The air quality and health impacts of projected long-haul truck and rail freight transportation in the United States in 2050

Final Report

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16. Abstract

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Abstract

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Keywords: freight transportation, diesel emissions, air quality, public health, particulate matter.

1. Introduction

Diesel engines are often used to power commercial freight transport vehicles such as truck and rail locomotives. However, emissions from diesel engines have substantial negative impacts on the environment and public health. Diesel exhaust emissions comprise significantly high amounts of particulate matter and its precursors, which can cause respiratory and cardiovascular problems (Bell et al., 2008) and premature death (Woodruff et al., 2006; Krewski et al., 2009; Lepeule et al., 2012). In order to reduce these impacts, the United States (US) has initiated several stringent regulatory standards (e.g., US EPA Heavy Duty Diesel Rules 2004/2007/2010 to limit emissions of new diesel engines, state laws calling on retrofitting older diesel engines (CARB, 2014; TERP, 2001; Craft, 2012), and regional public-private partnerships administered by the US Environmental Protection Agency (USEPA)'s National Clean Diesel Campaign (USEPA, 2008)). Recently, the California Sustainable Freight Action Plan (CSFAP, 2016) was initiated to improve freight efficiency and shift to zero-emission technologies. In 2015, a dedicated source of federal support for improving freight transportation and preserving the environment was included in the US Department of Transportation (USDOT)'s Fixing America's Surface Transportation (FAST) Act. Internationally, the Euro I through VI standards have been adopted in European countries to control emissions from heavy-duty vehicles, and equivalent standards have sprung up in countries such as China (Wu et al., 2017), Japan, and others (DieselNet, 2018; Anenberg et al., 2017).

Large-scale factors such as population, economic development, industrialization, and international trade affect demand for freight services, which has historically grown in proportion to gross domestic product (GDP) (Muratori et al., 2017). The GDP factor explained 89% of the variation (R^2=0.89) in road freight volumes based on a study of 28 countries at different development stages (Bennathan et al., 1992). Freight related activities accounted for 33% of industry jobs in California in 2014 (CFAC, 2016). Under a high GDP growth rate, freight activities (e.g., vehicle miles traveled (VMT)) are projected to double in 2050 over the US (Liu et al., 2015). Similar projections were also made by USDOT's Highway Performance Monitoring System (HPMS) and adopted in USEPA's Motor Vehicle Emissions Simulator (MOVES) (USEPA, 2015a). Road freight transportation today are mostly fueled by ultra-low sulfur diesel (ULSD). Still combustion of diesel fuel results in emissions of greenhouse gases (GHGs) as well as criteria air pollutants, like particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x), and air toxics such as polycyclic aromatic hydrocarbons (PAHs) that cause cancer (CDC, 2014).

Due to emission control policies and advancements in vehicle technologies and fuel refinements, new diesel truck engines under the latest standards emit 98% less PM and NO_x emissions than their pre-1990 counterparts (ICCT, 2013). These technologies include diesel oxidation catalyst (DOC) to control CO and hydrocarbons, diesel particulate filter (DPF) to control PM emissions, and selective catalytic reduction (SCR) to control NO_x emissions (Resitoglu et al., 2015). Other measures include implementing emission testing programs and anti-idling programs, and promoting cleaner fuels like ultra-low sulfur diesel (USEPA, 2006). Under these efforts, future diesel pollutant emissions are predicted to decrease substantially, despite the surging demand in freight transport. There are other factors that affect the future picture and estimation of freight emissions. Emissions from the freight sectors also depend on energy and carbon intensities. Climate mitigation policy, such as pricing of GHG emissions (i.e., carbon tax), can cause shift of freight to less energy-intensive modes (e.g., switching from truck to rail). In addition, trucks often degrade from normal to high-emitting conditions (i.e., super-emitters) as they age (Bond et al., 2004; Yan et al., 2011). The relative magnitude of emission factors from normal to high-emitting conditions can reach up to 70 times for PM (Liu et al., 2015). Also, Liu et al. (2015) reported that total US long-haul freight emissions could be reduced to ~30% with the elimination of super-emitters in 2050.

Transportation emissions are known to cause significant negative health impacts (USEPA, 2000; Tayarani et al., 2016). Total on-road mobile emission sources were estimated to induce ~29,000 premature deaths over the US in 2005 (Fann et al., 2013). Several other studies have examined the impact of technology development on transportation emissions (Nichols et al., 2015) or air quality (Thompson et al., 2009, 2011; Nopmongcol et al., 2017), but not many have assessed the resulting health and associated economic benefits. Wolfe et al. (2019) reported that heavy duty diesel sector is the largest emission producer, in term of primary fine particulate matter ($PM_{2.5}$) and NO_x emissions, among all the mobile source sectors; and rail sector is the fifth largest for primary $PM_{2.5}$ and second largest for NO_x, respectively. In this study, we focus on freight transportation sectors (e.g., long-haul trucks and locomotives), and link the evolution of freight emissions to air quality modeling and health impact assessment. The year 2050 is a substantially far horizon to assess the impacts of significant anticipated changes in fleet composition. By examining multiple emission scenarios based on varying policy assumptions, we systematically model the impacts of future freight emissions on $PM_{2.5}$ concentrations, and associated changes in health outcomes (e.g., premature mortality, morbidities) and economic benefits. To conduct this analysis, we use the USEPA Community Multi-scale Air Quality (CMAQ) and Environmental Benefits Mapping and Analysis Program (BenMAP) models. Specifically, we examine spatial distributions of health impacts at state and county levels, which can help policy-makers to identify regions in need of early regulatory actions.

2. Methodology

2.1. Design of the Scenarios

This study applied several emission scenarios to account for future freight transportation emissions under the effect of socioeconomic development, climate policy, and technology evolution. A simplified flow chart of the assessment system is presented in Figure 1. Liu et al. (2015) provided the freight emissions projections through 2050 by applying a combination of an economic model (Fisher-Vanden et al., 2012) and an engineering model (Yan et al., 2011). The economic model seeks supply-demand equilibrium across sectors and worldwide regions, and outputs activities (e.g., GDP and fuel consumption). The engineering model includes freight demand and emission calculations. We applied the emission projection rates to scale the diesel-fueled long-haul truck and rail sectors in the following simulation cases:

(1) Baseline (BASE) case – This serves as the base case to which future scenarios were compared. Bell et al. (2007) reported large seasonal variations of several $PM_{2.5}$ components in the US (e.g., highest sulfate $PM_{2.5}$ in summer, highest nitrate $PM_{2.5}$ in winter); other major components, such as organic carbon, ammonium, and elemental carbon, generally had much less variations across seasons. Overall, total $PM_{2.5}$ concentrations were highest in summer and comparable in winter, spring, and autumn. We used the winter month of Jan 2011 as our simulation episode in this study, to provide a relative average estimate of the $PM_{2.5}$ concentrations.

(2) Stringent Control (CTR) scenario – Stringent emission control policies are continuously applied under a high GDP growth rate. Increasingly rigorous rules with varying degrees of stringency (e.g., the US EPA 2004, 2007, and 2010 standards for heavy-duty vehicles) have been designed and adopted. Generally, vehicles manufactured under 2010 standards produce less emissions than those built for previous years (except for some pollutants such as NO_x). This scenario does not assume further emission control standards beyond the 2010 standards, that is, all the new vehicles manufactured after 2010 would follow the US 2010 standards.

(3) Climate policy (PO) scenario – This has the same GDP growth rate as the CTR scenario, but employs a climate policy in the form of a carbon tax to emulate a 450 ppm stabilization scenario. In this scenario \$30/tonne CO_2 in 2010 increases to \$130/tonne CO_2 in 2050. The carbon tax increases oil prices, causing 15% of freight fuel consumption to shift from truck to the more energy-efficient rail (Liu et al., 2015). For this analysis, the inter-modal shift was represented at the national level.

(4) No super-emitters (NS) scenario – Representing the phase-out of high-emitting vehicles in the truck fleet. Normal vehicles become high emitters at a rate of 5%-7% (Dallmann et al., 2012, Preble et al., 2018). The high-emitting conditions consider poor engine maintenance, non-compliance with stricter emission standards, or failure of emission control systems. Current regulations set limits on emissions from new vehicles, but they do not affect in-use vehicles. This scenario is equivalent to a retrofit policy that controls emissions from in-use vehicles. The retrofit policy can restrict emissions not covered by current or potential newer vehicle standards.

Both the PO and NS scenarios are superimposed on the CTR scenario, that is, the same stringent emission control in the CTR scenario are applied in the PO and NS scenarios, as depicted in Figure S1. The CTR, PO, and NS scenarios are directly adopted from Liu et al. (2015); they are same as the high GDP, high GDP combined with climate policy, and no super-emitters scenarios in the reference.

