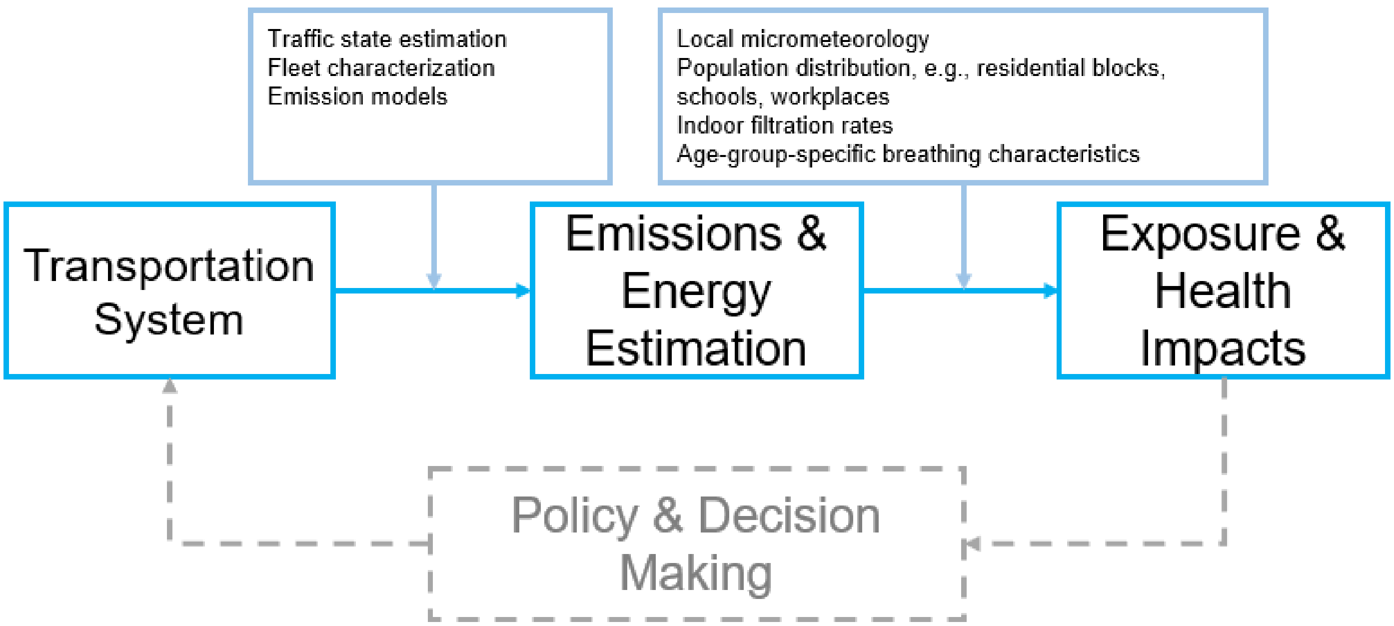
DEVELOP A PERFORMANCE METRIC TO QUANTIFY THE INHALATION OF TRAFFIC-RELATED AIR POLLUTANTS AT MESOSCALE



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16. Abstract

This study attempts to develop a health risk metric to quantify the inhalation of traffic-related air pollutants at a finer geographic level. In this study, northern Orange County and western Riverside County in California are selected as the study area. The concentration of particulate matter 2.5 microns or less in width (PM2.5) and the cancer risks based on 9-year exposure to traffic-related exhaust diesel PM2.5 are assessed at the census block level. The Orange County blocks generally have higher primary traffic-related PM2.5 concentration than the Riverside County blocks do. Within selected Orange County blocks, the gasoline and diesel PM2.5 concentrations are comparable. However, within selected Riverside County blocks, the average diesel PM2.5 concentration is slightly higher than the average gasoline PM2.5 concentration.

The estimated cancer risks show that to limit cancer risks to within the 75th percentile (14.5 in 1 million) of the study area, a "safe" distance would be 1,500 to 2,000 meters away from major freeways. The health risk values estimated in this study can be applied to evaluate cumulative health risks. For example, the values can be combined with existing screening tools to provide a layer of traffic-related air pollutant concentration and health risks that show detailed intra-urban variation.

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Executive Summary

Performance metrics to quantify traffic-related air pollutants and exposure disparities are critical for identifying disadvantaged populations and developing clean air policies. Existing screening tools generally estimate the overall ambient pollutants or traffic density at the census tract level or at a larger grid level. However, these tools do not reflect how much of the emissions actually reach and are inhaled by the localized population.

This study attempts to develop a health risk metric to quantify the inhalation of traffic-related air pollutants at a finer geographic level. In this study, northern Orange County and western Riverside County in California are selected as the study area. The concentration of particulate matter 2.5 microns or less in width ($PM_{2.5}$) and the cancer risks based on 9-year exposure to traffic-related exhaust diesel $PM_{2.5}$ are assessed at the census block level. The Orange County blocks generally have higher primary traffic-related $PM_{2.5}$ concentration than the Riverside County blocks do. Within selected Orange County blocks, the gasoline and diesel $PM_{2.5}$ concentrations are comparable. However, within selected Riverside County blocks, the average diesel $PM_{2.5}$ concentration is slightly higher than the average gasoline $PM_{2.5}$ concentration.

