Oregon Environmental Justice Community Framework (Index)

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List of Acronyms

ACS	American Community Survey
AHA	American Hospital Association
AHRF	Area Health Resources Files
BRFSS	Behavioral Risk Factor Surveillance System
CACES	Center for Air, Climate, & Energy Solutions
CBIAG	Community-Based Impacts Advisory Group
CBI	Community Benefits Indicator
CBRE	Community-Based Renewable Energy
CDC	Centers for Disease Control and Prevention
CO	Carbon Dioxide
EJ	Environmental Justice
EJI	CDC Environmental Justice Index
FEMA	Federal Emergency Management Agency
HDD	Heating Degree Days
NO_x	Nitrogen Dioxide
NRI	National Risk Index
OHA	Oregon Health Authority
PLACES	CDC Population Level Analysis and Community Estimates
$PM_{2.5}$	Particulate Matter 2.5
PRISM	Parameter-elevation Regressions on Independent Slopes Model
RRC	Rural Referral Center
SCP	Sole Community Provider
SES	Socioeconomic Status
SDoH	Social Determinants of Health
SO_2	Sulfur Dioxide
SoVI	Dynamic Disturbance Recorder
SVI	CDC Social Vulnerability Index
Tmax	Daytime Maximum Temperature
Tmin	Nighttime Minimum Temperature
USC	University of South Carolina

I. Introduction

The Environmental Justice (EJ) Community Framework is intended to be a structured method for identifying communities that face disproportionate social, health, environmental, and infrastructure burdens. The framework is a composite index - a combined measure built from a set of multiple indicators that capture socioeconomic stressors, health disparities, environmental exposures, climate sensitivity, infrastructure conditions, and other factors that contribute to cumulative disadvantage. By integrating these diverse indicators, the framework provides a multidimensional picture of community vulnerability, enabling a deeper understanding of where environmental risks and social determinants of well-being persist and how they intersect with PacifiCorp's Community Benefit Indicator (CBI) Framework.

The purpose of this type of framework within the context of reporting CBI outcomes, specifically, is to strengthen outcome evaluation and, potentially, guide more targeted investments. First, the framework may help to evaluate whether the benefits of programs tied to CBI outcomes are reaching EJ communities. A composite index such as the EJ Community Framework makes it possible to overlay vulnerability rankings with CBI outcomes to assess program alignment with areas of highest need. This allows for evaluation of distributional equity, or the equitable distribution of benefits, in keeping with HB 2021 and other equity-related regulatory guidance.

Second, the framework has the potential to support decision-making about where utility investments in customer programs could yield the most equitable return for EJ communities. By identifying communities with high socioeconomic, demographic, infrastructure, health, environmental, and/ or hazard vulnerability, the index can help target customer support programs to places where they can reduce burden most effectively.

Finally, the framework has the potential to provide insight into communities' capacity to benefit from actions tied to long-term planning and procurement. Vulnerability indices reveal not only existing disadvantages but also structural barriers to accessing the benefits of the transition to clean energy. Communities with layered vulnerabilities could benefit from, for example, tailored engagement and workforce development efforts tied to these programs.

II. Variable Selection

Developing a comprehensive vulnerability index requires integrating a wide range of indicators that reflect the interconnected social, economic, environmental, and health conditions shaping community vulnerability. The inclusion of local health outcomes, socioeconomic data, hazard exposure metrics, health system capacity indicators, environmental exposures, and climate variables - each drawn from reliable and validated sources - allows the index to capture the full spectrum of factors that influence exposure, sensitivity, and adaptive capacity.

In this framework, approximately eighty variables are included to represent the cumulative and layered nature of vulnerability, ensuring that it is not reduced to a single factor. This breadth prevents oversimplification, particularly for communities whose vulnerability is shaped by structural inequities, historic disinvestment, discriminatory policies, or persistent barriers to services and opportunity.

Selecting an expansive set of indicators also enhances the index's relevance across diverse geographies, which is necessary given the socioeconomic, demographic, geographic and climatological diversity of the company's Oregon service area. Additionally, communities experience vulnerability through different pathways, and a broader indicator set enables the index to detect these patterns accurately, as opposed to privileging one geographic context over another. Incorporating measures that reflect cumulative disadvantage also aligns the methodology with contemporary federal environmental justice and resilience indices, supporting consistent interpretation.

Using a variable set of this size further strengthens statistical validity and interpretive robustness. With a set of indicators of this size, it is possible to rigorously assess redundancy and explore the correlations between different sets of variables. These processes help to ensure that the index is reliable and capable of performing consistently across updates and differing levels of spatial granularity.

Although the underlying datasets do not align perfectly by year, the selected variables either represent slow-changing structural conditions - such as income, insurance coverage, or healthcare infrastructure - or were aggregated across multiple years to minimize the impact of short-term fluctuations. This approach ensures comparability across datasets and supports a consistent methodological foundation. Combined with cross walking to 2020 census tracts, these steps allow the index to provide a spatially coherent and methodologically reliable assessment of community vulnerability.

Variables included in the index were identified through a combination of extensive literature review and stakeholder input. Peer-reviewed studies and publicly available indices - including the Centers for Disease Control (CDC) Social Vulnerability Index (SVI), CDC Environmental Justice Index (EJI), University of South Carolina Social Vulnerability Index (SoVI), National Risk Index (NRI), and indicators from the Social Determinants of Health (SDoH) - were reviewed to assemble a list of candidate indicators across health, socioeconomic status, housing and built environment, environmental and hazard exposure, and race/ethnicity domains. Additionally, listening sessions with the company's Community Benefits and Impacts Advisory Group (CBIAG) and Tribal Nations CBIAG were conducted specifically to solicit input on variable selection, ensuring that included indicators reflected both empirical evidence and stakeholder priorities. A full list of variables, along with the rationale for their inclusion, is provided in Appendix I.

A. Socioeconomic Status

Socioeconomic Status (SES) variables from the American Community Survey (ACS) capture the structural conditions that shape community access to resources and resilience in response to stressors. Measures such as median income, poverty level, educational attainment, employment status, and housing and energy burden reflect long-standing economic patterns that influence a household's ability to prepare for, respond to, and recover from environmental or social stressors. SES indicators are fundamental to vulnerability assessment because they describe underlying economic vulnerability - such as limited financial flexibility, unstable employment, or reduced access to transportation - that decrease community resilience and the ability to fully benefit from the clean energy transition.

B. Household Composition and Demographics

Household composition and demographic characteristics, also derived from ACS data, describe populations that may require additional support during emergencies or other environmental stressors. Variables such as the age of residents, disability or veteran status, single-parent households, and linguistic isolation identify groups facing barriers to communication, mobility, and self-advocacy. These characteristics can influence an individual or household's functional capacity to receive alerts, access resources, evacuate, or maintain health during extreme weather events. Thus, incorporating household composition data ensures that the index accounts for population-level sensitivities that may amplify risk even when environmental and hazard exposures are similar across communities.

C. Housing and Built Environment

Built environment variables from the ACS characterize the conditions of the physical spaces where people live and directly influence exposure and resilience. Indicators such as housing age, overcrowding, mobile homes, incomplete kitchen/ plumbing, renters, and rurality provide insight into structural vulnerabilities that can affect indoor environmental quality and the ability to shelter safely during extreme weather or other hazard events. For example, older or poorly insulated housing contributes to heat retention, elevated energy costs, and difficulty maintaining safe indoor temperatures. Built environment metrics also reflect broader patterns of neighborhood stability, infrastructure quality, and historical disinvestment. Including these variables enables the index to capture how the condition of homes and neighborhoods can contribute to cumulative vulnerability beyond what socioeconomic or demographic indicators alone can convey.

D. Health Outcomes and Healthcare Accessibility

Health outcomes and behavioral indicators were derived from local and national health datasets. Low birthweight and pre-term birth data were obtained from the Oregon Health Authority (OHA) and aggregated over the years 2018 to 2024 to improve stability for small-area estimates. Health behavior and chronic disease prevalence data were sourced from the 2022 Behavioral Risk Factor Surveillance System (BRFSS) via CDC Population Level Analysis and Community Estimates (PLACES), representing a cross-sectional snapshot of adult health conditions and behaviors. Insurance status data was derived from the 2023 American Community Survey (ACS) 5-Year Estimates, covering the period 2019–2023. These datasets are all considered exceptionally reliable, as they are collected using standardized methodologies with rigorous quality controls and represent widely accepted sources for public health and health policy research.

Structural health system capacity data was sourced from the Area Health Resource Files (AHRF), which provide county-level indicators such as healthcare workforce availability, facility distribution, and population-to-provider ratios. AHRF data are compiled from multiple sources such as the American Hospital Association (AHA) and are regularly audited for completeness and accuracy. Incorporating AHRF data ensures that the index accounts for disparities in healthcare access, providing valuable insight into how differences in local health system capacity may influence community vulnerability.

E. Environmental and Climatological Exposure

Environmental exposure variables were derived from the Center for Air, Climate, & Energy Solutions (CACES) data, and include ambient $PM_{2.5}$, SO_2, CO, and NO_x concentrations, which are known contributors to respiratory, cardiovascular, and other adverse health outcomes. CACES estimates use land use regression modeling to produce high-resolution, reliable air quality data sets. These measures allow the index to reflect spatial variation in pollution exposure, complementing the other indicators.

Climate-related exposures were incorporated using Parameter-elevation Regressions on Independent Slopes Model (PRISM) data from Oregon State University, which provide high-resolution estimates of daytime maximum and nighttime minimum temperatures. PRISM combines ground-based meteorological observations with spatial interpolation to produce reliable climate metrics that capture extreme heat and overnight heat retention. These measures are essential for understanding heat-related health risks, especially for medically or socially vulnerable populations, and ensure that the index reflects both the intensity and temporal pattern of local heat stress.

Daily Maximum Temperature (Tmax)

Tmax represents peak daily heat intensity and is widely used to identify periods of hazardous heat-related exposure. High daytime temperatures are associated with acute heat stress and increased risk for individuals working or living in conditions with prolonged outdoor exposure, including agricultural workers, unhoused individuals, and workers in construction or transportation. Within the context of vulnerability, Tmax supports identification of groups experiencing the most intense daytime heat and, potentially, the acute exposure hazards associated with it.

Daily Minimum Temperature (Tmin)

Tmin reflects overnight cooling, which is critical for physiological recovery and indoor comfort during heat events. When nighttime temperatures remain elevated, the body cannot adequately dissipate heat, leading to cumulative strain that increases the likelihood of heat-related illness. Persistent high Tmin has been shown to drive hospitalizations and mortality during extended heat events. Tmin is particularly important for equity-focused analysis because insufficient overnight cooling disproportionately affects individuals who face high energy and housing burdens, inadequate housing insulation, limited access to cooling centers, chronic health conditions, or pronounced urban heat island effects. As such, Tmin serves as a key sensitivity indicator capturing how social, structural, and environmental conditions interact to heighten cumulative heat risk.

Heating Degree Days

Heating Degree Days (HDDs) quantify how much heating is required to maintain safe indoor temperatures, helping to identify communities that may face high energy burdens during colder seasons, particularly those with inefficient housing or limited financial resources. Higher HDDs also indicate greater exposure to cold temperatures, which can increase risks of hypothermia, respiratory illness, and cardiovascular events, especially among older adults, infants, and people with chronic health conditions. In places with elevated HDDs, poorly insulated homes, older housing stock, or inadequate heating systems can significantly increase vulnerability, making HDDs an important indicator of where building conditions may intensify cold-weather risk. Additionally, having a better understanding of the frequency and distribution of HDDs can further highlight communities that may benefit from targeted weatherization or other infrastructure upgrades aimed at reducing cold-related stress and improving energy efficiency.

F. Hazard Exposure

Hazard exposure data from the Federal Emergency Management Agency (FEMA) National Risk Index (NRI) were included to characterize community vulnerability to natural hazards with an emphasis on resilience. NRI indicators draw on well-established datasets and undergo extensive validation to ensure reliability. Incorporating NRI metrics allows the index to integrate the structural factors that shape a community's ability to withstand and recover from hazards.