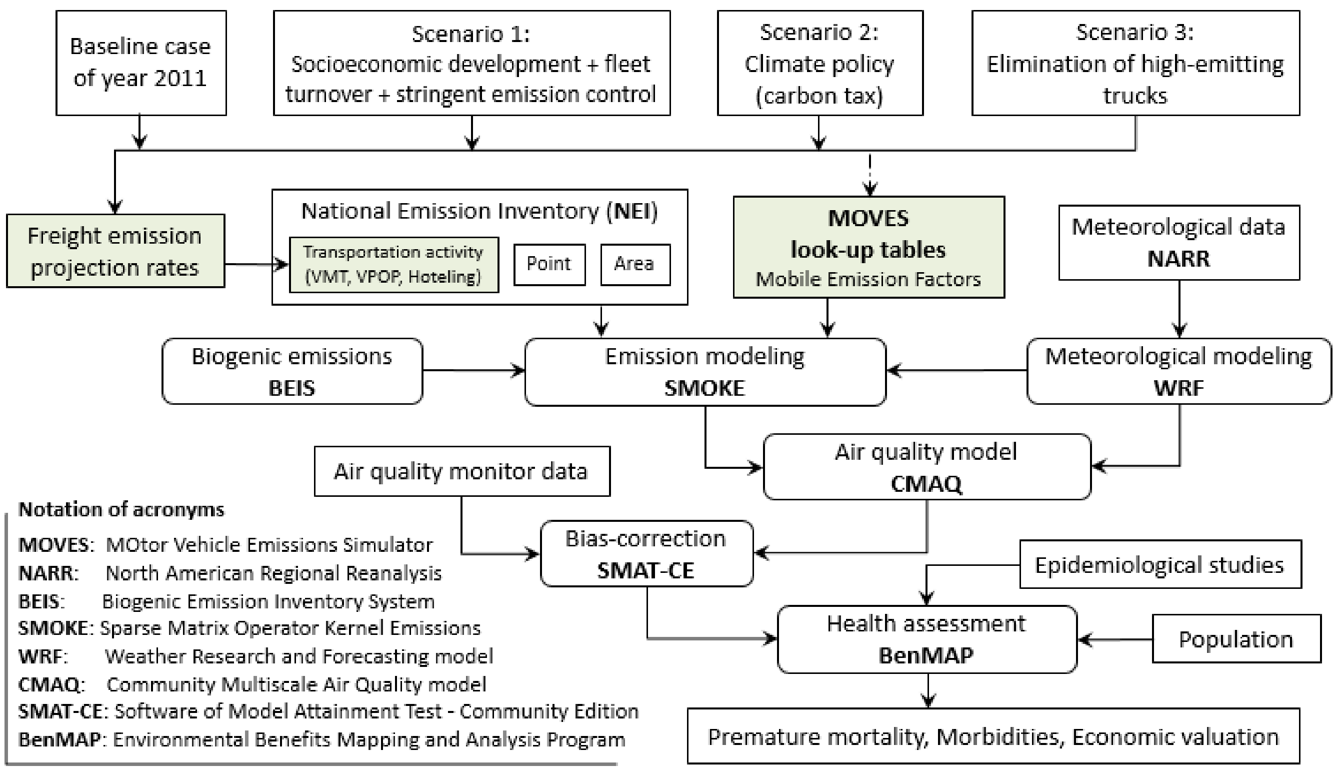

Figure 1. A simplified flow chart of the air quality and health assessment system.

2.2. Emission Inventories

Anthropogenic emissions inputs were developed using the USEPA National Emissions Inventory of 2011 (NEI2011) (USEPA, 2015b; 2015c) as a starting point. These inventories include mobile, point, and area sources. Mobile sources included on-road mobile emissions, for which the USEPA Motor Vehicle Emissions Simulator (MOVES) (USEPA, 2016a) provided emission factors (EF) look-up tables as functions of speed, fuel type, vehicle type, road type, and meteorological conditions. Motor vehicle activity data – such as vehicle miles traveled (VMT), population (VPOP), and hoteling hours (Hoteling) – were either submitted by state, local, and tribal air agencies, or estimated in-house by the USEPA. The on-road mobile emissions were calculated as EF multiply by activity, for each combination of fuel, vehicle, and road type. Point sources include electricity generating units (EGUs), oil and gas production processes, category 3 marine vessels, and remaining non-EGU industry sources. Area sources include agricultural activities, fugitive dust, locomotives, category 1 and 2 commercial marine vessels, oil and gas production processes, non-road vehicles, residential wood combustion, and remaining non-point sources. Gridded hourly biogenic emissions were estimated using the USEPA Biogenic Emission Inventory System (BEIS) (Pouliot and Pierce, 2009). For the baseline freight emissions, both activity and emission factors vary with fuel and vehicle types, hence diesel long-haul truck is one subgroup of the on-road mobile inventories. The rail sector is a subsector of the area sources.

A projection by Liu et al. (2015) suggested an approximate 100% to 140% increase of long-haul trucks and rail freight activity during 2010-2050. The projection for trucks is similar to the MOVES estimate (110%) during the same period, as plotted in Figure S2. Figure S3 plots the emissions of major air pollutants in each scenario from the truck and rail sectors, the projections are based on Liu et al. (2015). Compared to the base year case, PM emissions in all future year cases decrease substantially, as depicted in Figure 3(a) and (b). In the CTR case, the reduction rates are 60-70% for the truck sector and ~80% for the rail sector (Figures 3(c) and (d)). Reductions in truck emissions would result from the implementation of emission standards, fleet turnover, reduction in fuel intensity (fuel consumption per unit distance), and technological improvements. In the US, a majority of long-haul trucks have a lifespan of 4-15 years, as depicted in Figure S4. By 2050, almost all older and dirtier trucks built before the 2010 standard are projected to be retired. Locomotives have a longer lifetime than trucks and by 2050 most of the rail fleet would be built under Tier 4 emission standards. Comparing the PO case with the CTR case, the truck sector has a 35% decrease in PM emissions, while the rail sector sees a 25% increase. These reflect the effects of climate policy promoting a transition in freight demand from truck to rail, as the average fuel intensity of Class I railroads is only about one fifth that of trucks (AAR, 2011). In the NS case, PM emissions are significantly reduced (~70%) with respect to the CTR scenario in the truck sector due to the phase-out of super-emitters. Thus the potential proliferation of super-emitters must be addressed specifically in order to control PM emissions. The relative magnitude of emission factors between high-emitting and normal-emitting conditions is significantly bigger for PM than other pollutants. So PM has a larger reduction after eliminating high-emitting conditions. For the rail sector, emissions remain unchanged between the NS case and CTR case. As the truck emissions were calculated as EF multiply by activity, the truck emission projection rates in Figure S3 were used to scale EF database, which indirectly changed the truck freight emissions. The rail emission projection rates were directly applied to the rail inventories. The other anthropogenic emissions were held constant in the future.

2.3. Air Quality Modeling System

Chemical transport modeling

We used the USEPA Community Multi-scale Air Quality (CMAQ) model (Byun and Schere, 2006) version 5.0.2 to model atmospheric transformation processes. Here, the Carbon Bond 5 (CB05) (Yarwood et al., 2005) and AERO6 mechanisms simulate gas and aerosol chemistry, respectively. The CMAQ model solves the continuity mass-balance equation and simulates the atmospheric processes of emissions, advection, diffusion, dry and wet depositions, and chemistry for a given geographical region by discretizing the region into several horizontal, lateral, and vertical grid cells. The major CMAQ configuration options are listed in Table S1. In this study, the horizontal resolution of the model simulations is 12×12 km. The CMAQ simulation domain has 459×299 grid cells horizontally and 27 layers vertically.

Meteorological fields

The Weather Research and Forecasting (WRF) model (Skamarock and Klemp, 2008) version 3.7 provided meteorological fields. The WRF physics options are listed in Table S2. The National Centers for Environmental Prediction (NCEP) provided North American Regional Reanalysis (NARR) data (Mesinger et al., 2004) used as input for the WRF model. In this study, the meteorological conditions were held constant in the future year scenarios.

Emission modeling

To process emissions, we used the Sparse Matrix Operator Kernel Emissions (SMOKE) system (Houyoux et al., 2000) version 3.6. The SMOKE model performed spatial and temporal allocations and chemical speciation to transform annual or monthly county-level inventory data to hourly gridded model species. It also provided plume rise estimations to allocate point source emissions vertically. For the transportation sector, activity data and rail inventories were spatially allocated using GIS Shapefiles of TIGER/Line data for roads, and National Transportation Atlas Data for railways (USEPA, 2015b). These spatial surrogates were prepared by USEPA using the Surrogate Tools of the Spatial Allocator system (USEPA, 2016b). The SMOKE model took EF (the output from MOVES), county-level monthly activity data, and temperature data and produced hourly gridded CMAQ-ready emissions.

2.4. Health Impact Assessment Tool

To evaluate the impact of the various scenarios on health and economic benefits, we used the USEPA Environmental Benefits Mapping and Analysis Program (BenMAP) Community Edition version 1.3 (USEPA, 2017a; Sacks et al., 2018). The health impact calculations in BenMAP are based on concentration-response (C-R) functions (a.k.a. health impact functions), typically representing a decrease in adverse health effects with reduction of ambient air pollution concentrations resulting from the implementation of emission control policies (Fann et al., 2012, 2013; Kheirbek et al., 2013; Driscoll et al., 2015). One group of widely used C-R functions are in the log-linear format:

$$\Delta y = \left(1 - e^{-\beta \cdot \Delta x}\right) \times y_0 \times Pop \qquad (1)$$

where Δy represents the change in the incidence of adverse health effects, β the concentration-response coefficient, Δx change in air quality (e.g. $PM_{2.5}$ concentrations), y_0 the baseline incidence rates, and Pop the affected population. The concentration-response relationships (i.e., β) are usually assessed in epidemiological studies. The functional form of a C-R function is based on the statistical approach used in epidemiological study, and most often a log-linear statistical model is used. Additionally, the BenMAP model calculates the economic benefit of avoided premature mortality using a "value of statistical life" (VSL) approach, which is the aggregate monetary value that a large group of people would be willing to pay to slightly reduce the risk of premature death in the population (USEPA, 2017a; Fann et al., 2013).

