Life cycle air quality impacts of conventional and alternative light-duty transportation in the United States

Christopher W. Tessum[a], Jason D. Hill[b,1], and Julian D. Marshall[a,1]

[a]Department of Civil, Environmental, and Geo- Engineering, University of Minnesota, Minneapolis, MN 55455; and [b]Department of Bioproducts and Biosystems Engineering, University of Minnesota, St. Paul, MN 55108

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Commonly considered strategies for reducing the environmental impact of light-duty transportation include using alternative fuels and improving vehicle fuel economy. We evaluate the air quality-related human health impacts of 10 such options, including the use of liquid biofuels, diesel, and compressed natural gas (CNG) in internal combustion engines; the use of electricity from a range of conventional and renewable sources to power electric vehicles (EVs); and the use of hybrid EV technology. Our approach combines spatially, temporally, and chemically detailed life cycle emission inventories; comprehensive, fine-scale state-of-the-science chemical transport modeling; and exposure, concentration–response, and economic health impact modeling for ozone (O_3) and fine particulate matter ($PM_{2.5}$). We find that powering vehicles with corn ethanol or with coal-based or "grid average" electricity increases monetized environmental health impacts by 80% or more relative to using conventional gasoline. Conversely, EVs powered by low-emitting electricity from natural gas, wind, water, or solar power reduce environmental health impacts by 50% or more. Consideration of potential climate change impacts alongside the human health outcomes described here further reinforces the environmental preferability of EVs powered by low-emitting electricity relative to gasoline vehicles.

LCA | pollution | bioelectricity | externality | spatial

Society is in the midst of a great effort to understand and mitigate anthropogenic greenhouse gas (GHG) emissions and their effects on the global climate (1–5). However, GHG damages are not the only environmental impact of human activities, and are often not even the largest. In transportation, for example, non-GHG air pollution damage externalities generally exceed those from climate change (6–8). Here, we explore the air quality impacts of several proposed transportation fuel interventions: liquid biofuels (9), electric vehicles (EVs) powered by conventional and alternative energy sources (3), biomass feedstocks to power EVs (10, 11), compressed natural gas (CNG) powered vehicles (5), and improved vehicle fuel economy.

The air quality impacts of biofuels, transportation electrification, CNG vehicles, and improved fuel economy have been studied (refs. 7, 8, and 12–21; results are summarized in Table S1); our work advances prior research by combining estimates of life cycle emissions [i.e., emissions from production ("upstream") and consumption ("tailpipe") of the fuel] with an advanced air quality impact assessment. In addition, we incorporate greater spatial, temporal, and chemical detail than have prior research efforts. We also report non-GHG air quality life cycle impacts of biomass-powered EVs, which to our knowledge have not yet been described.

We use a spatially and temporally explicit life cycle inventory model (22) to estimate total fuel supply chain air pollutant emissions for scenarios where 10% of US projected vehicle miles traveled in year 2020 are driven in 1 of 11 types of passenger cars: (*i*) conventional gasoline powered vehicles (abbreviation: "gasoline"); (*ii*) grid-independent hybrid EVs ("gasoline hybrid"); (*iii*) diesel powered light-duty vehicles ("diesel"); (*iv*) internal-combustion CNG vehicles ("CNG"); (*v*) vehicles powered by ethanol from corn grain through natural-gas–powered dry milling ("corn ethanol"); (*vi*) vehicles powered by cellulosic ethanol from corn stover ("stover ethanol"); and battery EVs ("EV") powered by electricity from the following: (*vii*) the projected year 2020 US average electric generation mix ("EV grid average"); (*viii*) coal ("EV coal"); (*ix*) natural gas ("EV natural gas"); (*x*) the combustion of corn stover ("EV corn stover"); and (*xi*) wind turbines, dynamic water power, or solar power ("EV WWS"). Because year 2020 electric generation infrastructure is not predetermined, we explore a range of electricity technologies rather than attempting to predict future electrical generation and dispatch deterministically; our approach can inform transportation and electricity generation policies in tandem. Based on prior research, we assume that the difference among scenarios in emissions from manufacturing and disposal of vehicles and from upstream infrastructure is small relative to differences in vehicle operation emissions (8, 23, 24) with the exception of lithium ion EV battery production. To highlight battery-related impacts, we analyze them separately from fuel-related impacts.