The estimated cancer risks show that to limit cancer risks to within the 75th percentile (14.5 in 1 million) of the study area, a "safe" distance would be 1,500 to 2,000 meters away from major freeways. The health risk values estimated in this study can be applied to evaluate cumulative health risks. For example, the values can be combined with existing screening tools to provide a layer of traffic-related air pollutant concentration and health risks that show detailed intra-urban variation.

Acknowledgments

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Background and Introduction

> **CARTEEH QUICK FACTS**
>
> **CARTEEH** is a Tier 1 University Transportation Center, funded by the U.S. Department of Transportation's Office of the Secretary for Research and Technology.

Performance metrics to quantify traffic-related air pollutants and exposure disparities are critical for identifying disadvantaged populations and developing clean air policies. Currently, California has several related screening tools, such as CalEnviroScreen and Healthy Place Index. CalEnviroScreen4.0 evaluates a range of environmental factors, including drinking water contaminants, pesticide use, solid waste sites and facilities, and many other indicators [*1*]. Among those many indicators, ozone, diesel particulate matter (PM), and traffic density are highly pertinent to traffic-related air pollutants.

The Health Disadvantage Index includes diverse non-medical economic, social, political, and environmental factors that influence physical and cognitive health. These health determinants (or social determinants of health) form the root causes of disadvantage [*2*]. In 2018, the Health Disadvantage Index was updated and renamed the Healthy Place Index. The Healthy Place Index provides overall scores and more detailed data on specific policies that shape health, including but not limited to housing, transportation, and education [*3*].

Additionally, the U.S. Environmental Protection Agency (EPA) developed the BenMAP (Community Edition), an open-source computer program that can calculate the number and economic value of air-pollution-related illnesses and deaths. The software is able to quantify the burden to human health of total air pollution, and the potential benefits of policies reducing air pollution by a certain amount. The tool incorporates a database that includes the pollutant-concentration-response relationships, population data, and health and economic data needed to quantify these impacts [*4*].

Recently, Quan examined a range of screening tools used in California and analyzed their ability to guide housing and transportation resources [*5*]. The research found a positive relationship between housing production and transit proximate and low vehicle miles traveled (VMT) areas, which can support coordinated land use and transportation that help meet state climate and planning objectives. However, none of the maps include indicators related to these transportation characteristics that would intentionally direct resources toward those areas.

InMAP is a recently developed model that offers a new approach to estimating the human health impacts caused by air pollutant emissions and how those impacts are distributed among different groups of people [*6*]. InMAP uses annual total emissions as input to calculate annual average concentration of particulate matter 2.5 microns or less in width ($PM_{2.5}$) and the exposure values.

Vallamsundar et al. proposed a comprehensive modeling framework to assess traffic-related exposure [*7*]. Several limitations include:

- Aggregation methods are not well defined.
- The study uses the intake fraction as a metric, which can potentially be biased if evaluating a large geographic area.
- The intake fraction cannot be aggregated.

These tools generally estimate the overall ambient pollutants or traffic density at the census tract level or grid level. However, the tools do not reflect how much of the emissions reach and are inhaled by the localized population. For example, in a comparison of two communities in the Port of Long Beach area and Inland Empire, the communities may have similar levels of diesel PM emissions in terms of kilograms per day. However, depending on the local temperature; wind strength; location of homes, schools, and workplaces; and number of populations by age group; the level of exposure could be much different between the two communities. In this study, we attempt to fill in the gaps and address these issues.

Method and Modeling Experiment

Our objective was to develop a performance metric to quantify the inhalation of traffic-related air pollutants at both mesoscale (e.g., neighborhoods and cities) and macroscale (e.g., census tracts and metropolitan regions). The developed metric can assess the inhalation of specific primary traffic-related pollutants. The metric can be evaluated for a given population group (e.g., school children, stay-at-home residents, or the workforce), at a given microenvironment (e.g., indoor or outdoor), and at a given time span (e.g., a typical work day or the summer season). The metric can be readily aggregated and disaggregated at user-defined dimensions for different purposes. The metric can also reflect the influence of technology advancement (e.g., autonomous driving or clean trucks) and other driving factors.

To achieve such a goal, we unified the data format and developed an integrated framework. We applied a chaining approach to develop the metric as shown in Figure 1 and Figure 2. Figure 1 is also based on the research focus chart provided in the CARTEEH strategic plan [*8*].

