

## **TECHNICAL REPORT**

15 August 2025

For the project entitled:

### **Revisiting the Nature Gap**

**Quantifying the discrepancies in access to natural lands among diverse communities, in light of conservation momentum – and potential backsliding**

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# 1. Introduction

[The Nature Gap analysis](#) that CSP and Center for American Progress (CAP) carried out in 2020 confirmed the enormous scale of the racial and economic disparities in the distribution of nature in the US. The Biden administration’s “America the Beautiful” commitment spurred national momentum towards protecting more land and deliberately focusing on nature-deprived communities. Yet at the same time, sprawl and development—including the very necessary build-out of renewable energy—has continued to erode or degrade the natural lands that remain.

In response, the following analysis revisits our Nature Gap work with substantial updates to the methodology and additions to the underlying datasets so that we can more readily quantify the extent of the gap and to highlight current disparities among specific communities. Specifically, we have quantified how different human communities experience reduced nature by synthesizing and overlaying demographic indicators derived from the U.S. Census Bureau (race, ethnicity, income level, education level, housing affordability, and household composition) with two novel spatial data layers: (1) a machine learning-derived anthropogenic impact metric (hereafter referred to as ‘AIM’, or ‘impact’), or the degree to which humans are impacting the environment, across the conterminous U.S. (CONUS), and (2) contemporary measures of social vulnerability. Our contemporary AIM layer represents human impacts across four primary ‘stressor categories’: agriculture, transportation, urban development, and energy. Social vulnerability is characterized by indicators across three ‘vulnerability categories’: climate risk, pollution, and infrastructure. Both AIM and social vulnerability were summarized to 2020 U.S. Census tracts and normalized into percentile ranks to examine patterns in anthropogenic impact and social vulnerability relative to demographic indicators. With these updated and expanded datasets, our goal was to determine where and to what extent different communities experience disproportionately high levels of anthropogenic impact and/or social vulnerability throughout CONUS.

## 2. Data Sources and Methods

### 2.1 Anthropogenic impact metric (AIM)

#### *Land use footprint*

Our analysis focused solely on the conterminous U.S. and thus excluded Alaska and Hawaii. We quantified anthropogenic impact as the overall impact of human land use across four stressor categories: agriculture and managed forests, transportation, urban development, and energy development. AIM is the result of combining a ‘footprint’ layer identifying human land use within these four stressor categories with a continuous intensity layer quantifying the intensity of human land use types and activities within that footprint. Our methodology and the selection of datasets to represent both the footprint and intensity layers were also informed by feedback we solicited from external collaborators with subject-matter expertise.

The footprint layer was derived from the National Land Cover Database (NLCD), Hansen Global Forest Change, OpenStreetMap, and several energy development databases (e.g., Homeland Infrastructure Foundation-Level Data, US Energy Atlas, US Solar Photovoltaic Database, US Wind Turbine Database; see Table A1). This footprint was developed at a 90-m resolution and represents approximately present-day human land use. It is the precursor to developing a machine learning-based (i.e., deep learning) model,

specifically a convolutional neural network (CNN), to automatically detect these features in satellite imagery for different points in time. This footprint serves as the training data for the CNN, which is ideal for identifying specific features in remotely sensed imagery.

To capture radiating effects of human land use that may extend beyond the footprint, we allowed the value of each human land use pixel in the footprint to extend beyond the focal pixel itself. To smooth the footprint and remove spatial artifacts, we applied a focal mean with a radius of 90 m to our binary footprint layer (1 = within footprint, 0 = outside of footprint), then assigned a value of 1 to all pixels with value  $\geq 0.5$  and a value of 0 to all other pixels. We then allowed each pixel's value to decay with distance from the footprint, halving every 500 m out to a maximum distance of 10 km (Suraci, Littlefield, et al. 2023). This approach ensures that pixels within the footprint maintain a value of 1, and then values for pixels extending beyond that footprint decrease exponentially to 0 with distance from the footprint.

### ***Land use intensity***

We developed a continuous intensity layer using datasets representing intensity for each of our four stressor categories to reflect the degree of anthropogenic impact associated with our footprint (Table A2). This intensity layer accounts for the variability in the relative impacts of different land use types and human activities. We derived our intensity layer in a step-wise process. We first developed stressor category-specific intensity layers by standardizing each layer using z-scores, and computing the weighted linear sum of each intensity indicator for each category. This method involves first sampling a large number of indicators across CONUS to characterize the distribution of each indicator and then using an optimization routine to determine the relative influence of each indicator to contribute to the intensity layer (Suraci, Farwell, et al. 2023). This approach ensures that we are equalizing indicator influence in the composite intensity values (i.e., each indicator plays an equal role in producing the final intensity layer). We derived stressor category-specific intensity layers for agriculture, energy development, and transportation and urban development. However, due to collinearity in our proposed intensity indicators for both transportation and urban development (nightlights, traffic proximity and volume, major road density, minor road density, all paved road density, railroad density, percent cover commercial and industrial areas), we retained only nightlights for the most parsimonious representation of transportation and urban development intensity.

Once we derived intensity layers for both agriculture and energy development, we then once again performed the same optimization routine on these new datasets to determine the set of weights to apply to (1) agricultural intensity, (2) energy development intensity, and (3) nightlights (i.e., transportation and urban development intensity) when computing a weighted linear sum across these three final layers. The resulting intensity layer was normalized 0 - 1 to represent the overall intensity of human land use across all four stressor categories, and was then applied to the footprint of human land use. We found that intensity for some remote and rural locations with small areas of low-intensity human land use was estimated to be 0, despite representing human land use. This was largely due to instances where, for example, a minor road was present, but there were no nightlights detected. To ensure that these areas still contributed to AIM, we modified our final intensity layer such that any pixels within the footprint had a minimum intensity value of 0.00001.

### ***Integrating the footprint and intensity***

Finally, we multiplied our footprint and intensity layer values to generate AIM for each pixel across CONUS at a 90-m resolution. We computed the mean value of AIM for all 2020 census tracts across CONUS, and then generated both CONUS-wide and statewide percentile ranks for AIM by census tract for comparison with our social vulnerability and demographic datasets. In addition, we classified census

tracts as urban or rural using the U.S. Census 2020 urban area boundaries. Tracts with more than half of their land area within an urban boundary were designated as urban; all others were designated as rural. To assess spatial variation in anthropogenic impacts within these groups, we then also calculated percentile ranks for AIM separately for urban and rural tracts.

## **2.2 Social vulnerability**

### ***Indicator selection***

We identified indicators of social vulnerability across three categories: climate risk, pollution, and infrastructure. These categories were also broken out into themed subcategories, for example the climate risk category included groups such as flooding, temperature, and storms as subcategories (Table B1). Climate risk indicators represent factors that may predispose a community to heightened risk of climate-related disasters, such as the frequency of hurricanes or tornadoes. Pollution indicators encompass factors that contribute to a community's exposure to various pollutants, such as proximity to brownfields, superfund sites, or oil and gas wells. Infrastructure indicators capture lack of access to transportation and recreational infrastructure, such as access to a vehicle, road quality and maintenance, and proximity to parks and other 'protected nature' (i.e., USGS GAP 1 and 2 lands, which are primarily managed for biodiversity and permanently protected from conversion and extractive uses (USGS GAP 2024)). In all cases, higher values of social vulnerability indicators suggest greater vulnerability. In cases where a higher value for a certain indicator would in fact mitigate vulnerability, we would invert that indicator such that higher values represent greater social vulnerability in alignment with all other datasets across our vulnerability categories. We solicited feedback from collaborators with subject-matter expertise in refining our final list of indicators, which in total encompasses 57 indicators of social vulnerability (Table B1).

### ***Data processing***

We summarized indicators within our three vulnerability categories to U.S. Census 2020 boundaries and converted all values to percentile ranks for direct comparison. We also aggregated vulnerability indicators at the subcategory level by computing the census tract mean of all percentile-ranked indicators for that subcategory and then generating a new percentile rank. For example, we calculated the mean of the percentile-ranked values for access/proximity to water, proximity to protected nature, and amount of parks and greenspace within the 'Nature/green space accessibility' subcategory (which sits under the 'Infrastructure' category) to generate a single new 'Nature/green space accessibility' metric that was then also percentile ranked. This approach is robust to missing data values, meaning that it does not require us to impute missing values, and instead only incorporates available data in the computation. This means that we did not estimate new values to fill gaps in our contributing datasets, and all summarized, or 'rolled up', metrics were only informed by the data available. For cases in which census tract level data were not available (e.g., deaths from climate disasters), we used data from the smallest available administrative unit (i.e., state-level datasets) and applied those values to all census tracts within that administrative unit. We adapted raster layers and datasets summarized within other polygon boundaries (e.g., HUC12 watersheds, 2010 census tracts, urban areas) to 2020 census tracts using an area-weighted mean. We also produced a data availability metric summing the total number of indicators for which data were available at each census tract.

In order to ensure indicators were not over-emphasized in our metrics, we primarily used individual indicators as opposed to pre-computed composite indices. The only exceptions to this rule were our Forests to Faucets composite metrics: ability to produce clean drinking water, relative water yield risk to important drinking water watersheds, and relative development risk to important drinking watersheds.

These datasets were included given their role in representing risks to drinking water resources under different climate and development scenarios. All social vulnerability indicators were assigned two percentile rank values: (1) CONUS-wide percentile ranks, and (2) statewide percentile ranks, specific to each state. When summarizing our social vulnerability metrics, we used the statewide percentile ranks when comparing against demographic indicators. We used the CONUS-wide percentile ranks when comparing social vulnerability metrics to one another or to AIM, unless otherwise specified.