The air quality inputs of the model include a baseline scenario (without control) and a control scenario (with emission control policy implemented). In this study, the base year case is the baseline scenario and the future year cases represent varying control scenarios. The air quality spatial fields from CMAQ model were bias-corrected using the Software for Model Attainment Test - Community Edition (SMAT-CE) Version 1.2 (SCUT, 2017) and $PM_{2.5}$ federal reference methods (FRM) monitoring data. The SMAT-CE model typically uses $PM_{2.5}$ monitoring data in a five-year period to adjust the model spatial fields. In our study, the monitoring data for 2009-2013 (winter) were used. As depicted in Figure S5, the adjusted baseline model $PM_{2.5}$ concentrations are about half of the original CMAQ output data. We then assessed the changes in premature mortality and a few morbidities (e.g., hospital admissions, emergency room visits, and asthma exacerbation) attributable to $PM_{2.5}$ under various future year scenarios. As an extended analysis of the American Cancer Society cohort study, Krewski et al. (2009) included a large population (about 500,000 adults, aged over 30) in 116 US cities and reported relative risks of 1.06 (95% CI: 1.04 – 1.08) for a 10 $\mu g\ m^{-3}$ increase in $PM_{2.5}$ concentration for all-cause. These mortality risk estimates have been used to assess the health burden attributed to $PM_{2.5}$ exposure in the US (Punger and West, 2013; Li et al., 2016) and globally (Anenberg et al., 2010). In this study, we mainly adopted the C-R relationships from Krewski et al. (2009) to quantify the premature mortality change in the future. The baseline incidence rates for premature mortality analyses were taken from the Center for Disease Control and Prevention (CDC, 2016). The spatial scale for health impact assessment is 12×12 km, same as the air quality simulations. Additional details of the selections of health impact functions and source of the input parameters are listed in Tables S3 and S4 in Supplemental Information. For the base year population, the 2010 block-level US Census population data were allocated to our study domain using the PopGrid program (USEPA, 2017a). The county-level population growth rates for each year from 2000 through 2050 were developed by Woods & Poole (2015) and pre-installed in the BenMAP model.

3. Results

3.1. Changes in Freight Transportation Emissions

An investigation of the distributions of changes in freight emissions will enhance our understanding of changes in predicted air quality. Figure 2 plots the distributions of differences in emissions between the CTR case and the BASE case. These differences in emissions are only due to changes in freight emissions. Here we use elemental carbon as an example, as it is a tracer for diesel emissions (Roy et al., 2011; Lane et al., 2007). The predominant changes in long-haul truck emissions take place along roadway networks and in large urban areas. The rail sector shows widespread reductions in emissions over railway tracks. One notable difference between the two is that the truck sector exhibits substantial reductions over metropolitan areas while the rail sector shows relatively high reductions along several main line tracks.

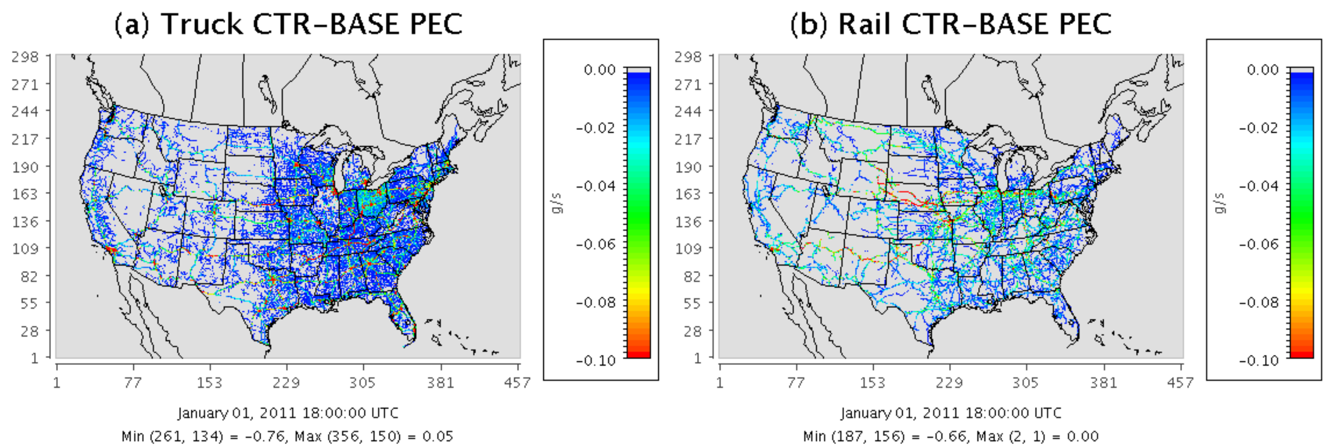

Figure 2. Changes in elemental carbon emissions between the CTR case and BASE case (CTR minus BASE) from the two freight transportation sectors: (a) truck and (b) rail. Note: the color-bars depict only negative/decrease because of the substantial reductions (60-80 %) in emissions in the CTR case. Both panels are snapshots and the units "g/s" represent the amount of emissions (in gram) produced per second.

3.2. Changes in Air Quality

We studied CMAQ outputs to examine the spatial patterns of changes in ground-level $PM_{2.5}$ concentrations. As illustrated in Figure 3, reductions of $PM_{2.5}$ concentrations are generally attained over the eastern US, similar to the regions demonstrating major reductions of freight emissions. The greatest reductions (1-1.5 μg m^{-3}), however, appear in the Midwest and California. The large reduction over the Midwest may be the result of several factors. First, temperatures are lower in the north than south. The northern US, particularly the Midwest, are frequently impacted by winter cold fronts and high pressure systems. As depicted in Figure S6, regions with the lowest surface temperature highly coincide with Midwest states experiencing the largest $PM_{2.5}$ reduction. Due to lower temperatures, the planetary boundary layer (PBL) is thinner over these regions, which reduces vertical mixing, and hence the dilution rates of $PM_{2.5}$ species. A similar phenomenon was described by Wang et al. (2014). Second, large concentrations of secondary $PM_{2.5}$ species can be generated under high humidity and reduced advection (Walker et al., 2012; Heo et al., 2016). In particular, greater amounts of secondary inorganic aerosols, such as nitrate and ammonium, are produced during the cold season (Jeon et al., 2015; Souri et al., 2017).

Fine nitrate is produced by the gas-phase reaction of nitric acid (HNO_3) with ammonia (NH_3). The chemistry favors the production of ammonium nitrate (NH_4NO_3, a component of $PM_{2.5}$) at low temperature and high humidity. The reaction product NH_4NO_3 is also less volatile in cold weather than in hot weather. The regions with higher post-policy difference of pollutant concentration usually coincide with those with higher initial concentration.

Since differences between other policy scenarios (i.e., PO and NS) and the BASE case, as plotted in Figure S7, are hard to distinguish from those between CTR and the BASE in Figure 3, we then used the CTR as a benchmark, and subtracted CTR from PO and NS to understand the incremental impact of climate policy and further technology improvement. As seen in Figure S8, for the relative changes between PO and CTR, $PM_{2.5}$ concentration reductions coincide with areas where the decrease in truck emissions larger than the increase in rail emissions (relative emissions changes in Figure S10), causing net reductions in $PM_{2.5}$ concentrations. In contrast, the increase in $PM_{2.5}$ concentrations in states such as Nebraska and North Dakota is due to the net increase in rail emissions in these regions. The positive values outside US borders could be due to the atmospheric transport and complex nonlinear atmospheric chemistry. The NS case predicts general reduction of $PM_{2.5}$ concentrations over the US, due to further reduction of truck emissions compared to the CTR case. The percentage changes in $PM_{2.5}$ concentrations between different cases are plotted in Figure S9. The percentage changes in air quality are significant smaller than those changes in emissions. These are due to the interplay of various atmospheric processes (e.g. emission, transport, and chemistry) (Pan et al., 2017).

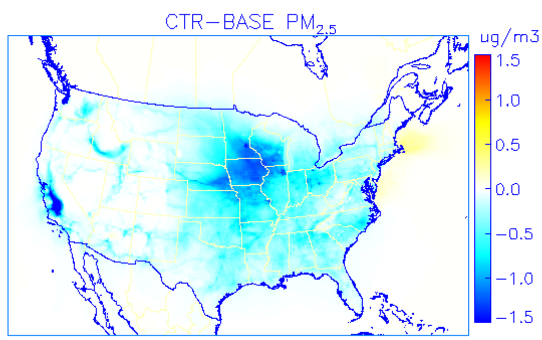

Figure 3. Changes in $PM_{2.5}$ concentrations resulting from the changes in freight emissions between the CTR case and BASE case (CTR minus BASE).

3.3. Changes in Premature Mortality, Morbidities, and Economic Benefits

We studied $PM_{2.5}$ concentrations from CMAQ air quality simulations of various scenarios over the continental US and compared them with the 2011 reference case to assess the health co-benefits for each of the future policy/technology scenarios. As depicted in Figure S11 and Table 1, based on the C-R relationships from Krewski et al. (2009), emissions reductions from freight transportation provide substantial prevented premature mortality, including 3,600 (95% CI: 2,400 – 4,800) cases of avoided early deaths in the CTR case and 4,400 (95% CI: 2,900 – 5,800) cases in the NS case. The associated economic benefits range from \$38 (95% CI: \$3.5 – \$100) to \$45 (95% CI: \$4.2 – \$120) billion (in inflation-adjusted 2015 dollars). Compared to the CTR case, the prevented premature mortality and benefits are estimated to be ~9% and ~20% higher in the PO and NS cases, respectively. Liu et al. (2019) reported the prevented premature mortality of 2060 cases vis-à-vis 3600 (95% CI: 2,400 – 4,800) cases in this study, due to stringent freight emission control. Since both studies used the same C-R relationships from Krewski et al. (2009), the differences in health results could be partly resulted from the different approaches in simulating air quality. Liu et al. (2019) used a reduced-from air quality model, the Intervention Model for Air Pollution (InMAP) (Tessum et al., 2017). While this study used the CMAQ model, a tool for regulatory impact analysis recommended by the USEPA. Nevertheless, both models predicted highest freight-contributed $PM_{2.5}$ concentrations in the Midwest and West Coast.

