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What are the best combinations of fuel-vehicle technologies to mitigate climate change and air pollution effects across the United States?

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Abstract

The transportation sector is the largest contributor to CO₂ emissions and a major source of criteria air pollutants in the United States. The impact of climate change and that of air pollution differ in space and time, but spatially-explicit, systematic evaluations of the effectiveness of alternative fuels and advanced vehicle technologies in mitigating both climate change and air pollution are lacking. In this work, we estimate the life cycle monetized damages due to greenhouse gas emissions and criteria air pollutant emissions for different types of passenger-moving vehicles in the United States. We find substantial spatial variability in the monetized damages for all fuel-vehicle technologies studied. None of the fuel-vehicle technologies leads simultaneously to the lowest climate change damages and the lowest air pollution damages across all U.S. counties. Instead, the fuel-vehicle technology that best mitigates climate change in one region is different from that for the best air quality (i.e. the trade-off between decarbonization and air pollution mitigation). For example, for the state of Pennsylvania, battery-electric cars lead to the lowest population-weighted-average climate change damages (a climate change damage of 0.87 cent/mile and an air pollution damage of 1.71 cent/mile). In contrast, gasoline hybrid-electric cars lead to the lowest population-weighted-average air pollution damages (a climate change damage of 0.92 cent/mile and an air pollution damage of 0.77 cent/mile). Vehicle electrification has great potential to reduce climate change damages but may increase air pollution damages substantially in regions with high shares of coal-fired power plants compared to conventional vehicles. However, clean electricity grid could help battery electric vehicles to achieve low damages in both climate change and air pollution.

1. Introduction

The transportation sector is currently the most significant contributor to CO₂ emissions in the United States (U.S.) (U.S. Energy Information Administration (EIA) 2017). Similarly, the health and environmental consequences associated with the transportation sector are of critical importance, since the transportation sector accounts for more than half of carbon monoxide (CO) and nitrogen oxides (NO_x) emissions in the U.S., as well as nearly a quarter of volatile organic compounds (VOCs), and 6% of primary PM_{2.5} (particulate matter less than

2.5 micrometers in diameter) emissions (Davis *et al* 2016). Increased emissions and concentrations of greenhouse gases and criteria air pollutants are of concern to society and policymakers, as they lead to poor urban air quality, increasing hazards of infrastructure, and elevated risks of mortality and morbidity in exposed populations (Pope *et al* 2002, Krewski *et al* 2009, Lepeule *et al* 2012). However, the social impacts of these pollutants are not the same across pollutant type, space, or time. Greenhouse gases, for example, have global dispersion, stay in the atmosphere for decades to centuries, and their impacts are the same regardless of the location of the source

(Intergovernmental Panel on Climate Change (IPCC) 2014). Criteria air pollutants, on the other hand, have a much shorter lifespan, and their consequences depend on the location of the source (Heo *et al* 2016a, Gilmore *et al* 2019). Emissions of criteria air pollutants result in higher concentrations of PM_{2.5} and ground-level ozone, which lead to substantial health consequences for the exposed population (Heo *et al* 2016a, Gilmore *et al* 2019).

The impact of air pollution and that of climate change differ in space (local versus global) and time (short-term versus long-term). This divergent nature of air pollution and climate change has led to different perceptions, rates of technology adoption, and effectiveness of technology options and policy actions to tackle air pollution and climate change (Maione *et al* 2016, Sergi *et al* 2018). Whereas efforts to clean the polluted air in the United States and many other developed countries have been hailed as victories (U.S. Environmental Protection Agency (EPA) 2011, Carnell *et al* 2019), efforts to mitigate climate change have yet to make substantial progress (Peters *et al* 2017, van Renssen 2018). One promising way to increase the effectiveness of climate change actions is to identify co-benefits (such as health benefit from the reduction of air pollution) which are achieved by technology options or policy actions that are designed initially to tackle climate change (Bain *et al* 2016, Chang *et al* 2017, Deng *et al* 2017). In particular, health co-benefits have been identified for carbon mitigation strategies and policies in the transportation sector (Shindell *et al* 2011, Balbus *et al* 2014, Shaw *et al* 2014, Thompson *et al* 2014), in the electricity sector (Balbus *et al* 2014, Thompson *et al* 2014, Driscoll *et al* 2015), and across the economy (Zapata *et al* 2013, Thompson *et al* 2014, Buonocore *et al* 2018).

Alternative fuels and advanced vehicle technologies have been widely regarded as a potential solution for sustainable transportation with negligible climate change and air pollution impacts (U.S. National Research Council (NRC) 2010, Creutzig *et al* 2015, Gearhart 2016). However, quantifications of climate change or air pollution effects of alternative fuels and advanced vehicle technologies are only available recently and limited in scope. In 2010, a U.S. National Academies report estimated that air emissions from on-road vehicles resulted in a cost of ~\$110 billion for climate change and air pollution damages in the U.S. (U.S. National Research Council (NRC) 2010). Around the same time, several studies have examined climate change damages or air pollution damages caused by alternative fuels and advanced vehicle technologies such as biofuels, compressed natural gas (CNG) vehicles, diesel vehicles, plug-in hybrid electric vehicles, and battery electricity vehicles, and hydrogen electric vehicles (Ogden *et al* 2004, Jacobson *et al* 2005, Jacobson 2007, Keefe *et al* 2008, Hill *et al* 2009, Sun *et al* 2010, Michalek *et al* 2011,

Tessum *et al* 2014, Luk *et al* 2015, Barrett *et al* 2015, Tamayao *et al* 2015, Tong *et al* 2015a, 2015b, 2017, Weis *et al* 2015, 2016, Yuksel *et al* 2016, Holland *et al* 2016a, 2016b).

For a detailed summary of existing literature in terms of fuel-vehicle technologies considered, data sources for emissions inventories, details about air quality modeling (e.g. species, scope, endpoints), and climate change modeling (species and endpoints), we refer the reader to table S1 in the *supplementary document* (available online at stacks.iop.org/ERL/15/074046/mmedia). In general, these studies find that only a few fuel-vehicle technologies, including hybrid-electric vehicles and battery electric vehicles powered by dedicated natural gas or renewable electricity sources, could reduce climate change damages or air pollution damages compared to incumbent petroleum fuels. However, none of these studies has explicitly quantified the effectiveness of alternative fuels and advanced vehicle technologies in mitigating climate change and air pollution simultaneously in a spatially-explicit manner.

Except for a few recent studies (Hill *et al* 2009, Tessum *et al* 2014, Barrett *et al* 2015, Holland *et al* 2016a), most existing studies ignored the spatial distributions of air pollution damage. This omission could lead to biased findings because the air pollution impact of criteria air pollutants depends critically on where they are emitted and, subsequently, how many people are exposed. As a result, although many studies estimated and compared air pollution damages and climate change damages for certain fuel-vehicle technologies at the national level (i.e. using a representative estimate), quantification and comparison of air pollution damages and climate change damages at the appropriate spatial context (local versus global) is lacking.