## 2.3 Demographic Indicators

### *Indicator selection and processing*

We also quantified demographic indicators from the U.S. Census Bureau within 2020 census tracts across six key themes: race, ethnicity, income level, education level, housing affordability, and household composition (Table B2). We used a thresholding approach to determine whether a tract fell into a specific demographic group. For each demographic indicator, we calculated the state mean for the proportion of the population represented by each indicator. Tracts belonging to a particular demographic group were defined as those with a proportion of the population falling in that demographic group that was greater than the state mean for that particular indicator. For example, the average proportion of the population identifying as Black is 31.7% in Georgia and 9.2% in Nevada, so then any census tract with a Black population greater than 31.7% in Georgia would be considered a Black community, as would any census tracts with a Black population greater than 9.2% in Nevada. This approach was applied to all demographic indicators with the exception of median household income and the proportion of property owners, which were adjusted such that any census tract with values below the state means for these two indicators were identified as communities with lower income and less property ownership, respectively.

## 3. Results

The results provided here are just a subset of the full suite of results generated in this study. For an overview of all results, please contact us for access to a detailed spreadsheet containing several different statistical summaries, all provided for CONUS and state-by-state (more information on how to use this spreadsheet is provided in Appendix C).

### 3.1 Top-line summary statistics

#### *Anthropogenic impact*

Considering all of CONUS, communities of color are almost twice as likely to live in areas with relatively high anthropogenic impact (Table 1). In fact, 45% of communities of color live in areas with some of the highest (top 25%) anthropogenic impacts across CONUS, as opposed to only 11% of white communities (Table 2). Communities that live in these highly impacted/built up areas are also 1.8 times more likely to live in closer proximity to pollution sources and face greater pollution risks and exposures than their counterparts in less impacted areas. In addition, highly impacted areas are 10% more likely to have reduced access to protected nature and green spaces, however these impacts are disproportionately felt. Living close to development, without nearby nature, can lead to worse health outcomes. This is most prevalent in states like Michigan, where communities living in highly impacted/built-up areas are 1.5 times more likely to experience less nearby protected nature and are more than twice as likely to experience greater risks and exposure to pollution.

Among census tracts across all of CONUS that are the most impacted and that have the least access to protected nature and green space (top 25% of both metrics, which equates to 7% of all census tracts in CONUS), 78% are communities of color, 79% have a low median income, and 79% are housing cost-burdened. Likewise, among census tracts that are the most impacted, have the least access to protected nature and green space, and are also the most exposed to pollution risks (top 25% of each metric, which equates to 5% of all census tracts in CONUS), 80% are communities of color, 78% have a low median income, and 79% are housing cost-burdened. Communities that are largely property renters (as opposed to property owners) are also almost twice as likely to live in areas with high anthropogenic impact, with 50% of these communities living in areas with some of the highest anthropogenic impacts compared to only 8% of property owners. Among census tracts that are the most impacted, have the least access to protected nature and green space, and are also the most exposed to pollution risks, 85% are property renters.

**Table 1.** Relative risk for the top 15 demographic groups experiencing higher levels of anthropogenic impact (based on statewide percentile ranks) across all of CONUS. For the relative risk values of all demographic group and AIM/social vulnerability metric pairings, please see the ‘CONUS Risk Vulnerability/Demographics (SP)’ tab in the spreadsheet shared above. Note that for all racial groups (with the exception of white communities), the relative risks calculated are the product of comparing that racial group against white communities. These results can be interpreted as “[demographic group] is X times more likely to experience greater anthropogenic impact”.

| Demographic group   | Relative risk of higher anthropogenic impact |
|---|--|
| Less ownership of occupied housing units (and thus more renters)  | 1.93   |
| Communities of color  | 1.75   |
| Black communities   | 1.75   |
| Housing cost-burdened communities (housing costs > 30% of household income for renters and owners)          | 1.70   |
| Asian communities   | 1.68   |
| Severely housing cost-burdened communities (housing costs > 50% of household income for renters and owners) | 1.57   |
| Hispanic or Latinx communities  | 1.49   |
| American Indian communities   | 1.47   |
| Household income below the poverty line   | 1.31   |
| Severely cost-burdened renters (gross rent is 50% or more of income)  | 1.28   |
| Cost-burdened renters (gross rent is 30-49.9% or more of income)  | 1.19   |
| High median gross rent as a percentage of income  | 1.19   |
| Communities with no high school diploma   | 1.18   |
| Low median household income   | 1.16   |
| Communities near the coast  | 1.01   |

**Table 2.** The percent of each demographic group falling within the top 25% of AIM (based on statewide percentile ranks). The values in ‘% of group’ were calculated as the number of tracts falling within a demographic group *and* where AIM is within the top 25% of values divided by the total number of tracts across CONUS that fall into that demographic group. The values in ‘% of ‘other’” were calculated as the number of tracts *not* in that demographic group *and* where AIM is within the top 25% of values divided by the total number of tracts across CONUS that are *not* in that demographic group. For example, for ‘no high school diploma’, ‘% of group’ represents the percent of communities with no high school diploma that live within highly impacted areas, and ‘% of ‘other’” represents the percent of communities that do have a high school diploma that live within highly impacted areas. The only exception to this is racial groups, which were instead compared to the % of white communities (indicated with an asterisk \*). These results can be interpreted as “[% of group]% of [demographic group] live in areas with some of the highest (top 25%) anthropogenic impacts across CONUS, as opposed to only [% of ‘other’]% of [‘other’ group]”.

| Demographic group   | % of group | % of ‘other’ |
|---|------------|--------------|
| White communities   | 11.27      | 45.45        |
| Black communities   | 46.41      | 11.27*       |
| American Indian communities   | 34.11      | 11.27*       |
| Asian communities   | 37.34      | 11.27*       |
| Communities of color  | 45.36      | 11.27*       |
| Hispanic or Latinx communities  | 41.87      | 17.49        |
| Household income below the poverty line   | 39.22      | 16.78        |
| Low median household income   | 32.02      | 16.17        |
| No high school diploma  | 34.50      | 19.57        |
| High median gross rent as a percentage of income  | 31.22      | 20.89        |
| Cost-burdened renters (gross rent is 30-49.9% or more of income)  | 30.21      | 21.27        |
| Severely cost-burdened renters (gross rent is 50% or more of income)  | 33.03      | 19.05        |
| Housing cost-burdened communities (housing costs > 30% of household income for renters and owners)          | 43.92      | 10.78        |
| Severely housing cost-burdened communities (housing costs > 50% of household income for renters and owners) | 42.78      | 13.02        |
| Less ownership of occupied housing units (and thus more renters)  | 49.52      | 7.55         |
| Households with children  | 21.01      | 29.51        |

### **Climate risk**

Across CONUS, white communities and housing cost-burdened communities are most likely to live on the coast (including both along oceans and the Great Lakes), where they are increasingly experiencing more impacts of climate change-driven nature loss, like sea level rise and associated flooding. These coastal areas are 1.9 times more likely to experience flooding and 1.7 times more likely to experience hurricanes. However, the demographic breakdown of coastal communities varies significantly by state. In Mississippi, American Indian communities are 2.2 times more likely to live on the coast, and Hispanic and Latinx communities are 9.3 times as likely. These coastal communities in Mississippi are also 2.1 times more likely to experience urban heat island effects. In Indiana, Black communities are 4.1 times as likely and communities with income below the poverty line are 2.9 times as likely to live in coastal areas, which

are also 1.8 times as likely to experience premature ozone-related mortalities and 1.8 times as likely to experience winter weather events. Housing cost-burdened communities are also more likely to live in coastal areas across several states, but most notably in Illinois, Pennsylvania, South Carolina, and Virginia (5, 4.8, 2, and 2 times more likely, respectively).

### **Pollution**

Black communities and communities of color are 1.6 times more likely to live in close proximity to brownfields and to experience overall heightened risks and exposure to pollution than white communities (Table 3). Across CONUS, 42% of communities of color live within close proximity to a brownfield, compared to only 14% of white communities. At the state level, this is most prominent in Maine, where 71% of communities of color live within close proximity to a brownfield, compared to only 10% of white communities. Other states with notable differences are Connecticut (60% and 3%, respectively), Vermont (57% and 6%, respectively), Rhode Island (52% and 3%, respectively), and Wisconsin (59% and 11%, respectively). Asian communities are 1.6 times more likely to live in close proximity to other pollution risks and potential exposures than white communities, and Hispanic and Latinx communities are 1.4 times more likely to live in close proximity to pollution sources than communities that are not Hispanic or Latinx. Areas with the highest pollution risks and exposures (top 25% of values) are also 1.8 times more likely to coincide with some of the highest anthropogenic impacts, and among the census tracts where top 25% of values for those two metrics coincide, 76% are communities of color, 84% are renters, 77% are housing cost-burdened, and 72% have a low median household income.

**Table 3.** Relative risk of each demographic group experiencing each social vulnerability metric (based on statewide percentile ranks) across all of CONUS. Here only the highest risk pairings (top 20) were retained. For the relative risk values of all demographic group and AIM/social vulnerability metric pairings, please see the ‘CONUS Risk Vulnerability/Demographics (SP)’ tab in our results spreadsheet. For racial groups other than white communities, relative risk was calculated by comparing each group to white communities (indicated with an asterisk \*). For all other demographic metrics, relative risk was calculated by comparing each group to its complementary “other” group (e.g., communities with low median household incomes were compared to those with higher median household incomes). These results can be interpreted as “[demographic group] is X times more likely to experience [social vulnerability metric]”.

