Estimating environmental co-benefits of U.S. low-carbon pathways using the GCAM-USA integrated assessment model

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Supplementary Information

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Section S1. Approaches for incorporating impacts

Previous studies have used either chemical transport models, response surface models, or impact factors for co-benefit analysis. Chemical transport models simulate the emission of air pollutants, their transformation via atmospheric chemical reactions, and their transport and removal processes in the atmosphere. Chemical transport models could theoretically be incorporated as a module within an IAM, with the resulting pollutant concentrations and their impacts considered endogenously during the IAM solution process. However, chemical transport models are too computationally intensive to be run in such an iterative fashion.

An alternative to integrating a full-scale chemical transport model is the integration of a model emulator. An emulator is a simplified or "reduced form" model that can serve as a surrogate for the more complex model, sacrificing detail while still being able to capture the key relationships pertinent to the application. One type of emulator is a response surface model (RSM), which is developed from a set of sensitivity runs of the full-scale model. Fann et al. [1] developed an RSM to link emission changes to changes in $PM_{2.5}$ concentrations, and thence to health benefits. Such model emulators for air quality and other environmental impacts are computationally intensive to develop, requiring multiple runs to characterize complex and nonlinear model behavior. Model emulators for air quality have not yet been integrated widely into IAMs such as GCAM to represent air quality, although they have been used to characterize climate impacts of emissions. For example, the Model for the Assessment of Greenhouse Gas Induced Climate Change (MAGICC) simple climate model [2], was used iteratively within GCAM to develop the RCP4.5 scenarios [3], and Hector, an open-source, object-oriented, simple climate carbon-cycle model has been coupled with GCAM to offer an even more rapid solution [4].

An even simpler approach is the use of impact factors to represent individual environmental impacts associated with economic activities [5,6] or aggregating multiple climate and environmental impacts into a single metric such as the social cost of atmospheric release [7]. Impact factors can be derived from a chemical transport model or a RSM. Recently, impact factors have also been developed using adjoint models that use a numerical derivative-based approach to link impacts to sources. For example, Lee et al. [8] quantified the effects on global premature mortality of changes to $PM_{2.5}$ precursor emissions using the adjoint of the GEOS-Chem chemical transport model. Akhtar et al. [9] used radiative forcing factors developed from the GEOS-Chem model as well. Potentially, impact factors can be integrated into an IAM and endogenized within the solver so that their values can be constrained and their costs can be considered in the model's solution process.

In this study, exogenously developed impact factors are integrated into GCAM-USA. The technology-rich representation in GCAM-USA provides detailed information about human and natural earth systems and the interactions between these systems, so the emission response to both climate polices and technological assumptions can be well captured and represented. The impact factors then allow for rapid estimation of the associated impacts due to the responses of each sector. This improvement allows us to explore a broader set of modeling scenarios with higher flexibility and computational efficiency.

Section S2. Development of $PM_{2.5}$ health impact factors

Fann et al. [5] calculate the monetized benefits of decreased premature mortality associated with a 1-ton reduction in directly emitted $PM_{2.5}$ or $PM_{2.5}$ precursor emissions (SO_2 and NO_x) from 17 sectors in 2005 and 2016. This analysis is extended to 2020, 2025 and 2030 by the US EPA [10]. These factors consider both population growth, which affects the total incidence from exposure to air pollution, and economic growth, which affects the willingness to pay to reduce health risk. The Value of Statistical Life (VSL) is used to monetize mortality, which is adjusted in future years to account for income growth. However, the 2025 and 2030 estimates in US EPA [10] both used 2024 VSLs because income growth projections were unavailable beyond that year.

The current paper estimates the health impact factors through 2050, considering impacts from both population growth and economic growth. Therefore, a two-step process has been conducted to develop the health impact factors based on the approach of Fann et al. [5] and US EPA [10].

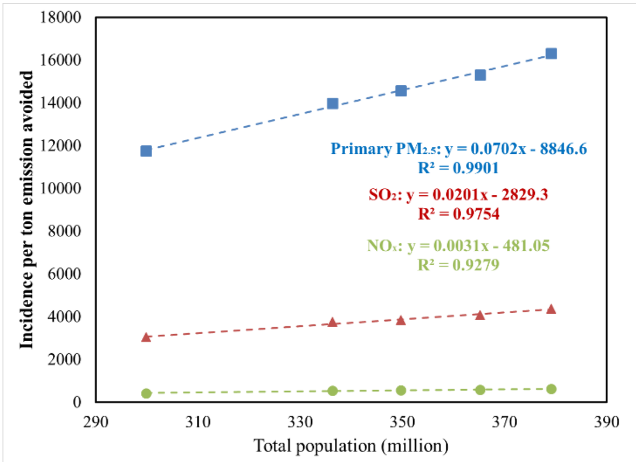
Step 1: Extrapolation of "deaths per ton" factors based on population growth

Fann et al. [5] and US EPA [10] report both health impact factors ($/ton) and the VSLs ($/death) applied for each analysis year. The "incidence per ton" factors, which reflect population growth, are obtained through dividing the former by the latter (Fig S1). The "incidence per ton" factors for other modeling years (2010, 2035, 2040, 2045, and 2050) are then calculated using the linear relation in Fig S1 with GCAM-USA population projections (Table S1).

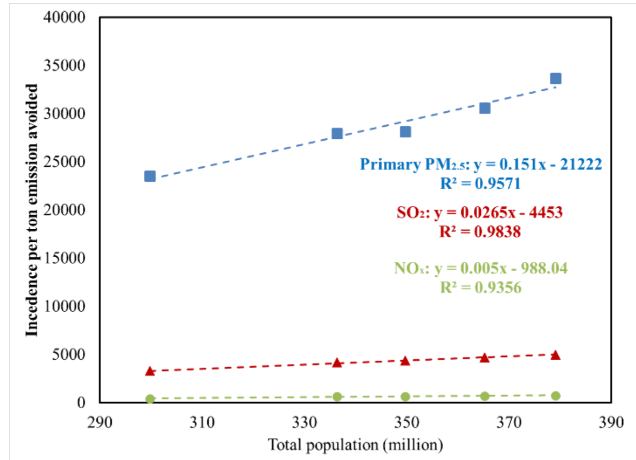
Step 2: Adjustment for income growth (willingness to pay)

To be more consistent with GCAM-USA socioeconomic assumptions, we projected U.S. per capita income (GDP, in 2010 dollars) using GCAM-USA and calculated VSLs for all modeling years (Table S2). The estimation is based on a benchmark of $8.3 million in 2005 [11] and an income elasticity of 0.5 [12].

Finally, the dollar per ton health impact factors (Table S3) are calculated by multiplying the income-adjusted incidence per ton values by the VSLs projected for each modeling year. The estimates for 2005, 2015, 2020, 2025 and 2030 are slightly lower than those of Fann et al. [5] and US EPA [10], since this paper applied VSL projections based on the per capita income projected by GCAM-USA and a lower benchmark VSL in 2005. The estimates in this paper consider income growth to 2050, while US EPA [10] adjusted VSL based on income growth only to 2024, so that their 2025 and 2030 values are likely underestimates.



(a)



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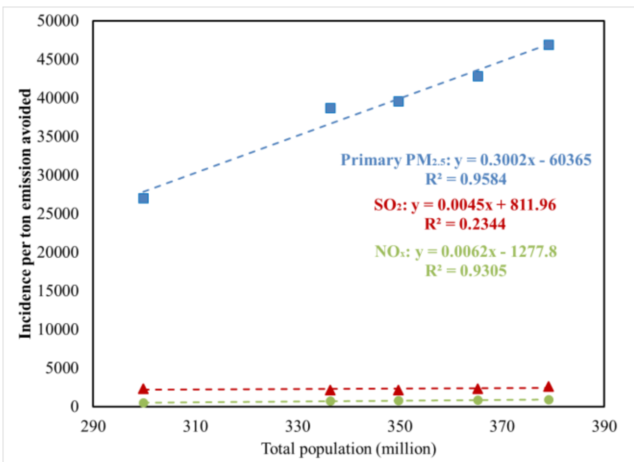

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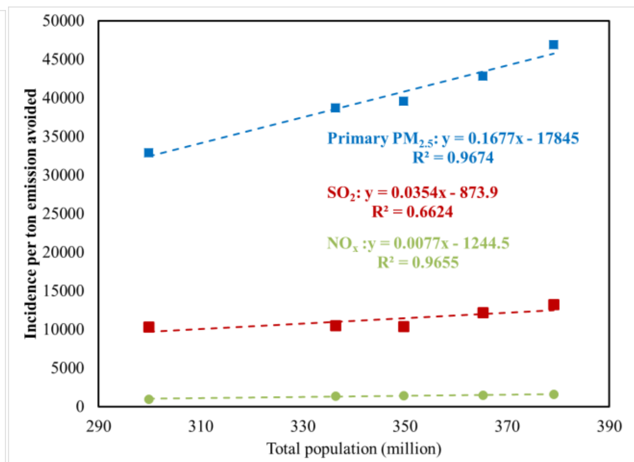


(d)

Figure S1 Linear regression between incidence (mortality) per ton emission avoided (2005, 2016, 2020, 2025 and 2030) and total population for four sectors from Fann et al. [5]. Panes: (a) Electric generating units; (b) Industrial point source; (c) On-road; and (d) Residential wood combustion.

Table S1 U.S. population projection in GCAM-USA for all scenarios[1].

Year	Population (Thousand)
2005	299,839
2010	321,813
2015	336,377
2020	349,743
2025	365,229
2030	379,129
2035	393,438
2040	407,489
2045	421,987
2050	437,264

[1] In GCAM-USA, population is a prescribed input, which does not vary across these modeling scenarios.

Table S2 Projected U.S. per capita income (GDP) and value of a statistical life (VSL) in all the modeling years.

Year	Per capita GDP[1]	VSL[2]
2005	51.9	**8.3**
2010	51.0	8.2
2015	54.7	8.5
2020	58.3	8.8
2025	61.7	9.0
2030	65.2	9.3
2035	68.8	9.6
2040	73.3	10.0
2045	77.7	10.3
2050	83.1	10.7

[1] In million 2010 dollars at a Market Exchange Rate basis

[2] In million 2010 dollars; 2005 VSL in bold red is used as benchmark to translate VSLs in future years.

Table S3 Economic value of 1-ton reduction in directly emitted $PM_{2.5}$ or $PM_{2.5}$ precursor emissions from electricity, transportation and industry sectors from 2010 to 2050 (2010 $/ton avoided).

		Sector			
Emissions	Year	Electricity[1]	Transportation[2]	Industry[3]	Building[4]
Primary $PM_{2.5}$	2010	112,542	296,761	224,121	295,776
	2015	118,534	328,247	237,067	328,247
	2020	127,804	346,897	246,480	346,897
	2025	138,319	387,293	276,638	387,293
	2030	152,124	437,356	313,756	437,356
	2035	180,270	554,512	366,701	462,224
	2040	196,808	617,176	401,491	502,908
	2045	214,161	683,559	438,056	545,505
	2050	234,676	761,530	481,234	595,937
SO_2	2010	29,797	18,506	33,367	86,124
	2015	31,913	17,324	35,560	89,356
	2020	33,777	19,171	38,341	91,289
	2025	36,885	21,209	42,418	110,655
	2030	40,883	24,720	46,588	123,601
	2035	48,770	24,798	57,358	125,352
	2040	53,400	26,352	63,203	134,975
	2045	58,266	27,943	69,367	144,972
	2050	64,011	29,855	76,629	156,870
NO_x	2010	4,230	5,874	5,085	10,100
	2015	4,741	6,656	5,562	11,853
	2020	4,930	7,029	5,934	12,780
	2025	5,348	7,746	6,455	13,832
	2030	5,895	8,652	7,226	15,212
	2035	7,093	11,154	9,403	17,141
	2040	7,791	12,437	10,452	18,857
	2045	8,526	13,797	11,564	20,665
	2050	9,392	15,394	12,870	22,796

[1] Derived from values reported in "Electric generating units" sector in Fann et al. [5]
[2] Derived from values reported in "On-road" sector in Fann et al. [5]
[3] Derived from values reported in "Industrial point source" sector in Fann et al. [5]
[4] Derived from values reported in "Residential wood combustion" sector in Fann et al. [5]

Section S3. Development of biomass supply restrictions

One previous GCAM study by Calvin et al. [13] explored the trade-offs of different land and bioenergy policies to achieve climate targets, in which one scenario greatly restricted the end-use and transformative consumption to 100 EJ per year in the U.S. by 2100. This work adopts the same assumption in our NUC/CCS scenarios from 2010 to 2050, which leads to a total biomass consumption of 21 EJ per year by 2050. No biomass supply constraints were applied to BASE and RE scenarios.

