.

Graphic – A map showing the percentile score for that indicator. To zoom in on areas of interest, users can isolate these factors in the online PennEnviroScreen mapping tool by selecting only this factor. These static maps are provided only for a snapshot reference and use of the dynamic online tool is suggested for any detailed analysis of individual indicator.

Future Considerations – Additional data that were considered but not included because they did not meet the inclusion criteria. If these data meet the inclusion criteria in the future, they may be considered for future iterations of PennEnviroScreen. This section may also include possible changes to the methodological calculations that may be made in the future. Items included in this section may also be useful to other researchers with different aims than the PennEnviroScreen team in order to conduct more localized analysis of various factors.

POLLUTION BURDEN: EXPOSURE INDICATORS

Ozone

Rationale

Ground-Level (tropospheric) Ozone (O_3) is the major component of smog (American Lung Association, 2022[vii]) and is associated with several adverse human health effects (EPA, 2022a[viii]). Population-based studies have shown that exposure to ozone is associated with a range of health complications, including decreased lung function, bronchial inflammation, oxidative stress, asthma, and increased mortality and morbidity from cardiovascular and respiratory diseases (Zu et al., 2018[ix]; Kim et al., 2020[x]). Some of these adverse health outcomes include decreased lung function, particularly in children (Holm & Balmes, 2022[xi]). Along with fine particulate matter, ozone is one of the most important criteria air pollutants for environmental justice screening, as it is the most widespread and poses significant health risks (EPA, 2022b[xii]). Recent studies conducted in Pennsylvania have shown that exposure to high levels of $PM_{2.5}$ and O_3 is associated with increased odds of childhood asthma aggravation (Huang et al., 2021[xiii]) and that high ozone concentrations worsen childhood asthma symptoms (Sousa et al., 2009[xiv]). While all individuals are susceptible to the adverse health effects of ozone, individuals who are asthmatic, elderly, work outside, or are young are at a higher risk (Toskala & Kennedy, 2015[xv]). According to the Centers for Disease Control and Prevention (CDC), the latest asthma data places the national asthma prevalence among adults over 18 years of age at 8.4% and school-age children (5-17 years of age) at 7.2%. Pennsylvania ranks higher than the national average, with 10.2% of its residents suffering from asthma (CDC, 2022[xvi]). It is important to note that despite the high prevalence of asthma in Pennsylvania, sampled ozone values have significantly decreased over the past twenty years, with only one area of the state (Southeastern Pennsylvania) currently in noncompliance with the National Ambient Air Quality Standards (NAAQS). It is important to note that despite the high prevalence of asthma in Pennsylvania, sampled ozone values have significantly decreased over the past twenty years, with only one area of the state (Southeastern Pennsylvania) currently in nonattainment with the National Ambient Air Quality Standards (NAAQS).

Data Source[xvii]

Data	Temporal Resolution	Agency	Source
Daily summary data of- ozone concentrations (ppm) at air monitor points	1 year	EPA	https://aqs.epa.gov/aqsweb/airdata/download_files.html

Methods

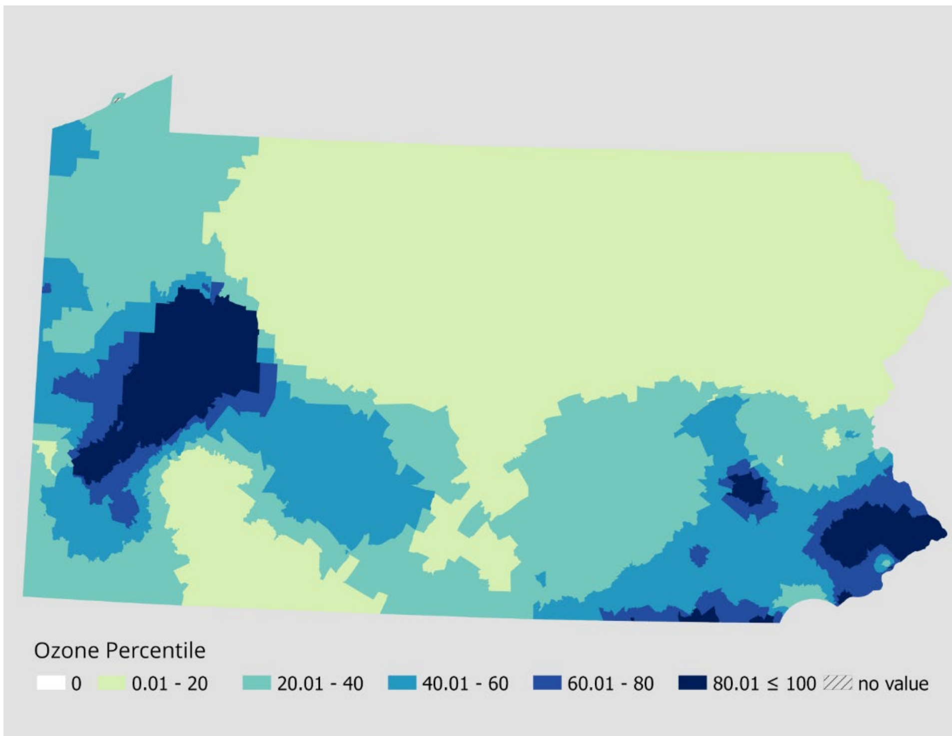
- The three most recent available years of daily summary ozone concentrations were downloaded from the EPA, then merged into one data set.

- Data were selected to only include monitor measurements taken during the summer months (June, July, and August) at monitors within 50 km of Pennsylvania.

- For each air monitor, all daily maximum ozone values were averaged (mean) into one value.

  Using a distance of within 50 km of each air monitor, Inverse Distance Weighting (IDW) spatial interpolation was used to generate a raster grid estimation of ozone concentrations throughout the state (Wong et al., 2004[xviii]); in areas not within 50 km of any air monitor, a 200-km IDW was generated.

- Using zonal statistics, the mean IDW raster value was calculated for each census block group.
- Each census block group was assigned a percentile based on the statewide distribution of values.



Percentiles of Ozone concentrations in Pennsylvania.

Future Considerations

In order to generate ozone concentrations outside of within 50 km of air monitors, satellite-generated ozone measurements were considered in addition to the data used, akin to the methodology of the $PM_{2.5}$ indicator, rather than generating a 200-km IDW. However, such satellite data was not available at the desired 1-km resolution. If such data becomes available in the future, the methodology may be altered to include it.

Fewer air monitors tend to be in rural areas relative to urban areas, leading to potential issues with accuracy of concentration estimates in rural areas.

Fine Particulate Matter of 2.5 micrometers or less in diameter ($PM_{2.5}$)

Rationale

Airborne fine particulate matter (PM) can cause serious health consequences and is categorized as particles less than 2.5 micrometers ($PM_{2.5}$) in diameter (Xing et al, 2016[xix]). $PM_{2.5}$ makes up a range of hazardous materials such as soot, dust, smoke, fluids, and even non-hazardous materials such as sea-salt (EPA, 2022d[xx]). Fine particulate pollution sourced from industrial combustion is particularly troublesome and is shown to cause several negative health outcomes including cardiovascular disparities, asthma attacks, and premature deaths (Slawsky et al., 2021[xxi]). $PM_{2.5}$ is capable of penetrating deep into the lung and is readily transferred to the blood, increasing the risk of respiratory, cardiovascular, and cerebrovascular disease (Lawal. & Araujo., 2012[xxii]). Epidemiological studies have shown an increased association between ultra-fine particulates and impaired lung function in both adults and children (Li et al., 2021[xxiii]; Lim et al., 2016[xxiv]). Racial and ethnic disparities in preterm births remain a major public health issue, and environmental exposures may contribute to these disparities (Burris et al., 2011[xxv]). The World Health Organization (WHO) estimates 4.2 million premature deaths globally are linked to outdoor air pollution (WHO, 2022[xxvi]). These deaths are mainly from heart disease, stroke, chronic obstructive pulmonary disease, lung cancer, and acute respiratory infections in children (Pun et al., 2017[xxvii]). Significant sources of fine particulate pollution stem from both stationary and mobile sources which include combustion engines, wood and coal burning, and wildfires (Unger et al., 2010[xxviii]). Both short-term and long-term exposure to fine particulates are associated with adverse health effects (Atkinson et al., 2014[xxix]). The WHO estimates that fine particulates contribute to over 800,000 premature deaths each year (WHO, 2022[xxx]). $PM_{2.5}$ is considered important for environmental justice screening and is part of criteria air pollutants considered in health standards (EPA, 2012[xxxi]). Furthermore, communities that are low-income and non-minority white are disproportionately exposed to higher levels of fine particulates than the overall population at both the state and national level (Mikati et al., 2018[xxxii]). A 2019 Pennsylvania study provided evidence that $PM_{2.5}$ concentrations as measured at the county level have positive direct and indirect effects on asthma hospitalization, indicating a major environmental health concern in the Commonwealth (Erfanian & Collins, 2019[xxxiii]). The University of Pittsburgh Medical Center, which provides 41% of health services to the Western Pennsylvania region conducted a cohort study of 31,414 individuals with Atrial Fibrillation (AF) to investigate the association of fine particulate matter and the risk of stroke in patients with AF. This 2020 study concluded that there is an association between residential-level pollution and increased risk of stroke in this population, suggesting that individuals with AF consider the contributions of environmental exposures (Rhinehart et al., 2020[xxxiv]).

Data Source [xxxv]

Data	Temporal Resolution	Agency	Source
Annual average $PM_{2.5}$ concentrations (micrograms / cubic meter) at air monitor points	1 year	EPA	https://aqs.epa.gov/aqsweb/airdata/download_files.html
Satellite-generated, 1-km resolution, surface $PM_{2.5}$ concentration raster	1 year	NASA	https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod-v4-gl-03/data-download

Methods

- A 1-km resolution raster of satellite-derived $PM_{2.5}$ measurements for the most recent year of available data was downloaded from NASA, then clipped to the extent of Pennsylvania.

- Annual average concentrations for the three most recent available years of air monitor data were downloaded from the EPA; the three years of data were then merged together.

- Air monitor data were selected to only include monitors within 50 km of Pennsylvania, within the "$PM_{2.5}$ - Local Conditions" parameter and the "$PM_{2.5}$ Annual 2012" pollutant measurement standard.

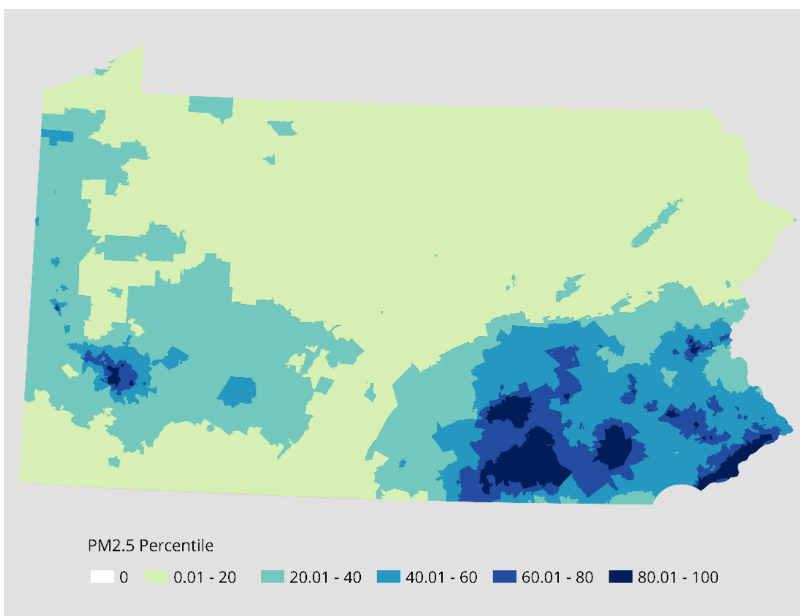
- For each air monitor, the three $PM_{2.5}$ arithmetic mean concentration values, each representing one summary year, were averaged into one mean value.

- Using a distance of within 50 km of each air monitor, Inverse Distance Weighting (IDW) spatial interpolation was used to generate a raster grid estimation of $PM_{2.5}$ concentrations throughout the state (Wong et al., 2004[xxxvi]).

- The 50 km IDW values were averaged with the NASA raster values. For areas not within 50 km of any air monitor, only the NASA raster values were used.

- Using zonal statistics, $PM_{2.5}$ values were averaged into one value for each census block group.

- Each census block group was assigned a percentile based on the statewide distribution of values.



Percentiles of $PM_{2.5}$ concentration levels in Pennsylvania.

Future Considerations

Fewer air monitors tend to be in rural areas relative to urban areas, leading to potential issues with accuracy of concentration estimates in rural areas.

Diesel Particulate Matter (DPM)

Rationale

Diesel Particulate Matter (DPM) is a type of fine particulate matter that is emitted from mobile and stationary diesel combustion sources, such as ships, generators, farm machinery, trucks, buses, and trains (Elkelawy et al., 2021[xxxvii]). It is composed of a complex mixture of gases and fine particulates, including mutagenic carcinogens from the polycyclic aromatic hydrocarbon (PAH) class, such as nitroarene compounds (Consonni et al., 2018[xxxviii]; McKeon et al., 2021[xxxix]; Gharibvand et al., 2017[xl]). Despite improvements in diesel technology that have aimed to reduce harmful DPM emissions, diesel pollution remains a significant contributor to ambient air pollution (Nabi et al., 2006[xli]). Exposure to DPM has been linked to a variety of negative health effects, including airway inflammation, vascular dysfunction, developmental toxicity, neuroinflammation, respiratory mortality, and lung cancer (Weitekamp et al., 2020[xlii]). DPM is commonly used as an indicator in environmental justice screening tools due to the extensive evidence of the adverse health impacts of diesel combustion (Patterson & Harley, 2021[xliii]). In the Mid-Atlantic region of the United States, research has shown that non-white communities have a 60%-75% increased risk of exposure to DPM from mobile and stationary diesel combustion sources (Union of Concerned Scientists, 2019[xliv]). A study conducted in 2003, analyzed traffic-related air pollution in Philadelphia, Pennsylvania, including the presence of DPM. The study found that traffic-related air pollution, including DPM, was highest near major roadways and in densely populated areas. The study also found that individuals living near major roadways had higher levels of DPM in their homes, indicating that residential proximity to traffic was a significant predictor of DPM exposure. The study concluded that traffic-related air pollution, including DPM, was a significant public health concern in Philadelphia and called for the implementation of policies to reduce emissions from vehicles (Henderson et al., 2003[xlv]). A study conducted in Pittsburgh, Pennsylvania in 2018 found that rush-hour emissions may largely determine the overall spatial variance in diesel-related pollution (Tunno et al., 2018[xlvi]).

Data Source

Data	Temporal Resolution	Agency	Source
Census Tract-level AirToxScreen Diesel PM_{10} pollutant-specific exposure concentrations	1 year	EPA	https://www.epa.gov/AirToxScreen/2019-airtoxscreen-assessment-results

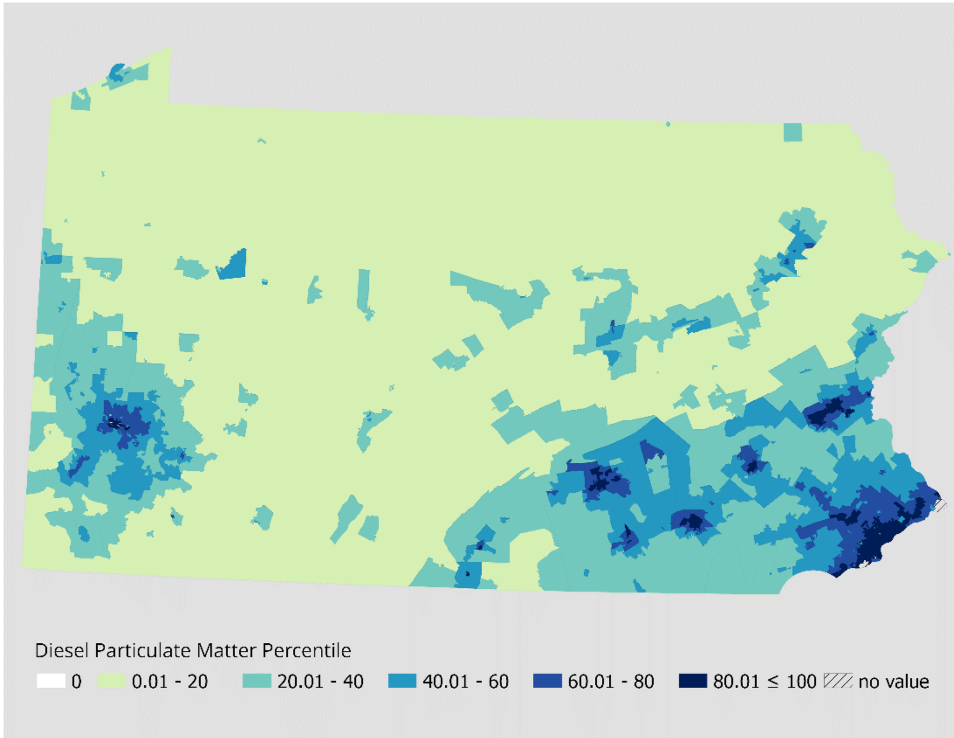
Methods

- 2018 Diesel PM_{10} pollutant-specific results, presented as a Microsoft Access file, were downloaded at the census tract level. The Exposure Concentration (µg/m3) table was used in this analysis.

- Data were selected to include only census tracts in Pennsylvania.

- Tract-level PM_{10} concentration values were assigned to the block groups falling within each tract.

- Each census block group was assigned a percentile based on the statewide distribution of values.



Percentiles of DPM concentration levels in Pennsylvania.

Future Considerations

DPM data are sourced from AirToxScreen which is presented at the census tract level. This indicator would benefit from higher-resolution data, such as block-group-level data. Additionally, satellite measurements of DPM levels could increase the accuracy of this indicator. If such data become available in the future, this indicator may be changed to include them.

Toxic Air Emissions

Rationale

The EPA's Risk Screening Environmental Indicators (RSEI) models the impacts of air pollution on the population (citation). The RSEI results were derived from the Toxics Release Inventory (TRI), an EPA program that tracks the release, reported by facilities across the United States, of 770 individual toxic chemicals that may pose a threat to human health and the environment (EPA, 2022[xlvii]). The data consist of the geographic location of each TRI-reporting facility and the amount of each chemical (in pounds or grams) released into water, land, or air by each reporting year (PA Department of Labor, 2020[xlviii]). Studies examining the relationship between adverse human health effects and proximity to TRI-reporting facilities have found increased risks of preterm birth, cancer, and other health disparities (Gong et al., 2018[xlix]; De Roos et al., 2010[l]; Hanchette et al., 2018[li]; Miller, 2004[lii]; Landrigan et al., 2010[liii]). Environmental justice research has documented disproportionate socioeconomic differences in exposure to air emissions reported by the TRI (Johnson et al., 2016[liv]; Wilson et al., 2012[lv]). Research has found that the statewide level percent minority increases with proximity to, and density of, TRI facilities (Mennis, 2002[lvi]). These disparities in the distribution of TRI facilities have been documented at the block and census-tract level by race/ethnicity and socioeconomic status (SES) (Johnson et al., 2016[lvii]). For example, a substantially higher proportion of African American children aged five years or younger living in low-income households are located near one or more industrial sources of air pollution compared to white children (Perlin et al., 2001[lviii]; Ash & Boyce, 2018[lix]; Kershaw et al., 2013[lx]). A study in 2022 investigated whether higher ambient air concentrations of arsenic (As) and cadmium (Cd), which are commonly reported toxic air emissions, were associated with lower overall and prostate cancer-specific survival among prostate cancer cases in Pennsylvania, suggesting that increasing ambient air exposures to As and Cd may increase overall and prostate cancer-specific mortality risk (McDonald et al., 2022[lxi]). A study conducted at the Children's Hospital of Philadelphia identified air quality as a risk factor for pediatric multiple sclerosis using RSEI-classified counties at risk of exposure to environmental toxic releases (Lavery et al., 2018[lxii]).

