Eliminating Health Disparities in Disadvantaged Communities: Assessing the Prospective Air Quality and Health Benefits of California’s Transition to Zero-Emission Vehicles

Clients: Office of Environmental Health Hazard Assessment (OEHHA),
Center for Biological Diversity (CBD)

Advisor: Pablo Saide Peralta

Team Members:

Isha Khalid

Elisa Kolek

Kaylin Ng

David Park

Sam Rutledge

Marlen De Silva

Anvin Tang

Sophia Wang

University of California, Los Angeles

Abstract

The focus of this study was to determine the prospective health effects of the transition to zero-emission vehicles (ZEVs) in California. To do so, the California on-road vehicle population estimates from a fleet database were organized with their corresponding emission factors and CalEnviroScreen (CES) scores using RStudio. The Advanced Clean Cars II (ACC II) regulations require all new passenger vehicles in California to be zero-emissions by 2035. This will drastically decrease the emissions produced by light-duty vehicles and trucks. However, it is unclear how the resulting air pollution reduction and avoided health impacts will be distributed across California's communities. To investigate this transition, four future scenarios were created using the varying ZEV adoption rates provided by ACC II. The emissions data was projected through 2035 and then run through a new modeling program that combines InMap and BENMap software, called the ISRM Tool. The results highlight the unequal air pollution burden and environmental injustices based on CES scores, ethnicity, and income across disadvantaged communities (DACs). The data on fine particulate matter ($PM_{2.5}$) health effects was connected to the selected communities and respective scenarios. From our study, we were able to see that the transition to ZEVs at today's current rates will increase existing disparities. It is crucial to introduce future policies that alleviate the disproportionate impact on disadvantaged communities.

Introduction

The transportation sector is the largest contributor to greenhouse gas (GHG) emissions in the state of California and the United States as a whole. These emissions primarily come from the burning of fossil fuels to power cars, trucks, ships, trains, and planes (U.S. Environmental Protection Agency, 2020). In 2020, approximately 140 million metric tonnes of carbon dioxide (CO_2) were emitted from the transportation sector in California, and about 70% of these emissions came just from passenger vehicles (CARB, 2022-a). Carbon dioxide is the GHG most responsible for our warming planet. In less than 200 years, since the Industrial Revolution, human activities have raised atmospheric CO_2 by 50%, leading to global climate change (NASA, 2023). Internal combustion engine vehicles (ICEVs) also emit harmful air pollutants such as fine particulate matter, also known as $PM_{2.5}$. Small enough to penetrate deep into the lungs and the bloodstream, long term exposure to $PM_{2.5}$ contributed to 4.14 million deaths worldwide in 2019, which made up 62% of all deaths attributable to air pollution (HEI, 2020). Acute exposure can lead to exacerbated lung and heart ailments as well as asthma attacks. Chronic exposure has been linked to both cardiovascular and respiratory diseases, has increased risk of affecting reproductive outcomes and cancer outcomes, and has been found to cause mortality (U.S. EPA, 2009). Previous research has estimated that $PM_{2.5}$ emissions from transportation lead to approximately 3,100 premature deaths per year in California due to cardiovascular disease, heart attacks, and other illnesses (Tessum, et al., 2014; Krewski et al., 2009). Thus, transportation contributes to both climate change and air pollution, two environmental hazards that undoubtedly threaten public health and need to be addressed.

In their "State of the Air" 2023 Report, the American Lung Association (ALA) (2023) determined that more than one in three Americans live in counties with unhealthy levels of ozone or particulate pollution. The report specifically looked at levels of ozone, short-term particle pollution, and year-round particle pollution, and California cities occupied the top three slots for ozone and year-round particle pollution. They also occupied the top two slots for short-term particle pollution. The report also re-emphasized that exposure to air pollution is not evenly distributed amongst communities. They found that people of color are 3.7 times more likely than white people to live in a county with a failing grade for at least one pollutant (ALA, 2023). This is a clear environmental injustice, and it is the result of discriminatory practices (e.g. redlining). A recent UCLA-led study similarly found that the most disadvantaged communities in Los Angeles not only contained a greater amount of pollution, but also that the pollution in these areas was more toxic than in other parts of Los Angeles (J. Shen et al., 2022). This study's definition of disadvantaged referred to census tracts in the 25 percent of LA communities facing the most socioeconomic disadvantages. They also determined that in the LA areas sampled, 42% of total air toxicity came from tailpipe emissions, and pollution in high-traffic areas was about 50% higher due to vehicle-related pollution than it was in other urban communities located further from streets or highways. Thus, these communities are disproportionately put at a higher risk for many health conditions due to the air pollution emitted from vehicles.

In August 2022, the California Air Resources Board (CARB) approved the Advanced Clean Cars II Rule, which mandates that all new vehicle sales in California must be ZEVs by 2035, along with intermediate ZEV milestones until that date. This rulemaking codifies the light-duty vehicle (LDV) goals described in Governor Newsom's Executive Order N-79-20 (CARB, 2022-c). Our practicum team aims to model multiple scenarios of this zero emission vehicle (ZEV) transition where rates of ZEV adoption vary among communities in California. ZEVs are expected to reduce emissions and concentrations of pollutants such as CO_2 and $PM_{2.5.}$

These reductions will not only help combat climate change but also reduce premature mortalities and improve the state's overall public health. CARB estimates that this regulation will lead to a 25% reduction in smog-causing pollution from LDVs, which will benefit "all Californians but especially the state's most environmentally and economically burdened communities along freeways and other heavily traveled thoroughfares" (CARB, 2022-c, para. 6). However, the cost of current ZEVs is mostly inaccessible to California's disadvantaged communities (DACs) who are the most burdened by air pollution. Adoption of new ZEVs in these communities occur at an extremely low rate – only 5.7% of total ZEV sales in the state for the period between 2010 and 2017, despite accounting for approximately 23.6% of the population (CARB, 2022-b). While we expect the ACC II transition to reduce air pollution in disadvantaged communities even at these low rates, it is unclear if the transition will be enough to eliminate the pre-existing disparity. Our goal was to determine the air quality and health benefits these communities would experience from possible future scenarios of ZEV adoption. To do this, we compared the current adoption rates with more equitable adoption rates by projecting vehicle emissions to 2035. We then used the new modeling program, the ISRM tool, to observe how the distribution of $PM_{2.5}$ concentrations and the corresponding health benefits varied across the scenarios. We hope that this work will quicken an equitable transition that reduces existing disparities in ZEV access and air pollution exposure.

Methodology

1.1 Data Sources

Emissions Factor Data

We sourced emissions factor data from the EMission FACtor (EMFAC) Emissions Inventory website, a database provided by the California Air Resources Board (CARB). We downloaded datasets for 2019 to 2036, and these datasets were used for our baseline data and also for the projections. The annual onroad emission factors data was downloaded at the county level using the EMFAC2021 v1.0.2 model version. The data was filtered to only include emission factors for passenger cars (LDA) and light-duty trucks (LDT1, LDT2) since these are the vehicle categories that will be included under the ACC II regulations (CARB, 2022-b). While this study does not include medium duty vehicles (MDV), future studies should since this category is also included under the ACC II's light duty vehicle regulations. Therefore, MDVs are also expected to transition to zero emission by 2035, which will be further discussed in the limitations section. We chose to aggregate the "speed" variable, but selected all available options for the "fuel" variable. Lastly, the output unit for these emissions was chosen at tons per year.

Provided Emissions Data for Validation

We also utilized a high-resolution emission dataset (1km x 1km) from 2019 that was provided by CARB in order to check the validity of our data method which we will refer to as EMFAC 2019 throughout the rest of the report. This dataset aggregates total vehicle emissions for an area and then redistributes emissions to the streets based on traffic data. In comparison, our data method assigns emissions to the census block group that a vehicle is registered in. This means our method attributes emissions to the home of the vehicle and not necessarily where the vehicle is being driven.

Vehicle Fleet Data

We sourced vehicle fleet data from the EMFAC Fleet Database website of the same CARB database. We downloaded the 2020 dataset which includes vehicles with model years between 1975 and 2021. This was the most recent year included in the database at the time of download. We filtered the vehicle category to only include passenger cars (P) and light-duty trucks (T1, T2). Similar to the emission factors data, our study did not include medium duty vehicles (T3), however, future studies should since they are also expected to transition. We chose to aggregate the "electric mile range variable", but included every option for the "fuel type, fuel technology, model year, and number of vehicles registered at the same address" variables. Lastly, we chose the "vehicle population output aggregation" to be given by census block group code, since this was the highest level of spatial resolution available.

2020 Census Block Group Data

We downloaded the 2020 vintage of Census block group data from the United States Census Bureau. Since the vehicle fleet data utilizes 2020 Census block groups to spatially assign vehicles, we sourced 2020 block group data to provide an appropriate spatial component for the emissions data.

CalEnviroScreen (CES) 4.0

CalEnviroScreen is a mapping tool created by one of our stakeholders, the Office of Environmental Health Hazard Assessment (OEHHA), that can help identify which communities are most affected by various types of pollution. It uses environmental, health, and socioeconomic information to produce a “burden” score for every census tract in the state of California (OEHHA, 2023). A census tract with a high score corresponds to a much higher pollution burden than those with a low score. The tool considers cumulative impacts from all pollution sources and accounts for vulnerable subpopulations such as young children (OEHHA, 2023). These scores are projected onto a map of California for visual analysis but can also be downloaded as an Excel spreadsheet which is what we utilized for this project. This data was last updated in October 2021.

Median Household Income Data/Non-White Population Data

Median Household Income and the Non-White Population in California were taken from the American Community Survey (ACS) provided by the United States Census Bureau. The American Community Survey release of 2020 provides a wide range of statistical data on the people and housing of every census tract in the United States.

RStudio was used to extract the median household income and non-white population from the ACS provided by the Census Bureau. Selected variables were chosen from ACS 2020 including the median household income in the past 12 months (B19013_001E), total population (B02002_001E), non-Hispanic white population (B03002_003E), Black or African American population (B03002_004E), American Indian and Alaska Native Population (B03002_005E), Asian population (B03002_006E), Native Hawaiian and Other Pacific Islander population (B03002_007E), some other race, non-Hispanic population (B03002_008E), two or more races, non-Hispanic population (B03002_009E), Hispanic or Latino population (B03002_012E). All of the preceding race variables were imported into RStudio to filter the non-white population. This was done by calculating the percent of non-white population over the total population. Both of the income and non-white values were converted into percentiles to create a consistent system of measurement.

1.2 Preparing the Baseline Data

To prepare the total emissions data for our baseline year of 2020 and the future projections, we used RStudio data analysis. As previously mentioned, we prepared the 2020 fleet data from the California Air Resources Board (CARB) database, EMission FACtor (EMFAC) Fleet Database Website. This data was filtered to only include passenger cars (P) and light-duty trucks (T1, T2). The large number of vehicles in California resulted in large datasets, thus, the data was downloaded county by county and then combined into one dataset in R. Once combined, the raw data required cleaning and processing. We first removed any rows with census block group codes that were “scrubbed” or removed, since this is the main geographic census unit utilized in this study for pollution distribution and health impacts. We also removed any “NA” row values under the model year variable. Without values for these variables, we could not assign the vehicles a location or emission rate.

We then prepared the 2020 emission factors data from the EMFAC Emissions Inventory website of the same CARB database. This data was also filtered to only include passenger cars (LDA) and light-duty trucks (LDT1, LDT2). Additionally, it was filtered to pollutants that contribute to primary or secondary formation of $PM_{2.5}$. This includes the running emissions for NH_3, the total exhaust emissions for NO_x and SO_x, and the total emissions for $PM_{2.5}$ and reactive organic gases (ROG). ROGs are the most similar to the Environmental Protection Agency’s (EPA) definition for volatile organic compounds (VOC). For simplicity, the VOC term will be used when referring to this class of pollutant moving forward. The emissions inventory provides total emissions for each type of vehicle based on its model year, fuel, county, etc. Therefore, we first needed to calculate the emission rates for each type of vehicle, and this was done by dividing the total emissions of each pollutant class by the vehicle population variable. Additionally, there were some discrepancies between the fleet and emissions data. For example, the fleet data from the year 2020 includes vehicles with model years between 1975 and 2021. However, the emission factors data from 2020 only includes vehicles with model years between 1976 and 2020. To solve this issue, we also downloaded emission factors data from the years 2019 and 2021, and these years provided us with the emission factors for vehicles with model years 1975 and 2021, respectively.

In order to join the fleet data to the emissions data, the names of the vehicle categories in the fleet data needed to be recoded to match. This was done by renaming the passenger cars and light-duty trucks to “LDA, LDT1, and LDT2”. The fuel type names for the fleet data also needed to be changed to match the fuel names in the emissions data. This was done by renaming the “Electric” fuel type to “Electricity” and by renaming any “PHEV” fuel technology vehicles to include a fuel type of “Plug-in Hybrid.” After additional minor processing, the fleet data and the emissions data were joined by model year, fuel type, vehicle type, and county. Once done, we could perform calculations for total vehicle emissions for the 2020 year. The previously calculated emission rates were multiplied by the vehicle population in each census block group code. There were missing emission rates in the data, for example, the emissions data did not contain values for natural gas vehicles with a 2017 model year. When joined, these vehicles had “NA” values, so we chose to also remove these rows. Finally, emissions for $PM_{2.5}$, VOC, NH_3, NO_x and SO_x were collapsed by census block group codes.

The CalEnviroScreen (CES) 4.0 data was the last dataset needed before the projections and subsequent analysis could be performed. We downloaded the data in the form of an Excel spreadsheet which we then imported into RStudio. Some processing of the raw data was needed, such as removing any variables beyond the scope of this study like exposure to pesticides or linguistic isolation. The main variable used from this dataset was the CES 4.0 percentile values, which tells us how a specific census tract scored in comparison to other tracts. Tracts with a higher percentile score experienced a higher cumulative pollution burden. Under Senate Bill (SB) 535, the California Environmental Protection Agency (CalEPA) designated census tracts receiving the highest 25 percent of overall scores in CES 4.0 as disadvantaged communities (OEHHA, 2022-a). We chose to follow this designation and similarly divide our census block groups into four quartiles based on their CES 4.0 percentile (0-25.99, 26-50.99, 51-75.99, and 76-100). This quartile approach was also utilized in an AB32 report (OEHHA, 2022-b). Like SB 535, the 76-100 quartile contains the most disadvantaged communities, and the 1-25 quartile contains the least disadvantaged. It is important to add this CES data so that $PM_{2.5}$ concentrations and their corresponding health impacts can be linked to the quartile and percentile score. This allows for environmental justice analysis and the direct comparison between various communities. We also used this quartile approach for additional variables such as median household income and non-white population which allowed us to perform further analysis. It is important to note that CalEPA has additional definitions under SB 535 for disadvantaged communities. This includes lands under the control of federally recognized tribes and tracts identified in the 2017 DAC designation as disadvantaged, regardless of their scores in CalEnviroScreen 4.0 (OEHHA, 2022-a). Tracts lacking overall CES scores due to data gaps, but receiving the highest 5 percent of CES 4.0 cumulative pollution burden scores are also considered disadvantaged. These communities are equally important, however, this study does not include any additional criteria in our designation of disadvantaged communities. Therefore, our designation is an oversimplification, and a more inclusive study should be done in the future.

In order to join the CES data, the census block group codes in the fleet and emissions data needed to be converted into census tracts, which is the geographic census unit used in CES. A census block group is a subdivision of a census tract and as such, it has an additional digit at the end of its numerical identifier. To perform the conversion, we simply divided each census block group code by 10 to remove the extra digit and then rounded down the decimal to calculate the whole number. Once completed, the fleet and emissions data could successfully be joined to the CES scores by census tract. It is important to note that some census tracts did not have a CES score or percentile value. CalEnviroScreen analyzes data for 8,035 census tracts across the state. Of these census tracts, 103 did not have an assigned percentile value. This could mean that no monitoring or reporting was conducted in these tracts or no population was reported. We opted to remove any census block group codes that did not have a CES percentile value, since we could not designate it as advantaged or disadvantaged. This resulted in the removal of 5,311 census block groups and their corresponding vehicles. Overall, we removed 5,027,629 vehicles–approximately 23% of the original data– however, these removals were deemed necessary due to the design of this study.

After modeling our combined fleet, emission factors, and CES 2020 data, we noticed that our $PM_{2.5}$ concentrations were slightly smaller than the 2019 CARB EMFAC modeled data. This was not unexpected, as our data is from a year heavily impacted by the COVID-19 pandemic.

For a substantial portion of the year, California was in lockdown, many people were working remotely, and travel was restricted. This led us to analyze the annual trends in the emissions inventory data, where we observed a significant dip in vehicle miles traveled during 2020, as shown in Figure 1 below. Vehicle miles traveled is directly related to the vehicle emission factors (U.S. EPA, n.d.). Therefore, we decided to perform a singular adjustment to account for the reduced emissions in 2020 from the COVID-19 pandemic so that this did not impact our projections moving forward. Total emissions were increased by 16.23%—a percentage proportional to the change in vehicle miles traveled—and modeling the adjusted data showed similar $PM_{2.5}$ concentrations and spatial patterns when compared to the 2019 CARB data.

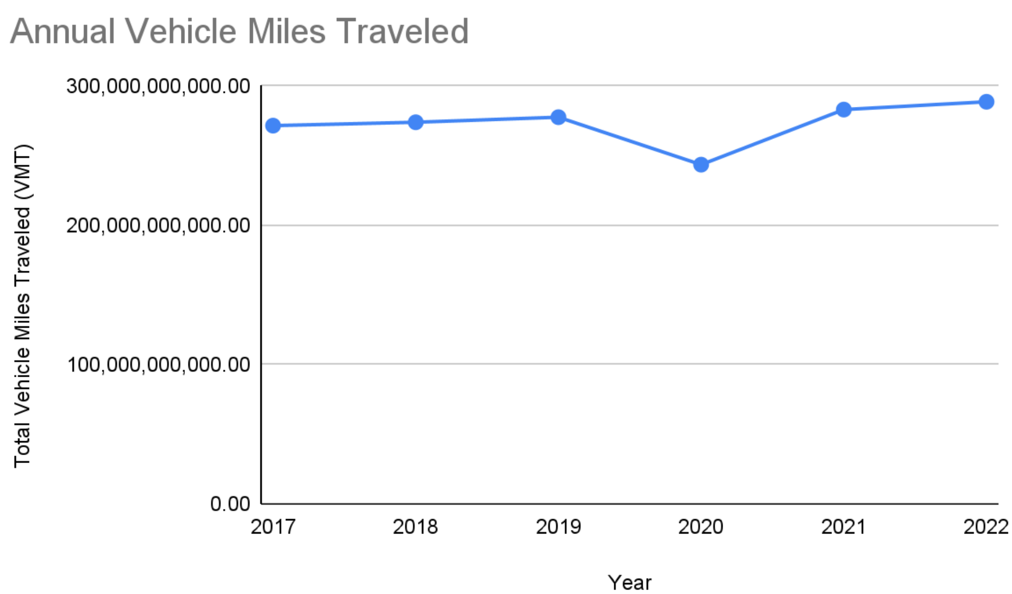


Figure 1. The graph above shows total vehicle miles traveled per year. This data was sourced from the CARB EMFAC Emissions Inventory website. There is a clear decrease in the year 2020 and then a recovery in the years following.

The combined fleet, emissions and CES data with the COVID-19 adjustment acted as our baseline for our projections. This provided the current $PM_{2.5}$ concentrations in the state for 2020 as well as the corresponding health impacts. From here, we removed vehicles and their corresponding emissions year by year and then replaced them with new combustion and zero emission vehicles. Details of this process are included in the following section. The projected data was then modeled and compared to the baseline to see how the ZEV transition will affect air pollution in California.

1.3a Projecting for Future Scenarios

To start our projections, we first needed to decide how many cars should be removed from and added to the fleet each year. This represents vehicles being retired from the fleet each year and being replaced by newly bought vehicles. Using the same EMFAC Emissions Inventory website, we downloaded statewide data for the years 2016 to 2022. When analyzing the data, we observed that total vehicle population for passenger vehicles and light duty trucks stayed fairly constant throughout this time period, as shown in Figure 2 below. Therefore, we assumed that the total vehicle population will stay approximately the same throughout all of our projections. The number of new vehicles introduced into the fleet each year is equal to the number of vehicles being retired from the fleet. To calculate the number of new vehicles added to the fleet each year, we sourced data from the California New Car Dealers Association (CNCDA) for the same years, 2016 to 2022. Since we are assuming the vehicle population stays constant, we took the average of the light duty vehicle registrations for these years and obtained a result of 2,007,143 new light duty registrations each year. We used data for new registrations instead of new sales to stay consistent with the EMFAC Fleet Database, which provides vehicle registrations as well. Registrations are also more likely to accurately represent where vehicles are driven and emissions occur in comparison to sales, since people will often travel beyond their cities of residence to buy vehicles. Since 2,007,143 new vehicles are registered each year, then the same number must be removed from the baseline data along with a proportionate amount of emissions. To calculate the percentage of emissions being removed each year, we took the average of the total vehicle population from the EMFAC Emissions Inventory data from 2016 to 2022. This yielded an average vehicle population of approximately 21,463,965 vehicles. We divided the number of new vehicles per year by this number, and we determined that approximately 9.35% of the fleet is being removed each year. Since it is possible for any vehicle in the fleet to be "retired," regardless of model year, we decided to remove these emissions uniformly across vehicle classes. To project this, we removed 9.35% of the $PM_{2.5}$, VOC, NH_3, NO_x and SO_x emissions each year from 2020 to 2035. With this method, we assume that the removal of vehicles from the fleet is proportional to the removal of emissions.

