Technical Documentation for the Environmental Justice Index 2022

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Contents

Glossary of Terms

Census Tract – the smallest subdivisions of land for which demographic and health data are consistently available. Each census tract is part of a particular county and is home to an average of 4,000 people.

Cumulative Impacts – see the *Introduction* below for a definition.

Disparity – a difference in conditions or outcomes across subgroups of the population that are often linked to social, economic, or environmental conditions.

Distributive Environmental Justice – seeks to address place-based disparities in exposures to environmental hazards and access to environmental amenities and other resources.

Environmental Amenities – environmental goods or benefits that may reduce poor health among populations or promote their economic welfare.

Environmental Burden – all features of the environment, both positive and negative, that contribute to human and environmental health.

Environmental Justice/Injustice – see the *Introduction* below for a definition.

Health Equity/Inequity – see the *Introduction* below for a definition.

Health Vulnerability – intrinsic biological factors such as chronic, pre-existing conditions that can worsen the effects of environmental burden.

Module Domains – functional groups representing distinct aspects of environmental burden and social vulnerability.

Pathogenic features – features of the environment that may be detrimental to human health.

Prevalence – the proportion of a population who have a specific characteristic or disease in a given time period.

Procedural Environmental Justice – seeks the equitable involvement of all people in environmental decision-making, with a focus on addressing unequal power structures.

Salutogenic features – features of the environment that contribute to good health.

Social Vulnerability – the combined demographic and socioeconomic factors that adversely affect communities that encounter hazards and other community-level stressors.

Tertile – any of the two points that divide an ordered distribution into three parts, each containing a third of the population.

Introduction

What is Environmental Justice?

Environmental justice is the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income to develop, implement, and enforce environmental laws, regulations, and policies. This goal will be achieved when everyone enjoys the same degree of protection from environmental and health hazards, and equal access to the decision-making process to live, learn, and work in a healthy environment.

Environmental justice issues are often divided into issues of "procedural justice" and issues of "distributive justice" (Kuehn, 2000). Procedural justice seeks the equitable involvement of all people in environmental decision-making, with a focus on addressing unequal power structures. Distributive justice seeks to address place-based disparities in exposures to environmental hazards and access to environmental amenities and other resources. Distributive environmental injustice can have profound cumulative impacts on human health and well-being. Addressing these cumulative impacts is a key part of promoting health equity.

What is Health Equity?

Health equity is the state in which everyone has a fair and just opportunity to attain their highest level of health. Achieving this requires focused and ongoing societal efforts to address historical and contemporary injustices, overcoming economic, social, and other obstacles to health and healthcare, and eliminating preventable health disparities.

What are Cumulative Impacts?

Cumulative impacts are the total harm to human health that occurs from the combination of environmental burden, pre-existing health conditions, and social factors. Cumulative impacts can result from long-term exposure to environmental pollution and community stress such as noise pollution, odor pollution, loss of natural resources, or lack of access to quality healthcare or other resources. These factors can have long-term effects on human health and well-being in communities experiencing the worst cumulative impacts. Degraded environmental conditions within an area can lead to economic disinvestment in highly polluted areas, also known as "sacrifice zones." This can lead to further environmental degradation in these areas of low economic value and can perpetuate generational economic and health inequities for residents of such areas.

The terms *impact* and *risk* are sometimes used synonymously, but there are important differences between the two (Faust, 2010; Murphy et al., 2018; Sexton, 2012; Solomon et al., 2016). Nor should a representation of cumulative impacts be confused with an exposure assessment, which quantifies exposure in an individual or community and is often coupled with detailed information on environmental mediators and dose-response relationships to determine whether a toxic exposure could have health implications for an affected individual or community. Health risk assessments seek to quantify the likelihood that a population will experience harm due to a hazardous event or chemical exposure using detailed data on factors such as chemical exposure levels, dose-response relationships, and contaminant fate and transport (Murphy et al., 2018). Risk, exposure, and public health assessments[1] are critical tools for public health professionals and communities alike, but the level of data collection required to produce such assessments at a large scale is prohibitive (Faust, 2010). Cumulative impact assessment was designed as an alternative to traditional risk and exposure assessment, and uses a combination of the quantitative and semi-quantitative information to compare the relative and synergistic impacts of social factors, environmental factors, and pre-existing chronic conditions on community health and well-being (Alexeeff et al., 2012; Morello-Frosch et al., 2011; Murphy et al., 2018; Solomon et al., 2016).

Development of the EJI

Recent concerns about health equity in the United States have motivated policy makers as well as environmental and public health experts to emphasize the importance of promoting EJ to achieve health equity goals. Place-based EJ screening and mapping tools allow government agencies and other entities to identify communities experiencing high environmental burden in order to prioritize these communities for policies and interventions designed to reduce inequities. There have been calls for state and federal tools that address the cumulative impacts of environmental injustice on health. The Environmental Justice Index (EJI) is the first place-based nationwide index designed to address cumulative impacts through the lens of EJ and health equity. This work builds on previous efforts to create EJ screening and mapping tools at state and federal levels, including the Environmental Justice Screening Method (EJSM), CalEnviroScreen, and the U.S. Environmental Protection Agency's (EPA's) EJSCREEN. The EJI was created to help public health officials, policy makers, and communities identify communities that experience the greatest cumulative impacts of environmental burdens on their health, as these communities may need additional help responding to environmental and health hazards. An additional Social-Environmental Ranking (SER) was developed for secondary analysis and research purposes, as detailed below.

Purpose and Uses of the EJI

The EJI can help public health officials, policy makers, and communities identify and respond to the varied environmental and social factors that affect a community's health and well-being.

[1] For more information on the ATSDR public health assessment process, please visit https://www.atsdr.cdc.gov/hac/products/pha.html

EJI databases and maps can be used to:

- Identify areas that may require special attention or additional resources to improve health and health equity
- Characterize the unique, local factors driving cumulative impacts on health to inform policy and decision-making
- Establish meaningful goals and measure progress towards EJ and health equity

While the full EJI Ranking is useful for the purposes designated above, it is not designed for use in secondary analysis. The EJI SER, which is provided within the EJI database, is the appropriate value to use for secondary data analysis where disease is an outcome of interest. The EJI SER was constructed using only the Environmental Burden and Social Vulnerability Modules of the EJI so that health outcome prevalence estimations would not be included in the construction. As a result, the EJI SER is useful in studying associations with health outcomes. For example, exploratory analysis into correlations between asthma prevalence and the EJI should not use the EJI score because estimates for asthma prevalence are already included in the health vulnerability module. However, the EJI SER does not include estimates for asthma prevalence and thus can be used for this analysis. Flags for 'high' estimated prevalence of health outcomes included in the overall EJI are provided in the database and can be visualized in a map over the EJI SER values to inform whether areas that experience high levels of cumulative environmental burden and social vulnerability also experience high levels of chronic disease burden.

EJI and CDC/ATSDR

CDC and ATSDR are committed to promoting health equity and to integrating practices that promote health equity into the fabric of all of their activities (Agency for Toxic Substance and Disease Registry, 2021; Centers for Disease Control and Prevention, 2022). Promoting EJ is key to advancing health equity. The EJI can help to inform and focus public health interventions aimed at alleviating health disparities by identifying communities facing the worst cumulative impacts of environmental burdens on health, and to track the success of programs and interventions across time by providing iterative updates for comparison.

Limitations and Considerations of the EJI

The EJI is intended as a high-level mapping and screening tool that characterizes cumulative impacts and patterns of environmental injustice across the U.S. The EJI is a useful starting place for investigating issues of distributive and procedural justice and their effects on health and well-being. However, like all high-level tools, the EJI is subject to several limitations that should govern proper use of the tool.

First, it is important to recognize that injustice occurs locally. High-level tools such as the EJI cannot capture all social, environmental, or health issues that a community may face. Data for some issues, such as indoor air pollution or septic system failure and associated soil contamination, are not available as national datasets. Other data representing drinking water quality, low infant birth weights, pesticide use, or other issues are available nationally but at a coarser spatial resolution than what was targeted for creation of the EJI (e.g., county level). Future iterations of the EJI may incorporate these and other important environmental and health concerns, but for now, these issues are best addressed using supplementary data when and where it is available. Several state-level cumulative impacts tools, such as CalEnviroScreen 4.0, the Washington Environmental Health Disparities Map, and others, incorporate datasets not available at the national level and are often tailored to state-level environmental justice issues and concerns. As such, these tools may offer a more complete picture of the relative contributions of individual factors to cumulative impacts when making state-level comparisons.

Second, there are inherent limitations in the kind of data used by the EJI and other screening-level tools. The EJI relies on historical data generated by various institutions on varying time scales, meaning that the EJI is not entirely reflective of current or future conditions. This may be particularly important to consider with data representing air quality, as the US has seen an overall decline in levels of pollutants like ozone and PM 2.5 in the last decade (US Environmental Protection Agency, 2022a, 2022b). However, aside from some measures of air quality, most EJI indicators use data collected within the last 5 years. Details on the years represented by each dataset can be found in the indicator descriptions and in the data dictionary. Additionally, many indicators used to construct the EJI rely on estimates that involve some level of uncertainty. Where possible, measurements of uncertainty are made available within the EJI database, as with Census-calculated margins of error (MOEs), but this uncertainty is not factored into EJI calculations. Thus, when using the EJI, it is important to note that modest differences in tract-level rankings should not necessarily be interpreted as definitively meaningful. Where possible, the EJI should be supplemented by more detailed local data as well as risk and exposure assessments.

The environmental indicators included in the EJI do not represent detailed measures of risk or exposure assessments. These indicators are intended to provide only a screening-level overview of environmental burdens facing a community. For example, proximity to a hazardous site alone does not constitute an exposure but is nonetheless important to characterize because these sites may be significant sources of pollution not captured by other indicators, such as noise or odor pollution, that can lead to community stress or otherwise negatively affect community health and well-being.

The decision to measure proximity to environmental hazards and amenities using a uniform 1-mile buffer was rooted in a desire to facilitate interpretation of index measures and results by a general audience. Furthermore, 1-mile buffers are commonly used in research on proximity to such sites as an issue of environmental burden or environmental justice (Flores et al., 2021; Huang & London, 2012). This is an approach that is well-suited to high-level screening but may not be suitable for measuring potential risk or exposure. It is also important to note that proximity measures used to construct indicators within the Proximity to Potentially Hazardous & Toxic Sites domain represent proximity to points within a site rather than polygons representing the entire site area due to a lack of nationally representative polygon data. This could lead to misclassification of potential impacts from large sites. However, these measures are still useful for a high-level screening approach.

Health indicators represented within the EJI are derived from PLACES estimates produced by the Division of Population Health within the CDC's National Center for Chronic Disease Prevention and Health Promotion (NCCDPHP). Because of certain methodological considerations outlined in the *Methods* section of this document, these estimates were incorporated into the EJI as "flags" representing tracts identified by our methodology as experiencing a high burden of chronic disease prevalence. Users who wish to view more detailed and nuanced estimates of chronic disease prevalence or learn more about the small area estimation techniques used to produce PLACES estimates should visit https://www.cdc.gov/places/index.html.

Finally, a lack of data for many key environmental indicators led to the exclusion of Alaska, Hawaii, the Commonwealth of Puerto Rico, and all other Island Territories (the U.S. Virgin Islands, American Samoa, Commonwealth of the Northern Mariana Islands, Guam) from the EJI 2022 calculations. The EJI 2022 includes only the Continental U.S. (48 states plus the District of Columbia). It is expected that future iterations of the EJI will include jurisdiction-specific indices for Alaska, Hawaii, and Puerto Rico. These indices will be calculated using indicators for which data are available. At this time, there are no plans to produce indices for other U.S. Island Territories due to a lack of data collected for these entities.

In summary, the EJI is **not** intended as the following:

- A definitive tool for labeling "EJ Communities" or characterizing all EJ issues
- A full representation of current or future social, environmental, or health characteristics
- A representation of risk or exposure for a given community or area

Next Steps for the EJI

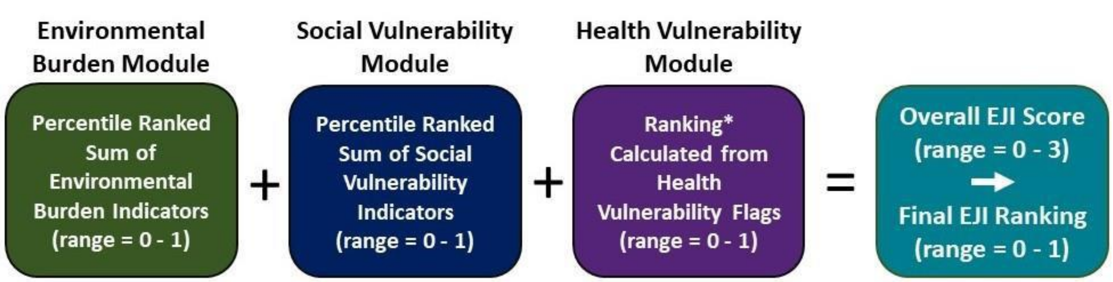
Going forward, the EJI will be updated every other year using the most recent data available from the U.S. Census Bureau, the U.S. Environmental Protection Agency, the U.S. Mine Safety and Health Administration, and the Centers for Disease Control and Prevention. CDC/ATSDR is committed to engaging with communities, EJ advocates, public health partners, and academic subject matter experts as part of the development and improvement of this tool. The EJI will be presented to a wide array of interested parties to gather comments on index construction and presentation. Comments and recommendations received during this community engagement process will be addressed within the documentation of the next iteration of the EJI and recommended changes will be made where feasible and appropriate. For more information on how to provide feedback and engage with the EJI team, please visit us at https://www.atsdr.cdc.gov/placeandhealth/eji/index.html.

Methods

EJI Model

The EJI model incorporates place-based measurements of factors related to distributive and procedural justice and to the cumulative impacts of injustice on health and well-being. The place-based unit of analysis for the EJI is the census tract. Census tracts are subdivisions of counties for which the U.S. Census Bureau collects statistical data and are commonly used as a proxy for neighborhoods in place-based epidemiological research (Akwo et al., 2018; Mujahid et al., 2008; Vutien et al., 2019) and for many other spatial indices and screening tools (California Office of Environmental Health Hazard Assessment, 2021; Flanagan et al., 2011; Huang & London, 2012; Min et al., 2019; Sadd et al., 2011).

