Air quality and health impacts of potential nuclear electricity generator closures in Pennsylvania and Ohio

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Summary

Air pollution is a major burden to human health, and electricity generation is a major source of air pollution. Nuclear electricity generators do not emit significant amounts of air pollution during operation. Within the area governed by the PJM electrical interconnection, three currently operating nuclear plants have submitted plans for closure. In this report, we investigate the air pollution implications of the potential closure of these plants, as well as the implications of the potential decommissioning of other nuclear plants in PJM. We assume that if a nuclear plant is decommissioned, its historical generation will be replaced by other generators currently in PJM. We model the air pollution caused by generating this replacement electricity, then use standard epidemiological and economic relationships to estimate health impacts and monetized damages from this additional air pollution. We find that if the three nuclear plants in PJM that are currently scheduled to close (providing 3% of total PJM generation) are replaced with generation with the average emissions intensity and locations of existing non-nuclear PJM generators, the result would be an increase of 126 (range: 73–196) human deaths per year, equivalent to \$806 (interquartile range: \$431-\$1,404) million per year in economic damages (year-2017 USD). The types of plants that provide replacement generation may be different than the grid average, however. If replacement generation is provided by all natural gas plants, damages would be $\sim$5$\times$ lower; if it comes from all coal plants, damages would be $\sim$1.5$\times$ higher. If additional nuclear plants close, additional damages are expected.

1 Introduction

Human inhalation of fine particulate matter air pollution ($PM_{2.5}$; particles less than 2.5 μm in diameter) is responsible for more than 60% of deaths from environmental causes and 3% of deaths from all causes in the US. More people die each year in the US from $PM_{2.5}$ exposure than from car crashes and murders combined [1]. Electricity generation is a major source of air pollution, responsible for ∼8% of deaths from $PM_{2.5}$ exposure [2].

Not all types of electricity generating units (EGUs) contribute equally to air pollution. $PM_{2.5}$ concentrations result from direct emissions of $PM_{2.5}$, and also from particles formed in the atmosphere by emissions of gases including sulfur dioxide (SO_2), oxides of nitrogen (NO_x), volatile organic compounds (VOCs) and ammonia (NH_3). Within the area governed by the PJM Interconnection — an organization that coordinates electrical generation in the Northeastern and Mid-Atlantic US (Fig. 1) — generators fueled by nuclear power, coal and natural gas contributed 34%, 34% and 27% respectively of total generation [3]. However, coal generators contributed 94% of SO_2 emissions and 78% of NO_x emissions, and natural gas generators contributed 2% of SO_2 emissions and 9% of NO_x emissions [4]. Nuclear-fueled generators do not emit significant amounts of air pollution as they operate and therefore contributed 0% of emissions [4].

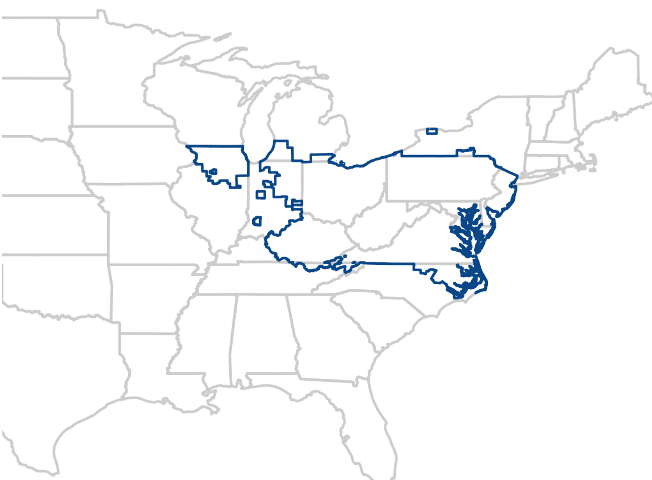

Figure 1: The boundaries of the PJM Interconnection regional transmission organization (blue lines).

As of the end of year 2018, nine nuclear plants in PJM had not recovered their avoidable costs in at least two of the last three years, and three plants are not expected to cover their avoidable costs on average during the next four years. These three plants — providing 3% of total generation in PJM — have submitted plans to deactivate [5].

