

California Air Toxics Assessment (CATA)

Technical Report

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Executive Summary

A. Background

In 2017, the California Air Resources Board (CARB) initiated the California Air Toxics Assessment (CATA) program to provide a comprehensive and state-of-the-science assessment of toxic air contaminants (TACs) in California. The first CATA study (referred to as CATA 2012) began in 2017 and was completed in 2019, using an integrated modeling approach based on the emission inventory and meteorological conditions for the year 2012. The goals of CATA align with CARB's Community Air Protection Program (AB 617) established in 2017. One component of the AB 617 program is the identification of environmental justice communities that are disproportionately impacted by TACs. Air toxics modeling can help identify those communities with elevated air pollution exposure and health impacts for actions as required by AB 617. Another component of the program is the enhancement of air quality monitoring in those communities impacted most by air pollution. Since deploying air toxic monitors in all communities statewide is not feasible, air toxics modeling can complement the present monitoring network by filling spatial and temporal data gaps and improving network design. AB 617 also requires that community emission reduction plans (CERPs) be developed and various measures to reduce emissions be implemented for various emission sources. CATA can help to: 1) identify areas within a community most impacted by air pollution and populations most vulnerable to air pollution impacts; 2) quantify the relative contributions of emission categories/sources to overall impacts; and 3) assess the cost, effectiveness, and benefits of mitigation measures.

This report presents the 2017 CATA study based on the emissions of air toxics and meteorology from 2017. At the time of this iteration, 2017 was the most recent year for which both the emissions data and meteorological data had gone through a rigorous QA/QC process. Through regularly updated modeling and analysis, this and future iterations of CATA represent a comprehensive air toxic risk modeling assessment for California that aims to provide statewide cumulative exposure and associated cancer risks at the census block and tract levels and track their trends over time based on on-going and future emission reduction plans and strategies.

B. Approach

CATA uses an innovative integrated modeling approach. A comprehensive inventory of TACs emission sources for 2017 was categorized into four main groups: on-road mobile, off-road mobile, areawide, and stationary sources. Two USEPA air quality models were used: the CALPUFF (Scire *et al*, 2000) dispersion model, which accurately represents source-to-receptor relationships, was used to simulate diesel particulate matter (DPM) and heavy metals, while the grid-based Community Multiscale Air Quality (CMAQ) version 5.3.2 (USEPA, 2020) photochemical model was used for the chemically reactive toxic volatile organic compounds (VOCs). Concentrations of DPM and heavy metals were computed at the centroids of census blocks, while CMAQ produced grid volume averaged hourly concentrations for subsequent analysis.

A total of twelve air toxics were simulated: DPM, six toxic VOCs (benzene, 1,3-butadiene, formaldehyde, acetaldehyde, p-dichlorobenzene, and perchloroethylene), and 5 toxic heavy metals (lead, hexavalent chromium, arsenic, cadmium, and nickel). These TACs cumulatively account for more than 95% of air toxic contaminant emissions available in California based on their toxic potency weighted values. With a balanced approach to cover most populated areas in California at a reasonable computational cost, the modeling was conducted in six modeling domains, covering San Diego County, Imperial County, South Coast Air Basin, San Joaquin Valley, Bay Area, and Sacramento Valley (Figure ES-1).

The results from CATA provide a wide range of information for TACs at various scales in California. On a state and regional level, it provides an overview of how toxic pollutants affect public health, the spatial distribution of the impact, and source apportionment of the overall impact by individual emission categories/sources for different toxic pollutants emitted within a county, an air basin, and statewide. The spatially refined results from CATA also assist in understanding unique TACs emission sources and public exposures in different communities across the state.

A health risk assessment based on the CATA modeling is used to evaluate the potential health impacts (long-term cancer and non-cancer) from exposure to toxic substances in the air. In this study, cumulative cancer risks were estimated following the procedures recommended in the 2015 California Office of Environmental Health Hazard Assessment's (OEHHA) "Air Toxics Hot Spots Program Guidance Manual for Preparation of Health Risk Assessments" (Guidance). An exposure duration of 30 years with the Risk Management Policy (RMP) method (95th/80th percentile daily breathing rate (DBR)) was used for assessing potential cancer risk (inhalation only). Note that the analysis presented in this report does not estimate impacts on mortality risk or other health effects from DPM and criteria air pollutant exposures, such as PM_{2.5} and ozone.

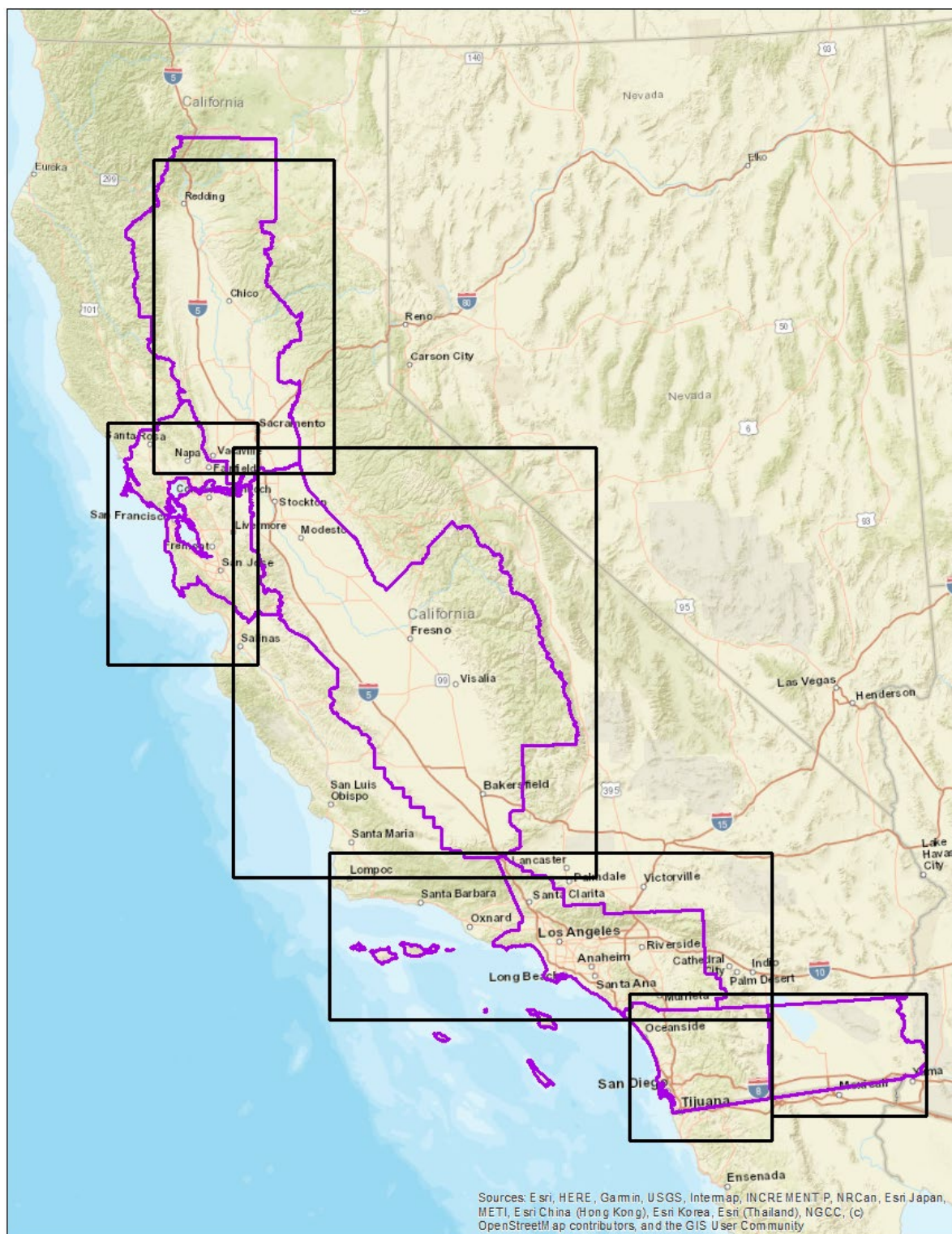


Figure ES-1. Map of the six major air basins (purple) and corresponding modeling domains (black).

C. Key Findings

The key findings from this study are summarized as follows:

Emissions. The total TACs (DPM potency equivalent) emissions amount to an estimated 7694 tons per year (TPY) statewide in 2017. On-road, off-road, area and stationary point sources accounted for 36%, 9%, 54% and 1% of DPM emissions statewide, respectively. Table ES-1 summarizes total TACs emissions for each air basin. Figure ES-2 shows the breakdown of annual total emissions by species. DPM accounted for about 75% of the total TACs emissions. Other significant TAC species (i.e., contribution >1%) included 1,3-butadiene (8%), benzene (5%), formaldehyde (4%), cadmium (1.8%), arsenic (1.6%), acetaldehyde (1.6%), and p-Dichlorobenzene (1.4%).

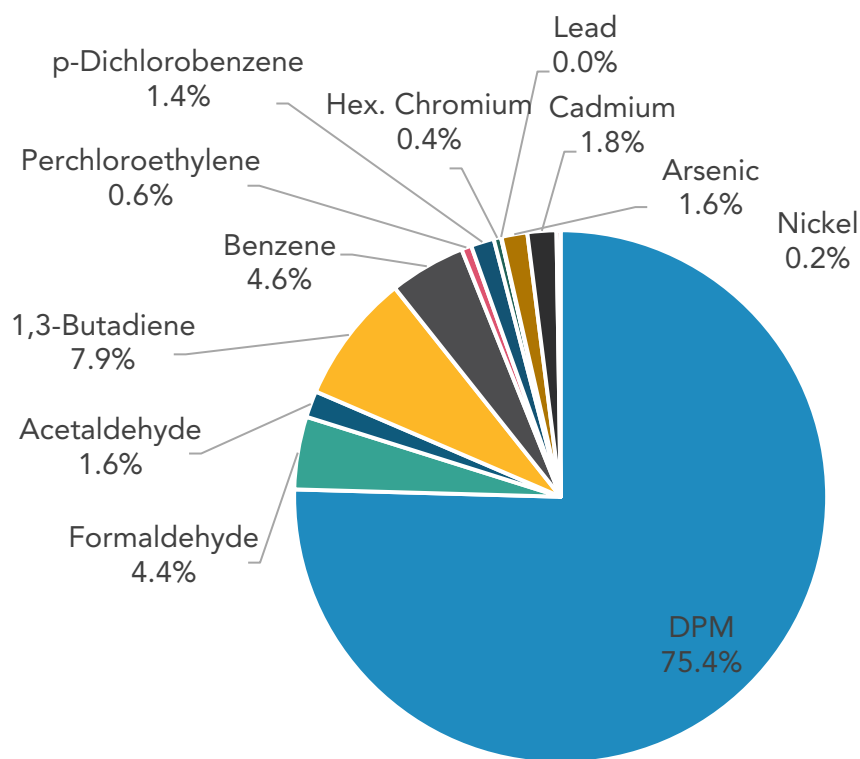


Figure ES-2. Breakdown of statewide total DPM potency equivalent emissions of TACs by species for 2017.

Table ES-1. Summary of DPM potency equivalent TACs emissions for each air basin and statewide in (TPY) for 2017.

TACs	Sac Valley	Bay Area	SJV	SC	SD	Imperial	Total
<u>DPM</u>							
<i>On-road</i>	270	349	543	744	160	34	2100
<i>Off-road</i>	56	70	82	209	40	20	476
<i>Area</i>	544	359	1272	741	195	51	3163
<i>Point</i>	5	6	7	33	11	1	65
<i>Total</i>	876	785	1,903	1727	407	106	5,804
<u>VOCs</u>							
<i>Formaldehyde</i>	40.0	84.2	132.5	62.9	17.0	2.8	339.4
<i>Acetaldehyde</i>	22.7	18.0	58.4	15.0	6.7	3.0	123.8
<i>1,3-Butadiene</i>	67.2	100.4	112.9	241.6	74.4	7.9	604.4
<i>Benzene</i>	51.0	85.8	72.3	172.5	41.6	4.7	355.6
<i>Perchloroethylene</i>	4.3	2.1	6.4	29.4	4.5	0.3	47.1
<i>p-Dichlorobenzene</i>	8.9	36.6	55.2	6.2	1.1	0.1	108.0
<u>Heavy Metals</u>							
<i>Hexavalent Chromium</i>	1	6.9	0.1	22.7	3.3	0.2	34.3
<i>Lead</i>	0.2	0.3	0.4	0.5	0.2	0.6	2.2
<i>Arsenic</i>	9.2	21.3	33.6	16.1	6.4	34.1	120.7
<i>Cadmium</i>	7.5	59.4	14.8	28.2	7.4	17.6	134.9
<i>Nickel</i>	2.9	4	3.5	6.2	1.3	1.2	19.1

Model Evaluation. The simulated concentrations of individual TACs by CALPUFF and CMAQ were evaluated by comparing with observational data available in our model domains in 2017. Monitored concentrations of elemental carbon (EC) were used as a surrogate for

modeled DPM evaluation. Overall, the model evaluation suggested satisfactory performance of the two models in representing TACs at monitoring sites across the state, considering observational and modeling uncertainties. It also highlighted some issues, such as the markedly higher observed concentrations of heavy metals compared to modeled values at a limited number of monitors. Future CATA will benefit from improved emissions inventories as well as increased observational data of heavy metals and other TACs.

Cancer Risk and Burden. The statewide population weighted average cancer risk from inhalation of TACs was estimated to be 598 cases per million in 2017. This means that, on average, aside from other possible causes, inhalation exposure to the estimated levels of air toxics over a time span of 30 years would be responsible for about 598 cancer cases out of a population of 1 million people. While this estimate represents a statewide average, some areas of the state have higher risks than other areas (Figure ES-3 and Figure ES-4). Figure ES-5 and Figure ES-6 show the spatial patterns of cancer burdens and their ranking across all census tracts statewide, which represent the number of cancer cases among a population for the estimated cancer risk (calculated as a product of population and cancer risk at a 70-yr exposure level). Overall, the spatial pattern of cancer burdens largely follows that of cancer risk, despite some differences, reflecting collocated hot spots of population and emission sources of TACs.

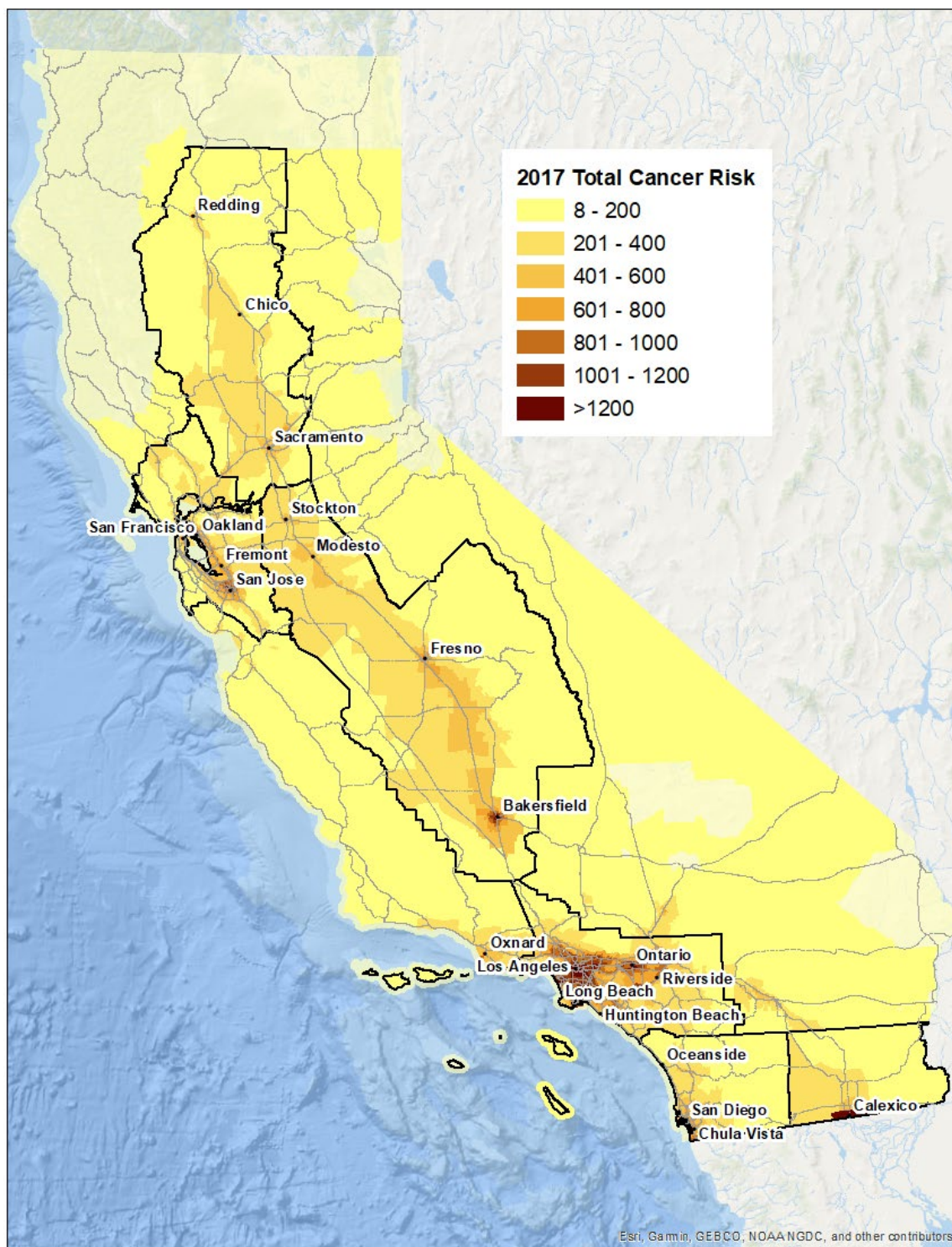


Figure ES-3. Map of total cancer risks from all TACs at the census tract level for 2017. Major freeways are shown in pale gray lines, and the six air basins are outlined in black. Cream color indicates areas outside of the modeling domains.

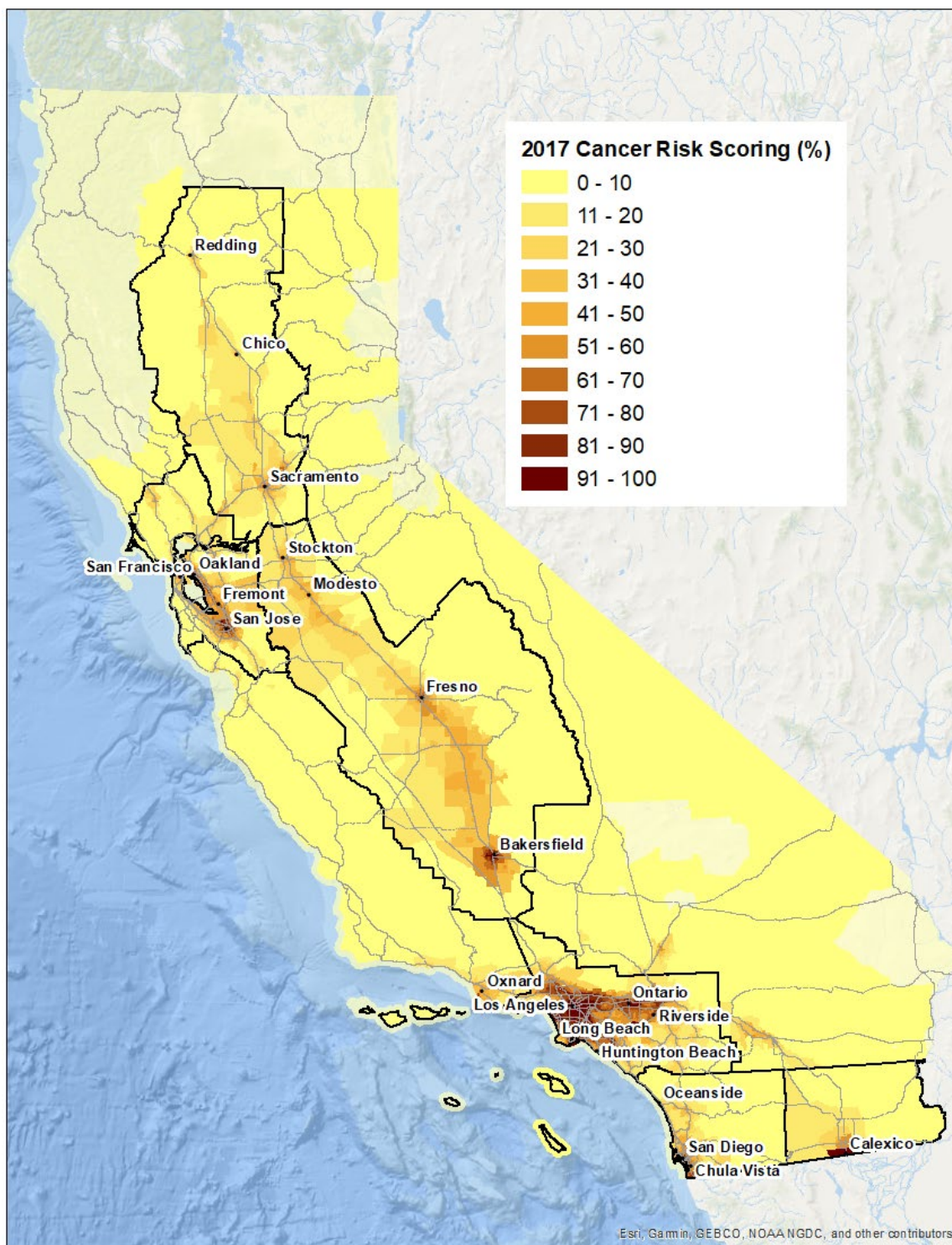


Figure ES-4. Map of cancer risk scoring (percentile in %) at the census tract level for 2017. Major freeways are shown as pale gray lines. Cream color indicates areas outside of the modeling domains.

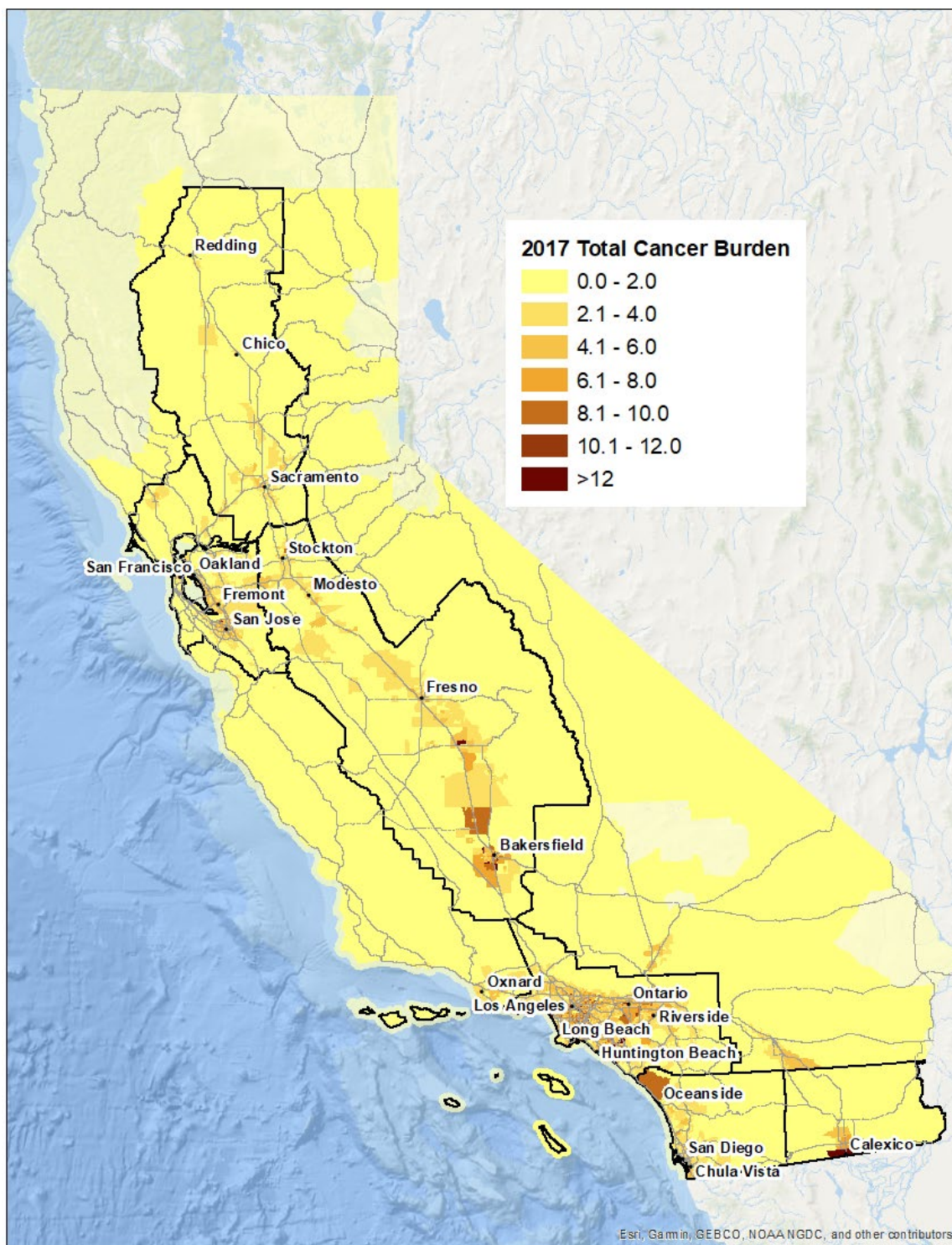


Figure ES-5. Map of cancer burdens at the census tract level for 2017. Major freeways are shown in pale gray lines, and the six air basins are outlined in black. Cream color indicates areas outside of the modeling domains.

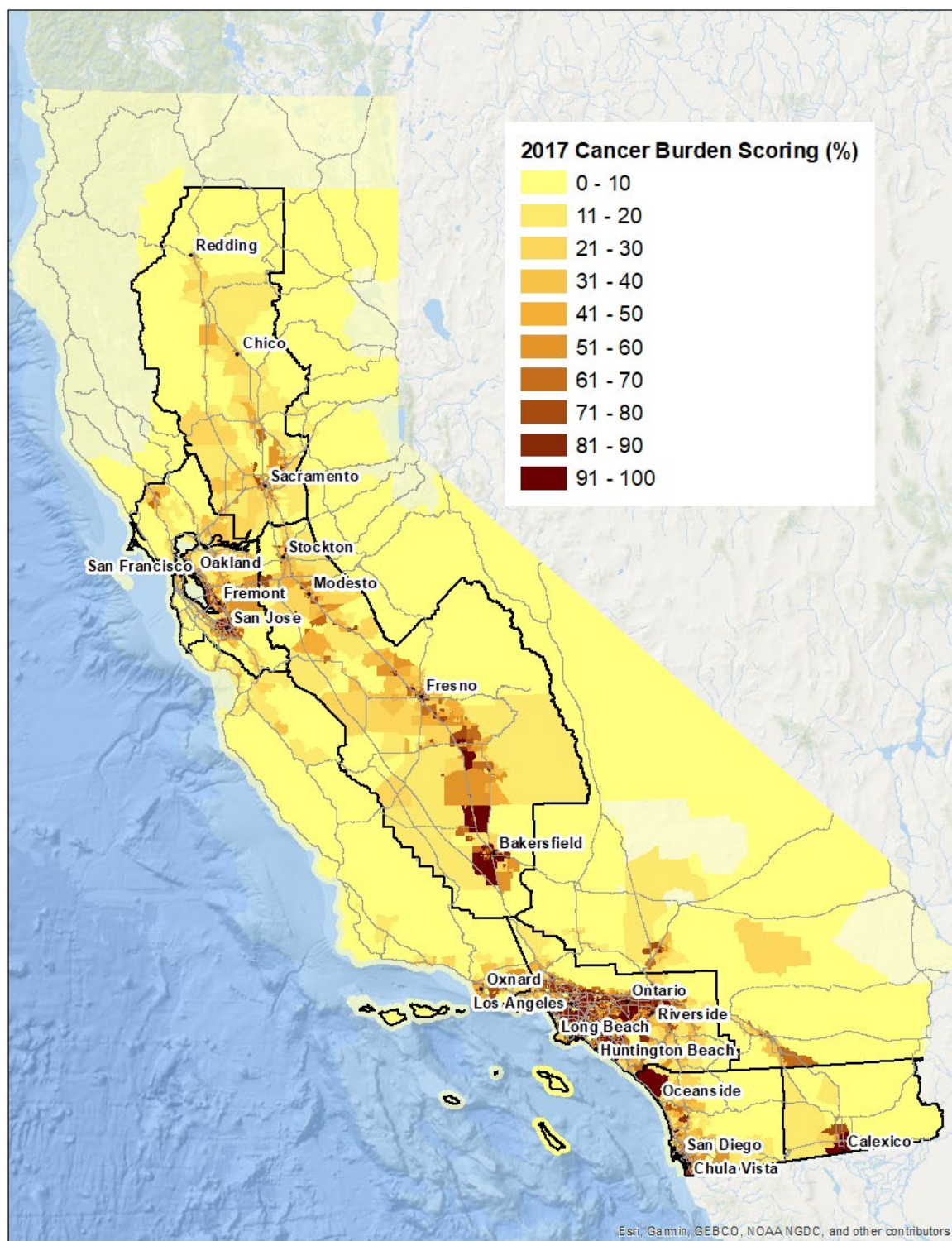


Figure ES-6. Map of cancer burden scoring (percentile in %) at the census tract level for 2017. Major freeways are shown as pale gray lines, and the six air basins are outlined in black. Cream color indicates areas outside of the modeling domains.

Among all TAC species considered in CATA, DPM was the main contributor (82%) to statewide population weighted average cancer risk, of which more than half come from on-road mobile sources, followed by benzene (6%), 1,3-butadiene (4%), and other TACs (Figure ES-7).

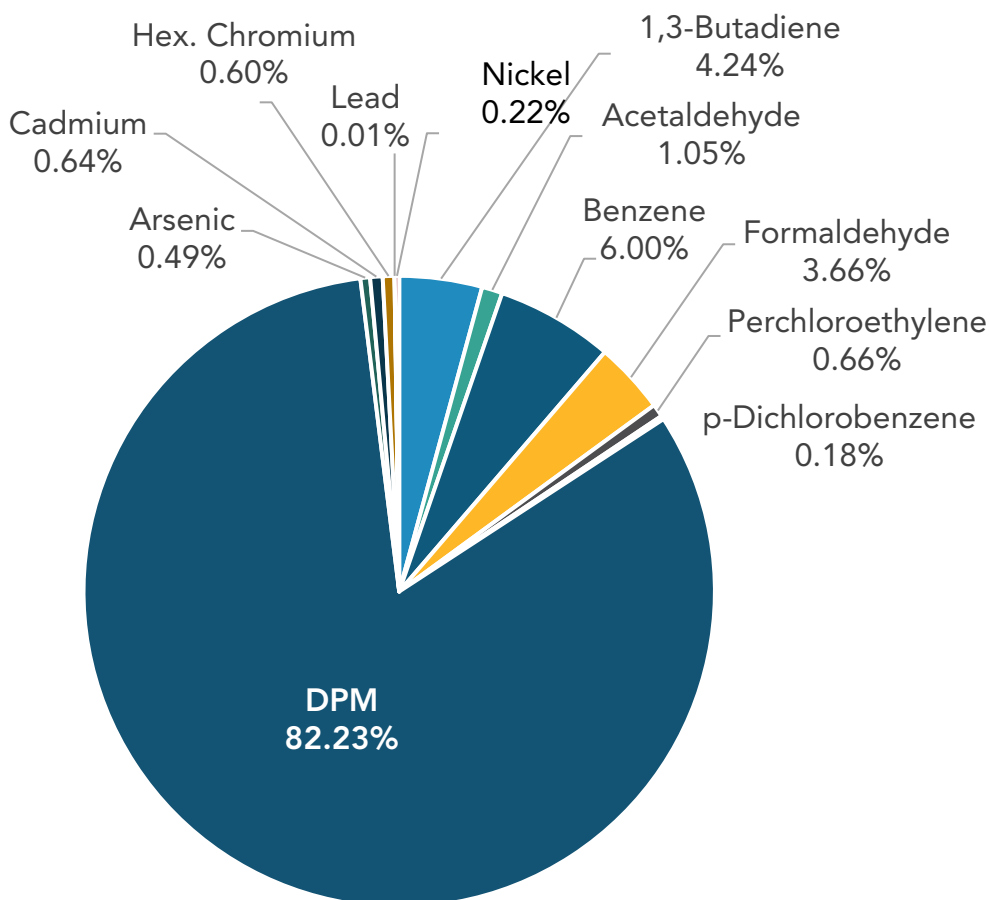


Figure ES-7. Relative contributions of individual TACs to total population weighted average cancer risk across the state for 2017.

Risk Reduction. As an illustration of using CATA to track TACs reductions over time, Figure ES-8 depicts the estimated change (in %) of TACs cancer risks at the census tract level. Overall, TACs cancer risks decreased by 32% statewide from 2012 to 2017 with marked spatial differences within the state. The largest reduction came from the on-road DPM mobile sources, which is also the largest contributor to the total cancer risk. While substantial reductions can be seen near major cities and transportation pathways, there are also areas with little reduction or increase of modeled cancer risks, such as the western San Diego County and the northern part of the Bay Area Air Basin. An inspection of the modeling

results showed relatively small overall cancer risks (Figures ES-6 and 7) as well as small on-road contributions in these regions. These increases may be due to a combination of low emission reductions, and updates and improvements in the emission inputs including a more complete inventory of sources and improved processing methodology (e.g., spatial allocation and resolution).

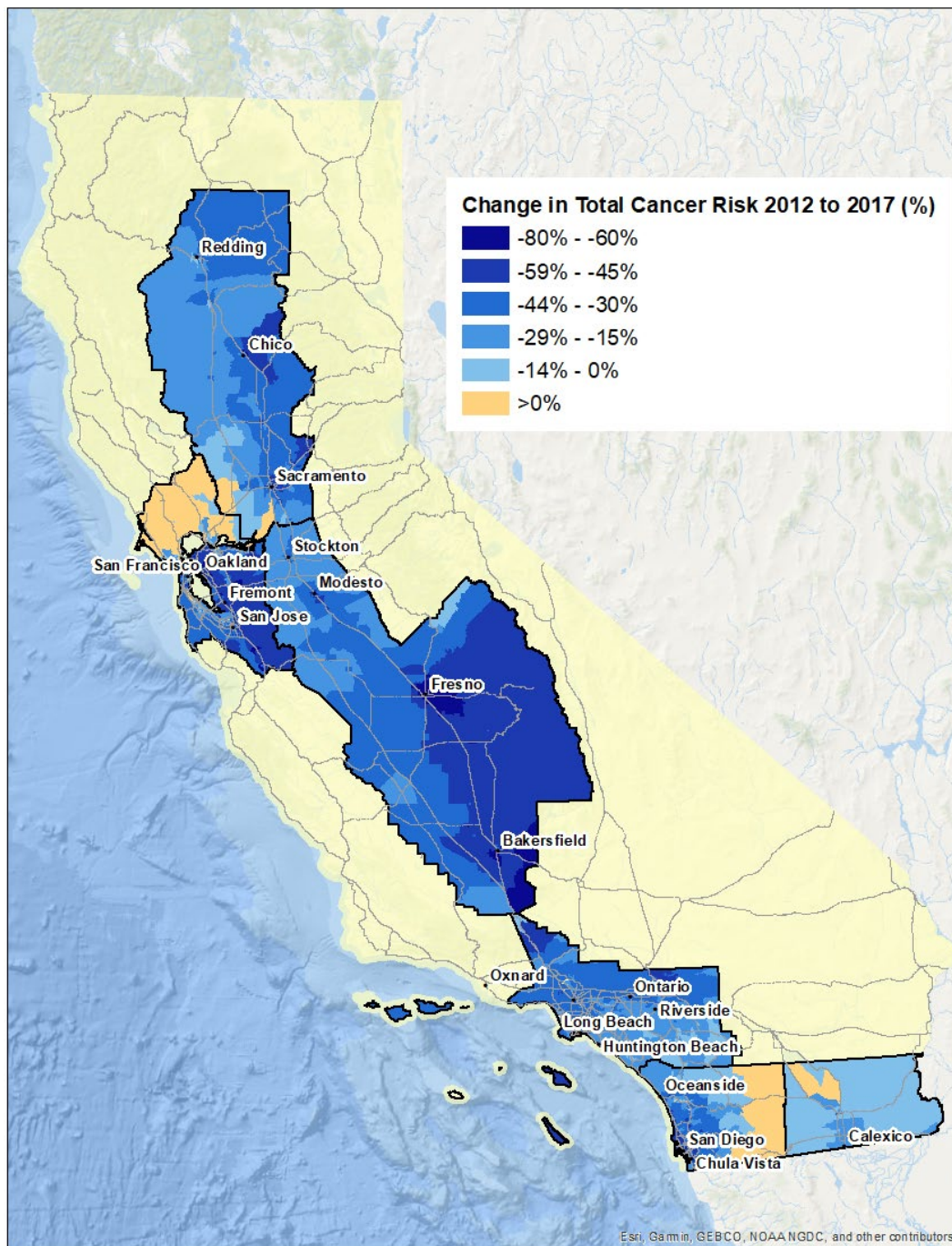


Figure ES-8. Map of the change in total modeled cancer risks from 2012 to 2017 on the census tract level, in percentage of 2012 risks. Only areas within the six air basins are shown.

Visualization and Mapping Tool. To facilitate public access of the CATA results, a GIS-based interactive visualization and mapping tool has been developed. The tool allows visualization, statistical analysis, and data downloading at different scales and levels of the CATA database. Access to the online tool can be found [here](#).

Cancer Risk Change in the Future. In the future, it is projected that the cancer risk associated with on-road DPM emissions will drop substantially statewide. This reduction is attributed to DPM emission reductions primarily from the On-road Truck and Bus rule and other programs. In addition, programs designed to reduce emissions from ocean going vessels (OGV), commercial harbor craft (CHC), cargo handling equipment (CHE), transport refrigeration units (TRU) and other sources have also been and/or will be implemented. However, reductions in those sectors from existing emission reduction programs are estimated to be much less than those from on-road mobile sources. As such, their relative contributions to total cancer risk are projected to increase with time, even though the absolute exposure and cancer risk values will decrease.

D. Recommended Use of This Study

- This CATA study can be used to identify general spatial pattern of air toxics and subsequent health impacts at the statewide, regional, and local levels, and to identify which pollutants and emission sources may require further scrutiny. It is also expected that through future CATA updates, trends in air toxics and associated health risk can be tracked over time.
- At the local scale, the modeling results are best used in a qualitative manner to inform which source categories and pollutants are contributing the most to the overall risk within a community, which can then be used to inform and prioritize emission reduction strategies that target the sources most likely to lead to reductions in risk over time.
- For those toxic air pollutants assessed as part of CATA, the incidence-per-ton (IPT) of emissions is a measure of the number of cancer cases due to exposure to a specific air toxic over 30 years per ton of emissions per year. It can be used directly to estimate the reduction in health outcomes (potential excess cancer risk and cancer burden) achieved by any newly proposed or existing air toxics regulation. These factors may also be used to inform the toxic emission and exposure reduction strategies in support of the districts' CERPs. While this metric can provide valuable information about the health impacts of air toxics, it is important to note that there are a number of uncertainties associated with the IPT approach. There are many factors that can influence the relationship between emissions and health outcomes, including the specific mix of pollutants in the air, the health status of the population, and the presence of other environmental stressors (such as noise pollution or lack of access to healthy food).
- Future-year risk estimates are best used to help focus on those sources that are not already projected to decrease significantly due to existing regulations, so as to achieve the greatest overall reduction in risk over time.

- Since this study is different from a health risk assessment (HRA) under the “Hot Spots” program of CARB (AB 2588), we don’t expect that the results from the current study to be used: 1) as a definitive means to pinpoint specific risk values at a specific location; 2) to compare risks among communities in the state; and 3) as part of a “Hot Spots” program or HRA in a permitting application.
- Note that individual risks within a census block may vary significantly from average risk within the block due to differences in proximity to sources and how pollutants are emitted from a source (e.g., near surface or aloft). For example, if a census block covers a city block, residents within that block that live immediately next to a source having ground-level emissions may be exposed to significantly higher concentrations than the average concentration over the entire census block.

E. Caveats and Uncertainties

Although this study reflects the state-of-the-science in modeling techniques and analytical tools, it is important to recognize caveats and limitations to avoid misinterpretation of the modeling results. In this study, the emission inventory was developed based on the best-established datasets and methods to quantify emissions from many diverse emission sources that were available at that time. However, there may be circumstances where emissions were under- or over-estimated. This may be because there are sources of air toxics that have not yet been identified or that are episodic and difficult to represent in the inventory. Diesel PM was the major contributor to cancer risk in this study. However, there are no existing techniques to directly measure diesel PM, so validating the diesel PM emission inventory from direct measurements is problematic. The modeling methods used in this study were designed specifically to provide the best estimates of cumulative exposures to air toxics from the multitude of emission sources and known air toxics. Cancer risks were estimated at the center of census blocks, and analyses of major air pollutants and emission sources were developed based on population-weighted averages within the state, air basins and communities. Thus, the results may not necessarily reflect near-source impacts for any emission source.