The EJI uses data from the U.S. Census Bureau, the U.S. Environmental Protection Agency, the U.S. Mine Safety and Health Administration, and the U.S. Centers for Disease Control and Prevention to determine the cumulative impacts of environmental injustice for over 71,000 U.S. census tracts. The EJI ranks each tract on 36 environmental, social, and health factors and groups them into three overarching modules and ten different domains. The overall EJI score is calculated by summing the ranked scores of three modules: the Environmental Burden Module, the Social Vulnerability Module, and the Health Vulnerability Module. Each module represents an important aspect of cumulative impacts as defined above. The final EJI ranking is, then, produced using this score.



Environmental Burden Module (Percentile Ranked Sum of Environmental Burden Indicators (range = 0 – 1)) + Social Vulnerability Module (Percentile Ranked Sum of Social Vulnerability Indicators (range = 0 - 1)) + Health Vulnerabilty Module (Ranking* Calculated from Health Vulnerability Flags (range = 0 - 1))= Overall EJI Score (range = 0-3) ➔ Final EJI Ranking (range = 0-1)

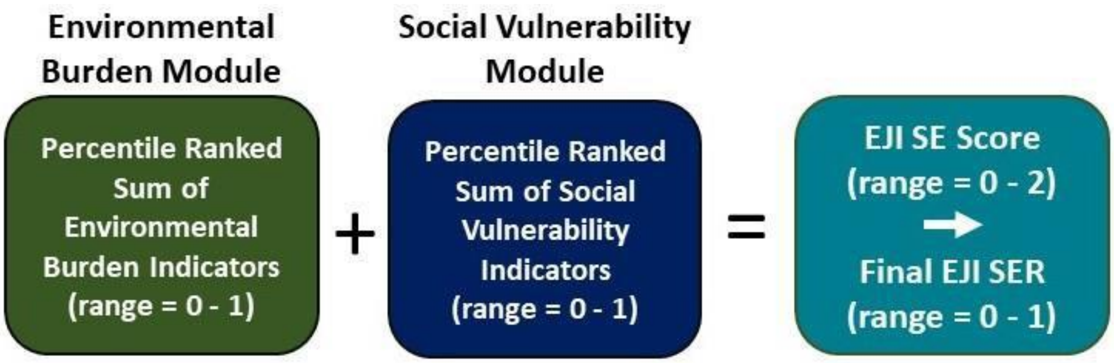
*Ranking calculated by multiplying the sum of health vulnerability flags (n = 5) by 0.2 to produce a number between 0 - 1.

Note: Due to a lack of scientific evidence supporting a specific weighting scheme, all modules are weighted equally in calculating the Overall EJI Score. This method of equal weighting for all modules aligns with that used by the Environmental Justice Screening Method (Sadd et al., 2011). Overall EJI Scores are percentile ranked to produce a final EJI Ranking with a range of between 0 - 1.

This model differs from the widely used CalEnviroScreen model, which combines social and health vulnerability into a single measure of population characteristics and measures cumulative impacts by multiplying pollution burden scores by population characteristics scores (California Office of Environmental Health Hazard Assessment, 2021). The EJI model also differs from the CalEnviroScreen model in that environmental factors representing exposures are not given more weight than factors representing other environmental characteristics. By 1) weighting all environmental indicators equally, 2) including social vulnerability and health vulnerability as distinct constructs, and 3) summing rather than multiplying measures of burden and vulnerability, the EJI more closely resembles the Environmental Justice Screening Method (EJSM) developed by environmental justice advocates and scholars in California prior to the development of CalEnviroScreen (Sadd et al., 2011). While the CalEnviroScreen method is very useful and has proven effective in California and beyond (J. Faust et al., 2021; Lee, 2020; Min et al., 2019), the decision to align the EJI model more closely with the EJSM came out of a desire to 1) facilitate easy interpretation of the EJI by a range of stakeholders with varying technical expertise, and to 2) facilitate easy adaptation of EJI rankings and scores to local needs and circumstances.

Maintaining a higher level of independence among modules by using an additive method of index calculations is intended to make the EJI easy for users to understand and to adapt to their own needs. While there is often significant overlap between additive models like the EJSM and the EJI and multiplicative models like CalEnviroScreen (California Office of Environmental Health Hazard Assessment, 2013), additive models allow for a greater influence of individual modules on the overall model. In the case of the EJI, this means that a community that experiences high levels of social vulnerability and environmental burden could receive a high overall EJI score, even if it does not score high for health vulnerability. This feature may be seen as a strength or a weakness of the model, something which has been a topic of debate in states which have implemented a multiplicative model (California Office of Environmental Health Hazard Assessment, 2017).

The EJI database also includes a Social-Environmental Ranking (SER) that is calculated by combining rankings from only the Environmental Burden Module and the Social Vulnerability Module, while excluding the Health Vulnerability Module (see figure below). The EJI SER represents a measure of distributive and procedural environmental justice factors that may influence human health and well-being. The EJI SER is more suitable than the full EJI for research and secondary analyses where health outcomes are of interest. The EJI SER can also be visualized alongside High-Prevalence Flags to gain an overall view of how specific health outcomes may be related to issues of distributive and procedural environmental justice.



Environmental Burden Module (Percentile Ranked Sum of Environmental Burden Indicators (range = 0 – 1)) + Social Vulnerability Module (Percentile Ranked Sum of Social Vulnerability Indicators (range = 0 - 1))= EJI SE Score (range = 0-2) ➔ Final EJI SER (range = 0-1)

Note: Social-Environmental Scores are percentile ranked to produce a final Social-Environmental Ranking (EJI SER) with a range of between 0 - 1.

Indicator Selection

Indicators representing environmental burden, social vulnerability, and health vulnerability were selected based on a thorough literature review conducted by the EJI research team between December 2020 and December 2021. This included a scoping review of the environmental justice literature as well as a review of a number of existing tools measuring aspects of environmental justice and cumulative impacts, including the U.S. EPA's EJSCREEN, the California Office of Community Health and Hazard Assessment's CalEnviroScreen, CDC/ATSDR's Social Vulnerability Index (CDC/ATSDR SVI), and others (Driver et al., 2019; Huang & London, 2012; Maizlish et al., 2019; Min et al., 2019; Sadd et al., 2011; Shrestha et al., 2016).

Indicators identified by the scoping review were evaluated for inclusion based on a series of data criteria designed to ensure index quality, reproducibility, and longevity. To be considered for inclusion in the EJI, indicators had to be linked to national data sources that satisfied our following global data criteria:

1. Accurate and reliable – the data must be from a trusted source and must be stable across time and space
2. Analytically sound – the data must be a quality measure of the phenomenon it is intended to capture (e.g., household lead exposure, harmful exposure to ozone, etc.)
3. Available at scale – the data must be calculated at the census tract level or below or must be easily manipulatable to that scale
4. Timely – data must be regularly updated to allow for future updates to the index

Following application of the data criteria, indicators were evaluated for inclusion in each module through a series of module-specific theoretical inclusion criteria.

Environmental Burden Module

Indicators representing environmental burden are intended to capture features of the environment that contribute either negatively or positively to human health and well-being. The inequitable distribution of negative and positive features of the environment among populations with greater or lesser capacity to influence environmental decision-making is the foundation behind the concept of distributive environmental justice (Kuehn, 2000). Some indicators represent potential exposures to harmful substances, while others represent proximity to various features of the environment that may be associated with toxic exposures or general environmental degradation. Other indicators represent environmental amenities, the lack of which can negatively impact human health and well-being. All indicators included in the Environment Burden Module satisfied the following criteria:

1. The presence or absence of the environmental characteristics represented by this variable has a quantifiable negative effect on human health
2. The mechanism by which the presence or absence of the environmental characteristics represented by this variable affects health is understood
3. The environmental characteristics represented by this variable are not already represented within another environmental burden variable

Social Vulnerability Module

Indicators representing social vulnerability are intended to capture population characteristics that may influence the ability of a community to respond to environmental hazards or influence environmental decision-making. These are key factors in producing procedural environmental justice. These social characteristics are also risk factors for various health outcomes. Where multiple social stressors persist and, in combination, render communities more socially vulnerable, such communities are also increasingly susceptible to the adverse effects of economic fluctuations, environmental burden, and emergencies such as natural disasters and disease outbreaks (Cutter et al., 2003; Cutter & Emrich, 2006; Flanagan et al., 2011; Juntunen, 2004). When coupled, chronic environmental burden and social vulnerability work synergistically to create more severe cumulative impacts affecting health and well-being, including increasing existing disease burden and exacerbating health inequities (Clougherty & Kubzansky, 2009; Huang & London, 2012; Morello-Frosch et al., 2011; Sadd et al., 2011). All indicators included in the Social Vulnerability Module were required to satisfy the following criterion:

1. The populations represented in the indicator have less capacity to improve environmental conditions or advocate against unwanted land uses in their communities because of historical or ongoing discrimination or other factors.

Health Vulnerability Module

Indicators characterizing health vulnerability are intended to capture the prevalence of certain pre-existing health conditions, which represent a measurable form of biological susceptibility that can influence morbidity and mortality associated with environmental burden. Other "intrinsic biological traits," such as age, disability, or genetic predisposition, may also represent aspects of biological susceptibility (Morello-Frosch et al., 2011), but genetic factors are difficult to measure at a large scale, and age and disability are already captured within the EJI Social Vulnerability Module. Thus, only pre-existing health conditions were considered as candidate indicators for the health vulnerability module. The only nationwide data on the prevalence of pre-existing conditions available at the census tract level is the PLACES dataset produced by the

CDC's National Center for Chronic Disease Prevention and Health Promotion (NCCDPHP). Thus, only indicators for which PLACES estimates were available were considered for inclusion in the EJI. All indicators included in the Health Vulnerability Module were required to satisfy the following criteria:

1. Indicator must represent a chronic health condition
2. Indicator must represent a health condition that increases susceptibility to the negative health effects of environmental hazards and pollution

Some measures initially identified as candidates for inclusion using these criteria (prevalence of chronic obstructive pulmonary disease, prevalence of obesity, prevalence of coronary heart disease, and prevalence of stroke) were ultimately excluded from the EJI due to significant correlations with other indicators of health vulnerability which were deemed to be more appropriate for inclusion. For example, obesity was found to be highly correlated with diabetes while coronary heart disease was highly correlated with high blood pressure.

EJI Scoring Method

Tract-level rankings for individual indicators, modules, and overall scores are based on percentile ranks. For a given census tract, ranks for the Environmental Burden Module and Social Vulnerability Module are calculated as described below:

- Percentile ranks for all individual indicators in each module were summed, producing a module score
- Module scores were then ranked, producing a module ranking between 0-1, with zero representing the lowest relative burden/vulnerability and 1 representing the highest relative burden/vulnerability

Tract-level rankings for the Health Vulnerability Module were calculated differently than the other modules due to data considerations. The PLACES estimates used in the Health Vulnerability Module are based on survey data collected as part of the CDC's Behavioral Risk Factor Surveillance System (BRFSS) and calculated using a method known as small area estimation (SAE) that incorporates demographic data, including data on age, race/ ethnicity, education, and poverty. Because these data are used to produce each estimate, directly combining these estimates would lead to overweighting of underlying demographic variables. To avoid this, health indicators are incorporated into the EJI by using the estimates to flag census tracts with disease prevalence estimates in the top tertile (33.33%) of all census tracts included in the EJI. The process for calculating Health Vulnerability Module ranking scores based on this method is described below:

- A tract receives a score of 1 for a given indicator if the indicator estimate for that tract (e.g., diabetes prevalence) is flagged as being in the top tertile, otherwise the tract receives a score of 0
- All indicator flags for a tract are summed, creating a flag score between 0-5 (5 meaning all 5 indicators were flagged)
- Because the flag score is not continuous and cannot be assigned a percentile rank, the score is multiplied by 0.2 to create a final Health Vulnerability ranking between 0-1 (0.0, 0.2, 0.4, 0.6, 0.8, or 1.0)

These module ranking scores were then used to calculate the overall EJI and EJI SER scores and rankings, as described in the section above. Additionally, rankings were calculated for domains representing different aspects of environmental burden and social vulnerability, as described below.