Data Source

Data	Time Period	Agency	Source
Risk Screening Environmental Indicators (RSEI) block-group-level geographic air microdata	1 year	EPA	https://www.epa.gov/rsei/ways-get-rsei-results#microdata
AirToxScreen nation-wide results: National Cancer Risk by Pollutant (tract-level)	1 year	EPA	https://www.epa.gov/AirToxScreen/2019-airtoxscreen-assessment-results
AirToxScreen nation-wide results: National All Hazard Indexes, tract-level (non-cancer health risk indices)	1 year	EPA	https://www.epa.gov/AirToxScreen/2019-airtoxscreen-assessment-results

Methods

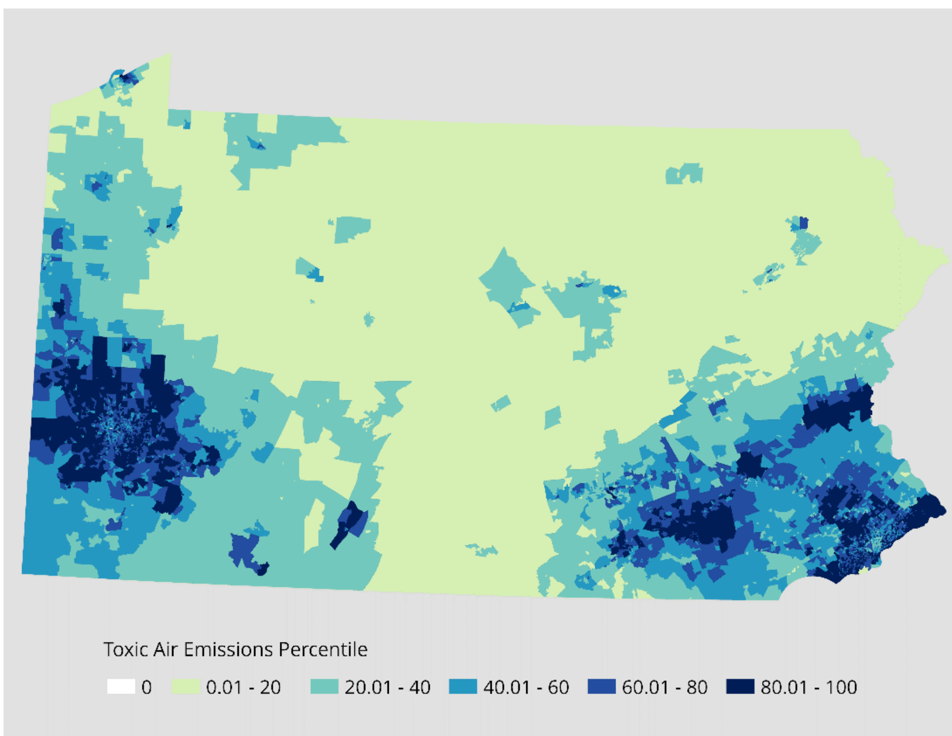
- RSEI block-group-level data were downloaded from the EPA; The three most recent available years of data were used.

- The three risk scores representing each year were averaged together to obtain a three-year risk score for each block group.

- Using the three-year RSEI average score, a percentile was calculated for each block group based on the statewide distribution of values.

- Two tract-level AirToxScreen data sets were downloaded from the EPA: cancer risk per million people for each census tract, and a non-cancer whole-body health risk index; data representing the most recent available year of data were used. For each data set, tract-level values were assigned to the block groups falling within each tract, and a percentile was calculated for each block group based on the statewide distribution of values. These two percentiles were averaged together for each block group, and using this average, a new percentile was calculated to produce one AirToxScreen percentile.

- The RSEI and AirToxScreen percentiles were averaged together, and using this average, a new percentile was calculated to produce the Toxic Air Emissions indicator percentile.



Percentiles of Toxic Air Emissions in Pennsylvania.

Future Considerations

The RSEI and AirToxScreen models are widely recognized as robust and reliable tools for assessing air pollution. These models incorporate a range of different sources of pollution, including point sources such as industrial facilities and mobile sources such as vehicles. This means that they provide a comprehensive and nuanced picture of the air pollution in a given area.

One of the key strengths of these models is their ability to incorporate data from multiple sources. For example, the RSEI model uses data from the EPA on emissions of toxic chemicals from industrial facilities, as well as data on weather patterns, population density, and other factors that can affect how pollutants are dispersed in the air.

Similarly, the AirToxScreen model uses data from a variety of sources, including EPA monitoring stations, traffic counts, and land use patterns. This allows it to capture the complex interactions between different sources of air pollution and the environment, providing a more accurate and detailed assessment of air quality.

Given the strengths of these models, they are an excellent choice for developing an air pollution indicator. However, as new data becomes available, it may be possible to refine and expand this indicator to include additional sources of pollution.

Compressor Stations

Rationale

Residents of Pennsylvania who live near natural gas compressor stations may be at risk for experiencing adverse health effects due to air pollution, noise, and increased truck traffic (Boyle et al., 2017[lxiii]). A study conducted in 2019 found elevated noise levels near compressor stations in Southwestern Pennsylvania, recommending that healthcare professionals be aware of the impact of noise stressors on populations in these areas (Richburg & Slagley, 2019[lxiv]). Research using Pennsylvania as a case study has provided evidence of several potential harms associated with the long-term contamination of soil and water with known carcinogens used in the industry (Wollin et al., 2020[lxv]). With the rapid expansion of compressor stations in communities near natural gas extraction, further research is needed to investigate the relationship between compressor stations and human health.

Data Sources [lxvi]

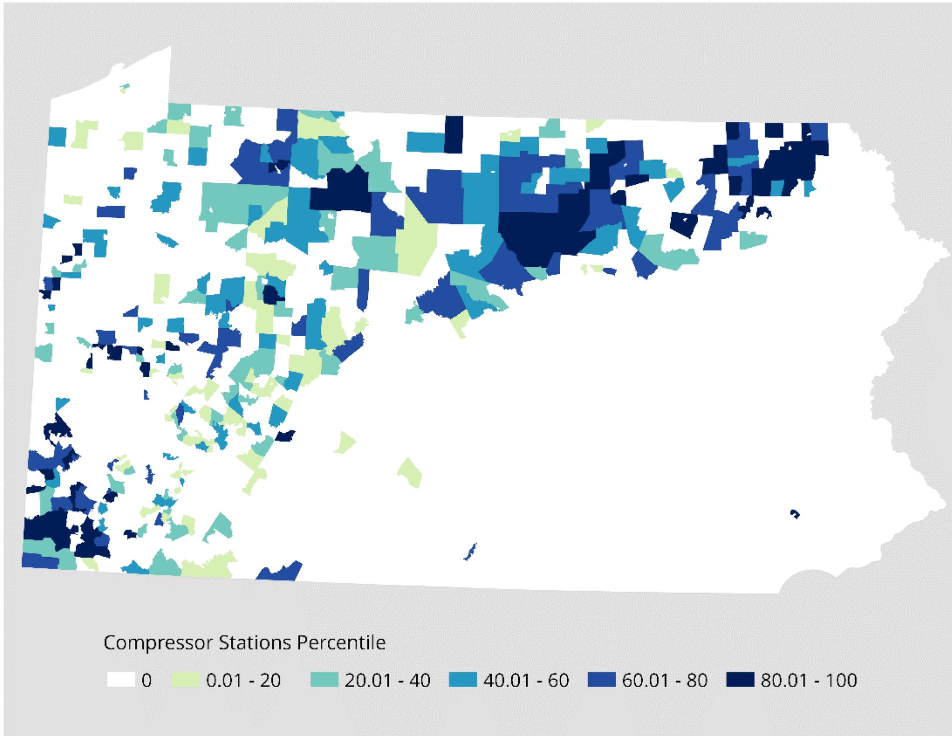
Data	Time Period	Agency	Source
Compressor Station point emissions	Continuously updated; points labeled by emissions year	DEP	http://cedatareporting.pa.gov/reports/powerbi/Public/DEP/AQ/PBI/Air_Emissions_Report

Methods

- Compressor Station points for each facility and emitted chemical were obtained by filtering and downloading all emissions points with a Facility Type of "CompressorStation." After downloading, data were selected to include only the three most recent available years.

- Within each block group, emissions values were added to obtain an emissions sum for each chemical.

- For each block group, separate percentiles were calculated for each chemical based on the statewide distribution of values; these percentiles were then averaged together into one score. Using this average, a new percentile was calculated to obtain the final indicator percentile.



Percentiles of Compressor Stations in Pennsylvania.

Future Considerations

As more information about compressor stations and their associated processes become available, consider updating the type of data collected.

Toxic Water Emissions

Rationale

The discharge of pollution into surface water bodies, including rivers, lakes, and coastal waters, can have negative impacts on the quality and safety of natural ecosystems and humans who use these spaces (Rahman & Naidu, 2009[lxvii]; Cantor, 1997[lxviii]). Surface waters are used for a variety of commercial and recreational purposes, such as swimming, fishing, boating, wastewater treatment, and drinking water (EPA, 2022[lxix]). Pollution that is discharged into surface waters can impact the entire watershed, compromising the health of both humans and ecosystems downstream. These downstream networks may cross between urban and rural areas, affecting many people (Hill et al., 2018[lxx]). There is a significant amount of industrial water pollution reported in the Toxic Release Inventory that can impact human health through inhalation and ingestion of contaminated water (Hendryx et al., 2012[lxxi]). While there is limited research on the connection between health and permitted surface water discharges, there is substantial evidence showing that groundwater contamination is correlated with higher population cancer mortality rates and other health disparities (Griffith et al., 1989[lxxii]; Vrijheid, 2000[lxxiii]). Surface and groundwater are interconnected, and surface water has been shown to contaminate groundwater, emphasizing the importance of monitoring both surface and groundwater pollution (Winter et al., 1998[lxxiv]). A study conducted by the Public Interest Network and PennEnvironment analyzed EPA's TRI data for water emissions in Pennsylvania. The study found that large quantities of chemicals linked to cancer and developmental harm are released around the Pittsburgh rivers, and Pennsylvania ranks among the top ten states by toxicity-weighted chemicals released in 2020 (Rumpler et al., 2022[lxxv]).

Data Source [lxxvi]

Data	Time Period	Agency	Source
Risk Screening Environmental Indicators (RSEI) geographic water (stream segment) microdata	1 year	EPA	https://www.epa.gov/rsei/ways-get-rsei-results#microdata

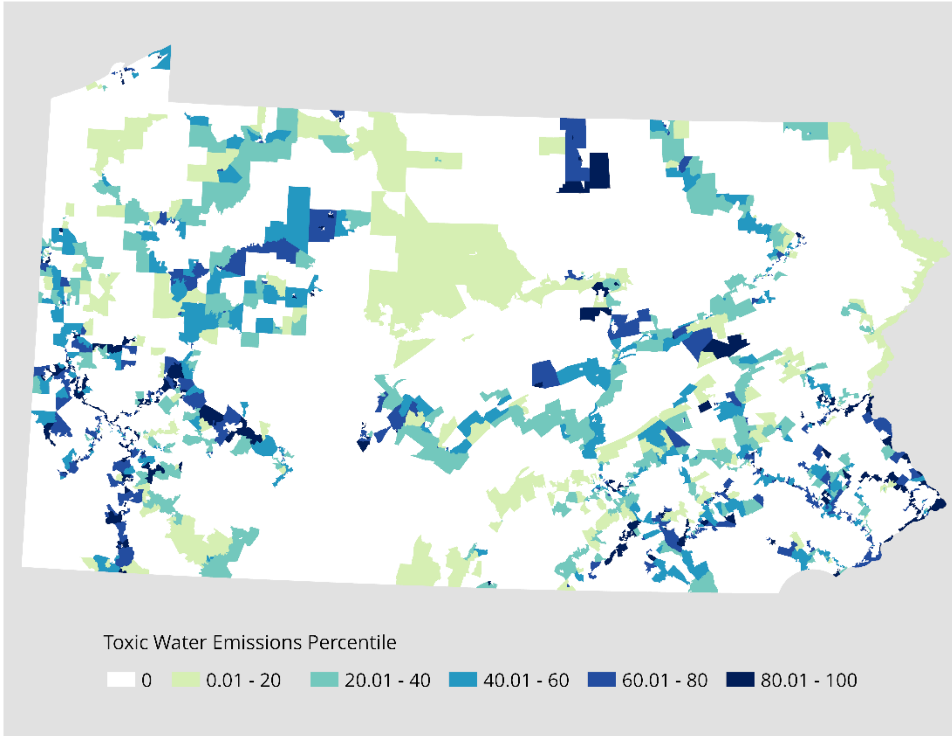
Methods

- RSEI aggregated water stream microdata files containing modeled chemical concentrations downstream of separate on-site and off-site chemical releases were downloaded from the EPA for the three most recent available years.

- On-site and off-site concentration values were summed to obtain a total concentration for each stream segment.

- Within each census block group, the total stream segment concentrations were averaged into one concentration value. This concentration value was multiplied by the total length of streams for each block group, then divided by the area of the block group, resulting in a value of miles of concentration-weighted stream segment length per square mile of land area.

- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Toxic Water Emissions in Pennsylvania.

Future Considerations

The data used for this indicator contain modeled concentrations of chemicals in surface water, but measurements of toxic substances in drinking water would be more ideal in order to quantify exposure to these substances. Such data do exist, but these measurements are recorded at the municipal level and could not be obtained on a comprehensive statewide level for this analysis. Additionally, these measurements generally do not include private water wells. If measurements from municipal water sources and private wells become widely available in the future, this indicator may be updated to be include these data.

Pesticides

Rationale

Environmental pollution, including pesticides, is known to disproportionately affect non-white minorities and low-income and wealthy communities (Donley et al., 2022[lxxvii]). Pennsylvania migrant farmworkers and communities near agricultural fields, particularly farmworker communities, may be at risk of exposure to pesticides (Edelson et al., 2018[lxxviii]). Drift or volatilization of pesticides from agricultural fields can be a significant source of pesticide exposure. There is growing concern about the effects of chronic low-level pesticide exposure during childhood on the development of childhood cancers (Chen et al., 2015[lxxix]). A systematic review and meta-analysis that looked at the relationship between residential pesticides and childhood leukemia, including data from research on Pennsylvania's cancer registry, found increased associations between childhood leukemia and residential pesticide exposures (Dell, 2004[lxxx]; Turner et al., 2010[lxxxi]). Fifteen pesticides were identified as being of particular concern by our stakeholder advisory groups and are listed in the following table.

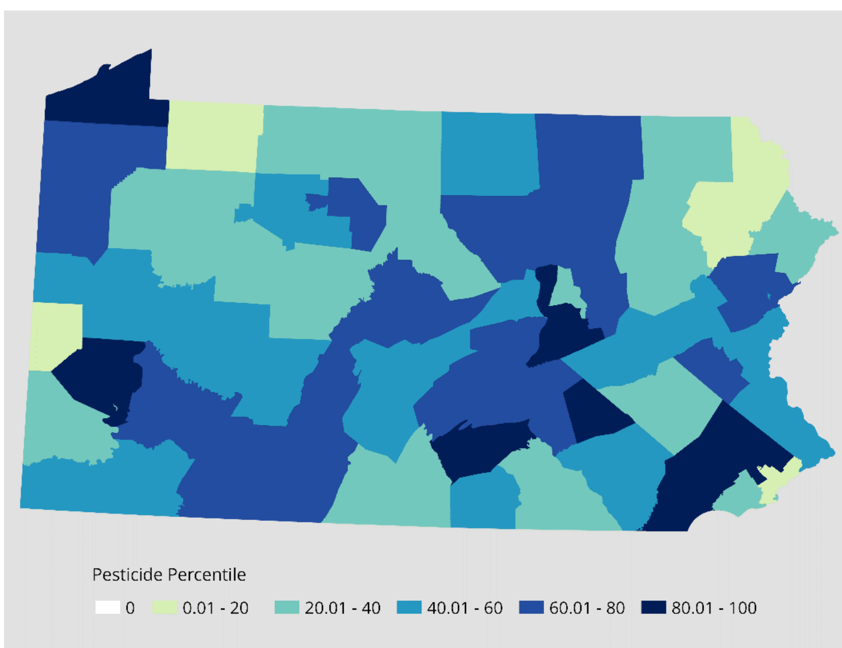
Pesticides of Importance identified by stakeholder advisory group	
Pesticide	**Toxicity Profile**
Aldrin[lxxxii]	Acute Toxic, Health Hazard, Environmental Hazard, suspected carcinogen
Benzo(g,h,i,)perylene[lxxxiii]	Environmental Hazard, Health Hazard, suspected carcinogen
Chlordane[lxxxiv]	Irritant, Health Hazard, Environmental Hazard
Heptachlor[lxxxv]	Acute Toxic, Health Hazard, Environmental Hazard, suspected carcinogen
Hexabromocyclododecane[lxxxvi]	Health Hazard, Damage to fertility or unborn child, environmental hazard
Hexachlorobenzene[lxxxvii]	Health Hazard, Environmental Hazard, Carcinogen, organ damage
Isodrin[lxxxviii]	Fatal if swallowed, skin contact, and inhaled, acute toxic, environmental hazard
Methoxychlor[lxxxix]	Irritant, Health Hazard, Environmental Hazard, Carcinogen, organ damage
Octachlorostyrene[xc]	Environmental Hazard, carcinogen
Pendimethalin[xci]	Irritant, Environmental Hazard, allergic reactions, possible carcinogen
Pentachlorobenzene[xcii]	Flammable, irritant, environmental hazard, health hazard
Polychlorinated biphenyl (PCBs)[xciii]	Organ damage, health hazard, environmental hazard, possible carcinogen
Tetrabromobisphenol[xciv]	Environmental Hazard
Toxaphene[xcv]	Acute Toxic, Health Hazard, Environmental Hazard, irritant, suspected carcinogen
Trifluralin[xcvi]	Irritant, Health Hazard, Environmental Hazard, suspected carcinogen

Data Source [xcvii]

Data	Time Period	Agency	Source
County-level estimated annual agricultural pesticide use	5 years	USGS	https://www.sciencebase.gov/catalog/item/5e95c12282ce172707f2524e
Toxic Release Inventory (TRI) points	1 year	EPA	https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-present

Methods

- County-wide pesticide use totals in pounds for years 2013 to 2017 (the most recent 5-year data set available) were summed to obtain a 5-year total weight for all pesticides within each county, and each county total was assigned to all block groups falling within that county. Values were multiplied by 0.6 to approximate the three-year range of the TRI data.
- Within each county, each block group's county-level pesticide use value was divided by the number of block groups within that county to obtain an estimate of each block group's portion of the county total.
- The three most recent years of TRI data were downloaded from the EPA, then selected to only include the 15 pesticides provided by stakeholder recommendation and TRI documentation.
- TRI chemical release values were summed with the county-level USGS values assigned to each census block group to obtain one total pesticide value.
- Each census block group was assigned a percentile based on the statewide distribution of values.



Percentiles of Pesticides in Pennsylvania.

Future Data Considerations

Pesticide use data were only available at the county level. If higher resolution data becomes available in the future, this indicator may be updated to include this data. Additionally, the two data sets used represent different concepts: pesticide use, and pesticides inadvertently released (from the Toxic Release Inventory) as part of industrial production, transportation, etc. The latter data were added to produce more granular variation in block group-level values; however, these data contain relatively few pesticide releases and therefore have little impact on the resulting indicator percentiles. If higher resolution pesticide use data become available, it may be ideal to remove the TRI data from this indicator in the future.

Children's Lead Risk

Rationale

Lead (Pb) is a toxic heavy metal that can have detrimental effects on human health, particularly in children. Children exposed to lead can experience developmental delays, learning disabilities, and behavioral problems (Centers for Disease Control and Prevention, 2021[xcviii]). Lead exposure can also cause anemia, hypertension, and kidney damage in adults (World Health Organization, 2019[xcix]).

In Pennsylvania, lead soil contamination from legacy sources in urban environments represents a significant health risk for exposed populations, particularly in communities facing environmental justice concerns (O'Shea et al., 2021[c]). A study conducted in Philadelphia found that the presence of lead paint in homes and the number of demolitions of older properties were the highest correlations to elevated blood lead levels in children (Caballero-Gomez et al., 2022[ci]). In addition, the Pennsylvania Department of Health conducts annual lead surveillance reports, monitoring elevated blood levels in children. Childhood lead poisoning is a significant issue in Pennsylvania, particularly in older cities like Philadelphia, Lancaster, Reading, and Scranton (Pennsylvania Department of Health, 2022[cii]). Despite efforts by the Philadelphia Department of Public Health to address systemic childhood lead poisoning, children continue to be identified with elevated blood lead levels.

Data Source [ciii]

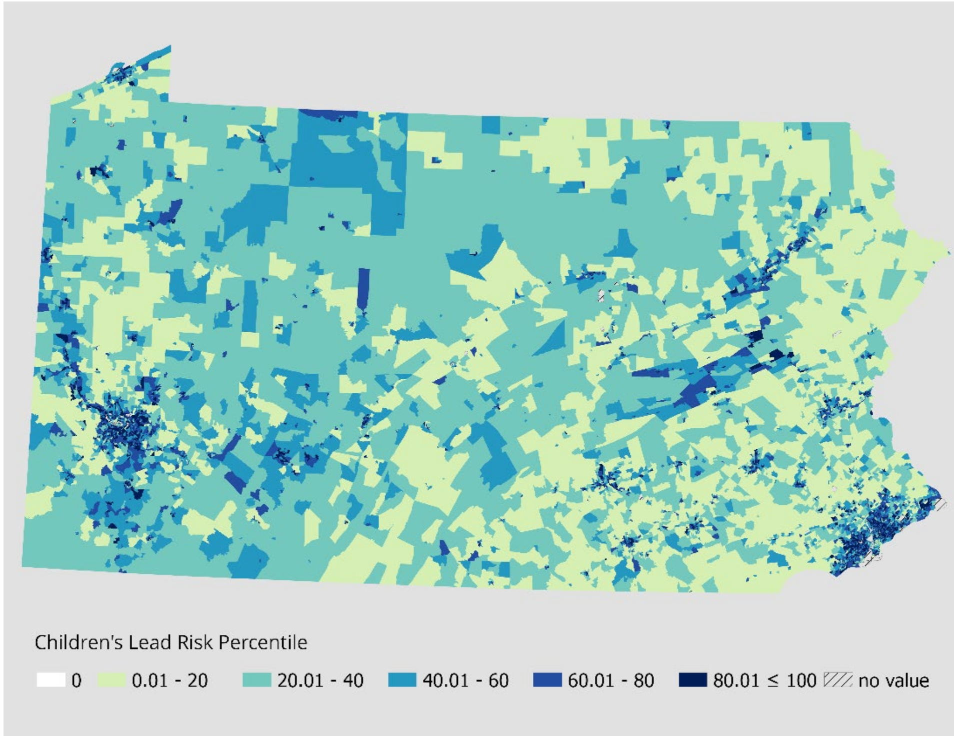
Data	Time Period	Agency	Source
US Census American Community Survey 2019 5-year data (ACS Table B25034), containing the number of households built before 1979 in each block group	2019 5-year data	U.S. Census Bureau	https://data.census.gov/table?q=b25034&g=0400000US42$1500000&tid=ACSDT5Y2019.B25034

Methods

- In ACS Table B25034, the number of households built before 1979 in each block group was divided by the total number of existing households in the block group to obtain a percentage.

