Environmental Science & Technology

pubs.acs.org/est

Policy Analysis

Designing Retirement Strategies for Coal-Fired Power Plants To Mitigate Air Pollution and Health Impacts

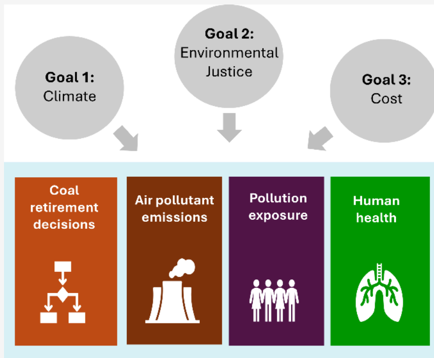
Carla Campos Morales,[‖] Emily L. Pakhtigian,[*,‖] Joel R. Landry, Hannah Wiseman, An T. Pham, and Wei Peng[*]

Cite This: https://doi.org/10.1021/acs.est.4c00704

Read Online

ACCESS | Metrics & More | Article Recommendations | Supporting Information

ABSTRACT: Retiring coal power plants can reduce air pollution and health damages. However, the spatial distribution of those impacts remains unclear due to complex power system operations and pollution chemistry and transport. Focusing on coal retirements in Pennsylvania (PA), we analyze six counterfactual scenarios for 2019 that differ in retirement targets (e.g., reducing 50% of coal-based installed capacity vs generation) and priorities (e.g., closing plants with higher cost, closer to Environmental Justice Areas, or with higher CO_2 emissions). Using a power system model of the PJM Interconnection, we find that coal retirements in PA shift power generation across PA and Rest of PJM, leading to scenario-varying changes in the plant-level release of air pollutants. Considering pollution transport and the size of the exposed population, these emissions changes, in turn, give rise to a reduction of 6−136 $PM_{2.5}$-attributable deaths in PJM across the six scenarios, with most reductions occurring in PA. Among our designed scenarios, those that reduce more coal power generation yield greater aggregate health benefits due to air quality improvements in PA and adjacent downwind regions. In addition, comparing across the six scenarios evaluated in this study, vulnerable populations—in both PA and Rest of PJM—benefit most in scenarios that prioritize plant closures near Environmental Justice Areas in PA. These results demonstrate the importance of considering cross-regional linkages and sociodemographics in designing equitable retirement strategies.



KEYWORDS: *Coal retirement, air quality, human health, environmental justice*

1. INTRODUCTION

The United States is in the midst of a significant energy transition. The past decade has seen a national decline in coal-fired electricity generation of nearly 50%.[1,2] Pennsylvania (PA) mirrors this trend due to its policy landscape and access to cheap and plentiful natural gas and renewable energy sources.[3−5] Coal plant retirements in PA provide a potential avenue for mitigating emissions of not only carbon dioxide (CO_2) but also criteria air pollutants such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and fine particulate matter ($PM_{2.5}$).[6,7] Accordingly, such closures are expected to improve air quality and reduce health damages.[8−11]

Prior studies have found that air quality and health benefits from coal generation are unevenly distributed across regions and sociodemographic groups.[8,12−18] Optimizing coal-fired power plant closures based on climate, cost, or health objectives can lead to substantial variation in both the magnitude and distribution of health benefits.[9,19−21,23] In practice, coal retirement decisions in PA and much of the country are largely based on economic and feasibility considerations and thus unlikely to address long-standing environmental justice concerns. This motivates a need to understand the equity implications of coal plant retirements—in particular, how to better design coal retirements so as to more effectively mitigate disproportionate environmental burdens historically borne by disadvantaged communities.

In addition, research into how cross-regional linkages across power systems, air pollution transport, and sociodemographics influence the distribution of health impacts is fairly limited. PA provides an exceptional setting to examine such linkages. First, PA is a major power exporter in the PJM Interconnection, a Regional Transmission Organization managing a wholesale electricity market spanning 13 states that is one of the largest in the world. Thus, coal retirements in PA affect power generation and flows throughout the PJM grid, leading to potentially significant emissions impacts elsewhere.[16,19,22] Second, due to historical plant siting decisions, chemical formation, and wind transport of pollution, reducing PA's emissions provides a means to also improve air quality in downwind states.[23,24] These complex dynamics and resulting distributional outcomes are not

Received: January 22, 2024
Revised: July 5, 2024
Accepted: July 8, 2024

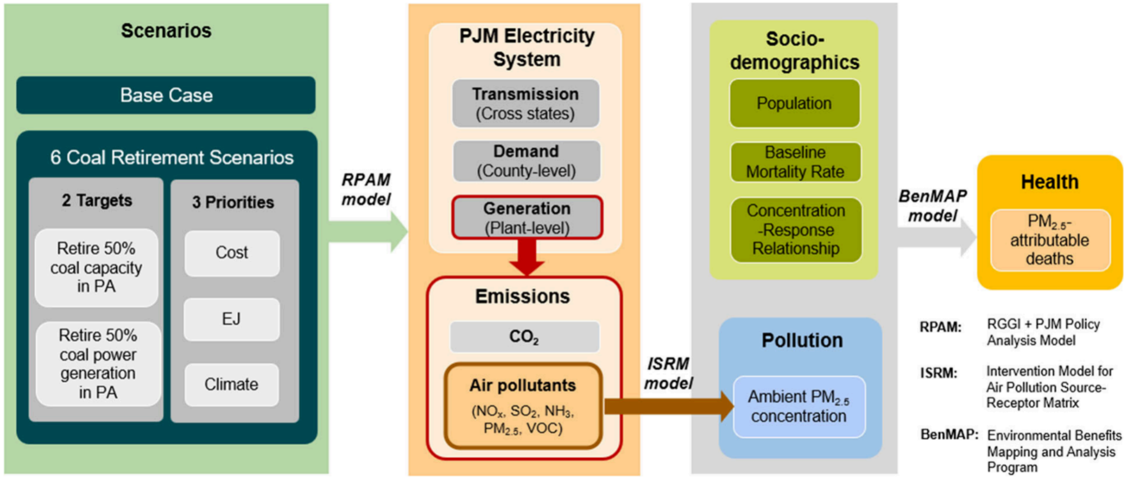


Figure 1. Schematic diagram of our modeling framework and coal retirement scenarios.

Table 1. Summary of Scenarios

	Scenario Name	Target	Explanation / Priority
	Base Case		All coal power plants active based on actual 2019 generation
		Target	**Priority**
Retirement scenarios	*Capacity-based_Cost*	Capacity-based retirement: retire ∼50% of total installed coal power capacity in PA	*Cost* Policy relevance: current practice of retirements based primarily on economic and feasibility considerations Method: plants with the highest marginal costs of generation are retired first Intention: assess how closures of high marginal cost plants affect emissions, air quality, and health throughout PJM
	Capacity-based_EJ		*EJ* Policy relevance: efforts to prioritize EJ in PA such as revisions to the Environmental Justice Policy Method:[a] plants with the largest number of EJ areas[b] within a 10 mile radius are retired first Intention: assess how closures of plants close to EJ areas affect emissions, air quality, and health throughout PJM
	Capacity-based_Climate		*Climate* Policy relevance: policy efforts to reduce emissions such as the Regional Greenhouse Gas Initiative (RGGI) Method: plants with the highest CO_2 emission rates are retired first Intention: assess how closures of high CO_2 emitting plants affect emissions, air quality, and health throughout PJM
	Generation-based_Cost *Generation-based_EJ* *Generation-based_Climate*	Generation-based retirement: retire ∼50% of total coal power generation in PA	Same as above

[a]See alternative EJ scenarios with varying radii and based on population size in SI2: Section I.C (SI2: Figure C.3 and Figure D.4). [b]EJ areas are defined by the Pennsylvania Department of Environmental Protection's (PA DEP) as census tracts where at least 20% of individuals live at or below the federal poverty line and/or where at least 30% of the population identifies as a nonwhite minority.[25]

well understood nor incorporated into coal retirement decisions in PA.

