Environmental Science & Technology

pubs.acs.org/est

Article

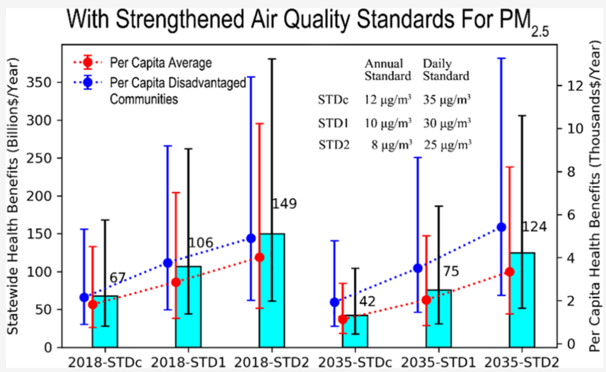
Health Benefits in California of Strengthening the Fine Particulate Matter Standards

Shupeng Zhu, Michael Mac Kinnon, Andre Paradise, Donald Dabdub, and G. Scott Samuelsen*

Cite This: *Environ. Sci. Technol.* 2021, 55, 12223−12232

Read Online

ABSTRACT: The Clean Air Act requires the United States Environmental Protection Agency to review routinely the National Ambient Air Quality Standards, including fine particulate matter ($PM_{2.5}$). A non-governmental Independent Particulate Matter Review Panel recently concluded that the current $PM_{2.5}$ standards do not protect public health adequately and recommended revising the daily standard from 35 to 25−30 $\mu g/m^3$ and the annual standard from 12 to 8−10 $\mu g/m^3$. To assess the public health implications of adopting the $PM_{2.5}$ standards proposed by the panel, the health benefits are quantified from their implementation based on both current (observed) and future (simulated) air quality data for California. The findings indicate that strengthening the standards would provide significant public health benefits valued at \$42−\$149 billion. Additionally, the stronger standards are shown to benefit environmental justice via health savings that are allocated more within environmentally and socioeconomically disadvantaged communities.



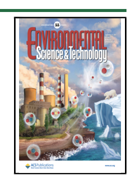
KEYWORDS: *$PM_{2.5}$, regulation, health benefits, environmental justice*

1. INTRODUCTION

Epidemiological studies have confirmed that exposure to fine particulate matter ($PM_{2.5}$) has an adverse impact on human health, resulting in an increased risk of morbidity and mortality.[1−3] Indeed, a scientific consensus confirms a causal relationship between premature mortality and both long- and short-term $PM_{2.5}$ exposure.[4] As a result, the National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$ are set by the United States Environmental Protection Agency (EPA) to protect public health under the Clean Air Act. The current NAAQS, set in 2012, mandates that levels of $PM_{2.5}$ do not exceed an annual average of 12 $\mu g/m^3$ and a 24 h average of 35 $\mu g/m^3$. According to the Clean Air Act, the NAAQS is subject to a routine review by the Clean Air Scientific Advisory Committee (CASAC) to “accurately reflect the latest scientific knowledge” regarding “the kind and extent of all identifiable effects on public health”. In 2019, the CASAC concluded that the available evidence does not reasonably call into question the adequacy of the current $PM_{2.5}$ standard and they should be retained.[5] However, a non-governmental Independent Particulate Matter Review Panel (IPMRP) questioned CASAC’s conclusions and further determined that the current $PM_{2.5}$ standards do not protect public health adequately.[6] Based on the scientific evidence and with the acknowledgment that a continuum of adverse effects decreases as the level of the standards strengthen, the IPMRP recommends tighter standards with the $PM_{2.5}$ concentrations not exceeding an annual average of 8−10 $\mu g/m^3$ and a 24 h average of 25−30 $\mu g/m^3$.

In addition to ensuring that NAAQS protects the public’s health, assessing that the potential economic impact of strengthening the standard is essential for policymakers to evaluate the cost benefits of adjustment. Marshall et al.[7] conducted a health benefit assessment for different annual $PM_{2.5}$ standards at the national level for the year 2010 and concluded that lowering the standard to 8−10 $\mu g/m^3$ would reduce $PM_{2.5}$ attributable mortality by 44−69% compared to 25% with the current standard. Also, for locations where ambient $PM_{2.5}$ concentrations would meet the annual standard but not the daily standard, the EPA estimates[8] relative risk reductions of 21 to 27% by changing the standard from 12 to 9 $\mu g/m^3$. However, the potential health benefits of meeting potentially revised daily and annual standards have not been assessed in California for current and future years. Also, how the attainment of stronger $PM_{2.5}$ standards can provide environmental justice (EJ) benefits within socially and environmentally vulnerable populations representing disadvan-

Received: May 22, 2021
Published: September 10, 2021



https://doi.org/10.1021/acs.est.1c03177
Environ. Sci. Technol. 2021, 55, 12223−12232

Table 1. Scenario Design

scenarios	annual standard (μg/m^3)	daily standard (μg/m^3)	baseline	BenMAP population set
2018-STDc	12	35	2018-observation	2018-LandScan
2018-STD1	10	30	2018-observation	2018-LandScan
2018-STD2	8	25	2018-observation	2018-LandScan
2035-STDc	12	35	2035-simulation	2035-CDoF
2035-STD1	10	30	2035-simulation	2035-CDoF
2035-STD2	8	25	2035-simulation	2035-CDoF

taged communities (DAC)[9] has not been evaluated previously. To provide insights into these questions, the potential public health benefits from implementing the IPMRP proposed $PM_{2.5}$ standards are evaluated based on both current (observed) and future (simulated) air quality (AQ) data for California. The health benefits are then analyzed within an EJ framework by allocating health benefits at the census tract level based on an EJ scoring system developed by the California EPA (CalEnviroScreen 3.0[10]).

2. METHODS

2.1. Scenario Design and the Dynamic Threshold Capping. The potential health benefits from implementing the proposed AQ standards were quantified and valued for California based on both observation and simulated AQ data. Two baselines were generated for hourly $PM_{2.5}$ concentrations at 4 km × 4 km resolution grids (see Figure S1): (1) a 2018 case constructed using satellite and ground-based observational data (see Data set S1) based on the random forest model widely used in previous studies to estimate high-resolution full-coverage $PM_{2.5}$ concentrations[11,12] and (2) a 2035 case based on California Air Resources Board emission projections and simulated using the Community Multiscale Air Quality (CMAQ) model.[13] For both temporal horizons, three scenarios were assessed for statewide attainment of (1) the current AQ standards (STDc: 12 μg/m^3 annually and 35 μg/m^3 daily), (2) AQ standards (STD1: 10 μg/m^3 annually and 30 μg/m^3 daily) that are more restrictive than the current, and (3) even more stringent AQ standards (STD2: 8 μg/m^3 annually and 25 μg/m^3 daily). Table 1 summarizes the design and naming of each scenario.

To simulate the minimum $PM_{2.5}$ concentration reduction needed to satisfy different regulation standards, a dynamic threshold capping method was developed to calculate the adjusted $PM_{2.5}$ concentration for each scenario. In detail, the following methodology is applied to each grid cell within the modeling domain:

Assuming that the annual AQ standard to be satisfied is C_A μg/m^3 and the annually averaged $PM_{2.5}$ concentration from the baseline is C_a μg/m3. Then, the annual adjustment factor is $F_a = C_A/C_a$ ($F_a = 1$ if $F_a \geq 1.0$).

For each $PM_{2.5}$ concentration record (hourly) in the baseline C_0, the annual threshold capping is performed: $C_1 = C_0 \times F_a$.

Assuming that the daily AQ standard to be satisfied is C_D μg/m3.

For each day in the baseline, a daily-averaged $PM_{2.5}$ concentration (C_d μg/m^3) is calculated based on the record after annual adjustment data C_1. Then, a daily adjustment factor can be calculated: $F_d = C_D/C_d$ ($F_d = 1$ if $F_d \geq 1.0$).

The daily threshold capping is performed for each hourly record within that day: $C_2 = C_1 \times F_d$.

