Technical Documentation for the 2024 Environmental Justice Index

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Glossary of Terms

Census Tracts – 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 – the total harm to human health that occurs from the combination of environmental burdens, pre-existing health conditions, and social factors. See the *Key Concepts* section for more information.

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

Distributive Justice – seeks to address place-based disparities in exposure to environmental hazards, as well as access to environmental amenities and other resources.

Domains – functional groups within modules (e.g., environmental burden) that represent distinct aspects of that module (e.g., air pollution).

Environmental Amenities – environmental goods or benefits that may improve health or promote the economic welfare of a community.

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

Environmental Justice – typically defined by the just treatment and meaningful involvement in environmental decision making and equitable protections from environmental burdens. See the *Key Concepts* section below for more information.

Exposure – coming into contact with something that can harm human health.

Health Equity – the state in which everyone has a fair and just opportunity to attain their highest level of health. See the *Key Concepts* section for more information.

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

Impact – the effect that an activity has on the environment, and subsequently, on health and wellbeing.

Indicator – a measure of an environmental, social, or health condition used to represent that condition for the purposes of index calculation.

Modules – functional groups within the EJI, representing environmental burden, social vulnerability, health vulnerability, and climate burden.

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

Quantitative – information about the amount or measured level of something.

Race – a social construct used to group people. Race was constructed as a hierarchal human grouping system, that uses racial classifications to identify, distinguish, and marginalize some groups across nations, regions, and the world. Race divides human populations into groups that are often based on physical appearance, social factors, and cultural backgrounds.

Racism – a system consisting of structures, policies, practices, and norms, that assigns value and determines opportunity based on the way people look, the color of their skin, or their cultural background. Racism results in conditions that unjustly disadvantages particular groups, while unfairly creating advantages for others.

Risk – the possibility that something will cause harm.

Sacrifice Zones – Communities that have experienced economic disinvestment due to highly degraded environmental conditions in these communities.

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 environmental hazards and other community-level stressors.

Tertile – one of three equal groups that a set of data can be divided into. Often used to categorize the data into "low," "medium," or "high."

Key Abbreviations

ACS - U.S. Census Bureau's American Community Survey

ATSDR - Agency for Toxic Substances and Disease Registry

CDC - U.S. Centers for Disease Control and Prevention

CONUS - Continental United States

COPD - Chronic Obstructive Pulmonary Disease

DOT - U.S. Department of Transportation

EBM - Environmental Burden Module

EJ - Environmental Justice

EJI - Environmental Justice Index

EJSM - Environmental Justice Screening Method

EPA - U.S. Environmental Protection Agency

HAPs - Hazardous Air Pollutants

HUC - Hydrologic Unit Code

HVM - Health Vulnerability Module

NTAD - U.S. Department of Transportation's National Transportation Atlas Database

PM $_{2.5}$ - Fine particulate matter ≥ 2.5 microns in diameter

SER - Social-Environmental Ranking

SVI - CDC/ATSDR Social Vulnerability Index

SVM - Social Vulnerability Module

Key Concepts

What is Environmental Justice?

Environmental justice is the just treatment and meaningful involvement of all people, regardless of income, **race**, color, national origin, Tribal affiliation, or disability, in agency decision-making and other Federal activities that affect human health and the environment so that people:

  i. are fully protected from disproportionate and adverse human health and environmental effects (including risks) and hazards, including those related to climate change, the cumulative impacts of environmental and other burdens, and the legacy of **racism** or other structural or systemic barriers; and

 ii. have equitable access to a healthy, sustainable, and resilient environment in which to live, play, work, learn, grow, worship, and engage in cultural and subsistence practices.[1]

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 burdens**, pre-existing health conditions, and social factors. Cumulative impacts can result from long-term **exposure** to environmental pollution and community stressors, such as noise pollution, odor pollution, loss of natural resources, and the lack of access to quality healthcare or other resources. These factors can have long-term effects on human health and well-being for people living in communities experiencing cumulative impacts. Degraded environmental conditions within a community can also lead to economic disinvestment in highly polluted areas, otherwise known as "**sacrifice zones**." This can lead to further environmental degradation in these areas and can perpetuate generational economic and health inequities for residents of those communities.

The terms **impact** and **risk** are sometimes used synonymously, but there are important

differences between cumulative impacts assessment and traditional risk assessment (Faust, 2010; Murphy et al., 2018; Sexton, 2012; Solomon et al., 2016). Traditional risk and exposure assessments, including health risk assessments, use detailed data on factors such as chemical exposure levels, dose-response relationships, and contaminant fate and transport, in order to quantify the likelihood that a population will experience harm due to a hazardous event or chemical exposure (Murphy et al., 2018). Risk, exposure, and public health assessments[*] 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 can be prohibitive (Faust, 2010).

Cumulative impacts assessment methods build upon traditional risk and exposure assessment, using a combination of **quantitative** and semi-quantitative information to compare the relative and combined impacts of social factors, environmental factors, and pre-existing chronic health conditions on community health and well-being.[2-4] Cumulative impacts assessments should be informed by community experience and community narratives, and should account for not only chemical exposures, but also factors in the built and social environments that can worsen or add to the effects that pollution has on health. [4,5]

Important Note on "Minority Status"

The EJI includes an **indicator** representing racial and ethnic "minority status." This indicator is included in the EJI as a measure of **social vulnerability**, because of an overwhelming consensus that an accounting for the impacts of racism and discrimination on populations and communities is critical to accurately measure social vulnerability and the cumulative impacts of environmental injustice in those communities.[5-7] This is due to a legacy of systematic discrimination and political marginalization that has resulted in economic and health disparities.[8] Studies spanning nearly four decades consistently point to racial and ethnic characteristics of communities as the single most important predictor of the location of hazardous waste sites in the U.S., with racial and ethnic minorities disproportionately represented in populations surrounding these sites.[9,10] This history, as well as ongoing discrimination, at both structural and interpersonal levels, make it critical to incorporate considerations of race and ethnicity in systematic response to health inequities.[11]

It is critical to note that the EJI's measure of racial and ethnic minority status is intended as a measure of the effects of racism and discrimination on populations and is intended to empower action to address these disparities. This measure is not intended to suggest a unified "minority" population or a set of shared characteristics among the diverse groups included in this measure. People of color and other minoritized populations are not a uniform group. Lived experiences and histories of racism and discrimination vary widely between and among racial and ethnic groups,

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

as do present-day disparities. Disaggregation, or measuring race and ethnicity using culturally relevant definitions of race and ethnicity that reflect the lived experience of those facing racism and discrimination, should always be the goal of data meant to promote health equity.[12,13]

Limitations in how data on race and ethnicity are measured within nationally consistent datasets, such as those provided by the U.S. Census Bureau, can limit disaggregation of race and ethnicity data in tools such as the EJI, but there are still ways to account for important social and cultural differences when using the EJI data. Disaggregated measures of community race and ethnicity from the U.S. Census Bureau's American Community Survey are available as part of the EJI database. Additionally, EJI data may be supplemented at the local level by more granular data on race and ethnicity. Finally, the EJI Explorer offers the ability to overlay important historical, cultural, and political boundaries over the EJI data. These include boundaries of sovereign Tribal Nations, Indigenous lands, and historical neighborhood redlining maps used by the U.S. Home Owners' Loan Corporation (HOLC) to discriminate against minoritized populations in the 20th century.

Additionally, although race and ethnicity status are key historic and ongoing contributors to the social vulnerability of communities, there may be instances when neither is relevant to a given study or action. A key feature of the EJI is that indicators or **domains** may be removed or added to the database and re-rankings made with relatively minimal effort. This is to empower communities to adapt the EJI to local needs and circumstances. In cases where law or best practice prevent the consideration of race and ethnicity in decision-making processes, the EJI may be modified to remove the minority status indicator.

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Introduction
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 environmental justice (EJ) to achieve health equity goals. Place-based EJ screening and mapping tools allow government agencies and other entities to identify communities experiencing high cumulative impacts from environmental burdens, in order to prioritize these communities for policies and interventions designed to reduce inequities. Additionally, 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.[1-3] 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.

EJI and CDC/ATSDR

The 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.[4,5] 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 their health.

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Using the EJI

Purpose and Uses of the EJI

The EJI can help public health officials, policy makers, and communities identify and respond to the various environmental and social factors that affect a community's health and well-being. The 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, and to
- establish meaningful goals and measure progress towards EJ and health equity.

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, or
- a representation of risk or exposure for a given community or area.

For more information on EJI limitations and considerations, please see Limitations and Considerations of the EJI.

The EJI Social-Environmental Ranking (SER)

While the full EJI ranking is useful for the purposes described above, it is not designed for use in secondary analysis where a health condition or disease is the outcome of interest. However, the EJI Social-Environmental Ranking (SER) could be used for this purpose, as it only includes the Social Vulnerability and Environmental Burden **modules** of the EJI and does not include any of the health outcome **prevalence** estimations that are included in the full EJI.

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 full EJI ranking, 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 EJI database and can be visualized in a map over the EJI SER values to assess if areas experiencing high levels of cumulative environmental burdens and social vulnerability also experience high levels of chronic disease burden.

EJI and Justice40

The Justice40 Initiative was created to ensure that federal agencies deliver 40 percent of the overall benefits of climate, clean energy, affordable and sustainable housing, clean water, and other investments to disadvantaged communities to the maximum extent permitted by applicable statutes, regulations, and guidance. The Justice40 Initiative, outlined in Section 223 of

Executive Order (EO) 14008 on Tackling the Climate Crisis at Home and Abroad,[1] is a critical part of the Administration's whole-of-government approach to environmental justice, and is one of the key tools in the Administration's comprehensive approach to advancing equity for all. The U.S. Department of Health and Human Services (HHS) has thirteen programs covered under the Justice40 Initiative.

The HHS advises that, under its Justice40 programs, the EJI can be used along with tools like the White House's Climate and Economic Justice Screening Tool (CEJST)[2] to identify and prioritize disadvantaged communities for environmental justice purposes. The EJI may help to broaden focus beyond a binary question of whether a community is disadvantaged or not and may help compare the relative cumulative impacts of multiple environmental, social, and health factors in these communities.

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 United States. 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, like 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 low birth weight, pesticide use, or other issues are available nationally, but at a coarser spatial resolution than what is used by 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[3], the Washington Environmental Health Disparities Map[4], 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.

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 U.S. has seen an overall decline in levels of pollutants like ozone and PM 2.5 in the last decade.[5,6] However, except for some measures of air quality, most EJI indicators use data that has been collected within the last 5 years. Details on the years represented by each dataset can be found in the EJI

Indicators descriptions and in the Data Dictionary.

Additionally, many indicators used to construct the EJI rely on estimates that involve some level of uncertainty. Many data used to calculate EJI indicators include measurements of uncertainty, such as 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 **census 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 only intended to provide a screening-level overview of environmental burdens facing a community. For example, simply living near a hazardous site does not constitute an exposure to a toxic substance. It is nonetheless important to characterize proximity to potentially hazardous sites, as 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 the proximity to environmental hazards and amenities using a uniform 1-mile buffer was rooted in a desire to facilitate the interpretation of EJI indicators and rankings by a general audience. Furthermore, 1-mile buffers are commonly used in research on the proximity to such sites, as an issue of environmental burden or environmental justice.[7,8] This is an approach that is well-suited to high-level screening tools but may not be suitable for measuring potential risk or exposure. It is also important to note that the proximity measures used to construct some indicators, such as those within the Proximity to Potentially Hazardous & Toxic Sites domain, represent the 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 the misclassification of the potential impacts from large sites. However, these types of measures are still useful for a high-level screening approach.

The 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). Due to certain methodological considerations that are further outlined in the *Methods* section of this document; these estimates were incorporated into the EJI as "flags" that represent census tracts that experience high chronic disease prevalence burden. 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 CDC | PLACES.

There are also several important limitations to note when using EJI to explore data for Tribal

lands. While the EJI includes data for Tribal lands that intersect U.S. census tracts, census tracts do not directly align with the jurisdictional boundaries of Tribal nations. This means that, in some cases, data for Tribal lands are combined with data for land that is just outside of Tribal nation boundaries.

Additionally, it is important to note that while the EJI always endeavors to use the most accurate and authoritative data available, authoritative datasets do not always accurately reflect Tribal lands, Tribal nations, and the lived experiences of Tribes and Indigenous peoples. Improvements to the EJI are intended to be an ongoing process that includes partnership and meaningful engagement with Tribes, Indigenous experts, and Indigenous Knowledge holders. Additional engagement with Tribes will be necessary to ensure: (1) future versions of the EJI more closely reflect the lived experiences of Tribes more accurately, (2) Indigenous Knowledge and values are incorporated into the EJI in a way that protects the intellectual property of Indigenous experts and Indigenous Knowledge holders, and (3) that the EJI is more useful and empowering for Tribal nations experiencing environmental injustice.

Finally, a lack of data for some key environmental indicators led to the exclusion of Alaska, Hawaii, the Commonwealth of Puerto Rico, and all other Island Territories (e.g., the U.S. Virgin Islands, American Samoa, Commonwealth of the Northern Mariana Islands, Guam) from the 2024 EJI calculations. The 2024 EJI only includes the Continental U.S. (48 states and the District of Columbia). It is expected that future iterations of the EJI will include jurisdiction-specific indices for Alaska, Hawaii, and Puerto Rico, using relevant 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.

EJI 2024 Updates and Change Log

The 2024 EJI includes updated data, methods, and documentation that are based on feedback received through community engagement. For more information on EJI community engagement efforts, including information on the major questions and comments the EJI team has received and updates that have been made in response to community feedback, please see the EJI 2022 Community Engagement Report at our EJI Community Engagement page. Changes to the EJI include:

- Updated from 2010 to 2020 census tract geographies, resulting in the addition of more than 10,000 census tracts.
    - For Connecticut, census tract identifiers were updated to 2022 Census Bureau designations due to a change to county-equivalents in the 2022 American Community Survey. This change did not alter census tract geographies, on geographic identifiers (GEOIDs). For more information on this change, please see U.S. Census Bureau | Change to County-Equivalents in the State of Connecticut for 2022 ACS.

- The prefix for several indicators in the Data Dictionary have been updated, so that all estimates begin with the prefix "E_" while all percentile ranks begin with "EPL_".
    - Variables with the prefix of "EP_" were changed to "E_" to match all other estimates included in the EJI dataset. An additional column of "2022 Variable Name" has been added in order to allow for the easy identification of variable names that have changed.
    - Please note that these new field names are unique to the EJI and that fields in similar tools, such as the Social Vulnerability Index and the Environmental Burden Index, may not always align with the field names here. When comparing fields between tools it is always recommended to compare the description and table calculation fields to ensure that all variables are being understood and used correctly.
- Added several adjunct fields to the EJI database:
    - GEOID_20
        - This field represents the GEOID for tracts as of the 2020 decennial census/ American Community Survey, which is identical to GEOID except for the state of Connecticut.
    - Several flagged fields (fields beginning with "F_") in the Environmental Burden Module and Climate Burden Module.
        - These fields denote true null values, true zeros, and values excluded from percentile rankings. See the Data Dictionary for more information.
    - Several fields representing estimated populations and percentage populations disaggregated by race and ethnicity.
    - Several fields denoting census tract overlap with State or Federally recognized Tribal lands or other indigenous areas.
- Updated data for all indicators, except for the Lack of Walkability indicator.
    - Data for the National Walkability Index, the source of the Lack of Walkability indicator, has not been updated by the U.S. Environmental Protection Agency since 2021.
- Renamed several Social Vulnerability Module Indicators, however, database field codes and the underlying data sources were not altered.
    - Housing Tenure → Renters
    - Housing Burdened, Lower-Income Households → Housing Cost Burden
    - Lack of Broadband Access →Lack of Internet Access
    - Speaks English "Less than Well" → English Language Proficiency
- Changed the Health Vulnerability Module indicator of High Blood Pressure to Coronary Heart Disease.
    - This change was necessary as measures of the crude prevalence of high blood pressure included in the CDC PLACES' 2024 data release were not available for the state of Florida and would have otherwise excluded Florida from EJI calculations.
        - For more information on CDC PLACES, please see CDC PLACES | Current Release

[Notes](#).
- Updated data sources for several Environmental Burden Module indicators, where applicable, including updating several proprietary data sources to more publicly available ones, including:
  - Diesel Particulate Matter
    - Updated from U.S. EPA National Air Toxics Assessment (NATA) to the U.S. EPA's AirToxScreen database, as EPA has archived NATA.
  - Air Toxics Cancer Risk
    - Updated from U.S. EPA National Air Toxics Assessment (NATA) to the U.S. EPA's AirToxScreen database, as EPA has archived NATA.
  - Lead Mines
    - Discontinued use of data from the U.S. Geological Survey's (USGS) Mineral Resources Data System and the sole source for the current indicator is now the Mine Safety and Health Administration's (MSHA) Mine Data Retrieval System.
  - Lack of Recreational Parks
    - Updated from TomTom MultiNet®, a proprietary dataset, to the publicly available U.S. Geospatial Survey's PAD-US 4.0 dataset.
  - Railways
    - Updated from TomTom MultiNet®, a proprietary dataset, to the publicly available U.S. Department of Transportation's National Transportation Atlas Database (NTAD).
  - Airports
    - Updated from TomTom MultiNet®, a proprietary dataset, to the publicly available OpenStreetMap and U.S. Department of Transportation's National Transportation Atlas Database (NTAD).
  - High Volume Roads
    - Updated from TomTom MultiNet®, a proprietary dataset, to the publicly available U.S. Department of Transportation's National Highway System (NHS).
- The addition of the EJI Climate Burden Module and the supplementary EJI + Climate Burden Ranking.
  - Both are now available to view and download through the EJI Explorer or on our EJI Data Download page.
- The addition of the EJI County Map Series, which provides a downloadable snapshot of EJI data for all census tracts within each county in the continental United States.
  - County Maps of EJI census tract rankings are available through the EJI Explorer or on our EJI Data Download page.
- Updates to the EJI Explorer to improve design and functionality of the tool in response to community engagement efforts.