As national and local decision-makers may care about different types of negative consequences, it becomes increasingly important to understand if one particular type or a combination of alternative fuels and advanced vehicle technologies could deliver health benefits as well as climate change benefits compared to the incumbent petroleum fuels. This is particularly relevant since vehicles rely on the refueling or charging infrastructure to support their use (Tong *et al* 2019). If different alternative fuels or advanced vehicle technologies are favored under different policy goals, it is hard to form joint forces from all the stakeholders and end-use consumers.

To fill this knowledge gap, we present a systematic, spatially-explicit assessment of environmental externalities caused by alternative fuels and advanced vehicle technologies in the United States, using a coupled modeling framework linking life cycle assessment and reduced-form air quality models. We study three typical types of passenger-moving vehicles, passenger cars, SUVs, and transit buses. We include SUVs because their sale has grown to be comparable

Table 1. Life cycle stages and fuel-vehicle technologies considered.

Stage	Gasoline	Diesel	CNG	Grid electricity
Primary energy extraction	Crude oil production and transportation ¹		Natural gas production, processing, and transmission ¹	Fossil fuels (coal, natural gas, crude oil) production and transportation ¹
Fuel production and transportation	Oil refining ¹		Natural gas compression ²	Electricity generation ²
	Petroleum product transportation ¹		On-site production at refueling stations. ²	Transmission & distribution lines (line losses considered) ²
Vehicle technology	Conventional ICEVs and HEVs. ³		ICEVs ³	BEVs ³
Vehicle type	passenger car, SUV	transit bus	passenger car, SUV, transit bus	passenger car, SUV, transit bus

Notes: CNG = compressed natural gas, ICEV = internal combustion engine vehicle, HEV = hybrid electric vehicle, BEV = battery electric vehicle, SUV = sports utility vehicle; ¹ = Continental U.S. estimate; ² = NERC region estimate; ³ = county estimate.

to that of passenger cars over the last two decades (Davis *et al* 2016). Although transit buses represent a small share of vehicle fleets, they are essential mobility service providers in urban areas and are early adopters for alternative fuel and advanced vehicle technologies (Tong *et al* 2017). We include four transportation fuels—gasoline, diesel, CNG, and grid electricity—which are paired with three vehicle technologies—internal combustion engine vehicles (ICEVs), hybrid electric vehicles (HEVs), and battery electric vehicles (BEVs)—based on fuel properties and market availability.

2. Methods

2.1. Life cycle scope, boundary, and functional unit

Table 1 summarizes the life cycle stages for the fuel-vehicle technologies considered. The life cycle boundary includes primary energy extraction, fuel production and transportation, and vehicle use. We also include the manufacturing of lithium-ion batteries for HEVs and BEVs following recent literature (Michalek *et al* 2011, Tessum *et al* 2014). We assume all other vehicle components are similar across vehicle technologies for a given vehicle type. The functional unit is one vehicle mile traveled (VMT), and the study reference year is 2014 for which we have the complete data.

2.2. Marginal damage approach

We use a marginal damage approach to estimate climate change monetized damages associated with greenhouse gases (CO₂, CH₄, N₂O) and health and environmental monetized damages caused by criteria air pollutants (SO₂, NO_x, CO, PM_{2.5}, and VOCs). We assume that an incremental VMT is small enough to be treated as marginal so that the induced climate change and air pollution damages are calculated as the product of emissions factors and the marginal damages for the emissions species for the same location and height (U.S. National Research Council (NRC) 2010). The marginal damages of a mass of greenhouse gas are the same regardless of source location and

height. However, the marginal damages of criteria air pollutants are sensitive to where they are emitted. We then attribute the monetized costs associated with each fuel-vehicle technology to one vehicle mile. The metric for comparison is monetized damages per vehicle mile. All monetary values are converted to the 2010 dollar using the consumer price index (CPI) (U.S. Bureau of Labor Statistics 2016).

We use two state-of-the-art reduced-form air quality models (the AP2 model and the EASIUR model) (Heo *et al* 2016a, Gilmore *et al* 2019, Muller 2011) to estimate marginal damages for criteria air pollutants. We present the results with the EASIUR model in the main text and leave the results with the AP2 model in the *supplementary document* (section 4.4). Critical economic assumptions in our analysis include a statistical life value of \$₂₀₁₀ 8 million and a social cost of carbon of \$₂₀₀₇36/t CO₂e. Given the uncertainty and discussions in the literature regarding these values, we perform a sensitivity analysis to understand the implication of these assumptions on our results.

2.3. Greenhouse gas (GHG) emissions and damages

We expand the GHG emissions inventories as reported in Tong *et al* (Tong *et al* 2015a, 2015b) by considering upstream and on-site GHG emissions for electricity generation for different NERC (North American Electric Reliability Corporation) regions (see the *supplementary document* for region boundaries and details on the upstream emissions). In particular, a 1.3% methane leakage in the natural gas supply chain was considered (Tong *et al* 2015a, 2015b). We use the 100-year global warming potential (GWP) from the IPCC (Intergovernmental Panel on Climate Change (IPCC) 2014) to convert non-CO₂ emissions to CO₂-equivalent emissions (36 for fossil fuel methane and 298 for fossil fuel N₂O). We use the social cost of carbon (\$₂₀₀₇ 36/t CO₂e) to monetize the damages associated with GHG emissions (Interagency Working Group on Social Cost of Carbon United States Government 2015). We assess the sensitivity of our

results for a range of SCCs from \$₂₀₀₇ 0/t CO₂ to \$₂₀₀₇ 105/t CO₂.

2.4. Criteria air pollutant (CAP) emissions and damages

The life cycle CAP emissions and the resulting damages estimates include those from primary energy extraction, fuel production, vehicle operation, and battery manufacturing.

2.4.1. Primary energy extraction emissions and damages

We calculate the national average air pollution damages producing primary energy products (coal, natural gas, or crude oil) in the U.S. following the approach outlined in (Jaramillo and Muller 2016). We aggregate the county-level criteria air pollutant emissions for these energy sub-sectors from the raw emissions data in the National Emissions Inventory (NEI) (U.S. Environmental Protection Agency (EPA) 2016b) based on the source classification code database developed in (Tschofen *et al* 2019). We multiply criteria air pollutant emissions and the marginal damage estimates for the same species at the same county to calculate the total damages for energy activities, which are then divided by total energy production to quantify the damages per energy unit. For primary energy extraction, we use national weighted-average damage in the analysis. Although domestic production of coal and natural gas accounts for the largest share of supply of these fuels, the U.S. continues to import crude oil (U.S. Energy Information Administration (EIA) 2016c) and, like previous studies (Michalek *et al* 2011, Weis *et al* 2016), we assume that imported crude oil has the same air pollution damages as U.S. crude oil. We account for air pollution damages due to electricity used for powering crude oil pipelines and natural gas pipelines using pipelines' electricity intensity data (Hooker 1981, Davis *et al* 2016) and the electricity damages calculated in this paper.

2.4.2. Fuel production emissions and damages

We construct emissions inventories of the four transportation fuels, gasoline, diesel, grid electricity, and CNG, as follows.