Finally, the minimum $PM_{2.5}$ concentration reduction is calculated for health benefit analysis: $\Delta C = C_2 - C_0$.

Additional justification of the methods used to estimate minimum $PM_{2.5}$ reductions is provided in the Supporting Information. However, it should be noted that the calculated attainment concentrations for a single year likely yield higher health benefits than would the use of the standard method for calculating attainment with NAAQS, which includes data for 3 consecutive years.[5]

2.2. 2018 $PM_{2.5}$ Concentrations. Hourly mean $PM_{2.5}$ concentrations at 4 km spatial resolution over California for the year 2018 used in this study were estimated using random forest models that incorporated information from multiple sources, including ground measurements, satellite remote sensing, chemical transport model simulations, meteorological fields, and land-use variables. This method was widely used in previous studies on estimating high-resolution full-coverage $PM_{2.5}$ concentrations (e.g., Hu et al.[12] and Xiao et al.[11]). The primary daily estimation of $PM_{2.5}$ concentrations for 2018 using this method has been applied in our previous wildfire study.[14]

The satellite-based observation was obtained from the NASA Earthdata portal (https://search.earthdata.nasa.gov/), including aerosol optical depth (AOD) data at 1 km spatial resolution retrieved by the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm.[15,16] Ground-based $PM_{2.5}$ observations for 2018 were obtained from the U.S. Environmental Protection Agency's Air Quality System (https://www.epa.gov/outdoor-air-quality-data/). Additional information on $PM_{2.5}$ distribution was generated based on $PM_{2.5}$ simulations from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA2) at 0.5° × 0.625° resolution. Other variables compiled in this study included pressure, temperature, wind speed, specific humidity, precipitation, shortwave and longwave fluxes, and evaporation at ∼13 km spatial resolution from the North American Land Data Assimilation Systems, elevation at 30 m spatial resolution from the National Elevation Data set (NED, http://ned.usgs.gov), forest cover, shrub cover, and cultivated land cover at 30 m spatial resolution from the 2011 National Land Cover Database (NLCD, http://www.mrlc.gov), road lengths of major roads, highways, and interstate highways extracted from ESRI StreetMap USA (Environmental Systems Research Institute, Inc., Redland, CA), and population data from 2018 LandScan data. All data were integrated into the 1 km MAIAC grid, and the $PM_{2.5}$ concentrations were first estimated at 1 km and then aggregated into a 4 km grid.

Random forest models are initially proposed by Breiman et al.[17] Generally, the random forest algorithm is a decision tree-based ensemble learning method. It has the advantage of allowing both continuous and categorical input variables with high robustness against outliers. It also provides variable importance rankings and out-of-bag errors for variable

https://doi.org/10.1021/acs.est.1c03177
Environ. Sci. Technol. 2021, 55, 12223−12232

selection and model evaluation.[18] Two random forest models were built for this study (i.e., with and without satellite inputs) and then merged their predictions to obtain full spatial and temporal coverage of $PM_{2.5}$ data because AOD has missingness in a certain time and places. Our models achieved good performance, with an out-of-bag R2 of 0.94 and a normalized mean bias of −1.6% (see Figure S2) compared to the AQS observation data.[19]

2.3. 2035 $PM_{2.5}$ Concentrations. Hourly mean $PM_{2.5}$ concentrations at 4 km spatial resolution over California for the year 2035 were generated based on simulation results from a chemical transport model. First, the emissions were projected to 2035 from the 2012 California Air Resources Board inventory[20] for all sources using the California Air Resources Board's CEPAM: 2016 SIP—Standard Emission Tool.[21] Emissions representative of each case were applied and resolved in space and time using the Sparse Matrix Operator Kernel Emissions (SMOKE) modeling system.[22] Then, the Community Multi-scale Air Quality model (CMAQ, v5.2)[13] was used to simulate atmospheric chemistry and transport and fully resolve distributions of hourly ground-level $PM_{2.5}$ concentrations. CMAQ is a widely accepted model used for various AQ assessment needs, including regulatory compliance and atmospheric research associated with tropospheric ozone, PM, acid deposition, and visibility.[23,24] For gas-phase chemistry, we used the SAPRC-07 chemical mechanism[25] and the AERO6 module to provide aerosol dynamics.[26] The model domain was the same as given in the study by Zhu et al.,[27] covering the entire state of California with 4 km × 4 km horizontal resolution (see Figure S2 for simulation domain). Boundary conditions were generated via the Model for Ozone and Related Chemical Tracers (Mozart v4.0).[28] We generated meteorological input data for the modeling period through the Advanced Research Weather Research and Forecasting Model (WRF-ARW, 3.7), with the MODIS land-use database.[29] Baseline meteorological conditions were obtained from the (Final) Operational Global Analysis data.[30] The boundary conditions and meteorology were held constant from 2012 to 2035; thus, impacts of transported pollution and climate change were not considered. We verified model performance by comparing the 2012 baseline simulation with observational data from the U.S. EPA Air Quality System for hourly $PM_{2.5}$ (Supporting Information Figure S3), with acceptable performance demonstrated through the criteria recommended in ref 31.

2.4. Health Benefits Assessment. It is well understood that reducing ambient concentrations of outdoor air pollution attains improvements in health within exposed populations, including incidences of premature mortality and a wide range of morbidity endpoints.[32−34] Public health benefits attributable to reductions in $PM_{2.5}$ from meeting the proposed NAAQS were assessed using the environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) version 1.528. BenMAP-CE was developed by the US Environmental Protection Agency and is widely used in both research and regulatory purposes requiring the quantification of the social-economic health impacts of air pollution.[27,35−37]

The selection of appropriate concentration−response functions (CRFs) to numerically quantify the avoided incidence of mortality across the study population resulting from reduced $PM_{2.5}$ concentrations was primarily guided by the methods used in an analogous study conducted by a pre-eminent AQ management district in California.[38] BenMAP applies the relationship between the CRF and the quantified $PM_{2.5}$ delta and the exposed population to calculate health impacts, as shown in Supporting Information Figure S4. The selected CRF was based upon a methodical and comprehensive review of the epidemiological literature for applicability to populations within Southern California, including peer review, date, geography, population characteristics, and study design.[39] While our study considers populations in other areas of California, the lack of regional granularity in the available epidemiological literature precludes using the CRF with increased specificity and other studies for California have used the same CRF.[40] The avoided all-cause mortality incidence associated with reductions in long-term $PM_{2.5}$ exposure was estimated based on pooling log-linear CRF estimated by Jerrett et al.[41] and Jerrett et al.[42] (California studies), and the kriging and land use regression results are obtained from Krewski et al.[43] (US study). While log-linear CRFs were selected for consistency with several recent studies,[38,40,44,45] it has been suggested that log−log supralinear CRFs (i.e., an upward curving slope) may be more appropriate for estimating mortality incidence at lower $PM_{2.5}$ concentrations.[2,46] Therefore, avoided mortality incidences are also estimated using the supralinear CRF from Burnett et al. (global study).[46] Relative to the results for log-linear CRFs, 46−57% increases in health benefits are estimated with the increasing difference between supralinear and linear CRF estimations, as the standard is reduced, which agrees with the findings of Marshall et al.[7]

It should be noted that no concentration threshold is assumed and health benefits continue to accrue with reduced exposure at all concentrations of $PM_{2.5}$, including those below the regulatory standards. We utilize baseline incidence rates for mortality from local health data based on public administrative data wherever possible and then calculate the additional incidence occurring from increased pollutant exposure. Moreover, one long-term morbidity endpoint (acute bronchitis),[47] one short-term mortality endpoint,[48] and ten short-term mortality endpoints (e.g., respiratory symptoms, myocardial infarctions, ischemic stroke, and so forth)[49−62] are also evaluated. Socioeconomic costs are then estimated using willingness-to-pay and cost-of-illness valuation functions from a comprehensive review of the health economic literature for mortality and morbidity.[63,64] The value of statistical life selected for application with avoided mortality incidents was \$10 million as a midpoint of a range of \$4.7−\$15.4 million from Robinson and Hammitt,[65] expressed in 2018 dollars and based on 2018 income levels as recommended for an analogous work in California.[64]

To evaluate how strengthening AQ standards could improve EJ, the health benefits are further analyzed at the census tract level using the CalEnviroScreen 3.0[10] EJ screening tool developed by California's Office of Environmental Health Hazard Assessment (OEHHA). CalEnviroScreen identifies communities burdened by a disparate share of air pollution in addition to socioeconomic and health challenges that increase their vulnerability to environmental health effects. CalEnviroScreen ranks each of the state's 8000 census tracts according to multiple endpoints associated with pollution, environmental quality, and socioeconomic and public health conditions. Organizations ranking within the final 25% (score ≥ 75) are considered DAC.

