Supporting Information

Tessum et al. 10.1073/pnas.1406853111

SI Results

Sensitivity Analyses. We perform several sensitivity analyses to evaluate the impact of key assumptions. The results of the sensitivity analyses are shown in Figs. S3–S5 and are described below and in the main text. All sensitivity analyses in Fig. S3 are performed for $PM_{2.5}$-related health impacts for the month of September only; as shown in Fig. S6, health impacts based on September $PM_{2.5}$ concentrations for the scenarios are similar to health impacts based on annual average concentrations. The grid resolution sensitivity analysis shown in Fig. S5 was performed for the month of July to capture summer peak O_3 conditions.

As shown in Fig. S2, not all emissions from the fuel life cycles occur within our spatial modeling domain, and therefore some emissions are excluded from our analysis. Refer to Tessum et al. (1) for more information. The electric vehicle (EV) battery production scenario has the most substantial fraction of emissions assumed to occur outside of the United States, with around 30–40% of emissions of most pollutants from battery production being excluded from the analysis (Fig. S2). We explore the sensitivity of our results to this assumption by doubling health impacts from battery production (Fig. S3) and find that the rank order of impacts among the different scenarios remains unchanged. For scenarios other than battery production, in most cases more than 90% of emissions occur inside the spatial modeling domain (Fig. S2). A fraction (30–45%) of SO_x and NO_x emissions from the petroleum scenarios (gasoline, gasoline hybrid, and diesel) are also excluded from the analysis, but because the excluded emissions are mainly from the extraction of crude oil (1), which largely occurs over the open ocean or far from population centers, their exclusion is not likely to impact our overall conclusions. These international upstream emissions are also excluded from fossil fuel use in the corn grain and stover ethanol scenarios.

Additionally, as emissions from coal mining and cleaning cause a substantial fraction of the total health impacts for some scenarios, and recent estimates of emissions factors for coal mining and cleaning for surface mining (2) and for underground mining (3) exist, we explore updating the GREET model with the new emission factors and rerunning all analyses for the month of September. We find that the change in coal mining and cleaning emissions factors does not affect the rank order of scenario impacts (Fig. S3) but does substantially reduces the air pollution impacts of some scenarios.

We additionally compare the impacts from the full life cycle of the fuels to impacts from either the vehicle tailpipe only for internal combustion vehicles or the electrical generation units only for EVs. As shown in Fig. S3, this sensitivity analysis affects the rank order of scenario impacts, further demonstrating the importance of including the emissions entire life cycle when performing environmental impact assessment for transportation fuels.

We also perform a set of sensitivity analyses investigating the effects climate-related assumptions on our results as shown in Fig. S4.

i) Fig. 3 in the main text excludes emissions occurring outside the United States for pollutants affecting both air quality and climate change. We investigate the effects of including these international emissions (exclusive of indirect land-use change) on climate change impacts. We find that including international climate-related emissions does not change overall damage costs by more than \$0.02 per gallon gasoline equivalent for any scenario.

ii) We investigate the impact of including indirect land-use change emissions as calculated by Plevin et al. (4) (using a value of 80 g $CO_2e \cdot MJ^{-1}$, which is near the middle of the range of estimates in that paper) for the corn ethanol scenario. This substantially increases the overall externality damages from that scenario and reinforces the overall conclusion that corn ethanol is not an attractive alternative fuel in terms of air pollution or climate change impacts.

iii) We investigate the sensitivity of our results to carbon pricing using market-based carbon price of \$6.19 Mg^{-1} CO_2 (from www.pointcarbon.com/productsandservices/carbon/ as of March 9, 2013, adjusted to 2012\$) as opposed to the \$49 Mg^{-1} CO_2 price used in Fig. 3. We find that this changes the sign of the net externality damages of the EV corn stover scenario from negative to positive but does not impact the overall conclusions presented in this paper.

