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Health and air pollutant emission impacts of net zero CO2 by 2050 scenarios from the energy modeling forum 37 study

Daniel H. Loughlin [a,*], Alexander R. Barron [b], Charavee Basnet Chettri [b], Abigail O'Meara [b], Luis Sarmiento [c,j,k], Danni Dong [d], David L. McCollum [e,f], Sharon Showalter [g], Robert H. Beach [h], John Bistline [i], G. Joyce Kim [a], Christopher G. Nolte [a], Johannes Emmerling [c], P. Ozge Kaplan [a]

[a] U.S. Environmental Protection Agency, 109 T.W. Alexander Dr., Research Triangle Park, NC 27711, United States
[b] Smith College, 10 Elm Street, Northampton, MA 01063, United States
[c] RFF-CMCC European Institute on Economics and the Environment, Via Bergognone 34, 20144 Milan, Italy
[d] Emory University, 1256 Briar Cliff Road NE, Atlanta, GA 30322, United States
[e] Oak Ridge National Laboratory, Oak Ridge, TN 37830, United States
[f] University of Tennessee, Knoxville, TN 37996, United States
[g] OnLocation, 501 Church Street, Vienna, VA 22180, United States
[h] RTI International, 3040 East Cornwallis Road, Durham, NC 27709, United States
[i] EPRI, 3420 Hillview Avenue, Palo Alto, CA 94304, United States
[j] Centro Euro-Mediterraneosui Cambiamenti Climatici, Via Bergognone 34, 20144 Milan, Italy
[k] Banco de México, Paseo de Montejo 475, 97000, Merida, Mexico

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ABSTRACT

Carbon dioxide and non-greenhouse gas air pollutants are emitted from many of the same sources. Decarbonization actions thus typically yield air pollutant emission reductions, resulting in significant air quality benefits. Although several studies have highlighted this connection, including in the context of net zero carbon emission targets, substantial uncertainty remains regarding how alternative technological pathways to this goal will affect the spatial distribution and magnitude of air pollutants. Comprehensive multi-model and multi-scenario analyzes are needed to explore the relative impacts of alternative pathways. Our study begins to address this gap by leveraging the results from the recent Energy Modeling Forum 37 inter-model comparison exercise on U.S. decarbonization pathways. Comparing the results of the six teams who submitted air pollutant emissions suggests that strategies that target net zero U.S. carbon emissions would yield significant reductions in many air pollutants, and that this finding is generally robust across pathways. However, some energy sources, such as biomass and fossil fuels with carbon capture, will emit air pollutants and can potentially influence the magnitude, spatial distribution, and even sign of localized air pollutant emission changes. In the second part of this analysis, a simplified air quality and health impacts screening model is used to evaluate the air quality impacts in 2035 of sectoral emission changes from the three models that provided sectoral detail. Relative to a reference scenario, a net zero pathway is estimated to reduce fine particulate matter concentrations across the contiguous U.S., with health benefits from reduced mortality ranging from $65 billion to $250 billion in 2035 alone (2023$s). These benefits would be expected to grow over time as the net zero trajectory becomes more stringent. Both the magnitude of potential benefits and the substantial variation of the projections across models underscore the need for an EMF-like inter-model comparison exercise focused on air quality.

1. Introduction

Decarbonization pathways have additional impacts beyond reducing greenhouse gas emissions, including effects on trade, employment, energy security, and grid reliability. One of the prominent anticipated impacts of decarbonization is on environmental quality, particularly air quality. In this study, we investigate the impact of decarbonization on an array of non-greenhouse gas (GHG) air pollutant emissions, as well as

* Corresponding author.
E-mail address: loughlin.dan@epa.gov (D.H. Loughlin).

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the associated monetary benefit of reduced premature mortality.

In the United States, 85 million people live in areas that do not meet one or more National Ambient Air Quality Standards[1] [1] (see Figure S1 for a map). Since many of the same sources emit both air pollutants and carbon dioxide (CO_2), the conventional wisdom is that shifting to technologies and fuels that emit less or no CO_2 will significantly reduce other pollutants and improve air quality. A handful of energy system and integrated assessment modeling studies over the past two decades have corroborated this outcome for the U.S. and other countries [2–6], although some indicate the potential for regional disbenefits [5,7–11]. Many of these studies rely on air pollutant projections from a single model (e.g., typically an energy systems or integrated assessment model) and often evaluate decarbonization scenarios that do not reach net zero CO_2 emissions.

Considerable uncertainty exists regarding the technological pathway that will be employed to decarbonize, especially in the context of reaching net zero emissions across the economy. Uncertainties include the relative roles of renewables, hydrogen, advanced nuclear power, bioenergy, and carbon dioxide removal (CDR) technologies. Many of these technologies have not yet been deployed at a commercial scale, and their roles will depend upon future technology costs, technical performance and readiness levels, markets, and policy, all of which are uncertain. Therefore, projections must rely on expert judgment about future costs and performance, as well as assumptions about the future planning environment. Another source of uncertainty is how accurately the model formulations and parameterizations simulate consumer and corporate behavior for complex decisions such as adopting more efficient and emerging technologies, conserving energy, and switching to electricity and fuels with lower carbon intensity. Furthermore, there are unknowns about the specific policy designs that will be employed to reach economy-wide net zero targets, which could lead to very different technology pathways and air quality impacts.

In practice, various model formulations are used to explore decarbonization scenarios, including least-cost optimization, agent-based, system dynamics, and logit-based models. Some models are “myopic”, stepping through time optimizing decisions based upon conditions in that period, while others have “perfect foresight” and thus can consider exogenously assumed future conditions and make optimal decisions across the entire time horizon. Other differences include spatial scale and resolution, modeling time horizon and temporal resolution, sectoral coverage, and data sources. As a result of these differences, even the baseline projections from which policy impacts are evaluated can be quite different [12]. However, this heterogeneity provides opportunity. Exploring commonalities and differences in results across models can yield insights about the robustness of specific outcomes and highlight possible outcomes that some models may have missed.

Using such an approach, we conduct an analysis of the air pollution impacts of decarbonization via an inter-model comparison exercise involving a suite of models and scenarios. To our knowledge, the literature currently lacks multi-model comparisons of net zero decarbonization scenarios that evaluate U.S. air pollution emissions or U.S. air quality as an endpoint. In this manuscript, results from the recent Energy Modeling Forum (EMF) 37 exercise [13] are analyzed to begin to fill this gap.

EMF is a series of comparative modeling exercises that began in 1976. These exercises tackle emerging and important topics, such as the potential energy impacts of shale gas and the degree to which the energy system can be electrified. In each EMF exercise, many sectoral, energy system, economy-wide, and integrated assessment modeling teams participate. The 37th EMF exercise, or EMF 37, addressed the topic of deep decarbonization in North America. Modeling teams targeted net zero CO_2 emissions in the U.S. by 2050 and explored various technological pathways for achieving that goal. The study was enhanced by sectoral teams that worked to improve the treatment of specific sectors, including the electric sector, industry, transportation, buildings, and carbon management.

EMF 37 thus provides a rich set of U.S. net zero scenarios that we can use to examine how projected air pollutant emission co-reductions vary across models and decarbonization pathways. The EMF 37 results also provide a means for identifying factors that could influence air quality benefits. While similar analyses have been conducted from a global perspective [14], a key aspect of our study is the translation of air pollutant emission changes from the net zero scenario into monetized health benefits in the U.S. using the reduced-form air quality model embedded within the CO-Benefits Risk Assessment tool [15]. COBRA outputs provide insights into the magnitude of such benefits and geographical differences in these benefits. The results are discussed in the context of some important differences among models, leading to conclusions about how those differences could be driving discrepancies in air pollutant emission projections. A brief statistical analysis is conducted to develop insights regarding some of the factors that drive differences across models and scenarios. Inherent challenges of using energy and integrated assessment models to project air pollutants are highlighted, and recommendations are made about how these challenges could be addressed.

Our research team utilized the data that the EMF modeling teams submitted to the EMF database. Since characterizing air pollutant emissions was not a primary focus of the larger EMF exercise, many EMF modeling teams did not report air pollutant emissions. Those that did used the data reporting template, which did not include sub-national or sectoral detail. We requested sub-national and sectoral data that several of the modeling teams were able to provide.

2. Methods

2.1. Scenarios

For a detailed description of the modeled scenarios in the EMF 37 exercise, see Browning et al. [13]. In this study, we include 41 scenarios for which at least one model reported air pollutant emissions (see Table S1 for a full listing of scenarios).

All EMF modeling teams simulated a Reference scenario, designed to capture U.S. climate policy as of early 2022, and a Net Zero CO_2 emissions scenario, which overlays a linearly-declining, economy-wide CO_2 emissions cap. Potential land sinks for CO_2(-800 Mt-CO_2/yr in 2050) were allowed to contribute to the net zero CO_2 cap through 2050. The Net Zero scenario also includes endogenous Carbon Capture and Sequestration (CCS) and Carbon Dioxide Removal (CDR) technologies. Unlike wind and solar, many CCS and CDR technologies emit air pollutants during their operation. Furthermore, CDR technologies such as biomass with carbon capture and storage (BECCS) and direct air capture (DAC) may allow some residual CO_2 and co-emitted air pollutants to be emitted from the energy system while still reaching the 2050 net zero target.

