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Diesel particulate matter health impacts in California: Trends, source apportionment, and policy implications[☆]

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ABSTRACT

Diesel particulate matter (DPM) has been recognized as a carcinogen and identified as a toxic air contaminant (TAC) in California and other jurisdictions. In response to this identification, the California Air Resources Board (CARB) has adopted numerous regulations aimed at reducing DPM emissions from various sources. This study utilized an integrated modeling approach to simulate ambient DPM concentrations for individual emission sectors separately for the two years 2012 and 2017. The associated health impacts, including cancer risk and non-cancer effects, were then assessed. This assessment provided a basis for apportioning emission sources, analyzing reduction trends, and informing further regulatory efforts when combined with future emissions projections.

Our results showed a significant reduction in DPM-related cancer risk in California between 2012 and 2017. Specifically, population weighted DPM cancer risk decreased by 42 %, and mortality attributable to DPM exposure decreased by about 50 % statewide. Additionally, census tracts with higher population densities consistently experienced more significant reductions in DPM cancer risk from 2012 to 2017.

Source apportionment analysis indicated that, as of 2017, on-road mobile sources were the largest contributor to overall DPM risk, followed by off-road mobile, area, and stationary sources. Our findings further suggest that while the overall health risk from DPM will continue to decline with emissions, the relative contributions of each emission sector to DPM risk may shift over time depending on the major regulations in place, and how the emission reductions impact nearby population. When accounting for how emissions have changed since 2017 and are projected to change in the future, new emission reduction efforts will likely need to prioritize off-road mobile sources (e.g., seaports, airports, locomotives) and area sources (e.g., construction and agricultural sectors) to achieve further risk reductions, especially beyond 2025.

1. Introduction

Diesel particulate matter (DPM) is widely recognized for its significant health impacts due to containing over 40 known carcinogenic substances (CARB, 2025). In 1998, the California Air Resources Board (CARB) identified and classified DPM as a Toxic Air Contaminant (TAC) (CARB, 1998), prompting a concerted effort to reduce its emissions. CARB adopted the Diesel Risk Reduction Plan (DRRP) in 2000 (CARB, 2000), leading to the adoption of various regulations targeting emissions from heavy-duty diesel engines, trucks, buses, and other sources.

The implementation of these regulations has yielded tangible results, with reported reductions in emission rates of elemental carbon (EC), a major component of DPM, and other pollutants from trucks operating on California roadways (Kozawa et al., 2014; Bishop et al., 2015; Dallmann et al., 2012; Preble et al., 2015; Kuwayama et al., 2013). Additionally, California enacted diesel fuel regulations aimed at reducing sulfur and aromatic hydrocarbons in both vehicular and non-vehicular emissions to address regional air quality issues related to ozone (O_3) and particulate matter (PM) pollution. Lower sulfur content in diesel fuel has been linked to reduced DPM emissions (Weaver et al., 1986; Saiyasitpanich et al., 2005; Ristovski et al., 2006; Zhang et al., 2009).

DPM has been considered as a major contributor to excess cancer risk

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in California due to its high carcinogenic potency and substantial emission levels. Additionally, DPM poses other health concerns such as negative effects on immunological or inflammatory systems (Sydbom et al., 2001), the cardiovascular system (Campen et al., 2003), and respiratory system (Ristovski et al., 2012). Progress in reducing health risks associated with DPM is typically assessed based on the magnitude of emission reductions (Lloyd and Cackette, 2001; Schwarzman et al., 2021). However, it is important to recognize that the health risk linked to DPM is more closely tied to ambient concentrations than simply to emission rates. This is because exposure and subsequent risk are determined by the ambient concentration of DPM, which can be significantly different from magnitude and spatial distribution of emissions because of the transport and diffusion processes in the atmosphere. The focus of the present study is to accurately estimate statewide ambient concentrations of DPM and inhalation health risks from DPM using an air quality modeling approach. It is crucial to use ambient concentrations, instead of emissions, to evaluate past, present, and future exposure levels, as well as to track the efficacy of efforts to reduce DPM emissions. Furthermore, DPM emissions originate from various sources, including on-road mobile, off-road mobile, area, and stationary sources. In this study, area sources represent all emission sources that are not classified as on-road mobile, off-road mobile or major stationary sources. Examples include farm equipment and portable engines; they are treated as area sources because they don't have unique locations over time, making it difficult to precisely specify where and when pollutants are released. Each emission source may contribute differently to the overall health impacts of DPM. Therefore, there is a pressing need to not only assess the absolute contribution of each emission source but also to understand their relative importance. Investigating the relative contribution of different emission sources can provide valuable insights for prioritizing and targeting mitigation efforts effectively.

The concentration of DPM in the atmosphere is influenced by the magnitude of emissions as well as by factors such as the location of emission sources relative to receptors, terrain features, and meteorological conditions. To more accurately assess the health impacts of DPM on both regional and local scales in California, high-resolution datasets of DPM concentrations that are both spatially and temporally resolved are essential. However, it is not possible at present to directly measure ambient DPM. Researchers have employed indirect methods to estimate these concentrations. For example, one approach involves using EC and nitrogen oxides (NOx) as surrogates for DPM and estimating DPM concentrations by scaling EC or NOx concentrations. However, these methods have been implemented without rigorous justifications (Verma, 2003; Propper et al., 2015; Hedmer et al., 2017). Even when the means of directly measuring DPM in the atmosphere becomes available, obtaining comprehensive measurements of DPM concentrations on regional and fine spatial scales over an extended period, such as an entire year, is extremely labor- and instrument-intensive, posing significant challenges due to resource constraints and high costs. Therefore, alternative approaches, such as air quality modeling, are necessary and often used to estimate DPM concentrations and assess associated long-term health impacts.

The U.S. EPA's National Air Toxics Assessment (NATA) (U.S. Environmental Protection Agency, 2016) uses a combination of the Community Multiscale Air Quality Modeling (CMAQ) system (U.S. Environmental Protection Agency, 2025a) and the AERMOD dispersion model (U.S. Environmental Protection Agency, 2025b) to estimate ambient hazardous air pollutant (HAP) concentrations at the national level, with CMAQ employing grid resolutions of 12 km $\times$ 12 km or coarser. Regional assessments in California, such as the South Coast Air Quality Management District's (SCAQMD) MATES studies (SCAQMD, 2021) and the Bay Area Air Quality Management District (BAAQMD) efforts (BAAQMD, 2014) utilize photochemical models, i.e., Comprehensive Air Quality Model with Extensions (CAMx) and CMAQ, at resolutions of 2 km $\times$ 2 km and 1 km $\times$ 1 km, respectively. While these models effectively simulate reactive toxins, they have limitations in accurately characterizing local exposures such as at community levels due to their coarse resolutions. Conversely, modeling at finer spatial resolutions can provide more detailed and accurate assessments of pollutant concentrations at the local level (Hamilton and Harley, 2021).

In this study, we employed an integrated modeling approach (Fig. 1) to quantify DPM exposure and assess associated health risks across California, from local communities to the statewide level. This approach accommodated emission sources by sector and allowed us to analyze trends in exposure and health impacts over time, providing a means to evaluate the effectiveness of California's DPM emissions regulations. By quantifying the contributions of different emission source categories to overall DPM impact, we can prioritize future emission reduction efforts. The overarching aim of this study is to inform and support the development of targeted regulations and policies that further reduce DPM emissions in California.

The objectives of our study are threefold: 1) to quantify ambient exposure to diesel particulate matter (DPM) and assess associated health impacts in California; 2) to analyze the trend in exposure and health impacts over time to evaluate the effectiveness of California's DPM emissions regulatory efforts; and 3) to quantify the relative contributions of each emission source category/sector to the overall DPM impact. The analysis also aims to inform and support the development of further regulations and policies targeting specific emission sources.

2. Materials and Methods

2.1. Modeling domains

Six separate modeling domains, covering the most populous regions of California, were used to simulate statewide ambient DPM concentrations. This approach was chosen over a single statewide modeling domain due to limitations in present-day computational resources, such as processing time, storage capacity, and memory requirements. The domains are listed from north to south as follows: Sacramento Valley (SV), Bay Area (BA), San Joaquin Valley (SJV), South Coast (SC), San Diego (SD), and Imperial County (IMP) (*SI Appendix* Fig. S1). The population within these modeling domains accounted for approximately 99 % of the state's total population based on 2010 census data. Based on our current understanding of toxic pollutant emissions, these domains should cover all populated areas significantly impacted by toxic air contaminants. *SI Appendix* Fig. S1 shows the six modeling domains along with the major on-road sources (traffic links) in each domain. Additional information is provided in *SI Appendix* Table S1 including population, and the number of census tracts and census blocks. The modeling periods for this study were selected to cover the years 2012 and 2017, which were the years with the most complete and recent regulatory emission inventory and meteorology at the time of this study.