Next Steps for the EJI

Going forward, the EJI will be updated every other year using the most recent data available. The 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 also be presented to a wide array of interested parties to receive feedback related to the construction and presentation of the EJI. 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.

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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. Census tracts are commonly used as a proxy for neighborhoods in place-based epidemiological research and for many other spatial indices and screening tools.[1-4]

The EJI uses data from the U.S. Census Bureau, the U.S. Environmental Protection Agency, the U.S. Mine Safety and Health Administration, the U.S. Department of Transportation, OpenStreetMap, the U.S. Geospatial Survey, the U.S. Department of Agriculture, the U.S. Federal Emergency Management Agency, the National Aeronautics and Space Administration, the National Oceanic and Atmospheric Administration, and the U.S. Centers for Disease Control and Prevention to determine the cumulative impacts of environmental injustice for more than 82,000 U.S. census tracts. The base EJI ranks each tract on 36 environmental, social, and health factors and groups them into three overarching modules and ten domains. The overall EJI score is calculated by summing the ranks 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.
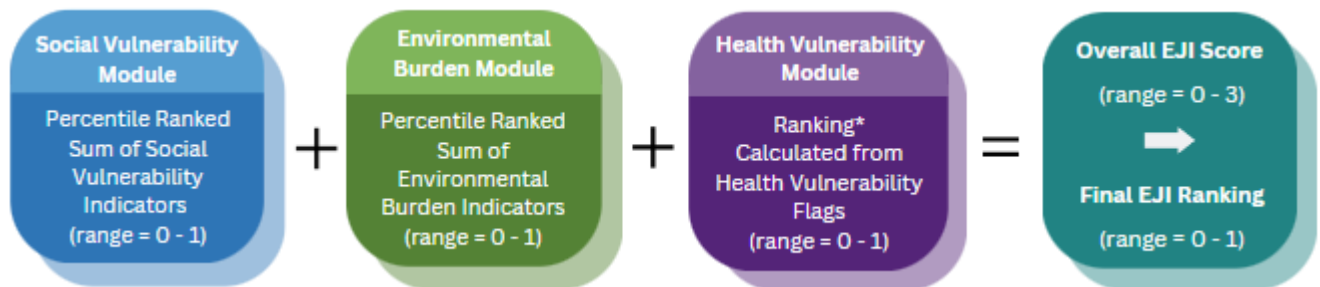
Social Vulnerability Module (Percentile Ranked Sum of Social Vulnerability Indicators (range = 0 - 1)) + Environmental Burden Module (Percentile Ranked Sum of Environmental Burden Indicators (range = 0 - 1)) + Health Vulnerability Module (Ranking* Calculated from Health Vulnerability Flags (range = 0 - 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.

Due to a lack of scientific evidence supporting a specific weighting scheme, all modules are weighted equally to calculate the Overall EJI Score. This method of equal weighting for all modules aligns with that used by the Environmental Justice Screening Method.[11] Overall EJI Scores are percentile ranked to produce a final EJI Ranking with a range of between 0 - 1.

The EJI database also includes an EJI + Climate Burden Ranking, which is calculated by combining the ranks for all three base EJI modules (the Environmental Burden Module, the Social Vulnerability Module, and the Health Vulnerability Module) as well as a new EJI Climate Burden Module. The EJI + Climate Burden Ranking is intended to represent the cumulative impacts of environmental burdens, including the impacts of climate-related burdens, on health and well-being. It is important to note that the Climate Burden Module and the EJI + Climate Burden Ranking are supplemental additions to the base EJI, and that the calculation of the base EJI was not changed. This decision was made in order to make it easier to compare base EJI releases to one another and to help clarify which EJI datasets are comparable.

Social Vulnerability Module (Percentile Ranked Sum of Social Vulnerability Indicators (range = 0 - 1)) + Environmental Burden Module (Percentile Ranked Sum of Environmental Burden Indicators (range = 0 – 1)) + Health Vulnerability Module (Ranking* Calculated from Health Vulnerability Flags (range = 0 - 1)) + Climate Burden Module (Percentile Ranked Sum of Climate Burden Indicators (range = 0 - 1)) = Overall EJI + Climate Burden Score (range = 0 - 4) ➔ Final EJI + Climate Burden 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.

Finally, the EJI database 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 the High Prevalence Flags of the Health Vulnerability Module to gain an overall view of how specific health outcomes may be related to issues of distributive and procedural environmental justice.
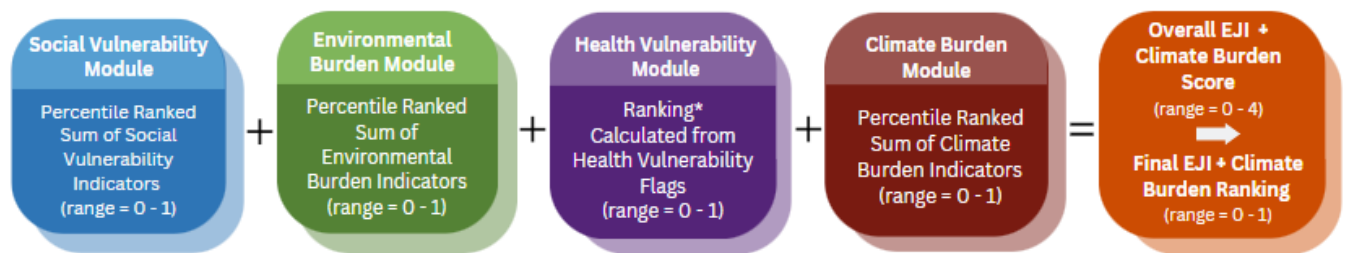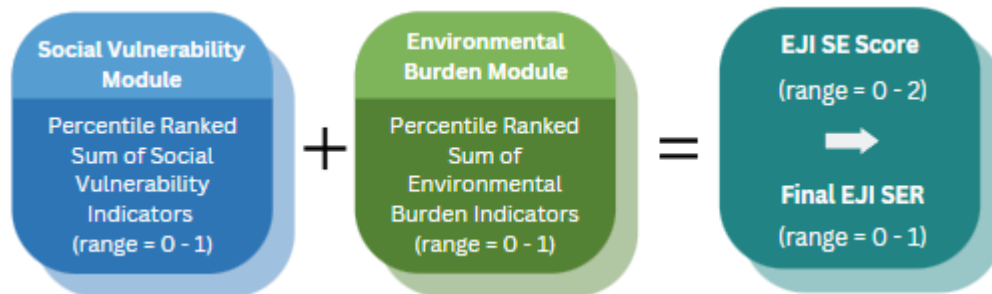
Social Vulnerability Module (Percentile Ranked Sum of Social Vulnerability Indicators (range = 0 - 1)) + Environmental Burden Module (Percentile Ranked Sum of Environmental Burden Indicators (range = 0 - 1)) = EJI SE Score (range = 0 - 2) ➔ Final EJI Social-Environmental Ranking (SER) (range = 0 - 1)

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 involved 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.[4,-12]

Indicators representing climate burden were selected based on a literature review conducted by the EJI research team between May 2023 and July 2023. Existing tools characterizing climate-related burdens, including the Council on Environmental Quality's Climate and Economic Justice Screening Tool (CEJST), Cal-Adapt, the Environmental Defense Fund's Climate Vulnerability Index (CVI), and the Federal Emergency Management Agency's National Risk Index (NRI),[3,13-15] were also reviewed, and constituent indicators were considered for inclusion. Subject matter experts on climate and health were also consulted to help identify indicators for inclusion.

Indicators identified through these review and consultation processes 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 from 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.
3. Available at scale – the data must be calculated at the census tract level or must be easily manipulatable to that scale.
4. Timely – data must be regularly updated to allow for future updates to the index.

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

Environmental Burden Module

Indicators representing environmental burden are intended to capture features of the environment that either negatively or positively contribute 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.[16] 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 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. [7,17-19] When coupled, chronic environmental burden and social vulnerability factors work synergistically to create more severe cumulative impacts that negatively affect human health and well-being, such as by increasing existing disease burden and exacerbating health inequities.[8,20,21] 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, due to 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, but genetic factors are difficult to measure at a large scale, and age and disability are already captured within the EJI Social Vulnerability Module.[21] 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 health 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).[22] 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. The indicator must represent a chronic health condition.
2. The 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, and the 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.

Climate Burden Module

The purpose of the Climate Burden Module is to capture the additional environmental burdens that communities face with extreme climate events. Data in this module represent the additional cumulative impacts that factors related to climate change have on health and well-being. The Climate Burden Module captures historic data from past climate events. Data are divided into three domains: 1) Heat, 2) Extreme events, and 3) Wildfires. All indicators included in the Climate Burden Module were required to satisfy the following criteria:
1. The indicator must represent a climate-related hazard.
2. The indicator must represent a hazard that causes significant public health burden.
3. The indicator must represent a unique climate-related hazard not already represented by another indicator in terms of effects.

Some measures initially identified as candidates for inclusion were ultimately excluded for one of the reasons listed above.

EJI Ranking 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 values 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), which incorporates demographic data, including data on age, race/ ethnicity, education, and poverty. As these data are used to produce each estimate, directly combining these estimates would lead to the 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 the Health Vulnerability Module flag scores based on this

method is described below:

- A tract receives a flag, or 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 Module ranking between 0-1 (0.0, 0.2, 0.4, 0.6, 0.8, or 1.0).

Module rankings for Environmental Burden and Social Vulnerability were used to calculate the EJI SER scores and rankings and combined with Health Vulnerability Module flag scores to create overall EJI scores and rankings as described in the section above. Climate Burden Module rankings were summed with all three other module rankings and flag scores to calculate the EJI + Climate Burden ranking. Additionally, rankings were calculated for domains, representing different aspects of each module (as described below), however, domain rankings are not used in final index calculation.

Module Domains

Module domains were constructed as a way of easily summarizing indicators into functional groups representing distinct aspects of each module. For example, the Environmental Burden Module contains 5 domains of air pollution, potentially hazardous and toxic sites, the built environment, transportation infrastructure, and water pollution. Domains allow users to easily interpret patterns within each module for a community of interest, without needing to deeply explore each indicator included in the EJI. Domains in the Social Vulnerability Module are largely organized around existing themes described in the CDC/ATSDR Social Vulnerability Index (SVI).[7] 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. Domains in the EBM line up with the domains used in the CDC/ATSDR Environmental Burden Index.[23] Domains in the Climate Burden Module were determined based on expert input and impacts to health.

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Example Census Tract: Indicator and Index Calculation

Documented below is an example calculation for the EJI for two census tracts (A and B), with GEOIDs (i.e., geographic identifiers) 48039664501 and 53033029203. This example illustrates the methodology used to calculate final EJI rankings.

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.
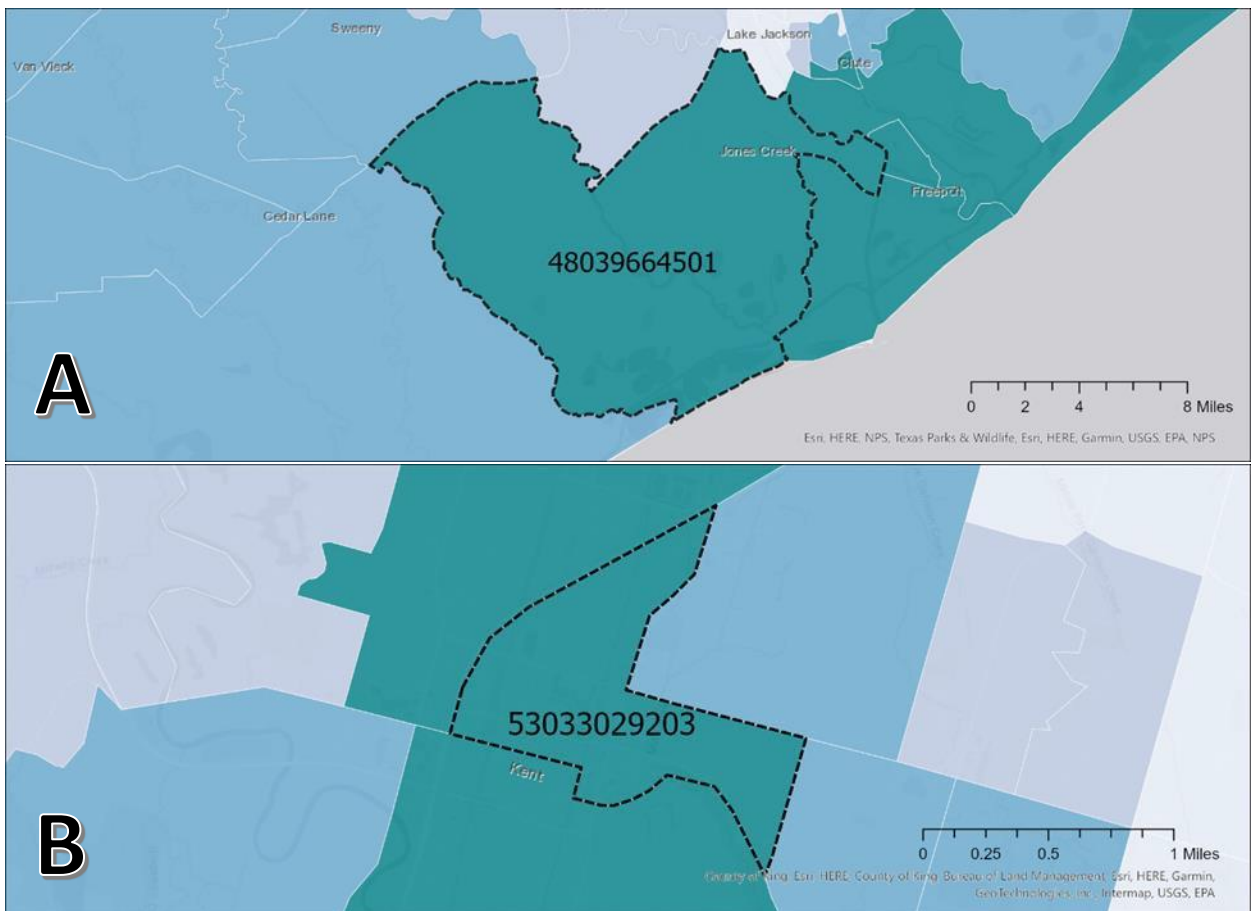
Social Vulnerability Module (SVM) Ranks				
Indicator	**Census Tract A**		**Census Tract B**	
Indicator name (unit)	Raw Value	Percentile Ranks	Raw Value	Percentile Ranks
Minority Status (%)	33.1	0.54	60.5	0.75
Poverty (%)	38.2	0.65	38.73	0.64
No High School Diploma (%)	15.8	0.71	16.6	0.73
Unemployment (%)	12.3	0.93	1.8	0.09
Renters (%)	6.5	0.24	23.5	0.84
Housing Cost Burden (%)	26.8	0.52	38.73	0.81
Lack of Health Insurance (%)	14.4	0.83	7.4	0.52
Lack of Internet 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
English Language Proficiency (%)	3.0	0.67	5.2	0.77
Group Quarters (%)	0	0.87	25.9	0.98
Mobile Homes (%)	17.3	0	0	0
Total Percentile Rank (Sum)		9.18		7.45

