Designing retirement strategies for coal-fired power plants to mitigate air pollution and health impacts

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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 the Rest of PJM region, leading to scenario-varying changes in the plant-level release of air pollutants. Considering pollution transport and size of the exposed population, these emissions changes, in turn, give rise to a reduction of 6 to 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 socio-demographics in designing equitable retirement strategies.

Keywords: Coal retirement, air quality, human health, environmental justice

Synopsis

Retiring coal power plants in Pennsylvania can improve air quality and health outcomes throughout the PJM Interconnection.

1. Introduction

The U.S. is in the midst of a significant energy transition. The last 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 socio-demographics influence the distribution of health impacts is fairly limited. PA provides a distinctive setting to examine such linkages. First, PA is a major power exporter in the PJM Interconnection, a Regional Transmission Organization that manages a wholesale electricity market spanning thirteen states which 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 provide an avenue to also improve air quality in downwind states.[23,24] These complex dynamics and resulting distributional outcomes are not 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 tradeoffs between aggregate and distributional effects across different coal plant retirement strategies.

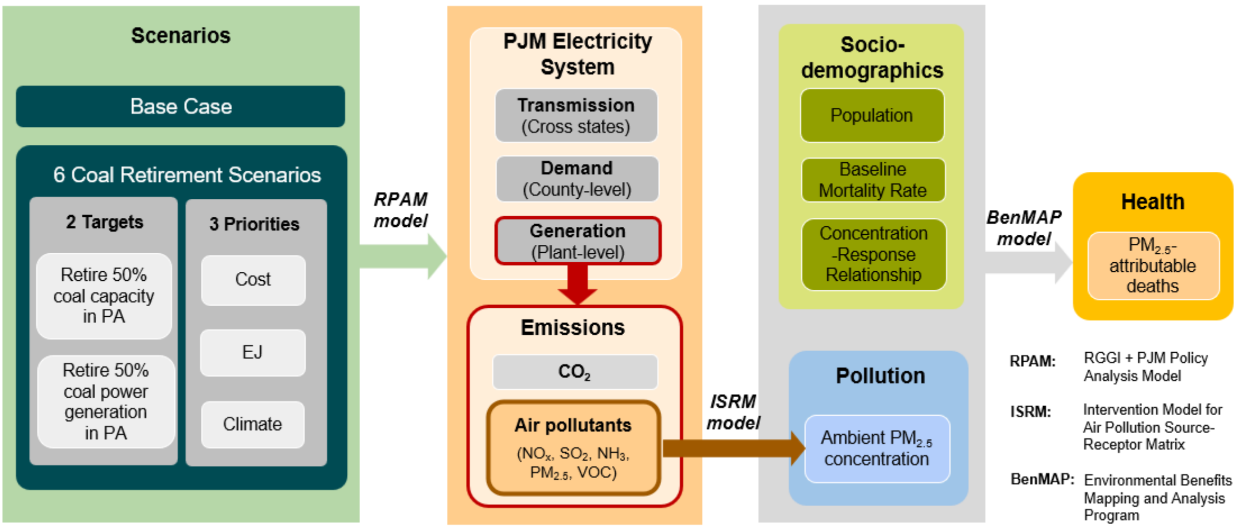

Figure 1. Schematic diagram of our modeling framework and coal retirement scenarios.

2. Methodology

2.1 Scenario design

Based on the 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 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 file, SI2: Section I.A and I.B (including Figure A.1 and Table A.1).

Table 1. Summary of scenarios

Scenario Name		Explanations	
Base Case		All coal power plants active based on actual 2019 generation	
		Target	**Priority**
Retirement Scenarios	*Capacity-based_Cost*	**Capacity-based retirement**: Method: 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 the revisions to the Environmental Justice Policy Method: * Plants with the largest number of EJ Areas** 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 retirement**: Method: Retire ~50% of total coal power generation in PA	Same above
	Generation-based_EJ		
	Generation-based_Climate		

** 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).*
*** 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 non-white minority.*[25]

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 region (see Supporting Information 1 (SI1) for detailed model description and validation).

