Washington Environmental Health Disparities Map

Cumulative Impacts of Environmental Health Risk Factors Across Communities of Washington State

DOH 311-011 July 2022
Updated July 2022
Version 2.0

Washington State Department of Health

ENVIRONMENTAL & OCCUPATIONAL HEALTH SCIENCES
SCHOOL OF PUBLIC HEALTH
UNIVERSITY of WASHINGTON

This technical report was prepared by the University of Washington (UW) Department of Environmental & Occupational Health Sciences and edited by UW and the Washington State Department of Health (DOH) to document the methodology of the Washington Environmental Health Disparities Map, version 2.0.

The UW Environmental Health Disparities Map Team included Tripura Talagadadeevi, Joey Frostad, Esther Min, and Edmund Seto.

The DOH Washington Tracking Network Team included Alli Ertl, Jennifer Sabel, Chris Ahmed, and Jeff Bryant.

Suggested citation: University of Washington Department of Environmental & Occupational Health Sciences and Washington State Department of Health. Washington Environmental Health Disparities Map: Cumulative Impacts of Environmental Health Risk Factors Across Communities of Washington State: Technical Report Version 2.0. 2022.

* For questions, comments, and feedback, please contact DOH team: Washington Tracking Network Team at EHDmap@doh.wa.gov or UW EHD Map Team envmap@uw.edu.

Version 1.0 of the Washington Environmental Health Disparities Map was the result of a collaborative effort among partners from the University of Washington Department of Environmental & Occupational Health Sciences (DEOHS), Front and Centered, the Washington State Department of Health (DOH), the Washington State Department of Ecology (ECY) and the Puget Sound Clean Air Agency (PSCAA). The research team included: Esther Min, Edmund Seto, Michael Yost (DEOHS); Deric Gruen, Front and Centered; Tina Echeverria, Lauren Freelander, Lauren Jenks, Paj Nandi, Glen Patrick, Jennifer Sabel (DOH); Millie Piazza (ECY); Erik Saganic and Michael Schmeltz (PSCAA).

Washington Environmental Health Disparities Map Comparing Environmental Health Risk Factors Across Communities

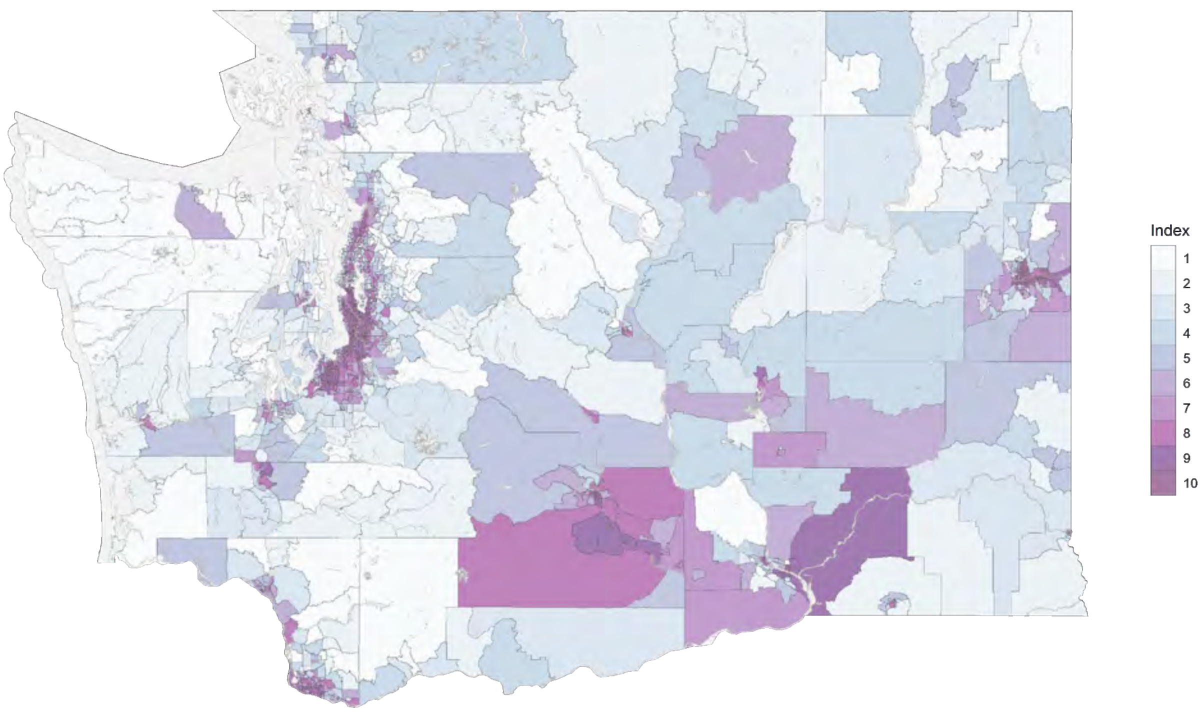


Table of Contents

Acknowledgments

This Environmental Health Disparities Map (EHD) 2.0 version relies heavily on the workgroup that launched the inaugural version 1.0 of the EHD map. Version 1.0 of the Washington EHD Map was the result of a collaborative effort among partners from the University of Washington Department of Environmental & Occupational Health Sciences (DEOHS), Front and Centered, the Washington State Department of Health (DOH), the Washington State Department of Ecology (ECY) and the Puget Sound Clean Air Agency (PSCAA).

The research team included: Esther Min, Edmund Seto*, Michael Yost (DEOHS); Deric Gruen, Front and Centered; Tina Echeverria, Lauren Freelander, Lauren Jenks, Paj Nandi, Glen Patrick, Jennifer Sabel (DOH); Millie Piazza (ECY); Erik Saganic and Michael Schmeltz (PSCAA).

Jill Schulte, Farren Thorpe and Rylie Ellison at the Department of Ecology Air Quality Program provided updates to the air quality indicators and documentation, based on the discussion from an air quality indicator meeting June 2021 including Jill Schulte, Millie Piazza, Rob Dengel, Sean Lundblad (ECY), Elise Rasmussen, Jennifer Sabel, Julie Fox, Lauren Freelander, Rad Cunningham (DOH), Erik Saganic (PSCAA), Edmund Seto, Esther Min, Joel Kaufman, Jon Wakefield, Lianne Sheppard, Michael Young, Mike Yost, and Nancy Carmona (UW).

We also acknowledge the contributions of the people statewide who participated in the 11 community listening sessions in 2017 that directly shaped the development of the first Washington EHD Map. Your contributions made this tool significantly more robust, comprehensive, and useful.

List of Abbreviations

ACS: American Community Survey

AIRPACT: Air Indicator Report for Public Awareness and Community Tracking

CalEPA: California Environmental Protection Agency

CDC: US Centers for Disease Control and Prevention

CERCLIS: Comprehensive Environmental Response, Compensation, and Liability Information System

CNT: Center for Neighborhood Technology

COPD: Chronic Obstructive Pulmonary Disease

DEOHS: University of Washington Department of Environmental & Occupational Health Sciences

DOH: Washington State Department of Health

ECY: Washington State Department of Ecology

EJ: Environmental Justice

HEAL: Healthy Environment for All Act (SB 5141, 2021)

IBL: Information By Location tool on the Washington Tracking Network

MOE: Margin of Error

NPL: National Priorities List

OFM: Washington State Office of Financial Management

PM: Particulate Matter

PSCAA: Puget Sound Clean Air Agency

RMP: Risk Management Plan

RSEI: Risk-Screening Environmental Indicators

TRI: Toxic Release Inventory

TSDF: Hazardous Waste Treatment Storage and Disposal Facilities

US EPA: US Environmental Protection Agency

WTN: Washington Tracking Network (Washington State Department of Health)

Executive Summary

People living in Washington state experience environmental risks and their related health effects in measurably different ways, depending on the neighborhood where they live.

People in communities that have lower incomes, less access to education and health care, and poorer overall health also shoulder a disproportionate share of the burden of environmental pollution. This is because their neighborhoods are more often located near pollution sources, such as vehicle traffic or hazardous waste facilities.

In short, where you live, your income, your race, or your language ability may put you at greater risk for exposure to the harmful health effects of environmental pollution.

The Washington Tracking Network's Environmental Health Disparities Map is an interactive tool that combines the most comprehensive data available to rank Washington communities according to the risk each faces from environmental factors that influence health outcomes.

The tool uses state and national data to map 19 indicators of community and environmental health, including traffic density, proximity to hazardous waste facilities, income and race. The data are combined into a cumulative score reflecting environmental and socioeconomic risk factors that allows for comparison across Washington's 1,458 US census tracts.

The result is a statewide view of the cumulative risks each neighborhood in Washington state faces from environmental burdens that contribute to inequitable health outcomes and unequal access to healthy communities.

The Environmental Health Disparities Map can help policymakers and the public visualize and compare how pollution and other environmental risks affect the health and wellbeing of Washington residents and where people experience the greatest health impacts.

The tool was developed in response to community interest by an innovative, cross-sector collaboration among academic researchers, government agencies and community-based organizations representing disadvantaged and underrepresented populations seeking to use data to advance environmental health equity.

About the Washington Environmental Health Disparities Map

The version 2.0 of the EHD Map reflects on the cumulative health impacts of environmental risk on communities. The map highlights pollution burden and vulnerabilities to inform state environmental policy, budgeting priorities and regulation enforcement to reduce health inequities across communities. We urge state and local decision-makers, in particular, to use this tool in tandem with direct community engagement to shape environmental policies and priorities and to support investments that would update, expand, and improve the mapping tool so that it can reach its full potential as a resource for the people of Washington.

Key details about the map:

- This online tool is hosted by the Washington State Department of Health through its Washington Tracking Network, a platform featuring publicly accessible data on more than 300 measures of state environmental and public health.
- Version 1 of the tool was developed through a two-year iterative process that was directly shaped by input from affected communities through a series of 11 statewide listening sessions. Participants included community groups representing communities of color, immigrants, tribes, farmworkers, the elderly and other groups disproportionately impacted by pollution.
- The mapping tool is modeled after a similar, widely used tool in California but is unique to Washington state. It offers customizable views using data from the Washington State Department of Health and other state and federal sources to pinpoint where people experience the greatest environmental health risk factors.
- The evidence and approaches used to develop the map are built on decades of science documenting cumulative environmental impacts and the role environmental hazards and social conditions play in magnifying those impacts.
- The map will be regularly refreshed and updated with the most current and relevant data available and through ongoing conversations with communities and users. It is important to highlight the tool's limitations. It relies on currently available statewide data. There are gaps in the data that prevent us from characterizing the full scope of environmental risks and health impacts experienced by people living in Washington. Parallel projects that capture data at the local level and that focus on environmental resilience to climate impacts are also needed.

Introduction

Washington state has a long history of efforts led by tribes, community-based organizations, policymakers, local governments and state agencies to document and act on reducing environmental health inequalities.

Tracking these efforts and ensuring decision-makers and advocates have access to current, easy-to-understand data on environmental hazards, exposure to pollution, and vulnerable populations is vital to inform state policy and budget decisions that can best address environmental justice issues.

The primary goal for the EHD map is to identify communities most affected by cumulative environmental health impacts. The resulting tool ranks environmental health risks by census tract to identify communities burdened by the cumulative impacts of pollution. In addition, this tool identifies environmental health indicators by census tract, providing useful, data-driven insights for communities, policymakers, government leaders and others.

The EHD Map depicts cumulative health impact as a ranking from 1 to 10, with 10 indicating the highest impact. These rankings reflect the risk each community faces from multiple environmental hazards and the degree to which a community is more vulnerable to those hazards because of sociodemographic factors.

The rankings represent environmental health “risk”—the potential or probability for harm from a combination of environmental and vulnerability factors.

The map does not depict the more complex concept of environmental health “burden”—typically defined as the magnitude of poor health due to injuries or illnesses caused by environmental hazards. Measuring environmental health burden would also require consideration of genetic, behavioral, or other types of risk.

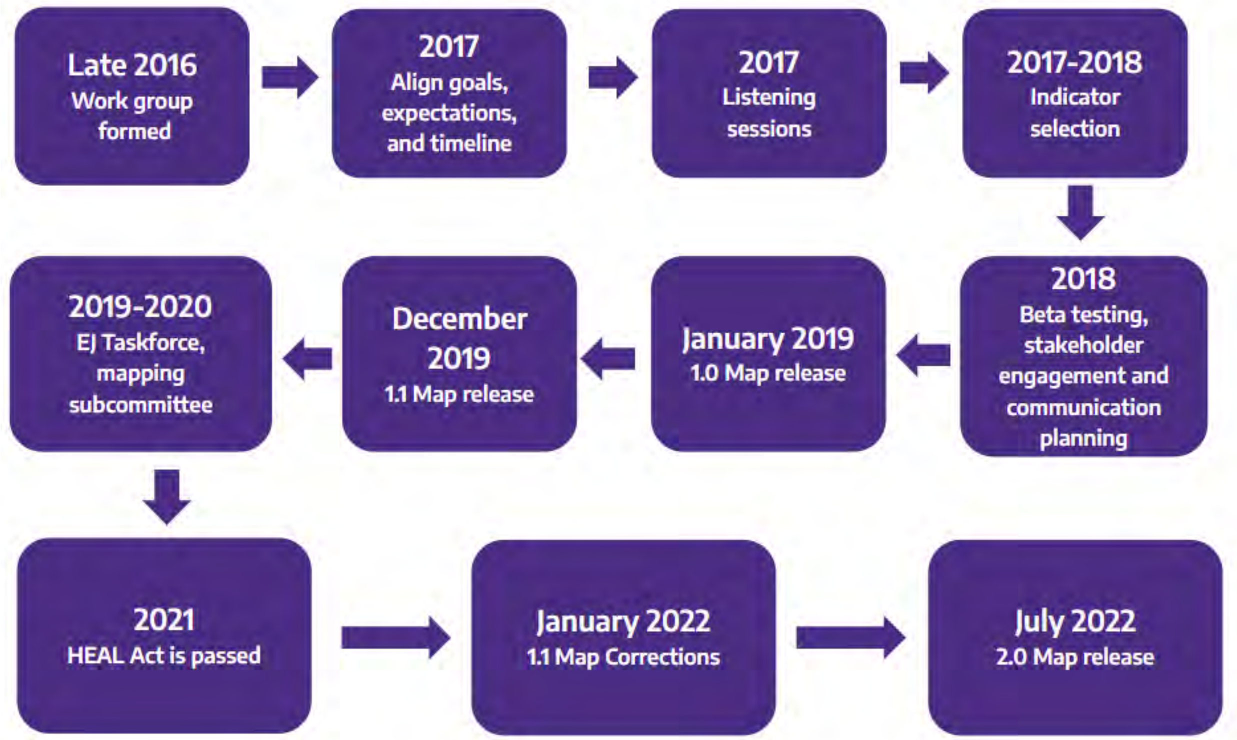
In a limited sense, the tool incorporates health outcomes as a vulnerability. For example, a high level of chronic disease in a community could increase the risk that exposures to environmental hazards lead to even greater harm to the community.

Timeline

In preparation for version 1.0, in fall 2016, the Washington Environmental Justice Mapping Work Group was initiated by Front and Centered, an environmental justice coalition of organizations rooted in communities of color, in partnership with the University of Washington Department of Environmental & Occupational Health Sciences. Through this coalition, we brought together partners from the Washington State Department of Health, the state Department of Ecology and the Puget Sound Clean Air Agency. In 2017, the EJ Mapping Work Group began with a process of listening to communities and engaging stakeholders. The work group listened to Washington state residents who responded to prompts about the environmental issues that are most concerning to their communities. We reviewed existing methods and tools that modeled environmental health impacts and disparities on communities, such as US EPA EJSCREEN and CalEPA CalEnviroScreen. The work group conducted a literature review on the relationship between the proposed indicators and environmental health and identified possible data sources for the proposed indicators. Once a data source was identified for an indicator, it was evaluated and assessed for reliability and quality of data. The 1.0 version was released in January 2019.

The Washington Department of Health (DOH) released two updates to version 1.0, which were identified as version 1.1. The first was published in December 2019. In this version, the indicators from the American Community Survey and the sensitive populations theme were updated. Version 1.1 was updated again in January 2022, which corrected some identified errors.

Under the Healthy Environment for All (HEAL) Act (SB5141, 2021), the DOH is tasked with continuing to develop and maintain the EHD map with the most current available information necessary to identify cumulative environmental health impacts and overburdened communities. The Washington State Department of Health began developing an updated version of the EHD map. This updated 2.0 version incorporates new indicators and updated methodology.



Summary of Changes for Version 2.0

DOH initiated an update in 2021. This updated 2.0 version incorporates modified methodology and new indicators. In addition, there are updated methods and indicators for Particulate matter 2.5 (PM2.5), diesel emission, and ozone. DOH updated indicators, assessed data, and is releasing version 2.0 of the EHD Map.

Environmental Exposures

- Ozone concentration and $PM_{2.5}$ concentration were updated from 2009 – 2011 3-year estimates to 2014 – 2017 3-year estimates (not aligned with the calendar year to avert the extreme wildfire smoke event in summer 2017).
- Diesel Emissions were previously based on estimated NOx (Annual Tons/Km2) emissions from Washington State Department of Ecology's 2014 Comprehensive Emissions Inventory. EHD Map version 2.0 uses estimated $PM_{2.5}$ emissions from diesel sources derived from Washington State Department of Ecology's 2014 Comprehensive Emissions Inventory, because diesel $PM_{2.5}$ emissions are a more relevant measure for human health and a more significant environmental health exposure than emissions of NOx from diesel.

- The previous version used a Populations Near Heavy Traffic Roadways indicator estimating the percentage of people living near a busy roadway from 2017 WSDOT roadway traffic data. EHD Map version 2.0 improves upon previous methods by using a Proximity to Heavy Traffic Roadways indicator, which is a continuous estimate and provides more accurate traffic variation, especially in rural areas and uses 2019 WSDOT roadway traffic data.
- Toxic Releases from Facilities (RSEI) was updated from 2012 – 2014 3-year average to a 2018 – 2020 3-year average.

Environmental Effects

- Lead Risk from Housing was updated from 2013 – 2017 5-year American Community Survey (ACS) estimates to 2015 – 2019 5-year ACS estimates.
- Proximity to Hazardous Waste Treatment Storage and Disposal Facilities (TSDFs) and Proximity to Risk Management Plan (RMP) facilities indicators were updated from 2017 to 2021 EPA EJSCREEN data.
- Proximity to National Priority List Facilities (Superfund Sites) was updated from 2016 to 2021 EPA EJSCREEN data.
- Wastewater Discharge was updated from 2015 to 2021 EPA EJSCREEN data.

Socioeconomic Factors

- Limited English Proficiency, No High School Diploma, Population Living in Poverty, Unaffordable Housing, and Unemployment indicators were updated from 2013 – 2017 5-year ACS estimates to 2015 – 2019 5-year ACS estimates.
- The People of Color indicator was updated from 2017 to 2019 estimates from the Office of Financial Management.

Sensitive Populations

- The Low Birthweight and Cardiovascular Disease Mortality indicators were updated from 2014 – 2018 5-year estimates to 2015 – 2019 5-year estimates obtained from the Washington State Department of Health Center for Health Statistics.

Definitions

Burden refers to the magnitude of poor health that exists within a community that is attributable to the risk factors that are present.

Census tracts are areas designated for taking the United States Census. Census tracts generally have a population size between 1,200 and 8,000 people.

Cumulative impact refers to the combined impact of multiple environmental health indicators on a population.

An **environmental hazard or risk factor** refers to a specific source or concentration of pollution in the environment. Polluted air, water and soil are examples of environmental hazards.

Environmental health refers to the processes by which environmental conditions affect human health.

An **environmental health indicator** refers to either a specific environmental risk factor or a specific measure of population susceptibility or vulnerability.

Environmental justice is defined differently by different groups. While some define environmental justice as the equitable distribution of environmental risks and benefits, others, like the US EPA, consider environmental justice to be the fair treatment and meaningful involvement of all people with respect to developing, implementing and enforcing environmental laws, regulations and policies.

Environmental effect refers to poor environmental quality generally, even when population contact with an environmental hazard is unknown or uncertain.

Environmental exposure refers to how a person comes into contact with an environmental hazard. Examples of exposure include breathing air, eating food, drinking water or living near to where environmental hazards are released or are concentrated.

Indicator refers to the measure of a condition that we are tracking/assessing. These conditions fall under the categories of sensitive populations, socioeconomic factors, environmental effects or environmental exposures. Examples of indicators include proximity to toxic waste, poverty, and unaffordable housing.

Morbidity is the occurrence of disease, injury, and/or disability.

Mortality is the occurrence of death in a defined population.

Particulate Matter is called particle pollution and refers to a mixture of solid particles and liquid droplets found in air. Some particles are so small they can only be seen with an electron microscope and are measured in micrometers. Particulate matter$_{2.5}$ or $PM_{2.5}$ are fine particles with diameters that are generally 2.5 micrometers and smaller.

Population characteristics refer to intrinsic and extrinsic vulnerabilities in communities that can modify the environmental risk factors. Risk refers to how likely exposure to environmental hazards will result in poor health for a population.

Risk refers to the chance of harmful effects to human health resulting from coming into contact with a stressor/concerning factor/irritant.

Susceptibility refers to a person's (or population's) inherent biology that affects their risk. Examples of susceptibility include youth or old age, or whether a person is already affected by a disease—such as asthma or heart disease—that places them at increased risk when exposed to environmental hazards.

Sensitive populations refers to those who are at greater risk due to biological/intrinsic vulnerability.

Threat is represented by indicators that account for pollution burden, which is a combination of environmental effects and environmental exposures in communities.

Uncertainty when referring to data, this may describe when the data is unclear or unreliable

Vulnerability refers to a person's (or population's) non-biological situation that affects their ability to cope with risk factors. Examples of vulnerability include low income, language barriers or poor access to health care.

Methodology

The framework and model

The EHD Map evaluates the cumulative impacts of environmental health risk factors in communities. The model was specifically adapted from CalEnviroScreen—a cumulative environmental impacts assessment mapping tool developed by CalEPA and used in California. It estimates a cumulative environmental health impact score for each census tract reflecting pollutant exposures and factors that affect people's vulnerability to environmental pollution.

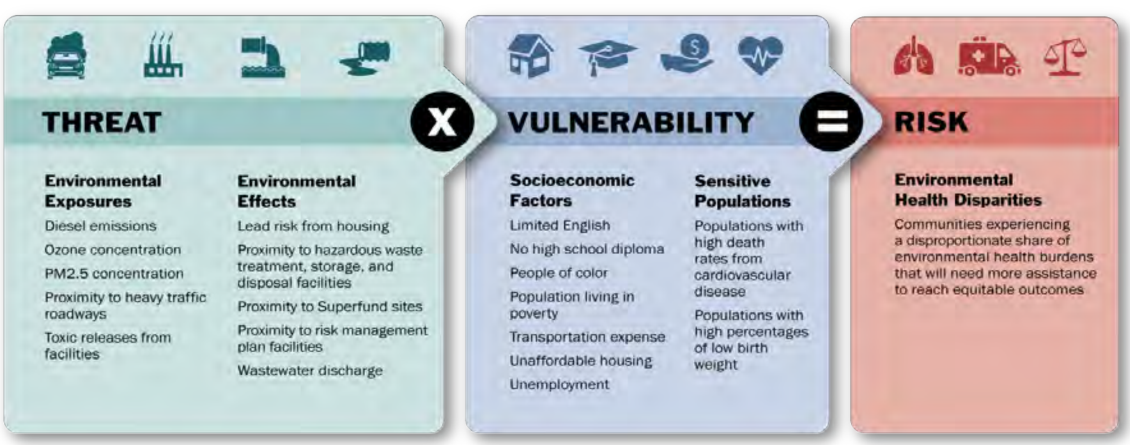
The model is based on a conceptual formula of Risk = Threat x Vulnerability. The pollution burden on a community may harm or increase their vulnerability. This degree of harm and vulnerability is calculated to understand the cumulative risk on each census tract.

Threat is represented by indicators that account for pollution burden, which is a combination of environmental effects and environmental exposures in communities. **Vulnerability** is represented by indicators of socioeconomic factors and sensitive populations for which there is clear evidence that they may affect susceptibility or vulnerability to an increased pollution burden.

Indicators in socioeconomic factors measure population characteristics that modify the pollution burden itself. Sensitive populations refer to those who are at greater risk due to intrinsic biological vulnerability to environmental stressors.

In the model, threat is multiplied by vulnerability in order to reflect the scientific literature that indicates population characteristics often modify and amplify the impact of pollution exposures on certain vulnerable populations. For each indicator, we created a score for each census tract by its raw value, then assigned percentile based on rank-order. For a detailed description of each indicator, see Part II section.

Threat x Vulnerability = Risk



Pollution burden

This category includes indicators related to the environmental health risk factors in communities of Washington state. Indicators within this category include environmental exposures and environmental effects.

Environmental exposures include the levels of certain pollutants that populations come into contact with. **Environmental exposure indicators** use data from measured environmental concentrations and releases of contaminants from pollution sources as a way to quantify pollution burden from exposure to pollutants.

Examples of indicators in this theme include ozone concentrations or diesel emissions. The average decile ranking for each indicator is weighted equally within this theme.

Environmental effects include indicators that account for poor environmental quality generally, even when population contact with an environmental hazard is unknown or uncertain. **Environmental effects indicators** illustrate the potential risk of the environmental hazard on communities nearby (Brender, Maantay & Chakraborty, 2011).

Examples of indicators in this theme include proximity to hazardous waste sites or Superfund sites. The average percentile for each indicator is weighted equally within this theme.