Note that neither the Reference nor the Net Zero scenario includes potential impacts related to the Inflation Reduction Act of 2022 and the Bipartisan Infrastructure Law of 2021 [16]. Several teams simulated scenarios that represent some of the major provisions in these legislative acts, and those results are included in our study (the IRA and Net Zero/IRA scenarios). We also include scenarios that were developed to explore assumptions regarding specific sectors, including carbon management, buildings, industry, and transportation. For the net zero scenarios, we include only scenarios with a target in 2050, excluding

[1] The National Ambient Air Quality Standards (NAAQS) are pollutant concentration limits set by the U.S. Environmental Protection Agency to regulate air pollutants that affect public health and the environment. These standards specifically target major pollutants including ozone (O3), particulate matter (PM) of diameter below 10 micrometers (PM_{10}) and 2.5 micrometers ($PM_{2.5}$), carbon monoxide (CO), nitrogen oxides (NOx), sulfur dioxide (SO2), and lead (Pb).

EMF37 scenarios with net zero targets for 2060 and 2080.

CO_2 trajectories for the Reference, IRA, and Net Zero scenarios are provided in the SI (Figure S2) for the models that participated in our study. Under Reference, most of the models suggest early declines, followed by a leveling off of CO2 emissions. CO2 trajectories for the IRA scenario were evaluated by fewer models and are more varied. The Net Zero trajectories all reach the same end point of zero by 2050, however, the paths to achieve that target differ by model.

2.2. Models and air pollutant reporting

While sixteen models participated in the U.S.-focused EMF 37 exercise, only five submitted air pollutant emission outputs to the results database and chose to have their results included in this study (Table 1). Some of the other models that are not represented do not output air pollutant emissions. In addition, while not a participant in EMF 37, one modeling team (WITCH) simulated the Reference and Net Zero scenarios and provided their results. Table S2 indicates which scenarios were evaluated by each model.

Of these models, EPA-TIMES, FECM-NEMS, and MARKAL-NETL are energy system models, focusing on energy supply and demand across the economy. Thus, their coverage includes energy resource extraction and import, the electric sector, refineries, and energy consumption within manufacturing and other industries, commercial and residential buildings, and on-road and non-road transportation. EPS also has a focus on energy supply and demand and includes a representation of GHG mitigation options in the agricultural sector. GCAM and WITCH are integrated assessment models that link energy supply and demand with representations of agriculture and land use.

In Table 2, coverage of common air pollutants by model is summarized, including for nitrogen oxides (NOx), sulfur dioxide (SO_2), volatile organic compounds (VOCs), carbon monoxide (CO), particulate matter of sizes less than 10 μm (PM_{10}) and less than 2.5 μm ($PM_{2.5}$) in diameter, black and organic carbon (BC+OC), and ammonia (NH_3), and whether those pollutants are reported nationally (N), regionally (R), or by energy sector (S). The $PM_{2.5}$ emission projections reflect "direct $PM_{2.5}$", implying that these particles are emitted directly via processes such as combustion, friction, and weathering. However, note that ambient $PM_{2.5}$ is comprised of both direct $PM_{2.5}$ and secondary $PM_{2.5}$, which is formed through atmospheric reactions of precursor pollutant species such as NOx, SO_2, VOCs, and NH_3. Energy and integrated assessment models that project emissions generally do not estimate ambient $PM_{2.5}$ concentrations. In this paper, we estimate these concentrations using a reduced-form air quality model that approximates pollutant chemistry and transport.

Table 1
Modeling teams submitting air pollutant emissions projections. See Browning et al. [13] for additional information about each model.

Model	Institution	Type of model	Spatial coverage and resolution	Reference
EPA-TIMES	U.S. Environmental Protection Agency *Office of Research and Development*	Least-cost optimization	U.S. at Census Division resolution	[17]
EPS	Energy Innovation	System dynamics model with logit-based choice	U.S. at national resolution	[18]
FECM-NEMS*	OnLocation	Least-cost optimization	U.S. at Census Division resolution	[19]
GCAM	Pacific Northwest National Laboratory	Dynamic recursive with logit-based choice	Global at U. S. national resolution	[20]
MARKAL-NETL	U.S. Department of Energy *National Energy Technology Laboratory*	Least-cost optimization	U.S. at Census Division resolution	[21]
WITCH	CMCC-RFF: European Institute on Economics and the Environment	Welfare maximization	Global at U. S. national resolution	[22]

Note: * FECM-NEMS model used in this analysis is a modified version of the U.S. Energy Information Administration's National Energy Modeling System (EIA NEMS), developed by OnLocation, with funding by the U.S. Department of Energy Office of Fossil Energy and Carbon Management.

Note that while FECM-NEMS represents the entire energy system, air pollutant emissions are produced only for the electric sector. All six models provided NOx and SO_2 emissions (Table 2). The largest anthropogenic source of NH_3 is agriculture, and thus, NH_3 was reported only by the models with detailed agricultural representations, GCAM and WITCH.

Direct $PM_{2.5}$ emissions were reported by EPS and MARKAL-NETL. GCAM and WITCH submitted estimates of black carbon (BC) and organic carbon (OC) emissions, which represent a subset of direct $PM_{2.5}$. The relationship between these components and direct $PM_{2.5}$ is complicated [23]. For example, the contribution from OC differs by fuel, with biomass-derived fuels having a higher coefficient, and solid fuels also differing as a function of their ash content [24]. This study assumes that total direct $PM_{2.5}$ emissions can be estimated using the formula:

$$\text{direct}\,PM_{2.5} = 1.66\,BC + 2.10\,OC \quad (1)$$

This equation is developed using regression from anthropogenic national BC, OC, and direct $PM_{2.5}$ emissions data for 2022 that are reported by the U.S. Environmental Protection Agency [25]. Emissions associated with energy supply, industry, buildings, transportation, and agriculture, forestry, and land use (AFOLU) are included in the calculation, while road dust is excluded.

3. Analysis

Our analysis is comprised of four parts. First (Section 3.1), the national emission totals for six pollutants are compared across the models and scenarios, as well as against recent estimates for 2022 [26]. Next (Section 3.2), economy-wide fuel use and the fuel use in electricity production are examined to characterize similarities and differences among the models. An econometric approach is then applied (Section 3.3) to develop correlations between fuel use and emissions, as well as to understand more fully the linkages between fuel substitution and emission changes. Finally (Section 3.4), sectoral air pollutant emission changes from three models are examined using COBRA to estimate air quality changes and associated health benefits in 2035 for the Net Zero scenario relative to the Reference scenario.

3.1. National-scale emission trajectories

At the national level, air pollutant projections by model, scenario, and pollutant differ significantly across the set of models and from U.S. EPA estimates [25] (Fig. 1). Some of these differences are attributable to differences in data sources, assumptions, calibration processes, modeled time horizon, and sectoral definitions and coverage. For each model, Reference, Net Zero, and IRA scenario results are indicated with solid, dashed, and dotted lines, respectively. Lighter solid lines represent alternative net zero scenarios designed by the various EMF sector-specific study groups. Circles reflect EPA emission estimates for several combinations of sectors. Note that not all modeling teams ran all scenarios (Table S2) or produced results for all pollutants (Table 2). Trends are discussed over the short (2020–2025), medium (2025–2035), and long term (2035–2050). Results are also summarized in Table S4. Plots showing emission trends relative to the year 2020, as well as

Table 2
Air pollutant emission coverage in the EMF 37 database. Shading represents that the model results for that pollutant species were submitted to the database. The "Detail" column indicates the spatial resolution associated with the submission. National scale results (N) were submitted by all models, while sectoral (S) and sub-national regional (R) results are available for some models.

		Pollutant coverage							
Model	**Detail**	**NOx**	**VOC**	**SO_2**	**CO**	**direct $PM_{2.5}$**	**PM_{10}**	**BC+OC**	**NH_3**
EPA-TIMES	N	■		■			■		
EPS	N, S	■	■	■	■	■	■	■	
FECM-NEMS*	N, S, R	■		■					
GCAM	N, S	■	■	■	■			■	■
MARKAL-NETL	N	■	■	■	■	■	■	■	
WITCH	N, S	■	■	■	■			■	■

Note: * FECM-NEMS provided results for the electric sector only

historical data from 2002 to 2022, are also provided in the SI (Figures S3 and S4).

