Latino Policy & Politics Institute
Climate & Health Dashboard

Technical Documentation for the Latino Climate and Health Dashboard County Factsheets

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Acronyms and Abbreviations

ACS	American Community Survey
BLS	Bureau of Labor Statistics
CARB	California Air Resources Board
CDC	Centers for Disease Control and Prevention
CES	CalEnviroScreen
CHD	Coronary Heart Disease
CHIS	California Health Interview Survey
CNK	Center for Neighborhood Knowledge
DAC	Disadvantaged Communities
FPL	Federal Poverty Level
LEP	Limited English Proficiency
NARR	North American Regional Reanalysis
NL	Non-Latino
OEHHA	Office of Environmental Health Hazard Assessment
OMB	U.S. Office of Management and Budget
PM	Particulate Matter
SNAP	Supplemental Nutrition Assistance Program
ZCTA	ZIP Code Tabulation-Area

Introduction

Project Background & Objectives

California's Latino communities face disproportionate health risks from environmental hazards, such as air pollution and extreme heat. This project builds on a foundation of prior research and policymaking to create an actionable framework for understanding and addressing environmental health disparities in California.

This report documents the UCLA Latino Policy and Politics Institute's development and construction of county-level factsheets highlighting environmental, health, and socioeconomic disparities between neighborhoods. The factsheets contain county-level and census tract-level indicators identified based on their relevance to environmental justice, climate vulnerability, and public health disparities. This project aligns with California's legislative efforts, including SB 535 (Disadvantaged Communities), AB 32 (California Global Warming Solutions Act), and AB 617 (Community Air Protection). Our factsheets are designed to support decision makers, public agencies, philanthropic partners, and community groups as they address systemic environmental health disparities.

The project's main objectives are: (1) identify key indicators related to environmental, health, and climate burdens at the county and census tract level, (2) create a series of factsheets that highlight disparities by demographic groups and neighborhood types, and (3) develop tools for stakeholders, policymakers, and advocacy groups to use in addressing inequalities to ensure historically marginalized neighborhoods benefit from the state's climate change policies.

This project aims to advance sustainable, inclusive solutions to California's most pressing environmental and health challenges by centering the lived experiences and needs of Latinos.

Advisory Committee

Throughout this project, we engaged stakeholders through an Advisory Committee that included representatives from academic institutions, public agencies, and community-based organizations with expertise in environmental justice, public health, and public policy. The committee met quarterly over the course of 2 years and provided input at key stages of the project. Their feedback helped us to refine our county selection process, prioritize which indicators to include in our factsheets, and decide the best approach for visualizing our data through county-level maps.

Overview of County Factsheets

For this project, we developed two sets of factsheets that present data on extreme heat and air pollution. In both sets of factsheets, we present environmental, sociodemographic, and health data specific to each topic.

Extreme Heat

The increasing frequency and intensity of extreme heat events pose significant health risks, particularly for Latino communities. California has experienced record temperatures in recent years, with heat waves becoming more frequent and prolonged.[1] Climate change is likely to continue this trend, further exacerbating challenges for vulnerable populations.[2] For example, Latinos face higher risks of experiencing heat-related illnesses that range from mild heat cramps to severe heat strokes due to their limited access to cooling resources and a greater likelihood of working in industries that require outdoor work.[3] Additionally, Latino communities often face poor housing conditions and limited health care access, which increases vulnerability to heat-related illnesses.[4] These communities are also less likely to have air conditioning.[5] By understanding vulnerabilities faced by Latinos and other underserved communities, it is possible to reduce the health impacts of extreme heat and help build more resilient communities for the future.

Air Pollution

Traffic and power generation are the primary sources of air pollution in developed countries.[6] In California, metropolitan areas such as Los Angeles, the San Francisco Bay Area, and the San Joaquin Valley experience the highest levels of air pollution.[7] Research about air pollutants, such as particulate matter (this includes ozone, nitrogen dioxide, and sulfur dioxide) and mixed traffic-related air pollutants, has found that exposure to pollutants exacerbates pre-existing conditions such as cardiovascular disease and asthma, with several studies suggesting exposure also contributes to new-onset asthma as well.[8] Recent studies have also found racial and ethnic disparities in exposure, with Black, Latino, and Asian communities experiencing higher levels of exposure than non-Latino (NL) white populations.[9] Researchers have linked disparate exposure to air pollution with significant health disparities. For example, studies have attributed disproportionate exposure to air pollution to the excess burden of childhood asthma among children of color compared to white children.[10] Exposure to air pollution is also unevenly distributed by socioeconomic status, with low-income neighborhoods facing greater exposure to pollutants than high-income neighborhoods.[11]

Primary Unit of Analysis: Census Tract

For this project, we analyzed data at both the county and census tract levels. The primary unit of analysis for our factsheets is the census tract, a geographic unit commonly used as a proxy for neighborhoods. We use the terms “census tract” and “neighborhood” interchangeably throughout this report. The U.S. Census Bureau defines census tracts as small, relatively homogeneous geographic units based on population characteristics, housing, and economic status. Each tract typically contains between 2,500 and 8,000 people, with an average population of about 4,000.[12] Census tract boundaries are reviewed and updated every 10 years with the decennial enumeration. If a census tract's population grows beyond 8,000, the U.S. Census Bureau may split it into two or more tracts. Likewise, if neighboring tracts experience a significant population decline, the Census Bureau may combine them into a single tract.[13]

For this project, we use multiple data sources that rely on different boundary years, based on either the 2010 or 2020 enumerations. The vintage of tract boundaries varies depending on the data source, but for each data source described later, we explicitly report the boundary year of each indicator.

County Selection Process

The research team produced county-level factsheets for 23 counties in California. We began by identifying the top 20 counties with the highest number of census tracts where Latinos represent more than 70% of the population (see Table 1). We chose this threshold to ensure a clear and consistent definition of Latino neighborhoods. However, as noted by our Advisory Committee, this approach excluded counties with few Latino neighborhoods but large Latino populations. To address this, we expanded our inclusion criteria to also include the top 20 counties with the largest Latino populations. This approach ensured broader geographic representation and alignment with stakeholder priorities. As a result, we selected counties that ranked in the top 20 by either the number of Latino neighborhoods or the total Latino population.

A total of 23 counties met at least one of the following inclusion criteria:

1. **Number of Latino-Majority Census Tracts:**
   We ranked counties by the number of census tracts in which Latinos make up more than 70% of the population. We ranked and selected the top 20 counties with the highest number of Latino-majority tracts..
2. **Total Latino Population:**
   We ranked counties by their total Latino population and included the 20 counties with the highest Latino populations.

Combining these two lists results in 23 counties representing approximately 93% of California's Latino population,[14] providing comprehensive coverage of the state's Latino population.

Although Sacramento County has no census tracts where Latinos make up more than 70% of the population, we included it in our analysis because it ranks ninth statewide in total Latino population (see Table 1). For our neighborhood-level analysis (explained in more detail below), we lowered the threshold for defining Latino neighborhoods in Sacramento County to a simple majority. In other words, we define Latino neighborhoods in Sacramento County as census tracts where more than 50% of the population is Latino (16 tracts meet this threshold).

Table 1 presents the 23 counties we selected for analysis, detailing the number of neighborhoods where Latinos make up more than 70% of the population, each county's total Latino population, and each county's ranking based on these two criteria.

Table 1. County Rankings by Latino Neighborhoods and Total Latino Population

County	Neighborhoods with a Latino Population >70%	Total Latino Population	Ranking by Latino Neighborhoods	Ranking by Latino Population
Los Angeles	685	4,837,594	1	1
Riverside	108	1,233,277	3	2
San Bernardino	127	1,200,147	2	3
San Diego	68	1,134,647	5	4
Orange	67	1,077,367	6	5
Fresno	61	546,774	7	6
Kern	74	501,705	4	7
Santa Clara	10	476,352	18	8
Sacramento	0	378,350	46	9
Alameda	5	369,603	22	10
Ventura	43	367,039	9	11
San Joaquin	16	331,382	15	12
Tulare	46	312,954	8	13
Contra Costa	8	306,895	19	14
Stanislaus	21	268,427	14	15
Monterey	41	261,954	10	16
Santa Barbara	25	207,576	12	17
San Mateo	6	180,393	21	18
Merced	22	174,732	13	19
Imperial	34	153,382	11	20
Madera	15	93,855	16	24
Santa Cruz	15	91,923	17	25
Kings	8	85,622	20	26

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Notes: In our analysis, we refer to census tracts as neighborhoods. Sacramento County has zero neighborhoods with a Latino population greater than 70%. It was included among the 23 counties for analysis because it is ranked the ninth county with the greatest Latino population.

Source: LPPI analysis of data from the Census Bureau’s American Community Survey 2022 5-year Estimates

Map 1 highlights the 23 counties selected for analysis, primarily located in Southern California and the Central Valley. Most Northern and Bay Area counties did not meet either of our two selection criteria.

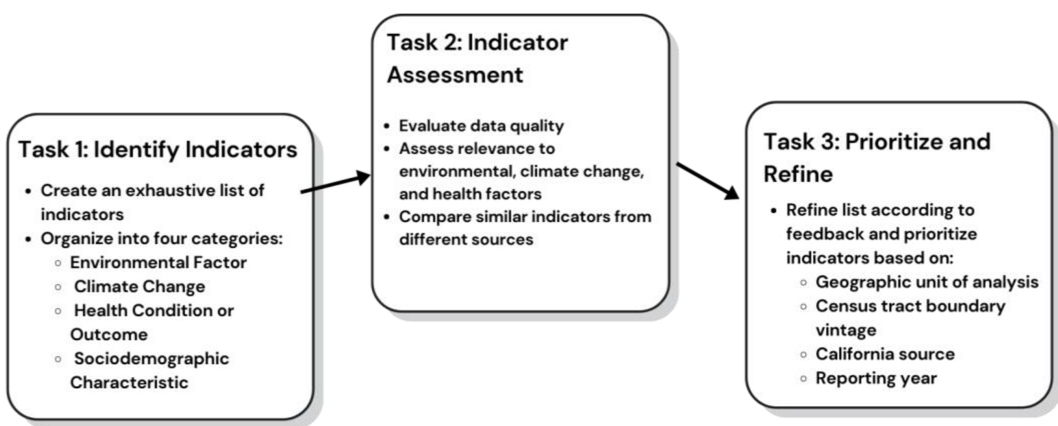
Map 1. 23 Counties Selected for Analysis

Source: LPPI analysis of data from the Census Bureau’s American Community Survey 2022 5-year Estimates

Indicator Selection Process

The following section describes our research team's step-by-step process of selecting the indicators in our county-level factsheets (see Figure 1). We first created an exhaustive list of potential indicators to understand the relationship between climate change, environmental factors, and health in California. We organized indicators into four categories: environmental factors, climate change, health, and sociodemographic characteristics. We then conducted an initial indicator assessment to check for data quality and relevance. We also compared similar indicators from different sources to check for inconsistencies in reporting. Finally, we refined our list based on feedback from our Advisory Committee, and prioritized indicators that reported data at the census tract level, have a 2020 boundary vintage, are developed by California agencies and organizations, and by reporting year (most recent). See Table 2 for a complete list of all 35 indicators included in our factsheets.