Fig S2 shows the total biomass consumption under each technology and policy scenario in the U.S. In 2010 the total biomass consumption is 2.8 EJ per year. When no CO_2 target was applied, biomass consumption increased by 5.0 EJ/yr and 4.7 EJ/yr in 2050 relative to 2010 in BASEREF and REREF, respectively, while NUC/CCSREF increased only 1.8 EJ/yr. Under a 50% CO_2 reduction target, the biomass consumption grows rapidly in BASE50 and RE50, but increases only slightly in NUC/CCS50. Under an 80% CO_2 reduction target, the biomass consumptions in 2050 are significantly different across technological assumptions, ranging from 47 EJ/yr in RE80 to 21 EJ/yr in NUC/CCS80, as a result of limited biomass supply. Therefore, limited bioenergy supply could have considerable impact in achieving low-carbon goals.

Fig S3 further shows the biomass supply by sector. In BASEREF, the majority of biomass supply comes from purpose-grown biomass after 2030, while under 50% and 80% reduction scenarios, residue biomass dominates the biomass supply. Consistent with the biomass consumption pattern, NUC/CCS scenarios have significantly limited biomass supply relative to BASE and RE.

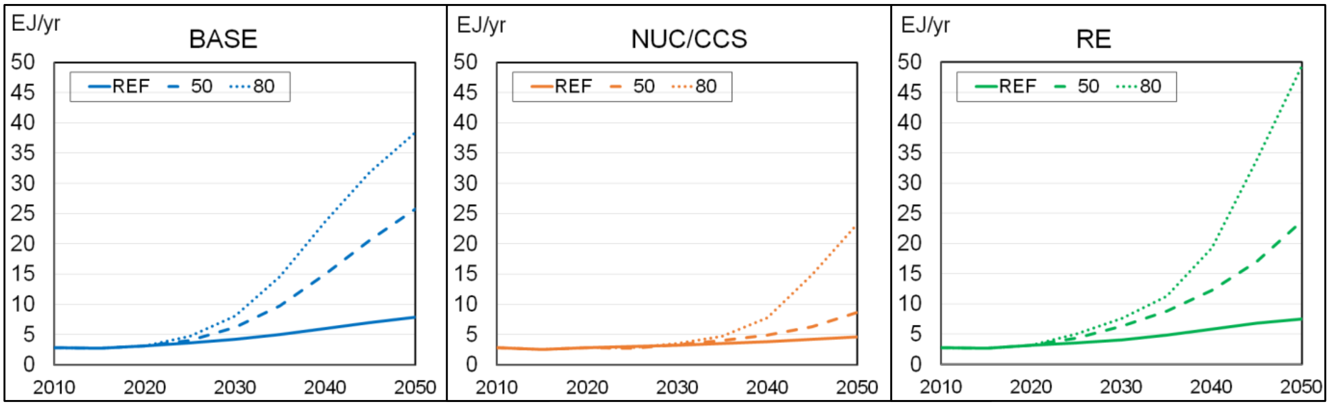


Figure S2 Total biomass consumption (EJ per year) for each technology and policy scenario in the U.S.

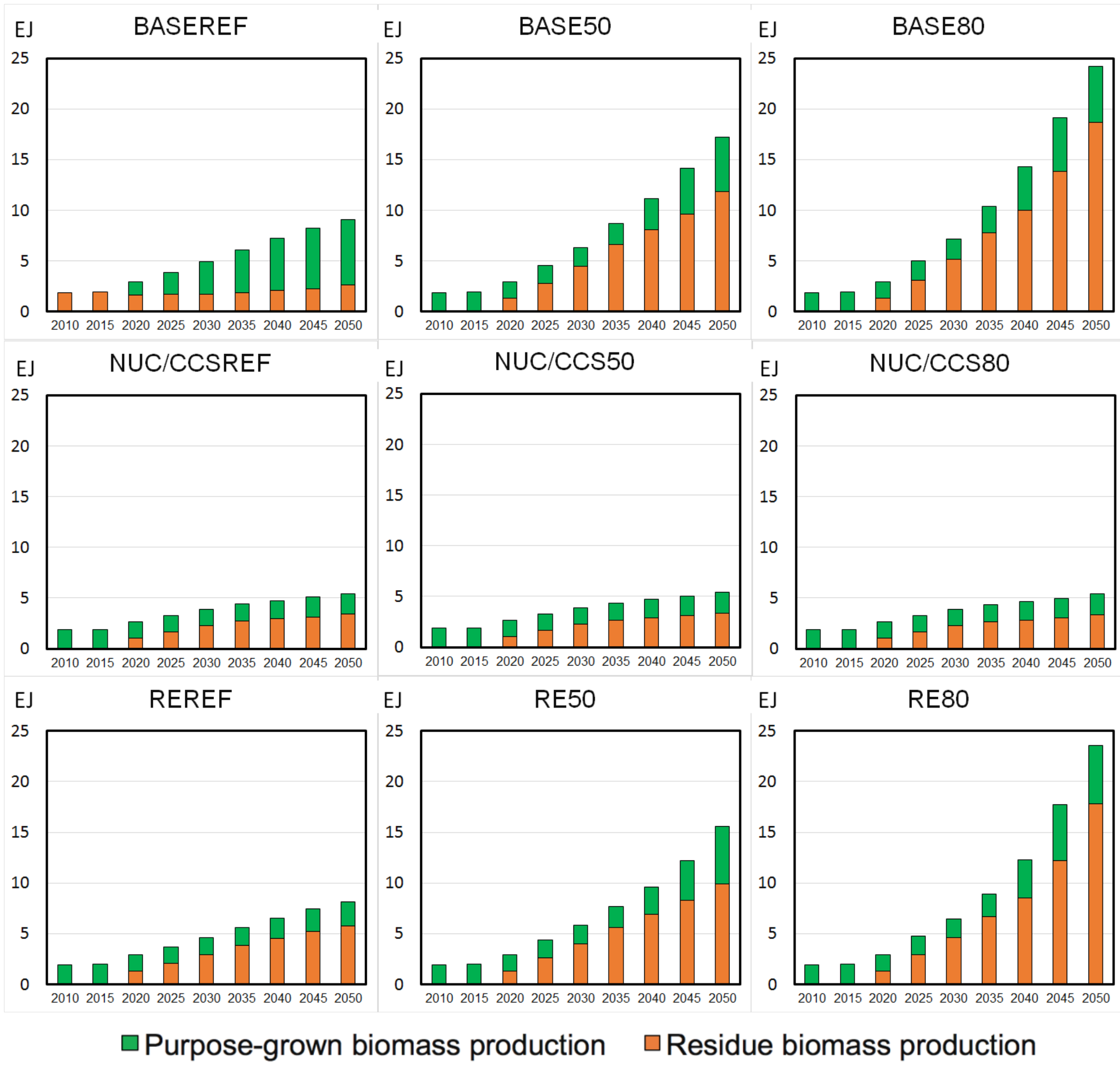


Figure S3 Biomass production (EJ per year) by sector for each technology and policy scenario.

Section S4. Electric sector technology assumptions

Electric sector capital cost assumptions that were used in the BASE, NUC/CCS, and RE sets of scenarios are summarized in Table S4 for 2015, 2030 and 2050. BASE values are the default costs assumed in GCAM-USA v4.3. These values are obtained from Muratori et al. [14]. See the notes below Table S4 for additional information about assumptions. These values in Table S4 do not capture some of the recent capital cost reductions in onshore wind and solar PV. In Section S9 we provide a sensitivity analysis in which alternative cost trajectories for onshore wind and solar PV are evaluated. The results from those sensitivity runs suggest that our conclusions in the manuscript are robust when considering uncertainty in renewable costs. Updating electric sector capital costs across the model in a consistent manner is a larger endeavor and beyond the scope of the work presented in the manuscript.

Electric sector, technology-specific water withdrawal and consumption factors are summarized in Table S5. These factors are derived from Macknick et al. [15].

Emission factors for post-2010-vintage electric sector technologies are provided in Table S6. These data come from two sources. NO_x and SO_2 data were derived from the documentation for the Integrated Planning Model (IPM), version 5.13. IPM is an electric sector model used in U.S. Environmental Protection Agency (US EPA) regulatory modeling activities [16]. $PM_{2.5}$ values are instead obtained from the "Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation" (GREET) model. The factors from GREET were derived from US EPA data.

Table S4 Capital cost assumptions for electricity generation technologies (2010$/kW).

Technologies[1]	BASE[2]			NUC/CCS[3]			RE[4]		
	2015	2030	2050	2015	2030	2050	2015	2030	2050
Coal (conventional pulverized)	1010	975	936						
Coal (IGCC)	1394	1241	1121						
Coal (IGCC CCS)	2301	1953	1724	1504	1337	1081			
Gas (CC)	366	353	339						
Gas (CC CCS)	732	640	583	673	579	511			
Nuclear (Gen_II_LWR)	1917	1917	1917						
Nuclear (Gen_III)	1917	1850	1775	1377	1181	945			
CSP	1673	1314	1115				1199	918	817
PV	650	579	523				716	253	224
Wind	698	620	560				586	421	419

[1] All technologies not presented are assumed to be the same as GCAM-USA default values
[2] BASE scenarios assume the same cost assumptions as GCAM-USA default values
[3] Adopted from Iyer et al. [17] - advanced technology scenario cost assumptions for nuclear and CCS technologies. Cells with blanks indicate the same value as the BASE.
[4] Adopted from Iyer et al. [17] - advanced technology scenario cost assumptions for wind, PV and CSP technologies. Cells with blanks indicate the same value as the BASE.

Table S5 Water use factors (withdrawal and consumption) for electricity generation technologies adopted in this study (trillion gallon/EJ output), modified from Macknick et al. [15]

GCAM-USA technology	Withdrawal		Consumption	
	2010	Future	2010	Future
biomass (conventional)	3.49	0.24	0.11	0.15
biomass (IGCC CCS)	0.16	0.16	0.15	0.15
biomass (IGCC)	0.11	0.11	0.10	0.10
coal (conventional pulverized CCS)	0.16	0.16	0.15	0.15
coal (conventional pulverized)	4.14	0.28	0.14	0.19
coal (IGCC CCS)	0.16	0.16	0.15	0.15
coal (IGCC)	0.11	0.11	0.10	0.10
CSP	0.13	0.24	0.13	0.24
CSP storage	0.24	0.24	0.24	0.24
gas (CC CCS)	0.14	0.14	0.11	0.11
gas (CC)	1.38	0.07	0.05	0.06
gas (steam/CT)	3.50	0.24	0.12	0.15
nuclear (Gen_II_LWR)	4.71	0.31	0.15	0.19
nuclear (Gen_III)	0.31	0.31	0.19	0.19
geothermal	0.54	1.00	0.54	1.00
refined liquids (CC CCS)	0.16	0.16	0.15	0.15
refined liquids (CC)	0.11	0.11	0.10	0.10
refined liquids (steam/CT)	3.58	0.33	0.17	0.23

Table S6 Future (new build) electric EFs (Tg/EJ) (NO_x and SO_2 from coal, gas and biomass are from IPM; $PM_{2.5}$ are from GREET).

Technologies	**NO_x**	**SO_2**	**$PM_{2.5}$**
Coal (conventional pulverized)	3.0E-02	2.6E-02	1.6E-02
Coal (IGCC)	5.6E-03	6.5E-03	7.0E-02
Coal (IGCC CCS)	5.6E-03	6.5E-03	7.0E-02
Gas (CC)	4.7E-03	0.0E+00	1.3E-04
Gas (CC CCS)	4.7E-03	0.0E+00	1.3E-04
Gas (steam/CT)	4.7E-03	0.0E+00	3.4E-03
Refined liquids (CC)	1.1E-01	2.6E-01	9.4E-03
Refined liquids (steam/CT)	2.4E-01	3.1E-02	6.2E-03
Biomass boiler	8.6E-03	3.4E-02	3.1E-02

Section S5. Global carbon prices for GHG reduction scenarios

While GCAM-USA has state-level resolution for the U.S., it also represents 31 additional global regions. These regions can trade energy resources, including biomass. Trade has the potential to affect how the model opts to meet GHG reduction targets for the U.S. For example, when faced with an 80% target, GCAM-USA could potentially import large quantities of biomass from other regions. In the real world, however, it is unlikely that the U.S. would institute such a target without other many other countries around the world also seeking to reduce GHG emissions. In such a scenario, those other countries would be competing with the U.S. for biomass and other low-carbon energy resources. Blanford et al. [18] used a CO_2 tax applied to the rest of the globe (excluding the U.S.) to simulate competition for resources. We adopt this approach and derive our values from Blanford et al. Values used in this study are shown in Table S7.

Table S7 CO_2 prices (2010$/tC) applied for all GCAM regions except the US for CO_2 reduction targets, modified from Blanford et al. [18]

Year	50% CO2 reduction	80% CO2 reduction
2010	0	0
2015	57.98	85.24
2020	74.00	115.11
2025	94.46	146.93
2030	120.54	187.51
2035	153.84	239.33
2040	196.34	305.44
2045	250.60	389.83
2050	319.84	497.53

Section S6. Time series model results

Within the manuscript, results are typically shown for 2010 and 2050. Understanding the trajectories of results for intermediate years may be of interest to some readers. This section includes time series results for sectoral CO_2 emissions (Fig S4), electricity generation by technology (Fig S5), water withdrawal and consumption for electricity production (Figs S6 and S7, respectively), and monetized $PM_{2.5}$ health costs and benefits (Figs S8 and S9, respectively).