iv) Recent analysis by Brandt et al. (5) suggests that CH_4 emissions may be systematically underestimated in emissions inventories, especially for natural gas extraction. We update the GREET model with the middle value for CH_4 leakage during natural gas extraction from Brandt et al. (5), resulting in 1.2% leakage on average instead of the GREET 1.8d1 default of 0.35%. We find that this does not affect the overall conclusions presented here. Although increased CH_4 emissions may also impact O_3 concentrations, we assume the effect on our overall conclusions to be negligible because O_3 health impacts are small relative to $PM_{2.5}$ health impacts.

v) Because almost all oil extraction from oil sands occurs outside of our geographic modeling domain, our baseline analysis assumes all oil is extracted conventionally (0% oil sands oil). This sensitivity analysis assumes that the GREET 1.8d1 year 2020 default value of 21% of crude oil comes from oil sands. We find that this does not affect the overall conclusions presented here. The use of oil sands oil instead of conventionally extracted crude may also affect air pollution concentrations, but the difference in health impacts is likely small because both the Canadian oil sands and most conventional extraction locations are typically located far from population centers.

The final sensitivity analysis investigates the impact of model spatial resolution on calculated health impacts (Fig. S5). For $PM_{2.5}$, total estimated impacts increase ~10–15% when going from 36- to 12-km resolution, and another 5% when going from 12- to 4-km resolution. (O_3 impacts are not highly dependent on grid resolution owing to the comparatively smaller spatial gradients in O_3 concentrations.) Our contiguous-United States, 12-km resolution analysis is an improvement over previous studies, which used 36-km or county-level resolution or considered only part of the United States; Table S1); still, our approach is potentially susceptible to underestimation of near-source exposures. This dependence of impacts on model spatial resolution is likely caused by numerical dispersion and is likely most pronounced in scenarios where the most emissions occur in urban areas (i.e., the gasoline, diesel, and gasoline hybrid scenarios). It currently is not computationally practical to perform the full methodology reported here at 4-km or finer resolution; current models capable of higher resolution analyses (e.g., Gaussian plume models) do so at the expense of the chemical and physical representation of processes that our findings suggest are important (e.g., formation of secondary $PM_{2.5}$).

Comparison with Michalek et al. (6). An analysis by Michalek et al. (6) finds that, in terms of air quality-related health impacts, EVs do not compare favorably to conventional gasoline vehicles: when only emissions from battery production and from brake and tire wear during vehicle use are considered (which is equivalent to the WWS EV scenario presented here), they find that EVs cause air quality-related damages 150% greater than do conventional gasoline vehicles. [Michalek et al., table S25, adjusted to make equivalent for comparison by excluding the following: (*i*) vehicle and battery production for gasoline vehicles; (*ii*) vehicle and electricity production for EVs; and (*iii*) GHG, CO, and oil premium impacts for both vehicles.] Our analysis, however, finds that WWS EVs reduce impacts by 70% compared with conventional gasoline vehicles. In both studies, the main source of WWS EV impacts is battery production. We are aware of two major reasons for the difference between our and Michalek et al.'s results: (*i*) differences in the estimates of amounts of emissions, and (*ii*) differences in the modeled locations of battery manufacturing processes.

i) Michalek et al. use a customized version of GREET 2.7 to calculate emissions from battery production, whereas we use the default settings in the more recently released GREET2_2012. (Note: GREET 2 is not an updated version of GREET 1. GREET 1.x models fuel pathways, and GREET 2.x models vehicle production pathways.) Comparing our emissions results (Dataset S1) to those of Michalek et al. (table S3 in their study), our emissions estimates are substantially lower than theirs—87% lower for SO_2 emissions (80% lower if international emissions are included). The battery size used in both studies is similar (66.1 kWh in Michalek et al.; 63 kWh in our study). The differences in emissions instead appear to be caused by differences between GREET versions—among other differences, GREET2_2012 uses $LiMn_2O_4$ batteries in place of the $LiCoO_2$ batteries used in GREET 2.7 (7)—and our use of year 2020 grid-average electric generation mix for electricity used in battery production, which is cleaner than the year 2010 mix used by Michalek et al.

