Update to the California Communities Environmental Health Screening Tool

Draft CalEnviroScreen 5.0

Public Review Technical Report

DATE JANUARY 2026

CALIFORNIA ENVIRONMENTAL PROTECTION AGENCY

OFFICE OF ENVIRONMENTAL HEALTH HAZARD ASSESSMENT

PREFACE TO VERSION 5.0 DRAFT

The Office of Environmental Health Hazard Assessment (OEHHA) is releasing draft CalEnviroScreen (CES) 5.0, the latest iteration of the California Communities Environmental Health Screening Tool. This version of CES incorporates the most recent publicly available data for all indicators and improves in the way some indicators are calculated to better reflect environmental conditions or a population's vulnerability to environmental pollutants. Two new indicators —Small Air Toxic Sites, and Diabetes Prevalence — have been added to help capture additional environmental burdens and disease that contribute to pollution burden and population sensitivity to pollution. The indicator of Small Air Toxic Sites accounts for the presence of oil and gas wells and other sites reporting air toxic releases that are not already captured in the existing indicator of toxic releases. A Diabetes Prevalence indicator reflects sensitivity to pollution as exposure to pollution leads to worsening health outcomes for individuals with diabetes.

This version of CES has been updated with additional information to incorporate pollution concerns in the California-Mexico border region, continuing the efforts to address Assembly Bill 1059 (Garcia, Statutes of 2015). For the latest iteration of CES, OEHHA partnered with community-based organizations (CBOs) to co-design key updates to the tool and to continue its commitment to meaningful community engagement. A full report on the co-design process and a short overview report summarizing changes and updates proposed in this draft are available on the draft CES 5.0 webpage along with this technical report. Further recognizing the importance of transparency and public input in government decision-making, this draft of CES 5.0 is being released for public review and comment. OEHHA will be holding a series of public webinars and community workshops to discuss the proposed updates, share results, and collect feedback on this draft. The workshop dates will be in February and information on how to get involved will be announced through the OEHHA listserv and provided on our website. Written comments and suggestions on this draft CES 5.0 will be accepted until March 23, 2026. Comments may be uploaded through the 5.0 webpage or sent by mail to:

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INTRODUCTION

To address the cumulative effects of both pollution burden and factors of population vulnerability, and to identify which communities might be in need of particular policy, investment, or programmatic interventions, the Office of Environmental Health Hazard Assessment (OEHHA) developed and maintains and updates the CalEnviroScreen (CES) tool on behalf of the California Environmental Protection Agency (CalEPA). From its inception, the CES tool has helped identify overburdened communities and direct resources and attention to these impacted communities. CES applies a framework for assessing cumulative impacts that OEHHA developed in 2010, based on input from a statewide working group consisting of scientists, academic experts, government representatives, as well as community-based organizations (CBOs) that pointed out the unmet need to assess cumulative burdens and vulnerabilities affecting California communities (OEHHA 2010). This framework was incorporated into the first (1.0) version of CES, providing the first statewide assessment of cumulative impacts across California communities. Subsequent versions updated the assessment tool using the most current available data and incorporating various improvements and recommendations from residents, stakeholders, and government partners. CES 2.0 was released in 2014, 3.0 in 2017, and 4.0 in 2021.

This draft update to CES, 5.0, continues to evolve as a science-based method for identifying impacted communities by taking into consideration pollution exposure and its effects, as well as health and socioeconomic status, at the census-tract level. Draft CES 5.0 includes more recent data, improved methodology, and two additional indicators. The changes proposed for draft CES 5.0 are described in more detail in the summary of major changes chapter later in this technical report.

Assessing Cumulative Impacts

Many factors, often referred to as stressors, contribute to an individual or a community's pollution burden and vulnerability. Standard risk assessment protocols used by regulatory agencies cannot always account for the full range of factors that may contribute to risk and vulnerability. Risk assessments are often primarily designed to quantify health risks from a single pollutant or single source at a time, often in one specific medium (e.g., air or water). Many community groups and scientists have highlighted the fact that this approach fails to consider the totality of the health risks that communities face.

In reality, people are simultaneously exposed to multiple contaminants from multiple sources and also have multiple stressors based on their health status as well as living conditions, together known as "cumulative impacts". Thus, their resulting health risk is influenced by nonchemical factors such as socioeconomic and health status of the people living in a community. In such situations, risk assessment has a limited ability to quantify the resulting cumulative risk, and other tools, such as cumulative impact assessment, are needed.

The concept of cumulative impacts assessment has advanced significantly in recent years, both in science and in policy. Recent reports from the US EPA— *Cumulative Impacts Research: Recommendations for EPA's Office of Research and Development* (2022) and *Interim Framework for Advancing Consideration of Cumulative Impacts* (2024)— along with the National Science, Engineering and Medicine (NASEM) recent report *State-of-the-Science and the Future of*

Cumulative Impact Assessment (2025), and with growing use of state-level screening tools such as CES, collectively advance cumulative impacts science and guide its application in permitting, enforcement, and the prioritization of resources in overburdened communities. These applications allow decision-makers to better target protections and investments to areas of greatest need, thereby helping reduce health and environmental inequities. The field of cumulative impacts is a rapidly growing field, with expanding tools and practices that increasingly shape environmental health and equity policy.

Prior to the initial release of CES, a methodology did not exist to fully integrate multiple sources of pollution burden with various community vulnerability factors into a composite indicator. Hence, OEHHA and CalEPA developed the CES tool to conduct statewide evaluations of community-scale impacts.

The NASEM also recently published a landmark report titled *Constructing Valid Geospatial Tools for Environmental Justice,* which serves as a guidance document for federal, state, and other organizations to improve the design and application of environmental justice mapping tools (NASEM 2024). The recommendations from the 2024 NASEM report highlight creating a structured, collaborative process for building composite indicators, including a clear concept definition, careful selection and analysis of data, community engagement, and transparency in decision-making. These are all principles that have guided and continue to guide the development of CES to best reflect real-world conditions and the lived experiences of Californians.

Community Engagement

Community engagement plays a crucial role in the development and refinement of cumulative impacts tools, ensuring that these tools accurately reflect the experiences and needs of the communities they are designed to serve. These efforts ensure that local knowledge and lived experiences are integrated into the tool's development, making it a more accurate, trustworthy, and effective resource for assessing the true burdens of a community.

Leading to the draft CES 5.0 update, OEHHA collaborated with environmental justice CBOs from mid-2024 through mid-2025 through a co-design approach to better understand community needs and priorities. See the *CalEnviroScreen 5.0 Community Co-Design Report* for more details and information on this effort. This process also aligns with the recent NASEM guidance on cumulative impact assessment and best practices for geospatial tool development, which recommends meaningful engagement throughout the entire tool development process (NASEM 2024; NASEM 2025).

Organization of the Report

This report includes a chapter providing a detailed explanation of the proposed changes between CES 4.0 and draft CES 5.0. The remainder of this report follows the same format as previous CES reports, beginning with methodology, selection criteria for the 23 indicators, and calculation of the CES score for an individual census tract. This is followed by chapters for each indicator that define the indicator and explain how the data for each indicator were selected and analyzed. The scores for each indicator and the final CES scores for different areas of the state are presented as maps.

The report concludes by providing the overall draft results of the statewide analysis, presented as maps showing the census tracts with highest draft CES scores.

METHODOLOGY

The CalEnviroScreen Model

CalEnviroScreen (CES) is a composite indicator aiming to quantify cumulative impacts in California communities. A composite indicator is created by combining individual indicators into a single index based on an underlying model, aiming to measure multi-dimensional concepts beyond the scope of a single indicator (OECD 2005). Both the Organization for Economic Co-operation and Development and NASEM provide recommendations for how to approach the development of a composite indicator (NASEM 2024; OECD 2005). These steps include developing a theoretical framework, selecting and analyzing datasets, normalizing individual indicator datasets, aggregating the data, and then visualizing and presenting the data. The following section outlines the framework defining the concept for CES, determines subgroups for the model, documents the selection criteria for including data, provides the rationale on a decision to choose a method of normalizing indicator scores, and documents the process of aggregating the indicators to a single composite index score of cumulative impacts. OEHHA recently published a paper documenting key technical issues that are generally applicable to all cumulative impacts tools, where the tradeoffs between methodological rigor and model simplicity and transparency are explored and all framed within the context of prioritizing community engagement (Ranjbar et al. 2025).

Definition of Cumulative Impacts

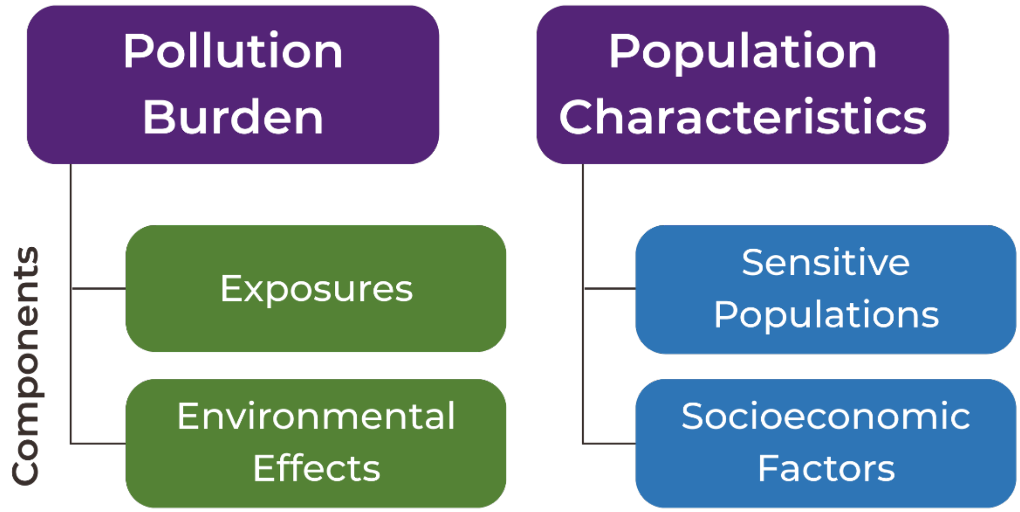
CalEPA adopted the following working definition of cumulative impacts in 2005:

“Cumulative impacts means exposures, public health or environmental effects from the combined emissions and discharges, in a geographic area, including environmental pollution from all sources, whether single or multi-media, routinely, accidentally, or otherwise released. Impacts will take into account sensitive populations and socioeconomic factors, where applicable and to the extent data are available.”

CalEnviroScreen Model

The CES model is based on the CalEPA working definition in that:

- The model is place-based and provides information for the entire State of California on a geographic basis. The geographic scale selected is intended to be useful for a wide range of decisions.
- The model is made up of multiple components cited in the above definition as contributors to cumulative impacts. The model includes two categories representing Pollution Burden – Exposures and Environmental Effects – and two components representing Population Characteristics – Sensitive Populations (in terms of health status) and Socioeconomic Factors.



Model Characteristics

- Uses 23 statewide indicators to characterize both Pollution Burden and Population Characteristics.
- Uses percentiles to normalize and assign scores for each of the indicators in a given geographic area. The percentile represents a relative score for the indicators.
- Aggregates scores by using a system in which the percentiles are averaged for the set of indicators in each of the four components (Exposures, Environmental Effects, Sensitive Populations, and Socioeconomic Factors).
- Combines the component scores to produce a CES score for a given place relative to other places in the state, using the formula below (see Formula for Calculating CalEnviroScreen Score).

Geographic Scale

Draft CES 5.0 uses the census tract as the unit of analysis. Census tract boundaries are available from the Census Bureau. CES uses the Bureau's 2020 boundaries, updated from the 2010 boundaries used in past versions. There are approximately 9,100 census tracts in California, representing a relatively fine scale of analysis. Census tracts are made up of multiple census blocks, which are the smallest geographic unit for which population data are available. Some census blocks have no people residing in them (unpopulated blocks).

CES uses census tracts to represent communities because indicator data is available or can be aggregated to the census tract level and tracts are designed to have roughly equal population sizes for better comparison. While census blocks may allow for more granular indicator data, they often experience greater challenges related to data quality and wider margins of error than tracts, particularly in areas with very low or very high population densities. Census tracts have advantages over larger geographies like ZIP codes, as they are spatially defined, consistent over time, and easier to update. Despite some limitations, census tracts offer a balanced approach by providing adequate spatial detail while maintaining data reliability.

Normalizing Data

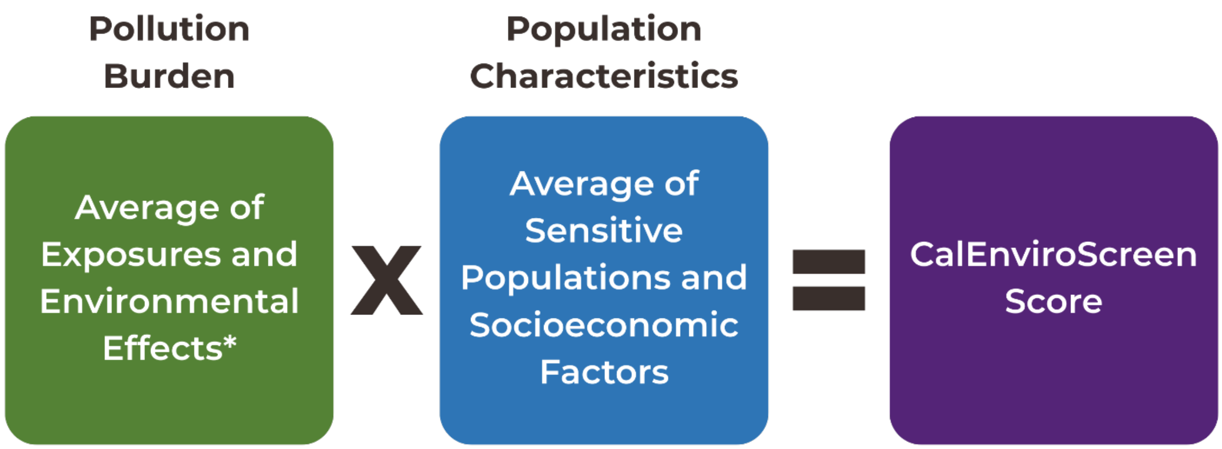
To combine different CES indicator data into a single score that can represent pollution burden or population vulnerability, the indicator values must first be transformed to a common scale. Normalization is transforming values measured on different units into a common scale for comparison and aggregation.

CES uses the percentile method to transform indicator values to a common scale. Each census tract receives a percentile score for each indicator value. Some of the reasons why this method was chosen:

1. *Ease and transparency*: Percentiles are straightforward to explain and easily understandable for a wide variety of audiences. A geographic area's percentile for a given indicator simply tells the percentage of areas with lower values of that indicator.
2. *Varying data distributions*: Indicators used in CES have varying underlying distributions, and percentile rank calculations provide a useful way to describe data without making any potentially unwarranted assumptions about those distributions.
3. *Consistency:* Percentile scores can be applied as the normalization method to all indicators in both pollution components and population characteristic components making it a consistent approach to transform the data for every data distribution.
4. *Confidence in ranking of data, not in impact of magnitude*: A percentile score is based on rank, not the magnitude of difference between values. For instance, an area in the 30th percentile isn't necessarily three times more impacted than one in the 10th. Preserving magnitude through normalization requires confidence in both raw data accuracy and the differences between values.
5. *Emphasis on cumulative burden*: The CES score emphasizes cumulative impacts based on consistently high values across multiple indicators, not just a few extreme ones. Using a normalization method that accounts for magnitude could raise scores for tracts with fewer but extreme indicators which would be inconsistent with the model and definition of cumulative impacts.

Formula for Calculating CalEnviroScreen Score

After the components are scored within Pollution Burden or Population Characteristics, the scores are combined as follows to calculate the overall CalEnviroScreen Score:



* The Environmental Effects score was weighted half as much as the Exposures score.

Rationale for Formula

Scores for the Pollution Burden and Population Characteristics categories are multiplied (rather than added, for example). Although this approach may be less intuitive than simple addition, there is scientific support for this approach to scoring.

Multiplication was selected for the following reasons:

1. *Scientific Literature*: Numerous studies have shown that socioeconomic and sensitivity factors amplify the health risks posed by environmental pollutants, making a simple sum an inaccurate representation of the total impacts. For example, analyses of long-term exposure to particulate matter in postmenopausal women found associations with cardiovascular disease that were 50% stronger among those living in lower socioeconomic status neighborhoods, than those in higher socioeconomic neighborhoods (Chi et al. 2016). Similarly, children in deprived areas experienced greater asthma morbidity in response to air pollution compared with those in more advantaged neighborhoods (O'Lenick et al. 2017). In another study, maternal stress magnified the adverse effects of prenatal lead exposure on child neurodevelopment, with children of highly stressed mothers showing the largest deficits (Tamayo Y Ortiz et al. 2017).

2. *Risk Assessment Principles*: Some people (such as children) may be 10 times more sensitive to some chemical exposures than others. Risk assessments, using principles first advanced by the NASEM apply numerical factors or multipliers to account for potential human sensitivity (as well as other factors such as data gaps) in deriving acceptable exposure levels (NASEM 2009; US EPA 2012).

3. *Established Risk Scoring Systems*: Priority rankings done by various emergency response organizations to score threats have used scoring systems with the formula: Risk = Threat × Vulnerability (Brody et al. 2012). These formulas are widely used and accepted, in part because multiplication creates a wider range of scores than addition, creating more granularity in differentiating risks and creating distinctions that would be overlooked by addition.

Future Directions

Climate Change Indicators and Climate Impacts

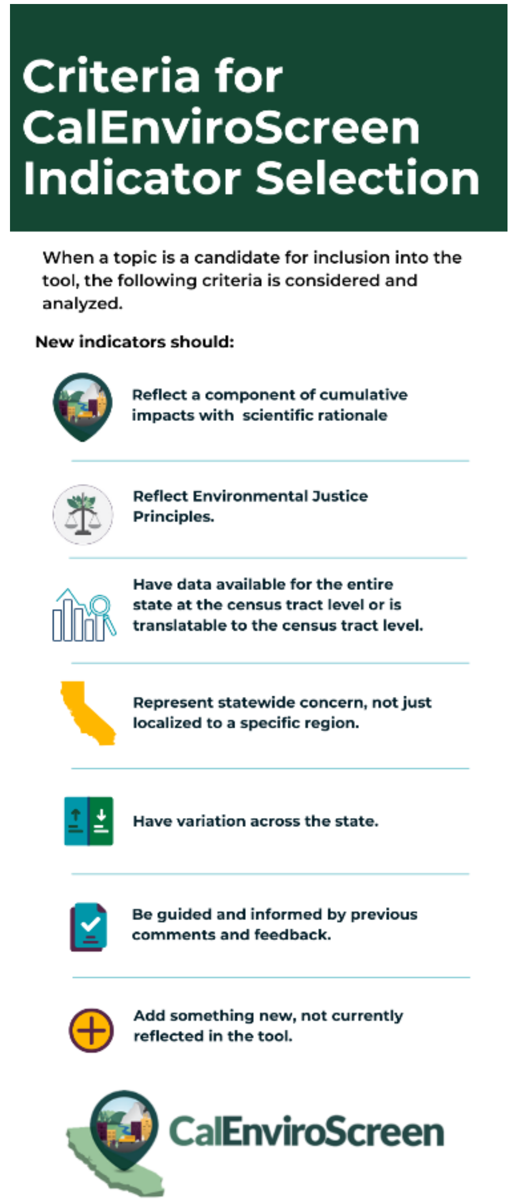
A strategy for evaluating climate data for use in CES will be developed for the longer term, and climate will be prioritized for consideration in CES 6.0. The next steps to assess the suitability of climate change in CES will involve reviewing publicly available data sources, evaluating methodologies, collaborating with scientific experts in the climate and cumulative impacts fields, and developing a plan based on collaboration with CBO and community input. In addition, when considering whether to incorporate a climate scoring component, decisions will have to be made on whether to include individual climate components into existing indicators (such as flood risk as an additional scoring component of an environmental effects indicator), or whether to add supplemental datasets to CES maps.

The incorporation of climate data into CES was a topic of interest during the public process of the CES 4.0 release. It has also been raised as a key priority during discussions with community-based organizations as part of the co-design effort on the continued development of the CES tool. There is general acknowledgement that communities are facing increasing risk from environmental hazards and vulnerability to pollution due to climate related events that already occur and are likely to worsen in the coming years. There is a lot of work being done at the state to assess issues of community vulnerability to climate change in California and how to incorporate this into CES will be a major consideration for the future direction of CES.

Indicator Selection and Scoring

The overall CalEnviroScreen Score for communities is driven by indicators. Here are the steps in the process for selecting indicators and using them to produce scores:

1. Identify potential indicators for each component.
2. Find sources of data to support indicator development (see Guiding Criteria for Indicator Selection below).
3. Select and develop the indicators, assigning a value for each census tract.
4. Assign a percentile for each indicator for each census tract, based on the rank-order of the value.
5. Generate maps to visualize data.
6. Derive scores for Pollution Burden and Population Characteristics components (see Indicator and Component Scoring below).
7. Derive the overall CalEnviroScreen Score by combining the component scores (see Scoring Overview below).
8. Generate maps to visualize overall results.



Guiding Criteria for Indicator Selection

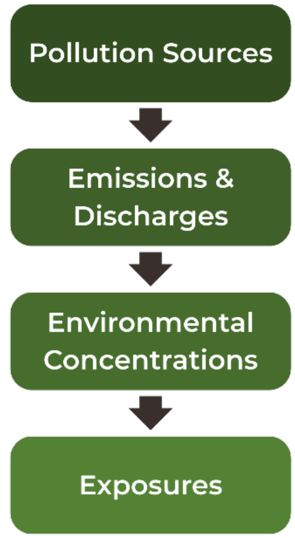
The selection of specific indicators requires consideration of both the type of information that will best represent statewide Pollution Burden and Population Characteristics, and the availability and quality of such information at the necessary geographic scale statewide.

The figure on the right describes the CES criteria for indicator selection utilized across the different versions of the tool. The criteria were used to guide the evaluation and discussion of indicators with CBO partners as part of the CBO co-design effort developing updates for draft CES 5.0.

CES practices for indicator selection are consistent with NASEM recommendations published more recently. In the report on constructing geospatial tools, NASEM states that the selection of indicators and datasets should be part of a structured approach. NASEM Recommendation 5 (NASEM 2024):

"Adopt systematic, transparent, and inclusive processes to identify and select indicators and datasets that consider technical criteria (validity, sensitivity, specificity, robustness, reproducibility, and scale) and practicality (measurability, availability, simplicity, affordability, credibility, and relevance). Evaluate measures in consultation with [government] agencies, technical experts, and community partners."

Exposure Indicators



People may be exposed to a pollutant if they come in direct contact with it, by breathing contaminated air, for example.

No data are available statewide that provide direct information on exposures. Exposures generally involve movement of chemicals from a source through the environment (air, water, food, soil) to an individual or population. CES uses data relating to pollution sources, releases, and environmental concentrations as indicators of potential human exposures to pollutants. Eight indicators have been identified and found consistent with the criteria for Exposure indicator development. They are:

- Air Quality: Ozone
- Air Quality: PM2.5
- Children's Lead Risk from Housing
- Diesel Particulate Matter
- Drinking Water Contaminants
- Pesticide Use
- Toxic Releases from Facilities
- Traffic Impacts

Environmental Effect Indicators

Environmental effects are adverse environmental conditions caused by pollutants.

Environmental effects include environmental degradation, ecological effects and threats to the environment and communities. The introduction of physical, biological and chemical pollutants into the environment can have harmful effects on different components of the ecosystem. Effects can be immediate or delayed. The environmental effects of pollution can also affect people by limiting their ability to make use of ecosystem resources (e.g., eating fish or swimming in local rivers or bays). Also, living in an environmentally degraded community can lead to stress, which may affect human health. In addition, the mere presence of a contaminated site or high-profile facility can have tangible impacts on a community, even if actual environmental degradation cannot be documented. Such sites or facilities can contribute to perceptions of a community being undesirable or even unsafe.

Statewide data on the following topics have been identified and found consistent with criteria for environmental effect indicator development:

- Cleanup Sites
- Groundwater Threats
- Hazardous Waste Generators and Facilities

- Impaired Waters
- Small Air Toxic Sites
- Solid Waste Sites and Facilities

Sensitive Population Indicators

Sensitive populations are populations with physiological conditions or health status that result in increased vulnerability to pollutants.

Sensitive individuals may include those with impaired health status, such as people with heart disease, asthma, or diabetes. Other sensitive individuals include those with physiological conditions like infants of low birth weight.

Pollutant exposure is a likely contributor to many observed adverse outcomes, and has been demonstrated for some outcomes such as asthma, low birth weight, and heart disease. People with these health conditions are also more susceptible to health impacts from pollution. With few exceptions, adverse health conditions are difficult to attribute solely to exposure to pollutants. High quality statewide data related to sensitive populations affected by toxic chemical exposures have been identified and found consistent with criteria for sensitive population indicator development:

- Asthma
- Cardiovascular Disease
- Diabetes Prevalence
- Low-Birth-Weight Infants

Socioeconomic Factor Indicators

Socioeconomic factors are community characteristics that result in increased vulnerability to pollutants.

A growing body of literature provides evidence of the heightened vulnerability of people of lower socioeconomic status to environmental pollutants. Here, socioeconomic factors that have been associated with increased population vulnerability were selected.

Data on the following socioeconomic factors have been identified and found consistent with criteria for socioeconomic factor indicator development:

- Educational Attainment
- Housing Burden
- Linguistic Isolation
- Poverty
- Unemployment

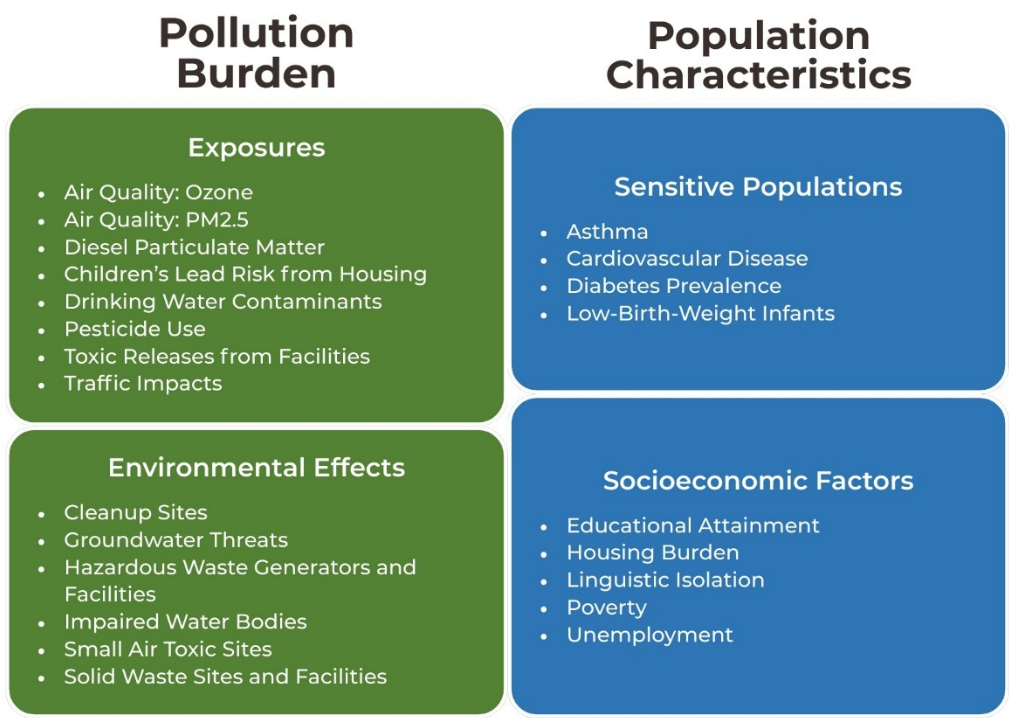
Indicator and Component Scoring

Indicator values were normalized by assigning percentile scores based on the order of census tracts' indicator values from highest to lowest for the entire state. A percentile score was calculated from the ordered values for all tracts that have a score. Each tract's percentile rank for a specific indicator is relative to the ranks for that indicator in the rest of the tracts in the state.

When a census tract has no indicator value (for example, the tract has no hazardous waste generators or facilities), it is excluded from the percentile calculation and assigned a score of zero for that indicator. When data are missing for a geographic area, such as census data in unpopulated census tracts, it is excluded from the percentile calculation and is not assigned any score for that indicator. The percentile score can be thought of as a comparison of one geographic area to other localities in the state where the hazard effect or population characteristic is present.

Indicators from Exposures and Environmental Effects components were grouped together to represent Pollution Burden. Indicators from Sensitive Populations and Socioeconomic Factors were grouped together to represent Population Characteristics (see figure below).

Scoring Overview



For a given census tract, scores for the Pollution Burden and Population Characteristics are calculated as described below (an example calculation is provided later in this report):

- First, the percentiles for all the individual indicators in a component are averaged. This becomes the score for that component. When combining the Exposures and Environmental Effects components, the Environmental Effects score was weighted half as much as the Exposures score. This was done because the contribution to possible pollutant burden from the Environmental Effects component is considered less than those from sources in the Exposures component. More specifically, the Environmental Effects components represent the presence of pollutants in a community rather than exposure to them. The Exposure component receives twice the weight of the Environmental Effects component.

- The Population Characteristics score is the average of the Sensitive Population score and Socioeconomic Factors score.
- The Pollution Burden and Population Characteristics scores are then scaled so that they have a maximum value of 10 and a possible range of 0 to 10. A value of zero typically implies that monitoring or reporting was conducted, but no impacts were present.

Each average was divided by the maximum value observed in the state and then multiplied by 10. The scaling ensures that the pollution component and population component contribute equally to the overall CalEnviroScreen Score.

CalEnviroScreen Score and Maps

The overall CalEnviroScreen Score is calculated by multiplying the Pollution Burden and Population Characteristics scores. Since each group has a maximum score of 10, the maximum CalEnviroScreen Score is 100.

The census tracts are ordered from highest to lowest, based on their overall score. A percentile for the overall score is then calculated from the ordered values. As for individual indicators, a census tract's overall CalEnviroScreen percentile equals the percentage of all ordered CalEnviroScreen Scores that fall below the Score for that area.

Maps are developed showing the percentiles for all the census tracts of the state. Maps are also developed highlighting the census tracts scoring the highest.

Uncertainty and Error

There are different types of uncertainty that are likely to be introduced in the development of any indicator screening method for evaluating pollution burden and population vulnerability in different geographic areas. Important ones are:

- The degree to which the data that are included in the model are correct.
- The degree to which the data and the indicator metric selected provide a meaningful measure of the pollution burden or population vulnerability.
- The degree to which data gaps or omissions influence the results.

Efforts were made to select datasets for inclusion that are complete, accurate and current. Nonetheless, uncertainties may arise because environmental conditions change over time, or large databases may contain errors or be incomplete, among others. Some of these uncertainties were addressed in the development of indicators. For example, clearly erroneous place-based information for facilities or sites have been removed when identified.

Other types of uncertainty, such as those related to how well indicators measure what they are intended to represent, are more difficult to measure quantitatively. For example:

- How well data on chemical uses or emissions reflect potential contact with pollution.
- How well vulnerability of a community is characterized by demographic data.

Generally speaking, indicators are surrogates for the characteristic being modeled, so a certain amount of uncertainty is inevitable. That said, the CES model is comprised of a suite of indicators considered useful in identifying places burdened by multiple sources of pollution with populations that may be especially vulnerable. Places that score highly for many of the indicators are likely to be identified as impacted. Since there are tradeoffs in combining different sources of information, the results are considered most useful for identifying communities that score highly using the model.

CES uses relatively straightforward methods, making it sensitive to changes such as how data are aggregated or which indicators are used. Concerns have been raised this could lead to unfair outcomes, such as excluding vulnerable communities from funding or enabling political manipulation. However, the tool's methods are shaped by public input, transparency, ease of use, and reproducibility. Ongoing community engagement helps with accountability and preventing misuse. CES developers continue to aim to clearly document and explain how sensitivity analyses guide decisions on updates and changes to the tool (Ranjbar et al. 2025).

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PROPOSED UPDATES AND SUMMARY OF MAJOR CHANGES FOR DRAFT CALENVIROSCREEN 5.0

Overview of Proposed Updates

The Office of Environmental Health Hazard Assessment (OEHHA) proposes to update CalEnviroScreen (CES) 4.0 to draft CES 5.0 in a variety of ways. The proposed updates include:

- Updates to the newest available census tract geography, reflecting the 2020 decennial census population.
- The most recently available data for all indicators.
- Two new indicators to better reflect on-the-ground conditions across California, which include:
    - **Diabetes Prevalence** in adults.
    - **Small Air Toxic Sites,** including oil and gas wells and other sites reporting air toxic releases.
- Improved calculations of several indicators, which include:
    - **Drinking Water Contaminants** indicator refinements, including refinement of methodology for calculating the drinking water index, the addition of per- and polyfluoroalkyl substances (PFAS) chemical monitoring data, and the incorporation of additional tribal water system data.
    - **Children's Lead Risk from Housing** indicator now incorporates the measured levels of children with elevated blood lead levels (BLLs).
    - Buffer distances for **Hazardous Waste Generators and Facilities** indicator expanded for larger hazardous waste facilities to better account for impacts to nearby communities.
- Suppression criteria that excluded census tracts with high margins of error in data estimates have been removed to improve methodological transparency and ease, as these criteria had only a minor influence on overall scoring.

With these changes, draft CES 5.0 has 23 indicators of pollution burden and drivers of vulnerability within California's approximately 9,100 census tracts. There are no changes to the overall model or to the method for calculating cumulative impacts (CalEnviroScreen Scores).

The following chapter provides more detail on the proposed changes between the draft CES 5.0 and the prior 4.0 version. Full details on the methods used to calculate each indicator can be found in the specific indicator chapters.

2020 Census Tract Geography Update

Draft CES 5.0 results have been analyzed at the 2020 decennial census tract geography. The previous version, CES 4.0, used the 2010 decennial census tract geography. During each census, geographic boundaries are adjusted to account for changes in population distribution. Census tracts typically contain about 2,500 to 8,000 residents. In 2020, California gained nearly 1,100 additional tracts, increasing from 8,035 to 9,106, from census tract boundary changes. This results in a finer scale of spatial analysis and a more accurate representation of the shifting population distribution of California. All indicators were analyzed using the 2020 census tract geography.

Indicator Update Details

Air Quality: Ozone

The air monitoring data have been updated to reflect ozone measurements for the years 2021–2023. The measure for draft CES 5.0 is the daily maximum 8-hour average ozone concentration of summer months (May to October). This is the same measure used for CES 4.0. For draft CES 5.0, ozone values were considered valid if 75 percent or more of the May through October time period was represented. Data for a monitoring site with a year that didn't meet this requirement were not included in the average for that site. Sites with two or more valid years were included in the final results.

Air Quality: PM 2.5

The air monitoring and satellite data have been updated to reflect fine particle pollution (particles less than 2.5 microns in diameter, PM2.5) measurements for the years 2021-2023. As in CES 4.0, PM2.5 concentration estimates were generated from a 1-kilometer (km) square grid layer. The grid layer concentrations were estimated by blending, as a weighted average, monitor measurements of PM2.5 concentrations, with 1-km square PM2.5 concentration estimates from a machine learning model leveraging satellite, meteorology, and other data to predict ground-level PM2.5. This model makes several improvements on the model by Lee and colleagues, referenced in the Method section of the PM2.5 indicator chapter, that was used to generate gridded PM2.5 estimates for CES 4.0, such as removing spatially static prediction variables like air basin boundaries and elevation that caused overfitting and replacing them with spatiotemporally varying predictors such as satellite-based estimates of carbon monoxide concentrations. Additionally, the 5.0 model is a random forest model, allowing for non-linearity in combining the predictor variables, as opposed to the 4.0 model which assumed linearity. The value of these improvements was confirmed by the fact that the CES 5.0 model's estimates for PM2.5 were closer to ground monitor measurements of PM2.5 than the model used in CES 4.0. As in CES 4.0, grid cells closer to monitors received a higher weight from monitor measurements, while grid cells further away received a higher weight from satellite model-based estimates. PM2.5 concentration data for census tract centers more than 10 km from the nearest PM2.5 monitor were based solely on satellite model-based estimates, whereas this radius was 50 km in CES 4.0, reflecting increased reliability of the modeled estimates in draft CES 5.0.

To generate a spatially stable distribution of statewide PM2.5 concentrations that reflects persistent PM2.5 burden, the impact of wildfire smoke PM2.5, whose spatial distribution can vary dramatically year-to-year based on the locations of large wildfires, must be minimized. In CES 4.0, this was accomplished by excluding satellite data from 2015 and 2017 in their entirety, as these years were strongly affected by wildfire smoke. In draft CES 5.0, to maximize data retention, days where wildfire smoke affected air quality across all three years (2021-2023) anywhere in the state, as detected by satellite smoke imagery data, were flagged and removed prior to aggregation of grid layer estimates to the census tract level. The differences in the PM2.5 indicator scores that are observed with the inclusion of wildfire smoke days in the data distribution can be viewed as a supplemental mapping application with the use of a slider or toggle map.

Diesel Particulate Matter

Diesel PM emissions data were updated to reflect emissions estimates for the year 2021, using largely the same data sources and methods as in CES 4.0. As in the previous version, emissions for the Diesel PM indicator for draft 5.0 include area, point, on-road, and ocean-going vessel sources, and account for emissions from sources of diesel PM in Mexico. Data for draft CES 5.0 included on-road emissions for each day in calendar year 2021 while data for CES 4.0 included on-road emissions estimates for a typical summer week in July of 2016.

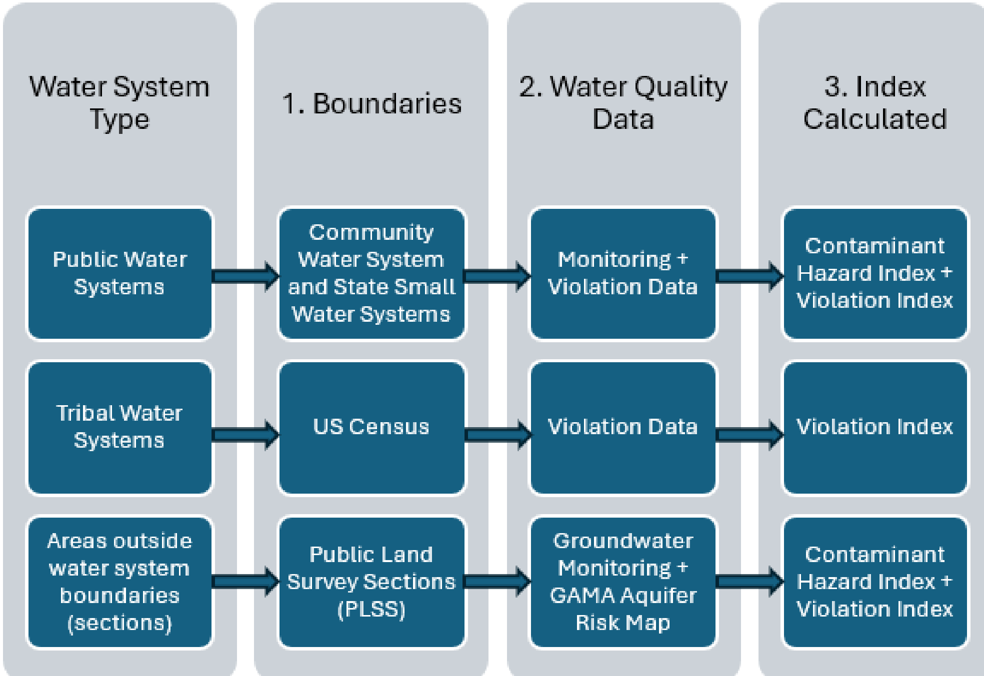
Drinking Water Contaminants

The Drinking Water Contaminants indicator methods have been updated significantly for draft CES 5.0. In addition to the full coverage of community water systems and the state small water systems included in CES 4.0, draft CES 5.0 now incorporates water quality data for 61 tribal areas.

Water contaminant data from 2014-2022 were collected, representing the three most recent compliance periods. In CES 4.0, the drinking water indicator included a census tract contaminant index that was calculated as the sum of the percentiles for all contaminants. For draft CES 5.0, an updated cumulative water contaminant hazard index and violation component is proposed. This was calculated by dividing each contaminant's average concentration by half the contaminant's California maximum contaminant level (MCL), or federal maximum contaminant level goal (MCLG). Ideally, the benchmark for each contaminant would be the contaminant's Public Health Goal (PHG), but many PHGs are below instrumentation detection limits. Although regulations require a contaminant's MCL to be established at a level as close to its PHG as is technologically and economically feasible, the MCL takes into account a chemical's detectability and treatability, as well as the costs of treatment. The value of half the MCL as a benchmark is both more health protective than the MCL (closer to the PHG), and measurable for each contaminant.

Contaminant ratios were summed per water system to create the contaminant hazard index. The violation component is the sum of maximum contaminant level violations, treatment technique violations, total coliform rule violations, and action level exceedances. The percentile ranking of both the contaminant hazard index and the violation component was summed using a 0.75 weight for the contaminant hazard index and a 0.25 weight for the violation component. The final indicator score was calculated using a weighted sum and assigned percentiles. A visual representation of the types of water systems and data analyzed is included below.

In addition to the 14 contaminants tested in drinking water that were included for 4.0, six federally regulated per- and polyfluoroalkyl substances (PFAS) were added to the indicator. PFOS, PFOA, PRHxS, PFBS, PFNA, and HFPO-DA were included as part of the drinking water contaminants for draft CES 5.0, as these are considered PFAS and are now EPA-regulated (US EPA 2021). The MCLG was used as the regulatory benchmark for PFBS.



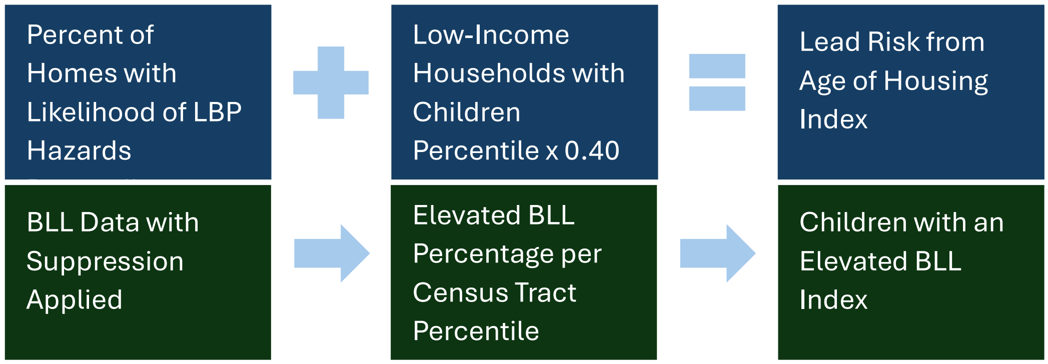
Illustrated steps for calculating the drinking water contaminant indexes in the Drinking Water Contaminants Indicator.

For federally recognized tribes with at least one federally regulated tribal water system, tribal land boundaries were used in lieu of water system boundaries to protect tribal sovereignty and data sharing concerns. Data from the US EPA's Enforcement and Compliance History Online (ECHO) allowed the incorporation of MCL violations, TCR violations, and LCR violations for 61 tribal water systems. Like CES 4.0, in cases where tribal water systems purchase water from public wholesale systems, the wholesale system's water quality was used to calculate both the contaminant hazard index and violation component.

Children's Lead Risk from Housing

The indicator of Children's Lead Risk from Housing has been updated with 2024 California parcel data and American Community Survey (ACS) 5-year estimates for 2019–2023 (age of housing) and 2017–2021 (percentage of low-income households with children). In addition, OEHHA proposes the inclusion of California Department of Public Health (CDPH) Childhood Lead Poisoning Prevention Branch (CLPPB) blood lead level (BLL) data from 2018-2022. This dataset provides census tract-level counts of children under six who received a blood lead test and the number with elevated BLLs of 3.5 microgram per deciliter (μg/dL) or greater. Each child is only counted once per year using their highest recorded BLL. Including this information adds a direct measure of lead exposure in children, complementing the existing housing-based risk factors.

To integrate the BLL dataset, OEHHA excluded all tracts with fewer than 10 total tests due to variability in coverage of testing. For remaining tracts in the dataset, the percent of elevated tests was calculated, ranked, and assigned a percentile (see figures below). Separately, the updated age of housing and low-income households with children data were combined following the CES 4.0 methodology. In the final indicator, the housing-based index contributes to 90% of the score, while the new BLL data accounts for 10%, using a weighted sum approach, highlighting both long-term risk and current evidence of exposure.



Illustrated steps to create Lead Risk from Age of Housing Index and Children with an Elevated BLL Index for final indicator calculation.

Illustrated steps to create the final Children's Lead Risk from Housing score.

Pesticide Use

The Pesticide Use indicator was updated with reported pesticide use (PUR) data used in production agriculture for the years 2021–2023. OEHHA revisited the hazard and volatility-based pesticide selection criteria from CES 4.0 to account for more recent data and updated information around hazard and volatility. For the proposed draft CES 5.0 update, OEHHA used the California Department of Pesticide Regulation's (DPR) full annual PUR data as the pesticide selection starting point instead of its "Pounds Sold" list, as was used in CES 4.0. The remaining methods of the selection criteria were followed as per CES 4.0.

The draft CES 5.0 includes 124 pesticide chemicals, compared to 132 pesticide chemicals in CES 4.0. Of the 124 pesticide chemicals currently included in the analysis, 107 were included in the previous version and 17 are new. There were 25 pesticide chemicals from the previous version that no longer met the inclusion criteria and were therefore not included in this current analysis. In most instances, these chemicals were dropped from analysis if they did not have production agricultural use between 2021 and 2023.

Toxic Releases from Facilities

Data from the US EPA's Risk Screening Environmental Indicators (RSEI) on toxicity-weighted concentrations of modeled chemicals that are released into the air were updated to incorporate an average of the emission data for the years 2020–2022.

As with CES 4.0, data on toxic release emissions from Mexico were incorporated to address the data gap for cross-border pollution and were incorporated into the RSEI model by Abt Associates, US EPA contractors for the RSEI program. Data from Mexico's Registry of Emissions and Pollutant Transfer (RETC, for its initials in Spanish) were from the years 2020–2022.

Traffic Impacts

The Traffic Impacts indicator was updated with traffic volume estimates for 2019 and incorporates data from an updated roadway network. The traffic volume data for draft CES 5.0 were acquired from the Caltrans Traffic Census and the Caltrans Highway Performance Monitoring Systems, both for 2019. Tracking California performed the analysis, adapting their Tracking California Traffic Tool, to update the road network and model of statewide traffic data, following a similar approach to that used in CES 4.0.

To account for the impact of traffic at the California-Mexico border, 2019 data on traffic volume for trucks, buses, and personal vehicles at six ports of entry were downloaded from the U.S. Customs and Border Protection website. In addition, data about traffic impacts from parallel roads in Mexico that are within 150 meters of the California-Mexico border were included for the two major parallel roads in Tijuana (Via Internacional and Blvd. Aeropuerto), using the same data from the San Diego Association of Governments (SANDAG) that was used for CES versions 2.0, 3.0, and 4.0. OEHHA is evaluating updated data for these roads received from SANDAG for potential inclusion into the final version of CES 5.0. Updated data for Mexicali parallel roads were not located.

Cleanup Sites

Data for cleanup sites have been updated with information on the location and status of cleanup sites from the EnviroStor database of the Department of Toxic Substances Control (DTSC) and Region 9 National Priority List Sites (Superfund Sites) Polygons from the US EPA, downloaded in July 2024.

Groundwater Threats

Updated information on the location and status of groundwater cleanup sites was downloaded from the State Water Resources Control Board's (SWRCB) GeoTracker database in March 2025. Data for dairies and feedlots data were downloaded from the SWRCB's California Integrated Water Quality System Project database in February 2025.

Hazardous Waste Generators and Facilities

Data from hazardous waste generators were updated for the years 2021-2023 with information provided by DTSC. Updated information on the location and status of permitted hazardous waste facilities was also acquired from DTSC in October 2024.

A change to buffer distances around hazardous waste facilities is proposed for draft CES 5.0. The proposal includes extending inverse distance weighted buffers up to 4-km around treatment, storage, and disposal facilities (TSDFs). Recent iterations of other environmental justice (EJ) tools, both national and state, have increased buffer distances around hazardous waste facilities, setting scientific precedent to evaluate using larger buffers in CES. As part of the CBO co-design for CES 5.0, CBOs provided direct input into the methodology and structure of the hazardous waste indicator, ensuring the indicator reflects real-world environmental and health burdens experienced by frontline communities. Throughout the evaluation of alternative buffers, OEHHA also consulted with other tool developers including US EPA EJScreen and Colorado EnviroScreen on best practices. Scientific rationale detailed in the indicator chapter supports a precedent set by other national and state environmental health tools, and the proposal was considered a priority for co-design CBOs. Please see the co-design report for additional details on the process. As well, information on the updated TSDF buffers proposed can be found in the appendix of the indicator chapter of this report.

Impaired Waters

The Impaired Waters indicator was updated with the most recent available data. SWRCB released its Final 2024 California Integrated Report (Clean Water Act Section 303(d) List /305(b) Report) on impaired water bodies in 2024. Every two years, the Regional Water Boards characterized as "on-cycle" are rotated so that each Regional Water Board is fully assessed once every six years. This Impaired Waters indicator update includes information from the SWRCB 2024 report and 2020-2022 report, incorporating new data for regions 2 (San Francisco), 4 (Los Angeles), Regions 3 (Central Coast), 5 (Central Valley), 9 (San Diego), and 8 (Santa Ana). Data for Regions 1 (North Coast), 6 (Lahontan), and 7 (Colorado River Basin) remain the same as CES 4.0.

OEHHA evaluated the indicator scoring and investigated alternative methods of characterizing data from the SWRCB Integrated Report and ultimately used the same method for counting unique pollutants per census tract as CES 4.0.

