Washington Environmental Health Disparities Map

Comparing environmental health risk factors across communities

ENVIRONMENTAL & OCCUPATIONAL HEALTH SCIENCES
SCHOOL OF PUBLIC HEALTH
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The Washington Environmental Health Disparities Map is 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).

This technical report was prepared by the UW Department of Environmental & Occupational Health Sciences to document the methodology of the map.

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).

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Table of contents

About the Washington Environmental Justice Mapping Work Group

The Washington Environmental Health Disparities Map is a new tool to assess multiple, combined environmental risks in Washington state. The tool was developed through a collaborative effort among community organizations, researchers and regional and state agencies.

There have been numerous important local, regional and statewide efforts to model environmental health that focus on specific environmental risks. This project does not replace those valuable tools. Rather, it is an interactive tool that compares various environmental health impacts across communities and provides a composite score for each census tract in Washington that reflects the combined impacts of various risk factors.

We describe the data used to develop robust environmental indicators, methods used to synthesize these indicators into an overall cumulative impact score and how these scores may be used to rank communities within the state with respect to environmental risk factors. While it is ready to use, it is also very much a work in progress—and likely always will be. That is partly because data are currently not available for several environmental indicators we would like to include.

We expect the current version of the map to improve over time as data and methods are improved. As we release this and future versions of the map, we appreciate feedback to improve the work and welcome suggestions and feedback on additional data to investigate or methodology to incorporate.

Washington Environmental Justice Mapping Work Group

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Acknowledgments

Project partners are individuals from the University of Washington Department of Environmental & Occupational Health Sciences (DEOHS), Front and Centered (a coalition of community organizations in Washington), the Washington State Department of Health (DOH), the Washington State Department of Ecology (ECY) and the Puget Sound Clean Air Agency (PSCAA).

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

List of abbreviations

ACS: American Community Survey
CalEPA: California Environmental Protection Agency
CDC: US Centers for Disease Control and Prevention
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
IBL: Information By Location tool on the Washington Tracking Network
NPL: National Priorities List
NTN: CDC National Tracking Network
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 new Washington 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 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 Washington Environmental Health Disparities Map can help policymakers and the public visualize and compare how pollution and other environmental risks affect the health and well-being 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

This inaugural version of the Washington Environmental Health Disparities Map reflects the interest of diverse stakeholders in understanding the effects of their local environment on their health.

It also highlights how data can and should be used 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 stakeholder 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.
- 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 state Department of Health and other state 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.


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Mother Africa
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Front and Centered
ABERCROMBIE & FITCH

Part I: Project overview

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.

In 1995, the state of Washington published a statewide environmental justice study that showed low-income populations and communities of color are disproportionately burdened by contaminated sites and facilities that are regulated by the government (Ridgway, 1995).

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.

In winter 2017, 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.

They brought together partners from the Washington State Department of Health, the state Department of Ecology and the Puget Sound Clean Air Agency.

This report describes the two-year process undertaken by this work group to develop a statewide mapping tool that accurately reflects Washington's environmental health disparities.

Our primary goal was to develop a way 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.
- Identifies and monitors trends in environmental health indicators by census tract over time, providing useful, data-driven insights for communities, policymakers, government leaders and others.

The Washington Environmental Health Disparities 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.

Next steps

This project has continued for more than two years through the dedication of work group partners and by leveraging the resources of work group organizations. The work group is looking for funding opportunities as this project moves to the next phase of listening sessions and development.

We welcome opportunities to partner with others in continuing this work. Please contact us: envmap@uw.edu.

While there are currently no dedicated funding sources for this project, the work group is committed to continuing community engagement and listening sessions. In 2019, our goal is to expand listening sessions to engage more communities, especially in tribal and rural communities.

In addition, we continue to explore additional indicators such as asthma, noise pollution, proximity to state-specific clean-up sites and quality of surface water. Other potential indicators require more development, such as drinking water quality, the effects of inequality and the effects of the built environment.

The map will be updated regularly by the Washington Tracking Network as new data become available, with new data layers added to the map. For more details on additional indicators under consideration, see the Indicators under exploration section.

Definitions

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

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 of all people with respect to developing, implementing and enforcing environmental laws, regulations and policies.

Environmental effect refers to adverse 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.

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.

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.