The estimates of prevented premature mortality and benefits using other epidemiological references for different age groups are also presented in Table 1. Compared to Krewski et al. (2009), estimates using Lepeule et al. (2012) provide higher prevented premature mortality values because they report higher C-R coefficients. We also provide the estimates of prevented early deaths for infants based on Woodruff et al. (1997). The results are 13 (95% CI: 4.9 – 20) in the CTR case, 14 (95% CI: 5.3 – 22) in the PO case, and 15 (95% CI: 5.9 – 24) in the NS case.

Table 1. Estimates of prevented premature mortality and benefits attributable to freight emission reductions in future year scenarios. The unit of Incidence is [Number of Deaths], and the unit of Benefit is [Billion Dollars, in 2015 currency year].

Epidemiological Reference		**Stringent Control**	**Climate Policy (carbon tax)**	**No Super-emitters**
Krewski et al. (2009) (Age: 30-99)	Incidence	3,600 (2,400 – 4,800)	3,900 (2,700 – 5,200)	4,400 (2,900 – 5,800)
Krewski et al. (2009) (Age: 30-99)	Benefit	$38 ($3.5 – $100)	$41 ($3.8 – $110)	$45 ($4.2 – $120)
Lepeule et al. (2012) (Age: 25-99)	Incidence	8,200 (4,100 – 12,000)	8,800 (4,400 – 13,000)	9,800 (4,900 – 15,000)
Lepeule et al. (2012) (Age: 25-99)	Benefit	$85 ($7.5 – $240)	$92 ($8.2 – $260)	$100 ($9.1 – $290)
Woodruff et al. (1997) (Age: 0; infants)	Incidence	13 (4.9 – 20)	14 (5.3 – 22)	15 (5.9 – 24)
Woodruff et al. (1997) (Age: 0; infants)	Benefit	$0.13 ($0.011 – $0.38)	$0.14 ($0.012 – $0.42)	$0.16 ($0.013 – $0.46)

Notation: (1) the BASE scenario is the baseline case in the BenMAP model, and the future year scenarios are the different control cases; (2) In the 3rd to 5th columns, the numbers in parentheses represent 95% confidence intervals, which are resulted from a full Monte-Carlo analysis performed by BenMAP, by randomly sampling an uncertainty distribution around the C-R coefficients or willingness to pay estimates.

In addition, the results for prevented morbidities in the future year scenarios are listed in Table S5. The morbidities include hospitalizations (from asthma, chronic lung, all respiratory, and all cardiovascular (less myocardial infarctions)), emergency room visits, asthma exacerbation (cough, wheeze, shortness of breath, and upper respiratory symptoms), and minor effects (e.g., acute bronchitis, work loss days, minor restricted activity days, and lower respiratory symptoms). Similarly, these results suggest significant health benefits from continuous implementation of emission control standards, further benefits from climate policy, and more from the removal of high-emitting conditions in the truck fleet. All of the future scenarios yield considerable health benefits in terms of prevented morbidities, from a few hundred to thousands of prevented hospitalizations and emergency room visits, as well as hundreds of thousands to several million cases of prevented asthma exacerbation and minor effects over the US. The magnitudes of these morbidity results are consistent with those provided in the "Pyramid of Effects" from air pollution (USEPA, 2018), suggested by the USEPA. The economic costs of morbidities can be estimated using the cost of illness, which includes direct medical costs and lost earnings associated with illness. The economic values from morbidity reduction are not provided here as the prevented premature mortality accounts for more than 90% of the monetized benefits (USEPA, 2018).

3.4. Geographic Distribution of Prevented Premature Mortality

The spatial distributions of health impacts provide useful information to identify the high impact regions of freight emission reductions. The spatial distributions of prevented premature mortality are plotted in Figure 4. These are the results at county- and state-levels, respectively. Recalling the formula of C-R functions, for a given epidemiological study (Krewski et al., 2009) and a given health endpoint (mortality), the corresponding C-R coefficient and the baseline incidence rates are fixed, so the change in the incidence of the health endpoint is mainly attributable to the change in air quality and the population affected. As illustrated in the county-level map in Figure 4, higher values of prevented premature mortality mostly coincide with large metropolitan areas. While the change in air quality can vary significantly across the continental United States, as illustrated in Figure 3, metropolitan areas or large cities can benefit from a large number of prevented early deaths due to their high population densities (Heo et al., 2017). Some examples include: Los Angeles and the San Joaquin Valley, California; Houston and Dallas, Texas; Chicago, Illinois; and Phoenix, Arizona. The bar-plots of state-level prevented premature mortality are presented in Figure S12. The top five states that have the highest prevented early deaths from freight emission reductions are California (1123), Texas (266), Illinois (260), Ohio (169), and Florida (154).

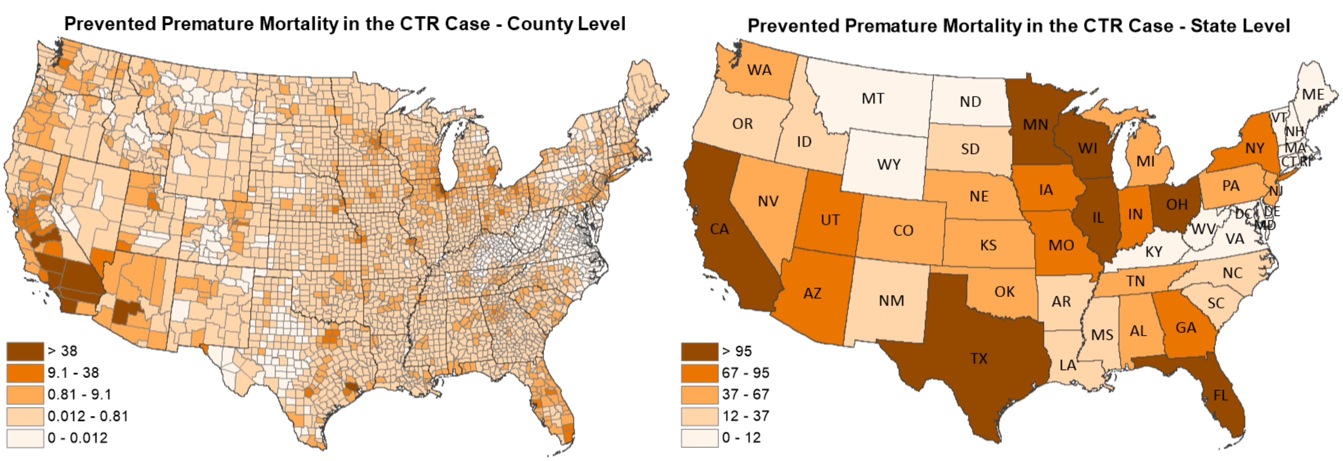

Figure 4. Distributions of the prevented premature mortality due to the changes in freight emissions between the CTR case and BASE case (CTR minus BASE). These are the prevented premature mortality attributable to $PM_{2.5}$ at county-level (left panel) and state-level (right panel).

To investigate the health impact of climate policy, we used the CTR case as the baseline case, and the PO case as the control case for the input of BenMAP. The result is presented in Figure 5. The health impact calculations in BenMAP are based on concentration-response functions, typically expressed as a decrease in health incidence (or response) due to a decrease in concentration of air pollutant, and vice versa. Thus, the increase in $PM_{2.5}$ concentrations in Nebraska and North Dakota (Figure S10) would result in more premature deaths in the same regions (Figure 5). Climate policy shifts freight from truck to rail, which causes reductions in total emissions and health impacts. But the policy also affects public health geographically. Table S6 lists the top fifteen counties that have the highest estimates of prevented premature mortality in each future year scenario. For each listed county, compared with the CTR case, the PO and NS cases estimate a greater number of prevented early deaths. However, the relative efficiency of the policy strategies varies across those counties. For instance, implementation of climate policy and further technology improvement to remove high-emitting trucks can increase lives saved by 7% and 15% in Cook County, Illinois; and such benefit would rise to 10% and 23% in Los Angeles County, California.

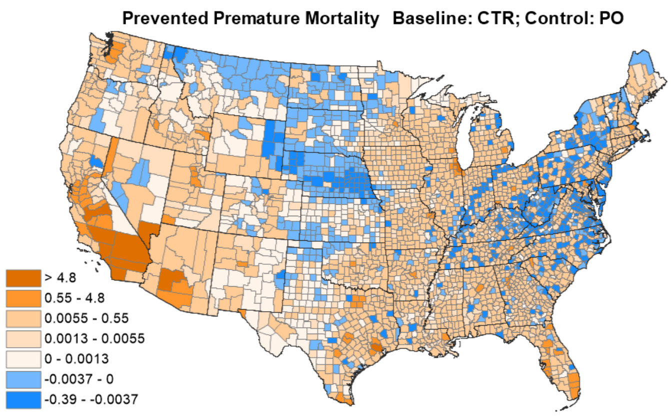

Figure 5. Prevented premature mortality due to the changes in $PM_{2.5}$ concentrations between the PO case and CTR case (PO minus CTR) at the county-level.

4. Discussion and conclusions

This study employed an integrated emissions-air quality-health impact assessment system to quantify the impact of projected freight transportation emissions (long-haul truck and rail emissions) over the US in 2050. Multiple scenarios with varying policy assumptions were considered. In general, the findings show that $PM_{2.5}$ concentrations will decrease by 2050 thanks to reduction in freight transportation emissions. The estimated mortality, morbidities, and economic benefits follow the trends in the change in $PM_{2.5}$ concentrations. Large metropolitan areas with high population density would particularly be the winners from freight emission reductions.