In the NRI, hazard exposure quantifies the extent to which people, buildings, and infrastructure are physically located within areas susceptible to specific hazards, independent of economic loss or vulnerability assumptions. Higher scores indicate a greater concentration of people and infrastructure located within hazard-prone areas, supporting consistent assessment of risk and informing mitigation planning, emergency preparedness, and risk-reduction strategies across hazard types. For hazards such as heat waves, ice storms, wildfire, and coastal/ riverine flooding, exposure values reflect the concentration of population and built environment within hazard-prone areas. Heat wave exposure captures the number of people and structures in areas that regularly experience prolonged extreme heat. Ice storm exposure reflects the extent of assets located in zones prone to freezing rain events that can lead to extended power outages or transportation failures. Similarly, strong wind exposure reflects the extent of assets located in zones prone to high wind events that can lead to extended power outages. Wildfire exposure measures the population, housing, infrastructure, and land area in locations where ignition and spread are likely, including wildland–urban interface regions. Coastal flooding exposure reflects population and property in low-lying coastal areas susceptible to storm surge, high-tide flooding, and episodic inundation.

III. Methodology

The methodology for University of South Carolina's Social Vulnerability Index, or SoVI, forms the conceptual foundation of the EJ Community Index. It was developed by researchers at the Hazards Vulnerability & Resilience Institute (HVRI) at the University of South Carolina (USC). First published in 2003, SoVI was created to provide a systematic, data-driven measure of how different U.S. counties vary in their social vulnerability to environmental hazards. Its purpose is to capture and compare across places the social, economic, and demographic conditions that influence a community's capacity to prepare for, respond to, and recover from disasters or other environmental stressors.

The SoVI method has been widely used across hazard research and planning contexts because its underlying steps - standardizing variables, extracting orthogonal components, rotating for interpretability, and summing component scores - are statistically sound and well documented. This long-standing precedent helps support it as an appropriate methodological approach for building the EJ Community Index.

A key strength of the SoVI method is its use of Principal Component Analysis (PCA) to reduce dimensionality and address multicollinearity, which occurs when two or more variables are highly correlated. PCA prevents highly correlated indicators from disproportionately influencing results and ensures that each retained component represents a distinct underlying dimension of vulnerability. PCA-derived loadings also provide a deeper understanding how indicators interact.

The defensibility of the SoVI approach lies in its methodological structure rather than any specific set of variables. It provides a transparent, statistically grounded framework for developing a composite vulnerability index using a consistent sequence of operations: data standardization, PCA, component interpretation, and score aggregation. Because the method relies on statistical properties of the dataset instead of expert weighting or subjective importance assignments which can introduce bias, it offers a reproducible, data-driven way to quantify vulnerability.

Additionally, masking - or the existence of hidden vulnerable populations - occurs when one variable suggests low vulnerability while other indicators reveal underlying disadvantage, causing some communities to appear average or non-vulnerable when viewed through a narrower set of measures. PCA helps address masking by capturing shared variance across indicators and identifying patterns where multiple factors co-occur. It reveals latent vulnerability structures that are not visible when examining indicators individually, making it easier to surface communities facing compounding disadvantages. Finally, PCA also enhances comparability across geographies by elevating consistent structural patterns that might otherwise obscure vulnerability in rural or small-population urban communities.

In this particular application of the SoVI method, Principal Component Analysis (PCA) was used to reduce dimensionality within each vulnerability domain, producing a single composite score that represents the degree of community vulnerability for that domain. All scores were then normalized to a common 0–1 scale to ensure comparability, and the final vulnerability index score was calculated as the sum of domain scores, providing an integrated measure of community-level vulnerability. A percentile ranking was subsequently applied to rank census tracts from least to most vulnerable for data visualization and interpretability.

Census tracts in or partially in Tribal Land were automatically assigned a percentile ranking of ≥90% to ensure their status as high-priority communities. Tribes and Indigenous communities have historically been subjected to a myriad of social and cultural injustices that may not be fully captured in commonly used vulnerability indices and are not captured in widely used data sets like the ACS. Manually assigning a high ranking to these census tracts helps to ensure that Tribal communities are recognized and prioritized.

IV. Variable Robustness, Index Validation, and Sensitivity Analysis

A. Multicollinearity Assessment

Multicollinearity was assessed as part of the exploratory data analysis using the Variance Inflation Factor (VIF) and network diagramming for each dimension of the index. This was performed to get a better understanding of the interactions between variables, the extent of the correlation prior to performing PCA, and to provide confirmation that the indicators in each dimension would contribute unique information to the final, composite index.

B. Spearman Rank Correlation Analysis and Validation

Spearman rank correlation coefficients (ρ) were calculated to compare the constructed index against well-established vulnerability indices, including the CDC Social Vulnerability Index (SVI), the CDC Environmental Justice Index (EJI), and the University of South Carolina (USC) Social Vulnerability Index (SoVI). The purpose of comparing the newly developed EJ Community Index to each of these well-established and peer-reviewed indices was to assess both general alignment and conceptual distinctness. SoVI has served as a foundational academic measure of social vulnerability for over two decades and is widely used in hazards and resilience research, while the CDC Social Vulnerability Index (SVI) is widely used by public agencies such as FEMA, the CDC, and state and county governments. These indices also align closely with the theoretical basis of the broader EJ Community Index , whereas hazard-specific indices, like the CDC Heat & Health Index do not provide such comprehensive vulnerability assessments. Both SoVI and SVI also offer a comparison between distinct but complementary methodological approaches. The SoVI uses data-driven PCA, while the SVI relies on a theory-driven additive scoring approach, enabling cross-validation across different conceptual and statistical frameworks.

The EJI was used to provide a comparison with an established environmental justice index that captures cumulative environmental and social burdens, allowing evaluation of whether the EJ Community Index also aligns with a widely recognized environmental justice index. Like the SoVI and SVI, the EJI is well-established, peer-reviewed, and integrates multiple indicators to provide a robust measure of environmental justice. Its explicit consideration of cumulative environmental exposures alongside social vulnerabilities makes it a useful complement for validating the new index.

The use of Spearman's ρ is particularly appropriate for comparison between composite vulnerability indices, which are typically derived from heterogeneous variables that may be non-normally distributed. In this case, Spearman's correlation was used to assess whether the ranking of census tracts in both indices tended to change in alignment with one another.

Additionally, vulnerability indices often employ distinct normalization methods, weights, and aggregation procedures, making absolute values difficult to compare directly. Spearman's ρ focuses on the relative ranking of spatial units, allowing for a scale-independent comparison that emphasizes whether the same areas are identified as more or less vulnerable across different indices. In all comparisons, the newly developed EJ Community Index showed Moderate-Strong correlation, indicating close alignment with the indices selected for comparison.

Strong correlation values ($\rho \approx 0.7$–0.9) indicate high concordance in the relative ordering of spatial units (census tracts) across indices. Similarly, moderate correlation values ($\rho \approx 0.5$–0.7) also indicate that the indices tend to rank spatial units in a similar order of vulnerability. In both cases, the strength of the correlations reflects that there are key differences, such as indicator selection or weighting, or conceptual framing. This suggests that the EJ Community Index captures core vulnerability patterns shared with established indices yet also highlights unique aspects resulting from its specific indicator selection and methodology. Overall, Spearman correlation provides a statistically sound and interpretable basis for evaluating the consistency and robustness of vulnerability assessment frameworks, as depicted below.

Table 1: Summary of Positive Spearman's Correlations and Their Interpretation

Spearman's ρ	Strength of Association	Interpretation in Index Comparison
0.00 – 0.30	Weak / Low	Little or no agreement in spatial rankings; indices likely measure different aspects of vulnerability or rely on divergent indicator sets.
0.30 – 0.50	Moderate–Low	Some shared spatial patterns, but substantial differences in relative rankings, indicating partial conceptual overlap.
0.50 – 0.70	Moderate	Indices exhibit general agreement in ranking patterns, though differences remain; suggests partial convergence in captured dimensions.

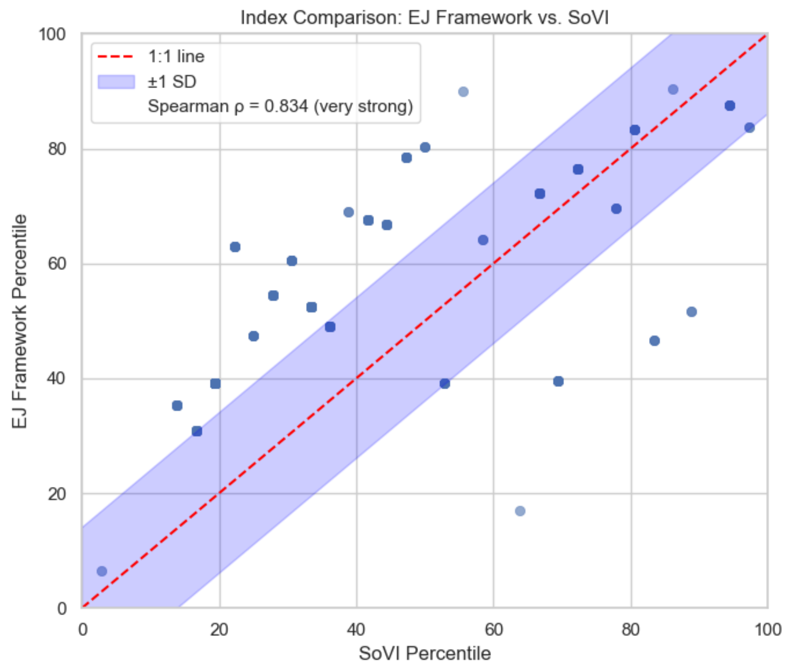
0.70 – 0.90	Strong	High degree of agreement in spatial rankings; indices likely measure similar constructs with consistent methodological assumptions.
0.90 – 1.00	Very Strong / Nearly Identical	Near-perfect concordance; indices produce almost identical spatial rankings and likely capture the same underlying vulnerability patterns.

Results

Comparison with the USC SoVI

The comparison between the EJ Community Framework and original SoVI yielded a ρ value of 0.834. This ranking shows a strong, positive correlation between the indices, indicating that census tracts ranked as more vulnerable by SoVI also tend to be ranked as more vulnerable in the EJ Community Index. However, the distribution of percentile scores between the two indices does differ, suggesting that while they move in the same general direction, the ranking of specific census tracts is not identical. A contributing cause for this could be that although both indices measure related constructs and use the same methodological approach, the EJ Community Index introduces distinct variation due to its inclusion of additional context-specific indicators, such as environmental exposures, and energy and housing burden that are not represented in SoVI. Regardless, the strong correlation demonstrates that the new index both aligns with and extends the conceptual framework of the original USC Social Vulnerability Index.

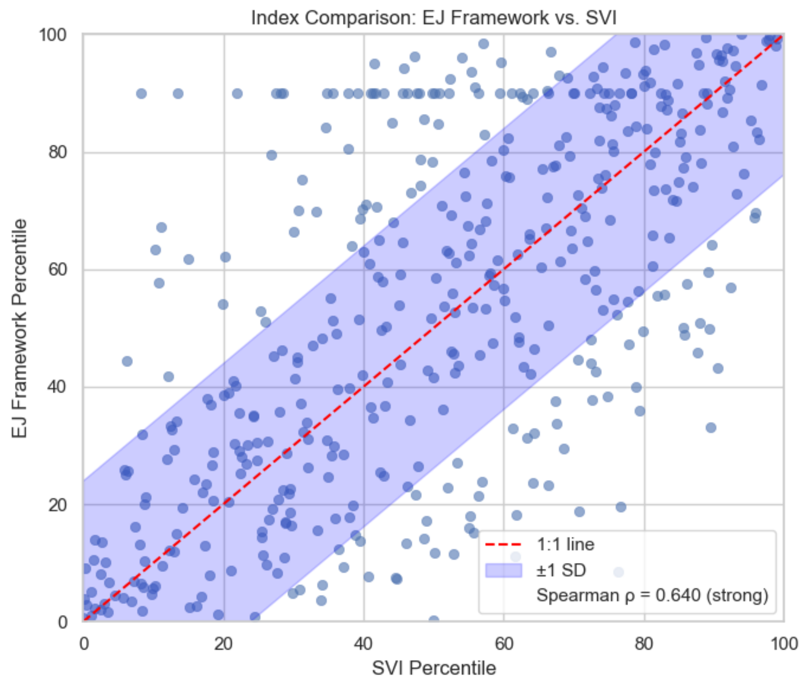
Figure 1: Comparison with SoVI



Comparison with the CDC SVI

Comparison with the CDC SVI resulted in a ρ value of 0.575. This indicates the presence of a moderate positive correlation, which means that areas ranked as more vulnerable by the CDC SVI also tend to be ranked as more vulnerable in the EJ Community Framework. The distribution of percentile scores between the two indices also did not differ significantly, which suggests that while they also tend to move in the same direction, the specific rankings of individual census tracts show some variation. Thus, although both indices measure related constructs, the EJ Community Framework introduces distinct variation which, like the comparison with the SoVI, could be reflective of the incorporation of additional context-specific indicators not captured by the CDC SVI, such as energy burden. Nonetheless, the moderate correlation indicates that the EJ Community Framework both aligns with and extends the conceptual framework of the SVI by adding unique, locally relevant insights gathered from the advisory groups and literature review.

