Nuclear and Coal Power Generation Phaseouts Redistribute U.S. Air Quality and Climate Related Mortality Risk

Lyssa M. Freese[1], Guillaume P. Chossière[2], Sebastian Eastham[3], Alan Jenn[4], and Noelle E. Selin[1]

[1]Department of Earth
[2]Massachusetts Institute of Technology
[3]Laboratory for Aviation and the Environment, Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[4]Institute of Transportation Studies, University of California, Davis

November 24, 2022

Posted on 24 Nov 2022 — CC-BY-NC-ND 4 — https://doi.org/10.1002/essoar.10510994.1 — This a preprint and has not been peer reviewed. Data may be preliminary.

Abstract

Nuclear and coal power use in the United States are projected to decline over the coming decades. Here, we explore how simultaneous phase-outs of these energy sources could affect air pollution and distributional health risk with existing grid infrastructure. We develop an energy grid dispatch model to estimate the emissions of CO2, NOx and SO2 from each U.S. electricity generating unit. We couple the emissions from this model with a chemical transport model to calculate impacts on ground-level ozone and fine particulate matter (PM2.5). Our yearlong scenario removing nuclear power results in compensation by coal, gas and oil, leading to increased emissions that impact climate and air quality nationwide. We estimate that changes in PM2.5 and ozone lead to an additional 9,200 yearly mortalities, and that changes in CO2 emissions over that period lead to an order of magnitude higher mortalities throughout the 21st century. Together, air quality and climate impacts incur between \$80.7-\$126.1 billion of annual costs. In a scenario where nuclear and coal power are shut down simultaneously, air quality impacts due to PM2.5 are larger and those due to ozone are smaller, because of more reliance on high emitting gas and oil, and climate impacts are substantially smaller than that of nuclear power shutdowns. With current reliance on non-coal fossil fuels, closures of nuclear and coal plants shift the distribution of health risks, exemplifying the importance of multi-system analysis and unit-level regulations when making energy decisions.

Nuclear and Coal Power Generation Phaseouts Redistribute U.S. Air Quality and Climate Related Mortality Risk

Lyssa M. Freese[a,1], **Guillaume P. Chossière**[b], **Sebastian Eastham**[b], **Alan Jenn**[c], **and Noelle E. Selin**[a,d,1]

[a]Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, MA, United States of America; [b]Laboratory for Aviation and the Environment, Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA 02139, USA; [c]Institute of Transportation Studies, University of California, Davis ; [d]Institute for Data, Systems and Society, Massachusetts Institute of Technology, Cambridge, MA, United States of America

Nuclear and coal power use in the United States are projected to decline over the coming decades. Here, we explore how simultaneous phase-outs of these energy sources could affect air pollution and distributional health risk with existing grid infrastructure. We develop an energy grid dispatch model to estimate the emissions of CO_2, NO_x and SO_2 from each U.S. electricity generating unit. We couple the emissions from this model with a chemical transport model to calculate impacts on ground-level ozone and fine particulate matter ($PM_{2.5}$). Our yearlong scenario removing nuclear power results in compensation by coal, gas and oil, leading to increased emissions that impact climate and air quality nationwide. We estimate that changes in $PM_{2.5}$ and ozone lead to an additional 9,200 yearly mortalities, and that changes in CO_2 emissions over that period lead to an order of magnitude higher mortalities throughout the 21st century. Together, air quality and climate impacts incur between \$80.7-\$126.1 billion of annual costs. In a scenario where nuclear and coal power are shut down simultaneously, air quality impacts due to $PM_{2.5}$ are larger and those due to ozone are smaller, because of more reliance on high emitting gas and oil, and climate impacts are substantially smaller than that of nuclear power shutdowns. With current reliance on non-coal fossil fuels, closures of nuclear and coal plants shift the distribution of health risks, exemplifying the importance of multi-system analysis and unit-level regulations when making energy decisions.

The United States relies on nuclear and coal for 38% of its electricity generation (1). Analysis of pathways for the U.S. to reach a net zero carbon emissions energy grid focus on reduction of fossil fuels and increased use of renewable energy (2). Nuclear power, which is expected to decline in the future, has historically provided many parts of the United States with low emission (both direct and indirect) energy that has had lower health and accident related illnesses and deaths when compared to coal, gas, and oil (3). Nuclear power has also been evaluated for its role in reducing historical carbon emissions at the global scale (4, 5), but it remains of public and government concern due to potential safety risks. At the same time, coal has long been one of the highest polluting sources of electricity, contributing to hundreds of thousands of premature deaths globally each year (other fossil fuel use brings this up to millions of deaths) (6, 7). Even in scenarios without substantial new climate action, it is still estimated that coal use will decline rapidly over the coming decades. There is little comprehensive work on the potential air quality impacts of reducing the role of nuclear power in the U.S. energy system, and how this reduction will interact with other aspects of energy transitions. Here, we explore the complex feedbacks of the energy system, air quality, climate and human health in response to changes in nuclear and coal power, which are traditional base-load electricity generating units (EGUs).

Recent closures of nuclear power plants are due to a combination of economic impracticability because of inexpensive gas (8), as well as health and safety concerns, and have historically led to increased use of fossil fuels to fill the gap in energy production. For example, in New York, the Indian Point Energy Center's second reactor was shut down in April, 2021 because of environmental and safety concerns due to its proximity to New York City (9), and the Diablo Canyon power plant in California is expected to shut down by 2025 because it did not seek to renew its license to operate (10). Tennessee Valley's Browns Ferry and Sequoyah nuclear power plant shutdowns in 1985 led to increased coal use (11), as determined by regressions comparing power plant level production in the Tennessee Valley Area before and after nuclear plant closures. Using similar regressions to assess generation by plants before and after California's San Onofre Nuclear Plant shutdown in 2012, Davis and Hausman found nuclear power plant closure led to increased gas use, as well as increased costs of electricity generation (12). Recent work has shown that Germany's phase out of nuclear power from 2011-2017 led to replacement by fossil fuels (13).

The fossil fuels that have historically replaced nuclear power have emissions that contribute to air pollution and climate change. Fossil fuels emit nitrogen oxides (NO_x) and sulfur dioxide (SO_2), both of which are precursors for fine particulate matter ($PM_{2.5}$), and NO_x is a precursor for ozone formation (14). Air pollution due to ozone and $PM_{2.5}$ is associated with adverse health outcomes and premature mortality (15, 16). The potential for increased use of fossil fuels (17) from the closure of the Diablo Canyon nuclear power plant has led to calls to stop the shutdown (18), citing the climate impacts of such decisions. Previous work has addressed sub-national level response to nuclear power shutdowns, and has quantified regional and global average avoided mortalities from nuclear power use. Using the InMAP reduced form model, Tessum and Marshall (19) found that the shutdown of three nuclear power plants in the Pennsylvania-New Jersey-Maryland (PJM) region led to increases in $PM_{2.5}$ resulting in 126 additional mortalities, and that replacing nuclear power with only gas in this region leads to 24 additional mortalities. Kharecha and Hansen (5) quantified the global historical prevented mortalities and CO_2

Conceptualization: LF, NS; Energy Modeling: LF, GC, AJ; Chemical Transport Modeling: LF, SE; Analysis: LF, SE, NS; Writing-original draft: LF; Writing-edits and review: LF, SE, AJ, GC, NS.

[1]To whom correspondence should be addressed. E-mail: lyssamfreese@gmail.com or selin@mit.edu

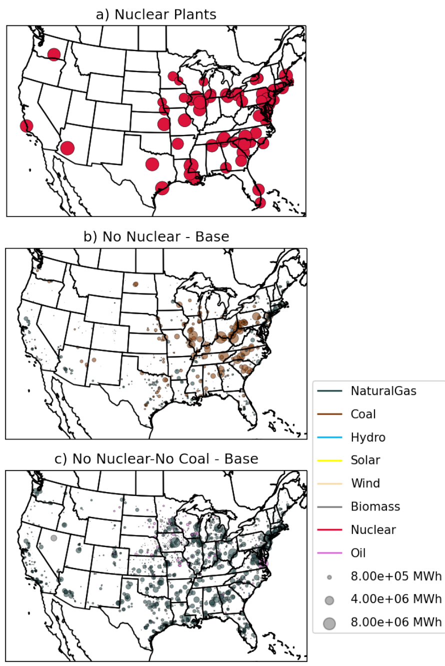

Fig. 1. a) Annual energy production (MWh) by each nuclear plant in the *Base* b) Difference in annual energy production (MWh) by unit under *No Nuclear* compared to the *Base* and c) Difference in annual energy production by unit (MWh) under *No Nuclear-No Coal* compared to the *Base*. In b and c we only plot the increases, which excludes nuclear power from b and nuclear and coal power from c.

emissions due to historical and potential future nuclear power generation, using average mortality rates and CO_2 emissions rates by electricity type. They project mortalities and CO_2 emissions based on energy projections by the UN International Atomic Energy Agency (IAEA) out to 2050, finding between 4.39-7.04 million deaths would be prevented by using nuclear power, rather than fossil fuels due to lower emissions of air pollutants.

Here, we construct three national-scale energy scenarios in order to better characterize the potential response of the existing energy grid and resulting air quality impacts to nuclear shutdowns. We compare three scenarios in which: 1) the U.S. shuts down all nuclear power (*No Nuclear*), 2) the U.S. shuts down all coal and nuclear power (*No Nuclear-No Coal*), and 3) the U.S. continues at an existing baseline (*Base*) (see Figures S3 and S4 for maps of the EGUs used in each scenario). These scenarios allow us to characterize a maximum potential impact of shutdowns, explore the dynamics of the energy system in response to loss of coal and nuclear power, assess the importance of timing and location in these decisions, and estimate the impacts of oil and gas on climate and human health. We also examine the impact of these closures on people of different races and ethnicities, as prior research has shown that people of color are not only disproportionately exposed to air pollution (20–23), but also experience up to three times the impact of $PM_{2.5}$ on mortality (15, 24). To do this, we couple an energy grid/dispatch model and a chemical transport model to calculate the economic and health impact of both climate and air quality changes, and further quantify shifts in exposure amongst different communities.

Results

We compare our two scenarios, *No Nuclear* and *No Nuclear-No Coal*, to the *Base*, which reflects the energy system in year 2016. We first present results of our energy grid/dispatch model (US-EGO), which estimates hourly emissions of NO_x, SO_2, and CO_2 from every power plant in the United States (US-EGO model evaluation can be found in the supplementary material). We then show the results of coupling the emissions from these scenarios to a chemical transport model (GEOS-Chem (25)), quantifying the impact of these emission changes on $PM_{2.5}$ and ozone. We present estimates of spatially explicit mortality impacts of the changes in $PM_{2.5}$ and ozone for each scenario, as well as the impact of pollution on different racial and ethnic groups and on those living near coal and nuclear power plants. We then show the change in mortalities due to the changes in carbon emissions. We conclude this section with quantified estimates of the monetary impacts of the various pollutants based on 1) the economic impacts of the changes in CO_2 using a range of social costs of carbon, and 2) the monetized impact of the mortalities due to changes in air quality using a value of statistical life.