In this report, we investigate the $PM_{2.5}$ air pollution implications of the potential closure of eleven generating units spread across seven nuclear plants in PJM (providing 12% of total generation), including the three plants mentioned above. Because existing nuclear plants were running at 94% capacity in 2018 and there are not currently any new nuclear plants under construction in PJM [5], replacement electricity generation is likely to be provided by natural gas or coal-fired plants. Combined cycle natural gas plants in PJM were running at 64% capacity in 2018 and coal plants are running at 44% [5].

Although previous research has studied the economic and climate effects of nuclear plant closure [6] and the avoided air pollution health effects of continued nuclear plant operation [7], the air pollution and health effects of potential nuclear plant closures in PJM have not been previously reported.

2 Methods

To estimate the air quality and resulting health impacts of the potential closure of nuclear power plants, we start with the assumption that if a nuclear plant closes, its year-2017 electric generation will be replaced by generation from other fuel types. This assumption is warranted because existing nuclear plants are currently running at nearly full capacity — while other types of generators are not — and there are not currently any new nuclear plants under construction in PJM [5]. We investigate two hypothetical scenarios, wherein replacement generation is provided by either:

1. All existing PJM non-nuclear generators proportionately to existing generation ("PJM average" scenario), or

2. Existing natural gas-fueled generators in PJM proportionately to existing generation ("PJM NG" scenario).

We then model the impact of each replacement emissions scenario on ambient $PM_{2.5}$ concentrations, estimate the health damages that would result from those $PM_{2.5}$ concentrations, and finally translate the health damages into economic damage costs.

2.1 Emissions estimation

To estimate the emissions that would occur to replace the electricity generated by a given nuclear plant, we use the eGRID database [4] to calculate year-2016 emissions per TWh electricity generated in each scenario. eGRID is useful because it contains information on amounts of both electric generation and pollutant emissions for each power plant. The eGRID database contains emissions of SO_2 and NO_x, which are the $PM_{2.5}$ precursors most emitted from power plants, but it does not contain emissions $PM_{2.5}$ itself ("primary $PM_{2.5}$") or of VOCs or NH_3, the other potential sources of $PM_{2.5}$ concentrations. Therefore we augment the eGRID database by adding emissions of $PM_{2.5}$, VOCs, and NH_3 to each eGRID power plant from the geographically nearest power plant in the US Environmental Protection

Agency's (US EPA's) year-2014 National Emissions Inventory [8].

For the PJM average scenario, we select all electric generators listed by eGRID as being managed by PJM and as not being powered by nuclear fuel, and then divide the emissions from each generator by the sum of electricity generation by all of the selected generators. This gives us the average mass of emissions at each generator location per TWh generated by the sum of all non-nuclear generators in PJM.

For the PJM NG scenario, we follow the steps above but only select generators powered by natural gas rather than all non-nuclear generators. This gives us the average mass of emissions at each generator location per TWh generated by the sum of all natural gas fired generators in PJM.

For both scenarios, we assume that all electricity generated per year by a nuclear plant would, if that plant shuts down, be replaced with generation from other pre-existing plants. In other words, we assume that plant closures would not cause any change in demand for electricity and would not cause the contruction of new plants. We consider emissions from the operation of the power plants only, and do not consider "life cycle" or "upstream" emissions (for example caused by the extraction and refining of natural gas or nuclear fuels), nor do we consider impacts other than health impacts from long-term inhalation of $PM_{2.5}$. We do not consider impacts related to handling, transporting, or storing spent fissile material.

2.2 Air quality modeling

After air pollution is emitted from electricity generators, it can be transported by wind, it can react with other pollutants — including, potentially, to form $PM_{2.5}$— and eventually it is removed from the air via wet or dry deposition.

The average $PM_{2.5}$ concentration at a person's location of residence over the course of a year has been determined to affect that person's health [9, 10]. Therefore, our goal is to estimate the effect of our emissions scenarios on annual average $PM_{2.5}$ concentrations at people's places of residence.