However, as proximity to a potential exposure does not necessarily reflect actual exposure, this theme is down-weighted by one-half when averaged with environmental exposures in the pollution burden category.

Population characteristics

This category includes indicators related to intrinsic and extrinsic vulnerabilities in communities that can modify the environmental risk factors.

Sensitive populations indicators in this theme relate to biological susceptibility. People with pre-existing cardiovascular disease or low-birth-weight infants may be more vulnerable to environmental risk factors. The average percentile for each indicator in this theme is weighted equally within this category.

Socioeconomic factors indicators in this theme are often found to be associated with environmental justice conditions, such as poverty or unemployment, which modify the effects of environmental exposures on health. The average percentile for each indicator in this theme is weighted equally within this category.

Total Score and Rankings

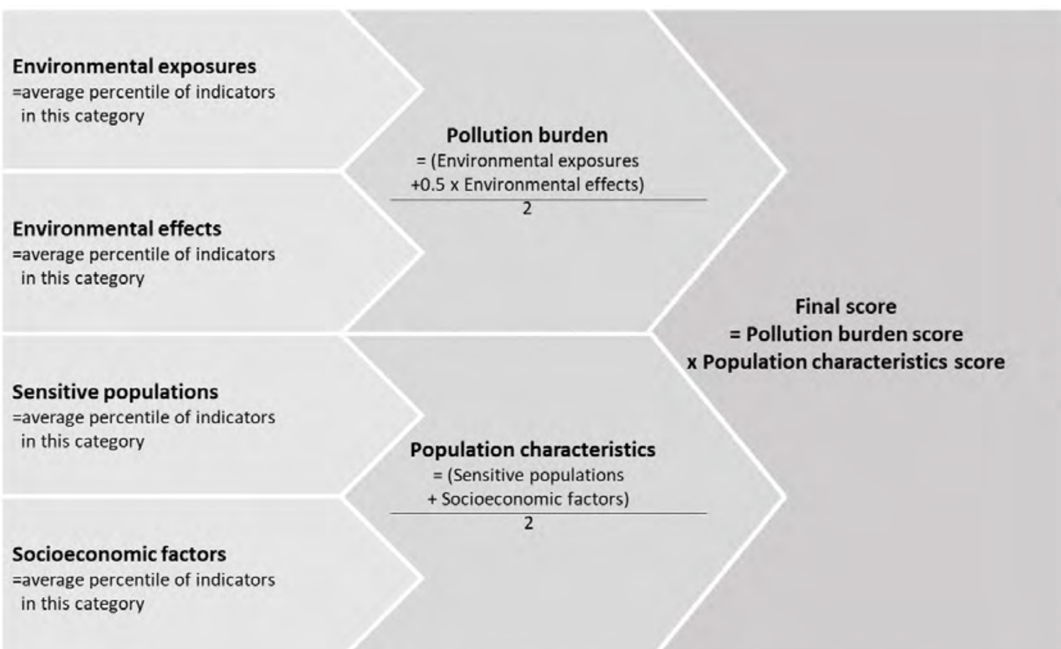
The EHD Map is displayed on the Washington State Department of Health's Washington Tracking Network (WTN). WTN is supported by the US Centers for Disease Control and Prevention's National Environmental Public Health Tracking Program and state funding from the HEAL Act. For each indicator, the raw data values are ranked by census tract. Each census tract is assigned a decile rank based on the ranking of the indicator. The decile rank for all indicators are then averaged within each theme for a given tract.

Pollution burden score = (Average decile rank of environmental exposures indicators +(0.5 × average decile rank of environmental effects indicators)) / 2

Population characteristics score = (Average decile rank of sensitive population indicators + average decile rank of socioeconomic factors indicators) / 2

The final composite score is based on the product of the pollution burden and population scores: Final composite score = pollution burden score × population characteristics score

The Information By Location (IBL) tool on WTN ranks all of the indicators, themes and final scores using decile (1 decile = 10 percent) ranks. Each decile represents about 10 percent of the values in the dataset. There are 1,458 census tracts in Washington as of 2018. This results in approximately 146 census tracts in each rank for the final EHD ranking. For details on the number of census tracts in each rank for each individual indicator, refer to Appendix A.

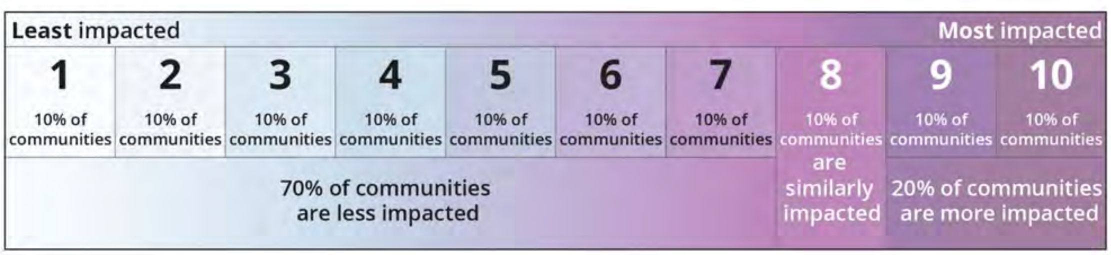


Rankings

The ranking provides a common scale to compare various issues at the community level and to assess the cumulative impact of the indicators across communities. The use of rankings also allows health information to be displayed for each community, while protecting confidentiality in communities with small numbers. The IBL tool does not show the actual numeric difference between each rank. The ranks only show that there is a difference, not how much. Because the final composite scores are approximately equally distributed across 10 ranks, the resulting rankings shown on the map range from 1 (least impacted) to 10 (most impacted).

How to Interpret the Map

Rankings for this map can be interpreted as a way to measure relative environmental risk factors in communities. The rankings help compare health and social factors that may contribute to disparities within a community or between communities and should not be taken to be an absolute value. For example, if a community has a rank of 8 for the diesel emissions indicator, it means about 10 percent of communities are similarly impacted by diesel emissions, approximately 70 percent of communities are less impacted, and 20 percent of communities are more impacted. To see the range of data used to create the ranks, you can select the graph icon next to the indicator within the IBL to export the data table for the specific indicator.



This map does not model resilience or asset-based indicators contributing to environmental health. This map also does not model the overall burden on communities, nor does it reflect the actual number of individuals affected by environmental risk factors. (Burden refers to the magnitude of poor health that exists within a community that is attributable to the risk factors that are present.) This map also does not model the positive or negative likelihood of an individual health outcome.

Therefore, it should not be used to diagnose a community health issue, to label a community or to impute risk factors and exposures for specific individuals. Additional analysis is needed to make decisions on health outcomes that may be affiliated with the environmental risk factors. This map is intended to be a dynamic, informative tool. Decisions on the cumulative impact of environmental risk should not solely be based on this map.

Limitations

This map is based on a specific model for risk and cumulative environmental impact. Models have inherent uncertainty associated in the methodology of the tool. There is no single way to truly capture the level of uncertainty associated with environmental risk factors. This map represents one of many ways to quantify the risk factors.

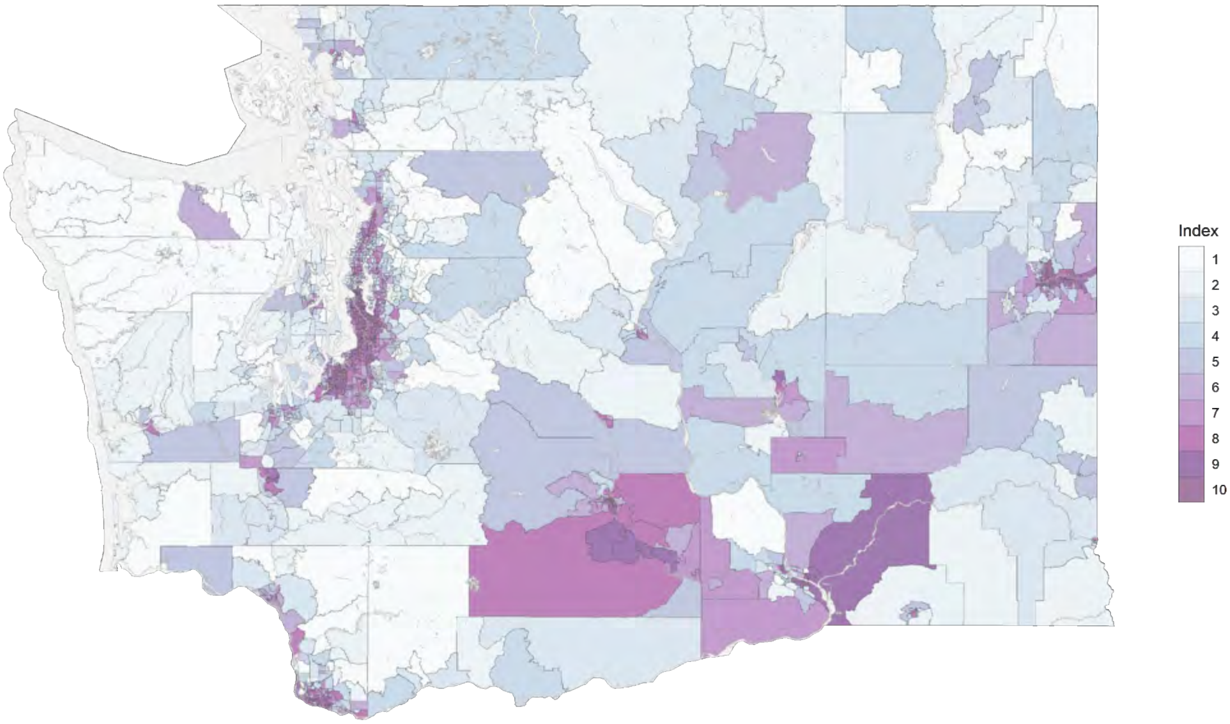
Many of the indicators in this map rely on national data sources. While nationwide data provide insight on environmental health burdens at the national level, these data may not capture the nuances that state-specific data would. Similarly, local data may better capture nuances than state-level or nationwide data. This map relies only on data that are available for the entire state. County and city data and maps, if they exist, can provide a more granular level of information for decisions that are being made at that scale.

This map does not include all environmental risk factors, only indicators for existing data. This map will be updated as statewide data for additional indicators become available.

The 2017 listening sessions included 11 communities and did not adequately cover all geographic regions or communities within Washington state. As a result, the topics discussed in the listening sessions that informed the development of these indicators may not have covered all environmental health impacts faced by all Washington communities. DOH plans to continue to include input from more communities in the future to address this limitation. Please see the “Next Steps” section for more information on plans for continual community and stakeholder engagement.

Environmental risk factors vary depending on a community’s characteristics, such as rural or urban communities. Data gaps also vary depending on the nature of the environmental risk factors. Sensitivity analysis was conducted as a way to reduce inherent bias due to data availability.

Washington State EHD Map – Color Coded



Map 1: Final Environmental Health Disparities Ranking of Washington state (version 2.0).

Indicators

Table 1. List of EHD map indicators

Indicators	**Description of indicator**	**Source of data**	**Years**
Sensitive Populations			
Death from Cardiovascular Disease	Age adjusted death rate due to cardiovascular disease per 100,000 population	Washington State DOH Center for Health Statistics, Community Health Assessment Tool (CHAT)	2015-2019
Low birth weight	The number of live born singleton (one baby) infants born at term (at or above 37 completed weeks of gestation) with a birth weight of less than 2,500 grams	Washington State DOH Center for Health Statistics, Community Health Assessment Tool (CHAT)	2015-2019
Socioeconomic Factors			
No High School Diploma	% of people without a high school diploma by age 25 per household	American Community Survey (ACS) 5-year, DP02 - Selected Social Characteristics	2015 – 2019
Unaffordable Housing	% of households spending great than 30 percent of their income on housing costs	American Community Survey (ACS) 5-year, DP04	2015 – 2019
Transportation Expense	Transportation costs based on percentage of income for the regional moderate household	Center for Neighborhood Technology	2017
Limited English	% of limited English-speaking households	American Community Survey (ACS) 5-year, B16004 - Age by Language Spoken at Home by Ability to Speak English	2015 – 2019
People Living in Poverty	% of the total population whose income was less than or equal to 185% of the federal poverty level within the past 12 months	American Community Survey (ACS) 5-year, S1701 - Poverty Status in the Past 12 Months	2015 – 2019
Race (people of color)	Summary of communities of color, specific race/ethnicity composition for census tracts	Office of Financial Management	2019
Unemployment	The population of people 16 years and older that are in the labor force and registered as unemployed	American Community Survey (ACS) 5-year, DP03 - Selected Economic Characteristics	2015 – 2019

Environmental Exposures			
Diesel Exhaust $PM_{2.5}$ Emissions	Diesel exhaust $PM_{2.5}$ emissions estimates were mapped to the AIRPACT modeling domain, which uses 4km x 4km grid cells	Washington State Department of Ecology's 2014 Comprehensive Emissions Inventory, AIRPACT	2014
Ozone	8-hour ozone design values interpolated at 4km x 4km grid cells	**NW-AIRQUEST Regional Background Design Values,** AIRPACT	2014-2017
Particulate matter 2.5 ($PM_{2.5}$)	Mean and 98th percentile daily $PM_{2.5}$ concentrations estimated at 4km x 4km grid cells	**NW-AIRQUEST Regional Background Design Values,** AIRPACT	2014-2017
Toxic Releases from Facilities (RSEI Model)	The Geographic Microdata is a model of Air pollution releases that are plotted on 810-meter grid cells	EJSCREEN (based on RSEI)	2018 – 2020
Proximity to Heavy Traffic Roadways	Maximum distance-weighted traffic along Washington highways for each census tract	Washington State Office of Financial Management's 2010 census boundaries highway traffic from WSDOT geodatabase	2019
Environmental Effects			
Lead Risk from Housing	Proportion of estimated housing unit with proportionate lead risk for the housing unit era	American Community Survey (ACS) 5-year, DP04 - Selected Housing Characteristics	2015-2019
Proximity to Hazardous Waste Treatment Storage and Disposal Facilities	Count of TSDFs (hazardous waste management facilities) within 5 km (or nearest beyond 5 km), each divided by distance in kilometers	EJSCREEN (based on RCRAInfo)	2021
Proximity to National Priorities List Facilities (Superfund Sites)	Count of proposed and listed NPL sites within 5 km (or nearest one beyond 5 km), each divided by distance in kilometers	EJSCREEN (based on CERLIS)	2021
Proximity to Risk Management Plan	Count of RMP (potential chemical accident management plan) facilities within 5 km (or nearest one beyond 5 km), each divided by distance in kilometers	EJSCREEN (based on RMP)	2021
Wastewater discharge	Toxicity-weighted stream concentrations at stream segments within 500 meters, divided by distance in kilometers	EJSCREEN (based on RSEI)	2021

Indicators in Population Characteristics

Sensitive populations

Sensitive populations are likely at a greater risk for poor health outcomes due to their developed physiological and/or biological predispositions. Sensitive populations accounted for in this theme include those with conditions such as cardiovascular disease or low birth weight. Individuals with these conditions experience greater vulnerability to environmental pollutants as pollution is a significant contributor to poor health outcomes experienced by sensitive populations. The statewide data displays the effect of pollution exposure experienced by sensitive population indicators.

Death from cardiovascular disease

Justification

Cardiovascular disease (CVD) is a life-long health condition that threatens the lives of thousands in Washington state. Cardiovascular diseases are caused by the narrowing of or blockage of heart muscles and vessels. Most common CVDs include coronary heart disease, strokes, aortic disease, and peripheral arterial disease.

Cardiovascular disease has many risk factors, including diet, lack of exercise, smoking, and air pollution. According to the American Heart Association, there is strong evidence that air pollution contributes to cardiovascular morbidity and mortality, including exposure to environmental stressors (Brook et al., 2010; Pope III et al., 2006). Exposure to long-term pollution can increase the risk of cardiovascular mortality. Furthermore, the effect of pollution is more pronounced among the elderly and those that have pre-existing health conditions.

Literature

Individuals with pre-existing heart disease are at higher risk of mortality when exposed to various environmental stressors (Bateson & Schwartz, 2004; Berglind et al., 2009; Brook et al., 2010; Chen et al., 2016). For example, a study found individuals who survived an acute coronary event to have a higher mortality rate when exposed to higher levels of particulate matter (Berglind et al., 2009).

Studies have also found short-term exposure to particulate matter to be linked to acute coronary events (Pope et al., 2006; Schwartz, 1994; von Klot et al., 2009). In addition, long-term exposure to particulate matter was found to reduce life expectancy in people with pre-existing cardiovascular disease (Brook et al., 2010).

Data Source

Department of Health's Center for Health Statistics, Community Health Assessment Tool (CHAT), 2015 - 2019 5-year estimates. Published February 2022.

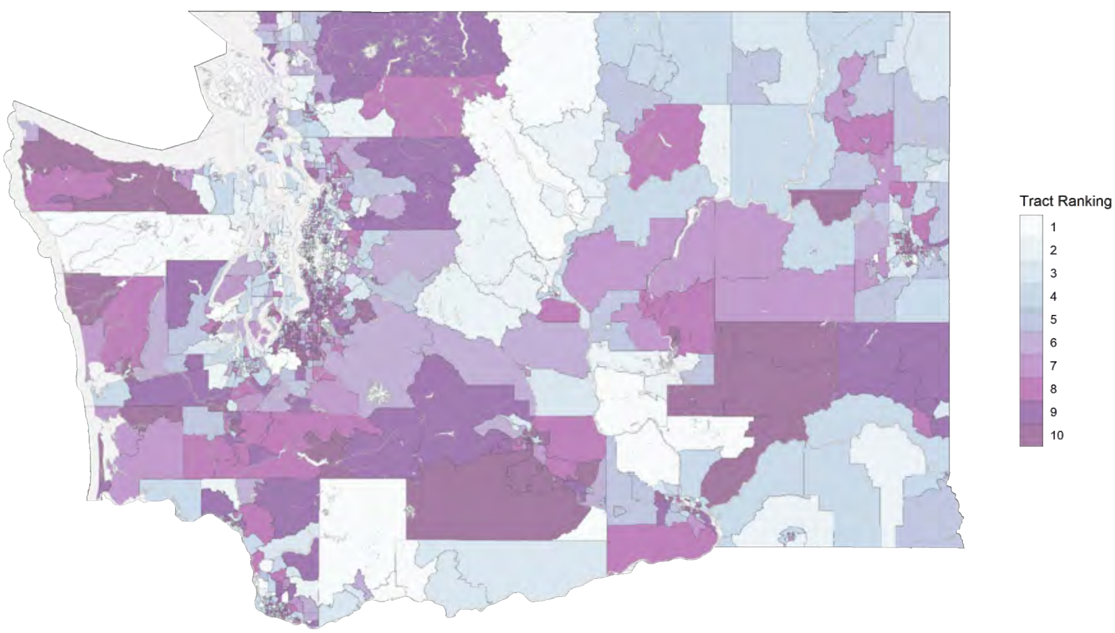
Method

Mortality from cardiovascular diseases (NCHS 113: Major cardiovascular diseases) represents the proportion of deaths in a population due to cardiovascular disease. The rate represents the age adjusted rate per 100,000 population.

This indicator was developed using cardiovascular disease mortality data from the Washington State DOH Center for Health Statistics. The Center for Health Statistics collects information on the deaths of Washington state residents from their death certificates, including the deaths of Washington state residents that died in other states or in Canada.

The prevalence of cardiovascular disease in a community truly captures the population susceptible to environmental risk factors; however, no such publicly available data exists. Mortality data may underestimate the true population with pre-existing heart disease in the community. In addition, the DOH Center for Health Statistics estimates that data gathered from death certificates are 99 percent complete.

Map 2: Decile ranking of deaths from cardiovascular disease indicator



Low birth weight

Justification

Infants that weigh less than 2,500 grams (about 5.5 pounds) when they are born are classified as low birth weight (LBW). Conditions such as nutritional status, lack of prenatal care, stress, and maternal smoking are risk factors for LBW.

LBW is a globally recognized marker for population health due to existing disparities because certain demographics puts infants at risk of LBW. For example, Black or Hispanic women have a higher risk of giving birth to a LBW baby, or older women have higher risk of delivering a LBW baby. There is evidence displaying environmental stressors not only impact LBW infants throughout their lifetime but also put infants at risk for LBW before birth.

Literature

Studies have found that children who had a low birth weight are at risk of developing health comorbidities, including coronary heart disease, type 2 diabetes and asthma later in life, in addition to being at risk for infant mortality (Barker et al., 2002; Lu & Halfon, 2003; McGauhey et al., 1990; Nepomnyaschy & Reichman, 2005).

Studies have shown that additional environmental factors such as exposure to air pollution, traffic pollution, lead, and pesticides are be linked to lower socioeconomic status and low birth weights (Ghosh et al., 2012; Harley et al., 2011; Laurent et al., 2013, Westergaard et al., 2017).

Data Source

The Department of Health Center for Health Statistics, Community Health Assessment Tool (CHAT), 2015 - 2019 5-year estimates.

Method

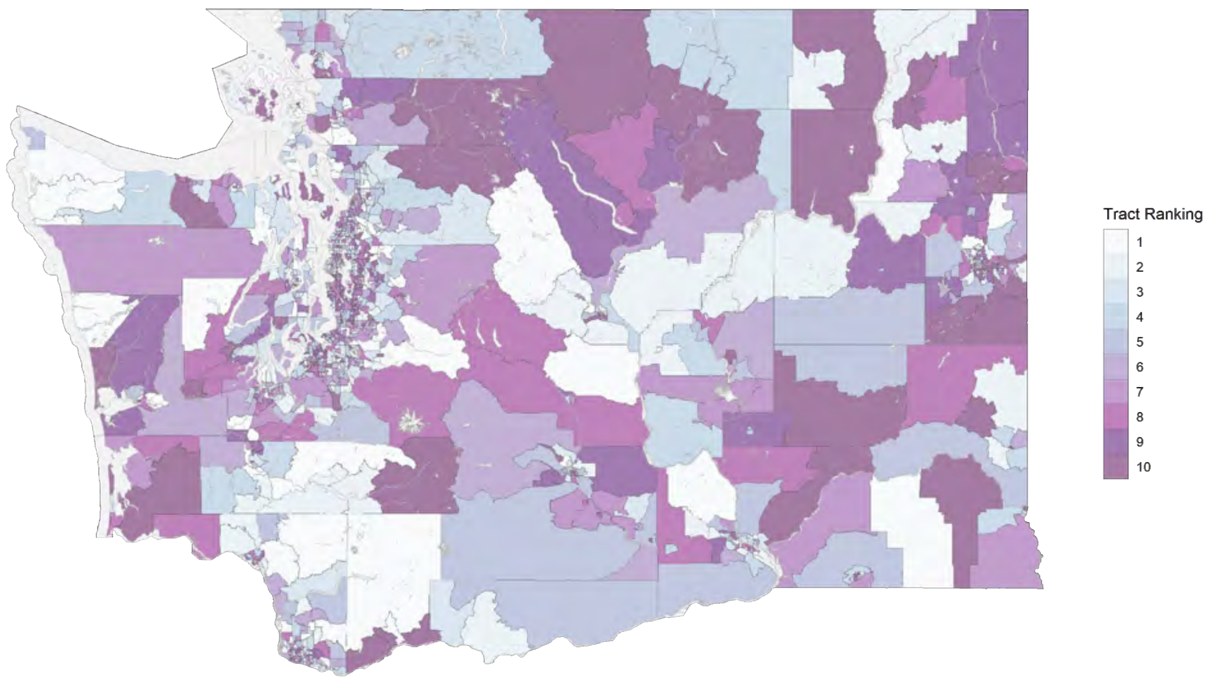
Birth and fetal death data on WTN come from the Washington State Department of Health's Center for Health Statistics (CHS), which compiles the information from birth and fetal death certificates. Formal interstate agreements assure that CHS receives the certificates from other states for WA residents. Abortions include induced abortions from abortion providers in Washington State, and through agreement, other states and Canada for Washington State residents.

This indicator depicts the number of live born singleton (one baby) infants born at term (at or above 37 completed weeks of gestation) with a birth weight of less than 2,500 grams (about 5.5 lbs).

The rate represents the count of low birth weight, live-born singleton infants divided by the total number of live-born singleton infants born at term to Washington state resident mothers. This indicator was developed using data collected by the Washington State DOH Center for Health Statistics from birth certificates.

This indicator does not account for individuals who were born outside of Washington that had low birth weight and are currently residing in Washington.

Map 3: Decile ranking of births associated with low birth weight indicator



Socioeconomic Factors

Socioeconomic factors are social and economic characteristics that affect the well-being and vulnerability of an individual in a community. Particularly with environmental pollutants, those that have lower income, lower education, or belong to a community of color are at a heightened vulnerability or mortality. In this report, various socioeconomic factors have been identified that display an association with risk of poor health outcomes when exposed to environmental pollutants.

The socioeconomic factor theme includes the following indicators in Washington State:

Low educational attainment, unaffordable housing, and transportation expense, linguistic isolation, poverty, race (people of color), and unemployment.

No high school diploma

Justification

Educational attainment is a very important social determinant of health as it provides insight into individual and community health and well-being for various health outcomes. With environmental pollution as well, studies display a strong inverse association between education level and exposure to environmental pollutants. Those who have a high school diploma or higher have less risk of mortality caused by particulate matter pollution. In addition, communities with lower educational attainment are more susceptible to developing asthma and other air pollution related cardiopulmonary health outcomes.