2.4.1. Uncertainties. Sensitivity analysis of parameters in the epidemiological model: in addition to a mean value, BenMAP

https://doi.org/10.1021/acs.est.1c03177
Environ. Sci. Technol. 2021, 55, 12223−12232

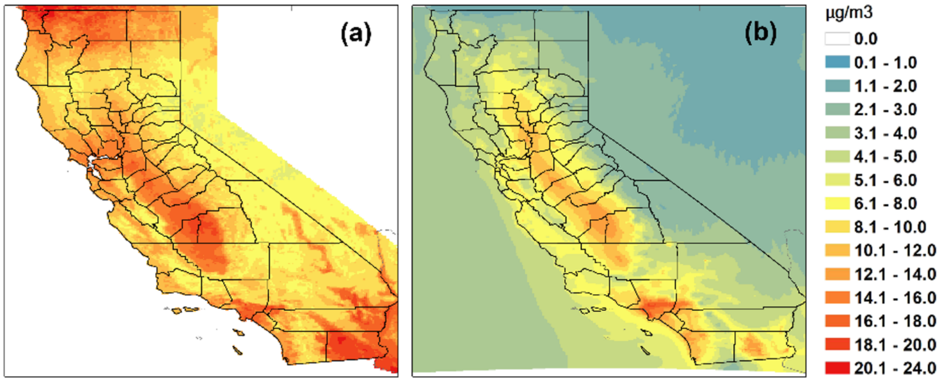


Figure 1. Baseline annually averaged $PM_{2.5}$ concentrations for (a) 2018 satellite and ground-based observational reconstruction data and (b) 2035 CMAQ simulation results.

also provides a 95% confidence interval (CI) estimation via a Monte Carlo analysis around the mean incidence and valuation estimations, which includes the pooling of uncertainties, including the avoided incidence of health endpoints quantified through the CRF, which are derived from epidemiological literature. Each CRF is associated with an uncertainty parameter, which is then pooled for all studies within the final 95% CI. As there are numerous studies providing an input to the results (e.g., several CRFs are pooled to quantify avoided incidence of premature mortality), the pooled distribution can be significant and also reflects the uncertainties associated with epidemiological studies.

Although the long-term health effects of $PM_{2.5}$ exposure dominate the valuation impacts and are presented in the main text, additional results for short-term exposure effects are also reported in the Supporting Information (see Tables S1−S4). No concentration threshold is assumed for the main health impact assessment modeling, consistent with the current methods applied by regulatory agencies, including the US Environmental Protection Agency and South Coast Air Quality Management District.[66] However, health benefits estimated for lower $PM_{2.5}$ concentrations may be sensitive to the application of thresholds. Therefore, additional threshold-based analyses were conducted for the 2035 STD_2 scenario, which has the lowest average concentrations and would be most impacted by the assumption of a threshold. The results demonstrate no impact on the health benefit estimation for a 2.4 $\mu g/m^3$ threshold (the lowest observed concentration in any of the 41 cohorts reported by Burnett et al.[42]) and a minimal 0.05% decrease in mortality by including a 5.8 $\mu g/m^3$ threshold (the minimum annual average concentration assigned to subjects in the American Cancer Society (ACS) CPS-II cohort study by Krewski et al.[2]). Even if a threshold of 8 $\mu g/m^3$ (the annual standard set for STD2) is assumed, only a −0.7% decrease in avoided mortality is estimated between the STD2 scenario and the baseline relative to the results without assuming a threshold. Figure S5 provides an overview of the framework used to quantify the avoided incidence of mortality and morbidity endpoints. As this study focused on the avoided incidence between the baseline and the attainment scenarios (i.e., the delta) and a threshold value should always be lower than the existing standard, the assumption of a threshold does impact the estimated health impacts of both the baseline and the attainment scenarios in the singular but has a minor impact on the delta between them.

2.4.2. Limitations. Comparing baselines generated with different methods. Although comparisons are made between the current (2018) and future (2035) scenarios in this study, it should be noted that the comparison of the health benefits evaluated under the two baselines is complicated by the different methodologies utilized. For 2018, the estimated $PM_{2.5}$ concentrations were largely based on observational data, while the resolution of $PM_{2.5}$ concentrations in 2035 was strictly model-based. Although a sophisticated and state-of-the-art modeling method is used, which satisfies statistical performance criteria established by the scientific community, there are still limitations that prevent perfect modeling of real-world dynamics associated with pollutant formation and fate. Therefore, simulated concentrations are not as accurate as observational data, and this should be considered in the interpretation of the results. Furthermore, uniformly adjusting $PM_{2.5}$ concentrations at each hourly time step does not necessarily achieve a realistic scenario, particularly when baseline concentrations are very low. However, it provides a feasible method for determining the minimum reduction needed for attainment.

Additionally, a major limitation of this work includes the lack of wildfire emissions present in the 2035 simulated baseline concentrations due to the difficulty of predicting future wildfire characteristics, including occurrence, spatial distributions, and emissions' chemical and physical properties. In contrast, the 2018 baseline concentrations are derived from observational data, which does include $PM_{2.5}$ contributed from several wildfires occurring during that period. Neither of these assumptions is ideal, as a complete lack of wildfire emissions is not realistic. On the other hand, $PM_{2.5}$ from wildfires is not controllable in the same manner, as other sources comprising mitigation efforts and including health benefits from reductions in wildfire $PM_{2.5}$ in 2018 are not necessarily realistic. However, the methods for both 2018 and 2035 are limited by these constraints, and the results should be interpreted with this caveat.

3. RESULTS AND DISCUSSION

Annually averaged $PM_{2.5}$ concentrations for both baselines are shown in Figure 1. Due to the significant emission reduction from the California State Implementation Plans (SIPs),[67] concentrations in 2035 (3.9 $\mu g/m^3$ on average) are generally much lower (6.0 $\mu g/m^3$ on average), including being almost halved in the San Joaquin Valley (SJV) and San Francisco Bay Area (SFBA) (see Figure S1 in the Supporting Information for