| Demographic group   | Social vulnerability metric   | Relative risk |
|---|---|---------------|
| Coastal communities already experiencing coastal flooding impacts | Climate risk: Flooding (exposure to coastal flooding and riverine flooding plus greater flooding risk to roads, sea level rise in meters, proportions of property at risk of permanent inundation from 50 cm of sea level rise, and share of properties at risk of flood in 30 years) | 1.91          |
| Less ownership of occupied housing units (and thus more renters)  | No access to a vehicle  | 1.85          |
| Low median household income                                       | Lower life expectancy   | 1.84          |
| Less ownership of occupied housing units (and thus more renters)  | Traffic proximity and volume  | 1.74          |
| Less ownership of occupied housing units (and thus more renters)  | Road, rail, and aviation noise  | 1.73          |

| Demographic group   | Social vulnerability metric   | Relative risk |
|---|---|---------------|
| Coastal communities already experiencing coastal flooding impacts   | Annualized frequency of hurricanes  | 1.71          |
| Low median household income   | No access to a vehicle  | 1.71          |
| Household income below the poverty line   | No access to a vehicle  | 1.68          |
| Less ownership of occupied housing units (and thus more renters)  | Proximity to brownfields  | 1.66          |
| Household income below the poverty line   | Lower life expectancy   | 1.64          |
| Less ownership of occupied housing units (and thus more renters)  | Pollution: Pollution sources (proximity to brownfields, chemical manufacturers, energy infrastructure, hazardous waste sites, landfills, superfund sites, oil and gas wells, wastewater and other waste treatment facilities, and greater wastewater discharge and transportation noise (road, rail, aviation)) | 1.62          |
| Housing cost-burdened communities (housing costs > 30% of household income for renters and owners)          | No access to a vehicle  | 1.62          |
| Asian communities   | Pollution: Potential risks and exposures (potential lead exposure, agricultural pesticides, PM2.5 in the air, traffic proximity and volume, air tox indicators, relative development risk to important drinking water watersheds, relative water yield risk to important drinking water watersheds)             | 1.61*         |
| Black communities   | Proximity to brownfields  | 1.60*         |
| Severely housing cost-burdened communities (housing costs > 50% of household income for renters and owners) | No access to a vehicle  | 1.59          |
| Black communities   | Pollution: Pollution sources (proximity to brownfields, chemical manufacturers, energy infrastructure, hazardous waste sites, landfills, superfund sites, oil and gas wells, wastewater and other waste treatment facilities, and greater wastewater discharge and transportation noise (road, rail, aviation)) | 1.58*         |
| Less ownership of occupied housing units (and thus more renters)  | Proximity to hazardous waste sites  | 1.58          |
| Communities of color  | Pollution: Potential risks and exposures (potential lead exposure, agricultural pesticides, PM2.5 in the air, traffic proximity and volume, air tox indicators, relative development risk to  | 1.57*         |

| Demographic group    | Social vulnerability metric   | Relative risk |
|----------------------|---|---------------|
|                      | important drinking water watersheds, relative water yield risk to important drinking water watersheds)  |               |
| Communities of color | Pollution: Pollution sources (proximity to brownfields, chemical manufacturers, energy infrastructure, hazardous waste sites, landfills, superfund sites, oil and gas wells, wastewater and other waste treatment facilities, and greater wastewater discharge and transportation noise (road, rail, aviation)) | 1.57*         |
| Black communities    | Pollution: Potential risks and exposures (potential lead exposure, agricultural pesticides, PM2.5 in the air, traffic proximity and volume, air tox indicators, relative development risk to important drinking water watersheds, relative water yield risk to important drinking water watersheds)             | 1.57*         |
| Black communities    | Road, rail, and aviation noise  | 1.57*         |

### **Infrastructure**

Among census tracts with some of the least transportation access, 55% are occupied by families with children and 54% are white communities. Note that transportation access in this context represents the “rolled up” composite of all indicators in the transportation access vulnerability category (see Table B1). Communities of color are 1.5 times more likely to not have access to a vehicle than white communities, however communities of color do tend to live in more walkable and bikeable areas. In fact, white communities are 1.5 times more likely to live in an area that is not walkable or bikeable. Across CONUS, 41% of communities of color do not have access to a vehicle, compared to only 14% of white communities. This is most pronounced at the state level in New Jersey, where 50% of non-white communities do not have access to a vehicle compared to only 5% of white communities. Likewise in Pennsylvania, this is 56% and 12%, respectively, and in Michigan this is 54% and 11%. Some of the greatest disparities in overall transportation access are felt at the state level as well. For example, in Washington, DC, communities with a low median household income are twice as likely to have limited access to transportation and Black communities are 1.8 times as likely to experience limited access. Likewise, Black communities in Nebraska and Wyoming are both 1.6 times as likely to have limited access to transportation. In terms of protected nature and green space access, communities with a low median household income are the most likely to experience limited access to these outdoor spaces. Across CONUS, 31% of communities with a median household income below the state average experience less access to protected nature/green spaces, compared to only 20% of communities with a median household income above the state average.

### **3.2 All data summaries**

The overall representation of white communities and households with children in highly impacted/built up areas tends to decrease as anthropogenic impact increases, however the proportion of all other racial

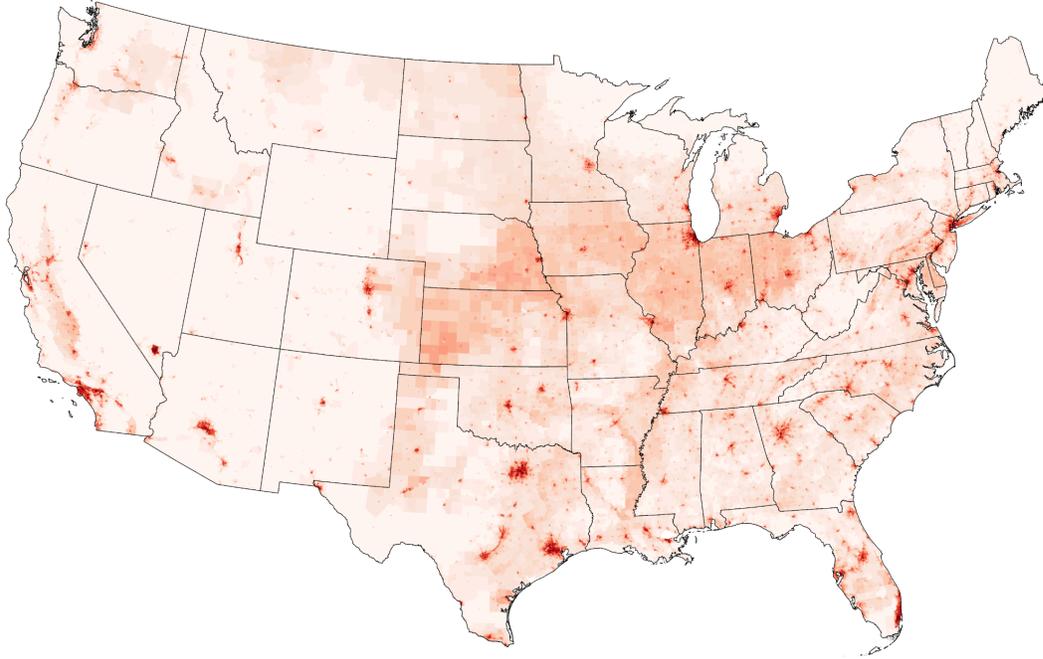
and ethnic groups, as well as the proportion of communities with low income, no high school diploma, and any degree of housing cost burden increases as anthropogenic impact increases (Table 4).

**Table 4.** The percent of census tracts within the top X% of AIM (based on statewide percentile ranks) that fall within each demographic group, as well as the percent of census tracts that are nature deprived (i.e., values of AIM above the state mean) that fall within each demographic group

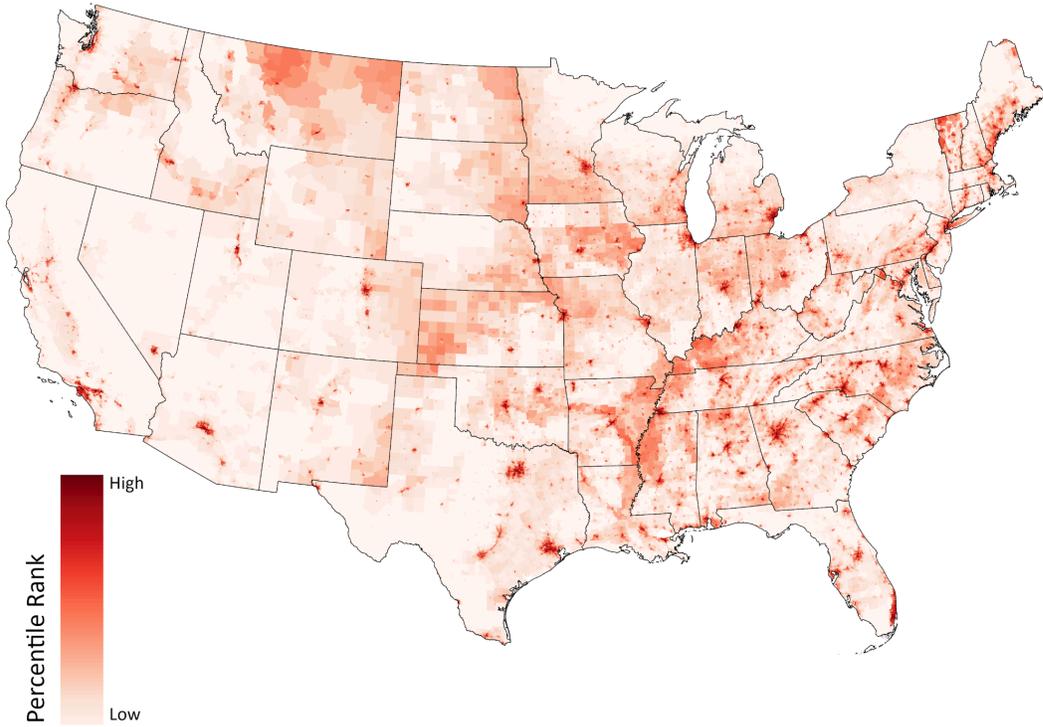
| Demographic group   | Top 10% | Top 25% | Top 50% | Nature deprived |
|---|---------|---------|---------|-----------------|
| White communities   | 22.8    | 26.0    | 37.0    | 31.0            |
| Black communities   | 58.5    | 55.0    | 45.8    | 50.4            |
| American Indian communities   | 41.5    | 40.6    | 36.2    | 38.8            |
| Asian communities   | 47.2    | 43.9    | 43.1    | 43.9            |
| Communities of color  | 76.8    | 73.9    | 63.1    | 69.1            |
| Hispanic or Latinx communities  | 53.8    | 53.6    | 46.9    | 50.8            |
| Household income below the poverty line   | 67.0    | 59.5    | 48.4    | 53.5            |
| Low median household income   | 76.7    | 73.5    | 64.5    | 69.1            |
| No high school diploma  | 55.0    | 53.3    | 45.8    | 49.9            |
| High median gross rent as a percentage of income  | 54.6    | 54.2    | 50.6    | 52.3            |
| Cost-burdened renters (gross rent is 30-49.9% or more of income)  | 55.8    | 55.4    | 53.1    | 54.2            |
| Severely cost-burdened renters (gross rent is 50% or more of income)  | 60.4    | 59.4    | 55.0    | 57.1            |
| Housing cost-burdened communities (housing costs > 30% of household income for renters and owners)          | 82.2    | 76.4    | 64.3    | 70.4            |
| Severely housing cost-burdened communities (housing costs > 50% of household income for renters and owners) | 76.0    | 70.2    | 58.7    | 64.4            |
| Less ownership of occupied housing units (and thus more renters)  | 91.8    | 83.0    | 67.0    | 74.4            |
| Households with children  | 32.4    | 39.6    | 46.2    | 43.3            |

The highest anthropogenic impacts are largely concentrated around major metropolitan areas (Figure 1). Large clusters of moderate anthropogenic impact tend to be focused within the Midwestern US, largely in agricultural areas. In the Western US, heavily impacted areas tend to be more concentrated, leaving far greater expanses with very little anthropogenic impact. When exploring AIM percentile rankings relative to urban and rural areas across CONUS, we see far more rural areas with extensive agricultural activity exhibiting relatively high impact values, especially across the Midwest (Figure 2).