Significance

Our assessment of the life cycle air quality impacts on human health of 10 alternatives to conventional gasoline vehicles finds that electric vehicles (EVs) powered by electricity from natural gas or wind, water, or solar power are best for improving air quality, whereas vehicles powered by corn ethanol and EVs powered by coal are the worst. This work advances the current debate over the environmental impacts of conventional versus alternative transportation options by combining detailed spatially and temporally explicit emissions inventories with state-of-the-science air quality impact analysis using advanced chemical transport modeling. Our results reinforce previous findings that air quality-related health damages from transportation are generally comparable to or larger than climate change-related damages.

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[1]To whom correspondence may be addressed. Email: hill0408@umn.edu or julian@umn.edu.

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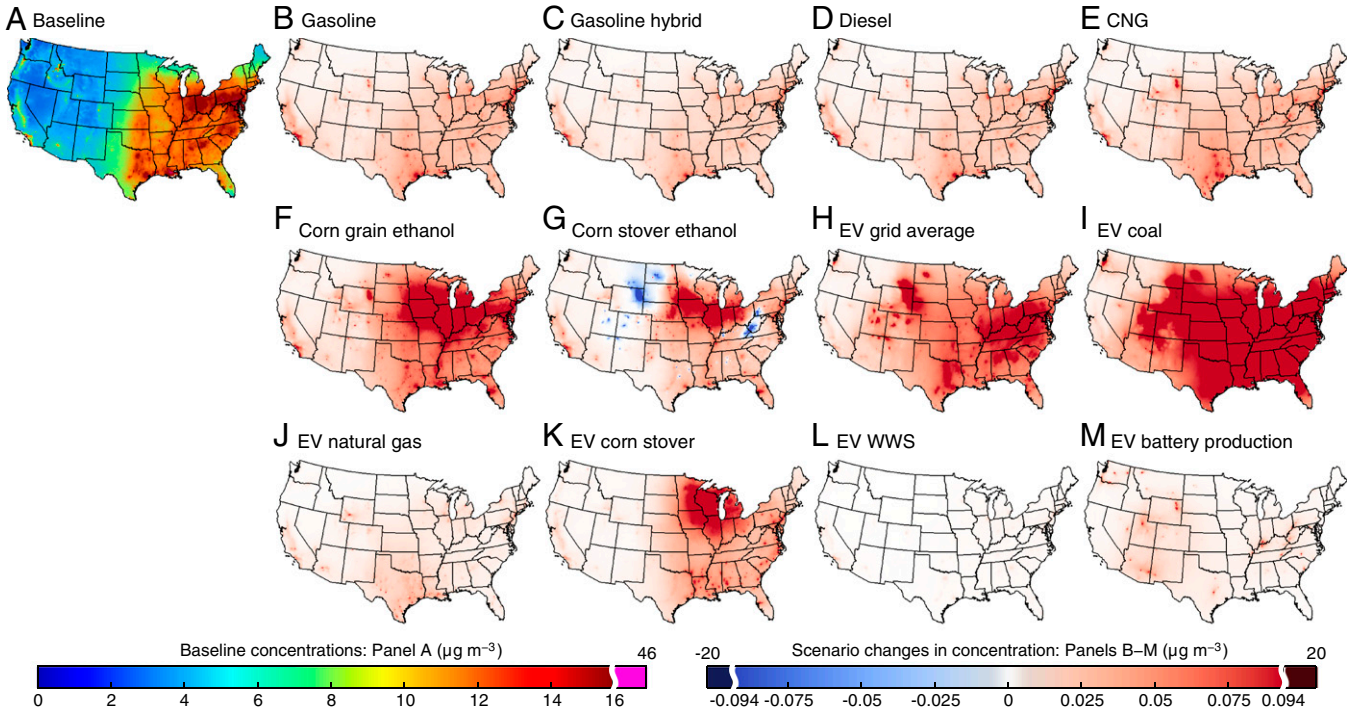