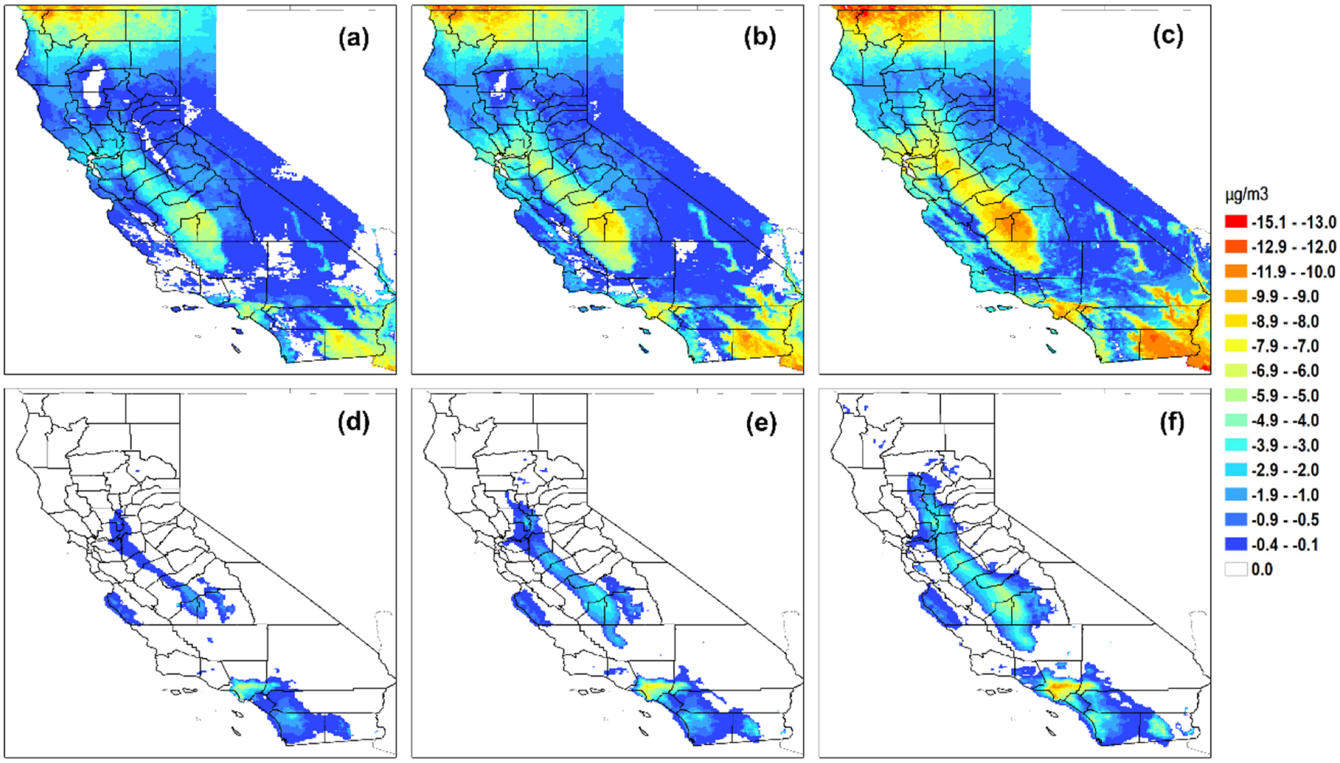


Figure 2. Annually averaged $PM_{2.5}$ concentration differences between the 2018 baseline and (a) 2018-STDc, (b) 2018-STD1, and (c) 2018-STD2 and between the 2035 baseline and (d) 2035-STDc, (e) 2035-STD1, and (f) 2035-STD2.

geographical locations). However, concentrations over the South Coast Air Basin of California (SoCAB) are only slightly reduced, which is notable, given the large, dense populations present. In 2018, high concentrations in northern regions of California were likely due to wildfire events,[14] and high concentrations in rural southwestern areas represent biogenic source impacts from the soil and transported pollution from Mexico.[68] Those sources are not represented in the emissions utilized for the 2035 simulations due to both uncertainties associated with future projections and the focus on emission control applicable to anthropogenic sources. Therefore, the 2035 results are likely conservative. A dynamic threshold capping method is designed to reduce the baseline concentrations to satisfy the designated daily and annually AQ standards for each scenario, as detailed in the Methods section. The annually averaged delta $PM_{2.5}$ concentration for each scenario compared to its corresponding baseline is presented in Figure 2. For the 2018 scenarios, the affected regions (i.e., the spatial distribution of impact) do not experience significant changes. However, the total amount of $PM_{2.5}$ within those regions is reduced significantly (e.g., STDc: −15.3%, STD1: −21.7%, STD2: −31.1%). For the 2035 scenarios, both the spatial distribution and quantitative total of $PM_{2.5}$ reduced are notably impacted (e.g., STDc: −0.7%, STD1: −1.7%, STD2: −3.9%).

Results indicate that significant health benefits are attained if the $PM_{2.5}$ standards are adjusted to either of the proposed standards. Here, only avoided mortality incidence associated with long-term $PM_{2.5}$ exposure is considered, as it is responsible for approximately 87% of AQ -driven health savings, which is consistent with our previous studies.[27,69] Meanwhile, the reduced incidence of morbidity health endpoints is discussed in the Supporting Information. Figure 3a shows that the avoided mortality incidence approximately doubles if the more restrictive standards are being met and nearly triples under the most stringent set of standards. For the most restrictive standards, ∼10,000 incidences of mortality would be avoided in 2018. In 2035, the avoided mortality is ∼25% lower than for 2018 due to two competing drivers: (1) expected reductions in baseline $PM_{2.5}$ concentrations in response to regulatory efforts (55.8% lower, see Figure 1) and (2) growth in the total population, which increases both total exposure and exposure within older age cohorts, which are more vulnerable to the health effects of exposure. Figure 3b shows the monetized health benefits quantified for each scenario. In 2018, annual health savings increased from \$67 billion with STDc to \$106 billion with STD1 and \$149 billion with STD2 in 2018 US dollar. The health benefits in 2035 are smaller than the 2018 baseline when converted to 2018 dollars, with \$42 billion for STDc, \$75 billion for STD1, and \$124 billion for STD2.

To frame these findings within potential implications for EJ, the health savings within DAC, including minority and low-income groups[70] are considered. Figure 3b compares the per capita health benefits for the statewide average (red) to those allocated only to DAC (blue). For all scenarios, the health benefits within DAC are higher than the state average, and this ratio of benefits increases favorably with increasingly more stringent standards, especially for the 2035 scenarios. Figure 3c shows the distribution of health benefits within communities in relation to their CalEnviroScreen score. Generally, health benefits increase with higher (i.e., more disadvantaged) CalEnviroScreen scores, indicating an improvement in environmental inequality. The results for the 2035 scenarios show more rapid growth, as the $PM_{2.5}$ standards strengthen

https://doi.org/10.1021/acs.est.1c03177
Environ. Sci. Technol. 2021, 55, 12223−12232