In this study, we respond to the above-mentioned knowledge gaps by evaluating the air quality and health effects of various coal retirement scenarios in PA. In particular, we contribute by (i) establishing a modeling system with improved representation of cross-regional linkages as key determinants of distributional air quality and health effects from coal plant retirements (Figure 1) and (ii) assessing trade-offs between aggregate and distributional effects across different coal plant retirement strategies.

2. METHODOLOGY

2.1. Scenario Design. Based on generation and emissions for the year 2019 (i.e., *Base Case*), we design six counterfactual scenarios that vary across two dimensions: targets and priorities. We consider two targets—"Capacity-based" (retiring coal-fired power plants until at least 50% of PA's 2019 coal-fired baseline capacity is eliminated) and "Generation-based" (retiring coal-fired power plants until at least 50% of PA's 2019 coal-fired baseline generation is eliminated)—and three priorities—*Cost* (sorting PA's 2019 coal-fired power plants by average annual cost ($/MWh) and retiring highest cost plants until reaching the target), *Environmental justice* (sorting by the number of environmental justice (EJ) areas within 10 miles of a plant

https://doi.org/10.1021/acs.est.4c00704
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

and retiring plants with the most EJ areas until reaching the target), and *Climate* (sorting by CO_2 emissions intensity and retiring the highest emitting plants until reaching the target). Notably, our EJ scenario design is driven by the fact that 73% of PA's population and 64% of EJ communities in PA resided within 25 miles from a coal power plant in 2019 (Supporting Information 2 (SI2): Figure B.2). We therefore use 10 miles in our main EJ scenarios with sensitivity analyses exploring 5–25 miles. Additional information on scenario design and policy relevance is provided in Table 1, the Supplementary data, and SI2: Section I.A and I.B (including Figure A.1 and Table A.1).

2.2. Electricity Market Modeling (RPAM). We use the RGGI + PJM Policy Analysis Model (RPAM) to examine how each coal retirement scenario induces changes in power market and plant-level emissions outcomes within PA and Rest of PJM (see Supporting Information 1 (SI1) for detailed model description and validation).

RPAM is a multimarket equilibrium model that accounts for critical features of the wholesale power market operated by PJM Interconnection, preexisting state and federal policies, the supply of external renewable energy credits (RECs) from outside of PJM, and abatement and banking from the partially overlapping RGGI allowance market (see SI1: Section II for data sets used to calibrate and estimate RPAM).[4,26] On the demand side, there are five aggregate load zones connected by five aggregate transmission lines (SI1: Section II.A). On the supply side, the model captures capacity and maintenance constrained supply from 845 representative electric generation units (EGUs) aggregated from 3,095 existing power plants in PJM (SI1: Section II.B). The model also predicts new capacity expansion for natural gas, wind, and solar on a state-by-load zone basis (SI1: Section II.C) considering anticipated annual profits net of annualized capital and financing costs. See SI1 Section II for data sets used to calibrate and estimate RPAM which come from several dozen data sets (SI1: Section II) including PJM Interconnection, S&P Global, EPA, EIA, and the U.S. Census. Subject to capacity, transmission, and policy/market clearing constraints, RPAM maximizes the sum of net benefits to PJM's wholesale customers (i.e., consumer surplus), total profits to PJM electricity producers (i.e., producer surplus) net of the costs of adding new capacity, total abatement costs from non-PJM RGGI states, and total net benefits to holders of RGGI banked allowances. This consideration of net welfare implications distinguishes RPAM from other electricity dispatch models that typically only consider costs assuming inelastic demand.[18,20,21,27]

RPAM is solved on an annual time step from 2016 to 2019. Our analysis focuses on 2019, including the Base Case, which considers the observed generation fleet and six counterfactual scenarios that update the generation fleet with coal retirements in PA. RPAM reports plant-level emissions from existing power plants in 2019 (CO_2, SO_2, NO_x, $PM_{2.5}$, NH_3, and VOC) (SI1: Section II.I). Emissions from new natural gas power plants added in each state-load zone are assumed to be released evenly across the corresponding subregion. Emissions from new solar and wind are assumed to be zero.

2.3. Air Quality Modeling (ISRM). Based on plant-level emissions from RPAM, we use the InMAP Source-Receptor Matrix (ISRM) to simulate the impacts on annual average ambient $PM_{2.5}$ concentrations. ISRM is derived from thousands of simulations of a reduced form air quality model, InMAP, which uses meteorology and emissions data from 2005 and average population data spanning from 2008 to 2012 (SI2: Section II.A). ISRM quantifies the impact of 1 ton of precursor emissions from each individual source location on the ambient $PM_{2.5}$ concentration in each receptor location. ISRM assumes a linear relationship between changes in precursor emissions and $PM_{2.5}$ concentrations. Despite these simplifications, ISRM provides reasonable estimates for $PM_{2.5}$ pollution levels when compared to observational data[28,29] and has been used to assess pollution impacts in many different contexts.[12,22,30]

ISRM includes approximately 52 ,411 spatial grid cells across the contiguous United States, including roughly 2,297 grid cells in PA and 13, 228 grid cells over rest of PJM. The grid resolution increases with population density, ranging from 1 km × 1 km in densely populated urban areas to 48 km × 48 km in remote or rural areas. ISRM inputs are precursor annual emissions of NO_x, SO_2, NH_3, primary $PM_{2.5,}$ and VOC for each grid cell or the sum of plant-level emissions of these pollutants from RPAM for each grid cell. ISRM outputs are the grid-level simulated ambient concentrations of $PM_{2.5}$, including primary and secondary $PM_{2.5}$. Based on the distribution of smokestack heights of coal power plants in PA (see SI2: Figure F.6), we use high smokestack height (>379 m) in ISRM.

The following equation describes the change in $PM_{2.5}$ concentration at receptor location b (ΔC_b) as a result of changes in emissions in location a

$$\Delta C_b = \sum_{p} \sum_{a=1}^{N} \Delta E_{a,p} \cdot f_{(a,p)-b} \tag{1}$$

where p is the primary emitted pollutant (an element of P = {primary $PM_{2.5}$, NH_3, NO_x, SO_2, VOC}), $\Delta E_{a,p}$ is the change in emissions for source grid cell a for pollutant type p emitted, and $f_{(a,p)\text{-}b}$ is the relationship between annual total emissions of pollutant type p in location a and annual average $PM_{2.5}$ in location b. Each InMAP simulation used to generate ISRM involves altering emissions of a specific pollutant from a single source by 1 ton. Thus, it generates a vector, $f_{(a,p)}$, representing impacts on all N receptors; the bth component of this vector is denoted $f_{(a,p)\text{-}b}$. The total change in ambient $PM_{2.5}$ concentration ($\mu g/m^3$) at location b is the aggregate impact from all precursor emissions from all locations.[28]

2.4. Health Impact Assessment (BenMAP). We use the U.S. EPA's Benefits Mapping and Analysis Program (BenMAP) model[31] to assess premature deaths associated with long-term exposure to ambient $PM_{2.5}$.[32] BenMAP has been applied widely in health impact assessment.[10,21,33−37] BenMAP inputs include county- and census tract-averaged $PM_{2.5}$ concentrations calculated using the gridded concentrations from ISRM; outputs are annual total $PM_{2.5}$-attributable deaths at the county and census tract levels (SI2: Section II.B). For our county-level analysis, we use gridded ISRM results to calculate population-weighted county-average $PM_{2.5}$ concentrations. If the ISRM grid size is smaller than a county, we calculate the population-weighted average $PM_{2.5}$ concentrations for the county covering multiple ISRM grids. For the geographic analysis in Section 3.4, we use ISRM results to calculate census tract-level $PM_{2.5}$ concentrations. If the census tract size is smaller than the ISRM grid, we use the same $PM_{2.5}$ concentration for all census tracts within one ISRM grid.