Figure 1. Indicator Selection Process



Criteria Considered:

- **Geographic Unit of Analysis:** We prioritized indicators with data available at the census tract level as this was our primary geographic unit of analysis.
- **Boundary Vintage:** Census tract boundaries change every 10 years during the decennial census. Data sources report using either the updated 2020 boundaries or 2010 boundaries. For our factsheets, we prioritized indicators reported with 2020 boundaries to identify the most current geography of Latino neighborhoods. However, not all data sources have updated their datasets to include 2020 boundaries, and some indicators included in our factsheets are reported using 2010 boundaries. For each data source described later, we explicitly report the boundary year of each indicator.
- **California Coverage:** We prioritized indicators created by California-based organizations rather than national organizations. State-specific datasets are often

created using California-specific data, while nationwide sources are more likely to use statistical models to estimate values for smaller geographies.

  - We conducted correlation analyses for indicators available from multiple sources to assess consistency between data sources. When indicators showed strong agreement across sources, we prioritized California-based datasets to enhance regional relevance and specificity.

- **Reporting Year:** We prioritized datasets with the most up-to-date reporting year. This approach ensures the data reflects the most current environmental risks, health issues, and climate change impacts affecting communities. That said, there is a general lack of timeliness for several indicators included in our factsheets, including data on tree canopy coverage, exposure to particulate matter 2.5 (PM2.5), and diesel emissions, which is unavoidable because of the time required for agencies to collect, assemble, review, and release information.

Table 2 presents all 35 indicators we analyzed and included in the county-level factsheets, the thematic factsheet they are included in, their source, their reporting year, geographic coverage, and their census tract-boundary vintage, when applicable. Additional information on how we analyzed each indicator, the weight variable used, and the rationale for including each indicator can be found in the final section of this report, labeled "Indicators".

Table 2. Indicators Included in the Latino Climate and Health County Factsheets

Indicator Name	Factsheet	Source	Reporting Year	Geographic Coverage	Boundary Vintage
Median Age	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Noncitizen Population	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Renter Households	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Poverty Rate	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Median Income (Household)	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Latino, Non-Latino white, and Other	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Limited English Proficiency	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
SNAP Benefits	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Food Insecurity	Extreme Heat Air Pollution	Feeding America	2016-2020	County	NA
Uninsured Rate	Extreme Heat Air Pollution	American Community Survey	2018-2022	County	NA
Fair/Poor Health Status	Extreme Heat Air Pollution	California Health Interview Survey	2018-2022	County	NA
Life Expectancy	Extreme Heat Air Pollution	County Health Rankings & Roadmaps	2019-2021	County	NA
Annual Number of Extreme Heat Days	Extreme Heat	CDC: National Environmental Public Health Tracking Network	2018-2022	Census Tract	2020
Longest Period of Consecutive Extreme Heat Days	Extreme Heat	Census Bureau’s Community Resilience Estimates for Heat, 2022	2022	Census Tract	2020
Projected Number of Extreme Heat Days by Mid-Century (2035-2064)	Extreme Heat	California Healthy Places Index 3.0	-	Census Tract	2010

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Table 2 (cont'd). Indicators Included in the Latino Climate and Health County Factsheets

Indicator Name	Factsheet	Source	Reporting Year	Geographic Coverage	Boundary Vintage
Tree Canopy	Extreme Heat	California Healthy Places Index 3.0	2011	Census Tract	2010
Impervious Surfaces	Extreme Heat	CDC: National Environmental Public Health Tracking Network	2021	Census Tract	2010
Older Housing Units	Extreme Heat	American Community Survey	2018-2022	Census Tract	2020
Heat-Related Emergency Department Visits (per 10,000 people)	Extreme Heat	UCLA Health Maps	2009-2018	Census Tract	2020
Workers in Heat-Exposed Industries	Extreme Heat	American Community Survey	2018-2022	Census Tract	2020
Emergency Department Visits (per 10,000 people) for Asthma Attacks	Extreme Heat Air Pollution	CalEnviroScreen 4.0	2015-2017	Census Tract	2010
Emergency Department Visits (per 10,000 people) for Heart Attacks	Extreme Heat Air Pollution	CalEnviroScreen 4.0	2015-2017	Census Tract	2010
Adults (18+) with Pre-Existing Condition: Obesity	Extreme Heat Air Pollution	CDC PLACES: Local Data for Better Health	2019-2021	Census Tract	2010
Adults (18+) with Pre-Existing Condition: Diabetes	Extreme Heat Air Pollution	CDC PLACES: Local Data for Better Health	2019-2021	Census Tract	2010
Age Groups (0-5, 0-18, 65+)	Extreme Heat Air Pollution	American Community Survey	2018-2022	Census Tract	2020
Disadvantaged Communities	Extreme Heat Air Pollution	CalEnviroScreen 4.0	2015-2017	Census Tract	2010
Particulate Matter 2.5	Air Pollution	CalEnviroScreen 4.0	2015-2017	Census Tract	2010
Diesel Particulate Matter	Air Pollution	CalEnviroScreen 4.0	2016	Census Tract	2010
Traffic Density	Air Pollution	CalEnviroScreen 4.0	2018	Census Tract	2010
Cleanup Sites	Air Pollution	CalEnviroScreen 4.0	2021	Census Tract	2010
Hazardous Waste Facilities	Air Pollution	CalEnviroScreen 4.0	2018-2020	Census Tract	2010
Low Birth Weight Babies	Air Pollution	CalEnviroScreen 4.0	2009-2015	Census Tract	2010
Risk Management Plan (RMP) Facilities	Air Pollution	Environmental Protection Agency Environmental Justice Screening Tool 2.3	2024	Census Tract	2020

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Table 2 (cont'd). Indicators Included in the Latino Climate and Health County Factsheets

Indicator Name	Factsheet	Source	Reporting Year	Geographic Coverage	Boundary Vintage
Clunker Vehicles	Air Pollution	UCLA Center for Neighborhood Knowledge - California Air Resources Board	2017	Census Tract	2010
Low-Emission Vehicles	Air Pollution	UCLA Center for Neighborhood Knowledge - California Air Resources Board	2017	Census Tract	2010

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Notes: Reporting year(s) represent the time frame for data collection and analysis. The reporting years do not always align with the publishing year of a data source, which represents when an indicator is made publicly available or the most recent year the data source has been updated. Data on "Projected Number of Extreme Heat Days by Mid-Century (2035-2064)" are estimated using data from 1950-2013. There were no boundary changes for California counties between 2010 and 2020; therefore, listing a boundary vintage does not apply to indicators reported at the county level.

Analytical Approach

In our county-level factsheets, we present statistics at both the county and neighborhood levels, with distinct approaches for analyzing data at both geographic levels.

At the **county level**, we report statistics that compare indicators specifically for Latino and NL white populations. These comparisons focus on population-level characteristics, such as age, rates of uninsurance, and income, and are drawn from datasets that allow for disaggregation by race and ethnicity.

At the **neighborhood level**, our analysis focuses on all residents, households, and workers within neighborhoods. Our population of interest is Latino neighborhoods, which are defined as census tracts with a predominantly Latino population. The outcomes of our neighborhood-level analyses represent everyone living or working in these neighborhoods, regardless of race or ethnicity. This distinction is crucial because, while these neighborhoods are predominantly Latino, they also include individuals from other racial and ethnic groups.

Our approach to our neighborhood-level analysis is largely driven by data availability. Many indicators, such as exposure to PM2.5, are available at the census tract level but are not disaggregated by race or ethnicity due to sample size limitations. Instead, these data reflect characteristics of all residents or households within a given census tract. By explicitly acknowledging these limitations and clarifying the scope of the analysis, we aim to provide a nuanced and accurate portrayal of neighborhood-level characteristics.

Both county-level and neighborhood-level data included in the factsheets provide unique insights into the characteristics and conditions of Latino communities, offering complementary perspectives on their experiences and challenges.

Neighborhood-Level Analysis

Within each county factsheet, we report and compare weighted averages for indicators by neighborhood type (described below). Weighted averages allow us to account for differences in neighborhood types, such as population size. For example, we report the annual average number of extreme heat days that Latino neighborhoods are exposed to in Los Angeles County, weighted by the population size of all residents in Latino neighborhoods in Los Angeles County. We compared this data point to the annual average number of extreme heat days that NL white neighborhoods are exposed to, weighted by the population size of all residents in NL white neighborhoods. This approach enables more accurate comparisons of indicators across neighborhoods while accounting for the unique characteristics of each group.

The choice of weighting variable depends on the specific indicator being analyzed. In most cases, we calculated weighted averages using population size to ensure more accurate comparisons across neighborhoods. However, when analyzing the distribution of older vehicles across neighborhoods, for example, the weight we applied was the total vehicle count within each neighborhood. The nature of the indicator and the available data guided the selection of the appropriate weighting variable. We specify the variable used to weight the analysis for each indicator in the factsheets later in this report. Finally, output for the neighborhood-level analysis only includes neighborhoods with populations greater than zero.

Comparison Groups

For our neighborhood-level analysis, we compared outcomes between the following types of neighborhoods:

- **Latino neighborhoods:** More than 70% of residents identify as Latino.
    - Sacramento County has no neighborhoods with a Latino population greater than 70%. Therefore, we define Latino neighborhoods in Sacramento County as census tracts where more than 50% of residents are Latino.
- **NL white neighborhoods:** More than 70% of residents identify as NL white.
    - We also define NL white neighborhoods in Sacramento County using a 50% threshold for consistency between comparison groups.
- **NL neighborhoods:** These neighborhoods do not meet the 70% population threshold for Latino or NL white neighborhoods. In other words, less than 70% of residents identify as either Latino or NL white. This definition applies to neighborhoods in Imperial, Kings, and Merced counties.
    - No neighborhoods in Imperial, Kings, or Merced Counties have NL white populations greater than 70%.

To classify neighborhoods into our comparison groups, we analyzed population data from the Census Bureau's American Community Survey (ACS) disaggregated by race and ethnicity. For indicators reported using 2010 boundaries, we used population data from the ACS 2019 5-year estimates, as this is the latest ACS dataset that utilizes a 2010 vintage for census tract boundaries. For indicators reported using 2020 boundaries, we used population data from the 2022 5-year ACS estimates.

Our factsheets contain the following groupings of neighborhood types:

- **Primary Comparison (70%+ NL white neighborhoods):** For 19 counties, we compared Latino neighborhoods to NL white neighborhoods with NL white populations greater than 70% (see Table 2).
- **Alternative Comparison (NL neighborhoods):** For Imperial, Kings, and Merced Counties, we compared outcomes for Latino neighborhoods to NL neighborhoods.
- **Sacramento County Exception (50%+ NL white neighborhoods):** For Sacramento County, we compared outcomes for Latino neighborhoods to NL white neighborhoods, both defined using a greater than 50% threshold of Latino and NL white populations, respectively.

Table 3 presents the number of neighborhoods that fall into each neighborhood type and the total number of neighborhoods in each county. It's important to note that although "NL neighborhoods" are designations for tracts that do not meet the 70% Latino or NL white population threshold, these tracts may still have significant Latino populations.