This study used the risk assessment guidance recommended by OEHHA and the annual average modeled air toxics concentration to calculate health risks. However, any toxic health risk assessment requires the use of certain assumptions, which are based on current scientific knowledge and designed to be conservative and health protective. These assumptions may simplify things to make an assessment possible, but they may also introduce uncertainties. As noted in the OEHHA risk assessment guidelines, sources of uncertainty in risk estimates include: (1) extrapolation of toxicity data in animals to humans; (2) uncertainty in the estimation of emissions; (3) uncertainty in the air dispersion models; and (4) uncertainty in the exposure estimates. Uncertainty may be defined as what is not currently known and may be reduced with further scientific studies. In addition to uncertainty, there is a natural range or variability in the human population for things such as height, weight, breathing rate, and susceptibility to chemical toxics. Future updates to CATA will include improvements and updates to the emission inventories, the spatial and temporal allocation of emissions data,

and more robust evaluations of the modeling performance as additional toxics monitoring data become available.

It is important to note that while these limitations are an important consideration, the study results here do provide the best estimate of the health risk impacts in California given the current emission inventory, OEHHA guidance, and USEPA recommended modeling systems.

F. Conclusions and Policy Implications

- Based on the 2017 emission inventory of air toxics, a total of 12 air toxics were simulated over six air basins using the integrated modeling approach. The simulated individual TAC concentrations were compared against available observations for the purpose of validating the CALPUFF and CMAQ models. Results showed that the simulated EC concentrations by CALPUFF (used as surrogate for DPM for evaluation purposes) and VOCs concentrations by CMAQ have a reasonable agreement with observations, while the simulated heavy metal concentrations were underestimated compared to the observations.
- Population-weighted cancer risks for 2017 were estimated for individual air toxics species as well as for all species combined at a 30-year exposure level. The statewide population weighted average cancer risk was estimated to be 598 cases per million.
- Among those simulated air toxics, DPM was the main contributing pollutant to total average risk and accounted for 82% of the total cancer risk. The on-road mobile sources were the top contributor with 60% of the total DPM risk.
- Compared with the 2012 CATA study (emission inventory and meteorology of 2012), statewide population-weighted average risk has been reduced by 32% from 2012 to 2017. However, people living near the ports, railyards, the US-Mexico border, and major transportation corridors continue to experience higher air toxics cancer risks. The results from this study support a continued effort on the reduction of toxic emissions, especially for those areas mentioned above.
- Incidence-per-ton of emissions (IPT) factors for DPM and toxic VOCs are developed from this study's results. They can be used to estimate the reduction in health outcomes achieved by any newly proposed or existing CARB toxic regulation. Those factors may also be used to inform the toxic emission and exposure reduction strategies in support of the districts' CERPs.
- In the future, the risk associated with on-road DPM emissions will be significantly reduced. This reduction is attributed to DPM emission reductions primarily from the On-road Truck and Bus rule. Programs designed to reduce emissions from OGV, CHC, CHE, TRU and other sources have also been and/or will be implemented. However, the relative contributions from these sources (compared to on-road mobile) are projected to increase with time, even though absolute risks will decrease.
- Future related work may include improving the emission inventories of air toxics and their spatial distribution, especially for heavy metals because of their underestimation in the current study. From a regulatory perspective, more attention may be needed towards toxic VOCs and heavy metals because both exhibited relatively smaller

reductions compared to DPM. In the near future, if an updated Criteria and Toxics Reporting emission inventory is developed, it will be included in future modeling.

I. Introduction

A. Overview

This report documents the first formal iteration of the California Air Toxics Assessment (CATA) study, a triennial statewide air toxics modeling effort conducted by CARB staff. This modeling effort provides an assessment of human exposure to air toxics throughout California and their potential cancer risks in support of CARB's various toxics programs, including the Community Air Protection Program (Program). At the time of this effort, the Program has identified 13 disadvantaged communities that are disproportionately impacted by air pollution. To help these and other communities identify the major toxics emission sources contributing to negative health outcomes in their community, the exposure and risk assessment had to be scalable to both regional and local-scale analyses. Traditional photochemical models, such as the Community Multiscale Air Quality Modeling System (CMAQ) and the Comprehensive Air Quality Model with Extensions (CAMx), are not entirely suitable for this purpose because those models are grid-based models. These models cannot generally resolve the variation, or gradient, of pollutant concentrations below a few square kilometers, which is necessary when considering exposure to air toxics. Therefore, an innovative approach was adopted that utilizes two different models to calculate concentrations of air toxics: CMAQ is used to simulate transport and diffusion of chemically reactive toxic air contaminants (TACs) such as benzene, 1,3-butadiene, formaldehyde, acetaldehyde, perchloroethylene and p-dichlorobenzene; and the CALPUFF dispersion model is used to study chemically inert TACs including diesel particulate matter (DPM) and metals such as hexavalent chromium, lead, arsenic, cadmium and nickel.

In doing so, the modeling approach remains regional in nature, and photochemical reactions are properly represented for reactive VOCs, while the results still have the capability of depicting fine details of concentration variations for DPM and metals as long as appropriate emissions data are available as input to the CALPUFF model. As a result, hot spots and even the spatial variation of DPM and metals within the hot spots can be revealed by the modeling results. This is because dispersion models such as CALPUFF have the ability to represent emission sources more accurately in space (e.g., the actual location of a source compared to the area averaging that is required by grid-based models). Furthermore, concentrations can be calculated at any specified location or receptor, such as centroids of census blocks, and sensitive receptors like senior care homes, kindergartens, and hospitals.

The first air toxics assessment was done for the 2012 base year with 2012 emissions and meteorology. Year 2017 was chosen for this first formal CATA analysis because it was, at the beginning of this modeling endeavor, the latest year that both emissions data and meteorological data had gone through rigorous quality control process.

The remainder of this report is organized as follows: The rest of Section I gives an overview of the air toxics of interest in this modeling work and their health impact, as well as a summary of the methodology and main objectives of this work. Sections II and III describe the inputs to the air quality models, namely the emission inventory and emission processing, and the meteorological conditions, respectively. Section IV summarizes the modeling

methodology and estimates of exposure to the different air pollutants on a statewide level. Section V gives an evaluation of model performance, before jumping into Sections VI and VII which show the major modeling results for risk assessment at the statewide, air basin, and community levels, with potential application of those results for regulatory development, respectively. Finally, Section VIII lists the literature referenced in the study.

B. Toxic Air Contaminants (TACs) and Their Health Impact

According to section 39655 of the California Health and Safety Code, a toxic air contaminant (TAC) is "an air pollutant which may cause or contribute to an increase in mortality or an increase in serious illness, or which may pose a present or potential hazard to human health". Long-term exposures to TACs can cause a wide variety of health effects, including cancer and birth defects. Other adverse health effects can include damage to immune, neurological, reproductive (reduced fertility), developmental, and respiratory systems. For example, diesel PM (DPM) is a known human carcinogen and was identified as a TAC by CARB in 1998, based on its potential to cause cancer and other health problems, including respiratory illnesses, and increased risk of heart disease. Benzene is also a known human carcinogen, but unlike DPM, the main types of cancer associated with benzene are blood cancers. Arsenic is a typical metal TAC that can cause certain types of cancer such as lung, skin and bladder cancer, as well as skin lesions, diabetes and high blood pressure. Detailed information about the various health effects associated with the specific TACs can be found on the website of the Office of Environmental Health Hazard Assessment (OEHHA).

TACs are emitted from many sources in California, including diesel engines, vehicles (e.g., cars, trucks), industrial processes, and gas stations. Types of TACs include DPM, toxic heavy metals such as lead and hexavalent chromium, and toxic volatile organic compounds (VOCs) such as benzene, formaldehyde, etc. A complete list of known TACs can be found from the OEHHA web site (<https://oehha.ca.gov/air/general-info/toxic-air-contaminant-list-staff-reportsexecutive-summaries>).

C. Exposure and Potential Cancer Risk of the TACs

Exposure represents the extent of public exposure to a TAC. An exposure assessment can involve quantification of emissions from emission sources, modeling of environmental transport and fate, and estimation of exposure levels over a certain period of time. In this study, the modeled annual average concentrations of TACs are used to represent exposure. Exposure to TACs can occur through multiple pathways, including inhalation and non-inhalation pathways (e.g., soil ingestion, ingestion of mother's milk, etc.). The South Coast Air Quality Management District' MATES-V study¹ showed that including risk from multiple

¹ http://www.aqmd.gov/docs/default-source/planning/mates-v/appendixix_final.pdf?sfvrsn=4, see Table IX-7-11.

pathways increased overall risk by approximately 7.3% compared to the inhalation-only risk. CARB staff has conducted sensitivity analyses on risk associated with various exposure pathways and found that the inhalation pathway can account for over 95% of the total exposure, which is consistent with MATES-V findings. Thus, only inhalation exposure was considered in this study.

Cancer risk represents the probability of a person developing cancer if exposed continuously to a TAC over their lifetime (70 years, in units of cases per million people²), but it does not necessarily mean that any specific individual will develop cancer due to TACs exposure. In other words, the risk number is not an actual number of cancer cases. Cancer risk calculation in this study is for TACs only and does not include other risk factors for developing cancer, such as age, genetics/predisposition, etc. Cancer risk calculations account for daily inhalation rates, age, the frequency of time spent at home (for residents only), the duration of exposure, and cancer potency of the TAC to yield the excess cancer risk. For residential inhalation exposure, the excess potential cancer risk is calculated separately by age group and then summed to yield an overall cancer risk at the receptor locations. Cancer risk due to all TACs is the sum of potential cancer risk for all individual TACs. Note that an exposure duration of 30 years with the Risk Management Policy (RMP) method (95th/80th percentile daily breathing rate (DBR)) was used for assessing potential lifetime cancer risk (inhalation only) in this study.

D. Steps of Air Toxics Assessment

Conducting a model based toxic health analysis includes four main steps (Figure I-1): 1) prepare an emission inventory and meteorological data, 2) estimate ambient concentrations of individual TACs using air quality modeling, 3) estimate population exposures, and 4) characterize potential health risks from inhalation.

² Often, scientific notation is used, and you may see it expressed as 1×10^{-5} or 10^{-5} . Therefore, if you see a potential cancer risk of 10 cases per million, that means if one million people were exposed to a certain level of a TAC there is a chance that 10 of them may develop cancer over their 70-year lifetime. This would be 10 new/excess cases of cancer above the expected rate (background) of cancer in the population.

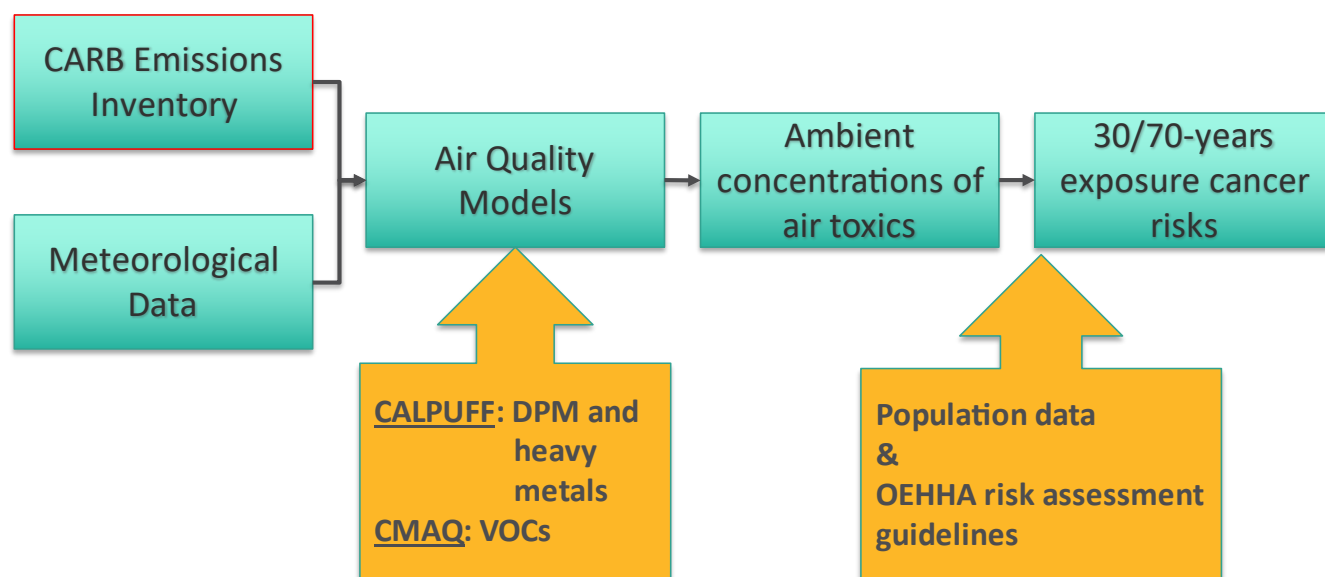


Figure I-1. Flowchart of the CATA process.

Part of the first step is assembling a temporally, spatially, and chemically speciated detailed emission inventory. All emission sources quantified in the official CARB emission inventory are considered in this modeling, including the following four major emission source categories:

- On-road mobile sources: major freeways and traffic links
- Off-road mobile sources: locomotives, railyards, seaports, airports, commercial harbor crafts, etc.
- Area sources: all other areawide emission sources, including small point sources (e.g., gasoline stations, dry cleaners, etc.), minor on-road mobile traffic links (centroid connectors), charbroils, livestock, various fires (wildfires, agricultural fires, prescribed fires, structure fires, residential wood combustion), paved and nonpaved road dust, biogenic, etc.
- Stationary Sources: major point sources from industrial facilities.

After preparing the emissions and other needed data (e.g., prognostic meteorological data, see Section III for more details), we use them as inputs to two air quality models used to calculate ambient air concentrations of air toxics: the CALPUFF dispersion model and the Community Multiscale Air Quality (CMAQ) photochemical model. CALPUFF is used to model inert toxics, namely DPM and 5 toxic heavy metals (cadmium, hexavalent chromium, lead, arsenic, and nickel), while CMAQ is utilized to simulate six reactive toxic VOCs (benzene, 1,3-butadiene, formaldehyde, acetaldehyde, perchloroethylene and p-dichlorobenzene). We then use these ambient concentrations to develop exposure concentrations, while accounting for exposure variables such as human activity patterns, etc.

Risk characterization is the final step of a health risk assessment (HRA). In this step, information developed through the exposure assessment is combined with information from the dose-response assessment to characterize risks to the public from emissions. The OEHHA's most recent risk assessment guidelines - Guidance Manual for Preparation of Health Risk (2015) are used to characterize cancer risks resulting from exposure to the modeled TACs in this study. Cancer risk is calculated by multiplying the daily inhalation or oral dose by a cancer potency factor, the age sensitivity factor, the frequency of time spent at home (for residents only), and the exposure duration divided by averaging time, to yield the excess cancer risk. For residential inhalation exposure, the excess cancer risk is calculated separately by age groups and then summed to yield an overall cancer risk at the receptor locations. Cancer risk due to all pollutants is the sum of cancer risks for all individual pollutants. Cancer burden can be calculated by multiplying the cancer risk at a census block (tract) centroid by the number of people who live in the census block (tract). Note that exposure duration of 30 years with the Risk Management Policy (RMP) method (95th/80th percentile DBR) is used for assessing potential cancer risk (inhalation only), and 70-year evaluation period is used to estimate potential cancer burden.

E. Objectives

In California, air quality and public health have improved from reductions of toxic emissions in the air due to regulatory actions and mitigation measures implemented over the past decades. However, the pollution reduction and resulting health benefits are not uniformly distributed across the state. Some communities are still disproportionately impacted by toxic air contaminants (TACs) emitted from various sources, such as on-road motor vehicles, off-road equipment, and industrial facilities. This study can help provide the information needed to assess public exposure to TACs at various spatial scales (communities, air basins, and statewide), assess the overall impact of current air toxic control measures, and help inform control strategy development for reducing exposure to air toxics associated with significant public health risks. Through regular updates to CATA (currently on a triennial basis), the statewide air quality improvement and trends in air toxics reductions over time can be tracked.

CATA can also be used to support AB 617 activities by: 1) screening, identifying and prioritizing the communities most impacted by air toxics, 2) quantifying the relative contribution of emission sources/categories to the overall health impact from TACs, identifying geographic areas with higher pollution burden, and assessing population exposures and the benefits of emission controls in impacted communities in support of the community emission reduction programs (CERP), and 3) filling data gaps by complementing observational data from the monitoring network, which are often costly to deploy and maintain, in support of community air monitoring programs. Deploying a large number of monitors in communities statewide is not practical because of the operational costs, human resources needs, and instrument limitations.

Additionally, CATA can be used to improve tools such as OEHHA's CalEnviroScreen, which uses DPM emissions inventories as a surrogate for a major air toxic exposure indicator. This

study can provide air toxic health risk indices as supplemental indicators to CalEnviroScreen with improved representation of exposure and cancer risk metrics.

Lastly, this study can provide technical support for the Board's regulatory development (such as the Airborne Toxics Control Measures (ATCMs), environmental justice, and many other programs).

II. Development of Toxics Emission Inventory

The emission inventory used in this modeling work was based on 2017 emission levels/estimates. Emissions data for CMAQ and CALPUFF modeling were processed differently to maximally take advantage of each model's strength. California's emission inventory is an estimate of the amounts and types of pollutants emitted from thousands of industrial facilities, millions of motor vehicles, and myriad emission sources such as consumer products and fireplaces. The emissions data in the emission inventory come from different sources maintained by CARB, local Districts, and other agencies.

The basic principle for estimating county-wide regulatory emissions is to multiply an, per-unit emission factor by an estimate of typical usage or activity. For example, on-road motor vehicle emission factors are estimated for a specific vehicle type and applied to all applicable vehicles. The estimates are based on dynamometer tests of a small sample for a vehicle type. The activity for any given vehicle type is based on an estimate of typical driving patterns, number of vehicle starts, and typical miles driven. Assumptions are also made regarding typical usage: it is assumed that all vehicles of a certain vehicle type are driven under similar conditions in each region of the state.

Developing emission estimates for stationary sources involves the use of per unit emission factors and activity levels. Under ideal conditions, facility-specific emission factors are determined from emission tests for a particular process at a facility. A generic emission factor is developed by averaging the results of emission tests from similar processes at several different facilities. This generic factor is then used to estimate emissions from similar types of processes when a facility-specific emission factor is not available. Activity levels from stationary sources can be derived from the amount of product produced, solvent used, or fuel consumed.

The district-reported and CARB-estimated emissions totals are stored in the California Emissions Inventory Data Analysis and Reporting System (CEIDARS) database for any given pollutant. Both criteria and toxic air pollutant emission inventories are stored in this complex database. These are typically annual average emissions for each county, air basin, and district. The emissions are temporally resolved by month, week, day, and hour to gauge model performance more accurately and ultimately to provide accurate estimates of pollutant concentrations.

Since air quality models attempt to replicate the physical (e.g., transport and diffusion) and chemical processes that occur in the atmosphere, it is important that the physical location of emissions be specified as accurately as possible. Ideally, the actual location of all emissions

would be known exactly, but this is generally only possible for some emissions sources and categories. To the extent possible, the spatial allocation of emissions in a modeling inventory approximates as closely as possible the actual location of emissions.

Spatial allocation is typically accomplished by using spatial surrogates. These spatial surrogates are processed into spatial allocation factors in order to geographically distribute county-wide area source emissions to individual grid cells. Spatial surrogates are developed based on demographic, land cover, and other data that exhibit patterns that vary geographically.

Three basic types of surrogate data were used to develop the original spatial allocation factors: land use and land cover, facility location, and demographic and socioeconomic data. Land use and land cover data are associated with specific land uses, such as agricultural harvesting or recreational boats. Facility locations are used for sources such as gas stations and dry cleaners. Demographic and socioeconomic data, such as population and housing, are associated with residential, industrial, and commercial activity (e.g., residential fuel combustion). To develop spatial allocation factors of high quality and resolution, local socioeconomic and demographic data were used when available.

A. Emission Data for CMAQ Modeling

County based reported annual emissions that are spatially, temporally, and chemically, resolved are needed as inputs for the photochemical air quality model. Point sources and area sources (area-wide, off-road mobile, and aggregated stationary) are processed into emissions inventories for photochemical modeling using the Spars Matrix Operator Kernel Emissions (SMOKE) modeling system.

The EMFAC emissions model is used to assess emissions from on-road vehicles including cars, trucks, and buses. EMFAC is designed to produce county-level, average-day estimates. These estimates are disaggregated spatially and temporally into gridded, hourly estimates for air quality modeling.

Emissions were distributed into the 2-km by 2-km modeling grids, mostly in the first layer but for emissions from tall stacks or other sources that have significant buoyancy the emissions are allocated above the surface layer.

B. Emission Data for CALPUFF Modeling

Many emission sources can be represented more accurately with a dispersion model such as CALPUFF, because the spatial representation of the emissions is not restricted to a specified modeling grid. Major stationary sources are characterized as point sources, most of the emissions from on-road motor vehicles are represented as individual traffic links which are modeled as narrow area sources (referred to as line sources since they are long and narrow), additionally emissions from ocean going vessels in the transiting and maneuvering modes are also represented in the modeling as line sources. Emissions from aircrafts landing/taking off

and taxiing are also treated as line sources. All remaining emission sources are modeled as 1-km x 1-km area sources. Future modeling work will include improvements to the spatial representation of some sources currently treated as area source emissions, such as emissions from line-haul locomotives, which will be treated as line sources. It should be noted that in CALPUFF modeling, the dimensions of area sources do not have to coincide with the modeling grids. This flexibility improves the accuracy of emission locations in the air dispersion modeling.

Release parameters for stationary point sources need to be specified in the modeling. These parameters are source specific for location, base elevation, release height, stack inside diameter, temperature and velocity of the exit effluent. For line sources, source length and width, release height and the initial vertical spread are needed. For area sources, the vertices of the area need to be specified along with the initial vertical spread.

The methodologies of emission inventory development are detailed in Appendix B. The sources of emission data and emission modeling used in this study are summarized in Table II-1.

Table II-1. 2017 emission data sources and emission modeling information.

	CMAQ	CALPUFF
Grid Resolution	Statewide 2-km	
Area Source Inventory	CEPAM 2019v1.01 RF3043 Criteria Pollutants, DPM, Speciated VOC & Metals	CEPAM 2019v1.01 RF3043 Criteria Pollutants, DPM, Speciated toxic VOC & Metals
Stationary Source Inventory	CEPAM 2019v1.01 RF3043 Criteria Pollutants, DPM, Speciated VOC & Metals	CEPAM 2019v1.01 RF3043 Criteria Pollutants, DPM, Speciated VOC & Metals
California Toxics Inventory (Stationary source heavy metals only)	CTI_snp20191024 Heavy Metals: Hexavalent Chromium, Lead, Arsenic, Cadmium & Nickel	CTI_snp20191024 Heavy Metals: Hexavalent Chromium, Lead, Arsenic, Cadmium & Nickel
Onroad Inventory	EMFAC 2017 with MPO v008 and spatial allocation using ESTA	EMFAC 2017 with MPO v008 and spatial allocation using link level ITN VMT
Spatial Surrogates	SRGDESC_2017_2km_20200323	SRGDESC_2017_1km_20200520
Speciation	gspro.WithInvpols.toxics.S07TT.072618.extra	gspro.WithInvpols.toxics.S07TT.072618.extra
Temporal Profiles	ATREF_pro2017_snp20190508_Rev20190605-CHC-replaced.csv	ATREF_pro2017_snp20190508_Rev20190605-CHC-replaced.csv

C. Summary of Emissions in the Six Air Basins

There are many sources that produce toxic air emissions in this state but not all sources contribute to air pollution equally. Contributing sources were grouped into four major categories and 33 subcategories: on-road mobile sources (freeways and local major roads/streets), off-road mobile sources (locomotives, railyards, airports, ocean going vessels (OGVs), commercial harbor crafts (CHC), cargo handling equipment (CHE), transport refrigeration units, etc.), area sources (construction, agricultural activities, small point sources (e.g., gasoline stations, dry cleaners, etc.), minor on-road mobile sources, charbroils, livestock, various fires (wildfires, agricultural fires, prescribed fires, structure fires, residential wood combustion), paved and nonpaved road dust, biogenic, etc.), and stationary point sources. Note that some emission sources, including commercial and industrial equipment such as forklift, air compressors, generators, etc. were included in area sources because they were not explicitly categorized. The stationary sources (businesses regulated by local air districts) included, but were not limited to, refineries, power generation plants, cement plants, chemical processing plants, food processing plants, electric utilities, metal fabrication and coating operations, petroleum bulk terminals, medicinal and botanical manufacturing and many others.

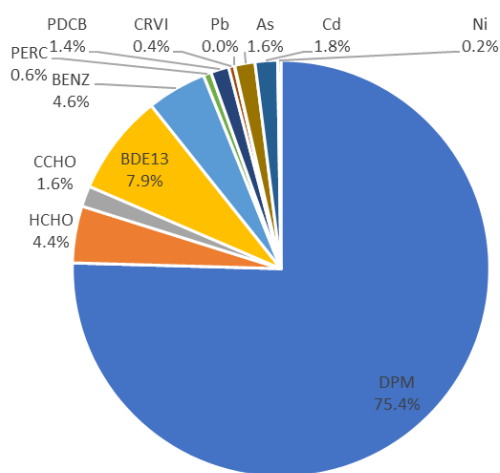
Table II-2 provides the breakdown of the 12 TACs emissions by species, major emission categories for DPM, and air basins. The annual DPM emissions total 5804 TPY in the six air basins, in which on-road, off-road, area and point sources accounted for 36%, 8%, 54% and 1%, respectively. Note that these summaries include emissions located within the six air basins' jurisdiction boundaries (not modeling domains).

Figure II-1 shows the breakdown of annual total emissions by each TAC statewide and in each air basin. Note that in Figure II-1, other TACs' emissions have been weighted into DPM potency equivalent emissions based on their inhalation cancer potency values. The emissions from species less potent than DPM (e.g., benzene, perchloroethylene) are weighted less, while emissions from species more potent than DPM (e.g., hexavalent chromium, arsenic) are weighted more. These weighted emissions are referred to as DPM potency equivalent emissions. Statewide, DPM accounts for about 75% of the total TACs emissions (DPM potency equivalent). The other significant TAC species (i.e., contribution >1%) are 1,3-butadiene (8%), benzene (5%), formaldehyde (4%), cadmium (1.8%), arsenic (1.6%), acetaldehyde (1.6%), and p-dichlorobenzene (1.4%). The breakdown into species differs slightly across air basins, reflecting unique characteristics of emission sources in each air basin. The spatial patterns of DPM emissions within the modeling domains are shown in Figures II-2 to II-5 by major source groups, i.e., on-road, stationary, off-road and area sources, respectively. The gridded emissions of the six VOC species within the modeling domains are mapped in Figure II-6.

Additional emission tables and figures are presented in Appendix C.

Table II-2. Summary of 2017 emissions by air basin and TAC (in TPY).

TACs	Sac Valley	Bay Area	SJV	SC	SD	Imperial	Total
<u>DPM</u>							
On-road	270	349	543	744	160	34	2100
Off-road	56	70	82	209	40	20	476
Area	544	359	1272	741	195	51	3163
Point	5	6	7	33	11	1	65
Total	876	785	1,903	1727	407	106	5,804
<u>VOCs</u>							
Formaldehyde	2,096	4,408	6,940	3,297	890	145	17,776
Acetaldehyde	2,500	1,976	6,426	1,650	735	333	13,620
1,3-Butadiene	123.2	184	207	443	136.4	14.4	1,108
Benzene	561.2	944	795.3	1,897	458	51.5	3,912
Perchloroethylene	223.3	112	337.1	1,540.5	238.3	15.3	2,467
p-Dichlorobenzene	244	1,007	1,518	170	30.2	2.2	2,971
<u>Heavy Metals</u>							
Hexavalent Chromium	0.0021	0.0149	0.0002	0.049	0.0071	0.0005	0.0739
Lead	5.5	8.5	9.4	12.6	5	16.1	57
Arsenic	0.8	1.9	3.1	1.5	0.6	3.1	11.1
Cadmium	0.5	4.4	1.1	2.1	0.5	1.3	9.9
Nickel	3.5	4.8	4.2	7.5	1.6	1.5	23.1



Nickel (Ni)
Cadmium (Cd)
Arsenic (As)
Lead (Pb)
Hexavalent Chromium (CRVI)
1,3-Butadiene (BDE13)
Benzene (BENZ)
Formaldehyde (HCHO)
Acetaldehyde (CCHO)
Perchloroethylene (PERC)
p-Dichlorobenzene (PDCB)

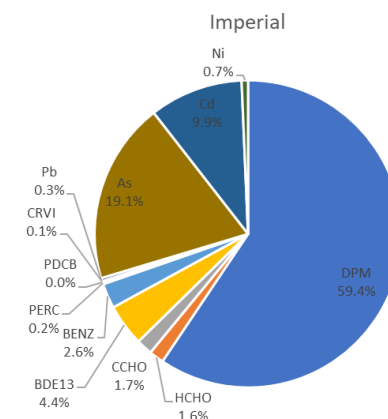
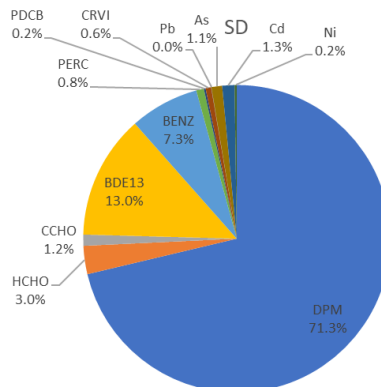
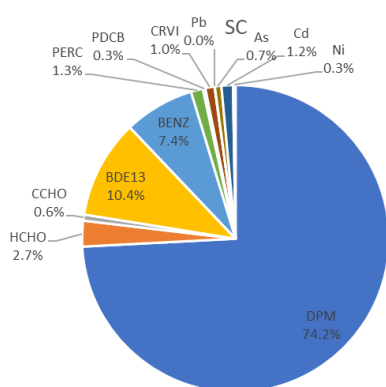
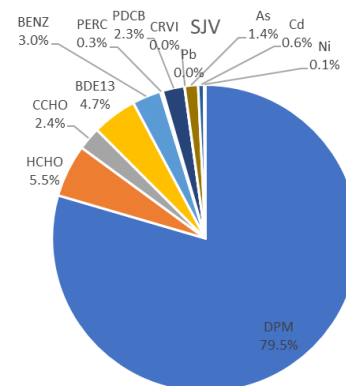
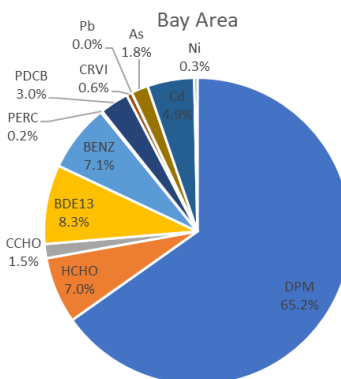
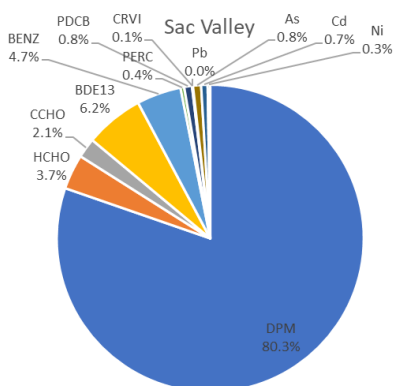


Figure II-1. Distribution of annual total emissions by TAC species (the emissions of VOCs and metals are expressed in DPM potency equivalent). The top pie chart shows TACs' statewide contributions and bottom 6 charts show their contributions for each air basin.

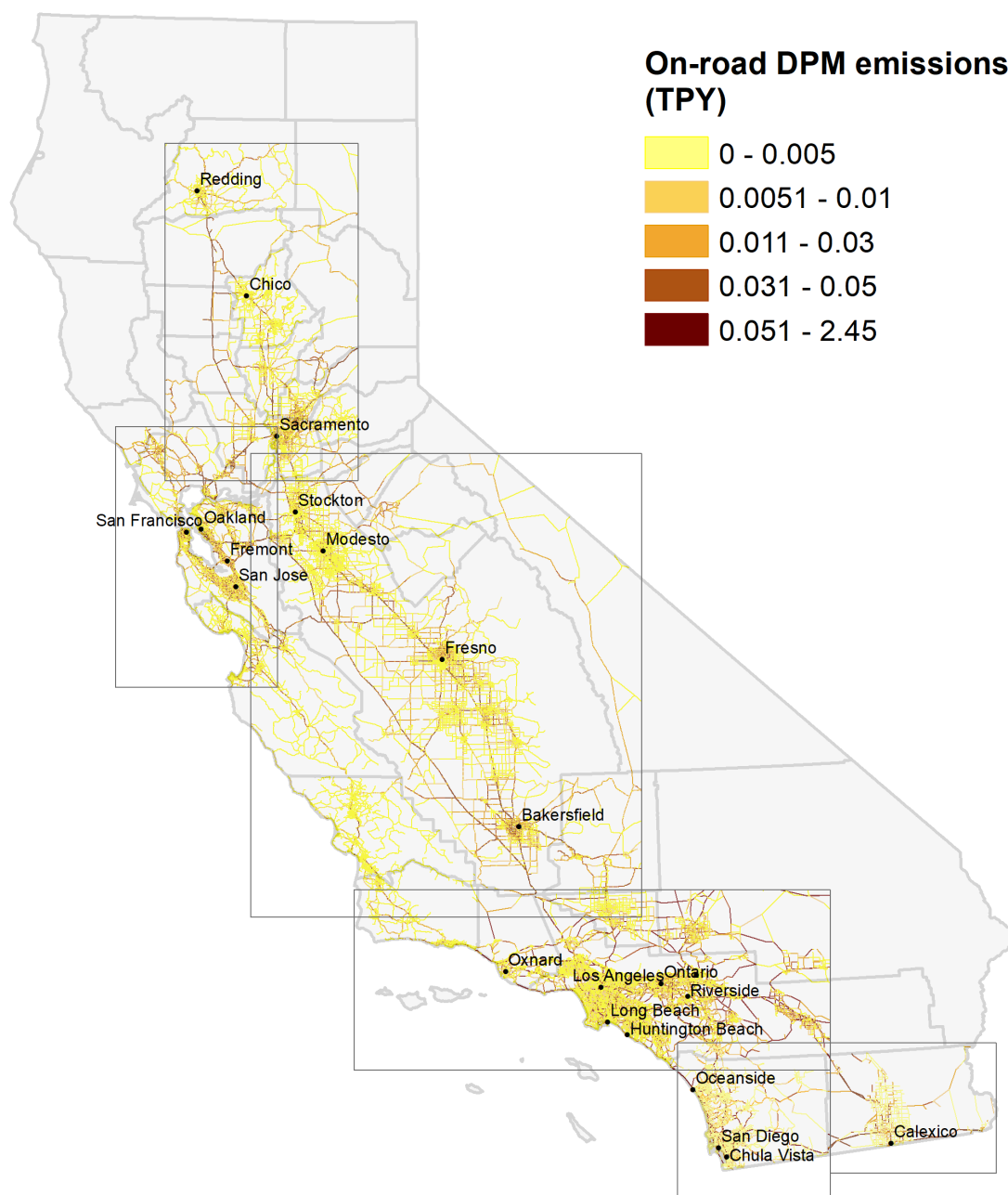


Figure II-2. Statewide Spatial Distribution of Annual Total On-road DPM Emissions (TPY) in 2017.

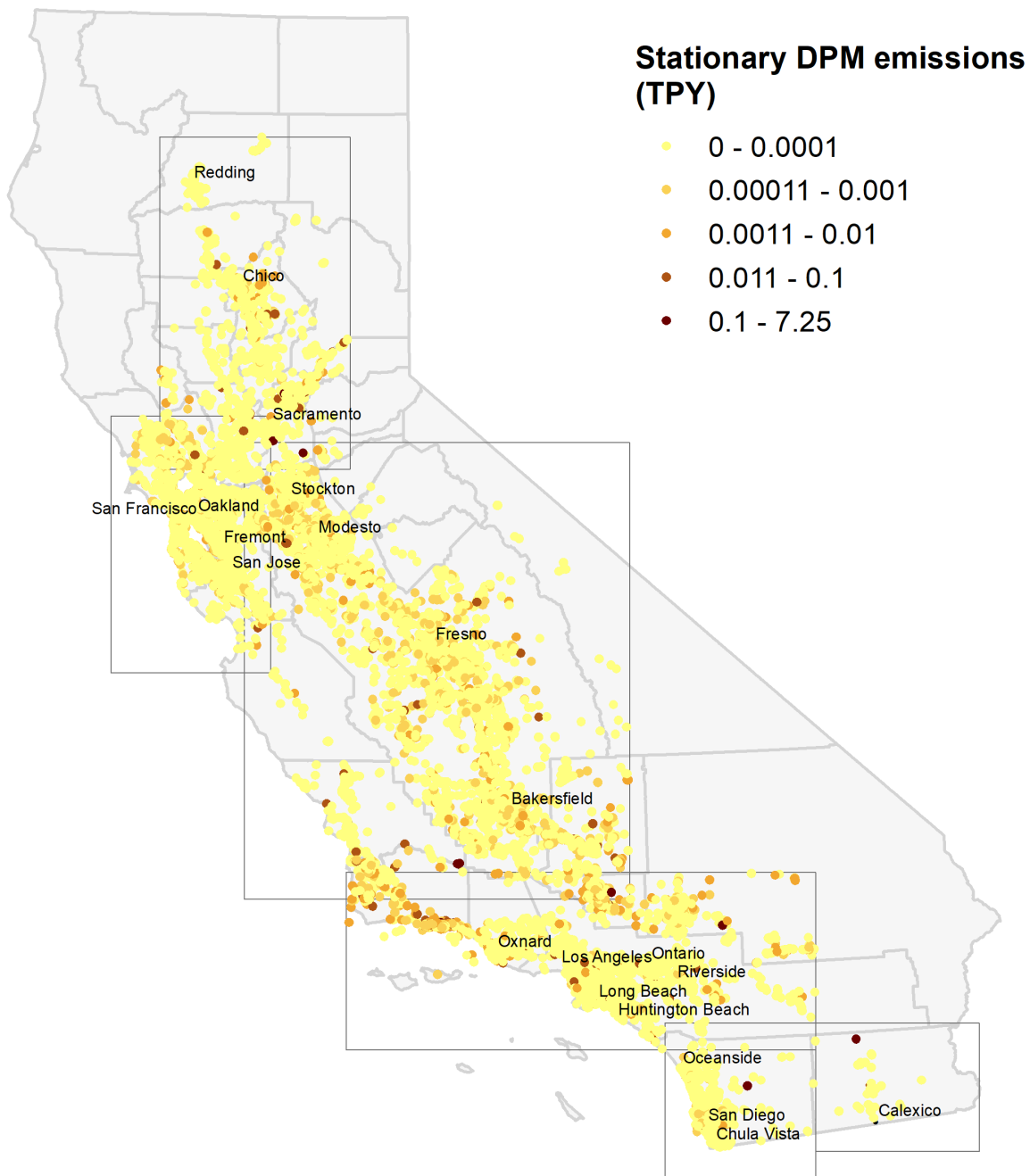


Figure II-3. Statewide Spatial Distribution of Annual Total Stationary DPM Emissions (TPY) in 2017.

