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Electric vehicle fleet penetration helps address inequalities in air quality and improves environmental justice

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Accelerated penetration of on-road electric vehicles offers regional and community-scale air quality benefits; however, such benefits have not been previously quantified regarding environmental justice communities near major roads. This study evaluated six 2040 electric vehicle scenarios and quantified concentration reductions of nitrogen dioxide and fine particulate matter (diameter less than 2.5 μm) for southern California environmental justice communities near Interstate 710. Findings showed that aggressive electric vehicle penetration (85% electric vehicle share) reduced nitrogen dioxide and fine particulate matter concentrations more in communities with more people of color (1.9 ppb and 1.1 μg m^{-3}) than in communities with more White residents (1.6 ppb and 0.94 μg m^{-3}). Aggressive electric vehicle penetration reduced pollution exposure disparity by 30% for nitrogen dioxide and 14% for fine particulate matter. Disparity reductions were also found based on educational attainment. Results suggest policies that encourage accelerated electric vehicle penetration will address inequalities in air pollution and help achieve environmental justice.

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There is recognition that U.S. environmental management programs and air pollution control in particular have not produced equitable outcomes. A growing literature shows communities more heavily populated by people of color (POC) and those with lower incomes are disproportionately located near major roads and other pollution sources. The location of such communities reflects development patterns set in place decades ago through discriminatory policies such as those involving home ownership and mortgage financing. Historic and ongoing outcomes in these settings include greater exposure to environmental hazards such as air pollution[1–7].

In response, agencies are addressing disparities to improve environmental justice (EJ), defined by the U.S. Environmental Protection Agency (EPA) as, "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies"[8]. An important contributor to exposure disparities is traffic-related air pollutants (TRAPs). Studies show TRAP concentrations within a few hundred meters of a major road can be two to four times higher than regional background concentrations[9,10]. Moreover, U.S. near-road communities are populated more heavily by POC and those with lower incomes[11]. As on-road vehicle emissions have dropped over time[12], pollution exposure has declined, but disparities persist. For example, one land use study showed, from 2000 to 2010, that nitrogen dioxide (NO_2) concentrations, an indicator of on-road vehicle emissions, declined more for communities with non-White (non-Hispanic) populations (−6.9 ppb) than communities with White (non-Hispanic) populations (−4.7 ppb). However, resulting 2010 NO_2 exposures were still higher for non-White communities[1]. A separate study used 2017 data from 20 U.S. cities to document that concentrations of particulate matter with diameter less than 2.5 μm ($PM_{2.5}$) continue to be higher adjacent to major roads than in surrounding communities[13]. Therefore, continued on-road vehicle emissions reductions are needed to reduce exposure disparities and address EJ.

Vehicle electrification is considered a central component of plans to reduce on-road vehicle emissions, improve urban-scale air quality, and reduce greenhouse gas (GHG) emissions[14–17]. Previous studies document that electric vehicle (EV) penetration in the light duty vehicle (LDV) and medium- and heavy-duty vehicle (MHDV) fleets reduces on-road emissions. Although EVs contribute road dust and brake and tire wear emissions, they lack exhaust emissions[18–24].

Erdakos et al.[25] reported the most important factor to accelerate EV adoption is achieving cost parity between EVs and internal combustion engine (ICE) vehicles; this can be achieved via lower EV manufacturing costs and higher gasoline prices. Their study showed a reduction of 3% to 15% in emissions of urban-scale air pollutants in the LDV fleet by 2040 across a range of accelerated cost parity scenarios. Raju et al.[18] showed achieving California's GHG emissions goals requires aggressive EV penetration in the MHDV fleet. U.S. federal and state actions therefore seek to accelerate EV penetration. For example, in August 2021, the Biden administration announced a goal to achieve a 40% to 50% new-vehicle EV sales share in 2030[26]. In California, Advanced Clean Car (ACC), Advanced Clean Truck (ACT), and Advanced Clean Fleet (ACF) regulations seek to reduce GHG and Nitrogen Oxide (NO_x) emissions via EV sales mandates for the LDV and MHDV fleets. Under the U.S. Clean Air Act, other states can adopt California vehicle requirements, and studies have documented the emission reduction benefits for states increasing EV penetration by adopting California rules[27].

Studies from the U.S.[28–32], Europe[33–35], and Asia[36] have also assessed regional air quality impacts from EV penetration from on-road emissions reductions and resulting changes in electricity generation emissions. In general, EV penetration is forecast to reduce regional $PM_{2.5}$, ozone (O_3), and NO_x concentrations. However, in some situations, EV penetration and resulting NO_x emissions reductions have been simulated to increase O_3 concentrations in areas such as Colorado, Houston, and Los Angeles, since vehicular NO_x emissions would have otherwise chemically reacted with and titrated O_3[28,31,32]. For example, Skipper et al.[32] found that by fully electrifying on-road vehicles in California, the statewide population-weighted annual $PM_{2.5}$ concentration would decrease 0.5 μg m^{-3} in both 2016 and 2028, and the fourth highest 8-h maximum daily O_3 concentration would decrease 6.6 ppb in 2016 and 4.3 ppb in 2028, although reduced on-road NO_x emissions led to O_3 increases in some areas. Modeling by Skipper et al. showed that the O_3 disbenefit however, was reduced by 2028 compared to 2016 (increased O_3 levels were up to 3 ppb in 2016 versus 0.5 ppb in 2028), and they concluded $PM_{2.5}$ and O_3 concentration reductions scale approximately linearly with increasing EVs. In a different study, Pan et al.[28] modeled EV penetration leading to O_3 increases along highways and reductions further downwind. Additional research has shown that even in regions where fossil-fuel based power generation is important to regional air quality, the net regional impact of increased penetration of EVs will be a benefit (reduced concentrations) for regional pollutants such as O_3 and total $PM_{2.5}$[37,38]. Schnell et al. found that U.S. O_3 levels generally decreased with EV penetration, regardless of the source of electricity used to charge the vehicles, except in locations where marginal power generation increased NO_x emissions, or where O_3 production was likely VOC-limited (e.g., Los Angeles)[23]. The same study found EV-related $PM_{2.5}$ concentration changes depended on electricity source, but had a lesser impact on O_3. See Supplementary Note S1 for additional research examples.

In summary, previous studies assessed EV-related changes in electricity generation and transportation emissions. Prior work supported regional-scale air quality analyses, including changes in $PM_{2.5}$ (direct emissions and atmospheric formation) and ozone concentrations using regional-scale (photochemical) air quality models to assess metropolitan-area exposure changes. However, most prior studies did not investigate the impact of EV penetration for near-road settings where primary vehicular pollutants contribute to exposure disparities[39].

This study quantified air quality benefits of EV penetration with respect to EJ by differentiating EV-related air pollution changes between communities with and without EJ concerns. The analysis focused on southern California communities adjacent to and heavily impacted by traffic on Interstate 710 (Fig. 1), one of California's busiest roadways and a travel corridor serving the largest port complex in the United States. The study region has long been characterized by poor air quality; for example, air quality monitoring adjacent to Interstate 710 measured the highest near-road $PM_{2.5}$ levels in the U.S. in 2017[13], and earlier work documented air pollution exposure concerns in communities near the Ports of Los Angeles and Long Beach[40]. The work described here builds on prior studies forecasting EV use[18,25] and California Air Resources Board (CARB) policies to reduce vehicle emissions, including the Advanced Clean Cars II rule, adopted August 25, 2022. This rule requires that by 2035, 100% of new cars and light trucks sold in California will be zero-emission vehicles, including plug-in hybrid electric vehicles[41]. Six calendar year (CY) 2040 EV penetration scenarios were evaluated (Table 1). Analyses focused on transportation-related NO_x, NO_2, and $PM_{2.5}$ direct (primary) emissions since those pollutants are important contributors to adverse health outcomes.

Although they also contribute to adverse health outcomes, photochemically formed pollutants such as O_3 and secondary

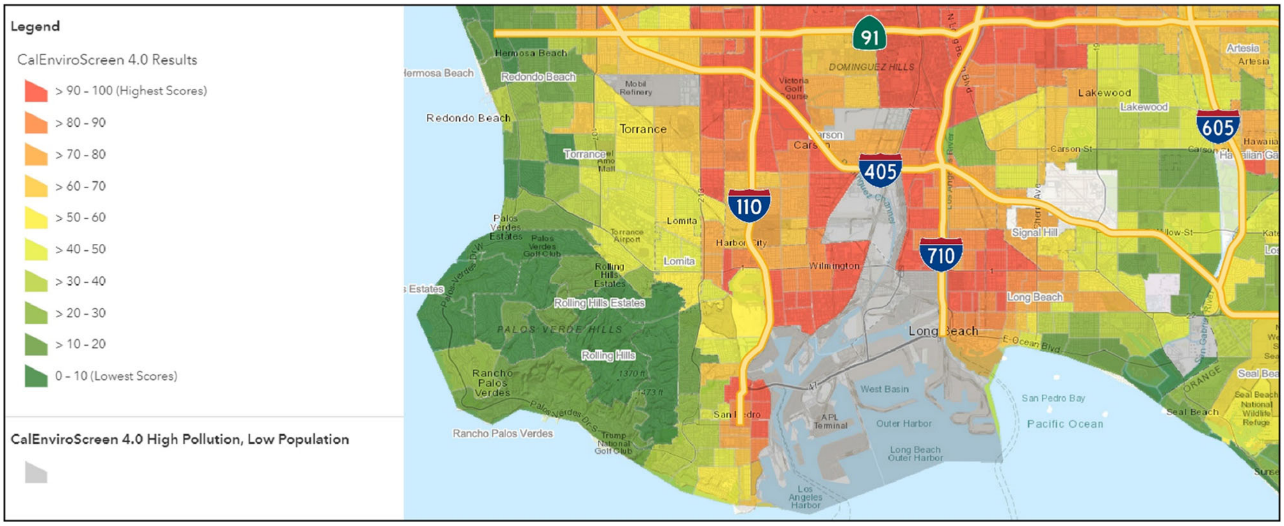

Fig. 1 The modeling domain. Image source https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40. On this figure, the I-710 freeway runs north to south just west of the Lakewood, Signal Hill, and Long Beach communities; it then joins Highway 47 and turns west (towards the area marked Rolling Hills). Permission to use this map was granted by the Office of California Environmental Health and Hazard Assessment.