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 ($\mu g/m^3$)	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

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 Coronary Heart Disease (%)	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

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

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

Climate Burden Module (CBM) Ranks				
Indicator	**Census Tract A**		**Census Tract B**	
Indicator name (unit)	Raw Value	Percentile Ranks	Raw Value	Percentile Ranks
Extreme Heat Days (Days)			14.6	0.64
Wildfire Smoke (Days)	9	0.58	13.4	0.74
Wildfire Proximity (%)	0	0	0	0
Coastal Flooding Frequency (Events/ Year)	3.71	0.84	0	0
Drought Frequency (Events/ Year)	31.18	0.72	0	0
Riverine Flooding Frequency (Events/ Year)	2.13	0.54	0.29	0.02
Hurricane Frequency (Events/ Year)	0.22	0.86	0	0
Tornado Frequency (Events/ Year)	0.08	0.96	0.01	0.04
Strong Winds Frequency (Events/ Year)	0.97	0.28	0.01	0
Total Percentile Rank (Sum)		5.71		1.44

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

Terms used in tables above:

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

Example Calculation Steps (Excel)

1. Within excel run a PERCENTRANK.INC on all raw variable values
   - **Note:** Zeros denote the actual absence of a characteristic, rather than missing data. Tracts where data were missing were excluded from overall ranking, however, the Environmental Burden Module (EBM) Impaired Surface Water indicator and the Climate Burden Module indicators are exceptions to this rule, as many census tracts that were null after calculations or in the original dataset were changed to zero to ensure those tracts would not be excluded from index calculations. All values that have been changed from null to zero have an associated "flag" field in the data and Data Dictionary that provides more information about this change.
   - **Note:** Because the EJI is calculated in SQL, percentile values calculated in Excel using the PERCENTRANK.INC function may differ slightly from values in the EJI database due to differences in rounding and sorting order of raw data. However, this small difference is unlikely to cause a significant change in overall rank order.
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 EJI (EBM + SVM + HVM), EJI SER (EBM + SVM), and EJI + CB (EBM + SVM + HVM + CBM)
5. Run PERCENTRANK.INC for sum of EJI, EJI SER, and EJI + CB individually

What is being calculated	Environmental Burden Module (EBM)	Social Vulnerability Module (SVM)	Health Vulnerability Module (HVM)	Climate Burden Module (CBM)
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	In Excel For all Variables: PERCENTRANK.INC on CBM_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)	Not applicable
Individual Modules - SUM	SUM(PR_VAR1,…, PR_VARN)	SUM(PR_VAR1,…, PR_VARN)	SUM(flag_VAR1,…, flag_VARN)*0.2	SUM(PR_VAR1,…, PR_VARN)

What is being calculated	Environmental Justice Index (EJI)	EJI Social Environmental Ranking (EJI SER)	EJI + Climate Burden Ranking (EJI + CB)
Combined Ranks	RPL_EBM + RPL_SVM + RPL_HVM = SPL_EJI	RPL_EBM + RPL_SVM = RPL_SER	RPL_EBM + RPL_SVM + RPL_HVM + RPL_CBM = SPL_EJI_CB
Final Rank	In Excel: PERCENTRANK.INC on SPL_EJI array with 4 significant digits	In Excel: PERCENTRANK.INC on SPL_SER array with 4 significant digits	In Excel: PERCENTRANK.INC on SPL_EJI_CB array with 4 significant digits

Indicators

Modules	Domains	Indicators	Data Sources
Social Vulnerability	Racial/ Ethnic Minority Status	Minority Status	U.S. Census Bureau American Community Survey (ACS)
	Socioeconomic Status	Poverty	
		No High School Diploma	
		Unemployment	
		Renters	
		Housing Cost Burden	
		Lack of Health Insurance	
		Lack of Internet Access	
	Household Characteristics	Age 65 and Older	
		Age 17 and Younger	
		Civilian with a Disability	
		English Language Proficiency	
	Housing Type	Group Quarters	
		Mobile Homes	
Environmental Burden	Air Pollution	Ozone	U.S. EPA Air Quality System (AQS)
		Particulate Matter 2.5 (PM2.5)	
		Diesel Particulate Matter	U.S. EPA AirToxScreen
		Air Toxics Cancer Risk	
	Potentially Hazardous & Toxic Sites	National Priority List Sites	U.S. EPA Facility Registry Service (FRS)
		Toxic Release Inventory Sites	
		Treatment, Storage, and Disposal Sites	
		Risk Management Plan Sites	
		Coal Mines	U.S. Mine Safety and Health Administration Mine Data Retrieval System (MDRS)
		Lead Mines	
	Built Environment	Lack of Recreational Parks	U.S. Geospatial Survey PAD-US 4.0
		Houses Built Pre-1980	U.S. Census Bureau American Community Survey (ACS)
		Lack of Walkability	U.S. EPA National Walkability Index
	Transportation Infrastructure	High Volume Roads	U.S. Department of Transportation National Highway System (NHS)
		Railways	U.S. Department of Transportation National Transportation Atlas Database (NTAD)
		Airports	OpenStreetMap and the U.S. Department of Transportation National Transportation Atlas Database (NTAD)
	Water Pollution	Impaired Surface Water	U.S. EPA Watershed Index Online (WSIO)
Health Vulnerability	Pre-existing Chronic Disease Burden	Asthma*	U.S. CDC PLACES Estimates
		Cancer*	
		Coronary Heart Disease*	
		Diabetes*	
		Poor Mental Health*	

(Leftmost spanning column: Overall Environmental Justice Rank)

*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 only represent whether or not a given census tract experiences a high estimated prevalence of disease.

EJI Indicators Text-Only Version

Social Vulnerability Module

- Racial/Ethnic Minority Status
    - Minority Status
- Socioeconomic Status
    - Poverty
    - No High School Diploma
    - Unemployment
    - Renters
    - Housing Cost Burden
    - Lack of Health Insurance
    - Lack of Internet Access
- Household Characteristics
    - Age 65 and Older
    - Age 17 and Younger
    - Civilian with a Disability
    - English Language Proficiency
- Housing Type
    - Group Quarters
    - Mobile Homes

Environmental Burden Module

- Air Pollution
    - Ozone
    - Particulate Matter 2.5 (PM2.5)
    - 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
    - Lack of Recreational Parks
    - Houses Built Pre-1980
    - Lack of Walkability

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

Health Vulnerability Module
- Pre-existing Chronic Disease Burden
    - Asthma*
    - Cancer*
    - Coronary Heart Disease*
    - Diabetes*
    - Poor Mental Health*

Modules	Domains	Indicators	Data Sources
Climate Burden	Heat	Extreme Heat Days	U.S. CDC National Environmental Public Health Tracking (NEPHT)
	Wildfire	Wildfire Smoke	U.S. NOAA Hazard Mapping System (HMS)
		Wildfire Proximity	Monitoring Trends in Burn Severity (MTBS)
	Extreme Events	Coastal Flooding Frequency	U.S. FEMA National Risk Index (NRI)
		Drought Frequency	
		Riverine Flooding Frequency	
		Hurricane Frequency	
		Strong Winds Frequency	
		Tornado Frequency	U.S. CDC National Environmental Public Health Tracking (NEPHT)

EJI Climate Burden Indicators
Text-Only Version

Climate Burden Module
- Heat
    - Extreme Heat Days
- Wildfire
    - Wildfire Smoke
    - Wildfire Proximity
- Extreme Events
    - Coastal Flooding Frequency
    - Drought Frequency
    - Riverine Flooding Frequency
    - Hurricane Frequency
    - Strong Winds Frequency
    - Tornado Frequency

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.[1-3] As a result, these communities are more likely to be exposed to harmful pollutants and experience poor health outcomes, such as cardiovascular disease, asthma, perinatal outcomes, and mental health impacts.[2,4] 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,[5] or have the social capital or resources to influence environmental decision-making;[6] making socially vulnerable communities particularly vulnerable to procedural environmental injustices.

References:
1. Bullard RD, Mohai P, Saha R, Wright B. Toxic wastes and race at twenty: Why race still matters after all of these years. Envtl. L.. 2008;38:371.
2. Morello-Frosch R, Zuk M, Jerrett M, Shamasunder B, Kyle AD. Understanding the cumulative impacts of inequalities in environmental health: implications for policy. Health affairs. 2011 May 1;30(5):879-87.
3. Mascarenhas M, Grattet R, Mege K. Toxic waste and race in twenty-first century America: Neighborhood poverty and racial composition in the siting of hazardous waste facilities. Environment and Society. 2021 Sep 1;12(1):108-26.
4. Johnston J, Cushing L. Chemical exposures, health, and environmental justice in communities living on the fenceline of industry. Current environmental health reports. 2020 Mar;7:48-57.
5. Tate E, Emrich C. Assessing social equity in disasters. Eos (United States). 2021 Mar;102(3):24-8.
6. Pearsall H. From brown to green? Assessing social vulnerability to environmental gentrification in New York City. Environment and Planning C: Government and Policy. 2010 Oct;28(5):872-86.

Racial/Ethnic Minority Status: Minority Status

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

Data Year: 2018-2022

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

Rationale:

In April 2021 CDC, declared racism a serious public health threat.[1] Historical and ongoing racial residential segregation, race-related income inequality, and other forms of institutional and systemic racism, often limit the ability of minoritized populations to advocate against unwanted land uses or influence environmental decision-making. Minoritized populations are also more likely to be located near hazardous waste sites.[2,3] A growing body of research also suggests 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.[4] Racial and ethnic minorities experiencing negative health effects associated with environmental pollution may also experience barriers to accessing health care due to discrimination and may suffer disproportionately adverse outcomes.

Processing Method:

1. 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 2018-2022 American Community Survey.
2. The number of persons designated as "white, non-Hispanic" were subtracted from the total population.
    a. Estimate total population - White, non-Hispanic population is equivalent to summing Estimate; Hispanic or Latino, Total Population + Estimate; Black and African American Not Hispanic or Latino + Estimate; American Indian and Alaska Native Not Hispanic or Latino + Estimate; Asian Not Hispanic or Latino + Estimate; Native Hawaiian and Other Pacific Islander Not Hispanic or Latino + Estimate; Two or More Races Not Hispanic or Latino + Estimate; Other Races Not Hispanic or Latino.
    b. We used the Estimate total population – White, non-Hispanic because this more direct calculation provides a smaller margin for error and a simpler calculation as recommended in the ACS guidance document [U.S. Census Bureau | Understanding and Using American Community Survey Data: What All Data Users Need to Know](#)
3. The remaining number, representing all persons who identify as Hispanic or Latino,

Black and African American Not Hispanic or Latino, American Indian and Alaska Native Not Hispanic or Latino, Asian Not Hispanic or Latino, Native Hawaiian and Other Pacific Islander Not Hispanic or Latino, Two or More Races Not Hispanic or Latino, or Other Races Not Hispanic or Latino, was divided by the total population, and multiplied by 100 to get the percentage estimate.

4. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).

5. Estimates of the percent of population that identifies as Hispanic or Latino, Black and African American Not Hispanic or Latino, American Indian and Alaska Native Not Hispanic or Latino, Asian Not Hispanic or Latino, Native Hawaiian and Other Pacific Islander Not Hispanic or Latino, Two or More Races Not Hispanic or Latino, or Other Races Not Hispanic or Latino in each census tract were then sorted and assigned a percentile ranking.

References:

1. Centers for Disease Control and Prevention. Atlanta, GA. Racism and Health. 2024 June 20. Accessed 9/8/2024.

2. Bullard RD, Mohai P, Saha R, Wright B. Toxic wastes and race at twenty: Why race still matters after all of these years. Envtl. L.. 2008;38:371.

3. Mascarenhas M, Grattet R, Mege K. Toxic waste and race in twenty-first century America: Neighborhood poverty and racial composition in the siting of hazardous waste facilities. Environment and Society. 2021 Sep 1;12(1):108-26.

4. Boateng A, Aslakson RA. Navigating the Complex Ecosystem of Race, Ethnicity, Structural Racism, Socioeconomic Factors, Medical Care Delivery, and End-of-Life Care—Casting Away the Compass to Make a Map. JAMA Network Open. 2021 Sep 1;4(9):e2126348-.

5. Rhee TG, Marottoli RA, Van Ness PH, Levy BR. Impact of perceived racism on healthcare access among older minority adults. American Journal of Preventive Medicine. 2019 Apr 1;56(4):580-5.

6. Furtado K, Verdeflor A, Waidmann TA. A conceptual map of structural racism in health care. Urban Institute. 2023 Oct 25.

Socioeconomic Status: Poverty

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

Data Year: 2018-2022

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

Rationale:

Poverty is an indication of economic hardship. The lack of financial resources may hinder a community's ability to influence environmental decision-making, leading to more hazardous and toxic waste sites being located in impoverished areas.[1-3] Low-income populations are also particularly susceptible to adverse health outcomes, due to psychosocial and chronic stress and lack of healthcare access.[4,5] Research also indicates that mothers from low-income neighborhoods are also more likely to suffer the negative effects of air pollution on birth outcomes than mothers from wealthier neighborhoods.[6]

Processing Method:

1. Data on the number of persons with income below 200% of the federal poverty level 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 2018-2022 American Community Survey.
2. An estimate of percent of persons with income below 200% of the federal poverty level was created by dividing the number of persons with income below 200% of the federal poverty level by the number of persons for whom poverty status was determined and then multiplying the result by 100.
3. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
4. 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.

References:

1. Mohai P, Bryant B. Race, poverty & the distribution of environmental hazards: Reviewing the evidence. Race, Poverty & the Environment. 1991 Oct 1:3-27.
2. Mohai P, Saha R. Which came first, people or pollution? Assessing the disparate siting and post-siting demographic change hypotheses of environmental injustice. Environmental Research Letters. 2015 Nov 18;10(11):115008.
3. Tanzer R, Malings C, Hauryliuk A, Subramanian R, Presto AA. Demonstration of a low-cost multi-pollutant network to quantify intra-urban spatial variations in air pollutant source impacts and to evaluate environmental justice. International journal of environmental research and public health. 2019 Jul;16(14):2523.
4. Smith KE, Pollak SD. Early life stress and development: potential mechanisms for adverse outcomes. Journal of neurodevelopmental disorders. 2020 Dec;12:1-5.
5. Parolin Z, Lee EK. The role of poverty and racial discrimination in exacerbating the health consequences of COVID-19. The Lancet Regional Health–Americas. 2022 Mar 1;7.
6. do Nascimento FP, de Almeida MF, Gouveia N. Individual and contextual socioeconomic status as effect modifier in the air pollution-birth outcome association. Science of The Total

Environment. 2022 Jan 10;803:149790.

Socioeconomic Status: No High School Diploma

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

Data Year: 2018-2022

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

Rationale:
Educational attainment is an important factor of socioeconomic status and may influence a community's ability to navigate and comprehend information about pollution, environmental law, and community-scale resources to influence environmental decision-making (Helfand & Peyton, 1999).[1] Education attainment also influences how susceptible an individual is to the health impacts of negative environmental conditions, as lack of educational attainment can be a barrier in navigating healthcare.[2] Low educational attainment has also been shown to be associated with increased risk of adverse birth outcomes and overall mortality.[3,4]

Processing Method:
1. Data on the percent of persons (age 25+) with no high school diploma or equivalent (i.e., a GED) 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 2018-2022 American Community Survey estimates.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Estimates of the percent of the population (age 25+) with no high school diploma in each census tract were then sorted and assigned a percentile ranking.