Small Air Toxics Sites

A new environmental effects indicator of proximity to Small Air Toxics Sites (SmATS) is proposed for inclusion in draft CES 5.0. This indicator captures the cumulative exposure burden from oil and natural gas (ONG) wells and other facilities reporting air toxic releases reported to the California Emissions Inventory Development and Reporting System (CEIDARS). CEIDARS is a database used by the California Air Resources Board (CARB) to store and maintain criteria and toxic air pollutants statewide. Because exposure levels vary with distance, the indicator accounts for proximity to populated census blocks when calculating census tract scores.

The SmATS indicator was added to address several important considerations. A growing body of scientific evidence shows that communities living closer to emission sources face higher pollution burdens, and that active ONG wells are causally linked to adverse health outcomes, including prenatal and respiratory impacts. Reliable, statewide data for ONG wells from CalGEM are available, addressing key gaps in previous CES versions. Facilities such as gas stations, dry cleaners, and autobody shops—common in communities and known to emit pollutants—are now captured using CARB’s CEIDARS database. While mandated facility reporting to CARB is currently undergoing phased implementation, the inclusion of CEIDARS data significantly improve neighborhood-level exposure estimates by accounting for sources previously excluded.

In addition, pollution burdens from SmATS sites are not evenly distributed. Socioeconomically disadvantaged people and people of color are more likely to live near these sources, compounding existing vulnerabilities. The CBOs that participated in the co-design of draft CES 5.0 emphasized that for communities living near ONG wells, this represents a significant part of the lived experience of disadvantaged communities and strongly supported their inclusion in the tool.

Solid Waste Sites and Facilities

Updated information on (1) active solid waste sites, (2) closed, illegal, or abandoned waste sites, (3) waste tires, and (4) violations at solid waste facilities was obtained from California's Department of Resources Recycling and Recovery (CalRecycle) in February 2025. Data about scrap metal recyclers that were active from 2022–2024 were obtained from DTSC. These data were all incorporated into draft CES 5.0.

(North American Industry Classification System) NAICS codes for DTSC's scrap metal recyclers were updated to reflect a more current categorization. New codes are 42193, 42393, and 56292, changed from only 42193. Overall, the analysis and scoring processes were streamlined without major methods changes.

Asthma

The Asthma indicator has been updated with data for the years 2022–2023 and represents the age-adjusted and spatially modeled rates of emergency department (ED) visits for asthma. Previous versions used three years of data instead of two, but 2021 was excluded in this case due to significant influence from the COVID-19 pandemic. If new data is available when CES 5.0 is finalized, OEHHA will consider using three years of data instead of two. Tracking California had calculated these rates for CES 4.0 and developed the original methods. For draft CES 5.0, OEHHA followed Tracking California's analysis with some minor updates to outdated software packages in the statistical program R.

Cardiovascular Disease

The Cardiovascular Disease (CVD) indicator has been updated with data for the years 2021–2023 for rates of ED visits for heart attacks. Tracking California had calculated these rates for CES 4.0 and developed the original methods. For draft CES 5.0, OEHHA followed Tracking California's analysis with some minor updates to outdated software packages in the statistical program R.

Diabetes Prevalence

OEHHA proposes adding a new sensitive population indicator for the draft CES 5.0: prevalence of adult diabetes. This indicator is proposed for inclusion because: a significant base of scientific evidence now indicates that the pathophysiology of diabetes increases an individual's sensitivity to the adverse effects of pollution on outcomes such as diabetes progression, cardiovascular complications, and mortality; validated census tract-level estimates of diabetes prevalence have recently become available for California; and CBOs in the co-design expressed that diabetes is an important part of the lived experience of disadvantaged communities in California, affecting 11% of Californians.

The indicator is developed from the Centers for Disease Control and Prevention's (CDC) PLACES data initiative, which uses nationally-representative individual-level survey data on diabetes prevalence from the 2021 Behavioral Risk Factor Surveillance System to impute population-level prevalence at the census tract scale. PLACES was chosen due to its accessibility as a free and publicly available tool and its spatial coverage at the census tract scale. OEHHA also evaluated a California-specific data set from the California Health Interview Survey (CHIS), but ultimately chose not to use it because the raw values could not be publicly displayed. The CBOs in the co-design process were supportive of the inclusion of this dataset to represent the indicator of diabetes prevalence and were involved in the decision to use the CDC PLACES data. Please see the co-design report for more information on this decision.

Low-Birth-Weight Infants

The draft CES 5.0 indicator for the percentage of low-birth-weight (LBW) infants uses data from more recent years (2017–2023). Tracking California produced this indicator for CES 4.0. For this version, OEHHA obtained and analyzed the data for this indicator in-house using identical methods.

Educational Attainment

The Educational Attainment indicator has been updated with 2019–2023 ACS estimates for the percentage of the adult population without a high school degree. For draft CES 5.0, OEHHA removed the suppression criteria applied in earlier versions, improving methodological transparency and ease of use. ACS data were obtained directly from the Census Bureau using an application programming interface (API) in R, allowing variables to be pulled programmatically. These variables were then used to calculate the final indicator. The removal of suppression criteria has only a minor effect on overall scoring, and there is little precedent for applying such suppression in other cumulative impact screening tools. All other methods remain consistent with those used in CES 4.0.

Housing Burden

The Hosing Burden indicator has been updated with 2017–2021 estimates from HUD's CHAS data. The measure is the percentage of households in a census tract that are both low income and severely burdened by housing costs. For draft CES 5.0, OEHHA removed the suppression criteria previously applied in CES 4.0 and earlier versions, improving methodological transparency and ease of use. The removal of suppression criteria has only a minor effect on overall scoring, and there is little precedent for applying such suppression in other cumulative impact screening tools. All other methods remain consistent with those used in CES 4.0.

Linguistic Isolation

The Linguistic Isolation indicator has been updated with 2019–2023 estimates from the ACS for the percentage of limited English-speaking households. For draft CES 5.0, OEHHA removed the suppression criteria applied in earlier versions, improving methodological transparency and ease of use. ACS data were obtained directly from the Census Bureau using an API in R, allowing variables to be pulled programmatically. These variables were then used to calculate the final indicator. The removal of suppression criteria has only a minor effect on overall scoring, and there is little precedent for applying such suppression in other cumulative impact screening tools. All other methods remain consistent with those used in CES 4.0.

Poverty

The Poverty indicator has been updated with 2019–2023 estimates from the ACS for the percentage of the population living below half the federal poverty level. For draft CES 5.0, OEHHA removed the suppression criteria applied in earlier versions, improving methodological transparency and ease of use. ACS data were obtained directly from the Census Bureau using an API in R, allowing variables to be pulled programmatically. These variables were then used to calculate the final indicator. The removal of suppression criteria has only a minor effect on overall scoring, and there is little precedent for applying such suppression in other cumulative impact screening tools. All other methods remain consistent with those used in CES 4.0.

Unemployment

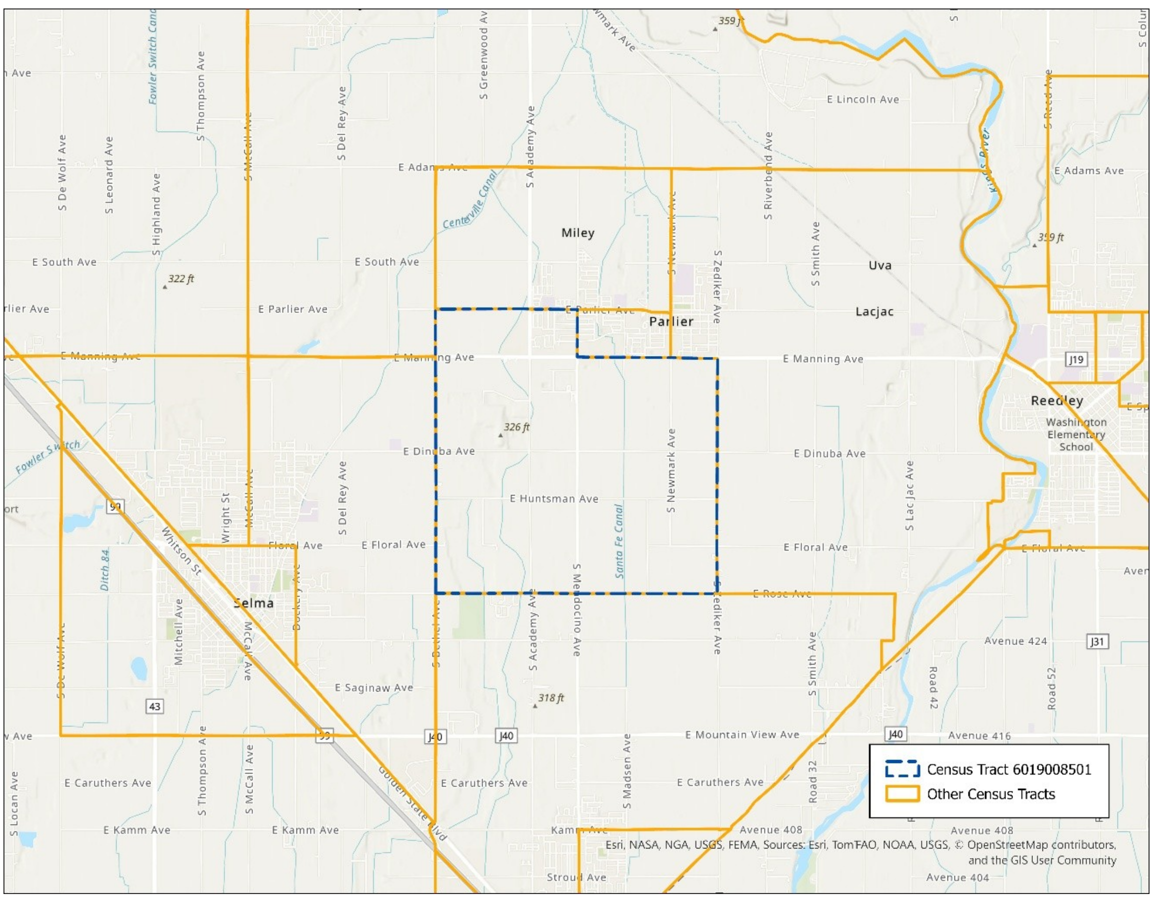
The Unemployment indicator has been updated with 2019–2023 estimates from the ACS for the percentage of the population over age 16 that is unemployed and eligible for the labor force. For draft CES 5.0, OEHHA removed the suppression criteria applied in earlier versions, improving methodological transparency and ease of use. ACS data were obtained directly from the Census Bureau using an API in R, allowing variables to be pulled programmatically. These variables were then used to calculate the final indicator. The removal of suppression criteria has only a minor effect on overall scoring, and there is little precedent for applying such suppression in other cumulative impact screening tools. All other methods remain consistent with those used in CES 4.0.

EXAMPLE CENSUS TRACT: INDICATOR RESULTS AND CALENVIROSCREEN SCORE

One example census tract in Parlier, southeast of Fresno, was selected to illustrate how an overall CalEnviroScreen Score is calculated using the CalEnviroScreen (CES) tool. Its census tract number is 6019008501.

Shown below are:

- An area map for the census tract and surrounding tracts.
- Tables for the indicators of Pollution Burden and Population Characteristics with percentile scores for each of the indicators.
- A table showing how a CalEnviroScreen Score was calculated for the example area, using draft CES 5.0.
- Example census tract map.



Exposure Indicators		
Indicator	**Raw Value**	**Percentile**
Ozone (ppm)	0.06	**87.18**
PM2.5 (μg/m3)	9.49	**58.77**
Diesel PM (tons/year)	0.03	**29.21**
Drinking Water (index)	96.98	**99.85**
Children's Lead Risk from Housing (index)	75.90	**79.14**
Pesticide Use (lbs/sq. mi.)	4160.70	**96.19**
Toxic Releases (RSEI toxicity-weighted releases)	255.19	**45.47**
Traffic (vehicle-km/ hour/km)	249.02	**11.58**
AVERAGE COMPONENT SCORE*	--	**63.42**

*A score here is calculated by averaging the percentiles within the component.

Environmental Effects Indicators		
Indicator	**Raw Value**	**Percentile**
Cleanup Sites (weighted sites)	1.70	**19.87**
Groundwater Threats (weighted sites)	6.00	**35.43**
Hazardous Waste Facilities/ Generators (weighted sites)	5.10	**98.01**
Impaired Water Bodies (number of pollutants)	0.00	**0.00**
Small Air Toxic Sites (weighted sites)	61.55	**62.43**
Solid Waste Sites/Facilities (weighted sites and facilities)	2.00	**49.98**
AVERAGE COMPONENT SCORE	--	**44.29**

Sensitive Population Indicators		
Indicator	**Raw Value**	**Percentile**
Asthma (rate per 10,000)	63.88	**90.97**
Cardiovascular Disease (heart attacks per 10,000)	16.21	**66.19**
Diabetes Prevalence (modeled population per tract)	18.8	**98.82**
Low Birth Weight (percent)	8.98	**96.65**
AVERAGE COMPONENT SCORE	--	**88.16**

Socioeconomic Factor Indicators		
Indicator	**Raw Value**	**Percentile**
Educational Attainment (percent)	37.39	**90.58**
Housing Burden (percent)	16.68	**46.32**
Linguistic Isolation (percent)	35.50	**97.88**
Poverty (percent)	67.38	**97.77**
Unemployment (percent)	8.27	**73.12**
AVERAGE COMPONENT SCORE	--	**81.13**

The approach used to calculate the CalEnviroScreen Score for census tract 6019008501is shown below in tabular form.

	Pollution Burden		**Population Characteristics**	
	Exposure Indicators	**Environmental Effects Indicators***	**Sensitive Population Indicators**	**Socioeconomic Factor Indicators**
Component Score	63.42	(0.5 × 44.29) =22.15	88.16	81.13
Average of Component Score	85.57 ÷ (1 + 0.5) = **57.05** *Pollution Burden is calculated as the average of its two component scores, with the Environmental Effects component half-weighted.*		169.29 ÷ 2 = **84.65** *Population Characteristics is calculated as the average of its two component scores.*	
Scaled Component Scores (Range 0-10)	(57.05 ÷ 82.12**) × 10 = **6.95** *The Pollution Burden percentile is scaled by the statewide maximum Pollution Burden scores.*		(84.65 ÷ 96.10***) × 10 = **8.81** *The Population Characteristics percentile is scaled by the statewide maximum Population Characteristics scores.*	
CalEnviroScreen Score	6.95 x 8.81 = **61.23** A score of **61.23** puts this census tract in the 95-100 percentile or **top 5%** of all CalEnviroScreen Scores statewide.			

* The Environmental Effects component was given half the weight of the Exposures component.
** The tract with the highest Pollution Burden score in the state had a value of 82.1.
*** The tract with the highest Population Characteristics score in the state had a value of 95.2.

INDICATORS

Pollution Burden: Exposure Indicators

AIR QUALITY: OZONE

Ozone pollution causes numerous adverse health effects, including respiratory irritation and exacerbation of lung disease. The health impacts of ground level ozone and other criteria air pollutants (carbon monoxide, lead, nitrogen dioxide, particulate matter (PM), and sulfur dioxide) have been considered in the development of health-based standards. Of the six criteria air pollutants, ozone and particle matter pose the most widespread and significant health threats. The California Air Resources Board maintains a wide network of air monitoring stations that provides information that may be used to better understand exposures to ozone and other air pollutants across the state.

Indicator

Mean of summer months (May-October) of the daily maximum 8-hour ozone concentration (ppm), averaged over three years (2021 to 2023).

Data Source

Air Monitoring Network, California Air Resources Board (CARB)

CARB, local air pollution control districts, tribes and federal land managers maintain a wide network of air monitoring stations in California. These stations record a variety of different measurements including concentrations of the six criteria air pollutants and meteorological data. In certain parts of the state, the density of the stations can provide high-resolution data for cities or localized areas around the monitors. However, not all cities have stations.

The information gathered from each air monitoring station audited by CARB includes maps, geographic coordinates, photos, pollutant concentrations, and surveys. Data are available at the link below:

http://www.arb.ca.gov/aqmis2/aqmis2.php

Rationale

Ozone is an extremely reactive form of oxygen. In the upper atmosphere, stratospheric ozone provides protection against the sun's ultraviolet rays. In contrast to ozone in the upper atmosphere, tropospheric ozone at ground level is harmful and is the primary component of smog. Ground-level ozone is formed from the reaction of oxygen-containing compounds with other air pollutants in the presence of sunlight. Ozone levels are typically at their highest in the afternoon and on hot days (NRC 2008).

Adverse effects of ozone have been studied extensively since the late 1960s (Lippmann 1989). Population-based studies have documented that acute ozone exposure is associated with a decrease in lung function, worsening of asthma, increase in hospital admissions as well as daily deaths (Last et al. 2017). Prolonged exposure to ozone in both animal and human studies show progressive inflammatory and cellular or tissue injury responses (Last et al. 2017). Reflecting the strong body of evidence, the US Environmental Protection Agency (EPA) determined that there is a causal relationship for short-term ozone exposure and respiratory effects, and a likely causal relationship for long-term exposure (US EPA 2020).

People with asthma and chronic obstructive pulmonary disease (COPD) are generally considered to be sensitive to the effects of ozone, long-term exposure increasing the risk of mortality for these diseases (Kehrl et al. 1999; Kim et al. 2024; Thurston et al. 1997; White et al. 1994).

Studies have shown that long-term ozone exposure also influences total respiratory and cardiovascular mortality (Crouse et al. 2015; Turner et al. 2016). A 2019 study estimates 13,700 deaths (95% CI: 6,100-23,700) in California in the year 2012 were attributable to long-term ozone exposure (Wang et al. 2019). Of these deaths, 7,300 and 6,400 were from respiratory and cardiovascular causes, respectively.

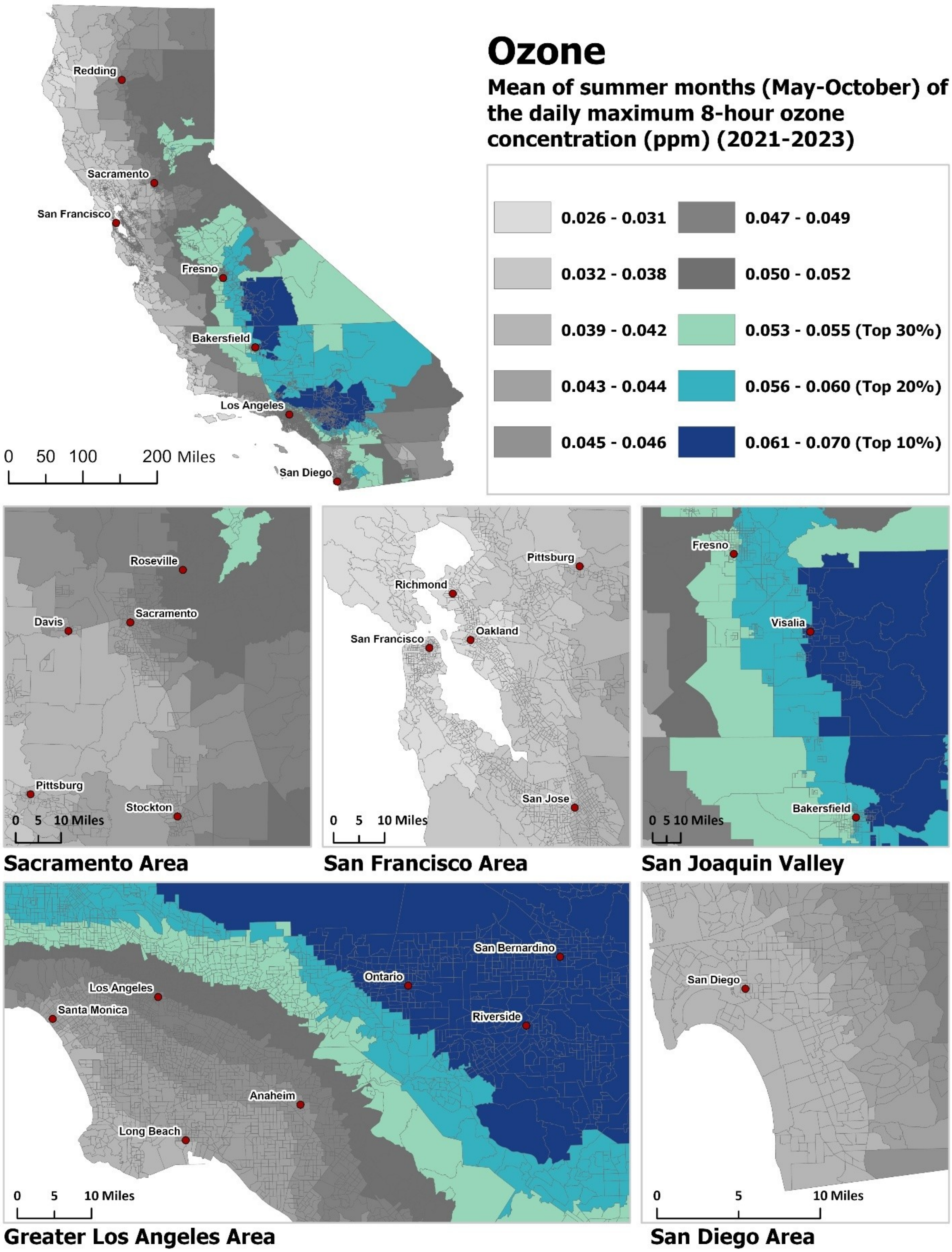
The lung irritation, decrements in lung function, inflammation and exacerbation of existing chronic conditions are seen at even low-level ozone exposures (Alexis et al. 2010; Fann et al. 2012; Schelegle et al. 2009; Zanobetti and Schwartz 2011). A long-term study in southern California found that rates of asthma hospitalization for children increased during warm season episodes of high ozone concentration (Moore et al. 2008). A Central Valley study found an association between ozone exposure and emergency department visits, with children aged 6-18 years, adults 19-40 years, and Blacks having the greatest increased odds (Gharibi et al. 2019). Additional studies have shown that the increased risk is higher among children under 2 years of age, young males, and African American children (Burnett et al. 2001; Lin et al. 2008). Increases in ambient ozone have also been associated with higher mortality, particularly in the elderly, women and African Americans (Medina-Ramon and Schwartz 2008).

A California study found an association between ozone and asthma, acute respiratory infection, pneumonia, COPD, and upper respiratory tract inflammation emergency department visits, with particularly large associations during the warm season (Malig et al. 2016). A study in New Mexico found an association between ozone and both cardiovascular and respiratory emergency room visits during spring and summer months when ambient ozone concentrations are highest (Rodopoulou et al. 2014). Together with PM2.5, ozone is a major contributor to air pollution-related morbidity and mortality (Fann et al. 2012).

Method

- Daily maximum 8-hour average concentrations for all monitoring sites in California were extracted from CARB’s air monitoring network database for the summer months (May to October) for the years 2021 to 2023.
- The means of summer months (May to October) were calculated by averaging the daily maximum 8-hour ozone concentrations during those months over three years (2021 to 2023).
- The mean concentrations from the monitoring stations were used to model ozone concentrations across the state of California. A model using a spatial interpolation method that incorporates the monitoring data from nearby monitors (ordinary kriging) was used to estimate concentrations for census tracts.

- Using the kriging model, daily maximum 8-hour concentrations were estimated for the center of each census tract. These were averaged to obtain a single value for each census tract.
- Ozone values were considered valid if 75 percent or more of the May-October time period was represented. Data for a monitoring site with a year with less than 75 percent of values were considered invalid and not included in the average for that site. Sites with two or more valid years were included.
- Census tracts were ordered by ozone concentration values and assigned a percentile based on the statewide distribution of values.


Ozone
Mean of summer months (May-October) of the daily maximum 8-hour ozone concentration (ppm) (2021-2023)
0.026 - 0.031
0.032 - 0.038
0.039 - 0.042
0.043 - 0.044
0.045 - 0.046
0.047 - 0.049
0.050 - 0.052
0.053 - 0.055 (Top 30%)
0.056 - 0.060 (Top 20%)
0.061 - 0.070 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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AIR QUALITY: PM2.5

Particulate matter pollution, and fine particle pollution (particles less than 2.5 microns in diameter, PM2.5) in particular, has been shown to cause numerous adverse health effects, including heart and lung disease. PM2.5 contributes to substantial mortality across California. The health impacts of PM2.5 and other criteria air pollutants (ground-level ozone, nitrogen dioxide, carbon monoxide, sulfur dioxide, and lead) are considered in the development of air quality standards. Of the six criteria air pollutants, particulate matter and ozone pose the most widespread and significant health threats. The California Air Resources Board (CARB) maintains a wide network of air monitoring stations that provides information that may be used to better understand exposures to PM2.5 and other pollutants across the state.

Indicator

Annual mean concentration (microgram per meter cubed - $\mu g/m^3$) of PM2.5 from 2021 to 2023, excluding days where wildfire smoke was detected by satellite anywhere in the state.

Data Source

Air Monitoring Network; Satellite Remote Sensing Data; Meteorological Data; Fire Detection Data, California Air Resources Board (CARB)

CARB, local air pollution control districts, tribes and federal land managers maintain a network of ~170 air monitoring stations in California. These stations record a variety of measurements, including concentrations of the six criteria air pollutants and meteorological data. The density of the stations is such that specific cities or localized areas around monitors may have high resolution. However, not all cities have stations.

Satellite data are available for California from the Moderate Resolution Imaging Spectroradiometer (MODIS), onboard NASA's Terra and Aqua satellites. The satellites are polar-orbiting and retrieve time-series MODIS measurements for up to 16 days in each fixed 1 km grid. Satellite data can also be used to detect the presence of smoke plumes in an area, enabling the identification of days where wildfire smoke may affect ground-level air quality. More information is available at the links below:

http://www.arb.ca.gov/aqmis2/aqmis2.php

https://ww2.arb.ca.gov/resources/documents/air-quality-research-using-satellite-remote-sensing

Rationale

Particulate matter (PM) is a complex mixture of aerosolized solid and liquid particles including such substances as organic chemicals, dust, allergens, and metals. These particles can come from many sources, including cars and trucks, industrial processes, wood burning, or other activities involving combustion. The composition of PM depends on the local and regional sources, time of year, location, and weather. The behavior of particles and the potential for PM to cause adverse health effects is directly related to particle size. The smaller the particle size, the more deeply the particles can penetrate the lungs. Some fine particles have also been shown to enter the bloodstream (Brook et al. 2010). Those most susceptible to the effects of PM exposure include children, the elderly, and persons suffering from cardiopulmonary disease, asthma, and chronic illness (US EPA 2019).

PM2.5 refers to particles that have a diameter of 2.5 micrometers or less. Particles in this size range can have adverse effects on the heart and lungs, including lung irritation, exacerbation of existing respiratory disease, and cardiovascular effects. The International Agency for Research on Cancer (IARC) determined PM to be carcinogenic to humans and causally associated with lung cancer (IARC 2015). Under the Clean Air Act, US EPA regulates ambient PM2.5 levels to manage its public health and economic impacts. On February 7, 2024, US EPA made the decision to lower the 2019 standard for ambient annual PM2.5 concentration from 12 $\mu g/m^3$ to 9 $\mu g/m^3$ (US EPA 2024). However, many studies have shown that levels of PM2.5 exposure below this standard can cause significant health impacts, including mortality (Crouse et al. 2012; Peralta et al. 2025; Wu et al. 2020; Zeger et al. 2008). In a large nationwide cohort of Medicare beneficiaries, increases in PM2.5 exposure even at lower levels (below 9 μ/m^3) were associated with a significant increase in the risk of death (Di et al. 2017). Both acute and chronic low-concentration PM2.5 exposures are associated with mortality (Shi et al. 2016; Shi et al. 2022). The association between long-term PM2.5 exposure and mortality are also influenced by individual-level, neighborhood-level variables, temperature, and chemical composition (Wang et al. 2017; Wang et al. 2022).

Deaths from all-causes and cardiovascular and respiratory illnesses stemming from PM2.5 exposures continue to be of major global concern. Results from a 2019 meta-analysis of 652 cities across the globe indicated that rises in ambient PM2.5 concentrations increase mortality more significantly in the United States than in countries like China that have very high ambient PM2.5 levels (Liu et al. 2019), reflecting their finding showing that the association between PM2.5 concentration and mortality is stronger at lower concentrations and tends to level off when higher concentrations are reached. Another study estimates that PM2.5 was associated with 26,700 (95% CI: 18,800–35,000) deaths in California in 2012 (Wang et al. 2019).

People with metabolic syndrome (having three or more of the five heart disease risk factors) also exhibit a systemic inflammatory response after PM2.5 exposure (Dabass et al. 2018). An increase in acute coronary syndrome (ACS) is associated with same-day PM2.5 exposure, and long-term survival following ACS is reduced with long-term PM2.5 exposure (Rajagopalan et al. 2018). In addition, studies continue to report the associated risk of insulin resistance and diabetes with PM2.5 exposure (Paul et al. 2020; Rao et al. 2015).

A meta-analysis combining data from 94 studies reports that the risk for admission to a hospital with stroke or death due to stroke increased by one percent when ambient PM2.5 levels increased by 10 $\mu g/m^3$ (Rajagopalan et al. 2018). Living close to roadways was found to be positively associated with the risk and severity of stroke (Rajagopalan et al. 2018). A cohort study of 3.7 million adults in Northern California found that long-term $PM_{2.5}$ exposure was associated with increased risks of acute myocardial infarction and cardiovascular mortality, particularly in low socioeconomic status communities (Alexeeff et al. 2023).

PM2.5 is particularly harmful to children as it can alter lung development, increasing the risk of chronic respiratory disease, such as asthma (Hazlehurst et al. 2021). In a seminal early study of this association, researchers linked high ambient levels of PM2.5 in Southern California with adverse effects on lung development (Gauderman et al. 2004). Additionally, a follow-up study showed that in recent years, declining levels of PM2.5 were associated with improvements in children's lung development (Gauderman et al. 2015). Another study in California found an association between PM2.5 and increased hospitalizations for several childhood respiratory diseases (Ostro et al. 2009). In adults, studies have demonstrated increased hospital admissions for respiratory and cardiovascular diseases (Wei et al. 2019), premature death after long-term exposure (Li et al. 2018), decreased lung function and pulmonary inflammation due to short-term exposures (Pope 2009), and losses to work productivity (Alexeeff et al. 2023).

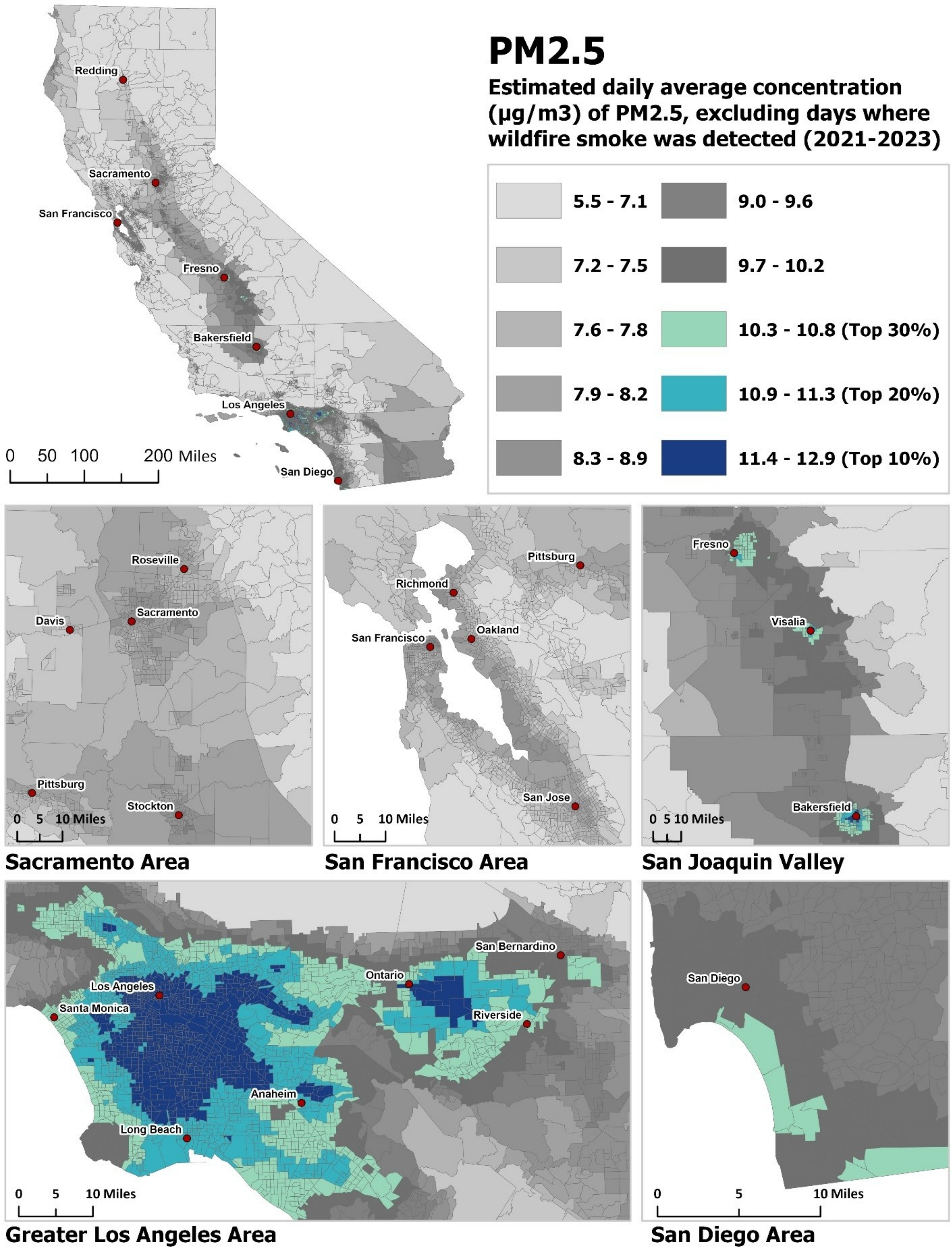
Fetal exposure to PM2.5 during pregnancy has also been associated with low birth weight, premature birth, and higher body mass index (BMI) in early childhood (Bekkar et al. 2020; Lee et al. 2022; Zhou et al. 2023). A Los Angeles County study found that the odds of full-term low birth weight increased with entire pregnancy exposure to PM2.5 from diesel and gasoline combustion and paved road dust (Wilhelm et al. 2012). These adverse effects are even more pronounced among black women (Bekkar et al. 2020; Salihu et al. 2012).

Wildfires are an additional source of PM2.5 in California, which are of growing concern as they become more frequent and severe. Smoke particles fall almost entirely within the size range of PM2.5. Aguilera and colleagues found that wildfire-specific PM2.5 exposure in Southern California led to significantly higher increases in respiratory hospitalizations compared to PM2.5 from other sources, highlighting the greater health risks associated with wildfire smoke (Aguilera et al. 2021). Data from the 2008 northern California wildfires were used in a recent study which found that during the active fire periods, PM2.5 was significantly associated with asthma and worsening chronic obstructive pulmonary disease (COPD) (Reid et al. 2019). During the 2007 San Diego wildfires, respiratory diagnoses, particularly asthma, were elevated in the population of Medi-Cal beneficiaries, with related healthcare utilization persisting after the initial high-exposure period (Hutchinson et al. 2018). Analyses of exposure to California wildfire smoke in the 2015 season found it to be associated with cardiovascular and cerebrovascular emergency department visits for all adults, particularly over 65 years of age (Wettstein et al. 2018), as well as an increased risk of out-of-hospital cardiac arrest (Jones et al. 2020). Although the short-term risks from exposure to smoke during a wildfire have been studied, long-term risks are still largely unknown (Black et al. 2017). As is the case with exposures to other pollution sources, sensitive populations are more likely to experience severe symptoms, both acute and chronic, from wildfire events (Ma et al. 2024; Lipsett et al. 2019).

The implications of wildfire smoke PM2.5 for health equity in California are complex. A recent study of the patterns of wildfire PM2.5 burden in California from 2006 to 2020 revealed that the burden can vary greatly from year to year, depending on the locations of the fires and meteorological conditions that distribute the smoke (Casey et al. 2024). Overall, however, non-Hispanic American Indian and Alaska Native, non-Hispanic White, and multiracial groups were found to be disproportionately exposed, in contrast to non-wildfire PM2.5, which is known to disproportionately impact people of color in California (Casey et al. 2024; Thilakaratne et al. 2023). As described below under "Method", we therefore removed wildfire days from the PM2.5 indicator, to best represent a stable distribution of statewide PM2.5 concentrations to serve as an indicator of pollution burden for communities in any given year. In affected areas, wildfire smoke events skew the average concentrations of the PM2.5 data, resulting in a down-weighting of low-income communities burdened by non-wildfire PM2.5 sources, such as traffic and industrial activity.

Method

- Daily mean PM2.5 concentration measurements were extracted for all ground-level air monitoring sites in California from CARB's air monitoring network database for the years 2021-2023.
- Satellite-based daily mean PM2.5 concentrations for 2021-2023 were estimated from Aerosol Optical Depth (AOD) measurements, Tropomi satellite observations of carbon monoxide levels, land use, and meteorology data via a random forest machine learning model trained on ground-level monitor data. The model developed was adapted from the model by Lee and colleagues (Lee 2019).
- Daily visible imagery and fire detection products from NASA's Terra and Aqua satellites were used to identify days where wildfire smoke affected ground-level air quality in California. These days were flagged, and the subsequent steps were followed using only the remaining days not affected by wildfires. This was done in order to represent a stable distribution of statewide PM2.5 concentrations, given the geographic distribution of wildfire smoke varies greatly each year.
- Concentrations were estimated for each 1 km satellite grid cell. They were computed as a weighted average of the satellite-based concentration and the concentrations recorded by air monitors within 10 km of the center of the grid cell. Estimates were blended using an inverse-distance weighting method where grid cells closer to monitors receive a higher weight from the monitor measurements and grid cells further away receive higher weight from satellite-based estimates. Beyond 10 km from the nearest PM2.5 monitor, monitor concentrations are given weight zero and estimated concentrations are based solely on satellite data.
- Annual means were then computed for each year by averaging the daily estimates to monthly estimates, then averaging the monthly estimates to annual estimates, and then averaging the annual estimates over the three-year period. These averaging steps were taken to avoid overrepresentation of the peak season because of uneven sampling frequency.
- Census tract PM2.5 estimates are calculated by taking the average of the grid cell estimates within a census tract boundary. Grid cells were considered within a tract boundary if the centroid of the grid cell was located within the tract boundary. For census tracts with no grid cell centroids within the tract boundary, the closest grid cell to the centroid of the tract was assigned.
- Census tracts were ordered by the PM2.5 concentration values and assigned a percentile based on the statewide distribution of values.


PM2.5
Estimated daily average concentration (μg/m3) of PM2.5, excluding days where wildfire smoke was detected (2021-2023)
5.5 - 7.1
7.2 - 7.5
7.6 - 7.8
7.9 - 8.2
8.3 - 8.9
9.0 - 9.6
9.7 - 10.2
10.3 - 10.8 (Top 30%)
10.9 - 11.3 (Top 20%)
11.4 - 12.9 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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CHILDREN'S LEAD RISK FROM HOUSING

Exposure to lead through paint is one of the most significant sources of lead exposure for children (CDC 2025a). Lead is a toxic heavy metal and occurs naturally in the environment. However, most of the high levels of lead found in our environment result from human activities. Historically, lead was used as an additive in gasoline and as a primary ingredient in house paint. Lead levels in the United States have declined over the past five decades due to various regulations. However, lead still persists in older buildings containing lead paint, as well as old plumbing and contaminated soil.

Factors such as age of housing, income, race, and enrollment in public assistance programs have been significantly associated with elevated blood lead levels (BLLs). Data are available for two of the most significant known risk factors: age of housing and children living in low-income households. Combining these data serves to identify communities that have a high potential for children's exposure to lead paint in older housing. While there are multiple sources of exposure to environmental lead, such as proximity to hazardous waste sites, contaminated soil, or older water pipes, the datasets relied upon here represent an indicator of potential exposure to lead due to older housing. Other CalEnviroScreen indicators can account for some of these other sources such as drinking water contaminants, toxic releases, and cleanup sites indicators. Additionally, state regulations require children who are at high-risk for environmental exposure or in publicly funded programs for low-income children (e.g., Medi-Cal, Healthy Families) to be tested for blood lead levels at ages 12 and 24 months. Although only a subset of California children, incorporating this dataset in the indicator serves to further identify communities currently burdened by elevated BLLs.

Indicator

Potential risk for lead exposure in children living in low-income communities with older housing.

Percentage of households within a census tract with likelihood of lead-based paint (LBP) hazards from the age of housing (2024 California parcel data and 5-year estimates 2019-2023) and the percentage of households that are both low-income (household income less than 80% of the county median family income) and have children under six years old (5-year estimates 2017-2021) combined with the percentage of elevated BLL tests by census tract for children under the age of six required to get tested by state regulations (5-year estimates 2018-2022).

Data Source

California Residential Parcel Data – Digital Map Products

Parcel data for 2024 were obtained from Digital Map Product's SmartParcels, a nationwide parcel database that combines parcel boundaries with property and tax attributes.

https://www.digmap.com/platform/smartparcels/

American Community Survey (ACS), United States Census Bureau

The ACS is an ongoing survey of the US population conducted by the US Census Bureau and has replaced the long form of the decennial census. Unlike the decennial census, which attempts to survey the entire population and collects a limited amount of information, the ACS releases results annually based on a sample of the population and includes more detailed information on individuals and households. Multiple years of data are pooled together to provide more reliable estimates for geographic areas with small population sizes. The most recent results available at the census tract scale are the 5-year estimates for 2019-2023. The data are available through the US Census data download website.

https://data.census.gov/

Comprehensive Housing Affordability Strategy (CHAS), United States Department of Housing and Urban Development (HUD)

Each year, HUD receives custom tabulations of ACS data from the US Census Bureau. These data, known as the "CHAS" data, demonstrate the extent of housing problems and housing needs, particularly for low-income households. The most recent results available at the census tract scale are the 5-year estimates for 2017-2021. The data are available from the HUD user website.

https://www.huduser.gov/portal/datasets/cp.html

Childhood Lead Poisoning Prevention Branch (CLPPB) Blood Lead Level (BLL) Data by Census Tract, California Department of Public Health (CDPH)

The CDPH is the reporting body for all results from blood drawn lead tests performed in California. Each year, the CDPH publishes the compiled data for lead tests performed on children under age six by zip code and census tract. The most recent aggregate data available at the census tract scale are the 2018 - 2022 report containing the total number of children under six with a reported BLL test and the number of children under six with an elevated BLL of 3.5 microgram per deciliter (µg/dL) or greater within the data timeframe. Each child is only included once per year in the data, using their highest BLL test from each year.

https://www.cdph.ca.gov/Programs/CCDPHP/DEODC/CLPPB/Pages/data.aspx

Rationale

Young children are especially susceptible to the effects of lead exposure and can suffer profound and permanent adverse health effects, particularly in the brain and nervous system (World Health Organization 1995). This increased susceptibility is due to their unique exposure pathways (e.g., dust-to-hand-to-mouth), developing brains, and differences in the absorption of ingested lead (CDC 2025c) Researchers have concluded that even with an elevated BLL lower than 10 µg/dL, children have a higher likelihood of lower IQ and educational performance outcomes, poorer language skills, and symptoms of attention-deficit hyperactivity disorder (ADHD) which can persist into early adolescence and even adulthood (Daneshparvar et al. 2016; Eubig et al. 2010; Ha et al. 2009; Lewis et al. 2018; Miranda et al. 2007; Reuben et al. 2017; Shadbegian et al. 2019; Surkan et al. 2007). Particularly strong evidence for an association between low BLL and cognitive impairment comes from a large international study which concluded that environmental lead exposure is associated with intellectual deficits (Lanphear et al. 2005). This association was especially apparent even among children who had BLLs less than 7.5 µg/dL.

There are no known safe levels of lead exposure, and levels that were previously considered safe are now known to cause subtle, chronic health effects (Lanphear 2017). In 2012, the US Centers for

Disease Control and Prevention (CDC) introduced a blood lead reference value for children at which they recommend public health actions be initiated. The blood lead reference value represents children ages 1-5 with the top 2.5% of blood lead levels in the US. In 2021, this reference value was reduced from 5 μg/dL to 3.5 μg/dL (CDC 2025b).

Childhood blood lead levels in the United States have steadily declined over the past five decades due to various regulations. However, among 419,000 California children tested in 2022, more than 9,000 children had elevated BLL (>3.5 ug/dL) (California Department of Public Health 2024). Lead persists in the environment in lead paint, old plumbing and contaminated soil, and can also be reintroduced through new pathways, like consumer products or through manufacturing-related exposures (California Department of Public Health 2024). As an example, in one California city, more than one half of the areas sampled had soil lead levels in excess of the California EPA recommended levels (Masri et al. 2020).

Older housing and higher levels of poverty are associated with elevated BLL (Egan et al. 2021; Ricciardi 2024; Schultz et al. 2017). Although residential LBP was banned in the US in 1978, paint chips and flaking paint remain a major source of lead exposure for young children living in these homes. In California, much of the housing was built prior to the lead paint ban, with 62% built prior to 1980 and 16% before 1950 (California Environmental Health Tracking Program 2015). In addition, approximately 15% of all California children under the age of five live in poverty, putting them at particularly high risk of lead exposure (California Department of Public Health 2025b; 2024)

Despite reduced exposures and declining BLLs in the US, results from blood testing show that children still experience elevated BLL (Egan et al. 2021; McClure et al. 2016). In 2023, 2.71% of children under age 6 (or 11,248 out of the 403,795) had a BLL over 3.5 μg/dL reported to California's statewide reporting system (California Department of Public Health 2025a). However, recent estimates show that only 37% of all children with elevated BLL in California are identified as such, indicating a clear need for increased testing (Roberts et al. 2017). All California children enrolled in Medi-Cal and other publicly funded programs for low-income children are required to receive blood lead testing.

Method

This indicator is a combination of the percentage of homes with higher likelihood of LBP hazards, the percentage of households that are both low-income and have children in a given area, and the percentage of elevated BLL tests for children who meet state testing requirements. The indicator was calculated for each census tract following five main steps (detailed more fully below and in the Appendix):

1. Calculate the percentage of homes with likelihood of LBP hazards using the construction period for each housing unit in the census tract.
2. Calculate the percentage of households that are low-income with children in each census tract.
3. Combine the percentage of homes with likelihood of LBP hazards with the low-income percentage to form a metric of potential lead exposure risk for each census tract.

4. Calculate the percentage of children under age six with an elevated BLL test in each census tract to form a metric of lead exposure.
5. Combine the metric of potential lead exposure risk and the percentage of elevated BLL tests to create the final indicator value.

Additional detail for each of these steps is described below:

1. Percentage of Homes with Likelihood of LBP Hazards:

- Data on the year residential housing units (HUs) were built was obtained from the California residential parcel data. For each census tract, the number of residential HUs in each of five different age categories was calculated. The number of housing units in each housing age category were summed for each census tract. Housing age categories are listed in Table 2 of the Appendix.
- The percentage of homes in each census tract with likelihood of LBP hazards was calculated using a weighted average approach. The number of HUs in each age category were multiplied by the reported percentage of homes with LBP hazards extracted from a study on LBP in West Coast homes (Jacobs et al. 2002; Clickner et al. 2001) (see Table 2 in the Appendix for the reported values). The number of HUs with likelihood of LBP hazards in each age category were summed and then divided by the total housing units in the census tract.
- For census tracts without adequate parcel data, age categories were assigned from the 2019-2023 5-year ACS estimates. More information on how adequate parcel data is defined is in the Appendix.

2. Low Income Households with Children:

- A dataset containing information for households by percent HUD-adjusted median family income (HAMFI) category was downloaded from the 2017-2021 HUD CHAS by census tract. For each census tract, the data was analyzed to estimate the number of households with household incomes less than 80% of the county median with one or more children under six years of age. The percentage of the total households in each tract that are both low-income with one or more children was then calculated.

3. Lead Risk from Age of Housing Index Calculation:

- Percentage homes with likelihood of LBP hazards and percentage households that are low-income households with children were individually ranked and assigned percentile scores. The two measures were then combined using a weighted sum approach, with a weight of 0.6 assigned to housing and 0.4 assigned to low-income.
- Census tracts were ordered by their combined lead risk from housing score and assigned a percentile based on the statewide distribution of values.

4. Children with an Elevated BLL Index Calculation:

- A dataset containing information on children with a BLL from 2018-2022 by census tract was downloaded from CDPH's website. The data included the total number of children under six with a BLL and the number of children under six with a BLL of 3.5 µg/dL or greater (i.e., elevated BLL) for each census tract.
- Due to some census tracts having a low total number of children tested and artificially inflating the percentage of children under six with an elevated BLL for those tracts, census tracts that had less than 10 children for the total number of children under six with a BLL were not included.
- The percentage of children with an elevated BLL was calculated per census tract. The resulting percentages were sorted and assigned percentiles based on their position in the distribution.

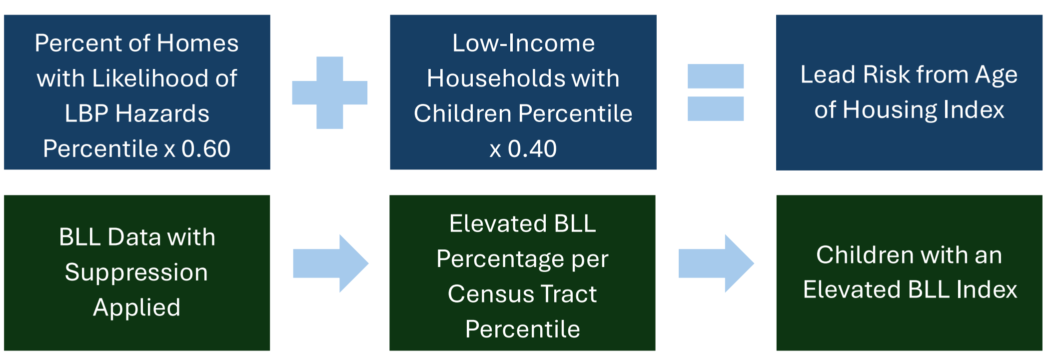
5. Final Indicator Calculation

- Percentile scores from the Lead Risk from Housing Index and the Children with an elevated BLL Index were combined using a weighted sum approach, with a weight of 0.9 and 0.1 respectively.
- Census tracts were ordered by their combined score and assigned a percentile based on the statewide distribution of values.

