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CalEnviroScreen
4.0

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Preface to Version 4.0

CalEnviroScreen 4.0 is the latest iteration of the California Communities Environmental Health Screening Tool. The original and subsequent versions were developed by the Office of Environmental Health Hazard Assessment, or OEHHA, an office within the California Environmental Protection Agency.

This version of CalEnviroScreen incorporates the recent publicly available data for all indicators. It also improves in the way some indicators are calculated to better reflect environmental conditions or a population's vulnerability to environmental pollutants. One new indicator — Children's Lead Risk from Housing — has been added to help capture another exposure that affects health and contributes to the pollution burden communities face.

CalEnviroScreen 4.0 has also been updated with additional information on the California-Mexico border region, pursuant to Assembly Bill 1059 (Garcia, Statutes of 2015). These changes affect the indicators for PM2.5, Diesel Particulate Matter, Traffic Impacts, Toxic Releases from Facilities, Solid Waste Sites and Facilities, and Hazardous Waste Generators and Facilities.

The CalEnviroScreen 4.0 draft report and draft mapping tool were released in February 2021 for public review and input. OEHHA convened a webinar and six workshops on the draft version to share the proposed updates of the tool, answer questions, and take public comment. Five workshops focused on different regions of the state. A sixth workshop covered statewide issues. OEHHA also received written public input on the report. OEHHA updated the tool and made changes based on written comments and verbal input received in the workshops.

A full discussion of the basis for the indicators and data sources is given in the main body of this document. A description of updates to the tool is provided in a Summary of Changes document available on the CalEnviroScreen 4.0 webpage.

Message from the Secretary

I am pleased to present this fourth version of CalEnviroScreen, which continues California's commitment to advancing equity and environmental justice.

Low-income communities, communities of color, tribal nations and other disadvantaged groups continue to be overburdened by unacceptable levels of pollution. CalEPA and the entire Newsom Administration is dedicated to shifting this dynamic, and CalEnviroScreen has become the national gold standard of geospatial data tools than can help drive more equitable decision-making.

Developed by CalEPA and its Office of Environmental Health Hazard Assessment (OEHHA), CalEnviroScreen includes an online mapping tool, a supplemental race analysis and related documents. It analyzes data on environmental, public health and socioeconomic conditions in California's 8,000 census tracts to provide a clear picture of cumulative pollution burdens and vulnerabilities in communities throughout the state.

When CalEPA released the initial version of the California Communities Environmental Health Screening Tool (CalEnviroScreen) in 2013, it marked the first time a state used a science-based screening tool to demonstrate, from a geospatial perspective, who is most affected by environmental injustice. Since then, CalEnviroScreen has guided significant public investments aimed at improving environmental conditions in California's disadvantaged communities and ameliorating environmental injustice. The tool has helped CalEPA and other local, state and federal agencies ensure their activities address these pollution burdens and protect those communities from additional ones. CalEPA uses CalEnviroScreen to prioritize enforcement and outreach in vulnerable communities. The City of Fresno used CalEnviroScreen data to prioritize the funding of parks in overburdened neighborhoods. Non-profit organizations have used the tool to advance the concept of green zones and identify neighborhoods for tree planting. Several states, including

Washington, New York, and Michigan, have used CalEnviroScreen to inform the development of their own state-specific environmental justice tools. The US Environmental Protection Agency studied CalEnviroScreen in developing its own national screening tool, EJSCREEN.

CalEnviroScreen shines a bright light on the shameful legacy of our past as well as continued injustices. It shows a direct, persistent relationship between exposure to environmental burdens and socio-economic and health vulnerabilities affecting largely, and at times almost exclusively, communities of color, as shown in the supplemental race analysis. California's history of racism and discrimination is visible in many of the maps contained in the tool. Segregation, redlining, and discriminatory land use, permitting and enforcement practices resulted in industrial facilities, landfills, ports and railyards, and high pesticide use clustered around low-income communities of color. Continued discriminatory practices, inequities in decision-making, disinvestment, poverty and other socioeconomic factors magnify the effects of pollution on these communities.

We seek to continuously improve our protection of public health and the environment and the programs and tools that support that work. CalEnviroScreen is no exception. CalEnviroScreen 4.0 reflects the input and comments received on prior versions of the tool and the 4.0 draft. This latest version features a new indicator reflecting children's risk of lead exposure from older housing stock, a burden disproportionately impacting low-income communities. CalEnviroScreen 4.0 also incorporates the most recent data produced by CalEPA's boards, departments and offices, the California Health and Human Services Agency and federal entities.

CalEnviroScreen is a powerful tool that can help us address historical and continued inequality. We encourage government agencies and private and non-governmental organizations alike to use CalEnviroScreen to continue to develop their own innovative ways to address pollution and related public health concerns and further environmental justice in California. We must continue progress toward making the California Dream accessible for all.

Sincerely,

Jared Blumenfeld
California Secretary for Environmental Protection

Introduction

In California, environmental quality has improved over the last few decades as evidenced by improved water quality, reduced air pollution, decrease in pesticide use, continued cleanup of hazardous waste sites as well as increased recycling and reduction of solid waste going into landfills. These improvements are observed and well documented at the state and regional level. However, the pollution reduction and resulting health and environmental benefits are not uniformly distributed across the state, within a region, or among all population segments.

Many communities continue to bear a disproportionate burden of pollution not only from multiple nearby sources, but also from pollution in multiple media (e.g., air or water). Some of these communities experience the additional burden of socioeconomic stressors and health conditions that render them more vulnerable to the impacts of pollution. . In order to address the cumulative effects of both pollution burden and these additional factors, and to identify which communities might be in need of particular policy, investment, or programmatic interventions, OEHHA developed and now maintains and updates the CalEnviroScreen tool on behalf of CalEPA. This tool applies a framework for assessing cumulative impacts that OEHHA developed in 2010, based in large part on input from a statewide working group on environmental justice 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 CalEnviroScreen, 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. CalEnviroScreen 2.0 was released in 2014 and 3.0 in 2017.

This update to CalEnviroScreen, Version 4.0, 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. This updated version includes more recent data, improved methodology, and an additional indicator.

Similar to previous versions, CalEnviroScreen 4.0 continues to:

- Present a relative, rather than an absolute, evaluation of pollution burdens and vulnerabilities in California communities by providing a relative ranking of communities across the state of California.

- Provide a methodology consistent with previous versions of the tool, and an assessment that is up-to-date with additional and most recent data.
- Evaluate multiple pollution sources, and stressors that measure a community's vulnerability to pollution.

CalEnviroScreen 4.0 changes over the previous version include:

- An update of all indicators with the most recent available data.
- Improved methods for calculating some indicators, including:
  - Refining the criteria for selecting Drinking Water Contaminants, updating water system service areas used in calculating the indicator's value, and improving the methodology for assessing water quality for areas outside of public water systems.
  - Adding multiple pesticides to the Pesticide Use indicator.
  - Adding dairy and feedlot locations to the Groundwater Threats indicator
  - Adding chrome metal plating facility locations to the Hazardous Waste indicator
  - Improving the methodology used to create the PM2.5 and Diesel PM air quality indicators
- Adding one new indicator to reflect potential exposure of children to lead-based paint, indicative of children's lead risk in low-income communities with older housing stock.

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. Thus, the resulting cumulative 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. Furthermore, risk assessment requires extensive characterization of the chemicals present, the routes and levels of exposure, and the dose-response relationship for hundreds of chemicals for which data are neither currently available nor likely to be generated in the foreseeable future.

A methodology did not exist to fully integrate, for a community in given geographic location, the spectrum of pollutants (such as simultaneous exposure to numerous

pollutants from multiple pollution sources), intrinsic factors (health status), and extrinsic factors (socioeconomic status) into risk assessment. Hence, OEHHA and CalEPA developed CalEnviroScreen to conduct statewide evaluations of community-scale impacts through this screening tool.

Impact vs. Risk

A core purpose of developing CalEnviroScreen is to characterize "*impacts*" of pollution in communities with respect to factors that are not routinely included in risk assessment. Often, the terms *risk* and *impact* are used synonymously, suggesting that they describe the same outcome. However, the term *risk* means a probability of an injury or loss that is quantified, while *impact* in this context refers more broadly to the overall burden that affects health and quality of life. While risk assessment suggests a quantitative approach to evaluating injury or loss, impact assessment implies integrating both quantitative factors and those less readily measured or estimated, but that may increase the magnitude of adverse effects. *Impact assessment* is increasingly used in land-use planning, resource allocation, and permitting.

Organization of the report

This report follows the same format as previous CalEnviroScreen versions beginning with methodology, selection criteria for the 21 indicators, and calculation of the CalEnviroScreen score for an individual census tract. This is followed by sections for each indicator that define the indicator and explain how the data for each indicator were selected and analyzed. The scores of each indicator and the final CalEnviroScreen scores for different areas of the state are presented as maps. The report concludes by providing the overall results of the statewide analysis, presented as maps showing the census tracts with highest CalEnviroScreen scores.

References

Office of Environmental Health Hazard Assessment (OEHHA, 2010). Cumulative Impacts: Building A Scientific Foundation. OEHHA, California Environmental Protection Agency. Available online at: https://oehha.ca.gov/media/downloads/calenviroscreen/report/cireport123110.pdf

Method

THE CALENVIROSCREEN MODEL

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 CalEnviroScreen 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 components representing Pollution Burden – Exposures and Environmental Effects – and two components representing Population Characteristics – Sensitive Populations (e.g., in terms of health status and age) and Socioeconomic Factors.
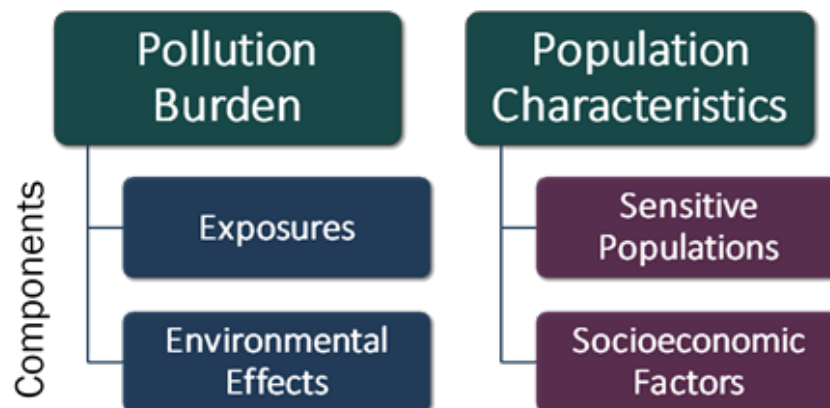
Model Characteristics

The model:

- Uses 21 statewide indicators to characterize both Pollution Burden and Population Characteristics.

- Uses percentiles to assign scores for each of the indicators in a given geographic area. The percentile represents a relative score for the indicators.

- Uses a scoring 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 CalEnviroScreen score for a given place relative to other places in the state, using the formula below.

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:

Pollution Burden   **Population Characteristics**

Average of Exposures and Environmental Effects* ✖ Average of Sensitive Populations and Socioeconomic Factors ═ CalEnviroScreen Score
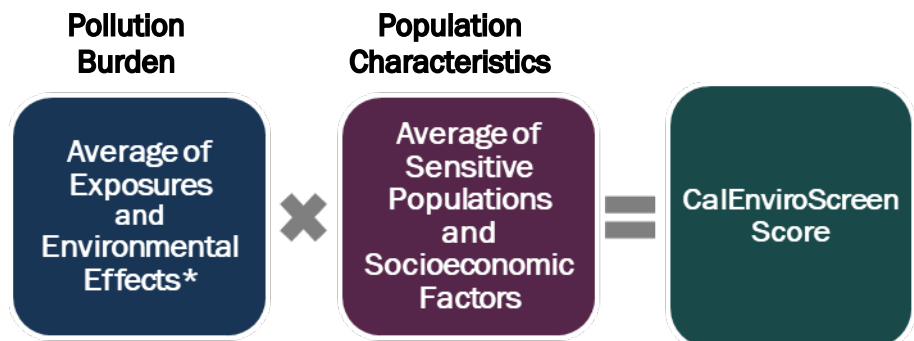
* The Environmental Effects score was weighted half as much as the Exposures score.

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*: Existing research on environmental pollutants and health risk has consistently identified socioeconomic and sensitivity factors as "effect modifiers" that multiply the risks posed by the pollutants. For example, numerous studies on the health effects of particulate air pollution have found that low socioeconomic status is associated with about a 3-fold increased risk of morbidity or mortality for a given level of

particulate pollution (Samet and White, 2004). Similarly, sensitivity to an air pollutant was up to 7-fold greater in asthmatics than non-asthmatics (Horstman *et al.*, 1986). Low-socioeconomic status African-American mothers exposed to traffic-related air pollution were twice as likely to deliver preterm babies (Ponce *et al.*, 2005). Studies of increased risk in vulnerable populations can often be described by effect modifiers that amplify the risk. This research suggests that the use of multiplication makes sense.

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 National Academy of Sciences, 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 (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.

Maximum Scores for Combined Components

Component Group	Maximum Score*
Pollution Burden *Exposures and Environmental Effects*	10
Population Characteristics *Sensitive Populations and Socioeconomic Factors*	10
CalEnviroScreen Score	Up to 100 (= 10 × 10)

* Enough decimal places were retained in the calculation to eliminate ties.

Notes on Scoring System

In the CalEnviroScreen model, the Population Characteristics are a modifier of the Pollution Burden. In mathematical terms, the Pollution Burden is the multiplicand and Population Characteristics is the multiplier, with the CalEnviroScreen score as the product. The final ordering of the communities is independent of the magnitude of the scale chosen for the Population Characteristics (without rounding scores). That is, the communities would be ordered the same in their final score if the

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Population Characteristics were scaled to 3, 5, or 10, for example. Here, a scale up to 10 was chosen for convenience.

Selection of Geographic Scale

CalEnviroScreen 4.0 uses the census tract as the unit of analysis. Census tract boundaries are available from the Census Bureau. CalEnviroScreen uses the Bureau's 2010 boundaries. New boundaries will be drawn by the Census Bureau as part of the 2020 Census but will not be available until 2022. OEHHA will address updates to census tract geography in CalEnviroScreen at that time.

There are approximately 8,000 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).

Race/Ethnicity, and Young and Elderly Populations

The relationship between CalEnviroScreen scores of the state's census tracts and their race/ethnicity compositions and children and elderly populations is an important context with which to understand environmental inequity in California. A analysis available on the CalEnviroScreen website shows clear disparities with respect to the racial makeup of the communities with the highest pollution burdens and vulnerabilities. People of color, especially Latino and Black people, disproportionately reside in highly impacted communities in California. The results using the CalEnviroScreen 4.0 scores are consistent with earlier versions of the tool, and reflect racial disparities, with the highest percentages of people of color living in the most highly impacted communities. After releasing each finalized version of CalEnviroScreen, OEHHA conducts a further analysis on race and age and provides the data and report on the CalEnviroScreen website.

References

Brody TM, Bianca PD, Krysa J (2012). Analysis of inland crude oil spill threats, vulnerabilities, and emergency response in the midwest United States. *Risk Analysis: An International Journal* **32**(10):1741-9.

Horstman D, Roger LJ, Kehrl H, Hazucha M (1986). Airway sensitivity of asthmatics to sulfur dioxide. *Toxicology and Industrial Health* **2**(3):289-98.

Ponce NA, Hoggatt KJ, Wilhelm M, Ritz B (2005). Preterm birth: the interaction of traffic-related air pollution with economic hardship in Los Angeles neighborhoods. *American Journal of Epidemiology* **162**(2):140-8.

Samet J, White R (2004). Urban air pollution, health, and equity. *Epidemiology & Community Health* **58**(1).

US EPA (2012). Conducting a Human Health Risk Assessment [Available at URL: https://www.epa.gov/risk/conducting-human-health-risk-assessment].

INDICATOR SELECTION AND SCORING

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

Overview of the Process

1. Identify potential indicators for each component.
2. Find sources of data to support indicator development (see Criteria for Indicator Selection below).
3. Select and develop the indicators, assigning a value for each geographic unit.
4. Assign a percentile for each indicator for each geographic unit, 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 below).
8. Generate maps to visualize overall results.

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.

Criteria for Indicator Selection

- Indicators should provide a measure that is relevant to the component it represents, in the context of the 2005 CalEPA cumulative impacts definition.

- Indicators should represent widespread concerns related to pollution burden or population characteristics in California.

- The indicators combined together should provide a good representation of each component.

- Pollution burden indicators should relate to issues that may be potentially actionable by CalEPA boards and departments.

- Population characteristics indicators should represent demographic factors known to modify vulnerability to impacts of pollution.

- Data for each indicator should be available for the entire state at the census tract level or be translatable to the census tract level.

- Data should be of sufficient quality, and be:
    - Complete
    - Accurate
    - Current

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. CalEnviroScreen 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 criteria for exposure indicator development. They are:

- Ozone concentrations in air

- PM2.5 concentrations in air

- Diesel particulate matter emissions

- Drinking water contaminants

- Children's lead risk from housing

- Use of certain high-hazard, high-volatility pesticides

- Toxic releases from facilities

Pollution Sources → Emissions & Discharges → Environmental Concentrations → Exposures
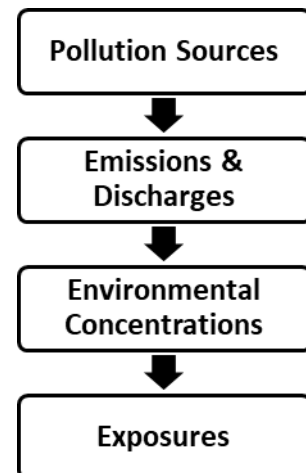
- Traffic impacts

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 indicator development:

- Toxic cleanup sites
- Groundwater threats from leaking underground storage sites and cleanups
- Hazardous waste facilities and generators
- Impaired water bodies
- Solid waste sites and facilities

Sensitive Population Indicators

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

Sensitive individuals may include those with impaired physiological conditions, such as people with heart disease or asthma. Other sensitive individuals include those with lower protective biological mechanisms due to genetic factors.

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 development of these indicators:

- Asthma emergency department visits

- Cardiovascular disease (emergency department visits for heart attacks)

- 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 color and lower socioeconomic status to environmental pollutants. For example, a study found that individuals with less than a high school education who were exposed to particulate pollution had a greater risk of mortality. 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 indicator development:

- Educational attainment

- Housing-burdened low-income households

- Linguistic isolation

- Poverty

- Unemployment

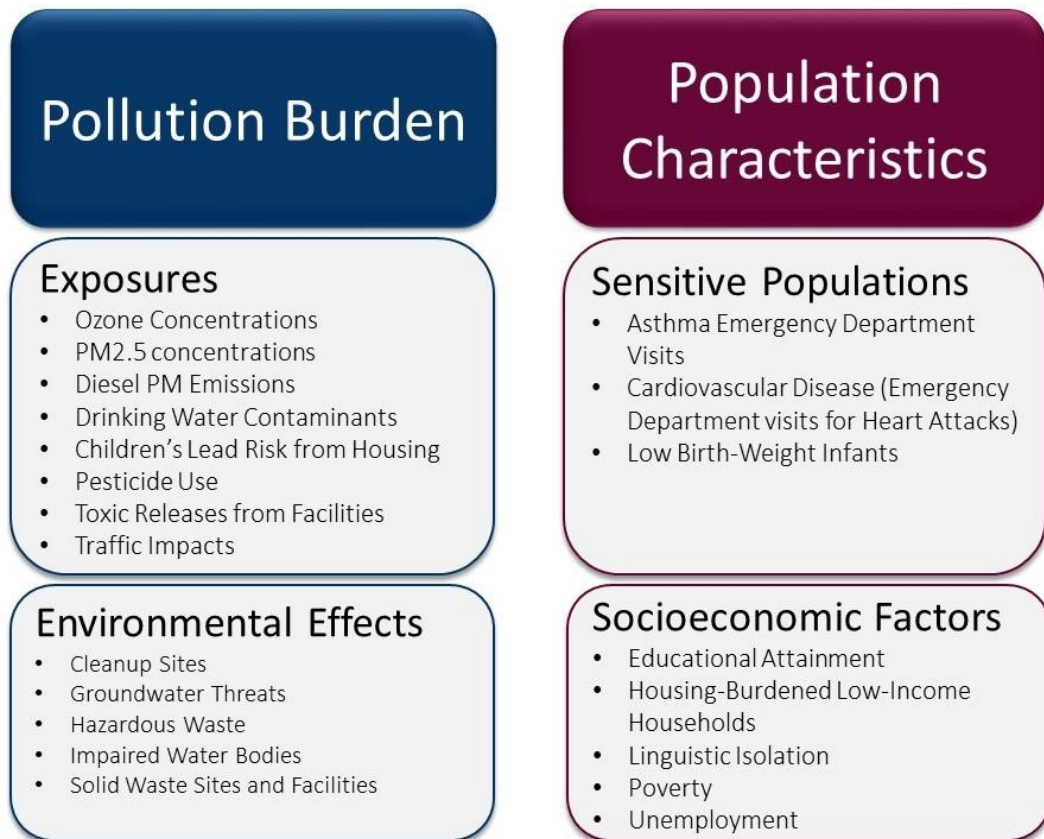## Indicator and Component Scoring

The indicator values for the census tracts for the entire state are ordered from highest to lowest. A percentile is calculated from the ordered values for all areas that have a score.* Thus each area's percentile rank for a specific indicator is relative to the ranks for that indicator in the rest of the places in the state.

- The indicators used in this analysis have varying underlying distributions, and percentile rank calculations provide a useful way to describe data without making any potentially unwarranted assumptions about those distributions.

- A geographic area's percentile for a given indicator simply tells the percentage of areas with lower values of that indicator.

- A percentile does not describe the magnitude of the difference between two or more areas. For example, an area

ranked in the 30th percentile is not necessarily three times more impacted than an area ranked in the 10th percentile.

* When a geographic area has no indicator value (for example, the census 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 unreliable or missing for a geographic area, such as census data with large uncertainties, it is excluded from the percentile calculation and is not assigned any score for that indicator. Thus 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).

Pollution Burden

Exposures
- Ozone Concentrations
- PM2.5 concentrations
- Diesel PM Emissions
- Drinking Water Contaminants
- Children's Lead Risk from Housing
- Pesticide Use
- Toxic Releases from Facilities
- Traffic Impacts

Environmental Effects
- Cleanup Sites
- Groundwater Threats
- Hazardous Waste
- Impaired Water Bodies
- Solid Waste Sites and Facilities

Population Characteristics

Sensitive Populations
- Asthma Emergency Department Visits
- Cardiovascular Disease (Emergency Department visits for Heart Attacks)
- Low Birth-Weight Infants

Socioeconomic Factors
- Educational Attainment
- Housing-Burdened Low-Income Households
- Linguistic Isolation
- Poverty
- Unemployment

For a given census tract, scores for the Pollution Burden and Population Characteristics are calculated as described below. An example calculation is provided on at the end of this chapter:

- 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 was considered to be 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. Thus the Exposure component receives twice the weight as 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 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 has been removed.

- Highly uncertain measurements have been excluded from the analysis (for example, socioeconomic measures with high margins of error).

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, this model comprised of a suite of indicators is 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. Using a limited data set, an analysis of the sensitivity of the model to changes in weighting showed it is relatively robust in identifying more impacted areas (Meehan August *et al.*, 2012). Use of broad

groups of areas, such as those scoring in the highest 10 and 25 percent, is expected to be the most suitable application of the CalEnviroScreen results.

Reference

Meehan August L, Faust JB, Cushing L, Zeise L, Alexeeff GV (2012). Methodological considerations in screening for cumulative environmental health impacts: Lessons learned from a pilot study in California. *International Journal of Environmental Research and Public Health* **9**(9):3069-84.

# EXAMPLE CENSUS TRACT: INDICATOR RESULTS AND CALENVIROSCREEN SCORE

One example census tract in western Fresno was selected to illustrate how an overall CalEnviroScreen score is calculated using the California Communities Environmental Health Screening Tool. Its census tract number is 6019000300.

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 CalEnviroScreen 4.0.

Example Census Tract

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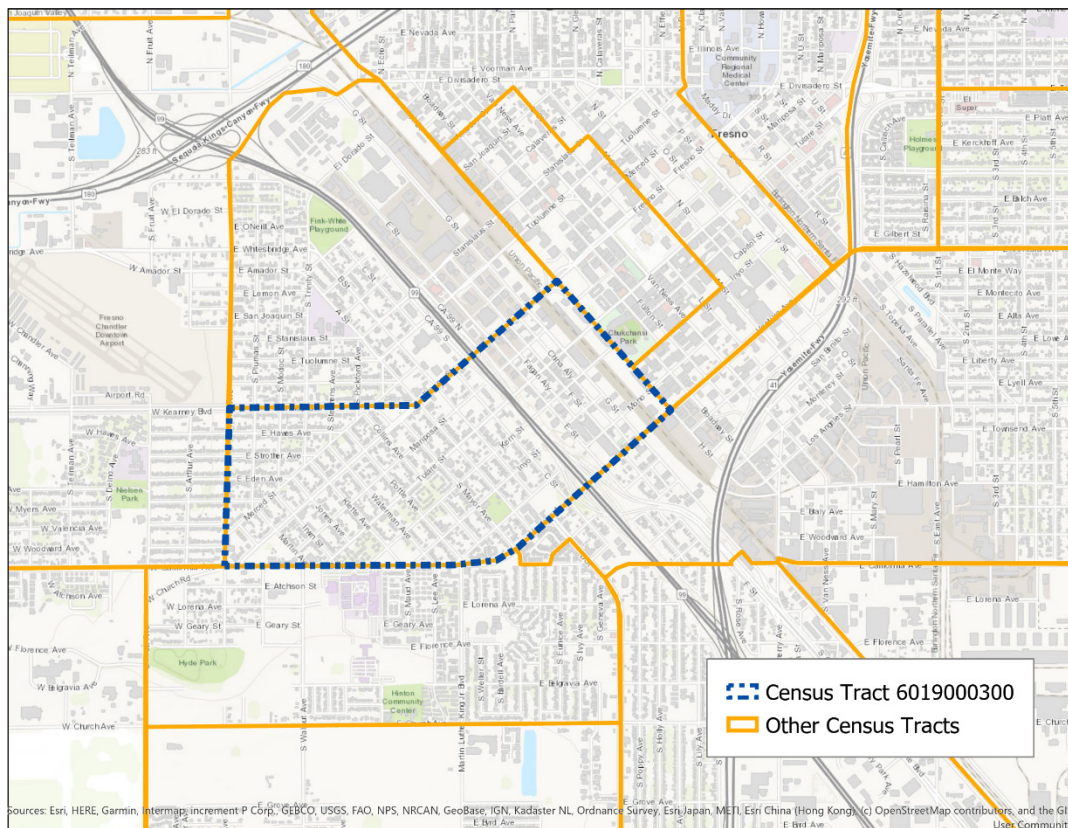
Exposure Indicators		
Indicator	Raw Value	Percentile
Ozone (concentration)	0.06	**82.48**
PM2.5 (concentration)	13.78	**97.36**
Diesel PM (emissions)	0.69	**95.22**
Drinking Water (index)	733.95	**84.39**
Children's Lead Risk from Housing (index)	82.05	**91.09**
Pesticide Use (lbs/sq. mi.)	59.94	**73.38**
Toxic Releases (RSEI toxicity-weighted releases)	2385.27	**81.92**
Traffic (impacts)	641.60	**31.51**
AVERAGE COMPONENT SCORE*	--	**79.67**

Environmental Effects Indicators		
Indicator	Raw Value	Percentile
Cleanup Sites (weighted sites)	15.00	**74.93**
Groundwater Threats (weighted sites)	22.5	**71.69**
Hazardous Waste Factilities/ Generators (weighted sites)	0.29	**47.41**
Impaired Water Bodies (number of pollutants)	0.00	**0.00**
Solid Waste Sites/Facilities (weighted sites and facilities)	1.00	**35.72**
AVERAGE COMPONENT SCORE	--	**45.95**

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

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Sensitive Population Indicators		
Indicator	Raw Value	Percentile
Asthma (rate per 10,000)	139.35	**98.23**
Cardiovascular Disease (heart attacks per 10,000)	22.68	**94.57**
Low Birth Weight (percent)	8.07	**96.74**
AVERAGE COMPONENT SCORE	--	**96.51**

Socioeconomic Factor Indicators		
Indicator	Raw Value	Percentile
Educational Attainment (percent)	38.40	**88.71**
Housing Burden (percent)	18.80	**57.85**
Linguistic Isolation (percent)	14.20	**75.19**
Poverty (percent)	70.20	**97.37**
Unemployment (percent)	NA	**NA**
AVERAGE COMPONENT SCORE	--	**79.78**

The approach used to calculate the CalEnviroScreen Score for census tract 6019000300 is shown below in tabular form.

	Pollution Burden		Population Characteristics	
	Exposure Indicators	Environmental Effects Indicators*	Sensitive Population Indicators	Socioeconomic Factor Indicators
Component Score	79.67	(0.5 × 45.95) =22.98	96.51	79.78
Average of Component Score	102.65 ÷ (1 + 0.5) = **68.43** *Pollution Burden is calculated as the average of its two component scores, with the Environmental Effects component half-weighted.*		176.29 ÷ 2 = **88.15** *Population Characteristics is calculated as the average of its two component scores.*	
Scaled Component Scores (Range 0-10)	(68.43 ÷ 81.9**) × 10 = **8.36** *The Pollution Burden percentile is scaled by the statewide maximum Pollution Burden scores.*		(88.15 ÷ 96.4***) × 10 = **9.14** *The Population Characteristics percentile is scaled by the statewide maximum Population Characteristics scores.*	
CalEnviroScreen Score	8.36 x 9.14 = **76.4** A score of **76.4** 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 81.9.
*** The tract with the highest Population Characteristics score in the state had a value of 96.4.

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 (2017 to 2019).*
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). People with asthma and chronic obstructive pulmonary disease (COPD) are generally considered to be sensitive to the effects of ozone (Kehrl *et al.*, 1999; 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 is 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 (Lin *et al.*, 2008; Burnett *et al.*, 2001). Increases in ambient ozone have also been associated with higher mortality, particularly in the elderly, women and African Americans (Medina-Ramon, 2008).
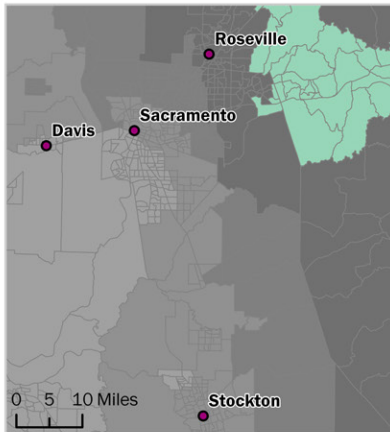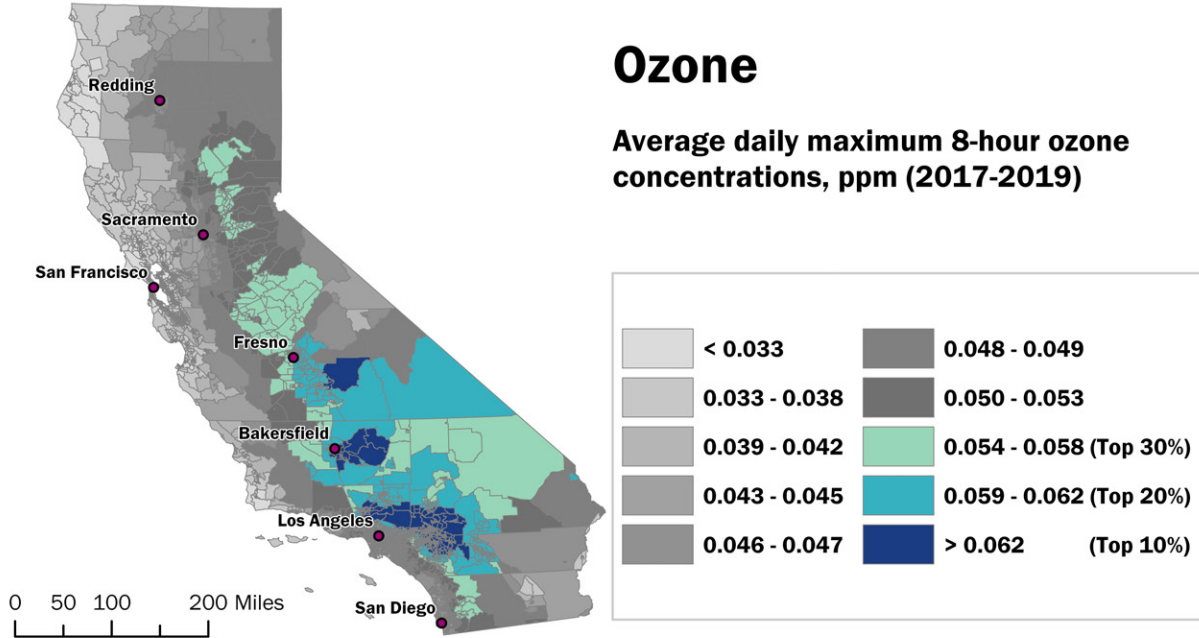
A California study found an association between ozone and asthma, acute respiratory infection, pneumonia, COPD, and upper respiratory tract inflammation emergency department visits, with particularly large associations during the warm season (Malig *et al.*, 2016). A study in New Mexico found an association 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).
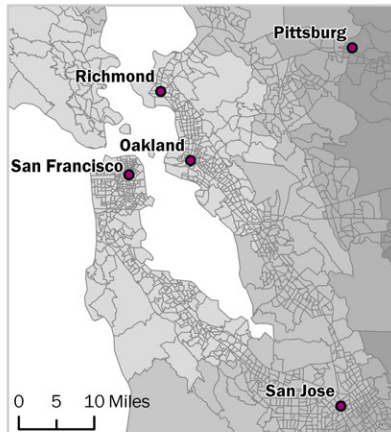
Method

- 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 2017-2019.

- The means of summer months (May-October) were calculated by averaging the daily maximum 8-hour ozone concentrations during those months over three years (2017 to 2019).

- 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 at census tracts with centers more than 50 km from the nearest monitor were not estimated using the model. For these tracts, the ozone value of the nearest air monitor was used.

- Census tracts were ordered by ozone concentration values and assigned a percentile based on the statewide distribution of values.
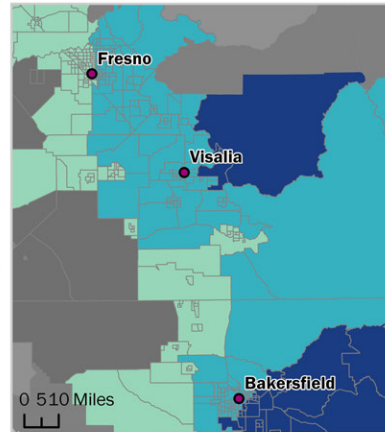
Ozone

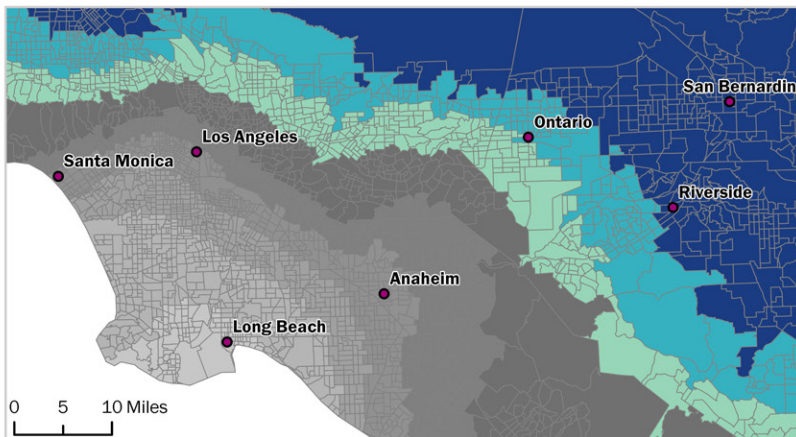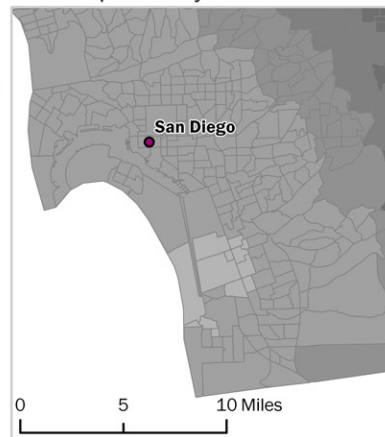## Average daily maximum 8-hour ozone concentrations, ppm (2017-2019)

< 0.033		0.048 - 0.049	
0.033 - 0.038		0.050 - 0.053	
0.039 - 0.042		0.054 - 0.058 (Top 30%)	
0.043 - 0.045		0.059 - 0.062 (Top 20%)	
0.046 - 0.047		> 0.062 (Top 10%)	

Redding

Sacramento

San Francisco

Fresno

Bakersfield

Los Angeles

San Diego

0   50 100   200 Miles

Roseville

Davis   Sacramento

Stockton

Sacramento Area

Pittsburg

Richmond

Oakland

San Francisco

San Jose

San Francisco Area

0   5   10 Miles

Fresno

Visalia

Bakersfield

San Joaquin Valley

0 5 10 Miles

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 4.0

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References

Alexis NE, Lay JC, Hazucha M, Harris B, Hernandez ML, Bromberg PA*, et al.* (2010). Low-level ozone exposure induces airways inflammation and modifies cell surface phenotypes in healthy humans. *Inhal Toxicol* **22**(7):593-600.

Crouse DL, Peters PA, Hystad P, Brook JR, van Donkelaar A, Martin RV*, et al.* (2015). Ambient PM2. 5, O3, and NO2 exposures and associations with mortality over 16 years of follow-up in the Canadian Census Health and Environment Cohort (CanCHEC). *Environl Health Perspect* **123**(11):1180-6.

Fann N, Lamson AD, Anenberg SC, Wesson K, Risley D, Hubbell BJ (2012). Estimating the national public health burden associated with exposure to ambient PM2.5 and ozone. *Risk Anal* **32**(1):81-95.

Gharibi H, Entwistle MR, Ha S, Gonzalez M, Brown P, Schweizer D*, et al.* (2019). Ozone pollution and asthma emergency department visits in the Central Valley, California, USA, during June to September of 2015: a time-stratified case-crossover analysis. *Journal of Asthma* **56**(10):1037-48.

Kehrl HR, Peden DB, Ball B, Folinsbee LJ, Horstman D (1999). Increased specific airway reactivity of persons with mild allergic asthma after 7.6 hours of exposure to 0.16 ppm ozone. *Journal of Allergy and Clinical Immunology* **104**(6):1198-204.

Last JA, Pinkerton KE, Schelegle ES (2017). Ozone and Oxidant Toxicity. In: *Respiratory Toxicology.* Elsevier Inc., pp. 389-402.

Lippmann M (1989). Health effects of ozone a critical review. *JAPCA* **39**(5):672-95.

Malig BJ, Pearson DL, Chang YB, Broadwin R, Basu R, Green RS*, et al.* (2016). A Time-Stratified Case-Crossover Study of Ambient Ozone Exposure and Emergency Department Visits for Specific Respiratory Diagnoses in California (2005-2008). *Environ Health Perspect* **124**(6):745-53.

Moore K, Neugebauer R, Lurmann F, Hall J, Brajer V, Alcorn S*, et al.* (2008). Ambient ozone concentrations cause increased hospitalizations for asthma in children: an 18-year study in Southern California. *Environ Health Perspect* **116**(8):1063-70.

Rodopoulou S, Chalbot M-C, Samoli E, DuBois DW, San Filippo BD, Kavouras IG (2014). Air pollution and hospital emergency room and admissions for cardiovascular and respiratory diseases in Doña Ana County, New Mexico. *Environmental Research* **129**(0):39-46.

Schelegle ES, Morales CA, Walby WF, Marion S, Allen RP (2009). 6.6-hour inhalation of ozone concentrations from 60 to 87 parts per billion in healthy humans. *Am J Respir Crit Care Med* **180**(3):265-72.

Thurston GD, Lippmann M, Scott MB, Fine JM (1997). Summertime haze air pollution and children with asthma. *American Journal of Respir and Critical Care Medicine* **155**(2):654-60.

Turner MC, Jerrett M, Pope III CA, Krewski D, Gapstur SM, Diver WR, *et al.* (2016). Long-term ozone exposure and mortality in a large prospective study. *American J Respir Crit Care Med* **193**(10):1134-42.

Wang T, Zhao B, Liou K-N, Gu Y, Jiang Z, Song K, *et al.* (2019). Mortality burdens in California due to air pollution attributable to local and nonlocal emissions. *Environment International* **133**:105232.

White MC, Etzel RA, Wilcox WD, Lloyd C (1994). Exacerbations of childhood asthma and ozone pollution in Atlanta. *Environmental Research* **65**(1):56-68.

Zanobetti A, Schwartz J (2011). Ozone and survival in four cohorts with potentially predisposing diseases. *Am J Respir Crit Care Med* **184**(7):836-41.