Energy Grid Response. There is more fossil fuel generation in both *No Nuclear* and *No Nuclear-No Coal* than in the *Base*. In the *Base*, gas is 32% of the energy generation, coal is 31% and oil is <1%; in *No Nuclear*, gas is 39% of the energy generation, coal is 45% and oil is <1%; and in *No Nuclear-No Coal*, gas is 75% of the energy generation, and oil is 1.9%. These larger shares of gas and oil are due to the need to cover the lost generation by coal power plants, and the generally low use of oil in the *Base*. Figure 1 shows the differences in fossil fuel use between these scenarios and the *Base*, which are largely concentrated in the Eastern U.S. because of the high concentration of nuclear power there. The interconnected nature of the energy grid can be seen through the differences in the location of increased fossil fuel generation–when coal or nuclear power plants in one county or state are not available, fossil fuel generators in other counties and states make up the difference in demand.

We calculate the ability to meet demand under each scenario and estimate the gaps, showing that the U.S. does not have the necessary capacity to close all of its nuclear power and meet current demand. In *No Nuclear*, this gap occurs in Texas during the summer; in *No Nuclear-No Coal*, this gap occurs across 35 National Electric Energy Data System (NEEDS) regions (see the user guide in (26) for a map of the regions). The gap is regionally dependent, but in the majority of these regions the largest gap is during the summer (see Materials and Methods for how this gap is filled, and Figure S2 for plots of this gap by region).

Under *No Nuclear-No Coal*, there is more reliance on oil and gas plants that have high NO_x emissions factors, and less reliance on the higher SO_2 and CO_2 emitting EGUs. In the U.S., there are 29 EGUs with emissions factors that emit one standard deviation more than the national mean of CO_2, 16 for NO_x and 19 for SO_2. The majority of these high emitting plants are oil and gas plants, many of which have no generation under *No Nuclear* and the *Base*, and are only needed under *No Nuclear-No Coal* (further evaluation of this can be found in the supplementary material). These plants also account for a higher fraction of the national total electricity generation under *No Nuclear-No Coal*, as well as a much higher fraction of the overall emissions of each pollutant. For example, 43% of the national NO_x emissions are from these 15 EGUs under *No Nuclear-No Coal* , while only 1 of these plants is used in *Base* and it accounts for 0.2% of national NO_x emissions. All 15 of these high NO_x EGUs in *No Nuclear-No Coal* are oil and gas plants, while the one used in the *Base* is a biomass plant. A similar picture is seen for SO_2, where 50% of the national SO_2 emissions come from the 15 high SO_2 emitting EGUs, but they provide less than 0.1% of nationwide electricity generation.

We compare the US-EGO results from *No Nuclear-No Coal* to two additional US-EGO sensitivity tests: A) *No Nuclear-No Coal* plus renewable generators scenario, and B) *No Nuclear-No Coal* under the Cross State Air Pollution Rule (CSAPR). In all of our scenarios (*Base*, *No Nuclear*, *No Nuclear-No Coal*), some states exceed their annual 2018 CSAPR ozone budget, and the largest exceedances are under *No Nuclear-No Coal* due to the increased reliance on these high emitting oil and gas plants (see Figure S5 for the emissions from these tests). If additional renewable generators are available, the loss of nuclear and coal power is replaced by renewables rather than high emitting fossil fuels. The CSAPR cap does not change generation, but does change emissions, as explored in the next section.

Emissions Changes. Both *No Nuclear* and *No Nuclear-No Coal* are characterized by more fossil fuel use, and changes in emissions of NO_x, SO_2 and CO_2, compared to the *Base*. In *No Nuclear* there are 42% more NO_x emissions, 45% more SO_2 emissions than, and 41% more CO_2 emissions than in the *Base*. In *No Nuclear-No Coal* there are 194% more NO_x emissions, 23% less SO_2 emissions, and 5% more CO_2 emissions than in the *Base*. *No Nuclear* and *No Nuclear-No Coal* have larger emissions of both NO_x and CO_2 than in the *Base* because of the greater generation by fossil fuels. Due to the closure of coal plants, in *No Nuclear-No Coal* compared to the *Base* there are lower nationwide average SO_2 concentrations, with more SO_2 only in a few regions, particularly the Georgia/South Carolina border and Indiana. Higher SO_2 regions are found where oil and gas plants with higher than average emissions factors of these pollutants provide more generation to fill the production gap (see Figure S7). In both scenarios as compared to the *Base*, the largest differences in NO_x and SO_2 concentrations occur in the Eastern U.S. and during the summer, due to changes in emissions in these regions/locations (Figures S12 and S13). Under our sensitivity test of *No Nuclear-No Coal* with CSAPR caps, emissions are approximately the same as the *Base* (see Figure S1), however the spatial and temporal distribution of emissions is altered due to the closure of coal power.

$PM_{2.5}$ concentrations. Figure 2 shows that annual average $PM_{2.5}$ concentrations are higher nationwide under *No Nuclear*, and lower in some locations while higher in others under *No Nuclear-No Coal* compared to the *Base*. These variations in $PM_{2.5}$ are driven by the changes in NO_x and SO_2 emissions. $PM_{2.5}$ concentrations are larger in *No Nuclear* than the *Base* throughout the Eastern half of the United States during both summer and winter. The concentration differences between *No Nuclear* or *No Nuclear-No Coal* and the *Base* are larger in the summer than in the winter (Figure S17, S18 and S19). Summertime (JJA) $PM_{2.5}$ concentrations are lower in *No Nuclear-No Coal* compared to the *Base* in regions that have a large number of coal plants and lower in SO_2 or NO_x concentrations (see Figure 1 for locations of coal plants and Figure S13 for SO_2 and NO_x concentration changes). $PM_{2.5}$ concentrations are larger in the Southeast and Midwest Great Lake region in *No Nuclear-No Coal* compared to the *Base*.

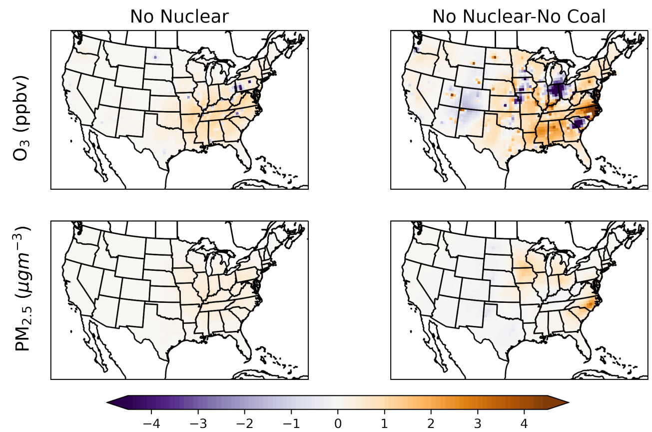

Fig. 2. Changes in annual average $PM_{2.5}$ and summer (JJA) local daytime average (10 A.M.- 6 P.M. JJA) ozone between*No Nuclear* or *No Nuclear-No Coal* and the *Base*.

Ozone concentrations. Summer (JJA) local daytime (10 A.M- 6 P.M.) average ozone concentrations are larger on average nationwide under both *No Nuclear* and *No Nuclear-No Coal* than in the *Base* scenario. In *No Nuclear*, the Eastern U.S. experiences higher changes in ozone than the West, as compared to the *Base*. In *No Nuclear-No Coal*, some regions where there are larger concentrations of NO_x as compared to the *Base* are VOC limited (Figure S14), so increased NO_x emissions lead to decreases in ozone concentrations (Figure 2) due to NO_x titration (27). However, the majority of regions in *No Nuclear-No Coal* still have larger summer local daytime ozone concentrations than the *Base*.

Health Impacts. We calculate two mortality metrics – those due to air quality exposure and those due to CO_2 emissions. Those due to changes in air quality are total mortalities in one year, expected to be incurred in the year of exposure as a result of concurrent emissions. Mortalities calculated due to changes in CO_2 are integrated mortalities, expected to be incurred throughout the 21st century as a result of a single year's emissions. Emissions changes that persist beyond a single year would incur additional mortalities due to both air quality and CO_2 emissions.

The differences between all-cause mortality due to changes in $PM_{2.5}$ and summer local daytime ozone concentrations in *No Nuclear* and *No Nuclear-No Coal* compared with the *Base*, are shown in Figure 3. We find that *No Nuclear-No Coal* has more yearly mortalities due to $PM_{2.5}$ air pollution than *No Nuclear*, and that *No Nuclear* has more yearly mortalities due to ozone than *No Nuclear-No Coal*. Due to changes in $PM_{2.5}$ concentrations in *No Nuclear* compared with the *Base*, there are 7800 (95% CI, 5800-9800) additional premature mortalities. The majority of the increase in mortalities is in the Eastern U.S., due to the higher $PM_{2.5}$ in the Eastern U.S. than the West. Yearly mortalities due to the change in summer local daytime ozone are larger in the Eastern U.S., where *No Nuclear* has 1400 (95% CI, 700-2800) additional premature mortalities as compared to the *Base*.

In *No Nuclear-No Coal*, there are an additional 8200 (95% CI, 6400-10,000) premature mortalities due to differences in $PM_{2.5}$ concentrations compared to the *Base*. In *No Nuclear-No Coal* the two regions with the largest differences in premature mortality are the Great Lakes Region and the Southeast. *No Nuclear-No Coal* has an additional 200 (95% CI 100-400) premature mortalities due to summer local daytime ozone, compared to the *Base*.

There is a more substantial difference among the three scenarios with respect to CO_2, and the related climate impacts due to these emissions also leads to differing premature mortalities over a longer timescale. We use the mortality cost of carbon (MCC) (28) to calculate the integrated mortalities until 2100 of the yearly CO_2 emissions. Under the range of MCC scenarios, CO_2 emissions due to *No Nuclear* lead to an additional 80,000 or 160,000 mortalities throughout the rest of the 21st century, and emissions due to *No Nuclear-No Coal* lead to 11,000-22,000 mortalities over the same time period, compared to the *Base*.

Monetization of Impacts Consistent with Regulatory Approaches. Using regulatory approaches (29), we monetize the annual impact of the increased carbon emissions as well as the health impacts of the changes in air quality from *No Nuclear* and *No Nuclear-No Coal* compared to the *Base*. We use a Value of Statistical Life (VSL), as defined by the EPA, to monetize the changes in mortalities, and a Social Cost of Carbon (SCC), to monetize the changes in carbon emissions.

We calculate the annual cost of mortalities due to changes in summer local daytime ozone and $PM_{2.5}$ using the EPA's current estimate for the VSL of $7.4 million (in 2007 dollars) (30). For *No Nuclear* there are $70.1 billion in monetized externalities ($11.0 billion due to ozone and $59.1 billion due to $PM_{2.5}$), and for *No Nuclear-No Coal* there are $63.8 billion due to changes in mortalities from shutting down both nuclear and coal power plants ($1.6 billion due to ozone and $62.2 billion due to $PM_{2.5}$).

We also quantify a range of values for the annual monetized social impact of the change in carbon emissions according to the 2020 social cost of carbon (SCC) (in 2007 dollars) across a range of discount rates (31) in order to account for uncertainty. The annual mean monetized social cost of carbon due to *No Nuclear* is between $10.6 and $56.0 billion, and due to *No Nuclear-No Coal* is between $1.4 and $7.5 billion (for discount rates of 5% and 2.5%, respectively). This is likely an underestimate of the total impact of GHG emissions from this transition, as we do not include changes in methane emissions due to the high uncertainties in their emission factors (see Figure S1). Overall, *No Nuclear* leads to costs between $85.6 to $131 billion due to climate and health impacts nationwide, and *No Nuclear-No Coal* leads to costs between $86.4 and $92.5 billion.