There are many aspects of low educational attainment that impacts daily life and affect individual susceptibility to environmental pollution. For instance, low educational attainment may lead to stress, lack of social support, limited occupational opportunities, reduced access to nutritious food, and limited access to healthcare services which can contribute to vulnerability to environmental pollution.

Literature

Low educational attainment, along with other socioeconomic status indicators such as income, are stressors that can lead to poorer health outcomes (Lewis et al., 2011; Neidell, 2004).

Communities with lower educational attainment can be more vulnerable to environmental risk factors such as air pollution (Cakmak, Dales, & Judek, 2006; Krewski et al., 2003).

Additionally, studies found higher educational attainment to be associated with higher life expectancy and reduction of risks for diseases associated with aging (Adler et al., 2013; Hummer & Hernandez, 2013).

Data Source

2015 - 2019 ACS 5-year estimates, DP02 - Selected Social Characteristics

Method

In addition to the census of every U.S. household every 10 years, as required by the U.S. Constitution, the Census Bureau has a sub-sample, yearly survey called the ACS. This representative sample-based survey gathers characteristics for a subset of the entire population of the U.S. each year.

The ACS asks respondents a variety of detailed questions on social and economic topics. WTN displays a selected subset of these indicators. This indicator displays the percent of people who have not received a high school diploma or GED by the age of 25.

This indicator was developed using data on the percent of population over age 25 with less than a high school education collected from the U.S. Census Bureau's ACS 5-year estimates for 2015–2019. The ACS 5-year estimate is recommended by the US Census Bureau as the most reliable estimate measure of census variables for small populations.

For more information, refer to ACS General Data Users Handbook. The ACS General Data Users Handbook documentation is a useful resource, however there are limitations of sampling and non sampling errors. Sampling error represents ACS sampling variation within counties between the surveyed and general population while non sampling variation represents data collection errors.

Variables used:
DP02_0058, DP02_0059, DP02_0060, DP02_0061

Calculations performed:

Pre-2019:
People with No High School Diploma = DP02_0060 + DP02_0059
Population (Ages 25 and Older) = DP02_0058
% People with No High School Diploma = (DP02_0060 + DP02_0059) / DP02_0058

2019-onwards:
People with No High School Diploma = DP02_0060 + DP02_0061,
Population (Ages 25 and Older) = DP02_0059,
% People with No High School Diploma = (DP02_0060 + DP02_0061) / DP02_0059

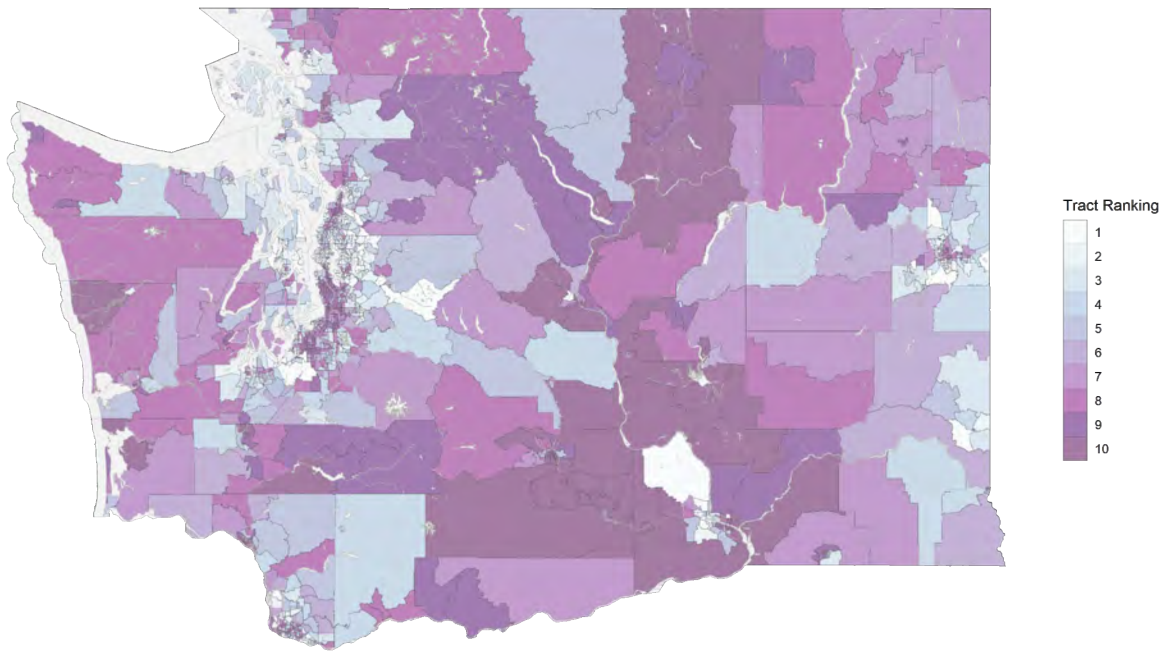
* For tracts with zero population, ACS will list some variables as missing data. For our calculations we changed these missing data to zeros.

Additional Resources

Certain published ACS estimates, such as total population estimates for counties and states, exactly match Census Data controls. These estimates, which have five asterisks (*****) in the Margin of Error (MOE) column in data.census.gov, are by definition fixed, and were considered to have no sampling error as instructed in Understanding and Using American Community Survey Data.

For MOE calculations, refer to U.S. Census Bureau, A Compass for Understanding and Using American Community Survey Data Appendix 1. For MOEs in which either the numerator or denominator of a proportion were derived from multiple ACS variables, see "Calculating MOEs for Aggregated Count Data;" for MOEs derived from proportions, see "Calculating MOEs for Derived Proportions."

Map 4: Decile ranking of population with no high school diploma indicator



Unaffordable housing

Justification

Housing burden captures many of the socioeconomic conditions that affect social health and well-being. As a social determinant of health, this indicator may influence the effect of exposure to environmental pollution. Those that live with a housing burden may be at a greater risk of living in areas of environmental degradation and increased levels of air pollution. Thus, individuals experiencing a housing burden are at greater risk of exposure to air pollution and higher mortality (Finkelstein et al., 2003).

Additionally, those that experience housing burden may delay medical care and services and suffer more long-term impacts due to financial insecurity. Low income and financially vulnerable households may also experience greater periods of residential instability and increased vulnerability to chronic and acute health conditions. Such health effects include stress and depression (Anderson et al., 2003; Harkness and Newman, 2005; Meltzer and Schwartz, 2016; Newman and Holupka, 2016).

Literature

Housing burden (both mortgage and rent) influence health in many ways, including financial stress and the unaffordability of basic necessities such as healthy food or health care services (Harkness & Newman, 2005; Meltzer & Schwartz, 2015).

Studies have found associations between housing burden and health disparities such as asthma hospitalization and hypertension (Lin et al., 2003; Meltzer & Schwartz, 2015; Pollack, Griffin & Lynch, 2010). In recent years, increasing levels of income inequality have affected the housing burden on communities (Dunn, 2000).

Data Source

2015 - 2019 ACS 5-year estimates, DP04 - Selected Housing Characteristics

Method

In addition to the census of every U.S. household every 10 years, as required by the U.S. Constitution, the Census Bureau has a sub-sample, yearly survey called the ACS. This representative sample-based survey gathers characteristics for a subset of the entire population of the U.S. each year.

The ACS asks respondents a variety of detailed questions on social and economic topics. WTN displays a selected subset of these indicators. This indicator represents the percent householders spend on housing costs. There are three categories under "Selected Monthly Costs as Percentage of Household Income": households with mortgages, households without mortgages, and rentals. “Unaffordable housing” is defined as households spending greater than 30 percent of their income on housing costs.

The housing burden indicator displays the modeled percent of income spent on housing for a four-person household making the median household income, based on U.S. Census Bureau’s ACS 5-year estimates for 2015–2019. The ACS 5-year estimate is recommended by the US Census as the most reliable estimate indicator of census variables for small populations.

For more information, refer to ACS General Data Users Handbook documentation. The ACS General Data Users Handbook documentation is a useful resource, however there are limitations of sampling and non sampling errors. Sampling error represents ACS sampling variation within counties between the surveyed and general population while non sampling variation represents data collection errors.

Variables used:

DP04_0002, DP04_0114, DP04_0115, DP04_0123, DP04_0124, DP04_0141, DP04_0142

Calculations performed:
Unaffordable Housing Units = sum of: DP04_0114, DP04_0115, DP04_0123, DP04_0124, DP04_0141, DP04_0142,

Total Occupied Housing Units = DP04_0002,

Unaffordable Housing Unit Percentage = (sum of DP04_0114, DP04_0115, DP04_0123, DP04_0124, DP04_0141, DP04_0142) / DP04_0002

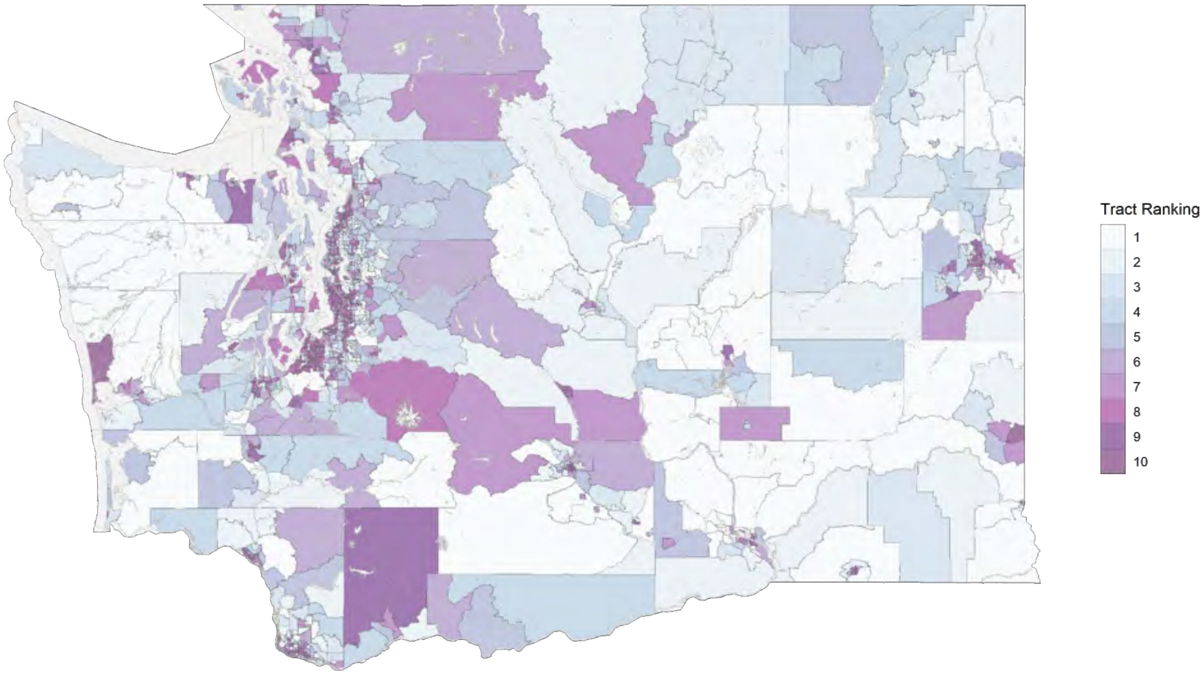
* For tracts with zero population, ACS will list some variables as missing data. For our calculations we changed these missing data to zeros.

Additional Resources

Certain published ACS estimates, such as total population estimates for counties and states, exactly match Census Data controls. These estimates, which have five asterisks (*****) in the MOE column in data.census.gov, are by definition fixed, and were considered to have no sampling error as instructed in Understanding and Using American Community Survey Data.

For MOE calculations, refer to U.S. Census Bureau, A Compass for Understanding and Using American Community Survey Data Appendix 1. For MOEs in which either the numerator or denominator of a proportion were derived from multiple ACS variables, see "Calculating MOEs for Aggregated Count Data;" for MOEs derived from proportions, see "Calculating MOEs for Derived Proportions."

Map 5: Decile ranking of population with unaffordable housing indicator per census tract



Transportation expense

Justification

Transportation expense captures many of the socioeconomic conditions that affect social health and well-being. As a social determinant of health, this indicator may influence the effect of exposure to environmental pollution. Those that experience a transportation burden may be at a greater risk of living in areas of environmental degradation and increased levels of air pollution. Individuals living in areas of heavy traffic and limited transportation options may be exposed to a greater extent of air pollution and experience vulnerability to respiratory health outcomes and increased mortality (Finkelstein et al., 2003).

Additionally, those that experience transportation burden may delay medical care and services and suffer more long-term impacts due to financial insecurity or distance to resources. Low income and financially vulnerable individuals may also experience greater periods of instability, resulting in increased vulnerability to chronic and acute health conditions. Such health effects include stress and depression.

Literature

Studies have found transportation burden on a household’s income has an inverse relationship with housing burden (Renne et al., 2015). Those with low housing burden often have high transportation costs due to where affordable homes may be located.

Data Source

2017 data release from Center for Neighborhood Technology (CNT), based on 2015 ACS estimates

Method

The transportation expense indicator displays transportation costs based on percentage of income for the regional moderate household. The CNT defines regional moderate household income as a household income of 80 percent of the area median, the regional average household size and the regional average commuters per household.

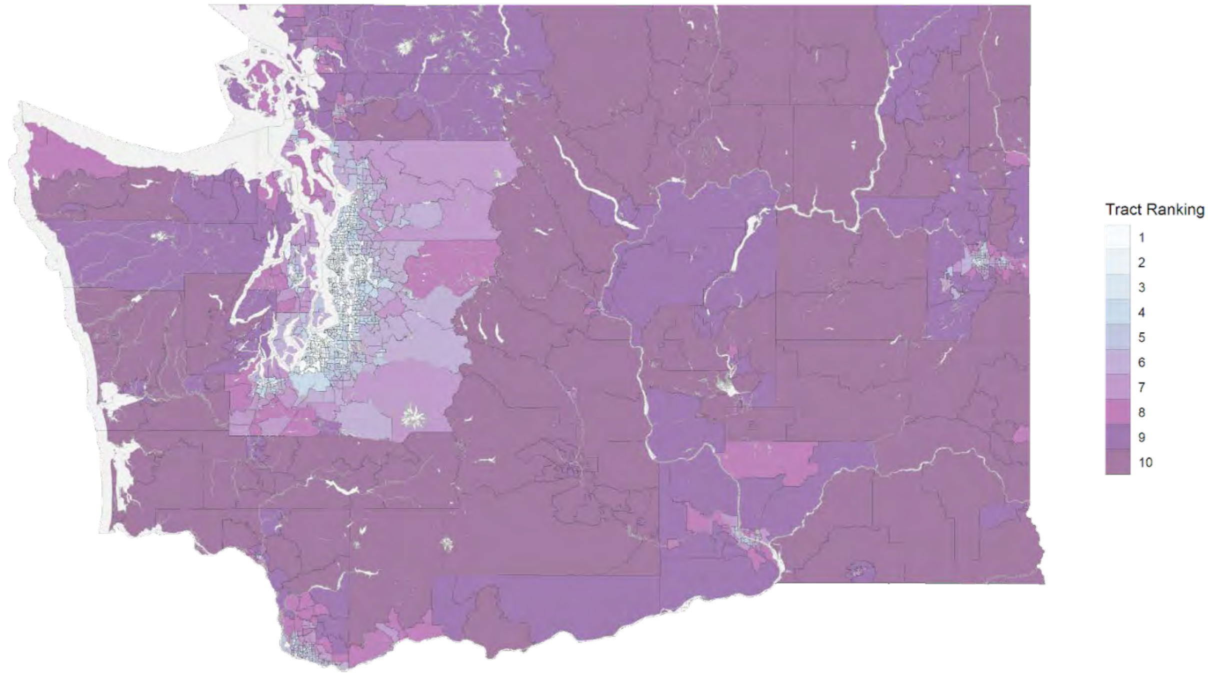
Transportation burden on a household's income has an inverse relationship with housing burden. Those with low housing burden often have high transportation costs due to where affordable homes may be located. Due to this paradox, comparing both housing and transportation burden provide valuable insight for assessing affordability.

The way the CNT processes their data there is a 2-year lag. For example, data published by them in 2017 would show up on the data portal as 2015.

Additional Resources

For more information, refer to CNT Methodology documentation.

Map 6: Decile ranking of transportation expense indicator



Limited English

Justification

Linguistic isolation is measured by the US Census Bureau in households to assess if all members 14 years of age or above have at least some difficulties speaking English. Among individuals and communities that have high levels of linguistic isolation, there is concern of limited access to health education and health services. Lack of proficiency may place individuals at loss of clear communication at times of environmental risk or emergencies such as with hazards and air pollution. In addition, households that are linguistically limited might experience greater racial discrimination, social isolation, and increased exposure to environmental pollution.

Literature

In the US, people with limited English may have poorer quality of life than those with proficient English (Gee & Ponce, 2009).

The same population may also have limited access to health care, including mental health care, and may be unable to participate in key national health surveillance surveys such as the

Behavioral Risk Factor Surveillance System (BRFSS) (Link et al., 2006; Sentell, Shumway & Snowden, 2007; Shi, Lebru & Tsai, 2009).

Communities with higher levels of linguistic isolation live in closer proximity to Toxic Release Inventory (TRI) sites than those that have lower levels of linguistic isolation in the community (Pastor Jr., Morello-Frosch & Sadd, 2010).

Linguistic isolation may also affect a community's capacity for civic engagement affecting environmental policies, which can lead to environmental health disparities (Pastor Jr., Morello-Frosch & Sadd, 2010).

Data Source

2015 - 2019 ACS 5-year estimates, B16004 - Age by Language Spoken at Home by Ability to Speak English

Method

In addition to the census of every U.S. household every 10 years, as required by the U.S. Constitution, the Census Bureau has a sub-sample, yearly survey called the ACS. This representative sample-based survey gathers characteristics for a subset of the entire population of the U.S. each year.

The ACS asks respondents a variety of detailed questions on social and economic topics. WTN displays a selected subset of these indicators. This indicator displays the percentage of the population five years and older that speak English less than "very well" and "not at all".

This indicator was developed using census tract-level data on the percent of limited English-speaking households from the U.S. Census Bureau's ACS for 2015– 2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate indicator of census variables at the census tract level of geography.

For more information, refer to ACS General Data Users Handbook. The ACS General Data Users Handbook documentation is a useful resource, however there are limitations of sampling and non sampling errors. Sampling error represents ACS sampling variation within counties between the surveyed and general population while non sampling variation represents data collection errors.

Variables used:
B16004_001, B16004_006, B16004_007, B16004_008, B16004_011, B16004_012, B16004_013, B16004_016, B16004_017, B16004_018, B16004_021, B16004_022, B16004_023, B16004_028, B16004_029, B16004_030, B16004_033, B16004_034,

B16004_035, B16004_038, B16004_039, B16004_040, B16004_043, B16004_044, B16004_045, B16004_050, B16004_051, B16004_052, B16004_055, B16004_056, B16004_057, B16004_060, B16004_061, B16004_062, B16004_065, B16004_066, B16004_067

Calculations performed:

Speaks English less than Very Well = sum of (B16004_006, B16004_007, B16004_008, B16004_011, B16004_012, B16004_013, B16004_016, B16004_017, B16004_018, B16004_021, B16004_022, B16004_023, B16004_028, B16004_029, B16004_030, B16004_033, B16004_034, B16004_035, B16004_038, B16004_039, B16004_040, B16004_043, B16004_044, B16004_045, B16004_050, B16004_051, B16004_052, B16004_055, B16004_056, B16004_057, B16004_060, B16004_061, B16004_062, B16004_065, B16004_066, B16004_067)

Population 5+ = B16004_001
% Speaks English less than Very Well = (sum of B16004_006, B16004_007, B16004_008, B16004_011, B16004_012, B16004_013, B16004_016, B16004_017, B16004_018, B16004_021, B16004_022, B16004_023, B16004_028, B16004_029, B16004_030, B16004_033, B16004_034, B16004_035, B16004_038, B16004_039, B16004_040, B16004_043, B16004_044, B16004_045, B16004_050, B16004_051, B16004_052, B16004_055, B16004_056, B16004_057, B16004_060, B16004_061, B16004_062, B16004_065, B16004_066, B16004_067)/ B16004_001

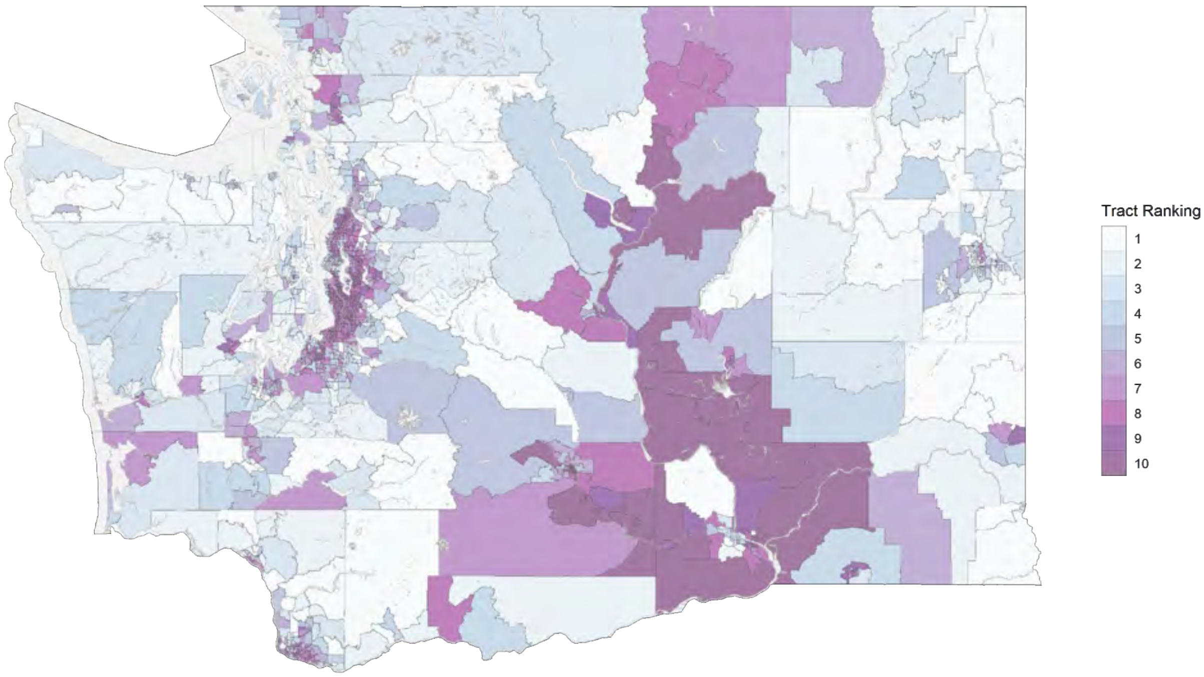
* For tracts with zero population, ACS will list some variables as missing data. For our calculations we changed these missing data to zeros.

Additional Resources

Certain published ACS estimates, such as total population estimates for counties and states, exactly match Census Data controls. These estimates, which have five asterisks (*****) in the MOE column in data.census.gov, are by definition fixed, and were considered to have no sampling error as instructed in Understanding and Using American Community Survey Data.

For MOE calculations, refer to U.S. Census Bureau, A Compass for Understanding and Using American Community Survey Data Appendix 1. For MOEs in which either the numerator or denominator of a proportion were derived from multiple ACS variables, see "Calculating MOEs for Aggregated Count Data;" for MOEs derived from proportions, see "Calculating MOEs for Derived Proportions."

Map 7: Decile ranking of population with limited English proficiency indicator



People living in poverty

Justification

Poverty is a primary social determinant of health and is strongly associated with exposure to environmental pollutants. Low-income communities are significantly impacted by their socioeconomic status. Economic status shapes one's nutrition, occupation, housing, access to healthcare resources, and more. Due to increased psychosocial stress and decreased resilience, individuals experiencing poverty bear poor mental and physical health. Furthermore, many do not have the resources or access to healthcare services or delay healthcare due to financial insecurity. Thus, underlying pre-existing health conditions in low-income communities may be exacerbated by exposure to environmental pollutants.

In addition, low-income communities are at higher risk of exposure to environmental pollution (Hajat et al., 2015). Individuals in low socioeconomic status face higher concentrations of air pollutants, making them more susceptible to chronic respiratory health outcomes such as asthma. In addition, those experiencing poverty may not have access to safe or healthy living conditions, leading to additional vulnerability to infectious diseases and exposure to environmental hazards.

Literature

Low-income communities have higher rates of chronic diseases (Marmot & Wilkinson, 2006) and can be more vulnerable to environmental risk factors (Cakmak, Dales, & Judek, 2006; Forastiere et al., 2006; Yi, Kim & Ha 2009; Zeka, Melly & Schwartz, 2008).

Living in poverty creates chronic stress for individuals, modifying their biological susceptibility or extrinsic vulnerabilities (O'Neill et al., 2003).

When faced with environmental risk factors, communities with more low-income households may also have lower resilience (Forastiere et al., 2006; Marmot & Wilkinson, 2006; O'Neill et al., 2003).

Data Source

2015 - 2019 ACS 5-year estimates, S1701 - Poverty Status in the Past 12 Months

Method

In addition to the census of every U.S. household every 10 years, as required by the U.S. Constitution, the Census Bureau has a sub-sample, yearly survey called the ACS. This representative sample-based survey gathers characteristics for a subset of the entire population of the U.S. each year.

The ACS asks respondents a variety of detailed questions on social and economic topics. WTN displays a selected subset of these indicators. This indicator represents the percent of the total population whose income was less than or equal to 185% of the federal poverty level within the past 12 months. See 'How the Census Bureau Measures Poverty' for more information on how poverty was measured. Note that in this indicator the population is the population for whom poverty status was determined.