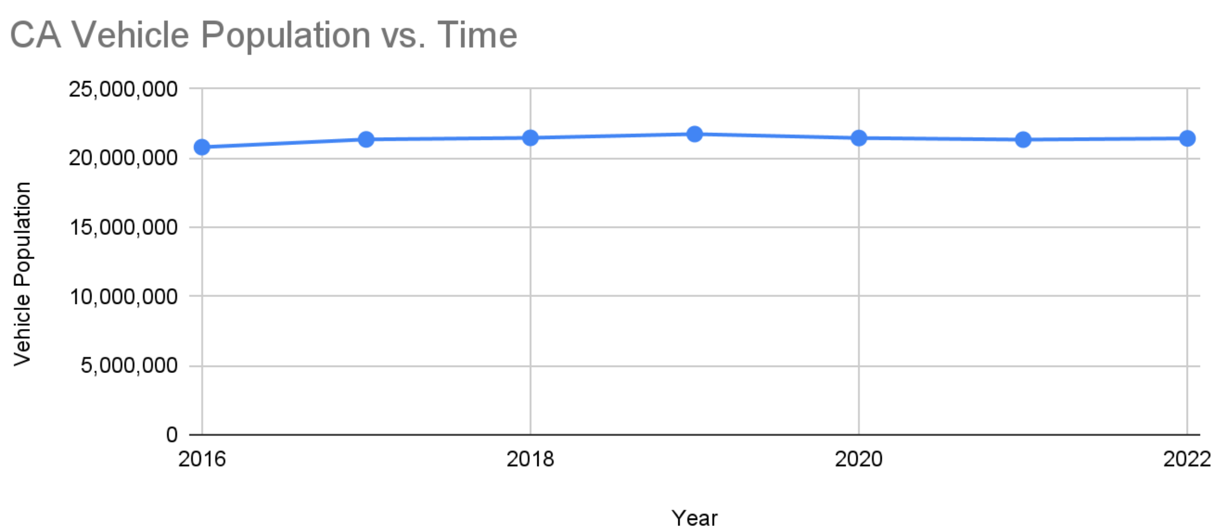


Figure 2. The graph above shows the total vehicle population for passenger vehicles and light duty trucks in California per year. This data was sourced from the CARB EMFAC Emissions Inventory website. We can observe that the vehicle population remains fairly constant throughout the years.

Once we determined how many new vehicles were being added to the fleet each year, we then needed to calculate how many of these vehicles would be zero emission. To make this calculation, we used the following projection provided by CARB in the ACC II document. This states the percentage of new vehicles that must be zero emission vehicles each year. This percentage increases annually until 2035, when 100 percent of new vehicle sales must be zero emission. However, this projection does not start until the year 2026. So, in order to perform our projections starting in 2020, we needed to calculate the years in between the CARB projection and the last year of observed data through linear interpolation. For this, we sourced data from the same CNCDA data report on ZEV sales for the years 2017 to 2021. At the time of download, 2021 was the most recent year of data available. We used the average increase per year from 2017 to 2021 and then linearly interpolated from 2021 to 2026. This yielded the percentage of new vehicle sales each year that will be ZEVs. The CARB projection is shown below in Figure 3, and an updated projection from our linear interpolation is shown in Figure 4.

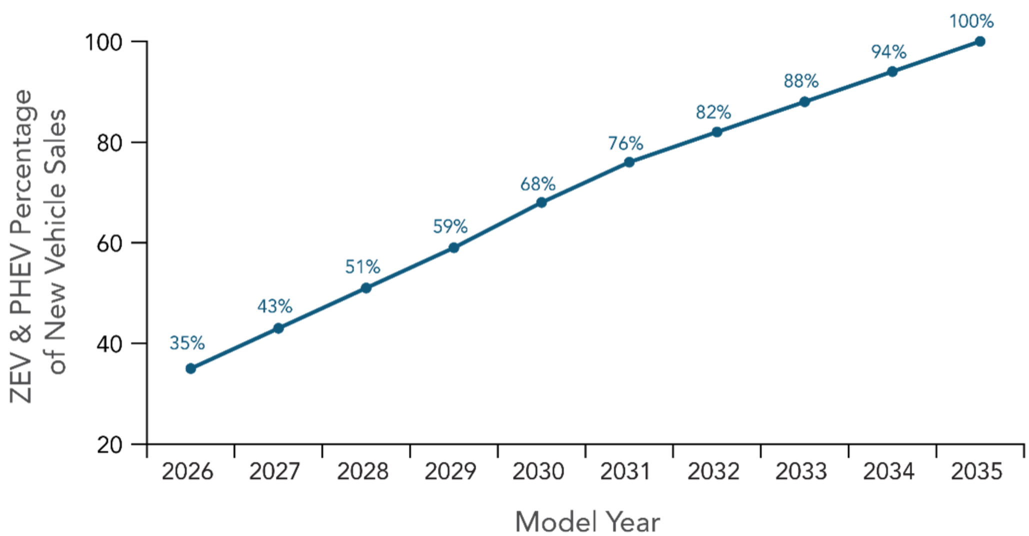


Figure 3. This projection was sourced from the CARB ACC II document (2022). It shows the ZEV and PHEV percentages of new vehicle sales each year as it ramps up to 100 percent in 2035.

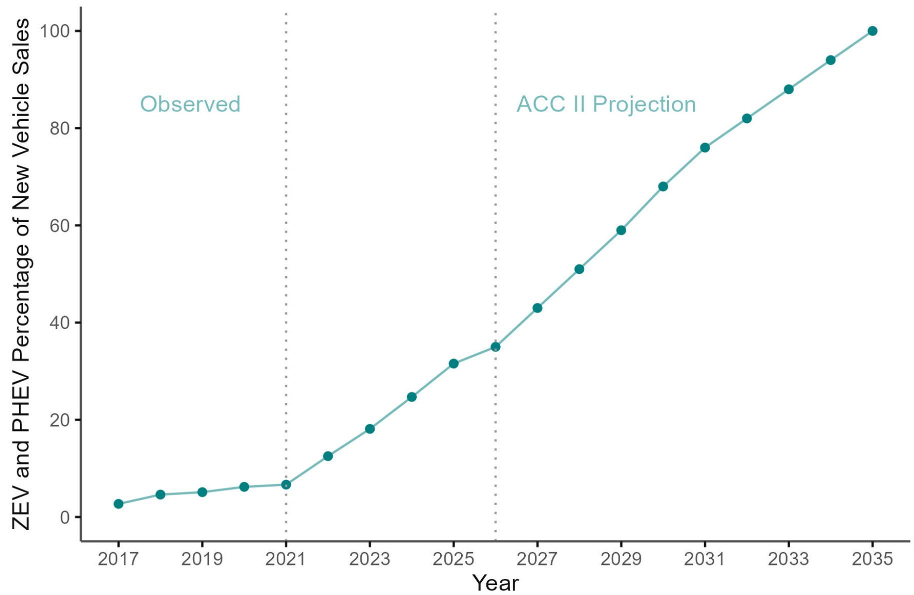


Figure 4. This projection was performed by our team and shows a linear interpolation between observed data sourced from the CNCDA and the previously shown CARB ACC II projection. This provides us with the ZEV and PHEV percentage of new vehicle sales for the years between 2021 and 2026.

1.3b The Four Scenarios

Table 1. Percentage of Total California ZEV Sales Distributed to Each Quartile Through All Scenarios

CES Percentile Scores	Business as Usual (Scenario 1)	Equal Spread of ZEVs (Scenario 2)	Half to DACs (Scenario 3)	Three-Fourths to DACs (Scenario 4)
0 - 25 (Most Advantaged)	54.6.%	28.47%	29.30%	14.63%
26 - 50	25.50%	25.55%	13.30%	6.65%
51 - 75	13.90%	24.97%	7.50%	3.72%
76 - 100 (Most disadvantaged)	6.10%	21.01%	50%	75%

Scenario 1 - Business as Usual

Once we calculated the number of new electric vehicles being added each year, we needed to figure out how they would be distributed. We created four scenarios, and each scenario has a different ZEV adoption rate for each CES quartile, as seen in Table 1. This also applies to the additional variables previously mentioned: median household income and non-white population. We chose these scenarios to highlight the potential effects of different proposed adoption rates amongst California's communities. This is the core of our research question, and this allowed us to analyze the differences in air pollution reductions and avoided health impacts. The first scenario was developed based on the current rate of ZEV adoption rates and is a scenario modeling "business as usual." ACC II assumes that adoption of new electric vehicles in disadvantaged communities occurs at an extremely low rate, only making up 5.7 percent of total ZEV sales in the state (CARB, 2022-b). To calculate the adoption rates in the other three quartiles, we summed all pre-existing ZEVs in our 2020 baseline fleet data from the EMFAC Fleet Database website. We found that approximately 6 percent of pre-existing ZEVs were located in disadvantaged communities (76-100 percentile), which aligned with the rate stated in the ACC II document. Then, we found 14 percent were located in the next quartile (51-75 percentile), 25 percent in the next quartile (26-50 percentile), and 55 percent in the most advantaged communities (1-25 percentile). We used these same percentages for our first projection scenario. However, by 2035, 100 percent of new vehicle sales going into all quartiles are expected to be electric. Due to the larger percentage going into the most advantaged quartile (1-25 percentile), their share of new vehicles quickly becomes completely electric. In order to keep the total number of vehicles balanced, we had to avoid adding extra ZEVs into this quartile. To do this, we redirected any extra ZEVs into the adjacent quartile (26-50 percentile). Once this quartile's share of new vehicles also reaches 100 percent electric, we redirected it to the next quartile (51-75 percentile) and then finally to the most disadvantaged communities (76-100 percentile). For this reason, the initial percentages for scenario one evolved over the years until 2035. For this scenario, the first quartile (1-25 percentile) reached 100% ZEV sales by 2030, quartile two (26- 50 percentile) reached 100% by 2031, quartile three (51-75 percentile) reached 100% by 2033, and quartile four (76 - 100 percentile) reached 100% by 2035.

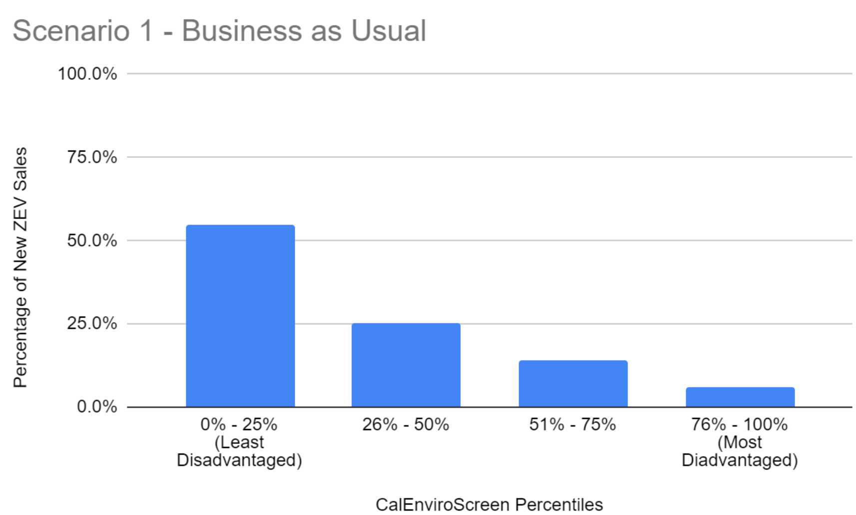


Figure 5. This figure represents scenario one, where current ZEV adoption rates remain the same until 2035. This is "business as usual," and we have included this figure for easier visualization of the adoption rates per percentile.

Scenario 2 - Equal Spread of ZEVs

Our second scenario was developed to investigate the effects of a more equitable transition to ZEVs. In this scenario, the adoption rate is equal to the pre-existing vehicle percentage in each quartile. The vehicle percentage was also calculated using the 2020 baseline fleet data from the EMFAC Fleet Database website. We summed the pre-existing vehicles in each quartile and then divided it by the total number of vehicles in the state of California. Therefore, our definition of equity for this scenario is having an adoption rate in a quartile equal its vehicle percentage. These calculations determined that 21.01 percent of vehicles are registered in disadvantaged communities (76-100 percentile). 24.97 percent of vehicles are in the next quartile (51-75 percentile), 25.55 percent are in the next quartile (26-50), and finally, 28.47 percent are in the most advantaged communities (1-25 percentile). These percentages are close to 25 percent, however, we can see that disadvantaged communities have the smallest percentage while most advantaged communities have the largest. Since these adoption rates are based on the pre-existing vehicle percentages, we did not run into the same problem from scenario one, where one quartile reaches 100 percent adoption of ZEVs before the others.

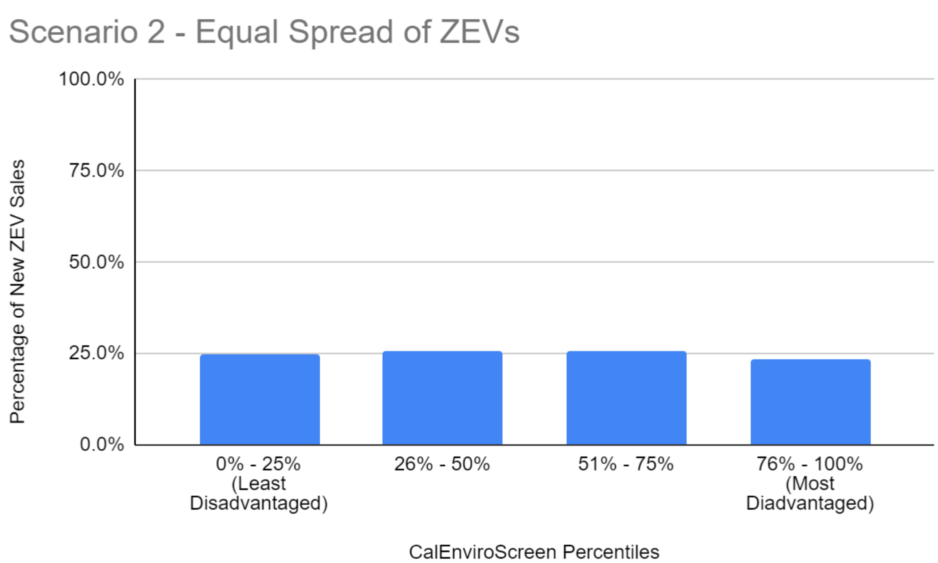


Figure 6. This figure represents scenario two, where ZEV adoption rates are equal to the pre-existing vehicle percentage in each quartile. This is "equal spread of ZEVs" until 2035, and we have included this figure for easier visualization of the adoption rates per percentile.

Scenario 3 - Half to DACs

Our third scenario shifted most of the ZEVs to the most disadvantaged quartile while continuing to keep a similar ratio of new ZEV adoption in the other quartiles. We chose this scenario to investigate how aggressive ZEV adoption must be in DACs in order to erase the pre-existing air pollution disparity. For this, we decided 50 percent of ZEVs would enter disadvantaged communities (76-100 percentile), 7.5 percent would enter the next quartile (51-75 percentile), 13.3 percent would enter the next quartile (26-50 percentile), and 29.3 percent of new ZEVs would go to the most advantaged communities (1-25 percentile). Similar to scenario one, the most disadvantaged quartile (76-100 percentile) quickly had new car sales at 100 percent electric due to its larger percentage of sales. To compensate for this, we used a similar method to scenario one by redirecting any extra ZEVs into the adjacent quartile. However, in this scenario, extra ZEVs from the fourth quartile (76-100 percentile) were added to the third quartile (51-75 percentile), then to the second, and finally to the most advantaged communities. For this scenario, the fourth quartile (76 - 100 percentile) reached 100% ZEV sales by 2028, quartile three (51-75 percentile) reached 100% by 2032, and both quartile one (1 - 25 percentile) and quartile two (26 - 50 percentile) reached 100% by 2035. In order for there to be such a large percentage of new ZEV sales in disadvantaged communities, as seen in this scenario, there would likely have to be some form of new legislation or incentives to increase sales so dramatically. If this were the case, we would likely see higher new ZEV counts in the next most disadvantaged communities than in the most advantaged. Thus, the excess ZEV redistribution in scenario three is formatted to reflect this concept. Therefore, the initial percentages for this scenario also evolved over the years.

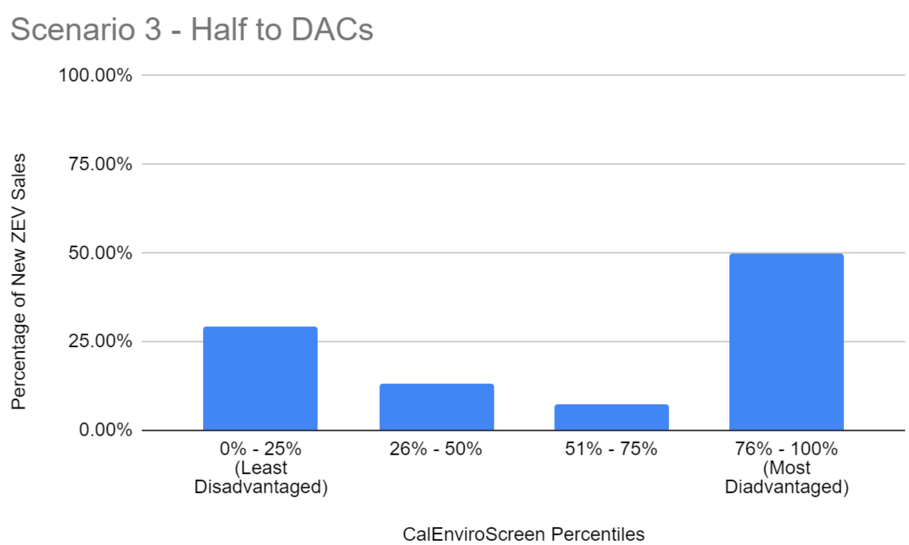


Figure 7. This figure represents scenario three, where ZEV adoption rates prioritize disadvantaged communities who experience the highest air pollution burden . This is "half to DACs," and we have included this figure for easier visualization of the adoption rates per percentile.

Scenario 4 - Three-Fourths to DACs

Our fourth and final scenario investigates even more aggressive rates than seen in scenario three. For this, we decided 75 percent of ZEVs would enter disadvantaged communities (76-100 percentile), 3.7 percent would enter the next quartile (51-75 percentile), 6.7 percent would enter the next quartile (26-50 percentile), and 14.6 percent of new ZEVs would go to the most advantaged communities (1-25 percentile). With such a large percentage of new ZEV sales in the most disadvantaged communities, we will see how a drastic decrease in ICEs and their emissions in these areas can affect the overall California population. Like scenario three, we kept the ZEV adoption rates in the other three quartiles similar to their current ratio. Scenario four ran into the same complication as scenario three, where excess of ZEVs needed to be redistributed to the next most disadvantaged communities. We applied the same logic with this scenario as well, and extra ZEVs from the fourth quartile (76-100 percentile) were added to the third quartile (51-75 percentile), then to the second, and finally to the most advantaged communities. For this scenario, the fourth quartile (76 - 100 percentile) reached 100% ZEV sales by 2025, quartile three (51-75 percentile) reached 100% by 2030, quartile two (26 - 50 percentile) reached 100% by 2033, and quartile one (1 - 25 percentile) reached 100% by 2035.

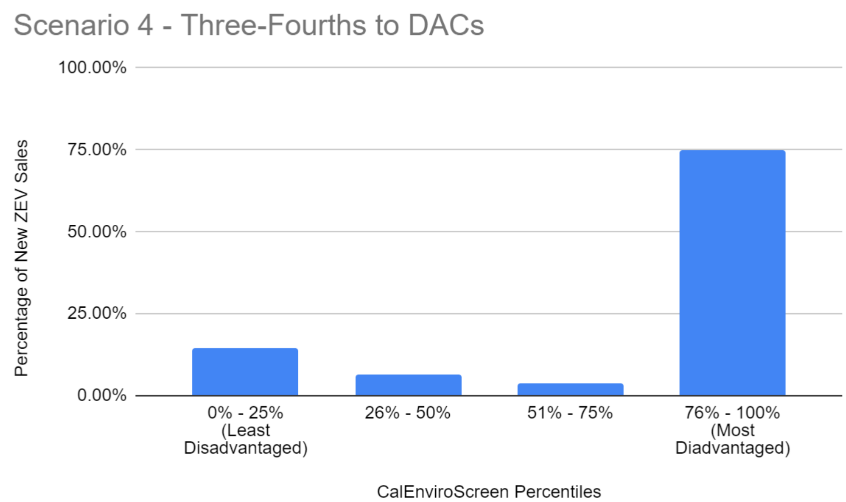


Figure 8. This figure represents scenario four, where current ZEV adoption rates are even more aggressive in prioritizing disadvantaged communities. This is "three-fourths to DACs," and we have included this figure for easier visualization of the adoption rates per percentile.