We use emissions data from the National Emissions Inventory (NEI) at the county level to estimate air pollution damages associated with the production of gasoline and diesel. These emissions are normalized to oil refinery capacity (barrel of crude oil inputs) before being converted to the actual outputs of petroleum products (gasoline and diesel) using the energy allocation method (Wang *et al* 2004, U.S. Energy Information Administration (EIA) 2016b, 2016c).

For CNG, we assume compression of natural gas takes place at refueling stations. Thus, compressors use the electricity from the NERC region in which

they are located. The energy efficiency of the compression process is 96% (Tong *et al* 2015a, 2015b).

We model GHG and CAP emissions for the U.S. electricity grid in the year 2014. To explore the impact of the evolving electricity grid, we also model a hypothetical case 'alternative electricity grid' in which coal-fired and oil-fired power plants in the 2014 electricity grid are replaced by new natural gas combined cycle power plants at the same location and for the same net generation. For both electricity grids, we use NERC regions as independent geographical units of analysis (U.S. Environmental Protection Agency (EPA) 2015). In the *supplementary document*, section 2, we include a map of NERC regions for the readers' reference. We account for line losses using U.S. EPA's eGRID data (U.S. Environmental Protection Agency (EPA) 2015), and for battery-electric vehicles, we assume a vehicle charging efficiency of 86.5% (Tong *et al* 2015a).

To calculate climate change damages and air pollutant damages for electricity generation, we use data from U.S. EPA's Continuous Emissions Monitoring System (CEMS) (U.S. Environmental Protection Agency (EPA) 2016a) (net electricity generation, CO₂, SO₂ and NO_x emissions for fossil fuel power plants) and U.S. EPA's NEI for PM_{2.5} emissions. We calculate the air pollution damages from each electric generation units (EGU) by multiplying emissions and their respective county-level marginal damages. To calculate the weighted-average damages associated with the average electricity generation, we sum up the individually-calculated damages for EGUs in each NERC region, which are then divided by the net electricity generation (for the year 2014) in each NERC region. We compile U.S. EIA's Form-923 (U.S. Energy Information Administration (EIA) 2016a) for net generation data for non-fossil fuel power plants, which is not included in U.S. EPA's CEMS.

In the *supplementary document*, we consider three additional electricity grid scenarios for 2014 electricity grid to understand the likely impacts of electric vehicle charging: (1) the average electricity generation from all fossil fuel power plants ('average fossil-fuel electricity'); (2) marginal fossil fuel electricity that has the lowest combined air pollution and climate change damages for an hour ('cleanest marginal fossil fuel electricity'), and (3) marginal fossil fuel electricity that has the highest combined damages for an hour ('dirtiest marginal fossil fuel electricity').

Data and estimates for net generation, emissions factor, and climate change and air pollution damages associated with electricity generation are available in the *supplementary document* (section 3.3).

2.4.3. Vehicle operation

Emissions come directly from the combustion of fossil fuels as well as tire and brake wear during vehicle operation. For passenger cars and SUVs, we

Table 2. Comparison of reduced-form air quality models.

Model	Data Year	Approach	Spatial resolution	Temporal resolution	Pollutants	Damage endpoints
AP2	Emissions: 2011; Population: 2011	Source-receptor matrix and damage functions.	County centroid (3109 counties)	Annual average	PM _{2.5} , SO _x , NO _x , NH ₃ , VOC	Health (short-term and long-term mortality and morbidity) and environmental impacts due to primary and secondary PM _{2.5} and ozone.
EASIUR	Emissions: 2005; Population: 2010	Reduced-form chemical transport model and damage functions.	Grid cell size of 36 km × 36 km (148*112 cells)	Seasonal and annual average	PM _{2.5} , SO _x , NO _x , NH ₃	Health impacts (long-term mortality) due to primary and secondary PM _{2.5} .

use the GREET model (ANL 2019) for vehicle operation emissions. For transit buses, we use chassis emissions tests of CO, NO_x, and VOC from the Altoona Bus Research & Testing Center (ABTRC) reports (Altoona Bus Research and Testing Center 2016) and use the GREET model for PM_{2.5} and SO₂ emissions. Transit buses tested followed U.S. EPA's 2010 emissions standards for heavy-duty engines (U.S. Environmental Protection Agency (EPA) 2001). Besides, we include low-NO_x CNG transit buses (whose NO_x emissions are 1/10 of those from a conventional diesel bus) to account for the 2015 California Optional Low NO_x Standard (California Air Resources Board (CARB) 2013). Our assumptions on transit bus's vehicle operation emissions are in agreement with the GREET model (section 3.4 in the *supplementary document*).

The vehicle fuel efficiency determines the amount of fuel used per mile. We use the fuel economy assumptions from Tong *et al* (2015a, 2015b). We also rely on Tong *et al* (2015a, 2015b) for vehicle mileage, battery size, and replacement (for HEVs and BEVs only) assumptions. While outside the scope of this work, other factors, such as temperature and driving profiles, may also affect the overall damages associated with the operation of BEVs as discussed in (Weiss *et al* 2016) and (Yuksel *et al* 2016).

2.4.4. Battery manufacturing

We use the literature estimates for the air pollution damages associated with battery manufacturing. In particular, the estimated damages between the two literature (Michalek *et al* 2011, Tessum *et al* 2014) differed by a factor of three. While the two sources used similar emissions inventories (GREET model), they assumed different locations of production processes and, as a result, found different air pollution damages. We assume an \$8.68 kWh⁻¹ damage (the lower estimate) from the more recent source (Tessum *et al* 2014) in the baseline analysis, and we perform sensitivity analysis with the alternative source (Michalek *et al* 2011). Battery manufacturing damages are allocated to vehicle miles traveled with the consideration of vehicle lifetime mileage, battery size,

and number of batteries per vehicle lifetime (Section 3.4.2 in the *supplementary document*).

2.4.5. Marginal damages of air pollutants

We use the AP2 model (Muller and Mendelsohn 2007, Muller 2011) and the EASIUR model (Heo *et al* 2016a, 2016b) to estimate the marginal damages of air pollutants. Both models use a damage function approach and use similar concentration-response relationships for PM_{2.5} (Pope *et al* 2002, Krewski *et al* 2009). A key modeling difference is that the AP2 model used a source-receptor matrix framework derived from a Gaussian Plume model, whereas the EASIUR model used a regression method to obtain reduced-form outputs from a tagged chemical transport model (Gilmore *et al* 2019). The models also differ in baseline emissions inventory, baseline population data, spatial and temporal resolutions, pollutants considered, and damage endpoints assumed (table 2). As a result, there are significant differences in the spatial distributions of their respective marginal damage estimates (see (Heo *et al* 2016a) and (Gilmore *et al* 2019) for details). Ongoing work aims to resolve the mentioned differences between the two models.

The EASIUR and AP2 models estimate different marginal damages for ground-level and elevated emissions sources. We use the elevated-level marginal damages for fossil fuel power plants and the ground-level marginal damages for all other emissions sources.

Carbon monoxide is known to affect cardiovascular health and leads to secondary effects from ground-level ozone (Michalek *et al* 2011), but neither social cost model includes these effects. Thus, we use the national-average CO damage estimate from (Matthews and Lave 2000) of \$520/metric ton CO in \$₁₉₉₂, which after inflation adjustment is \$₂₀₁₀808/metric ton CO.