Module Domains

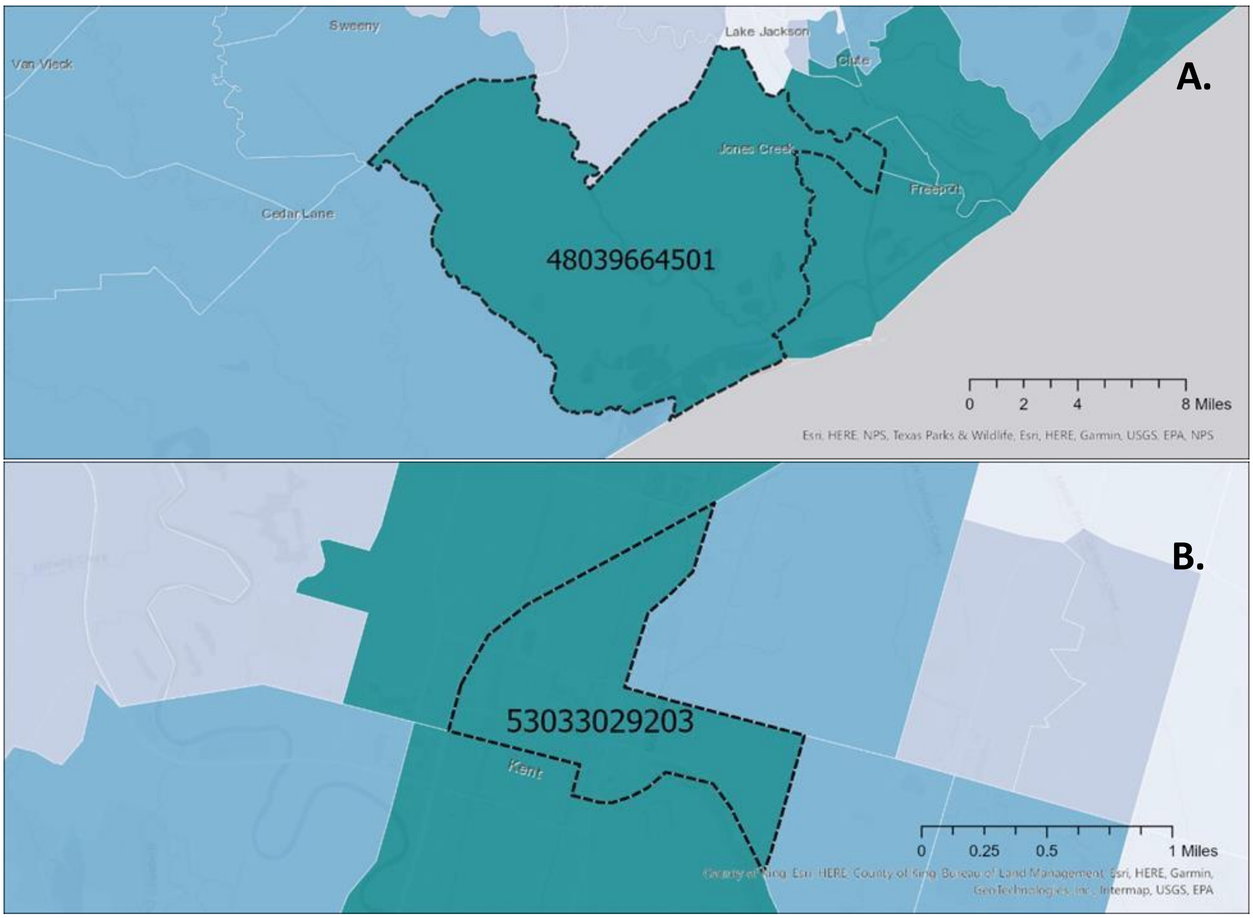
Module domains were constructed as a way of easily summarizing indicators into functional groups representing distinct aspects of environmental burden and social vulnerability. These domains represent discrete aspects of the social vulnerability and environmental burden, such as socioeconomic status and air pollution, that allow users to easily interpret patterns of vulnerability and burden for communities of interest without deeply exploring each of the 31 indicators that constitute these modules. Domains in the Social Vulnerability Module are largely organized around existing themes described in the CDC/ATSDR SVI (Flanagan et al., 2011). The CDC/ATSDR SVI uses themes to group indicators into less granular units of analysis. Domains in the Environmental Burden Module are constructed based on environmental media (i.e., air, soil, water, noise, odor) affected by pollution and land use indicators.

Example Census Tract: Indicator and Index Calculation

Documented below is an example calculation for the EJI for two census tracts (A and B). The census tract GEOIDs being used are 13089021907 and 53033029203. This document will illustrate the values and calculations that are used to create a final EJI score.

Contained within this section are:

1. Maps of census tract A (48039664501) and census tract B (53033029203)
2. Tables of all indicator variables
3. The values used to calculate the final EJI
4. Instructions on calculating individual tracts



Social Vulnerability Module (SVM) Ranks				
Indicator	**Census Tract A**		**Census Tract B**	
Indicator name (unit)	**Raw Value**	**Percentile Ranks**	**Raw Value**	**Percentile Ranks**
Minority Status (%)	33.1	0.54	60.5	0.75
Poverty (%)	38.2	0.65	38.73	0.64
No High School Diploma (%)	15.8	0.71	16.6	0.73
Unemployment (%)	12.3	0.93	1.8	0.09
Housing Tenure (%)	6.5	0.24	23.5	0.84
Housing Burdened Lower-Income Households (%)	26.8	0.52	38.73	0.81
Lack of Health Insurance (%)	14.4	0.83	7.4	0.52
Broadband Access (%)	24.8	0.75	16.9	0.51
Age 65 and Older (%)	21.1	0.79	8.4	0.12
Age 17 and Younger (%)	28.0	0.85	19	0.29
Civilian with Disability (%)	18.6	0.84	11.1	0.4
Speaks English "Less than Well" (%)	3.0	0.67	5.2	0.77
Mobile Homes (%)	17.3	0	0	0
Group Quarters (%)	0	0.87	25.9	0.98
Total Percentile Rank (Sum)		9.18		7.45

Health Vulnerability Module (HVM) Ranks						
Indicator	**Census Tract A**			**Census Tract B**		
Indicator name (unit)	**Raw Value**	**Percentile Ranks**	**High Prevalence (>0.6666)**	**Raw Value**	**Percentile Ranks**	**High Prevalence (>0.6666)**
High Prevalence of High Blood Pressure (%)	39.3	0.84	1	28.2	0.28	0
High Prevalence of Asthma (%)	9.6	0.46	0	11.2	0.82	1
High Prevalence of Cancer (%)	7.5	0.69	1	5.2	0.21	0
High Prevalence of Poor Mental Health (%)	14.8	0.59	0	18.1	0.86	1
High Prevalence of Diabetes (%)	14.6	0.84	1	11.4	0.58	0
Total Prevalence (Sum)			3			2

Environmental Burden Module (EBM) Ranks				
Indicator	**Census Tract A**		**Census Tract B**	
Indicator name (unit)	**Raw Value**	**Percentile Ranks**	**Raw Value**	**Percentile Ranks**
Ozone (Days)	0.67	0.46	0	0
PM2.5* (Days) *particulate matter < 2.5 microns in diameter	8.49	0.36	7.06	0.13
Diesel Particulate Matter (µg/m^3)	0.15	0.11	0.93	0.91
Air Toxics Cancer Risk (%)	25.83	0.27	43.62	0.93
National Priority List Sites (%)	0	0	0	0
Toxic Release Inventory Sites (%)	3.3	0.38	100	0.86
Treatment, Storage, and Disposal Sites (%)	1.11	0.92	1.01	0.92
Risk Management Plan Sites (%)	2.02	0.68	100	0.98
Coal Mines (%)	0	0	0	0
Lead Mines (%)	0	0	0	0
Lack of Recreational Parks (%)	52.93	1-0.41	100	1-0.61
Houses Built Pre-1980 (%)	44.8	0.31	49.38	0.36
Lack of Walkability (index value)	2.87	1-0.02	16.42	1-0.97
High-Volume Roads (%)	0	0	100	0.77
Railways (%)	2.4	0.28	100	0.79
Airports (%)	0	0	0	0
Impaired Surface Water (%)	13.86	0.26	86.83	0.73
Total Percentile Rank (Sum)		5.6		7.78

Total Percentile Ranks by EJI Module						
Calculation	**Census Tract A**			**Census Tract B**		
Calculation	**EBM**	**SVM**	**HVM**	**EBM**	**SVM**	**HVM**
Percentile Rank Sum	5.6	9.18	3	7.78	7.45	2
Percentile Rank	0.39	0.85	(3*0.2)	0.84	0.6	(2*0.2)

Total Percentile Ranks for the EJI and the EJI SER				
Calculation	**EJI** (EBM+SVM+HVM)	**EJI SER** (EBM+SVM)	**EJI** (EBM+SVM+HVM)	**EJI SER** (EBM+SVM)
Percentile Rank Sum	1.84	1.24	1.84	1.44
Final Score Percentile Rank	0.76	0.69	0.76	0.81

Terms used in table above:

- EJI – Environmental Justice Index
- EJI SER – Environmental Justice Index Social-Environmental Ranking
- EBM – Environmental Burden Module
- SVM – Social Vulnerability Module
- HVM – Health Vulnerability Module

Example Calculation Steps (Excel)

1. Within excel run a PERCENTRANK.INC on all raw variable values
   - *Note: Zeros mark actual absence of a characteristic, rather than missing data. Tracts where data were missing were excluded from overall ranking.*
2. For HVM flag (1) all percentile rank results that are above 0.6666
3. Sum all individual module percentile rank results excluding tracts with missing values
   - For HVM multiple cumulative health impact by 0.2
4. Sum cumulative module PR for CI (EBM + SVM + HVM) and for EJI (EBM + SVM)
5. Run PERCENTRANK.INC for sum of EJI and EJI SER individually

What is being calculated	**Environmental Burden Module (EBM)**	**Social Vulnerability Module (SVM)**	**Health Vulnerability Module (HVM)**
Individual Modules - Ranks	In Excel For all Variables: PERCENTRANK.INC on EBM_VarN array with 4 significant digits	In Excel For all Variables: PERCENTRANK.INC on SVM_VarN array with 4 significant digits	In Excel For all Variables: PERCENTRANK.INC on HVM_VarN array with 4 significant digits
Individual Modules - Flags	Not applicable	Not applicable	In Excel For all Variables: If(PR_VarN>0.6666,1,0)
Individual Modules - SUM	SUM(PR_VAR1,…, PR_VARN)	SUM(PR_VAR1,…, PR_VARN)	SUM(flag_VAR1,…, flag_VARN)*0.2

What is being calculated	**Environmental Justice Index (EJI)**	**EJI Social Environmental Ranking (EJI SER)**
Combined Scores	EBM_SUM_PR + SVM_SUM_PR + HVM_SUM_PR = SPL_SER	EBM_SUM_PR + SVM_SUM_PR = SPL_EJI
Final Score	In Excel: PERCENTRANK.INC on SPL_SER array with 4 significant digits	In Excel: PERCENTRANK.INC on SPL_EJI array with 4 significant digits

Indicators

Social Vulnerability	Racial/ Ethnic Minority Status	Minority Status
	Socioeconomic Status	Poverty
		No High School Diploma
		Unemployment
		Housing Tenure
		Housing Burdened Lower-Income Households
		Lack of Health Insurance
		Lack of Broadband Access
	Household Characteristics	Age 65 and Older
		Age 17 and Younger
		Civilian with a Disability
		Speaks English "Less than Well"
	Housing Type	Group Quarters
		Mobile Homes
Environmental Burden	Air Pollution	Ozone
		PM2.5
		Diesel Particulate Matter
		Air Toxics Cancer Risk
	Potentially Hazardous & Toxic Sites	National Priority List Sites
		Toxic Release Inventory Sites
		Treatment, Storage, and Disposal Sites
		Risk Management Plan Sites
		Coal Mines
		Lead Mines
	Built Environment	Lack of Recreational Parks
		Houses Built Pre-1980
		Lack of Walkability
	Transportation Infrastructure	High-Volume Roads
		Railways
		Airports
	Water Pollution	Impaired Surface Water
Health Vulnerability	Pre-existing Chronic Disease Burden	Asthma*
		Cancer*
		High Blood Pressure*
		Diabetes*
		Poor Mental Health*

*Health vulnerability measures are marked with asterisks because they are calculated differently than other indicators. While most indicators can have a range of values, the health vulnerability indicators represent only whether a given census tract experiences a high estimated prevalence of disease or not.

EJI Indicators

Text-Only Version

Social vulnerability module

- Racial/Ethnic Minority Status
  - Minority Status
- Socioeconomic Status
  - Poverty
  - No High School Diploma
  - Unemployment
  - Housing Tenure
  - Housing Burdened Lower-Income Households
  - Health Insurance
  - Broadband Access
- Household Characteristics
  - Age 65 and Older
  - Age 17 and Younger
  - Civilian with a Disability
  - Speaks English “Less than Well”
- Housing Type
  - Group Quarters
  - Mobile Homes

Environmental burden module

- Air Pollution
  - Ozone
  - PM2.5 (Fine Particulate Matter)
  - Diesel Particulate Matter
  - Air Toxics Cancer Risk
- Potentially Hazardous and Toxic Sites
  - National Priority List Sites
  - Toxic Release Inventory Sites
  - Treatment, Storage, and Disposal Sites
  - Risk Management Plan Sites
  - Coal Mines
  - Lead Mines
- Built Environment
  - Recreational Parks
  - Houses Built Pre-1980

    - Walkability
- Transportation Infrastructure
    - High-Volume Roads
    - Railways
    - Airports
- Water Pollution
    - Impaired Surface Water

Health vulnerability module

- Pre-existing Chronic Disease Burden
    - Asthma*
    - Cancer*
    - High Blood Pressure*
    - Diabetes*
    - Poor Mental Health*

Environmental Burden Module

Cumulative environmental burden can be understood as the sum of activities that cause environmental pollution or negatively affect environmental and human health (Owusu et al. 2022). The approach taken here to quantify cumulative environmental burden includes assessments of both features of the environment that contribute to good health (salutogenic features) and features of the environment that may be detrimental to human health (pathogenic features). While many cumulative impacts and EJ mapping tools consider only pathogenic features of the environment (California Office of Environmental Health Hazard Assessment, 2021; Min et al., 2019; United States Environmental Protection Agency, 2019), a growing body of literature has documented the importance of salutogenic features in determining environmental quality and measuring health disparities attributable to environmental conditions (Brulle & Pellow, 2006; Maizlish et al., 2019; Pastor et al., 2005; Shrestha et al., 2016).

Air Pollution: Ozone

Indicator: Mean annual number of days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard (NAAQS), averaged over three years (2014-2016)

Data Year: 2014-2016

Data source: U.S. Environmental Protection Agency Air Quality System (AQS; combined monitoring and modeled data)

Rationale:

Both acute and long-term exposure to elevated levels of ozone in air are associated with negative health effects ranging from increased morbidity and mortality due to respiratory and cardiovascular disease (Crouse et al., 2015; Last et al., 2017). Together with PM2.5, ozone is a major contributor to air pollution-related morbidity and mortality, with an estimated 4,700 ozone-related deaths in the United States in 2005 (Fann et al., 2012).