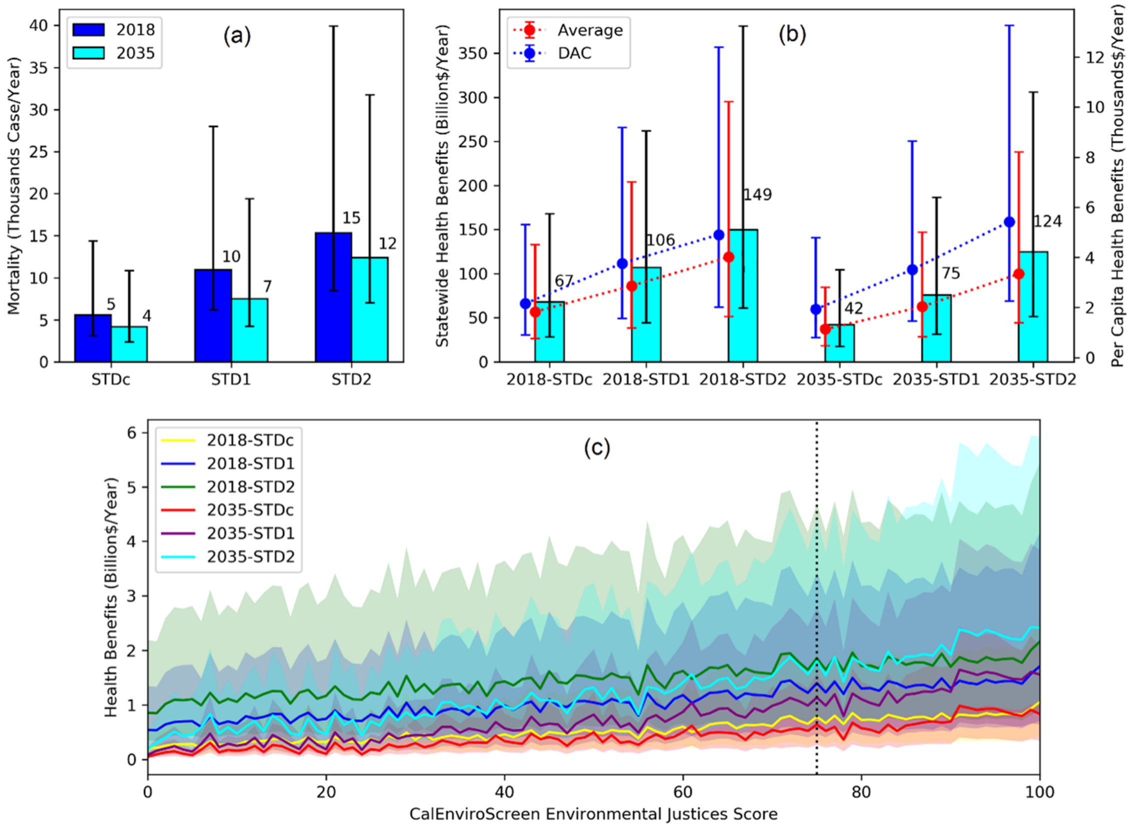


Figure 3. (a) Avoided mortality incident bar plots with 95% CI (mean values marked), for the attainment of proposed standards relative to 2018 and 2035 baselines [the same for plot (b,c)]; (b) bar plot with 95% CI showing mean monetized health benefits (left axis) and the line plot showing the health benefits per capita (right axis) for both the statewide average (average) and DAC; and (c) health benefit distribution for aggregated communities based on their CalEnviroScreen score (shading areas mark 95% CI and the dashed line marks 75%), where communities above it are considered as DAC (in 2018 US dollar).

compared to the 2018 scenarios, indicating more progressive/ efficiency in improving environmental inequalities.

Figure 4a−f shows the spatial distribution of per capita health savings at the Census Tract community level. As would be expected, for both 2018 (see Figure 4a−c) and 2035 (see Figure 4d−f), an expansion and increased magnitude of monetary benefits can be observed, indicating a universal improvement in California if $PM_{2.5}$ NAAQS are strengthened. However, between the 2018 and 2035 scenarios, the distribution patterns are different. The 2018 scenarios are more equally weighted throughout the modeling domain, and the 2035 distribution is more concentrated in the highly populated SoCAB and the SJV Air Basins. A key factor in this difference is the lack of wildfire emissions in the 2035 simulations. The 2018 data include multiple large wildfires that impacted particulate levels in California as a whole and the SFBA area. As the increased incidence of wildfires is expected due to climate change and other factors,[71] the results for 2035 are conservative. For SoCAB, results indicate more significant health benefits for 2035 than 2018, especially over the northeast Los Angeles (LA) and San Bernardino region (see Figure S1 in the Supporting Information for geographical locations). Considering the health benefits distribution over the highlighted DACs, most benefits are allocated to DACs in the SJV and SoCAB. Some of the most impacted communities are in downwind regions west of LA, for example, Fontana.

The conclusions of the IPMRP are supported by these results, which states that strengthening of the $PM_{2.5}$ standards would yield significant socioeconomic benefits and better protect public health than current standards. The substantial monetary value generated by health savings should be considered against the potentially increased costs of deploying emission mitigation strategies within impacted sectors. While a direct cost/benefit assessment is not provided here, the results support a previous work demonstrating that the public health benefits often exceed additional costs.[38,72] Notably, health savings occur with a higher frequency in environmentally and socioeconomically DACs. EJ concerns remain a major focus of AQ regulators and demonstrate the current inequality associated with AQ-related health burdens in California. Given the disparity, stronger NAAQS provides greater benefits in regions that currently experience the most degraded AQ and other vulnerabilities, which represents an optimal outcome for AQ regulators.

The impact of wildfire-contributed $PM_{2.5}$ pollution in California cannot be overstated due to the damages incurred to public health and other aspects of the economy[14] and the expected increase in the occurrence and severity of wildfire events in response to climate change and other factors.[73−76] Wildfire smoke wave events cannot be controlled in the same manner as anthropogenic sources, and therefore present as a significant confounding factor in current and future NAAQS. This is notable in the results, as the 2018 scenarios attain benefits in regions of Northern California that are likely influenced by assumed reductions in $PM_{2.5}$ contributed by wildfires, as the same pattern is not observed for the 2035

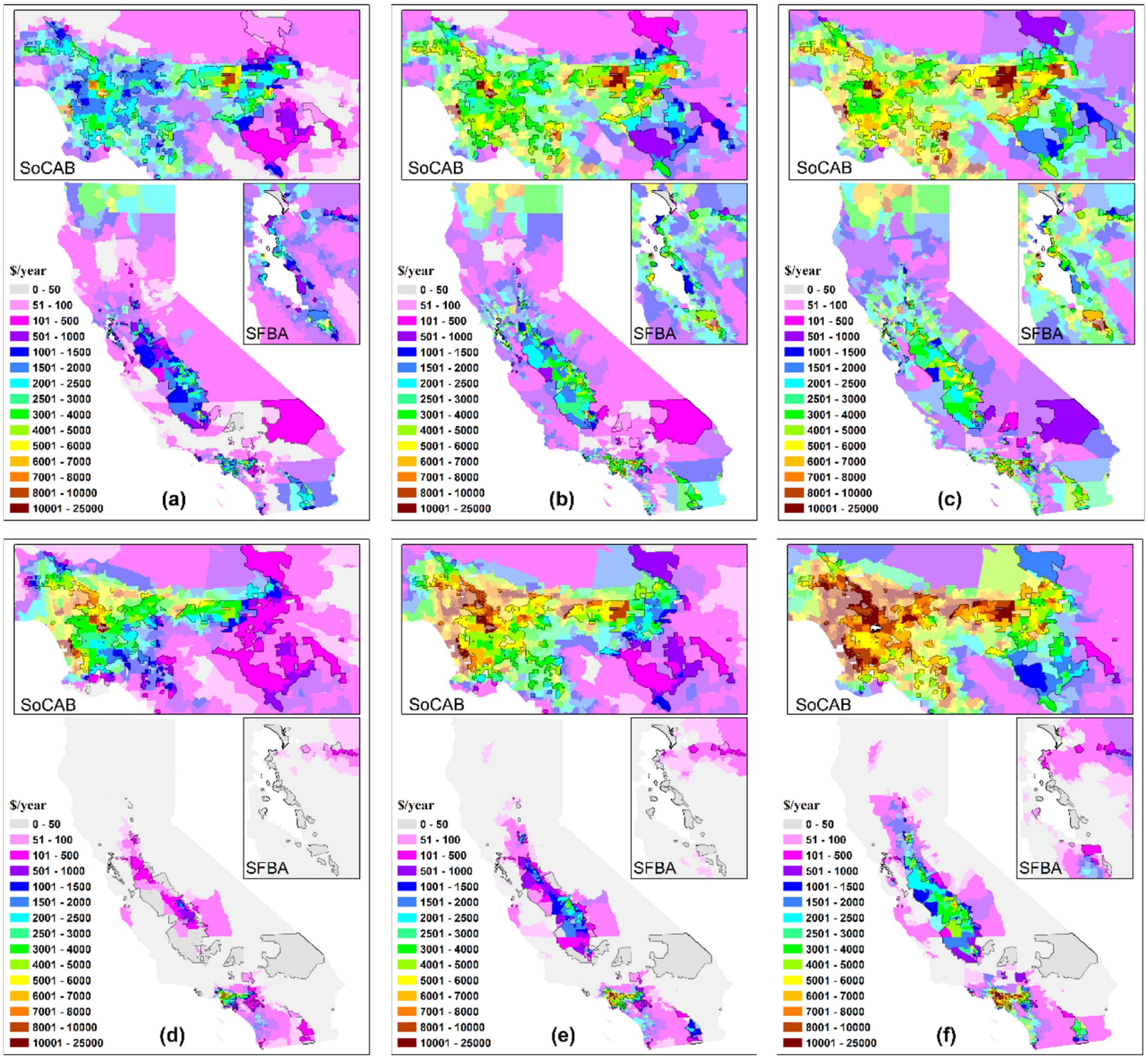


Figure 4. Spatial distribution of per capita health savings for (a) 2018-STDc, (b) 2018-STD1, (c) 2018-STD2, (d) 2035-STDc, (e) 2035-STD1, and (f) 2035-STD2. Highlighted regions indicate the presence of DAC.

scenarios, which assume no impacts from wildfires. Therefore, establishing stronger NAAQS to help offset increased contributions to regional air pollutant burdens from wildfire smoke could be necessary to limit detrimental health effects in exposed populations. This consideration should be addressed in future work, including the quantification and spatial resolution of wildfire contributed $PM_{2.5}$ from total regional burdens in relation to the attainment of NAAQS.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c03177.