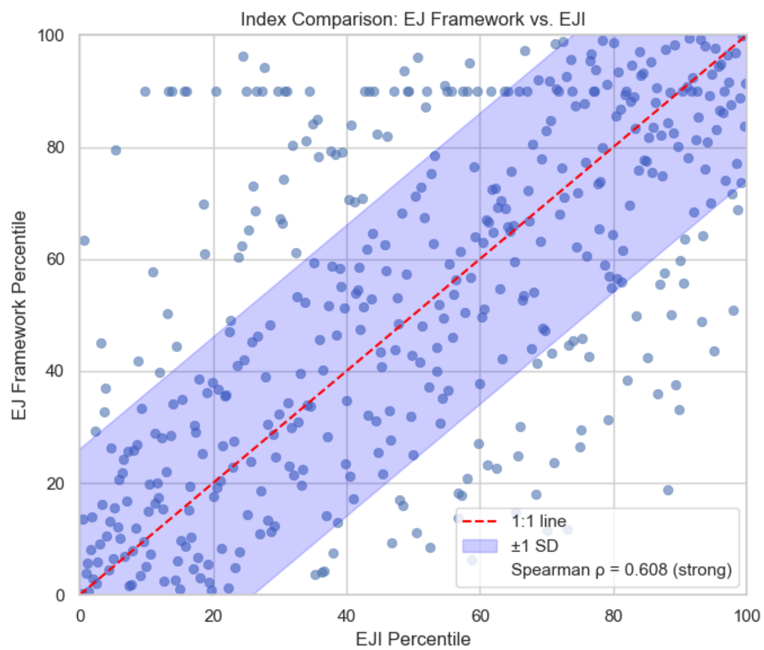
Figure 2: Comparison with CDC SVI



Comparison with the EJI

The comparison between the EJI and EJ Community Index resulted in a ρ value of 0.608, indicating the presence of a moderate positive correlation in which areas ranked as more vulnerable by the EJI also tend to be ranked as more vulnerable in the EJ Community Index. The distribution of percentile scores between the two indices does not differ significantly, suggesting that while they generally move in the same direction, the specific rankings of individual census tracts show some variation. Here again, although both indices measure related constructs, the EJ Community Index introduces distinct variation, likely reflecting its incorporation of additional context-specific indicators such as hazard exposure (as opposed to frequency of hazard events) from the National Risk Index. Overall, the degree of correlation indicates that the new index extends the conceptual framework of the EJI with the addition of advisory groups insights and other indicators. It should be noted that this is positive, as the developers of the EJI themselves noted that it is not intended to be used as a definitive tool for "labeling EJ communities" or characterizing all EJ issues.

Figure 3: Comparison with CDC EJI



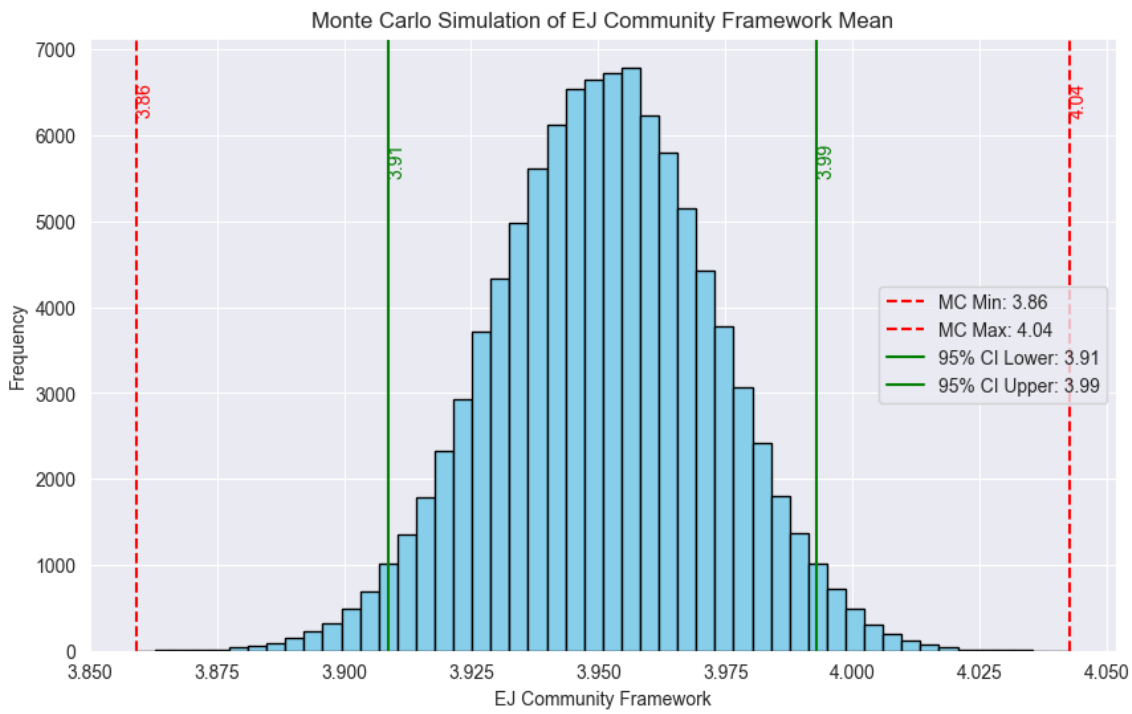
C. Monte Carlo Simulation

To complement Spearman correlation analysis with well-established indices, a Monte Carlo simulation was applied, in which 100,000 iterations were run to evaluate the stability and reliability of the EJ Community Index under uncertainty in model assumptions. Composite indices rely on methodological choices such as indicator weights, normalization methods, and aggregation procedures, making it essential to understand how these decisions influence final results. Using Monte Carlo simulation is a common practice in index development and robustness testing, as it allows researchers to quantify the sensitivity of results to variations in inputs and assess the consistency of rankings or scores under different scenarios.

The simulation works by repeatedly recalculating the index across thousands of iterations, and randomly varying key parameters within defined ranges. Each iteration produces a new set of index values, generating a distribution of outcomes rather than a single deterministic result. Analysis of these outcomes allows quantification of variability, estimation of confidence intervals, assessment of rank stability across areas, and identification of parameters that most strongly influence index behavior. This approach provides a probabilistic understanding of index performance, ensuring that observed spatial patterns of vulnerability are robust and not artifacts of specific weighting or aggregation choices. By systematically evaluating the impact of parameter uncertainty, Monte Carlo simulation enhances the transparency, reproducibility, and credibility of the index.

The results of the Monte Carlo simulation indicate that the EJ Community Index is statistically stable under repeated random sampling. Across 100,000 simulations, the distribution of simulated means is normal, centered around 3.95, with a 95% confidence interval ranging from 3.91 to 3.99. The simulated minimum and maximum values, 3.86 and 4.04 respectively, indicates a narrow overall range of variation, confirming low sensitivity to input uncertainty. The resulting bell-shaped distribution demonstrates that the index behaves predictably and is not overly sensitive to random variation in the input data, as shown in Figure 4 below.

Figure 4: Monte Carlo Simulation



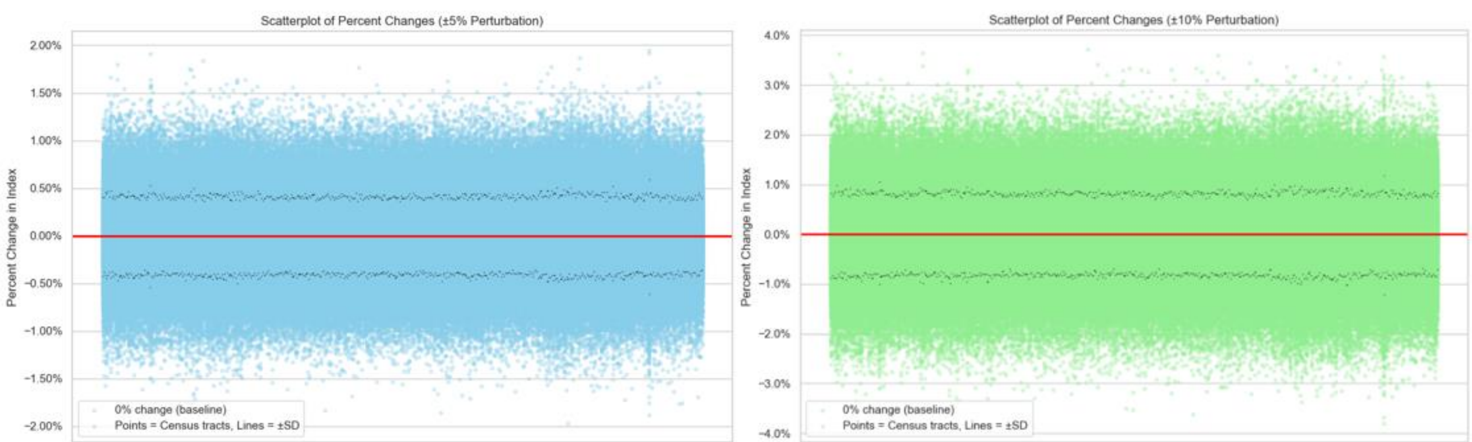
This stability is critical for outcome evaluation because it indicates that small changes or uncertainties in the underlying data do not materially alter the overall result. A metric that varies only slightly under repeated simulation provides confidence that the ranking or relative prioritization of communities will remain consistent, even if underlying data shift slightly, and that investment, planning, or regulatory decisions informed by the index will be reliable rather than vulnerable to statistical noise.

Overall, the Monte Carlo results show that the EJ Community Index is statistically reliable and suitable as a decision-support tool. Its stability suggests low propagation of error, meaning that variability in underlying component indicators does not meaningfully shift the aggregated score. In other words, the index output exhibits high reliability with respect to data perturbation, indicating that weighting, normalization, and aggregation procedures are functioning as intended and are not amplifying noise.

D. Sensitivity Analysis

The sensitivity testing performed on the EJ Community Framework indicates that the index is robust to variations in input data. A ±5% perturbation was first applied to the input variables, resulting in minimal change to the overall index. This suggested that the framework is not extremely sensitive to small fluctuations, which is desirable given that real-world data often contains minor noise or variability. When the perturbation was increased to ±10%, the index continued to demonstrate low sensitivity, with results remaining stable even under these larger adjustments. Across both levels of testing, the standard deviation of percent changes was low, further confirming that no single variable dominates the index. The results of sensitivity testing are presented below.

Figure 5: Sensitivity Analysis



In practical terms, this stability means that census tract rankings behave consistently, with no communities shifting dramatically or unexpectedly. In other words, the EJ Community Index produces reliable, reproducible results and maintains stable relative rankings at the census tract level.