Distributional Consequences. We quantify the difference in $PM_{2.5}$ and ozone population weighted exposure amongst racial and ethnic groups due to *No Nuclear* and *No Nuclear-No Coal* compared to the *Base*, finding that Black and African American people experience both the largest difference in exposure and mortalities under both scenarios (see Figures S20, S21, S22, S23 for county specific exposures by state). Table S5 shows the mortality rate per 1 million people due to changes in $PM_{2.5}$ and Table S4 shows population weighted exposure changes in $PM_{2.5}$. Table S7 shows the mortality rate per 1 million people due to changes in ozone and Table S6 shows the average population weighted changes in exposure to ozone.

In both *No Nuclear* and *No Nuclear-No Coal*, population weighted exposure to $PM_{2.5}$ and related mortality rates are higher for those living in a county adjacent to a nuclear power plant than those living in non-adjacent counties, while they are lower for ozone and related mortality rates (see Materials and Methods for details on adjacent county definitions). Tables S11 and S9 show the detailed mortality rates and Tables S10 and S8 show the population weighted exposures in both scenarios for both county types. In *No Nuclear* compared to the *Base*, mortality rates due to changes in $PM_{2.5}$ in nuclear adjacent counties are 1.6 times that in non-adjacent counties, while ozone related mortalities decrease by 1.2 times. In *No Nuclear-No Coal* compared to the *Base*, mortality rates due to differences in $PM_{2.5}$ in nuclear adjacent counties are 3.3 times that in non-adjacent counties, and those due to differences in ozone decrease in nuclear adjacent counties, while they increase slightly in non-adjacent counties.

Closures of coal plants benefit those living in counties with coal plants; these counties have lower mortality rates due to changes in $PM_{2.5}$ and ozone in *No Nuclear-No Coal* compared to the *Base*, than *No Nuclear* compared to the *Base*. Counties with coal power plants have larger differences in mortalities per 1 million people due to $PM_{2.5}$, compared with the *Base*: 12.6 in *No Nuclear*, and 11.5 in *No Nuclear-No Coal*, with a population weighted exposure to $PM_{2.5}$ increase of $0.21 \mu g m^{-3}$ and $0.19 \mu g m^{-3}$ in *No Nuclear* and *No Nuclear-No Coal*, respectively. There is a difference in population weighted exposure to ozone for counties containing coal plants of 0.11 ppb in *No Nuclear* and -0.45 in *No Nuclear-No Coal*, leading to changes in mortality rates of 1.8 and -7.8 compared to the *Base* for *No Nuclear* and *No Nuclear-No Coal*, respectively. In some locations, ozone differences are caused by NO_x increases in VOC limited regimes, while in other locations they are due to NO_x decreases in VOC abundant regimes, leading to lower ozone concentrations.

Discussion and Conclusion. Closure of all nuclear power plants across the United States (*No Nuclear*) leads to more mortalities due to air pollution and climate compared to a baseline scenario (*Base*). There are an additional 9,200 mortalities due to changes in $PM_{2.5}$ and ozone under *No Nuclear*. These health impacts are roughly three times those estimated in studies on the impact of proposed carbon policies such as the Clean Power Plan on air quality (3500 avoided premature mortalities from implementation of the Clean Power Plan) (32).

Compared to the *Base*, a scenario where all nuclear and coal power plants are shut down (*No Nuclear-No Coal*) leads to more yearly mortalities from $PM_{2.5}$ related pollution than *No Nuclear*. However, this is offset by lower mortalities due to ozone pollution, and the potential for higher mortality rates over the 21st century due to annual CO_2 emissions, using MCC estimates, under *No Nuclear* than *No Nuclear-No Coal* as compared to the *Base*. Due to changes in $PM_{2.5}$ and ozone, *No Nuclear-No Coal* leads to an additional 8,400 mortalities compared to the *Base*. Compared to the *Base*, the estimated mortality impacts over the entire 21st century of changes in CO_2 from one year for *No Nuclear* are 80,000-160,000 mortalities, and for *No Nuclear-No Coal* are 11,000-22,000 mortalities. These mortalities compound with each year of continued emissions.

Our scenarios illustrate that oil and gas, particularly plants with high emissions factors that are currently rarely used, could be increasingly called upon to meet demand in the electricity system if there is not adequate planning to replace nuclear and coal plants as they shut down. Not only does the generation and emissions from these plants become a larger percentage of the overall system, but there is a net increase in emissions of NO_x, SO_2, and CO_2 due to the reliance on these plants. If low cost renewables are deployed at scale, particularly in regions with plants that have high emissions factors (see Figures S6, S7 and S8) these downstream effects could potentially be mitigated.

Our scenarios suggest an increased risk of non-compliance with relevant regulations such as the Cross State Air Pollution Rule (CSAPR) (33), which limit the amount of total emissions from individual states to reduce the transport of pollutants across state borders. Although CSAPR could constrain the emissions from these plants in the long term–either by limiting their generation or enforcing installation of scrubbers–our analysis of the energy system response and potential air quality and climate impacts nevertheless aids in mitigation planning ahead of potential closures. CSAPR permits emission allowance trading, and there have been recent scenarios where states have paused their emission requirements in order to meet demand during electricity shortages (34, 35). Changes in baseload energy can lead to spatial shifts in the risk of mortality due to air pollution, depending on the types of EGUs that fill in gaps in generation, and their emission factors. Even if CSAPR emissions limits reduce the total emissions from each state, there would still be a shift in counties that are at risk for air pollution related mortalities, which are likely to be more similar to those seen in *No Nuclear-No Coal* than in the *Base* because of the transition to reliance on gas and oil. This shows the importance of at least maintaining existing caps, even where current emissions are well below caps, as future changes in the electricity grid could lead to potential exceedances. This analysis also suggests that technology-based controls, rather than emissions trading schemes, could better ensure air quality outcomes in transitioning energy systems which retain EGUs with high emissions factors.

We show here an example where local risk management can redistribute risk and vulnerability, both at the local and national level, consistent with findings of previous sustainability analyses (36). Closures of nuclear power plants often aim to reduce risk to those living near the power plant, and the closures of coal power plants often have the desired impact of reducing both air quality and climate impacts. We show here that this risk calculation is complicated by the electricity grid's current reliance on fossil fuels beyond coal, the presence of simultaneous energy transitions, and subsequent adjustments of the electricity grid to these closures. Nuclear power has had significant historical impacts on human health and the environment, which has led to concern for those living near power plants or working in the industry. There is extensive research on the social and historical context of the nuclear power industry, which points to high risk accidents, inadequate safety measures from uranium mining (particularly within Navajo Nation), health impacts of living near the radiation of a plant, and waste management as some of the safety concerns with continued use of nuclear power (37–40). Here, we show that a calculation of risk-related benefits of nuclear shutdowns is complicated by our finding that closing nuclear power plants under the current electricity system would lead to a higher increase in mortalities from air pollution for those living within the 50 mile radius ingestion exposure pathway. In contrast, those living near coal power plants benefit the most from closures of coal power plants, but the potential reliance on the dirtiest oil and gas plants to help fill the gap in production with simultaneous phase-outs leads to redistribution of health risks. Further work could explore additional energy transition strategies, particularly in light of the Executive Order 14057's clean electricity by 2030 goals and Justice40 initiative (41), and could identify other measures that could help mitigate the risks imposed on the most disadvantaged communities.

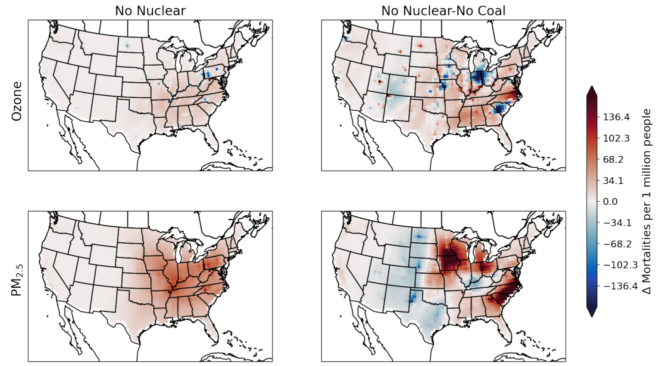

Fig. 3. Changes in mortalities per 100,000 people between *No Nuclear* or *No Nuclear-No Coal* and the *Base* for ozone and $PM_{2.5}$.

Materials and Methods

We combine an energy grid model and a chemical transport model to assess the impact of nuclear plant shutdowns in the United States.

We create a total of six scenarios: three coupled model scenarios for the analysis, and three additional scenarios for model evaluation. Four of these are generated through US-EGO: 1. A no nuclear scenario (*No Nuclear*), 2. A no nuclear or coal scenario (*No Nuclear-No Coal*), 3. A base scenario (*Base*), and 4. A scenario with EPA's Emissions and Generation Resource Integrated Database (eGRID). The other two use existing emissions inventories: 5. A scenario using the National Emissions Inventory (NEI) from 2011, and 6. A scenario using the most recently available NEI data from 2016. Scenarios 1-3 are used for analysis, and scenarios 4-6 are used for evaluation. Table S1 shows the six scenarios and associated data, and the evaluation of US-EGO with scenarios 4-6 are discussed in the supplement. Associated $PM_{2.5}$ and ozone related premature mortalities due to the nuclear power plant shutdowns are calculated according to concentration response functions from Vodonos et al. (42) and Turner et al. (16), respectively. We calculate the mortality cost of carbon (MCC) (28) across the 21st century due to one year's emissions. The monetized social impact of carbon is calculated using 2020 social costs of carbon (SCC) across a range of discount rates (31), and the monetized health impacts are calculated using the value of statistical life (VSL)(30).

Energy Grid Optimization Model. We extend and evaluate the United States energy grid optimization model (US-EGO) based on Jenn (43). Model evaluation can be found in the supplementary material. Data for this model is from the EPA's National Electric Energy Data

System (NEEDS) model v.5.16 (26), which provides the generation costs, capacity, electricity demand, and emissions factors for every energy generating unit (EGU) in the United States. We assume no change in demand. We use this data to set up a cost optimization, which is based on the Security Constrained Unit Commitment model (44) for the energy market. This optimization is solved such that the supply of energy satisfies demand at every hour in 64 regions (as based on NEEDS), allowing for transmission between certain regions. It runs across T time periods with 1) x_i^{gen} generation for generator i at cost c_i^{gen} with N total generators, and 2) x^{trans} transmission power between regions d and o at cost $c_{o\to d}$. We run the model for 8760 hours throughout the year, optimizing at each time step (43).

$$\min_{x^{gen},x^{trans}} \sum_{i=1}^{N}\sum_{t=1}^{T} x_i^{gen}(t)c_i^{gen}(t) + \sum_{o,d}\sum_{t=1}^{T} x_{o\to d}^{trans}(t)c_{o\to d}^{trans}(t) \quad [1]$$

Constraints for the model can be found in the supplemental material.

We take the hourly output of generation from the model and calculate the hourly emissions of SO_2, NO_x and CO_2 by

$$x_i^{gen} EF_i \quad [2]$$

Where EF_i is the emissions factor specific to that EGU. These hourly emissions are merged onto a 0.5° by 0.625° grid to allow for their input into the chemical transport model, GEOS-Chem.

In order to generate the *No Nuclear* scenario, we remove all nuclear power plants from the possible set of EGUs. US-EGO requires sufficient supply to meet demand in order to calculate a solution to its optimization. To close the optimization, we implement additional zero emissions generation capacity which is available in each of the 64 regions. The pricing of the additional generation we implement is high, such that it is only triggered when the existing grid is at complete capacity. With a shutdown of all nuclear power, south eastern Texas demand exceeds supply for 20 hours in the month of May, and we discuss the closure of this gap in the supplemental material. When both coal and nuclear power are shut down, 35 regions (26) have to use additional generators to meet demand. The use of these generators is influenced by the pricing, which is explored in a lower cost "renewable generator" scenario below.