Fig. 1. Annual average $PM_{2.5}$ concentrations. (*A*) Year 2005 baseline modeled concentrations. (*B–L*) Increase in concentration above the baseline attributable to replacement of 10% of year 2020 vehicle use with the given technology. (*M*) Increase in concentration attributable to EV battery manufacturing. Color scales contain a discontinuity at the 99th percentile of emissions. Abbreviations: CNG, compressed natural gas vehicle; EV, electric vehicle; WWS, wind, water, or solar. Analogous plots for O_3 are in Fig. S1.

We use spatially and temporally explicit simulations, including a state-of-the-science mechanistic meteorology and chemical transport model, to estimate for each scenario the changes in annual-average concentrations of the regulated pollutants fine particulate matter ($PM_{2.5}$) and ground-level ozone (O_3). We use spatially explicit population data (25) and results from major epidemiological studies (26, 27) to estimate increases in mortalities attributable to each scenario. We estimate monetized externalities from mortalities using a value of statistical life (VSL) metric. Results are given next; methods are described thereafter.

Results

Fig. 1 shows the spatial distributions of the background $PM_{2.5}$ concentrations (Fig. 1*A*) and of the changes in $PM_{2.5}$ concentrations for each scenario (Fig. 1 *B–L*). Spatial distributions of concentrations of O_3 (Fig. S1) and other species are in *SI Results*. As all scenarios represent increases in vehicle miles traveled, concentrations increase in almost all cases, as shown in Fig. 1. Changes in concentrations caused by alternative scenarios (Fig. 1 *C–L*) may be larger or smaller than the changes caused by the business-as-usual gasoline scenario (Fig. 1*B*). For the petroleum scenarios (gasoline, gasoline hybrid, and diesel; Fig. 1 *B–D*), vehicle tailpipe emissions are the largest source of impacts. Impacts from vehicle tailpipe emissions for the CNG (Fig. 1*E*) and ethanol (Fig. 1 *F* and *G*) scenarios are similar to those from the petroleum scenarios, but upstream processes, such as natural gas processing and compression (mainly in Texas) for the CNG scenario and agriculture (mainly in the upper Midwest) for the ethanol scenarios, cause additional substantial impacts. Industrial electricity use in the corn ethanol and CNG scenarios creates additional impacts in Wyoming and in the Appalachian Mountains owing to emissions from coal mining; emission credits from excess electricity generation in the stover ethanol scenario cause decreases in concentrations in the same geographic areas. Impacts are lower for the EV natural gas scenario (Fig. 1*J*) than for the CNG scenario (Fig. 1*E*) for several reasons: emissions per vehicle-kilometer are lower for natural gas combustion in electricity generators than for CNG combustion in vehicles; natural gas must be compressed for use in CNG vehicles but not in electricity generation; and combustion emissions generally occur further from population centers for electricity generation than for vehicle tailpipe emissions. The EV corn stover scenario (Fig. 1*K*) causes farming-related impacts in the Midwest. Coal mining and combustion in the EV coal (Fig. 1*I*) and EV grid average (Fig. 1*H*) scenarios cause large impacts in Wyoming and the Appalachian Mountains; long-range transport of sulfur dioxide (SO_2) emitted during coal combustion causes impacts distributed over wide areas in those scenarios. Excluding battery production, impacts from wind, water, and solar (WWS) EVs (Fig. 1*L*) are notably lower than from the other scenarios because WWS electrical generators do not produce emissions while in use. Emissions from battery production for the EV scenarios are tracked separately. The main emission sources for EV battery production (Fig. 1*M*) are coal mining in Wyoming and the Appalachian Mountains and the extraction and refinement of raw material inputs, including copper in Arizona and Utah and aluminum in Washington State and the Appalachian Mountains.