We use U.S. EPA's recommended value of a statistical life (VSL), \$₂₀₁₀ 8 million (U.S. Environmental Protection Agency (EPA) 2014). In the sensitivity analysis, we vary this value from \$0 to \$16 million (Viscusi and Aldy 2003, U.S. Environmental Protection Agency 2010). We

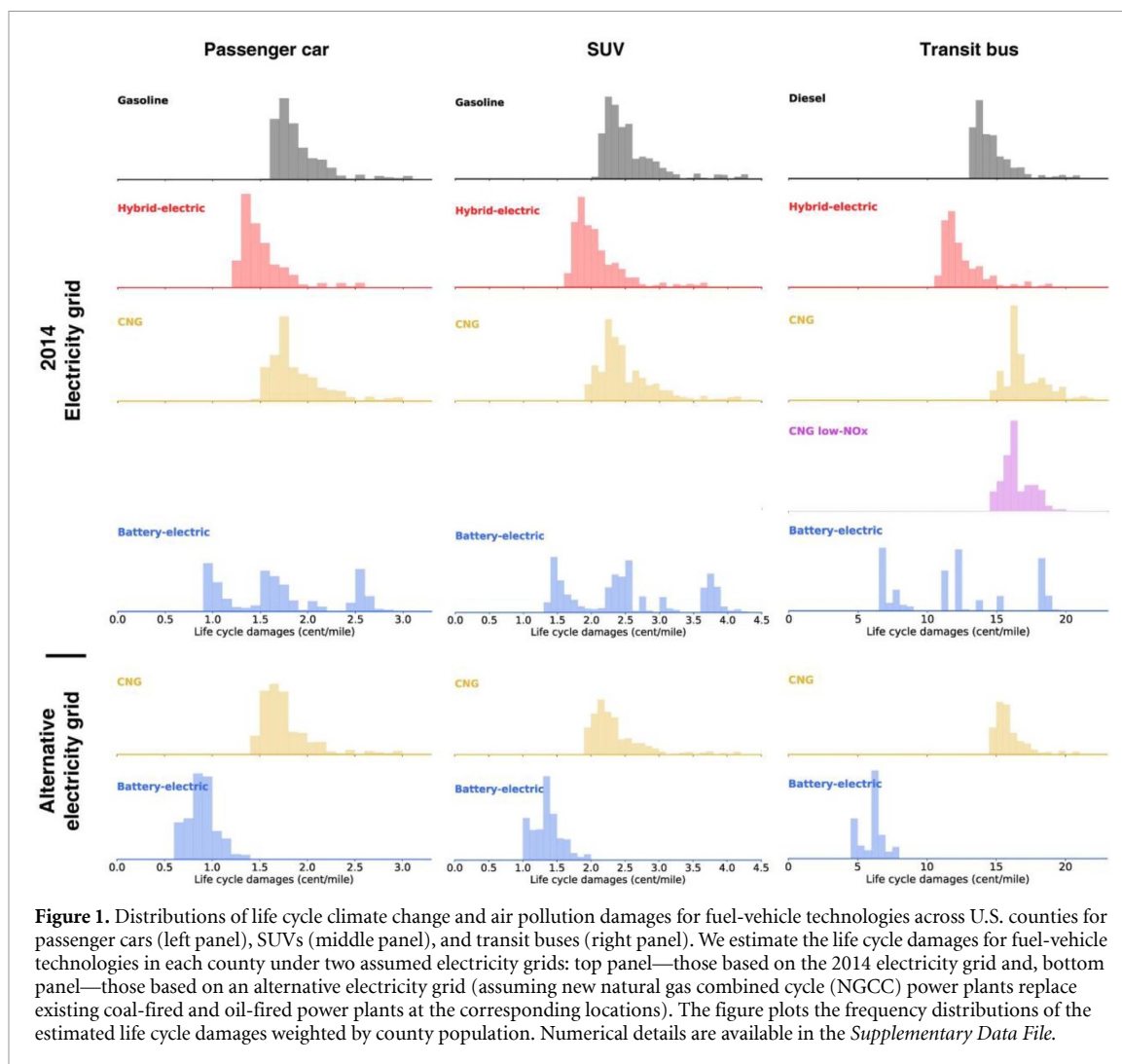


Figure 1. Distributions of life cycle climate change and air pollution damages for fuel-vehicle technologies across U.S. counties for passenger cars (left panel), SUVs (middle panel), and transit buses (right panel). We estimate the life cycle damages for fuel-vehicle technologies in each county under two assumed electricity grids: top panel—those based on the 2014 electricity grid and, bottom panel—those based on an alternative electricity grid (assuming new natural gas combined cycle (NGCC) power plants replace existing coal-fired and oil-fired power plants at the corresponding locations). The figure plots the frequency distributions of the estimated life cycle damages weighted by county population. Numerical details are available in the *Supplementary Data File*.

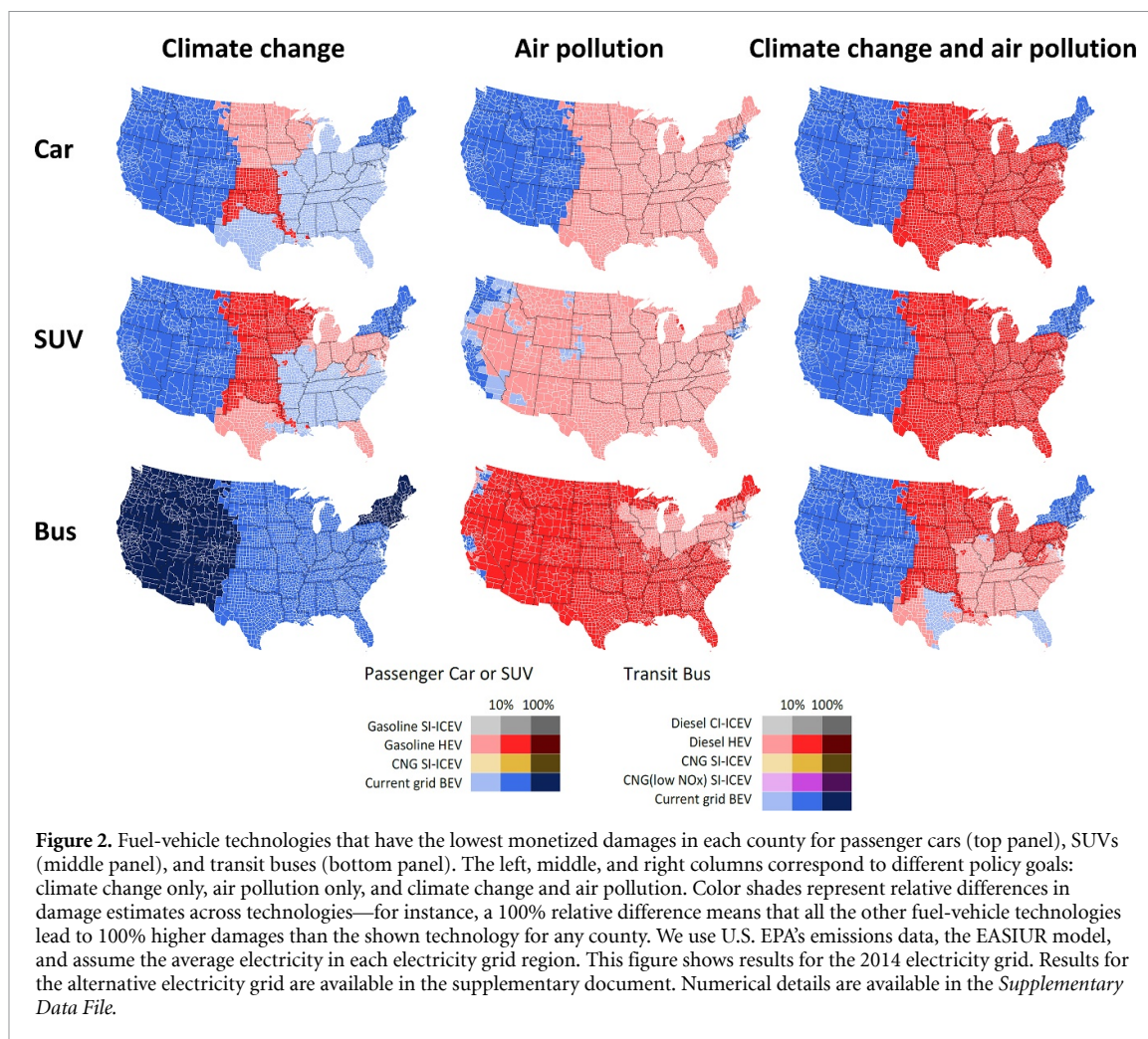
Table 3. Weighted-average life cycle damages of fuel-vehicle technologies for the Contiguous U.S. (weighted by county population) assuming the average electricity in 2014. (Unit: cent per vehicle mile traveled).