This indicator uses data on the percent of the population living below 185 percent of the federal poverty level from the U.S. Census Bureau's ACS for 2015–2019. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables.

For more information, refer to ACS General Data Users Handbook. The ACS General Data Users Handbook documentation is a useful resource, however there are limitations of sampling and non sampling errors. Sampling error represents ACS sampling variation within counties between the surveyed and general population while non sampling variation represents data collection errors.

Variables used:
S1701_C01_041, S1701_C01_001

Calculations performed:
Living at or below 185% of Federal Poverty Level = S1701_C01_041,
Total Population = S1701_C01_001,
% Living at or below 185% of Federal Poverty Level = S1701_C01_041/S1701_C01_001

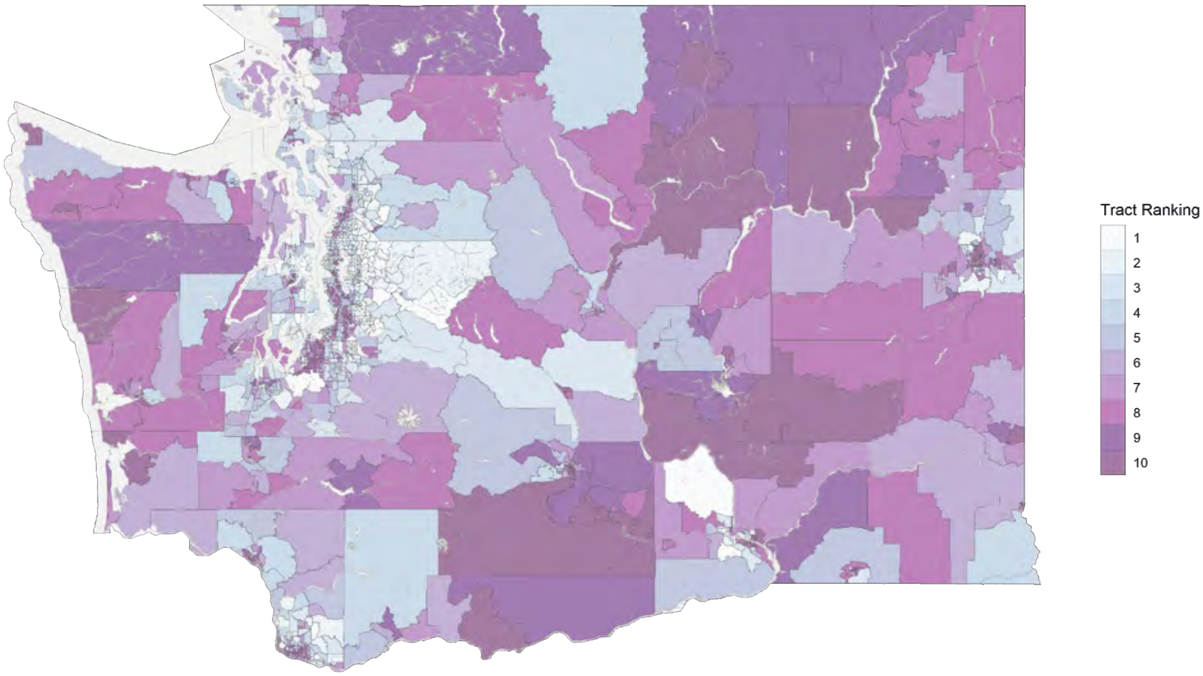
* For tracts with zero population, ACS will list some variables as missing data. For our calculations we changed these missing data to zeros.

Additional Resources

Certain published ACS estimates, such as total population estimates for counties and states, exactly match Census Data controls. These estimates, which have five asterisks (*****) in the MOE column in data.census.gov, are by definition fixed, and were considered to have no sampling error as instructed in Understanding and Using American Community Survey Data.

For MOE calculations, refer to U.S. Census Bureau, A Compass for Understanding and Using ACS Data Appendix 1. For MOEs in which either the numerator or denominator of a proportion were derived from multiple ACS variables, see "Calculating MOEs for Aggregated Count Data;" for MOEs derived from proportions, see "Calculating MOEs for Derived Proportions."

Map 8: Decile ranking of population living in poverty indicator



Race (people of color)

Justification

An individual's race/ethnicity is a primary social determinant of health and is strongly associated with exposure to environmental pollutants. Race and ethnicity significantly impact an individual's exposure to environmental hazards and air pollution. An individual's race/ethnicity shapes one's access to nutrition, occupation, housing, healthcare resources, and more. Among communities of color, increased chronic and psychosocial stress persist, and disparities in chronic and infectious diseases are evident. Communities of color and ethnic minorities are disproportionately exposed to environmental hazards well across the socioeconomic spectrum.

Pre-existing factors such as housing, geographic location, occupation, and financial stability significantly influence the extent of exposure to hazards such as toxic waste, exposure to ozone, proximity to Superfund sites, etc. Landfills, toxic waste facilities, hazardous waste sites and industrial facilities are more likely to be in areas with a high population of people of color (Kravitz-Wirtz et al., 2016).

In addition, in conditions of water pollution, lead exposure, and climate change communities of color experience higher vulnerability than their white counterparts. Children and women of color are most susceptible to negative health outcomes resulting from exposure to environmental pollutants such as poor birth outcomes, cardiopulmonary diseases, and increased hospitalizations due to chronic health conditions. The association of racial status and environmental exposure is complex but is rooted in racial discrimination and disparities.

Literature

Different racial and ethnic groups are disproportionately affected by environmental risk factors (Bell & Dominici, 2008; Cushing et al., 2015; Kravitz-Wirtz et al., 2016; Balazs & Ray, 2014). Superfund sites and other hazardous sites are more likely to be found near communities of color (Pollock & Vittas, 1995).

When exposed to pollutants, certain racial groups are more likely to have poor health outcomes such as asthma (DOH, 2013; Smith et al., 2005). A mother's racial and ethnic background can be negatively associated with poor birth outcomes such as low birth weights for some racial and ethnic groups more than others (Lu & Halfon, 2003).

In addition, certain racial and ethnic groups are more vulnerable to wildfire (Davies et al., 2018).

Data Source

2019 population estimates from Washington State Office of Financial Management

Method

The data for People of Color is comes from the Washington State Office of Financial management (OFM). It is a sum of all race/ethnicity categories EXCEPT White/Non-Hispanic, this includes: Black, American Indian/Alaskan Native, Asian, Native Hawaiian-Other Pacific Islander, Two or more races and the ethnicity grouping of "Spanish/Hispanic/Latino". You can access the website for any updated tables.

The OFM uses mathematical models of births, deaths, and migration to make forecasts based on numbers obtained from the Census Bureau. WTN terms these numbers "estimates" because they are not based on an actual count of people.

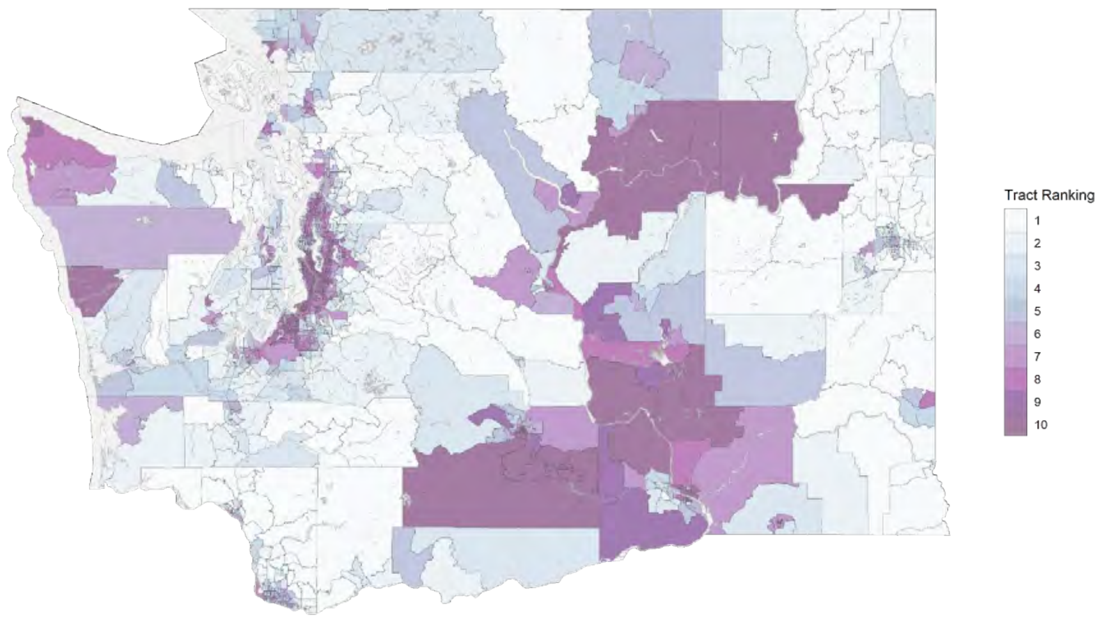
The population numbers included in WTN are used for rate calculations elsewhere in this site: a count is the numerator and the population estimate is the denominator.

Population data on WTN differ slightly from population data on the CDC National Tracking Network (NTN) portal, due to differences in methods for estimation. NTN uses the annual population estimates from the U.S. Census Bureau, which produces estimates every year between the 10-year censuses. Census Bureau methods are described on their Population Estimates website.

Additional Resources

Further information on collection and use of population estimates at the DOH are in the [Technical Appendix to the Health of Washington State report] (see section on "Census Population Counts and Intercensal and Postcensal Estimates").

Map 9: Decile ranking of population that are people of color indicator



Unemployment

Justification

Unemployment is a major factor when considering individual health and well-being. Unemployment can significantly impact mental and physical health as financial and emotional stress increases. This stress may lead to an increased susceptibility to environmental pollutants. With unemployment, individuals may experience the burden of financial strain, resulting in reduced access to healthcare resources, insurance, and nutritious food, leading to an increased risk of poor health outcomes related to environmental pollutants (DeFur et al., 2007).

When experiencing unemployment, individuals experience high levels of biological stress and long-term unemployment may lead to increased morbidity and mortality. Unemployment may lead individuals to seek housing in lower-income areas, which are often associated with higher levels of air pollution and environmental decline. In addition, in communities with high rates of unemployment, increased cardiovascular disease persists.

Literature

Economic activities including unemployment rates are closely associated with stressors that contribute to negative environmental health impacts (deFur et al., 2007; Premji et al., 2007). Unemployment rates are often used as a proxy indicator for vulnerability to environmental burden (Davis et al., 2010).

Unemployment is also closely tied to negative health outcomes (Athar et al., 2013; Dragano et al., 2008; Hafkamp-de Groen et al., 2013; Tapia Granados et al., 2014; Turner, 1995). Long term unemployment may be associated with increased risk for developing diseases associated with aging (Ala-Mursula et al., 2013). Areas with high unemployment rate are associated with higher rates of coronary heart disease (Dragano et al., 2008).

Data Source

2015 - 2019 ACS 5-year estimates, DP03 - Selected Economic Characteristics

Method

In addition to the census of every U.S. household every 10 years, as required by the U.S. Constitution, the Census Bureau has a sub-sample, yearly survey called the ACS. This representative sample-based survey gathers characteristics for a subset of the entire population of the U.S. each year.

The ACS asks respondents a variety of detailed questions on social and economic topics. WTN displays a selected subset of these indicators. This indicator represents the population of people 16 years and older that are in the labor force and registered as unemployed.

This indicator uses the percent of the population over the age of 16 that is unemployed and eligible for the labor force from the U.S. Census Bureau's ACS for 2015– 2019. This indicator excludes retirees, students, homemakers, institutionalized persons except prisoners, those not looking for work and military personnel on active duty. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables at the census tract level of geography.

For more information, refer to ACS General Data Users Handbook. The ACS General Data Users Handbook documentation is a useful resource, however there are limitations of sampling and non sampling errors. Sampling error represents ACS sampling variation within counties between the surveyed and general population while non sampling variation represents data collection errors.

Variables used:
DP03_0002, DP03_0005, DP03_0009P

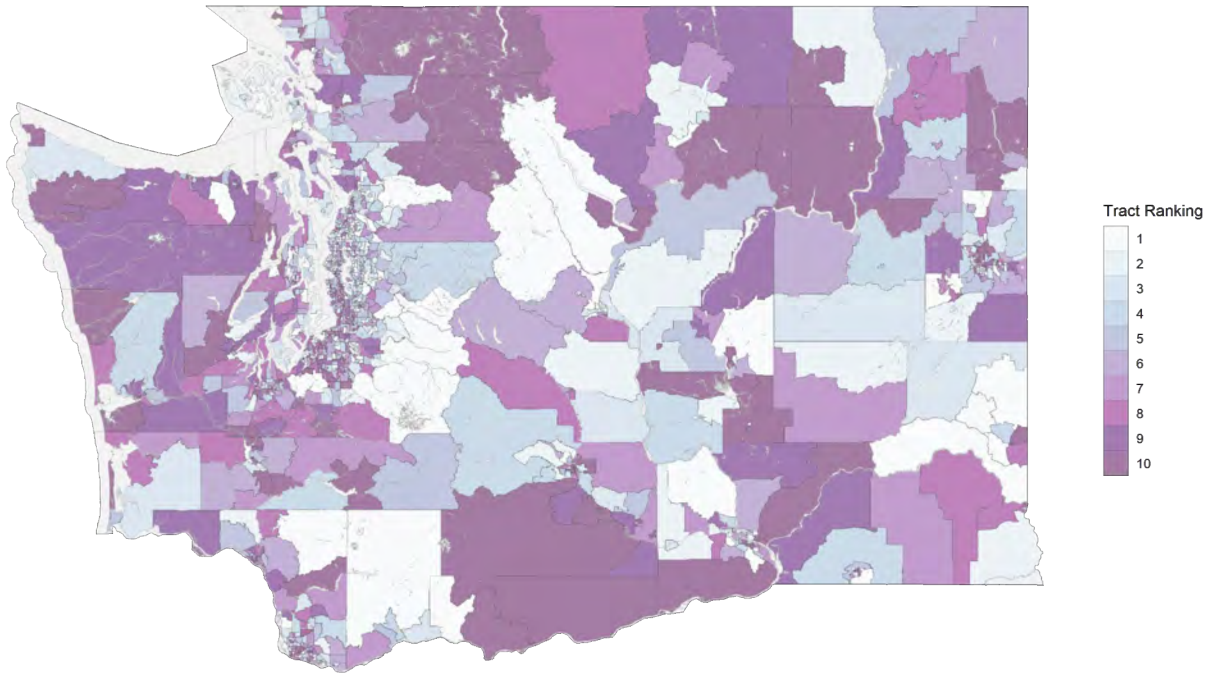
Calculations performed:
Unemployed People Over 16 Years Old = DP03_0005
Employable Population Over 16 Years Old = DP03_0003
Percent Unemployed Over 16 Years Old = DP03_0009P
* For tracts with zero population, ACS will list some variables as missing data. For our calculations we changed these missing data to zeros.

Additional Resources

Certain published ACS estimates, such as total population estimates for counties and states, exactly match Census Data controls. These estimates, which have five asterisks (*****) in the MOE column in data.census.gov, are by definition fixed, and were considered to have no sampling error as instructed in Understanding and Using American Community Survey Data.

For MOE calculations, refer to U.S. Census Bureau, A Compass for Understanding and Using American Community Survey Data Appendix 1. For MOEs in which either the numerator or denominator of a proportion were derived from multiple ACS variables, see "Calculating MOEs for Aggregated Count Data;" for MOEs derived from proportions, see "Calculating MOEs for Derived Proportions."

Map 10: Decile ranking of population that is unemployed indicator



Indicators in Pollution Burden

Environmental exposures

Engagement with environmental exposure occurs when pollution sources get into the environment and affect individuals or populations. Direct contact or prolonged contact with an environmental exposure could lead to poor health outcomes. This theme captures common/everyday environmental exposures and the risk of developing poor health outcomes.

In this report, environmental exposures include airborne pollutants such as diesel emissions, Ozone, $PM_{2.5}$, and Traffic density. Environmental exposure data on pollution sources, polluted areas and pollution concentrations were gathered to identify risk.

Diesel exhaust $PM_{2.5}$ emissions

Justification

Diesel emissions are the released gases and particulate matter from the combustion of diesel fuel. The most common sources of emissions are cars, trucks, buses, trains, ships and other vehicles. High levels of diesel exhaust circulate near ports, busy trafficways, and railyards. Constant exposure to diesel emissions leads to various health effects ranging from eye and skin irritation to respiratory and cardiovascular diseases.

Literature

Diesel engines emit harmful compounds such as ultrafine particles, nitrogen dioxide, benzene and formaldehyde (Betha & Balasubramanian, 2012). Studies have found that short-term exposure to these compounds can cause oxidative stress, increased airway inflammation and acute cardiovascular events (Krishnan et al., 2013; Patel et al., 2012).

Both acute and chronic exposure to diesel emissions can cause poor respiratory outcomes in children with asthma and in people with chronic obstructive pulmonary disease (Krivoshto et al., 2008; Löndahl et al., 2012; McCreanor et al., 2007; Spira-Cohen et al., 2011). Long-term exposure to diesel emissions was associated with higher rates of lung cancer and related mortality in those working near diesel exhaust (Garshick et al., 2004; Garshick et al., 2008).

Data Source

Field Diesel $PM_{2.5}$ annual tons 2014 estimates, Washington State Department of Ecology's 2014 Comprehensive Emissions Inventory; AIRPACT

Method

The estimates of $PM_{2.5}$ emissions from diesel exhaust were derived from the Washington State Department of Ecology's 2014 Comprehensive Emissions Inventory. All diesel exhaust $PM_{2.5}$ emissions estimates were mapped to the AIRPACT modeling domain, which uses 4km x 4km grid cells. Major point source emissions were directly allocated to the grid cell in which they are located. Other emission sources (e.g. non-point and mobile) were allocated to grid cells based on spatial surrogates developed for AIRPACT. These spatial surrogates allocate total county emissions to individual grid cells by source classification codes, based on various available spatial datasets. Each census tract was assigned the maximum emissions estimate of any grid cells that intersect it.

The census tracts and boundaries used in this analysis may be viewed in the feature layer map. Please note that the feature layer map includes additional census tracts (water-only tracts) and that the boundaries for coastline tracts include portions of the adjacent body of water in order to account for emissions from other sources (shipping channels, ferry routes, and ports) that would not have otherwise been captured in an analysis of land-only tracts.

There is no spatial variability within the 4km x 4km grid provided by AIRPACT. Even if a small community only covers a fraction of the overlapping grid cell, the concentration of that community's monitor will be assigned to the entire grid cell. Local weather patterns happen at finer scales than this, and that can mean mischaracterized air quality on a neighborhood level.

Additional Resources

Tract boundaries used in this analysis come from the United States Census Bureau and are available for download here: https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2010&layergroup=Census+Tracts

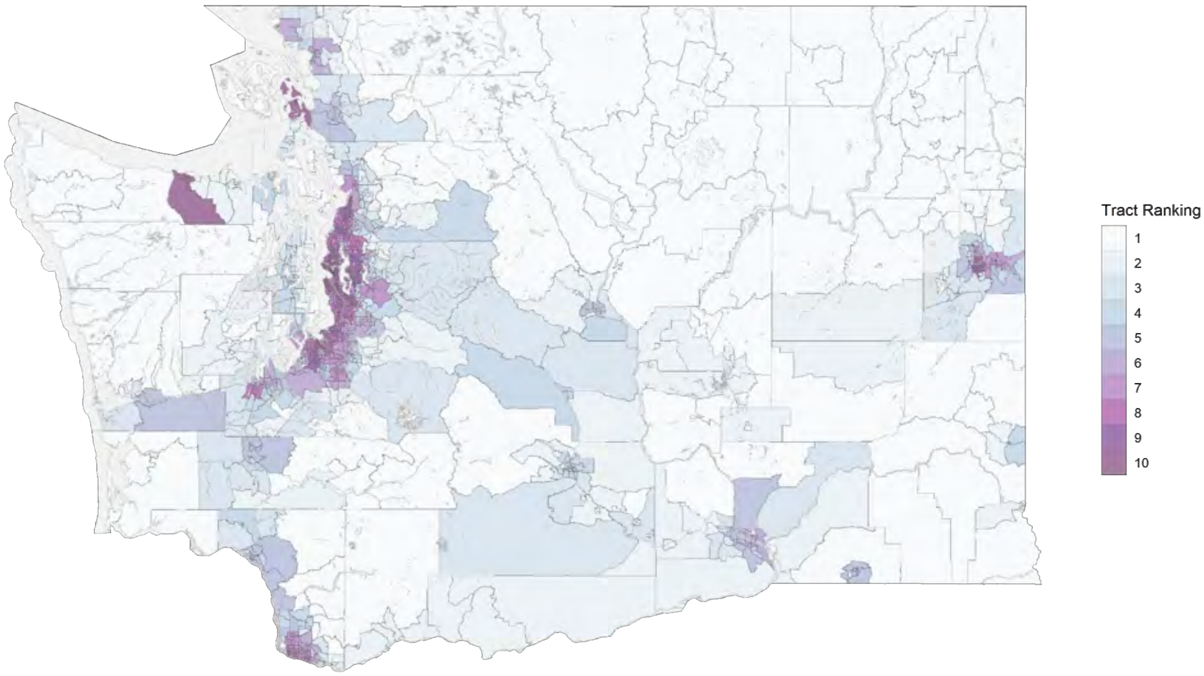
The current Washington Comprehensive Emissions Inventory is available at: https://ecology.wa.gov/Air-Climate/Air-quality/Air-quality-targets/Air-emissions-inventory

The US EPA Spatial Surrogate Workbook was the basis for AIRPACT surrogates. The Department of Ecology made custom updates as well. The original EPA workbook is: ftp://ftp.epa.gov/EmisInventory/surrogates/shapefiles_2010/US_SpatialSurrogate_Workbook_v093013.xlsx

The AIRPACT website is: http://lar.wsu.edu/airpact/index.html

Contact Washington State Department of Ecology with any questions about these data: airemissions@ecy.wa.gov

Map 11: Decile ranking of diesel exhaust PM2.5 emissions indicator



Ozone

Justification

Ozone is a highly reactive gas consisting of oxygen atoms. Ozone is both anthropogenic and naturally occurring in the upper atmosphere, in both the stratosphere and the troposphere (ground level). While ozone is naturally occurring in the stratosphere, significant amounts of ozone in the troposphere is formed primarily from photochemical reactions between air pollutants such as volatile organic compounds (VOC) and nitrogen oxides (NOx). Sources of these air pollutants include motor vehicles, biogenic sources, solvent use, residential wood combustion, gasoline pumps, and industrial point sources. Depending on sunlight and emission patterns, ozone levels shift.

Significant health threats exist with exposure to high levels of ozone. For those living in areas of serious ozone exposure, health risks include higher rates of asthma, and increased daily deaths. In addition, exposure to ozone has been associated with increased cardiovascular and respiratory mortality.

Literature

Ozone is one of six criteria air pollutants (US EPA, "Criteria Air Pollutants"). Exposure to ozone pollution can result in adverse health outcomes including increased risk of mortality in people (Fann et al., 2012). Ozone levels, even at low levels, can increase airway inflammation (Alexis et al., 2010), and in children, increased ozone levels are positively associated with higher incidence of respiratory distress leading to emergency and hospital admissions (Burnett et al., 2011; Lin, Le & Hwang, 2008; Moore et al., 2008).

Certain sociodemographic characteristics also affect vulnerability to ozone-related mortality, including sex, age and race (Bell & Dominici, 2008; Medina-Ramon & Schwartz, 2008).

Airborne dust and wildfires have been associated with higher levels of ozone and $PM_{2.5}$, leading to a higher number of emergency room visits (Rodopoulou et al., 2013).

Data Source

NW-AIRQUEST Regional Background Design Values, 2014-2017 estimates

Method

This indicator uses 8-hour ozone design values interpolated at 4km x 4km grid cells from July 2014-June 2017. The form of the ozone design value is the annual fourth-highest daily maximum 8-hour concentration (D8M), averaged over three years. Design values were interpolated using the relationship between ozone design values measured at air quality agency monitoring sites and median forecast D8M ozone from the AIRPACT forecast model. Ozone design values were interpolated across Washington with Empirical Bayesian Kriging Regression Prediction using measured design values as the dependent variable and median forecast D8M as the explanatory variable.

Each census tract was assigned the interpolated ozone design value of the most populated grid cell that intersects that tract. Population estimates at grid cells were derived from 2010 census data at the block group level, assigned to grid cells based on the proportion of each block group intersecting the grid cell.

The value in each 4km by 4km grid is the same within each grid cell. This means within the large 16 km^2 area of the cell, there is no spatial variability. Even if a small community only covers a fraction of the overlapping grid cell, the concentration of that community's monitor will be assigned to the entire grid cell. Local weather patterns happen at finer scales than this, and that can mean mischaracterized air quality on a neighborhood level.