Table 3. Breakdown of Neighborhood Comparison Groups Across 23 Counties

County	Comparison Group	Neighborhoods with a Latino Population >70%	Neighborhoods with a NL white Population >70%	Non-Latino Neighborhoods	Total Neighborhoods
Los Angeles	70%+ NL White	685	163	1,791	2,476
San Bernardino	70%+ NL White	127	22	339	466
Riverside	70%+ NL White	108	38	409	517
Kern	70%+ NL White	74	20	162	236
San Diego	70%+ NL White	68	130	667	735
Orange	70%+ NL White	67	79	546	613
Fresno	70%+ NL White	61	5	164	225
Tulare	70%+ NL White	46	2	57	103
Ventura	70%+ NL White	43	28	146	189
Monterey	70%+ NL White	41	18	61	102
Imperial	NL Neighborhoods	34	0	6	40
Santa Barbara	70%+ NL White	25	20	82	107
Merced	NL Neighborhoods	22	0	41	63
Stanislaus	70%+ NL White	21	6	91	112
San Joaquin	70%+ NL White	16	6	158	174
Madera	70%+ NL White	15	6	19	34
Santa Cruz	70%+ NL White	15	27	54	69
Santa Clara	70%+ NL White	10	6	398	408
Contra Costa	70%+ NL White	8	30	233	241
Kings	NL Neighborhoods	8	0	23	31
San Mateo	70%+ NL White	6	13	166	172
Alameda	70%+ NL White	5	12	372	377
Sacramento	50%+ NL White	0	47	363	363

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Notes: In our analysis, we refer to census tracts as neighborhoods. In Sacramento County, 16 Latino neighborhoods and 147 NL white neighborhoods are defined using the greater than 50% population threshold, respectively.

Source: LPPI analysis of the Census Bureau's American Community Survey 2022 5-year Estimates

Limitations

While this project uses reliable and detailed data, several limitations should be considered when interpreting the factsheets and information included in the dashboard:

Geographic Boundary Differences
The indicators showcased in our factsheets are reported using either 2010 or 2020 census tract boundaries. Some indicators, such as PM2.5 and diesel PM, are only available using the older (2010) boundary vintage. This may affect comparability across indicators, particularly in areas that experienced significant population growth or redistricting between 2010 and 2020.

Census Tracts as Proxies for Neighborhoods
We focused on census tracts as the primary geographic unit of analysis and as proxies for neighborhoods. While census tracts are designed to reflect relatively homogenous populations, they do not always align with community-identified boundaries or reflect the full diversity of residents' lived experiences.

Population-Based Neighborhood Definitions
We define neighborhood types using population thresholds (e.g., a Latino population greater than 70%), simplifying complex demographic compositions. We use these definitions to examine place-based exposures, not to imply homogeneity within neighborhoods. Areas labeled "Latino neighborhoods" or "NL white neighborhoods" include residents from various racial and ethnic backgrounds.

Data Availability and Reporting Years
Some indicators reflect older periods due to data collection, processing, and release delays. For example, the reporting years for tree canopy and impervious surfaces are 2011 and 2021, respectively. Additionally, some health indicators are based on multi-year averages to increase reliability. For example, data on emergency department visits for asthma and heart attacks, report data from 2015 to 2017. Because of delays in releasing more up-to-date data, data included in our factsheets may not reflect more recent trends.

Race and Ethnicity Disaggregation
Due to sample size limitations, environmental and health indicators at the neighborhood level are not disaggregated by race or ethnicity. As a result, our place-based analyses describe conditions affecting all residents within majority-Latino and NL white-majority neighborhoods rather than isolating impacts specific to individuals.

County Comparability
To ensure Sacramento County's inclusion, we used a 50%, simple majority threshold for identifying Latino-majority and NL white-majority neighborhoods, in contrast to the 70% threshold used for the other 22 counties we included in our analyses. This exception may affect comparability across counties and should be interpreted with caution.

Survey-Based Estimates and Small Sample Sizes
Several indicators rely on survey-based data, including the ACS and the California Health Interview Survey (CHIS). Small sample sizes in some counties may lead to greater margins of error, especially for estimates disaggregated by race and ethnicity. These estimates are provided as the best available data but should not be interpreted as precise counts.

Modeled and Imputed Data
Certain indicators, such as heat-related emergency department visits and projected extreme heat days, rely on statistical models or imputation methods to estimate values at the census tract level. These models introduce uncertainty and should be interpreted as estimates, not direct measurements.

Verification Process

The research team implemented a two-step verification process to ensure consistency and accuracy in our analyses. Each indicator was first assigned to a research team member responsible for constructing the indicator and producing output for each county and neighborhood type. A second research team member then repeated the process of constructing an indicator and producing output independently to compare results. After meeting consensus, we recorded final values in a flat file documenting output for each county, neighborhood type, and indicator. This verification approach helped identify discrepancies and confirm results through reproducibility.

Tools and Software Used

The research team used statistical and geospatial tools for data processing, analysis, and map development. We utilized R Studio as the primary statistical program for data management, constructing indicators, and calculating weighted averages. Members of the research team also conducted analyses using the Statistical Analysis System program to independently verify results generated in R Studio. Finally, team members used Python to produce the county factsheets, develop county-level maps, and design the dashboard that hosts the factsheets. Together, these tools supported a reproducible analytical workflow across all project phases.

Indicators

In the following section, we describe, in detail, the indicators we included in the county-level factsheets, how we analyzed and presented each indicator, and the rationale for including each one.

Demographic Indicators

The following demographic indicators are included in both the extreme heat and air pollution factsheets.

Demographic Indicator: Latino, Non-Latino white, and Other
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: Data on ethnicity and race were collected through questions five (ethnicity) and six (race) in the American Community Survey (ACS). These questions follow the guidelines set by the U.S. Office of Management and Budget (OMB) and are based on self-identification.

Ethnicity
Individuals identifying as Hispanic, Latino, or Spanish may be of any race.

Race
The ACS collects data on race using the following OMB-defined categories, which reflect sociocultural concepts rather than biological definitions: White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, Some Other Race, and Two or More Races (any combination of the above).

In this analysis, data for Latinos include individuals of any race, while data for white populations are limited to non-Latino white individuals. The "Other" category represents individuals who identify as a racial or ethnic background other than Latino or non-Latino white. Presenting each group's population share establishes the baseline against which all subsequent indicators are interpreted. To calculate the percentage of Latinos, NL white, and "Other", in each county, we divided the population size for each group by the total population in the county.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Limited English Proficiency
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: The U.S. Census Bureau defines individuals with Limited English Proficiency (LEP) as those ages 5 and older who report speaking English "less than very well" in the American Community Survey (ACS).

The ACS reports English proficiency using the following categories:

- Speaks only English
- Speaks English "very well"
- Speaks English "well"
- Speaks English "not well"
- Speaks English "not at all"

Residents who speak English “less than very well” often encounter language barriers to preventive care,[15] and are more likely to be uninsured,[16] which intensifies the health impacts of extreme heat and air pollution on these communities. To calculate the total population with LEP in a county, we summed all individuals who report speaking English "well," "not well," or "not at all." The percentage of individuals with LEP is the number of individuals with LEP divided by the total civilian noninstitutionalized population aged 5 years and older.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Uninsured Rate
Source: Census Bureau’s American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: The U.S. Census Bureau defines "No Health Insurance Coverage" as not being covered by any type of health insurance for the entire reference period. In the American Community Survey (ACS), respondents report their health insurance status for the calendar year preceding the survey.

This information is collected for the civilian noninstitutionalized population, which includes individuals residing in households and noninstitutional group quarters, such as college dormitories, but excludes individuals in institutional settings like prisons, nursing homes, or long-term care facilities.

We obtained data on health insurance coverage from Question 16, which asked respondents to indicate current coverage by marking “yes” or “no”. The ACS classifies individuals as uninsured if they lacked any of the following types of coverage during the reference year:

Private Insurance Coverage:

- Employer-provided health insurance
- Union-provided health insurance
- Directly purchased health insurance

Public Insurance Coverage:

- Medicare
- Medicaid

- Children's Health Insurance Program
- Veteran Affairs health care
- TRICARE or other military health care

Residents without health coverage have fewer opportunities for preventive care or timely treatment, which can lead to chronic conditions going unmanaged and increase vulnerability to illnesses[17] triggered or worsened by extreme heat and air pollution. The percentage of individuals without health insurance coverage at the county level is calculated as the number of uninsured individuals in the specified group divided by the total civilian noninstitutionalized population of that group.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Noncitizen Population
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: We obtained data on citizenship status from the American Community Survey, where respondents are able to select one of five categories:

1. Born in the United States
2. Born in Puerto Rico, Guam, the U.S. Virgin Islands, or the Northern Mariana Islands
3. Born abroad to a U.S. citizen parent(s)
4. U.S. citizen by naturalization (respondents also reported their year of naturalization)
5. Not a U.S. citizen

We include the noncitizen share because residents without U.S. citizenship often face restricted or inconsistent access to health insurance and care. Poor access to healthcare limits the prevention and treatment of chronic conditions that are aggravated by extreme heat and polluted air.[18]

The percentage of noncitizens for their respective groups in each county was calculated as follows: Non-Latino (NL) white noncitizens divided by the total NL white population. Hispanic or Latino noncitizens divided by the total Hispanic or Latino population.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Poverty Rate
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: Poverty rate measures the proportion of individuals whose income, over the past 12 months, was below the Federal Poverty Level (FPL). Individuals are categorized as being in poverty if their income-to-poverty ratio is below 1.00 FPL.[19]

The Census Bureau collects this information from individuals living in households, excluding those in institutionalized group quarters such as correctional facilities, nursing homes, and long-term care hospitals. Respondents report their household income, which is then compared to the FPL thresholds and adjusted for household size and composition. For reference, the FPL for a single individual in 2022 was $13,590 per year. For households with more members, the threshold increases (i.e., the FPL for a 2-person household is $18,310, and the FPL for a 3-person household is $23,030).

Households living below the FPL have fewer financial resources for air-conditioning, health care, and relocation, leaving them more exposed to and less able to mitigate the health impacts of extreme heat and air pollution.[20] For our factsheets, we analyzed poverty data at the county level and disaggregated the data by race and ethnicity to examine poverty among Latino and non-Latino white populations.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Median Income (Household)
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: We derived data for median household income from Question 47 of the American Community Survey, which asks respondents to report their total household income over the past 12 months from all sources. The median value is the "middle value" when data is ordered in ascending order. Half of the observations fall below the middle value (median) and one-half above it. For households, the median income is based on the distribution of the total number of households, including those with no income.

Multiple studies show that higher-income households are more likely to live in cooler, less polluted neighborhoods and can afford protective measures such as air-conditioning, while lower-income households experience greater exposure to extreme heat and air pollution and have fewer financial resources to respond.[21] In our factsheets, we report the median household income for Latino householders and non-Latino white householders at the county level.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Renter Households
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: Renter households include all occupied housing units that are not owner-occupied, regardless of whether rent is paid. These households are classified as:

- Renter Units: Units leased under traditional renter agreements or life care arrangements.
- No Rent Paid Units: These are units occupied without payment, such as those provided by friends or relatives or in exchange for services (e.g., resident manager, caretaker).

We include data on renter occupancy because tenants typically have limited control over insulation, air-conditioning, and other building upgrades, leaving them more exposed to extreme heat and outdoor pollutants than homeowners.[22] We report the percentage of renter-occupied households as the number of renter-occupied households divided by the total number of households for a given group at the county level.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Median Age
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: We obtained data on median age from Question 4 of the 2023 American Community Survey. Respondents provided their age in completed years, as well as their date of birth, to ensure accuracy. The median value is the "middle value" when data is ordered in ascending order. One-half of the observations fall below the middle value (median) and one-half above the middle value. Median age is based on a standard distribution of the population by single years of age and is shown to the nearest tenth of a year.