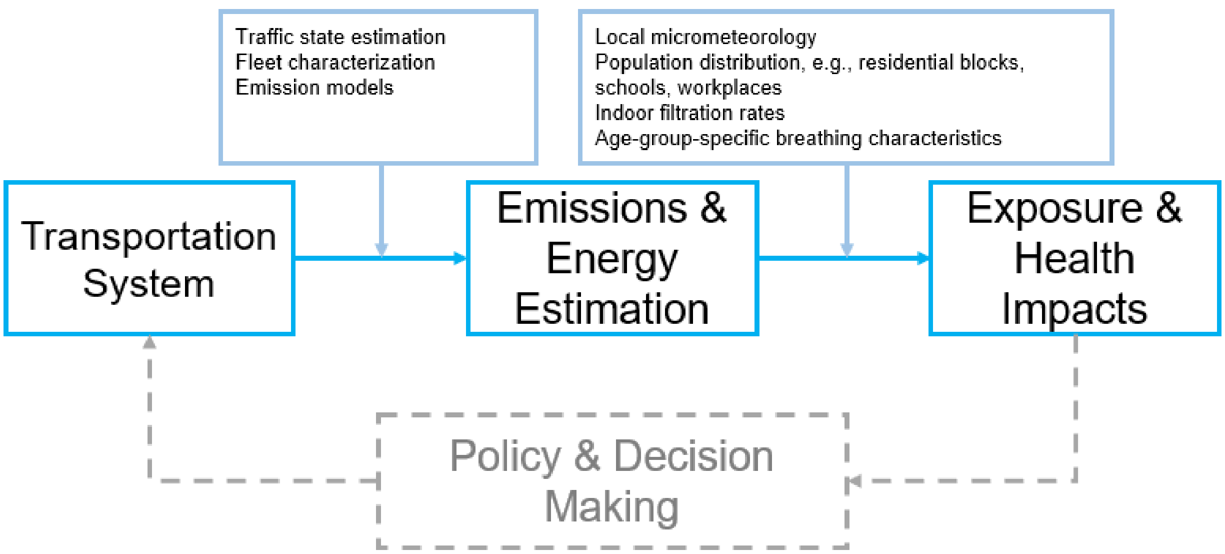

Figure 1. Method flowchart proposed in the study (adapted from CARTEEH [*8*]).

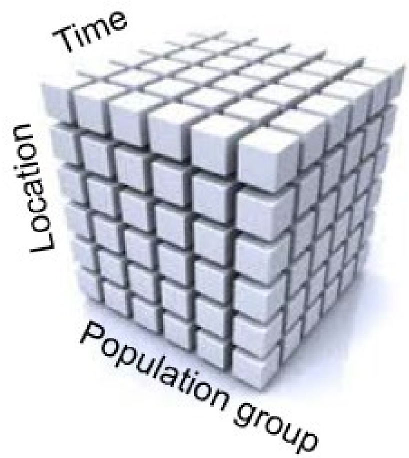

Figure 2. Aggregation dimension proposed in the study (adapted from Hou et al. [*9*]).

In this study, we selected northern Orange County and western Riverside County in southern California as the study area. Orange County borders the Pacific Ocean, is the third most populated county in the state, and has several of the largest job centers in southern California. Riverside County is located east of Orange County and is connected with Orange County through a number of freeways and transit systems. The two areas are home to more than 4 million people and have an enormous number of VMT per day. Additionally, the two areas have quite different urban development patterns and climate conditions. Therefore, it is of great interest to study the traffic-related air pollution and associated health risks. In this study, 14,951 Orange County census blocks (2.3 million population) and 14,044 Riverside County census blocks (1.8 million population) were selected as the study area. The blocks that have no residential population were filtered out and not included in this study.

Traffic Activity and Emissions Modeling

Traffic activity data (in terms of traffic flow and speed) on roadway links in and around Riverside County and Orange County were obtained directly from the Southern California Association of Government Regional Transportation Model (SCAG RTM), which is the regional transportation model of the southern California region. The data were available for four periods:

- Morning (6 to 9 a.m.).
- Midday (9 a.m. to 3 p.m.).
- Afternoon (3 to 7 p.m.).
- Nighttime (7 p.m. to 6 a.m.).

Traffic flow data included separate values for six vehicle types:

- DA: passenger car, driving alone.
- SR2: passenger car, shared ride with two persons.
- SR3: passenger car, shared ride with three or more persons.
- LHDT: light heavy-duty trucks.
- MHDT: medium heavy-duty trucks.
- HHDT: heavy heavy-duty trucks.

The total flow is the summation of the flow values of all six vehicle types. Traffic speed data have only one value that represents the speed for all vehicle types.

To estimate traffic emissions, emission factors were obtained from the California Air Resources Board's EMFAC model version 2021 for the fleet composition in Riverside and Orange Counties in 2016. EMFAC is the regulatory emission model for California. For example, fine particle ($PM_{2.5}$) emission factors for speed from 5 mph to 70 mph were obtained for multiple vehicle categories in EMFAC, which were then matched with vehicle types in the SCAG RTM model according to Table 1. Then the total $PM_{2.5}$ emission on each roadway link was calculated using Equation 1.

$$E_i = \sum_j q_{i,j} \cdot e(v_i)_j \qquad \forall\, i = 1, 2, 3, \ldots, 743 \qquad \text{Equation 1}$$

where E_i is the total emission on roadway link i (grams), $q_{i,j}$ is the flow of vehicle type j on roadway link i (vehicles per hour), and $e(v_i)_j$ is the emission factor of vehicle type j for the speed on roadway link i (grams per mile).