1.4 Calculating Future Emissions

For every year until 2035, new vehicle sales include both new electric vehicles and new ICE vehicles. Once we calculated the number of new ZEVs going into each quartile, we next needed to calculate the number of new ICEVs. Recall that the total number of new vehicles entering the fleet each year is equal to 2,007,143. To calculate the "Equal Spread of ZEVs" scenario, we also calculated the vehicle percentages in each of the four quartiles. We then multiplied these percentages by the total number of new vehicles in order to calculate the total number of new vehicles going into each quartile every year. Table 2 below shows the results of these calculations detailing the new vehicle distribution per CES percentile.

Table 2. "Equal Spread of ZEVs" Scenario - New Vehicle Distribution

CES Percentile	0 - 25.99	26 - 50.99	51 - 75.99	76 - 100 (DACs)	Total
Number of New Vehicles	571,472	512,866	501,151	421,654	2,007,143

Once done, we subtracted the calculated number of ZEVs each year from these numbers which gave us the number of new ICEs each year, since the total number of vehicles must remain balanced. Finally, we needed to distribute these new vehicles to each census block group, since this was the geographic census data used. To keep vehicles balanced, we decided to distribute these based on the pre-existing vehicle proportion in each census block group. The proportion of vehicles for each census block group was calculated by dividing the number of vehicles in each census block group by the total number of vehicles in the quartile. This proportion was then multiplied by the number of new ZEVs and ICEs which gave us the number of each in every census block group.

After this, the next step of the projection was to find emission factors for these projected cars. To do this, we sourced data from the same EMFAC Emissions Inventory website. CARB provides projected emission factors for vehicles, likely based on technological advancements or stricter legislative standards coming down the pipeline. We downloaded statewide emission factors data from the year 2022 to 2035. For simplicity, we decided that a "new vehicle" would refer only to vehicles with a model year for the following year. For example, when projecting for 2021, we introduced new vehicles to the fleet that had a model year of 2022. We chose this method since this is standard practice for car dealerships. One limitation to adding new vehicles in this manner is that we are unable to account for an increase in pollution from vehicles as they age. A car will have the same emissions throughout its entire lifetime in the fleet, regardless that it will age and become "dirtier". There is currently not enough information regarding at what age most vehicles are retired and in which communities to allow for accurate estimates regarding an increase in pollution. Therefore, we are assuming the emission rates of existing vehicles remain constant.

Once the emissions data was downloaded and imported, we first needed to calculate the emission rates for each type of vehicle. Like our baseline data, the emissions inventory provides total emissions for each type of vehicle based on its model year, fuel, county, etc. This was done in the same manner–by dividing the total emissions of each pollutant class by the vehicle population variable. We added this emissions data to our baseline data by county, before collapsing the data down by vehicle type (gasoline, diesel, etc.) and county. This was done so that every county has only one NO_x emission rate for a new gasoline vehicle, for example. Then, we needed to calculate one combined electric vehicle rate, since electric vehicles consist of both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). The ACC II regulation considers both BEVs and PHEVs to be electric vehicles, and both types of vehicle have their own corresponding emission factors. The same is true for ICE vehicles, which consist of both gasoline and diesel vehicles. This category also contains natural gas vehicles, however they typically make up less than 1 percent of ICEV sales. Additionally, the EMFAC Emissions Inventory website is missing data on natural gas vehicles, therefore, we decided to omit them in this study. To calculate the proper ratios of BEVs to PHEVs, as well as gasoline to diesel vehicles, we sourced data from the EMFAC Emissions Inventory website. This time, we downloaded statewide data for the years 2015 to 2019, in order to avoid any skewed data from the unique COVID-19 years. We found that the ratio for gasoline to diesel sales was roughly constant at 9:1. The ratio of BEV to PHEV sales did change throughout the years, with the number of PHEVs decreasing each year. Additionally, the ACC II states that although PHEVs count as a zero emission vehicle, they can only make up 20 percent of the annual zero-emission vehicle requirement. Therefore, we linearly interpolated between the last year of 2019 to the year 2026, when PHEVs can only account for 20 percent. This is shown in the figure below.

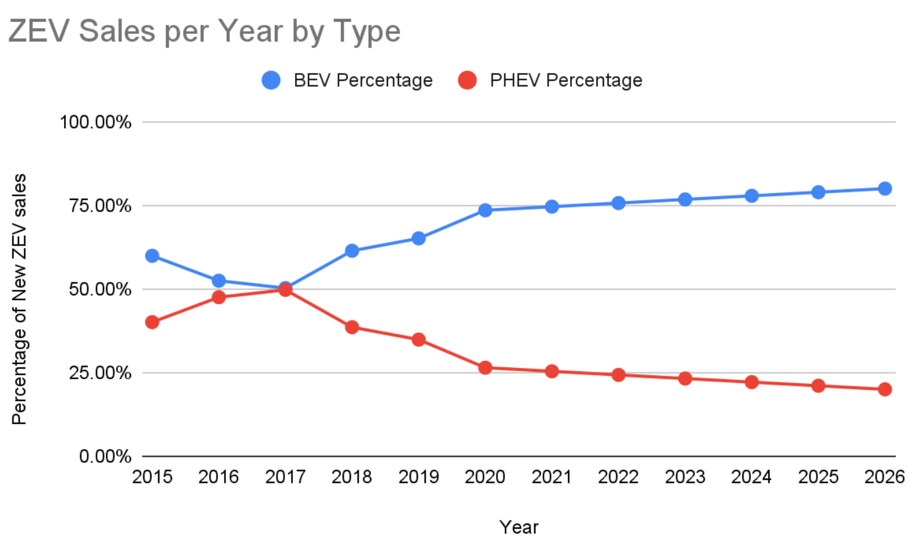


Figure 9. This figure shows the percentage of new vehicle sales every year that can be attributed to either BEVs or PHEVs. We performed a linear interpolation between the years of 2019 and 2026.

Finally, we used these calculated ratios to find combined emissions rates for electric and combined emissions rates for ICE vehicles. This was done by multiplying the emission rates for each fuel type by the corresponding ratio. For example, to find the ICE emission rate for NO_x, we performed the following calculation:

(NO_x gasoline emission rate*0.9) + (NO_x diesel emission rate*0.1) = total NO_x ICE emission rate

This was done for both the electric and ICE vehicles, with the ratio for electric vehicles changing every year until 2026. For the last step of our projections, we multiplied these rates by the corresponding number of new electric and ICE vehicles for each census block group code, which was already previously calculated. This yielded the new emissions being added to the fleet for a given year which was added to the reduced emission values from vehicles being taken out. In the end, this gave us the projected $PM_{2.5}$, VOC, NH_3, NO_x and SO_x emissions for the year. Once one year was projected, it became the starting point data for the next year, and so on. An example of a projected dataset in R is included below for visualization.

	census_block	ces_4_0_percentile	county	red_NOX	electric_NOX_in	ice_NOX_in	NOX_new
1	60014001001	2.79878971	Alameda	1.6016052	0.0048325400	0.028231335	1.6346691
2	60014001002	2.79878971	Alameda	0.8554784	0.0032558858	0.019020640	0.8777549
3	60014002001	2.87443268	Alameda	0.9251066	0.0024390650	0.014248834	0.9417945
4	60014002002	2.87443268	Alameda	0.7986645	0.0022263117	0.013005945	0.8138967
5	60014003001	15.93545134	Alameda	0.8265515	0.0020705458	0.012095973	0.8407181
6	60014003002	15.93545134	Alameda	0.9595470	0.0026670150	0.015580501	0.9777945
7	60014003003	15.93545134	Alameda	0.8738725	0.0026442200	0.015447334	0.8919641
8	60014003004	15.93545134	Alameda	1.0825521	0.0029139608	0.017023140	1.1024892
9	60014004001	18.97377711	Alameda	1.0837857	0.0028911658	0.016889973	1.1035668
10	60014004002	18.97377711	Alameda	0.8394961	0.0021541275	0.012584251	0.8542345
11	60014004003	18.97377711	Alameda	0.7539963	0.0021503283	0.012562056	0.7687087
12	60014037011	23.28542612	Alameda	0.4488286	0.0013525033	0.007901223	0.4580823
13	60014037012	23.28542612	Alameda	0.6765335	0.0022073158	0.012894973	0.6916358
14	60014037021	25.52950076	Alameda	0.4244364	0.0012765200	0.007457334	0.4331703
15	60014037022	25.52950076	Alameda	0.8412678	0.0025530400	0.014914667	0.8587355

Figure 10. This figure shows an example of a projected dataset in R and includes projected NO_x emissions. From this figure, we can see the spatial resolution utilized is the census block group. The dataset also includes the CES percentile scores for each census block group, as well as the county it belongs to, which is how we joined the projected emission factors data. The "red_NOX" column contains the reduced values of the original emissions data, which symbolizes the remaining fleet after cars have been removed. The next two columns represent the emissions for new ZEVs and new ICEVs being introduced into the fleet. Finally, the "NOX_new" column contains the annual projected emissions for a given year. This value was calculated by adding the reduced original emissions to the emissions for new ZEVs and ICEVs–the three columns prior. This process was repeated for each pollutant.

1.5 Modeling with the ISRM Tool

The ISRM Tool

Modeling of our baseline and scenario datasets was performed through the newly developed InMap Source-Receptor Matrix (ISRM) Tool, created by UC Berkeley graduate student Libby Koolik. As our team is one of the first testers of this tool, we closely consulted with Koolik on how to use it and provided feedback for its future development. Essentially, the ISRM Tool combines the functions of the Intervention Model for Air Pollution (InMAP), created by Christopher Tessum, Jason Hill, and Julian Marshall, with the EPA's Environmental Benefits Mapping and Analysis Program (BenMAP). InMAP is a reduced complexity model that predicts annual average changes in $PM_{2.5}$ concentrations that result from small perturbations in emissions (Tessum et al., 2017). One detail to note is that the ISRM tool is based on the ISRM developed by Goodkind et al. (2019) and not InMAP itself. Goodkind et al. (2019) used InMAP to collect estimates of the perturbations brought about by small changes in emissions in various locations. Through this integration, Goodkind et al. (2019) created matrices to derive linear associations between emissions and locations, and formed the ISRM for various pollutants. BenMAP then associates these changes in $PM_{2.5}$ concentrations with estimated changes in health endpoints, such as changes in the number of illnesses and deaths caused by air pollution (U.S. EPA, 2022). Utilizing the ISRM Tool simplified our methodology as it only requires users to supply an emissions file that has a spatial component and contains values for the emissions of $PM_{2.5}$, VOC, NH_3, NO_x and SO_x, two unique identification columns (I_CELL, J_CELL), and an optional 'Height_M' column indicating source release height, for the tool to perform the calculations of both InMAP and BenMAP. The other requirements of the tool, such as the ISRM health calculation files and a population file, are included by default after installing the tool. The ISRM Tool performs a regridding process from the emissions data input to ISRM grid cells and calculates changes in $PM_{2.5}$ concentrations and health endpoints like excess mortality and excess ischemic heart disease per these ISRM grids. Specifically for our purposes, we used the ISRM Tool to determine the changes in $PM_{2.5}$ concentrations and excess mortality as a result of alterations to the baseline distribution of ZEVs among the different CES score quartiles.

<u>Accessing the ISRM Tool Through Google Cloud</u>

The ISRM Tool was accessed through the Google Cloud platform. Detailed information about the ISRM Tool's methodology and the code for running the tool were provided by Koolik through the GitHub Readme file and the ISRM Tool on Linux & Google Cloud manual, respectively. To set up the tool properly, we started a virtual machine in Google Cloud, which gave us access to a Secure Shell (SSH) where most of the coding took place. The essential inputs required for the ISRM Tool were the emissions shapefile, ISRM files, and population file. The tool has other capabilities, but only these three inputs and the 'Run Health' setting were applied for our purposes. Buckets were created in Google Cloud to store the emissions file inputs, data files necessary for running the ISRM Tool, and population files, as well as the output files from the ISRM Tool.

For the ISRM files and the population file, we utilized the tool's native datasets that included the California ISRM grid and 2010 Census population data. The emissions shapefiles were created from the baseline and scenario datasets and included data on emissions for $PM_{2.5}$, VOC, NH_3, NO_x and SO_x. As aforementioned, the emissions shapefile had additional spatial requirements and needed specific column names and formatting in order for the tool to read it correctly. Thus, we made sure to correctly match the required column names of the emissions data files with the ISRM Tool's desired format. In order to run any emissions data, the ISRM Tool requires its input files to be shapefiles or feather files. As our baseline and scenario emissions data were originally csv files, we had to give them a spatial component by joining the data with 2020 block group data using the QGIS mapping software. Through this process, we were able to convert our data into shapefiles. After these steps, the emissions shapefiles were ready to be exported and inputted into the ISRM Tool.

We proceeded to run each set of emissions data (EMFAC 2019, baseline, and projected scenarios) through the ISRM Tool following the aforementioned manual, and our control files have been included in the appendix. We selected that the tool provides $PM_{2.5}$ concentrations per ISRM grid, which assigns a variable grid ranging from 1 to 48 km based on population density, since this would provide a higher resolution in more populated regions than other options like per county or per air basin. The output files from each ISRM Tool run consisted of a line graph depicting $PM_{2.5}$ exposure percentiles by racial and ethnic groups; a map of $PM_{2.5}$ concentrations across California; maps regarding total all cause excess mortality, total ischemic heart disease excess mortality, and total lung cancer excess mortality; as well as shapefiles for all map outputs.

Accessing the ISRM Tool Locally

Alternatively, we were also able to access the ISRM Tool locally on a Mac operating system. Detailed instructions for this method were similarly provided by Koolik through the Running the ISRM Tool on Mac manual. The methodology listed was comparable to that of the Linux & Google Cloud manual, with a few modifications. To run the tool, we first ensured the latest version of Python was installed to the system. Due to the system's limited processing capabilities, we connected to a Linux server via Mac's Terminal. Once we connected to the server via a SSH, we created a virtual environment that stored the libraries necessary for us to run the code pipeline. From there, we cloned the ISRM Github repository through the Mac Terminal, downloaded the data files necessary for running the tool, and were able to run the ISRM Tool in a similar fashion to the Google Cloud Platform. Further details of this process can be found in our Running the ISRM Tool Locally on a Linux Server (Mac OS) document.

Processing the ISRM Tool Outputs

After each run of the ISRM Tool, it provided six different outputs for each of our scenarios: a copy of the control file, a copy of all logging statements printed on the terminal, a map which depicted changes in the dispersal of $PM_{2.5}$ exposure concentrations, maps of their health incidences (e.g., lung cancer), a line graph that depicted the distribution of $PM_{2.5}$ exposure by population group percentile, and a sub-directory of shapefiles ("shapes") that detailed exposure concentrations and/or health incidences.

Of the outputs that were produced from the tool, the map of California illustrated the dispersal of changing $PM_{2.5}$ exposure concentrations with the use of a continuous color scale. However, the low resolution of these values, whose distribution was auto-generated by the tool, made it difficult to distinguish and analyze areas whose $PM_{2.5}$ concentrations were greater than the lowest recorded values. To best define and provide greater insight to our data, we imported the corresponding shapefiles that were exported with each map output from the ISRM Tool into

QGIS. Within each shapefile's layer properties, we used graduated color symbols to reflect each area's "PM25_UG_M3" values. As QGIS uses graduated symbology to divide data into classes, we selected a color ramp that best accounted for and illustrated each area's values (e.g., the ramp's darkest color represented larger areas with the lowest $PM_{2.5}$ concentrations, and the lightest color represented smaller areas with higher recorded $PM_{2.5}$ concentrations). To best display the wide range of values we were working with, as well as analyze each scenario's results from a comparative distance, the same logarithmic scale was applied to each scenario's revised maps. The values used for this scale were derived from our baseline data, as it accounts for California's most current (i.e., highest) $PM_{2.5}$ concentrations and corresponding health impacts, and is the standard by which our projected scenarios have been modeled and compared to. Further details of this process can be found in our [Processing the ISRM Tool's PM2.5 Exposure Concentration Maps in QGIS] document.

Then, we selected each run's respective shapefiles for $PM_{2.5}$ exposure concentrations, and total excess mortality due to $PM_{2.5}$ exposure. We reapportioned $PM_{2.5}$ concentrations and mortality from the ISRM grids to the block group level using RStudio. With regards to $PM_{2.5}$ concentrations, if a block group was completely within an ISRM grid, we assigned the block group to have the same $PM_{2.5}$ concentration as the ISRM grid. If the block group overlapped with multiple ISRM grids, we calculated a weighted average for the $PM_{2.5}$ concentration in the block group based on land area (for each overlap, we multiplied $PM_{2.5}$ concentration of ISRM grid by proportion of land area in block group intersecting with the ISRM grid, and found total sum of all contributing portions to a block group). As for mortality, we distributed mortality based on land area to ensure proper mass balance for all calculations. If the block group was completely within an ISRM grid, we multiplied the total mortality in the ISRM grid by the proportion of land area in the ISRM grid intersecting with the block group. If the block group overlapped with multiple ISRM grids, we summed mortality values from the overlaps based on land area intersections (for each overlap, multiplied total mortality in ISRM grid by proportion of land area in block group intersecting with ISRM grid, and found total sum of all contributing portions to a block group). The purpose of the reapportionment was to allocate changes in $PM_{2.5}$ concentrations and mortality per ISRM grid to the block group level to allow for further analysis on the changes specifically experienced in block groups. This way, we could more easily highlight changes in $PM_{2.5}$ and excess mortality in disadvantaged communities and consider the community characteristics related to race/ethnicity and other socioeconomic variables, like income.

Additionally, we generated summary maps of each run's $PM_{2.5}$ exposure concentrations with most disadvantaged communities overlaid. This utilized identified communities, as defined by CES scores, that were in the highest quartile and overlaid the borders of these communities on top of the aforementioned map outputs specific to Greater Los Angeles and the San Francisco Bay Area. This allowed us to provide more context in our analysis to these regions with higher $PM_{2.5}$ concentrations.

1.6 Assessing Health Disparities on Disadvantaged Communities Using Bar Graphs

Bar Graph Outline

The bar graphs we created looked at four agents that may portray any health disparities. Those are $PM_{2.5}$ exposure, average premature mortality, $PM_{2.5}$ emissions, and NO_x emissions. $PM_{2.5}$ exposure and average premature mortality were used to determine the health effects from mobile sources. Additionally, we included NO_x emissions and $PM_{2.5}$ emission to analyze its importance as an emission from mobile sources.

We grouped each agent to either CalEnviroScreen scores, non-white population, or median household income. To do this we joined by the census tract variable. Some datasets were in a geoid form, because of this we had to manually mutate the geoids into census tracts.

Creating Bar Graphs

We created bar graphs to represent the average $PM_{2.5}$ exposure levels, average premature mortality, $PM_{2.5}$ emissions, and NO_x emissions across the baseline 2020 data, business as usual scenario, equal spread of ZEVs scenario, half to DACs scenarios, three-fourths to DACs scenario. We did this to analyze the differences in distribution across each scenario. We used three different parameters to sort the levels of $PM_{2.5}$ exposures to a quartile group. Those parameters were decided on what we considered to be disadvantaged in our report; including CalEnviroScreen scores, non-white population, and median household income. Each parameter had its scores on a percentile format, this was done through RStudio to keep everything under the same metric system. The percentile scores had been coupled to a census tract in California.

Based on the emissions provided by the EMFAC CARB data, emission levels had been obtained for each prospective scenario. The predicted emissions levels were then reapportioned to $PM_{2.5}$ exposure levels and premature mortality deaths.

We then joined our disadvantaged group (CES, non-white population, median household income) to $PM_{2.5}$ exposure, mortality, $PM_{2.5}$ emissions, or NO_x emissions separately by census tract. Our quartiles were formed by sorting each disadvantaged parameter from low to high on Google Sheets. Our four quartiles ranged from <25, 25-<50, 50-<75, 76-100. The agent values within each quartile range were averaged for each scenario. The values from the 76-100 percentile is what we deemed as disadvantaged.

In addition to the statewide analysis described above, we further analyzed highly populated areas to determine if similar disparity trends follow. Those areas include Los Angeles and San Francisco counties. In total we created 32 bar graphs for California, Los Angeles County, San Francisco County and the respective $PM_{2.5}$ exposure, mortality, $PM_{2.5}$ emissions, and NO_x emissions. This was done for CalEnviroScreen scores, non-white population, and the median household income.

Results and Discussion

2.1 Projected Trends in Pollutants from 2020 Through 2035

Using the projected fleet and emissions data we created through forming our scenarios, we were able to highlight the expected trends in NOx, VOC, PM2.5, SOx, and NH3 emissions from 2020 - 2035. We then compared those trends to see the differences in reductions between disadvantaged and advantaged communities in each scenario.