References:
1. Helfand GE, Peyton LJ. A conceptual model of environmental justice. Social science quarterly. 1999 Mar 1:68-83.
2. Nguyen NH, Subhan FB, Williams K, Chan CB. Barriers and mitigating strategies to healthcare access in indigenous communities of Canada: a narrative review. In Healthcare 2020 Apr 26 (Vol. 8, No. 2, p. 112). MDPI.
3. Thayamballi N, Habiba S, Laribi O, Ebisu K. Impact of maternal demographic and socioeconomic factors on the association between particulate matter and adverse birth outcomes: a systematic review and meta-analysis. Journal of Racial and Ethnic Health Disparities. 2021 Jun;8:743-55.

4. Halpern-Manners A, Helgertz J, Warren JR, Roberts E. The effects of education on mortality: Evidence from linked US Census and administrative mortality data. Demography. 2020 Aug;57:1513-41.

Socioeconomic Status: Unemployment

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

Data Year: 2018-2022

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

Rationale:

Unemployment is an important marker of a community's socioeconomic status. Lack of employment often means limited financial resources as well as decreased social capital due to the stigma of being unemployed. 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 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.[1,2] Unemployment is also associated with stress and stress-related inflammation, potentially rendering these populations more vulnerable to health effects worsened or caused by stress (Ala-Mursula et al., 2013; Dettenborn et al., 2010; Heikkala et al., 2020).[3-5]

Processing Method:
1. Data on the percent of persons 16 and older who are unemployed 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 2018-2022 American Community Survey estimates.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. 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.

References:
1. Bullard RD. Anatomy of environmental racism and the environmental justice movement. Confronting environmental racism: Voices from the grassroots. 1993;15:15-39.
2. Banzhaf HS, Ma L, Timmins C. Environmental justice: Establishing causal relationships. Annual Review of Resource Economics. 2019 Oct 5;11(1):377-98.

3. Dettenborn L, Tietze A, Bruckner F, Kirschbaum C. Higher cortisol content in hair among long-term unemployed individuals compared to controls. Psychoneuroendocrinology. 2010 Oct 1;35(9):1404-9.

4. Ala-Mursula L, Buxton JL, Ek E, Koiranen M, Taanila A, Blakemore AI, Järvelin MR. Long-term unemployment is associated with short telomeres in 31-year-old men: an observational study in the northern Finland birth cohort 1966. PLoS One. 2013 Nov 20;8(11):e80094.

5. Heikkala E, Ala-Mursula L, Taimela S, Paananen M, Vaaramo E, Auvinen J, Karppinen J. Accumulated unhealthy behaviors and psychosocial problems in adolescence are associated with labor market exclusion in early adulthood–a northern Finland birth cohort 1986 study. BMC Public Health. 2020 Dec;20:1-3.

Socioeconomic Status: Renters

Indicator: Percent of occupied housing units that are renter-occupied

Data Year: 2018-2022

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

Rationale:

Renters are often seen as more transitory, and as a result, they may have less social capital within the context of environmental decision-making than homeowners, who have more vested rights and interests in defending local environmental quality and land values.[1-3] Additionally, research consistently supports the idea that renters experience worse health outcomes associated with a range of conditions when compared to homeowners.[4,5]

Processing Method:
1. Data on the percent of renter-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 2018-2022 American Community Survey estimates.

2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).

3. Estimates of the percent of housing units that are renter-occupied in each census tract were then sorted and assigned a percentile ranking.

References:
1. Mullenbach LE, Baker BL. Environmental justice, gentrification, and leisure: A systematic review and opportunities for the future. Leisure Sciences. 2020 Nov 23;42(5-6):430-47.

2. Dundon LA, Camp JS. Climate justice and home-buyout programs: renters as a forgotten

population in managed retreat actions. Journal of Environmental Studies and Sciences. 2021 Sep;11(3):420-33.

3. Anyanwu C, Beyer KM. Intersections among housing, environmental conditions, and health equity: A conceptual model for environmental justice policy. Social Sciences & Humanities Open. 2024 Jan 1;9:100845.

4. Mawhorter S, Crimmins EM, Ailshire JA. Housing and cardiometabolic risk among older renters and homeowners. Housing studies. 2023 Aug 9;38(7):1342-64.

5. Kim SD, Carswell AT. The mediation effect of indoor air quality on health: a comparison of homeowners and renters. Indoor air. 2022 Sep;32(9):e13108.

Socioeconomic Status: Housing Cost Burden

Indicator: Percent of occupied housing units with less than $75,000 in annual household income who are considered burdened by housing costs (i.e., pay greater than 30% of monthly income on housing expenses)

Data Year: 2018-2022

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 their monthly income on housing costs. Housing costs represent a significant financial burden for most households, and populations burdened by housing costs and debt may lack the financial resources or time required to devote to improving their environmental conditions. Additionally, research indicates that persons experiencing housing burden may be less likely to have access to preventative care and more likely to postpone health care.[1,2] The instability associated with housing cost burden can also exacerbate stress and poor mental health and is associated with worse developmental and educational outcomes for children.[3] High housing cost burden is also associated with worse cardiovascular health and worse overall health in seniors.[4,5]

Processing Method:

1. 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 2018-2022 American Community Survey estimates.

2. Estimates of the 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 annual income levels under $75,000.

3. 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 the result by 100.

4. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).

5. 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.

References:

1. Martin P, Liaw W, Bazemore A, Jetty A, Petterson S, Kushel M. Adults with housing insecurity have worse access to primary and preventive care. The Journal of the American Board of Family Medicine. 2019 Jul 1;32(4):521-30.

2. Westbrook M. "I Don't have a Pile of Money to Take Care of Things": Financial Stress and Housing Insecurity Among Low-Income Hispanic/Latinx Immigrant Families During COVID-19. Journal of Family and Economic Issues. 2024 Jun;45(2):315-26.

3. Leung CW, Farooqui S, Wolfson JA, Cohen AJ. Understanding the cumulative burden of basic needs insecurities: associations with health and academic achievement among college students. American Journal of Health Promotion. 2021 Feb;35(2):275-8.

4. Sims M, Kershaw KN, Breathett K, Jackson EA, Lewis LM, Mujahid MS, Suglia SF, American Heart Association Council on Epidemiology and Prevention and Council on Quality of Care and Outcomes Research. Importance of housing and cardiovascular health and well-being: a scientific statement from the American Heart Association. Circulation: Cardiovascular Quality and Outcomes. 2020 Aug;13(8):e000089.

5. Jenkins Morales M, Robert SA. Housing cost burden and health decline among low-and moderate-income older renters. The Journals of Gerontology: Series B. 2022 Apr 1;77(4):815-26.

Socioeconomic Status: Lack of Health Insurance

Indicator: Percent of civilian, non-institutionalized population with no health insurance

Data Year: 2018-2022

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

Rationale:
The total population of insured persons in the U.S. has almost consistently declined since

1997with about 8.2% of the population uninsured as of March, 2024.[1] Uninsured persons are commonly of families with low income (with typically only one person working in the family), people of color, and undocumented immigrants.[2] The financial burdens associated with healthcare may the reduce uninsured populations' ability to engage in the environmental decision-making process. Individuals without health insurance also experience barriers with accessing healthcare following adverse environmental events, resulting in an increased risk of morbidity and mortality among uninsured populations.[3,4]

Processing Method:

1. Data on the percent of the non-institutionalized population who have no health insurance, 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 2018-2022 American Community Survey estimates.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Estimates of the percent of civilian, non-institutionalized population who have no health insurance in each census tract were then sorted and assigned a percentile ranking.

References:

1. Cohen RA and Briones EM. Health insurance coverage: Early release of quarterly estimates from the National Health Interview Survey, January 2023–March 2024. National Center for Health Statistics. August 2024. Available from: https://www.cdc.gov/nchs/nhis/releases.htm
2. Tolbert J, Singh R, Drake P. Key Facts about the Uninsured Population. KFF Health News. May 2024. Accessed September 17, 2024. https://www.kff.org/health-policy-101-the-uninsured-population-and-health-coverage/
3. Woolhandler S, Himmelstein DU. The relationship of health insurance and mortality: is lack of insurance deadly?. Annals of Internal Medicine. 2017 Sep 19;167(6):424-31.
4. Mulchandani R, Smith M, Armstrong B, English National Study of Flooding and Health Study Group, Beck CR, Oliver I. Effect of Insurance-Related factors on the association between flooding and mental health outcomes. International journal of environmental research and public health. 2019 Apr;16(7):1174.

Socioeconomic Status: Lack of Internet Access

Indicator: Percent of households with no internet subscription

Data Year: 2018-2022

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

Rationale:

Lack of access to internet 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 a barrier to accessing healthcare through telehealth, and an important communication barrier during environmental emergencies, for which outreach through internet sources can be a key strategy for public health officials.[1-3]

Processing Method:
1. Data on the percent of households with no internet subscription, 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 2018-2022 American Community Survey estimates.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Estimates of the percent of households with no internet subscription in each census tract were then sorted and assigned a percentile ranking.

References:
1. Woolhandler S, Himmelstein DU. The relationship of health insurance and mortality: is lack of insurance deadly?. Annals of Internal Medicine. 2017 Sep 19;167(6):424-31.
2. Lokmic-Tomkins Z, Bhandari D, Bain C, Borda A, Kariotis TC, Reser D. Lessons learned from natural disasters around digital health technologies and delivering quality healthcare. International journal of environmental research and public health. 2023 Mar 3;20(5):4542.
3. Marshall A, Wilson CA, Dale A. Telecommunications and natural disasters in rural Australia: The role of digital capability in building disaster resilience. Journal of Rural Studies. 2023 May 1;100:102996.

Household Characteristics: Age 65 and Older
Indicator: Percent of population aged 65 and older

Data Year: 2018-2022

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

Rationale:

Approximately 24% of adults aged 65 and older face social isolation, which can lead to worse health outcomes and can affect their ability to affect change or influence environmental

decision-making in their communities.[1-3] Additionally, older populations may be more susceptible to environmental pollution due to lowered immune function and accumulated oxidative stress from a lifetime of exposures.[4]

Processing Method:

1. Data on the percent of persons aged 65 and older, provided directly by the 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 2018-2022 American Community Survey estimates.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Estimates of the percent of population aged 65 and older in each census tract were then sorted and assigned a percentile ranking.

References:

1. National Academies of Sciences, Division of Behavioral, Social Sciences, Medicine Division, Board on Behavioral, Sensory Sciences, Board on Health Sciences Policy, Committee on the Health, Medical Dimensions of Social Isolation, Loneliness in Older Adults. Social isolation and loneliness in older adults: Opportunities for the health care system. National Academies Press; 2020 Jun 14.
2. Barnes TL, MacLeod S, Tkatch R, Ahuja M, Albright L, Schaeffer JA, Yeh CS. Cumulative effect of loneliness and social isolation on health outcomes among older adults. Aging & Mental Health. 2022 Jul 3;26(7):1327-34.
3. Ravi KE, Fields NL, Dabelko-Schoeny H. Outdoor spaces and buildings, transportation, and environmental justice: A qualitative interpretive meta-synthesis of two age-friendly domains. Journal of Transport & Health. 2021 Mar 1;20:100977.
4. Bektas A, Schurman SH, Sen R, Ferrucci L. Aging, inflammation and the environment. Experimental gerontology. 2018 May 1;105:10-8.

Household Characteristics: Age 17 and Younger

Indicator: Percent of population aged 17 and younger

Data Year: 2018-2022

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

Rationale:

Persons below voting age have limited ability to influence environmental decision-making, as well as limited resources, knowledge, and life experience necessary to affect change (Flanagan

et al., 2011).[1] 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. Physiological factors, such as rates of absorption, distribution, metabolism, and excretion of chemicals, make children more vulnerable to environmental pollution than adults.[2]

Processing Method:

1. 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 2018-2022 American Community Survey estimates.
2. 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.
3. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
4. Estimates of the percent of population aged 17 and younger in each census tract were then sorted and assigned a percentile ranking.

References:

1. Flanagan BE, Gregory EW, Hallisey EJ, Heitgerd JL, Lewis B. A social vulnerability index for disaster management. Journal of homeland security and emergency management. 2011 Jan 5;8(1):0000102202154773551792.
2. Etzel RA. The special vulnerability of children. International journal of hygiene and environmental health. 2020 Jun 1;227:113516.

Household Characteristics: Civilian with a Disability

Indicator: Percent of civilian, non-institutionalized population with a disability

Data Year: 2018-2022

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

Rationale:

Those living with a disability may experience social or physiological barriers, preventing them from fully participating in the environmental decision-making process. Persons with disabilities are often disproportionately affected at every stage of disaster events and disaster recovery .[1,2] Furthermore, certain types of disability are associated with increased physiological susceptibility to environmental pollution, particularly to PM2.5 and other forms of air pollution (Dales &

Cakmak, 2016; H. Lin et al., 2017; Weuve et al., 2016).[3-5]

Processing Method:
1. Estimates of percent of the civilian, non-institutionalized population with a disability 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 2018-2022 American Community Survey.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Estimates of the percent of civilian, non-institutionalized population with a disability in each census tract were then sorted and assigned a percentile ranking.

References:
1. Stough LM, Kelman I. People with disabilities and disasters. Handbook of disaster research. 2018:225-42.
2. Chakraborty J, Grineski SE, Collins TW. Hurricane Harvey and people with disabilities: Disproportionate exposure to flooding in Houston, Texas. Social Science & Medicine. 2019 Apr 1;226:176-81.
3. Dales RE, Cakmak S. Does mental health status influence susceptibility to the physiologic effects of air pollution? A population based study of Canadian children. PloS one. 2016 Dec 28;11(12):e0168931.
4. Weuve J, Kaufman JD, Szpiro AA, Curl C, Puett RC, Beck T, Evans DA, Mendes de Leon CF. Exposure to traffic-related air pollution in relation to progression in physical disability among older adults. Environmental health perspectives. 2016 Jul;124(7):1000-8.
5. Lin H, Guo Y, Zheng Y, Zhao X, Cao Z, Rigdon SE, Xian H, Li X, Liu T, Xiao J, Zeng W. Exposure to ambient PM2. 5 associated with overall and domain-specific disability among adults in six low- and middle-income countries. Environment international. 2017 Jul 1;104:69-75.

Household Characteristics: English Language Proficiency

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

Data Year: 2018-2022

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.[1] Furthermore, discrimination against non-English speakers can lead to exclusion from decision making and is correlated with increased stress and reduced quality of life.[2,3] 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.[4,5]

Processing Method:
1. Data on the number of persons who speak languages other than English and speak English either not at all or less than 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 2018-2022 American Community Survey estimates.
2. A total number of persons who speak languages other than English and speak English either not at all or less than well was calculated by combining Estimate; Native, Speak Spanish, Speak English "not well"+ Estimate; Native, Speak Spanish, Speak English "not at all" + Estimate; Native, Speak other Indo-European languages, Speak English "not well" + Estimate; Native, Speak other Indo-European languages, Speak English "not at all" + Estimate; Native, Speak Asian and Pacific Island languages, Speak English "not well" + Estimate; Native, Speak Asian and Pacific Island languages, Speak English "not at all" + Estimate; Native, Speak other languages, Speak English "not well" + Estimate; Native, Speak other languages, Speak English "not at all" + Estimate; Foreign Born, Speak Spanish, Speak English "not well"+ Estimate; Foreign Born, Speak Spanish, Speak English "not at all" + Estimate; Foreign Born, Speak other Indo-European languages, Speak English "not well" + Estimate; Foreign Born, Speak other Indo-European languages, Speak English "not at all" + Estimate; Foreign Born, Speak Asian and Pacific Island languages, Speak English "not well" + Estimate; Foreign Born, Speak Asian and Pacific Island languages, Speak English "not at all" + Estimate; Foreign Born, Speak other languages, Speak English "not well" + Estimate; Foreign Born, Speak other languages, Speak English "not at all"
3. An estimate of percent of persons who speak English less than well was created by dividing the number of persons with income below 200% of the federal poverty level by the number of persons for whom poverty status was determined and then multiplying the result by 100.
4. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
5. 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.