RPAM is a multi-market 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 datasets 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 datasets used to calibrate and estimate RPAM come from several dozen datasets (SI1: Section II) including from PJM Interconnection, S&P Global, EP, EIA, and 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 total welfare implications distinguishes the RPAM model from other electricity dispatch models that typically only considers the physical cost.[18,20,21,27]

RPAM is solved on an annual time-step from 2016 to 2019. This analysis focuses on 2019, including the Base Case that 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 sub-region. 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 one 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 the PJM region. The grid resolution increases with population density, ranging from 1km x 1km in densely populated urban areas to 48 km x 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 the smokestack height of coal power plants in PA (see SI2: Figure F.6), we use high smokestack height (>379m) 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*:

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

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 $f_{(a,p)-b}$ is the relationship between annual total emissions 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 one ton. Thus, it generates a vector, $f_{(a,p)}$, representing impacts on all N receptors; the b^{th} component of this vector is denoted $f_{(a,p)-b}$. The total change in ambient $PM_{2.5}$ concentration ($\mu g/m^3$) at location *b* is the aggregate impact from all precursor emissions and 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 using multiple ISRM grids. For the geographic analysis in 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:

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

Table 2. Summary of input data for the health impact assessment

Variable*	Definition	Data Source
$\boldsymbol{Y_0}$	All-cause baseline mortality rate for 2019	Center for Disease Control (CDC) WONDER database.
$\boldsymbol{Pop}$	Population in 2019	2010 U.S. Census Bureau census block data with projection to 2019
$\boldsymbol{\beta}$	Concentration-Response coefficient from epidemiological studies. Changes in mortality risk resulting from changes in $PM_{2.5}$ exposure level	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]
$\boldsymbol{\Delta PM}$	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

* For more detailed information on these variables, see the BenMAP manual.[38]

** For additional information on sensitivity analyses using other concentration-response functions and β values, see Figure 6 and SI2: Section IV.

3. Results

3.1 Impacts on electricity generation

Coal-fired power plants account for 13% and 12% of total generation in PA and the 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 by 2.1 TWh, 13 TWh, 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 utilization rates.

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.