An initial observation is how strikingly different the emissions are in magnitude across the set of pollutants and models, even for historical years (Fig. 1). However, comparison of each model's emission projections with various aggregations of EPA 2022 estimates provides insights about sectoral coverage that explain many of these differences. For example, EPA-TIMES and MARKAL-NETL are energy system models, and their projections line up best with EPA estimates from energy system sources (blue circles). In contrast, GCAM and WITCH also incorporate agriculture, and the closer proximity of the $PM_{2.5}$ and NH_3 projections to the pink circle is indicative of the impact of this expanded coverage. In some instances, model projections exceed the inventory significantly, such as for NOx and SO_2. In the U.S., the period between 2010 and 2024 saw large transformations across the energy system, including a transition in the electric sector from coal to natural gas and renewables, as well as the implementation of emission standards on many stationary sources and on onroad vehicles and fuels. The degree to which this transformation is captured in the models may also be an underlying source of differences across models and with EPA estimates. This topic is explored further in Section 3.2.

Despite the differences from one model to another, several trends are evident. For the Reference scenario, most pollutant-model combinations result in emission reductions across the entire 30-year time horizon. This trend reflects technology changes that reduce emissions intensity (e.g., additional replacement of coal-fired power plants with gas and renewables) or improve energy efficiency, as well as regulations that lower the emissions of future technologies. Many of these reductions reach 40 % to 80 % relative to 2020 levels by 2050. In contrast, EPS suggests the potential for relatively small short-term increases in NOx, SO_2, VOC, and CO, as well as the potential for small long-term increases in VOCs and $PM_{2.5}$. GCAM and WITCH suggest increases in NH_3 in the Reference scenario over time, driven by increasing demand for agricultural products and the associated use of fertilizer.

In general, the IRA scenarios lead to emission reductions relative to Reference. However, emission reductions associated with Net Zero relative to Reference are considerably greater across most pollutant-model combinations, generally supporting the notion that decarbonization results in additional reductions of co-emitted air pollutants (Table S4). For instance, for the Reference scenario, economy-wide NOx emissions in 2050 are reduced by 11 to 68 % relative to 2020 levels. Over the set of net zero scenarios, these reductions range from 37 to 80 %. Similar reduction trends are witnessed for $PM_{2.5}$(-5 to 51 % vs. 10 to 49 %), VOC (-7 to 40 % vs. 3 to 62 %), SO_2(-3 to 75 % vs. 38 to 87 %), and CO (23 to 52 % vs. 34 to 62 %). Notable exceptions include the short-to-mid-term increases in direct $PM_{2.5}$ emissions from GCAM and MARKAL-NETL, with the GCAM estimate growing by as much as 70 % in one scenario, and the short-to-mid-term NH_3 projection from GCAM. The GCAM modeling team indicated that GCAM's response reflects mitigation target-induced changes in land use, including the conversion of unmanaged land to managed land for bioenergy production. This result, unique to GCAM, highlights a potentially interesting dynamic that is not captured in models that do not simulate agriculture and land use change.

The air pollutant emission trends described here are generally robust across the EMF 37 scenarios and models. However, EPS tends to report muted responses relative to the other models. Also, WITCH tends to indicate greater emission reductions over time. The NH_3 trajectories are notable as well. NH_3 tends to go up over the long-term, and the Net Zero scenario results in additional growth over most of the timeline.

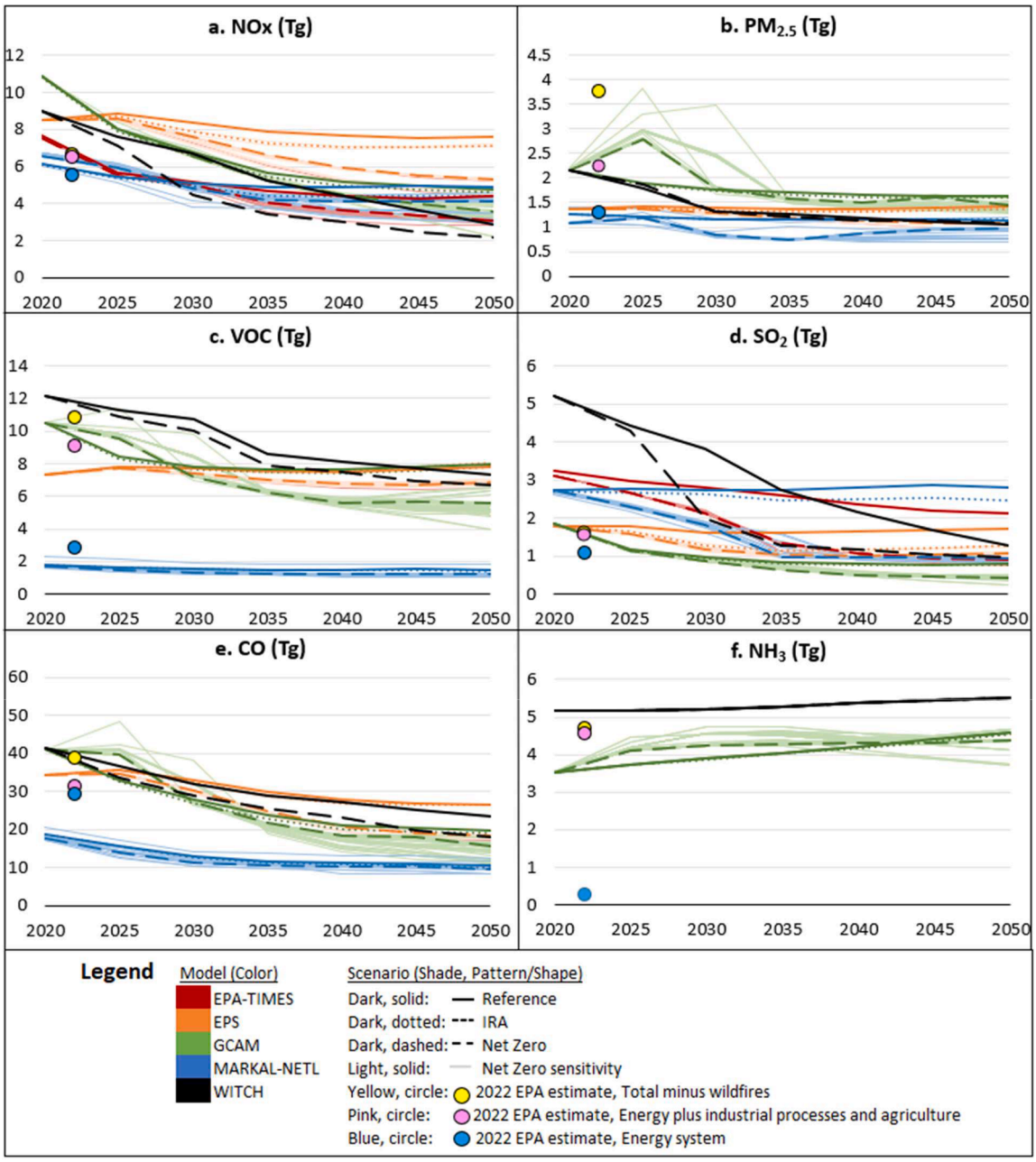

Fig. 1. *National-scale air pollutant emission projections by model and scenario.* Results indicate significant heterogeneity across models. For comparison, the yellow, pink, and blue circles reflect groupings of emissions from U.S. EPA air pollutant emission trends data [25]. $PM_{2.5}$ emissions in this figure represent direct $PM_{2.5}$ only since the energy and integrated assessment models included in this study do not output secondary $PM_{2.5}$, which is formed in atmospheric reactions.

3.2. Assessment of underlying drivers of emission differences

Next, the underlying scenario data describing sectoral fuel use over time is examined to investigate the similarities and differences in technology pathways across scenarios. Results from all EMF models are included, although results for the specific models included in our study are highlighted. We examine fuels that are likely to impact specific sets of pollutants. For example, coal and oil (e.g., diesel and fuel oil) combustion would be expected to emit SO_2, the combustion of any fossil fuel or biomass would emit NOx, and biomass use in buildings and for power generation has relatively high direct $PM_{2.5}$ intensity compared to other fuels. The emission rates for various pollutants also depend upon the degree to which emissions controls are applied. EMF modeling teams did not submit information about the emission rates or emission control assumptions to the EMF database. We focus on 2035 and 2050 since these reflect middle-to-long-term trends. Results for 2025 and 2030 are provided in the SI (see Figure S5 and S6).