Processing Method:

- Data from monitoring and modeled predictions for ozone from 2014 to 2016 were obtained from the National Environmental Health Tracking Program which uses estimates from the U.S. EPA's Downscaler model
- The daily standard used for ozone was 0.075 ppm for year 2015 and 0.070 ppm for years 2015 and 2016, reflecting a change in EPA daily standards (U.S. EPA, 2021).
- A 3-year mean of the number of days above this standard for ozone was computed for each census tract for which data were available
- Mean annual percent of days with daily 24-hour average ozone concentrations over the National Ambient Air Quality Standard in each census tract were then sorted and assigned a percentile ranking

Air Pollution: PM2.5

Indicator: Mean annual percent of days with daily 24-hour average $PM_{2.5}$ concentrations over the National Ambient Air Quality Standard (NAAQS), averaged over three years (2014-2016)

Data Year: 2014-2016

Data source: U.S. Environmental Protection Agency Air Quality System (AQS; combined monitoring and modeled data)

Rationale:

Inhalation of particulate matter with a diameter of 2.5 microns or less (PM2.5) can have a number of adverse effects on health and well-being. Acute exposure to elevated levels of PM2.5 can lead to irritation of eyes, nose, throat and lungs , and increases relative risk of acute cardiovascular events including admission to a hospital for stoke (Rajagopalan et al., 2018). Long-term exposure to elevated levels of PM2.5 is associated with higher rates of mortality from a number of conditions ranging from cancer to cardiopulmonary disease (Dockery & Pope, 1994). In the U.S. in 2005, an estimated 130,000 deaths were attributable to PM2.5-related causes (Fann et al., 2012).

Processing Method:

- Data from monitoring and modeled predictions for PM2.5 from 2014 to 2016 were obtained from the National Environmental Health Tracking Program which uses estimates from the U.S. EPA's Downscaler model
- A 3-year mean number of days above the U.S. EPA's daily standard for PM 2.5 (35 $\mu g/m^3$) was computed for each census tract for which data were available
- Mean annual percent of days with daily 24-hour average PM2.5 concentrations over the National Ambient Air Quality Standard in each census tract were then sorted and assigned a percentile ranking

Air Pollution: Diesel Particulate Matter

Indicator: Diesel particulate matter concentrations in air, $\mu g/m^3$

Data Year: 2014

Data source: U.S. Environmental Protection Agency National Air Toxics Assessment (NATA: modeled data)

Rationale:

Diesel particulate matter (DPM) is a particle emission from a diesel motor made of an elemental carbon core and various adsorbed organics compounds and other chemical components

(Wichmann, 2007). Evidence indicates that DPM exposure may cause respiratory symptoms via inflammation and oxidative stress (Ristovski et al., 2012). Acute exposure to DPM has been associated with acute coronary syndrome (ACS) and other cardiovascular issues (Peters et al., 2001) and DPM contains carcinogens such as benzene and formaldehyde that may lead to the development of certain kinds of cancer (Krivoshto et al., 2008).

Processing Method:

- Data from modeled predictions of ambient diesel particulate matter concentrations at the census tract level were downloaded from the U.S. EPA's 2014 National Air Toxics Assessment database
- Estimates of diesel particulate matter concentrations in air in each census tract were then sorted and assigned a percentile ranking

Air Pollution: Air Toxics Cancer Risk

Indicator: Lifetime cancer risk from inhalation of air toxics

Data Year: 2014

Data source: U.S. Environmental Protection Agency National Air Toxics Assessment (NATA; modeled data)

Rationale:

Air toxics cancer risk is a composite measure assessing the cancer risk associated with inhaling 140 different hazardous air pollutants (HAPs). HAPs such as benzene, dioxin, formaldehyde, and ethylene oxide are known carcinogens which, at various concentrations, contribute to lifetime risk of developing certain types of cancer (Loh et al., 2007; Reynolds et al., 2003; Whitworth et al., 2008; Wu et al., 2009). The cancer risks estimated by NATA are based on modeled exposure concentrations, assessments of each pollutant's unit risk estimate, and inhalation reference concentration. It is important to note that diesel particulate matter (DPM), which is another EJI indicator, is one of the HAPs included in the 2014 NATA lifetime cancer risk model. However, the DPM indicator is represented as distinct from the air toxics cancer risk indicator because DPM is only one of the 140 HAPs used to create the 2014 NATA lifetime cancer risk estimate and is associated with many health issues other than cancer. For more information on the 2014 NATA, including a full list of HAPs included in the lifetime cancer risk model, please visit https://www.epa.gov/national-air-toxics-assessment/2014-nata-assessment-results.

Processing Method:

- Data from modeled predictions of total lifetime cancer risk associated with air toxics at the census tract level were downloaded from the U.S. EPA's 2014 National Air Toxics Assessment database

- Estimates of lifetime cancer risk from inhalation of air toxics in each census tract were then sorted and assigned a percentile ranking

Potentially Hazardous & Toxic Sites: National Priority List Sites

Indicator: Proportion of tract area within 1-mi buffer of EPA National Priority List (NPL) sites

Data Year: 2021

Data source: U.S. Environmental Protection Agency Facility Registry Service (FRS)

Rationale:

Sites on the EPA's National Priorities List (NPL), which are designated by the U.S. EPA as priorities through hazard assessment, nomination by states or territories, or issuance of a health advisory by the Agency for Toxic Substances and Disease Registry, can present several potential hazards to the health and well-being of neighboring communities. While actual risks to health vary by sites, proximity to these sites can have important and complex effects on community stress and perceptions of risk (Kiel & Zabel, 2001; Pearsall, 2010). Furthermore, legacy contaminants associated with many of these sites can affect multiple environmental media, becoming airborne with windblown dust or leaching into soil and groundwater and possibly exposing surrounding communities through drinking water or vapor intrusion.

Processing Method:

- Point level data representing locations of NPL sites were downloaded through the U.S. EPA's Facility Registry Service
- 1-mile buffers were calculated for each site
- Site buffers were combined into a single layer representing a 1-mile buffer around all NPL sites in the U.S.
- The NPL buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a NPL site in each census tract were then sorted and assigned a percentile ranking

Potentially Hazardous & Toxic Sites: Toxic Release Inventory Sites

Indicator: Proportion of tract area within 1-mi buffer of Toxic Release Inventory (TRI) sites

Data Year: 2021

Data source: U.S. Environmental Protection Agency Facility Registry Service (FRS)

Rationale:

Sites listed through the EPA's Toxic Release Inventory (TRI) include all facilities with 10 or more full time employees which operate within certain industrial sectors and annually either 1) manufacture more than 25,000 pounds of listed chemicals or 2) used more than 10,000 pounds of listed chemicals. These sites can affect the health of neighboring communities through routine chemical releases into air, soil, or water. Residential proximity to TRI sites has been linked to higher rates of hospitalization for COPD (Brown-Amilian & Akolade, 2021) as well as increased risks for certain kinds of cancer (Bulka et al., 2016). Additionally, TRI sites and other noxious and unwanted land uses can produce noise and odor pollution and, particularly in communities burdened by multiple such land uses, can lead to increased burden of community stress (Wilson et al., 2012).

Processing Method:

- Point level data representing locations of TRI sites were downloaded through the U.S. EPA's Facility Registry Service
- 1-mile buffers were calculated for each site
- Site buffers were combined into a single layer representing 1-mile buffers around all TRI sites in the U.S.
- The TRI buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a TRI site in each census tract were then sorted and assigned a percentile ranking

Potentially Hazardous & Toxic Sites: Treatment, Storage, and Disposal Facilities

Indicator: Proportion of tract area within 1-mi buffer of EPA Treatment, Storage, and Disposal Facilities (TSDF)

Data Year: 2021

Data source: U.S. Environmental Protection Agency Facility Registry Service (FRS)

Rationale:

Sites listed as Treatment, Storage, and Disposal Facilities (TSDF) are responsible for handling hazardous wastes such as manufacturing by-products, cleaning fluids, or pesticides throughout the process of collection, transfer, and ultimately disposal. Volatile substances generated by waste may become aerosolized or migrate into soil and water, leading to vapor intrusion or contamination of groundwater (Johnston & MacDonald Gibson, 2015; Marshall et al., 1993). Proximity to hazardous waste sites has been linked to increased rates of hospitalizations for diseases such as stroke, diabetes, and coronary heart disease (Kouznetsova et al., 2007; Sergeev & Carpenter, 2005; Shcherbatykh et al., 2005).

Processing Method:

- Point level data representing locations of TRI sites were downloaded through the U.S. EPA's Facility Registry Service
- 1-mile buffers were calculated for each site
- Site buffers were combined into a single layer representing a 1-mile buffer around all TRI sites in the U.S.
- The TRI buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a TSD facility in each census tract were then sorted and assigned a percentile ranking

Potentially Hazardous & Toxic Sites: Risk Management Plan Sites

Indicator: Proportion of tract area within 1-mi buffer of EPA Risk Management Plan (RMP) sites

Data Year: 2021

Data source: U.S. Environmental Protection Agency Facility Registry Service (FRS)

Rationale:

The EPA's Risk Management Plan (RMP) program covers ~12,500 of the nation's most high-risk facilities that produce, use, or store significant amounts of certain highly toxic or flammable chemicals. These facilities must prepare plans for responding to a worst-case incident such as a major fire or explosion that releases a toxic chemical into the surrounding community (US Environmental Protection Agency, 2016). There are many negative health effects associated with residing in proximity to RMP sites. The EPA estimates that about 150 "reportable" incidents of unplanned chemical releases occur each year at RMP facilities, separate from the daily toxic emissions that are allowed under most operating permits. The EPA notes that these incidents "pose a risk to neighboring communities and workers because they result in fatalities, injuries, significant property damage, evacuations, sheltering in place, or environmental damage" (US Environmental Protection Agency, 2021). Besides direct deaths and injuries caused by chemical release and explosion incidents, research shows increased risk of cancer and respiratory illness from toxic air pollution exposure at these sites. Although the effects of proximity to RMP sites on community stress has not formally been assessed, it is also reasonable to assume that fear of potential chemical plant disasters contributes to the burden of psychosocial stress imposed on communities by cumulative environmental and social stressors (Hynes & Lopez, 2007).

Processing Method:

- Point level data representing locations of RMP sites were downloaded through the U.S. EPA's Facility Registry Service
- 1-mile buffers were calculated for each site

- Site buffers were combined into a single layer representing a 1-mile buffer around all RMP sites in the U.S.
- The RMP buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of an RMP site in each census tract were then sorted and assigned a percentile ranking

Potentially Hazardous & Toxic Sites: Coal Mines

Indicator: Proportion of tract area within 1-mi buffer of a coal mine

Data Year: 2021

Data source: U.S. Mine Safety and Health Administration Mine Data Retrieval System (MDRS)

Rationale:

Coal mining, while on the decline in the United States, is still of substantial concern for the health of exposed communities, including both traditional underground mining methods and surface mining methods, such as mountaintop removal (MTR). Studies have observed elevated blood inflammation levels, increased cardiopulmonary, lung, and kidney disease, and increased rates of lung cancer mortality in heavy Appalachian coal mining communities as a result of air pollution from mining activity (Hendryx et al., 2010; Hendryx & Ahern, 2008; Hendryx & Luo, 2015). Proximity to MTR sites has been linked to impaired respiratory health, including increased occurrence of chronic obstructive pulmonary disease (COPD)(Hendryx & Luo, 2015) and may predict increased risk for depressive and substance use disorders (Canu et al., 2017). Air pollution from coal mining has also been connected to adverse effects in-utero for pregnant women, including low-birthweight (Ahern et al., 2011). Exposure pathways to coal contamination are also multifactorial. Coal slurry (the practice of disposing liquified coal wastes underground) can leach coal-related pollutants into well and ground water, potential drinking water sources for residents (Ducatman et al., 2010).

Processing Method:

- Point level data representing locations of coal mines were downloaded through the U.S. Mine Safety and Health Administration's Mine Data Retrieval System (MDRS)
- Sites were filtered to remove mines designated metal mines (var: COAL_METAL_IND) and as "abandoned" and "abandoned sealed" to avoid capturing sites at which coal is not being extracted or handled and which no longer constitute an environmental hazard
- Note: other forms of non-active coal mines, such as those listed as "temporarily idled," were not excluded from the dataset because these sites can produce environmental harm from remaining slag piles and other forms of residual contamination
- 1-mile buffers were calculated for each site

- Site buffers were combined into a single layer representing a 1-mile buffer around all active or intermittent coal mines in the U.S.
- The coal mine buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a coal mine in each census tract were then sorted and assigned a percentile ranking

Potentially Hazardous & Toxic Sites: Lead Mines

Indicator: Proportion of tract area within 1-mi buffer of an active lead mine

Data Year: 2021

Data source: U.S. Mine Safety and Health Administration Mine Data Retrieval System (MDRS)

Rationale:

Lead mines constitute an important health risk for surrounding communities. Studies in the U.S. have suggested that soil and dust contaminated from lead mining as well as other waste-byproducts of mining pose a health hazard to nearby communities, particularly to children (Malcoe et al., 2002; Murgueytio et al., 1998). Studies outside of the U.S. evaluating health risks associated with communities in close proximity to active lead mines have found evidence of elevated blood lead levels in children (Schirnding et al., 2003; Zhang et al., 2012).

Processing Method:

- Point level data representing locations of lead mines were downloaded through the U.S. Mine Safety and Health Administration's Mine Data Retrieval System (MDRS)
- 1-mile buffers were calculated for each site
- Sites were filtered to only include mines labelled as "producers" to avoid capturing sites which no longer constitute an environmental hazard
- 116 sites were determined to have inadequate location descriptions to verify accuracy and were removed from the dataset
- Site buffers were combined into a single layer representing a 1-mile buffer around all active or intermittent lead mines in the U.S.
- The lead mine buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a lead mine in each census tract were then sorted and assigned a percentile ranking

Built Environment: Lack of Recreational Parks

Indicator: Proportion of tract area not within 1-mi buffer of a park, recreational area, or public forest

Data Year: 2020

Data source: TomTom MultiNet® Enterprise Dataset

Rationale:

Parks and greenspaces represent important healthy features of the built environment, providing spaces for physical recreation and promoting physical activity (Bedimo-Rung et al., 2005; Cohen et al., 2007), though evidence that parks promote physical activity in rural areas is mixed (Reuben et al., 2020; Roemmich et al., 2018). Parks and greenspaces also play an important role in mitigating urban heat island effects (P. Lin et al., 2017; Shishegar, 2014) and can offer refuge on extreme heat days (Brown et al., 2015; Voelkel et al., 2018). Proximity and access to parks and greenspaces can also have important implications for mental health, with studies indicating that measures of proximity and access to these spaces are associated with better overall mental health (Bojorquez & Ojeda-Revah, 2018; Sturm & Cohen, 2014; Wood et al., 2017). While park design quality, and neighborhood perceptions of safety can have important mediating effects on these benefits (Cohen et al., 2010; Cutts et al., 2009; Rigolon et al., 2018), and while there are concerns associated with "greening" and gentrification (Mullenbach & Baker, 2020; Wolch et al., 2014), these spaces nearly always provide an overall benefit to neighboring communities and lack of access constitutes an important issue for health and environmental justice (Boone et al., 2009; Jennings et al., 2012; Rigolon, 2017; Rigolon et al., 2018).