2.2. Air quality and meteorological models

Air Quality Model. The objective of the air quality modeling was to assess the current state of DPM exposure across California and trends in ambient DPM concentrations over time. Traditionally, for regional-scale air quality modeling, grid-based regional-scale photochemical models, such as CMAQ and CAMx are usually the preferred modeling platform (e.g., Buonocore et al., 2014). Since the major portion of DPM mass like EC, ash and metallic abrasion particles is inert and the chemical reaction pathways among the reactive components are essentially not known, it is reasonable to treat DPM as an inert pollutant. For inert pollutants, air dispersion models have several advantages over grid-based photochemical models. In dispersion modeling, the location and spatial extent of emission sources can be more accurately represented. For example, on-road mobile sources can be treated as "road-segment-like" line sources instead of area sources with dimensions coincident with the modeling grids. Another advantage is that in dispersion modeling, receptors (places where concentrations are computed) can be placed

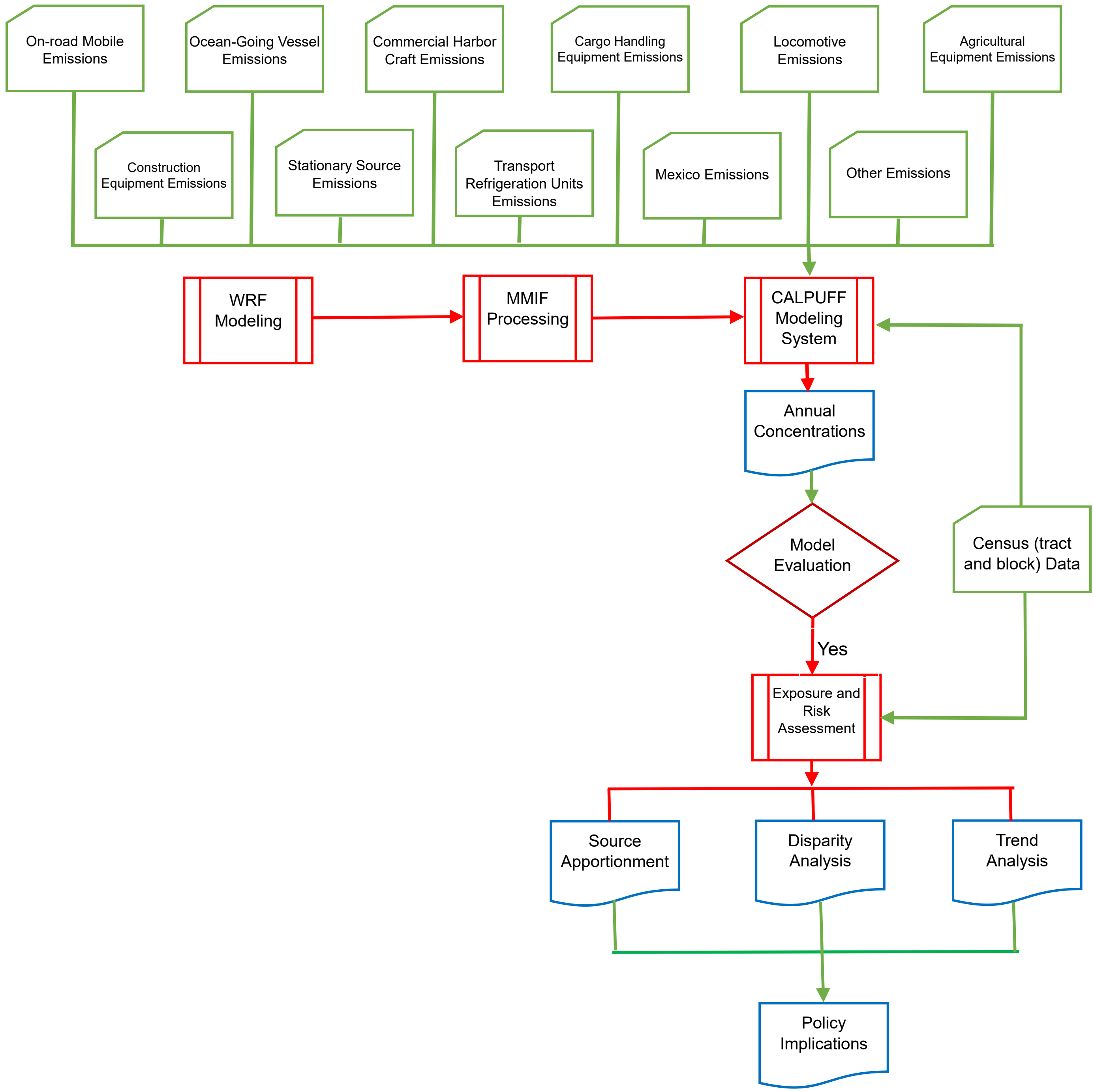

Fig. 1. Integrated modeling framework. Flowchart of the methodology to calculate DPM concentrations and to estimate health risks. Further analyses of source apportionment and geographic disparity as well as policy implications are also major components of the present study.

anywhere in the modeling domain, such as centroids of census blocks and census tracts, as well as places of interest and sensitive receptors (i.e., monitoring sites, schools, hospitals, senior homes, daycare centers, etc.). In grid-based models however, modeled concentrations represent averaged values over grid cells. In short, dispersion models can characterize source-receptor relationships more accurately.

In this study, CALPUFF was selected due to its thorough evaluation (U.S. Environmental Protection Agency, 1998a; Rzeszutek, 2019) and its suitability for regional-scale air quality assessments (U.S. Environmental Protection Agency, 1998b). CALPUFF is a three-dimensional non--steady-state puff dispersion model. It can incorporate time- and space-varying meteorological conditions caused by weather systems as well as the complexity of surface geophysical features like terrain variations and inhomogeneity of land cover. As such, CALPUFF can be utilized in scales from local up to regional applications.

CALPUFF version 5.8.5 (U.S. Environmental Protection Agency, 2017a) was used in this study. Concentrations were estimated at the centroids of census blocks, at sites where sensitive population groups are located, such as senior homes, schools, hospitals, and daycare centers, as well as regulatory air quality monitoring sites in the state.

Meteorology Model. In this study, meteorological fields generated by the Weather Research and Forecast (WRF) (Skamarock et al., 2005) version 3.9.1.1 (NCAR, 2017), a prognostic model, were processed with the Mesoscale Model Interface Program (MMIF), version 3.4.1. (U.S.

Environmental Protection Agency, 2017b). MMIF converts WRF output fields to the parameters in the CALPUFF-ready format.

The WRF meteorological modeling domain consisted of four nested Lambert projection grids of 36 km (D01), 12 km (D02), 4 km (D03), and 2 km (D04) uniform horizontal grid spacing (see *SI Appendix* Fig. S2). WRF was run simultaneously for the four nested domains with two-way feedback between the parent and nested grids, where the parent (outer) domain provides lateral boundary conditions to the next interior domain, while the interior domain provides higher resolution feedback to its parent domain. 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, which stretched from the surface to 100 hPa and contained ten layers within the first kilometer above the surface (*SI Appendix* Table S2). Initial and boundary conditions (IC/BCs) were based on North American Regional Reanalysis (NARR) data at 32 km horizontal resolution. The IC/BCs were further amended with surface and upper air observations obtained from the National Center for Atmospheric Research (NCAR). The major physics options for each domain are listed in *SI Appendix* Table S3.

2.3. DPM emissions inventory

In this study, DPM emission data were categorized into four major groups: on-road mobile, off-road mobile, area sources and major point sources. Each category was further processed into multiple emission sectors (*SI Appendix* Table S4), around 30 sectors in total. For example, off-road mobile sources were subcategorized into commercial harbor craft (CHC), cargo handling equipment (CHE), locomotive (LOC), transport refrigeration unit (TRU), airports, seaports including port trucks (drayage), ocean-going vessels (OGV), etc. Doing so allowed us to conduct dispersion modeling for emissions of each sector separately so that their contributions to the overall exposure and excess cancer risk could be quantified. The emission data for off-road mobile sources, area sources and stationary sources were obtained from the California Emissions Projection Analysis Model (CEPAM) (CARB, 2019) and the emissions for on-road mobile sources were developed using the California On-road Emission Factor Model system (EMFAC2017) (CARB, 2023). The spatial distributions of the four categories' emissions (on-road, off-road, area-wide, and major stationary) are mapped in *SI Appendix* Figs. S3-S6. A summary table of annual total emissions by sector is presented in Table 1. To consider potential impacts from the emissions in Mexico that were transported into California, a DPM emission inventory for regions in Mexico closest to the California-Mexico border was also developed based on U.S. EPA's 2017NEI (U.S. Environmental Protection Agency, 2017c). Detailed emission source treatment and model parameters are presented in *SI Appendix* Note S1.