The chemical and physical processes impacting the transport, transformation and removal of pollution are complex. As a result, the spatial patterns of $PM_{2.5}$ concentrations are not always closely related to the spatial patterns of the emissions that cause them. Therefore, we use models that represent the physical and chemical phenomena that drive the relationship between emissions and annual-average concentrations of $PM_{2.5}$. To provide an estimate of the range of uncertainty in our air quality modeling, we use two separate models, ISRM and APSCA, to create independent estimates of the $PM_{2.5}$ concentrations caused by each emissions scenario.

The Intervention Model for Air Pollution (InMAP; [11]) splits up a three-dimensional spatial area into grid cells that vary in size according to population density. It then numerically solves equations representing air pollution transport, transformation, and removal to provide spatially-explicit estimates of annual-average $PM_{2.5}$ concentrations resulting from an emissions scenario. The predictive performance of InMAP has been evaluated in a number of different situations [2, 11, 12, 13]. Here, we use the InMAP Source-Receptor Matrix (ISRM), a version of InMAP described by Goodkind et al. [12].

The Air Pollution Social Cost Accounting (APSCA; [14]) model also splits up a three-dimensional spatial area into grid cells. However, instead of solving air-pollution-related equations, it estimates the spatial relationships between emissions and concentrations using empirical methods which attempt to reproduce the predictions of a more complex air quality model.

Because the two models use fundamentally different methods to make predictions, we expect they do not share structural biases and therefore the range of predictions made by the two models provides a useful estimate of uncertainty in the relationship between emissions and concentrations.

After running the air quality models, we have spatially-explicit estimates of $PM_{2.5}$ concentrations resulting from each emissions scenario, per TWh electricity generated.

Both air quality models make predictions of $PM_{2.5}$ concentrations throughout the continental US, even though the emission scenarios focus on the PJM region.

2.3 Health damages

We estimate the number of mortalities that would be caused by changes in $PM_{2.5}$ concentrations resulting from the closure and replacement of nuclear power plants. We do not estimate non-mortality (i.e., morbidity) health impacts of $PM_{2.5}$ exposure, such as the increased prevalence of nonfatal ischemic heart disease, stroke, lung cancer, chronic obstructive pulmonary disease, diabetes [1] or childhood asthma [15].

The $PM_{2.5}$ concentration at a person's location of residence is commonly used as a surrogate for the amount of pollution they inhale [9, 10]. To predict the health impacts of each emission scenario, we combine information about where people live from the US Census [16] with baseline mortality rate information [17] and information on the relationship between $PM_{2.5}$ concentrations and mortality rate to estimate the number of deaths caused by each emissions scenario (in units of deaths per TWh generation) as in Eq. 1:

$$D = \sum_{i=1}^{N} \left\{ \left[\exp\left(\frac{\ln R}{10} C_i \right) - 1 \right] P_i r_P M_i r_M \right\}, \quad (1)$$

where D is the the number of deaths caused by the emissions scenario and R is the mortality change ratio caused by a $PM_{2.5}$ concentration change of $10\,\mu g\,m^{-3}$. Here we use two values of R, 1.06 [9] and 1.14 [10], to provide an estimate of the uncertainty in the relationship between $PM_{2.5}$ concentration and mortality. C_i is the concentration estimate in air quality model grid cell i (out of N total grid cells), P_i is the human population count in grid cell i, and M_i is the baseline mortality rate in grid cell i. The functional form of Eq. 1, the choice of $PM_{2.5}$ as the pollutant studied, and the values of R we use are common choices for quantifying health impacts of air pollution [18]. The vast majority of total health damages from air pollution are typically attributed to $PM_{2.5}$ [1], therefore in this study we exclusively quantify damages from $PM_{2.5}$.

Population data in the ISRM model [19] are based on the five-year period 2008–2012 (mid-point 2010); we include an adjustment factor $r_P = 1.047$ (the ratio of year-2016 to year-2010 US total population [17]))), reflecting that the population was 4.7% greater in 2016 than in 2010. Similarly, for mortality data, the ISRM model uses data for year 2005; we include an adjustment factor of $r_M = 1.025$ (the ratio of year-2016 to year-2005 US overall baseline mortality rate [17]), reflecting that the mortality rate was 2.5% greater in 2016 than in 2005. As of this writing, 2016 is the most recent year for which baseline mortality rates are available [17].