ii) Michalek et al. assume processes upstream from EV battery manufacturing are colocated with automobile manufacturing facilities, but our more detailed analysis shows that, for example, copper ore smelting, which causes the majority of battery production SO_2 emissions, mainly occurs in the sparsely populated southwestern United States (8). Because the production of copper and other raw materials for batteries occurs far from people, even if impacts from battery production as calculated here are doubled to adjust for emissions that occur outside of our spatial modeling domain, impacts from WWS EVs would still be 57% lower than conventional gasoline vehicle impacts. We test this hypothesis by using the ratio of population-weighted average ground-level concentrations to area-weighted average ground-level concentrations as an imperfect surrogate for the proximity of emissions sources to people. The ratio for our results for EV battery production is 1.9, lower than any of the other scenarios. The ratios for the other scenarios range between 3 and 9. If emissions from battery production were located so as to give a population-weighted average to domain average ratio of 9 instead of 1.9, impacts from WWS EVs would be ~30% greater than impacts from conventional gasoline vehicles, which is closer to the result reported by Michalek et al. GREET assumes zero transportation emissions between mining operations and smelting facilities. This implies that smelting occurs at the mining site; to maintain consistency with GREET, we have maintained that assumption in our analyses. Given the potentially large importance of those emissions in estimating the impacts of battery EVs, further investigation of this topic is warranted.

Sensitivity of Results to EV Battery Life. In these analyses, we use the GREET default assumption that EV battery life is 160,000 miles: the same as the life of the rest of the vehicle. To explore a hypothetical scenario where battery life is only 100,000 miles, we multiply our results for air quality impacts from battery production by a factor of 1.6. This gives results similar to the sensitivity analysis in Fig. S3 where we double battery impacts: the air quality impacts of the EV scenario increase (WWS EVs, 34% increase; natural gas EVs, 18%; corn stover EVs, 7%; grid average EVs, 5%; coal EVs, 2%), but the rank order of scenarios does not change.

Model Availability. The GREET model is available at greet.es.anl.gov/. GREET-cst is freely available upon request. WRF-Chem is available at www2.mmm.ucar.edu/wrf/users/. The SMOKE model is available at www.cmascenter.org/smoke/. Our program used to convert between SMOKE and GREET-cst output and WRF-Chem input formats is available at bitbucket.org/ctessum/emcnv/.

Additional Data. Additional supporting data files are available:

- Dataset S1: A Microsoft Excel file containing emissions amounts disaggregated by life cycle stage for each scenario. For more information on emissions, refer to Tessum et al. (1).
- DatasetS2.pdf: Maps of annual average ground-level concentrations of $PM_{2.5}$, O_3, PM_{10}, NO_x, HCHO, NH_3, particulate SO_4, particulate NH_4, particulate NO_3, organic aerosol, elemental carbon aerosol, particle number, and CO; maps of annual average daily peak O_3 concentrations; and maps of $PM_{2.5}$ and O_3 concentrations animated by month of year, day of week, and hour of day for the baseline simulation and each scenario. A PDF viewer that allows embedded JavaScript, such as Adobe Acrobat, is required to view the animations. Available in an external repository at dx.doi.org/10.13020/D6159V.
- VideoS1.mp4: A video showing temporal variation in $PM_{2.5}$ concentrations attributable to each scenario. Available in an external repository at dx.doi.org/10.13020/D6159V.
- VideoS2.mp4: A video showing temporal variation in O_3 concentrations attributable to each scenario. Available in an external repository at dx.doi.org/10.13020/D6159V.