We compare the US-EGO results from *No Nuclear-No Coal* to two additional US-EGO sensitivity tests: A) *No Nuclear-No Coal* plus renewable generators, and B) *No Nuclear-No Coal* under the Cross State Air Pollution Rule. For test A, we create generator capacity in all 64 NEEDS regions with zero emissions at the cost necessary for renewables to provide baseload, intermediate and peaker electricity (\$0.01/MWh) following Ziegler et al. (45). We run the *No Nuclear-No Coal* scenario with these "renewable generators", and our "renewable generators" fill the gaps, while also taking the place of many gas and oil EGUs for generation, as compared to *No Nuclear-No Coal*. For test B, we run *No Nuclear-No Coal*, capping emissions of the relevant plants to hourly estimates of their allowances under the 2018 annual NO_x CSAPR budgets (46), by dividing their annual allowance by the hours in a year. This is a simplification as emissions caps allow for trading, and these emissions factors may not be achievable in practice, but we use these scenarios as a way to explore the potential role of CSAPR in these transitions.

Chemical Transport Model. We use the GEOS-Chem model v13.2.1 (47) to simulate SO_2, NOx, $PM_{2.5}$ and ozone concentrations. GEOS-Chem is a global three-dimensional chemical transport model that includes aerosol chemistry (48) and tropospheric oxidant chemistry (25). We use a global horizontal resolution of 4°x 5°to create boundary conditions for a nested North American run with horizontal resolution of 0.5° by 0.625° between 140°- 40°W and 10°- 70°N (49). This resolution is similar to that of other studies examining air quality impacts and disparities (e.g. (42, 50–52)). GEOS-Chem is driven by meteorological data from the MERRA-2 reanalysis (53). Emissions data come from the Harvard–NASA Emission Component (HEMCO) (54). We use six months for spin-up, and we analyze daily concentration outputs for the year of 2016.

Within HEMCO, we make a few key modifications to the inputs of emissions for EGUs. For our *NEI 2011* simulation, the EGU emissions for GEOS-Chem are from the 2011 NEI that are scaled to the relevant year as described in the GEOS-Chem wiki (55). In the *NEI 2016* simulation, we use recently developed emissions inventories for the NEI in 2016. The *eGRID* simulation utilizes the EPA's Emission and Generation Resource Integrated Database (eGRID) (56) SO_2 and NOx emissions gridded onto a 0.5° by 0.625° grid. *Base* uses the emissions profiles of SO_2 and NOx created through the US-EGO model, *No Nuclear* uses emissions profiles of SO_2 and NOx created through the US-EGO model in the *No Nuclear* scenario, and *No Nuclear-No Coal* uses emissions profiles of SO_2 and NOx created through the US-EGO model in the *No Nuclear-No Coal* scenario. In the *Base*, *No Nuclear*, *No Nuclear-No Coal*, *eGRID* and NEI 2016 scenarios, all emissions other than the EGU SO_2 and NOx emissions are from the 2016 NEI emission inventory.

Health Impact Assessment. We calculate the differences in annual mean $PM_{2.5}$ concentrations between the *Base* and *No Nuclear* or *No Nuclear-No Coal*. Mortalities due to changes in $PM_{2.5}$ exposure are calculated using the concentration response function (CRF) from a recent meta-analysis of the association between $PM_{2.5}$ and mortality (42). For each grid box, we calculate $\overline{\beta}(\mathrm{PM}_{2.5})$, the long-term $PM_{2.5}$ concentration response, as:

$$\overline{\beta}(\mathrm{PM}_{2.5}) = \frac{1}{\Delta \mathrm{PM}_{2.5}} \int_{\mathrm{PM}_{2.5\,a}}^{\mathrm{PM}_{2.5\,b}} \beta(\mathrm{PM}_{2.5}{}') \delta \mathrm{PM}_{2.5}{}'$$

where β is based on Figure 2 in Vodonos et al. (42), such that its value depends on $\Delta PM_{2.5}$, a is the *Base* scenario and b is *No Nuclear* or *No Nuclear-No Coal* scenario, and $\Delta PM_{2.5}$ is the annual average change in $PM_{2.5}$ between scenario a and b. We calculate the 95% CI for $\overline{\beta}(\mathrm{PM}_{2.5})$ based on this same method, using the upper and lower bounds on the 95% CI from Vodonos et al. (42)

We calculate the incidence, I, for each grid box as:

$$I = \frac{\exp^{\overline{\beta}\Delta \mathrm{PM}_{2.5}} - 1}{\exp^{\overline{\beta}\Delta \mathrm{PM}_{2.5}}}$$

Based on the change in concentration and incidence, we calculate the change in all-cause mortality for each GEOS-Chem grid cell as (7):

$$\Delta M = p_{af} I M_0$$

where p_{af} is the affected population, for which we use the Gridded Population of the World data for all ages (57), and M_0 is the United States' baseline all-cause mortality rate taken from the 2017 Global Burden of Disease Study (58).

For ozone, we similarly quantify the differences in concentration between *Base* and *No Nuclear* or *No Nuclear-No Coal*. Mortalities due to ozone changes are calculated following the methods used in the latest Regulatory Impact Analysis for the Final Revised CSAPR by the Environmental Protection Agency (EPA) (16, 59). From this, we calculate three β values (the mean and 95% confidence interval [CI]), the long-term ozone concentration response, as $\frac{\log \mathrm{RR}}{\Delta \mathrm{ozone}}$, where RR = 1.02 [1.01, 1.04] is the relative risk per 10ppb (Δozone) increase in summertime ozone in a two-pollutant model accounting for $PM_{2.5}$ (16). We use daily 10am-6pm local summer daytime average (June-August) ozone concentrations from our GEOS-Chem data as a proxy for the EPA's maximum daily 8 hour average (MDA8) ozone (60) as is done in (61). We calculate a change in mortality for each β and grid cell as:

$$\Delta M = p_{aff} I_{obs} \Delta \chi \beta$$

In which the mean mortality is based in the mean β, and our 95% CI mortality is based on the 95% CI for β.

We aggregate our gridded $PM_{2.5}$ and ozone data to county levels using area-weighted averages (using the python module, xesmf (62)) across the United States. We use U.S. Census Bureau Demographic Analysis Data for the year 2016 (63) to attribute changes in mortality at the county level based on race (Asian or Pacific Islander, American Indian, Black or African American, and White) and Hispanic origin/ethnicity (not Hispanic or Latino, and Hispanic or Latino). These categories are chosen based on the Center for

Disease Control's (CDC) race and ethnicity categories. The mortality rates from the census based aggregations use an average RR based on (15), so differences in mortality rates are due solely to exposure. For calculating exposure in counties adjacent to nuclear power plants, we define adjacent as a county that has a border within 50 miles of a nuclear power plant. We assess counties within a 50 mile radius, which is considered by the Nuclear Regulatory Committee as being at risk for enhanced exposure in case of a nuclear power plant accident (64, 65). To calculate exposure in coal containing counties, we find counties that contain a coal EGU, and compare the population weighted exposure and mortality rates to those without a coal plant.

We apply the same aggregation method to the Center for Disease Control (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER) data (66) baseline mortality data, so that we can compare the use of an average RR to race and ethnicity specific values (15). WONDER data is restricted in scenarios where mortalities are fewer than 10 people per county, so we use the census data in our main analysis, even though it does not take race and ethnicity specific exposure response curves (see S8, S9, S10 and S11 for differences in exposure and mortality between the two aggregation methods).

Mortality Cost of Carbon. We calculate the total mortality cost due to changes in carbon emissions between our two scenarios as a global total, based on the total change in CO_2 emissions multiplied by a range of MCC values. We calculate the central mortality estimate under both a baseline and optimal emissions scenario, leading to 2.4°and 4.1°C of warming by 2100, respectively (see Table 1 in Bressler (28)). We assume that emissions from the year 2016 would lead to similar responses across the 21st century as those of emissions in 2020, as the MCC is based on the impact of emissions from 2020 on mortalities from 2020-2100.

Monetized Social Impact of Carbon. We calculate a monetized social impact of carbon using a range of values for the social cost of carbon (SCC) based on different discount rates (31, 67). We use an emission year of 2020, with the 5%, 3%, and 2.5% average discount rates corresponding to 14, 51 and 76 dollars per metric ton of CO_2 (in 2007 dollars). The use of different discount rates allows us to address issues of inter-generational justice and governance (68), but all of our values have some form of discounting. We calculate the monetized impact as:

$$\Delta S_d = \mathrm{SCC}_d \Delta E_{CO_2}$$

for the entire frequency distribution of the SCC across each discount rate (d), where ΔE_{CO_2} is the change in emissions between the two scenarios. The average monetized social impact for each discount rate is the mean of ΔS.

Value of Statistical Life. We calculate the VSL due to changes in ozone and $PM_{2.5}$ using the EPA's current estimate for the VSL of $7.4 million (in 2006 dollars) (30). We convert the VSL to 2007 dollars, and multiply the VSL by our mortalities due to changes in ozone and $PM_{2.5}$ to calculate a total economic impact of lives lost across the United States.

ACKNOWLEDGMENTS. L.F. acknowledges support from the NIEHS Toxicology Training Grant #T32-ES007020, and the MIT Martin Family Society of Fellows for Sustainability. This publication was supported by US EPA grant RD-835872-58201. Its contents are solely the responsibility of the grantee and do not necessarily represent the official views of the USEPA. Further, USEPA does not endorse the purchase of any commercial products or services mentioned in the publication.