Vehicle	Technology	Climate change	Air pollution	Climate change and air pollution
Passenger car	Gasoline	1.25	0.65	1.90
	Gasoline hybrid-electric	0.92	0.60	1.52
	CNG	1.18	0.70	1.88
	Battery-electric	0.78	0.91	1.69
SUV	Gasoline	1.65	0.90	2.55
	Gasoline hybrid-electric	1.25	0.84	2.09
	CNG	1.54	0.97	2.51
	Battery-electric	1.14	1.36	2.50
Transit bus	Diesel	11.74	2.93	14.67
	Diesel hybrid-electric	9.79	2.72	12.51
	CNG	11.39	5.62	17.01
	CNG low-NOx	11.39	5.05	16.44
	Battery-electric	5.82	6.16	11.99

assume the air pollution damages are proportional to VSL, but the VSL does not impact climate change damages.

For the results shown in figure 1, table 3, and figure 4, we use the population as a proxy for vehicle miles traveled in U.S. counties for passenger-moving

vehicles considered in this paper. County population data is available from the U.S. Census Bureau (National Bureau of Economic Research 2017). The formula to calculate the weight-averaged damages is available in the *supplementary document* (section 3.5).



3. Results

3.1. Spatial variability in life cycle damages

We estimate the life cycle climate change damages and air pollution damages for fuel-vehicle technologies used in U.S. counties. In the discussion below, ‘damages’ or ‘life cycle damages’ refer to ‘life cycle air pollution damages and life cycle climate change damages’, unless otherwise specified. In figure 1, we present the frequency plots (weighted by county population) of county-level damages for each fuel-vehicle technology option considered for passenger cars, SUVs, and transit buses. The estimated life cycle damages show significant heterogeneity across U.S. counties. For instance, the most serious damage is twice as significant as the lowest damage of driving the same gasoline car across counties. However, no matter where the vehicle is driven, the damages are no smaller than 1.5 cents per vehicle mile traveled. For population-weighted-average damages for the Contiguous U.S., gasoline hybrid-electric vehicles lead to the lowest damages for passenger cars and SUVs, whereas battery-electric buses achieve the lowest damages for transit buses (table 3). Weighted-average damage estimates for U.S. states and electricity grid regions are available in the *Supplementary Data File*.

Hybrid-electric vehicles have lower damages than conventional gasoline/diesel vehicles (baseline technologies) across all counties. This is because hybrid-electric vehicles operate more energy-efficiently, thus consuming fewer fuels and leading to lower energy use and emissions from the upstream activities. CNG vehicles or battery-electric vehicles do not always lead to damage reductions. With the 2014 electricity grid, battery-electric vehicle is the preferred technology in some counties while the least-preferred technology in other counties for cars and SUVs (Figure S4 in the *supplementary document*). However, if coal power plants are entirely phased out (‘alternative electricity grid’), the distributions of damages for battery-electric vehicles would move entirely to the left of those for the other technologies. In other words, battery-electric vehicles powered by coal-phased-out electricity grid would deliver substantial health and climate benefits across the United States. Furthermore, as natural gas compressors, used in the transportation and storage of natural gas as well as compression of natural gas to make CNG fuel, consume electricity for operation, the life cycle damages of CNG vehicles would also reduce under the ‘alternative electricity grid.’

The frequency distributions of life cycle damages of any specific fuel-vehicle technology are similar for passenger cars and for SUVs. But this is not the case for transit buses. First, CNG transit buses are more likely to increase damages compared to conventional diesel buses due to fuel efficiency penalty and methane leakage along the natural gas supply chain (Tong *et al* 2015b, 2017). Second, battery-electric buses are more likely to reduce damages compared to conventional diesel buses thanks to stop-and-go duty cycles (that are more beneficial to battery-electric vehicles) and higher tailpipe emissions of criteria air pollutants for conventional diesel buses (Tong *et al* 2015b, 2017).

3.2. 'Best' fuel-vehicle technology for each county

To facilitate decision-making, we compare and rank the fuel-vehicle technologies by their life cycle damages for the same vehicle type in the same county. In figure 2, we show the preferred fuel-vehicle technologies that lead to the lowest damages in any county. In particular, we consider three environmental goals: climate change only, air pollution only, and climate change and air pollution. We find that battery-electric buses are the preferred technology across the country for the climate change goal. However, for other goals and other vehicle types, preferred fuel-vehicle technologies depend on the environmental goal considered as well as where vehicles are used.

Looking across environmental goals (i.e. different columns in figure 2), for passenger cars, SUVs, or transit buses, there is no fuel-vehicle technology that achieves the lowest climate change damages *and* the smallest air pollution damages in all counties. Instead, we identify a trade-off for technology solutions that mitigate climate change damages and those that reduce air pollution damages. Although alternative fuel and advanced vehicles almost always reduce climate change damages compared to conventional gasoline/diesel vehicles, they can increase air pollution damages in some regions (see *supplementary document*, section 4.4, and *Supplementary Data File* for quantitative details). It is worth noting, however, that battery-electric passenger car could lead to co-benefits (mitigating both climate change and air pollution damages) for the west coast, Rocky Mountain, and New England. Similarly, gasoline/diesel hybrid-electric cars and SUVs would provide co-benefits in the Midwest.