2.4 Economic damages

We translate the health impacts attributable to each emissions scenario into economic damage costs using standard economic methods. The approach here follows recommendations by the US EPA [20]. Following this recommendation, we assume a stochastic, Weibull-distributed Value of a Statistical Life (VSL) with a central estimate of 4.8 million year-1990 US dollars (USD) — updated for year 2017 by adjusting for inflation [21] to yield 9.0 million — with a Weibull shape parameter equal to 1.51 [20].

Economic damages calculated using VSL values represent estimates of the amount of money people would be willing to pay to avoid a small increase in their risk of death, or the amount of money they would accept in exchange for doing something that increases their risk of death, scaled to the risk in question. For example, suppose that people on average were willing to take a job that increased their risk of death in any given year by 0.1%, if the salary is at least \$10,000 per year more than a comparable job that didn't have the added risk. The value of a statistical life would then be \$10,000 / 0.1% = \$10 million. In this example, if a hypothetical improvement in air pollution caused 100 fewer people to die per year, then using the calculated VSL of \$10 million, the reduction of 100 deaths per year would be equivalent to an economic benefit of 100 deaths $\times$ \$10 million per death = \$1 billion per year.

2.5 Uncertainty assessment

As described above, for each emissions scenario we estimate damages using two air quality models, two estimates of the relationship between $PM_{2.5}$ and mortality rate, and a stochastic (Weibull) distribution of VSL values, with the purpose of quantifying uncertainty in our estimates of health and economic impacts.

Because our mortality calculations are based on four point estimates (two air quality models and two concentration-mortality relationships) for each scenario, we represent uncertainty in the number of deaths as the median and range (smallest and largest value) of the four estimates.

To represent uncertainty in economic damages, we combine these different methods in a Monte Carlo analysis using 10,000 random samples from the VSL distribution for each combination of air quality model and concentration-mortality relationship. We present the median of the resulting 40,000 values as a central estimate of the impacts and the interquartile range (IQR; 25th to 75th percentile) as a characteristic range of uncertainty.

3 Results

3.1 Emissions

Table 1 shows that in 2016, emissions per TWh of electricity produced in the PJM average scenario were 16 times greater for SO_2 (and 4 times greater for NO_x) than in the PJM NG scenario. Emissions of SO_2 and NO_x are substantially greater than emissions of primary $PM_{2.5}$, NH_3, and VOCs in both scenarios. In the PJM average scenario, emissions are dominated by coal generators along the Ohio River Valley, whereas in the PJM NG scenario a larger fraction of pollution is emitted from the large natural gas generators near the eastern and western edges of the domain (Fig. 2).

Table 1: Emissions (short tons) per TWh Generation in PJM

Pollutant	PJM Average	PJM NG
SO_2	657	40
NO_x	528	119
$PM_{2.5}$	34	11
NH_3	4	3
VOCs	2	1

3.2 Concentrations

Ambient $PM_{2.5}$ concentrations caused by the PJM average emissions scenario are spatially diffuse, reflecting that SO_2 emissions from coal combustion can take several days to react to form particulate SO_4 (a type of $PM_{2.5}$), and can travel long distances during that time (Fig. 3). For the PJM NG scenario, concentrations are more localized around emissions sources, reflecting the shorter reaction time required for NO_x — the main type of $PM_{2.5}$ precursor emissions from natural gas combustion — to form $PM_{2.5}$ (Fig. 3).