- The census block groups were assigned a percentile based on the statewide distribution of values.

- Census block groups were excluded based on high uncertainty of estimates. To determine this, the Standard Error (SE) was calculated for each census block group following the ACS procedure for calculating the SE of column proportions (US Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each tract by dividing the standard error by the pre-1979 housing percentage. A tract was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50 percent of the estimate), and SE greater than the mean of all tracts' SE values.



Percentiles of Children's Lead Risk in Pennsylvania.

Future Considerations

The proportion of housing constructed prior to 1979 serves as a proxy for estimating the risk of lead exposure for young children. However, it must be noted that this metric does not provide a direct measurement of the occurrence or magnitude of lead exposure in children. To obtain a more precise measurement of lead exposure, data on Elevated Blood Lead Levels (EBLLs) would be beneficial. Such data, while available in more urban areas, is not universally available at a state-wide level.

In addition to data on EBLLs, information on soil lead levels would also provide valuable insight into the extent of lead contamination in the state. However, such data is currently not available at a state-wide level, and even if it were, it would not directly measure EBLLs. This data, if it becomes available in the future, could be incorporated into this indicator.

It is important to note that the indicators related to child lead exposure and soil testing should be continuously monitored and evaluated in the future as they are critical components in understanding and addressing the issue of lead exposure in the state.

The indicator presented here was calculated using data from the American Community Survey's (ACS) 5-year data set from 2019. While more recent data is available, the 2019 data aligns with the 2010 US Census block group geometries used in this analysis. As data for certain indicators is still based on the 2010 census geometries and has not yet been made available at the 2020 geometries, using data from both the 2010 and 2020 census geometries would result in data mismatches between certain tracts. Therefore, the decision was made to use the 2010 census data for this analysis. As soon as data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Traffic Density

Rationale

According to Tian et al. (2013)[civ], lower-income and minority populations in the United States are more likely to live near major roads. Noise pollution is a common issue in these areas, as high-traffic roads can generate levels of noise often measured above 70 dBA, which is the threshold at which hearing damage may occur over time (Kapp et al., 2015[cv]). This is especially concerning considering that research in Allegheny County found an association between ambient air pollution and the rate of hospitalization for congestive heart failure among Medicare recipients aged 65 or older (Wellenius et al., 2005[cvi]). This suggests that air pollution from traffic-related sources can be a trigger for this health outcome, and that these patients may be more susceptible to its effects.

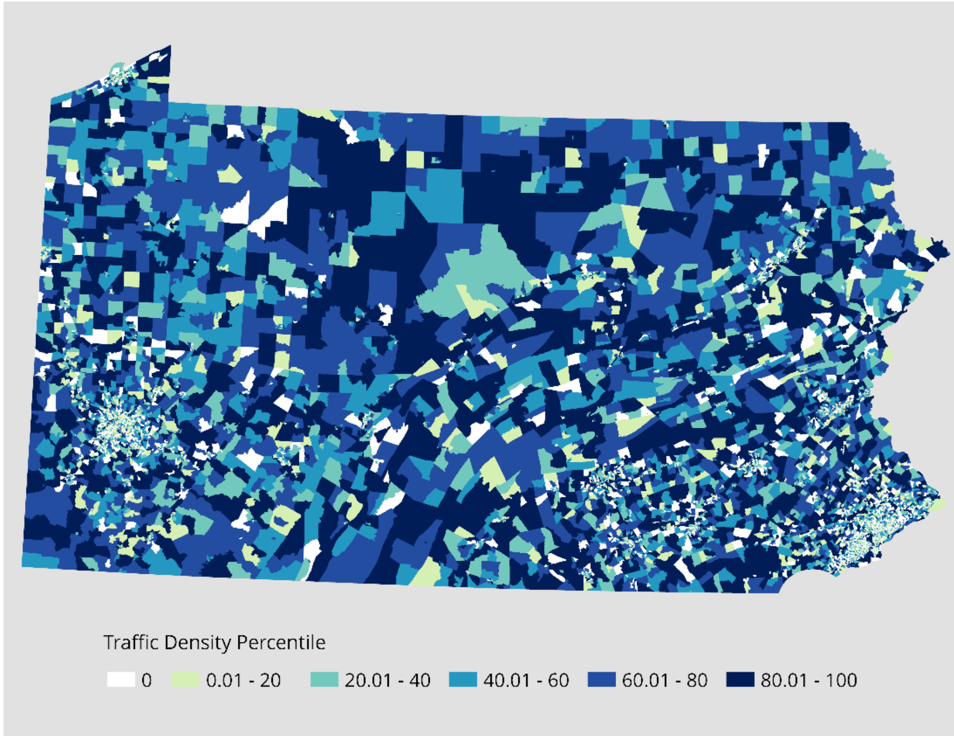
A 2020 study investigating road dust in Philadelphia found that sites with high traffic densities had higher mean concentrations of Fe, Cr, Cu, and Zn (O'shea et al., 2020[cvii]). This, combined with the fact that low-income and racial minorities are disproportionately skewed towards areas of high exposure, suggests that these populations, often referred to as environmental justice (EJ) residents, bear a greater risk for air pollution-related disease compared to other residents (Fabisiak et al., 2020[cviii]).

Data Source[cix]

Data	Time Period	Agency	Source
Annualized daily traffic (AADT) counts from PennDOT containing traffic volume measurements for each road segment	Continuous	PennDOT	https://data-pennshare.opendata.arcgis.com/datasets/PennShare::rmstraffic-traffic-volumes/explore

Methods

- Annualized daily traffic (AADT) counts from PennDOT were downloaded as a polyline shapefile containing the most recent traffic volume measurement for each road segment.
- Truck and car traffic values were summed within a 150-meter buffer of each census block group.
- Traffic sums were multiplied by the total length of roads within each buffer polygon to obtain a figure of traffic-miles.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Traffic Density in Pennsylvania.

Future Considerations

Additional PennDOT data on Transportation Systems Management and Operation (TSMO) truck bottleneck rankings (available at PennDOT OneMap) and Transit Improvement Projects lines and points were considered but not included in this analysis, because the traffic data used contains truck traffic counts and provide geographically comprehensive measurements across the state. Such additional data may be useful to include in this indicator in the future.

POLLUTION BURDEN: ENVIRONMENTAL EFFECTS INDICATORS

Oil and Gas – Unconventional Wells

Rationale

Hughes (2013)[cx] notes that modern technological advancements in extracting natural gas from shale formations have led to rapid growth in natural gas production in the United States in previously inaccessible areas. One such technological advancement, hydraulic fracturing, is utilized in the Marcellus shale formation in the Commonwealth of Pennsylvania. As of 2022, there are approximately 13,000 unconventional natural gas wells drilled in the state (PADOH, 2022[cxi]).

However, natural gas drilling has raised public concerns about the extraction process and its potential negative impacts on the environment and human health (Finkel & Law, 2013[cxii]; Witter et al., 2013[cxiii]; Clough & Bell, 2016[cxiv]). Hydraulic fracturing uses a mixture of fluids that contain chemicals known to be harmful to human health, such as corrosion inhibitors, biocides, surfactants, friction reducers, gels, and scale inhibitors (Aminto & Olson, 2012[cxv]). These fracturing fluids can expose humans through various means, including surface leaks, releases from storage tanks, well pad accidents, transportation, flowback, and flooding events (Rozell & Reaven, 2012[cxvi]). Research has found that air quality around unconventional well pads is often worse, particularly during the pre-operational phase when there is an increase in heavy traffic, energy generation, and construction work on site (Wilde et al., 2022[cxvii]; Field et al., 2014[cxviii]).

Many chemical compounds used in the hydraulic fracturing process are unknown or understudied, making it difficult to fully assess the public health risks (Colborn et al., 2011[cxix]; Stringfellow et al., 2017[cxx]). As unconventional extraction techniques have expanded in recent decades, more people are living near oil and gas development (Blinn et al., 2020[cxxi]). In Pennsylvania, unconventional oil and gas drilling has been associated with increased hospital utilization rates in areas with a high density of wells (Jemielita et al., 2015[cxxii]). A study investigating the associations between county-level socio-economic and demographic factors and oil and gas drilling in Pennsylvania between 2004-2016 found higher numbers of oil and gas complaints filed, as well as an increase in the number and proportion of state investigations of water supply complaints yielding a confirmed water supply impairment in these vulnerable communities (Clark et al., 2021[cxxiii]).

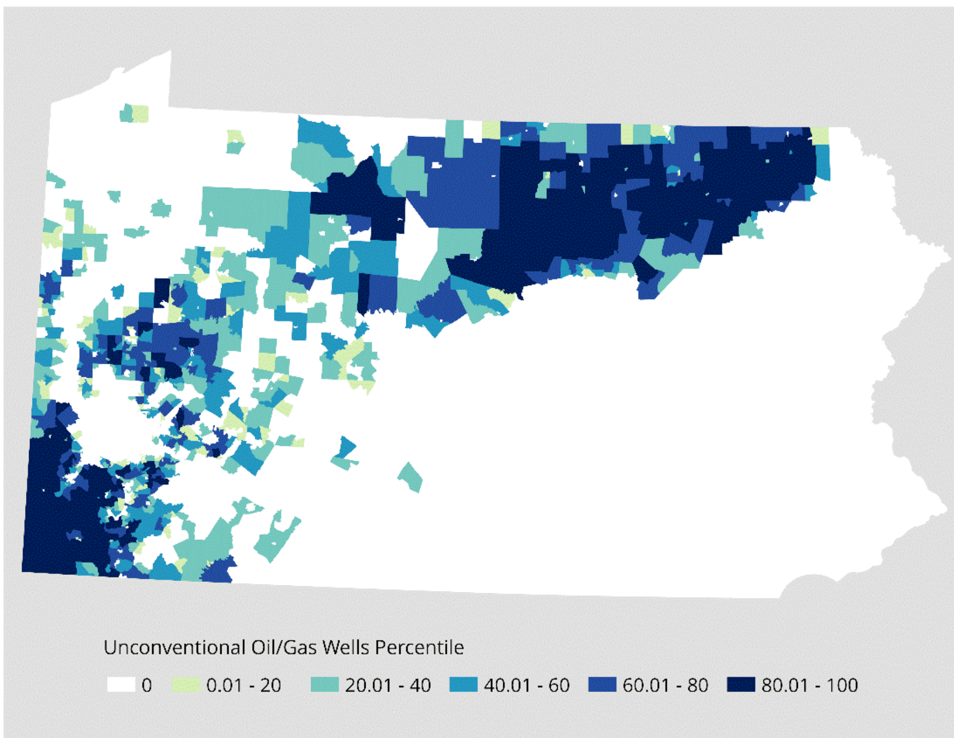
Data Source[cxxiv]

Data	Temporal Resolution	Agency	Source
DEP point data on locations of unconventional wells	Continuously updated	DEP	https://newdata-padep-1.opendata.arcgis.com/maps/oil-gas-unconventional-well-locations/about

Methods

- Unconventional Oil and Gas well points were selected to include only those with a status of “active” or “abandoned.”

- Wells within 1 km of each census block group were assigned weights based on proximity:
  - $0 \leq$ site ≤ 250 meters = 1
  - $250 \leq$ site ≤ 500 meters = 0.5
  - $500 \leq$ site ≤ 750 meters = 0.25
  - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group.
- A percentile was then calculated for each block group based on the statewide distribution of values.



Percentiles of Unconventional Wells concentration levels in Pennsylvania.

Future Considerations

In the future, it may be useful to consider wells with a status besides "active" and "abandoned."

Oil and Gas – Conventional Wells

Rationale

Operations to bring crude oil to the surface, including exploratory processes, frequently occur near human populations (Kang et al., 2016[cxxv]; PADOH, 2022[cxxvi]). Oil and natural gas production are a significant industry in Pennsylvania, with approximately 350,000 conventional oil and natural gas wells drilled in the state (PADOH, 2022[cxxvii]). Many Pennsylvanians live in census tracts with a high concentration of these operations, and those living near these sites are disproportionately exposed to their potential environmental harms (PADOH, 2022[cxxviii]).

Conventional oil and gas facilities can pose risks to human and environmental health (Johnston et al., 2019[cxxix]). These operations have been known to release a range of harmful chemicals, including particulates, benzene, heavy metals, radioactive materials, and polycyclic aromatic hydrocarbons (PAHs) into the water, soil, and air (Pichtel, 2016[cxxx]; Costa et al., 2017[cxxxi]). This type of pollution has been linked to a number of adverse health outcomes, including pregnancy complications, cardiovascular and respiratory illness, multiple cancers, neurological issues, and other adverse developmental outcomes (Elliott et al., 2017[cxxxii]; Bamber et al., 2019[cxxxiii]).

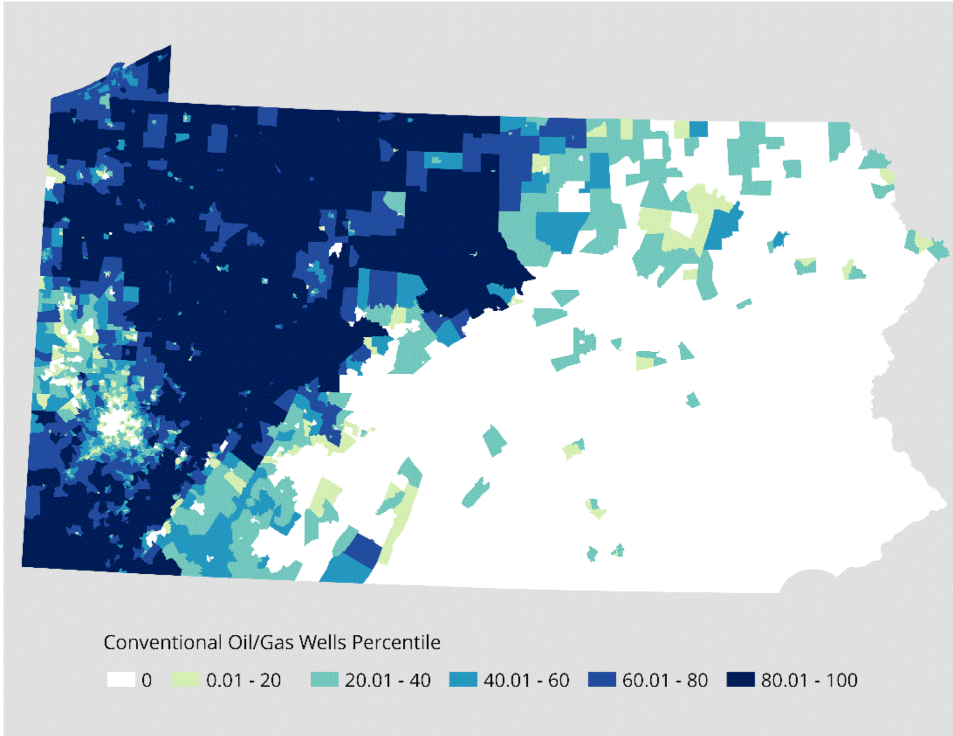
Conventional oil and gas operations remain a major industry in Pennsylvania, with operations present in much of the state (PADOH, 2022[cxxxiv]).

Data Source [cxxxv]

Data	Temporal Resolution	Agency	Source
Conventional Wells location points	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/54

Methods

- Conventional Oil and Gas sites were selected to include only those with a status of "Active," "Abandoned," "DEP Orphan list," "DEP Abandoned list," "plugged unverified," or "uncharted mined through."
- Sites within 1 km of each census block group were assigned weights based on proximity:
  - $0 \leq$ site ≤ 250 meters = 1
  - $250 \leq$ site ≤ 500 meters = 0.5
  - $500 \leq$ site ≤ 750 meters = 0.25
  - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Conventional Wells in Pennsylvania.

Future Considerations

In the future, it may be useful to consider wells with a status other than those selected for this analysis.

Proximity to Railroads

Rationale

According to the U.S. Bureau of Transportation Statistics (BTS), at the end of 2020 there were just over 23,500,000 freight and 484 passenger rail locomotives in operation in the U.S. (USDOT Bureau of Transportation, 2020[cxxxvi]). Diesel remains the predominant source of energy used to power passenger and freight rail in the U.S. In Pennsylvania, exposure to air pollution near freight rail lines is higher in minority communities (Popovich et al., 2021[cxxxvii]).

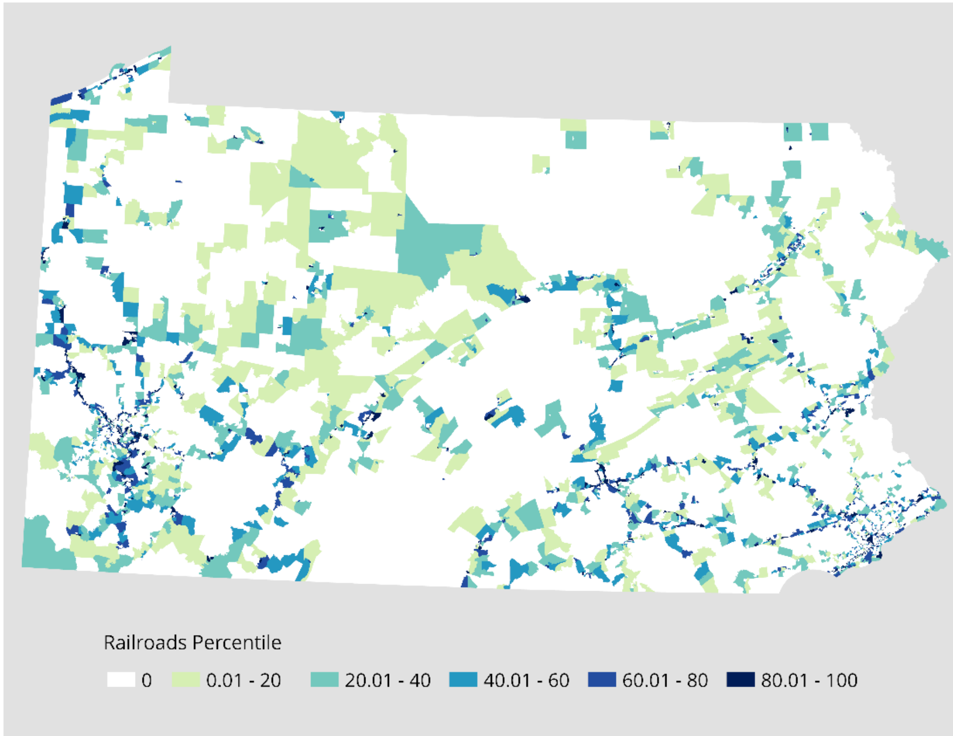
A report by the Public Interest Network found that a disproportionate number of non-white minority and low-income people in Philadelphia, Pittsburgh, Harrisburg, and Reading reside within dangerous oil train blast zones (The Public Interest Network, 2016[cxxxviii]). These individuals face increased risks from emissions, spills, and derailments, especially on Class 1 railroads, which have a higher volume of trains and cargo compared to Class 2 or 3 railroads. Along with toxic cargo, Class 1 railroads also pose greater risks in terms of traffic, noise, pollution, and overall risk compared to other classes of railroads.

Data Source [cxxxix]

Data	Temporal Resolution	Agency	Source
Rail line segments	Continuously updated	PennDOT	https://data-pennshare.opendata.arcgis.com/datasets/pennsylvania-rail-lines-1/explore

Methods

- Railroad lines were downloaded from PennDOT.
- The length of each line segment was multiplied by an assigned weight based on its rail class value:
  - 'Class I' = 1
  - 'Class II' = 0.5
  - 'Class III' = 0.25
  - 'Regional,' 'Short Line,' 'Yard,' 'Other,' 'None' = 0.1
- Weighted rail line lengths were summed within each census block group; this sum was divided by the area of the block group to obtain a density measure of weighted railroad length (miles) per square mile.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Proximity to Railroads in Pennsylvania.