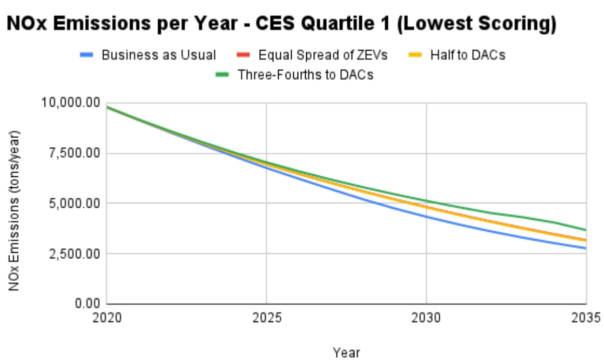


Figure 11a. NOx Emissions per year from 2020 - 2035, for the most **advantaged** communities in each projected scenario.

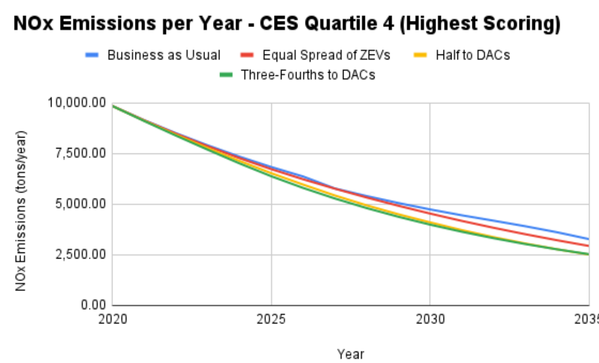
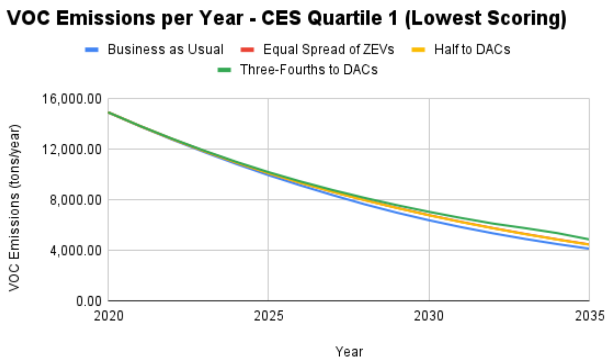


Figure 11b. NOx Emissions per year from 2020 - 2035, for the most **disadvantaged** communities in each projected scenario.

Figure 11 shows the differences between trends in NOx emissions for advantaged vs disadvantaged communities over time. The overall decrease in this pollutant over time is projected to be very similar in both community types shown. However, figure 11b shows larger decreases of NOx emissions in disadvantaged communities for scenarios that heavily favor ZEV sales in DACs with advantaged communities seeing the opposite for these scenarios.



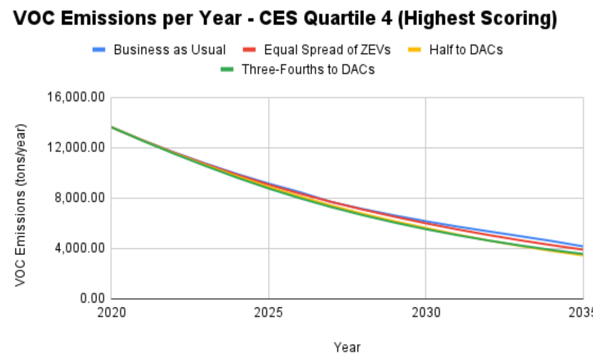
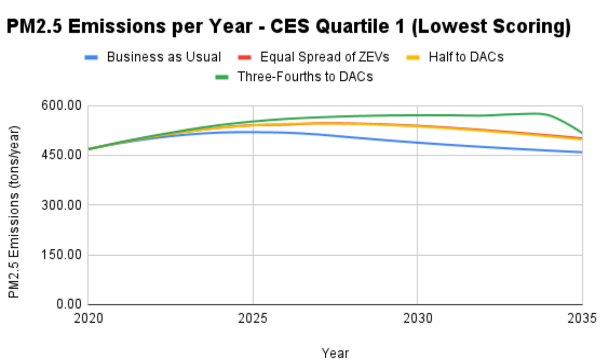


Figure 12a. VOC Emissions per year from 2020 - 2035, for the most **advantaged** communities in each projected scenario.

Figure 12b. VOC Emissions per year from 2020 - 2035, for the most **disadvantaged** communities in each projected scenario.

Figure 12 shows the differences between trends in VOC emissions for advantaged vs disadvantaged communities over time. The trends in this figure are nearly identical to those shown in figure 11, with a steady decrease in emissions overtime.



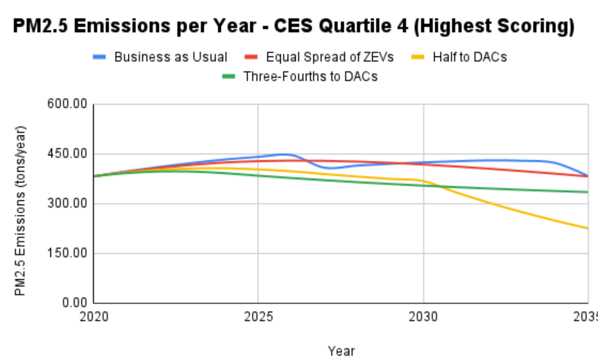


Figure 13a. PM2.5 Emissions per year from 2020 - 2035, for the most **advantaged** communities in each projected scenario.

Figure 13b. PM2.5 Emissions per year from 2020 - 2035, for the most **disadvantaged** communities in each projected scenario.

Figure 13 shows the differences between trends in PM2.5 emissions for advantaged vs disadvantaged communities over time. 13b shows a slightly larger overall decrease in PM2.5 emissions for disadvantaged communities when compared to advantaged communities through all scenarios.

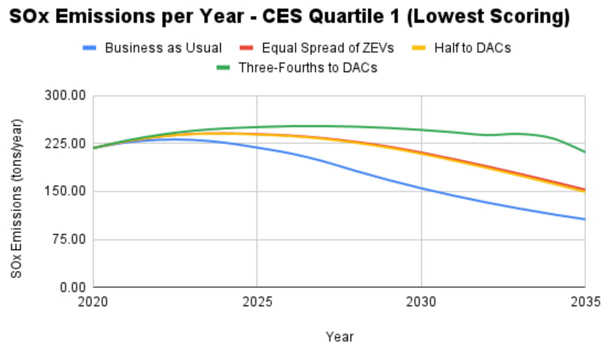


Figure 14a. SOx Emissions per year from 2020 - 2035, for the most **advantaged** communities in each projected scenario.

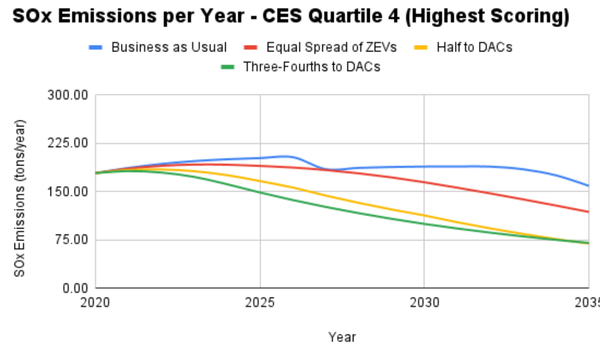


Figure 14b. SOx Emissions per year from 2020 - 2035, for the most **disadvantaged** communities in each projected scenario.

Figure 14 shows the differences between trends in SOx emissions for advantaged vs disadvantaged communities over time. 14b shows a slightly larger overall decrease in PM2.5 emissions for disadvantaged communities when compared to advantaged communities through all scenarios.

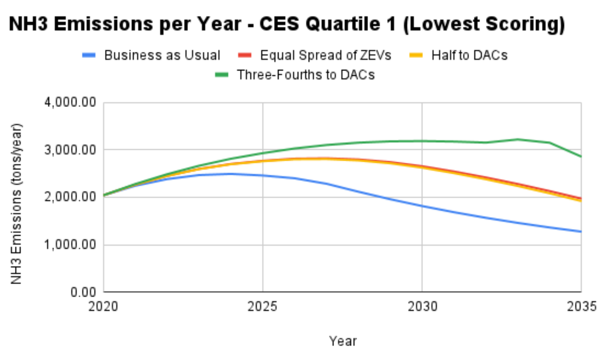


Figure 15a. NH3 Emissions per year from 2020 - 2035, for the most **advantaged** communities in each projected scenario.

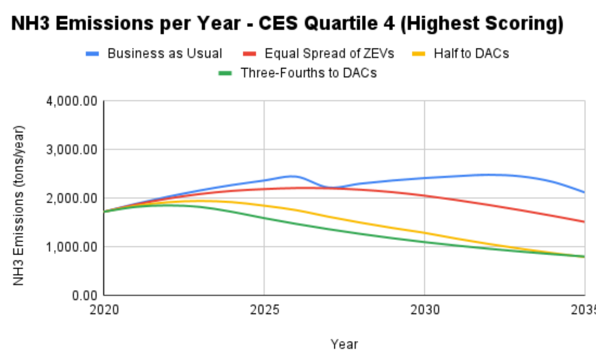


Figure 15b. NH3 Emissions per year from 2020 - 2035, for the most **disadvantaged** communities in each projected scenario.

Figure 15 shows the differences between trends in NH3 emissions for advantaged vs disadvantaged communities over time. The trends in this figure are nearly identical to those shown in figure 11, with an overall decrease in emissions overtime. Scenarios that favor ZEV sales in DACs saw larger decreases on NH3 in those areas but saw increases in advantaged communities.

2.2 Tracking Annual Pollutant Emissions

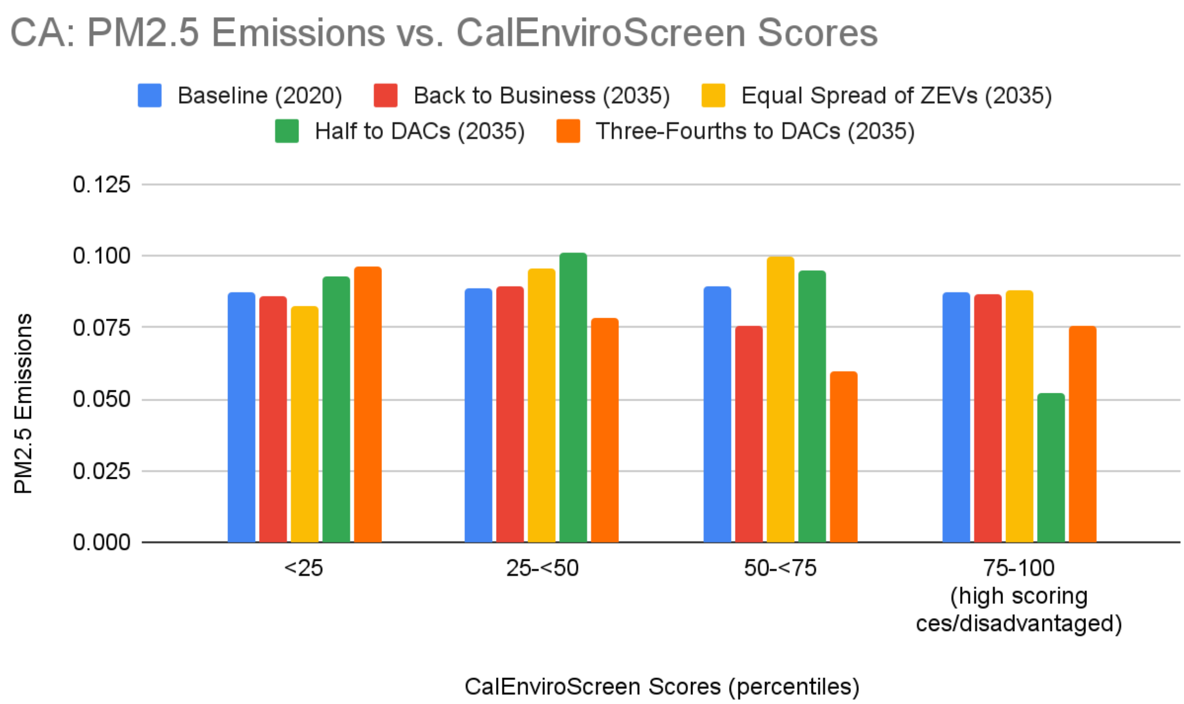


Figure 16. Relationship between the CalEnviroScreen scores and the average $PM_{2.5}$ emissions in California.

In Figure 16, we are looking at California's average $PM_{2.5}$ emissions and establishing our disadvantaged groups by CalEnviroScreen scores. In the baseline scenario, there is a .4% decrease in the upper quartile from the lower quartile. In the business as usual scenario, there is a 1% increase in the upper quartile from the lower quartile. In the equal spread scenario, there is a 6% increase in the upper quartile from the lower quartile. In the half to DACs scenario, there is a 44% decrease in the upper quartile from the lower quartile. In the three-fourths to DACs scenario, there is a 22% decrease in the upper quartile from the lower quartile. In this graph, it can be seen that the scenarios that introduce a greater proportion of ZEVs into the most disadvantaged communities show results that reduce the disparity between those communities and the least disadvantaged; with the scenario where half of ZEV sales go to disadvantaged communities being the most effective scenario in doing this.

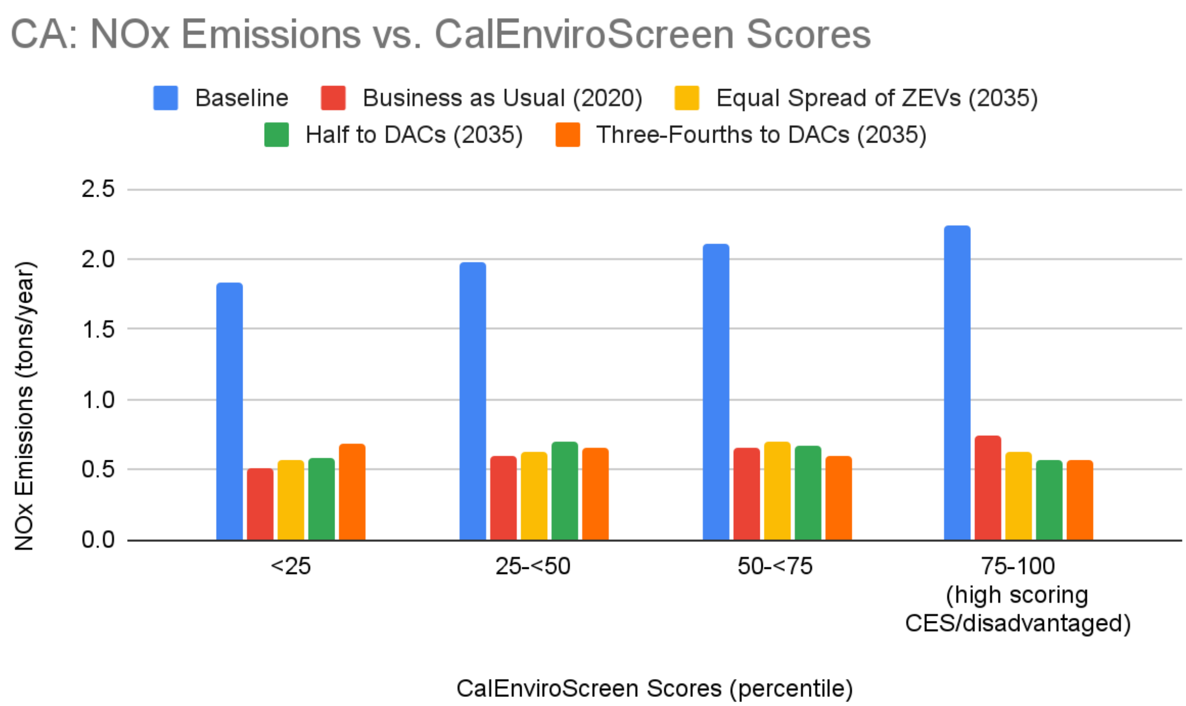


Figure 17. Relationship between the CalEnviroScreen Scores and the average NO_x emissions in California.

In Figure 17, we are looking at the average NO_x emissions and establishing our disadvantaged groups by CalEnviroScreen scores. In the baseline scenario, there is a 23% increase in the upper quartile from the lower quartile. In the business as usual scenario, there is a 44% increase in the upper quartile from the lower quartile. In the equal spread scenario, there is a 10% increase in the upper quartile from the lower quartile. In the half to DACs scenario, there is a 2% decrease in the upper quartile from the lower quartile. In the three-fourths to DACs scenario, there is a 16% decrease in the upper quartile from the lower quartile. At first glance, it can be seen that the baseline has an exponentially higher level of emissions than the other scenarios. Again, we see that the two scenarios that introduce a greater proportion of ZEVs into the most disadvantaged communities show results that reduce exposure disparity. The fact that these scenarios see decreases in the differences between the most and least disadvantaged communities shows just how much of an impact the introduction of ZEVs can make. The three-fourths of ZEVs to disadvantaged communities looks to be the most efficient at reducing exposure disparity.

2.3 UCLA Statewide Estimates Validated Against CARB EMFAC 2019 Data

According to CARB's EMFAC 2019 output (Figure 18A), the highest $PM_{2.5}$ concentrations occur at more densely populated areas, like the San Francisco Bay Area and the Greater Los Angeles Area, which have respective concentrations of around 1.0 μg/m^3 and from 2.0 to upwards of 2.5 μg/m^3.

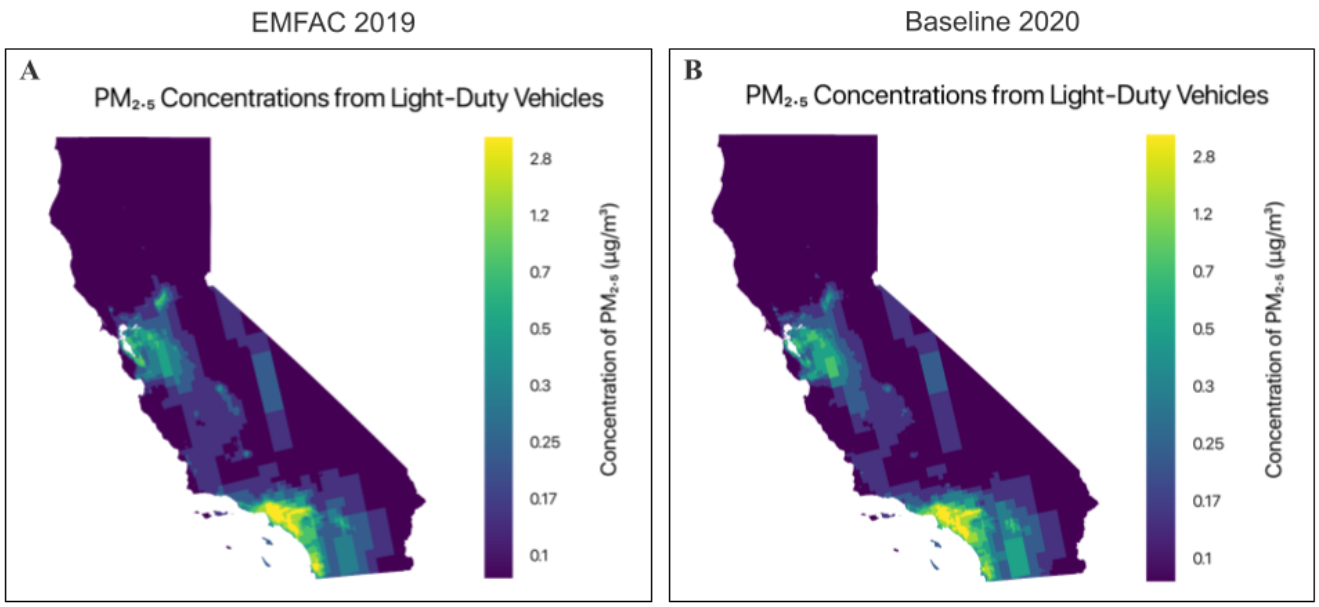


Figure 18. EMFAC 2019 (18A) and Baseline 2020 (18B) $PM_{2.5}$ concentrations (μg/m^3) from light-duty vehicles.

These same observations remained consistent for our baseline scenario (Figure 18B) based on fleet data combined with emission factors. This indicates that our methods were validated per the EMFAC 2019 run since the same locales were identified as experiencing the highest $PM_{2.5}$ concentrations.