1. Tessum CW, Marshall JD, Hill JD (2012) A spatially and temporally explicit life cycle inventory of air pollutants from gasoline and ethanol in the United States. *Environ Sci Technol* 46(20):11408–11417.
2. US Environmental Protection Agency (2013) *Fugitive Dust from Mining and Quarrying (2325000000)*. Available at ftp://ftp.epa.gov/EmisInventory. Accessed August 12, 2013.
3. Xstrata Coal (2012) *Ravensworth Underground Mine—Coal Mine Particulate Matter Control Best Management Practice Determination*. Available at www.xstratacoalravensworth.com.au/EN/RavensworthUndergroundMine/Publications/Mt plans and programs/RUM%20Coal%20Mine%20PM%20BMP%20Determination.pdf. Accessed September 26, 2013.
4. Plevin RJ, O'Hare M, Jones AD, Torn MS, Gibbs HK (2010) Greenhouse gas emissions from biofuels' indirect land use change are uncertain but may be much greater than previously estimated. *Environ Sci Technol* 44(21):8015–8021.
5. Brandt AR, et al. (2014) Energy and environment. Methane leaks from North American natural gas systems. *Science* 343(6172):733–735.
6. Michalek JJ, et al. (2011) Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proc Natl Acad Sci USA* 108(40):16554–16558.
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8. Edelstein BDL (2010) *US Geological Survey 2010 Minerals Yearbook: Copper* (US Geological Survey, Reston, VA). Available at minerals.usgs.gov/minerals/pubs/commodity/copper/myb1-2010-coppe.pdf. Accessed January 28, 2013.

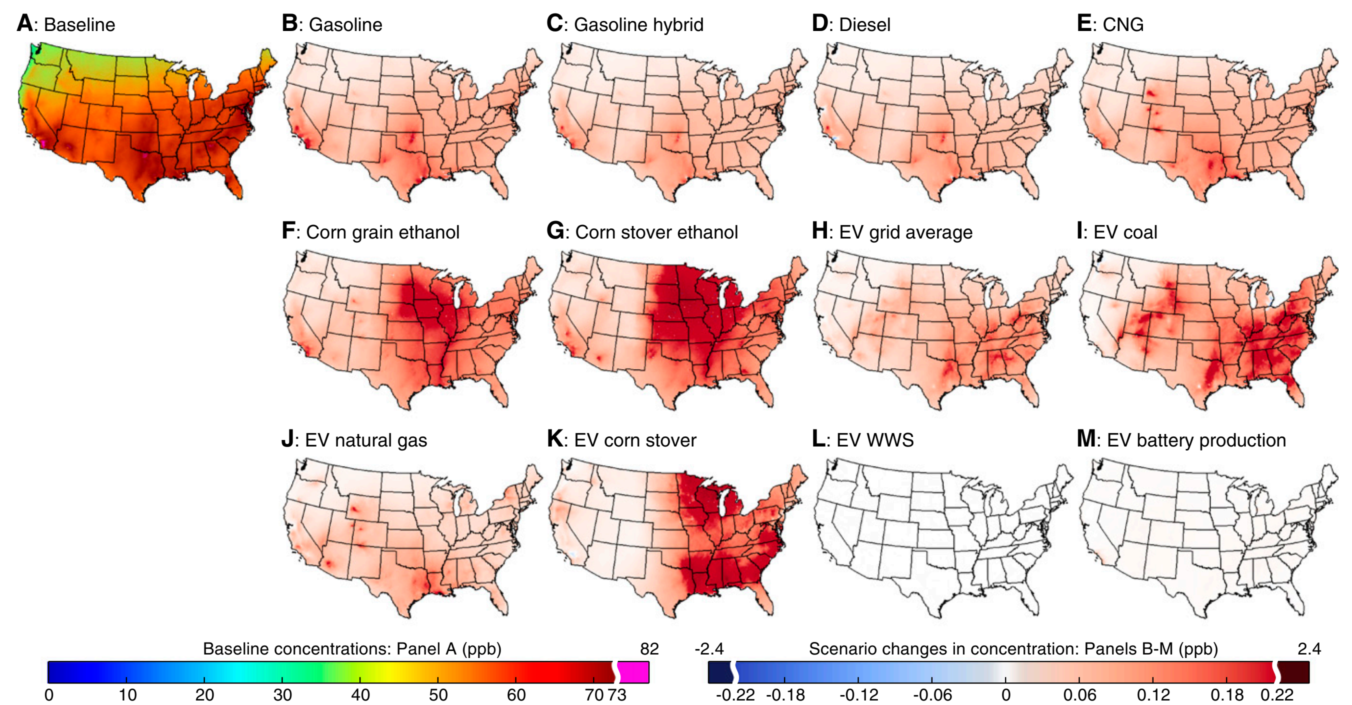

Fig. S1. April to September average daily peak O_3 concentrations. (*A*) Year 2005 baseline modeled concentrations. (*B–L*) Increase in concentration above the baseline attributable to replacement of 10% of year 2020 vehicle use with the given technology. (*M*) Increase in concentration attributable 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.