Lead Risk from Housing Index Calculation

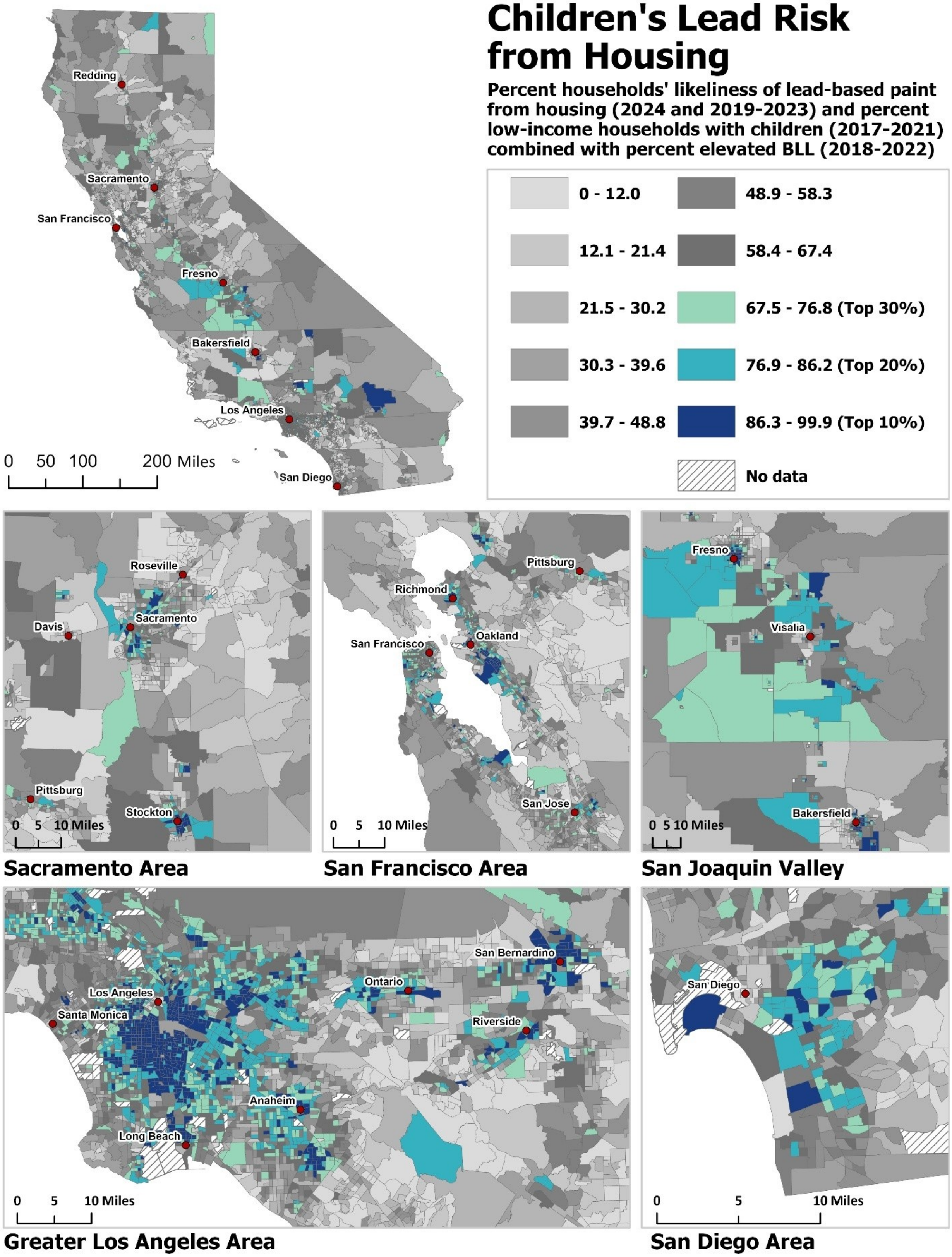
Index Calculations

Figure 1: Illustrated steps to create Lead Risk from Age of Housing Index and Children with an Elevated BLL Index for final indicator calculation.



Final Indicator Calculation

Figure 2: Illustrated steps to create the final Children's Lead Risk from Housing score.


Children's Lead Risk from Housing
Percent households' likeliness of lead-based paint from housing (2024 and 2019-2023) and percent low-income households with children (2017-2021) combined with percent elevated BLL (2018-2022)
0 - 12.0
12.1 - 21.4
21.5 - 30.2
30.3 - 39.6
39.7 - 48.8
48.9 - 58.3
58.4 - 67.4
67.5 - 76.8 (Top 30%)
76.9 - 86.2 (Top 20%)
86.3 - 99.9 (Top 10%)
No data
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

I. Estimating Number of Housing Units and Year Built

Residential parcel data on housing attributes used in the analysis included use code (single-family residence, duplex, multi-family unit, etc.), number of units, and year built.

Residential use codes were used to determine the number of households in each census tract. For most residential parcels statewide, the number of units for each parcel in the residential parcel dataset was used. For residential parcels with a missing "number of units" field (other than multifamily units and mobile home parks), the residential use code was imputed based on the categories in Table 1.

Table 1: Residential parcels use codes and associated number of units.

Use Code	Description	Number of Units
<1100, 1999	Single-family residence (single-family residences, condominium, rural residence, etc.)	1
1101	Duplex	2
1102	Triplex	3
1103	Quadruplex	4

For multifamily residential parcels missing the number of units, a systematic approach to assign a value was developed. Since apartment buildings vary greatly in size, the median apartment unit number was calculated for each county using the available parcel data for counties with over 25% of apartment unit data available (33 of 58 counties). For counties with less than 25% apartment unit data available (21 of 58 counties), the statewide median apartment unit number of 8 was used for missing apartment unit number values.

Residential parcels classified as mobile home parks (MHPs) did not include data on the number of MHP units on the parcel. To fill this gap, the county median number of units for mobile home parks was calculated using a dataset from the U.S. Department of Security (Department of Homeland Security 2022).

II. Estimating Year Built

To estimate the year built for each residential HU, parcel year built data was used for counties with available data greater than 50% data. This accounts for the majority of counties (53 out of 58 counties).

For counties with more than 50% of missing year built parcel data, ACS data was used (5 out of 58 counties: Humboldt, Mariposa, Mendocino, San Benito, and Trinity).

ACS year built data was also used if the census tract had fewer than 20 housing units or the amount of available parcel unit data was less than 20% of the total units listed in the ACS data. This accounted for 116 census tracts including the five counties above that used ACS housing data.

III. Estimating Percentage of Homes with Likelihood of LBP by Census Tract

Percentage of homes with likelihood of LBP was calculated in R 4.3.2 by summing up the number of units in each age of housing category within each census tract. Residential HUs were divided into the five age categories shown in Table 2 by census tract in order to calculate the associated percentage of homes with LBP hazards.

Hazard weights were derived from the percentage of LBP hazards (for example, on walls, ceilings, windows, play areas and doors) in 18,841 West Coast homes in a study sponsored by HUD (Jacobs et al. 2002; Clickner et al. 2001).

Table 2: Age of housing categories based on estimated prevalence or homes with lead hazards.

Year of Construction Age of HUs Categories (For tracts using parcel data)*	Year of Construction Age of Hus Categories (For tracts using ACS data)**	Homes with LBP Hazards (%)*
HUs built after 1998	HUs built after 1999	0
HUs built 1978-1998	HUs built 1980-1999	4
HUs built 1960-1977	HUs built 1960-1979	22
HUs built 1940-1959	HUs built 1940-1959	69
HUs built before 1940	HUs built before 1940	71

*The age of housing categories and LBP hazard weights come from the HUD 2001 and Jacobs et al., 2002 studies.
**ACS estimates were matched as closely to the parcel categories.

The number of residential HUs in each category and their associated hazard percentage were multiplied. The products were summed and divided by the total HUs in the census tract. HUs without age of housing parcel data were excluded from the total HUs calculation. Lastly, the calculated value was multiplied by 100 for a total percentage of homes with LBP hazards. This process is described in the equation below.

The weighted average calculated for each census tract:

[∑ (Total HUs in each category x % homes with LBP hazards) / ∑ (HUs)] x 100

Table 3: Example of housing metric calculation for census tract.

Construction Year	Number of Housing Units	Homes with LBP Hazards (%)	Estimate of Homes with a Lead Risk
After 1998	150	0	0
1978-1998	150	4	6
1960-1977	150	22	33
1940-1959	150	69	103.5
Before 1940	150	71	106.5
Total HU in census tract	750		249
Proportion and percentage of homes with LBP hazard:		249/750 x 100 =	**33.20%**

IV. Low Income Households Calculation

The percentage of the total households in each census tract that are both low-income (household incomes less than 80% of the county median) and contain one or more children was calculated from the 2017-2021 HUD CHAS. This dataset contains information for households by percentage of HUD-adjusted median family income (HAMFI).

V. Lead Risk from Age of Housing Index Calculation

Percentage of homes with a likelihood of LBP hazards and percentage low-income with children were individually ranked and assigned percentile scores. The two measures were combined using a weighted sum approach, with a weight of 0.6 assigned to percentage of homes with likelihood of LBP hazards and 0.4 assigned to poverty. The weights selected are based on national studies that examined characteristics associated with elevated BLL in children (McClure et al. 2016; Wheeler 2013). This sum is the Lead Risk from Age of Housing Index as shown in Figure 1.

VI. Children with an Elevated BLL Index Calculation

The BLL dataset was suppressed to exclude census tracts that contained less than 10 children for the total number of children under six with a BLL. This removed 318 census tracts from the dataset. The percentage of children tested with an elevated BLL (i.e., BLL of 3.5 µg/dL or greater) was taken by dividing the number of children with an elevated BLL by the number of children with a BLL per census tract. These percentages were individually ranked and assigned percentile scores to contribute to the final indicator calculation as shown in Figures 1 and 2.

VII. Final Children’s Lead Risk from Housing Indicator Calculation

The Lead Risk from Age of Housing Index and the Children with an elevated BLL Index were combined using a weighted sum approach applied to their percentile scores, with a weight of 0.9 and 0.1 respectively. The weights were selected based on the reliability of the data and to account for the variability in testing across the state the BLL data introduces. This sum is the final Children’s Lead Risk from Housing score as shown in Figure 2.

DIESEL PARTICULATE MATTER

Diesel particulate matter (diesel PM) occurs throughout the environment from both on-road and off-road mobile sources and some stationary sources. Major sources of diesel PM include trucks, buses, cars, ships and locomotive engines. Diesel PM is concentrated near ports, rail yards and freeways where many such sources exist. Exposure to diesel PM has been shown to have numerous adverse health effects including irritation to the eyes, throat and nose, cardiovascular and pulmonary disease, and lung cancer. California regulations enacted since 1990 have led to a steady decline in diesel emissions that continues today.

Indicator

Spatial distribution of gridded diesel PM emissions from on-road, stationary, area, and ocean-going vessel sources in 2021 (tons/year).

Data Source

EMission FACtors (EMFAC) 2021; California Emission Projection Analysis Model (CEPAM) rf3089; Sparse Matrix Operator Emissions (SMOKE) 5.0; Metropolitan Planning Organizations (MPO) via Emissions Spatial and Temporal Allocator (ESTA); California Toxics Inventory (CTI); Automatic information system (AIS) 2021 ship counts, California Air Resources Board (CARB)

CARB produces grid-based emission estimates for a variety of pollutants by emissions category on a 1km by 1km statewide Cartesian grid system to support specific regulatory and research programs. Diesel PM emissions were generated from four source sectors that were created using different approaches: area, point, on road mobile, and ocean-going vessels. The data source does not account for meteorological dispersion of emissions at the neighborhood scale, which can have local-scale and year-to-year variability, or significant local-scale spatial gradients known to exist within a few hundred meters of a high-volume roadway or other large sources of diesel PM. Nevertheless, it is a reasonable regional metric of exposure to diesel PM emissions. More information and data available at the links below:

https://ww2.arb.ca.gov/msei-modeling-tools

https://arb.ca.gov/emfac

Rationale

Diesel PM is the particle phase of exhaust emitted from diesel engines commonly used to power trucks, buses, cars, trains, and heavy-duty equipment. This phase, sometimes referred to as “soot”, is composed of a mixture of compounds, including sulfates, nitrates, metals and carbon particles. Diesel engine exhaust has been classified as carcinogenic to humans by the International Agency for Research on Cancer (IARC) in 2012, based on sufficient scientific evidence showing the association between exposure and elevated risk of lung cancer (IARC 2014). Diesel PM contains known carcinogens, such as benzene and formaldehyde (Krivoshto et al. 2008; National Toxicology Program 2016) and 50 percent or more of the particles are in the ultrafine range (US EPA 2002).

Although diesel emissions have been substantially reduced, modern diesel vehicles still emit ultrafine PM (Liati et al. 2018). As particle size decreases, the particles may have increasing potential to deposit in the lungs (Löndahl et al. 2012). The ultrafine fraction of diesel PM (aerodynamic diameter less than 0.1 μm) is of particular concern because these particles penetrate deeper into the lung, can carry toxic compounds on particle surfaces, and are more biologically reactive than larger particles (Betha and Balasubramanian 2013; Nemmar et al. 2007). In urban areas, diesel PM is a major component of the particulate air pollution from traffic (McCreanor et al. 2007).

Children and those with existing respiratory disease, particularly asthma, appear to be especially susceptible to the harmful effects of exposure to airborne PM from diesel exhaust, resulting in increased asthma symptoms and attacks along with decreases in lung function (Fitzpatrick et al. 2024; McCreanor et al. 2007). Studies have found strong associations between diesel particulate exposure and exacerbation of asthma symptoms in asthmatic children who attend school in areas of heavy truck traffic (Patel et al. 2011; Spira-Cohen et al. 2011). Diesel PM exposure in children has also been linked to altered immune responses, such as reduced functioning of T-cells and reduced cytokine secretion (Fitzpatrick et al. 2024), and emerging evidence suggests diesel PM may cause adverse effects on neurodevelopment and the central nervous system (Reis et al. 2018). https://pubmed.ncbi.nlm.nih.gov/39074656/?utm_source=chatgpt.com

Studies of both men and women demonstrate cardiovascular effects of diesel PM exposure, including coronary vasoconstriction and premature death from cardiovascular disease (Krivoshto et al. 2008; Zychowski et al. 2020). A study of diesel exhaust inhalation by healthy non-smoking adults found an increase in blood pressure and other potential triggers of heart attack and stroke (Krishnan et al. 2013). Exposure to diesel PM, especially following periods of severe air pollution, can lead to increased hospital visits and admissions due to worsening asthma and emphysema-related symptoms (Krivoshto et al. 2008).

People that live or work near heavily traveled roadways, ports, railyards, bus yards, or trucking distribution centers may experience a high level of diesel PM exposure (Krivoshto et al. 2008; National Toxicology Program 2016; US EPA 2002). A study of US workers in the trucking industry found an increasing risk for lung cancer with increasing years on the job (Garshick et al. 2008; 2012). The same trend was seen among railroad workers, who showed a 40% increased risk of lung cancer (Garshick et al. 2004; Garshick and Hart 2020). Using elemental carbon as a proxy for diesel engine exhaust, one study found that for three groups of truckers and miners, diesel engine exhaust exposure at occupational levels appears to pose a substantial excess lifetime risk of lung cancer (Vermeulen et al. 2014). Workers in jobs with diesel exhaust exposure also have an increased risk of chronic obstructive pulmonary disease mortality relative to those in unexposed jobs (Hart et al. 2009). Another study of truck drivers in Beijing that leveraged personal air samplers found that increased black carbon exposure was associated with epigenetic alterations in drivers' blood samples, biochemical processes linked to carcinogenesis and cardiovascular disease (Sanchez-Guerra et al. 2015).

Method

Diesel PM emissions were generated from four (on-road mobile area, point, and ocean-going vessels) source sectors as follows:

- On-road: Gridded (1km x 1km) diesel PM emissions from on-road sources were calculated for the calendar year of 2021 using CARB's EMFAC2021, which is the latest approved on-road emissions model for California, based on the distribution of regional vehicle activity. The latest version of the Vehicle Miles Traveled (VMT) database was also incorporated, obtained from the different Metropolitan Planning Organizations (MPOs). Day of week factors for light-duty vehicles, light- and medium-duty trucks and daily factors for the heavy-heavy duty trucks were applied, and emissions were summed over each day of calendar year 2021 to obtain emissions in units of tons/year.

- Area: The California Emission Projection Analysis Model (CEPAM) rf3089 planning inventory was used to estimate diesel PM emissions from area sources. The inventory was spatially disaggregated into 1km x 1km spatial resolution using the Sparse Matrix Operator Emissions (SMOKE) 5.0 modeling system. This disaggregation was based on a variety of gridded spatial surrogate datasets. Each category of emissions is mapped to a spatial surrogate that generally represents the expected sub-county locations of source-specific activities. The surrogates include, for example: Lakes and Coastline; Population; Housing and Employment; Industrial Employment; Irrigated Cropland; Unpaved Roads; Single-Housing Units; Forest Land; Military Bases; Non-irrigated Pasture Land; Rail Lines; Non-Urban Land; Commercial Airports; and Ports.

- Point: The point or stationary source inventory consists of California Toxics Inventory (CTI) containing reported diesel PM, and CEPAM rf3089 planning inventory containing PM from exhaust emissions. As with area sources, SMOKE 5.0 was used to spatially distribute point source emissions to 1km x 1km grid cells, typically based on the latitude and longitude of the emitting stack or facility.

- Ocean-going vessels: Ocean-going vessel sources were obtained from the planning inventory used for area and point sources (CEPAM rf3089). Using Automatic Information System (AIS) data (consisting of recorded vessel locations transmitted to satellites by onboard transponders) from 2021, all ship lines and locations of anchorage and docking of vessels over the year were aggregated to create spatial surrogates. SMOKE 5.0 was then used to distribute emissions to 1km x 1km grid cells.

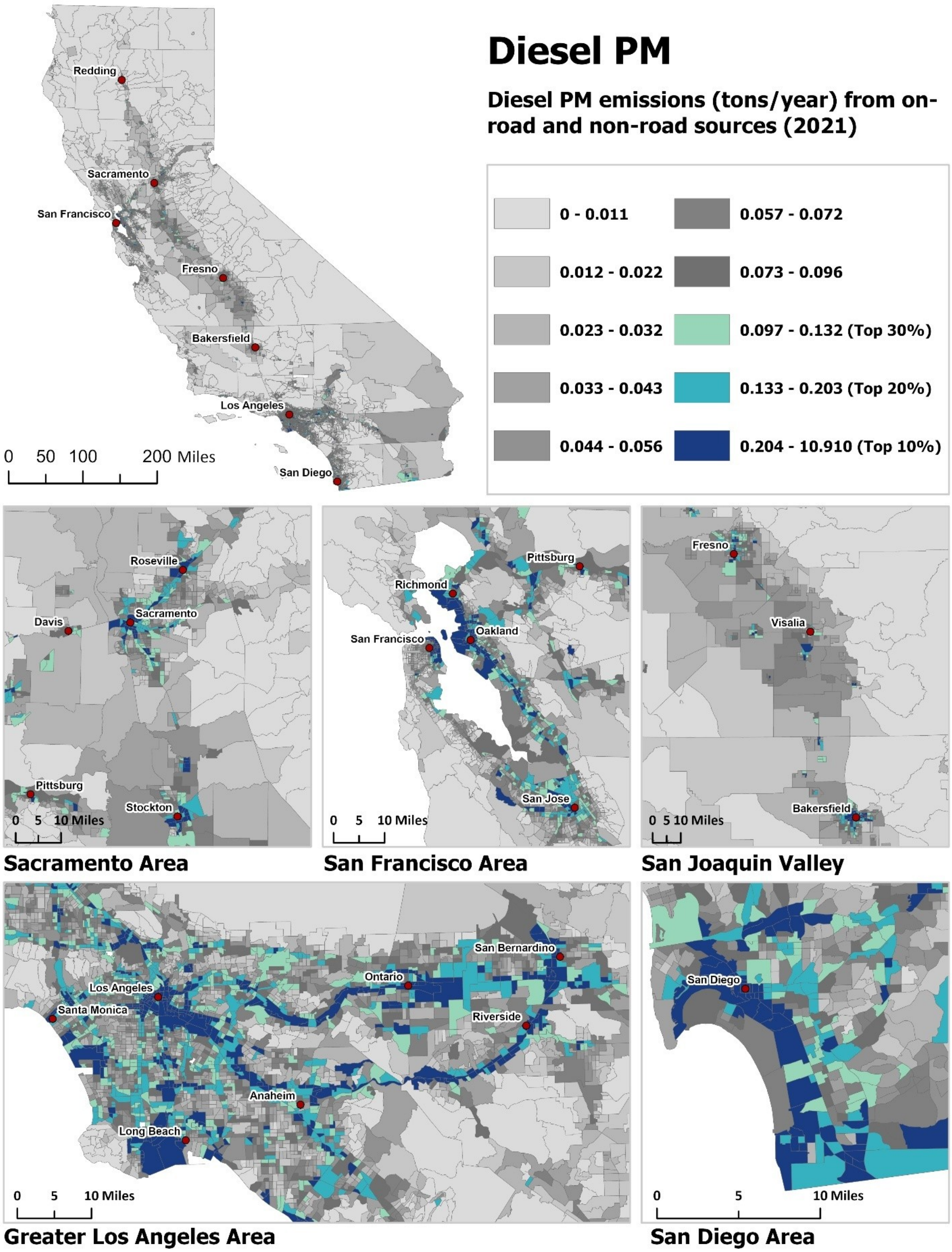
- Resulting gridded emission estimates from the on-road and non-road (point, area, and ocean-going vessels) categories were summed into a single gridded dataset. Gridded diesel PM emission estimates were then allocated to census tracts in ArcGIS Pro using a weighted apportionment. The proportion of a grid cell intersecting populated census blocks was used as the weight of that grid cell's diesel PM value to the census tract estimate. Weighted values were then summed across the census tract, and divided by the sum of the weights, to generate the census tract estimate.

- Emission estimates were then adjusted for emissions at the US-Mexico border that impact tracts in San Diego and Imperial counties, as follows:
    - Recent air quality modeling work demonstrates that emissions from Mexico can impact air quality in communities north of the border (Quintana et al. 2015). To account for additional diesel PM emissions from sources on the Mexico side of the US-Mexico border, results from CARB's California Air Toxics Assessment (CATA)

were used. CATA uses air quality models to simulate how emissions disperse and transform in the atmosphere before reaching a population.

  - First, the impact of Mexico diesel PM (DPM) emissions transported into US communities was estimated. Then, the total cumulative impact from all emission sources on both sides of the US-Mexico border, including on-road mobile, off-road mobile, area and stationary point sources, was estimated. The ratio between the two assessments is the percentage of total DPM impact in near-border communities that can be attributed to transport from Mexico. The Mexico transport versus total DPM impact ratios were calculated at the 2020 US Census block level and population-weighted to the tract level, based on 2017 meteorology and emissions.
  - For each census tract in the San Diego and Imperial counties, the initial DPM emission estimate (DPM_{unadj}) was adjusted to calculate the final DPM emission estimate (DPM_{adj}) by adding the Mexico transport percentage (Transport%) estimated by CATA to local DPM emissions, as follows: DPM_{adj} = (Transport%/(100-Transport%) + 1)*DPM_{unadj}

- After adjustment for emissions at the border, the estimates for diesel PM for census tracts were sorted and assigned percentiles based on their position in the distribution.


Diesel PM
Diesel PM emissions (tons/year) from on-road and non-road sources (2021)
0 - 0.011
0.012 - 0.022
0.023 - 0.032
0.033 - 0.043
0.044 - 0.056
0.057 - 0.072
0.073 - 0.096
0.097 - 0.132 (Top 30%)
0.133 - 0.203 (Top 20%)
0.204 - 10.910 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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DRINKING WATER CONTAMINANTS

Californians receive their drinking water from a wide variety of sources and distribution systems. An estimated 86% of Californians received their water from public sources in 2022, while a small fraction of the population rely on small water systems not regulated by the state or privately operated groundwater wells with little to no treatment (Pace et al. 2022). In 2025, public water systems, serving approximately 98% of Californians, delivered water that met all federal and state drinking water standards (SWRCB 2025).

However, drinking water quality varies with location, water source, treatment method, and the ability of the water purveyor to remove contaminants before distribution. Because water is universally consumed, drinking water contamination has the potential to result in widespread exposures. Contaminants may be introduced into drinking water sources in many ways, including natural occurrence, accidental discharge, industrial release, agricultural runoff, and certain water disinfection methods. Cumulative exposure to contaminants, even at low levels, may affect health (Stoiber et al. 2019; Kolpin et al. 2002). California water systems have a high rate of compliance with drinking water standards. In 2023, systems serving an estimated 6% of the state's population were in violation of one or more federal drinking water standards (SWRCB 2024).

The drinking water contaminant hazard index indicator is a combination of contaminant data that accounts for the relative concentrations of different contaminants, the highest level of a contaminant that is allowed in drinking water - the maximum contaminant level (MCL), and data on violations (See the Appendix for the list of drinking water contaminants included). The indicator does not indicate whether water is safe to drink. Specific local water quality data may be available for public water systems through annual Consumer Confidence Reports. These Consumer Confidence Reports provide drinking water quality information directly to the public. The U.S. Environmental Protection Agency offers guidance on finding water quality data in California:

https://www.epa.gov/wqs-tech/water-quality-standards-regulations-california

Indicator

Drinking water contaminant hazard index for selected contaminants (2014-2022)

Data Source

Geography and Boundaries

Service Area Boundary Layer (SABL) Plus Tool, State Water Resources Control Board (SWRCB)

Community water system and state small water system service area boundaries were extracted from the SABL Plus Tool. To provide an accurate data set of service area boundaries for California drinking water systems, the Division of Drinking Water of SWRCB has an ongoing project to verify the data collected by Tracking California's Water Boundary Tool (WBT) that was used in previous versions of CalEnviroScreen.

https://gis.data.ca.gov/content/0e4c019a46454725b058edd90538732a/about

American Indian Areas Related National Geodatabase - Census TIGER/Line Geodatabase

Geodatabase of federally recognized tribal boundaries within California, 2021. This layer has been updated through CalEPA's tribal consultation process where a Tribe may establish that a particular area of land is under its control by requesting a consultation with the CalEPA Deputy Secretary for Environmental Justice, Tribal Affairs and Border Relations.

https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-geodatabase-file.html

Sections and Townships - Public Land Survey System (PLSS)

Sections (approximately one by one mile grid) were used to characterize ambient groundwater quality in areas outside community and state small water systems. The larger townships (six by six-mile grid) were only used to characterize water quality when no ambient water quality data was available for a section or its surrounding sections. The layer is based on the PLSNET layer that the Department of Water Resources hosts.

https://gis.water.ca.gov/arcgis/rest/services/Environment/i07_WellCompletionReports/FeatureServer/1

Public Water System and Water Quality Data

Safe Drinking Water Information System (SDWIS), California State Water Resources Control Board

SDWIS houses a wide range of information about water systems, such as population served, types of facilities, and sampling points within the distribution system. MCL violations, Total Coliform Rule (TCR) violations, Lead and Copper Rule (LCR) sampling results were extracted from this database. The data is available through request.

SAFER Clearinghouse, California State Water Resources Control Board

The SAFER Clearinghouse tracks source water inventory and source conditions for public water systems and a small selection of state small water systems. With the SAFER Clearinghouse, water systems record source flow rates, total volume, and water usage.

https://wbappsrv.waterboards.ca.gov/safer/login?returnUrl=%2Fhome

EDT Library and Water Quality Analyses Data and Download Page, California State Water Resources Control Board

Drinking water monitoring data reported from laboratories was extracted from this database.

https://www.waterboards.ca.gov/drinking_water/certlic/drinkingwater/EDTlibrary.html

Enforcement and Compliance History Online, US Environmental Protection Agency (US EPA)

ECHO data focuses on compliance and enforcement related information for US EPA-regulated facilities. Violation and enforcement data for federally regulated tribal water systems are reported quarterly to the data system of record no later than the quarter following the quarter in which the events occur. Tribal water systems' MCL violations, LCR Violations, and TCR Violations were extracted from this database.

https://echo.epa.gov/facilities/facility-search?mediaSelected=sdwa

Groundwater Data

Groundwater Ambient Monitoring and Assessment (GAMA) Program's Groundwater Information System, California State Water Resources Control Board

This online mapping tool integrates ambient groundwater sample results from multiple sources. Ambient groundwater sample results were utilized from GAMA projects to characterize areas outside community and state small water system service boundaries. The GAMA projects are listed below.

- Monitoring Wells (Water Board Regulated Sites)
- Local Groundwater Projects
- Public Water System Wells
- Department of Water Resources
- GAMA - Domestic Wells
- National Water Information System (NWIS)
- GAMA – Priority Basin Project
- GAMA – Special Studies
- Cleanup and Permitted Sites – Domestic wells only (Water Board Regulated Sites)
- Irrigated Lands and Regulatory Programs (Water Board Regulated Sites)

https://gamagroundwater.waterboards.ca.gov/gama/gamamap/public/Default.asp

GAMA Aquifer Risk Map Depth Filter Dataset, California State Water Resources Control Board

A depth filter was applied to ambient groundwater to incorporate data most likely to capture domestic well depths. The methodology is detailed in the link below.

https://www.waterboards.ca.gov/water_issues/programs/gama/docs/armmethods25.pdf

Rationale

Low income and rural communities, particularly those served by small community water systems, can be disproportionately exposed to contaminants in their drinking water (VanDerslice 2011; Balazs et al. 2011; Pace et al. 2022). These systems tend to have the largest number of MCL violations for a variety of contaminants (Allaire et al. 2018; Marcillo and Krometis 2019; Wallsten and Kosec 2005).

Much of California relies on groundwater for drinking. In agricultural areas, nitrate from fertilizer application or animal waste can leach into groundwater and cause contamination of drinking water wells (Lockhart et al. 2013). Rural residents of the San Joaquin Valley receive water primarily from shallow domestic wells. Elevated levels of nitrate in drinking water are associated with methemoglobinemia (blue baby syndrome) and may be associated with birth defects and miscarriages (Ruckart et al. 2007). In an earlier study of nitrate concentrations and socioeconomic characteristics of water consumers, investigators found that small community water systems serving Latinos and renters supplied drinking water with higher levels of nitrate than systems serving fewer Latinos and a higher proportion of homeowners (Balazs et al. 2011).

Perchlorate, a groundwater contaminant that can come from geologic, industrial and agricultural sources, is common in drier regions of the state (Fram and Belitz 2011). Although for most people, ingested perchlorate comes primarily from food, on average, across all age groups, 20 percent comes from drinking water (Huber et al. 2011). Perchlorate exposure during pregnancy appears to affect thyroid hormone levels in newborns, which can disrupt normal development (Hershman 2005; Steinmaus et al. 2013). A study of bladder cancer in the US found that drinking surface water was associated with an increased risk of mortality, and the authors suspected a link to low-level pesticide contamination (Colli and Kolettis 2010).

Arsenic, a known human carcinogen, is a naturally occurring contaminant often found in groundwater in arid and semiarid regions, particularly in the San Joaquin Valley. Exposure to arsenic through drinking water is associated with elevated lung and bladder cancer rates, especially with early-life exposures (Steinmaus et al. 2013). Based on a robust epidemiological evidence base, arsenic exposure also causes ischemic heart disease and diabetes. Evidence from human studies supports a high level of confidence in this conclusion (US EPA 2025). It has also been found that communities with lower socioeconomic-status residents were more likely to be exposed to arsenic in their drinking water and more likely to receive water from systems with high numbers of water quality compliance violations (Balazs et al. 2012; Pace et al. 2022).

Further contamination may occur through commonly used water treatment methods and post-treatment leaching in the distribution system. Chlorination and other treatment methods that are used to control microbial contamination can introduce by-products such as trihalomethanes (THMs), which have been linked to an increased risk of bladder cancer (Cantor et al. 2010; Richardson and Postigo 2011). Tap water ingestion is the principal source of THM exposure in the US (ATSDR 1997; National Toxicology Program 2016).

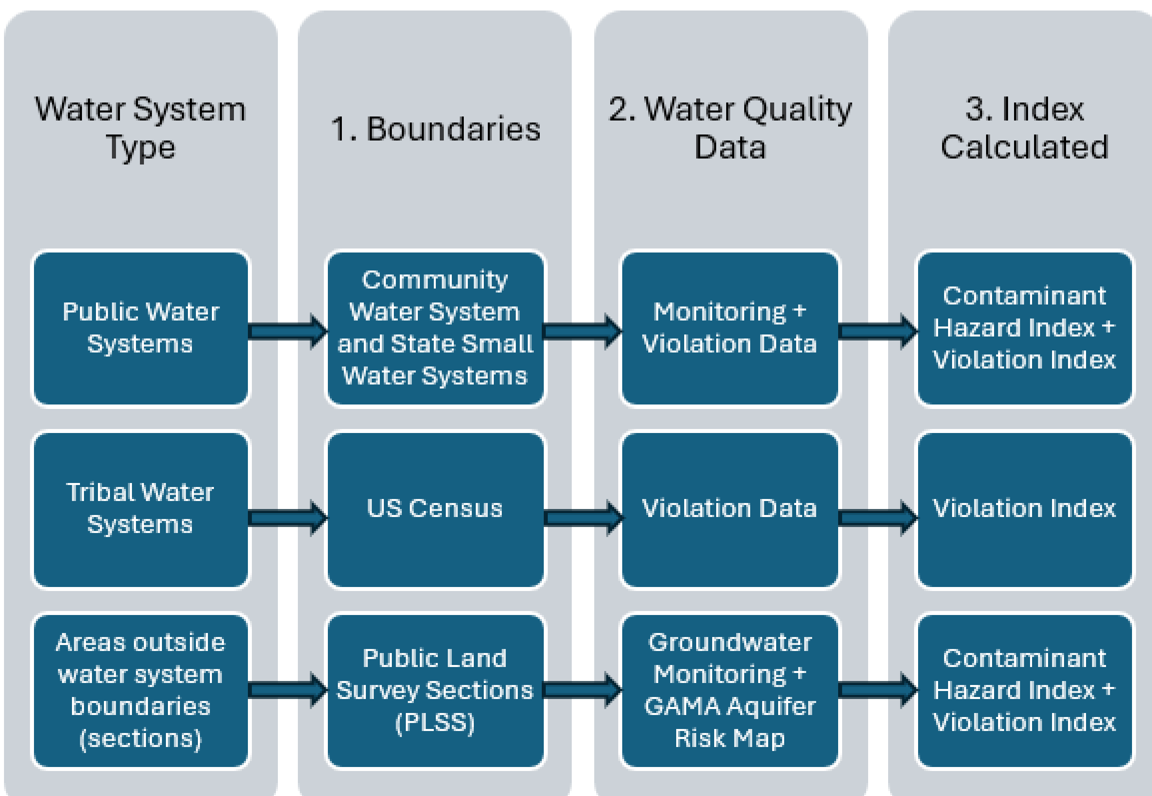
Lead can leach into drinking water post-treatment when pipes and fixtures made from lead corrode, contributing to at least 20 percent of lead ingestion (US EPA 2019). Lead pipes are most commonly found in older cities and homes built before 1986 (US EPA 2019). Although lead is harmful to all age groups, children who are exposed to lead are at significant risk of brain and nervous system damage, developmental disorders, and learning and behavioral problems (ATSDR 2020; Bellinger et al. 1984; Dietrich 1999; Lanphear et al. 2005). There is no known safe level of lead exposure (ATSDR 2020; NTP 2012).

Method

Method Overview

A drinking water contaminant hazard index was calculated for all census tracts through the main steps shown in the figure below. The steps and available data vary by water system type: public water systems, tribal water systems, and areas outside public water systems. More detailed information on the methodology is provided in the following section.

1. **Boundary Selection**: Public water system boundaries (community water systems and state small water systems), tribal boundaries, and sections were downloaded and cleaned.
2. **Water Quality Data (Monitoring Data and Violations)**: Average concentrations for the 20 contaminants, lead concentrations from the LCR, and MCL and TCR violations were calculated and associated with each water system type. (See the Appendix for the list of drinking water contaminants included.)
3. **Index Calculation**: For each water system type (public water system, tribal water system, or areas outside water systems), average concentrations and/or violations were calculated for census tracts. For public water systems and areas outside water systems, a contaminant hazard index was calculated as each contaminant's concentration divided by half its MCL and summed across. A violation index was calculated for public water systems, areas outside water systems, and tribal water systems. For public water systems and areas outside water systems, the indices were combined to create the drinking water index.



Detailed Methodology

Boundary Selection

- Public water system boundaries were downloaded from the SABL plus tool. The water systems in this set comprise all 2,945 community water systems in California and a subset of 122 state small water systems.
- For tribal water systems with publicly available violation data through ECHO, census boundaries of federally recognized Tribes were used to approximate the water system boundaries, as water system boundaries are not publicly available for tribal water systems.
- One-mile by one-mile sections from the Public Land Survey System (PLSS) were treated as boundaries for the purpose of assigning water quality to areas outside water system boundaries. It is assumed that people living in these areas drink water from very small water systems (under 15 connections) or from private wells.

Contaminant Concentrations and Violations

Public Water Systems:

- A subset of 20 contaminants tested in drinking water across California was selected for the contaminant hazard index analysis (see Appendix) based on a set of criteria that included frequency of tests, detections in drinking water, and toxicity concerns. Monitoring data for these chemicals was obtained from SWRCB's Water Quality Monitoring database from 2014-2022.
- LCR data was used to evaluate lead contamination during the same time. The LCR requires water systems to report the 90th percentile results of lead sampling. Therefore, the average lead concentration represents the average of the 90th percentile results
- Within a public water system, information on the type of sampling location, called a source, is available. Water quality data from sources representing treated water was associated with their water system first. If no treated water quality data for a system was available, then raw source samples were used. If the system purchased water from wholesalers, the wholesaler's water quality data were incorporated with the retail system. Lastly, if there were samples taken in the distribution system (mostly for post-treatment by-products), then those samples were given priority over any other sample.
- Time-weighted average concentrations of each contaminant were calculated for each year for each sample source within a system. The average yearly concentrations were then averaged to create a source concentration. Then, the source concentrations within a system were averaged to calculate one concentration value for each contaminant in each system.
- If purchased water from wholesalers was included, the average calculation was weighted by the fraction purchased by each wholesale or local water system. Weights assigned to local or wholesale water systems were determined based on a combination of online research and SAFER Clearinghouse data on gallons supplied from water sources.

- For the violation index, the number of MCL violations for any chemical contaminant (not limited to the 20 selected for the contaminant hazard index), the number of TCR violations, and the number of lead action level exceedances (from the LCR) were summed for each water system.

Tribal Water Systems:

- For federally regulated tribal water systems, information on violations and population served are available on EPA's ECHO. Since water system boundaries are not available for federally recognized Tribes, census tribal boundaries were used in lieu of water system boundaries, and MCL violations, treatment technique violations, TCR violations, and LCR lead action level exceedances were summed for each census boundary.
- If a Tribe has multiple water systems associated with a single census boundary, the violations were population weighted to the tribal census boundary.
- If Tribes purchase water from public water system wholesalers, the wholesaler's water quality data was incorporated into the tribal water system's data.

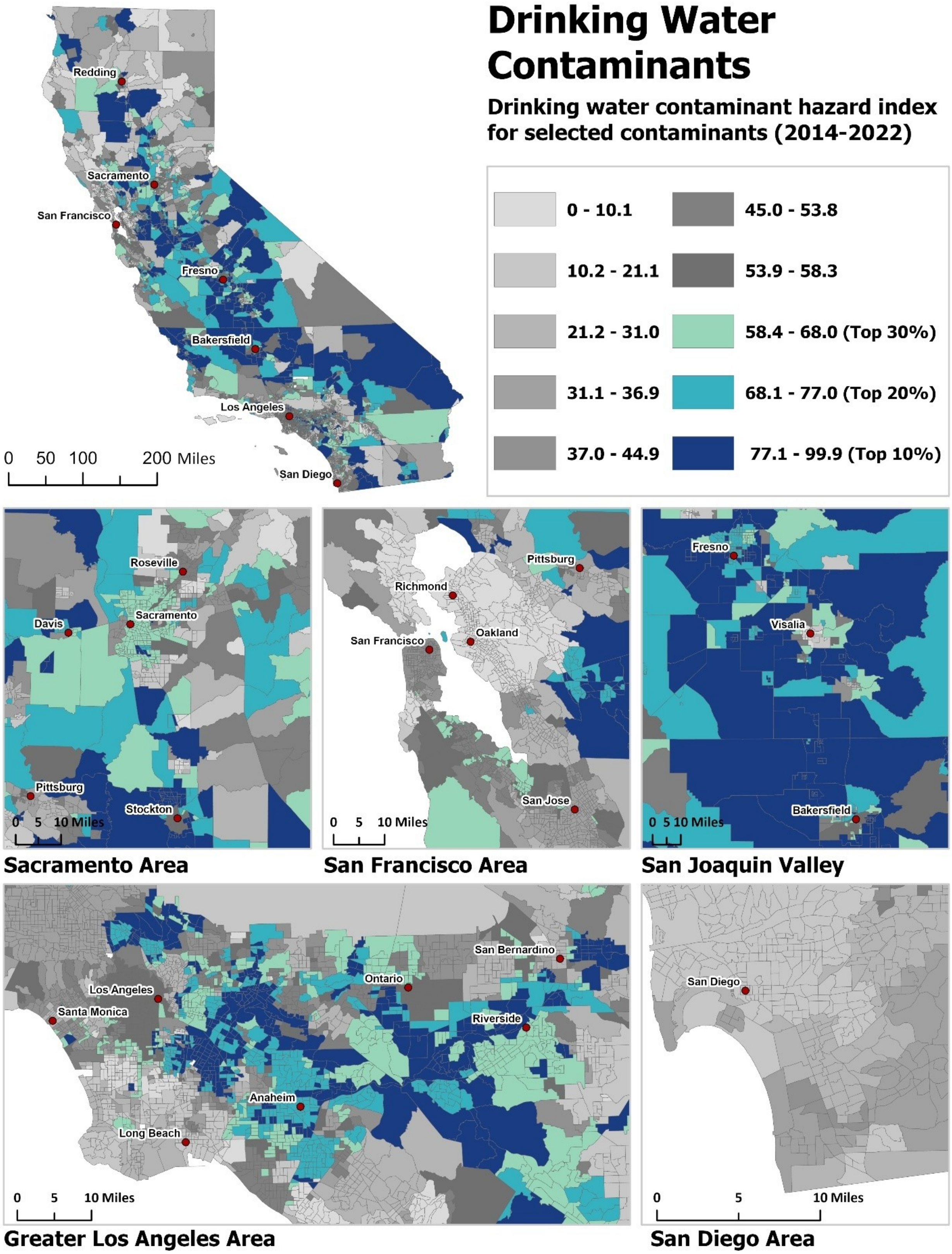
Areas Outside Water System Boundaries:

- For areas of the state outside the public water system and tribal boundaries, the contamination concentration index was calculated at the section geography using ambient groundwater well data from the eight GAMA projects (see data sources). Both domestic and non-domestic wells were incorporated. A methodology was used that filtered non-domestic wells based on their well depth in relation to known domestic well depths in the area. This methodology was adapted from SWRCB's GAMA Aquifer Risk Map:
    - Areas outside system service areas were assigned an average groundwater quality data by PLSS section. Average water quality was calculated for sections with wells that have data. For areas outside water systems with wells that have data, the 90th percentile of the well's lead concentration averages represented the PLSS section's lead result.
    - If a section did not have data, an average of wells in neighboring sections with data were utilized.
    - If a section lacks data and all neighboring sections lack data, the section was assigned the average water quality of the larger township the sections reside in.
- For each PLSS section, average contaminant concentrations were then compared to the MCL or AL for each contaminant. The number of exceedances of regulatory standards are summed to create a violation index for each section.

Contaminant Hazard Index and Violation Index Calculation

- Populated 2020 census blocks were intersected with water system boundaries from the SABL plus tool to determine the proportion of each populated block within a water system boundary. The intersected blocks were then used to calculate a population-weighted estimate of how many people were served by each water system.

- The contaminant hazard index was created as follows. Census tract concentrations for each contaminant were calculated as the population-weighted sum of the contaminant concentration for the census blocks (or partial blocks) within the tract. The average contaminant concentrations were then divided by half the MCL. This method was adapted from Pace et al., 2022, by dividing each contaminant's mean concentration from 2014-2022 by half the contaminant's MCL.
- The violation index is a sum of violations for public water systems and tribal water systems, including MCL violations, TCR violations, and LCR violations. For areas outside public water systems, the violation index is the sum of the number of groundwater contaminants above the MCL per section.
- The drinking water hazards contaminant index is calculated from the weighted sum of the index percentiles, where the contaminant hazard index receives 75% of the weight and the violation index receives 25%.



Drinking Water Contaminants
Drinking water contaminant hazard index for selected contaminants (2014-2022)
0 - 10.1
10.2 - 21.1
21.2 - 31.0
31.1 - 36.9
37.0 - 44.9
45.0 - 53.8
53.9 - 58.3
58.4 - 68.0 (Top 30%)
68.1 - 77.0 (Top 20%)
77.1 - 99.9 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Contaminant	Unit	MCL	PHG	DL
1,2,3-Trichloropropane*	µg/L	0.005	0.0007	0.005
1,2-Dibromo-3-chloropropane (DBCP)	µg/L	0.2	0.003	0.01
Arsenic	µg/L	10	0.004	2
Cadmium	µg/L	5	0.04	1
Chromium, Hexavalent	µg/L	10	0.02	0.1
Ethylene dibromide (EDB)	µg/L	0.05	0.01	0.02
Gross Alpha	pCi/L	15	none	3
Lead**	µg/L	15	0.2	5
Nitrate as N	µg/L	10000 as N	10000 as N	400
Perchlorate	ng/L	6	1	1
Tetrachloroethylene (PCE)	µg/L	5	0.06	0.5
Trichloroethylene (TCE)	µg/L	5	1.7	0.5
Disinfection Byproducts				
HAAS, Haloacetic Acids (five) (HAA5)	µg/L	60	*none*	0
Total Trihalomethanes (TTHM)	µg/L	80	*none*	
PFAS (Per- and Polyfluoroalkyl Substances)				
2,3,3,3-Tetrafluoro-2-(heptafluoropropoxy)propanoate (HFPO-DA or GenX Chemicals)	ng/L	10		
Perfluorohexane sulfonic acid (PFHxS)	ng/L	10		
Perfluorononanoate (PFNA)	ng/L	10		
Perfluorooctane sulfonic acid (PFOS)	ng/L	4	1	
Perfluorooctanoic acid (PFOA)	ng/L	4	0.007	
Perfluorobutane sulfonate (PFBS)***	ng/L	2000		

**Notification level*
***Action Level established under the Lead and Copper Rule (LCR).*
**** Maximum Contaminant Level Goal used (MCLG)*
Nitrate as N refers to a method for testing nitrate, where nitrate is expressed in terms of its concentration as nitrogen (N).
Blank PHGs may not be developed yet (for PFAS) or determined to not be practical (Gross Alpha).
Groups of chemicals, such as HAAS and TTHM, do not have a PHG.

Violation types evaluated

Violation Type
MCL Violations + LCR Action Level Exceedances

Total Coliform Rule Violations

Certain assumptions, data gaps, and limitations within the indicator score methodology may affect the calculation of scores. For example, the indicator score is calculated using average contaminant concentrations over the 9-year compliance cycle (2014-2022). Therefore, the average concentration may not be representative of the current concentration in treated drinking water. Although the indicator compares concentrations to MCLs, MCLs are established considering financial and technical feasibility, and therefore the indicator results do not provide a basis for determining when differences between scores are significant in relation to human health (US EPA 2015). Census tracts can encompass multiple public drinking water systems, and therefore, their scores may represent a combination of water contaminant data from several public drinking water systems and groundwater sources. As such, the drinking water contaminant score may not reflect the water that an individual resident of that tract is drinking. More specific local water quality data may be available for public water systems through annual Consumer Confidence Reports. These Consumer Confidence Reports provide drinking water quality information directly to the public. The U.S. Environmental Protection Agency offers guidance on finding water quality data in California: http://water.epa.gov/drink/local/ca.cfm.

PESTICIDE USE

Communities near agricultural fields, primarily farm worker communities, may be at risk for exposure to pesticides. Drift or volatilization of pesticides from agricultural applications are a significant source of pesticide exposure. Complete statewide data on human exposures to pesticides do not exist, however the California Department of Pesticide Regulation (DPR) maintains the most robust pesticide data available statewide, showing where and when pesticides are used across the state. Pesticide use, especially use of volatile chemicals that can easily become airborne, can serve as an indicator of potential exposure. Similarly, unintended environmental damage from the use of pesticides may increase in areas with greater use.

Indicator

Total pounds of 124 selected active pesticide ingredients (filtered for hazard and volatility) used in production agriculture per square mile, averaged over three years (2021 to 2023).

Data Source

Pesticide Use Reporting (PUR), California Department of Pesticide Regulation (DPR)

In California, all agricultural pesticide use must be reported monthly to county agricultural commissioners, who report the data to DPR. California has a broad legal definition of agricultural pesticide use: production agricultural use is defined as pesticides used on any plant or animal to be distributed in the channels of trade, and non-production agricultural use includes pesticide applications to parks and recreational lands, rights-of-way, golf courses, and cemeteries, for example. Non-agricultural control includes home, industrial, institutional, structural, vector control, and veterinary uses. The production agricultural pesticide use data used to create this indicator are publicly available for each Meridian-Township-Range-Section (MTRS) in California. An MTRS, or section, is roughly equivalent to one square mile. Data are available statewide except for some areas that are exempt from reporting, such as some military and tribal lands.