The two air quality models — ISRM and APSCA — broadly agree on the magnitude and spatial patterns of concentrations in both emissions scenarios, although ISRM predicts concentrations that are larger and more spatially diffuse in the PJM

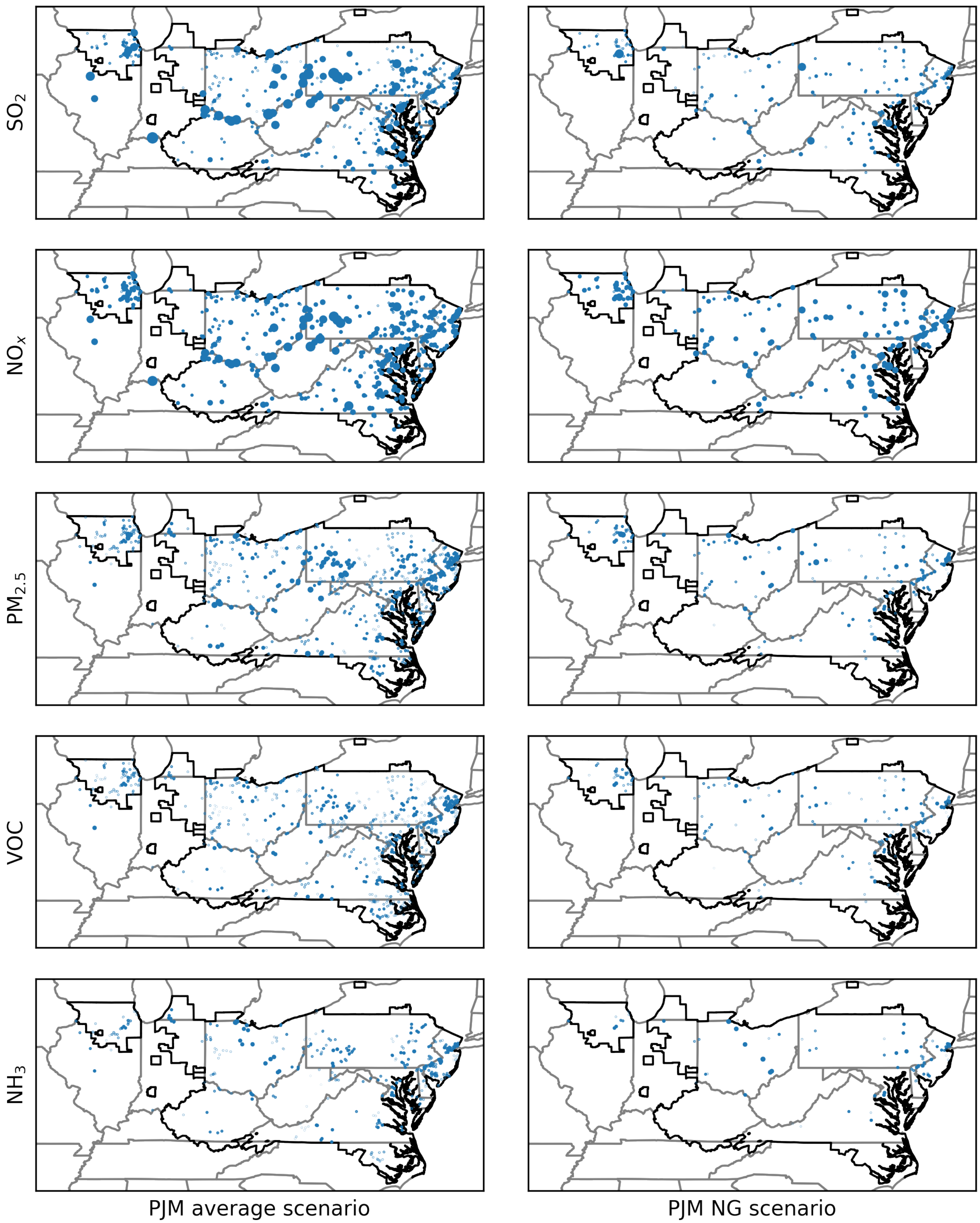

Figure 2: Locations of electrical generators in the eGRID database [4] (blue dots) attributed to PJM in "PJM average" and "PJM NG" scenarios (columns). The area of each dot is proportional to the emissions of each pollutant per TWh generated (rows).

average scenario (Fig. 3). Because the two models have similar predictive accuracy [11, 14], areas where they disagree can be considered to represent a range of uncertainty in the relationship between emissions and concentrations.

