

## **ASTHO Climate Change Population Vulnerability Screening Tool** *Prepared by the California Environmental Health Tracking Program (CEHTP)*

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### **INTRODUCTION**

Population vulnerability assessments are a key tool for climate change preparedness and are needed to guide policy makers in planning efforts to address climate change impacts. As climate change mitigation and adaptation strategies move from legislation to regulation, there will be a need to identify communities with elevated health risks from climate change, allowing for regulatory structures and regional and municipal planning efforts that protect communities vulnerable to climate change.

In California, the State has recently initiated a cap-and-trade program as a regulatory method to mitigate greenhouse gas (GHG) emissions. As part of the regulatory process, decision-makers must determine whether there are ways to target program benefits in a manner that maximizes community-level health benefits from co-pollutant reductions and minimizes the likelihood that market-based GHG reductions will produce or exacerbate disparities in public health. Recommendations from the California Department of Public Health and other health and environmental justice stakeholders have pointed to the need to use a portion of revenue raised from the cap-and-trade program to promote climate adaptation programs in communities vulnerable to climate change. Understanding existing community health risks and population vulnerabilities to climate change at the sub-county level is a core need when planning for future climate risks and community adaptation plans.

The California Department of Public Health's Environmental Health Tracking Program (CEHTP) utilized an existing environmental justice screening method (EJSM) and adapted it to two counties likely to experience substantial climate change impacts—Los Angeles and Fresno Counties. The EJSM method maps cumulative impacts and community health vulnerabilities at the census tract level using data for existing land uses, air pollution sources, and demographic traits. CEHTP supplemented the EJSM with metrics associated with climate change impacts and adaptive capacity, such as population sensitivities (eg. elderly living alone; car access), air conditioning ownership, green space, and ecological risks (eg. flood risk; fire risk).

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### **Indicators of Climate Change Vulnerability in California**

The indicators chosen are consistent with the expected climate change impacts in California—including increased extreme heat events, increased flooding, and more frequent and intense wildfires. The indicators include air conditioning (AC) ownership, land cover characteristics (tree canopy and impervious surfaces), access to transportation (transit and household car access), social vulnerabilities (elderly living alone), flood risk, and wildfire risk.

### *Air Conditioning Ownership*

Heat waves are one of the more certain impacts of climate change, and will likely increase in California.<sup>1,2</sup> In the 2006 heat wave in California, 16,166 excess emergency department visits and 1,182 excess hospitalizations occurred statewide.<sup>3</sup> Air conditioning is an important protective factor during heat waves.<sup>4</sup> Low-income households and communities of color—populations that are already face greater health risks—often have diminished access to air conditioning, as basic adaptation tool for climate change.<sup>3,5</sup> Adults over 50 years of age are at increased risk for mortality during heat waves, and children may be at increased risk for morbidity due a decreased capacity to thermoregulate.<sup>4</sup>

### *Impervious Surfaces and Tree Canopy*

Urban heat islands (UHIs) develop in areas where buildings, roads, and other impervious surfaces replace land and vegetative cover. UHIs increase peak energy demand, contribute to air pollution and GHG emissions, and diminish water quality. UHIs can increase daytime temperatures 1–3°C and nighttime temperatures<sup>i</sup> up to 12°C.<sup>6</sup> In addition, impervious surfaces can increase flood risks and decrease water quality due to excessive water runoff in urban areas. Increasing tree and vegetative cover, promoting green roofs, and innovative infrastructure (such as cool pavements or permeable surfaces) can diminish the impacts of UHIs, reduce GHG emissions, and reduce water runoff.<sup>6</sup>

Minority and low-income communities often live in neighborhoods with greater exposure to heat stress. This is in part due to higher densities of settlement and increased impervious surfaces, diminished vegetative cover, and a lack of open space.<sup>7,8,9,10</sup> Diminished green space in urban areas reduces a community's adaptive capacity to climate change.

### *Transportation Access*

Transportation access is a critical tool during heat waves and other extreme weather events, allowing individuals to commute to cooling stations or other safe areas.<sup>10</sup> In addition, transportation access is a critical component in emergency preparedness, and as witnessed with Hurricane Katrina, emergency transportation is often least accessible to low-income minority communities.<sup>11</sup> Access to public transit and household vehicles are each indicators of a household's overall mobility.

Minority and low-income populations are less likely to own cars and far more reliant on public transportation for everyday activities, including school and work.<sup>12</sup> And a widening spatial gap between where people live and where people work, and the inability to get to work, impedes socioeconomic progress in many communities of color.<sup>13</sup> Public transit generally receives only 20 cents for every 80 cents earmarked for highways, and many states use gas tax revenue only for highway funding, resulting in the disinvestment in transit systems in many urban communities.<sup>14</sup>

The transportation sector also generates one-third of U.S. emissions. Improving public transit and land use patterns that support transit use and access will be essential for climate change mitigation, and will also reap other health benefits, including decreases in pollution and automobile collisions, as well as increases in physical activity.<sup>15,16</sup>

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<sup>i</sup> Nighttime temperatures are critical for cooling during prolonged heat waves.

### *Flooding*

Flooding will likely increase in California due to climate change as a result of melting snowpack and earlier water runoff. Flood risks can be compounded by impervious surfaces and wildfires—each of which exacerbate water runoff. In addition, sea rise will contribute to coastal flooding. Flooding has a direct health impact for communities at immediate risk during a flood, and can also impact the safety of food and water supplies for a wider region.<sup>17</sup> Flooding can place individuals at risk of residential displacement, drowning, injury, illness and infections, carbon monoxide poisoning, mold exposure, food and water contamination, and hypothermia.<sup>18</sup>

Equity issues are of importance in all disaster scenarios, as socially and economically vulnerable populations—including elderly, children, and immune-compromised individuals—often have less capacity to “anticipate, cope with, resist, and recover” from environmental hazards.<sup>19</sup> Racial and ethnic disparities play a role in all major stages of a disaster, including preparedness, communication and response, physical and psychological impact, emergency response, recovery, and reconstruction.<sup>20</sup>

### *Wildfires*

Climate change is expected to increase the frequency of wildfires in California.<sup>21 22</sup> Health effects from wildfire include mortality, respiratory illness and eye irritations associated with smoke, displacement from one’s home, and increased risk for erosion, flooding, and landslides.<sup>23 24 25 26</sup>

Individuals with pre-existing respiratory illnesses are at the greatest risk for adverse health impacts associated with wildfires. In addition, populations living in urban-wildfire boundaries are at increased risk for wildfire injury.<sup>25</sup> Overall, a community’s adaptive capacity will impact their ability to respond and recover to disasters such as wildfires.<sup>19</sup>

### *Other High-Risk Populations*

Chronic disease exacerbations (CDE) account for one of the largest patient populations during natural disasters, and medical complications can arise from the inability to deliver basic medical services.<sup>27</sup> Heat waves can exasperate chronic illnesses, such as cardiovascular and respiratory diseases.<sup>28</sup> Furthermore, existing chronic diseases can increase susceptibility to heat-related illnesses.<sup>29</sup> Disease outbreaks related to flooding may pose particular risks to immunocompromised individuals.<sup>19</sup>

Individuals with limited mobility, pregnant women, the elderly (who often have multiple chronic conditions and comorbidities), individuals with low socioeconomic status, and individuals without insurance may be at increased risk during disasters or other emergency events. Reducing basic human vulnerabilities will be a core strategy to minimizing climate change risk.<sup>30</sup>

## **DATA + METHODS**

The method described here for assessing population to vulnerability offers community organizations, local health departments, legislators, regulators, and other decision makers a relatively simple, transparent, and flexible tool to screen for population vulnerabilities. As described above, certain populations will be at increased risk for negative health impacts from climate change, but these population risks will vary throughout the State. Thus, the flexibility of this screening method can be adapted to local needs and existing data resources. This method

can support future planning needs and guide regulatory decisions to minimize the negative health risks and maximize health benefits in local communities with existing community health vulnerabilities.

The EJSM developed by Sadd et al. maps cumulative impacts using a set of 23 health, environmental, and social indicators organized into three categories: 1) hazard proximity and land use, 2) air pollution exposure and health risk, and 3) social and health vulnerabilities. We developed a 4th category, population vulnerability to climate change, using 8 indicators (plus a 9th indicator—sea rise—for Los Angeles County) to supplement the existing categories of the EJSM. Our methodology was developed in accordance with the methods used by Sadd et al. Our methodology for compiling climate change risks is explained here, and the full methodology from Sadd et al., developed with considerable community input, is described in Appendix A (and the results from Sadd et al. are described in Appendix B).

### **Climate Change Population Vulnerability Indicator**

The climate change population vulnerability indicators were piloted for two counties that are expected to be impacted by climate change—Los Angeles and Fresno County. Data were compiled from various sources, and all data were publicly accessible online with the exception of data on AC prevalence and Fresno transit lines (these had to be requested because the data were not available online). Data points were summarized at the census tract level, using tract boundaries from year 2000 Census data. Each discrete indicator for each county was ranked into quintiles and scored 1 (low vulnerability) to 5 (high vulnerability). A final score was created by averaging across indicator rankings for each county, then re-scoring from 1 to 5.

Data on the prevalence of central AC ownership (excluding swamp coolers and window cooling units) were obtained from the California Energy Commission (CEC), based on the 2009 Residential Appliance Saturation Survey.<sup>31</sup> Data from the CEC were reported at the zip code level. Using 2009 ESRI zip codes, AC data were projected for the State using a spatial empirical Bayes model, and then projected onto year 2000 Census tracts using an area weighted average for Los Angeles and Fresno Counties to derive tract-level estimates for AC ownership. These estimates were ranked into quintiles and scored 1 (high AC ownership) to 5 (low AC ownership).<sup>ii</sup>

Data on land cover characteristics were collected from the United States Environmental Protection Agency's (US EPA) 2001 National Land Cover Data.<sup>32</sup> Data included tree canopy and impervious surface characteristics. For each data set, the percent of land coverage based on raster pixel values was averaged across year 2000 Census block groups. Using population weighted averages, the values were summarized at the census tract level. Both tree canopy coverage and impervious surface averages were ranked into quintiles and scored 1 (high canopy coverage; low impervious surfaces) to 5 (low canopy coverage; high impervious surfaces).

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<sup>ii</sup> All rankings were made using quintiles. Other methods to classify and rank the data—such as Jenks natural breaks—could also be employed. Sadd et al. found that for most data points included in the EJSM, quintiles and Jenks natural breaks produced very similar results. However, community workshops found that quintile rankings were much easier to understand and more transparent for community stakeholders, thus Sadd et al. employed quintile rankings throughout. We too have employed quintile rankings for a more transparent and consistent methodology. Calculations were programmed in SAS. When rankings were tied, the default was to assign the lower score as the final ranking (in order to not overestimate population vulnerabilities).

Spatial data on bus and light rail lines were collected from the Southern California Association of Governments and from the Council of Fresno County Governments (Fresno COG).<sup>33 34</sup> All transit lines, covering multiple transit jurisdictions and/or agencies for each county were overlaid with year 2000 census tracts. A simple indicator of transit access was created by counting the number of unique transit routes per census tract, without regard to transit stops, the type of service (eg. bus or rail), or headway times. The route counts per census tract were ranked into quintiles and scored 1 (greater number of transit routes) to 5 (fewer transit routes).

Household car access provided another measure of transportation access. The proportion of households per census tract with at least one car was collected from year 2000 Census data. The proportions for each census tract were ranked into quintiles and scored 1 (higher proportion of households with at least one car) to 5 (lower proportion of households with at least one car).

The proportion of elderly living alone highlights a community vulnerable to extreme weather events—particularly heat—and other emergencies. Data were gathered from the year 2000 Census for the percent of households within a tract consisting of one individual age 65+ years old living alone. The census tracts were ranked into quintiles and scored 1 (fewer proportion of elderly living alone) to 5 (higher proportion of elderly living alone).

Data on wildfire threat is available from the CAL FIRE Fire and Resource Assessment Program (FRAP).<sup>35</sup> CAL FIRE's Wildland Urban Interface (WUI) data describes wildfire threat to developed areas, ranking 100 meter cells from "little to no threat" to "extreme threat". Categorical rankings from CAL FIRE were assigned values of 1 (no threat) to 5 (extreme threat) and used to calculate area weighted averages for each census tract. These averages were then ranked into quintiles and scored 1 (lower fire threat) to 5 (higher fire threat).

Flood risks were obtained from the Federal Emergency Management Agency's (FEMA) Digital Flood Insurance Rate Maps (DFIRM).<sup>36</sup> Flood risk categories include 'areas of minimal risk' (outside the 500 year flood zone), 'areas of moderate risk' (within 500 year and 100 year flood zones), and 'areas of increased risk' (within the 100 year flood zone). Each category was assigned a value of 1, 3, or 5, respectively. DFIRM maps were then overlaid with census tract polygons for each county, and an area weighted average was calculated for each tract. These averages were ranked into quintiles and scored 1 (low flood risk) to 5 (high flood risk).

Population susceptibility to coastal flooding due to sea level rise was included for Los Angeles County, but excluded for landlocked Fresno County. Projections on the impact of coastal flooding were obtained from the Pacific Institute.<sup>37</sup> Projections from the Pacific Institute assume a 1.4 m rise in sea level, and assess the proportion of individuals in each census tract to be inundated by rising coastal waters. Non-impacted tracts in Los Angeles County were assigned a zero for the proportion of population impacted. Census tracts were ranked 1 (no impact from sea rise) to 5 (high impact from sea rise).

A summary of all climate change population vulnerability indicators is shown in Table 1. A more detailed summary of the data used is included in appendix C. Indicators are given a score of 1 (low population vulnerability) to 5 (high population vulnerability). To create a final composite climate change population vulnerability score for each census tract, the scores of each indicator

are averaged for each census tract. The average scores are then divided into quintiles and re-ranked 1 to 5, representing a final composite score for population vulnerability to climate change. This score is also then added as a fourth category to the EJSM developed by Sadd et al., for a total Cumulative Impact score of 4 to 20.