The calculation was performed for all roadway links in and around the study area so that the effect of traffic-related air pollution carried into the study area by wind would be accounted for.

Furthermore, to develop a performance metric to quantify the inhalation of traffic-related air pollutants, this study separated gasoline exhaust and diesel exhaust due to the significant health effects reported for the two. To separate gasoline and diesel emissions, this study used VMT data for gasoline-fueled and diesel-fueled vehicles and calculated a gasoline emission rate and a diesel emission rate for each roadway link. By separating gasoline and diesel emissions, this study was able to apply different health risk factors for gasoline and diesel concentration at a receptor. This study reduced the risk of overestimating the health risks due to gasoline emissions and was able to view the health risks from the perspectives of both gasoline and diesel emissions.

Table 1. Vehicle Type Mapping

This Project	SCAG RTM	EMFAC2007 Category
LDV	DA, SR2, SR3	LDA, LDT1, LDT2, MDV
LHDT	LHDT	LHDT1, LHDT2
MHDT	MHDT	MHDT
HHDT	HHDT	HHDT

* Notes: LDV: Light-duty vehicle LHDT: light heavy-duty trucks MHDT: medium heavy-duty trucks
DA: passenger car, driving alone
SR2: passenger car, shared ride with two persons
SR3: passenger car, shared ride with three or more persons
HHDT: heavy heavy-duty trucks LDA: light duty automobile LDT1: light duty truck Class 1
LDT2: light duty truck Class 2 MDV: medium duty vehicles
LHDT: light heavy duty truck Class 1 LHDT2: light heavy duty truck Class 2

Air Pollutant Dispersion Modeling

Recently, EPA released R-LINE, a research-grade dispersion model for near-roadway assessments. R-LINE is based on a steady-state Gaussian formulation and is designed specifically to simulate air dispersion of emissions from line sources [*10*, *11*]. Compared to AERMOD, which is one of the air dispersion models preferred/recommended by EPA and is required in modeling and analysis for regulatory purposes, R-LINE requires a similar level of data inputs but computes much faster—an attribute that is important for the modeling work in this project. In addition, R-LINE has a succinct input configuration. Therefore, R-LINE was selected for use in this project.

R-LINE treats traffic-related emissions as line sources. That is, roadway links are represented by lines in the model, and on each link the level of traffic emissions is evenly distributed along the lines. The underlying relationship between air pollutant concentration and the line sources in R-LINE can be expressed as in Equation 2.

$$C(x, y, z) = f(Q, source\ location, meterology\ ) \quad \text{Equation 2}$$

where *C(x,y,z)* is the emission concentration at a receptor location and *Q* is the average emission rate of on-road vehicles (grams/meter/second) obtained from traffic emission modeling in the previous step.

For the source location, each line segment's node coordinates are required. R-LINE provides options for analytical solution and numerical integration for concentration calculation. In this study, we chose the analytical solution for better performance. Typical meteorological data for R-LINE, such as air temperature, wind speed, wind direction, surface friction velocity, Monin-Obukhov length, etc., are available from the South Coast Air Quality Management District [*12*].

In regulatory analyses, it is desirable to use the 5-year history of hourly meteorological data to calculate the hourly average and maximum concentration in order to capture any extreme concentration values that may result from certain meteorological conditions. This adds up to a combination of 5 years times 365 days times 24 hours, which is 43,800 hourly meteorological scenarios. However, due to the large number of roadway links (more than 68,000) and receptors (28,955) in this project, it would be computationally expensive to calculate hourly concentration for that many meteorological scenarios.

In a previous study, 36 different temporal scenarios were modeled with methods similar to those mentioned, where the traffic and meteorological parameters were obtained for the 36 temporal scenarios and traffic-related $PM_{2.5}$ was modeled for 48,000 receptors in the city of Riverside [*13*]. The concentration between all 36 different temporal scenarios were highly correlated, and the R-squared (R^2) of the concentration between all the temporal scenarios were more than 0.7. This finding shows that if the concentrations are calculated for all receptors for one temporal scenario, the set of values can potentially be used to predict concentration for another temporal scenario given an appropriate multiplication factor. The data for meteorological parameters are readily available from 2012 to 2016. To keep the computation time reasonable, this study selected one typical day in August 2016 and used the meteorological data at 6:00 p.m. of that day after confirming that no abnormal weather conditions were present.