3.3 Health impacts

We estimate 5.1 (range: 3.0–8.0) deaths per TWh generated for the PJM average scenario and 1.0 (range: 0.6–1.4) for the PJM NG scenario. We find that the PJM average scenario caused more deaths than the PJM NG scenario by a factor of 5.4 on average, predictions made by the two air quality models differ by 12% on average (with a maximum difference of 18%), and predictions made with the two concentration-mortality relationships differ on average by a factor of 2.3 (Table 2).

Table 2: Deaths per TWh Generation in PJM

Scenario	PJM Average		PJM NG	
AQM/C-M[a]	Krewski	LePeule	Krewski	LePeule
APSCA	3.0	6.7	0.6	1.4
ISRM	3.5	8.0	0.6	1.3

[a]Rows: Air quality model (AQM); Columns: Relationship between $PM_{2.5}$ concentration and mortality (C-M), as estimated by either Krewski et al. [9] or LePeule et al. [10].

3.4 Economic damages

We estimate median (and IQR) economic damages of $33.1 (17.7–57.7) million year-2017 USD per TWh generated for the PJM average scenario and $6.2 (3.3–10.7) million per TWh generated for the PJM NG scenario. Our uncertainty range for economic damages includes uncertainty in the emissions-concentration and concentration-mortality relationships as well as in the VSL.

3.5 Total closure damages by generator

We estimate the health damages — and the related economic externality damages — that could result from the potential closure of each of eleven generating units across seven plant locations in PJM. Combined, these plants generated 101 TWh of electricity in 2017, which is 13% of the total generation in PJM [22]. If all eleven plants were closed and replaced with generation with the emission intensity and locations of the PJM average scenario, we estimate that would result in 516 excess deaths per year (range: 301–802), causing $3 billion per year in economic externality damages (IQR: $1.8–5.8 billion). If the plants were instead all closed and replaced with generation with PJM NG emission intensity and locations, the result would be 98 (range: 59–143) excess deaths per year and $624 million (IQR: $334–1,084 million) per year in economic damages (Table 3).

If the three plants that have already submitted plans to close (Davis Besse, Perry, and Three Mile Island [5], with a combined generation of 27 TWh, or 3% of the PJM total [first three rows of Table 3]) are replaced with PJM average scenario generation, we estimate that would result in 126 (range: 73–195) excess deaths per year and $812 (IQR: $436–$1,417) million per year in economic damages. If, however, those plants were all replaced with PJM NG scenario generation, it would cause 24 (range: 14–35) excess deaths per year and $152 (IQR: $81–264) million per year in economic damages (Table 3).

4 Discussion

If nuclear plants cease operating in PJM, the loss in electricity generation would likely be replaced by generation from non-nuclear plants, a change that would impact air pollution and health. We find that, if the three nuclear plants in PJM that are currently scheduled to cease operation do close, and if they are replaced with generation from the PJM average (non-nuclear) scenario, the result would be an increase of 126 (range: 73–195) deaths per year, equivalent to $812 (IQR: $436–$1,417) million per year in economic damages. If they are replaced with generation from the PJM natural gas scenario, the result would be 24 (range: 14–35) excess deaths per year, equivalent to $152 (IQR: $81–$264) million per year in economic damages. If additional plants close, predicted damages would increase proportionately. Damage estimates depend on which power plant fuel replaces the nuclear plant; estimated damages would be $\sim 5\times$ lower if the electricity generation comes exclusively from natural gas than if it comes from the grid average fuel mix.

The results presented here are consistent with other studies. For example, we calculate that 1 TWh of non-nuclear generation in PJM causes on average $29.6 (IQR: $15.7–$51.6) million in externality damages. An equivalent number based on a widely used estimate of the economic benefits per unit emissions reduction from the electricity generating sector as a whole [23] is $34.2 million. Although this estimate is for the average of all electricity generation in the US rather than just PJM, it is within our estimated uncertainty range.

As an additional check, extrapolating our estimates of damages from PJM average emissions to match the total electrical generation in the US would yield an estimate of 20,300 (range: 13,900–27,800) deaths per year. If we adjust that estimate by multiplying by 0.66 to reflect that PJM generates 34% of its electricity with emission-free nuclear plants, we get a value of 13,400 (range: 9,200–18,300) which is comparable to a previous estimate of 10,400 deaths per year [2].