BenMAP uses the following log−linear health impact function to calculate changes in all-cause mortality attributable to ambient $PM_{2.5}$ exposure[38] described in Table 2:

$$\Delta Y = (1 - e^{-\beta \cdot \Delta PM}) \cdot Y_0 \cdot Pop \tag{2}$$

https://doi.org/10.1021/acs.est.4c00704
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

Table 2. Summary of Input Data for the Health Impact Assessment

Variable[a]	Definition	Data Source
Y_0	All-cause baseline mortality rate for 2019	Center for Disease Control (CDC) WONDER database available from BenMAP
Pop	Population in 2019	2010 U.S. Census Bureau census block data with projection to 2019
β	Concentration−Response coefficient from epidemiological studies; changes in mortality risk resulting from changes in $PM_{2.5}$ exposure level[b]	The main results use the estimate from the American Cancer Society;[39] the sensitivity analyses use the estimates from Laden et al. (2006)[40] and Thurston et al. (2016)[41]
ΔPM	Changes in $PM_{2.5}$ concentration in a coal retirement scenario relative to the Base Case	County or census-tract level $PM_{2.5}$ concentrations averaged from gridded concentrations simulated by ISRM

[a]For more detailed information on these variables, see the BenMAP user's manual.[38] [b]For additional information on sensitivity analyses using other concentration−response functions and β values, see Figure 6 and SI2: Section IV.

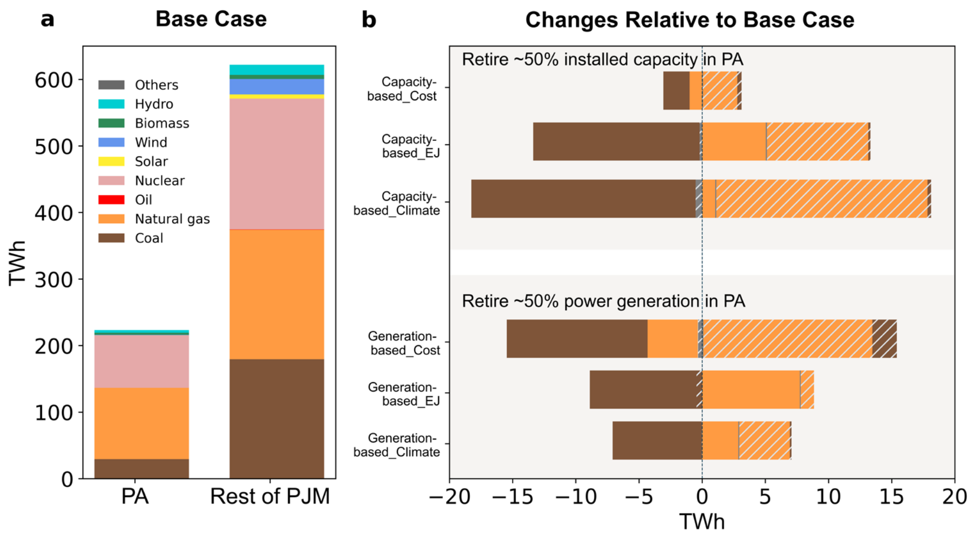


Figure 2. Electricity generation (TWh) by fuel source. (a) *Base Case* electricity generation in PA and Rest of PJM. (b) Changes in generation relative to the *Base Case* for the six scenarios in PA and Rest of PJM by power plant source (coal, natural gas, and others). "Others" in b refers to generation from all non-coal or natural gas sources.

3. RESULTS

3.1. Impacts on Electricity Generation. Coal-fired power plants account for 13% and 12% of total generation in PA and Rest of PJM, respectively, in the *Base Case* (Figure 2a). Retiring coal-fired power plants in PA based on capacity or generation targets have different impacts on the power system. For the "Capacity-based" scenarios, declines in coal-fired electricity generation in PA vary substantially from 2.1, 13, and 18 TWh in the *Cost*, *EJ*, and *Climate* scenarios, respectively, relative to the *Base Case* (Figure 2b). This variation is primarily influenced by disparities in *Base Case* utilization rates. For instance, coal plants retired in the *Capacity-based_Cost* scenario have lower utilization rates on average than the other two "Capacity-based" scenarios. However, reductions in coal-fired electricity generation are roughly the same across all "Generation-based" scenarios, which implicitly control for variation in the amount of reduced generation from coal.

Coal power plant retirements in PA drive changes in the transmission-constrained dispatch of power both within and between PA and Rest of PJM. These changes are driven by (i) the amount of coal generation displaced by retirements, (ii) the marginal costs and available capacities of remaining units, and (iii) the location of retired generation and associated transmission constraints. Generally, our results are similar to findings in previous studies[42] that coal retirements in PA lead to an increase in dispatch from natural gas plants because dispatching existing plants is cheaper than installing new capacity to make up for foregone generation, and natural gas plants are dispatched more often due to their cost advantage (Figure 2b). However, the scale and location of additional generation may be affected by changes in transmission congestion. For instance, in the *Generation-based_Cost* scenario, natural gas-based generation in PA also declines slightly when the coal-and gas-based generation in Rest of PJM increases.

3.2. Impacts on Emissions of CO_2 and Other Air Pollutants. Our main results focus on emissions of CO_2 due to its climate impacts and of SO_2, NO_x, and $PM_{2.5}$ because prior studies found these three pollutants to be the most important precursors from the power sector, contributing to 81%, 12%, and 6% of ambient $PM_{2.5}$, respectively at the national level.[28] (SI2: Figure D.4 provides results for NH_3 and VOC, which contribute 0.2% and 0.1% to ambient $PM_{2.5}$, respectively). In the *Base Case*, we estimate annual total CO_2, NO_x, SO_2, and $PM_{2.5}$ emissions from all power plants in PJM to be 426 million tons, 206, 187 , and 38 thousand tons, respectively, of which 17−25% are from PA plants (Figure 3a).

Although all six scenarios reduce CO_2 and air pollutant emissions in aggregate across PJM relative to the *Base Case*, the spatial distribution of emissions changes varies considerably across scenarios (Figure 3b and 3c). As noted above, changes in the spatial pattern of precursor emissions follow from changes in power generation. Reductions in coal power generation in PA largely explain observed declines in emissions there. For example, the *Capacity-based_Climate* scenario leads to the largest reduction in coal-fired electricity generation and thus emissions in PA of 18% for CO_2, 50% for SO_2, 32% for NO_x, and

https://doi.org/10.1021/acs.est.4c00704
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