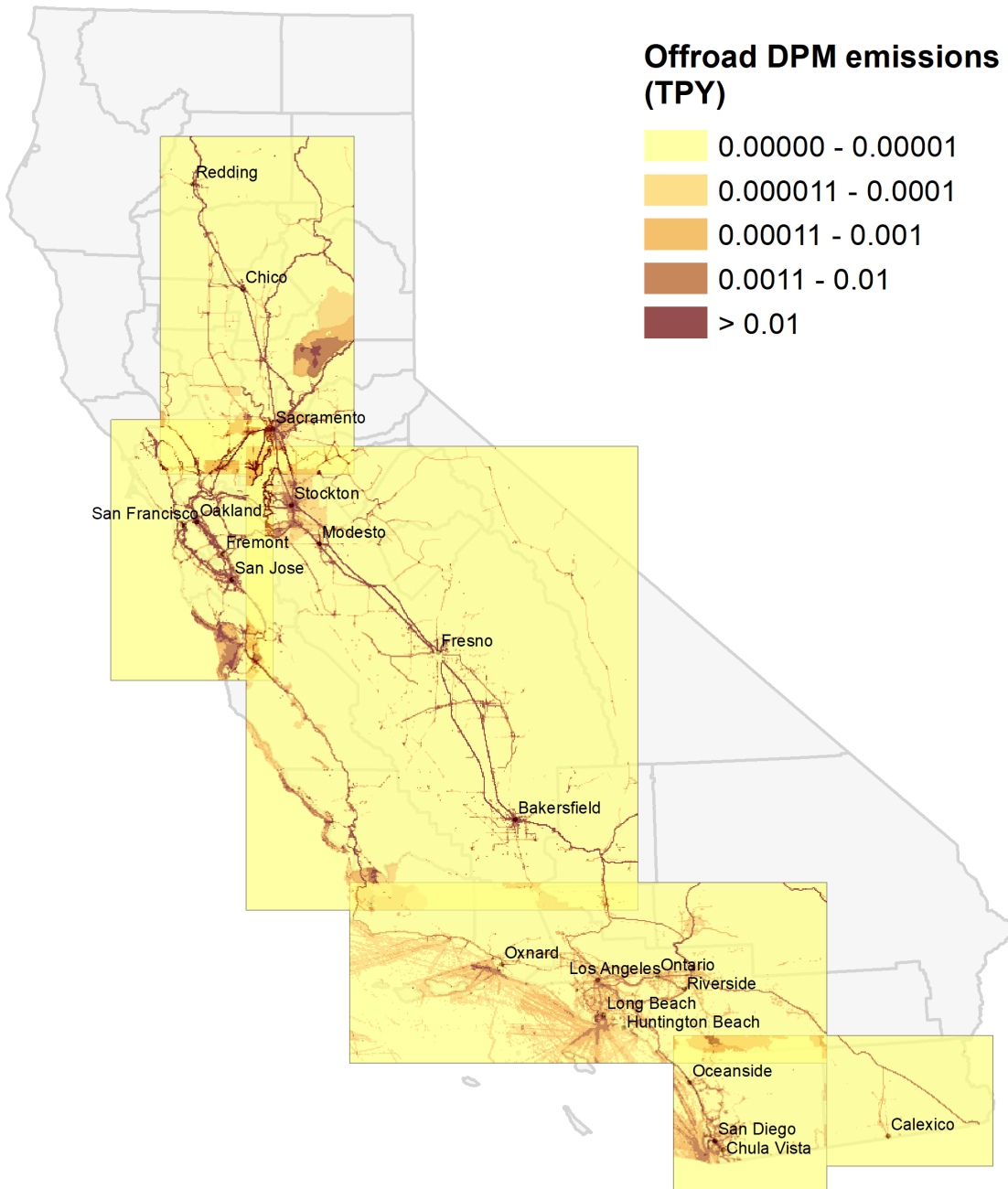


Figure II-4. Statewide Spatial Distribution of Annual Total Off-road DPM Emissions (TPY) in 2017.

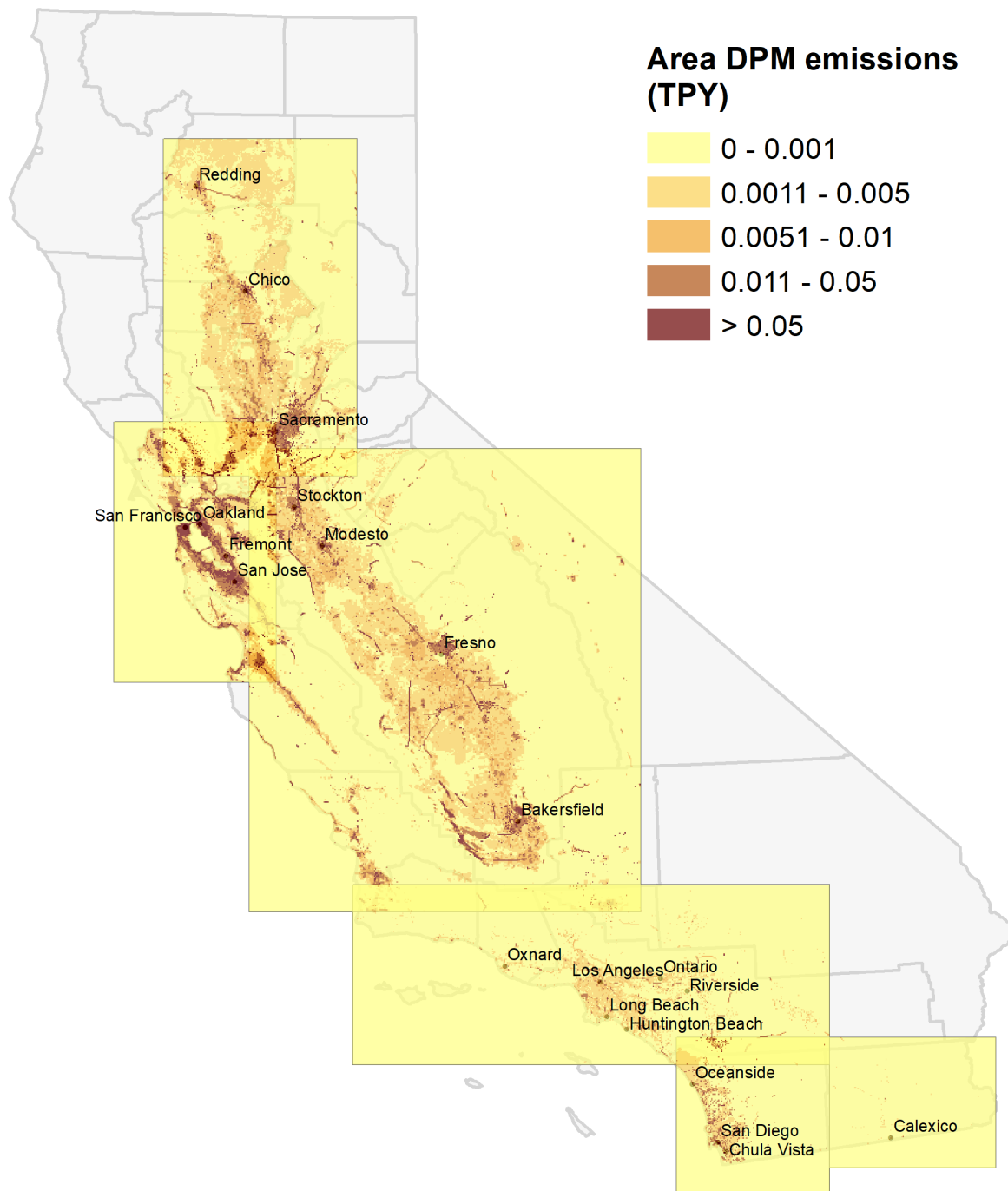
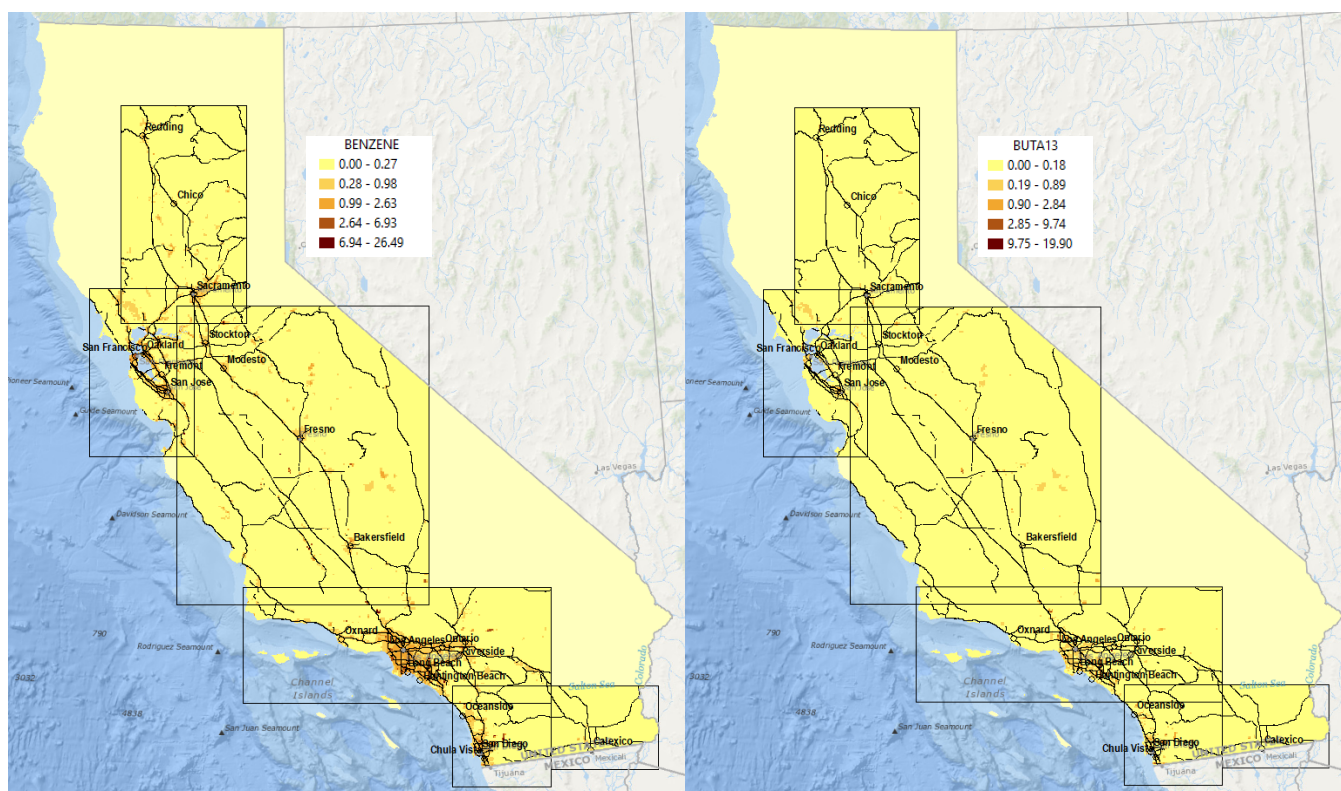
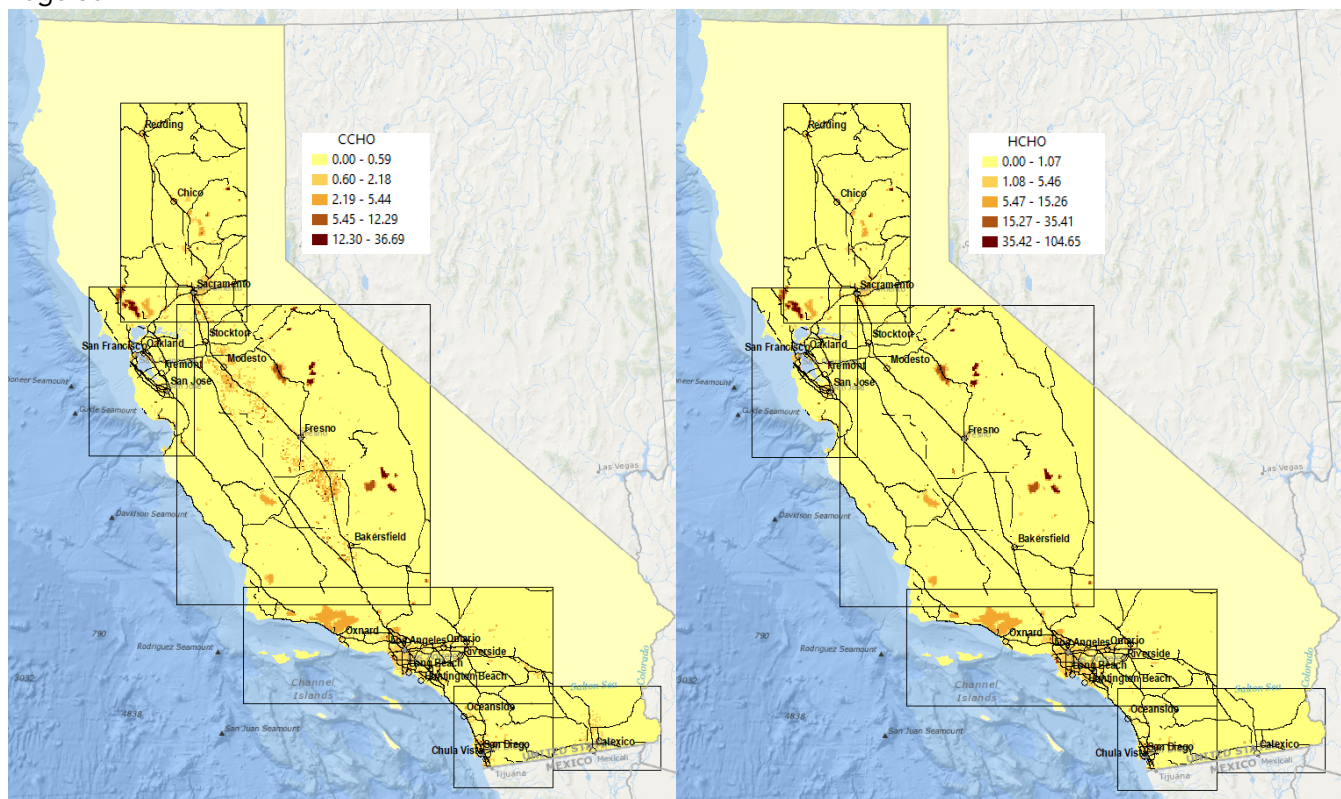


Figure II-5. Statewide Spatial Distribution of Annual Total Area DPM Emissions (TPY) in 2017.



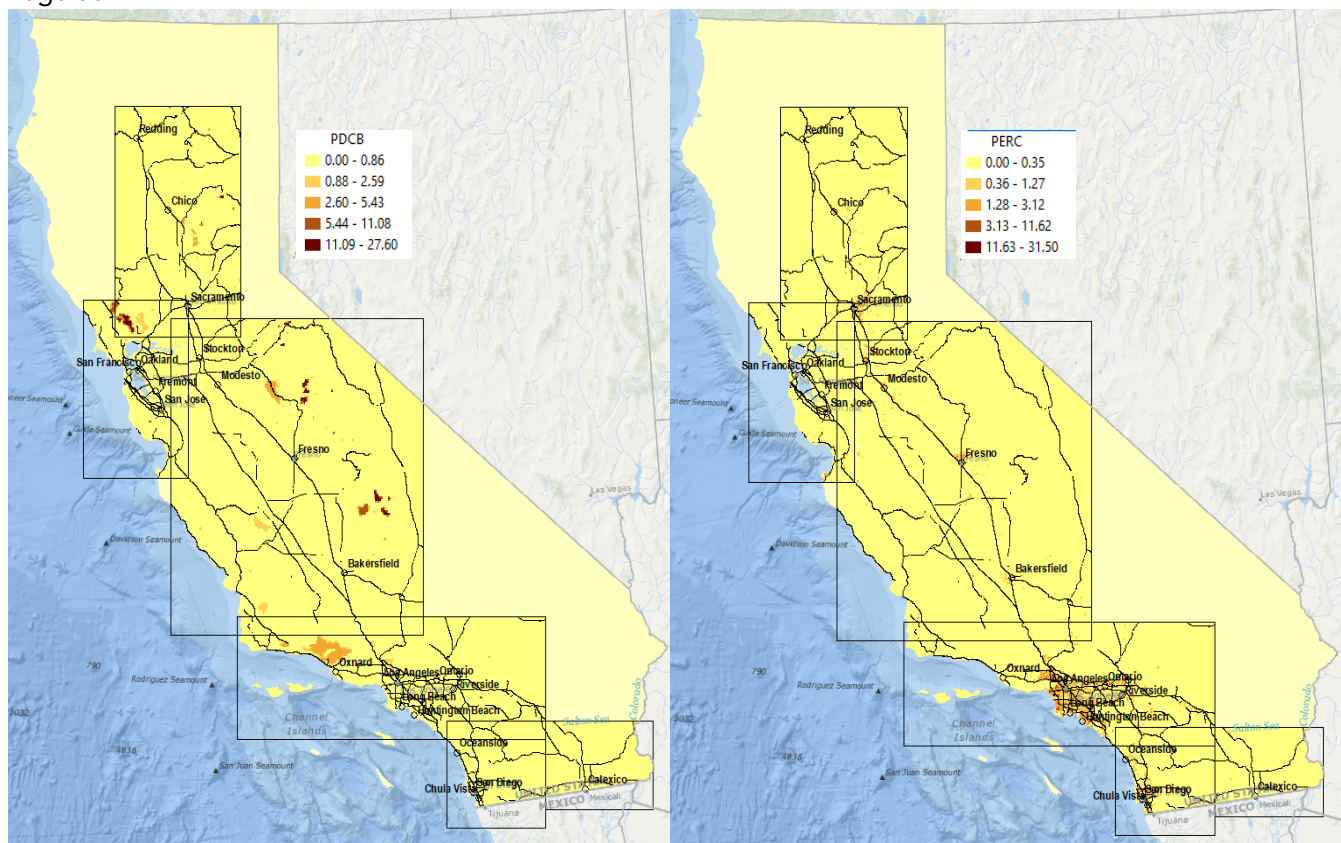


Figure II-6. Distributions of annual emissions (TPY) of the six modeled toxic VOCs in California for 2017: acetaldehyde, formaldehyde, benzene, 1,3-butadiene, p-dichlorobenzene, and perchloroethylene, respectively.

III. Meteorological Inputs

California's proximity to the ocean, its complex terrain and diverse climate present a unique challenge for developing meteorological fields that adequately represent the synoptic and mesoscale features of the regional meteorology. To provide reasonable meteorological data for air quality modeling, the state-of-the-science Weather and Research Forecasting (WRF) prognostic model (version 3.9.1.1 of the Advanced Research WRF [ARW] core) was utilized to develop the meteorological fields needed for the air quality simulations and for processing specific emissions categories, which respond to changes in meteorology.

WRF has previously been applied in California to study meteorological phenomena unique to the region, including complex wind flows due to topographical features. In addition, WRF is commonly used to simulate meteorological fields for air quality modeling studies in California, including large scale field studies and regulatory modeling activities (South Coast, 2016; San Diego, 2016; San Joaquin Valley 2016). The simulation results from WRF have been shown to accurately represent the meteorological phenomena relevant to air quality.

A. WRF Model Setup

The major meteorological parameters required by air quality models include hourly wind speed and direction, temperature, humidity, cloud cover, rain and solar radiation levels, etc. Wind speed determines how rapidly pollutants are transported away from the source, while wind direction determines where pollutants are transported to. The difference in ambient temperature and the exhaust temperature determines the initial buoyancy of emissions from point sources. Air quality models also require some boundary layer parameters to estimate air dispersion of pollutants in the atmosphere, including, but not limited to, atmospheric stability (a measure of atmospheric turbulence that determines the rate at which pollutants are mixed laterally and vertically), the vertical temperature gradient, and the convective and mechanical boundary layer heights (the vertical depth through which pollutants may be dispersed).

The WRF meteorological modeling domains used for this study consist of four nested Lambert projection gridded domains with 36-km (D01), 12-km (D02), 4-km (D03), and 2-km (D04) uniform horizontal grid spacing (Figure III-1). WRF was run simultaneously for the four nested domains with two-way feedback between the parent and the nest grids. The D01 and D02 grids were used to resolve the larger scale synoptic weather systems, while the D03 and D04 grids resolved the finer details of the atmospheric conditions and were used to drive the air quality model simulations, depending on the need of air quality modeling. In this work, meteorological fields on the 2-km grids were used. Vertical variations of meteorological fields were resolved by 30 vertical hybrid sigma-pressure levels (Table III-1), which stretched from the surface to 100 hPa and contained ten layers within the first kilometer above the surface. For the two-way nesting, the parent (outer) domain provided lateral boundary conditions to the inner nested domain, while the inner domain provided higher resolution feedback to its parent domain. Initial and boundary conditions (IC/BCs) were based on the North American Regional Reanalysis (NARR) data with 32-km horizontal resolution.

The IC/BCs were further adjusted with surface and upper air observations obtained from the National Center for Atmospheric Research (NCAR). To prevent any large deviations from reality, analysis nudging was applied to the outermost domain (D01) above the planetary boundary layer (PBL) for moisture and above 2-km for wind and temperature using reanalysis data. Reanalysis datasets are post-processed products that combine model fields with best-available observations. No nudging was used on the three inner domains to allow model physics to work fully without externally imposed forcing. Boundary conditions on the outermost domain were updated every 6 hours, while WRF was reinitialized every 6 days with one day overlap, where the first day after being reinitialized was discarded as model spin-up. The major physics options for each domain are listed in Table III-2.

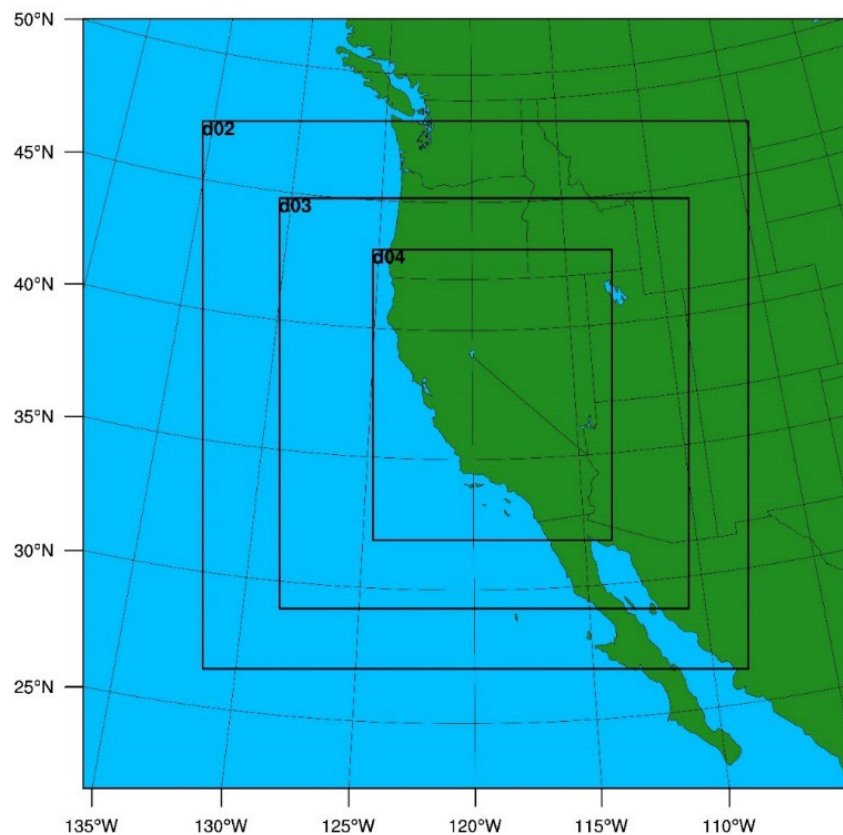


Figure III-1. WRF modeling domains (D01- 36-km; D02- 12-km; D03- 4-km; D04- 2-km).

Table III-1. WRF vertical layer structure.

Layer Number	Height (m)	Layer Thickness (m)	Layer Number	Height (m)	Layer Thickness (m)
30	16082	1192	14	1859	334
29	14890	1134	13	1525	279
28	13756	1081	12	1246	233
27	12675	1032	11	1013	194
26	11643	996	10	819	162
25	10647	970	9	657	135
24	9677	959	8	522	113
23	8719	961	7	409	94
22	7757	978	6	315	79
21	6779	993	5	236	66
20	5786	967	4	170	55
19	4819	815	3	115	46
18	4004	685	2	69	38
17	3319	575	1	31	31
16	2744	482	0	0	0
15	2262	403			

Table III-2. WRF Physics options.

Physics Option	D01 (36-km)	D02 (12-km)	D03 (4-km)	D04 (2-km)
Microphysics	WSM 6-class	WSM 6-class	WSM 6-class	WSM 6-class
Longwave Radiation	RRTM	RRTM	RRTM	RRTM
Shortwave Radiation	Dudhia	Dudhia	Dudhia	Dudhia
Surface Layer	Revised MM5 Monin-Obukhov	Revised MM5 Monin-Obukhov	Revised MM5 Monin-Obukhov	Revised MM5 Monin-Obukhov
Land Surface	Pleim-Xiu LSM	Pleim-Xiu LSM	Pleim-Xiu LSM	Pleim-Xiu LSM
Planetary Boundary Layer	YSU	YSU	YSU	YSU
Cumulus Parameterization	Kain-Fritsch Scheme	Kain-Fritsch Scheme	N/A (explicitly resolved)	N/A (explicitly resolved)

B. WRF to CMAQ Interface

CMAQ-ready meteorological data set was obtained by processing WRF data with the Meteorology-Chemistry Interface Processor (MCIP) (Otte and Pleim, 2010). WRF data were extracted for the six air quality modeling domains.

MCIP is a vital piece of software within the CMAQ modeling system. MCIP acts as both a post-processor to the meteorological model and a pre-processor to the CMAQ modeling system. MCIP's functions are to ingest the meteorological model output fields in their native formats, perform horizontal and vertical coordinate transformations, diagnose additional atmospheric fields, define gridding parameters, and prepare the meteorological fields in a format that is common to the CMAQ modeling system.

C. WRF to CALPUFF Interface

CALPUFF-ready meteorological data set was obtained from processing WRF data with the Mesoscale Model Interface Program (MMIF) version 3.4 (Karamchandani et al, 2022). WRF data were extracted for the six air toxics modeling domains.

MMIF converts prognostic meteorological model output fields to the parameters and formats required for direct input into dispersion models. Supported dispersion models include AERMOD, SCICHEM, and CALPUFF. The MMIF has the capability to process geophysical and meteorological output fields from the WRF model and diagnose certain parameters required by the dispersion models that are not directly available from WRF. It also offers the option to read derived planetary boundary layer (PBL) heights from the meteorological models, or to independently diagnose them from other variables.

D. WRF Modeling Performance Evaluation

To ensure the WRF model reasonably captures the meteorological conditions for 2017 in California, we conducted an extensive evaluation for simulated surface wind speeds, temperatures, and relative humidity at 2-km grid spacing against hourly observations. The hourly observations include surface measurements from Federal Aviation Administration (FAA), Remote Automatic Weather Stations (RAWS), California Irrigation Management Information System (CIMIS), Aerometric Information Retrieval System (AIRS), and National Data Buoy Center (Buoy) within California. Model performance was evaluated based on three metrics: the root-mean-square error (RMSE), absolute bias (bias), and correlation coefficient (CC), as defined by the equations below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N ||x(i)-y(i)||^2}{N}} \quad (1)$$

$$BIAS = \frac{1}{N} \sum_{i=1}^N x(i) - y(i) \quad (2)$$

$$CC = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} \quad (3)$$

where N is the number of data points, $x(i)$ is the i -th measurement, and $y(i)$ is its corresponding modeled value, $\bar{x}$ is the mean of the values of x , and $\bar{y}$ is the mean of the values of y .

A summary of the statewide evaluation is presented in Figure III-2. A more detailed evaluation was done as well for each of the 14 individual air basins mapped in Figure III-3, including Great Basin Valleys (GBV), Lake Tahoe (LT), Mountain Counties (MC), Mojave Desert (MD), North Central Coast (MCC), North Coast (NC), Northeast Plateau (NEP), Sacramento Valley (SV), Salton Sea (SS), San Diego (SD), San Francisco Bay Area (SB), San Joaquin Valley (SJV), South Central Coast (SCC), and South Coast (SC). The results for all air basins are presented in Figure III-4. Note that these results are comparable to other WRF

modeling efforts in California investigating ozone formation in Central California³ and modeling analysis for the CalNex (Angevine et al⁴; Baker et al⁵; Kelly et al⁶), CARES⁷ and Discover-AQ field Studies⁸.

i. 2-m surface temperature evaluation

There are 689 station measurements available for statewide temperature comparison. Figures III-2 and III-4 show that WRF can reproduce reasonably well the spatial and temporal variation of surface temperature in California. Specifically, simulated temperatures have the smallest RMSE over coastal regions, with increased RMSE further inland. Simulated temperatures have warm bias over coastal and nearby regions and cold bias over inland regions. It is also shown that the Central Valley has higher CC, with decreased CC moving further inland and toward coastal regions.

Further looking into comparisons among the 14 air basins, the results show that simulated temperatures in GBV have the largest RMSE, and SD has the smallest RMSE. Three coastal basins, NC, NCC, and SCC, have warm bias with the lowest CC, while other 11 air basins have cold bias with relatively higher CC. This suggests that WRF reasonably reproduced the 2-m surface temperatures for the six air basins this study focuses on, namely SC, SD, SS, SB, SJV and SV, with low bias and RMSE, and high CC.

ii. 10-m surface winds evaluation

For wind speed evaluation, there are 244 station measurements available statewide (Figure III-4). Like surface temperatures, Figures III-2 and III-4 show that WRF can reproduce

³ Hu, J., C. J. Howard, F. Mitloehner, P. G. Green, and M. J. Kleeman. 2012. "Mobile Source and Livestock Feed Contributions to Regional Ozone Formation in Central California." *Environmental Science and Technology* (46): 2781-2789

⁴ Angevine, W. M., L. Eddington, K. Durkee, C. Fairall, L. Bianco, and J. Brioude. 2012. "Meteorological model evaluation for CalNex 2010." *Monthly Weather Review* (140): 3885-3906.

⁵ Baker, K. R., C. Misenis, M. D. Obland, R. A. Ferrare, A. J. Scarino, and J. T. Kelly. 2013. "Evaluation of surface and upper air fine scale WRF meteorological modeling of the May and June 2010 CalNex period in California." *Atmospheric Environment* (80): 299-309.

⁶ Kelly, J. T., K. R. Baker, J. B. Nowak, J. G. Murphy, Z. M. Milos, T. C. VandenBoer, R. A. Ellis, et al. 2014. "Fine-scale simulation of ammonium and nitrate over the South Coast Air Basin and San Joaquin Valley of California during CalNex-2010." *Journal of Geophysical Research* (119): 3600-3614. doi:doi:10.1002/2013JD021290.

⁷ Fast, J. D., W. I. Gustafson Jr, L. K. Berg, W. J. Shaw, M. Pekour, and M. Shrivastava et al. 2012. "Transport and mixing patterns over Central California during the carbonaceous aerosol and radiative effects study (CARES)." *Atmospheric Chemistry and Physics* (12): 1759-1783.

⁸ Chen, J., D. Yin, Z. Zhao, A. P. Kaduwela, J. C. Avise, J. A. DaMassa, A. Beyersdorf, and S. Burton et al. 2020. "Modeling air quality in the San Joaquin Valley of California during the 2013 DISCOVER-AQ field campaign." *Atmospheric Environment* (5): 100067.

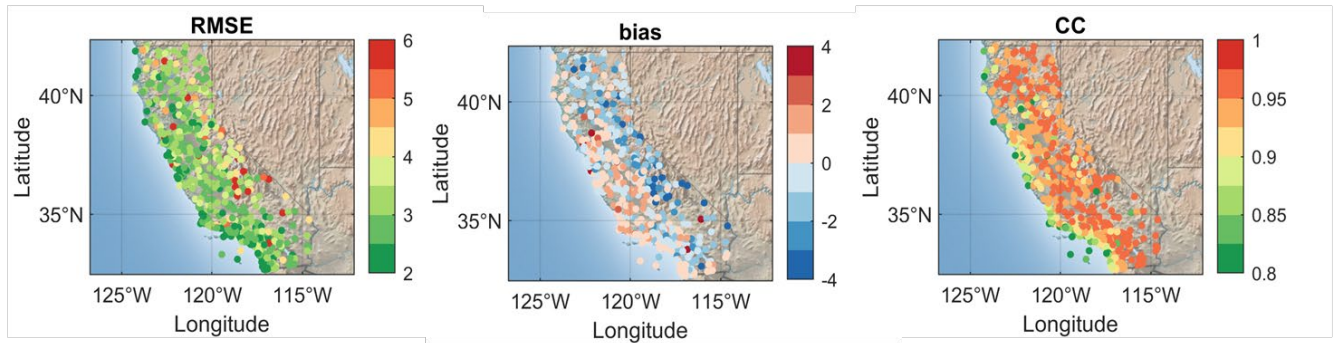
reasonably well the spatial and temporal variation of surface wind speeds in California. We do notice that the WRF model generally underestimates wind speed in most of California, except for LT, MC, NC, NEP, and SCC. The underestimated wind speeds from WRF could contribute to overestimated pollutant concentrations in some areas. The simulated wind speeds have relatively larger RMSE over inland regions, particularly in GBV. In contrast, simulated wind speeds have relatively smaller RMSE over coastal and nearby regions, in particular SD which has the smallest RMSE among all air basins. A similar pattern is seen in the CC comparison, where high CC values are located over coastal areas and decreasing further inland. This suggests that WRF provides reasonable 10-m surface winds for the six air basins of interest in this study.

iii. 2-m surface relative humidity comparison

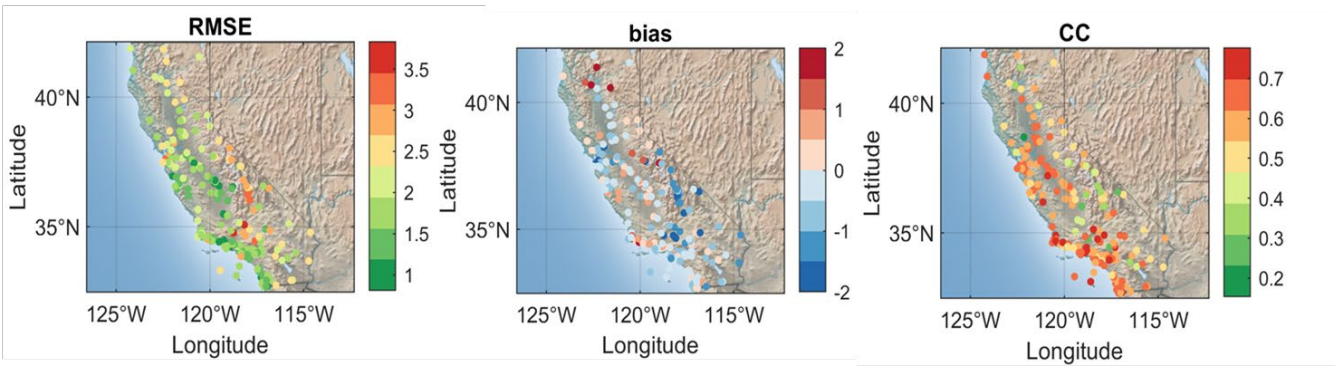
For relative humidity, there are 233 station measurements available statewide. Overall, WRF can reproduce reasonably well the spatial and temporal variation of surface relative humidity in California. Like surface temperatures and wind speeds, the results show that mountain regions have larger RMSE values than coastal regions, where GBV has the largest RMSE, and SS has the smallest. We notice that there is a wet bias over Southern California and a dry bias over Northern California. The CC are highest over the Central Valley with decreasing CC toward further inland and coastal regions, where LT and GBV have lower CCs than other basins. This again suggests that WRF provides reasonable 2-m relative humidity for SC, SD, SS, SB, SJV, and SV with low bias and RMSE, and high CC.

In summary, WRF can reasonably simulate the spatial and temporal variation of surface temperatures, wind speeds, and relative humidity in California, especially in the six air basins of importance for this study, namely SC, SD, SS, SB, SJV, and SV, with low bias and RMSE and high CC. This provides us confidence that WRF can provide reasonable meteorological conditions for simulating air toxic concentrations in these regions and can be a valuable tool for understanding the atmospheric transport and dispersion of air pollutants.

(a) Temperature



(b) Wind Speed



(c) Relative Humidity

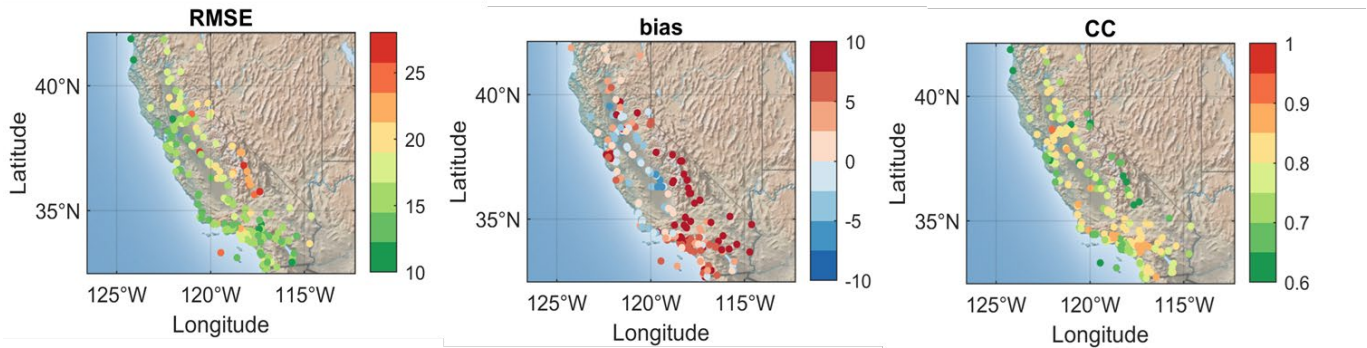
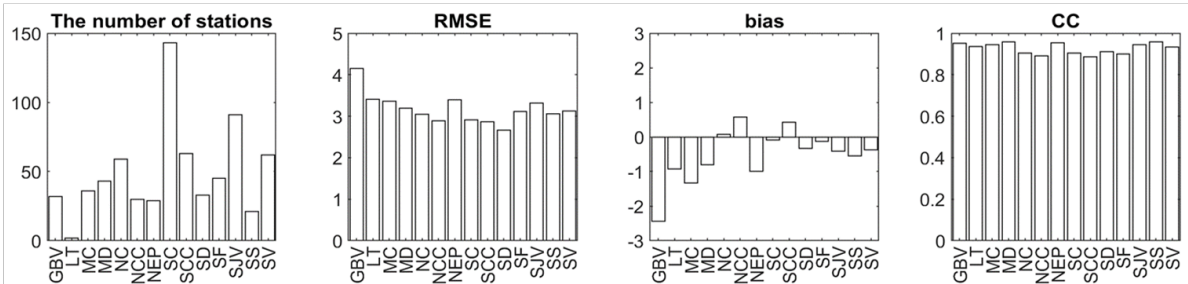


Figure III-2. WRF model performance evaluation for (a) temperature, (b) wind speed, and (c) relative humidity using RMSE (left columns), bias (middle columns), and CC (right columns).

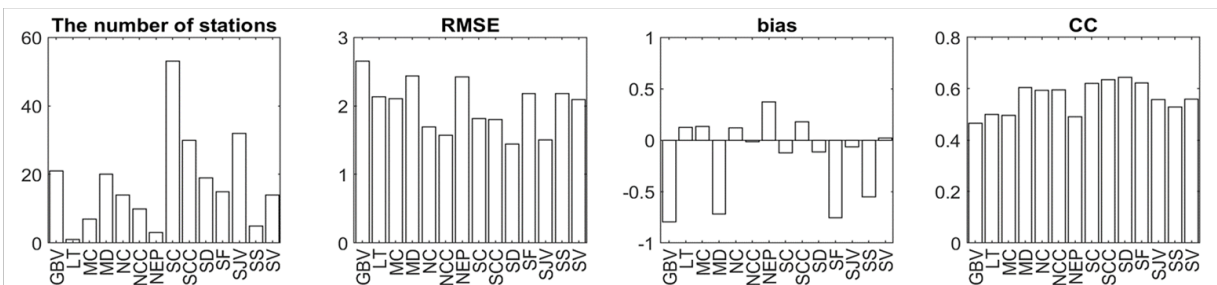


Figure III-3. California air basin boundaries, including Great Basin Valleys (GBV), Lake Tahoe (LT), Mountain Counties (MC), Mojave Desert (MD), North Central Coast (MCC), North Coast (NC), Northeast Plateau (NEP), Sacramento Valley (SV), Salton Sea (SS), San Diego (SD), San Francisco Bay Area (SB), San Joaquin Valley (SJV), South Central Coast (SCC), and South Coast (SC).

(a) Temperature



(b) Wind Speed



(c) Relative Humidity

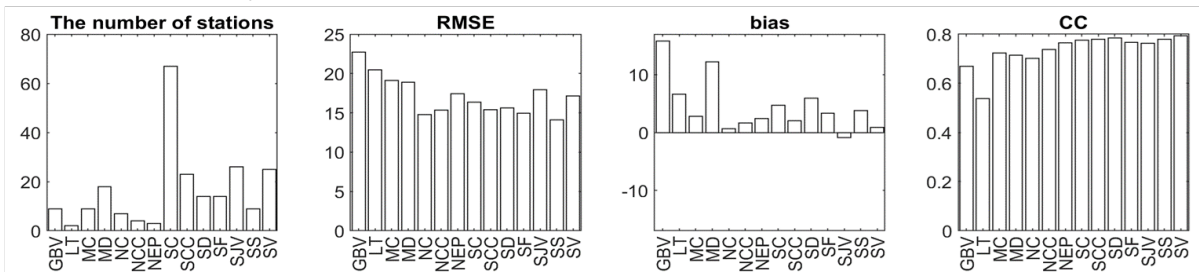


Figure III-4. WRF model performance evaluation for (a) temperature, (b) wind speed, and (c) relative humidity. The columns from left to right are the number of stations, RMSE, bias, and CC, respectively, for different air basins (x axis), including Great Basin Valleys (GBV), Lake Tahoe (LT), Mountain Counties (MC), Mojave Desert (MD), North Central Coast (MCC), North Coast (NC), Northeast Plateau (NEP), Sacramento Valley (SV), Salton Sea (SS), San Diego (SD), San Francisco Bay Area (SB), San Joaquin Valley (SJV), South Central Coast (SCC), and South Coast (SC).