1. EIA, Annual Energy Outlook 2021 with projections to 2050, Technical report (2021).
2. E. Larson, et al., Net-Zero America: Potential Pathways, Infrastructure, and Impacts (2021).
3. A Markandya, P Wilkinson, Electricity generation and health. *The Lancet* **370**, 979–990 (2007).
4. H Fell, A Gilbert, JD Jenkins, M Mildenberger, Nuclear power and renewable energy are both associated with national decarbonization. *Nat. Energy* **7**, 25–29 (2022).
5. PA Kharecha, JE Hansen, Prevented Mortality and Greenhouse Gas Emissions from Historical and Projected Nuclear Power. *Environ. Sci. & Technol.* **47**, 4889–4895 (2013) Publisher: American Chemical Society.
6. E McDuffie, R Martin, H Yin, M Brauer, Global Burden of Disease from Major Air Pollution Sources (GBD MAPS): A Global Approach. *Heal. Eff. Inst.*, 62 (2021).
7. K Vohra, et al., Global mortality from outdoor fine particle pollution generated by fossil fuel combustion: Results from GEOS-Chem. *Environ. Res.* **195**, 110754 (2021).
8. J Jenkins, What's Killing Nuclear Power in US Electricity Markets? Drivers of Wholesale Price Declines at Nuclear Generators in the PJM Interconnection (2018).
9. EIA, New York's Indian Point nuclear power plant closes after 59 years of operation - Today in Energy - U.S. Energy Information Administration (EIA) (2021).
10. M Specth, Countdown to Shutdown | Union of Concerned Scientists (2021).
11. E Severnini, Impacts of nuclear plant shutdown on coal-fired power generation and infant health in the Tennessee Valley in the 1980s. *Nat. Energy* **2**, 1–9 (2017).
12. L Davis, C Hausman, Market Impacts of a Nuclear Power Plant Closure. *Am. Econ. Journal: Appl. Econ.* **8**, 92–122 (2016).
13. S Jarvis, O Deschenes, A Jha, The Private and External Costs of Germany's Nuclear Phase-Out (2019).
14. J Seinfeld, S Pandis, *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change.* Second edition, (2006).
15. Q Di, et al., Air Pollution and Mortality in the Medicare Population. *New Engl. J. Medicine* **376**, 2513–2522 (2017).
16. MC Turner, et al., Long-Term Ozone Exposure and Mortality in a Large Prospective Study. *Am. J. Respir. Critical Care Medicine* **193**, 1134–1142 (2016).
17. J Aborn, et al., An Assessment of the Diablo Canyon Nuclear Plant for Zero-Carbon Electricity, Desalination, and Hydrogen Production (2021).
18. Letter to Gavin Newsom RE Diablo Canyon.pdf (2022).
19. CW Tessum, JD Marshall, Air quality and health impacts of potential nuclear electricity generator closures in Pennsylvania and Ohio (2019).
20. CW Tessum, et al., Inequity in consumption of goods and services adds to racial–ethnic disparities in air pollution exposure. *Proc. Natl. Acad. Sci.* **116**, 6001–6006 (2019) Publisher: National Academy of Sciences Section: Physical Sciences.
21. A Hajat, C Hsia, MS O'Neill, Socioeconomic Disparities and Air Pollution Exposure: a Global Review. *Curr. Environ. Heal. Reports* **2**, 440–450 (2015).
22. J Liu, et al., Disparities in Air Pollution Exposure in the United States by Race/Ethnicity and Income, 1990–2010. *Environ. Heal. Perspectives* **129**, 127005 (2021).
23. CW Tessum, et al., PM2.5 polluters disproportionately and systemically affect people of color in the United States. *Sci. Adv.* (2021) Publisher: American Association for the Advancement of Science.
24. E Spiller, J Proville, A Roy, NZ Muller, Mortality Risk from PM2.5: A Comparison of Modeling Approaches to Identify Disparities across Racial/Ethnic Groups in Policy Outcomes. *Environ. Heal. Perspectives* **129**, 127004 (2021) Publisher: Environmental Health Perspectives.
25. I Bey, et al., Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation. *J. Geophys. Res. Atmospheres* **106**, 23073–23095 (2001) _eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2001JD000807.
26. EPA, Power Sector Modeling Platform v.5.15 (2016).
27. S Sillman, The relation between ozone, NOx and hydrocarbons in urban and polluted rural environments. *Atmospheric Environ.* **33**, 1821–1845 (1999).
28. RD Bressler, The mortality cost of carbon. *Nat. Commun.* **12**, 4467 (2021).
29. Executive Order 12866 of September 30, 1993 Regulatory Planning and Review (1993).
30. EPA, Mortality Risk Valuation (2014).
31. USG Interagency Working Group on Social Cost of Greenhouse Gases, Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide (2021).
32. CT Driscoll, et al., US power plant carbon standards and clean air and health co-benefits. *Nat. Clim. Chang.* **5**, 535–540 (2015) Number: 6 Publisher: Nature Publishing Group.
33. EPA, CSAPR Allowance Allocations (2016).
34. Federal Power Act Section 202(c): CAISO, September 2021 (2021).
35. Department of Energy, Order No. 202-21-1 (2021).
36. WC Clark, AG Harley, Sustainability Science: Toward a Synthesis. *Annu. Rev. Environ. Resour.* **45**, 331–386 (2020) _eprint: https://doi.org/10.1146/annurev-environ-012420-043621.
37. D Kyne, B Bolin, Emerging Environmental Justice Issues in Nuclear Power and Radioactive Contamination. *Int. J. Environ. Res. Public Heal.* **13**, 700 (2016).
38. VL Kuletz, *The Tainted Desert: Environmental and Social Ruin in the American West.* (1998).
39. JW Stoutenborough, SG Sturgess, A Vedlitz, Knowledge, risk, and policy support: Public perceptions of nuclear power. *Energy Policy* **62**, 176–184 (2013).
40. D Brugge, R Goble, The History of Uranium Mining and the Navajo People. *Am. J. Public Heal.* **92**, 1410–1419 (2002).
41. Catalyzing Clean Energy Industries and Jobs Through Federal Sustainability (2021).
42. A Vodonos, YA Awad, J Schwartz, The concentration-response between long-term PM2.5 exposure and mortality; A meta-regression approach. *Environ. Res.* **166**, 677–689 (2018).
43. A Jenn, The Future of Electric Vehicle Emissions in the United States. (2018).
44. E Ela, et al., Evolution of Wholesale Electricity Market Design with Increasing Levels of Renewable Generation (2014).
45. MS Ziegler, et al., Storage Requirements and Costs of Shaping Renewable Energy Toward Grid Decarbonization. *Joule* **3**, 2134–2153 (2019).
46. EPA, Cross-State Air Pollution Rule (CSAPR) State Budgets, Variability Limits, and Assurance Provisions (2016).
47. TIGCU Community, geoschem/GCClassic: GEOS-Chem 13.2.1 (2021).
48. RJ Park, Natural and transboundary pollution influences on sulfate-nitrate-ammonium aerosols in the United States: Implications for policy. *J. Geophys. Res.* **109**, D15204 (2004).
49. YX Wang, MB McElroy, DJ Jacob, RM Yantosca, A nested grid formulation for chemical transport over Asia: Applications to CO. *J. Geophys. Res. Atmospheres* **109** (2004).
50. Y Zhang, SD Eastham, AK Lau, JC Fung, NE Selin, Global air quality and health impacts of domestic and international shipping. *Environ. Res. Lett.* **16**, 084055 (2021) Publisher: IOP Publishing.
51. H Wang, et al., Trade-driven relocation of air pollution and health impacts in China. *Nat. Commun.* **8**, 738 (2017) Number: 1 Publisher: Nature Publishing Group.

52. Y Xie, et al., Comparison of health and economic impacts of PM2.5 and ozone pollution in China. *Environ. Int.* **130**, 104881 (2019).
53. MERRA-2: File Specification (2016).
54. CA Keller, et al., HEMCO v1.0: a versatile, ESMF-compliant component for calculating emissions in atmospheric models. *Geosci. Model. Dev.* **7**, 1409–1417 (2014) Publisher: Copernicus GmbH.
55. GEOS-Chem, EPA/NEI11 North American emissions (2019).
56. EPA, Emissions & Generation Resource Integrated Database (eGRID) (2016).
57. Center for International Earth Science Information Network - CIESIN - Columbia University, Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11 (2018) Place: Palisades, NY.
58. GB of Disease Collaborative Network., Global Burden of Disease Study 2017 (GBD 2017) Results (2018).
59. Regulatory Impact Analysis for the Final Revised Cross-State Air Pollution Rule (CSAPR) Update for the 2008 Ozone NAAQS (2021).
60. EPA, Ozone National Ambient Air Quality Standards (NAAQS) (2020).
61. M Li, D Zhang, CT Li, NE Selin, VJ Karplus, Co-benefits of China's climate policy for air quality and human health in China and transboundary regions in 2030. *Environ. Res. Lett.* **14**, 084006 (2019).
62. J Zhuang, r dussin, A Jüling, S Rasp, xESMF: v0.3.0 (2020).
63. UC Bureau, County Population by Characteristics: 2010-2019 (2021) Section: Government.
64. U.S. Nuclear Regulatory Commission, Emergency Planning Zones (2020).
65. U of Concerned Scientists, Emergency Planning for Nuclear Disasters (2011).
66. NCfHS Centers for Disease Control and Prevention, Compressed Mortality File 1999-2016 on CDC WONDER Online Database (2017).
67. Social Cost of Greenhouse Gases Complete Data Runs (2021).
68. A Jerneck, et al., Structuring sustainability science. *Sustain. Sci.* **6**, 69–82 (2011).

Supplementary Information for

Nuclear and Coal Power Generation Phaseouts Redistribute U.S. Air Quality and Climate Related Mortality Risk

Lyssa M. Freese, Guillaume P. Chossière, Sebastian Eastham, Alan Jenn, Noelle E. Selin

Corresponding Author Lyssa Freese.
E-mail: lyssamfreese@gmail.com

This PDF file includes:

- Supplementary text
- Figs. S1 to S23
- Tables S1 to S11
- SI References

Supporting Information Text

Energy Grid Optimization Model

As described in the Methods and Materials Section, the United States Energy Grid Optimization model (US-EGO) uses data from the National Electric Energy Data System (NEEDS) to perform a cost optimization to meet energy demand in every one of 64 NEEDS regions at every hour of the year. There is transmission between regions, and we have isolated the Texas (ERCOT), Eastern and Western Interconnections in order to represent the limitation on transmission between these regions, and to better match the real-world generation and emissions data (1), meaning that there is no transmission between these regions. We limit hydro-power to maximum capacity factors based on region (Southwest at 56%, Midwest at 68%, Southeast at 49% and Northeast at 73%) (2), aside from the Northwest, for which the model under-predicts hydro-power generation, so we allow it to use 100% of available hydro-power. Finally, we adjust the fuel price of refined coal to be $3 less than the listed price in order to better match refined coal use in the real-world data (based on the fact that refined coal is subsidized (3)).

Constraints for generation in the optimization are:

$$gen_{solar} - capacity_{solar} * pattern <= 0 \quad [1]$$

$$gen_{wind} - capacity_{wind} * pattern * 0.85 <= 0 \quad [2]$$

$$gen_{nuclear} - capacity_{nuclear} * 0.95 <= 0 \quad [3]$$

and for all other fuel types:

$$gen_{fuel} - capacity_{fuel} <= 0 \quad [4]$$

Where gen is generation, capacity is the maximum capacity of the EGU, and the *pattern* is the renewable capacity pattern, taken from NEEDS.

Constraints setting $generation + imports = load + exports$ for region, i at time, t:

$$(\sum(gen_i) + trans_{to_i} - trans_{from_i} - load >= 0)_t \quad [5]$$

Constraints on transmission:

$$trans_i - trans_{capacity} <= 0 \quad [6]$$

Comparison to EPA Data. We evaluate US-EGO by comparing our generation and emissions output from our 2016 baseline (*Base*) US-EGO scenario to the generation and emissions data from our *eGRID* scenario. To evaluate the model, we use annual mean generation and emissions for SO_2, NO, NO_2, and CO_2 by fuel type (biomass, coal, fossil waste, geothermal, hydro, landfill gas, municipal solid waste, natural gas, non-fossil waste, nuclear, oil, petroleum coke, solar, waste coal, and wind) and NEEDS region (64 regions) (4), as seen in Figure S1. We calculate the Pearson correlation coefficient between the annual model generation and *eGRID* generation across both region and fuel types of 0.99 and 1.0, respectively. Correlations for the emissions averaged by region and fuel type vary between 0.82 and 1.0. We do not evaluate methane (CH_4) emissions in our paper because the model largely under-estimates the emissions by region and fuel type (see Figure S1, e). As shown in the results, many oil and gas plants that are the highest emitters have little to no generation in our *Base* and *No Nuclear* scenarios– this is consistent with the generation for these specific EGUs in the *eGRID* generation data. The majority of the high emissions plants in the *Base* scenario have annual generation within a 200 MWh range of *eGRID*, and a few have larger or smaller generation.