2.4. Model evaluations

CALPUFF. Prior to using the modeling results for assessing potential excess cancer risks, it is essential to evaluate the simulated annual average concentrations of DPM against measurement data. However, DPM concentrations in ambient air cannot be measured directly. Elemental carbon (EC) has widely been recognized as the most suitable surrogate for DPM (Schauer, 2003), given its abundance in diesel exhaust. Two sets of EC emissions were generated using the same methodology and data sources as those for DPM: total EC and fossil-fuel EC. The annual average concentrations of total EC and fossil-fuel EC were simulated using CALPUFF with identical model configurations as those for DPM across the model domains for each emission category and sector. Subsequently, the monitored black carbon (BC) concentrations were converted to EC concentrations based on the relationships of BC and EC established in MATES-V study (SCAQMD, 2021) at the same monitoring locations.

WRF Meteorology. To ensure that the WRF model simulations used in this study accurately captured meteorological conditions for 2017 in California, a comprehensive evaluation was conducted for simulated surface wind speeds, temperatures, and relative humidity at a 2-km grid spacing, compared against hourly observations. Detailed evaluations are provided in *SI Appendix* Note S2.

2.5. Characterization of potential cancer risk

We adhered to the methodology outlined 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) (OEHHA, 2015) to assess the cancer risk associated with exposure to modeled DPM. Specifically, cancer risks were determined by multiplying the daily inhalation or oral dose by a cancer potency factor, age sensitivity factor, frequency of time spent at home (for residents only), and exposure duration divided by averaging time. This process yielded the excess cancer risk that results from the modeled DPM concentrations. For residential inhalation exposure, excess cancer risk was calculated for each age group and then summed to determine the overall cancer risk at the receptor locations. The following equations demonstrate the calculation of residential inhalation cancer risk:

$$Risk_{inh-res} = DOSE_{air} \times CPF \times ASF \times \frac{ED}{AT} \times FAH \qquad \text{(Eq. 1)}$$

$$DOSE_{air} = C_{air} \times \frac{BR}{BW} \times A \times EF \times 10^{-6} \qquad \text{(Eq. 2)}$$

where:

$Risk_{inh-res}$ = Residential inhalation cancer risk
$DOSE_{air}$ = Daily inhalation dose (mg/kg-day)

Table 1
Annual emission totals (in ton/year) of DPM in each modeling domain in 2017.

Category		Sac	BA	SJV	SC	SD*	IMP*
On-road		270.21	349.28	542.51	743.82	160.42	33.76
Off-road	Commercial Harbor Craft	11.09	85.1	6.24	26.98	17.40	0.08
	Cargo Handling Equipment	0.02	1.67	0.03	10.49	0.22	0.00
	Locomotives	28.54	27.89	55.92	110.24	10.33	18.98
	Transport refrigeration units	16.35	30.76	18.76	55.43	11.45	0.92
	Ocean-going vessels	0.01	10.03	0.62	5.92	2.44	0.00
Area	Agriculture	362.32	75.42	923.29	47.86	41.90	36.70
	Construction	93.89	139.05	183.47	415.14	84.09	10.76
	Point without exact location	0.05	0.00	0.00	0.00	0.00	0.00
	Aggregated area-point	88.15	144.73	164.99	278.09	67.28	3.54
Stationary point		5.34	6.41	7.31	33.45	11.24	0.84

Note: The emissions from Mexico are not included.

CPF = Inhalation cancer potency factor ($(mg/kg\text{-}day)^{-1}$)
ASF = Age sensitivity factor for a specified age group (unitless)
ED = Exposure duration (in years) for a specified age group.
AT = Averaging time for lifetime cancer risk (years)
FAH = Fraction of time spent at home (unitless)
C_{air} = Daily average concentration in air ($\mu g/m^3$)
BR/BW = Daily breathing rate normalized to body weight (L/kg body weight-day)
A = Inhalation absorption factor (unitless)
EF = Exposure frequency (unitless), days/365 days.

We used a 30-year exposure duration and the Risk Management Policy (RMP) method with 95th/80th percentile daily breathing rate (DBR) to assess residential potential cancer risk.

DPM exposure and associated cancer risks, as generated by the model, were initially reported at the census block level statewide. These exposure levels and associated cancer risks were then aggregated to the census tract level using a population weighted approach. Spatially resolved cancer risks at the census tract level were calculated as follows:

$$PWRi = \sum_j risk_i(j) \times pop_i(j) \Big/ \sum_j pop_i(j) \quad \text{(Eq. 3)}$$

where.

$risk_i$ – risk at census tract i
$pop_i(j)$ - population in j-th block within census tract i
$risk_i(j)$ - cancer risk at j-th block within census tract i

$\sum_j pop_i(j)$ – total population within census tract i.

Population data for year 2010 were used to calculate population weighted cancer risk. The U.S. Census Bureau publishes population data every ten years.

2.6. Calculation of non-cancer health impact

DPM, a component of ambient $PM_{2.5}$, is widely recognized as a significant contributor to air pollution-related health effects, including premature mortality. In this part, we utilized the Environmental Benefits Mapping and Analysis Program (BenMAP-CE v1.5.8) (Coffman et al., 2024) developed by the U.S. EPA to estimate the reduction in mortality resulting from decreased DPM exposure between 2012 and 2017. This analysis aimed to assess the effectiveness of CARB's regulatory programs in reducing DPM's non-cancer health impact. We used the following concentration-response function:

$$M = baseline\ incidence\ x\ population\ x\ \left(1 - e^{-\beta C_{DPM}}\right) \quad \text{(Eq. 4)}$$

where β is a coefficient value for $PM_{2.5}$ cardiopulmonary mortality, and C_{DPM} is the annual average concentration of DPM. β values, population data and baseline incidence rates for health impact functions were obtained from the BenMAP database (2010 census data for population, and 2015 incidence were used for both 2012 and 2017 calculation). We used Eq. (4) to calculate the cardiopulmonary mortality impact of DPM for each age group in each census tract for the years of 2012 and 2017. These values were then summed to get the total mortality impact of ambient DPM for each air basin and the whole state of California for 2012 and 2017. Note that other health impacts such as cardiovascular or respiratory hospitalization, and respiratory emergency room visits, including for asthma, due to exposure to DPM were not included in this study.

3. Results and discussion

3.1. Spatial distribution of DPM exposure and comparison with observations

Fig. 2 illustrates the spatial distributions of 2017 DPM concentrations in the modeling domains, sampled and plotted at census block resolution. The figure clearly indicates elevated concentrations primarily in major urban areas such as Los Angeles, San Francisco, and San Diego. These concentrations align with transportation corridors including freeways, major arterials, seaports, and railyards. Higher DPM levels are also observed along State Route 99 and major urban centers like Bakersfield and Fresno, attributed to on-road mobile sources and heavy agricultural activities in the San Joaquin Valley. Additionally, elevated concentrations are evident in the communities adjacent to the Mexico-United States border, which result from DPM emissions in Mexico transported into the U.S.

To evaluate our CALPUFF modeling, we compared modeled EC concentrations with monitoring data detailed in Materials and Methods. *SI Appendix* Fig. S7 presents the comparison between our modeled total and fossil-fueled EC annual average concentrations against observed BC provided by the SCAQMD (2022). Studies indicated that BC and EC concentrations are similar within the measurement accuracy range (Pileci et al., 2021). In order to compare with modeled EC concentrations, BC concentrations were converted to EC concentrations based on EC and BC relationships derived from EC and BC data observed at the same monitoring locations. Overall, the model performance is reasonable. Several statistics of model performance were calculated. The normalized mean errors (NME) were 0.311 and 0.333, respectively, for total and fossil EC. The corresponding normalized mean biases (NMB) were −0.018 and −0.094, and the coefficients of determination (R^2) were 0.460 and 0.468, respectively. This level of performance for EC modeling can be considered satisfactory (Simon et al., 2012).

In summary, CALPUFF demonstrates reasonable performance in simulating annual average EC concentrations. Given that DPM and EC emission inventories were developed using the same methodology and data sources, the confidence level of modeled DPM annual concentrations by CALPUFF should be comparable to that of EC.

3.2. Characterization of cancer risk and trend analysis

Potential excess cancer risk of DPM was calculated by multiplying the annual average concentrations of DPM with the inhalation unit risk factor. Note that only inhalation exposure was considered in this study, which was shown to be the major exposure pathway by SCAQMD's MATES-V study (93 %) (SCAQMD, 2021) and our internal studies at CARB (over 95 %). The results were expressed as potential cancer incidences per million people, or chances per million.

Fig. 3A depicts the spatial distribution of estimated DPM cancer risk in 2017 at the census block level statewide. Not surprisingly, the spatial pattern of DPM cancer risk closely mirrors that of DPM concentrations. High risks are distributed along major freeways and urban centers, as well as in communities near the California-Mexico border, where pollution transported from Mexico contributes to higher risks. In essence, areas with heightened risk tend to align with transportation and goods movement corridors, such as major freeways, seaports, airports, railyards, and near the border.