Animated versions of Fig. 1 showing temporally explicit concentrations for $PM_{2.5}$ and O_3 are available in *SI Results*. Notable trends include spikes in $PM_{2.5}$ for the corn ethanol, corn stover ethanol, and EV corn stover scenarios caused by fertilizer application and nitrification emissions during the spring planting season. For these same scenarios, owing to complexities in the chemistry of O_3 formation and removal, O_3 concentrations in the Midwest "corn belt" tend to be increased relative to the baseline in the summer months, but decreased in the winter months.

Air pollution-related human health impacts for each scenario ($PM_{2.5}$- and O_3-related mortalities, and the corresponding monetized damages) are shown in Fig. 2. Total impacts range

from 230 mortalities per year ($0.14 per gallon gasoline-equivalent) for the WWS EV scenario to 3,200 mortalities per year ($1.94 per gallon gasoline-equivalent) for the coal EV scenario. Estimated mortality impacts from $PM_{2.5}$ are approximately an order of magnitude greater than those from O_3. Damages from the production of EV batteries are shown separately in Fig. 2. Scenarios with substantially decreased air quality-related health impacts compared with gasoline include gasoline hybrid vehicles (30% decrease) and EVs powered by natural gas or by WWS (50% and 70% decrease, respectively); scenarios with substantially higher damages than gasoline include corn ethanol (80% increase) and EVs powered by grid average or coal electricity (200% and 350% increase, respectively).

Changes in combined air pollution and climate damages attributable to each alternative scenario, relative to gasoline, are shown in Fig. 3. For most scenarios, air pollution impacts are comparable to or larger than climate change impacts. Although corn ethanol as modeled here emits marginally less GHGs than does gasoline, the combined climate and air quality impacts are greater than those from gasoline vehicles. (Our corn ethanol GHG results exclude impacts of indirect land-use change, and so likely are lower-bound GHG emission estimates.) EVs powered by grid-average electricity also have greater negative impacts than do vehicles powered by gasoline. Previous studies (3, 5) have argued that to meet stated goals for GHG emission reductions, it is necessary to both electrify vehicles and decarbonize electricity generation, for example through WWS electric generation. Our results suggest that such a strategy would have the strong cobenefit of substantially reducing air quality-related mortalities (by ~70%).

Given the considerable computational demands of our mechanistic meteorology and chemical transport modeling, comprehensive quantification of uncertainty within our analyses is impractical. Rather, we explore uncertainty via sensitivity analyses for several factors that are important in our analyses and that could impact the relative rankings of scenarios. Results are described below; additional detail, methods, and figures are in *SI Results*.

As shown in Fig. S2 and discussed in *SI Results*, EV battery production is unique among the life cycles investigated here in that up to about half of all emissions occur outside of our spatial modeling domain and are thus excluded from this analysis. We test the impact of this exclusion by doubling the impacts from EV battery production (Fig. S3). We find that this increases damage costs for EVs by $0.08 per gasoline gallon-equivalent, which is between a 4% increase for the coal EV scenario and a 57% increase for the WWS EV scenario, but does not change the rank order of air quality impacts among scenarios.

As emissions from coal mining are a major source of impacts in many of the scenarios we study, we examine the impact on our results of using lower coal mining emission factors (28, 29). As shown in Fig. S3, this shift does not change the rank order of air quality impacts among scenarios, although it decreases overall impacts from EVs powered by coal or grid average electricity by 37% and 33%, respectively.

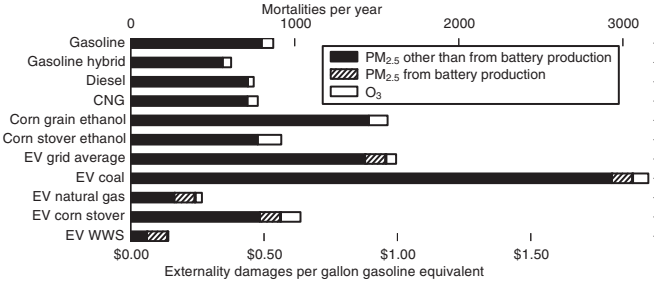

Fig. 2. Air quality health impacts in the United States for each scenario: attributable increases in annual mortality (upper scale) and the resulting monetized health impacts (lower scale).