AIR QUALITY: PM2.5

Particulate matter pollution, and fine particle (PM2.5) pollution 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) have been considered in the development of health-based standards. Of the six criteria air pollutants, particulate matter and ozone 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 PM2.5 and other pollutants across the state.

Indicator	*Annual mean concentration of PM2.5 (weighted average of measured monitor concentrations and satellite observations, µg/m³), over three years (2015 to 2017).*
Data Source	*Air Monitoring Network, Satellite Remote Sensing Data; 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. 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.

The site information gathered from each air monitoring station audited by CARB includes maps, location coordinates, photos, pollutant concentrations, and surveys.

Satellite data are available for California from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the Aqua satellite. The satellite is polar-orbiting and retrieves time-series MODIS measurements for up to 16 days in each fixed 1 km grid. More information 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 into the lungs. Some fine particles have also been shown to enter the bloodstream. 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, 2019b).

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). In 2020, US EPA made the decision to retain the 2012 standard for ambient PM2.5 concentration of 12 μg/m^3 (US EPA, 2020). According to US EPA's Air Quality System databases, six of the ten counties nationwide with PM2.5 concentrations exceeding this standard are in California as of 2019 (US EPA, 2019a). Because adverse health effects are seen at concentrations below the US EPA's current standard, residents in more counties than these six could be facing health risks.

Many studies have shown that levels of PM2.5 exposure below the current US EPA standard can cause significant health impacts. Studies found that mortality was associated with long-term exposure to PM2.5 at relatively low levels (Crouse *et al.*, 2012; Wu *et al.*, 2020; Zeger *et al.*, 2008). In an open cohort of Medicare beneficiaries, increases in PM2.5 exposure even at lower levels (below 12 μg/m^3) were associated with a significant increase in the risk of death, especially among men, African Americans, and people with Medicaid eligibility (Di *et al.*, 2017). Both acute and chronic low-concentration PM2.5 exposures are associated with mortality (Shi *et al.*, 2016). The association between long-term PM2.5 exposure and mortality is also influenced by individual-level, neighborhood-level variables, temperature, and chemical composition (Wang *et al.*, 2017).

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). This reflects 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 (Liu *et al.*, 2019). Another recent 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 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 µg/m³ (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 study of six US communities, including Los Angeles, found an association between increased PM2.5 concentration and an increased risk of stroke (Adar *et al.*, 2013).

In children, researchers associated 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 relationships between daily PM2.5 and mortality (Ostro *et al.*, 2006), 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 work loss/restricted activity days (Ostro, 1983, 1987).

A study of prior year PM2.5 exposure in women found significant associations with biomarkers of inflammation that can indicate increased risk of cardiovascular disease (Green *et al.*, 2016). Exposure to PM during pregnancy has also been associated with low birth weight and premature birth (Bekkar *et al.*, 2020; Brauer *et al.*, 2008; Kloog *et al.*, 2012; Wu *et al.*, 2011). 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. During the wildfires that spread throughout the state in June 2008, PM2.5 concentrations at a site in the northeast San Joaquin Valley not only far exceeded air quality standards, but were also much more toxic than normal ambient PM2.5 (Wegesser *et al.*, 2009). 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). In addition, adverse health events increased even at slightly degraded air quality levels (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 (Lipsett *et al.*, 2008).
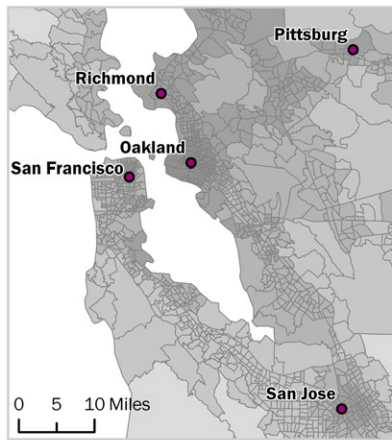
Method

- PM2.5 annual mean monitoring data were extracted for all monitoring sites in California from CARB's air monitoring network database for the years 2015-2017, with the exception of the special purpose monitor at San Ysidro where data were available only for 2015 and part of 2016. For San Ysidro, estimated 2015-2017 values were supplemented using regression relationships with nearby sites to estimate missing values.

- Satellite-based annual average PM2.5 concentrations were derived from Aerosol Optical Depth (AOD) measurements, land use and meteorology data via regression on ground level monitor data (Lee, 2019).

- Concentrations were estimated for each 1 km satellite grid cell. They were computed as a weighted average of the satellite-derived concentration and the concentrations of monitors within 50 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 measured monitor concentrations and grid cells further away receive higher weight from satellite estimates. Beyond 50 km from the nearest PM2.5 monitor, monitor concentrations are given weight zero and estimated concentrations are based solely on satellite data. Concentrations were estimated at the center of the 1×1 km grid layer.

- For the air monitor in Portola (Plumas County), California, satellite data were used for areas beyond 10 km from the Portola monitor due to the localized nature of the particulate pollution in Portola.

- Annual means were then computed for each year by averaging quarterly estimates and then averaging those over the three year period to avoid overrepresentation of the peak season because of uneven sampling frequency.

- Census tract estimates are calculated by taking the average of each grid cell value within a census tract boundary. All grid cell values that had a grid cell centroid point located within a census tract boundary contribute to the tract PM2.5 score. 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.
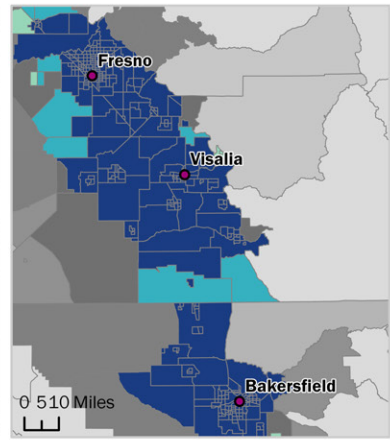
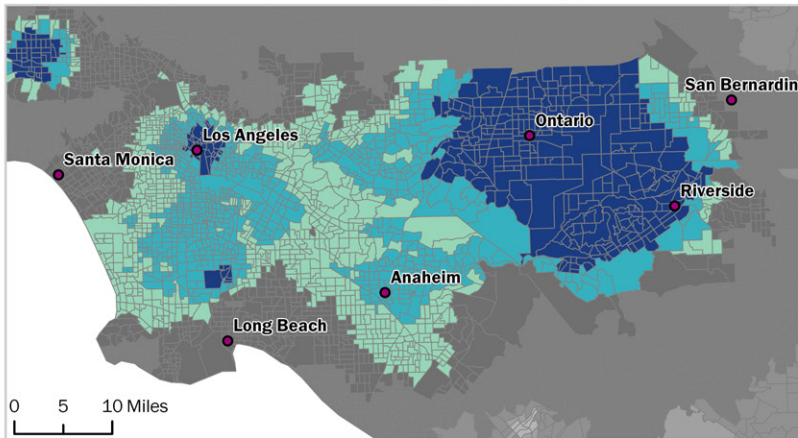# PM2.5

Annual mean PM2.5 concentration, μg/m3 (2015-2017)
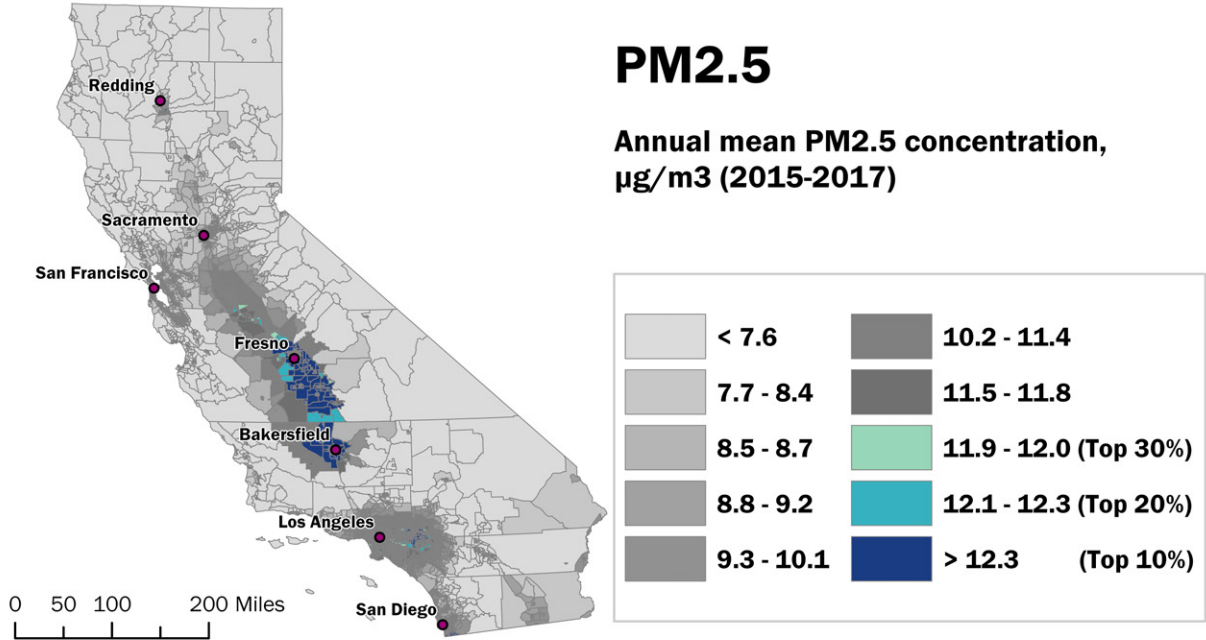
< 7.6	10.2 - 11.4
7.7 - 8.4	11.5 - 11.8
8.5 - 8.7	11.9 - 12.0 (Top 30%)
8.8 - 9.2	12.1 - 12.3 (Top 20%)
9.3 - 10.1	> 12.3 (Top 10%)

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

San Diego Area

CalEnviroScreen 4.0

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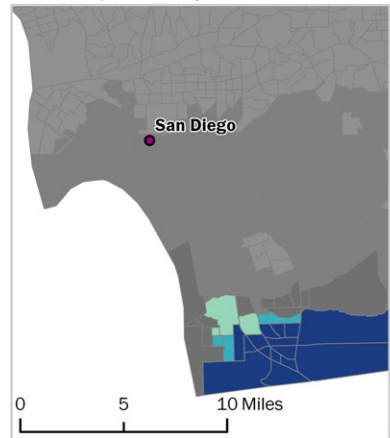
References

Adar SD, Sheppard L, Vedal S, Polak JF, Sampson PD, Diez Roux AV*, et al.* (2013). Fine particulate air pollution and the progression of carotid intima-medial thickness: a prospective cohort study from the multi-ethnic study of atherosclerosis and air pollution. *PLoS Med* **10**(4):e1001430.

Bekkar B, Pacheco S, Basu R, DeNicola N (2020). Association of Air Pollution and Heat Exposure With Preterm Birth, Low Birth Weight, and Stillbirth in the US: A Systematic Review. *JAMA Network Open* **3**(6):e208243-e.

Black C, Tesfaigzi Y, Bassein JA, Miller LA (2017). Wildfire smoke exposure and human health: Significant gaps in research for a growing public health issue. *Environmental Toxicology and Pharmacology* **55**:186-95.

Brauer M, Lencar C, Tamburic L, Koehoorn M, Demers P, Karr C (2008). A cohort study of traffic-related air pollution impacts on birth outcomes. *Environ Health Perspect* **116**(5):680-6.

Crouse DL, Peters PA, van Donkelaar A, Goldberg MS, Villeneuve PJ, Brion O*, et al.* (2012). Risk of nonaccidental and cardiovascular mortality in relation to long-term exposure to low concentrations of fine particulate matter: a Canadian national-level cohort study. *Environ Health Perspect* **120**(5):708-14.

Dabass A, Talbott EO, Rager JR, Marsh GM, Venkat A, Holguin F*, et al.* (2018). Systemic inflammatory markers associated with cardiovascular disease and acute and chronic exposure to fine particulate matter air pollution (PM2. 5) among US NHANES adults with metabolic syndrome. *Environmental Research* **161**:485-91.

Di Q, Wang Y, Zanobetti A, Wang Y, Koutrakis P, Choirat C*, et al.* (2017). Air pollution and mortality in the Medicare population. *N Engl J Med* **376**(26):2513-22.

Gauderman WJ, Avol E, Gilliland F, Vora H, Thomas D, Berhane K*, et al.* (2004). The effect of air pollution on lung development from 10 to 18 years of age. *N Engl J Med* **351**(11):1057-67.

Gauderman WJ, Urman R, Avol E, Berhane K, McConnell R, Rappaport E*, et al.* (2015). Association of improved air quality with lung development in children. *N Engl J Med* **372**:905-13.

Green R, Broadwin R, Malig B, Basu R, Gold EB, Qi L*, et al.* (2016). Long-and short-term exposure to air pollution and inflammatory/hemostatic markers in midlife women. *Epidemiology (Cambridge, Mass)* **27**(2):211.

Hutchinson JA, Vargo J, Milet M, French NH, Billmire M, Johnson J*, et al.* (2018). The San Diego 2007 wildfires and Medi-Cal emergency department presentations, inpatient hospitalizations, and outpatient

visits: An observational study of smoke exposure periods and a bidirectional case-crossover analysis. *PLoS medicine* **15**(7):e1002601.

IARC (2015). IARC monographs on the evaluation of carcinogenic risks to humans: vol. 109, outdoor air pollution. *Lyon, France: International Agency for Research on Cancer*.

Jones CG, Rappold AG, Vargo J, Cascio WE, Kharrazi M, McNally B, *et al.* (2020). Out-of-Hospital Cardiac Arrests and Wildfire-Related Particulate Matter During 2015–2017 California Wildfires. *JAMA* **9**(8):e014125.

Kloog I, Melly SJ, Ridgway WL, Coull BA, Schwartz J (2012). Using new satellite based exposure methods to study the association between pregnancy PM 2.5 exposure, premature birth and birth weight in Massachusetts. *Environmental Health* **11**(1):1-8.

Lee HJ (2019). Benefits of High Resolution PM2. 5 Prediction using Satellite MAIAC AOD and Land Use Regression for Exposure Assessment: California Examples. *Environmental Science & Technology* **53**(21):12774-83.

Li T, Zhang Y, Wang J, Xu D, Yin Z, Chen H, *et al.* (2018). All-cause mortality risk associated with long-term exposure to ambient PM2· 5 in China: a cohort study. *The Lancet Public Health* **3**(10):e470-e7.

Lipsett M, Materna B, Stone SL, Therriault S, Blaisdell R, Cook J (2008). Wildfire Smoke: A Guide for Public Health Officials (pp. 53).

Liu C, Chen R, Sera F, Vicedo-Cabrera AM, Guo Y, Tong S, *et al.* (2019). Ambient particulate air pollution and daily mortality in 652 cities. *N Engl J Med* **381**(8):705-15.

Ostro B, Broadwin R, Green S, Feng WY, Lipsett M (2006). Fine particulate air pollution and mortality in nine California counties: results from CALFINE. *Environ Health Perspect* **114**(1):29-33.

Ostro B, Roth L, Malig B, Marty M (2009). The effects of fine particle components on respiratory hospital admissions in children. *Environ Health Perspect* **117**(3):475-80.

Ostro BD (1983). The effects of air pollution on work loss and morbidity. *Journal of Environmental Economics and Management* **10**(4):371-82.

Ostro BD (1987). Air pollution and morbidity revisited: a specification test. *Journal of Environmental Economics and Management* **14**(1):87-98.

Paul LA, Burnett RT, Kwong JC, Hystad P, van Donkelaar A, Bai L, *et al.* (2020). The impact of air pollution on the incidence of diabetes

and survival among prevalent diabetes cases. *Environment international* **134**:105333.

Pope CA, 3rd (2009). The expanding role of air pollution in cardiovascular disease: does air pollution contribute to risk of deep vein thrombosis? *Circulation* **119**(24):3050-2.

Rajagopalan S, Al-Kindi SG, Brook RD (2018). Air pollution and cardiovascular disease: JACC state-of-the-art review. *Journal of the American College of Cardiology* **72**(17):2054-70.

Rao X, Montresor-Lopez J, Puett R, Rajagopalan S, Brook RD (2015). Ambient air pollution: an emerging risk factor for diabetes mellitus. *Current Diabetes Reports* **15**(6):1-11.

Reid CE, Considine EM, Watson GL, Telesca D, Pfister GG, Jerrett M (2019). Associations between respiratory health and ozone and fine particulate matter during a wildfire event. *Environment International* **129**:291-8.

Salihu HM, Ghaji N, Mbah AK, Alio AP, August EM, Boubakari I (2012). Particulate pollutants and racial/ethnic disparity in feto-infant morbidity outcomes. *Maternal and Child Health Journal* **16**(8):1679-87.

Shi L, Zanobetti A, Kloog I, Coull BA, Koutrakis P, Melly SJ*, et al.* (2016). Low-concentration PM2. 5 and mortality: estimating acute and chronic effects in a population-based study. *Environ Health Perspect* **124**(1):46-52.

US EPA (2019a). Air Quality Statistics by County [internet database] available via https://www.epa.gov/air-trends/air-quality-cities-and-counties. Accessed September 17, 2020.

US EPA (2019b). *Integrated Science Assessment (ISA) for Particulate Matter (Final Report, 2019)*. Washington, DC: U.S. Environmental Protection Agency

US EPA (2020). EPA Proposes to Retain NAAQS for Particulate Matter: News Releases from Headquarters, Air and Radiation (OAR).

Wang T, Zhao B, Liou K-N, Gu Y, Jiang Z, Song K*, et al.* (2019). Mortality burdens in California due to air pollution attributable to local and nonlocal emissions. *Environment International* **133**:105232.

Wang Y, Shi L, Lee M, Liu P, Di Q, Zanobetti A*, et al.* (2017). Long-term exposure to PM2. 5 and mortality among older adults in the southeastern US. *Epidemiology (Cambridge, Mass)* **28**(2):207.

Wegesser TC, Pinkerton KE, Last JA (2009). California wildfires of 2008: coarse and fine particulate matter toxicity. *Environ Health Perspect* **117**(6):893-7.

Wei Y, Wang Y, Di Q, Choirat C, Wang Y, Koutrakis P*, et al.* (2019). Short term exposure to fine particulate matter and hospital admission risks and costs in the Medicare population: time stratified, case crossover study. *BMJ* **367**.

Wettstein ZS, Hoshiko S, Fahimi J, Harrison RJ, Cascio WE, Rappold AG (2018). Cardiovascular and cerebrovascular emergency department visits associated with wildfire smoke exposure in California in 2015. *JAMA* **7**(8):e007492.

Wilhelm M, Ghosh JK, Su J, Cockburn M, Jerrett M, Ritz B (2012). Traffic-related air toxics and term low birth weight in Los Angeles County, California. *Environ Health Perspect* **120**(1):132-8.

Wu J, Wilhelm M, Chung J, Ritz B (2011). Comparing exposure assessment methods for traffic-related air pollution in an adverse pregnancy outcome study. *Environmental Research* **111**(5):685-92.

Wu X, Braun D, Schwartz J, Kioumourtzoglou M, Dominici F (2020). Evaluating the impact of long-term exposure to fine particulate matter on mortality among the elderly. *Science Advances* **6**(29):eaba5692.

Zeger SL, Dominici F, McDermott A, Samet JM (2008). Mortality in the Medicare population and chronic exposure to fine particulate air pollution in urban centers (2000–2005). *Environ Health Perspect* **116**(12):1614-9.

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 and non-road sources 2016 (tons/year).

Data Source

EMission FACtors (EMFAC) model2017, the 2016 CEPAMv1.05 Inventory for criteria pollutants, and the California Emissions Inventory Development and Reporting System (CEIDARS) 2012 database, 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 source of diesel PM. Nevertheless, it is a reasonable regional metric of exposure to diesel PM emissions. Data available at the links below:

http://www.arb.ca.gov/diesel
http://www.arb.ca.gov/msei/modeling.htm
https://ww2.arb.ca.gov/emission-inventory-data
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. The diesel PM indicator is distinct from

other air pollution indicators in CalEnviroScreen, such as PM2.5 generated from non-diesel sources. Diesel engine exhaust has been classified as carcinogenic to humans by the International Agency for Research on Cancer 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; NTP, 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 lung (Löndahl *et al.*, 2012). The ultrafine fraction of diesel PM (aerodynamic diameter less than 0.1 µm) is of 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 (McCreanor *et al.*, 2007; Wargo *et al.*, 2002). 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.*, 2013; Spira-Cohen *et al.*, 2011). Diesel exposure may also lead to reduced lung function in children living in close proximity to roadways (Brunekreef *et al.*, 1997).

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). 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; NTP, 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.*, 2012; Garshick *et al.*, 2008). The same trend was seen among railroad workers, who showed a 40% increased risk of lung cancer (Garshick, 2020; Garshick *et al.*, 2004). 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).

Method

Gridded diesel PM emissions from on-road sources were calculated for a typical summer week in July as follows:

- CARB's on-road emissions model, EMFAC2017, was used to calculate county-wide estimates of diesel PM emissions for each representative day of the summer week and multiplied by the total number of days for the corresponding day of the week in 2016. The average day emissions reported in this layer is the sum of the above emissions divided by the total number of days in 2016. The average day emissions are multiplied by 365 to represent a yearly average.

- EMFAC2017 county-wide emission estimates are spatially distributed to 1×1 km grid cells based on the distribution of regional vehicle activity. Transportation networks are produced from travel demand modeling conducted by metropolitan planning organizations, local agencies and Caltrans.

Gridded diesel PM from non-road sectors is based on CEPAMv1.05 for a 2016 year except for the stationary source sector, which comes from a 2012 CEIDARS database which contains information relevant to the AB 2588 Air Toxics "Hot Spots" Program. These two sectors were spatially allocated using the Sparse Matrix Operator Kerner Emissions (SMOKE) Modeling System.

- Area source sector emissions are spatially distributed to 1×1 km grid cells 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 source sector emissions are spatially distributed to 1×1 km grid cells based on the latitude and longitude of the emitting stack or facility.

- The Ocean going vessel (OGV) sector was obtained in gridded format. Pre-gridded at 1km resolution, the OGV data were based on CEPAMv1.05.
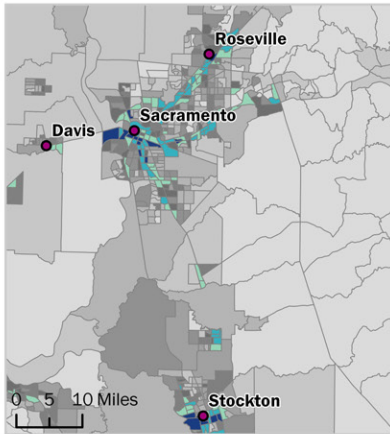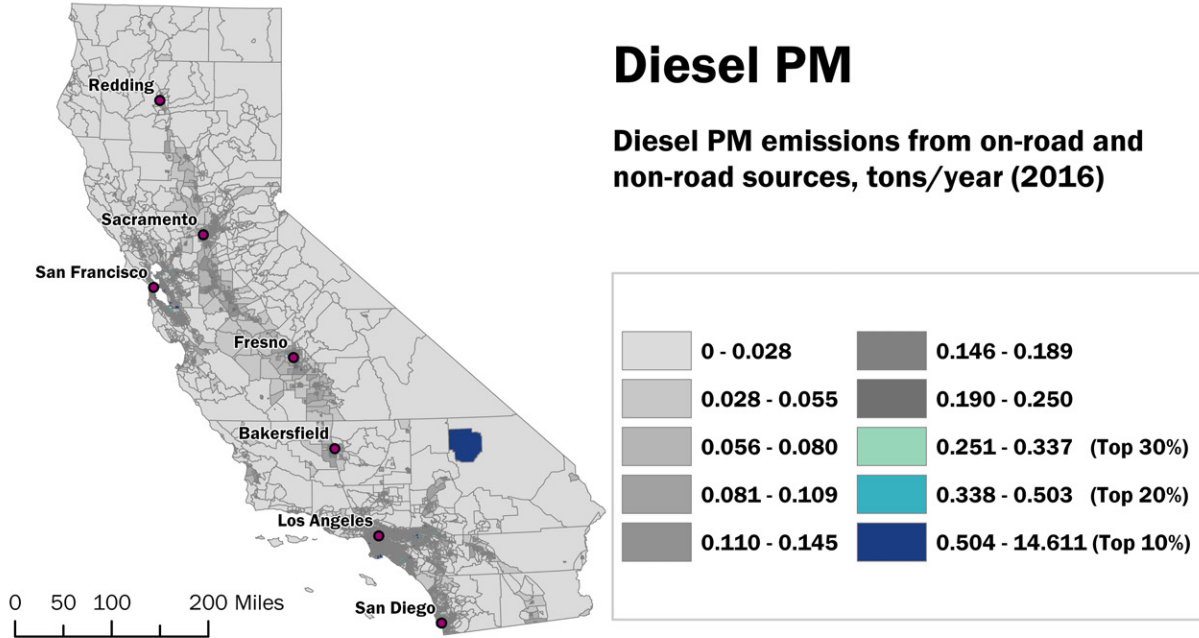
Adjustment for emissions at the US-Mexico border:

- 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, CARB compared the results of its gridded diesel PM calculation with estimated diesel PM measurements from San Diego and Imperial County air monitors using measured nitrogen oxides (NOX) as a surrogate. Emissions in the Calexico area of Imperial County were adjusted higher based on additional air monitoring data showing cross-border pollution impacts.

- Comparison with other NOx monitors in the area suggested that the emissions in the Calexico area underestimate the true impacts of diesel PM by a factor of 2.7. Accordingly, emissions for Calexico were multiplied by 2.7. The NOx concentrations in San Diego County matched the estimated diesel PM emissions more closely and did not require any adjustment.

Resulting gridded emission estimates from the on-road and non-road 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 to contribute the weight of that grid cell value. Weighted values were then summed across the census tract. The estimates for diesel PM for census tracts were sorted and assigned percentiles based on their position in the distribution.
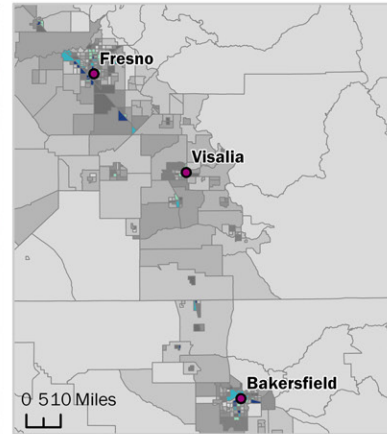
Diesel PM

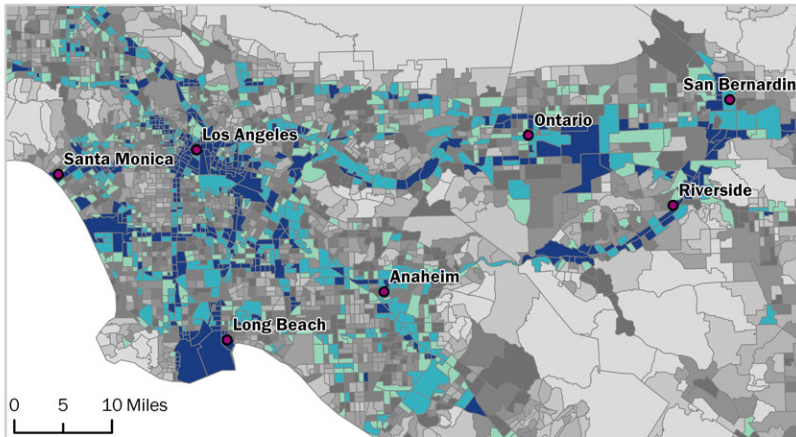**Diesel PM emissions from on-road and non-road sources, tons/year (2016)**
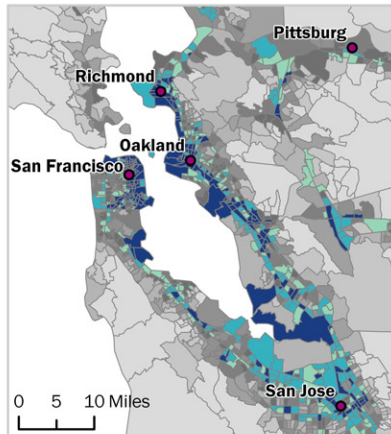
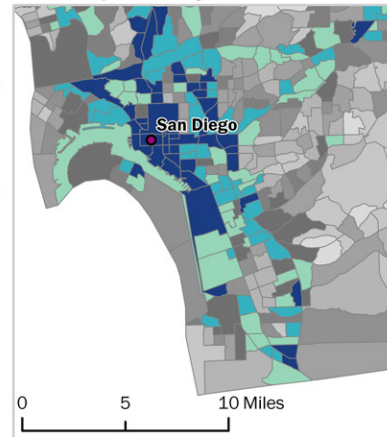|			
	0 - 0.028		0.146 - 0.189
	0.028 - 0.055		0.190 - 0.250
	0.056 - 0.080		0.251 - 0.337 (Top 30%)
	0.081 - 0.109		0.338 - 0.503 (Top 20%)
	0.110 - 0.145		0.504 - 14.611 (Top 10%)

0 50 100   200 Miles

Sacramento Area

0   5   10 Miles

San Francisco Area

0   5   10 Miles

San Joaquin Valley

0 5 10 Miles

Greater Los Angeles Area

0   5   10 Miles

CalEnviroScreen 4.0

San Diego Area

0   5   10 Miles

References

Betha R, Balasubramanian R (2013). Emissions of particulate-bound elements from biodiesel and ultra low sulfur diesel: size distribution and risk assessment. *Chemosphere* **90**(3):1005-15.

Brunekreef B, Janssen NA, de Hartog J, Harssema H, Knape M, van Vliet P (1997). Air pollution from truck traffic and lung function in children living near motorways. *Epidemiology* **8**(3):298-303.

Garshick E, Hart, J.E. (2020). DIESEL EXHAUST AND LUNG CANCER RISK. In: *Environmental Toxicants.* pp. 515-33.

Garshick E, Laden F, Hart JE, Davis ME, Eisen EA, Smith TJ (2012). Lung cancer and elemental carbon exposure in trucking industry workers. *Environ Health Perspect* **120**(9):1301-6.

Garshick E, Laden F, Hart JE, Rosner B, Davis ME, Eisen EA*, et al.* (2008). Lung cancer and vehicle exhaust in trucking industry workers. *Environ Health Perspect* **116**(10):1327-32.

Garshick E, Laden F, Hart JE, Rosner B, Smith TJ, Dockery DW*, et al.* (2004). Lung cancer in railroad workers exposed to diesel exhaust. *Environ Health Perspect* **112**(15):1539-43.

Hart JE, Laden F, Eisen EA, Smith TJ, Garshick E (2009). Chronic obstructive pulmonary disease mortality in railroad workers. *Occupational and Environmental Medicine* **66**(4):221-6.

IARC (2014). DIESEL AND GASOLINE ENGINE EXHAUSTS AND SOME NITROARENES. IARC MONOGRAPHS ON THE EVALUATION OF CARCINOGENIC RISKS TO HUMANS. *IARC Monographs on the Evaluation of Carcinogenic Risks to Humans* **105**:9.

Krishnan RM, Sullivan JH, Carlsten C, Wilkerson HW, Beyer RP, Bammler T*, et al.* (2013). A randomized cross-over study of inhalation of diesel exhaust, hematological indices, and endothelial markers in humans. *Part Fibre Toxicol* **10**:7.

Krivoshto IN, Richards JR, Albertson TE, Derlet RW (2008). The toxicity of diesel exhaust: implications for primary care. *J Am Board Fam Med* **21**(1):55-62.

Liati A, Schreiber D, Dasilva YAR, Eggenschwiler PD (2018). Ultrafine particle emissions from modern Gasoline and Diesel vehicles: An electron microscopic perspective. *Environmental Pollution* **239**:661-9.

Löndahl J, Swietlicki E, Rissler J, Bengtsson A, Boman C, Blomberg A*, et al.* (2012). Experimental determination of the respiratory tract deposition of diesel combustion particles in patients with chronic obstructive pulmonary disease. *Part Fibre Toxicol* **9**:30.

McCreanor J, Cullinan P, Nieuwenhuijsen MJ, Stewart-Evans J, Malliarou E, Jarup L*, et al.* (2007). Respiratory effects of exposure to

diesel traffic in persons with asthma. *N Engl J Med* **357**(23):2348-58.

Nemmar A, Al-Maskari S, Ali BH, Al-Amri IS (2007). Cardiovascular and lung inflammatory effects induced by systemically administered diesel exhaust particles in rats. *Am J Physiol Lung Cell Mol Physiol* **292**(3):L664-70.

NTP (2016). 14th Report on Carcinogens, National Toxicology Program. *US Department of Health and Human Services*, from https://ntp.niehs.nih.gov/pubhealth/roc/index-1.html

Patel MM, Chillrud SN, Deepti KC, Ross JM, Kinney PL (2013). Traffic-related air pollutants and exhaled markers of airway inflammation and oxidative stress in New York City adolescents. *Environ Res* **121**:71-8.

Quintana PJ, Ganster P, Stigler Granados PE, Muñoz-Meléndez G, Quintero-Núñez M, Rodríguez-Ventura JG (2015). Risky borders: traffic pollution and health effects at US–Mexican ports of entry. *Journal of Borderlands Studies* **30**(3):287-307.

Spira-Cohen A, Chen LC, Kendall M, Lall R, Thurston GD (2011). Personal exposures to traffic-related air pollution and acute respiratory health among Bronx schoolchildren with asthma. *Environ Health Perspect* **119**(4):559-65.

US EPA (2002). Health Assessment Document For Diesel Engine Exhaust. EPA/600/8-90/057F, 2002.

Vermeulen R, Silverman DT, Garshick E, Vlaanderen J, Portengen L, Steenland K (2014). Exposure-response estimates for diesel engine exhaust and lung cancer mortality based on data from three occupational cohorts. *Environ Health Perspect* **122**(2):172-7.

Wargo J, Brown D, Cullen MR (2002). *Children's exposure to diesel exhaust on school buses*ed.: Environment & Human Health, Inc.

DRINKING WATER CONTAMINANTS

Californians receive their drinking water from a wide variety of sources and distribution systems. An estimated 98% of Californians received their water from public sources in 2013 (SOR, 2015), 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. In 2018, 95% of public water systems, serving approximately 88% of Californians, delivered water that met all federal and state drinking water standards (SWRCB, 2018).

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 (Kolpin *et al.*, 2002; Stoiber *et al.*, 2019).

California water systems have a high rate of compliance with drinking water standards. In 2017, systems serving an estimated 1.6 percent of the state's population were in violation of one or more federal drinking water standards (SWRCB, 2018). The drinking water contaminant index in CalEnviroScreen 4.0 is not a measure of compliance with these or California's state standards. The drinking water contaminant index is a combination of contaminant data that takes into account the relative concentrations of different contaminants and whether multiple contaminants are present. The indicator does not indicate whether water is safe to drink.

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 one compliance cycle (2011-2019). Therefore, those average concentrations may not be representative of current concentrations in treated drinking water. The indicator results do not provide a basis for determining when differences between scores are significant in relation to human health. 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. For a location within a census tract, more specific local water quality data may be available from the public water system serving that area. Public water systems are required to prepare annual Consumer Confidence Reports that provide detailed, system-specific information on water quality, health impacts and compliance with drinking water standards. These Consumer Confidence Reports provide drinking water quality information directly to the public. The

US Environmental Protection Agency offers guidance on finding water quality data in California: http://water.epa.gov/drink/local/ca.cfm

Indicator	*Drinking water contaminant index for selected contaminants (2011 to 2019)*

Data Source

Water Boundary Tool – Tracking California

Community water system and state small water system service area boundaries were extracted from the Water Boundary Tool. Although the mapping tool was retired on July 1, 2020, it was the most complete tool for system boundaries at the time of updating this indicator. The website is at the link below.

https://trackingcalifornia.org/water-boundary-tool/water-boundary-tool-landing

Sections and Townships - Public Land Survey System

Sections (approximately 1 by 1 mile grid) and townships (6 by 6 mile grid) were used to characterize ambient groundwater quality in areas outside of community and state small water systems. The layer is based on the PLSNET layer that the Department of Pesticide Regulation hosts and is provided in the link below.

https://gis.water.ca.gov/arcgis/rest/services/Environment/i07_Well CompletionReports/FeatureServer/1

High-Resolution Populated Areas Map of California (Pace et al., 2013)

Water system and section boundaries were intersected with a high-resolution map layer of residential or parcel areas within census blocks. The population estimate for each census block or portion of block was used in calculating water quality estimates at the census tract level.

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 and types of facilities and sampling points within the distribution system. Additionally, MCL violations, TCR violations and sample results from the Lead and Copper Rule were extracted from this database. The data are available through request.

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

Drinking water monitoring data reported from laboratories were extracted from this database. The data are available at the link below.
https://www.waterboards.ca.gov/drinking_water/certlic/drinkingwater/EDTlibrary.html

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 8 GAMA projects to characterize areas outside of community and state small water system service boundaries.

- Monitoring Wells (Water Board Regulated Sites)

- Local Groundwater Projects

- Public Water System Wells

- Department of Water Resource

- GAMA - Domestic Wells

- National Water Information System (NWIS)

- GAMA – Priority Basin Project

- GAMA – Special Studies

The link to the mapping tool is below.

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

GAMA Aquifer Risk Map Depth Filter Dataset

A depth filter was applied to ambient groundwater data in order to capture well depths most similar to domestic wells using the dataset:
https://gispublic.waterboards.ca.gov/portal/home/item.html?id=55258176731a4cefb24fc571d8136276

Rationale

Low income and rural communities, particularly those served by small community water systems, can be disproportionately exposed to contaminants in their drinking water (Balazs *et al.*, 2011; VanDerslice, 2011). 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).

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.*, 2010). 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). It has also been found that communities with more low 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). 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).

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; NTP, 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

A drinking water contaminant metric was calculated for each census tract through four broad steps (detailed more fully below):

1. Drinking water system boundaries and townships were downloaded and cleaned.

2. Average concentrations for each contaminant were calculated and associated with each water system and township.

3. The systems' and townships' average water contaminant concentrations were re-allocated from the associated boundaries to census tracts. The census tracts were then ranked to obtain a percentile score for each contaminant and tract.

4. A census tract contaminant index was calculated as the sum of the percentiles for all contaminants.

Drinking Water System Boundaries

- Water system boundaries were downloaded from Tracking California's Water Boundary Tool. The 2,933 water systems in this set comprise all community water systems and about 90 state small water systems.

- For areas without known water systems and source locations, township boundaries from the Public Land Survey System (approximately 6 miles square) were treated as the boundaries for the purpose of assigning water quality to people living in that area. It is assumed that people living in these areas drink water from very small water systems (under 15 connections) or from private wells.

Drinking Water Contaminant Metric Calculation

- A subset of contaminants tested in drinking water across California was selected for the analysis (see Appendix) based on a set of criteria, such as frequency of tests, detections in drinking water and toxicity concerns. Monitoring data for these chemicals were obtained from SWRCB's Water Quality Monitoring database from 2011-2019, the most recent 9-year compliance cycle.

- Data from the Lead and Copper Rule (LCR) were used to evaluate lead contamination during the same time period. 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. For areas outside of water systems, lead sample results were averaged by drinking water well first and then the 90th percentiles of the well concentrations within each township were calculated.

- Water quality data representing treated/delivered water were associated with their water system first. If no treated/delivered water quality data for a system was available, but the system purchased water from wholesalers, the wholesaler's water quality was associated with the system. If no treated/delivered water data were reported in that time period for a given contaminant and system, water quality data from untreated or raw sources were used for that contaminant and system.

- For large water systems serving more than 20,000 people that rely on local sources of water and purchase water from wholesalers, the fraction of water that was purchased was identified from publicly available information (e.g., water quality reports). If no information was found on fraction purchased, it was assumed that half of the water was purchased (including all systems serving less than 20,000 people that purchase water from wholesalers).

- 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 chemical in each system. If purchased water from wholesalers was included, the calculation was adjusted by the fraction purchased.

- Water quality for areas outside of system service areas were characterized by 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 of system service areas were assigned an average groundwater quality data by PLSS section. First, an average water quality was calculated for sections with wells that have data. Then, an average of wells in neighboring sections with data were used for sections without data. Lastly, sections still without data were assigned the average of the township that the sections were within (ambient groundwater data from 8 GAMA sources).