E. Summary

Collectively, these diagnostic and validation steps demonstrate that the vulnerability index is robust, reliable, and interpretable at the census tract level. Multicollinearity assessment using VIF confirmed that each dimension contributed unique information to the composite index. Spearman rank correlation analysis with established indices (CDC SVI, CDC EJI, and USC SoVI) provided external validation, indicating general agreement with recognized vulnerability indices while also highlighting the unique contributions of the constructed index. Monte Carlo simulation showed that the index is stable under methodological uncertainty, and sensitivity analysis of the overall index confirmed minimal impact from moderate perturbations in indicator weights. Together, these analyses provide a transparent, defensible framework for index construction and confirm that the resulting measure can be confidently used for research, policy, and planning purposes.

V. Exploratory Data Analysis

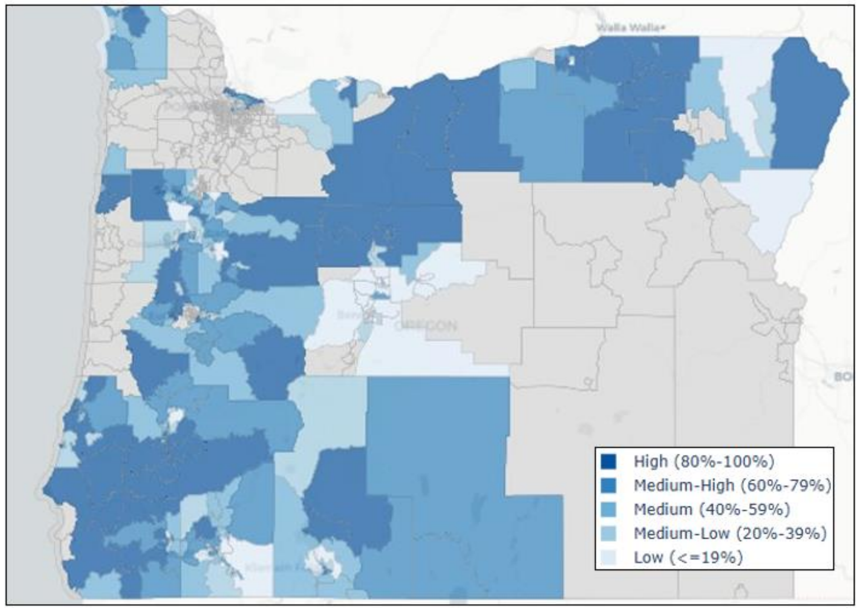
The following maps present visualizations of the selected dimensions and indicators related to identifying environmental justice communities. They are intended to illustrate how underlying social, economic, and demographic conditions vary across geographic areas and to support development of a better understanding of communities' lived experience of equity. To complement the maps, the accompanying tables identify the ten census tracts with the highest degree of relative vulnerability in each dimension, providing a focused reference to support their interpretation.

As described above, the barriers and challenges that contribute to the vulnerability of Tribes and Indigenous communities were incorporated during the final stage of the analysis to ensure their status as high priority communities was fully captured. As a result, the individual dimensions of vulnerability (socioeconomic, health, household, race/ ethnicity, housing, environmental, and hazard) shown below do not include explicit consideration of the unique risks and equity considerations applicable to Tribes and Indigenous communities.

Figure 6 below provides a visualization of the Environmental Justice Community Framework. The map shows census-tract–level vulnerability across Oregon, with darker blue indicating higher vulnerability and lighter blue indicating lower vulnerability. Overall, vulnerability is highest in rural, coastal, southern, and eastern parts of the state, while lower vulnerability clusters along the urbanized Willamette Valley. Multnomah, Washington, and Clackamas Counties generally exhibit low to medium vulnerability, particularly in Portland and its suburbs, though pockets of higher vulnerability remain outside urban cores. Similar urban–rural contrasts appear in Marion, Lane, Linn, and Benton Counties, with lower vulnerability near Salem, Eugene, Corvallis, and Albany and higher vulnerability in surrounding tracts. Coastal counties including Clatsop, Tillamook, Lincoln, Coos, and Curry show widespread medium-high to high vulnerability. In southern Oregon, Douglas, Josephine, and Jackson Counties display consistently high vulnerability beyond Medford and Grants Pass. Central Oregon reflects mixed conditions, with lower vulnerability near Bend in Deschutes County and predominantly high vulnerability in Jefferson County. Eastern Oregon contains large contiguous areas of high vulnerability, with some pockets of low vulnerability near the Idaho border.

Figure 6: The Environmental Justice Community Framework

Tract	County	Percentile Ranking
41035971500	Klamath County	100
41035971600	Klamath County	99.77
41035971800	Klamath County	99.55
41029000100	Jackson County	99.32
41051008100	Multnomah County	99.1
41031960201	Jefferson County	98.87
41011001101	Coos County	98.65
41011001102	Coos County	98.42
41033361601	Josephine County	98.19
41011000505	Coos County	97.97

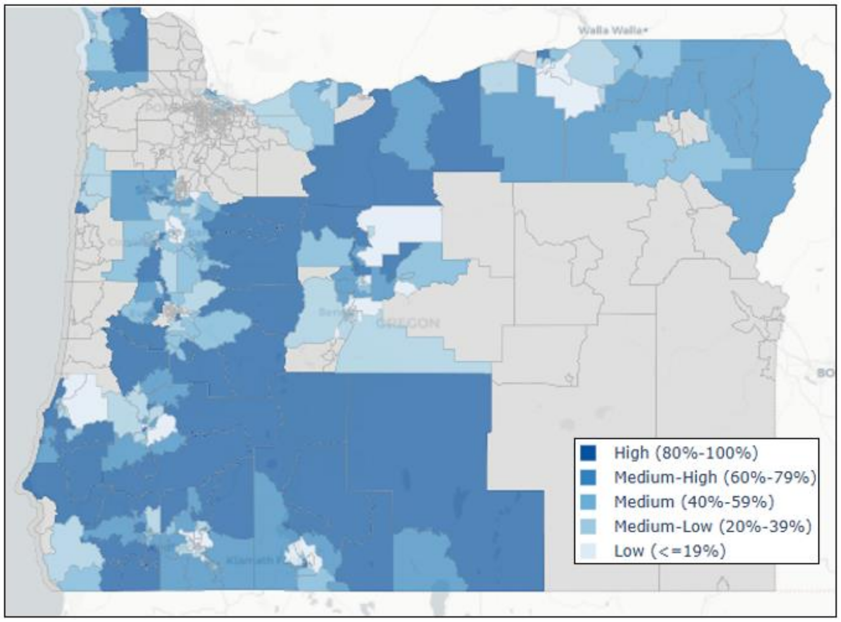


Socioeconomic Status

As shown in Figure 7, socioeconomic vulnerability in Oregon is unevenly distributed across the state, with the highest concentrations of vulnerability occurring in southern, southwestern, coastal, and eastern counties. Census tracts with higher vulnerability (dark blue) are prevalent in Josephine, Douglas, Coos, Klamath, Lake, and Jefferson Counties, reflecting greater economic and social challenges in these largely rural areas. In contrast, census tracts with lower vulnerability (light blue) are concentrated in the Portland metropolitan area, particularly in Washington, Clackamas, and much of Multnomah County, as well as parts of the northern Willamette Valley. Counties such as Lane, Marion, Linn, Polk, Yamhill, and Deschutes exhibit a mix of vulnerability levels, with lower vulnerability near urban centers and higher vulnerability in surrounding rural tracts. Overall, the map highlights a clear urban–rural divide in socioeconomic conditions across the state.

Figure 7: Socioeconomic Status

Tract	County	Percentile Ranking
41039001500	Lane County	100.00%
41035971800	Klamath County	99.77%
41011001101	Coos County	99.55%
41033360100	Josephine County	99.32%
41015950100	Curry County	99.10%
41043030404	Linn County	98.87%
41033361601	Josephine County	98.65%
41035970201	Klamath County	98.42%
41033361602	Josephine County	98.19%
41007950900	Clatsop County	97.97%

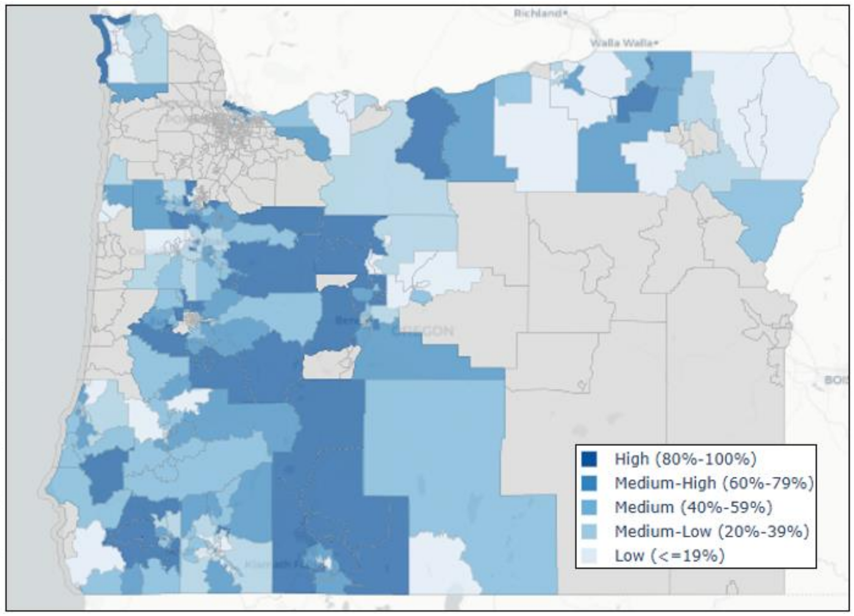


Health Status and Healthcare Accessibility

Figure 8 indicates that health vulnerability - related to healthcare access and health outcomes - is concentrated primarily in southern, southwestern, central, and some parts of eastern Oregon, while lower vulnerability appears more common in urban and suburban areas. Census tracts with higher health vulnerability (dark blue) are prominent in Clatsop, Josephine, Douglas, and Klamath Counties, suggesting greater barriers to healthcare access and poorer overall health outcomes in these primarily rural regions. Portions of Jefferson, Deschutes, and eastern Lane County also show elevated vulnerability. In contrast, lower health vulnerability (light blue) is concentrated in the Portland metropolitan area, including Washington, Clackamas, and much of Multnomah County, where healthcare infrastructure and access are stronger. Counties such as Lane, Marion, Linn, Polk, Yamhill, and Deschutes display mixed patterns, with lower vulnerability near population centers and higher vulnerability in more remote or rural census tracts. Overall, the map highlights the existence of persistent geographic health disparities across Oregon that are closely aligned with rurality and limited access to healthcare services.