Processing Method:

- Polygons representing areas of parks, recreational areas and public forests were obtained from TomTom's MultiNet® Enterprise Dataset
- 1-mile buffers were calculated for each polygon
- Polygon buffers were combined into a single layer representing a 1-mile buffer around all parks, recreational areas, or public forests in the U.S.
- The parks buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Because this indicator is intended to represent lack of access to parks and greenspaces, the final value for this indicator was calculated by subtracting the percentile ranking from 1 to get the inverse score – thus the indicator value for a tract with greater access to parks and greenspace than 95% of all other tracts would be calculated as 1 - 0.95 = 0.05

- Proportions of tract area not within 1-mi buffer of a park, recreational area or public forest in each census tract were then sorted and assigned a percentile ranking

Built Environment: Housing Built Pre-1980

Indicator: Proportion of occupied housing units built prior to 1980

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Age of housing units has important implications for potential exposure to lead. While lead-based paint was banned in 1978, housing built around that time or prior often contain underlying layers of lead-based paint. While underlying layers of lead-based paint do not necessarily constitute a health risk, chipping or flaking that exposes underlying layers of lead-based paints may lead to ingestion by children (Lanphear et al., 1996). Measures of housing built prior to the ban on lead-based paint have repeatedly been identified as one of the leading predictors of blood-lead levels in children (Kim et al., 2002; Sadler et al., 2017; Schultz et al., 2017). There are no known safe levels of lead exposure, especially among children, who are highly susceptible to neurological and developmental issues associated with lead exposure.

Processing Method:

- Estimates of renter- and owner-occupied housing units built by decade for each census tract in the U.S. were downloaded from the 2015-2019 American Community Survey
- Estimates of both renter- and owner-occupied housing units built after 1980 were subtracted from the overall and housing built from the overall estimates of occupied housing units
- The resulting measure of renter- and owner-occupied housing units built before 1980 was divided by the total estimate of renter- and owner-occupied housing units to calculate the proportion
- Proportions of occupied housing units built prior to 1980 in each census tract were then sorted and assigned a percentile ranking

Built Environment: Lack of Walkability

Indicator: National Walkability Index Score

Data Year: 2021

Data source: U.S. Environmental Protection Agency National Walkability Index

Rationale:

The U.S. Centers for Disease Control and Prevention (CDC) considers walkability as 'the idea of quantifying the safety and desirability of the walking routes' (Smith, 2015). This conceptualization of walkability, stemming from the scientific evidence that walking can boost metabolism, lower blood sugar and improve mental health (Barton et al., 2009), has become a quantifiable variable to study health-promoting effects of the built environment. Research shows that nearby available locations for walking and biking promote physical activity. Higher residential neighborhood walkability has been associated with more walking, higher overall physical activity, lower body mass index (BMI), lower incidence of diabetes, improved glycemic control among residents, and lower premature mortality (Awuor & Melles, 2019; Chen & Kwan, 2015; L. Frank et al., 2010; L. D. Frank et al., 2004, 2005, 2006; Freeman et al., 2013; Hirsch et al., 2014; US Environmental Protection Agency, 2014, 2017). Measures of neighborhood walkability that include measures of street connectivity, transit stop density, and land use mix, all features of the EPA's National Walkability Index, have also been shown to be positively associated with various measures of accessibility for older adults and persons with disabilities (King et al., 2011; Kwon & Akar, 2022; Mahmood et al., 2020). While it is important to note that the associations between built environment measures of walkability on health may be different in rural and urban neighborhoods (Stowe et al., 2019), and while these measures may not account for physical or social factors that could mediate the effects of walkability on physical activity and health benefits (Bracy et al., 2014; Forsyth, 2015), walkability nevertheless constitutes an important environmental amenity.

Processing Method:

- National Walkability Index values were downloaded at the census tract level for the entire U.S.
- Because this indicator is intended to represent lack of walkability, the final value for this indicator was calculated by subtracting the percentile ranking from 1 to get the inverse score – thus the indicator value for a tract with greater walkability than 95% of all other tracts would be calculated as 1 - 0.95 = 0.05
- The inverse walkability scores for each census tract were then sorted and assigned a percentile ranking

Transportation Infrastructure: High Volume Roads

Indicator: Proportion of tract area within 1-mi buffer of a high-volume street or road

Data Year: 2020

Data source: TomTom MultiNet® Enterprise Dataset

Rationale:

High-volume roads, such as interstate highways, can constitute major hazards to surrounding communities. Vehicular emissions are a major source of air pollutants such as ozone and diesel particulate matter, and proximity to busy roads has been associated with a number of adverse respiratory symptoms, childhood cancers, adverse birth outcomes, and overall mortality (Boothe & Shendell, 2008). Water runoff from roads can also lead to deposition of heavy metals and other pollutants in nearby soils and waters (Khalid et al., 2018; Sutherland & Tolosa, 2001). Noise pollution associated with traffic is also associated with significant increases in community stress (Barbaresco et al., 2019) and can lead to elevated risk of cardiovascular disease (Münzel et al., 2021) and adverse mental health outcomes (Díaz et al., 2020).

Processing Method:

- Shapefiles representing all street and highway features were obtained from TomTom's MultiNet® Enterprise Dataset
- Features were filtered by arterial classification code to include only continental/ inter-state (ACC 1) or inter-metropolitan area (ACC 2) roads
- 1-mile buffers were produced for each road segment
- Road buffers were combined into a single layer representing a 1-mile buffer around all continental/ inter-state and inter-metropolitan area roads in the U.S.
- The roads buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a high-volume street or road in each census tract were then sorted and assigned a percentile ranking

Transportation Infrastructure: Railways

Indicator details: Proportion of tract area within 1-mi buffer of a railway

Data Year: 2020

Data source: TomTom MultiNet® Enterprise Dataset

Rationale:

Like roads, railways can also present a significant source of noise pollution to nearby communities. This noise pollution can constitute a major annoyance and source of community stress, especially when combined with noise pollution from traffic (Öhrström et al., 2007). Among all transportation-associated sources of noise pollution, railway noise is associated with the most significant levels of sleep disruption and associated increases in stress and diastolic blood pressure (Elmenhorst et al., 2019; Petri et al., 2021).

Processing Method:

- Shapefiles representing railway features were obtained from TomTom's MultiNet® Enterprise Dataset
- 1-mile buffers were produced for each rail segment
- Railroad buffers were combined into a single layer representing a 1-mile buffer around all railways in the U.S.
- The railway buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of a railway in each census tract were then sorted and assigned a percentile ranking

Transportation Infrastructure: Airports

Indicator: Proportion of tract area within 1-mi buffer of an airport

Data Year: 2020

Data source: TomTom MultiNet® Enterprise Dataset

Rationale:

Airports are important sources of noise pollution. Studies indicate that noise pollution associated with residential proximity to airports can constitute a significant nuisance, and can lead to elevated levels of stress and sleep disturbance (Elmenhorst et al., 2019; Ogneva-Himmelberger & Cooperman, 2010; Ozkurt et al., 2015). Airports are also important sources of air, soil, and groundwater contamination. Accidental releases from leaky storage tanks, use of hazardous chemicals in rescue and firefighting training, and stormwater runoff all contribute to infiltration of chemicals such as benzene, trichloroethylene, carbon tetrachloride, and a range of perfluorochemicals into soil and groundwater (Nunes et al., 2011).

Processing Method:

- Polygons representing areas of airports with at least one runway were obtained from TomTom's MultiNet® Enterprise Dataset
- 1-mile buffers were calculated for each airport polygon
- Polygon buffers were combined into a single layer representing a 1-mile buffer around all airports in the U.S.
- The airport buffer layer was then intersected with geographic boundaries of census tracts and proportion of tract area intersecting with buffer was calculated
- Proportions of tract area within 1-mi buffer of an airport in each census tract were then sorted and assigned a percentile ranking

Water Pollution: Impaired Surface Water

Indicator: Percent of tract watershed area classified as impaired

Data Year: 2019

Data source: U.S. Environmental Protection Agency Watershed Index Online (WSIO)

Rationale:

Surface waters such as rivers and lakes are important for recreation and fishing, and impairment of these waters can constitute a potential nuisance or even hazard to nearby residents. Waters may be classified as impaired due to elevated levels of waterborne pathogens or significant contamination by toxic substances. Waterborne pathogens can pose a significant health risk through recreational exposure (McKee & Cruz, 2021), while ingestion of fish from chemically-impaired waters can be a significant exposure pathway for a number of pollutants that bioaccumulate in tissues (Dórea, 2008).

Processing Method:

- Data on impaired water sources was obtained from the EPA Watershed Index Online (WSIO) database. The data contains information on the level of degraded water quality for each watershed hydrographic unit (HUC-12) in the U.S.
- Impaired water source values were translated from HUC-12 to census tract by estimating the proportion of each watershed's area intersecting each census tract's area. This process was repeated for each tract to approximate the percentage of area overlapping any intersecting HUC-12 watershed
- Once the HUC-12 watershed proportions for each tract's area were obtained, the percentage of water deemed impaired in each tract was calculated

- Percentages of water deemed impaired in each census tract were then sorted and assigned a percentile ranking

Social Vulnerability Module

Literature regarding environmental injustice documents the disproportionate placement of hazardous waste sites, industrial facilities, busy roads and railways, and sewage treatment plants in socially vulnerable neighborhoods (Bullard et al., 2008; Mohai et al., 2009; Mohai & Saha, 2007; Morello-Frosch et al., 2011). These communities are thus more likely to be exposed to harmful pollutants and experience poor health outcomes, such as cardiovascular disease, asthma, perinatal outcomes, and mental health impacts (Morello-Frosch et al., 2011). Given the inequities associated with social vulnerability, these communities are also less likely to receive financial assistance for environmental and disaster recovery, have access to mental and physical health services (Tate & Emrich, 2021), or have the social capital or resources to influence environmental decision-making (Pearsall, 2010). Thus, socially vulnerable communities may be particularly vulnerable to procedural environmental injustices.

Racial/Ethnic Minority Status: Minority Status

Indicator: Percent of population that is a racial/ethnic minority (all persons except white, non-Hispanic)

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Historical and ongoing racial residential segregation, race-related income inequality, and other forms of institutional and systemic racism have often limited the ability of these populations to advocate against unwanted land uses or influence environmental decision-making, as borne out by the disproportionate location of contamination sites near non-white populations (Bullard et al., 2008; Cutter et al., 2003; Ernst, 1994; Lee, 1992). Racism has been labeled by the CDC as a serious public health threat (see statement here: https://www.cdc.gov/media/releases/2021/s0408-racism-health.html). A growing body of data suggest that aspects of systemic and structural racism contribute to health disparities, including those associated with environmental pollution, through a number of pathways, including discrimination by the institutional medical system (Boateng & Aslakson, 2021). Minorities experiencing negative health effects associated with environmental pollution may experience barriers to accessing health care due to discrimination and other factors and may suffer disproportionately adverse outcomes (Neighbors et al., 2007; Smedley, 2012; Williams & Mohammed, 2009).

Processing Method:

- Data on the number of persons, stratified by race/ethnicity, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey
- The number of persons designated as "white, non-Hispanic" were subtracted from the total population
- The remaining number, representing all persons except "white, non-Hispanic" persons, was divided by the total population, and multiplied by 100 to get the percentage estimate
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of population that is a racial/ethnic minority in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: Poverty

Indicator: Percent of population with income below 200% of federal poverty level

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Poverty is an indication of economic hardship. Lack of financial resources may hinder a community's ability to influence environmental decision-making, leading to contamination sites being disproportionately located in impoverished areas (Mohai & Bryant, 1991; Mohai & Saha, 2015; Tanzer et al., 2019). Low-income populations are also particularly susceptible to adverse health outcomes, at least in part due to psychosocial and chronic stress and lack of healthcare access (Evans & Kim, 2013; Haushofer & Fehr, 2014; Wright et al., 1998). Research indicates that negative effects of air pollution on birth outcomes are greater for mothers from low-income neighborhoods (Padula et al., 2014; Yi et al., 2010).

Processing Method:

- Data on the percent of persons with income below 200% of the federal poverty level, provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)

- Estimates of the percent of population with income below 200% of federal poverty level in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: No High School Diploma

Indicator: Percent of population (age 25+) with no high school diploma

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Educational attainment is an important factor of socioeconomic status and may influence communities' ability to navigate information about pollution, environmental law, and community-scale resources to influence environmental decision-making (Helfand & Peyton, 1999). Education also influences populations' susceptibility to health impacts of negative environmental conditions. Low educational attainment has been shown to be associated with increased risk of adverse birth outcomes (Gray et al., 2014; Thayamballi et al., 2021) and overall mortality (Kan et al., 2008).

Processing Method:

- Data on the percent of persons (age 25+) with no high school diploma or equivalent (e.g. a GED), provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of population (age 25+) with no high school diploma in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: Unemployment

Indicator: Percent of population age 16 and older who are unemployed

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Unemployment is an important marker of community socioeconomic status. Lack of employment often means limited financial resources as well as decreased social capital due to stigma. These factors can reduce this population's ability to influence environmental decision-making. Furthermore, fear of unemployment can prevent communities from advocating against unwanted land uses that provide employment opportunities (Bullard, 1993), and communities with high rates of unemployment may be more receptive to incoming industrial facilities that offer jobs, essentially trading employment for environmental pollution to avoid extreme poverty (Shrader-Frechette, 2002). Unemployment is also associated with stress and stress-related inflammation, potentially rendering these populations more vulnerable to health effects mediated by stress (Ala-Mursula et al., 2013; Dettenborn et al., 2010; Heikkala et al., 2020).