- Violations of the Maximum Contamination Level (MCL) for any chemical contaminant and Total Coliform rule were also summed for each water system, serving as a basis for a "violation index." A system's number of lead action level exceedances (from the Lead and Copper Rule) was added to MCL violations.
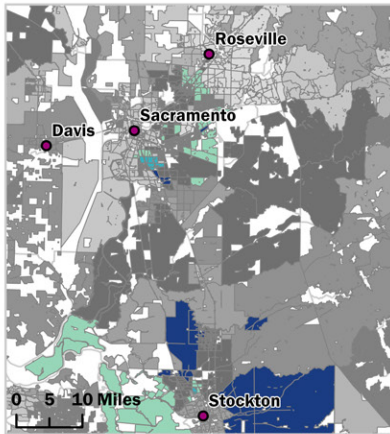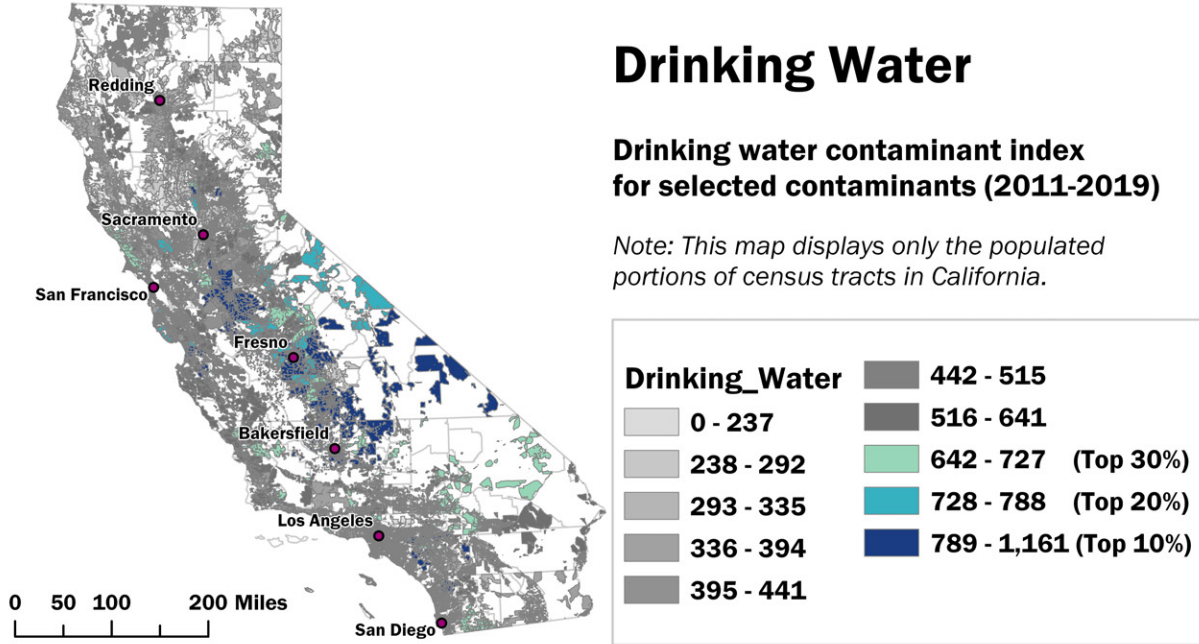
Re-allocation from Water System Boundaries to Census Tracts

- Residential areas from a high-resolution populated census block file (see data sources) were assigned the contaminant concentration or violation index of the systems in which they fell. Partial census blocks were apportioned by area.

- Census tract concentration estimates for each contaminant were calculated as the population-weighted sum of the contaminant concentration for the census blocks (or partial blocks) within the tract. Violation index data were similarly calculated.

- The census tracts were ordered by the value of their contaminant concentrations or violation index. Percentiles were calculated.

- The overall drinking water contaminant score for a census tract is the sum of its percentiles for all contaminants and violations.

Drinking Water

Drinking water contaminant index for selected contaminants (2011-2019)

Note: This map displays only the populated portions of census tracts in California.
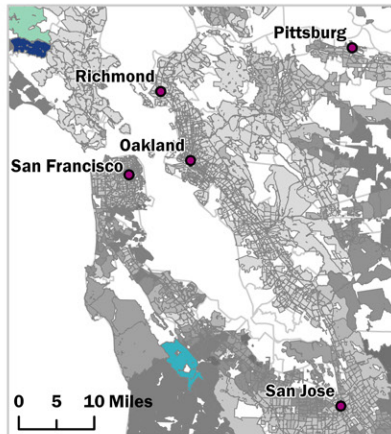
Drinking_Water

- 0 - 237
- 238 - 292
- 293 - 335
- 336 - 394
- 395 - 441
- 442 - 515
- 516 - 641
- 642 - 727 (Top 30%)
- 728 - 788 (Top 20%)
- 789 - 1,161 (Top 10%)

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

61
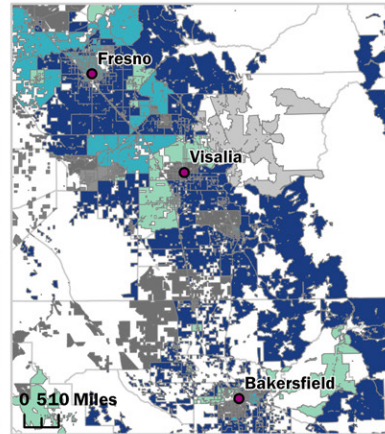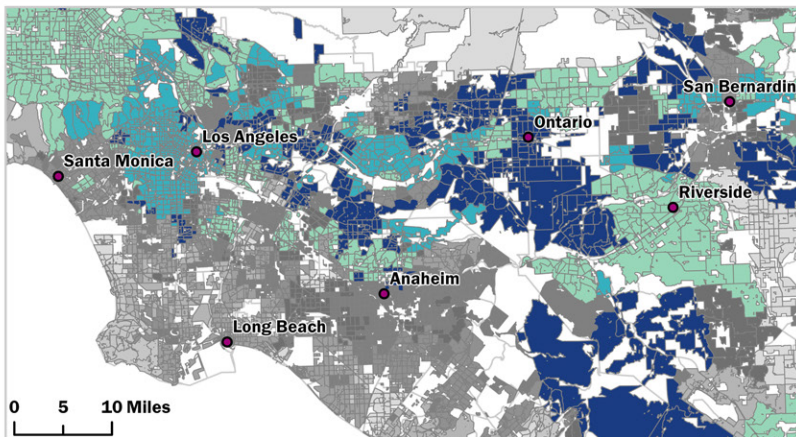
References

Allaire M, Wu H, Lall U (2018). National trends in drinking water quality violations. *Proceedings of the National Academy of Sciences* **115**(9):2078-83.

ATSDR (1997). *Toxicological profile for chloroform*. Agency for Toxic Substances and Disease Registry, U.S. Department of Health and Human Services, Atlanta, GA. Available from: http://www.atsdr.cdc.gov/toxprofiles/tp6.pdf.

ATSDR (2020). *Toxicological Profile for Lead*: Agency for Toxic Substances and Disease Registry, U.S. Department of Health and Human Services, Atlanta, GA. Available from: https://www.atsdr.cdc.gov/toxprofiles/tp13.pdf.

Balazs C, Morello-Frosch R, Hubbard A, Ray I (2011). Social Disparities in Nitrate Contaminated Drinking Water in California's San Joaquin Valley. *Environ Health Perspect*.**119** (9): 1272-1278

Balazs CL, Morello-Frosch R, Hubbard AE, Ray I (2012). Environmental justice implications of arsenic contamination in California's San Joaquin Valley: a cross-sectional, cluster-design examining exposure and compliance in community drinking water systems. *Environ Health* **11**:84.

Bellinger D, Needleman HL, Bromfield R, Mintz M (1984). A followup study of the academic attainment and classroom behavior of children with elevated dentine lead levels. *Biological Trace Element Research* **6**(3):207-23.

Cantor KP, Villanueva CM, Silverman DT, Figueroa JD, Real FX, Garcia-Closas M*, et al.* (2010). Polymorphisms in GSTT1, GSTZ1, and CYP2E1, disinfection by-products, and risk of bladder cancer in Spain. *Environ Health Perspect* **118**(11):1545-50.

Colli JL, Kolettis PN (2010). Bladder cancer incidence and mortality rates compared to ecologic factors among states in America. *International Urology and Nephrology* **42**(3):659-65.

Dietrich KN (1999). Environmental chemicals and child development. *The Journal of Pediatrics* **134**(1):7-9.

Fram MS, Belitz K (2011). Probability of detecting perchlorate under natural conditions in deep groundwater in California and the southwestern United States. *Environ Sci Technol* **45**(4):1271-7.

Hershman JM (2005). Perchlorate and thyroid function: what are the environmental issues? *Thyroid* **15**(5):427-31.

Huber DR, Blount BC, Mage DT, Letkiewicz FJ, Kumar A, Allen RH (2011). Estimating perchlorate exposure from food and tap water based on US biomonitoring and occurrence data. *J Expo Sci Environ Epidemiol* **21**(4):395-407.

Kolpin DW, Furlong ET, Meyer MT, Thurman EM, Zaugg SD, Barber LB, *et al.* (2002). Pharmaceuticals, hormones, and other organic wastewater contaminants in US streams, 1999– 2000: A national reconnaissance. *Environmental science & Technology* **36**(6):1202-11.

Lanphear BP, Hornung R, Khoury J, Yolton K, Baghurst P, Bellinger DC, *et al.* (2005). Low-level environmental lead exposure and children's intellectual function: an international pooled analysis. *Environ Health Perspect* **113**(7):894-9.

Lockhart KM, King AM, Harter T (2013). Identifying sources of groundwater nitrate contamination in a large alluvial groundwater basin with highly diversified intensive agricultural production. *J Contam Hydrol* **151**:140-54.

Marcillo CE, Krometis LAH (2019). Small towns, big challenges: does rurality influence Safe Drinking Water Act compliance? *AWWA Water Science* **1**(1):e1120.

NTP (2012). Monograph on Health Effects of Low-Level Lead. *National Toxicology Program, U.S. Department of Health and Human Services*, from https://ntp.niehs.nih.gov/ntp/ohat/lead/final/monographhealtheffe ctslowlevellead_newissn_508.pdf

NTP (2016). 14th Report on Carcinogens, National Toxicology Program. *US Department of Health and Human Services*, from https://ntp.niehs.nih.gov/pubhealth/roc/index-1.html

Pace C, Balazs C, Bangia K, Depsky N, Renteria A, Morello-Frosch R, Cushing L (2021). Advancing California's Human Right to Water: Characterizing inequities in drinking water quality among domestic well communities and community water systems [Manuscript submitted for publication].

Richardson SD, Postigo C (2011). Drinking water disinfection by-products. In: *Emerging organic contaminants and human health.* Springer, pp. 93-137.

Ruckart PZ, Henderson AK, Black ML, Flanders WD (2007). Are nitrate levels in groundwater stable over time? *J Expos Sci Environ Epidemiol* **18**(2):129-33.

SOR (2015). *The Water We Drink, Part I: What is California Doing to Ensure Its Water is Safe?* California Senate Office of Research. Available from: https://sor.senate.ca.gov/sites/sor.senate.ca.gov/files/FINAL%20dr aft%20Part%201%20Drinking%20Water.pdf.

Steinmaus C, Miller MD, Smith AH (2010). Perchlorate in drinking water during pregnancy and neonatal thyroid hormone levels in California. *J Occup Environ Med* **52**(12):1217-524.

Steinmaus CM, Ferreccio C, Romo JA, Yuan Y, Cortes S, Marshall G*, et al.* (2013). Drinking water arsenic in northern chile: high cancer risks 40 years after exposure cessation. *Cancer Epidemiol Biomarkers Prev* **22**(4):623-30.

Stoiber T, Temkin A, Andrews D, Campbell C, Naidenko OV (2019). Applying a cumulative risk framework to drinking water assessment: a commentary. *Environmental Health* **18**(1):1-8.

SWRCB (2018). *2018 Annual Compliance Report* California Drinking Water Program. Available from: https://www.waterboards.ca.gov/drinking_water/certlic/drinkingwater/documents/dwdocuments/acr_2018_final_20191220.pdf.

US EPA (2019). Basic Information about Lead in Drinking Water. from https://www.epa.gov/ground-water-and-drinking-water/basic-information-about-lead-drinking-water#main-content

VanDerslice J (2011). Drinking water infrastructure and environmental disparities: evidence and methodological considerations. *Am J Public Health* **101 Suppl 1**:S109-14.

Wallsten S, Kosec K (2005). Public or private drinking water? The effects of ownership and benchmark competition on US water system regulatory compliance and household water expenditures. *The Effects of Ownership and Benchmark Competition on US Water System Regulatory Compliance and Household Water Expenditures (March 2005) AEI-Brookings Joint Center Working Paper* (05-05).

Appendix

Contaminants Evaluated

Contaminant	Unit	MCL	PHG	DL
1,2,3-Trichloropropane*	UG/L	0.005	0.0007	0.005
Arsenic	UG/L	10	0.004	2
Cadmium	UG/L	5	0.04	1
Dibromochloropropane (DBCP)	UG/L	0.2	0.0017	0.01
Gross Alpha	PCI/L	15		3
Lead (Lead and Copper Rule)**	UG/L	15	0.2	5
Nitrate as N	MG/L	10	10	0.4
Perchlorate	UG/L	6	1	4
Chromium, Hexavalent	UG/L		0.02	1
Ethylene Dibromide (EDB)	UG/L	0.05	0.01	0.02
Total Haloacetic Acids (HAAs)	UG/L	60		0
Tetrachloroethylene (PCE)	UG/L	5	0.06	0.5
Total Trihalomethanes (THM)	UG/L	80		1
Trichloroethylene (TCE)	UG/L	5	1.7	0.5

*Action Level established under the Lead and Copper Rule (LCR).
**Notification level

Violation Types Evaluated

Violation Type
MCL Violations + LCR Action Level Exceedances
Total Coliform Rule Violations

CHILDREN'S LEAD RISK FROM HOUSING

Exposure to lead through paint is the most significant source of lead exposure for children (CDC, 2019b). 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.

Data on elevated blood lead levels (BLLs) in children is limited because universal testing of children for lead is not required in California. However, factors such as age of housing, income, race, and enrollment in public assistance programs have been significantly associated with EBLLs and have been used to screen for places where children may be at high risk for lead exposure. Data exists for two of the most significant measures of 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 stock, though it is not a measure of true exposure to lead in a community. 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.

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 (2017 California parcel data and 5-year estimates 2015-2019) combined with the percentage of households that are both low-income (household income less than 80% of the county median family income) and have children under 6 years old (5-year estimates 2013-2017).
Data Source	*California Residential Parcel Data – Digital Map Products*
	Parcel data for 2017 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/
	United States Census Bureau – American Community Survey

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 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 2015-2019. The data are available through the US Census data download website.

http://www.census.gov/acs/

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

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

Each year, the US Department of Housing and Urban Development (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 2013-2017. The data are available from the HUD user website.

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

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 (WHO, 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, 2019a). 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, and symptoms of attention-deficit hyperactivity disorder (ADHD) (Canfield *et al.*, 2003; Eubig *et al.*, 2010; Ha *et al.*, 2009; 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. In 2012, the US Centers for Disease Control and Prevention (CDC) lowered the reference level at which they recommend public health actions be initiated from 10 µg/dL to a BLL of 5 µg/dL (CDC, 2019a).

Childhood blood lead levels in the United States have steadily declined over the past five decades due to various regulations. However, among 675,000 California children tested in 2011, more than 17,000 children had elevated BLL (>5 ug/dL) (California Environmental Health Tracking Program, 2015). 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 (CDC, 2020). 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 (Kim *et al.*, 2002; Sargent *et al.*, 1995; 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, nearly one quarter of all California children under the age of five live in poverty, putting them at particularly high risk of lead exposure (California Environmental Health Tracking Program, 2015).

Despite reduced exposures and declining BLLs in the US, results from blood testing show that children still experience elevated BLL (McClure *et al.*, 2016; Wheeler, 2013). In 2018, about 1.5 percent of children under age 6 (or 7,141 out of the 473,813) had a BLL over 4.5 µg/dL reported to California's statewide reporting system. (Childhood Lead Poisoning Prevention Branch, 2020). 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 and the percentage of households that are both low-income and have children in a given area. The indicator was calculated for each census tract following three 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.

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; Westat, 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 2015-2019 5-year ACS estimates. More information on how adequate parcel data is defined and how the reliability of the ACS data was assessed 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 2013-2017 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.

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- CHAS data estimates which come from a sample of the population. They may be unreliable if they are based on a small sample or population size. Details on the selection of reliable estimates is provided in the Appendix.

3. Lead Risk from 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. The result is the final lead risk from housing score.

- Census tracts were ordered by their combined lead risk from housing score and assigned a percentile based on the statewide distribution of values.

Percent of Homes with Likelihood of LBP Hazards Percentile × 0.60 **+** Low-Income Households with Children Percentile × 0.40 **=** Final Lead Risk from Housing Score
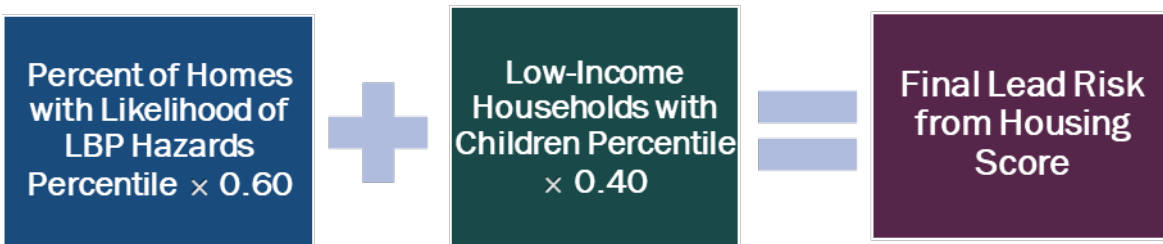
Lead Risk from Housing Index Calculation

Children's Lead Risk from Housing

Percent households with likelihood of lead-based paint hazards based on age of housing (2017 parcel data and 5-year estimate 2015-2019) and percent low-income households with children (5-year estimate 2013-2017)
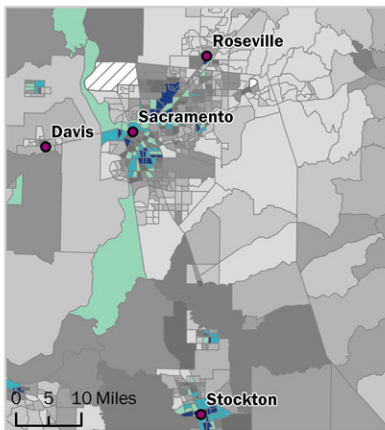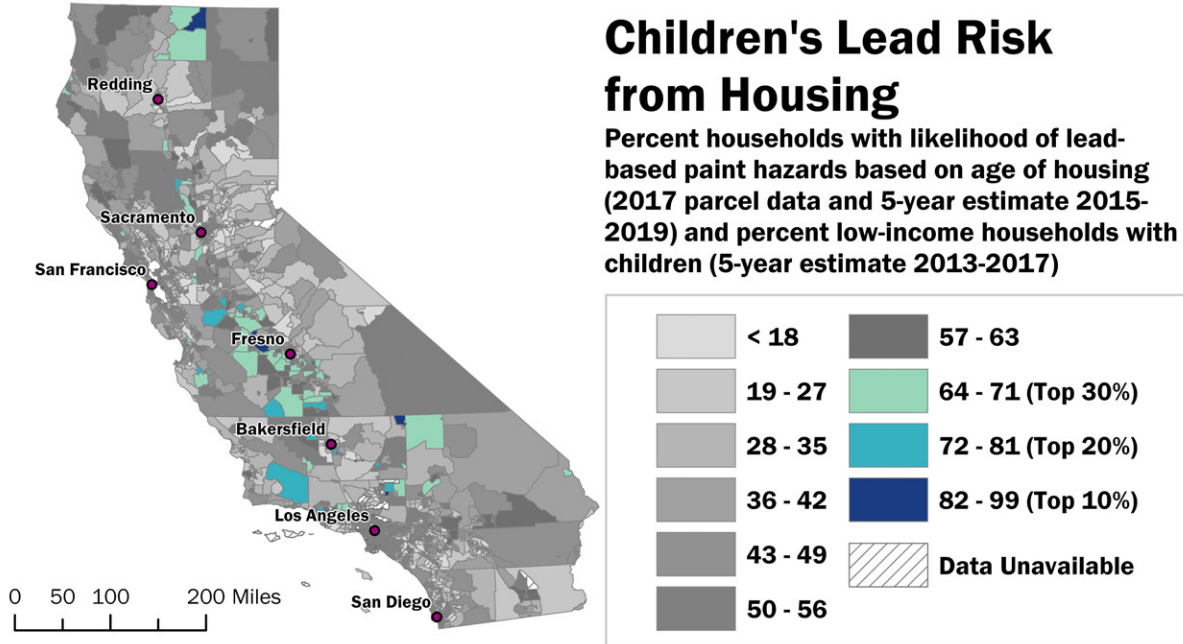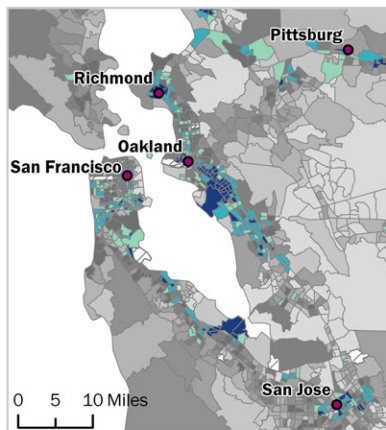
< 18	57 - 63
19 - 27	64 - 71 (Top 30%)
28 - 35	72 - 81 (Top 20%)
36 - 42	82 - 99 (Top 10%)
43 - 49	Data Unavailable
50 - 56	

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

San Diego Area

71
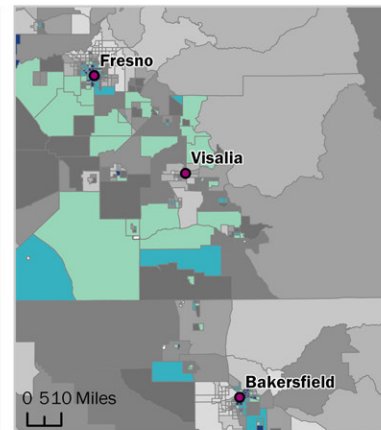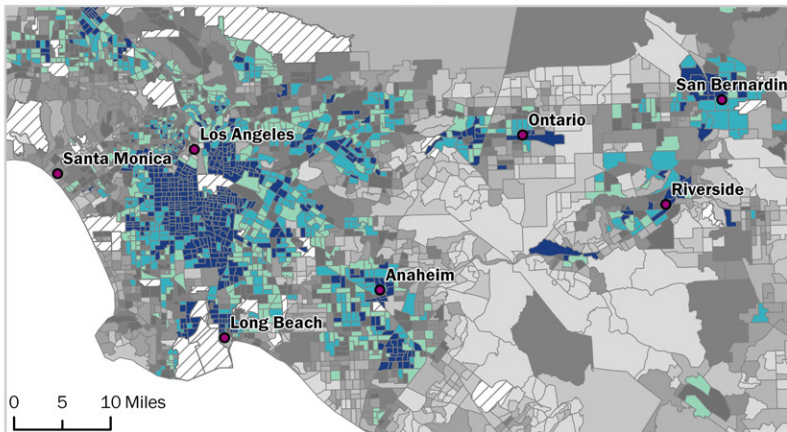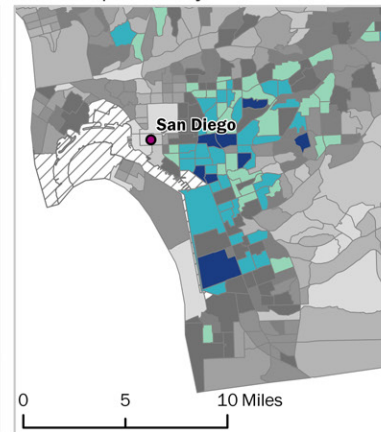
References

California Environmental Health Tracking Program PHI (2015). *Costs of Environmental Health Conditions in California Children*.

Canfield RL, Henderson CR, Cory-Slechta DA, Cox C, Jusko TA, Lanphear BP (2003). Intellectual Impairment in Children with Blood Lead Concentrations below 10 µg per Deciliter. *N Engl J Med* **348**(16):1517-26.

CDC (2019a). Lead Poisoning Prevention - Blood Lead Levels in Children.   Retrieved February 22, 2020, from https://www.cdc.gov/nceh/lead/prevention/blood-lead-levels.htm

CDC (2019b). Lead Poisoning Prevention - Lead in Paint.   Retrieved August 3, 2020, from https://www.cdc.gov/nceh/lead/prevention/sources/paint.htm

CDC (2020, April 7, 2020). Sources of Lead Exposure.   Retrieved October 28, 2020, from https://www.cdc.gov/nceh/lead/prevention/sources.htm

Childhood Lead Poisoning Prevention Branch C (2020). 2018 Blood Lead Level Maps and Data. from https://www.cdph.ca.gov/Programs/CCDPHP/DEODC/CLPPB/Pages/BLLMapsTables.aspx

Department of Homeland Security (2019, December 2, 2019). Mobile Home Parks Data. from https://catalog.data.gov/dataset/mobile-home-parks

Eubig PA, Aguiar A, Schantz SL (2010). Lead and PCBs as risk factors for attention deficit/hyperactivity disorder. *Environ Health Perspect* **118**(12):1654-67.

Ha M, Kwon H-J, Lim M-H, Jee Y-K, Hong Y-C, Leem J-H*, et al.* (2009). Low blood levels of lead and mercury and symptoms of attention deficit hyperactivity in children: a report of the children's health and environment research (CHEER). *Neurotoxicology* **30**(1):31-6.

Jacobs DE, Clickner RP, Zhou JY, Viet SM, Marker DA, Rogers JW*, et al.* (2002). The prevalence of lead-based paint hazards in U.S. housing. *Environ Health Perspect* **110**(10):A599-A606.

Kim DY, Staley F, Curtis G, Buchanan S (2002). Relation Between Housing Age, Housing Value, and Childhood Blood Lead Levels in Children in Jefferson County, Ky. *American Journal of Public Health* **92**(5):769-72.

Lanphear BP, Hornung R, Khoury J, Yolton K, Baghurst P, Bellinger DC*, et al.* (2005). Low-level environmental lead exposure and children's intellectual function: an international pooled analysis. *Environ Health Perspect* **113**(7):894-9.

Masri S, LeBrón A, Logue M, Valencia E, Ruiz A, Reyes A, *et al.* (2020). Social and spatial distribution of soil lead concentrations in the City of Santa Ana, California: Implications for health inequities. *Science of The Total Environment* **743**:140764.

McClure LF, Niles JK, Kaufman HW (2016). Blood Lead Levels in Young Children: US, 2009-2015. *The Journal of Pediatrics* **175**:173-81.

Roberts EM, Madrigal D, Valle J, King G, Kite L (2017). Assessing child lead poisoning case ascertainment in the US, 1999–2010. *Pediatrics* **139**(5).

Sargent JD, Brown MJ, Freeman JL, Bailey A, Goodman D, Freeman DH (1995). Childhood lead poisoning in Massachusetts communities: its association with sociodemographic and housing characteristics. *American Journal of Public Health* **85**(4):528-34.

Schultz BD, Morara M, Buxton BE, Weintraub M (2017). Predicting Blood-Lead Levels Among U.S. Children at the Census Tract Level. *Environmental Justice* **10**(5):129-36.

Surkan PJ, Zhang A, Trachtenberg F, Daniel DB, McKinlay S, Bellinger DC (2007). Neuropsychological function in children with blood lead levels< 10 µg/dL. *Neurotoxicology* **28**(6):1170-7.

Westat (2001). National Survey of Lead and Allergens in Housing. Final Report, Volume I: Analysis of Lead Hazards. In U.S. Department of Housing and Urban Development (Ed.) (Vol. s). Washington, DC.

Wheeler W (2013). Blood Lead Levels in Children Aged 1–5 Years — United States, 1999–2010. *Morbidity and Mortality Weekly Report*

WHO (1995). Inorganic Lead (Environmental health criteria, No. 165). In International Programme on Chemical Safety (Ed.).

Appendix

Determining age categories for housing

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 (36 of 58 counties). For counties with less than 25% apartment unit data available (19 of 58 counties), the statewide median apartment unit number of 8 was used for missing apartment unit number values. For counties with no data on number of units or year built (3 of 58 counties), ACS data was used for the entire analysis.

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, 2019).

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 (51 out of 58 counties).

For counties with more than 50% of missing year built parcel data, ACS data was used (7 out of 58 counties: Del Norte, Humboldt, Imperial, 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 158 census tracts including the 7 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 SAS 9.4 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; Westat, 2001).

Table 2: Age of housing categories based on estimated prevalence of 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.

Standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of ACS data for census tracts which relied on ACS data to calculate percentage of homes with LPB from age of housing. This approach was undertaken because ACS estimates come from a sample of the population and may be unreliable if they are based on a small sample size. The SE was calculated for each census tract by dividing the margin of error reported in the ACS by 1.645, the statistical value associated with a 90% confidence interval. The RSE was then calculated as the absolute value of the census tract's SE divided by its estimated value. Census tract estimates that met either of the following criteria were considered reliable and included in the calculation of the percentage of homes with LBP hazards:

- o Relative standard error was less than 50 or

- o Standard error was less than the mean standard error of all California census tract estimates for the age of housing category

A census tract percentage of homes with LBP hazards estimate calculated from the ACS was deemed reliable if the census tract had reliable estimates from at least three of the five age categories shown in Table 2. An exception was made if a single age category estimate held at least 80% of the tract's total number of houses and that estimate was established as reliable by the above criteria using

RSE or SE. There were 87 census tracts in which the overall score could not be calculated due to unreliable parcel and ACS data.

For census tracts with reliable data, 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:

$[\Sigma$ (Total HUs in each category x % homes with LBP hazards) / Σ (HUs)] x 100

Table 3 shows an example calculation for the percentage of homes with likelihood of LBP hazards.

Table 3: Example of a housing metric calculation for a 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 a 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 2012-2016 HUD CHAS. This dataset contains information for

households by percentage of HUD-adjusted median family income (HAMFI).

Reliability of the low-income households with children estimates from CHAS was also assessed since these are estimates provided by ACS. The standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of each estimate. Because of the further complexity of only selecting household data with a child under 6 years old, the estimates and margins of error from the low-income housing data alone were used to establish data reliability. This maximizes available data and reduce the number of null results while still maintaining consistent exclusion criteria.

The SE was calculated for each census tract low income household estimate by dividing the margin of error reported in the CHAS data by 1.645, a statistical value associated with a 90% confidence interval. The RSE was then calculated by dividing a census tract's SE by its estimated value and taking the absolute value as the result. Census tract estimates that met either of the following criteria were considered reliable and included in the analysis:

- o Relative standard error was less than 50 or

- o Standard error was less than the mean standard error of all California census tract estimates for the particular variable

If a census tract did not meet either criteria for the low-income household estimates, it was considered null and excluded from the analysis. If it was established to have a reliable percentage low-income household estimate, then the corresponding percentage low-income household with one or more child estimate was considered reliable enough to use in the metric. Four census tracts, which had reliable housing data, were excluded due to unreliable CHAS estimates, resulting in the exclusion of 91 tracts from the indicator.

V.   Combining the data

There were 7944 census tracts out of 8035 with reliable data on housing and low-income households. 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 EBLL in children (McClure *et al.*, 2016; Wheeler, 2013). This sum is the final lead exposure risk from housing score as shown in Figure 1.

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 fields can be a significant source of pesticide exposure. Complete statewide data on human exposures to pesticides do not exist. The most robust pesticide information available statewide are data maintained by the California Department of Pesticide Regulation 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 132 selected active pesticide ingredients (filtered for hazard and volatility) used in production-agriculture per square mile, averaged over three years (2017 to 2019).*
Data Source	*Pesticide Use Reporting, 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. Production agricultural pesticide use data are publicly available for each Meridian-Township-Range-Section (MTRS) in California and were used to create this indicator. 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. Data and the MTRS is available at the link below:

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

https://www.cdpr.ca.gov/docs/emon/grndwtr/gis_shapefiles.htm

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 Latinas residing 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). 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 Pesticide Use Report (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). 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).

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). 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). 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. Soil fumigation accounted for most of the cases (Lee *et al.*, 2011). In 2016 alone, DPR recorded 127 incidents of illnesses caused by agricultural pesticide drift (DPR, 2016). 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 2016 it showed that 25 of the 37 pesticides and breakdown products sampled were detected (DPR, 2017). Although none were found to be above health screening levels, 1,3-dichloropropene reached a 4-week average concentration that was 97.6% of its subchronic health screening level (DPR, 2017). Similarly, in 2017 and 2018, 27 and 28 of the 36 sampled pesticides and breakdown products were detected respectively, although none exceeded health or regulatory screening levels (DPR, 2018, 2019). In 2018, 1,3-dichloropropene was found to have 4-week and 13-week average concentrations that exceeded health screening levels (DPR, 2019).

Method

Specific pesticides included in the measure of pesticide use were narrowed from the list of all registered pesticides in use in California to focus on a subset of 132 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 2017, 2018, and 2019.

- 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 ArcMap.

- 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, pounds per square mile (2017-2019)
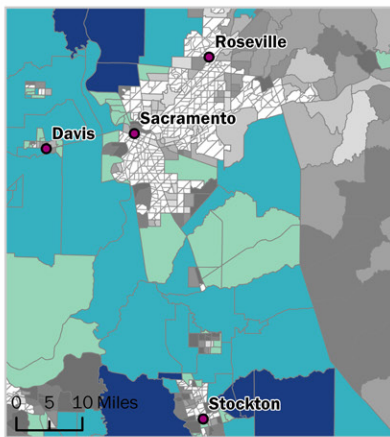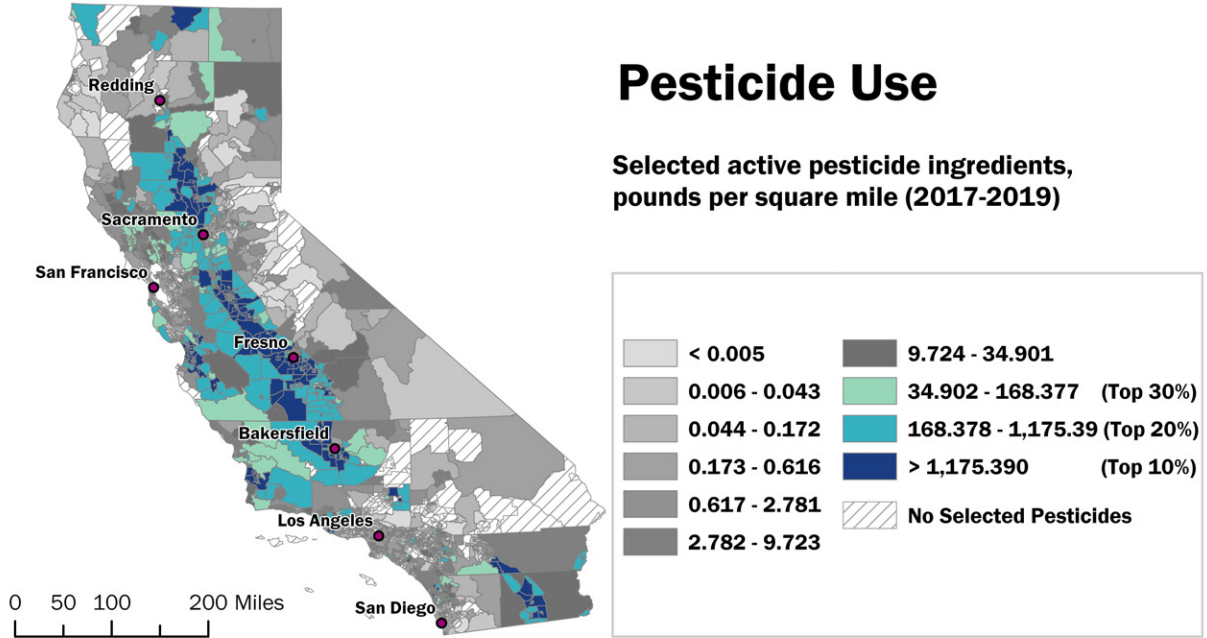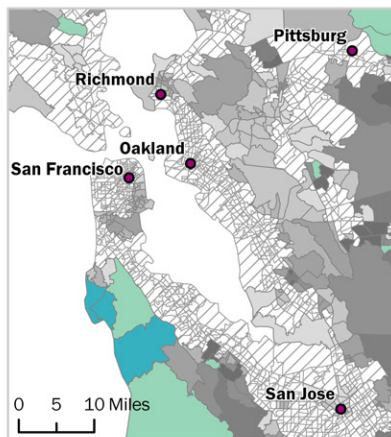
< 0.005	9.724 - 34.901
0.006 - 0.043	34.902 - 168.377 (Top 30%)
0.044 - 0.172	168.378 - 1,175.39 (Top 20%)
0.173 - 0.616	> 1,175.390 (Top 10%)
0.617 - 2.781	No Selected Pesticides
2.782 - 9.723	

0   50   100   200 Miles

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

82
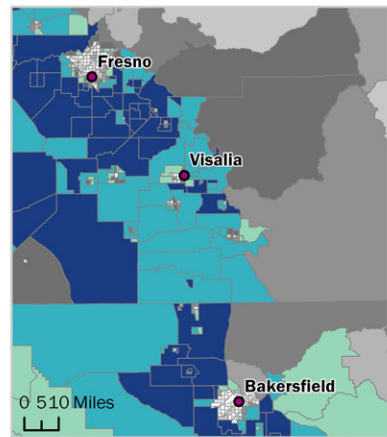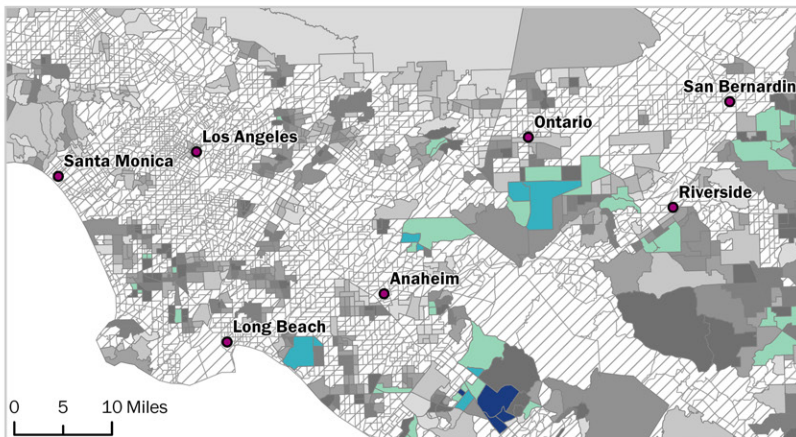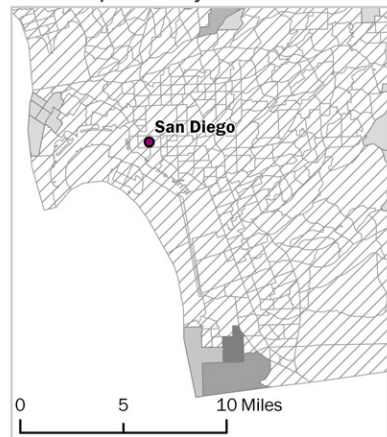
Appendix

Pesticide Use – Filter for Hazard and Volatility

Specific pesticides included in the measure of pesticide use were identified from DPR's 2018 list of pesticides active ingredients by pounds used in California through consideration of 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, the number of species affected, the 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 March 2020 were evaluated. For the purpose of developing an exposure indicator, 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. Higher volatility was considered to increase the likelihood of exposures. A list of pesticide volatilities was obtained from DPR. Pesticides not appearing on this list were researched for chemical properties in PubChem and the open literature. Pesticides with volatility less than 10^{-6} mm Hg were removed from the indicator analysis.