Future Considerations

Continue to monitor updated databases for railroads. Consider different weight assignments and rail class values.

Land Remediation

Rationale

The EPA has recognized the need to address environmental justice issues and has included land protection and cleanup programs in their 2022 Environmental Justice Action Plan (Environmental Protection Agency, 2022[cxl]). This is particularly important for communities living in close proximity to land remediation sites, such as brownfields and superfund sites, which can be vulnerable to the negative impacts of toxic chemicals. As Kiaghadi et al. (2021)[cxli] have noted, these communities may experience unique burdens, including an increased likelihood of exposure to toxic chemicals and a decrease in life expectancy. These chemicals can contaminate various environmental media, including air, soil, water, and buildings (Raid et al., 2018[cxlii]). Studies have even found that certain areas with high densities of superfund sites have elevated rates of gastrointestinal cancers (Griffith et al. 1989[cxliii]; Kiaghadi et al. 2021). In one example, research conducted in EPA Region 3 found that several counties in Pennsylvania had a cancer incidence relative risk of 1.17 in relation to superfund site density (Kiaghadi et al. 2021[cxliv]).

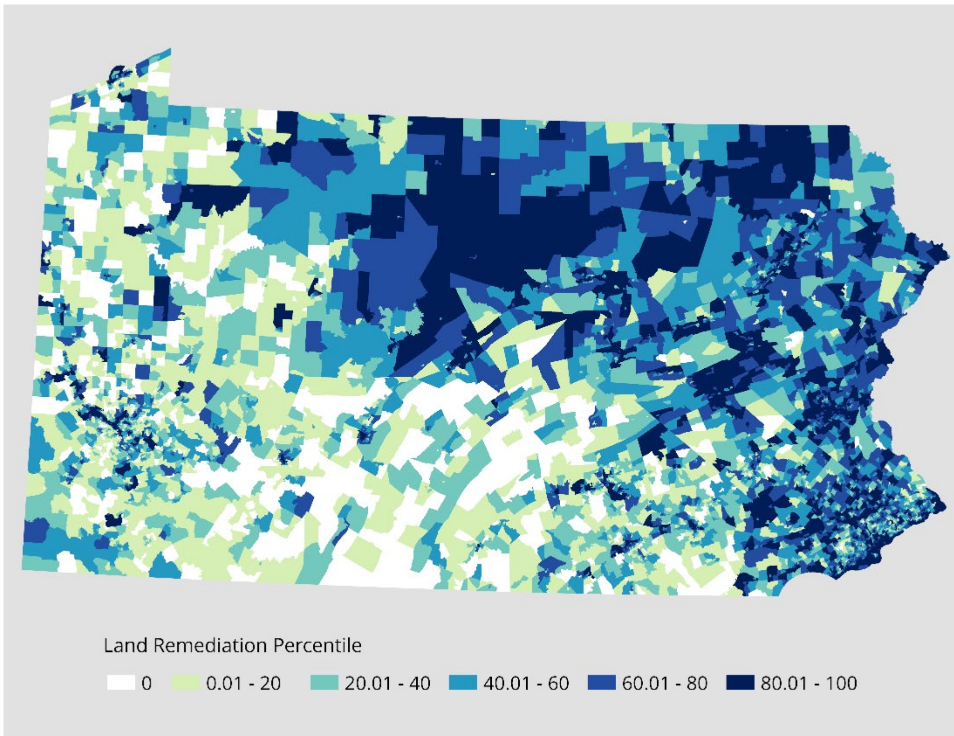
Data Source

Data	Temporal Resolution	Agency	Source
Superfund Sites points	Continuously updated	EPA	https://geodata.epa.gov/arcgis/rest/services/OEI/FRS_INTERESTS/MapServer/21
Brownfields Sites points	Continuously updated	EPA	https://geodata.epa.gov/arcgis/rest/services/OEI/FRS_INTERESTS/MapServer/0
Surface Mine Reclamation Sites points	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/25
Land Recycling Cleanup sites points	Continuously updated	DEP	Air Media: (link) Contained Release Or Abandoned: (link) Groundwater Media: (link) Sediment Media: (link) Soil Media: (link) Surface Water Media: (link) Waste Media: (link)

Methods

- Data for each site type was downloaded, and all data sets were merged into one data set.
- Data were selected to only include active sites.

- Sites within 1 km of each census block group were assigned weights based on proximity:
    - $0 \leq$ site ≤ 250 meters = 1
    - $250 \leq$ site ≤ 500 meters = 0.5
    - $500 \leq$ site ≤ 750 meters = 0.25
    - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Land Remediation in Pennsylvania.

Future Considerations

Continue to monitor updated databases and additional sources for land remediation. Consider different weights and including or excluding sub-indicators included in this metric.

Hazardous Waste and Storage Sites

Rationale

In the state of Pennsylvania, the Hazardous Waste Program is responsible for regulating the generation, storage, transportation, treatment, and disposal of hazardous waste (DEP, 2022). These hazardous wastes can take various forms, including liquids, solids, and contained gases, and are often generated through the production of consumer goods, such as plastics. One example of a hazardous chemical commonly found in hazardous waste and storage sites is hexavalent chromium, which has been identified as a carcinogen and can cause damage to multiple organs in the human body when ingested or inhaled (Pellerin & Booker, 2000[cxlv]). A population-based case-control study from Pennsylvania found an association between in utero exposure to hexavalent chromium and autism spectrum disorders (Wise et al. 2022[cxlvi]; Talbott et al. 2015[cxlvii]).

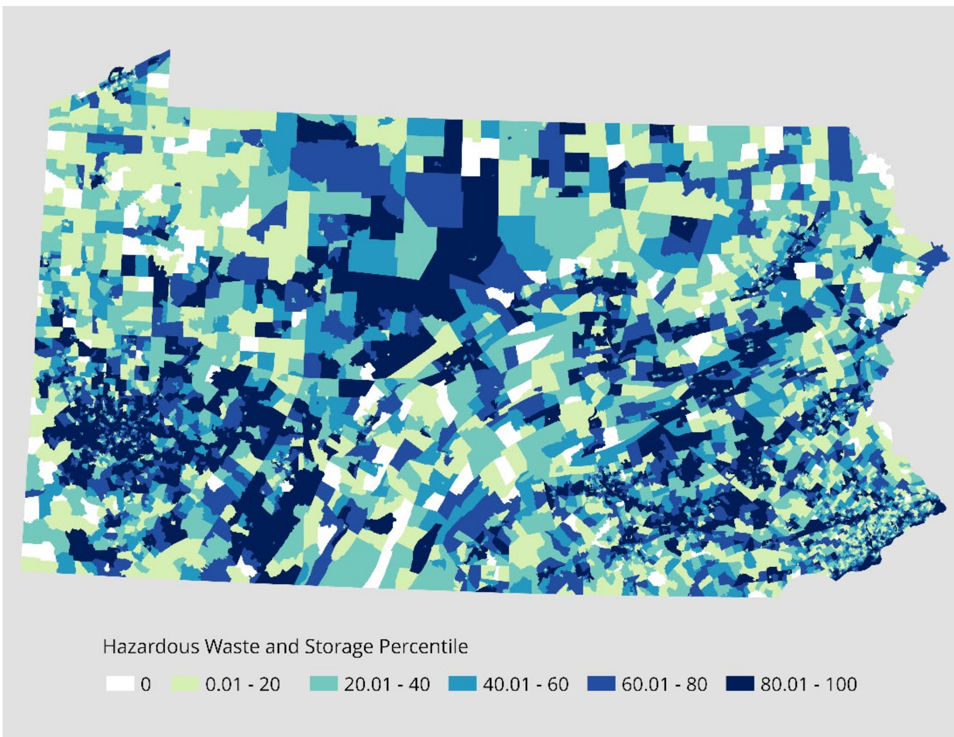
In the United States, smaller generators of hazardous waste typically send their waste an average distance of 200 miles for treatment or disposal (Hazen et al., 2018[cxlviii]) (McGlinn, 200). The presence of hazardous waste has the potential to harm both human and environmental health. Many studies have investigated the disproportionate impact of hazardous waste treatment, storage, or disposal on minority and low-income communities (Shrader-Frechette, 2022[cxlix]; Bullard et al., 2002[cl]). Although most hazardous waste treatment, storage, and disposal sites are located in areas with few minority or low-income residents, there are some that are in heavily populated, minority or low-income areas, leading to disadvantaged populations living in close proximity to these sites (Atlas, 2001[cli]). Research has shown that living near hazardous waste sites can have negative health effects, including an increased risk of conditions such as diabetes, asthma, respiratory diseases, and cardiovascular disease (Kouznetsova et al., 2007[clii]; Best el al., 2015[cliii]).

Data Source

Data	Temporal Resolution	Agency	Source
Coal above-ground storage tanks points	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/29
Active storage tanks points	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/118
Captive Hazardous Waste Sites points	Continuously updated	DEP	Generator (link) Incinerator (link) Recycling (link) Treatment (link) Disposal (link) Storage (link) Boiler/Industrial Furnace (link)
Commercial Hazardous Waste Sites points	Continuously updated	DEP	Generator (link) Recycling (link) Treatment (link) Disposal (link) Storage (link) In-Transit Storage (link)

Methods

- Data for each site type were downloaded, and all data sets were merged into one data set.
- Sites were selected to include only active sites.
- Sites within 1 km of each census block group were assigned weights based on proximity:
  - $0 \leq$ site ≤ 250 meters = 1
  - $250 \leq$ site ≤ 500 meters = 0.5
  - $500 \leq$ site ≤ 750 meters = 0.25
  - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Hazardous Waste and Storage Sites in Pennsylvania.

Future Considerations

Continue to monitor updated databases and additional sources for hazardous waste and storage sites.

Coal Mining

Rationale

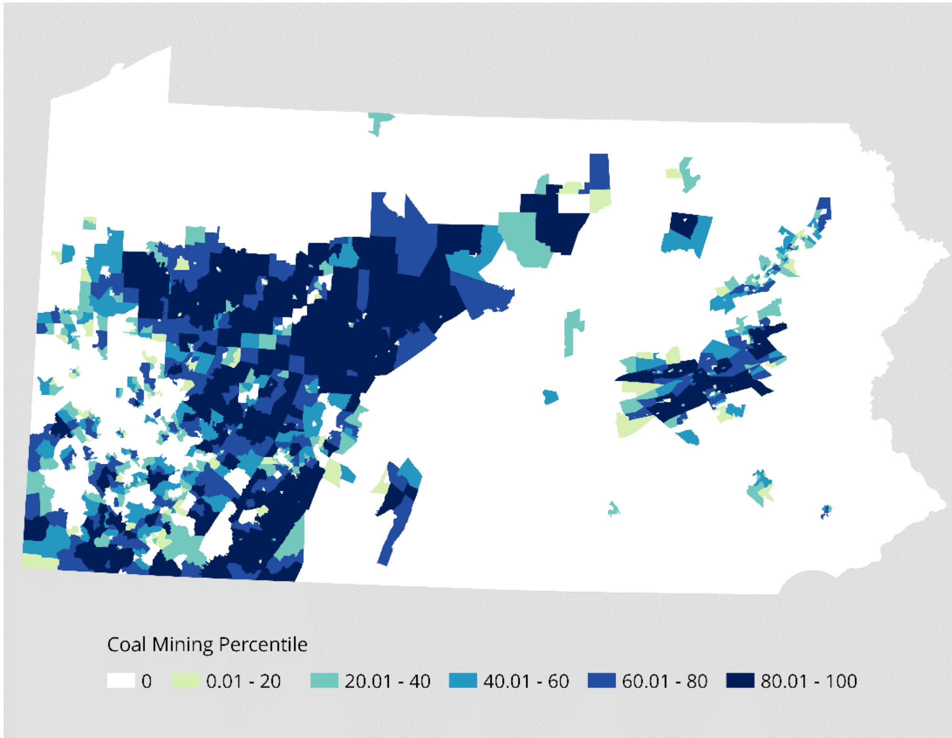
Coal is a nonrenewable source of energy that is often used in the production of electricity through combustion. Communities located near coal mining sites may also be at risk for negative health impacts due to exposure to pollution from coal mining activities. This can include air and water pollution, such as heavy metals, nitrogen oxides, and fine particulate matter (Gasparotto & Da Boit Martinello, 2021[cliv]). Studies have found that communities with coal mining activity experience higher levels of pollution in Pennsylvania (Niu et al., 2017[clv]). The improper disposal of waste derived from coal mining can contribute to environmental contamination (Russell et al., 2017[clvi]). Additionally, coal miners are often exposed to high levels of respirable coal dust during working hours, and guidelines for safe exposure levels have been established by the Centers for Disease Control and Prevention (CDC, 2020[clvii]).

Data Source

Data	Temporal Resolution	Agency	Source
Aggregate of multiple DEP sources	Continuously updated	DEP	Refuse Reprocessing (link) Anthracite River Dredge (link) Discharge Point (link) Mineral Preparation Plant (link) Mining Stormwater General Permit (link) NPDES Discharge Point (link) Post Mining Treatment (link) Refuse Disposal Facility (link) Refuse Reprocessing (link) Surface Mine (link) Underground Anthracite Exploration (link) Underground Mine (link)

Methods

- All data sets were downloaded and merged into one data set.
- Sites were selected to include only active sites.
- Sites within 1 km of each census block group were assigned weights based on proximity:
  - $0 \leq$ site ≤ 250 meters = 1
  - $250 \leq$ site ≤ 500 meters = 0.5
  - $500 \leq$ site ≤ 750 meters = 0.25
  - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Coal Mining in Pennsylvania.

Future Considerations

Continue to monitor updated databases and additional sources for coal mining data. Consider redefining this category and group sub-indicators into another indicator.

Municipal Waste

Rationale

DEP manages the Municipal Waste Program, which regulates the storage, transportation, processing, beneficial use, composting, and disposal of municipal waste (DEP, 2022[clviii]). However, communities located near municipal waste sites may be at increased risk for degraded environmental health. For example, a study examining soil toxicity in samples from municipal landfill sites found that the soil samples from these sites were more toxic than organic soil extract (Roelofs et al., 2012[clix]). Other research has also found that individuals living near landfill and other municipal waste sites may have increased exposure to hazardous chemicals such as hydrogen sulfide, dioxins, and other chemicals (Mataloni et al., 2016[clx]; Vassiliadou et al., 2009[clxi]).

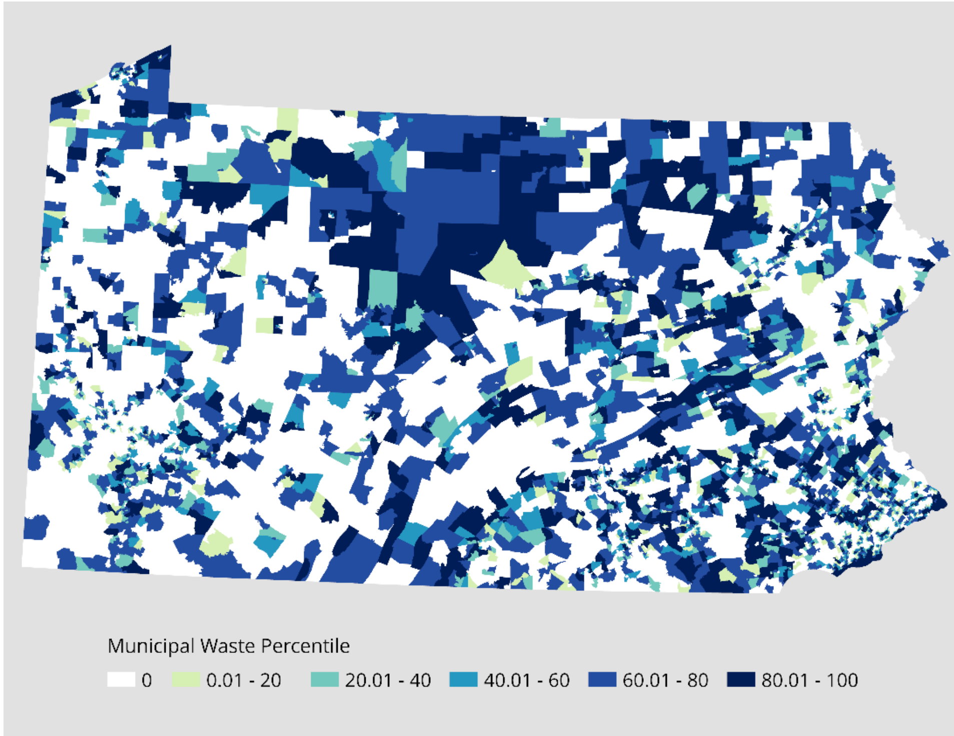
In response to these concerns, the General Assembly of the Commonwealth of Pennsylvania enacted the Municipal Waste Planning, Recycling, and Waste Reduction Act in 1988. This act was designed to reduce improper municipal waste practices in Pennsylvania and was based on the legislative finding that such practices create public health hazards, environmental pollution, and economic loss, and can cause irreparable harm to the public health, safety, and welfare (Commonwealth of Pennsylvania, 1988[clxii]).

Data Sources

Data	Temporal Resolution	Agency	Source
Municipal Waste Program Sites	Continuously updated	DEP	Composting (link) Land Application (link) Abandoned Landfill (link) Landfill (link) Multiple Waste Generator (link) Processing (link) Resource Recovery (link) Transfer Station (link)

Methods

- All data sets were downloaded and merged into one data set.
- Sites within 1 km of each census block group were assigned weights based on proximity:
    - 0 ≤ site ≤ 250 meters = 1
    - 250 ≤ site ≤ 500 meters = 0.5
    - 500 ≤ site ≤ 750 meters = 0.25
    - 750 ≤ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of Municipal Waste Sites in Pennsylvania.

Future Considerations

Continue to monitor updated databases and additional sources for municipal waste sites.

Impaired Lakes and Streams

Rationale

An impaired water body is one that does not meet the designated uses set by the state's water quality standards, such as being too polluted for drinking or swimming, or not having sufficient oxygen levels to support aquatic life. These bodies of water can be contaminated by various pollutants, including agricultural or urban runoff, industrial discharges, and untreated sewage (EPA, 2002[clxiii]).

Low-income and minority communities may be disproportionately affected by impaired water bodies, as they often rely on these bodies of water for their economic, cultural, recreational, and nutritional needs. These communities may also be more vulnerable to the negative health impacts of water pollution (EPA, 2002[clxiv]).

In Pennsylvania, DEP is responsible for monitoring water quality in the state. In 2022, the DEP released an updated Integrated Water Quality Report, which assessed the health of over 80,000 miles of streams in the state. The report found that over 27,000 miles of these streams were impaired, with over 2,400 miles becoming polluted in the past two years. Urban areas within the Pittsburgh and Philadelphia regions had the highest percentage of polluted streams. In addition, the report found that just under two-thirds of the state's 110,000 lakes were polluted. Alleghany County had the highest percentage of impaired streams, with about two-thirds of the county's streams being reported as impaired (DEP, 2022[clxv]).

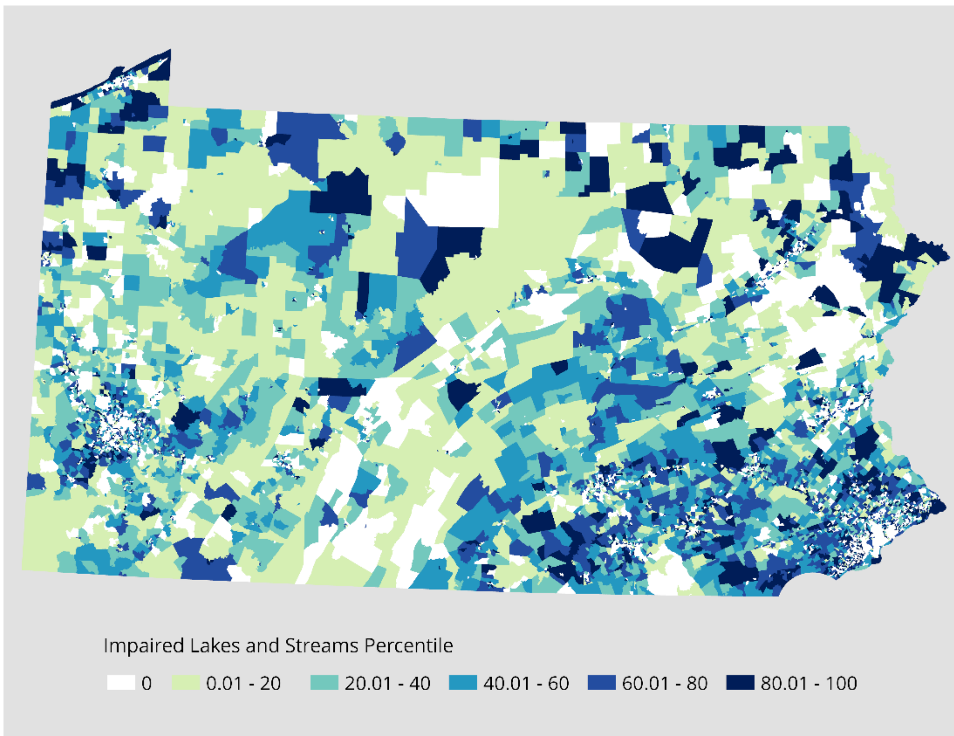
Data Source

Data	Temporal Resolution	Agency	Source
Non-Attaining Streams	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/107 https://newdata-padep-1.opendata.arcgis.com/maps/PADEP-1::water-quality-integrated-list-non-attaining-streams/about
Non-Attaining Lakes	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/114

Methods

- Non-attaining lakes within 1 km of each census block group were assigned weights based on proximity:
  - $0 \leq$ site ≤ 250 meters = 1
  - $250 \leq$ site ≤ 500 meters = 0.5
  - $500 \leq$ site ≤ 750 meters = 0.25
  - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all lakes within 1 km of each block group.