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

To create this map, we began with a process of listening to communities and engaging stakeholders. The work group listened to residents from around the state who responded to prompts about the environmental issues that are most concerning to their communities.

We then reviewed existing methods and tools that modeled environmental health impacts and disparities on communities. US EPA EJSCREEN and CalEPA CalEnviroScreen are two examples of existing tools that model national and California state environmental health impacts, respectively.

The work group conducted a literature review to determine the relationship with the proposed indicators and environmental health. Secondary data collection occurred to identify 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. For more details, see chart on page 17.

Listening sessions

Front and Centered and its affiliated organizations held a series of community listening sessions throughout Washington state in 2017. To date, 11 listening sessions have taken place. The first round of listening sessions informed the work group on the environmental health risk factors each community faces and how each community is affected by them.

More listening sessions will take place to regularly inform the project and check the accuracy of the map generated by this project. For more details, see the Next steps section.

A full report of the listening sessions can be downloaded here: http://frontandcentered.org/pollution-listening-2017/

Symposium

In February 2018, 50 participants from research, government and community-based organizations convened for a daylong work session to identify potential indicators for the tool.

Symposium participants represented a range of perspectives on the methods for determining and illustrating the severity of environmental health disparities and the impact of climate change on environmental factors in communities across the state. A portion of the symposium included break-out sessions with participants discussing four key areas: population characteristics, environmental effects and exposures, climate impacts and application of policy in practice.

The discussion groups then came together to share summaries from each group discussion and propose new key indicators of health, such as inequality; flag concerns (such as accounting for undocumented and indigenous people); and identify the need for actionable data and information at the community level.

A full report from the symposium can be downloaded here: http://frontandcentered.org/wp-content/uploads/2018/05/Blog-post_-Symposium-Report.pdf

Webinar

Once a draft map was created for this project, the work group members hosted a webinar in September 2018 to share the findings in the draft report.

More than 90 people attended the webinar or listened to the webinar record to provide feedback on ways to frame the map, interpret findings and model environmental risk factors.

The model

The Washington Environmental Health Disparities Map evaluates 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 Vulnerability*, where threat and vulnerability are based on several indicators.

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

Environmental effects include indicators that account for adverse environmental quality generally, even when population contact with an environmental hazard is unknown or uncertain.

Environmental exposures include the levels of certain pollutants that populations come into contact with.

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.

Indicators

The indicators below are included in the Washington Environmental Health Disparities Map.

Final composite score

Final composite score = Pollution Burden score × Population Characteristics score

Pollution burden

$$\text{Polution burden score} = \frac{\left(\textit{Average percentile of Environmental Exposures indicators} + 0.5 \times \textit{Average percentile of Environmental Effects indicators}\right)}{2}$$

Environmental exposures

Diesel emissions

Ozone

Particulate Matter 2.5 (PM2.5)

Toxic releases from facilities

Traffic density

Environmental effects

Lead risk and exposure

Proximity to hazardous waste generators and facilities

Proximity to Superfund sites

Proximity to facilities with highly toxic substances

Wastewater discharge

Population characteristics

$$\text{Population characteristics score} = \frac{\left(\textit{Average percentile of Sensitive Population indicators} + \textit{Average percentile of Socioeconomic Factors indicators}\right)}{2}$$

Sensitive populations

Cardiovascular disease

Low birth weight infants

Socioeconomic factors

Poor educational attainment

Housing burden

Linguistic isolation

Poverty

Race (People of color)

Transportation expense

Unemployment

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

Indicators in the environmental exposures theme 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 percentile for each indicator is weighted equally within this theme.

Environmental effects

Indicators in the environmental effects theme 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-rank 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 (see Part II for more details). The average percentile for each indicator in this theme are 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 are weighted equally within this category.

Total score and rankings

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

$$\text{Polution burden score} = \frac{(\text{Average percentile of environmental exposures indicators} + 0.5 \times \text{average percentile of environmental effects indicators})}{2}$$

$$\text{Population characteristics score} = \frac{(\text{Average percentile of sensitive population indicators} + \text{average percentile of socioeconomic factors indicators})}{2}$$

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

$$\text{Final composite score} = \text{pollution burden score} \times \text{population characteristics score}$$

The Information By Location (IBL) tool on WTN ranks all of the indicators, themes and final scores using deciles (1 decile = 10 percent). Each decile represents about 10 percent of the values in the dataset. There are 1,463 census tracts in Washington as of 2018. This results in approximately 146 census tracts in each rank.