References:

1. Teron L. Sustainably speaking: considering linguistic isolation in citywide sustainability planning. Sustainability: The Journal of Record. 2016 Dec;9(6):289-94.
2. Gee GC, Ponce N. Associations between racial discrimination, limited English proficiency, and health-related quality of life among 6 Asian ethnic groups in California. American journal of public health. 2010 May;100(5):888-95.
3. Carl Y, Frias RL, Kurtevski S, Copo TG, Mustafa AR, Font CM, Blundell AR, Rodriguez EC, Sacasa R. The correlation of English language proficiency and indices of stress and anxiety in migrants from Puerto Rico after Hurricane Maria: a preliminary Study. Disaster medicine and public health preparedness. 2020 Feb;14(1):23-7.
4. Nepal V, Banerjee D, Perry M, Scott D. Disaster preparedness of linguistically isolated populations: Practical issues for planners. Health promotion practice. 2012 Mar;13(2):265-71.
5. White-Newsome J, O'Neill MS, Gronlund C, Sunbury TM, Brines SJ, Parker E, Brown DG, Rood RB, Rivera Z. Climate change, heat waves, and environmental justice: Advancing knowledge and action. Environmental Justice. 2009 Dec 1;2(4):197-205.

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: 2018-2022

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

Rationale:

Institutionalized persons, including 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.[1] Persons institutionalized in nursing homes or mental hospitals face similar issues of autonomy and lack of social capital or the physical ability to influence environmental decision-making. Furthermore, persons in institutional facilities are often neglected in environmental decision-making and hazard response.[2]

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.[3] People living in group homes, missions, and shelters may have limited legal status, limited time, and limited resources, and therefore may also have a diminished ability to influence environmental decision-making.[4]

Processing Method:
1. Data on the percentage of persons living in group quarters at the census tract level were downloaded for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2018-2022 American Community Survey estimates.
2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Estimates of persons living in group quarters (including 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.

References:
1. Pellow DN. Struggles for environmental justice in US prisons and jails. Antipode. 2021 Jan;53(1):56-73.
2. Cutter SL. Hazards vulnerability and environmental justice. Routledge; 2012 May 4.
3. Broomandi P, Guney M, Kim JR, Karaca F. Soil contamination in areas impacted by military activities: a critical review. Sustainability. 2020 Oct 29;12(21):9002.
4. Intersecting hazards, intersectional identities: A baseline Critical Environmental
5. Justice analysis of US homelessness

Housing Type: Mobile Homes

Indicator: Percentage of total housing units designated as mobile homes

Data Year: 2018-2022

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.[1] Mobile homes are also often inhabited by farm workers, who are beholden to the environmental decisions made by the landowners, such as the use of agricultural pesticides.[2] 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 the negative health effects associated with air pollution and extreme heat ,[3,4] while the observed unreliability of access to drinking water poses further risks to residents' health.[5]

Processing Method:

1. Data on the percentage of housing units designated as mobile homes at the census tract level were downloaded for all 50 U.S. States, the District of Columbia, and the Commonwealth of Puerto Rico from the 2018-2022 American Community Survey estimates.

2. Data for Alaska, Hawaii, and the Commonwealth of Puerto Rico were removed from the dataset prior to index calculation, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).

3. Estimates of total housing units designated as mobile homes in each census tract were then sorted and assigned a percentile ranking.

References:

1. Sullivan E. Manufactured insecurity: Mobile home parks and Americans' tenuous right to place. Univ of California Press; 2018 Aug 7.

2. Early J, Davis SW, Quandt SA, Rao P, Snively BM, Arcury TA. Housing characteristics of farmworker families in North Carolina. Journal of Immigrant and Minority Health. 2006 Apr;8:173-84.

3. MacTavish K, Eley M, Salamon S. Housing vulnerability among rural trailer-park households. Geo. J. on Poverty L. & Pol'y. 2006;13:95.

4. Phillips LA, Solís P, Wang C, Varfalameyeva K, Burnett J. Engaged convergence research: An exploratory approach to heat resilience in mobile homes. The Professional Geographer. 2021 Sep 21;73(4):619-31.

5. Pierce G, Jimenez S. Unreliable water access in US mobile homes: evidence from the American Housing Survey. Housing Policy Debate. 2015 Oct 2;25(4):739-53.

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,[2-4] a growing body of literature has documented the importance of salutogenic features in determining environmental quality and measuring health disparities attributable to environmental conditions.[5-7]

References:

1. Owusu C, Flanagan B, Lavery AM, Mertzlufft CE, McKenzie BA, Kolling J, Lewis B, Dunn I, Hallisey E, Lehnert EA, Fletcher K. Developing a granular scale environmental burden index (EBI) for diverse land cover types across the contiguous United States. Science of The Total Environment. 2022 Sep 10;838:155908.
2. Min E, Gruen D, Banerjee D, Echeverria T, Freelander L, Schmeltz M, Saganić E, Piazza M, Galaviz VE, Yost M, Seto EY. The Washington State Environmental Health Disparities Map: Development of a community-responsive cumulative impacts assessment tool. International journal of environmental research and public health. 2019 Nov;16(22):4470.
3. California Office of Environmental Health and Hazard Assessment. CalEnviroScreen 4.0. Updated May 1, 2023. Accessed September 12, 2024. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40
4. U.S. Environmental Protection Agency. Environmental Justice Screening and Mapping Tool (EJScreen). Updated September 9, 2024. Accessed September 12, 2024. https://www.epa.gov/ejscreen
5. Maizlish N, Delaney T, Dowling H, Chapman DA, Sabo R, Woolf S, Orndahl C, Hill L, Snellings L. California healthy places index: frames matter. Public Health Reports. 2019 Jul;134(4):354-62.
6. Ige-Elegbede J, Pilkington P, Orme J, Williams B, Prestwood E, Black D, Carmichael L. Designing healthier neighbourhoods: a systematic review of the impact of the neighbourhood design on health and wellbeing. Cities & health. 2022 Sep 3;6(5):1004-19.
7. Forsyth A. What is a healthy place? Models for cities and neighbourhoods. InUrban Design and Human Flourishing 2021 Apr 12 (pp. 6-22). Routledge.

Air Pollution: Ozone

Indicator: Mean annual percent of days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard (NAAQS), averaged over three years (2018- 2020)

Data Year: 2018-2020

Data Source: U.S. Environmental Protection Agency (EPA) Air Quality System (AQS), combined monitoring and modeled data

Rationale:

Both acute and long-term exposure to elevated levels of ground-level ozone is associated with negative health effects ranging from increased morbidity and mortality due to respiratory and cardiovascular.[1-3] Together with PM2.5, ozone is a major contributor to air pollution-related morbidity and mortality. Long term exposure to ground-level ozone contributed to an estimated 490,000 deaths worldwide in 2021, including 14,000 deaths in the United States.[4] The number of deaths associated with ozone is projected to increase over the next several decades due to climate change.[5]

Processing Method:

1. Data from monitoring and modeled predictions for ozone from 2018 to 2020 were obtained from the National Environmental Health Tracking Program, which uses estimates from the U.S. EPA's Downscaler model.
2. Data from 2018 and 2019 used 2010 census tracts and were converted to 2020 census tracts, using the 2020 Census Tract relationship file. The data was averaged when there wasn't a 1:1 match between 2010 and 2020 census tracts.
3. A 3-year mean of the number of days above the EPA standard for ozone (> 0.070 ppm) was computed for each census tract for which data were available. This matches the calculations used by other agencies, including the U.S. EPA.
4. The mean annual percent of days with daily 24-hour ozone concentrations over the National Ambient Air Quality Standard (NAAQS) in each census tract were then sorted and assigned a percentile ranking.

References:

1. Lim CC, Hayes RB, Ahn J, Shao Y, Silverman DT, Jones RR, Garcia C, Bell ML, Thurston GD. Long-term exposure to ozone and cause-specific mortality risk in the United States. American journal of respiratory and critical care medicine. 2019 Oct 15;200(8):1022-31. https://doi.org/10.1164/rccm.201806-1161OC
2. U.S. Environmental Protection Agency. Health Effects of Ozone Pollution. Updated April 9, 2024. Accessed September 16, 2024. https://www.epa.gov/ground-level-ozone-pollution/health-effects-ozone-pollution

3. Zhang J, Wei Y, Fang Z. Ozone pollution: a major health hazard worldwide. Frontiers in immunology. 2019 Oct 31;10:2518. https://doi.org/10.1007/s11356-017-9239-3
4. Health Effects Institute. 2024. State of Global Air 2024. Data source: Global Burden of Disease Study 2021. IHME, 2024. Accessed 9/16/2024. www.stateofglobalair.org
5. Domingo NG, Fiore AM, Lamarque JF, Kinney PL, Jiang L, Gasparrini A, Breitner S, Lavigne E, Madureira J, Masselot P, Da Silva SD. Ozone-related acute excess mortality projected to increase in the absence of climate and air quality controls consistent with the Paris Agreement. One Earth. 2024 Feb 16;7(2):325-35. https://doi.org/10.1016/j.oneear.2024.01.001

Air Pollution: Particulate Matter (PM2.5)

Indicator: Mean annual percent of days with daily 24-hour average PM2.5 concentrations over the National Ambient Air Quality Standard (NAAQS), averaged over three years (2018-2020)

Data Year: 2018-2020

Data Source: U.S. Environmental Protection Agency (EPA) Air Quality System (AQS), combined monitoring and modeled data

Rationale:

Inhaling 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. Exposure to elevated levels of PM2.5 can lead to irritation of eyes, nose, throat, and lungs, and increases the relative risk of acute cardiovascular events, including admission to a hospital for stroke.[1] Long-term exposure to elevated levels of PM2.5 is associated with higher rates of mortality from a number of conditions, including cancer and cardiopulmonary disease.[2] Exposure to ambient PM2.5 contributed to an estimated 4.7 million deaths worldwide in 2021, including 50,000 deaths in the United States.[3,4]

Processing Method:

1. Data from monitoring and modeled predictions for PM2.5 from 2018 to 2020 were obtained from the National Environmental Health Tracking Program, which uses estimates from the U.S. EPA's Downscaler model.
2. Data from 2018 and 2019 used 2010 census tracts and were converted to 2020 census tracts, using the 2020 Census Tract relationship file. The data was averaged when there wasn't a 1:1 match between 2010 and 2020 census tracts.
3. A 3-year mean of the percent of days above the EPA daily standard for PM2.5 ($>=35.5 \mu g/m^3$) was computed for each census tract for which data were available. This matches the calculations used by other agencies, including the U.S. EPA.
4. The mean annual percent of days with daily 24-hour average PM2.5 concentrations over the National Ambient Air Quality Standard (NAAQS) in each census tract were then sorted and assigned a percentile ranking.

References:

1. U.S. Environmental Protection Agency. Health and Environmental Effects of Particulate Matter (PM). Updated July 16, 2024. Accessed September 16, 2024. https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm
2. Shi L, Zanobetti A, Kloog I, Coull BA, Koutrakis P, Melly SJ, Schwartz JD. Low-concentration PM2.5 and mortality: estimating acute and chronic effects in a population-based study. Environmental health perspectives. 2016 Jan;124(1):46-52. https://doi.org/10.1289/ehp.1409111
3. Fann, N., Lamson, A. D., Anenberg, S. C., Wesson, K., Risley, D., & Hubbell, B. J. (2012). Estimating the National Public Health Burden Associated with Exposure to Ambient PM2.5 and Ozone. Risk Analysis, 32(1), 81–95. https://doi.org/10.1111/j.1539-6924.2011.01630.x
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Air Pollution: Diesel Particulate Matter

Indicator: Diesel particulate matter concentrations in air, μg/m^3

Data Year: 2019

Data Source: U.S. Environmental Protection Agency (EPA) AirToxScreen modeled data

Rationale:

Diesel particulate matter is a particle emission from a diesel motor made of an elemental carbon core and various adsorbed organics, compounds, and other chemical components.[1] Evidence indicates that diesel particulate matter exposure may cause respiratory symptoms via inflammation and oxidative stress.[2] Acute exposure to diesel particulate matter has been associated with acute coronary syndrome and other cardiovascular issues.[3] Diesel particulate matter contains carcinogens, such as benzene and formaldehyde, that may lead to the development of certain kinds of cancer.[2]

Processing Method:

1. Data from modeled predictions of ambient diesel particulate matter concentrations at the census tract level were downloaded from the U.S. EPA's AirToxScreen database for 2019.
2. As the data used 2010 census tracts, census tracts were converted to 2020 census tracts, using the 2020 Census Tract relationship file. The data was averaged when there wasn't a 1:1 match between 2010 and 2020 census tracts. (Note: 150 census tracts were null, as those census tracts were not included in the AirToxScreen data. Additionally, 4 census tracts were in the AirToxScreen data, but did not line up with a matching census tract in the 2020 census tract boundary file. These tracts were

manually added to the table.)

3. Estimates of diesel particulate matter concentrations in air for each census tract were then sorted and assigned a percentile ranking.

References:

1. Wichmann, H.-E. (2007). Diesel Exhaust Particles. Inhalation Toxicology, 19(sup1), 241–244. https://doi.org/10.1080/08958370701498075
2. Wu D, Zhang F, Lou W, Li D, Chen J. Chemical characterization and toxicity assessment of fine particulate matters emitted from the combustion of petrol and diesel fuels. Science of the Total Environment. 2017 Dec 15;605:172-9. https://doi.org/10.1016/j.scitotenv.2017.06.058
3. Hime NJ, Marks GB, Cowie CT. A comparison of the health effects of ambient particulate matter air pollution from five emission sources. International journal of environmental research and public health. 2018 Jun;15(6):1206. https://doi.org/10.3390/ijerph15061206

Air Pollution: Air Toxics Cancer Risk

Indicator: Lifetime cancer risk from inhalation of air toxics

Data Year: 2019

Data Source: U.S. Environmental Protection Agency (EPA) AirToxScreen 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.[1-4] Cancer risks estimated by AirToxScreen are based on modeled exposure concentrations, assessments of each pollutant's unit risk estimate, and inhalation reference concentration.

It is important to note that while diesel particulate matter, which is another EJI indicator, is one of the HAPs included in the 2019 AirToxScreen lifetime cancer risk model, it is represented as distinct from the air toxics cancer risk indicator because it is only one of the 140 HAPs used to create the 2019 AirToxScreen lifetime cancer risk estimate and is associated with many other health issues other than cancer. For more information on the 2019 AirToxScreen, including a full list of hazardous air pollutants included in the lifetime cancer risk model, please visit: https://www.epa.gov/AirToxScreen/2019-airtoxscreen-assessment-results#nationwide.

Processing Method:

1. Data from the modeled predictions of total lifetime cancer risk associated with air toxics at the census tract level were downloaded from the U.S. EPA's AirToxScreen

database.

2. As the data used 2010 census tracts, census tracts were converted to 2020 census tracts, using the 2020 Census Tract relationship file. (**Note:** 150 census tracts were null, as those census tracts were not included in the AirToxScreen data. Additionally, 4 CONUS census tracts were in the AirToxScreen data, but did not line up with a matching census tract in the 2020 census tract boundary file. These tracts were manually added to the table.)

3. Values were rounded to one significant figure to match EPA's methodology and to avoid adding false precision to the results.