Additionally, pesticides that did not make 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://www.cdpr.ca.gov/docs/enforce/permitting.htm
https://www.cdpr.ca.gov/docs/emon/pubs/tac/tac_prog.htm

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

The filtering of pesticides for both hazard and volatility resulted in a list of 147 pesticides, of which 132 had agricultural use during this time. These 132 were included in the analysis here. The pesticides that are included in the indicator calculation are identified below.
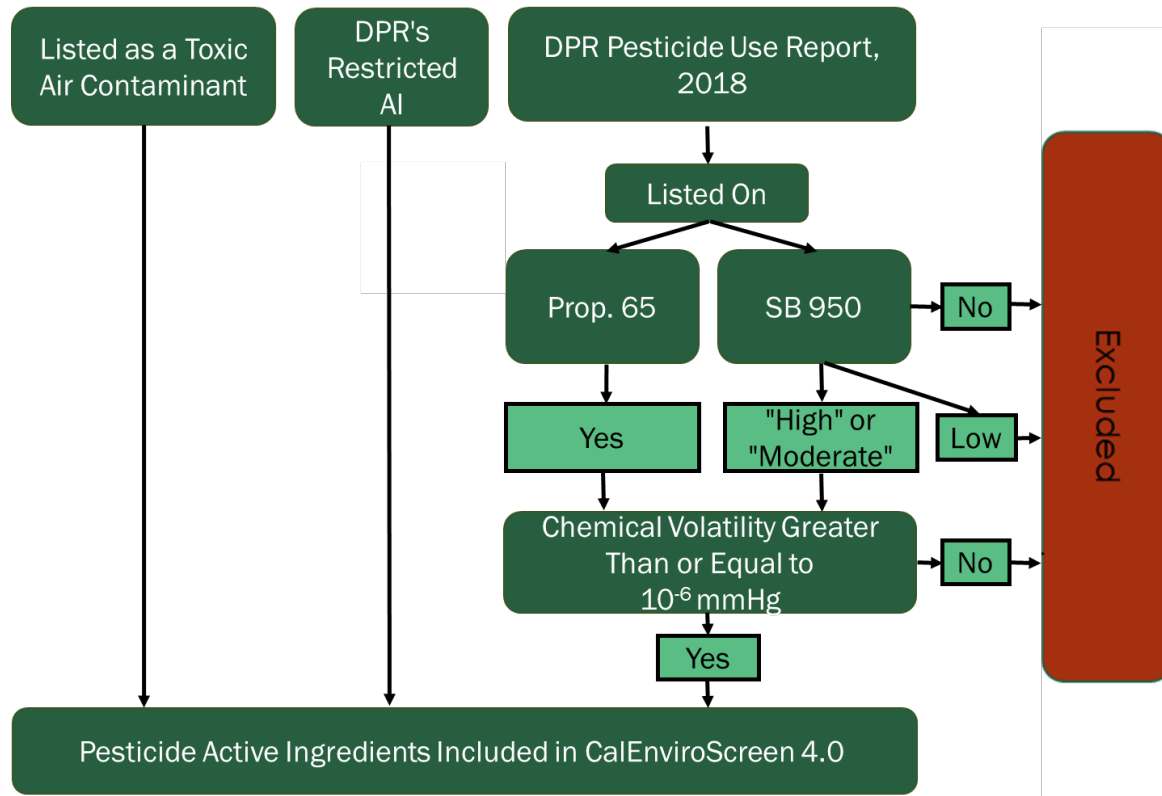
Flowchart of Pesticide Active Ingredients used in CalEnviroScreen 4.0

Pesticide Active Ingredients	Total Production Agricultural Use (Pounds: 2017-19)	Rank in CalEnviroScreen 4.0
1,3-DICHLOROPROPENE	56,009,225	1
2,4-D	16,921	67
2,4-D, 2-ETHYLHEXYL ESTER	36,930	55
2,4-D, ALKANOLAMINE SALTS (ETHANOL AND ISOPROPANOL AMINES)	287	90
2,4-D, BUTOXYETHANOL ESTER	1,662	79
2,4-D, BUTYL ESTER	50	106
2,4-D, DIETHANOLAMINE SALT	11,773	70
2,4-D, DIMETHYLAMINE SALT	1,175,604	16
2,4-D, ISOOCTYL ESTER	106	98
2,4-D, ISOPROPYL ESTER	56,007	49
2,4-D, TRIISOPROPANOLAMINE SALT	294	89
2,4-D, TRIISOPROPYLAMINE SALT	519	86
2,4-DP-P, DIMETHYLAMINE SALT	24	108

Pesticide Active Ingredients	Total Production Agricultural Use (Pounds: 2017-19)	Rank in CalEnviroScreen 4.0
3-CHLORO-P-TOLUIDINE HYDROCHLORIDE	1	120
4-(2,4-DB), DIMETHYLAMINE SALT	229,529	33
ACETAMIPRID	257,861	32
ACIBENZOLAR-S-METHYL	16,286	68
ACROLEIN	4,635	78
ALACHLOR	180	93
ALUMINUM PHOSPHIDE	27,530	60
AMITRAZ	127	96
ATRAZINE	81,574	47
ATRAZINE, OTHER RELATED	1,650	80
BENTAZON, SODIUM SALT	39,088	53
BORIC ACID	201,605	38
BRODIFACOUM	<1	129
BROMACIL	22,822	63
BROMADIOLONE	<1	121
BROMOXYNIL OCTANOATE	165,243	42
BUPROFEZIN	1,004,867	17
CACODYLIC ACID	1	116
CAPTAN	2,630,831	11
CAPTAN, OTHER RELATED	21,286	65
CARBARYL	464,812	25
CHLOROPICRIN	46,094,550	2
CHLOROTHALONIL	4,396,860	9
CHLORPYRIFOS	2,063,470	13
CHLORTHAL-DIMETHYL	961,385	18
CLOMAZONE	181,312	40
CYCLOATE	207,826	37
CYMOXANIL	38,659	54
CYPRODINIL	870,240	21
DAMINOZIDE	43,283	51
DAZOMET	7,010	76
DDVP	74	103
DIAZINON	200,567	39
DICAMBA	393	87
DICAMBA, DIMETHYLAMINE SALT	23,693	62
DICAMBA, SODIUM SALT	17,793	66
DICHLOBENIL	96	100
DIFENACOUM	<1	132

Pesticide Active Ingredients	Total Production Agricultural Use (Pounds: 2017-19)	Rank in CalEnviroScreen 4.0
DIFETHIALONE	<1	130
DIMETHENAMID-P	61,766	48
DIMETHOATE	688,052	22
DIMETHOMORPH	147,117	45
DINOSEB	56	105
DINOTEFURAN	49,538	50
DITHIOPYR	10,293	72
DIURON	455,674	26
ENDOSULFAN	97	99
EPTC	879,422	20
ESBIOTHRIN	<1	131
ETHALFLURALIN	170,765	41
ETHOFUMESATE	25,283	61
ETHOPROP	21,667	64
FENAMIPHOS	77	102
FLUDIOXONIL	161,460	44
FLUMIOXAZIN	314,139	31
FORMALDEHYDE	<1	123
GLUTARALDEHYDE	192	92
HYDROGEN CHLORIDE	<1	124
IMAZALIL	1	118
LINURON	226,643	34
MAGNESIUM PHOSPHIDE	117	97
MALATHION	1,509,690	14
MANCOZEB	6,363,283	6
MANEB	8,137	75
MCPA, 2-ETHYL HEXYL ESTER	1,338	82
MCPA, DIMETHYLAMINE SALT	337,510	30
MCPA, ISOOCTYL ESTER	1	115
MEFENOXAM	416,012	27
META-CRESOL	8	112
METALAXYL	551	85
METAM-SODIUM	16,141,566	4
METHAMIDOPHOS	3	114
METHIDATHION	172	94
METHOMYL	952,551	19
METHOXYCHLOR	<1	122
METHYL BROMIDE	5,231,947	8

Pesticide Active Ingredients	Total Production Agricultural Use (Pounds: 2017-19)	Rank in CalEnviroScreen 4.0
METHYL IODIDE	19	109
METHYL PARATHION	29	107
METHYL PARATHION, OTHER RELATED	<1	125
METRAFENONE	225,553	35
MEVINPHOS	241	91
MEVINPHOS, OTHER RELATED	160	95
MYCLOBUTANIL	220,071	36
NITRAPYRIN	318	88
NORFLURAZON	36,314	56
ORTHO-BENZYL-PARA-CHLOROPHENOL	<1	128
ORTHO-PHENYLPHENOL	3	113
OXYDEMETON-METHYL	4,904	77
PARAQUAT DICHLORIDE	5,304,452	7
PARATHION	16	110
PCNB	341,271	29
PCP, OTHER RELATED	9	111
PENTACHLOROPHENOL	78	101
PHORATE	103,671	46
PHOSPHINE	72	104
POTASSIUM N-METHYLDITHIOCARBAMATE	33,164,122	3
PROMETON	1	119
PROPANIL	6,623,895	5
PROPOXUR	<1	126
PYRETHRINS	31,925	58
PYRIDABEN	15,319	69
PYRIMETHANIL	346,408	28
S,S,S-TRIBUTYL PHOSPHOROTRITHIOATE	30,588	59
SIMAZINE	468,900	24
SODIUM FLUOROACETATE	<1	127
STRYCHNINE	753	84
SULFUR DIOXIDE	10,821	71
SULFURYL FLUORIDE	40,345	52
TERRAZOLE	1,317	83
TETRACONAZOLE	32,360	57
THIOBENCARB	2,266,300	12

Pesticide Active Ingredients	Total Production Agricultural Use (Pounds: 2017-19)	Rank in CalEnviroScreen 4.0
THIRAM	586,434	23
TRIALLATE	8,453	74
TRIBUTYLTIN OXIDE	1	117
TRIFLUMIZOLE	162,768	43
TRIFLURALIN	1,348,481	15
XYLENE	1,409	81
ZINC PHOSPHIDE	9,548	73
ZIRAM	2,920,604	10

References

Bradman A, Eskenazi B, Barr DB, Bravo R, Castorina R, Chevrier J, *et al.* (2005). Organophosphate urinary metabolite levels during pregnancy and after delivery in women living in an agricultural community. *Environ Health Perspect* **113**(12):1802-7.

Bradman A, Whitaker D, Quiros L, Castorina R, Claus Henn B, Nishioka M, *et al.* (2007). Pesticides and their metabolites in the homes and urine of farmworker children living in the Salinas Valley, CA. *J Expo Sci Environ Epidemiol* **17**(4):331-49.

Coronado GD, Holte S, Vigoren E, Griffith WC, Barr DB, Faustman E, *et al.* (2011). Organophosphate pesticide exposure and residential proximity to nearby fields: evidence for the drift pathway. *J Occup Environ Med* **53**(8):884-91.

DPR (2016). California Department of Pesticide Regulation. Summary of Results from the California Pesticide Illness Surveillance Program 2016. https://www.cdpr.ca.gov/docs/whs/pisp/2016/2016summary.pdf.

DPR (2017). California Department of Pesticide Regulation. Air Monitoring Network Results for 2016. Volume 6. [Available by request at: https://www.cdpr.ca.gov/docs/emon/airinit/air_network_results.htm].

DPR (2018). California Department of Pesticide Regulation. Air monitoring Network Results for 2017. Volume 7. [Available by request at: https://www.cdpr.ca.gov/docs/emon/airinit/air_network_results.htm].

DPR (2019). California Department of Pesticide Regulation. Air Monitoring Network Results for 2018. Volume 8. [Available at URL: https://www.cdpr.ca.gov/docs/emon/airinit/air_monitoring_results/2018/full_report.pdf].

Gunier RB, Bradman A, Harley KG, Kogut K, Eskenazi B (2017). Prenatal residential proximity to agricultural pesticide use and IQ in 7-year-old children. *Environ Health Perspect* **125**(5):057002.

Gunier RB, Ward MH, Airola M, Bell EM, Colt J, Nishioka M, *et al.* (2011). Determinants of agricultural pesticide concentrations in carpet dust. *Environ Health Perspect* **119**(7):970-6.

Harnly ME, Bradman A, Nishioka M, McKone TE, Smith D, McLaughlin R, *et al.* (2009). Pesticides in dust from homes in an agricultural area. *Environ Sci Technol* **43**(23):8767-74.

Koutros S, Beane Freeman LE, Lubin JH, Heltshe SL, Andreotti G, Barry KH, *et al.* (2013). Risk of total and aggressive prostate cancer

and pesticide use in the Agricultural Health Study. *Am J Epidemiol* **177**(1):59-74.

Lee SJ, Mehler L, Beckman J, Diebolt-Brown B, Prado J, Lackovic M*, et al.* (2011). Acute pesticide illnesses associated with off-target pesticide drift from agricultural applications: 11 States, 1998-2006. *Environ Health Perspect* **119**(8):1162-9.

Quiros-Alcala L, Bradman A, Nishioka M, Harnly ME, Hubbard A, McKone TE*, et al.* (2011). Pesticides in house dust from urban and farmworker households in California: an observational measurement study. *Environ Health* **10**:19.

Raanan R, Harley KG, Balmes JR, Bradman A, Lipsett M, Eskenazi B (2015). Early-life exposure to organophosphate pesticides and pediatric respiratory symptoms in the CHAMACOS cohort. *Environ Health Perspect* **123**(2):179-85.

Rauh VA, Perera FP, Horton MK, Whyatt RM, Bansal R, Hao X*, et al.* (2012). Brain anomalies in children exposed prenatally to a common organophosphate pesticide. *Proc Natl Acad Sci U S A* **109**(20):7871-6.

Shrestha S, Parks CG, Goldner WS, Kamel F, Umbach DM, Ward MH*, et al.* (2018). Pesticide use and incident hypothyroidism in pesticide applicators in the Agricultural Health Study. *Environ Health Perspect* **126**(9):097008.

Wang A, Cockburn M, Ly TT, Bronstein JM, Ritz B (2014). The association between ambient exposure to organophosphates and Parkinson's disease risk. *Occupational and Environmental Medicine* **71**(4):275-81.

Winchester P, Proctor C, Ying J (2016). County-level pesticide use and risk of shortened gestation and preterm birth. *Acta Paediatrica* **105**(3):e107-e15.

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 2017 to 2019 and including releases from Mexican facilities averaged over 2014 to 2016).*
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 (593 individually listed chemicals and 30 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)

The Registry of Emissions and Transfer of Contaminants (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/index.html

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." (U.S. 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 (Lam *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 California, a study that modeled concentrations of air toxic chemicals found significant levels of risk (Morello-Frosch *et al.*, 2000). Although this study found that mobile sources accounted for a major portion of the risk, the authors pointed out that for some communities, local industrial sources were a major contributor.

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 (Szasz and Meuser, 1997). 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 (Morello-Frosch *et al.*, 2002; Sadd *et al.*, 1999).

Method

- California TRI air releases for years 2017 through 2019 were modeled using RSEI Version 2.3.7 code by Abt Associates, US EPA contractors for the RSEI program. (Releases to land and water were not included.)

- Locations of facilities reporting emissions to RETC were 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).

- RETC emissions for the years 2014 to 2016 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 2010 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

Toxicity-weighted concentrations of modeled chemical releases to air from facilities (2017-2019)
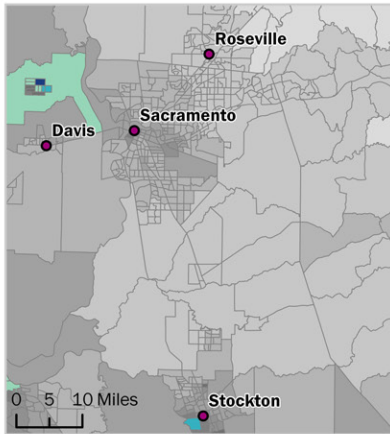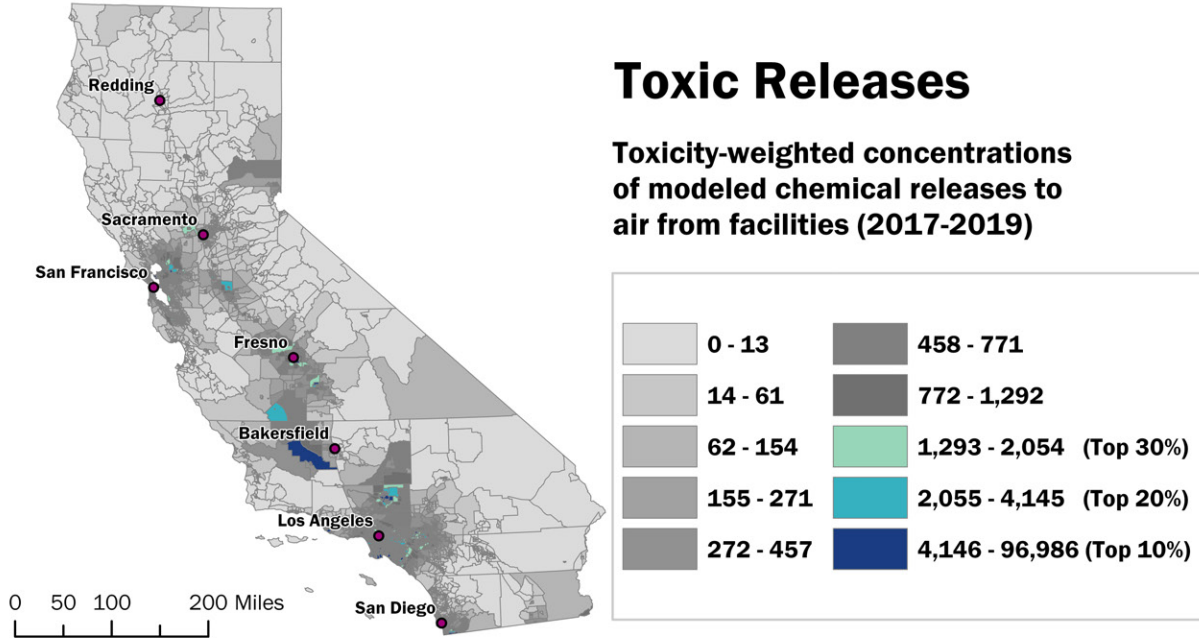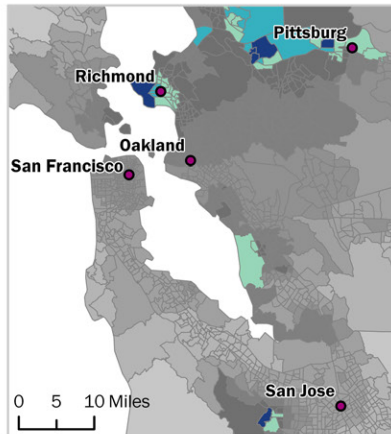
0 - 13	458 - 771
14 - 61	772 - 1,292
62 - 154	1,293 - 2,054 (Top 30%)
155 - 271	2,055 - 4,145 (Top 20%)
272 - 457	4,146 - 96,986 (Top 10%)

0   50 100   200 Miles

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

95
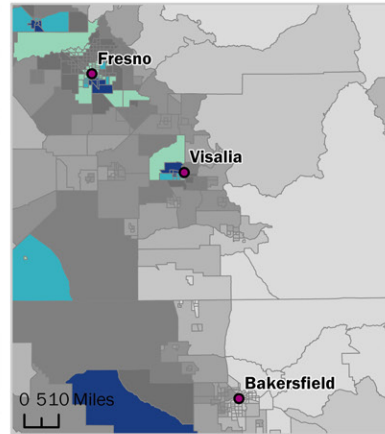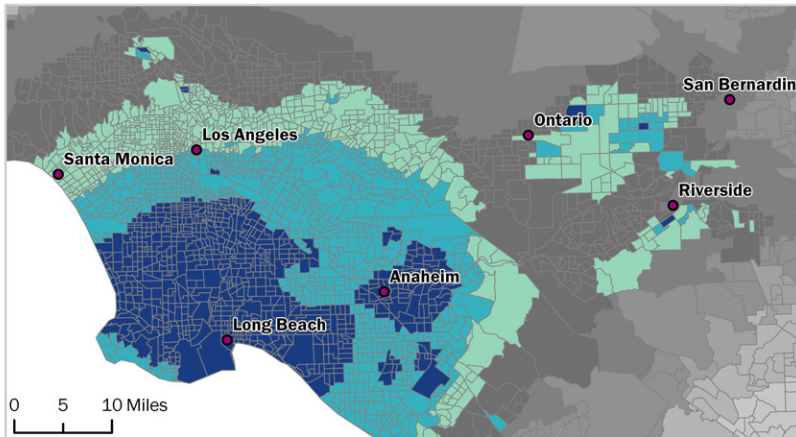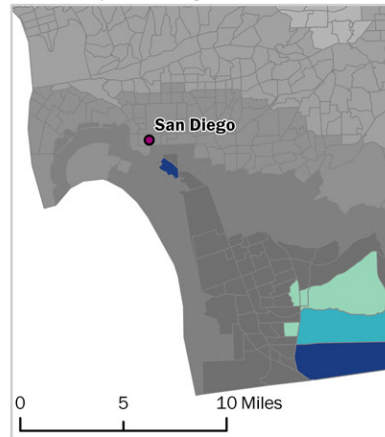
References

Agarwal N, Banternghansa C, Bui L (2010). Toxic exposure in America: Estimating fetal and infant health outcomes from 14 years of TRI reporting. *Journal of Health Economics* **29**(4):557-74.

Choi HS, Shim YK, Kaye WE, Ryan PB (2006). Potential residential exposure to toxics release inventory chemicals during pregnancy and childhood brain cancer. *Environ Health Perspect* **114**(7):1113-8.

Collins MB, Munoz I, JaJa J (2016). Linking 'toxic outliers' to environmental justice communities. *Environmental Research Letters* **11**(1):015004.

Gong X, Lin Y, Zhan FB (2018). Industrial air pollution and low birth weight: a case-control study in Texas, USA. *Environ Sci Pollut Res Int* **25**(30):30375-89.

Hendryx M, Fedorko E (2011). The relationship between toxics release inventory discharges and mortality rates in rural and urban areas of the United States. *The Journal of Rural Health* **27**(4):358-66.

Hendryx M, Luo J, Chen B-C (2014). Total and cardiovascular mortality rates in relation to discharges from toxics release inventory sites in the United States. *Environmental Research* **133**:36-41.

Kleindorfer PR, Belke JC, Elliott MR, Lee K, Lowe RA, Feldman HI (2003). Accident epidemiology and the U.S. chemical industry: accident history and worst-case data from RMP*Info. *Risk Anal* **23**(5):865-81.

Lam CW, Lim SR, Schoenung JM (2011). Environmental and risk screening for prioritizing pollution prevention opportunities in the U.S. printed wiring board manufacturing industry. *J Hazard Mater* **189**(1-2):315-22.

McCarthy MC, O'Brien TE, Charrier JG, Hafner HR (2009). Characterization of the chronic risk and hazard of hazardous air pollutants in the United States using ambient monitoring data. *Environ Health Perspect* **117**(5):790-6.

Morello-Frosch R, Pastor M, Jr., Porras C, Sadd J (2002). Environmental justice and regional inequality in southern California: implications for future research. *Environ Health Perspect* **110 Suppl 2**:149-54.

Morello-Frosch RA, Woodruff TJ, Axelrad DA, Caldwell JC (2000). Air toxics and health risks in California: the public health implications of outdoor concentrations. *Risk Anal* **20**(2):273-91.

Sadd JL, Pastor Jr M, Boer JT, Snyder LD (1999). "Every Breath You Take…": The Demographics of Toxic Air Releases in Southern California. *Economic Development Quarterly* **13**(2):107-23.

Szasz A, Meuser M (1997). Environmental inequalities: Literature review and proposals for new directions in research and theory. *Current Sociology* **45**(3):99-120.

U.S. EPA (2010). Toxic Release Inventory. National Analysis Overview.35 pp.

Zwickl K, Ash M, Boyce JK (2014). Regional variation in environmental inequality: Industrial air toxics exposure in US cities. *Ecological Economics* **107**:494-509.
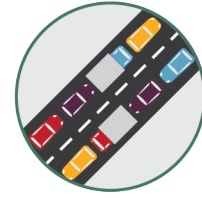
TRAFFIC IMPACTS

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 a large number of 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 2017).

Data Source

TomTom Find/Route/Display

A 2018 digital roadway network, TomTom Find/Route/Display, was purchased through American Digital Cartography *inc.*
https://www.adci.com/tomtom/gis/

TrafficMetrix® Traffic Count Database

Traffic volume data for the year 2017 was purchased from TrafficMetrix®.
https://www.kalibrate.com/solutions/traffic-count-data

University of California, Riverside College of Engineering – Center for Environmental Research and Technology

Bernie Beckerman, PhD, independent contractor

Researchers at the University of California, Riverside's Center for Environmental Research and Technology conducted much of the analysis of the road network and traffic volume data in collaboration with Dr. Bernie Beckerman

https://www.cert.ucr.edu/

US Customs and Border Protection, Border Crossing Entry Data; San Diego Association of Governments (SANDAG)

Data on northbound border crossing counts for the year 2017 was downloaded from the US Customs and Border Protection website. 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://explore.dot.gov/views/BorderCrossingData/Annual?:isGuestRedirectFromVizportal=y&:embed=y

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 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 (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). A recent 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).

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).

Method

- A 150 meter buffer was placed around each of the 2010 census tracts in California. The area of the buffered census tract was calculated. 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).

- ArcGIS was used to link the 2017 traffic volume data from TrafficMetrix® to the corresponding road segment of the digital roadway network from 2018 TomTom Find/Route/Display.

- ArcGIS was used to intersect (or link) the buffered census tracts with traffic volumes and the road network data. For each road within the buffered census tract, a length-adjusted volume was calculated and summed for all roads within the buffered area of

the census tract. The total road length within the buffered census tract was also calculated.

- For roadways with missing traffic data, spatial interpolation modeling was performed (Beckerman, 2014).

- Due to differences in the length of road segments across the state, a length-adjusted traffic volume metric was calculated by indicator multiplying the traffic volumes by the length of the road segment.

- 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 (km).

- 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 2017 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

Traffic volumes adjusted by road segment length (vehicle-km per hour) divided by total road length (km) within 150 meters of each census tract, 2017.
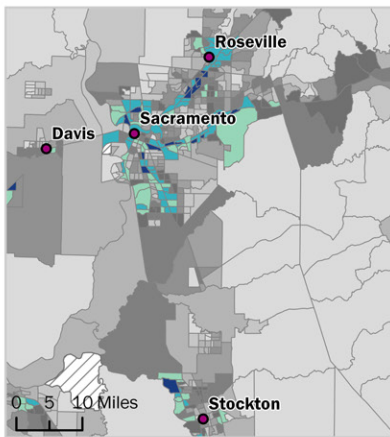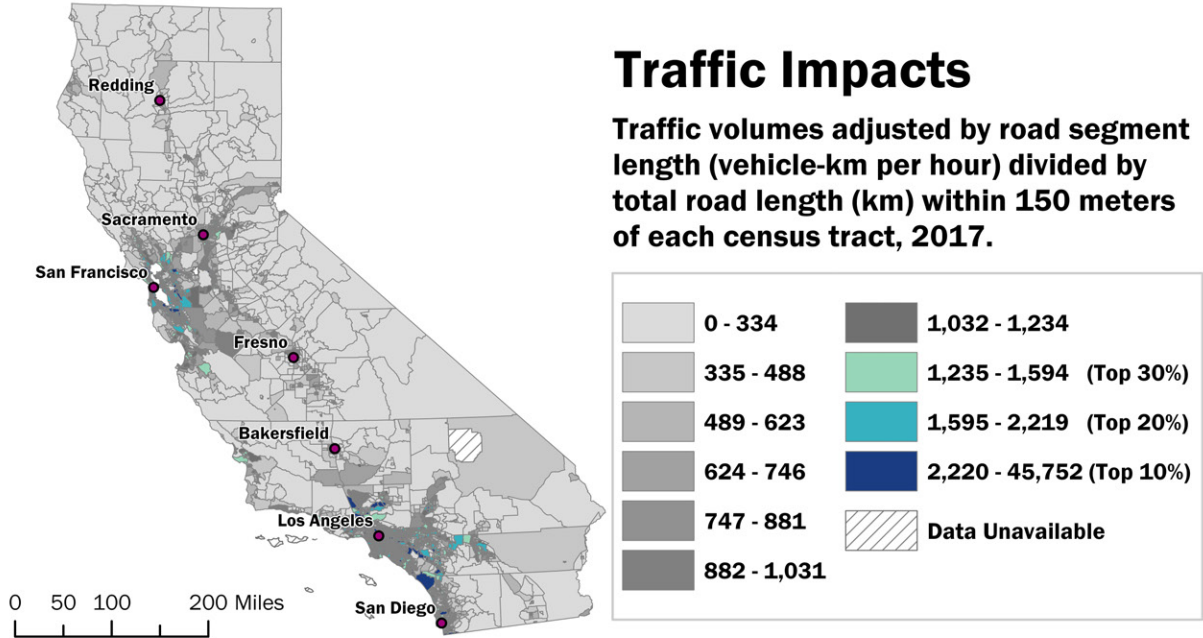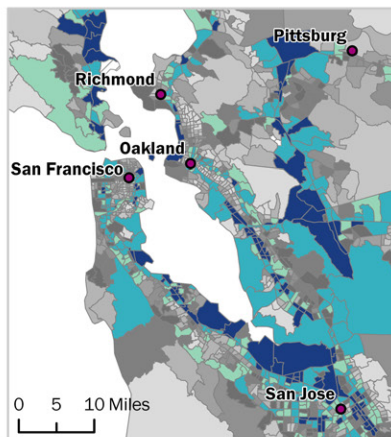
0 - 334		1,032 - 1,234	
335 - 488		1,235 - 1,594	(Top 30%)
489 - 623		1,595 - 2,219	(Top 20%)
624 - 746		2,220 - 45,752	(Top 10%)
747 - 881		Data Unavailable	
882 - 1,031			

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0
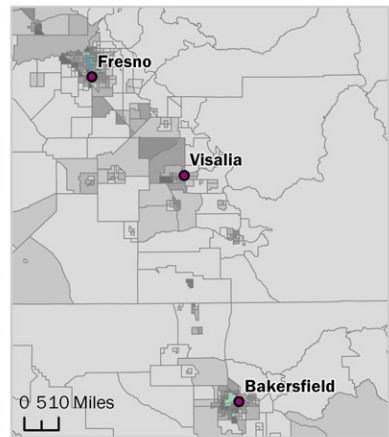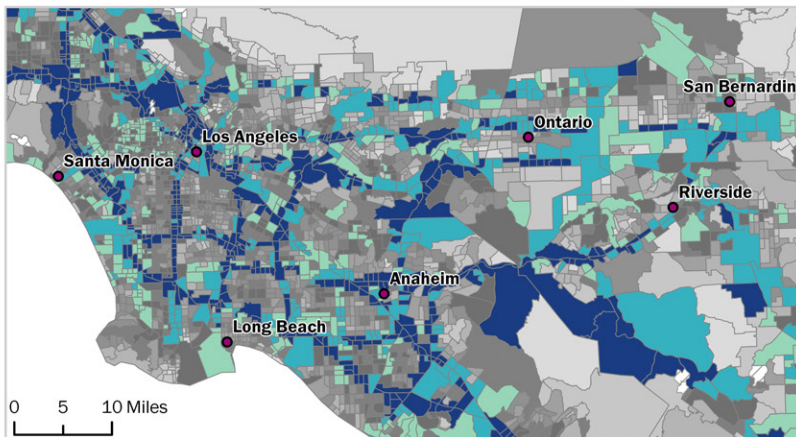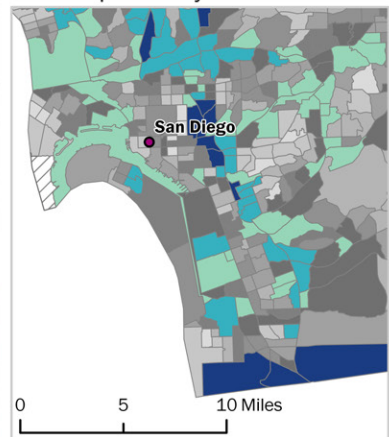
San Diego Area

References

Alexeeff SE, Roy A, Shan J, Liu X, Messier K, Apte JS, *et al.* (2018). High-resolution mapping of traffic related air pollution with Google street view cars and incidence of cardiovascular events within neighborhoods in Oakland, CA. *Environmental Health* **17**(1):38.

Baumann LM, Robinson CL, Combe JM, Gomez A, Romero K, Gilman RH, *et al.* (2011). Effects of distance from a heavily transited avenue on asthma and atopy in a periurban shantytown in Lima, Peru. *J Allergy Clin Immunol* **127**(4):875-82.

Becerra TA, Wilhelm M, Olsen J, Cockburn M, Ritz B (2013). Ambient air pollution and autism in Los Angeles County, California. *Environ Health Perspect* **121**(3):380-6.

Beckerman BS (2014). *Improving Exposure-Response Estimation in Air Pollution Health Effects Assessments (Doctoral dissertation).* UC Berkeley.

Berger K, Malig BJ, Hasheminassab S, Pearson DL, Sioutas C, Ostro B, *et al.* (2018). Associations of source-apportioned fine particles with cause-specific mortality in California. *Epidemiology* **29**(5):639-48.

Blount RJ, Pascopella L, Catanzaro DG, Barry PM, English PB, Segal MR, *et al.* (2017). Traffic-related air pollution and all-cause mortality during tuberculosis treatment in California. *Environ Health Perspect* **125**(9):097026.

Boehmer TK, Foster SL, Henry JR, Woghiren-Akinnifesi EL, Yip FY (2013). Residential proximity to major highways - United States, 2010. *MMWR Surveill Summ* **62 Suppl 3**:46-50.

CARB (2005). *Air quality and land use handbook: A community health perspective*: California Environmental Protection Agency, Air Resources Board.

Ebisu K, Malig B, Hasheminassab S, Sioutas C (2019). Age-specific seasonal associations between acute exposure to PM2. 5 sources and cardiorespiratory hospital admissions in California. *Atmospheric Environment* **218**:117029.

Ebisu K, Malig B, Hasheminassab S, Sioutas C, Basu R (2018). Cause-specific stillbirth and exposure to chemical constituents and sources of fine particulate matter. *Environmental Research* **160**:358-64.

Garcia E, Berhane KT, Islam T, McConnell R, Urman R, Chen Z, *et al.* (2019). Association of changes in air quality with incident asthma in children in California, 1993-2014. *JAMA* **321**(19):1906-15.

Ghosh JK, Wilhelm M, Su J, Goldberg D, Cockburn M, Jerrett M, *et al.* (2012). Assessing the influence of traffic-related air pollution on risk of term low birth weight on the basis of land-use-based regression

models and measures of air toxics. *Am J Epidemiol* **175**(12):1262-74.

Green RS, Smorodinsky S, Kim JJ, McLaughlin R, Ostro B (2004). Proximity of California public schools to busy roads. *Environ Health Perspect* **112**(1):61-6.

Gunier RB, Hertz A, Von Behren J, Reynolds P (2003). Traffic density in California: socioeconomic and ethnic differences among potentially exposed children. *J Expo Anal Environ Epidemiol* **13**(3):240-6.

Habermann M, Gouveia N (2012). Motor vehicle traffic and cardiovascular mortality in male adults. *Rev Saude Publica* **46**(1):26-33.

IARC (2010). *Some non-heterocyclic polycyclic aromatic hydrocarbons and some related exposure*sed. (Vol. 92): IARC Press, International Agency for Research on Cancer.

Kan H, Heiss G, Rose KM, Whitsel E, Lurmann F, London SJ (2007). Traffic exposure and lung function in adults: the Atherosclerosis Risk in Communities study. *Thorax* **62**(10):873-9.

Ng C, Malig B, Hasheminassab S, Sioutas C, Basu R, Ebisu K (2017). Source apportionment of fine particulate matter and risk of term low birth weight in California: exploring modification by region and maternal characteristics. *Science of The Total Environment* **605**:647-54.

Patel MM, Quinn JW, Jung KH, Hoepner L, Diaz D, Perzanowski M*, et al.* (2011). Traffic density and stationary sources of air pollution associated with wheeze, asthma, and immunoglobulin E from birth to age 5 years among New York City children. *Environ Res* **111**(8):1222-9.

Ritz B, Wilhelm M, Hoggatt KJ, Ghosh JK (2007). Ambient air pollution and preterm birth in the environment and pregnancy outcomes study at the University of California, Los Angeles. *Am J Epidemiol* **166**(9):1045-52.

Schultz ES, Gruzieva O, Bellander T, Bottai M, Hallberg J, Kull I*, et al.* (2012). Traffic-Related Air Pollution and Lung Function In Children At 8 Years Of Age - A Birth Cohort Study. *Am J Respir Crit Care Med*.

Tian N, Xue J, Barzyk TM (2013). Evaluating socioeconomic and racial differences in traffic-related metrics in the United States using a GIS approach. *J Expo Sci Environ Epidemiol* **23**(2):215-22.

Weaver GM, Gauderman WJ (2018). Traffic-related pollutants: exposure and health effects among Hispanic children. *American Journal of Epidemiology* **187**(1):45-52.

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.

Indicator

Sum of weighted sites within each census tract.
(Data downloaded July 2021)

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 (2021 Draft Data) –
US Environmental Protection Agency, Region 9

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). More recently, it was found that Superfund sites contribute to increased rates of elevated blood lead levels in children (Klemick *et al.*, 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 *et al.*, 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). Some of the relationships between CalEnviroScreen scores and race have been added to the final section of this report.

It generally takes many years for a site to be certified as clean, and cleanup work is often delayed 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 instead of points.

- 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 evaluations, for example. 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.

- 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.
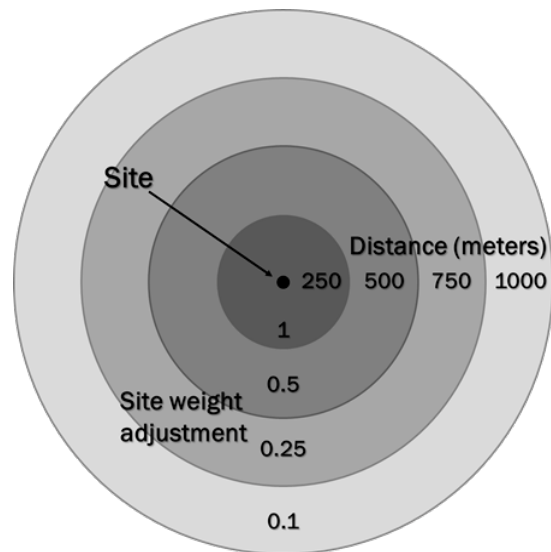
- Each census tract was scored based on the sum of the adjusted weights (in ArcMap).

- 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 2021)
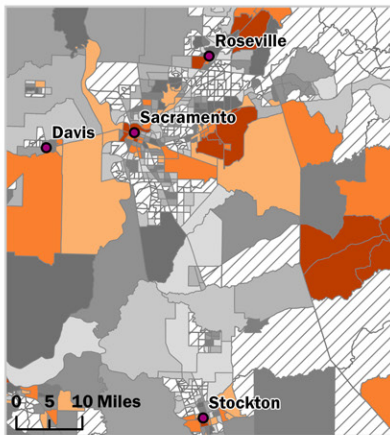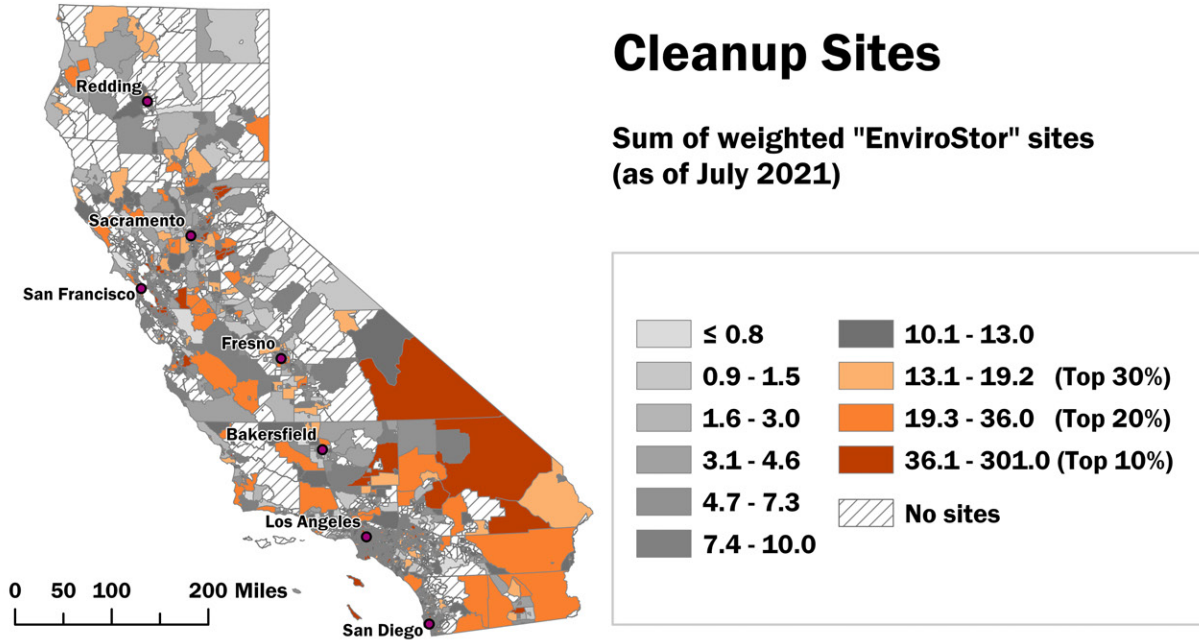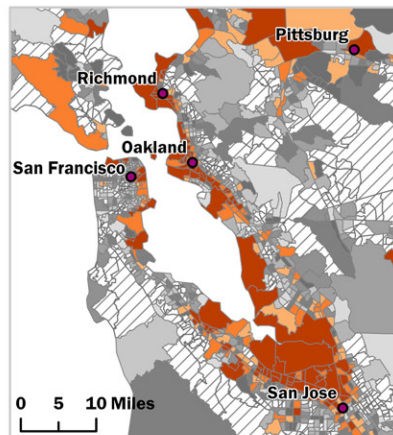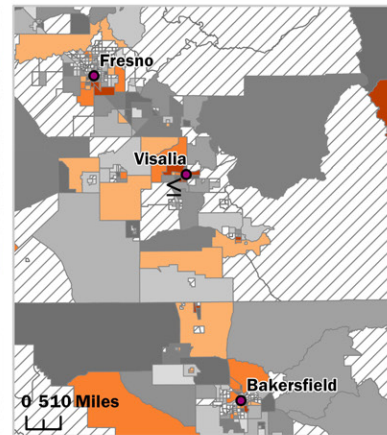
≤ 0.8	10.1 - 13.0
0.9 - 1.5	13.1 - 19.2 (Top 30%)
1.6 - 3.0	19.3 - 36.0 (Top 20%)
3.1 - 4.6	36.1 - 301.0 (Top 10%)
4.7 - 7.3	No sites
7.4 - 10.0	

Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego

0   50   100   200 Miles

Sacramento Area

Roseville
Sacramento
Davis
Stockton
0   5   10 Miles

San Francisco Area

Pittsburg
Richmond
Oakland
San Francisco
San Jose
0   5   10 Miles

San Joaquin Valley

Fresno
Visalia
Bakersfield
0 5 10 Miles

Greater Los Angeles Area

San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0   5   10 Miles

San Diego Area

San Diego
0   5   10 Miles

CalEnviroScreen 4.0

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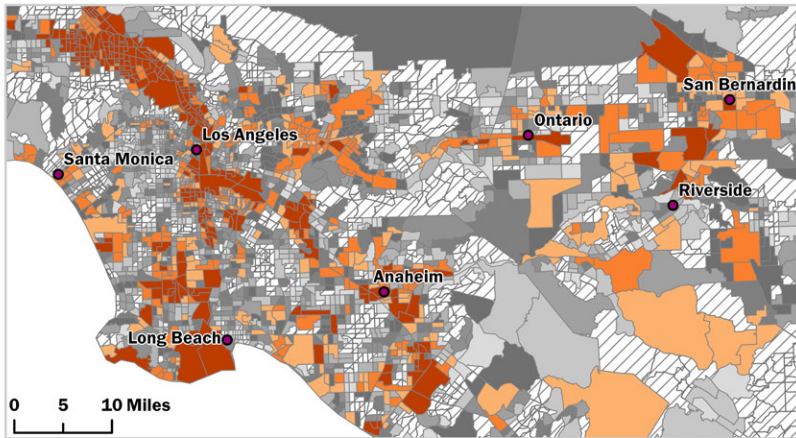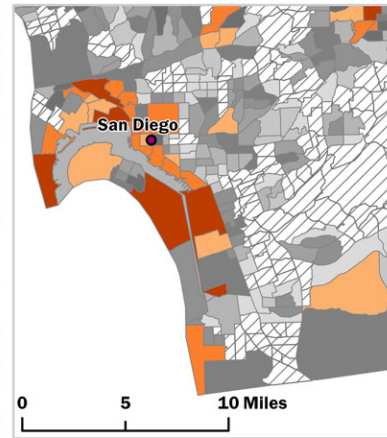
References

Ala A, Stanca CM, Bu-Ghanim M, Ahmado I, Branch AD, Schiano TD, *et al.* (2006). Increased prevalence of primary biliary cirrhosis near Superfund toxic waste sites. *Hepatology* **43**(3):525-31.

