TECHNICAL NOTE

Modeling the societal health and climate benefits associated with transitioning the US school bus fleet from diesel to electric

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Technical notes document the research or analytical methodology underpinning a publication, interactive application, or tool.

Suggested Citation: Oztaner, Y.B., M. Soltanzadeh, A. Todd, B. Zepka, and A. Hakami. 2025. "Modeling the societal health and climate benefits associated with transitioning the US school bus fleet from diesel to electric." Technical Note. Washington, DC: World Resources Institute. Available online at doi.org/10.46830/writn.24.00024.

Abstract

Approximately 90 percent of the half-million school buses operating in the United States run on diesel, a fossil fuel known to emit harmful pollutants such as particulate matter, nitrogen oxides, and volatile organic compounds. These emissions, particularly from older buses, pose significant health risks to children and drivers, including respiratory and cognitive impairment. Diesel exhaust has been classified as a carcinogen by the World Health Organization. Research shows that older diesel buses emit substantially more pollution than newer models, exacerbating public health burdens. In contrast, electric school buses produce zero tailpipe emissions and have the lowest greenhouse gas emissions of any school bus type, even when accounting for electricity generation. As a result, there is growing momentum toward electrifying school bus fleets, supported by increased public funding and policy interest.

This study is one of the first to model and quantify the health and climate impacts of replacing aging diesel school buses with either new diesel or new electric buses, incorporating both upstream and tailpipe emissions at the US county level. Using reverse source influence modeling, the research estimates the societal benefits of various fleet renewal scenarios. Key questions include which regions would benefit most from electrification and what the national emissions would be under different replacement strategies. The findings are intended to inform policymakers, school districts, manufacturers, and utilities by providing monetized estimates of health and climate impacts, enabling data-driven decisions about school bus fleet modernization.

Introduction

With about half a million school buses nationwide driving a total of 3.16 billion miles per year, school buses are among the most ubiquitous and visible vehicles in the United States. In the 2022–23 school year, more than 21 million students rode the bus to school each day (*School Bus Fleet Magazine* 2024).

An estimated 90 percent of the half-million US school buses are powered by fossil fuels, primarily diesel (Lazer et al. 2022). Diesel exhaust—classified as a carcinogen by the World Health Organization—contains particulate matter, cancer-causing air toxins, nitrogen oxides, and volatile organic compounds (WHO 2012; US EPA 2015). The pollution levels of school buses are closely tied to the age of the bus fleet. Past research has found that a 30-year-old diesel bus produces two to three times more onboard pollution than a three-year-old bus across similar time frames (Austin et al. 2019). Similarly, an old bus can impose significantly higher public health burdens on society than a new bus (Hakami et al. 2024a). Specifically, buses manufactured before 2010 produce significantly more exhaust, which infiltrates the bus cabin and exposes children and drivers to diesel exhaust pollution that negatively impacts their health and cognition.

The World Health Organization estimates that outdoor air pollution caused an estimated 4.2 million premature deaths worldwide in 2019 (WHO 2024). A study by Anenberg et al. (2019) found that transportation emissions contributed to 11.4 percent of deaths related to particulate matter and ozone. Diesel vehicles contributed to the majority of these mortalities and health impacts.

In addition to cancer, exposure to diesel exhaust can lead to increased asthma symptoms and a host of other respiratory illnesses and health impacts such as reduced lung function, more frequent asthma attacks, and impaired cognitive development (US EPA 2025a). Children are especially susceptible to these risks due to their ongoing respiratory development, smaller average lung size, and increased activity levels (Beatty and Shimshack 2011). Further, diesel exhaust can directly impact student academic performance, since it can lead to shortened attention spans and respiratory illnesses that result in absenteeism. Reducing students' exposure to air pollution from school buses while riding, near bus stops, and along bus routes, in contrast, has had positive and significant effects on student English and math test scores (Austin et al. 2019).

Conversely, electric school buses have zero tailpipe emissions, so students and the public aren't exposed to toxic diesel exhaust pollution that contributes to the adverse health outcomes described above. Electric school buses also have the lowest greenhouse gas (GHG) emissions of any school bus type, even when accounting for emissions from the generation of electric power (WRI 2025). Due in part to their associated health and climate benefits, there has been a growing demand for the electrification of school bus fleets (Lazer and Freehafer 2024) as well as a large increase in public funding for electric school buses in the United States (Levinson and Achury 2024). Compared to diesel, electric school buses are attractive to school districts and communities for reasons including decreased operating costs, quieter rides, and opportunities to support grid resiliency. Specifically, about 14,000 electric school buses were on the road or on the way in the United States as of January 2025. At the beginning of 2021, there were just over 1,400 electric school buses on the road or on the way in the United States—meaning we have seen a 10-fold increase in electric school bus commitments in four years (Lazer and Freehafer 2024).

The harms of aging diesel school buses that electric school buses often replace are well documented. However, many of the health and climate impacts of *new electric buses compared to new diesel buses* are not clear. This technical note is currently one of only two known published studies to model and quantify such climate and health impacts for new electric and new diesel school buses from both upstream and tailpipe emissions, specifically at the US county level. A recent study by Choma et al. (2024) follows a similar approach in monetizing climate and public health impacts of diesel school buses and the benefits associated with electrifying school bus fleets, but it uses different models and methodologies, leading to somewhat different results. We compare these results and discuss the differences later in this note.

In this technical note, we define climate impact as the atmospheric release of GHGs and their warming potential, while the health impact is the change in excess mortality due to exposure to fine particulate matter. In estimating these impacts, we account for the atmospheric release of pollutants during school bus operations and, wherever possible, for the emissions associated with upstream generation of the school bus fuel, diesel or electricity. We use a state-of-the-art technique for reverse influence modeling, termed adjoint modeling, to quantify the location-specific impact of operational and upstream school bus emissions (Errico 1997). Depending on the type of school bus—diesel or electric—the overall estimated impact consists of various climate or public health components. For example, the health impact from diesel school buses consists of emissions from the bus's tailpipe and upstream emissions, while the health impact from electric school buses only consists of emissions from upstream electricity generation, since there are zero tailpipe emissions from electric buses.

Estimating the climate footprint of school buses is a straightforward process, as the impact is not dependent on the location of the release of GHGs. GHGs last in the atmosphere for decades, and their impact on the climate is therefore evenly spread across the globe. Consequently, estimating the climate impact of a school bus, diesel or electric, is reduced to estimating GHG emissions associated with its operation.

By contrast, air pollutants such as fine particulate matter (i.e., particulate matter with an aerodynamic diameter smaller than 2.5 mm, or $PM_{2.5}$) have much shorter atmospheric lifetimes, and as a result their impact is heavily dependent on where they are released. The public health impact of these short-lived air pollutants can vary by orders of magnitude depending on proximity to populations, weather patterns, and various atmospheric transport and transformation processes that they can undergo. To cover such complexities, estimating the public health impact of diesel or electric school buses is best carried out by using photochemical air quality models (AQMs) that can account for various atmospheric processes and provide spatial distribution of air pollutants (US EPA 2025b).

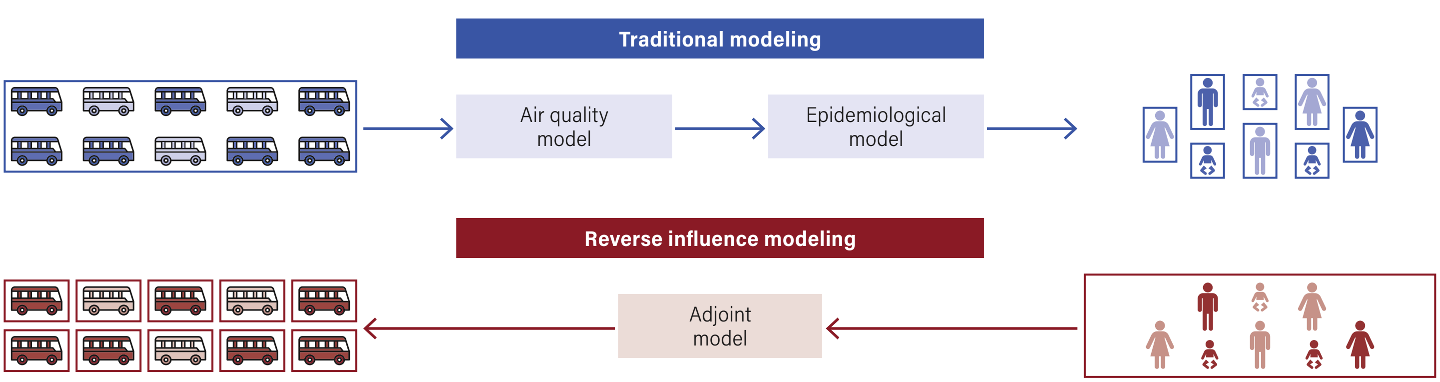
There are various approaches to using AQMs in air pollution health impact assessments. The most common approach is to use AQMs to simulate atmospheric concentrations of pollutants with and without certain sources, or under various intervention scenarios, to elicit the air quality impacts from pollution sources of concern, such as school buses. The results from this approach, schematically depicted in Figure 1, are then used in epidemiological modeling and/or a benefit assessment tool to estimate the resulting population health outcomes, such as asthma exacerbations, emergency room visits, premature mortality, and so on. These health outcomes can be expressed as incident counts, or as valuated or monetized estimates to facilitate benefit-cost analyses. This approach is straightforward and has the advantage that it provides a distribution of health outcomes in the population. However, in this approach (Figure 1, top panel) it is not easy to distinguish between specific polluters, such as school buses in different districts, or school buses of different types or age (vintage) in the same district.

We use a different and more recent technique—reverse source influence modeling—to estimate the impact of emissions associated with school buses in various counties in the contiguous United States. Reverse influence modeling uses an augmented version of a photochemical model, known as an adjoint model, as it traces the overall health impact on the entire population back to individual polluting sources at all locations. In that sense, reverse influence modeling using an adjoint model starts from the overall population health impact as characterized by the combination of a regular AQM and an epidemiological model (Figure 1, bottom panel). The adjoint model then attributes these impacts to emissions from each school bus at each location (i.e., each US county). Contrary to the traditional approach, an adjoint model provides location-specific health impact estimates for school buses.

The primary objective of this research was to model the monetized health and climate impacts associated with replacing aging diesel school buses with new diesel buses or new electric buses in each county in the United States to better understand the impacts from a range of school bus fleet renewal scenarios. These findings would then help us further understand where electrification of school buses entails largest public health benefits. We posed two research questions:

- What estimated monetized health impacts would be associated with replacing old diesel school buses with either new electric or new diesel school buses in each US county?
- What estimated monetized climate impacts would be associated with replacing old diesel school buses with either new electric or new diesel school buses in each US county?

Figure 1 | **Traditional health impact assessment using air quality models (top) versus reverse influence modeling using an adjoint model (bottom)**



Note: The traditional approach provides more information about the locations where health impacts occur, while the adjoint model provides far more detail about the impacts of various sources on the overall population.

Source: WRI authors.

This research is targeted toward policymakers, advocates, researchers, school districts, school bus operators, school bus manufacturers, and utilities who are interested in the health and climate impacts of school bus fleet renewals in the United States. These audiences will be able to use the national or county-level data to compare the total monetized health and climate impacts of replacing older diesel school buses with new diesel buses or electric buses, incorporating both upstream and tailpipe emissions in their respective county or region. This will help users appreciate the health and economic burden of continuing to use aging diesel buses across different counties and states and how new buses may impact health and climate outcomes. Local users can incorporate these data into funding applications and educational materials, as well as use the findings to inform their fleet renewal strategies. While this study uses a novel approach to address some of the questions involving the overall societal impacts of old and new school buses, it should be taken as a first attempt at such quantification since it only addresses certain aspects of the problem; future work exploring other aspects (e.g., other pollutants such as ozone, impact on vulnerable and marginalized groups, higher-resolution estimates, etc.) is needed and may be guided by the findings shown in this technical note.

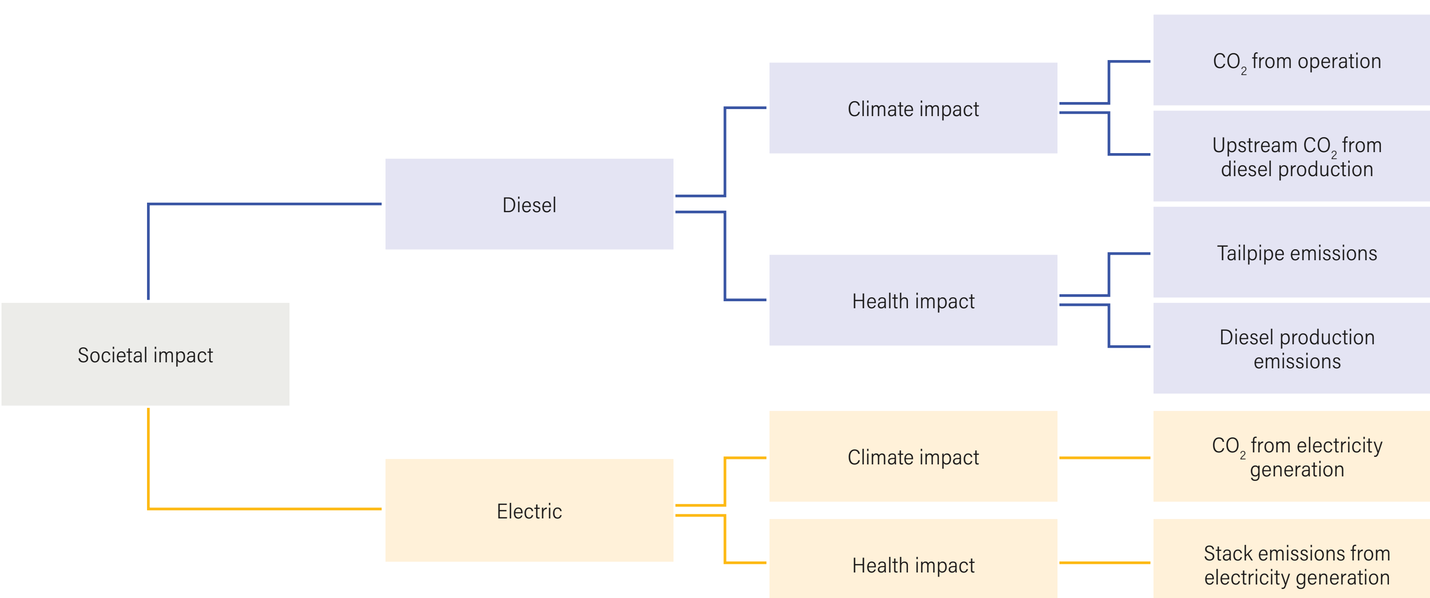
Methods

Our aim in this methodology is to evaluate the societal impacts of the release of pollutants associated with school bus powering and operations. In so doing, we consider climate impacts due to the release of GHGs, as well as the public health impact due to excess mortality from long-term exposure to fine particulate matter. In estimating these impacts, we account for the atmospheric release of pollutants during school bus operation, as well as for the emissions associated with upstream production of diesel fuel or electricity (Figure 2).

Population health impacts

We use a novel approach for reverse-source influence modeling to estimate the impact of emissions associated with school buses county by county across the contiguous United States. We do so by employing an augmented version of the Community Multiscale Air Quality (CMAQ) model developed by the US Environmental Protection Agency (EPA) (Byun and Schere 2006), referred to as the adjoint model, or CMAQ-ADJ (Zhao et al, 2020). Traditional methods for health impact assessment follow emissions from various sources to the location where the population health impact takes place, or at various receptor locations (Figure 1). Adjoint models provide the opposite perspective for source impact quantification. Adjoint simulations

Figure 2 | **Components of the societal impacts (i.e., climate or public health impacts) of school bus operations, and type**



Note: CO_2 = carbon dioxide.
Source: WRI authors.

start with the impact on a receptor, or on a group of receptors. These impacts are then traced back to preceding times, all the way to the initial time and location of the release of the pollutant from any and all sources. Contrary to traditional methods, an adjoint model provides location-specific source impact estimates, and therefore can help distinguish between the health impacts of school buses at various locations across the country.

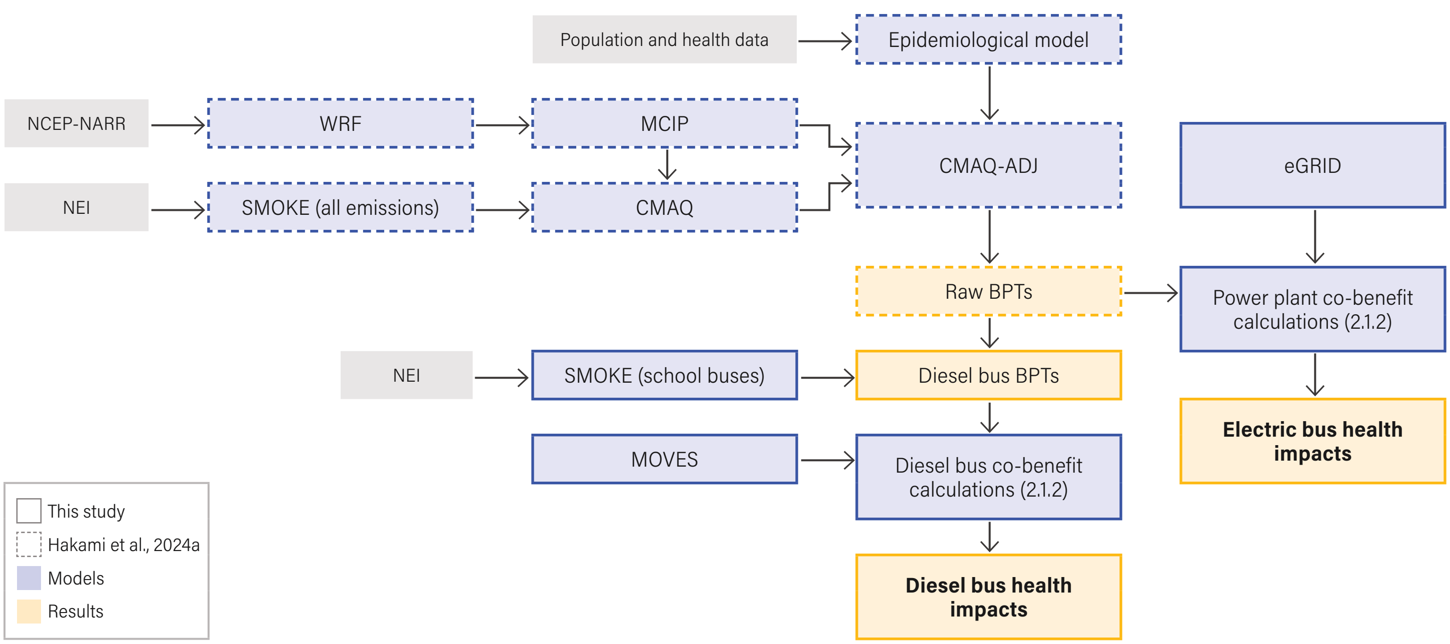
Reverse influence modeling is an effective approach for answering policy questions when the following two conditions are met:

- The policy question can be condensed into a single number (e.g., the number of premature deaths across the country).
- That single number has a known dependence on ambient concentrations.