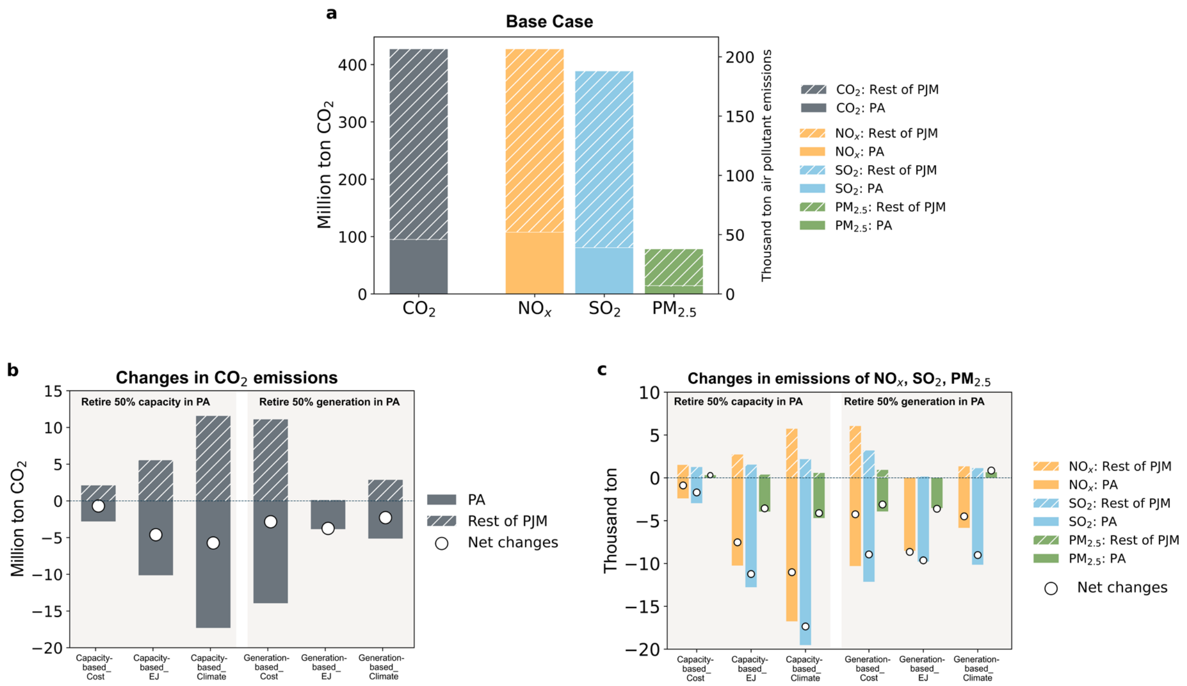


Figure 3. Annual total emissions of CO_2, NO_x, SO_2, and $PM_{2.5}$ from all power plants located in PA and Rest of PJM. (a) Emissions under the *Base Case*; (b and c) changes in CO_2 and criteria air pollutants in each of the six retirement scenarios relative to the *Base Case*. The white circles show the net change across the whole PJM . Results for NH_3 and VOC are reported in SI2: Figure G.7.

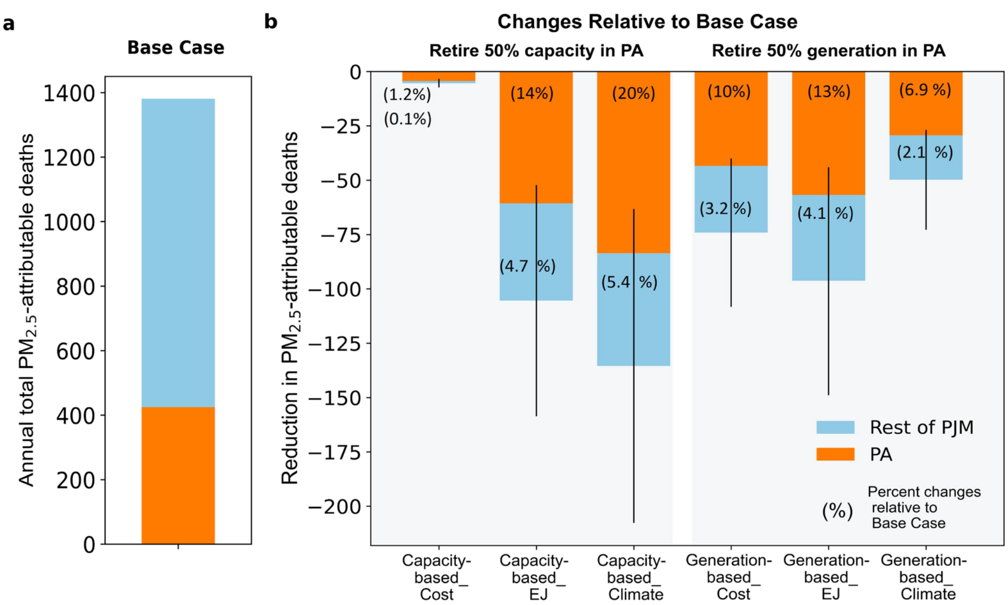


Figure 4. Annual total $PM_{2.5}$-attributable deaths from power sector emissions in the *Base Case* (a) and the changes in the six coal retirement scenarios relative to the *Base Case* in PA and Rest of PJM (b). Here, we use the concentration−response coefficients from Krewski et al. (2009).[39] Error bars represent the estimates based on the 95% confidence interval of the concentration−response coefficients for the total deaths throughout the whole PJM.

75% for $PM_{2.5}$. Changes in power generation in Rest of PJM also largely explain changes in emissions there. For example, we find almost no emissions increase in Rest of PJM in the *Generation-based_EJ* scenario (Figure 3b and 3c) consistent with the negligible change in generation there (Figure 2b). However, in the *Capacity-based_Cost* scenario, we find small increases in CO_2 (0.6%), NO_x (0.9%), SO_2 (0.8%), and $PM_{2.5}$ (0.6%) emissions due to more substantial increases in natural gas generation in Rest of PJM (Figure 2b).

3.3. Impacts on Ambient $PM_{2.5}$ Concentrations and $PM_{2.5}$-Attributable Deaths.

In the *Base Case*, power sector emissions from all electricity generation in PJM result in an annual $PM_{2.5}$ concentration of up to 5.7 $\mu g/m^3$ across PJM counties, which is associated with 1300 $PM_{2.5}$-attributable deaths annually (95% confidence interval = 1200−1600) (Figure 4a). The low concentration level results from estimating the effects only from power sector emissions, while other sectors,

https://doi.org/10.1021/acs.est.4c00704
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

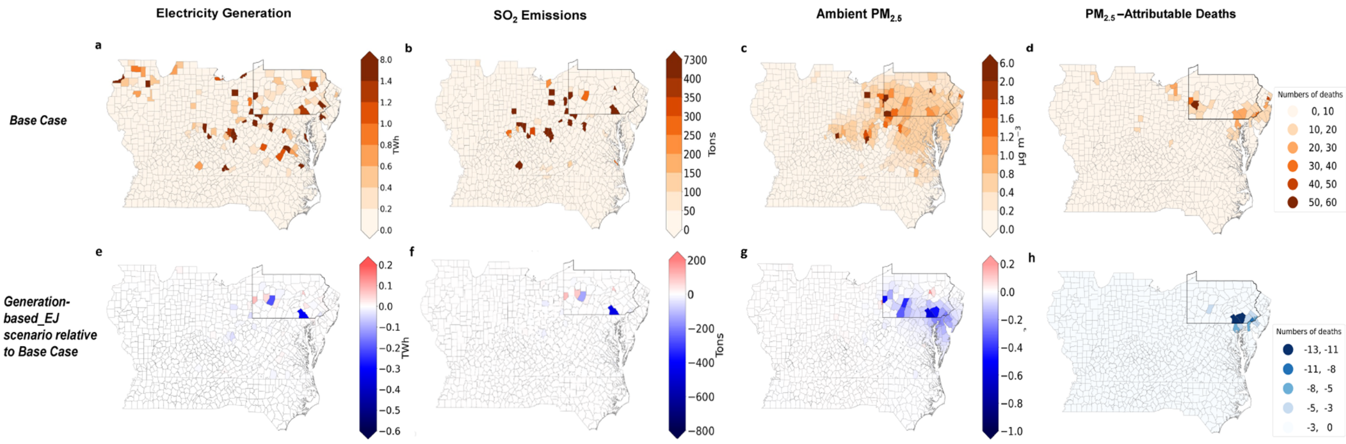


Figure 5. Geographical distribution of impacts. The first row provides results for the *Base Case*. The second row shows the changes in the *Generation-based_EJ* scenario relative to the *Base Case*. From left to right, the four columns depict county-level annual total electricity generation, annual total SO_2 emissions from power generation, simulated county-level annual average ambient $PM_{2.5}$ concentrations, and annual total $PM_{2.5}$-attributable deaths. SI2: Figures H.8 and I.9 provide results for other five scenarios SI2: Figures J.10 and K.11 report results for NO_x and primary $PM_{2.5}$ emissions for all scenarios.

such as transportation and residential, contribute additional pollution in this region.[10,42,43]

Although changes in precursor emissions are negative in some counties and positive in others depending on the scenario, almost all counties experience a reduction in ambient $PM_{2.5}$ concentrations and associated deaths relative to the *Base Case* (see SI2: Table B.2 for population-weighted annual average $PM_{2.5}$ concentrations by scenario). This is because retired coal plants are often more polluting than the generation that replaces them (such as natural gas), causing precursor emissions to fall in aggregate across PJM. Despite spatial variation in precursor emissions from retired and replacement generation predicted by RPAM and corresponding spatial variation in emissions arising from air pollution formation and transport via ISRM, the aggregate decline in precursor emissions dominates, leading to lower ambient $PM_{2.5}$ concentrations and associated deaths for most counties in southeastern PA.