- A percentile was calculated for each block group based on the statewide distribution of values.
- The length of non-attaining stream segments within each block group was summed. This total length (miles) was divided by the total area of the block group (square miles), resulting in a density measure of miles of stream per square mile.
- The percentiles for non-attaining streams and lakes were averaged to obtain a non-attaining bodies of water score for each block group. Using this score, a new percentile was calculated to obtain the indicator percentile.



Percentiles of Impaired lakes and streams in Pennsylvania.

Future Considerations

Stakeholders recommended the consideration of data from the Chesapeake Bay Watershed Public School Stream Best Management Practice Evaluation Program. This data was not used because it only covers part of the state. If similar data become available across the whole state, certain indicators may be updated to include this data, or a new indicator may be created. DEP Water Pollution Control points were also considered, notably the Sewage Discharge Points subtype, but they were not included because the impairment status of lakes and streams was a more concrete measurement the outcome of water pollution. This indicator or other water related-indicators may be improved by including these data in the future.

Abandoned Mining Concerns

Rationale

Abandoned mine lands (AMLs) are areas that have been impacted by ore and mineral extraction, beneficiation, or processing activities (EPA, 2022[clxvi]). These sites may contain high concentrations of toxic elements such as copper, nickel, lead, mercury, cadmium, arsenic, chromium, and antimony (Peco et al., 2021[clxvii]). The presence of these toxic materials in AMLs can pose significant risks to the surrounding environment and human health, as they can be carried by the wind or water to nearby areas (Sengupta, 2021[clxviii]).

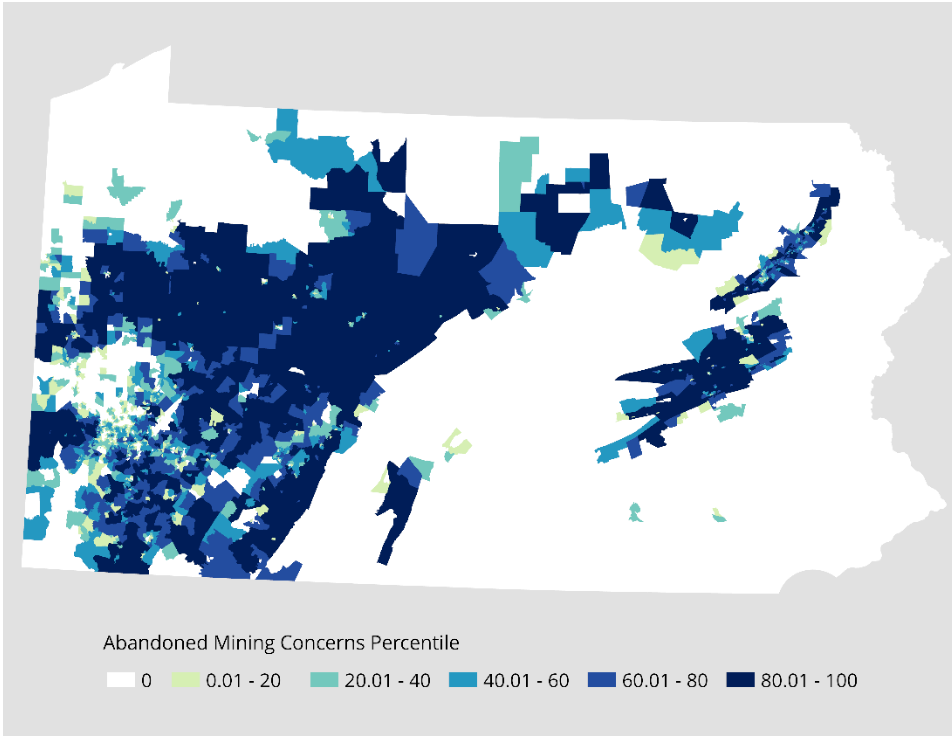
DEP's Bureau of Abandoned Mine Reclamation is responsible for addressing the impacts of abandoned mines in the state, including mining-impacted water supplies and other hazards resulting from past mining practices (DEP, 2022[clxix]). This Bureau operates in accordance with the federal Surface Mining Control and Reclamation Act (Senate and House of Representatives of the United States of America, 1977[clxx]). To date, the AML program in Pennsylvania has reclaimed thousands of AML sites, but an additional 287,000 acres of land are still in need of reclamation (DEP, 2022[clxxi]).

Data Source

Data	Temporal Resolution	Agency	Source
Abandoned Mine Land Inventory Sites	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/50
Mine Drainage Treatment Sites	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/15
Orphan Mine Discharge Sites	Continuously updated	DEP	https://gis.dep.pa.gov/depgisprd/rest/services/emappa/eMapPA_External_Extraction/MapServer/201

Methods

- All data sets were downloaded, then merged into one data set.
- Sites were selected to only include active sites and those where reclamation is not complete.
- Sites within 1 km of each census tract were assigned weights based on proximity:
  - $0 \leq$ site ≤ 250 meters = 1
  - $250 \leq$ site ≤ 500 meters = 0.5
  - $500 \leq$ site ≤ 750 meters = 0.25
  - $750 \leq$ site ≤ 1000 meters = 0.1
- Weights were summed for all sites within 1 km of each block group. A percentile was then calculated based on the statewide distribution of values.



Percentiles of Abandoned Mining Concerns in Pennsylvania.

Future Considerations

Continue to monitor updated databases and additional sources for Abandoned Mining Concerns.

Flood Risk

Rationale

The anticipated increase in severe flood events and sea-level rise caused by climate change presents a pressing environmental concern (Marcantonio et al. 2020[clxxii]; Edmonds et al. 2020[clxxiii]). The link between clean water and human health has long been recognized in environmental health research (Li & Wu 2019[clxxiv]; Levallois & Villanueva 2019 [clxxv]). This is of particular concern in both urban and rural areas where sea-level rise will inundate land and redistribute chemical and biological contaminants (Erickson et al. 2019[clxxvi]). Chemical contaminants that may be carried by floodwaters include heavy metals, pesticides, carcinogens, and other industrial pollution (Euripidou & Murray 2004[clxxvii]), while biological contaminants may include pathogens from combined sewer overflow, manure from farmlands, dead animals, and other organic materials (Lim & Foo 2021[clxxviii]). Some specific biological contaminants that can cause illness through water exposure include Vibrio species, Salmonella species, pathogenic E. coli, hepatitis A, norovirus, Listeria monocytogenes, and Cryptosporidium (Murphy et al. 2016[clxxix]).

Many regions in Pennsylvania have been contaminated by decades of toxic discharges and urban pollution, with a significant number of hazardous sites located in areas at high risk of flooding due to sea-level rise (Kekeh et al. 2020[clxxx]; Habel et al. 2020[clxxxi]). Flooding contaminated with toxic chemicals can result in a range of acute and chronic health consequences for those who are exposed to the pollution in flood water (Sayers et al. 2018[clxxxii]). Flooding is a growing concern in the literature on environmental justice (Razzaghi & Pearsall, 2023[clxxxiii], Walker et al. 2011[clxxxiv]; Herreros-Cantis et al. 2020[clxxxv]), and it is important to recognize the vulnerability of certain communities to environmental threats from flooding in order to advance the definition of environmental justice communities in future research.

Data Source

Data	Temporal Resolution	Agency	Source
National Flood Hazard Layer, containing polygons representing flood risk in each area	Continuously updated	FEMA	https://www.fema.gov/flood-maps/national-flood-hazard-layer

Methods

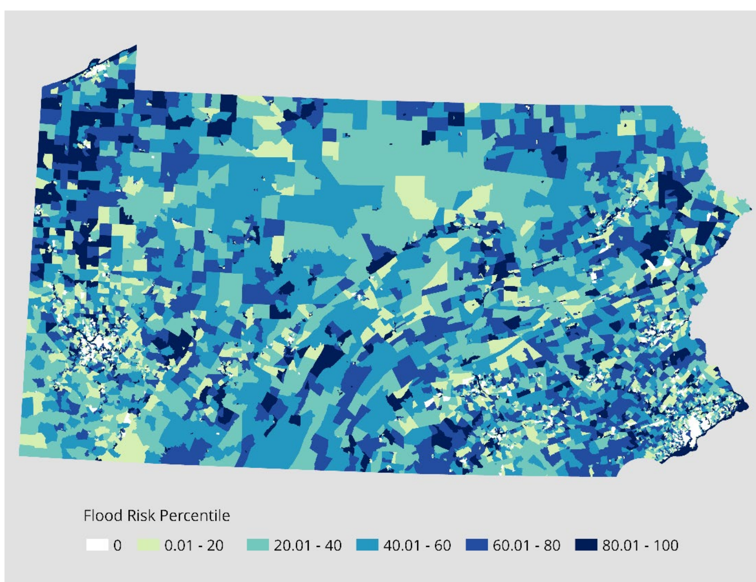
- Polygons representing flood risk zones were weighted by the degree of flood risk:
- Flood risk is defined by these categories:
  - 1% chance of flooding in any given year, otherwise known as a 100-year flood (FEMA zone types AH, AE, AO, A)
  - 0.2% chance of flooding in any given year, otherwise known as a 500-year flood (FEMA zone type X)
  - Minimal flood risk

Flood Zone Type	Weight
100-year flood zones (1%; zone type AH, AE, AO, A)	1
500-year flood zones (0.2; zone type X)	0.2
Protected by Levee*	0.05
Floodway/Floodway Contained in Channel**	0
Minimal Flood Risk	0

*FEMA does not assign a specific flood probability to areas protected by levees. A weight of 0.05% was assigned based on an assumed small but nonzero flood risk.

**FEMA assigns various flood probability values to floodways, defined as "the channel of a river or other watercourse and the adjacent land areas that must be reserved in order to discharge the base flood without cumulatively increasing the water surface elevation more than a designated height" (FEMA, 2022). Given that these areas are specifically designated for floods, a weight of 0 was assigned.

- Flood risk zones were intersected with census block groups to identify the portion of each zone falling within each block group.
- The weight of each zone was multiplied by its area to obtain a flood-risk-weighted area.
- Flood-risk weighted area was divided by block group area, resulting in a weighted proportion of a block group occupied by a certain flood zone. This proportion was summed for all flood risk zones within a block group.
- Using the flood risk sum for each block group, a percentile was calculated based on the statewide distribution of values.



Percentiles of Flood Risk in Pennsylvania.

Future Considerations

Continue to monitor updated databases and additional sources for Flood Risk. Different weights may be used for the flood risk categories in the future.

SENSITIVE POPULATION INDICATORS

Asthma

Rationale

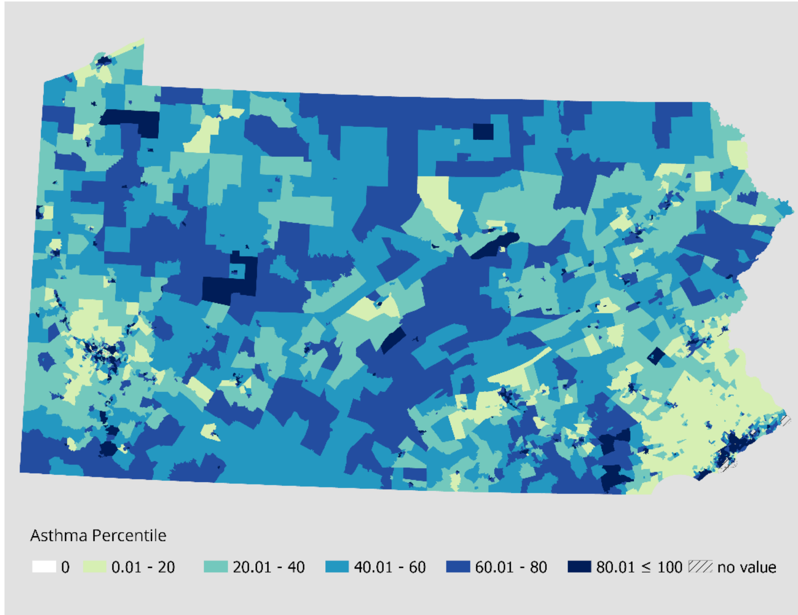
Asthma is a chronic lung disease exacerbated by outdoor air pollution, including particulate matter, ozone, and diesel exhaust, characterized by episodic breathlessness, wheezing, coughing, and tightening of the chest (CDC, 2022[clxxxvi]). Although asthma can be managed as a chronic disease, asthma can be a life-threatening condition, and emergency department (ED) visits for asthma are a very serious outcome, both for patients and for the medical system. Pennsylvania's Department of Health (DOH) reports that lifetime asthma prevalence is up 28% in males and 19% in females from 2011 to 2019 in Pennsylvania. Asthma prevalence is higher in low-income households (less than $15,000) during the 2011 to 2019 time-period. Child lifetime asthma decreased among children 0 to 17 years of age from 13.8% in 2011 to 12.3% in 2019, although by racial breakdowns, non-Hispanic White children had the lowest lifetime asthma prevalence (DOH, 2021[clxxxvii]).

Data Source

Data	Temporal Resolution	Agency	Source
CDC PLACES census-tract-level data containing a percentage of the population over 18 with asthma	Results aggregate data from different periods; see Source for details.	CDC	https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-Census-Tract-D/cwsq-ngmh

Methods

- Tract-level data were downloaded for Pennsylvania from the most recent CDC PLACES data set.
- Each tract's asthma percentage value was assigned to all block groups falling within that tract.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of population over 18 with asthma in Pennsylvania.

Future Considerations

CDC PLACES data are available not at the block group level, but instead at the tract level. If block group-level data become available in future, this indicator may be updated to include them.

The CDC PLACES data only measures asthma rates in the population above age 18. Pediatric asthma data would be useful in showing regional impact of and susceptibility to pollutants, but such data are only available in certain localities such as Allegheny County rather than at the statewide level. If such data become more widely available, this indicator may be updated to include these data.
https://www.phila.gov/media/20191219114641/Health_of_City_2019-FINAL.pdf
https://www.health.pa.gov/topics/programs/Asthma/Pages/Surveillance-Reports.aspx

No Health Insurance

Rationale

Health insurance is a crucial tool for providing affordable access to healthcare and protecting individuals from financial burdens caused by unexpected medical costs (McWilliams, 2009[clxxxviii]). In Pennsylvania, the uninsured rate among nonelderly individuals has been decreasing in recent years, with a rate of 6.8% in 2018, which is lower than the national average of 10.4% (Kaiser Family Foundation, 2021[clxxxix]).

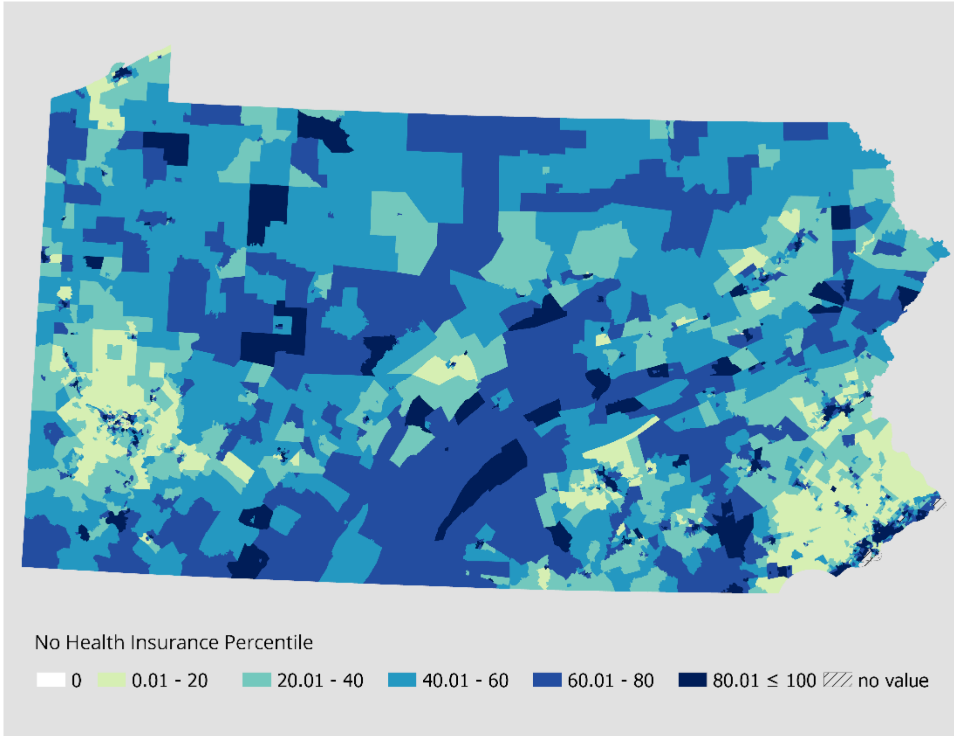
It is important to examine communities with high rates of adults (18 to 64 years of age) without health insurance, as these communities may be impacted by social determinants of health that are relevant to environmental justice issues. Research has shown that uninsured adults generally have less access to recommended care, receive lower quality care, and experience poorer health outcomes compared to adults with insurance (Kilbourn et al, 2006[cxc]). Studies have also found that lack of health insurance coverage can have negative impacts on specific health outcomes, such as reduced blood pressure control among adults with hypertension and increased mortality among adults with HIV (Goldman et al., 2001[cxci]; Lurie et al., 1984[cxcii]). Environmental justice communities may be disproportionately affected by environmental health risks and may also experience other social determinants of health that contribute to health disparities (Prochaska et al., 2014[cxciii]).

Data Source

Data	Temporal Resolution	Agency	Source
CDC PLACES census-tract-level data containing a percentage of the population ages 18-64 without health insurance	Results aggregate data from different periods; see Source for details.	CDC	https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-Census-Tract-D/cwsq-ngmh

Methods

- Tract-level data were downloaded for Pennsylvania from the most recent CDC PLACES data set.
- Each tract's value was assigned to all block groups falling within that tract.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of percentage of the population ages 18-64 with no health insurance in Pennsylvania.

Future Considerations

CDC PLACES data are available not at the block group level, but instead at the tract level. If block group-level data become available in future, this indicator may be updated to include this.

Cancer

Rationale

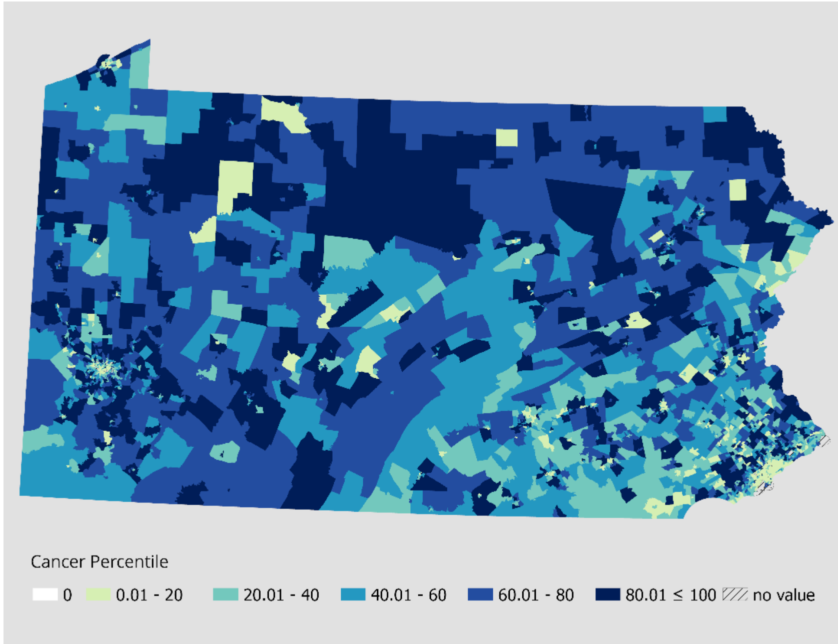
Cancer is a leading cause of death in the Commonwealth of Pennsylvania. In 2019, the Pennsylvania Department of Health estimated that over 79,000 Pennsylvanians were diagnosed with an invasive form of cancer and over 28,000 people died from the disease (DOH, 2019[cxciv]). Disparities in cancer screening have been observed along racial and socioeconomic lines, including differences in eligibility, utilization, and post-screening behavior and care (Sosa et al., 2021[cxcv]). In addition, research has shown that race is a significant predictor of cancer risk distribution, even after controlling for other socioeconomic and demographic factors, including exposures to outdoor mobile and stationary sources of pollution (Morello-Frosch et al., 2002[cxcvi]).