In the scenario with high GDP growth and fleet turnover, relatively strict controls on fuel and emissions are assumed. This scenario assumes no new policies on vehicle emissions and fuel quality beyond those currently implemented or adopted. The scenario did consider approximately 30% and 25% reductions in fuel intensity from 2007 to 2050 for long-haul trucks and locomotives, respectively. These reductions are based on historical trends and projections from the literature (Fulton et al., 2009; Vyas et al., 2013). Future fuel intensity reductions, which indirectly lessen emissions factors, reflect the development and manufacture of new, highly effective technology. Therefore, in order to achieve emission reduction goals and the co-benefit in public health, stringent emission standards and fuel policies should be continuously and effectively implemented. In addition, the social benefits of reduced freight emissions are expected to largely exceed the implementation costs of such standards/policy. For instance, the cumulative costs for compliance with US 2010 or Euro VI standards (compared to US 1994 or Euro II) are the same, both at $6,937 (in inflation-adjusted 2015 dollars) per vehicle (ICCT, 2016). Assuming an average lifespan of 10 years for long-haul diesel trucks and a complete fleet turnover each decade, that is, a population of about (2.0 + 2.5 + 2.8 + 3.2 = 10.5) million (USEPA, 2015a), the total compliance costs from 2011 to 2050 would be around $73 billion (about $1.8 billion year^{-1}), which is less than the low-end of calculated health benefits ($3.5 billion year^{-1} based on Krewski et al. (2009)) from this study. Also, the compliance costs are one-twentieth of the calculated mean health benefits ($38 billion year^{-1}). Moreover, current diesel vehicles still produce much more NO_x emissions under real-world operating conditions than during laboratory certification testing. Anenberg et al. (2017) estimated that nearly one-third of on-road heavy-duty diesel vehicle emissions were in excess of certification limits in global leading markets including the US. They suggested that adopting and enforcing newer standards (e.g., more stringent than Euro VI for heavy-duty vehicles) could nearly eliminate real-world diesel NO_x emissions in these regions.

Climate policy that shifts freight demand from truck to rail can attain further health benefits nationally, but could make certain regions worse off due to geographic variability of freight activities, and hence influence health endpoints. With carbon tax of climate policy, regions with fewer trucks could gain in health benefits, while regions with added rail freight may potentially cut their local air quality improvement in terms of $PM_{2.5}$ pollution. The climate policy scenario assumes that a 450 ppm CO_2 concentration will be achieved by 2050, which represents the low end of CO_2 concentrations in Representative Concentration Pathways (RCP) scenarios (i.e., RCP2.6). As the policy scenario favors the transition from diesel truck to rail, future investments are required in the rail system and infrastructure. However, the RCP2.6 is an aggressive global greenhouse gas mitigation scenario. Therefore, in the event that such stringent climate policy controlling the level of CO_2 concentration were not established, that would reduce the truck-to-rail shift of freight transportation. Then the changes in air quality and health benefits would be between the numbers reported in the CTR case and PO case. Besides carbon tax, other forms of policy strategies, such as motor fuel taxes, tolls, other emission-based fees, and tighter truck size and weight restrictions, may incentivize a freight modal shift (Brogan et al., 2013). These may lead to similar trends of changes in air quality and health effects as those from climate policy.

The removal of high-emitting trucks provides substantial further reductions in particulate matter emissions. Tighter standards for new vehicles alone (i.e., the CTR case) may not sufficiently protect environmental quality and public health. The phasing-out of super-emitters (i.e., the NS case) should be particularly addressed and accelerated if possible. High-emitting conditions could be eliminated through the identification and repair of individual vehicles, or improvements in durability standards. Financial resources – the Volkswagen settlement (USEPA, 2017b; NASEO, 2017) as an example – can be used to subsidize technological changes, including vehicle repair/retrofit/replacement, along with the application of cost minimization strategies across the fleet (Gao and Stasko, 2009; Stasko and Gao, 2012). We have provided an estimation of the costs for fully replacement of super-emitters using new vehicles. Assuming an average rate of 6% of super-emitters in the truck fleet (a population of ~0.6 million), the 2015 fleet average US truck price was $157,000 (ICCT, 2016), then the costs for high-emitting truck replacement from 2011 to 2050 would be around $94 billion. Adding to the $73 billion in CTR case, the total policy costs in the NS case would be $167 billion (~$4.2 billion year^{-1}), which is about one-tenth of the calculated mean health benefits ($45 billion year^{-1} based on Krewski et al. (2009)).

Our results suggest that a complete fleet turnover under the latest emission standards/policies would significantly reduce harmful emissions and attain improved air quality and health benefits. Such fleet turnover, however, would have to take place over several decades. Before the complete turnover is achieved, emissions from long-haul freight transportation would contribute to thousands of premature deaths. Therefore, populated states (e.g., California, Texas, etc.) and metropolitan areas (e.g., Los Angeles, Houston, Chicago, etc.) should take early actions to control freight emissions. Incentive programs, such as California Air Resources Board's Carl Moyer Program, Proposition 1B, and Low Carbon Fuel Standard, can help to accelerate fleet replacement/turnover.

The findings from the above-mentioned air quality and health assessments of different control policies in this study can provide useful information for reducing air pollution from diesel-powered freight activities not only in the US but also other countries. For instance, in January 2019, the Ministry of Ecology and Environment of China published new guidelines on regulating highly-polluting diesel trucks (MEE, 2019). China set goals to substantially increase the compliance rate (at least 90%) of in-use diesel trucks by 2020. Highly-polluted regions, such as the northern regions near the capital Beijing, will be mandated to implement advanced "China VI" standards starting in July 2019. And more than one million outdated diesel trucks in the northern regions will be eliminated by the end of 2020. Thus, similar to the stringent control and no super-emitters scenarios in this study, it would be interesting to see how the implementation of such strict control policies could impact the air quality and health in China. It would be expected to obtain vast health benefits from freight emission control, considering the large population densities in Chinese cities and current high pollution levels. In addition, both China and European countries expressed their commitments on increasing the rail freight modal share (MEE, 2019; RFFC, 2018). In this study, we highlighted the potential environmental injustice resulted from the modal shift, implying the necessity of rail freight planning under careful environmental impact assessment.

An alternative approach to mitigating freight emissions is to replace diesel fuel in the trucking sector, for example, by adopting alternative fuels or via electrification (Peng et al., 2018). There are recent efforts on fuel cell heavy duty. Toyota just deployed a fuel cell tractor-trailer, as did Nikola. Hydrogenics recently came up with fuel cell light rail. Electric/fuel cells have significantly higher fuel economy. For example, the Argonne National Laboratory's AFLEET model indicates an electric tractor-trailer with fuel economy of 19 mpg, as opposed to 7 mpg for diesel, in diesel gallon equivalent. However, because electrification of freight transport would increase energy demands on the electricity generation infrastructure, efforts in renewable or cleaner energy production would also need to be promoted (Elgowainy et al., 2010; Tessum et al., 2014). The adoption of electric vehicles may also be impacted by factors such as consumer preference, government intervention (Walsh, 2018; Peng et al., 2018), vehicle purchase price and operating cost, and technology advancement. Further, other emerging transportation innovations, such as the advent of connected and autonomous vehicles (Sperling, 2018), are expected to have a vast impact on the current transportation infrastructure, and hence on emissions. Thus, the future reduction of emissions from the freight transportation sectors requires a combination of systems actions involving the corporate, public, academic, and government.

It should be noted that this study poses several limitations and uncertainties. One important limitation about the climate policy assessment in this study is that the policy was applied at the national level, that is, the same fractional changes of emissions (about 25% increase in rail and 35% decrease in truck) were conducted over the entire continental US. The emission adjustment factors would be unfixed if the inter modal shift were represented either with sub-national or commodity-level detail (Bickford et al., 2013). Future air quality and health impact assessments need to consider these points to evaluate a more realistic regional-scale emissions change. In addition, the climate policy scenario assumes an increase of carbon price from $30 in 2010 to $130 in 2050. A recent energy modeling comparison study, the Stanford Energy Modeling Forum (EMF) 32 study, used a set of different carbon price trajectories in the US from year 2020 to 2050: $25 to $34, $50 to $67, $25 to $108, and $50 to $216. Their results indicate higher reductions in CO_2 emissions under more ambitious carbon prices (McFarland et al., 2018). The carbon price path used in our study is halfway between the two more aggressive carbon price paths in the EMF 32 study.

In order to investigate the sensitivity of change in freight emissions within the US, we focused on the emissions from the long-haul truck and rail sectors; emissions from other major sectors were fixed to their present levels. This may induce some uncertainty in our predictions. For instance, as population grows in the urban areas, besides the rising demand of freight activity, the demand for buildings and power generation will largely increase, and hence impact on the emission amount of area and point sectors. However, the emissions from area and point sectors do not necessarily increase as future projections also indicate increase in energy efficiency of the buildings and de-carbonization of the power system (USDOE, 2015). Another uncertainty not considered is the potential changing weather conditions in 2050, as in this study the meteorological factors were kept unchanged across scenarios. The climate impact resulting from change in emissions of GHGs due to evolution of freight and other sectors will be likely to alter the future weather conditions. In addition, the year 2011 was selected as the reference year because NEI 2011 was used as the base inventory. However, the meteorological conditions usually vary year by year and using the meteorological input of this limited time period could possibly lead to uncertainty in the simulated results for air quality. This uncertainty could be potentially partly reduced in this study from the bias-correction of the air quality model fields using monitoring data in 2009-2013. It should be noted that the uncertainties in air quality modeling system are higher than the freight-induced air quality change in future year scenarios. For instance, the differences in simulated $PM_{2.5}$ concentrations between PO and NS compared to CTR are very small (lower than 0.1 ug/m^3). Hence, the comparison between CTR and PO can be largely affected by the modeling system associated uncertainties. This becomes a more important issue as the health impact estimation is based on the change in concentrations.