Non-production agricultural and non-agricultural pesticide use data are available only at the county scale and were not included in the indicator due to the large geographic scale. PUR data and the MTRS file are available at the links below:

https://www.cdpr.ca.gov/docs/pur/purmain.htm

https://calpip.cdpr.ca.gov/plssFiles.cfm

Rationale

High use of pesticides has been correlated with both exposure and acute pesticide-related illness, and there is evidence for an association with chronic disease outcomes. Pregnant, low-income Latina residents in an agricultural area of California had pesticide metabolite levels in their urine up to 2.5 times higher than a representative sample of US women (Bradman et al. 2005). A study in the California San Joaquin Valley found that 22% of adult participants' air monitor found detectable levels of at least one pesticide, including chlorpyrifos, which had already been banned in California at that time of sampling (Bennett et al. 2025). Exposures among children in preschools were found to be higher in counties with higher agricultural or commercial pesticide use or when children lived near agricultural fields (Alkon et al. 2022). Some research indicates that proximity to agricultural fields is correlated with measured concentrations in homes (Bradman et al. 2007; Harnly et al. 2009). A study in California comparing farmworker homes to homes of low-income urban residents found indoor concentrations of an agricultural pesticide only in homes of farmworkers (Quiros-Alcala et al. 2011). Another study, based on data from the California PUR database, found that nearby agricultural pesticide use was significantly associated with pesticide concentrations in carpet dust (Gunier et al. 2011).

A large cohort study of male pesticide applicators found a significant association between the use of four specific insecticides and aggressive prostate cancer (Koutros et al. 2013). The same study cohort also found that an elevated risk of hypothyroidism was significantly associated with the use of seven pesticides (Shrestha et al. 2018). Studies have also found significant associations between decreased sperm quality and pesticide exposure (Knapke et al. 2022). Ambient exposure to pesticides was also found to be associated with increased risk of developing Parkinson's Disease in a California-based study (Wang et al. 2014). Chronic, moderate pesticide exposure has also been associated with cognitive and psychomotor dysfunction, as well as other neurodegenerative diseases (Kamel and Hoppin 2004).

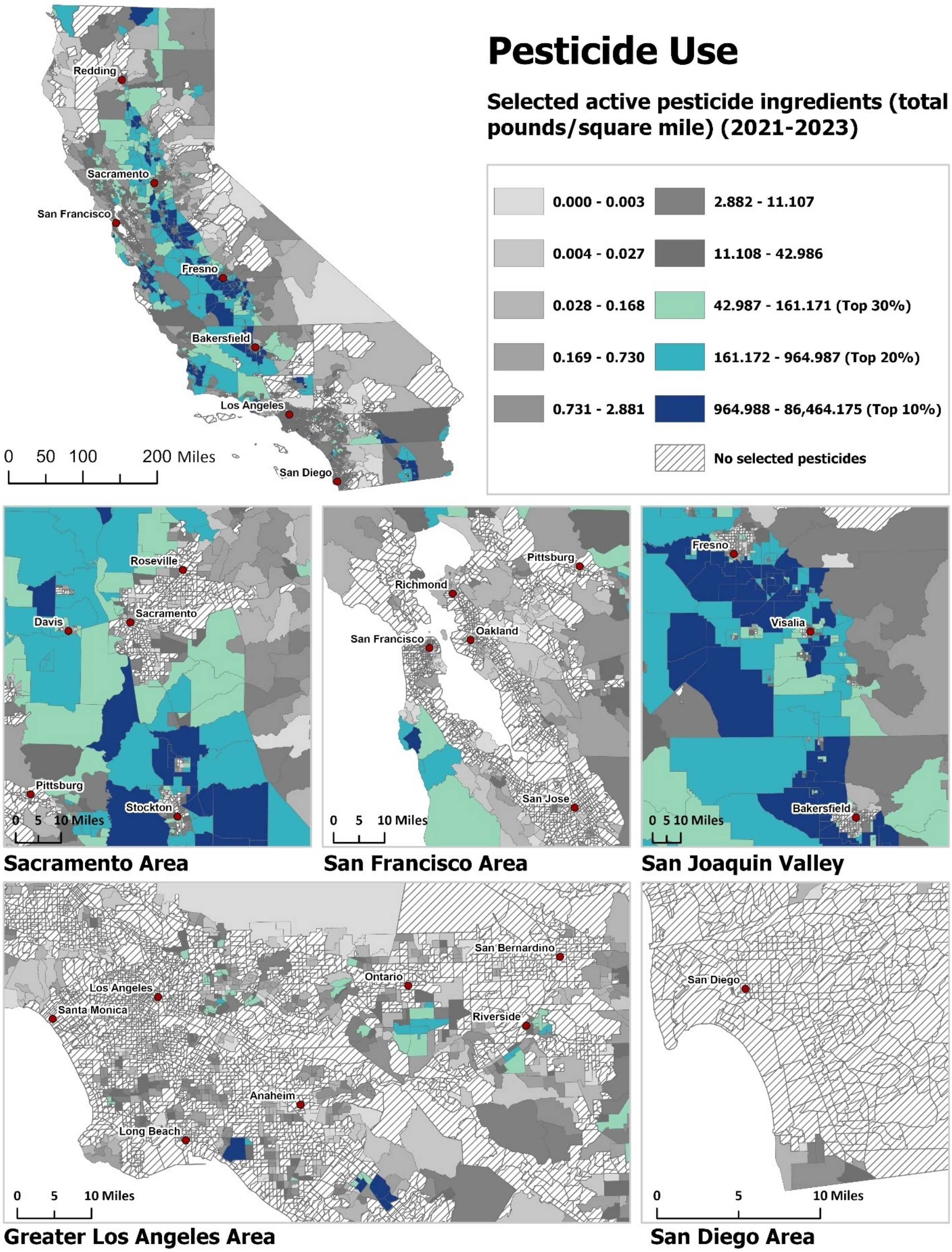
A study of California births found that rates of preterm birth by county increased significantly as country-wide pesticide use increased, using pesticide information from the California PUR database (Winchester et al. 2016). Prenatal exposure to the organophosphate chlorpyrifos has been associated with abnormalities in brain structure in children (Rauh et al. 2012). In an agriculture-intensive area of California, children prenatally exposed to several pesticides were found to have significant decreases in Full-Scale IQ (Gunier et al. 2017). Children are at increased risk of pesticide toxicities because of exposures through hand-to-mouth behaviors, higher ratio of body surface area to volume, higher respiratory rates, and closer proximity to the ground. Early life exposures to pesticides, measured as urinary metabolite concentrations, were significantly associated with childhood respiratory symptoms, such as exercise-induced coughing (Raanan et al. 2015). Residential proximity to agricultural pesticide applications has also been linked to childhood cancer (Lombardi et al. 2021; Park et al. 2020).

An examination of national pesticide illness data concluded that agricultural workers and residents near agriculture had the highest rates of pesticide poisoning from drift incidents, with soil fumigation accounting for most of the cases (Lee et al. 2011). In 2021 alone, DPR recorded 158 cases of illnesses caused by agricultural pesticide drift (DPR 2021). Because of their physical and chemical characteristics, fumigants and other volatile pesticides are most likely to be involved in pesticide drift incidents and illnesses. However, any pesticide that is applied by air or sprayed during windy conditions can drift over neighboring communities (Coronado et al. 2011; Lee et al. 2011).

Although pesticide air monitoring data are not available statewide, DPR has established a pesticide air monitoring network for eight agricultural areas as of 2018 where there is high use of pesticides likely to concentrate in air. This network tracks concentrations of 30-40 pesticides and compares monitored ambient air concentrations of individual pesticides with their health screening level. In 2021 it showed that 22 of the 36 pesticides and breakdown products sampled were detected, and although none were found to be above acute health screening levels, 13-week average concentrations for 1,3-dichloropropene and chloropicrin exceeded their sub-chronic health screening levels (DPR 2023a). Similarly, in 2022 and 2023, 19 of the 40 sampled pesticides and breakdown products were detected, with none exceeding health or regulatory screening levels (DPR 2023b, 2024). In 2023, chloropicrin was found to have a 13-week average concentration that reached 95.4% of its sub-chronic screening level (DPR 2024).

Method

- Specific pesticides included in this indicator were narrowed from the list of all registered pesticides in use in California to focus on a subset of 124 chemicals that are filtered for hazard and volatility. Volatility is indicative of higher likelihood of drift and exposure. (See Appendix)
- Production agricultural pesticide use records were obtained for the entire state for the years 2021, 2022, and 2023.
- Production agricultural pesticide use (total pounds of selected active ingredient) for MTRS records were matched to census tracts using a match file created in the GIS software ArcGIS Pro.
- Production pesticide use for each census tract was divided by each census tract's area.
- Census tracts were ordered by pesticide use values and assigned a percentile based on the statewide distribution of values.


Pesticide Use
Selected active pesticide ingredients (total pounds/square mile) (2021-2023)
0.000 - 0.003
0.004 - 0.027
0.028 - 0.168
0.169 - 0.730
0.731 - 2.881
2.882 - 11.107
11.108 - 42.986
42.987 - 161.171 (Top 30%)
161.172 - 964.987 (Top 20%)
964.988 - 86,464.175 (Top 10%)
No selected pesticides
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Pesticide Use – Filter for Hazard and Volatility

Specific pesticides included in the Pesticide Use indicator were identified from pesticide active ingredients found in DPR's PUR database for years 2021-2023. These pesticides were further filtered for both hazard and likelihood of exposure.

Potentially hazardous pesticides were identified using a list generated under the Birth Defect Prevention Act of 1984 (SB 950) and the Proposition 65 list (Safe Drinking Water and Toxic Enforcement Act of 1986). As part of a review process of active ingredients under the SB 950 program, pesticides were classified as "High", "Moderate", or "Low" priority in 2011 for potential adverse health effects using studies of sufficient quality to characterize risk. For SB 950, the prioritization of each pesticide is a subjective process based upon the nature and number of potential adverse effects, number of species affected, no observable effect level (NOEL), potential human exposure, use patterns, quantity used, and US EPA evaluations and actions, among others. Proposition 65 requires the state to maintain a list of chemicals that cause cancer or reproductive toxicity. Pesticides on the Proposition 65 list as of February 2025 were evaluated. Because this indicator is intended to capture pesticide exposure risk, pesticides that were prioritized as "Low," not prioritized under SB 950, or not on the Proposition 65 list were removed from the analysis.

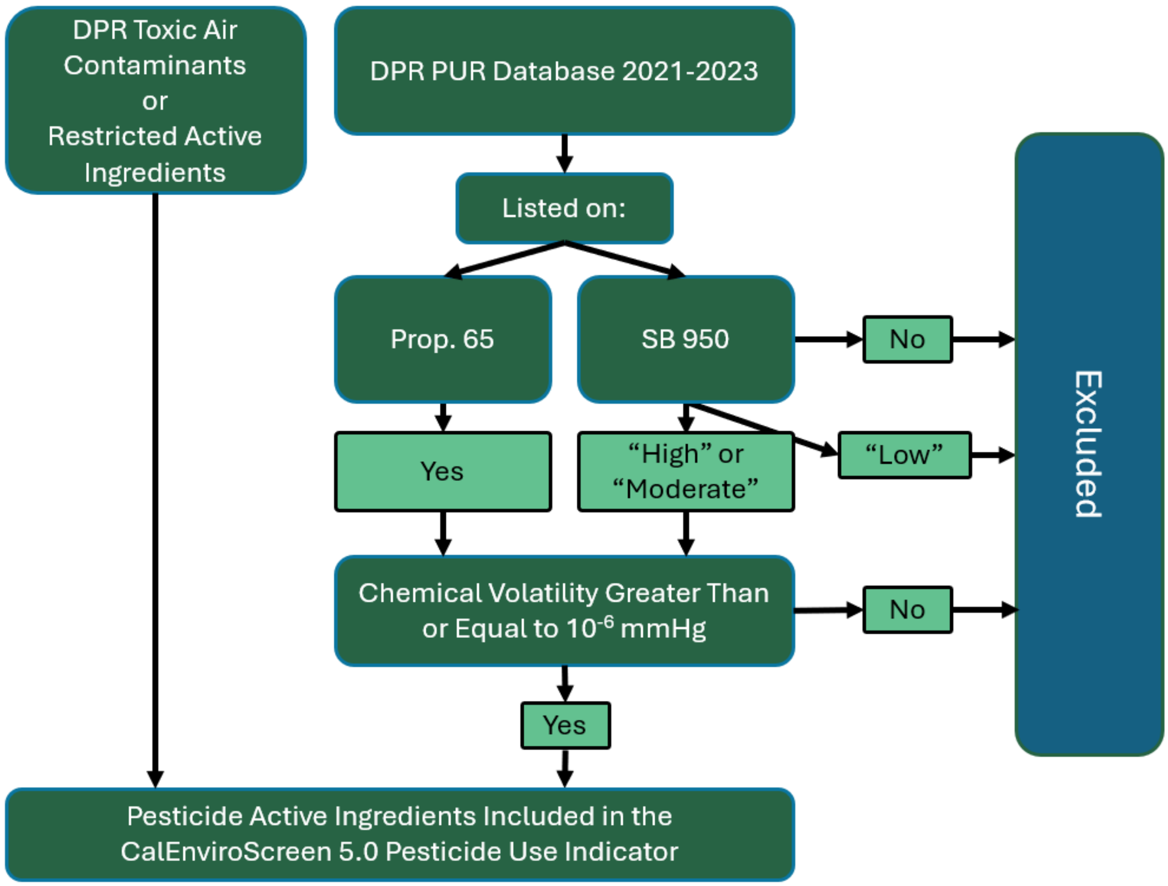
The analysis was further limited to pesticides of high or moderate volatility, as higher volatility increases the likelihood of exposure through air. A list of pesticide volatilities was obtained from DPR. Pesticides not appearing on this list were researched for chemical properties in PubChem and other open literature sources. Pesticides with a vapor pressure of less than 10^{-6} millimeters of mercury (mmHg), indicating low volatility, were removed from analysis.

Additionally, pesticides that did not meet the hazard and volatility criteria, but that are listed as Toxic Air Contaminants (TACs) or restricted active ingredients based on DPR's, TAC or restricted use lists were also included in the analysis. The DPR lists of restricted materials and TACs are available at:

https://apps.cdpr.ca.gov/label/restricted.cfm

https://www.cdpr.ca.gov/environmental-monitoring/air-monitoring/

See the figure below for a flow chart on how pesticide active ingredients were selected for inclusion.



The above selection criteria resulted in a list of 166 pesticides, of which 124 had production agricultural use greater than zero during this time. These 124 pesticides were included in the final indicator analysis. The pesticides included in the indicator calculation are identified below.

Pesticide Active Ingredient	Total Production Agricultural Use (Pounds: 2021-23)	Rank in CalEnviroScreen 5.0
1,3-DICHLOROPROPENE	27,862,040	1
2,4-D	22,077	53
2,4-D, 2-ETHYLHEXYL ESTER	16,506	59
2,4-D, BUTOXYETHANOL ESTER	2,949	77
2,4-D, DIETHANOLAMINE SALT	7,288	71
2,4-D, DIMETHYLAMINE SALT	856,082	12
2,4-D, ISOOCTYL ESTER	26	96
2,4-D, ISOPROPYL ESTER	37,070	47
2,4-D, TRIETHYLAMINE SALT	11	97
2,4-D, TRIISOPROPANOLAMINE SALT	<1	113
2,4-DB, DIMETHYLAMINE SALT	184,709	25

2,4-DICHLOROPHENOXYACETIC ACID, CHOLINE SALT	88,912	40
2,4-DP-P, 2-ETHYLHEXYL ESTER	416	84
2,4-DP-P, DMA SALT	<1	114
ACETAMIPRID	178,703	26
ACIBENZOLAR-S-METHYL	6,829	72
ACROLEIN	9,738	66
ALACHLOR	27	94
ALUMINUM PHOSPHIDE	35,129	49
AMITRAZ	4	104
ATRAZINE	50,818	43
ATRAZINE, OTHER RELATED	967	80
BENTAZON, SODIUM SALT	21,192	55
BORIC ACID	42,440	45
BROMACIL	3,488	76
BROMOXYNIL OCTANOATE	124,180	33
BUPROFEZIN	737,856	14
CACODYLIC ACID	<1	120
CAPTAN	1,033,571	10
CAPTAN, OTHER RELATED	11,226	64
CARBARYL	257,588	22
CHLORDANE	<1	118
CHLOROPICRIN	25,792,417	2
CHLOROTHALONIL	2,624,340	7
CHLORPYRIFOS	5,429	74
CHLORTHAL-DIMETHYL	498,503	16
CLOMAZONE	90,715	39
CYCLOATE	122,473	34
CYMOXANIL	19,622	58
CYPRODINIL	385,689	19
DAMINOZIDE	12,688	62
DAZOMET	20,740	56
DDVP	2	112
DIAZINON	118,119	35
DICAMBA	340	85
DICAMBA, DIMETHYLAMINE SALT	11,171	65
DICAMBA, DIMETHYLAMINE SALT, OTHER RELATED	2	106
DICAMBA, SODIUM SALT	11,979	63
DICHLOBENIL	10	99

DIGLYCOLAMINE SALT OF 3,6-DICHLORO-O-ANISIC ACID	117,423	36
DIMETHENAMID-P	41,082	46
DIMETHOATE	290,569	20
DIMETHOMORPH	67,218	42
DIMETHYLAMINE 2-(2,4-DICHLOROPHENOXY)PROPIONATE	<1	116
DINOCAP	2	109
DINOSEB	2	111
DINOTEFURAN	34,191	50
DITHIOPYR	6,526	73
DIURON	133,412	30
ENDOSULFAN	105	91
EPTC	426,528	17
ETHALFLURALIN	76,276	41
ETHOFUMESATE	15,326	60
ETHOPROP	36,435	48
FLUDIOXONIL	132,924	31
FLUMIOXAZIN	282,148	21
GLUTARALDEHYDE	254	87
HYDROGEN CHLORIDE	7	100
IMAZALIL	201	88
LINDANE	4	103
LINURON	132,810	32
MAGNESIUM PHOSPHIDE	10	98
MALATHION	788,667	13
MANCOZEB	2,750,381	6
MANEB	777	81
MCPA, 2-ETHYL HEXYL ESTER	1,118	79
MCPA, DIMETHYLAMINE SALT	233,869	24
MEFENOXAM	255,074	23
META-CRESOL	2	110
METALAXYL	8,003	70
METAM-SODIUM	9,705,472	4
METHIDATHION	3	105
METHOMYL	683,439	15
METHOXYCHLOR	45	93
METHOXYCHLOR, OTHER RELATED	6	101
METHYL BROMIDE	4,248,887	5
METHYL PARATHION	27	95
METRAFENONE	144,356	29

MYCLOBUTANIL	98,883	38
NAPHTHALENE	<1	124
NITRAPYRIN	118	90
NORFLURAZON	8,209	69
ORTHO-PHENYLPHENOL	<1	115
OXYDEMETON-METHYL	<1	123
PARA-DICHLOROBENZENE	2	108
PARAQUAT DICHLORIDE	1,175,932	9
PARATHION	68	92
PCNB	30,621	51
PCP, OTHER RELATED	<1	121
PENTACHLOROPHENOL	2	107
PHORATE	24,164	52
PHOSPHINE	179	89
POTASSIUM N-METHYLDITHIOCARBAMATE	25,152,512	3
PROPOXUR	<1	119
PYRETHRINS	19,924	57
PYRIDABEN	4,286	75
PYRIMETHANIL	171,566	27
S,S,S-TRIBUTYL PHOSPHOROTRITHIOATE	14,279	61
SEDAXANE	<1	117
SIMAZINE	150,179	28
STRYCHNINE	752	82
SULFUR DIOXIDE	9,726	67
SULFURYL FLUORIDE	99,174	37
TERRAZOLE	333	86
TETRACONAZOLE	21,580	54
THIRAM	414,383	18
TRIALLATE	2,095	78
TRICHLORFON	<1	122
TRIFLUMIZOLE	50,047	44
TRIFLURALIN	890,475	11
UNICONAZOLE-P	5	102
XYLENE	445	83
ZINC PHOSPHIDE	9,248	68
ZIRAM	1,307,805	8

TOXIC RELEASES FROM FACILITIES

There is widespread concern regarding exposures to chemicals that are released from industrial facilities. Statewide information directly measuring exposures to toxic releases has not been identified. However, some data on the release of pollutants into the environment are available and may provide some relevant evidence for potential subsequent exposures. The US Environmental Protection Agency (US EPA) maintains a Toxic Release Inventory (TRI) of on-site releases to air, water, and land and underground injection of any classified chemical, as well as quantities transferred off-site. The data are reported by each facility. US EPA has a computer-based screening tool called Risk Screening Environmental Indicators (RSEI) that analyzes these releases and models potential toxic exposures.

Indicator

Toxicity-weighted concentrations of modeled chemical releases to air from facility emissions and off-site incineration (averaged over 2020 to 2022 and including releases from Mexican facilities averaged over the same time three-year period.

Data Source

Toxics Release Inventory (TRI), US Environmental Protection Agency (US EPA)

The TRI program was created by the federal Emergency Planning and Community Right-to-Know Act (EPCRA) and Pollution Prevention Act. The program maintains a database of emissions and other releases for certain toxic chemicals. The database is updated annually and includes:

- Chemicals identified in EPCRA Section 313 (799 individually listed chemicals and 33 chemical categories); and
- Persistent, Bioaccumulative and Toxic (PBT) Chemicals (16 specific chemicals and 4 chemical classes).

Facilities are required to report if they have 10 or more full-time employees, operate within a set of industrial sectors outlined by TRI, and manufacture more than 25,000 pounds or otherwise use more than 10,000 pounds of any listed chemical during the calendar year. Lower reporting thresholds apply for PBT chemicals (10 or 100 pounds) and dioxin-like chemicals (0.1 gram).

https://www.epa.gov/toxics-release-inventory-tri-program

Mexico Registry of Emissions and Transfer of Contaminants (RETC)

RETC is Mexico's national database, similar to US EPA's TRI, with information on pollutants released into the environment, including air, water, and soil. Current Mexican environmental regulations include a list of 200 chemicals that have mandatory reporting requirements to RETC, with their respective reporting thresholds.

http://sinat.semarnat.gob.mx/retc/retc/index.php

Risk Screening Environmental Indicators (RSEI), US Environmental Protection Agency (US EPA)

RSEI is a computer-based screening tool that analyzes factors related to toxic releases that may result in chronic human health risks. RSEI analyzes these factors and calculates a numeric score. To give the score meaning, it must be ranked against other RSEI scores. RSEI combines TRI release data with toxicity estimates and models the dispersion of chemicals in air by incorporating physicochemical properties, weather and geography. RSEI gives each chemical release and potential exposure pathway a toxicity weight. The toxicity weights are drawn from various programs of the US EPA, CalEPA, and the Agency for Toxic Substances and Disease Registry and consider both cancer and non-cancer endpoints. The resulting measure of exposure is additive across chemicals.

For all air releases, a US EPA plume model is used to estimate long-term pollutant concentrations downwind of a stack or area source. The air releases resulting from incineration of waste after transfers to off-site facilities are modeled in the same manner. RSEI assigns the toxicity weighted concentrations to an 810 m by 810 m grid cell system. The total concentration-based hazard scores for the entire grid cell system are available from US EPA as RSEI Geographic Microdata. The data are available at the link below:

https://www.epa.gov/rsei

Rationale

The Toxics Release Inventory (TRI) provides public information on emissions and releases into the environment from a variety of facilities across the state. TRI data do not, however, provide information on the extent of public exposure to these chemicals. That said, US EPA has stated that “[d]isposal or other releases of chemicals into the environment occur through a range of practices that could ultimately affect human exposure to the toxic chemicals” (US EPA 2010). A study of pollution in the printed wiring board industry found that among states with high TRI emissions in 2006, RSEI risk scores for California were by far the highest. According to the study, California combines high toxic emissions with a high-risk score, based on location, composition of emissions and population exposure modeling (Lim et al. 2011).

Air monitoring data at hundreds of locations across the United States have identified over a dozen hazardous air pollutants at concentrations that exceed California cancer or non-cancer benchmarks (McCarthy et al. 2009). Many of the locations that these authors found to have elevated levels are near major industrial sources, and many of the chemicals monitored are emitted from these facilities. In a study of national cancer risk from hazardous air pollutants from 2013-2017, Los Angeles had an estimated annual average cancer risk of nearly 100 in 1 million; the second highest of the cities studied (Weitekamp et al. 2021). The largest contributor to cancer risk was formaldehyde, a carcinogen commonly emitted from industrial activities (CARB 2020). However, air toxics cancer risks across California, especially in urban areas, have been declining due to regulatory and incentive-based air toxics reduction programs (Maestas et al. 2024; Propper et al. 2015; Weitekamp et al. 2021).

In addition to routine chemical releases, some communities located near TRI facilities are at risk from exposure to accidental chemical releases. A study of self-reported accident rates at US chemical facilities over a five-year period reported that 1,205 facilities (7.8% of facilities in the database) had at least one accident during the reporting period, and an additional 355 facilities

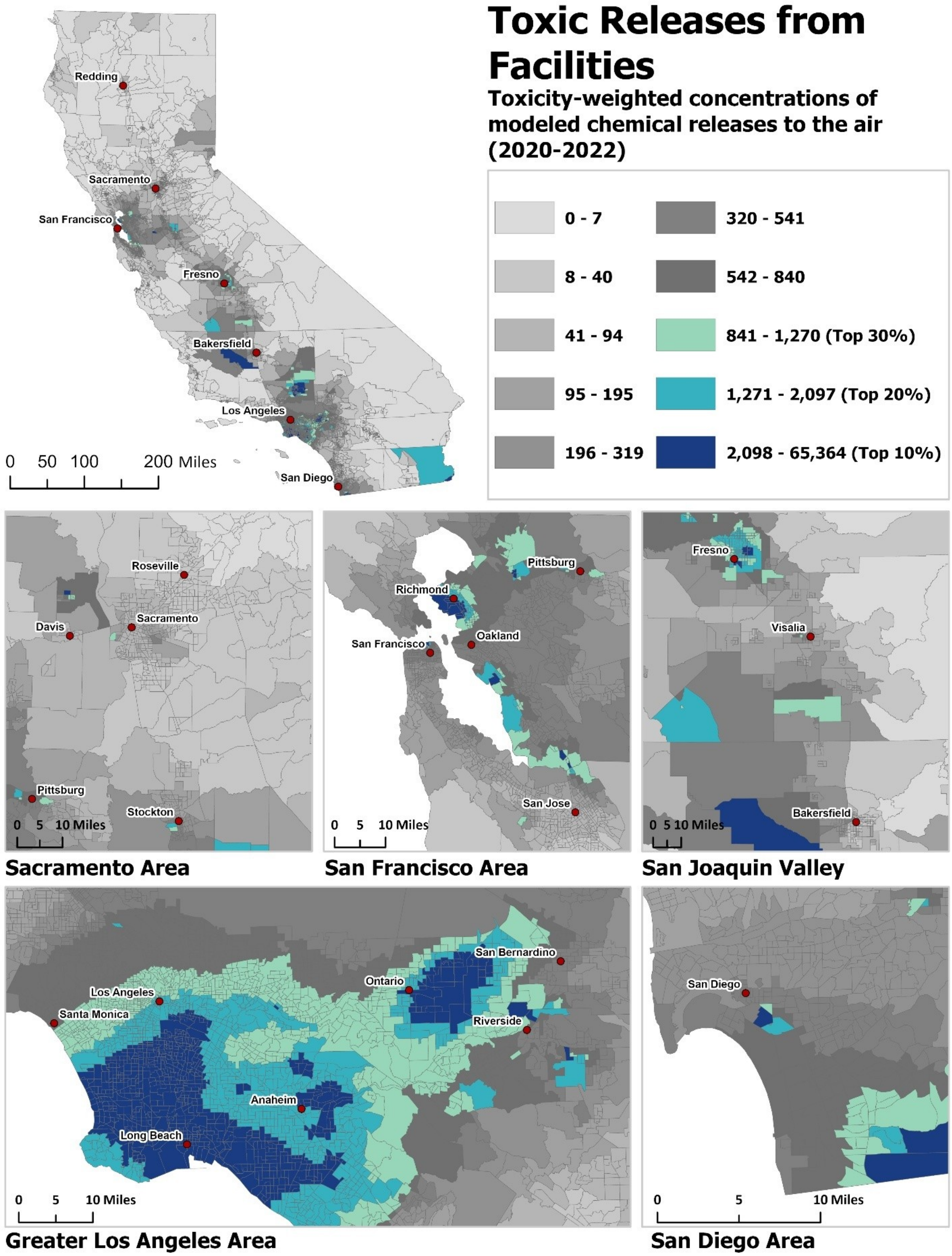
(2.3%) had multiple accidents during the reporting period (Kleindorfer et al. 2003). Associated with these events were a total of 1,987 injuries and 32 deaths among workers, and 167 injuries among nonemployees, including emergency responders. There were 215 total hospitalizations and 6,057 individuals given other medical treatments. Over 200,000 community residents were involved in evacuations and shelter-in-place incidents over that five-year period.

Several studies have examined the potential for health effects from living near TRI facilities. For example, a case-control study reported an increase in risk for diagnosis of brain cancer in children of mothers living within a mile of a TRI facility that released carcinogens (Choi et al. 2006). In another study, TRI air and water concentrations were associated with an increase in infant, but not fetal, mortality rates (Agarwal et al. 2010). In one Texas study, maternal residential exposures to five TRI chemicals were positively associated with low birth weight in offspring (Gong et al. 2018). A study that compared county-level TRI releases and health data found that increased chemical releases to air were significantly associated with higher total mortality as well as mortality from cardiovascular disease (Hendryx et al. 2014). In addition, significantly higher adjusted mortality rates have been associated with greater water and air releases in both rural and urban counties (Hendryx and Fedorko 2011).

Multiple studies have observed greater emissions in low-income and disadvantaged areas (Brooks and Sethi 2009; Pastor Jr et al. 2005; Szasz and Meuser 1997; Weitekamp et al. 2021). Additionally, race and ethnicity have been correlated with the presence of toxic release facilities. One 2016 study found that the worst polluting facilities disproportionally expose communities of color and low-income populations to chemical releases (Collins et al. 2016). Furthermore, these racial and ethnic disparities in exposure are stronger in neighborhoods with median incomes below $25,000, and income-based disparities stronger in neighborhoods with median incomes above that level (Zwickl et al. 2014). People of color in studied regions of southern California were found to have a greater likelihood of living in areas with higher toxic releases (Marshall 2008; Morello-Frosch 2002; Sadd et al. 1999).

Method

- California TRI air releases for years 2020 through 2022 were modeled using RSEI Version 2.3.12 code by Abt Associates, US EPA contractors for the RSEI program (releases to land and water were not included).
- RETC emissions for the years 2020 to 2022 were provided to Abt Associates for inclusion in the RSEI model.
- Census tract-level estimates for RSEI hazard-weighted concentrations were made by taking a land-area weighted average of the block-level values for each tract. Land area information was obtained from a 2020 Census Tiger Line block shapefile.
- The average of the toxicity-weighted concentration estimates for census tracts were sorted and assigned a percentile based on their position in the distribution.


Toxic Releases from Facilities
Toxicity-weighted concentrations of modeled chemical releases to the air (2020-2022)
0 - 7
8 - 40
41 - 94
95 - 195
196 - 319
320 - 541
542 - 840
841 - 1,270 (Top 30%)
1,271 - 2,097 (Top 20%)
2,098 - 65,364 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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TRAFFIC IMPACTS

While California has the strictest auto-emission standards in the US, the state is also known for its freeways and heavy traffic. Traffic is a significant source of air pollution, particularly in urban areas, where more than 50% of particulate emissions come from traffic. Exhaust from vehicles contains many toxic chemicals, including nitrogen oxides, carbon monoxide, and benzene. Traffic exhaust also plays a role in the formation of photochemical smog. Health effects of concern from these pollutants include heart and lung disease, cancer, and increased mortality.

Indicator

Sum of traffic volumes adjusted by road segment length (vehicle-kilometers per hour) divided by total road length (kilometers) within 150 meters of the census tract (traffic volumes estimates for 2019).

Data Source

Caltrans Functional Classification California Road System (CRS) (November 2022)

Dataset provides authoritative statewide road system information for general public use, providing road geometries and classification of road segments into associated Functional Classification. Dataset is openly available for download and use.

https://gisdata-caltrans.opendata.arcgis.com/datasets/cf4982ddf16c4c9ca7242364c94c7ad6_0/about

Caltrans TrafficCensus Traffic Volumes (2019)

Traffic volume data from the TrafficCensus program for the year 2019 was requested in shapefile format from Caltrans. The TrafficCensus Traffic Volumes provides Annual Average Daily Traffic (AADT) counts for state highways in California, i.e. roads with a functional classification between 1 to 3.

Caltrans Highway Performance Monitoring Systems (HPMS) Traffic Volumes (2019)

Traffic volume data from the HPMS database for the year 2019 was requested in shapefile format from Caltrans. The Traffic Census Traffic Volumes provides AADT counts for state highways in California, i.e. roads with a functional classification between 3 to 6.

Tracking California, Public Health Institute: 2019 California Traffic Volume Estimates

Analysis of the road network and traffic volumes was conducted by Dr Joanna Wilkin at Tracking California, a program of the Public Health Institute. The analysis was adapted from their 2019 Traffic Tool.

https://ext.trackingcalifornia.org/traffic

US Customs and Border Protection, Border Crossing Entry Data

Data on northbound border crossing counts for the year 2019 was downloaded from the US Customs and Border Protection website.

https://explore.dot.gov/views/BorderCrossingData/Annual?:isGuestRedirectFromVizportal=y&:embed=y

San Diego Association of Governments (SANDAG)

Data on traffic volumes for vehicles crossing the US-Mexico border and from roadways in Mexico that are within 150 meters of the US-Mexico border was obtained for the Tijuana area for the year 2008 from SANDAG.

https://www.sandag.org/

Rationale

Traffic impacts represent the vehicles in a specified area, resulting in human exposures to chemicals that are released into the air by vehicle exhaust, as well as other effects related to large concentrations of motor vehicles. Major roadways have been associated with a variety of effects on communities, including noise, vibration, injuries, and local land use changes such as increased numbers of gas stations. For example, motorists often detour through residential streets near major roads in order to avoid congestion or traffic controls and this phenomenon can increase risk of injuries among pedestrians or bicyclists in these communities. Vehicle speed is directly associated with risk of pedestrian fatality, and speeds along major roadways tend to be higher than normal speeds on residential streets.

Studies have shown that non-white and low-income people make up the majority of residents in high-traffic areas (Gunier et al. 2003; Tian et al. 2013) and that schools that are located near busy roads are more likely to be in low-income neighborhoods than those farther away (Green et al. 2004). A US Centers for Disease Control and Prevention study based on the 2010 Census found that Latinos, non-whites, foreign born and people who speak a language other than English at home were most likely to live within 150 meters of a major highway (Boehmer et al. 2013). In a California study on the effects of traffic-related pollution and respiratory effects in children, Hispanic children, particularly those with Native American ancestry, were more likely to live close to a freeway or major road compared with white children (Weaver and Gauderman 2018). Hispanic children with more than 50% Native American ancestry who also live close to a major road were more than twice as likely to have ever reported asthma compared with those who lived further away (Weaver and Gauderman 2018). In Southern California, decreases in ambient levels of specific traffic-related pollutants were significantly associated with lower asthma incidence (Garcia et al. 2019). In addition, children who live near or attend schools near busy roads are more likely to suffer from asthma and bronchitis than children in areas with lower traffic density. This relationship has been seen in both developed (Patel et al. 2011; Schultz et al. 2012) and developing countries (Baumann et al. 2011).

Exposure to air pollutants from vehicle emissions has been linked to adverse birth outcomes, such as low birth weight, stillbirth, and preterm birth (Costello et al. 2022; Ebisu et al. 2018; Ghosh et al. 2012; Ritz et al. 2007). These associations are affected by region, as well as maternal race/ethnicity and education (Ng et al. 2017). Current evidence also suggests that childhood leukemia is associated with residential traffic exposure during the postnatal period (Boothe et al. 2014). A study of children in Los Angeles found that those with the highest prenatal exposure to traffic-related pollution were up to 15% more likely to be diagnosed with autism than children of mothers in the lowest quartile of exposure (Becerra et al. 2013). One study also found smaller improvement in cognitive development among children attending schools with higher traffic-related air pollution (Sunyer et al. 2015).

The Atherosclerosis in Communities study, a cohort study with over 15,000 participants, found that traffic density and distance to roadways were associated with reduced lung function in adult women (Kan et al. 2007). A California study found that vehicular emissions were associated with cardiovascular hospitalizations for elderly, as well as respiratory hospitalizations for children (Ebisu et al. 2019). One study using street-level traffic-related air pollutant data showed an association between long-term exposure and higher risk of cardiovascular events among the elderly (Alexeeff et al. 2018). Vehicular emissions were associated with increased cardiovascular mortality, and warm season traffic was associated with all-cause and cardiovascular mortality (Berger et al. 2018). Road density and traffic volume were associated with adult male mortality from cardiovascular disease in an urban area in Brazil (Habermann and Gouveia 2012). Traffic volume and density have also been associated with all-cause mortality during tuberculosis treatment in California (Blount et al. 2017). Motor vehicle exhaust is also a major source of polycyclic aromatic hydrocarbons (PAHs), which can damage DNA and may cause cancer (IARC 2010). A multiethnic California study found an association between lung cancer and traffic-related air pollution exposure, particularly within low-socioeconomic status neighborhoods (Cheng et al. 2022). Overall, there is high confidence in the association between long-term exposure to traffic-related air pollution and asthma onset in children and adults, acute lower respiratory infections in children, ischemic heart disease, and lung cancer mortality (Boogaard et al. 2022).

Method

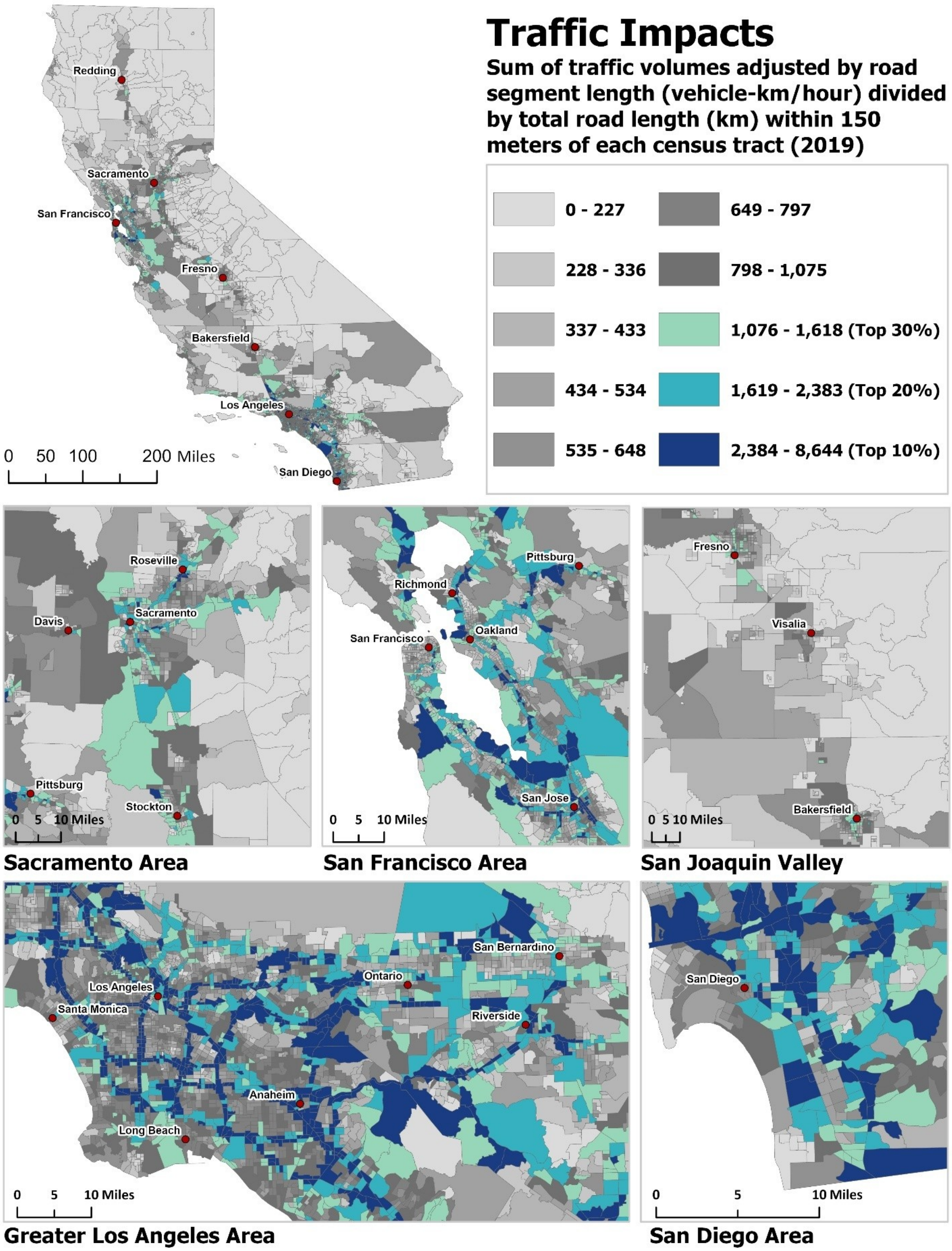
- A 150 meter buffer was placed around each of the 2020 census tracts in California. A buffer was used to account for impacts from roadways within the buffered census tract boundaries. The selected buffer distance of 150 meters, or about 500 feet, is taken from the California Air Resources Board Air Quality and Land Use Handbook recommendations, which states that most particulate air pollution from traffic drops off beyond approximately 500 feet from roadways (CARB 2005).
- Python 3 -based programming, including pandas (version 1.5.3) and geopandas (version 1.0.1), was used for all data processing and analysis.
- The Caltrans TrafficCensus was provided as a point-based shapefile, containing up to two average annual daily traffic (AADT) counts (a back AADT and ahead AADT) for each point. For those points with two AADT counts, an average calculated to obtain a single count at each recorded point.
- The Caltrans HPMS AADT dataset was provided as a line-based geospatial database, containing individual road segments with a single AADT count. The dataset was transformed to point data by taking the midpoint of the line segment.
- The two datasets were merged into a single point-based spatial dataset and checked for duplicates.

- The Caltrans California Road System (CRS) road network dataset was regenerated to provide a consistent segmentation by initially merging the road network into a single feature and re-splitting the network at intersections as well as road segment starts and ends. Road segments designated as ramps were removed from the dataset.
- The combined AADT dataset was snapped to the regenerated road network dataset; an average AADT was calculated for roads with multiple snapped points.
- For road segments with missing traffic data, spatial interpolation modeling was used. Two approaches, kriging and nearest neighbor, were used to provide estimated AADT values.
- The resulting AADT road network dataset was clipped to the buffered census tracts and aggregated values were calculated:
    - The total road length of each road segment within the buffered census tract in kilometers within the buffered census tract was calculated.
    - An hourly traffic volume for each road segment within the buffered census tract was calculated by dividing the AADT value by 24.
    - A length-adjusted hourly traffic volume was calculated for each road segment within the buffered census tract by multiplying the hourly traffic volume by the clipped road length.
    - The length-adjusted hourly traffic volumes for all road segments were summed into a single total volume for the buffered census tract.
    - The clipped road length for all road segments were summed into a single total road length for the buffered census tract.
- The final traffic impacts indicator value, vehicles per hour, was calculated by dividing the sum of all length-adjusted traffic volumes within the buffered census tract (vehicle-km/hr) by the sum of the length of all road segments within the buffered census tract.

  Traffic impacts, or vehicles per hour (vehicles/hr), represents the number of vehicles (adjusted by road segment lengths in kilometers) per hour per kilometer of roadways within the buffered census tract.
- Two adjustments were made to account for the impacts of traffic on communities along the US-Mexico border. Impacts from parallel roads near border crossings and roads crossing the border.
- Traffic impacts from parallel roads in Mexico within 150 meters of the US-Mexico border were incorporated with traffic data obtained from SANDAG for the Tijuana area for the year 2008.Information on parallel roads near other border crossings, such as Mexicali, was not available at the time of this update.
- Data on the number of trucks, buses and personal vehicles crossing the six ports of entry at the US-Mexico border was incorporated into this indicator. Data on northbound border crossing counts for the year 2019 was downloaded from the US Customs and Border

Protection website. To account for vehicles traveling southbound into Mexico, the northbound counts were multiplied by two.

The estimates for traffic impacts for census tracts were sorted and assigned percentiles based on their position in the distribution.


Traffic Impacts
Sum of traffic volumes adjusted by road segment length (vehicle-km/hour) divided by total road length (km) within 150 meters of each census tract (2019)
0 - 227
228 - 336
337 - 433
434 - 534
535 - 648
649 - 797
798 - 1,075
1,076 - 1,618 (Top 30%)
1,619 - 2,383 (Top 20%)
2,384 - 8,644 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Richmond
Pittsburg
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Pollution Burden: Environmental Effects Indicators

CLEANUP SITES

Sites undergoing cleanup actions by governmental authorities or by property owners have suffered environmental degradation due to the presence of hazardous substances. Of primary concern is the potential for people to come into contact with these substances. Some of these "brownfield" sites are also underutilized due to cleanup costs or concerns about liability. The most complete set of information available related to cleanup sites and brownfields in California is maintained by the Department of Toxic Substances Control (DTSC).

Indicator

Sum of weighted sites within each census tract.

(Data downloaded July 2024)

Since the nature and the magnitude of the threat and burden posed by hazardous substances vary among the different types of sites as well as the site status, the indicator takes both into account. Weights were also adjusted based on proximity to populated census blocks.

Data Source

EnviroStor Cleanup Sites Database, Department of Toxic Substances Control (DTSC)

EnviroStor is a public database that provides access to information maintained by DTSC on site cleanup. The database contains information on numerous types of cleanup sites, including Federal Superfund, State Response, Corrective Action, School Cleanup, Voluntary Cleanup, Tiered Permit, Evaluation, Historical, and Military Evaluation sites. The database contains information related to the status of the site such as required cleanup actions, involvement/land use restriction, or "no involvement." Data available at the link below:

http://www.envirostor.dtsc.ca.gov/public/

Region 9 NPL Sites (Superfund Sites) Polygons (2024) –US Environmental Protection Agency, Region 9 (US EPA)

US EPA maintains and distributes the dataset for National Priorities List (NPL) Superfund sites nationwide. The data come in polygon format and generally represent the parcel boundaries of the sites or the estimated extent of contamination. Data is currently in draft format and was obtained from US EPA Region 9.

Rationale

Contaminated sites can pose a variety of risks to nearby residents. Hazardous substances can move off-site and impact surrounding communities through volatilization, groundwater plume migration, or windblown dust. Studies have found levels of organochlorine pesticides in blood (Gaffney et al. 2005) and toxic metals in house dust (Zota et al. 2011) that were correlated with residents' proximity to contaminated sites.

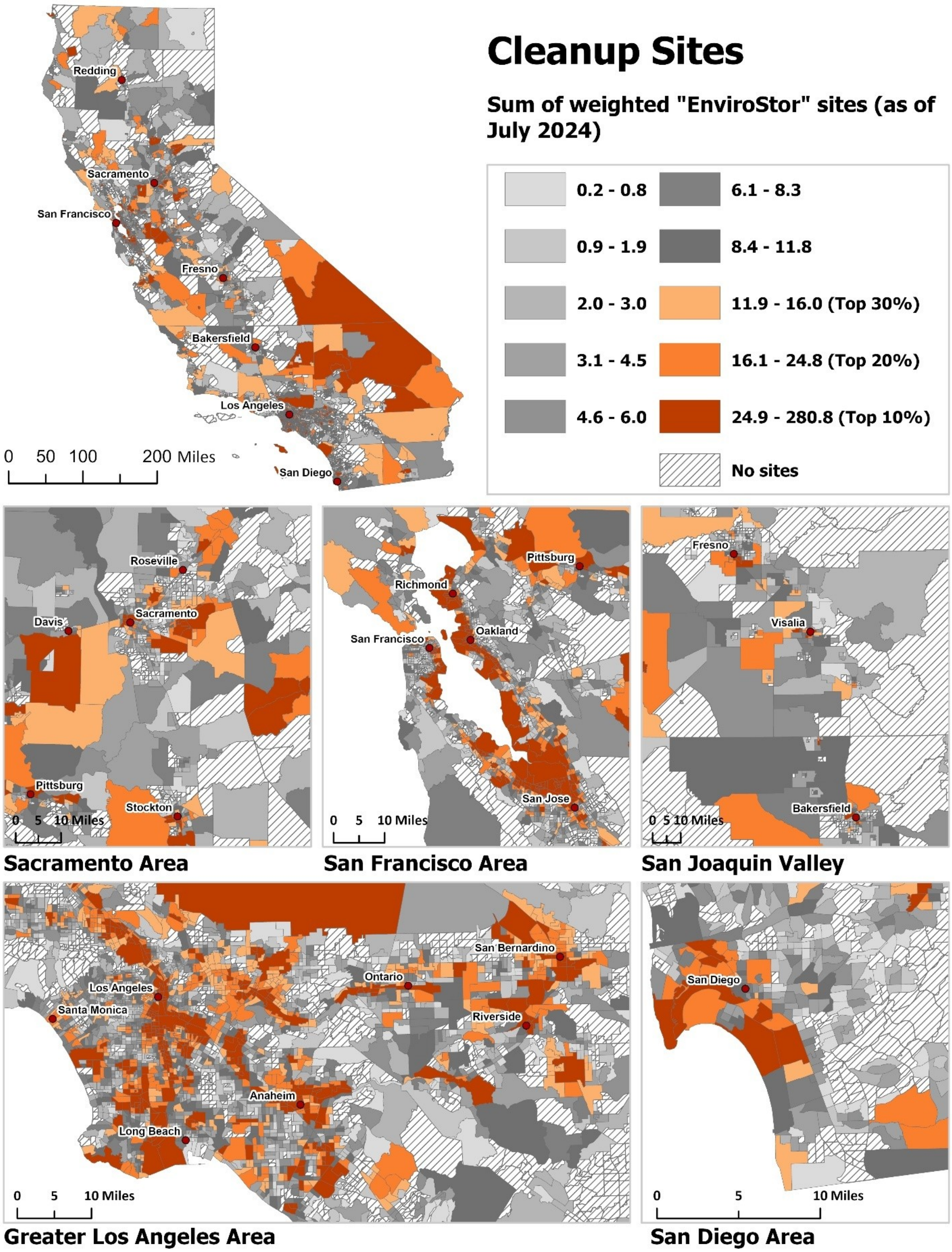
A study of pregnant women living near Superfund sites in New York state showed an increased probability of having a low-birth-weight child (Baibergenova et al. 2003). A later study of cities in New York saw an association between prevalence of liver disease and the number of Superfund sites per 100 square miles (Ala et al. 2006). A 2020 study found that Superfund sites contribute to increased rates of elevated blood lead levels in children (Klemick, Mason, and Sullivan 2020). Additionally, children born to mothers living within two miles of a Superfund site were more likely to experience cognitive and behavioral problems than their siblings who were conceived after the site was cleaned (Persico, Figlio, and Roth 2020). A demographic study of socioeconomic factors in communities in Florida found that census tracts with Superfund sites had significantly higher proportions of African Americans, Latinos and people employed in "blue collar" occupations than census tracts that did not contain a Superfund site (Kearney and Kiros 2009).