IV. Air Toxics Modeling

Regional photochemical models such as CMAQ and CAMx, are not entirely sufficient for our purpose because those models are grid-based, and cannot resolve the variation, or gradient, of pollutant concentrations within an area of a few square kilometers (typical size of a model grid cell). Therefore, an innovative approach was used in this study that utilizes two different models to calculate concentrations of air toxics: CMAQ and CALPUFF. CALPUFF was selected as the air dispersion model that estimates concentrations of inert TACs including DPM and metals, and CMAQ was the choice of grid-based photochemical model in this study to simulate chemically reactive toxic VOCs. CALPUFF can provide more accurate source-receptor relationships without unwanted area averaging that occurs in models such as CMAQ. Locations of emissions sources can be as exact as the data allows and are represented as such in the models, while TACs concentrations can be estimated at any locations/receptors of interest, such as centroids of census blocks and census tracts as well as sensitive receptors such as senior care homes, kindergartens, and hospitals as opposed to grid-cell wide releases and average concentrations from grid-based air quality models. However, CALPUFF cannot accurately characterize chemical reactions among various pollutants and their precursors in the atmosphere. CMAQ contains sophisticated and state-of-the-science chemical reaction mechanisms to simulate atmospheric chemical reactions. For the above reasons, an integrated modeling approach was used in this study.

A. CALPUFF

CALPUFF is a multi-layer, multi-species non-steady-state puff dispersion model that simulates the effects of time- and space-varying meteorological conditions on pollution transport, transformation, and removal (Scire et al, 2000a,b). CALPUFF can be applied on scales of tens to hundreds of kilometers. It includes algorithms for sub-grid scale effects (such as terrain impingement) as well as longer range effects (such as pollutant removal due to wet deposition/scavenging and dry deposition, chemical transformation, and visibility impact from particulate matter concentrations).

CALPUFF is one of three main components of a modeling system that also include a number of preprocessing and post-processing programs. The other two main components of the modeling system are CALMET (a diagnostic three-dimensional meteorological model) and CALPOST (a post-processing package). In addition to these main components, there are numerous other processors that may be used to prepare geophysical (land use and terrain) data in many different formats; meteorological data (surface, upper air, precipitation, and buoy data); and interfaces to other models such as the Penn State/NCAR Mesoscale Model (MM5), the National Centers for Environmental Prediction (NCEP) Eta/NAM and RUC models, the Weather Research and Forecasting (WRF) model and the RAMS model. CALPUFF has been extensively used by staff for many CARB programs (e.g., OGV at-berth and CHC ATCM regulations). In this study, version 5.8.5 level 151214 was used.

In this study, traffic links including all interstates and other freeways, expressways, arterials, and major collectors were explicitly modeled as individual line sources (or narrow area sources analogous to road links). This is important because it allows the health impact of on-road mobile emissions on the population to be directly calculated. Additionally, some other emission sources were also treated as individual line emission sources including ocean-going vessels in transit and maneuvering activities, aircraft landing, takeoff and taxiing (more details found in Appendix D). All other sources including minor collector roads, off-road mobile emissions, distribution centers, airports and seaport, agricultural activities, and construction were modeled as 1-km x 1-km area sources. In the future, emissions from locomotives will be treated as individual line sources. All stationary sources and OGV-at berth were treated as point sources. Concentrations of DPM and metals were calculated at discrete receptors such as at the centroids of every census tract and census block as well as sensitive locations such as hospitals, schools, kindergartens, and senior care homes. Emission source types, categories and sectors used in CALPUFF modeling are summarized in Table IV-1. Hourly emissions were processed to resolve diurnal variations as well as seasonal and weekday/weekend emission changes as inputs to CALPUFF.

Table IV-1. Emission source types, categories and sectors used in CALPUFF modeling.

Source Type	Source Categories	Source Sectors
Point sources	Off-road mobile Stationary	- OGV at berth - Stationary Toxics - Hotspots program
Line sources	On-road mobile Off-road mobile	- On-road major traffic - OGV (maneuvering / transit) - Aircraft 3D - Locomotives (in progress)
Area sources (1km x 1km)	Off-road mobile Area sources Mexico sources	- Commercial harbor craft, cargo handling equipment, aircraft (military), locomotive (current), OGV (military), TRU - Ag burn, agriculture activities, construction, managed burns, residential wood combustion, structural burns, wildfires / prescribed burn, charbroil - Others: off-road equipment such as forklifts, generator sets, pumps, air compressors, food and agricultural processing, manufacturing and industrial equipment, etc. - Mexico (on-road, off-road, point and areas)

B. CMAQ

CMAQ is an active open-source development project from the U.S. EPA (1999) that consists of a suite of programs for conducting air quality model simulations. CMAQ combines current knowledge in atmospheric science and air quality modeling, multi-processor computing techniques, and an open-source framework to deliver fast, technically sound estimates of ozone, particulates, toxics, and acid deposition. CMAQ is a first-principles scientific computer

model that comprehensively represents the most important processes affecting air quality and atmospheric chemistry. Emissions from a wide range of sources are included, as well as meteorological processes such as transport by winds and deposition due to precipitation events. CMAQ uses an extensive database of atmospheric chemical reactions to predict the chemical production and loss of hundreds of pollutants as they are carried downwind from their sources. In addition to gas-phase species, many pollutants exist partially or wholly as airborne particles, giving them the potential to interact with incoming solar radiation and clouds in complicated ways.

The model has been extensively used by staff in many CARB programs, most notably in developing State Implementation Plans (SIPs) for ozone and PM_{2.5}. In this study, CMAQv5.3.2 with SAPRC07tc_ae6_aq chemical mechanism and AERO7 aerosol module was applied. The large-scale output from CAM-CHEM model simulations conducted at the National Center for Atmospheric Research (NCAR) was used to represent lateral chemical boundary conditions for the statewide 12-km simulations, while output from the 12-km simulations was used as chemical boundary conditions for the 2-km simulations.

Model ready speciated and gridded hourly emissions were generated by combining biogenic emissions from the Model of Emissions of Gases and Aerosols from Nature (MEGAN; <https://ww2.arb.ca.gov/biogenic-emissions-inventory>) and CARB's anthropogenic emission inventory (CEPAM 2019v1.01 RF3043). The anthropogenic inventory was processed as follows: area source emissions were processed through the SMOKE emissions processor; on-road emissions were based on EMFAC2017; point source emissions were processed using CMAQ's in-line processing. Final simulations were carried out at a 2-km horizontal resolution and model calculated concentrations were grid-cell averaged.

C. Modeling Domains and Period

A larger modeling domain, for example one that covers the entire state, requires extensive computational resources (e.g., longer model run time and storage requirements). To make modeling feasible in a reasonable amount of time, six modeling domains were used to cover the most populous areas of California. The domains are listed from north to south as follows: Sacramento Valley, Bay Area, San Joaquin Valley, South Coast, San Diego, and Imperial County (Figure IV-1). The population within these modeling domains accounts for about 99% of total population of the state based on 2010 census data (36,727,572 vs. 37,253,956). Although some areas in the state are not covered by these modeling domains, it is unlikely that the domains are missing any populated areas significantly impacted by toxic air contaminants. Figure IV-1 shows the six modeling domains along with the major on-road sources in each domain. Additional information is provided in Table IV-1 including domain sizes, population, and the number of census tracts and census blocks. Note that some tracts and blocks are in more than one modeling domain.

The modeling period for this study was selected to be the entire year of 2017, which was the year we had the most complete and recent regulatory emission inventory and meteorology.

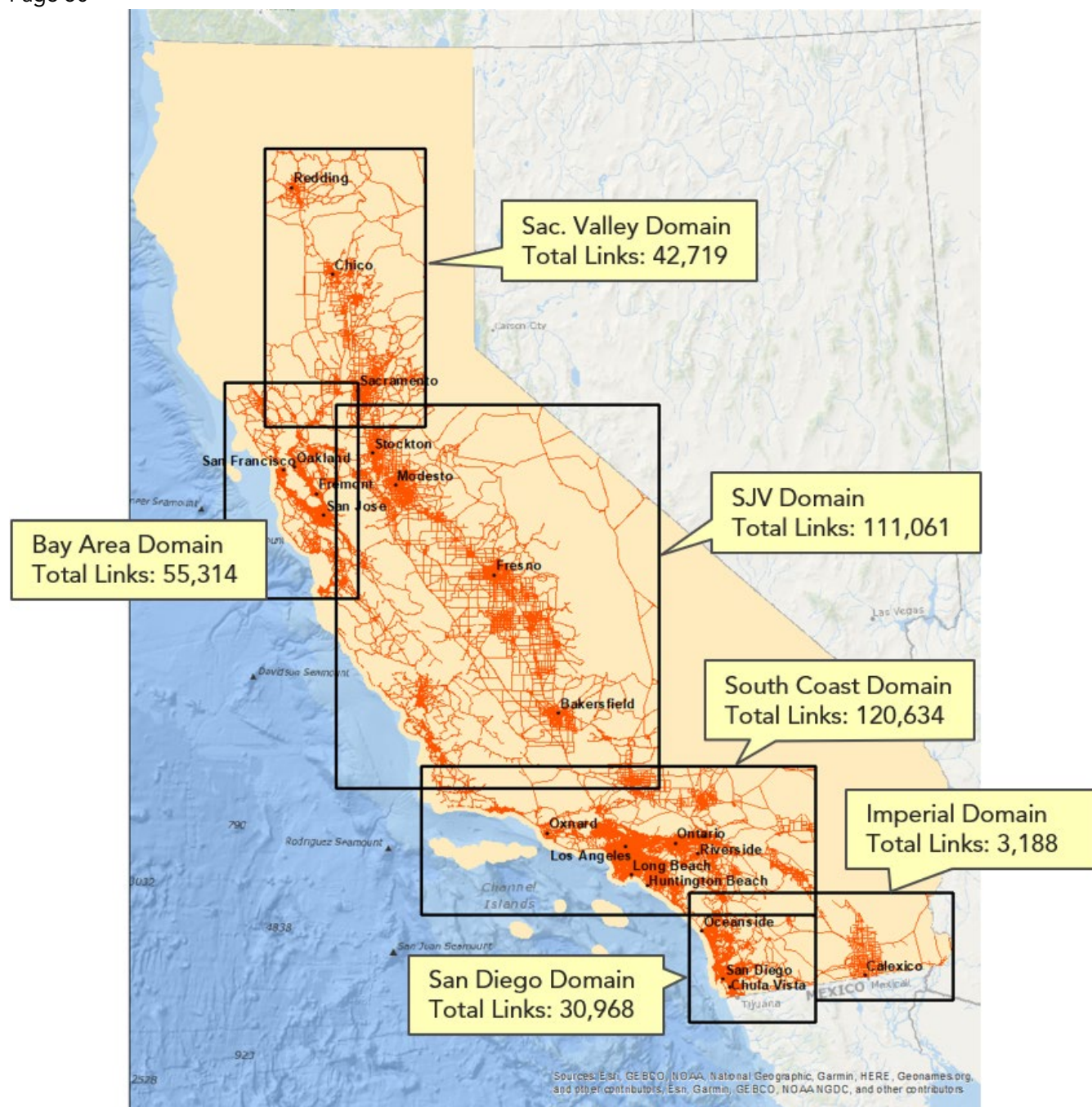


Figure IV-1. Statewide six modeling domains with traffic links in each domain.

Table IV-2. Characteristics of the six modeling domains.

Domain	Cell size	X direction	Y direction	Grid cells	Traffic links	Census blocks	Census tracts	Total population
Bay Area	2-km	72	116	8,352	55,314	123,884	1,809	8,159,238
Sac Valley	2-km	86	150	12,900	42,719	90,367	809	3,605,388
San Joaquin Valley	2-km	174	206	35,844	111,061	167,743	1,134	5,799,051
South Coast	2-km	212	80	16,960	120,634	244,912	3,998	18,259,717
San Diego	2-km	68	70	4,760	30,968	46,247	667	3,350,307
Imperial	2-km	74	58	4,292	3,188	9,050	35	202,646

Note that CMAQ and meteorology fields were run on 2-km x 2-km grids.

D. Modeling results

Annual average concentrations of TACs were calculated and their spatial distributions within the six domains are plotted at the census block level for DPM and metals and at 2-km grid level for VOCs using GIS mapping tools. Figure IV-2 depicts the modeled annual average concentration of DPM in the model domains. In general, the distribution of DPM exposure is aligned with the transportation corridors including major freeways, major arterials, railyards and seaports. Figures IV-3 through IV-6 provide the distributions of benzene, 1,3-butadiene, formaldehyde, and acetaldehyde, respectively, and Figure IV-7 shows the annual average concentration of cadmium as an example of spatial distribution of heavy metals. The spatial patterns of benzene and 1,3-butadiene reflect light-duty vehicle traffic pattern since benzene and 1,3-butadiene emissions are mostly from gasoline combustion. Benzene emissions are primarily from on- and off-road mobile sources, with portions emitted from refineries. High concentrations of cadmium are mostly found near industrial facilities.

The spatial distributions of formaldehyde and acetaldehyde concentrations (Figures IV-5 and IV-6) around primary emission sources with additional elevated levels in the downwind areas of their primary sources indicate that the ambient concentrations of formaldehyde and acetaldehyde are attributed to direct emissions, such as combustion sources, and secondary formation in the atmosphere. The modeling results in the SJV domain show that secondary formation of formaldehyde and acetaldehyde in the atmosphere through chemical transformation contributed ~80% and ~60% to the total concentrations, respectively.

Name

Date

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Additional spatial distributions of annual concentrations of DPM and heavy metals are included in Appendix H.

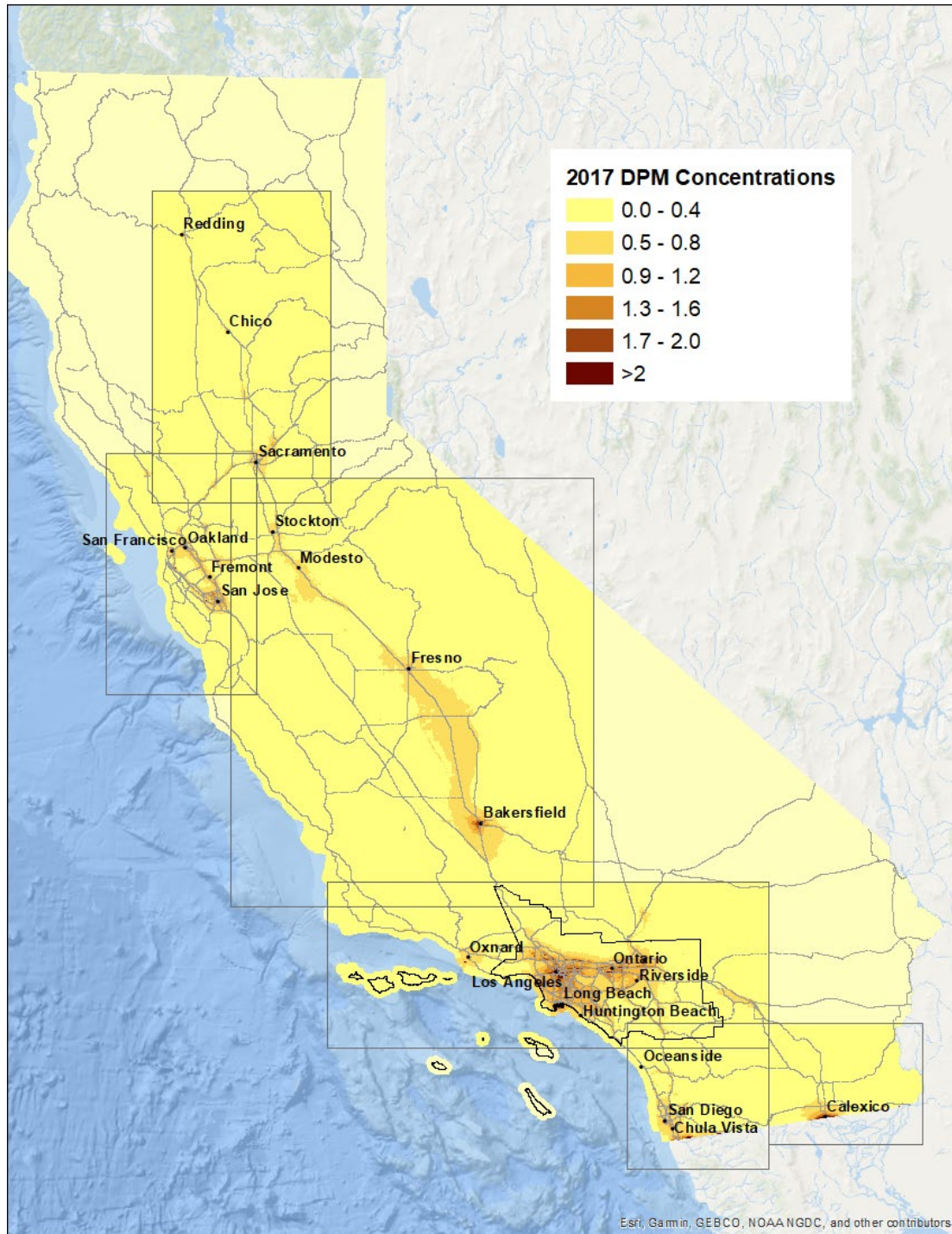


Figure IV-2. Map of the 2017 annual average DPM concentrations ($\mu\text{g}/\text{m}^3$) in census blocks. Major freeways are drawn as gray lines. Black boxes outline the six modeling domains where concentrations were estimated.

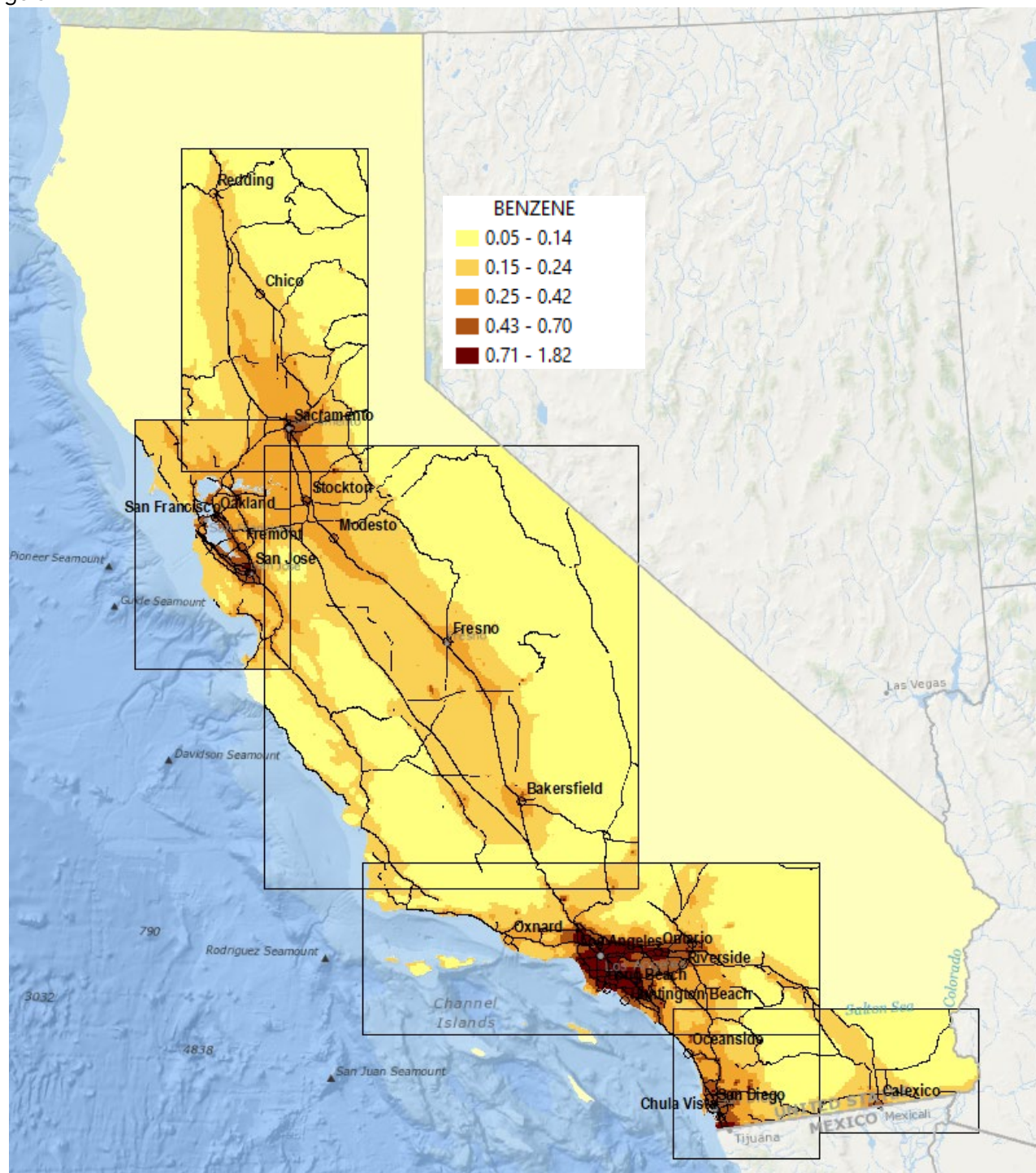


Figure IV-3. Map of the 2017 annual average benzene concentrations ($\mu\text{g}/\text{m}^3$). Black boxes outline the six modeling domains where concentrations were estimated.

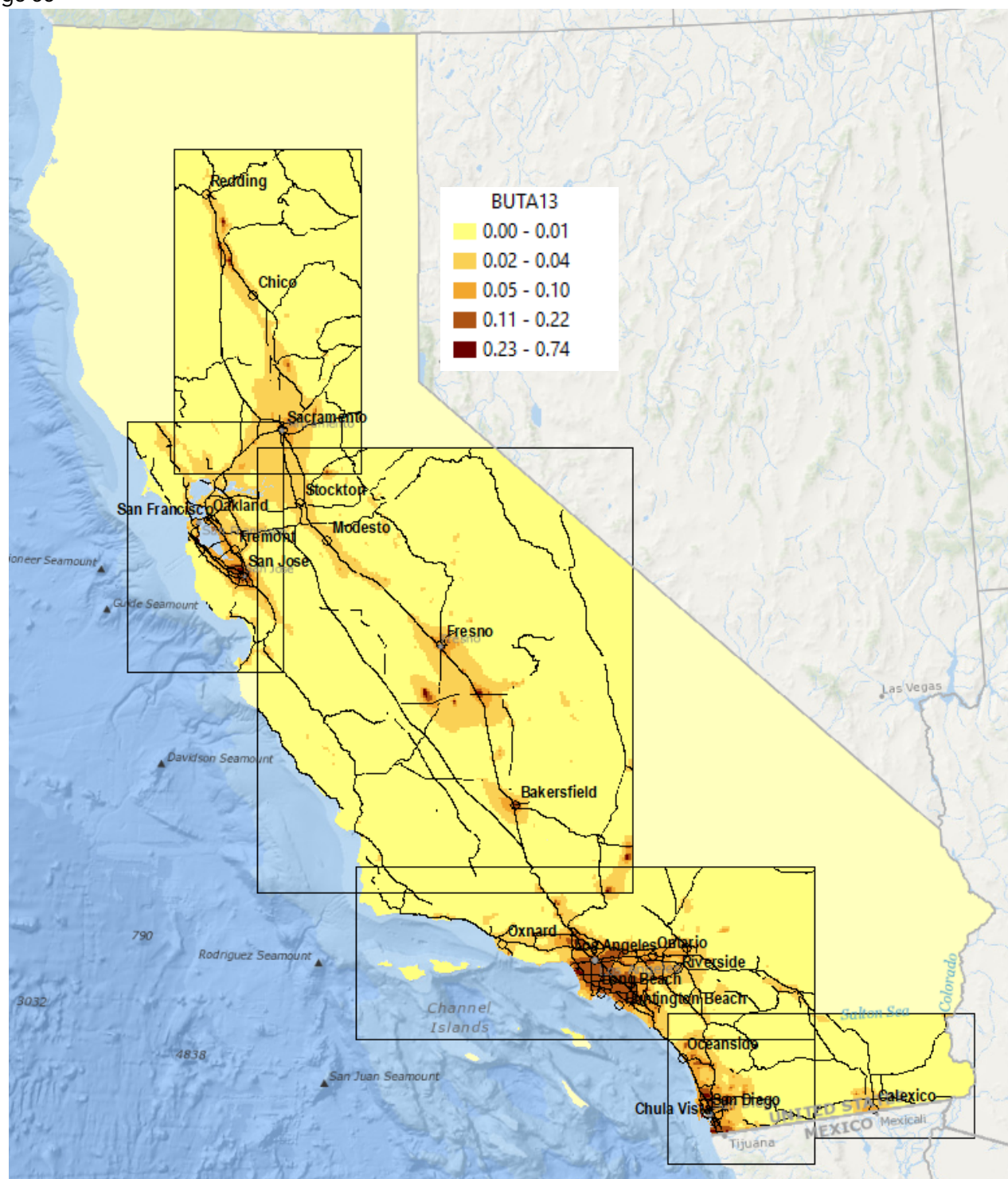


Figure IV-4. Map of the 2017 annual average 1,3-butadiene concentrations ($\mu\text{g}/\text{m}^3$). Black boxes outline the six modeling domains where concentrations were estimated.

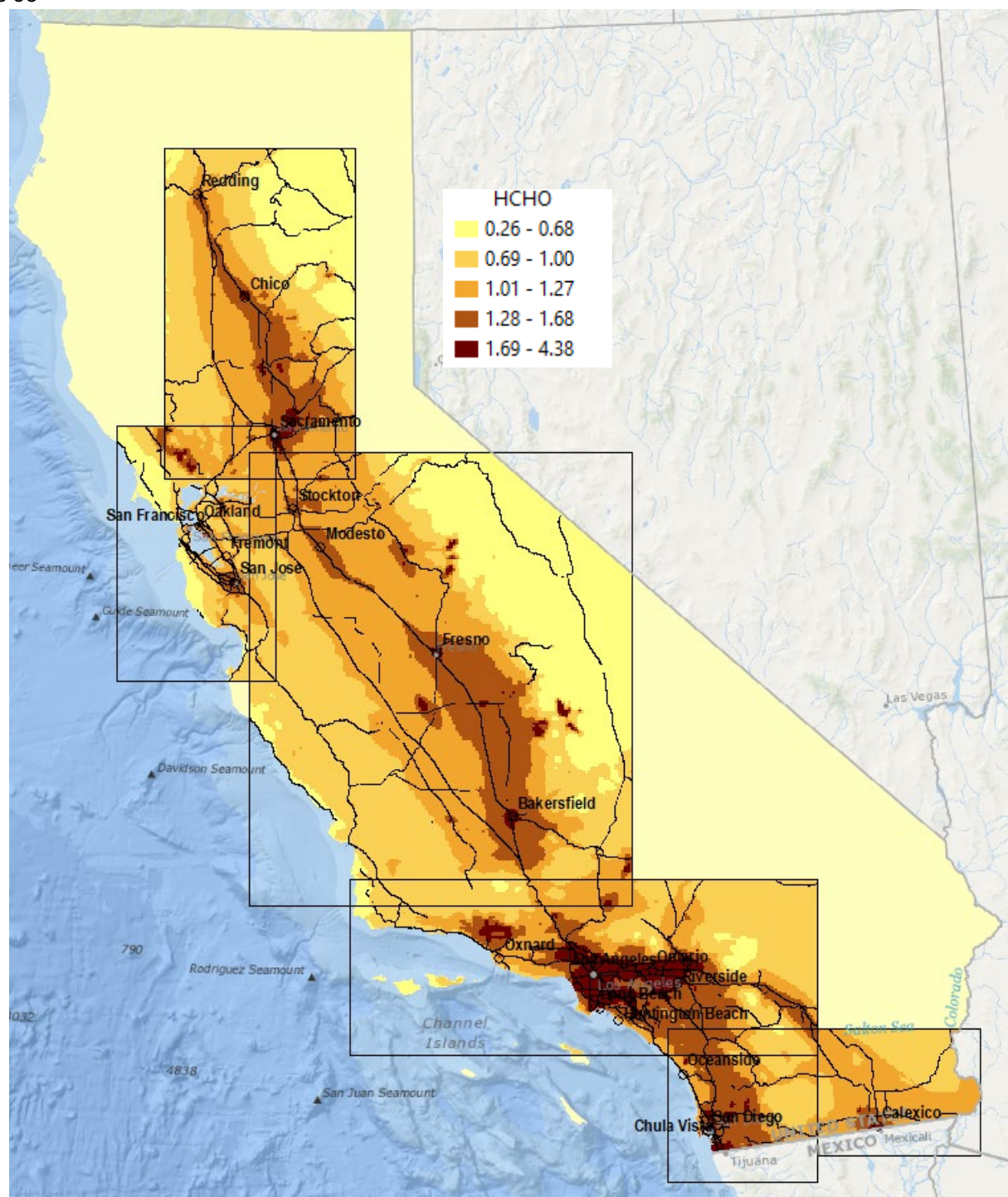


Figure IV-5. Map of the 2017 annual average formaldehyde concentrations ($\mu\text{g}/\text{m}^3$). Black boxes outline the six modeling domains where concentrations were estimated.

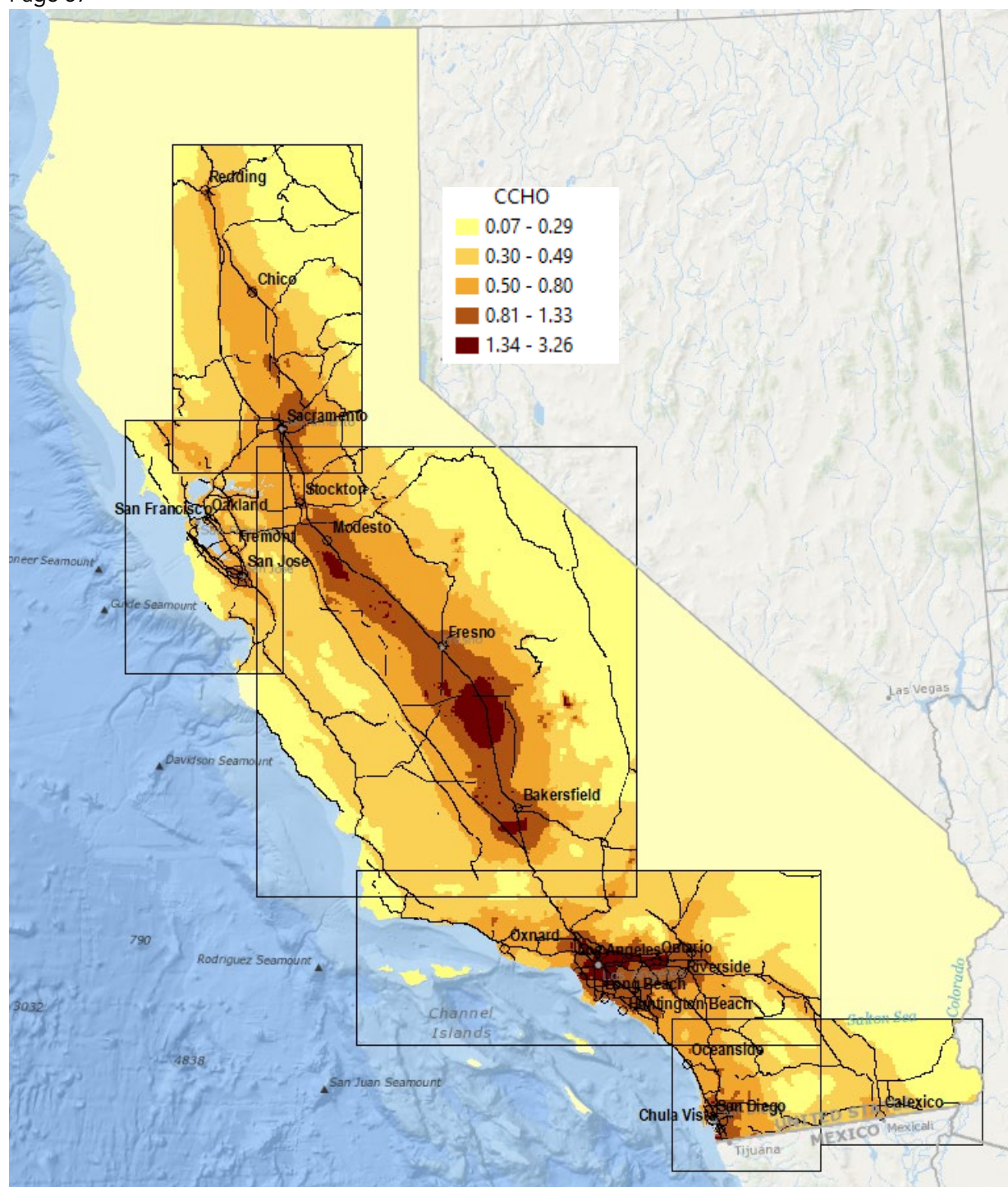


Figure IV-6. Map of the 2017 annual average acetaldehyde concentrations ($\mu\text{g}/\text{m}^3$). Black boxes outline the six modeling domains where concentrations were estimated.

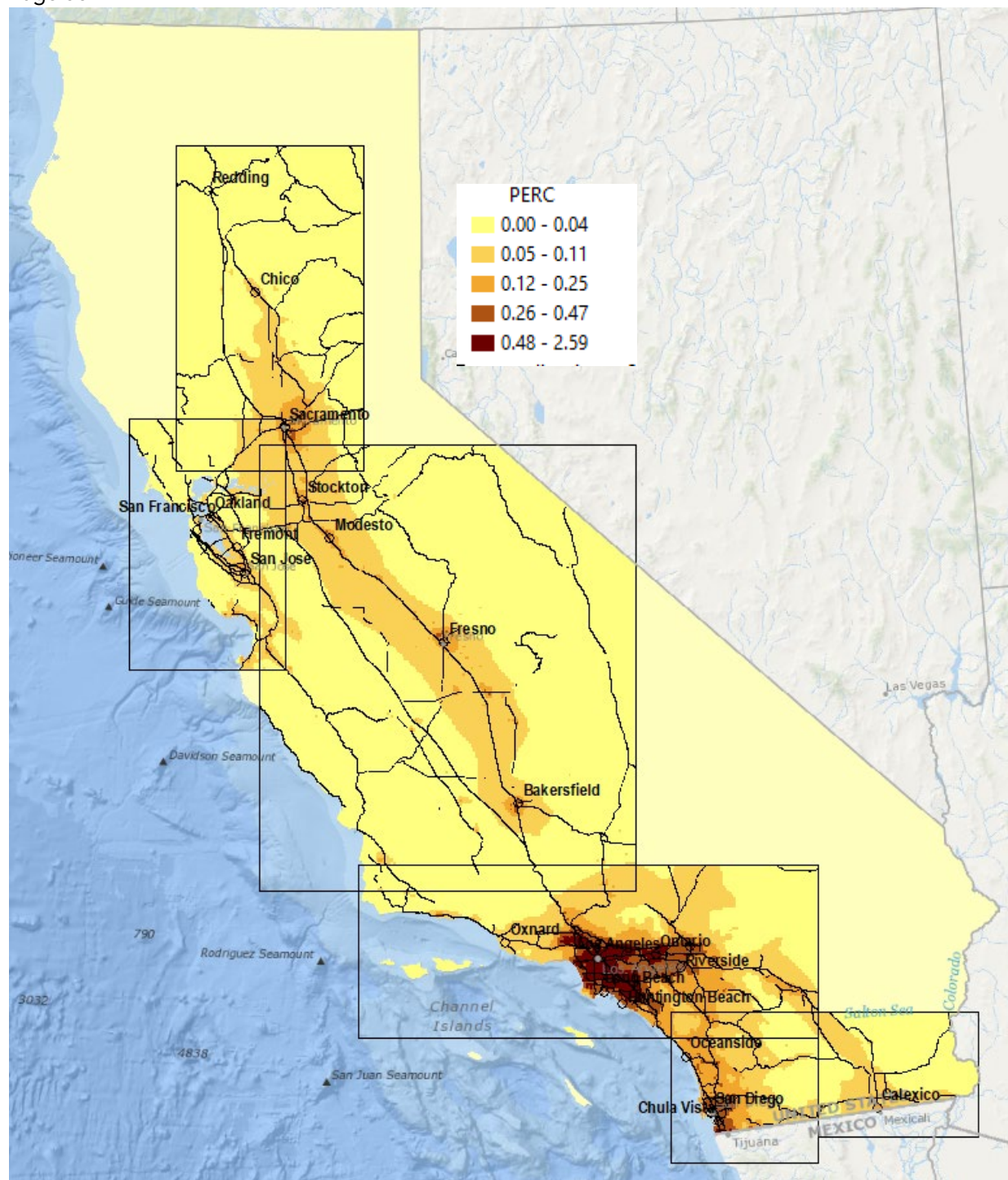


Figure IV-6. Map of the 2017 annual average perchloroethylene concentrations ($\mu\text{g}/\text{m}^3$). Black boxes outline the six modeling domains where concentrations were estimated.

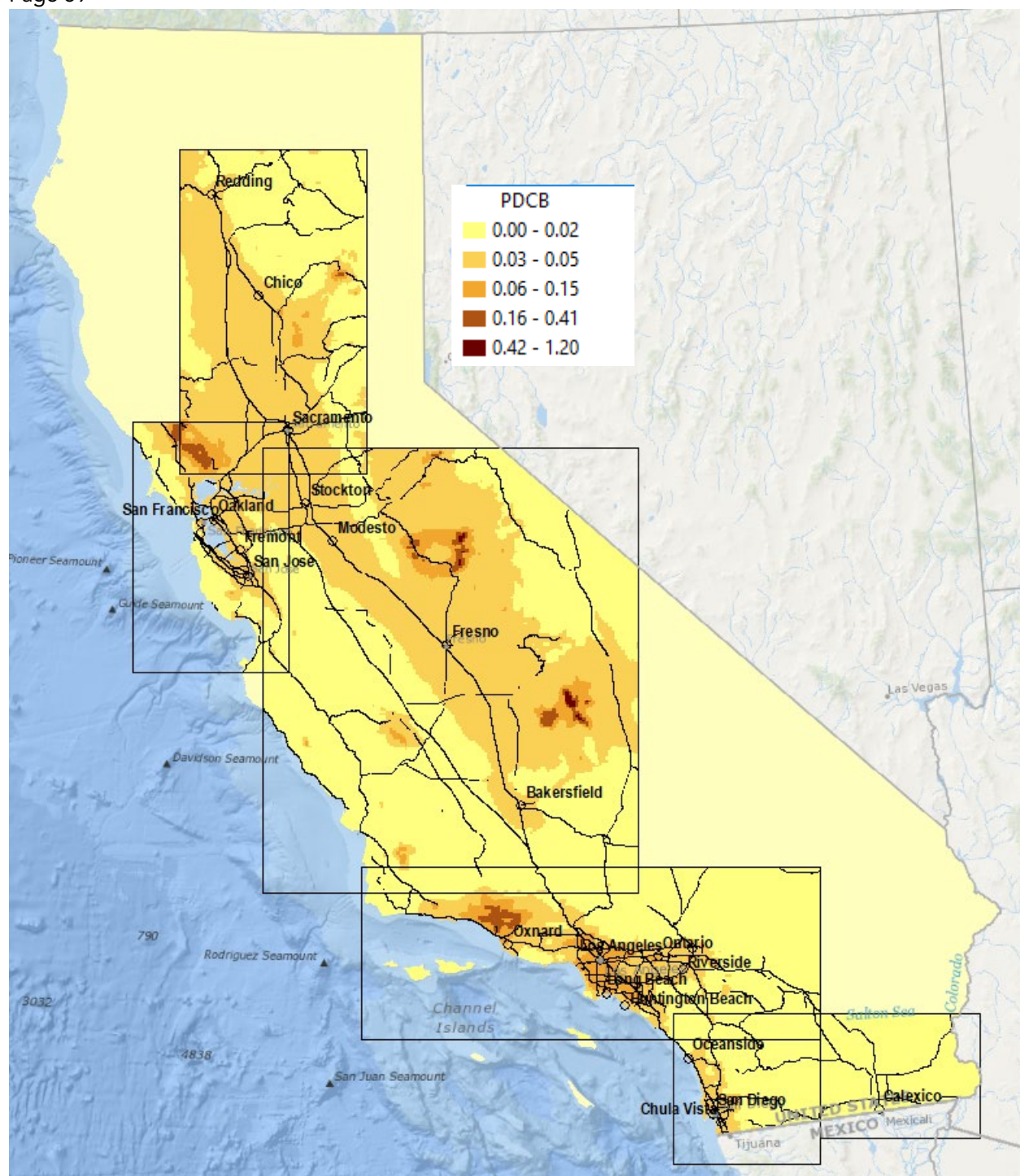


Figure IV-6. Map of the 2017 annual average p-dichlorobenzene concentrations ($\mu\text{g}/\text{m}^3$). Black boxes outline the six modeling domains where concentrations were estimated.