Rankings

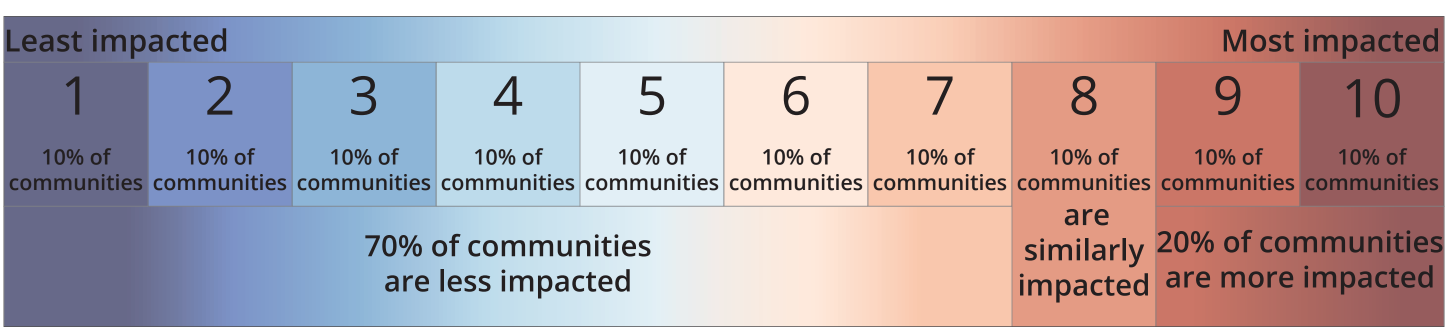
The ranking provides a common scale to compare various issues at the community level and to assess the cumulative impact of the indicators across communities. The use of rankings also allows health information to be displayed for each community, while protecting confidentiality in communities with small 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 ranked by deciles, 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 there are about 10 percent of other communities in the same rank. It also means 20 percent of communities have a higher level of diesel emissions, while 70 percent of communities have a lower level of diesel emissions. 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

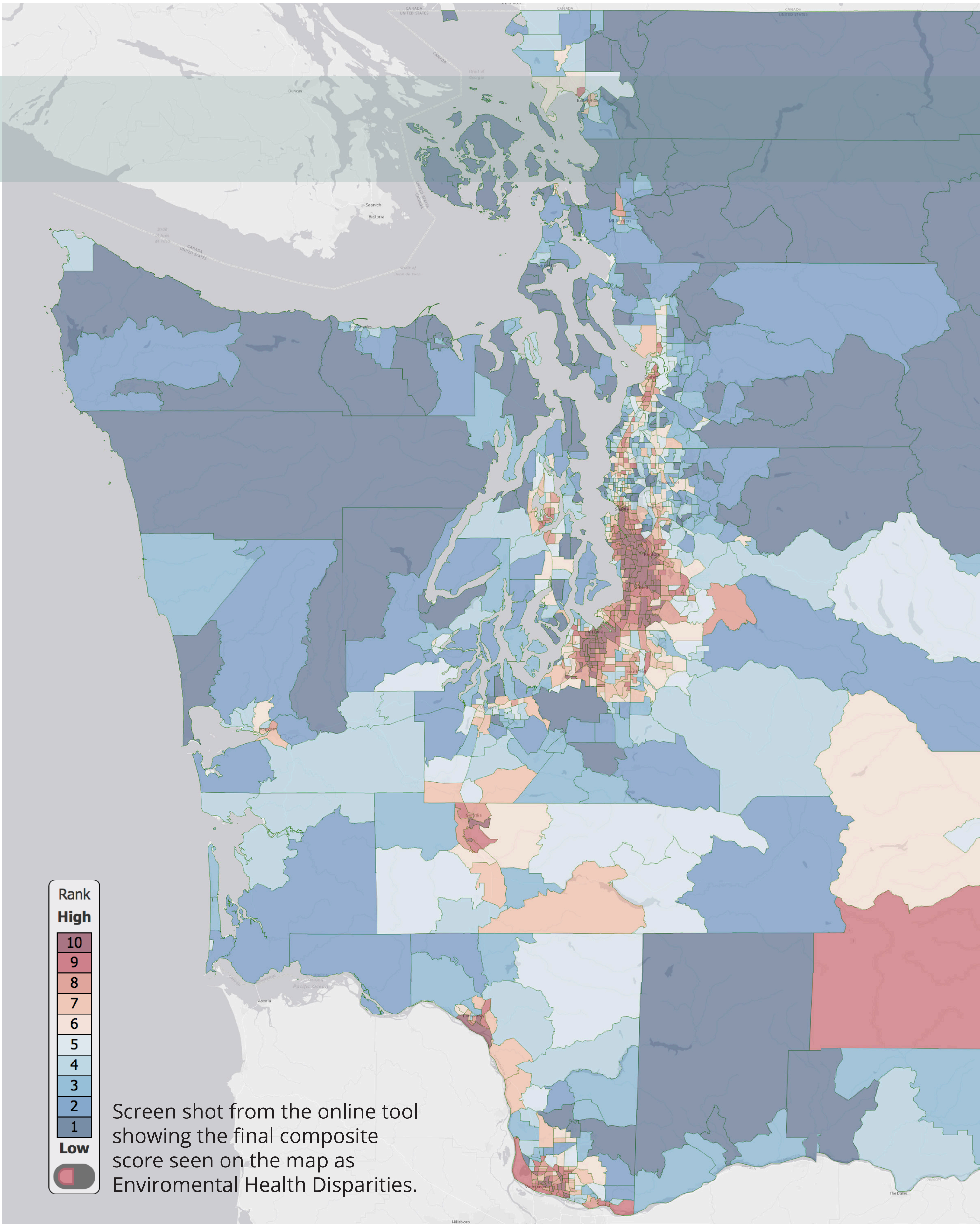
This map is based on a specific model for risk and cumulative environmental impact. Models have inherent uncertainty associated in the methodology of the tool. There is no single way to truly capture the level of uncertainty associated with environmental risk factors. This map represents one of many 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. See the "Indicators under Exploration" section for additional information.