It generally takes many years for a site to be certified as clean, and cleanup work is often prolonged due to cost, litigation, concerns about liability, or detection of previously unrecognized contaminants.

Method

- Data on cleanup site type, status, and location (coordinate or address) for the entire state were obtained from DSTC's EnviroStor database.
- Sites with a valid latitude and longitude were mapped in ArcGIS Pro.
- US EPA Region 9 National Priority List polygon shapefile boundary data were acquired from US EPA Region 9.
- Polygon boundaries of California Superfund sites were identified. Active sites were assigned a score of 12 (as a federal Superfund site).
- EnviroStor sites with a Superfund polygon representation were used.
- Several types of sites and statuses were excluded from the analysis because they indicate neither the presence of hazardous waste nor potential environmental risk (See Appendix).
- Each remaining site was scored on a weighted scale of 0 to 12 in consideration of both the site type and status (See Appendix). Higher weights were applied to Superfund, State Response sites, and cleanups compared to site evaluations (evaluations identify suspected, but unconfirmed, contaminated sites that need or have gone through a limited investigation and assessment process). Similarly, higher weights were applied to sites that are undergoing active remediation and oversight by DTSC, relative to those with little or no state involvement. See appendix for additional information on scoring and weighting.
- The weights for all sites were adjusted based on the distance they fell from populated census blocks. Sites further than 1000m from any populated census block were excluded from the analysis.
- Site weights were adjusted by multiplying the weight by 1 for sites less than 250m, 0.5 for sites 250-500m, 0.25 for sites 500-750m, and 0.1 for sites 750-1000m from the nearest populated census blocks within a given tract.

- Each census tract was scored based on the sum of the adjusted weights (in ArcMap).
- Summed census tract scores were sorted and assigned percentiles based on their position in the distribution.


Cleanup Sites
Sum of weighted "EnviroStor" sites (as of July 2024)
0.2 - 0.8
0.9 - 1.9
2.0 - 3.0
3.1 - 4.5
4.6 - 6.0
6.1 - 8.3
8.4 - 11.8
11.9 - 16.0 (Top 30%)
16.1 - 24.8 (Top 20%)
24.9 - 280.8 (Top 10%)
No sites
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Weighting Matrix for Cleanup Sites

Cleanup Sites from the EnviroStor Cleanup Sites database were weighted on a scale of 0 to 12 in consideration of both the site type and status. The table below shows the weights applied for each site type and status.

Site and status types excluded from the analysis:

School Investigation and Border Zone/Hazardous Waste Evaluation site types were not included in the analysis. Sites with the following statuses were also not included in the analysis: Agreement – Work Completed, Referrals, Hazardous Waste Disposal Land Use, and De-listed. Sites with statuses of Certified, Completed, and No Further Action were assigned a weight of zero and were effectively not included in the analysis. These sites and status types were excluded because they are not indicative of hazardous waste or potential environmental risk.

For a given census tract, the weighted scores of all facilities in the area were summed. Definitions used in the table are defined below.

	Status		
Site Type	Low • Certified • Completed • No Further Action • No Evidence of Release	Medium • Inactive – Needs Evaluation • Inactive • Certified Operation & Maintenance	High • Active • Backlog • Inactive – Action Required
Low • **Historical** • **Evaluation** • **Military Evaluation**	**0**	**4**	**6**
Medium • **Corrective Action** • **School Cleanup** • **Voluntary Cleanup** • **Tiered Permit**	**1**	**7**	**9**

High • **State Response** • **Superfund or NPL**	**2**	**10**	**12**

Definitions*

- *Active*: Identifies that an investigation and/or remediation is currently in progress and that DTSC is actively involved, either in a lead or support capacity.
- *Certified Operation and Maintenance (O&M)*: Identifies sites that have certified cleanups in place but require ongoing O&M activities.
- *Certified*: Identifies completed sites with previously confirmed releases that are subsequently certified by DTSC as having been remediated satisfactorily under DTSC oversight.
- *Corrective Action*: Identifies sites undergoing "corrective action," defined as investigation and cleanup activities at hazardous waste facilities (either Resource Conservation and Recovery Act (RCRA) or State-only) that either were eligible for a permit or received a permit. These facilities treat, store, dispose and/or transfer hazardous waste.
- *Evaluation*: Identifies suspected, but unconfirmed, contaminated sites that need or have gone through a limited investigation and assessment process.
- *Inactive – Action Required*: Identifies non-active sites where, through a Preliminary Endangerment Assessment (PEA) or other evaluation, DTSC has determined that a removal or remedial action or further extensive investigation is required.
- *Inactive - Needs Evaluation*: Identifies inactive sites where DTSC has determined a Preliminary Endangerment Assessment or other evaluation is required.
- *No Further Acti*on: Identifies completed sites where DTSC determined after investigation, generally a PEA (an initial assessment), that the property does not pose a problem to public health or the environment.
- *School Cleanup*: Identifies proposed and existing school sites that are being evaluated by DTSC for possible hazardous materials contamination at which remedial action occurred.
- *State Response*: Identifies confirmed release sites where DTSC is involved in remediation, either in a lead or oversight capacity. These confirmed release sites are generally high-priority and high potential risk.
- *Superfund*: Identifies sites where the US EPA proposed, listed, or delisted a site on the National Priorities List (NPL).
- *National Priorities List (NPL):* The list of sites of national priority among the known releases or threatened releases of hazardous substances, pollutants, or contaminants throughout the United

States and its territories. The NPL is intended primarily to guide the EPA in determining which sites warrant further investigation.

- *Tiered CA Permit Sites*: These facilities manage waste not regulated under RCRA, but regulated as a hazardous waste by the State of California. These facilities include but are not limited to recyclers, oil transfer stations, and precious metals recyclers.
- *Voluntary Cleanup*: Identifies sites with either confirmed or unconfirmed releases, and the project proponents have requested that DTSC oversee evaluation, investigation, and/or cleanup activities and have agreed to provide coverage for DTSC's costs.

* EnviroStor Glossary of Terms (http://www.envirostor.dtsc.ca.gov/public/EnviroStor%20Glossary.pdf)

Number of Cleanup Sites in CalEnviroScreen 5.0: Approximately 6,800

Site Type	Number of Sites	Percent of Sites
Voluntary Cleanup	1699	25%
Military Evaluation	1121	16%
State Response	951	14%
Tiered Permit	907	13%
Evaluation	876	13%
Corrective Action	543	7%
School Cleanup	417	6%
Historical	312	5%
Federal Superfund	42	0.5%
National Priorities List (NPL) Sites	112	1.6%

GROUNDWATER THREATS

Many activities can pose threats to groundwater quality. These include the storage and disposal of hazardous materials on land and in underground storage tanks at various types of commercial, industrial, and military sites. Thousands of storage tanks in California have leaked petroleum or other hazardous substances, degrading soil and groundwater. Storage tanks are of particular concern when they can affect drinking water supplies. In addition, the land surrounding these sites may be taken out of service due to perceived cleanup costs or concerns about liability. Dairy farms and concentrated animal-feeding operations, which produce large quantities of animal manure pose a threat to groundwater. Other activities that pose threats to groundwater quality include produced water ponds, which are generated as a result of oil and gas development. The most complete sets of information related to sites that may impact groundwater and require cleanup are maintained by the State Water Resources Control Board (SWCB).

Indicator

Sum of weighted scores for sites within each census tract.

(Data downloaded March 2025)

The nature and the magnitude of the threat and burden posed by sites maintained in GeoTracker vary significantly by site type (e.g., leaking underground storage tank or cleanup site) and status (e.g., Completed Case Closed or Active Cleanup). The indicator takes into account information about the type of site, its status, and its proximity to populated census blocks.

Data Source

GeoTracker Database, State Water Resources Control Board (SWRCB)

GeoTracker is a public web site that allows the SWRCB, regional water quality control boards and local agencies to oversee and track projects at cleanup sites that can impact groundwater. The GeoTracker database contains information on locations and water quality of wells that could be contaminated, as well as potential sources of groundwater contamination. These include leaking underground storage tanks (LUSTs), leaking military underground storage tanks (USTs) cleanup and land disposal sites, produced water ponds, industrial sites, airports, dairies, dry cleaners, and publicly owned sewage treatment plants. For each site, there is additional information on the status of cleanup activities. Groundwater quality data are extracted from monitoring and records maintained by SWRCB, the Department of Water Resources, Division of Oil, Gas & Geothermal Resources, Department of Public Health, Department of Pesticide Regulation, US Geological Survey and Lawrence Livermore National Laboratory. The database is constantly updated and sites are never deleted from the database, where they may ultimately be designated 'clean closed.'

A separate GeoTracker database contains information on the location of underground storage tanks (not leaking), which was not used. Data available at the link below:

https://geotracker.waterboards.ca.gov/

California Integrated Water Quality System Project (CIWQS), State Water Resources Control Board (SWRCB)

The California Integrated Water Quality System (CIWQS) is a computer system used by the State and Regional Water Quality Control Boards to track information about places of environmental interest, manage permits and other orders, track inspections, and manage enforcement activities. CIWQS also allows online submittal of information by permittees within certain programs and makes data available to the public through reports. CIWQS contains data on confined animal facilities, including dairies and feedlots. Confined animal facilities include farms or ranches where livestock are held for a significant period of time and provided food in the facility (as opposed to grazing), and whose discharges are regulated by the SWRCB and/or one of the nine Regional Water Quality Control Boards. Discharges include manure, wastewater, and storm water runoff that may contain waste constituents. Users can access relevant information such as location, status, and number of animals permitted per facility. Data available at the link below:

https://www.waterboards.ca.gov/water_issues/programs/ciwqs/

Rationale

Common groundwater pollutants found at LUST and cleanup sites in California include gasoline and diesel fuels, chlorinated solvents and other volatile organic compounds (VOCs) such as benzene, toluene, and methyl tert-butyl ether (MTBE); heavy metals such as lead, chromium and arsenic; polycyclic aromatic hydrocarbons (PAHs); persistent organic pollutants like polychlorinated biphenyls (PCBs); DDT and other insecticides; and perchlorate (DPR 2025; SWRCB 2012; US EPA 2002). An assessment of benzene exposure from a fuel leak concluded that soil and groundwater contamination could put nearby residents at risk and could have caused adverse health effects (Santos et al. 2013). Dioxins and dioxin-like substances have been detected in groundwater in areas where treated wastewater has been used for irrigation (Mahjoub et al. 2011) and near wood treatment facilities (Karouna-Renier et al. 2007).

The occurrence of storage tanks, leaking or not, provides a good indication of potential concentrated sources of some of the more prevalent compounds in groundwater. For example, the detection frequency of VOCs found in gasoline is associated with the number of UST or LUST sites within one kilometer of a well (Squillace and Moran 2007). The occurrence of chlorinated solvents in groundwater is also associated with the presence of cleanup sites (Moran et al. 2007). Some of these cancer-causing compounds have in turn been detected in drinking water supplies in California (Williams et al. 2002). People who live near shallow groundwater plumes containing VOCs may also be exposed via the intrusion of vapors from soil vapor into indoor air (Picone et al. 2012; Yao et al. 2013).

In addition to LUSTs and cleanup sites, confined animal feeding operations (CAFOs) can pose a threat to groundwater via nitrate contamination. Although nitrate contamination can originate from several possible sources, such as synthetic fertilizers and septic waste, manure from dairy farms is a significant contributor (Ransom et al. 2016). Socioeconomically disadvantaged communities in the Central Valley bear a disproportionate burden of nitrate groundwater contamination (Francis and Firestone 2010). Another threat to surface groundwater is produced water ponds from oil and gas production, which have been shown to contain PAHs, metals, and alkylphenols (Chittick and Srebotnjak 2017), as well as increases in the salinity of underground sources of drinking water in California (Gillespie et al. 2019).

Method

Cleanups, Land Disposal, Underground Storage Tanks, and Produced Water Ponds:

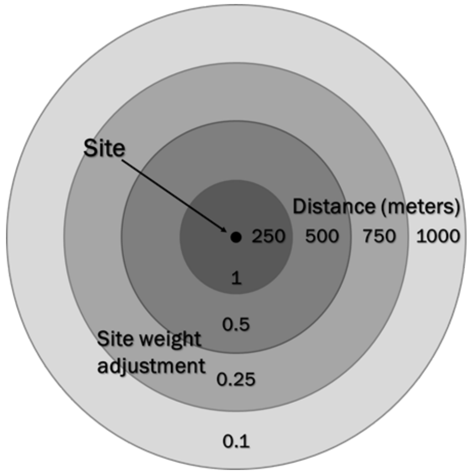
- Data on cleanup site type, status, and location (coordinate or address) for the entire state were downloaded from GeoTracker (http://geotracker.waterboards.ca.gov/data_download.asp; GeoTracker Cleanup Sites).
- Sites with a valid latitude and longitude were mapped and sites with address only were geocoded in ArcGIS Pro.
- Certain types of sites and statuses were excluded from the analysis because they are not indicative of a hazard or a potential environmental risk (See Appendix). Each remaining site was scored on a weighted scale of 1 to 15 in consideration of both the site type and status (See Appendix).

Dairies and Feedlots:

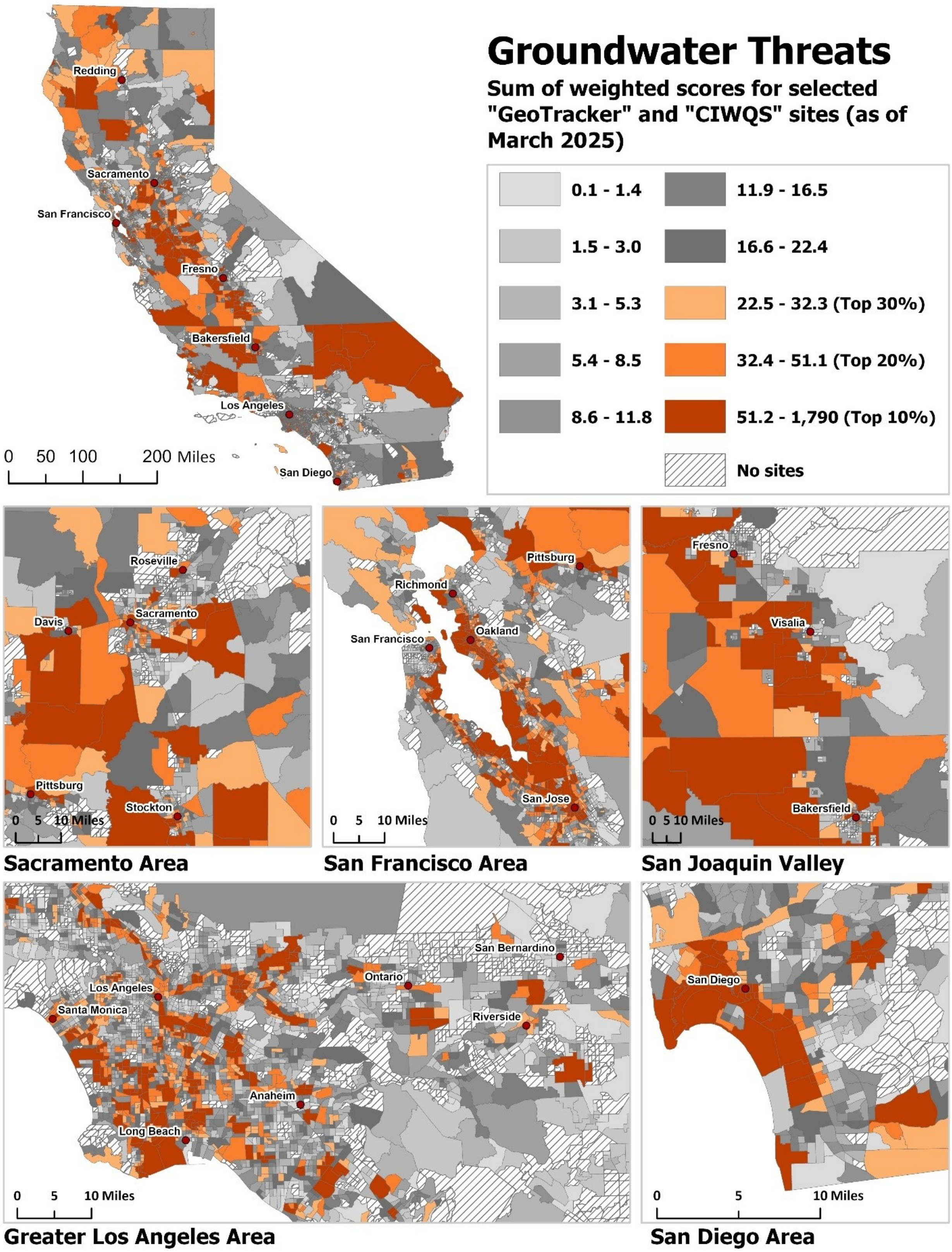
- Data on confined animal feeding operation type, status, location, and permitted population were downloaded from CIWQS. (https://www.waterboards.ca.gov/ciwqs/publicreports.html#facilities ; Interactive Regulated Facilities Report).
- Sites with a valid latitude and longitude were mapped and sites with address only were geocoded in ArcGIS Pro.
- Pasture-based dairies were removed from the analysis because they are less indicative of a hazard or potential environmental risk. Inactive and historical site types were also removed from the analysis. Each remaining site was scored on a weighted scale of 1 to 5 in consideration of the permitted animal population (See Appendix).

Proximity Adjustment:

- The weights for all sites, except LUST Cleanup Program and military UST sites, were adjusted based on their distance from populated census blocks. Sites further than 1000m from any populated census block were excluded from the analysis. LUST Cleanup Program and military UST sites were not adjusted, but if these sites fell further than 250m from populated census blocks, they were excluded.
- Site weights were adjusted by multiplying the weight by 1 for sites less than 250m, 0.5 for sites 250-500m, 0.25 for sites 500-750m, and 0.1 for sites 750-1000m from the nearest populated census blocks within a given tract. Sites outside of a census tract, but less than 1000m from one of that tract’s populated blocks were similarly adjusted based on the distance to the nearest block from that tract (See image below).



- Each census tract was scored based on the sum of the adjusted weights for sites it contains or is near (in ArcGIS Pro).
- Summed census tract scores were sorted and assigned percentiles based on their position in the distribution.


Groundwater Threats
Sum of weighted scores for selected "GeoTracker" and "CIWQS" sites (as of March 2025)
0.1 - 1.4
1.5 - 3.0
3.1 - 5.3
5.4 - 8.5
8.6 - 11.8
11.9 - 16.5
16.6 - 22.4
22.5 - 32.3 (Top 30%)
32.4 - 51.1 (Top 20%)
51.2 - 1,790 (Top 10%)
No sites
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Weighting Matrix for Groundwater Threats

Groundwater threats from the GeoTracker and CIWQS database were weighted on a scale of 1 to 15 in consideration of both the site type and status. The following table shows the weights applied for each site type and status.

Sites with a status type of Completed – Case Closed and Open-Referred were excluded from the analysis because they are completed or were referred and tracked by another agency.

For a given census tract, the weighted scores of all facilities in the area were summed after adjusting for proximity to populated census blocks.

Cleanups, Land Disposal, Underground Storage Tanks, and Produced Water Ponds

Site Type	Status	Weight
Land Disposal Sites [Military Privatized Site*]	Open – Remediation	10
	Open - Assessment & Interim Remedial Action	10
	Open - Site Assessment	6
	Open	3
	Open – Operating	3
	Open - Verification Monitoring	3
	Open - Closed / Monitoring	2
	Open – Inactive	2
	Open - Eligible for Closure	Exclude
	Open – Proposed	Exclude
Produced Water Ponds	Active	5
	Inactive	2
LUST Sites [Military UST Site*]	Open – Remediation	3
	Open - Assessment & Interim Remedial Action	3
	Open - Site Assessment	2
	Open - Verification Monitoring	2
	Open – Inactive	1
	Open - Eligible for Closure	Exclude
Cleanup Program Sites [Military Cleanup Site*]	Open - Assessment & Interim Remedial Action	15
	Open – Remediation	15
	Open - Site Assessment	10
	Open - Reopen Case	10
	Open - Verification Monitoring	6
	Open – Inactive	3
	Open - Eligible for Closure	Exclude

*Military sites have unique site types, but receive the same weights as their Land Disposal, Cleanup, and LUST site types of the same status.

Dairies and Feedlots

Site Type	Weight	CAFO Population
Dairies	1	0 - 299
	3	300 - 999
	5	1,000 or more
Feedlots	1	0 - 499
	3	500 – 2,999
	5	3,000 or more

Approximately 11,400 Groundwater Threat Sites

Facility Type	% of Total
Cleanup Program Site	46%
Military Cleanup Site	15%
LUST Site	10%
Land Disposal Site	10%
Dairy	9%
Produced Water Pond	4%
Feedlot	3%
Military UST Site	2%
Military Privatized Site	1%

Glossary

Site Type Definitions*:

- *Cleanup Program Site* (Site Cleanup Program): In general, Site Cleanup Program sites are areas where a release of pollutants has occurred that is not addressed in the other core regulatory programs (e.g., permitted facilities, USTs). The funding for the Program is primarily cost reimbursement from responsible parties.
- *Land Disposal Site*: The Land Disposal program regulates water quality aspects of discharges to land for disposal, treatment, or storage of waste at waste management facilities and units such as landfills, waste piles and land treatment units under California Code of Regulations, Title 27. A land disposal unit is an area of land, or a portion of a waste management facility, at which waste is discharged.

- *Produced Water Ponds*: Produced water is the water that is produced as a byproduct during oil and gas extraction. The major constituents in produced water are salts, oil, inorganic and organic chemicals, and sometimes heavy metals or traces of naturally occurring radioactive materials. The Regional Water Quality Control Boards require waste discharge permits for produced water ponds.
- *Military Cleanup Site*: Military Cleanup Program sites are areas where a release of pollutants from an active or closed military facility has occurred. The military fully funds for the Program oversight.
- *Military Privatized Site*: These sites are within the Site Cleanup Program. They are unique because these sites have been transferred by the military into non-military ownership with or without further cleanup necessary.
- *Military Underground Storage Tanks* (UST): Military UST Program sites are areas where a release of pollutants from an underground storage tank has occurred at a military or former military installation. The military fully funds for the Program oversight costs.

Status Definitions for Land Disposal Sites*:

- *Open - Operating*: A land disposal site that is accepting waste. These sites have been issued waste discharge requirements by the appropriate Regional Water Quality Control Board.
- *Open - Proposed*: A land disposal site that is in the process of undergoing the permit process by several agencies. These sites have not been issued waste discharge requirements by the appropriate Regional Water Quality Control Board and are not accepting waste.
- *Open – Closing/with Monitoring*: A land disposal site that is no longer accepting waste and is undergoing all operations necessary to prepare the site for post-closure maintenances in accordance with an approved plan for closure.
- *Open – Closed/with Monitoring*: A land disposal site that has ceased accepting waste and was closed in accordance with applicable statutes, regulations, and local ordinances in effect at time of closure. Land disposal site in post closure maintenance period as waste could have an adverse effect on the quality of the waters of the state. Site has waste discharge requirements.
- *Open – Inactive*: A land disposal site that has ceased accepting waste but has not been formally closed or is still within the post-closure monitoring period. Site does not pose a significant threat to water quality and does not have groundwater monitoring. Site may or may not have waste discharge requirements.
- *Completed – Case Closed/No Monitoring*: A land disposal site that ceased accepting waste and was closed in accordance with applicable statutes, regulations, and local ordinances in effect at time of closure. The land disposal site was monitored for at least 30 years, and Water Board staff has determined that wastes no longer pose a threat to water quality. Site does not have waste discharge requirements.

Status Definitions for Other Site Types*:

- *Completed – Case Closed*: A closure letter or other formal closure decision document has been issued for the site.
- *Open – Assessment & Interim Remedial Action*: An "interim" remedial action is occurring at the site AND additional activities such as site characterization, investigation, risk evaluation, and/or site conceptual model development are occurring.
- *Open – Inactive*: No regulatory oversight activities are being conducted by the Lead Agency.
- *Open – Remediation*: An approved remedy or remedies has/have been selected for the impacted media at the site and the responsible party (RP) is implementing one or more remedy under an approved cleanup plan for the site. This includes any ongoing remedy that is either passive or active or uses a combination of technologies. For example, a site implementing only a long-term groundwater monitoring program, or a "monitored natural attenuation" (MNA) remedy without any active groundwater treatment as part of the remedy, is considered an open case under remediation until site closure is completed.
- *Open – Site Assessment*: Site characterization, investigation, risk evaluation, and/or site conceptual model development are occurring at the site. Examples of site assessment activities include, but are not limited to, the following: 1) identification of the contaminants and the investigation of their potential impacts; 2) determination of the threats/impacts to water quality; 3) evaluation of the risk to humans and ecology; 4) delineation of the nature and extent of contamination; 5) delineation of the contaminant plume(s); and 6) development of the Site Conceptual Model.
- *Open – Verification Monitoring* (use only for UST, Chapter 16 regulated cases): Remediation phases are essentially complete, and a monitoring/sampling program is occurring to confirm successful completion of cleanup at the Site. (e.g.. No "active" remediation is considered necessary or no additional "active" remediation is anticipated as needed. Active remediation system(s) has/have been shut off and the potential for a rebound in contaminant concentrations is under evaluation).
- *Open – Reopen Case* (available selection only for previously closed cases): This is not a case status. This field should be selected to record the date that the case was reopened for further investigation and/or remediation. A case status should immediately be selected from the list of case status choices after recording this date.
- *Open – Eligible for Closure*: Corrective action at the Site has been determined to be completed and any remaining petroleum constituents from the release are considered to be a low threat to Human Health, Safety, and the Environment. The case in GeoTracker is going through the process of being closed.

*Available through Geotracker website: http://geotracker.waterboards.ca.gov/

(except the Produced Water Pond definition available at http://www.waterboards.ca.gov/water_issues/programs/groundwater/sb4/oil_field_produced/index.shtml).

Definition of Confined Animal Facilities:
Includes farms or ranches where livestock are held for a significant period of time and provided food in the facility (as opposed to grazing), and whose discharges are regulated by the State Water Resources Control Board and/or one of the nine Regional Water Quality Control Boards. Discharges include manure, wastewater, and storm water runoff that may contain waste constituents.

Available at: https://geotracker.waterboards.ca.gov/site_type_definitions

HAZARDOUS WASTE GENERATORS AND FACILITIES

Most hazardous waste must be transported from hazardous waste generators to permitted recycling, treatment, storage, or disposal facilities (TSDF) by registered hazardous waste transporters. Shipments are accompanied by a hazardous waste manifest. There are widespread concerns for both human health and the environment from sites that serve to process or dispose of hazardous waste. Many newer facilities are designed to prevent the contamination of air, water, and soil with hazardous materials, but even newer facilities may negatively affect perceptions of surrounding areas in ways that have economic, social and health impacts. The Department of Toxic Substances Control (DTSC) maintains data on permitted facilities that are involved in the treatment, storage, or disposal of hazardous waste as well as information on hazardous waste generators.

Indicator

Sum of weighted permitted hazardous waste facilities, hazardous waste generators, and chrome plating facilities within each census tract.

(Permitted hazardous waste facilities data was received October 2024, Hazardous waste data are from 2021-2023, and chrome plating facilities data was received in August 2024).

Data Source

EnviroStor Hazardous Waste Facilities Database and Hazardous Waste Tracking System, Department of Toxic Substances Control (DTSC)

EnviroStor is a public website that provides access to detailed information on hazardous waste permitted facilities. Information included in the database includes the facility name and address, geographic location, facility type and status.

DTSC also maintains information on the manifests created for the transport of hazardous waste from generators in its Hazardous Waste Tracking System. Manifests include the generator's name and identification number, the transporter, the designated recipient and description of the type and quantity of waste classified by a coding system. Data are currently available for 2021-2023. Data are available at the links below:

http://hwts.dtsc.ca.gov/

Chrome Plating Airborne Toxics Control Measure, California Air Resources Board (CARB)

The 2023 Chrome Plating Airborne Toxics Control Measure (ATCM) requires CARB to reduce and eventually eliminate hexavalent chromium emissions from California chrome plating facilities. Since 1988, CARB has regulated chrome plating operations for both decorative and hard chrome plating facilities, as well as chromic acid anodizing operations. The ATCM was amended in 1998 and again in 2007 to accommodate changes in federal regulations as well as improve ways to further reduce chrome emissions. Information on CARB's Chrome Plating ATCM webpages provides information on the regulation, the announcements of Work Group meetings and public workshops, as well as how interested parties can get involved in the Chrome Plating ATCM amendment development process. This data of chrome plating facilities is based on survey data from 2018, and updated data was received in August 2024. More details about the Chrome Plating ATCM can be found at:

https://ww2.arb.ca.gov/our-work/programs/chrome-plating-atcm

Rationale

Hazardous waste is potentially dangerous or harmful to human health or the environment. The US Environmental Protection Agency and DTSC both have standards for determining when waste materials must be managed as hazardous waste. Hazardous waste can be liquids, solids, or contained gases. It can include manufacturing by-products and discarded used or unused materials such as cleaning fluids (solvents) or pesticides. Hexavalent chromium, a hazardous waste of particular human health concern, is generated as part of the chrome plating process (Pellerin and Booker 2000). Used oil and contaminated soil generated from a site clean-up can be hazardous wastes (DTSC 2012). In 1995, 97% of toxic chemicals released nationwide came from small generators and facilities (McGlinn 2000). Generators of hazardous waste may treat waste onsite or send it elsewhere for disposal.

The potential health effects that come from living near hazardous waste disposal sites have been examined in a number of studies (Vrijheid 2000). Studies have found adverse health effects, including diabetes and cardiovascular disease, associated with living in proximity to hazardous waste sites (Kouznetsova et al. 2007; Sergeev and Carpenter 2005). Living near hazardous waste sites has also been associated with adverse birth outcomes (Kihal-Talantikite et al. 2017). Hexavalent chromium can be ingested or inhaled and can cause damage to the respiratory system and other organs. Hexavalent chromium compounds have been found to be carcinogenic (OEHHA 2016; Pellerin and Booker 2000; US EPA 2024b).

The hazardous waste indicator uses a 4 km (~2.5 mi) buffer around treatment, storage, and disposal facilities (TSDFs), compared to 1 km for large quantity generators, to reflect concerns for both human health and the environment from sites that process or dispose of hazardous waste. The indicator uses a distance decay method of weighting, with substantial weight from each TSDF facility concentrated within 1km (see the updated 4km buffer image below). While adverse birth outcomes like low birth weight and prematurity have been linked to living within 1 km of TSDFs (Berry and Bove 1997), broader studies show health risks extend farther. For example, low and very low birth weights were associated with residence within 2 km of landfills (Elliott et al. 2001), congenital anomalies within 3 km of hazardous waste landfill sites in Europe's EUROHAZCON study (Dolk et al. 1998; Vrijheid et al. 2002), and fetal malformations up to 8 km away from hazardous waste sites in Washington State (Kuehn et al. 2007).

Several cumulative impacts tools, including US EPA's EJScreen at the national level and states such as Washington and Colorado, apply 5 – 10km buffers to account for environmental justice concerns, including psychological stress, fear, and other reactions to the presence of these facilities (US EPA 2024a). State and national tools that use larger buffers are not directly comparable to CES because some use smaller census geography or do not include scoring of facilities by permit type and size. However, US EPA's EJScreen, which uses a 10km buffer intended to represent more than only real or potential human health adverse effects coming from exposure, indicates that a smaller buffer size may be more appropriate for state-specific applications and US

EPA documentation has suggested less than 5 km may be more suitable for state-specific applications (US EPA, 2024a).

The location of hazardous waste sites near communities has long been an environmental justice concern in California. For example, a study of 82 hazardous waste treatment, storage, and disposal facilities in Los Angeles County found that the communities most affected by the facilities are composed of working-class and ethnic minority populations living near industrial areas (Aliyu et al. 2011). A 1997 study correlated race/ethnicity with the location of hazardous waste treatment, storage and disposal facilities for both African-American and Latino populations (Boer et al. 1997).

Electronic waste is defined as universal waste rather than hazardous waste by California law and is subject to different rules for handling and transportation. However, some components of electronic devices contain hazardous materials, and facilities that collect or recycle electronic waste are potential sources of exposure to toxic chemicals (DTSC 2010).

Method

Permitted hazardous waste facilities:

- Permitted facility data were obtained from the DTSC website.
- Facilities were scored on a weighted scale in consideration of the type, permit status, and compliance history for the facility (See Appendix).
- Site locations were mapped or geocoded (in ArcGIS Pro).

Hazardous waste generators:

- Generator data were obtained from DTSC from the Hazardous Waste Tracking System for 2021 to 2023.
- Only large quantity generators (producing at least 1,000 kg of non-RCRA waste or at least 1 kg of RCRA waste for at least one month during the three years) were included. The threshold of large quantity generators is based on the following definition from DTSC: https://dtsc.ca.gov/large-quantity-generator-of-hazardous-waste-definition/
- To more fully account for cross-border pollution, one brick kiln in Mexico was identified within 1000 meters of a community in California. Without data on volume of waste generated, this brick kiln was classified as a large hazardous waste generator, weighted with a score of ‘2’ (See Appendix). This site was independently validated by San Diego State University researchers as part of a California Air Resources Board contract to improve data quality at the California-Mexico border (Contract number 16RD010).
- Facilities were scored on a weighted scale in consideration of the volume of waste generated (See Appendix).
- Site locations were mapped or geocoded (in ArcGIS Pro).

Chrome plating facilities:

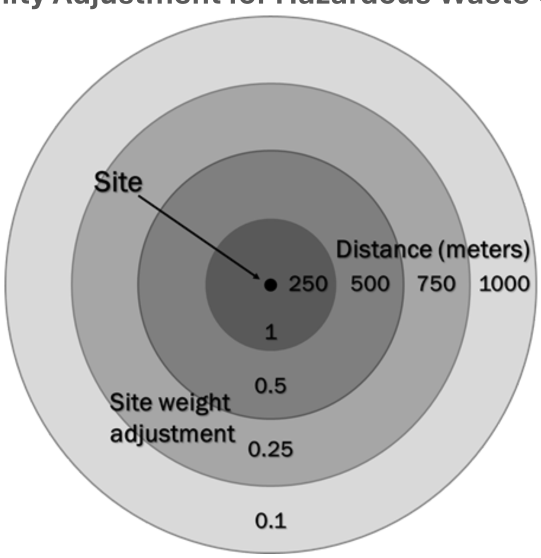
- Chrome plating facility data were obtained from CARB, which maintains a list of chrome plating facilities.

- Only active chrome plating facilities were included in the analysis.
- Facilities were scored based on the number of annual amperage hours permitted at that facility.
- Site locations were mapped or geocoded (in ArcGIS Pro).

Proximity Adjustment:

- The weights for all facilities were adjusted based on the distance they fell from populated census blocks.
- Site weights for hazardous waste generators and chrome plating facilities were adjusted by multiplying the weight by 1 for facilities less than 250m, 0.5 for sites 250-500m, 0.25 for sites 500-750m, and 0.1 for sites 750-1000m from the nearest populated census blocks within a given tract. Facilities outside of a census tract, but less than 1000m from one of that tract's populated blocks were similarly adjusted based on the distance to the nearest block from that tract.
- Site weights for permitted hazardous waste facilities were adjusted by multiplying the weight by 1 for facilities less than 250m, 0.5 for sites 250-500m, 0.25 for sites 500-1000m, 0.1 for sites 1000m-2000m, and 0.05 for sites 2000m-4000m.

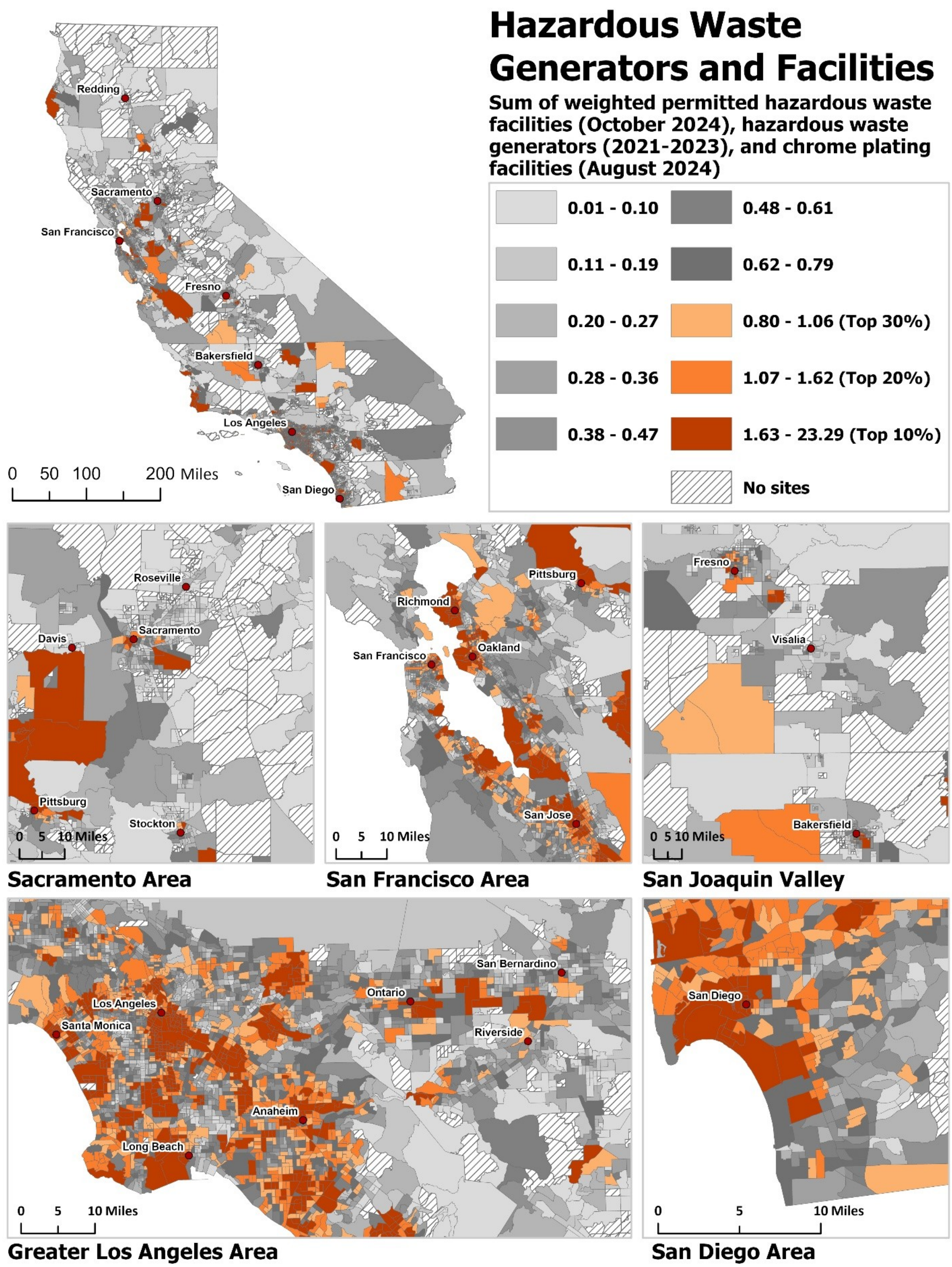
Proximity Adjustment for Hazardous Waste Generators and Chrome Plating Facilities



*not to scale

Proximity Adjustment for Transfer, Storage, and Disposal Facilities (TSDFs)

- Each census tract was scored based on the sum of the adjusted weights for sites it contains or is near (in ArcGIS Pro).
- Summed census tract scores were sorted and assigned percentiles based on their position in the distribution.


Hazardous Waste Generators and Facilities
Sum of weighted permitted hazardous waste facilities (October 2024), hazardous waste generators (2021-2023), and chrome plating facilities (August 2024)
0.01 - 0.10
0.11 - 0.19
0.20 - 0.27
0.28 - 0.36
0.38 - 0.47
0.48 - 0.61
0.62 - 0.79
0.80 - 1.06 (Top 30%)
1.07 - 1.62 (Top 20%)
1.63 - 23.29 (Top 10%)
No sites
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Weighting Matrix for Permitted Hazardous Waste Facilities, Hazardous Waste Generators, and Chrome Plating Facilities

Permitted Hazardous Waste Facilities from DTSC's permitted facilities database were weighted on a scale of 1 to 15 in consideration of the facility activity and permit type. The score for any given Permitted Hazardous Waste Facility represents the sum of its Facility Activity and Permit Type. Compliance history is now a component of the permitted facility scoring. OEHHA worked with DTSC during their SB 673 (Permitting Criteria) process and used data from the Violations Scoring Procedure (VSP) to assign scores to facilities with more violations in a rolling ten-year period. OEHHA assigned additional weights to facilities that fell within VSP Compliance Tiers of "Conditionally Acceptable" or "Unacceptable". The new facility scoring weights can be found further down in the appendix.

Hazardous waste generators were assigned weights from 0.1 to 2 based on the yearly amount of waste generated. Chrome plating facilities were weighted on a scale of 0.1 to 2 based on the annual amperage-hours permitted at that site.

The following tables show the weights applied to the facilities, generators, and chrome platers. Greater concerns were identified for permitted hazardous waste facilities that handle much of the hazardous waste generated from the ~100,000 generators in California. Only large quantity generators (>1,000 kg of non-RCRA waste or at least 1 kg of RCRA waste) were included due to the large number of hazardous waste generators producing small amounts of less hazardous types of waste. In 2021 to 2023 this represents about 12,000 generators. Higher weights were given to generators that produced larger volumes of waste. For all census tracts, the weighted and proximity adjusted scores of all facilities and generators in the area were summed.

Permitted Hazardous Waste Facilities

Facility Activity weight + Permit Type weight + Violation Scoring Procedure weight = Facility Weight

Facility Activity	Weight
Landfill	10
Treatment	7
Storage	4

Permit Type	Weight
RCRA	2
Non-RCRA	1
Large	1
Disposal	1

Violation Scoring Procedure Compliance Tier	Weight
Unacceptable	3
Conditionally Acceptable	1

Hazardous Waste Generators

Quantity of Waste	Weight
> 1,000 tons/ year	2
100 – 1,000 tons/ year	0.5
> 100 tons/ year	0.1

Chrome Plating Facilities

Permitted Amperage-Hours	Weight
> 500,000 amp-hrs/ year	2
> 50,000 amp-hrs/ year	0.5
<= 50,000 amp-hrs/ year	0.1

Number of Chrome Plating Facilities, Hazardous Waste Generators, and Permitted Facilities: Approximately 12,200

Facility Type	N(%)
Large hazardous waste generator or hazardous waste generator with RCRA waste	12,008 (98%)
Permitted hazardous waste storage facility	71 (1%)*
Active Chrome Plating Facility	108 (1%)

**Permitted storage facilities are weighted much higher than generators and chrome platers*

IMPAIRED WATERS

Contamination of California streams, rivers, lakes, and coastal waters by pollutants can compromise the use of the water body for drinking, swimming, fishing, aquatic life protection, and other beneficial uses. When this occurs, such water bodies are considered "impaired." Information on impairments to these water bodies can help determine the extent of environmental degradation within an area.

Indicator

Summed number of pollutants across all water bodies designated as impaired within the area (2024) .

Data Source

2024 303(d) List of Impaired Water Bodies, State Water Resources Control Board (SWRCB)

The SWRCB provides information relevant to the condition of California surface waters. Such information is required by the Federal Clean Water Act. Every two years, State and Regional Water Boards assess and report on the quality of California surface waters. Lakes, streams and rivers, and coastal waters that do not meet water quality standards, or are not expected to meet water quality standards, are listed as impaired under Section 303(d) of the Clean Water Act. The 2024 303(d) List was based on water quality data collected prior to December 9, 2020. The 2024 California Integrated Report was partially approved and partially disapproved by US EPA on December 13, 2024. US EPA approved the majority of the 303(d) list but identified 44 waterbody-pollutant combinations they are considering adding to the 303(d) List due to benthic community effects, and nine waterbodies that were misclassified, but still included in the analysis(Torres 2024). Data and information about the 303(d) list are available at the link below:

https://www.waterboards.ca.gov/water_issues/programs/water_quality_assessment/

Rationale

Rivers, lakes, estuaries and marine waters in California are important for many different uses. Water bodies used for recreation may also be important to the quality of life of nearby residents if subsistence fishing is critical to their livelihood (CalEPA and OEHHA 2002). Water bodies also support abundant flora and fauna. Alterations in natural conditions in aquatic environments can affect biological diversity and overall health of ecosystems. Aquatic species important to local economies may be impacted if the habitats where they seek food and reproduce are changed. Marine wildlife like fish and shellfish that are exposed to toxic substances may potentially expose local consumers to toxic substances as well (CalEPA and OEHHA 2002). Excessive hardness, unpleasant odor or taste, turbidity, color, weeds, and trash in the waters are types of pollutants affecting water aesthetics (CalEPA and OEHHA 2002), which in turn can affect nearby communities.

Communities of color, low-income communities, and tribes generally depend on the fish, aquatic plants, and wildlife provided by nearby surface waters to a greater extent than the general population (NEJAC 2002). Some communities that rely on resources provided by nearby surface waters have populations of lower socioeconomic status and higher ethnic diversity than the general population. For example, certain fishing communities along California's northern coast have lower educational attainment and median income than California as a whole (Pomeroy et al. 2010). In a study of 500 women in the Sacramento–San Joaquin Delta, it was found that Asian and African American women consumed the highest number of sport-caught fish (Silver et al. 2007). Increased levels of certain surface water pollutants have been associated with lower per capita income, low housing values, and a higher percentage of minorities and people of color (Farzin and Grogan 2013; Liévanos 2018). In addition, a study in the Sacramento-San Joaquin Delta found that fish consumption for certain subsistence fishers was higher than rates used for planning and regulation of polluted waters, and that mercury consumption from fish was significantly above US EPA advisory levels (Shilling et al. 2010).

Two studies, one in England and one in San Antonio, Texas, found that people who lived near water bodies with significant impairments were more likely to believe that the water bodies were safe, and therefore to visit them more often, than people who lived further away (Brody et al. 2004; Georgiou et al. 2000).

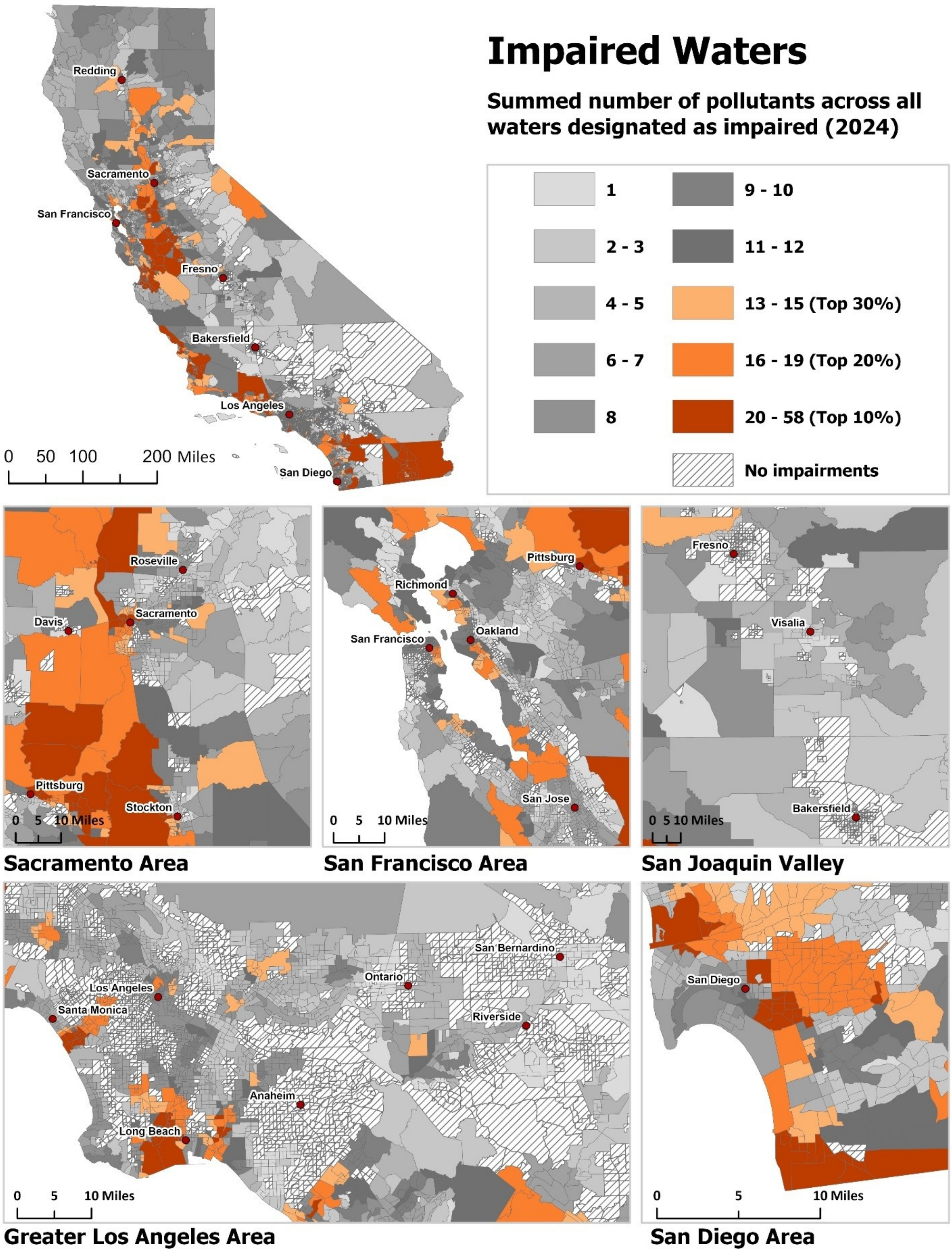
Method

Data on water body type, water body ID, and pollutant type were downloaded in Excel format, and GIS data showing the visual representation of all water bodies were downloaded from the SWRCB website.