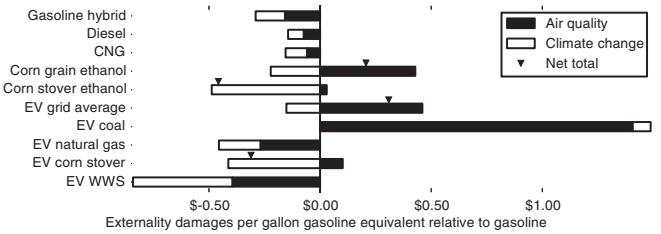

Fig. 3. Combined air quality plus climate change externalities attributable to each scenario, relative to the gasoline scenario. [The gasoline scenario impacts (air quality, $0.53/gallon; climate change, $0.46/gallon) would equal zero on this plot.] EV scenarios include battery production. Air quality impacts include $PM_{2.5}$ and O_3. For bars with both positive and negative values, the triangle above each bar shows the net total impact. GHG emissions from indirect land-use change are not included. See Fig. S4 for the impact of including indirect land-use change on net GHG emissions.

To test the importance of incorporating full life cycle supply chain information when performing air quality impact assessment, we perform a sensitivity analysis that considers only emissions from the single phase of each life cycle most frequently associated with its environmental impacts (for internal combustion vehicles: on-road emissions; for EVs: emissions from electricity generation). This change causes corn ethanol to appear substantially less damaging because emissions during production and transport are overlooked (Fig. S3).

We also investigate the sensitivity of our results to a range of assumptions related to climate change (Fig. S4). We investigate the use of a lower carbon price, the inclusion of international emissions of climate forcers, the inclusion of indirect land-use change, the recently reported possibility of additional gas leakage during natural gas extraction (30), and sourcing crude oil from oil sands rather than from conventional sources (31). As illustrated in Fig. S4, conclusions of this study are generally robust to these perturbations.

Finally, we investigate the impact of model spatial resolution on estimated health impacts (Fig. S5). Higher resolution analyses tend to produce larger estimates for health impacts but do not alter the overall conclusions presented here.

Discussion

Results provided here combine spatially and temporally explicit life cycle assessment with state-of-the-science air quality modeling for a range of potential transportation technology interventions. The updated emissions estimates, better spatial resolution and coverage, better disaggregation of process locations, and more detailed air quality impact analysis incorporated here yield different overall conclusions from a similar recent study by Michalek et al. (8). For instance, when only air quality impacts are considered, Michalek et al. found that WWS EVs increase impacts by 160% compared with gasoline, whereas we find that WWS EVs reduce impacts by 70% compared with gasoline. Two major factors contributing to this difference are our use of a more recent version of the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model and Michalek et al.'s assumption that all emissions from EV battery manufacturing are colocated with automobile manufacturing facilities; our more detailed analysis places many of the most polluting processes in the battery production life cycle in remote areas. Additional discussion of this comparison is in *SI Results*.

We have considered here 10 alternative transportation fuel and technology options that have been put forward as potentially

environmentally preferable to conventional gasoline-powered vehicles based largely on reductions in fossil fuel use and GHG emissions. We find that, in some cases, such as for EVs powered by natural gas or WWS, considering air quality impacts alongside climate impacts increases the apparent environmental benefit of the alternative fuel relative to gasoline; in both cases (EVs from natural gas; EVs from WWS), the air pollution benefits relative to gasoline are larger than the climate-related benefits. Other fuels, such as corn ethanol [the climate impact of which is unclear (32)], are more damaging than conventional vehicles when air pollution impacts are considered alone or when air pollution and climate impacts are considered together. The difference between the least- and most-polluting electricity generation options for EVs increases almost sixfold when air pollution damages are considered alongside climate impacts, instead of when climate impacts are considered alone. Our findings thus reinforce the benefit of pairing EVs with clean electricity (3, 5).