Processing Method:

- Data on the percent of persons 16 and older who are unemployed, provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of population (age 25+) with no high school diploma in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: Housing Tenure

Indicator: Percent of housing units that are renter-occupied

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Renters are often seen as more transitory and, thus, may have less social capital within the context of environmental decision-making, especially within the context of environmental efforts specifically geared towards homeowners who have vested rights and interests in defending local environmental quality and land values (Perkins et al., 2004; Shapiro, 2005). Additionally, research consistently supports the idea that renters experience worse health outcomes associated with a range of conditions when compared to homeowners, likely due to complex interactions between general socioeconomic status associated with housing tenure and aspects of the physical and meaning-based environments represented by rented and owned housing units (Hiscock et al., 2003; Mawhorter et al., 2021).

Processing Method:

- Data on the number of renter-occupied housing units and the total number of occupied housing units were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates

- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of renter-occupied housing units were divided by estimates of total occupied housing units to calculate a percent of units that are renter-occupied
- Estimates of the percent of housing units that are renter-occupied in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: Housing Burdened, Lower-Income Households

Indicator: Percent of households with annual income less than $75,000 who are considered burdened by housing costs (pay greater than 30% of monthly income on housing expenses)

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

The U.S. Department of Housing and Urban Development (HUD) and the U.S. Census Bureau define a household as "housing cost burdened" if that household pays greater than 30% of monthly income on housing costs. Housing costs represent a significant financial burden for most households, and populations burdened by housing costs and associated debt may lack financial resources or time to devote to improving environmental conditions. Additionally, research indicates that persons experiencing housing burden may be less likely to have access to preventative care or to postpone health care (Meltzer & Schwartz, 2016). Instability associated with housing cost burden can also exacerbate issues of stress and poor mental health and are correlated with worse developmental and educational outcomes for children (Burgard et al., 2012; Newman & Holupka, 2016; Suglia et al., 2011).

Processing Method:

- Data on the monthly housing costs as a percent of household income in the past 12 months were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Estimates of number of households with monthly housing costs greater than 30% of household income in the past 12 months by income level were added together for all income levels under $75,000
- Estimated percentage of households with annual income less than $75,000 and housing costs greater than 30% of income was calculated by divided the estimate above by the total estimated number occupied housing units and then multiplying by 100
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)

Estimates of the percent of households with annual income less than $75,000 who are considered burdened by housing costs (pay greater than 30% of monthly income on housing expenses) in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: Lack of Health Insurance

Indicator: Percent of civilian, noninstitutionalized population who have no health insurance

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

The total population of insured persons in the US has consistently declined since 1997, despite the recent uptick in 2018-2019, where about 11% of the population at the time remained uninsured. This population of uninsured persons are commonly of families with low income (with typically one person working in the family), people of color, and undocumented immigrants (Tolbert et al., 2020). Financial burdens associated with healthcare may the reduce uninsured populations' ability to engage in the environmental decision-making process. Further, individuals without insurance have barriers to accessing preventative care following adverse environmental events, increasing risk of morbidity and mortality among uninsured populations (Mulchandani et al., 2019; Woolhandler & Himmelstein, 2017).

Processing Method:

- Data on the percent of noninstitutionalized population who have no health insurance, provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of civilian, noninstitutionalized population who have no health insurance in each census tract were then sorted and assigned a percentile ranking

Socioeconomic Status: Lack of Internet Access

Indicator: Percent of households with no internet subscription

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Lack of access to broadband services can impede populations' ability to be engaged in decision-making and to be informed on environmental issues in their communities. The inability to access the internet can also be an important communication barrier during environmental emergencies, for which outreach through internet sources can be a key strategy for public health officials (Houston et al., 2015; Jha et al., 2016; Nguyen et al., 2017; Wong et al., 2017).

Processing Method:

- Data on the percent of households with no internet subscription, provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of households with no internet subscription in each census tract were then sorted and assigned a percentile ranking

Household Characteristics: Age 65 and Older

Indicator: Percent of population aged 65 and older

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Adults aged 65 and older face higher rates of social isolation than the general population, which can affect their ability to affect change or influence environmental decision-making in their communities (Andrew & Keefe, 2014). Additionally, older populations may be more susceptible to environmental pollution due to lowered immune function and accumulated oxidative stress associated with a lifetime of exposures (Cakmak et al., 2007; Hong, 2013; Morello-Frosch et al., 2011).

Processing Method:

- Data on the percent of persons aged 65 and older, provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of population aged 65 and older in each census tract were then sorted and assigned a percentile ranking

Household Characteristics: Age 17 and Younger

Indicator: Percent of population aged 17 and younger

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Persons below voting age have a limited ability to influence environmental decision-making as well as limited resources, knowledge, or life experiences necessary to affect change (Flanagan et al., 2011). Additionally, children are particularly susceptible to negative health effects associated with a range of environmental pollution due to a combination of physiological sensitivity and behaviors that put them at greater risk (Morello-Frosch et al., 2011). Physiological factors, such as rates of absorption, distribution, metabolism, and excretion of chemicals, make children more vulnerable to environmental pollution than adults (Faustman et al., 2000).

Processing Method:

- Data on the total number of persons 17 and younger were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- The estimate of persons 17 and younger for each tract was divided by the tracts' estimated total population and multiplied by 100 to calculate the estimated percentage of the tracts population that was 17 and younger
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of population aged 17 and younger in each census tract were then sorted and assigned a percentile ranking

Household Characteristics: Civilian with a Disability

Indicator: Percent of civilian, noninstitutionalized population with a disability

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Those living with a disability may experience social or physiological barriers to full participation in the environmental decision-making process. Persons with disabilities are often disproportionately affected at every stage of disaster events and disaster recovery (Chakraborty et al., 2019; Peek & Stough, 2010). Furthermore, certain types of disability are associated with increased physiological susceptibility to environmental pollution, particularly PM2.5 and other forms of air pollution (Dales & Cakmak, 2016; H. Lin et al., 2017; Weuve et al., 2016).

Processing Method:

- Estimates of percent of civilian, noninstitutionalized population with a disability, provided directly by the Census Bureau, were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of the percent of civilian, noninstitutionalized population with a disability in each census tract were then sorted and assigned a percentile ranking

Household Characteristics: Speaks English "Less than Well"

Indicator: Percent of persons (age 5 and older) who speak English "less than well"

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

The ability to communicate in English can be an important factor in determining a community's ability to participate in civil discourse surrounding environmental decision-making. Documents and news sources covering environmental issues are often not available in languages other than English, hampering non-English speakers' ability to inform themselves and engage in these issues (Teron, 2016). Furthermore, discrimination against non-English speakers can lead to exclusion from decision making and is correlated with increased stress and reduced quality of life (Gee & Ponce, 2010). Non-English speakers may also be more vulnerable during disasters or extreme climate events if materials aimed at dissemination of emergency information are available only in English (Nepal et al., 2012; White-Newsome et al., 2009).

Processing Method:

- Data on the percentage of persons who speak languages other than English and speak English either not at all or less that well were downloaded at the census tract level for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of persons (age 5 and older) who speak English "less than well" in each census tract were then sorted and assigned a percentile ranking

- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were added back into the final database following index calculation

Housing Type: Group Quarters

Indicator: Percentage of persons living in group quarters (includes college residence halls, residential treatment centers, group homes, military barracks, correctional facilities, and worker's dormitories)

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Institutionalized persons, those in correctional facilities, nursing homes, and mental hospitals, are particularly vulnerable to environmental injustice and often have limited ability to influence environmental decision-making. For example, persons who are incarcerated or detained often face disproportionate exposures to environmental contaminants due to poor institutional conditions, exposures through hazardous work programs, and a lack of social capital to improve conditions for themselves (Pellow, 2021). Persons institutionalized in nursing homes or mental hospitals face similar issues of autonomy and lack of social capital or physical ability to influence environmental decision-making. Furthermore, persons in institutional facilities are often neglected in environmental decision making and hazard response (Cutter, 2012).

Non-institutionalized persons living in group quarters are also vulnerable to environmental injustice, though perhaps not as clearly as institutionalized persons. Military bases share some characteristics with correctional facilities in that they are often sites of concentrated environmental contamination and many of their residents come from similar socioeconomic backgrounds and have similarly little influence over the day to day operations that result in contamination (Broomandi et al., 2020). People living in group homes, missions, and shelters may have limited legal status, limited time, and limited resources, and thus diminished ability to influence environmental decision-making (Goodling, 2020).

Processing Method:

- Data on the percentage of persons living in group quarters at the census tract level, provided directly by the Census Bureau, were downloaded for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of persons living in group quarters (includes college residence halls, residential treatment centers, group homes, military barracks, correctional facilities, and

worker's dormitories) in each census tract were then sorted and assigned a percentile ranking
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were added back into the final database following index calculation

Housing Type: Mobile Homes

Indicator: Percentage of total housing units designated as mobile homes

Data Year: 2015-2019

Data source: U.S. Census Bureau American Community Survey (ACS)

Rationale:

Mobile homes are often clustered in communities confined to low-value areas due to zoning laws and stigma (Maantay, 2002). Mobile homes are also often inhabited by farm workers, who are beholden to landowners for environmental decision-making such as use of agricultural pesticides (Early et al., 2006). These aspects of stigma, zoning, and lack of land ownership can inhibit these populations' ability to influence local environmental policy. Furthermore, issues of poor construction and energy inefficiency can render residents of mobile homes more susceptible to negative health effects associated with air pollution (MacTavish et al., 2006) and extreme heat (Phillips et al., 2021), while observed unreliability of access to drinking water poses further risks to residents' health (Pierce & Jimenez, 2015).

Processing Method:

- Data on the percentage of housing units designated as mobile homes at the census tract level, provided directly by the Census Bureau, were downloaded for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2015-2019 American Community Survey estimates
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Estimates of total housing units designated as mobile homes in each census tract were then sorted and assigned a percentile ranking
- Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were added back into the final database following index calculation

Health Vulnerability Module

High Estimated Prevalence of Asthma

Indicator: Estimated prevalence of asthma among adults 18 and older greater than for 66.66% of U.S. census tracts (2020)

Data Year: 2020

Data source: U.S. Centers for Disease Control and Prevention PLACES Estimates

Rationale:

Outdoor air pollution is associated with increases in asthma attacks (Centers for Disease Control and Prevention, 2020; Peel et al., 2005) and asthma-related ED visits (Norris et al., 1999; Slaughter et al., 2005; Stieb et al., 1996; P. E. Tolbert et al., 2000; Villeneuve et al., 2007). Inhalation of pollutants such as PM2.5, ozone, and diesel particulate matter can lead to oxidative stress which inflames the airways and exacerbates asthma symptoms, and both acute and long-term exposure to asthma are associated with worsening asthma symptoms (Guarnieri & Balmes, 2014).

Processing Method:

- Data on asthma prevalence at the census tract level was downloaded for all 50 U.S. States and the District of Columbia from the 2020 PLACES estimates
- Data for Alaska and Hawaii were removed from the dataset due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Tracts were assigned percentile ranks based on the estimated asthma prevalence
- Tracts were assigned a score of 1 if the estimated asthma prevalence was flagged as being in the top tertile (greater than 66.66% of all tracts in dataset), otherwise the tract received a score of 0

High Estimated Prevalence of Cancer

Indicator: Estimated prevalence of all-cause cancer (excluding skin cancer) among adults 18 and older greater than for 66.66% of U.S. census tracts (2020)

Data Year: 2020

Data source: U.S. Centers for Disease Control and Prevention PLACES Estimates

Rationale:

Increases in PM2.5 are also associated with increased all-cause mortality for young adult cancer patients diagnosed with all cancer types (Ou et al., 2020). Long-term exposure to PM2.5, ozone, and other air pollutants is associated with increased morbidity and mortality in persons diagnosed with cancer, including lung cancer (Jerrett et al., 2013; Pope III et al., 2002), liver cancer (Deng et al., 2017), pediatric lymphomas, and CNS tumors (Ou et al., 2020). Experimental research suggests that intermediate to long-term exposure to both fine and coarse particulate matter may accelerate oncogenesis (the formation of tumors) and cause increased expression of inflammation and oncogenesis-related genes in rat brains (Ljubimova et al., 2018).

Processing Method:

- Data on cancer prevalence at the census tract level was downloaded for all 50 U.S. States and the District of Columbia from the 2020 PLACES estimates
- Data for Alaska and Hawaii were removed from the dataset due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Tracts were assigned percentile ranks based on the estimated cancer prevalence
- Tracts were assigned a score of 1 if the estimated cancer prevalence was flagged as being in the top tertile (greater than 66.66% of all tracts in dataset), otherwise the tract received a score of 0
- Data for Alaska and Hawaii were added back into the final database following index calculation

High Estimated Prevalence of High Blood Pressure

Indicator: Estimated prevalence of high blood pressure among adults ≥ 18 greater than for 66.66% of U.S. census tracts (2020)

Data Year: 2020

Data source: U.S. Centers for Disease Control and Prevention PLACES Estimates

Rationale:

Elevated levels of ambient PM2.5, ozone, and other air pollutants are associated with the increased prevalence and elevated risk of adverse health outcomes like heart attack and overall increases in blood pressure, including hypertension (Coogan et al., 2012; Giorgini et al., 2016; Lee, 2020). Long-term exposure to particulate matter, other traffic-related air pollution, and traffic noise pollution have been associated with increased blood pressure and a higher risk of developing hypertension (Dong et al., 2013; Foraster et al., 2014; Fuks et al., 2014). Hypertension is an established risk factor for a number of negative cardiovascular health outcomes, including coronary heart disease and stroke, but cardiovascular complications related to high blood pressure can occur before the onset of established hypertension (Go et al., 2013).