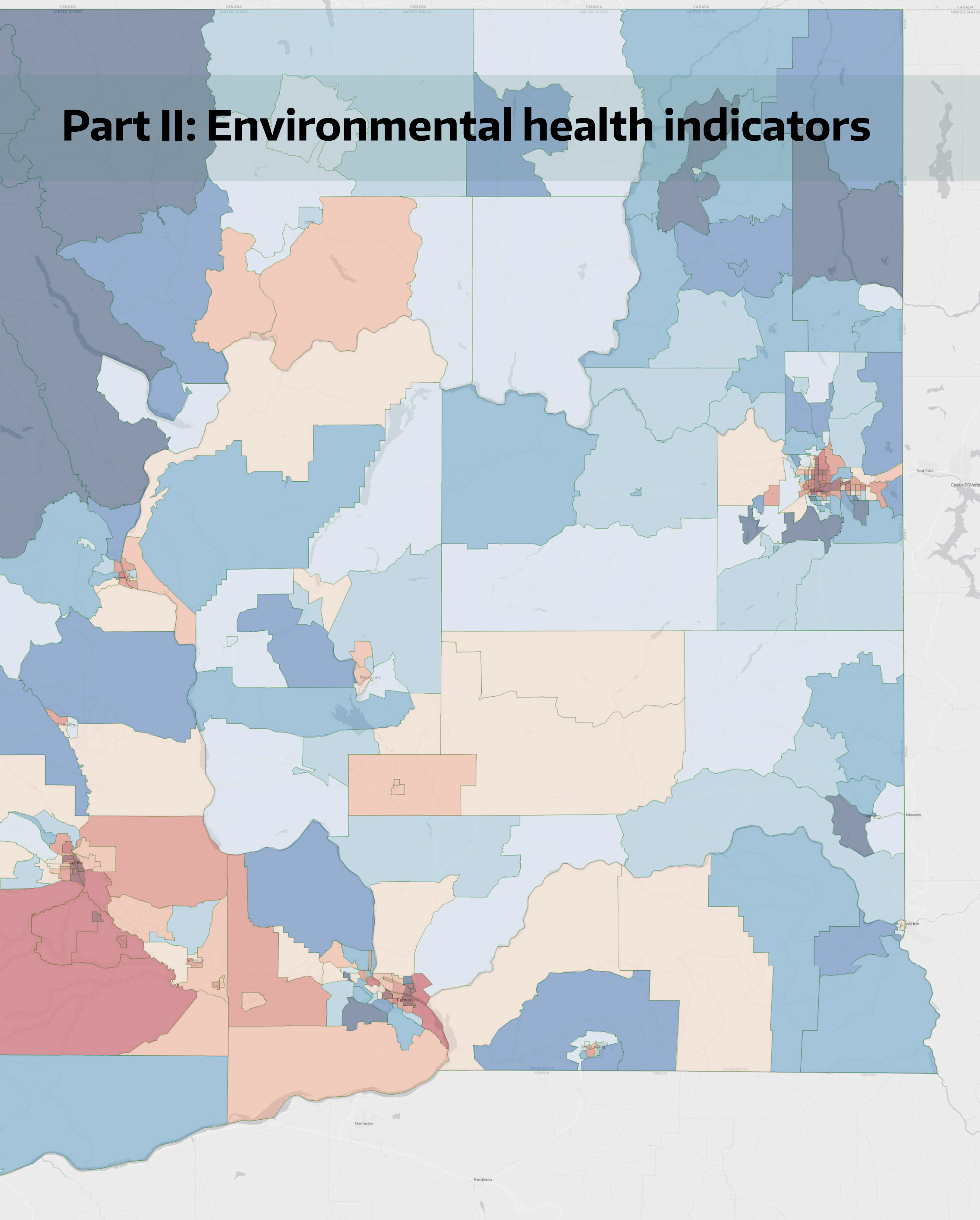
The 2017 listening sessions included 11 communities and did not adequately cover all geographic regions or communities within Washington state. As a result, the topics discussed in the listening sessions that informed the development of these indicators may not have covered all environmental health impacts faced by all Washington communities. The work group 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.