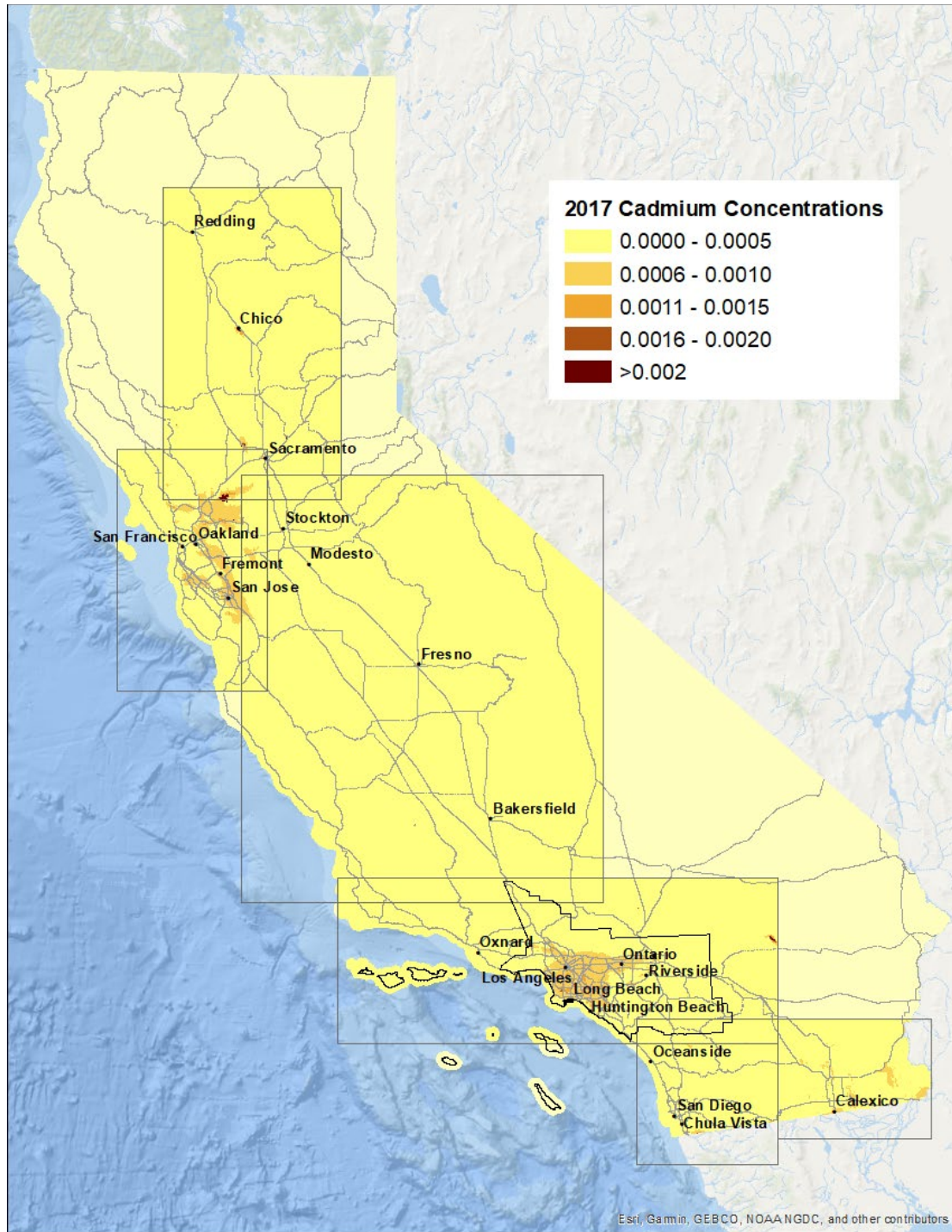


Figure IV-7. Map of the 2017 annual average cadmium concentrations ($\mu\text{g}/\text{m}^3$) in census blocks. Major freeways are drawn as gray lines. Black boxes outline the six modeling domains where concentrations were estimated.

V. Model Performance Evaluation

A. VOCs and Heavy Metals

Before modeling results can be used reliably to support various programs, they need to be evaluated against observational data. For heavy metals and toxic VOCs, direct comparisons between modeled and measured values at monitor sites are conducted for both annual and daily average concentrations (Figures V-1 and V-2, Appendix E). For VOCs, model performance is evaluated based on the root-mean-square error (RMSE), absolute bias (bias), and index of agreement (Table V-1). The index of agreement (IA) is a statistical measure used to evaluate the accuracy of a model by comparing its modeled values with the observed values. The formula for IA is:

$$IA = 1 - \left[\frac{\sum_{i=1}^N (|x_i - y_i|)}{\sum_{i=1}^N (|x_i - \bar{x}|)} \right] \quad (4)$$

where N is the number of data points, $x(i)$ is the i -th measurement, $y(i)$ is its corresponding modeled value, and $\bar{x}$ is the mean of the values of x . IA ranges from 0 to 1, with 1 indicating perfect agreement between the observed and modeled values, while values closer to 0 indicate poorer agreement. For heavy metals, considering emission uncertainties and the sparseness of the monitored data, five different ways were used to compare modeled values against observations, including (1) closest receptor to the monitoring site, (2) mean of closest 3 sites, (3) mean of closest 10 sites, (4) maximum of closest 3 sites, and (5) maximum of closest 10 sites.

The comparison between modeled and monitored annual average concentrations for four major VOCs (1,3-butadiene, benzene, formaldehyde, and acetaldehyde) is shown in Figure V-1. There are 31 sites for 1,3-butadiene, 17 sites for formaldehyde, 43 sites for benzene, and 17 sites for acetaldehyde in California that provide sufficient data points for evaluation. The modeled results for 1,3-butadiene and benzene show good agreement with the observed data, with an index of agreement of 0.7 and 0.6, respectively (Table V-1). The model underestimated the annual concentration of formaldehyde and acetaldehyde, particularly during extreme events such as wildfires. The modeling results show that the majority of formaldehyde and acetaldehyde (70-80%) are formed via secondary formation, which CMAQ was not able to capture with predefined emission source data.

Examining CMAQ's capability of simulating seasonal variation of 1,3-butadiene, benzene, formaldehyde, and acetaldehyde using time series and scatter plots of daily average concentrations shows that CMAQ captured the seasonal variation relatively well. However, the model underestimated daily average concentrations, especially during fall months. In addition to secondary formation processes, a lack of appropriate representation of emissions from wildfires that occurred in 2017 might be another potential factor for the underestimation.

For heavy metal concentrations shown in Figure V-2, the CALPUFF model and the measurements broadly agree with each other, despite considerable uncertainties in the emission inventories of these species, as well as the sparseness and uncertainties of the

monitored data (discussed in detail in Appendix E). In general, our results of statewide model performance evaluation are in agreement with previous work in the Bay area and South Coast using other models, which also show similar magnitude of model discrepancies in these heavy metals. Future work is warranted to improve model representations of these heavy metal species and gather more measurement data for a more robust model performance evaluation.

The overall performance of both CMAQ and CALPUFF is satisfactory, therefore modeling results can be used to estimate the impact on air quality by various TACs.

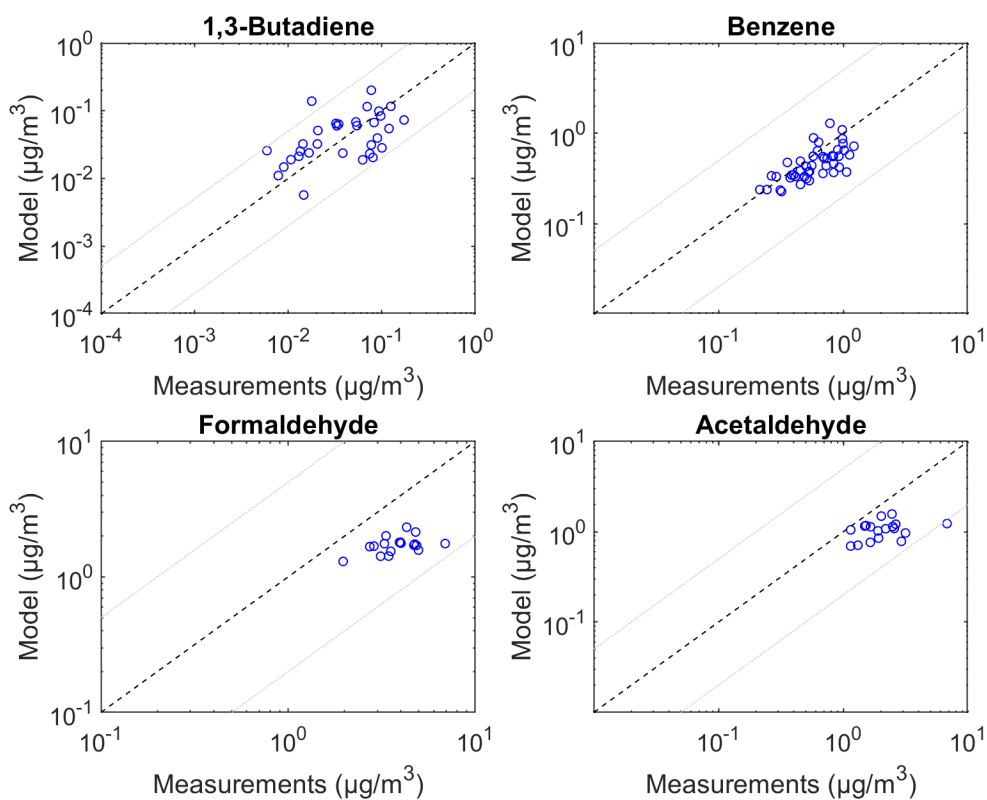


Figure V-1. Comparison between modeled and monitored annual average concentrations ($\mu\text{g}/\text{m}^3$) for VOCs: (a) 1,3-Butadiene, (b) Benzene, (c) Formaldehyde, and (d) Acetaldehyde. Each blue dot represents one monitor site. 1:1, 1:5 and 5:1 lines are shown to guide the comparison.

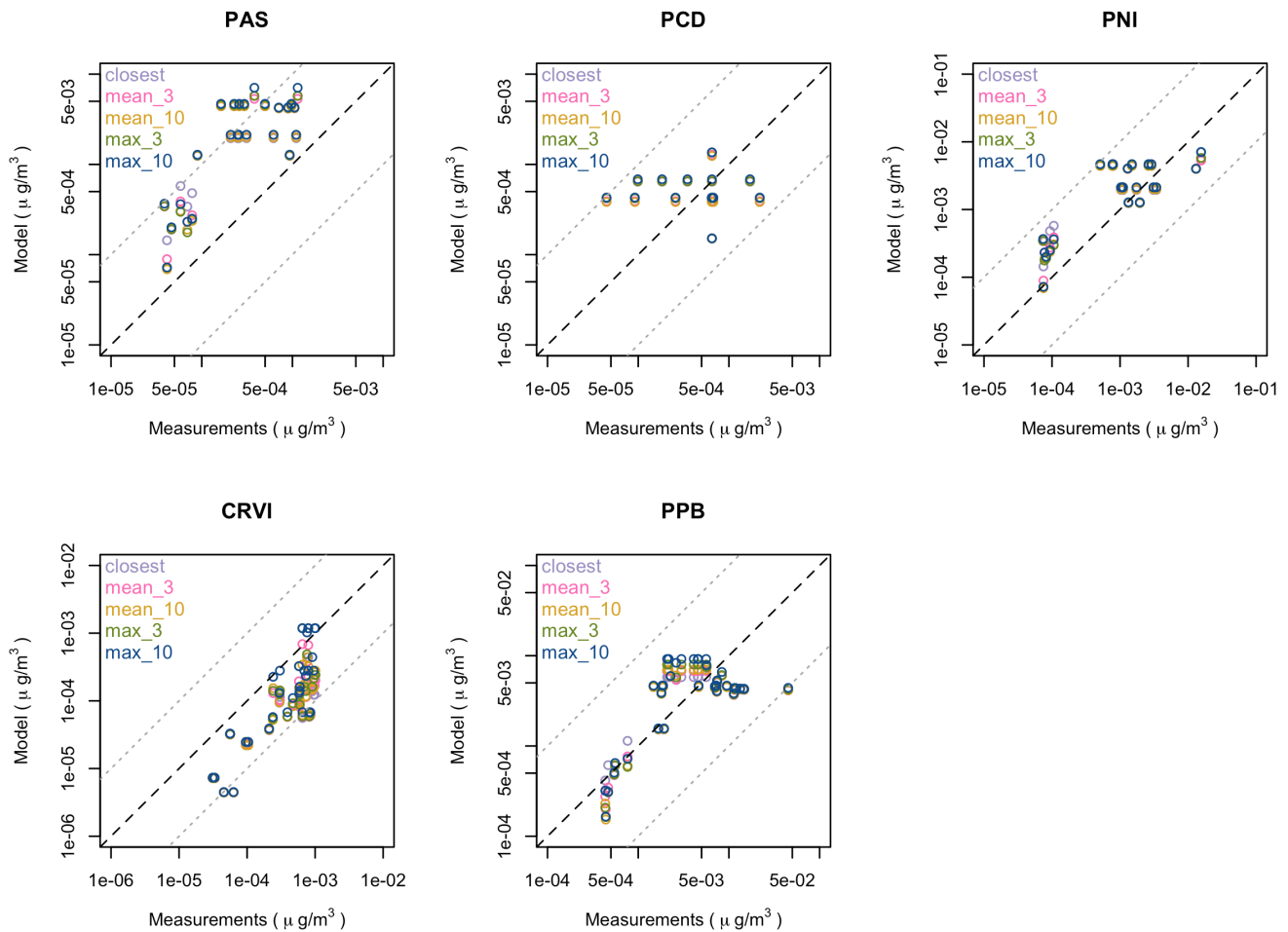


Figure V-2. Comparison between modeled and monitored annual average concentrations of heavy metals (arsenic (PAS), cadmium (PCD), nickel (PNI), hexavalent chromium (CRVI), and lead (PPB)). Five different ways were used to estimate modeled values for comparison, including (1) closest receptor to the monitoring site, (2) mean of closest 3 sites, (3) mean of closest 10 sites, (4) maximum of closest 3 sites, and (5) maximum of closest 10 sites. 1:1, 1:10 and 10:1 lines are shown to guide the comparison.

Table V-1. Comparison between modeled and monitored annual average concentrations of major VOCs.

VOCs	RMSE	bias	Index of agreement
Acetaldehyde	1.75	-1.26	0.41
Benzene	0.33	-0.18	0.59
1,3-Butadiene	0.05	0.01	0.70
Formaldehyde	2.52	-2.29	0.39

B. DPM (EC)

Evaluating the model's ability to simulate DPM is not trivial, since DPM cannot be measured directly. Elemental carbon (EC) has been widely considered as the best surrogate for DPM (Schauer, 2003) since EC is the most abundant component of diesel exhaust.

In some observational datasets, fossil EC can be separated from non-fossil EC. The sum of modeled EC from fossil fuel combustion activities such as on-road mobile and off-road mobile and equipment was used to compare against fossil EC observations. If fossil EC and non-fossil EC are not separable, then the total EC concentrations from CALPUFF including all emission sources such as wildfires, agricultural burns, charbroiling and residential wood combustions is used to compare against total observed EC.

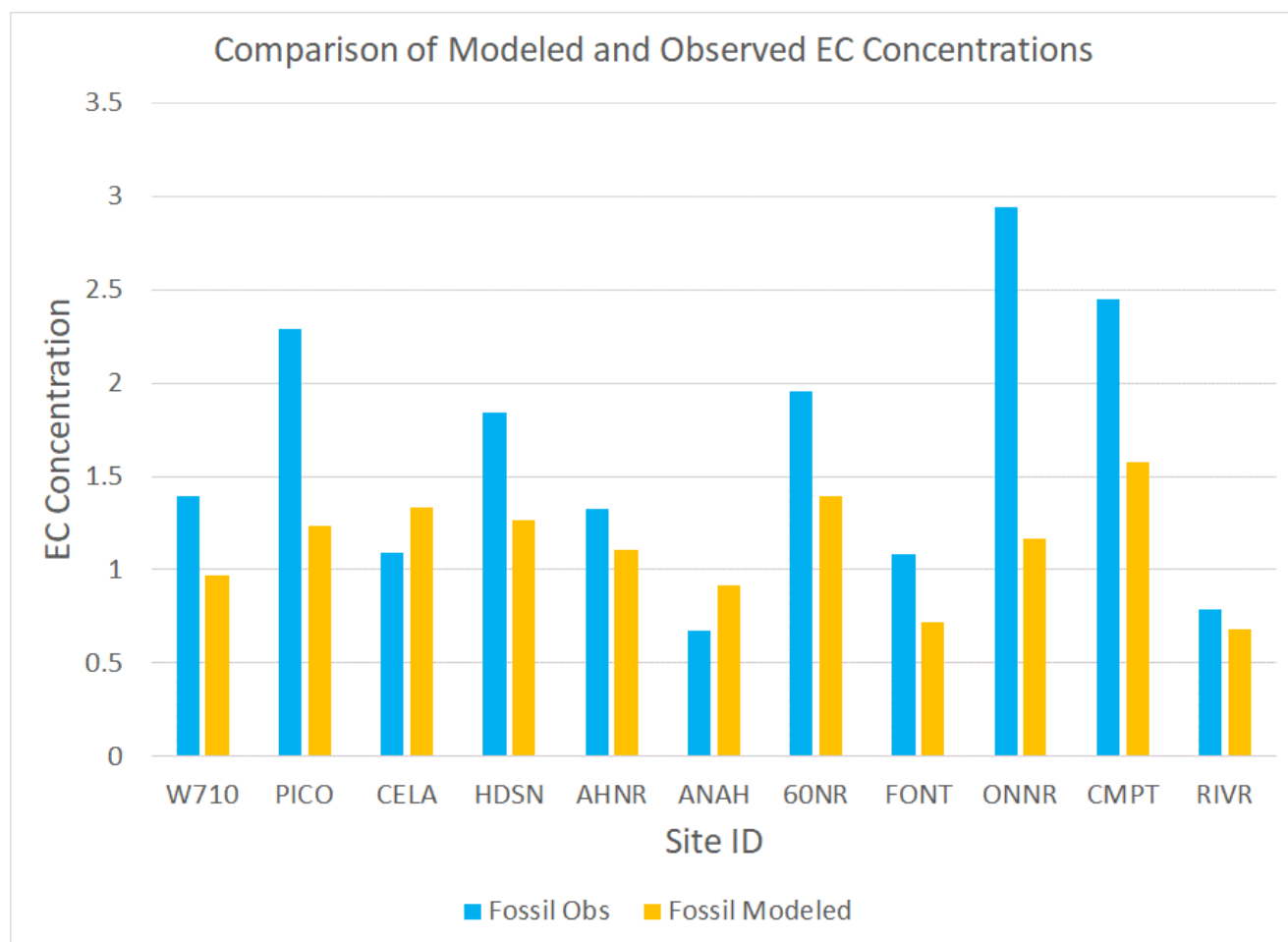
In order to model EC concentrations for 2017, EC emissions were processed with the same methodology and data source as those for diesel PM. Annual average concentrations of EC modeled by CALPUFF were compared with the observed counterparts. First, we used the Chemical Speciation Network (CSN) data for year 2017 in California to evaluate model results. CSN data are collected once every 3-6 days (different monitors can have different sampling frequencies) and each sample represents 24-hours sampling (24-hour mean EC concentrations). Table V-1 compares the modeled and the monitored EC annual average concentrations. Given that there may be some uncertainties involved in the EC measurements (low frequency) and the EC emission inventory, the general agreement between modeled and monitored EC annual average concentrations is acceptable, even though at several sites the model overestimated EC concentrations.

Table V-2. Comparison between modeled and monitored annual average concentrations of total EC. Observational data are from the CSN.

Site Name	Modeled	CSN Data	Latitude	Longitude
San Jose – Jackson St	1.888	0.617	37.3485	-121.895
Chico – East Ave	1.245	0.517	39.76168	-121.84
Sacramento – Del Paso Manor	1.350	0.676	38.61378	-121.368
Sacramento – T St	1.703	0.557	38.56844	-121.493
Modesto – 14th St	1.087	0.577	37.64217	-120.994
Fresno - Garland	1.123	0.728	36.78532	-119.774
Visalia – N Church St	0.911	0.595	36.34507	-119.291
Bakersfield – 5558 California Ave	1.778	0.762	35.35609	-119.041
Los Angeles – North Main St	1.904	0.793	34.06659	-118.227
Riverside Rubidoux	0.840	0.827	33.99958	-117.416
El Cajon – Lexington Elementary School	0.926	0.588	32.81798	-116.968
Calexico – Ethel St	0.954	0.843	32.67887	-115.483

Additionally, fossil and non-fossil EC data collected in the South Coast air basin by the South Coast Air Quality Management District (SCAQMD) were used in the model performance evaluation for DPM. The separation of fossil and non-fossil EC provides an opportunity to

evaluate CALPUFF for its ability to simulate fossil EC concentrations that are more closely related to DPM. Figure V-3 presents the comparison between monitored and modeled EC annual average concentrations for the fossil EC and total EC (sum of fossil and non-fossil EC). The monitoring dataset includes the following sites: Anaheim (ANAH), Anaheim near-road (AHNR), Central LA (CELA), Compton (CMPT), Fontana (FONT), Pico Rivera (PICO), Rubidoux (RIVR), Ontario near-road (ONNR), W710 near-road (W710), 60 near-road (60NR).



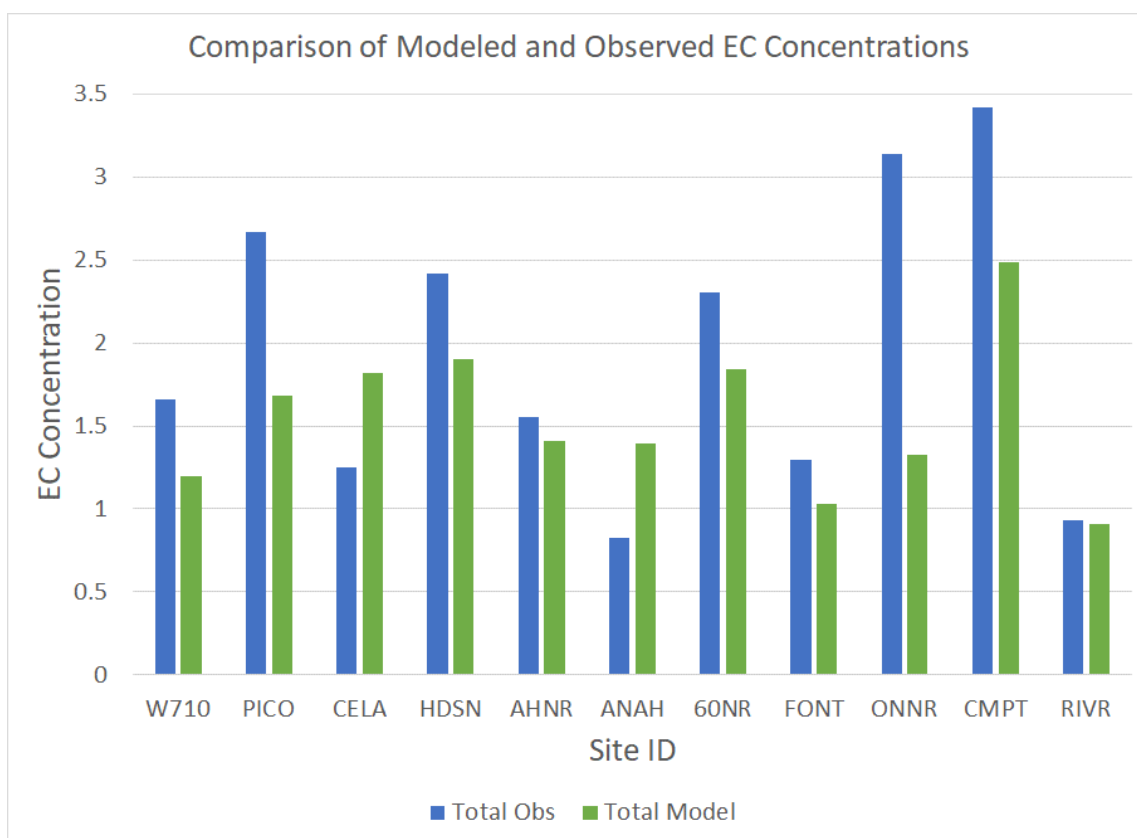


Figure V-3. Comparison of monitored and modeled annual average of EC concentrations ($\mu\text{g}/\text{m}^3$). (a) the upper panel, fossil EC and (b) the lower panel, total EC.

The overall performance of CALPUFF is satisfactory in terms of simulating annual average EC concentrations. The model tends to overestimate EC concentrations when compared with CSN data while it tends to underestimate compared to the EC data collected by the SCAQMD. It is not clear what may have caused this inconsistent behavior in the model. It is nonetheless an indication that the model may not be systematically biased.

As previously discussed, diesel PM and EC emission inventories were developed based on the same data sources and were processed with the same methodology. This strongly suggests that the CALPUFF model and DPM emission data are dependable for the purpose of computing annual average DPM concentrations, which are used to estimate excess cancer risk due to DPM exposure.

VI. Risk Characterization

A. Statewide level

Risk characterization can be derived from the annual average concentrations of TACs. The California Environmental Protection Agency's Office of Environmental Health Hazard Assessment's (OEHHA) most recent risk assessment guidelines - Guidance Manual for Preparation of Health Risk (2015) were used to characterize cancer risk resulting from exposure to the modeled TACs. Cancer risk is expressed in units of chances per million (i.e., the excess probability of a person developing cancer due to air toxics exposure per million people). It is calculated by multiplying the daily inhalation or oral dose by a cancer potency factor, the age sensitivity factor, the frequency of time spent at home (for residents only), and the exposure duration divided by averaging time. For residential inhalation exposure, the excess potential cancer risk is calculated separately by age group and then summed to yield an overall cancer risk at the receptor locations. Cancer risk due to all TACs is the sum of potential cancer risks for all individual TACs. Note that an exposure duration of 30 years with the Risk Management Policy (RMP) method (95th/80th percentile DBR) was used for assessing potential cancer risk (inhalation only). Further, with census population data, cancer burden can also be calculated, where a 70-year exposure period is used to estimate potential cancer burden (details of the calculation method are presented in Appendix F).

Figures VI-1 and VI-2 depict maps of average DPM cancer risk and burden in census tracts across California, respectively. These averages were calculated as the average of all census block receptors within each census tract, weighted by block population. Not surprisingly, the spatial distribution of DPM cancer risk in the state is similar to that of DPM. Higher risks are distributed along major freeways and urban centers, as well as near the California-Mexico border from transported pollution from Mexico. In other words, the higher-risk areas tend to be along transportation corridors, such as major freeways, ports and railyards, and near the border.

Figures VI-3-VI-4 are similar maps of average cancer risk and burden from all heavy metals. Higher risks are found in urban industrial areas from stationary sources such as power plants and industrial facilities, aggregated area-point sources modeled as area sources such as off-road equipment, and near ports from OGV at-berth emissions.

Figures VI-5-VI-6 are maps of average cancer risk and burden for total VOCs. The South Coast, San Joaquin Valley, Sacramento Valley, and San Francisco Bay show the highest levels of cancer risks due to the combined effects of toxic VOCs. Significant levels of cancer risks are also seen in areas in San Diego and Imperial County near the California-Mexico border due to high emissions from the Mexican side. The combined population weighted cancer risk from toxic VOCs in the South Coast was approximately 129 in a million, which was the highest followed by the risk of about 103 in a million in San Diego. A significant part of the combined risk from VOCs in the southern air basins such as San Diego and Imperial Counties can be attributed to the cross-border emissions from Mexico. The combined toxic VOCs risks in the Sacramento Valley, San Francisco and San Joaquin Valley were 68, 74, and 65 in a million, respectively.

Name

Date

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The population-weighted potential cancer risks for DPM, metals (hexavalent chromium, lead, arsenic, cadmium and nickel) and toxic VOCs (benzene, 1,3-butadiene, formaldehyde, acetaldehyde, perchloroethylene and p-Dichlorobenzene) across all six basins as well as cancer burden totals are presented in Table VI-1.

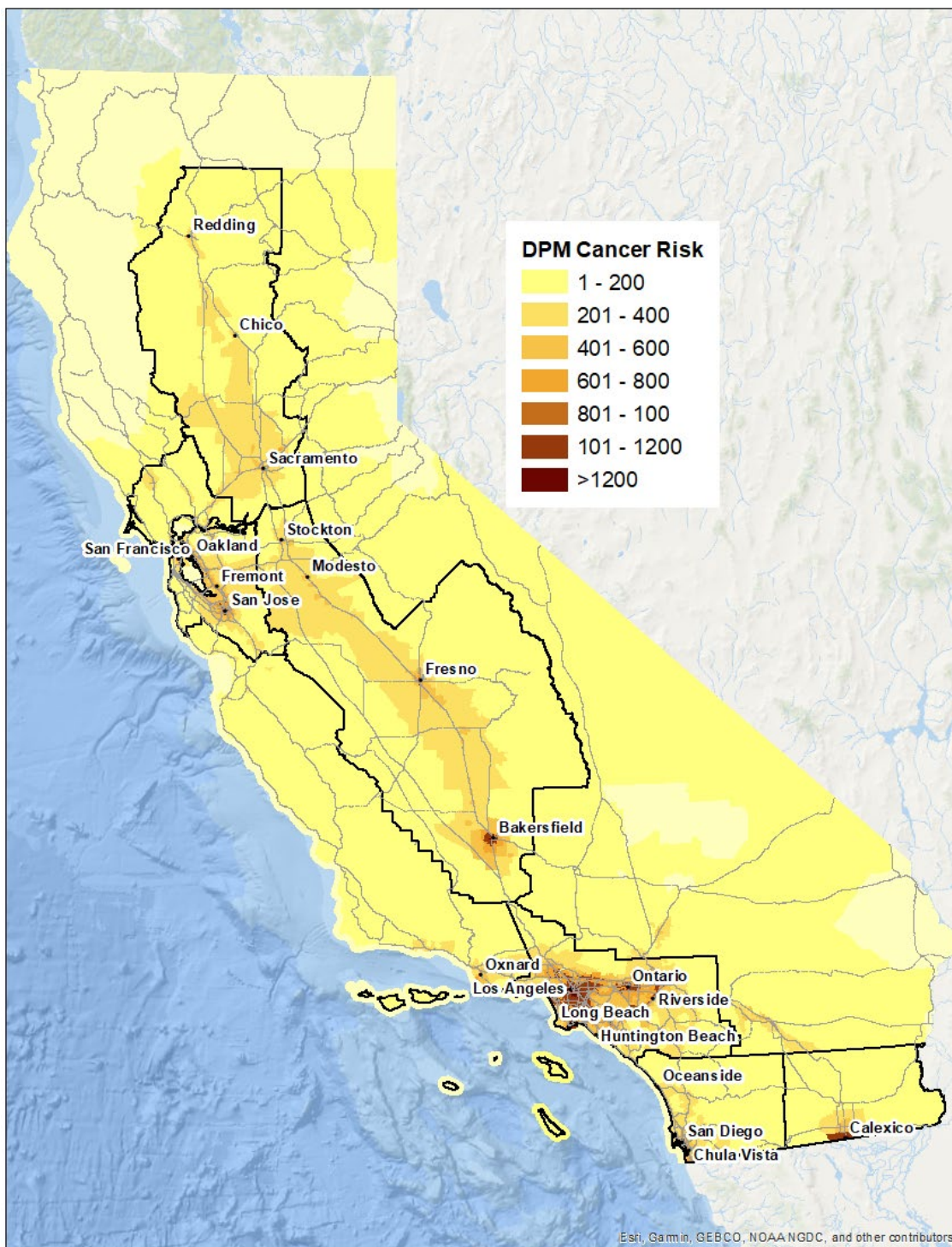


Figure VI-1. Map of the 2017 DPM cancer risks (in chances per million) by census tract. Black contours outline the six air basins of interest.

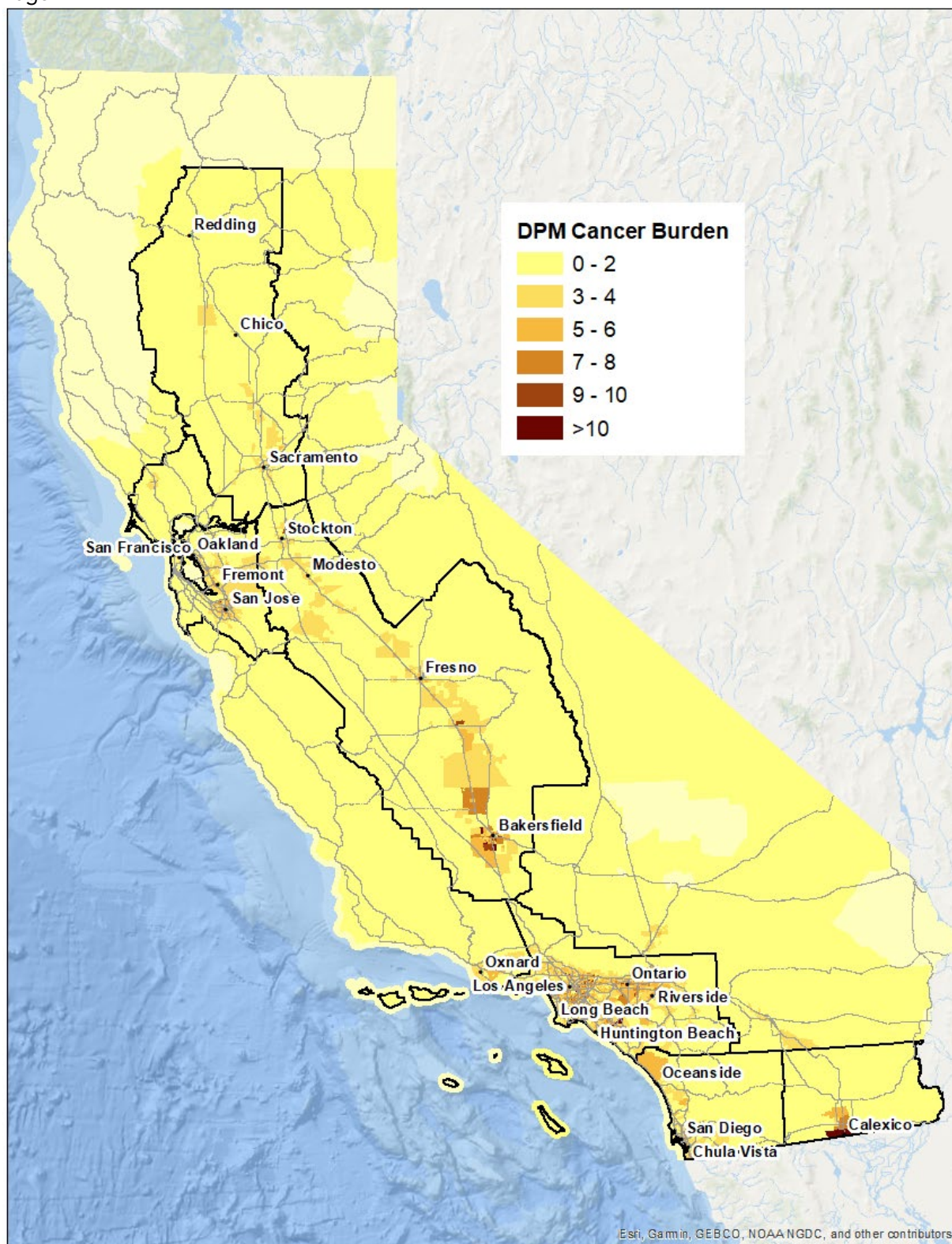


Figure VI-2. Map of the 2017 DPM cancer burden (cases) by census tract. Black contours outline the six air basins of interest.

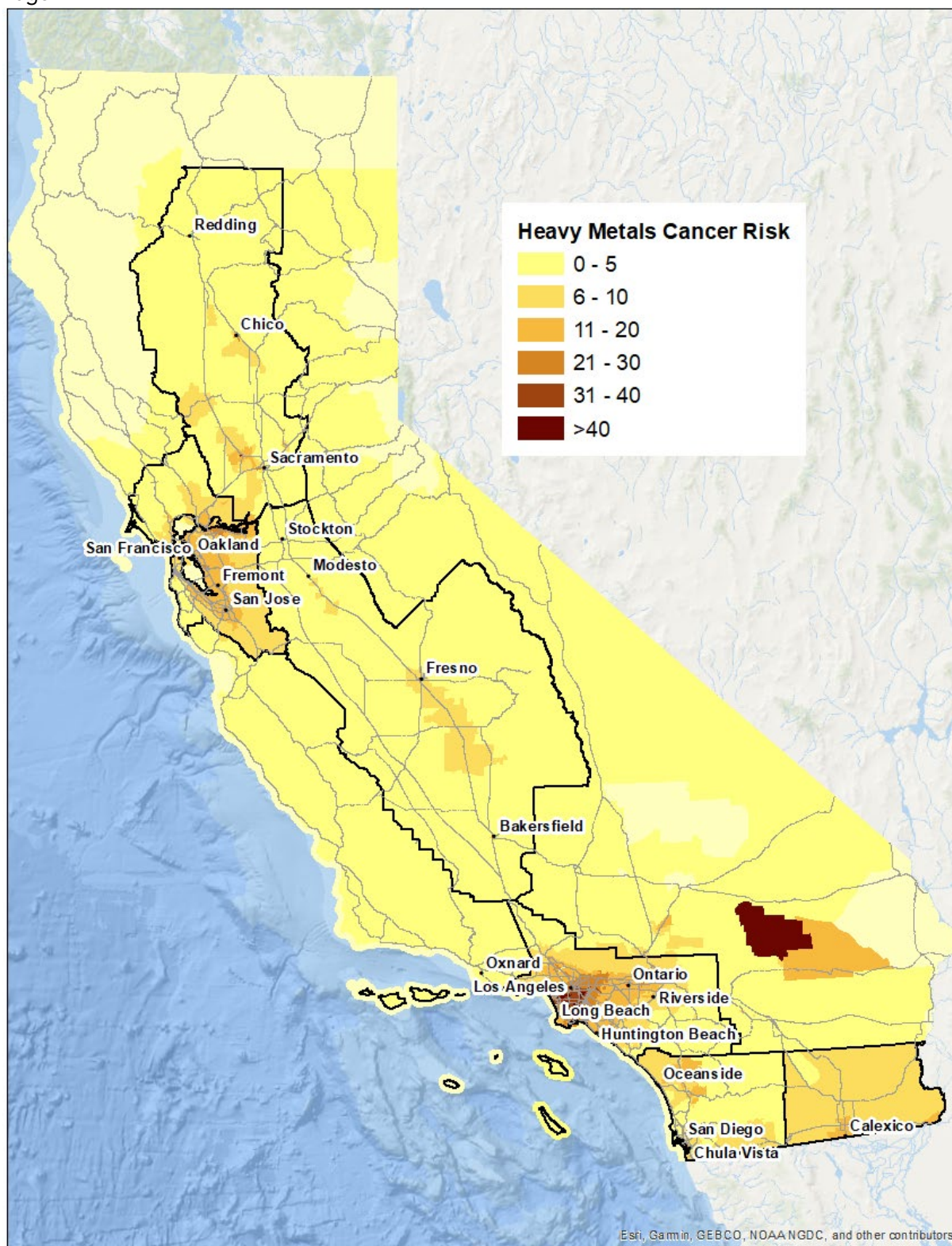


Figure VI-3. Map of the 2017 total heavy metals cancer risk (in chances per million) by census tract. Black contours outline the six air basins of interest.