Nonetheless, these complex linkages together with differences in sociodemographics that characterize pollution exposure across counties cumulatively determine the magnitude and distribution of avoided $PM_{2.5}$-attributable deaths (see SI2: Table C.3 for absolute changes in $PM_{2.5}$-attributable deaths relative to the *Base Case*). Of the six scenarios, *Capacity-based_Climate* reduces $PM_{2.5}$ concentrations and associated deaths the most: by 84 in PA (95% CI = 52−118) or 20% relative to the *Base Case*; Rest of PJM also observes a reduction of 52 $PM_{2.5}$-attributable deaths (95% CI = 41−85) or 5% relative to the *Base Case* (Figure 4b).

3.4. Insights on the Geographic Distribution of Impacts and Environmental Justice Communities. We find important spatial variation across PJM regarding the patterns of electricity generation, air pollutant emissions, ambient concentrations of $PM_{2.5}$, and $PM_{2.5}$-attributable deaths. We focus on the results for the *Generation-based_EJ* scenario (Figure 5) with results for the other scenarios in SI2: Figures H.8 and I.9. Under this scenario, the majority of health benefits in Rest of PJM occur in PA's southern neighbors Delaware, Maryland, and New Jersey. Thus, regional impacts are still largely determined by close proximity to PA's coal plant closures (see SI2: Figure L12 for an expanded air quality assessment that also includes states outside PJM).

To further understand the distributional implications of PA coal plant closures, we compare the health effects in EJ areas and non-EJ areas (Figure 6). To assess impacts in EJ areas outside of PA, we apply the PA DEP EJ area definition to census tracts in Rest of PJM. Because EJ areas are defined at the census tract level, we perform the health impact assessment at the census tract-level using gridded $PM_{2.5}$ concentrations from ISRM. As some census tracts are smaller than ISRM grids, we are unable to identify exposure disparities across different census tracts in these circumstances.

For "Capacity-based" scenarios, we find that the *Climate* scenario provides the largest overall reduction as well as the largest benefit to EJ areas, driven again by the largest reduction in coal power generation from the same capacity retirement. In comparison, for "Generation-based" scenarios, we find that the *EJ* scenario provides the largest overall reduction in deaths as well as the largest benefit to EJ areas. In particular, 61% of the avoided deaths occur within 10 miles from coal plant closures (the relevant distance based on our scenario design), of which 77% occur within EJ areas (SI2: Figure E.5). This result demonstrates potential equity-improving outcomes by prioritizing EJ areas in coal retirement decisions. While the *EJ* scenarios do not consider constraints to "safeguard" EJ areas in Rest of PJM from experiencing worse exposure outcomes, we observe distributional cobenefits to these areas. This result is largely driven by the unique spatial feature that the EJ areas outside PA happen to be downwind of some retired plants, suggesting that cross-regional linkages may impact distributional impacts outside PA too.

We further consider sensitivity in concentration−response coefficients (β) as one of the largest sources of uncertainty in health assessment.[44−46] Using higher or lower values for β increases and decreases the level of avoided deaths, respectively, yet we observe similar patterns in terms of the spatial distribution of health benefits in PA and Rest of PJM as well as in EJ and non-EJ areas.

Finally, recognizing that closing plants based on their proximity to EJ areas may not protect the largest number of vulnerable people, we also investigate the sensitivity of EJ scenario design by (i) varying the radius (15, 20, and 25 miles in addition to 10 miles in the main EJ scenarios) and (ii) considering the population size of EJ areas instead of the number

https://doi.org/10.1021/acs.est.4c00704
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

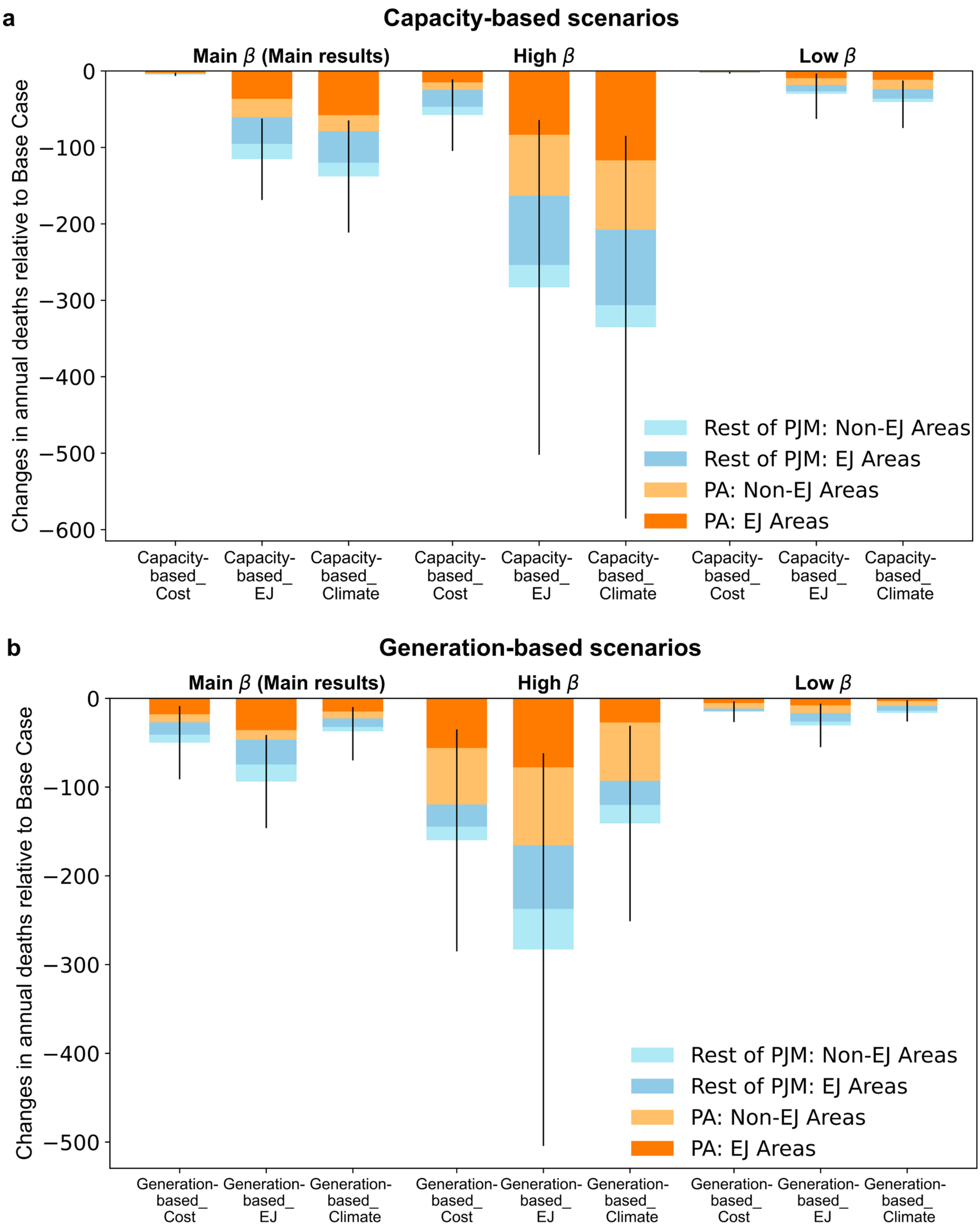


Figure 6. Sensitivity analysis using different concentration−response coefficients (β). (a and b) Reduction in deaths for "Capacity-based" scenarios and "Generation-based" scenarios, respectively. We show the estimates based on the concentration−response coefficients in Krewski et al. (2009, main β),[39] Laden et al. (2006, high β),[40] and Thurston et al. (2016, low β).[41] Here, we categorize census tracts based on their location (PA vs Rest of PJM) and if they are EJ areas or non-EJ areas. We apply PA DEP's EJ Area definition to the census tracts outside the state to define non-EJ areas in Rest of PJM. Error bars show the 95% confidence interval of the concentration−response coefficients.