Table 1. Indicators of population vulnerability to climate change

INDICATOR	ORIGINAL SPATIAL UNIT	FINAL RANKED SPATIAL UNIT	SOURCE
Central AC ownership	ESRI 2009 zip codes	Census tract	CEC 2009
Impervious surfaces	Raster grid (30m cell)	Census tract	NLCD 2001
Tree canopy	Raster grid (30m cell)	Census tract	NLCD 2001
Public transit routes	Line	Census tract	SCAG 2011; Fresno COG 2011
Household car access	Census tract	Census tract	Census 2000
Elderly living alone	Census tract	Census tract	Census 2000
Flood risk	Flood zone polygons	Census tract	FEMA (Fresno 2009; LA 2008)
Wildfire Urban Interface	Raster grid (100m cell)	Census tract	CAL FIRE 2003
Sea rise inundation	Census block	Census tract	Pacific Institute 2009 (using year 2000 Census data); LA only

### Validation of Indicator

The climate change population vulnerability indicator was validated against emergency room data from a recent extreme weather event—the 2006 California heat wave. Heat related emergency room visits were compiled at the zip code level for the time period during the heat wave (July 15 - August 1, 2006) and compared to heat related visits in a reference period (July 8-14 and August 12 – 22, 2006). Climate change population vulnerability scores from each census tract were averaged across host zip codes based on census tract centroids. These subsequent zip code level vulnerability scores were then ranked into quintiles. Relative risks for heat related emergency room visits were calculated for each vulnerability score.

### FINAL RESULTS

Results from the climate change population vulnerability screening tool were very similar to those from Sadd et al.’s EJSM methodology, showing elevated risks in urbanized areas, particularly those areas with a high proportion of persons of color. Our climate change screening tool also highlighted areas of risk along coastal areas of Los Angeles County, largely from risks due to sea level rise, but also partially attributable to poor public transit, wildfire risk, and a large proportion of elderly living alone. Utilizing the cumulative impact polygons derived from Sadd et al. (Figure 1), attention is focused to geographical areas where people live and where sensitive populations reside (such as schools, hospitals, and senior centers).

The final results from the climate change population vulnerability screening tool are similar to results from the EJSM in Fresno County as well (Figure 2<sup>iii</sup>). The EJSM and climate change vulnerability method both highlight areas of increased risk in western Fresno County and in urbanized areas. These pockets of greater risk persist when the two methods are combined

<sup>iii</sup> The cumulative impact polygon mask is not shown here for Fresno County to enhance map visualization. It is included, however, in Appendix D Figure D16.

(shown in Appendix D, Figure D15). A much more detailed discussion of results can be found in Appendix D, including additional high resolution maps of the final results.

Figure 1. Final climate change population vulnerability scores, including cumulative impact polygons, Los Angeles County

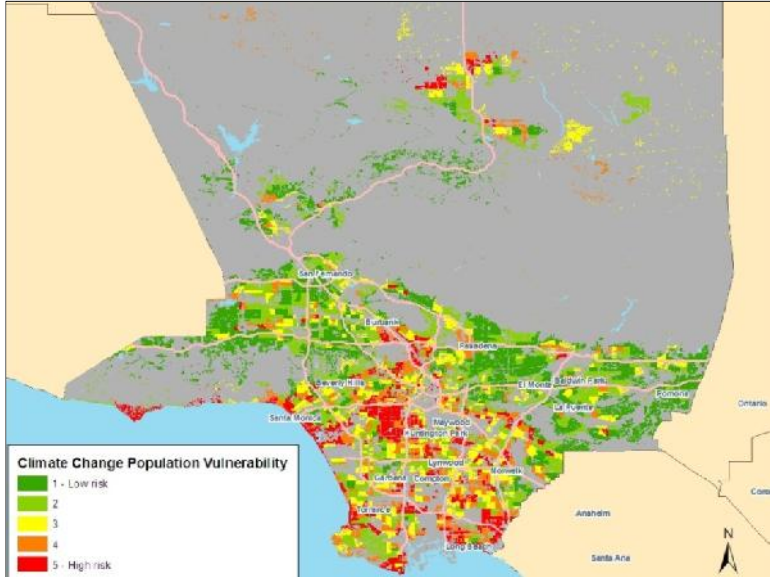
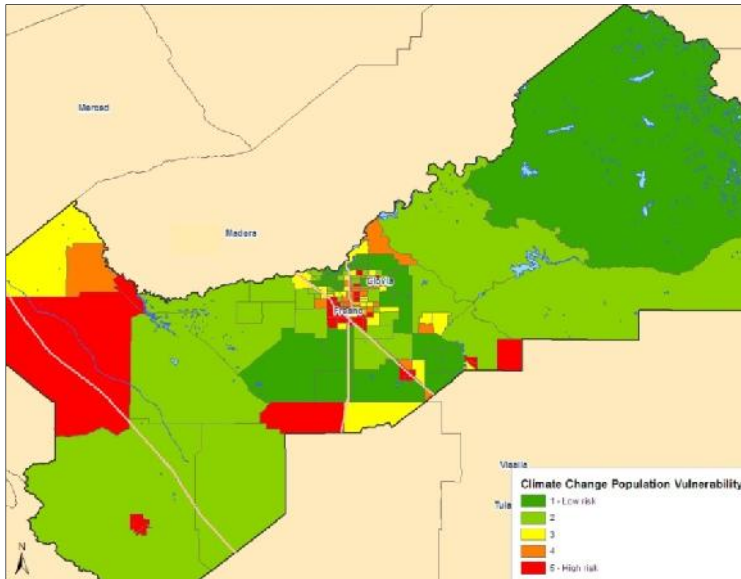


Figure 2. Final climate change population vulnerability risk scores at the census tract level, Fresno County



We also found strong racial disparities in each county for climate change vulnerability. In Los Angeles County, 46% of African Americans and 36% of Latinos reside in the two highest risk categories (those tracts with scores of 4 or 5), while 30% of whites live in these high risk census tracts (Table 2). In Fresno County, 49% of African Americans and 45% of Latinos reside in the two highest risk categories for climate change vulnerability, compared to just 26% of Fresno’s

white population (Table 3). These racial disparities are similar to those found using the environmental justice screening methodology.

Table 2. Proportion of population by race by climate change vulnerability score, Los Angeles County

Climate Change Vulnerability	Proportion of black population (%)	Proportion of Latino population (%)	Proportion of white population (%)	Proportion of total population (%)
1	12	17	28	22
2	22	26	25	25
3	20	21	18	19
4	19	18	14	16
5	27	18	16	18
<b>Total</b>	100	100	100	100

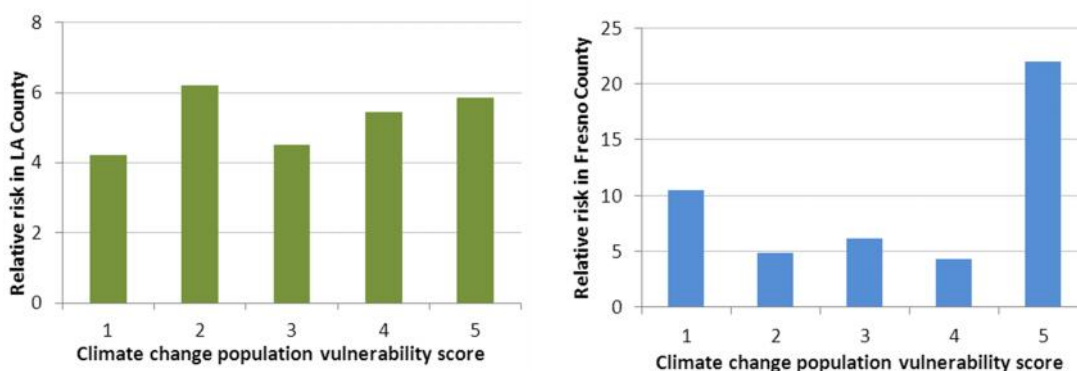
Table 3. Proportion of population by race by climate change vulnerability score, Fresno County

Climate Change Vulnerability	Proportion of black population (%)	Proportion of Latino population (%)	Proportion of white population (%)	Proportion of total population (%)
1	8	12	29	19
2	20	21	29	24
3	23	22	17	20
4	15	18	12	15
5	34	27	14	21
<b>Total</b>	100	100	100	100

## DATA VALIDATION

Data validations for each county show some correlation between the climate change population vulnerability scores and risks for heat related illness during the 2006 California heat wave. Los Angeles County displays a subtle dose-response pattern. Higher climate change population vulnerability scores show some correlation to elevated relative risk for heat related emergency room (ER) visits during the 2006 heat wave (with the exception of elevated risk for vulnerability category 2). In Fresno County, vulnerability category 5 has nearly twice the relative risk for heat related ER visits as category 1, though results are mixed for categories 2-4 (Figure 3).

Figure 3. Relative risk for heat related emergency room visits during the 2006 California heat wave by climate change population vulnerability score for Los Angeles and Fresno Counties





Validation results are promising, but as expected, the correlations are noisy. First, the climate change population vulnerability score includes many variables not related to health impacts from heat waves, such as flood risk or sea level rise. Likewise, no single climate change related event will be related to the entirety of the screening tool's underlying data. However, it still may be useful to assess a wide range of risks for broader planning purposes, as many emergency response planning efforts will complement each other. Secondly, there are limited ER data points to use for validation. Ideally, multiple heat waves could be combined or the validation could be performed across many counties for a large heat wave. Validating any indicator tool is a key step in assessing the tool's accuracy and usefulness for planning purposes.

### **METHODOLOGICAL CHALLENGES**

Manipulating and merging geospatial data across diverse data sources presents many challenges, particularly when working with sub-county data. Sub-county data are often not available, particularly in more rural counties. For example, there was not a reliable source of data on existing chronic disease burden for Fresno County. For Los Angeles County, data on disease burden were available at the sub-county level, but not at the census tract level.<sup>iv</sup> Overall, few counties in California maintain a detailed surveillance system of local disease burden. Other data points—such as data on transit systems—will vary from county to county in accessibility, and will likely exist in varying degrees of quality.

There is also a substantial investment in time and skilled labor to develop a screening tool such as this one. Data exist in a variety of geographic units, and any census tract level vulnerability indicator will rely on data points in a common geographic unit. In order to assign an indicator score to a census tract for some data points, moderate geospatial analyses are required.

In addition, climate change is a public health issue that will unfold over many future decades. However, the geospatial data used here are not prospective in nature (with the exception of data relating to sea level rise). Therefore, the tool captures existing population vulnerability to climate change, and does not capture actual future impacts. Similarly, populations and neighborhoods will change over time. While many of the traits that describe a vulnerable community will be the same over time (eg. a concentration of elderly living alone; high rates of chronic disease), the distribution of these traits will change over time. Therefore, a screening tool can inform future planning efforts, but should be refreshed with the most current data available, and needs a core understanding of how communities are changing on the ground.

### **SUCCESSSES**

Despite the data limitations listed above, this general approach to screening for population vulnerabilities to climate change advances many positive practices. First, the indicator was developed with data that were readily available on publicly accessible web sites (with the exceptions of AC ownership and Fresno County transit lines, which were easily requested). The implication is that other organizations could easily develop their own method with little costs

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<sup>iv</sup> The Los Angeles County Department of Public Health aggregates health data into 26 Health Districts, and each Health District is composed of 28-168 census tracts. These data were not included in the final indicator because of their granular geographic resolution.

outside of staff time to manipulate existing data sets and software. No original data collection would be needed. In addition, because many of these same data sets are collected nationally, similar screening tools could be developed in other states or regions of the country.

Second, we were able to link our climate change population vulnerability screening method with an existing screening tool that was well vetted by many community based organizations and other research groups in California. By employing a consistent method, we are confident that our screening tool will be accessible and understandable to many of these same community groups.

Finally, the method is very simple and transparent. This allows other groups to adopt this screening tool as is, or to assign weights to certain indicators in order to best assess the risks that are of the greatest concern in their communities.

### **RECOMMENDATIONS FOR BEST PRACTICES**

Based on the above success and data limitations, best practice recommendations would include:

- Use publicly available data and a transparent method to increase accessibility and adaptability by outside stakeholders.
- Developing a transparent and simple tool with no weighting allows stakeholders to use the screening tool “as is”, or to adjust it to best fit the needs of their communities.
- Building upon existing screening tools, emergency plans, etc. limits the data workload necessary to complete a screening tool, while avoiding duplicative efforts.
- Ideally, processed data layers could be held and maintained by a central source, such as a state department of public health, limiting the need for skilled labor on the user end.

### **RECOMMENDATIONS FOR FUTURE WORK**

Several steps that can be taken to improve the accessibility and usability of this screening tool, increasing the potential for uptake by outside organizations. Recommendations include:

- Reviewing and revising the screening tool with input from local health departments, community groups, planning groups, and other relevant stakeholders.
- Editing and analyzing data in advance for outside users would better assist stakeholders with fewer data skills to develop their own indicator system. Ideally, the data could be housed online and be readily available for download. Future efforts could be made to include the data in a dynamic online mapping tool, such as Google Fusion, and allow stakeholders to interactively change weights and/or turn data layers off and on, and zoom in and out of specific areas. This would greatly increase accessibility.
- Bridging data regarding existing vulnerabilities/susceptibilities with projected future climate change impacts will add to the relevancy of the screening methodology. Currently, local climate related data projections are limited, therefore the screening tool relies almost exclusively on existing conditions, not future projections.
- Building this work upon existing emergency and community planning tools and/or plans may increase the relevancy of this methodology to city, county, and state health officials, and decrease the workload needed to gather data and produce community vulnerability assessments.