We include data on median age because older adults have a reduced ability to cool their bodies during heat waves, while young children have developing lungs that are especially sensitive to air pollution; in both cases, age structure shapes vulnerability to extreme heat and unhealthy air quality.[23] For this project, we report the median age for Latino residents and non-Latino white residents at the county level.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Supplemental Nutrition Assistance Program (SNAP) Benefits
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: County

Definition: We obtained data on SNAP benefits from Housing Question 15 in the 2023 American Community Survey. Respondents were asked whether one or more members of their household received SNAP benefits in the past 12 months.

The Food Stamp Act of 1977 defines this federally-funded program as one intended to "permit low-income households to obtain a more nutritious diet" (from Title XIII of Public Law 95-113, The Food Stamp Act of 1977, Declaration of Policy). Food purchasing power is increased by providing eligible households with cards that can be used to purchase food. SNAP, administered by the Food and Nutrition Service of the U.S. Department of Agriculture, is distributed through state and local welfare offices. SNAP serves as the major national income support program to which all low-income and low-resource households, regardless of household characteristics, are eligible. Note: In California, this program is called CalFresh.

Program participation in SNAP is a direct marker of low household resources, and research shows these households are less likely to spend on energy, cooling, and medical care,[24] conditions that place residents at greater risk during extreme heat days and make them more vulnerable when exposed to unhealthy air quality. We report the percentage of households receiving SNAP benefits at the county level by dividing the number of SNAP recipient households by the total number of households in a given demographic group.

For more information on the underlying data, visit the U.S. Census Bureau website.

Demographic Indicator: Fair/Poor Health Status
Source: California Health Interview Survey, 2018-2022
Geographic Unit of Analysis: County

Definition: We obtained data on self-reported fair/poor health status from the California Health Interview Survey (CHIS). As part of this survey, participants are asked to select one of the following options when reporting their perception of their overall health:

- Excellent
- Very Good
- Good
- Fair
- Poor
- Refused
- Don't Know

For our analysis, we combined responses to "Fair" and "Poor" to indicate the percentage of individuals reporting a fair or poor health status across counties. We pooled data from 2018 to 2022 to have a larger sample size. This approach also aligns with the American Community Survey methodology for 5-year estimates. Results for the following counties were flagged for data quality concerns by CHIS: Contra Costa, Madera, Monterey, San Joaquin, Santa Cruz, and Stanislaus. Concerns about data quality are usually due to small sample sizes.

Individuals who rate their overall health as fair or poor often live with chronic conditions[25] that increase their risk of illness during extreme heat and periods of poor air quality, making this measure a useful proxy for baseline vulnerability. For our project, we calculated the percentage of individuals reporting a poor or fair health status by dividing the number of respondents who selected "fair" or "poor" by the total number of valid responses, excluding refusals and "don't know" answers.

For more information, visit the AskCHIS website.

Demographic Indicator: Life Expectancy
Source: County Health Rankings & Roadmaps, 2024
Geographic Unit of Analysis: County

Definition: Life expectancy measures the average number of years a person is expected to live from birth, based on current age-specific mortality rates. It is an age-adjusted indicator, ensuring fair comparisons across counties with differing age structures. Life expectancy reflects the cumulative impact of social and environmental conditions, and research shows that counties with lower life expectancy also tend to have higher fine-particle pollution burdens, making longevity a useful indicator of vulnerability to environmental hazards.[26] In our factsheets, we report the life expectancy for Latino and non-Latino (NL) white populations at the county level.

The County Health Rankings & Roadmaps report data on life expectancy, sourced from the National Center for Health Statistics via the National Vital Statistics System. The data is reported from 2019 to 2021. Life expectancy is calculated using the total number of deaths and the average population at risk of dying during a specified time period. Deaths are attributed to the county of residence, regardless of where the death occurred.

Note: According to County Health Rankings & Roadmaps, in most California counties, Latino life expectancy is higher than that of NL white populations. However, according to life expectancy data from the California Department of Public Health, Latino life expectancy in San Mateo and Santa Cruz counties is lower than that of their NL white counterparts. This contradicts data from County Health Rankings & Roadmaps. Despite this noted difference, we decided to use County Health Rankings & Roadmaps data based on its more comprehensive data coverage.

For additional details, visit the County Health Rankings & Roadmaps website.

Demographic Indicator: Food Insecurity
Source: Feeding America, 2022
Geographic Unit of Analysis: County

Definition: Food insecurity refers to the lack of consistent access to enough food for an active, healthy life. This measure reflects economic and social conditions at the household level that limit food access, rather than a measure of hunger.

Feeding America developed an indicator to represent food insecurity rates at the county level using Current Population Survey data from 2009 to 2020, the American Community Survey 2020 5-Year Estimates, and 202 data from the Bureau of Labor Statistics. We include food insecurity because unstable access to food tends to have other resource limitations; households that struggle to buy groceries often cut back on cooling, energy costs, and medical care,[27] leaving residents more vulnerable to extreme heat and air pollution.

In our factsheets, we report overall food insecurity rates for Latino and non-Latino white populations at the county level.

For more information, refer to the Map the Meal Gap 2022 Technical Brief by Feeding America.

Extreme Heat Indicators

Extreme Heat Indicator: Annual Number of Extreme Heat Days (2018-2022)
Source: Centers for Disease Control and Prevention: National Environmental Public Health Tracking Network, 2023
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: Values for extreme heat days represent the total number of days in a calendar year where the daily temperature reached an absolute threshold of 90°F. Studies show that census tracts with larger shares of people of color and low-income residents experience significantly higher urban-heat-island effects compared to wealthier, predominantly white tracts, evidence of long-standing inequities in heat exposure.[28] In our factsheets, we report the annual average number of extreme heat days by neighborhood type. We averaged data from 2018 to 2022 and used the total population size at the census tract level to weigh the data.

The Centers for Disease Control and Prevention (CDC): National Environmental Public Health Tracking Network reports historical temperature data. According to the CDC, their data is derived using estimates for air temperature, humidity, and surface pressure from the North American Land Data Assimilation System. Raw data is available for 103,936 grid cells covering the U.S. (excluding Alaska and Hawaii; approximately 14km x 14km in size) and is summarized to the census tract and county level to estimate population exposure to extreme heat.

For additional details, visit the Centers for Disease Control and Prevention website.

Extreme Heat Indicator: Longest Period of Consecutive Extreme Heat Days (2022)
Source: Census Bureau's Community Resilience Estimates for Heat, 2022
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: Consecutive heat waves are events when the air temperature reaches or exceeds 90°F for at least two consecutive days. Extended heat waves impose long-term physiological stress, and research shows that low-income and minority neighborhoods experience higher mortality during these events than wealthier, predominantly white areas, evidence of unequal heat-wave exposure and vulnerability.[29] In our factsheets, we report the average duration, in days, of consecutive heat waves by neighborhood type. Averages are weighted using the total population size at the census tract level.

The Census Bureau reports data for heat waves that is sourced from the North American Regional Reanalysis (NARR) and provided by the National Oceanic and Atmospheric Administration's Physical Science Laboratory. NARR data includes detailed daily measurements for air temperature and humidity across North America, using a grid system with cells approximately 32 kilometers wide. Any grid cell where the maximum daily temperature exceeded 90°F for two or more consecutive days was flagged. These flagged areas were then matched to census tracts and counties to estimate the population living in heat-exposed areas.

For more detailed information on the data sources and methods, refer to the Community Resilience Estimates for Heat 2022 technical document.

Extreme Heat Indicator: Projected Number of Extreme Heat Days by Mid-Century (2035-2064)
Source: California Healthy Places Index 3.0, 2022
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: This indicator represents the projected number of days per year where the daily temperature is expected to exceed 90°F for the mid-21st century (2035–2064). Climate model studies show that census tracts with larger shares of low-income and minority residents are expected to experience the greatest increase in dangerously hot days by mid-century, highlighting the growing exposure gap in the future.[30] In our factsheets, we report the average number of projected days above 90°F by neighborhood type using the total population size at the census-tract level as our weight.

Projections are based on the Representative Concentration Pathway 8.5 scenario, utilizing data from California's four priority global climate models: HadGEM2-ES, CNRM-CM5, CanESM2, and MIROC5. The California Healthy Places Index reports these projections from Cal-Adapt, a platform providing climate change data to support California's adaptation planning.

For detailed information on the data and models used, refer to Cal-Adapt's website.

Extreme Heat Indicator: Tree Canopy
Source: California Healthy Places Index 3.0, 2022
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Data for tree canopy represents the percentage of land in a census tract covered by deciduous, evergreen, and mixed forest types. This measure is crucial for assessing environmental quality, urban planning, and public health, as higher tree canopy coverage is associated with reduced urban heat islands, improved air quality, and enhanced mental well-being.[31] In our factsheets, we report the population-weighted percentage of tree canopy coverage by neighborhood type.

The data for this indicator are from 2011. The Healthy Places Index reports tree canopy data provided by the National Land Cover Database (NLCD), which provides nationwide land cover data at a 30-meter resolution and classifies land into categories such as developed areas, forests, and wetlands.

For more detailed information, refer to the NLCD website.

Extreme Heat Indicator: Impervious Surfaces
Source: Centers for Disease Control and Prevention: National Environmental Public Health Tracking Network, 2023
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Impervious surfaces, such as roads, sidewalks, and buildings, prevent water infiltration and help retain heat. Studies have found that census tracts with more than 40% of land categorized as an impervious surface are on average 2–6°C hotter during summer days than adjacent, less-paved tracts.[32] In our factsheets, we report the average percentage of land characterized as an impervious surface by neighborhood type using the total population size at the census-tract level as our weight.

The Centers for Disease Control and Prevention reports data on impervious surfaces developed by the Multi-Resolution Land Characteristics Consortium using data from the 2021 National Land Cover Database (NLCD). The NLCD provides high-resolution (30-meter) land cover data across the U.S., including impervious surface estimates. The share of land characterized as an impervious surface is calculated by aggregating pixel-level impervious cover data (30m x 30m) for each census tract. Each pixel is assigned a value representing the proportion of impervious cover, which is then averaged across the tract area.

For more information, refer to the NLCD website.

Extreme Heat Indicator: Older Housing Units
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: This indicator represents the proportion of housing units within a census tract that were constructed before 1970, and serves as a proxy for identifying older housing stock. We calculated this measure using "Year Structure Built" data from the American Community Survey, which records the original construction year of housing units, regardless of subsequent remodeling or updates. We summed the number of housing units constructed before 1970 and divided by the total number of housing units in that census tract to calculate the percentage of housing units built before 1970 within a given census tract. In our factsheets, we report the average percentage of older housing units by neighborhood type, weighted using the total number of housing units in each census tract.

This indicator is important for understanding vulnerability to extreme heat, as older housing units often lack modern features that are critical for managing indoor temperatures, such as central air conditioning, effective insulation, and energy-efficient double-pane windows.[33] These deficiencies increase the vulnerability of residents to heat-related risks, especially in areas with an aging housing stock.[34] The year 1970 is used as a threshold for identifying older housing units because it marks a notable transition in residential construction practices and infrastructure. Central air conditioning became more widespread in the 1970s,[35] and homes built prior to this period were less likely to include it, leaving residents more susceptible to heat.