Fig. 3B shows the reduction of DPM cancer risk from 2012 to 2017. It is evident that a significant reduction in DPM risk is observed across most areas within the six air basins. The most substantial percentage decrease in risk is noted in major urban areas with high population density, as well as transportation and goods movement corridors. This reduction reflects the decline in DPM emissions from trucks on major freeways and off-road mobile sources such as ports and railyards, among others, which can be linked to major past and current regulations such as the On-Road Truck and Bus Rule and regulations of OGV and port

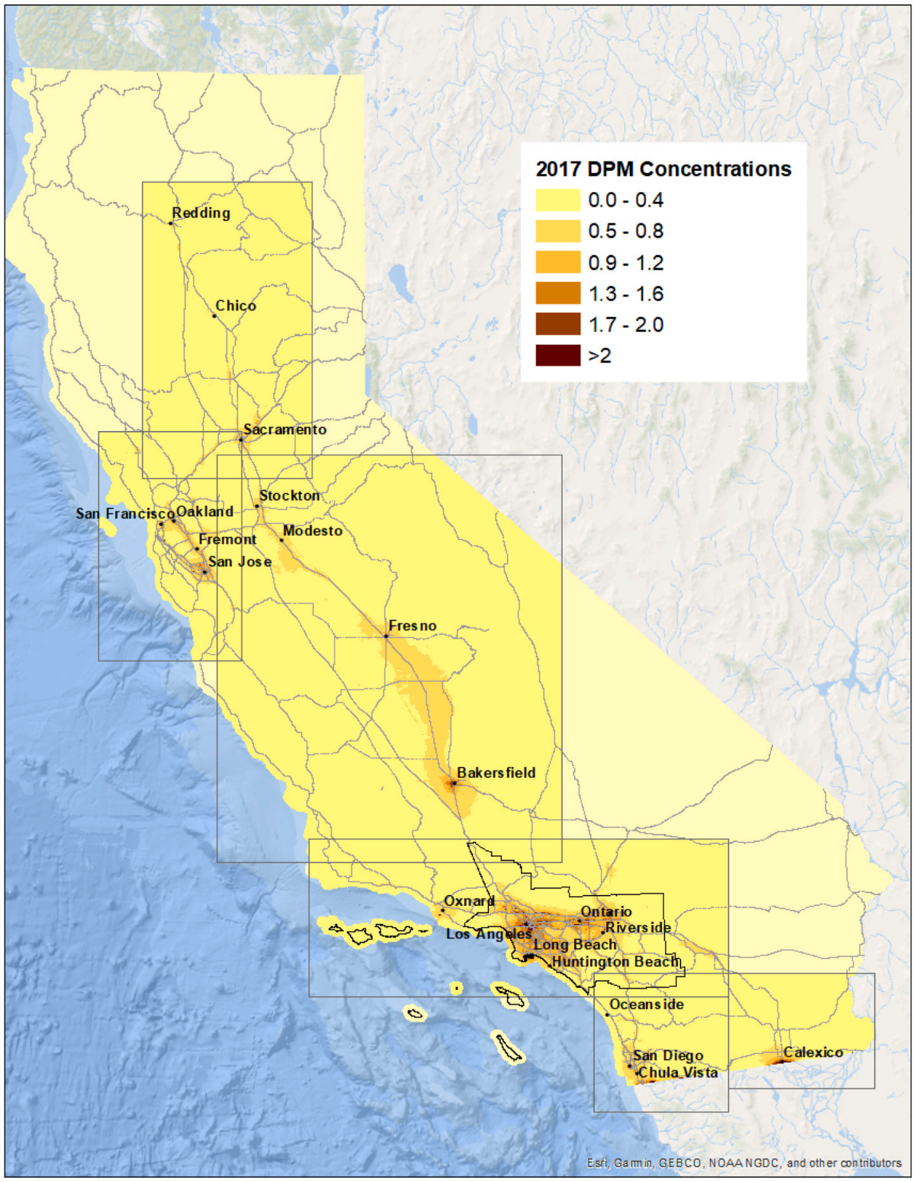

Fig. 2. Annual average DPM concentrations (μg/m^3) obtained with 2017 meteorology and DPM emissions data. Also shown are the six modeling domains and major cities and freeways.

activities.

Some increases in cancer risk are seen in certain low-risk areas (warm-colored areas in Fig. 3B), including the northern Bay Area and the eastern regions of the San Diego air basin near the San Diego-Mexico border, as well as the northwest corner of Imperial County. These unexpected increases in cancer risk could be attributed to improvements in the emission inventory. For example, improvements in reporting of emissions, and emission sources that were present in the 2017 inventory but not in the 2012 inventory. Another reason is that some sources commenced to emit between 2012 and 2017. Examples include rezoning properties that had a net emission increase, e.g., rezoning an agricultural land into industrial zone, and relocation of some industrial facilities to the area where cancer risk is found to have increased. Additionally, due to the nature of construction activities, some projects that were active in 2017 might not have existed in 2012.

Another notable finding is that communities in San Diego and Imperial Counties near the California-Mexico border show relatively small reductions in risk. This can be attributed to updates in the Mexican emission inventory, which can change substantially over time. Despite significant reductions within San Diego and Imperial Counties, the overall reduction in risk was minimal since over 2/3 of the risk in these communities was caused by emissions transported from Mexico.

The population weighted potential cancer risks of DPM for each of the six air basins are presented in Fig. 4. Also shown are the percentage reductions in each air basin. Please note that the population weighted risk was calculated with population in every census block within each air basin's jurisdiction, not the entire modeling domain. Clearly, cancer risks were quite different in different air basins and the South Coast had the highest cancer risk among all air basins. Basin-wide reductions in cancer risk were also different and the greatest reduction from 2012 to 2017 occurred in the San Joaquin Valley. Overall, the risk reduction from 2012 to 2017 in California was significant. The population weighted DPM cancer risk was reduced by 42 % statewide with a range from 19 % to 59 % in individual air basins. Supplementary to the population weighted risk, Fig. 5 presents how the cancer risk was distributed in 2017. It is seen that the highest cancer risk in the Sacramento Valley corresponds to about 50th percentile of the risk in the South Coast air basin, revealing the disparity in cancer risk among air basins. Another

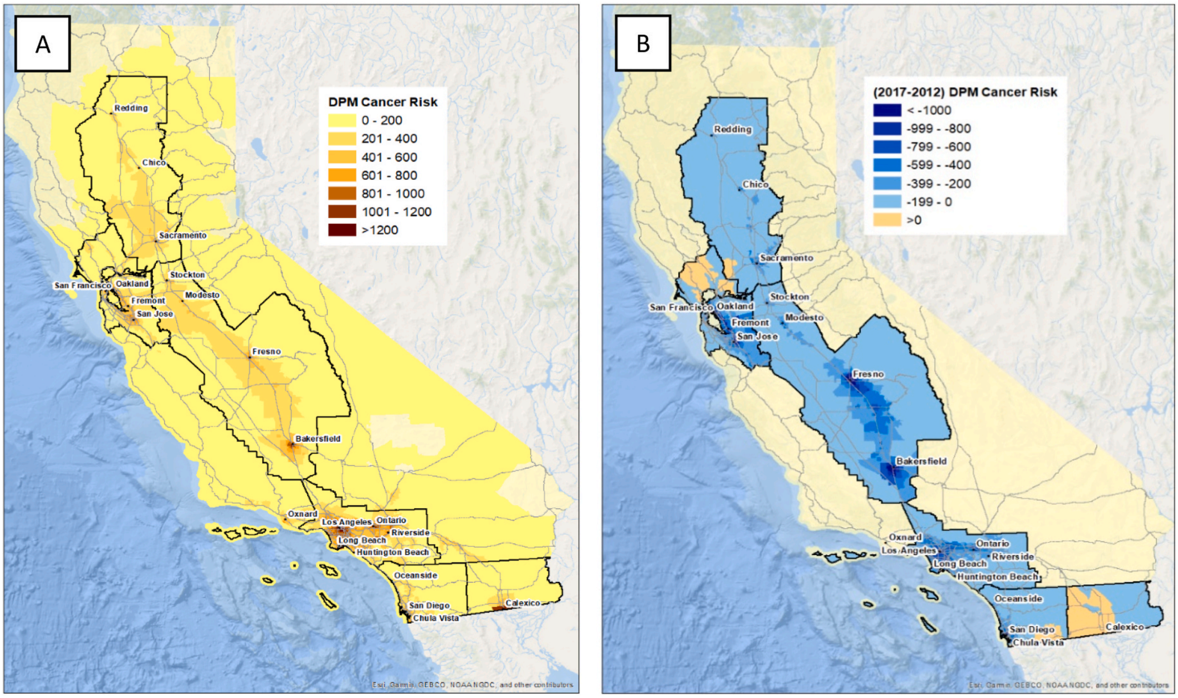

Fig. 3. A. DPM cancer risk (per million) for 2017 (left). B. Cancer risk reduction (%) from 2012 to 2017 (right).