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## Appendix A: Environmental Justice Screening Method (EJSM)—Methodology

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The method described here summarizes the methodology presented by Sadd et al. in *Playing it Safe: Assessing Cumulative Impact and Social Vulnerability through an Environmental Justice Screening Method in the South Coast Air Basin, California*.<sup>i</sup> Please refer to the full report for a more detailed methodology.

The EJSM followed a basic 4-step geospatial process:

- 1) Developing a regional base map of hazard proximity indicators according to hazard sources and sensitive land uses;
- 2) Using GIS to summarize the resulting hazard proximity indicators for each of the region's census tracts;
- 3) Coupling the resulting census tract scores with census tract level data on a) health risk exposures and b) social and health vulnerabilities; and
- 4) Scoring a cumulative tract-level score based on all indicators.

### **Base Map**

The base map was constructed using specific residential and sensitive land use classes as classified by the California Air Resources Board (CARB).<sup>ii</sup> Doing so focused the cumulative impact (CI) screening to areas where people live and to areas with sensitive receptors—such as children, the elderly, pregnant women, and those with existing respiratory disease—reside (including schools, hospitals, day care centers, and parks). Areas that are strictly industrial, commercial, or undeveloped open space were excluded.

Residential and sensitive land use polygons were intersected with census block polygons from the 2000 Census, creating a base map of neighborhood-sized CI polygons, each with a known land use class and census information.

### **Summarizing Hazard Proximity Indicators**

A set of hazard proximity indicators was attached to each CI polygon, then summarized to create scores at the tract level. This category captures the location of stationary emission sources and sensitive land uses based, including buffer distances to separate residential and other sensitive land uses from environmental health hazards, based on CARB recommendations. A summary of sensitive land uses is shown in Table A1.

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<sup>i</sup> Sadd JL, Pastor M, Morello-Frosch R, Scoggins J, Jesdale B. "Playing it Safe: Assessing Cumulative Impact and Social Vulnerability through an Environmental Justice Screening Method in the South Coast Air Basin, California". *International Journal of Environmental Research and Public Health*. 2011. 8:1441-1159.

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Table A1. Sensitive land use indicators

INDICATOR	GIS SPATIAL UNIT	SOURCE
Childcare facilities	Land use polygons	Southern California Association of Government (SCAG 2005)
	Buffered points	Dunn and Bradstreet, by Standard Industrial Code (SIC) 8350 and 8351 (2006)
Healthcare facilities	Land use polygons	SCAG (2005); California Spatial Information Library
Schools	Land use polygons	SCAG (2005)
	Buffered points	California Department of Education (2005)
Urban playgrounds	Land use polygons	SCAG (2005)
Senior housing	Buffered points	Dunn and Bradstreet, by SIC 8361 (2006)

Residential and sensitive land uses were mapped using several data sources (Table A1). Residential land uses were more straightforward, clearly delineated in the Southern California Association of Governments (SCAG) 2005 land use data layer. However, not all sensitive land uses are available as polygon features. For example, some commercial and other facilities contain childcare centers or health care facilities that are not mapped separately. Therefore, point locations were identified from other data sources and geocoded to create a point spatial feature layer. Any point feature that intersected with an equivalent polygon feature was dropped. A minimum area was then assigned to each point, with the buffer selected equaling the smallest equivalent polygon from the SCAG data layer.

Point source locations prioritized by CARB and in community scoping sessions as significant pollution sources were then mapped. These pollution sources are shown in Table A2.

Table A2. Hazardous facilities and land uses

INDICATOR	GIS SPATIAL UNIT	SOURCE
Facilities in the CA Community Health Air Pollution Information System (CHAPIS)	Point locations	CARB (2001)
Chrome-platers	Point locations	CARB (2001)
Hazardous waste sites	Point locations	CA Department of Toxic Substances Control (2004)
Railroad facilities	Land use polygons	SCAG (2005)
	Line features	National Transportation Atlas Database—NTAD (2001)
Ports	Land use polygons	SCAG (2005)
Airports	Land use polygons	SCAG (2005)
	Line features	NTAD (2001)
Refineries	Land use polygons	SCAG (2005)
Intermodal distribution	Land use polygons	SCAG (2005)
	Line features	NTAD (2001)

Each CI polygon, consisting of either residential or sensitive land uses, was then scored. First, buffers were constructed at 1000, 2000, and 3000 feet from the boundary of each CI polygon. The 1000 foot buffer is the standard applied by CARB. Additional buffers of 1000-2000 and 2000-3000 feet were included to compensate for GIS inaccuracies and the reality that some hazardous points are actually polygons.

The number and type of hazards within these buffered areas was tabulated for each CI polygon. Distance-weighted scoring was used, with the influence of the hazard diminishing with distance from the CI polygon (hazards within the 1000 foot buffer were valued as 1; hazards within the 1000-2000 foot buffer were valued as 0.5; hazards within the 2000-3000 buffer were valued as 0.1). Using this method, the summed score for polygons in the Southern California area ranged from 0-9.8.

A binary dummy variable was then added to each CI polygon depending on if it was residential (0) or non-residential sensitive land use (1). To create tract-level hazard proximity scores, a population weight from the underlying and intersecting census block was attached to each CI polygon. That value was then used to weight the scores to a census tract average score for hazard proximity/sensitive land use. Alternatively, an area-weighting approach could have also been used. The authors report that results were generally similar, and since the focus was on community impacts, population-weighting was ultimately used to assign tract-level scores.

Finally, a quintile ranking from 1 (low impact/risk) to 5 (high impact/risk) was applied to finalize the tract-level scores. More complex rankings—such as Jenks’ natural breaks, or the application of standard deviations—were available. However, quintile rankings yielded similar results and were simpler and more transparent to community stakeholders, so quintile rankings were used for assigning hazard/sensitive land use scores (as well as other variables to be discussed below).

Tract-level quintile scores were then calculated for health risk exposures and social and health vulnerabilities, as described below.

**Health Risk and Exposure Indicators**

The health risk and exposure indicators consist of five metrics of air pollution or health risk estimates associated with air toxics (Table A3). The metrics are assessed at the census tract level.

Table A3. Health risk and exposure indicators

INDICATOR	GIS SPATIAL UNIT	SOURCE
Risk Screening Environmental Indicators (RSEI) toxic concentration hazard score	Census tract	US Environmental Protection Agency—US EPA (2005)
National Air Toxics Assessment respiratory hazard for air toxics from mobile and stationary emissions	Census tract	US EPA (1999)
Estimated cancer risks from modeled ambient air toxics concentrations—mobile and stationary emissions	Census tract	CARB (2001)
PM <sub>2.5</sub> estimated concentrations (interpolated from CARB monitoring data)	Census tract	CARB (2004-06)
Ozone estimated concentrations (interpolated from CARB monitoring data)	Census tract	CARB (2004-06)

Each metric above was assigned an intermediate score by ranking 1 (lowest impact) through 5 (highest impact) based on quintiles. These intermediate scores were then summed across all health risk and exposure metrics (for a potential score ranging from 5 to 25). These totaled intermediate scores were reranked into quintiles by tract to produce a final health risk and



exposure score ranging from 1 to 5. As each metric is at the tract level, the CI polygons receive scores correspondent to their host census tract.

**Social and Health Vulnerability Indicators**

The social and health vulnerability indicators include tract-level metrics identified in the social epidemiology and environmental justice literature as important determinants of health outcomes and statistically significant determinants of disparate patterns of disease distribution (Table A4).

Table A4. Social and health vulnerability indicators

INDICATOR	GIS SPATIAL UNIT	SOURCE
% people of color (total population non-Hispanic white)	Census tract	US Census (2000)
% below 2x the national poverty level	Census tract	US Census (2000)
Home ownership—% living in rented households	Census tract	US Census (2000)
Housing value—median housing value	Census tract	US Census (2000)
Educational attainment—% >24 yrs with <high school degree	Census tract	US Census (2000)
Age of residents—% <5 yrs	Census tract	US Census (2000)
Age of residents—% > 60 yrs	Census tract	US Census (2000)
Linguistic isolation—% residents <4 yrs in households where no one >15 yrs speaks English well	Census tract	US Census (2000)
Voter turnout—% votes cast in general election	Census tract	UC Berkeley Statewide Database (2000)
Birth outcomes—% preterm and small for gestational age	Census tract	CA Dept of Public Health (1996-2003)

Each metric above was assigned an intermediate score by ranking 1 (lowest impact) through 5 (highest impact) based on quintiles. To ensure that social and health vulnerability scores were not distorted, tracts with fewer than 50 people and those with fewer than six indicator values were not scored (about 1% of all census tracts); some tracts had already been eliminated since they did not have any residential land. To insure comparability, final cumulative scores were calculated by dividing the sum by the number of non-missing metrics. These totaled intermediate scores were reranked into quintiles by census tract to produce a final social health and vulnerability score ranging from 1 to 5. As each metric is at the tract level, the CI polygons receive scores correspondent to their host census tract.

**Assigning a Final Cumulative Score**

To assign a final score to the census tracts, and subsequently to the CI polygons, the three quintile scores (the Hazard Proximity Indicator, the Health Risk and Exposure Indicator, and the Social and Health Vulnerability Indicator) were summed to create a Total Cumulative Impact Score that ranged from 3 to 15. These scores were attached to each CI polygon for GIS visualization, focusing attention to residential areas and sensitive land uses.

To supplement this research, we created a fourth indicator—Population Vulnerability to Climate Change—using a similar method to score census tracts based on quintile rankings. Our methods and findings are described in the main body of this report.

## Appendix B: Environmental Justice Screening Method (EJSM)—Final Results

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The following results discussed here summarize the findings presented by Sadd et al. in *Playing it Safe: Assessing Cumulative Impact and Social Vulnerability through an Environmental Justice Screening Method in the South Coast Air Basin, California*.<sup>i</sup> Please refer to the full report for a more complete description of their assessment. Their methodology is explained in Appendix A. The results shown are only for Los Angeles County (results for Fresno County were not yet ready for publication in the article cited above).

The images below are shown for the Los Angeles County area for the calculate Hazard Proximity and Land Use Indicator, the Air Pollution Exposure and Estimated Health Risk Indicator, the Social Vulnerability Indicator, and finally, the Cumulative Impact (CI) Score.

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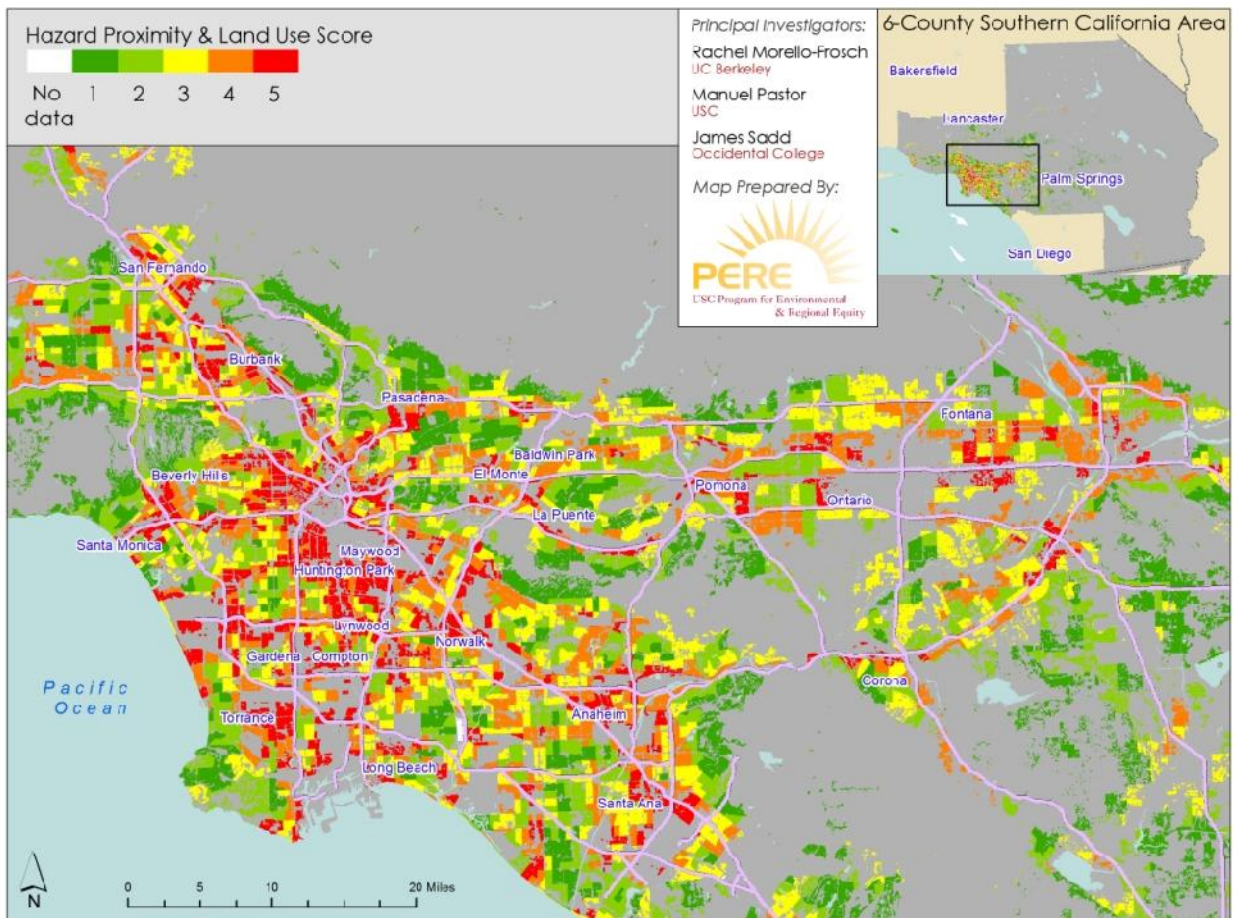
<sup>i</sup> Sadd JL, Pastor M, Morello-Frosch R, Scoggins J, Jesdale B. "Playing it Safe: Assessing Cumulative Impact and Social Vulnerability through an Environmental Justice Screening Method in the South Coast Air Basin, California". *International Journal of Environmental Research and Public Health*. 2011. 8:1441-1159.