Baibergenova A, Kudyakov R, Zdeb M, Carpenter DO (2003). Low birth weight and residential proximity to PCB-contaminated waste sites. *Environ Health Perspect* **111**(10):1352-7.

Gaffney SH, Curriero FC, Strickland PT, Glass GE, Helzlsouer KJ, Breysse PN (2005). Influence of geographic location in modeling blood pesticide levels in a community surrounding a U.S. Environmental protection agency superfund site. *Environ Health Perspect* **113**(12):1712-6.

Kearney G, Kiros GE (2009). A spatial evaluation of socio demographics surrounding National Priorities List sites in Florida using a distance-based approach. *Int J Health Geogr* **8**:33.

Klemick H, Mason H, Sullivan K (2020). Superfund cleanups and children's lead exposure. *Journal of Environmental Economics and Management* **100**:102289.

Persico C, Figlio D, Roth J (2020). The developmental consequences of Superfund sites. *Journal of Labor Economics* **38**(4):1055-97.

Zota AR, Schaider LA, Ettinger AS, Wright RO, Shine JP, Spengler JD (2011). Metal sources and exposures in the homes of young children living near a mining-impacted Superfund site. *J Expo Sci Environ Epidemiol* **21**(5):495-505.

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.

Site Type	Status		
	Low • Certified • Completed • No Further Action	**Medium** • Inactive-Needs Eval. • Inactive • Certified Operation & Maintenance – Land Use Restrictions • Certified Operation & Maintenance	**High** • Active • Backlog • Inactive- Action Required
Low • Evaluation • Historical • Military Evaluation	0	4	6
Medium • Corrective Action • School Cleanup • Voluntary Cleanup • Tiered Permit	1	7	9
High • State Response • Superfund	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 Action*: 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).
- *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 4.0: Approximately 5,600

Site Type	% of Sites
Voluntary Cleanup	26%
Military Evaluation	15%
State Response	15%
Tiered Permit	14%
Evaluation	12%
Corrective Action	8%
School Cleanup	7%
Historical	1%
National Priorities List (NPL) (with boundaries)	1%
Federal Superfund (boundaries unavailable)	1%
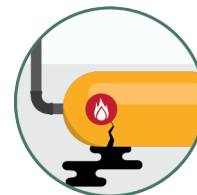
GROUNDWATER THREATS

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.

Indicator

Sum of weighted scores for sites within each census tract.
(Data downloaded July 2021)

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, 2011; EPA, 2002; SWRCB, 2012). 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 Mdos *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 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 polycyclic aromatic hydrocarbons (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 ArcMap.

- 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 ArcMap.

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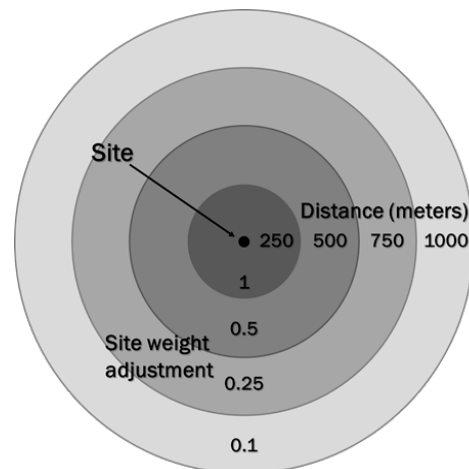
- Each census tract was scored based on the sum of the adjusted weights for sites it contains or is near (in ArcMap).

- 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 July 2021)
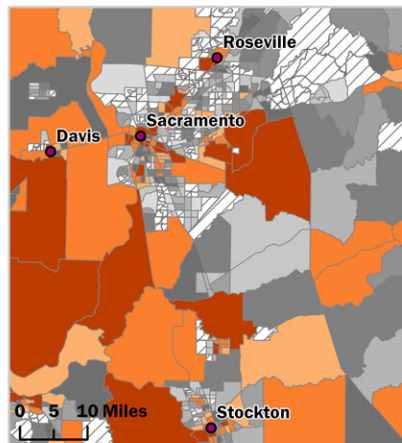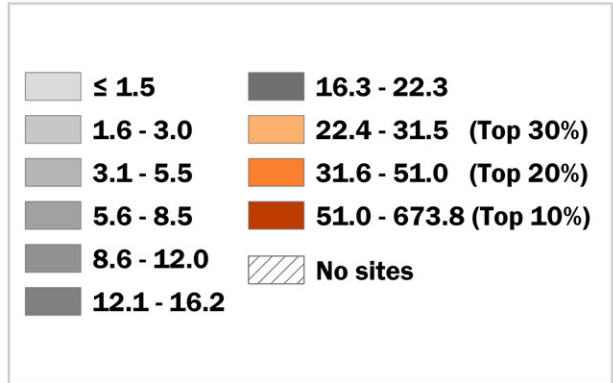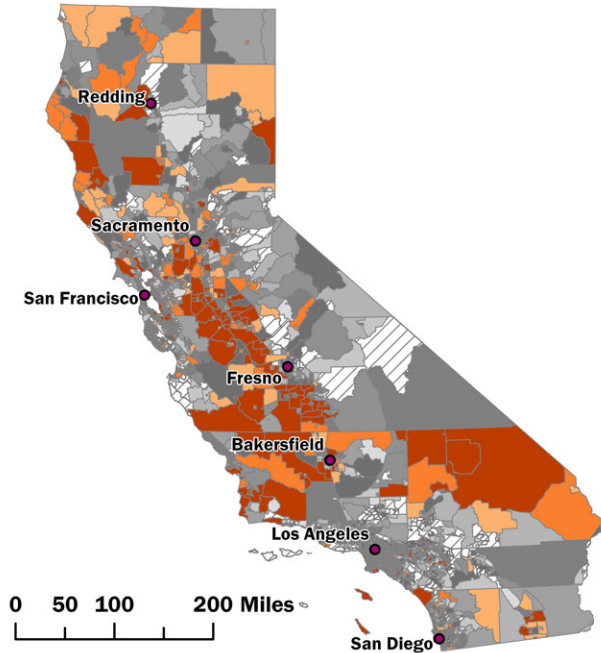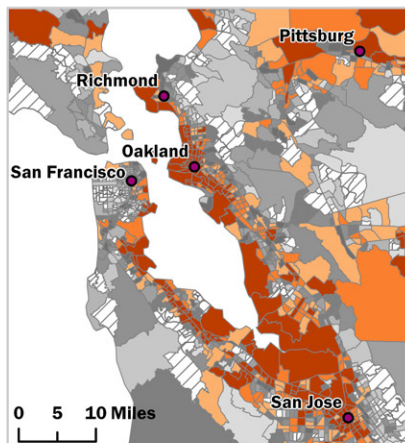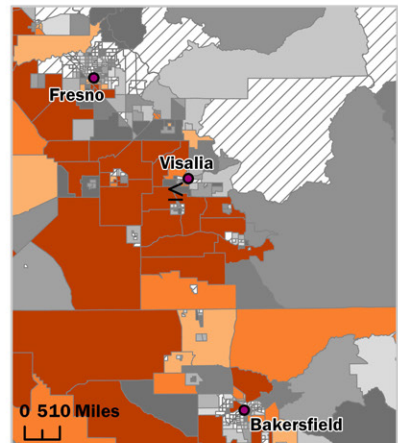
Legend:
- ≤ 1.5
- 1.6 - 3.0
- 3.1 - 5.5
- 5.6 - 8.5
- 8.6 - 12.0
- 12.1 - 16.2
- 16.3 - 22.3
- 22.4 - 31.5 (Top 30%)
- 31.6 - 51.0 (Top 20%)
- 51.0 - 673.8 (Top 10%)
- No sites

Sacramento Area

San Francisco Area

San Joaquin Valley
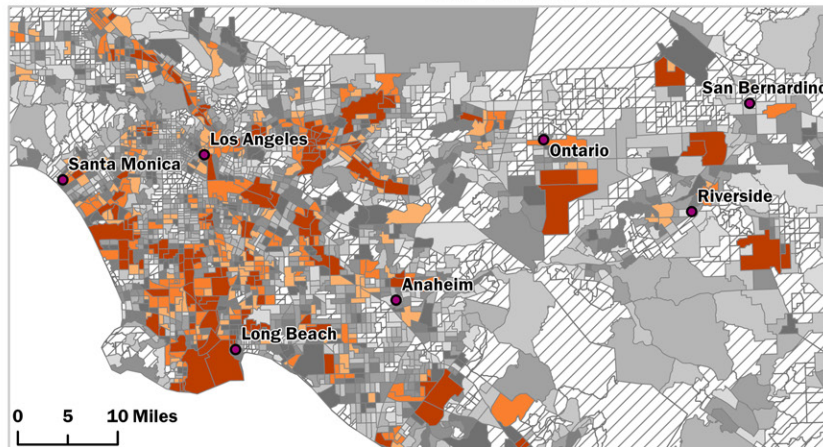
Greater Los Angeles Area
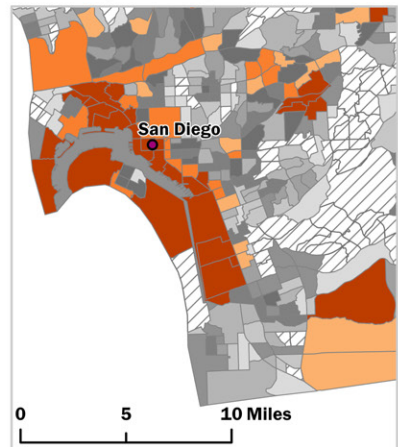
CalEnviroScreen 4.0

San Diego Area

References

Chittick EA, Srebotnjak T (2017). An analysis of chemicals and other constituents found in produced water from hydraulically fractured wells in California and the challenges for wastewater management. *Journal of Environmental Management* **204**:502-9.

DPR (2011). Sampling for pesticide residues in California well water: 2010 update of the well invento ry database. In DoP Regulation (Ed.). Sacramento: Department of Pesticide Regulation.

US EPA (2002). Health Assessment Document For Diesel Engine Exhaust.EPA/600/8-90/057F, 2002.

Francis R, Firestone L (2010). Implementing the human right to water in California's Central Valley: building a democratic voice through community engagement in water policy decision making. *Willamette L Rev* **47**:495.

Gillespie JM, Davis TA, Stephens MJ, Ball LB, Landon MK (2019). Groundwater salinity and the effects of produced water disposal in the Lost Hills–Belridge oil fields, Kern County, California. *Environmental Geosciences* **26**(3):73-96.

Karouna-Renier NK, Rao KR, Lanza JJ, Davis DA, Wilson PA (2007). Serum profiles of PCDDs and PCDFs, in individuals near the Escambia Wood Treating Company Superfund site in Pensacola, FL. *Chemosphere* **69**(8):1312-9.

Mahjoub O, Escande A, Rosain D, Casellas C, Gomez E, Fenet H (2011). Estrogen-like and dioxin-like organic contaminants in reclaimed wastewater: transfer to irrigated soil and groundwater. *Water Sci Technol* **63**(8):1657-62.

Moran MJ, Zogorski JS, Squillace PJ (2007). Chlorinated solvents in groundwater of the United States. *Environ Sci Technol* **41**(1):74-81.

Picone S, Valstar J, van Gaans P, Grotenhuis T, Rijnaarts H (2012). Sensitivity analysis on parameters and processes affecting vapor intrusion risk. *Environ Toxicol Chem* **31**(5):1042-52.

Ransom KM, Grote MN, Deinhart A, Eppich G, Kendall C, Sanborn ME*, et al.* (2016). Bayesian nitrate source apportionment to individual groundwater wells in the Central Valley by use of elemental and isotopic tracers. *Water Resources Research* **52**(7):5577-97.

Santos Mdos A, Tavora BE, Koide S, Caldas ED (2013). Human risk assessment of benzene after a gasoline station fuel leak. *Rev Saude Publica* **47**(2):335-44.

Squillace PJ, Moran MJ (2007). Factors associated with sources, transport, and fate of volatile organic compounds and their mixtures in aquifers of the United States. *Environ Sci Technol* **41**(7):2123-30.

SWRCB (2012). Leaking underground fuel tank guidance manual. In SWRC Board (Ed.) (pp. 366). Sacramento, CA: SWRCB.

Williams P, Benton L, Warmerdam J, Sheehans P (2002). Comparative risk analysis of six volatile organic compounds in California drinking water. *Environ Sci Technol* **36**(22):4721-8.

Yao Y, Shen R, Pennell KG, Suuberg EM (2013). Examination of the Influence of Environmental Factors on Contaminant Vapor Concentration Attenuation Factors Using the U.S. EPA's Vapor Intrusion Database. *Environ Sci Technol* **47**(2):906-13.

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.

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

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 from 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

Number of Groundwater Threat Sites: Approximately 12,000

Facility Type	% of Total
Cleanup Program Site	43%
Military Cleanup Site	15%
LUST Site	14%
Dairy	10%
Land Disposal Site	9%
Produced Water Pond	3%
Military UST Site	3%
Feedlot	2%
Military Privatized Site	1%

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 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 were downloaded July 2021, Hazardous waste data are from 2018-2020, and chrome plating facilities are based on a survey from 2018.)
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 2018 - 2020. Data are available at the links below:

http://www.envirostor.dtsc.ca.gov/public/data_download.asp
http://hwts.dtsc.ca.gov/

Chrome Plating Airborne Toxics Control Measure – California Air Resources Board

The California Air Resources Board (CARB) is in the process of amending the Chrome Plating Airborne Toxics Control Measure (ATCM) for reducing 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 in 2018. 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 by definition 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). While there is sometimes limited assessment of exposures that occur in nearby populations, there are studies that have found health effects, including diabetes and cardiovascular disease, associated with living in proximity to hazardous waste sites (Kouznetsova *et al.*, 2007; Sergeev and Carpenter, 2005). 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 (Pellerin and Booker, 2000).

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 (CalRecycle, 2020; 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 2018 to 2020.

- 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, OEHHA identified one brick kiln in Mexico 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. All facilities further than 1,000m from any populated census block were excluded from the analysis.

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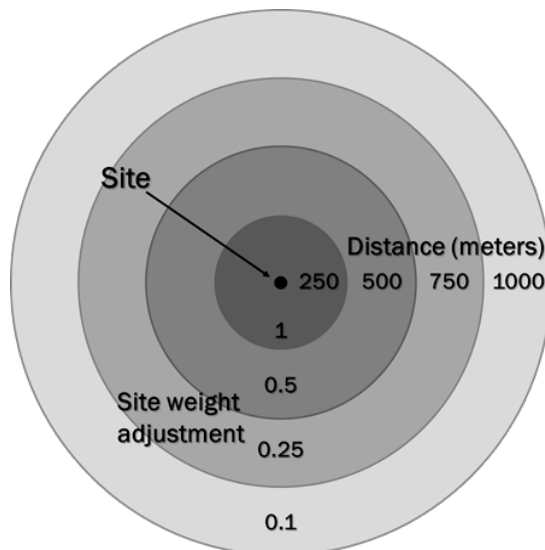
- Each census tract was scored based on the sum of the adjusted weights for sites it contains or is near (in ArcGIS Pro).

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

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Hazardous Waste Generators and Facilities

Sum of weighted permitted facilities and chrome platers in 2021, and generators over three years (2018-2020)
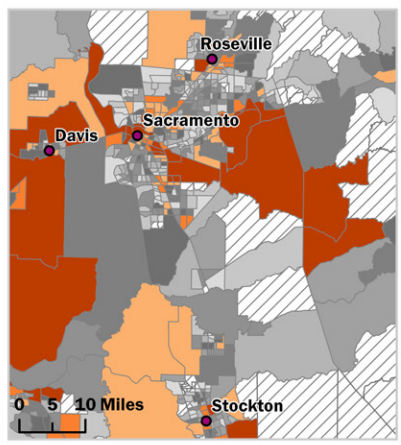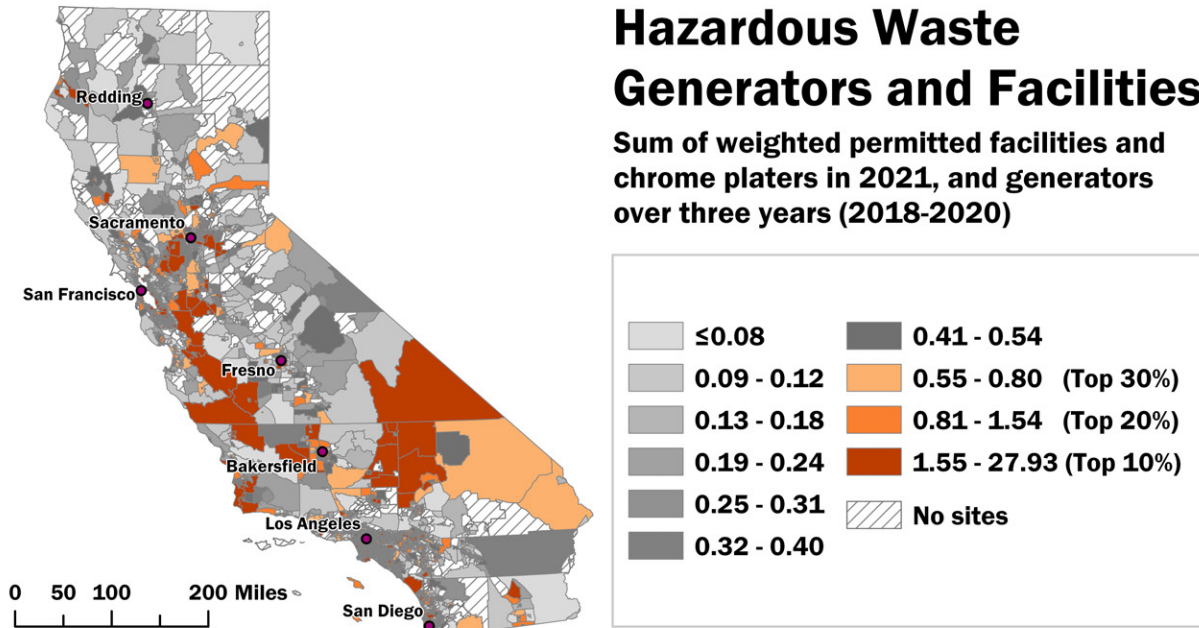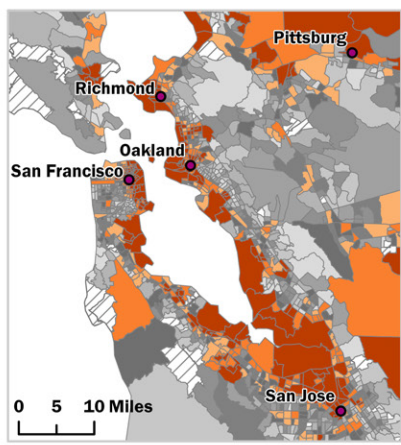
≤0.08	0.41 - 0.54
0.09 - 0.12	0.55 - 0.80 (Top 30%)
0.13 - 0.18	0.81 - 1.54 (Top 20%)
0.19 - 0.24	1.55 - 27.93 (Top 10%)
0.25 - 0.31	No sites
0.32 - 0.40	

0 50 100   200 Miles

Sacramento Area

0   5   10 Miles

San Francisco Area

0   5   10 Miles

San Joaquin Valley

0 5 10 Miles

Greater Los Angeles Area

0   5   10 Miles

CalEnviroScreen 4.0

San Diego Area

0   5   10 Miles

130
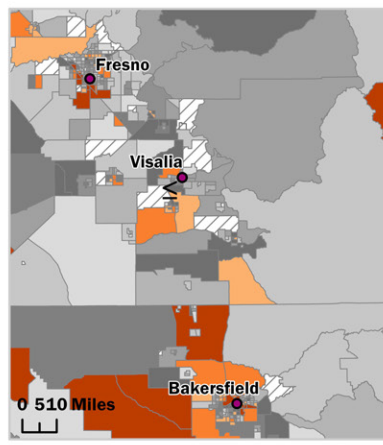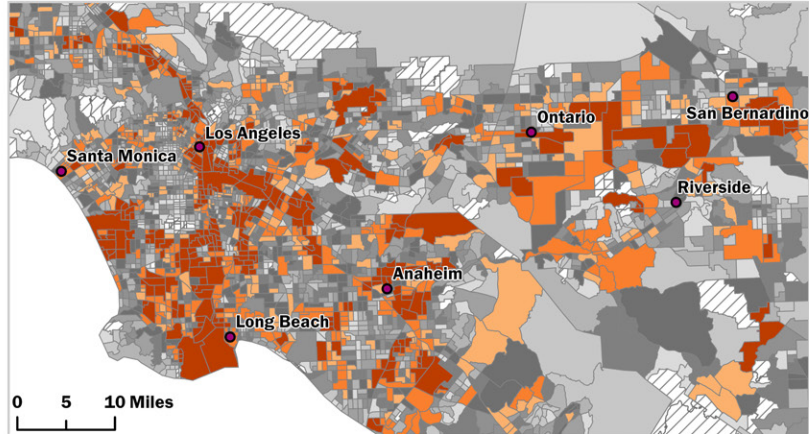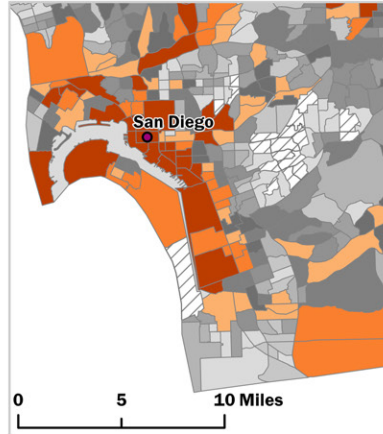
References

Aliyu AA, Kasim R, Martin D (2011). Siting of hazardous waste dump facilities and their correlation with status of surrounding residential neighbourhoods in Los Angeles County. *Property Management* **29**(1):87-102.

Boer JT, Pastor Jr M, Sadd JL, Snyder LD (1997). Is there environmental racism? The demographics of hazardous waste in Los Angeles County: Research on the environment. *Social Science Quarterly* **78**(4):793-810.

CalRecycle (2020). What Is E-Waste.   Retrieved 9 October 2020, from https://www.calrecycle.ca.gov/Electronics/WhatisEwaste.

DTSC (2010). Electronic Hazardous Waste (E-Waste). Retrieved 9 October 2020, from https://dtsc.ca.gov/electronic-hazardous-waste/

DTSC (2012). Defining Hazardous Waste.   Retrieved 9 October 2020, from https://dtsc.ca.gov/defining-hazardous-waste/.

Kouznetsova M, Huang X, Ma J, Lessner L, Carpenter DO (2007). Increased rate of hospitalization for diabetes and residential proximity of hazardous waste sites. *Environ Health Perspect* **115**(1):75-9.

McGlinn L (2000). Spatial Patterns of Hazardous Waste Generation and Management in the United States. *The Professional Geographer* **52**(1):11-22.

Pellerin C, Booker SM (2000). Reflections on hexavalent chromium: health hazards of an industrial heavyweight. *Environmental Health Perspect* **108**(9):A402-A7.

Sergeev AV, Carpenter DO (2005). Hospitalization rates for coronary heart disease in relation to residence near areas contaminated with persistent organic pollutants and other pollutants. *Environ Health Perspect* **113**(6):756-61.

Vrijheid M (2000). Health effects of residence near hazardous waste landfill sites: a review of epidemiologic literature. *Environ Health Perspect* **108 Suppl 1**:101-12.

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)[1] 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[2] (>1,000 kg of non-RCRA[3] 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 2018 to 2020 this represents about 11,000 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.

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[2] DTSC Large Quantity Generators of Hazardous Waste at https://dtsc.ca.gov/large-quantity-generator-of-hazardous-waste-definition/

[3] RCRA: Resource Conservation and Recovery Act governs the federal management of hazardous wastes; (List of RCRA waste: https://www.epa.gov/hw/defining-hazardous-waste-listed-characteristic-and-mixed-radiological-wastes)

Permitted Hazardous Waste Facilities

	Weight	Activity or Status
Facility Activity (base weight)	10	Landfill
	7	Treatment
	4	Storage
	2	Post-closure
Permit Type (additional weight)	1	Large facilities
	1	Non-RCRA facilities
	2	RCRA facilities
Violation Scoring Procedure Compliance Tier (additional weight)	3	Tier: "Unacceptable"
	1	Tier: "Conditionally Acceptable"

Hazardous Waste Generators

Generator Type	Weight	Quantity of Waste
Large Quantity Hazardous Waste Generators (> 1,102 tons in one calendar month)	0.1	< 100 tons/yr
	0.5	100 – 1,000 tons/yr
	2	>1,000 tons/yr

Chrome Plating Facilities

Facility Type	Weight	Permitted Amperage-Hours
Active Chrome Plating Facilities	0.1	<=50,000 amp-hrs/yr
	0.5	> 50,000 – 500,000 amp-hrs/yr
	2	>500,000 amp-hrs/yr

Number of Chrome Plating Facilities, Hazardous Waste Generators, and Permitted Facilities: Approximately 11,300

Facility Type	% of Total
Large hazardous waste generator or hazardous waste generator with RCRA waste	98%
Permitted hazardous waste storage facility	1%*
Active chrome plating facility	1%

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

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IMPAIRED WATER BODIES

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 (2018).*
Data Source	*2018 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 2018 303(d) List was based on water quality data collected prior to May 3, 2017. 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, 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, 2002). Excessive hardness, unpleasant odor or taste, turbidity, color, weeds, and trash in the waters are types of pollutants affecting

water aesthetics (CalEPA, 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.

  https://www.waterboards.ca.gov/water_issues/programs/water_quality_assessment/2018_integrated_report.html

- 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 Water Bodies

Summed number of pollutants from water bodies designated as impaired (2018)
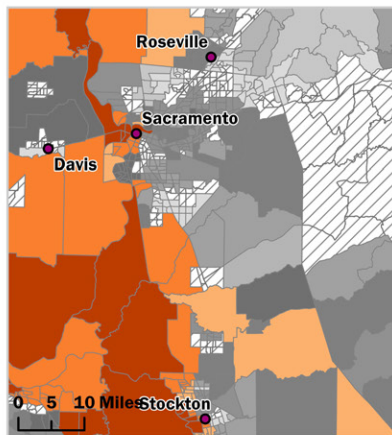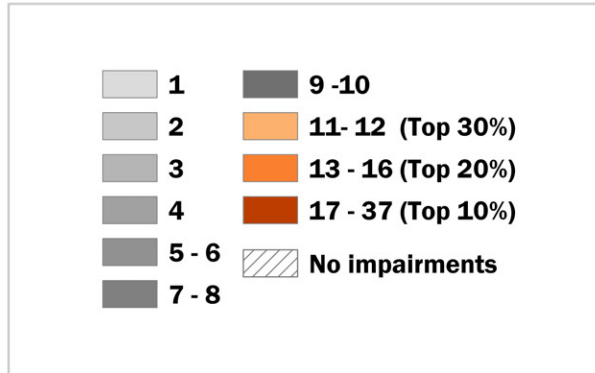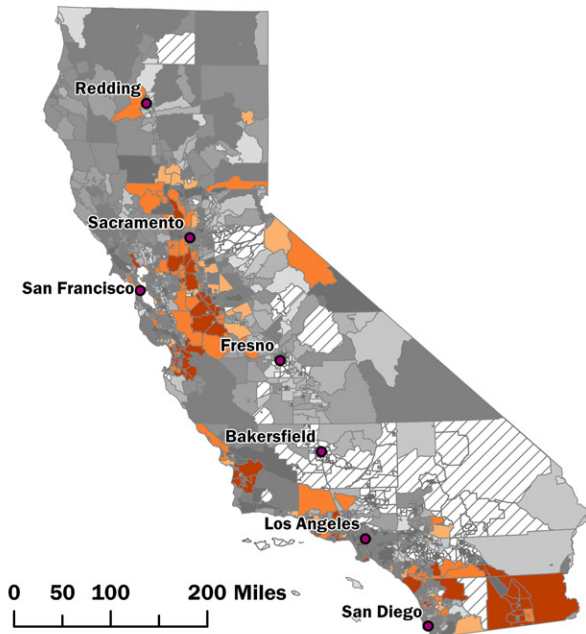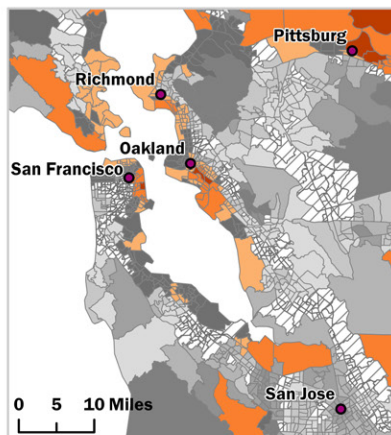
1		9 -10	
2		11- 12 (Top 30%)	
3		13 - 16 (Top 20%)	
4		17 - 37 (Top 10%)	
5 - 6		No impairments	
7 - 8			

0 50 100 200 Miles

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

San Diego Area

CalEnviroScreen 4.0

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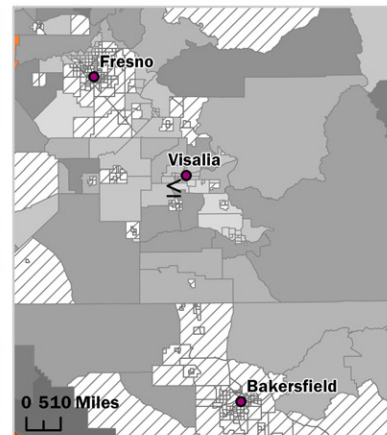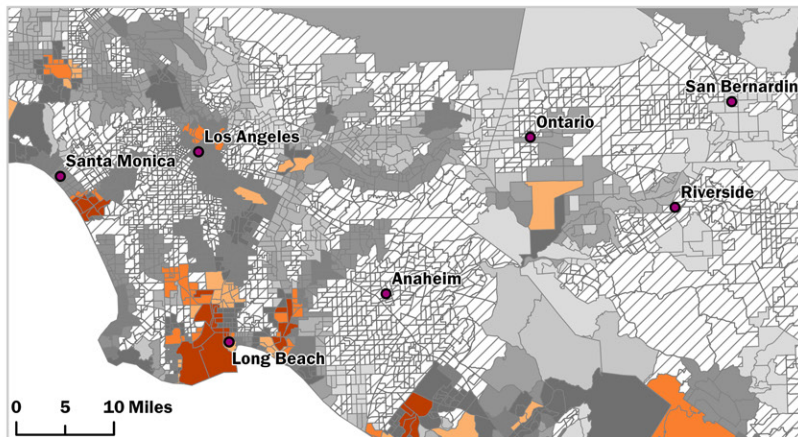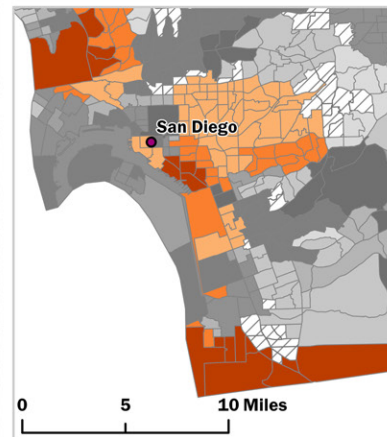
References

Brody SD, Highfield W, Alston L (2004). Does location matter? Measuring environmental perceptions of creeks in two San Antonio watersheds. *Environment and Behavior* **36**(2):229-50.

CalEPA (2002). Environmental Protection Indicators for California. In OEHHA (Ed.) (2002 ed., pp. 303). Sacramento: CalEPA. Available at URL: http://oehha.ca.gov/multimedia/epic/Epicreport.html.

Farzin YH, Grogan KA (2013). Socioeconomic factors and water quality in California. *Environmental Economics and Policy Studies* **15**(1):1-37.

Georgiou S, Bateman I, Cole M, Hadley D (2000). Contingent ranking and valuation of river water quality improvements: Testing for scope sensitivity, ordering and distance decay effects. *Centre for Social and Economic Research on the Global Environment*.

Liévanos RS (2018). Impaired water hazard zones: Mapping intersecting environmental health vulnerabilities and polluter disproportionality. *ISPRS International Journal of Geo-Information* **7**(11):433.

NEJAC (2002). National Environmental Justice Advisory Council. Fish Consumption and Environmental Justice. A Report Developed from the National Environmental Justice Advisory Council Meeting of December 3-6, 2001. Available at URL: http://www.epa.gov/environmentaljustice/resources/publications/nejac/fish-consump-report_1102.pdf.

Pomeroy C, Thomson CJ, Stevens MM (2010). California's North Coast Fishing Communities: Historical Perspective and Recent Trends. *Scripps Institution of Oceonography* (T-072).

Shilling F, White A, Lippert L, Lubell M (2010). Contaminated fish consumption in California's Central Valley Delta. *Environ Res* **110**(4):334-44.

Silver E, Kaslow J, Lee D, Lee S, Tan ML, Weis E*, et al.* (2007). Fish consumption and advisory awareness among low-income women in California's Sacramento–San Joaquin Delta. *Environ Res* **104**(3):410-9.

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. 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 siting 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 July 2021).*
Data Source	*Solid Waste Information System (SWIS) and Closed, Illegal, and Abandoned (CIA) Disposal Sites Program, California Department of Resources Recycling and Recovery – CalRecycle*

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, waste tire sites, and closed disposal sites.

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 links below:

https://www2.calrecycle.ca.gov/SolidWaste/Activity
http://www.calrecycle.ca.gov/SWFacilities/CIA/

Hazardous Waste Tracking System – Department of Toxic Substances Control (DTSC)

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 2017-2019. Data are available at the link below:

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

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 (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, 2010a; USFA, 2002). 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).

Although all active solid waste sites 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, 2010b).

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 in the laboratory. New ecological test methods have demonstrated that exposure 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, 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, primarily meat, milk and olives, from an area near the landfill (Vassiliadou *et al.*, 2009). A recent 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:

- CIA data were obtained from CalRecycle for all priorities. (Only high priority CIA sites data are available online.)

- Unconfirmed and non-solid waste sites were removed from the analysis.

- Each remaining site was scored on a weighted scale in consideration of CalRecycle's prioritization categories (see table in Appendix).

- To account for cross-border pollution, OEHHA identified one closed solid waste site in Mexico within 1000 meters of a

community in California. This site was given a weight of '1', the same as a closed solid waste site within CalRecycle's database. 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).

- Site locations were mapped or geocoded (in ArcMap).

Active Solid Waste Information (SWIS) sites:

- SWIS data 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 on a weighted scale in consideration of the category type of solid waste operation (see table in Appendix).

- Site locations were mapped or geocoded (in ArcMap).

- CalRecycle provided site boundaries (based on parcel boundaries and aerial photo inspection) for most of the 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 (NAICS code 42193) were obtained from DTSC's Hazardous Waste Tracking System for 2017 to 2019.

- Any facility that was active between 2017 and 2019 was included.

- All scrap metal recyclers were weighted the same as large volume permitted transfer/processing facility (see weighting matrix below).