Figure 8: Health Status and Healthcare Accessibility

Tract	County	Percentile Ranking
41035970201	Klamath County	100.00%
41051007300	Multnomah County	99.77%
41017001802	Deschutes County	99.55%
41039001400	Lane County	99.32%
41047010600	Marion County	99.10%
41007990000	Clatsop County	98.87%
41035971600	Klamath County	98.65%
41035970600	Klamath County	98.42%
41033360601	Josephine County	98.19%
41051010602	Multnomah County	97.97%

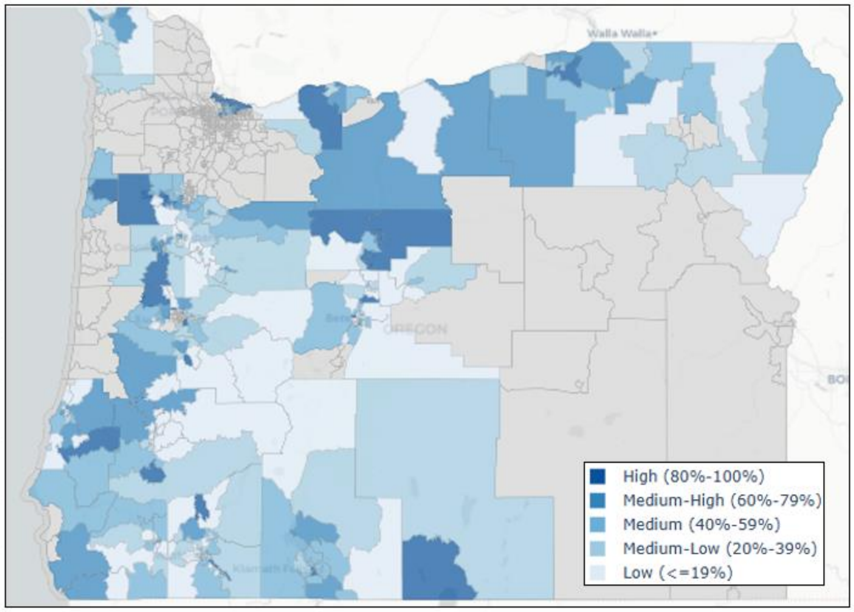


Racial, Ethnicity, Language

Figure 9 below demonstrates clear geographic clustering of racial and ethnic diversity across Oregon census tracts, with the highest diversity concentrated in western Oregon along the Interstate 5 corridor. High diversity tracts are most prominent in Multnomah County, particularly within Portland, and extending into Washington and Clackamas Counties, reflecting the state's largest and most diverse metropolitan area. Additional pockets of moderate to high diversity appear in Marion County (Salem) and Lane County (Eugene–Springfield), where diversity is highest near urban centers and decreases in surrounding rural areas. Coastal counties such as Clatsop, Tillamook, Lincoln, Coos, and Curry are dominated by low-diversity tracts. Along the Columbia River Gorge and in Eastern Oregon, most counties - including Union and Baker - exhibit low diversity overall, though Hood River and Wasco County stand out with moderate diversity in areas associated with agricultural employment. Overall, these patterns reflect the influence of urbanization, the role of agricultural and food-processing labor markets in specific corridors, and longstanding settlement dynamics in more remote rural areas.

Figure 9: Racial, Ethnic, and Linguistic Diversity

Tract	County	Percentile Ranking
41051009501	Multnomah County	100.00%
41051010200	Multnomah County	99.77%
41051008100	Multnomah County	99.55%
41051009204	Multnomah County	99.32%
41051005201	Multnomah County	99.10%
41051007700	Multnomah County	98.87%
41051007900	Multnomah County	98.65%
41051007201	Multnomah County	98.42%
41035971600	Klamath County	98.19%
41051009302	Multnomah County	97.97%

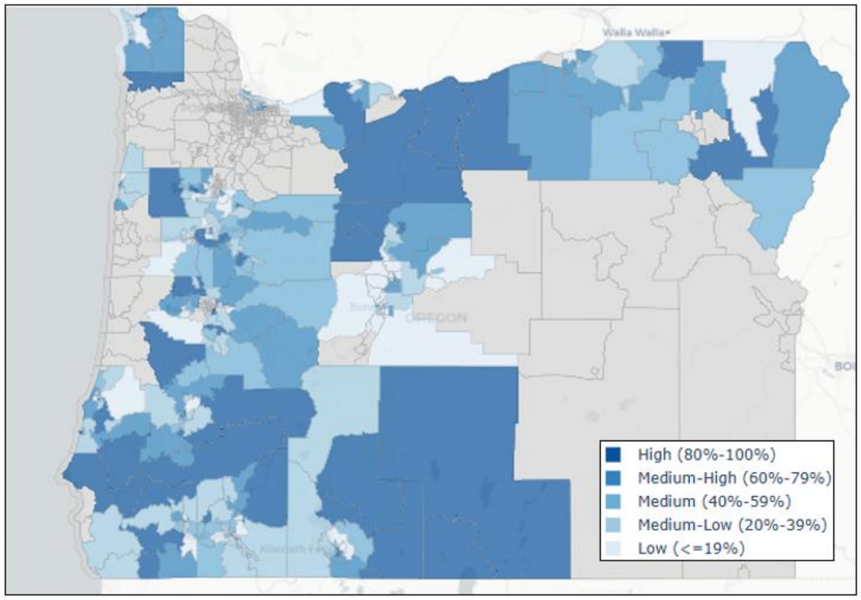


Housing

Figure 10 shows pronounced spatial variation in housing vulnerability across Oregon census tracts, with the highest vulnerability concentrated in specific western, southern, and northeastern areas of the state. Dark blue tracts indicating high housing vulnerability are especially prominent in Multnomah County, particularly within Portland, and extend into parts of Washington and Clackamas Counties, reflecting known housing cost pressures and rental instability in the Portland metropolitan area. Elevated vulnerability also appears in Marion County (Salem), Lane County (Eugene–Springfield), and Josephine County (Medford), where high-vulnerability tracts cluster around urban cores and along major transportation corridors. In southern Oregon, portions of Lake and Klamath County show high housing vulnerability, while Jackson County exhibits moderate but more dispersed patterns. In eastern Oregon, notable concentrations of high vulnerability are visible in Umatilla and Wallowa Counties, likely reflecting housing stock limitations and affordability challenges tied to agricultural economies. Coastal counties, including Clatsop, Tillamook, Lincoln, and Coos, display a mix of medium to high vulnerability, particularly near population centers, while lower vulnerability tracts are more common in less urbanized areas. Collectively, these patterns underscore the combined effects of urban affordability pressures in urban centers and growth hubs, persistent structural challenges in rural southern and eastern Oregon, and distinct coastal housing dynamics associated with seasonal economies and limited infrastructure.

Figure 10: Quality of Housing and the Built Environment

Tract	County	Percentile Ranking
41029000100	Jackson County	100.00%
41051005103	Multnomah County	99.77%
41051001101	Multnomah County	99.55%
41061970200	Union County	99.32%
41031960201	Jefferson County	99.10%
41011001101	Coos County	98.87%
41035971600	Klamath County	98.65%
41033361601	Josephine County	98.42%
41051008203	Multnomah County	98.19%
41019120002	Douglas County	97.97%

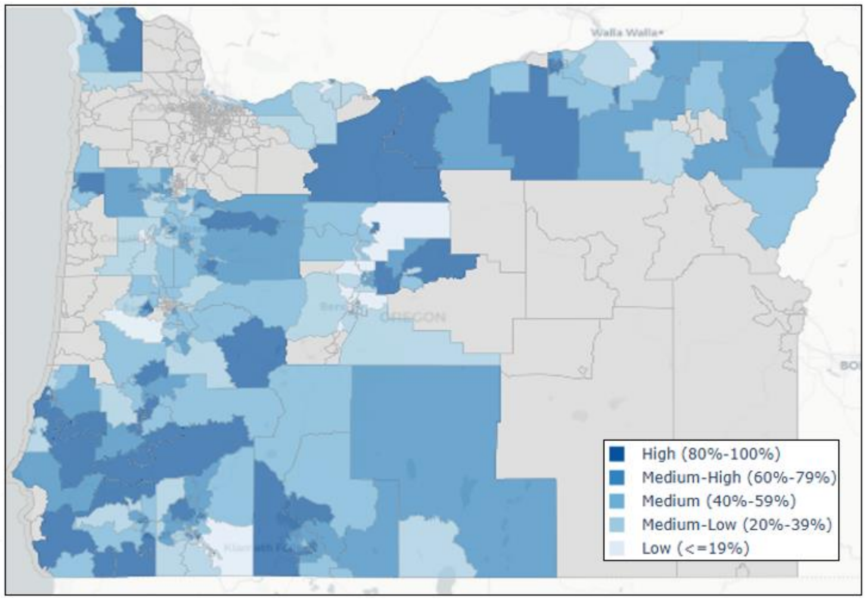


Household Composition

Figure 11 illustrates clear geographic patterns in household composition vulnerability across Oregon census tracts, with darker blue areas indicating higher concentrations of vulnerable household characteristics such as disability, older age, veteran status, and single-parent households. Along the Columbia River Gorge, high vulnerability tracts are most prominent in Wasco, Gilliam, and Wallowa Counties, likely reflecting a concentration of aging populations. In southern Oregon, Klamath County shows notable concentrations of high household vulnerability, while Josephine County exhibits moderate but widespread vulnerability. Coastal counties such as Columbia, Coos, and Curry show a mix of medium and high vulnerability. In general, the map highlights both urban and rural dimensions of household composition vulnerability, with elevated levels of vulnerability occurring in more rural areas of the state.

Figure 11: Household Composition

Tract	County	Percentile Ranking
41019050004	Douglas County	100.00%
41059950700	Umatilla County	99.77%
41035971500	Klamath County	99.55%
41015950301	Curry County	99.32%
41011001101	Coos County	99.10%
41033360601	Josephine County	98.87%
41011000505	Coos County	98.65%
41039001500	Lane County	98.42%
41019140000	Douglas County	98.19%
41033361601	Josephine County	97.97%

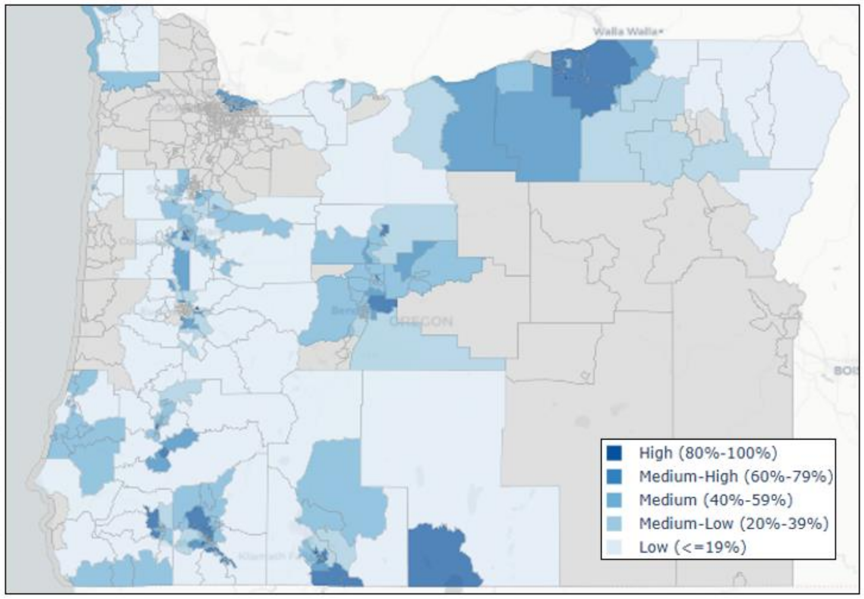


Environmental Exposure

Figure 12 highlights gradients of environmental exposure across Oregon, with higher exposure concentrated in inland urban and agricultural regions and lower exposure in coastal and sparsely populated areas. Dark blue tracts with higher exposure are concentrated in urban and agricultural areas. These areas are most prominent in Multnomah County, particularly within the Portland metropolitan area, where emissions and the presence of urban heat islands contribute to elevated exposure. Additional clusters of high exposure appear along the I-5 corridor in the Willamette Valley, likely reflecting a combination of population density, transportation-related emissions, and temperature variability. In southern Oregon, parts of Jackson and Lake County show higher exposure, likely associated with warmer daytime temperatures and susceptibility to wildfire. Along the Columbia River Gorge, elevated exposure is visible in Umatilla County and portions of Gilliam and Morrow County, where agricultural activity and transportation-related emissions contribute to higher values. Coastal counties, including Clatsop, Tillamook, Lincoln, Coos, and Curry, are largely characterized by lower environmental exposure, consistent with milder coastal climates and fewer major emissions sources.