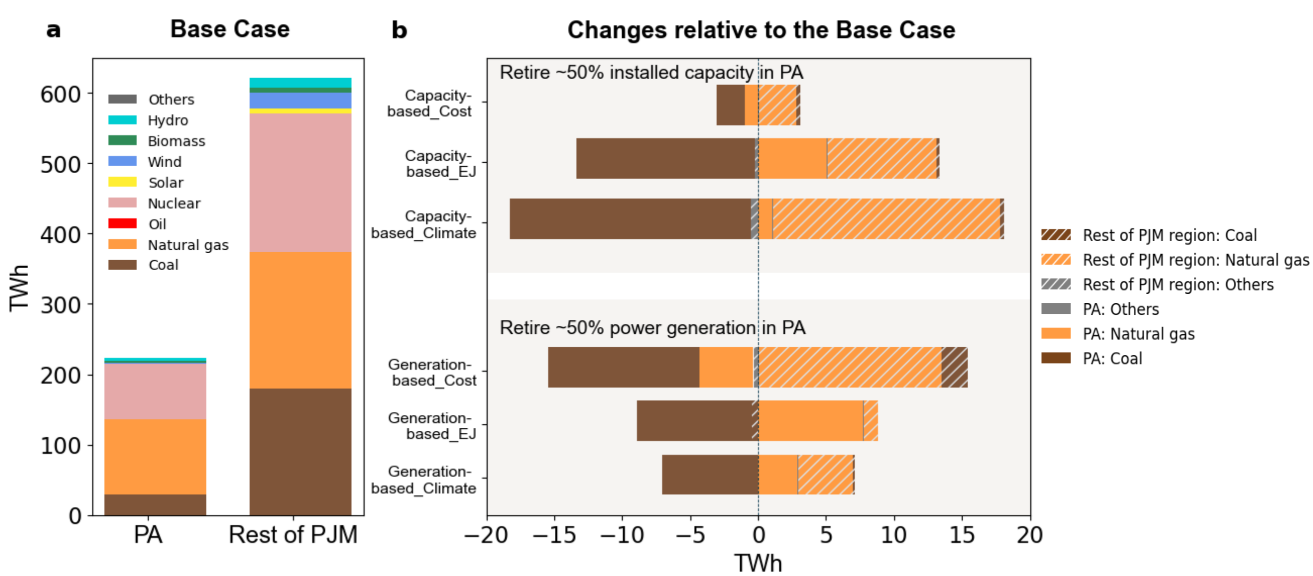

Figure 2. Electricity generation (TWh) by fuel source. Panel (a) depicts *Base Case* electricity generation in PA and Rest of PJM. Panel (b) reports changes in generation relative to the *Base Case* for the six scenarios in PA and Rest of PJM by power plant source (Coal, Natural Gas, and Others). "Others"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

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 the PJM region to be 426 million tons, 206 thousand tons, 187 thousand tons, and 38 thousand tons, respectively, of which 17 to 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 Figure 3c). As noted above, changes in the spatial pattern of precursor emissions follow from changes in power generation which, in turn, through ISRM, correspond to changes in the spatial pattern of receptor emissions. 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 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 Figure 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).

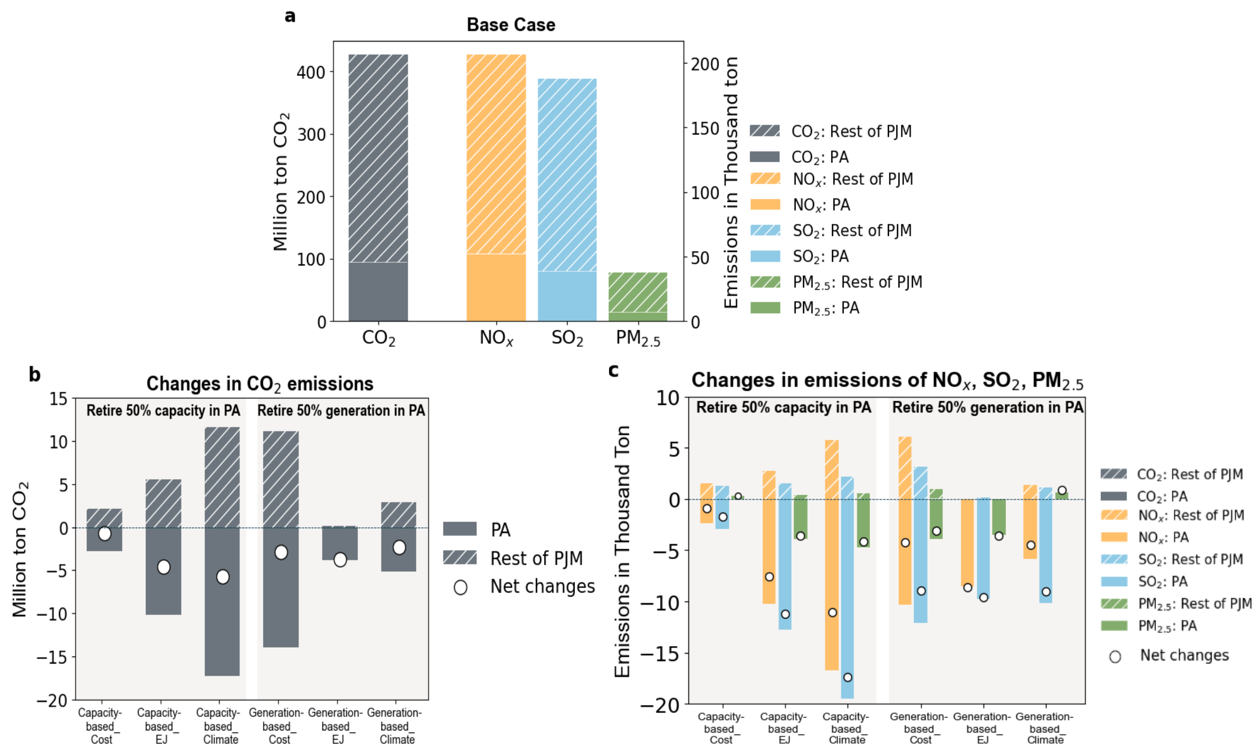

Figure 3. Annual total emissions of CO_2, NO_x, SO_2, and $PM_{2.5}$ from all power plants located in PA and Rest of PJM. Panel (a) reports emissions under the *Base Case*; Panels (b) and (c) show the changes in CO_2 and criteria air pollutants in each of the six retirement scenarios relative to the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