All sites:

- The weights for all sites, including the large landfill perimeters, 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. Sites outside of

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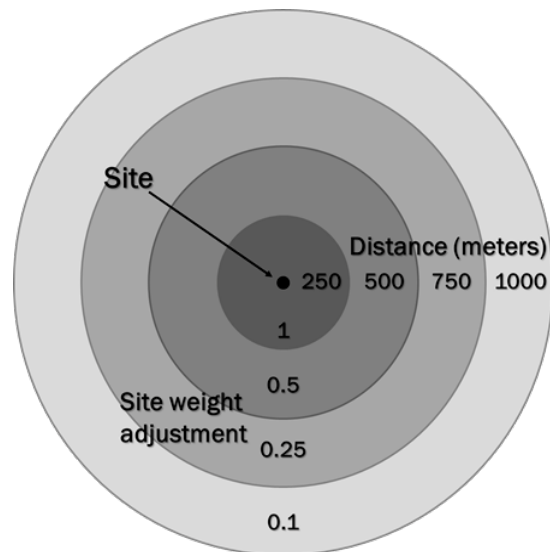
- Odor complaints regarding composting facilities are commonly made more than 1000 m from these facilities. Because of this concern the buffer distances (and site weights) for composting sites were adjusted as follows: 1 for sites less than 500m, 0.5 for sites 500 – 1000m, 0.25 for sites 1000 – 1500m,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

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

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

Solid Waste Sites and Facilities

Sum of weighted solid waste sites and facilities (as of July 2021)
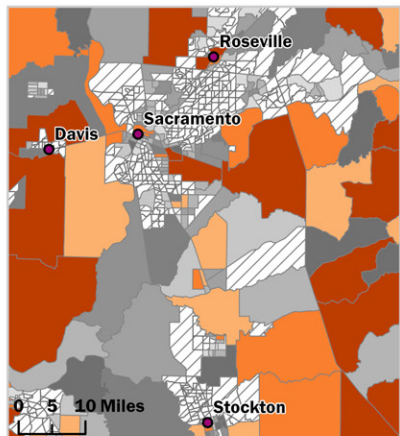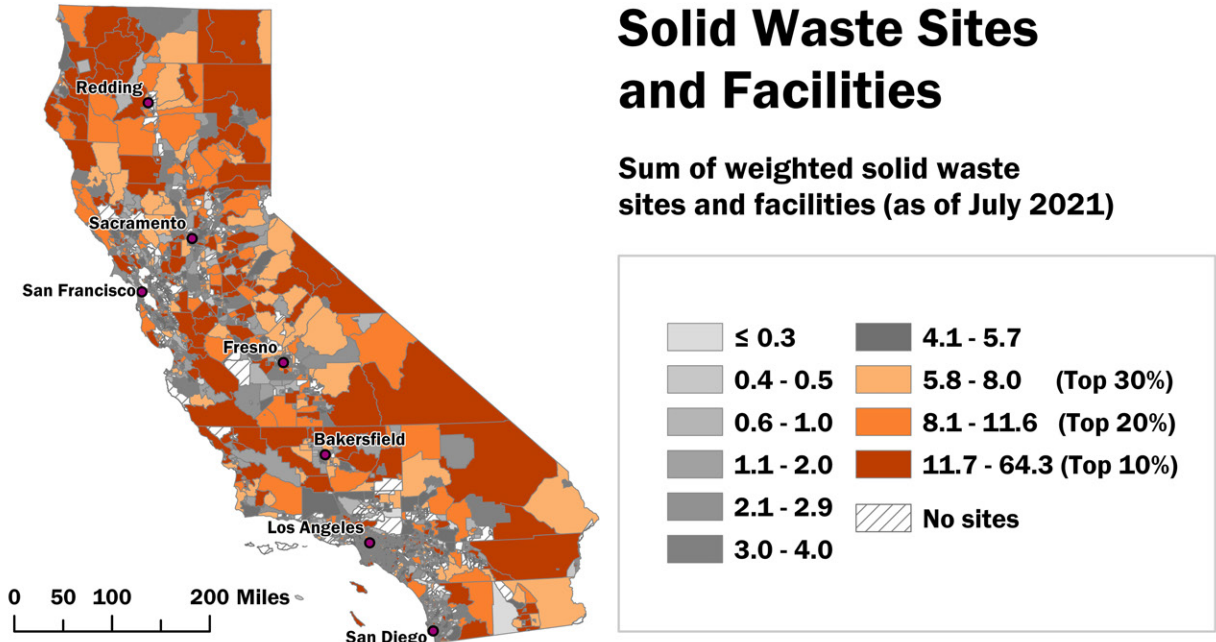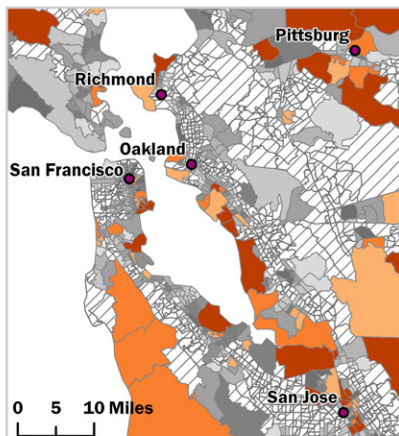
≤ 0.3	4.1 - 5.7
0.4 - 0.5	5.8 - 8.0 (Top 30%)
0.6 - 1.0	8.1 - 11.6 (Top 20%)
1.1 - 2.0	11.7 - 64.3 (Top 10%)
2.1 - 2.9	No sites
3.0 - 4.0	

0   50   100   200 Miles

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0
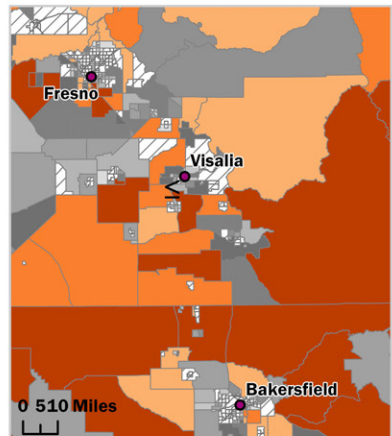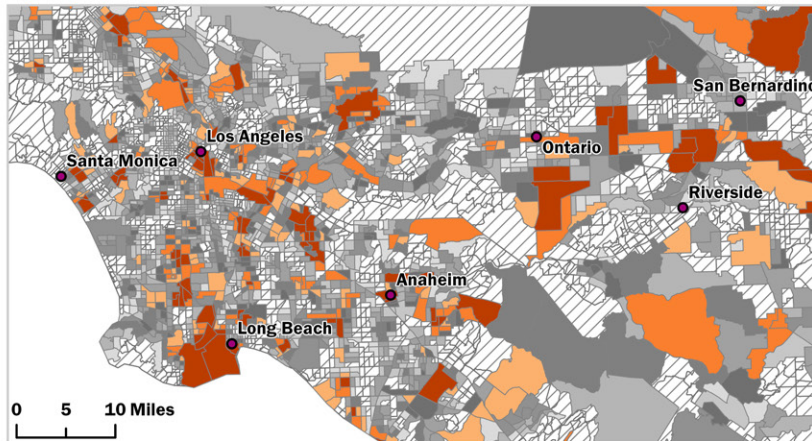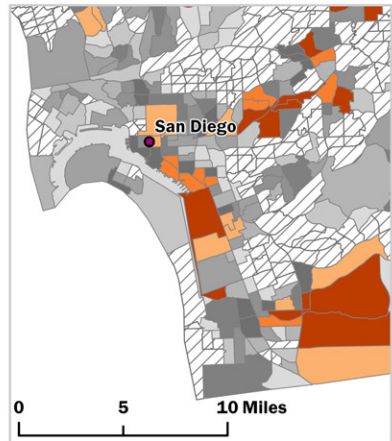
San Diego Area

References

CalRecycle (2010a, March 3, 2020). Fires at Solid Waste Facilities. Retrieved September 28, 2020, from https://www.calrecycle.ca.gov/SWFacilities/Fires/

CalRecycle (2010b, July 15, 2019). Former Landfill and Disposal Site Investigations.   Retrieved September 28, 2020, from https://www2.calrecycle.ca.gov/Publications/Download/1410

Heaney CD, Wing S, Campbell RL, Caldwell D, Hopkins B, Richardson D*, et al.* (2011). Relation between malodor, ambient hydrogen sulfide, and health in a community bordering a landfill. *Environ Res* **111**(6):847-52.

Lou X, Nair J (2009). The impact of landfilling and composting on greenhouse gas emissions–a review. *Bioresource Technology* **100**(16):3792-8.

Mataloni F, Badaloni C, Golini MN, Bolignano A, Bucci S, Sozzi R*, et al.* (2016). Morbidity and mortality of people who live close to municipal waste landfills: a multisite cohort study. *International Journal of Epidemiology* **45**(3):806-15.

Ofungwu J, Eget S (2006). Brownfields and health risks--air dispersion modeling and health risk assessment at landfill redevelopment sites. *Integr Environ Assess Manag* **2**(3):253-61.

Palmer SR, Dunstan FD, Fielder H, Fone DL, Higgs G, Senior ML (2005). Risk of congenital anomalies after the opening of landfill sites. *Environ Health Perspect* **113**(10):1362-5.

Roelofs D, de Boer M, Agamennone V, Bouchier P, Legler J, van Straalen N (2012). Functional environmental genomics of a municipal landfill soil. *Front Genet* **3**:85.

USFA (2002). Landfill Fires: Their magnitude, characteristics, and mitigation. In USF Administration (Ed.). Washington, DC: Federal Emergency Management Agency, U.S. Fire Administration.

Vassiliadou I, Papadopoulos A, Costopoulou D, Vasiliadou S, Christoforou S, Leondiadis L (2009). Dioxin contamination after an accidental fire in the municipal landfill of Tagarades, Thessaloniki, Greece. *Chemosphere* **74**(7):879-84.

Weitz KA, Thorneloe SA, Nishtala SR, Yarkosky S, Zannes M (2002). The impact of municipal solid waste management on greenhouse gas emissions in the United States. *Journal of the Air & Waste Management Association* **52**(9):1000-11.

Appendix

Weighting Matrix for Solid Waste Sites and Facilities

Solid Waste Sites and Facilities from the Solid Waste Information System were weighted on a scale of 1 to a maximum of 13 in consideration of both the site type and violation history. The following table shows the weights applied to the facilities and sites. The score for any given Solid Waste Site or Facility represents the sum of its 'Site or Facility Type' and 'Violations'. For all census tracts, the weighted scores of all facilities in the area were summed after adjusting for proximity to populated census blocks.

Category	Criteria	Site or Facility Type	Violations (any in 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 Landfill *or* Construction, Demolition and Inert (CDI) Debris Waste Disposal (active) [3]	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)	**3** (gas) **1** (each for litter, dust, noise, vectors, and site security)
Solid Waste Disposal Site (closed, closing, inactive) [4]	Tonnage	**1** (All)	**3** (gas) **1** (each for litter, vector, site security)
Inert Debris: Engineered Fill	Regulatory Tier [5]	**2** (Notification)	**1** (each for dust, noise, vectors, site security)
Inert Debris: Type A Disposal	Regulatory Tier [5]	**3** (Permitted)	**1** (each for dust, noise, vectors, site security)
Composting	Regulatory Tier [5]	**4** (Permitted) **3** (Permitted: Chipping & Grinding, 200 to ≤500 tpd) **2** (Notification)	**1** (each for vector, odor, litter, hazard, nuisance, noise, dust, site security) **1** (fire)
In-Vessel Digestion Facility	Regulatory Tier [5]	**5** (Permitted: large volume, > 100 tpd, or average > 700 tpw) **3** (Registration, 15 to ≤ 100 tpd, not to exceed 700 tpw) **2** (Notification)	**1** (vector, odor, litter, hazard, nuisance, noise, dust, site security)
Transfer/Processing	Regulatory Tier [5]	**5** (Permitted: large vol.) **3** (Permitted: medium vol.; direct transfer) **2** (Notification) **3** (Permitted: medium vol.; direct transfer) **2** (Notification)	**1** (each for dust, litter, vector/bird/animal, fire, site security)

Waste Tire	Regulatory Tier [5]	**4** (Major) **2** (Minor)	**2** (each for storage, fire) **1** (each for vectors, site security)
Scrap Metal Recycler		**5** (Active 2017-2019)	NA

[1] Violations: Recurring requirements ensures only facilities that exhibit a pattern and practice of non-compliance receive a higher impact score and reduces point-in-time fluctuations. 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 weighted per established CIA Site Priority Code scoring methodology (A through D; additional information available at https://www.calrecycle.ca.gov/swfacilities/cia/prioritize).

[3] Active landfills (other than Contaminated Soil Disposal Sites and Nonhazardous Ash Disposal/Monofill Facilities) are all in the Full Permit tier, so permitted tonnage (from SWIS) is used to scale impact score.

[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] Regulatory Tier used to weight the site or facility. 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.

Number of Solid Waste Sites and Facilities in CalEnviroScreen 4.0: Approximately 4,000

Facility Type	% of Total
Disposal (closed)	58%
Transfer/Processing (open)	15%
Composting	10%
Scrap Metal Recyclers	10%
Disposal (active)	4%
Waste Tire	1%
In-Vessel Digestion Facility	<1%
Transfer/Processing (closed)	<1%

SCORES FOR POLLUTION BURDEN

(RANGE OF POSSIBLE SCORES: 0.1 TO 10)

Pollution Burden scores for each census tract are derived from the average percentiles of the seven Exposures indicators (ozone and PM2.5 concentrations, diesel PM emissions, drinking water contaminants, children's lead risk from housing, pesticide use, toxic releases from facilities, and traffic density) and the five Environmental Effects indicators (cleanup sites, impaired water bodies, groundwater threats, hazardous waste facilities and generators, and solid waste sites and facilities).

Indicators from the Environmental Effects component were given half the weight of the indicators from the Exposures component. The calculated average pollution burden score (average of the indicators) was divided by 10 and rounded to one decimal place for a Pollution Burden score ranging from 0.1 – 10.

Note: The map on the following page shows pollution scores divided into deciles.

Pollution Burden

Percentile of combined Exposures and Environmental Effects* indicators
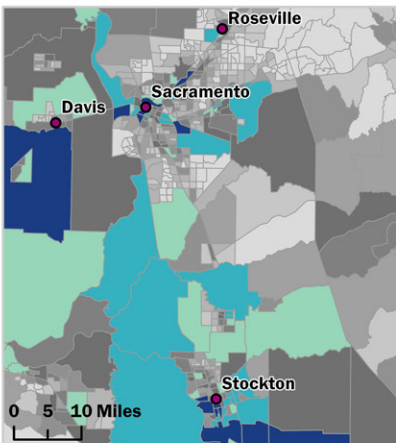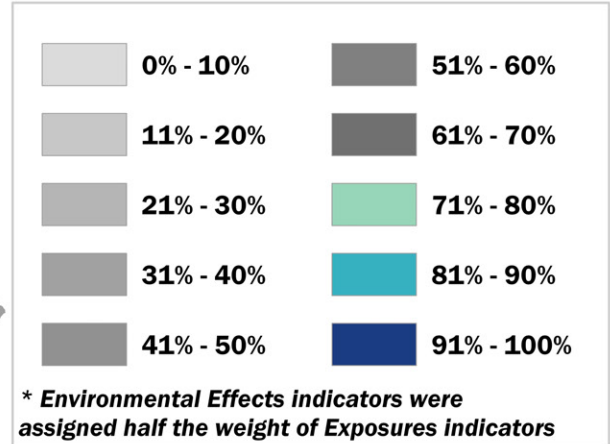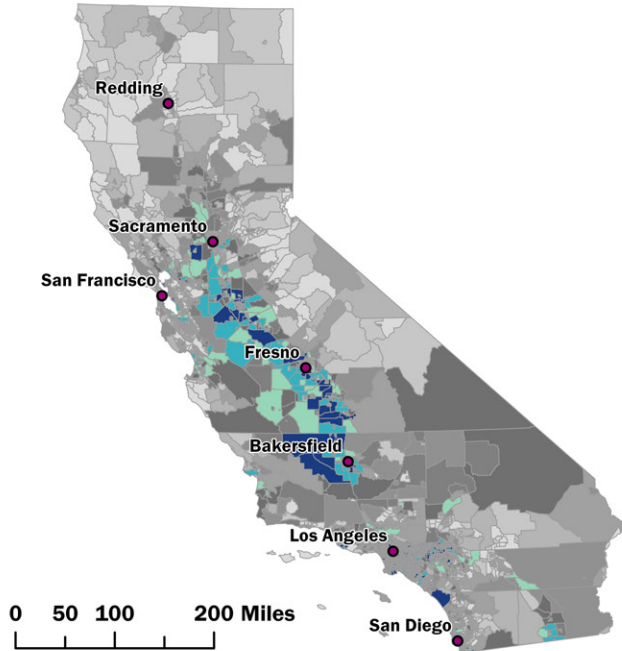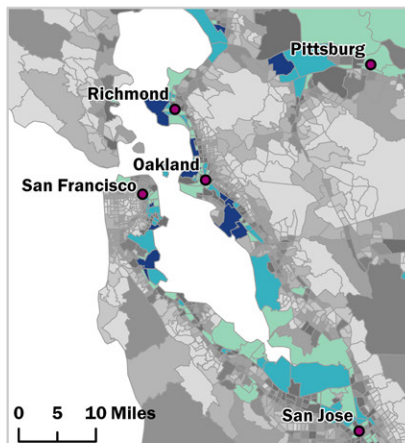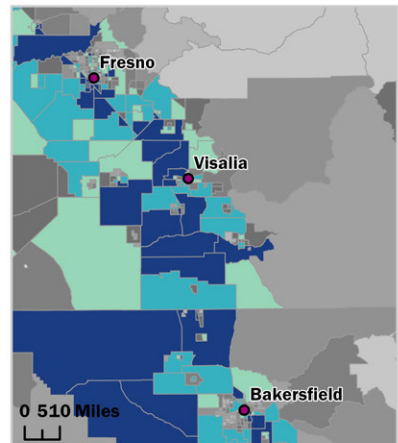
0% - 10%	51% - 60%
11% - 20%	61% - 70%
21% - 30%	71% - 80%
31% - 40%	81% - 90%
41% - 50%	91% - 100%

Environmental Effects indicators were assigned half the weight of Exposures indicators

0   50   100   200 Miles

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

San Diego Area

149
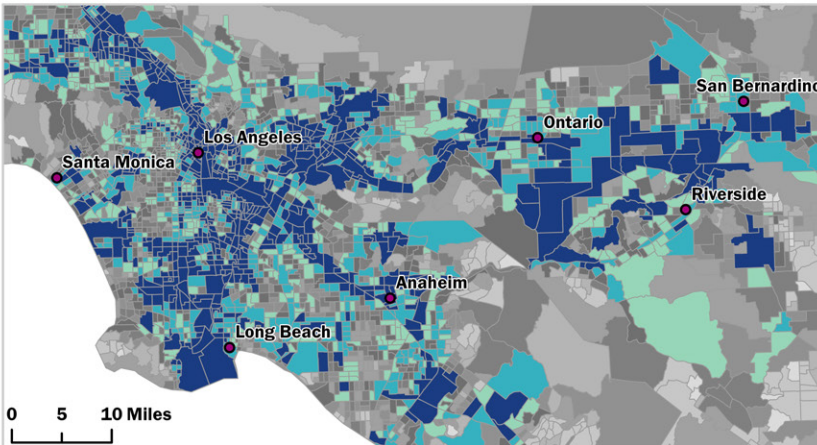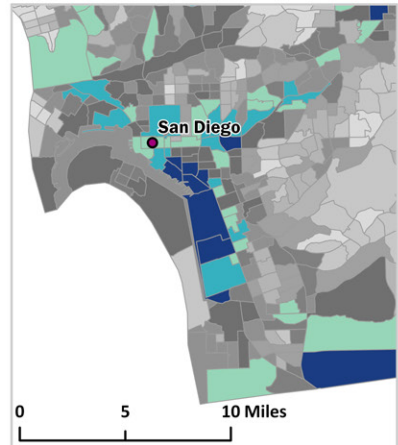
POPULATION CHARACTERISTICS: SENSITIVE POPULATION INDICATORS

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 (UCLA, 2009). 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.

Indicator   Spatially modeled, age-adjusted rate of ED visits for asthma per 10,000 (averaged over 2015-2017).

Data Source   *Emergency Department and Patient Discharge Datasets from the State of California, Office of Statewide Health Planning and Development (OSHPD)*

Since 2005, hospitals licensed by the state of California to provide emergency medical services are required to report all ED visits to OSHPD. 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.

ED utilization does not capture the full burden of asthma in a community because not everyone with asthma requires emergency care, especially if they 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. Some ED visits result in hospitalization. OSPHD collects data on hospitalization due to asthma in addition to ED visits. ED visits are thought to provide a better comparative measure of asthma burden than hospitalizations and deaths because the data capture a larger portion of the overall burden and include less severe occurrences.
https://oshpd.ca.gov/data-and-reports/

Tracking California

Tracking California processed OSHPD's data to calculate age-adjusted rates of asthma ED visits for California ZIP codes. These

estimates make use of 2017 ZIP code level population estimates from ESRI and the US 2000 Standard Population to derive age-adjusted rates. Age-adjustment takes the age distribution of a population into account and allows for meaningful comparisons between ZIP codes with different age structures. ZIP code estimates are assigned to 2010 census blocks using areal apportionment. Population-weighted census block estimates are then combined to arrive at a census tract estimate.
https://trackingcalifornia.org/asthma/query

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 (Meng *et al.*, 2011). 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 (Hernandez *et al.*, 2011) and increases risk of asthma morbidity in children with asthma (Benka-Coker *et al.*, 2020).

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). The severity of symptoms and the likelihood of needing hospital care decrease with access to regular medical care and asthma medication (CDC, 2013; Grineski *et al.*, 2010). Asthma-related ED visits provide an underestimate of total asthma cases because not all cases require emergency care. However, using those cases requiring emergency care as an indicator also captures 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 performed the following steps to calculate the rate of ED visits for asthma:

- Records for ED visits occurring during 2015-2017 were obtained from OSHPD's Emergency Department and Ambulatory Surgery files for patients listed as residing in California and principle diagnostic of asthma.

- International Classification of Diseases (ICD) codes were used to extract ED visits for asthma. In 2015, ICD-9 was replaced by ICD-10.

- ICD-9 code 493, which identifies asthma, was used for quarters 1-3 in 2015.

- ICD-10 code J45, which identifies asthma, was used for quarter 4 of 2015 and for the years 2016 and 2017.

- Hospitalizations were included if the hospitalization is described as originating from the hospital's own ED.

- An age-adjusted rate of asthma ED visits was calculated for each ZIP code. ZIP code rates were then reapportioned to census tract rates.

- 2017 population data used for the age-adjustment were obtained from ESRI and rates reported are standardized to the 2000 US population using five-year age groupings (0-4, 5-9, etc.). The rates are per 10,000 residents per year.

- Age-adjusted rates were spatially modeled to provide estimates for ZIP codes with fewer than 12 ED visits, which were considered statistically unreliable. A modeling technique that incorporates information about both local and statewide rates into the calculations was used (Mollié, 1996).

- Census blocks were assigned the average rate of the ZIP code they intersected using areal apportionment. Census tract rates were then estimated by the population-weighted average of the rates of the census blocks that it contains.

- Census tracts were sorted by the spatially modeled apportioned rate and were assigned percentiles based on their position in the distribution.

Asthma

Spatially modeled, age-adjusted rate of emergency department visits for asthma per 10,000 (2015-2017)
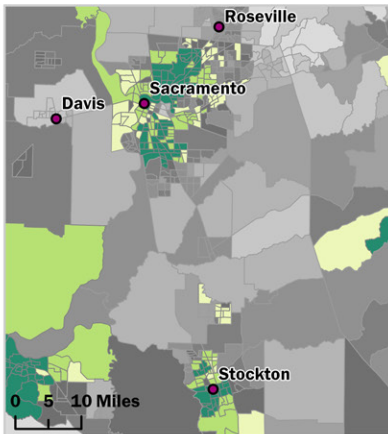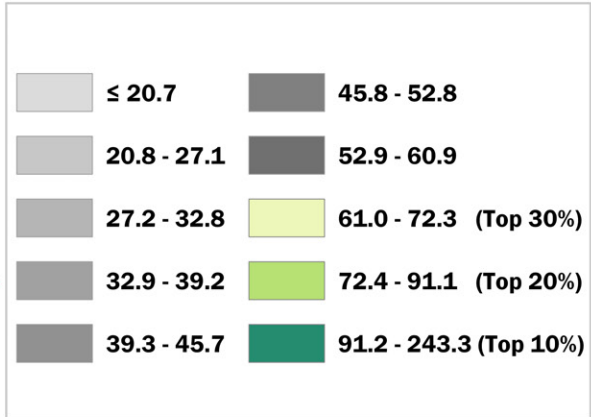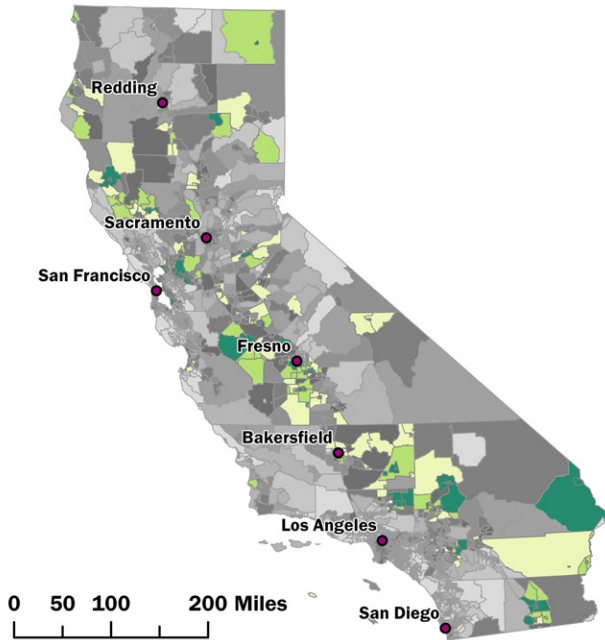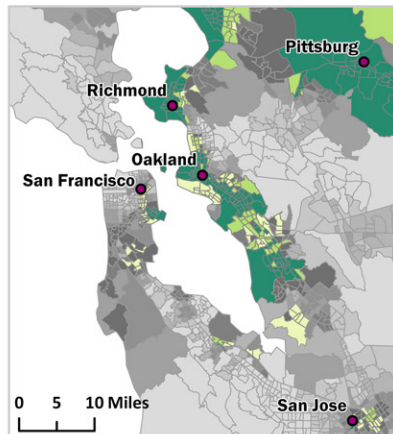
≤ 20.7	45.8 - 52.8
20.8 - 27.1	52.9 - 60.9
27.2 - 32.8	61.0 - 72.3 (Top 30%)
32.9 - 39.2	72.4 - 91.1 (Top 20%)
39.3 - 45.7	91.2 - 243.3 (Top 10%)

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

San Diego Area

CalEnviroScreen 4.0

154
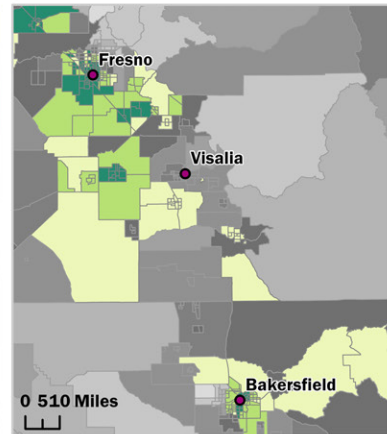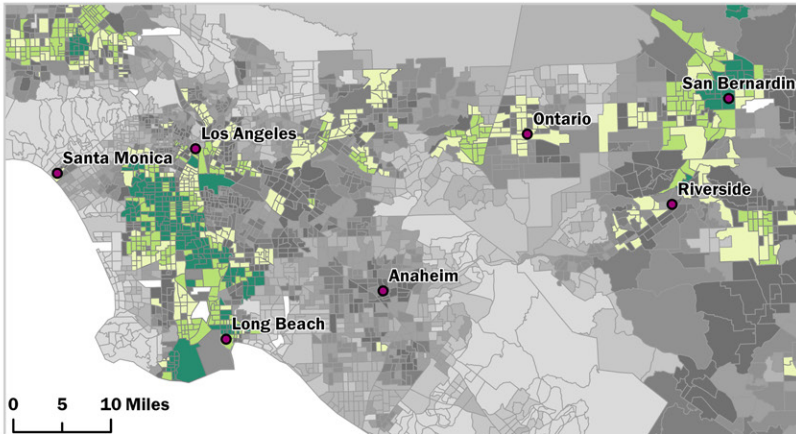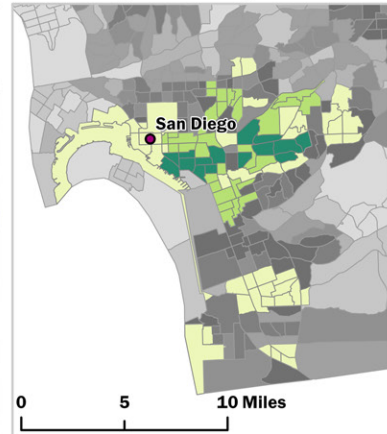
References

Benka-Coker W, Loftus C, Karr C, Magzamen S (2020). Association of Organophosphate Pesticide Exposure and a Marker of Asthma Morbidity in an Agricultural Community. *Journal of Agromedicine* **25**(1):106-14.

CDC (2013). *Centers for Disease Control and Prevention Asthma facts: CDC's National Asthma Control Program grantees.* http://www.cdc.gov/asthma/pdfs/asthma_facts_program_grantees.pdf.

Grineski SE, Staniswalis JG, Peng Y, Atkinson-Palombo C (2010). Children's asthma hospitalizations and relative risk due to nitrogen dioxide (NO2): effect modification by race, ethnicity, and insurance status. *Environ Res* **110**(2):178-88.

Guarnieri M, Balmes JR (2014). Outdoor air pollution and asthma. *The Lancet* **383**(9928):1581-92.

Hernandez AF, Parron T, Alarcon R (2011). Pesticides and asthma. *Curr Opin Allergy Clin Immunol* **11**(2):90-6.

Kloepfer KM, Olenec JP, Lee WM, Liu G, Vrtis RF, Roberg KA*, et al.* (2012). Increased H1N1 infection rate in children with asthma. *Am J Respir Crit Care Med* **185**(12):1275-9.

McConnell R, Islam T, Shankardass K, Jerrett M, Lurmann F, Gilliland F*, et al.* (2010). Childhood incident asthma and traffic-related air pollution at home and school. *Environ Health Perspect* **118**(7):1021-6.

Meng YY, Wilhelm M, Ritz B, Balmes JR, Lombardi C, Bueno A*, et al.* (2011). *Is disparity in asthma among Californians due to higher pollutant exposures, greater susceptibility, or both?* Sacramento, CA: UCLA Center for Health Policy Research.

Mollié A (1996). Bayesian mapping of disease. In: *Markov Chain Monte Carlo in Practice.* Springer, pp. 359-79.

Spira-Cohen A, Chen LC, Kendall M, Lall R, Thurston GD (2011). Personal exposures to traffic-related air pollution and acute respiratory health among Bronx schoolchildren with asthma. *Environ Health Perspect* **119**(4):559-65.

UCLA (2009). California Health Interview Survey 2012, from http://www.chis.ucla.edu/main/default.asp

Wendt JK, Symanski E, Stock TH, Chan W, Du XL (2014). Association of short-term increases in ambient air pollution and timing of initial asthma diagnosis among medicaid-enrolled children in a metropolitan area. *Environmental Research* **131**(0):50-8.

Zanobetti A, Schwartz J, Gold D (2000). Are there sensitive subgroups for the effects of airborne particles? *Environ Health Perspect* **108**(9):841-5.

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 a 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 2015-2017).

Data Source *Emergency Department and Patient Discharge Datasets from the State of California, Office of Statewide Health Planning and Development (OSHPD)*

Since 2005, hospitals licensed by the state of California to provide emergency medical services are required to report all ED visits to OSHPD. 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.

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

Tracking California

Tracking California processed OSHPD's data to calculate age-adjusted rates of AMI ED visits for California ZIP codes. These estimates make use of 2017 ZIP code scale population estimates from ESRI and the US 2000 Standard Population to derive age-adjusted rates. Age-adjustment takes the age distribution of a population into account and allows for meaningful comparisons between ZIP codes with different age structures. ZIP code estimates are assigned to 2010 census blocks using areal apportionment. Population-weighted census block estimates are then combined to arrive at a census tract estimate.
https://trackingcalifornia.org/mi/query

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). One more recent study found that exposure to ambient gases at current National Ambient Air Quality Standards may increase CVD risks in midlife women (Basu *et al.*, 2017).

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 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, although the research is less conclusive. A recent 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 µg/m³ increase in PM 2.5. This suggests that long-term exposure to particulate matter may play a role in decreasing the likelihood of survival following a heart attack (Chen *et al.*, 2016). It has also been found that long-term exposure to ambient PM 2.5 may increase CVD risks in midlife

women (Broadwin *et al.*, 2019). Another study found that long-term exposure to PM 2.5 was associated with ischemic heart disease and stroke mortality, with excess risk occurring even below the US standard for PM 2.5 exposure (Hayes *et al.*, 2020).

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.

Method

Tracking California performed the following steps to calculate the rate of ED visits for CVD:

- Records for ED visits occurring during 2015-2017 were obtained from OSHPD's Emergency Department and Ambulatory Surgery files for patients listed as residing in California and principle diagnostic of AMI.

- International Classification of Diseases (ICD) codes were used to extract ED visits for AMI. In 2015, ICD-9 was replaced by ICD-10.

- ICD-9 code 410, which identifies AMI, was used for quarters 1-3 in 2015.

- ICD-10 code I21 and I22, which identifies AMI, was used for quarter 4 of 2015 and for the years 2016 and 2017.

- Hospitalizations were included if the hospitalization is described as originating from the hospital's own ED.

- An age-adjusted rate of AMI ED visits was calculated for each ZIP code using data obtained from OSHPD. ZIP code rates were then reapportioned to census tract rates.

- 2017 population data used for the age-adjustment were obtained from ESRI and rates reported are standardized to the 2000 US population using five-year age groupings. The rates are per 10,000 residents per year.

- The age-adjusted rates were spatially modeled to provide estimates for ZIP codes with fewer than 12 ED visits, which are considered statistically unreliable. A modeling technique that incorporates information about both local and statewide rates into the calculations was used (Mollié, 1996).

- Census blocks were assigned the average rate of the ZIP code they intersected using areal apportionment. Census tract rates were then estimated by the population-weighted average of the rates of the census blocks that it contains.

- Census tracts were sorted by the spatially modeled apportioned rate and were 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 (2015-2017)
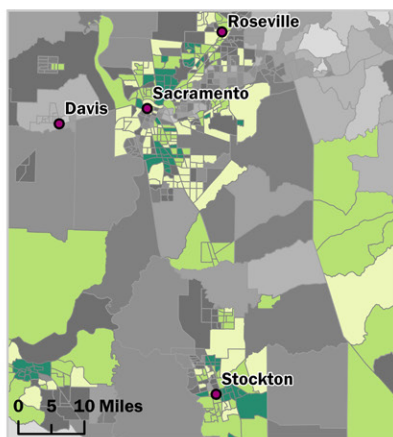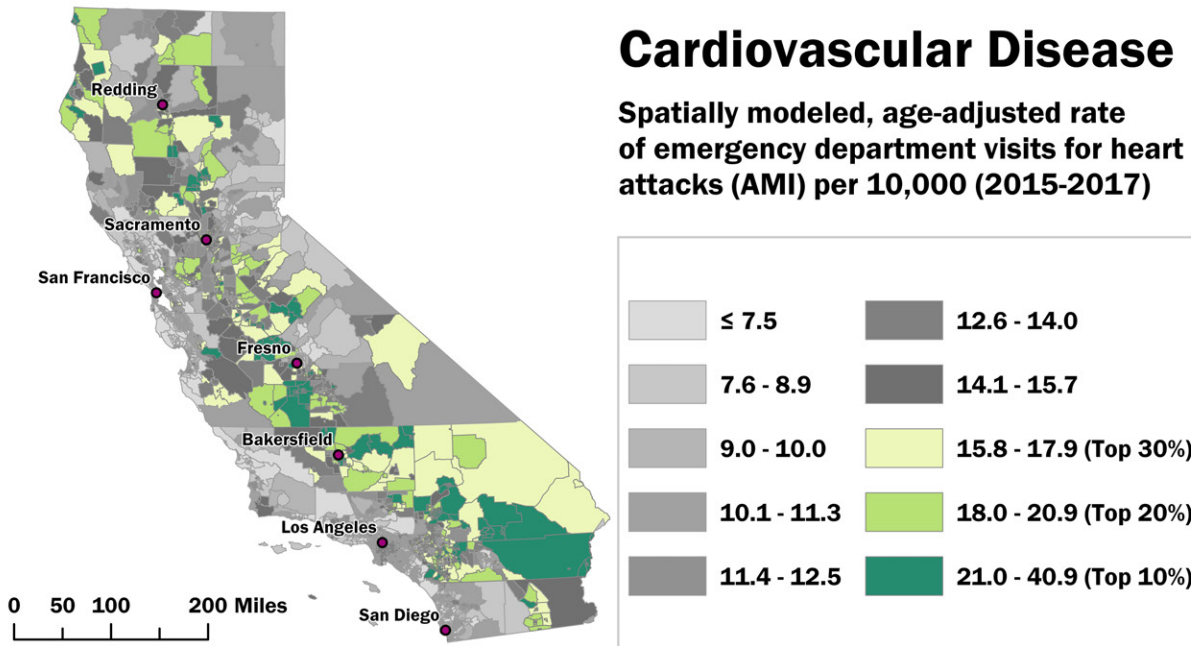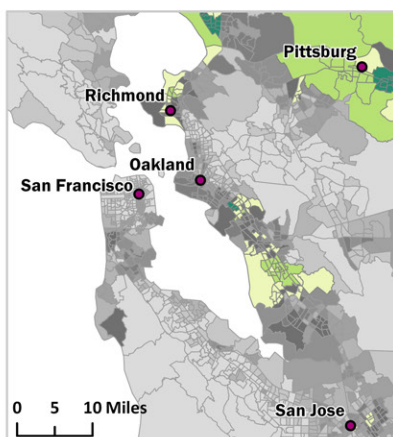
≤ 7.5	12.6 - 14.0
7.6 - 8.9	14.1 - 15.7
9.0 - 10.0	15.8 - 17.9 (Top 30%)
10.1 - 11.3	18.0 - 20.9 (Top 20%)
11.4 - 12.5	21.0 - 40.9 (Top 10%)

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

159
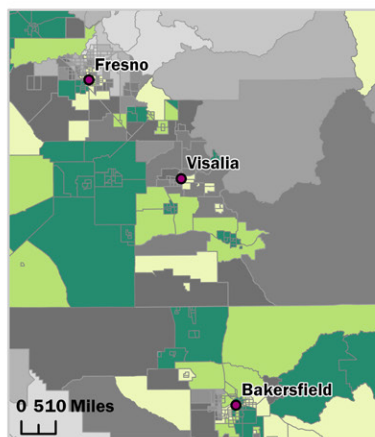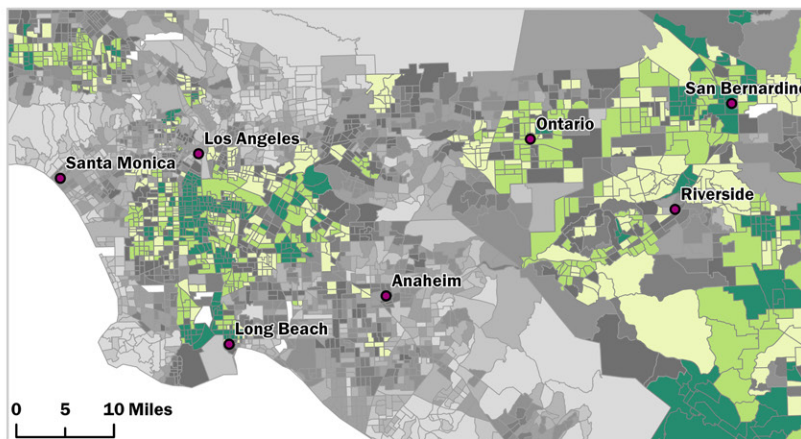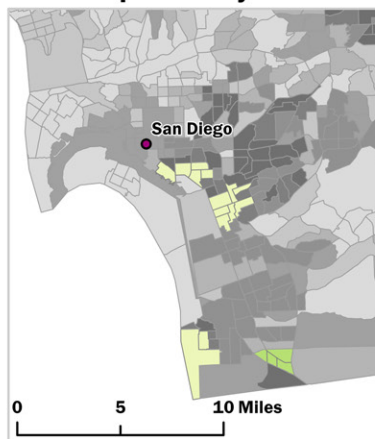
References

Basu R, Malig B, Broadwin R, Ebisu K, Gold EB, Qi L, *et al.* (2017). Association between gaseous air pollutants and inflammatory, hemostatic and lipid markers in a cohort of midlife women. *Environment International* **107**:131-9.

Bateson TF, Schwartz J (2004). Who is sensitive to the effects of particulate air pollution on mortality? A case-crossover analysis of effect modifiers. *Epidemiology* **15**(2):143-9.

Berglind N, Bellander T, Forastiere F, von Klot S, Aalto P, Elosua R, *et al.* (2009). Ambient air pollution and daily mortality among survivors of myocardial infarction. *Epidemiology*:110-8.

Broadwin R, Basu R, Malig B, Ebisu K, Gold EB, Qi L, *et al.* (2019). Associations between fine particulate matter and changes in lipids/lipoproteins among midlife women. *Science of the Total Environment* **654**:1179-86.

Brook RD, Rajagopalan S, Pope III CA, Brook JR, Bhatnagar A, Diez-Roux AV, *et al.* (2010). Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. *Circulation* **121**(21):2331-78.

Chen H, Burnett RT, Copes R, Kwong JC, Villeneuve PJ, Goldberg MS, *et al.* (2016). Ambient fine particulate matter and mortality among survivors of myocardial infarction: population-based cohort study. *Environ Health Perspect* **124**(9):1421-8.

Hayes RB, Lim C, Zhang Y, Cromar K, Shao Y, Reynolds HR, *et al.* (2020). PM2. 5 air pollution and cause-specific cardiovascular disease mortality. *International Journal of Epidemiology* **49**(1):25-35.

Mollié A (1996). Bayesian mapping of disease. In: *Markov chain Monte Carlo in practice.* Springer, pp. 359-79.

Pope III C, Muhlestein JB, May HT, Renlund DG, Anderson JL, Horne BD (2006). Ischemic heart disease events triggered by short-term exposure to fine particulate air pollution. *Circulation* **114**(23):2443-8.

Schwartz J (1994). What are people dying of on high air pollution days? *Environmental Research* **64**(1):26-35.

Von Klot S, Gryparis A, Tonne C, Yanosky J, Coull BA, Goldberg RJ, *et al.* (2009). Elemental carbon exposure at residence and survival after acute myocardial infarction. *Epidemiology*:547-54.

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, (averaged over 2009-2015).*

Data Source

California Department of Public Health (CDPH)

The Health Information and Research Section of CDPH 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 are available at the link below:

http://www.cdph.ca.gov/data/dataresources/requests/Pages/BirthandFetalDeathFiles.aspx

Tracking California

Information about the geographic location of births was used by OEHHA in compliance with the State of California Committee for the Protection of Human Subjects. The data were analyzed by Tracking California. More information on Tracking California at the link below:

https://trackingcalifornia.org/

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 birthweight (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). A recent study found that proximity to higher production oil and gas development in rural areas of California was associated with increased odds of LBW (Tran *et al.*, 2020). There also is a significant association between heat, ozone, and fine particulate matter with adverse pregnancy outcomes, including LBW (Bekkar *et al.*, 2020).

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

- Low birth weight (LBW) was calculated from California birth records as the percent of live, singleton births during the 2009-2015 period weighing less than 2,500 grams.

- Multiple births (non-singletons) and births with an improbable combination of gestational age and birth weight were excluded (Alexander et al., 1996). Out-of-state births, and births with no known residential address (including P.O. boxes) were also excluded. These exclusions lead to lower statewide LBW percentage than that reported by other organizations who do not apply this criterion.

- Births were geocoded based on the mother's residential address at the time of birth by Tracking California. A small number (less than 1%) of addresses could not be geocoded and were excluded.

- Estimates derived from places with few births are considered unreliable because they often produce extreme 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 (2009-2015) were excluded. The percentage of low birth weight births was calculated using the seven years of data to minimize the number of excluded census tracts.

- Census tracts were sorted by percentage low birth weight and were assigned percentiles based on their position in the distribution.