Vehicle electrification has great potential to reduce climate change damages. Battery-electric vehicles lead to the lowest climate change damages for passenger cars and transit buses in the majority of U.S. regions (except the Midwest). Battery-electric SUVs have lower climate change damages than gasoline and CNG SUVs in all areas. However, significant variability and uncertainty exist in the air pollution damages caused by battery-electric vehicles across the U.S. For regions where clean power

plants are already in place, such as the west coast and Rocky Mountain region, battery-electric passenger cars achieve lower air pollution damages than other fuel-vehicle technologies. It is also worth noting that battery-electric SUVs and battery-electric transit buses only lead to the smallest air pollution damages for densely-populated regions on the west coast. The differences in the relative air pollution damages of battery-electric vehicles across vehicle types suggest the need to consider vehicle type in the policymaking.

The emissions profiles of natural gas vehicles are different from conventional gasoline/diesel vehicles. Although natural gas vehicles have lower tailpipe CO₂ emissions and NO_x emissions than gasoline/diesel vehicles, they have more substantial life cycle methane emissions (a potent greenhouse gas) and much higher tailpipe CO emissions (a criteria air pollutant). As a result, when comparing life cycle damages of CNG vehicles with gasoline/diesel vehicles, the spatial variability in marginal air pollution damages (primarily determined by baseline emissions, wind speed and direction, and population density) plays an important role. In this study, CNG vehicles always lead to greater damages than gasoline/diesel hybrid-electric vehicles for climate change damage or air pollution damage.

3.3. Sensitivity to time of charging

In contrary to petroleum and natural gas fuels, the environmental impact of battery-electric vehicles is much more sensitive to time of vehicle charging. This is because the cost-minimized dispatch of electric power grid varies from hour to hour due to changes in demand, generator availability, renewable energy generation, and transmission line congestion (Siler-Evans *et al* 2012). The preceding discussion so far highlights the potential of battery-electric vehicles in reducing climate change and air pollution damages, assuming the average emissions from all electricity generation sources in 2014. The concept of 'average electricity' may apply if the adoption of battery-electric vehicles leads to a sizable electricity load comparable to existing electricity loads. For a limited penetration of battery-electric vehicles, the expected charging load is more likely to cause a 'consequential' change (or perturbation) in the grid operation. To quantify these 'consequential' impacts, we estimate the 'consequential' generation at the margin following the regression-based approach proposed in (Siler-Evans *et al* 2012). In figure 3, we show that the 'consequential' life cycle climate change and air pollution damages of battery-electric vehicles vary substantially depending on when vehicle charging happens during a day. In Dallas, for instance, the life cycle air pollution damages of battery-electric cars would vary by three times between charging at 4 am and 11 am. In any county within a given electricity grid region, the relationship between the consequential impacts and hour of charging is similar because we assume

electrons flow freely within each grid region. However, we find inconsistent patterns regarding the effect of charging time across electricity grid regions (figure 3). This finding further highlights the need to follow a regionalized strategy to incentivize vehicle charging at certain times to maximize social benefits. Finally, to bound the impact of charging time, we estimated the range of 'consequential' life cycle damages of battery-electric vehicles when charged at the 'cleanest' and the 'dirtiest' hours in each electricity grid region across the country in the *supplementary document* (sections 3.3 and 4.2).

3.4. Sensitivity to monetary valuation

Subjective judgments of decision-makers further complicate the trade-offs of technology solutions for different environmental goals. Two examples are the value of a statistical life (an economic valuation of lost life due to premature morbidity and mortality) and the social cost of carbon (the marginal damages of an additional metric ton of carbon dioxide emissions). These assumptions are crucial in converting physical health outcomes to monetary values, but they are inherently subjective and uncertain. Indeed, the estimates of the value of a statistical life could range from ~\$1 million to ~\$24 million (Viscusi and Aldy 2003, U.S. Environmental Protection Agency 2010). Furthermore, U.S. federal agencies have the discretion to choose VSLs appropriate for their rulemaking (Viscusi and Aldy 2003, U.S. Environmental Protection Agency 2010). The social cost of carbon is profoundly uncertain because it depends on climate change impacts happening in the future as well as the valuation of the impacts (Pizer *et al* 2014, Interagency Working Group on Social Cost of Carbon United States Government 2015). While the social cost of carbon would be impacted by the assumed value of a statistical life, we assume, in the following parametric analysis, that they are independent of each other.

In figure 4, we show fraction of the U.S. population with the preferred fuel-vehicle technologies (i.e. achieving the lowest climate change and air pollution damages) in their home counties. For instance, for passenger cars (the first column), with the baseline assumptions of the value of statistical life and social cost of carbon (the dashed vertical line), 30% of U.S. population would find battery-electric vehicles to have the lowest life cycle damages in their home county whereas the other 70% of residents would prefer gasoline hybrid-electric vehicles for the same goal. This result relies on the same underlying results as those shown in figures 1 and 2 but is presented in a compressed way to allow for a visual comparison of results over any changed assumption.

For passenger cars and SUVs, battery-electric vehicles and gasoline-hybrid vehicles are preferred technologies, and their relative shares as the preferred

technology for U.S. populations are largely stable across the assumed range of either social cost of carbon or value of a statistical life. However, for transit buses, the preferred technology choices change dramatically depending on the social cost of carbon and the value of a statistical life used.

As we assume the climate change damages are proportional to the social cost of carbon and the air pollution damages proportional to the value of a statistical life, different assumptions for these two variables represent varying weights between climate change damages and air pollution damages in decision-making. In the extreme case, a \$0/metric ton social cost of carbon indicates that only air pollution damages are considered, and a \$0 value of a statistical life suggests that only climate change damages matter. Since different fuel-vehicle technologies are preferred for transit buses under different goals (figure 2), divergent subjective judgments of decision-makers only amplify this trade-off in decision-making.

3.5. Sensitivity to air pollution damage model

There is a considerable difference in the estimated life cycle air pollution damages using the EASIUR model or the AP2 model (Heo *et al* 2016a, Gilmore *et al* 2019). In particular, the two models differ by multiple times in their respective valuations of NO_x and SO_x across the United States due to different baseline emissions inventories and population data, and distinct approaches in calculating the resulting airborne concentrations of PM_{2.5} and ozone in the response of criteria air pollutant emissions (Heo *et al* 2016a, Gilmore *et al* 2019). For the scope of this paper, the implications of inconsistent estimates from these two models include different damage estimates for the same fuel-vehicle technologies, and, as a result, different rankings of fuel-vehicle technologies in some counties.

3.6. Sensitivity to emissions inventory

As summarized in the *supplementary document* (table S1), all existing studies used the GREET model for emissions inventories. In the *supplementary document* (section 4.4), we estimated the life cycle air pollution and climate change damages using the emissions data from the GREET model. The GREET model reported higher criteria air pollutant emissions from oil refining than the National Emissions Inventory, so using the GREET model's emissions data would favor alternative fuels and advanced vehicle technologies.