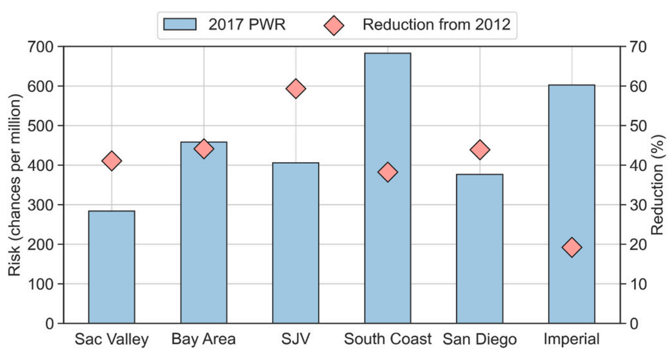

Fig. 4. Population weighted excess cancer risk for 2017 (vertical coordinate on the left-hand side) and its reduction from 2012 to 2017 (vertical coordinate on the right-hand side) in Six air basins. The reduction is in percentage, defined as $(PWR_{2017} - PWR_{2012})/PWR_{2012}$.

aspect worth noting is the long tail of the cancer risk distribution in Imperial County where the mode is the lowest among all air basins, the long tail makes Imperial the air basin to have the second highest population weighted cancer risk.

Fig. 6 presents DPM risk histograms and cumulative population percentage exposed to certain levels of cancer risk for 2012 and 2017, respectively. It shows clearly the general downward trend of cancer risk and in particular much fewer people being exposed to any given level of high risk. For example, in 2012, about 10 % of the population lived in areas with 1500 per million cancer risk, in 2017 the level was reduced to about 750 per million.

Overall, the risk reduction from 2012 to 2017 in California was significant. The population weighted DPM cancer risk was reduced by 42 % statewide with a range from 19 % to 59 % in individual air basins (Fig. 4). As shown in Figs. 5 and 6, the percentage of cumulative population exposed to high-level of DPM risk shrank from 2012 to 2017, demonstrating the overall benefit of DPM emission reduction. For example, in 2012 half of the population in the state were exposed to cancer risk levels below (and above) 800 chances per million, while in 2017 the level was reduced to less than 500 chances per million. The histograms show a shift of the population distribution toward lower cancer risks, further revealing the benefit of emission reduction.

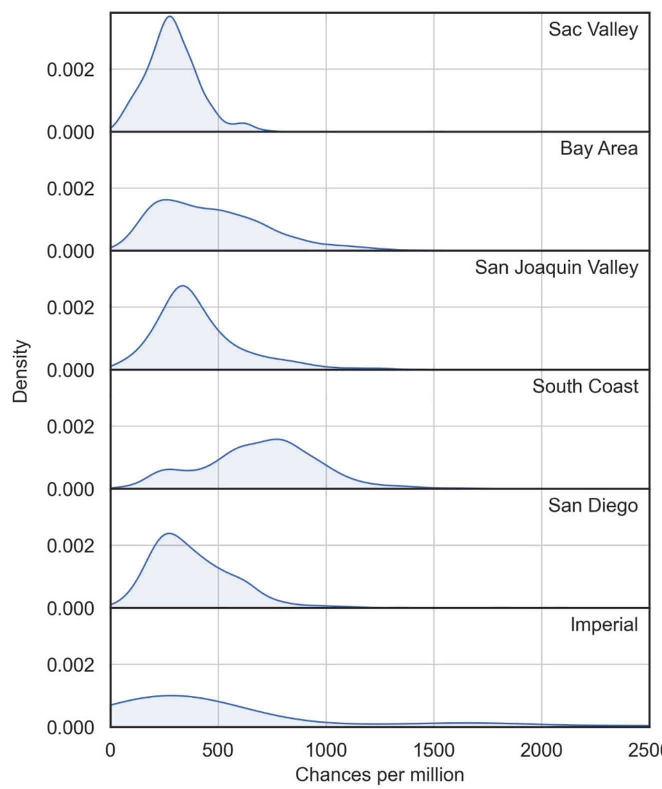

Fig. 5. DPM cancer risk distribution (chances per million) for each air basin at the census tract level in 2017.

A further analysis of the cancer risk reduction distribution reveals that census tracts with higher population densities tended to have more

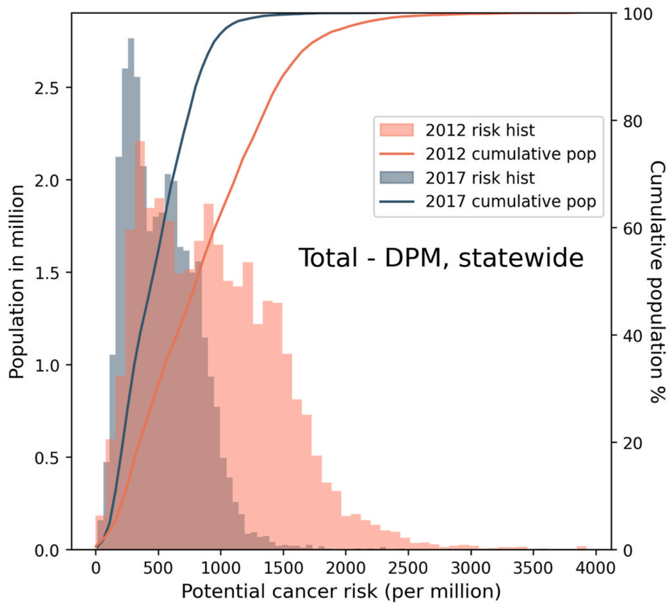

Fig. 6. DPM risk histograms for total population across the state, representing the cancer risk (per million) distribution across the statewide population at the census tract level. Coral and dark blue shadings represent 2012 and 2017 results, respectively. Lines represent the cumulative population percentage (right y-axis), where 50 % indicates the risk level that separates half of the population. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

significant reductions in DPM cancer risk from 2012 to 2017. Fig. 7 shows that the reduction in DPM cancer risk from 2012 to 2017 monotonically increased with population density, i.e., more densely populated areas tended to gain more reduction in cancer risk. In order words, the geographical disparity in DPM cancer risk decreased with time. *SI Appendix* Fig. S8 further shows that this statewide trend of reduction in disparity holds in each of the air basins. The reduction may be attributable to the fact that high population density areas coincided with major on-road emission sources (*SI Appendix* Figs. S3 and S9), and the on-road emission sector experienced the largest risk reduction from 2012 to 2017 (*SI Appendix* Table S5). This suggests that regulatory measures like the Truck and Bus Rule have successfully targeted the most impactful emission sources and thus led to meaningful improvements for communities facing a disproportionate burden of DPM exposure. On the other hand, the extent of correlation varies in different air basins (*SI Appendix* Fig. S8). The highest correlation between risk reductions and population densities was observed in Imperial and the lowest was observed in Bay Area.

3.3. Characterization of non-cancer risk and trend analysis

Statewide and air-basin wide non-cancer health impacts, i.e., all-cause mortality, from DPM exposure for the years 2012 and 2017 were estimated by treating DPM as part of $PM_{2.5}$ (shown in Fig. 8a and b). In the BenMAP calculation, BenMAP default 2015 incidence and 2010 census track level population were used. Two all-cause mortality health impact functions (HIF) were chosen to avoid bias caused by choosing one HIF over the other. One is from Turner et al. (2016), and the other is from Pope et al. (2015). Similar results were obtained with these two HIFs (Fig. 8a vs. Fig. 8b), suggesting that the outcome of the BenMAP calculation is not affected by the choice of HIF. For the year 2012, the statewide mortality attributable to DPM exposure was estimated at 70 premature deaths per 1 million population (1290 total deaths) based on Turner et al. (2016) and 81 premature deaths per 1 million population (1495 total deaths) based on Pope et al. (2015). Our analysis showed an approximate 50 % decrease statewide in mortality due to exposure to the diesel portion of $PM_{2.5}$ from 2012 to 2017 (Fig. 8c). For the year 2017, we estimated 36 premature deaths per 1 million population based on Turner et al. (2016) and 42 premature deaths per 1 million population based on Pope et al. (2015), as shown in Fig. 8a and b.