Mathematical justification for dynamic threshold capping; maps for the simulation domain; data validation; schematic diagram of the BenMAP model; sketch explaining threshold effects; and detailed health incidence and valuation for both mobility and mortality endpoints (PDF)

■ AUTHOR INFORMATION

Corresponding Author

G. Scott Samuelsen − *Advanced Power and Energy Program, University of California, Irvine, California 92697-3550, United States;* orcid.org/0000-0002-0420-3951; Email: gss@apep.uci.edu

Authors

Shupeng Zhu − *Advanced Power and Energy Program, University of California, Irvine, California 92697-3550, United States;* orcid.org/0000-0002-8446-9329

Michael Mac Kinnon − *Advanced Power and Energy Program, University of California, Irvine, California 92697-3550, United States*

https://doi.org/10.1021/acs.est.1c03177
Environ. Sci. Technol. 2021, 55, 12223−12232

Andre Paradise − *Computational Environmental Sciences Laboratory, University of California, Irvine, California 92697-3975, United States;* orcid.org/0000-0002-8503-3500

Donald Dabdub − *Computational Environmental Sciences Laboratory, University of California, Irvine, California 92697-3975, United States;* orcid.org/0000-0002-5130-4122

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.1c03177

Author Contributions

S.Z., D.D., and G.S.S. conceived the presented idea. S.Z. designed the method and carried out the health and DAC analyses. S.Z. took the lead in writing the manuscripts. M.M.K. contributed significantly to the development of this work and to the writing and editing of the manuscript. A.P. programmed the dynamic threshold capping model. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

The authors would like to acknowledge the assistance from the UCI High-Performance Computing group and the UCI Research Computing group and funding support from the UCI Advanced Power and Energy Program. The authors would like to acknowledge Dr. Guannan Geng of the Tsinghua University to provide the initial observation based on 2018 $PM_{2.5}$ daily concentrations using random forest models.

■ REFERENCES

(1) U.S. Environmental Protection Agency. *Quantitative Health Risk Assessment for Particulate Matter*; U.S. Environmental Protection Agency, Air Quality Planning and Standards: Research Triangle Park, NC, 2010; pp 1−596.

(2) Krewski, D.; Jerrett, M.; Burnett, R. T.; Ma, R.; Hughes, E.; Shi, Y.; Turner, C.; Pope, C.; Calle, E.; Thunt, M. *Extended Follow-up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality*; Health Effects Institute, 2009; Vol. *140*.

(3) Ezzati, M.; Lopez, A. D.; Rodgers, A. A.; Murray, C. J. *Comparative Quantification of Health Risks: Global and Regional Burden of Disease Due to Selected Major Risk Factors*; World Health Organization: Geneva, 2004; Vol. *2*.

(4) U.S. Environmental Protection Agency. *Integrated Science Assessment (ISA) for Particulate Matter (Final Report, 2019)*, 2019.

(5) U.S. Environmental Protection Agency. *Policy Assessment for the Review of the Particulate Matter National Ambient Air Quality Standards*; U.S. Environ. Prot. Agency, Off. Air Qual. Plan. Stand., 2020. No. EPA-452/R-20-002.

(6) Wachter, R. M.; Pronovost, P. J. The Need for a Tighter Particulate-Matter Air-Quality Standard. *N. Engl. J. Med.* **2020**, *383*, 680−683.

(7) Marshall, J. D.; Apte, J. S.; Coggins, J. S.; Goodkind, A. L. Blue Skies Bluer? *Environ. Sci. Technol.* **2015**, *49*, 13929−13936.

(8) U.S. Environmental Protection Agency. *Policy Assessment for the Review of the National Ambient Air Quality Standards for Particulate Matter (External Review Draft—September 2019)*, Washington D.C., 2019, EPA-CASAC-20-001.

(9) Fowlie, M.; Walker, R.; Wooley, D. *Climate Policy*; Environmental Justice, and Local Air Pollution, 2020.

(10) OEHHA. CalEnviroScreen 3.0. Available at: https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30 (accessed Sept 2, 2020).

(11) Xiao, Q.; Chang, H. H.; Geng, G.; Liu, Y. An Ensemble Machine-Learning Model To Predict Historical PM 2.5 Concentrations in China from Satellite Data. *Environ. Sci. Technol.* **2018**, *52*, 13260−13269.

(12) Hu, X.; Belle, J. H.; Meng, X.; Wildani, A.; Waller, L. A.; Strickland, M. J.; Liu, Y. Estimating PM 2.5 Concentrations in the Conterminous United States Using the Random Forest Approach. *Environ. Sci. Technol.* **2017**, *51*, 6936−6944.

(13) U.S. Environmental Protection Agency Office of Research and Development. *CMAQ (Version 5.2)*; Zenodo, 2017.

(14) Wang, D.; Guan, D.; Zhu, S.; Kinnon, M. M.; Geng, G.; Zhang, Q.; Zheng, H.; Lei, T.; Shao, S.; Gong, P.; Davis, S. J. Economic Footprint of California Wildfires in 2018. *Nat. Sustain.* **2020**, *4*, 252−260.

(15) Lyapustin, A.; Martonchik, J.; Wang, Y.; Laszlo, I.; Korkin, S. Multiangle Implementation of Atmospheric Correction (MAIAC): 1. Radiative Transfer Basis and Look-up Tables. *J. Geophys. Res.* **2011**, *116*, D03210.

(16) Lyapustin, A.; Wang, Y.; Laszlo, I.; Kahn, R.; Korkin, S.; Remer, L.; Levy, R.; Reid, J. S. Multiangle Implementation of Atmospheric Correction (MAIAC): 2. Aerosol Algorithm. *J. Geophys. Res.* **2011**, *116*, D03211.

(17) Breiman, L. *Random Forests. Machine Learning* **2001**, *45*, 5−32.

(18) Geng, G.; Meng, X.; He, K.; Liu, Y. Random Forest Models for PM 2.5 Speciation Concentrations Using MISR Fractional AODs. *Environ. Res. Lett.* **2020**, *15*, 034056.

(19) U.S. Environmental Protection Agency. *Air Quality System (AQS)*. 2019.

(20) California Air Resources Board. *Current CARB Emissions Inventory (Ver. 2012)*.

(21) California Air Resources Board. *CEPAM: 2016 SIP-Standard Emissions Tool*.

(22) Houyoux, M.; Vukovich, J.; Brandmeyer, J. E. Sparse Matrix Operator Kernel Emissions (SMOKE) v3.7 User's Manual; University North Carolina Chapel Hill, 2015. Available https//www.cmascenter.org/smoke/documentation/3.7/manual_smokev37.pdf (accessed June 22, 2016).

(23) Foley, K. M.; Dolwick, P.; Hogrefe, C.; Simon, H.; Timin, B.; Possiel, N. Dynamic Evaluation of CMAQ Part II: Evaluation of Relative Response Factor Metrics for Ozone Attainment Demonstrations. *Atmos. Environ.* **2015**, *103*, 188−195.

(24) Foley, K. M.; Roselle, S. J.; Appel, K. W.; Bhave, P. V.; Pleim, J. E.; Otte, T. L.; Mathur, R.; Sarwar, G.; Young, J. O.; Gilliam, R. C.; Nolte, C. G.; Kelly, J. T.; Gilliland, A. B.; Bash, J. O. Incremental Testing of the Community Multiscale Air Quality (CMAQ) Modeling System Version 4.7. *Geosci. Model Dev.* **2010**, *3*, 205−226.

(25) Carter, W. P. L. Development of the SAPRC-07 Chemical Mechanism. *Atmos. Environ.* **2010**, *44*, 5324−5335.