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

References:

1. Grineski SE, Collins T. Lifetime cancer risks from hazardous air pollutants in US public school districts. J Epidemiol Community Health. 2019 Sep 1;73(9):854-60. https://doi.org/10.1136/jech-2018-211832

2. Weitekamp CA, Lein M, Strum M, Morris M, Palma T, Smith D, Kerr L, Stewart MJ. An examination of national cancer risk based on monitored hazardous air pollutants. Environmental health perspectives. 2021 Mar 24;129(3):037008. https://doi.org/10.1289/EHP8044

3. Hutchings H, Zhang Q, Grady SC, Cox J, Popoff A, Wilson CP, Zhu S, Okereke I. Lung Cancer and Air Quality in a Large Urban County in the United States. Cancers. 2024 Jun 5;16(11):2146. https://doi.org/10.3390/cancers16112146

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Potentially Hazardous & Toxic Sites: National Priority List Sites

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

Data Year: 2024

Data Source: U.S. Environmental Protection Agency (EPA) 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.[1-2] 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:
1. Point level data representing the location of NPL sites were downloaded through the U.S. EPA's Facility Registry Service on January 26, 2024.
2. 1-mile buffers were calculated for each NPL site.
3. The NPL site buffers were combined into a single layer, representing a 1-mile buffer around all NPL sites in the nation.
4. The NPL buffer layer was then intersected with geographic boundaries of census tracts and the proportion of the tract area that intersected each buffer was calculated.
5. The proportion of tract area within 1-mile of a NPL site for each census tract was then sorted and assigned a percentile ranking.

References:
1. Kiaghadi A, Rifai HS, Dawson CN. The presence of Superfund sites as a determinant of life expectancy in the United States. Nature communications. 2021 Apr 13;12(1):1947. https://doi.org/10.1038/s41467-021-22249-2
2. Nagisetty RM, Autenrieth DA, Storey SR, Macgregor WB, Brooks LC. Environmental health perceptions in a superfund community. Journal of environmental management. 2020 May 1;261:110151. https://doi.org/10.1016/j.jenvman.2020.110151

Potentially Hazardous & Toxic Sites: Toxic Release Inventory Sites

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

Data Year: 2024

Data Source: U.S. Environmental Protection Agency (EPA) 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 either: (1) manufacture more than 25,000 pounds of listed chemicals annually, or (2) used more than 10,000 pounds of listed chemicals annually. 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[1], as well as increased risks for certain kinds of

cancer.[2,3] Additionally, TRI sites and other noxious and unwanted land uses can produce noise and odor pollution and, particularly in communities burdened by multiple land uses, can lead to the increased burden of community stress.[4]

Processing Method:

1. Point level data representing locations of TRI sites were downloaded through the EPA's Facility Registry Service on January 26, 2024.
2. 1-mile buffers were calculated for each TRI site.
3. The TRI site buffers were combined into a single layer, representing a 1-mile buffer around all TRI sites in the nation.
4. The TRI buffer layer was intersected with geographic boundaries of census tracts and the proportion of the tract area that intersected each buffer was calculated. In some cases, this calculation resulted in an estimate greater than 100% by a matter of 12 decimal places. In these cases, the proportions were capped at 100%.
5. The proportion of tract area within 1-mile of a TRI site for each census tract was then sorted and assigned a percentile ranking.

References:

1. Brown-Amilian S, Akolade Y. Disparities in COPD hospitalizations: a spatial analysis of proximity to toxics release inventory facilities in Illinois. International Journal of Environmental Research and Public Health. 2021 Dec 13;18(24):13128. https://doi.org/10.3390/ijerph182413128
2. Chen Y, Van Deventer D, Nianogo R, Vinceti M, Kang W, Cockburn M, Federman N, Heck JE. Maternal residential exposure to solvents from industrial sources during pregnancy and childhood cancer risk in California. International journal of hygiene and environmental health. 2024 Jun 1;259:114388. https://doi.org/10.1016/j.ijheh.2024.114388
3. Madrigal JM, Pruitt CN, Fisher JA, Liao LM, Graubard BI, Gierach GL, Silverman DT, Ward MH, Jones RR. Carcinogenic industrial air pollution and postmenopausal breast cancer risk in the National Institutes of Health AARP Diet and Health Study. Environment International. 2024 Aug 24:108985. https://doi.org/10.1016/j.envint.2024.108985
4. Wilson SM, Fraser-Rahim H, Williams E, Zhang H, Rice L, Svendsen E, Abara W. Assessment of the distribution of toxic release inventory facilities in metropolitan Charleston: an environmental justice case study. American Journal of Public Health. 2012 Oct;102(10):1974-80. https://doi.org/10.2105/AJPH.2012.300700

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

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

Data Year: 2024

Data Source: U.S. Environmental Protection Agency (EPA) 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.[1,2] Proximity to hazardous waste sites has been linked to increased rates of hospitalizations for diseases such as stroke, diabetes, and coronary heart disease.[3-5]

Processing Method:

1. Point level data representing the locations of TSDFs, including Large Quantity Generators (LQGs), were downloaded through the EPA's Facility Registry Service on January 26, 2024.
2. 1-mile buffers were calculated for each TSDF.
3. The TSDF buffers were combined into a single layer, representing a 1-mile buffer around all TSDFs in the nation.
4. The TSDF buffer layer was intersected with geographic boundaries of census tracts and the proportion of the tract area that intersected each buffer was calculated.
5. The proportion of tract area within 1-mile of a TSDF site for each census tract was then sorted and assigned a percentile ranking.

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

Data Year: 2024

Data Source: U.S. Environmental Protection Agency (EPA) 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 worse-case scenario, such as a major fire or explosion that releases a toxic chemical into the surrounding community.[1] 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 at RMP facilities each year, these releases are separate from the daily toxic emissions that are allowed under most operating permits.

The EPA notes that these incidents "can result in catastrophic accidents that cause fatalities and serious injuries, evacuation, and shelter-in-place orders."[2] 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.[3]

Processing Method:
1. Point level data representing the locations of RMP sites were downloaded through the EPA's Facility Registry Service on January 26, 2024.
2. 1-mile buffers were calculated for each RMP site.
3. The RMP site buffers were combined into a single layer, representing a 1-mile buffer around all RMP sites in the nation.
4. The RMP buffer layer was intersected with geographic boundaries of census tracts and the proportion of the tract area that intersected each buffer was calculated.
5. The proportion of tract area within 1-mile of a RMP site for each census tract was then sorted and assigned a percentile ranking.

References:
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Potentially Hazardous & Toxic Sites: Coal Mines

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

Data Year: 2024

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

Rationale:

Coal mining includes both traditional underground mining methods and surface mining methods, such as mountain top removal (MTR). While on the decline in the United States, coal mining is still of substantial concern for the health of exposed communities. 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.[1-3] Proximity to MTR sites has been linked to impaired respiratory health, including increased occurrence of chronic obstructive pulmonary disease (COPD)[3] and may predict increased risk for depressive and substance use disorders.[4] Air pollution from coal mining has also been connected to adverse effects in-utero for pregnant women, including low-birthweight.[5] 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.[6]

Processing Method:

1. Point level data representing the locations of coal mines were downloaded through the U.S. Mine Safety and Health Administration's Mine Data Retrieval System (MDRS) on April 29, 2024.

2. Sites were filtered to remove mines designated as metal mines (var: COAL_METAL_IND) and as "abandoned" and "abandoned sealed" to avoid capturing sites at which coal is not being extracted/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. Unlike lead mines, facilities and non-producing locations were not excluded from the dataset, as these locations likely still process or handle coal. Additionally, four sites with inaccurate location information (latitude and/or longitude) were excluded.

Please note, there were 43 coal mines in this data set that were located in a different state than what was listed in the 'STATE' field in the original data source. In some cases, this was because the address listed was referring to the main office of the coal mine, rather than the actual location of the mine. Upon further inspection, these mine locations were unable to be ruled out as actual locations, as it does appear that they represent valid mine locations when compared to satellite imagery.

3. 1-mile buffers were calculated for each coal mine location.
4. The coal mine buffers were combined into a single layer, representing a 1-mile buffer around all active or intermittent coal mines in the nation.
5. The coal mine buffer layer was intersected with the geographical boundaries of census tracts and the proportion of tract area intersecting each buffer was calculated.
6. The proportion of tract area within 1-mile of a coal mine in each census tract were then sorted and assigned a percentile ranking.

References:

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Potentially Hazardous & Toxic Sites: Lead Mines

Indicator: Proportion of census tract area within a 1-mile buffer of an active lead mine

Data Year: 2024

Data Source: U.S. Mine Safety and Health Administration (MSHA) 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- by-products of mining pose a health hazard to nearby communities, particularly to children.[1-2] Studies outside of the U.S. that evaluated health risks associated with communities in close proximity to active lead mines have found evidence of elevated blood lead levels in children.[3-4]

Processing Method:
1. Point level data representing the locations of lead mines were downloaded through the U.S. Mine Safety and Health Administration's Mine Data Retrieval System (MDRS) on April 29, 2024.
2. Sites were filtered to include only active lead mines (i.e., PRIMARY_SIC or SECONDARY_SIC included "lead"). Active lead mines were determined to be mines with a current mine status (CURRENT_MINE_STATUS) of active, intermittent, new mine, or temporarily idled. The current mine type (CURRENT_MINE_TYPE) field was also filtered to only active lead mines that were either surface or underground mines.
3. 1-mile buffers were calculated for each lead mine location.
4. Site buffers were combined into a single layer, representing a 1-mile buffer around all active or intermittent lead mines in the nation.
5. The lead mine buffer layer was then intersected with geographic boundaries or census tracts and the proportion of tract area intersecting each buffer was calculated.
6. The proportion of tract area within 1-mile of a lead mine in each census tract were then sorted and assigned a percentile ranking.

References:

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Built Environment: Lack of Recreational Parks

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

Data Year: 2024

Data Source: United States Geospatial Survey (USGS) PAD-US 4.0

Rationale:

Parks and greenspaces are important healthy features of the built environment, providing spaces for physical recreation and promoting physical activity.[1-2] However, the effect of parks and greenspaces on physical activity may differ in rural contexts and by individual user characteristics.[3-4] Parks and greenspaces may also mitigate urban heat island effects[5-6] and can offer refuge on extreme heat days.[7] Close proximity and access to parks and greenspaces can also have important implications for positive mental and physical health outcomes.[8] Park design, quality, and neighborhood perceptions of safety may mediate these effects.[9-11] Additionally, while there are concerns associated with "greening" and gentrification,[12-13] parks and greenspaces provide an overall benefit to neighboring communities and the lack of access is an important issue for health equity and environmental justice.[14-16,12]

Processing Method:

1. Polygons representing areas of parks, recreational areas and public forests were downloaded from the United States Geospatial Survey PAD-US 4.0 dataset on May 13, 2024. The PAD-US 4.0 dataset contains 4 layers (Marine, Fee, Designation, and Easement Areas).

2. Park polygons were filtered from each layer, using the following criteria:
   a. For the Marine Areas layer, large open-ocean areas that are considered federally managed outer continental shelf lands that are sometimes used for natural resource extraction were excluded, as these areas are unlikely to be used for large-scale recreational use. Areas that are considered closed to the public were also removed from the dataset. The following queries were used to exclude these areas from the dataset:
      i. Open Ocean (OCS) areas were excluded from the Designation Type (Des_Tp) field.
      ii. Only areas listed as Open Access (OA), Restricted Access (RA), and Unknown Access (UA) in the Public Access (Pub_Access) field were included.
   a. For the Fee, Designation, and Easement Area layers any park or recreational area that is not openly accessible to the public was excluded from the dataset, using the following queries:
      i. State Resource Management Areas (SRMA), Local Resource Management Areas (LRMA), Private Conservation (PCON) areas, Private Parks (PPRK), Private Recreation of Education (PREC) areas, Private Historic or Cultural Areas (PHCA), Private Agricultural (PAGR) areas, Private Ranch (PRAN) areas, Private Forest Stewardship (PFOR) areas, Private Other or Unknown (POTH) areas, and Resource Management Areas (RMA) were excluded from the Designation Type (Des_Tp) field.
      ii. Only areas listed as Open Access (OA), Restricted Access (RA), and Unknown Access (UA) in the Public Access (Pub_Access) field were included.
3. The four layers were then merged together into one park polygon layer in ArcPro.
4. 1-mile buffers were calculated for each park polygon.
5. Polygon buffers were combined into a single layer, representing a 1-mile buffer around all parks, recreational areas, or public forests in the nation.
6. The parks buffer layer was intersected with the geographic boundaries of census tracts and the proportion of tract area that intersected with each buffer was calculated.
7. The proportion of tract area within a 1-mile buffer of a park, recreational area, or public forest in each census tract was sorted and assigned a percentile ranking.
8. As this indicator is intended to represent the lack of access to parks and greenspaces, the final value for this indicator was calculated by subtracting the percentile ranking from 1, in order to get the inverse score. For example, 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.

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Built Environment: Housing Built Pre-1980

Indicator: Proportion of occupied housing units built prior to 1980

Data Year: 2018-2022

Data Source: U.S. Census Bureau American Community Survey (ACS) S2504

Rationale:

Although lead-based paint was banned in 1987, older houses may pose a health risk to children who may accidently ingest lead-based paint chips.[1] Living in housing built before the ban on lead-based paint is one of the leading predictors of blood lead levels in children.[2-3] 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.[4]

Processing Method:

1. Percentage estimates of occupied housing units built prior to 1980 for each census tract in the U.S. were downloaded from the 2018-2022 American Community Survey.

2. Percentage estimates of occupied housing units built from 1960 to 1979, 1940 to 1959, and prior to 1940 for each tract were summed to determine a percentage estimate of occupied housing units built prior to 1980. (Note: ACS percentage estimates are rounded to the first decimal place.)

3. The proportion of occupied housing units built before 1980 in each census tract

were then sorted and assigned a percentile ranking.

Notes:

- The U.S. Census Bureau officially recognized Connecticut's planning regions as county equivalents beginning in 2022. As a result, the 879 Connecticut tract GEOIDs in the 2018-2022 American Community Survey (ACS) are different than in the 2020 cartographic boundary file that serves as the geography used throughout this EBI release. The EJI team used a table found at https://github.com/CT-Data-Collaborative/2022-tract-crosswalk/blob/main/2022tractcrosswalk.csv to reassign the 2020 equivalents to the 2022 ACS tracts at the variable level prior to index calculation.
- Summing the percentage estimate variables for 31 tracts yielded 100.1%. The value was capped at 100.0% as those values can be explained by margins of errors in the components.
- 750 CONUS tracts were assigned null values as ACS could not compute an estimate, due to insufficient numbers of sample observations in them.

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Built Environment: Lack of Walkability

Indicator: National Walkability Index Score

Data Year: 2021

Data Source: U.S. Environmental Protection Agency (EPA) National Walkability Index (NWI)

Rationale:

Walking is one of the most accessible methods of physical activity, due to its low cost and reduced barriers to entry. Walking for leisure or transportation can improve metabolism, lower blood sugar, and positively impact mental health.[2] Higher residential neighborhood walkability has been associated with positive health outcomes, including lower premature mortality[3], walking[4], higher overall physical activity[5], reduced obesity[5], and lower prevalence of coronary artery disease (CAD)[6]. Measures of neighborhood walkability that include street connectivity, transit stop density, and land use mix, which are all features of the EPA's National Walkability Index[7], are positively associated with various measures of accessibility for older adults[8] and persons with disabilities.[9-10] Associations between the built environment measures of walkability on health may be different in rural and urban neighborhoods[11] and may not account for physical or social factors that could mediate the effects of walkability on physical activity and health benefits.[12] Walkability nevertheless constitutes an important environmental amenity.

Processing Method:

1. National Walkability Index (NWI) scores were downloaded at the census block level for the entire nation from the U.S. EPA's NWI.
2. Census tract IDs were parsed from the census block IDs and the block level data was aggregated to the census tract level to get the average NWI score for each census tract.
3. As the data used 2010 census tracts, census tracts were converted to 2020 tracts, using the 2020 Census Tract relationship file. The data was averaged when there wasn't a 1:1 match between 2010 and 2020 census tracts.
4. The NWI scores for each census tract were sorted and assigned a percentile ranking.
5. As this indicator is intended to represent the lack of walkability, the final value for this indicator was calculated by subtracting the percentile ranking from 1 to get the inverse score. For example, the indicator value for a tract with greater walkability than 95% of all other tracts would be calculated as $1 - 0.95 = 0.05$.