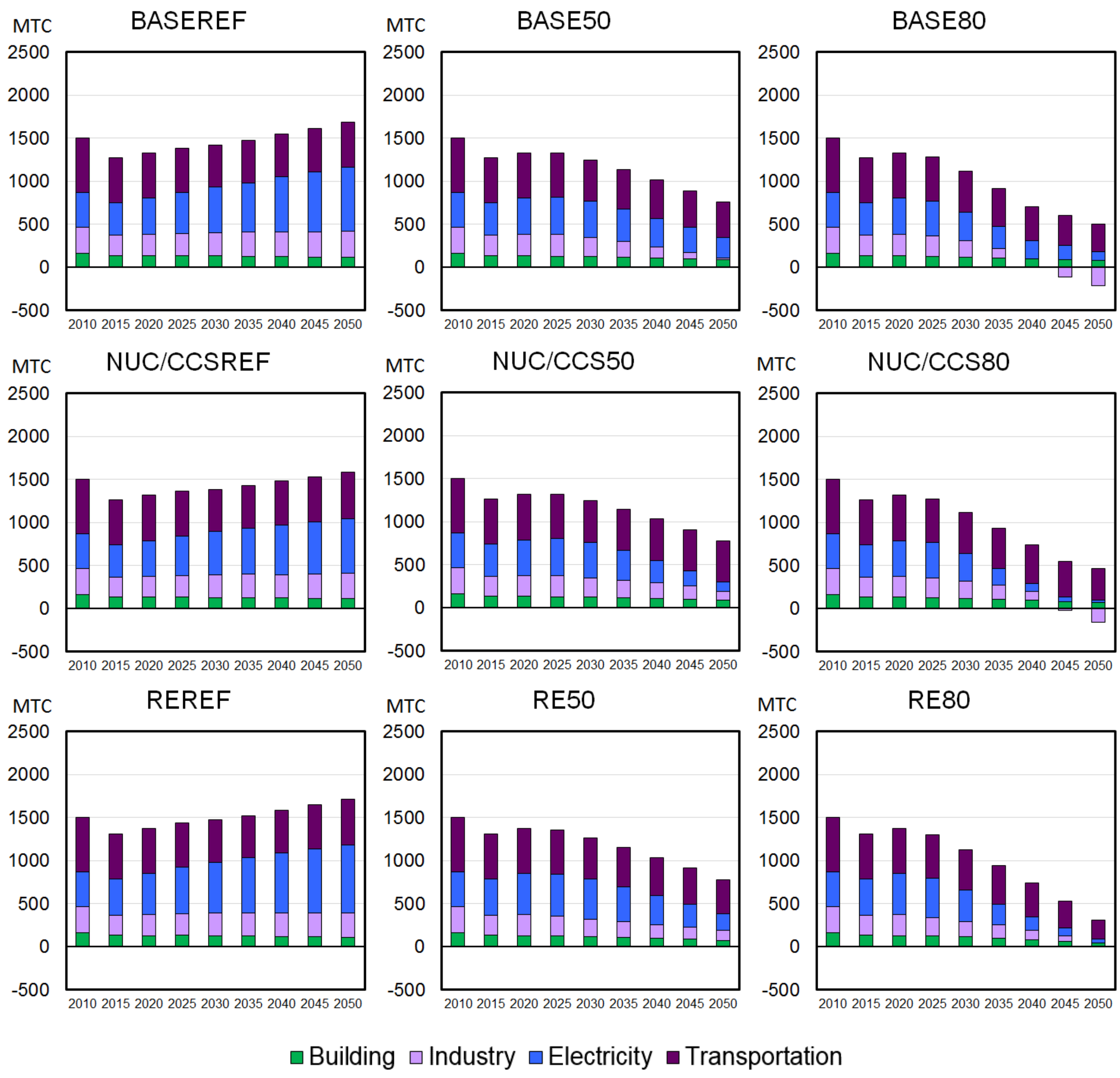


Figure S4 CO_2 emissions (million tonnes C per year) by sector for each technology and policy scenario.

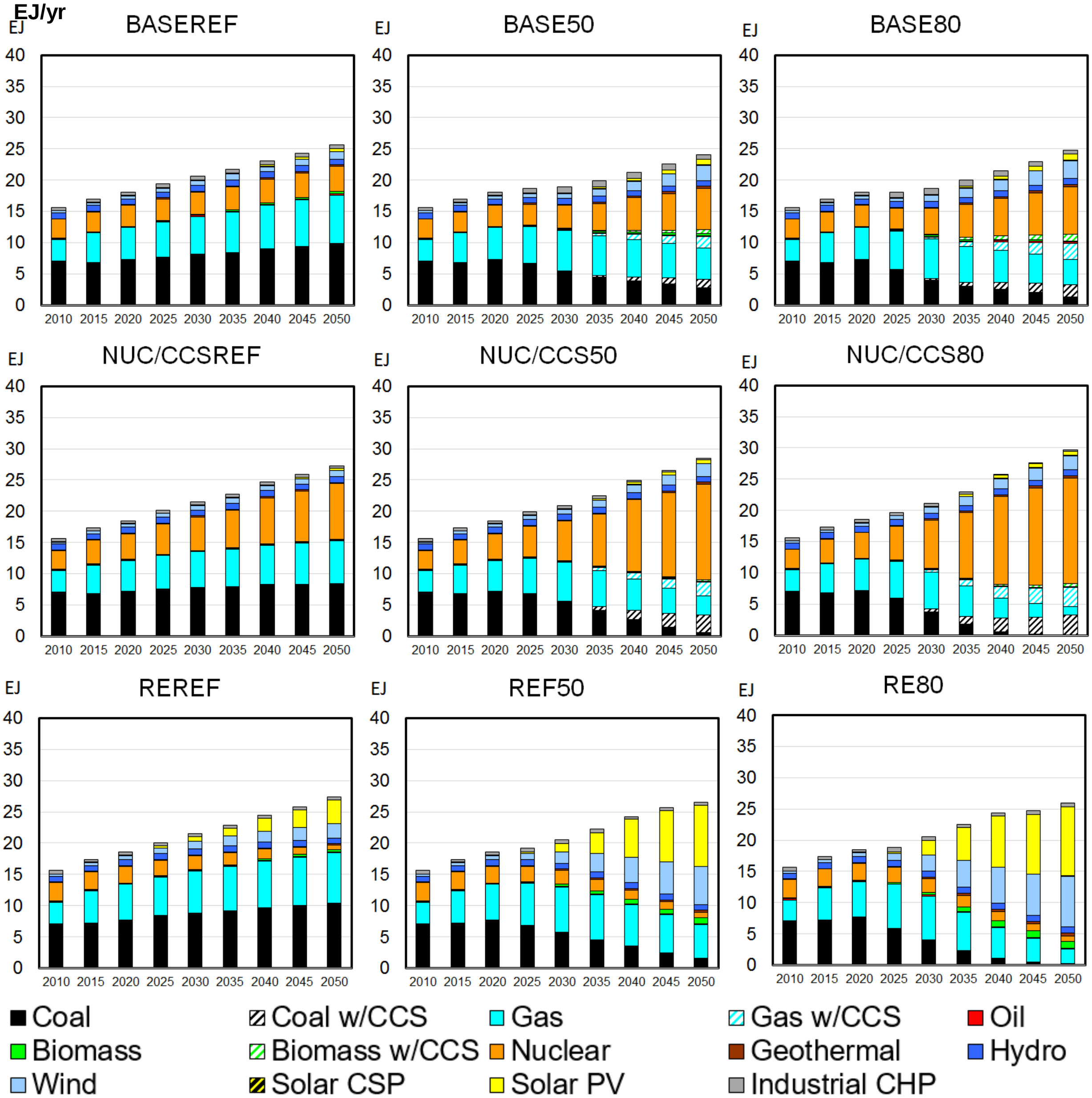


Figure S5 Electricity generation (EJ per year) by technology and policy scenario.

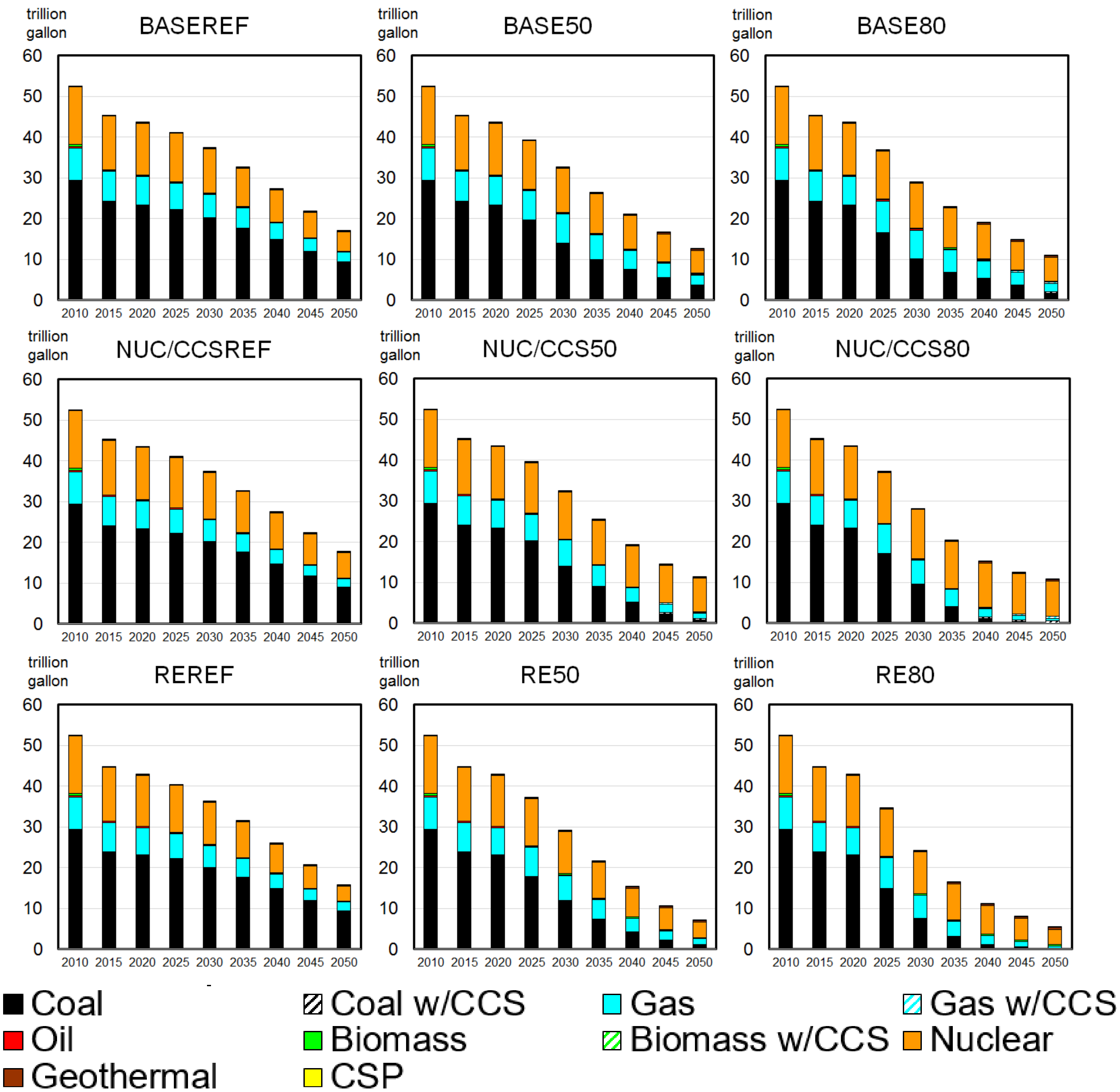


Figure S6 Water withdrawal for electricity generation (trillion gallons per year) by technology for each scenario.