In the health impact analysis, all the $PM_{2.5}$ species were assumed to have equal toxicity. It is possible that certain species are more toxic than others, but there is no adequate data that can be used to assess the $PM_{2.5}$-related health impacts differentiated by speciated components. In addition, the concentration-response relationships from epidemiological references were usually developed based on long-term average $PM_{2.5}$ exposure levels (Krewski et al., 2009; Fann et al., 2012; Punger and West, 2013). In order to apply these relationships for health impact assessment, one has to use proxies for annual average exposure levels. While in this study we conducted one-month winter simulations. So the emissions and air quality changes here are only representative of wintertime conditions. Hence, the health impacts reported here may be under- or over- estimated regionally, considering the variability of particle mass concentrations across seasons. Future studies should at least take the average of four representative months (Jan, Apr, Jul, Oct) to proxy for average exposure. Also as reported by Bell et al. (2007) that $PM_{2.5}$ concentrations were highest in summer, then the change in $PM_{2.5}$ concentrations between baseline case and control case would possibly also be highest in summer, the subsequent health responses in summer would be higher than those calculated using change of annual average concentrations. Thus, the assessments using a winter month in this study could avoid an over-prediction of the health outcomes at national level. What's more, even the greatest concentration changes appear in the Midwest (in Figure 3), still the population density is a critically important factor in the health impact calculations (or C-R functions) that populated states (e.g., Texas, Florida) can obtain substantial health benefits without having the largest change in air quality (Figures 3 and 4). Therefore, findings from the cross-scenario comparisons and geographic distributions of health impact results can be considered effective given the consistency of the assumptions across the scenarios. These findings can provide useful information for policy-makers to identify national, regional, and local control strategies to achieve sustainable freight goals noted earlier.

Acknowledgements

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Supplemental Information

S1. Emission scenarios, and the WRF and CMAQ model configuration options

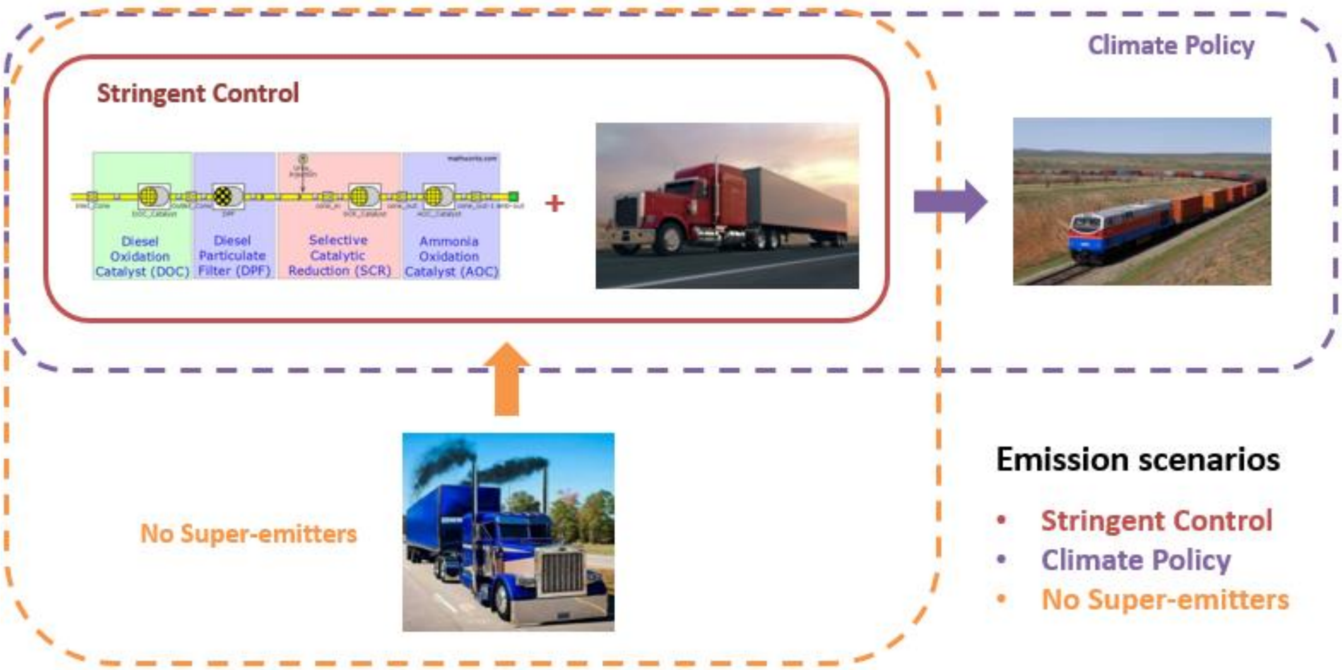

Figure S1. The relationships of the emission scenarios.

Table S1. Major CMAQ options.

CMAQ version	v5.0.2
Chemical mechanism	CB05 gas-phase mechanism with active chlorine chemistry, updated toluene mechanism, sixth-generation CMAQ aerosol mechanism with sea salt, aqueous/cloud chemistry
Horizontal advection	YAMO
Vertical advection	WRF omega formula
Horizontal diffusion	Multiscale
Vertical diffusion	Asymmetric Convective Model (ACM) version 2
Deposition	M3dry
Chemistry solver	SMVGEAR
Aerosol chemistry	AERO6
Lightning NO_x emission	Included inline
Cloud option	ACM cloud processor for AERO6

Table S2. WRF physics options.

WRF version	v3.7
Microphysics	Lin et al. scheme
Long-wave radiation	RRTMG
Short-wave radiation	New Goddard scheme
Surface layer option	Monin-Obukhov with Carlson-Boland viscous sublayer scheme
Land-surface option	Unified Noah LSM
Urban physics	None
Boundary layer	YSU
Cumulus cloud option	Kain-Fritsch
FDDA	Grid analysis nudging

S2. Changes in Freight Transportation Activity, Emissions, and Air Quality

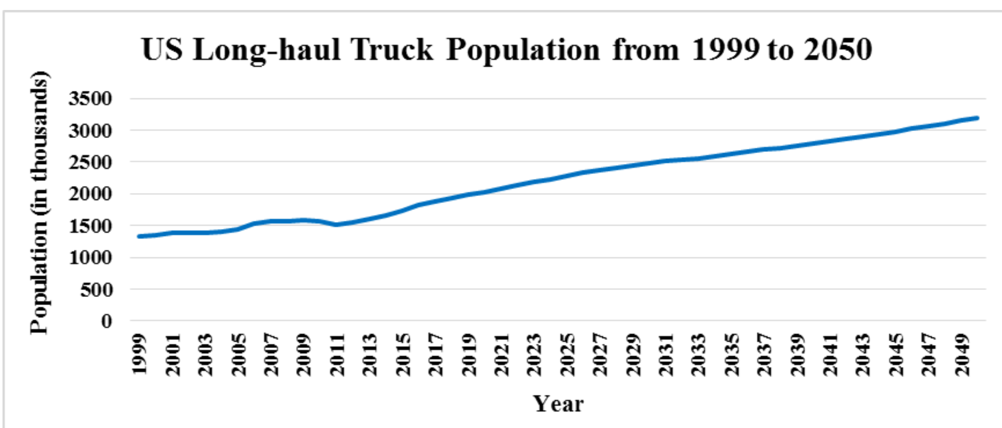

Figure S2. The US long-haul truck population from 1999 to 2050. The population data during 1999-2011 were derived from registration data from the Federal Highway Administration's annual Highway Statistics report. The data between 2012 and 2050 are projected values from EPA MOVES (USEPA, 2015). The population of long-haul trucks would increase by 110% during 2010-2050.

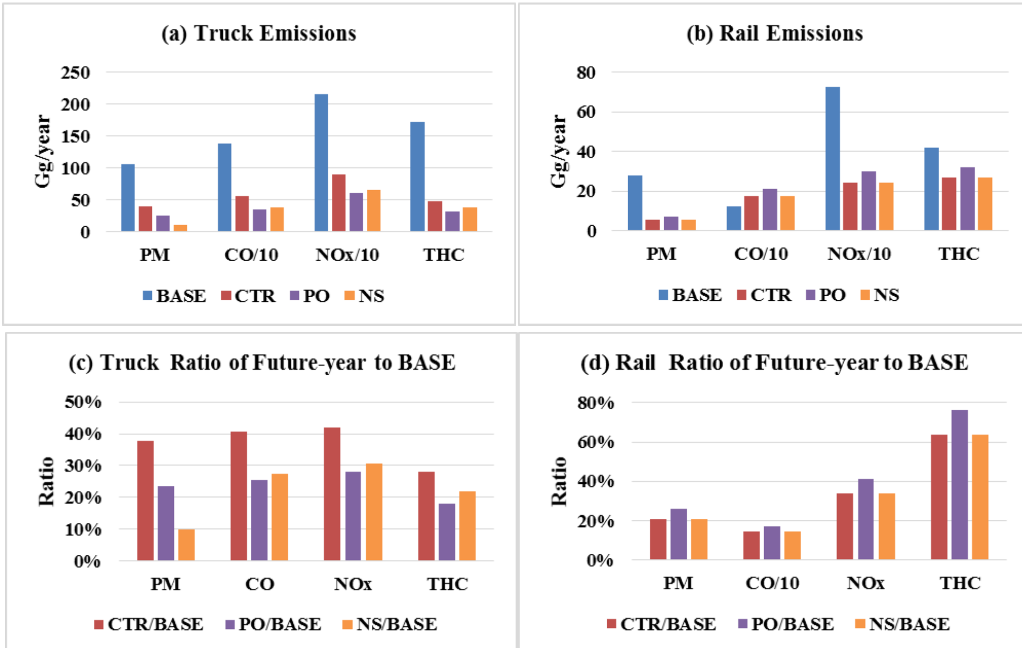

Figure S3. Freight emissions in each simulation scenario for particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x), and total hydrocarbon (THC). (a) Total long-haul truck emissions, (b) total rail emissions, (c) the ratio of emissions of each future year case compared to BASE case for long-haul truck sector, and (d) similar as (c) but for rail sector. (Acronyms of the names of simulation cases: BASE - baseline, CTR - stringent control, PO - climate policy, NS - no super-emitters). These projections are based on Liu et al. (2015).