Our work supports the inclusion of air pollution health impacts when assessing the environmental impact of transportation; in monetized terms, the health impacts can be as great, or greater than, effects on climate change. We also demonstrate the importance of spatial, temporal, and chemical detail and precision in life cycle air quality impact assessment. Although climate change and air quality are often considered the two main transportation-related environmental externalities (6), inclusion of other life cycle impact categories not considered here, such as environmental justice, water quality and availability (e.g., 33, 34), biodiversity, or vehicle safety could add additional insight.

Results given here should not be taken as a final statement that environmental improvements are best achieved by replacing existing light-duty vehicles with less-polluting light-duty vehicles, nor that EVs are the best technology for every transportation need. Instead, these results can be seen as an indication of how light-duty transportation fuels could shift to reduce or increase pollution, and as an encouragement into the research of less polluting, more sustainable transportation options for the future.

Materials and Methods

Scenario Selection. We use a functional unit of 388 billion miles per year, which is 10% of year 2020 projected US vehicle miles traveled (35). For the ethanol scenarios, this value corresponds to blending an average of 10% ethanol with gasoline on an energy equivalent basis. For EV scenarios, it corresponds to aggressive but plausible adoption of EVs (36).

We do not consider constraints on the availability or cost of resources (e.g., the viability of increased ethanol production; availability of WWS electricity). However, we have found that the air quality impacts we consider scale approximately linearly with changes in the size of the functional unit, so as a first approximation air quality impacts from different amounts of miles traveled or fuel produced could be interpolated from our results.

Life Cycle Inventory. We create a chemically, spatially, and temporally detailed life cycle inventory for each scenario using the GREET-chemical, spatial, and temporal (GREET-cst) model (22), which is based on the GREET model, version 1.8d1, from Argonne National Laboratory (31). It is worth noting that subsequent versions of GREET have been released since version 1.8d1. We investigate the sensitivity of our results to some of the changes in subsequent GREET versions, as well as to other important factors; investigating the effect of GREET version on the estimated air quality impacts is an area for future research. GREET-cst outputs emissions that are spatially allocated to a 12-km grid covering the continental United States and surrounding waters, chemically speciated according to the CB05 chemical mechanism (37), and temporally disaggregated in 1-h time increments. The GREET model can be obtained at greet.es.anl.gov/.

For assumptions specific to GREET-cst, including spatial modeling domain, spatial locations of emissions, chemical speciation, and temporal profiles, we configure the model as described by Tessum et al. (22). Briefly, we use the continental United States and its surrounding waters as a spatial model domain and exclude from the analysis all emissions occurring outside of the domain. We assume all emissions from individual processes, including vehicle end use, occur at existing production or activity locations. For material transport emissions, we use network analysis and linear optimization to simulate transport behavior along roadways, rails, and navigable water routes between source and destination locations. We apply temporal and chemical speciation profiles from the 2005 National Emissions Inventory (NEI) (38) to the emissions from each process. We use the results of Bashash et al. (39) for EV battery charging temporal profiles, which assume batteries would be charged to optimize for long battery life and low electricity costs. We use these charging profiles only to determine the timing for emissions release from power plants; for the mix of electrical generation sources, we use the hypothetical scenarios discussed in the Introduction.

For most processes that use electricity, such as electricity generation for use in EVs in the EV coal and EV natural gas scenarios, we assume that electricity generation comes from the same North American Electrical Reliability Corporation (NERC) electrical grid region as the end use process as in Tessum et al. (22) and that the mix of generation fuels and technologies in each NERC region is the same as the national average. For electricity generation in the EV corn stover scenario, however, because of the logistical difficulty in transporting corn stover, we assume that electricity generation for EVs occurs in the same electrical grid region as the corn stover production instead of vehicle end use. For the EV grid average scenario, we assume that electricity generation for EV use is distributed according to total generation amounts in the year 2007 (40) so as to preserve the difference in fuel mixes for electric generation across NERC regions. Further details are in *SI Results*.