Additional Resources

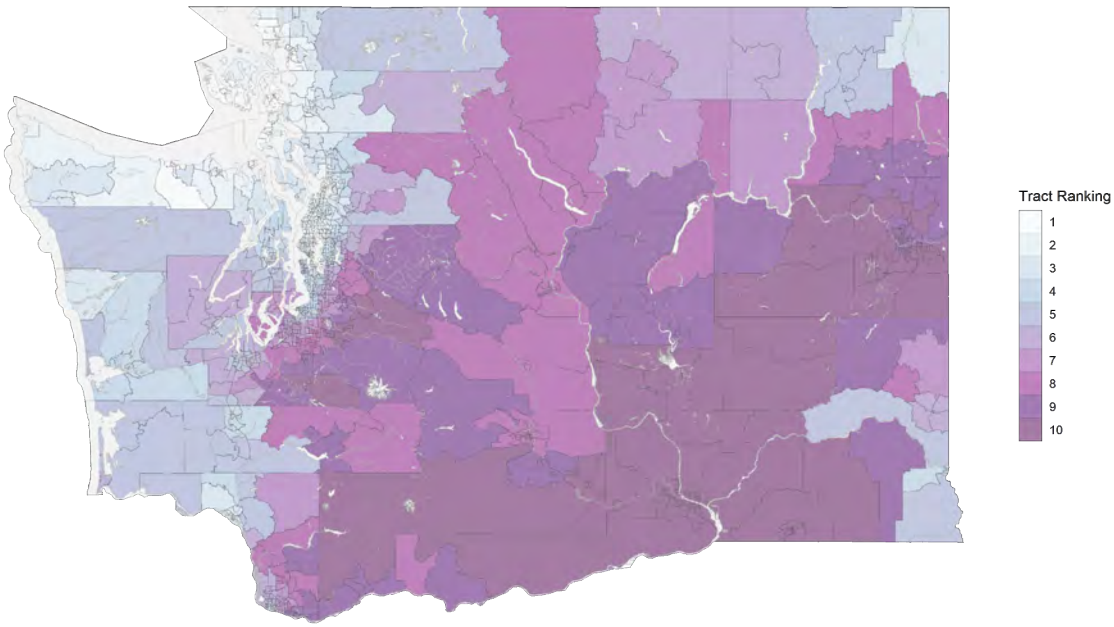
The 4km x 4km ozone dataset and detailed explanation of methods are available at https://idahodeq.maps.arcgis.com/apps/MapSeries/index.html?appid=0c8a006e11fe4ec5939804b873098dfe

More information about ozone design values can be found at https://www.epa.gov/ground-level-ozone-pollution/timeline-ozone-national-ambient-air-quality-standards-naaqs

Ozone monitoring data are available from the Washington Department of Ecology at https://enviwa.ecology.wa.gov/home/map

The AIRPACT website is: http://lar.wsu.edu/airpact/index.html

Map 12: Decile ranking for ozone indicator



Particulate Matter 2.5 ($PM_{2.5}$)

Justification

Particulate matter is a chemical mixture of particles with diameters that are 2.5 micrometers and smaller. These particles come from many different sources such as residential wood combustion, wildfires and other outdoor burning, dust, industrial point sources, commercial cooking and motor vehicles. Particulate matter can be emitted directly from a source or form through secondary chemical reactions of chemicals like sulfur oxides and nitrogen oxides. The composition of $PM_{2.5}$ depends on seasonal periods, geography, and weather patterns, on both local and regional scales.

Particulate matter is extremely hazardous because the small particles can penetrate the bloodstream and be absorbed deep into organs, resulting in poor health outcomes. The elderly, those with preexisting respiratory health conditions, and children are most susceptible to the significant health impacts posed by $PM_{2.5}$.

Literature

$PM_{2.5}$ (fine particles) is one of six criteria air pollutants (EPA, “Criteria Air Pollutants”). Similar to ozone, the relationship between exposure to $PM_{2.5}$ and negative health outcomes, such as respiratory and cardiovascular disease, is well documented (Adar et al., 2013; Bell, Ebisu & Belanger, 2007; Kaufman et al., 2016).

Exposure to $PM_{2.5}$ can elevate the risk of mortality and adverse birth outcomes such as low birth weight (Bell, Ebisu & Belanger, 2007; Fann et al., 2012; Morello-Frosch et al, 2010). In addition, short-term exposure can lead to higher rates of hospitalization in susceptible populations such as children (Dominici et al., 2006; Ostro et al., 2008).

Airborne dust and wildfires have been associated with higher levels of $PM_{2.5}$ and found to increase emergency room visits (Rodopoulou et al., 2013; Wegesser, Pinkerton & Last, 2009). Long-term exposure to $PM_{2.5}$ can also lead to increased risk of cardiovascular disease morbidity and mortality (Kaufman et al., 2016; Kim et al., 2014).

Data Source

Field PM2.5 2014 – 2017 estimates from the Washington State Department of Ecology

Method

This indicator uses the mean and 98th percentile daily $PM_{2.5}$ concentrations estimated at 4km x 4km grid cells from July 2014-June 2017. The 3-year mean and 3-year 98th percentile daily $PM_{2.5}$ concentrations are surrogates for the annual and 24-hour $PM_{2.5}$ design values, respectively. Mean and 98th percentile concentrations were interpolated at grid cells using the relationship between mean/98th percentile $PM_{2.5}$ measured at air quality agency monitoring sites and median daily forecast $PM_{2.5}$ from the AIRPACT forecast model. The monitor/model ratio at each monitoring site was calculated and then interpolated across Washington using Empirical Bayesian Kriging. The interpolated ratios were multiplied by median daily forecast $PM_{2.5}$ from AIRPACT at each 4km x 4km grid cell to yield interpolated mean and 98th percentile $PM_{2.5}$.

Each census tract was assigned the maximum interpolated mean and 98th percentile $PM_{2.5}$ value of any grid cells that intersect it. Mean and 98th percentile values at census tracts were each normalized to a scale of [0-1] and summed to give each census tract a single $PM_{2.5}$ score. The value in each 4km by 4km grid is the same within each grid cell. This means within the large 16 km^2 area of the cell, there is no spatial variability. Even if a small community only covers a fraction of the overlapping grid cell, the concentration of that community's monitor will be assigned to the entire grid cell. Local weather patterns happen at finer scales than this, and that can mean mischaracterized air quality on a neighborhood level.

Additional Resources

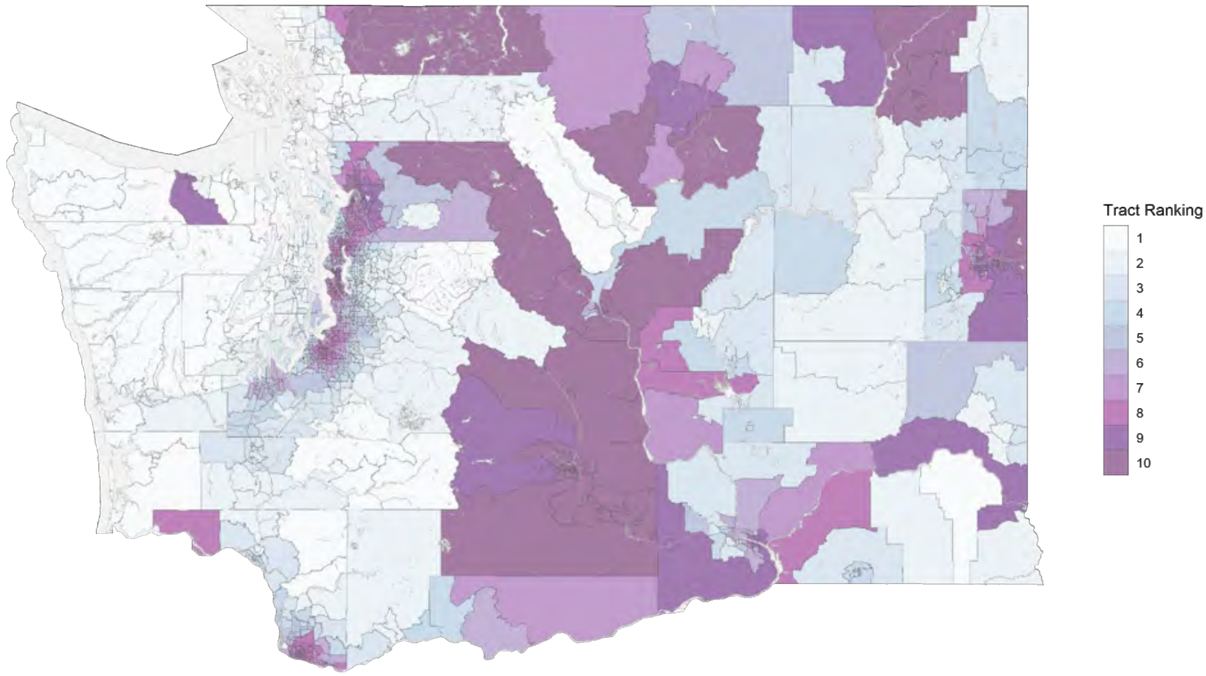
The 4km x 4km $PM_{2.5}$ datasets and detailed explanation of methods are available at https://idahodeq.maps.arcgis.com/apps/MapSeries/index.html?appid=0c8a006e11fe4ec5939804b873098dfe

More information about $PM_{2.5}$ design values can be found at https://www.epa.gov/pm-pollution/timeline-particulate-matter-pm-national-ambient-air-quality-standards-naaqs

$PM_{2.5}$ monitoring data are available from the Washington State Department of Ecology at https://enviwa.ecology.wa.gov/home/map

The AIRPACT website is http://lar.wsu.edu/airpact/index.html

Map 13: Decile ranking of PM2.5 concentrations indicator



Toxic releases from facilities (RSEI)

Justification

Toxic releases from facilities entail chemicals that are emitted into the air from industrial facilities. Quantities of these hazardous pollutants are monitored by the EPA in their Toxic Release Inventory (TRI) of on-site releases to air, land, water, and underground.

For those living near TRI facilities, high levels of TRI emissions lead to poor health outcomes. TRI emissions place individuals at risk for numerous cancers, cardiovascular mortality, and infant mortality. Disproportionately disadvantaged populations such as those in neighborhoods with low median incomes or communities of color have a greater likelihood of living in areas of high TRI air pollutants. In addition, those who are at an increased risk of exposure include employees, children, and the elderly.

Chemical releases from industrial facilities are tracked through the TRI, a program through the US EPA. Air releases are modeled by the TRI Program Risk Screening Environmental Indicator (RSEI).

Literature

People living near facilities with routine chemical releases have increased risk if toxic compounds are released into the environment (Agarwal, Banternghansa & Bui, 2010). A study has shown that TRI facilities are more prevalent in or near low-income communities or communities of color (Szasz & Meuser, 1997).

Studies have also shown increased toxic releases to be associated with increased risk of infant mortality, childhood cancers and cardiovascular mortality (Agarwal, Banternghansa & Bui, 2010; Choi et al., 2006; Hendryx, Luo & Chen, 2014).

Data Source

US EPA EJSCREEN 2021, based on RSEI 2018 - 2020 3-year average

Method

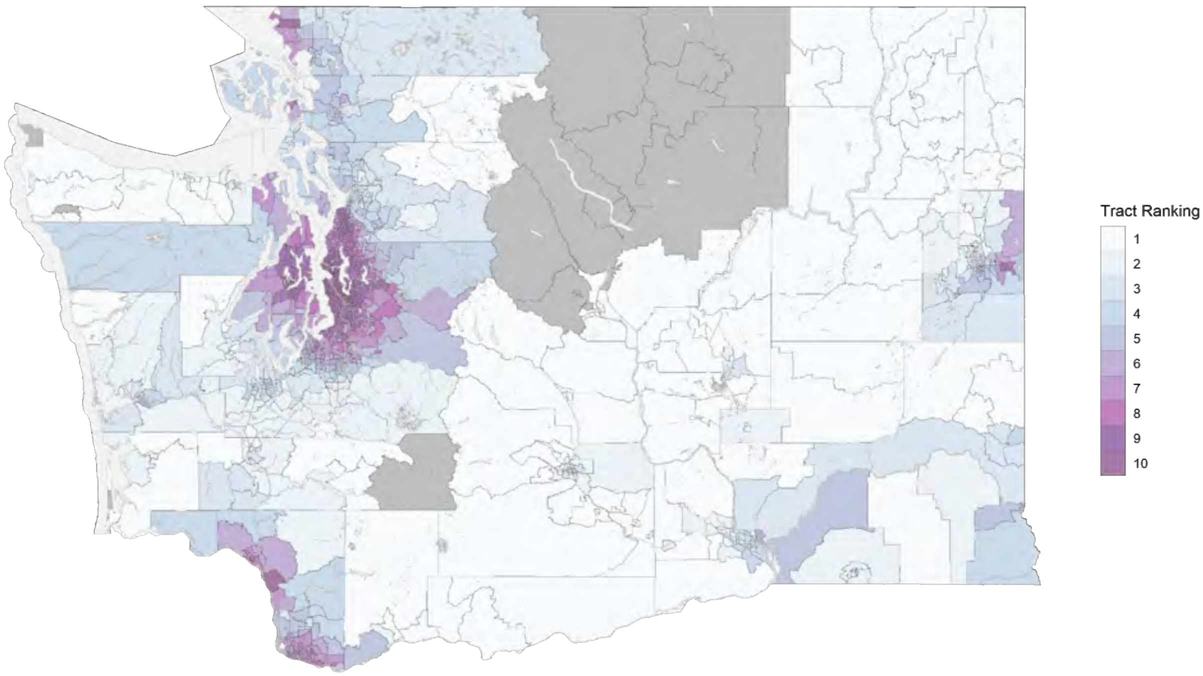
This indicator shows the toxicity-weighted concentrations of chemical releases to air from facility emissions and off-site incineration. Data was downloaded from RSEI where air releases are modeled by the TRI program.

The US EPA provided nationwide RSEI Microdata aggregated at the census tract level for 2018, 2019, and 2020. The Geographic Microdata is a model of air pollution releases that are plotted on 810-meter grid cells (RSEI Geographic Microdata (RSEI-GM) | US EPA). We selected the Washington state 2010 census tracts and calculated a 3-year-average for each.

RSEI models the toxicity-weighted concentration into air from TRI sites for census tracts. Although all models have uncertainty involved, studies have shown the RSEI model of toxicity weighted concentration into air and actual measured concentrations to be in good agreement (McCarthy et al., 2009).

This indicator only captures toxic releases into air but does not capture water or soil deposition of toxic releases, which may also occur.

Map 14: Decile ranking of toxic releases from facilities indicator



Proximity to heavy traffic roadways

Justification

Traffic density refers to the degree of exposure to vehicle exhaust based on the amount of traffic in a certain area. While busy trafficways affect communities through noise pollution, development of smog, and increased pedestrian injuries, trafficways can also increase air pollution in those areas. Vehicle exhaust contains very harmful chemicals that are detrimental to the human body. Traffic volume and density greatly impact health conditions and are associated with infant mortality, poor birth outcomes, cardiovascular disease, and cancers. Furthermore, the effect of pollution is more pronounced among the elderly and those that have preexisting health conditions.

Literature

Living near high traffic density may lead to increased exposure to noise, vibration, and local land use changes, in addition to traffic-related air pollution (Boehmer et al., 2013).

Noise pollution from high traffic roads can also cause sleep disturbances leading to poorer quality of life (Eze et al., 2017).

Exposure from traffic-related air pollution was associated with poor health effects such as cardiovascular disease mortality, respiratory health and an increased risk of low birth weight (Berglind et al., 2009; Ghosh et al., 2012; Habermann & Gouveia, 2012; Kan et al., 2007; von Klot et al., 2009).

Air pollution from traffic and major roadways may also predispose children to poor respiratory health outcomes (Gauderman et al., 2007; Gunier et al., 2003; Shultz et al., 2012). Long-term exposure to traffic-related air pollution can lead to increased risk of cardiovascular diseases (Kaufman et al., 2016).

Pregnant women exposed to traffic pollution are at greater risk of having a child born with a low birth weight. Noise pollution and the way land is organized and used in heavy traffic areas contribute to higher levels of stress, and poor sleep, which contribute to other physical and mental health problems (e.g., high blood pressure, anxiety, depression).

Data Source

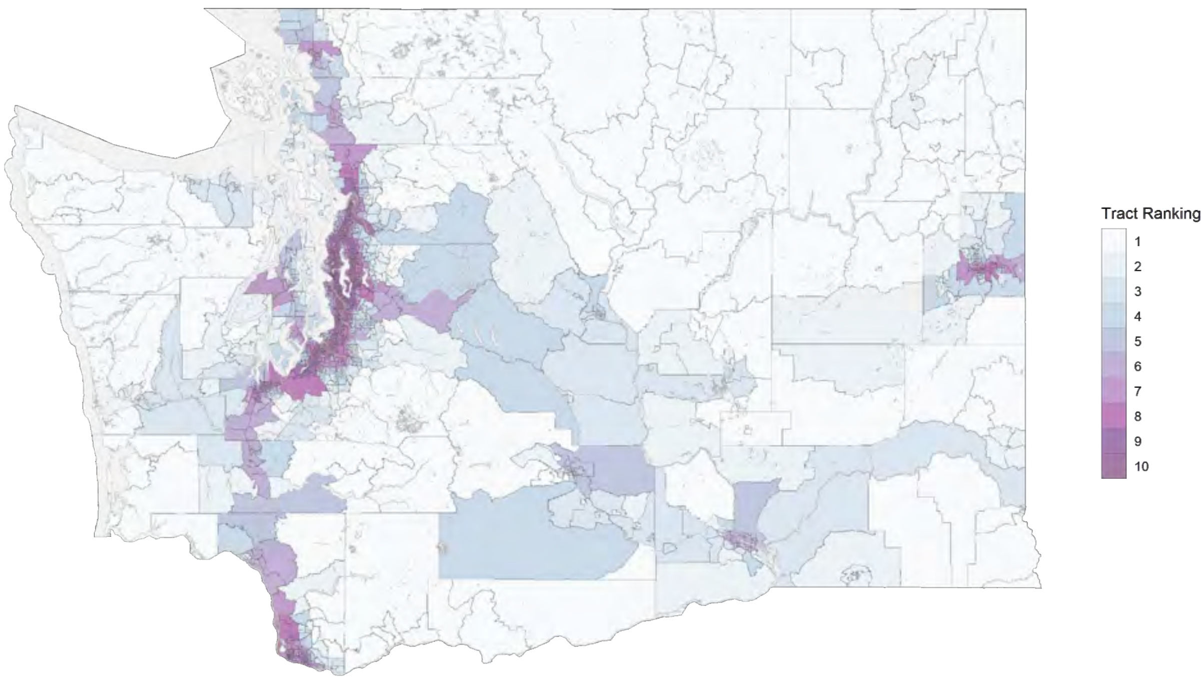
2019 traffic data from WSDOT

Method

This indicator shows the maximum distance-weighted traffic along Washington highways for each census tract. Average Annual Daily Traffic (AADT) on highways is from a network of permanent and short-duration traffic counters. Census tracts are the main boundaries used by the census bureau. The units for this indicator are maximum highway AADT (vehicles per day) / Distance to highway (km) or vehicles/day/km.

We used the Washington State Office of Financial Management's 2010 census boundaries (Census geographic files | Office of Financial Management (wa.gov), and 2019 roadway traffic from WSDOT map center (WSDOT - Traffic Sections (AADT) | WSDOT - Traffic Sections (AADT) | Washington State Geospatial Open Data Portal).

Map 15: Decile ranking of proximity to heavy traffic roadways indicator



Environmental Effects

Environmental effects capture poor environmental conditions. Pollutants can greatly diminish the interactions among the ecosystem and can lead to loss of resources or poor health outcomes. Environmental effects can be immediate or have a delayed impact and affect the well-being and access of nearby communities. Not only do environmental effects burden humans, they also affect natural wildlife and other biotic components of the ecosystem.

Environmental effect indicators reviewed in this report include: lead risk from housing, proximity to hazardous waste generators and facilities, proximity to Superfund sites, proximity to facilities with highly toxic substances, and wastewater discharge.

Lead risk from housing

Justification

Lead poisoning is a serious but preventable public health issue. Lead is a naturally occurring toxic heavy metal. However, much of the lead found in human environments is due to use of lead in products such as gasoline and house paint.

There are no known safe levels of lead exposure, and even small amounts can lead to significant health implications. Exposure to lead can lead to chronic health conditions, neurological defects, and nervous system damage. Those that live in low socioeconomic housing or in poverty are more likely to live in older homes and be exposed to lead poisoning. Children are at most risk of poor health outcomes as they are more susceptible to lead exposure due to their explorative nature.

Literature

Before 1978, paint used in houses had heavy traces of lead, until the federal government banned consumer use of lead-based paint. Lead paint in older homes can elevate indoor lead levels, which in combination with poor housing conditions can elevate the risk of lead exposure (Adamkiewicz et al., 2011; Jacobs et al., 2009; Roberts et al., 2003).

Lead exposure can cause learning disabilities, behavior problems, stunted physical growth and delayed mental development (AAP, 2005).

Data Source

2015 - 2019 ACS 5-year estimates, DP04 - Selected Housing Estimates

Method

In addition to the census of every U.S. household every 10 years, as required by the U.S. Constitution, the Census Bureau has a sub-sample, yearly survey called the ACS. This representative sample-based survey gathers characteristics for a subset of the entire population of the U.S. each year.

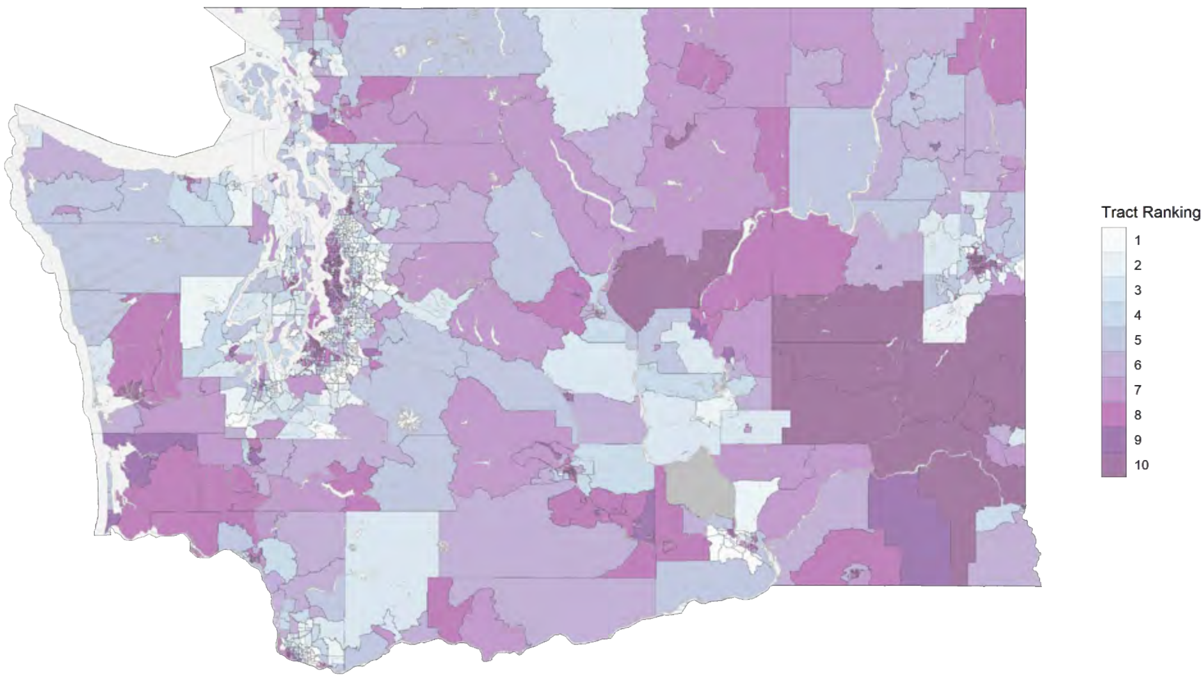
The ACS asks respondents a variety of detailed questions on social and economic topics. WTN displays a selected subset of these indicators. This indicator represents the proportion of estimated housing units with proportionate lead risk for each housing unit era.

This indicator provides the total number of houses and proportion of houses by year of construction from the U.S. Census Bureau's ACS for 2015 - 2019. These data were used in conjunction with national estimates of the proportion of housing from each era with lead risks.

This indicator models potential lead exposure. This indicator reflects the number and percent of housing units built before 1980, including single homes and multiple residence units such as apartments. Age of a building by itself does not reflect the actual exposure to lead. The age of a home is a marker of risk for presence of lead paint because paint typically contained high levels of lead in the decades leading up to 1980. In the early 1970s the paint industry issued voluntary standards limiting lead content in paint, and in 1978 lead was banned from use in the manufacture of residential paint.

Data on housing age come from the U.S. Census's ACS 5-year roll-up. This dataset provides the total number of houses and proportion of houses by year of construction. We adjust each era of housing with a factor that reflects proportionate risk for that era. The data is from Jacobs et al., 2002; the adjustment for housing built: before 1940 = 0.68; 1940-1959= 0.43; 1960-1979= 0.08.

Map 16: Decile ranking of lead risk from housing indicator



Proximity to hazardous waste treatment storage and disposal facilities

Justification

Hazardous waste is defined as having harmful properties that impact human health and the environment. Hazardous waste comes from industrial manufacturers and is generated in many forms such as liquids, solids, gasses, and sludges.

Hazardous waste generators and facilities can greatly affect the health of populations living in proximity. Due to the various forms of hazardous waste that is discarded, the area surrounding hazardous waste generators and facilities is at risk of contamination of air, water, and soil. Studies have shown that living near hazardous waste generators and facilities can be associated with health effects such as diabetes and cardiovascular disease. In addition, the locations of the generators and facilities are often in communities of color or low-income communities, making them susceptible to poor health outcomes.