Low Birth Weight Infants

Percent low birth weight (2009-2015)
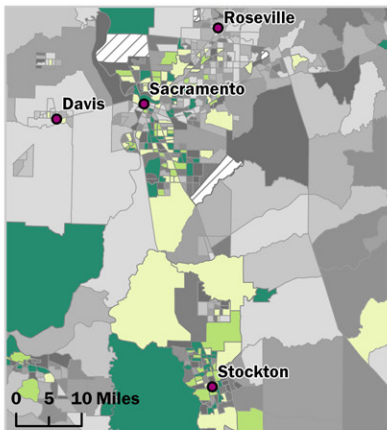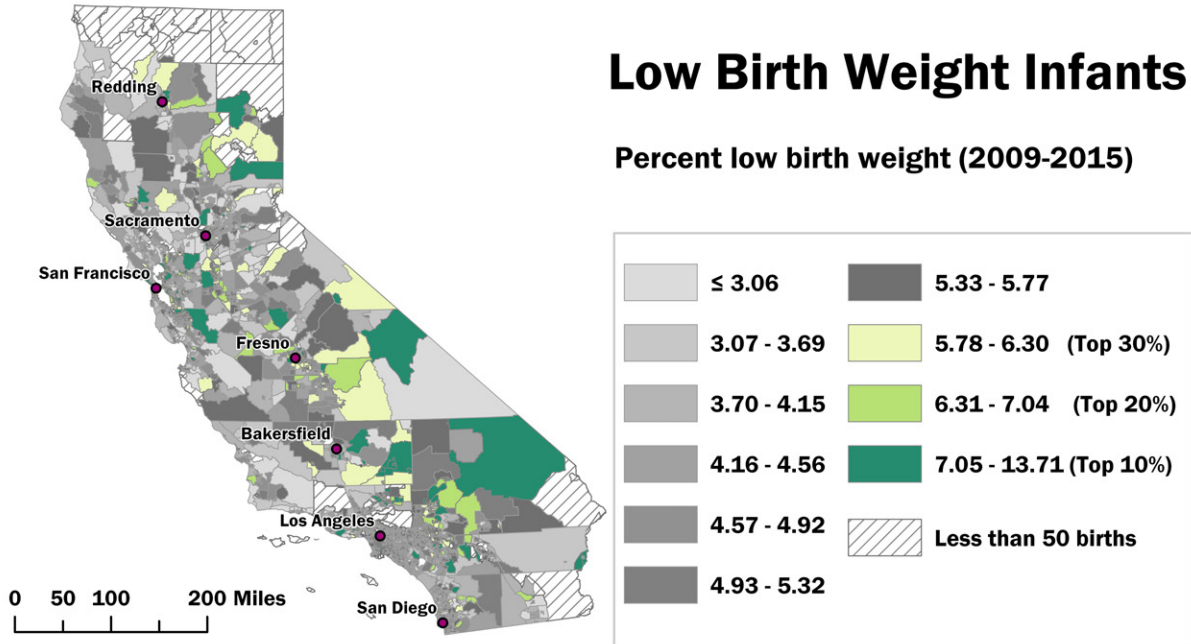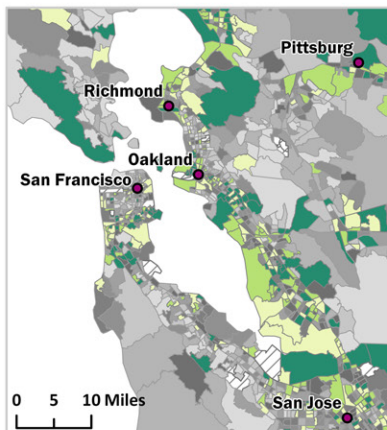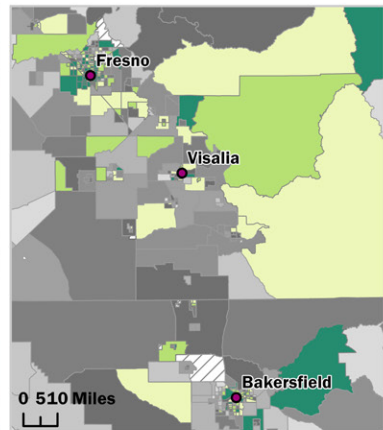
≤ 3.06	5.33 - 5.77
3.07 - 3.69	5.78 - 6.30 (Top 30%)
3.70 - 4.15	6.31 - 7.04 (Top 20%)
4.16 - 4.56	7.05 - 13.71 (Top 10%)
4.57 - 4.92	Less than 50 births
4.93 - 5.32	

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

164
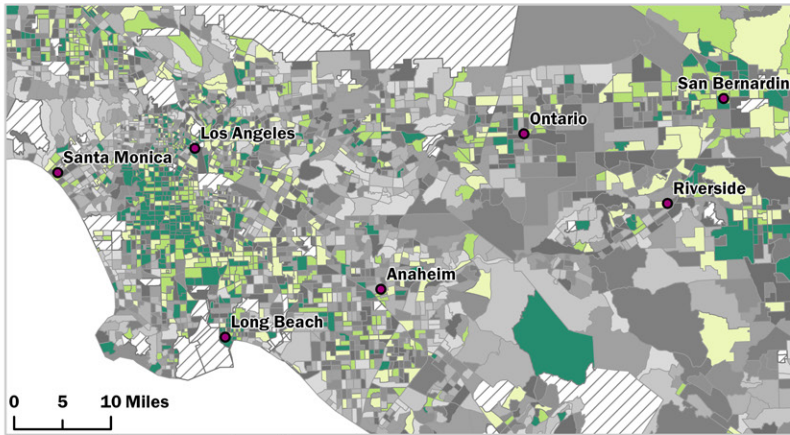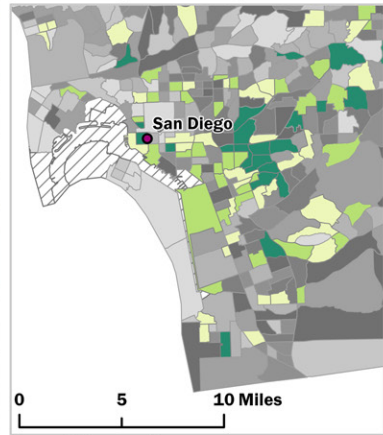
References

Alexander GR, Himes JH, Kaufman RB, Mor J, Kogan M (1996). A United States national reference for fetal growth. *Obstetrics & Gynecology* **87**(2):163-8.

Almeida J, Bécares L, Erbetta K, Bettegowda VR, Ahluwalia IB (2018). Racial/ethnic inequities in low birth weight and preterm birth: the role of multiple forms of stress. *Maternal and Child Health Journal* **22**(8):1154-63.

Ban J, Xu D, He MZ, Sun Q, Chen C, Wang W, *et al.* (2017). The effect of high temperature on cause-specific mortality: A multi-county analysis in China. *Environment International* **106**:19-26.

Basu R, Harris M, Sie L, Malig B, Broadwin R, Green R (2014). Effects of fine particulate matter and its constituents on low birth weight among full-term infants in California. *Environ Res* **128**:42-51.

Bekkar B, Pacheco S, Basu R, DeNicola N (2020). Association of Air Pollution and Heat Exposure With Preterm Birth, Low Birth Weight, and Stillbirth in the US: A Systematic Review. *JAMA Network Open* **3**(6):e208243-e.

Belbasis L, Savvidou MD, Kanu C, Evangelou E, Tzoulaki I (2016). Birth weight in relation to health and disease in later life: an umbrella review of systematic reviews and meta-analyses. *BMC medicine* **14**(1):147.

Franz AP, Bolat GU, Bolat H, Matijasevich A, Santos IS, Silveira RC, *et al.* (2018). Attention-deficit/hyperactivity disorder and very preterm/very low birth weight: a meta-analysis. *Pediatrics* **141**(1).

Ghosh JK, Wilhelm M, Su J, Goldberg D, Cockburn M, Jerrett M, *et al.* (2012). Assessing the influence of traffic-related air pollution on risk of term low birth weight on the basis of land-use-based regression models and measures of air toxics. *Am J Epidemiol* **175**(12):1262-74.

Harley KG, Huen K, Aguilar Schall R, Holland NT, Bradman A, Barr DB, *et al.* (2011). Association of organophosphate pesticide exposure and paraoxonase with birth outcome in Mexican-American women. *PLoS One* **6**(8):e23923.

Laurent O, Hu J, Li L, Kleeman MJ, Bartell SM, Cockburn M, *et al.* (2016). Low birth weight and air pollution in California: Which sources and components drive the risk? *Environment International* **92**:471-7.

Ratnasiri AW, Parry SS, Arief VN, DeLacy IH, Halliday LA, DiLibero RJ, *et al.* (2018). Recent trends, risk factors, and disparities in low birth weight in California, 2005–2014: a retrospective study. *Maternal Health, Neonatology and Perinatology* **4**(1):15.

Shah AS, Langrish JP, Nair H, McAllister DA, Hunter AL, Donaldson K*, et al.* (2013). Global association of air pollution and heart failure: a systematic review and meta-analysis. *The Lancet* **382**(9897):1039-48.

Tran KV, Casey JA, Cushing LJ, Morello-Frosch R (2020). Residential Proximity to Oil and Gas Development and Birth Outcomes in California: A Retrospective Cohort Study of 2006–2015 Births. *Environ Health Perspect* **128**(6):067001.

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, 2015-2019).*
Data Source	*American Community Survey – 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 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 2015-2019. The data are made available using the U.S. Census data download website and are available at the link below:

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

Rationale

Educational attainment is an important independent predictor of health (Cutler and Lleras-Muney, 2006; Zajacova and Lawrence, 2018). Individuals with lower education in the US have a lower life expectancy (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 (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

- From the *2015-2019* American Community Survey estimates, a dataset containing the percentage of the population over age 25 with a high school education or higher was downloaded by census tracts for the state of California.

- This percentage was subtracted from 100 to obtain the proportion of the population with less than a high school education.

- Unlike the US Census, ACS estimates come from a sample of the population and may be unreliable if they are based on a small sample or population size. The standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of each estimate.

- The SE was calculated for each census tract by dividing the margin of error (MOE) reported in the ACS by 1.645, a statistical value associated with a 90 percent confidence interval. The MOE is the difference between an estimate and the upper or lower bounds of its confidence interval. All ACS-published MOEs are based on a 90 percent confidence interval.

- The RSE is calculated by dividing a tract's SE by its estimate of educational attainment, and taking the absolute value of the result.

- Census tract estimates that met either of the following criteria were considered reliable and included in the analysis:

    o RSE less than 50 (meaning the SE was less than half of the estimate) OR

    o SE was less than the mean SE of all California census tract estimates for education.

- Census tracts with unreliable estimates received no score for the indicator (null). The indicator was not factored into that tract's overall CalEnviroScreen score.

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

Educational Attainment

Percent population over age 25 not having completed high school (2015-2019)
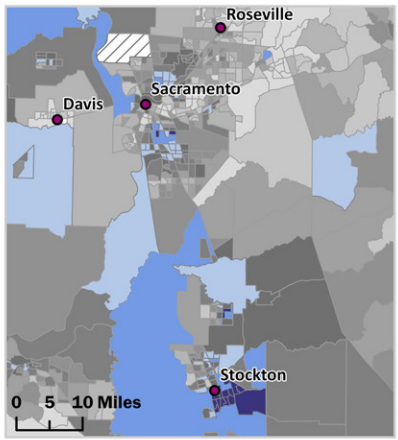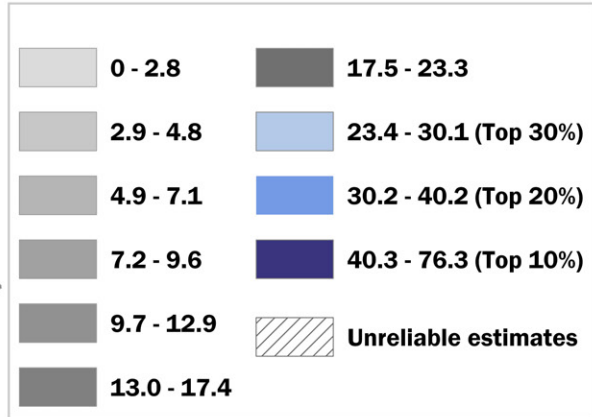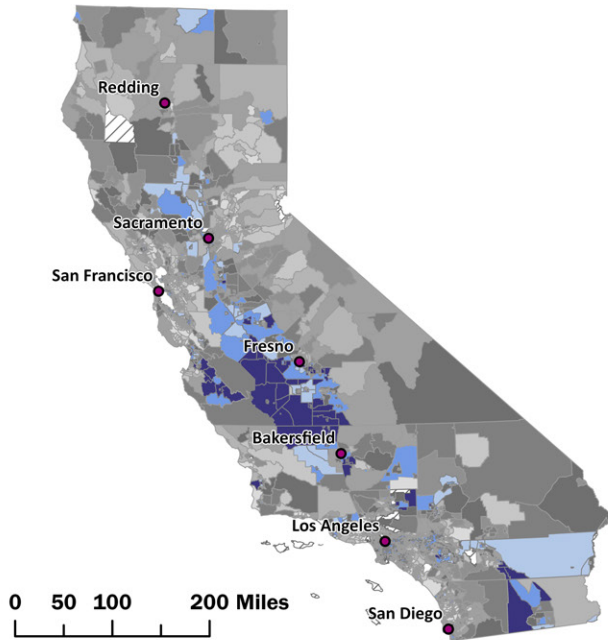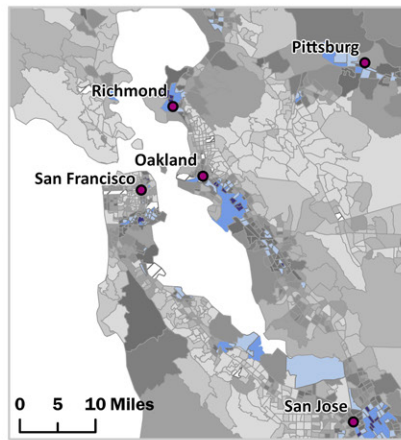
0 - 2.8	17.5 - 23.3
2.9 - 4.8	23.4 - 30.1 (Top 30%)
4.9 - 7.1	30.2 - 40.2 (Top 20%)
7.2 - 9.6	40.3 - 76.3 (Top 10%)
9.7 - 12.9	Unreliable estimates
13.0 - 17.4	

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0
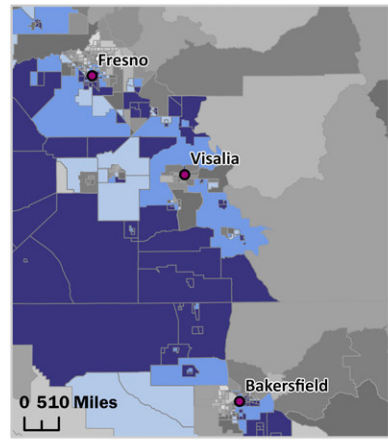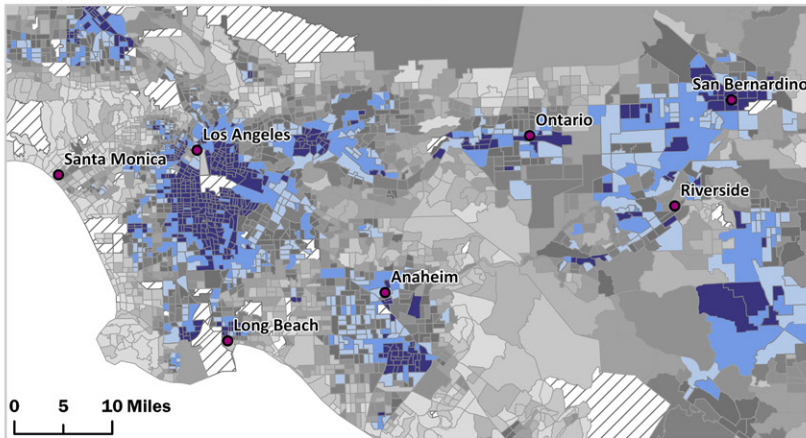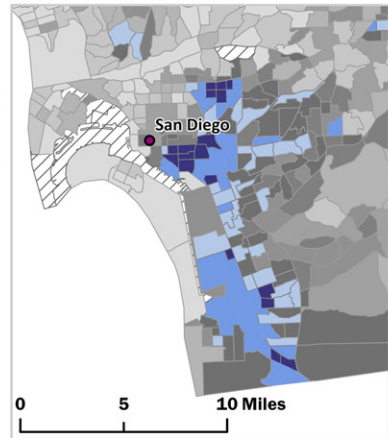
San Diego Area

References

Adler N, Pantell MS, O'Donovan A, Blackburn E, Cawthon R, Koster A, *et al.* (2013). Educational attainment and late life telomere length in the Health, Aging and Body Composition Study. *Brain Behav Immun* **27**(1):15-21.

Assari S (2018). Blacks' diminished return of education attainment on subjective health; mediating effect of income. *Brain Sciences* **8**(9):176.

Bell CN, Sacks TK, Tobin CST, Thorpe Jr RJ (2020). Racial Non-equivalence of Socioeconomic Status and Self-rated Health among African Americans and Whites. *SSM-Population Health* **10**:100561.

Cakmak S, Dales RE, Judek S (2006). Respiratory health effects of air pollution gases: modification by education and income. *Arch Environ Occup Health* **61**(1):5-10.

Cohen AK, Rai M, Rehkopf DH, Abrams B (2013). Educational attainment and obesity: a systematic review. *Obesity Reviews* **14**(12):989-1005.

Cutler DM, Lleras-Muney A (2006). *Education and health: evaluating theories and evidence*: National Bureau of Economic Research.

Erickson J, El-Gabalawy R, Palitsky D, Patten S, Mackenzie CS, Stein MB, *et al.* (2016). Educational attainment as a protective factor for psychiatric disorders: findings from a nationally representative longitudinal study. *Depression and Anxiety* **33**(11):1013-22.

Krewski D, Burnett RT, Goldberg MS, Hoover K, Siemiatycki J, Jerrett M, *et al.* (2000). Reanalysis of the Harvard Six Cities Study and the American Cancer Society Study of particulate air pollution and mortality. *Cambridge, MA: Health Effects Institute* **295**.

Lewis AS, Sax SN, Wason SC, Campleman SL (2011). Non-chemical stressors and cumulative risk assessment: an overview of current initiatives and potential air pollutant interactions. *Int J Environ Res Public Health* **8**(6):2020-73.

Neidell MJ (2004). Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. *J Health Econ* **23**(6):1209-36.

Sasson I (2016). Trends in life expectancy and lifespan variation by educational attainment: United States, 1990–2010. *Demography* **53**(2):269-93.

Shankardass K, McConnell R, Jerrett M, Milam J, Richardson J, Berhane K (2009). Parental stress increases the effect of traffic-related air pollution on childhood asthma incidence. *Proc Natl Acad Sci U S A* **106**(30):12406-11.

Thayamballi N, Habiba S, Laribi O, Ebisu K (2020). Impact of Maternal Demographic and Socioeconomic Factors on the Association Between Particulate Matter and Adverse Birth Outcomes: a Systematic Review and Meta-analysis. *Journal of Racial and Ethnic Health Disparities*:1-13.

van den Berg G, van Eijsden M, Vrijkotte TG, Gemke RJ (2012). Educational inequalities in perinatal outcomes: the mediating effect of smoking and environmental tobacco exposure. *PLoS One* **7**(5):e37002.

Zajacova A, Lawrence EM (2018). The relationship between education and health: reducing disparities through a contextual approach. *Annual Review of Public Health* **39**:273-89.

HOUSING-BURDENED LOW-INCOME HOUSEHOLDS

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 and paying greater than 50% of their income to housing costs. The indicator takes into account 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-Burdened Low-Income Households. 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, 2013-2017).*
Data Source	*Comprehensive Housing Affordability Strategy – Housing and Urban Development*
	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 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

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estimates for -2013-2017. 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 exposures, 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 (Lin *et al.*, 2004).

Low-income and financially vulnerable households that face high costs for housing can potentially suffer from health impacts (Beer *et al.*, 2006; Slatter and Beer, 2003). Households that experience high rent burden for longer periods of time are associated with greater disadvantage (Susin, 2007). Studies have shown that high rent burden can mean a higher likelihood of postponing medical services for financial reasons. 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 (Anderson *et al.*, 2003; 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 been on the rise in the US since 1970 (Chan and Jush, 2017; Quigley and Raphael, 2004). An analysis of US Census Bureau data on rent burden found that, in 2011, 53% of renter households in the US spent more than 30% of their income on housing (Colburn and Allen, 2018). 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 (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.

- Like ACS estimates, CHAS data come from a sample of the population and may be unreliable if they are based on a small sample or population size. The standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of each estimate.

- The SE was calculated for each census tract using the formula for approximating the SE of proportions provided by the ACS (American Community Survey Office, 2013, pg. 13, equation 4). When this approximation could not be used, the formula for approximating the SE of ratios (equation 3) was used instead.

- The RSE was calculated by dividing a tract's SE by its estimate of the percentage of housing-burdened low-income households, and taking the absolute value of the result.

- Census tract estimates that met either of the following criteria were considered reliable and included in the analysis:

  o RSE less than 50 (meaning the SE was less than half of the estimate) OR

  o SE was less than the mean SE of all California census tract estimates for housing-burdened low-income households.

- Census tracts with unreliable estimates receive no score for the indicator (null). The indicator is not factored into that tract's overall CalEnviroScreen score.

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

Housing Burdened

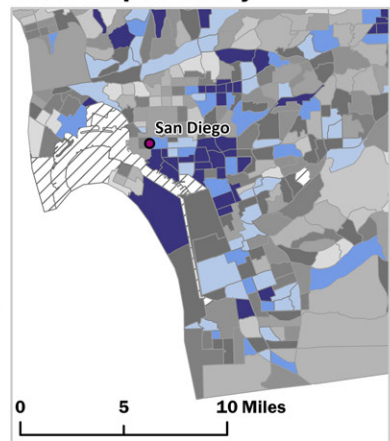Percent housing burdened
low income households (2013-2017)
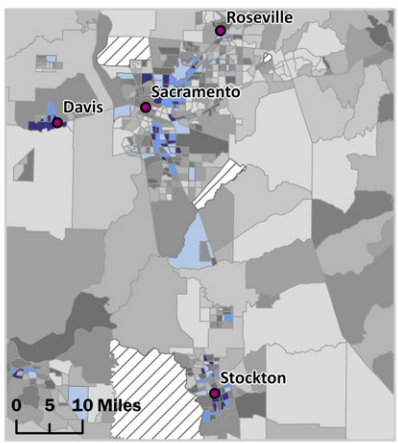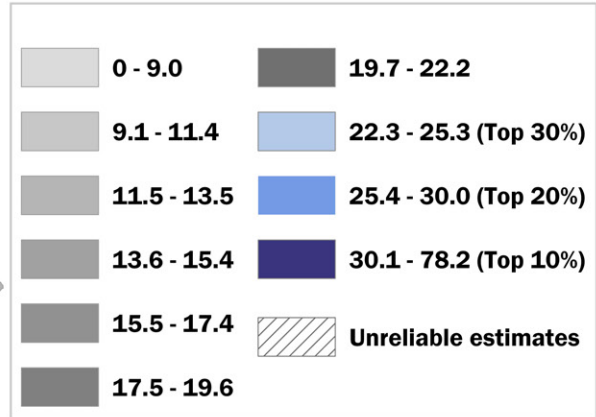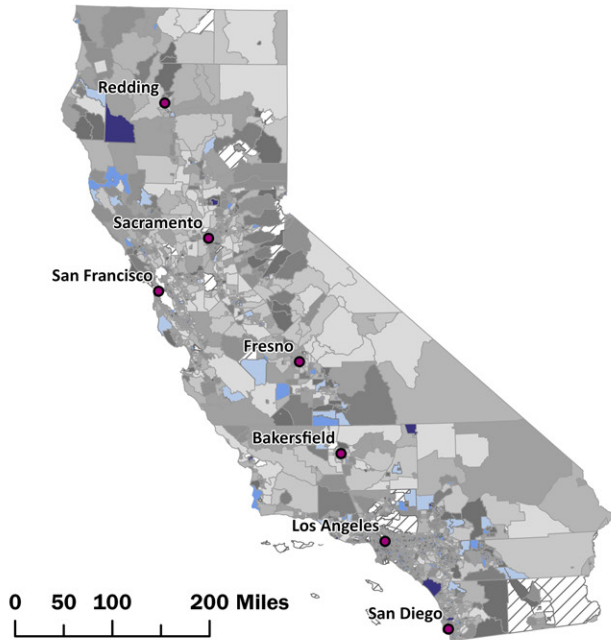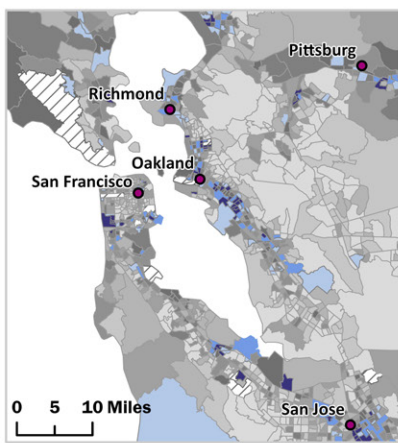
0 - 9.0
9.1 - 11.4
11.5 - 13.5
13.6 - 15.4
15.5 - 17.4
17.5 - 19.6
19.7 - 22.2
22.3 - 25.3 (Top 30%)
25.4 - 30.0 (Top 20%)
30.1 - 78.2 (Top 10%)
Unreliable estimates

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

178
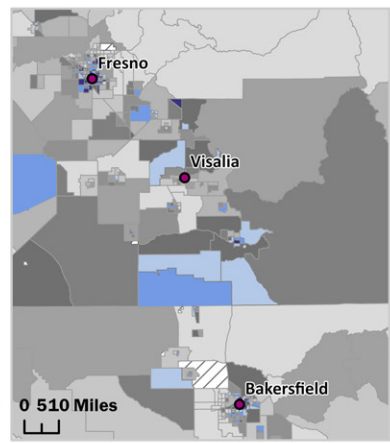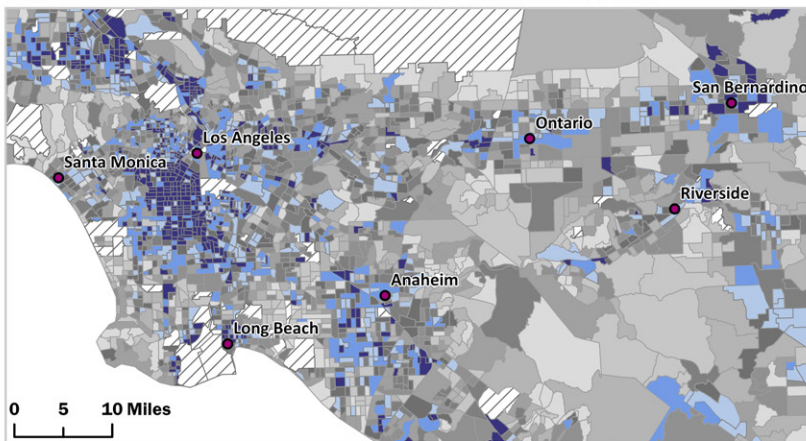
References

Anderson LM, Charles JS, Fullilove MT, Scrimshaw SC, Fielding JE, Normand J*, et al.* (2003). Providing affordable family housing and reducing residential segregation by income: a systematic review. *American Journal of Preventive Medicine* **24**(3):47-67.

Beer AP, Slatter MM, Baulderstone JM, Habibis D (2006). Evictions and housing management. *Australian Housing and Urban Research Institute Southern Research Centre*.

Braubach M (2011). Key challenges of housing and health from WHO perspective. *International Journal of Public Health* **56**(6):579-80.

Chan S, Jush GK (2017). 2017 National Rental Housing Landscape: Renting in the Nation's Largest Metros. *NYU Furman Center*.

Colburn G, Allen R (2018). Rent burden and the Great Recession in the USA. *Urban Studies* **55**(1):226-43.

Finkelstein MM, Jerrett M, DeLuca P, Finkelstein N, Verma DK, Chapman K*, et al.* (2003). Relation between income, air pollution and mortality: a cohort study. *CMAJ* **169**(5):397-402.

Harkness J, Newman SJ (2005). Housing affordability and children's well-being: Evidence from the national survey of America's families. *Housing Policy Debate* **16**(2):223-55.

Hess C, Colburn G, Crowder K, Allen R (2020). Racial disparity in exposure to housing cost burden in the United States: 1980–2017. *Housing Studies*:1-21.

Legislative Analyst's Office L (2015). California's high housing costs: Causes and consequences. Sacramento, CA: Legislative Analyst's Office.

Lin M, Chen Y, Villeneuve PJ, Burnett RT, Lemyre L, Hertzman C*, et al.* (2004). Gaseous air pollutants and asthma hospitalization of children with low household income in Vancouver, British Columbia, Canada. *Am J Epidemiol* **159**(3):294-303.

Marmot M, Friel S, Bell R, Houweling TA, Taylor S, Health CoSDo (2008). Closing the gap in a generation: health equity through action on the social determinants of health. *The Lancet* **372**(9650):1661-9.

Meltzer R, Schwartz A (2016). Housing affordability and health: evidence from New York City. *Housing Policy Debate* **26**(1):80-104.

Newman S, Holupka CS (2016). Housing affordability and children's cognitive achievement. *Health Affairs* **35**(11):2092-9.

Quigley JM, Raphael S (2004). Is housing unaffordable? Why isn't it more affordable? *Journal of Economic Perspectives* **18**(1):191-214.

Slatter M, Beer A (2003). *Housing Evictions in South Australia: A study of bailiff-assisted evictions*ed.: Australian Centre for Community Services Research Adelaide.

Susin S (2007). Duration of rent burden as a measure of need. *Cityscape: A Journal of Policy Development and Research* **9**(1):157-74.

LINGUISTIC ISOLATION

According to the most recent US Census Bureau's 2015-2019 American Community Survey (ACS), nearly 44% of Californians speak a language at home other than English, 18% of the state's population speaks English "less than very well," and 9% of all households in California are linguistically isolated. 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 difficulty speaking English. A high degree of linguistic isolation among members of a community raises concerns about access to health information and public services, and effective engagement with 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, (2015-2019).*
Data Source	*American Community Survey – 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 2015-2019. The data are made available using the U.S. Census data download website. Data are available at the link below:
	https://data.census.gov/cedsci/
Rationale	According to the most recent US Census Bureau's 2015-2019 ACS, nearly 44% of Californians speak a language at home other than English, 18% of the state's population speaks English ""less than very well," and 9% of all households in California are linguistically isolated. The inability to speak English well can affect an individual's communication with service providers and his or her ability to perform daily activities, leading to low-quality or ineffective medical care. For example, US kidney transplant candidates living in linguistically isolated ZIP codes are less likely to complete the follow-

up evaluations necessary in order to be deemed suitable to receive a kidney (Talamantes *et al.*, 2017).

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, and because in California 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 may also have higher community cultural capital than other communities, 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, and 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
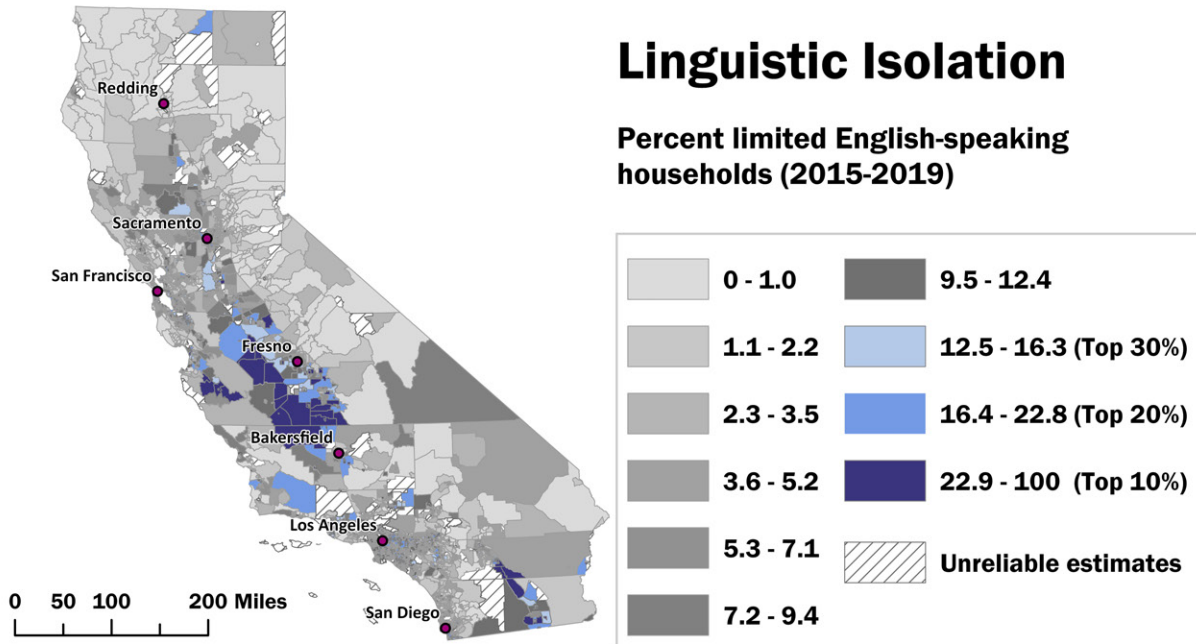
receive timely information on evacuation or shelter-in-place orders, and may therefore experience health risks that those who speak English can more easily avoid (Nepal *et al.*, 2012). Additionally, linguistic isolation was independently related to both proximity to a Toxics Release Inventory (TRI) 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

- From the 2015-2019 American Community Survey, a dataset containing the percentage of limited English-speaking households was downloaded by census tracts for the state of California. This variable is referred to as "linguistic isolation" and represents the fraction of households where no one age 14 and above speaks English well.

- Unlike the US Census, ACS estimates come from a sample of the population and may be unreliable if they are based on a small sample or population size. The standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of each estimate.

- The SE was calculated for each census tract by dividing the margin of error (MOE) reported in the ACS by 1.645, a statistical value associated with a 90 percent confidence interval. The MOE is the difference between an estimate and the upper or lower bounds of its confidence interval. All ACS-published MOEs are based on a 90 percent confidence interval.

- The RSE is calculated by dividing a tract's SE by its estimate of the percent of linguistically isolated households, and taking the absolute value of the result.

- Census tract estimates that met either of the following criteria were considered reliable and included in the analysis:

  o RSE less than 50 (meaning the SE was less than half of the estimate) OR

  o SE was less than the mean SE of all California census tract estimates for linguistic isolation.

- Census tracts with unreliable estimates received no score for the indicator (null). The indicator was not factored into that tract's overall CalEnviroScreen score.

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

Linguistic Isolation

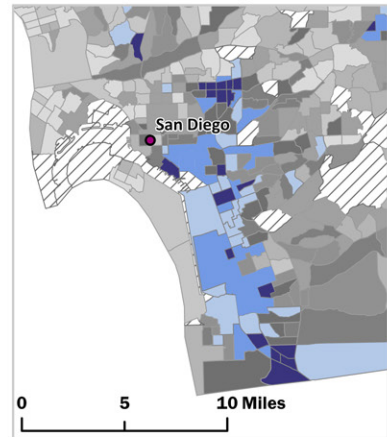## Percent limited English-speaking households (2015-2019)
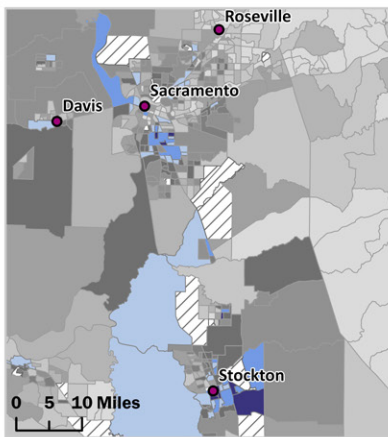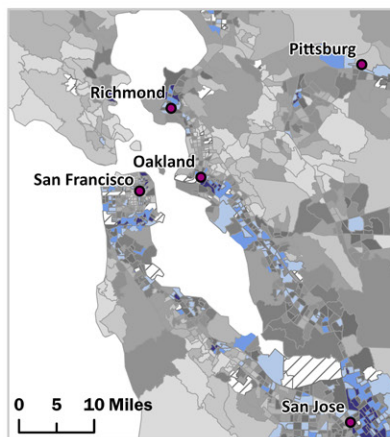
0 - 1.0	9.5 - 12.4
1.1 - 2.2	12.5 - 16.3 (Top 30%)
2.3 - 3.5	16.4 - 22.8 (Top 20%)
3.6 - 5.2	22.9 - 100 (Top 10%)
5.3 - 7.1	Unreliable estimates
7.2 - 9.4	

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

184
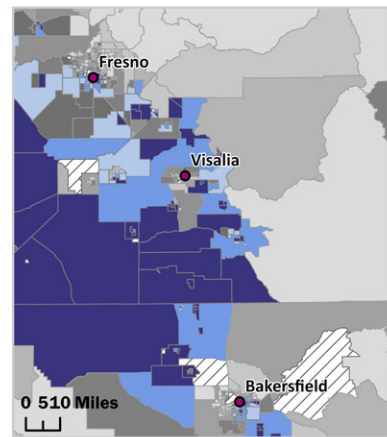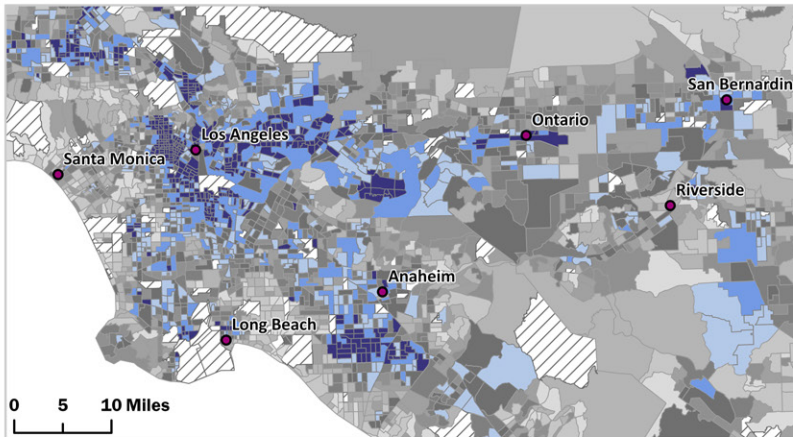
References

Drake TA (2014). The effect of community linguistic isolation on language-minority student achievement in high school. *Educational Researcher* **43**(7):327-40.

Feldmeyer B, Harris CT, Lai D (2016). *Language use and violence: Assessing the relationship between linguistic context and macrolevel violence.* Paper presented at the Sociological Forum.

Gee GC, Ponce N (2010). Associations between racial discrimination, limited English proficiency, and health-related quality of life among 6 Asian ethnic groups in California. *Am J Public Health* **100**(5):888-95.

Hill L (2011, March 2011). English Proficiency of Immigrants. *Just the Facts*, 2013, from www.ppic.org

Johnson H (2011, April 2011). Immigrants in California. *Just the Facts*, 2013, from www.ppic.org

Link MW, Mokdad AH, Stackhouse HF, Flowers NT (2006). Race, ethnicity, and linguistic isolation as determinants of participation in public health surveillance surveys. *Prev Chronic Dis* **3**(1):A09.

Lu T, Myerson R (2020). Disparities in Health Insurance Coverage and Access to Care by English Language Proficiency in the USA, 2006–2016. *Journal of General Internal Medicine*:1-8.

Nepal V, Banerjee D, Perry M, Scott D (2012). Disaster preparedness of linguistically isolated populations: Practical issues for planners. *Health promotion practice* **13**(2):265-71.

Pastor Jr M, Morello-Frosch R, Sadd JL (2010). *Air Pollution and Environmental Justice: Integrating indicators of cumulative impact and socio-economic vulnerability into regulatory decision-making.*CARB Research Contract 04-308, from https://ww3.arb.ca.gov/research/single-project.php?row_id=64727

Sentell T, Shumway M, Snowden L (2007). Access to mental health treatment by English language proficiency and race/ethnicity. *J Gen Intern Med* **22 Suppl 2**:289-93.

Shi L, Lebrun LA, Tsai J (2009). The influence of English proficiency on access to care. *Ethn Health* **14**(6):625-42.

Shihadeh ES, Barranco RE (2010). Latino immigration, economic deprivation, and violence: Regional differences in the effect of linguistic isolation. *Homicide Studies* **14**(3):336-55.

Shin HB, Bruno R (2003). Language Use and English-Speaking Ability: 2000. In USDo Commerce (Ed.) (pp. 1-11). Washington, DC: U.S. Census Bureau.

Talamantes E, Norris KC, Mangione CM, Moreno G, Waterman AD, Peipert JD*, et al.* (2017). Linguistic isolation and access to the active

kidney transplant waiting list in the United States. *Clinical Journal of the American Society of Nephrology* **12**(3):483-92.

Teron L (2016). Sustainably speaking: considering linguistic isolation in citywide sustainability planning. *Sustainability: The Journal of Record* **9**(6):289-94.