**Hazard Proximity and Land Use Indicator**

A set of hazard proximity indicators was attached to each cumulative impact polygons and summarized to create scores at the tract level. This category captures the location of stationary emission sources and sensitive land uses, including buffer distances to separate residential and other sensitive land uses from environmental health hazards, based on CARB recommendations. The final Hazard Proximity and Land Use Scores are shown in Figure B1.

Areas with high hazard proximity and sensitive land use scores tend to correspond with the more densely populated areas, and often cluster around major industrial centers or follow major transportation corridors. High scores are typical in areas characterized by minority, low income populations, and adjacent to sectors of concentrated industrial activity, such as the Ports of Los Angeles/Long Beach, the Los Angeles International Airport, and the industrial core of Los Angeles running from the ports to downtown L.A.

Figure B1. Final Hazard Proximity and Land Use Scores for the Los Angeles County area

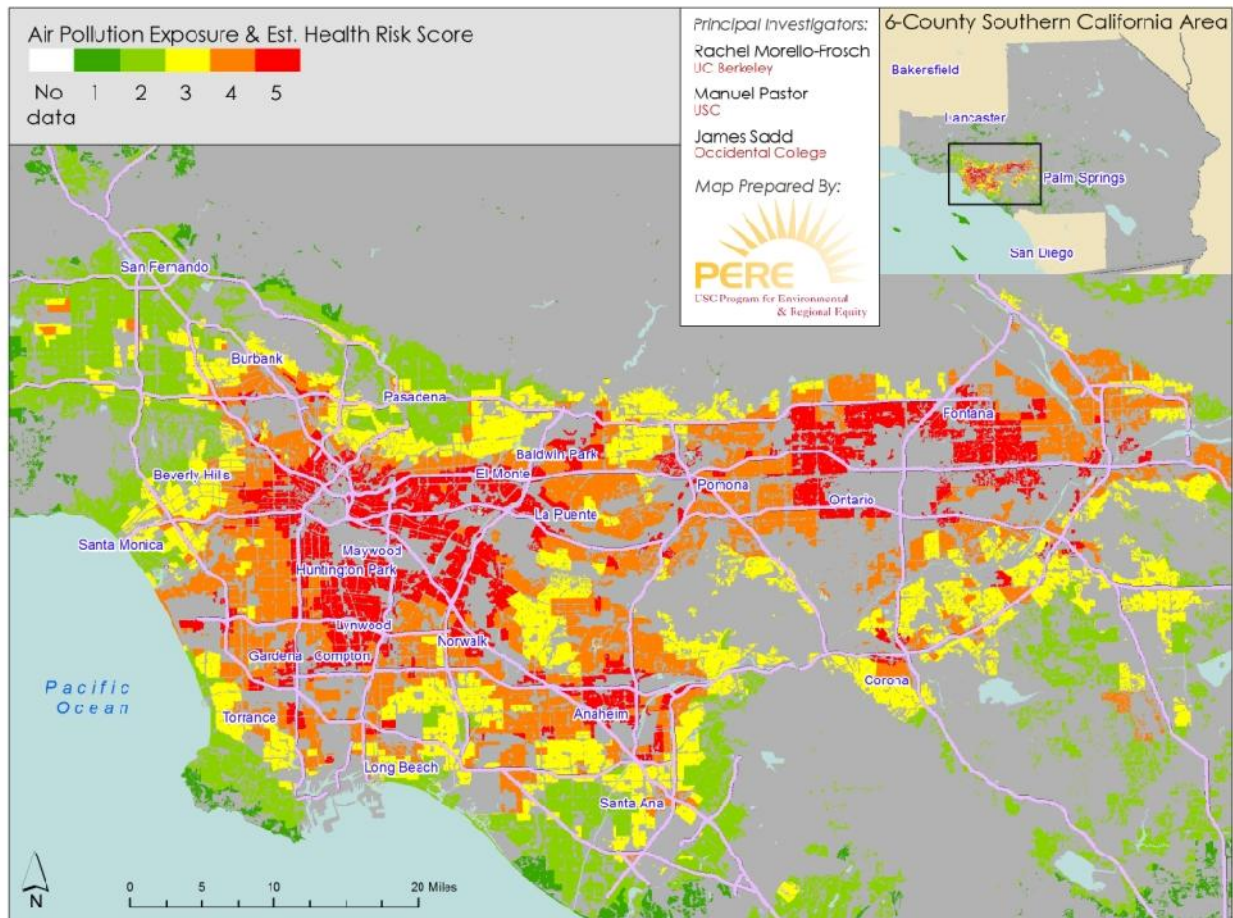


**Air Pollution Exposure and Estimated Health Risk Indicator**

The health risk and exposure indicators consist of five metrics of air pollution or health risk estimates associated with air toxics. The metrics are assessed at the census tract level, and assigned to the resident cumulative impact polygons of that tract. The final Air Pollution Exposure and Estimated Health Risk Scores are shown in Figure B2.

The geographic distribution of the Health Risk and Exposure scores is less complex, but with a clear concentric pattern with little fine-scale variation, resulting in broad areas with a single score. Areas with the highest scores surround heavily industrialized areas, including central and East Los Angeles, the Alameda corridor connecting downtown to the ports along the 710 transportation corridor, and the industrial centers in Baldwin Park and east of Ontario International Airport. Coastal and foothill neighborhoods are characterized by low scores, and the apparent effects of the freeway system on the overall pattern are minor. These results are similar to those from past exposure studies, suggesting that the results from the EJSM are consistent with other screening approaches.

Figure B2. Air Pollution Exposure and Estimated Health Risk Scores for the Los Angeles County Area

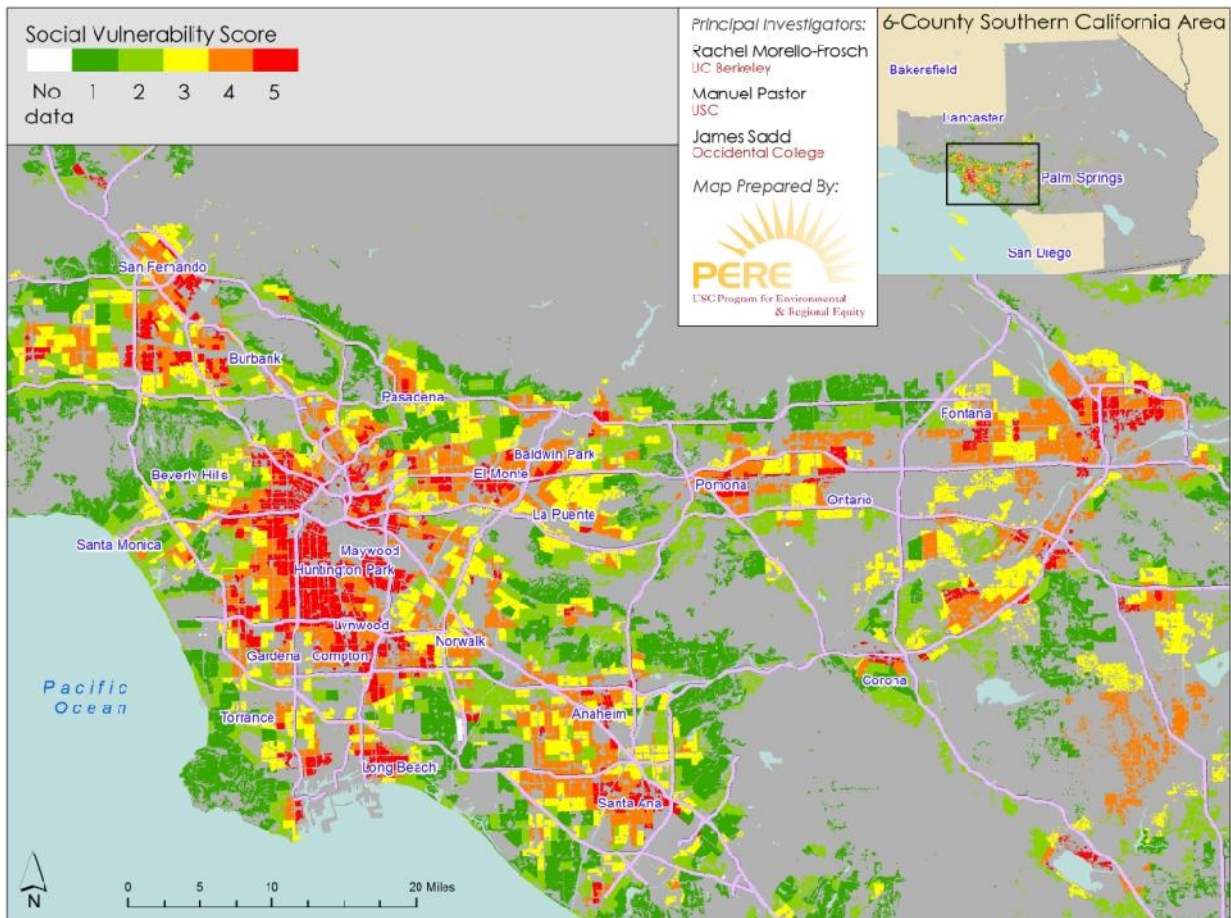


**Social Vulnerability Indicator**

The social and health vulnerability indicators include tract-level metrics identified in the social epidemiology and environmental justice literature as important determinants of health outcomes and statistically significant determinants of disparate patterns of disease distribution. To ensure that social and health vulnerability scores were not distorted, tracts with fewer than 50 people and those with fewer than six indicator values were not scored (about 1% of all census tracts). To insure comparability, final cumulative scores were calculated by dividing the sum by the number of non-missing metrics. The metrics are assessed at the census tract level, and assigned to the resident cumulative impact polygons of that tract. The final Social Vulnerability Scores are shown in Figure B3.

The Social Vulnerability Scores reflect the well documented pattern of residential segregation in metropolitan Los Angeles by race and class. Many of the same neighborhoods bearing the burden of high exposure to air pollution are also those where the most vulnerable populations are concentrated.

Figure B3. Social Vulnerability Scores for the Los Angeles County Area

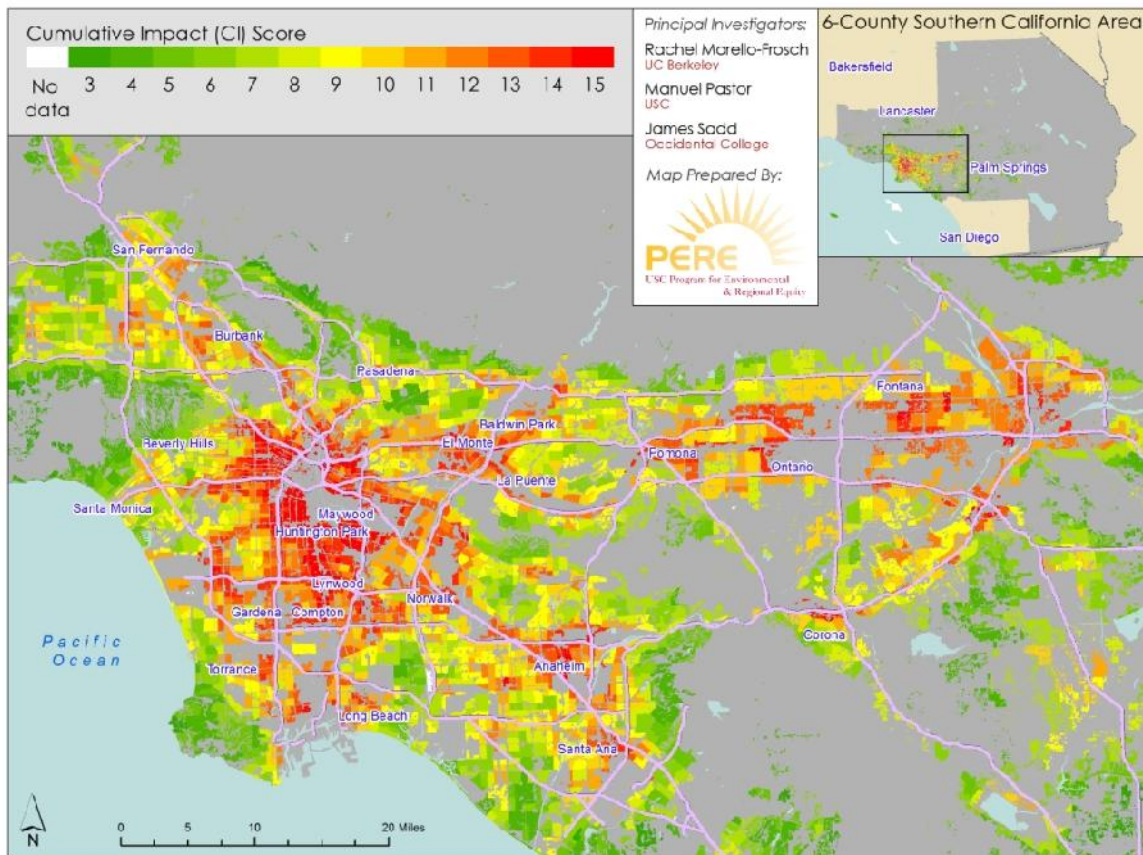


### Final Cumulative Impact (CI) Scores

To assign a final CI score to the census tracts, and subsequently to the cumulative impact polygons, the three quintile scores (the Hazard Proximity Indicator, the Health Risk and Exposure Indicator, and the Social and Health Vulnerability Indicator) were summed to create a Total Cumulative Impact Score that ranged from 3 to 15. These scores were attached to each CI polygon for GIS visualization, focusing attention to residential areas and sensitive land uses. The results of the final Cumulative Impact Scores are shown in Figure B4.