Figure 12: Environmental Exposure

Tract	County	Percentile Ranking
41029000300	Jackson County	100.00%
41029000202	Jackson County	99.77%
41029001001	Jackson County	99.55%
41029000201	Jackson County	99.32%
41029001002	Jackson County	99.10%
41029000203	Jackson County	98.87%
41029000100	Jackson County	98.65%
41029001301	Jackson County	98.42%
41029000406	Jackson County	98.19%
41029000405	Jackson County	97.97%

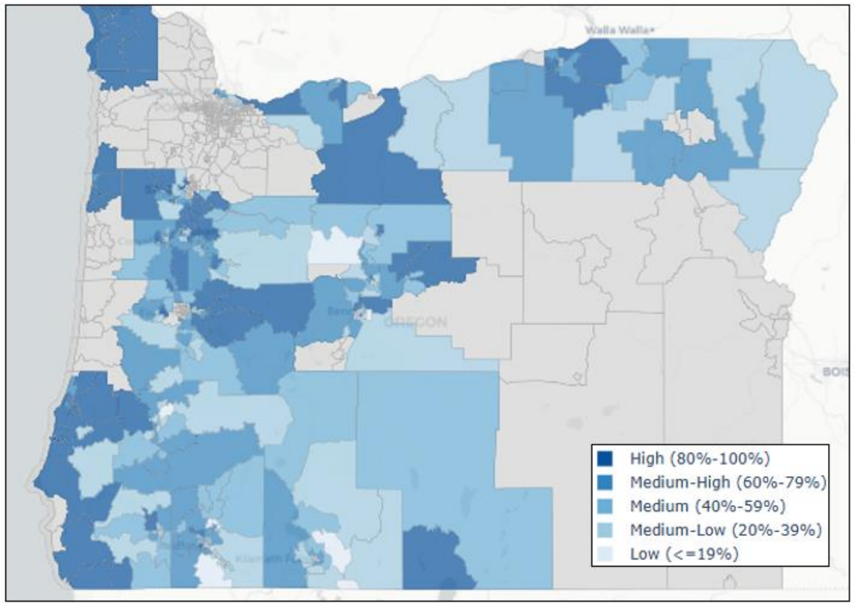


Hazard Exposure

Figure 13 represents spatial variation in hazard exposure across Oregon census tracts, with higher exposure concentrated in coastal, urban, and climatically sensitive regions. Dark blue tracts indicating high hazard exposure are prominent along the Oregon Coast, particularly in Clatsop, Tillamook, Lincoln, Coos, and Curry Counties, reflecting elevated risk from coastal flooding and strong wind events. Elevated exposure is also evident in the Portland metropolitan area, including Multnomah, Washington, and Clackamas Counties, where riverine flooding, earthquake risk, extreme heat, and wind hazards intersect. In the Willamette Valley, Marion and Lane Counties show moderate to high exposure near urban centers. Southern Oregon counties, including inland Curry, Josephine, and portions of Lake County display higher exposure driven by wildfire risk and temperature extremes, while parts of Klamath County also show elevated areas of exposure. In eastern Oregon, areas of Umatilla and Morrow County exhibit moderate to high hazard exposure, likely associated with strong wind and wildfire. Overall, the map highlights Oregon's multifaceted hazard landscape, with the highest exposure occurring in coastal counties, metropolitan areas, and the fire-prone regions of southern, central, and eastern Oregon.

Figure 13: Hazard Exposure

Tract	County	Percentile Ranking
41007950500	Clatsop County	100.00%
41007951100	Clatsop County	99.77%
41007950900	Clatsop County	99.55%
41007990000	Clatsop County	99.32%
41015950301	Curry County	99.10%
41011000701	Coos County	98.87%
41007950400	Clatsop County	98.65%
41007950600	Clatsop County	98.42%
41011001002	Coos County	98.19%
41011001001	Coos County	97.97%



VI. Next Steps

As a next step, modeling will be conducted to examine the relationship between program uptake and environmental justice community designation, in which CBI outcomes will be treated as the dependent variable and the EJ Community Index as an independent variable. This analysis will be used to assess alignment between CBI outcomes and EJ community designation, and to evaluate how well programs tied to CBI outcomes are reaching EJ communities. It is important to emphasize that modeling results will be interpreted as descriptive and predictive, indicating whether program participation rates are higher or lower in communities with greater relative equity burden. This approach is intended to evaluate associations between vulnerability rankings and program reach, not to establish causal relationships or to assess whether program outcomes improve or worsen equity.

Additionally, the index will be validated via feedback from advisory groups to ensure that the indicators, weighting, and aggregation methods used provide an accurate reflection of lived experience and local knowledge. This validation will help to improve accuracy and identify opportunities for refinement, supporting greater transparency, credibility, and usefulness of the index in informing decision-making.

VII. Limitations and Appropriate Use

This index is intended to inform planning and prioritization by summarizing relative patterns of equity across communities. As with any composite measure, it should be interpreted in light of several important considerations.

First, the index is based on a combination of multiple indicators, each of which represent only part of the lived experience of vulnerability. While the approach helps to capture broad, multi-dimensional patterns, it cannot reflect all local circumstances, historical context, or community strengths. For this reason, qualitative insights from advisory groups and other stakeholders will still be essential to understanding environmental justice communities, as they provide local expertise and community input that can support truly equitable decision-making relative to CBI outcomes.

Second, the index reflects relative vulnerability within a given area, not an absolute level of need. Communities are ranked in comparison to one another, meaning that a lower ranking does not imply the absence of need, nor does a higher ranking the full extent of challenges faced by a community. The index is therefore best used to inform comparative decision-making, such as identifying areas for more targeted interventions rather than a standalone assessment of environmental justice community designation.

Third, because the index is derived from available data, it is influenced by data coverage and quality. Some aspects of equity - such as social cohesion, informal support networks, or lived experience of discrimination/ historical disadvantage are difficult to quantify and may not be fully represented. Finally, the index is not designed to identify causal drivers of inequity or to predict outcomes under specific future scenarios. Instead, it provides a transparent, consistent framework for highlighting relative equity patterns and supporting more informed, equitable distribution of resources and evaluation of CBI outcomes.

VIII. References

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IX. Appendix I: Variable Choices and Justification for Including

Category/ Dimension	Data Source	Variable ID	Justification for Including
Socioeconomic Status	American Community Survey (ACS)	< Poverty %	• Many low-income households have a disproportionately high energy burden, spending more than 6% of their income on energy. This often forces hard choices between paying for energy, buying food, medication, or rent, creating long-term instability. • Low-income households are more likely to reside in older, less efficient homes with poor weatherization, outdated or inadequate heating and cooling systems, poor indoor air quality, and higher susceptibility to outdoor air pollution. • Importantly, households living below the poverty level are also frequently unable to take advantage of cost savings from energy efficiency incentive programs (because of high upfront costs).
	American Community Survey (ACS)	Deep Poverty (<50%) %	• Deep poverty reflects households with extremely limited financial resources, often insufficient to meet basic needs such as food, housing, utilities, and healthcare. This level of deprivation signifies significantly greater hardship than standard poverty measures alone. • Households in deep poverty face higher rates of energy insecurity, housing instability, chronic health conditions, and barriers to accessing transportation and care. These intersecting constraints reduce adaptive capacity. • In the context of environmental hazards, infrastructure disruptions, or economic shocks, households in deep poverty have fewer buffers and recovery options, leading to prolonged or more severe impacts compared to households with even slightly higher incomes.
	American Community Survey (ACS)	Median HH Income	• Median household income provides a measure of the typical financial resources available to households, influencing the ability to afford housing, utilities, healthcare, and adaptation measures. Lower median incomes indicate greater financial strain and reduced ability to absorb economic shocks. • Communities with lower median incomes experience higher energy burdens, greater likelihood of living in older or substandard housing, and increased difficulty accessing efficiency upgrades or resilient infrastructure, compounding vulnerability. • Lower-income communities are more likely to face prolonged recovery times following hazards or disruptions, as limited savings and credit access reduce options for relocation, repairs, or protective investments.

	American Community Survey (ACS)	Gini Index	• The Gini Index measures the degree of income inequality within a community. Higher inequality reflects a wider gap between high- and low-income households, signaling uneven access to resources, services, and opportunities. • Communities with high income inequality often exhibit greater health disparities, housing insecurity, and reduced social cohesion, all of which amplify sensitivity to environmental and economic stressors. • Higher income inequality is associated with weaker community adaptive capacity, meaning that during hazards or disruptions, burdens fall disproportionately on those with fewer resources, slowing recovery and deepening long-term impacts.
	American Community Survey (ACS)	Fixed Income HHs %	• Households on fixed incomes have limited ability to adjust spending in response to rising costs of energy, housing, healthcare, or other essential needs. This rigid income structure increases sensitivity to price shocks and utility rate changes. • Fixed-income households, particularly older adults, and individuals with disabilities, are more likely to face trade-offs between heating/cooling, medical care, food, and rent. These trade-offs increase exposure to health risks and economic instability. • Fixed-income households may have fewer options to relocate, repair homes, or invest in energy efficiency and resilience improvements, slowing recovery from disruptions/ climate adaptations.
	American Community Survey (ACS)	HHs w/ SNAP %	• Participation in the Supplemental Nutrition Assistance Program (SNAP) is a widely used indicator of social vulnerability in research and policy frameworks. • SNAP participation reflects lower socioeconomic status and is associated with higher vulnerability, including food and energy insecurity, reliance on the social safety net, reduced resilience, and barriers to accessing healthy foods and healthcare.
	American Community Survey (ACS)	Agriculture, forestry, fishing and hunting, and mining %	• Many agricultural workers earn low wages, experience unstable employment, and lack access to benefits such as health insurance or paid leave. • Their jobs frequently involve physically demanding labor in extreme weather conditions, which is becoming more dangerous due to rising temperatures and more frequent heatwaves. • Agricultural workers may also live in substandard or temporary housing with poor insulation or inadequate cooling and heating.

	American Community Survey (ACS)	Unemployed %	• Unemployed individuals/ households are more vulnerable economically, which directly influences their ability to access, afford, and benefit from energy systems. • Unemployed individuals or households typically have lower or no income, making it harder to pay for electricity, heating, and fuel. • Energy burden is disproportionately high for unemployed or low-income households and energy insecurity is more common. • Unemployed individuals are more likely to live in older, inefficient housing with poor insulation, outdated heating systems, or limited weatherization. • Participation in solar, efficiency upgrades, or rebate programs often requires upfront costs, steady income, or employment-based eligibility, making them inaccessible to the unemployed.
	American Community Survey (ACS)	<HS Grad %	• Lower education is strongly correlated with having lower income, higher unemployment/ job instability, and access to jobs with fewer benefits. • Educational attainment impacts the ability to access and adopt energy efficiency and clean energy programs and their associated energy savings. • Limited education can preclude participation in the clean energy economy, such as energy efficiency or solar incentive program participation.
	American Community Survey (ACS)	No Vehicle %	• In rural or poorly connected areas jobs, healthcare, education, and grocery stores can be difficult to access without a vehicle. • Lack of a vehicle can prevent timely evacuation during climate-related disasters (e.g., wildfires, storms). • Vehicle-less households often live in transit-poor areas or low-cost housing far from urban infrastructure, compounding disadvantage.
	American Community Survey (ACS)	Long Commute (>=45 Min) %	• A commute >=45 minutes can signal limited local opportunities, increasing economic and social stress. • Longer commutes increase transportation costs (fuel, maintenance, insurance), reducing disposable income for other essentials like housing, food, and healthcare. • A commute >=45 minutes can also reflect geographic isolation, which can exacerbate risks during emergencies.
	CDC PLACES	Food Insecurity % of Pop	• Food insecurity captures households struggling to afford sufficient, nutritious food, often signaling low income, unemployment, or reliance on social safety nets. • Food insecurity is associated with housing instability, energy insecurity, and limited access to healthcare, highlighting multiple dimensions of vulnerability. • Chronic food insecurity increases risk for poor physical and mental health, reducing capacity to withstand and recover from stressors.