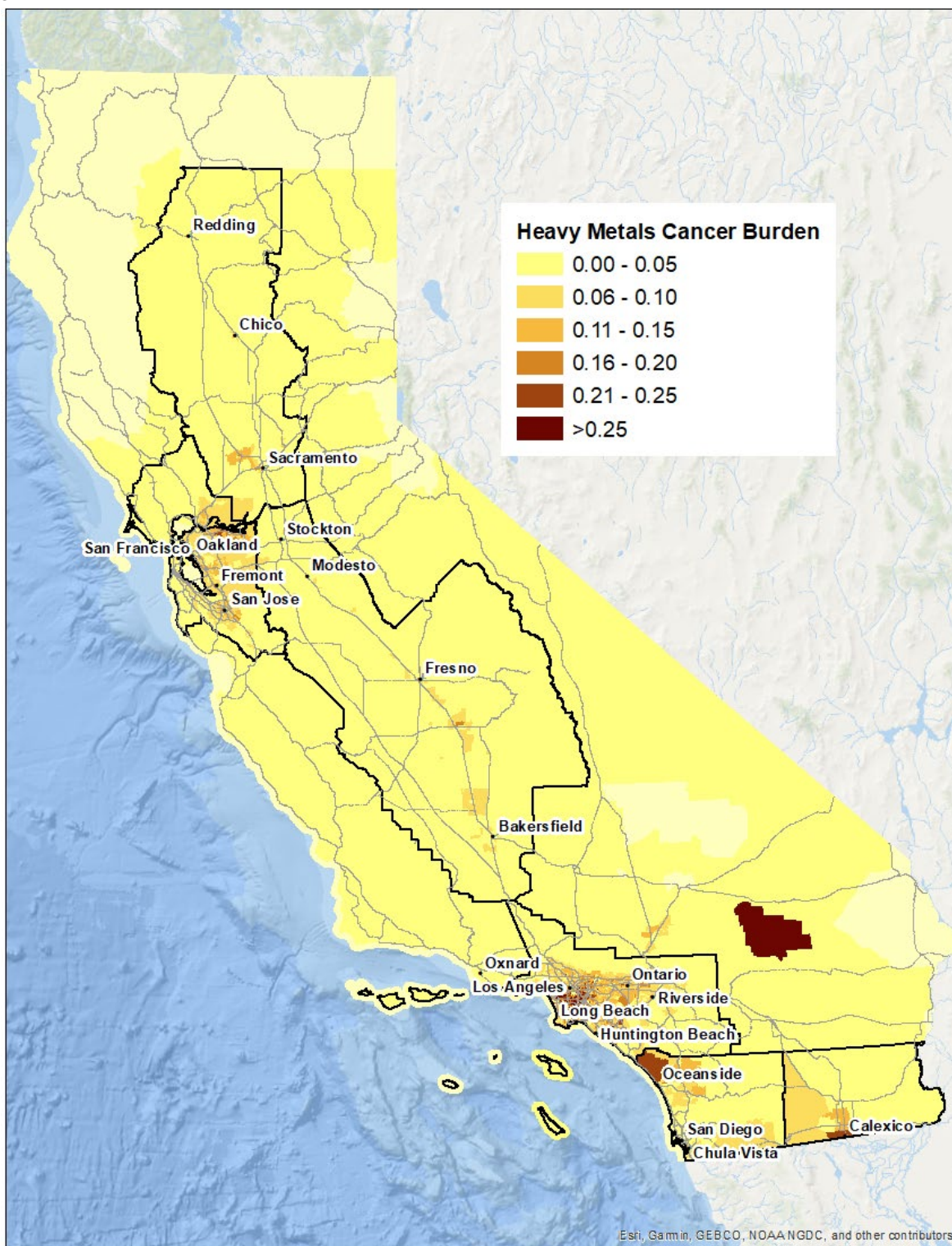


Figure VI-4. Map of the 2017 total heavy metals cancer burden (cases) by census tract. Black contours outline the six air basins on interest.

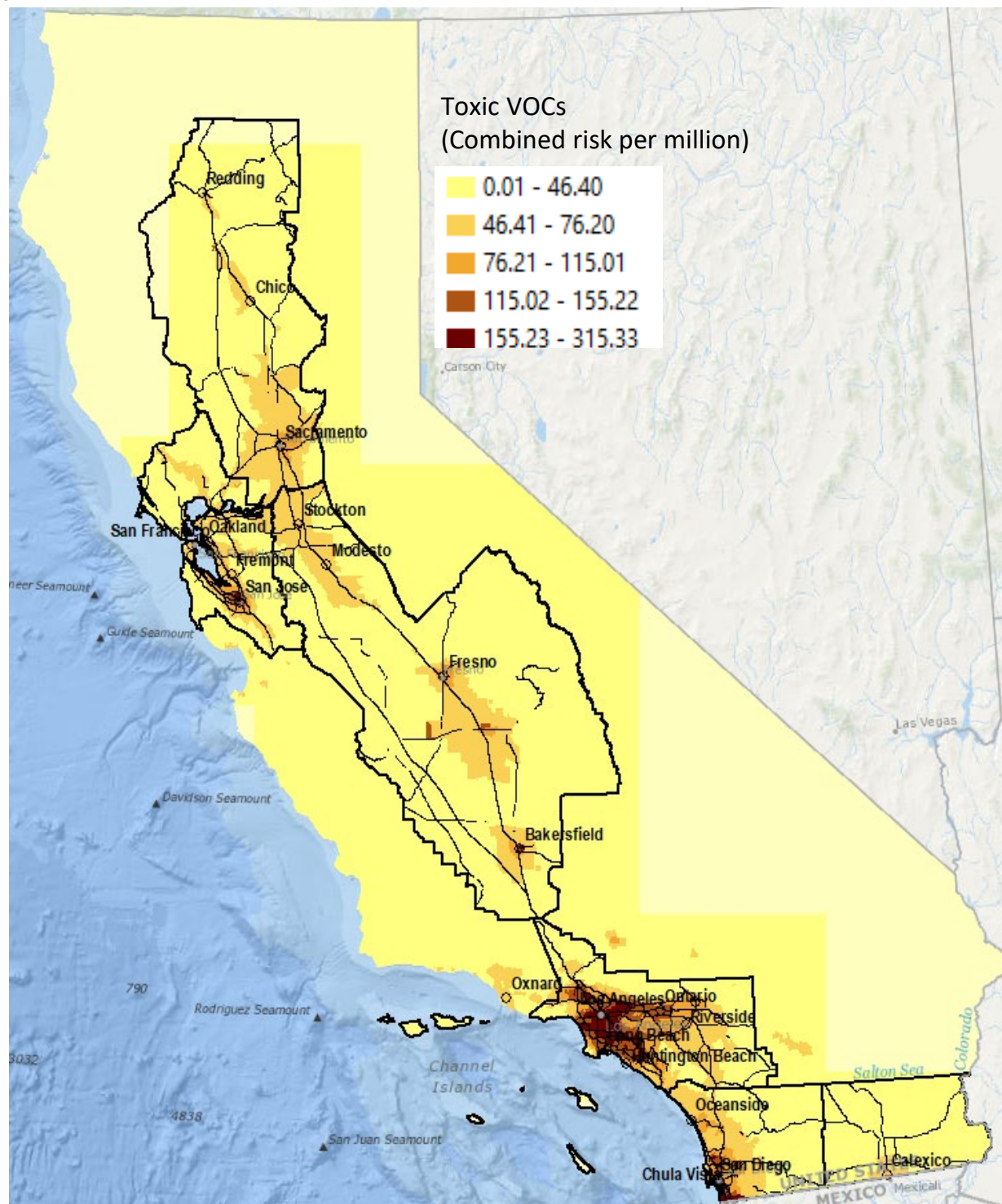


Figure VI-5. Map of the 2017 total VOCs cancer risk (in chances per million) by census tract. Black contours outline the six air basins of interest.

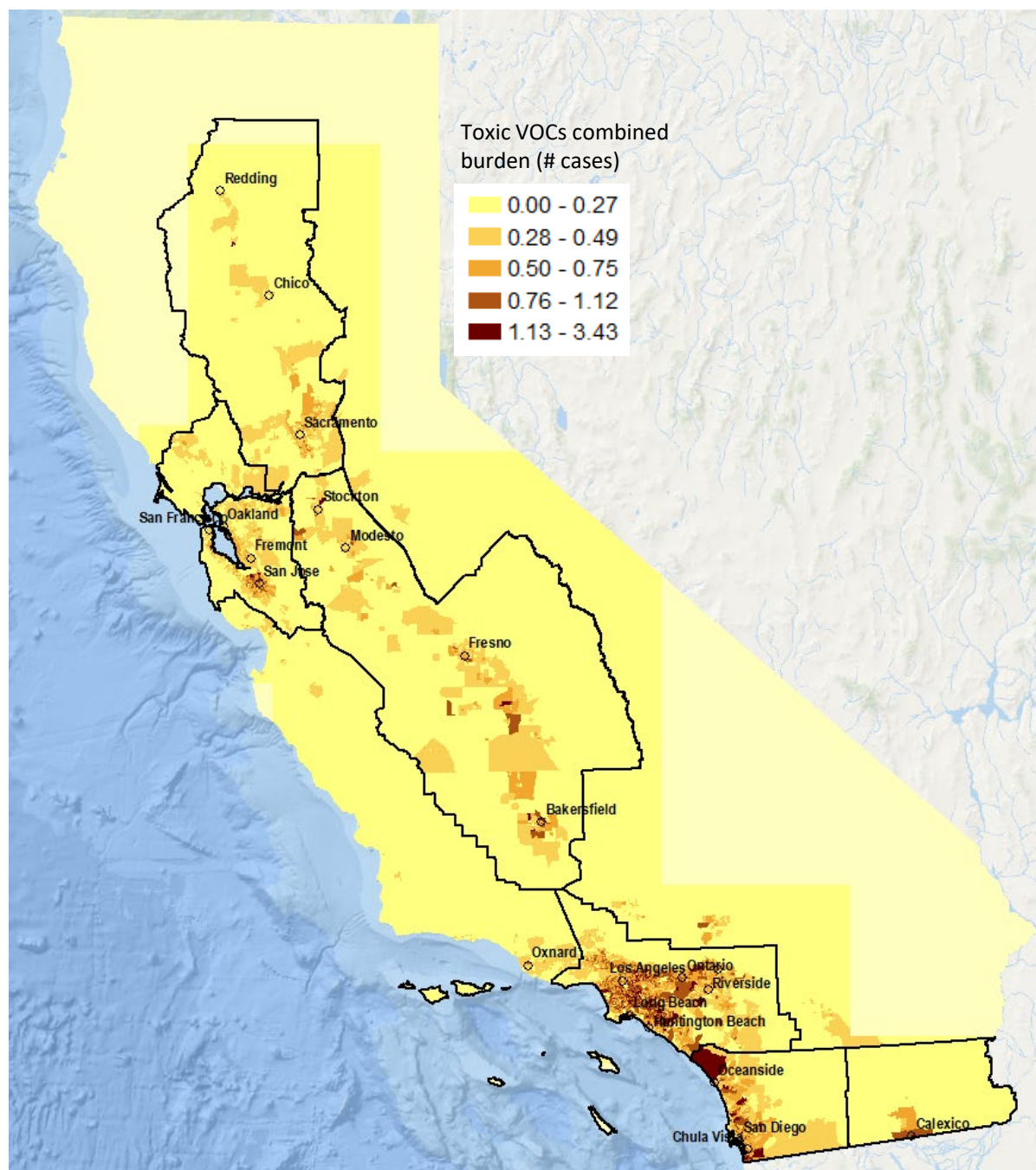


Figure VI-6. Map of the 2017 total VOCs cancer burden (cases) by census tract. Black contours outline the six air basins of interest.

Table VI-1. Population-weighted cancer risk (chances per million, 30-year exposure) and cancer burden (70-year exposure) across all six air basins from census tract averages.

<i>TACs/Emission Category</i>	<i>Cancer Risk (chances per million)</i>	<i>Cancer Burden (cases)</i>
<i>DPM</i>		
<i>On-road</i>	294.8	13000.8
<i>Off-road</i>	94.2	4153.9
<i>Area</i>	100.5	4432.4
<i>Point</i>	2.5	109.6
<i>Total</i>	491.9	21695.0
<i>VOCs</i>		
<i>Formaldehyde</i>	21.9	965.1
<i>Acetaldehyde</i>	6.3	278.1
<i>1,3-Butadiene</i>	25.3	1117.9
<i>Benzene</i>	35.9	1584.1
<i>Perchloroethylene</i>	4.0	174.5
<i>p-Dichlorobenzene</i>	1.1	48.6
<i>Heavy Metals</i>		
<i>Hexavalent Chromium</i>	3.6	157.6
<i>Lead</i>	0.1	3.9
<i>Arsenic</i>	3.0	130.2
<i>Cadmium</i>	3.8	168.0
<i>Nickel</i>	1.3	59.1
<i>Grand Total</i>	598.2	26382.1

For the 2017 base year, DPM was the dominant toxic, contributing around 82% of total cancer risk and burden across the state (Figure VI-7), followed by the VOCs which accounted for around 16% total, and 2% from heavy metals. Because each emission source category was modeled separately for DPM, we can investigate which sources were the most important for an area of interest. Figure VI-8 shows the relative contribution of each emission category to total cancer risks from DPM sources across all six air basins. On-road mobile sources were the most prominent emission category, accounting for about 60% of total DPM risk, followed by the aggregated area-point sources (16%) and locomotives (8%). Note that these toxics and source apportionment represent an average across the whole state.

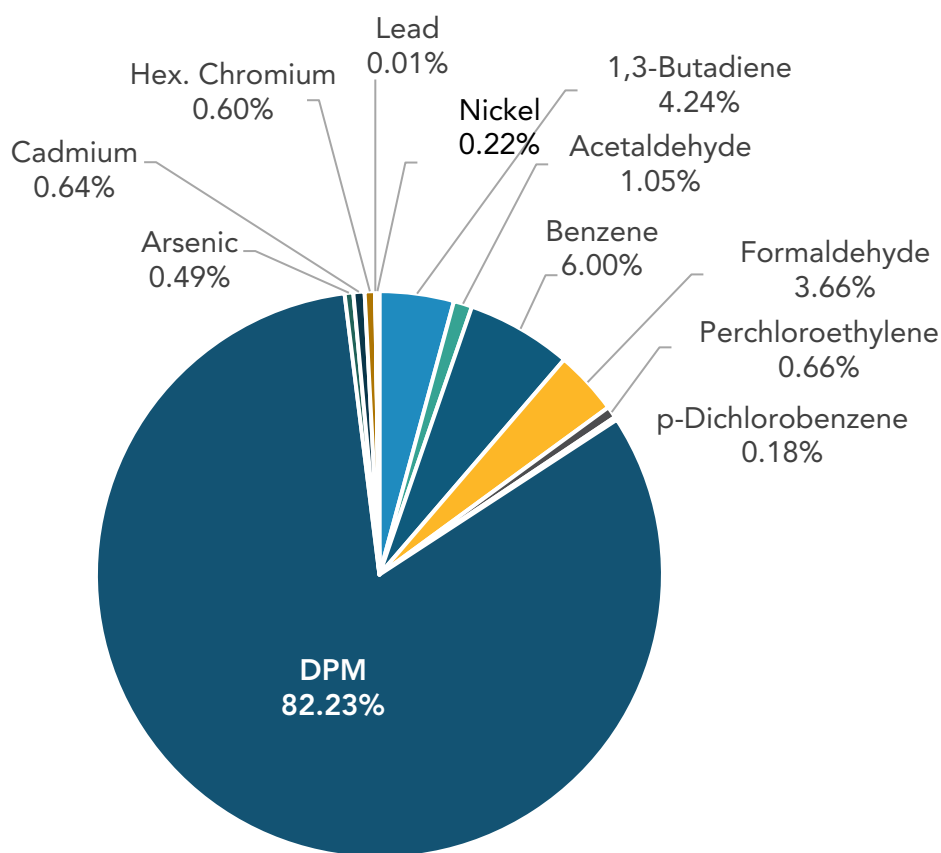


Figure VI-7. Relative contributions of air toxics to total cancer risk across the state.

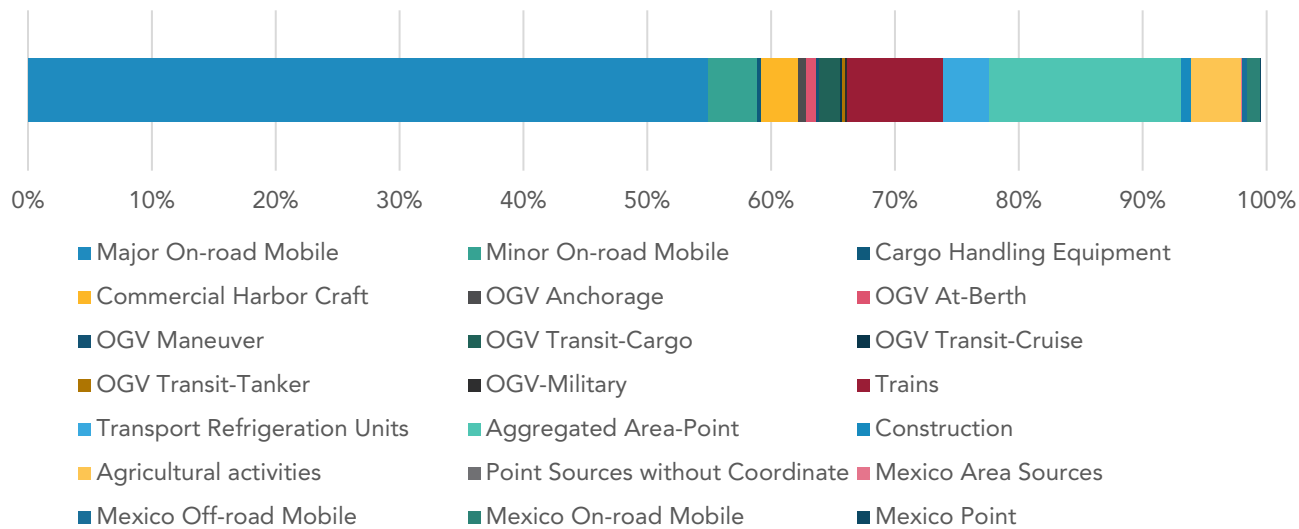


Figure VI-8. Relative contributions of emission sub-categories to total cancer risk from DPM sources across the state.

B. Regional Level

The above section presented cancer risks and burden statewide. In this section, we take a closer look at the air toxics and major emission sources in each air basin.

i. Overview by basin

Figures VI-9 through VI-20 provide close-up depictions of the overall risks in each of the six air basins. For each basin, a pie chart first presents the relative contribution of each toxic to total risk, followed by spatial maps of all TACs, DPM, VOCs, and heavy metals.

Bay Area

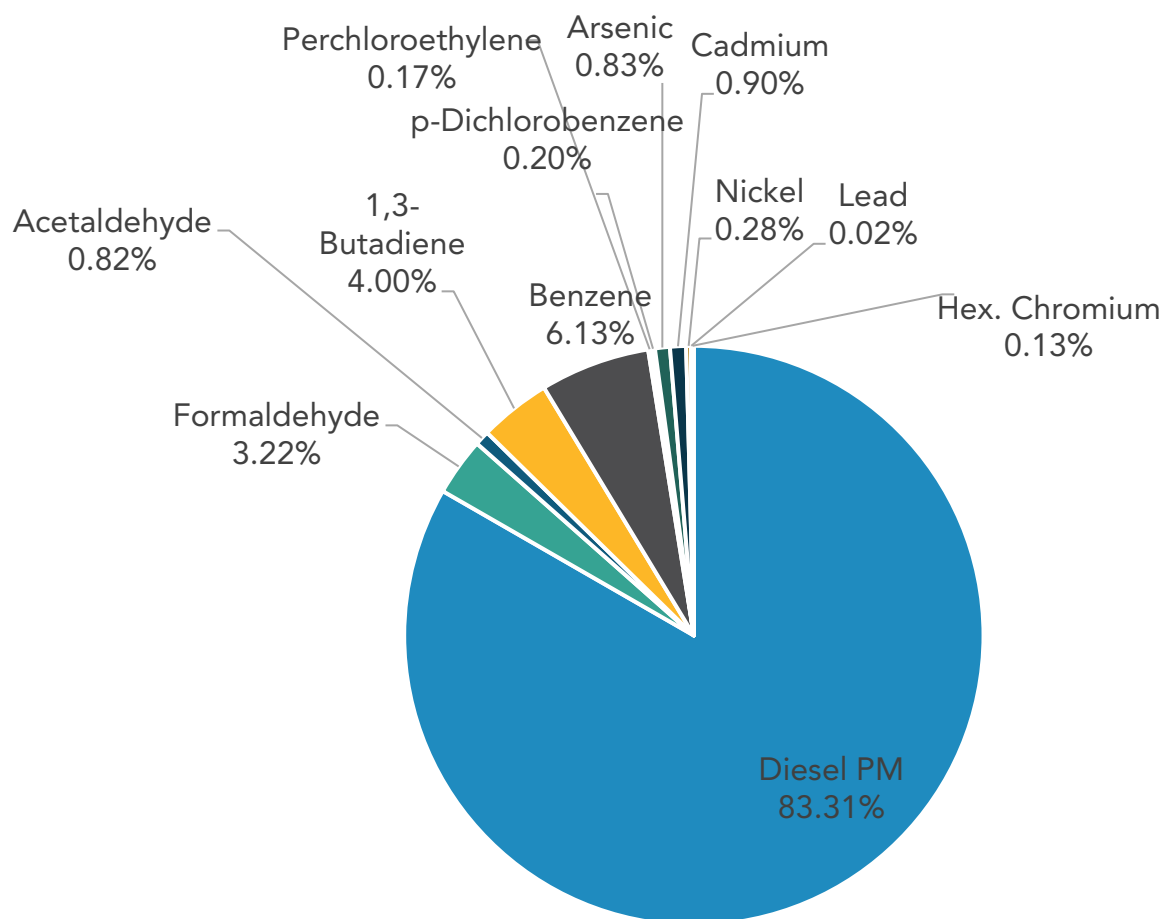
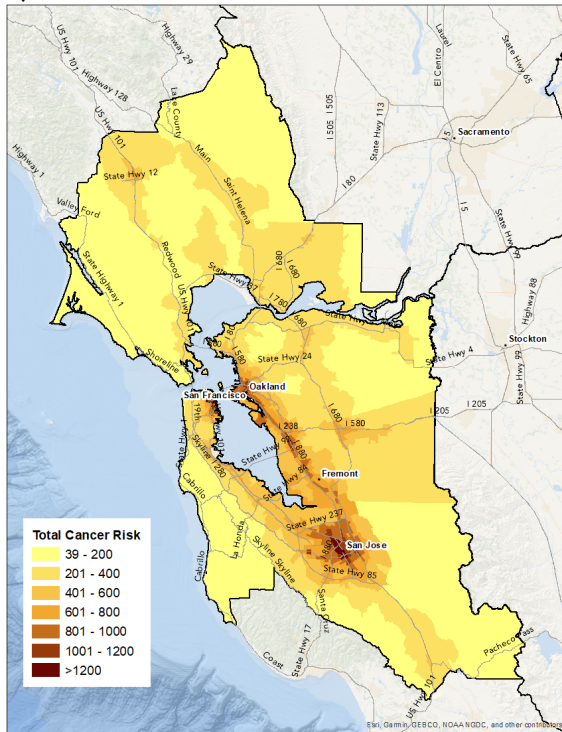
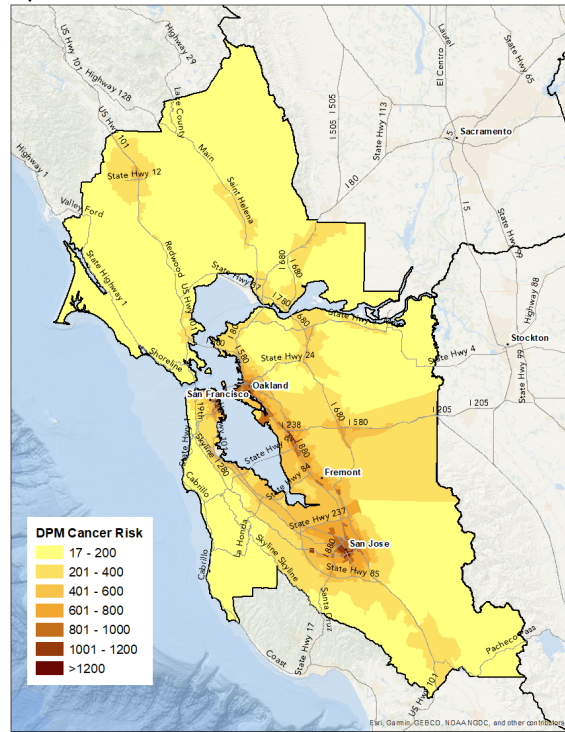


Figure VI-9. Relative contributions of air toxics to total cancer risk in the Bay Area air basin.

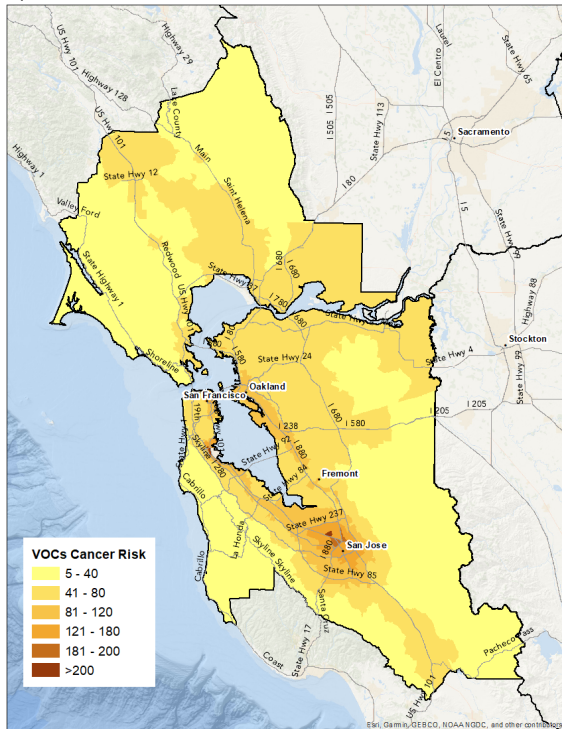
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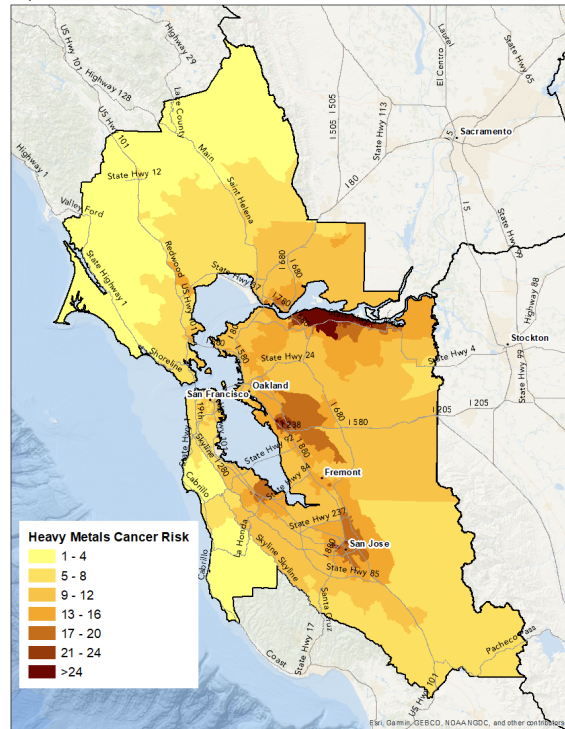


Figure VI-10. Maps of the 2017 cancer risks in Bay Area census tracts: a) Total cancer risk from all TACs (DPM + VOCs + heavy metals); b) Total cancer risk from all DPM sources; c) Total cancer risk from all VOCs; and d) Total cancer risk from all heavy metals.

Sacramento Valley

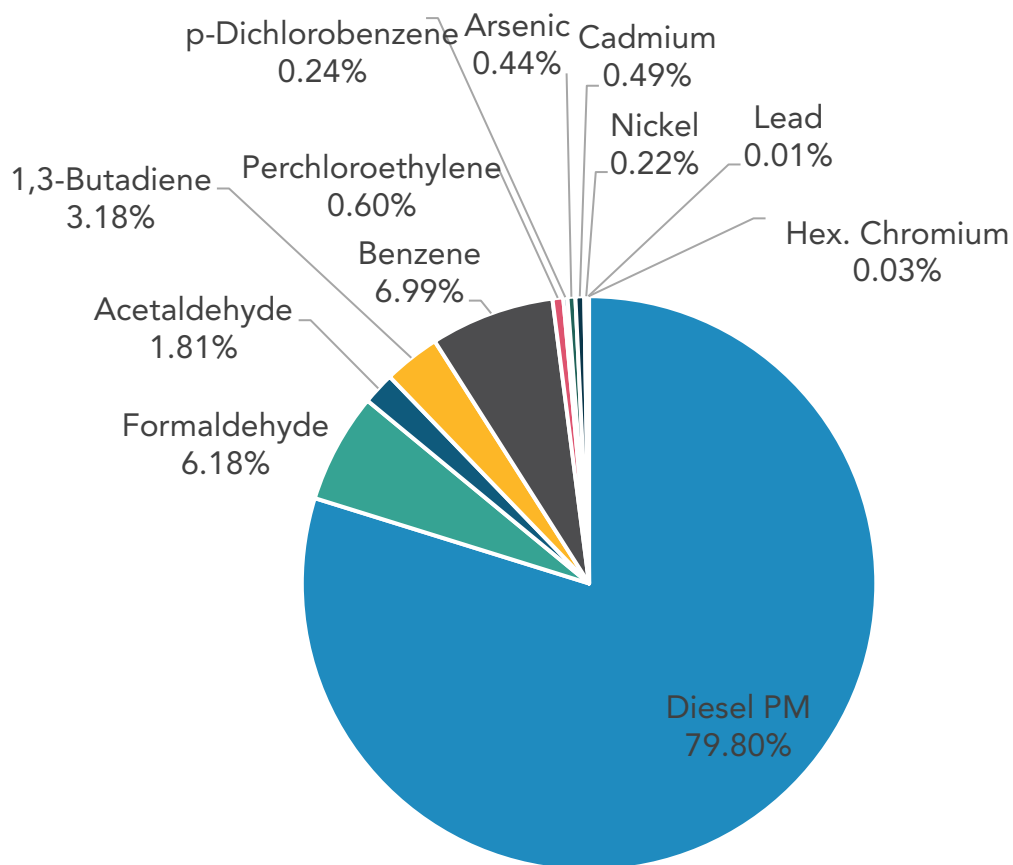
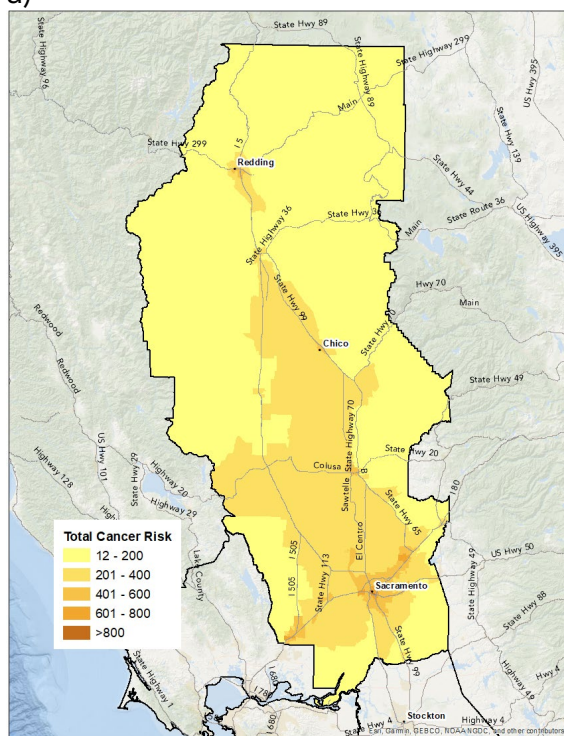
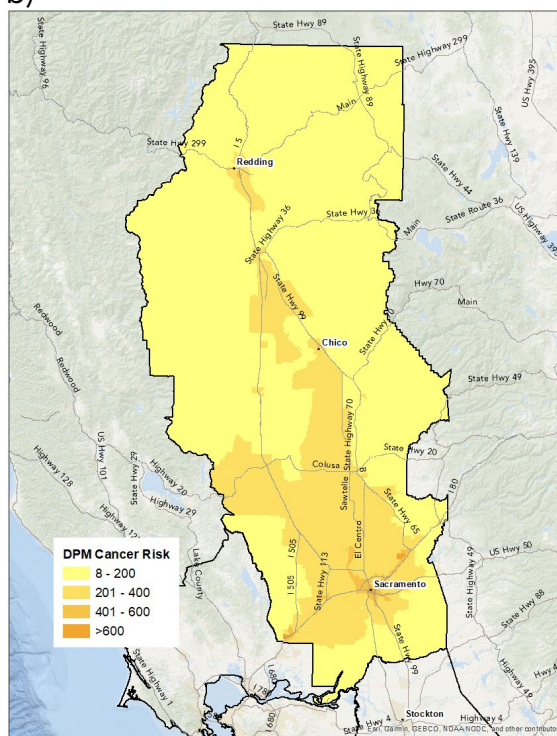


Figure VI-11. Relative contributions of air toxics to total cancer risk in the Sacramento Valley air basin.

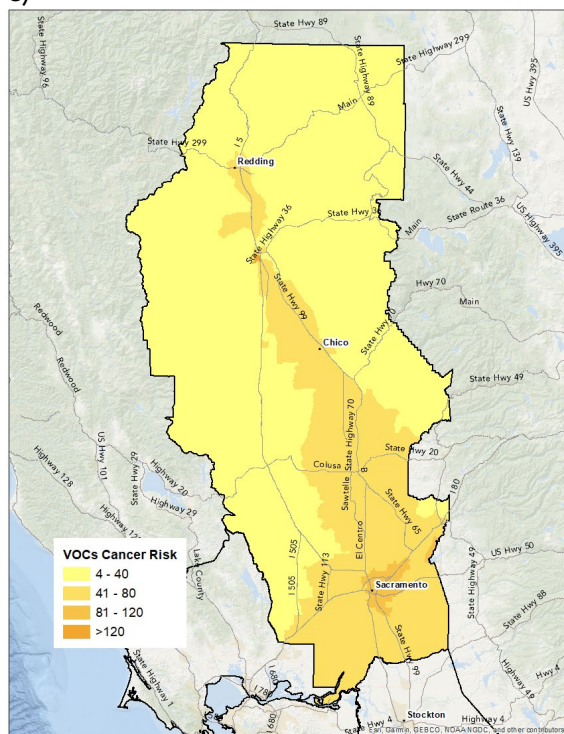
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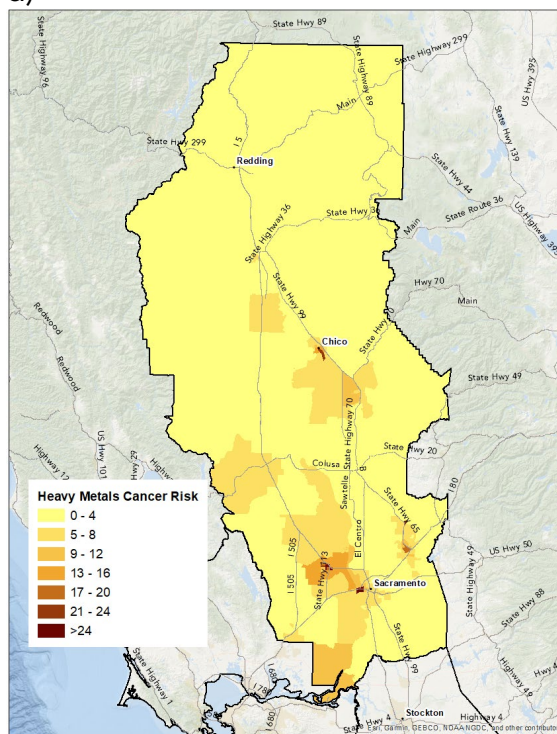


Figure VI-12. Maps of the 2017 cancer risks in Sacramento Valley census tracts: a) Total cancer risk from all TACs (DPM + VOCs + heavy metals); b) Total cancer risk from all DPM sources; c) Total cancer risk from all VOCs; and d) Total cancer risk from all heavy metals.

San Joaquin Valley

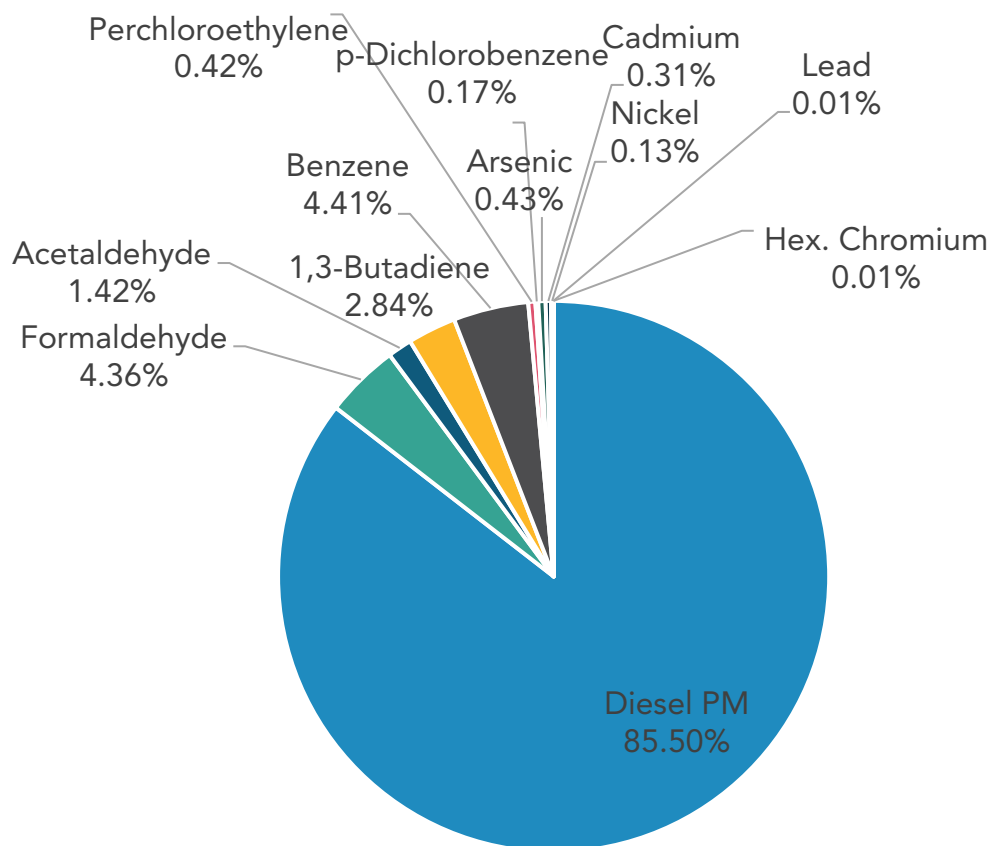
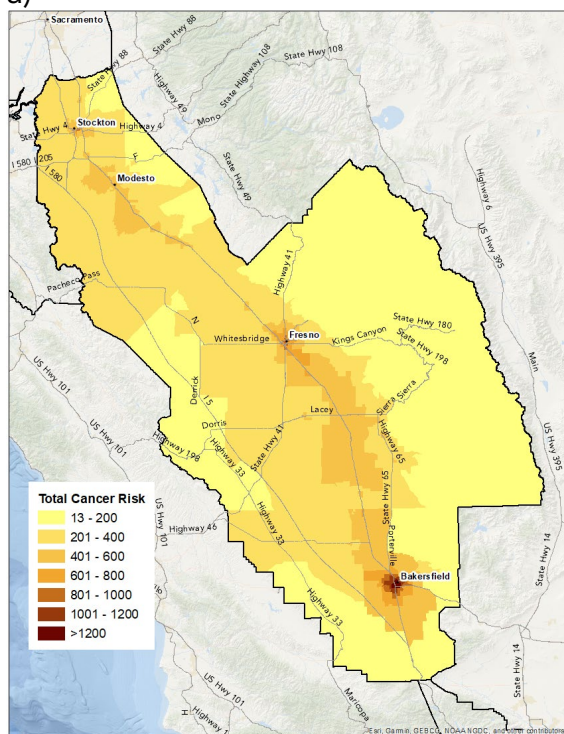
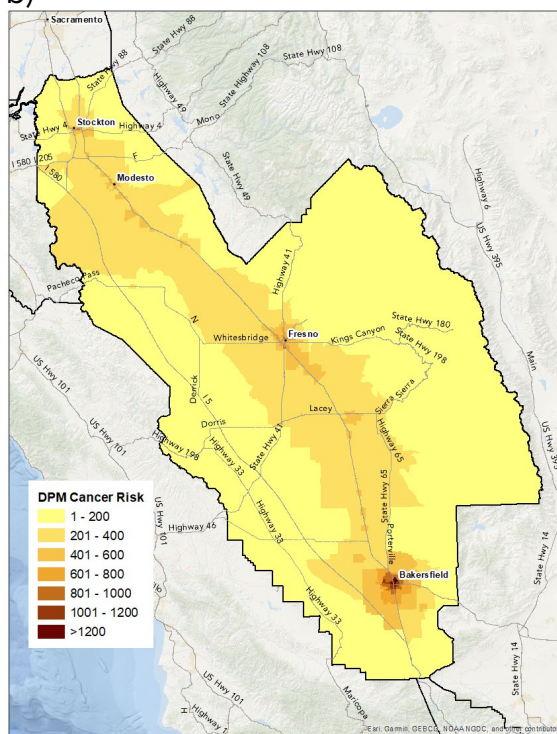


Figure VI-13. Relative contributions of air toxics to total cancer risk in the San Joaquin Valley air basin.