Data Source

Data	Temporal Resolution	Agency	Source
CDC PLACES data containing a percentage of the population over age 18 with cancer (excluding skin cancer) in each census trac	Results aggregate data from different periods; see Source for details.	CDC	https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-Census-Tract-D/cwsq-ngmh

Methods

- Tract-level data were downloaded for Pennsylvania from the most recent CDC PLACES data set.
- Each tract's value was assigned to all block groups falling within that tract.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of percentage of the population over age 18 with cancer (excluding skin cancer) in Pennsylvania.

Future Considerations

CDC PLACES data are available not at the block group level, but instead at the tract level. If block group-level data become available in future, this indicator may be updated to include this.

The CDC PLACES data only measures cancer rates in the population above 18. Pediatric cancer data would be useful in showing regional impact of and susceptibility to pollutants, but such data are only available in certain localities rather than at the statewide level. If such data become more widely available, this indicator may be updated to include these data.

Disability

Rationale

Disabled populations are often more vulnerable to harm, social, and economic disadvantages due to exposure to environmental burdens (Kosanic et al., 2022[cxcvii]). According to data from the Centers for Disease Control and Prevention (CDC, 2022[cxcviii]), 11% of adults in Pennsylvania have a mobility or cognition disability, 7% are unable to live independently, 6% have a hearing disability, 4% have a vision disability, and 3% have a self-care functional disability. Disabled adults in Pennsylvania also have higher rates of depression, obesity, smoking, diabetes, and heart disease. These increased health disparities, along with reduced ability to mitigate harm, increase the susceptibility of disabled populations in Pennsylvania to the negative effects of the environment.

The World Health Organization (WHO, 2022[cxcix]) estimates that approximately 15% of the global population is considered disabled, and this percentage is expected to increase as the population ages and the number of chronically ill individuals increases.

Data Source

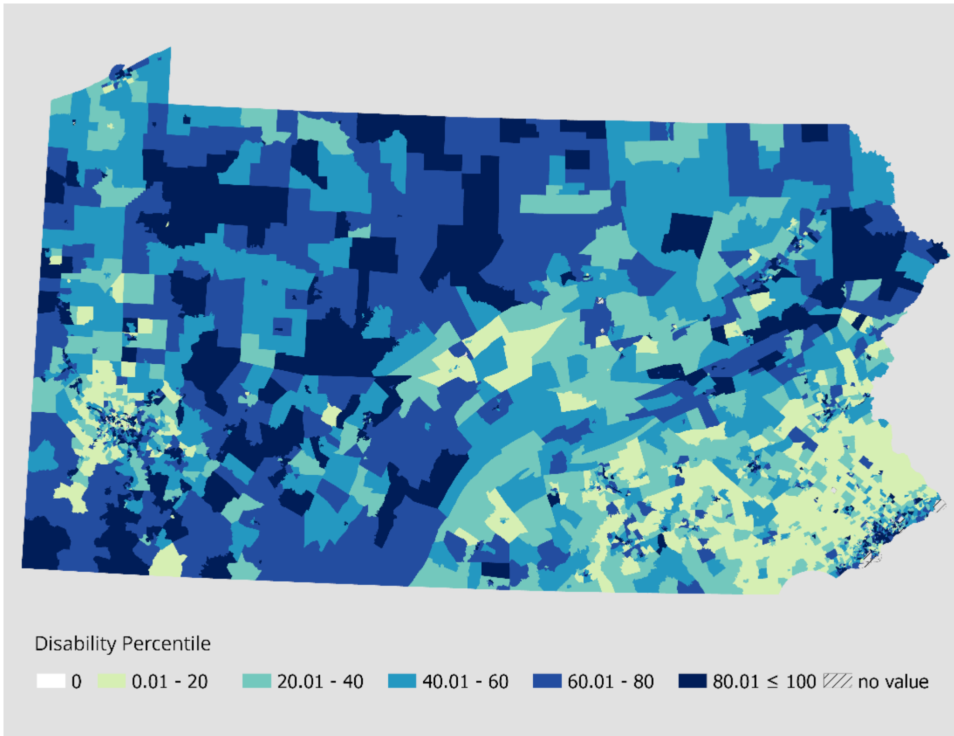
2019 5-year American Community Survey (ACS) tract-level data (Table S1810), containing the population (civilian, noninstitutionalized) with a disability in each census tract; disability types include hearing, vision, cognitive, ambulatory, self-care, and independent living difficulty.

Data	Temporal Resolution	Agency	Source
2019 5-year American Community Survey (ACS) tract-level data (Table S1810), containing the population (civilian, noninstitutionalized) with a disability in each census tract	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=S1810&g=0400000US42%241400000&tid=ACSST5Y2019.S1810

Methods

- Table S1810 was downloaded from the 2019 5-year ACS data set.
- The population with a disability was divided by the total population to obtain the percentage of people with a disability in each tract.
- Each tract's percentage value was assigned to all block groups falling within that tract.
- A percentile value was calculated for each block group based on its position in the distribution of all tract values.
- Census tracts were excluded based on high uncertainty of estimates. To determine this, the Standard Error (SE) was calculated for each census tract following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021[cc]). The Relative Standard Error (RSE) was calculated for each tract by dividing the standard error by the disabled

population percentage. A tract's disabled population percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50 percent of the estimate), and SE greater than the mean of all tracts' SE values.



Percentiles of percentage of the population with a disability in Pennsylvania.

Future Considerations

The ACS fields used for this analysis were only available at the census tract level. If block group-level data become available, this indicator may be updated in the future to include these data.
This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. Therefore the 2010 census geometries were used for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Coronary Heart Disease

Rationale

Trends in cardiovascular disease rates in Pennsylvania have remained around 10% from 2015 to 2020, consistently higher than the national rate of approximately 8% during the same time period (America's Health Rankings, 2022[cci]). In both Pennsylvania and nationally, populations with lower educational attainment have higher rates of cardiovascular diseases. For example, 18.3% of Pennsylvanians with less than a high school education has cardiovascular diseases, compared to 6.2% of those with a college education. Higher age and low-income are also associated with higher rates of cardiovascular diseases.

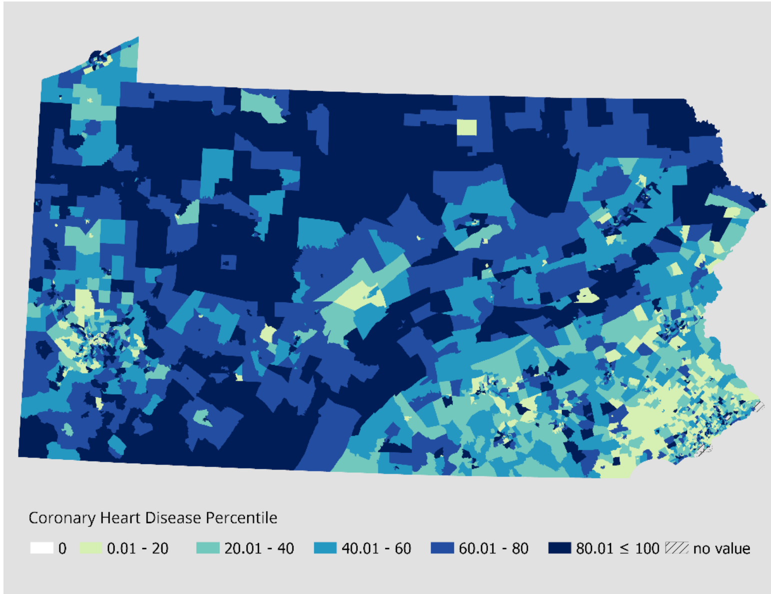
In a study investigating environmental justice (EJ) and non-EJ populations in Alleghany County, researchers developed a risk-based model to estimate the burden of black carbon and nitrogen dioxide on coronary heart disease (CHD). The results of the study found that, while EJ tracts accounted for about 40% of the CHD mortality attributed to each pollutant, these tracts bore a greater risk for disease related to air pollution (Fabisiak et al., 2020[ccii]).

Data Source

Data	Temporal Resolution	Agency	Source
CDC PLACES census-tract-level data containing the percentage of the population over 18 with coronary heart disease	Results aggregate data from different periods; see Source for details.	CDC	https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Local-Data-for-Better-Health-Census-Tract-D/cwsq-ngmh

Methods

- Tract-level data were downloaded for Pennsylvania from the most recent CDC PLACES data set.
- Each tract's value was assigned to all block groups falling within that tract.
- A percentile was calculated for each block group based on the statewide distribution of values.



Percentiles of percentage of the population over 18 with coronary heart disease in Pennsylvania.

Future Considerations

CDC PLACES data are available not at the block group level, but instead at the tract level. If block group-level data become available in future, this indicator may be updated to include them.

SOCIOECONOMIC POPULATION INDICATORS

Educational Attainment

Rationale

Educational attainment is an important factor of socioeconomic status and a social determinant of health, and a literature review conducted in 2018 on the association between education and health suggest higher education is associated with lower exposures to environmental pollution that damage health (Zajacova, & Lawrence, 2018[cciii]). Along with low-income, there is a relationship between lower educational attainment and risk of hospitalization for atrial fibrillation (AF), supporting the consideration of social determinants of socioeconomically disadvantaged individuals with AF to reduce hospitalization risk (Tertulien et al., 2021[cciv]).

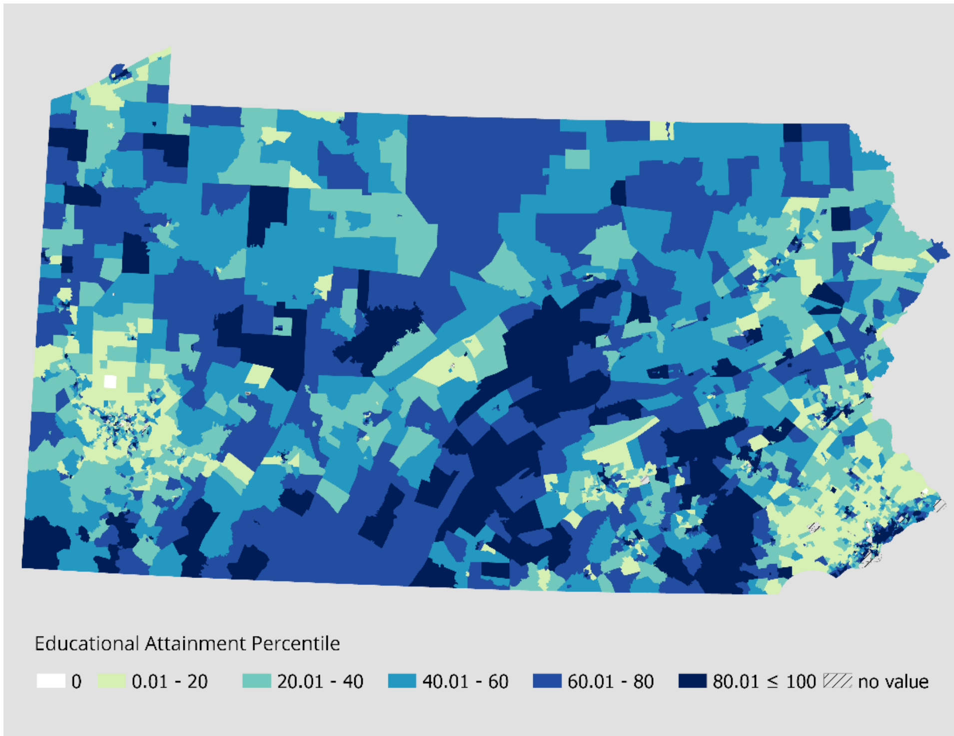
Data Source

Data	Temporal Resolution	Agency	Source
2019 5-year American Community Survey (ACS Table S1501) census-tract-level data containing two relevant values: 1. Population over age 25 whose highest educational attainment was below 9th grade. 2. Population over age 25 whose highest educational attainment was between 9th and 12th grade without graduating high school	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=S1501%3A%20EDUCATIONAL%20ATTAINMENT&g=0100000US_0400000US42%241400000&tid=ACSST5Y2019.S1501

Methods

- Table S1501 was downloaded from the ACS 2019 5-year data.
- The population of each tract over age 25 whose educational attainment was below 9th grade, and those whose educational attainment was between 9th and 12th grade without graduating, were added together and then divided by the total population over 25 to obtain the percentage with low educational attainment.
- The low educational attainment percentage for each tract was assigned to all block groups falling within that tract.
- A percentile was calculated for each block group based on its position within the statewide distribution of values.
- Census tracts were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each census tract following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was

calculated for each tract by dividing the standard error by the low educational attainment percentage. A tract's low educational attainment percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50 percent of the estimate), and SE greater than the mean of all tracts' SE values.



Percentiles of low educational attainment in Pennsylvania.

Future Considerations

Title 1 Schools were not included in this analysis due to conceptual overlap with the indicators for educational attainment, poverty, and housing-burdened low-income households. It may be useful to include Title 1 Schools in future analyses.

The ACS fields used for this analysis were only available at the census tract level. If block group-level data become available, this indicator may be updated in the future to include these data.

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Linguistic Isolation

Rationale

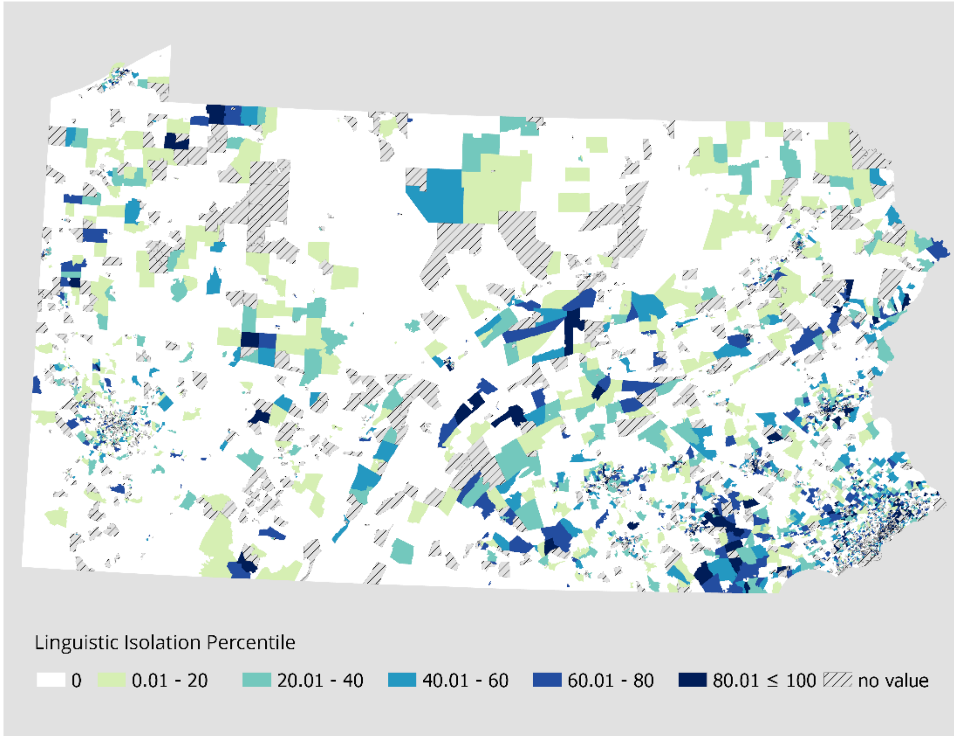
According to the US Census Bureau's 2010-2019 American Community Survey (ACS), 11.7% of Pennsylvanians five years and over spoke a language other than English at home. 1.8% of the state's population speaks English "less than very well," and 2.44% of all households in Pennsylvania are linguistically isolated. The US Census Bureau uses the term "linguistic isolation" to measure households where all members 14 years of age or above have at least some difficulties speaking English. A high degree of linguistic isolation among members of a community raises concerns about access to health information and public services, and effective engagement with regulatory processes (Link et al., 2006[ccv]).

Data Source

Data	Temporal Resolution	Agency	Source
2019 5-year American Community Survey (ACS Table C16002) block-group-level data containing the number of households speaking various primary languages without speaking English well	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=C16002&g=0400000US42%241500000&tid=ACSDT5Y2019.C16002

Methods

- Table C16002 was downloaded from the ACS 2019 5-year data set.
- Within each block group, columns representing the number of households speaking various primary languages, without speaking English well, were added together and then divided by the total number of households to obtain the linguistic isolation percentage.
- A percentile was calculated for each block group based on its position within the statewide distribution of values.
- Block groups were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each block group following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each block group by dividing the standard error by the linguistic isolation percentage. A block group's linguistic isolation percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50% of the estimate), and SE greater than the mean of all block groups' SE values.



Percentiles of linguistic isolation in Pennsylvania.

Future Considerations

ACS linguistic isolation data include information on which language is spoken in linguistically isolated areas, but the language categories are broad and were therefore not used in the methods for this indicator. This indicator map does not show information on specific languages, but the Pennsylvania Department of Health Pennsylvania Languages Map shows data on where specific languages are spoken. Comparing these two maps can help users identify which translation or interpretation services may be most useful in reaching populations in highly linguistically isolated communities.

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Housing-Burdened Low-Income Households

Rationale

The cost and availability of housing is an important determinant of well-being, and households with lower incomes spend a larger proportion of their income on housing (Swope et al., 2019[ccvi]). The inability of households to afford necessary non-housing goods after paying for shelter is known as housing-induced poverty and an important factor to evaluating environmental justice (Adamkiewicz et al., 2011[ccvii]). A comprehensive housing study conducted by the Pennsylvania Housing Finance Agency in 2020 found that increasing income inequality, combined with fewer low-cost housing options is causing an increased burden to low-income Pennsylvanians in recent years (Pennsylvania Housing Finance Agency, 2020[ccviii]).

Data Source

Data	Temporal Resolution	Agency	Source
The Comprehensive Housing Affordability Strategy (CHAS) data set, a custom tabulation of ACS tract-level data	5 years	U.S. Department of Housing and Urban Development	https://www.huduser.gov/portal/datasets/cp.html

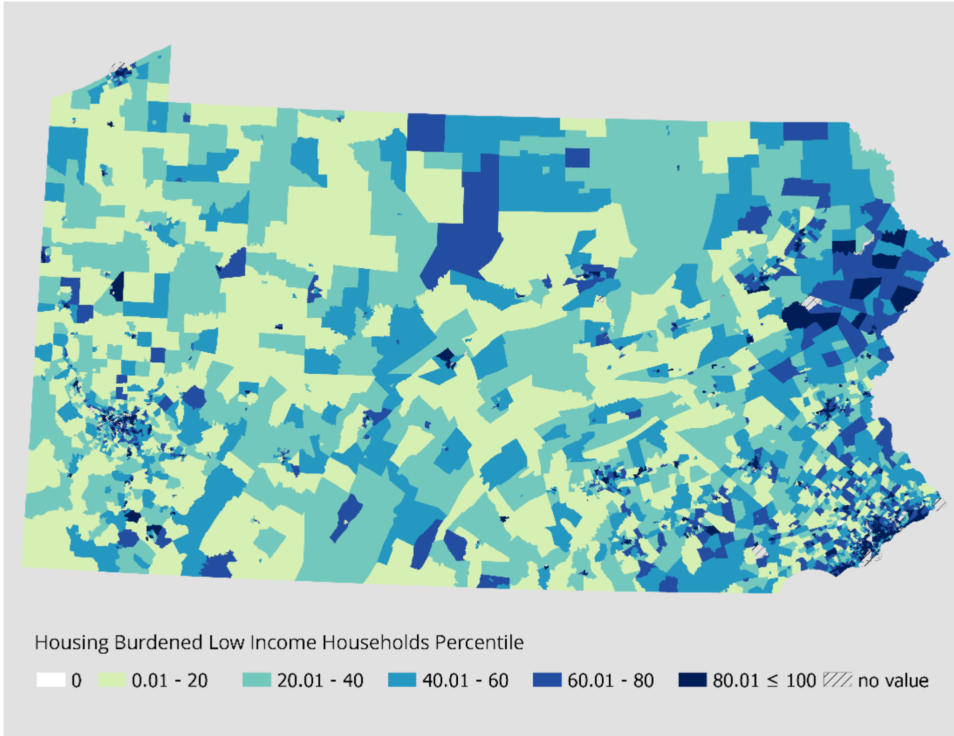
Methods

- Using Table 3 from the most recent CHAS data set, columns were added to obtain the number of households that were both housing-burdened (paying more than 50% of their income toward housing costs) and low-income (earning less than 80% of the HUD Area Median Family Income). This sum was divided by the total number of households to obtain the percentage of housing-burdened low-income households within each tract.

- Each tract's value was assigned to all block groups falling within that tract.

- A percentile value was calculated for each block group based on its position in the statewide distribution of values.

- Census tracts were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each tract following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each tract by dividing the standard error by the housing-burdened low-income household percentage. A tract's housing-burdened low-income percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50% of the estimate), and SE greater than the mean of all block groups' SE values.