These two conditions are met for certain types of air pollution health impact assessment studies. In the case of school bus health impacts, the health outcome (i.e., premature mortality) is cumulative across various locations and adds up to nationwide health burdens from $PM_{2.5}$ exposure; in addition, the relationship between pollutant concentrations and health outcomes is known from established epidemiological studies, which yield concentration-response functions (CRF). Overall, this approach takes location-specific emissions over time and outputs total health and economic impacts within the population residing in the entire domain of the model simulation. While these impacts are generally larger among populations closer to the emission locations, CMAQ-ADJ produces total impacts on the whole population, those near and far from the emission sources.

Adjoint modeling using CMAQ-ADJ relies on a range of upstream models (e.g., meteorological and emission models) and a variety of data sources (Figure 3). Adjoint simulations in our study are based on Hakami et al. (2024a) and Zhao et al. (2024) and have undergone an extensive quality-assurance process (the dashed area in Figure 3). While Hakami et al. (2024a) investigated various types of on-road vehicles and off-road engines, their study did not focus on school buses. Here, the raw results from that study are processed with more detailed data specific to school buses in the United States. While further details about the adjoint simulations and the underlying data can be found in Hakami et al. (2024a), here we apply their findings to the specific case of school bus impacts.

Figure 3 | **Data flow for calculation of health impacts from the replacement of older diesel school buses with new diesel or electric school buses**



Notes: BPT = benefit per ton; CMAQ = Community Multiscale Air Quality model; CMAQ-ADJ = Community Multiscale Air Quality, Adjoint model; eGRID = emissions and Generation Resource Integrated Database; MCIP = Meteorology-Chemistry Interface Processor; MOVES = Motor Vehicle Emission Simulator; NCEP-NARR = National Centers for Environmental Prediction North American Regional Reanalysis; NEI = National Emission Inventory; SMOKE = Sparse Matrix Operator Kernel Emissions; WRF = Weather Forecasting and Research. Terms in parentheses refer to the section in this technical note in which the item is discussed or introduced.

Source: WRI authors.

Health outcomes

Air pollution health impacts span a range of health outcomes from exposure to various pollutants such as $PM_{2.5}$ and ozone. While we recognize this wide range, this study focuses only on excess mortality due to long-term exposure to $PM_{2.5}$. It is important to note that our study evaluates the overall population health impact due to $PM_{2.5}$ excess mortality, and not the impact due to other factors or the impact on schoolchildren specifically. Mortality due to air pollution is by far the largest valuated health outcome, and $PM_{2.5}$ is the single most significant contributor to pollution-related premature mortality in the United States (Wolfe et al. 2019; Zhang et al. 2018). As a result, this study's focus covers the largest portion of the valuated air pollution health impact in the United States; however, since it does not cover all pollutants and health impacts, the derived estimates should be considered underestimations.

A number of epidemiological studies provide epidemiological relationships between $PM_{2.5}$ exposure and the excess risk of mortality. Our study uses the Global Exposure Mortality Model (GEMM) to characterize $PM_{2.5}$ mortality in the United States (Burnett et al. 2018). Reasons for choosing GEMM are described in Hakami et al., where the uncertainties associated with the choice of GEMM as the epidemiological model are also evaluated (Hakami et al. 2024a). GEMM is an epidemiological model from a pooled cohort of cohorts from across the globe, and as such covers a wider range of exposed concentrations than national cohorts. GEMM employs a sublinear concentration response function (CRF) that conforms with the growing evidence of larger relative risk reductions at lower concentrations (Pope et al. 2015; Weichenthal et al. 2022).

GEMM is a nonlinear CRF for the associations between premature mortality from noncommunicable diseases (NCDs) and lower respiratory infections (LRIs) in populations 25 years and older. The population data for exposure assessment were taken from the 2015 US census at the census block level. Baseline mortality rates for NCDs and LRIs were taken from the appropriate disease classification codes from the Centers for Disease Control databases. These data were mapped (gridded and/or aggregated) into CMAQ's 12-kilometer (km) computational domain from county-level data and county shapefiles.

School bus co-benefits

School bus impacts are quantified as benefits per ton (BPTs) and co-benefits for each county in the United States. The BPTs of a certain pollutant are the population health benefit of reducing school bus emissions or upstream emissions of that pollutant in a given county by one metric ton. Similarly, co-benefits are estimated from BPTs and are the cumulative population health benefits from reduction of all pollutants, but normalized to, and expressed per metric ton of, carbon dioxide (CO_2) emitted from the school bus. CMAQ-ADJ simulations provide estimates of BPTs for primary $PM_{2.5}$ emissions and nitrogen oxides (NO_x), sulfur dioxide (SO_2), ammonia (NH_3), and volatile organic compounds (VOCs) emitted from school buses that contribute to $PM_{2.5}$ exposure, such as primary $PM_{2.5}$, or NO_x emissions. Co-benefits refer to the ancillary benefits of reducing GHG emissions that are not directly related to the impacts of climate change, and therefore, are not accounted for in climate costs of GHGs. As an example in the case of school buses, electrification results in reduced tailpipe emissions of CO_2 from the replaced diesel bus, as well as the associated reduction in the emissions of CO_2's co-emitted pollutants, such as NO_x, SO_2, and $PM_{2.5}$ and VOCs. Like BPTs, co-benefits are defined as the monetized societal benefits associated with a reduction of one metric ton of emissions, but for CO_2 emissions rather than the emissions of its co-emitted pollutants. Co-benefits form the basis of our health impact estimations from school bus operations. Co-benefits are calculated from BPTs via the following equation,

$$\textit{Co-benefit} = \sum_{spc} BPT_{spc} \times \frac{Emission_{spc}}{Emission_{CO2}}$$

where *spc* is each of the co-emitted pollutants ($PM_{2.5}$, NO_x, SO_2, NH_3, and VOCs). Estimation of co-benefits requires information about emissions of CO_2 and co-emitted pollutants (i.e., intensity ratios on the right-hand side of the above equation). BPTs and co-benefits are estimated burdens of existing emissions from a source (e.g., a diesel bus), but similarly they can be construed as benefits of removing that source and its emissions.

Emissions modeling

Air quality simulations by CMAQ or CMAQ-ADJ and the processing of school bus health impacts require information about the release of pollutants into the atmosphere from different sources. Modeling of emissions for CMAQ and CMAQ-ADJ is conducted through the US EPA's Sparse Matrix Operator Kernel Emissions (SMOKE) modeling systems (Houyoux and Vukovich 1999). SMOKE allocates available inventories into temporal, gridded, and speciated CMAQ-ready emission files. SMOKE requires emission inventory information, and various data for spatial and temporal allocation of emissions, as well as for speciation to proper chemical species. These data are obtained from the National Emission Inventory

(NEI) 2016 platform (US EPA 2019). SMOKE is run for emissions from all sectors to produce BPTs as reported in Hakami et al. (2024a).

While BPT estimates are based on the 2016 NEI, school bus emissions are taken from the US EPA's 2020 NEI platform (US EPA 2023) for all counties in the contiguous United States, to reflect a later year. SMOKE is run separately for school buses only to allocate emissions to various locations in each county. Processing school bus emissions separately also ensures that the temporal allocation of emissions (time of the day, day of the week, and month of the year) matches the unique characteristics of school bus operations. However, NEI inventories do not provide fleet breakdowns across school bus vintages. To estimate impacts from school buses from different vintages, we conduct simulations with the US EPA's Motor Vehicle Emission Simulator, Version 3 (MOVES3). The breakdown between different years is based on MOVES's default databases. Operating procedures and technical documentation for MOVES are available from the US EPA (2019). MOVES is the EPA's state-of-the-art emissions modeling platform that provides default inventories and county-specific emission factors for on-road vehicles and off-road engines, including school buses. We use MOVES to produce emission factors for various model years of school buses (but running MOVES3 is the default mode for all US counties for school buses alone) and to provide fleet breakdown of school bus impacts. Emission factors from MOVES are used for estimation of intensity ratios (i.e., ratio of criteria contaminants to CO_2 emissions), as well as for burden estimates for various school bus vintages.

The use of MOVES in this study entails certain limitations. The version of MOVES used in the study does not include electric school buses, as the data for the vehicle type are not yet mature. While electric school buses have no tailpipe emissions, we assume that tire-wear and brake-wear emissions from these buses are similar to those from diesel school buses, and therefore those types of emissions are not included in the comparison between electric and diesel school buses. This assumption is made to isolate the impact from emissions that are linked to CO_2 and combustion (i.e., affected by electrification), and also because MOVES3 was considered inadequate to characterize differences between tire- and brake-wear emissions from diesel and electric buses. The MOVES database does not distinguish between different types of school buses (e.g., type C or D), and, as a result, our impact assessment does not differentiate between school bus types either. Finally, in our analysis, we run MOVES for all model years up to 2020. As our analysis of school bus models does not extend beyond 2020, we consider a 2020 model year diesel or electric school bus to be "new." Note that our underlying BPT estimates are for the year 2016, as available from Hakami et al. (2024a), while we calculate school bus impacts for 2020 emissions to provide more recent information. In other words, for our calculations, we assume that BPTs do not change significantly between 2016 and 2020, which has been found to be a reasonable assumption (Hakami et al. 2024b).

To evaluate the impact from electric school buses (i.e., upstream impact due to electricity generation), we use emission data for thermal electricity generating units in the United States. Emissions from all power plants are taken (on a facility basis) from the US EPA's emissions and the Generation Resource Integrated Database (eGRID). eGRID is a compilation of emissions of NO_x, SO_2, $PM_{2.5}$, ammonia, and CO_2 for most power plants in the United States. These emissions are used in combination with each power plant's location-specific BPTs to produce co-benefits for various coal and natural gas facilities in the United States. We use CO_2 inventory and electricity generation information from each of the 22 eGRID regions within the contiguous United States, in combination with facility-specific co-benefits from adjoint simulations, to estimate the upstream public health impact of the electricity use by electric school buses.

Atmospheric modeling

CMAQ (Byun and Schere 2006) is a community-based air quality model that is widely used across the globe. Most CMAQ applications use the same modeling platform configuration used for this study. CMAQ is a multiscale and multiphase model that accounts for various atmospheric processes. CMAQ produces spatial and temporal distributions of pollutants over a computational domain that consists of uniform grid cells. For this national study, the spatial resolution of the CMAQ grid was 12 × 12 km. Simulations for this study are conducted for the year 2016 and are taken to be representative of the recent atmospheric composition in North America. CMAQ and CMAQ-ADJ are used to estimate BPTs, and subsequently, co-benefits across the United States at the 12-km grid, which are then converted to county-level estimates of co-benefits for various school bus models.

CMAQ requires meteorological fields produced by a meteorological model. We use the National Center for Atmospheric Research's Weather Forecasting and Research (WRF) model (Skamarock et al. 2008), driven by the National Centers for Environmental Prediction North American Regional Reanalysis datasets to create initial and boundary values for our WRF simulations. The Meteorology-Chemistry Interface Processor (MCIP) is a crucial component of the CMAQ modeling system, used for air quality forecasting and research. MCIP processes meteorological data from the WRF and prepares them for use in the CMAQ modeling system.

The CMAQ-ADJ model was developed based on CMAQ v5.0 and includes all the atmospheric transport and transformation processes of that version. It has undergone extensive evaluation and is publicly available (Zhao et al. 2020). The evaluation process for CMAQ-ADJ used various comparative methods to verify that CMAQ-ADJ results are consistent with the underlying CMAQ model. CMAQ-ADJ has been used in various applications for health impact assessment across different domains (Hakami et al. 2024a, 2024b; Zhao et al. 2024). Further details about the use of adjoint modeling in air quality models can be found elsewhere (Hakami et al. 2007; Henze et al. 2007; Sandu et al. 2005).

School bus health impact calculations

County-level results are processed for existing and new diesel and new electric school buses. These results provide societal impacts (health, climate, or both health and climate) for each type of school bus of any vintage. The benefits of school bus replacements can then be calculated as the difference between the impacts of replaced and replacing buses. The CMAQ-ADJ model operates on a computational grid structure, and, as a result, co-benefit estimates and emissions are produced and stored in two dimensional gridded (2D, surface) files. Using SMOKE allocations, school bus emissions are also estimated at the grid level but are then mapped onto county values using a geographical information system based on area overlaps between grids and counties. These calculations are done for 3,108 counties in the contiguous United States, as well as 41 independent cities.

School bus health co-benefits (\$/ton-CO_2) are calculated directly from combining adjoint BPTs and NEI emissions, as described above, for each county in the contiguous United States. Values are estimated for model years up to 2020. Additionally, co-benefits and impacts are also estimated for school buses in the subfleet groups and across the entire fleet. We consider the following model year groupings: extremely old (XXOLD, before 2000), very old (XOLD, 2000–2006), old (OLD, 2007–10), existing or current (CUR, 2011–20), and the entire fleet (ALL, all model years). We consider this subfleet grouping to somewhat (but not fully) match the gradual trend of more stringent standards for diesel engines. In particular, beginning with the 2007 model year, PM emission standards were tightened significantly, while more strict NO_x emission standards were phased in between the years 2007 and 2010 (US EPA 2004). As noted above, we consider new school buses to be of the 2020 model year and onward. We produce the following summary results for the impact of school buses:

- *Fleet (and subfleet) impact* (\$/year): Fleet-level impacts (i.e., health burdens) associated with diesel school buses for each county in the contiguous United States are provided. Values are reported for model years 2000–2020 and for subfleet groupings. Total burden is calculated from co-benefit values (all values are at the county level).

$$Total\ burden\left(\frac{\$}{year}\right) = Co\text{-}benefit\left(\frac{\$}{ton-CO2}\right) \times CO2\ emissions\left(\frac{ton\text{-}CO2}{year}\right)$$

- *Unit impact* (\$/bus-year or \$/distance): The societal burden associated with one diesel school bus for each county in the contiguous United States is reported for model years 2000–2020 and for subfleet groupings. For a diesel school bus, this value can be used as the societal benefit of removing an existing diesel school bus from the fleet. Per-bus impacts are estimated from total burden estimates for each county:

$$Unit\ burden\left(\frac{\$}{bus-year}\right) = Total\ burden\left(\frac{\$}{year}\right) \div Bus\ number\ (bus)$$

Per–vehicle mile traveled (VMT) impacts are estimated in similar fashion:

$$Unit\ burden\left(\frac{\$}{1{,}000\ mi}\right) = Total\ burden\left(\frac{\$}{year}\right) \div Bus\ VMT\ (1{,}000\ mi/year)$$

- *Electrification benefits*: The difference between the societal health burden associated with a diesel school bus from a certain vintage or subfleet with that of a new electric school bus. Electrification benefits are provided on a per-bus basis, per 1,000 miles traveled, and for the subfleet groupings.
- Electric school bus impacts are assumed to be limited to the upstream impact from the electricity generation, which produces NO_x and $PM_{2.5}$ emissions, for the county's eGRID region. For example, per-bus upstream impacts for an electric bus are estimated as

$$Electric\ school\ bus\ burden\left(\frac{\$}{bus}\right) = Co\text{-}benefit\left(\frac{\$}{kwh}\right) \times Energy\ use\left(\frac{kwh}{mi}\right) \times VMT\left(\frac{mi}{bus}\right)$$

Where the per-kilowatt-hour (kWh) co-benefit is calculated using adjoint-based co-benefits for individual power plants and eGRID emission and generation data.

Diesel upstream impacts are estimated using adjoint-based co-benefit estimates for the oil and gas industry in the United States to be \$35/ton-CO_2, assuming that all diesel fuel used in the United States is produced domestically.

Similarly, upstream impacts for electric school buses are calculated as:

$$\textit{Co-benefit}\left(\frac{\$}{kwh}\right) = \textit{Co-benefit}\left(\frac{\$}{ton - CO2}\right) \times \textit{Emissions}\ (ton - CO2) \div \textit{Generation}\ (kwh)$$

Upstream CO_2 emission rates for diesel school buses (i.e., CO_2 emissions due to production and distribution) are taken from the Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) emission model (Burnham 2021):

$$\textit{Upstream diesel health impact}\left(\frac{\$}{bus}\right) = \textit{Oil and gas co-benefit}\left(\frac{\$}{ton - CO2}\right) \times \textit{Emissions}\left(\frac{ton - CO2}{mi}\right) \times VMT\left(\frac{mi}{bus}\right)$$

Climate impacts

To value climate impacts (i.e., excluding health impacts) of school buses, we assign estimates of the social cost of carbon (SCC) to CO_2 emissions. The SCC is an all-encompassing measure of the societal damage of GHG emissions and includes various endpoints such as health, extreme heat, sea level rise, food security, and the like. Similar to co-benefits, the SCC is expressed per metric ton of CO_2 (or CO_2-equivalent) emissions.