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 μg/m^3 across PJM counties, which is associated with 1,300 $PM_{2.5}$-attributable deaths annually (95% confidence interval: 1,200 to 1,600) (Figure 4a). The low concentration level results from estimating the effects only from power sector emissions, while other sectors, 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 receptor 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 socio-demographics 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 to 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 to 85) or 5% relative to the *Base Case* (Figure 4b).

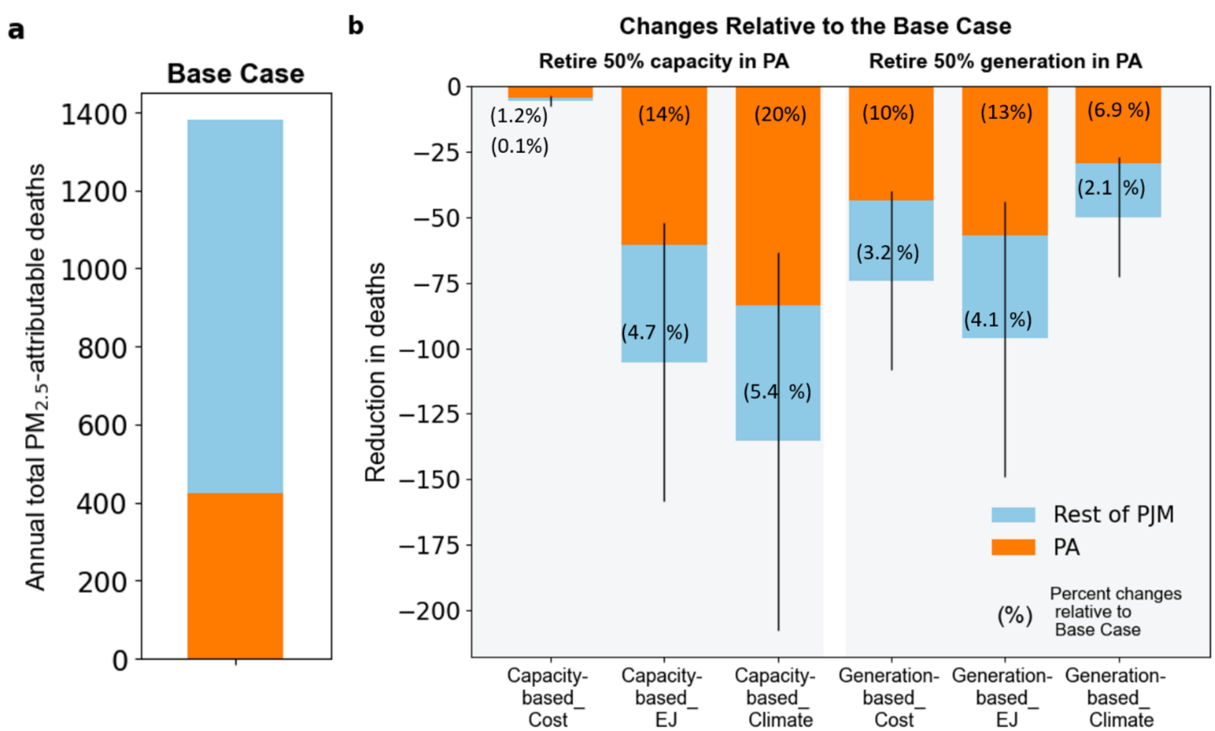

Figure 4. Annual total $PM_{2.5}$-attributable deaths from power sector emissions in the *Base Case* (Panel a) and the changes in the six coal retirement scenarios relative to the *Base Case* in PA and Rest of PJM (Panel b). Here we use the concentration-response coefficients from Krewski et al., 2009.[39]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

3.4 Insights on geographic distribution and environmental justice communities

We find important spatial variation across the PJM region 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-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 coal plant closures (see SI2: Figure L.12) for an expanded air quality assessment that also includes states outside PJM).