Percentiles of Housing-Burdened Low-Income Households in Pennsylvania.

Future Considerations

The United Way ALICE (Asset Limited, Income Constrained, Employed) data set was considered for this indicator, because these data take the variations in local expenses into account when determining people's ability to pay their expenses. The CHAS data used in this analysis do include variations in income and housing costs into account using the HUD Area Median Family Income, although these data do not address other costs besides housing. At this time, the ALICE data are only available at the county level. If these data become available at a higher resolution, such as the tract or block group level, this indicator may be updated to include these data.

Poverty

Rationale

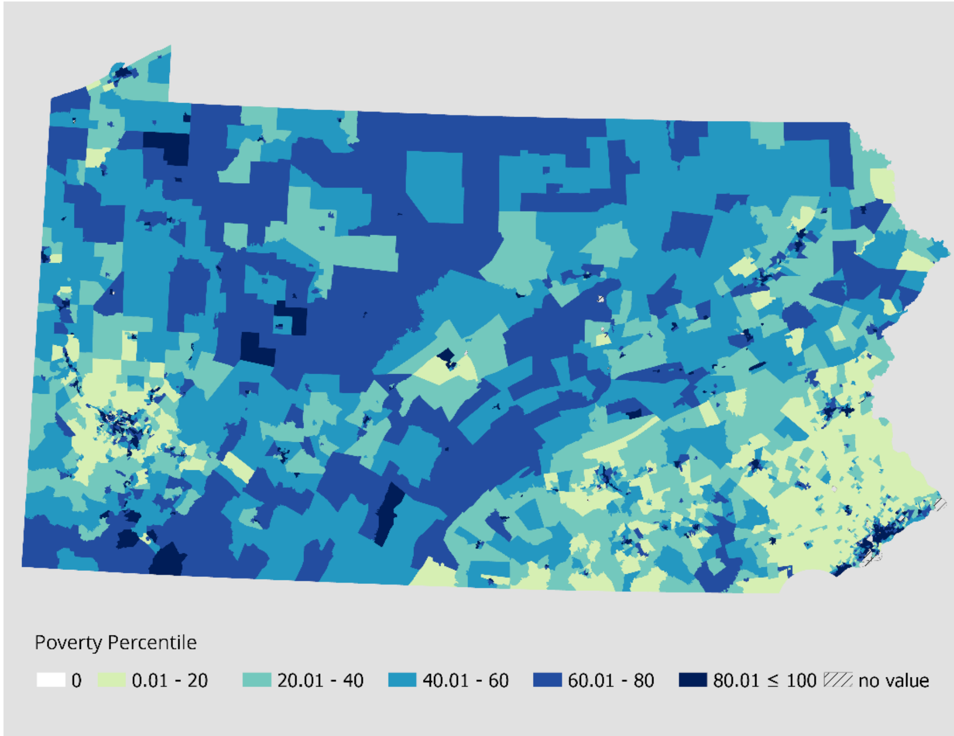
Poverty is an important social determinant of health and EJ indicator since lower-income populations are located more closely to sources of pollution and is associated with worsened health outcomes (Paster et al., 2005[ccix]; Huang & Barzyk, 2016[ccx]; Shusted &, Kane, 2020[ccxi]). Poverty is commonly emphasized in EJ studies, and impoverished populations are more likely than wealthier populations to experience adverse health outcomes when exposed to environmental pollution because of its close relationship to other EJ indicators such as proximity to contamination sites and pre-existing conditions (Linder et al., 2008[ccxii]; Huang & Barzyk, 2016[ccxiii]). According to 2021 estimates from U.S. Census, 12.1% of Pennsylvanians are in poverty (U.S. Census Bureau, 2021) [ccxiv].

Data Source

Data	Temporal Resolution	Agency	Source
2019 American Community Survey 5-year tract-level data (ACS Table S1701), containing the population with income under 200 percent of the federal poverty level in each census tract	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=S1701&g=0400000US42%241400000&tid=ACSST5Y2019.S1701

Methods

- In ACS Table S1701, the population with income below 200 percent of the federal poverty level was divided by the total population to obtain the low-income percentage for each tract.
- Each tract's value was assigned to all block groups falling within that tract.
- A percentile value was calculated for each block group based on its position in the distribution of all tract values.
- Census tracts were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each tract following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each tract by dividing the standard error by the low-income percentage. A block group's low-income percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50% of the estimate), and SE greater than the mean of all block groups' SE values.



Percentiles of poverty in Pennsylvania.

Future Considerations

The ACS fields used for this analysis were only available at the census tract level. If block group-level data become available, this indicator may be updated in the future to include these data.

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Unemployment

Rationale

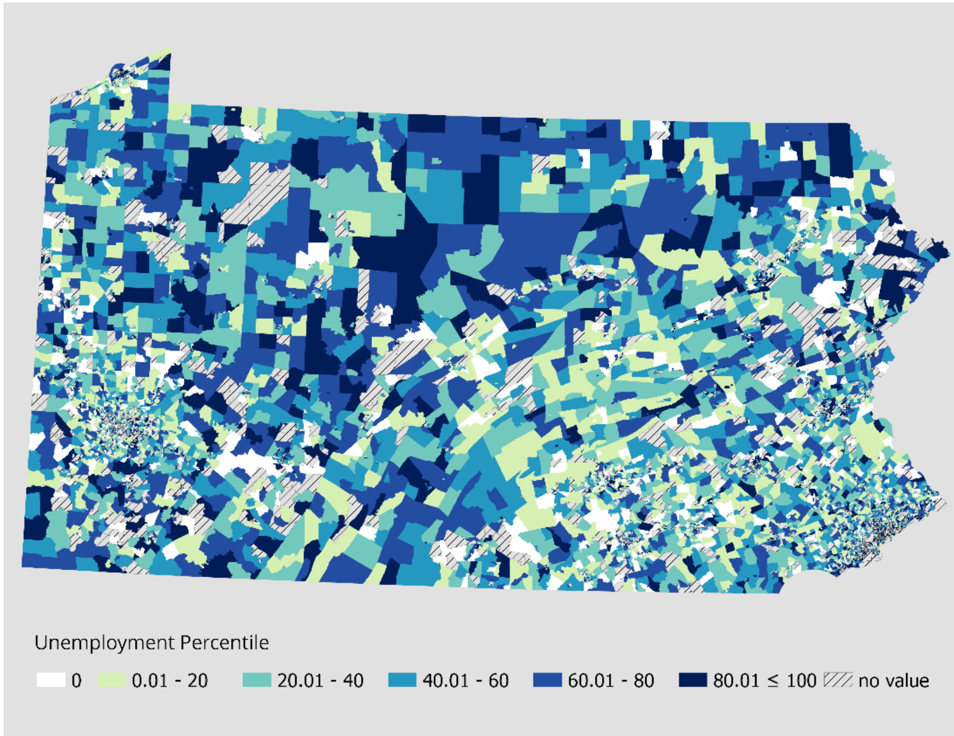
The unemployment rate in Pennsylvania as of October 2022 rests at 4.0%, slightly higher than the national unemployment rate of 3.7% (Bureau of Labor Statistics, 2021[ccxv]). Low socioeconomic status often goes together with high unemployment; thus, the rate of unemployment is a factor commonly used in describing disadvantaged communities (Tang et al., 2022[ccxvi]; Puig-Barrachina et al., 2011[ccxvii]). On an individual level, unemployment is a source of stress, which is implicated in poor health reported by residents of such communities (Silver et al., 2022[ccxviii]). Lack of employment and resulting low-income often constrain people to live in neighborhoods with higher levels of pollution and environmental degradation therefore an important indicator for environmental justice screening (Pratap et al., 2021[ccxix]).

Data Source

Data	Temporal Resolution	Agency	Source
American Community Survey 2019 5-year block group-level data (ACS Table B23025), containing the unemployed population in the labor force	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=B23025&g=0400000US42%241400000,42%241500000&tid=ACSDT5Y2019.B23025

Methods

- In ACS Table B23025, the unemployed population was divided by the total population in the labor force to obtain the unemployment percentage for each block group.
- A percentile value was calculated for each block group based on its position in the statewide distribution of values.
- Census block groups were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each census block group following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each block group by dividing the standard error by the unemployed population percentage. A block group's unemployed percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50% of the estimate), and SE greater than the mean of all block groups' SE values.



Percentiles of percentage containing the unemployed population in the labor force in Pennsylvania.

Future Considerations

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Race

Rationale

There is a well-documented correlation between majority non-white populations and environmental burdens in the environmental justice (EJ) literature, and this is often considered an essential indicator in EJ screening tools (Cutter, 1995[ccxx]; Mikati et al., 2018[ccxxi]; Banzhaf et al., 2019[ccxxii]). The EJ movement has its roots in the 1982 protests in Warren County, North Carolina, which opposed the implementation of a toxic waste facility in a predominately black and low-income community. This event brought attention to the concept of environmental racism and laid the foundations for the EJ movement.

In response to these protests, the US House of Representatives requested a study on the correlation between hazardous waste landfill locations and the racial and socioeconomic demographics of the surrounding communities. This study, published by the US Government Accountability Office (GAO) in 1983, found that race is the biggest predictor of communities and individuals living near a hazardous waste site in the United States (US Gen 1983[ccxxiii]; Martuzzi et al., 2010[ccxxiv]). Many types of waste facilities are disproportionately located in low-income and communities of color (Ash & Boyce, 2018[ccxxv]; Bullard, 2018[ccxxvi]).

Historical redlining practices, which were discriminatory mortgage lending practices that existed for decades in the 20th century, have also contributed to long-term environmental inequities for Black adults in Pennsylvania (Schuyler & Wenzel, 2022[ccxxvii]). According to US Census data, Pennsylvania is home to 12.2% Black residents, and urban areas such as Philadelphia (43.6% Black) and Pittsburgh (23% Black) have larger populations of non-white residents.

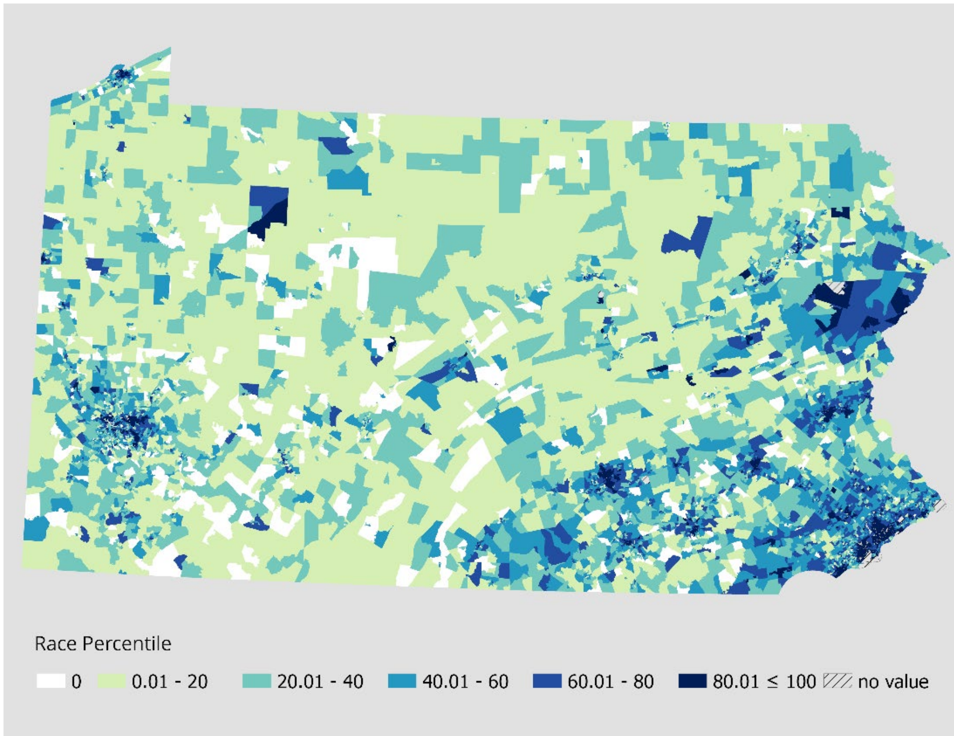
Data Source

Data	Temporal Resolution	Agency	Source
American Community Survey 2019 5-year block group-level data (ACS Table B03002), containing the population identifying as white, which was subtracted from the total population to obtain the population of people of color (POC)	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=B03002&tid=ACSDT5Y2019.B03002

Methods

- In ACS Table B03002, the POC population was obtained by subtracting the white population from the total population; the POC population was divided by the total population to obtain the percentage of POC in each block group.
- A percentile value was calculated for each block group based on its position in the distribution of all block group values.
- Census block groups were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each block group following the ACS procedure for calculating the

SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each block group by dividing the standard error by the POC population percentage. A block group's POC population percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50 percent of the estimate), and SE greater than the mean of all block groups' SE values.



Percentiles of POC population in Pennsylvania.

Future Considerations

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Age Over 64

Rationale

A review of studies identifying susceptible subgroups found that elderly populations showed greater evidence of sensitivity to environmental burdens, particularly ozone found the strongest evidence for greater sensitivity (Bell et al., 2014[ccxxviii]). Advancing age of populations increases the prevalence of age-related diseases (Hong, 2013[ccxxix]). Exposure to environmental threats is a modifiable risk factor to age-related diseases since the elderly are more sensitive because of deterioration in physiologic, biochemical, immunologic, and homeostatic parameters (Hong, 2013[ccxxx]; Lopez & Goldoftas, 2009[ccxxxi]).

Data Source

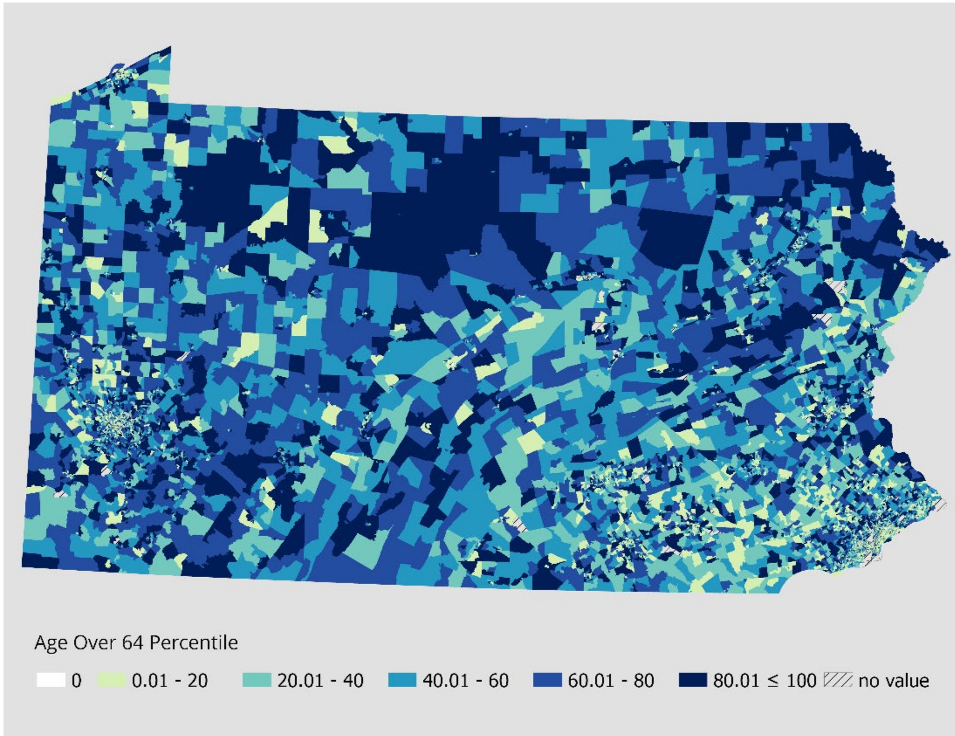
Data	Temporal Resolution	Agency	Source
American Community Survey 2019 5-year block group-level data (ACS Table B01001), containing values for the populations of different age groups	5 years	Census	https://data.census.gov/cedsci/table?q=B01001&g=0400000US42%241400000&tid=ACSDT5Y2019.B01001

Methods

- In ACS Table B01001, the percentage of the population over age 64 in each census block group was obtained by adding multiple age group columns, then dividing this sum by the total population of each block group.

- A percentile value was calculated for each block group based on its position in the statewide distribution of values.

- Census block groups were excluded based on high uncertainty. To determine this, the Standard Error (SE) was calculated for each block group following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each block group by dividing the standard error by the over-64 population percentage. A block group's over-64 population percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50% of the estimate), and SE greater than the mean of all block groups' SE values.



Percentiles of the population over 64 in Pennsylvania.

Future Considerations

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

Age Under 5

Rationale

Environmental risks have an impact on the health and development of children. The World Health Organization estimates that reducing environmental risks could prevent one in four child deaths (WHO, 2022[ccxxxii]). Children are more vulnerable to environmental hazards due to their size, physiology, and behavior. Their exposure to toxins is greater in proportion to their body weight, and they may suffer long-term effects from early exposure. Perinatal conditions influenced by the environment are responsible for 20% of deaths in children under age five. Fetal exposure to chemicals like lead can cause brain damage or developmental problems. Children of all ages are at greater risk than adults. They breathe more air, drink more water, and eat more food per unit of body weight, increasing their exposure to pathogens and pollutants. Childhood behaviors like crawling and putting objects in the mouth can also increase risks[ccxxxiii]. Research on environmental lead exposure found strong correlations between the percentage of children with elevated blood lead levels (percent EBLL) and percent minority population as well as between percent EBLL and percent children in poverty.[ccxxxiv]

Data Source

Data	Temporal Resolution	Agency	Source
American Community Survey 2019 5-year block group-level data (ACS Table B01001), containing the population by sex under age 5	5 years	Census Bureau	https://data.census.gov/cedsci/table?q=B01001&g=0400000US42%241400000&tid=ACSDT5Y2019.B01001

Methods

- In ACS Table B01001, the percentage of the population under age five in each census block group was obtained by adding the number of males and females under five, then dividing this sum by the total population of each block group.

- A percentile value was calculated for each block group based on its position in the statewide distribution of values.

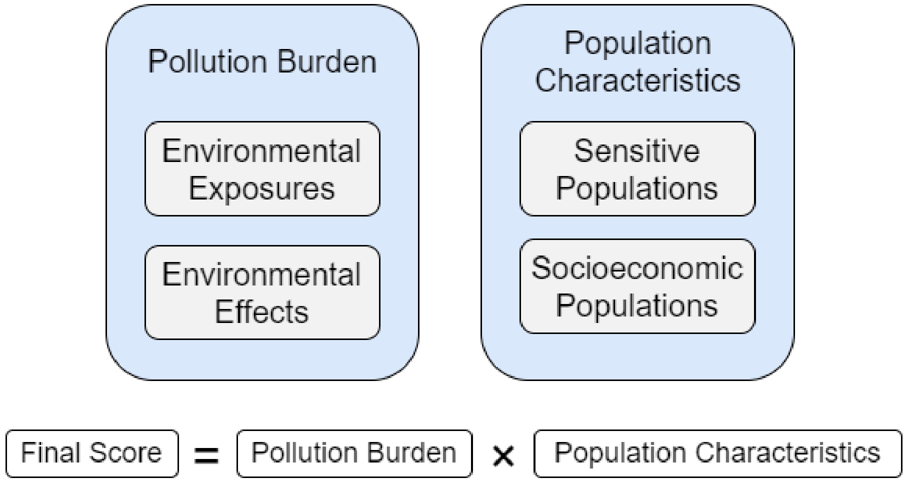
- Census block groups were excluded based on high uncertainty. To determine this The Standard Error (SE) was calculated for each block group following the ACS procedure for calculating the SE of column proportions (U.S. Census Bureau, 2021). The Relative Standard Error (RSE) was calculated for each block group by dividing the standard error by the under-5 population percentage. A block group's under-5 population percentage was excluded from analysis if both of the following conditions were met: RSE greater than 50 (SE greater than 50% of the estimate), and SE greater than the mean of all block groups' SE values.

Percentiles of the population under 5 in Pennsylvania.

Future Considerations

This indicator was calculated using data from the 2019 ACS 5-year data set. More recent data is available, but the 2019 data are the most recent that align with the 2010 census block group geometries that have been used in this analysis. Because data for certain indicators still use the 2010 census geometries and have not been made available at the 2020 geometries, using data from both 2010 and 2020 census geometries would result in data mismatches between certain tracts. The 2010 census geometries were therefore chosen for this analysis. When data for all indicators align with the 2020 census data, this indicator should be updated using more recent ACS 5-year data.