Note: The Census Bureau defines a housing unit as a structure intended for occupancy, including houses, apartments, mobile homes, and other living arrangements, provided they meet specific criteria such as completed exterior windows, doors, and floors.

For more information on the underlying data, visit the U.S. Census Bureau website.

Extreme Heat Indicator: Emergency Department Visits (per 10,000 people) for Asthma Attacks
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: This indicator represents the age-adjusted annual rate of emergency-department visits for asthma per 10,000 residents at the census-tract level. A meta-analysis published in 2023 found that extreme heat events are associated with a significant rise in asthma-related hospital visits.[36] By analyzing patterns in asthma emergency department visits, public health officials can identify communities at greater risk during heat events. In our factsheets, we report the average number of emergency department visits per 10,000 residents by neighborhood type using the total population size at the census-tract level as our weight.

CalEnviroScreen (CES) reports rates of emergency department visits for asthma using data from the Emergency Department and Patient Discharge Datasets maintained by the State of California's Office of Statewide Health Planning and Development. Data reported by CES represents the age-adjusted annual rate of emergency department visits for asthma per 10,000 residents and is averaged over 2015 to 2017.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Extreme Heat Indicator: Emergency Department Visits (per 10,000 people) for Heart Attacks
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: This indicator represents the age-adjusted annual rate of emergency-department visits for heart attacks per 10,000 residents at the census-tract level. Exposure to extreme heat has been linked to increased emergency department visits for several conditions, including heat stroke, kidney failure, and heart attacks.[37] In our factsheets we report the average number of emergency department visits for heart attack per 10,000 residents by neighborhood type using the total population size at the census tract level as our weight.

CalEnviroScreen (CES) reports rates of emergency department visits for heart attacks using data from the Emergency Department and Patient Discharge Datasets maintained by the State of California's Office of Statewide Health Planning and Development. This indicator specifically represents acute myocardial infarctions. Data reported by CES represents the age-adjusted annual rate of emergency department visits for heart attacks per 10,000 residents and is averaged over 2015 to 2017.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Extreme Heat Indicator: Adults (18+) with Pre-Existing Condition: Obesity
Source: Centers for Disease Control and Prevention: PLACES: Local Data for Better Health, 2023
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Data on obesity prevalence represents the percentage of adults (18 years and older) whose body mass index is 30 kg/m² or higher.[38] Individuals with obesity are at greater risk of developing comorbidities such as diabetes, cardiovascular disease, and asthma,[39] which increase vulnerability to heat-related illnesses.[40] Analyzing data on obesity prevalence can help advocates identify areas with vulnerable populations to help target these communities during heat waves. In our factsheets, we report the average crude prevalence of adult obesity by neighborhood type using the total adult population size at the census-tract level as our weight.

The Centers for Disease Control and Prevention (CDC) PLACES: Local Data for Better Health published estimates on obesity prevalence in 2023 with survey data from the 2019-2021 Behavioral Risk Factor Surveillance System and demographic data from the American Community Survey. This measure is derived from self-reported height and weight data.

For more information, refer to the CDC PLACES website.

Extreme Heat Indicator: Adults (18+) with Pre-Existing Condition: Diabetes
Source: Centers for Disease Control and Prevention: PLACES: Local Data for Better Health, 2023
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Data on diabetes prevalence represents the percentage of adults (18 years and older) who report being told by a healthcare professional that they have diabetes (excluding female respondents who report being diagnosed with diabetes during pregnancy). Individuals with type 1 and type 2 diabetes have an altered response to heat stress, including impaired vasodilation and sweating, and are especially vulnerable to climate change and exposure to extreme heat.[41] Additionally, responses to heat stress in diabetics can be affected by diabetes-related comorbidities, such as cardiovascular and chronic kidney disease, and the medications prescribed to manage the condition.[42] In our factsheets, we report the average crude prevalence of diagnosed diabetes by neighborhood type using the total adult population size at the census-tract level as our weight.

The Centers for Disease Control and Prevention (CDC) PLACES: Local Data for Better Health published estimates on diabetes prevalence in 2023 with survey data from the 2019-2021 Behavioral Risk Factor Surveillance System and demographic data from the American Community Survey.

For more information, refer to the CDC PLACES' website.

Extreme Heat Indicator: Heat-Related Emergency Department Visits (per 10,000 people)
Source: UCLA Health Maps, 2022
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: The Excess Daily Emergency Room Visits from Extreme Heat is the rate of emergency room visits per 10,000 persons per day that exceed expected levels on extreme heat days. This indicator was developed by the UCLA Center for Healthy Climate Solutions "Heat Maps" project, which derived tract-level values from 2009-2018 emergency-department discharge records in collaboration with the California Department of Health Care Access and Information. In our factsheets, we report the average excess-emergency-department-visit rate by neighborhood type using the total census tract population as the weight. Note: at the time of our data analysis, the rate of heat-related emergency department visits covered the period from 2009 through 2018. The latest iteration of this data source now covers the period from 2008 to 2018.

Excess emergency department visits capture the immediate health burden of extreme heat, particularly among residents with pre-existing cardiovascular or respiratory disease. Highlighting this outcome pinpoints neighborhoods where heat-related demand on hospitals is highest and where targeted cooling interventions can reduce emergency-care utilization.

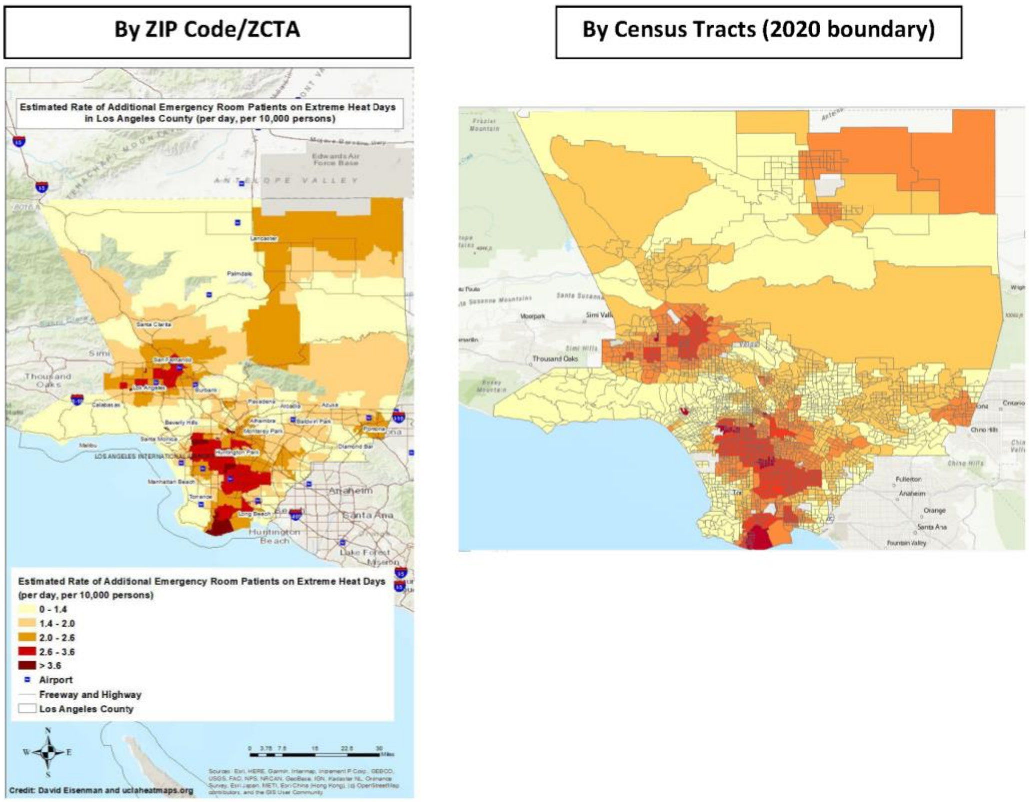
UCLA Center for Health Climate Solutions identified visits related to heat via diagnostic codes for heat illness, dehydration, electrolyte imbalance, and heat-exacerbated cardiovascular or respiratory conditions. Baseline ("expected") visit rates were modeled from non-heat days and age-adjusted to the 2000 U.S. standard population. Original values are published at the 2010 ZIP Code Tabulation-Area level (ZCTA).

For more information on how the indicator is defined and constructed, see the UCLA Heat Map website.

Note: The data is originally reported at the ZCTA level, based on 2010 ZCTA boundaries. Because our analysis focuses on neighborhoods defined by census tracts, we allocated the ZCTA-level data to 2020 census tract boundaries. This allocation was performed using a census block-to-ZCTA geographic crosswalk from the Missouri Geocorr tool, weighted by population to ensure proportional distribution of data.

To verify the accuracy of this allocation, we compared maps of the data displayed at the ZCTA and census tract levels. The spatial patterns between the two maps (see Map 2) were largely consistent, as expected when imputing ZCTA data to tracts. This visual inspection is part of our standard data verification process.

Map 2. Verification of Geographic Distribution of Emergency Room Visits from Extreme Heat



Sources: LPPI analysis of data from the UCLA Center for Healthy Climate Solutions, Health Maps 2009-2018, and the Census Bureau's American Community Survey 2022 5-Year Estimates

Extreme Heat Indicator: Age
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: We report data on two heat-vulnerable age groups: children (younger than 18 years) and older adults (65 years and older). These age groups are considered more vulnerable to extreme heat and other environmental hazards due to increased physiological sensitivity and potential limitations in mobility or resources.[43] For children, their higher surface-area-to-body-mass ratio and developing body increase their vulnerability to heat-related illnesses, particularly in areas with limited cooling infrastructure.[44] Additionally, older adults are especially vulnerable because they are more likely to have preexisting chronic health conditions and may take medications that reduce heat tolerance.[45] Including this indicator helps identify neighborhoods with higher concentrations of these vulnerable age groups to design targeted public health interventions. In our factsheets, we report the average share of children and older adults by neighborhood type using the total census-tract population as the weight.

We obtained data on age-group counts from the American Community Survey 2022 five-year estimates, Table B01001 (Sex by Age). We summed up the relevant age-specific population counts (male and female populations aged 0-18 and 65 or older). We divided them by the total population of the census tract to calculate the percentage of the population in each age group within a census tract.

For more information on the underlying data, visit the U.S. Census Bureau website.

Extreme Heat Indicator: Workers in Heat-Exposed Industries
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: The indicator "Workers in Heat-Exposed Industries" refers to the percentage of workers employed within industries identified by the Bureau of Labor Statistics (BLS) as having the highest average heat-related fatalities per year.[46] According to BLS data cited by the Occupational Safety and Health Administration, these industries include Agriculture, Forestry, Fishing, and Hunting; Mining; Construction; Administrative and Support and Waste Management and Remediation Services; and Transportation and Warehousing. These industries are particularly vulnerable to heat-related illnesses due to their work environments and physical demands. Outdoor and non-air-conditioned work environments expose workers to prolonged solar radiation, high radiant heat, and limited cooling breaks—conditions that elevate the risk of heat exhaustion, heat stroke, and occupational injury.