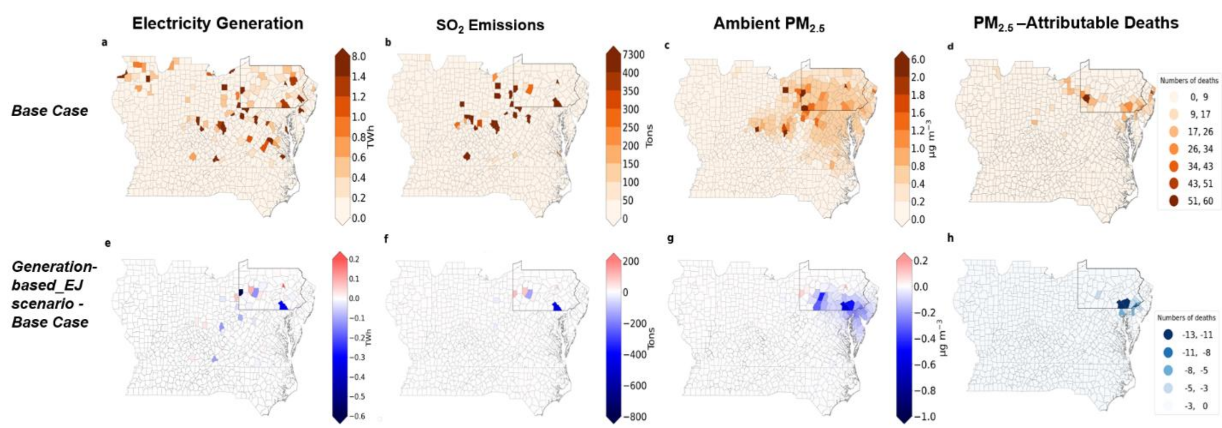

Figure 5. Geographical distribution of impacts. The first row provides results for the *Base Case*; The second row shows the changes in the *Generation-based_EJ* scenario relative to the *Base Case*. From left to right, the four columns depict county-level annual total electricity generation, annual 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, and SI2: Figures J.10 and K.11 report results for NO_x and Primary $PM_{2.5}$ emissions for all scenarios.

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 the 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 co-benefits in these areas. This result is largely driven by the unique feature that the EJ Areas outside PA happen to be the downwind areas of some retired plants, suggesting that cross-regional linkages may impact distributional impacts outside PA too.

We further consider sensitivity in concentration-response coefficients ($\boldsymbol{\beta}$), as one of the largest sources of uncertainty in health assessment[44–46]. Using higher or lower values for $\boldsymbol{\beta}$ increases and decreases the level of reduced 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 its 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 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 that scenarios generate more diffuse unit closures, suggesting that the geographical unit of aggregation is important for assessing distributional impacts (SI2: Figure D.4).