All water bodies were identified in all census tracts in the GIS software ArcGIS Pro.

The number of pollutants listed in streams or rivers that fell within 1 kilometer (km) or 2 km respectively of a census tract's populated blocks were counted. The 2 km buffer distance was applied to major rivers (>100 km in length, plus the Los Angeles River and Imperial Valley canals and drainage ways). The 1 km buffer distance was applied to all smaller streams/rivers

- The number of pollutants listed in lakes, bays, estuaries or shoreline that fell within 1 km or 2 km of a census tract's populated blocks were counted. The 2 km buffer distance was applied to major lakes or bays greater than 25 square kilometers in size, plus all the Sacramento/San Joaquin River Delta waterways. The 1 km buffer distance was applied for all other lakes/bays.
- The two pollutant counts were summed for every census tract.
- Each census tract was scored based on the sum of the number of individual pollutants found within and/or bordering it. For example, if two stream sections within a census tract were both listed for the same pollutant, the pollutant was only counted once.
- Summed census tract scores were sorted and assigned percentiles based on their position in the distribution.


Impaired Waters
Summed number of pollutants across all waters designated as impaired (2024)
1
2 - 3
4 - 5
6 - 7
8
9 - 10
11 - 12
13 - 15 (Top 30%)
16 - 19 (Top 20%)
20 - 58 (Top 10%)
No impairments
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Richmond
Oakland
San Jose
San Francisco Area
Visalia
San Joaquin Valley
San Bernardino
Ontario
Riverside
Santa Monica
Anaheim
Long Beach
Greater Los Angeles Area
0 5 10 Miles
San Diego Area

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SMALL AIR TOXIC SITES

People are impacted daily by a unique combination of pollutants from small air toxic sites (SmATS) emitting a variety of toxic air contaminants within, or in proximity to their community. On the individual scale, these point source emissions may pose a limited risk, but cumulatively can negatively impact environmental quality and human health. Examples of emission sites in California neighborhoods range from the more commonplace gas stations, autobody shops and oil and gas wells to larger emitters like food processing plants and oil refineries. Every community has its own diverse composition of pollution sources and pollutants that contribute to their overall pollution burden. The California Emission Inventory Development and Reporting System (CEIDARS) currently tracks over 25,000 of these air toxic sites and their emissions statewide. In addition to these sites, there are over 95,000 active and idle oil and natural gas (ONG) wells across the state tracked in the Well Statewide Tracking and Reporting System (WellSTAR). The drilling, construction, and extraction processes from active ONG wells expose residents to a combination of environmental pollutants, presenting health risks to these residents and long-term public health impacts to the community. Additionally, idle ONG wells, those that have been unused for 24 consecutive months or longer, can leak unpredictably and may impact nearby residents.

Indicator

Sum of weighted small air toxic sites and ONG wells within each census tract.

(ONG data downloaded February 2025, and CEIDARS data represent 2022 emission inventory year).

Data Source

California Emission Inventory Development and Reporting System (CEIDARS), California Air Resources Board (CARB)

CEIDARS is the primary database system used by CARB to collect, store, and manage criteria and non-criteria pollutant emissions data throughout California. Criteria pollutants are air pollutants designated and regulated by the US Environmental Protection Agency under the Clean Air Act. Local air districts, state agencies, and other sources collect and report emissions data to the CEIDARS database. Within the database, information on stationary points sources (e.g., power plants, manufacturing facilities, food processing plants) includes facility identification, location information, reporting air district, pollutant types, emissions totals by year, and the associated toxicity-weighted risk for each facility pollutant.

While not included in SmATS, the CEIDARS database also records aggregated stationary sources, areawide sources, on- and off-road mobile sources, and natural sources of air pollutants. CEIDARS currently includes approximately 25,000 smaller sources out of an estimated 60,000 statewide, as new reporting requirements are phased in. Under these new reporting requirements, annual reporting for all sources in large air districts will begin with 2026 emissions data reported in 2027, while smaller districts will start with 2028 emissions data reported in 2029.

https://ww2.arb.ca.gov/applications/facility-search-engine

Well Statewide Tracking and Reporting System (WellSTAR), California Geologic Energy Management Division (CalGEM)

The Well Statewide Tracking and Reporting System (WellSTAR) is a comprehensive public database maintained by CalGEM to regulate oil and gas operations in California. The WellSTAR database contains information on the location, unique well identification number (API), operator, field name, production and/or injection volume, well status (e.g., active, idle, plugged and abandoned, etc.), and individual well records and maintenance data among other information. WellSTAR is updated daily based on operator reports and permit filings in adherence with requirements in Oil and Gas Production: Water Use: Reporting, Senate Bill 1281 (Pavley-2014) and Oil and Gas: Well Stimulation, Senate Bill 4 (Pavley-2013), as well as other state and federal laws. Well sites are never deleted from the database, even when the well is permanently sealed and closed to standards (i.e., well status changed to 'Plugged and Abandoned').

https://data.ca.gov/dataset/wellstar-oil-and-gas-wells

Rationale

Air pollution is often experienced as a complex mixture of pollutants rather than single contaminants. Such mixtures can amplify health impacts beyond the effects of individual pollutants (Araki et al. 2020; Mauderly and Samet 2009). The burden of this pollution is strongly shaped by proximity to emissions sources, with fence line communities located near industries often experiencing the highest exposures and associated health risks (Brender et al. 2011; Chen et al. 2022; García-Pérez et al. 2016; Johnston and Cushing 2020). Smaller sources of emissions within neighborhoods (e.g., gas stations, autobody shops) may appear modest in isolation, but are widespread and cumulatively contribute to significant chronic, neighborhood-level exposures (Chen et al. 2022; Deshmukh et al. 2020; Hilpert et al. 2015). For example, gas stations are widely distributed throughout the built environment, existing near neighborhoods, businesses, and schools. Aof fuel during the delivery, storage, and dispensation can lead to toxic chemical exposure and adverse health impacts from vaporized fuel to surrounding populations (Hilpert et al. 2015). While CEIDARS only tracks routine emissions, the density and proximity of these types of sites to nearby communities can be a proxy for potential impacts to residents through both routine emissions as well as accidental discharges and unexpected incidents.

ONG wells are a prominent example of the health impacts from localized emission sources. During drilling, construction, and extraction, nearby communities are exposed to diverse combinations of stressors including air and water pollution, noise, and other environmental disturbances, adversely impacting residents' health and wellbeing (Allshouse et al. 2019; Garcia-Gonzales et al. 2019; Gonzalez et al. 2022; Johnston et al. 2019; McKenzie et al. 2018; Shonkoff and Morello-Frosch 2024). ONG activity at these sites releases toxic air contaminants (TACs), volatile organic compounds (VOCs), heavy metals, combustion byproducts, odorous compounds, and various chemical additives into the surrounding environment (Shonkoff and Morello-Frosch 2024). Additional hazards include disrupting noise and light pollution, induced seismic activity, exposure to radioactive materials, and even risks of fire or explosions (Shonkoff and Morello-Frosch 2024). Many of these pollutants are linked with adverse health outcomes.

The concentrations, and resulting risks, of pollutants associated with ONG wells increase with proximity (Garcia-Gonzales et al. 2019; McKenzie et al. 2018; Shonkoff and Morello-Frosch 2024; Tran et al. 2020; 2021). Roughly 2.1 million Californians live within 1 km of an active well (Czolowski et al. 2017). A 2021 response to CalGEM seeking expert opinion from the California Oil and Gas

Public Health Rulemaking Scientific Advisory Panel concluded with a high level of certainty that living near active ONG wells is casually associated with adverse perinatal and respiratory outcomes (Shonkoff et al. 2021). For example, prenatal exposure in the first and second trimester to ONG wells in the San Joaquin Valley was associated with elevated risk of preterm birth, particularly among Hispanic and Black populations (Gonzalez et al. 2020). Other studies show increased cancer risks for residents near ONG wells, linking exposure to carcinogenic pollutants emitted by ONG well activity (Epstein 2017; McKenzie et al. 2017; Onyije et al. 2021). Idle wells, or wells that have not been used for 24 consecutive months without being plugged, can leak methane, VOCs, and TACs, posing poorly understood but potentially significant health hazards (Secaira 2022; Shonkoff and Morello-Frosch 2024; Solis 2022; South Coast AQMD 2016).

Importantly, the health risks associated with living near ONG wells and other stationary sources of pollution found in the CEIDARS database are not evenly distributed. Race and socioeconomic status are key determinants of exposure (Proville et al. 2022; Shonkoff and Morello-Frosch 2024). In Los Angeles County, neighborhoods with the highest production volume from ONG wells had a 2.4 times higher number of Black compared to the statewide average, demonstrating disproportionate burden (González et al. 2023). Similar disparities exist for exposure to other stationary sources of pollution (Brooks and Sethi 2009; Marshall 2008; Morello-Frosch 2002; Morello-Frosch et al. 2001; Pastor et al. 2005). These inequities are compounded by underlying vulnerabilities (e.g., higher baseline health risks and reduced access to healthcare) that make affected populations more susceptible to pollution's harmful effects (Deguen et al. 2022; Hooper and Kaufman 2018; Morello-Frosch et al. 2011).

Method

Oil and Natural Gas Wells

- Data on ONG wells including their API, status (i.e., active, idle, plugged and abandoned), and location (i.e., coordinates, address, and geospatial data) were downloaded from CalGEM's WellSTAR database.
- ONG wells were filtered by well status to only include 'Active' or 'Idle' wells.
- Active and idle wells were assigned a weight of one.

CEIDARS Facilities

- Data on CEIDARS stationary point source facilities, including facility name, emissions, and location (e.g., coordinates and address), were obtained from CARB's CEIDARS database.
- Facility records were first cleaned in RStudio to remove entries with missing latitude or longitude values. Diesel engine exhaust emissions were excluded since they are already represented in the Diesel PM Indicator.
- To avoid double counting, Toxic Release Inventory (TRI) facilities (included in the CEIDARS database and the Toxic Releases Indicator) were removed. This process began in RStudio by

standardizing facility names and addresses (e.g., case formatting, removal of special characters) and then applying a two-step Jaro-Winkler matching process:

  - Step 1: CEIDARS facilities within 1 km of TRI facilities that matched both in name and address were removed using a maximum Jaro-Winkler matching distance of 0.15.

  - Step 2: Remaining unmatched TRI facilities were re-checked against CEIDARS facilities within 1 km by address name only, using a stricter maximum matching distance of 0.05.

- CEIDARS facilities were then mapped in ArcGIS Pro using latitude and longitude. Any remaining TRI facilities still embedded in the CEIDARS data were manually removed by cross-referencing facility names and addresses with TRI records.

- All final CEIDARS facilities were assigned a weight of one.

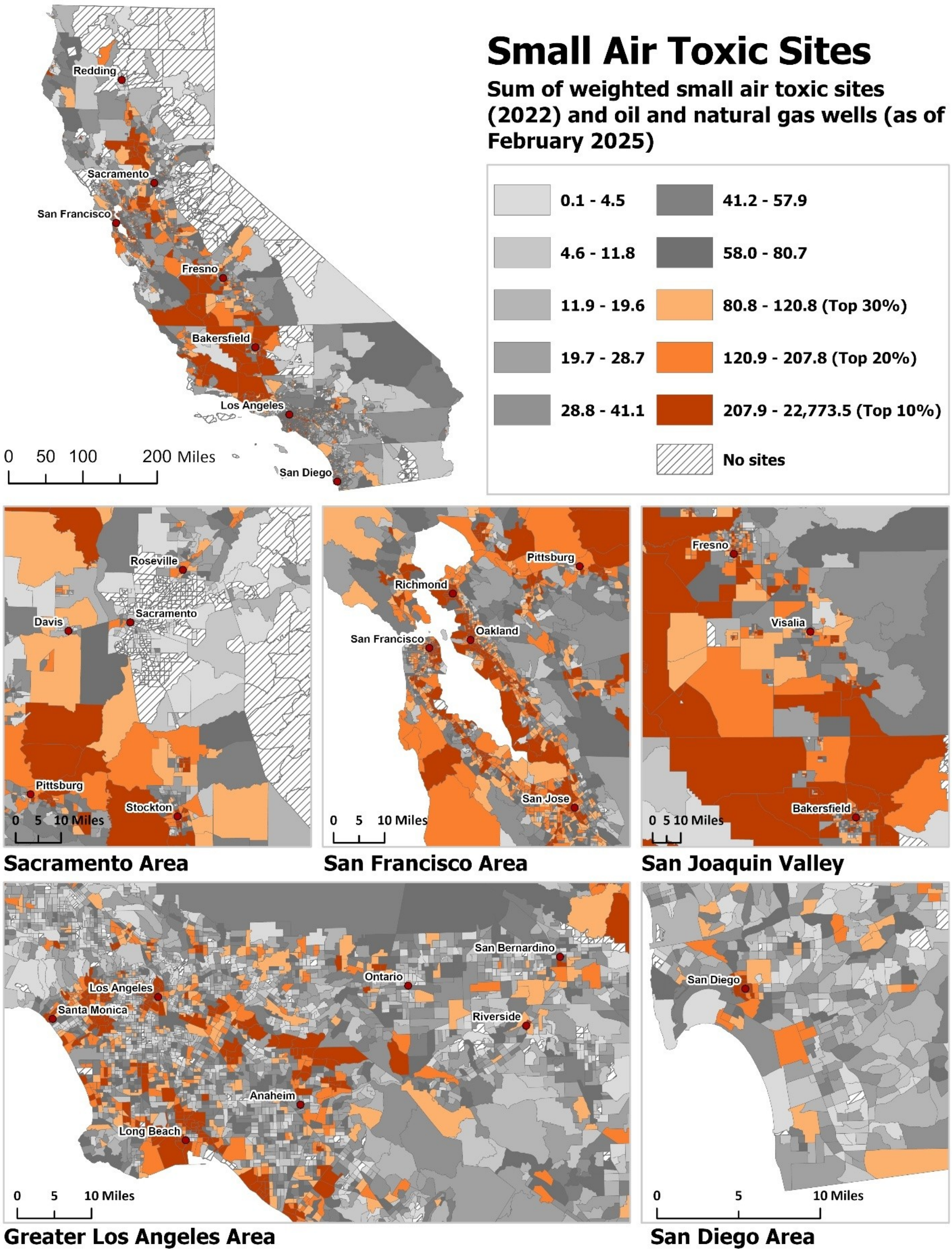
Proximity Adjustments

- The weights for the ONG wells and final CEIDARS facilities were adjusted based on their distance from populated census blocks. Sites further than 1000m from any populated census block were excluded from the analysis.

- Site weights were adjusted by multiplying the weight by 1 for sites less than 250m, 0.5 for sites 250-500m, 0.25 for sites 500-750m, and 0.1 for sites 750-1000m from the nearest populated census blocks within a given tract. Sites outside of a census tract, but less than 1000m from one of that tract's populated blocks were similarly adjusted based on the distance to the nearest block from that tract (See image below).

- Each census tract was scored based on the sum of the adjusted weights for sites it contains or is near (in ArcGIS Pro).

- Summed census tract scores were sorted and assigned percentiles based on their position in the distribution.


Small Air Toxic Sites
Sum of weighted small air toxic sites (2022) and oil and natural gas wells (as of February 2025)
0.1 - 4.5
4.6 - 11.8
11.9 - 19.6
19.7 - 28.7
28.8 - 41.1
41.2 - 57.9
58.0 - 80.7
80.8 - 120.8 (Top 30%)
120.9 - 207.8 (Top 20%)
207.9 - 22,773.5 (Top 10%)
No sites
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Breakdown by Location Type

Site Type	Number	Percent
CEIDARS Facilities	18,115	15%
ONG Well Sites	98,871	85%
Active Wells	*59,218*	*51%*
Idle Wells	*39,653*	*34%*
Total	**116,986**	**100%**

SOLID WASTE SITES AND FACILITIES

Many newer solid waste landfills are designed to prevent the contamination of air, water, and soil with hazardous materials. However, older sites that are out of compliance with current standards or illegal solid waste sites may degrade environmental conditions in the surrounding area and may expose nearby residents to hazards. Other types of facilities, such as composting, treatment and recycling facilities, may raise concerns about odors, vermin, and increased truck traffic. While data that describe environmental effects from the sites and operation of all types of solid waste facilities are not currently available, the California Department of Resources Recycling and Recovery (CalRecycle) maintains data on facilities that operate within the state, as well as sites that are abandoned, no longer in operation, or illegal.

Indicator

Sum of weighted solid waste sites and facilities (as of February 2025).

Data Source

Solid Waste Information System (SWIS), CalRecycle (February 2025)

SWIS is a database which tracks solid waste facilities, operations, and disposal sites throughout California. Solid waste sites found in this database include landfills, transfer stations, material recovery facilities, composting sites, transformation facilities, and closed disposal sites. Data available at the link below:

https://www2.calrecycle.ca.gov/SolidWaste/Activity

Closed, Illegal, and Abandoned (CIA) Disposal Sites Program, CalRecycle (February 2025)

The CIA Disposal Sites Program is a subset of the SWIS database and includes closed landfills and disposal sites that have not met minimum state standards for closure as well as illegal and abandoned sites. Sites within CIA have been prioritized to assist local enforcement agencies investigate the sites and enforce state standards. Data available at the link below:

http://www.calrecycle.ca.gov/SWFacilities/CIA/

Inspection Regulation Status List for Violations, CalRecycle (2023)

CalRecycle maintains records of various violations by the solid waste sites they assess. Some violation types include dust, fire, gas, hazard, litter, noise, nuisance, odor, site security, storage, and vector. Further information can be found at the link below:

https://calrecycle.ca.gov/swfacilities/enforcement/

Hazardous Waste Tracking System, Department of Toxic Substances Control (DTSC, 2022-2024)

DTSC also maintains information on the waste manifests created for scrap metal recyclers in its Hazardous Waste Tracking System. Manifests include the metal recycler's name, identification number, and address. Data are currently available for 2022-2024. Data are available at the link below:

http://hwts.dtsc.ca.gov/

Waste Tire Management System (WTMS), CalRecycle (2024)

CalRecycle maintains data on entities who store or stockpile more than 500 waste tires at a specific location, requiring that they acquire a major or minor waste tire facility permit and comply with certain safety and storage standards. Some facilities may qualify for excluded or exempt status from permitting requirements. Further information can be found at the link below:

https://calrecycle.ca.gov/Tires/

Rationale

Solid waste sites can have multiple impacts on a community. Waste gases like methane and carbon dioxide can be released into the air from disposal sites for decades, even after site closure (Cusworth et al. 2024; Lou and Nair 2009; Ofungwu and Eget 2006; Weitz et al. 2002). Fires, although rare, can pose a health risk from exposure to smoke and ash (CalRecycle 2025; USFA 2002). People living near solid waste disposal sites can experience significant annoyance from odors compared to those living further away (Aatamila et al. 2010). Odors and the known presence of solid waste may impair a community's perceived desirability and affect the health and quality of life of nearby residents (Heaney et al. 2011). Importantly, communities of color and low-income communities are more likely to be affected by illegal waste dumping from external entities looking to offload garbage cheaply (Hohl et al. 2023). While all active solid waste sites in California are regulated, CalRecycle has recorded a number of old, closed disposal sites and landfills that are monitored less frequently. Former abandoned disposal sites present potential for human or animal exposure to uncovered waste or burn ash. Such sites are of concern to state and local enforcement agencies (CalRecycle 2010).

Although less common with modern engineering, landfills can contaminate the surrounding environment and groundwater with leachate, the liquid that drains from waste material (Ozbay et al. 2021). In addition to toxic chemicals, landfill leachate also often contains microplastics, which potentially absorb other contaminants (Kabir et al. 2023). Many of the studies that address the potential toxicity of solid waste site emissions look at the biological effects of landfill leachate on selected species of animals and plants. Biodiversity, flora and fauna, and aquatic life have been found to be impacted by nearby landfills (Siddiqua et al. 2022). New ecological test methods have demonstrated that exposure of arthropods to landfill soil containing a mixture of hazardous chemicals can cause genetic changes that are associated with adverse effects on the reproductive system (Roelofs et al. 2012).

In addition to studies on the ecological effects of solid waste disposal sites, there has been a growing body of evidence for adverse health effects to humans. Living near landfills is associated with exposure to carcinogenic chemicals and heavy metals, leading to increased incidence of health outcomes like skin and respiratory conditions (Khoiron et al. 2020). An epidemiologic study of human births near landfills in Wales found an increase in the rate of birth defects after the opening or expansion of sites (Palmer et al. 2005). A study conducted after an accidental fire at a municipal landfill in Greece found unacceptably high levels of dioxins in food products from an area near the landfill (Vassiliadou et al. 2009). A cohort study of people living within 5 kilometers of a landfill in Italy found associations between exposure to hydrogen sulfide, a marker of airborne contamination from landfills, and slight increases in mortality and morbidity from respiratory diseases (Mataloni et al. 2016).

Method

Closed, Illegal, and Abandoned (CIA) sites:

- The CIA Site Investigation Status List (February 2025) was obtained from CalRecycle for all priority designations, as only high priority CIA sites data are available online.
- Unconfirmed and non-solid waste sites were removed from the analysis.
- Each remaining site was assigned a score in consideration of CalRecycle's prioritization categories (see table in Appendix).
- To account for cross-border pollution, one closed solid waste site in Mexico was identified within 1000 meters of a community in California. This site was independently validated in 2019 by San Diego State University researchers as part of a California Air Resources Board contract to improve data quality at the California-Mexico border (Contract number 16RD010). This site was scored the same as closed solid waste sites within CalRecycle's database and was assigned a 1, which is the lowest score,
- Site locations were geocoded and mapped in ArcGIS Pro.

Active Solid Waste Information System (SWIS) sites:

- SWIS data (February 2025) were obtained from the CalRecycle website.
- CIA records were filtered from the database because SWIS contains an inventory of both active and CIA sites.
- Of the remaining sites, Clean Closed, Absorbed, Inactive and Planned sites were not included.
- Each remaining site was scored in consideration of the site's activity type, regulation status, operational status, and/or throughput volume (see table in Appendix).
- Data on site violations were joined to the scored SWIS sites. Sites were assigned a violation score based on the number of unique violation types (gas, odor, nuisance, etc.) and their respective scores (see table in Appendix).
- Site locations were geocoded and mapped in ArcGIS Pro.
- Landfill boundaries based on parcel boundaries and aerial photo inspection were provided or drawn for most solid waste landfills in the SWIS database. These boundaries were used in the analysis in place of point location, when applicable.

Scrap Metal Recyclers:

- Scrap metal recyclers with NAICS codes 42193, 42393, or 56292 were obtained from DTSC's Hazardous Waste Tracking System.

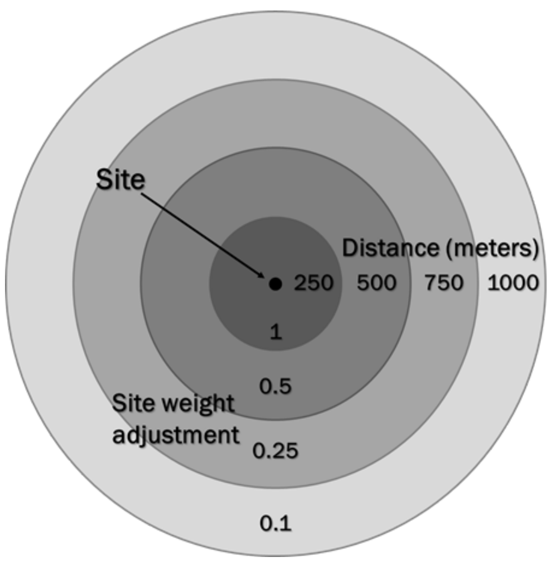
- Any facility that was active between 2022 and 2024 was included and assigned a score of 5 (see table in Appendix).

Waste Tire Facilities:

- Waste tire facility and violation data for permitted active sites were requested from CalRecycle.
- Sites were assigned a score based on their “major” or “minor” activity status (see table in Appendix).
- Sites were assigned a violation score based on information in the same dataset.

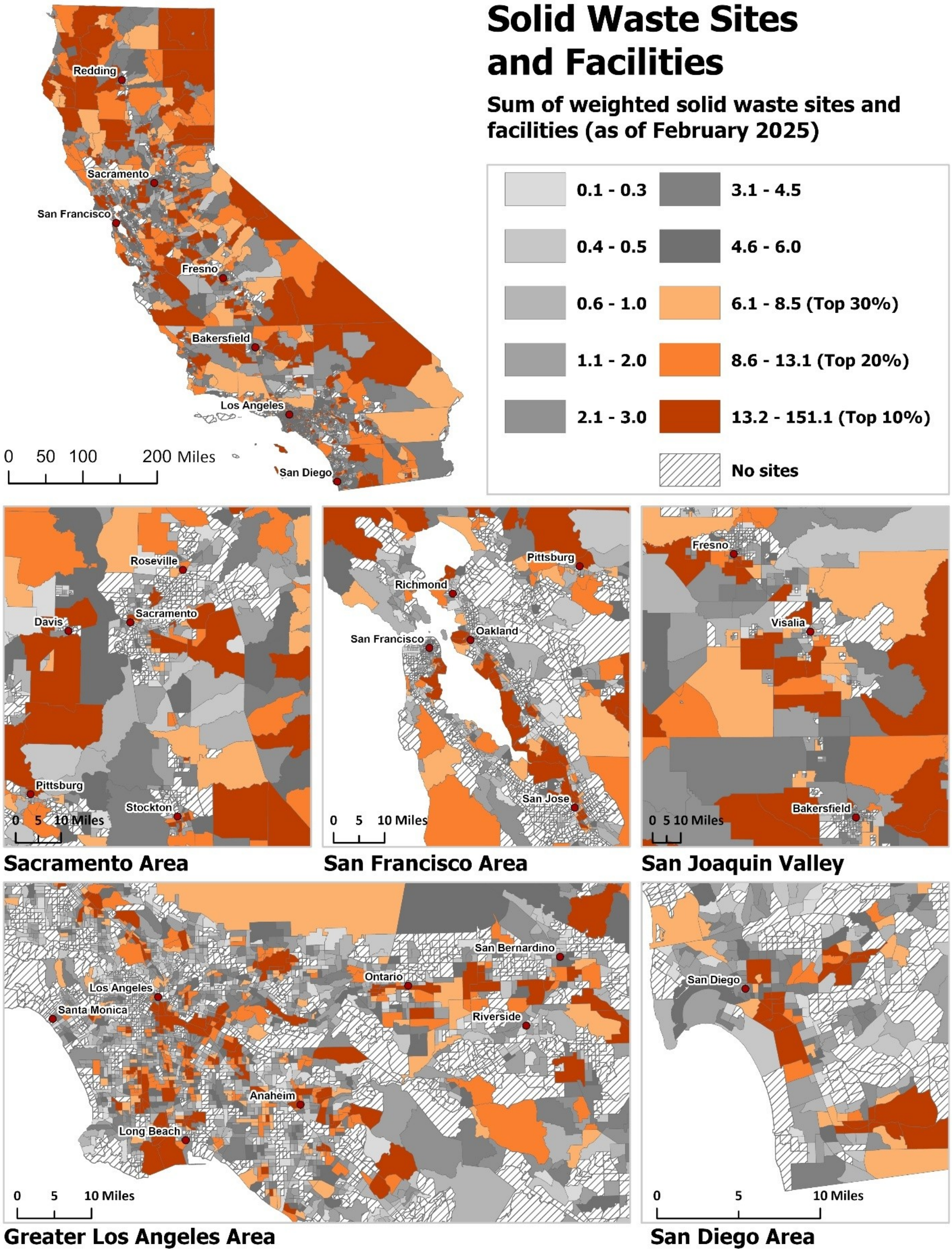
All sites:

- The scores for all sites, including the large landfill perimeters, were weighted based on the distance they fell from populated census blocks. Sites further than 1000m from any populated census block were excluded from analysis.
- Site scores were weighted for proximity to populated census blocks by multiplying the score by 1 for sites less than 250m away, 0.5 for sites 250-500m, 0.25 for sites 500-750m, and 0.1 for sites 750-1000m. Sites outside of a census tract, but less than 1000m from one of that tract’s populated blocks were similarly adjusted based on the distance to the nearest populated block from that tract.



- Odor complaints regarding composting facilities are commonly made more than 1000m from these facilities. Because of this concern the buffer distances and weights for composting sites were adjusted as follows: 1 for sites less than 500m, 0.5 for sites 500 – 1000m, 0.25 for sites 1000 – 1500m, and 0.1 for sites 1500 – 2000m from the nearest populated census blocks within a given tract.

- Census tracts were assigned final scores based on the sum of the highest proximity-weighted scores for each site the census tract contains or is near.
- Census tract scores were sorted and assigned percentiles based on their position in the statewide distribution.


Solid Waste Sites and Facilities
Sum of weighted solid waste sites and facilities (as of February 2025)
0.1 - 0.3
0.4 - 0.5
0.6 - 1.0
1.1 - 2.0
2.1 - 3.0
3.1 - 4.5
4.6 - 6.0
6.1 - 8.5 (Top 30%)
8.6 - 13.1 (Top 20%)
13.2 - 151.1 (Top 10%)
No sites
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Appendix

Table 1. Weighting Matrix for Solid Waste Sites and Facilities

Solid Waste Sites and Facilities were scored in consideration of activity type, regulation status, operational status, throughput volume, and violation history. Table 1 shows the scoring applied to the facilities and sites. The total score for any given Solid Waste Site or Facility represents the sum of its site score and violation score. For all census tracts, the scores of all facilities in the area were summed after weighting by proximity to populated census blocks.

Site or Facility Type	Criteria	Site Score	Violation Score (within previous 12 months)[1]
Closed, Illegal, or Abandoned Site[1]	Priority Code[2]	**6** (Priority Code A) 4 (Priority Code B) **2** (Priority Code C) **1** (Priority Code D)	NA
Solid Waste Disposal Site (closed, closing, inactive)[4]	Operational Status	**1** (Closed)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)
Solid Waste Landfill *or* Construction, Demolition and Inert Debris Waste Disposal (active)[3]	Throughput Tonnage	**8** (> 10,000 tpd) **7** (3,000 to 10,000 tpd) **6** (1,000 to 3,000 tpd) **5** (100 to 1,000 tpd) **4** (< 100 tpd) **0** (0 tpd or NA)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)
Inert Debris: Engineered Fill	Regulatory Tier[5]	**2** (Notification)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)
Inert Debris: Type A Disposal	Regulatory Tier[5]	**3** (Permitted)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)
Composting	Throughput Tonnage and Regulatory Tier[5]	**4** (> 500 tpd) **3** (200 to 500 tpd) **2** (0 to 200) **2** (Notification) **1** (0 tpd or NA)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)
In-Vessel Digestion Facility	Throughput Tonnage	**5** (> 100 tpd) **3** (< 100 tpd) **2** (Notification) **1** (0 tpd or NA)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)
Transfer/Processing	Regulatory Tier[5]	**5** (Permitted: large vol.) **3** (Permitted: medium vol.; small vol.; limited vol.; direct transfer) **2** (Notification)	**3** (gas) **1** (each for dust, fire, hazard, litter, noise, nuisance, odor, site security, storage, and vector)

Waste Tire	Regulatory Tier[5]	**4** (Major) **2** (Minor)	**1** (each violation)
Scrap Metal Recycler	Operational Status	**5** (Active)	NA

[1] Violations: Explosive gas violations have a greater potential environmental impact than dust, noise, and vectors (from SWIS and the Waste Tire Management System).

[2] CIA sites are scored per established CIA Site Priority Code scoring methodology (A through D).

[3] Active landfills (other than Contaminated Soil Disposal Sites and Nonhazardous Ash Disposal/Monofill Facilities) are all in the Full Permit regulatory tier, so permitted tonnage is used to assign site scores.

[4] Solid Waste Disposal Site (closed) means the site was closed pursuant to state closure standards that became operative in 1989. Closed sites associated with the CIA Site database were closed prior to 1989 in accordance with standards applicable at the time of closure.

[5] Placement within a regulatory tier accounts for the type of waste and amount of waste processed per day or onsite at any one time. See SWIS for compost and transfer/processing; Waste Tire Management System (WTMS) for waste tire sites.

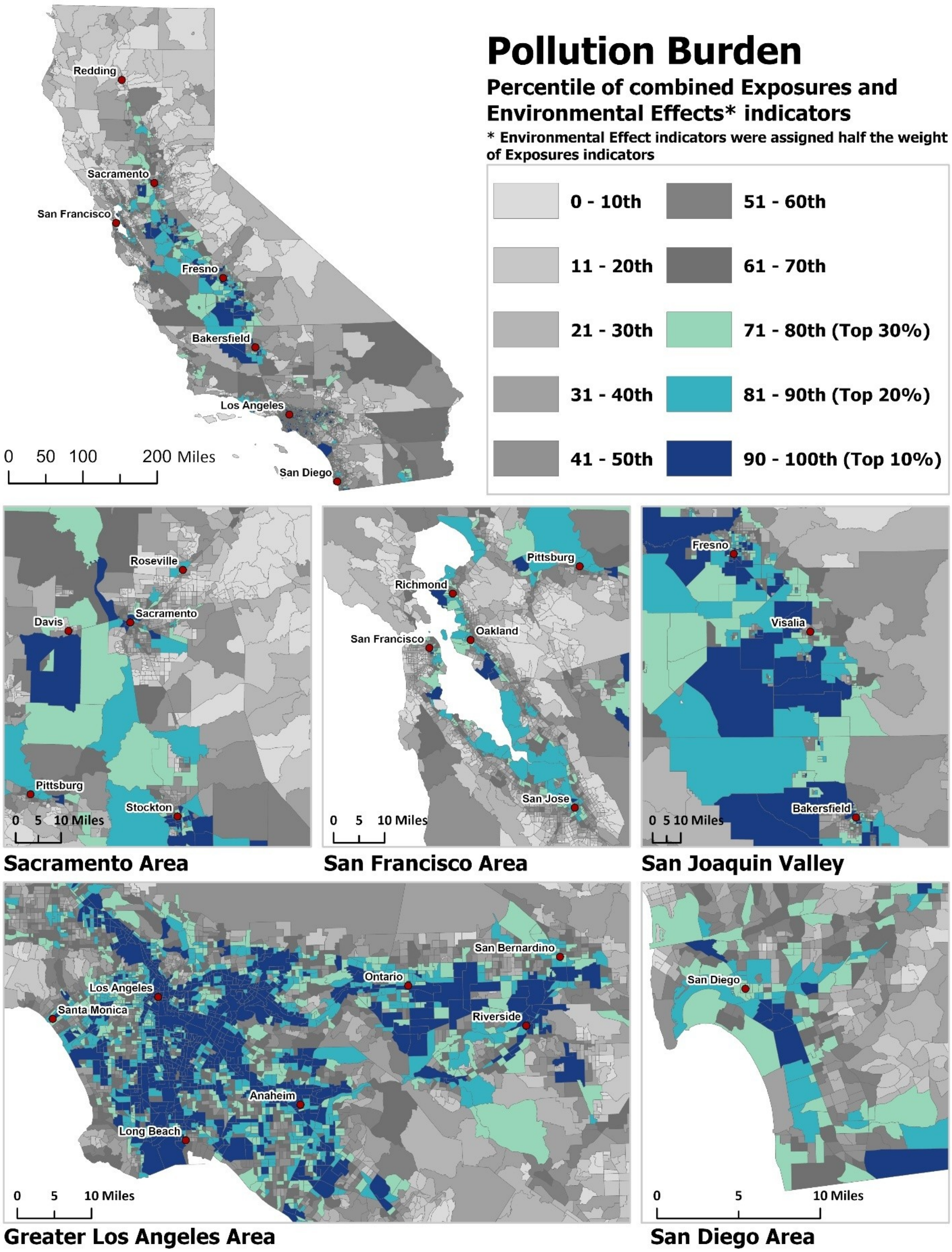
Table 2. Percentage of Total Sites Included by Type

Number of Solid Waste Sites and Facilities in CalEnviroScreen 5.0: Approximately 4,800

Facility Type	% of Total
Disposal Site (closed)	57%
Scrap Metal Recyclers	15%
Transfer/Processing (active)	13%
Composting Facility	8%
Disposal Site (active)	5%
Transfer/Processing (closed)	1%
Waste Tire Facility	1%
In-Vessel Digestion Facility	<1%

Scores for Pollution Burden

The map on the following page shows Pollution Burden scores divided into deciles.


Pollution Burden
Percentile of combined Exposures and Environmental Effects* indicators
* Environmental Effect indicators were assigned half the weight of Exposures indicators
0 - 10th
11 - 20th
21 - 30th
31 - 40th
41 - 50th
51 - 60th
61 - 70th
71 - 80th (Top 30%)
81 - 90th (Top 20%)
90 - 100th (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

Population Characteristics: Sensitive Population Indicators

ASTHMA

Asthma is a chronic lung disease characterized by episodic breathlessness, wheezing, coughing, and chest tightness. While the causes of asthma are poorly understood, it is well established that exposure to traffic and outdoor air pollutants, including particulate matter, ozone, and diesel exhaust, can trigger asthma attacks. More than three million Californians currently have asthma and nearly six million have had it at some point in their lives. Children, the elderly, and low-income Californians suffer disproportionately from asthma (Alcala et al. 2018). Although asthma can be managed as a chronic disease, asthma can be a life-threatening condition, and emergency department (ED) visits for asthma are a very serious outcome, both for patients and for the medical system. Asthma is included as an indicator of sensitive populations because it reflects an increased susceptibility to the harmful effects of certain environmental exposures.

Indicator

Spatially modeled, age-adjusted rate of ED visits for asthma per 10,000 (averaged over 2022-2023).

Data Source

Emergency Department (ED) and Patient Discharge Datasets (PDD) from the California Department of Health Care Access and Information (HCAI)

Since 2005, hospitals licensed by the state of California to provide emergency medical services are required to report all ED visits to HCAI. Federally owned facilities, including Veterans Affairs and Public Health Service hospitals, are not required to report. The ED dataset includes information on the principal diagnosis, which can be used to identify which patients visited the ED because of asthma. We excluded the year 2021 due to anomalous reductions in ED visits during the COVID-19 pandemic, which were not reflective of underlying asthma risk.

https://hcai.ca.gov/data/data-and-reports/

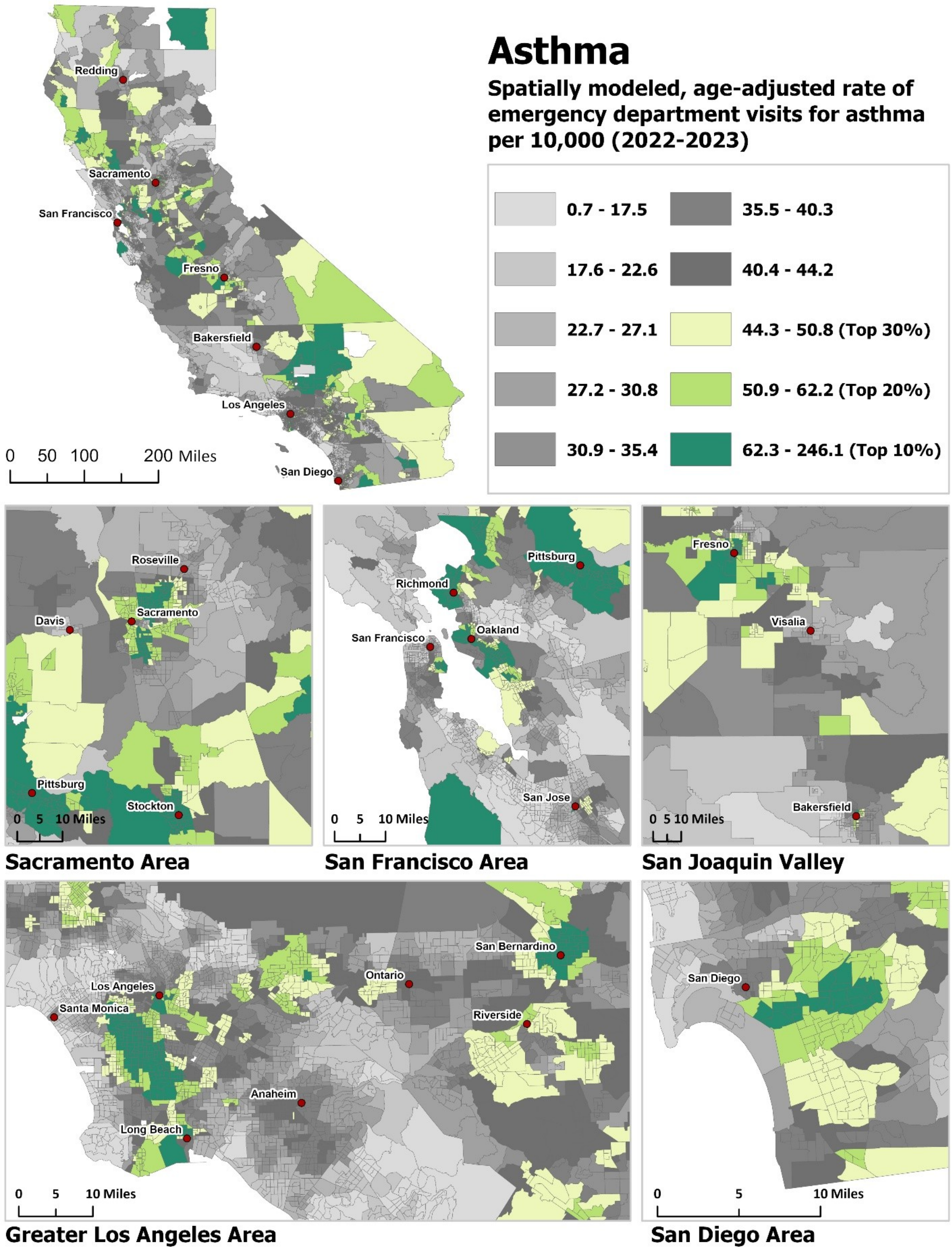
Rationale

Asthma increases an individual’s sensitivity to pollutants. Air pollutants, including particulate matter, ozone, nitrogen dioxide, and diesel exhaust, can trigger symptoms among asthmatics (Bronte-Moreno et al. 2023; Meng et al. 2012; Tiotiu et al. 2020; Zhou et al. 2024). Children living in areas with higher traffic-related pollution in California have been shown to suffer significantly increased rates of asthma (McConnell et al. 2010). Particulate matter from diesel engines has been shown to exacerbate asthma symptoms in children with asthma (Spira-Cohen et al. 2011). A study of low-income children who developed asthma found that there was an increase in asthma diagnosis following increases in ambient air pollution (Wendt et al. 2014). Exposure to certain pesticides can also trigger wheezing, coughing, and chest tightness (Gilden et al. 2023; Hernandez et al. 2011) and increased risk of asthma morbidity in children with asthma (Benka-Coker et al. 2020; Gilden et al. 2023). Asthma can increase susceptibility to respiratory diseases such as pneumonia and influenza (Kloepfer et al. 2012). For example, one study found that when ambient particulate pollution levels are high, persons with asthma have twice the risk of being hospitalized for pneumonia compared to persons without asthma (Zanobetti et al. 2000).

Asthma rates are a good indicator of population sensitivity to environmental stressors because asthma has been found to both be caused by and worsened by pollutants (Guarnieri and Balmes 2014; Tiotiu et al. 2020; Zhou et al. 2024). The severity of symptoms and the likelihood of needing hospital care decrease with access to regular medical care and asthma medication (Grineski et al. 2010; Mirabelli et al. 2024). Asthma-related ED visits provide an underestimation of total asthma cases because not all cases require emergency care, especially if individuals receive preventive care, avoid asthma triggers, and undertake disease maintenance. However, there is limited state-wide monitoring of other indicators, such as planned and unplanned doctor's visits, that might provide a better indication of overall disease burden. Using those cases requiring emergency care as an indicator has the benefit of capturing some aspects of access to care and can be seen as a marker of both environmental and social stressors. Potential biases in using ED visits as an indicator of sensitivity include the possibility that lower socioeconomic status or more isolated rural populations may not have access to nearby health care facilities. Conversely, populations without health insurance may turn to emergency departments for basic care.

Method

- Tracking California developed the original methods on which the following analysis was based.
- Records of ED visits and hospitalizations (PDD) for patients with a principal diagnosis relating to asthma were requested from HCAI for 2022 and 2023.
    - Visits for asthma were identified using International Classification of Diseases (ICD) code J45.
    - Hospitalizations were included if the hospitalization is described as originating from the hospital's own ED.
    - Only patients with residential ZIP codes within California were included.
- Age-adjusted rates of asthma ED visits were calculated using five-year age group-stratified population data from ESRI for each ZIP code.
- Age-adjusted rates were spatially modeled for all populated ZIP codes using a technique that incorporates information about both local and statewide rates (Mollié 1996).
- Zip codes with fewer than 12 total cases for the years considered were flagged as unreliable and their modeled rates were removed from analysis.
- 2020 census blocks with populations greater than zero were assigned rates by taking the average of the ZIP code modeled rates they intersected.
- Census tract rates were then calculated by taking the population-weighted average of the rates of the census blocks contained in each census tract.
- Census tracts were sorted by the spatially modeled apportioned rate and assigned percentiles based on their position in the distribution.


Asthma
Spatially modeled, age-adjusted rate of emergency department visits for asthma per 10,000 (2022-2023)
0.7 - 17.5
17.6 - 22.6
22.7 - 27.1
27.2 - 30.8
30.9 - 35.4
35.5 - 40.3
40.4 - 44.2
44.3 - 50.8 (Top 30%)
50.9 - 62.2 (Top 20%)
62.3 - 246.1 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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CARDIOVASCULAR DISEASE

Cardiovascular disease (CVD) refers to conditions that involve blocked or narrowed blood vessels that can lead to a heart attack or other heart problems. CVD is the leading cause of death both in California and the United States. Acute myocardial infarction (AMI), commonly known as a heart attack, is the most common cardiovascular event. Although many people survive and return to normal life after a heart attack, quality of life and long-term survival may be reduced, and these people are highly vulnerable to future cardiovascular events.

There are many risk factors for developing CVD including diet, lack of exercise, smoking, and air pollution. In scientific statements made by the American Heart Association, there is strong evidence that air pollution contributes to cardiovascular morbidity and mortality (Brook et al. 2010; Pope III et al. 2006). Short term exposure to air pollution, and specifically particulate matter, has been shown to increase the risk of cardiovascular mortality shortly following a heart attack. There is also growing evidence that long term exposure to air pollution may result in premature death for people that have had a heart attack. In addition to people with previous AMI, the effects of pollution on cardiovascular disease may be more pronounced in the elderly and people with other preexisting health conditions.

Indicator

Spatially modeled, age-adjusted rate of emergency department (ED) visits for AMI per 10,000 (averaged over 2021-2023).

Data Source

Emergency Department (ED) and Patient Discharge Datasets (PDD) from the California Department of Health Care Access and Information (HCAI)

Since 2005, hospitals licensed by the state of California to provide emergency medical services are required to report all ED visits to HCAI. Federally owned facilities, including Veterans Affairs and Public Health Service hospitals are not required to report. The ED dataset includes information on the principal diagnosis, which can be used to identify whether a patient visited the ED because of a heart attack.

https://hcai.ca.gov/data/data-and-reports/

Rationale

Recent studies have shown that individuals with preexisting heart disease or an AMI respond differently to the effects of pollution than individuals without heart disease. Specifically, individuals who have had an AMI may have a higher risk of dying after exposure to both short- and long-term increases in air pollution. An early paper on the subject of air pollution effects on sensitive subpopulations found the relative risk of dying on days with high levels of pollution was higher for people with chronic obstructive pulmonary disease (COPD), pneumonia, and existing heart disease or stroke (Schwartz 1994).

Multiple studies have found exposure to high levels of air pollution increased the risk of dying following an AMI. The effects of short-term exposure to coarse particulate matter (PM) with diameter <10 microns (PM10) or traffic-related air pollution following an AMI significantly increased the risk of death in a cohort study of almost 4,000 people in Massachusetts (Von Klot et al. 2009), in a multi-city European study of over 25,000 people (Berglind et al. 2009), and among over 65,000 elderly residents in Illinois (Bateson and Schwartz 2004).