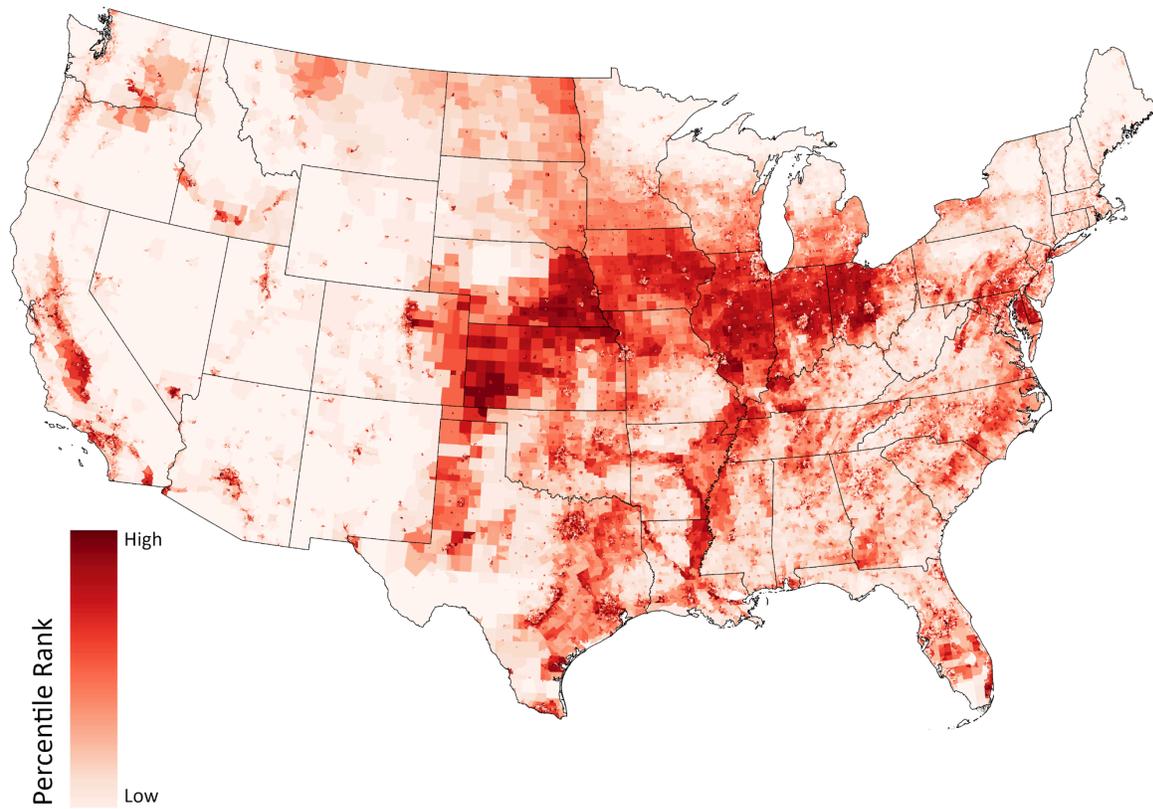
**A**



**B**

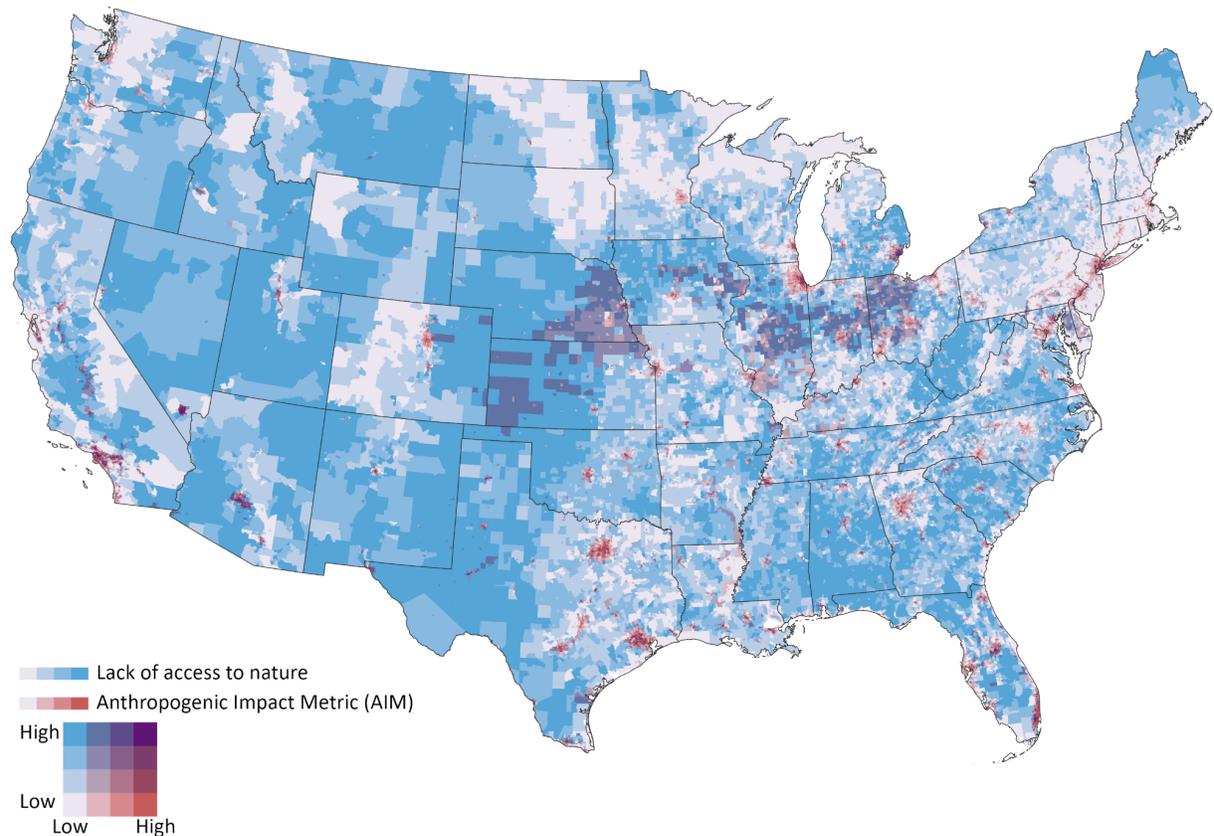


**Figure 1.** AIM across CONUS based on (A) nationwide percentile rankings and (B) statewide percentile rankings. Areas in darker red have greater overall anthropogenic impacts.



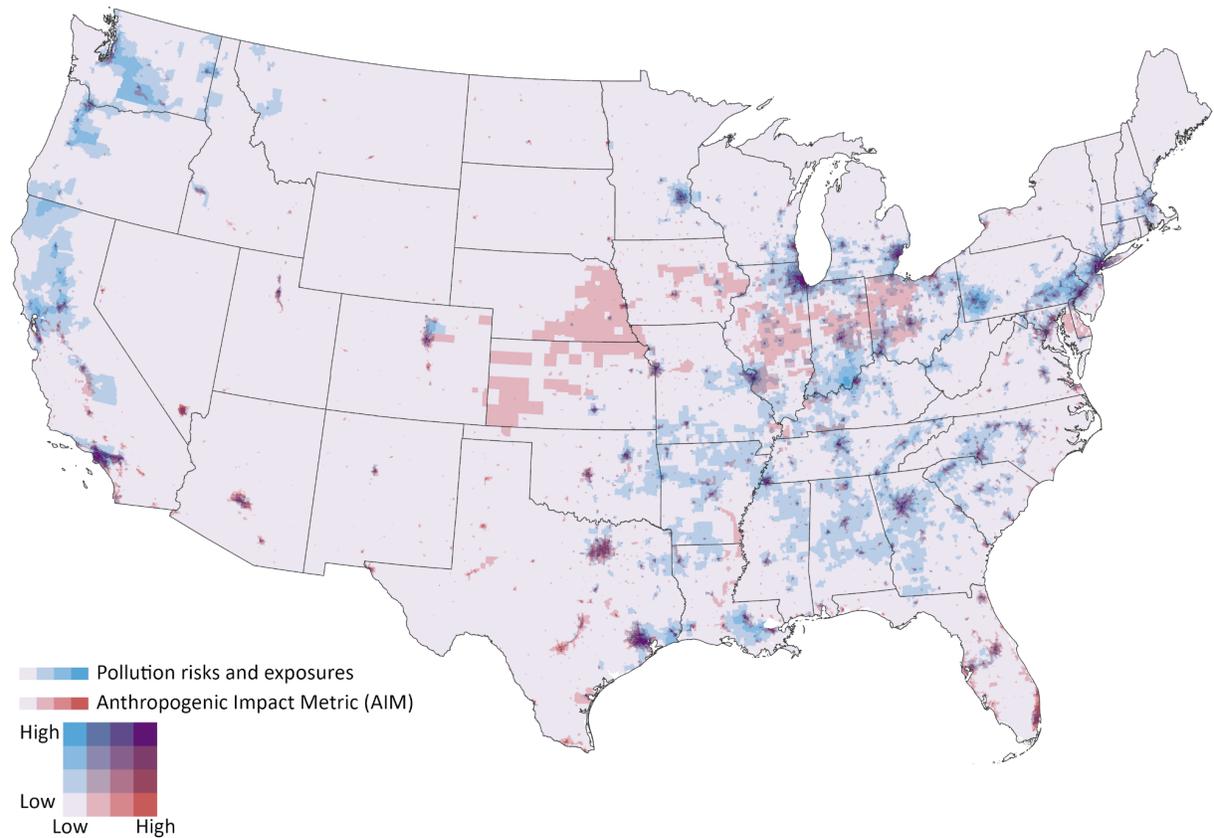
**Figure 2.** AIM across CONUS based on urban and rural percentile rankings. Here, census tracts were assigned 'urban' or 'rural' status based on whether the majority of their land area fell within a US Census urban area. AIM was then re-percentile ranked separately within these urban and rural designations to identify high-impact areas relative to all other urban and rural areas. Areas in darker red have greater anthropogenic impacts.