(26) Pye, H. O. T.; Pinder, R. W.; Piletic, I. R.; Xie, Y.; Capps, S. L.; Lin, Y.-H.; Surratt, J. D.; Zhang, Z.; Gold, A.; Luecken, D. J.; Hutzell, W. T.; Jaoui, M.; Offenberg, J. H.; Kleindienst, T. E.; Lewandowski, M.; Edney, E. O. Epoxide Pathways Improve Model Predictions of Isoprene Markers and Reveal Key Role of Acidity in Aerosol Formation. *Environ. Sci. Technol.* **2013**, *47*, 11056−11064.

(27) Zhu, S.; Horne, J. R.; Mac Kinnon, M.; Samuelsen, G. S.; Dabdub, D. Comprehensively Assessing the Drivers of Future Air Quality in California. *Environ. Int.* **2019**, *125*, 386−398.

(28) Emmons, L. K.; Walters, S.; Hess, P. G.; Lamarque, J.-F.; Pfister, G. G.; Fillmore, D.; Granier, C.; Guenther, A.; Kinnison, D.; Laepple, T.; Orlando, J.; Tie, X.; Tyndall, G.; Wiedinmyer, C.; Baughcum, S. L.; Kloster, S. Description and Evaluation of the Model for Ozone and Related Chemical Tracers, Version 4 (MOZART-4). *Geosci. Model Dev.* **2010**, *3*, 43−67.

(29) Friedl, M. A.; Sulla-Menashe, D.; Tan, B.; Schneider, A.; Ramankutty, N.; Sibley, A.; Huang, X. MODIS Collection 5 Global Land Cover: Algorithm Refinements and Characterization of New Datasets. *Remote Sens. Environ.* **2010**, *114*, 168−182.

(30) NCEP. NCEP FNL Operational Model Global Tropospheric Analyses, Continuing from July 1999. Research Data Archive at the

National Center for Atmospheric Research; Computational and Information Systems Laboratory, 2000.
(31) Emery, C.; Liu, Z.; Russell, A. G.; Odman, M. T.; Yarwood, G.; Kumar, N. Recommendations on Statistics and Benchmarks to Assess Photochemical Model Performance. *J. Air Waste Manage. Assoc.* **2017**, *67*, 582−598.
(32) Pascal, M.; Corso, M.; Chanel, O.; Declercq, C.; Badaloni, C.; Cesaroni, G.; Henschel, S.; Meister, K.; Haluza, D.; Martin-Olmedo, P.; Medina, S. Assessing the Public Health Impacts of Urban Air Pollution in 25 European Cities: Results of the Aphekom Project. *Sci. Total Environ.* **2013**, *449*, 390−400.
(33) Kampa, M.; Castanas, E. Human Health Effects of Air Pollution. *Environ. Pollut.* **2008**, *151*, 362−367.
(34) Goldberg, M. A Systematic Review of the Relation Between Long-Term Exposure to Ambient Air Pollution and Chronic Diseases. *Rev. Environ. Health* **2008**, *23*, 243−298.
(35) Driscoll, C. T.; Buonocore, J. J.; Levy, J. I.; Lambert, K. F.; Burtraw, D.; Reid, S. B.; Fakhraei, H.; Schwartz, J. US Power Plant Carbon Standards and Clean Air and Health Co-Benefits. *Nat. Clim. Change* **2015**, *5*, 535−540.
(36) Broome, R. A.; Fann, N.; Cristina, T. J. N.; Fulcher, C.; Duc, H.; Morgan, G. G. The Health Benefits of Reducing Air Pollution in Sydney, Australia. *Environ. Res.* **2015**, *143*, 19−25.
(37) Voorhees, A. S.; Wang, J.; Wang, C.; Zhao, B.; Wang, S.; Kan, H. Public Health Benefits of Reducing Air Pollution in Shanghai: A Proof-of-Concept Methodology with Application to BenMAP. *Sci. Total Environ.* **2014**, *485−486*, 396−405.
(38) Shen, E.; Oliver, A.; Dabirian, S. *Final Socioeconomic Report; South Coast Air Quality Management District*, 2017. Available at: http://www.aqmd.gov/docs/default-source/clean-air-plans/socioeconomic-analysis/final/sociofinal_030817.pdf?sfvrsn=2.
(39) Industrial Economics. Literature Review of Air Pollution-Related Health Endpoints and Concentration-Response Functions for Particulate Matter: Results and Recommendations; Memorandum; Industrial Economics, Inc.: Cambridge, MA, 2016 Available at: http://www.aqmd.gov/docs/default-source/clean-air-plans/socioeconomic-analysis/iec_pmlitreview_092916.pdf (accessed Sept 01, 2018).
(40) Alexander, M.; Alvarez-Gomez, A.; Bowermaster, D.; Grant, J.; Johnson, B.; Knipping, E.; Krishnamoorthy, S.; Liu, C.; Nopmongcol, U.; Stephens, P.; Vairamohan, B. *Air Quality Implications of an Energy Scenario for California Using High Levels of Electrification*, 2019.
(41) Jerrett, M.; Burnett, R. T.; Ma, R.; Pope, C. A.; Krewski, D.; Newbold, K. B.; Thurston, G.; Shi, Y.; Finkelstein, N.; Calle, E. E.; Thun, M. J. Spatial Analysis of Air Pollution and Mortality in Los Angeles. *Epidemiology* **2005**, *16*, 727−736.
(42) Jerrett, M.; Burnett, R. T.; Beckerman, B. S.; Turner, M. C.; Krewski, D.; Thurston, G.; Martin, R. V.; van Donkelaar, A.; Hughes, E.; Shi, Y.; Gapstur, S. M.; Thun, M. J.; Pope, C. A. Spatial Analysis of Air Pollution and Mortality in California. *Am. J. Respir. Crit. Care Med.* **2013**, *188*, 593−599.
(43) Krewski, D.; Jerrett, M.; Burnett, R. T.; Ma, R.; Hughes, E.; Shi, Y.; Turner, M. C.; Pope, C. A., III; Thurston, G.; Calle, E. E. *Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality*; Health Effects Institute Boston: MA, 2009.
(44) Zhao, B.; Wang, T.; Jiang, Z.; Gu, Y.; Liou, K.-N.; Kalandiyur, N.; Gao, Y.; Zhu, Y. Air Quality and Health Cobenefits of Different Deep Decarbonization Pathways in California. *Environ. Sci. Technol.* **2019**, *53*, 7163−7171.
(45) Zapata, C. B.; Yang, C.; Yeh, S.; Ogden, J.; Kleeman, M. J. Low-Carbon Energy Generates Public Health Savings in California. *Atmos. Chem. Phys.* **2018**, *18*, 4817−4830.
(46) Burnett, R.; Chen, H.; Szyszkowicz, M.; Fann, N.; Hubbell, B.; Pope, C. A.; Apte, J. S.; Brauer, M.; Cohen, A.; Weichenthal, S.; Coggins, J.; Di, Q.; Brunekreef, B.; Frostad, J.; Lim, S. S.; Kan, H.; Walker, K. D.; Thurston, G. D.; Hayes, R. B.; Lim, C. C.; Turner, M. C.; Jerrett, M.; Krewski, D.; Gapstur, S. M.; Diver, W. R.; Ostro, B.; Goldberg, D.; Crouse, D. L.; Martin, R. V.; Peters, P.; Pinault, L.; Tjepkema, M.; Van Donkelaar, A.; Villeneuve, P. J.; Miller, A. B.; Yin, P.; Zhou, M.; Wang, L.; Janssen, N. A. H.; Marra, M.; Atkinson, R. W.; Tsang, H.; Quoc Thach, T.; Cannon, J. B.; Allen, R. T.; Hart, J. E.; Laden, F.; Cesaroni, G.; Forastiere, F.; Weinmayr, G.; Jaensch, A.; Nagel, G.; Concin, H.; Spadaro, J. V. Global Estimates of Mortality Associated with Longterm Exposure to Outdoor Fine Particulate Matter. *Proc. Natl. Acad. Sci. U.S.A.* **2018**, *115*, 9592−9597.
(47) Raizenne, M.; Neas, L. M.; Damokosh, A. I.; Dockery, D. W.; Spengler, J. D.; Koutrakis, P.; Ware, J. H.; Speizer, F. E. Health Effects of Acid Aerosols on North American Children: Pulmonary Function. *Environ. Health Perspect.* **1996**, *104*, 506−514.
(48) Atkinson, R. W.; Kang, S.; Anderson, H. R.; Mills, I. C.; Walton, H. A. Epidemiological Time Series Studies of PM2.5 and Daily Mortality and Hospital Admissions: A Systematic Review and Meta-Analysis. *Thorax* **2014**, *69*, 660−665.
(49) Delfino, R. J.; Wu, J.; Tjoa, T.; Gullesserian, S. K.; Nickerson, B.; Gillen, D. L. Asthma Morbidity and Ambient Air Pollution. *Epidemiology* **2014**, *25*, 48−57.
(50) Ostro, B. D. Air Pollution and Morbidity Revisited: A Specification Test. *J. Environ. Econ. Manag.* **1987**, *14*, 87−98.
(51) Shin, H. H.; Fann, N.; Burnett, R. T.; Cohen, A.; Hubbell, B. J. Outdoor Fine Particles and Nonfatal Strokes. *Epidemiology* **2014**, *25*, 835−842.
(52) Zanobetti, A. Air Pollution and Emergency Admissions in Boston, MA. *J. Epidemiol. Community Health* **2006**, *60*, 890−895.
(53) Sullivan, J.; Sheppard, L.; Schreuder, A.; Ishikawa, N.; Siscovick, D.; Kaufman, J. Relation Between Short-Term Fine-Particulate Matter Exposure and Onset of Myocardial Infarction. *Epidemiology* **2005**, *16*, 41−48.
(54) Pope, C. A.; Muhlestein, J. B.; May, H. T.; Renlund, D. G.; Anderson, J. L.; Horne, B. D. Ischemic Heart Disease Events Triggered by Short-Term Exposure to Fine Particulate Air Pollution. *Circulation* **2006**, *114*, 2443−2448.
(55) Ostro, B.; Lipsett, M.; Mann, J.; Braxton-Owens, H.; White, a. M. Air Pollution and Exacerbation of Asthma in African-American Children in Los Angeles. *Epidemiology* **2001**, *12*, 200−208.
(56) Mar, T. F.; Larson, T. V.; Stier, R. A.; Claiborn, C.; Koenig, J. Q. An Analysis of the Association Between Respiratory Symptoms in Subjects with Asthma and Daily Air Pollution in Spokane, Washington. *Inhal. Toxicol.* **2004**, *16*, 809−815.
(57) Pope, C. A.; Dockery, D. W.; Spengler, J. D.; Raizenne, M. E. Respiratory Health and PM 10 Pollution: A Daily Time Series Analysis. *Am. Rev. Respir. Dis.* **1991**, *144*, 668−674.
(58) Schwartz, J.; Neas, L. M. Fine Particles Are More Strongly Associated than Coarse Particles with Acute Respiratory Health Effects in Schoolchildren. *Epidemiology* **2000**, *11*, 6−10.
(59) Moolgavkar, S. H. Air Pollution and Daily Mortality in Three U.S. Counties. *Environ. Health Perspect.* **2000**, *108*, 777−784.
(60) Moolgavkar, S. H. Air Pollution and Hospital Admissions for Diseases of the Circulatory System in Three U.S. Metropolitan Areas. *J. Air Waste Manage. Assoc.* **2000**, *50*, 1199−1206.
(61) Moolgavkar, S. H. Air Pollution and Hospital Admissions for Chronic Obstructive Pulmonary Disease in Three Metropolitan Areas in the United States. *Inhal. Toxicol.* **2000**, *12*, 75−90.
(62) Zanobetti, A.; Franklin, M.; Koutrakis, P.; Schwartz, J. Fine Particulate Air Pollution and Its Components in Association with Cause-Specific Emergency Admissions. *Environ. Health* **2009**, *8*, 58.
(63) Industrial Economics; Robinson, L. Review of Morbidity Valuation Estimates for Use in 2016 Socioeconomic Assessment; Memorandum; Industrial Economics, Inc.: Massachusetts, MA, 2016. Available: http://www.aqmd.gov/docs/default-source/clean-air-plans/socioeconomic-analysis/iecmemos_november2016/scmorbidityvaluation_112816.pdf (accessed Sept 20, 2018).
(64) Industrial Economics; Robinson, L. Review of Mortality Risk Reduction Valuation Estimates for 2016 Socioeconomic Assessment; Memorandum; Industrial Economics, Inc.: Massachusetts, MA, 2016. Available: http://www.aqmd.gov/docs/default-source/clean-air-plans/socioeconomic-analysis/iecmemos_november2016/evaluationcriteria_113016.pdf (accessed Sept 20, 2018).