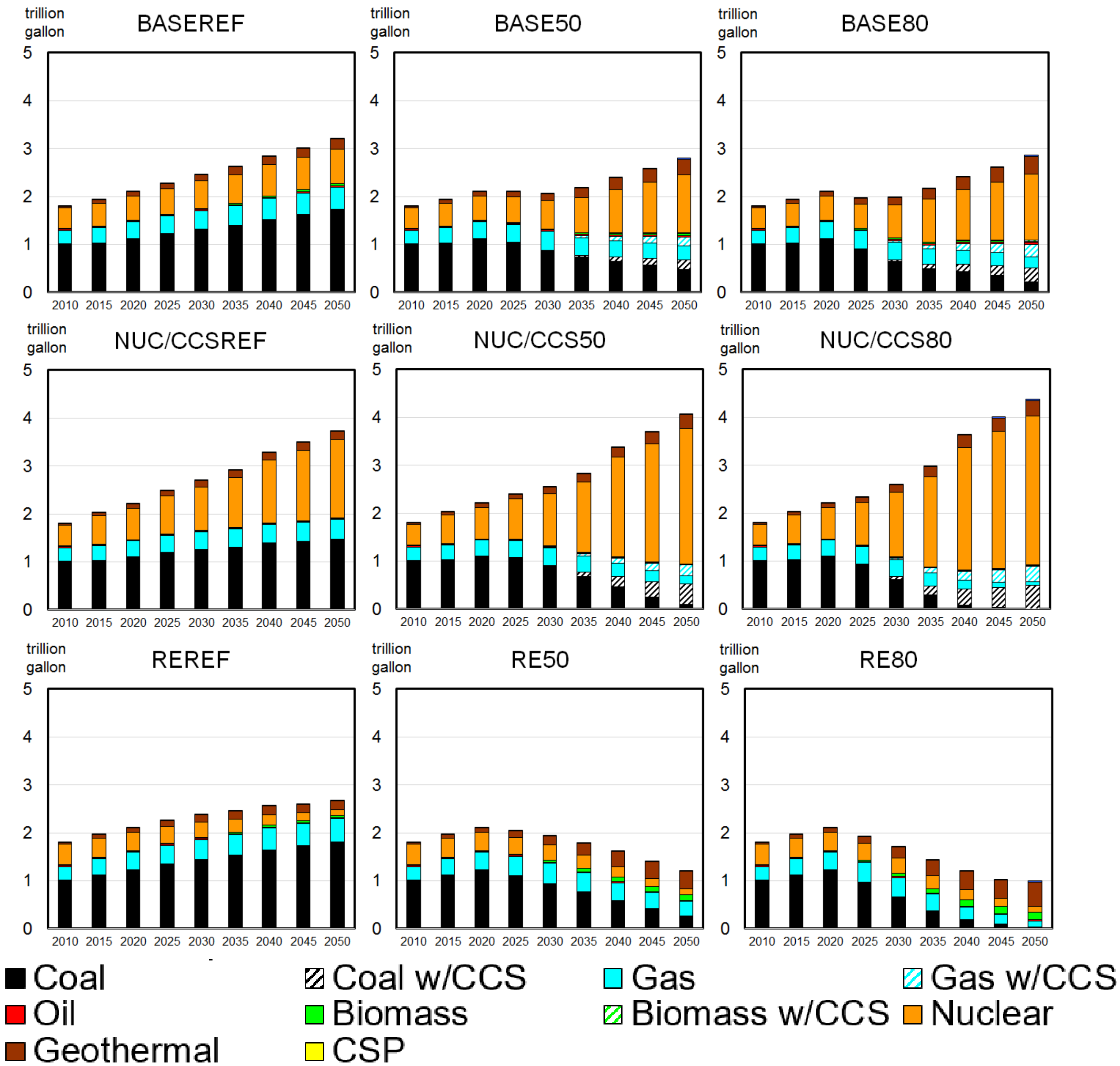


Figure S7 Water consumption for electricity generation (trillion gallons per year) by technology for each scenario.

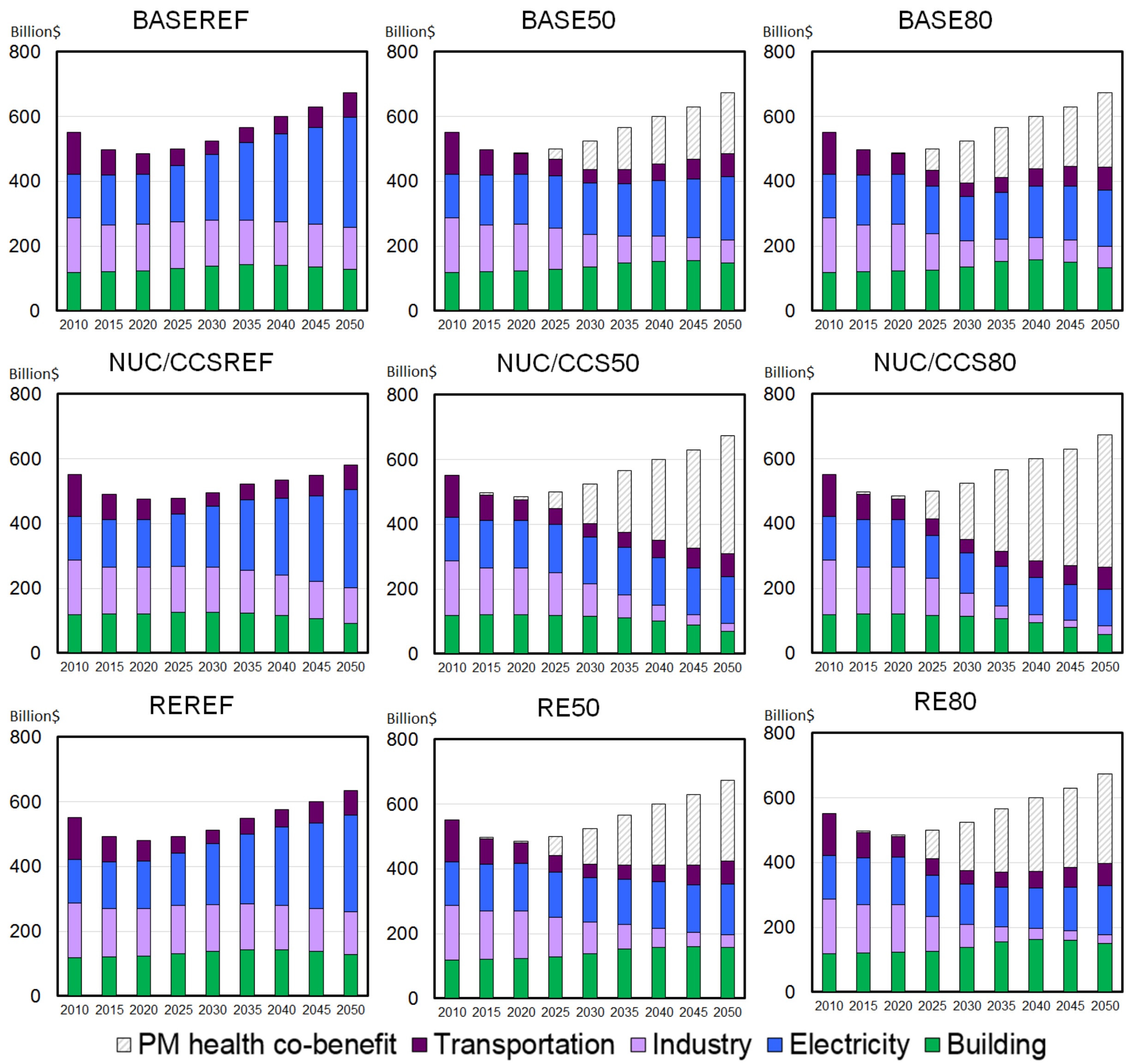


Figure S8 Monetized $PM_{2.5}$ health costs for different technology and policy scenarios (billion 2010$ per year) in U.S. energy system by sector in 2050. The difference between low-carbon scenarios and BASEREF (gray pattern) indicates the PM health co-benefits from CO_2 policies

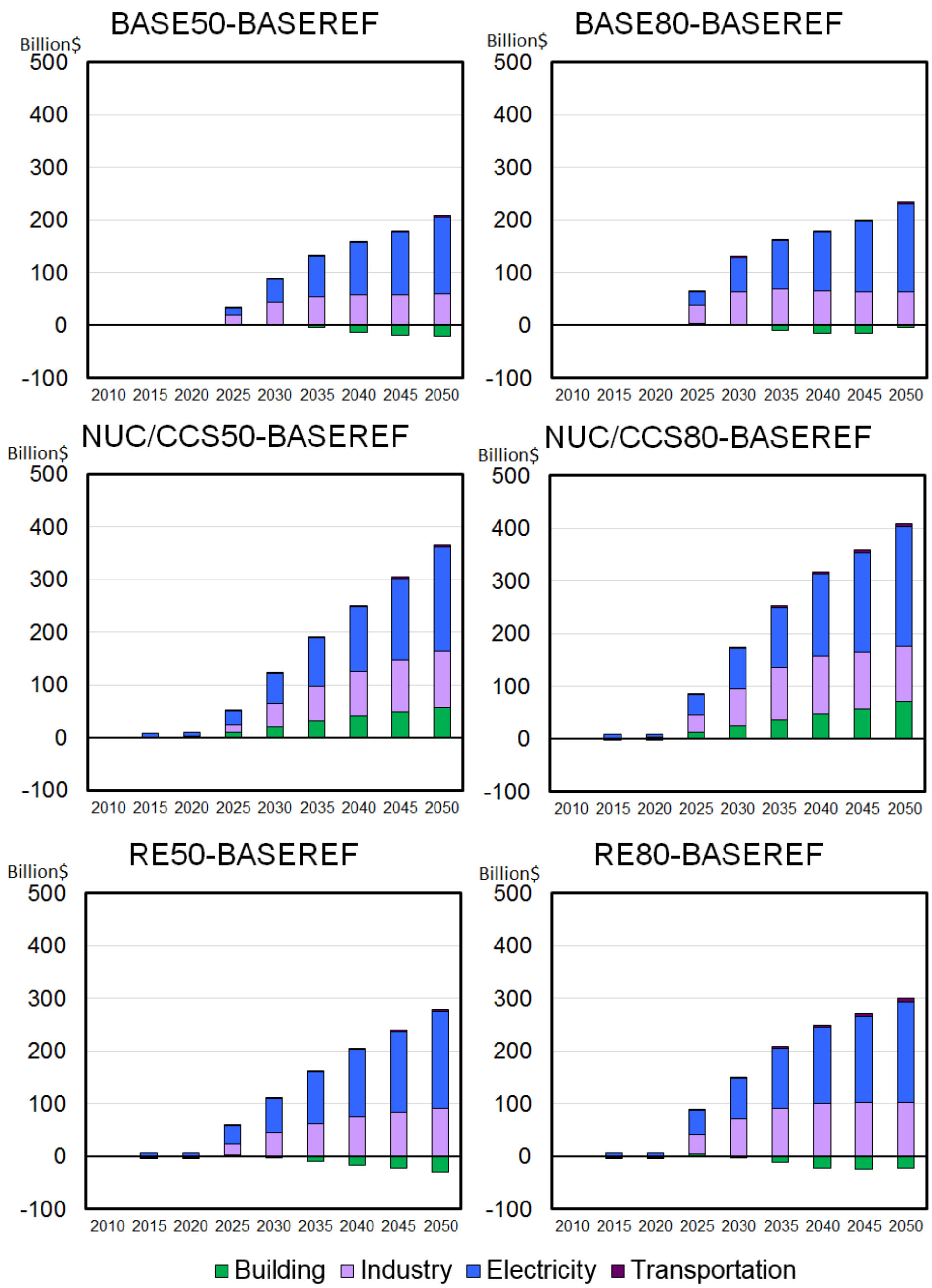


Figure S9 $PM_{2.5}$ health co-benefits relative to BASEREF (billion 2010$ per year) by sector for each low-carbon scenario.

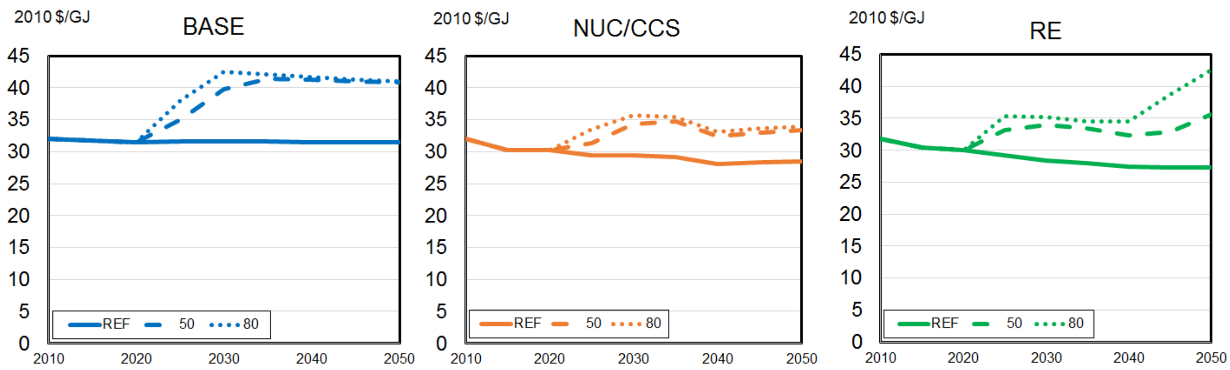


Figure S10 Electricity generation cost (2010 $/GJ) for each technology and policy scenario.

Section S7. Additional scenario comparison graphics

In this section, additional model results are provided. These figures illustrate changes in sectoral fuel use and technologies in the industrial (Fig S11), on-road vehicles (Fig S12), and buildings (Fig S13) sectors. Since residential wood combustion was found to be an important driver of $PM_{2.5}$ emissions, we also show the change in residential heating by technology relative to BASEREF for each scenario (Fig S14).