Table 1 EV penetration scenarios.

Scenario	Policies that impact light-duty fleet	Policies that impact medium- and heavy-duty fleet
Reference Case		
0. Reference case	No further policies to accelerate EV penetration	No further policies to accelerate EV penetration
Policy Cases		
1. High emissions reduction	The cost to manufacture light-duty EVs is comparable to internal combustion conventional vehicles starting in 2030	Advanced Clean Truck (ACT) and Advanced Clean Fleet (ACF) regulations
2. Medium emissions reduction	Medium gasoline price increases \$0.07 per gallon per year beginning in 2019	ACT regulation
3. Emission reduction for MHDVs only	No further policies to accelerate EV penetration	ACT and ACF regulations
Idealized Bounding Cases		
4. Customized EV-phase in schedule	Advanced clean car regulation phase II (ACC II)	Customized EV phase-in schedule starting in 2025 to achieve 56% EV on the road in 2040 (Ref.[18])
5. Maximum bounding scenario	100% new-vehicle EV market share starting from 2023	100% new-vehicle EV market share starting from 2023

ACT Advanced Clean Truck, *ACF* Advanced Clean Fleet, *ACC II* Advanced Clean Car Regulation Phase II.

$PM_{2.5}$ were not considered in this study. We focused on near-road settings, where studies show higher-than-average concentrations of directly emitted vehicular pollutants[9,42]. The impact from power generation was not considered because (a) California law requires phase-out of fossil-fueled electric power generation by 2045;[43] and (b) impacts from power plants are likely to be more regional in nature, especially for O_3 and secondary $PM_{2.5}$, and this work focused on neighborhood-scale impacts, including EJ communities near major roads. As noted above, some studies find that as EVs change on-road and electric power generation emissions, there can be cases of increased secondary pollutant formation. Secondary pollutant impacts from EV-related power generation will likely decrease over time, however. The U.S. Energy Information Administration forecasts that by 2050, the supply of renewably-generated electricity (solar, wind, hydro) will increase more rapidly than overall power demand[44].

For all scenarios, regional pollutant background concentrations and the contribution from on-road vehicles were assessed separately at a census block group level. We investigated the change in concentrations due to EV penetration considering different population characteristics depicted in CalEnviroScreen[45], a California mapping tool that ranks locations by EJ parameters, including population characteristics such as White population percentage, and education level. We tested the hypothesis that as EVs penetrate the vehicle fleet, communities with EJ concerns located near major roads would gain greater incremental air quality benefits than the population as a whole. We also used a health-based metric to quantify outcomes as fleet electrification reduced NO_2 and $PM_{2.5}$ concentrations across population groups. We concluded that EV penetration can reduce exposure disparity more for NO_2 and less for $PM_{2.5}$. Policies that encourage accelerated EV penetration will address inequalities in air pollution exposure and help achieve environmental justice.

Results

EV penetration and impacts on emissions. Among the six EV penetration scenarios, we modeled a reference case and five alternative futures. The reference case assumed no additional policies to accelerate EV penetration. The CARB EMission FACtor (EMFAC) model was used to model vehicle population and emissions. Based on EMFAC defaults, reference case results for CY 2040 EV fleet shares were 10.6% for the LDV fleet, 0% for the MHDV fleet, and 9.2% for the total vehicle fleet (Supplementary Table S1).

Scenarios 1–3 were policy cases that included assumed actions to accelerate EV penetration in both the LDV and the MHDV fleets. Scenarios were built on policies developed by CARB and prior work published for the U.S. National Cooperative Highway Research Program (NCHRP)[25]. Supplementary Table S1 summarizes the EV share for each scenario and vehicle fleet. In Scenario 1, we combined CARB-forecasted policy outcomes with NCHRP projections of how EV penetration would be affected by LDV fleet cost parity between EV and ICE vehicles. Scenario 1 increased the LDV EV share from 10.6% to 19%; also in Scenario 1, implementation of the CARB ACT[46] and ACF[47] regulations increased the EV share in the MHDV fleet from 0% to 30.1%. In total, the Scenario 1 fleetwide EV share increased from 9.2% to 17.5%. Scenario 2, based on the NCHRP work, showed that a gasoline price increase of $0.07 per gallon per year resulted in a 0.1% increase in the EV share for the LDV fleet compared to the reference case (10.7% vs. 10.6%); the ACT regulation increased the EV share in the MHDV fleet by 27.8%. By comparing Scenarios 1 and 2, we found the ACF regulation, added to assumed ACT implementation, increased the MHDV fleet EV share an additional 2.3%. Scenario 3 assumed no additional policy regarding the LDV fleet, and ACT and ACF regulations for the MHDV fleet, resulting in 10.8% total EV share - a 1.6% increase compared to the reference case (10.8% vs. 9.2%). Because of the limited incremental EV share from gasoline price increases and ACF, Scenario 2 and 3's total FY 2040 fleetwide EV share was almost identical (10.8%).

Scenarios 4 and 5 served as idealized bounding cases with assumed rapid EV penetration. Scenario 4's LDV fleet assumed implementation of Phase 2 of the CARB Advanced Clean Car rule (ACC II, adopted August 25, 2022)[48]. For ACC II, modeling assumed a phase-in of zero emission vehicle (ZEV) and plug-in hybrid electric vehicle (PHEV) new-vehicle sales starting in 2026, gradually increasing to 100% of sales by 2035 and beyond (see Methods). More information on the final ACC II rule is available at https://ww2.arb.ca.gov/news/california-moves-accelerate-100-new-zero-emission-vehicle-sales-2035[39]. In this study, we assumed the requirement applied only to ZEVs and also assumed all ZEVs were EVs. This assumption resulted in 69.7% EVs in the LDV fleet by 2040. Scenario 4's MHDV fleet followed a scenario in Raju et al.[18] (their Scenario 3) that assumed accelerated ZEV deployment with a focus on battery electric vehicles to assess the feasibility of achieving 80% GHG emissions reductions from trucks by 2050 in the California. Our modeling resulted in a 56.4% EV share for the MHDV fleet (for comparison, Raju et al.[18] modeled a CY 2040 HD vehicle EV share of 56.9%). Scenario 5 assumed that, starting from CY 2023, all new-vehicle sales were EVs, resulting by CY 2040 in an 89% EV share in the LDV fleet, 76.7% EV share in the MHDV fleet, and 85% EV share fleetwide. This case (Scenario 5) served as a what if scenario to bound the maximum EV share by 2040. The analysis approach used to estimate the EV share for these scenarios is detailed in the Methods section.

NO_x and $PM_{2.5}$ emissions reductions for each EV penetration scenario were modeled by combining EMFAC emissions estimates for the reference case and the EV market share for each scenario (see Methods section). The six EV penetration scenarios resulted in varying emissions reductions for NO_x and $PM_{2.5}$ (Fig. 2c, d). Note that $PM_{2.5}$ emissions modeled here include exhaust, tire wear, and brake wear. Our analysis used EMFAC2021 assumptions that EVs have half the brake wear emissions of ICE vehicles[49]. For this analysis, we assumed that emissions from re-suspended road dust, which are not estimated by EMFAC, are not affected by EV penetration, and therefore we did not vary or include those emissions as part of our scenario analyses. The analysis presented here, which focuses on year 2040, embeds a long-term assumption there is no material difference in weight, and therefore road dust emissions, for electric vs. conventional light-duty vehicles. For example, Argonne National Laboratory found battery electric vehicles, "…are significantly heavier than the conventional baseline vehicles in 2021 and 2027… however, battery technology improvements are expected to reduce the vehicle weight penalty as we get closer to 2050"[50]. Supplementary Table S2 shows the relative importance of exhaust, tire wear, brake wear, and road dust emissions to total $PM_{2.5}$. For the LDV fleet, Scenario 1 reduced 8% of NO_x emissions and 5% of $PM_{2.5}$ emissions compared to the reference case (8.4% EV increase compared to the reference case: 19% vs. 10.6%). Scenario 2 showed almost no NO_x or $PM_{2.5}$ emissions reductions, due to the limited EV share increase in the LDV fleet (a 0.1% increase). In Scenarios 4 and 5, EV penetrations in the LDV fleet resulted in 60% and 82% reductions of NO_x concentrations, and 32% and 40% reductions of $PM_{2.5}$ concentrations. For the MHDV fleet, the ACT and ACF regulations (Scenarios 1 and 3) reduced NO_x emissions by 32% and $PM_{2.5}$ emissions by 18%. The ACT regulation alone reduced NO_x emissions by 17% and $PM_{2.5}$ emissions by 14% for Scenario 2 in the MHDV fleet. This indicates that, although the ACF regulation only increased the MHDV fleet EV share by 2.3% in addition to the ACT regulation, the impact on exhaust NO_x emissions was substantial. In Scenarios 4 and 5, EV penetration in the MHDV fleet resulted in 47% and 65% reductions of NO_x concentrations, and 31% and 41% reductions of $PM_{2.5}$ concentrations.