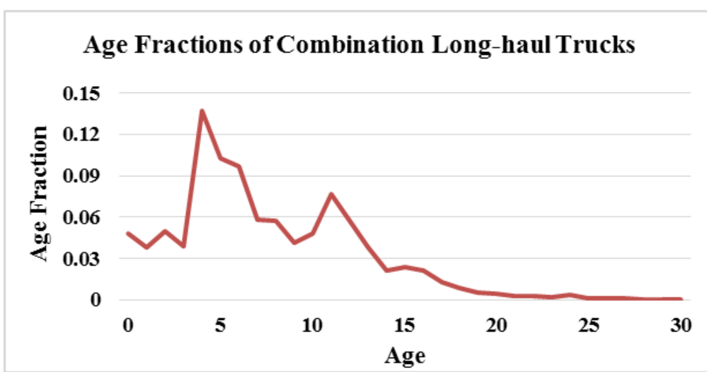

Figure S4. The 2011 age distributions of the US combination long-haul trucks from the EPA MOVES model (USEPA, 2015a). Note this figure indicates a typical lifespan of long-haul trucks. The age distributions would be different with varying conditions. For instance, under an economic crisis, total freight demand and vehicle travel tend to lower, and hence average lifetime periods for trucks would be longer. The Tier 4 locomotive is designed for a typical lifetime of 25-30 years.

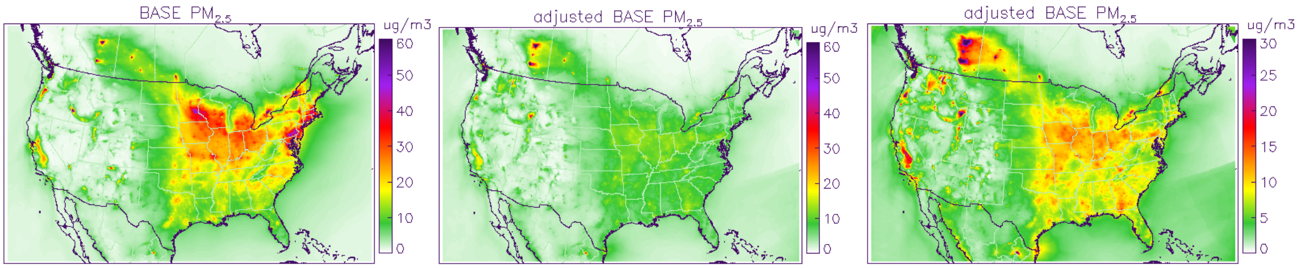

Figure S5. The episode average $PM_{2.5}$ concentrations in (a) the BASE case, (b) the adjusted BASE case (bias-corrected using SMAT-CE), and (c) similar to (b) but at different color scales.

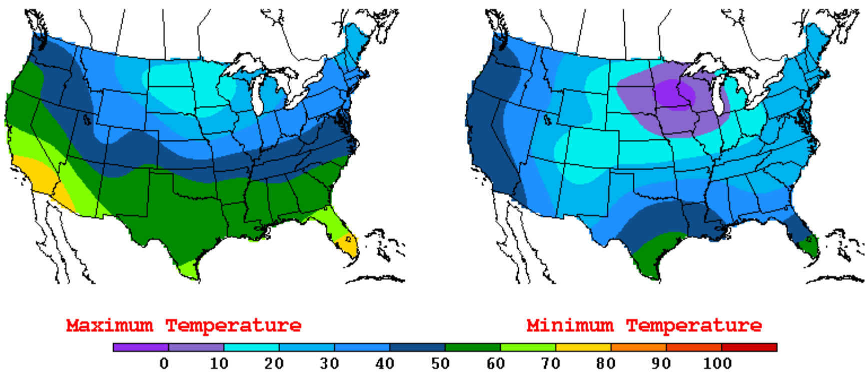

Figure S6. Surface distributions of maximum temperature (left panel) and minimum temperature (right panel) on 16th January 2011 (as reported by the National Centers for Environmental Prediction, Hydrometeorological Prediction Center, http://www.wpc.ncep.noaa.gov/dailywxmap/index.html), with units in ºF. Other days of the month showed generally similar patterns.

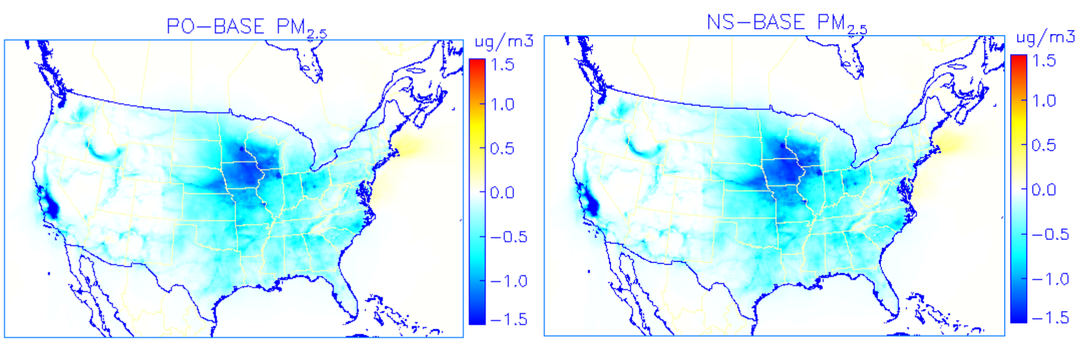

Figure S7. Distributions of the change in $PM_{2.5}$ concentrations due to the change in freight emissions between the future cases and the BASE case (future cases minus BASE).

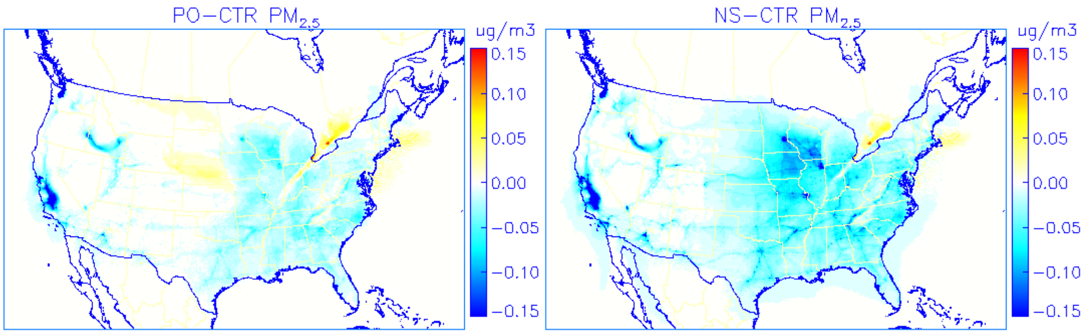

Figure S8. Distributions of the change in $PM_{2.5}$ concentrations due to the change in freight emissions between the future cases and CTR case (future cases minus CTR). Note: the color scales in Figure S8 are different from those in Figure S7 to show better clarity.

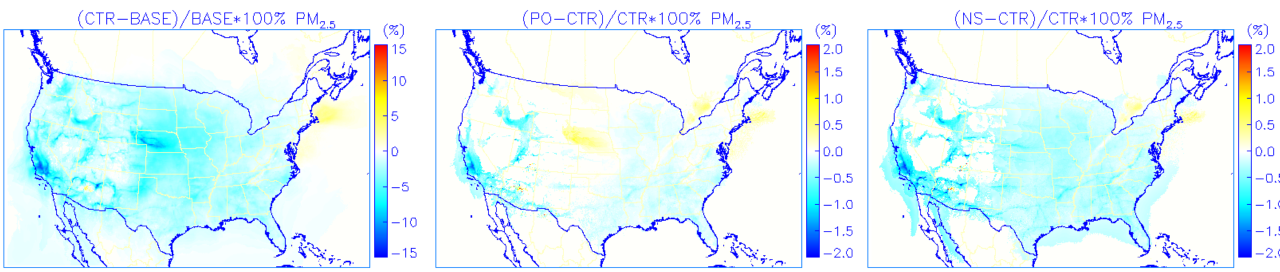

Figure S9. The fractional changes in $PM_{2.5}$ concentrations between different cases: (a) CTR-BASE, (b) PO-CTR, and (c) NS-CTR.

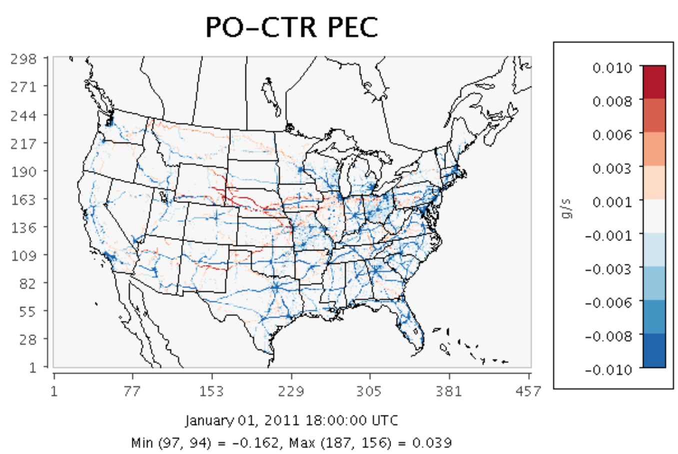

Figure S10. Distribution of the change in elemental carbon emissions between the PO case and CTR case (PO minus CTR).