The literature reported different cradle-to-grave air pollution damages for battery manufacturing (by a factor of three) (Michalek *et al* 2011, Tessum *et al* 2014). Using the higher battery manufacturing damage estimate leads to 13%–104% increases in the life cycle air pollution damages for battery-electric vehicles across vehicle types and counties compared

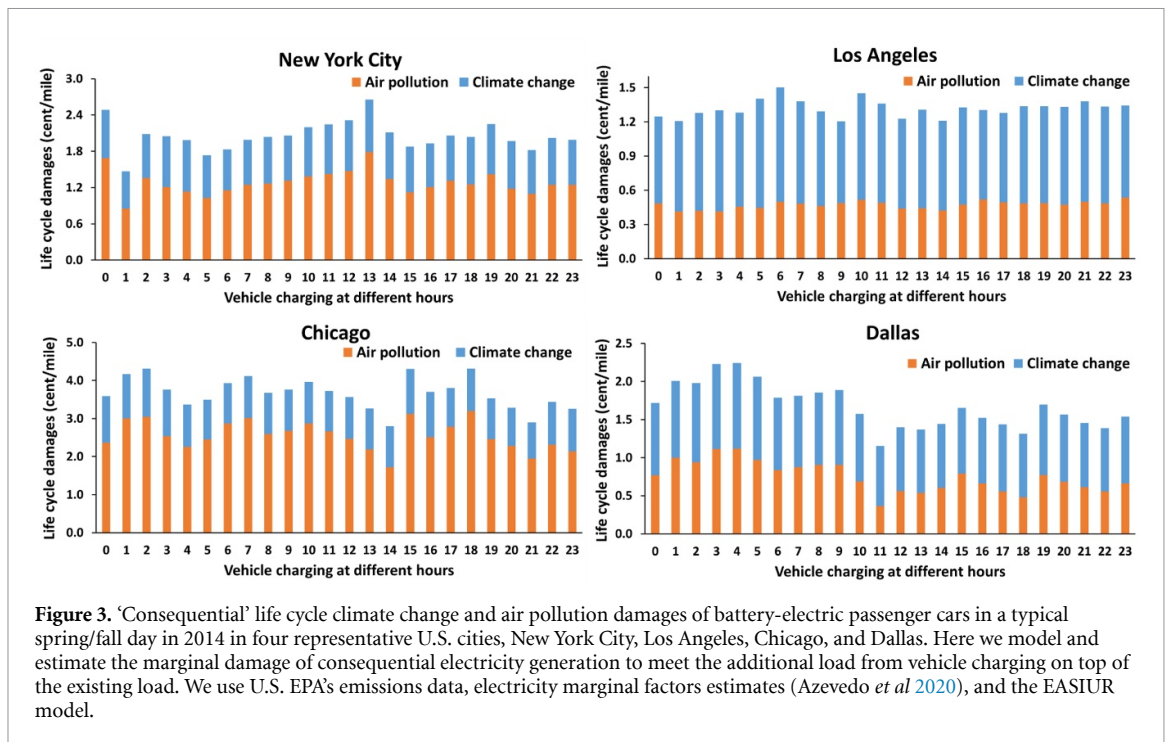


Figure 3. ‘Consequential’ life cycle climate change and air pollution damages of battery-electric passenger cars in a typical spring/fall day in 2014 in four representative U.S. cities, New York City, Los Angeles, Chicago, and Dallas. Here we model and estimate the marginal damage of consequential electricity generation to meet the additional load from vehicle charging on top of the existing load. We use U.S. EPA’s emissions data, electricity marginal factors estimates (Azevedo *et al* 2020), and the EASTUR model.

to those using the lower battery manufacturing damage estimate (section 4.3 in the *supplementary document*). Assuming more serious battery manufacturing damages, the trade-offs between climate change damages and air pollution damages become more evident, but battery-electric cars and buses used in regions with clean electricity still provide overall environmental benefits.

4. Conclusions and discussion

This paper presents a systematic, spatially-explicit assessment of environmental externalities caused by alternative fuels and advanced vehicle technologies in the United States. Using a coupled modeling framework linking state-of-the-art life cycle assessment, reduced-form air quality models, and integrated assessment models, we estimate the monetized damages in climate change and air pollution caused by the life cycle air emissions from passenger-moving vehicles (passenger cars, SUVs and transit buses). We find substantial spatial variability in the monetized damages for all fuel-vehicle technologies studied.

None of the fuel-vehicle technologies leads to the lowest climate change damages and the smallest air pollution damages across all U.S. counties. Trade-offs between air pollution mitigation and decarbonization for the fuel-switching strategy (replacement of incumbent petroleum fuels with alternative fuels or advanced vehicle technologies) are persistent across several spatial scales (counties, states, and electricity grid regions). These findings suggest that policy actions towards sustainable transportation should account for the spatial heterogeneity in

climate change and air pollution impacts as well as reflect stakeholders’ value judgment in terms of the relative importance between clean air and decarbonization goals. As a result, depending on the decision-making goal (clean air or stabilizing climate), the preferred technology choices are sensitive to economic assumptions such as the social cost of carbon and the value of a statistical life. We note that such trade-offs could be high hurdles for the adoption of and support for sustainable transportation technologies. Further research should study how these trade-offs impact consumer behaviors and real-world decision making.

Vehicle electrification has substantial potential to reduce climate change damages and air pollution damages. With the 2014 electricity grid, vehicle electrification can already mitigate climate change damages compared to conventional petroleum vehicles on the west coast and New England. However, battery-electric vehicles can lead to up to three point six times increases in air pollution damages for passenger cars and SUVs and up to six point three times increases for transit buses compared to conventional gasoline/diesel vehicles in U.S. regions with high shares of coal-fired power plants (such as Midwest and Southeast). Even in U.S. regions with a relatively clean electricity grid (such as the west coast and New England), battery-electric vehicles can only partially reduce air pollution damages. These findings highlight the importance of continually cleaning and decarbonizing electricity grid, such as with increased penetrations of renewable energy technologies and nuclear power (Wei *et al* 2013). A clean electricity grid with near-zero emissions not only benefits the electricity sector and traditional electricity consumers such