Figure 2 showed the estimated EV and ICE vehicle populations and the NOx and $PM_{2.5}$ emissions for each scenario. The major contributor for fleetwide NO_x emissions are MHDVs (Fig. 2c); therefore, total NO_x emissions reductions were largely controlled by the rate of EV penetration into the MHDV fleet. NO_x emissions reductions were 27% for Scenario 1, 14% for Scenario 2, 26% for Scenario 3, 44% for Scenario 4, and 62% for Scenario 5. The major contributor for 2040 modeled fleetwide $PM_{2.5}$ emissions, on the other hand, were LDVs. Policy cases had limited LDV fleet EV share changes compared to the Reference case (Supplementary Table S1) and thus did not substantially reduce $PM_{2.5}$ emissions (Reductions in $PM_{2.5}$ emissions were 8% for Scenario 1, 4% for Scenario 2, and 4% for Scenario 3; Fig. 2d). Idealized bounding cases (Scenarios 4 and 5) showed much greater $PM_{2.5}$ emissions reductions (29% and 40%).

Air quality impacts and EJ implications. Our analysis translated EV penetration scenarios and emissions changes into resulting air pollutant concentrations (air quality). Air pollutant concentrations were separated into two components: regional background concentrations based on monitored air quality and then forecasted to the year 2040, and modeled concentrations resulting solely from year 2040 on-road vehicle operations forecasted within the study area (the on-road contribution). The regional background concentrations were estimated based on hourly air quality data collected from ambient monitoring sites reported to U.S. EPA's Air Quality System[51]. These air quality data were projected to 2040 based on the 2000 to 2020 trend in monitored NO_x and interpolated to census block group centroids (see details in the Methods section). Concentration contributions from on-road vehicles were modeled with U.S. EPA's Research LINE (R-LINE)[52,53] source model; our R-LINE modeling employed scenario-specific emissions estimates for on-road vehicles and spatially resolved meteorological data (see Methods).

The modeled concentrations and the relative concentration change compared to the reference case are summarized in Table 2. In the reference case, the on-road contribution and total regional

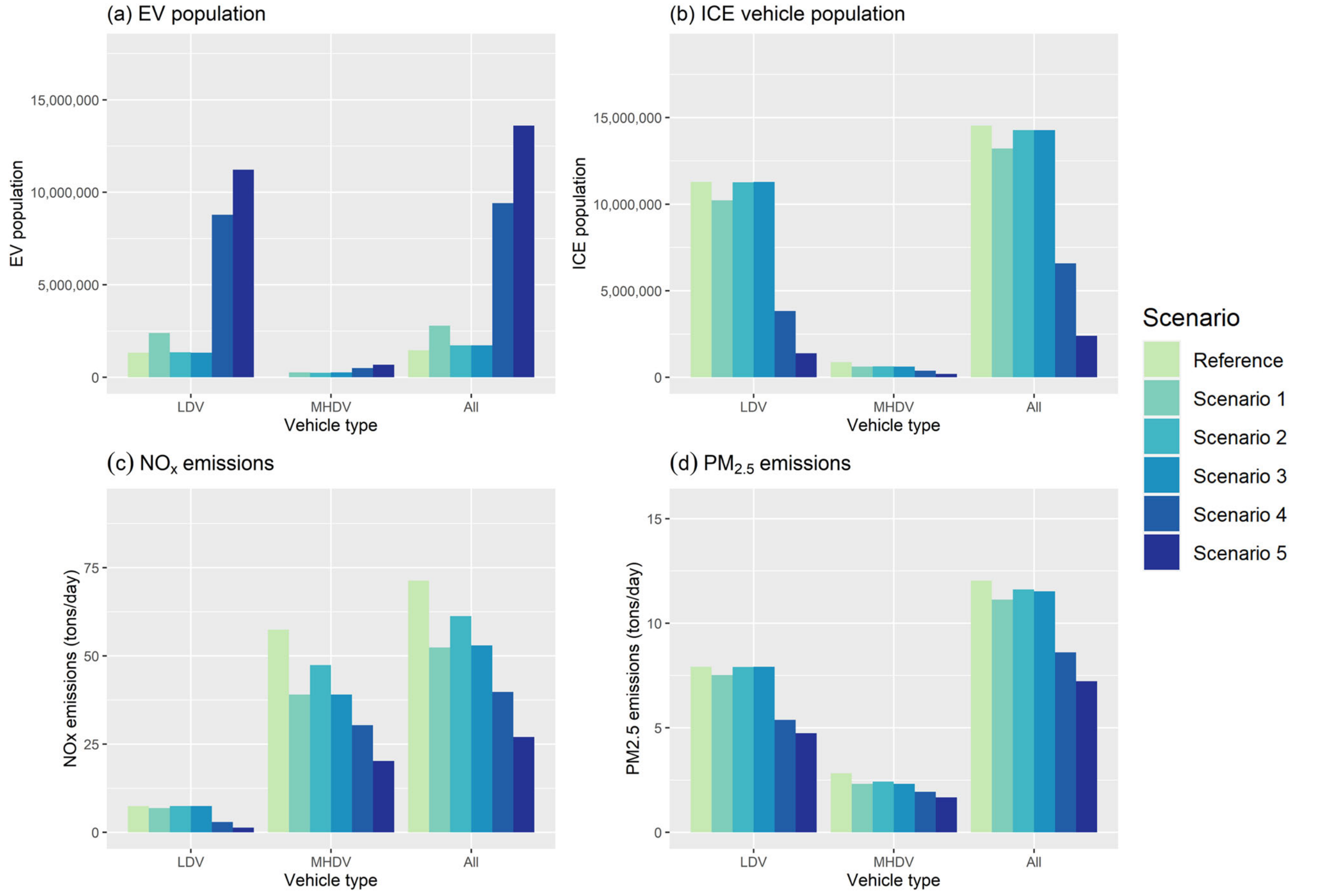

Fig. 2 Estimated vehicle population and emissions for each scenario in the South Coast region in 2040. a Electric vehicle (EV) population, **b** internal combustion engine (ICE) vehicle population, **c** NO_x emissions, and **d** $PM_{2.5}$ emissions. $PM_{2.5}$ emissions shown here represent the combination of exhaust, tire wear, and brake wear; road dust is not included. LDV light duty vehicles, MHDV medium- and heavy-duty vehicles. All = LDV + MHDV + all remaining vehicles (such as motor homes and motorcycles) not covered by policies to accelerate EV penetration among LDV and MHDV vehicles in Scenarios 1–4.

Table 2 Mean and standard deviation of modeled concentrations for CY 2040 at census block group centroids in the domain.

Scenario	**NO_2**			**$PM_{2.5}$**		
	On-road contribution (mean ± std ppb)	**Regional background (mean ± std ppb)**	**Total reduction compared to Reference (ppb [%])[a]**	**On-road contribution (mean ± std μg m^{-3})**	**Regional background (mean ± std μg m^{-3})**	**Total reduction compared to Reference (μg m^{-3} [%])[a]**
Reference	0.51 ± 1.12	8.08 ± 9.89	NA	1.88 ± 3.61	12.49 ± 7.93	NA
Scenario 1	0.38 ± 0.81	7.46 ± 9.12	−0.75 (−8.7%)	1.84 ± 3.54	12.33 ± 7.83	−0.2 (−1.4%)
Scenario 2	0.43 ± 0.92	7.76 ± 9.49	−0.40 (−4.7%)	1.87 ± 3.59	12.42 ± 7.89	−0.08 (−0.6%)
Scenario 3	0.39 ± 0.83	7.48 ± 9.15	−0.72 (−8.4%)	1.87 ± 3.58	12.42 ± 7.89	−0.08 (−0.6%)
Scenario 4	0.28 ± 0.62	7.06 ± 8.64	−1.25 (−14.6%)	1.70 ± 3.27	11.96 ± 7.60	−0.71 (−4.9%)
Scenario 5	0.20 ± 0.44	6.64 ± 8.13	−1.75 (−20.4%)	1.63 ± 3.13	11.76 ± 7.47	−0.98 (−6.8%)

[a]The total reduction represents the sum of reductions combining on-road contribution and regional background.

background concentrations are 0.51 ± 1.12 ppb and 8.08 ± 9.89 ppb for NO_2, and 1.88 ± 3.61 μg m^{-3} and 12.49 ± 7.93 μg m^{-3} for $PM_{2.5}$. On average, within the entire modeled area (Fig. 1), domain-wide NO_2 and $PM_{2.5}$ concentrations were dominated by regional background. However, on-road vehicles contributed to above-average pollutant concentrations for census block groups near major roadways – areas of particular concern from an EJ perspective (Fig. 3a, b). Concentration reductions in on-road emissions for each EV penetration scenario are approximately proportional to the emissions change for each scenario. The total concentration reductions ranged from −0.4 ppb to −1.75 ppb (−4.7% to −20.4%) for NO_2, and −0.08 μg m^{-3} to −0.98 μg m^{-3} (−0.6% to −6.8%) for $PM_{2.5}$. The reduction for $PM_{2.5}$ is higher than the values reported in Skipper et al. 2023[32], likely because the finer spatial resolution in this study (census block group level in this study vs. 12 km grids in Skipper et al., 2023) is able to better assess concentration hotspots near roadways[40]. Although domain-wide absolute concentration reductions were limited (less than 2 ppb for NO_2 and 1 μg m^{-3} for $PM_{2.5}$), greater reductions in NO_2 concentration were observed at census block groups near major roadways (Fig. 3c). For $PM_{2.5}$, the concentration reductions occurred at census block groups that spread farther away from