Exposure Assessment

Equations 3 and 4 were drawn from the California Office of Environmental Health Hazard Assessment (OEHHA) *Health Risk Assessment Guidelines* and were adjusted with values identified for this study.

$$\text{Cancer Risk} = CPF \times DOSE_{AIR} \times ASP \times ED/AT \times FAH \quad \text{Equation 3}$$

where:

- Cancer Risk = total individual excess cancer risk defined as the cancer risk a hypothetical individual faces if exposed to carcinogenic emissions from a particular source for specified exposure durations. This risk is defined as an excess risk because it is above and beyond the background cancer risk to the population. Cancer risk is expressed in terms of risk per million exposed individuals.
- CPF = inhalation cancer potency factor.
- ASP = age sensitivity factor (see Table 2).
- ED = exposure duration.
- AT = averaging time for lifetime cancer risk.
- FAH = fraction of time at home (see Table 2).

$$DOSE_{AIR} = C_{AIR} \times DBR \times A \times EF \quad \text{Equation 4}$$

where:

- C_{AIR} = toxic air contaminant concentration from the air dispersion model (μg/m^3).
- DBR = daily breathing rate (see Table 2).
- A = inhalation absorption factor (usually set as 1).
- EF = exposure frequency (see Table 2).

Table 2 provides the OEHHA-recommended values for the various cancer risk parameters, shown in Equations 3 and 4.

Table 2. Exposure Assumptions for Cancer Risk Calculations at Residential Receptors

Receptor Type	Fraction of Time at Home	Exposure Frequency (Days/Year)	Age Sensitivity Factors	Daily Breathing Rate (L/kg-day)
Infant Receptors				
3rd trimester	1	350	10	361
0 to 2 years	1	350	10	1,090
Child Receptors				
2 to 9 years	1	350	3	631
9 to 16 years	1	350	3	572
Adult Receptors				
16 to 30 years	0.73	350	1	261
30 to 70 years	0.73	350	1	233

Notes:
(L/kg-day) = liters per kilogram body weight per day.
Source: Office of Environmental Health Hazard Assessment, *Air Toxics Hot Spots Program Risk Assessment Guidelines,* 2015.

To provide a standardized platform for health risk assessment, the Hotspots Analysis and Reporting Program (HARP) was developed as a software suite that addresses the programmatic requirements of the Air Toxics Hot Spots Program (created by Assembly Bill 2588) [*14*]. HARP incorporates the information presented in the 2015 Air Toxics Hot Spots Program *Guidance Manual for Preparation of Health Risk Assessments*. In HARP, users are able to select a range of scenarios including type of pollutants, exposure pathway, population, and exposure duration [*15*]. If data are available, cancer risks, chronic risks, and acute risks can be estimated with the HARP software.

With the cancer risk calculated as shown in Equations 3 and 4 or in HARP, we can estimate the cancer risk from multiple traffic-related air pollutants for a certain population under an exposure scenario. Assuming that the cancer risks in this study can be added together, Equation 5 can be applied to summarize the health risks. Therefore, for certain pollutants, the effects could be synergetic, and Equation 5 needs to be adjusted to reflect such effects.

$$\text{Risk} = \sum_p \sum_t risk_{p,t} \qquad \text{Equation 5}$$

where $risk_{p,t}$ is the health risk of a certain pollutant *p* during a duration *t*. The risks can also be aggregated by population groups as needed.

With the risks calculated as shown in Equations 3 and 4 or in HARP, we estimated the cancer risk that resulted from several pollutants based on a time scale. HARP software is designed mainly for regulatory purposes, and the exposure duration, such as 9 years, 30 years, and 70 years, for residential receptors is recommended.

In this study, HARP was used, and 9-year exposure was selected. Concentration is proportionally related to the cancer risks when all other options are the same. In HARP, 1 µg/m³ of diesel exhaust PM is calculated to have a cancer risk of 434.5 in 1 million for 9-year exposure starting at the third trimester, and the cancer risk would be 373 in 1 million for 9-year exposure starting at 30 years old. Unfortunately, gasoline exhaust PM was limited and not studied as extensively as diesel gasoline exhaust [*16*]. For example, Roth et al. found that short-term exposure to gasoline exhaust may have no major toxic effects in bronchial epithelial cells and natural killer cells [*17*]. Since HARP does not have data for gasoline exhaust, the gasoline exhaust's health effects were not estimated with the concentration estimation.

Results and Discussion

Figure 3 shows the estimated gasoline $PM_{2.5}$ concentration in the study area. Dark gray marks census block centroids that have higher gasoline exhaust $PM_{2.5}$. The highlighted points represent the top 1 percent of the estimated concentration. Since the selected Orange County area is more densely populated than the selected Riverside County area, there are darker census block centroids in Orange County than in Riverside County.