RESULTS



The maps displayed in this section represent these model components:

- Environmental Exposures component score (percentile calculated for display)
- Environmental Effects component score (percentile calculated for display)
- Pollution Burden score, which is calculated from the Environmental Exposures and Environmental Effects scores (percentile calculated for display)
- Sensitive Populations component score (percentile calculated for display)
- Socioeconomic Populations component score (percentile calculated for display)
- Population Characteristics score, which is calculated from the Sensitive Populations and Socioeconomic Populations component scores (percentile calculated for display)
- The Final Score Percentile map shows the percentile values assigned to block groups based on the statewide distribution of Final Score values, which are calculated from the Pollution Burden and Population Characteristics scores

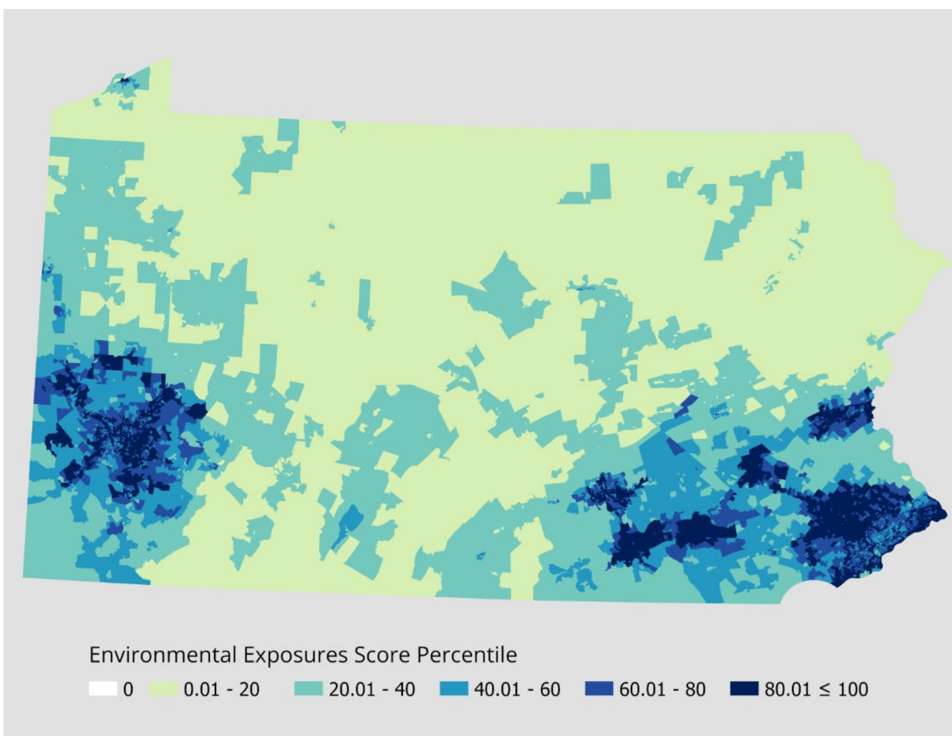
For details about model methodology, see the Methodology and Rationale section.

Pollution Burden: Environmental Exposures

The Environmental Exposures component score is the average of the percentiles of all indicators within the Environmental Exposures category:

- Ozone
- $PM_{2.5}$
- Diesel Particulate Matter
- Toxic Air Emissions
- Toxic Water Emissions
- Pesticides
- Children's Lead Risk
- Traffic Density

For display, a percentile was calculated for each block group based on the statewide distribution of Environmental Exposures Score values.



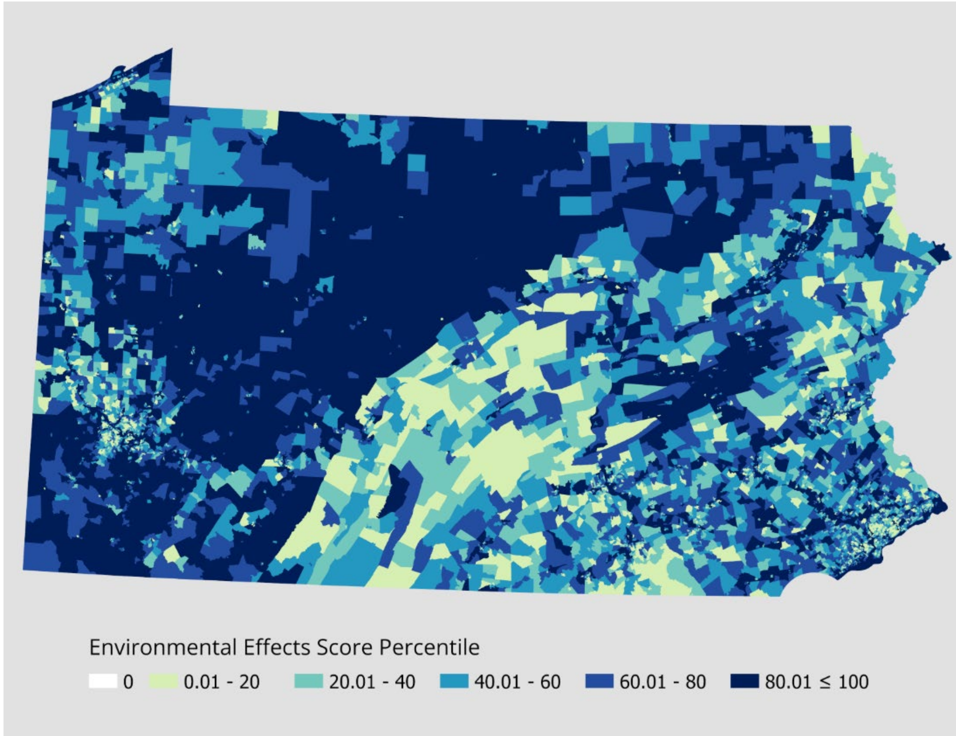
Environmental Exposures Component Score Percentile.

Pollution Burden: Environmental Effects

The Environmental Effects component score is the average of the percentiles of all indicators within the Environmental Effects category:

- Unconventional Oil/Gas Wells
- Conventional Oil/Gas Wells
- Proximity to Railroads
- Land Remediation
- Hazardous Waste and Storage Sites
- Coal Mining
- Municipal Waste
- Impaired Lakes and Streams
- Abandoned Mining Concerns
- Flood Risk

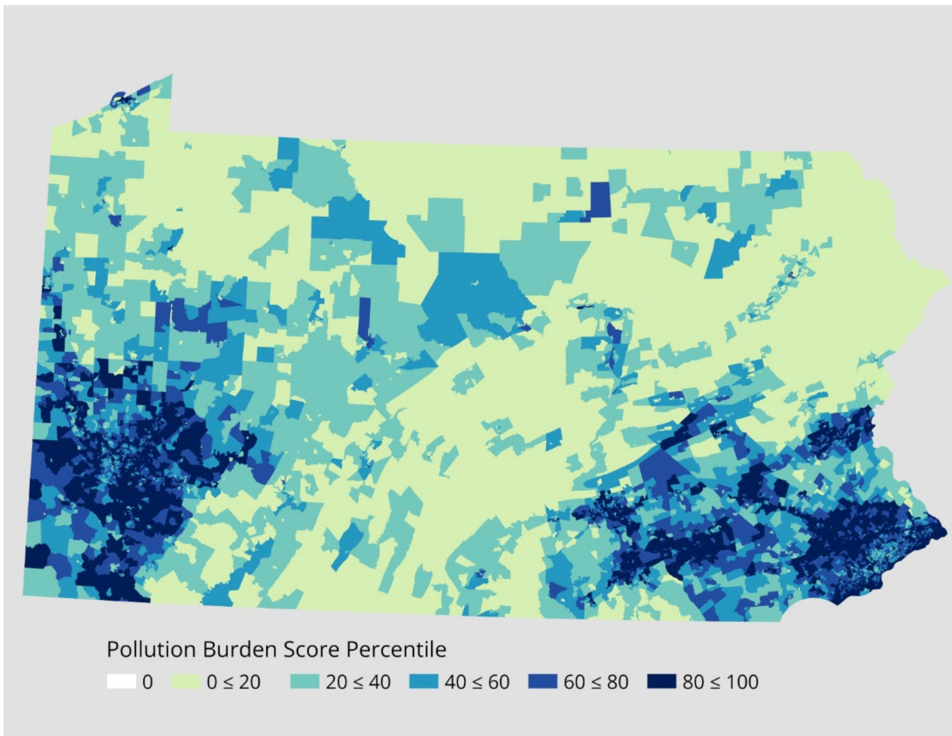
For display, a percentile was calculated for each block group based on the statewide distribution of Environmental Effects Score values.



Environmental Effects Component Score Percentile.

Pollution Burden

The Pollution Burden Score is a weighted average of the Environmental Effects and Environmental Exposures component scores, with Environmental Exposures being weighted by half relative to Environmental Effects (for more details, see the Methodology and Rationale section). For display, a percentile was calculated for each block group based on the statewide distribution of Pollution Burden Score values.



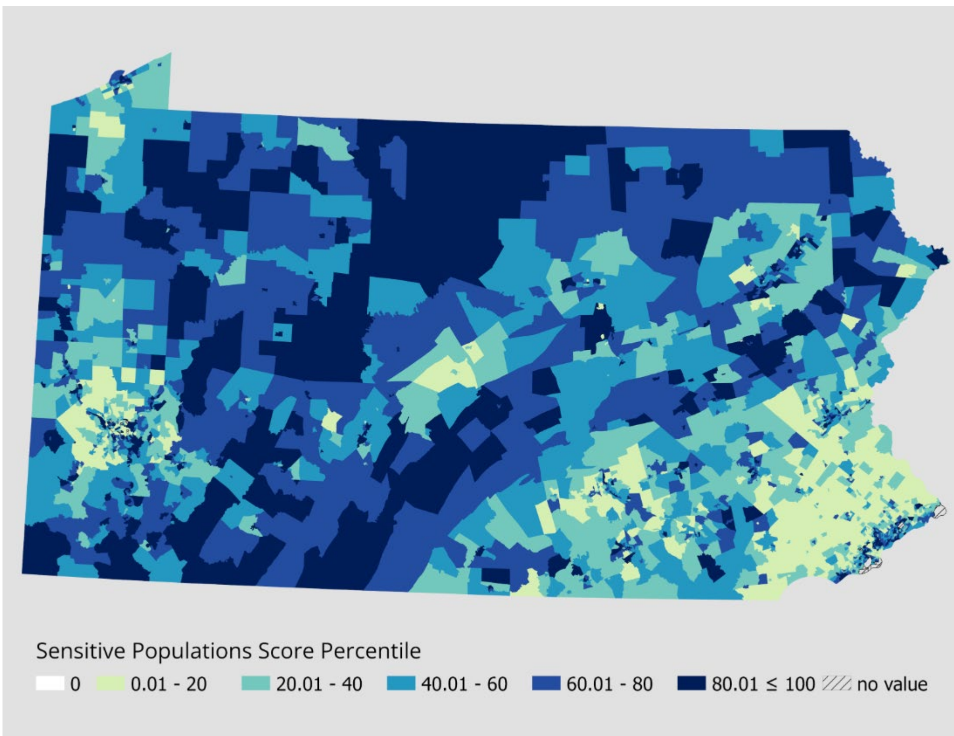
Pollution Burden Score Percentile.

Population Characteristics: Sensitive Populations

The Sensitive Populations component score is the average of the percentiles of all indicators within the Sensitive Populations category:

- Asthma
- No Health Insurance
- Cancer
- Disability
- Coronary Heart Disease

For display, a percentile was calculated for each block group based on the statewide distribution of Sensitive Populations Score values.



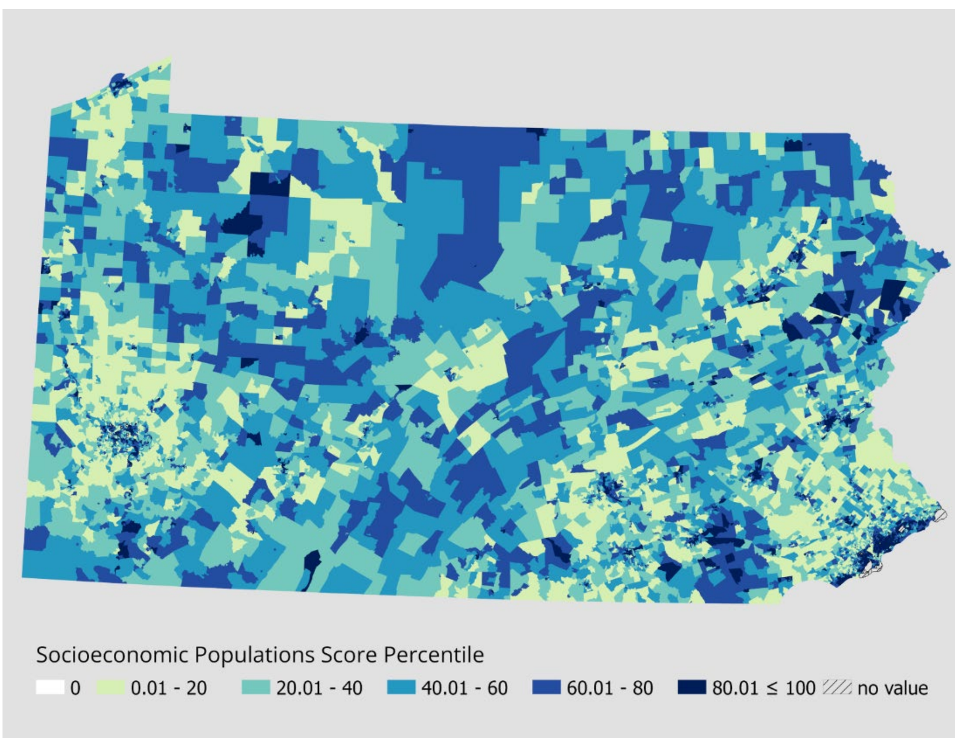
Sensitive Populations Component Score Percentile.

Population Characteristics: Socioeconomic Populations

The Socioeconomic Populations component score is the average of the percentiles of all indicators within the Socioeconomic Populations category:

- Educational Attainment
- Linguistic Isolation
- Housing-Burdened Low-Income Households
- Poverty
- Unemployment
- Race
- Age Over 64
- Age Under 5

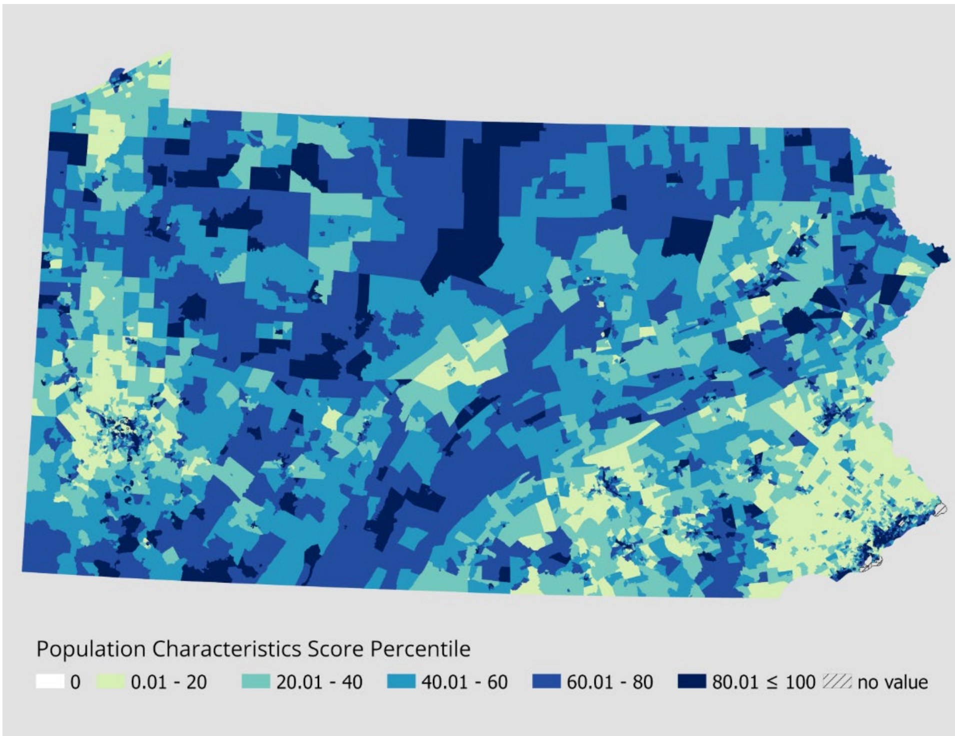
For display, a percentile was calculated for each block group based on the statewide distribution of Socioeconomic Populations Score values.



Socioeconomic Populations Component Score Percentile.

Population Characteristics

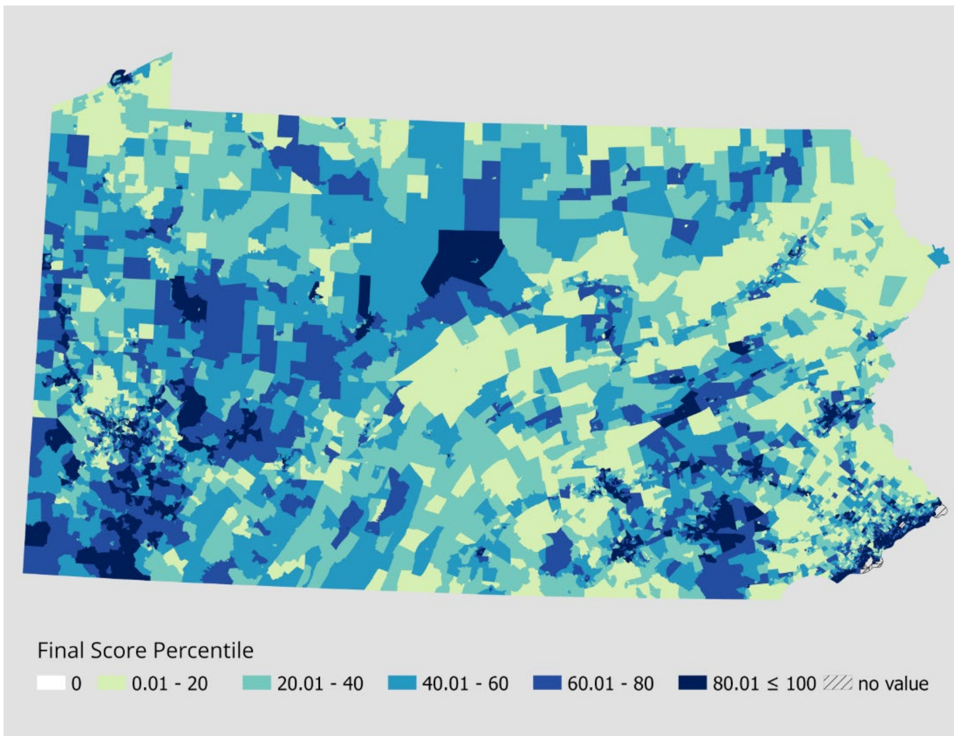
The Population Characteristics score is the average of the Sensitive Populations and Socioeconomic Populations component scores. For display, a percentile was calculated for each block group based on the statewide distribution of Population Characteristics Score values.



Population Characteristics Score Percentile.

Final Score Percentile

The Final Score was calculated by scaling the Pollution Burden and Population Characteristics scores to values between one and ten, then multiplying them together. A percentile value was then calculated for each block group based on the statewide distribution of Final Score values. These percentile values are used to determine whether a given block group qualifies as an EJ Area as pertaining to the EJ Policy; block groups at or above the 80th percentile threshold qualify as EJ Areas.



Final Score Percentile

Additional Future Considerations and Updates

This EJ screening tool is planned to be updated annually with the latest data for each indicator and census geographic boundaries. Older versions will be archived as a reference. Each indicator has information about future considerations which are data sources, and suggestions which currently do not meet the inclusion criteria but worth revisiting for future updates in the event data quality and availability improves.

Relative Weighting of Indicators

In comparing two given indicators with each other, one indicator may have a greater effect on overall health relative to the other, which might justify weighting certain individual indicators more highly when calculating the average. This weighting process exceeded the time and resource constraints of the current model. Such determinations may be approached in future analyses.

Hyperlocal Data

During the process of developing the updated EJ screening tool. Stakeholders expressed the need to incorporate more hyperlocal information. In areas around urban regions such as Philadelphia and Pittsburgh have more environmental justice and indicator data collection occurring at academic and non-governmental levels. Currently there are limitations in using statewide data only. In the future Pennsylvania may consider creating regional screening tools to incorporate hyperlocal information.

Broadband Internet Access

Limited broadband internet access is an indicator which has been discussed and may improve the model in the future. At this time, it was decided to not include this indicator due to the lack of consistently and regularly updated data on the source. Also due to conceptual overlap with other indicators that account for socioeconomic vulnerabilities.

Infant Mortality and Maternal Morbidity/Mortality

The intersection of environmental justice and health equity continues to be a growing highlight even as more health factors have been included in this version of the EJ viewer. It is integral to healthier community outcomes that the correlations (if any) between infant mortality, and maternal mortality/morbidity to EJ areas are better understood; like the mapping efforts corelating redlining impacts to EJ areas. The National institute of Health (NIH) describes maternal morbidity as any short or long-term health problems that result from being pregnant and giving birth. Maternal mortality refers to the death of a woman from complications of pregnancy or childbirth that occur during the pregnancy or within six weeks after the pregnancy ends. Infant mortality refers to the death of an infant between one day and one year of age. Having these layers as integrated aspects of the PennEnviroScreen would allow for more seamless analysis and visualization of EJ related health equity implications to vulnerable populations.

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