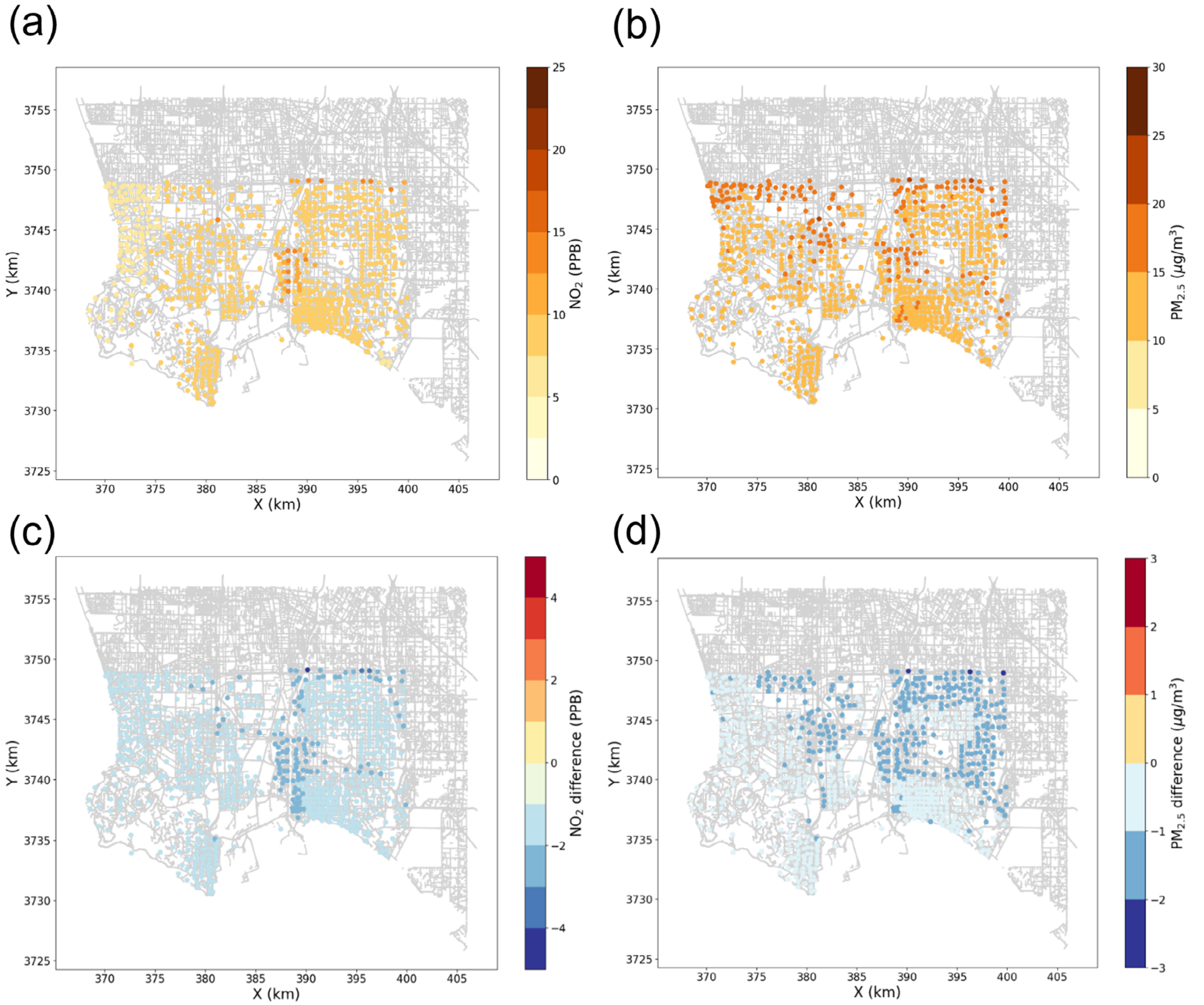

Fig. 3 Modeled NO_2 and $PM_{2.5}$ concentrations and concentrations differences. **a** NO_2 concentrations in the Reference Case, **b** $PM_{2.5}$ concentrations in the reference case, **c** NO_2 concentration differences between Scenario 5 and Reference Case, **d** $PM_{2.5}$ concentration differences between Scenario 5 and Reference. The circles represent census block group centroids, and the gray lines represent roadways.

major roadways (Fig. 3d). Compared to the reference case, maximum reductions in NO_2 and $PM_{2.5}$ for Scenario 5 at the near-road census block groups were above 3 ppb and 2 μg m^{-3}, respectively. Scenarios with smaller emissions reductions (policy cases, Scenarios 1–3) showed the same trend: greater concentration reductions were observed near major roadways compared to the modeling domain as a whole, but the modeled concentration reductions were smaller than in the idealized bounding cases (see Supplementary Figs. S1 and S2 for concentrations, and see Fig. 3 for concentration reductions). The concentration reduction maps for scenarios 1–4 can be found in Supplementary Figs. S3 and S4.

For each census block group in the modeling domain, we retrieved CalEnviroScreen (ver. 3.0) parameters used to identify communities with EJ concerns; we then summarized concentration distributions by EJ parameter. These parameters included race, White population percentage, education level, and the composite EJ score calculated in CalEnviroScreen. Reference case findings showed $PM_{2.5}$ and NO_2 concentrations were higher in communities with a greater percent of non-White population and with a greater percent of members over age 25 with less than a high school education (Figs. 4 and 5). For example, the average reference case NO_2 concentration for communities with more Latino members was 12% higher than communities with more White members (9.2 vs. 8.2 ppb, Fig. 4a). Similar trends were observed for $PM_{2.5}$, although the concentration disparity was smaller. For example, the average $PM_{2.5}$ concentration for communities with more Asian members was 8% higher than communities with more White members (15.2 vs. 14.2 μg m^{-3}, Fig. 5a). Findings were consistent with prior work evaluating demographics and pollutant concentrations at the census block scale[1].

EV penetration reduced air pollutant concentrations across the entire domain (Fig. 3), thus benefiting the whole population. Greater pollutant concentration reductions were observed for communities with more non-White members, as well as those with more members over the age of 25 with less than high school education. Figures 6 and 7 show the NO_2 and $PM_{2.5}$ concentration distributions for Scenario 5 (maximum bounding) and the mean concentration for the reference case. The NO_2 concentration reduction for communities with more White members was less than that of the communities with more Latino members (1.6 vs. 1.9 ppb, Fig. 6a). The $PM_{2.5}$ concentration reduction showed a similar trend although reductions were smaller. For example, the $PM_{2.5}$ reduction is 0.94 μg m^{-3} for communities with more White

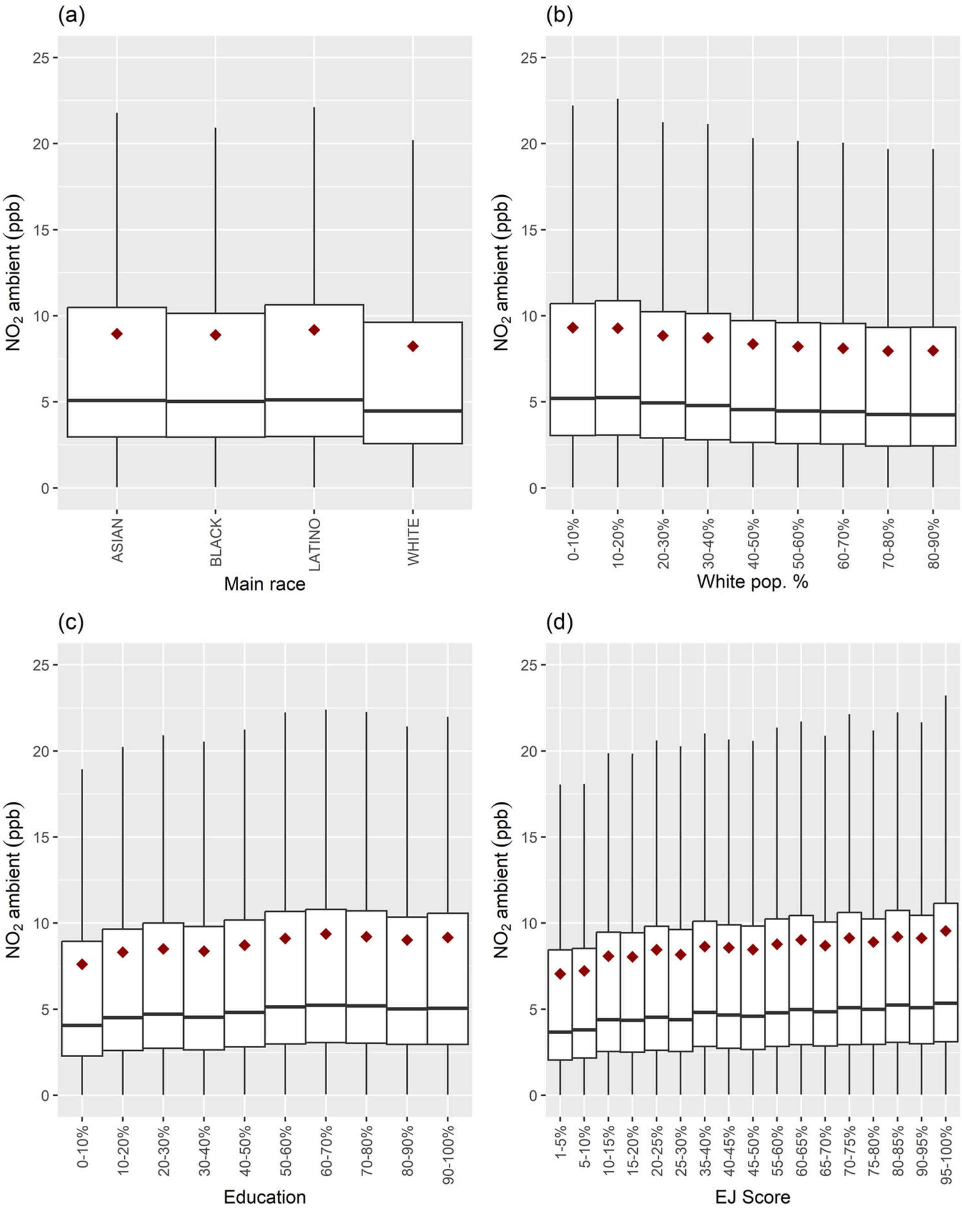

Fig. 4 NO_2 concentrations grouped by CalEnviroScreen EJ parameters for the Reference Case. EJ parameters include (**a**) race, (**b**) white population percentage, (**c**) percent of population with a degree lower than high school, and (**d**) the final score in CalEnviroScreen. Diamonds represent mean concentrations, and the horizontal lines represent the median. Boxes are bound by 25% and 75% ranges. The whiskers extend to 1.5 times of the inter quartile range (IQR) from the boxes.

members and 1.1 μg m^{-3} for communities with more Asian members (Fig. 7a). The same analyses for Scenarios 1–4 can be found in Supplementary Figs. S5–S12.