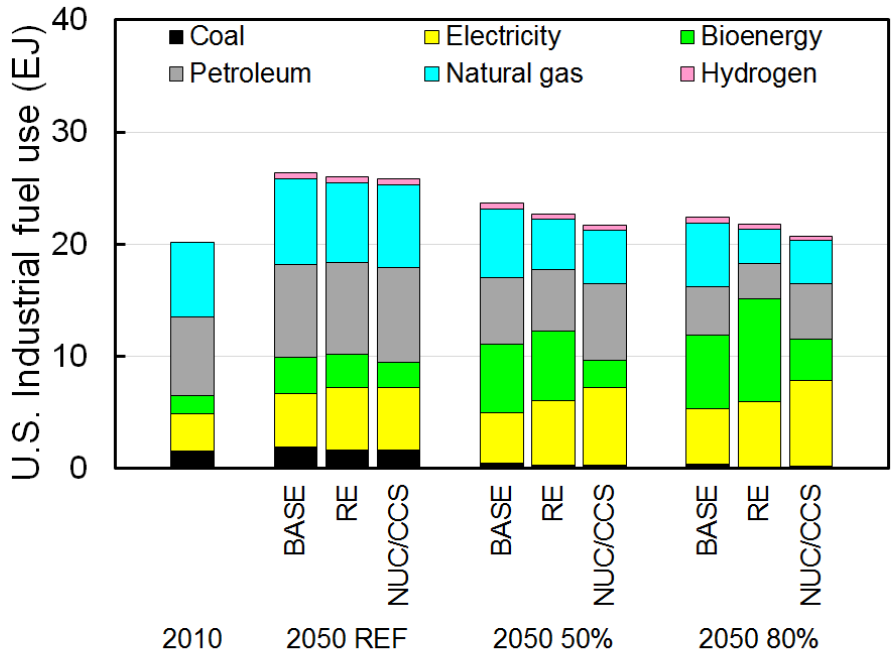
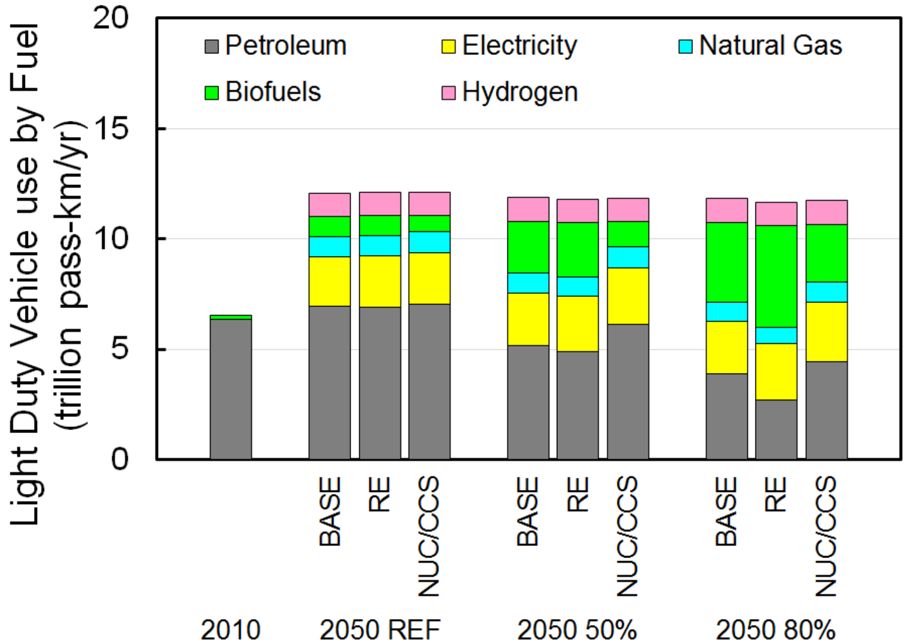
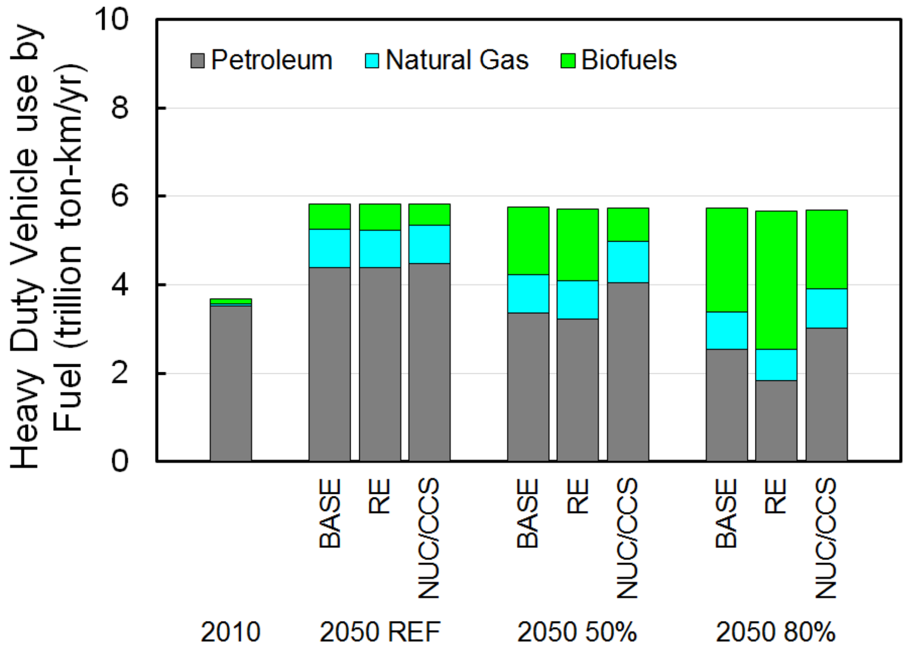


Figure S11 U.S. industrial final energy by fuel (EJ per year) in 2010 and for each of the technology and policy scenarios in 2050.



(a)



(b)

Figure S12 U.S. light duty vehicle (a) and heavy duty vehicle (b) service output by fuel in 2010 and for each of the technology and policy scenarios in 2050.

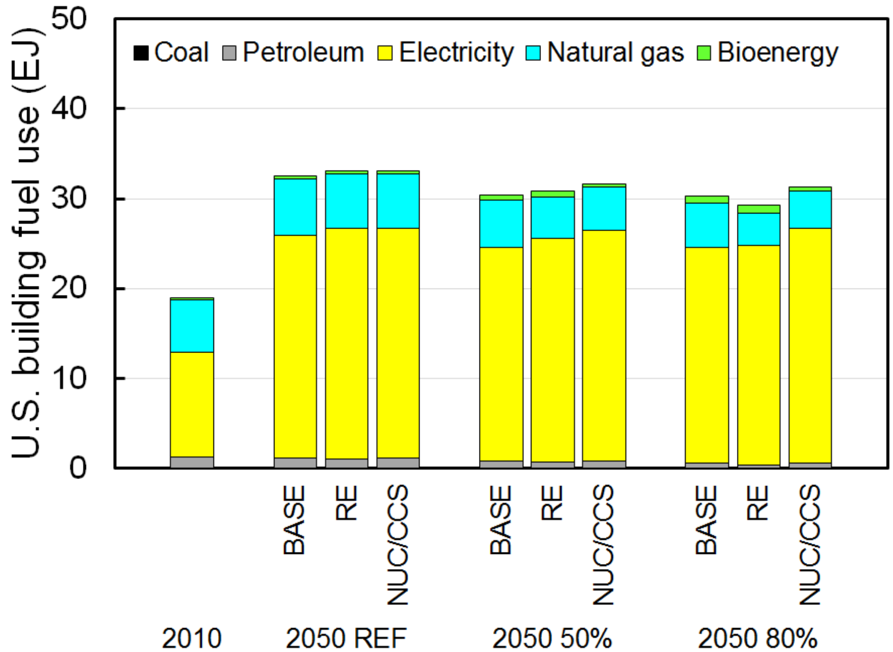


Figure S13 U.S. building final energy by fuel (EJ per year) in 2010 and for each of the technology and policy scenarios in 2050.

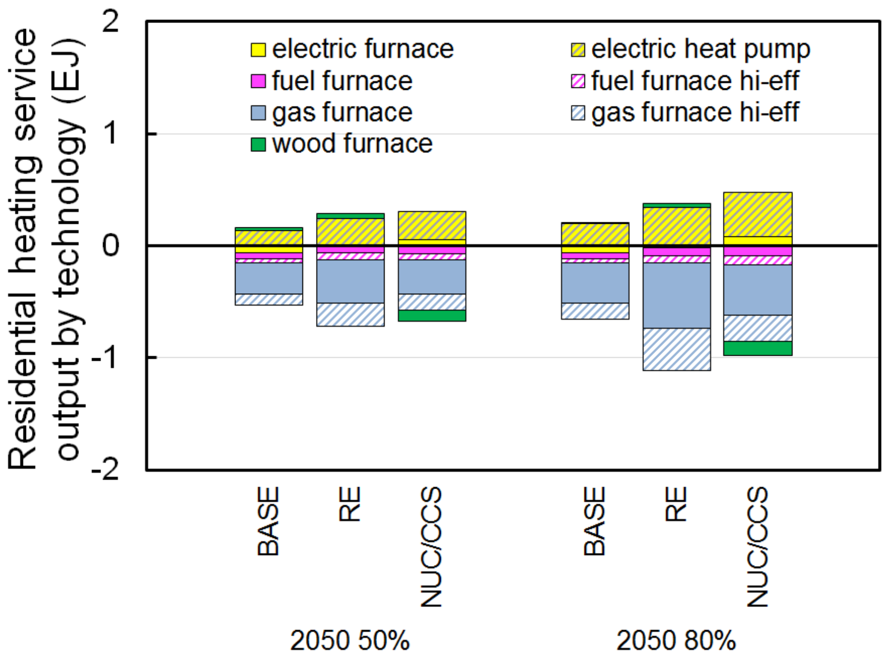


Figure S14 Changes of U.S. residential heating service output by technology under each low-carbon scenario relative to BASEREF in 2050 values for each scenario.

Section S8. State-level water results

While national, scenario-specific water withdrawal and consumption changes are shown in the manuscript, GCAM-USA also produces state-level results. In Fig S15, changes in withdrawals and consumption are shown relative to BASE80. General national trends are visible (e.g., NUC/CCS80 requires more withdrawals and has greater consumption, while RE80 has the opposite response). Differences in sign and magnitude are also apparent from state to state. Exploring these differences fully is beyond the scope of this study. However, we hypothesize that the differences are a result of state-specific conditions, including: initial technology stock, stock turnover, and access to fossil and renewable resources. These factors would influence the technologies and fuels used in BASE80, and thus would affect the technologies and fuels that are displaced under NUC/CCS80 and REF80.

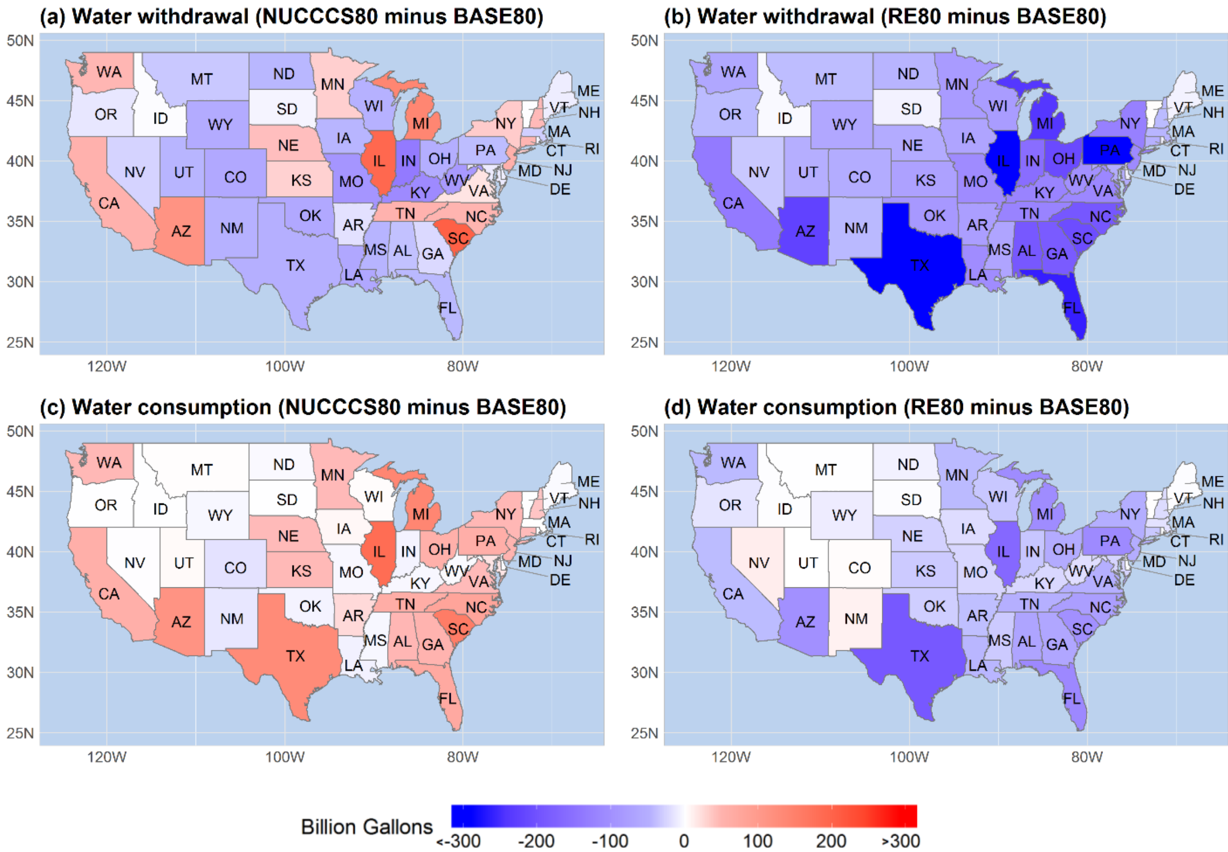


Figure S15 Water withdrawal and consumption of alternative pathways in 2050 for the continental U.S. states. Blue colors reflect lower water use compared with the BASE, red colors indicate higher water use compared with the BASE.