Communities near the ports and airports, as well as the Pacoima neighborhood in the San Fernando Valley, have the highest CI scores (shown in red). Community activism around environmental justice has occurred in these areas and these communities often receive targeted attention from regulators and policy makers. What is perhaps more useful is that the CI map also points to communities that do not have a record of organizing and have not brought themselves to the attention of regulators or decision-makers, such as East Los Angeles (which is intersected with freeways and populated with other smaller hazards), Pomona east of Los Angeles, and parts of the Inland Valley (reaching into Riverside and San Bernardino Counties). From the view of regulators, the map helps direct attention to places where specific attention may be needed to address environmental health concerns not usually considered; from the point of view of community stakeholders, the map highlights locations where residents may need to be educated and engaged to address environmental hazards.

Figure B4. Final Cumulative Impact Scores in the Los Angeles County Area



## Appendix C: Data Sources for Climate Change Population Vulnerability Screening Tool

The data described in Table C1 were used to develop the climate change population vulnerability screening tool. Additional data were collected on chronic disease for Los Angeles County (from a health assessment survey) and for Fresno County (from school health studies), but because the data were so sparse and too granular for analysis, they were not included in the final assessment. Increasing the surveillance of chronic disease conditions at the sub-county level will assist in future assessments and health evaluations.

Table C1. Data sources and definitions for data layers used to develop the climate change population vulnerability screening tool

Data Layer	Data Definition	Original Geographic Unit	Year	Final Geographic Unit	Data Source	Other Data Notes
<b>AC ownership</b>	The proportion of households with central air conditioning (does not include window units or swamp coolers as central AC units)	Data referenced by zip code; ESRI 2009 zip code polygons	2009	Census tract (2000)	California Energy Commission (CEC) Residential Appliance Saturation Survey: <a href="http://www.energy.ca.gov/applications/rass/">http://www.energy.ca.gov/applications/rass/</a> . Record level data had to be requested from CEC. Aggregate data available online.	A spatial empirical Bayes model was performed of AC prevalence by zip code. These figures were converted to census tract polygons using area weighted averages.
<b>Impervious surfaces</b>	Average percent of each raster pixel that is classified as an impervious surface	Raster data, 30m Landsat pixel cell	2001	Census tract (2000)	National Land Cover Database: <a href="http://www.epa.gov/mrlc/nlcd-2001.html">http://www.epa.gov/mrlc/nlcd-2001.html</a>	Pixel values were averaged across census block groups, then averaged up to census tracts using population weighting. Data courtesy Bill Jesdale and Rachel Morello-Frosch, UC Berkeley.

Data Layer	Data Definition	Original Geographic Unit	Year	Final Geographic Unit	Data Source	Other Data Notes
<b>Tree canopy</b>	Average percent of each raster pixel that is classified as tree canopy	Raster data, 30m Landsat pixel cell	2001	Census tract (2000)	National Land Cover Database: <a href="http://www.epa.gov/mrlc/nlcd-2001.html">http://www.epa.gov/mrlc/nlcd-2001.html</a>	Pixel values were averaged across census block groups, then averaged up to census tracts using population weighting. Data courtesy Bill Jesdale and Rachel Morello-Frosch, UC Berkeley. Processed using GIS overlays.
<b>Transit routes</b>	The number of unique transit routes per census tract	Line data by county	LA: 2007 Fresno: 2003-09	Census tract (2000)	LA: Southern California Association of Governments ( <a href="http://developer.metro.net/">http://developer.metro.net/</a> )  Fresno: Fresno Council of County Governments (requested via email)	
<b>Household car access</b>	The proportion of households with at least one vehicle	Census tract	2000	Census tract (2000)	US Census: <a href="http://www.census.gov/main/www/cen2000.html">http://www.census.gov/main/www/cen2000.html</a>	
<b>Flood risk</b>	Average flood risk as ascertained by the Federal Emergency Management Agency (FEMA)	Polygons assigned as low, moderate, or high risk areas	LA: 2008 Fresno: 2009	Census tract (2000)	FEMA: <a href="http://www.fema.gov/plan/prevent/fhm/index.shtm">http://www.fema.gov/plan/prevent/fhm/index.shtm</a>	



Data Layer	Data Definition	Original Geographic Unit	Year	Final Geographic Unit	Data Source	Other Data Notes
Sea rise	Proportion of population by census tract vulnerable to inundation from sea level rise	Census blocks	LA: 2000 Fresno: NA	Census tract (2000)	Pacific Institute: <a href="http://www.pacinst.org/reports/sea_level_rise/">http://www.pacinst.org/reports/sea_level_rise/</a>	Data were recalculated for census tracts.
Wildfire risk	Average wildfires along the wildfire-urban interface (WUI)	100m GRID data assigned to threat levels ranging from "little to moderate threat" to "extreme threat"	2003	Census tract (2000)	CAL FIRE: <a href="http://frap.cdf.ca.gov/data/frap_gisdata/download.asp?rec=wui">http://frap.cdf.ca.gov/data/frap_gisdata/download.asp?rec=wui</a>	Area weighted averages were calculated for each census tract.
Elderly living alone	The proportion of households consisting of an elderly individual (65+ years) living alone	Census tract	2000	Census tract (2000)	US Census: <a href="http://www.census.gov/main/www/cen2000.html">http://www.census.gov/main/www/cen2000.html</a>	

## Appendix D: Climate Change Population Vulnerability Screening Tool—Final Results

Overall, results from the CEHTP Climate Change population vulnerability screening tool are similar to those from the environmental justice screening methodology developed by Sadd et al. This suggests that environmental justice communities that currently experience many health disparities due to environmental hazards and socioeconomic inequities are also at greatest risk from the effects of climate change. The results from Los Angeles County and Fresno County are described below.

### **RESULTS FROM COMPONENT DATA SETS**

The climate change population vulnerability indicator for Los Angeles County was devised from 9 distinct data sets, and 8 data sets in Fresno County. The results from each data set are described and shown below.

#### **Central AC Ownership**

Data on AC ownership was the most incomplete data set in the final indicator (Los Angeles County—74% complete; Fresno County—78% complete). In Los Angeles County, census tracts near downtown Los Angeles and the southwestern coast have the lowest prevalence of central air conditioning ownership (Figure D1a). In Fresno County, central AC ownership tends to be more uniform, though there are areas with lower AC access in western Fresno and near downtown Fresno (Figure D1b). Tracts with greater access to central AC were assigned lower risk scores.

Figure D1a. Central AC ownership at the census tract level, Los Angeles County

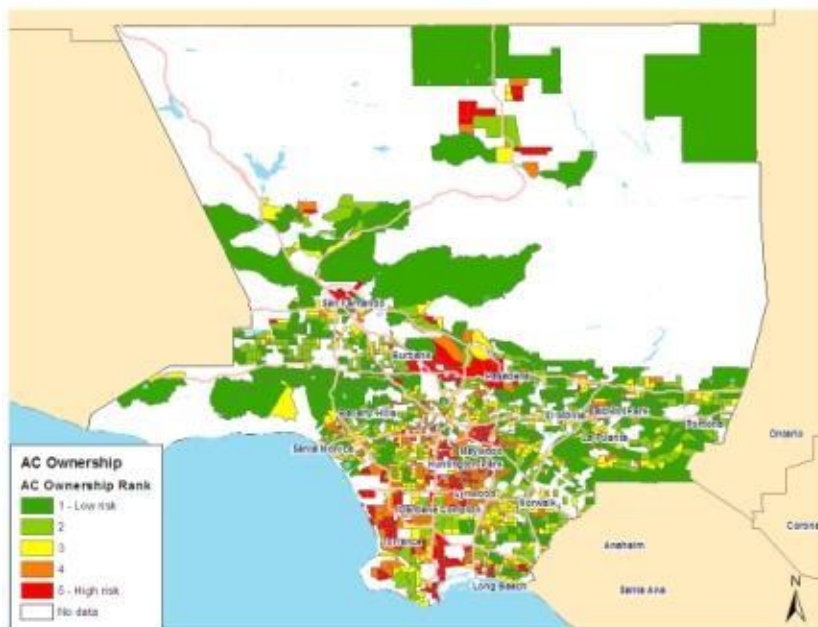
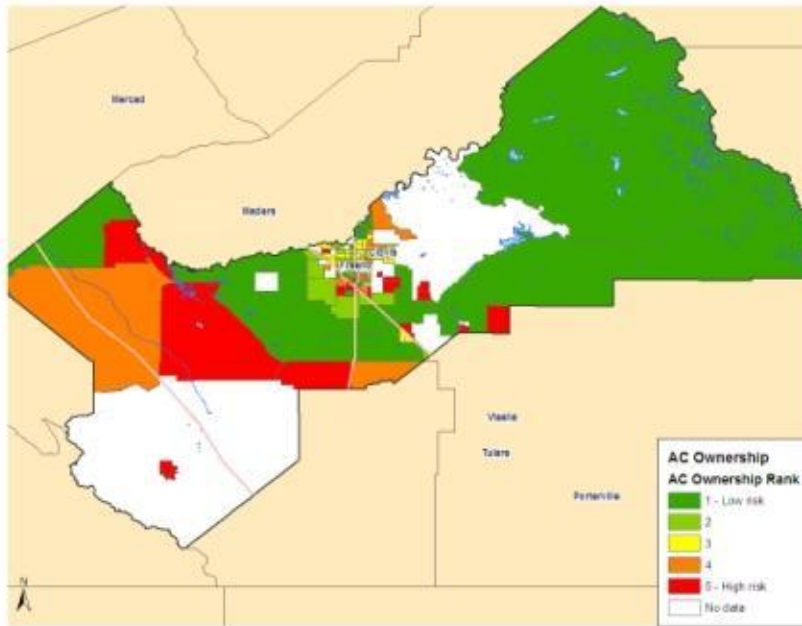


Figure D1b. Central AC ownership at the census tract level, Fresno County



Data on air conditioning access were the least complete of all indicators. Data came from the Residential Appliance Saturation Survey. To compensate for a low sample size and incomplete coverage, data were smoothed using a spatial empirical Bayes model. The model assumed a beta distribution for AC prevalence and uses the weighted count of respondents with and without air conditioning in each ZIP code as inputs. For each ZIP code  $i$ , the 'prior distribution' is calculated using all of the respondents in ZIP codes adjacent to  $i$ , and the 'posterior distribution' is the prior distribution updated by the counts in ZIP code  $i$  itself. Zip level AC prevalence was then transferred to the tract level using an area weighted average.

### Impervious Surfaces and Tree Canopy

For both Los Angeles and Fresno Counties, the most urbanized census tracts had the lowest tree canopy coverage (Figure D2a and D2b). Similarly, these same tracts often had a greater average of impervious surfaces (Figure D3a and D3b), though this is less pronounced for the more rural Fresno County. Tree canopy coverage in Los Angeles seems very binary because of the ranking method employed (assigning tied rankings to the lowest ranking possible), and the relatively modest range of the data. However, the map accurately conveys the location of Los Angeles County's most forested areas. Other users could reassign data ranks to better portray the range of the data.<sup>viii</sup>

Tracts with high canopy coverage have low risk scores, while tracts with high impervious surface coverage have high risk scores.

<sup>viii</sup> Maintaining a simple methodology was one goal of this research, increasing user access to the methods employed, as well as their ability to modify the methods to suit their local needs. However, at times, such a simplistic approach leads to minor data anomalies, such as the seemingly binary distribution of canopy coverage in Los Angeles County. Yet the simplicity of the method also allows for others to easily modify the approach to best fit their needs. The same methodology was used for Fresno County.

Figure D2a. Average tree canopy at the census tract level, Los Angeles County



Figure D2b. Average tree canopy at the census tract level, Fresno County

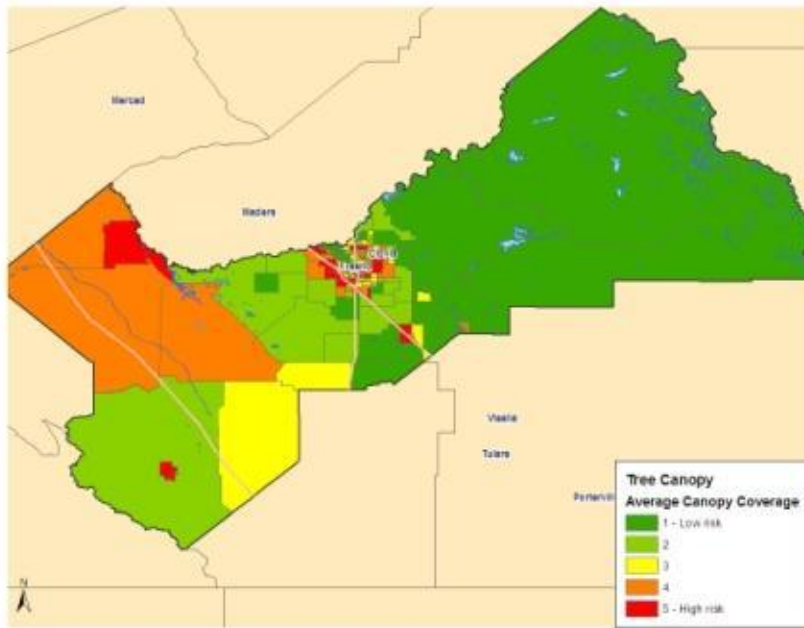
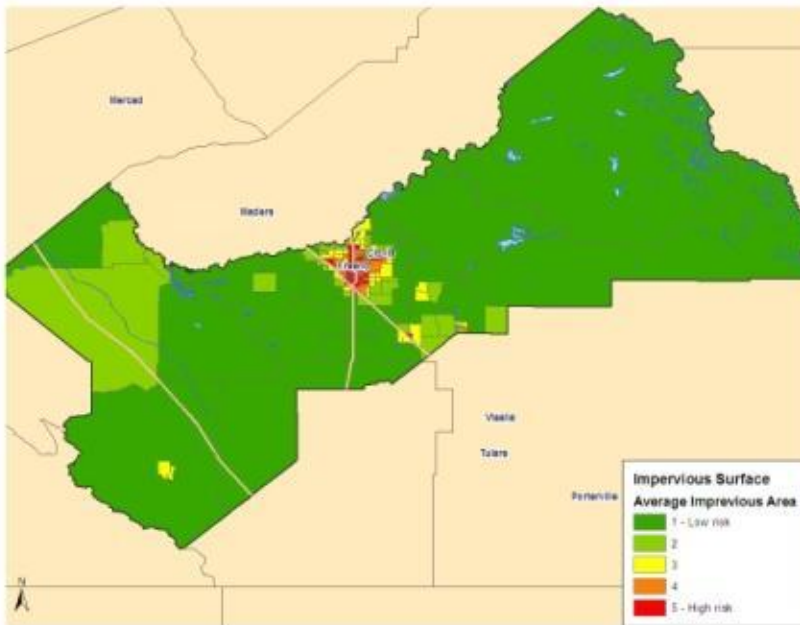


Figure D3a. Average impervious surface coverage at the census tract level, Los Angeles County



Figure D3b. Average impervious surface coverage at the census tract level, Fresno County



**Transportation Access**

Two metrics were used for transportation access: access to public transportation (measured as the number of unique transit routes per census tract) and the proportion of households with at least one vehicle. More urbanized census tracts and those with dense populations had lower risk scores for access to public transit (Figure D4a and D4b). Inversely, more rural or suburban

census tracts had greater access to personal vehicles (Figure D5a and D5b), and thus lower risk scores.