Breaking down the results by six air basins, South Coast accounts for the largest number of DPM-related premature deaths (Fig. 8a and b bar chart) due to its large population (*SI Appendix* Fig. S10a) and relative higher DPM concentration compared with other air basins (*SI Appendix* Fig. S10b), followed by Bay Area and San Joaquin Valley. In contrast, Imperial, Sacramento Valley and San Diego have fewer DPM-related premature deaths, either due to the small population share (Imperial, *SI Appendix* Fig. S10a), or relative lower DPM exposure (Sacramento Valley, *SI Appendix* Fig. S10b). When population size is normalized (expressed as deaths per 1 million residents), the pattern of deaths per 1 million aligns closely with the distribution of DPM exposure across the six air basins. South Coast still shows the highest mortality rate, followed by San Joaquin Valley and Bay Area. It is interestingly to note, while Imperial has the smallest area and population, it is not the least impacted air basin because of its high per-capita DPM exposure, most of

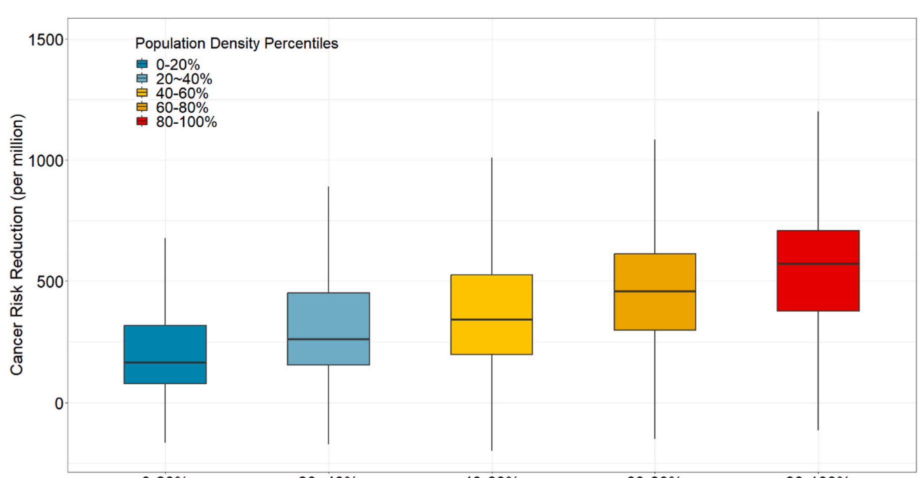

Fig. 7. Tract-level DPM cancer risk reduction by population density percentiles represented by colors. The horizontal axis represents population density percentiles, and the vertical axis shows the level of cancer risk reduction. Boxes are defined as the interquartile range (IQR) of each subgroup, including the median (central line), upper (75th) and lower (25th) quartiles (box hinges), and maximum and minimum values within 1.5 × IQR (whiskers). Clearly, the areas with higher population density had higher cancer risk reduction. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

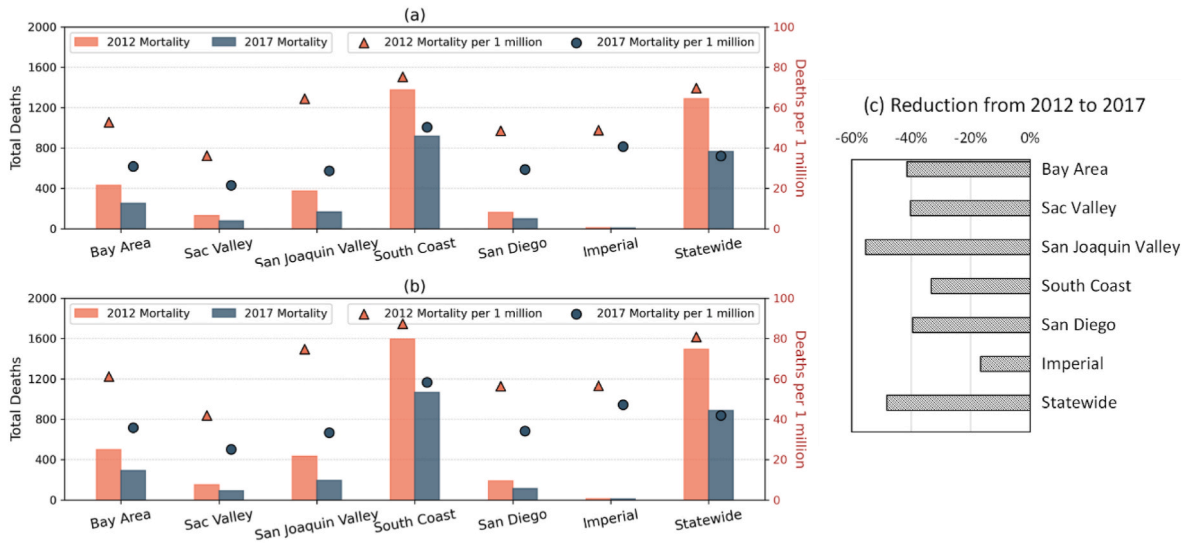

Fig. 8. Statewide and air basins all-cause mortalities of DPM for 2012 (Coral) and 2017 (dark blue) were calculated with BenMAP-CE v1.5 (a, b), as well as the reduction rate from 2012 to 2017 (c). Population data are from 2010 Census at census tract level. Two health impact functions (HIF) were chosen to avoid bias caused by choosing one HIF over the other – (a) HIF from Turner et al. (2016), $\beta = 0.005826891$; (b) HIF from Pope et al. (2015), $\beta = 0.00676586$. Results obtained with two different HIFs show similar trends and about 50 % mortality decrease from 2012 to 2017 (33 mortalities per million with Turner et al. (2016) HIF and 39 mortalities per million with Pope et al. (2015)) HIF, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

which comes from cross-border transport from Mexico.

Non-cancer risk reductions from 2012 to 2017 are shown in Fig. 8c. In general, premature death reduction rates in air basins follow the trend of cancer risk reduction rate (Fig. 4). The reductions in cancer and non-cancer health effects for DPM align with the reduction in DPM emissions over the same period. This reduction underscores the effectiveness of many of CARB's diesel-related emission control regulations implemented over the past 2-3 decades. For instance, regulations such as the On-road Trucks and Buses rule (CARB, 2008) have played a crucial role. This rule mandated the replacement and retrofit of diesel-fueled engines, including the installation of diesel particulate filters, as well as the use of ultra-low-sulfur (<15 ppm) diesel fuel. Other measures have included substituting electric power for diesel where feasible and tightening emissions limits for both new and existing diesel engines. These efforts collectively contributed to the decrease in DPM emissions and associated health impact across the state.

Although the focus of the present study is to characterize regional and statewide cancer risks, it is worthwhile noting that the modeled results contain fine scale variations of DPM concentrations, e.g., the granular information of DPM concentrations within communities. Getting detailed variations of DPM risk does not require any additional effort since all results needed for this purpose have already been included in the model output. One can simply choose a community of interest and zoom in on the map in our data portal and visualization mapping tool (https://california-air-toxics-assessment-californiaarb.hub.arcgis.com/). Fig. 9 shows an example of community level details of inhalation cancer risk caused by exposure to ambient DPM concentrations. The community is referred to as the Portside Environmental Justice Neighborhoods Community, which includes neighborhoods of Barrio Logan, West National City, Logan Heights, and Sherman Heights in South San Diego. The Community has been s**elected by California's Community Air Protection Program for** Community Air Monitoring Plan and Community Emissions Reduction Program. Clearly, spatial variation of DPM cancer risk in the community is strong, meaning that residents living in the same community can be impacted very differently by DPM. The detailed information of how DPM risk varies within the community and its source apportionment provides additional leverage to reduce DPM risk locally.

3.4. Source apportionment of DPM

In this study, each emission source sector was modeled separately to enable the quantification of contributions from each sector. This approach is valuable for informing future emission control efforts, particularly as DPM emission reductions are primarily achieved through sector-based policies at both the state and federal levels.

Fig. 10A illustrates the relative contribution of each sector to total statewide DPM cancer risk in 2017, with on-road mobile sources being the most significant at approximately 59 %, followed by aggregated area-point sources (16 %) and locomotives (8 %). Notably, source apportionments vary across air basins (Fig. 10B). In most air basins, on-road mobile sources contributed over 50 % to total risks, despite emitting less than half of the total DPM emissions (Table 1). The exception was Imperial County, where Mexico sources dominated due to large emission sources close to the border on the Mexico side, and higher population density near the border on the U.S. side.

The disproportionately higher contribution from on-road sources to cancer risk is attributed to their proximity to populated areas (*SI Appendix* Figs. S1 and S9). Conversely, emissions from agricultural activities in Sacramento Valley and SJV, while double that of on-road emissions, pose lower cancer risks due to their distance from populated urban areas. This underscores the importance of considering the spatial distribution of emissions and ambient concentrations over absolute emission rates in risk characterization. It also supports California's regulatory focusing on reducing DPM risk from on-road mobile sources.