When examining coincidence between AIM and a lack of access to protected nature and parks/green space, we find that metropolitan areas and portions of the Midwest (specifically, Nebraska, Illinois, Indiana, and Ohio) tend to experience the greatest combined effect (Figure 3). The Great Plains, West, and Southeastern US also tend to have large areas with relatively limited access to protected nature. It is important to note that here we are specifically focusing on protected nature (GAP 1 and 2 areas managed for biodiversity) as well as public parks and green space. As a result, we see many rural areas that have a relatively high lack of access to those protected areas, despite likely being in close proximity to natural lands that are either unprotected or not publicly accessible.



**Figure 3.** Coincidence of anthropogenic impacts and a lack of access to protected nature and parks/green space based on nationwide percentile rankings. Dark purple shading represents highly impacted areas where the nature gap is most pronounced.

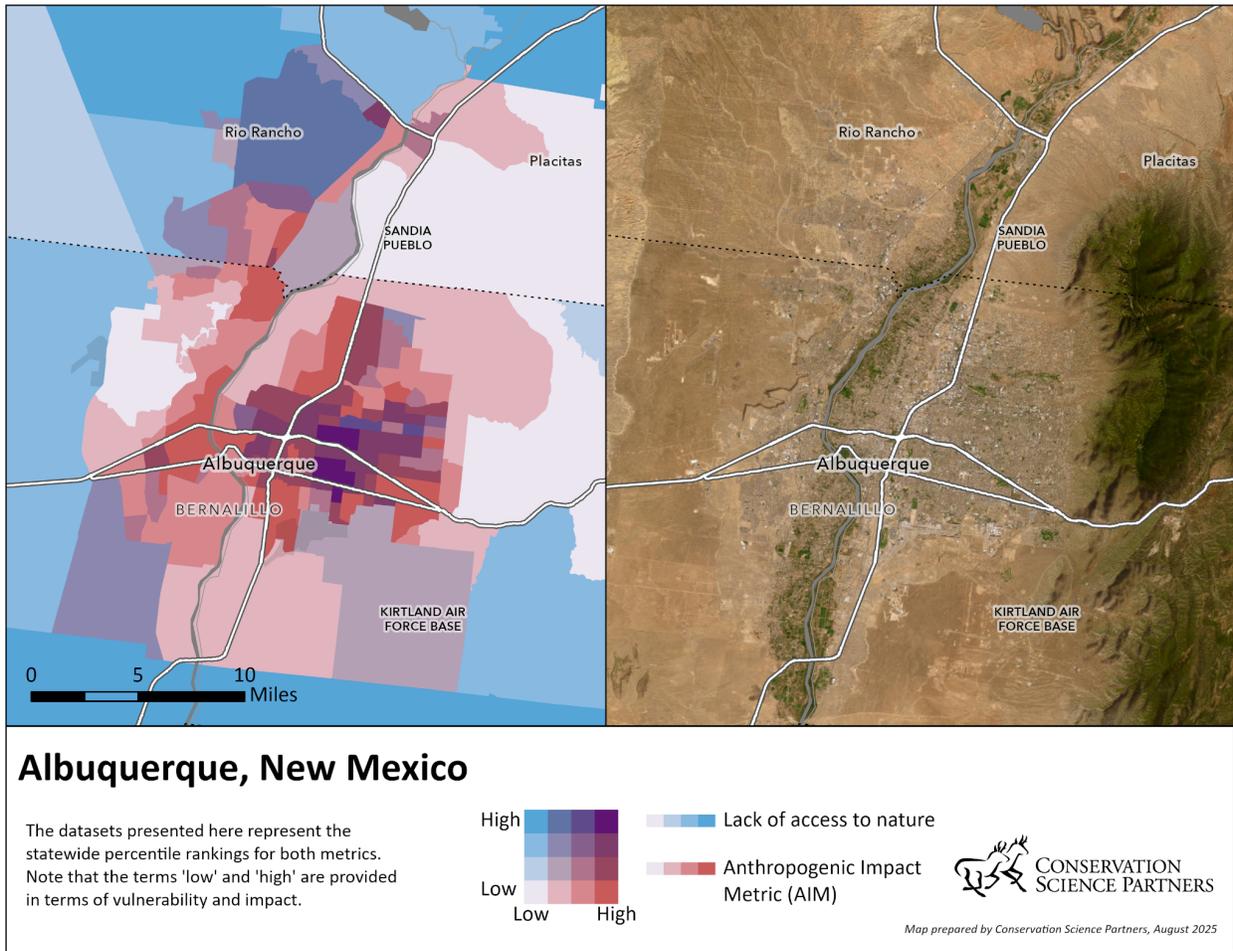
Lastly, when comparing AIM and pollution risks and potential exposures, we see a lot of concentration around metropolitan areas (Figure 4). Areas where pollution risk is high but AIM is low tend to be concentrated in the western and southeastern US, and the areas with high AIM but relatively low pollution risks tend to be concentrated in the Midwest where a large portion of anthropogenic impact is tied to agriculture.



**Figure 4.** Coincidence of anthropogenic impacts and pollution risks and potential exposures based on nationwide percentile rankings. Dark purple shading represents highly impacted areas where these risks are most pronounced.

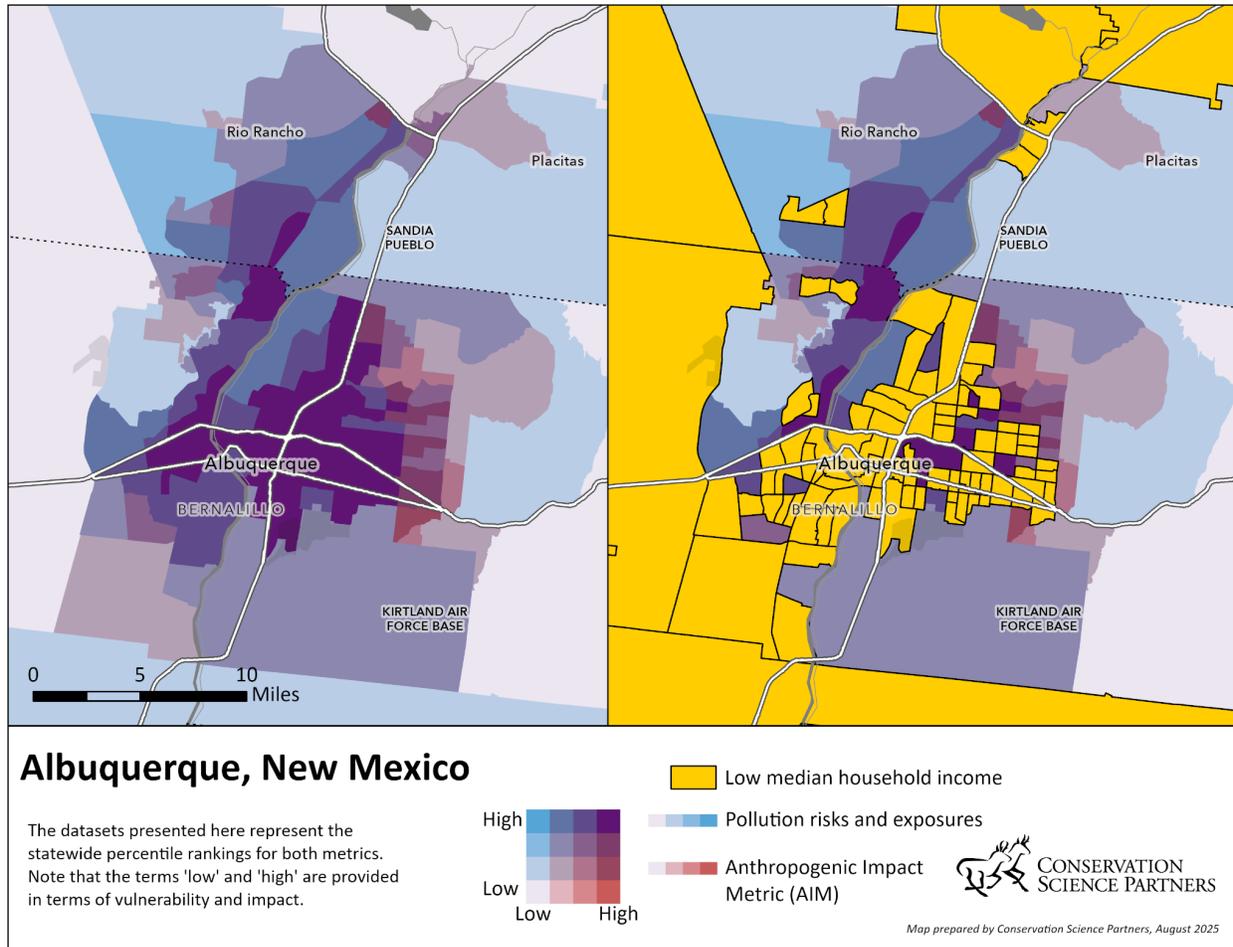
### 3.3 Focal area example: Albuquerque, NM

We used Albuquerque, NM as an example of a potential focal area. The region around Albuquerque has relatively low anthropogenic impact, however Uptown, which sits just north of the Albuquerque International Sunport airport and just east of the University of New Mexico campus, experiences some of the greatest combined anthropogenic impact and lack of access to protected nature and green spaces in the entire state of New Mexico (Figure 5). Of these most impacted and vulnerable census tracts (i.e., the darkest purple census tracts in Figure 5), 29% are communities of color and Hispanic or Latinx and 71% have low median household incomes.