Accounting of the climate footprint of school buses is a straightforward process, as the impact does not depend on where the GHGs are released. As a result, climate impact estimation will only require estimation of CO_2 emissions. Climate impacts are calculated from operational (diesel) and upstream CO_2 emission estimates (diesel and electric) by applying the SCC for monetization. Climate impacts are calculated using the latest estimate of the SCC: the 2022 value of \$190/ton-CO_2 (US EPA 2022). Operational CO_2 emissions for diesel school buses are taken from MOVES for each county, while their upstream emissions (diesel production and distribution) are the national-level value of 331 grams/mile from Argonne National Laboratory's AFLEET tool (Burnham 2021). Upstream CO_2 emissions for electric buses are based on an assumed national-level average electricity usage of 1.85 kWh/mile for electric buses (Levinson et al. 2023) and transition and charging losses of 15 percent (Choma et al. 2024), combined with generation and CO_2 emission data for each eGRID region. Climate impacts are reported in the same fashion as health impacts (i.e., fleet-level, per-bus, and per-VMT for diesel school buses) and as electrification benefits (i.e., diesel impact – electric impact).

Findings

Overview

We present a range of results that quantify the impacts of school bus operations in each county in the contiguous United States. Various forms of results are discussed in this technical note and its appendices. For all categories of results described below, they are provided for each model year and each subfleet grouping (XXOLD, XOLD, OLD, CUR, ALL). The datasets produced include the following:

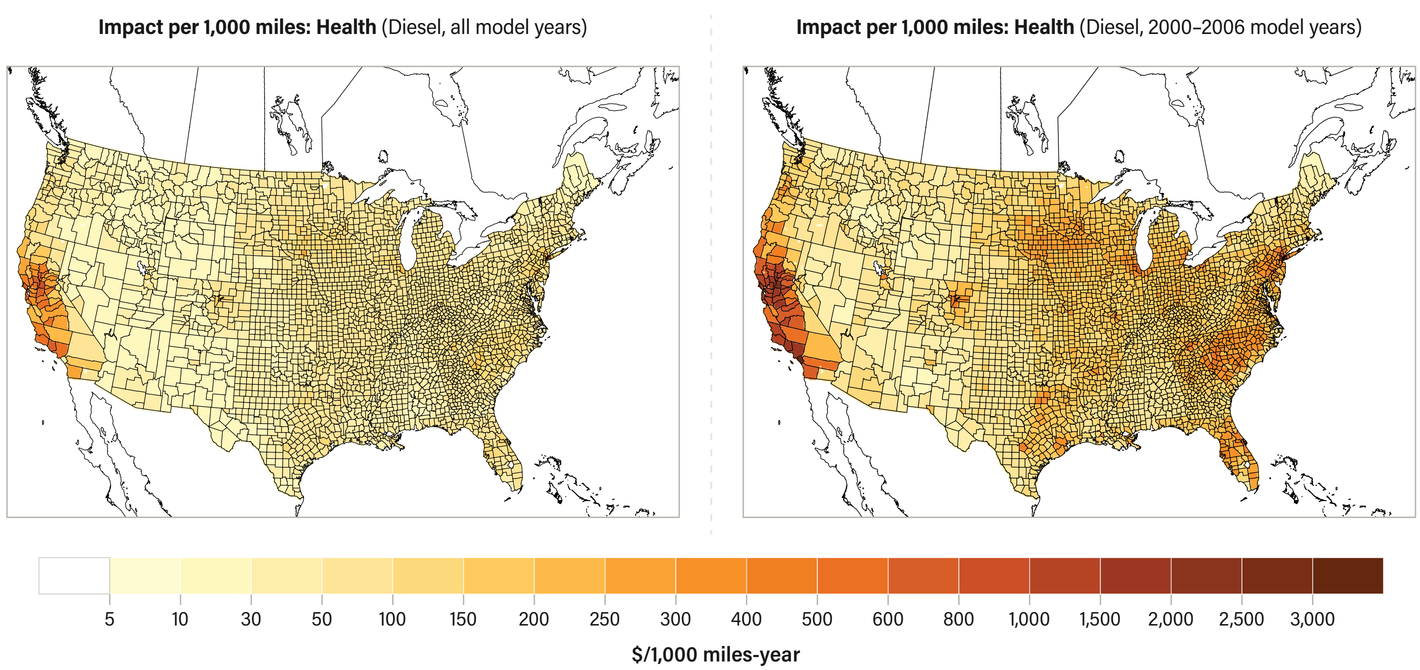
1. Diesel school bus impacts: Diesel school bus impacts are calculated as unit impacts and total impacts.
   i. Unit impacts for each county are provided in three forms: per ton-CO_2 emitted (i.e., co-benefits, in units of \$/ton-CO_2), per school bus (\$/bus-year), or per VMT (\$/1,000 VMT).
   ii. Total impacts for each county are impacts from all buses in a model year or subfleet category in that county and are expressed in units of \$/year. Total impacts are broken down to health, climate, or overall (health + climate) impacts.
2. Electrification benefits: Societal benefits of replacing diesel school buses with electric school buses are calculated as the difference between their respective societal impacts. Electrification benefits are made up of both climate and health benefits of school bus replacement. Similar to the diesel school bus results, these benefits are provided for all US counties, and as unit impacts (per bus or per VMT) and total impacts (\$/year) for model year or subfleet categories.

Health impacts of diesel school buses

Diesel school bus health impacts, expressed per bus, per VMT, or as co-benefits, vary significantly across counties and by bus vintage (Figure 4). Per VMT impacts range from less than $10/1,000 miles to nearly $4,000/1,000 miles across all counties and model years. As one would expect, larger impacts are from emissions in more populous counties, as school bus emissions in these counties affect a larger population, and older diesel school buses have greater impacts as they emit greater amounts of pollutants. Among the counties with the largest impacts are Kings County, Queens, and the Bronx (NY), Orange County and Sacramento (CA), Philadelphia (PA), and Washington (DC). There is a gradual reduction in health impacts in newer model years due to more stringent tailpipe emission control standards. This reduction is most significant starting in the 2007 model year, when new PM emissions standards for heavy-duty diesel vehicles took effect, while more stringent NO_x standards were phased in between 2007 and 2010.

The disparity in the health burden of school bus emissions (Figure 4) reveals the value of the adjoint model in providing location-specific source impact estimates. The extent of school bus health impact variability across counties and model years can also be seen in Figure 5, which depicts the share of health impacts borne by various fractions of school buses or their VMTs. Each point on the plot (also known as the Lorenz curve) corresponds to the share of the diesel school bus impact (*y*-axis value) that can be attributed to the share of the most damaging emissions by number of buses or their VMTs (*x*-axis value). If emissions from school buses were all equally impactful, then Figure 5 would reduce to the one-on-one (black) line. In other words, the significant curvature of the curves in Figure 5 indicate differences in school bus emission impacts across counties and vintages. For instance, the top 10 percent and 20 percent of the school buses with the highest impacts account for 49 percent and 65 percent of the health burden of the total diesel school bus fleet in the United States, respectively. Similarly, the top 10 percent and 20 percent of the most damaging miles traveled by school buses are responsible for 54 percent and 70 percent of the health burden of the fleet. School buses with the largest impacts are likely the result of two contributing factors: more polluting (i.e., older) buses and operation in more populous counties where a larger population is exposed to the emissions of the school bus. Note that impacts shown in Figure 5 only include health impacts of school bus operations, and not the climate

Figure 4 | **Per VMT impacts of diesel school buses for the all fleet average (left) and older (2000–2006, right)**

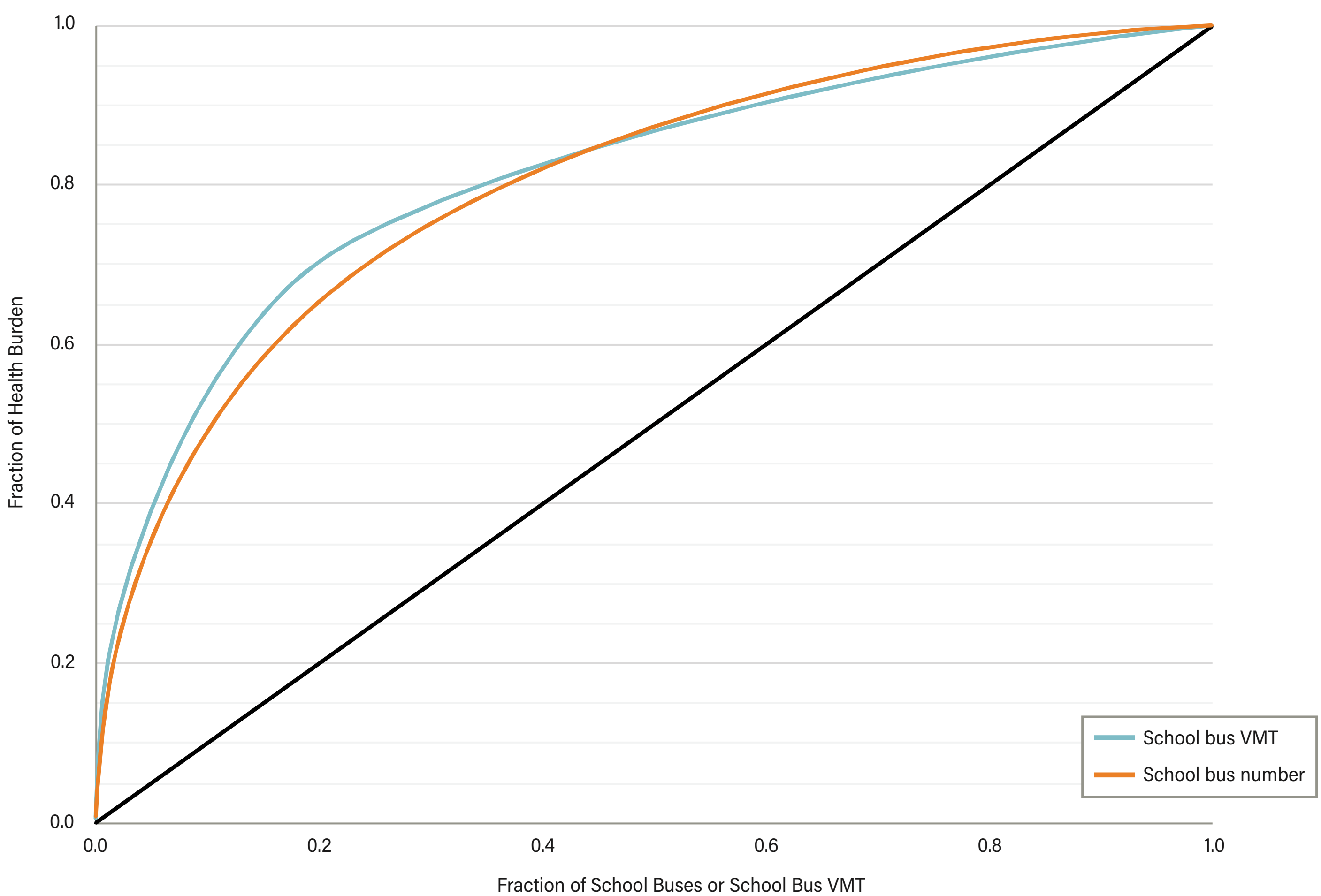


Notes: VMT = vehicle miles traveled.
Source: WRI authors.

impacts. There is significantly less variability of climate impacts of tailpipe CO_2 emissions from school buses across counties and model years. This is due to two facts: climate impacts are not location-dependent, and changes in fuel efficiency (and therefore CO_2 emissions) across different vintages are significantly less pronounced than the change in emissions of air pollutants.

Figure 6 shows the overall impact (climate and health) of school buses in all US counties for OLD (2000–2006) and newer (i.e., CUR, 2011–20) fleet segments, and for 2022 SCC values. As mentioned before, in 2007 new PM standards were enacted for heavy-duty diesel vehicles, resulting in significantly lower health impacts. However, these standards did not affect fuel efficiency as significantly, and therefore the climate impacts of these newer vehicles decreased only marginally. Higher VMTs for newer school buses result in comparable overall (i.e., climate and health) impacts for newer buses, despite their lower tailpipe emissions of criteria pollutants. The relative contribution of the health impact to the overall impact can be seen in Figure 7. Given the increase in the value of SCC in 2022, the overall impact is dominated by climate impacts under this higher value of SCC, where the contribution of health impacts is only comparable to that of climate impacts in some major urban areas.

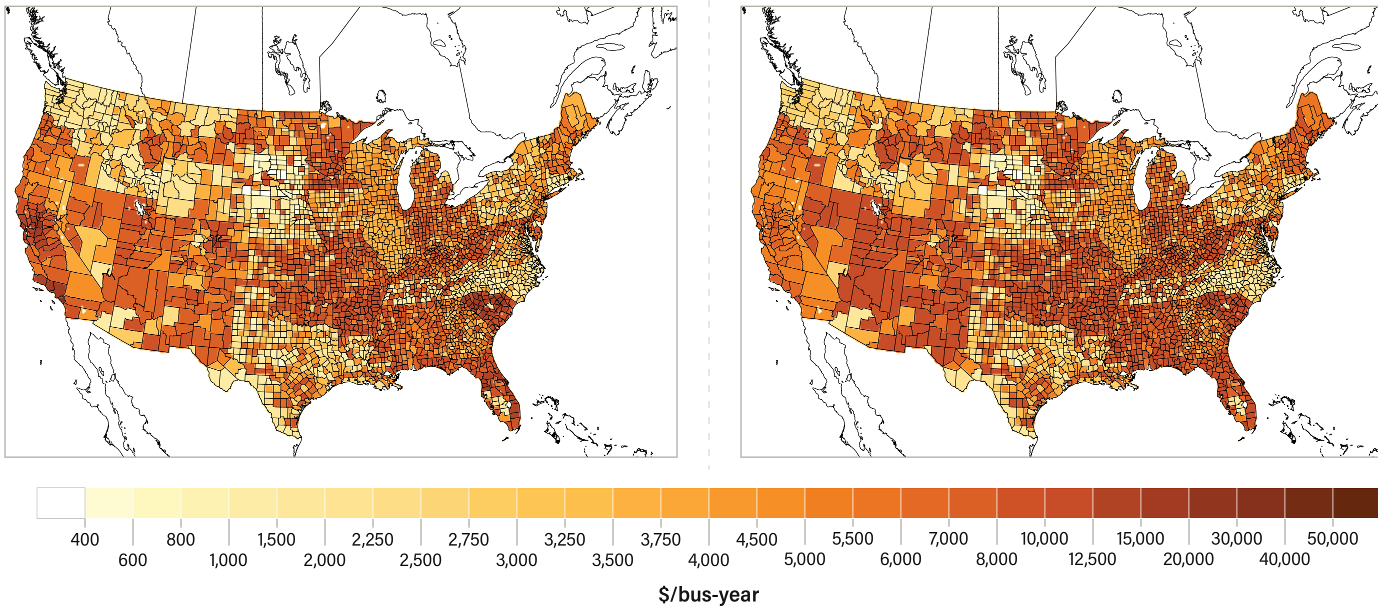
Figure 5 | **The share of the health burden imposed by fractions of the most polluting school buses (orange), or school bus VMTs (blue)**



Notes: VMTs = vehicle miles traveled. For example, nearly 50 percent of the health burden of all school buses is attributed to only 10 percent of the most polluting buses.
Source: WRI authors.

Figure 6 | **Per-bus impact of older (2000–2006, left) and newer (2011–20, right) school buses across the United States**

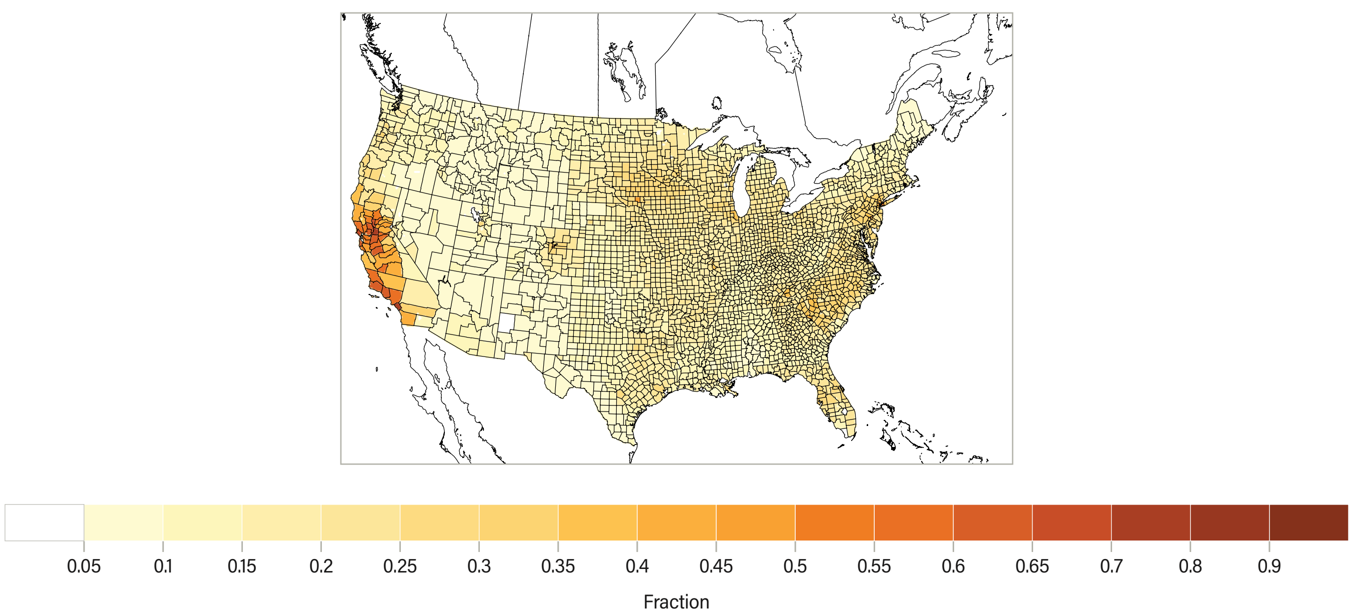
Impact per bus: Climate + health (Diesel, 2022 SCC, 2000–2006 model years) **Impact per bus: Climate + health** (Diesel, 2022 SCC, 2011–2020 model years)



Note: SCC = social cost of carbon.
Source: WRI authors.