Literature

Hazardous waste generators and facilities pose increased environmental risks to surrounding communities. These facilities produce various forms of hazardous compounds to human health (McGlinn, 2000; Fazzo et al., 2017). Living near hazardous waste generators and facilities may contribute to poor health effects such as diabetes and cardiovascular disease (Kouznetsova et al., 2007; Sergeev & Carpenter, 2005).

Hazardous waste generators and facilities are often located close to communities of color or low-income communities (Aliyu, Kasim & Martin, 2010; Boer et al., 1997).

Data Source

EJSCREEN 2021 estimates, based on RCRAInfo

Method

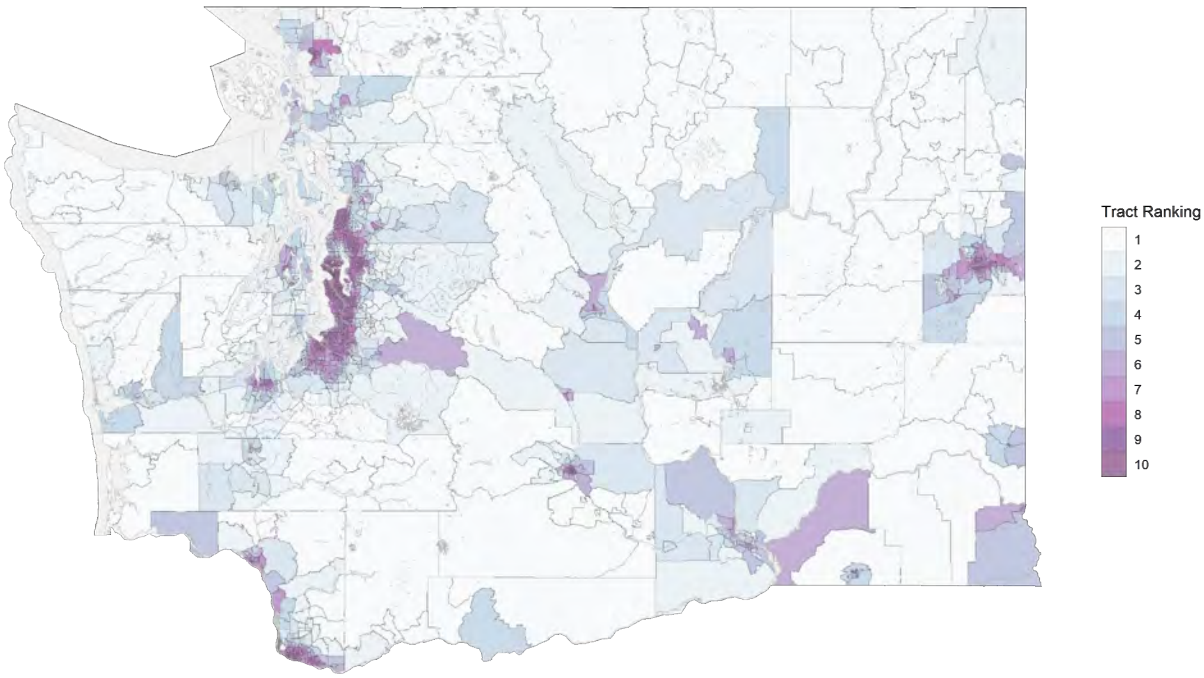
This indicator uses the count of all commercial Hazardous Waste Treatment, Storage and Disposal Facilities (TSDF) facilities within 5 km, divided by distance, presented as population weighted averages in each census tract. This indicator was directly downloaded from EJSCREEN.

This indicator was developed using nationwide databases and may not reflect the risk of living in close proximity to all hazardous waste sites in Washington. The 5km buffer used in this indicator was found to be appropriate for the national indicator. However, a smaller buffer size may be more appropriate for state-specific applications.

Additional Resources

For more information, refer to EJSCREEN Technical Documentation: https://www.epa.gov/ejscreen/technical-documentation-ejscreen.

Map 17: Decile ranking of Proximity to Hazardous Waste Treatment Storage and Disposal Facilities indicator



Proximity to national priorities list facilities (Superfund sites)

Justification

Superfund sites, also known as National Priorities List (NPL) sites, are areas where hazardous waste has been dumped or spilled historically. Efforts to clean out toxic waste are underway through the Superfund program. These sites typically include mining grounds, manufacturing sites, processing plants, and landfills.

Facilities that use highly toxic substances (substances with flammable or explosive potential) are required to establish a Risk Management Plan (RMP) with the Environmental Protection Agency (EPA). In the event of an accident, communities in close proximity to RMP facilities may be disproportionately burdened by the toxic releases. Studies have shown facilities with an RMP site are more likely to be near communities of color.

Literature

Communities near Superfund sites are at increased risk of being exposed to environmental contaminants from these sites (Zota et al., 2011). NPL sites are often situated near communities of color or low-income communities (Kearney & Kiros, 2009).

Studies have found proximity to Superfund sites to be closely associated with poor health effects such as low birth weight (Ala et al., 2006; Baibergenova et al., 2003).

Residents living closer to a NPL site were found with higher blood pesticide levels compared to those living further away (Gaffney et al., 2005).

Data Source

EJSCREEN 2021 estimates, based on CERCLIS

Method

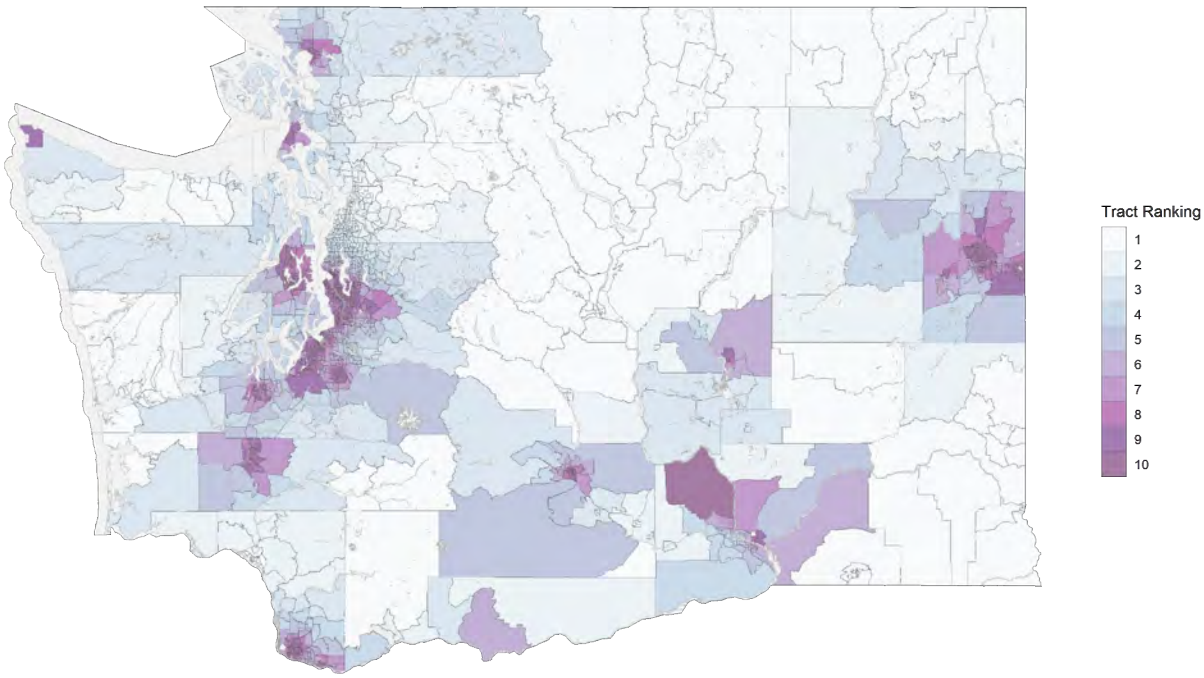
This indicator displays the count of sites proposed and listed on the NPL, directly downloaded from EJSCREEN. Each site is represented by a point on the map (latitude/longitude coordinate), within 5 km of the average resident in a block group, divided by distance and calculated as the population-weighted average in each census tract.

This indicator was developed using nationwide databases and may not reflect the risk of living within close proximity to all NPL sites in Washington. The 5km buffer used in this indicator was found to be appropriate for the national indicator. However, a smaller buffer size may be more appropriate for state-specific applications.

Additional Resources

For more information, refer to EJSCREEN Technical Documentation: https://www.epa.gov/ejscreen/technical-documentation-ejscreen

Map 18: Decile ranking of Proximity to National Priorities List Facilities (Superfund Sites) indicator



Proximity to risk management plan

Justification

Toxic releases from facilities entails the safe management of toxic substances and occupational risk. Limiting occupational exposure and occupational hazards is key to reducing accidents and unwanted toxic exposures.

Communities living in areas where facilities release toxic chemicals are at greater risk of poor outcomes caused by accidents or unsafe management practices. Studies have shown that communities of color and those of low socioeconomic backgrounds are more likely to live in surrounding areas, placing them at higher risk of potential health impacts such as cardiovascular disease and cancer.

According to the Clean Air Act, RMP plans are federally required for toxic facilities that release extremely hazardous chemical substances to develop a RMP that is updated every 5 years. These plans are valuable for first responders and ensure that safe practices are in place to respond to chemical emergencies in the community and improve accident prevention.

Literature

Facilities that use highly toxic substances or substances with flammable or explosive potential are required to establish a RMP with the EPA (Kleindorfer et al., 2003). In the event of an accident, communities in close proximity to RMP facilities may be exposed to increased levels of toxic releases (Elliot et al., 2003). Studies have shown facilities with an RMP site are more likely to be near communities of color (Elliot et al., 2003; Kleindorfer et al., 2003).

Data Source

EJSCREEN 2021 estimates, based on RMP

Method

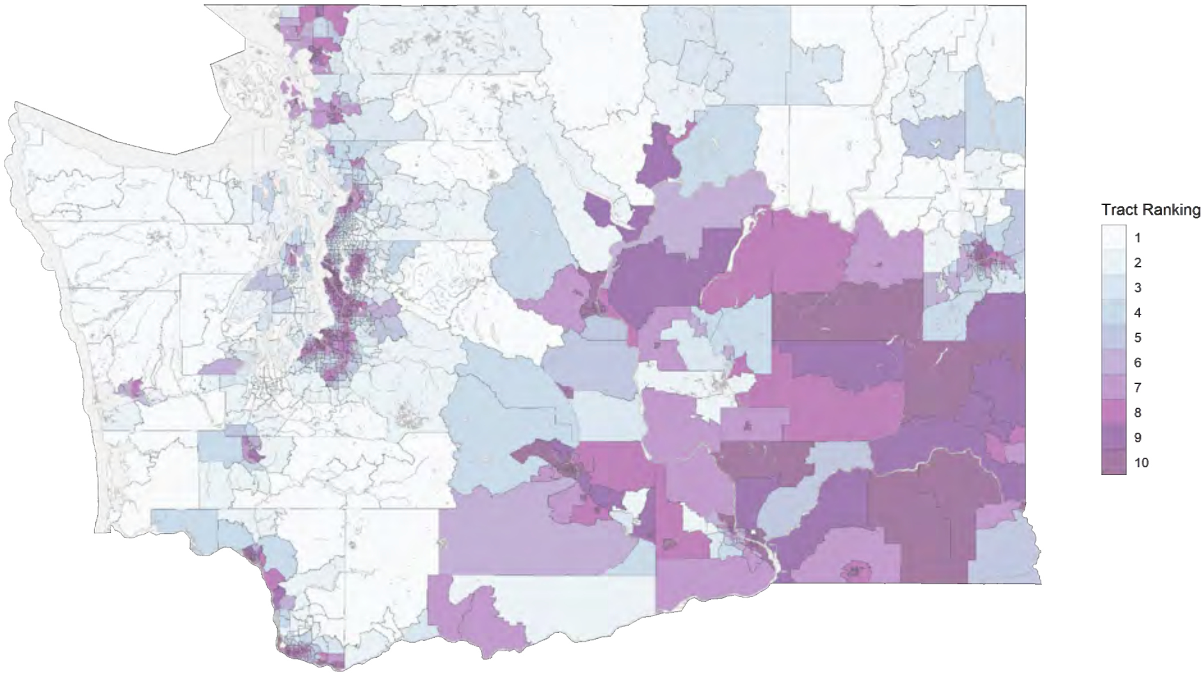
This indicator shows the count of RMP facilities within 5 km, divided by distance, presented as population-weighted averages in each census tract. The data was downloaded from EJSCREEN.

This indicator was developed using nationwide databases and may not reflect the risk of living within close proximity to all RMP facilities in Washington. The 5km buffer size used in this indicator was found to be appropriate for the national indicator. However, a smaller buffer size may be more appropriate for state-specific applications.

Additional Resources

Information on the EPA's RMP Methodology may be found here: https://www.epa.gov/rmp/risk-management-plan-rmp-rule-overview
For more information, refer to EJSCREEN Technical Documentation:
https://www.epa.gov/ejscreen/technical-documentation-ejscreen.

Map 19: Decile ranking of Proximity to Risk Management Plan indicator



Wastewater discharge

Justification

Wastewater refers to the used waste and solids that are released as household sewage. This wastewater flows into a wastewater treatment plant and is stored in underground tanks. The discharge from wastewater plants can pollute the nearby groundwater and surface water if not carefully managed. In such cases, the contaminated storage water can lead to poor health outcomes for many communities that use that water as their drinking water supply. In addition, leaked wastewater could poison soil and emit dangerous odors significantly impacting farmers.

Communities of color, ethnic minorities, and those in low socioeconomic conditions bear the burden of disease and are most vulnerable to poor health outcomes such as hypertension, cancer, and waterborne infections.

Literature

Discharge from wastewater facilities can directly contaminate surface water and groundwater and are associated with poor health outcomes such as the prevalence of hypertension (Karouna-Renier et al., 2007).

These contaminants can put nearby communities at greater vulnerability when the contaminated sites are used as irrigation or drinking water supplies (Balazs & Ray, 2014; Brender, Maantay & Chakraborty, 2011; VanDerslice, 2011).

Data Source

EJSCREEN 2021 estimates, based on RSEI

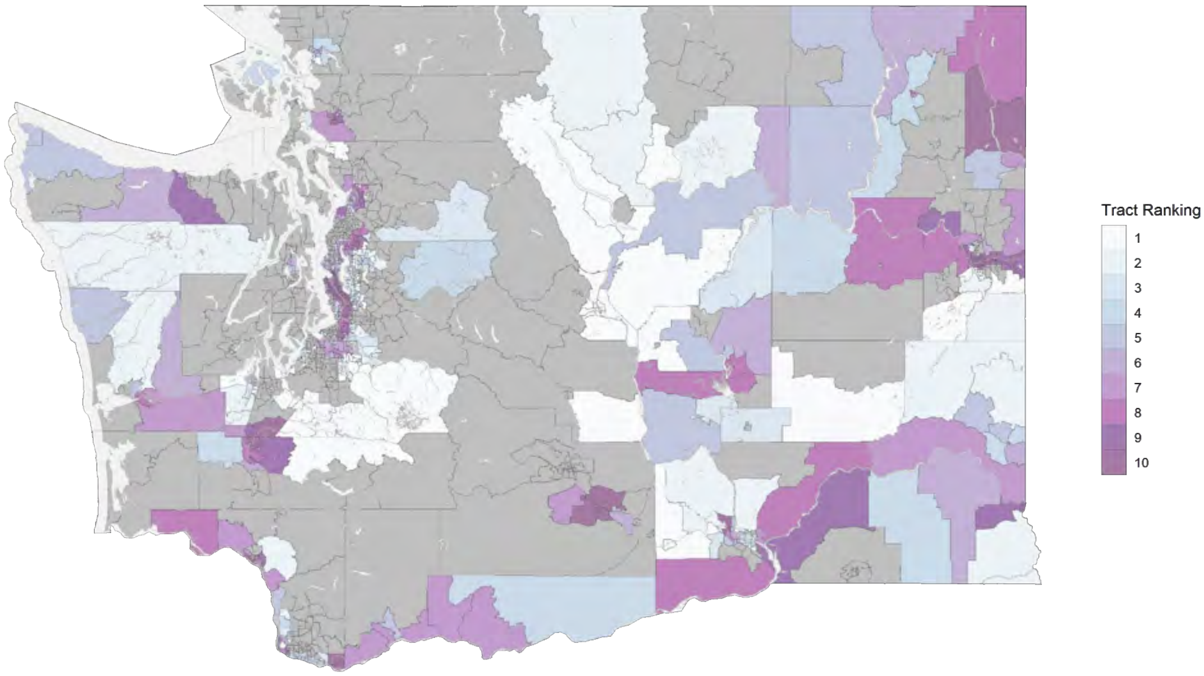
Method

This indicator displays toxicity-weighted concentration in stream reach segments within 500 meters of a block centroid, divided by distance in meters, presented as the population-weighted average in each census tract. Adjustments are made so that the minimum distance used is reasonable when very small. The data were downloaded from EJSCREEN. This indicator was developed using national databases and may not reflect the true risk of exposure to wastewater discharge within Washington.

Additional Resources

For more information, refer to EJSCREEN Technical Documentation: https://www.epa.gov/ejscreen/technical-documentation-ejscreen

Map 20: Decile ranking of wastewater discharge indicator



Next Steps

In accordance with the HEAL Act (2021), the Washington State Department of Health will continue to develop updated versions of the EHD map. The map will be updated regularly by the WTN as new data become available, with new data layers and indicators added to the map. The Washington State Department of Health WTN team continues to engage the stakeholders including but not exclusively the original workgroup that created the map. The HEAL Act provides funding to support engagement and future updates, including the development of a visualization to track environmental health disparities over time. Future development of the map will be done through consultation with the EJ Council, as outlined in the HEAL Act.

We welcome opportunities to partner with others in continuing this work.

To contact the University of Washington team, email envmap@uw.edu .
To contact the Department of Health WTN team, EHDMap@doh.wa.gov.

References

1. Adamkiewicz, G., Zota, A., Fabian, M., Chahine, T., Julien, R., Spengler, J., et al. (2011). Moving environmental justice indoors: Understanding structural influences on residential exposure patterns in low-income communities. American Journal of Public Health, 101 Suppl. 1(S1), S238-45.
2. Adar, S., Sheppard, L., Vedal, S., Polak, J., Sampson, P., Diez Roux, A., et al. (2013). Fine particulate air pollution and the progression of carotid intima-medial thickness: A prospective cohort study from the multiethnic study of atherosclerosis and air pollution (Air pollution and carotid IMT progression). PloS Med, 10(4), E1001430.
3. Adler, N., Pantell, MS., O'donovan, A., Blackburn, E., Cawthon, R., Koster, A., et al . (2013). Educational attainment and late life telomere length in the health, aging and body composition study. Brain Behavior and Immunity, 27(1), 15-21.
4. Agarwal, N., Banternghansa, C., & Bui, L. (2010). Toxic exposure in America: estimating fetal and infant health outcomes from 14 years of TRI reporting. Journal of Health Economics, 29(4), 557-74.
5. AIRPACT. Accessed 6 July, 2018. http://lar.wsu.edu/airpact/introduction.html.
6. Ala, A., Stanca, C., BuGhanim, M., Ahmado, I., Branch, A., Schiano, T., et al. (2006). Increased prevalence of primary biliary cirrhosis near superfund toxic waste sites. Hepatology, 43(3), 525-31.
7. Ala-Mursula, L., Buxton, J., Ek, E., Koiranen, M., Taanila, A., Blakemore, A., et al. (2013). 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, 8(11), E80094.
8. Alexis, N., Lay, J., Hazucha, M., Harris, B., Hernandez, M., Bromberg, P., et al. (2010). Low-level ozone exposure induces airways inflammation and modifies cell surface phenotypes in healthy humans. Inhalation Toxicology, 22(7), 593-600.
9. Aliyu, A., Kasim, R., & Martin, D. (2011). Siting of hazardous waste dump facilities and their correlation with the status of surrounding residential neighbourhoods in Los Angeles County. Property Management, 29(1), 87-102.
10. American Academy of Pediatrics (AAP). (2005). Lead exposure in children: prevention, detection, and management. Pediatrics, 116(4), 1036-46.
11. American Community Survey (ACS). Accessed 1 Aug, 2018. https://www.census.gov/programssurveys/acs/
12. Anderson, L., Charles, J., Fullilove, M., Scrimshaw, S., Fielding, J., Normand, J., et al. (2003). Providing affordable family housing and reducing residential segregation by income: a systematic review. American Journal of Preventive Medicine, 24(3), 47-67.

13. Athar, H., Chang, M., Hahn, R., Walker, E., & Yoon, P. (2013). Unemployment - United States, 2006 and 2010. MMWR-Morbidity and Mortality Weekly Report, 62(3), 27-32.

14. Baibergenova, A., Kudyakov, R., Zdeb, M., & Carpenter, D. (2003). Low birth weight and residential proximity to PCB-contaminated waste sites. Environmental Health Perspectives, 111(10), 1352-7.

15. Balazs, C., & Ray, I. (2014). The drinking water disparities framework: On the origins and persistence of inequities in exposure. American Journal of Public Health, 104(4), 603-11.

16. Barker, D., Eriksson, J., Forsn, T., & Osmond, C. (2002). Fetal origins of adult disease: Strength of effects and biological basis. International Journal of Epidemiology, 31(6), 1235-9.

17. Bateson, T., & Schwartz, J. (2004). Who is sensitive to the effects of particulate air pollution on mortality? A case-crossover analysis of effect modifiers. Epidemiology, 15(2), 143-9.

18. Bell, M., & Belanger, K. (2007). Ambient air pollution and low birth weight in Connecticut and Massachusetts. Environmental Health Perspectives, 115(7), 1118-24.

19. Bell, M., & Dominici, F. (2008). Effect modification by community characteristics on the short term effects of ozone exposure and mortality in 98 US communities. American Journal of Epidemiology, 167(8), 986-97.

20. Berglind, N., Bellander, T., Forastiere, F., Von Klot, S., Aalto, P., Elosua, R., et al. (2009). Ambient air pollution and daily mortality among survivors of myocardial infarction. Epidemiology, 20(1), 110-8.

21. Betha, R., & Balasubramanian, R. (2013). Emissions of particulate-bound elements from biodiesel and ultra low sulfur diesel: size distribution and risk assessment. Chemosphere, 90(3), 1005-15.

22. Boehmer, T., Foster, S., Henry, J., Woghiren-Akinnifesi, E., & Yip, F. (2013). Residential proximity to major highways - United States, 2010. Morbidity and Mortality Weekly Report, 62(3), 46-50.

23. Boer, J., Pastor, M., Sadd, J., & Snyder, L. (1996). Is there environmental racism? The demographics of hazardous waste in Los Angeles County. Abstracts with Programs - Geological Society of America, 28(7), 167.

24. Brender, J., Maantay, J., & Chakraborty, J. (2011). Residential proximity to environmental hazards and adverse health outcomes. American Journal of Public Health, 101 Suppl 1(S1), S37-52.

25. Brook, R., Rajagopalan, S., Pope, A., Brook, J., Bhatnagar, A., Diez-Roux, A., et al. (2010). Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association. Circulation, 121(21), 2331-78.

26. Burnett, R., Smith-Doiron, M., Stieb, D., Raizenne, M., Brook, J., Dales, R., et al. (2001). Association between ozone and hospitalization for acute respiratory diseases in children less than 2 years of age. American Journal of Epidemiology, 153(5), 444-52.

27. Cakmak, S., Dales, R., & Judek, S. (2006). Respiratory health effects of air pollution gases: modification by education and income. Archives of Environmental & Occupational Health, 61(1), 5-10.

28. Chen, H., Burnett, R., Copes, R., Kwong, J., Villeneuve, P., Goldberg, M., et al. (2016). Ambient fine particulate matter and mortality among survivors of myocardial infarction: population-based cohort study. Environmental Health Perspectives, 124(9), 1421-8.

29. Choi, H., Shim, Y., Kaye, W., and Ryan, P. (2006). Potential residential exposure to toxics release inventory chemicals during pregnancy and childhood brain cancer. Environmental Health Perspectives, 114(7), 1113-8.

30. Cushing, L., Faust, J., August, L., Cendak, R., Wieland, W., & Alexeeff, G. (2015). Racial/ethnic disparities in cumulative environmental health impacts in California: evidence from a statewide environmental justice screening tool (CalEnviroScreen 1.1). American Journal of Public Health, 105(11), 2341-8.

31. Davies, I., Haugo, R., Robertson, J., & Levin, P. (2018). The unequal vulnerability of communities of color to wildfire. PLoS ONE, 13(11), E0205825.

32. Davis, M., Laden, F., Hart, J., Garshick, E., & Smith, T. (2010). Economic activity and trends in ambient air pollution. Environmental Health Perspectives, 118(5), 614-9.

33. deFur, P., Evans, G., Hubal, E., Kyle, A., Morello-Frosch, R., & Williams, D. (2007). Vulnerability as a function of individual and group resources in cumulative risk assessment. Environmental Health Perspectives, 115(5), 817-24.

34. Dominici, F., Peng, R., Bell, M., Pham, L., Mcdermott, A., Zeger, S., et al. (2006). Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. JAMA, 295(10), 1127-34.

35. Dragano, N., Hoffmann, B., Stang, A., Moebus, S., Verde, P., Weyers, E., et al. (2009). Subclinical coronary atherosclerosis and neighbourhood deprivation in an urban region. European Journal of Epidemiology, 24(1), 25-35.

36. Dunn, J. (2000). Housing and Health Inequalities: Review and Prospects for Research. Housing Studies, 15(3), 341-66.

37. Elliott, M., Wang, Y., Lowe, R., & Kleindorfer, P. (2004). Environmental justice: frequency and severity of US chemical industry accidents and the socioeconomic status of surrounding communities. Journal of Epidemiology and Community Health, 58(1), 24-30.