Screen shot from the online tool showing the final composite score seen on the map as Enviromental Health Disparities.

Part II: Environmental health indicators



Indicators in population characteristics

Sensitive populations

Cardiovascular disease

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 higher mortality rate when exposed to higher level 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).

Indicator

This indicator depicts the mortality rate from cardiovascular diseases for 2012–2016 per 100,000 population. This rate represents the proportion of deaths in a population due to cardiovascular disease. This indicator uses an 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.

Caveats

The prevalence of cardiovascular disease in a community truly captures the population susceptible to environmental risk factors. However, no such publicly available data exist. 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.

Low birth weight

Studies found children who had a low birth weight are at risk of developing other health morbidities, including coronary heart disease, type 2 diabetes and asthma, later in life (Barker et al., 2002; Lu & Halfon, 2003; McGauhey et al., 1990; Nepomnyaschy & Reichman, 2005). In addition, studies also found exposure to air pollution and pesticides to 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).

Indicator

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.) for 2012–2016.

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.

Caveats

This indicator does not account for individuals who were born outside of Washington, had low birth weight and now reside in Washington.

Socioeconomic factors

Low educational attainment

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).

Indicator

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 American Community Survey 5-year estimates for 2012–2016. The ACS 5-year estimate is recommended by the US Census Bureau as the most reliable estimate measure of census variables for small populations.

Caveats

For more information, refer to ACS General Data Users Handbook.

Housing burden and transportation expense

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 also 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). 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 cost due to where affordable homes may be located. Due to this paradox, comparing both housing and transportation burden provide valuable insight for assessing affordability.

Indicator

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 American Community Survey 5-year estimates for 2012–2016. The ACS 5-year estimate is recommended by the US Census as the most reliable estimate indicator of census variables for small populations.

The transportation expense indicator displays transportation costs based on percentage of income for the regional moderate household. The Center for Neighborhood Technology (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.

Caveats

For more information, refer to ACS General Data Users Handbook or CNT Methodology documentation.

Linguistic isolation

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).

Indicator

This indicator was developed using census tract-level data on the percent of limited English-speaking households from the U.S. Census Bureau's American Community Survey for 2012–2016. 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.

Caveats

For more information, refer to ACS General Data Users Handbook.

Poverty

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).

Indicator

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 American Community Survey for 2012–2016. The ACS 5-year estimate is recommended by the U.S. Census Bureau as the most reliable estimate measure of census variables.