Section S9. Regional $PM_{2.5}$ health benefits for the 50% reduction low-carbon pathways

In the manuscript, regional health benefits are shown for the 80% reduction low-carbon pathways (Fig 6). In Fig S16, results of equivalent calculations for the 50% low-carbon pathways are shown. Patterns are similar between the two sets of graphics; however, the magnitudes of changes in the 80% results are greater.

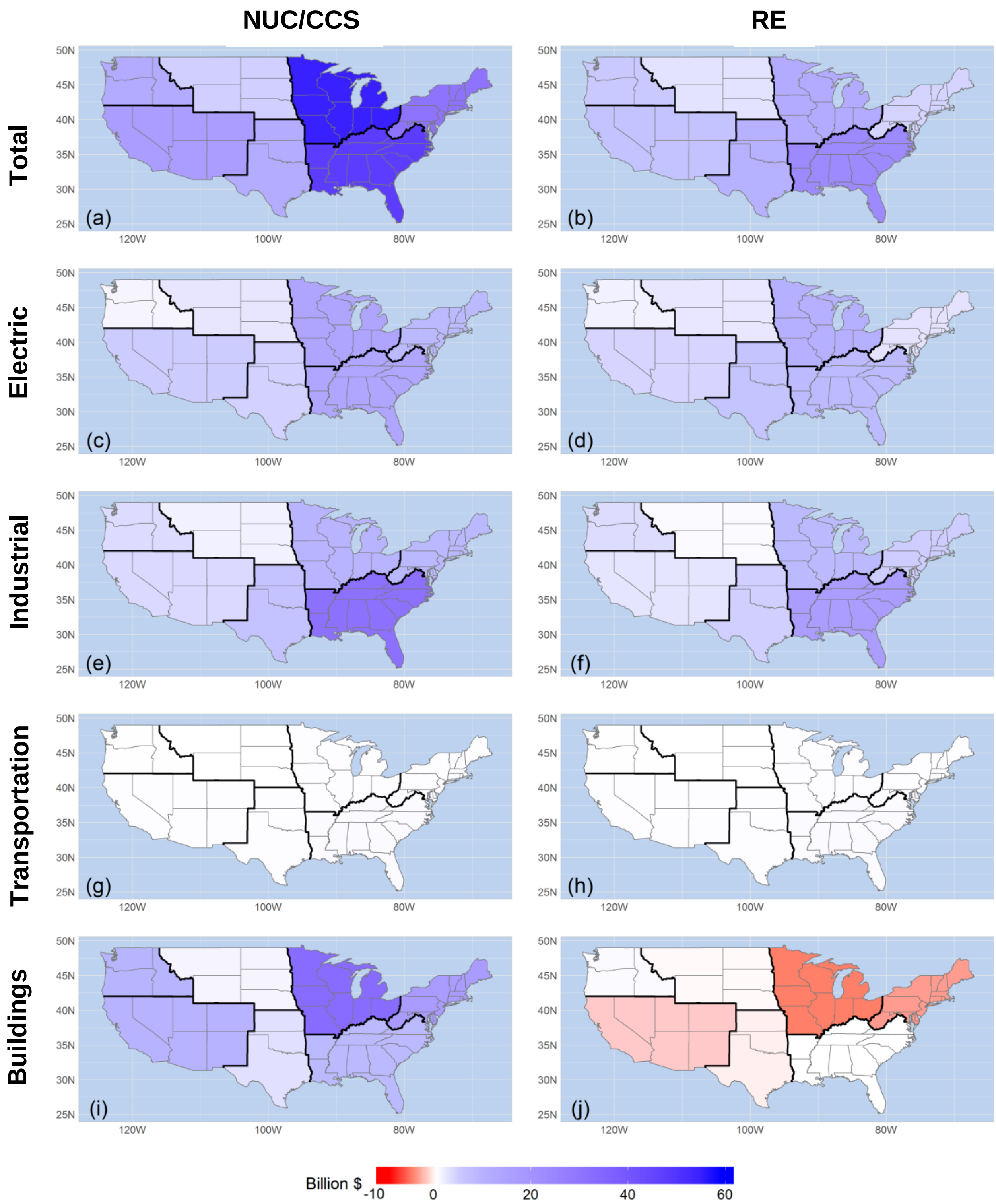


Figure S16 Regionally-aggregated estimates of annual $PM_{2.5}$ health benefits of NUC/CCS50 and RE50 relative to BASE50 in 2050. Blue colors represent additional health benefits; red colors represent damages (billion 2010$).

Section S10. Sensitivity analysis: Alternative cost assumptions for wind and solar

As discussed in Section 4 of this Supplemental Information, electric sector costs for GCAM-USA were developed from Muratori et al. [14]. These are the default values we use in our study. Cost projections into the future are based upon technology-specific improvement curves. However, these smooth curves do not capture some of the recent and substantial reductions in electric sector technology costs. We have made additional runs of GCAM-USA with updated costs for solar PV and wind power, with the goal of evaluating whether capturing these recent trends more fully would alter the conclusions of our study. A full update to electric sector costs would also involve re-evaluation of coal, nuclear, gas, and other technologies. Such an update is beyond the scope of this manuscript and Supplemental Information.

Updated wind capital cost assumptions are developed using the Department of Energy 2016 Wind Technologies Market Report, which was created by Lawrence Berkeley National Laboratory (LBNL) [19]. That report included historic wind costs, as well as projections into the future. The projections, which differed by wind class, included high, medium and low estimates. The resulting set of projections, starting in 2015, are shown in Fig S17. The GCAM-USA default trajectory is also shown on the figure in black.

To create an updated baseline trajectory, we averaged the medium projections across each wind class, then calculated the percent change relative to the 2010 starting point, the left-most end of the dashed line in Fig S17. These percent changes were then applied to the GCAM-USA 2010 starting value to develop a new baseline, BASE-updated, which is shown with a red line in Fig S17. A similar approach was applied to develop the RE-updated trajectory, which was based on an average of the lowest-cost projection for each wind class. RE-updated is indicated by a thick blue line. We used a straight average across wind classes as opposed to a weighted average. As our goal was to provide alternative sensitivity cases, we felt averaging across wind classes was sufficient.

Utility-scale solar PV costs were updated using a similar methodology. The source of the solar PV cost projections was the 2015 Utility-Scale Solar Report by LBNL [20]. See Fig S18 for Default and updated solar PV cost trajectories.

Percent reductions of the updated wind and solar PV costs relative to the default costs are summarized in Table S8. Solar PV capital cost reductions are much greater than those of wind, but both represent substantial reduction compared to GCAM-USA defaults. These differences suggest that a more formal update to GCAM-USA electric sector costs could be warranted to support future applications.

Results for 2050 that are generated using the updated BASE and RE costs are compared with those generated using Default costs in Figs S19 through S24.

Fig S19 shows electricity production by technology for the BASE80 and RE80 cases. For BASE80 (an 80% system-wide CO_2 reduction target), there are several noticeable differences in model response when using the updated solar PV and wind costs (Wind/PV). With these lower-cost renewables, the market shares for each increase substantially, and, together, wind and solar achieve approximately 50% of generation. This market share comes at the expense of coal and gas, both with and without CCS, and biomass with CCS. Furthermore, since electricity can be produced at lower cost, the total amount of electricity produced increases by nearly 20%. For the RE80 case, the Default and Wind/PV results in 2050 are much more similar to each other. These changes reduce electric sector water consumption, shown in Fig S21, since wind and solar have very little water requirements relative to most other technologies.

Refined liquid production, shown in Fig S20, does not change dramatically under the Wind/PV assumption. However, decreases in biomass-to-liquids does occur. Our hypothesis is that the lower wind and solar PV costs allow the model to target more of the necessary emission reductions to the electric sector.

Sectoral $PM_{2.5}$ emissions are shown in Fig S22. The greatest changes from Wind/PV occur in the electric sector, although there is also a decrease in industrial $PM_{2.5}$. Residential $PM_{2.5}$ emissions are largely unchanged. This is an important result since it reinforces a key conclusion from our manuscript: $PM_{2.5}$ emissions from residential wood combustion can offset a portion of the health benefits associated with the RE pathway. This result is further illustrated in Fig S23, where health disbenefits occur in the residential sector for both RE80 runs. Similarly, residential wood combustion plays an important role in offsetting the health co-benefits in RE scenarios (Fig S24).

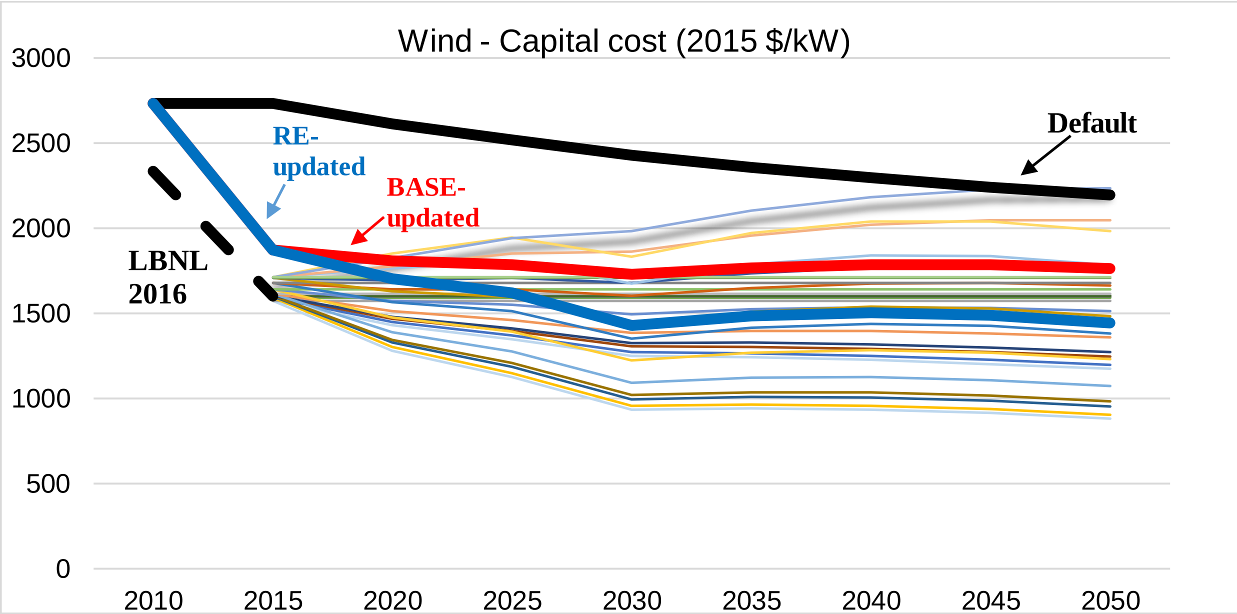


Figure S17. Default and updated cost assumptions for wind energy. The default GCAM-USA projection is shown by the thick black line. The updated BASE and RE values are shown by the thick red and blue lines, respectively. The thin lines represent the range of high, medium, and low projections across wind categories.

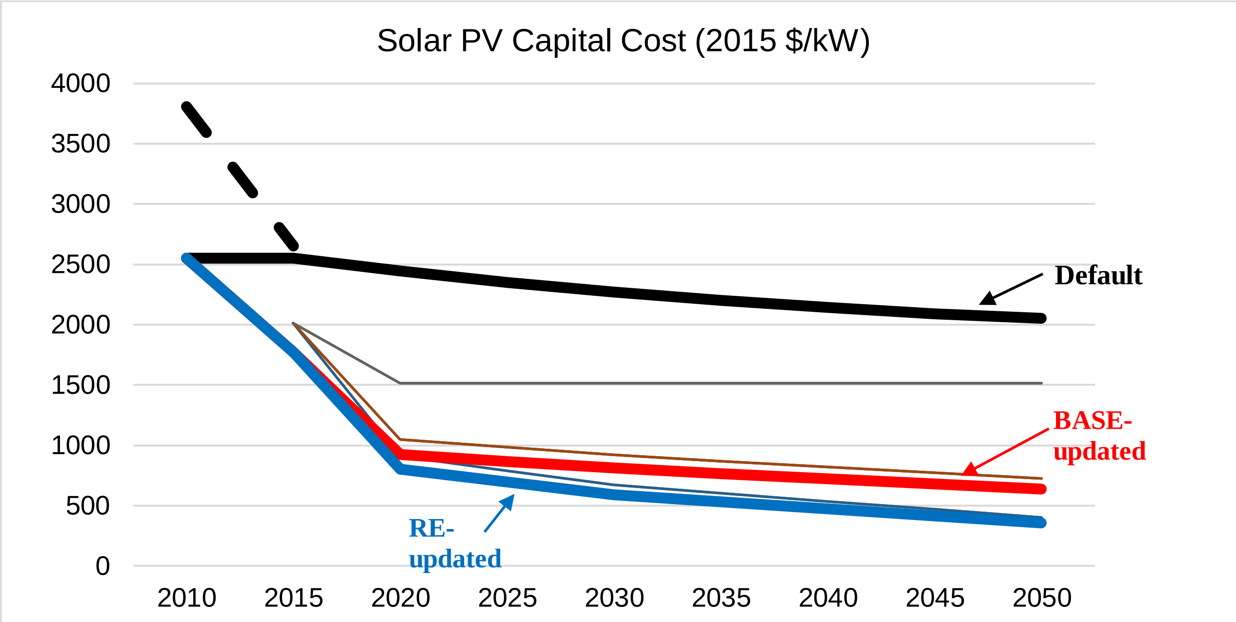


Figure S18. Default and updated cost assumptions for solar PV. The default GCAM-USA projection is shown by the thick black line. The updated BASE and RE values are shown by the thick red and blue lines, respectively. The thin lines represent the range of high, medium, and low projections from the 2015 Utility-Scale Solar Report by LBNL.