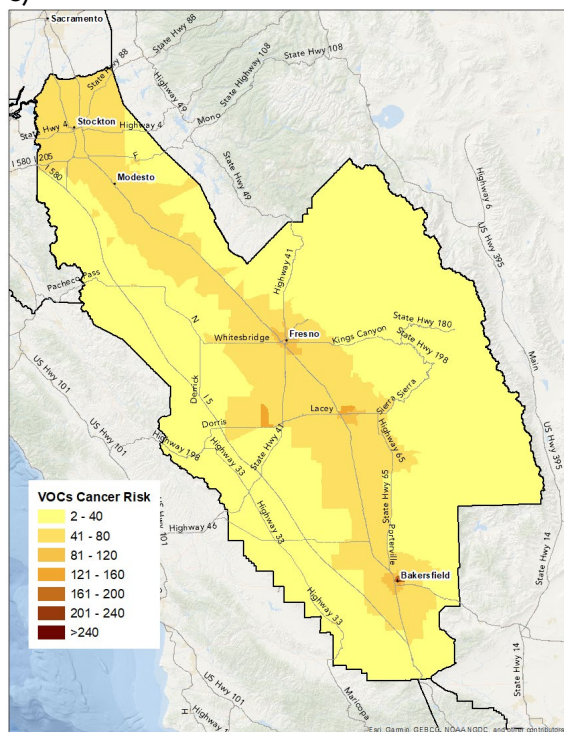
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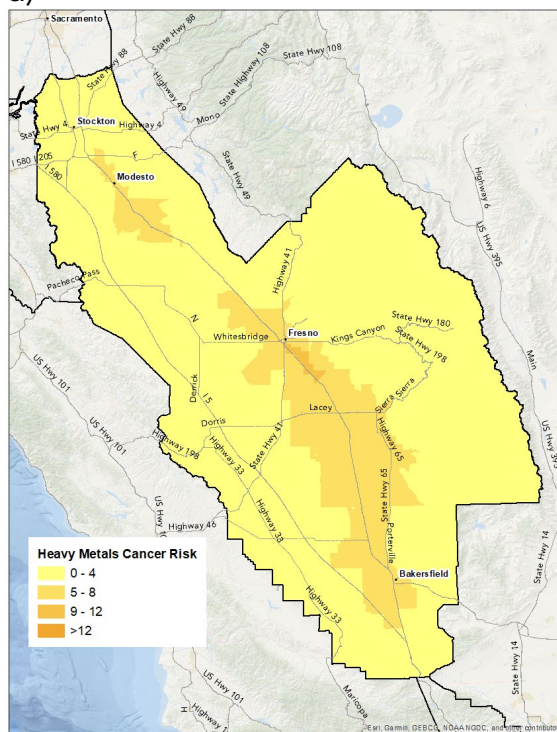


Figure VI-14. Maps of the 2017 cancer risks in San Joaquin Valley census tracts: a) Total cancer risk from all TACs (DPM + VOCs + heavy metals); b) Total cancer risk from all DPM sources; c) Total cancer risk from all VOCs; and d) Total cancer risk from all heavy metals.

South Coast

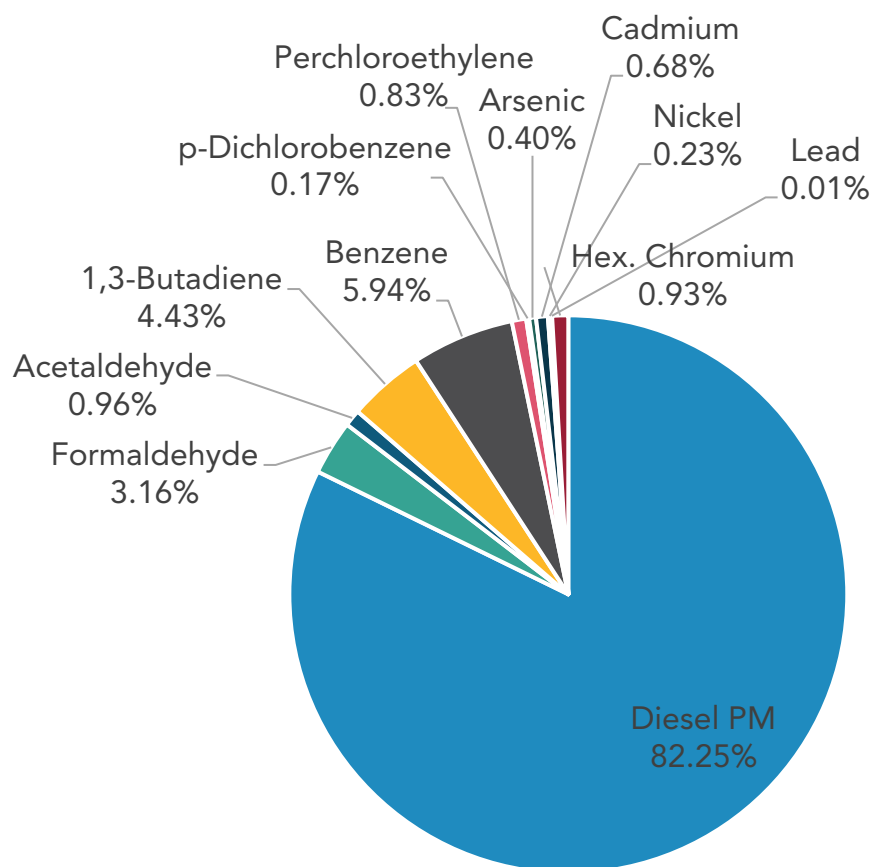
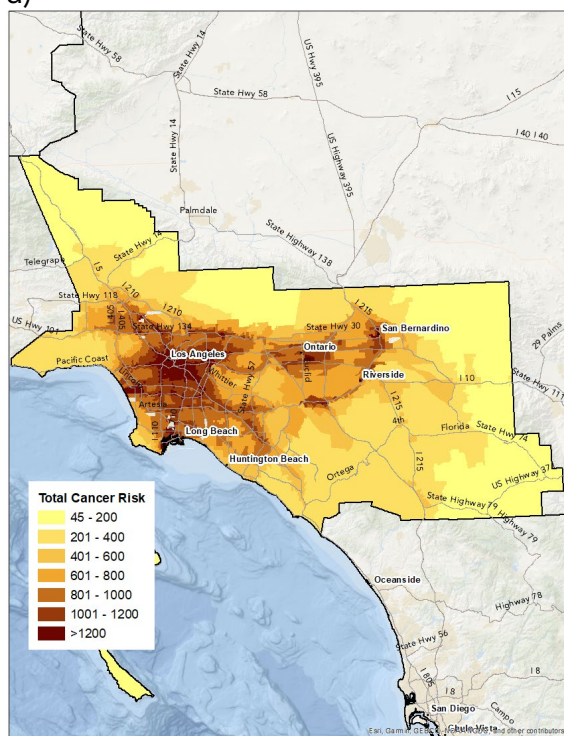
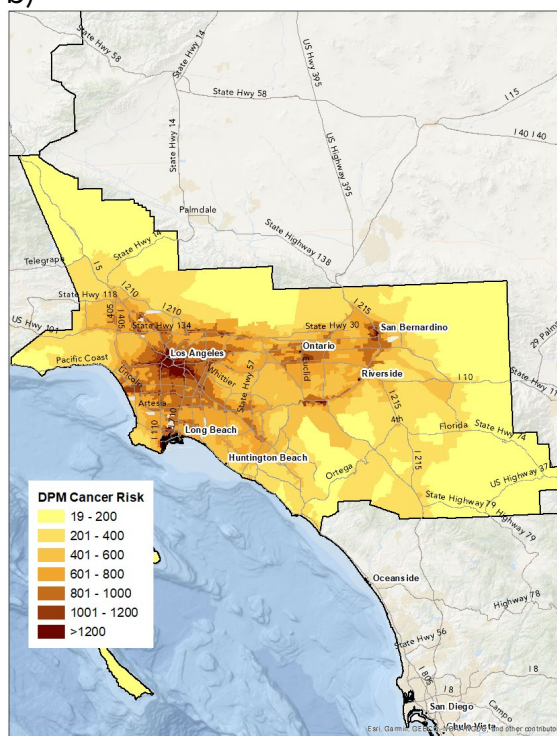


Figure VI-15. Relative contributions of air toxics to total cancer risk in the South Coast air basin.

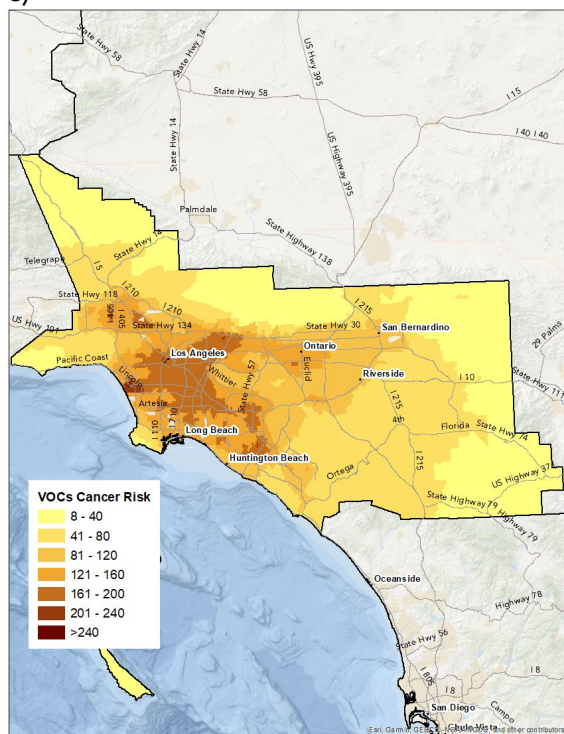
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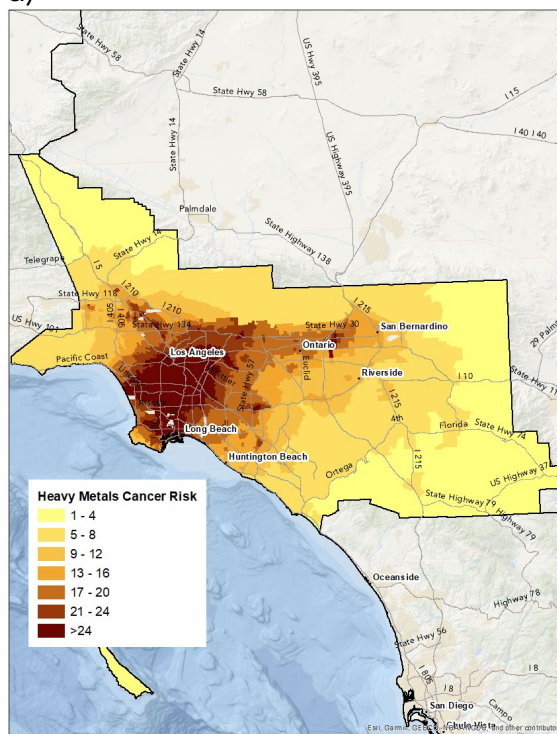


Figure VI-16. Maps of the 2017 cancer risks in South Coast census tracts: a) Total cancer risk from all TACs (DPM + VOCs + heavy metals); b) Total cancer risk from all DPM sources; c) Total cancer risk from all VOCs; and d) Total cancer risk from all heavy metals.

San Diego

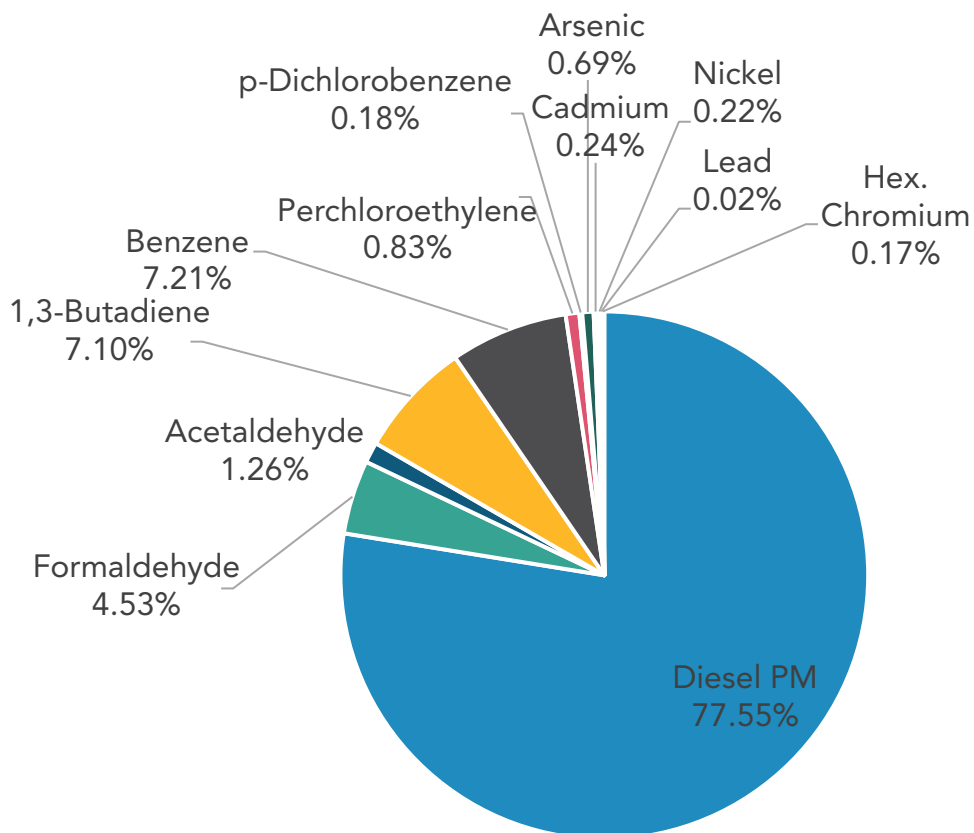
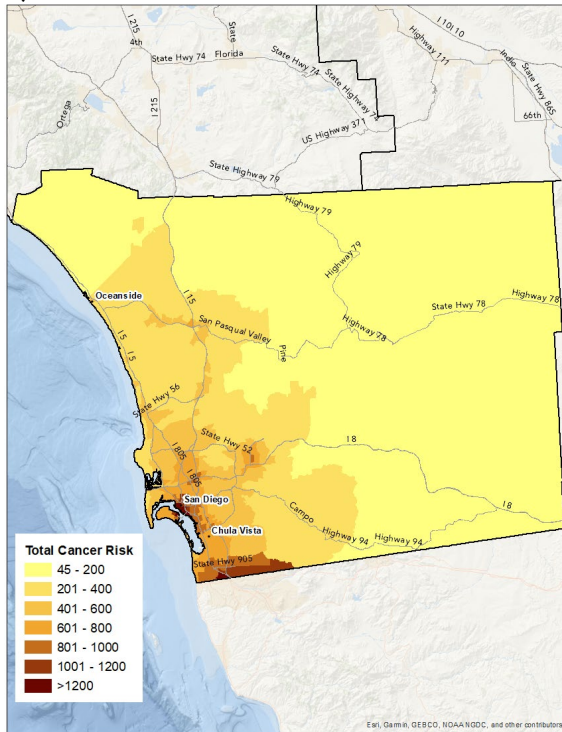
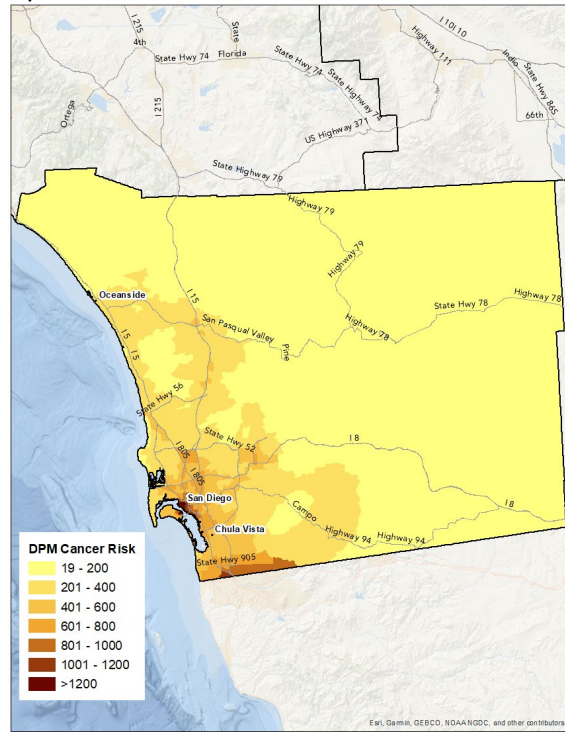


Figure VI-17. Relative contributions of air toxics to total cancer risk in the San Diego air basin.

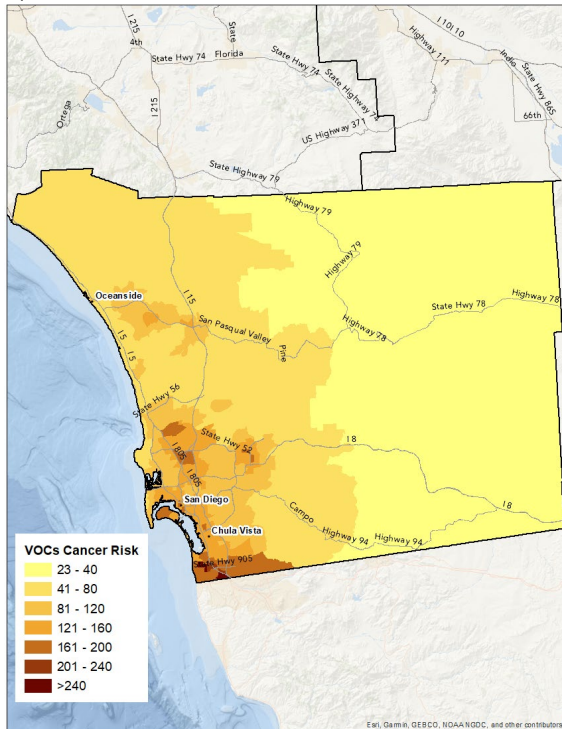
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d)

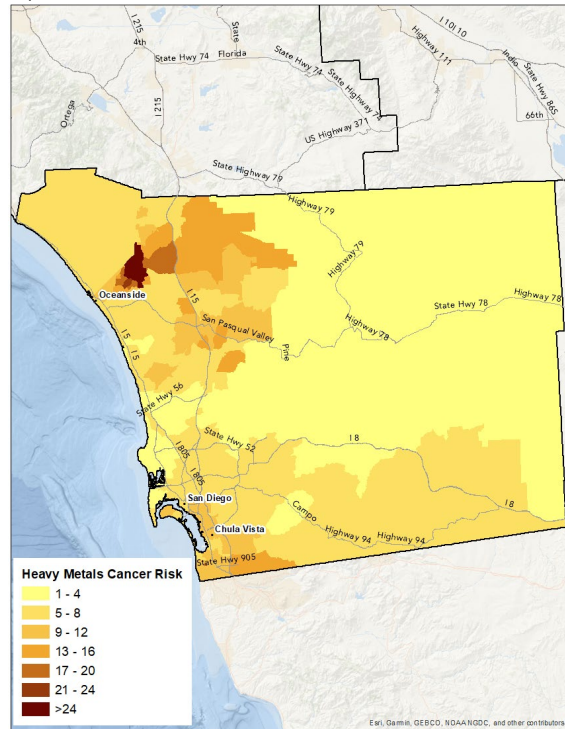


Figure VI-18. Maps of the 2017 cancer risks in San Diego census tracts: a) Total cancer risk from all TACs (DPM + VOCs + heavy metals); b) Total cancer risk from all DPM sources; c) Total cancer risk from all VOCs; and d) Total cancer risk from all heavy metals.

Imperial

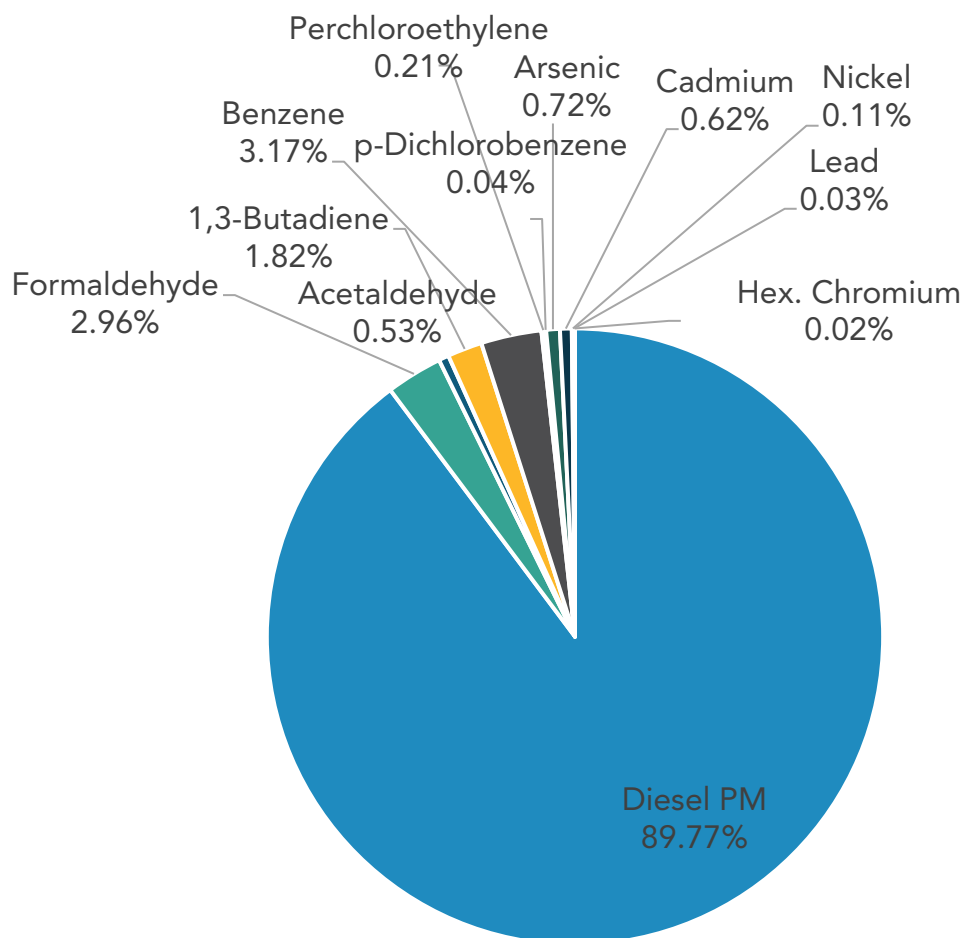


Figure VI-19. Relative contributions of air toxics to total cancer risk in the Imperial air basin.

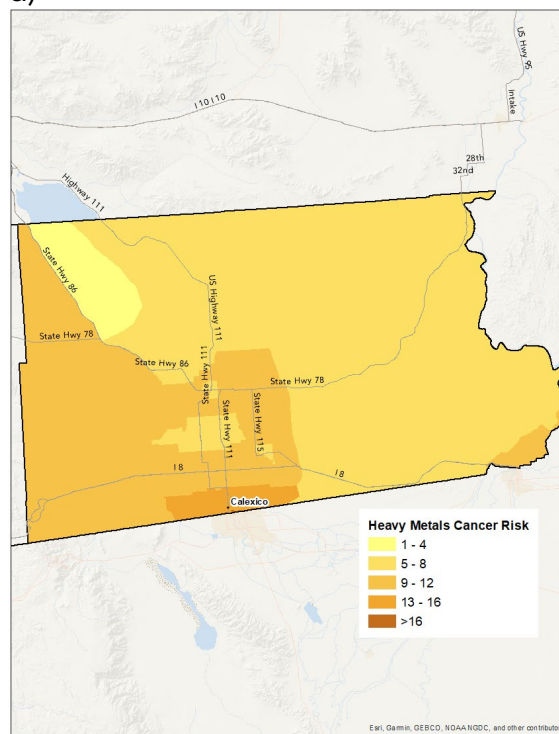
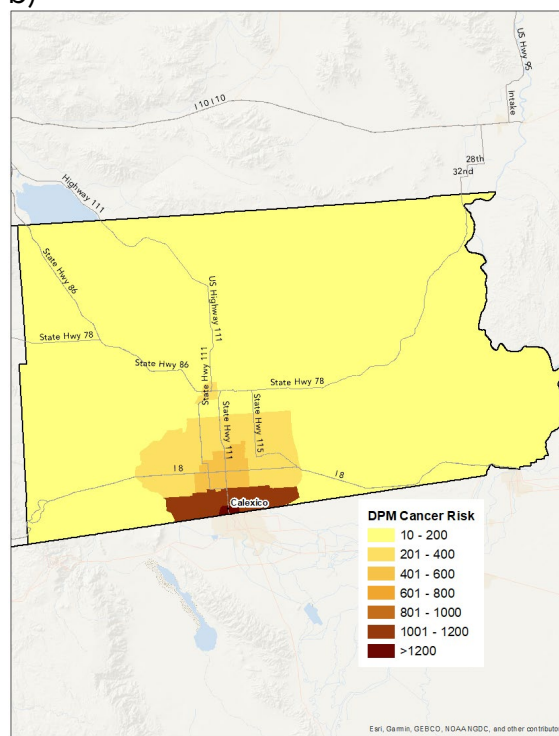


Figure VI-20. Maps of the 2017 cancer risks in Imperial census tracts: a) Total cancer risk from all TACs (DPM + VOCs + heavy metals); b) Total cancer risk from all DPM sources; c) Total cancer risk from all VOCs; and d) Total cancer risk from all heavy metals.

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Overall, DPM accounted for 80~90% of total cancer risk in air basins. High risk values are seen near major freeways and ports, in urban centers, and near the Mexican border for San Diego and Imperial. The population-weighted average cancer risk values are summarized by air basin and TAC in Table VI-2. Risks from DPM sources are further categorized into on-road mobile, off-road mobile, area, and stationary point sources. As we can see, even though on-road mobile sources are the top contributor of cancer risk in most air basins, the importance of other off-road and area sources such as agriculture, locomotives and port-related activities can vary substantially across air basins.

Table VI-2. Population-weighted cancer risk (chances per million) for each air basin from census tract averages.

<i>TACs/Emission Category</i>	<i>Bay Area</i>	<i>Sac Valley</i>	<i>San Joaquin Valley</i>	<i>South Coast</i>	<i>San Diego</i>	<i>Imperial</i>
<u>DPM</u>						
<i>On-road</i>	274.9	172.4	235.2	401.0	245.5	257.0
<i>Off-road</i>	56.3	32.6	38.8	152.5	63.2	296.3
<i>Area</i>	92.3	77.0	130.9	125.2	67.3	49.1
<i>Point</i>	1.5	2.3	0.6	4.1	0.6	0.2
<i>Total</i>	425.0	284.3	405.6	682.8	376.5	602.6
<u>VOCs</u>						
<i>Formaldehyde</i>	16.4	22.0	20.7	26.3	22.0	19.9
<i>Acetaldehyde</i>	4.2	6.4	6.7	8.0	6.1	3.6
<i>1,3-Butadiene</i>	20.4	11.3	13.5	36.8	34.5	12.2
<i>Benzene</i>	31.3	24.9	20.9	49.3	35.0	21.3
<i>Perchloroethylene</i>	0.9	2.2	2.0	6.9	4.0	1.4
<i>p-Dichlorobenzene</i>	1.0	0.8	0.8	1.4	0.9	0.3
<u>Heavy Metals</u>						
<i>Arsenic</i>	4.2	1.6	2.0	3.3	3.4	4.8
<i>Cadmium</i>	4.6	1.8	1.5	5.7	1.2	4.1
<i>Nickel</i>	1.4	0.8	0.6	1.9	1.1	0.8
<i>Lead</i>	0.1	0.0	0.0	0.1	0.1	0.2
<i>Hexavalent Chromium</i>	0.7	0.1	0.1	7.7	0.8	0.1
<u>Grand Total</u>	510.1	356.2	474.4	830.1	485.5	671.2

Table VI-3. Potential cancer burden (cases, 70-year exposure) from major air toxics groups.

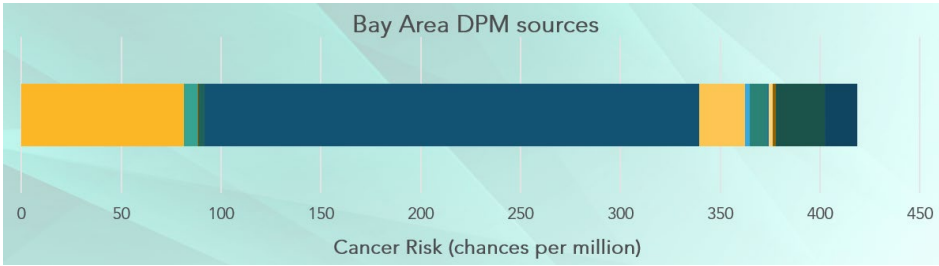
<i>Pollutant</i>	<i>Bay Area</i>	<i>Sac Valley</i>	<i>San Joaquin Valley</i>	<i>South Coast</i>	<i>San Diego</i>	<i>Imperial</i>
<i>DPM</i>	3554.6	936.0	1881.5	12896.0	1399.4	126.3
<i>Heavy Metals</i>	91.8	14.1	19.6	352.4	24.2	2.1
<i>Toxic VOCs</i>	620.6	222.9	299.6	2431.1	381.0	12.3

ii. Source apportionment of DPM sources

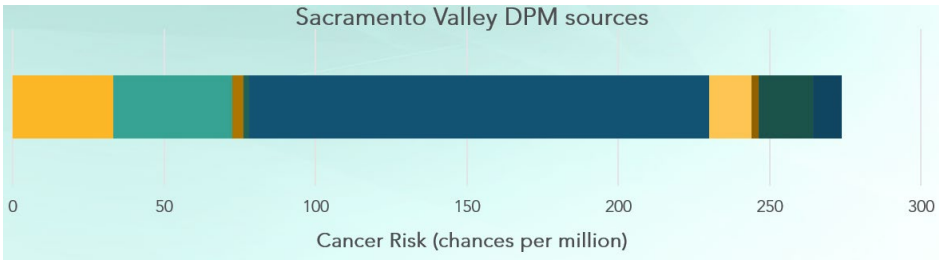
Figure VI-8 showed that on-road mobile sources were the most impactful DPM emission category. While it stands mostly true for each of the individual air basins, other categories had significant contributions to the overall risk and varied from basin to basin. Figure VI-21 shows the contributions of each emission category to total DPM cancer risk for each of the air basins. From left to right in the stacked bars, below were the major categories:

- Aggregated area-point sources (yellow color) were a noticeable source of cancer risk in most basins. It mostly consists of exhaust from industrial and commercial off-road equipment (air compressors, generators, welders, etc.), as well as small stationary sources like auto-body shops and gas stations that were aggregated into area sources.
- Risks associated to agricultural activities (teal color) were significant in the Sacramento and San Joaquin Valley.
- Impact from commercial harbor crafts (brown color) is noticeable in the South Coast and San Diego air basins.
- In-state major on-road mobile sources (freeways and major roads, in dark blue color) are the main contributors of risk across 5 of the 6 basins. Vehicles travelling on smaller, local roads (yellow bar right of the major on-road) had smaller but non-negligible contributions to the overall risk.
- Locomotives (dark green) and Transport Refrigeration Units (dark blue on the right end of bars) are both noticeable sources of risk in the Bay Area, Sacramento Valley, San Joaquin Valley, and in the South Coast.
- Transported on-road mobile emissions from Mexico are an important source of risk in both the San Diego and Imperial air basins, especially the latter, due to the proximity of in-state population to the border in those areas. Together, on-road and off-road mobile sources from Mexico accounted for about 73% of total DPM cancer risks in Imperial.

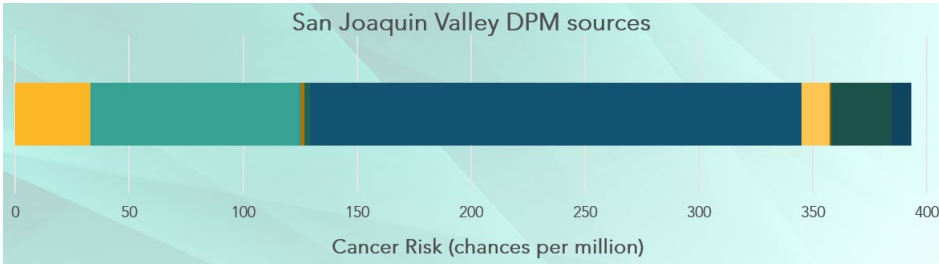
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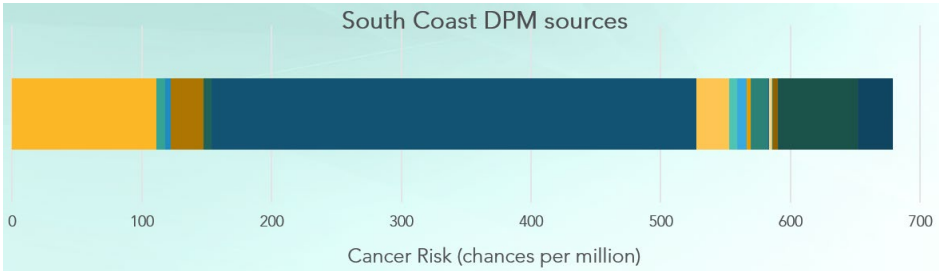
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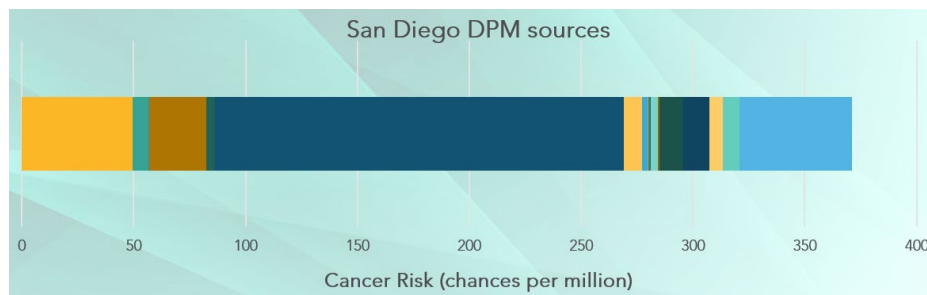


d)



- Aggregated Area-Point
- Agricultural activities
- Cargo Handling Equipment
- Commercial Harbor Craft
- Construction
- Major On-road Mobile
- Minor On-road Mobile
- OGV Anchorage
- OGV At-Berth
- OGV Maneuver
- OGV Transit-Cargo
- OGV Transit-Cruise
- OGV Transit-Tanker
- OGV-Military
- Point Sources without Coordinate
- Stationary Sources
- Trains
- Transport Refrigeration Units
- Mexico Area Sources
- Mexico Off-road Mobile
- Mexico On-road Mobile

e)



f)

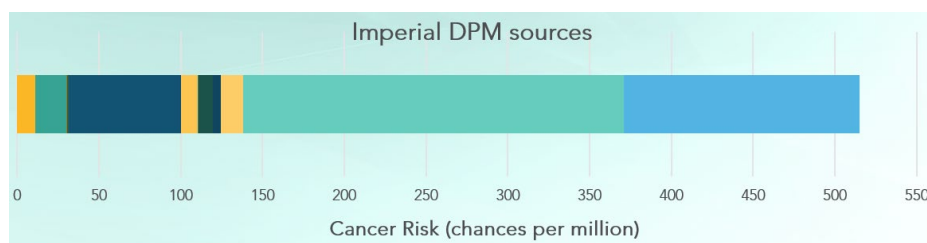


Figure VI-21. Bar charts showing the contributions of each emission source category to total DPM risks in the a) Bay Area, b) Sacramento Valley, c) San Joaquin Valley, d) South Coast, e) San Diego, and f) Imperial air basins.

iii. Trend analysis from 2012 to 2017

Prior to the 2017 CATA study presented here, an initial statewide air toxics study was conducted, which covered a 2012 base year. Combining results from the 2012 study with the 2017 CATA, means trends and changes in emissions and health impacts between 2012 and 2017 can be studied. Compared to the 2012 modeling results, total risks have been reduced by 17% to 55% in all air basins (Table VI-4). For both years, DPM sources were the major contributor to the overall risk. Figure VI-22 compares the change in total risk from 2012 to 2017 with change in DPM-related risks across the air basins. As we can see, DPM sources are also the main driver of the risk reductions we see from 2012 to 2017. In fact, the reduction of population-weighted average risk from DPM sources was larger than the reduction of overall risk (i.e., the statewide average risk from VOCs and heavy metals slightly increased from 2012 to 2017). More specifically, most of the reductions seen across the air basins are attributed to reductions in on-road mobile emissions in the past years due to implementation of the On-road Trucks and Bus rule and other programs. It is important to note here that improvements have been made to the modeling methodology and emissions in 2017, making it difficult to make a direct comparison of the results between the two modeling years, especially in low-risk areas where the impact of methodology changes may dominate the impact of real emission changes. One major improvement was a more complete emissions inventory of Mexico off-road emissions that were not available at the time of the 2012 base year modeling. To make a fairer assessment of trends for Imperial, where international transport is

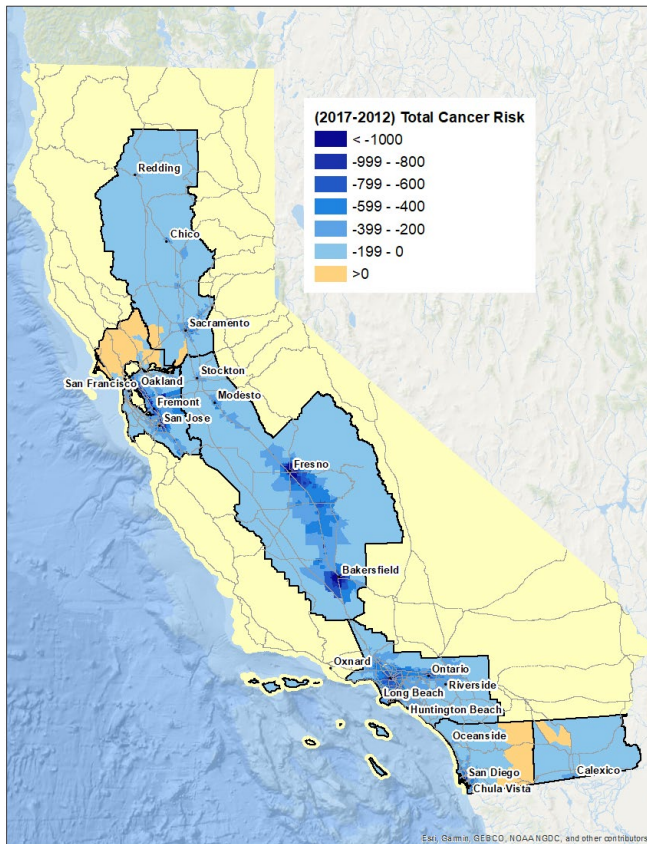
important, we estimated 2012 Mexico off-road DPM emissions and associated cancer risks by using back-projections from 2017 data and added them to the 2012 results, so that this emission sector is both present in the 2012 and 2017 modeling results. Another improvement in the 2017 modeling is the inclusion of wildfire emissions, which are a large contributor of certain TACs like formaldehyde and acetaldehyde but were not available for 2012. Therefore, the slight increases in cancer risks that are seen in certain low-risk areas such as northern Bay Area and western San Diego are partly due to the aforementioned improvements in the methodology, e.g., more complete emission inventories and modeling at a finer spatial resolution. Other areas where overall risk reductions are small reflect the much smaller reductions or increases in emissions in sectors other than on-road such as off-road mobile DPM sources, VOCs, and heavy metals.

Table VI-4. Population-weighted averages of census tract total cancer risks in 2017 and reduction from 2012 in the six air basins.