**Figure 5.** Coincidence of anthropogenic impacts and a lack of access to protected nature and parks/green space in Albuquerque, NM based on statewide percentile rankings. Dark purple shading represents highly impacted areas where the nature gap is most pronounced.

When examining the coincidence of some of the greatest anthropogenic impact and pollution risks and exposures in this region, we see that nearly all of downtown Albuquerque is ranked among the highest combined impacts and exposures across the state of New Mexico (Figure 6). This area also largely coincides with communities that have a median household income below the state average.



**Figure 6.** Coincidence of anthropogenic impacts and pollution risks and potential exposures in Albuquerque, NM based on statewide percentile rankings. Dark purple shading represents highly impacted areas where these risks are most pronounced. Yellow polygons represent census tracts with a median household income below the state average.

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## Appendix A

The following tables provide additional information on all datasets contributing to the AIM footprint and intensity layer.

**Table A1.** Datasets contributing to our anthropogenic impact footprint, organized by AIM stressor categories.

| Stressor category | Indicator       | Description  | Data source   | Year(s) represented |
|-------------------|-----------------|--|---|---------------------|
| Agriculture       | Croplands       | <b>Cultivated crops:</b> Land dedicated to growing annual crops including corn, soybeans, vegetables, tobacco, and cotton, as well as perennial woody crops such as orchards and vineyards   | <a href="#">NLCD</a>  | 2024                |
|                   | Pasture         | <b>Pasture/hay:</b> Land planted with grasses, legumes, or mixed grass–legume crops for livestock grazing or for seed or hay crops, generally maintained on a perennial cycle  | <a href="#">NLCD</a>  | 2024                |
|                   | Managed forests | <b>Managed forests:</b> All pixels that were recorded as experiencing non-fire loss in the Global Forest Loss Due to Fire dataset and as also experiencing loss in 2024 in Hansen Global Forest Change   | <a href="#">Hansen Global Forest Change</a> and <a href="#">GLAD lab's Global Forest Loss Due to Fire</a> | 2024                |
| Transportation    | Roads           | <b>Paved roads:</b> Roads where ‘fclass’ equals any of the following: primary, primary_link, secondary, secondary_link, motorway, motorway_link, trunk, trunk_link, tertiary, tertiary_link, residential, service, unclassified, living_street, busway. All linear features were buffered by 15 m on either side to represent an estimate of road coverage/width. This buffer size was determined based on a standard 2-lane road width of ~24 ft (12 ft per lane) plus a ~6-8 ft shoulder. This translates to a ~10 m width for a two lane road, ~17 m for a four lane road, and ~24 m for a 6-lane road. | <a href="#">OpenStreetMap</a>   | Up to May 2025      |
|                   | Railroads       | <b>Railroads:</b> Railways where ‘fclass’ equals any of the following: rail, light_rail, tram. All linear features were buffered by 15 m on either side to represent an estimate of railroad coverage/width.   | <a href="#">OpenStreetMap</a>   | Up to May 2025      |
| Urban             | Developed areas | <b>Developed-High Intensity:</b> Densely built areas with 80–100% impervious   | <a href="#">NLCD</a>  | 2024                |

| Stressor category | Indicator         | Description  | Data source  | Year(s) represented |
|-------------------|-------------------|--|--|---------------------|
| development       |                   | cover<br><b>Developed-Medium Intensity:</b> Residential or mixed development areas with 50–79% impervious cover<br><b>Developed-Low Intensity:</b> Residential or mixed development areas with 20–49% impervious cover<br><b>Developed-Open Space:</b> Mostly vegetated areas with some built structures, less than 20% impervious cover, such as large-lot housing, parks, golf courses, and landscaped spaces.   |  |                     |
|                   |                   | <b>Residential:</b> Land use polygons that are predominantly occupied by residential buildings such as houses or apartment buildings<br><b>Commercial:</b> Land use polygons predominantly consisting of offices and other structures used for non-retail services (offices, administration, laboratories, logistics, hotels, car repair stations, and associated infrastructure such as parking lots, service roads, and lawns)<br><b>Industrial:</b> Land use polygons used for industrial purposes, typically consisting of buildings like workshops, factories or warehouses and their associated infrastructure such as parking lots, service roads, and yards) | <a href="#">OpenStreetMap</a>  | Up to May 2025      |
| Energy            | Oil and gas wells | All oil and gas well points in the HIFLD dataset were retained regardless of status, and all were buffered by 134.34 m to target an area of ~5.67 ha per well as the average well footprint (Allred et al. 2015; Conservation Science Partners (CSP) 2019; McDonald et al. 2009)   | <a href="#">Homeland Infrastructure Foundation-Level Data</a> (HIFLD; accessed through <a href="#">Koordinates</a> ) | Through 2018        |
|                   | Surface mines     | <b>Surface coal mines:</b> All points representing surface coal mine locations were buffered by 300 m in order to capture a larger portion of the mine footprint   | <a href="#">U.S. Energy Atlas</a>  | 2022                |
|                   |                   | <b>Quarries, Mines, Gravel Pits and Oil Wells</b>  | <a href="#">USGS GAP Land Cover</a>  | 2011                |
|                   |                   | <b>Quarries:</b> Land use polygons used for surface extraction, such as open-pit mining, of mineral or organic materials (e.g., rock, gravel, sand, soil, clay, ore, coal, or peat)  | <a href="#">OpenStreetMap</a> Land use polygons: Quarries  | Up to May 2025      |

| Stressor category           | Indicator | Description  | Data source   | Year(s) represented |
|-----------------------------|-----------|--|---|---------------------|
| Other energy infrastructure |           | <p><b>Power plants:</b> All power plant points regardless of fuel type and with a status equal to any of the following: (L) Regulatory approvals pending. Not under construction but site preparation could be underway; (OA) Out of service – was not used for some or all of the reporting period but is expected to be returned to service in the next calendar year; (OP) Operating - in service (commercial operation) and producing some electricity. Includes peaking units that are run on an as needed (intermittent or seasonal) basis; (SB) Standby/Backup - available for service but not normally used (has little or no generation during the year) for this reporting period; (T) Regulatory approvals received. Not under construction but site preparation could be underway; (TS) Construction complete, but not yet in commercial operation (including low power testing of nuclear units); (U) Under construction, less than or equal to 50 percent complete (based on construction time to date of operation); or (V) Under construction, more than 50 percent complete (based on construction time to date of operation). All power plant points were buffered by 200 m.</p> | <a href="#">Homeland Infrastructure Foundation-Level Data</a> | Through Feb 2025    |
|                             |           | <p><b>Transmission lines:</b> All overhead transmission lines with a status equal to any of the following: 'in service', 'under construction', or 'not available'. All linear features were buffered by 15 m given the potential for access roads and other infrastructure below/around the transmission lines.</p>  |   | Through Sept 2024   |
|                             |           | <p><b>Terminals:</b> All points for port of loading (POL) terminals, liquified natural gas import and export terminals, and petroleum product terminals. All points were buffered by 200 m.</p>  |   | Through Oct 2024    |
|                             |           | <p><b>Natural gas processing plants:</b> All points for natural gas processing plants, which were buffered by 200 m.</p>   |   | Through June 2024   |
|                             |           | <p><b>Petroleum refineries:</b> All points for petroleum refineries, which were</p>  |   | Through 2022        |

| Stressor category | Indicator         | Description   | Data source   | Year(s) represented |
|-------------------|-------------------|---|---|---------------------|
|                   |                   | buffered by 200 m.  | <a href="#">Foundation-Level Data</a>                     |                     |
|                   | Solar facilities  | <b>Photovoltaic solar installations:</b> Footprint of all solar installations regardless of capacity  | <a href="#">U.S. Solar Photovoltaic Database (USPVDB)</a> | Up to 2024          |
|                   | Wind energy sites | <b>Wind turbine sites:</b> All points for wind energy sites, buffered based on capacity. The buffer is defined by the estimated direct land use of wind turbines, which is roughly 0.75 acres per megawatt of rated capacity (Denholm et al. 2009). | <a href="#">U.S. Wind Turbine Database (USWTDB)</a>       | Up to 2024          |

**Table A2.** Datasets selected to quantify human land use intensity, organized by AIM stressor categories.

| Stressor category                    | Indicator  | Description   | Data source  | Year(s) represented |
|--------------------------------------|--|---|--|---------------------|
| Agriculture                          | Agricultural pesticide use                                 | Application of the top 7 pesticides applied on agricultural lands across CONUS, dasymmetrically mapped at the county level to agricultural lands using NLCD. Pesticide use includes 3 insecticides (Chlorpyrifos, Cyfluthrin, Permethrin) and 4 herbicides (Glyphosate, 2, 4-D, Atrazine, Metolachlor). | <a href="#">County-level estimated annual agricultural pesticide use</a>             | 2017                |
|                                      | Crop diversity   | Shannon Index on all crop types in the Cropland Data Layer, inverted such that lower crop diversity (i.e., monocultures) indicates greater intensity  | <a href="#">Cropland Data Layer</a>  | 2023                |
| Transportation and urban development | Nightlights  | Median of all average day/night band radiance values (i.e., nighttime light) from 2024-01-01 to 2024-12-31  | <a href="#">Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime radiance</a> | 2024                |
| Energy                               | Oil and gas well density                                   | We computed a kernel density estimate of all oil and gas wells in the HIFLD dataset   | <a href="#">Homeland Infrastructure Foundation-Level Data</a> (HIFLD)                | Through 2018        |
|                                      | Other energy infrastructure density                        | Power plant density: We computed a kernel density estimate of all power plants meeting the same filtering requirements as described in Table A1   | <a href="#">Homeland Infrastructure Foundation-Level Data</a>                        | Through Feb 2025    |
|                                      |  | Transmission line density: We computed linear density of all overhead transmission lines meeting the same filtering requirements as described in Table A1   | <a href="#">Homeland Infrastructure Foundation-Level Data</a>                        | Through Sept 2024   |
|                                      |  | All other processing infrastructure density: We computed a kernel density estimate of all terminals, natural gas processing plants, and petroleum refineries  | <a href="#">Homeland Infrastructure Foundation-Level Data</a>                        | Up to 2024          |
|                                      | Percent cover of solar facilities                          | We computed the percent cover of all photovoltaic solar installations   | <a href="#">U.S. Solar Photovoltaic Database (USPVDB)</a>                            | Up to 2024          |
| Wind energy site density             | We computed a kernel density estimate of all wind turbines | <a href="#">U.S. Wind Turbine Database (USWTDB)</a>   | Up to 2024   |                     |

## Appendix B

The following tables provide additional information on all datasets contributing to social vulnerability and demographic indicators.