Figure 7 | **Ratio of health impacts to overall impacts (climate and health) for the 2022 SCC**

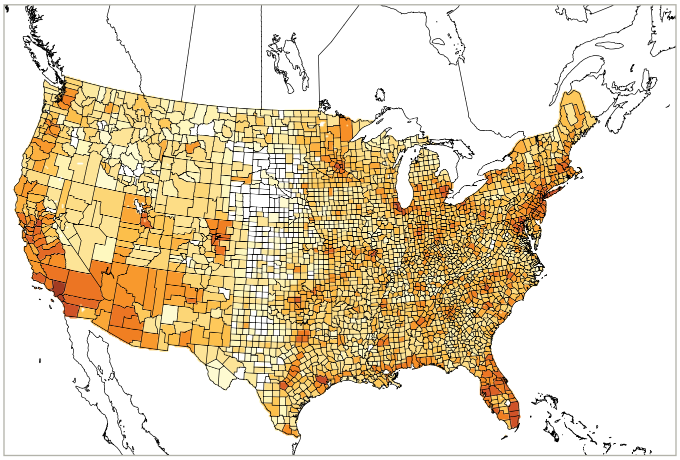
Fraction of health total benefits (2022 SCC)



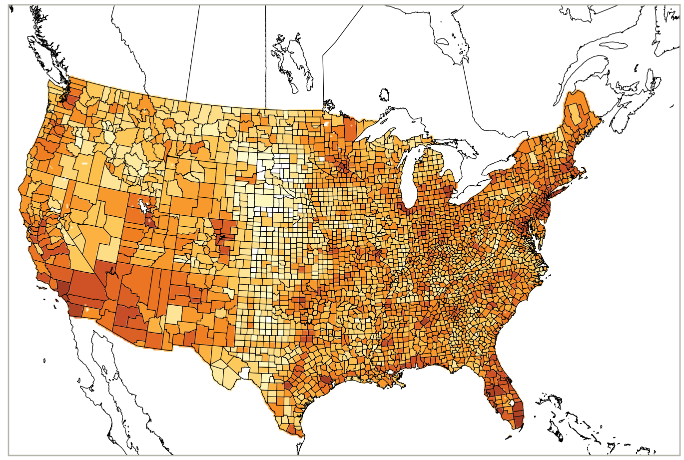
Note: SCC = social cost of carbon.
Source: WRI authors.

Figure 8 | **The total impact of diesel school bus fleets for very old (2000-2006) and newer (2011-20) fleet segments, and for the entire fleet of diesel school buses (bottom) in all counties in the United States**

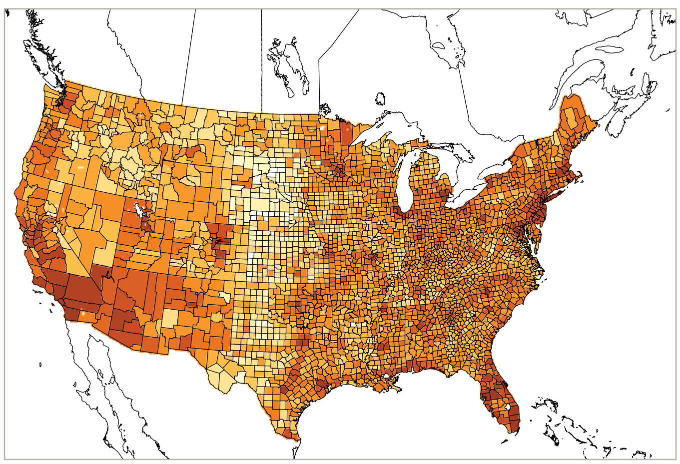
Impact, fleet: Climate + health (Diesel, 2022 SCC, 2000–2006 model years)

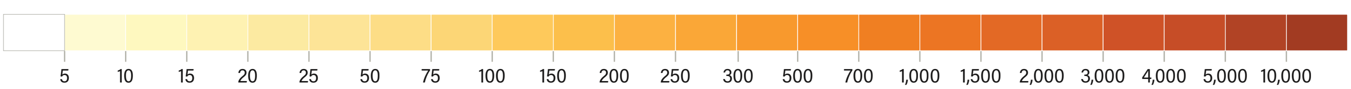


Impact, fleet: Climate + health (Diesel, 2022 SCC, 2011–2020 model years)



Impact, fleet: Climate + health (Diesel, 2022 SCC, all model years)





Note: SCC = social cost of carbon.

Source: WRI authors.

Table 1 | **Summary of nationwide (contiguous United States) diesel school bus statistics and impacts presented in this report**

FLEET	COUNT (1,000)	VMTS (M)	HEALTH IMPACT ($M)	CLIMATE IMPACT ($M)	TOTAL IMPACT ($M)
< 2000	40	300	150	90	**240**
2000–2006	100	1,000	290	300	**600**
2007–10	80	900	60	290	**350**
2011–20	300	4,400	170	1450	**1,620**
All fleet	**520**	**6,600**	**670**	**2,140**	**2,810**

Notes: M = million; VMTs = vehicle miles traveled. The table also includes the total count and VMTs of each school bus subfleet grouping.
Source: WRI authors.

The results shown in Figure 6 are per-bus impacts. The total impact for the full fleet population of school buses (i.e., the impact of all school buses in each county) or subfleet population (e.g., the impact of all buses from 2000–2006 model years in every county) can be calculated by accounting for the number of buses in each county (Figure 8). Newer diesel school buses are more numerous and have more VMTs, and therefore they pose greater societal impacts, particularly climate ones. The impact is noticeably larger for major urban areas, where both the health impacts and the number of buses operating are larger. Figure 8 also shows the impact of the entire fleet of diesel school buses for each county in the United States. Table 1 summarizes the nationwide impacts of diesel school buses for various subfleet groupings.

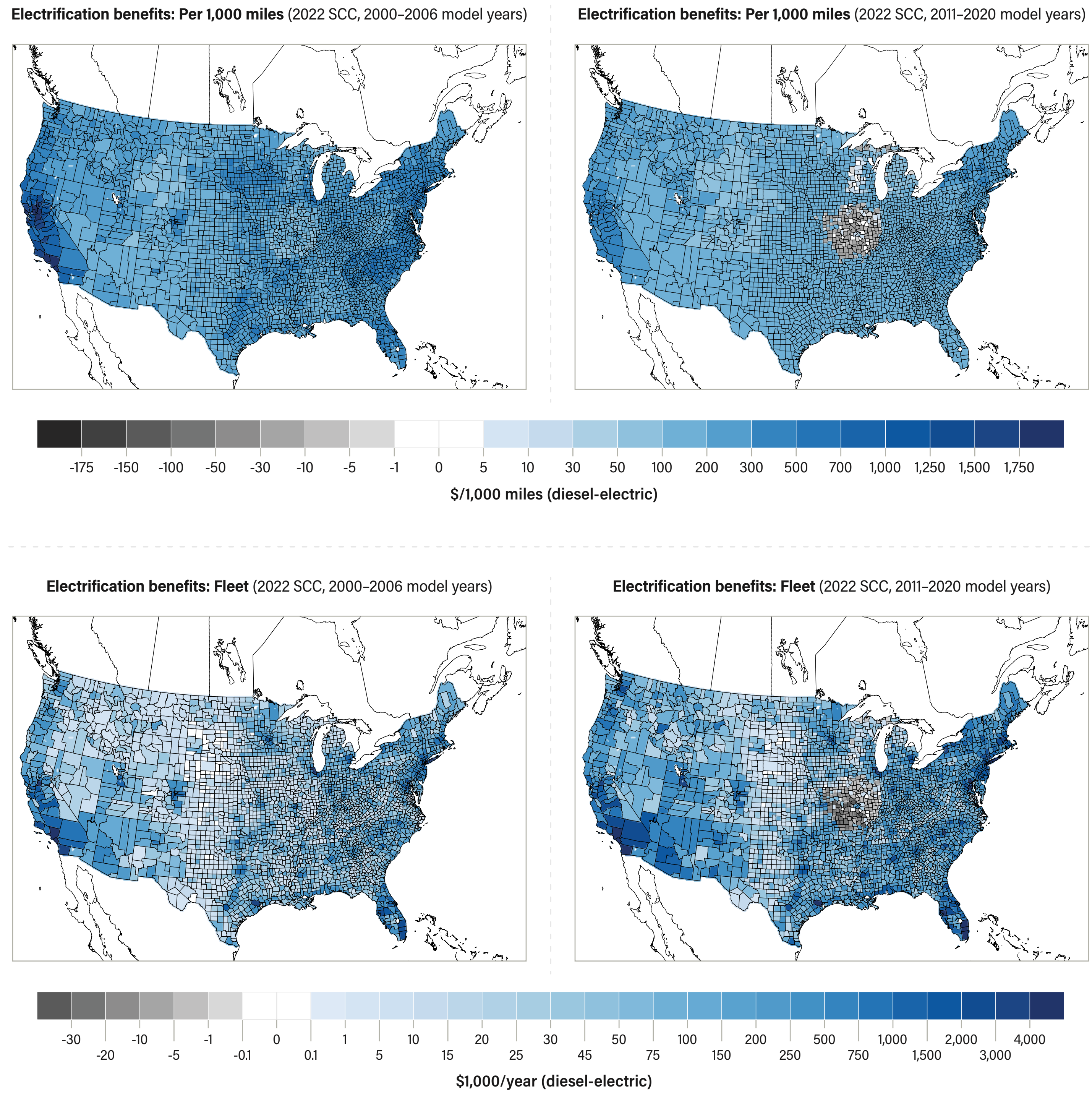
Benefits of school bus electrification

The benefits of school bus electrification are calculated as the difference between climate and health impacts of diesel and electric school buses. For electric school buses, those impacts would depend on the electricity market where the bus operates and is charged. We use eGRID reported emission levels for CO_2 and air pollutants, together with electricity production data, to account for climate and health impacts. All electric buses are assumed to be 2020 model year, and they are compared on a bus-to-bus basis with individual diesel school buses in any county. The resulting total benefits are compiled by aggregating benefits across individual buses for each fleet grouping and county.

The electrification of school buses generally results in benefits (Figure 9), with the largest benefits in larger cities, particularly along the coasts. However, there are occasional regions where electrification entails disbenefits (i.e., negative benefits); for example, in some Midwest US counties in Illinois, Missouri, Kentucky, Wisconsin, and so on. Electricity in these areas is serviced by two eGRID regions (Midwest Reliability Organization East and SRC Midwest) that relied most heavily on coal (in 2020) and have the highest CO_2 emissions rates. As a result, the health and climate impact of electricity generation through coal is larger than that of diesel school bus operations. In these areas, while electrification of older school buses is beneficial, electrification of newer (2011–20 model years) school buses entails small disbenefits due to the reliance of the electricity mix on coal. These disbenefits are the results of the current grid's reliance on coal; as the electricity grid becomes cleaner and/or less reliant on coal, they are likely to turn to benefits. We also note that the magnitude of occasional disbenefits are considerably smaller than the benefits provided in much of the United States.

Electrification of school buses is particularly beneficial in large urban areas, where the health benefits of electrification are more pronounced (Figure 10). This is primarily due to the proximity of the bus operation to population. In all major cities, the benefits of electrification are significantly larger than the benefits of fleet renewal with new diesel school buses. Nationwide, we estimate benefits of $1.6 billion/year for electrification of the entire US school bus fleet under the 2022 SCC values.

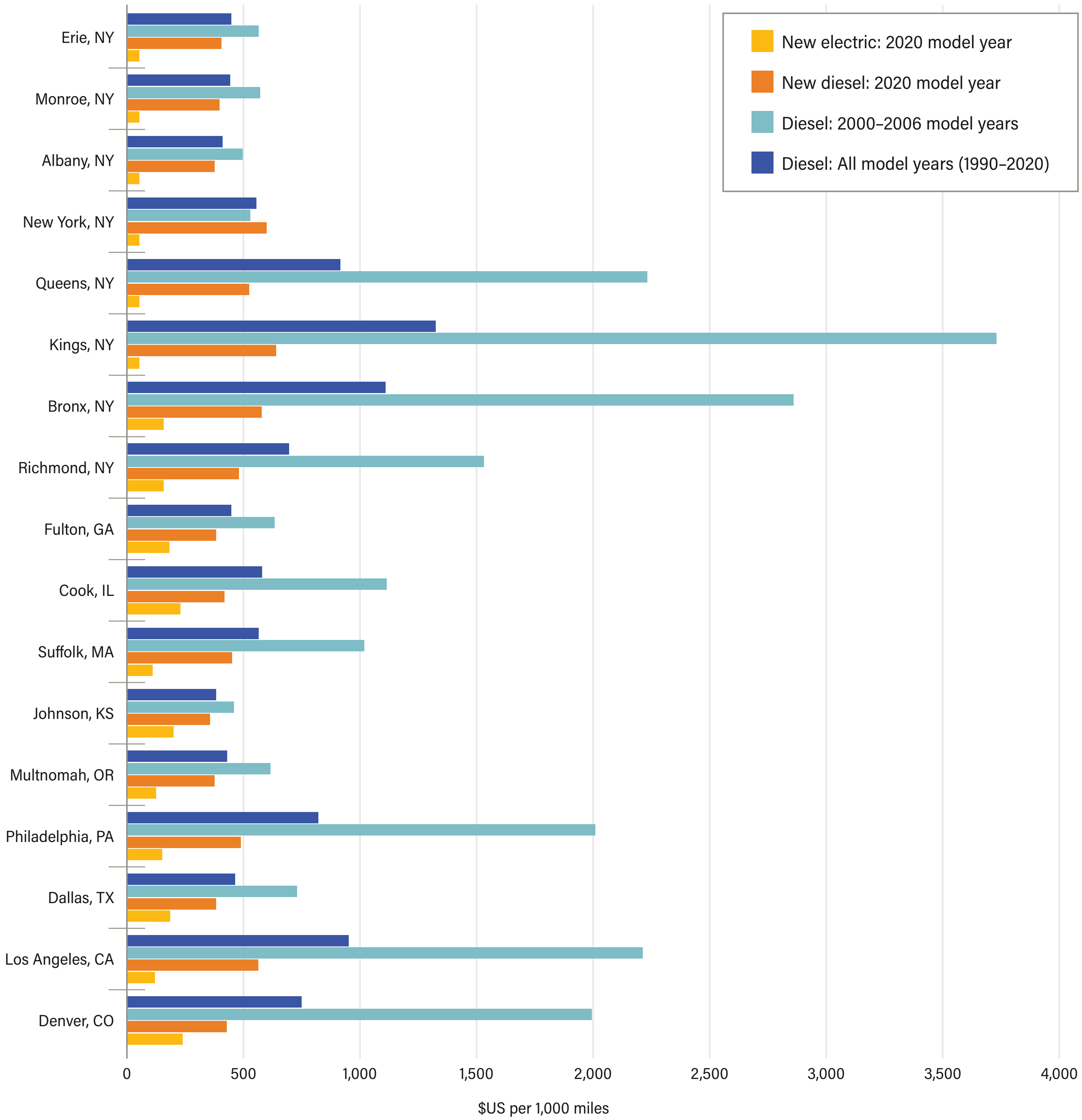
Figure 9 | **Benefits: Benefits of electrification of school buses for older (2000–2006, left) and newer (2011–20, right) buses**



Notes: SCC = social cost of carbon. Benefits are shown per 1,000 vehicle miles traveled (top) and as total fleet benefits (bottom). The color map is not symmetrical for positive and negative values.

Source: WRI authors.

Figure 10 | **Comparison of the yearly societal impacts of existing and new diesel and electric school buses in major urban areas in the United States**



Notes: SCC = social cost of carbon.

Source: WRI authors.

Discussion

We note that the most recent results presented here are estimates of the school bus impacts and the benefits of their electrification as of 2020, given available data from MOVES. Any school bus model year after 2020, diesel or electric, will have life cycle impacts that are not accounted for in this study. Also, the operational impacts of school buses are bound to change in time. The age of the fleet, and consequently its emissions characteristics, will change as old units are decommissioned and more stringent new vehicle standards take effect for new school buses. The electricity mix in the United States is likely to become cleaner and less reliant on fossil fuels, which would in turn help increase benefits of electrification. Changes in atmospheric composition will impact BPT and co-benefit estimates because of the changing chemical regimes, although these changes are likely to be small within the lifetime of the existing fleet.

While several studies have investigated the impact of diesel school buses on students, studies of the impact of school buses on general population health and climate are rather limited. The recent study by Choma et al. (2024) similarly investigates the benefits of electrifying school buses in the United States, but Choma et al. (2024) estimate substantially larger nationwide health impacts for diesel school buses (in 2017) and lower health impacts for electric school buses than this study, though the climate benefit estimates are generally comparable. Several factors contribute to these discrepancies. Choma et al. (2024) include asthma in their health outcomes (an increase of about 10 percent in their valuation) and use higher valuations (2023 US$ vs. 2016 US$) for the value of statistical life and the SCC (an increase of about 15 percent). Choma et al. (2024) estimate lifetime electrification benefits by projecting a nationwide average for future electricity generation impacts. Further, they use a simplified modeling platform that may not fully and adequately capture the response of the atmosphere to emissions, and that has a tendency to overestimate the health burden from transportation (Choma et al. 2021; Davidson et al. 2020; Fann et al. 2013). However, their modeling platform does employ higher spatial resolution in urban areas that better represents population distributions. Table 2 summarizes the differences between the two studies. Nonetheless, as climate benefits constitute a large portion of the total electrification benefits, the overall benefit estimates from both studies are generally comparable.