Figure D4a. Average public transit access at the census tract level, Los Angeles County



Figure D4b. Average public transit access at the census tract level, Fresno County

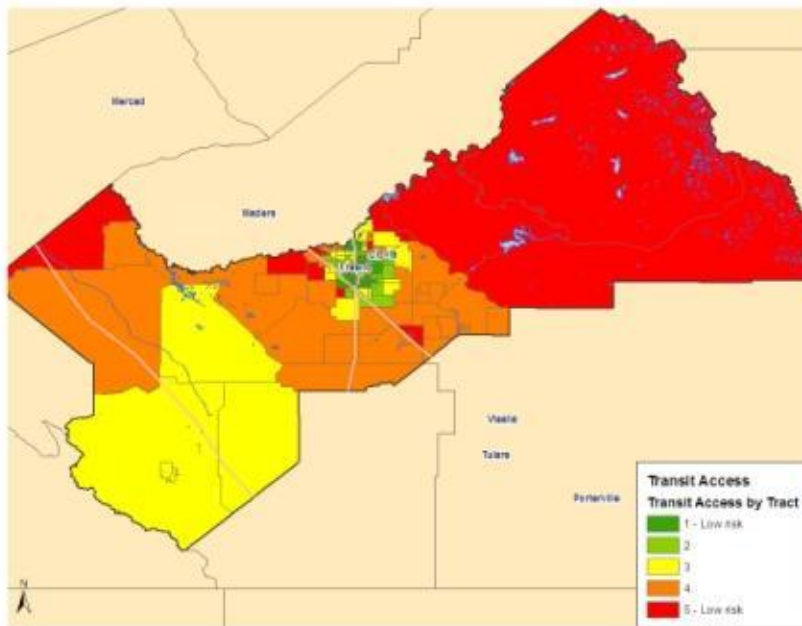
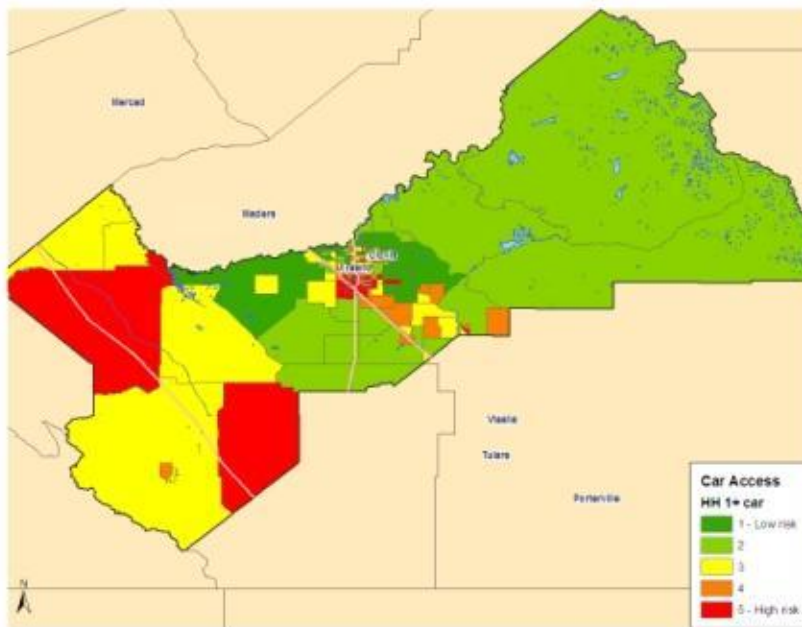


Figure D5a. Average car access at the census tract level, Los Angeles County



Figure D5b. Average car access at the census tract level, Fresno County



### Flood Risk & Sea Rise

Flood risk data was compiled from the Federal Emergency Management Agency (FEMA). Areas with the highest high flood risks are shown in red (Figure D6a and D6b). Flood risk is more sporadic than other metrics, impacting both rural and urban areas.

Figure D6a. Average flood risk at the census tract level, Los Angeles County

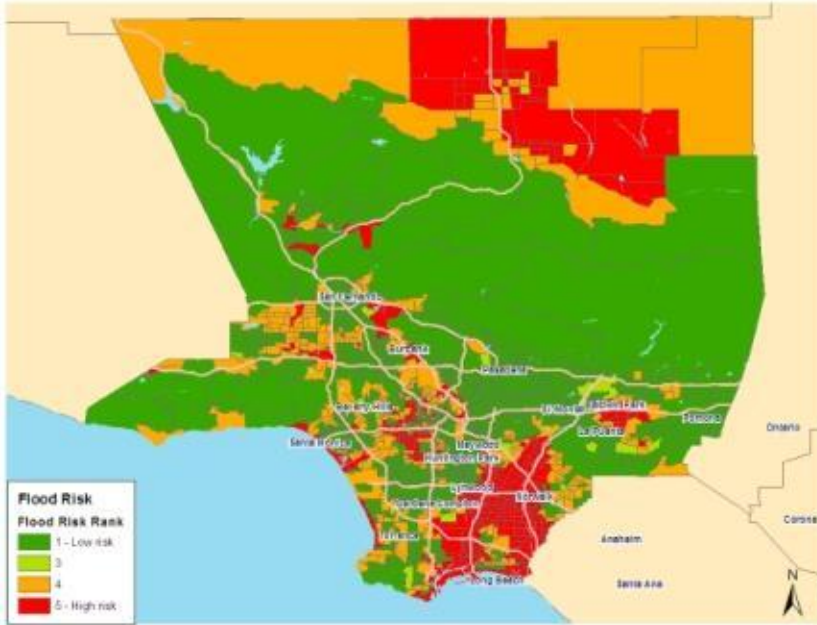
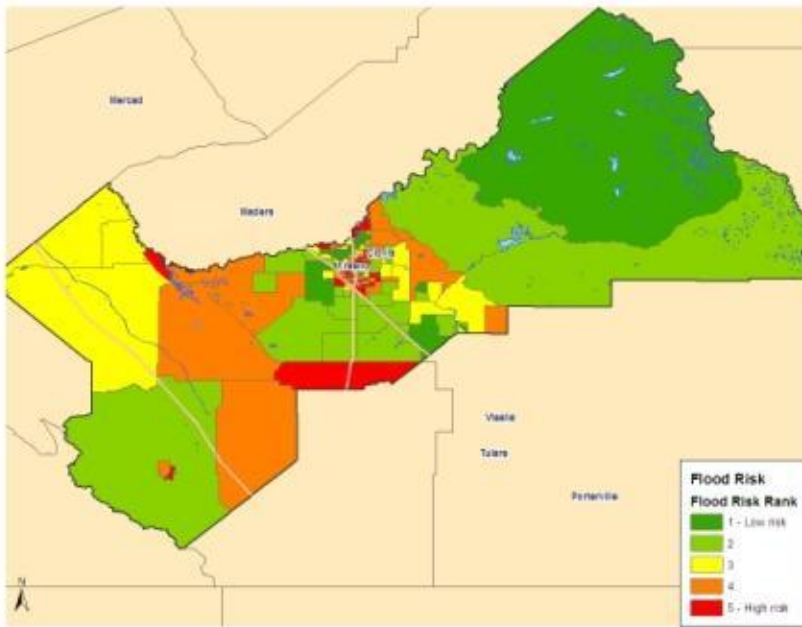


Figure D6b. Average flood risk at the census tract level, Fresno County



Sea rise is a risk unique to Los Angeles County and other coastal areas in California and throughout the world. Similar to the data for average tree canopy, the ranking method employed makes sea rise seem like a binary risk (Figure D7). A decision was made to include all census tracts in the calculation for ranking sea rise risk even when they were inland census tracts that would not be impacted, because all other metrics were ranked against all census tracts within the county, and because sea rise will very much impact coastal communities much

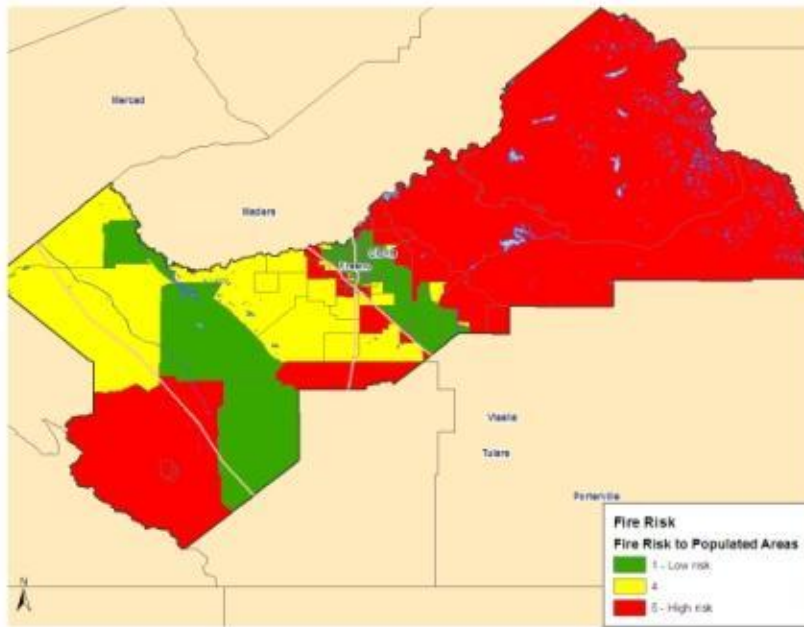




Figure D8a. Average fire risk at the census tract level, Los Angeles County



Figure D8b. Average fire risk at the census tract level, Fresno County



### Elderly Living Alone

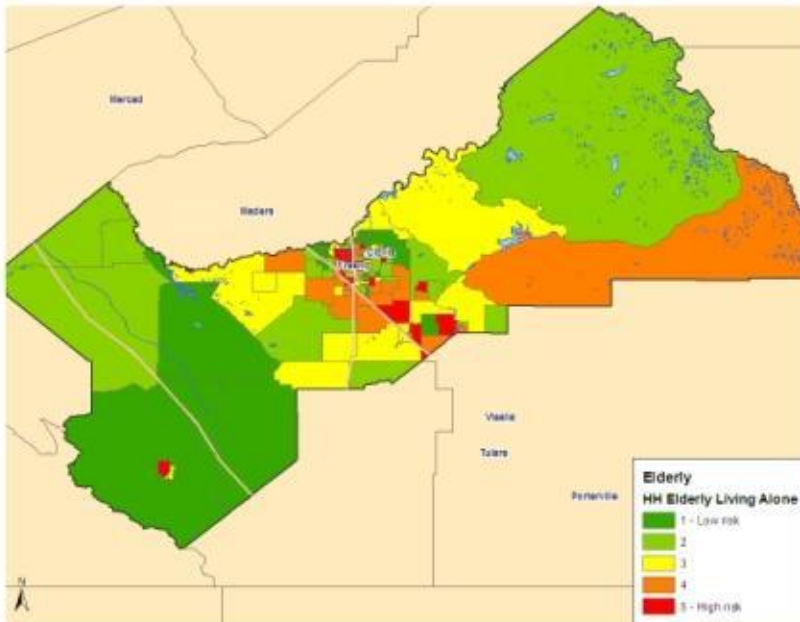
Census tracts with a relatively high proportion of elderly living alone (aged 65+ years) are at greater risk to weather events or other disasters related to climate change. In Los Angeles County, some rural areas and localized pockets in urban areas have a larger proportion of

elderly living alone (Figure D9a). In Fresno County, there is some clustering south of Fresno city center (Figure D9b).