Generation Closure. In both shutdown scenarios, *No Nuclear* and *No Nuclear-No Coal*, the demand in various regions exceeds possible supply at certain points in the year. In the nuclear shutdown, the demand in the NEEDS' ERC REST region, located in south eastern Texas, exceeds possible supply for a total of 20 hours in the month of May. Almost 20% of Texas' energy supply is from nuclear power, and we have constrained transmission to stay within the Texas Interconnection (ERCOT), which limits the ability of transmission to take on the shortage. In *No Nuclear-No Coal*, 35 regions have demand that exceeds supply throughout various times of the year. We close these gaps by adding generators that have prohibitive costs such that they are only utilized when the optimization cannot close. The generators have zero emissions, so that we do not impact our estimates on changes in emissions.

Limitations. Our multi-system model uses EGU specific data for explicit interpretation of spatial and temporal variation. However, our choice to use EGU-specific data introduces some tradeoffs relative to more complex energy grid models. We do not include ramp up or reserves for generation, and we do not account for investment into new electricity generation, beyond including emissions free generators without specific locations or limitations on capacity. More complex models incorporate quantification of where this type of investment would occur. The lack of ramp up and reserves have an impact on the amount of generation capacity and the speed with which new plants come on and offline, reducing the amount of capacity available when nuclear and coal power are shut down. This reduces the impact of estimations of future build out on our results. Future research could explore related questions combining chemical transport models with complex energy grid models.

GEOS-Chem

In addition to the comparisons between the *Base* and our two shutdown scenarios (*No Nuclear* and *No Nuclear-No Coal*), we have included the $PM_{2.5}$ and ozone summer (JJA) and winter (DJF) seasonal mean concentrations for each of our five scenarios in summer and winter time (Figures S15 and S16).

Comparison to Observations. We compare 2016 observational data from the IMPROVE network (5) and the EPA's Air Quality System (AQS) monitoring network (6) to our base model, *NEI 2011*, *NEI 2016* and *eGRID* GEOS Chem output. We use AQS daily average observations for $PM_{2.5}$, NO_2, SO_2 and ozone and IMPROVE observations for $PM_{2.5}$, sulfate, and nitrate. We interpolate our model data onto the locations of monitors using xarray's nearest method (7). We calculate the R-value based on interpolated values of our model runs compared to the observations from IMPROVE and AQS (Figures S9 and S10). We also calculate the normalized mean bias (NMB) of ozone and $PM_{2.5}$ for our base model and the observations. The NMB is calculated as $\frac{\sum(M_i - O_i)}{\sum(O_i)} \times 100\%$, where i denotes the seasonal mean at each observational site. The results can be seen in Tables S2 and S3. For ozone, our largest bias shows that the model is high compared to observations during the summer months in the Midwest, Northeast, and Southeast. For $PM_{2.5}$, we find biases during the winter in the Northeast and Southeast (where the model is biased high), and the Northwest, and Southwest (where the model is biased low), as well as being biased low during the summer in the Southwest. Our NMB and R-values are of similar magnitude to previous work (8–11). In S11, we compare the observational data for each of our pollutants with the model output by regional annual mean. The resulting concentrations from our *Base* and *eGRID* scenarios are within a similar range of the observational data as the typical GEOS-Chem emissions inventory, the *NEI 2011* scenario, which shows again that US-EGO does capture similar ranges of pollutant concentrations. We also can see that for the sulfate, $PM_{2.5}$, and SO_2, *NEI 2016* falls closer within the range of the observations than *NEI 2011*.

Ozone Regimes

We calculate a proxy to estimate whether or not a region is NO_x abundant, limited, or transitional by using the formaldehyde (CH_2O):NO_2 ratio (12). We define CH_2O):NO_2 of less than .5 as VOC limited, between .5 and .8 as Transitional, and as greater than .8 as NO_x limited. Figure S14 shows differences between the regimes for the nuclear shutdown and the coal and nuclear shutdown, particularly during the summer, which lead to differences in ozone formation. There is also a shift between VOC limited regimes dominating during the wintertime and NO_x limited regimes dominating during summertime.

Health Impact Assessments

Detailed information about the mean exposure, and mean mortality and 95% confidence intervals for each Race and Ethnicity are shown in tables S5 and S7. We show the mean exposure for the data aggregated by WONDER data and census data, which show similar trends in Tables S6 and S4. Mortality differences are larger than differences in exposure due to the use of race and ethnicity specific relative risks for mortalities using the WONDER data. Tables S8, S9, S10, and S11 show mean exposure and mean mortality rates for counties adjacent to or non-adjacent to nuclear power plants.

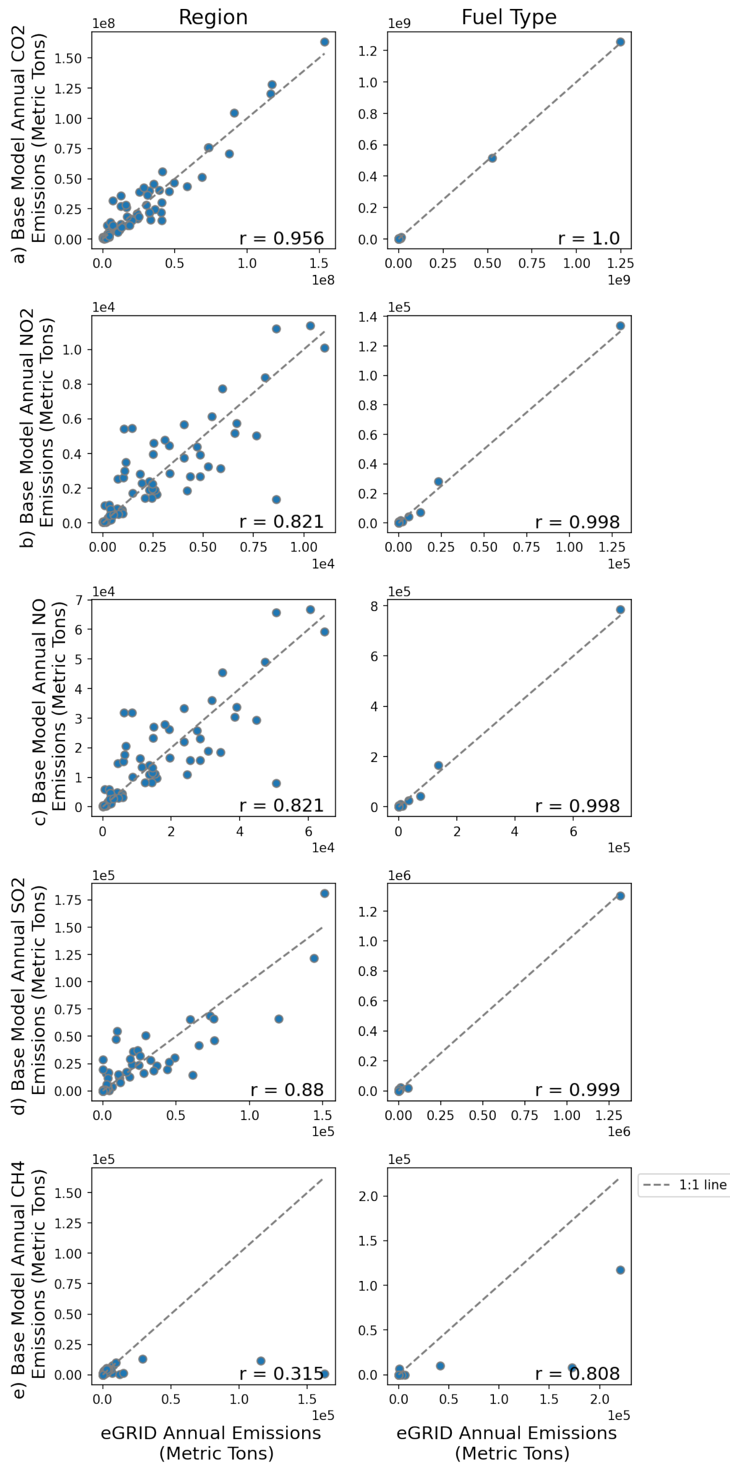

Fig. S1. Scatterplots of the emissions of CO_2 (a), NO_2 (b), NO (c), SO_2 (d), and CH_4 (e) by NEEDS region and fuel type. Pearson correlations (r) are calculated and shown in the bottom right of each plot.

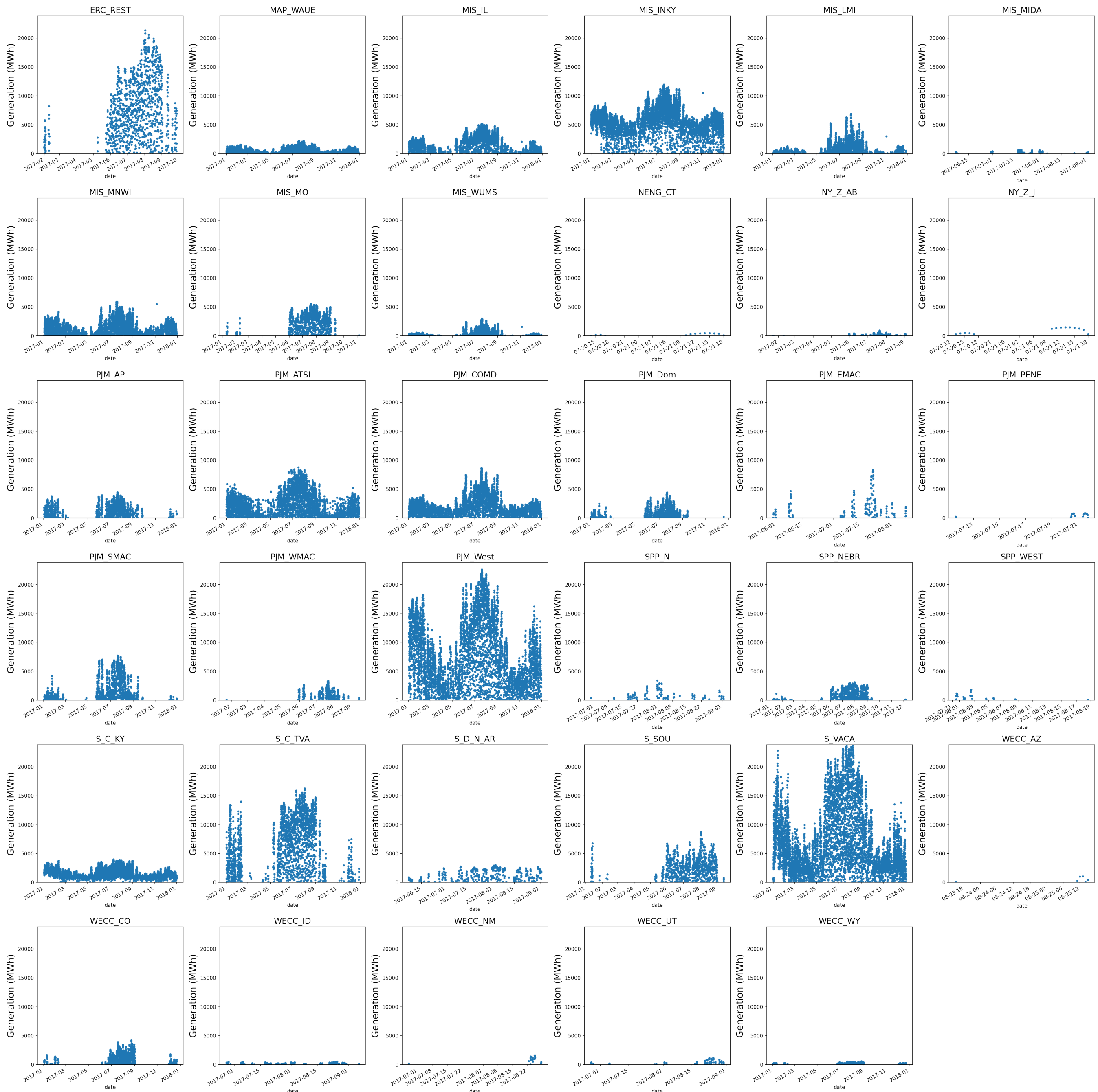

Fig. S2. Generator use by region throughout the year in the *No Nuclear-No Coal* scenario.