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Transportation Infrastructure: High Volume Roads

Indicator: Proportion of census tract area within a 1-mile buffer of high volume streets or roadways

Data Year: 2024

Data Source: U.S. Department of Transportation (DOT) National Highway System (NHS)

Rationale:

High volume roads, such as interstate highways, can constitute major hazards to surrounding communities. Vehicular emissions, including ozone and diesel particulate matter, are a major source of air pollutants and proximity to busy roads has been associated with a number of adverse respiratory symptoms[1], childhood cancers[2], adverse birth outcomes, and overall mortality.[3] Water runoff from roads can also lead to deposition of heavy metals and other

pollutants in nearby soils and waters.[4] Noise pollution associated with traffic is also associated with significant increases in community stress[5] and can lead to elevated risk of cardiovascular disease[6] and adverse mental health outcomes[7].

Processing Method:

1. Shapefiles representing major highways and roadways were downloaded from the Department of Transportation's National Highway System on May 10, 2024.
2. 1-mile buffers were calculated for each segment of road.
3. Road buffers were combined into a single layer, representing a 1-mile buffer around all major highways and roadways in the nation.
4. The buffered roadway layer was intersected with the geographic boundaries of census tracts and the proportion of census tract that intersected each buffer was calculated.
5. The proportion of census tract area within 1-mile of a high-volume highway or roadway in each census tract was then sorted and assigned a percentile ranking.

References:

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Transportation Infrastructure: Railways

Indicator: Proportion of census tract area within a 1-mile buffer of a railway

Data Year: 2024

Data Source: U.S. Department of Transportation (DOT) National Transportation Atlas Database (NTAD)

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 and anxiety.[1] Among all transportation-associated sources of noise pollution, railway noise is associated with the most significant levels of sleep disruption and is associated with increases in stress and diastolic blood pressure.[2-3]

Processing Method:

1. Shapefiles representing railway features were downloaded from the U.S. Department of Transportation's National Transportation Atlas Database (NTAD) on May 10, 2024.
2. Railways with a network type of Abandoned Rail Line (A), Abandoned Line That has Been Physically Removed (R), Out of Service Line (X), and Trail on Former Rail Right-of-Way (T) were excluded.
3. 1-mile buffers were calculated for each segment of railway.
4. Railway buffers were combined into a single layer, representing a 1-mile buffer around all railways in the nation.
5. The railway buffer layer was intersected with geographic boundaries of census tracts and the proportion of census tract area intersecting with each buffer was calculated.
6. The proportions of census tract area within 1-mile of a railway in each census tract was sorted and assigned a percentile ranking.

References:

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Transportation Infrastructure: Airports

Indicator: Proportion of census tract area within a 1-mile buffer of an airport

Data Year: 2024

Data Source: OpenStreetMap and the U.S. Department of Transportation (DOT) National Transportation Atlas Database (NTAD)

Rationale:

Airports are important sources of noise pollution. Studies indicate that noise pollution associated with residential proximity to airports can lead to elevated levels of stress and sleep disturbance.[1-3] Airports are also important sources of air, soil, and groundwater contamination. Accidental releases from leaky storage tanks, the use of hazardous chemicals in rescue and firefighting training, and stormwater runoff all contribute to the infiltration of chemicals such as benzene, trichloroethylene, carbon tetrachloride, and a range of perfluorochemicals into soil and groundwater.[4]

Processing Method:
1. Polygons representing areas of airports with at least one runway were downloaded from OpenStreetMap on May 13, 2024.
2. Point data representing airports with at least one runway were obtained from the U.S. Department of Transportation's National Transportation Atlas Database (NTAD) on May 10, 2024. Private Airports (Ownership Codes) were excluded from the dataset, and only airports with a status of "O" (Operational) and a site type code of "A" (Airport) were included.
3. Polygon data from OpenStreetMap was merged with the point data from NTAD. For airports present in both datasets, the polygon data from OpenStreetMap was kept, and the duplicated data from NTAD was removed, to provide a more accurate representation of the area that the airport covers. If an airport was only present in one dataset, that polygon or point was kept in the final dataset.
4. 1-mile buffers were calculated for the remaining polygon and point airport data.
5. The buffered airport data was combined into a single layer, representing 1-mile buffers around all airports in the nation.

6. The airport buffer layer was intersected with the geographic boundaries of census tracts and the proportion of census tract area intersecting with each buffer was calculated.
7. The proportion of tract area within 1-mile of an airport for each census tract was then sorted and assigned a percentile ranking.

References:

1. Elmenhorst EM, Griefahn B, Rolny V, Basner M. Comparing the effects of road, railway, and aircraft noise on sleep: Exposure–Response relationships from pooled data of three laboratory studies. International journal of environmental research and public health. 2019 Mar;16(6):1073. https://doi.org/10.3390/ijerph16061073
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Water Pollution: Impaired Surface Water

Indicator: Percentage of census tract watershed area classified as impaired

Data Year: 2023

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

Rationale:

Surface waters, such as rivers and lakes, are important for recreation and fishing. 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[1] and ingesting fish from chemically-impaired waters[2] can be a significant exposure pathway for a number of pollutants that bioaccumulate in tissues.

Processing Method:

1. Impaired surface water data was downloaded from the EPA's Watershed Index Online (WSIO) database. The data contains information on surface waters defined as "impaired" (i.e., the water did not meet water quality standards under Section 303(d) of the Clean Water Act), for each watershed hydrographic unit (HUC12) in the nation.
2. HUC12 area values were translated to census tracts with a Python script that estimates the proportion of each watershed area intersecting each census tract area. This process was repeated for each tract, to approximate the percentage of area overlapping any intersecting HUC12 watershed.
3. Once the HUC12 watershed proportions for each tract's area were obtained, the percentage of water deemed impaired in each tract was calculated. The final value was rounded to three decimal places to align with the precision of the EPA source variable of percent water that is impaired. If no water was present in a tract, then the tract was assigned a 0. If no WSIO HUC12 data intersected the census tract, a null value was assigned.
4. Each census tract was then assigned a percentile ranking based on the percentage of water deemed impaired. Tracts with null values were assigned a 0 and a flag value prior to percentile ranking. (Note: 2,042 out of 83,509 (2%) of tracts had no impaired water value ("NULL"), which indicates that WSIO had no impaired water data for any intersecting HUC12s. Seven additional tracts did not intersect a HUC12 in the watershed boundary file provided by WSIO.)

References:

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2. Barbo N, Stoiber T, Naidenko OV, Andrews DQ. Locally caught freshwater fish across the United States are likely a significant source of exposure to PFOS and other perfluorinated compounds. Environmental Research. 2023 Mar 1;220:115165. https://doi.org/10.1016/j.envres.2022.115165

Health Vulnerability Module

Health Vulnerability refers to pre-existing chronic health conditions that can make people more susceptible to the effects of pollution. This idea is closely linked with the idea of biological susceptibility, intrinsic traits, including pre-existing health conditions, that can have an influence on how much environmental factors like pollution actually affect people's health[1]. For example, people with asthma are more sensitive to outdoor air pollution, which can cause an increase in asthma attacks and asthma-related doctor visits. As conditions like asthma can modify the effects that environmental factors have on people's health, understanding how common conditions, like asthma, are in communities can tell us which communities might be the most affected by environmental pollution.

References:
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3. Centers for Disease Control and Controlling Asthma. Atlanta, GA: Centers for Disease Control and Prevention, National Center for Environmental Health, Division of Environmental Science and Practice, Asthma and Community Health Branch. 2024 January 22. Accessed 9/8/2024.

High Estimated Prevalence of Asthma

Indicator: Estimated prevalence of asthma among adults greater than for 66.66% of U.S. census tracts (2024)

Data Year: 2024

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

Rationale:
Outdoor air pollution is associated with increases in asthma attacks and asthma-related ED visits.[1] Inhaling pollutants, such as $PM_{2.5}$, ozone, and diesel particulate matter, can lead to oxidative stress, which inflames the airways and exacerbates asthma symptoms.[2-5]

Processing Method:
1. Data on asthma prevalence at the census tract level was downloaded for all 50 U.S. States and the District of Columbia from the 2024 PLACES estimates.
2. Data for Alaska and Hawaii were removed from the dataset, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the

EJI" above).

3. Tracts were assigned percentile ranks based on the estimated asthma prevalence.
4. Tracts were assigned a flag 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.

References:

1. Centers for Disease Control and Prevention. Atlanta, GA. Air Pollutants. 2024 February 16. Accessed 9/8/2024.
2. Orellano P, Quaranta N, Reynoso J, Balbi B, Vasquez J. Effect of outdoor air pollution on asthma exacerbations in children and adults: systematic review and multilevel meta-analysis. PloS one. 2017 Mar 20;12(3):e0174050.
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High Estimated Prevalence of Cancer

Indicator: Estimated prevalence of all-cause cancer (excluding skin cancer) among adults greater than for 66.66% of U.S. census tracts (2024)

Data Year: 2024

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

Rationale:

Increases in $PM_{2.5}$ are associated with increased all-cause mortality for young adult cancer patients diagnosed with all cancer types.[1] Long-term exposure to $PM_{2.5}$, ozone, and other air pollutants is associated with increased morbidity and mortality in persons diagnosed with cancer, including lung cancer,[2,3] liver cancer,[4] pediatric lymphomas, and CNS tumors.[1] 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.[5]

Processing Method:

1. Data on cancer prevalence at the census tract level was downloaded for all 50 U.S. States and the District of Columbia from the 2024 PLACES estimates.
2. Data for Alaska and Hawaii were removed from the dataset, due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Tracts were assigned percentile ranks based on the estimated cancer prevalence.
4. Tracts were assigned a flag 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.

References:

1. Ou JY, Hanson HA, Ramsay JM, Kaddas HK, Pope III CA, Leiser CL, VanDerslice J, Kirchhoff AC. Fine particulate matter air pollution and mortality among pediatric, adolescent, and young adult cancer patients. Cancer Epidemiology, Biomarkers & Prevention. 2020 Oct 1;29(10):1929-39.
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5. Ljubimova JY, Braubach O, Patil R, Chiechi A, Tang J, Galstyan A, Shatalova ES, Kleinman MT, Black KL, Holler E. Coarse particulate matter (PM2. 5–10) in Los Angeles Basin air induces expression of inflammation and cancer biomarkers in rat brains. Scientific reports. 2018 Apr 9;8(1):5708.

High Estimated Prevalence of Coronary Heart Disease

Indicator: Estimated prevalence of coronary heart disease among adults greater than for 66.66% of U.S. census tracts (2024)

Data Year: 2024

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

Rationale:
Research indicates associations between air pollution and higher rates of cardiovascular disease, as well as increased morbidity and mortality associated with cardiovascular disease.[1,2] Coronary heart disease (CHD) is a form of cardiovascular disease, caused by plaque buildup in arteries,

which can increase risk for heart attack or cardiac arrest.[3] Both acute and long-term exposure to air pollutants, including $PM_{2.5}$, nitrogen dioxide (NO^2), and measures of multiple air pollution have been associated with risk for hospitalization among those with CHD.[4-6]

Processing Method:

1. Data on the prevalence of coronary heart disease at the census tract level was downloaded for all 50 U.S. States and the District of Columbia from the 2024 PLACES estimates.
2. Data for Alaska and Hawaii were removed from the dataset due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Tracts were assigned percentile ranks based on the estimated prevalence of coronary heart disease.
4. Tracts were assigned a flag score of 1 if the estimated prevalence of coronary heart disease 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.

References:

1. Liang F, Liu F, Huang K, Yang X, Li J, Xiao Q, Chen J, Liu X, Cao J, Shen C, Yu L. Long-term exposure to fine particulate matter and cardiovascular disease in China. Journal of the American College of Cardiology. 2020 Feb 25;75(7):707-17.
2. Wolf K, Hoffmann B, Andersen ZJ, Atkinson RW, Bauwelinck M, Bellander T, Brandt J, Brunekreef B, Cesaroni G, Chen J, de Faire U. Long-term exposure to low-level ambient air pollution and incidence of stroke and coronary heart disease: a pooled analysis of six european cohorts within the ELAPSE project. Lancet Planet Health 5 (9): e620–e632, PMID: 34508683.
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High Estimated Prevalence of Diabetes

Indicator: Estimated prevalence of diabetes among adults greater than for 66.66% of U.S. census

tracts (2024)

Data Year: 2024

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

Rationale:

Research suggests that air pollution, such as $PM_{2.5}$, can cause oxidative stress and inflammation, leading to impairments in insulin signaling associated with diabetes.[1] Several meta-analyses show significant associations between $PM_{2.5}$ exposure and the risk of type 2 diabetes,[2,3] even when adjusted for obesity.[4] Proximity to hazardous sites and land use, including proximity to high volume roads and associated noise pollution, have also been associated with increased risk of hospitalization among individuals with diabetes.[5]

Processing Method:

1. Data on the prevalence of diabetes at the census tract level was downloaded for all 50 U.S. States and the District of Columbia from the 2024 PLACES estimates.
2. Data for Alaska and Hawaii were removed from the dataset due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Tracts were assigned percentile ranks based on the estimated prevalence of diabetes.
4. Tracts were assigned a flag 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.

References:

1. Meo SA, Memon AN, Sheikh SA, Rouq FA, Usmani A, Hassan A, Arain SA. Effect of environmental air pollution on type 2 diabetes mellitus. European Review for Medical & Pharmacological Sciences. 2015 Jan 1;19(1).
2. Liu F, Chen G, Huo W, Wang C, Liu S, Li N, Mao S, Hou Y, Lu Y, Xiang H. Associations between long-term exposure to ambient air pollution and risk of type 2 diabetes mellitus: a systematic review and meta-analysis. Environmental pollution. 2019 Sep 1;252:1235-45.
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heart association. 2020 Mar 17;9(6):e013021.

High Estimated Prevalence of Poor Mental Health

Indicator: Estimated prevalence of poor mental health for ≥ 14 days among adults greater than for 66.66% of U.S. census tracts (2024)

Data Year: 2024

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

Rationale:

Poor mental health can be caused and exacerbated by negative environmental quality. One study found that residential proximity to industrial activity negatively impacts mental health by impacting individual perceptions of neighborhood disorder and personal powerlessness, with these effects being most prominent in racial/ethnic minority populations and populations in poverty.[1] 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.[2] 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 increased stress and poor sleep.[3]

Processing Method:

1. 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 Columbia from the 2024 PLACES estimates.
2. Data for Alaska and Hawaii were removed from the dataset due to a lack of some key environmental data for these areas (see "Limitations and Considerations of the EJI" above).
3. Tracts were assigned percentile ranks based on the estimated prevalence of poor mental health.
4. Tracts were assigned a flag 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.

References:

1. Downey L, Van Willigen M. Environmental stressors: the mental health impacts of living near industrial activity. Journal of health and social behavior. 2005 Sep;46(3):289-305.
2. Khan A, Plana-Ripoll O, Antonsen S, Brandt J, Geels C, Landecker H, Sullivan PF, Pedersen CB, Rzhetsky A. Environmental pollution is associated with increased risk

of psychiatric disorders in the US and Denmark. PLoS biology. 2019 Aug 20;17(8):e3000353.

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Climate Burden Module

Climate change has led to the increase in extreme events over the last decade, greatly impacting the communities within them and increasing morbidity and mortality. These events include wildfires, flooding events, droughts, storms, and extreme heat, all which are expected to intensify with global warming. [1] Events can also exacerbate existing environmental conditions in an area, leading to higher burden within the community. The U.S. Global Change Research Program notes that climate variability and changes in weather extremes can affect much of the environment including air, food, water, shelter, and security.[2] Climate events will lead to higher risks for illnesses including heat-related illness, vector-borne diseases, worsening mental health, and chronic diseases.[3]

Not everyone is impacted equally by these events; some populations are more at risk for event related illness and mortality. Factors like age, socioeconomic status, and preexisting health conditions all contribute to how people are able to respond to and recover from climate-related events.[1] The EJI has added a climate burden module to be used with the existing EJI structure to be able to capture the additional environmental burden that exposure to historic climate related events adds to a community. Data in this module represent the additional cumulative impacts that measures of climate change have on health and well-being. The climate module captures historic data from past climate event occurrence. Data are divided into three domains: 1) Heat, 2) Extreme events, and 3) Wildfires.