Table S8. Percent reduction from default GCAM-USA wind and solar PV capital costs with alternative values

Technologies[1]	BASE[2]			RE[4]		
	2015	2030	2050	2015	2030	2050
Solar PV	30%	54%	64%	30%	67%	80%
Wind	31%	8%	6%	31%	24%	23%

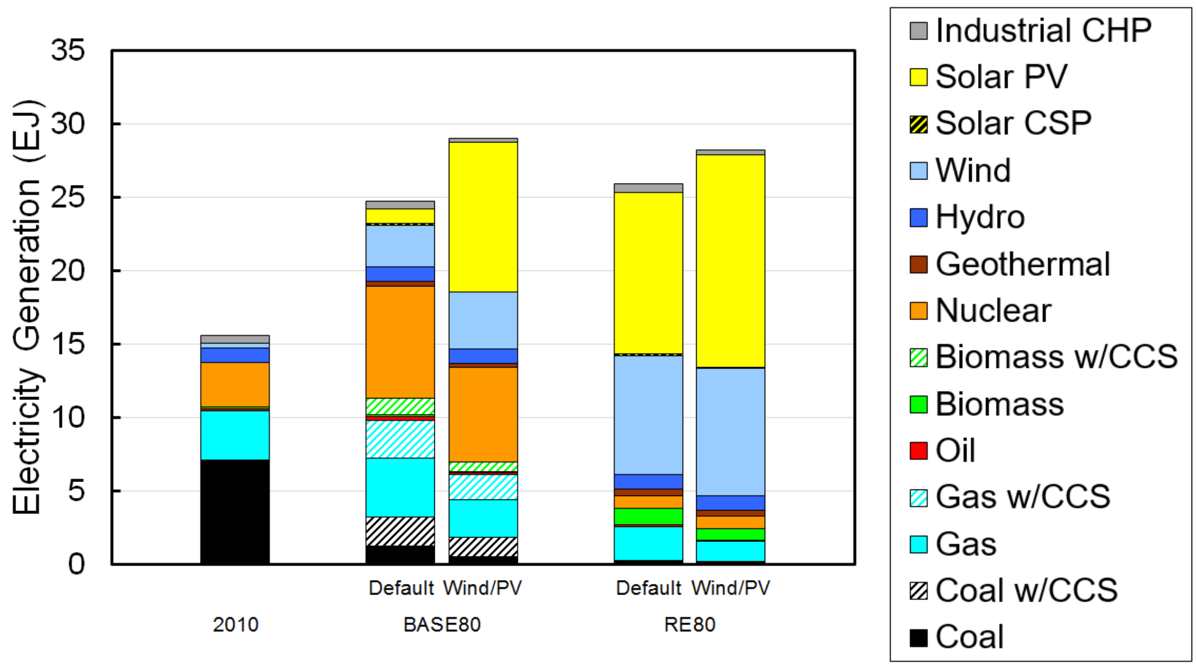


Figure S19. Comparison of U.S. electricity generation (EJ per year) by technology in 2010 and 2050. Generation in 2050 is shown for the BASE80 and REF80 scenarios, for both default GCAM-USA wind and solar PV capital costs (Default) as well as for revised costs (Wind/PV).

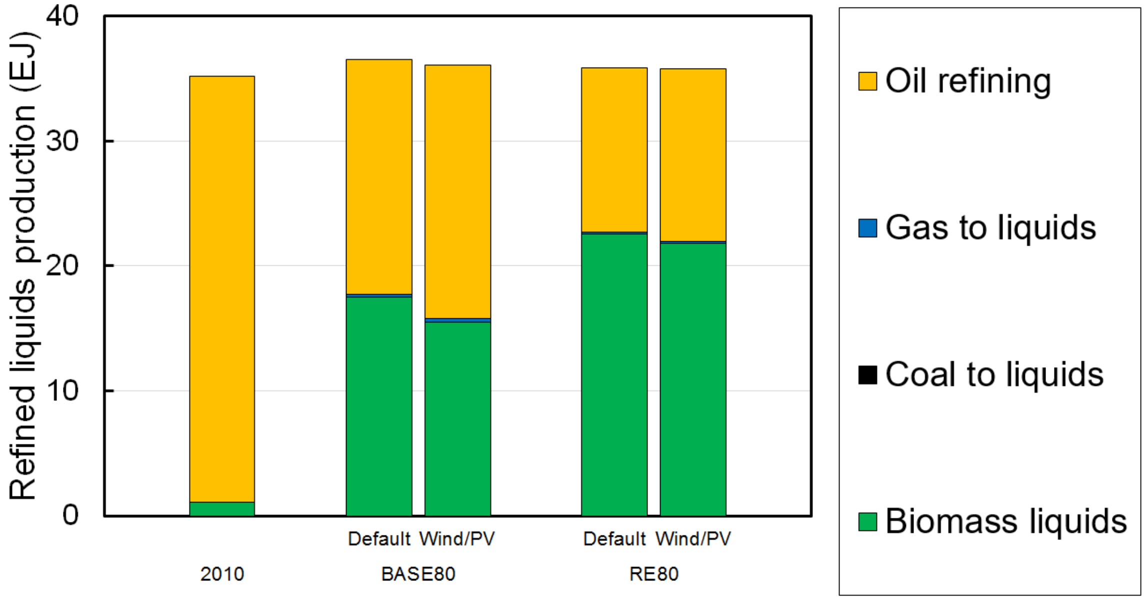


Figure S20. Comparison of U.S. liquid fuel production (EJ per year) by technology in 2010 and 2050. Production in 2050 is shown for the BASE80 and REF80 scenarios, for both default GCAM-USA wind and solar PV capital costs (Default) as well as for revised costs (Wind/PV).

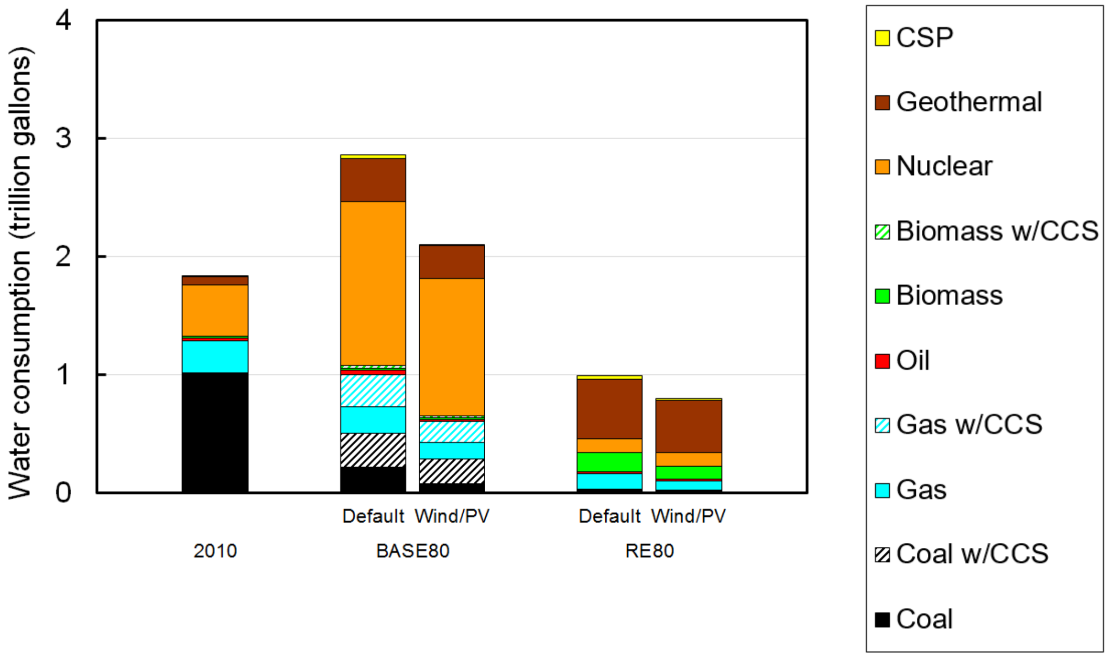


Figure S21. Comparison of U.S. water consumption (trillion gallons per year) for electricity production by technology in 2010 and 2050. Consumption in 2050 is shown for the BASE80 and REF80 scenarios, for both default GCAM-USA wind and solar PV capital costs (Default) as well as for revised costs (Wind/PV).

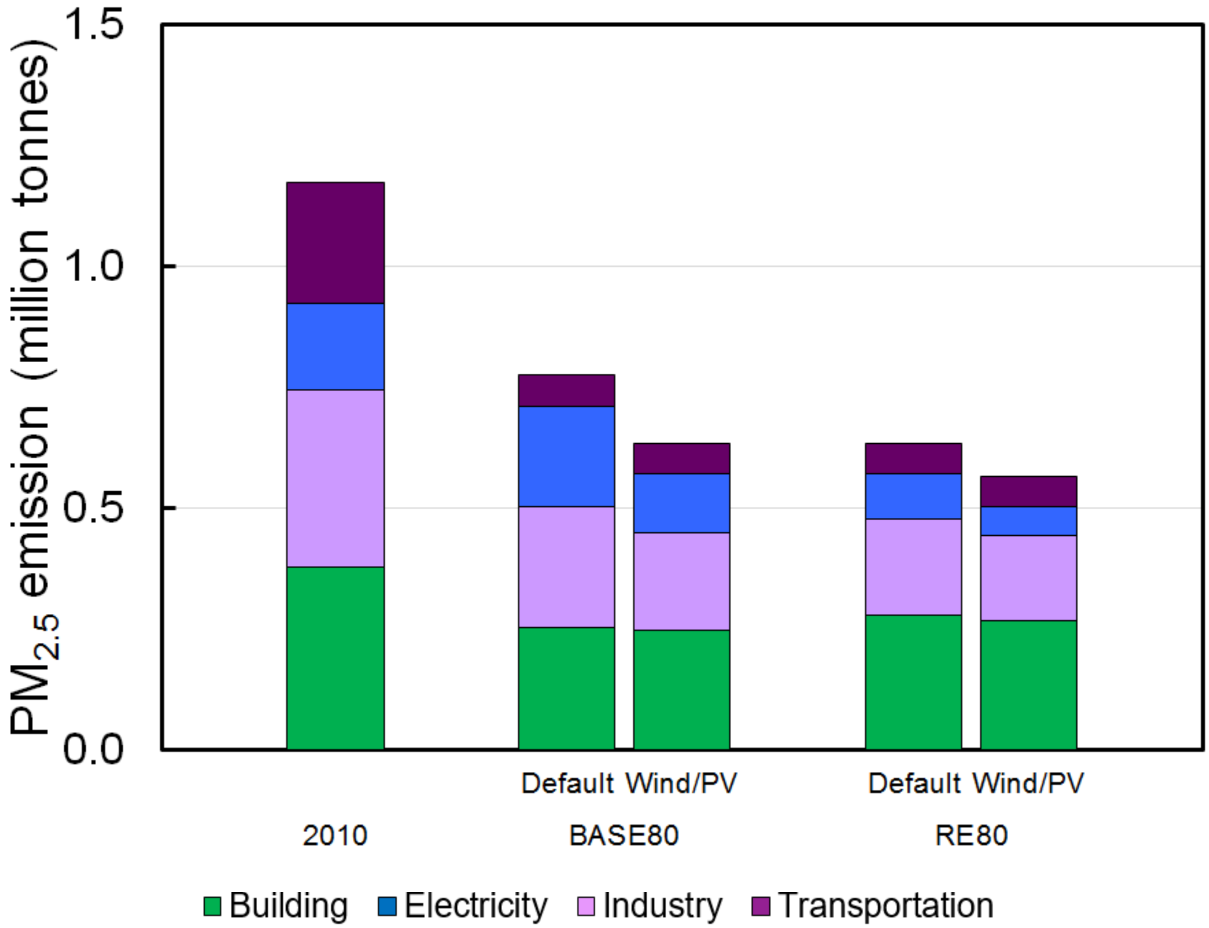


Figure S22. Comparison of $PM_{2.5}$ emissions by sector in 2010 and 2050. Emissions in 2050 are shown for the BASE80 and REF80 scenarios, for both default GCAM-USA wind and solar PV capital costs (Default) as well as for revised costs (Wind/PV).