An important question is whether the differences modeled here would be expected to have observable real-world outcomes. One way to answer that question is to assess whether the findings are statistically significant. The differences in NO_2 and $PM_{2.5}$ concentration reductions between racial groups were statically significant based on one-way Analysis of Variance (ANOVA) testing for all scenarios (p-value < 0.05; see Supplementary Table S3). A post-hoc Tukey–Kramer test also showed that the NO_2 and $PM_{2.5}$ concentrations reductions in the communities with more White members were significantly lower than other racial groups (see Supplementary Table S4). However, another way to address this question is to consider past work on near-road air quality. The literature clearly shows an incremental contribution of roadway emissions to air pollutant concentrations adjacent to major roadways[9,13]. Electrification of the vehicle fleet, with commensurate reductions in on-road emissions, would logically reduce the incremental roadway contribution to observed concentrations. Prior work by Karner et al., 2010, for example, showed NO_2 concentrations 0–80 m from the road edge were approximately two to six times above background concentrations, and more recent analysis of TRAPs noted consistent near-road enhancements of concentrations of NO_2 and other pollutants[54]. Therefore, substantial reductions through electrification are expected to have measurable near-road outcomes.

Overall, the findings of this study showed that as EV penetration increased, disparities in community-scale air pollutant concentrations were reduced. Figure 8 shows the maximum disparity for each EV penetration scenario by CalEnviroScreen EJ parameters. The maximum disparity for a given scenario and EJ parameter was calculated as the concentration difference between the census block groups with the highest and lowest concentrations. Racial

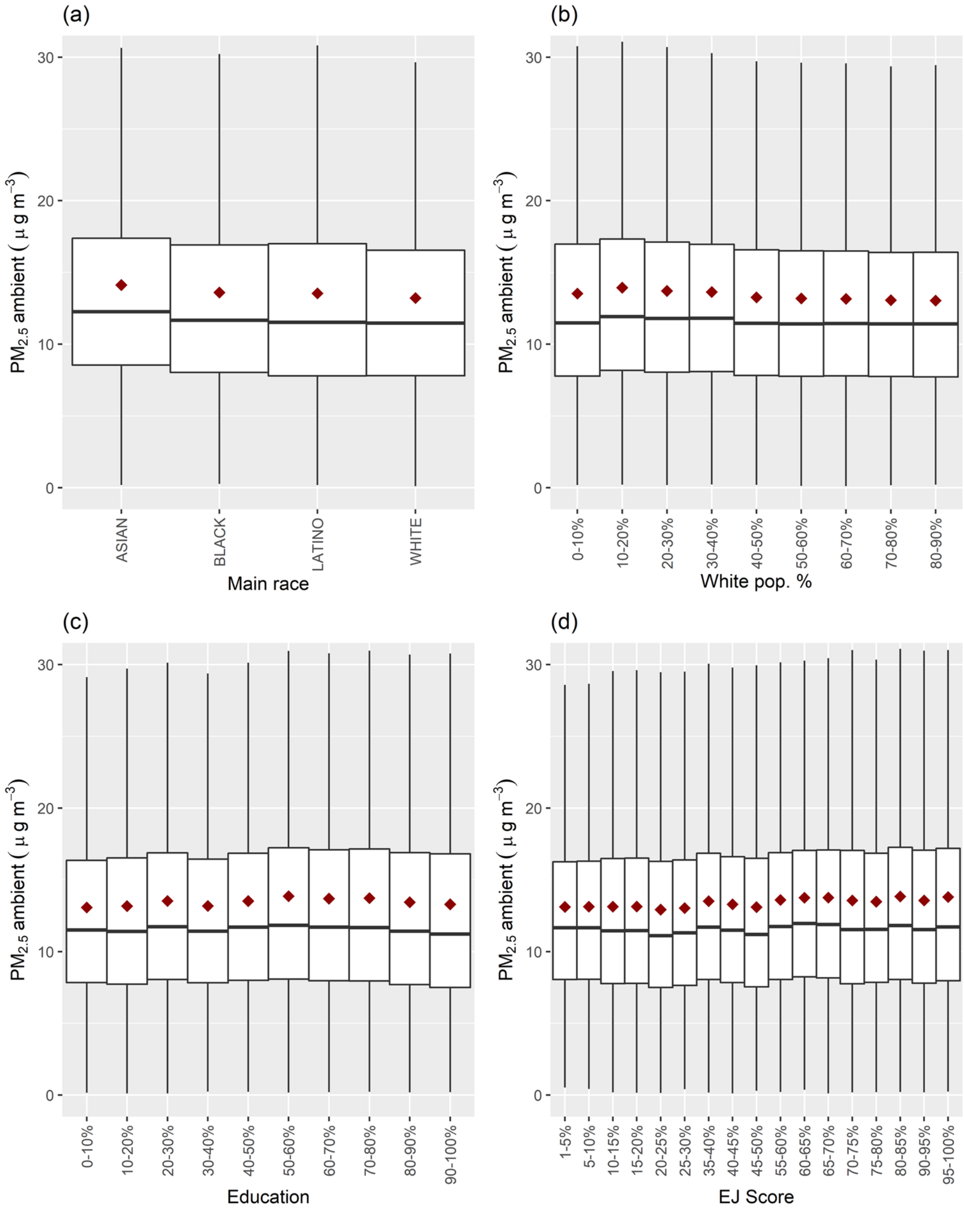

Fig. 5 $PM_{2.5}$ concentrations grouped by CalEnviroScreen EJ parameters for the Reference Case. The EJ parameters include (**a**) race, (**b**) white population percentage, (**c**) percent of population with a degree lower than high school, and (**d**) the final score in CalEnviroScreen. Diamonds represent mean concentrations, and the horizontal lines represent the median. Boxes are bound by 25% and 75% ranges. The whiskers extend to 1.5 times of the IQR from the boxes.

disparities were evaluated based on the racial grouping with the highest population percentage within a given census block (the main race). For NO_2, the scenario with the most aggressive EV penetration (Scenario 5) reduced the disparity by 30%. For example, the disparity in NO_2 census block concentrations between racial groups for the reference case was 0.95 ppb; in Scenario 5 the disparity was reduced to 0.67 ppb. Similar findings were observed for $PM_{2.5}$, but disparity reductions were smaller since, in future years, the on-road contribution to $PM_{2.5}$ concentrations is dominated by non-exhaust processes (e.g., brake and tire wear) and background concentrations. The disparity in $PM_{2.5}$ exposure between racial groups for the reference case was 1.06 $\mu g\,m^{-3}$ and was reduced by 14% to 0.91 $\mu g\,m^{-3}$ for Scenario 5. Scenario 4 in this study is largely structured on the California ACC II policy adopted August 25, 2022, requiring that by 2035, 100% of new cars and light trucks sold in California will be zero-emission vehicles, including plug-in hybrid electric vehicles. Scenario 4 also included an assumed EV phase-in schedule for battery electric vehicles in the medium- and heavy-duty vehicle (MHDV) fleet that resulted in approximately 56% of all on-road MHDVs being electric by 2040. This scenario results in disparity reductions of 22% for NO_2 and 10% for $PM_{2.5}$.

Discussion

In this study, we used a chain of modeling tools to quantify the outcomes of accelerated EV penetration on emissions, air quality, and EJ. Findings showed that greater rates of EV fleet penetration can further reduce on-road vehicle emissions by 2040. These results also suggest that while EV penetration is beneficial to all communities in terms of reducing exposure to air pollution, EJ communities near major roads stand to gain greater incremental air quality benefits than the population as a whole. Thus, policies that encourage accelerated EV penetration will work to address inequality in exposure to air pollution and help achieve