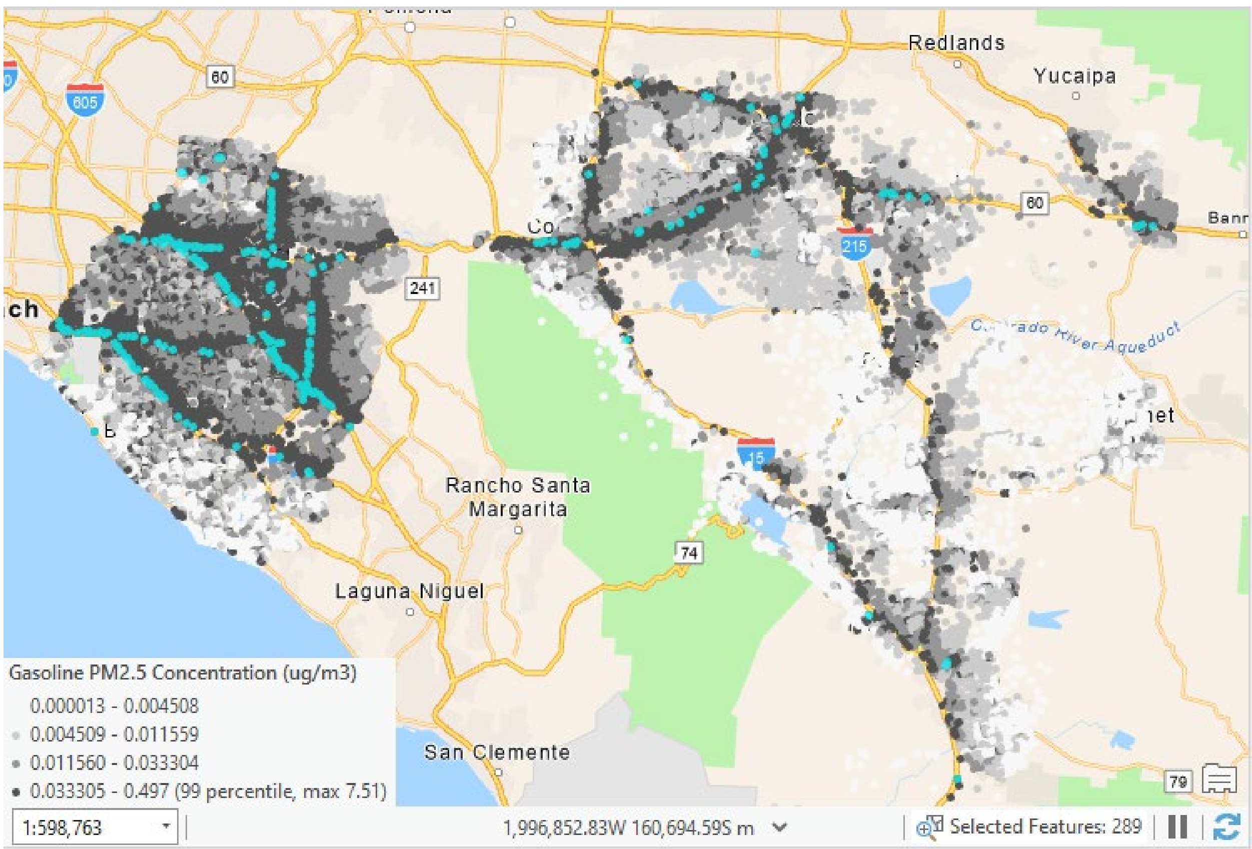

Figure 3. Gasoline exhaust $PM_{2.5}$ concentration modeling for 2016 (highlighted points represent the top 1 percent of the concentration).

Figure 4 shows the estimated diesel $PM_{2.5}$ concentration in the study area, which shows a pattern similar to that in Figure 3. This was anticipated because major freeways that carry the most gasoline-fueled vehicles are also heavily traveled by diesel-fueled vehicles. Therefore, the communities near major freeways are mostly impacted. The highlighted points represent the top 1 percent of the estimated concentration. The highlighted hot spots are the top 1 percent due to a number of reasons, including the traffic volume, traffic speed, diesel vehicle ratio, and micrometeorology data applied in the experiment. This does not necessarily mean that the traffic-related air pollutants at the highlighted points are always at higher concentration than at other points. However, this does indicate that the corresponding census blocks or tracts are heavily impacted by traffic-related air pollutants.