2.4 Evaluating PM2.5 Exposure from Light-Duty Vehicles by Population Group Percentile

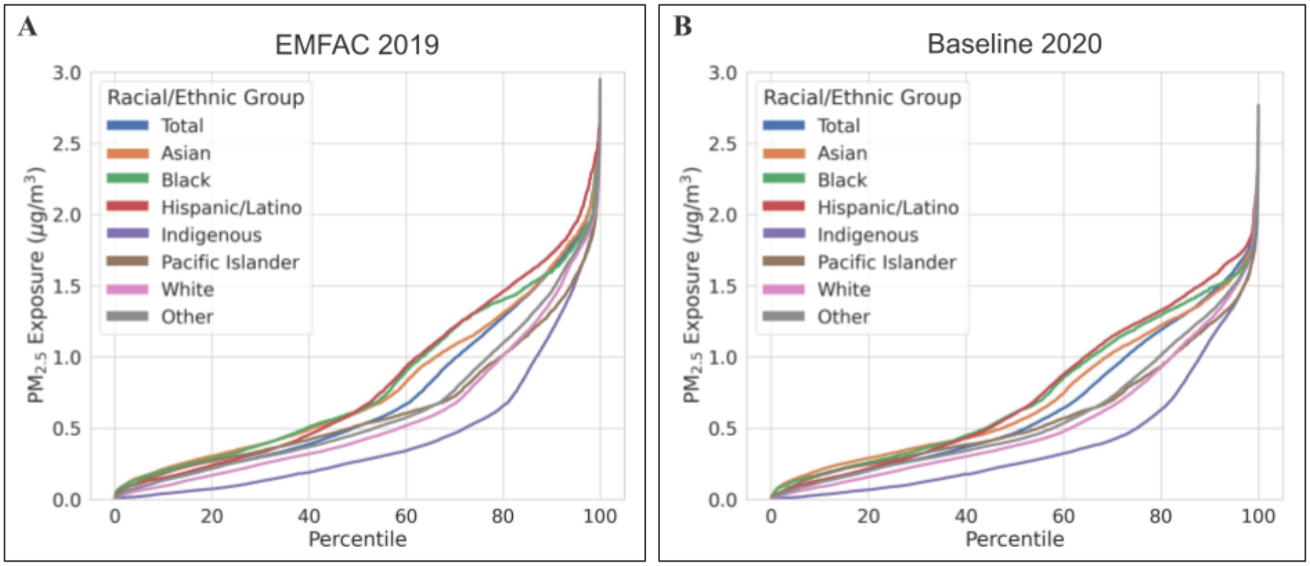


Figure 19. EMFAC 2019 and Baseline 2020 $PM_{2.5}$ exposure concentrations (μg/m^3) from light-duty vehicles with racial/ethnic breakdown. At the 50th and 75th percentile of exposure, racial/ethnic group disparities can be found for $PM_{2.5}$ exposure with relatively higher exposures for Hispanic/Latino, Black, and Asian populations compared to white and Indigenous populations.

The line graphs shown in Figures 19-21 display the $PM_{2.5}$ exposure experienced by percentiles of racial/ethnic groups, as produced from the ISRM Tool. An nth percentile indicates that people experience a $PM_{2.5}$ exposure greater than n% of their racial/ethnic group. For the baseline scenario, we observed that at the 25th percentile, all racial/ethnic groups experienced similar concentrations of $PM_{2.5}$ between 0.1 and 0.4 μg/m^3 (Figure 19B). At the 50th percentile, there was growing inequity among the racial/ethnic groups as $PM_{2.5}$ concentrations varied between 0.25 and 0.6 μg/m^3. This inequity was most prevalent at the 75th percentile where the exposure concentrations of $PM_{2.5}$ ranged from 0.5 to 1.25 μg/m^3. Throughout the various scenarios, the distribution of racial/ethnic groups is fairly consistent: Black and Hispanic/Latino populations experience the greatest amount of $PM_{2.5}$, although this is untrue at the lowest percentiles where Asians experience the greatest amount of $PM_{2.5}$. Asians, Pacific Islanders, and other racial/ethnic groups experience intermediate exposures and white and Indigenous populations experience the lowest amount of exposure.

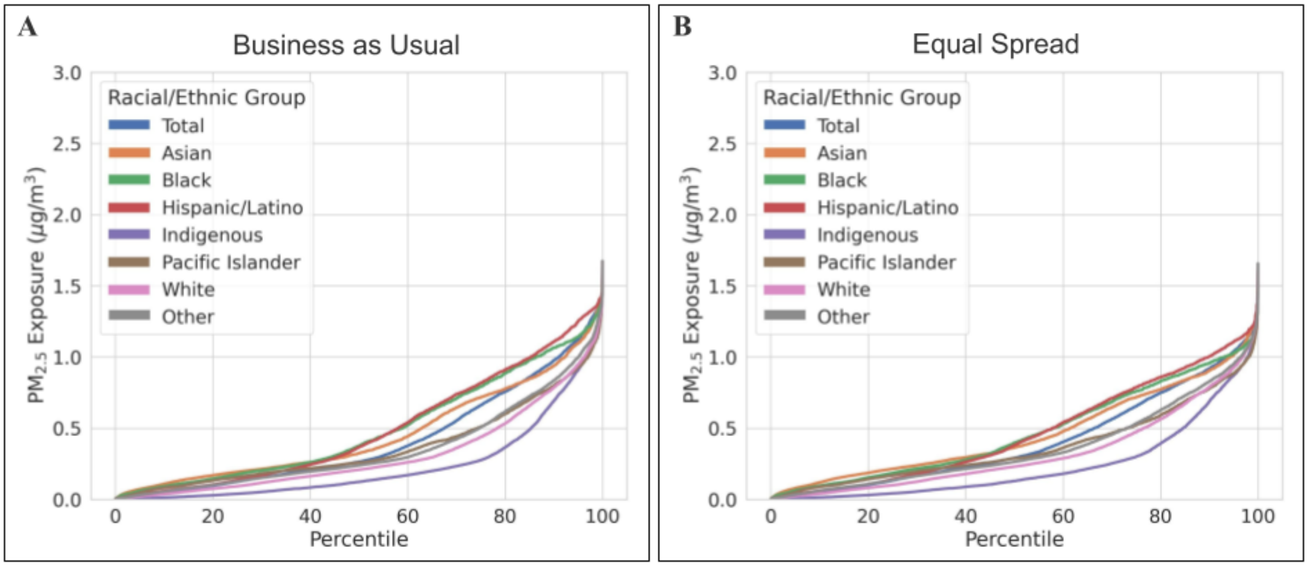


Figure 20. Business as Usual and Equal Spread $PM_{2.5}$ exposure concentrations (μg/m^3) from light-duty vehicles with racial/ethnic breakdown. At the 50th and 75th percentile of exposure, racial/ethnic group disparities can be found for $PM_{2.5}$ exposure with relatively higher exposures for Hispanic/Latino, Black, and Asian populations compared to white and Indigenous populations.

In the business as usual scenario, the 25th percentile displayed a much smaller range compared to the baseline, with $PM_{2.5}$ exposure ranging between 0.1 to 0.25 μg/m^3 (Figure 20). The 50th percentile showed an even more drastic decrease than the baseline with $PM_{2.5}$ exposure ranging between 0.2 to 0.45 μg/m^3. Once again, the 75th percentile displayed the most disparities between racial/ethnic groups, but $PM_{2.5}$ decreased compared to the baseline to a range of 0.3 to 0.85 μg/m^3. Interestingly, the line graph revealed that at the 75th percentile, $PM_{2.5}$ exposure disparities remained consistent between Black and Hispanic/Latino populations and white populations. This could imply that current ZEV distribution rates will not have a significant impact in reducing $PM_{2.5}$ exposure to vulnerable populations by 2035. Another noticeable difference with the baseline is that the Asian population experiences less $PM_{2.5}$ exposure compared to the Black and Hispanic/Latino populations in general between the 60th and 80th percentiles.

The equal spread scenario was fairly similar to the business as usual scenario (Figure 20). The 25th and 50th percentiles were almost identical to the business as usual scenario at 0.1 to 0.25 μg/m^3 and 0.2 to 0.45 μg/m^3, respectively, but another decrease was found at the 75th percentile. The 75th percentile now ranged from 0.3 to 0.8 μg/m^3, but disparities have noticeably reduced from the business as usual scenario. Less of a gap can be found between the Black, Hispanic/Latino, and Asian populations, as well as all three populations compared to the white population. This finding signifies that with about 25% of ZEVs getting distributed to disadvantaged communities, minority populations, specifically the Black, Hispanic/Latino, and Asian populations, experience reductions in $PM_{2.5}$ exposure by 2035 without being high outliers compared to other populations.

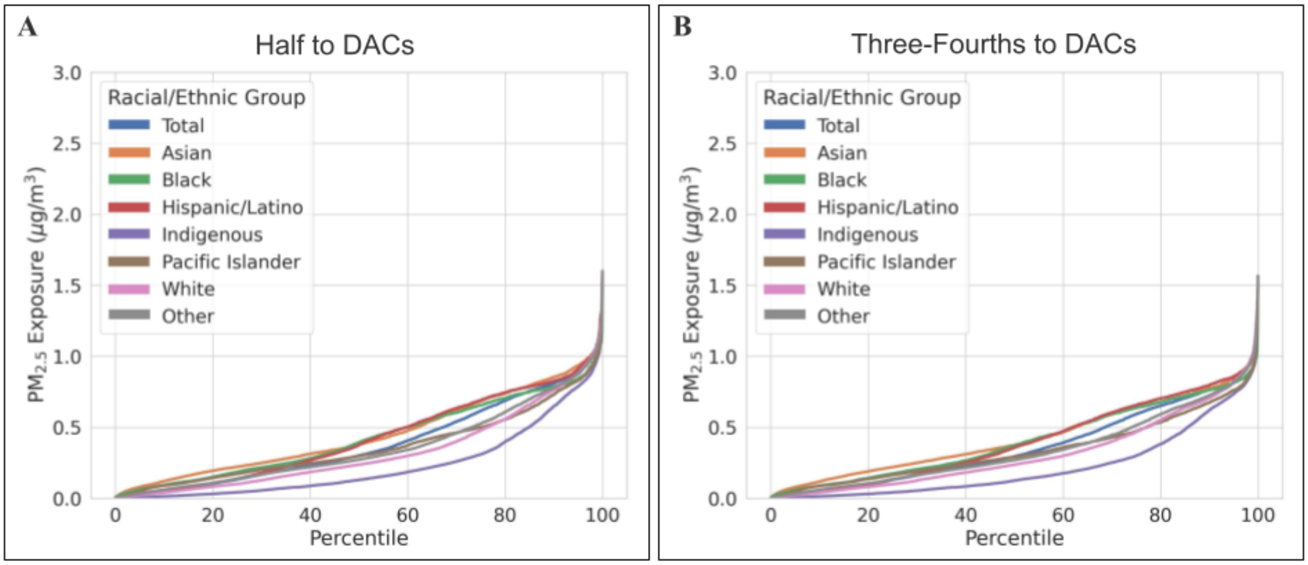


Figure 21. Half to DACs and Three-Fourths to DACs $PM_{2.5}$ exposure concentrations (μg/m^3) from light-duty vehicles in 2035 with racial/ethnic breakdown. At the 50th and 75th percentile of exposure, racial/ethnic group disparities can be found for $PM_{2.5}$ exposure with relatively higher exposures for Black, Hispanic/Latino, and Asian populations compared to white and Indigenous populations.

As greater proportions of new ZEV sales get distributed to disadvantaged communities, the line graphs showed less disparities in $PM_{2.5}$ exposure across all percentiles by 2035. In the half to DACs scenario, the 25th percentile was now at 0.05 to 0.25 μg/m^3, the 50th percentile was at 0.2 to 0.4 μg/m^3, and the 75th percentile was at 0.3 to 0.75 μg/m^3 (Figure 21). Most of the lines were in close proximity to each other, and it seemed that the Black and Hispanic/Latino populations showed no difference than the $PM_{2.5}$ experienced by the Asian population unlike the previous two scenarios.

The three-fourths to DACs scenario showed the least disparities among racial/ethnic groups. The 25th percentile was at 0.05 to 0.25 μg/m^3, the 50th percentile was at 0.2 to 0.4 μg/m^3, and the 75th percentile was at 0.3 to 0.7 μg/m^3. While the values were not very different from the half to DACs scenario, the line graph displayed even fewer disparities as now all racial ethnic groups were within 0.4 μg/m^3 of each other at the 75th percentile. In the business as usual scenario, the difference in disparities between the Black and Hispanic/Latino populations and the white population was about 0.4 μg/m^3, but by the three-fourths to DACs scenario, this difference was reduced in half to about 0.2 μg/m^3. Overall, the series of line graphs demonstrate that more ZEVs in disadvantaged communities reduces the disparities of $PM_{2.5}$ exposure experienced by vulnerable populations in California by 2035.

2.5 Evaluating the Greater Los Angeles Area Through Various Projections

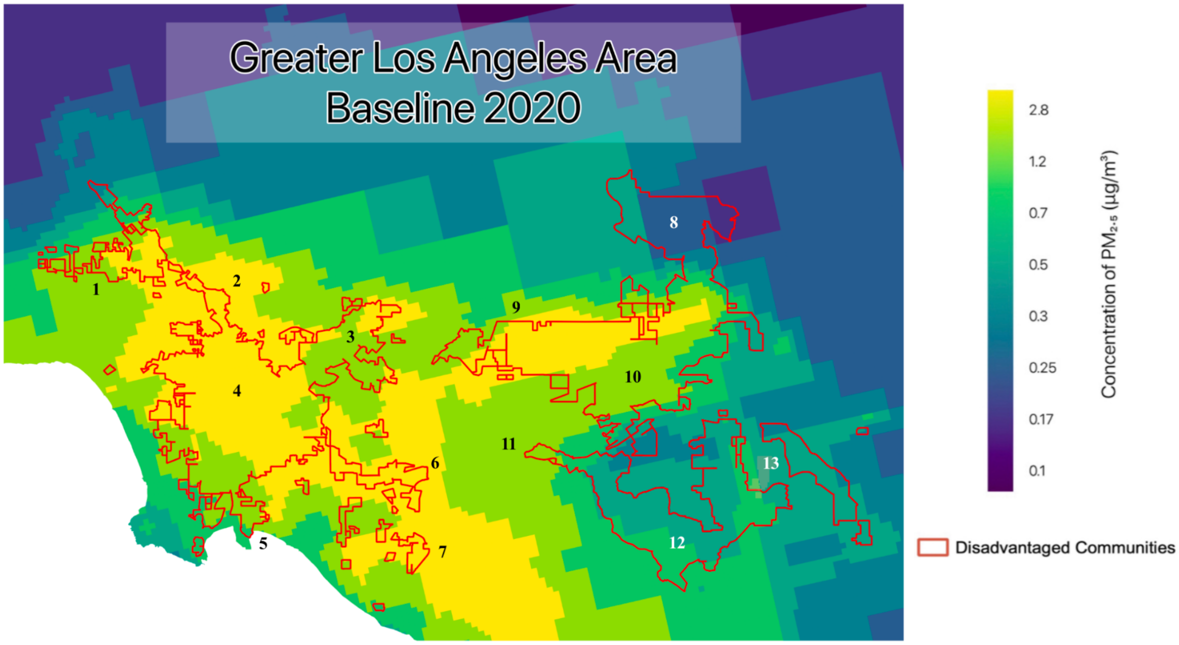


Figure 22. Greater Los Angeles Area $PM_{2.5}$ concentrations in 2020 with applied corrective factors to adjust for the COVID-19 pandemic. The disadvantaged communities outlined in red and labeled are as follows: (1) San Fernando Valley, (2) Glendale, (3) San Gabriel Valley, (4) Los Angeles, (5) Long Beach, (6) Anaheim, (7) Santa Ana, (8) San Bernardino, (9) southwestern San Bernardino, (10) Riverside, (11) Corona, (12) Perris, (13) Moreno Valley.

The Greater Los Angeles Area is shown to experience a wide range of $PM_{2.5}$ concentrations across its landscape (Figure 22). This is evidenced by the change in concentrations as one moves west from Riverside and San Bernardino, which experience $PM_{2.5}$ concentrations from as low as 0.17-0.7 μg/m^3, towards the San Fernando Valley, Los Angeles, and Santa Ana, which mainly experience concentrations between 1.2-2.8 μg/m^3. This noticeable increase in $PM_{2.5}$ concentrations can be attributed to these greater urban regions experiencing heavier, condensed traffic. However, these $PM_{2.5}$ hotspots are largely situated within disadvantaged communities.

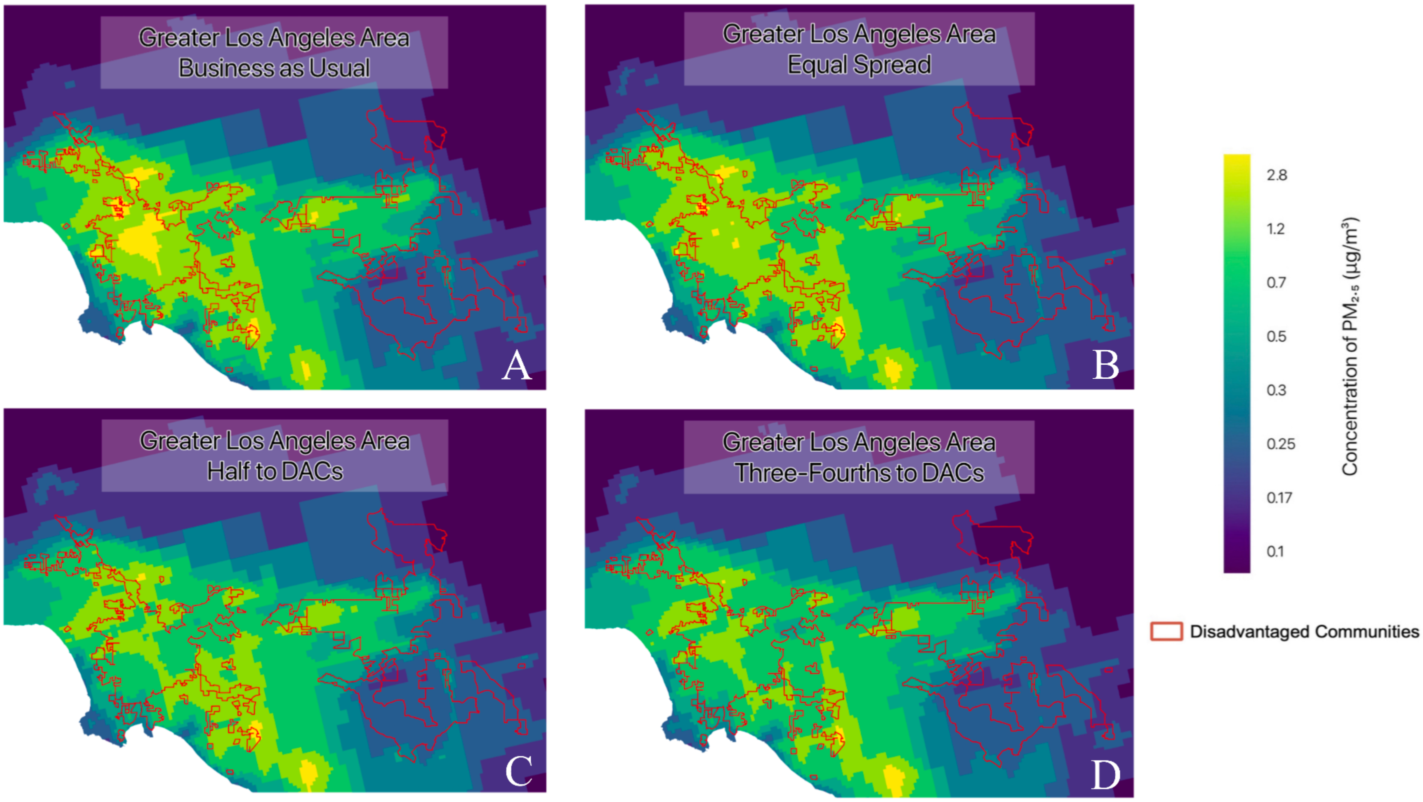


Figure 23. Greater Los Angeles Area projected $PM_{2.5}$ concentrations in 2035 based on the following ZEV adoption rates: the current ZEV adoption rate ("business as usual"), equal adoption rates across all communities ("equal spread"), half of ZEV adoption occurring in disadvantaged communities ("half to DACs"), and three-fourths of ZEV adoption occurring in disadvantaged communities ("three-fourths to DACs").

In the business as usual map (Figure 23A), we can see a drastic decrease in the projected $PM_{2.5}$ concentrations for 2035 compared to the baseline. This change is especially evident in the hotspot regions across Corona, Riverside, southwestern San Bernardino, San Gabriel Valley, Glendale, San Fernando Valley, Los Angeles, Long Beach, Anaheim, and Santa Ana: areas that experienced $PM_{2.5}$ concentrations that ranged from 1.2-2.8 $\mu g/m^3$ (Figure 22), now vary more between 0.7-1.5 $\mu g/m^3$. This is with the exception of a few areas that experience 2.8 $\mu g/m^3$ concentrations, notably Glendale, Los Angeles, Santa Ana, and southwestern San Bernardino. It is also noted that in the disadvantaged communities located in San Bernardino, Moreno Valley, and Perris, the range of $PM_{2.5}$ concentrations they experienced went down from 0.17-0.7 $\mu g/m^3$ to range between 0.1-0.5 $\mu g/m^3$.

In the equal spread map (Figure 23B), we continue to see decreases in $PM_{2.5}$ concentrations from the business as usual scenario, although not as drastic. Of the aforementioned hotspots where 2.8 $\mu g/m^3$ concentrations were still prominent (i.e. Glendale, Los Angeles, Santa Ana, and southwestern San Bernardino) they have notably gotten smaller. The disadvantaged communities situated in and nearby these hotspots still experience $PM_{2.5}$

concentrations that range up to 1.5 μg/m^3, but more within the range of 0.7-1.2 μg/m^3. However, we have interestingly started to see an increase in the $PM_{2.5}$ concentrations of advantaged communities, specifically located in Lake Forest and Mission Viejo, which are just southeast of Santa Ana. What ranged between 0.7-1.3 μg/m^3 in the “business as usual” scenario, has increased to range between 0.5-1.5 μg/m^3 here.