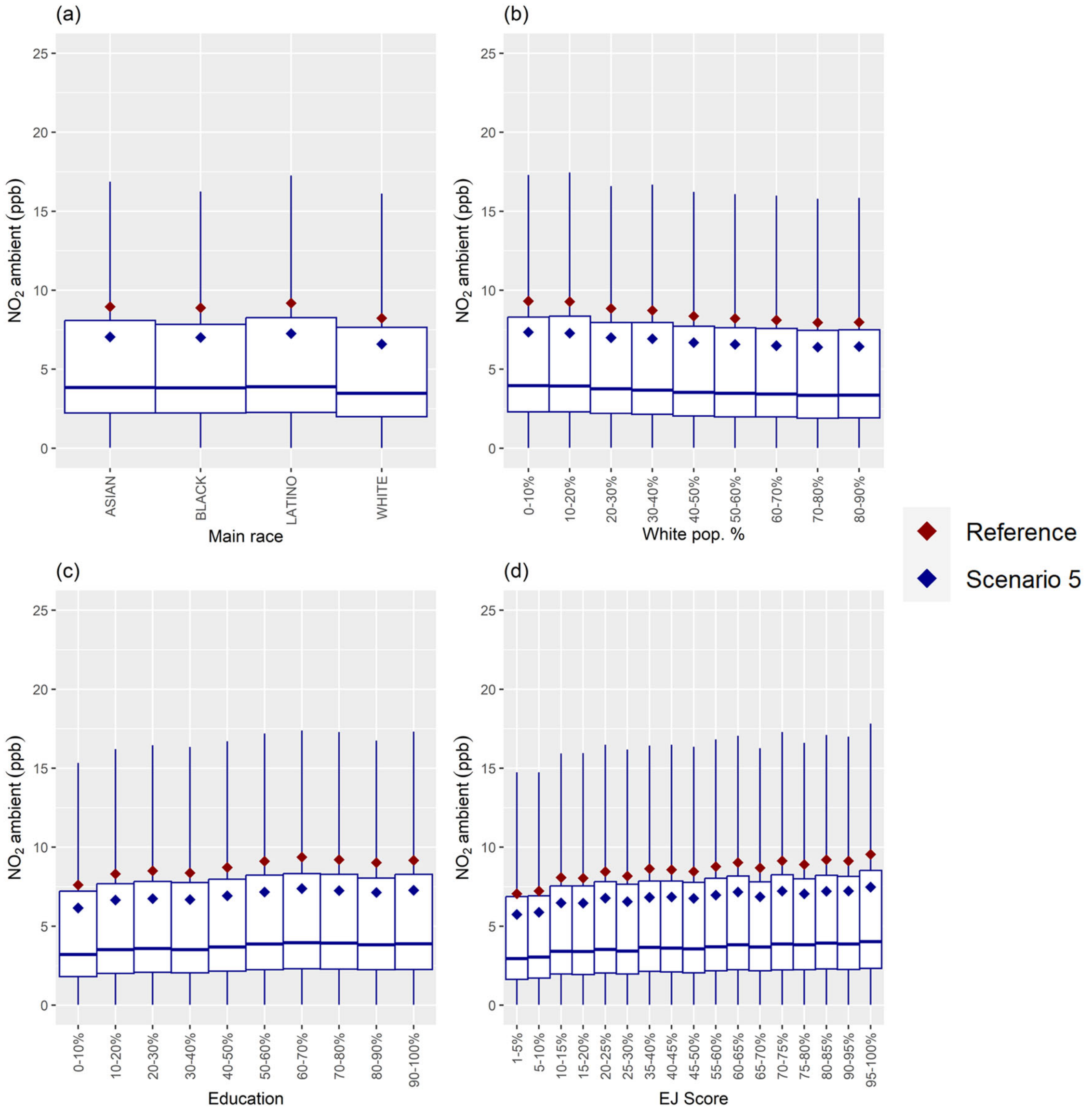

Fig. 6 NO_2 concentrations grouped by CalEnviroScreen EJ parameters for Scenario 5. The EJ parameters include (**a**) race, (**b**) white population percentage, (**c**) percent of population with a degree lower than high school, and (**d**) the final score in CalEnviroScreen. Blue diamonds represent mean concentrations, and the horizontal lines represent the median. Boxes are bound by the scenario's 25% and 75% ranges. Reference Case means shown as red diamonds for comparison. The whiskers extend to 1.5 times of the IQR from the boxes.

environmental justice. Previous work has shown that 19% of the U.S. population lives close to major roadways and that the percentage could be higher in urban areas[11]. The same study also documented that in near-road settings, the fraction of lower-income and minority residents increases with traffic volumes and road proximity. Results shown here, therefore, are expected to have applicability across many, if not most, U.S. near-road communities. In addition, prior work has shown that near-road air quality problems are observed throughout the world, with consistent findings regarding the rate at which pollutant concentrations decay as distance from the road increases[9]. Therefore, findings from this work should provide insights of international interest.

An important consideration is potential health outcomes and whether EVs can reduce disparities across population groups exposed to vehicle-related NO_2 and $PM_{2.5}$. Although a full health risk assessment was not completed, modeled air pollutant concentration differences allowed for health-related comparisons in a relative sense between communities with and without EJ concerns. To complete these relative comparisons, we used a metric from the health literature referred to as the attributable fraction (AF) of disease burden due to exposure to air pollutants (see Methods). Concentration reduction results in Scenario 5 provide an example where NO_2 reductions were 1.6 and 1.9 ppb, and $PM_{2.5}$ reductions were 0.94 and 1.1 $\mu g\, m^{-3}$ for communities with more White and more Asian members respectively. The resulting AF for avoided mortality was 19% (White versus Latino) and 16% (White versus Asian) higher for NO_2 and $PM_{2.5}$ for communities with more POC than with more White members. A complete health impact assessment would consider in greater depth issues such as population characteristics and baseline mortality. However, AF comparisons used here help place modeled air pollution concentration changes into a health framework and illustrate that the EV scenarios likely produce greater health benefits for the EJ communities studied (see Supplementary Note S2).

This study also reinforces prior work about the importance of early actions to encourage EV adoption[25]. Policies that take effect early replace older vehicles and yield greater emissions reductions, since older vehicles generate higher emissions per mile

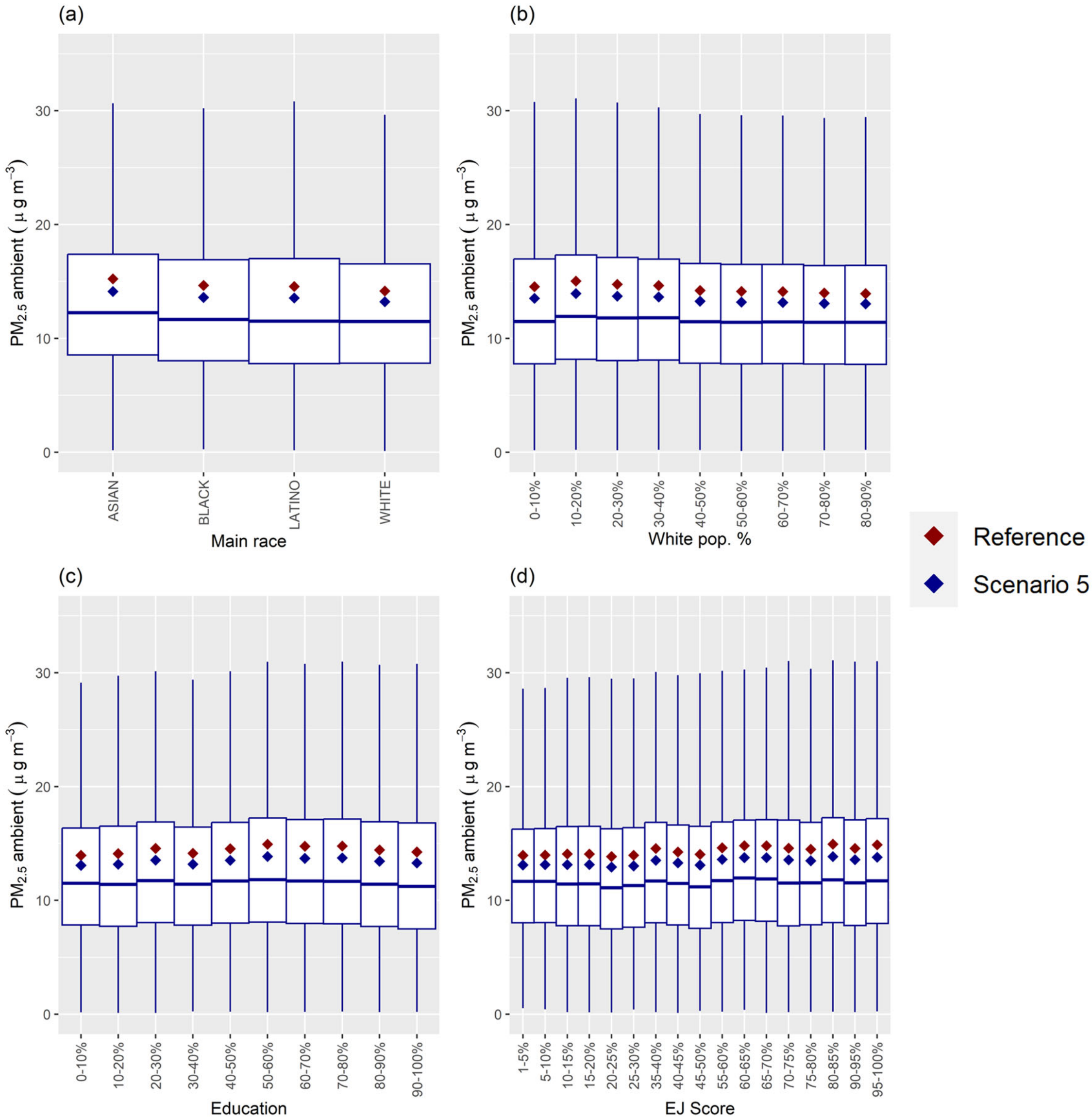

Fig. 7 $PM_{2.5}$ concentrations grouped by CalEnviroScreen EJ parameters for Scenario 5. The EJ parameters include (**a**) race, (**b**) white population percentage, (**c**) percent of population with a degree lower than high school, and (**d**) the final score in CalEnviroScreen. Blue diamonds represent mean concentrations. Boxes are bound by the scenario's 25% and 75% range. Reference Case means shown as red diamonds for comparison. The whiskers extend to 1.5 times of the IQR from the boxes.

driven than newer vehicles. The idealized bounding cases (Scenarios 4 and 5) benefited from their early (2023, 2025) starting points, as well as their substantial (60–85%) on-road EV share by 2040.