Using industry data from the American Community Survey (ACS), we summed counts of individuals (ages 16 and older) employed in these industries to represent a category of workers in high-heat-risk industries. In our factsheets, we report the average share of workers employed in these industries by neighborhood type, using the census-tract population ages 16 and older as the weight.

Industry descriptions and their increased exposure to extreme heat:

- **Agriculture, Forestry, Fishing, and Hunting**: Workers in this sector often work outdoors for long hours under direct sunlight, performing physically demanding tasks such as planting, harvesting, fishing, or handling livestock.
- **Mining**: Mining operations often expose workers to high temperatures in underground settings with limited ventilation, combined with physically strenuous labor and the operation of heat-generating equipment.

- **Construction**: Construction workers perform intense physical labor outdoors, frequently in direct sunlight, often wearing protective clothing that traps heat, increasing their vulnerability to heat-related illnesses.
- **Administrative and Support, and Waste Management and Remediation Services**: This category includes outdoor jobs like landscaping, waste collection, and pest control, where workers often wear protective gear and have limited access to shaded or cool areas.
- **Transportation and Warehousing**: Workers such as truck drivers and warehouse staff often operate in poorly ventilated spaces, such as vehicles or non-air-conditioned facilities, where heat can accumulate and pose significant risks.

Industry data in the ACS is collected for individuals aged 16 years and older who were employed at any time during the 12-month reference period preceding the survey. For more information on the underlying data, visit the U.S. Census Bureau website.

Extreme Heat Indicator: Disadvantaged Communities
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Disadvantaged communities (DACs) in California are neighborhoods identified for targeted investments through proceeds from the state's Cap-and-Trade Program under the California Global Warming Solutions Act of 2006 (AB 32). These investments aim to reduce greenhouse gas emissions, improve public health, and enhance the quality of life in the state's most burdened communities. In our factsheets, we report the share of residents living in Senate Bill 535-designated disadvantaged communities by neighborhood type using the total census-tract population as our weight.

CalEnviroScreen reports data on disadvantaged communities designations identified under the criteria in Senate Bill 535[47] and using the California Protection Agency's (CalEPA) pollution-and-population-vulnerability scoring system.[48] Census tracts are assessed using geographic, socioeconomic, public health, and environmental hazard criteria to determine those most impacted by pollution and vulnerable populations.

CalEnviroScreen identifies DACs using the following criteria:
- Tracts that received the highest 25% of overall scores in CalEnviroScreen 4.0.
- Tracts with data gaps but among the top 5% of pollution burden scores in CalEnviroScreen 4.0.
- Tracts identified as disadvantaged in the 2017 designation, regardless of their current scores in CalEnviroScreen 4.0.
- Lands under the control of federally recognized Tribes, which may be designated as DACs through consultation with CalEPA.

For more detailed information, see the SB 535 Disadvantaged Communities Report.

Development of Extreme Heat Maps

In the extreme heat factsheets, we include individual county-level maps displaying the geographic distribution of the extreme heat days at the neighborhood level (see Map 3 for an example). We mapped the average population-weighted annual number of extreme heat days from 2018 to 2022 for each neighborhood using the indicator for historical temperature at or above 90°F. We present data for historical temperature as three distinct categories:

1) Neighborhoods that experienced 0 extreme heat days.
2) Neighborhoods that experienced an annual number of extreme heat days greater than 0 and less than or equal to each respective county's average.
3) Neighborhoods that experienced an annual number of extreme heat days greater than the county average.

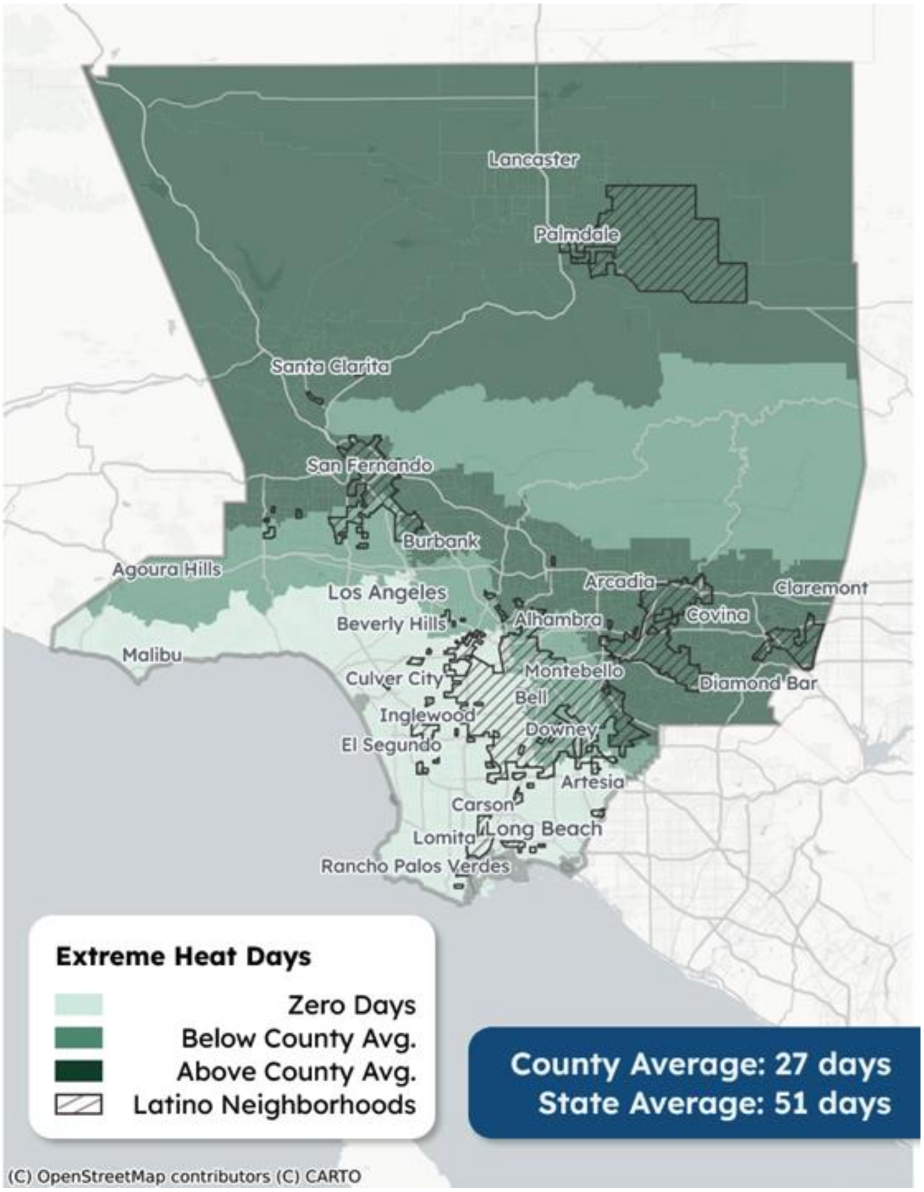
This indicator offers a clear, multi-year view of extreme heat exposure and provides a meaningful measure of how communities are currently experiencing extreme temperatures. This approach captures patterns of disparity at a neighborhood level and allows decision-makers to better address the health impacts of extreme heat.

Additionally, categorizing neighborhoods relative to their county's average provides insight into local disparities, as counties can have very different overall temperature distributions. This method allows us to:

- Highlight Localized Heat Disparities: Comparing neighborhoods within the same county reveals how heat exposure is unevenly distributed, even in regions sharing similar climates.
- Focus on Equity: By highlighting Latino neighborhoods, we can identify communities disproportionately affected by extreme heat and prioritize resources accordingly.

Map 3 displays the distribution of the average annual number of extreme heat (≥ 90 °F) days at the census tract level for Los Angeles County, overlaid with the outlines that represent Latino neighborhoods. The map shows that Latino neighborhoods are concentrated farther inland (away from the cooler coast) and largely fall in tracts that experience the county average of roughly 27 hot days per year or more; very few Latino neighborhoods lie in regions below the county average.

Map 3. Latino Neighborhoods and Exposure to Extreme Heat Days (≥ 90°F), 2018-2022



Notes: In our analysis, we refer to census tracts as neighborhoods. The county and state averages are population-weighted outputs using population data at the county and state levels, respectively. Census tracts reflect 2020 boundaries.

Sources: LPPI analysis of data from the Centers for Disease Control and Prevention National Environmental Public Health Tracking Network and the Census Bureau’s American Community Survey 2022 5-Year Estimates.

Air Pollution Indicators

Air Pollution Indicator: Particulate Matter 2.5 (PM2.5)
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Particulate Matter 2.5 is less than 2.5 microns (µm) in diameter and is expressed in micrograms per cubic meter (µg/m³). Particulate matter is a mixture of aerosolized liquid and solid substances that can include metals, allergens, and chemical materials. It is produced from several sources, including motorized vehicles and activities involving the combustion of materials. Due to their small size, PM2.5 particles can penetrate deep into the lungs and bloodstream, causing adverse health effects. Long-term exposure to PM2.5 has been linked to increased risk of developing asthma, especially in children.[49] In 2019, nearly one-third of global asthma cases were associated with PM2.5 exposure, demonstrating the effect the pollutant has on our health.[50] In our factsheets, we report the annual average PM2.5 concentration by neighborhood type using the total census-tract population as our weight.

CalEnviroScreen (CES) reports data for PM2.5 as an average over three years (2015-2017). According to CES, this indicator is developed using data from ground monitors from the U.S. Environmental Protection Agency Air-Quality System and satellite-derived PM2.5 estimates produced by the California Air Resources Board (CARB). The CARB air monitoring network uses data from over 50 air monitoring sites across the state. The system also uses satellite annual average PM2.5 computed through regression of Aerosol Optical Depth, land use, and meteorological data against ground-level measurements. Concentrations for each 1 km² grid cell were calculated as a weighted average, combining satellite data and monitoring site measurements using an inverse-distance weighting approach. These granular grid-level estimates were then averaged across census tracts to compute tract-level PM2.5 scores.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Diesel Particulate Matter (PM)
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Diesel particulate matter is the particle phase of exhaust produced from diesel engines and is also known as “soot”. Major producers of diesel PM include trucks, buses, cars, and ships. Diesel PM is a significant component of PM2.5 and is known to have serious health impacts, including respiratory and cardiovascular issues.[51] Exposure to diesel PM has been linked to an increased risk of lung cancer and can worsen conditions such as asthma and chronic bronchitis.[52] In our factsheets, we report the average diesel PM emissions by neighborhood type, expressed in tons per year, using the total census-tract population as our weight.

CalEnviroScreen reports data for diesel PM developed using 2016 on-road and non-road diesel PM emission estimates from the California Air Resources Board (CARB) statewide emissions inventory. Diesel exhaust is formally classified as a Toxic Air Contaminant under California law (CalEPA/OEHHA, 1998), underscoring its health significance.[53] Diesel emission estimates from on-road (trucks, buses) and non-road (ships, locomotives, construction equipment) sources were combined into a single 1 km gridded dataset. Gridded data were allocated to census tracts using weighted apportionment, based on the proportion of each grid cell intersecting census blocks. Resulting values were summed within census tracts and sorted into percentiles.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Traffic Density
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Traffic density represents the average number of vehicles passing a one-kilometer stretch of roadway per hour (vehicle-kilometers per hour). Exposure to traffic-related air pollution is linked to significant health risks, including respiratory issues such as asthma, cardiovascular diseases, and adverse birth outcomes.[54] Populations living near high-traffic roadways experience higher concentrations of pollutants like nitrogen dioxide (NO_2) and particulate matter, which worsen these health conditions.[55] In our factsheets, we report the average traffic-density value by neighborhood type using the total census-tract population as our weight.