Processing Method:

- Data on the prevalence of high blood pressure at the census tract level was downloaded for all 50 U.S. States and the District of Columbiafrom the 2020 PLACES estimates
- Data for Alaska and Hawaii were removed from the dataset due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Tracts were assigned percentile ranks based on the estimated prevalence of high blood pressure
- Tracts were assigned a score of 1 if the estimated prevalence of high blood pressure was flagged as being in the top tertile (greater than 66.66% of all tracts in dataset), otherwise the tract received a score of 0
- Data for Alaska and Hawaii were added back into the final database following index calculation

High Estimated Prevalence of Diabetes

Indicator: Estimated prevalence of diabetes among adults 18 and older greater than for 66.66% of U.S. census tracts (2020)

Data Year: 2020

Data source: U.S. Centers for Disease Control and Prevention PLACES Estimates

Rationale:

Research suggests that air pollution, such as PM2.5, can cause oxidative stress and inflammation, leading to impairments in insulin signaling associated with diabetes (Meo et al., 2015). PM2.5 is also associated with markers of systemic inflammation in individuals with diabetes (Dubowsky et al., 2006), which may lead to greater risk of diabetes-related negative health outcomes. Proximity to hazardous sites and land use have also been associated with increased risk of hospitalization among individuals with diabetes (Kouznetsova et al., 2007).

Processing Method:

- Data on the prevalence of diabetes at the census tract level was downloaded for all 50 U.S. States and the District of Columbiafrom the 2020 PLACES estimates
- Data for Alaska and Hawaii were removed from the dataset due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Tracts were assigned percentile ranks based on the estimated prevalence of diabetes
- Tracts were assigned a score of 1 if the estimated prevalence of diabetes was flagged as being in the top tertile (greater than 66.66% of all tracts in dataset), otherwise the tract received a score of 0

- Data for Alaska and Hawaii were added back into the final database following index calculation

High Estimated Prevalence of Poor Mental Health

Indicator: Estimated prevalence of poor mental health for ≥ 14 days among adults 18 and older greater than for 66.66% of U.S. census tracts (2020)

Time Period: 2020

Data source: U.S. Centers for Disease Control and Prevention PLACES Estimates

Rationale:

Poor mental health can be both caused by and exacerbated by negative environmental quality. One study found that residential proximity to industrial activity negatively impacts mental health directly and by mediating individual's perceptions of neighborhood disorder and personal powerlessness, with these effects being most prominent in racial/ ethnic minority populations and populations in poverty (Downey & Van Willigen, 2005). Another exploratory study in the U.S. found a strong positive link between exposure to environmental pollution and an increase of prevalence in psychiatric disorders in affected patients (Khan et al., 2019). Poor environmental quality may also affect the quality of life (i.e. the expectation and concern for one's own health and life) negatively through the mediating effects of increased stress and poor sleep (Chang et al., 2020).

Processing Method:

- Data on the prevalence of poor mental health at the census tract level was downloaded for all 50 U.S. States and the District of Columbiafrom the 2020 PLACES estimates
- Data for Alaska and Hawaii were removed from the dataset due to a lack of environmental data for these areas (see "Limitations and Considerations of the EJI" above)
- Tracts were assigned percentile ranks based on the estimated prevalence of poor mental health
- Tracts were assigned a score of 1 if the estimated prevalence of poor mental health was flagged as being in the top tertile (greater than 66.66% of all tracts in dataset), otherwise the tract received a score of 0
- Data for Alaska and Hawaii were added back into the final database following index calculation

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Notes and Information on the EJI Database

Important Notes on EJI Database

- The EJI cumulative impacts ranking (RPL_EJI) should not be used to explore relationships between environmental injustice and health phenomena because health vulnerability factors are already included within that ranking. Instead, the Social-Environmental Ranking (RPL_SER) can be used along with disease flags to explore areas where high social vulnerability and high environmental burden may be contributing to high rates of chronic disease.
- EJI 2022 does not include measures for Alaska, Hawaii, or U.S. territories and dependencies due to a lack of data for these states/territories. Future versions of the EJI will include state- and territory-specific rankings for Alaska, Hawaii, and the Commonwealth of Puerto Rico.
- For tracts with > 0 TOTPOP, a value of -999 in any field either means the value was unavailable from the original census data or we could not calculate a derived value because of unavailable census data.
- Any cells with a -999 were not used for further calculations. For example, total flags do not include fields with a -999 value.
- Questions? Please visit the EJI website at https://www.atsdr.cdc.gov/placeandhealth/eji/index.html for additional information or email the EJI Coordinator at eji@cdc.gov.