Table 2 | **Comparison of methods and results of this study with Choma et al. (2024)**

	ITEM	CHOMA ET AL. (2024)	THIS STUDY
Inputs, assumptions, and methods	Health outcomes	Mortality and asthma from $PM_{2.5}$	Mortality from $PM_{2.5}$
	Epidemiological model (mortality)	GEMM	GEMM
	VSL	$12.4M	$10.2M
	SCC	$228/ton-$CO_2$	$190
	VMT	6.8B miles	6.6B miles
	Number of buses	~500,000	520,000
	Emitted pollutants considered	$PM_{2.5}$, SO_2, NO_x, NH_3, VOCs	$PM_{2.5}$, SO_2, NO_x, NH_3, VOCs
	Air quality model	Reduced complexity (InMAP)	Full complexity (CMAQ)
	Model resolution	Variable, down to 1 km in cities	12 km
	Temporal variability (seasonality)	Not considered	Considered
	Electricity generation burden	Nationwide, projected	Grid-dependent, 2020
	Electricity losses	15%	15%
	Energy use by electric buses	1.54 kWh/mi	1.85 kWh/mi

Table 2 | **Comparison of methods and results of this study with Choma et al. (2024) (cont).**

	ITEM	CHOMA ET AL. (2024)	THIS STUDY
Results	Diesel school bus health burden*	$1.8B	$670M
	Diesel school bus health burden ($/mi)*	0.27 $/mi	0.1 $/mi
	Electrification benefits**	$1.9B	$1.6B
	Electrification benefits ($/mi)**	0.28 $/mi	0.24 $/mi
	Disparity (burden of worst 10% miles)	30%	54%

Notes: B = billion; CMAQ = Community Multiscale Air Quality model; CO_2 = carbon dioxide; GEMM = Global Exposure Mortality Model; InMAP = Intervention Model for Air Pollution; kWh = kilowatt-hours; km = kilometers; M = million; mi = miles; NH_3 = ammonia; NO_x = nitrogen oxides; PM = particulate matter; SCC = social cost of carbon; SO_2 = sulfur dioxide; VMT = vehicle miles traveled; VOC = volatile organic compound; VSL = value of statistical life; * Mortality only, i.e., asthma excluded; ** Climate and health benefits.

Source: WRI authors.

Limitations

The estimates provided in this study are subject to several limitations stemming from incomplete inputs, model errors and imperfections, and study assumptions. Like all modeling studies, our results are also subject to a range of uncertainties. Sources of these uncertainties include, but are not limited to, uncertainty in emissions, including those of school buses; uncertainty in epidemiological models; lack of detailed county-level information about school bus fleets and operations; and a lack of knowledge of the operational parameters of electric school buses. Our results are also subject to the following limitations due to modeling constraints or study design:

- Our health impact estimation only included mortality as the health endpoint due to chronic $PM_{2.5}$ exposure. Diesel school buses have significant NO_x emissions that can lead to ozone-induced health outcomes, including asthma and mortality. NO_x emissions also lead to increased NO_2 exposure, with its associated impacts on mortality or morbidity (Faustini et al. 2014; Khreis et al. 2017; Turner et al. 2016). Due to the magnitude of NO_x emissions from heavy-duty diesel engines, exclusion of ozone from the analysis is likely to result in a sizeable underestimation of the impact of diesel school buses or the benefits of their electrification. As a result, the inclusion of NO_x also has the potential to delineate a sharper contrast between population health impacts of new electric and diesel school buses. The adjoint model used here can also be employed in future studies to extend the estimates in this study to include ozone-related health outcomes.
- While the approach used in this study can be extended to estimate county-specific environmental justice benefits of school bus electrification, our study focused on the health and climate impacts of school buses. Like other transportation sources, school bus emissions are likely contributors to air pollution exposure disparities. Environmental justice and equity benefits are important considerations in the analysis of school bus electrification that are absent from the current study. An analysis of environmental justice benefits (e.g., with regards to race, ethnicity, gender, or income) is likely to result in its own differential delineation of impacts across different counties, adding another layer of differentiation between school bus electrification benefits in different counties.
- Our results at a 12-km resolution in major cities show school bus health impacts that are 20–40 times larger than the national average. While 12-km resolution is found to be generally sufficient for health impact assessment studies, in certain cities higher resolution simulations can lead to significantly higher estimates (Hakami et al. 2024b; Valencia et al. 2023).
- In our analysis we did not consider brake- and tire-wear emissions, assuming that they are similar for diesel and electric school buses. Due to operational differences between electric and diesel engines and weight differences between the vehicles, this assumption may not be justifiable, and as more data on emissions from electric heavy-duty vehicles become available, it should be revisited.

To address these limitations, we recommend that future studies using this methodology include the following:

- Estimation of cumulative health benefits (mortality and morbidity due to exposure to $PM_{2.5}$, ozone, and NO_2).
- Incorporation of environmental justice benefits of school bus electrification with population health and climate benefits.
- Conducting of higher-resolution simulations in select cities, particularly densely populated areas on the West Coast, as such areas are likely to be more sensitive to model resolution (Hakami et al. 2024b).

Conclusion

This study contributes important data to help policymakers, districts, advocates, and others understand the societal impacts of school bus fleets, particularly when deciding to purchase a new diesel or electric school bus. The data help fill a gap in the literature about the actual effects of school bus electrification in the United States. We recommend that future work use these county-level results to analyze the equity implications of the current societal impacts of school bus fleets nationwide, as well as the potential effects of electrification. These calculations can be done using county-level census data. Policymakers can also use the data and findings to promote public investments in school bus electrification.

Further work can also address the limitations listed above and build on this important foundational work. As interest and policy support grow for school bus electrification, it is important to maintain and expand the evidence base for the effects of diesel versus electric school buses. Federal, state, and local policy changes, as well as technological improvements in bus design, electricity procurement, and the energy grid, have the potential to shift outcomes over time. This reinforces the need for continued updates to these findings and associated modeling efforts.

Appendix A: Health and climate impacts ($/1,000 miles-year) of school buses (diesel and electric)

Figure A-1 | **Health and climate impact per 1,000 miles VMT of diesel school buses for model years**

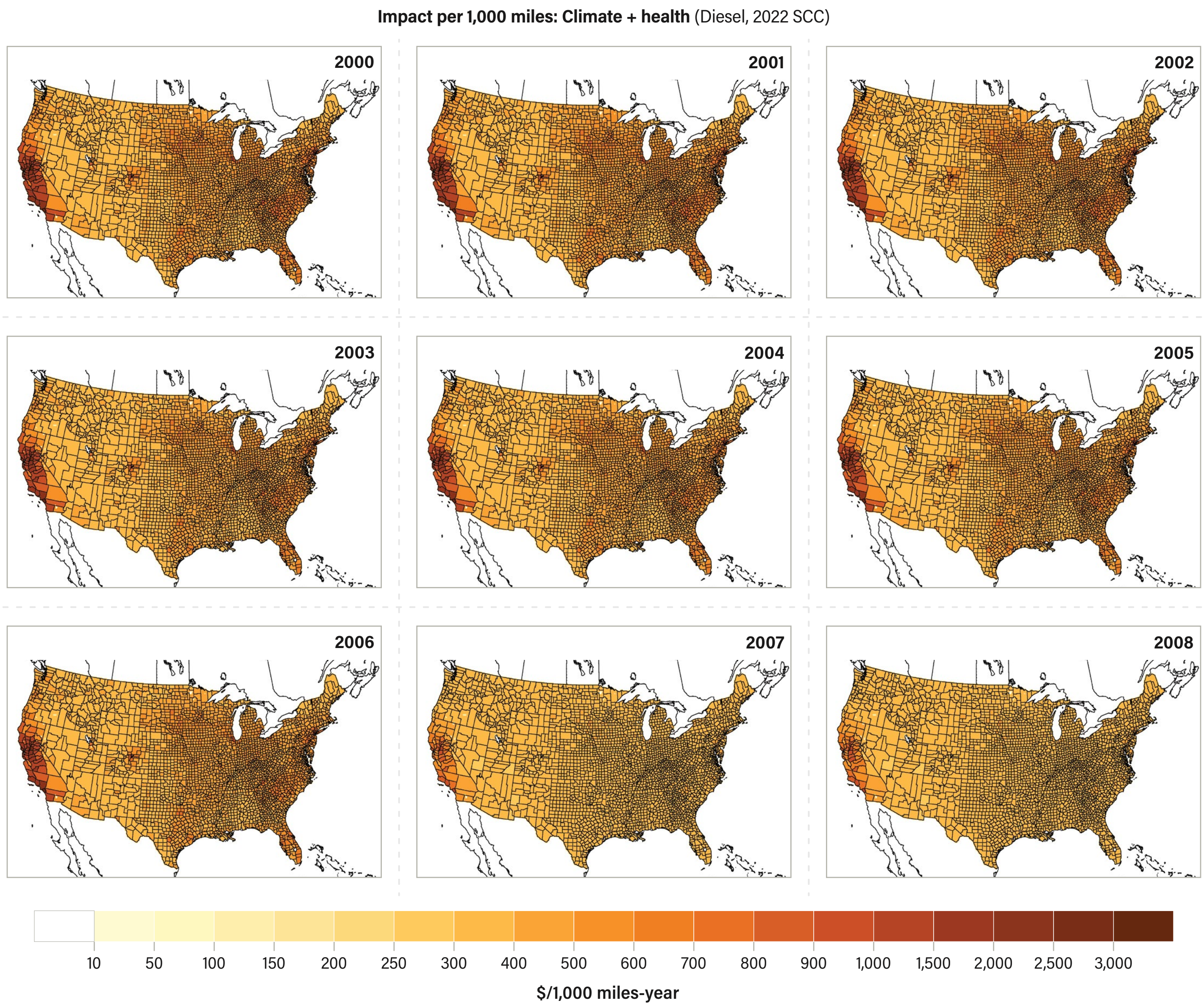
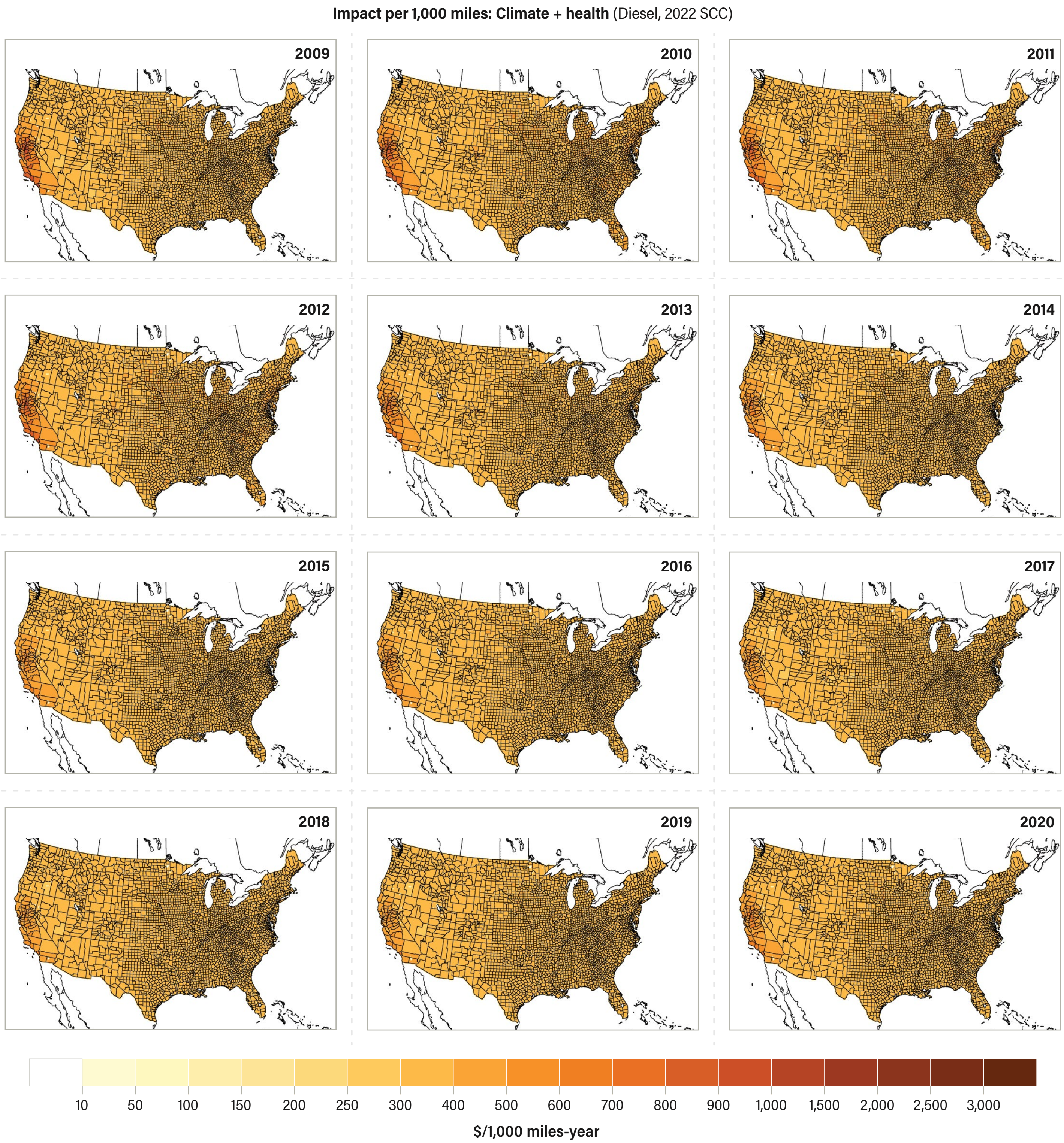
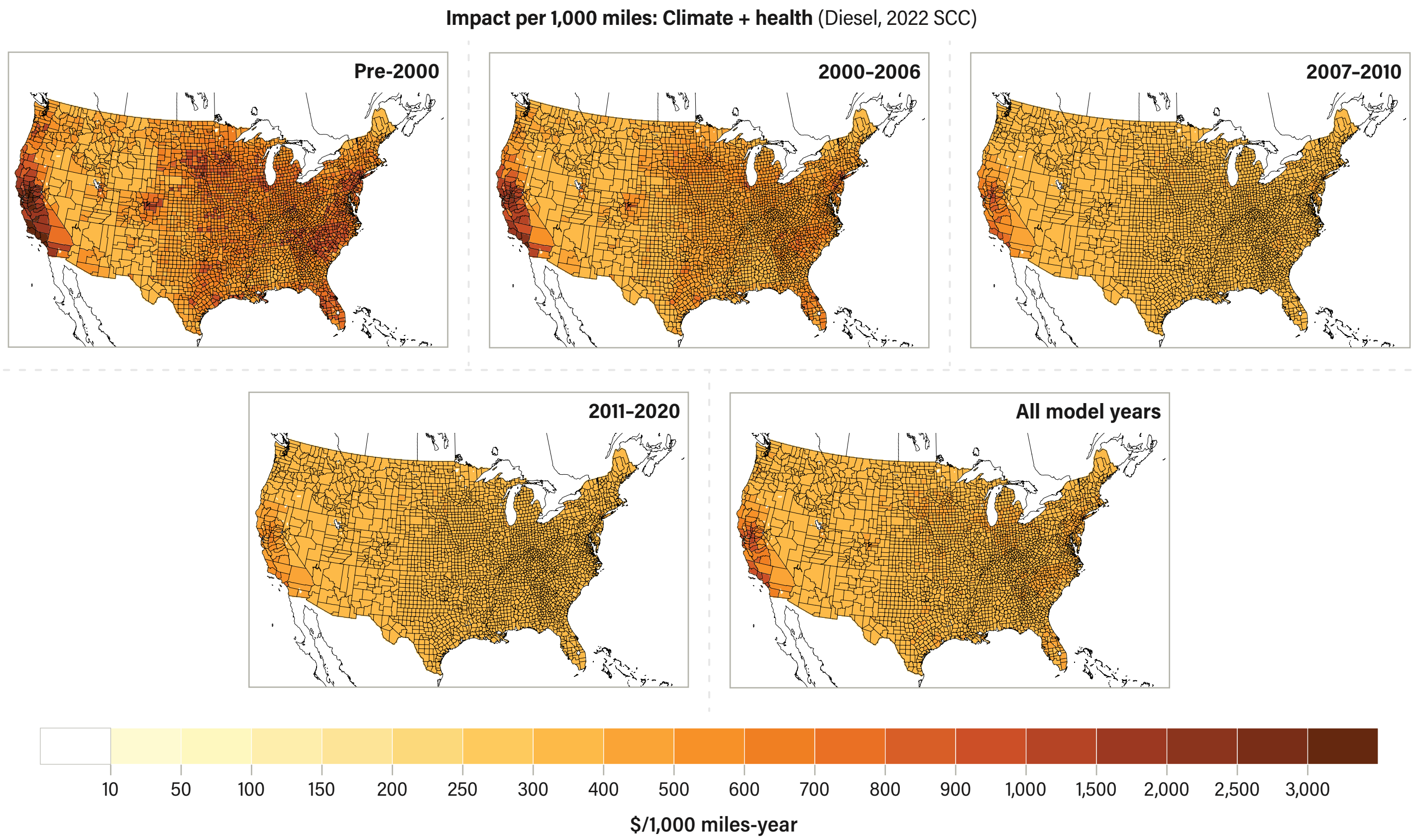


Figure A-1 | **Health and climate impact per 1,000 miles VMT of diesel school buses for model years (cont.)**



Note: VMT = vehicle miles traveled.
Source: Authors.