**Table B1.** Datasets selected to represent all social vulnerability categories and sub-categories. Any subcategories in which individual indicators were also ‘rolled up’ into a grouped metric for that sub-category have an asterisk (\*).

| Vulnerability category | Sub-category                        | Indicator  | Description   | Data Source   | Year(s) represented                        |
|------------------------|-------------------------------------|--|---|---|--|
| Climate risk           | General                             | Deaths from climate disasters  | We derived average annual deaths from climate disasters from 1980 through 2024 at the state level and then computed a rate (deaths per 100,000) | <a href="#">NOAA NCEI State-level climate disaster events</a>   | 1980-2024                                  |
|                        |                                     | Life expectancy  | Life expectancy in years (inverted such that lower life expectancy equals greater vulnerability)  | <a href="#">CEJST 2.0</a>   | 2010-2015                                  |
|                        | Air pollution-related impacts*      | Increased particulate matter (PM2.5) mortality   | Air quality related mortalities per 100,000 (ages 65+) under 2°C of warming   | <a href="#">EPA Climate Change and Social Vulnerability in the United States</a> : Appendix D: Air Quality and Health | Projections from 2000 (base year) to ~2100 |
|                        |                                     | Increased Ozone (O3) mortality   | Ozone-related premature mortalities per 100,000 (all ages) under 2°C of warming   | <a href="#">EPA Climate Change and Social Vulnerability in the United States</a> : Appendix D: Air Quality and Health | Projections from 2000 (base year) to ~2100 |
|                        |                                     | Increase in childhood asthma incidence   | New childhood asthma cases per 100k under 2°C of warming  | <a href="#">EPA Climate Change and Social Vulnerability in the United States</a> : Appendix D: Air Quality and Health | Projections from 2000 (base year) to ~2100 |
| Temperature            | Urban heat island extreme heat days | Number of extreme heat days per year (3 year average)  | <a href="#">EDF’s Climate Vulnerability Index</a> (primary source: CDC)   | 2018-2020   |  |
|                        | Heat Severity (urban areas)         | Relative heat severity for every pixel in all urban areas in the US. Heat severity is measured on a scale from 1 | Trust for Public Land: <a href="#">Heat severity</a>  | 2024  |  |

| Vulnerability category | Sub-category | Indicator                                  | Description   | Data Source  | Year(s) represented                       |
|------------------------|--------------|--|---|--|---|
|                        |              |  | (relatively mild heat area; i.e., slightly above the mean value for the urban area) to 5 (severe heat area; i.e., significantly above the mean for the urban area).   |  |   |
|                        |              | Heat Severity (cities)                     | Relative heat severity for every pixel in all cities in the US. Heat severity is measured on a scale from 1 (relatively mild heat area; i.e., slightly above the mean value for the urban area) to 5 (severe heat area; i.e., significantly above the mean for the urban area). | Trust for Public Land: <a href="#">Heat severity</a>   | 2024                                      |
|                        |              | Annualized frequency of cold waves         | The number of recorded cold wave occurrences (in event-days, to better capture hazards of varying durations) each year over the period of record (16.8 years)   | <a href="#">FEMA National Risk Index</a>   | 2005-2022                                 |
| Droughts               |              | Annualized frequency of drought            | The number of recorded drought occurrences (in event days, to better capture hazards of varying durations) each year over the period of record (21.9 years)   | <a href="#">FEMA National Risk Index</a> (U.S. Drought Monitor)  | 2000-2021                                 |
| Flooding*              |              | Annualized frequency of coastal flooding   | Modeled frequency of a coastal flooding occurrence (in events) per year   | <a href="#">FEMA National Risk Index</a>   | 1996-2019                                 |
|                        |              | Annualized frequency of riverine flooding  | The number of riverine flooding occurrences (in event days, to better capture hazards of varying durations) each year over the period of record (24 years)  | <a href="#">FEMA National Risk Index</a>   | 1996-2019                                 |
|                        |              | Sea level rise (permanent inundation risk) | The proportion of properties at risk of permanent inundation from 50 cm of sea level rise   | <a href="#">EPA Climate Change and Social Vulnerability in the United States</a> ; Appendix H: Coastal Flooding and Property | Projections from 2000 (base year) to 2100 |

| Vulnerability category | Sub-category                   | Indicator  | Description   | Data Source  | Year(s) represented         |
|------------------------|--------------------------------|--|---|--|-----------------------------|
|                        |                                | Share of properties at risk of flood in 30 years | Climate-adjusted model projecting future flood risk for properties. Represents how many structures are at risk of flooding due to tides, rain, riverine and storm surges over a 30-year period. | <a href="#">CEJST 2.0</a> (primary source: First Street Foundation)  | Projections (released 2022) |
|                        |                                | Sea level rise (in meters)                       | Sea level rise in meters  | <a href="#">EDF's Climate Vulnerability Index</a> (primary source: IPCC AR6, Scenario SSP5-8.5 Medium Term (2041-2060))                    | Projections 2041-2060       |
|                        |                                | Flooding risk to roads                           | Average flooding risk score by census tract   | <a href="#">EDF's Climate Vulnerability Index</a> <sup>1</sup> (primary source: Flood Factor Risk Statistics V2.0, Firststreet Foundation) | Projections (released 2020) |
|                        | Storms                         | Annualized frequency of hurricanes               | The estimated number of recorded hurricane occurrences (in events) each year  | <a href="#">FEMA National Risk Index</a>   | 1851-2020                   |
|                        |                                | Annualized frequency of tornadoes                | The estimated number of recorded tornado occurrences (in events) each year  | <a href="#">FEMA National Risk Index</a>   | 1950-2019                   |
|                        |                                | Annualized frequency of winter weather           | The number of recorded winter weather occurrences (in event-days, to better capture hazards of varying durations) each year over the period of record (16.8 years)                              | <a href="#">FEMA National Risk Index</a>   | 2005-2022                   |
| Pollution              | Potential risks and exposures* | Traffic proximity and volume                     | Count of vehicles at major roads within 500 meters, divided by distance in meters (compiled from 2017 DOT traffic data)   | <a href="#">CEJST 2.0</a>  | 2017                        |
|                        |                                | Air quality: Air toxics total cancer             | Hazard index for cancer health effects from air toxics and diesel particulate matter  | <a href="#">EDF's Climate Vulnerability Index</a> <sup>1</sup> (primary source: <a href="#">EPA</a> )                                      | 2017                        |

| Vulnerability category | Sub-category                          | Indicator   | Description | Data Source   | Year(s) represented |
|------------------------|---------------------------------------|---|-------------|---|---------------------|
|                        |                                       | risk  |             | <a href="#">AirToxScreen</a> )  |                     |
|                        | Air quality: Air toxics developmental | Hazard index for developmental health effects from air toxics and diesel particulate matter |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics immunological | Hazard index for immunological health effects from air toxics and diesel particulate matter |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics kidney        | Hazard index for kidney health effects from air toxics and diesel particulate matter        |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics liver         | Hazard index for liver health effects from air toxics and diesel particulate matter         |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics neurological  | Hazard index for neurological health effects from air toxics and diesel particulate matter  |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics reproductive  | Hazard index for reproductive health effects from air toxics and diesel particulate matter  |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics respiratory   | Hazard index for respiratory health effects from air toxics and diesel particulate matter   |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality: Air toxics thyroid       | Hazard index for thyroid health effects from air toxics and diesel particulate matter       |             | <a href="#">EDF's Climate Vulnerability Index<sup>1</sup></a> (primary source: <a href="#">EPA AirToxScreen</a> ) | 2017                |
|                        | Air quality (PM2.5)                   | Fine inhalable particulate matter (diameter less than                                       |             | <a href="#">CEJST 2.0</a>   | 2017                |