In general, the models show considerable variability with respect to changes in the use of carbon-based fuels (Fig. 2). Net Zero scenarios generally feature a decrease in fossil fuel use by 2035 (relative to 2020). Still, many models project fossil fuel use to be within the range of variability for the IRA scenario. There is very little agreement on the impact of decarbonization on bioenergy use through 2035, with differences even in the sign of the impact of the net zero target. For example, MARKAL-NETL indicates increases in both biomass liquids and biomass solids, while EPA-TIMES reports a decrease in biomass solids. GCAM suggests a transition from using biomass liquids to biomass solids through 2035 (Figures S3 and 2), reflecting a switch from biofuels to biomass combustion. Increases in biomass solids relative to 2020 provide some corroboration for the GCAM team explanation of the role of

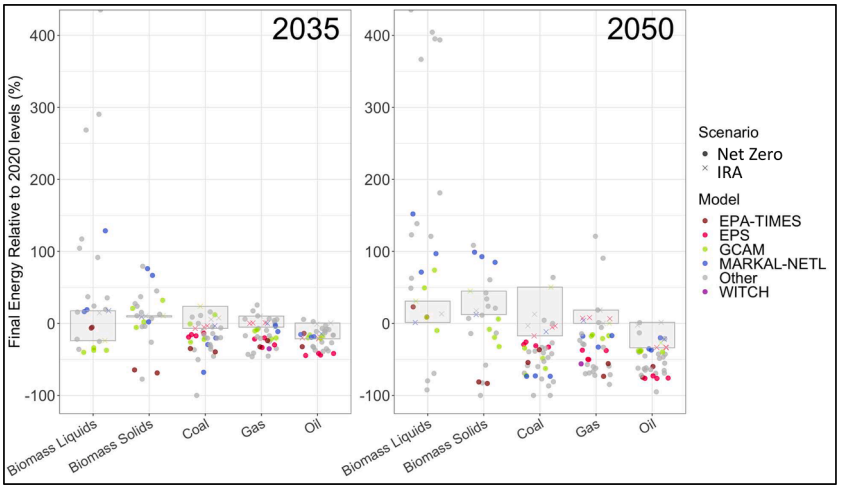

Fig. 2. *U.S. final energy use by fuel.* Final energy relative to 2020 levels (as %) for that model for coal, oil, and gas in 2035 and 2050. "Other" represents models that did not report air pollution ($n = 12$). Boxes show the range (max, min) for the IRA scenarios (23–25 in Table S1) and dots show the Net Zero scenarios (2 and 3 in Table S1). See the SI (Figure S5) for results for 2025 and 2030.

land use changes (including the repurposing of unmanaged lands) in driving $PM_{2.5}$ increases.

By 2050, the Net Zero scenarios generally show fossil reductions that fall outside of the IRA scenario range, with very little agreement across models for any particular fossil fuel. Liquid and solid biomass show even less agreement across the models, with the change in final energy across models ranging from nearly 100 % below 2020 levels to an infinite relative increase (i.e., the 2020 value was zero).

While all sectors impact air pollutant emissions, the electric sector provides a unique lens for comparing model behavior since it is a major source of both GHG and air pollutant emissions and one where the likely technology pathways are known and captured in most models. Thus, assumptions about overall generation, initial technology mix, retirement, and response to the Net Zero target in that sector are important in driving overall air pollutant emission trends.

Total electricity production in 2020 is compared across models in the SI (Figure S7). Total production differs by model, although production from coal and gas is similar for all except WITCH. The global integrated assessment model WITCH, calibrated using data through 2015, does not capture post-2015 coal plant retirements and also reports higher use of biomass. Coal use in the electric sector is typically a major source of SO_2 emissions, and both coal and biomass combustion are major sources of $PM_{2.5}$ emissions, explaining WITCH's relatively high levels of both pollutants compared to the other models (Fig. 2).

Projections of future fuel use in the electricity sector relative to 2020 are also quite variable across models (Fig. 3). Coal use shows clear declines, with the overall impact moderated by the deployment of coal with CCS. Wind and solar, which are zero-emitting variable renewables, show the largest increase in output. Nuclear tends to decline and geothermal and oil show little change. The range of projections for nuclear likely reflects alternative assumptions regarding retirement over time and the viability and cost of adding new nuclear capacity. None of the models project a significant role for hydrogen in the electric sector.

Projections of electricity production from coal for several key scenarios are explored further (Fig. 4). WITCH offers the largest opportunity to reduce CO_2 by decreasing coal use, although this is influenced by its greater reliance on coal in 2020. The rate of decline of coal use differs considerably by model. However, MARKAL-NETL is unique in showing a resurgence of coal use as CCS technologies come online for both the IRA and Net Zero scenarios.

Carbon capture technologies are expected to reduce the net energy efficiency of power plants. Impacts on air pollutant emissions are not

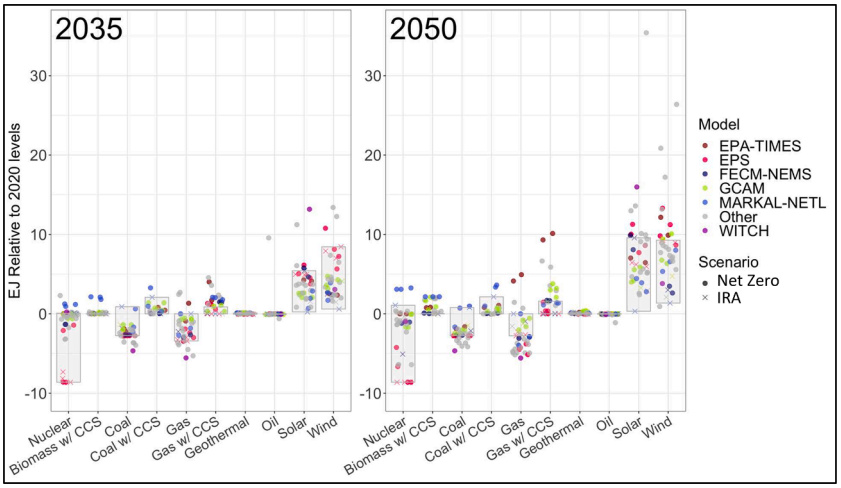

Fig. 3. Change in U.S. electricity production by fuel. Secondary energy relative to 2020 levels in EJ for each model in 2035 and 2050. "Other" represents models that did not report air pollution ($n = 13$). Boxes show the range (max, min) for the IRA scenarios (23–25 in Table S1) and dots show the Net Zero scenarios (2 and 3 in Table S1). See the SI (Figure S6) for 2025 and 2030.

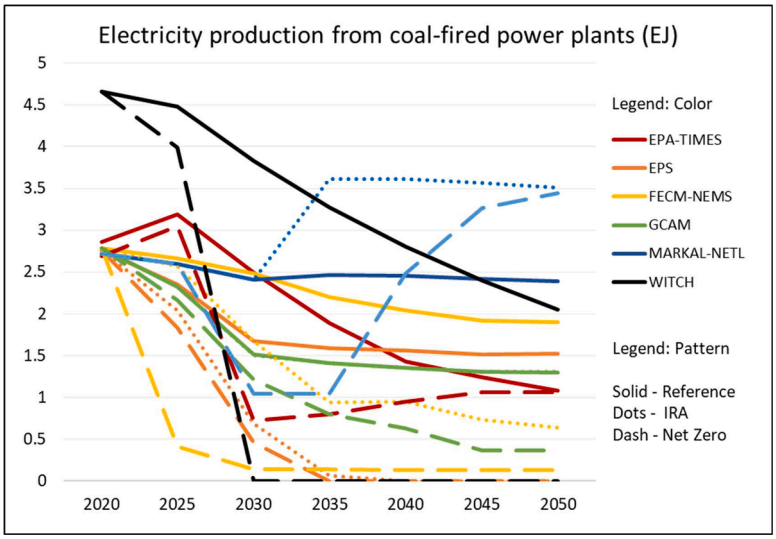

Fig. 4. *Electricity production (EJ) from coal-fired power plants, by model, totaled across those with and without CCS, for Reference, IRA, and Net Zero.* The EMF37 models have similar output from coal-fired power plants in 2020, but their trajectories differ significantly. In contrast, WITCH shows a continuation of the relatively higher share of 2015 due to its calibration year, and those plants are therefore more responsive to the Net Zero target. Increases in coal plant output for some models under Net Zero reflects adoption of coal with CCS.

fully known [26,27]. Thus, air pollution impacts will also depend upon the mix of carbon sequestration approaches deployed (Fig. 5) and upon control requirements. There is tremendous variability across models in how much BECCS, fossil CCS, DAC, and land use, land use change, and forestry (LULUCF) storage occurs in 2050. BECCS and fossil CCS are both combustion processes and thus generate pollutants such as NOx and direct $PM_{2.5}$. If DAC is powered by electricity, the net air pollutant signal would be reflective of the electric sector technology mix. Alternatively, DAC may be powered by natural gas, which would also result in air pollutant emissions.

CO_2 removal technologies can also have an indirect impact on the magnitude and spatial distribution of air pollutant emissions. For example, in scenarios with large-scale deployment of CO_2 removal technologies, the pressure to decarbonize other sectors decreases. As a result, some of the potential air pollutant benefits associated with electrifying transportation, buildings, and industry may not be fully realized.

3.3. Econometric estimates of underlying trends

Undoubtedly, there are differences in air pollutant emission factors and assumptions about the application of air pollution controls across models across the models. Cataloging and comparing those emission factors is beyond the scope of this paper. However, in this section, we take a top-down approach that uses simple econometric models to examine the technology and fuel trends that drive emission changes across models and scenarios. The approach is conducted on fuel use and emissions data covering 2025 to 2035 to identify short-term relationships and for 2040 through 2050 to identify long-term impacts.