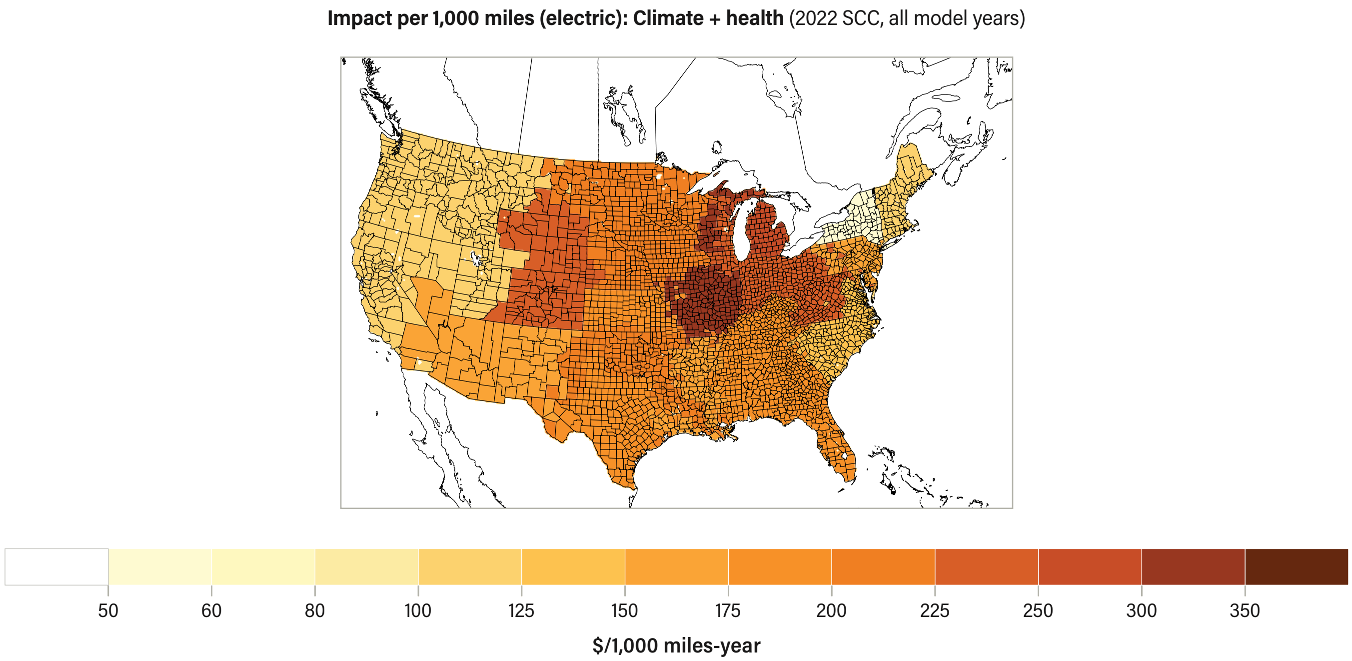
Figure A-2 | **Health and climate impact per 1,000 miles VMT of diesel school buses for fleet segments**



Note: VMT = vehicle miles traveled.

Source: Authors.

Figure A-3 | **Health and climate impact per 1,000 miles VMT for new electric school buses (2020 model year)**



Note: VMT = vehicle miles traveled.
Source: Authors.

Appendix B: Health and climate burden ($/year) of school buses (diesel)

Figure B-1 | **Health and climate burden ($/year) of diesel school buses for model years**

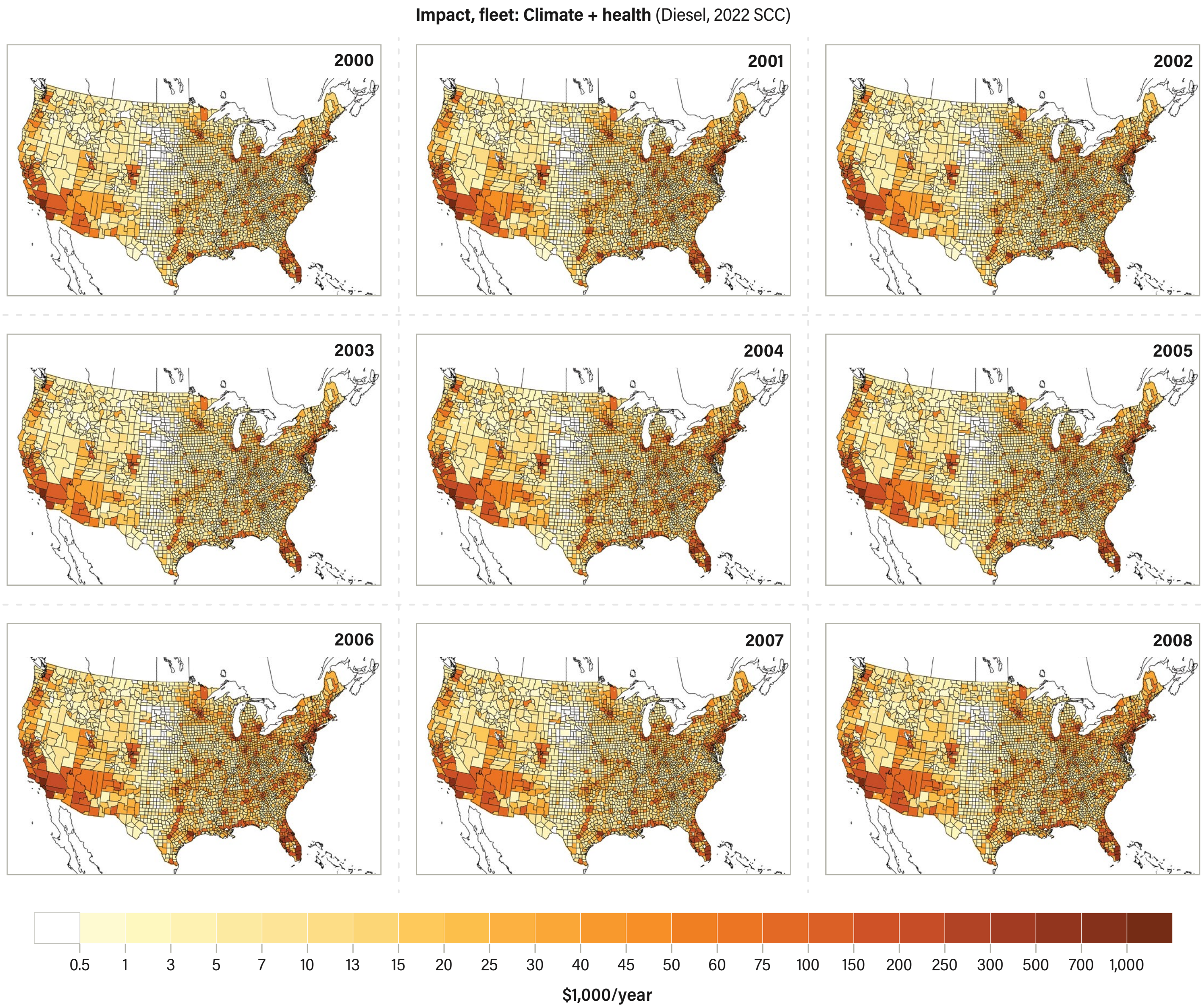
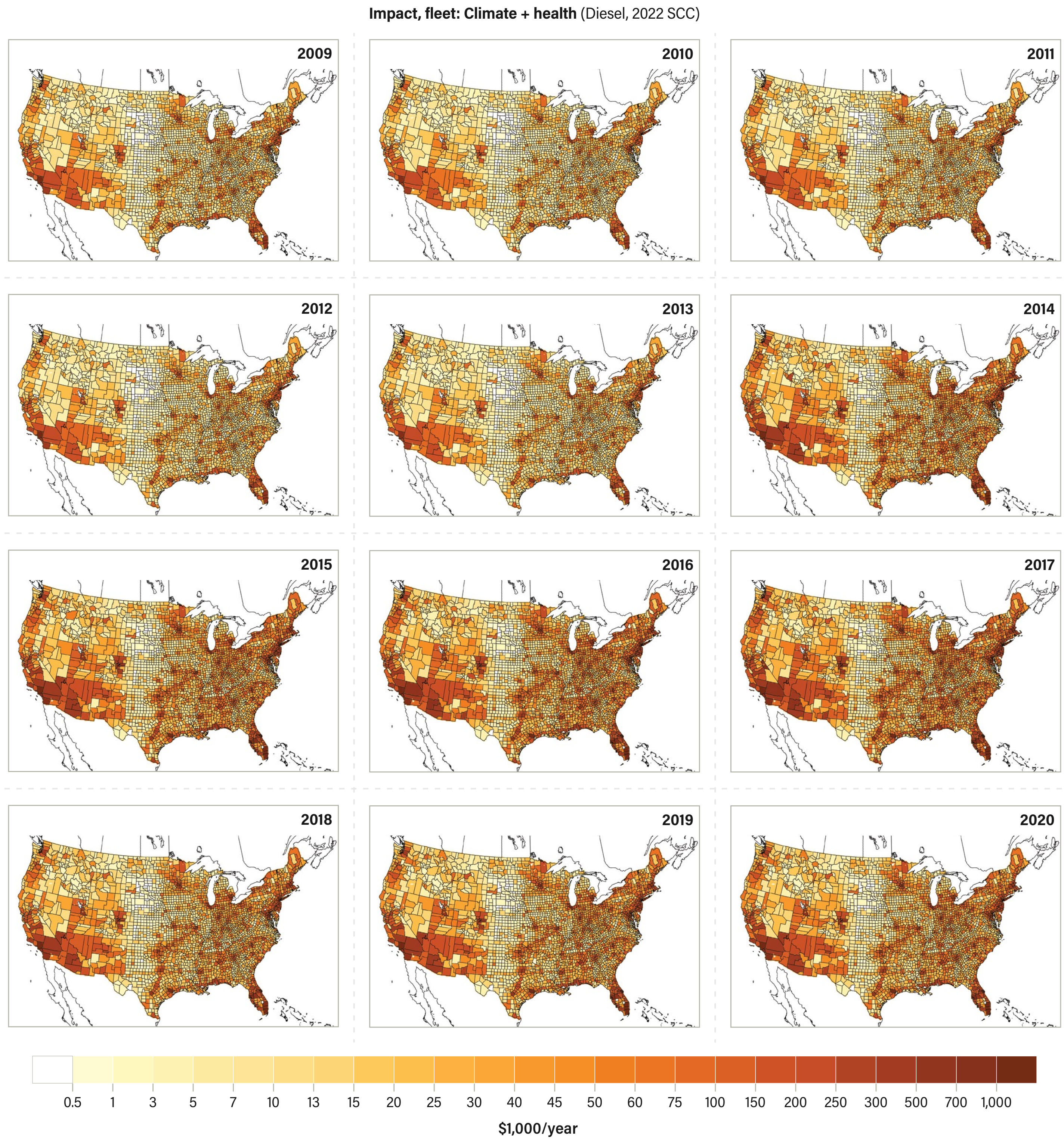
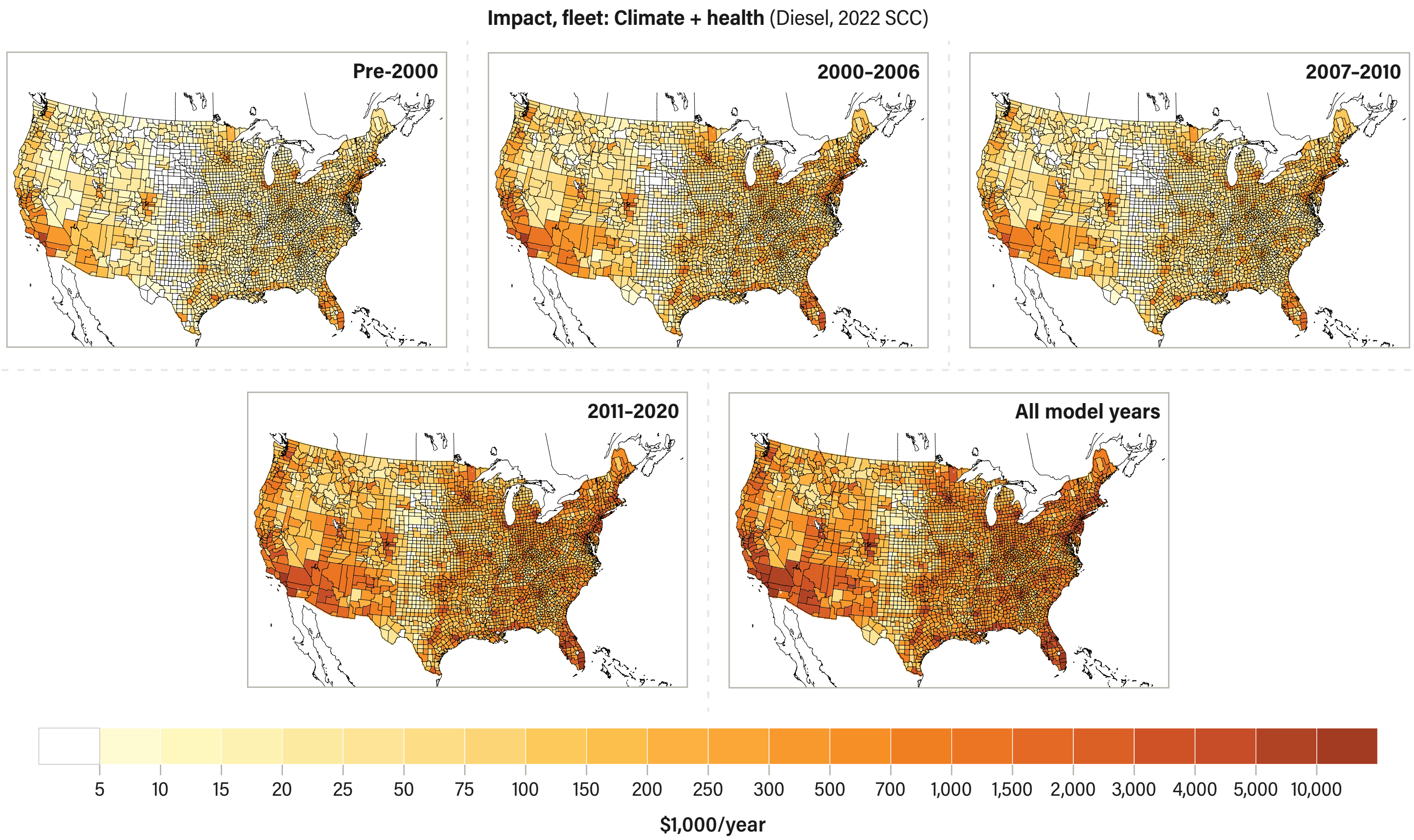


Figure B-1 | **Health and climate burden ($/year) of diesel school buses for model years (cont.)**



Source: Authors.

Figure B-2 | **Health and climate burden ($1,000/year) of diesel school buses for fleet segments**



Source: Authors.

Appendix C: Health and climate benefits of electrification ($/1,000 miles-year) of diesel school buses

Figure C-1 | **Health and climate benefits of electrification ($/1,000 miles-year) of diesel school buses for model years**