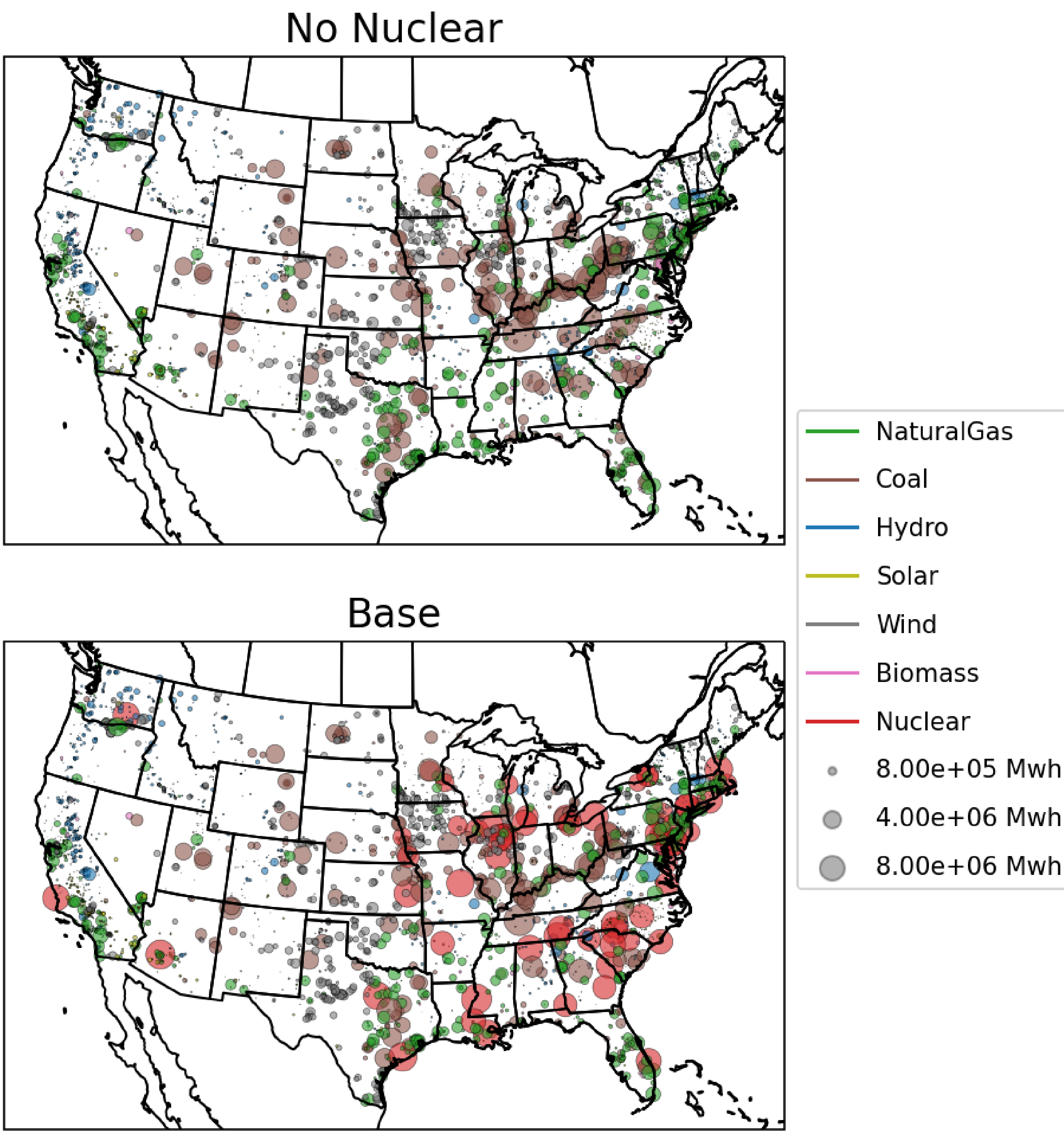

Fig. S3. Map of plants in the *Base* (top) and *No Nuclear* (bottom) scenarios, sized by their annual generation.

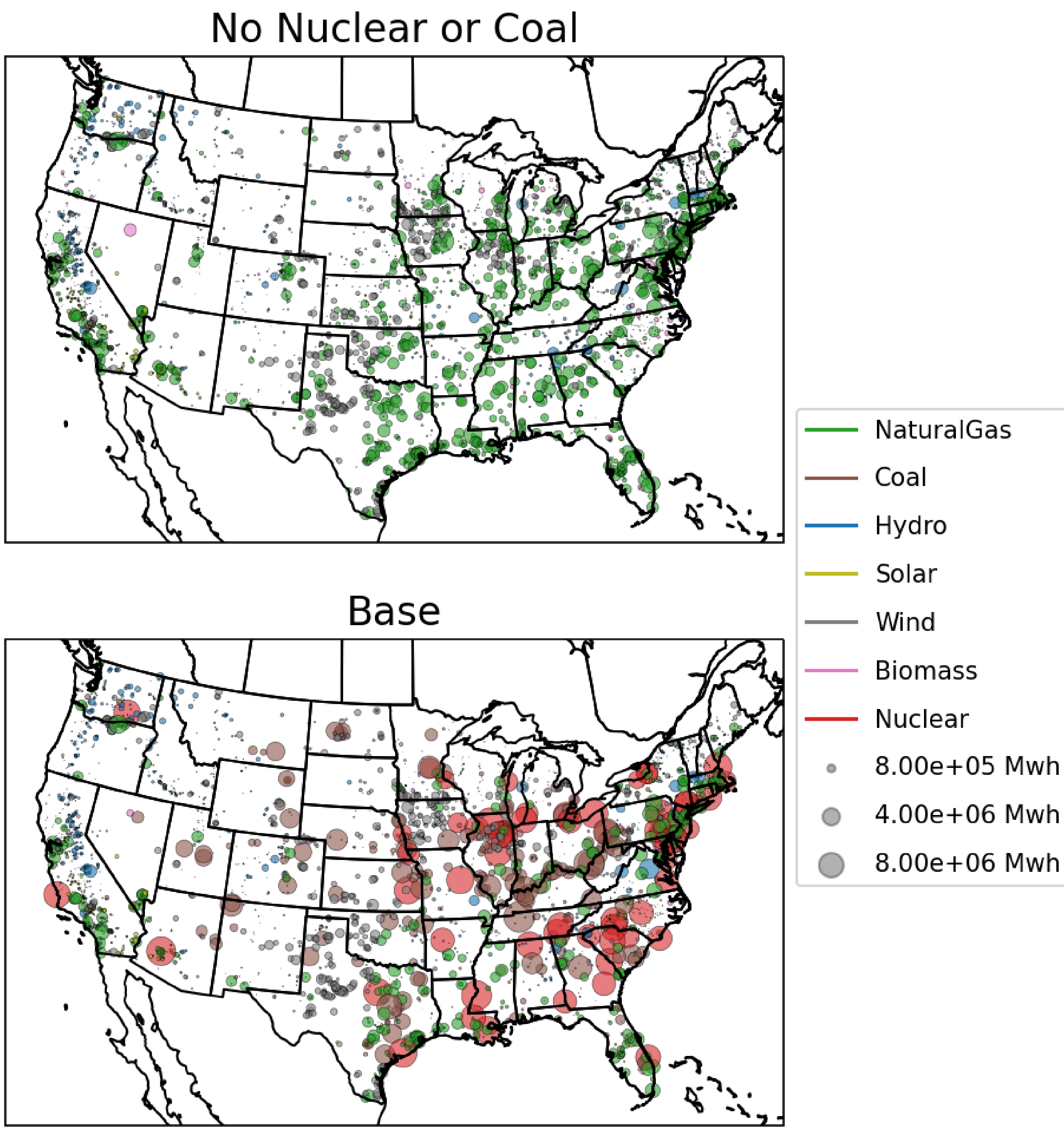

Fig. S4. Map of plants in the *Base* (top) and *No Nuclear-No Coal* (bottom) scenarios, sized by their annual generation.

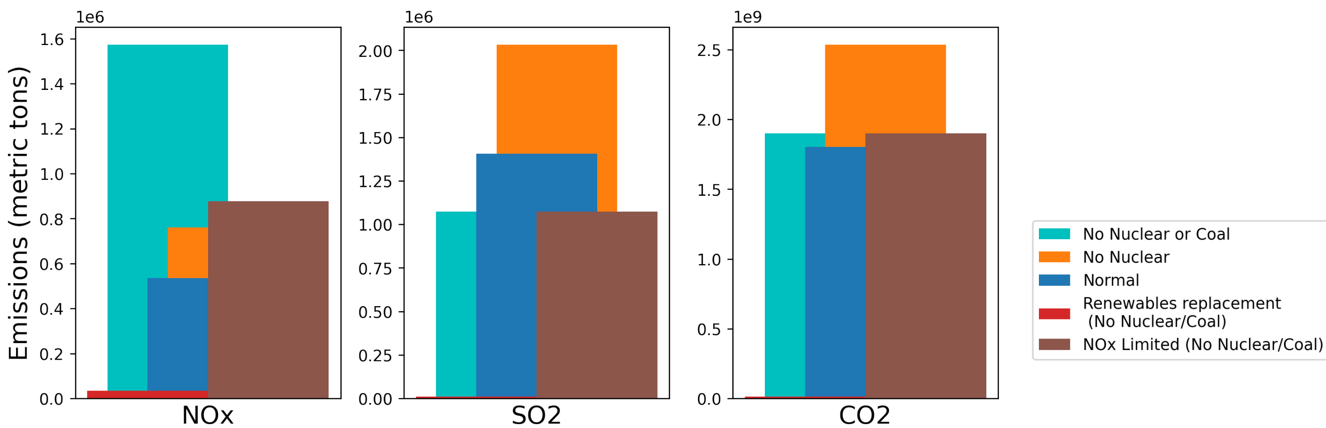

Fig. S5. Emissions of NO_x, SO_2 and CO_2 for the US-EGO simulations for our *No Nuclear-No Coal*, *No Nuclear*, *Base*, and two sensitivity tests of A) renewables replacement in *No Nuclear-No Coal* and B) CSAPR regulations in *No Nuclear-No Coal*

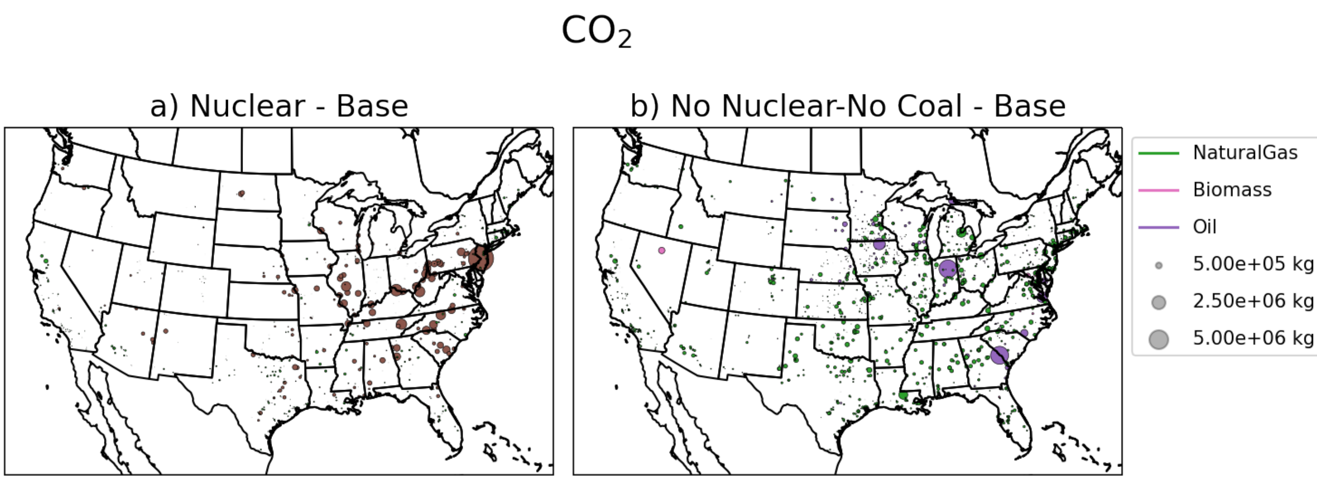

Fig. S6. *No Nuclear - Base* and *No Nuclear-No Coal - Base* annual emissions of CO_2 by each EGU.