| Vulnerability category | Sub-category       | Indicator                          | Description   | Data Source   | Year(s) represented |
|------------------------|--------------------|------------------------------------|---|---|---------------------|
|                        |                    | in the air)                        | or equal to 2.5 micrometers) in the air   |   |                     |
|                        |                    | Water quality: Development risk    | Relative development risk (e.g., due to urban expansion, land-use change, or increased impervious surfaces) to important drinking water watersheds (scenario: 2040, RCP 4.5)  | <a href="#">Forests to Faucets 2.0 Assessment</a>   | Projection (2040)   |
|                        |                    | Water quality: Yield risk          | Relative water yield risk to important drinking water watersheds due to climate change (scenario: 2040, RCP 4.5)  | <a href="#">Forests to Faucets 2.0 Assessment</a>   | Projection (2040)   |
|                        |                    | Potential lead paint exposure      | The percent of housing units built before 1960, which serves as a proxy for potential lead paint exposure   | <a href="#">CEJST 2.0</a>   | 2018-2022           |
|                        |                    | Agricultural pesticides            | Annual agricultural pesticide use per cropland area, by county (lbs/acre)   | <a href="#">EDF's Climate Vulnerability Index</a> <sup>1</sup> (primary source: <a href="#">County-level estimated annual agricultural pesticide use</a> )      | 2013-2017           |
|                        | Pollution sources* | Proximity to brownfields           | The inverse of distance to all brownfields. All points were buffered by 200 m to capture a larger portion of the brownfield footprint when computing distance.  | <a href="#">EPA ACRES</a>   | Up to 2024          |
|                        |                    | Proximity to NPL (superfund) sites | The inverse of distance to all superfund sites with a status of either 'F' (Currently on the Final NPL: These are sites that have been officially added to the National Priorities List and require cleanup due to hazardous substance releases) or 'P' (These sites have been identified as potentially needing cleanup and are currently being evaluated for inclusion on the NPL, according to the EPA). We utilized all superfund site boundary polygons meeting these filtering criteria, as well as any point locations that fell outside | EPA National Priorities List (NPL) Superfund Sites ( <a href="#">points</a> ; <a href="#">boundaries</a> ); <a href="#">EPA Facility Registry Service (FRS)</a> | Through Feb 2024    |

| Vulnerability category | Sub-category | Indicator  | Description   | Data Source   | Year(s) represented |
|------------------------|--------------|--|---|---|---------------------|
|                        |              |  | of those boundary polygons. All points were buffered by 200 m to capture a larger portion of the superfund site footprint when computing distance.  |   |                     |
|                        |              | Proximity to NPL (superfund) sites                           | Count of proposed or listed superfund (or NPL) sites within 5 km (or nearest outside of 5 km), each divided by distance in km   | <a href="#">CEJST 2.0</a>   | 2020                |
|                        |              | Proximity to landfills                                       | The inverse of distance to all landfills with a 'Current Landfill Status' of 'open'. All points were buffered by 200 m to capture a larger portion of the landfill footprint when computing distance. | <a href="#">EPA LMOP Landfill and Landfill Gas Energy Project Database</a>                          | Up to Sept 2024     |
|                        |              | Proximity to active oil and gas wells                        | The inverse of distance to all oil and gas wells. All points were buffered by 134.34 m to capture the mean oil and gas well footprint described in Table A1.  | <a href="#">Homeland Infrastructure Foundation-Level Data (HIFLD; accessed through Koordinates)</a> | Through 2018        |
|                        |              | Proximity to chemical manufacturers                          | The inverse of distance to all chemical manufacturers. All points were buffered by 200 m to capture a larger portion of the chemical manufacturing site footprint when computing distance.            | <a href="#">EPA Toxics Release Inventory (TRI) Program</a>  | 1987-2024           |
|                        |              | Proximity to hazardous waste management facilities           | Count of hazardous waste facilities (treatment, storage, and disposal facilities, and large quantity generators) within 5 km (or the nearest facility beyond 5 km), divided by distance in km         | <a href="#">CEJST 2.0</a>   | 2020                |
|                        |              | Proximity to wastewater and other waste treatment facilities | The inverse of distance to all wastewater and other waste treatment facilities. All points were buffered by 200 m to capture a larger portion of the site footprint when computing distance.          | <a href="#">HIFLD FRS ICIS Wastewater Treatment Plants</a>  | Through May 2025    |
|                        |              | Wastewater   | Modeled toxic concentrations at stream segments   | <a href="#">CEJST 2.0</a>   | 2020                |

| Vulnerability category | Sub-category            | Indicator                                  | Description  | Data Source  | Year(s) represented                              |
|------------------------|-------------------------|--|--|--|--|
|                        |                         | discharge                                  | within 600 meters, divided by distance in km   |  |  |
|                        |                         | Proximity to other energy infrastructure   | The inverse of distance to transmission lines, terminals, natural gas processing plants, and petroleum refineries (all as identified in our footprint in Table A1)       | <a href="#">Homeland Infrastructure Foundation-Level Data</a>  | Up to 2024                                       |
|                        |                         | Transportation noise                       | Mean road, rail, and aviation noise  | <a href="#">Bureau of Transportation Statistics</a>  | 2020   |
| Infrastructure         | Transportation access*  | Households with no vehicle                 | The percent of occupied housing units without a vehicle  | <a href="#">American Community Survey (ACS)</a>  | 2023   |
|                        |                         | Delay (congestion) per capita/census tract | Weighted yearly average commute delay (congestion) per commuter  | <a href="#">EDF's Climate Vulnerability Index</a> (primary source: <a href="#">Urban Mobility Report, Texas A&amp;M Transportation Institute</a> ) | 2019   |
|                        |                         | Lane miles per capita                      | The inverse of lane miles per capita to capture reduced travel lane availability   | <a href="#">EDF's Climate Vulnerability Index</a> (primary source: <a href="#">Highway Performance Monitoring System (HPMS)</a> )                  | 2018   |
|                        |                         | Road quality and maintenance               | International Roughness Index (quantifies road surface roughness), inverted to represent limited road quality and maintenance as high vulnerability                      | <a href="#">EDF's Climate Vulnerability Index</a> <sup>1</sup> (primary source: <a href="#">Highway Performance Monitoring System (HPMS)</a> )     | 2018   |
|                        |                         | Public transit performance                 | The inverse of the public transit score (original values from 1-10, with 1 being the lowest and 10 being the highest) for metropolitan areas with a population > 100,000 | <a href="#">AllTransit</a>   | Based on 2022 demographics and 2024 transit data |
|                        | Community accessibility | Walkability                                | The inverse of the score of walkability (original values from 0-100, with 0 being the least walkable and 100   | <a href="#">EDF's Climate Vulnerability Index</a> <sup>1</sup> (primary source:  | 2022   |

| Vulnerability category | Sub-category                      | Indicator   | Description   | Data Source  | Year(s) represented                           |
|------------------------|-----------------------------------|---|---|--|---|
|                        |                                   |   | being the most walkable)  | Walkscore)   |   |
|                        |                                   | Bikeability   | Score of bikeability (original values from 0-100, with 0 being the least bikeable and 100 being the most bikeable )   | <a href="#">EDF's Climate Vulnerability Index</a> <sup>1</sup> (primary source: Walkscore) | 2022  |
|                        |                                   | Isolation   | Linguistically isolated populations: The percent of the total population (5 years and over) that lives in households in which no one 14 and over speaks English only or speaks a language other than English at home and speaks English 'very well' | <a href="#">US Census/American Community Survey (ACS)</a>                                  | 2023  |
|                        | Nature/green space accessibility* | Access/proximity to water                                 | Distance to naturally occurring waterbodies (stream/river, sea/ocean, and bay/inlet from NHDArea and 'lake/pond' and 'estuary' from NDHWaterbody)   | <a href="#">NHDPlus</a>  | Up to July 2022                               |
|                        |                                   | Proximity to protected nature                             | Distance to all protected nature (GAP 1 and 2 lands, which are primarily managed for biodiversity and permanently protected from conversion and extractive uses)  | <a href="#">PAD-US 4.1</a> and <a href="#">National Conservation Easement Database</a>     | Up to 2024                                    |
|                        |                                   | Parks and greenspace as a percentage of each census tract | The inverse of the percent of each census tract occupied by parks and green space   | Trust for Public Land <a href="#">U.S. ParkServe Dataset</a>                               | Up to 2024                                    |
|                        |                                   | Ability of an area to produce clean drinking water        | The inverse of the relative ability of an area to produce clean drinking water. Note that this metric was not included in the aggregated 'Nature/green space accessibility' metric).  | <a href="#">Forests to Faucets 2.0 Assessment</a>  | Reflects watershed conditions from ~2010-2016 |

<sup>1</sup>These datasets provided via EDF's Climate Vulnerability Index already underwent a median imputation process to replace any missing data values with their median value (Tee Lewis et al. 2023) prior to inclusion in this analysis.

**Table B2.** Demographic indicators representing race, ethnicity, income level, education level, housing affordability, and household composition.

| Theme                 | Indicator  | Description (if needed)                        | Data source                                |
|-----------------------|--|--|--|
| Race                  | % White  |  | US 2020 Census                             |
|                       | % Black  |  | US 2020 Census                             |
|                       | % American Indian  |  | US 2020 Census                             |
|                       | % Asian  |  | US 2020 Census                             |
|                       | % Communities of color   | All non-white racial groups                    | US 2020 Census                             |
| Ethnicity             | % Hispanic or Latinx   |  | US 2020 Census                             |
| Income level          | % below the poverty line   |  | American Community Survey (ACS; 2019-2023) |
|                       | Median household income  |  | American Community Survey (ACS; 2019-2023) |
| Education level       | % without a high school diploma  |  | American Community Survey (ACS; 2019-2023) |
| Housing affordability | Median gross rent as a percentage of income                                  |  | American Community Survey (ACS; 2019-2023) |
|                       | % cost-burdened renters  | gross rent is 30-49.9% of income               | American Community Survey (ACS; 2019-2023) |
|                       | % severely cost-burdened renters   | gross rent is 50% or more of income            | American Community Survey (ACS; 2019-2023) |
|                       | % of owned and rented occupied housing units that are cost-burdened          | housing costs are over 30% of household income | American Community Survey (ACS; 2019-2023) |
|                       | % of owned and rented occupied housing units that are severely cost-burdened | housing costs are over 50% of household income | American Community Survey (ACS; 2019-2023) |
|                       | % owned housing units  |  | American Community Survey (ACS; 2019-2023) |
|                       | % rented housing units   |  | American Community Survey (ACS; 2019-2023) |
| Household composition | % of households with children  |  | American Community Survey (ACS; 2019-2023) |

## Appendix C

The information here provides guidance on how to use the accompanying results spreadsheet containing several different summary statistic breakdowns and formats for our final analysis outputs. The table of contents ('table-of-contents' tab) in the spreadsheet provides an overview of the information provided in each tab and the types of top-line statistics that may be derived from each table. The code lookup tab ('code-lookup') describes all codes used for social vulnerability metrics, demographic metrics, and AIM in all subsequent data tables in the spreadsheet. All remaining tabs in the spreadsheet provide various statistical summaries.