Figure D9a. Elderly living alone at the census tract level, Los Angeles County



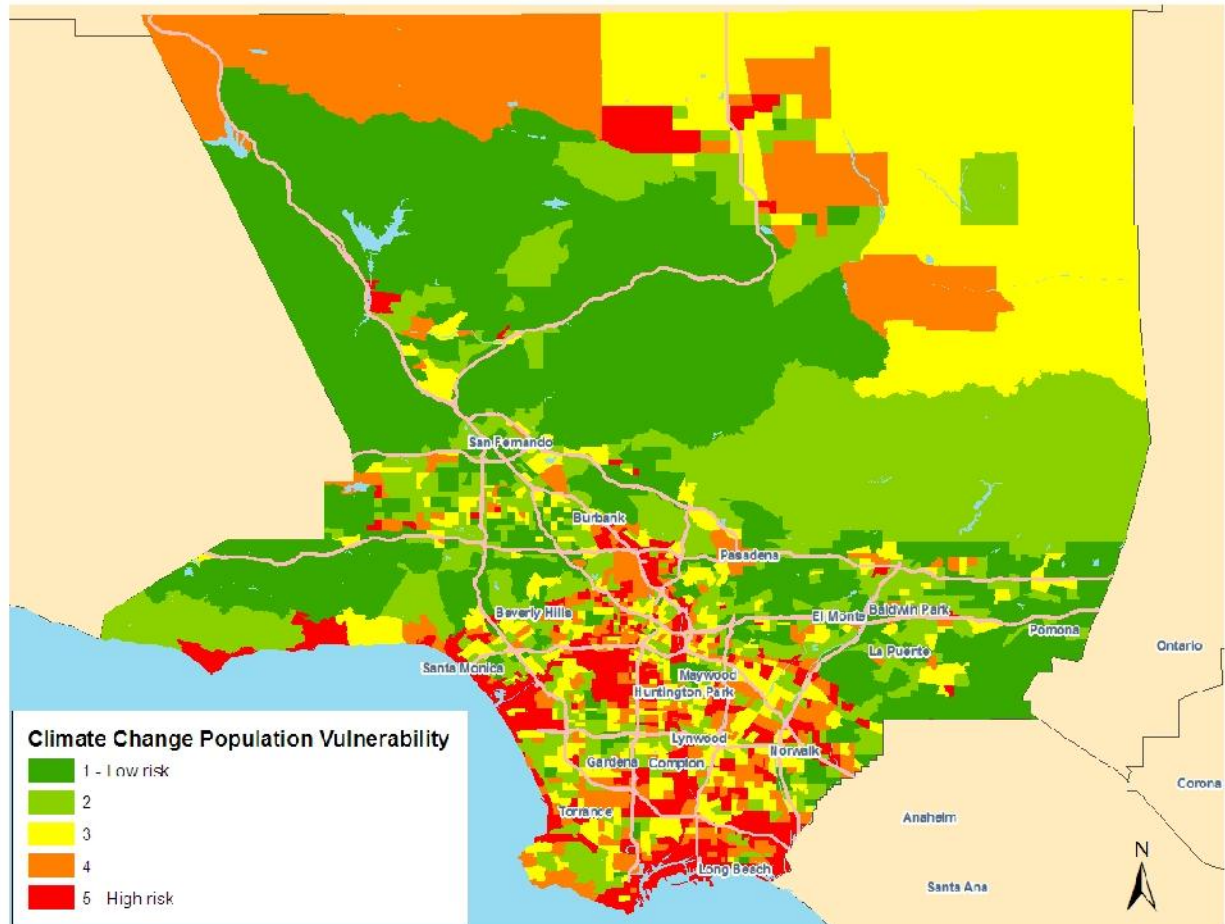
Figure D9b. Elderly living alone at the census tract level, Fresno County



## **FINAL INDICATOR RESULTS**

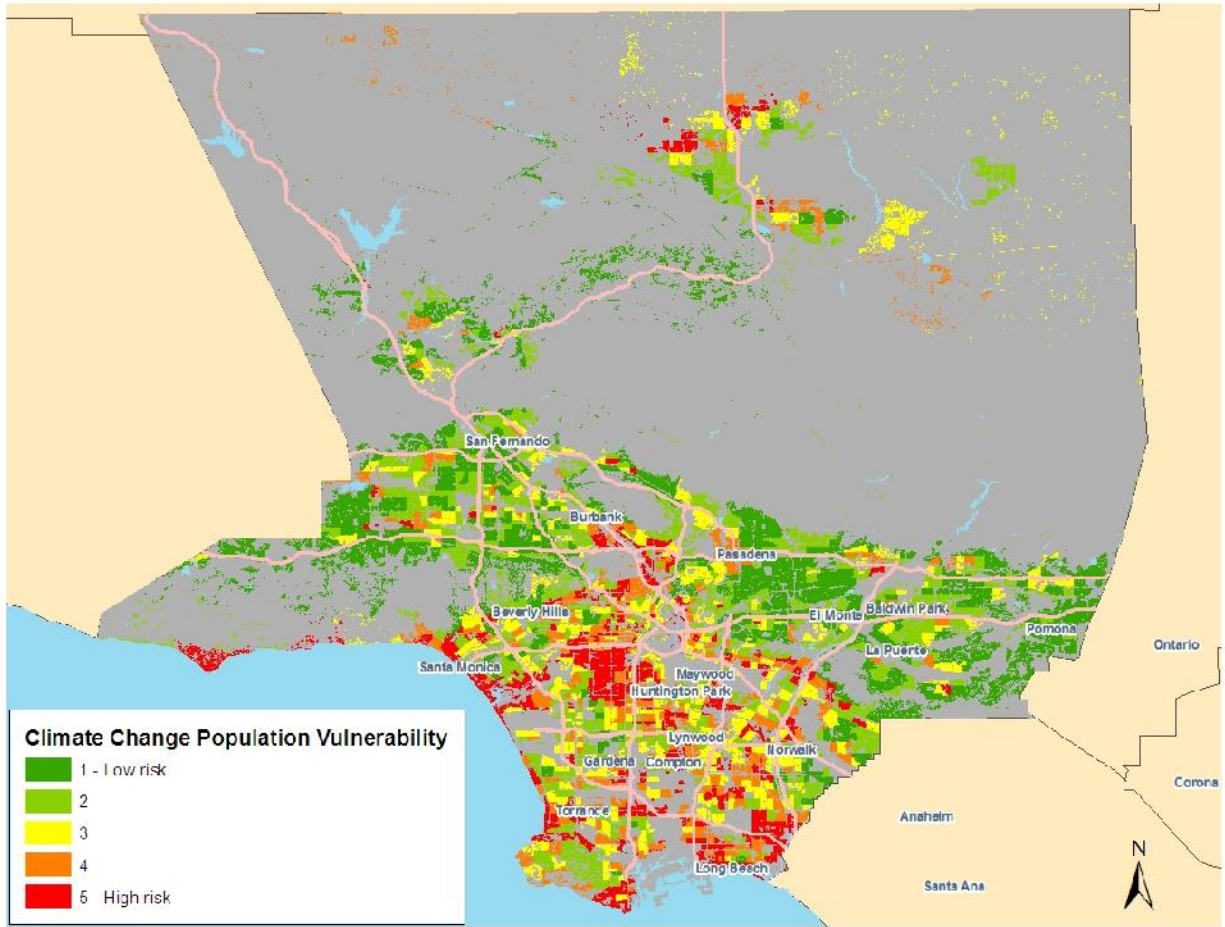
The data sets shown above were average for each census tract to create a final risk score for population vulnerability to climate change at the census tract level. The results for Los Angeles County are shown in Figure D10.

Figure D10. Final climate change population vulnerability risk scores at the census tract level, Los Angeles County



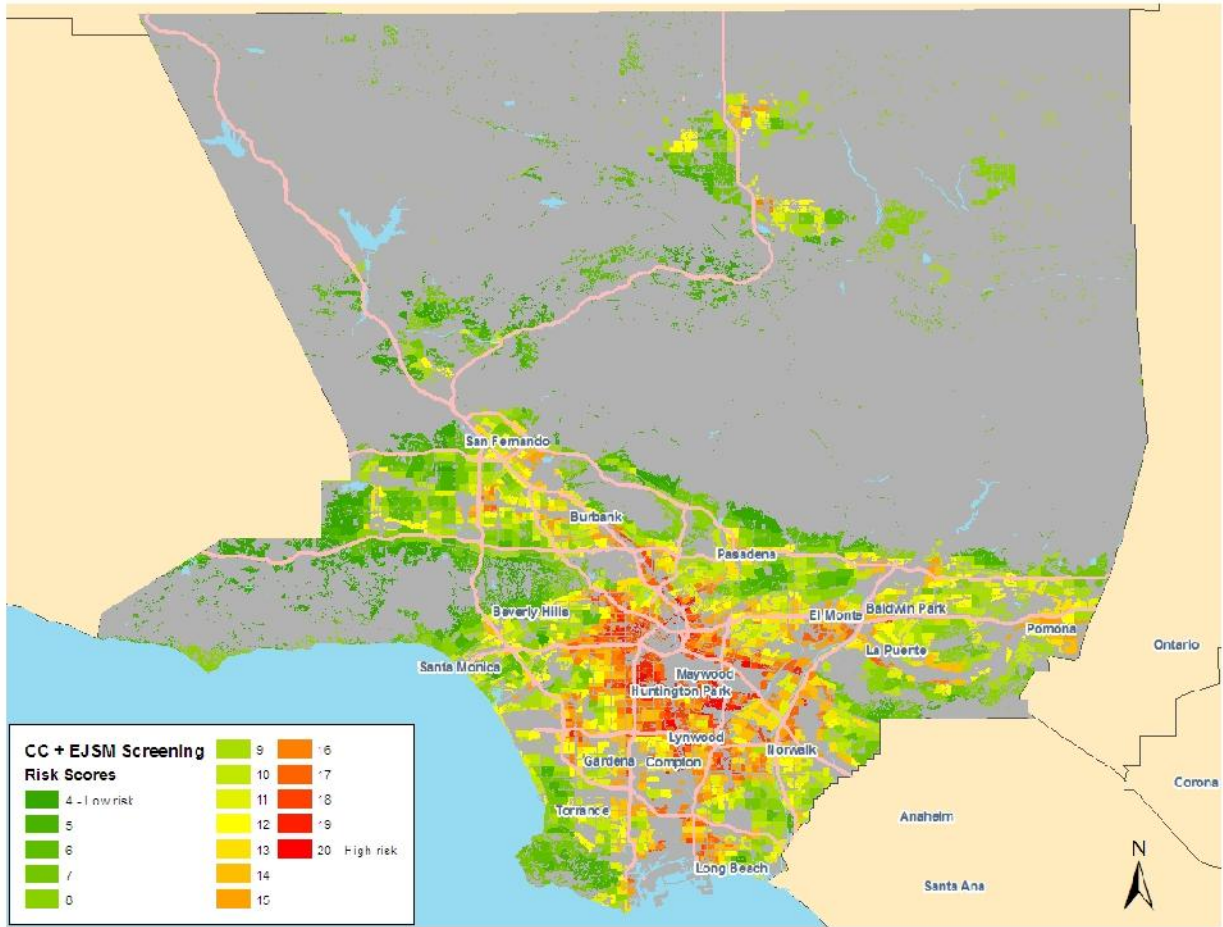
The results from our method are similar to those from the method employed by Sadd et al. Heavily urbanized areas tend to be at greater risk, though coastal areas (largely due to increased risk from sea level rise) tend to show greater population risks when employing our methodology. Figure D10 shows the entire census tract. A layer displaying Sadd et al.'s cumulative impact polygons can be placed over the county to focus attention to areas where individuals reside and where sensitive populations are (Figure D11), as described in Appendix A. Gray areas are land uses in which people do not live and sensitive populations do not reside. This visualization of the data is more useful for understanding where human risks are most pronounced.

Figure D11. Final climate change population vulnerability scores, including cumulative impact polygons, Los Angeles County



The same similarities and differences between our climate change impact screening method and the EJSM tool can be seen when the land use mask is imposed. When the scores from the climate change population vulnerability screening tool are added to the EJSM tool, the results converge more closely (Figure D12), and differences between the two become more muted. Most notably, the addition of the climate change screening tool slightly increases risk scores along coastal communities, most notably Santa Monica. In addition, the risk in downtown areas is reduced relative to the climate change screening method alone. The cumulative risks in areas to the east of San Fernando and in northern Los Angeles County are also reduced. Yet the overall similarities in outcomes between the two methods suggest that environmental justice communities in Los Angeles County also face the greatest challenges in terms of climate change preparedness.

Figure D12. Cumulative risk scores from the climate change population vulnerability and EJSM screening tools, Los Angeles County



The final results from the climate change population vulnerability screening tool are similar to results from the EJSM in Fresno County (Figure D13). Results for Fresno from the Sadd et al. methodology were not ready for their previous publication. However, the researchers have recently completed computing EJSM scores for Fresno County (Figure D14). Each method shows areas of increased risk in western Fresno County and in urbanized areas. These pockets of greater risk persist when the two methods are combined (Figure D15). A similar land use mask was employed for Fresno County to highlight where people live and sensitive populations reside. An example is shown in Figure D16. Such a map would be useful for planners and local health officers implementing local projects or policies.