In GREET, we model year 2020 passenger cars using default settings with the following exceptions:

- The gasoline used is 100% conventional (0% reformulated gasoline) so as to disentangle the effect of ethanol blends.
- Because almost all oil extraction from oil sands occurs outside of our geographic modeling domain, we assume all oil is extracted conventionally (0% oil sands oil). The sensitivity of our results to this assumption is explored in *SI Results*.
- For gasoline hybrid vehicles, GREET assumes that the tailpipe emission factors for volatile organic compounds, CO, PM_{10}, $PM_{2.5}$, and N_2O are the same as for conventional gasoline vehicles on a per-mile basis. We therefore adjust gasoline hybrid tailpipe emissions of these species to be 71% (the ratio of hybrid to conventional fuel efficiency) of the conventional vehicle emissions factors.
- We do not include land-use change emissions for the ethanol or bioelectricity scenarios.
- We assume all corn ethanol plants use dry milling and 100% natural gas for process heat.
- We assume that ethanol is produced as 100% ethanol with no denaturant, but for ethanol scenarios we use tailpipe emissions factors for a 10% blend of ethanol with gasoline ("E10").
- We update the year 2020 projection for electricity generation mix to a more recent Energy Information Administration projection (41).
- We add a corn stover bioelectricity pathway to the GREET 1.8d1 spreadsheet based on parameters from the other bioelectricity pathways and the corn stover ethanol pathway.

We do not assume that marginal emissions from electrical generation or other sources are subject to cap-and-trade or other regulation (e.g., as in refs. 12 and 42). We use the GREET default assumption that electricity from biomass (corn stover) is generated using a dedicated biomass boiler. Cofiring biomass with coal may yield different emissions.

We assume that impacts related to the manufacture and disposal of equipment used to supply fuel (e.g., electrical generating units, oil wells, manufacturing plants), as well as those from the manufacture and disposal of vehicles, do not differ among the scenarios investigated here (8, 23, 24), and we exclude them from this analysis. Although these emissions do not differ much among scenarios, their impact on the overall air quality-related damages from transportation may be important (8, 23) and is an area for future research. We do include, however, production of EV batteries, which we model as a separate scenario to show explicitly the contribution of EV battery manufacturing to total impacts. We model the emissions from the production of enough lithium ion batteries to power our functional unit of 10% of the projected year 2020 US vehicle miles traveled by expanding GREET-cst to include the GREET2 vehicle cycle model, version 2012 (23). We do this step using the methods of Tessum et al. (22) and including additional spatial data on the locations of aluminum manufacturing (43), copper manufacturing (44), plastics manufacturing (38), steel manufacturing (38), and battery assembly (38). Table S2 shows, for each process, the fractions of emissions from battery production processes that are excluded from the analysis because they occur outside our spatial modeling domain. Information on

international fractions for other processes is reported by Tessum et al. (22). Fig. S2 shows amounts of domestic (included) and international (excluded) emissions from battery production. Full GREET-cst results for battery production are included in Dataset S1. We use the GREET2 default EV battery life assumption of 160,000 miles.

Emissions of GHGs and radiatively active aerosols are calculated using the same assumptions as above (i.e., the exclusion of indirect, market-mediated effects and the exclusion of emissions occurring outside the United States), and reported as CO_2 equivalent emissions using global warming potential conversions reported by Bond et al. (45). We use GREET default values for all emissions factors and process relationships not otherwise mentioned here.

Chemical Transport Modeling. To estimate changes in $PM_{2.5}$ and O_3 concentrations attributable to each scenario, we run the Weather Research and Forecasting with Chemistry (WRF-Chem) Eulerian meteorology and chemical transport model, version 3.4 (46), using a 12-km resolution grid with 444 rows, 336 columns, and 28 vertical layers. The modeling domain (5,328 km × 4,032 km) covers the continental United States, southern Canada, and northern Mexico [see the study by Tessum et al. (47)].

Setup of WRF-Chem as used here is detailed elsewhere (47). We use the Regional Atmospheric Chemistry Mechanism (RACM) (48) for gas phase reactions, and the Modal Aerosol Dynamics for Europe (MADE) (49) module for aerosol chemistry and physics. We use the Volatility Basis Set (VBS) (50) to simulate formation and evaporation of secondary organic aerosols.