EV policies targeting the LDV fleet will have only modest impacts on reducing NO_x emissions, since MHDVs are the major on-road NO_x emissions source. Scenario 3, which focused solely on MHDVs, achieved virtually the same NO_x emissions reductions (26%) as Scenario 1 (27% reductions), even though Scenario 1 included an additional 9% share of LDV EV penetration (see Fig. 2c). Therefore, truck-focused polices such as ACT and ACF accelerate EV penetration in the MHDV fleet and reduce the disparity for exposure to NO_2. This finding is especially important for EJ communities adjacent to major roads with substantial truck traffic, such as the communities studied here along the I-710 goods movement corridor serving the Ports of Los Angeles and Long Beach.

On the other hand, by 2040, LDVs are the major contributor to $PM_{2.5}$ (Fig. 2d), due largely to brake wear emissions (e.g., see Supplementary Table S2). These findings are consistent with prior work that emphasized the growing importance of brake wear to California on-road vehicle $PM_{2.5}$ emissions in years 2015 and beyond[55]. CARB estimates that EV brake wear emissions are half that of ICE vehicles due to regenerative braking:[49] this implies that LDV EVs offer important $PM_{2.5}$ emission reduction benefits that extend beyond tailpipe exhaust. However, as illustrated by Supplementary Table S2, resuspended road dust contributes substantially to vehicular $PM_{2.5}$ emissions, assumed in this study to be unchanged with EV penetration[50]. Given the importance of non-exhaust emissions to $PM_{2.5}$, the implication is that the emission reduction and EJ benefits of EV adoption are more limited for $PM_{2.5}$ compared to NO_x. These findings are consistent with past work by Mehlig et al.[35], which found that EV penetration resulted in greater NO_x exposure reduction than $PM_{2.5}$ due to EV non-exhaust emissions.

The policy cases with actions to accelerate LDV fleet EV penetration (Scenarios 1 and 2) showed a limited EV share increase compared to the reference case. This finding is unique to California

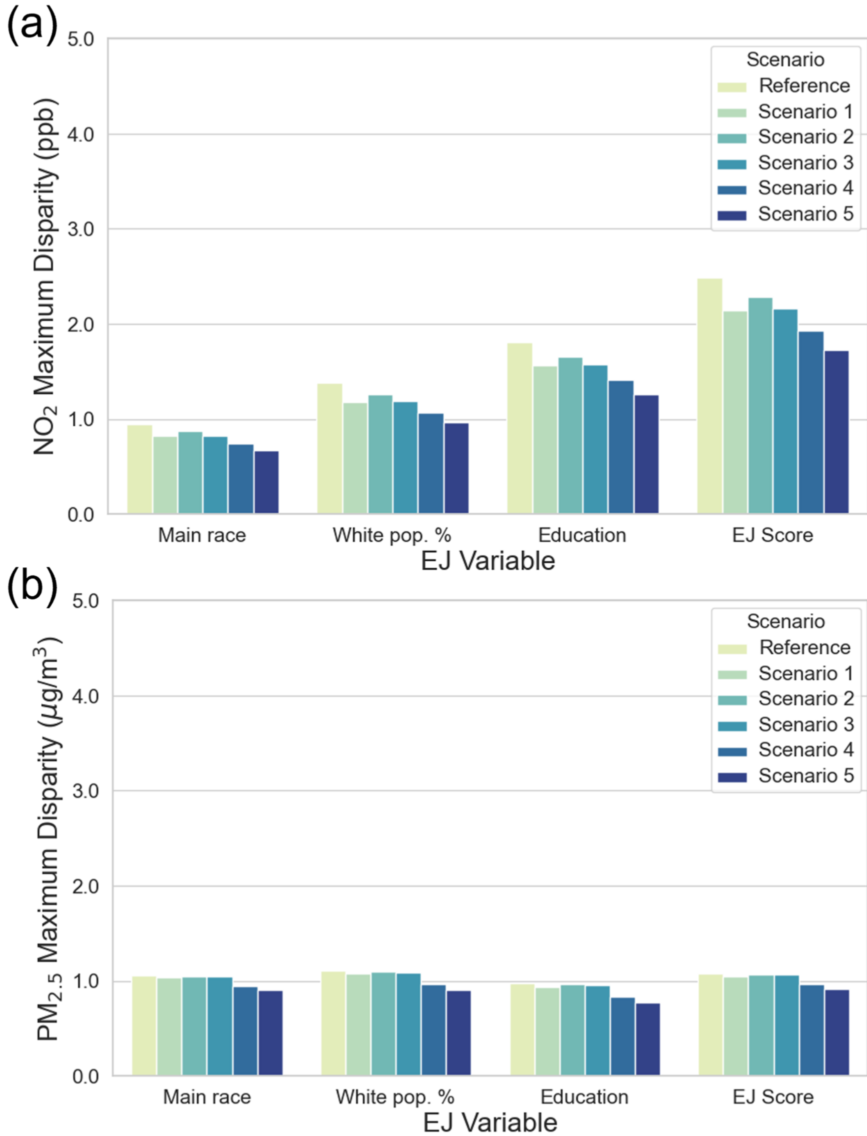

Fig. 8 The modeled maximum disparity in concentration. a Maximum disparity for NO_x and **b** maximum disparity for $PM_{2.5}$. The maximum disparity is defined as the average concentration difference between the group that is exposed to the highest concentration of a pollutant and the group that is exposed to the lowest concentration. Lower disparity represents a lower degree of disproportional exposure to air pollutants. Main race means the racial grouping with the highest population percentage within a given census block.

and states adopting California fleet requirements. These outcomes reflect that in California, LDV EV policies embedded in the reference case were more effective in early years (2030–2035) compared to (non-California) NCHRP-based assumptions included in Scenarios 1 and 2 (see Supplementary Note S3).

There are opportunities for additional research to address uncertainties in this study. First, work could further explore how changes in future background concentrations affect the findings presented here. Our approach extrapolated 2016 concentrations to 2040, but did not consider whether new regulations will further control emissions. Second, research is needed to examine how non-exhaust emissions affect $PM_{2.5}$ disparities. For example, research shows U.S. EPA road dust estimation methods may over-predict emissions[56]. Also, EV brake wear emissions could change as regenerative braking systems, brake pad materials, and vehicle weights evolve[49]. Third, work should examine how EVs change vehicle weights and tire wear emissions[57,58]. Fourth, exposure assessments using advanced models[59,60] could better consider human activities, time indoors[61–63], and demographic relationships to indoor exposure to outdoor pollutants[64]. Lastly, analyses could build on existing work to assess how national-scale electrification affects CO_2 emissions and other pollutants[65,66], actual vs. forecasted decarbonization of fuel sources to generate electricity[16], and effectiveness of efforts to promote energy justice in concert with fleet electrification and electricity generation decarbonization (e.g., see work by the U.S. Department of Energy)[67]. The Supplementary Note S4 expands on these points.

Methods

Future year EV population modeling. A Python-based tool was developed to estimate the future-year EV population based on vehicle model-year-specific EV market shares and a baseline vehicle population retrieved from EMFAC. EV penetrations in the LDV and MHDV fleets were modeled separately. In the policy cases, the EV market shares (Supplementary Table S3) in the LDV fleet for Scenarios 1 and 2 were estimated with Oak Ridge National Laboratory's Market Acceptance of Advanced Automotive Technologies model[68]. For the MHDV fleet in the policy cases, the ACT and ACF regulations' EV phase-in schedules (see Supplementary Tables S6 and S7) were used to estimate EV market share. Note that for the ACT and ACF scenarios, the EV phase-in schedules are only applied to vehicles that were first sold in California (Supplementary Table S9). In the idealized bounding cases, more rapid EV penetration was assumed. In Scenario 4, the Advanced Clean Car regulation Phase II[48] EV market share requirement was used to represent market share for the LDV fleet (Supplementary Table S5, Scenario 4). Modeling was completed prior to the August 25, 2022, CARB adoption of final ACC II requirements. The modeling analyses are generally consistent with the adopted rule, including a 100% zero emissions sales requirement beginning in 2035; however, modeling included early phase-in assumptions that are somewhat different from the final rule. The modeling assumed 30% ZEVs and plug-in hybrid electric vehicles for new-vehicle sales starting in 2026, as opposed to the 35% requirement included in the ACC II final rule. Given that the analysis focused on 2040 outcomes, these discrepancies do not introduce substantial differences between expected and modeled 2040 outcomes. For the Scenario 4's MHDV fleet, we customized an EV phase-in schedule that resulted in 56% of on-road MHDVs being EVs (Supplementary Table S8). This followed a scenario in Raju et al.[18] (their Scenario 3 assumed accelerated ZEV deployment with a focus on battery electric vehicles), which was developed based on the technology status of battery electric vehicles to assess if GHG emission reduction goals were met. For Scenario 5, the EV market share was assumed to be 100% starting in 2023 for both the LDV and MHDV fleets. The EV market shares for each scenario were then combined with the reference case's vehicle population retrieved from EMFAC to update the EV population. The number of EVs that were added to the fleet were removed from their ICE counterparts to ensure the total vehicle population across all scenarios stayed constant. To be conservative with the EV population estimates, we assumed additional EV penetration only occurred if the estimated scenario-specific EV market share was higher than the EV market share in the reference case. If the scenario-specific EV market share was lower than the reference case EV share, no additional EV penetration was assumed.