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, 2015-2019).*
Data Source	*American Community Survey – 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 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 2015-2019. The data are made available using the U.S. Census data download website. 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 $25,465 during 2018, 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. Data is 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 (Brunner and Marmot, 2005; Wright *et al.*, 1998).

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. 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 (Forastiere *et al.*, 2007), and childhood asthma (Meng *et al.*, 2011) in low-income communities. A multi-city study in Canada found that the effect of nitrogen dioxide (NO_2) on respiratory hospitalizations was increased among lower income households compared to those with higher incomes (Cakmak *et al.*, 2006). 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

- From the 2015-2019 American Community Survey, a dataset containing the number of individuals below 200 percent of the federal poverty level was downloaded by census tracts 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.

- Unlike the US Census, ACS estimates come from a sample of the population and may be unreliable if they are based on a small sample or population size. The standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of each estimate.

- The SE was calculated for each census tract using the formula for approximating the SE of proportions provided by the ACS (American Community Survey Office, 2013, pg. 13, equation 4).

When this approximation could not be used, the formula for approximating the SE of ratios (equation 3) was used instead.
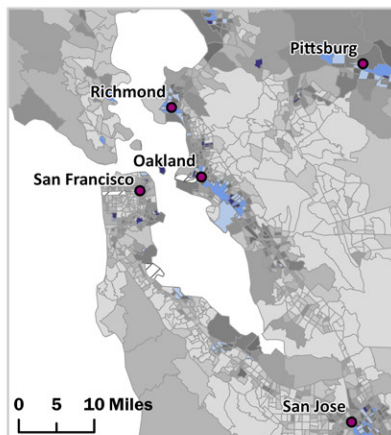
- The RSE is calculated by dividing a tract's SE by its estimate of the percentage of the population living below twice the federal poverty level, and taking the absolute value of the result.

- Census tract estimates that met either of the following criteria were considered reliable and included in the analysis:

    o RSE less than 50 (meaning the SE was less than half of the estimate) OR

    o SE was less than the mean SE of all California census tract estimates for poverty.

- Census tracts with unreliable estimates received no score for the indicator (null). The indicator was not factored into that tract's overall CalEnviroScreen score.

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

Poverty

Percent of population living below twice the federal poverty level (2015-2019)
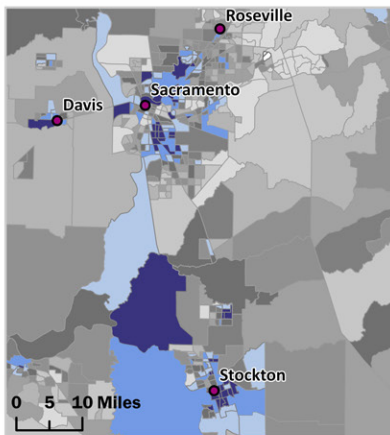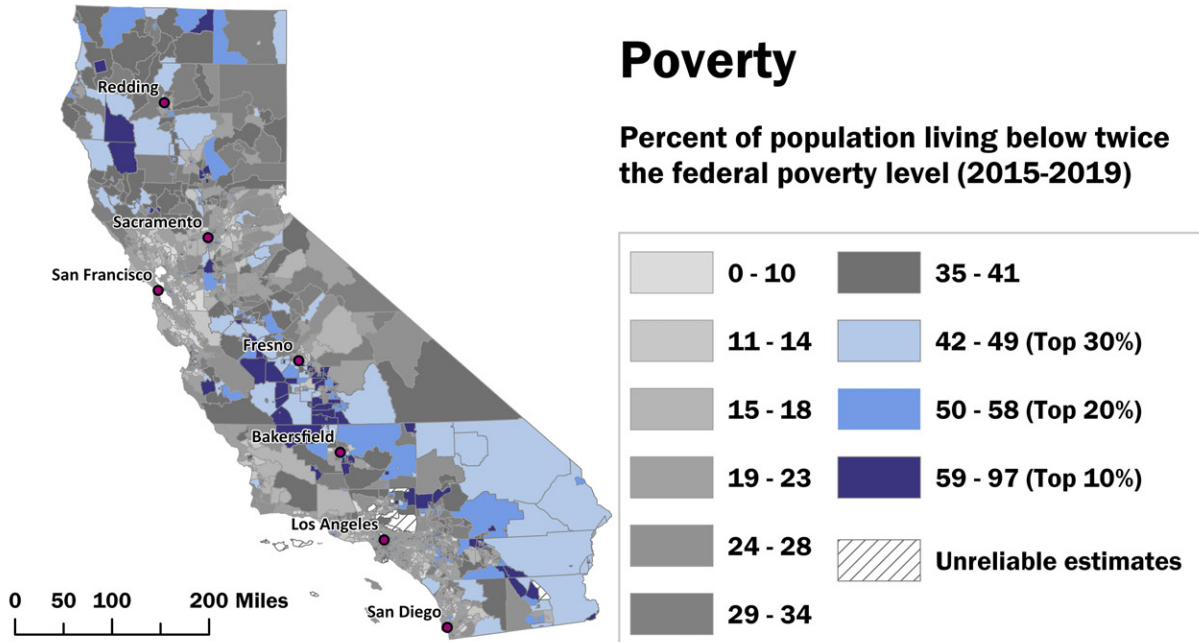
☐	0 - 10	☐	35 - 41
☐	11 - 14	☐	42 - 49 (Top 30%)
☐	15 - 18	☐	50 - 58 (Top 20%)
☐	19 - 23	☐	59 - 97 (Top 10%)
☐	24 - 28	☐	Unreliable estimates
☐	29 - 34		

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

190
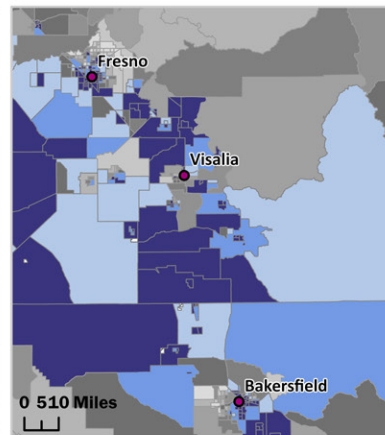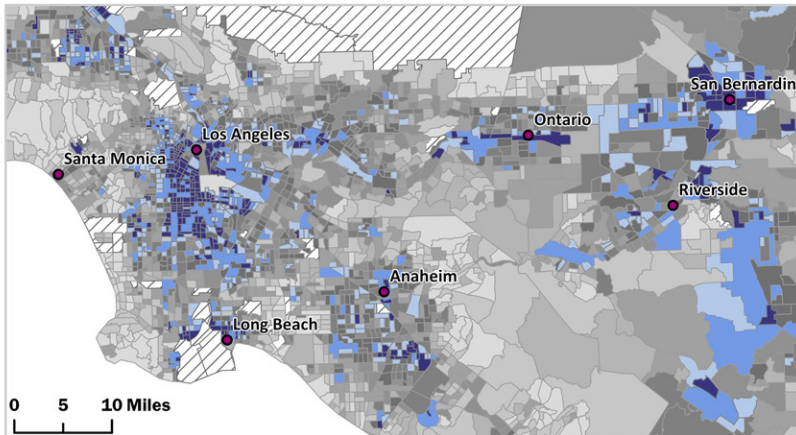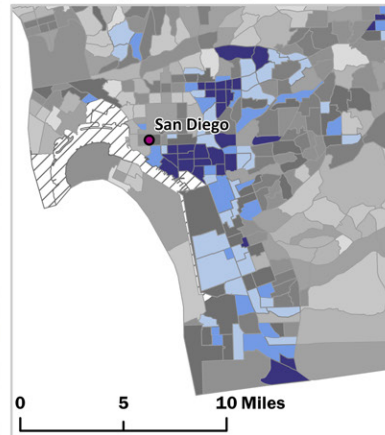
References

Ailshire J, Karraker A, Clarke P (2017). Neighborhood social stressors, fine particulate matter air pollution, and cognitive function among older US adults. *Social Science & Medicine* **172**:56-63.

Bernard P, Charafeddine R, Frohlich KL, Daniel M, Kestens Y, Potvin L (2007). Health inequalities and place: a theoretical conception of neighbourhood. *Social Science & Medicine* **65**(9):1839-52.

Marmot M, Wilkinson R (2005). Social organisation, stress and health. In: *Social determinants of health.* Oxford University Press.

Cakmak S, Dales RE, Judek S (2006). Respiratory health effects of air pollution gases: modification by education and income. *Arch Environ Occup Health* **61**(1):5-10.

Forastiere F, Stafoggia M, Tasco C, Picciotto S, Agabiti N, Cesaroni G*, et al.* (2007). Socioeconomic status, particulate air pollution, and daily mortality: differential exposure or differential susceptibility. *Am J Ind Med* **50**(3):208-16.

Hajat A, Hsia C, O'Neill MS (2015). Socioeconomic disparities and air pollution exposure: a global review. *Current Environmental Health Reports* **2**(4):440-50.

Meng YY, Wilhelm M, Ritz B, Balmes JR, Lombardi C, Bueno A*, et al.* (2011). *Is disparity in asthma among Californians due to higher pollutant exposures, greater susceptibility, or both?* Sacramento, CA: UCLA Center for Health Policy Research.

Morello-Frosch R, Shenassa ED (2006). The environmental "riskscape" and social inequality: implications for explaining maternal and child health disparities. *Environ Health Perspect* **114**(8):1150-3.

O'Neill MS, Jerrett M, Kawachi I, Levy JI, Cohen AJ, Gouveia N*, et al.* (2003). Health, wealth, and air pollution: advancing theory and methods. *Environ Health Perspect* **111**(16):1861-70.

Padula AM, Mortimer KM, Tager IB, Hammond SK, Lurmann FW, Yang W*, et al.* (2014). Traffic-related air pollution and risk of preterm birth in the San Joaquin Valley of California. *Annals of Epidemiology* **24**(12):888-95. e4.

Wright RJ, Rodriguez M, Cohen S (1998). Review of psychosocial stress and asthma: an integrated biopsychosocial approach. *Thorax* **53**(12):1066-74.

Yi O, Kim H, Ha E (2010). Does area level socioeconomic status modify the effects of PM10 on preterm delivery? *Environmental Research* **110**(1):55-61.

Zeka A, Melly SJ, Schwartz J (2008). The effects of socioeconomic status and indices of physical environment on reduced birth weight and preterm births in Eastern Massachusetts. *Environ Health* **7**:60.

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, 2015-2019).*
Data Source	*American Community Survey – US Census Bureau*
	The American Community Survey (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 *2015-2019*. The data are made available using the U.S. Census data download website. 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), and suicides (Gordon and Sommers, 2016; Paul and Moser, 2009; Ruhm, 2015). Unemployment is also associated with increases in physical morbidity as well as mortality.
	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 (including adequate insurance) to seek care for health conditions while they are treatable, and this leads to worse health outcomes, including outcomes cause by environmental pollutants.

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

- From the 2015-2019 American Community Survey, a dataset containing the unemployment rate by census tracts for the state of California was downloaded.

- 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.

- Unlike the US Census, ACS estimates come from a sample of the population and may be unreliable if they are based on a small sample or population size. The standard error (SE) and relative standard error (RSE) were used to evaluate the reliability of each estimate.

- The SE was calculated for each census tract using the formula for approximating the SE of proportions provided by the ACS (American Community Survey Office, 2013, pg. 13, equation 4). When this approximation could not be used, the formula for approximating the SE of ratios (equation 3) was used instead.

- The RSE is calculated by dividing a tract's SE by its estimate of unemployment rate, and taking the absolute value of the result.
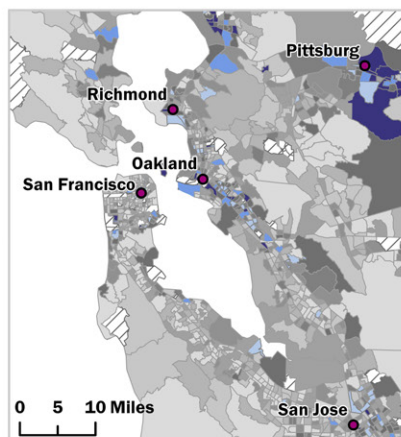
- Census tract estimates that met either of the following criteria were considered reliable and included in the analysis:

    - RSE less than 50 (meaning the SE was less than half of the estimate) OR
    - SE was less than the mean SE of all California census tract estimates for unemployment rate.

- Census tracts with unreliable estimates received no score for the indicator (null). The indicator was not factored into that tract's overall CalEnviroScreen score.

- Census tracts that met the inclusion criteria 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 (2015-2019)
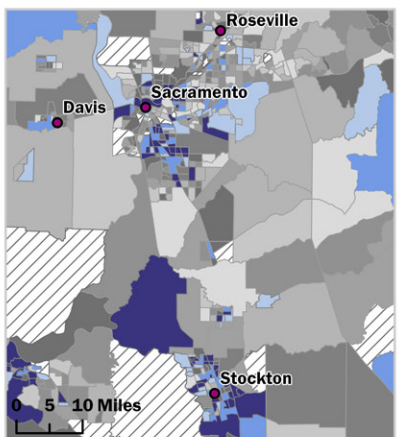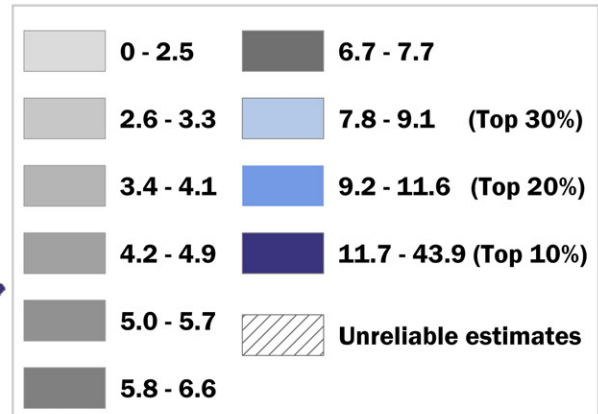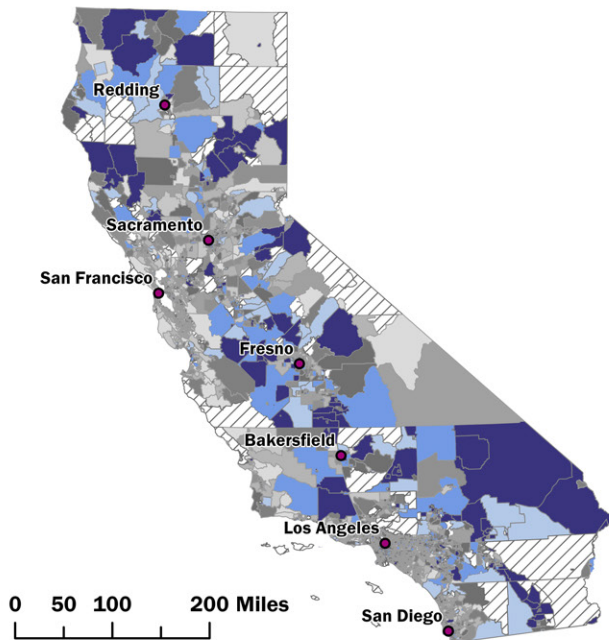
0 - 2.5		6.7 - 7.7	
2.6 - 3.3		7.8 - 9.1	(Top 30%)
3.4 - 4.1		9.2 - 11.6	(Top 20%)
4.2 - 4.9		11.7 - 43.9	(Top 10%)
5.0 - 5.7		Unreliable estimates	
5.8 - 6.6			

0 50 100 200 Miles

Sacramento Area

San Francisco Area

San Joaquin Valley

Greater Los Angeles Area

CalEnviroScreen 4.0

San Diego Area

196
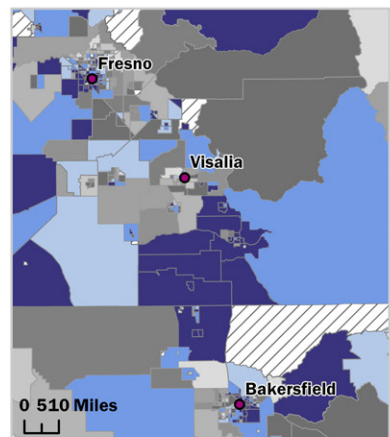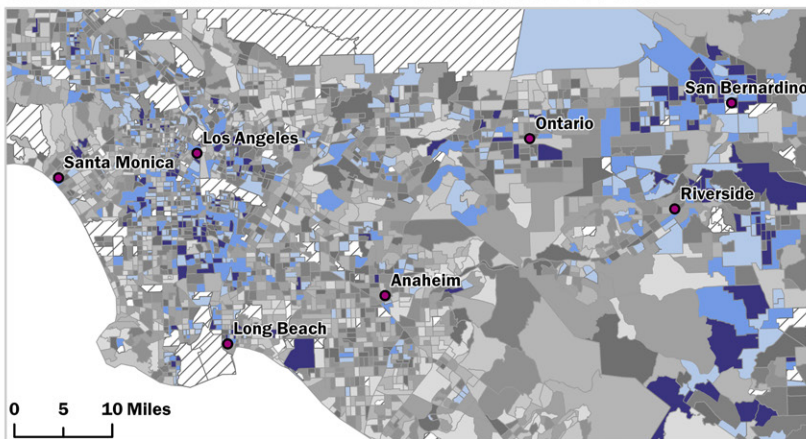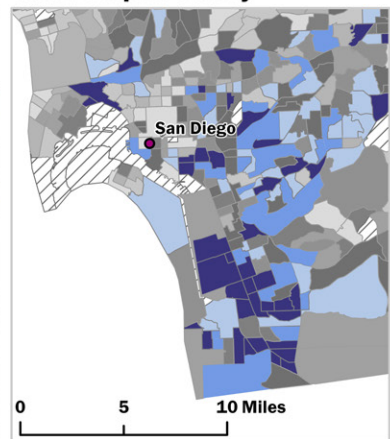
References

Ala-Mursula L, Buxton JL, Ek E, Koiranen M, Taanila A, Blakemore AI, *et al.* (2013). Long-term unemployment is associated with short telomeres in 31-year-old men: an observational study in the northern Finland birth cohort 1966. *PLoS One* **8**(11):e80094.

DeFur PL, Evans GW, Cohen Hubal EA, Kyle AD, Morello-Frosch RA, Williams DR (2007). Vulnerability as a function of individual and group resources in cumulative risk assessment. *Environ Health Perspect* **115**(5):817-24.

Dettenborn L, Tietze A, Bruckner F, Kirschbaum C (2010). Higher cortisol content in hair among long-term unemployed individuals compared to controls. *Psychoneuroendocrinology* **35**(9):1404-9.

Gordon SH, Sommers BD (2016). Recessions, poverty, and mortality in the United States: 1993–2012. *American Journal of Health Economics* **2**(4):489-510.

Hughes A, Kumari M, McMunn A, Bartley M (2017). Unemployment and inflammatory markers in England, Wales and Scotland, 1998–2012: Meta-analysis of results from 12 studies. *Brain, Behavior, and Immunity* **64**:91-102.

Paul KI, Moser K (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational behavior* **74**(3):264-82.

Ruhm CJ (2015). Recessions, healthy no more? *Journal of Health Economics* **42**:17-28.

Turner JB (1995). Economic Context and the Health Effects of Unemployment. *Journal of Health and Social Behavior* **36**(3):213-29.

Voigtlander S, Berger U, Razum O (2010). The impact of regional and neighbourhood deprivation on physical health in Germany: a multilevel study. *BMC Public Health* **10**:403.

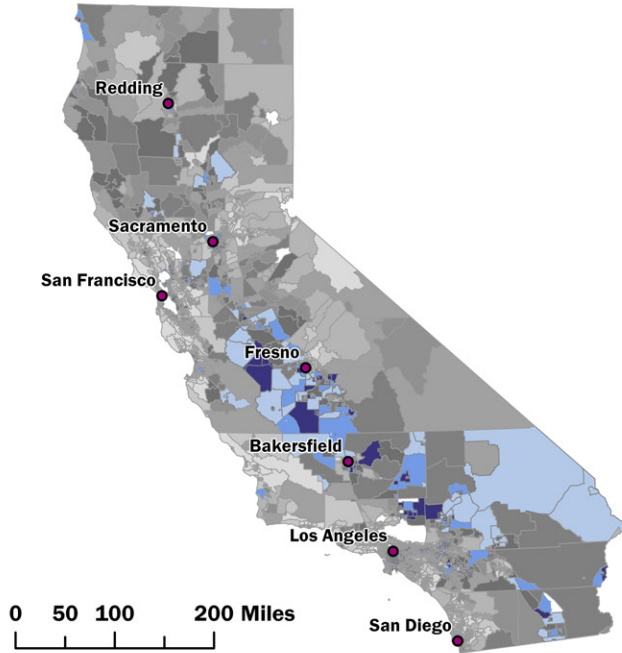# SCORES FOR POPULATION CHARACTERISTICS

(RANGE OF POSSIBLE SCORES: 0.1 TO 10)

Population Characteristics scores for each census tract are derived from the average percentiles for the three Sensitive Populations indicators (asthma, cardiovascular disease, and low birth weight) and the five Socioeconomic Factors indicators (educational attainment, housing-burdened low-income households, linguistic isolation, poverty, and unemployment). The calculated average percentile divided by 10 for a Population Characteristic score ranging from 0.1 – 10.

Note: The map on the following page shows population characteristic scores divided into deciles.

Population Characteristics

Percentile of combined Sensitive Populations and Socioeconomic Factors indicators
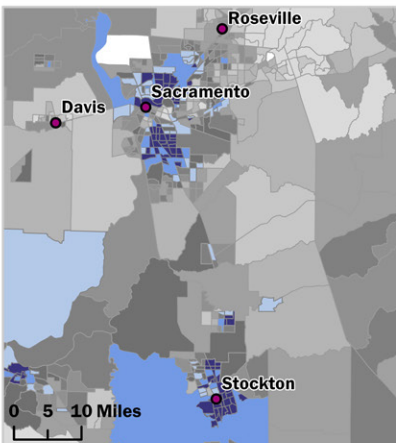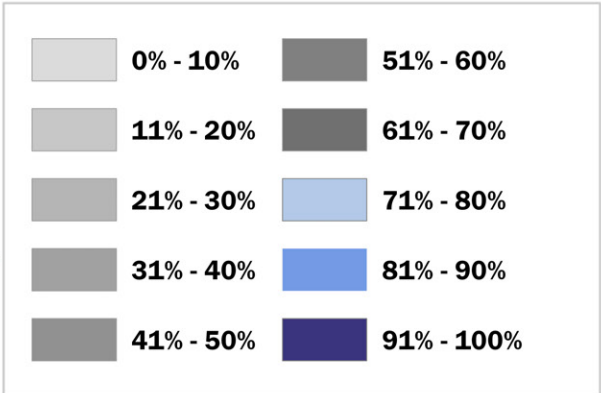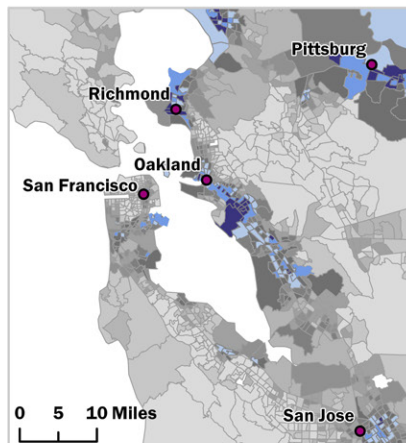
0% - 10%		51% - 60%	
11% - 20%		61% - 70%	
21% - 30%		71% - 80%	
31% - 40%		81% - 90%	
41% - 50%		91% - 100%	

0   50   100   200 Miles

Redding
Sacramento
San Francisco
Fresno
Bakersfield
Los Angeles
San Diego

Sacramento Area

Roseville
Davis
Sacramento
Stockton
0   5   10 Miles

San Francisco Area

Pittsburg
Richmond
Oakland
San Francisco
San Jose
0   5   10 Miles

San Joaquin Valley

Fresno
Visalia
Bakersfield
0 5 10 Miles

Greater Los Angeles Area

San Bernardino
Ontario
Los Angeles
Santa Monica
Riverside
Anaheim
Long Beach
0   5   10 Miles

San Diego Area

San Diego
0   5   10 Miles

CalEnviroScreen 4.0

199
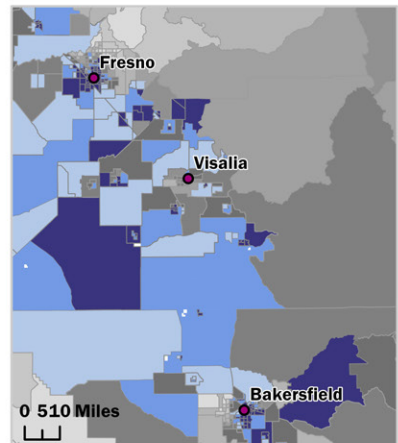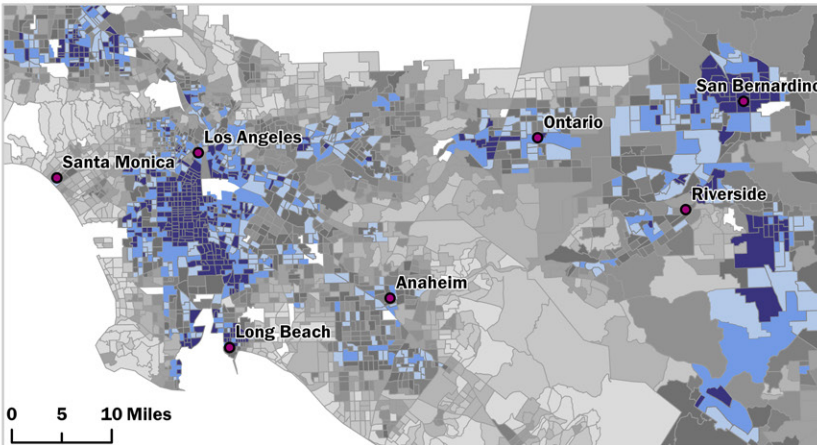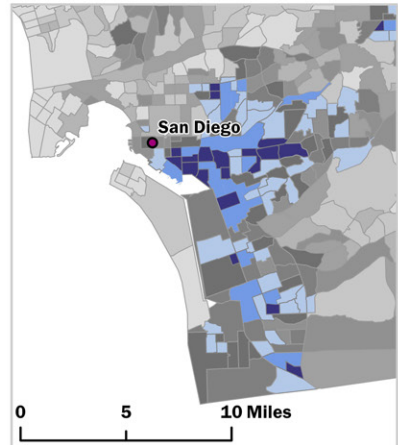
CalEnviroScreen Results

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.
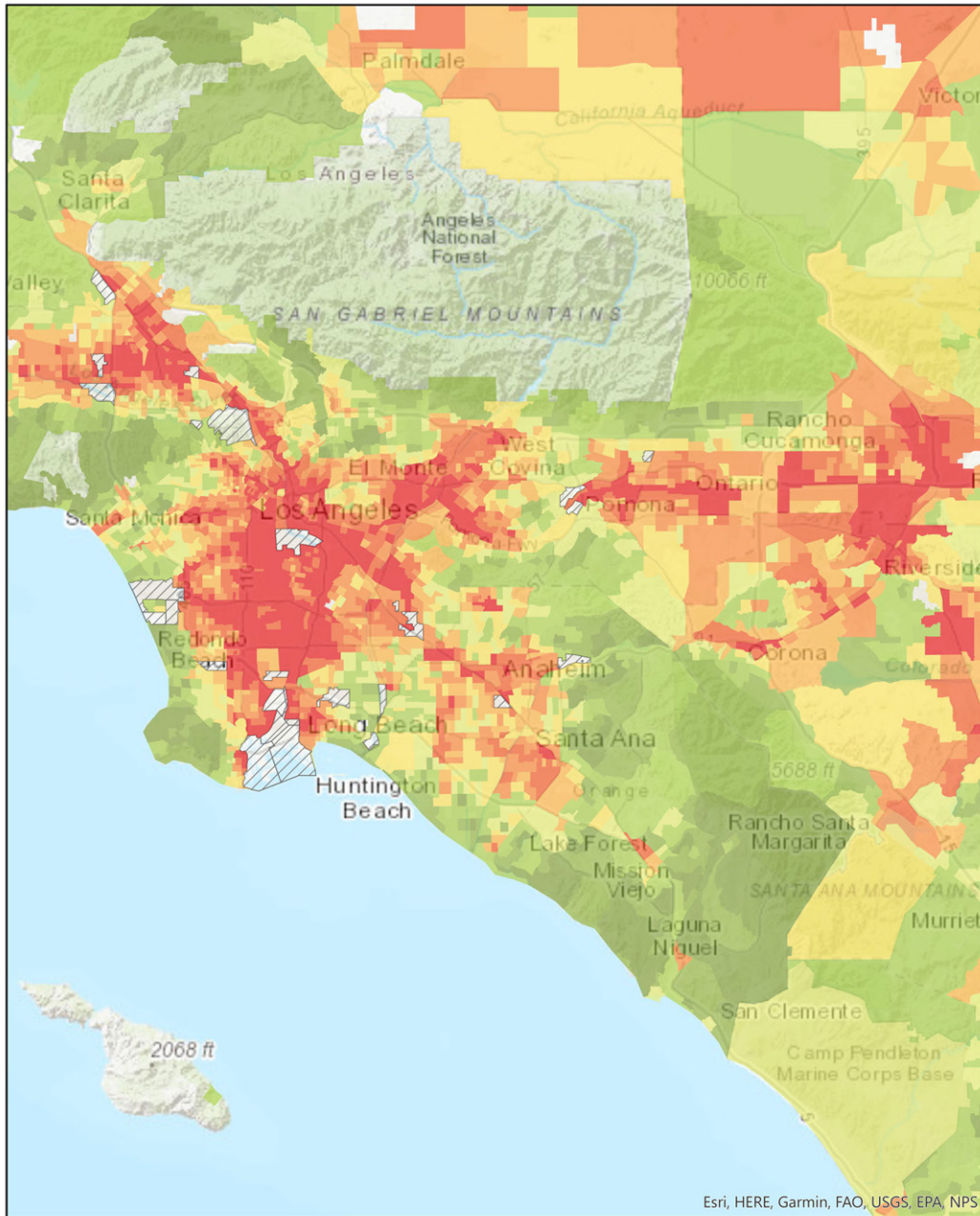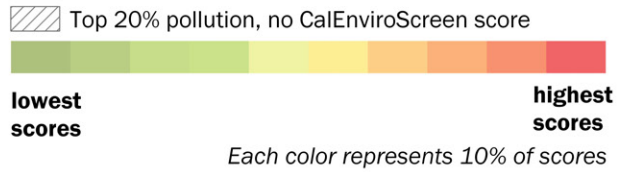
The maps of specific regions of the state (Los Angeles, San Francisco, San Diego, San Joaquin Valley, Sacramento and the Coachella and Imperial Region) are "close-ups" of the statewide map and are intended to provide greater clarity on the relative scoring of census tracts in those regions. Colors on 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 at OEHHA's website at http://oehha.ca.gov/calenviroscreen.
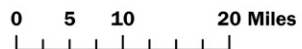
The information is available both in a Microsoft Excel spreadsheet format and as an online mapping application.
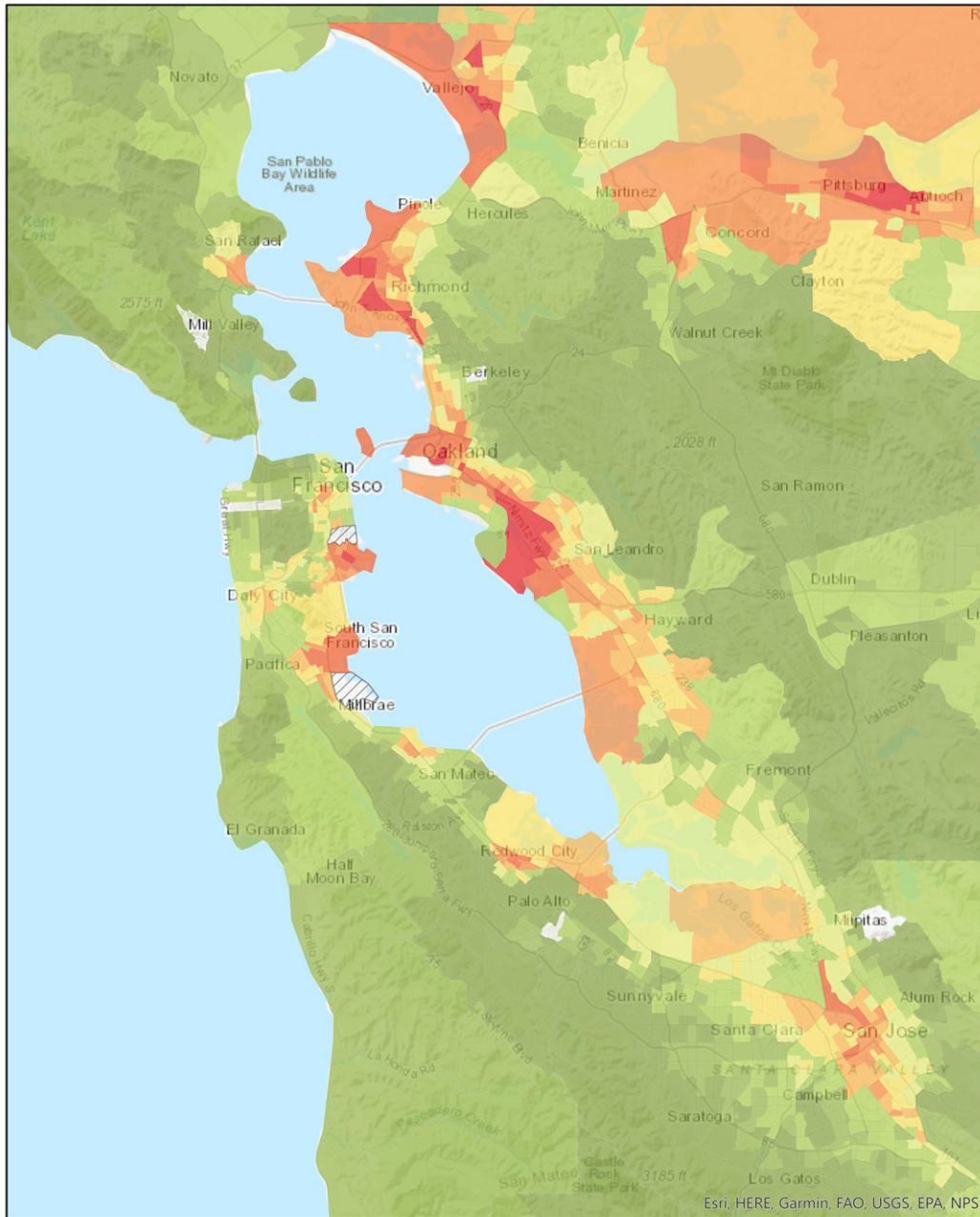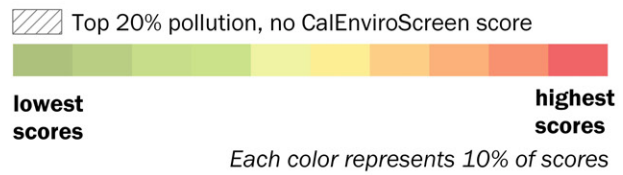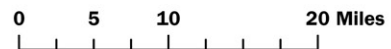
CalEnviroScreen
Version 4.0
Results

lowest scores

highest scores

Each color represents 10% of the scores

0 25 50   100 Miles

CalEnviroScreen Version 4.0 Results (September 2021)
Esri, HERE, Garmin, FAO, USGS, NGA, EPA, NPS

CalEnviroScreen Version 4.0 Results

Top 20% pollution, no CalEnviroScreen score

lowest scores

highest scores

Each color represents 10% of scores

Los Angeles Area

0   5   10   20 Miles
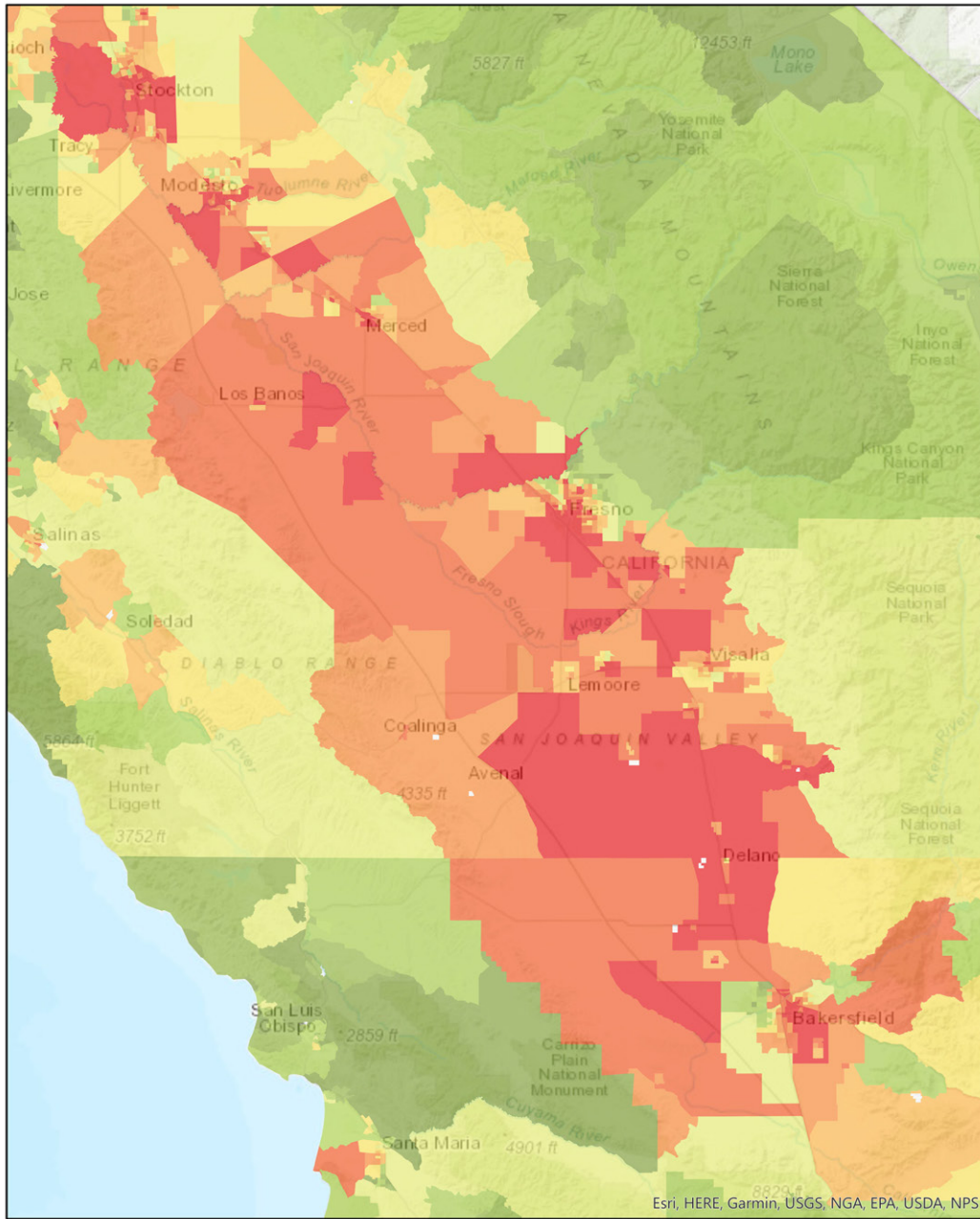
CalEnviroScreen 4.0

CalEnviroScreen Version 4.0 Results

Top 20% pollution, no CalEnviroScreen score

lowest scores

highest scores

Each color represents 10% of scores

San Francisco Bay Area

0   5   10   20 Miles

CalEnviroScreen 4.0

CalEnviroScreen Version 4.0 Results

Top 20% pollution, no CalEnviroScreen score

lowest scores — highest scores

Each color represents 10% of scores

San Diego Area

0   2.5   5   10 Miles

CalEnviroScreen 4.0

CalEnviroScreen Version 4.0 Results

Top 20% pollution, no CalEnviroScreen score

lowest scores — highest scores

Each color represents 10% of scores

Sacramento Area

0   2.5   5   10 Miles
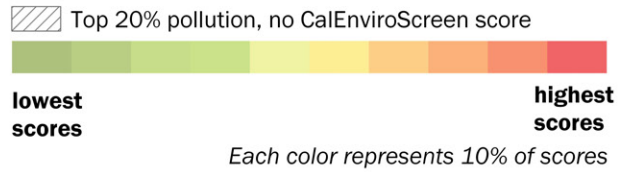
CalEnviroScreen 4.0

CalEnviroScreen Version 4.0 Results

Top 20% pollution, no CalEnviroScreen score

lowest scores

highest scores

Each color represents 10% of scores

San Joaquin Valley

0   15   30   60 Miles

CalEnviroScreen 4.0

CalEnviroScreen Version 4.0 Results

Top 20% pollution, no CalEnviroScreen score

lowest scores

highest scores

Each color represents 10% of scores

Imperial Area

0   10   20   40 Miles

CalEnviroScreen 4.0