	CDC PLACES	Housing Insecurity % of Pop	• Self-reported housing insecurity identifies households facing eviction, unaffordable rent, or unstable living conditions, often linked to low income and financial stress. • Housing instability is associated with limited access to healthcare, education, and community resources, highlighting multiple layers of vulnerability. • Chronic housing insecurity contributes to stress, poor mental and physical health, and reduced capacity to prepare for, respond to, or recover from stressors.
	CDC PLACES	Transportation Barriers % of Pop	• Self-reported transportation barriers identify households lacking reliable transportation, limiting access to work, healthcare, education, and essential services. • Transportation barriers are often linked to low income, rural location, or inadequate public transit, highlighting systemic inequities that increase vulnerability. • Limited transportation can reduce the ability to obtain medical care, food, or emergency resources.
	US Department of Energy (LEAD)	Energy Burden	• As the climate changes, extreme temperature changes, such as heat waves and deep freezes are becoming more common, forcing communities to adapt. • Adaptations include keeping homes at safe and comfortable temperatures; however, that often requires more energy-efficient heating and cooling. • Vulnerable households, especially those limiting energy use due to cost, are often left behind or struggle to make these changes.
	Department of Housing and Urban Development	QCT	• HUD QCTs identify areas with high poverty or low median income, capturing communities at elevated risk of housing and financial instability. • HUD qualified census tracts often face limited access to quality housing, healthcare, transportation, and other essential services, highlighting systemic inequities.
Housing and Built Environment	American Community Survey (ACS)	Renters %	• Renters typically cannot make energy efficiency improvements like insulation, new appliances, or solar panels because they do not have control over property. Property owners may also be unwilling to invest in upgrades that benefit tenants. • Rental units are often older or less efficient, leading to higher utility costs for tenants. • Renters may face eviction, rising rents, or displacement, limiting their ability to benefit from long-term programs or improvements. • Many weatherization or energy efficiency programs require landlord approval or focus on homeowners. • A growing body of research warns that renters are particularly vulnerable after disasters, in part because they are less likely to have relevant insurance and may not receive adequate assistance from the government in the immediate aftermath.

	American Community Survey (ACS)	Mobile Homes %	• Mobile homes are often clustered in communities confined to low-value areas due to zoning laws and stigma. • The aspects of stigma, zoning, and lack of land ownership can inhibit these populations' ability to influence local environmental policy. • Issues with poor construction and energy inefficiency can render residents of mobile homes more susceptible to emergencies and the negative health effects associated with air pollution and extreme heat.
	American Community Survey (ACS)	Bottled, tank, or LP gas %	• These fuels are often more expensive and sensitive to price fluctuations, which can impact accessibility and increase energy burden. • They can be subject to delivery disruptions (e.g., during storms or supply shortages), which can leave households without heat or cooking fuel. • Improper storage or aging equipment can pose fire or explosion risks, especially in lower-quality housing like mobile homes. • They are often used in homes that lack access to piped natural gas or electric infrastructure. • Tanks and related equipment require upkeep and inspections, which can be cost-prohibitive.
	American Community Survey (ACS)	No Internet %	• Many utilities and service providers are shifting to web-based customer tools. • Rural residents may lack reliable internet access. Limited internet access can create barriers to communication during emergencies. • Online outreach is often critical during hazard events, leaving those without access at risk.

	American Community Survey (ACS)	Overcrowded Housing %	• Housing with more than one occupant per room (overcrowding) can be indicative of:
			  ○ Economic hardship.
			  ○ Risk to health by increased spread of infectious diseases; namely respiratory illnesses.

	American Community Survey (ACS)	Incomplete Plumbing %	• Housing without complete plumbing or kitchen facilities signals vulnerability because it reflects poor living conditions and limited access to infrastructure to meet basic needs. • Lack of plumbing increases exposure to waterborne diseases and unsanitary conditions. • Incomplete kitchens limit the ability to store and prepare healthy meals, contributing to poor nutrition. • Incomplete facilities also indicate structural disrepair. • Homes without basic infrastructure are often ineligible for weatherization or energy efficiency programs.
	American Community Survey (ACS)	Incomplete Kitchen %	

	American Community Survey (ACS)	Units Built <=1980 %	• For energy efficiency and weatherization programs, many older homes have health and safety issues that need to be addressed before they can be safely retrofitted; for example, leaking roofs, electrical or plumbing issues, moisture issues or mold, loose asbestos, or other issues. • When programs do not have sufficient funds or are not allowed to spend retrofit funds on health and safety repairs, these homes can be excluded from receiving energy efficiency retrofits (known as deferrals or walkaways). • Older homes are also often more expensive to heat and cool than newer, more efficient housing.
	American Community Survey (ACS)	Multi-Unit Housing (Total) %	• Shared infrastructure can limit individual control over heating, cooling, and ventilation. • Older buildings may lack insulation, weatherization, or energy-efficient systems. • Tenants often cannot make upgrades (e.g., solar panels, new windows, efficient appliances). • High density can increase exposure to indoor air pollutants or heat. • Emergency evacuations can be more difficult in large or poorly maintained buildings.
	American Community Survey (ACS)	No Telephone %	• Households without phone service may struggle to access important energy assistance programs, bill payment plans, or energy-saving resources. • Programs like LIHEAP and shut-off protections rely on communication, so without a phone, individuals may miss notifications or the chance to apply for help. • During extreme weather or power outages, utilities often use phones to share safety updates (e.g., outages), and those without phones may be left unaware.
	Rural Urban Commuting Area Codes	PrimaryRUCA	• Climate change affects some populations more severely than others based on: ○ Geographic location ○ Capacity to manage climate-related hazards (e.g., wildfires, extreme weather events) • People living in rural areas may be particularly vulnerable because of: ○ Their geographic location. ○ Heavy reliance on natural resources for income and livelihoods. • Limited resources or infrastructure to adapt to changing climate conditions. • Rural communities often face specific barriers to participating in the clean energy transition, like: ○ High upfront costs to participate. ○ Limited infrastructure. ○ Insufficient access to information about clean energy technologies (e.g., rooftop solar, electric vehicles)

	American Community Survey (ACS)	Housing Burdened %	• A high housing burden—typically defined as spending more than 30% of income on housing—indicates vulnerability because:
			  ○ There are fewer resources left for food, healthcare, transportation, and energy bills.
			  ○ Energy bills may become unaffordable, especially during periods of extreme weather.
			  ○ Fewer financial resources mean less flexibility to invest in energy efficiency or respond to emergencies.
			  ○ High housing costs increase the risk of eviction or homelessness during financial setbacks.
			  ○ Chronic financial strain can also lead to mental and physical health issues.

Race/ Ethnicity/ Language	American Community Survey (ACS)	Black %	• Race is a strong indicator of disparities in energy cost burdens, with communities of color often allocating a disproportionately larger portion of their income to household energy expenses for a number of reasons. For example, non-white individuals and households: tend to have lower than average incomes and are more likely to live in under-resourced areas and/ or in homes that are less energy efficient. • Non-white individuals and households also often have limited access to clean energy incentive programs, frequently because of the high upfront cost to participate. • These communities also tend to be at higher risk of developing chronic health conditions and be located in areas with higher exposure to environmental pollutants, which can exacerbate these conditions.
	American Community Survey (ACS)	AI_AN %	
	American Community Survey (ACS)	Asian %	
	American Community Survey (ACS)	NH_PI %	
	American Community Survey (ACS)	Other %	
	American Community Survey (ACS)	2_Plus %	
	American Community Survey (ACS)	Hisp_Lat %	
	American Community Survey (ACS)	Foreign-Born %	• Foreign-born populations, especially those with lower incomes, are more likely to reside in substandard housing that is also often in high-risk areas relative to exposure to pollution (like poor indoor and outdoor air quality). • Foreign-born individuals are disproportionately represented in low-wage, high-risk jobs, including agriculture, construction, and waste management, which may expose them to environmental and occupational hazards, such as extreme heat, or frequent exposure to wildfire smoke or other

			pollutants. They may also have higher baseline health risks because of structural inequities, which can be exacerbated by environmental stressors. • Foreign born individuals often lack paid leave, job security, and/or health insurance, which increases vulnerability to environmental shocks and long-term health impacts. • Individuals without permanent legal status may avoid engaging with public agencies, including those responsible for public health, housing, or emergency management for fear of deportation. • Foreign-born individuals, particularly non-citizens, often have limited representation in policy-making processes, which can result in the under prioritization of their needs.
	American Community Survey (ACS)	Non-U.S. Citizen %	• Non-citizens often face barriers to employment, healthcare, and social services due to legal status, language barriers, or limited knowledge of available programs. • Limited access to public benefits, housing, and healthcare can increase economic and social vulnerability compared with citizen populations. • Non-citizen households may have reduced capacity to prepare for, respond to, or recover from hazards, including disasters, due to systemic, legal, and cultural barriers.
	American Community Survey (ACS)	LEP Households %	• Language barriers can easily prevent individuals from accessing important information about environmental risk, emergency warnings, and social services, even if it is readily available, because many communications are only available in English or do not capture appropriate cultural nuance. • Language barriers can also limit individuals' access to healthcare, legal aid, and/or other services, such as bill payment assistance. • Individuals that do not speak English or speak limited English may be underrepresented in community proceedings or other decision-making processes.

Household Composition	American Community Survey (ACS)	Single Parents %	• Single parents, and mothers in particular, often have lower income. This can lead to:
			  o Increased vulnerability to economic shock (job loss, illness, emergencies).
			  o Higher stress and susceptibility to mental illness (depression and anxiety).
			  o Lower access to healthcare and childcare.
			  o Housing instability.

	American Community Survey (ACS)	Veterans %	• Many veterans experience higher rates of chronic health conditions, disability, mental health challenges, and service-related injuries, which can increase sensitivity to environmental stressors and disruptions. • Veterans, particularly those with low income, limited-service connection benefits, or who live in rural areas, may face challenges accessing consistent medical care, behavioral health services, and affordable housing, compounding vulnerability. • Veterans with service-related trauma or chronic illness may have reduced ability to cope with extreme weather, energy insecurity, or displacement, and may require specialized support during emergencies or recovery efforts.
	American Community Survey (ACS)	Disabled %	• Those living with a disability may experience social or physiological barriers, preventing them from fully participating in the environmental decision-making process. • Persons with disabilities are often disproportionately affected at every stage of disaster events and disaster recovery. • Certain types of disability are associated with increased physiological susceptibility to environmental pollution.
	American Community Survey (ACS)	Population <5 Years %	• Young children have developing respiratory, immune, and thermoregulatory systems, making them more susceptible to air pollution, heat exposure, infectious disease, and environmental contaminants. • Children under five rely entirely on adult caregivers for mobility, healthcare access, and protection during emergencies; disruptions such as power outages, extreme heat events, or displacement can therefore have amplified consequences. • Early-childhood exposures to environmental or socioeconomic stressors can have long-term effects on cognitive, physical, and emotional development, reinforcing the importance of protective infrastructure and stable living conditions.
	American Community Survey (ACS)	Population 5-18 Years %	• Children in moderately energy-insecure households face higher risks of food insecurity and hospitalization. • Caregivers in energy insecure households more often rate children's health as fair or poor, or express concerns about child development. • Children facing both food and energy hardships are more likely to: show withdrawn or depressive behaviors, report physical symptoms and/ or engage in rule-breaking behavior.

	American Community Survey (ACS)	Population >=65 Years	• Older adults often face high energy burdens.
			• Barriers to accessing energy assistance may include:
			  ○ Mobility limitations that make it harder to access assistance programs, cooling/warming centers, or make home improvements.
			  ○ Lack of internet or other digital tools for assistance, alerts, or resources.
			  ○ Limited awareness of available programs.
			• They are especially vulnerable to extreme heat or cold events which can worsen chronic conditions like cardiovascular and respiratory illnesses (inability to afford adequate heating or cooling can also aggravate these conditions).

	American Community Survey (ACS)	Population >=65 Years Living Alone%	• Emerging evidence shows that households with strong social support networks are better able to manage the challenges of energy poverty. • Socially isolated household, especially those with older adults, may struggle more to cope with energy-related difficulties. • Older adults living alone are at higher risk of social isolation and may lack support systems for assistance or wellness checks. • Socially isolated individuals, particularly older adults, are more susceptible to hazards and emergencies due to limited support, reduced access to timely help, and fewer resources for preparedness.
Health	American Community Survey (ACS)	Uninsured %	• Populations without health insurance often face barriers to preventive care, treatment, and chronic disease management, leaving them especially vulnerable to respiratory distress, poor indoor air quality, and utility shutoffs. • Lack of insurance is associated with socioeconomic disadvantage and reduced access to medical services, highlighting communities that warrant targeted affordability and energy security interventions.
	Area Health Resource Files (AHRF)	# Active Providers (2yr Average)	• If there are too few providers relative to population, people face long wait times, travel burdens, or go without care, which can lead to delayed diagnoses, unmanaged chronic conditions, and preventable hospitalizations. • Provider shortages disproportionately affect rural areas, low-income communities, and communities of color. • Areas with low provider saturation often have lower rates of preventive care (immunizations, screenings, chronic disease management), which can shift care to emergency departments and hospitals. • In extreme weather or long duration outages, communities with weak provider access are less resilient to crises.