EJI Database Data Dictionary

Variables beginning with “E_” are estimates. Variables beginning with “EPL_” are percentile ranks for those estimates. Variables beginning with “SPL_” are summed indicator or module ranks for domains, modules, or overall scores, and variables beginning with “RPL_” are percentile ranks for domains, modules or overall scores. Values of -999 represent “null” or “no data.” Census tract boundaries are taken from 2019 TIGER/ Line Files and are based on the 2010 decennial census.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
STATEFP	State fips code	No value	No value	No value	No value	No value
COUNTYFP	County fips number	No value	No value	No value	No value	No value
TRACTCE	Census tract code	No value	No value	U.S. Census Bureau 2019 TIGER/ Line Files https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html	No value	No value
AFFGEOID	Census tract identifier; a concatenation of current state Federal Information Processing Series (FIPS) code, county FIPS code, and census tract code	No value	No value	No value	No value	No value
GEOID	County identifier; a concatenation of current state Federal Information Processing Series	No value	No value	No value	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
	(FIPS) code and county FIPS code					
COUNTY	County names	No value	No value	No value	No value	No value
StateAbbr	State abbreviations	No value	No value	No value	No value	No value
StateDesc	Full state name	No value	No value	No value	No value	No value
Location	Text description of tract, county, state	No value	No value	No value	No value	No value
E_TOTPOP	Population estimate, 2014-2018 ACS	No value	No value	No value	No value	No value
M_TOTPOP	Population estimate MOE, 2014-2018 ACS	No value	No value	No value	No value	No value
E_DAYPOP	Adjunct variable - Estimated daytime population, LandScan 2018	No value	No value	No value	No value	No value
SPL_EJI	Summation of the HVM, EBI, and SVI module percentile ranks	No value	No value	No value	RPL_EBM + RPL_HVM + RPL_SVM	Tract with null values were not included in the sum.
RPL_EJI	Percentile ranks of SPL_EJI	No value	No value	No value	In Excel: PERCENTRANK.INC on SPL_EJI array with 4 significant digits	Null values removed before calculating output rank.
SPL_SER	Summation of the EB, and SV module percentile ranks	No value	No value	No value	RPL_EBM + RPL_SVM	Tract with null values were not included in the sum.
RPL_SER	Percentile ranks of SPL_SER	No value	No value	No value	In Excel: PERCENTRANK.INC	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
					on SPL_SER array with 4 significant digits	
EPL_OZONE	Percentile rank of annual mean days above O3 regulatory standard - 3-year average	EBM	EBM DOM1	No value	In Excel: PERCENTRANK.INC on E_OZONE array with 4 significant digits	Null values removed before calculating output rank.
EPL_PM	Percentile rank of annual mean days above PM2.5 regulatory standard - 3-year average	EBM	EBM DOM1	No value	In Excel: PERCENTRANK.INC on E_PM array with 4 significant digits	Null values removed before calculating output rank.
EPL_DSLPM	Percentile rank of ambient concentrations of diesel PM/m3	EBM	EBM DOM1	No value	In Excel: PERCENTRANK.INC on E_DSLPM array with 4 significant digits	Null values removed before calculating output rank.
EPL_TOTCR	Percentile rank of the probability of contracting cancer over the course of a lifetime, assuming continuous exposure	EBM	EBM DOM1	No value	In Excel: PERCENTRANK.INC on E_TOTCR array with 4 significant digits	Null values removed before calculating output rank.
SPL_EBM_THEME1	Domain consisting of ozone, PM2.5, air toxics cancer risk, and diesel particulate matter.	EBM	EBM DOM1	No value	EPL_OZONE + EPL_PM + EPL_DSLPM + EPL_TOTCR	Tract with null values were not included in the sum.
RPL_EBM_DOM1	Percentile rank of domain consisting of ozone, PM2.5, air toxics cancer risk, and diesel particulate matter.	EBM	EBM DOM1	No value	In Excel: PERCENTRANK.INC on SPL_EBM_THEME1 array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EPL_NPL	Percentile rank of proportion of tract's area within 1-mi buffer of EPA National Priority List site	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on E_NPL array with 4 significant digits	Null values removed before calculating output rank.
EPL_TRI	Percentile rank of proportion of tract's area within 1-mi buffer of EPA Toxic Release Inventory site	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on E_TRI array with 4 significant digits	Null values removed before calculating output rank.
EPL_TSD	Percentile rank of proportion of tract's area within 1-mi buffer of EPA Treatment, Storage, and Disposal site	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on E_TSD array with 4 significant digits	Null values removed before calculating output rank.
EPL_RMP	Percentile rank of proportion of tract's area within 1-mi buffer of EPA risk management plan site	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on E_RMP array with 4 significant digits	Null values removed before calculating output rank.
EPL_COAL	Percentile rank of proportion of tract's area within 1-mi buffer of coal mines	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on E_COAL array with 4 significant digits	Null values removed before calculating output rank.
EPL_LEAD	Percentile rank of proportion of tract's area within 1-mi buffer of lead mines	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on E_LEAD array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
SPL_EBM_THEME2	Domain consisting of proximity to national priority list sites, proximity to release inventory sites, proximity to treatment, storage, and disposal sites, proximity to risk management plan sites, proximity to coal mines, and proximity to lead mines	EBM	EBM DOM2	No value	EPL_NPL + EPL_TRI + EPL_TSD + EPL_RMP + EPL_COAL + EPL_LEAD	Tract with null values were not included in the sum.
RPL_EBM_DOM2	Percentile rank of domain consisting of proximity to national priority list sites, proximity to release inventory sites, proximity to treatment, storage, and disposal sites, proximity to risk management plan sites, proximity to coal mines, and proximity to lead mines	EBM	EBM DOM2	No value	In Excel: PERCENTRANK.INC on SPL_EBM_THEME2 array with 4 significant digits	Null values removed before calculating output rank.
EPL_PARK	Percentile rank of proportion of tract's area within 1-mi buffer of green space	EBM	EBM DOM3	No value	In Excel: PERCENTRANK.INC on E_PARK array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EPL_HOUAGE	Percentile rank of percentage of houses built pre-1980 (lead exposure)	EBM	EBM DOM3	No value	In Excel: PERCENTRANK.INC on E_HOUSAGE array with 4 significant digits	Null values removed before calculating output rank.
EPL_WLKIND	Percentile rank of a nationwide geographic data resource that ranks block groups according to their relative walkability	EBM	EBM DOM3	No value	In Excel: PERCENTRANK.INC on E_WLKIND array with 4 significant digits	Null values removed before calculating output rank.
SPL_EBM_THEME3	Domain consisting of proximity to recreational parks, houses built pre-1980 (lead exposure), and walkability index	EBM	EBM DOM3	No value	EPL_PARK + EPL_HOUAGE + EPL_WLKIND	Tract with null values were not included in the sum.
RPL_EBM_DOM3	Percentile rank of domain consisting of proximity to recreational parks, houses built pre-1980 (lead exposure), and walkability index	EBM	EBM DOM3	No value	In Excel: PERCENTRANK.INC on SPL_EBM_THEME3 array with 4 significant digits	Null values removed before calculating output rank.
EPL_RAIL	Percentile rank of proportion of tract's area within 1-mi buffer of railroad	EBM	EBM DOM4	No value	In Excel: PERCENTRANK.INC on E_RAIL array with 4 significant digits	Null values removed before calculating output rank.
EPL_ROAD	Percentile rank of proportion of tract's area within 1-mi buffer of high-volume road or highway	EBM	EBM DOM4	No value	In Excel: PERCENTRANK.INC on E_ROAD array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EPL_AIRPRT	Percentile rank of proportion of tract's area within 1-mi buffer of airport	EBM	EBM DOM4	No value	In Excel: PERCENTRANK.INC on E_AIRPRT array with 4 significant digits	Null values removed before calculating output rank.
SPL_EBM_THEME4	Domain consisting of proximity to high volume roads, proximity to railways, and proximity to airports	EBM	EBM DOM4	No value	EPL_RAIL + EPL_ROAD + EPL_AIRPRT	Tract with null values were not included in the sum.
RPL_EBM_DOM4	Percentile rank of domain consisting of proximity to high volume roads, proximity to railways, and proximity to airports	EBM	EBM DOM4	No value	In Excel: PERCENTRANK.INC on SPL_EBM_THEME4 array with 4 significant digits	Null values removed before calculating output rank.
EPL_IMPWTR	Percentile rank of percent of tract that intersects an impaired/impacted watershed at the HUC12 level	EBM	EBM DOM5	No value	In Excel: PERCENTRANK.INC on E_IMPWTR array with 4 significant digits	Null values removed before calculating output rank.
SPL_EBM_THEME5	Domain consisting of impaired water bodies	EBM	EBM DOM5	No value	EPL_IMPWTR	Tract with null values were not included in the sum.
RPL_EBM_DOM5	Percentile rank of domain consisting of impaired water bodies	EBM	EBM DOM5	No value	In Excel: PERCENTRANK.INC on RPL_EBM_THEME5 array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
SPL_EBM	No value	No value	No value	No value	EPL_OZONE + EPL_PM + EPL_DSLPM + EPL_TOTCR + EPL_NPL + EPL_TRI + EPL_TSD + EPL_RMP + EPL_COAL + EPL_LEAD + EPL_PARK + EPL_HOUAGE + EPL_WLKIND + EPL_RAIL + EPL_ROAD + EPL_AIRPRT + EPL_IMPWTR	Tract with null values were not included in the sum.
RPL_EBM	The environmental burden module percentile ranks	EBM	No value	No value	In Excel: PERCENTRANK.INC on SPL_EBM array with 4 significant digits	Null values removed before calculating output rank.
EPL_MINRTY	Percentile rank of percentage of minority persons	SVI	SVI DOM1	No value	In Excel: PERCENTRANK.INC on E_MINRTY array with 4 significant digits	Null values removed before calculating output rank.
SPL_SVM_DOM1	Domain consisting of percentage of individuals who are a racial/ethnic minority	SVI	SVI DOM1	No value	EPL_MINRTY	Tract with null values were not included in the sum.
RPL_SVM_DOM1	Percentile rank of domain consisting of percentage of individuals who are a racial/ethnic minority	SVI	SVI DOM1	No value	In Excel: PERCENTRANK.INC on SPL_SVM_DOM1 array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EPL_POV200	Percentile rank of percentage below 200% poverty	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_POV200 array with 4 significant digits	Null values removed before calculating output rank.
EPL_NOHSDP	Percentile rank of percentile Percentage of persons with no high school diploma (age 25+) estimate	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_NOHSDP array with 4 significant digits	Null values removed before calculating output rank.
EPL_UNEMP	Percentile rank of percentage of persons who are unemployed	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_UNEMP array with 4 significant digits	Null values removed before calculating output rank.
EPL_RENTER	Percentile rank of percentage of persons who rent	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_RENTER array with 4 significant digits	Null values removed before calculating output rank.
EPL_HOUBDN	Percentile rank of percentage of households that make less than 75,000	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_HOUBDN array with 4 significant digits	Null values removed before calculating output rank.
EPL_UNINSUR	Percentile rank of percentage of persons who are uninsured	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_UNINSUR array with 4 significant digits	Null values removed before calculating output rank.
EPL_NOINT	Percentile rank of percentage of persons without internet	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on E_NOINT array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
SPL_SVM_DOM2	Domain consisting of below 200% poverty, no high school diploma, unemployed, housing tenure, housing cost, no health insurance, and not internet	SVI	SVI DOM2	No value	EPL_POV200 + EPL_NOHSDP + EPL_UNEMP + EPL_RENTER + EPL_HOUBDN + EPL_UNINSUR + EPL_NOINT	Tract with null values were not included in the sum.
RPL_SVM_DOM2	Percentile rank of domain consisting of below 200% poverty, no high school diploma, unemployed, housing tenure, housing cost, no health insurance, and not internet	SVI	SVI DOM2	No value	In Excel: PERCENTRANK.INC on SPL_SVM_DOM2 array with 4 significant digits	Null values removed before calculating output rank.
EPL_AGE65	Percentile rank of percentage of persons aged 65 and older estimate	SVI	SVI DOM3	No value	In Excel: PERCENTRANK.INC on E_AGE65 array with 4 significant digits	Null values removed before calculating output rank.
EPL_AGE17	Percentile rank of percentage of persons aged 17 and younger estimate	SVI	SVI DOM3	No value	In Excel: PERCENTRANK.INC on E_AGE17 array with 4 significant digits	Null values removed before calculating output rank.
EPL_DISABL	Percentile rank of percentage of civilian noninstitutionalized population with a disability estimate	SVI	SVI DOM3	No value	In Excel: PERCENTRANK.INC on E_DISABL array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EPL_LIMENG	Percentile rank of percentage of persons (age 5+) who speak English "less than well" estimate, 2014-2018 ACS	SVI	SVI DOM3	No value	In Excel: PERCENTRANK.INC on E_LIMENG array with 4 significant digits	Null values removed before calculating output rank.
SPL_SVM_DOM3	Domain consisting of English language proficiency, aged 65 or older, aged 17 or younger, and civilian with a disability	SVI	SVI DOM3	No value	EPL_AGE65 + EPL_AGE17 + EPL_DISABL + EPL_LIMENG	Tract with null values were not included in the sum.
RPL_SVM_DOM3	Percentile rank of domain consisting of English language proficiency, aged 65 or older, aged 17 or younger, and civilian with a disability	SVI	SVI DOM3	No value	In Excel: PERCENTRANK.INC on SPL_SVM_DOM3 array with 4 significant digits	Null values removed before calculating output rank.
EPL_MOBILE	Percentile rank of percentage of mobile homes estimate	SVI	SVI DOM4	No value	In Excel: PERCENTRANK.INC on E_MOBILE array with 4 significant digits	Null values removed before calculating output rank.
EPL_GROUPQ	Percentile rank of percentage of persons in group quarters estimate, 2014-2018 ACS	SVI	SVI DOM4	No value	In Excel: PERCENTRANK.INC on E_GROUPQ array with 4 significant digits	Null values removed before calculating output rank.
SPL_SVM_DOM4	Domain consisting of number of mobile homes and	SVI	SVI DOM4	No value	EPL_MOBILE + EPL_GROUPQ	Tract with null values were not included in the sum.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
	housing with group quarters					
RPL_SVM_DOM4	Percentile rank of domain consisting of number of mobile homes and housing with group quarters	SVI	SVI DOM4	No value	In Excel: PERCENTRANK.INC on SPL_SVM_DOM4 array with 4 significant digits	Null values removed before calculating output rank.
SPL_SVM	No value	No value	No value	No value	EPL_MINRTY + EPL_RENTER + EPL_HOUBDN + EPL_UNINSUR EPL_NOINT + EPL_AGE65 + EPL_AGE17 + EPL_DISABL + EPL_LIMENG + EPL_MOBILE + EPL_GROUPQ	Tract with null values were not included in the sum.
RPL_SVM	Social vulnerability module percentile rank	SVI	No value	No value	In Excel: PERCENTRANK.INC on SPL_SVM array with 4 significant digits	Null values removed before calculating output rank.
F_BPHIGH	Flag indicating tracts greater than 0.6666 percentile rank with high blood pressure	HVM	HVM DOM	No value	EPL_BPHIGH > 0.6666	No value
F_ASTHMA	Flag indicating tracts greater than 0.6666 percentile rank with asthma	HVM	HVM DOM	No value	EPL_ASTHMA > 0.6666	No value
F_CANCER	Flag indicating tracts greater than	HVM	HVM DOM	No value	EPL_CANCER > 0.6666	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
	0.6666 percentile rank with cancer					
F_MHLTH	Flag indicating tracts greater than 0.6666 percentile rank with not good mental health	HVM	HVM DOM	No value	EPL_MHLTH > 0.6666	No value
F_DIABETES	Flag indicating tracts greater than 0.6666 percentile rank with diabetes	HVM	HVM DOM	No value	EPL_DIABETES > 0.6666	No value
F_HVM	Total number of tertile flags (>0.6666)	HVM	HVM DOM	No value	F_BPHIGH + F_ASTHMA + F_CANCER + F_MHLTH + F_DIABETES	Tract with null values were not included in the sum.
RPL_HVM	Percentile rank of combined tertile flags	HVM	No value	No value	F_HVM * 0.2	No value
E_OZONE	Annual mean days above O3 regulatory standard - 3-year average	EBM	EBM DOM1	2014-2016 U.S. EPA Air Quality System (AQS) as available through the CDC's National Environmental Health Tracking Network https://ephtracking.cdc.gov/indicatorPages	No value	No value
E_PM	Annual mean days above PM2.5 regulatory standard - 3-year average	EBM	EBM DOM1	2014-2016 U.S. EPA Air Quality System (AQS) as available through the CDC's National Environmental Health Tracking Network https://ephtracking.cdc.gov/indicatorPages	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
E_DSLPM	Ambient concentrations of diesel PM/m3	EBM	EBM DOM1	2014 U.S. EPA National Air Toxics Assessment (NATA) - https://www.epa.gov/national-air-toxics-assessment/2014-nata-assessment-results#modeled	No value	No value
E_TOTCR	The probability of contracting cancer over the course of a lifetime, assuming continuous exposure	EBM	EBM DOM1	2014 U.S. EPA National Air Toxics Assessment (NATA) - https://www.epa.gov/national-air-toxics-assessment/2014-nata-assessment-results#modeled	No value	No value
E_NPL	Proportion of tract's area within 1-mi buffer of EPA National Priority List site	EBM	EBM DOM2	https://www.epa.gov/frs/geospatial-data-download-service	No value	No value
E_TRI	Proportion of tract's area within 1-mi buffer of EPA Toxic Release Inventory site	EBM	EBM DOM2	https://www.epa.gov/frs/geospatial-data-download-service	No value	No value
E_TSD	Proportion of tract's area within 1-mi buffer of EPA Treatment, Storage, and Disposal site	EBM	EBM DOM2	https://www.epa.gov/frs/geospatial-data-download-service	No value	No value
E_RMP	Proportion of tract's area within 1-mi buffer of EPA risk management plan site	EBM	EBM DOM2	https://www.epa.gov/frs/geospatial-data-download-service	No value	No value
E_COAL	Proportion of tract's area within 1-mi buffer of coal mines	EBM	EBM DOM2	U.S. Mine Safety and Health Administration Mine Data Retrieval System (MDRS)	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
E_LEAD	Proportion of tract's area within 1-mi buffer of lead mines	EBM	EBM DOM2	U.S. Mine Safety and Health Administration Mine Data Retrieval System (MDRS)	No value	No value
E_PARK	Proportion of tract's area within 1-mi buffer of green space	EBM	EBM DOM3	2020 TomTom MultiNet® Enterprise Dataset	No value	No value
E_HOUAGE	Percentage of houses built pre-1980 (lead exposure)	EBM	EBM DOM3	No value	No value	No value
E_WLKIND	A nationwide geographic data resource that ranks block groups according to their relative walkability	EBM	EBM DOM3	2021 U.S. EPA National Walkability Index - https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7B251AFDD9-23A7-4068-9B27-A3048A7E6012%7D	No value	No value
E_RAIL	Proportion of tract's area within 1-mi buffer of railroad	EBM	EBM DOM4	2020 TomTom MultiNet® Enterprise Dataset	No value	No value
E_ROAD	Proportion of tract's area within 1-mi buffer of high-volume road or highway	EBM	EBM DOM4	2020 TomTom MultiNet® Enterprise Dataset	No value	No value
E_AIRPRT	Proportion of tract's area within 1-mi buffer of airport	EBM	EBM DOM4	2020 TomTom MultiNet® Enterprise Dataset	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
E_IMPWTR	Percent of tract that intersects an impaired/impacted watershed at the HUC12 level	EBM	EBM DOM5	2022 U.S. EPA Watershed Index Online (WSIO) Tool - https://www.epa.gov/wsio/download-and-use-wsio-tool	No value	No value
EP_MINRTY	Percentage of minority persons	SVI	SVM DOM1	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table B01001H - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_POV200	Percentage below 200% poverty	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S1701 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_NOHSDP	Percentile Percentage of persons with no high school diploma (age 25+) estimate	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S0601 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_UNEMP	Percentage of persons who are unemployed	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table DP03 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EP_RENTER	Percentage of persons who rent	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S2502 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_HOUBDN	Percentage of households that make less than 75,000	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S2503 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_UNINSUR	Percentage of persons who are uninsured	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S2701 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_NOINT	Percentage of persons without internet	SVI	SVM DOM2	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S2801 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_AGE65	Persons aged 65 and older estimate MOE, 2014-2018 ACS	SVI	SVM DOM3	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table S0101 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EP_AGE17	Persons aged 17 and younger estimate, 2014-2018 ACS	SVI	SVM DOM3	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table B09001 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_DISABL	Percentage of civilian noninstitutionalized population with a disability estimate, 2014-2018 ACS	SVI	SVM DOM3	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table DP02 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_LIMENG	Percentage of persons (age 5+) who speak English "less than well" estimate, 2014-2018 ACS	SVI	SVM DOM3	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table B16005 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_MOBILE	Percentage of mobile homes estimate	SVI	SVM DOM4	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table DP04 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value
EP_GROUPQ	Percentage of persons in group quarters estimate, 2014-2018 ACS	SVI	SVM DOM4	2015-2019 Census Bureau American Community Survey (ACS) 5-year Data - Table B26001 - https://www.census.gov/data/developers/data-sets/acs-5year.html	No value	No value

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EP_BPHIGH	Percentage of individuals with Raw high blood pressures values	HVM	HVM DOM	2020 CDC PLACES Data - https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Census-Tract-Data-GIS-Friendly-Format-2020-/ib3w-k9rq	No value	No value
EP_ASTHMA	Percentage of individuals with asthma	HVM	HVM DOM	2020 CDC PLACES Data - https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Census-Tract-Data-GIS-Friendly-Format-2020-/ib3w-k9rq	No value	No value
EP_CANCER	Percentage of individuals with cancer	HVM	HVM DOM	2020 CDC PLACES Data - https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Census-Tract-Data-GIS-Friendly-Format-2020-/ib3w-k9rq	No value	No value
EP_MHLTH	Percentage of individual reporting not good mental health	HVM	HVM DOM	2020 CDC PLACES Data - https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Census-Tract-Data-GIS-Friendly-Format-2020-/ib3w-k9rq	No value	No value
EP_DIABETES	Percentage of individuals with diabetes	HVM	HVM DOM	2020 CDC PLACES Data - https://chronicdata.cdc.gov/500-Cities-Places/PLACES-Census-Tract-Data-GIS-Friendly-Format-2020-/ib3w-k9rq	No value	No value
EPL_BPHIGH	Percentile rank of percentage of individuals with Raw high blood pressures values	HVM	HVM DOM	No value	In Excel: PERCENTRANK.INC on EP_BPHIGH array with 4 significant digits	Null values removed before calculating output rank.
EPL_ASTHMA	Percentile rank of percentage of individuals with asthma	HVM	HVM DOM	No value	In Excel: PERCENTRANK.INC on EP_ASTHMA array with 4 significant digits	Null values removed before calculating output rank.

2022 VARIABLE NAME	2022 DESCRIPTION	MODULE	DOMAIN	DATA SOURCE	2022 TABLE FIELD CALCULATION	NOTES
EPL_CANCER	Percentile rank of percentage of persons with cancer	HVM	HVM DOM	No value	In Excel: PERCENTRANK.INC on EP_CANCER array with 4 significant digits	Null values removed before calculating output rank.
EPL_DIABETES	Percentile rank of percentage of individuals with diabetes	HVM	HVM DOM	No value	In Excel: PERCENTRANK.INC on EP_DIABETES array with 4 significant digits	Null values removed before calculating output rank.
EPL_MHLTH	Percentage of individual reporting not good mental health percentile rank	HVM	HVM DOM	No value	In Excel: PERCENTRANK.INC on EP_MHLTH array with 4 significant digits	Null values removed before calculating output rank.