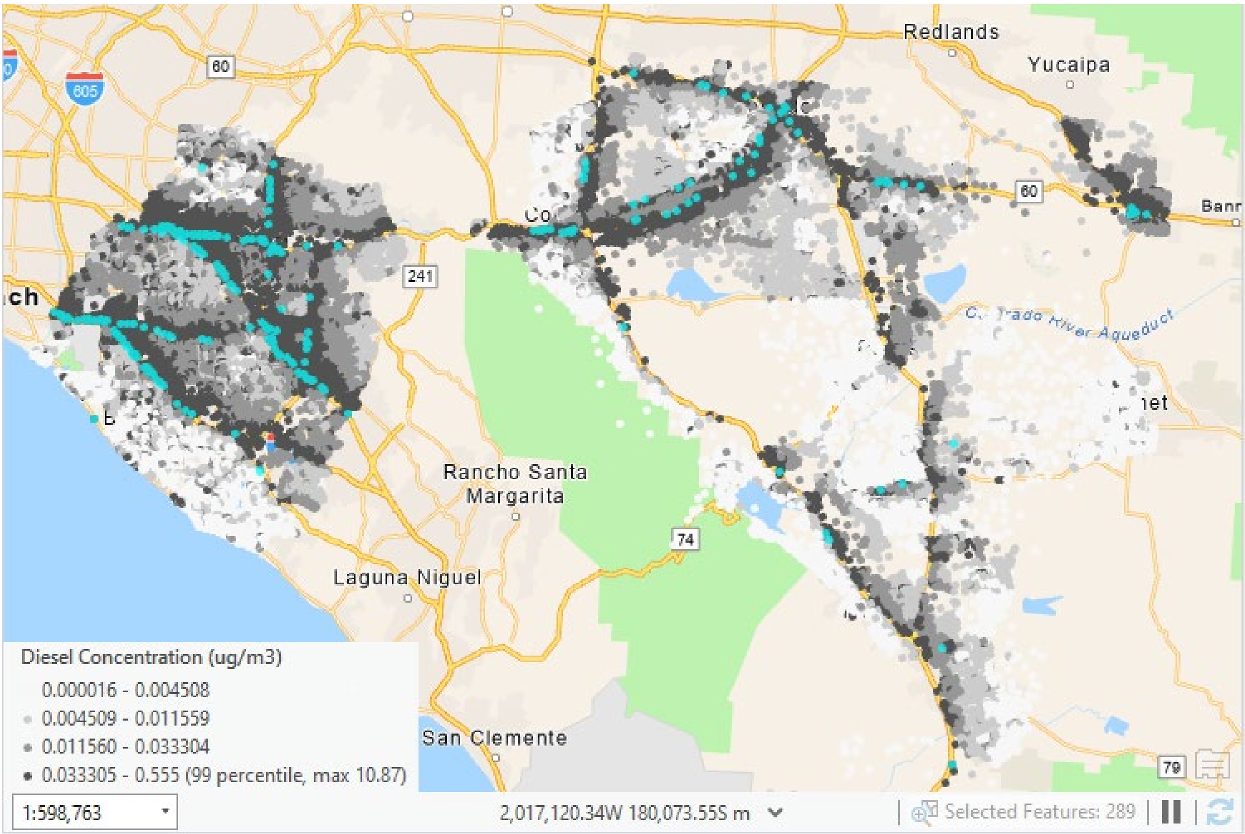

Figure 4. Diesel exhaust $PM_{2.5}$ concentration modeling for 2016 (highlighted points represent the top 1 percent of the concentration).

To compare the overall $PM_{2.5}$ concentration between the selected areas, Figure 5 shows the box plot of the gasoline $PM_{2.5}$ and diesel $PM_{2.5}$ between selected areas. The Orange County blocks generally have higher primary traffic-related $PM_{2.5}$ concentration than the Riverside County blocks do. Within selected Orange County blocks, the gasoline and diesel $PM_{2.5}$ concentrations are comparable. However, within selected Riverside County blocks, the average diesel $PM_{2.5}$ concentration is slightly higher than the average gasoline $PM_{2.5}$ concentration. The comparison results were anticipated because the selected Orange County area has more blocks near the road than the selected Riverside County area does, and this study provides a quantitative comparison.

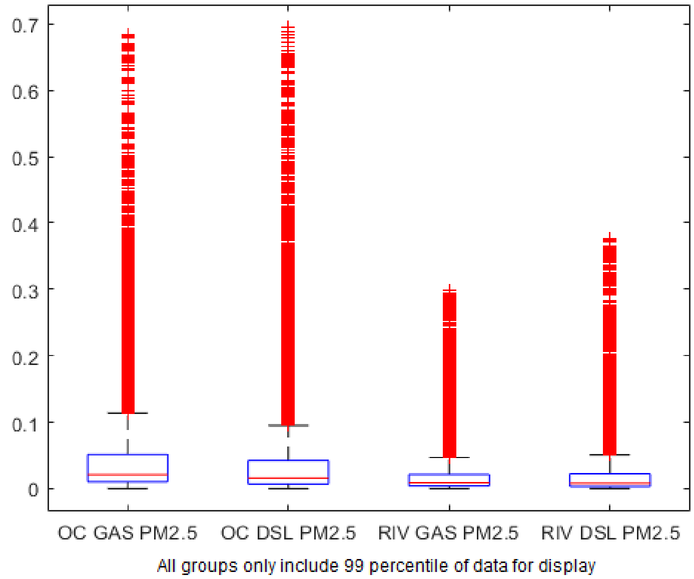

Figure 5. Box plot of estimated gasoline and diesel $PM_{2.5}$ concentration at selected Orange County (OC) and Riverside County (RIV) census block centroids.

This study only models the traffic-related exhaust emissions. Considering ambient air quality, the total pollutant concentration can be more substantial than the traffic-related exhaust emissions analyzed in this study, especially for inland California, where secondary PM and ozone pollution cause more health concern than primary air pollutants.