Figure D13. Final climate change population vulnerability risk scores at the census tract level, Fresno County

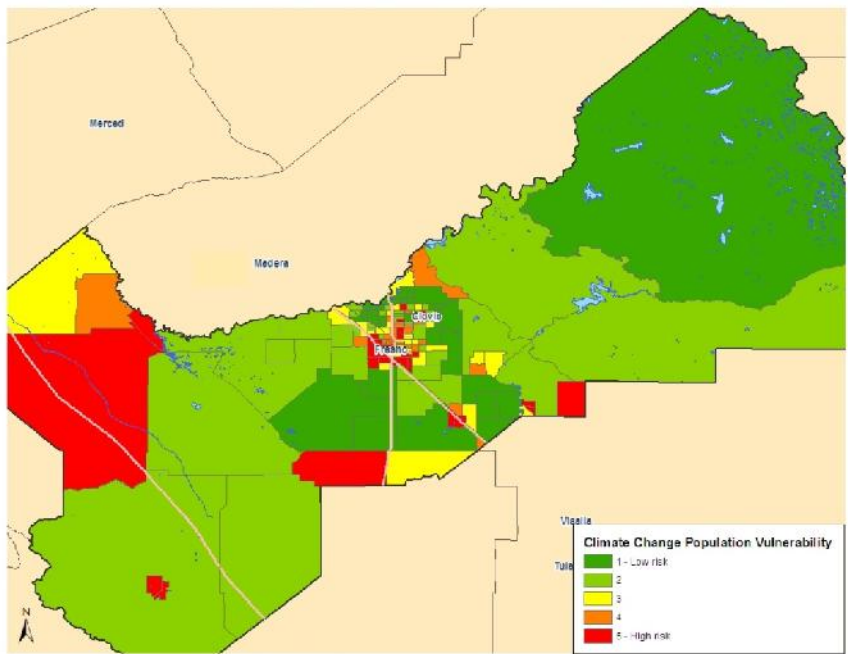


Figure D14. Final EJSM risk scores at the census tract level, Fresno County

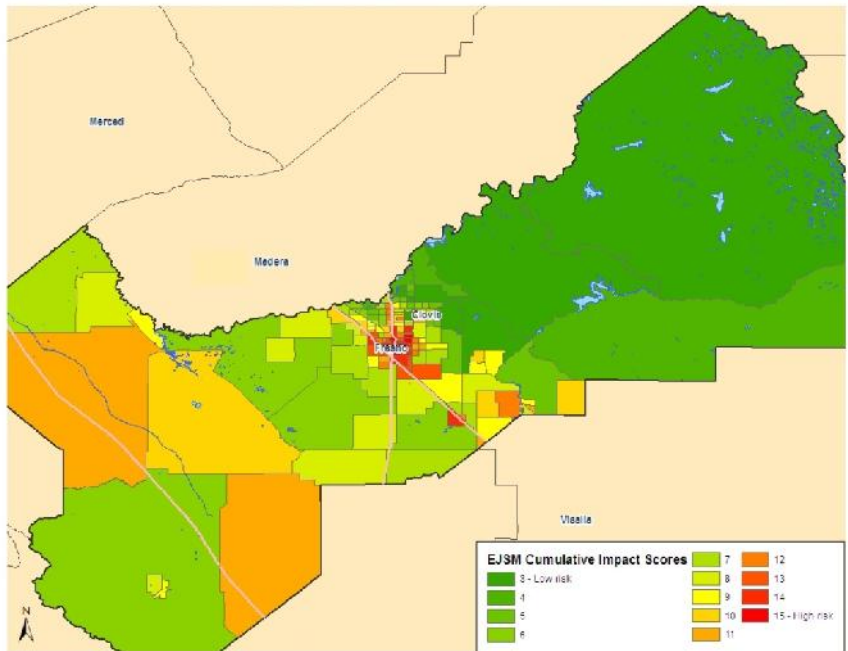


Figure D15. Cumulative risk scores from the climate change population vulnerability and EISM screening tools, Fresno County

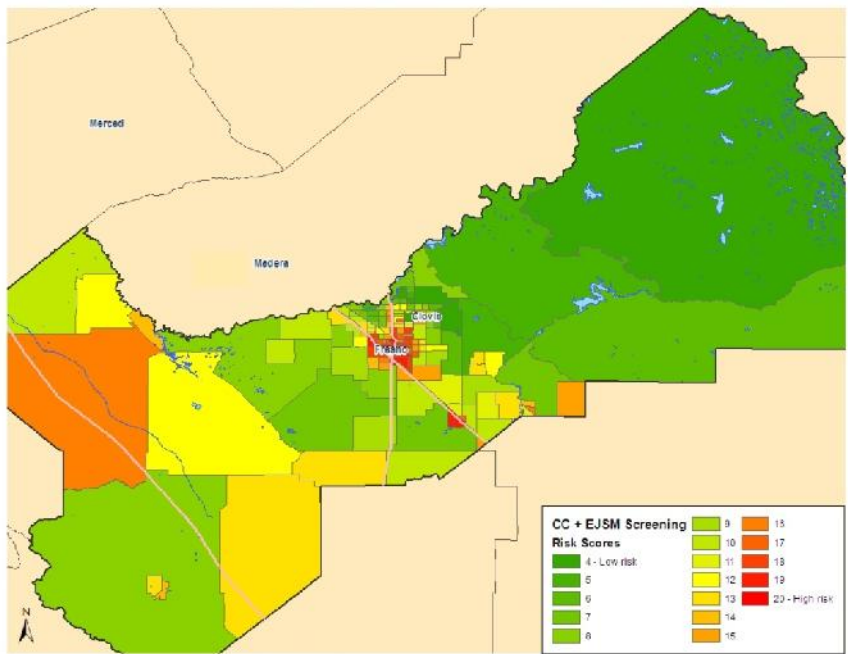
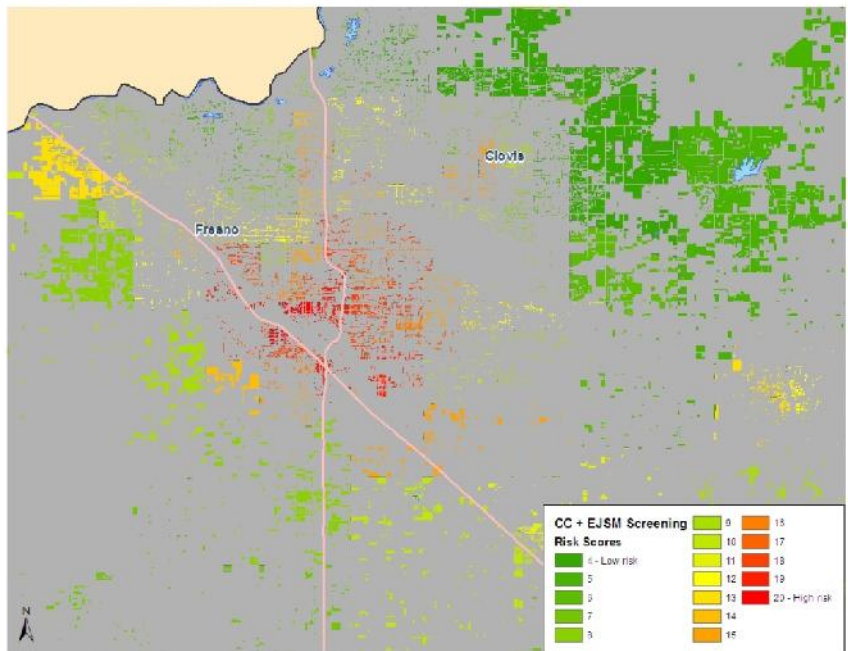


Figure D16. Cumulative risk scores from the climate change population vulnerability and EISM screening tools, Cities of Fresno and Clovis





## **RACIAL DISPARITIES**

Stratifying the climate change vulnerability scores by race shows clear racial disparities exist in Los Angeles and Fresno County. In Los Angeles County, 46% of African Americans and 36% of Latinos reside in the two highest risk categories (those tracts with scores of 4 or 5), while 30% of whites live in these high risk census tracts (Figure D17). The EJSM method by Sadd et al. shows similar racial disparities by risk score, with a higher proportion of African Americans and Latinos residing in high risk areas (Figure D18).

Figure D17. Percent of population by race by climate change vulnerability score, Los Angeles County

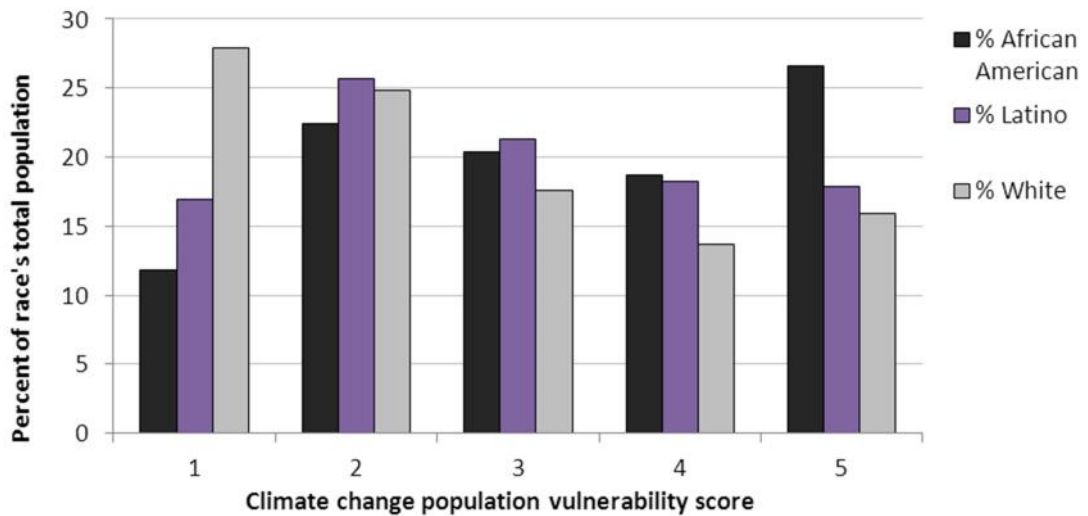
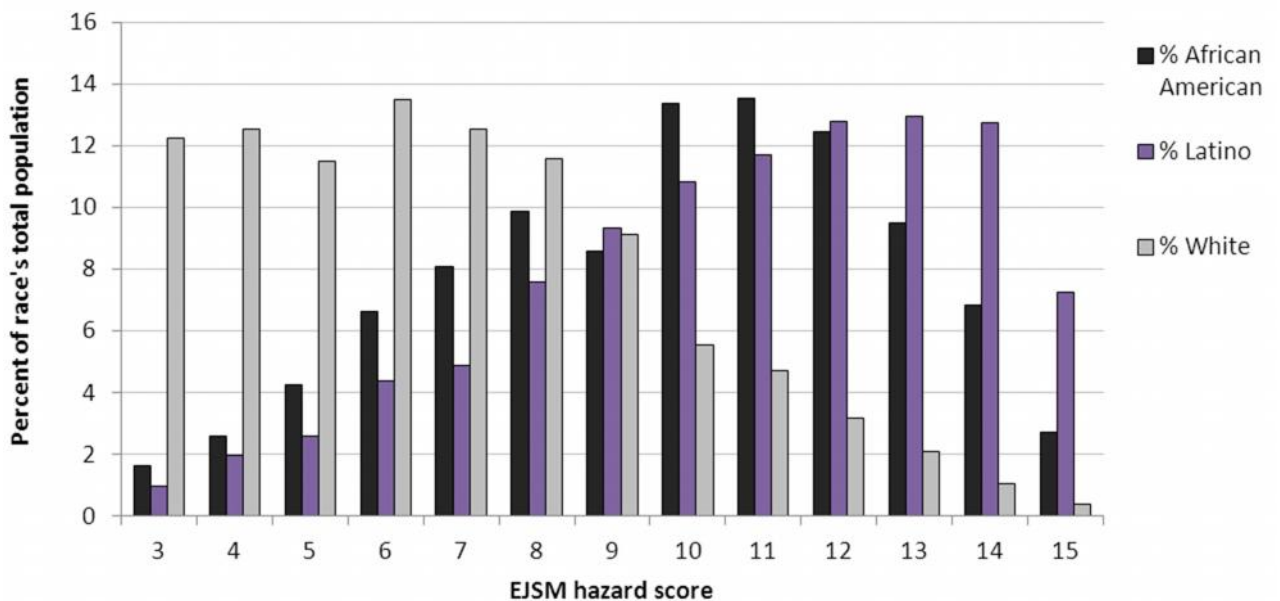


Figure D18. Percent of population by race by EJSM score, Los Angeles County



In Fresno County, 49% of African Americans and 45% of Latinos reside in the two highest risk categories for climate change vulnerability, compared to just 26% of Fresno’s white population (Figure D19). Again, the results are similar to those from Sadd et al. Using the EJSM method, a higher proportion of Latinos and African Americans reside in higher risk census tracts compared to whites (Figure D20).

Figure D19. Percent of population by race by climate change vulnerability score, Fresno County

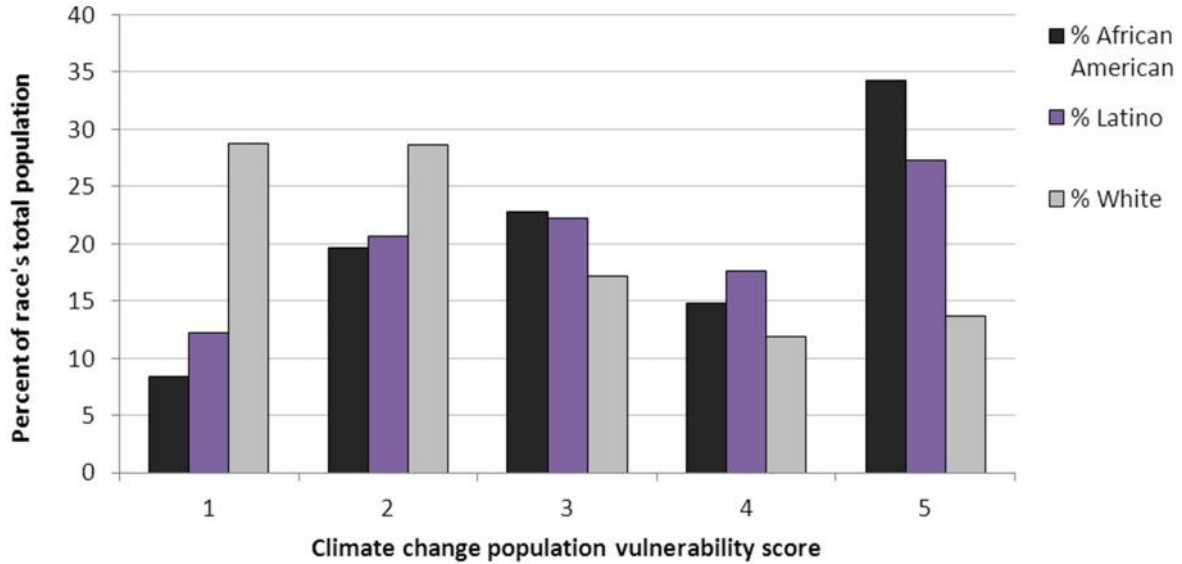


Figure D20. Percent of population by race by EJSM score, Fresno County