References:

1. USGCRP, 2023: Fifth National Climate Assessment. Crimmins, A.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, B.C. Stewart, and T.K. Maycock, Eds. U.S. Global Change Research Program, Washington, DC, USA. https://doi.org/10.7930/NCA5.2023
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Heat: Extreme Heat Days

Indicator: Annual Mean Number of Extreme Heat Days

Data Year: 2018-2022

Data Source: CDC's National Environmental Public Health Tracking Network

Rationale:

Heat exposure, occurring over a range of temperatures, can cause deaths and illnesses. In particular, extreme heat may contribute to additional negative health impacts where people are unable to cool off quickly or do not have access to air-conditioned areas. Heat can also exacerbate underlying health conditions, like cardiovascular disease and respiratory conditions like asthma.[1-3] Electrolyte imbalances due to dehydration can also lead to problems with kidneys, such as kidney stones and renal failure.[4,5] Disparities exist in how people experience heat, particularly in regard to socioeconomic status (ability to afford to cool off ones living quarters) and environmental exposures, such as air quality and built environment factors.[6,7]

Processing Method:

1. The number of extreme heat days were downloaded from the CDC's National Environmental Public Health Tracking Network for 2018-2022. The number of extreme heat days measure is derived from the census tract number of extreme heat days, using a threshold of the 95th percentile of temperature distribution that is specific to each census tract. (**Note**: For the estimates of the number of extreme heat days (E_NEHD), 13 tracts were missing data. These tracts were assigned a value by interpolating the average values of their neighboring tracts.)
2. The census tract measure was cross-walked from 2010 census tracts to 2020 census tracts.
3. The annualized frequency of tract-specific extreme heat days was calculated by taking the sum of the number of extreme heat days and dividing by the number of years observed (5 years).
4. Tracts were assigned percentile ranks based on the annualized frequency of extreme heat days.
5. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0 but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
6. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

References:

1. Liu J, Varghese BM, Hansen A, Zhang Y, Driscoll T, Morgan G, Dear K, Gourley M, Capon A, Bi P. Heat exposure and cardiovascular health outcomes: a systematic review and meta-analysis. The Lancet Planetary Health. 2022 Jun 1;6(6):e484-95.

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Wildfire: Wildfire Smoke

Indicator: Average annualized frequency of smoky days from wildfire smoke **Data Year:** 2013 - 2022

Data source: NOAA; OSPO (Office of Satellite and Product Operations)

Rationale:
Climate change has influenced the frequency, duration, and intensity of wildfires, presumably due to hotter temperatures and droughts.[1,2] Wildfires can impact human health in many ways. Wildfires in close proximity to residential areas can be exposed through flame and smoke-related impacts, and can result in loss of life and other severe physical and mental health consequences.
Wildfire smoke contains a hazardous mixture of air pollutants like fine and course particulate matter and ozone.[2-4] Smoke exposure can range far and wide from the actual fire source, often being documented hundreds of miles away from the fire source.[5,6] Studies have shown that hospital visits increase in areas exposed to wildfire smoke.[5-7] Smoke exposure primarily affects the respiratory system, including ear, nose, and throat, but can lead to eye irritation and have negative health consequences to the cardiovascular system. More serious respiratory disorders can also occur including reduced lung function, bronchitis, and asthma. Smoke exposure can also contribute to and exacerbate cardiovascular disease, including heart failure. Several populations are particularly

vulnerable to the effects of wildfire smoke, including the very young, pregnant women, older adults, and those with preexisting health conditions like asthma and cardiovascular disease.[4,8]

Processing Method:

1. Shapefiles representing wildfire smoke cover for every day were downloaded for years 2013 through 2022.
2. Only medium and heavy density smoke were used, 'light' smoke was filtered out.
3. All polygons were dissolved within each day's dataset to get rid overlapping data for each day.
4. The intersection between each census tract and the smoke cover for each day was calculated.
5. The sum of the intersections was calculated to get the total number of smoky days over the 10-year period for each census tract.
6. An annualized frequency was calculated by taking the sum of observed intersections and dividing by number of years observed (10 years) to get the average number of smoky days experienced by each census tract.
7. Tracts were assigned percentile ranks based on the annualized frequency of smoky days.
8. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
9. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

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Wildfire: Wildfire Proximity

Indicator: Average annualized burned area from wildfires

Data Year: 2013 - 2022

Data source: USGS EROS, USDA, GTAC; MTBS (Monitoring Trends in Burn Severity)

Rationale:

Climate change has influenced the frequency, duration, and intensity of wildfires, presumably due to hotter temperatures and droughts.[1,2] Wildfires can impact human health in many ways. Close proximity wildfires can cause loss of life and severe health outcomes. Loss of property and residences impact mental health, and the stress of experiencing these events can lead to other negative health consequences. Wildfire smoke contains a hazardous mixture of air pollutants like fine and course particulate matter and ozone, and closer proximity can lead to increased smoke exposure.[2-4] Studies have shown that hospital visits increase in areas exposed to wildfire smoke.[5-7] Smoke exposure primarily affects the respiratory system, including ear, nose, and throat, but can lead to eye irritation and have negative health consequences to the cardiovascular system. More serious respiratory disorders can also occur including reduced lung function, bronchitis, and asthma. Smoke exposure can also contribute to and exacerbate cardiovascular disease, including heart failure. Several populations are particularly vulnerable to the effects of wildfire smoke, including the very young, pregnant women, older adults, and those with preexisting health conditions, like asthma and cardiovascular disease.[4,8]

Processing Method:

1. Shapefiles representing burned areas were downloaded for years 1984 through 2022, however, only years 2013 through 2022 were used.
2. Additionally, only wildfires (Incid_Type = Wildfire) over 1,000 acres were used.

3. All polygons were dissolved within each year to rid the data of overlaps for each year.
4. The intersection between each census tract and the burned area for each year was calculated.
5. The sum of the intersection percentage was calculated.
6. The annualized average was calculated by taking the sum of the intersection percentage and dividing by the number of years observed (10 years).
7. Tracts were assigned percentile ranks based on the annualized average area burned by a wildfire.
8. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
9. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

References:

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Extreme Events: Coastal Flooding Frequency

Indicator: Modeled frequency of coastal flooding occurrence in events per year

Data Year: 1996-2019

Data Source: Federal Emergency Management Association, National Risk Index, Coastal Flooding Annualized Frequency Variable

Rationale:

Storm surges and coastal flooding are increasing in frequency and extent and are predicted to increase in the future.[1-3] Both coastal and riverine flooding are a related to many health outcomes. Drowning is a common flooding risk when people try to drive or walk through high waters. Flooded roads also limit access to critical resources and needed facilities and resources, including healthcare.[4] Bacteria can also spread through flood water exposure causing illnesses like gastrointestinal diseases.[5] A study of indoor mold found that coastal homes that have previously flooded are more prone to have mold, specifically Aspergillus and Penicillium, which can contribute to several health risks including upper respiratory tract symptoms.[6] Past coastal flooding events have also led to the release of industrial and hazardous waste from flooded contamination sites.[3,7] Studies have found that contaminant releases from flooding events are more likely to impact low-income households, as they are more likely to live near the hazardous facilities.[3,7]

Processing Method:

1. The annualized frequency of coastal flooding was downloaded at a census tract level.
2. Tracts were assigned percentile ranks based on the annualized frequency of coastal flooding.
3. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
4. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.
5. Any tract who had no data present for annualized frequency was then set to 0.

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Extreme Events: Drought Frequency

Indicator: Number of recorded drought occurrences in event-weeks each year for the period of record

Data Year: 2000 - 2021

Data Source: Federal Emergency Management Association, National Risk Index, Drought Annualized Frequency Variable

Rationale:
Drought conditions are changing across the U.S., with extended periods of drought becoming more frequent.[1,2] Exposure to drought can impact human health both directly and indirectly. The increase of drier conditions in areas due to drought can lead to adverse health outcomes, including asthma and allergies related to more dust in the air. Drought events can also contribute to reduced water quality for populations that rely on water sources that are within drought regions.[2] For example, a recent

study modeled arsenic concentrations in private wells and found higher levels of arsenic in well water associated with increasing durations of drought.[3] Drought can also contribute to the dry conditions that exacerbate wildfires, prolonging the events and making them more widespread, which as noted in the section above, can contribute to many health effects.[1]

Processing Method:
1. The annualized frequency of drought drought weeks was downloaded at a census tract level from the National Risk Index (NRI). The NRI only uses extreme and exceptional drought weeks for their annualized frequency measure.
2. Tracts were assigned percentile ranks based on the annualized frequency of drought.
3. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
4. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

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Extreme Events: Riverine Flooding Frequency

Indicator: Number of riverine flooding occurrences in event days each year over the period of record

Data Year: 1996 – 2019

Data Source: Federal Emergency Management Association, National Risk Index, Riverine Flooding Annualized Frequency Variable

Rationale:
The U.S. Global Research Program Climate and Health Assessment highlights that extreme events

leading to flooding have increased nationally over the last few decades, primarily in the Midwest and Northeast.[1] When flooding events occur more often and strain local infrastructures, populations are at risk for a multitude of related health outcomes. Similar to coastal flooding, riverine flooding can cause traumatic injury and drowning risk in high waters when people try to drive or walk through water. Mold growth due to sustained wet and moist conditions can exacerbate asthma and respiratory symptoms, particularly in people with suppressed immune systems.[2-5] Flooded roads limit access to needed resources including to needed facilities like healthcare. Additionally, disruption to water and sewage infrastructure can spread bacteria and parasitic infections through contact with flood water.[6] Studies have also shown that health burdens after floods are unequally distributed amongst age, minority, and socioeconomic groups after flooding events.[7-9]

Processing Method:
1. The annualized frequency of riverine flooding was downloaded at a census tract level.
2. Tracts were assigned percentile ranks based on the annualized frequency of riverine flooding.
3. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
4. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

References:

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Extreme Events: Hurricane Frequency

Indicator: Number of recorded hurricane occurrences in events each year

Data Year: 1851 – 2020

Data Source: Federal Emergency Management Association, National Risk Index,
Hurricane Annualized Frequency Variable

Rationale:
Hurricane frequency and intensity have increased in the last 30-40 years.[1] These events are predicted to increase as water and air temperatures warm. Both winds and floods from these events can lead to deaths and exacerbations of pre-existing health conditions. Similar to riverine and coastal flooding, hurricanes can cause water levels to rise, resulting in severe injuries and deaths due to drowning, traumatic injury, or bacteria or mold exposure. Mold growth due to sustained wet and moist conditions can exacerbate asthma and respiratory symptoms, particularly in people with suppressed immune systems.[2-5] Past hurricane and flooding events have also led to the release of industrial and hazardous waste from flooded contamination sites .[6,7] Studies have found that contaminant releases from flooding events are more likely to impact low-income households because they are more likely to live near the hazardous facilities.[6,7] Damages to property and infrastructure and loss of power can limit the ability of populations to access needed health care, medicine, and essentials like food and potable water.[8] Improper use of electrical generators can also lead to carbon monoxide poisoning, which can

cause severe health effects and death.[9,10]

Processing Method:

1. The annualized frequency of hurricanes was downloaded at a census tract level.
2. Tracts were assigned percentile ranks based on the annualized frequency of hurricanes.
3. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.
4. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.
5. Any tract who had no data present for annualized frequency was then set to 0.

References:

1. Ebi, K.L., J.M. Balbus, G. Luber, A. Bole, A. Crimmins, G. Glass, S. Saha, M.M. Shimamoto, J. Trtanj, and J.L. White-Newsome, 2018: Human Health. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 539–571. doi: 10.7930/NCA4.2018.CH14
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Extreme Events: Tornado Frequency

Indicator: Average Annual Number of Tornadoes

Data Year: 1986-2024

Data Source: CDC's National Environmental Public Health Tracking Network

Rationale:

Tornadoes can have profound impacts on public health and safety. Tornadoes of all scale ratings pose some risk of injury or death, mostly linked the strong winds, associated airborne debris, and direct damage to property and sheltering space. In particular, people who live in a mobile home, are aged 60 years and older, or who lack physical protection to shelter within, are more likely to experience injuries or die because of tornados.[1] Tornadoes can also cause indirect health effects when damages affect access to essential items and services such as medicines, health care, and potable water.[2] The influence of climate change on patterns of tornado occurrence is unclear. Since the 1970's, research suggests that there has not been a significant change in the number of tornadoes or tornado outbreaks occurring in the United States, however the frequency of large tornado outbreaks is increasing, potentially including an increase in the number of tornadoes associated with each outbreak.[3,4]

Processing Method:
1. The annualized frequency of tornadoes was downloaded at a census tract level.
2. Tracts were assigned percentile ranks based on the annualized frequency of tornadoes.
3. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0 but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.

4. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

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Extreme Events: Strong Winds Frequency

Indicator: Number of recorded strong wind occurrences in events each year over the period of record

Data Year: 1986 – 2019

Data Source: Federal Emergency Management Association, National Risk Index,
Strong Wind Annualized Frequency Variable

Rationale:
Similar to hurricane and tornadoes, strong winds can contribute to multiple direct or indirect injuries or death.[1,2] Winds can cause physical impalement and traumatic injury or death. The loss of power and damage to infrastructure can impair people's abilities to access needed care and resources. Research has found that during high wind events, emergency department visits for injuries increased overall, with greater risks in injuries in older adults and people on Medicaid.[3] Widespread and sustained windstorms, termed "derecho", have been responsible for a number of fatalities and injuries across the United States.[4] Infrastructure damage from strong winds has also led to electrocutions and burns from fires.[2] Improper use of electrical generators can also lead to carbon monoxide poisoning, which can cause severe health effects and death .[2,5]

Processing Method:
1. The annualized frequency of strong winds was downloaded at a census tract level.
2. Tracts were assigned percentile ranks based on the annualized frequency of strong wind.
3. Tracts were assigned a flag of 0 if the annualized frequency was 0. Tracts were

assigned a flag of 1 if there was no data present for the annualized frequency. Tracts were assigned a flag of 2 if their percentile rank was 0, but their annualized frequency was greater than 0. All other tracts were assigned a flag of 9.

4. After flags were set, the percentile rank was set to 0 for any tract whose annualized frequency was 0 for any tract that had no data present for the annualized frequency.

References:
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3. Sheridan SC, Zhang W, Deng X, Lin S. The individual and synergistic impacts of windstorms and power outages on injury ED visits in New York State. Sci Total Environ. 2021 Nov 25;797:149199. doi: 10.1016/j.scitotenv.2021.149199. Epub 2021 Jul 21. PMID: 34346383.
4. Ashley WS, Mote TL. Derecho hazards in the United States. Bulletin of the American Meteorological Society. 2005 Nov;86(11):1577-92.
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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.

- The EJI 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 are expected to 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.

- Source data for several indicators within the Environmental Burden Module and Climate Burden Module excluded tracts where specific environmental hazards or climate events were unlikely to occur. Rather than exclude these tracts, the EJI includes them with an assigned value of zero. Further details and identification of these tracts can be found in the "F_" variables within the Environmental Burden and Climate Burden Modules.

- Some data on extreme events from the Federal Emergency Management Agency's National Risk Index include adjustments for minimum annual frequency (MAF). MAFs are assigned to communities that have not experienced a hazard occurrence recorded by source data but are determined to be at some level of risk. EJI Indicators based on data where MAFs were applied are 1) Hurricane Frequency, and 2) Riverine Flooding Frequency. For more information on MAFs, how they were determined, and how they were applied, please see FEMA | National Risk Index Technical Documentation.

- Some indicators (e.g., ozone, PM2.5, diesel particulate matter, air toxics cancer risk, and lack of walkability) were only available using 2010 census tract geographies from the original data source. In these cases, the data were cross-walked to 2020 using the 2020 Census Tract relationship file from the U.S. Census Bureau. More information on how those indicators were cross-walked, including how data was cross-walked when there wasn't a 1:1 match between years can be found in the Processing Methods for those indicators.

- Many of the indicators included in the EJI represent estimates with unique methods and calculations. Caution should be taken when adapting, merging, or using estimates in additional calculations. Specific estimate calculations are detailed by agency of origin.

- Special considerations should be taken before using statistical hypothesis-based testing on ranked variables as parametric testing may not be appropriate.

- Questions? Please visit the EJI website at eji.cdc.gov for additional information or email the EJI Coordinator at eji_coordinator@cdc.gov.