Emissions modeling. The emissions from on-road vehicles for six EV penetration scenarios were estimated using EMFAC model version 2017. EMFAC is the California regulatory on-road emissions model developed by CARB. It is used by government agencies to support California's regulatory and air quality planning efforts for on-road mobile sources and to meet U.S. federal transportation and air quality planning requirements. EMFAC combines vehicular emission factors and vehicle activity data to calculate emissions for a given region in California. The emission factors used in EMFAC were based on measurement data collected from U.S. EPA's In-Use Vehicle Program and CARB's Vehicle Surveillance Program. EMFAC vehicle activity data are based on California travel surveys. These surveys collected information such as mileage accrual rates, travel speeds, vehicle starts per day, and temporal distribution of vehicle miles traveled and trips. More information on EMFAC is available from CARB[69].

Emissions were modeled combining the EMFAC-predicted emissions for the reference case and the EV market share described in the future year EV population modeling section. In this study, EMFAC's South Coast California region emissions were used to develop emission factors and then link-based emissions for use in the air quality model. The emissions for the EV penetration cases were modeled as follows:

1. For running exhaust for NO_x and $PM_{2.5}$ (i.e., total $PM_{2.5}$, which typically includes elemental carbon, organic carbon, sulfate particles, and other trace elements), the emissions from the portion of ICE vehicles that were replaced with EV were zeroed out.
2. For brake wear $PM_{2.5}$, EV emissions were assumed to be half of ICE vehicle emissions following assumptions embedded in the EMFAC2021 model[70]. Vehicles with regenerative braking may be 50% or less than those of conventional vehicles.
3. For tire wear $PM_{2.5}$, EV emissions were assumed to be the same as that of their ICE counterpart following assumptions embedded in the EMFAC2021 model.

The calculated emissions were combined with vehicle miles traveled and aggregated to create an emission rate (in gram/mile) look-up table by vehicle speed and heavy duty-truck percentage. Here, we assumed that the EV penetration into the on-road fleet does not impact the traffic flow; thus, the vehicle miles traveled and vehicle speed remains constant across the six scenarios. For road dust $PM_{2.5}$ emissions (see Supplementary Table S2), U.S. EPA methods[71] were used to develop the emission rate based on silt loading and average vehicle weight. The road dust $PM_{2.5}$ emission rates were developed for varying heavy duty-truck percentage and merged with running exhaust, brake wear, and tire wear emission rates to generate the total vehicular emission rates for the region. No change in vehicle weight was assumed for EVs compared to ICE vehicles.

To develop link-level emission rates for all roadways in the modeling domain, link-based activity data including vehicle speed and traffic volume in 2016 from Streetlytics™ data by Bentley Systems, Inc.[72], and heavy-duty truck volume from the California Transportation Department[73] were extracted. The roadway geometry was based on spatially detailed 2019 HERE Technologies roadway network data[74]. The 2016 traffic volume was projected to 2040 with a projection factor assuming 7% traffic volume growth. This factor was developed with EMFAC vehicle miles traveled estimates for 2016 and 2040 for the South Coast California region. The emission rate for a roadway segment at a given hour of a day was calculated as:

$$ER_h = TC_h \times EF_{s,T_{percent}} \tag{1}$$

Where ER is the emission rate of a roadway segment in gram per mile, TC is the traffic count, EF is the emission factor for one vehicle in gram per mile, h is the given hour, s is the speed of the vehicles, and $T_{percent}$ is the heavy-duty truck percentage.

Air quality modeling. Concentrations of traffic-related pollutants such as NO_x can drop by more than 50% within 150 meters from the edge of roadways[9]. To quantify the impact of traffic-related pollutants in near-road settings, highly spatially resolved pollutant concentration information is needed to characterize the sharp concentration gradients near roadways. Here, we used an improved Gaussian dispersion model called R-LINE, developed by the U.S. EPA, to model how on-road emissions affect near-road air quality (information on R-LINE development has been published previously; see, for example Venkatram et al., 2013[52]). To estimate total pollutant concentrations near roads, we paired R-LINE air quality outputs with urban background concentrations estimated using data from monitoring networks and geostatistical methods described previously in the literature[75].

R-LINE was used at a census block group level to model how EV penetration scenarios changed the NO_2 and $PM_{2.5}$ concentrations contributed from on-road vehicles. Regional NO_x, NO_2, and $PM_{2.5}$ levels were interpolated with Inverse Distance Weighting to census block group centroids based on hourly air quality data collected from ambient monitoring sites reported to EPA's Air Quality System. To avoid double counting the concentration contribution from local roadways, the sites categorized as near-road sites were removed before the Inverse Distance Weighting interpolation. The same approach has been used by others to estimate regional air pollution levels[35]. To estimate the regional concentration for 2040, the monitored NO_x trend between 2000 to 2020 was used to project 2016 concentrations to 2040. For NO_x, a 4% reduction per year was assumed. Regional $PM_{2.5}$ concentration was assumed to be at the same level as 2019 because of the less varying concentration level between 2010 to 2020 in the South Coast region. Scenario-specific regional air pollution levels were adjusted for the reduced traffic emissions due to EV penetration. Following the South Coast Air Quality Management District's Air Quality Management Plan[76], we assumed 29% of regional NO_x and 15% of regional $PM_{2.5}$ comes from non-local on-road sources. The estimated emissions reductions for on-road vehicles were deducted from the portion of regional concentrations that were from on-road sources. This approach introduces a relatively small amount of uncertainty in the overall study findings, since regional concentrations are not linearly correlated to emissions reductions. However, regional background concentrations, compared to pollutants directly emitted from on-road vehicles, tend to be spatially distributed more homogenously[75]. Since benefits of reduced background concentrations would be similar, if not identical, for both EJ and non-EJ communities, the analysis did not involve a more refined assessment of expected reductions in urban background concentrations.

As noted earlier, NO_x and $PM_{2.5}$ concentration contributions from on-road vehicles were modeled with R-LINE. R-LINE is incorporated into the American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD)[77]. The NO_2 concentrations were calculated using the polynomial approach in the version of R-LINE with NO_x chemistry[78]. R-LINE's model performance was previously evaluated against measurement data[10,52,79]. Besides emission data, R-LINE requires meteorological data as input to simulate downwind concentrations. Due to the modeling domain's off-shore and on-shore winds and resulting diverging and converging wind fields, meteorological data needed to be spatially resolved to improve R-LINE prediction accuracy. The U.S. National Weather Service's Real-Time Mesoscale Analysis[80] data provides meteorological information at a 2.5-km resolution. We used the hourly wind speed, wind direction, temperature, dew point, and cloud cover from RTMA as input to run the U.S. EPA's AERMOD meteorological processor, AERMET[81], to provide necessary inputs for R-LINE dispersion calculations used to estimate the concentration contribution from on-road vehicles. To adjust for the concentration overprediction by R-LINE under low wind speed conditions[82], lateral turbulent wind component, σ_v, was increased to allow more contribution from the meandering component for a Gaussian plume[83].

The modeling domain contains approximately 113,000 roadway segments. To reduce the computational burden, we grouped the roadway segments into 5 km by 5 km grids; each grid contained about 5000 roadway segments. The roadway segments in each grid were used as the emission sources to model the concentrations at the census block groups in the same grid. To account for the impact from roadways from adjacent grids, each grid included larger roadways within a 2-km buffer and smaller roadways within a 1-km buffer outwards. The same approach was used in previous health studies[84,85].

Heath related analysis. The health analysis used attributable fraction of disease burden due to exposure to air pollutants. The AF is based on a log-linear concentration-response function for mortality due to exposure to air pollutants[40,86,87]. The log-linear relationship between ambient air pollutant concentration and health outcome is defined as:

$$AF = 1 - \exp^{-\beta\Delta X} \quad (2)$$

where AF is the attributable fraction, β is the concentration-response coefficient (the slope of the log-linear relationship between concentration and relative risk (RR) reported in epidemiological studies), and ΔX is the change in concentration for $PM_{2.5}$ or NO_2. Here, β was calculated using a value for RR equal to 1.04 (95% confidence interval [CI] 1.02–1.06) for all-cause mortality associated with a 5.32 ppb (converted from the 10 $\mu g\,m^{-3}$ in the literature) increase in annual NO_2 concentration[88] and 1.03 (95% CI 1.01–1.05) for all-cause mortality associated with a 5 $\mu g\,m^{-3}$ increase in annual $PM_{2.5}$ concentration[89]. Also, ΔX is the change in concentrations of NO_2 and $PM_{2.5}$ for each racial group between the reference case and each sensitivity case.

Data availability

The modeled ambient (i.e., the sum of background concentrations modeled with Inverse Distance Weighting and on-road contributions modeled with R-LINE) NO_2 and $PM_{2.5}$ concentrations for each scenario are available to download from https://figshare.com/articles/dataset/Environmental_Justice_Implications_of_Accelerated_Electric_Vehicle_Penetration/21675092[90].

Code availability

R-Line is available through the American Meteorological Society/Environmental Protection Agency Regulatory Model's (AERMOD) beta option. It can be downloaded through EPA (https://www.epa.gov/scram/air-quality-dispersion-modeling-preferred-and-recommended-models#aermod). The meteorological data preprocessor, AERMET, is also available to download through EPA (https://www.epa.gov/scram/meteorological-processors-and-accessory-programs#aermet).

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S.Y.C.: Writing – original draft, air quality modeling – R-LINE, meteorological data modeling, data visualization, data analysis – modeled data, project administration, conceptualization, writing – review and editing. J.H.: Emissions modeling – regional emissions, air quality modeling – Inverse Distance Weighting for background concentration, data analysis – EJ related data and modeled data. M.C.: Geographical information system data processing. F.L.: Emissions modeling – link-level emissions. D.E.: Conceptualization, writing – review and editing, project administration, and supervision. A.M.: Data analysis – observed data. G.E.: Data analysis – EV penetration for future year scenario. M.A.: Data analysis – EV penetration for base year, resources. E.K.: Conceptualization, funding acquisition, writing – review and editing, supervision.

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The authors declare no competing interests.

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