	CH_4	CO	CO_2	N_2O	NH_3	NO_x	PM_{10}	$PM_{2.5}$	SO_x	VOC
Gasoline	96%	100%	97%	99%	100%	68%	86%	81%	55%	99%
Gasoline hybrid	96%	100%	97%	99%	100%	69%	87%	82%	55%	99%
Diesel	96%	98%	98%	99%	100%	71%	87%	83%	54%	97%
CNG	99%	100%	97%	99%	100%	89%	88%	92%	89%	99%
Corn grain ethanol	97%	100%	94%	96%	99%	93%	96%	94%	71%	97%
Corn stover ethanol	123%	100%	115%	95%	98%	97%	86%	91%	190%	97%
EV grid average	100%	98%	100%	100%	100%	98%	100%	100%	100%	99%
EV coal	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
EV natural gas	99%	96%	99%	99%	80%	93%	98%	98%	98%	98%
EV corn stover	86%	99%	76%	97%	97%	98%	97%	97%	90%	87%
EV WWS	X	X	X	X	X	X	100%	100%	X	X
EV battery production	53%	59%	64%	70%	80%	52%	75%	68%	63%	43%

Fig. S2. Fractions of emissions from each scenario that occur within the spatial modeling domain. Boxes marked with "X" indicate that total emissions are zero. Emissions outside of spatial modeling domain are not included in the above analyses.

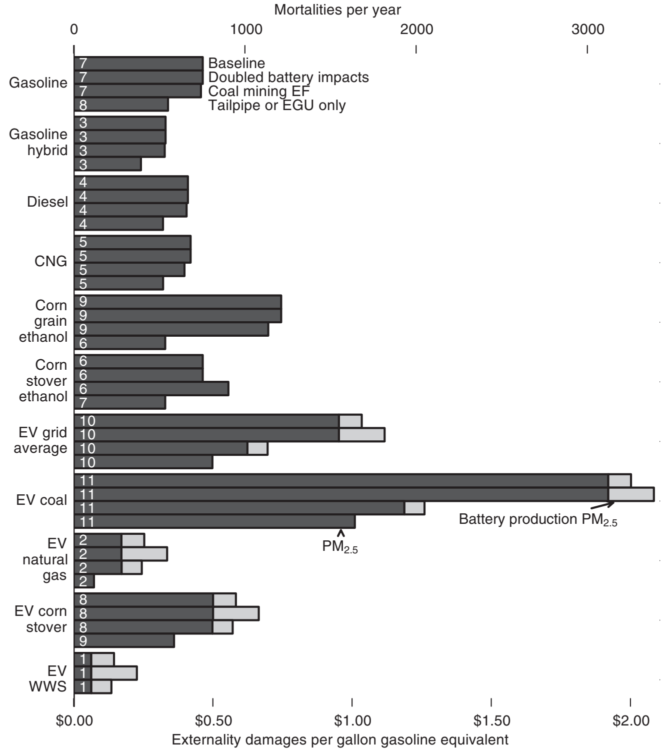

Fig. S3. Air pollution damages based on air quality modeling for the month of September for the baseline scenarios and sensitivity analyses where battery production impacts are doubled ("Doubled battery impacts"), where coal mining and cleaning emissions factors were updated to a recently published value ("Coal mining EF"), and where only emissions from vehicle tailpipes or electrical generation units are considered ("Tailpipe or EGU only"). The numbers at the base of each bar are rank orders where number 1 has the lowest impacts and number 11 has the highest impacts of all of the scenarios. Climate change and air pollution impacts of battery production are added to the EV scenarios assuming effects are additive. Abbreviations: CNG, compressed natural gas vehicle; WWS, wind, water, or solar.