3.5. Limitations and caveats

Although this study reflects the best state-of-the-science efforts in emissions processing and air quality modeling, it is important to recognize certain caveats and limitations to ensure the accurate interpretation of the modeling results. In this study, the emission inventory was developed using the best-available datasets and methodologies to quantify emissions from a wide range of sources. However, it's widely recognized that emission inventories are subject to uncertainties regarding the locations and release rates of emission sources (Davison et al., 2021). Missing emission sources and errors in emission estimates associated with stationary sources will be addressed by CARB's newly

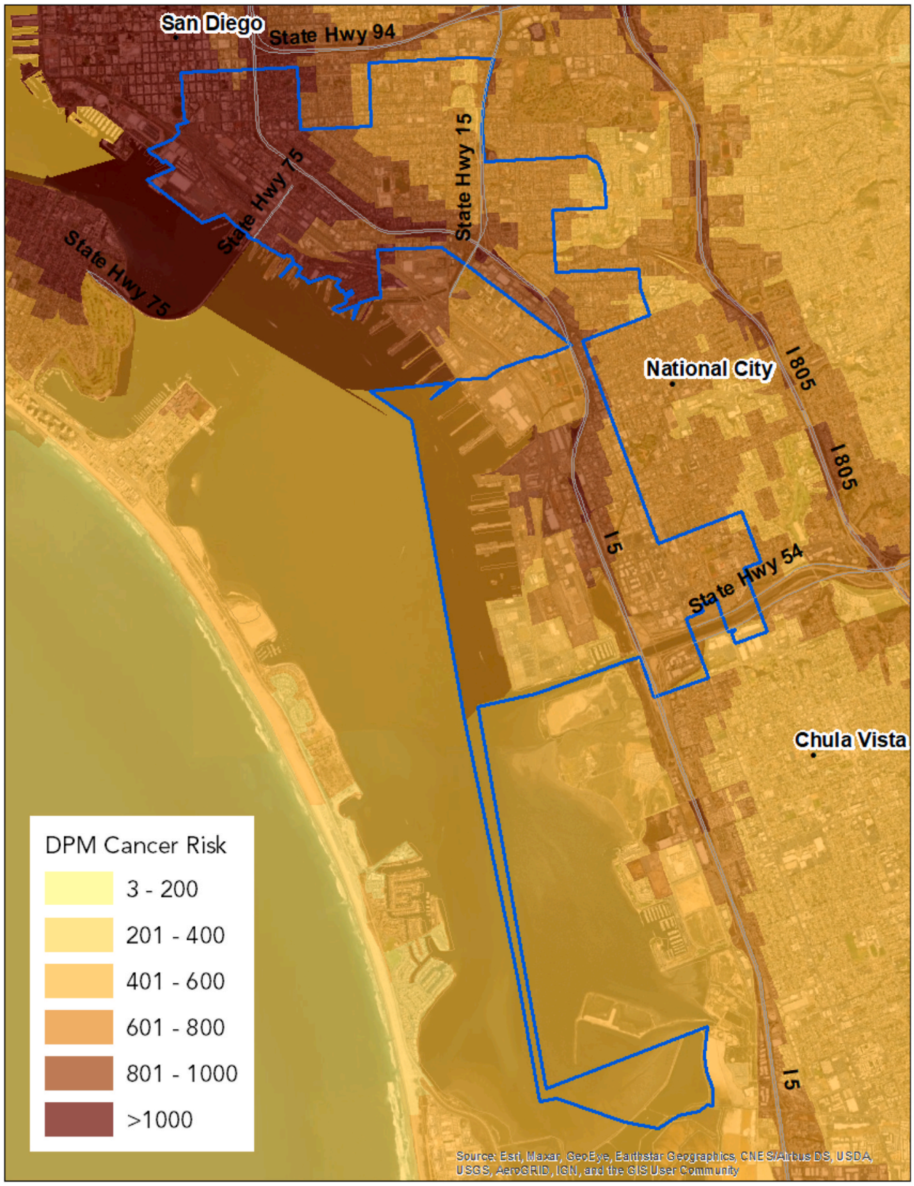

Fig. 9. DPM cancer risk in the Portside EJ Neighborhood, encircled by the blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

implemented Criteria Pollutant and Toxics Emissions Reporting (CTR) system (CARB, 2020). Additionally, air quality modeling, including the CALPUFF model utilized in this study, inherently involves numerous approximations (Hanna, 1988). For instance, uncertainties exist in how emission sources are represented in the modeling process and in the development of the meteorological field used to drive the air quality models. These uncertainties can lead to inaccuracies in the estimations of ambient DPM concentrations.

Another significant source of uncertainty arises from the calculation of cancer risk based on DPM concentrations, coupled with numerous parameters that influence the uptake of ambient DPM into human bodies. In this study, health risks were assessed using the risk assessment guidance developed by OEHHA, which involves numerous sources of uncertainty and tends to be overly conservative (OEHHA, 2015). As outlined in the OEHHA Guidance, sources of uncertainty in risk estimates include, but are not limited to: (1) extrapolating toxicity data from animals to humans; (2) uncertainty in estimating emissions; (3) uncertainty in air dispersion models; and (4) uncertainty in exposure estimates. These factors contribute to the overall uncertainty surrounding the assessment of health risks associated with DPM exposure.

Despite these limitations, this study offers the most reliable estimate of cancer risks in California based on a recent emissions inventory, OEHHA guidance, and U.S. EPA air quality modeling guidelines. It should be noted that this study is based on both 2012 and 2017 emissions data, which may differ significantly from current levels. Future studies will focus on more recent emission estimates, but the nature of inventory development and the time it takes to conduct the detailed modeling means there will always be a disconnect between the model assessment year and the present day.

Ideally, emissions data for the most recent years should be used so that the modeled results reflect the current status of air quality, and more importantly, provide more meaningful guidance for future emission reduction efforts. However, for statewide studies such as this one, a latency is not only expected, but necessary to develop comprehensive and detailed emissions inventories and conduct air quality modeling. This study represents a multi-year (3–5 years), iterative, comprehensive and resource-intensive effort at characterizing the health impact from

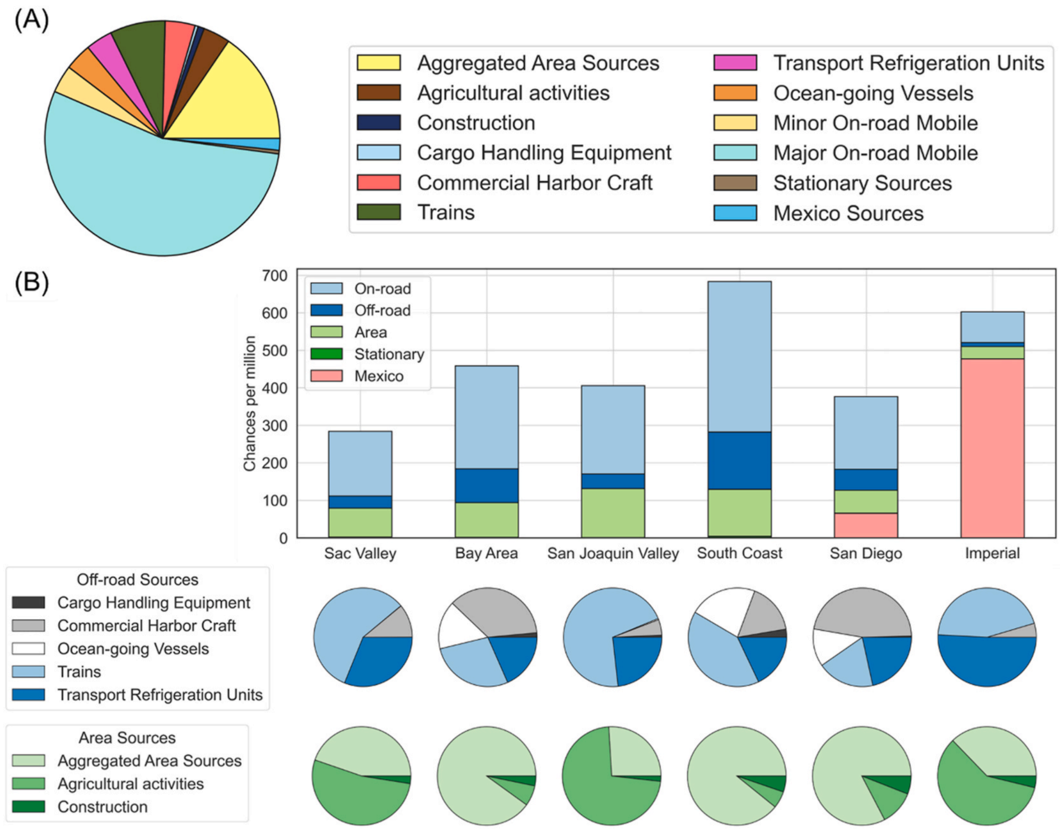

Fig. 10. Sources apportionment based on 2017 modeled results. A. Percentage contribution to the statewide population weighted excess DPM risk by emission source sectors. B. Source apportionment results at the air basin level. Each column represents one air basin. The bar chart shows the cancer risk due to each major emission source categories. In each column, the first pie chart outlines percentage contributions from each off-road source subcategory to the off-road source category as a whole, the second pie chart shows percentage contributions from each area source subcategory to the area source category as a whole.