Caveats

For more information, refer to ACS General Data Users Handbook.

Race (people of color)

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 adverse health outcomes such as asthma (DOH, 2013; Smith et al., 2005). A mother's racial and ethnic background can be negatively associated with adverse 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).

Indicator

This indicator is a sum of all race/ethnicity categories except White/Non-Hispanic. It includes Black, American Indian/Alaskan Native, Asian, Native Hawaiian-Other Pacific Islander and two or more races.

The data for this indicator is derived from the 2015 population estimates dataset at the Washington State Office of Financial Management (OFM). The OFM uses models of birth, death and migration in to make forecasts based on numbers obtained from the U.S. Census Bureau.

Caveats

Population counts in this indicator are estimates provided by the OFM and are not an actual count of people of color. The true number of people of color in Washington may vary from what is depicted here. Population data for this indicator may also differ slightly from population data provided in the CDC's National Environmental Public Health Tracking Network and in other tools, due to differences in methods for estimation in the data sources used.

Unemployment

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).

Indicator

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 American Community Survey for 2012–2016. 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.

Caveats

For more information, refer to ACS General Data Users Handbook.

Indicators in pollution burden

Environmental exposures

Diesel emissions

Diesel engines produce emissions, producing 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).

Indicator

The basis of the diesel NO_x data is the Washington State Department of Ecology's 2014 Comprehensive Emissions Inventory. All diesel emissions were mapped to the AIRPACT-5 modeling domain (NW-AIRQUEST and Washington State University), which uses 4km x 4km grid-cells. Major point source emissions were directly allocated to the grid-cell they correspond to. Other emission sources (e.g., non-point and mobile) were allocated to grid-cells based on spatial surrogates developed for AIRPACT-5. These spatial surrogates allocate total county emissions to individual grid-cells, based on the source classification codes. The combined gridded emissions were then re-allocated to census tracts using area-weighted spatial interpolation.

Caveat

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.

Ozone

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).

Indicator

This indicator uses the three-year mean concentration of daily maximum 8-hour rolling averaged ozone for 2009-2011 from AIRPACT. AIRPACT provides data that averages daily max ozone level for three years within 12km x 12km grid cells. Daily maximum ozone concentrations were calculated by using inverse distance weighting from the center of each 12km x 12km grid cell to model the average ozone concentration at the census block level. The block-level ozone concentrations were then averaged for all blocks within a census tract.

Caveat

The value in each 12km by 12km grid is the same within each grid cell. This means within the large 144 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.

Particulate matter 2.5 (PM2.5)

$PM_{2.5}$ (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, are 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 diseases morbidity and mortality (Kaufman et al., 2016; Kim et al., 2014).

Indicator

This indicator uses the three-year mean concentration of annual $PM_{2.5}$ for 2009-2011 from AIRPACT. AIRPACT provides data that data that averages daily mean concentration of $PM_{2.5}$ over three years within 12km x 12km grid cells. $PM_{2.5}$ levels were calculated by using inverse distance weighting from the center of each 12km x 12km grid cell to model average $PM_{2.5}$ at the census block level. Block-level concentrations were then averaged to the census tract level.

Caveat

The value in each 12km by 12km grid is the same within each grid cell. This means within the large 144 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.

Toxic releases from facilities

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 toxic release inventory (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).

Indicator

This indicator shows the toxicity-weighted concentrations of chemical releases to air from facility emissions and off-site incineration. Data was downloaded from Risk Screening Environmental Indicators (RSEI) where air releases are modeled by the TRI program (2014–2016).

Caveats

RSEI models the toxicity-weighted concentration into air from TRI sites for census blocks. Although any 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.

Traffic density

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 adverse 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 adverse 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).

Indicator

This indicator uses 2017 census block population estimates from the Washington State Office of Financial Management and 2017 roadway traffic density data from the Washington State Department of Transportation in the form of estimated annual average daily traffic volumes (AADT). This indicator displays the percentage of population exposed to busy roadways within each census tract. Traffic volumes for each tract were determined by the following formula:

$$\text{Traffic volume} = \frac{\text{annual average daily traffic volumes}}{\text{total road length}}$$

The AADT is adjusted by the road segment length and the total road length includes roads within 150 meters of a census tract boundary.