of census tracts that are defined by PA DEP as EJ areas. We find the main pattern of retirements is not sensitive to the radius choice despite some minor differences in plant retirements (SI2: Figure C.3). Using population size instead of number of EJ areas, we find these scenarios generate more diffuse unit closures, suggesting that the geographical unit of aggregation is important for assessing distributional impacts (SI2: Figure D.4).

4. DISCUSSION

We find that reducing coal capacity and generation in Pennsylvania would improve regional air quality and reduce premature deaths and that the distribution of these benefits depends on the targets and priorities set for power plant retirements. For example, among scenarios that use reduced capacity targets, retiring plants by their CO_2 intensity would

https://doi.org/10.1021/acs.est.4c00704
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

result in the largest shift in the composition of fuels used for energy generation—away from coal in PA and toward natural gas in Rest of PJM. This, in turn, generates the largest net CO_2 benefits under a "Capacity-based" reduction target. Alternatively, among scenarios that use reduced generation targets, retiring plants by marginal cost of operation would result in the largest shift in the composition of fuels—away from both coal and natural gas in PA and toward natural gas and, to a lesser extent, additional coal in Rest of PJM. Yet, the largest net CO_2 benefits under a "Generation-based" reduction target result from the scenario that prioritizes retirements near EJ census tracts. This is due to a smaller increase in natural gas generation in Rest of PJM in response to plant closures in PA.

Combining these fuel composition changes and the effects of pollution transport and population exposure, the air quality and health impacts also vary by retirement targets and priorities. We find that the largest reduction in deaths among "Capacity-based" scenarios comes from prioritizing retirements by CO_2 emissions, and the largest reduction in deaths among generation-based scenarios comes from prioritizing retirements by proximity to EJ census tracts. Furthermore, we find complex distributional implications for air quality and health. Geographically, among the EJ scenarios that we tested, more of these health benefits are found in EJ areas, highlighting the additional equity benefits achieved by placing vulnerable communities at the center of energy decision making. In addition, many of the air quality improvements occur in southern and eastern PA and neighboring states such as NJ and DE, suggesting that regional analysis is necessary for assessing air quality impacts of low-carbon energy transitions. Thus, it is important for regional transmission organizations and federal regulators to look beyond reliability rules that largely guide current coal retirement decisions[47] and start to consider electricity market operations and resulting air quality and health impacts as additional considerations for plant closures.

Notably, our results are driven by a few key features of PA and the PJM grid, including (i) spatial relationship between coal plant locations and population settlements, especially EJ communities (see SI2: Figure B.2), (ii) the characteristics of existing power plants and the transmission grid, and (iii) the wind transport pattern of the region. While our quantitative conclusions may not be generalizable, the underlying interconnected factors and the importance of considering plant closure targets and priorities are likely to be relevant to other regions and decision makers.

Finally, we highlight a few areas for future work. First, how can modeling frameworks be improved to assess finer scale decisions, impacts, and disparities? While our analysis focuses on annual aggregate impacts due to the time step of RPAM, a finer temporal resolution would be useful to understand power dispatch and transmission decisions, short-term pollution events, and acute health impacts such as morbidity and hospital admissions. Further, our current approach involves a one-way coupling from energy to air quality and then to health. Thus, our model takes predesigned scenarios that do not optimize the energy system to achieve health or equity objectives. Future research that optimizes coal retirement decisions based on aggregate health impacts, environmental improvements, or protections for the most vulnerable populations would provide valuable policy insights.[8,48] Second, how will coal retirement decisions interact with other trends in electricity and end-use sectors to collectively shape air quality and health outcomes? While we focus only on coal retirements in PA, increased renewable penetration and accelerated adoption of electric vehicles, heat pumps, and other energy efficient durable goods may significantly alter future electricity and energy consumption with difficult-to-predict impacts on air quality and health. Third, how do varying sources of uncertainty influence environmental impact assessment? Uncertainties exist in the energy system (policy implementation, behavioral response, future technology choices, etc.),[49−51] air quality modeling (chemical and physical transport processes, spatial distribution of different groups, etc.),[52−54] and health impact assessment (baseline health conditions, health attributes of different groups, etc.).[55,56] In addition, here, we conducted a simple monetization of health impacts (SI2: Tables F.6 and G.7) and the operational costs of the PJM electricity grid (SI2: Table E.5). Extending this analysis to conduct a comprehensive equity and cost-benefit assessment that includes climate damages, sunk capital costs, and broader economy-wide socioeconomic impacts of coal retirement may be a useful direction for future research.

In conclusion, shifts in U.S. electricity production demand a careful analysis of transitions in key states like PA and across wholesale electricity markets such as the PJM Interconnection. Using energy systems and health impact modeling, this study explores the consequences of retiring coal-fired power plants in PA. Natural gas often replaces coal, reducing overall air pollution. Spatial analysis highlights air pollution variation, emphasizing the need for preretirement impact assessments to understand the potential economic and distributional effects of plant closures in the region.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.4c00704.

RGGI + PJM Policy Analysis Model documentation; methods information, scenario design, additional results, sensitivity analysis, cost analysis, and supplementary data (PDF)

■ AUTHOR INFORMATION

Corresponding Authors

Emily L. Pakhtigian − *School of Public Policy, The Pennsylvania State University, University Park, Pennsylvania 16802, United States*; Email: emilypakhtigian@psu.edu

Wei Peng − *School of Public and International Affairs and Andlinger Center for Energy and the Environment, Princeton University, Princeton, New Jersey 08540, United States*; orcid.org/0000-0002-1980-0759; Email: weipeng@princeton.edu

Authors

Carla Campos Morales − *Department of Civil and Environmental Engineering, The Pennsylvania State University, University Park, Pennsylvania 16802, United States; School of Public and International Affairs and Andlinger Center for Energy and the Environment, Princeton University, Princeton, New Jersey 08540, United States*

Joel R. Landry − *College of Earth and Mineral Sciences, The Pennsylvania State University, University Park, Pennsylvania 16802, United States;* Present Address: CNA, Arlington, Virginia 22201, United States

Hannah Wiseman − *Penn State Law, The Pennsylvania State University, University Park, Pennsylvania 16802, United States*

An T. Pham − *School for Environment and Sustainability, University of Michigan, Ann Arbor, Michigan 48109, United States*

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.4c00704

Author Contributions

‖C.C.M. and E.L.P.: These authors contributed equally.

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This work was supported by a grant from the Pennsylvania State University Institutes of Energy and the Environment. C.C.M. and W.P. also received funding support from the Penn State College of Engineering and Princeton's Andlinger Center for Energy and the Environment. Stuart Vas and Anna Lee provided excellent research assistance.