CalEnviroScreen reports traffic-density estimates using 2017 TrafficMetrix® vehicle-count data linked to the 2018 TomTom digital road-network file. A 150-meter buffer was applied to each 2010 census tract in California to account for air pollution dispersal from roadways and calculate traffic impacts. The traffic density metric reflects the total number of vehicles per hour per kilometer of roadway within the buffered census tract. Traffic volume data from TrafficMetrix® (2017) were linked to road segments from TomTom's digital roadway network (2018) using ArcGIS. For roads missing traffic volume data, spatial interpolation modeling was performed. The length of each road segment was factored into the traffic volume calculations to create a length-adjusted traffic metric. This was summed across all roadways within the buffered census tract.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Cleanup Sites
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract

Boundary Vintage: 2010

Definition: Cleanup sites are polluted with hazardous materials like lead and asbestos and include old and abandoned processing plants, superfunds, state landfills, and brownfields. They are identified from the California Department of Toxic Substances Control's EnviroStor database, the U.S. Environmental Protection Agency Region 9 National Priorities List, and other state and federal remediation lists. Studies have found that communities living near contaminated sites have a higher exposure to hazardous substances, as pollutants can travel off-site through groundwater and windblown dust.[56] Research also indicates that pregnant women residing near Superfund sites are more likely to give birth to low birth weight babies.[57]

Data for this indicator represent both the number of sites and the severity of contaminated sites, as the burden of hazardous substances varies at the census tract level. In our factsheets, we present this indicator as a "neighborhood exposure score." We report the average exposure score by neighborhood type using the total census tract population as our weight. Higher scores indicate a closer proximity to and a greater number of toxic facilities.

CalEnviroScreen reports data on cleanup sites and developed its indicator using detailed geospatial and scoring methodologies to account for both the type and proximity of sites. Each site was assigned a score based on its type and remediation status, with higher weights given to more severe or active sites. These scores were adjusted for proximity to populated census blocks, with sites farther than 1,000 meters excluded. The adjusted scores were then summed up for each census tract to assess potential exposure risks to hazardous substances.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Hazardous Waste Facilities
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Hazardous waste generators and facilities include treatment, storage, and disposal sites for hazardous materials and chrome plating facilities, and can release toxic substances such as carcinogens, mercury, and asbestos into the air, water, and soil.[58] Living near hazardous waste sites has been associated with adverse health outcomes, including increased risks of congenital anomalies and types of cancers.[59] A review of epidemiological studies found that populations residing near hazardous waste sites may experience higher incidences of health issues due to exposure to toxic substances.[60]

Data for this indicator represents the weighted sum of large-quantity hazardous-waste generators, permitted hazardous-waste facilities, and active chrome-plating facilities, each weighted by distance to populated census blocks. In our factsheets, we present this data as a "neighborhood exposure score." We report the average exposure score by neighborhood type using the total census-tract population as our weight. Higher scores indicate a closer proximity to and a greater number of hazardous waste facilities.

CalEnviroScreen reports data on hazardous waste generators and facilities using 2018-2020 facility data from the California Department of Toxic Substances Control and other state remediation lists. This indicator was developed using detailed geospatial and scoring methodologies to assess potential exposure risk. The pooled sources are permitted hazardous waste facilities, hazardous waste generators (only large quantity generators were included), and chrome plating facilities (only active chrome plating facilities were included). Weights for all facilities were adjusted based on their distance from populated census blocks, where facilities further than 1,000 meters from any populated census block were excluded. Data were then aggregated to the census tract levels, and adjusted weights for facilities within or near each census tract were summed to produce an overall score.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Low Birth Weight Babies
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Data on low birth weight infants represents live births where infants weighed less than 2,500 grams (5.5 pounds). A high prevalence of low birth weight infants in a community can indicate potential exposure to environmental stressors, including air pollution, as studies have found that exposure to air pollutants during pregnancy is linked to an increased risk of low birth weight infants among other adverse outcomes.[61] Consequently, low birth weight is associated with an increased risk of infant mortality and long-term health issues.[62] Our factsheets report the average share of low-birth-weight births by neighborhood type using the census-tract population of children aged 0-5 as our weight. This weighting emphasises communities where more young children could be affected.

CalEnviroScreen reports low birth weight prevalence using 2009 to 2015 live birth records from the California Department of Public Health. This measure was calculated by summing the number of low birth weights in each census tract and dividing by the total number of live births in the same tract.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Risk Management Plan (RMP) Facilities
Source: Environmental Protection Agency EJ Screen 2.3, 2024
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: Sites where hazardous chemicals—like propane, pesticides, ammonia, and explosives—are present are required to implement a risk management plan under the Clean Air Act. Studies have shown that populations near such facilities face increased risk of harmful health effects, long-term illnesses, and environmental decline due to accidental chemical releases. These risks disproportionately affect vulnerable populations, including low-income communities and communities of color, demonstrating the need for targeted environmental efforts.[63]

Data for RMP facility proximity represent the proximity of populations to these sites. In our factsheets, we present this indicator as a "neighborhood proximity score" and report the average RMP-facility-proximity score by neighborhood type using the total census tract population as our weight. Higher scores indicate neighborhoods are closer to more facilities.

The Environmental Protection Agency (EPA) reports RMP-facility-proximity using facility locations in the EPA Facility Registry Service Risk-Management-Plan dataset. Proximity scores were calculated for each census block based on the inverse distance between block centroids and RMP facilities within a 10-kilometer radius and then aggregated to the census tract level. The maximum score of 10 was applied for distances under 0.1 km, with scores decreasing proportionally as distance increases.

For more detailed information on this indicator, refer to the EPA's EJScreen Technical Documentation.

Air Pollution Indicator: Age
Source: Census Bureau's American Community Survey, 2022 5-year Estimates
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2020

Definition: We report data on two age groups: children (0-5 years) and older adults (65 years and older) because of their heightened sensitivity to air pollution. The developing respiratory and immune systems in children, for example, make them more sensitive to air pollutants as their lungs are especially vulnerable to acute injury during childhood.[64] Additionally, older adults are more susceptible to air pollution-induced health effects because of a greater incidence of chronic conditions, including cardiovascular and respiratory disease,[65] as well as dementia.[66] Including this indicator helps identify neighborhoods with higher concentrations of these vulnerable age groups to design targeted public health interventions. Our factsheets report the average share of children and older adults by neighborhood type using the total census-tract population as the weight.

We obtained data on age-group counts from the American Community Survey 2022 five-year estimates, Table B01001 (Sex by Age). To calculate the percentage of the population in each age group within a census tract, we summed up the relevant age-specific population counts (male and female populations aged 0-5 and 65 or older) and divided them by the total population of the census tract.

For more information on the underlying data, visit the U.S. Census Bureau website.

Air Pollution Indicator: Emergency Department Visits (per 10,000 people) for Asthma Attacks
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: This indicator represents the age-adjusted annual rate of emergency-department visits for asthma per 10,000 residents at the census-tract level. Adults with asthma are highly sensitive to outdoor air pollution; a California time-series analysis found that short-term increases in source-specific fine-particulate matter were followed by significant rises in asthma-related emergency-department visits across eight metropolitan areas.[67] By analyzing patterns in asthma emergency department visits, public health officials can identify communities at greater respiratory risk during poor air quality. In our factsheets, we report the average number of emergency department visits per 10,000 residents by neighborhood type using the total population size at the census tract level as our weight.

CalEnviroScreen (CES) reports data for emergency department visits using data from the Emergency Department and Patient Discharge Datasets maintained by the State of California's Office of Statewide Health Planning and Development. The data reported by CES represents the age-adjusted annual rate of emergency department visits for asthma per 10,000 residents and is averaged over 2015 to 2017.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Emergency Department Visits (per 10,000 people) for Heart Attacks
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: This indicator represents the age-adjusted annual rate of emergency-department visits for heart attacks per 10,000 residents at the census-tract level. An increase in outdoor fine-particulate matter (PM2.5) can worsen cardiac events; a multicity U.S. case-crossover study reported that each 10 $\mu g/m^3$ increase in daily PM2.5 was associated with a statistically significant rise in emergency department visits for myocardial infarction.[68] By analyzing patterns in asthma emergency department visits, public health officials can identify communities at greater risk of heart attacks during poor air quality. In our factsheets we report the average number of emergency department visits for heart attack per 10,000 residents by neighborhood type using the total population size at the census tract level as our weight.

CalEnviroScreen (CES) reports rates of emergency department visits for heart attacks using data from the Emergency Department and Patient Discharge Datasets maintained by the State of California's Office of Statewide Health Planning and Development. This indicator specifically represents acute myocardial infarctions. Data reported by CES represents the age-adjusted annual rate of emergency department visits for heart attacks per 10,000 residents and is averaged over 2015 to 2017.

For detailed information on the data sources and calculation methods, please refer to the CES 4.0 website.

Air Pollution Indicator: Adults (18+) with Pre-Existing Condition: Asthma
Source: Centers for Disease Control and Prevention: PLACES: Local Data for Better Health, 2023
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Data on asthma prevalence represents the percentage of adults (18 years and older) who report being told by a healthcare professional that they have asthma and still have it at the time of the survey. Adults with asthma are highly sensitive to airborne pollutants; U.S. studies show exposure to fine-particulate matter is associated with an increased risk for emergency hospital admission among individuals with asthma.[69] Analyzing data on asthma prevalence can help advocates identify areas with vulnerable populations to help target these communities, whose residents are most likely to experience respiratory impacts during periods of poor air quality. In our factsheets, we report the average crude prevalence of adults' current asthma by neighborhood type, using the total population size at the census-tract level as our weight.

The Centers for Disease Control and Prevention (CDC) PLACES: Local Data for Better Health reports asthma prevalence. The CDC developed its 2023 estimates with survey data from the 2019-2021 Behavioral Risk Factor Surveillance System and demographic data from the American Community Survey.

For more information, refer to the CDC PLACES website.

Air Pollution Indicator: Adults (18+) with Pre-Existing Condition: Coronary Heart Disease
Source: Centers for Disease Control and Prevention: PLACES: Local Data for Better Health, 2023
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Data on coronary-heart-disease (CHD) prevalence represents the percentage of adults who report having been told by a health professional that they have angina or CHD. Air pollution disproportionately affects adults living with CHD as they are more vulnerable to negative health impacts.[70] Additionally, studies have also found that long-term exposure to air pollution increases the risk of CHD.[71] Analyzing data on CHD prevalence can help target neighborhoods whose residents face greater cardiovascular dangers when air quality worsens. In our factsheets we report the average crude prevalence of adult CHD by neighborhood type, using the total adult population at the census-tract level as our weight.

The Centers for Disease Control and Prevention (CDC) PLACES: Local Data for Better Health reports data on asthma prevalence. The CDC developed its 2023 estimates with survey data from the 2019-2021 Behavioral Risk Factor Surveillance System and demographic data from the American Community Survey.

For more information, refer to the CDC PLACES website.