A log-log model is used to characterize the unconditional relation-

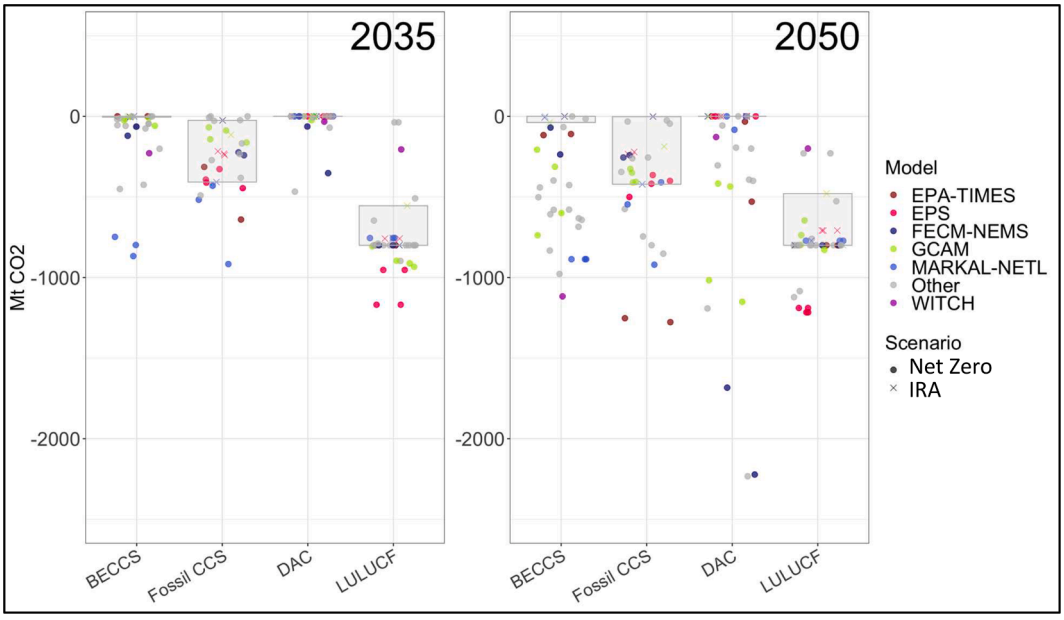

Fig. 5. CO_2 *captured in 2035 and 2050 by technology in the U.S.* Values are shown as negative to reflect removal. "Other" represents models that did not report air pollution ($n = 14$). Boxes show the range (max, min) for the IRA scenarios (23–25 in Table S1) and dots show the Net Zero scenarios (2 and 3 in Table S1).

ship between each air pollutant and the final energy demand for each fuel according to Eq. (2). Pol_{jmst} is the level of air pollutant j emitted by model m, for scenario s, and time t. Δ_{emst} is the final energy demand for fuel e. Various fixed effects are included to account for differences between models, time periods, and scenarios. λ_t captures shocks common to all models in period t. This is equivalent to subtracting for each period the average emissions reported across all models in that period. This partially accounts for the decreasing trend in fossil fuels reported by all models across scenarios, effectively identifying the elasticities from deviations of the average trend. λ_m and λ_s are model and scenario fixed effects that control (in an additive way) for level differences across models and scenarios. Finally, λ_{ms} accounts for cross-sectional differences between the model-scenario pairs.

$$\log(Pol_{jmst}) = \sum_e \beta_{ej} \log(\Delta_{emst}) + \lambda_t + \lambda_m + \lambda_s + \lambda_{ms} + \in_{emst} \quad (2)$$

Fig. 6 presents the β_{ej} coefficients for the effects of final energy demand increases of biomass, coal, electricity, gas, and oil on reported CO, OC, PM_{10}, VOC, NH_3, F Gases, BC, $PM_{2.5}$, methane (CH_4), and SO_2 (sulfur). These point estimates can be interpreted as elasticities. For example, a 1 % average increase in Δ_e across models and scenarios would increase Pol_j by β%. Note that these are unconditional elasticities that inherently ignore complementarities and substitutions among fuels. The coefficients include the effect of both increasing fuel e and its effect on the final energy demand for fuel e' ($\forall\ e' \neq e$).

Increasing biomass use for bioenergy increases the emission of most pollutants, including CO, OC, PM, and VOC. The increase in biomass demand comes hand-in-hand with a decrease in sulfur and CH_4, suggesting that higher demand for biomass substitutes coal. For the relationship between coal and air pollution, increasing coal use seems to increase all pollutants but PM_{10} and OC. This apparent OC decrease arises from the inverse relationship between biomass and coal. A key finding is the effect of electrification on air pollution. Across all air pollutants, increasing the electricity share of final energy demand significantly decreases the emissions of all reported pollutants. As expected, this happens because renewable technologies like wind and solar substitute for fossil fuel final energy demand.

To formally assess the cross-fuel unconditional elasticities that pin down the point estimates in Fig. 6, we estimate them with a similar model to Eq. (2). Specifically, we estimate these elasticities with a log-log model of the final energy demand of each energy source as a function of the final energy demand in the other sources. Fig. 7 presents the coefficients for the cross-fuel unconditional elasticities in final energy demand. The model accounts for period, model, scenario, and model-by-scenario fixed effects. We color insignificant coefficients gray, negative coefficients green, and positive coefficients purple. The point estimates are not symmetrical because unconditional elasticities are not necessarily bi-directional. That is, the effect of an increase of 1 % in electricity on oil is not the same as an increase of 1 % in oil on electricity. This happens because while electricity can substitute oil through electrification, it is more difficult for oil to substitute electricity.

As expected, increasing electricity demand by 1 % reduces oil, gas, and coal demand by 1.19 %, 1.74 %, and 1.51 %. This negative cross-sectional elasticity between electricity and fossil fuels drives the positive effects of electricity on air quality (Fig. 6). For gas, Fig. 6 suggests that increasing its final energy demand leads to generalized increases across air pollutants. This positive relationship happens because the final energy demand for gas is positively correlated with the final demand for all other fossil fuels plus biomass and negatively correlated with electricity (Fig. 7). While a higher demand for oil is positively associated with higher gas and biomass, it is negatively correlated with coal and electricity. This explains the slight negative association between oil final energy demand, sulfur, methane, black carbon, and VOCs.

3.4. Translation to health impacts

Several alternative approaches exist for translating the emission changes produced by energy models into air quality and health impacts. The gold standard for developing detailed regional air quality estimates is using a bias-corrected Chemical Transport Model (CTM) [28–30]). CTMs produce mechanistically driven and spatially detailed projections of air pollutant concentration changes, typically with a temporal resolution of minutes to hours and a spatial resolution of 20 km down to 1 km or finer. As a result of this level of detail, regional and national

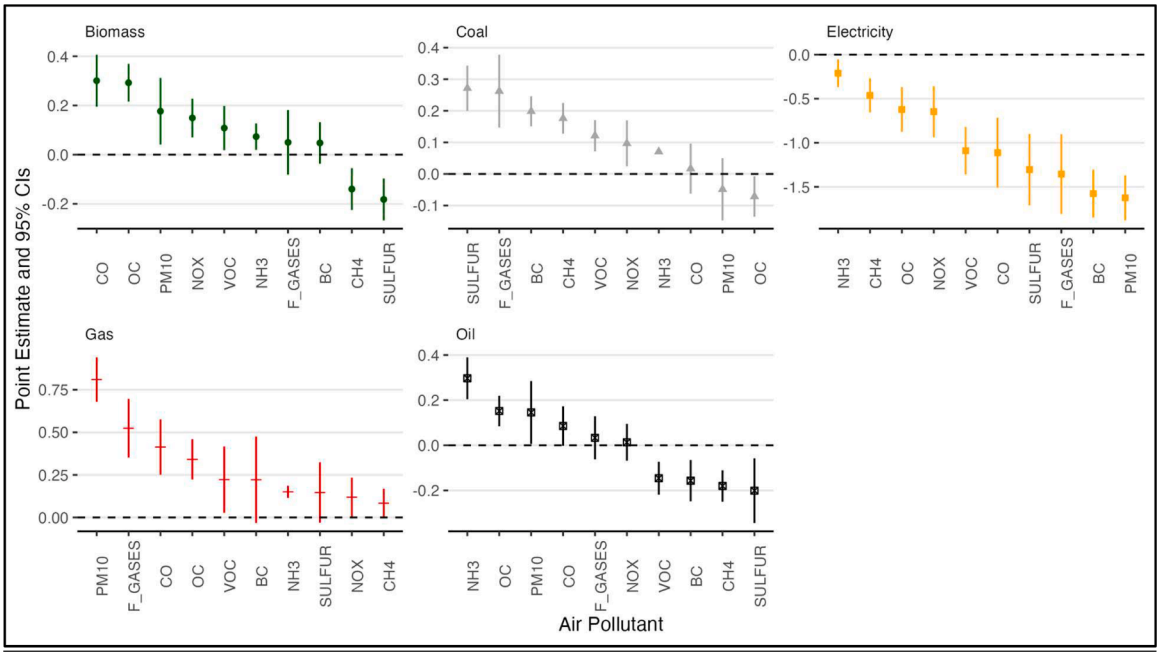

Fig. 6. *Relationship between final energy demand by source and air pollutant emission.* The coefficients come from a log-log model of each pollutant as a function of the final energy demand for each energy source. The statistical model accounts for period, model, scenario, and model-by-scenario fixed effects. We estimate the effect from the variation obtained from all reference, Net Zero, and IRA scenarios. Standard errors are clustered at the model level.