Air Basin	2012 Average Risk (chances per million)	2017 Average Risk (chances per million)	Change from 2012 (%)
Bay Area	870.7	510.1	-41.4
Sac Valley	596.6	356.2	-40.3
SJV	1063.2	474.4	-55.4
South Coast	1244.1	830.1	-33.3
San Diego	802.7	485.5	-39.5
Imperial	805.7	671.2	-16.7

Note that the total population in the six modeling domains where exposure and cancer risk are estimated is 36,727,572, which accounts for around 99% of total population in California.

a)



b)

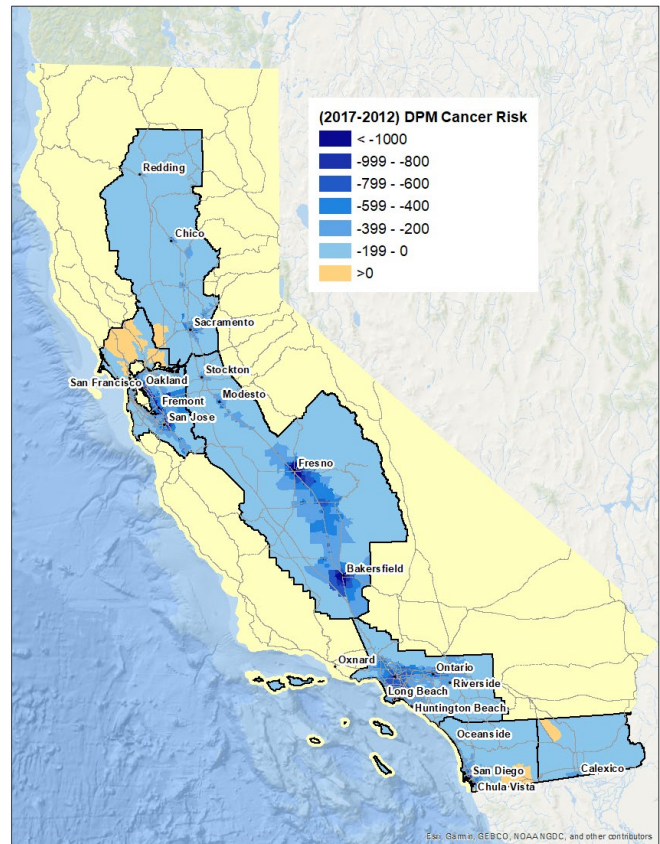


Figure VI-22. Maps of the change from 2012 to 2017 of a) total cancer risk, and b) DPM cancer risk on the same color scales. Blue (negative) values indicate reductions. Areas where risks were not estimated in 2012 are colored in cream.

C. Community Level

Our CALPUFF modeling for DPM and metals was able to capture fine scale concentrations and related risk variations for emission sources that can be accurately positioned in the modeling. For example, on-road sources were modeled as spatially accurate road following line sources. Along with high resolution receptors at census blocks, this allows model results to depict gradients of emission source impact at the community level. Figure VI-23 shows an example of such high-resolution gradients in the San Diego region, where the impact from major freeways is noticeably larger downwind. Dominant winds are generally from the west-northwest in that region based on surface meteorological monitor stations.

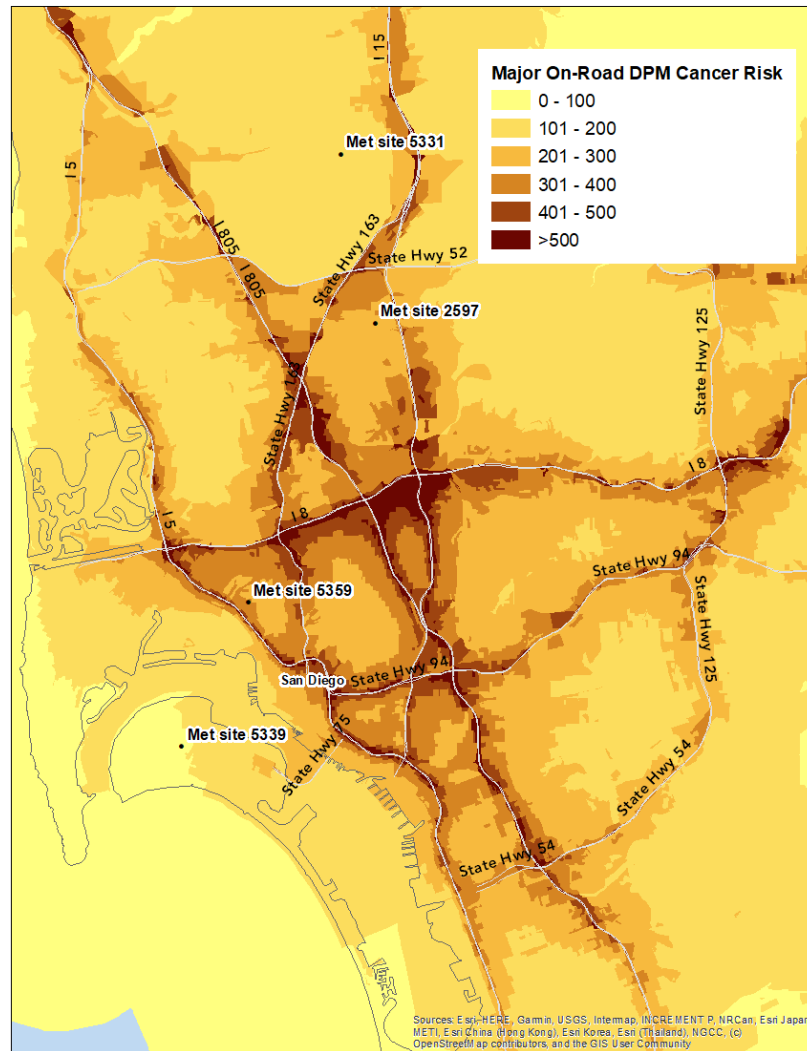


Figure VI-23. Zoomed-in map of a part of the San Diego region. Colors represent the potential cancer risk in census blocks from DPM emissions of major on-road mobile sources, risk in units of chances per million.

With the confidence that our modeling approach allows for the kind of qualitative community scale analysis detailed in the Executive Summary and in Section I, here we summarize the risk assessment for each of the Environmental Justice communities identified by AB 617 based on our statewide modeling. An overview of the cancer risks in each of the communities is presented in Table VI-5. Not surprisingly, the majority of the selected communities have significantly higher risks than the basin-wide averages.

Table VI-5. Population-weighted averages of total cancer risks in the AB 617 environmental justice communities.

Air Basin	Communities	Population (2010)	Average Risk (per million)
Bay Area	West Oakland	37,845	1052.3
	Richmond, North Richmond, San Pablo	138,983	387.2
Sac Valley	South Sacramento Florin	165,115	390.9
SJV	Shafter	18,072	492.5
	Stockton	82,120	599.8
	South Central Fresno	144,478	736.3
South Coast	East L.A., Boyle Heights, West Commerce	230,815	1604.8
	Southeast L.A.	243,086	1160.5
	San Bernardino, Muscoy	100,956	1046.1
	Wilmington, West Long Beach, Carson	409,551	995.6
San Diego	Portside Environmental Justice Communities	53,049	986.8
	International Border Community	34,594	1092.6
Imperial	Calexico, El Centro, Heber	97,710	1009.3

In addition, because the modeling in this study was done with highly detailed inputs such as categorized emission sources with high spatial resolution, along with high resolution meteorology, it is possible to extract useful community-level information such as the major source contributors to the community. Here we use Portside Environmental Justice

Communities (Portside), one community designated jointly by CARB's Office of Community Air Protection (OCAP) and the San Diego Air District, as an example of a detailed analysis at the community scale that this modeling work can support (Full report found in Appendix G).

Figure VI-24 depicts the overall risks in Portside resulting from all TACs and emission sources in the San Diego modeling domain. It is mapped to census tract level as a reconciliation between CMAQ and CALPUFF receptor resolutions by re-processing VOC results into census tract averages using GIS geoprocessing tools and adding them to the population-weighted tract averages of DPM and metal risks. Figures VI-25 through VI-27 show spatially distributed cancer risks for all TACs, total DPM, total VOCs and total metals, respectively, on their native model output resolution, i.e., at the centers of census blocks for DPM and heavy metals, and on 2-km x 2-km grids for VOCs.

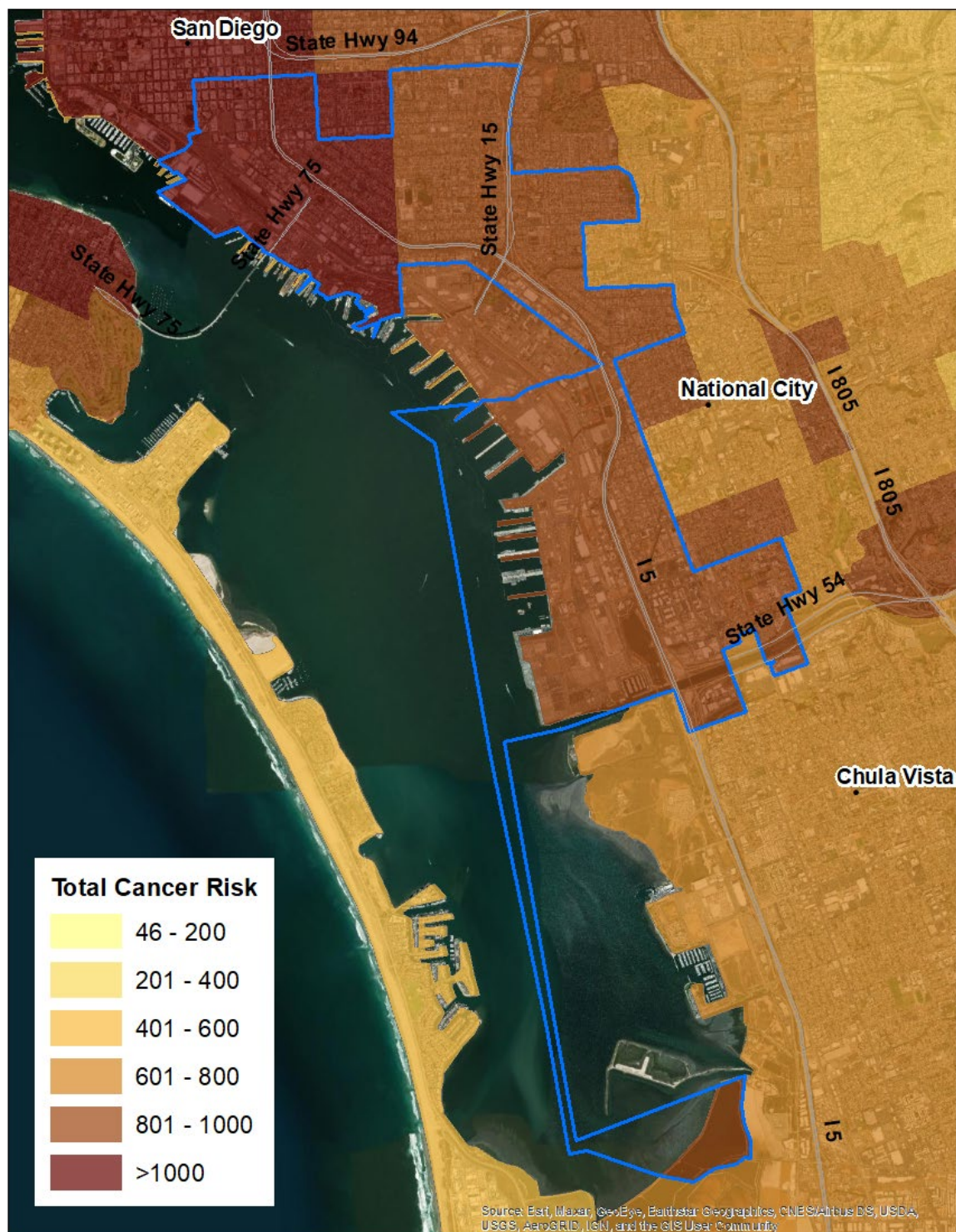


Figure VI-24. Simulated average cancer risk in census tracts from all TACs and all emission sources within the San Diego District, zoomed into Portside (2017). The community boundary is outlined in blue.

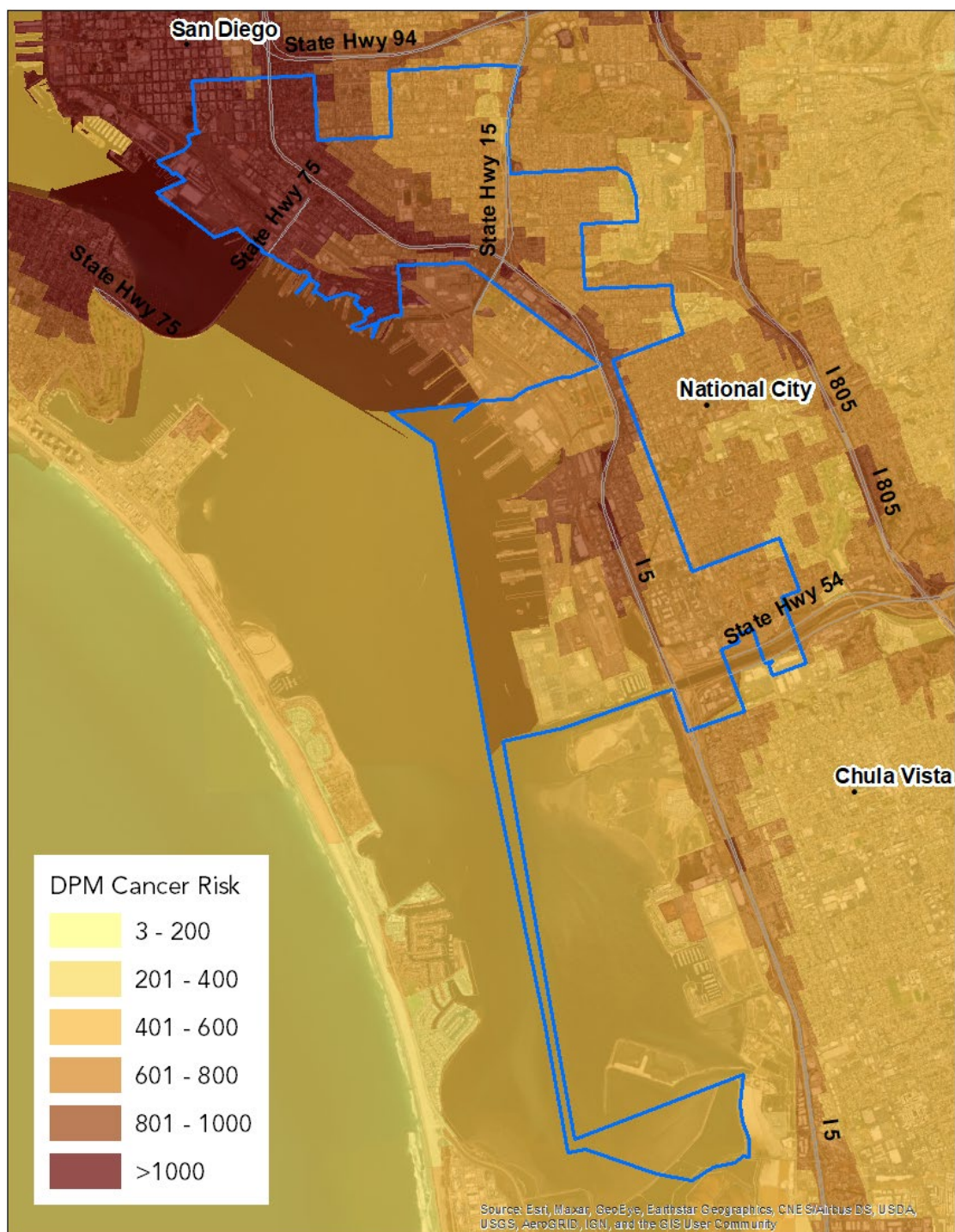


Figure VI-25. Simulated cancer risk at the center of census blocks from all DPM emission sources within the San Diego District, zoomed into Portside (2017). The community boundary is outlined in blue.

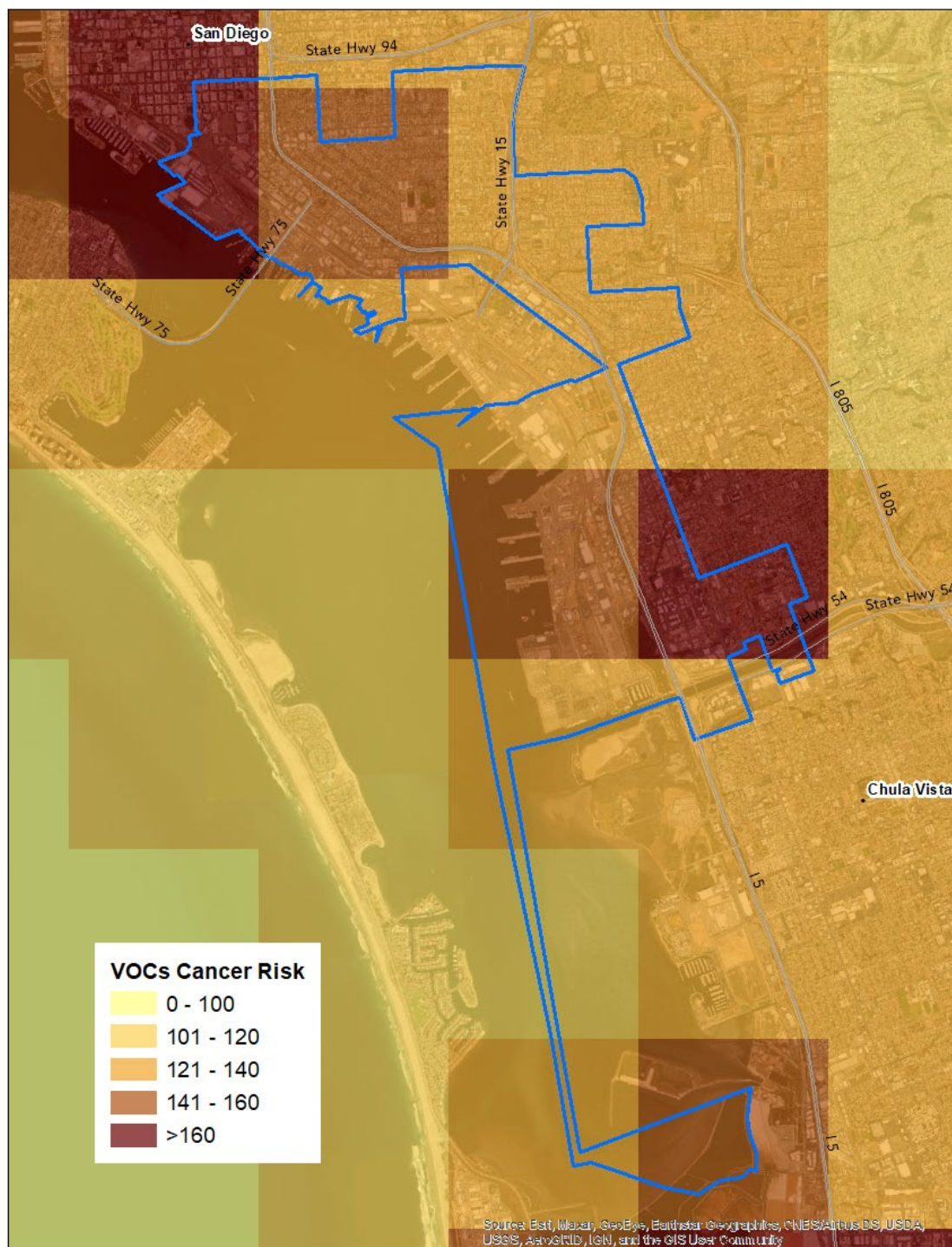


Figure VI-26. Simulated cancer risk on 2-km x 2-km grid from all VOC emission sources within the San Diego District, zoomed into Portside (2017). The community boundary is outlined in blue.

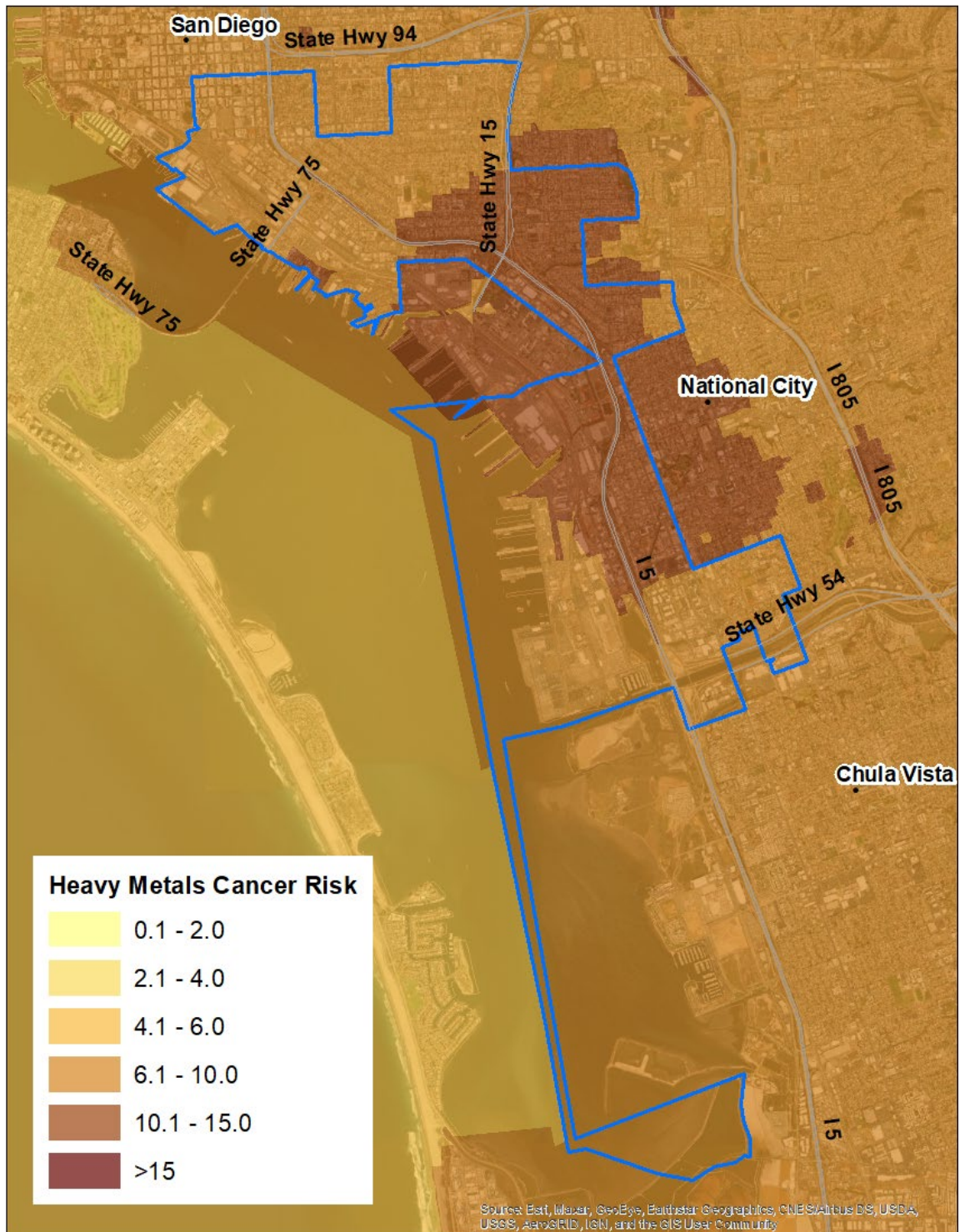


Figure VI-27. Simulated cancer risk at the center of census blocks from all heavy metals' emission sources within the San Diego District, zoomed into Portside (2017). The community boundary is outlined in blue.

Of the 13 TACs simulated, DPM ranks the highest (~85%) in terms of contribution to the overall cancer risk within Portside (Figure VI-28). The next three highest contributors include 1,3-butadiene (~5%), benzene (~5%) and formaldehyde (~3%). Together, these top-four TACs contribute to about 98% of total toxic risk. The remaining TACs combined accounted for about 2% of the total. The overall census tract-level population-weighted cancer risk is estimated to be about 987 per million within Portside.

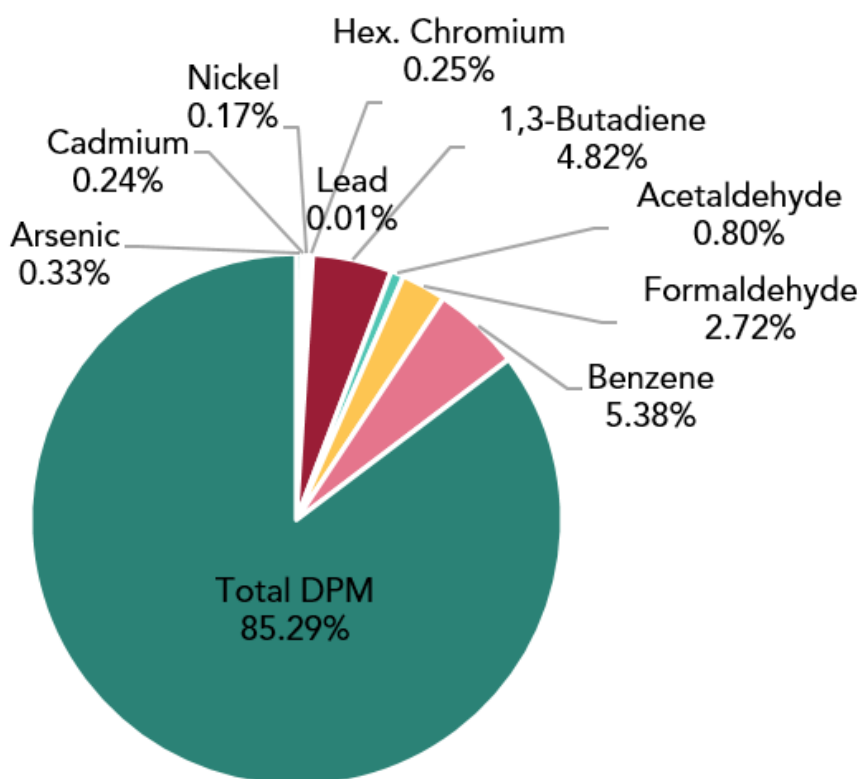


Figure VI-28. Relative contribution of individual TACs to overall excess cancer risk in Portside.

Figure VI-29 shows the relative contributions of each emission categories to the total population-weighted DPM risk in the Portside community for year 2017. The major source specific contributions to the overall DPM risk are on-road mobile sources (42%), CHC (19%), aggregated area-point sources (15%), Mexico on-road mobile sources (9%), TRU (6%), locomotives (3%), and OGV (3%).

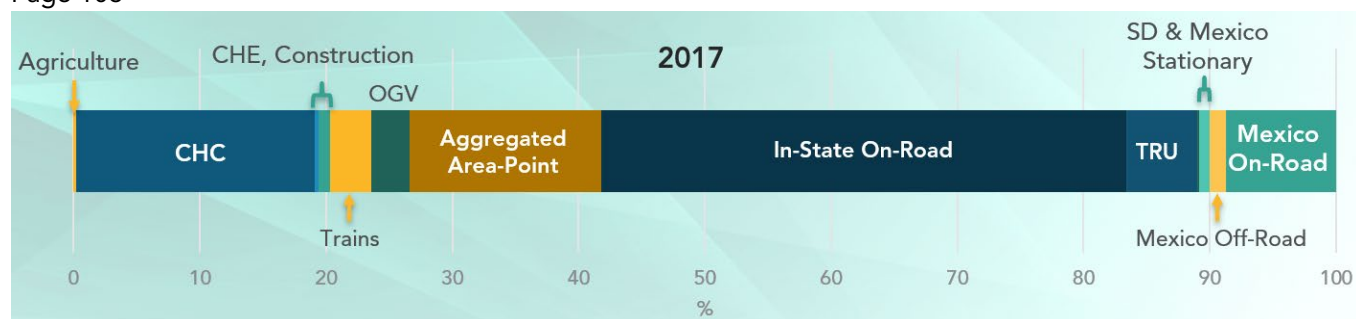


Figure VI-29. Relative contributions of emission categories to total DPM risk for the Portside community.

VII. Application for Regulatory Development

CARB staff have used a simplified method, called “*incidence-per-ton (IPT)*”, to estimate premature death and other health effects related to PM_{2.5} exposure. Originally, the method was developed by the U.S. EPA⁹ and used to estimate benefits of reductions in PM_{2.5} emitted directly from sources, and PM_{2.5} formed from precursors by chemical processes in the atmosphere. The basis/assumption of the IPT method is that changes in emissions are approximately proportional to changes in health outcomes. Mathematically an IPT factor equals the number of PM-related health effects divided by emissions of PM_{2.5} or a precursor, such as NO_x. By procedure, it essentially uses pre-calculated results, usually obtained by running a photochemical model (such as CMAQ) and a health effects model (such as BenMAP¹⁰) on a baseline scenario, to estimate the number of cases of adverse health outcomes. The IPT method allows users to input emission data due to emission reduction by a proposed regulation or a control measure to quickly estimate associated health benefits.

In Sections IV and VI we have presented the exposure and associated cancer risk for each TACs statewide and in the six major air basins. Here we apply the concept to develop toxic health related IPT factors based on the results presented in Section II (emissions) and VI (risk assessment). The IPT is defined as follows:

$$IPT = \frac{\text{Incidents (cases per million people, or cancer burden \#)}}{\text{Emissions for each TAC (tons per year)}}$$

IPT (i.e., cancer risk or burden per unit of toxic emissions) for DPM for each air basin and emission source category are summarized in Tables VII-1 and VII-2.

⁹ Fann N, Fulcher CM, Hubbell BJ. 2009. The influence of location, source, and emission type in estimates of the human health benefits of reducing a ton of air pollution Air Quality. Atmosphere & Health. 2:169-176.

¹⁰ <https://www.epa.gov/benmap>.

Table VII-1. IPT (risk/ton) of DPM sources by emission source category for each of the six air basins.

Source Category		Bay Area	Sac Valley	San Joaquin Valley	South Coast	San Diego	Imperial
On-Road		0.78	0.61	0.40	0.54	1.20	1.98
Off-Road	CHC	0.33	0.34	0.29	0.94	1.49	4.74
	CHE	0.46	0.53	0.55	0.39	0.98	4.62
	Locomotive	0.78	0.63	0.43	0.56	1.01	0.31
	OGV Anchorage	0.41	N/A	N/A	0.29	N/A	N/A
	OGV At-Berth	0.18	0.26	N/A	0.22	0.60	N/A
	OGV Maneuver	0.21	0.32	0.31	0.30	0.66	N/A
	OGV transit + military	0.12	0.25	0.22	0.11	0.24	N/A
	TRU	0.52	0.58	0.41	0.49	1.04	4.85
Area	Agriculture	0.08	0.11	0.10	0.14	0.17	0.43
	Construction	0.02	0.02	0.01	0.02	0.04	0.11
	Others	0.56	0.37	0.20	0.40	0.74	2.78
Stationary		0.23	0.41	0.09	0.12	0.22	0.05

Table VII-2. IPT (burden/ton) of DPM sources by emission source category for each of the six air basins.

Source Category		Bay Area	Sac Valley	San Joaquin Valley	South Coast	San Diego	Imperial
On-Road		6.63	2.08	1.93	10.19	4.51	0.51
Off-Road	CHC	2.90	1.16	1.38	17.85	5.58	1.22
	CHE	5.07	1.80	2.63	7.34	3.67	1.19
	Locomotive	6.60	2.16	2.08	10.56	3.79	0.08
	OGV Anchorage	3.52	N/A	N/A	5.47	N/A	N/A
	OGV At-Berth	1.55	0.88	N/A	4.23	2.26	N/A
	OGV Maneuver	1.76	1.10	1.51	5.72	2.46	N/A
	OGV transit + military	1.03	0.85	0.72	2.02	0.91	N/A
	TRU	4.38	1.98	1.99	9.33	3.90	1.25
Area	Agriculture	0.73	0.38	0.48	2.75	0.64	0.11
	Construction	0.18	0.07	0.06	0.30	0.16	0.03
	Others	4.72	1.27	0.94	7.59	2.79	0.72
Stationary		2.00	1.41	0.41	2.35	1.00	0.01

High cancer risk-based IPT values (Table VII-1) indicate emission sectors that are close to receptors and have relatively high health impact on that region's population. For example, it is seen that IPT values for DPM are higher for on-road mobile sources compared with other emission categories in all six domains, and IPT for locomotive is comparable to on-road mobile sources. This may be attributed to the fact that both on-road mobile sources and locomotives are in close proximity to residential areas, so their IPT values are similar, and higher than other sectors such as ocean-going vessels, for which much of the pollutants are emitted over bodies of water and away from residential areas. The general pattern of IPT is quite similar in all domains except in the Imperial County domain where values for CHC, CHE, and TRU are exceptionally high. The reason for high risk-based IPT values for the

Commercial Harbor Craft (CHC) and Cargo Handling Equipment (CHE) sectors in Imperial is, these emissions are located over in-land canals that serpent through populated areas, as opposed to being near ports and on the outskirts of city centers for the other basins. Another factor that may have led to higher IPT values in Imperial is the fact that the domain is very small, so the majority of the population in the domain is close to emission sources.

In contrast, cancer burden-based IPT values (Table VII-2) are dominated by population density. High values indicate emission sectors that are not only close to populations, but also close to highly dense populations. As we would expect, the Bay Area and South Coast have some of the highest values due to their large population. CHC emissions in South Coast in particular gave the highest burden-based IPT value, due to the high population density in the Long Beach area. In contrast, Imperial had relatively small burden-based IPT values even when pollutants are emitted near its population, because the total amount of population is relatively small compared to other basins.

The IPT values for toxic VOCs for each air basin are presented in Tables VII-3 and VII-4. It can be seen from Table VII-3 that 1,3-butadiene, benzene, and formaldehyde pose more threat to public health within all geographic locations. The San Diego County and San Francisco Bay Area air basins were estimated to have 0.253 and 0.107 chances per million per ton of 1,3-butadiene emissions, respectively. In other words, approximately 1 in 4 million people is likely to develop cancer per ton of 1,3-butadiene emissions per year due to exposure over a 30-yr period in San Diego. Overall, 1,3-butadiene is estimated to have 1 case in 41.8 million per ton of emissions per year within the regions encompassed by the six modeling domains in California. Other toxic VOC species such as perchloroethylene, formaldehyde, benzene, acetaldehyde, and p-dichlorobenzene are estimated to have 1 case in 625 million, 909 million, 126.6 million, 2 billion, and 3.3 billion per ton of emissions per year, respectively.

Comparing Table VII-3 with Table VII-1, we can see that IPT values for VOCs are much lower. This can be attributed to the two facts that 1) the unit risk factors (URFs) of the VOCs (the last column in Table VII-3) are smaller than that of DPM ($3.0\text{E-}4$); and 2) VOCs emissions are averaged over a larger area in the gridded modeling domains and are subject to chemical reaction in the atmosphere, thus their concentrations diluted and represent averages over larger areas.

Table VII-3. IPT (risk/ton) of VOC species for each of the six air basins.

Toxics	Sac Valley	Bay Area	SJV	SC	SD	Imperial	URF ($\mu\text{g}/\text{m}^3$) ⁻¹
Acetaldehyde	0.003	0.002	0.001	0.005	0.008	0.011	2.70E-06
Formaldehyde	0.011	0.004	0.003	0.008	0.025	0.137	6.00E-06
Benzene	0.044	0.033	0.026	0.026	0.077	0.413	2.90E-05
1,3-Butadiene	0.092	0.107	0.065	0.083	0.253	0.851	1.70E-04
p-Dichlorobenzene	0.003	0.001	0.001	0.008	0.028	0.120	1.10E-05
Perchloroethylene	0.010	0.008	0.006	0.004	0.017	0.090	6.10E-06

Table VII-4. IPT (burden/ton) of VOC species for each of the six air basins.

Toxics	Sac Valley	Bay Area	SJV	SC	SD	Imperial
Acetaldehyde	0.008	0.016	0.004	0.082	0.028	0.002
Formaldehyde	0.031	0.028	0.012	0.133	0.083	0.026
Benzene	0.131	0.247	0.109	0.437	0.255	0.078
1,3-Butadiene	0.272	0.803	0.272	1.401	0.846	0.160
p-Dichlorobenzene	0.010	0.008	0.002	0.139	0.095	0.023
Perchloroethylene	0.028	0.058	0.024	0.076	0.057	0.017

Note that these IPT factors are developed based on the air basin level. They can be used directly to estimate the reduction in health outcomes (potential health cancer and cancer burden) achieved by any newly proposed or existing CARB toxic reduction regulation in a particular air basin. As an example, suppose the hypothetical case where the proposed DPM emission reduction from the OGV-at berth regulation is 10 tons per year in San Diego County, the resulting cancer risk and burden reductions at the County level would be about 6 chances per million people and 22 cases, respectively.

These factors may also be used to inform the toxic emission and exposure reduction strategies in support of the districts' CERP with some caution. For those communities with greater pollution burden, the IPT factors for certain emission categories could be much

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higher. For a community near a seaport, the IPT factors for on-road and off-road may be much higher. Nevertheless, these factors can still be used to compare/screen relative effectiveness of different control measures.

There may be a need to estimate other health outcomes such as premature death from DPM exposure. These IPT factors can be easily converted into premature death and/or other health outcomes.

It is expected that these factors will change with time as populations grow and emissions change. The next triennial modeling iteration will update these factors and provide greater insight into the trends over time.

VIII. REFERENCES

Angevine, W. M., L. Eddington, K. Durkee, C. Fairall, L. Bianco, and J. Brioude, 2012, Meteorological model evaluation for CalNex 2010. *Monthly Weather Review* (140): 3885-3906.

Baker, K. R., C. Misenis, M. D. Obland, R. A. Ferrare, A. J. Scarino, and J. T. Kelly, 2013, Evaluation of surface and upper air fine scale WRF meteorological modeling of the May and June 2010 CalNex period in California. *Atmospheric Environment* (80): 299-309.

Chen, J., D. Yin, Z. Zhao, A. P. Kaduwela, J. C. Avise, J. A. DaMassa, A. Beyersdorf, and S. Burton et al., 2020, Modeling air quality in the San Joaquin Valley of California during the 2013 DISCOVER-AQ field campaign. *Atmospheric Environment* (5): 100067.

Fast, J. D., W. I. Gustafson Jr, L. K. Berg, W. J. Shaw, M. Pekour, and M. Shrivastava et al., 2012, Transport and mixing patterns over Central California during the carbonaceous aerosol and radiative effects study (CARES). *Atmospheric Chemistry and Physics* (12): 1759-1783.

Hu, J., C. J. Howard, F. Mitloehner, P. G. Green, and M. J. Kleeman, 2012, Mobile Source and Livestock Feed Contributions to Regional Ozone Formation in Central California. *Environmental Science and Technology* (46): 2781-2789

Karamchandani, P., Emery, C. and Brashers, B., 2022, User's Manual of the Mesoscale model interface (MMIF) program version 4.0, available at <https://www.epa.gov/scram/air-quality-dispersion-modeling-related-model-support-programs>

Kelly, J. T., K. R. Baker, J. B. Nowak, J. G. Murphy, Z. M. Milos, T. C. VandenBoer, R. A. Ellis, et al., 2014, Fine-scale simulation of ammonium and nitrate over the South Coast Air Basin and San Joaquin Valley of California during CalNex-2010. *Journal of Geophysical Research* (119): 3600-3614. doi:10.1002/2013JD021290.

OEHHA, 2015, *Air Toxics Hot Spots Program Guidance Manual for Preparation of Health Risk Assessments*, available at <https://oehha.ca.gov/air/cnr/notice-adoption-air-toxics-hot-spots-program-guidance-manual-preparation-health-risk-0>

Otte, T.L., Pleim, J.E., 2010, The Meteorology-Chemistry Interface Processor (MCIP) for the CMAQ modeling system: updates through MCIPv3.4.1, Geoscientific Model Development, <https://www.geosci-model-dev.net/3/243/2010/>

Schauer J.J., 2003, Evaluation of elemental carbon as a marker for diesel particulate matter. Journal of Exposure Analysis and Environmental Epidemiology. 13: 443-53.

Scire, J.S., F.R. Robe, M.E. Fernau, R.J. Yamartino, 2000, *A User's Guide for the CALMET Meteorological Model (Version 5)* Earth Tech, Inc, Concord, MA (2000)

Scire, J.S., D.G. Strimaitis, R.J. Yamartino, 2000b, *A User's Guide for the CALPUFF Dispersion Model (Version 5)*, Earth Tech, Inc, Concord, MA (2000)

San Diego, 2016, 2016 Plan for the 2008 8-Hour Ozone Standard, available at:

<https://www.sandiegocounty.gov/content/dam/sdc/apcd/PDF/Air%20Quality%20Planning/8-Hr-O3%20Attain%20Plan-08%20Std.pdf>

SJV, 2016, 2016 Plan for the 2008 8-Hour Ozone Standard, available at:

http://valleyair.org/Air_Quality_Plans/Ozone-Plan-2016.htm

South Coast, 2016, Final 2016 Air Quality Management Plan, available at:

<http://www.aqmd.gov/docs/default-source/clean-air-plans/air-quality-management-plans/2016-air-quality-management-plan/final-2016-aqmp/cover-and-opening.pdf?sfvrsn=6>

Skamarock, W. C., J. B. Klemp, J. Dudhia, D. O. Gill, D. M. Barker, W. Wang, and J. G. Powers, 2005: A description of the Advanced Research WRF Version 2. NCAR Tech Notes-468+STR.

U.S. EPA, 1999, *Science Algorithms of the EPA Models-3 Community Multiscale Air Quality (CMAQ) Modeling System*. EPA/600/R-99/030.

United States Environmental Protection Agency. (2020). CMAQ (Version 5.3.2) [Software]. Available from <https://doi.org/10.5281/zenodo.4081737>