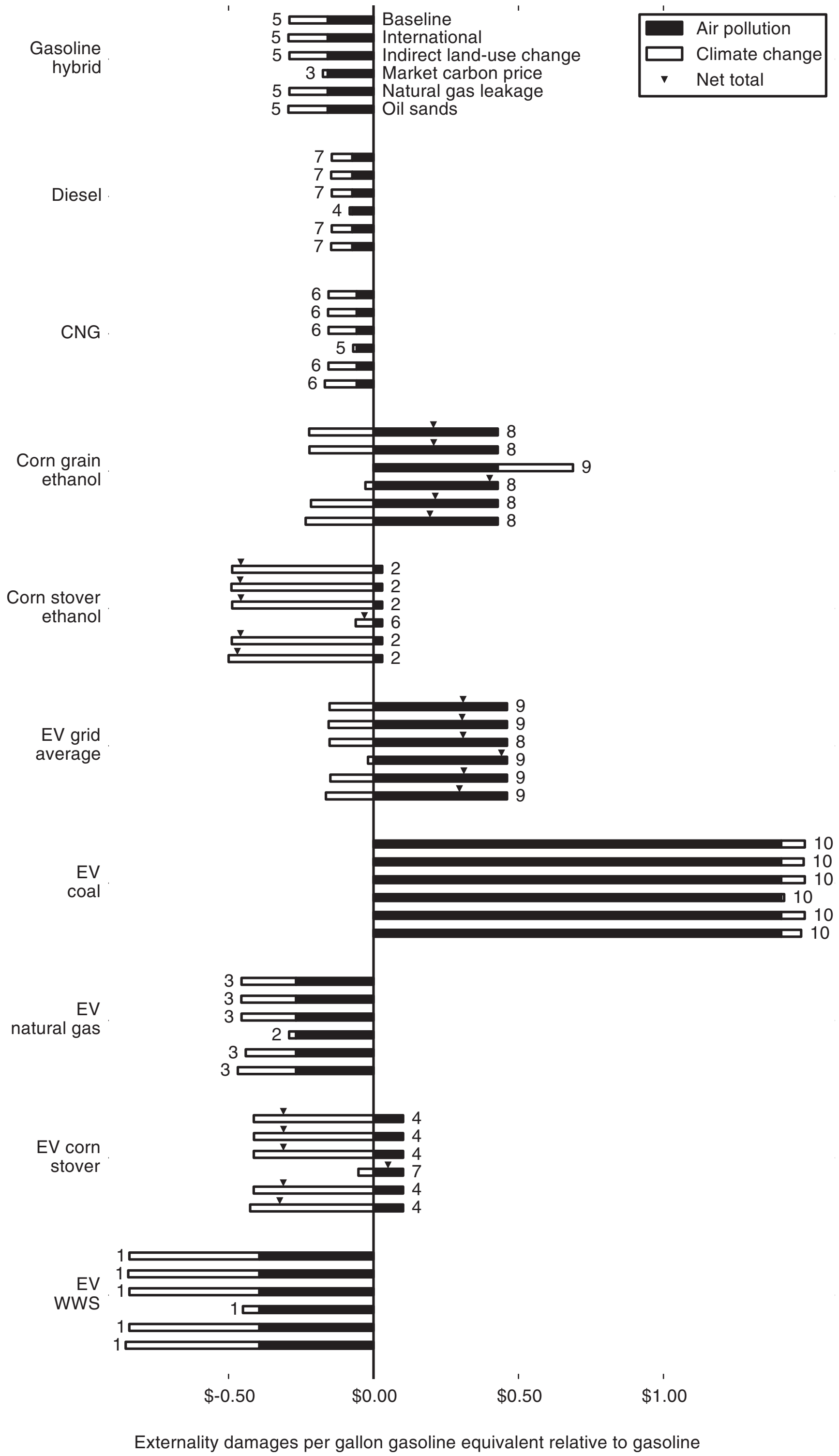

Fig. S4. Annual air pollution and climate change externalities attributable to each scenario relative to the gasoline scenario ("Baseline") and sensitivity analyses assessing the impacts of (*i*) "Indirect land-use change": including indirect land-use change emissions in the corn ethanol scenario; (*ii*) "International": including climate impacts of emissions outside of the United States; (*iii*) "Market carbon price": using a market-based carbon prices rather than the mitigation-based price used in the main analysis; (*iv*) "Natural gas leakage": assuming increased leakage of methane during natural gas extraction; and (*v*) "Oil sands": assuming 21% of crude oil comes from oil sands as opposed to the baseline assumption of 0%. The numbers at the end of each bar are rank