In the half to disadvantaged communities map (Figure 23C), we see a decrease in $PM_{2.5}$ concentrations in the hotspots located in Glendale, Los Angeles, and southwestern San Bernardino from the equal spread scenario, with more block groups’ $PM_{2.5}$ concentrations ranging between 0.5-1.2 μg/m^3. In the case of Lake Forest and Mission Viejo, the lower end of their $PM_{2.5}$ concentrations slightly increased from 0.5 μg/m^3 to 0.6 μg/m^3, and increased spatially.

In the three-fourths to disadvantaged communities map (Figure 23D), we find consistent findings with those in the half to DACs map. In the Greater LA Area and upper Riverside County, the 0.5-1.2 μg/m^3 range still holds strong, with more block groups’ concentrations settling around 0.5-1.0 μg/m^3. In the DACs located in San Bernardino, Perris, and Moreno Valley, $PM_{2.5}$ concentrations decreased from 0.1-0.5 μg/m^3 to about 0.06-0.3 μg/m^3. As for Orange County, the upper end of the range increased slightly from 1.5 μg/m^3 to 1.6 μg/m^3, and now covers more of the region.

From these findings, we're able to see that as equity of ZEV distribution increases in each subsequent map, decreases in $PM_{2.5}$ concentrations were initially greater, but became more gradual overtime. This was especially the case in disadvantaged communities situated in hotspots in Corona, Riverside, southwestern San Bernardino, San Gabriel Valley, Glendale, San Fernando Valley, Los Angeles, Long Beach, Anaheim, and Santa Ana. This initially had been the case for advantaged communities in Lake Forest and Mission Viejo, which experienced the same drastic decrease in $PM_{2.5}$ concentrations in the business as usual scenario. However, they alternatively saw an increase and spread in $PM_{2.5}$ concentrations in subsequent scenarios. Overall, considering the wide range of $PM_{2.5}$ concentrations experienced in the Greater Los Angeles Area, especially by disadvantaged communities located in $PM_{2.5}$ hotspots, the gradual introduction of more ZEVs could greatly improve the air quality of this region. However, areas where ZEVs may not be introduced at similar rates (e.g. like Lake Forest and Mission Viejo in this study) may see increases in $PM_{2.5}$ concentrations and signs of worsened air quality.

2.6 Evaluating the San Francisco Bay Area Through Various Projections

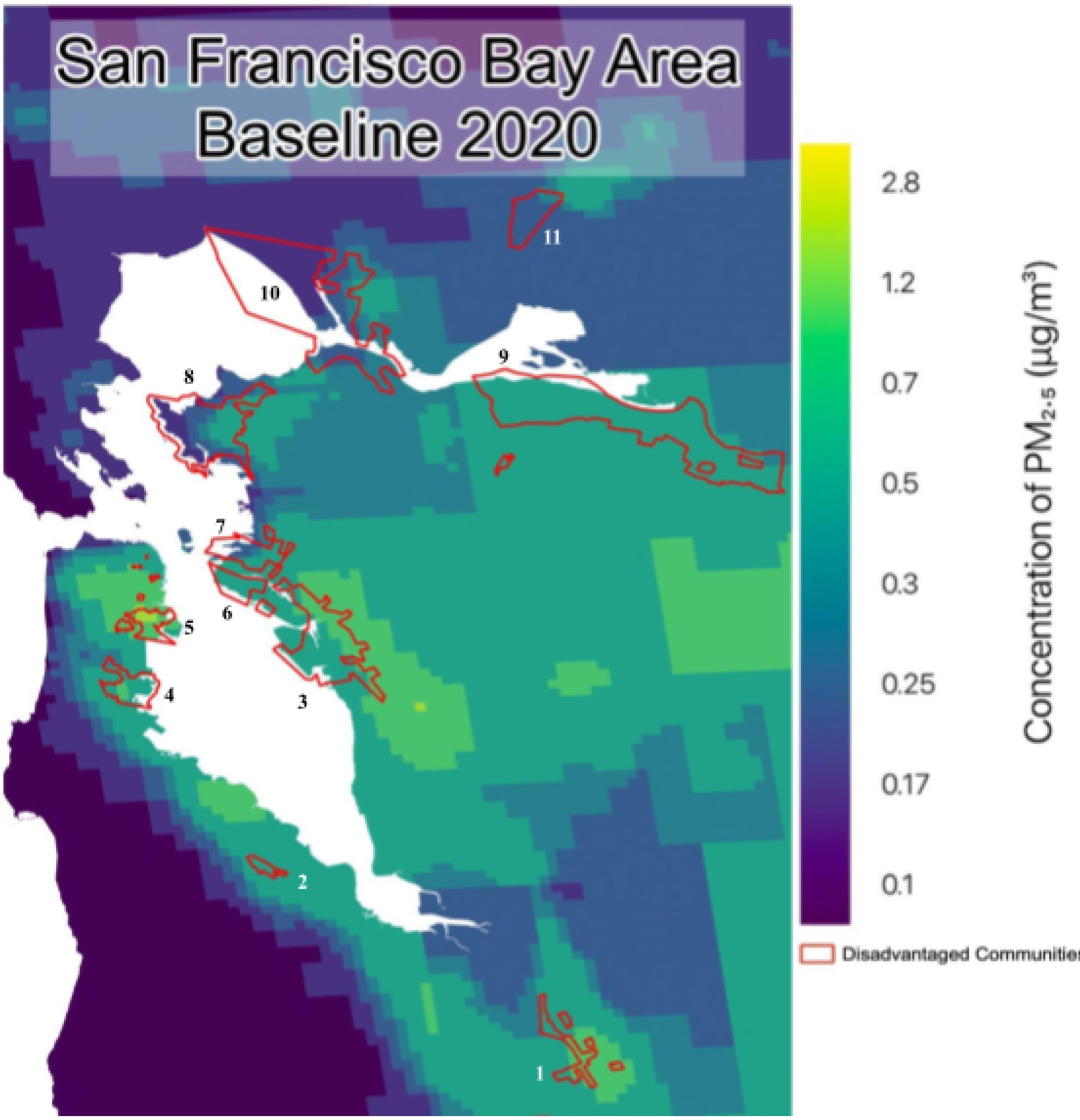


Figure 24. San Francisco Bay Area $PM_{2.5}$ concentrations in 2020 with applied corrective factors to adjust for the COVID-19 pandemic. The disadvantaged communities labeled are as follows: (1) San Jose, (2) Redwood City, (3) Greater Oakland, (4) South San Francisco, (5) San Francisco, (6) Alameda, (7) Downtown Oakland, (8) Richmond, (9) Pittsburg and Greater Stockton, (10) Vallejo.

In the baseline 2020 map output (Figure 24), the expected trend of greater urban regions experiencing more $PM_{2.5}$ concentrations was exemplified through hotspots of $PM_{2.5}$ clustered in San Francisco, the East Bay region, San Jose, and inland regions near Stockton. These concentrations are around 1.2 $\mu g/m^3$. The disadvantaged communities identified on this map experience variable $PM_{2.5}$ concentrations, ranging from 0.1 $\mu g/m^3$ to as high as 1.7 $\mu g/m^3$, which suggests that the San Francisco Bay Area may not be the best region to identify improvements in air quality, as compared to the Greater Los Angeles region, which will be discussed later.

Nevertheless, the majority of disadvantaged communities are associated with the higher end of $PM_{2.5}$ concentrations between 0.5 to 1.2 μg/m^3. This observation confirms that in recent years, disadvantaged communities have been residing in regions with relatively greater $PM_{2.5}$ concentrations compared to wealthier communities.

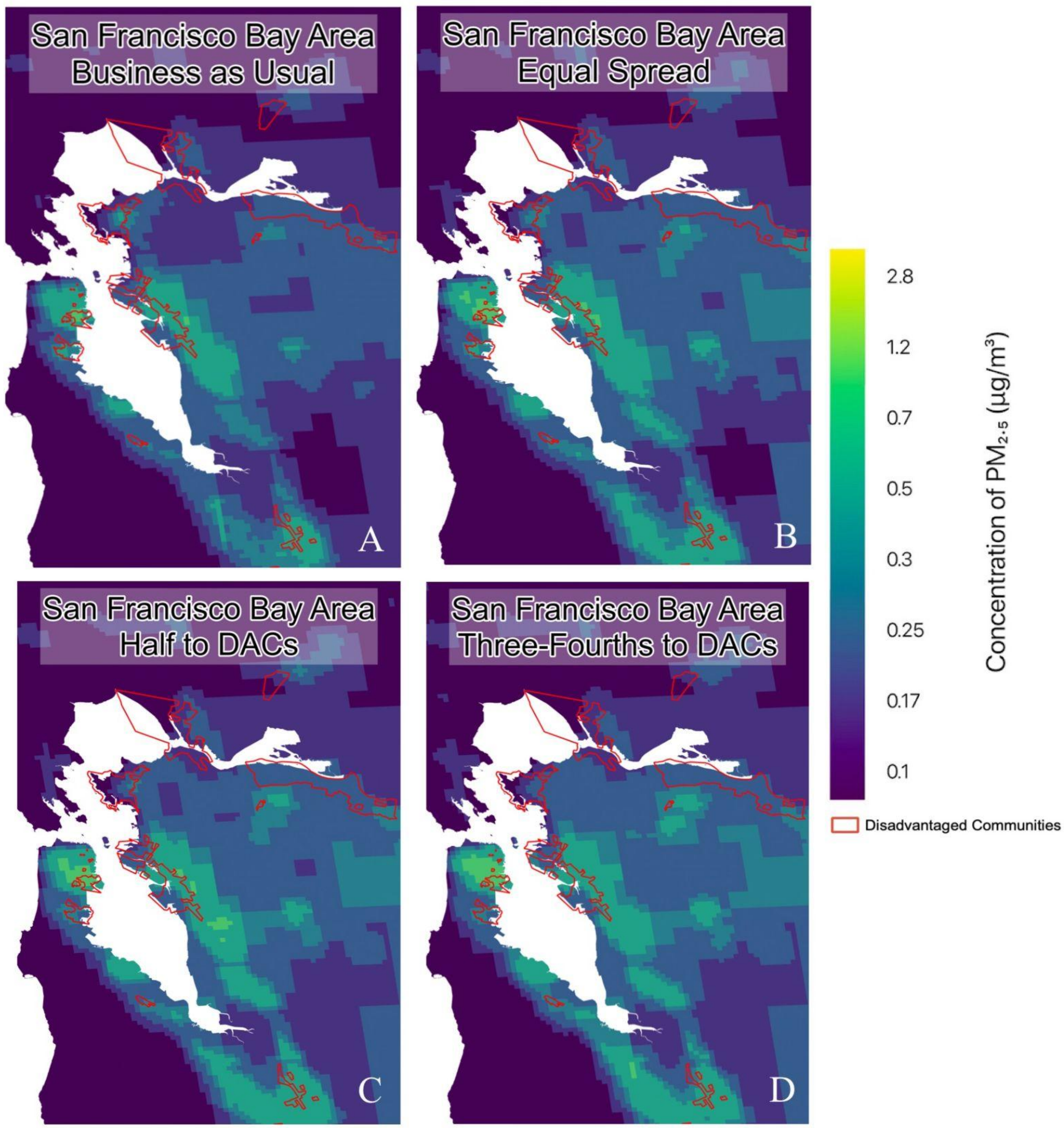


Figure 25. San Francisco Bay Area projected $PM_{2.5}$ concentrations in 2035 based on the following ZEV adoption rates: the current ZEV adoption rate ("business as usual"), equal adoption rates across all communities ("equal spread"), half of ZEV adoption occurring in disadvantaged communities ("half to DACs"), and three-fourths of ZEV adoption occurring in disadvantaged communities ("three-fourths to DACs").

In the business as usual map (Figure 25A), there is a noticeable projected decrease in $PM_{2.5}$ concentrations in 2035 from the baseline 2020 map, which is to be expected as ZEV sales increase. Once again, $PM_{2.5}$ concentrations are varied throughout the disadvantaged communities with the same hotspots in San Francisco, the East Bay region, and San Jose, although this time at lower concentrations of around 0.5 $\mu g/m^3$. The inland regions west of Stockton experience a notable decrease to the 0.3 $\mu g/m^3$ range. In the equal spread map (Figure 25B), we see noticeable decreases in $PM_{2.5}$ compared to the baseline 2020 map. Hotspots, with concentrations of 0.5-0.7 $\mu g/m^3$ arise in San Francisco, in the South Bay region, in the East Bay region, and in San Jose and once again, disadvantaged communities experience a wide range of $PM_{2.5}$ concentrations from as low as 0.1 $\mu g/m^3$ to as high as 0.7 $\mu g/m^3$. Interestingly, for this and subsequent scenarios, more inland regions display slight increases of PM2.5 concentration to the 0.5-0.7 $\mu g/m^3$ level. In the half to disadvantaged communities map (Figure 25C), we see similar findings to the equal spread scenario, but there are increases in $PM_{2.5}$ whereby more block groups in San Francisco and in the East Bay region experience 0.7 $\mu g/m^3$ of $PM_{2.5}$. This increase in $PM_{2.5}$ concentration is comparable in the three-fourths to disadvantaged communities map (Figure 25D). Greater amounts of block groups in San Francisco are experiencing 0.7 $\mu g/m^3$ of $PM_{2.5}$; however, East Bay has lower $PM_{2.5}$ concentrations at 0.5 $\mu g/m^3$.

Within disadvantaged communities, all four scenarios lead to observable decreases in $PM_{2.5}$ concentrations compared to the baseline scenario, which range on average from 0.5-1.2 $\mu g/m^3$ to about 0.25-0.7 $\mu g/m^3$. However, some findings are surprising in that as the equity of ZEV distribution increases from the business as usual scenario to the three-fourths to disadvantaged communities scenario, $PM_{2.5}$ concentrations actually increase in areas like East Bay and San Francisco. One possible explanation for the $PM_{2.5}$ exposure increases observed in advantaged communities could be that with a greater proportion of ZEVs distributed to disadvantaged communities, these other regions are receiving fewer ZEVs. With fewer ZEVs in each subsequent scenario attributed to regions with more advantaged communities, $PM_{2.5}$ exposure would be expected to increase relative to business as usual scenario for each subsequent scenario in these locations.

2.7 Evaluating the Average $PM_{2.5}$ Exposure and Health Effects Across California

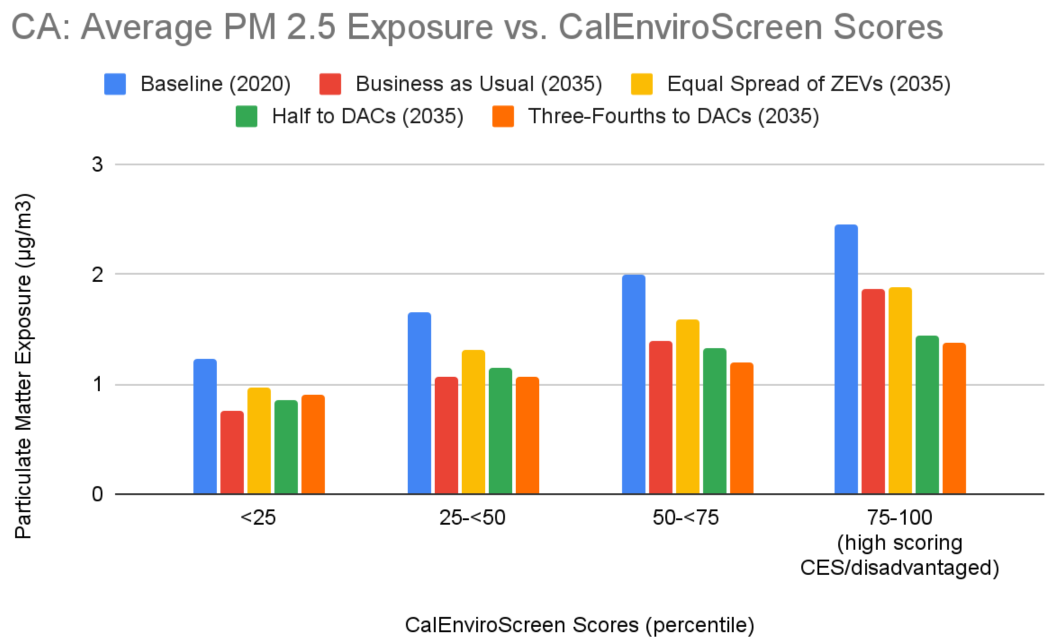


Figure 26. Relationship between the CalEnviroScreen scores and the average PM 2.5 exposure in California

In Figure 26, we are looking at the average $PM_{2.5}$ exposure in California and establishing our disadvantaged groups by CalEnviroScreen scores. One noticeable difference is that the baseline 2020 concentration displays a lower $PM_{2.5}$ exposure level than the respective scenarios. This is as expected, as gas-fueled vehicles are slowly being replaced with ZEVs, $PM_{2.5}$ emissions are decreasing concurrently with $PM_{2.5}$ exposure levels. Overall, the implementation of ZEVs does indicate a reduction in the concentration of $PM_{2.5}$. We then tested to see if the disparity between the upper quartile and lower quartile decreases. Again, the upper quartile refers to the most disadvantaged groups, and the lower quartile refers to the least disadvantaged group.

After testing the disparity we calculated a 100% increase in the upper quartile from the lower quartile in the baseline 2020 scenario. The business as usual scenario had a 149% increase in the upper quartile from the lower quartile. This is indicative in showing that with today's current rates, the health disparity will increase regardless of the overall reduction of $PM_{2.5}$ concentration. The equal spread of ZEVs scenario has a 94% increase in the upper quartile from the lower quartile. The half to DACs scenario has a 67% increase in the upper quartile from the lower quartile. The three-fourths to DACs scenario has a 54% increase in the upper quartile from the lower quartile. We see a reduction in disparities as the distribution of ZEVs caters towards disadvantaged communities. Even with the idealized scenario of the three-fourth distribution of ZEVs to disadvantaged communities, there is still a disparity over 50%. Although the disparity is expected to substantially reduce from the current rate, equity is still not reached. Other measures need to be taken in order to ensure the safety of disadvantaged communities.

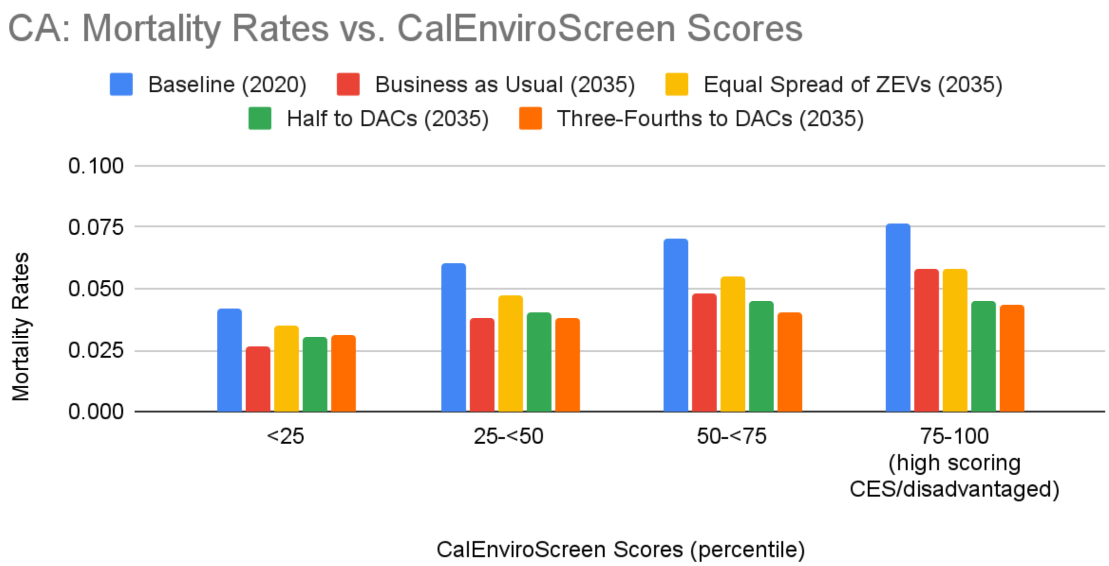


Figure 27. Relationship between the CalEnviroScreen scores and the calculated mortality in California.

Figure 27 is looking at the average mortality to its respective CalEnviroScreen score. The mortality is what we used to identify the health effects imposed from mobile sources. The trends of Figure 27 coincides with Figure 26. We can see there is an overall reduction of mortality in the 2035 scenarios. The baseline displays an 84% increase in upper quartile from the lower quartile. Additionally we see an even higher disparity in scenario 1, with a 118% increase in the upper quartile from the lower quartile. Following the business as usual scenario reveals a 65% increase in the upper quartile from the lower quartile. In the half to DACs scenario, we see a 49% increase in the upper quartile from the lower quartile. Lastly in the three-fourths to DACs scenarios, we see a 37% increase in the upper quartile from the lower quartile.