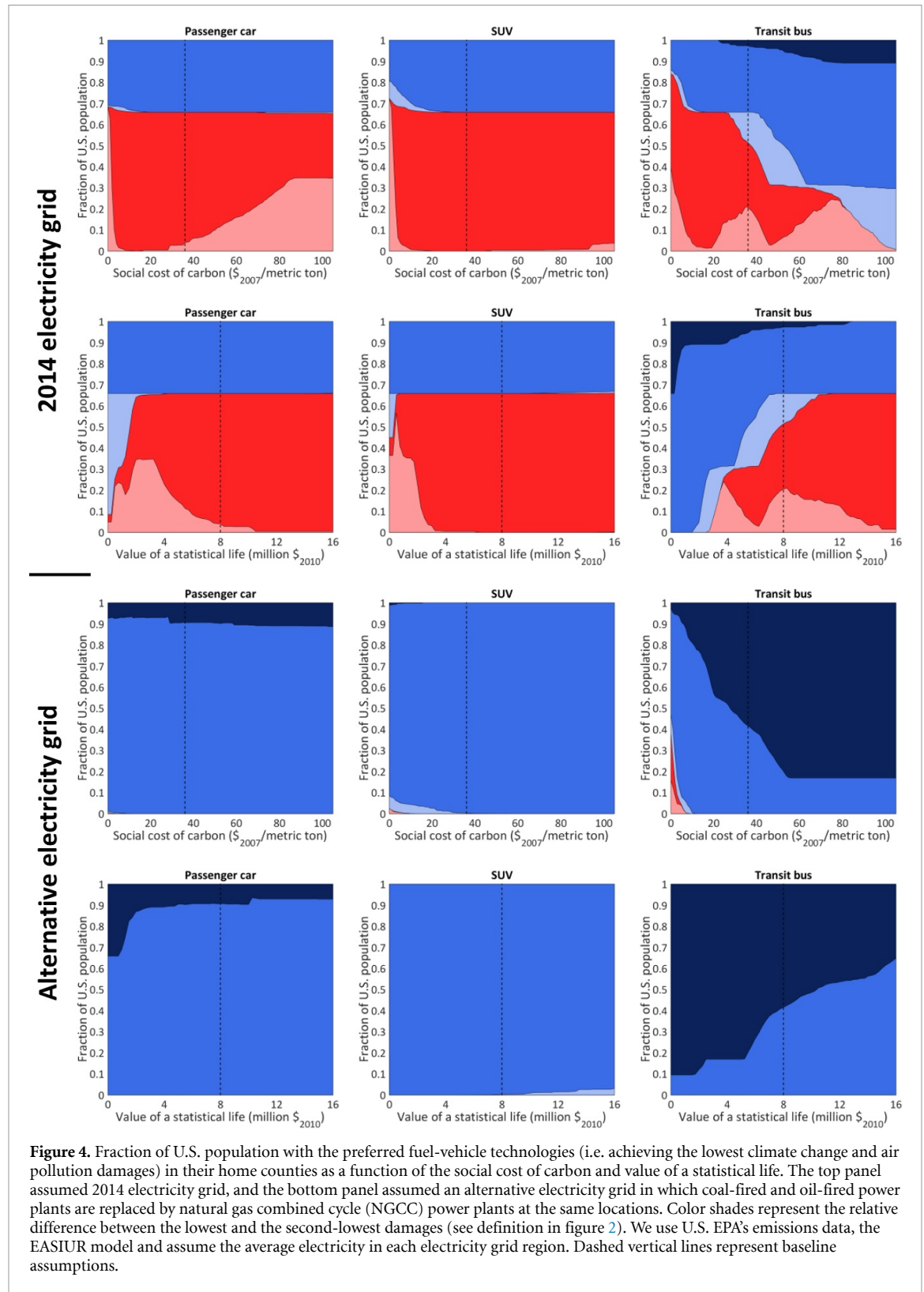


Figure 4. Fraction of U.S. population with the preferred fuel-vehicle technologies (i.e. achieving the lowest climate change and air pollution damages) in their home counties as a function of the social cost of carbon and value of a statistical life. The top panel assumed 2014 electricity grid, and the bottom panel assumed an alternative electricity grid in which coal-fired and oil-fired power plants are replaced by natural gas combined cycle (NGCC) power plants at the same locations. Color shades represent the relative difference between the lowest and the second-lowest damages (see definition in figure 2). We use U.S. EPA’s emissions data, the EASIUR model and assume the average electricity in each electricity grid region. Dashed vertical lines represent baseline assumptions.

as buildings but also becomes increasingly crucial for a sustainable transportation future (Wei *et al* 2013, McCollum *et al* 2014).

This work highlights the importance of considering the interactions between electricity grid operation and electric vehicle adoption and usage. However, given the limitation in time and scope, we were unable to model explicitly how vehicle electrification would

impact the operation of the grid in the near term or how vehicle electrification would lead to new generation assets and transmission lines over an extended time. As the adoption of battery-electric vehicles grows, the charging load from vehicle electrification would start to emerge beyond the ‘marginal’ electricity load in certain regions and specific hours. As a result, the optimal dispatch of the electricity grid

would change, and the new generation capacity would have to be built. Thus, if well planned, vehicle electrification could present new opportunities to decarbonize the electricity grid and the transportation sectors at the same time. Further research could shed light on how to plan and safeguard a sustainable transition of the electricity grid and vehicle fleets. Furthermore, future research should explore technology deployment, policy support, and infrastructure lock-in in the interconnected electricity and transportation systems.

Our work shows the effectiveness and importance of vehicle fuel efficiency and tailpipe emissions standards (Shindell *et al* 2011). Hybrid-electric vehicles provide tangible benefits in terms of reduced climate change damages and air pollution damages no matter where they are driven. They are also the preferred technologies for regions with relatively dirty electricity grid. More importantly, the increasing performance of energy-efficient vehicles would set the bar with which advanced and emerging vehicle technologies compete. Reducing vehicle tailpipe emissions has long been a strategy to solve the air quality issues in the U.S. (US EPA 2001, U.S. Environmental Protection Agency (EPA) and U.S. Department of Transportation (DOT) National Highway Traffic Safety Administration (NHTSA) 2012). Except for battery-electric vehicles, which eliminate tailpipe emissions, tailpipe emissions still account for a majority share in life cycle emissions inventory and the resulting life cycle monetized damages. Strengthening vehicle tailpipe emissions can be an effective means to reduce vehicles' environmental externalities as vehicles last for more than a decade on average.

Systems analysis that considers multiple different impacts across the life cycle of fuel-vehicle technologies would not be possible without the recent progress in the quantification of health and climate change damages. However, any air quality and impact model would still face the daunting challenge to balance accuracy, representation (e.g. temporal and spatial resolution and scope, atmospheric physics, and chemistry), and computational efficiency. Full-scale chemical transport models (such as CMAQ) strive to simulate the best atmospheric chemistry and quantify the most detailed spatial and temporal representations at the expense of high computational resources. As a result, the use of such models in our study would limit sensitivity analysis and fail to identify the most sensitive factors or variables. Reduced-form air quality and impact models, such as those we have used in this paper, significantly reduce the running time, but at the cost of coarser spatial representation and approximation of the atmospheric chemistry. In particular, the county-level spatial resolution of the EASIUR and AP2 models would underestimate the health impacts of tailpipe emissions to drivers, pedestrians, and residents who

are near road infrastructure. The lack of finer-scale representation would bias results in favor of gasoline/diesel vehicles versus battery-electric vehicles whose emissions occur at remote locations of power plants.

Finally, we note that a comprehensive analysis to determine fuel-vehicle technologies for passenger-carrying vehicles should include other fuel technologies (e.g. biofuels, hydrogen, and fuel cell electric vehicles) and consider different perspectives such as economics, consumer behavior, vehicle use patterns, and infrastructure planning (Wolinetz *et al* 2018, Tong *et al* 2019). Nevertheless, this work shows that the life cycle climate change and air pollution damages of fuel-vehicle technologies can and should be considered. Quantifying and internalizing externalities caused by greenhouse gas and air pollutant emissions from the life cycle of vehicles is essential to achieve sustainable transportation.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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