We reflect uncertainty in the types of electric generation that might replace shuttered nuclear plants, and the damages caused by that generation, using sensitivity and uncertainty analysis. Accurately predicting the type and location of electricity generation that would replace closed nuclear plants is outside the scope of this report. The mix of future electric generation might depend on future government policy, resource

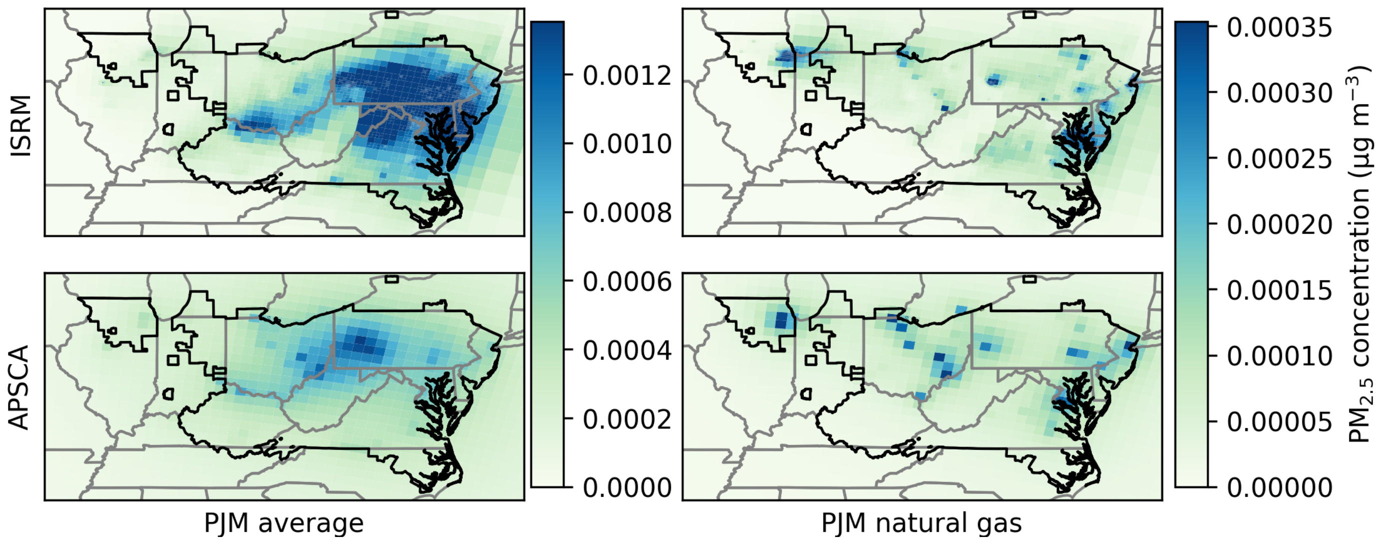

Figure 3: Ambient concentrations of $PM_{2.5}$ caused by 1 TWh of electricity generation for each each emissions scenario (columns) as predicted by each air quality model (rows). Although only the area near PJM is shown, both models predict concentrations throughout the contiguous US. To facilitate interpretation, color scales are truncated at the 99.5th percentile of values. The left and right columns have different color scales.

discovery, technological development, and individual business decisions, all of which are difficult to predict. We therefore present results based on two scenarios: 1) that generation is replaced proportionately by all existing non-nuclear plants in PJM ("PJM average"), and 2) that generation is replaced proportionately by all existing natural gas plants in PJM ("PJM NG"). (A third scenario, involving coal-only is mentioned below.) While we do not expect that either of these scenarios will be exactly correct, the scenarios are representative of the range of variability in emissions intensity and locations of near-term replacement generation, given current market conditions and technological constraints.

It might be desirable for closing nuclear plants to be replaced with generation from other non-emitting sources, such as wind or solar power. If that happened, the replacement electricity would also be emission-free. We do not investigate here the degree to which renewable energy might displace fossil fuel electricity in the long term. In the near term, wind and solar generators would typically not be considered as replacements for nuclear generators, which provide steady baseload generation.