REFERENCES

(1) Linn, J.; McCormack, K. The Roles of Energy Markets and Environmental Regulation in Reducing Coal-fired Plant Profits and Electricity Sector Emissions. *RAND Journal of Economics* **2019**, *50* (4), 733−767.

(2) *Electricity explained*. U.S. Energy Information Administration (EIA), https://www.eia.gov/energyexplained/electricity/ (accessed 2023−06−09).

(3) *U.S. Energy Information Administration-EIA-Independent Statistics and Analysis*. https://www.eia.gov/state/analysis.php?sid=PA#55 (accessed 2023−06−22).

(4) Landry, J. R.; Pham, A. T.; Blumsack, S. A. *Understanding The Direct and Strategic Effects Voluntary Entry into Regional Cap and Trade Systems*; https://drive.google.com/file/d/1SgLfBHHYmPg2Tx9ukB82_SQ6ODTYOv_X/view (accessed 2024−05−07).

(5) Blumsack, S.; Andrew, B.; Mingsong, C.; Seamus, G.; Landry, J.; Daniel, M.; Wei, P.; An, P.; Daniel, W.; Hui, Y. *Prospects for Pennsylvania in the Regional Greenhouse Gas Initiative* 2021, https://celp.psu.edu/projects/rggi/.

(6) *Coal and the environment*; U.S. Energy Information Administration (EIA), https://www.eia.gov/energyexplained/coal/coal-and-the-environment.php (accessed 2023−06−09).

(7) Filonchyk, M.; Peterson, M. P. An Integrated Analysis of Air Pollution from US Coal-Fired Power Plants. *Geoscience Frontiers* **2023**, *14* (2), 101498.

(8) Mayfield, E. N. Phasing out Coal Power Plants Based on Cumulative Air Pollution Impact and Equity Objectives in Net Zero Energy System Transitions. *Environ. Res.: Infrastruct. Sustain.* **2022**, *2* (2), 021004.

(9) Fan, M.; Wang, Y. The Impact of PM2.5 on Mortality in Older Adults: Evidence from Retirement of Coal-Fired Power Plants in the United States. *Environ. Health* **2020**, *19* (1), 28.

(10) Fann, N.; Fulcher, C. M.; Baker, K. The Recent and Future Health Burden of Air Pollution Apportioned Across U.S. Sectors. *Environ. Sci. Technol.* **2013**, *47* (8), 3580−3589.

(11) Fann, N.; Fulcher, C. M.; Hubbell, B. J. 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* **2009**, *2* (3), 169−176.

(12) Thind, M. P. S.; Tessum, C. W.; Azevedo, I. L.; Marshall, J. D. Fine Particulate Air Pollution from Electricity Generation in the US: Health Impacts by Race, Income, and Geography. *Environ. Sci. Technol.* **2019**, *53* (23), 14010−14019.

(13) Martenies, S. E.; Akherati, A.; Jathar, S.; Magzamen, S. Health and Environmental Justice Implications of Retiring Two Coal-Fired Power Plants in the Southern Front Range Region of Colorado. *GeoHealth* **2019**, *3* (9), 266−283.

(14) Henneman, L. R. F.; Rasel, M. M.; Choirat, C.; Anenberg, S. C.; Zigler, C. Inequitable Exposures to U.S. Coal Power Plant−Related PM2.5:22 Years and Counting. *Environ. Health Perspect* **2023**, *131* (3), 037005.

(15) Polonik, P.; Ricke, K.; Reese, S.; Burney, J. Air Quality Equity in US Climate Policy. *Proc. Natl. Acad. Sci. U.S.A.* **2023**, *120* (26), No. e2217124120.

(16) Goforth, T.; Nock, D. Air Pollution Disparities and Equality Assessments of US National Decarbonization Strategies. *Nat. Commun.* **2022**, *13* (1), 7488.

(17) Dimanchev, E. G.; Paltsev, S.; Yuan, M.; Rothenberg, D.; Tessum, C. W.; Marshall, J. D.; Selin, N. E. Health Co-Benefits of Sub-National Renewable Energy Policy in the US. *Environ. Res. Lett.* **2019**, *14* (8), 085012.

(18) Deetjen, T. A.; Azevedo, I. L. Climate and Health Benefits of Rapid Coal-to-Gas Fuel Switching in the U.S. Power Sector Offset Methane Leakage and Production Cost Increases. *Environ. Sci. Technol.* **2020**, *54* (18), 11494−11505.

(19) Bin Thaneya, A.; Horvath, A. Exploring Regional Fine Particulate Matter ($PM_{2.5}$) Exposure Reduction Pathways Using an Optimal Power Flow Model: The Case of the Illinois Power Grid. *Environ. Sci. Technol.* **2023**, *57* (21), 7989−8001.

(20) Sergi, B. J.; Adams, P. J.; Muller, N. Z.; Robinson, A. L.; Davis, S. J.; Marshall, J. D.; Azevedo, I. L. Optimizing Emissions Reductions from the U.S. Power Sector for Climate and Health Benefits. *Environ. Sci. Technol.* **2020**, *54* (12), 7513−7523.

(21) Luo, Q.; Copeland, B.; Garcia-Menendez, F.; Johnson, J. X. Diverse Pathways for Power Sector Decarbonization in Texas Yield Health Cobenefits but Fail to Alleviate Air Pollution Exposure Inequities. *Environ. Sci. Technol.* **2022**, *56* (18), 13274−13283.

(22) Yang, H.; Pham, A. T.; Landry, J. R.; Blumsack, S. A.; Peng, W. Emissions and Health Implications of Pennsylvania's Entry into the Regional Greenhouse Gas Initiative. *Environ. Sci. Technol.* **2021**, *55* (18), 12153−12161.

(23) Hernandez-Cortes, D.; Meng, K. C. Do Environmental Markets Cause Environmental Injustice? Evidence from California's Carbon Market. *Journal of Public Economics* **2023**, *217*, 104786.

(24) Peng, W.; Ou, Y. Integrating Air Quality and Health Considerations into Power Sector Decarbonization Strategies. *Environ. Res. Lett.* **2022**, *17* (8), 081002.

(25) *PA Environmental Justice Areas*. Department of Environmental Protection. https://www.dep.pa.gov:443/PublicParticipation/OfficeofEnvironmentalJustice/Pages/PA-Environmental-Justice-Areas.aspx (accessed 2023−06−15).

(26) *Welcome | RGGI, Inc.* https://www.rggi.org/ (accessed 2023−06−22).

(27) Kerl, P. Y.; Zhang, W.; Moreno-Cruz, J. B.; Nenes, A.; Realff, M. J.; Russell, A. G.; Sokol, J.; Thomas, V. M. New Approach for Optimal Electricity Planning and Dispatching with Hourly Time-Scale Air Quality and Health Considerations. *Proc. Natl. Acad. Sci. U. S. A.* **2015**, *112* (35), 10884−10889.

(28) Goodkind, A. L.; Tessum, C. W.; Coggins, J. S.; Hill, J. D.; Marshall, J. D. Fine-Scale Damage Estimates of Particulate Matter Air Pollution Reveal Opportunities for Location-Specific Mitigation of Emissions. *Proc. Natl. Acad. Sci. U.S.A.* **2019**, *116* (18), 8775−8780.

(29) Wang, Y.; Apte, J. S.; Hill, J. D.; Ivey, C. E.; Patterson, R. F.; Robinson, A. L.; Tessum, C. W.; Marshall, J. D. Location-Specific Strategies for Eliminating US National Racial-Ethnic PM2.5 Exposure Inequality. *Proc. Natl. Acad. Sci. U.S.A.* **2022**, *119* (44), No. e2205548119.