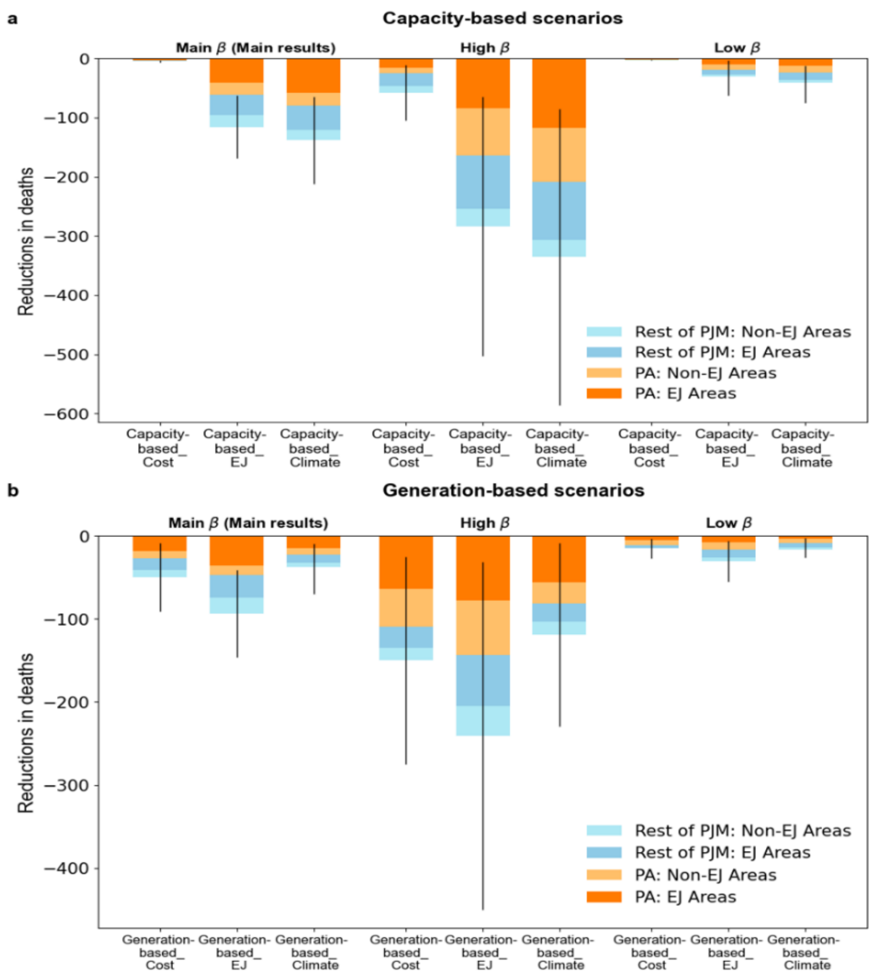

Figure 6. Sensitivity analysis using different concentration-response coefficients (β) Panel a and b show the reduction in deaths for "Capacity-based" scenarios and "Generation-based" scenarios, respectively. We show the estimates based on the concentration-response coefficients in Krewski et al. 2009 (main β)[39], Laden et al. 2006 (high β)[40], 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. Error bars show the 95% confidence interval of the concentration-response coefficients.

4. Discussion

We find that reducing coal capacity and generation in Pennsylvania would improve regional air quality and reduce premature deaths; 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 CO_2 emissions would result in the largest shift in the composition of fuels used for energy generation—away from coal in PA and towards natural gas in Rest of PJM. This, in turn, generates the largest net CO_2 benefits under a capacity-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 towards natural gas, and, to a lesser extent, additional coal in Rest of PJM. Yet, the largest net CO_2 benefits under a generation-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-oriented scenarios that we tested, more of these health benefits are found in EJ Areas, highlighting the additional equity benefits by placing vulnerable communities at the center of energy decision making. In addition, many of the air quality improvements occur in southern and eastern Pennsylvania 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 the current coal retirement decisions,[47] and start to consider the 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 PJM grid, including: i) the spatial relationship between where coal plants locate and where EJ communities live (see SI2: Figure B.2), ii) the characteristics of existing power plants and transmission grid, and iii) the wind transport pattern of the region. While our quantitative conclusions may not be generalizable, the key underlying 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 pre-designed scenarios that do not optimize the energy system to achieve health or equity objectives. Future research that optimizes scenario design 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 modelling (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 monetize air quality and health impacts (SI2: Table F.6 and Table G.7) and changes in operational costs across PJM (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 grid regions like 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 variations, emphasizing the need for pre-retirement impact assessments to estimate the economic and distributional effects of plant closures in the region.

Supporting Information

Supporting Information 1: RGGI + PJM Policy Analysis Model documentation

Supporting Information 2: Methods information, scenario design, additional results (tables and figures), sensitivity analysis, cost analysis

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