orders where number 1 has the lowest impacts and number 10 has the highest impacts of all of the scenarios. Impacts from the gasoline scenario equal zero on this plot. Climate change and air pollution impacts of battery production are added to the EV scenarios assuming effects are additive. Abbreviations: CNG, compressed natural gas vehicle; WWS, wind, water, or solar.

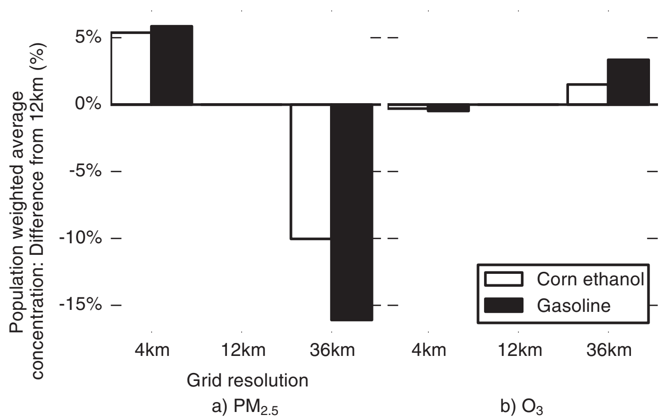

Fig. S5. Impact of grid resolution on apparent health impacts for two scenarios.

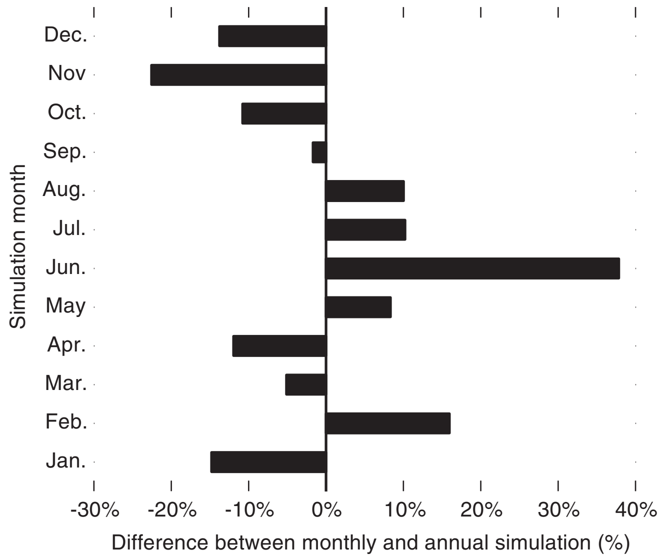

Fig. S6. Average percent differences in number of deaths among all scenarios when only considering air quality modeling results from one month compared with all 12 months.

Table S1. Results of previous studies of air quality impacts from alternative transportation fuels and technologies