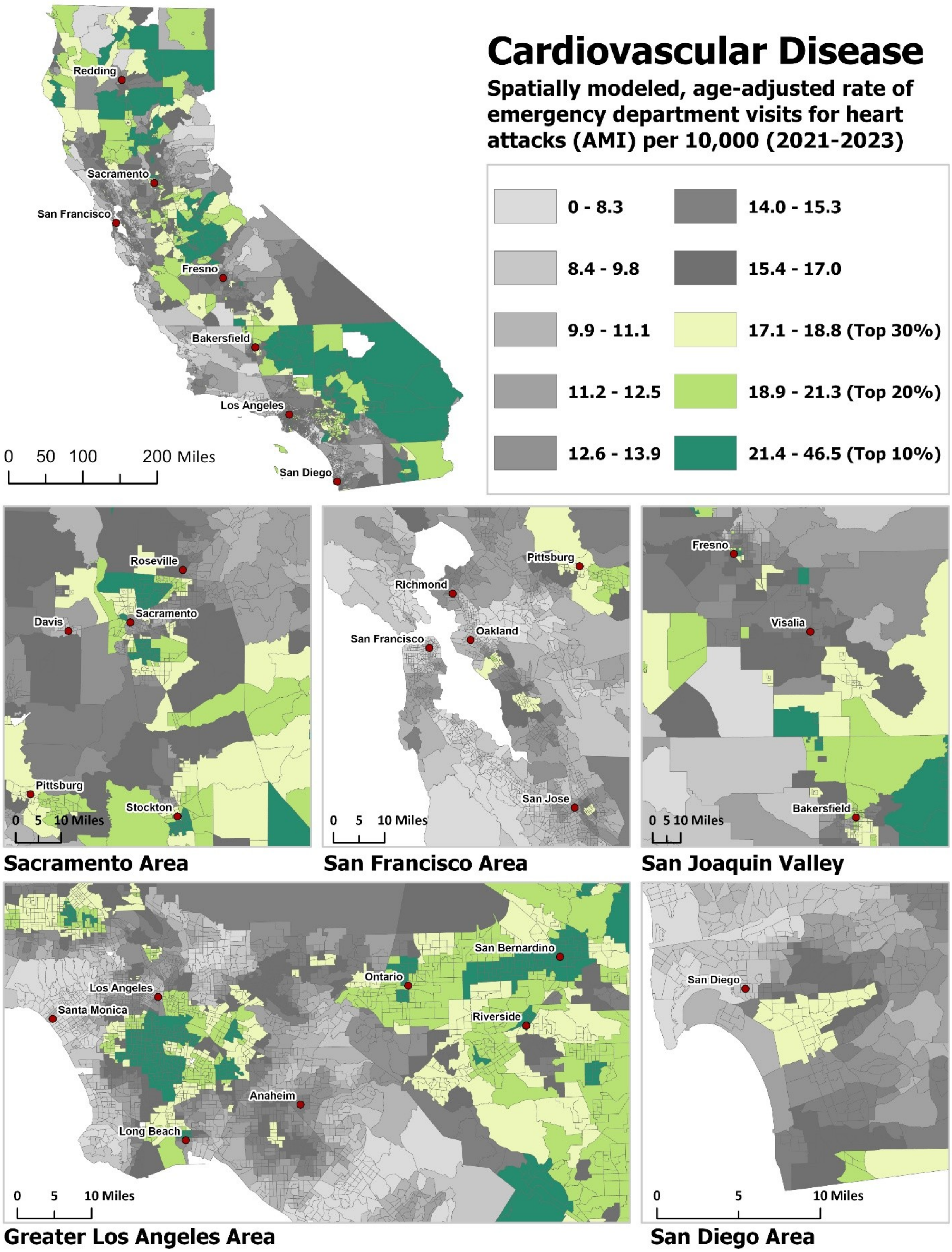
The influence of long-term exposure to pollution on survival following an AMI has also been examined. A cohort study examined mortality over 10 years for almost 9,000 patients with a previous AMI and found significant increases in non-accidental mortality for each 10 $\mu g/m^3$ increase in fine particulate matter (PM2.5)(Chen et al. 2016). This suggests that long-term exposure to particulate matter may play a role in decreasing the likelihood of survival following a heart attack. It has also been found that long-term exposure to ambient PM2.5 may increase CVD risks in midlife women (Broadwin et al. 2019). Additionally, exposure to ambient gases at current National Ambient Air Quality Standards may increase CVD risks in midlife women (Basu et al. 2017). Another study found that long-term exposure to PM2.5 was associated with ischemic heart disease and stroke mortality, with excess risk occurring even below the US standard for PM2.5 exposure (Hayes et al. 2020). One recent study also found that increases in PM2.5 exposure in adults with pre-hypertension were associated with aggravated progression from hypertension to CVD, and consequent death (Zhang et al. 2023). Several of these studies on the effects of air pollution on AMI survivors have examined whether different effects are observed by race or ethnicity. To date, no significant differences have been found.

ED visits for heart attacks do not capture the full burden of people living with CVD because not everyone with CVD has a heart attack. However, there is limited information on people with CVD, and therefore ED visits for a heart attack was selected as a good indicator of CVD. The selection of ED visits for AMI is likely to capture virtually the full burden of heart attacks because the abrupt nature and severity of the event would cause most individuals to visit the ED.

Method

- Tracking California developed the original methods on which the following analysis was based.
- Records of ED visits and hospitalizations (PDD) for patients with a principal diagnosis relating to AMI were requested from HCAI for 2022 and 2023.
    - Visits for AMI were identified using International Classification of Diseases (ICD) codes I21 and I22.
    - Hospitalizations were included if the hospitalization is described as originating from the hospital's own ED.
    - Only patients with residential ZIP codes within California were included.
- Age-adjusted rates of AMI ED visits were calculated using five-year age group-stratified population data from ESRI for each ZIP code.
- Age-adjusted rates were spatially modeled for all populated ZIP codes using a technique that incorporates information about both local and statewide rates (Mollié 1996).

- Zip codes with fewer than 12 total cases for the years considered were flagged as unreliable and their modeled rates were removed from analysis.
- 2020 census blocks with populations greater than zero were assigned rates by taking the average of the ZIP code modeled rates they intersected.
- Census tract rates were then calculated by taking the population-weighted average of the rates of the census blocks contained in each census tract.
- Census tracts were sorted by the spatially modeled apportioned rate and assigned percentiles based on their position in the distribution.


Cardiovascular Disease
Spatially modeled, age-adjusted rate of emergency department visits for heart attacks (AMI) per 10,000 (2021-2023)
0 - 8.3
8.4 - 9.8
9.9 - 11.1
11.2 - 12.5
12.6 - 13.9
14.0 - 15.3
15.4 - 17.0
17.1 - 18.8 (Top 30%)
18.9 - 21.3 (Top 20%)
21.4 - 46.5 (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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DIABETES PREVALENCE

Diabetes mellitus (DM) is a long-term health condition where the body can't properly control blood sugar levels, which can lead to dangerous health issues. In California, nearly 11% of adults have diagnosed DM, with almost half of adults showing signs of prediabetes or undiagnosed type 2 DM (Taylor et al. 2019). DM is especially common among Latino, African American, and Native American groups (Taylor et al. 2019). There are two main types of DM: type 1 DM (T1D) and type 2 DM (T2D). In T1D, the body's immune system mistakenly attacks the cells in the pancreas that make insulin, a hormone that helps lower blood sugar (CDC 2024). In T2D, which is the most common form of diabetes, the body becomes resistant to insulin over time, and the pancreas can't keep up with the demand, leading to high blood sugar levels (CDC 2024). While it is typically not possible to pinpoint the exact cause of an individual case of DM, research has shown that many factors, including exposure to environmental pollutants, poor diet, and physical inactivity, contribute to this condition (ElSayed et al. 2023). Low-income populations are at higher risk because they face challenges like limited access to healthy foods, healthcare, and safe places to exercise (McAlexander et al. 2022). If left untreated, DM can lead to serious health problems like kidney damage and vision loss. Exposure to pollution leads to worsening health outcomes for individuals with diabetes.

Indicator

Model-based prevalence of diabetes in adults (≥ 18 years), 2021.

Data Source

PLACES: Local Data for Better Health, Centers for Disease Control and Prevention (CDC)

Many local public health agencies rely on statistical modeling to determine the relative burden of a health condition in small geographic areas, such as census tracts, in order to effectively prioritize scarce public health resources. PLACES, a data science collaboration between the CDC, the Robert Wood Johnson Foundation, and the CDC Foundation, meets this need at a national scale. PLACES generates its estimates by using individual participant data from the most recent (2021 and 2022) iterations of the CDC's Behavioral Risk Factor Surveillance System (BRFSS), the largest continuous telephone-based health survey system in the world, to create a model for an individual's probability of having a particular health condition, typically based on basic demographic information that is available in the U.S. Census (e.g., age, sex, and race/ethnicity). This model is then used to predict how many people in a population are likely to have the condition, based on the distribution of those demographic factors in the population.

https://www.cdc.gov/places/index.html

Rationale

Exposure to traffic-related air pollutants, such as fine particulate matter (PM) and nitrogen dioxide (NO2), and other environmental contaminants, have been linked to an elevated risk of type 2 diabetes onset (Bowe et al. 2018). For example, in a cohort of over 1.7 million U.S. veterans, a 10 $\mu g/m^3$ increase in PM2.5 exposure was associated with a 15% increase in the risk of diabetes, with significant effects observed even at low concentrations (Bowe et al. 2018). Similarly, a study involving 11,208 participants in suburban and rural areas found that a 5 μg/m^3 increase in PM2.5 over two years was linked to diabetes onset (McAlexander et al. 2022). At the molecular level, particulate matter exposure has been shown to impair insulin function and glucose metabolism, potentially through oxidative stress and inflammation, thus promoting insulin resistance and type 2 diabetes onset (Rajagopalan et al. 2018). Cohort studies have explored these biological pathways; for example, a study of 314 Latino children in Los Angeles found that exposure to NO2 and PM2.5 reduced insulin sensitivity and impaired pancreatic β-cell function (Alderete et al. 2017). Another study of 1,775 women in Germany linked traffic-related pollution with increased type 2 diabetes risk, likely through inflammatory processes (Krämer et al. 2010).

Exposure to pollution is also known to worsen health outcomes in individuals who already have diabetes, further supporting the inclusion of diabetes as an indicator of population sensitivity to pollution exposure. Increased air pollution exposure has been associated with increased T2D progression, complications (including hospitalizations for cardiovascular disease), and mortality (Bonanni et al. 2024; Wu et al. 2022; Zanobetti and Schwartz 2002). For example, in a large retrospective study of California death records, a 10 μg/m^3 increase in PM2.5 exposure was associated with a 2.4% increase in diabetes-related mortality (Ostro et al. 2006), with a number of subsequent studies supporting this finding for PM2.5 and other pollutants in other regions and countries (Feng et al. 2024; Goldberg et al. 2006; Wu et al. 2021; Zeka et al. 2006). Proximity to toxic waste sites has also been associated with higher diabetes hospitalization rates (Kouznetsova et al. 2007).

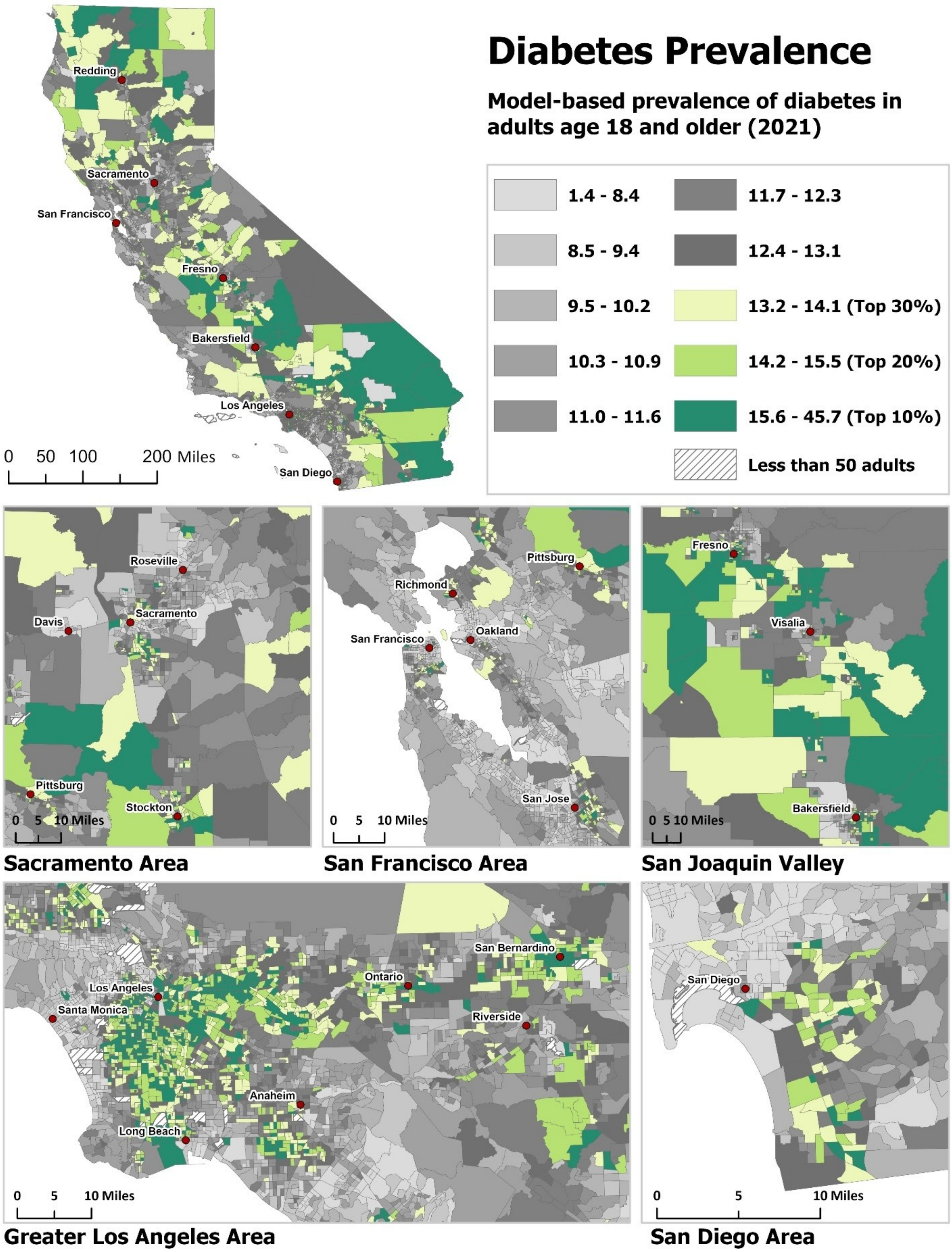
Method

- CDC PLACES estimates census tract-level adult diabetes prevalence as follows. First, CDC's 2021 and 2022 Behavioral Risk Factor Surveillance System (BRFSS) was used to create a model for probability of diabetes. Specifically, diabetes status was modeled as the outcome variable in a multi-level logistic regression model, which included the following variables as predictors: individual-level age, sex, race/ethnicity, and education level; county-level percentage of adults below 150% of the federal poverty level from the 5-year American Community Survey (ACS); and state- and county-level random effects.

- The fitted model was then applied to decennial 2020 census block-level population counts to compute a predicted prevalence of diabetes in the census block. The estimated prevalence was obtained by multiplying the model's probability of diabetes in the block, by the total adult population for the block. This census block-level prevalence was then aggregated to the census tract level.

- Both internal and external validation studies showed strong/moderate correlations between model-based estimates and direct survey estimates at state, county, and place levels (Wang 2017; 2018; Zhang et al. 2015).

- Estimates for all California census tracts were then ordered from smallest to largest, and assigned a percentile based on this ordering.


Diabetes Prevalence
Model-based prevalence of diabetes in adults age 18 and older (2021)
1.4 - 8.4
8.5 - 9.4
9.5 - 10.2
10.3 - 10.9
11.0 - 11.6
11.7 - 12.3
12.4 - 13.1
13.2 - 14.1 (Top 30%)
14.2 - 15.5 (Top 20%)
15.6 - 45.7 (Top 10%)
Less than 50 adults
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Richmond
Oakland
San Jose
San Francisco Area
Visalia
San Joaquin Valley
San Bernardino
Ontario
Santa Monica
Riverside
Anaheim
Long Beach
Greater Los Angeles Area
San Diego Area

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LOW-BIRTH-WEIGHT INFANTS

Infants born weighing less than 2,500 grams (about 5.5 pounds) are classified as low birth weight (LBW), a condition associated with increased risk of health problems later in life as well as infant mortality. Most LBW infants are small because they were born early, but infants born at full term (after 37 complete weeks of pregnancy) can also be LBW if their growth was restricted during pregnancy. Nutritional status, lack of prenatal care, stress, and maternal smoking are known risk factors for LBW. Studies also suggest that environmental exposures to lead, air pollution, toxic air contaminants, traffic pollution, pesticides, and polychlorinated biphenyls (PCBs) are all linked to LBW. These children are at higher risk of chronic health conditions that may make them more sensitive to environmental exposures after birth.

Indicator

Percent low-birth-weight births (averaged over 2017-2023)

Data Source

California Comprehensive Birth File (CCBF), California Department of Public Health (CDPH) Vital Statistics Application (VSA)

The CDPH Center for Health Statistics and Informatics is responsible for the stewardship and distribution of birth records in the state. Medical data related to a birth, as well as demographic information related to the infant, mother, and father are collected from birth certificates. Personal identifiers are not released publicly to protect confidentiality. Data was requested and handled in compliance with the State of California Committee for the Protection of Human Subjects.

https://www.cdph.ca.gov/Programs/CHSI/Pages/Data-Applications.aspx

Rationale

LBW is considered a key marker of overall population health. Being born low weight puts individuals at higher risk of health conditions that can subsequently make them more sensitive to environmental exposures. For example, children born low weight are at increased risk of developing asthma wheezing disorders in childhood (Belbasis et al. 2016). LBW can also put one at increased risk of coronary heart disease (Belbasis et al. 2016), which can predispose one to mortality associated with particulate air pollution or excessive heat (Ban et al. 2017; Shah et al. 2013). There is also evidence that children born early or with low birth weight have a higher risk of developing ADHD and other behavioral problems compared to children born near or at normal birth weight (Franz et al. 2018).

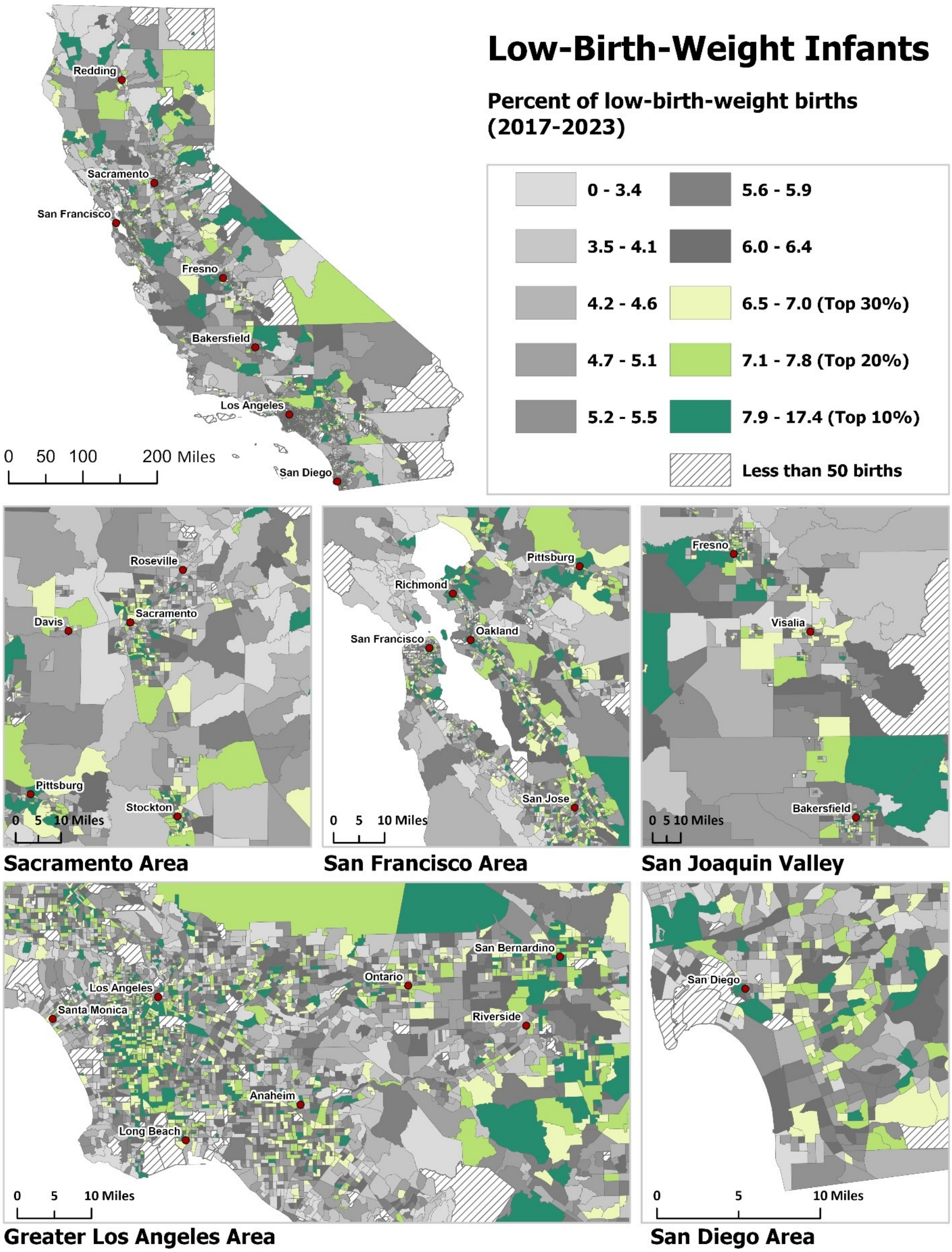
Risk of LBW is increased by certain environmental exposures and social factors and can therefore be considered a marker of the combined impact of environmental and social stressors. For example, exposures to fine particulate matter, heavy traffic, and toxic air contaminants such as benzene, xylene, and toluene have been linked to LBW in California (Basu et al. 2014; Ghosh et al. 2012). In addition, non-Hispanic Black women and Hispanic women are at higher risk of giving birth to a child who is LBW relative to non-Hispanic White women, even among those with comparable socioeconomic status, prenatal care, behavioral risk factors (Almeida et al. 2018).

Living in close proximity to freeways or highly trafficked roadways has been associated with an increased risk for LBW term infants (Laurent et al. 2016). Latina women exposed to pesticides in California in low-income farmworker communities were found to be at risk for LBW infants that were small for gestational age, with smaller than average head circumference, an indicator of brain development (Harley et al. 2011). Recent studies found that proximity to oil and gas development in rural areas was associated with increased odds of LBW (Tran et al. 2020; Willis et al. 2021). There also is a significant association between heat, ozone, and fine particulate matter with adverse pregnancy outcomes, including LBW (Bekkar et al. 2020; Niu et al. 2022).

In addition to these environmental risk factors, LBW is also influenced considerably by certain demographic characteristics. Women aged 40 to 54 years are twice as likely to have LBW infants compared to women aged 20 to 24, and African American women have a 2.4-fold greater prevalence of having LBW infants compared with white women (Ratnasiri et al. 2018).

Method

- Data on all California births occurring between 2017 and 2023 were obtained from CDPH VSA.
- Out-of-state births, births with no known residential address (including P.O. boxes), multiple births (non-singletons), and births with an improbable combination of gestational age and birth weight (Alexander et al. 1996) were excluded from analysis.
    - These exclusions lead to a lower statewide LBW percentage than those reported by other organizations who do not apply this criterion.
- Births were coded as LBW if the recorded weight at birth was less than 2,500 grams.
- Births were geocoded based on the mother's residential address at the time of birth.
    - A small number (less than 1%) of addresses could not be geocoded and were excluded.
- Geocoded births were assigned to the census tract they fell within.
- For each census tract, percent LBW was calculated by dividing the total number of LBW births by the total number of births and multiplying by 100.
- Estimates derived from places with few births are considered statistically unreliable because they often produce values much higher or lower than expected and can vary greatly from year to year. For this reason, census tracts with fewer than 50 live births over the seven years (2017-2023) were excluded. The percentage of LBW births was calculated using the seven years of data to minimize the number of excluded census tracts.
- Census tracts were sorted by percent LBW and were assigned percentiles based on their position in the distribution.


Low-Birth-Weight Infants
Percent of low-birth-weight births (2017-2023)
0 - 3.4
3.5 - 4.1
4.2 - 4.6
4.7 - 5.1
5.2 - 5.5
5.6 - 5.9
6.0 - 6.4
6.5 - 7.0 (Top 30%)
7.1 - 7.8 (Top 20%)
7.9 - 17.4 (Top 10%)
Less than 50 births
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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Population Characteristics: Socioeconomic Factor Indicators

EDUCATIONAL ATTAINMENT

Educational attainment is an important element of socioeconomic status and a social determinant of health. Numerous studies suggest education is associated with lower exposures to environmental pollutants that damage health. Information on educational attainment is collected annually in the US Census Bureau's American Community Survey (ACS). In contrast to the decennial census, the ACS surveys a small sample of the US population to estimate more detailed economic and social information for the country's population.

Indicator

Percentage of the population over age 25 with less than a high school education (5-year estimate, 2019-2023).

Data Source

American Community Survey (ACS), US Census Bureau

The ACS is an ongoing survey of the US population conducted by the US Census Bureau and has replaced the long form of the decennial census. Unlike the decennial census, which attempts to survey the entire population and collects a limited amount of information, the ACS releases results annually based on a sample of the population and includes more detailed information on socioeconomic factors such as educational attainment. Multiple years of data are pooled together to provide more reliable estimates for geographic areas with small population sizes. The most recent results available at the census tract scale are the 5-year estimates for 2019-2023. The data are made available using the US Census data download website and via the US Census Bureau API. Data are available at the links below:

https://data.census.gov/

https://data.census.gov/cedsci/

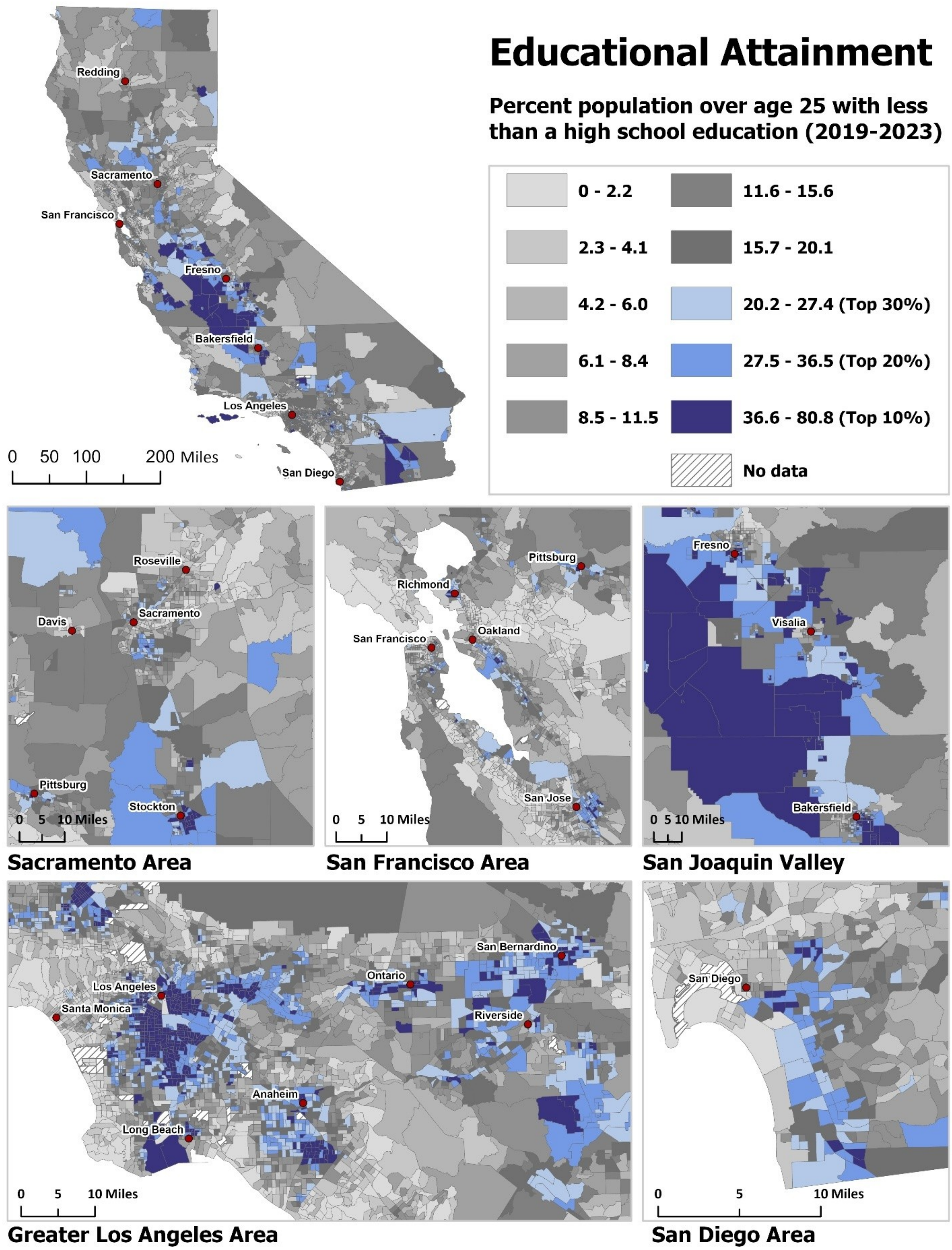
Rationale

Educational attainment is an important independent predictor of health (Cutler and Lleras-Muney 2006; Hahn and Truman 2015; Zajacova and Lawrence 2018). Individuals with lower education in the US have a lower life expectancy (Balaj et al. 2024; Sasson 2016), are more likely to be obese (Cohen et al. 2013), and are more likely to experience psychiatric disorders (Erickson et al. 2016) compared to individuals with higher education. Education is often inversely related to the degree of exposure to indoor and outdoor pollution. Several studies have associated educational attainment with susceptibility to the health impacts of environmental pollutants. For example, individuals without a high school education appear to be at higher risk of mortality associated with particulate air pollution than those with a high school education (Krewski et al. 2000). There is also evidence that the effects of air and traffic-related pollution on respiratory illness, including childhood asthma, are more severe in communities with lower levels of education (Cakmak et al. 2006; Neidell 2004; Shankardass et al. 2009). In studies evaluating air pollution related risks of adverse birth outcomes, mothers with low educational attainment were found to be more vulnerable (Ha et al. 2014; Thayamballi et al. 2020). While there is a positive association between educational attainment and health, racial and ethnic minorities gain fewer health benefits from educational attainment than Whites (Assari 2018; Bell et al. 2020).

The ways in which lower educational attainment can decrease health status are not completely understood, but may include economic hardship, stress, fewer occupational opportunities, lack of social support, and reduced access to health-protective resources such as medical care, prevention and wellness initiatives, and nutritious food. In a study of pregnant women in Amsterdam, smoking and exposure to environmental tobacco smoke were more common among women with less education. These women also were at significantly increased risk of preterm birth, low birth weight and small for gestational age infants (van den Berg et al. 2012). A review of studies tying social stressors with the effects of chemical exposures on health found that level of education was related to mortality and incidence of asthma and respiratory diseases from exposure to particulate air pollution and sulfur dioxide (Lewis et al. 2011). A study of older adults, aged 70 to 79, found that those with less than a high school education had significantly shorter leukocyte telomere length, a genetic marker linked to stress, than those with more education (Adler et al. 2013).

Method

- Data were obtained from the 2019-2023 ACS 5-year estimates via the US Census Bureau Data API at the census-tract level for the state of California. Data on each education level were downloaded (i.e., no education, nursery education, grade levels Kindergarten through 11th, and grade 12 with no diploma) for the population over age 25 who received that maximum level of educational attainment.
- For each census tract, data of the population over age 25 with less than a high school education were summed and then divided by the total population over 25 to create a final educational attainment percent for the census tract.
- Census tracts were sorted and assigned percentiles based on their position in the distribution.


Educational Attainment
Percent population over age 25 with less than a high school education (2019-2023)
0 - 2.2
2.3 - 4.1
4.2 - 6.0
6.1 - 8.4
8.5 - 11.5
11.6 - 15.6
15.7 - 20.1
20.2 - 27.4 (Top 30%)
27.5 - 36.5 (Top 20%)
36.6 - 80.8 (Top 10%)
No data
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Richmond
Oakland
San Jose
San Francisco Area
Visalia
San Joaquin Valley
San Bernardino
Ontario
Riverside
Santa Monica
Anaheim
Long Beach
Greater Los Angeles Area
San Diego Area

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HOUSING BURDEN

The cost and availability of housing is an important determinant of well-being. Households with lower incomes may spend a larger proportion of their income on housing. The inability of households to afford necessary non-housing goods after paying for shelter is known as housing-induced poverty. California has very high housing costs relative to much of the country, making it difficult for many to afford adequate housing. Within California, the cost of living varies significantly and is largely dependent on housing cost, availability, and demand.

Areas where low-income households may be stressed by high housing costs can be identified through the Housing and Urban Development (HUD) Comprehensive Housing Affordability Strategy (CHAS) data. We measure households earning less than 80% of HUD Area Median Family Income by county while paying greater than 50% of their income to housing costs. The indicator considers the regional cost of living for both homeowners and renters and factors in the cost of utilities. CHAS data are calculated from US Census Bureau’s American Community Survey (ACS).

Indicator

Housing Burden. Percent of households in a census tract that are both low income (making less than 80% of the HUD Area Median Family Income) and severely burdened by housing costs (paying greater than 50% of their income to housing costs) (5-year estimates, 2017-2021).

Data Source

Comprehensive Housing Affordability Strategy (CHAS), Housing and Urban Development (HUD)

The ACS is an ongoing survey of the US population conducted by the US Census Bureau and has replaced the long form of the decennial census. Unlike the decennial census, which attempts to survey the entire population and collects a limited amount of information, the ACS releases results annually based on a sub-sample of the population and includes more detailed information on socioeconomic factors. Multiple years of data are pooled together to provide more reliable estimates for geographic areas with small population sizes. Each year, the HUD receives custom tabulations of ACS data from the US Census Bureau. These data, known as the "CHAS" data (Comprehensive Housing Affordability Strategy), demonstrate the extent of housing problems and housing needs, particularly for low-income households. The most recent results available at the census tract scale are the 5-year estimates for 2017-2021 The data are available from the HUD user website. Data available at the link below:

https://www.huduser.gov/portal/datasets/cp.html

Rationale

Housing affordability is an important part of the framework of social and economic conditions that shape the health and well-being of individuals (Braubach 2011; Marmot et al. 2008). Socioeconomic variables may influence response to pollutants or modify the effect of exposure to pollution. Several scientific studies have examined the relationship between income level, pollution exposure, and health outcomes. Individuals with low income exposed to high levels of air pollution had higher mortality rates than higher income individuals (Finkelstein et al. 2003).

Children of low-income families had greater asthma hospitalization rates when exposed to air pollutants (Neidell 2004).

Low-income and financially vulnerable households that face high costs for housing disproportionately suffer from negative physical and mental health outcomes (Grewal et al. 2024). Households that experience a high rent burden for longer periods of time are associated with greater disadvantage (Susin 2007). High rent burden can mean a higher likelihood of postponing medical services for financial reasons (Pollack et al. 2010). High rent burden is also associated with worse self-reported health conditions (Meltzer and Schwartz 2016). High housing cost burdens and unaffordable housing situations can also contribute to residential instability, increase vulnerability to acute and chronic health problems, worsen stress and depression, and can lead to poor educational outcomes for children (Baker et al. 2020; Grewal et al. 2024; Harkness and Newman 2005; Meltzer and Schwartz 2016; Newman and Holupka 2016).

The fraction of low-income households paying greater than 30 percent of their income to housing expenditures has doubled in the US since the 1960’s (Chan and Jush 2017). In 2022, a record 22.4 million households were cost-burdened by rent, 12.1 million of those households spending more than 50% of their income on housing, and in total, accounting for half of all renter households in the US (Joint Center for Housing Studies 2024). Rent-burdened households in the US are disproportionately non-white and very low income. An examination of racial disparities in housing cost burden in the US found that Black households were significantly more likely to experience housing cost burden than White households for every year between 1981 and 2017 (Hess et al. 2020).

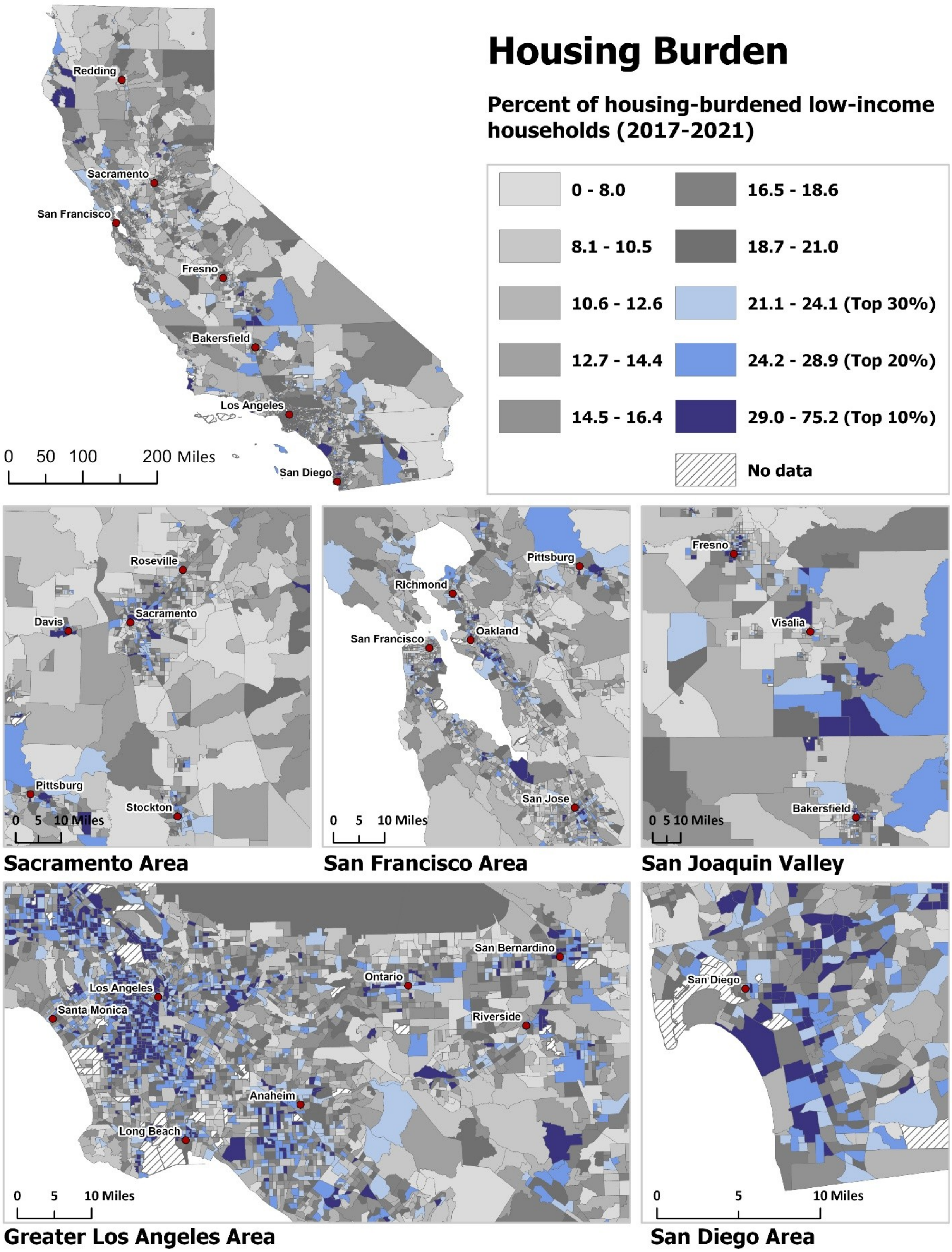
Geographic differences in housing costs are not accounted for in the official poverty measure calculated by the US Census Bureau. Research has found that renter households in the Western US are more likely to experience high rent burden than renters in other areas of the US, such as the Midwest or South (Colburn and Allen 2018). California has some of the highest housing costs in the nation as well as substantial differences in housing costs within the state (Bentz 2025; Legislative Analyst’s Office 2015).

Housing cost burden accounts for differences in rent or homeowner costs across different areas of California. By restricting the measure to low-income households on a county-by-county basis, the measure retains the focus on those who are most financially vulnerable in specific geographic regions of California.

Method

- From the 2013-2017 HUD CHAS, a dataset containing cost burdens for households by HUD-adjusted median family income (HAMFI) category was downloaded by census tract for the state of California.
- For each census tract, the data were analyzed to estimate the number of households with household incomes less than 80% of the county median and renter or homeowner costs that exceed 50% of household income. The percentage of the total households in each tract that are both low-income and housing-burdened was then calculated.

- Census tracts were sorted and assigned percentiles based on their position in the distribution.


Housing Burden
Percent of housing-burdened low-income households (2017-2021)
0 - 8.0
8.1 - 10.5
10.6 - 12.6
12.7 - 14.4
14.5 - 16.4
16.5 - 18.6
18.7 - 21.0
21.1 - 24.1 (Top 30%)
24.2 - 28.9 (Top 20%)
29.0 - 75.2 (Top 10%)
No data
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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LINGUISTIC ISOLATION

Linguistic isolation is an important social determinant of health. The US Census Bureau uses the term "linguistic isolation" to measure households where all members 14 years of age or above have at least some difficulties speaking English. Communities with high levels of linguistic isolation may face barriers to accessing health information, public services, and participating effectively in regulatory processes. Information on language use is collected annually in the ACS. In contrast to the decennial census, the ACS surveys a small sample of the US population to estimate more detailed economic and social information for the country's population.

Indicator

Percentage of limited English-speaking households, (2019-2023).

Data Source

American Community Survey (ACS), US Census Bureau

The American Community Survey (ACS) is an ongoing survey of the US population conducted by the US Census Bureau and has replaced the long form of the decennial census. Unlike the decennial census, which attempts to survey the entire population and collects a limited amount of information, the ACS releases results annually based on a sample of the population and includes more detailed information on socioeconomic factors such as linguistic isolation. Multiple years of data are pooled together to provide more reliable estimates for geographic areas with small population sizes. The most recent results available at the census tract scale are the 5-year estimates for 2019-2023. The data are made available using the US Census data download website and via the US Census Bureau API. Data are available at the link below:

https://data.census.gov/

Rationale

According to the most recent US Census Bureau's 2019-2023 ACS, nearly 44% of Californians speak a language at home other than English, 17% of the state's population speaks English "less than very well," and 8% of all households in California are linguistically isolated. The inability to speak English well can be a key determinate of an individual's healthcare access, utilization, and overall health outcomes (Flores and Tomany-Korman 2008; Kim et al. 2011; Kimbro et al. 2014; Rasi 2020). In California, linguistic isolation was shown to be significantly associated with increased lengths of stay and mortality rates for pediatric oncology patients when controlling for other factors (Ennett et al. 2024).

People with limited English are less likely to have health insurance or a usual source of care compared to English speakers (Lu and Myerson 2020). They are also less likely to have regular medical care and are more likely to report difficulty getting medical information or advice than English speakers (Lu and Myerson 2020). Communication is essential for many steps in the process of obtaining health care, and limited English speakers may delay care because they lack important information about symptoms and available services (Shi et al. 2009). Non-English speakers are also less likely to receive mental health services when needed (Kim et al. 2011; Sentell et al. 2007). In California, because non-English speakers are concentrated in minority ethnic communities, limited

English proficiency may contribute to further ethnic and racial disparities in health status and disability (Sentell et al. 2007).

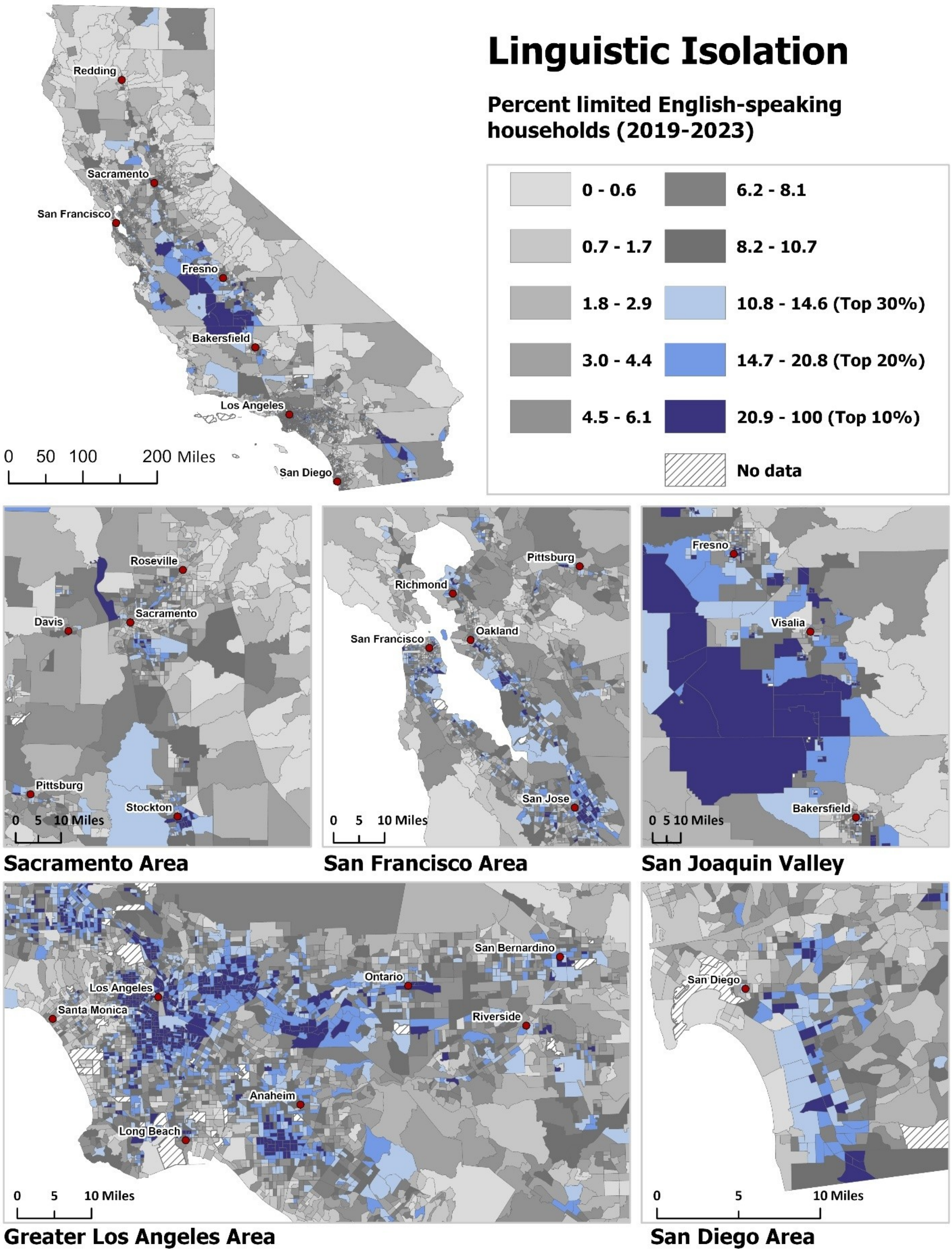
Linguistic isolation is also an indicator of a community's ability to participate in decision-making processes and the ability to navigate the political system. A study examining the linguistic accessibility of the sustainability planning process in the US found that only 13 of the 28 most populated cities in the US had web translation tools or translated documents available for their sustainability plans (Teron 2016). It is also important to note, however, that linguistically isolated communities can also have higher community cultural capital, which can reduce some of the negative outcomes associated with linguistic isolation. Community linguistic isolation is associated with a decreased achievement gap among 10th grade students whose native language is not English in the US, potentially due to community cultural capital (Drake 2014).

Lack of proficiency in English often results in racial discrimination, where both language difficulties and discrimination are associated with stress, low socioeconomic status, and reduced quality of life (Gee and Ponce 2010). In addition, limited-English speakers living in areas that are not ethnic enclaves (areas with a shared language and culture) can be targets of violence. Latinx immigrants who move to areas in the US that are not ethnic enclaves experience higher rates of homicides than those who move to ethnic enclaves (Feldmeyer et al. 2016; Shihadeh and Barranco 2010). Linguistic isolation also hampers the ability of the public health sector to reduce racial and ethnic disparities because non-English-speaking individuals participate in public health surveillance studies at very low rates, even when there is translation available (Link et al. 2006).

In the event of an emergency, such as an accidental chemical release or a spill, households that are linguistically isolated may not receive timely information on evacuation or shelter-in-place orders and may experience health risks that those who speak English can more easily avoid (Nepal et al. 2012). Additionally, linguistic isolation was independently related to both proximity to a Toxics Release Inventory (TRI) facility and cancer risks by the National Air Toxics Assessment (NATA) in an analysis of the San Francisco Bay Area, suggesting that linguistically isolated communities may bear a greater share of health risks from air pollution hazards (Pastor Jr et al. 2010).

Method

- Data for each race/ethnic group containing the number of limited English-speaking households were obtained from the 2019-2023 ACS 5-year estimates via the US Census Bureau Data API at the census-tract level for the state of California. "Linguistic isolation" refers to households in which no individual age 14 or older speaks English well.
- For each census tract, the number of linguistically isolated households across race/ethnic groups was summed and divided by the total number of households in the tract to calculate the percentage of linguistically isolated households.
- Census tracts were sorted assigned percentiles based on their position in the distribution.


Linguistic Isolation
Percent limited English-speaking households (2019-2023)
0 - 0.6
0.7 - 1.7
1.8 - 2.9
3.0 - 4.4
4.5 - 6.1
6.2 - 8.1
8.2 - 10.7
10.8 - 14.6 (Top 30%)
14.7 - 20.8 (Top 20%)
20.9 - 100 (Top 10%)
No data
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Richmond
Oakland
San Jose
San Francisco Area
Visalia
San Joaquin Valley
San Bernardino
Ontario
Riverside
Santa Monica
Anaheim
Long Beach
Greater Los Angeles Area
San Diego Area

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POVERTY

Poverty is an important social determinant of health. Numerous studies have suggested that impoverished populations are more likely than wealthier populations to experience adverse health outcomes when exposed to environmental pollution. Information on poverty is collected annually in the US Census Bureau's American Community Survey (ACS). In contrast to the decennial census, the ACS surveys a small sample of the US population to estimate more detailed economic and social information for the country's population.