(30) Bin Thaneya, A. S.; Apte, J.; Horvath, A. A Human Exposure-Based Traffic Assignment Model for Minimizing Fine Particulate Matter ($PM_{2.5}$) Intake from on-Road Vehicle Emissions. *Environ. Res. Lett.* **2022**, *17* (7), 074034.

(31) *Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE)*; U.S. EPA, https://www.epa.gov/benmap (accessed 2023−06−15).

(32) Sacks, J. D.; Lloyd, J. M.; Zhu, Y.; Anderton, J.; Jang, C. J.; Hubbell, B.; Fann, N. The Environmental Benefits Mapping and Analysis Program − Community Edition (BenMAP−CE): A Tool to Estimate the Health and Economic Benefits of Reducing Air Pollution. *Environmental Modelling & Software* **2018**, *104*, 118−129.

(33) Mirzaei, A.; Tahriri, H.; Khorsandi, B. Comparison between AirQ+ and BenMAP-CE in Estimating the Health Benefits of PM2.5 Reduction. *Air Qual Atmos Health* **2021**, *14* (6), 807−815.

(34) Yang, P.; Zhang, Y.; Wang, K.; Doraiswamy, P.; Cho, S.-H. Health Impacts and Cost-Benefit Analyses of Surface O3 and PM2.5 over the U.S. under Future Climate and Emission Scenarios. *Environmental Research* **2019**, *178*, 108687.

(35) Fann, N.; Risley, D. The Public Health Context for PM2.5 and Ozone Air Quality Trends. *Air Qual Atmos Health* **2013**, *6* (1), 1−11.

(36) Punger, E. M.; West, J. J. The Effect of Grid Resolution on Estimates of the Burden of Ozone and Fine Particulate Matter on Premature Mortality in the USA. *Air Qual Atmos Health* **2013**, *6* (3), 563−573.

(37) Li, Y.; Henze, D. K.; Jack, D.; Kinney, P. L. The Influence of Air Quality Model Resolution on Health Impact Assessment for Fine Particulate Matter and Its Components. *Air Qual Atmos Health* **2016**, *9* (1), 51−68.

(38) *BenMAP-CE Manual and Appendices*; ; U.S. EPA, https://www.epa.gov/benmap/benmap-ce-manual-and-appendices (accessed 2023−06−15).

(39) Krewski, D.; Jerrett, M.; Burnett, R. T.; Ma, R.; Shi, Y.; Turner, M. C.; Pope, C. A., III; Thurston, G.; Calle, E. E.; Thun, M. J. Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality. *Research Report 140*; Health Effects Institute, 2009.

(40) Laden, F.; Schwartz, J.; Speizer, F. E.; Dockery, D. W. Reduction in Fine Particulate Air Pollution and Mortality: Extended Follow-up of the Harvard Six Cities Study. *Am. J. Respir Crit Care Med.* **2006**, *173* (6), 667−672.

(41) Thurston, G. D.; Ahn, J.; Cromar, K. R.; Shao, Y.; Reynolds, H. R.; Jerrett, M.; Lim, C. C.; Shanley, R.; Park, Y.; Hayes, R. B. Ambient Particulate Matter Air Pollution Exposure and Mortality in the NIH-AARP Diet and Health Cohort. *Environ. Health Perspect* **2016**, *124* (4), 484−490.

(42) Russell, M. C.; Belle, J. H.; Liu, Y. The Impact of Three Recent Coal-Fired Power Plant Closings on Pittsburgh Air Quality: A Natural Experiment. *J. Air Waste Manage. Assoc.* **2017**, *67* (1), 3−16.

(43) Tessum, C. W.; Apte, J. S.; Goodkind, A. L.; Muller, N. Z.; Mullins, K. A.; Paolella, D. A.; Polasky, S.; Springer, N. P.; Thakrar, S. K.; Marshall, J. D.; Hill, J. D. Inequity in Consumption of Goods and Services Adds to Racial−Ethnic Disparities in Air Pollution Exposure. *Proc. Natl. Acad. Sci. U.S.A.* **2019**, *116* (13), 6001−6006.

(44) Kodros, J. K.; Carter, E.; Brauer, M.; Volckens, J.; Bilsback, K. R.; L'Orange, C.; Johnson, M.; Pierce, J. R. Quantifying the Contribution to Uncertainty in Mortality Attributed to Household, Ambient, and Joint Exposure to $PM_{2.5}$ From Residential Solid Fuel Use. *GeoHealth* **2018**, *2* (1), 25−39.

(45) Burnett, R.; Cohen, A. Relative Risk Functions for Estimating Excess Mortality Attributable to Outdoor PM2.5 Air Pollution: Evolution and State-of-the-Art. *Atmosphere* **2020**, *11* (6), 589.

(46) Burnett, R. T.; Pope, C. A.; Ezzati, M.; Olives, C.; Lim, S. S.; Mehta, S.; Shin, H. H.; Singh, G.; Hubbell, B.; Brauer, M.; Anderson, H. R.; Smith, K. R.; Balmes, J. R.; Bruce, N. G.; Kan, H.; Laden, F.; Prüss-Ustün, A.; Turner, M. C.; Gapstur, S. M.; Diver, W. R.; Cohen, A. An Integrated Risk Function for Estimating the Global Burden of Disease Attributable to Ambient Fine Particulate Matter Exposure. *Environ. Health Perspect* **2014**, *122* (4), 397−403.

(47) *Ensuring a Reliable Energy Transition*; PJM, https://www.pjm.com/about-pjm/ensuring-a-reliable-energy-transition (accessed 2023−12−12).

(48) Heleno, M.; Sigrin, B.; Popovich, N.; Heeter, J.; Jain Figueroa, A.; Reiner, M.; Reames, T. Optimizing Equity in Energy Policy Interventions: A Quantitative Decision-Support Framework for Energy Justice. *Applied Energy* **2022**, *325*, 119771.

(49) Bridges, A.; Felder, F. A.; McKelvey, K.; Niyogi, I. Uncertainty in Energy Planning: Estimating the Health Impacts of Air Pollution from Fossil Fuel Electricity Generation. *Energy Research & Social Science* **2015**, *6*, 74−77.

(50) Bistline, J. E. Electric Sector Capacity Planning under Uncertainty: Climate Policy and Natural Gas in the US. *Energy Economics* **2015**, *51*, 236−251.

(51) Bistline, J. E. Natural Gas, Uncertainty, and Climate Policy in the US Electric Power Sector. *Energy Policy* **2014**, *74*, 433−442.

(52) Molitor, J.; Jerrett, M.; Chang, C.-C.; Molitor, N.-T.; Gauderman, J.; Berhane, K.; McConnell, R.; Lurmann, F.; Wu, J.; Winer, A.; Thomas, D. Assessing Uncertainty in Spatial Exposure Models for Air Pollution Health Effects Assessment. *Environ. Health Perspect.* **2007**, *115* (8), 1147−1153.

(53) Özkaynak, H.; Frey, H. C.; Burke, J.; Pinder, R. W. Analysis of Coupled Model Uncertainties in Source-to-Dose Modeling of Human Exposures to Ambient Air Pollution: A PM2.5 Case Study. *Atmos. Environ.* **2009**, *43* (9), 1641−1649.

(54) Gerharz, L. E.; Klemm, O.; Broich, A. V.; Pebesma, E. Spatio-Temporal Modelling of Individual Exposure to Air Pollution and Its Uncertainty. *Atmos. Environ.* **2013**, *64*, 56−65.

(55) Mesa-Frias, M.; Chalabi, Z.; Vanni, T.; Foss, A. M. Uncertainty in Environmental Health Impact Assessment: Quantitative Methods and Perspectives. *International Journal of Environmental Health Research* **2013**, *23* (1), 16−30.

(56) Briggs, D. J.; Sabel, C. E.; Lee, K. Uncertainty in Epidemiology and Health Risk and Impact Assessment. *Environ. Geochem Health* **2009**, *31* (2), 189−203.