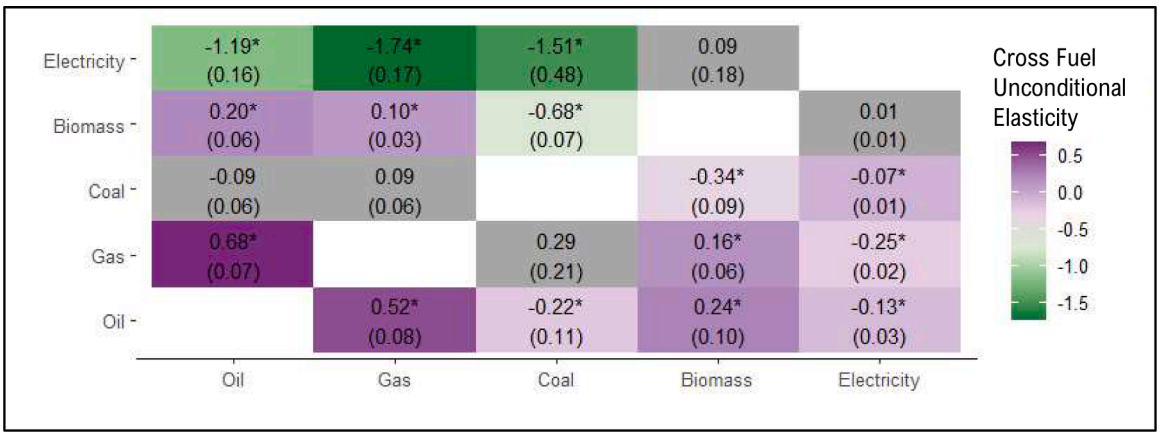

Fig. 7. *Cross-sectional relationship of final energy demand for various energy sources.* The coefficients come from a log-log model of the final energy demand of each energy source as a function of the final energy demand in the other sources. Standard errors are in parentheses and are clustered at the model level.

simulations using CTMs often require weeks of computational time on a high-performance computer, limiting the number of scenarios that can be analyzed and which groups can perform them. Gridded air pollutant concentrations can be translated into health impacts using a tool such as BenMAP [31].

Alternatives have emerged to address the computational burden associated with CTMs [32–36]. Many utilize linear air pollution impact factors or health impact factors, typically represented as a source-receptor (S-R) matrix [37]. These reduced-form models can provide spatially detailed results but at a potential loss of accuracy, especially for pollutants undergoing large emissions changes and those with nonlinear chemistry. An example of one such model is the CO-Benefits and Risk Assessment (COBRA) tool [15], which includes an S-R matrix derived from sensitivity simulations of the Comprehensive Air Quality Model with extensions (CAMx) CTM [30]. Inputs to COBRA include county-level population projections, incidence functions, and county- and source category-specific emission changes of air pollutants. COBRA then estimates county-level air quality for both the base case and policy case, as well as the monetized health impacts associated with the changes in concentration between the two cases.

Note that the S-R matrix in COBRA was developed using sensitivity runs of a CTM, but captures concentration responses using linear, additive coefficients. Atmospheric chemistry involves nonlinear processes, so this representation may not adequately capture air quality changes in some locations. Also, while the grow-in-place assumption is used to address uncertainty in the specific locations of emission reductions, this assumption does not resolve spatial uncertainty. Other sources of uncertainty include those associated with the "emissions inventory, health impact functions, and economic values" [15]. The U.S. Environmental Protection Agency considers COBRA to be a screening model and indicates that regulatory modeling applications require more sophisticated modeling approaches.

COBRA 5.1 is used in this study. This version includes an updated S-R matrix that translates changes in NOx, SO_2, CO, VOCs, and direct $PM_{2.5}$ emissions into ambient $PM_{2.5}$ and tropospheric ozone concentration differences. Note that COBRA 5.1 does not consider NH_3 or VOC emissions in predicting $PM_{2.5}$ concentrations, nor does it consider changes in emissions from non-anthropogenic sources such as wildfires and biogenic emissions. In this study, we focus on ambient $PM_{2.5}$ concentrations and impacts since monetized $PM_{2.5}$ health costs tend to dominate other air pollution health costs [38]. As described previously, $PM_{2.5}$ emissions reported by the energy models are "direct $PM_{2.5}$ emissions". The ambient $PM_{2.5}$ concentration estimates produced by COBRA include both direct emissions and secondary $PM_{2.5}$ (formed through atmospheric reactions). Direct $PM_{2.5}$ is an important source of mortality, but secondary $PM_{2.5}$ is typically responsible for more particle mass and mortality [39].

Each of the six modeling teams that participated in this study provided estimates of national totals for various air pollutants through time, allowing the development of pollutant-specific growth and control factors. However, COBRA includes a much more detailed representation of the U.S. air pollutant emissions inventory, representing sources at the county and source category levels. This detail is important since the sector-specific contributions to emissions can differ significantly from one part of the country to another. Furthermore, the impacts of pollutants can differ by location and source type. For example, sources within the electric sector tend to have tall smokestacks, distributing emissions over a wide area. In contrast, emissions from motor vehicles and buildings can have a much greater impact-per-ton since the emissions are not as widely dispersed, and there may be many people in close proximity to the source.

Our team decided that using sectoral-, pollutant-specific emission growth-and-control factors would capture more of these details than national-scale factors. The modeling teams were contacted and asked to provide air pollutant emissions at the subnational and sectoral levels. One team (FECM-NEMS) submitted subnational data, although several others had this capability. Four (EPS, FECM-NEMS, GCAM, and WITCH) of the six modeling teams provided sectoral emissions for at least two pollutants. One (FECM-NEMS) only provided emissions for the electric sector. Based on this response, we chose to evaluate air quality impacts for the sectoral results of EPS, GCAM, and WITCH.

Obtaining sector-based emissions provided an additional opportunity for refining the estimates of direct $PM_{2.5}$ emissions for the models that did not output it directly (GCAM and WITCH). While Eq. (1) represented the relationship across source categories, the new dataset, combined with historical sectoral emissions data from the EPA, supported the development of sector-specific OC-to-direct $PM_{2.5}$ conversion factors (Table S3). Excluding road dust (15.9), these factors ranged from 1.6 in the commercial sector to 4.75 for power generation, reflecting the different mix of fuels used across sectors.

An important methodological step involves matching the emission outputs from each model with the inventory categories represented in COBRA. Table S5 provides the crosswalk used to perform this matching. The emission categories represented in each model differ from those of the inventory in COBRA, so this mapping process undoubtedly introduces uncertainty.

In developing emission changes to apply within COBRA, we chose the year 2035 to allow significant mitigation-driven technological change while still being relevant from an air quality management perspective that currently is typically more focused on deadlines through 2032 for attaining the National Ambient Air Quality Standards (NAAQS) [40]. COBRA allows users to select which population,

valuation, and incidence function files to use, including options for 2016, 2023, and 2028, as well as 2030 through 2050 in 5-year increments. Note that COBRA uses estimates of future population that may not be consistent with the EMF 37 models. For example, the future county-level population estimates in COBRA were developed from the 2010 census projections [41] and the 2015 Woods and Poole forecasting model [42] using a four-step process involving national-level variables, employment data, net migration rates, and finally regional level variables. In contrast, the EMF modeling teams were allowed to develop their own assumptions about population growth, potentially introducing some inconsistency that could be addressed via harmonizing assumptions.

For each of COBRA's emission categories, we developed emission scalars from Reference results to grow the COBRA base-year inventory from 2023 to 2035. However, the models did not report 2023 results, so the scalars were based on emission changes between 2025 and 2035. Similarly, emission scalars for 2035 were developed to reflect emission differences between Reference and Net Zero results in that year. The scalars were used to develop the "BASE" and "CONTROL" case emissions for 2035 that were used in COBRA. Selected COBRA results are presented (Table 3), including avoided mortality and overall monetized benefits. The Reference scenario was chosen as the baseline for these analyzes since of the three models only EPS and GCAM simulated the IRA scenario. Despite the differences in model structure and emission projections, the estimates of avoided mortality and overall monetized benefits are very similar across all three models.