Mortality and the $PM_{2.5}$ exposure both show that there is an increase in disparity for the business as usual scenario, and a declining disparity from scenarios two to four. Mortality does show a slight lower disparity than the $PM_{2.5}$ exposure. Although the mortality is lower, it is worth mentioning that we are only checking for the most extreme health outcome, death. $PM_{2.5}$ concentration can also cause short term effects such as damage to the respiratory tract and lung irritation. This bar graph does not consider all the health effects from the $PM_{2.5}$ exposure. If we did, then we would expect to see a slightly high disparity.

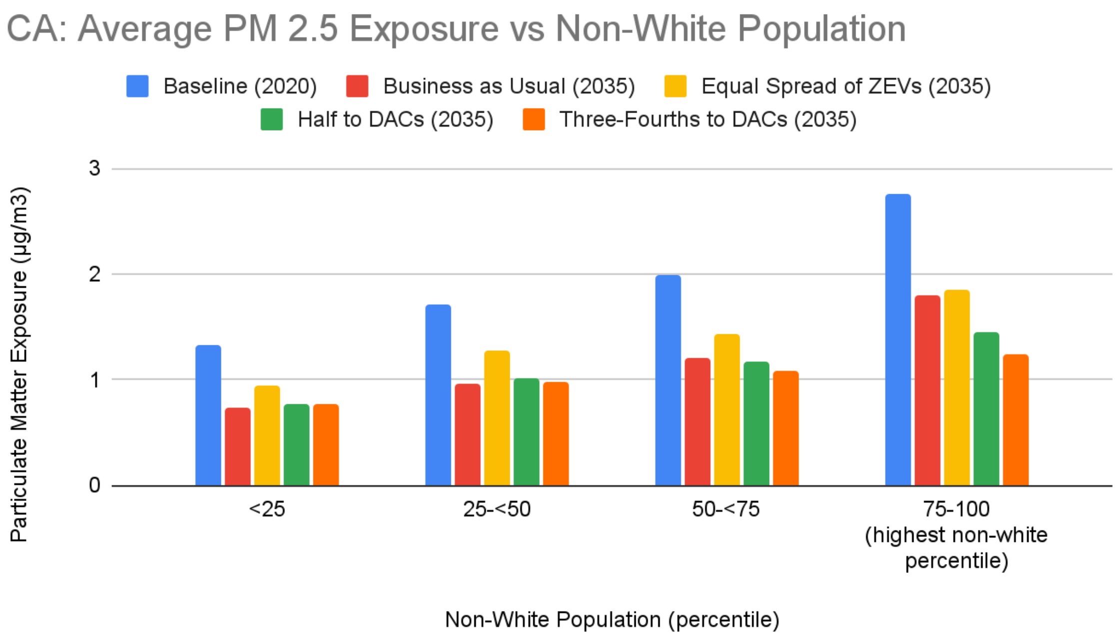


Figure 28. Relationship between the non-white population and the average PM 2.5 exposure in California

Alternatively, we will now be looking at the non-white population (Figure 28) to define our disadvantaged groups. Once again we see the same sharp increase in the back to business disparity, and a declining disparity in the next three scenarios.

In the baseline scenario, there is a 106% increase in the upper quartile from the lower quartile. In the business as usual scenario, there is a 147% increase in the upper quartile from the lower quartile. In the equal spread scenario, there is a 97% increase in the upper quartile from the lower quartile. In the half to DACs scenario, there is an 87% increase in the upper quartile from the lower quartile. In the three-fourths to DACs scenario, there is a 61% increase in the upper quartile from the lower quartile.

One striking observation in the non-white population graph is that the disparity difference between the half to DACs scenario and the three-fourths to DACs scenario drops by 25%. Whereas in the CalEnviroScreen graph (Figure 26), scenarios 3 and 4 have a disparity difference of 12%. The larger drop in the non-white population graph indicates that the highest quartile experiences the largest disparity and unequal consequences. This finding indicates that race is a critical framework to be considered and there seems to be a clear correlation between the non-white population and the $PM_{2.5}$ exposure levels.

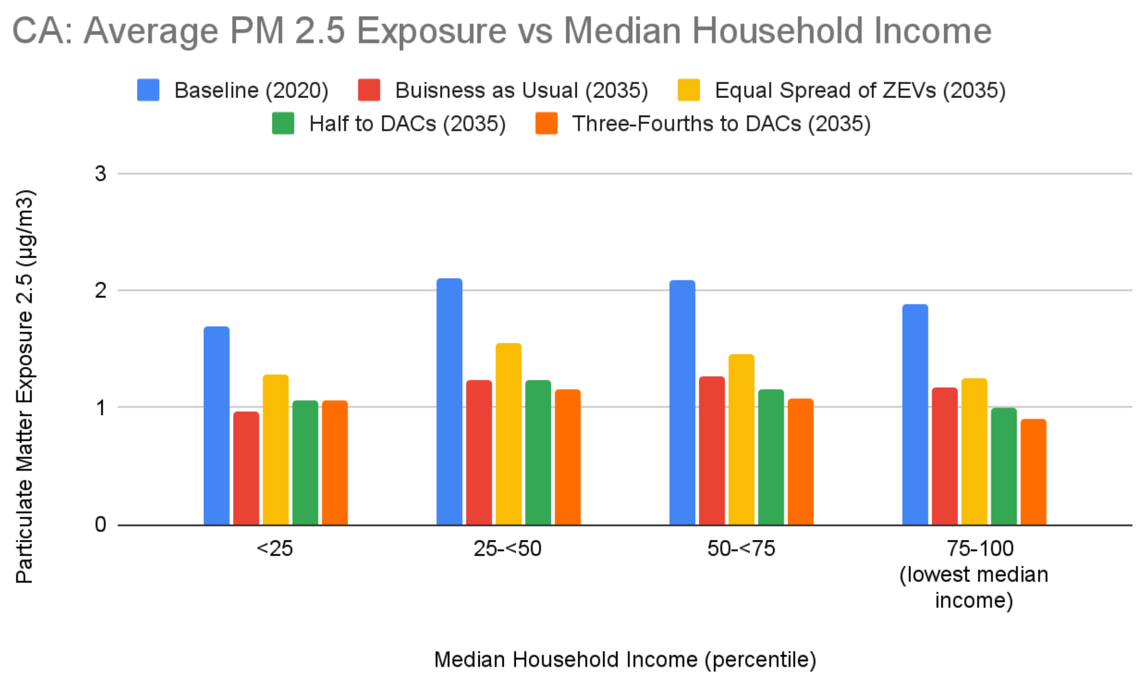
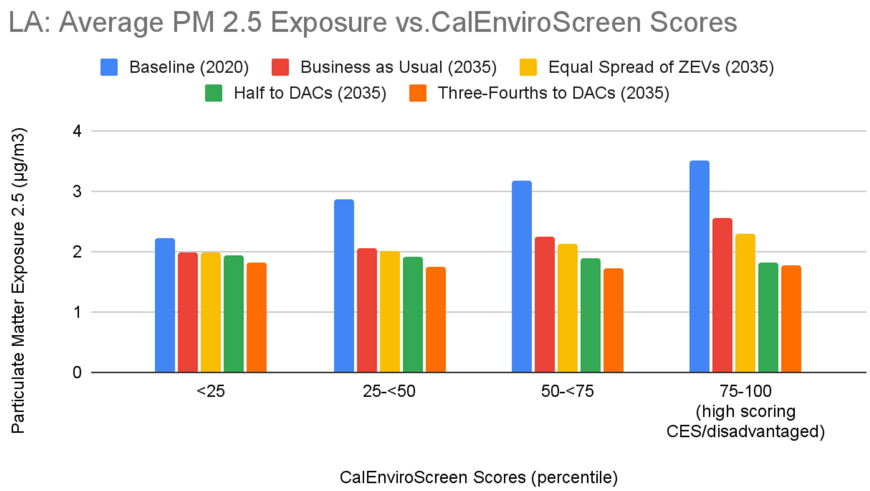


Figure 29. Relationship between the median household income and the average PM 2.5 exposure in California**.**

The last parameter we will be diving into is the median household income. Figure 29 showcases the trends of income and its respective $PM_{2.5}$ exposure. Once again we see an increase in disparity in the back to business scenario and a declining disparity in the following scenarios.

In the baseline scenario, there is a 10% increase in the upper quartile from the lower quartile. In the business as usual scenario, there is a 18% increase in the upper quartile from the lower quartile. In the equal spread scenario, there is a 2% decrease in the upper quartile from the lower quartile. In the half to DACs scenario, there is a 6% increase in the upper quartile from the lower quartile. In the three-fourths to DACs scenario, there is an 18% increase in the upper quartile from the lower quartile.

The disparity in the income analysis is drastically lower than the disparity shown in both the CalEnviroScreen score graph and the median household income graph. Comparatively the income disparity does not exceed a 20% difference. Moreover, we can now see an effective decreased risk in disadvantaged communities from the equal spread scenario to the three-fourths to DACs scenario. Those in the least disadvantaged quartile are now facing higher $PM_{2.5}$ exposure than the most disadvantaged quartile. In this prospective analysis, the equal spread scenario displays the most equity with only a 2% difference between the upper and lower quartile. Income may not be the best representation for the disadvantaged, as multiple other components are not considered. Because of this, we assume that the decreased disparity is not indicative of equity.



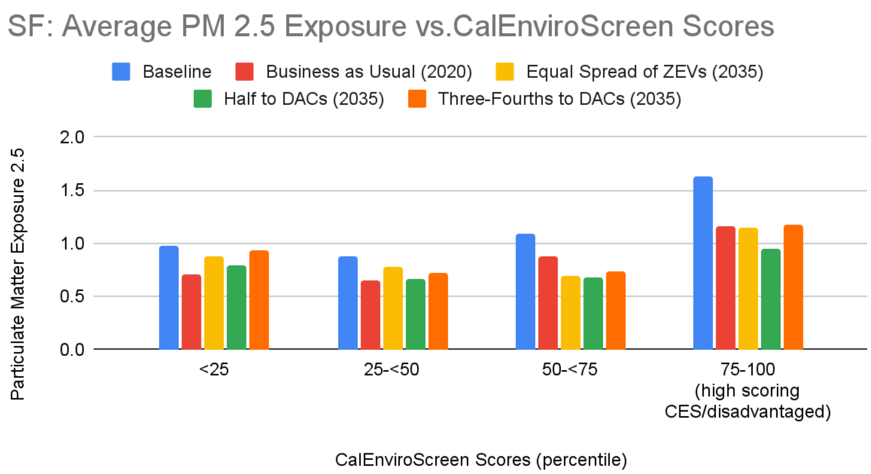


Figure 30. Relationship between CalEnviroScreen scores and the Average PM 2.5 Exposure in Los Angeles and San Francisco.

We decided to focus on two California regions, to see how our scenarios would impact specific areas. Figure 30 displays our $PM_{2.5}$ exposure in relation to CalEnviroScreen scores of Los Angeles County and San Francisco County respectively.

For Los Angeles County, the baseline scenario shows a 59% increase in the upper quartile from the lower quartile. The business as usual scenario shows a 28% increase in the upper quartile from the lower quartile. The equal spread scenario shows a 15% increase in the upper quartile from the lower quartile. The half to DACs scenario shows a 6% decrease in the upper quartile from the lower quartile. The three-fourths to DACs scenario, shows a 2% decrease in the upper quartile from the lower quartile. Our last two scenarios boasting decreases between the upper and lower quartiles is significant as it illustrates the potential ZEV's have in reducing $PM_{2.5}$ exposure.

For San Francisco County, the baseline scenario shows a 67% increase in the upper quartile from the lower quartile. The business as usual scenario shows a 64% increase in the upper quartile from the lower quartile. The equal spread scenario shows a 31% increase in the upper quartile from the lower quartile. The half to DACs scenario shows a 19% increase in the upper quartile from the lower quartile. The three-fourths to DACs scenario, shows 25% increase in the upper quartile from the lower quartile. San Francisco County's results suggest that an approach of half ZEV sales to the most disadvantaged communities might be the most effective in reducing the disparity between them and the least disadvantaged.

2.8 Average $PM_{2.5}$ Exposure, Mortality, $PM_{2.5}$ Emissions, NO_x Emissions Across California

We organized our bar graphs into four figures. Each figure focuses on either $PM_{2.5}$ exposure, mortality, $PM_{2.5}$ emissions, and NO_x emissions. Within each figure we also looked at the results in California, Los Angeles, and San Francisco. Additionally we combined it to the three indicators of disadvantaged groups including CES, race, and income.

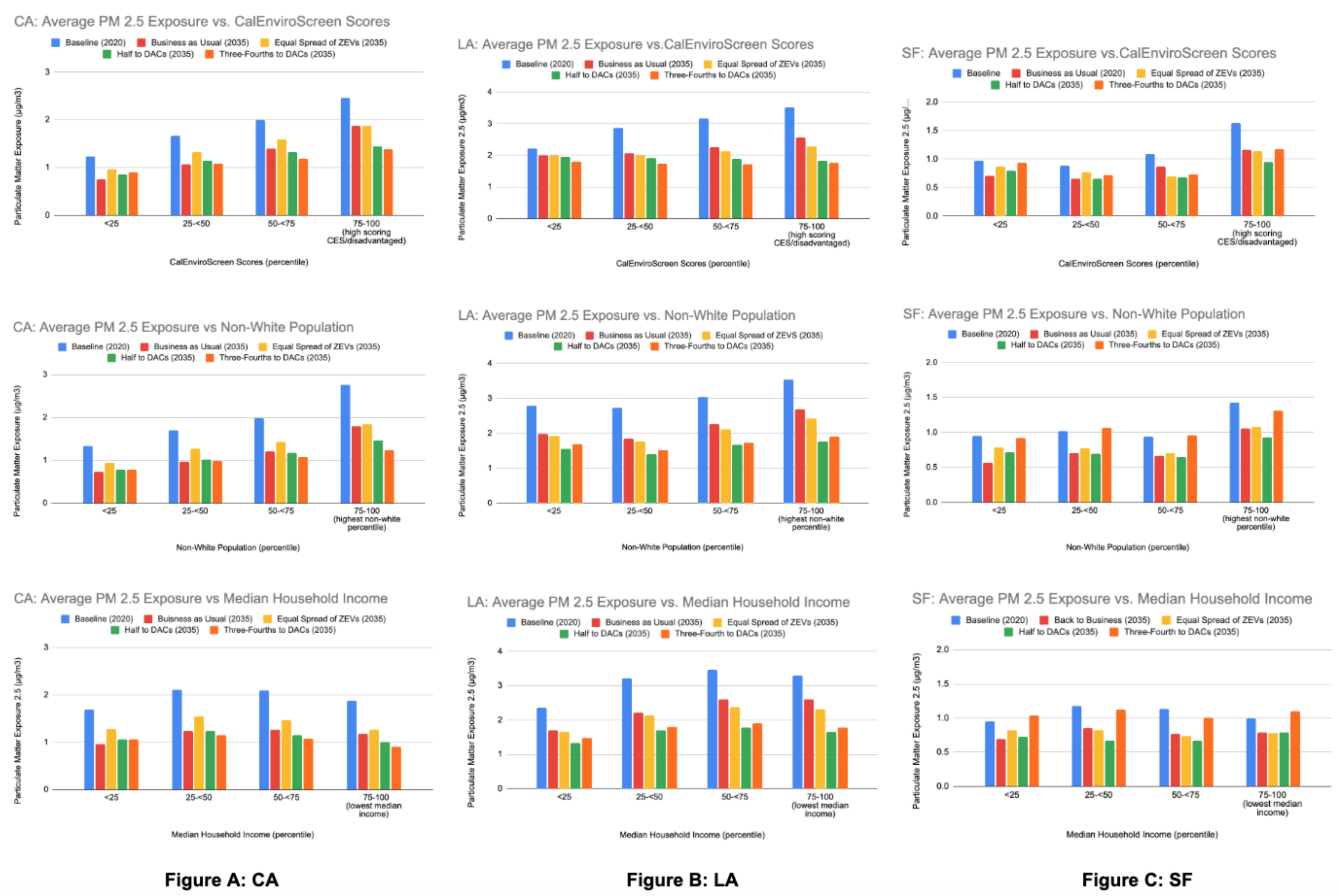


Figure 31. Average $PM_{2.5}$ Exposure in Varying Disadvantaged Groups
Figure 31A: California, Figure 31B: Los Angeles, Figure 31C: San Francisco

Figure 31 looks at the $PM_{2.5}$ exposure levels. $PM_{2.5}$ exposure levels are the highest in the 76-100 quartile when looking at the CalEnviroScreen scores and the non-white population. The income raises uncertainty with its reliability as a disadvantaged implication as there is little trend across each quartile. California, statewide, shows the largest disparity between the upper and lower quartile.

Table 3. California: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 31A)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	100% increase	107% increase	10% increase
Back to Business	149% increase	147% increase	18% increase
Equal Spread of ZEVs	94% increase	97% increase	2% decrease
Half to DACs	67% increase	88% increase	6% decrease
Three-fourths to DACs	54% increase	61% increase	18% decrease

Table 4. Los Angeles: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 31B)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	59% increase	27% increase	40% increase
Back to Business	28% increase	36% increase	53% increase
Equal Spread of ZEVs	15% increase	26% increase	39% increase
Half to DACs	6% decrease	13% increase	25% increase
Three-fourths to DACs	2% decrease	12% increase	20% increase

Table 5. San Francisco Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 31C)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	67% increase	50% increase	4% increase
Back to Business	65% increase	85% increase	14% increase
Equal Spread of ZEVs	31% increase	37% increase	4% decrease

Half to DACs	20% increase	29% increase	9% increase
Three-fourths to DACs	25% increase	42% increase	6% increase

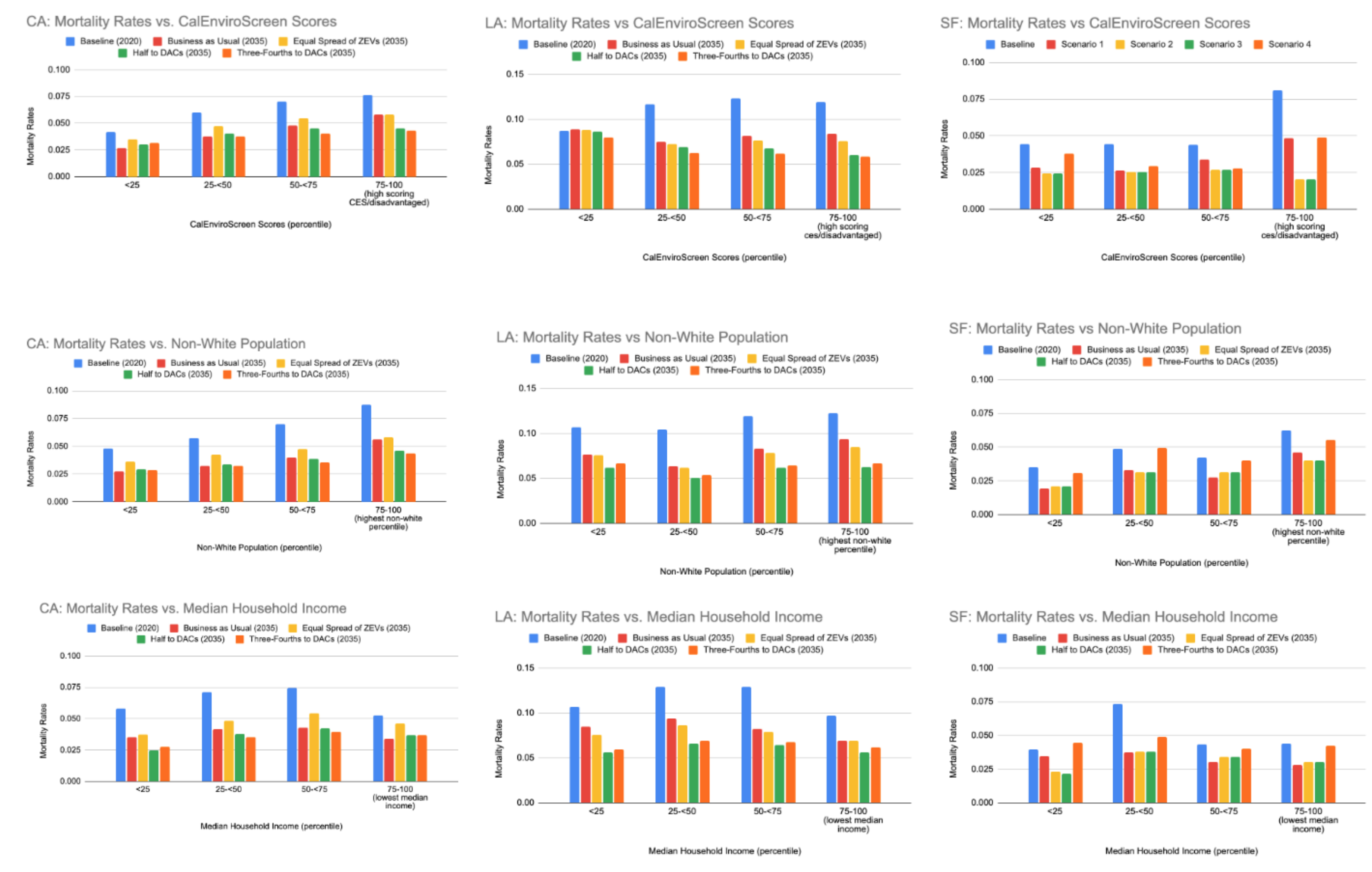


Figure A: CA **Figure B: LA** **Figure C: SF**

Figure 32. Average Mortality in Varying Disadvantaged Groups
Figure 32A: California, Figure 32B: Los Angeles, Figure 32C: San Francisco

Figure 32 looks at the average mortality across California, Los Angeles, and San Francisco. The mortality graphs follow similar trends as the PM 2.5 exposure graphs. However we see a slight decrease across all disparties.