Conversely, it is possible that decommissioned nuclear plants would be replaced with generation from only coal plants. Using the methods above, with replacement generation assumed to come from existing coal plants in PJM proportionately to historical generation, we find that this scenario would cause 7.7 (range: 4.3–12.7) deaths/TWh replacement generation, equivalent to \$50.3 (IQR: \$26.7–\$87.9) million USD per TWh in economic damages. These damages are $\sim$1.5$\times$ larger damages than in the PJM average scenario, mainly caused by 1.9$\times$ and 1.5$\times$ increases in SO_2 and NO_x emissions intensity, respectively.

Relationships between emissions, concentrations, and health impacts are complex; we represent uncertainty in these relationships using interquartile ranges of Monte Carlo simulations. Although we have attempted to quantify the major sources of uncertainty in these relationships, there remain other sources of uncertainty, for example in emission rates, population counts and baseline mortality rates. We expect these unquantified sources of uncertainty to be smaller than the sources we have quantified. Additionally, owing to limitations in available data, in different parts of the analysis we have used data from years 2014, 2016, and 2017. This is a limitation of our analysis, but we do not expect it to be a large source of error. As above, the reported uncertainty ranges are not meant to be firm bounds regarding the actual value of damages, but rather to provide general estimates of the variability to be expected.

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Table 3: Health and Economic Damages Caused by Potential Electricity Generating Unit Closures

Plant (Location) Unit #	2017 Gen. (TWh)	Replacement Deaths[a] PJM Average	Replacement Deaths[a] PJM NG	Replacement Damages (2017$ millions[b]) PJM Average	Replacement Damages (2017$ millions[b]) PJM NG
Davis Besse (Oak Harbor, OH) #1	7.9	40.3 (23.5–62.6)	7.6 (4.6–11.1)	260.5 (139.7–454.6)	48.7 (26.0–84.6)
Perry (Perry, OH) #1	9.8	50.2 (29.2–78.0)	9.5 (5.7–13.9)	324.6 (174.1–566.4)	60.7 (32.4–105.4)
3 Mile Island (Middletown, PA) #1	6.9	35.1 (20.4–54.5)	6.6 (4.0–9.7)	227.0 (121.7–396.0)	42.4 (22.7–73.7)
Beaver Valley (Shippingport, PA) #1	8.0	40.9 (23.8–63.6)	7.7 (4.7–11.3)	264.6 (141.9–461.8)	49.5 (26.4–85.9)
Beaver Valley (Shippingport, PA) #2	7.3	37.4 (21.8–58.1)	7.1 (4.3–10.3)	241.9 (129.7–422.1)	45.2 (24.2–78.6)
Limerick (Sanatoga, PA) #1	10.0	51.1 (29.8–79.5)	9.7 (5.8–14.1)	330.6 (177.3–576.9)	61.8 (33.0–107.4)
Limerick (Sanatoga, PA) #2	8.6	43.8 (25.5–68.1)	8.3 (5.0–12.1)	283.2 (151.9–494.2)	53.0 (28.3–92.0)
Peach Bottom (Delta, PA) #2	11.3	57.9 (33.7–89.9)	11.0 (6.6–16.0)	374.2 (200.7–652.9)	70.0 (37.4–121.5)
Peach Bottom (Delta, PA) #3	10.4	53.3 (31.0–82.8)	10.1 (6.1–14.7)	344.5 (184.7–601.1)	64.4 (34.4–111.9)
Susquehanna (Berwick, PA) #1	11.0	56.2 (32.7–87.4)	10.6 (6.4–15.5)	363.6 (195.0–634.5)	68.0 (36.3–118.1)
Susquehanna (Berwick, PA) #2	9.8	49.9 (29.1–77.6)	9.5 (5.7–13.8)	322.9 (173.2–563.5)	60.4 (32.3–104.9)
Total	**101**	**516 (301–802)**	**98 (59–143)**	**3338 (1790–5824)**	**624 (334–1084)**

[a] Median (Range)
[b] Median (IQR)

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