38. EPA, “Criteria Air Pollutants”, Accessed 16 Nov, 2018. https://www.epa.gov/criteria-air-pollutants

39. Eze, I., Foraster, M., Schaffner, E., Vienneau, D., Héritier, H., Rudzik, F., et al. (2017). Long-term exposure to transportation noise and air pollution in relation to incident diabetes in the SAPALDIA study. International Journal of Epidemiology, 46(4), 1115-25.

40. Fann, N., Lamson, A., Anenberg, S., Wesson, K., Risley, D., & Hubbell, B. (2012). Estimating the national public health burden associated with exposure to ambient PM2.5 and ozone. Risk Analysis, 32(1), 81-95.

41. Fazzo, L., Minichilli, F., Santoro, M., Ceccarini, A., Della Seta, M., Bianchi, F., et al. (2017). Hazardous waste and health impact: A systematic review of the scientific literature. Environmental Health: A Global Access Science Source, 16(1), 1-11.

42. Finkelstein, M., Jerrett, M., DeLuca, P., Finkelstein, N., Verma, D., Chapman, K., et al. (2003). Relation between income, air pollution and mortality: a cohort study. Canadian Medical Association Journal, 169(5), 397-402.

43. Forastiere, F., Stafoggia, M., Tasco, C., Picciotto, S., Agabiti, N., Cesaroni, G., et al. (2007). Socioeconomic status, particulate air pollution, and daily mortality: differential exposure or differential susceptibility. American Journal of Industrial Medicine, 50(3), 208-16.

44. Gaffney, S., Curriero, F., Strickland, P., Glass, G., Helzlsouer, K., & Breysse, P. (2005). Influence of geographic location in modeling blood pesticide levels in a community surrounding a U.S. Environmental Protection Agency Superfund site. Environmental Health Perspectives, 113(12), 1712-6.

45. Garshick, E., Laden, F., Hart, J., Rosner, B., Davis, M., Eisen, E., & et al. (2008). Lung cancer and vehicle exhaust in trucking industry workers. Environmental Health Perspectives, 116(10), 1327-32.

46. Gauderman, W., Vora, H., McConnell, R., Berhane, K., Gilliland, F., Thomas, D. et al. (2007). Effect of exposure to traffic on lung development from 10 to 18 years of age: A cohort study. The Lancet, 369(9561), 571-7.

47. Gee, G., & Ponce, N. (2010). Associations between racial discrimination, limited English proficiency, and health-related quality of life among 6 Asian ethnic groups in California. The American Journal of Public Health, 100(5), 888-95.

48. Ghosh, J., Wilhelm, M., Su, J., Goldberg, D., Cockburn, M., Jerrett, M., et al. (2012). Assessing the influence of traffic-related air pollution on risk of term low birth weight on the basis of land-use-based regression models and measures of air toxics. American Journal of Epidemiology, 175(12), 1262-74.

49. Gunier, R., Hertz, A., Von Behren, J., & Reynolds, P. (2003). Traffic density in California: Socioeconomic and ethnic differences among potentially exposed children. Journal of Exposure Analysis and Environmental Epidemiology, 13(3), 240-6.

50. Habermann, M., & Gouveia, N. (2012). Motor vehicle traffic and cardiovascular mortality in male adults. Revista de Saude Publica, 46(1), 26-33.

51. Hafkamp-de Groen, E., Sonnenschein-van der Voort, A., Mackenbach, J., Duijts, L., Jaddoe, V., Moll, H., et al. (2013). Socioeconomic and sociodemographic factors associated with asthma related outcomes in early childhood: the Generation R study. PLoS ONE, 8(11), E78266.

52. Harkness, J., & Newman, S. (2005). Housing affordability and children's well-being: Evidence from the national survey of America's families. Housing Policy Debate, 16(2), 223-55.

53. Harley, K., Huen, K., Schall, R., Holland, N., Bradman, A., Barr, D., et al. (2011). Association of organophosphate pesticide exposure and paraoxonase with birth outcome in Mexican-American women. Plos One, 6(8), e23923.

54. Hendryx, M., Luo, J., & Chen, B-C. (2014). Total and cardiovascular mortality rates in relation to discharges from toxics release inventory sites in the United States. Environmental Research, 133, 36-41.

55. Hummer, R., & Hernandez, E. (2013). The effect of educational attainment on adult mortality in the United States. Population Bulletin, 68(1), 1-16.

56. Jacobs, D., Clickner, R., Zhou, J., Viet, S., Marker, D., Rogers, J., et al. (2002). The prevalence of lead-based paint hazards in U.S. housing. (Children's Health Articles). Environmental Health Perspectives, 110(10), A599-606.

57. Kan, H., Heiss, G., Rose, K., Whitsel, E., Lurmann, F., & London, S. (2007). Traffic exposure and lung function in adults: The Atherosclerosis Risk in Communities study. Thorax, 62(10), 873-9.

58. Karouna-Renier, N., Rao, K., Lanza, J., Davis, D., & Wilson, P. (2007). Serum profiles of PCDDs and PCDFs, in individuals near the Escambia Wood Treating Company Superfund site in Pensacola, FL. Chemosphere, 69(8), 1312-9.

59. Kaufman, J., Adar, S., Barr, R., Budoff, M., Burke, G., Curl, C., et al. (2016). Association between air pollution and coronary artery calcification within six metropolitan areas in the USA (the Multi-Ethnic Study of Atherosclerosis and Air Pollution): A Longitudinal Cohort Study. The Lancet, 388(10045), 696-704.

60. Kearney, G., & Kiros, G-E. (2009). A spatial evaluation of socio demographics surrounding National Priorities List sites in Florida using a distance-based approach. International Journal of Health Geographics, 8, 33.

61. Kim, S-Y., Sheppard, L., Kaufman, J., Bergen, S., Szpiro, A., Larson, T., et al. (2014). Individual level concentrations of fine particulate matter chemical components and subclinical atherosclerosis: A cross-sectional analysis based on 2 advanced exposure

prediction models in the multi-ethnic study of atherosclerosis. American Journal of Epidemiology, 180(7), 718-28.

62. Kleindorfer, P., Belke, J., Elliott, M., Lee, K., Lowe, R., & Feldman, H. (2003). Accident epidemiology and the U.S. chemical industry: Accident History and Worst-Case Data from RMP*Info. Risk Analysis, 23(5), 865-81.

63. Kouznetsova, M., Huang, X., Ma, J., Lessner, L., & Carpenter, D. (2007). Increased rate of hospitalization for diabetes and residential proximity of hazardous waste sites. Environmental Health Perspectives, 115(1), 75-9.

64. Kravitz-Wirtz, N., Crowder, K., Hajat, A., & Sass, V. (2016). The long-term dynamics of racial/ethnic inequality in neighborhood air pollution exposure, 1990-2009. Du Bois Review, 13(2), 237-59.

65. Krewski, D., Burnett, R., Goldberg, M., Hoover, B., Siemiatycki, J., Jerrett, M., et al. (2003). Overview of the reanalysis of the Harvard six cities study and American Cancer Society study of particulate air pollution and mortality. Journal of Toxicology and Environmental Health, Part A, 66(19), 1507-52.

66. Krishnan, R., Sullivan, J., Carlsten, C., Wilkerson, H-W., Beyer, R., Bammler, T., et al. (2013). A randomized cross-over study of inhalation of diesel exhaust, hematological indices, and endothelial markers in humans. Particle and Fibre Toxicology, 10(1), 7.

67. Krivoshto, I., Richards, J., Albertson, T., & Derlet, R. (2008). The toxicity of diesel exhaust: Implications for primary care. Journal of The American Board of Family Medicine, 21(1), 55-62.

68. Laurent, O., Wu, J., Li, L., Chung, J., & Bartell, S. (2013). Investigating the association between birth weight and complementary air pollution metrics: A cohort study. Environmental Health: A Global Access Science Source, 12(1), 18.

69. Lewis, A., Sax, S., Wason, S., & Campleman, S. (2011). Non-chemical stressors and cumulative risk assessment: An overview of current initiatives and potential air pollutant Interactions. International Journal of Environmental Research and Public Health, 8(6), 2020-73.

70. Lin, S., Liu, X., Le, L., & Hwang, S. (2007). Chronic exposure to ambient ozone and asthma hospital admissions among children. American Journal of Epidemiology, 165(11), S99.

71. Link, M., Mokdad, A., Stackhouse, H., & Flowers, N. (2005). Race, ethnicity, and linguistic Isolation as determinants of participation in public health surveillance surveys. Preventing Chronic Disease, 3(1), A09.

72. Löndahl, J., Swietlicki, E., Rissler, J., Bengtsson, A., Boman, C., Blomberg, A., et al. (2012). Experimental determination of the respiratory tract deposition of diesel combustion

particles in patients with chronic obstructive pulmonary disease. Particle and Fibre Toxicology, 9(1), 30.

73. Lu, M., & Halfon, C. (2003). Racial and ethnic disparities in birth outcomes: A life-course perspective. Maternal and Child Health Journal, 7(1), 13-30.

74. Marmot, M., & Wilkinson, R. (2005). Social organization, stress, and health. In Social Determinants of Health (Chapter 02). Oxford University Press.

75. Mccarthy, M., O'Brien, T., Charrier, J., & Hafner, H. (2009). Characterization of the chronic risk and hazard of hazardous air pollutants in the United States using ambient monitoring data. Environmental Health Perspectives, 117(5), 790-6.

76. McCreanor, J., Cullinan, P., Nieuwenhuijsen, M., Stewart-Evans, J., Malliarou, E., Jarup, L., et al. (2007). Respiratory effects of exposure to diesel traffic in persons with asthma. The New England Journal of Medicine, 357(23), 2348-58.

77. McGauhey, P., Starfield, B., Alexander, C., & Ensminger, M. (1991). Social environment and vulnerability of low birth weight children: A social-epidemiological perspective. Pediatrics, 88(5), 943-53.

78. McGlinn, L. (2000). Spatial patterns of hazardous waste generation and management in the United States. The Professional Geographer 52(1), 11-22.

79. Medina-Ramón, M., & Schwartz, J. (2008). Who is more vulnerable to die from ozone air pollution? Epidemiology, 19(5), 672-9.

80. Meltzer, R., & Schwartz, A. (2015). Housing affordability and health: evidence from New York City. Housing Policy Debate, 26(1), 1-25.

81. Moore, K., Neugebauer, R., Lurmann, F., Hall, J., Brajer, V., Alcorn, S., et al. (2008). Ambient ozone concentrations cause increased hospitalizations for asthma in children: An 18-year study in southern California. Environmental Health Perspectives, 116(8), 1063-70.

82. Morello-Frosch, R., Jesdale, B., Sadd, J., & Pastor, M. (2010). Ambient air pollution exposure and full-term birth weight in California. Environmental Health, 9(1), 44-4.

83. Neidell, M. (2004). Air pollution, health, and socio-economic status: The effect of outdoor air quality on childhood asthma. Journal of Health Economics, 23(6), 1209-36.

84. Nepomnyaschy, L., & Reichman, N. (2006). Low birthweight and asthma among young urban children. American Journal of Public Health, 96(9), 1604-10.

85. Newman, S., & Holupka, C. (2016). Housing affordability and children's cognitive achievement. Health Affairs, 35(11), 2092-9.

86. O'Neill, M., Jerrett, I., Kawachi, J., Levy, A., Cohen, N., Gouveia, P., et al. (2003). Health, wealth, and air pollution: Advancing theory and methods. Environmental Health Perspectives, 111(16), 1861-70.

87. Ostro, B., Roth, L., Malig, B., & Marty, M. (2009). The effects of fine particle components on respiratory hospital admissions in children. Environmental Health Perspectives, 117(3), 475-80.

88. Pastor Jr, M., Morello-Frosch, R., & Sadd., J. (2010). Air pollution and environmental justice: Integrating indicators of cumulative impact and socio-economic vulnerability into regulatory decision-making. Final report. California Air Resources Board.

89. Patel, M., Chillrud, S., Deepti, K., Ross, J., & Kinney, P.. (2012). Traffic-related air pollutants and exhaled markers of airway inflammation and oxidative stress in New York City adolescents. Environmental Research, 121, 71-8.

90. Pollack, C., Griffin, B., & Lynch, J. (2010). Housing affordability and health among homeowners and renters. American Journal of Preventive Medicine, 39(6), 515-21.

91. Pollock, P., & Vittas, M. (1995). Who bears the burdens of environmental pollution? Race, ethnicity, and environmental equity in Florida. Social Science Quarterly, 76(2), 294-310.

92. Pope, C., Muhlestein, J., May, H., Renlund, D., Anderson, J., & Horne, B. (2006). Ischemic heart disease events triggered by short-term exposure to fine particulate air pollution. Circulation, 114(23), 2443-8.

93. Premji, S., Bertrand, F., Smargiassi, A., & Daniel, M. (2007). Socioeconomic correlates of municipal-level pollution emissions on Montreal Island. Canadian Journal of Public Health, 98(2), 138-42.

94. Renne, J., Tolford, T., Hamidi, S., & Ewing, R. (2016). The cost and affordability paradox of transitoriented development: A comparison of housing and transportation costs across transit oriented development, hybrid and transit-adjacent development station typologies. Housing Policy Debate, 26(4-5), 819-34.

95. Ridgway, J. (1995). Environmental equity study in Washington state. Washington Department of Ecology. Publication number 95-413.

96. Roberts, J., Hulsey, T., Curtis, G., & Reigart, J. (2003). Using geographic information systems to assess risk for elevated blood lead levels in children. Public Health Reports, 118(3), 221-9.

97. Rodopoulou, S., Chalbot, M-C., Samoli, E., Dubois, D., San Filippo, B., & Kavouras, I. (2014). Air pollution and hospital emergency room and admissions for cardiovascular and respiratory diseases in Doña Ana County, New Mexico. Environmental Research, 129, 39-46.

98. Schultz, E., Gruzieva, O., Bellander, T., Bottai, M., Hallberg, J., Kull, I., Svartengren, M., Melen, E., & Pershagen, G. (2012). Traffic-related air pollution and lung function in children at 8 years of age: A birth cohort study. American Journal of Respiratory and Critical Care Medicine, 186(12), 1286-91.

99. Schwartz, J. (1994). What are people dying of on high air pollution days? Environmental Research, 64(1), 26-35.

100. Sentell, T., Shumway, M., & Snowden, L. (2007). Access to mental health treatment by English language proficiency and race/ethnicity. Journal of General Internal Medicine, 22 Suppl 2(Suppl 2), 289-93.

101. Sergeev, A., and Carpenter, D. (2005). Hospitalization rates for coronary heart disease in relation to residence near areas contaminated with persistent organic pollutants and other pollutants. Environmental Health Perspectives, 113(6), 756-61.

102. Shi, L., Lebrun, L., & Tsai, J. (2009). The influence of English proficiency on access to care. Ethnicity & Health, 14(6), 625-42.

103. Smith, L., Hatcher-Ross, J., Wertheimer, R., & Kahn, R. (2005). Rethinking race/ethnicity, income, and childhood asthma: Racial/ethnic disparities concentrated among the very poor. Public Health Reports, 120(2), 109-16.

104. Spira-Cohen, A., Chen, L., Kendall, M., Lall, R., & Thurston, G. (2011). Personal exposures to traffic-related air pollution and acute respiratory health among Bronx school children with asthma. Environmental Health Perspectives, 119(4), 559-65.

105. Szasz, A., & Meuser, M. (1997). Environmental inequalities: literature review and proposals for new directions in research and theory. Current Sociology, 45(3), 99-120.

106. Tapia Granados, J., House, J., Ionides, E., Burgard, S., & Schoeni, R. (2014). Individual joblessness, contextual unemployment, and mortality risk. American Journal of Epidemiology, 180(3), 280-7.

107. Turner, J. (1995). Economic context and the health effects of unemployment. Journal of Health and Social Behavior, 36(3), 213-29.

108. Vanderslice, J. (2011). Drinking water infrastructure and environmental disparities: Evidence and methodological considerations. American Journal of Public Health, 101 Suppl 1(S1), S109-14.

109. Von Klot, S., Gryparis, A., Tonne, C., Yanosky, J., Coull, B., Goldberg, R., et al. (2009). Elemental carbon exposure at residence and survival after acute myocardial infarction. Epidemiology, 20(4), 547-54.

110. Washington State Department of Health (DOH). (2013) The burden of asthma in Washington state: 2013 update. Accessed 17 Nov, 2018. https://www.doh.wa.gov/Portals/1/Documents/Pubs/345-240-AsthmaBurdenRept13.pdf

111. Wegesser, T., Pinkerton, K., & Last, J. (2009). California wildfires of 2008: Coarse and fine particulate matter toxicity. Environmental Health Perspectives, 117(6), 893-7.

112. Westergaard, N., Gehring, U., Slama, R., & Pedersen, M. (2017). Ambient air pollution and low birth weight—are some women more vulnerable than others? Environment International, 104, 146-54.

113. Yi, O., Kim, H., & Ha, E. (2010). Does area level socioeconomic status modify the effects of PM10 on preterm delivery? Environmental Research, 110(1), 55-61.

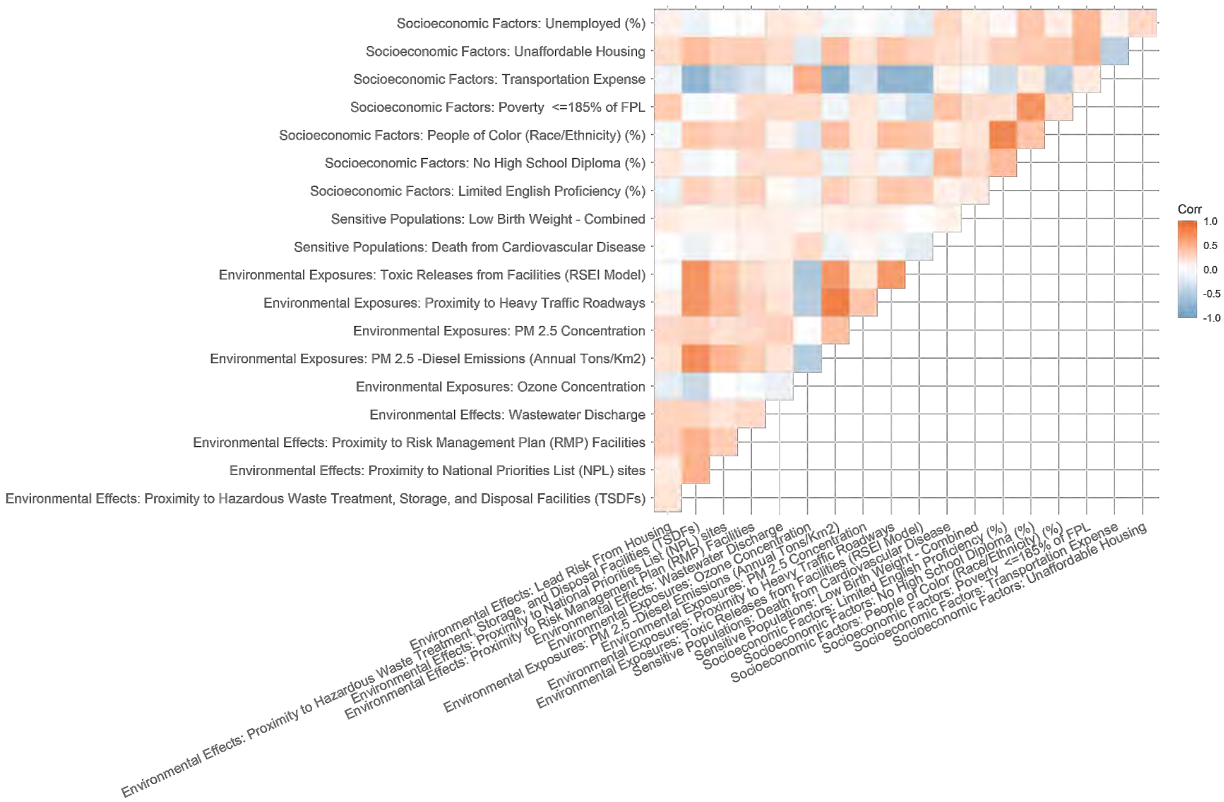
114. Zeka, A., Melly, S., & Schwartz, J. (2008). The effects of socioeconomic status and indices of physical environment on reduced birth weight and preterm births in Eastern Massachusetts. Environmental Health, 7(1), 60.

115. Zota, A., Schaider, L., Ettinger, A., Wright, R., Shine, J., & Spengler, J. (2011). Metal sources and exposures in the homes of young children living near a mining-impacted Superfund site. Journal of Exposure Science and Environmental Epidemiology, 21(5), 495-505.

Appendix A - Changes from Version 1.1 to 2.0

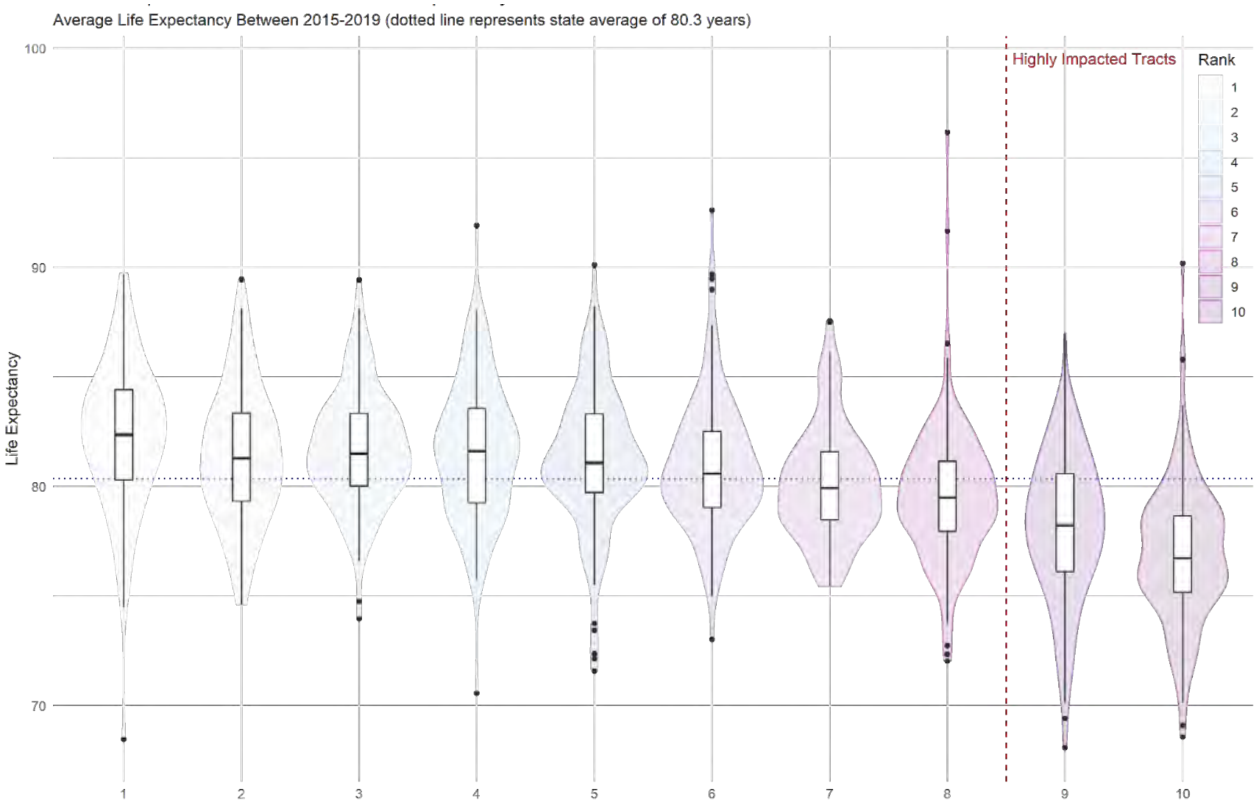
DEOHS conducted a sensitivity analysis to assess how each of the current indicators used in the Washington EHD Map impact the scoring and ranking results.