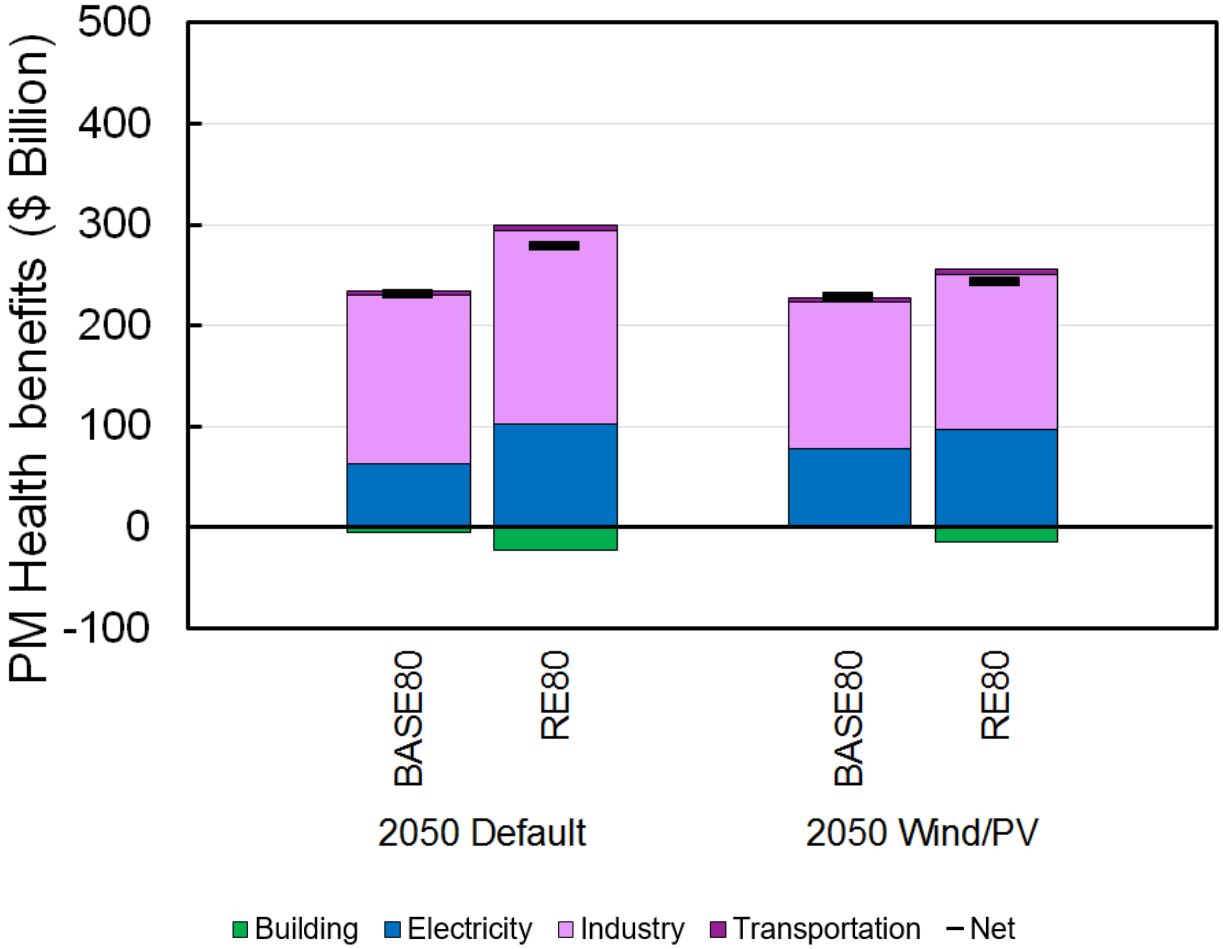


Figure S23. Comparison of monetized $PM_{2.5}$-related health benefits for BASE80 and RE80 in 2050, relative to BASEREF. Positive values indicate health benefits from pollutant emissions reductions; negative values indicate health damages; the Net value is the sum of positive and negative values for each scenario. Values are shown both when using default GCAM-USA wind and solar PV capital costs (Default) as well as for revised costs (Wind/PV).

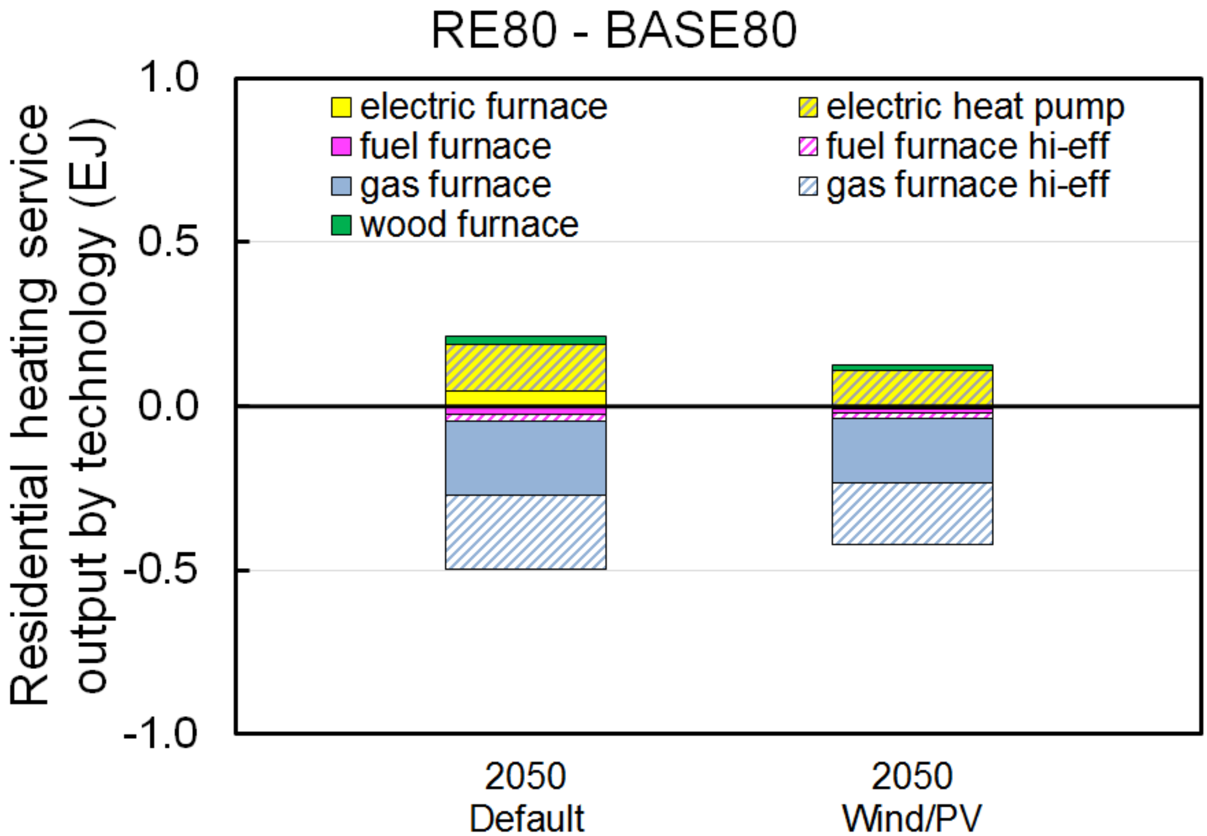


Figure S24. Change in fuel use for residential heating, RE80-BASE80, for both default GCAM-USA wind and solar PV capital costs (Default) as well as for revised costs (Wind/PV).

Section S11. References

[1] Fann, N., Fulcher, C. M., & Hubbel, B. J. (2009). The influence of location, source, and emission type in estimates of the human health benefits of reducing a ton of air pollution. Air Qual Atmos Health, 2, 169-176. doi:10.1007/s1186900900440

[2] Wigley, T.M.L., & Raper, S.C.B. (2002). Reasons for larger warming projections in the IPCC Third Assessment Report. Journal of Climate 15:2945-2952. dot:10.1175/1520-0442

[3] Thomson, A.M., Calvin, K.V., Smith, S.J. et al. (2011). RCP4.5: a pathway for stabilization of radiative forcing by 2100. Climatic Change. 109: 77. doi:10.1007/s105840110151-4

[4] Hartin, C.A., Patel, P., Schwarber, A., Link, R.P., & Bond-Lamberty, B.P. (2015). A simple object-oriented and open-source model for scientific and policy analyses of the global climate system – Hector v1.0. Geoscientific Model Development, 8, 939-955. doi: 10.5194/gmd-8-939-2015

[5] Fann, N., Baker, K. R., & Fulcher, C. M. (2012). Characterizing the PM2.5-related health benefits of emission reductions for 17 industrial, area and mobile emission sectors across the U.S. Environment International, 49, 141-151. doi: 10.1016/j.envint.2012.08.017

[6] Meldrum, J., Nettles-Anderson, S., Heath , G., & Macknick, J. (2013). Life cycle water use for electricity generation: a review and harmonization of literature estimates. Environmental Research Letters, 8. doi:10.1088/1748-9326/8/1/015031

[7] Shindell, D. T. (2015). The social cost of atmospheric release. Climatic Change, 130, 313-326. doi:10.1007/s10584015-13430

[8] Lee, C. J., Martin, R. V., Henze, D. K., Brauer, M., Cohen, A., & Donkelaar, A. (2015). Response of Global Particulate-Matter-Related Mortality to Changes in Local Precursor Emissions. Environmental Science & Technology, 49(7), 4335-4344. doi:10.1021/acs.est.5b00873

[9] Akhtar, F. H., Pinder, R.W., Loughlin, D.H., & Henze, D. K. (2013). GLIMPSE: A Rapid Decision Framework for Energy and Environmental Policy. Environmental Science and Technology, 47(21), 12011-12019. doi:10.1021/es402283j

[10] US EPA. (2013). Technical Support Document- Estimating the Benefit per Ton of Reducing PM2.5 Precursors from 17 Sectors. Retrieved from https://www.epa.gov/sites/production/files/2014-10/documents/sourceapportionmentbpttsd.pdf [accessed Jan 31, 2018]

[11] US EPA. (2016). Technology transfer network – economics and cost analysis support: Regulatory Impact Analyses (RIAs). Retrieved from EPA websites: https://www.epa.gov/economic-and-cost-analysis-air-pollution-regulations [accessed Jan 31, 2018]

[12] Viscusi, W. K. & Aldy, J. E. (2003). The value of a statistical life: A critical review of market estimates throughout the world. J. Risk and Uncertainty 27, 5-76.

[13] Calvin, K., Wise, M., Kyle, P., Patel, Clarke, L., & Edmonds, J. (2014). Trade-offs of different land and bioenergy policies on the path to achieving climate targets. Climaic Change (2014), 123:691. doi: 10.1007/s10584-013-0897-y

[14] Muratori, M., Ledna, C., McJeon, H., Kyle, P., Patel, P., Kim, S.H., Wise, M., Kheshgi, H.S., Clarke, L.E., & Edmonds, J. (2017). Cost of power or power of cost: A U.S. modeling perspective. Renewable and Sustainable Energy Reviews, 77(2017), 861-874.

[15] Macknick, J., Newmark, R., Heath, G., Hallett, K. C., Meldrum, J., and Nettles-Anderson, S. (2012). Operational water consumption and withdrawal factors for electricity generating technologies: a review of existing literature. Environmental Research Letter, 7(4)

[16] US EPA. (2015). Base case v.5.15 incremental documentation. Retrieved from https://www.epa.gov/airmarkets/base-case-v515-incremental-documentation [accessed Jan 31. 2018]

[17] Iyer, G., Ledna, C., Clarke, L.E., McJeon, H., Edmonds, J., & Wise, M. (2017). GCAM-USA Analysis of US Electric Power Sector Transitions, Pacific Northwest National Laboratory, Richland, Washington.

[18] Blanford, G.J., Kriegler, E. and Tavoni, M. (2014). Harmonization vs. fragmentation: overview of climate policy scenarios in EMF27. Climatic Change, 123: 383. doi:10.1007/s10584-013-0951-9

[19] Wiser, Ryan., & Bolinger, Mark. (2017). 2016 Wind Technologies Market Report. U.S. Department of Energy. Prepared by the Lawrence Berkeley National Laboratory (LBNL). DOE/GO-102917-5033. August 2017.

[20] Bolinger, Mark., & Seel, Joachim. (2016). Utility-Scale Solar 2015 – An empirical analysis of project cost, performance, and pricing trends in the United States. U.S. Department of Energy SunShot. Prepared by the Lawrence Berkeley National Laboratory (LBNL). LBNL-1006037. August 2016.