The exposure zone used in this indicator is defined as the area within 600 meters of a roadway (i.e., 300 meters on either side of the roadway). The population exposed to a busy roadway was determined first at the census-block level using the following formula:

$$\text{Population exposed} = \frac{\text{proportion of census block within exposure zone}}{\text{population within the exposure zone}}$$

The population exposed per census block within a tract was summed in order to get the exposed population within each census tract. The percentage of population exposed to busy roadways within each tract was then determined by the following formula:

$$\text{Population exposed} = \frac{\text{exposed population within each tract}}{\text{total population within each tract}} \times 100$$

Caveats

Population numbers within this indicator are estimates provided by the Washington State Office of Financial Management and should not be taken to be absolute values. There may be some differences when comparing these results to population counts provided by the U.S. Census Bureau's American Community Survey.

Environmental effects

Lead risk and exposure

Lead poisoning is a serious but preventable public health issue. 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).

Indicator

This indicator provides the total number of houses and proportion of houses by year of construction from the U.S. Census Bureau's American Community Survey for 2012–2016. These data were used in conjunction with national estimates of the proportion of housing from each era with lead risks. The ACS five-year estimate is recommended by the US Census Bureau as the most reliable estimate measure of census variables for small populations. The reliability of the estimates was calculated based on standard error and relative standard error recommended by US Census Bureau.

Caveats

This indicator models potential lead exposure. Age of a building by itself does not reflect the actual exposure to lead.

Proximity to hazardous waste generators and facilities

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 adverse 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).

Indicator

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 of blocks in each census tract. The data used to calculate this indicator were downloaded from EJSCREEN in 2017.

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

Caveats

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.

Proximity to Superfund sites

Communities near Superfund sites, also known as National Priorities List (NPL) 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 adverse 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).

Indicator

This indicator displays the count of sites proposed and listed on the National Priorities List (NPL), directly downloaded from EJSCREEN in 2017. 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 of blocks in each census tract.

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

Caveats

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.

Proximity to facilities with highly toxic substances

Facilities that use highly toxic substances or substances with flammable or explosive potential are required to establish a Risk Management Plan (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).

Indicator

This indicator shows the count of RMP facilities within 5 km, divided by distance, presented as population-weighted averages of blocks in each census tract. The data was downloaded from EJSCREEN 2017.

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

Caveats

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.

Wastewater discharge

Discharge from wastewater facilities can directly contaminate surface water and groundwater and are associated with adverse 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).

Indicator

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 of blocks in each block group. Adjustments are made so that the minimum distance used is reasonable when very small. The data were downloaded from EJSCREEN in 2017.

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

Caveats

This indicator was developed using national databases and may not reflect the true risk of exposure to wastewater discharge within Washington.

Indicators under exploration

We are currently working on the following additional indicators: asthma, noise pollution, proximity to state-specific cleanup sites and surface water quality.

Asthma

Individuals with asthma are prone to acute attacks from various environmental factors. Interactions between asthma and pollution (such as PM, diesel exhaust and traffic-related air pollution) have been well documented. Currently, the only dataset available at a statewide level is asthma hospitalization rate at the census-tract level.

Noise pollution

During the first round of listening sessions, noise pollution was brought up in various communities as a concern. We are investigating data sources and strategies for modeling noise pollution.

Proximity to state-specific cleanup sites

In addition to NPL sites, Washington state monitors additional sites that are considered to be cleanup sites, based on state requirements and regulations. We are currently evaluating the best method to weigh and rank state cleanup sites.

Surface water quality

Surface water quality impacts aquatic life, biodiversity and communities nearby or ones that rely on the health of aquatic life. We are currently investigating various ways to model the health of surface water including biological or chemical contaminants.

We maintain a list of environmental risk factors that are currently not included in this version of the map. Potential future indicators include:

- Various built environment indicators and tree canopy.
- Climate change, health risk and vulnerability.
- Drinking water contaminants.
- Food access.
- Wealth inequality.
- Marine water quality.
- Occupational risk.
- Pesticide exposure.

Sensitivity analysis

DEOHS conducted a sensitivity analysis to assess how each of the current indicators used in the Washington Environmental Health Disparities Map impact the scoring and ranking results. Additional analysis is in progress.

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