Indicator

Percent of the population living below two times the federal poverty level (5-year estimate, 2019-2023).

Data Source

American Community Survey (ACS), US Census Bureau

The ACS is an ongoing survey of the US population conducted by the US Census Bureau and has replaced the long form of the decennial census. Unlike the decennial census, which attempts to survey the entire population and collects a limited amount of information, the ACS releases results annually based on a sub-sample of the population and includes more detailed information on socioeconomic factors such as poverty. Multiple years of data are pooled together to provide more reliable estimates for geographic areas with small population sizes. The most recent results available at the census tract scale are the 5-year estimates for 2019-2023.

The Census Bureau uses income thresholds that are dependent on family size to determine a person's poverty status during the previous year. For example, if a family of four with two children has a total income less than $30,900 during 2023, everyone in that family is considered to live below the federal poverty line. A threshold of twice the federal poverty level was used in this analysis because California's cost of living is higher than many other parts of the country. In addition, the methods for determining the federal poverty thresholds have not changed since the 1980s despite increases in the cost of living. The data are made available using the US Census data download website and via the US Census Bureau API. Data are available at the link below:

https://data.census.gov/cedsci/

Rationale

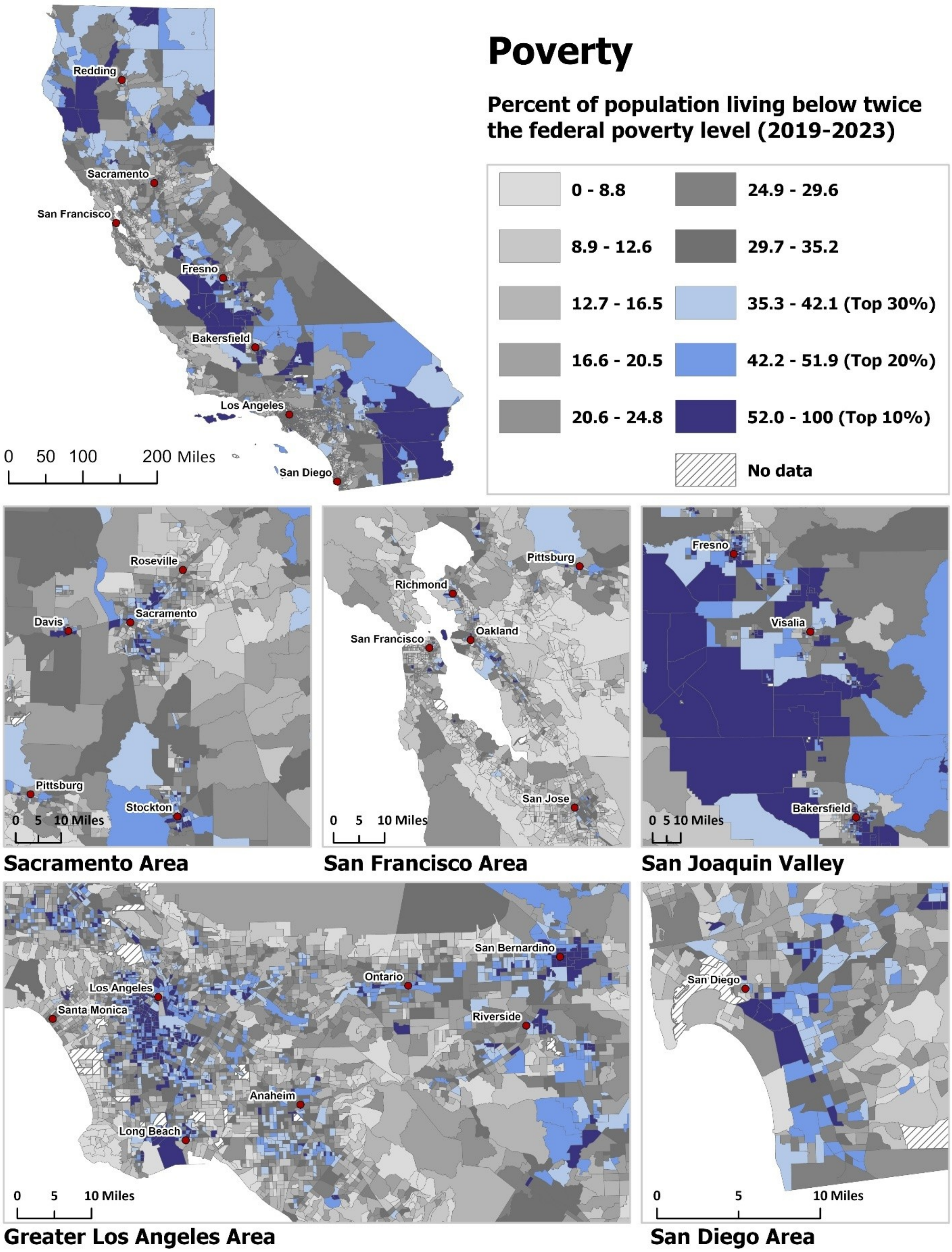
Wealth influences health by determining one's living conditions, nutrition, occupation, and access to health care and other health-promoting resources. Low-income communities face a double threat to their health (Morello-Frosch and Shenassa 2006). First, they have a higher exposure to pollutants and environmental hazards (Hajat et al. 2015). Second, they experience increased susceptibility to poor health due to factors such as psychosocial and chronic stress (Bell et al. 2013; Clougherty et al. 2014; Marmot and Wilkinson 2005).

Psychosocial stressors, like social crowding, social/family disorder, racial discrimination, and economic insecurity are more common in low-income neighborhoods (Bernard et al. 2007). These factors combine to create environmental health disparities in low-income communities (Santiago et al. 2011). For example, a 2017 study conducted in the US found that neighborhood social stressors like perceived breakdown of order and social control, abandoned buildings, trash, and vacant lots increased the association between fine particulate matter and lower cognitive function in older adults (Ailshire et al. 2017). Other studies, including one conducted in California's San Joaquin Valley, found that traffic-related air pollution and particulate matter had a larger effect on preterm birth and low birth weight among mothers from low-socioeconomic status (SES) neighborhoods (Padula et al. 2014; Yi et al. 2010; Zeka et al. 2008).

Air pollution also has a strong impact on mortality (Di et al. 2017; Forastiere et al. 2007; Josey et al. 2023; Kioumourtzoglou et al. 2015), heart disease (Carlsson et al. 2016), and childhood asthma (Kravitz-Wirtz et al. 2018; Meng et al. 2012) in low-income communities. A study of children in Central California found children from low-income households disproportionately experience possibly preventable hospitalizations from conditions usually treated in outpatient facilities (e.g., asthma, pneumonia, conditions with available vaccines) (Lessard et al. 2016). Differential underlying burdens of pre-existing illness and co-exposure to multiple pollutants are other factors that can contribute to increased susceptibility in low-income communities (O'Neill et al. 2003).

Method

- A dataset containing the number of individuals below 200 percent of the federal poverty level was obtained from the 2019-2023 ACS 5-year estimates via the US Census Bureau Data API at the census-tract level for the state of California.
- The number of individuals below 200% of the poverty level was divided by the total population for whom poverty status was determined.
- Census tracts were sorted and assigned percentiles based on their position in the distribution.


Poverty
Percent of population living below twice the federal poverty level (2019-2023)
0 - 8.8
8.9 - 12.6
12.7 - 16.5
16.6 - 20.5
20.6 - 24.8
24.9 - 29.6
29.7 - 35.2
35.3 - 42.1 (Top 30%)
42.2 - 51.9 (Top 20%)
52.0 - 100 (Top 10%)
No data
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Francisco
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

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UNEMPLOYMENT

Because low socioeconomic status often goes hand-in-hand with high unemployment, the rate of unemployment is a factor commonly used in describing disadvantaged communities. On an individual level, unemployment is a source of stress, which is implicated in poor health reported by residents of such communities. Lack of employment and resulting low income often constrain people to live in neighborhoods with higher levels of pollution and environmental degradation.

Indicator

Percentage of the population over the age of 16 that is unemployed and eligible for the labor force. Excludes retirees, students, homemakers, institutionalized persons except prisoners, those not looking for work, and military personnel on active duty (5-year estimate, 2019-2023).

Data Source

American Community Survey (ACS), US Census Bureau

The ACS is an ongoing survey of the US population conducted by the US Census Bureau. Unlike the decennial census, which attempts to survey the entire population and collects a limited amount of information, the ACS releases results annually based on a sub-sample of the population and includes more detailed information on socioeconomic factors such as unemployment. Multiple years of data are pooled together to provide more reliable estimates for geographic areas with small population sizes. The most recent results available at the census tract level are the 5-year estimates for 2019-2023. The data are made available using the US Census data download website and via the US Census Bureau API. Data are available at the link below:

https://data.census.gov/cedsci/

Rationale

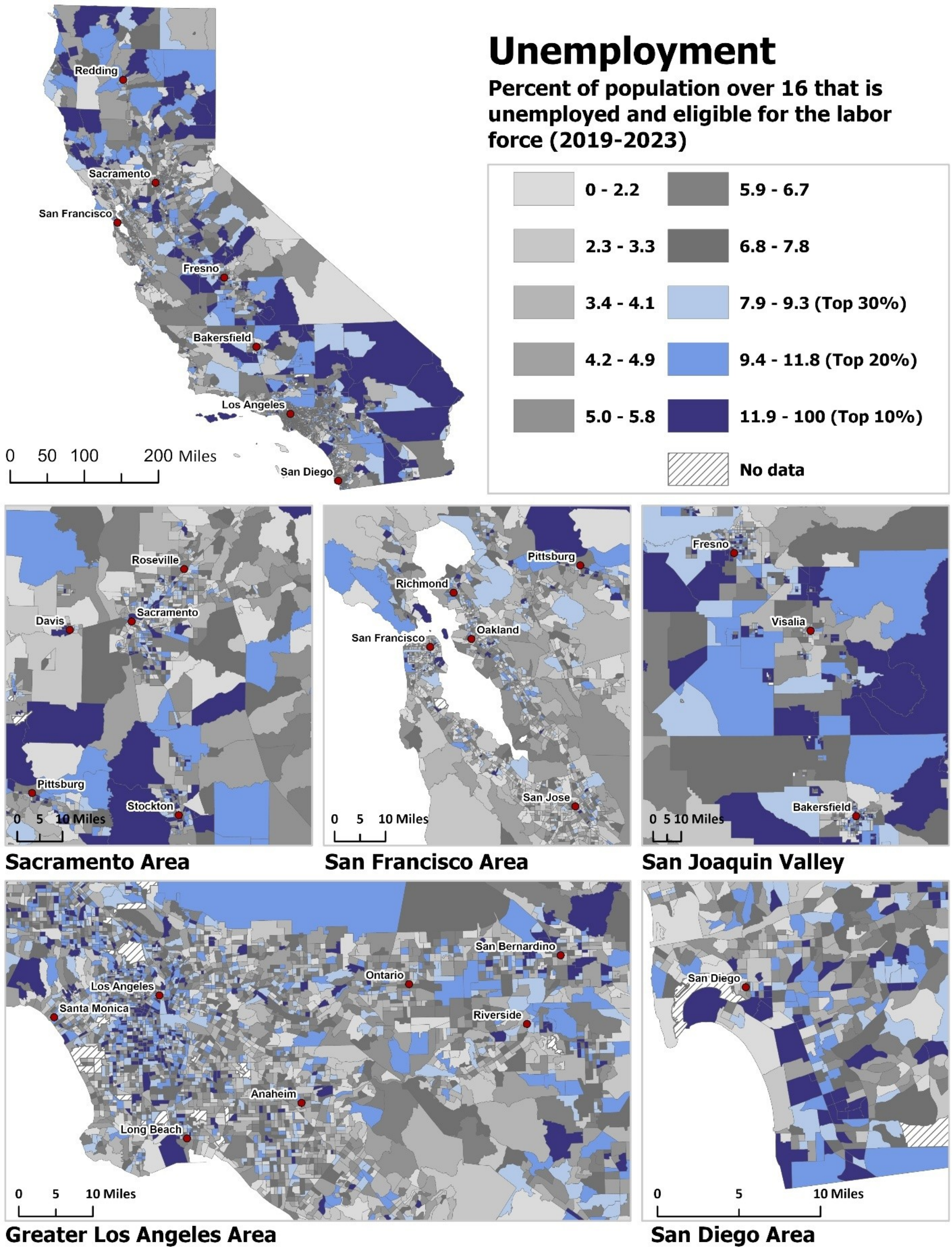
Unemployment has a wide range of effects on health which contribute to the burden placed on vulnerable communities. It has been shown to negatively impact mental and physical health. Higher rates of unemployment are associated with overall mortality, as well as mortality specifically due to transport accidents, poisonings (which include drug overdoses), psychological distress and suicides (Gordon and Sommers 2016; Paul and Moser 2009; Picchio and Ubaldi 2024; Ruhm 2015). Unemployment is also associated with increases in physical morbidity as well as mortality. The negative impacts of unemployment on health, especially mental health, increase with the duration of unemployment, which can contribute to a cycle of unemployment (Herbig et al. 2013; Picchio and Ubaldi 2024).

Unemployment has been shown to be associated with the biological effects of stress. Compared to men who are consistently employed, men who experience long-term unemployment have shorter leukocyte telomere length, which is associated with domestic stress (Ala-Mursula et al. 2013). One UK meta-analysis found that inflammatory markers, often associated with stress, were elevated for jobseekers in studies between 1998 and 2012 (Hughes et al. 2017). In another study, unemployed individuals had higher cortisol content in hair samples, compared with employed individuals (Dettenborn et al. 2010). This stress may then lead to poor health, increased susceptibility to toxic effects of pollution, and reduced capacity to cope and recover from adverse effect of environmental exposures (DeFur et al. 2007). Finally, the unemployed often lack the resources, such as income and adequate insurance, to seek care for health conditions while they are treatable or continue medically necessary prescriptions, leading to worse health outcomes, including outcomes caused by environmental pollutants (Nguyen et al. 2022; Samoli et al. 2019; Tefft and Kageleiry 2014).

There is also evidence that an individual's health is at least partly determined by neighborhood and regional factors. Unemployment is frequently used as a surrogate for neighborhood deprivation, which is associated with pollution exposure as well as poor health (Voigtlander et al. 2010). Studies of neighborhood socioeconomic factors have found stress to be a major factor in reported poor health among residents of disadvantaged communities, and both financial and emotional stress are direct results of unemployment (Turner 1995).

Method

- A dataset containing the unemployment rate by was obtained from the 2019-2023 ACS 5-year estimates via the US Census Bureau Data API at the census-tract level for the state of California.
- The Census Bureau calculates an unemployment rate by dividing the 'Population Unemployed in the Civilian Labor Force' by 'Population in the Civilian Labor Force' and then converts this to a percentage.
- Census tracts were sorted and assigned percentiles based on their position in the distribution.


Unemployment
Percent of population over 16 that is unemployed and eligible for the labor force (2019-2023)
0 - 2.2
2.3 - 3.3
3.4 - 4.1
4.2 - 4.9
5.0 - 5.8
5.9 - 6.7
6.8 - 7.8
7.9 - 9.3 (Top 30%)
9.4 - 11.8 (Top 20%)
11.9 - 100 (Top 10%)
No data
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Visalia
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
0 5 10 Miles
San Diego Area

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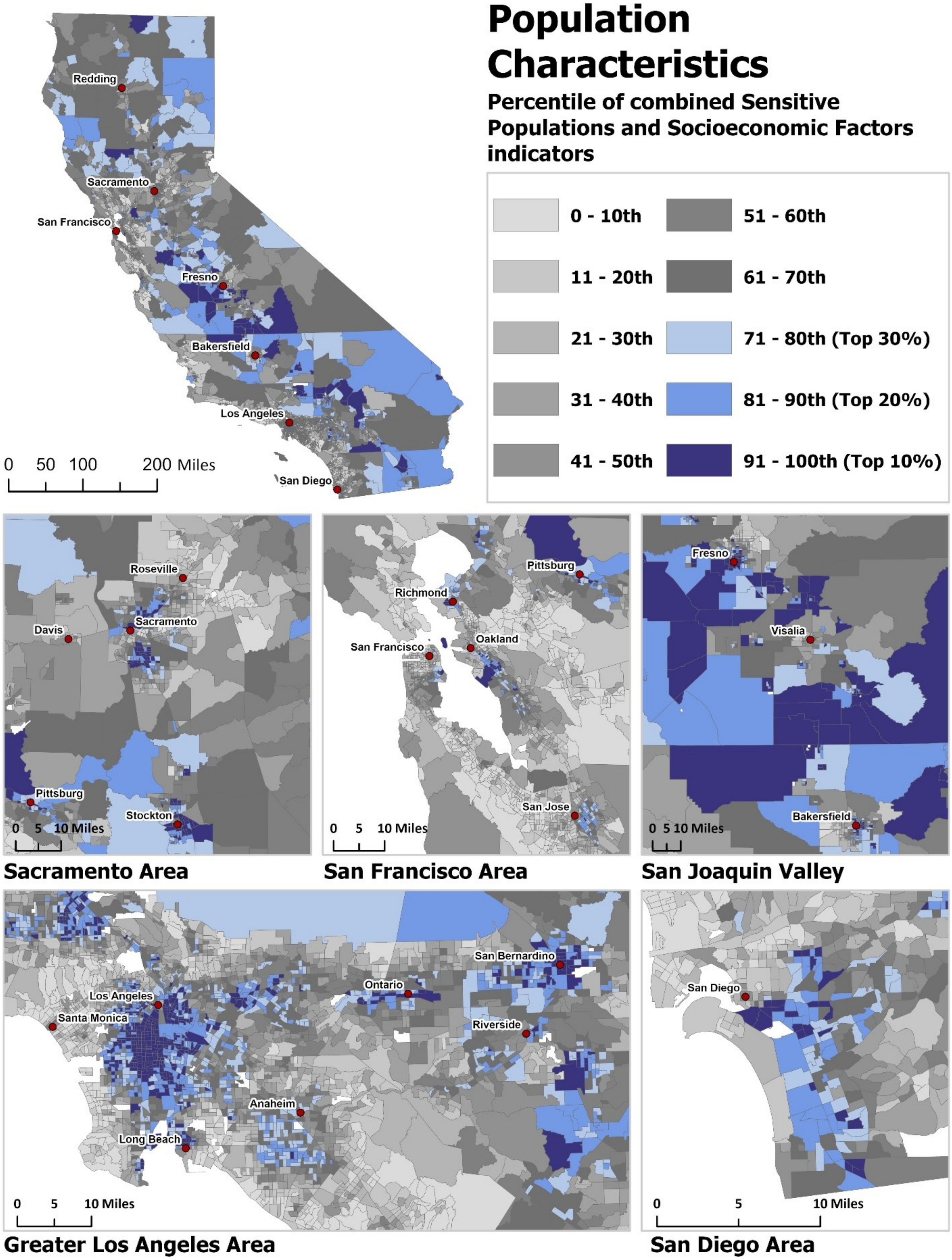
Scores for Population Characteristics

The map on the following page shows Population Characteristics scores divided into deciles.



Population Characteristics
Percentile of combined Sensitive Populations and Socioeconomic Factors indicators
0 - 10th
11 - 20th
21 - 30th
31 - 40th
41 - 50th
51 - 60th
61 - 70th
71 - 80th (Top 30%)
81 - 90th (Top 20%)
91 - 100th (Top 10%)
Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego
0 50 100 200 Miles
Roseville
Davis
Sacramento
Pittsburg
Stockton
0 5 10 Miles
Sacramento Area
Pittsburg
Richmond
San Francisco
Oakland
San Jose
0 5 10 Miles
San Francisco Area
Fresno
Visalia
Bakersfield
0 5 10 Miles
San Joaquin Valley
San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0 5 10 Miles
Greater Los Angeles Area
San Diego
0 5 10 Miles
San Diego Area

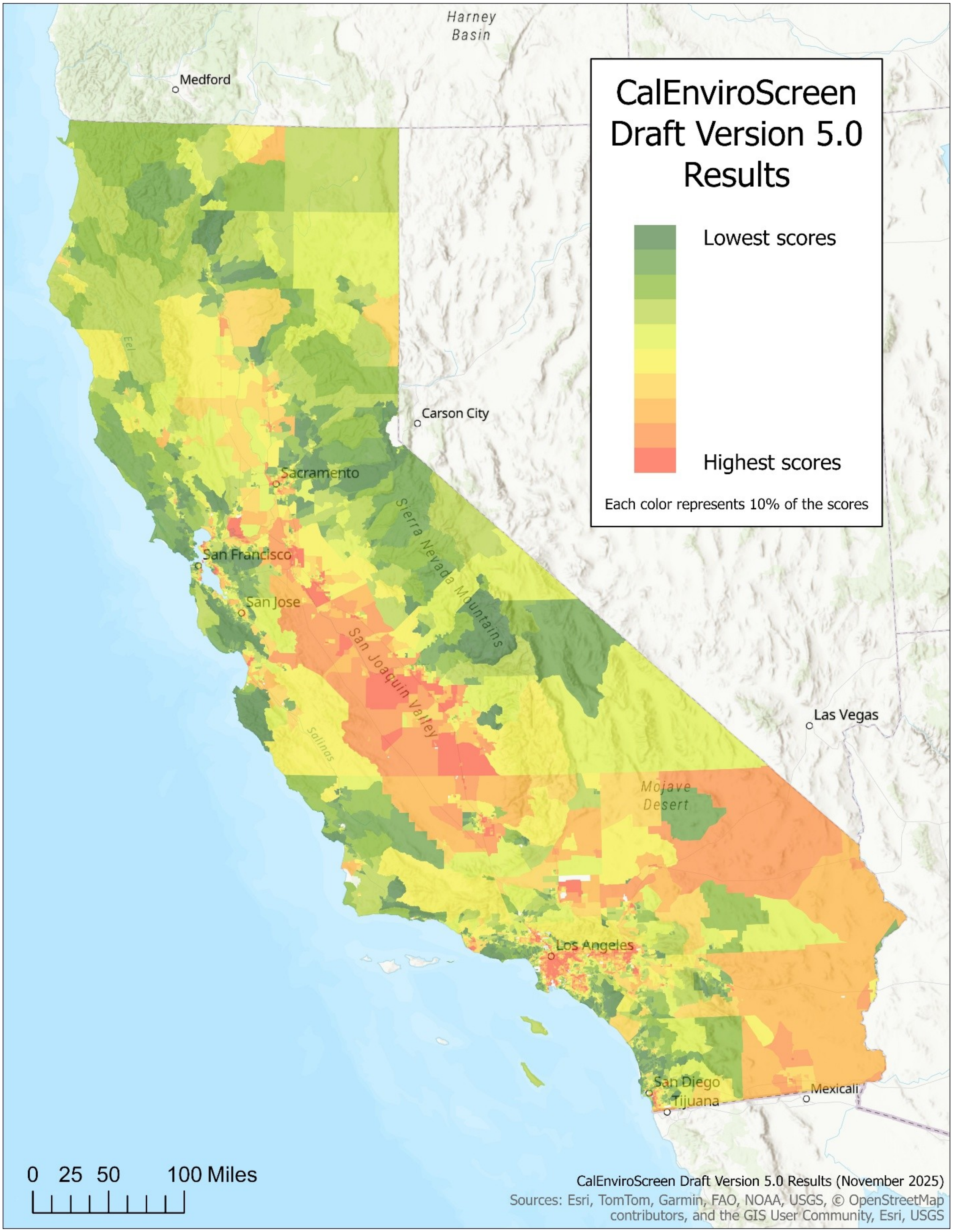
CALENVIROSCREEN RESULTS

The maps on the following pages depict the relative scoring of California's census tracts using the CalEnviroScreen methodology described in this report. Census tracts with darker red colors have the higher CalEnviroScreen Scores and therefore have relatively high pollution burdens and population sensitivities. Census tracts with lighter green colors have lower scores, and correspondingly lower pollution burdens and sensitivities.

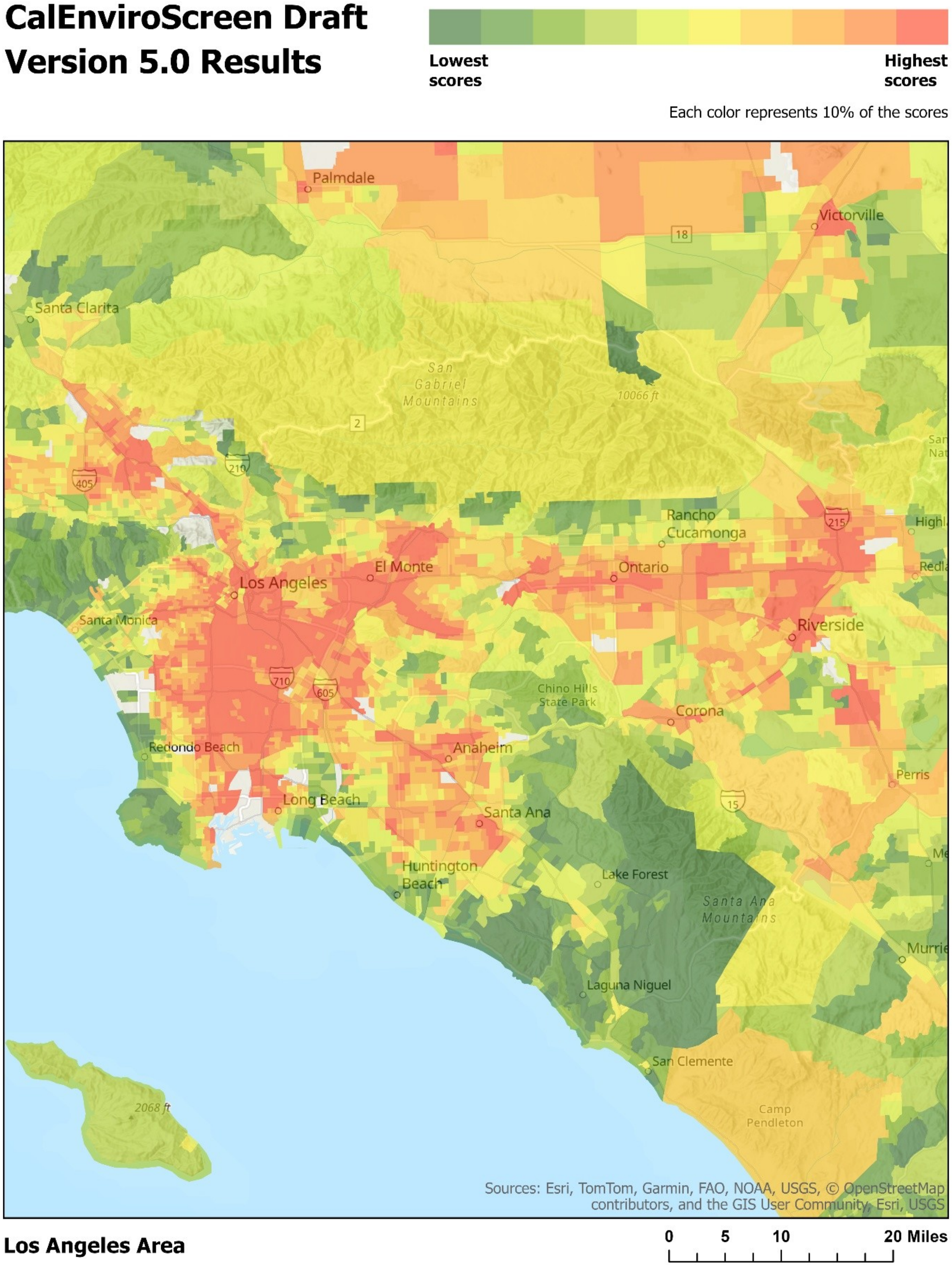
The maps of specific regions of the state (Los Angeles, San Francisco, San Diego, San Joaquin Valley, Sacramento and the Coachella and Imperial Region) are "close-ups" of the statewide map and are intended to provide greater clarity on the relative scoring of census tracts in those regions. Colors on these maps reflect the relative statewide scoring of individual census tracts.

Numerical scores for each census tract, as well as the individual indicator scores for each census tract, may be found online on the CalEnviroScreen website at http://oehha.ca.gov/calenviroscreen.

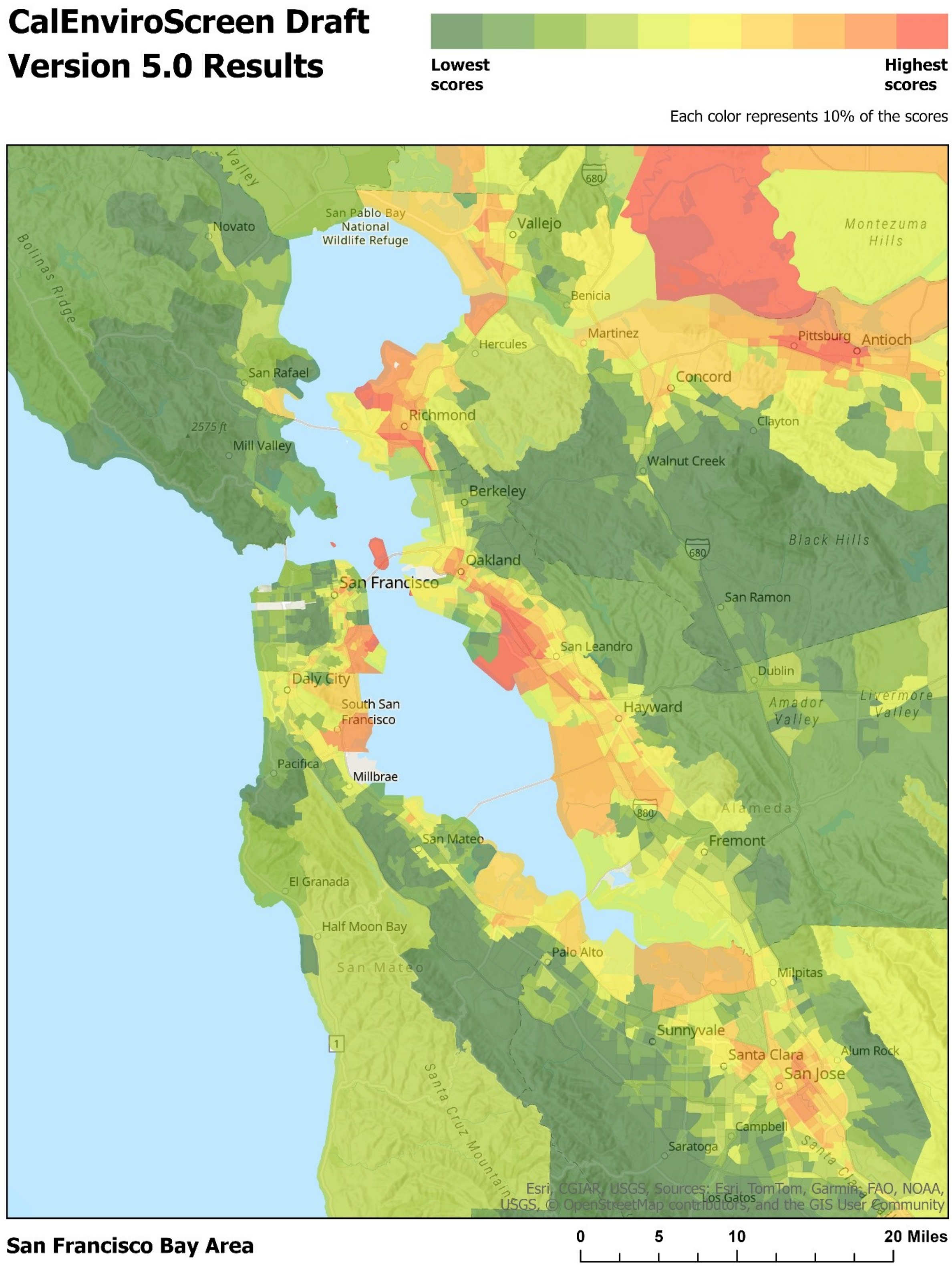
The information is available both in a Microsoft Excel spreadsheet format and as an online mapping application.

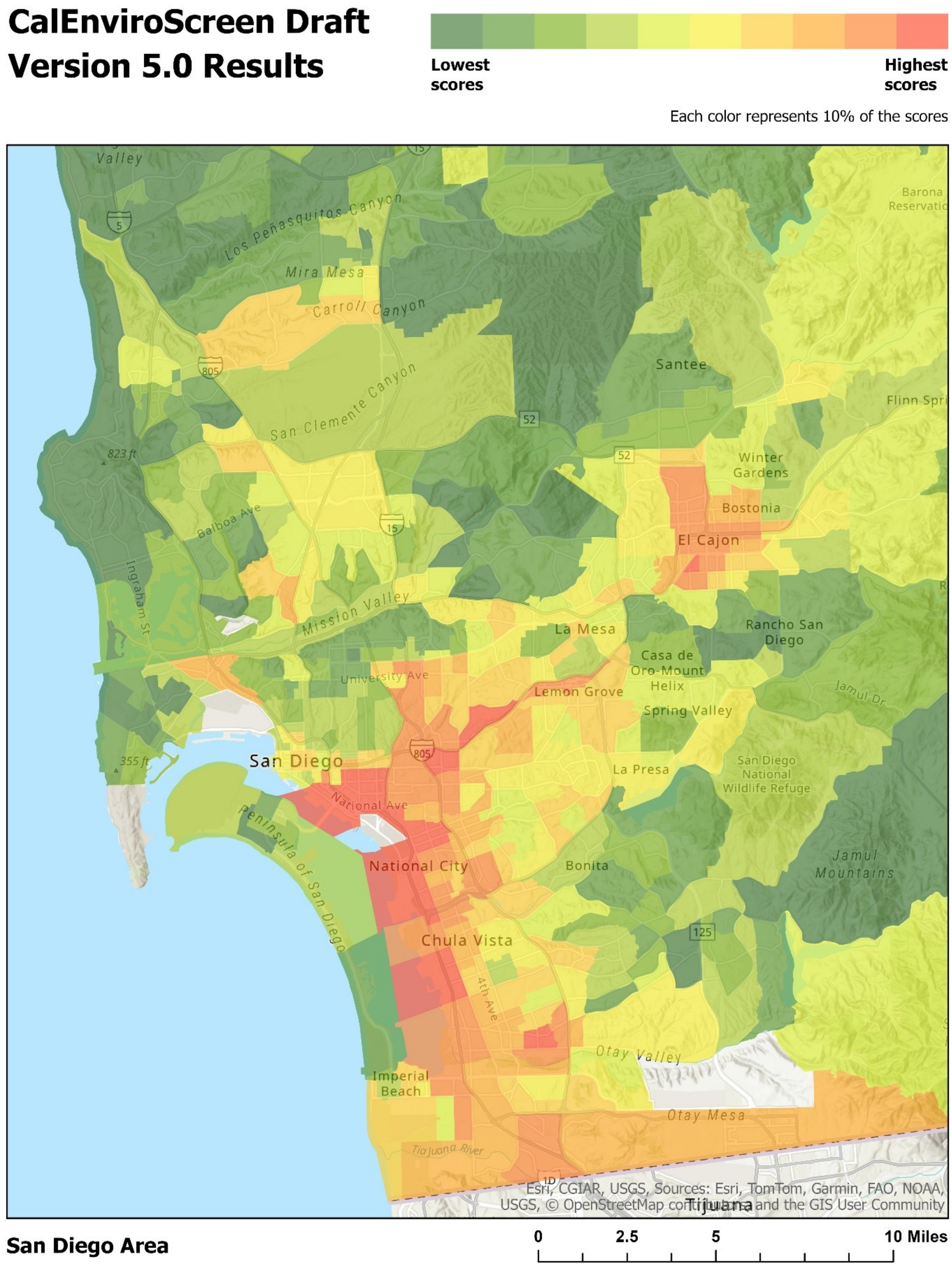

Harney Basin
Medford
CalEnviroScreen Draft Version 5.0 Results
Lowest scores
Highest scores
Each color represents 10% of the scores
Carson City
Sacramento
Sierra Nevada Mountains
San Francisco
San Jose
San Joaquin Valley
Salinas
Eel
Las Vegas
Mojave Desert
Los Angeles
San Diego
Tijuana
Mexicali
0 25 50 100 Miles
CalEnviroScreen Draft Version 5.0 Results (November 2025)
Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community, Esri, USGS

CalEnviroScreen Draft Version 5.0 Results

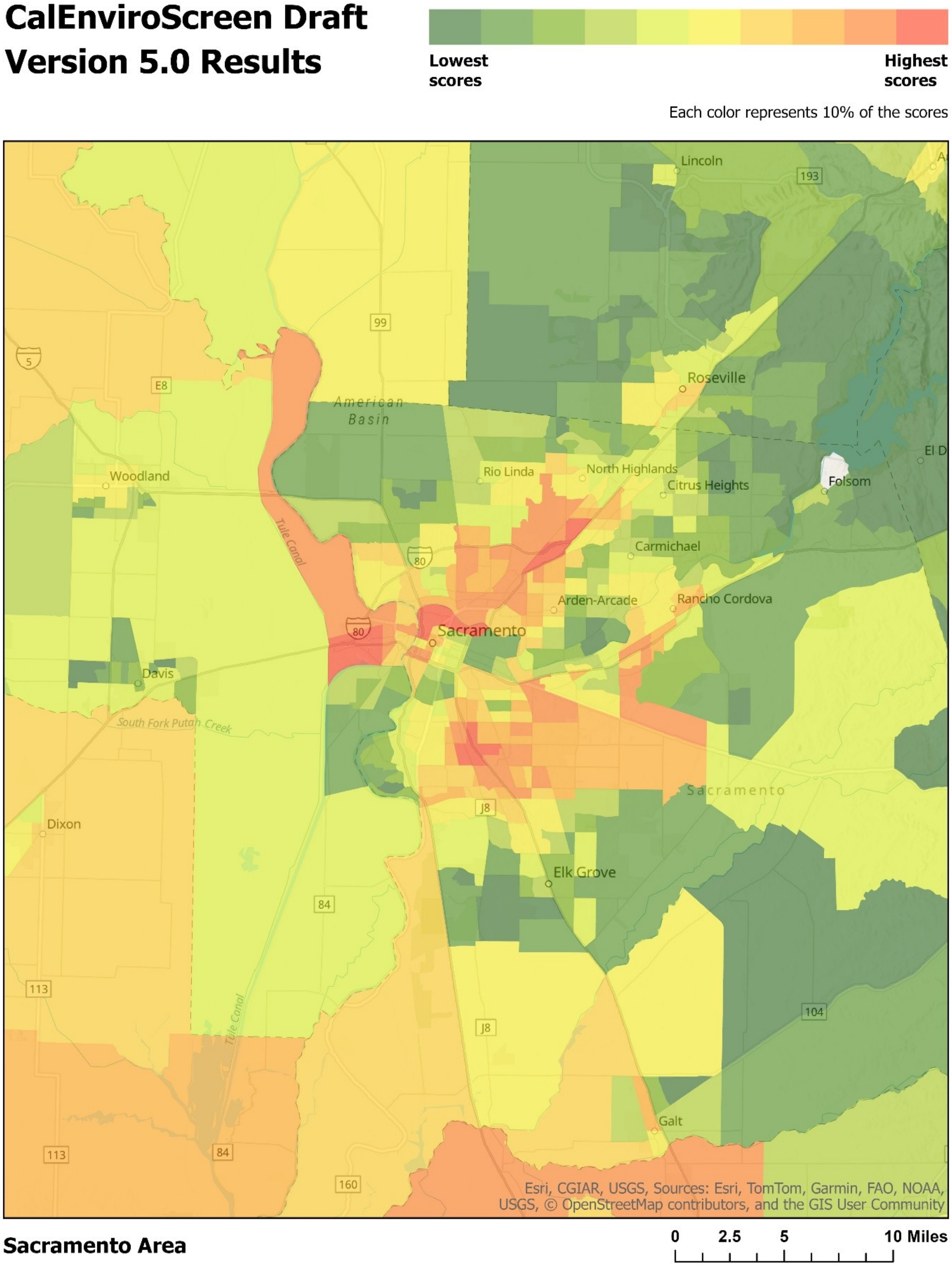


Los Angeles Area

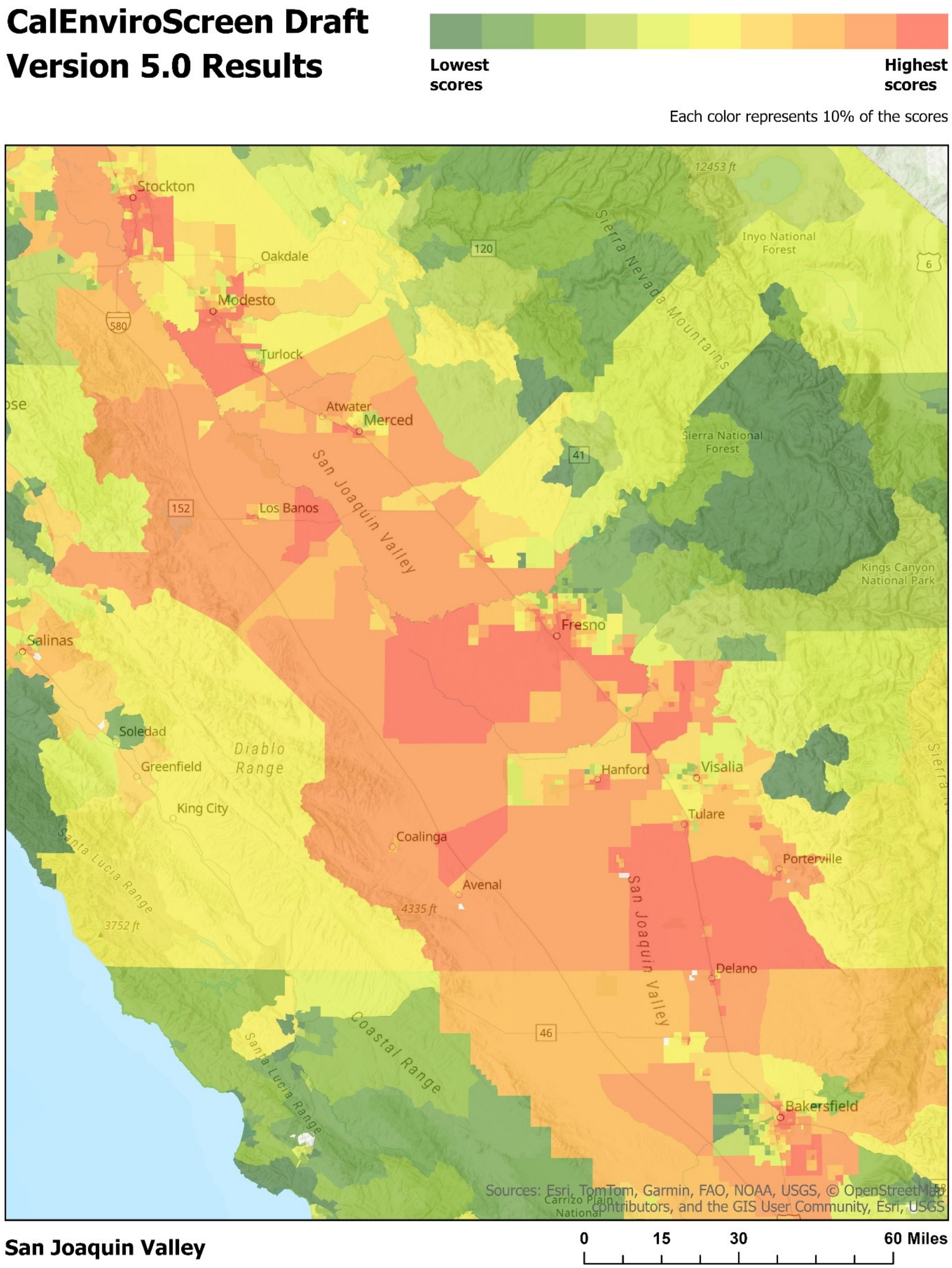

CalEnviroScreen Draft
Version 5.0 Results
Lowest scores
Highest scores
Each color represents 10% of the scores
Novato
San Pablo Bay National Wildlife Refuge
Vallejo
Montezuma Hills
Bolinas Ridge
Benicia
Hercules
Martinez
Pittsburg
Antioch
San Rafael
Concord
Richmond
2575 ft
Mill Valley
Clayton
Walnut Creek
Berkeley
Black Hills
Oakland
San Francisco
San Ramon
San Leandro
Daly City
Dublin
South San Francisco
Hayward
Amador Valley
Livermore Valley
Pacifica
Millbrae
Alameda
San Mateo
Fremont
El Granada
Half Moon Bay
Palo Alto
San Mateo
Milpitas
Sunnyvale
Santa Clara
Alum Rock
San Jose
Santa Cruz Mountains
Campbell
Saratoga
Los Gatos
Esri, CGIAR, USGS, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community
San Francisco Bay Area
0
5
10
20 Miles


CalEnviroScreen Draft Version 5.0 Results
Lowest scores
Highest scores
Each color represents 10% of the scores
Valley
Los Peñasquitos Canyon
Mira Mesa
Carroll Canyon
San Clemente Canyon
823 ft
Balboa Ave
Ingraham St
Mission Valley
University Ave
San Diego
355 ft
National Ave
Peninsula of San Diego
National City
Chula Vista
4th Ave
Imperial Beach
Tia Juana River
Santee
Winter Gardens
Bostonia
El Cajon
La Mesa
Rancho San Diego
Casa de Oro-Mount Helix
Lemon Grove
Spring Valley
La Presa
San Diego National Wildlife Refuge
Jamul Dr
Jamul Mountains
Bonita
Otay Valley
Otay Mesa
Flinn Spri
Barona Reservatio
Tijuana
Esri, CGIAR, USGS, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community
San Diego Area
0 2.5 5 10 Miles

CalEnviroScreen Draft Version 5.0 Results



Sacramento Area



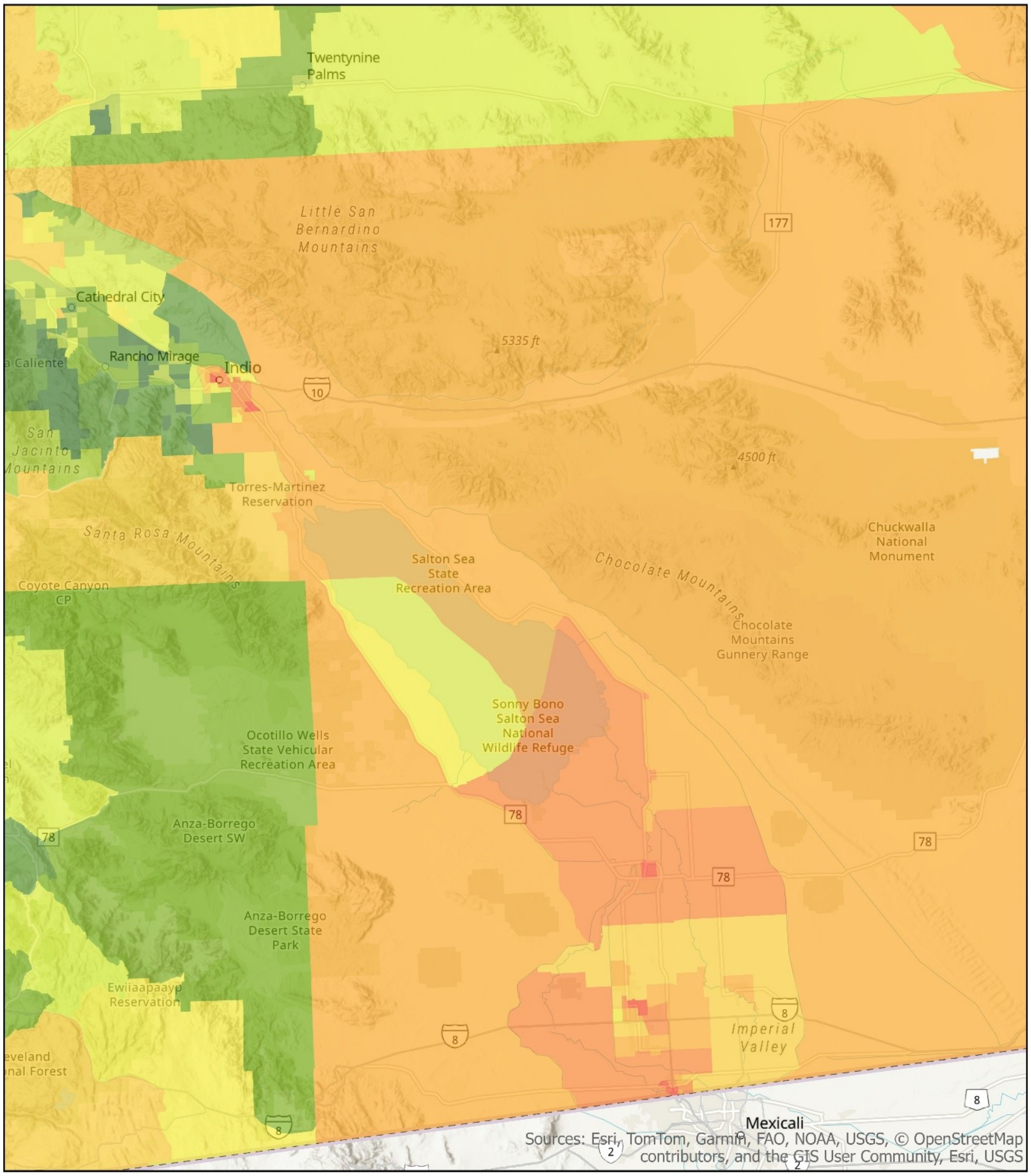
San Joaquin Valley

CalEnviroScreen Draft Version 5.0 Results

Lowest scores

Highest scores

Each color represents 10% of the scores



Imperial Area

0 5 10 20 Miles