Next, we examine the spatial distribution of air quality impacts. COBRA produces $PM_{2.5}$ concentrations by county, and the results suggest that Net Zero would potentially reduce ambient concentrations in all counties across the U.S. by 2035 relative to Reference. To illustrate regional patterns, we use population weighting to aggregate county-level results to the state level (Fig. 8). For Reference in 2035, the three models all indicate higher PM concentrations in the central states. While the reductions in $PM_{2.5}$ concentrations appear to be widespread, the greatest reductions are in the central and northeastern states. The median state-level decrease in population-weighted ambient $PM_{2.5}$ concentrations in 2035 due to the application of the Net Zero target ranged from 4.4 % (WITCH) to 8.4 % (GCAM). GCAM indicated that these reductions would be homogenous, while in WITCH and EPS reductions were limited to the south and mountain regions.

4. Discussion

Considerable heterogeneity is witnessed across models for fuel use (Fig. 2) and the associated air pollutant emissions (Figs. 1). Coal combustion is shown to be positively correlated with many air pollutants, including SO_2, BC, VOC, and NOx (Fig. 6), and differences in model-specific assumptions about coal-fired power plant capacity and retirement (Figs. 4) appear to be critical in driving differing air pollutant emission responses. While most modeling teams have very similar retirement assumptions through 2020 (Figure S7), their projections for future coal generation under the Reference, IRA, and Net Zero scenarios are quite different (Fig. 4). Another factor driving differences in air pollutant projections is biomass utilization (Fig. 2), which is shown to be positively correlated with the emissions of air pollutants, including CO, OC, NOx, VOCs, NH3, and BC (Fig. 6). Depending upon emissions controls, substituting biomass for coal could offset some of the air pollutant benefits of coal plant retirement (Fig. 7). Total natural gas combustion is also correlated with increases in a wide range of air pollutant emissions, while electrification of end-uses is associated with their decrease (Fig. 6). Together, these results suggest that there are greater air pollutant emission benefits from combining electrification with zero-emissions electricity (primarily from new wind and solar power capacity in these scenarios).

Differences in sectoral coverage and representation of intra-sector dynamics were sources of variance among air pollutant emission projections. For example, GCAM indicated the potential for near-term (2025 and 2030) increases in direct $PM_{2.5}$ emissions linked to the conversion of unmanaged lands to other uses, including the production of biomass for bioenergy (Figures S2 and S3). This dynamic is not reflected in the other models, likely because most do not include an explicit representation of agriculture or land use. Previous global-scale modeling supports this result: although climate policy-triggered reductions in fossil fuels lead to large public health improvements, low-pollution areas (e.g., where coal is already phased out) can experience increases in pollution from bioenergy and land use change [43].

Several additional factors likely drove differences in air pollutant projections among models that we were not able to explore explicitly in this manuscript, but that we raise for consideration in potential follow-up work. One such factor is that there currently is no standard set of emissions factors (EFs) suitable for use across the wide range of energy and integrated assessment models. As a result, the modeling teams have taken a myriad of approaches to developing air pollutant EFs. For example, the GCAM modeling team develops 2015 base-year EFs by dividing sectoral-, fuel-, and pollutant-specific emissions totals from the U.S. EPA's National Emissions Inventory [44] by an estimate of sectoral fuel use. The resulting average emission factors are applied at the technology level. For many source categories, EFs for future vintages of the same technology are adjusted downward with each vintage, reflecting the generalized impact of current and expected future regulation [45]. In contrast, the EPA-TIMES team took a more varied approach toward base-year EF development [17]. For some source categories, technology-specific EFs were obtained from EPA emission testing activities, while for other categories, EFs were calculated from various EPA Regulatory Impact Analyses. These EFs are carried forward from the base year, with the exception of instances where they would be impacted by a specific regulation or rule, such as New Source Performance Standards [46], the Tier 3 standards for on-road vehicle emissions [47], and various other regional control requirements (e.g., the EPA's Good Neighbor Plan [48]). Updating EFs to reflect various rules is a complicated and time-consuming process, which is made more difficult since the regulatory environment is non-static. Thus, not all regulations that would affect air pollutant EFs are included.

With any EF development approach, adopting or developing EFs for new and emerging technologies is necessary, introducing uncertainty. For example, there is uncertainty about how the application of CCS to a power plant will impact conventional pollutant emissions. The energy penalty associated with CCS (e.g., from the cycling of entrainment liquid and the compression of captured CO_2) would be expected to result in a higher level of these pollutants per unit of output than fossil fuels without CCS. Most CCS technologies require the removal of sulfur from the emissions stream, resulting in near-zero SO_2 emissions. However, since these technologies have had limited commercial deployment, there is considerable uncertainty in their real-world emissions and the extent to which those can or will be controlled. The net impact of these factors will be a function of the specific capture method employed and whether additional controls are applied [27,49].

Table 3
Avoided premature $PM_{2.5}$-attributable mortality and total monetized $PM_{2.5}$ health benefits in 2035 (2023$s), developed using national-scale emission changes by pollutant, applied to all sources. Benefit estimates represent the total monetized benefits of reducing $PM_{2.5}$ concentrations for Net Zero relative to Reference. Benefit values are dominated by reduced premature deaths. The COBRA default 2 % discount rate is used.

	Avoided premature deaths in 2035		Monetized Benefits (2023$s) in 2035 using a 2 % discount rate	
Model	Low estimate	High estimate	Low estimate	High estimate
EPS	7000	14,000	$130 billion	$250 billion
GCAM	6900	15,000	$120 billion	$250 billion
WITCH	3700	7400	$65 billion	$130 billion

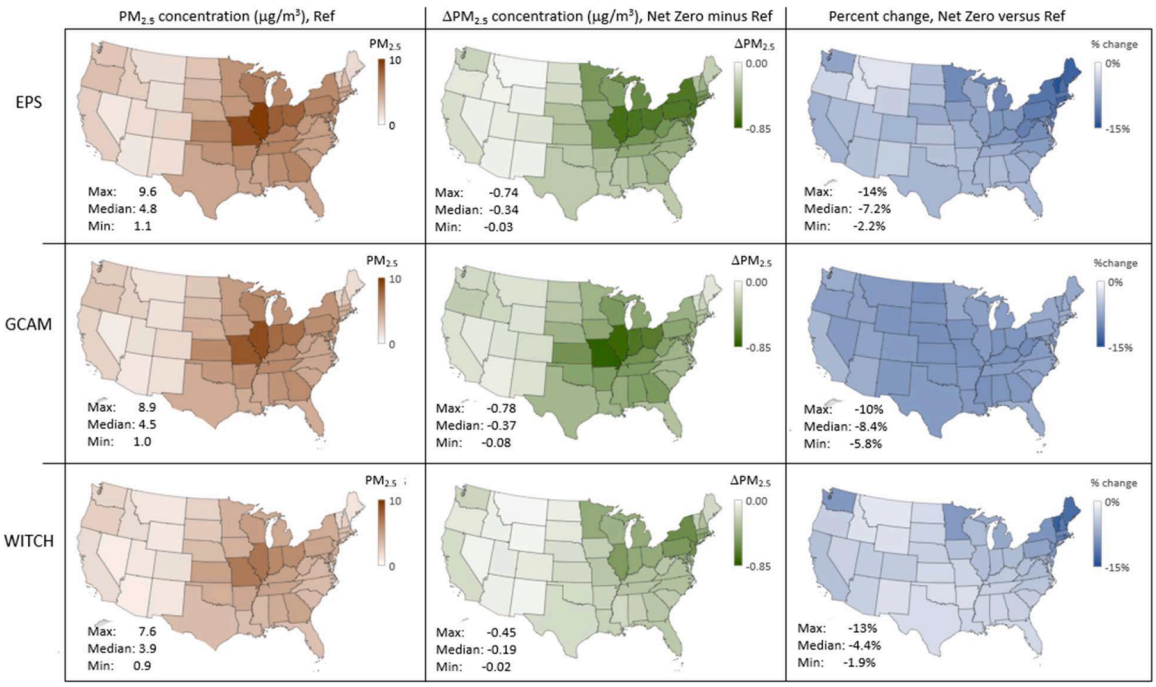

Fig. 8. Population-weighted $PM_{2.5}$ concentration (developed from county-level estimates) in 2035 in each state for Reference and for the absolute and percent change in concentration resulting from the implementation of the net zero constraint. Maps were generated using Excel and Bing, © GeoNames, Microsoft, and TomTom.

Even if a standard source of EFs is developed, complications arise in its use. One reason is that many of these models have often been developed for overlapping but slightly different purposes, and their spatial and temporal resolution, sectoral coverage, and technological detail differ as a result. For example, if the primary purpose of a model is to estimate energy use and greenhouse gas emissions, that model may focus on the quantities of fuels that are used and the carbon content of those fuels. For natural gas, such a model may not track whether that natural gas is combusted in a boiler, turbine, or engine. From an air quality perspective, however, those applications typically have very different emission signatures. NOx emissions from a stationary reciprocating engine may be more than 20 times greater than those of a turbine per unit of fuel combusted [50]. An energy or integrated assessment model developed from the "ground up" to inform air quality decision-making would likely include this differentiation. Otherwise, the model would need to aggregate across categories and lose this distinction or adjust emissions to account for assumed technology market shares as a post-processing step.