DPM across California, involving extensive emissions inventory preparation, large-scale and fine-resolution modeling for over 30 emission sectors, and post-processing. Consequently, the findings presented in this paper should be interpreted with caution, and extrapolations from 2012 to 2017 results are not recommended, as new emission reduction plans implemented since 2017 are not being accounted for. In addition, Fig. 11A and B shows that the combined effect of past and current emission control measures and regulations as we knew them will cause shifts in emission trends, in particular around year 2025, for both total and major categories of DPM sources across the state, and the general trend of cancer risk reductions are expected to change accordingly. Therefore, to verify whether these projected changes in emission trends occur, it is recommended that the status of DPM pollution be reassessed every few years with the most recent emissions data.

As more source testing, refined emission inventory, advanced modeling technologies, and updated health data become available, exposure and risk assessment for 2025 and beyond will be more robust and accurate.

3.6. Conclusions and policy implications

To our knowledge, this is the first study to quantify DPM exposure and associated health risks using an integrated modeling approach at scales ranging from local communities to statewide, incorporating all emission sources. This level of detail and computational intensity has not been previously reported in the literature. CARB's comprehensive DPM emission inventories provided a valuable foundation for this novel research, offering a more accurate and reliable foundation for source apportionment, trend analysis, and guiding regulatory efforts.

Source apportionment analysis revealed that different emission sources contributed variably to overall risk: on-road mobile sources accounted for 59 %, off-road mobile sources for 19 %, area sources for 21 %, and stationary sources for 1 % of the overall risk in 2017. Compared to 2012, the statewide population weighted cancer risk associated with DPM exposure decreased by 43 %, largely due to various CARB DPM emission control regulations and policies. Future emissions projections indicate significant reductions in on-road DPM emissions, primarily driven by ongoing efforts like the On-road Truck and Bus Rule. More specifically, as shown in Fig. 11, between 2018 and 2025, the contribution of on-road sources to inhalation cancer risk continues to decline and is eventually surpassed by the combined contributions from off-road and area-wide emission sources. In contrast, the reduction in health risk from off-road mobile and area sources was relatively slow from 2012 to 2017 (*SI Appendix* Table S5) and that is projected to continue. Therefore, future emission reduction efforts will likely need to prioritize off-road mobile sources, including cargo-handling equipment (CHE), transport refrigeration units (TRUs), and locomotives. Although the bulk of ocean-going vessel (OGV) emissions arise far away from population centers, the rapid growth of the OGV sector (Fig. 11B) from a net increase in activity and fewer regulations means a future focus on reducing emissions from that sector is warranted. Additionally, California could benefit from reducing emissions from area sources, such as construction and agriculture sectors, which have benefited from incentive programs in the past that have led to a reduction in emissions through the replacement of older and higher emitting equipment. In particular, the agriculture sector becomes increasingly relevant in terms of its contribution to total inhalation cancer risk due to its slower reduction rate compared to on-road mobile sources. After 2025, total DPM emissions are projected to level off. This change in the trends implies that additional measures will have to be developed and

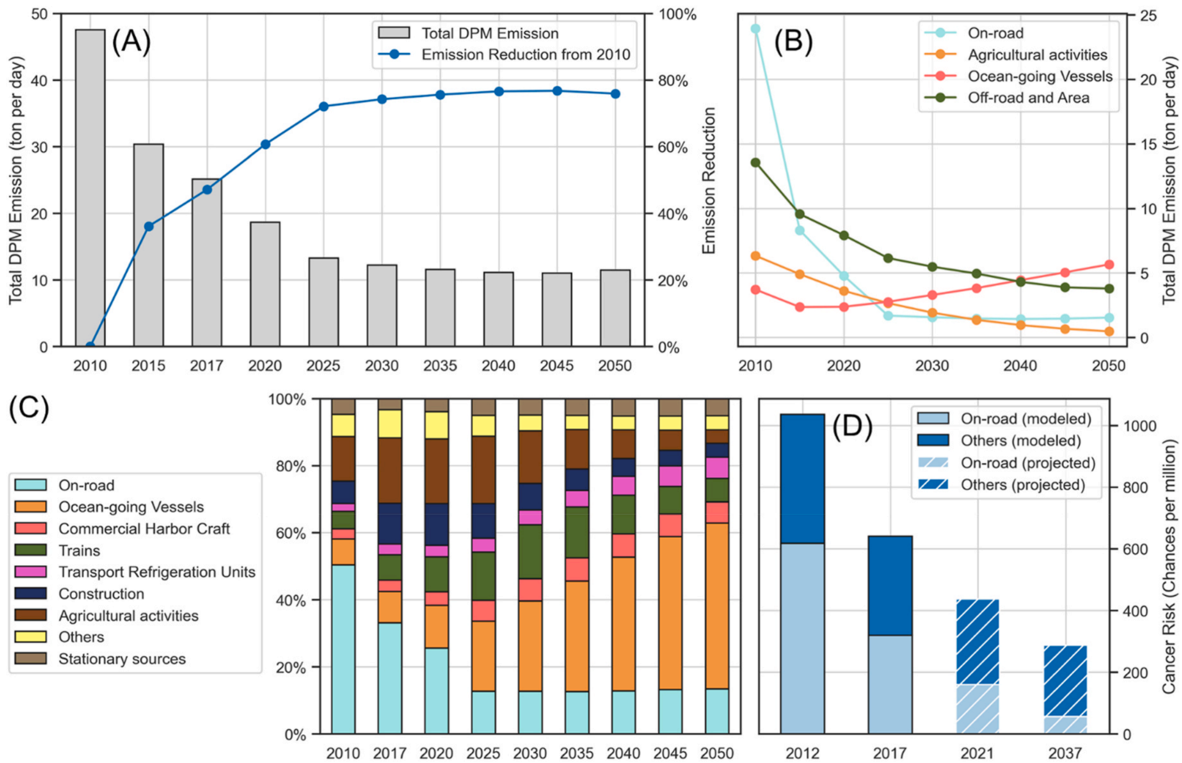

Fig. 11. Trend of DPM emissions. A. Daily emission total from all sectors and reduction scaled by the 2010 level. B. Daily emissions from on-road mobile, off-road mobile and area (excluding agricultural sector and OGV), agricultural section and OGV. C. Percentage of contribution from each emission sector to the emission total. D. Trend of DPM cancer risk reduction (modeled for 2012 and 2017; projected for 2021 and 2037).

implemented so that the cancer risk associated with DPM will continue to decrease. Advances in technology will facilitate the promotion and adoption of zero-emission technologies across all emission sectors.

In summary, although significant progress has been made in reducing DPM emissions over the past few decades, DPM-related health risks remain high and continue to be a major toxic air pollutant in California. Therefore, further reductions in DPM emissions are essential. Since DPM particles are smaller than 2.5 μm, they are a part of $PM_{2.5}$. As shown in Fig. 2, some localized areas have annual average DPM concentrations exceeding 2 $\mu g/m^3$, constituting a significant fraction of total $PM_{2.5}$ at that time (https://www.arb.ca.gov/aqmis2/aqdselect.php). Consequently, reduction in DPM emissions since 2017 has not only reduced overall risk but also contributed to lowering overall $PM_{2.5}$ levels.

While the present study focused on California, the methodology can be applied to other regions. It is likely that these general findings could be relevant across the United States, as some states have adopted similar regulatory efforts after California's initiatives.

CRediT authorship contribution statement

Shuming Du: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pingkuan Di:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **XueMeng Chen:** Visualization, Validation, Investigation, Formal analysis, Data curation. **Yiting Li:** Visualization, Validation, Investigation, Formal analysis, Data curation. **Yunle Chen:** Visualization, Validation, Investigation, Formal analysis, Data curation. **Karry Liu:** Visualization, Validation, Investigation, Formal analysis, Data curation. **Zhen Liu:** Visualization, Validation, Investigation, Formal analysis, Data curation. **Abdullah Mahmud:** Visualization, Validation, Investigation, Formal analysis, Data curation. **Melissa Venecek:** Investigation, Formal analysis, Data curation. **Daniel Chau:** Investigation, Formal analysis, Data curation. **Wenli Yang:** Investigation, Formal analysis, Data curation. **Roger Kwok:** Investigation, Formal analysis, Data curation. **Leonardo Ramirez:** Supervision, Project administration, Investigation, Formal analysis, Data curation. **Jeremy Avise:** Supervision, Resources, Project administration, Investigation.

Disclaimer

Although all authors are affiliated with the California Air Resources Board (CARB), the view expressed in the article is solely that of the authors and does not necessarily reflect the views of CARB.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2025.127182.

Data availability

Data will be made available on request.

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