Air Pollution Indicator: Clunker Vehicles
Source: California Neighborhood Knowledge/California Air Resources Board (CNK-CARB) Transportation Disparity Tool, 2022
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: This indicator represents the proportion of vehicles registered within a census tract over 20 years old, classified as "clunkers" based on their model year (1997 or earlier). These older vehicles typically lack modern emission control technologies that, in modern vehicles, help to reduce the emission of pollutants.[72] Thus, older vehicles contribute significantly to air pollution due to less stringent emission standards at the time of manufacture. Our factsheets report the average share of older vehicles by neighborhood type using the total number of registered vehicles in each census tract as our weight.

The UCLA Center for Neighborhood Knowledge (CNK) and California Air Resources Board (CARB) developed the older-vehicle indicator using 2017 vehicle registration data from the California Department of Motor Vehicles. Their indicator only includes vehicles registered to individuals and excludes corporate-owned vehicles. The indicator was constructed by dividing the count of vehicles with model years 1997 or earlier by the total vehicle stock within each census tract.

For more information, refer to the CNK-CARB Screening Technical Report.

Air Pollution Indicator: Low-Emission Vehicles
Source: California Neighborhood Knowledge/California Air Resources Board (CNK-CARB) Transportation Disparity Tool, 2022
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Low-emission vehicles include battery electric vehicles, plug-in hybrid electric vehicles, and hybrid electric vehicles. Low-emission vehicles, particularly newer models, have reduced emissions compared to traditional internal combustion vehicles, contributing to better air quality and lower greenhouse gas emissions.[73] Our factsheets report the average share of low-emission vehicles by neighborhood type using the total number of registered vehicles in each census tract as our weight.

The UCLA Center for Neighborhood Knowledge (CNK) and California Air Resources Board (CARB) developed data for low-emission vehicles, originally named the “clean-vehicle indicator,” using 2017 vehicle registration data from the California Department of Motor Vehicles. Their indicator only includes vehicles registered to individuals and excludes corporate-owned vehicles. The indicator was constructed by dividing the count of low-emission vehicles with 2013–2017 model years by the total vehicle stock within each census tract.

For more information, refer to the CNK-CARB Screening Technical Report.

Air Pollution Indicator: Disadvantaged Communities
Source: CalEnviroScreen 4.0, 2021
Geographic Unit of Analysis: Census Tract
Boundary Vintage: 2010

Definition: Disadvantaged communities (DACs) in California are neighborhoods identified for targeted investments through proceeds from the state’s Cap-and-Trade Program under the California Global Warming Solutions Act of 2006 (AB 32). These investments aim to reduce greenhouse gas emissions, improve public health, and enhance the quality of life in the state’s most burdened communities. Our factsheets report the share of residents living in Senate Bill 535-designated disadvantaged communities by neighborhood type using the total census-tract population as our weight.

CalEnviroScreen reports data on disadvantaged communities designations identified under the criteria in Senate Bill 535[74] and using the California Protection Agency’s (CalEPA) pollution-and-population-vulnerability scoring system.[75] Census tracts are assessed using geographic, socioeconomic, public health, and environmental hazard criteria to determine those most impacted by pollution and vulnerable populations.

CalEnviroScreen identifies DACs using the following criteria:

- Tracts received the highest 25% of overall scores in CalEnviroScreen 4.0.
- Tracts with data gaps but among the top 5% of pollution burden scores in CalEnviroScreen 4.0.
- Tracts identified as disadvantaged in the 2017 designation, regardless of current scores in CalEnviroScreen 4.0.
- Lands under the control of federally recognized Tribes may be designated as DACs through consultation with CalEPA.

For more detailed information, see the SB 535 Disadvantaged Communities Report.

Development of Air Pollution Maps

In the air pollution factsheets, we include individual county-level maps showing the geographic distribution of the concentration of fine particulate matter 2.5 (PM2.5) at the neighborhood level (see Map 4 for an example). We mapped the population-weighted concentration of PM2.5 for each neighborhood using the indicator for annual mean concentration of PM2.5 (averaged over 2015-2017). We present data for PM2.5 as three distinct categories:

1) Neighborhoods exposed to PM2.5 concentrations below each respective county average.
2) Neighborhoods exposed to PM2.5 concentration near the county average (explained in more detail below).
3) Neighborhoods exposed to PM2.5 concentrations above the county average.

This indicator offers a clear, multi-year view of air pollution exposure trends and provides a meaningful measure of how communities are currently experiencing poor air quality. This approach captures patterns of disparity and allows decision-makers to better address the impacts of air pollution.

Note: We categorize observations of PM2.5 as “near” the county average if they are less than or greater than the value for the county average by 2.5% (see Table 4). We adopted this category after taking into account feedback from members of the Advisory Committee to create three distinct categories for the readability of our maps. Additionally, we settled on a ± 2.5% buffer after testing several buffer widths and reviewing the Office of Environmental Health Hazard Assessment’s (OEHHA) statewide standard-deviation analysis of PM2.5. A fixed 2.5% buffer captures tracts “statistically similar” to the mean without masking meaningful differences. County-level standard deviations range from ≈ 0.2 to 3 μg/m³, and a ± 2.5% is smaller than most standard deviations but large enough to avoid overgeneralization.

Table 4. Bins for Particulate Matter 2.5 on County-Level Maps

Bin	Rule
Above county average	PM2.5 > μ + 2.5%
Near county average	μ − 2.5 % ≤ PM2.5 ≤ μ + 2.5%
Below county average	PM2.5 < μ − 2.5%

Created with Datawrapper

Notes: μ = population-weighted county mean for PM2.5 (μg/m³). The ± 2.5 % buffer is small enough to work in bimodal or skewed county distributions, and at least one tract falls into each of the three bins for all counties.

Categorizing neighborhoods relative to their county’s average provides insight into local disparities, as countries can have very different exposure to air pollution. This method allows us to:

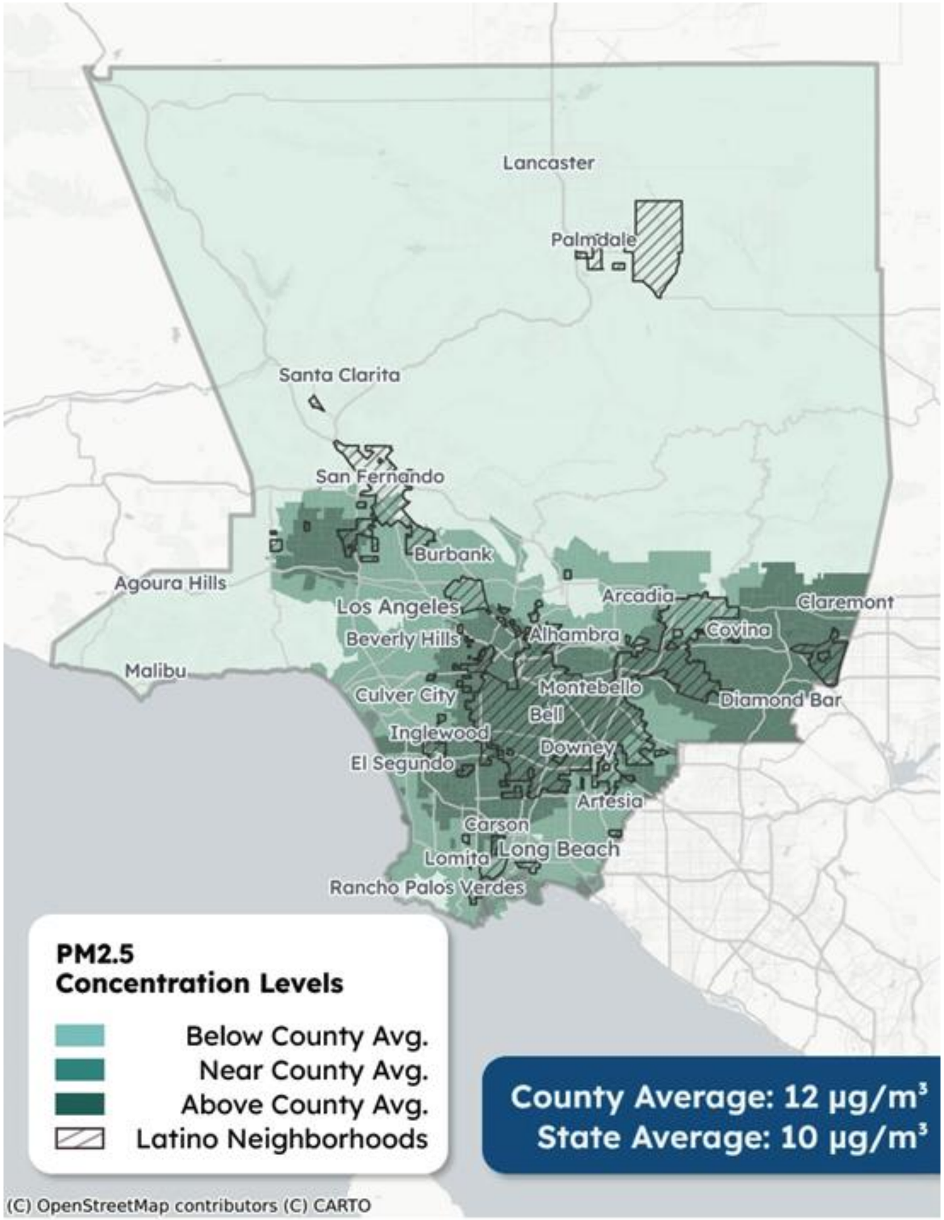
- Highlight localized air quality disparities: Comparing neighborhoods within the same county reveals how air pollution exposure is unevenly distributed, even in regions with exposure to pollutants.
- Focus on equity: Comparing neighborhoods within the same county reveals uneven distribution of air pollution, even in regions affected by similar pollutants and environmental hazards.

Technical Note: Below are the alternative classification methods we evaluated for displaying PM2.5:

1. Using state or federal standards (9 μg/m³) to categorize neighborhoods collapsed many counties into one color, eliminating neighborhood-level variation.
2. Equal-interval bins were too wide, leaving the middle bin category ("near" average) empty in most counties.
3. Categorizing observations into ± 1 standard deviations worked poorly for counties with standard deviations < 1 μg/m³ and was hard to explain to non-technical readers.
4. Geometric-interval breaks also produced an empty middle bin category ("near" average), offering very little intuition for technical and non-technical audiences.

Map 4 displays the distribution of PM2.5 at the census tract level for Los Angeles County, overlaid with the outlines that represent Latino neighborhoods. These maps also include primary roads to identify neighborhoods near high-traffic corridors, where vehicle emissions may contribute to higher air pollution levels. The map shows that Latino neighborhoods are concentrated farther inland (away from the coast) and largely fall in tracts exposed to an annual concentration of PM2.5 greater than the county average of 12 μg/m³; very few Latino neighborhoods lie in regions below the county average.

Map 4. Latino Neighborhoods and Exposure to Particulate Matter 2.5, 2015-2017



Notes: In our analysis, we refer to census tracts as neighborhoods. The county and state averages are population-weighted outputs using population data at the county and state levels, respectively. Census tracts reflect 2010 boundaries. Census tracts classified as "near" the county average fall within a ± 2.5% buffer of the county average.

Sources: LPPI analysis of data from CalEnviroScreen 4.0, 2021, and the Census Bureau's American Community Survey 2019 5-Year Estimates

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