	Area Health Resource Files (AHRF)	# Hospitals (2yr Average)	• Limited facility availability often forces residents to delay or forgo preventive care, such as screenings, vaccinations, and early interventions. • Delayed preventive care increases the likelihood that health issues go undetected until they become more serious and costly to treat. • Inadequate access to primary or specialty care leads individuals to rely more heavily on emergency services as a primary point of care. • Chronic conditions become harder to manage without consistent provider access, follow-up care, medication adjustments, and patient education. • Unmanaged or worsening chronic conditions accumulate at the community level, compounding vulnerabilities and increasing strain on health and social support systems.
	Area Health Resource Files (AHRF)	# Rural Referral Centers (2yr Avg)	
	Area Health Resource Files (AHRF)	# Sole Community Providers (2yr Avg)	• Rural communities without Sole Community Providers, rural health clinics, or NHSC sites have extremely limited access to primary and preventive care, which increases reliance on distant or emergency services. • The absence of these facilities often correlates with rural location, low-income populations, and historically underserved areas, highlighting disparities in healthcare infrastructure.
	Area Health Resource Files (AHRF)	# Rural Health Clinics (2yr Avg.)	
	Area Health Resource Files (AHRF)	# NHSC Sites (2yr Avg.)	
	Area Health Resource Files (AHRF)	# Nursing Facilities (2yr Avg.)	• Communities with fewer nursing facilities have reduced access to long-term care and specialized health services for older adults and medically vulnerable populations. • Limited nursing facility availability often affects rural, low-income, or underserved areas, highlighting disparities in healthcare infrastructure and eldercare access. • Reduced local access to nursing facilities decreases a community's ability to support medically vulnerable populations during emergencies, chronic illness management, or disaster response, increasing overall vulnerability.

	Area Health Resource Files (AHRF)	# ED Visits	• Average Emergency Department (ED) visits are:
			  ○ An indicator of unmet primary care needs. High ED visit rates can mean that communities are relying on the ED for conditions that could have been managed by outpatient or preventive care.
			  ○ Signals barriers to healthcare access. Frequent ED use can reflect shortages of primary care providers, long waiting times for appointments, transportation barriers, or lack of insurance.

	Oregon Health Authority	Low Birth Wt. %	• Low birth weight is a well-established, population-level indicator of underlying structural inequities in health and social conditions. • Elevated rates of low birth weight in a community are strongly associated with limited access to quality prenatal care, chronic maternal stress, nutritional instability, and exposure to environmental hazards.
	Area Health Resource Files (AHRF)	# Pre-Term Births	• Communities with elevated rates of pre-term birth often experience limited access to quality prenatal care, high levels of maternal stress, inadequate nutrition, and exposure to environmental hazards. • Pre-term birth is associated with increased risk of chronic health conditions, developmental delays, and long-term medical needs for affected infants, reflecting both immediate and intergenerational vulnerability. • Pre-term births are an indicator of health inequities that stem from social, economic, and environmental stressors, complementing other indicators such as low birth weight and chronic disease prevalence to provide a more comprehensive picture of community vulnerability.
	Area Health Resource Files (AHRF)	# Preventable Stays (2yr Avg)	• High preventable stay rates typically indicate insufficient primary care or preventive services, poor chronic disease management, and structural barriers that limit timely access to medical care. • These hospitalizations often reflect underlying social determinants of health, including economic hardship, limited transportation, and disparities in healthcare coverage. • This measure highlights areas where inadequate healthcare infrastructure and systemic inequities contribute to increased vulnerability.

	CDC PLACES	Asthma % of Pop	• Vulnerable communities face disproportionately high rates of respiratory illnesses such as asthma. These health disparities are linked to:
			  o Exposure to outdoor air pollutants from traffic and industrial facilities
			  o Poor indoor air quality caused by:
			  o Inadequate ventilation
			  o Moisture issues (e.g., mold and mildew)
			  o Smoke
			  o Household chemicals

	CDC PLACES	Heart Disease % of Pop	• Prevalence of heart disease indicates populations at higher risk of morbidity and mortality, particularly during environmental or social stressors such as extreme temperatures or poor air quality. • Higher rates of heart disease often correlate with limited access to healthcare, lower socioeconomic status, and lifestyle or environmental risk factors, highlighting systemic disparities. • Communities with elevated heart disease prevalence may have reduced capacity to withstand, respond to, or recover from hazards, emergencies, or health crises.

	CDC PLACES	Annual Checkup % of Pop	• Annual health exam rates serve as a proxy for access to preventive care and the ability of residents to maintain consistent engagement with the healthcare system. • Lower rates often reflect structural barriers, including lack of insurance, limited availability of providers, transportation challenges, or mistrust due to historical inequities, which contribute to poorer long-term health outcomes. • Including this measure captures differences in underlying healthcare access that are not reflected by disease prevalence alone.
	CDC PLACES	COPD % of Pop	• Individuals with COPD are particularly vulnerable to indoor air pollutants such as smoke from cooking or heating, mold, dust, and chemicals. • Low-income households often rely on older, inefficient appliances or combustion-based heating sources like wood stoves, which can further degrade indoor air quality. • Due to high electricity costs, energy-insecure households may avoid using ventilation systems or air purifiers, increasing their exposure to harmful irritants. • Extreme temperatures can trigger COPD symptoms, leading to respiratory distress or hospitalization. However, maintaining safe indoor temperatures is often difficult for energy-insecure households that may forgo heating or air conditioning due to cost.
	CDC PLACES	Diabetes % of Pop	• Energy insecurity (unreliable electricity, shutoffs, outages) can compromise medication storage and effectiveness, putting the health of individuals with diabetes at serious risk. • "Tradeoffs" from energy insecurity may limit the ability to cook healthy meals, forcing reliance on processed or fast foods high in sugar and salt. • Lack of access to heating or cooling due to energy insecurity can make diabetes more difficult to manage and can lead to complications.
	CDC PLACES	Poor Health % of Pop	• Self-reported poor health captures how individuals perceive their own physical and mental well-being, providing insight into the real-world impacts of illness and chronic conditions. • Poor self-reported health often correlates with limited access to healthcare, low income, environmental stressors, and systemic barriers, highlighting disparities across communities.
	CDC PLACES	Mental Distress (>=14 days) % of Pop	• Self-reported mental distress captures individuals' experiences of anxiety, depression, or emotional strain, providing insight into how stressors affect day-to-day well-being. • Higher rates of mental distress often correlate with economic hardship, limited access to mental healthcare, social isolation, and systemic barriers, highlighting underlying community vulnerabilities.

	CDC PLACES	Physical Distress (>=14 days) % of Pop	• Self-reported physical distress captures individuals' experiences of pain, fatigue, or functional limitations, providing insight into how health conditions affect daily life. • Higher rates of physical distress often correlate with limited access to healthcare, chronic disease prevalence, low income, and environmental stressors, highlighting systemic disparities.
Environment	PRISM 30-year Climate Normals	TMAX_mean	• High daytime maximum temperatures capture the frequency and severity of heat events, which can threaten human health, especially in communities lacking cooling resources. • Populations living in poorly insulated housing, without air conditioning, or with high energy burdens are disproportionately affected by extreme heat. • Exposure to high daytime temperatures increases risks of heat exhaustion, heat stroke, cardiovascular stress, respiratory complications, and mortality, particularly among older adults, children, and medically vulnerable groups.
	PRISM 30-year Climate Normals	HDD	• HDDs quantify how much heating is required to maintain safe indoor temperatures, which helps identify communities that may face high energy burdens during cold seasons—especially those with inefficient housing or limited financial resources. • Higher HDDs can also signal greater exposure to cold temperatures, which can increase risks of hypothermia, respiratory illness, and cardiovascular events, particularly among older adults, infants, and people with chronic conditions. • In areas with high HDDs, poorly insulated homes, older housing stock, or inadequate heating systems can significantly worsen vulnerability, making HDDs a useful indicator of where building conditions may intensify cold-weather risk. • Understanding the frequency of HDDs can help identify communities that may benefit from targeted weatherization, heating assistance programs, or infrastructure upgrades to reduce cold-related stress and improve energy resilience.
	PRISM 30-year Climate Normals	TMIN_mean	• Elevated nighttime minimum temperatures capture the persistence of heat during the night, which can prevent recovery from daytime heat stress. • Communities without adequate cooling, insulation, or access to energy for air conditioning are disproportionately affected by warm nights. • High nighttime temperatures are linked to sleep disruption, increased cardiovascular and respiratory stress, and higher mortality during heat waves, particularly among older adults, children, and medically vulnerable populations.

	Center for Air, Climate, and Energy Solutions (CACES)	Mean_PM25	• Elevated PM2.5 concentrations, including from wildfire smoke, increase the risk of respiratory distress, asthma exacerbation, heart attacks, and other health complications. • Low-income, elderly, and chronically ill populations are more susceptible to adverse health outcomes from PM2.5 exposure. • High PM2.5 exposure reduces a community's capacity to cope with additional stressors, such as extreme heat or other environmental hazards, compounding overall vulnerability.
	Center for Air, Climate, and Energy Solutions (CACES)	Mean_O3	• Ambient ground-level ozone serves as a key measure of air quality, with well-documented impacts on respiratory and cardiovascular systems, particularly among sensitive subpopulations. • Elevated ozone concentrations are associated with increased incidence of asthma exacerbation, reduced pulmonary function, and higher rates of respiratory morbidity and mortality. • Vulnerable groups, including children, older adults, and individuals with pre-existing respiratory conditions, experience disproportionately adverse health outcomes from ozone exposure. • Chronic exposure to elevated ozone may undermine a community's adaptive capacity to additional environmental stressors, contributing to overall social and health vulnerability.
	Center for Air, Climate, and Energy Solutions (CACES)	Mean_SO2	• SO_2, NO_x, and CO are pollutants with direct, documented health impacts that disproportionately affect sensitive and vulnerable populations. • SO_2, NO_x, and CO come primarily from traffic, industrial combustion, and power generation—sources that are often concentrated near vulnerable communities. • Unlike some regional pollutants, SO_2, NO_x, and CO show strong local spatial gradients, making them effective for identifying local level disparities in air quality. • All three are EPA criteria pollutants with national standards and robust monitoring networks, which provide reliable, comparable data across census tracts. • Chronic exposure to these pollutants contributes to cumulative environmental stress and are correlated with other environmental hazards.
	Center for Air, Climate, and Energy Solutions (CACES)	Mean_NOx	
	Center for Air, Climate, and Energy Solutions (CACES)	Mean_CO	
Hazard Exposure	National Risk Index	Coastal Flooding Exposure	• Understanding hazard exposure is essential to equity assessment because it identifies which communities face the greatest environmental risks, independent of wealth, enabling a clear evaluation of how those risks intersect with social vulnerability and adaptive capacity. Total Exposure, specifically:
	National Risk Index	Cold Wave Exposure	

	National Risk Index	Heat Wave Exposure	○ Measures the physical extent of hazard exposure without relying on property values or economic activity. ○ Reveals where hazards are most prevalent, providing a clearer picture of environmental stressors across communities regardless of local economic conditions. ○ Serves as a direct measure of hazard presence and preserves the analytical separation between the hazard environment and community vulnerability/ adaptive capacity, allowing socioeconomic, housing, health, and demographic indicators to appropriately capture adaptive/ resilience capacity.
	National Risk Index	Drought Exposure	
	National Risk Index	Strong Wind Exposure	
	National Risk Index	Ice Storm Exposure	
	National Risk Index	Tsunami Exposure	
	National Risk Index	Earthquake Exposure	
	National Risk Index	Riverine Flooding Exposure	
	National Risk Index	Wildfire Exposure	