S3. Health Impact Functions and Morbidities Results

The relationship between changes in air pollutant concentrations and incidence of health outcome (i.e., β) are usually assessed in epidemiological studies. These studies have produced a number of C-R functions that have been incorporated into the EPA BenMAP model and can be selected by the user. The selections of health impact functions and source of the input parameters in this study, listed in Table S3 and S4, are based on an approach recommended by USEPA (USEPA, 2012; 2017a). Because the health impact functions for morbidities were derived from fewer cities or smaller time-scale sample sizes, results from multiple epidemiological studies were used to estimate the morbidity risk outcome.

Table S3. The health endpoints quantified in this study and the risk estimates from epidemiological studies.

Health Endpoint	Start Age	End Age	Risk Estimate, β	Epidemiological Reference
Mortality, All Cause	30	99	0.00583	Krewski et al., 2009
Mortality, All Cause	25	99	0.01310	Lepeule et al., 2012
Mortality, All Cause	0	0	0.00392	Woodruff et al., 1997
Hospital Admissions (HA), Asthma	0	64	0.00200 0.00332	Babin et al., 2007 Sheppard, 2003
HA, All Respiratory	65	99	0.00070 0.00207	Kloog et al., 2012 Zanobetti et al., 2009
HA, Chronic Lung Disease	18	64	0.00220	Moolgavkar, 2000
HA, All Cardiovascular (less Myocardial Infarctions)	65	99	0.00080 0.00068 0.00071 0.00189	Bell et al., 2008 Peng et al., 2008 Peng et al., 2009 Zanobetti et al., 2009
HA, All Cardiovascular (less Myocardial Infarctions)	18	64	0.00140	Moolgavkar, 2000
Emergency Room Visits, Asthma	0	99	0.00392 0.00560 0.00296	Glad et al., 2012 Mar et al., 2010 Slaughter et al., 2005
Acute Bronchitis	8	12	0.02721	Dockery et al., 1996
Asthma Exacerbation, Wheeze, Cough, Shortness of Breath	6	18	Wheeze: 0.00194 Cough: 0.00099 Shortness of Breath: 0.00257	Ostro et al., 2001
Asthma Exacerbation, Wheeze, Cough, Shortness of Breath	6	18	Cough: 0.01906 Shortness of Breath: 0.01222	Mar et al., 2004
Work Loss Days	18	64	0.00460	Ostro, 1987
Minor Restricted Activity Days	18	64	0.00741	Ostro and Rothschild, 1989
Upper Respiratory Symptoms	9	11	0.00360	Pope et al., 1991
Lower Respiratory Symptoms	7	14	0.01901	Schwartz and Neas, 2000

Table S4. The baseline incidence rates used in the health impact functions.

Health Endpoint	Parameter	Incidence Rates	Source
Mortality, All Cause	Daily or annual mortality rate	Age-, cause-, and county- specific rate	Centers for Disease Control and Prevention, 2016
Hospital Admissions	Daily hospitalization rate	Age-, cause-, and county- specific rate	Agency for Healthcare Research and Quality, 2007
Emergency Room Visits, Asthma	Daily emergency room visit rate	Age-, cause-, and county- specific rate	Agency for Healthcare Research and Quality, 2007
Acute Bronchitis	Annual bronchitis incidence rate, children	0.043	American Lung Association, 2002
Asthma Exacerbation, Wheeze, Cough, Shortness of Breath	Incidence among asthmatic African-American children: daily wheeze daily cough daily shortness of breath	 0.173 0.145 0.074	Ostro et al., 2001
Work Loss Days	Daily incidence rate per person: Aged 18-24 Aged 25-44 Aged 45-64	 0.00540 0.00678 0.00492	Adams et al., 1999
Minor Restricted Activity Days	Daily incidence rate per person	0.02137	Ostro and Rothschild, 1989
Upper Respiratory Symptoms	Daily incidence rate among asthmatic children	0.3419	Pope et al., 1991
Lower Respiratory Symptoms	Daily incidence rate among children	0.0012	Schwartz et al., 1994

Table S5. Estimates of prevented $PM_{2.5}$-induced morbidities in the future year scenarios.

Health Endpoint	Stringent Control	Climate Policy (carbon tax)	No Super-emitters
Hospital Admissions (HA), Asthma	64	69	77
HA, All Respiratory	704	763	850
HA, Chronic Lung Disease	159	172	192
HA, All Cardiovascular (less Myocardial Infarctions) (65-99)	664	720	801
HA, All Cardiovascular (less Myocardial Infarctions) (18-64)	291	316	352
Emergency Room Visits, Asthma	1,660	1,800	2,000
Acute Bronchitis	4,720	5,120	5,660
Asthma Exacerbation, Wheeze, Cough, Shortness of Breath	101,000	109,000	121,000
Work Loss Days	418,000	453,000	502,000
Minor Restricted Activity Days	2,470,000	2,680,000	2,960,000
Upper Respiratory Symptoms	86,200	93,400	103,000
Lower Respiratory Symptoms	60,200	65,200	72,100

S4. Changes in Premature Mortality at National-, State- and County- Level

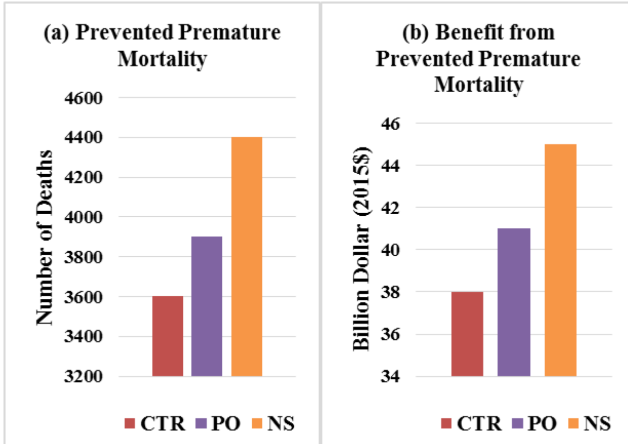

Figure S11. Estimates of prevented premature mortality and benefits attributable to $PM_{2.5}$ reductions in the future year scenarios. These are based on the concentration-response functions from Krewski et al. (2009).

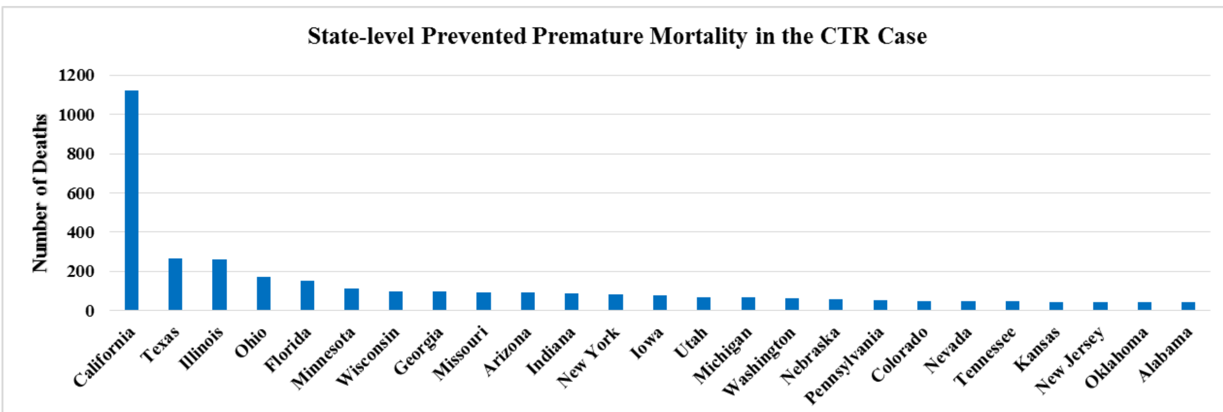

Figure S12. The state-level prevented premature mortality in the CTR case (sorted by number of prevented deaths, from highest to lowest; listed here are states with numbers > 40). The top five states are California (1123), Texas (266), Illinois (260), Ohio (169), and Florida (154).

Table S6. The fifteen counties that have the highest estimates of prevented premature mortality attributable to $PM_{2.5}$ reductions in the future year scenarios.

County, State	Incidence CTR	Rank-CTR	Incidence PO	Rank-PO	Efficiency PO	Incidence NS	Rank-NS	Efficiency NS
Los Angeles, California	305	1	336	1	10%	374	1	23%
Orange, California	127	2	142	2	12%	156	2	23%
Riverside, California	115	3	130	3	13%	146	3	27%
Cook, Illinois	110	4	117	4	7%	126	4	15%
San Bernardino, California	98	5	108	5	10%	122	5	24%
San Diego, California	89	6	99	6	12%	112	6	26%

Fresno, California	67	7	74	8	11%	78	8	17%
Maricopa, Arizona	65	8	77	7	19%	91	7	40%
Kern, California	55	9	60	9	9%	65	9	17%
Harris, Texas	42	10	47	10	11%	52	10	23%
Clark, Nevada	38	11	44	11	16%	51	11	34%
Sacramento, California	30	12	32	12	7%	35	13	16%
Tarrant, Texas	28	13	31	13	10%	34	14	21%
Dallas, Texas	28	14	30	14	7%	35	12	25%
Will, Illinois	28	15	29	15	4%	32	15	15%

Notation: (1) the unit of Incidence is [Number of Deaths]; (2) we first sorted the US counties in the Stringent Control scenario by incidence results (from highest to lowest), then the counties in other scenarios were listed using the same order; (3) For each future year sensitivity case ii, $Efficiency_{ii} = 100\% \times (Incidence_{ii} - Incidence_{CTR})/Incidence_{CTR}$.

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