Article	Result	Notes	Peer-reviewed journal?
Alhajeri et al. (1)	Seventeen percent plug-in hybrid EV (PHEV) adoption leads to greater decreases in O_3 than 100% biofuel (E85) adoption.	Use detailed photochemical model, but only consider vehicle tailpipe and EGU emissions, and only estimate impacts in Austin, TX.	Yes
Boureima et al. (2)	Battery EVs greatly decrease air quality impacts compared with gasoline or hybrid vehicles.	Full life cycle analysis including battery production but does not include any spatial information and uses generalized emissions impact functions. Electric generation mix is Belgium average.	Yes
Brinkman et al. (3)	PHEVs decrease O_3 concentrations compared with gasoline vehicles.	Use detailed photochemical model, but only consider vehicle tailpipe and EGU emissions, and only estimate impacts in Denver, CO.	Yes
Cook et al. (4)	Increased ethanol use in the United States will increase O_3 concentrations in most areas, but decrease concentrations in some highly populated areas with poor air quality.	Full life cycle analysis with spatially explicit emissions, but the degree of spatial disaggregation is not clear. Impacts on $PM_{2.5}$ concentrations are not reported. Air quality model uses two separate 12-km resolution domains, each covering half of the United States.	Yes
EPA (5)	Standard mandating biofuel (both corn grain-based and cellulosic) production and consumption will cause 35–85 cases of adult $PM_{2.5}$ mortality and 36–160 cases of adult O_3 mortality compared with business as usual.	Use detailed air quality model for contiguous United States with life cycle inventory, and spatial data are included in the life cycle inventory. Impacts of corn grain and cellulosic ethanol are not reported separately.	No
EPRI (6)	PHEV adoption decreases O_3 and $PM_{2.5}$ levels compared with business-as-usual in almost all urban areas.	Use detailed photochemical model for contiguous United States, but only consider tailpipe, EGU, and petroleum supply chain emissions. Assume no marginal SO_x or NO_x emissions from EGUs. Air quality model uses 36-km spatial resolution.	No
Hill et al. (7)	$PM_{2.5}$ impacts from corn ethanol are ~60% greater than from gasoline, impacts from cellulosic ethanol are slightly better than from gasoline, and $PM_{2.5}$ impacts are larger than GHG impacts.	Full life cycle analysis at county-level spatial resolution for contiguous United States, with reduced-form air quality model.	Yes
Jacobson (8)	Ethanol vehicles cause increased O_3-related mortalities compared with business-as-usual.	Use detailed photochemical model for contiguous United States, but only consider tailpipe emissions. Air quality model uses 0.5 by 0.75° (~50 km × 75 km) spatial resolution.	Yes
NRC (9)	For year 2030, corn ethanol causes similar air quality impacts to gasoline; cellulosic ethanol, diesel vehicles, and compressed natural gas vehicles cause decreased impacts; EVs cause increased impacts.	Use reduced-form air quality model with full life cycle emissions inventory. Emissions inventory and air quality model have county-level spatial resolution.	No
Michalek et al. (10)	Using "base case" assumptions, EVs do not improve $PM_{2.5}$ and O_3 air quality impacts compared with gasoline, owing largely to emissions from battery production.	Use reduced-form air quality model with full life cycle emissions inventory. Emissions inventory and air quality model have county-level spatial resolution.	Yes
Thompson et al. (11)	PHEVs decrease O_3 concentrations compared with gasoline vehicles.	Use detailed photochemical model, but only consider vehicle tailpipe and EGU emissions, and only estimate impacts in Pennsylvania, New Jersey, and Maryland.	Yes
Thompson et al. (12)	PHEVs decrease O_3 concentrations compared with gasoline vehicles.	Use detailed photochemical model, but only consider vehicle tailpipe and EGU emissions, and only estimate impacts in Texas.	Yes

1. Alhajeri NS, McDonald-Buller EC, Allen DT (2011) Comparisons of air quality impacts of fleet electrification and increased use of biofuels. *Environ Res Lett* 6(2):024011.
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12. Thompson TM, King CW, Allen DT, Webber ME (2011) Air quality impacts of plug-in hybrid electric vehicles in Texas: Evaluating three battery charging scenarios. *Environ Res Lett* 6(2):024004.

Table S2. Fractions of processes related to battery production that occur outside of the spatial modeling domain

Process	Percent excluded, %	Data source, ref.
Steel production	9	1
$LiMn_2O_4$	100	2
Graphite production	100	1
Copper production	35	1
Aluminum production	13	1
$LiPF_6$	100	2

The spatial modeling domain includes the continental United States and surrounding waters. Processes not included in this table are assumed occur 100% inside the spatial modeling domain. Refer to Dataset S1 for total emissions for each of these processes after the excluded fractions have been removed.

1. US Geological Survey (2012) *Mineral Commodity Summaries 2012.* Available at minerals.usgs.gov/minerals/pubs/mcs/. Accessed January 28, 2012.
2. Wang M, Burnham A, Wu Y (2012) *The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model v2_2012*. Available at greet.es.anl.gov/. Accessed November 24, 2014.

Other Supporting Information Files

Dataset S1 (XLS)