With the $PM_{2.5}$ concentration calculated, the health risk can be assessed using the previously described methods. Using HARP, we found that the cancer risks are linearly related to diesel $PM_{2.5}$ concentration, provided that all other options are the same. A diesel exhaust PM of 1 $\mu g/m^3$ was calculated to cause a cancer risk of 434.5 in 1 million for 9-year exposure starting at the third trimester. This value was applied to estimate cancer risks resulting from traffic-related primary diesel $PM_{2.5}$ as shown in Figure 6. The gasoline $PM_{2.5}$ health risks were not evaluated in this study because the risk factors were not available yet. However, for the future work, the gasoline $PM_{2.5}$ health risks can also be assessed given more health studies or using other surrogates such as benzene or formaldehyde.

The health risk values estimated in Figure 6 can be combined with screening tools to provide more detailed resolution. If secondary PM and ozone concentration can be mapped at a regional scale, this study can provide a layer of concentration and health risks that shows detailed intra-urban variation.

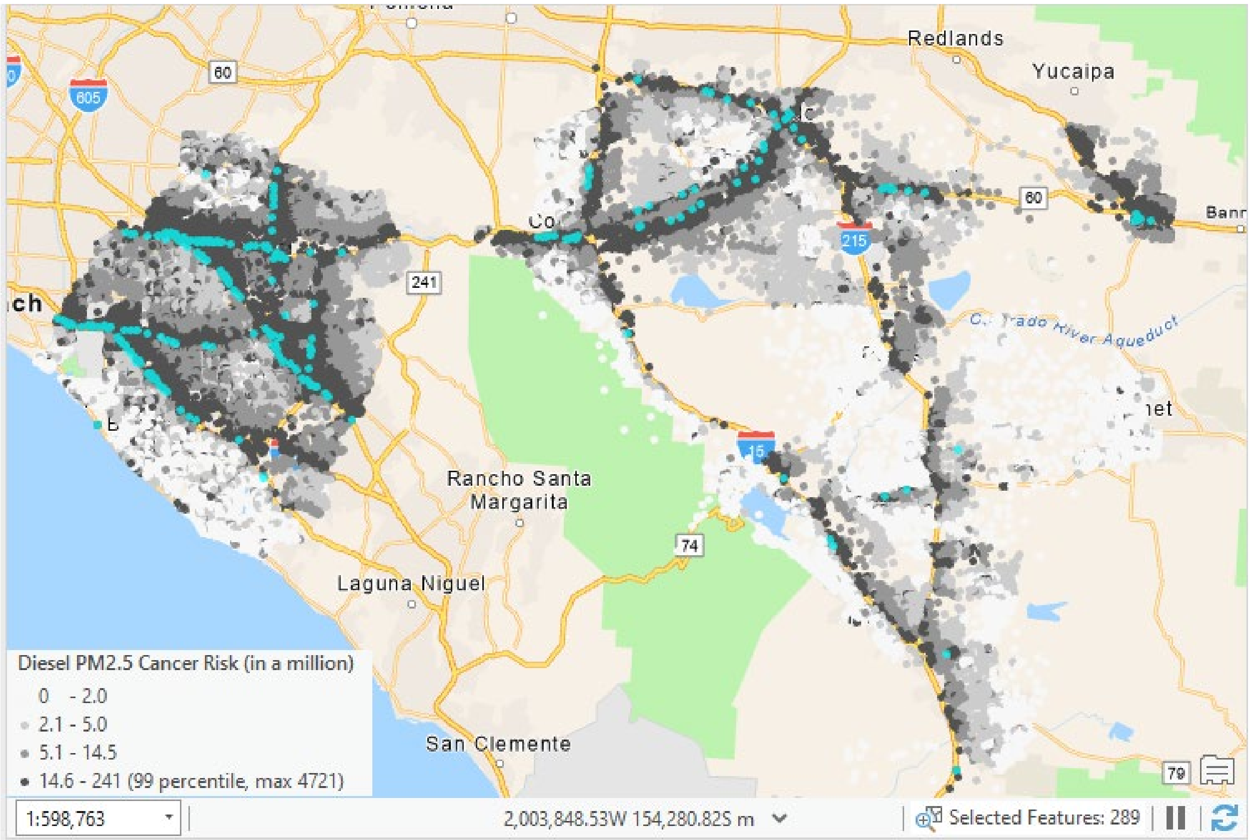

Figure 6. Estimated cancer risks based on 9-year diesel $PM_{2.5}$ exposure starting at the third trimester.

Conclusions and Recommendations

The cancer risks shown in Figure 6 are limited to traffic-related exhaust emissions based on a range of assumptions. Figure 6 provides quantitative health risk values among residential communities. For example, the map shows that to limit cancer risk within the 75th percentile (14.5 in a million) of the study area, a "safe" distance would be 1,500 to 2,000 meters away from major freeways in a number of neighborhoods. While the California Air Resource Board recommends sensitive receptors, such as homes and schools, be located 300 meters away from major sources such as freeways [*18*], this study shows that a "safe" distance could be much more than 300 meters, given various other pollutants are not included in this study.

Therefore, more work is needed to evaluate the health risks related to traffic sources and measures that can help communities reduce such health risks. Future work can be directed to perform cohort health studies with modeling studies, explore technology breakthroughs that can significantly reduce exhaust emissions, and evaluate mitigation measures such as household air filters.

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