Another complication is that EFs can differ considerably from one part of the country to another. Some emission rates are impacted by temperature and climate [51], but another source of differences is location-specific regulatory requirements. In the U.S., the Clean Air Act Amendments [52] are the primary regulatory framework impacting air pollutant emissions through ambient air quality standards and emission limits on new technologies and some existing technologies. While the federal government sets ambient standards, states typically develop and implement plans to meet those standards. The resulting control requirements may be specific to a facility, to a county, or to a metropolitan area. In other instances, states may work together to set control requirements specific to a multi-state region [53]. Models at the spatial resolution of those in this study thus cannot fully capture key U.S. air pollution requirements (e.g. New Source Review and Prevention of Significant Deterioration requirements - including air quality offsets, RACT for existing sources and BACT for new sources [54]) or future requirements that may alter the distribution of air pollution. Furthermore, these models do not capture the impacts of state and local policies that might, for example, limit the siting of certain generation types (e.g. fossil CCS, and bioenergy) or infrastructure (e.g., CO_2 pipelines) in some locations [55,56].

The historical period over which the models are calibrated, as well as any constraints applied to reflect subsequent historical data, also can differ from one model to another. In the rapidly changing electric sector, the impact is particularly evident. In the U.S., electricity from coal declined from 1850 TWh in 2010 to 1350 TWh in 2015 and 770 TWh in 2020 [57]. Thus, a model calibrated or constrained to 2010 or 2015 data could produce a very different electric sector generation mix than one calibrated or constrained to 2020. Generation from coal plants in all the models except WITCH reflect 2020 historical levels (Figure S7), while WITCH's value is roughly equivalent to the 2015 historical levels. Note that WITCH was not part of the U.S. portion of the EMF 37 exercise, and thus did not benefit from the coordination of assumptions among other modeling teams.

In summary, the models represented in this study reflect a variety of formulations and parametrizations. There are differences in how the models were calibrated, whether and how demands are elastic to price, whether the model solution process has perfect foresight or is myopic, whether the model is seeking to optimize decisions or simulate choices, and internal constraints such as limits on market share for specific technologies or fuels. The models themselves are non-static, with development and additional considerations (e.g., representation of the IRA) being added even during the EMF 37 exercise. In light of all these factors, the emission magnitudes, emission trends, and estimated health benefits shown in Figures 1 and S2 and in Table 3 are remarkably consistent in their projection of air pollutant trends and air quality improvements.

The scope of our initial health benefits analysis limits firm conclusions about magnitude and geographic distribution. For example, we evaluated impacts between a single Reference scenario and Net Zero scenario for only one year (2035) and used only three EMF models. Evaluating impacts over a broader set of scenarios, years, and models would improve the robustness of the exercise and resulting observations. The magnitude of estimated benefits indicate that a more detailed

analysis is worth pursuing.

5. Conclusions

Despite differences in model structure, level of attention paid to air pollutants, sources of emissions factors, differing baseline policy assumptions, and other factors, this study finds, consistent with previous work, that many air pollutant levels are expected to decrease over time due to existing policies and market trends, and that net zero policies will yield additional reductions. Furthermore, we expect these emission changes will result in widespread improvements in air quality, and that these improvements have significant monetary benefits.

Air pollutant emissions have not traditionally been a core focus of most climate/energy modeling efforts [58,59] and were similarly not the core focus of the overall EMF 37 effort. Thus, it is not surprising that there was limited reporting of air pollutant emissions. However, given the salience of air quality to policy makers (both as an important social concern and a near-term benefit of climate action), efforts to improve the ability to quickly learn about the air quality impacts of different policy or technology pathways will be valuable. This is especially true given the increasing focus on equity in climate policy transitions [60]), which requires attention to the spatial distribution of both legacy and future air pollution. The tremendous variability in the future trajectory of combustion fuels (Fig. 2) further emphasizes how variable future impacts on human health from air quality could be [61]. Approaches to reduce building and industrial emissions could cut $PM_{2.5}$ emissions by nearly half in 2050 [11], highlighting the need for a cross-sector focus for decarbonization and air quality management (even before accounting for shifts in emissions across sectors). Similarly, failure to pay attention to co-pollutants could leave black and low-income communities continuing to carry a higher pollution burden [62].

Developing an accurate picture of future air quality is far from straightforward. Models at this level of resolution often do not represent key federal, state, and local air pollution requirements or future requirements that may alter the magnitude and distribution of emissions. Similarly, models do not capture political considerations. Understanding air quality impacts of emissions changes is complicated by complex atmospheric transport and transformation, typically requiring the use of an air quality model. This process requires mapping emission categories from an energy system or integrated assessment model into the categories represented in an air quality model, and differences in emission categories between models introduces uncertainty.

Nonetheless, developing a picture of air quality benefits is critical. To the extent that policymakers are considering the costs of climate policies, they should also consider the benefits [63]. The monetized benefits to air quality from climate policies are often of a similar order of magnitude or greater than the monetized climate benefits, with significant benefits unquantified in both cases [4,64]. In addition, decarbonization actions that move the energy system away from fossil fuel combustion negate the need for investing in more advanced, ultra-clean air pollution control equipment (scrubbers, particulate traps, etc.); this can lead to enormous cost savings system-wide [65]. Knowing the differential impacts on the amount or distribution of air quality between technology pathways or policy designs could lead policymakers to select different options.

In general, if air pollutant emissions are to be a commonly used endpoint of energy and integrated assessment modeling, efforts could be taken to improve these models for this purpose. A few recommendations for the modeling community include:

- Develop a standard set or database of air pollutant EFs (or EF ranges) for current and future technologies that include the impacts of current regulations (as in [3]). This would encourage teams to keep EFs updated and would provide additional transparency about assumptions.
- Use this database of EFs to add sources of air pollution mentioned in the text above but that may need to be more thoroughly treated in their model (e.g., NH_3, brake and tire wear, and emerging CCS technologies) to standard outputs.
- Identify the critical factors that drive air pollutant emission trends and develop a set of scenarios to explore these factors further. Based on the results here, topics of particular interest may include the air pollutant emission implications of bioenergy in buildings, industry, fuel production, and electricity production, as well as those of fossil fuels and biomass paired with CCS.
- Explore the potential to endogenize the monetized value of health impacts into models. Endogenization would allow these impacts to be more fully considered in designing decarbonization strategies.
- Facilitate analysis of air quality impacts by streamlining or automating workflows for the handoff of results to reduced form or more complex air quality models, including disaggregating results by sector and region.
- Clearly communicate which air quality impacts, if any, are quantified by the model and which ones are likely to be missing. Uncertainty in these impacts should also be articulated.

Addressing these recommendations would require major efforts for many modeling teams and perhaps warrant an inter-model comparison exercise under or similar to the EMF.

Policymakers and other funders of modeling could, where possible, seek out models that can demonstrate a capacity to produce air pollution output with realistic emissions factors at the regional and/or sectoral scale. However, they should review those results with an eye to the fact that there is considerable heterogeneity across models and scenarios regarding the mix of fuels and strategies that are employed to achieve deep decarbonization (Figs. 2–5).

There also is a gap between the spatial resolution typical of energy-economic models [66] and the resolution required to accurately model air quality and project its spatial impacts at the scale of environmental justice communities. Emerging tools may prove useful in partially bridging this gap. For example, some high-resolution electric sector models can simulate the siting of new facilities [67] and land use change models have been used to develop spatial surrogates for other sectors [68]. These approaches themselves can introduce uncertainty, however, and their application may be most useful as part of a well-designed probabilistic or scenario analysis that identifies and explores the impacts of key uncertainties.

Ultimately, some uncertainty is irreducible when translating from policy scenarios to air pollutant emissions to local air quality to health and other impacts. In light of this uncertainty, policymakers may wish to combine broad policy tools with more targeted air quality strategies (enforcement, grants, performance standards, etc.) if they wish to ensure that decarbonization is accompanied by equitable improvements in air quality at subregional and community scales, as well as to target hotspots of inequality.

CRediT authorship contribution statement

Daniel H. Loughlin: Conceptualization, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Alexander R. Barron:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Conceptualization. **Charavee Basnet Chettri:** Writing – review & editing, Visualization. **Abigail O'Meara:** Writing – review & editing, Visualization. **Luis Sarmiento:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis. **Danni Dong:** Visualization, Investigation. **David L. McCollum:** Conceptualization, Writing – review & editing. **Sharon Showalter:** Writing – review & editing, Conceptualization. **Robert H. Beach:** Writing – review & editing, Conceptualization. **John Bistline:** Writing – review & editing. **G. Joyce Kim:** Writing – review & editing. **Christopher G. Nolte:** Writing – review & editing. **Johannes**

Emmerling: Writing – review & editing. **P. Ozge Kaplan:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.egycc.2024.100165.

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