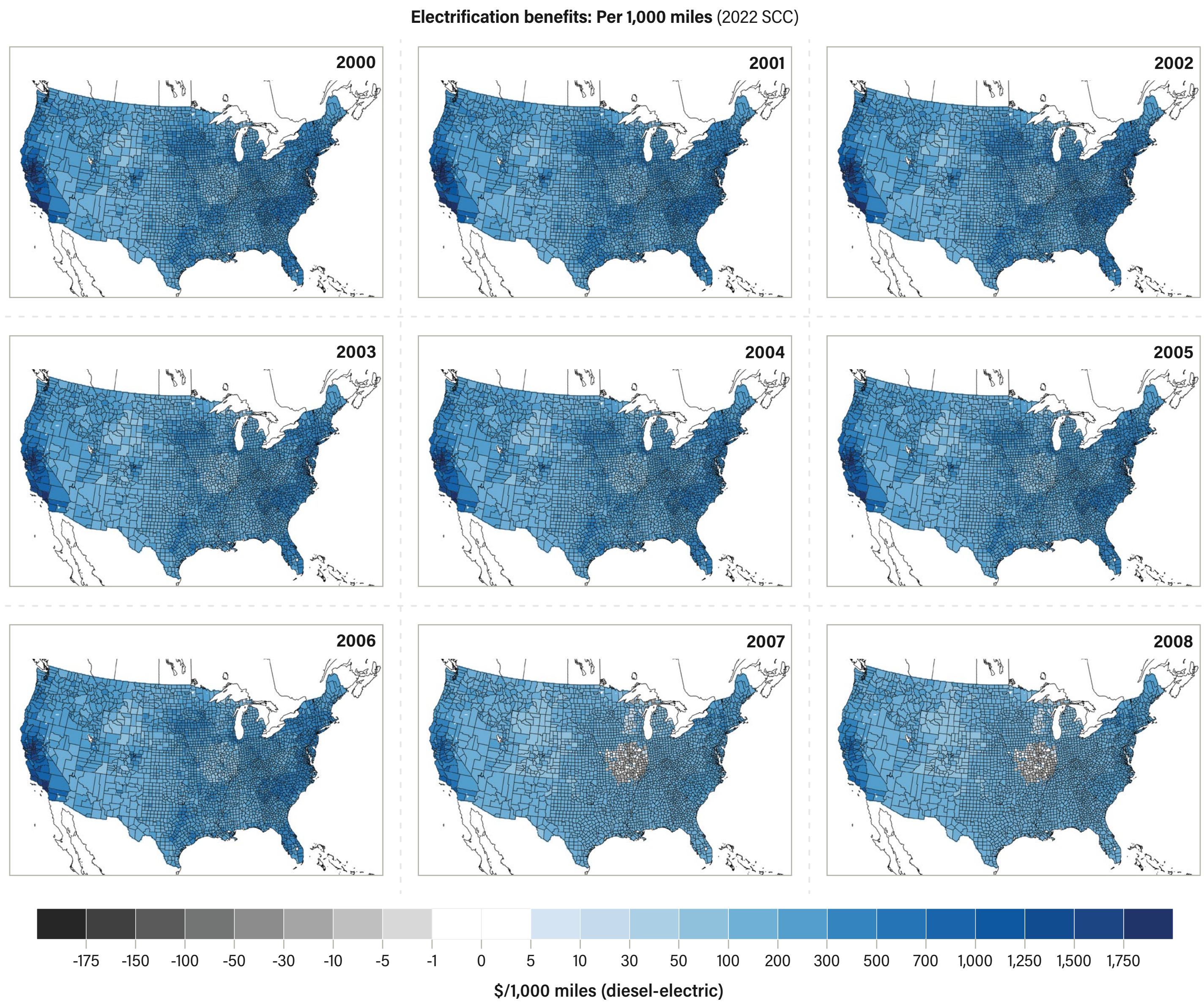
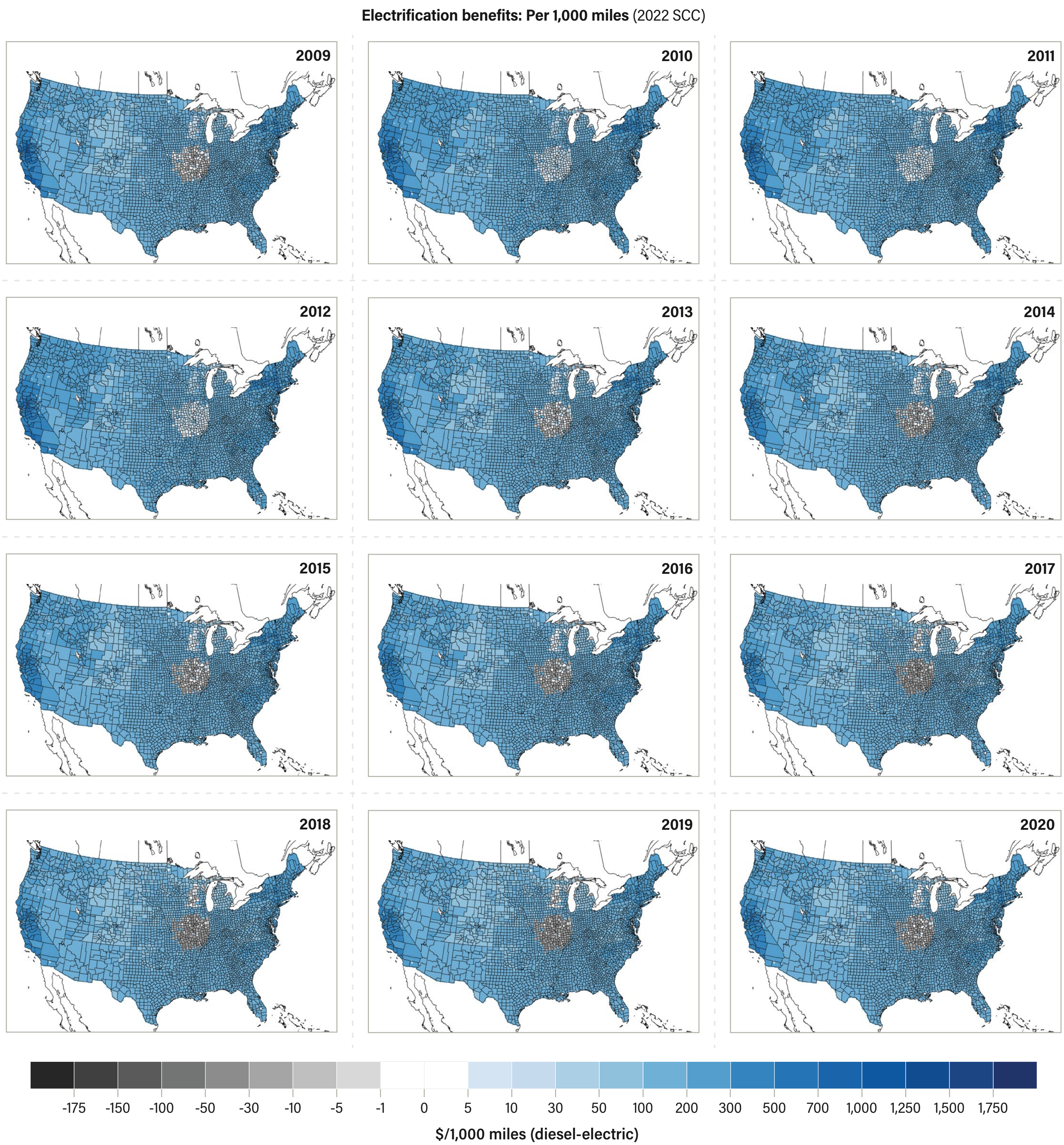
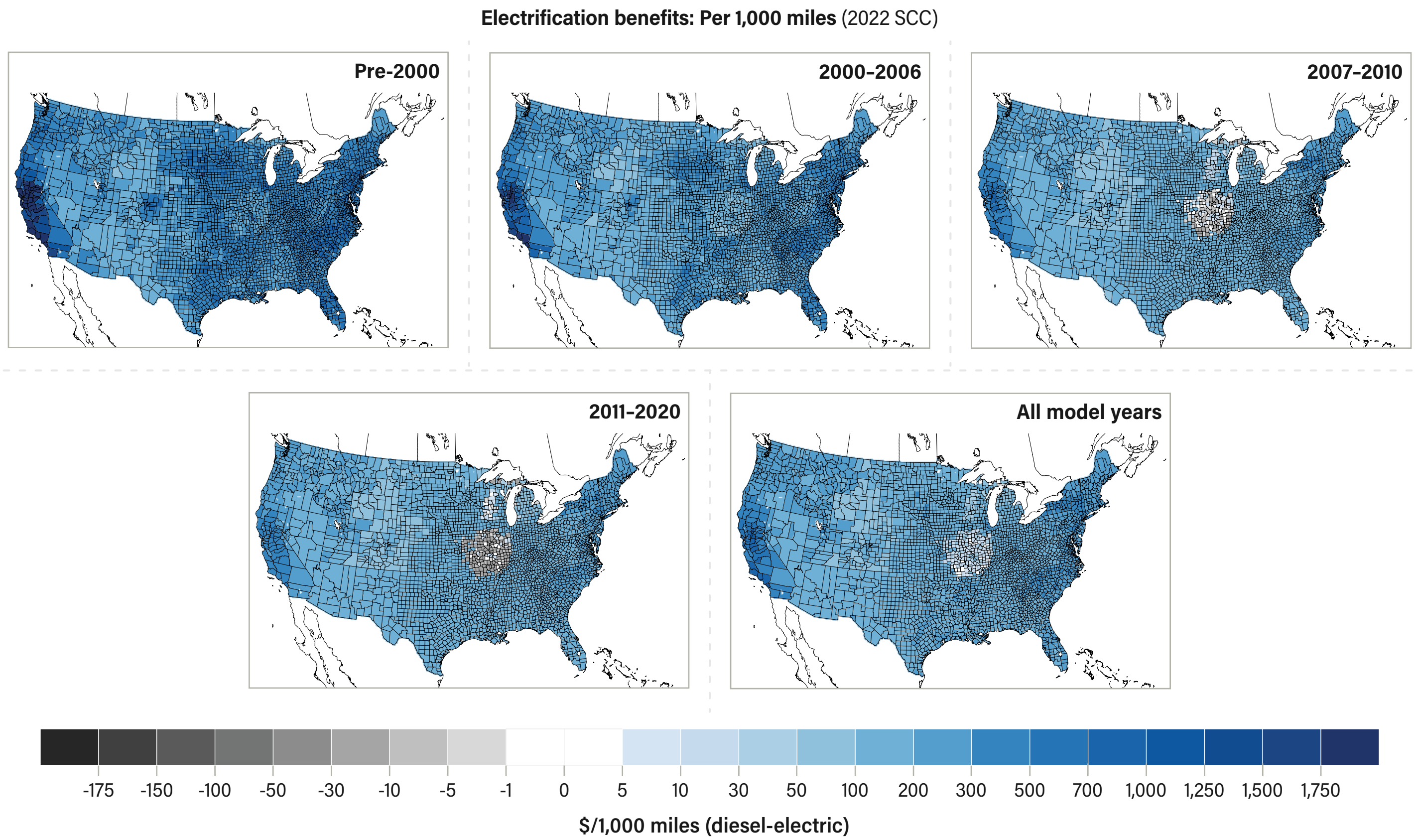


Figure C-1 | **Health and climate benefits of electrification ($/1,000 miles-year) of diesel school buses for model years (cont.)**



Source: Authors.

Figure C-2 | **Health and climate benefits of electrification ($/1,000 miles-year) of diesel school buses for fleet segments**



Source: Authors.

Appendix D: Health and climate benefits of electrification ($/bus-year) of diesel school buses

Figure D-1 | **Health and climate benefits of electrification ($/bus-year) of diesel school buses for model years**

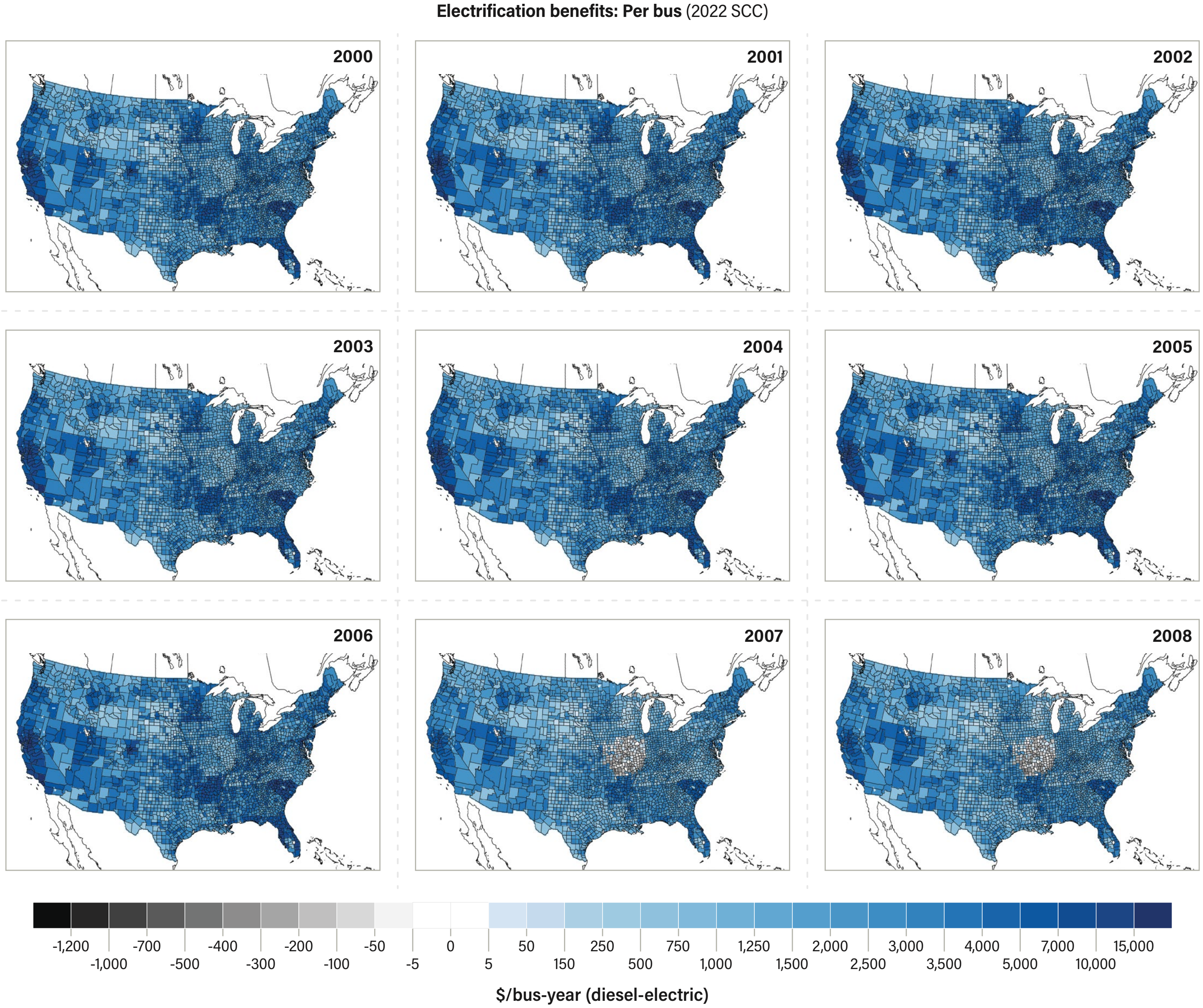
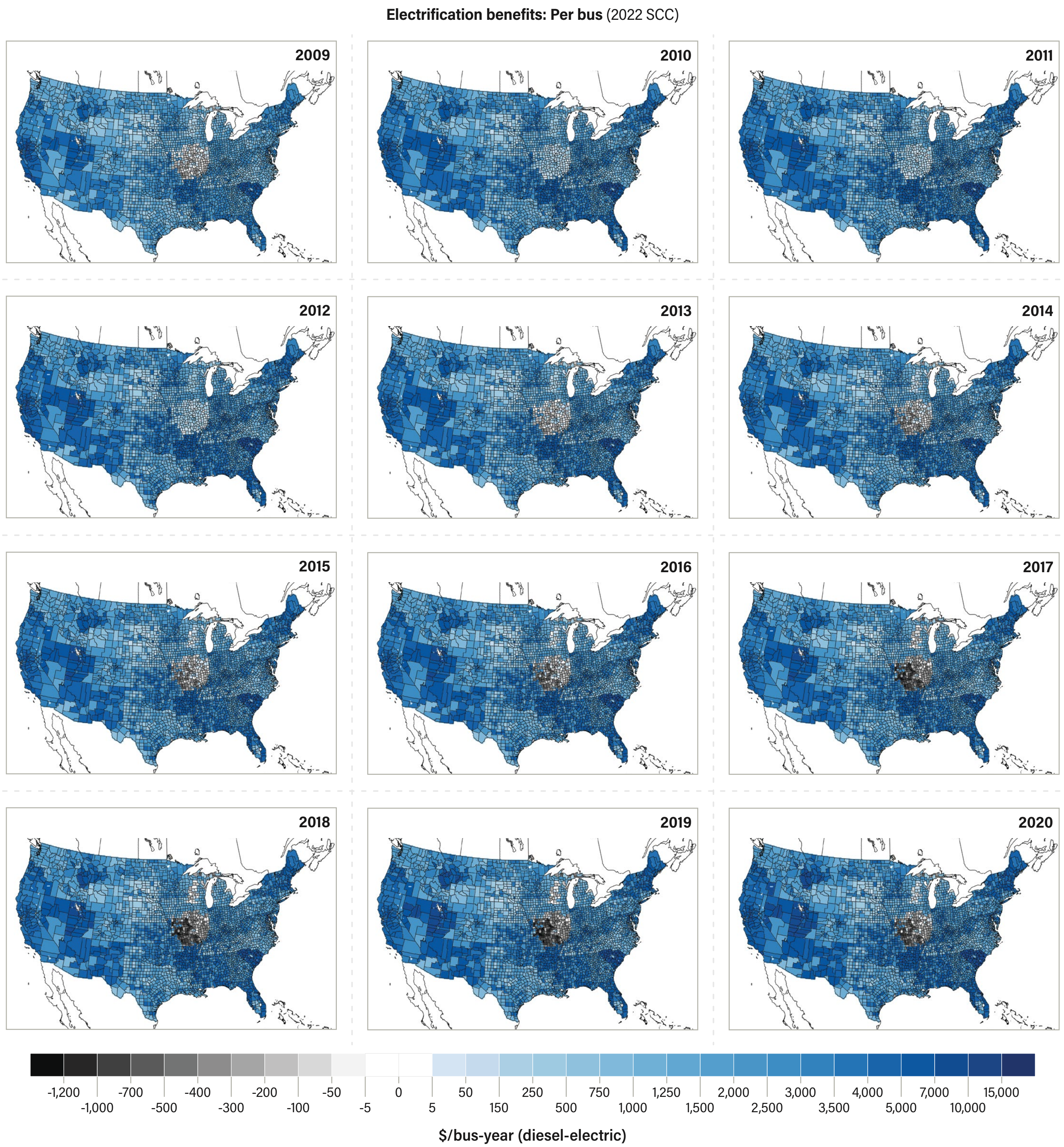
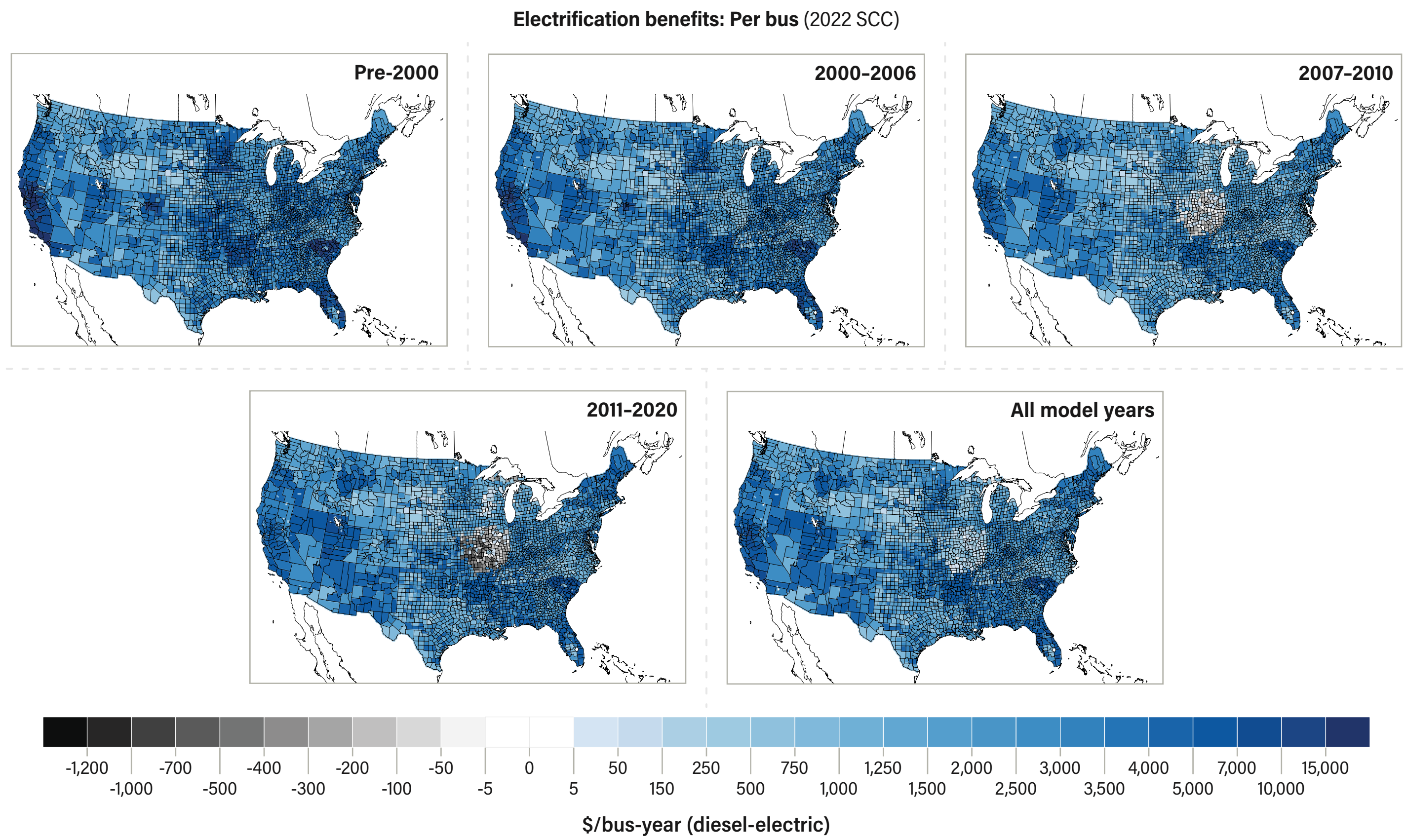