Table 6. California: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 32A)

	CalEnviroScreen Scores	Non-White Population	Median Household Income
Baseline	84% increase	83% increase	33% decrease
Back to Business	118% increase	105% increase	47% decrease
Equal Spread of ZEVs	65% increase	61% increase	23% increase
Half to DACs	49% increase	58% increase	4% increase
Three-fourths to DACs	37% increase	52% increase	9% decrease

Table 7. Los Angeles: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 32B)

	CalEnviroScreen Scores	Non-White Population	Median Household Income
Baseline	36% increase	15% increase	4% increase
Back to Business	6% decrease	22% increase	1% increase
Equal Spread of ZEVs	16% decrease	13% increase	9% decrease
Half to DACs	30% decrease	2% increase	18% decrease
Three-fourths to DACs	27% decrease	0.5% increase	9% decrease

Table 8. San Francisco: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 32C)

	CalEnviroScreen Scores	Non-White Population	Median Household Income
Baseline	83% increase	78% increase	11% increase
Back to Business	72% increase	135% increase	18% decrease
Equal Spread of ZEVs	17% decrease	91% increase	31% increase
Half to DACs	17% decrease	91% increase	43% increase
Three-fourths to DACs	29% increase	79% increase	5% decrease

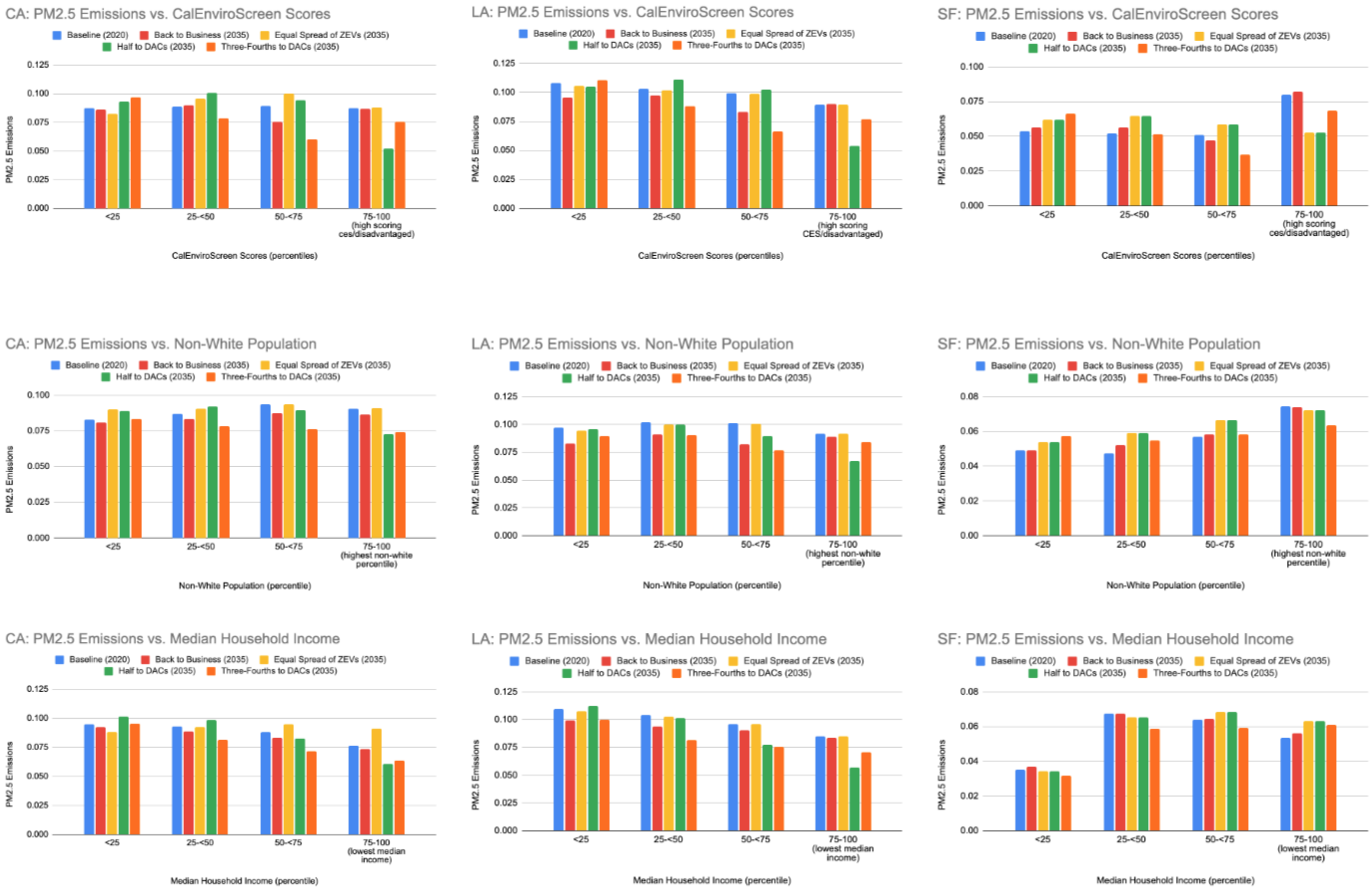


Figure A: CA Figure B: LA Figure C: SF

Figure 33. Average PM 2.5 Emissions in Varying Disadvantaged Groups
Figure 33A: California, Figure 33B: Los Angeles, Figure 33C: San Francisco

Figure 33 looks at the $PM_{2.5}$ exposure levels across California, Los Angeles, and San Francisco. $PM_{2.5}$ exposure levels are higher in the California and Los Angeles graphs compared to San Francisco. Los Angeles sees the most reduction in disparities after the scenarios. After each scenario, San Francisco, statewide, shows the most disparity between the upper and lower quartile.

Table 9. California: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 33A)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	.4% decrease	9% increase	19% decrease
Back to Business	1% increase	7% increase	20% decrease
Equal Spread of ZEVs	6% increase	1% increase	4% increase

Half to DACs	44% decrease	19% decrease	40% decrease
Three-fourths to DACs	22% decrease	11% decrease	34% decrease

Table 10. Los Angeles: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 33B)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	17% decrease	6% decrease	23% decrease
Back to Business	6% decrease	7% increase	16% decrease
Equal Spread of ZEVs	15% decrease	3% decrease	21% decrease
Half to DACs	49% decrease	30% decrease	49% decrease
Three-fourths to DACs	30% decrease	6% decrease	29% decrease

Table 11. San Francisco: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 33C)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	49% increase	52% increase	52% increase
Back to Business	46% increase	51% increase	53% increase
Equal Spread of ZEVs	15% decrease	34% increase	84% increase
Half to DACs	15% decrease	34% increase	84% increase
Three-fourths to DACs	3% increase	11% increase	94% increase

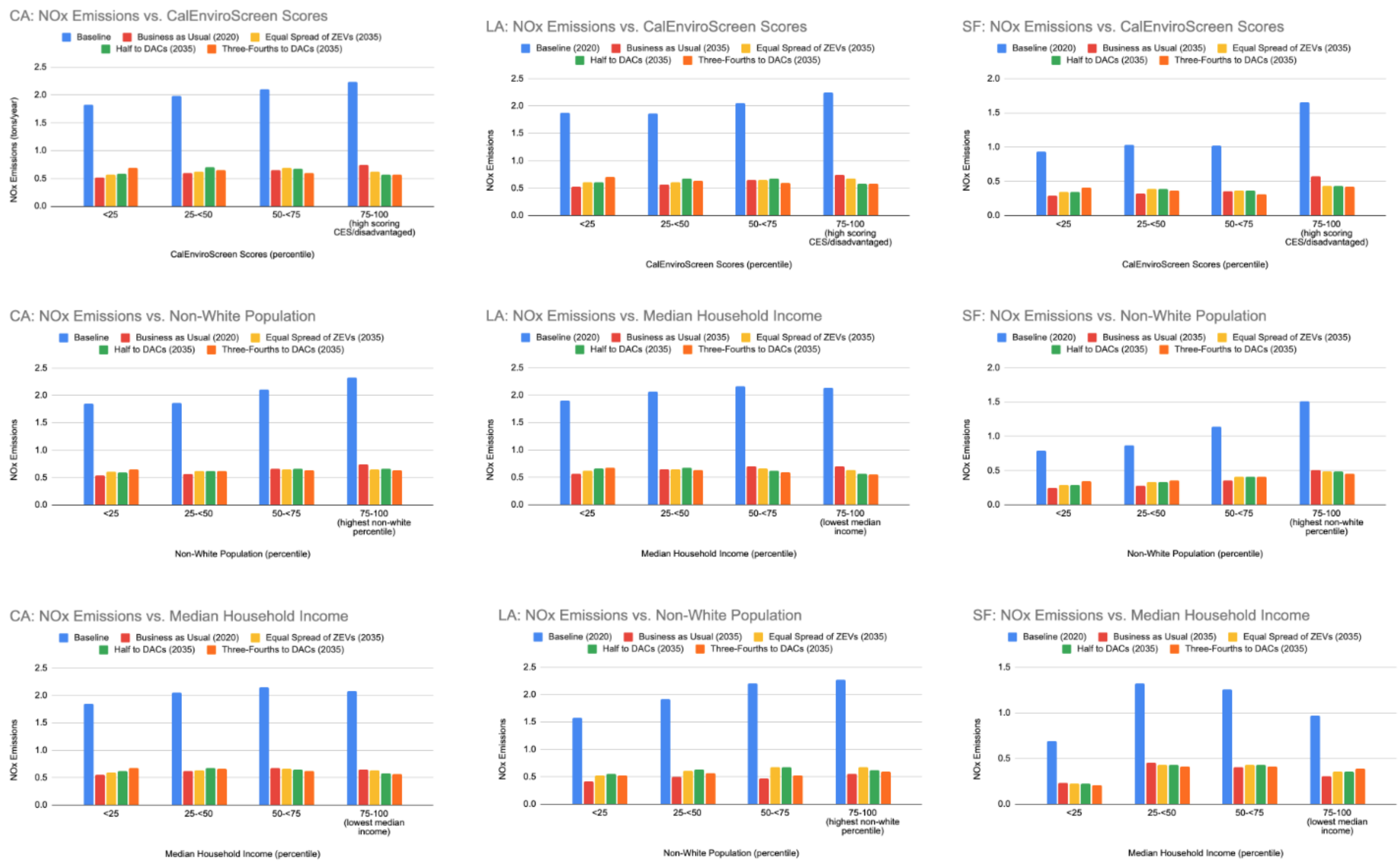


Figure A: CA **Figure B: LA** **Figure C: SF**

Figure 34. Average NO_x Emissions in Varying Disadvantaged Groups
Figure 34A: California, Figure 34B: Los Angeles , Figure 34C: San Francisco

Figure 34 looks at the NO_x emissions across California, Los Angeles, and San Francisco. NO_x emissions levels are the highest in the baseline scenario and exponentially decrease in every scenario. Again, after each scenario, San Francisco, statewide, shows the most disparity between the upper and lower quartile.

Table 12. California: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 34A)

	CalEnviroScreen Scores	**Non-White Population**	**Median Household Income**
Baseline	23% increase	26% increase	12% increase

Back to Business	43% increase	39% increase	19% increase
Equal Spread of ZEVs	10% increase	6% increase	7% increase
Half to DACs	2% decrease	9% increase	8% decrease
Three-fourths to DACs	12% decrease	2% decrease	17% decrease

Table 13. Los Angeles: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 34B)

	CalEnviroScreen Scores	Non-White Population	Median Household Income
Baseline	20% increase	44% increase	12% increase
Back to Business	40% increase	34% increase	22% increase
Equal Spread of ZEVs	10% increase	30% increase	3% increase
Half to DACs	5% decrease	13% increase	14% decrease
Three-fourths to DACs	18% decrease	12% increase	17% decrease

Table 14. San Francisco: Disparity between the 76-100 Quartile and <25 Quartile (in reference to Figure 34C)

	CalEnviroScreen Scores	Non-White Population	Median Household Income
Baseline	77% increase	90% increase	41% increase
Back to Business	96% increase	104% increase	30% increase
Equal Spread of ZEVs	26% increase	69% increase	58% increase
Half to DACs	26% increase	69% increase	58% increase
Three-fourths to DACs	4% increase	33% increase	86% increase

Limitations

There were several limitations that were encountered in our project that may have impacted our results. One is that the term “disadvantaged” in our study did not include all considerations, such as failing to account for poverty and the most targeted race groups. While we looked at income as a way to define disadvantaged, there were very little trends found. This may have been because we did not look at which income brackets were experiencing poverty. Two households may have been making the same income, however the household size could have been indicative over which household was more vulnerable. We also looked at the entire non-white race. We extracted every race, besides the white population. This may have been an inaccurate representation for the term disadvantaged, as research has shown that Hispanic/Latino and Black Americans are more likely to be exposed to higher levels of PM 2.5. In addition, income and non-white population data were taken from the American Community Survey, this survey is conducted through mail in questionnaires, with telephone and phone visit collection used as a follow-up to mail non-response. The most disadvantaged groups are less likely to take the survey, often underrepresenting particular groups. Consequently, our study may have not collected the entire population of those who are considered disadvantaged and underestimate the $PM_{2.5}$ exposure and mortality rates found in disadvantaged communities, as well as the reductions in these two metrics with more equitable ZEV distribution to these communities. A third limitation was that our study did not consider that disadvantaged communities are more likely to buy used cars instead of new vehicles. Used electric vehicles would not be as effective in reducing $PM_{2.5}$ emissions compared to new electric vehicles, so this could imply that our reductions in $PM_{2.5}$ exposure concentrations may be an overestimate of the actual $PM_{2.5}$ reductions by 2035.

With regards to the fleet data, our study included light duty automobiles (LDAs) and two categories of light duty trucks (LDT1 & LDT2), but did not involve medium duty vehicles (MDVs). Although the CARB website classifies these as medium duty vehicles, they are still included in the light duty vehicle emissions regulations. Therefore, they are regulated by the ACC II rule and are expected to transition to zero emission by 2035 as well. Using the EMFAC 2019 data as a reference, the total emissions for all pollutant classes was 92,454 tons/year when MDVs were not included. When including MDVs, the new total was 118,418 tons/year for all pollutant classes.Therefore, we believe adding MDVs to our analysis would have increased our emissions by 20-30% and could have produced larger $PM_{2.5}$ exposures and mortality rates as the different scenarios of ZEV distribution were applied. However, we do believe the trends and conclusions shown in this study would be consistent with a future study including MDVs. Furthermore, an assumption made in the study was that the removal of vehicles is proportional to the removal of emissions. This, however, may not be true, since ZEVs are responsible for fewer emissions than ICEVs. Since vehicles were uniformly removed, a percentage of those would be ZEVs. If a large percentage of the vehicle population becomes ZEVs in the future, the removal of vehicles would not be proportional to the removal of emissions. Thirdly, in our methodology, new vehicles were assigned emission factors based on the upcoming model year. For example, when modeling the year 2030, new vehicles referred to those with a model year of 2031. These new vehicles were assigned this emission factor when they entered the fleet, and this emission factor stayed constant throughout its entire lifetime. This is a simplification of reality since this assumption does not consider the age of vehicles. As vehicles age, they tend to emit more pollution due to decreased efficiency, so emission factors, and their subsequent emissions total, might not be as accurate when vehicles become older. Lastly, it is likely that we overestimated the proportion of new zero emission vehicles made up by PHEVs. The ACC II rule mandates that PHEVs can only make up 20% of the annual zero-emission vehicle requirement. However, this percentage will likely be lower since some manufacturers, such as Tesla, only offer BEVs and not PHEVs.

With regards to the ISRM tool, one limitation is the use of the default 2010 population data to establish trends in $PM_{2.5}$ concentrations and mortality rates across different scenarios. The 2010 population underestimates the population in 2020, which may have led to underestimates of the mortalities due to $PM_{2.5}$. Additionally, it is possible that between 2010 and 2020, more communities were assigned the disadvantaged status. Therefore, if 2020 population data was used in the modeling process, the maps would have been more representative of the mortalities and the number of disadvantaged communities affected by the varying $PM_{2.5}$ concentrations. Another limitation mentioned by the developer of the ISRM tool is that it relies on relatively old chemical transport modeling data. This fact indicates that updated knowledge about interactions between chemical pollutants and their dispersal would not be reflected in the calculations performed by the ISRM tool. With this mind, the ISRM tool is continuously being developed, and updating the calculations to the latest knowledge about chemical transport can be a way to more accurately model the changes brought about by more equitable ZEV distributions.

Conclusions and Recommendations

In our study, we found that California's transition to zero emission vehicles will lead to an overall decrease in concentrations of $PM_{2.5}$. This decrease was observed statewide as well as in smaller subregions such as the Los Angeles and San Francisco Bay areas. This reaffirms the state's prediction that the transition will yield cleaner air for Californians and subsequently reduce pollution-induced health impacts. However, disadvantaged communities, especially those with a high proportion of Black and Hispanic/Latino populations, are still expected to experience a higher air pollution burden than their counterparts if current rates of ZEV adoption continue. While the exposures will be smaller, the pre-existing disparity will only grow larger. This would reinforce current environmental injustices instead of using the transition as an opportunity to prioritize the communities who are the most negatively impacted. With more aggressive rates of ZEV adoption in disadvantaged communities, the pre-existing disparity significantly lessens or even disappears fully. However, the rates necessary for this effect are unlikely to occur naturally due to the current high costs of ZEVs.

Therefore, in the switch to zero emission vehicles in California, we highly recommend that policymakers focus on making ZEVs more accessible to disadvantaged communities, especially those with a high proportion of Hispanic/Latinos or Black populations. This could be done by improving financial incentives to help overcome higher upfront costs. Historically, many incentives have been offered in the form of rebates or tax credits that act retrospectively, leaving customers to front the initial cost. This is an unrealistic option for disadvantaged communities and needs to be improved to work prospectively instead. Incentives also need to include community outreach and engagement to ensure that community leaders and residents are aware and understand the resources available to them.

While a full discussion of charging infrastructure is beyond the scope of this study, accessible charging options is a crucial step in expanding ZEV ownership. This could include building more charging stations in homes, workplaces, or public areas. Since ZEV adoption rates in disadvantaged communities have been historically low, it is likely that they also currently have less access to charging infrastructure. A lack of chargers would act as an additional barrier to ZEV adoption in the future, and more charging needs to be built immediately. Future studies could be performed to investigate the current distribution of charging stations and to identify target areas for future implementation. Iit is also important to address the future of the power grid in California. While ZEVs eliminate tailpipe emissions on the streets, they place an increased load on the electric grid. In densely populated areas like Los Angeles, this could be beneficial for air quality, since it would relocate emissions to a potentially distant power plant. While California may use a fair amount of renewable energy, ZEVs will not be truly clean until the grid is entirely powered by renewables. For the time being, it is important to investigate how increased charging demand could harm communities near power plants. Further studies will also need to be done to include medium duty vehicles and to investigate additional scenarios of ZEV adoption. Finally, it would be helpful to research how these $PM_{2.5}$ reductions could potentially help regions in California reach attainment for National Ambient Air Quality Standards

(NAAQS) established by the EPA under the Clean Air Act. These reductions could possibly be offset by an increased amount of dust or particulate matter from drought or wildfires as climate change is expected to worsen. We hope our work can be built upon to help answer these important research questions.

Overall, the transition to zero emission vehicles in California is expected to lead to an overall decrease in $PM_{2.5}$ concentrations and related health impacts. However, current ZEV adoption rates are low in California's disadvantaged communities that already experience a disproportionately high amount of air pollution. This transition presents an opportunity to remedy this environmental injustice, but it is not possible without intervention from the government. The results presented in this study call for immediate policy changes to prioritize the introduction of ZEVs into the communities who need it most.

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Appendix

A. ISRM Tool on Linux & Google Cloud

Link to Libby Koolik's ISRM Tool on Linux & Google Cloud manual.

B. Running the ISRM Tool on Mac OS

Link to Libby Koolik's Running the ISRM Tool on Mac manual.

C. Running the ISRM Tool Locally on a Linux Server (Mac OS)

Link to Running the ISRM Tool Locally on a Linux Server (Mac OS) document.

D. Processing the ISRM Tool's $PM_{2.5}$ Exposure Concentration Maps in QGIS

Link to Processing the ISRM Tool's PM2.5 Exposure Concentration Maps in QGIS document.