Table 2: Correlation matrix between each indicator



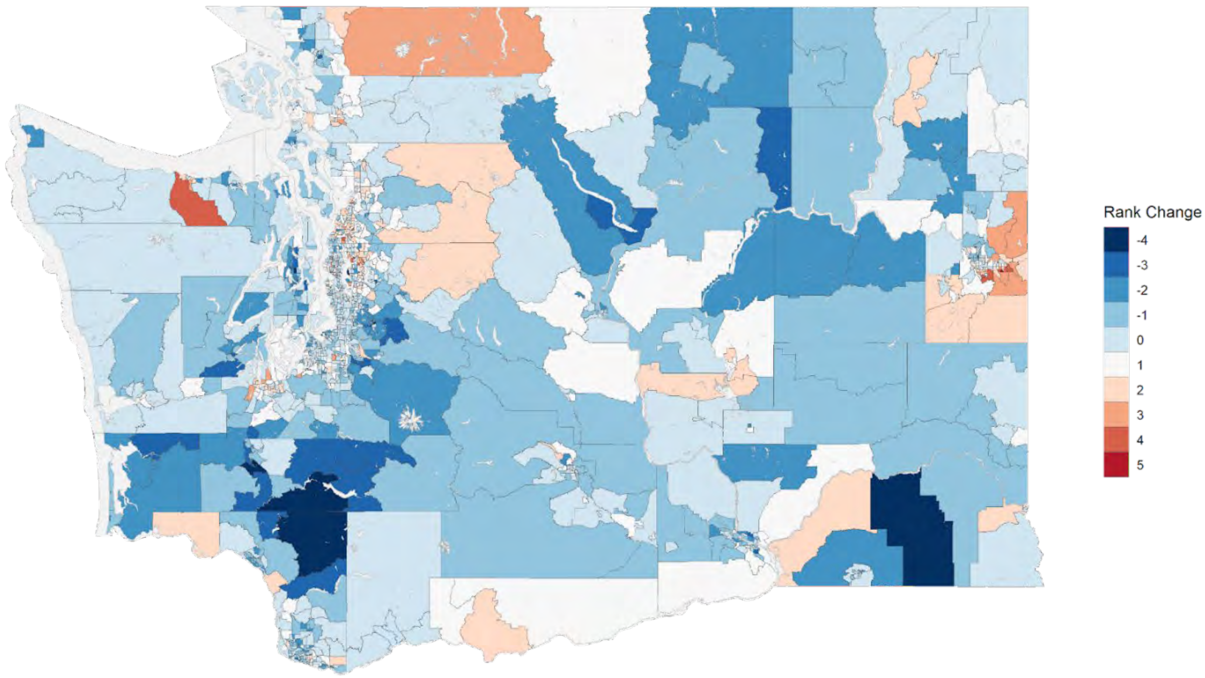
Caption: Correlation between the underlying indicators is visualized with darker red representing a stronger positive correlation, and darker blue representing a stronger negative correlation. The indicators are sorted alphabetically within the four themes. Transportation expense is observed to be negatively correlated with indicators associated with urban living, such as $PM_{2.5}$ concentrations, diesel emissions, and proximity to heavy traffic roadways. Conversely, demographic indicators are illustrated to have strong positive correlation: for example, the association between poverty and the percentage of people of color.

Figure 1: Relationship between EHD rank and life expectancy at birth by rank



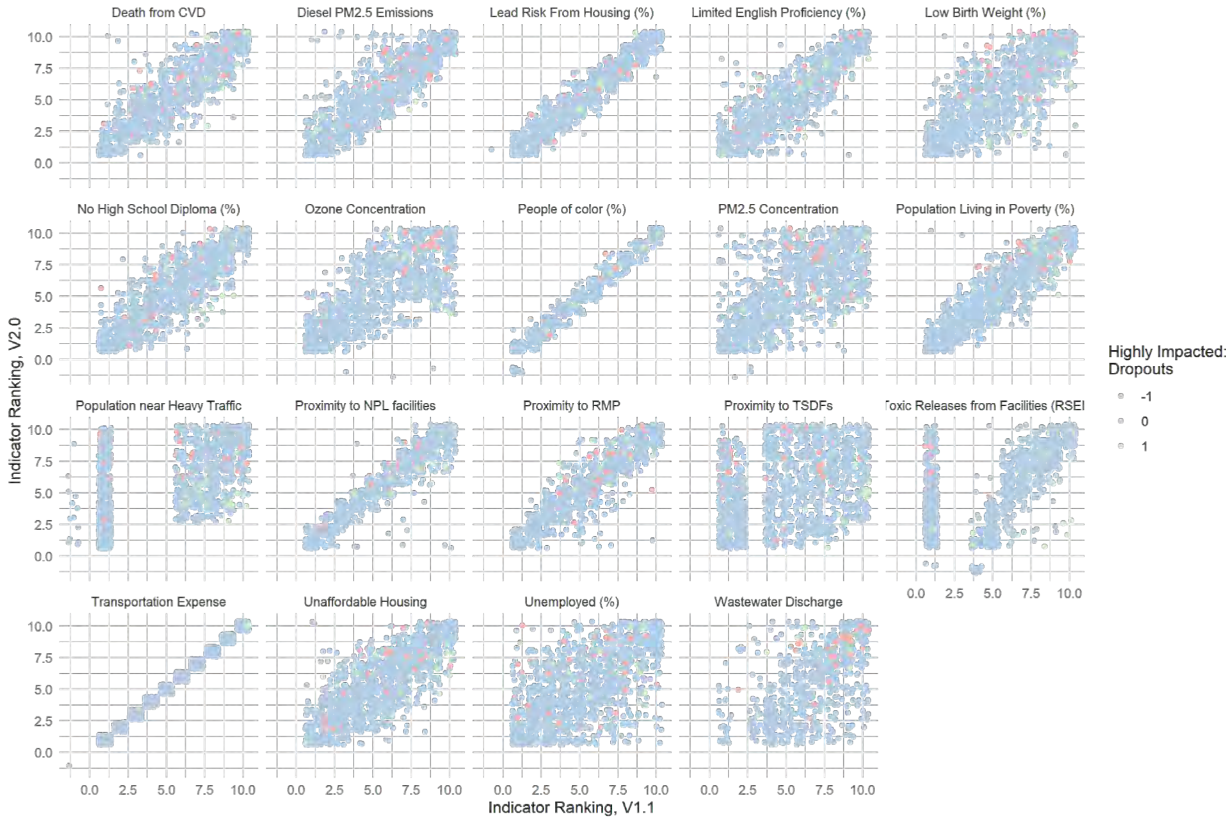
Caption: The distribution of life expectancy is visualized across deciles of the overall EHD rank. The ranks are sorted with increasing impact from left to right and from the lightest purple to darker purple, with dark purple representing the most highly impacted tracts. A negative correlation is illustrated between life expectancy and environmental impact, indicating that as environmental health disparities increase, the life expectancy decreases. The distributions of life expectancy are nearly equivalent in the tracts that are below the median impact, with a monotonic decrease in the average life expectancy beginning for tracts that are above the median impact and continuing through to the maximum impact. The statewide average of 80.3 years is displayed as a horizontal dotted line; the entire inner-quartile range for life expectancy in the most impacted tracts is observed to be below this average, with the mean life expectancy in tracts that are highly impacted being substantially below average.

Map A1: Map of overall EHD rank change from version 1.1 to version 2.0



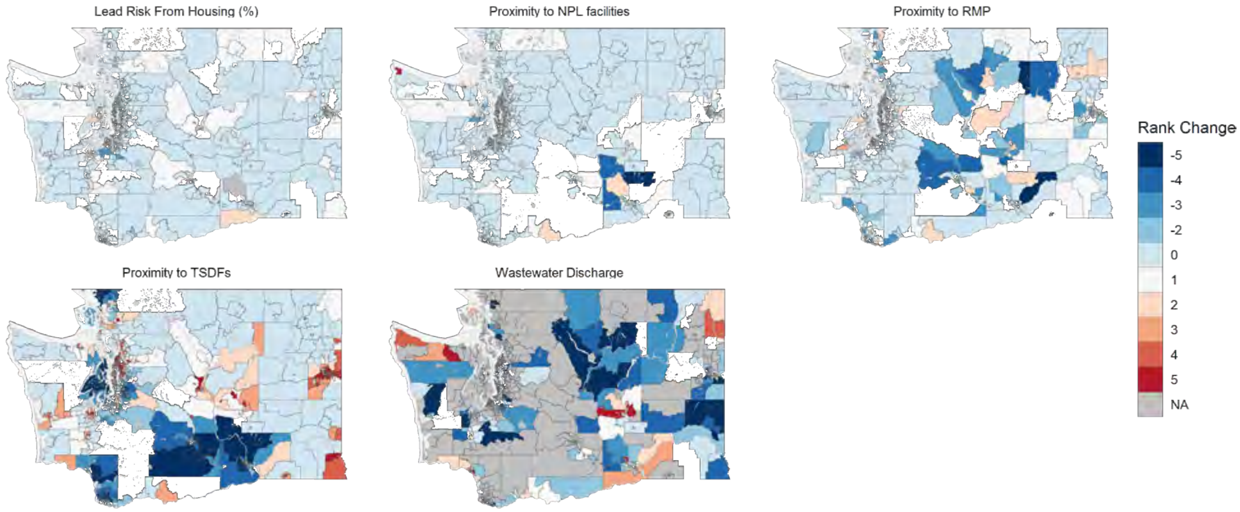
Caption: The relative change in the overall EHD rank is visualized statewide at the census tract level. This map was calculated by subtracting the version 1.1 from the version 2.0, meaning that more negative values (darker blue) mean the rank has decreased and more positive values (darker red) mean that the rank has increased. White tracts denote where the rank was stable across versions. We observe substantial increases in north King County, in the areas surrounding Spokane, and near Olympia. The larger decreases are focused in more rural areas, such as Lewis and Cowlitz counties.

Figure 2: Scatterplot comparison of EHD map indicators from version 1.1 to version 2.0



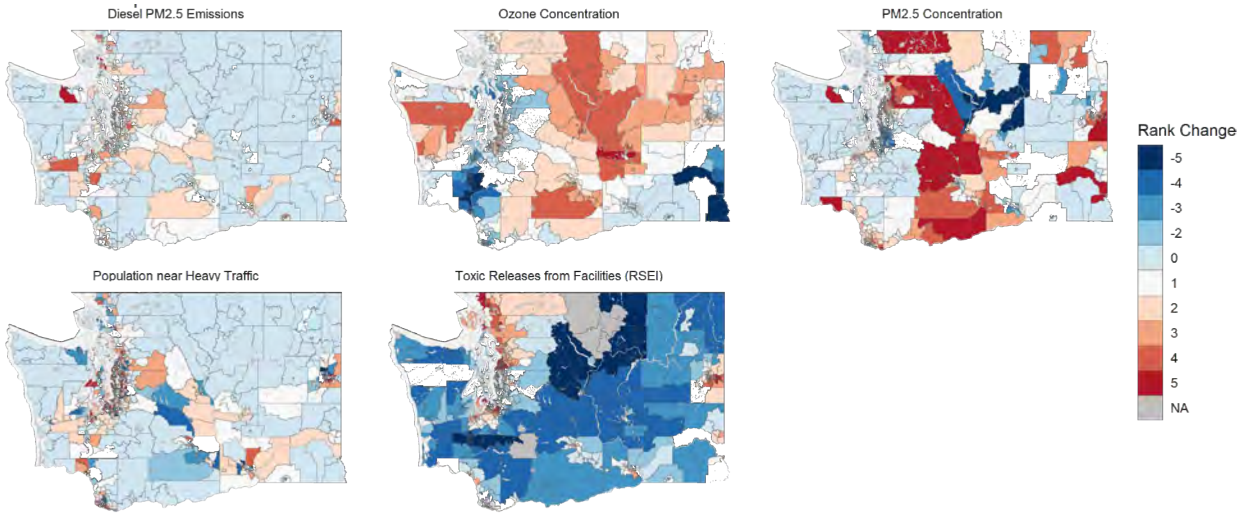
Caption: The versions 1.1 and 2.0 of the EHD indicator ranks are scattered against each other, with version 1.1 on the X axis and version 2.0 on the Y - where the 45-degree line represents perfect alignment (demonstrated by transportation expense, which did not change between versions). We observe minimal change in lead risk from housing, percent of the population that are people of color, and proximity to NPL or RMP sites. Substantial changes in both directions are observed for unemployment percentages, $PM_{2.5}$ and ozone concentrations. The values for wastewater discharge are generally lower in version 2.0, as observed by the density of points below the 45-degree line, while proximity to heavy traffic roadways and toxic releases from facilities are observed to have many cases where zeros in version 1.1 are updated to a wide range of values across the spectrum for the version 2.0.

Maps A2-6: Maps of environmental effects indicator rank change from version 1.1 to 2.0



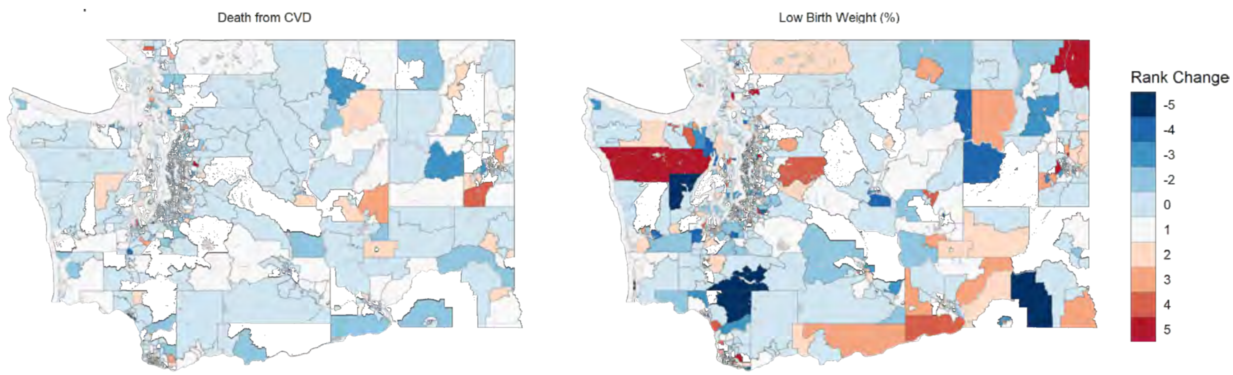
Caption: The relative change in the environmental effects indicator ranks is visualized statewide at the census tract level. These maps were calculated by subtracting the version 1.1 ranks from version 2.0 ranks, meaning that more negative values (darker blue) mean the rank decreased and more positive values (darker red) mean that the rank increased. White tracts denote where the rank was stable across versions. For environmental effects, most changes were decreases in the rank, especially for proximity to hazardous waste, RMP facilities, and wastewater discharge. For wastewater discharge, there are many tracts that now have null values due to a new exclusion framework based on distance to the wastewater network. There are some notable increases in the proximity to hazardous waste facilities indicator for the census tracts surrounding Spokane.

Maps A7-11: Maps of environmental exposures indicator rank change from version 1.1 to 2.0



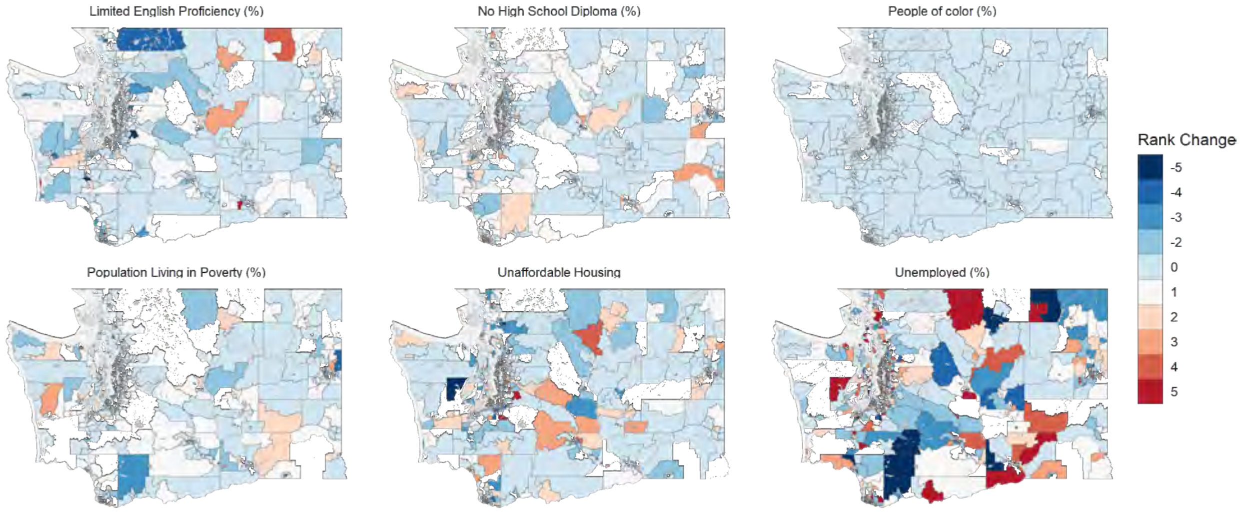
Caption: The relative change in environmental exposure indicator ranks is visualized statewide at the census tract level. These maps were calculated by subtracting version 1.1 ranks from version 2.0, meaning that more negative values (darker blue) mean the rank decreased and more positive values (darker red) mean that the rank increased. White tracts denote where the rank was stable across versions. The PM2.5 and ozone concentration indicators have substantially increased for many tracts in version 2.0, while toxic releases from facilities has broadly decreased except for in the northern part of the I5 corridor and the census tracts near Spokane.

Maps A12-13: Maps of sensitive population indicator rank change from version 1.1 to 2.0



Caption: The relative change in sensitive population indicator ranks is visualized statewide at the census tract level. These maps were calculated by subtracting version 1.1 from version 2.0, meaning that more negative values (darker blue) mean the rank decreased and more positive values (darker red) mean that the rank increased. White tracts denote where the rank was stable across versions. The changes in death from cardiovascular disease were small and distributed in both directions across the state. The low birth weight indicator had some large changes in rural areas, including some substantial increase on the Olympic peninsula and a notable decrease in Cowlitz county.

Maps A14-19: Maps of socioeconomic factors indicator rank change from version 1.1 to 2.0



Caption: The relative change in socioeconomic factors indicator ranks is visualized statewide at the census tract level. These maps were calculated by subtracting version 1.1 ranks from version 2.0 ranks, meaning that more negative values (darker blue) mean the rank decreased and more positive values (darker red) mean that the rank has increased. White tracts denote where the rank was stable across versions. Transportation expenses was not included in this figure due to the lack of change between versions. Large shifts were observed in the employment percentages, especially a notable decrease in the indicator for the southwest and northeast areas of the state and some large increases in King County. The other indicators were largely stable across versions.

Appendix B - IBL Rank Replication Instruction

Instructions for Replicating the IBL Rank in Excel*

WTN – February 2022

Notes for Replication

1. IBL ranks are not true deciles. Although the goal is to have the census tracts approximately equally distributed across 10 ranks, IBL rank calculation is more complex than deciles.
2. The same IBL rank calculation is used for all 19 indicators, 4 themes, and overall index for the EHD map.
3. IBL ranks cannot be replicated using the exported comma delimited (.csv) files from the WTN data portal, because the underlying data is rounded to two decimal places in the exported file. Additionally, due to unreliable data, some indicators have census tracts with suppressed data. IBL ranks are generated using the unrounded and unsuppressed data initially imported into the platform.
4. The total number of census tracts varies by indicator. When calculating IBL ranks at the indicator level, use the total number of census tracts with valid data. When calculating the four themes and overall IBL ranks, 1,459 unique Geocodes must be used, capturing the 1,458 census tracts in the state and the Geocode for the state (i.e., Geocode 53000000000).
5. The state average should be included for all IBL rank calculations (i.e., Geocode 53000000000).
6. Theme rank replication:
    a. All indicators must have an IBL rank for 1,459 Geocodes (1,458 census tracts and the overall state Geocode).
    b. For indicators where a Geocode is present but there is no data: values of "--" will be ranked "**" at the indicator level; however, "**" must be replaced with a rank of "-1" to calculate the theme average and rank.
    c. If the Geocode is missing, add the Geocode with a rank of "0" to calculate the theme average and rank. For example, if the indicator only has 1,455 census tracts, add the remaining 4 census tracts to that indicator and assign them a rank of "0" prior to calculating the theme average and rank. These 4 census tracts are: 53027990000, 53031990000, 53033990100, 53061990002.
    d. The average for the Socioeconomic Factors theme must be rounded to 2 decimal places prior to ranking using the "**=Round(___,2)**" function in Excel.

7. Overall EHD rank replication:
    a. The Final Composite Score = Pollution Burden x Population Characteristics.
    b. When calculating the Final Composite Score used to generate the overall ranking, the theme averages must be used in the calculation, not the theme ranks.
    c. Use the rounded Socioeconomic Factors theme average in the calculation for the Final Composite Score.
    d. Do <u>not</u> round the Population Characteristics score prior to calculating the Final Composite Score.
    e. Round the Final Composite Score to 2 decimal places prior to calculating the overall rankings using the "**=Round(___,2)**" function in Excel.
8. Do not sort the data. This will make it easier to create one sheet in Excel with data for all indicators to generate the theme and overall ranks.
9. Columns reference in the IBL Rank Excel Formula:
    a. Column B: this is referencing the data to be ranked. If the data to be ranked are not in column B, replace "B" in the Excel Formula with column letter containing the data to be ranked.
10. To use the Excel Formula:
    a. Either: (1) make sure the data to be ranked are in column B and then place the formula in any open column, or (2) place the formula in any open column, and then change any reference to column B in the formula so the column of data to be ranked is referenced.
    b. Drag the field down and ranks will be calculated for all census tracts.

<u>The Excel Formula</u>

=IF(B2="--","**",IF(ROUNDUP((RANK.EQ(B2,B:B,1)/ROUNDDOWN((COUNTA(B:B)-COUNTIF(B:B,"--")-1)/10,0)),0)=11,10,ROUNDUP((RANK.EQ(B2,B:B,1)/ROUNDDOWN((COUNTA(B:B)-COUNTIF(B:B,"--")-1)/10,0)),0)))

<u>What does the Excel Formula do?</u>

1. The formula first looks through the field to be ranked (e.g. % children living in poverty) to see if any values are "- -," which is how WTN indicates missing values. If a census tract has a missing value, the formula will not rank this census tract and instead will give the tract rank a value of "**."
2. The formula uses an "IF" statement to make sure census tracts with the same value are given the same rank (e.g. if 400 census tracts have 0% of their population living near

heavy traffic roadways, all 400 should have the same rank). How these two statements are doing this will be discussed next.

3. The formula is checking to see if the census tract being ranked has the same value (e.g. % children living in poverty) as the previous census tract. If this is true, both census tracts would have the same rank.
4. "**ROUNDUP(__,0)**": The "0" means we will round up and not have any decimal places, so if we have a value of 0.3, that will be round up to a value of 1. This is needed because all our ranks are whole numbers between 1 and 10.
5. "**ROUNDDOWN((COUNTA(B:B)-COUNTIF(B:B,"--")-1)/10,0))**": This part of the formula is trying to determine how many census tracts would there be per rank, if the formula tried to put the exact number of census tracts in each rank (e.g. if there were 1,000 census tracts, and 10 ranks, we would want to place 100 census tracts in each of the 10 ranks). To count the number of census tracts we use "**COUNTA(B:B).**" But that counts both the header row and any cells that have missing data in them (indicated by a value of "- -"). That's why we then subtract the number of cells with missing values as well as subtract 1 for the headers: "-COUNTIF(B:B,"--")-1". We are rounding down because if we have 1,454 tracts that need to go into 10 ranks, we can't have 145.4 tracts per rank, we can only have 145 tracts per rank with 4 tracts left over. The "**ROUNDDOWN(__,0)**" let's us do this.
6. Putting the above parts together, we are: determining the census tract's place in line (let's say that place is 145th), we are then determining how many census tracts should exist in each rank if we want to have the same number of tracts in each rank (let's say there are 1,450 tracts, so we will want 145 tracts in each rank), then the formula divides these two values (146/145 = 1.01), and rounds this value up (so 1.01 turns into 2) which places this census tract in rank 2. This is what we want because the first 145 census tracts should go to rank 1, the 146th census tract in this situation should go to rank 2.
   a. Note: As discussed earlier, if this part of the formula wants to give the census tract a rank of 2, but the census tract has a value equal to the previous census tract which has a rank of 1, the formula knows to give this tract a rank of 1 as well.
7. "IF(ROUNDUP((RANK.EQ(B2,B:B,1)/ROUNDDOWN((COUNTA(B:B)-COUNTIF(B:B,"--")-1)/10,0)),0)**=11,10**": If we have 1,454 tracts to rank, the formula determines 145 tracts will perfectly fit into 10 ranks, with 4 tracts remaining. The formula will by default assign these 4 tracts into rank 11, but we don't have a rank 11, so this "**IF**" statement will change any tract that the formula wants to assign to rank 11, a rank of 10.

8. “=IF(B2="--","**",IF(ROUNDUP((RANK.EQ(B2,B:B,1)/ROUNDDOWN((COUNTA(B:B)-COUNTIF(B:B,"--")-1)/10,0)),0)=11,10,**ROUNDUP((RANK.EQ(B2,B:B,1)/ROUNDDOWN((COUNTA(B:B)-COUNTIF(B:B,"--")-1)/10,0)),0)))”**: Finally, we see the ranking part of the equation for the last time. This is the last part of the final “IF” statement, which means that the formula has already checked if the values are the same and the census tract should be given the same rank as the previous census tract. The formula has also already checked if it needs to change an assigned rank of 11 to a rank of 10. Now that these decisions have been already carried out, the ranking formula runs and assigns the rest of the ranks.
9. Other notes on the IBL rank formula:
    a. The ranking calculation pretends the same number of census tracts can exist in 10 ranks (see the “**ROUNDDOWN**” parts of the formula above), and when this does not hold true, it places the remaining tracts into rank 10. This can make rank 10 larger than you would expect if using another relative ranking method.
    b. The ranking calculation determines what rank to give each census tract before considering duplicate values. This is interesting because after then placing duplicate values in the same rank, it uses those original ranks for the rest of the census tracts. This creates the following situation: if we had 1,000 census tracts, the formula would want to place 100 tracts in each of the 10 ranks. If 400 census tracts had a value of 0, the formula would then assign all 400 tracts a rank of 1, but then, instead of distributing the remaining tracts in ranks 2 through 10, the formula will place zero tracts in rank 2 and 3, and then start with the 401st tract in rank 4.

*R Code available upon request (EHDMap@doh.wa.gov)

Contact Information

Access the mapping tool
https://fortress.wa.gov/doh/wtn/WTNIBL

UW project website
deohs.washington.edu/washington-state-envmap

DOH EHD map webpage
https://doh.wa.gov/data-statistical-reports/washington-tracking-network-wtn/washington-environmental-health-disparities-map

Email
envmap@uw.edu
EHDmap@doh.wa.gov