Figure D-1 | **Health and climate benefits of electrification ($/bus-year) of diesel school buses for model years (cont.)**



Source: Authors.

Figure D-2 | **Health and climate benefits of electrification ($/bus-year) of diesel school buses for fleet segments**



Source: Authors.

Appendix E: Health and climate benefits of electrification ($/year) of diesel school buses

Figure E-1 | **Health and climate benefits of electrification ($1,000/year) of diesel school buses for model years**

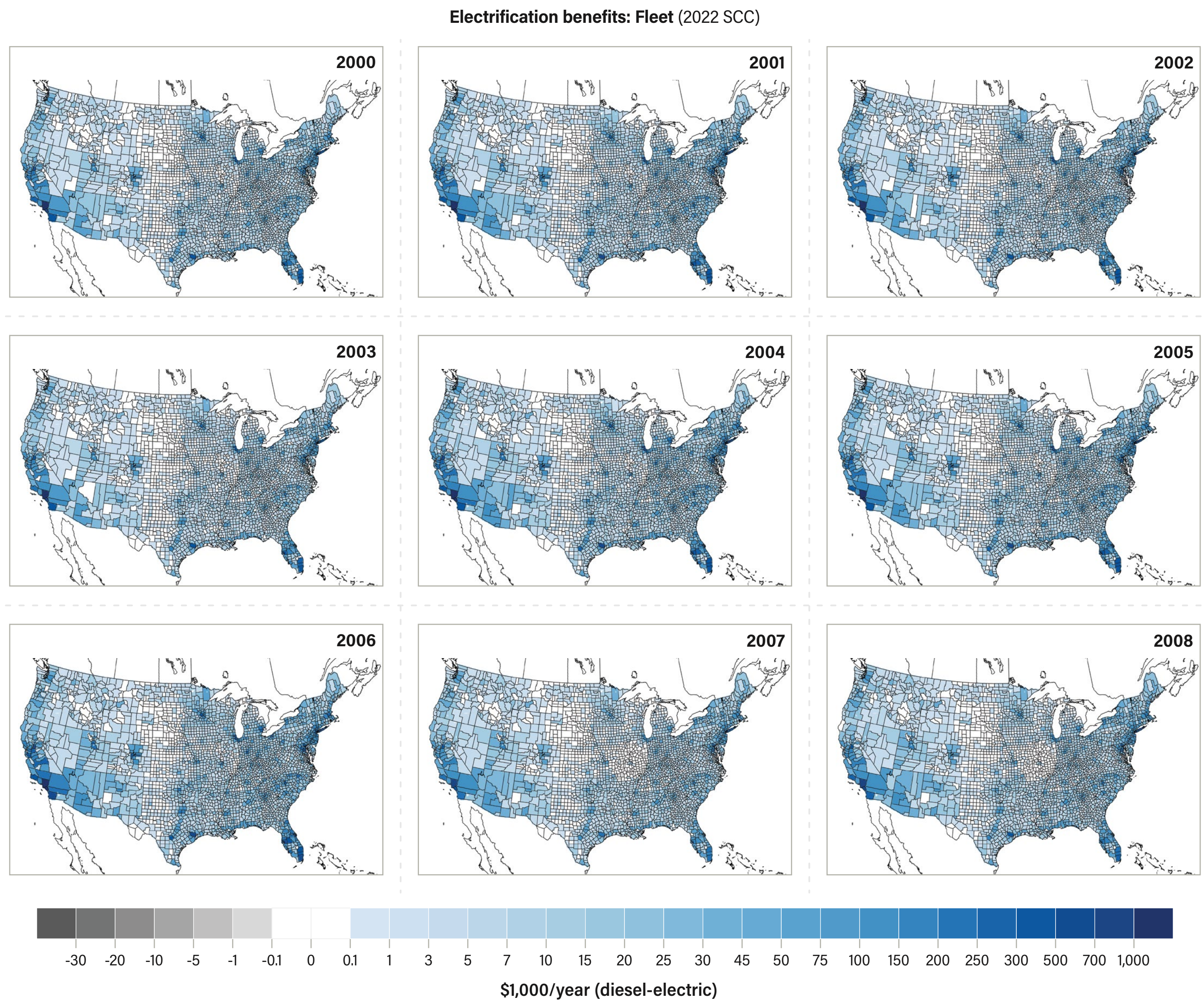
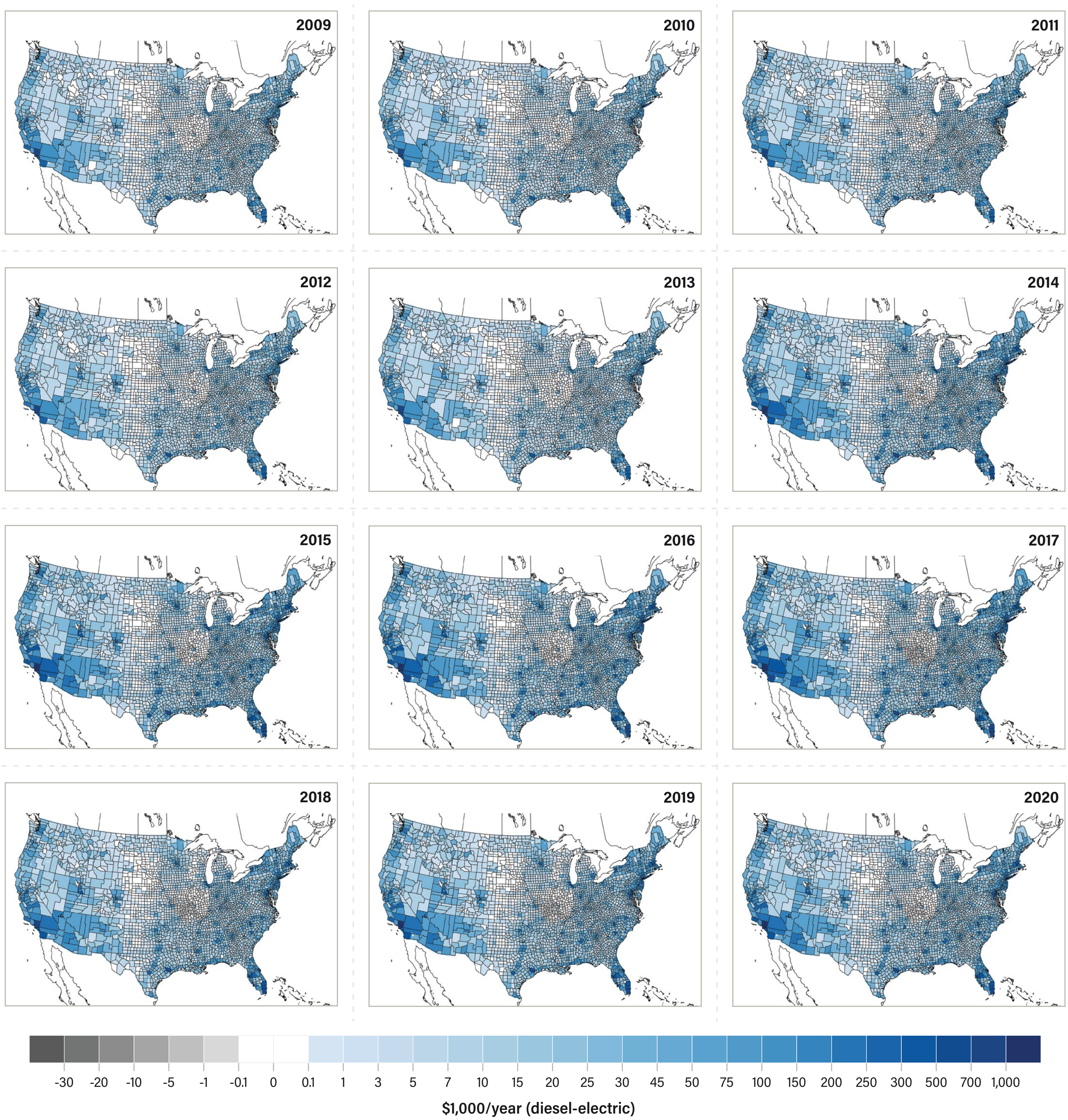


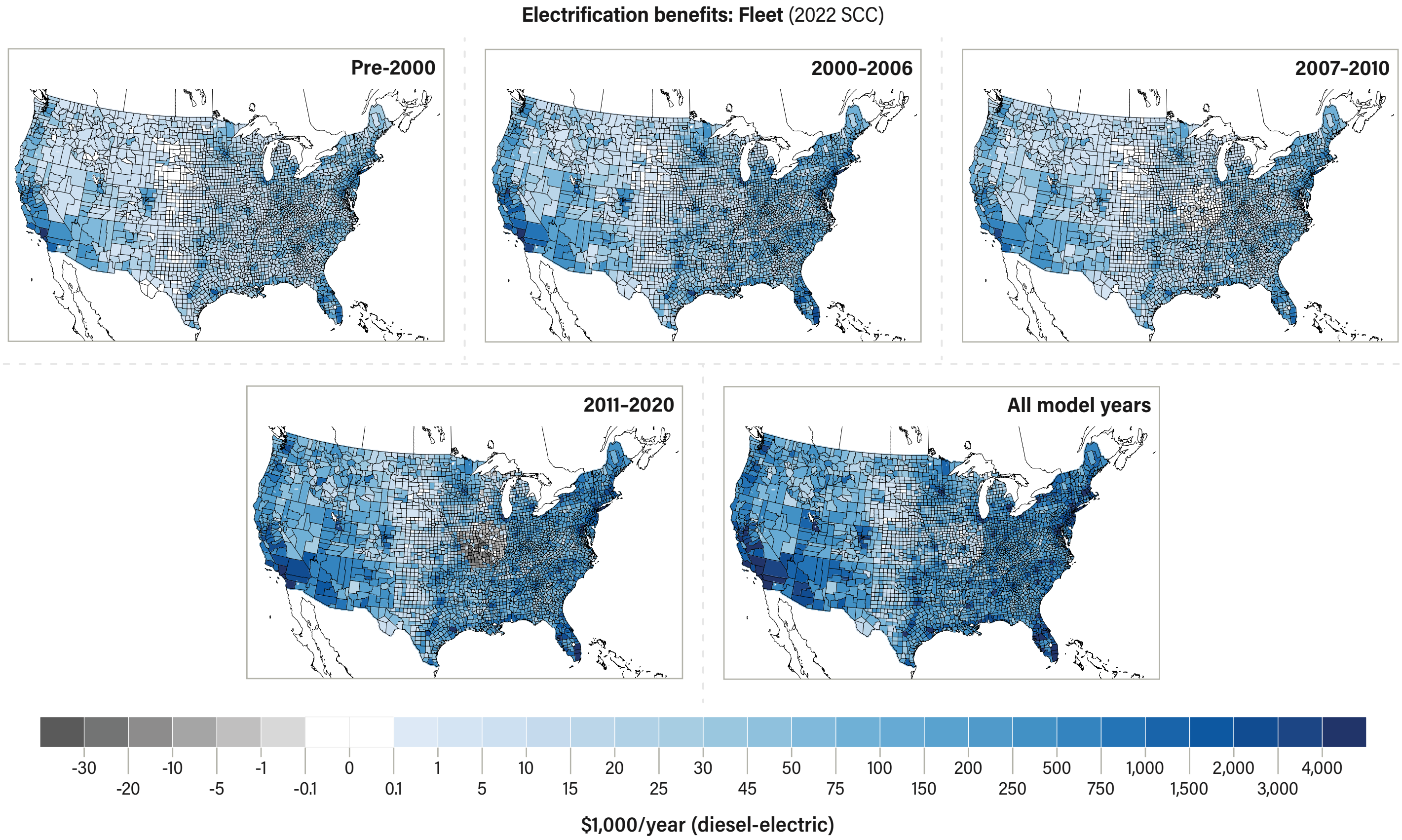
Figure E-1 | **Health and climate benefits of electrification ($1,000/year) of diesel school buses for model years (cont.)**

Electrification benefits: Fleet (2022 SCC)



Source: Authors.

Figure E-2 | **Health and climate benefits of electrification ($1,000/year) of diesel school buses for fleet segments**



Source: Authors.

Glossary

Air contaminants: Co-emitted pollutants with CO_2, other than greenhouse gases.

Benefits per ton (BPTs): Monetized societal benefits of a metric ton reduction in emissions of a pollutant (e.g., primary particles, or precursors such as nitrogen oxides, volatile organic compounds, or ammonia). Expressed in units of $/ton-pollutant.

Co-benefits: In this technical note, the monetized societal health benefits of a metric ton reduction in CO_2 emissions. Co-benefits in this note refer to health benefits from reduced emissions of co-emitted criteria pollutants, regardless of the impact of a changing climate. Similar to BPTs, co-benefits refer to health benefits but are expressed per units of emitted CO_2 ($/ton-$CO_2$).

Concentration response function: Epidemiological relationship between increased risk of mortality and exposure.

Intensity ratios: Mass ratios of criteria air contaminants to CO_2 emissions from an emissions source.

Social cost of carbon (SCC): Aggregated monetized impact of climate change attributed to a metric ton of CO_2 emissions. SCC only accounts for impacts due to climate change and does not include air pollution health co-benefits from reduced emissions of co-emitted pollutants, as defined above. Expressed in units of $/ton-$CO_2$.

Valuation (valuated benefits): Monetizing intangible burdens and external costs.

Value of statistical life (VSL): A widely used willingness-to-pay measure for monetization of a statistical life in governmental cost-benefit analysis.

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Acknowledgments

We are pleased to acknowledge our institutional strategic partners that provide core funding to WRI: the Netherlands Ministry of Foreign Affairs, Royal Danish Ministry of Foreign Affairs, and Swedish International Development Cooperation Agency.

This research was conducted in collaboration between WRI's Electric School Bus Initiative and Carleton University, with generous support from the Bezos Earth Fund, which funds WRI's Electric School Bus Initiative. The authors extend their gratitude to the many individuals who contributed their time and expertise to review and provide feedback on this technical note. In particular, we thank the following reviewers for their invaluable insights: Simone Athayde, Sarav Arunachalam, Beatriz Cardenas, Ken Davidson, Amanda Gian, Sue Gander, Arya Harsono, Heather Holmes, Rohit Jaikumar, Joel Jaeger, Adriana Kocornik-Mina, Tirthankar Mandal, Anne Maassen, Fernando Menendez, Mehri Mohebbi, Meredith Pedde, Elizabeth Wesley, and Sophie Young.

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About WRI

World Resources Institute works to improve people's lives, protect and restore nature, and stabilize the climate. As an independent research organization, we leverage our data, expertise, and global reach to influence policy and catalyze change across systems like food, land and water; energy; and cities. Our 2,000+ staff work on the ground in more than a dozen focus countries and with partners in over 50 nations.

About WRI's Electric School Bus Initiative

In collaboration with partners and communities, the Electric School Bus Initiative aims to build unstoppable momentum toward an equitable transition of the US school bus fleet to electric, bringing health, climate, and economic benefits to children and families across the country and normalizing electric mobility for an entire generation. The Electric School Bus Initiative was founded in partnership with the Bezos Earth Fund in late 2020. We work with key stakeholders at all levels and across areas, including school districts, private fleet operators, electric utilities, public and private lenders, manufacturers, policymakers, equity and environmental advocacy groups, program administrators, community members, and communitybased organizations.