We compare the change in emissions attributable to each scenario to a baseline or reference case. For the baseline emissions we use the 2005 NEI (38), which includes area, point, and mobile emissions from year 2005 for the United States, year 2006 for Canada, and year 1999 for Mexico. The performance of WRF-Chem as used here in reproducing observed $PM_{2.5}$ and O_3 concentrations is reported by Tessum et al. (47); the annual mean fractional bias and error, respectively, are −1% and 21% for $PM_{2.5}$, and 11% and 14% for daily peak O_3.

We use year 2005 baseline emissions and meteorology inputs. The NEI has been projected to future years, but we are only able to compare our model predictions to observed pollutant levels for years for which there is an available emissions inventory, pollution monitoring data, and meteorological observations. At the time the simulations described here were run, 2005 was the most recent year for which all of these inputs existed.

To predict changes in pollutant concentrations attributable to each scenario, we combine the emissions from each scenario with the baseline NEI, rerun WRF-Chem with the resulting emissions, and then subtract the baseline NEI-derived concentrations from the concentrations calculated using the combined emissions. Because some scenarios involve credits for displaced coproducts that we model as negative emissions, and because negative emissions cannot be represented in WRF-Chem, we deal with any grid cell with net negative emissions (where the baseline NEI value plus the scenario value is negative) by subtracting emissions from nearby cells, thereby zeroing out the negative cells while achieving the targeted local total mass of emissions.

Health Impact Assessment. We use as health endpoints respiratory mortalities attributable to ambient O_3 concentrations and mortalities from all causes attributable to ambient $PM_{2.5}$ concentrations. We use concentration–response values reported by Jerrett et al. (27) for O_3 and Krewski et al. (26) for $PM_{2.5}$. Jerrett et al. reported that, after accounting for covariation with $PM_{2.5}$ concentrations, a 10-ppb increase in April to September average daily peak-hour O_3 concentration causes a 4% increase in respiratory mortalities. Krewski et al. reported that a 10 $\mu g \cdot m^{-3}$ increase in annual average $PM_{2.5}$ concentration causes a 7.8% increase in all-cause mortalities; the Krewski et al. model does not account for covariance with O_3 concentrations. Both results are based on the Cox proportional hazards model, which assumes that the risk ratio (*RR*) varies exponentially with change in pollutant concentration (ΔC) as in Eq. **1**, where the β coefficients for O_3 (0.00392 ppb^{-1}) and $PM_{2.5}$ [0.00751 $(\mu g\ m^{-3})^{-1}$] are calculated from the results of Jerrett et al. and Krewski et al., respectively. WRF-Chem is configured to output instantaneous concentrations at the beginning of each hour, rather than hourly average concentrations; when calculating ΔC for each scenario, we use the instantaneous concentrations output by WRF-Chem as a surrogate for hourly average concentrations. We use Eq. **2** to calculate total annual mortalities (*D*) attributable to each scenario, where *n* is the total number of ground-level grid cells, *P* is the population in each cell based on year 2000 US Census block group-level data (25), and *M* is the county-specific population average baseline all-cause (for $PM_{2.5}$) or respiratory (for O_3) mortality rate (51):

$$RR = \exp(\beta \Delta C), \quad [1]$$

$$D = \sum_{i=1}^{n} (\exp(\beta \Delta C_i) - 1) P_i M_i. \quad [2]$$

Economic Valuation. We estimate economic damages from the deaths attributable to air pollution impacts of each scenario using a VSL of $10.1 million (2012$) using US Environmental Protection Agency methodology for income year 2020 (52). We assume no lag time between pollutant emissions and the resulting health effects. We estimate the economic damages from emissions GHGs and radiatively active aerosols using a social cost of carbon of \$180 MgC^{-1} (\$49 $MgCO_2^{-1}$) (53) (mean value, 1% discount rate, adjusted to 2012$) in the main analyses and \$23 MgC^{-1} (\$6.19 $MgCO_2^{-1}$) (2012$) in a sensitivity analysis.

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