(65) Robinson, L. A.; Hammitt, J. K. Valuing Reductions in Fatal Illness Risks: Implications of Recent Research. *Health Econ.* **2016**, *25*, 1039−1052.
(66) Shen, E.; Oliver, A.; Dabirian, S. Final 2016 Socioeconomic Report (South Coast Air Quality Management District, 2017) http://www.aqmd.gov/docs/default-source/clean-air-plans/socioeconomic-analysis/final/sociofinal_030817.pdf?sfvrsn=2 (accessed Dec 11, 2019).
(67) CARB. California State Implementation Plans; California Air Resources Board https://ww2.arb.ca.gov/our-work/programs/california-state-implementation-plans (accessed Dec 21, 2020).
(68) Lee, H. J. Benefits of High Resolution PM2.5 Prediction Using Satellite MAIAC AOD and Land Use Regression for Exposure Assessment: California Examples. *Environ. Sci. Technol.* **2019**, *53*, 12774−12783.
(69) Samuelsen, S.; Zhu, S.; Kinnon, M. M.; Yang, O. K.; Dabdub, D.; Brouwer, J. An Episodic Assessment of Vehicle Emission Regulations on Saving Lives in California. *Environ. Sci. Technol.* **2021**, *55*, 547.
(70) Morello-Frosch, R.; Pastor, M.; Sadd, J. Environmental Justice and Southern California's "Riskscape". *Urban Aff. Rev.* **2001**, *36*, 551−578.
(71) Running, S. W. Climate Change: Is Global Warming Causing More, Larger Wildfires? *Science* **2006**, *313*, 927−928.
(72) U.S. Environmental Protection Agency. The Benefits and Costs of the Clean Air Act from 1990 to 2020: Summary Report: Research Triangle Park, NC. Available at: http://www.epa.gov/cleanairactbenefits/feb11/summaryreport.pdf (accessed Sept 20, 2018), 2011.
(73) Westerling, A. L. *Wildfire Simulations for California's Fourth Climate Change Assessment: Projecting Changes in Extreme Wildfire Events with a Warming Climate*, 2018.
(74) Westerling, A. L.; Bryant, B. P.; Preisler, H. K.; Holmes, T. P.; Hidalgo, H. G.; Das, T.; Shrestha, S. R. Climate Change and Growth Scenarios for California Wildfire. *Clim. Change* **2011**, *109*, 445−463.
(75) Holden, Z. A.; Swanson, A.; Luce, C. H.; Jolly, W. M.; Maneta, M.; Oyler, J. W.; Warren, D. A.; Parsons, R.; Affleck, D. Decreasing Fire Season Precipitation Increased Recent Western US Forest Wildfire Activity. *Proc. Natl. Acad. Sci.* **2018**, *115*, E8349−E8357.
(76) Abatzoglou, J. T.; Williams, A. P. Impact of Anthropogenic Climate Change on Wildfire across Western US Forests. *Proc. Natl. Acad. Sci.* **2016**, *113*, 11770−11775.

https://doi.org/10.1021/acs.est.1c03177
Environ. Sci. Technol. 2021, 55, 12223−12232