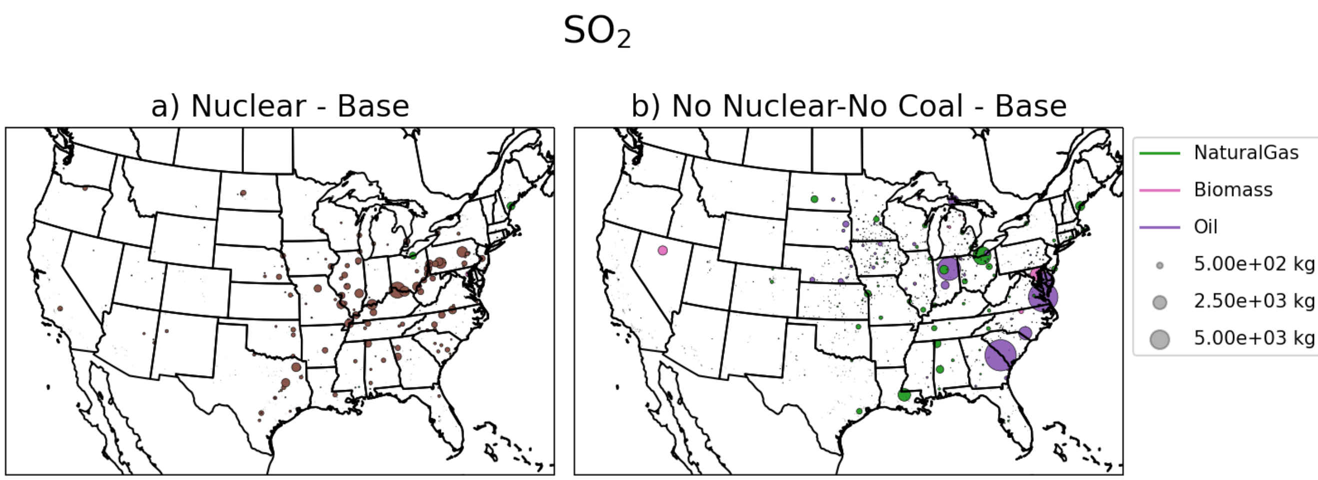

Fig. S7. *No Nuclear - Base* and *No Nuclear-No Coal - Base* annual emissions of SO_2 by each EGU.

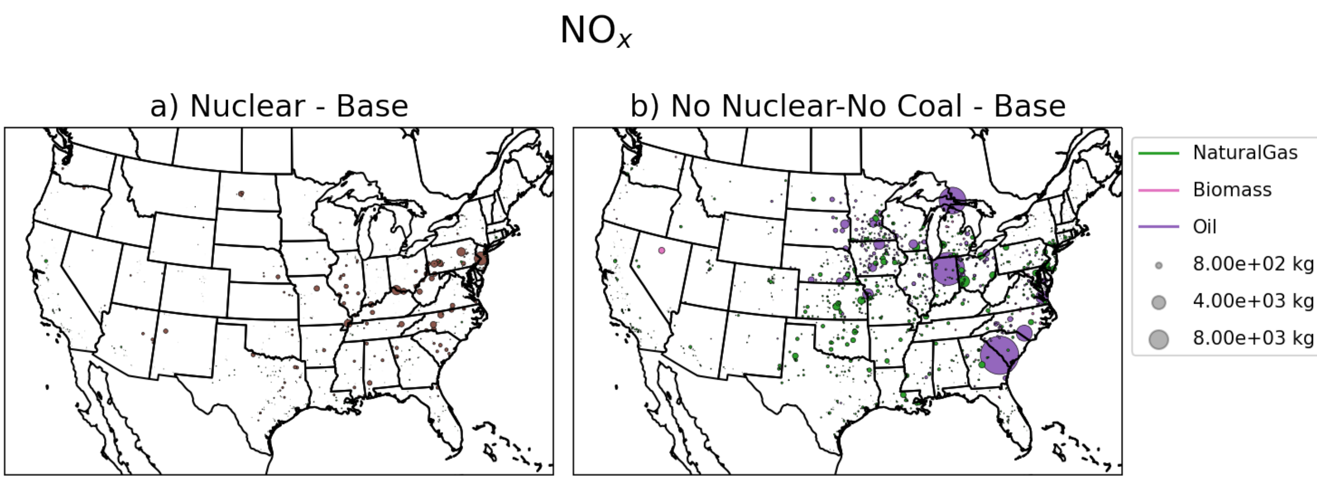

Fig. S8. *No Nuclear - Base* and *No Nuclear-No Coal - Base* annual emissions of NO$_x$ by each EGU.

Table S1. GEOS-Chem Simulations

Name	Data
NEI 2011	National Emissions Inventory, 2011
NEI 2016	National Emissions Inventory, 2016
eGRID	Emissions and Generation Resource Integrated Database
No Nuclear	US-EGO No Nuclear Scenario
No Nuclear- No Coal	US-EGO No Nuclear-No Coal Scenario
Base	US-EGO Base Scenario

Table S2. GEOS-Chem AQS Observation Comparison for Ozone, and the Normalized Mean Bias (NMB) between interpolated GEOS-Chem data and the observational data

Region	Season	NMB (%)
Midwest	DJF	-6.6
Midwest	JJA	36.3
Northeast	DJF	-18.5
Northeast	JJA	34.4
Southeast	DJF	8.1
Southeast	JJA	60.8
Northwest	DJF	13.6
Northwest	JJA	13.7
Southwest	DJF	13.1
Southwest	JJA	12.1

Table S3. GEOS-Chem AQS Observation Comparison: $PM_{2.5}$, and the Normalized Mean Bias (NMB) between interpolated GEOS-Chem data and the observational data

Region	Season	NMB (%)
Midwest	DJF	11.4
Midwest	JJA	-7.4
Northeast	DJF	41.3
Northeast	JJA	13.2
Southeast	DJF	28.3
Southeast	JJA	-4.2
Northwest	DJF	-42.1
Northwest	JJA	-12.0
Southwest	DJF	-37.3
Southwest	JJA	-31.3

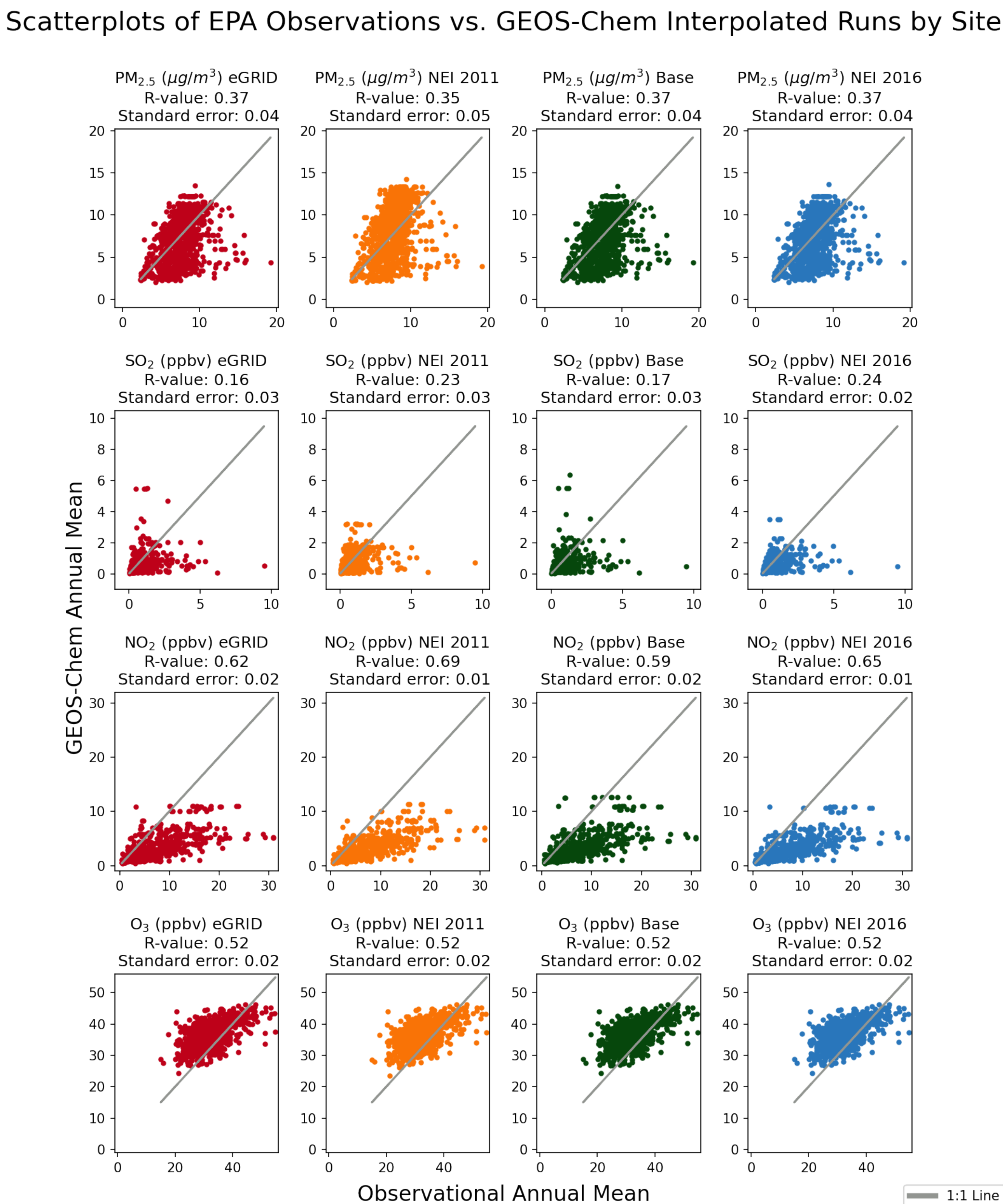

Fig. S9. Scatter plot of the interpolated annual mean GEOS-Chem data as compared to the AQS observational annual mean for the *eGRID*, *NEI 2016*, *Base*, and *NEI 2011*.

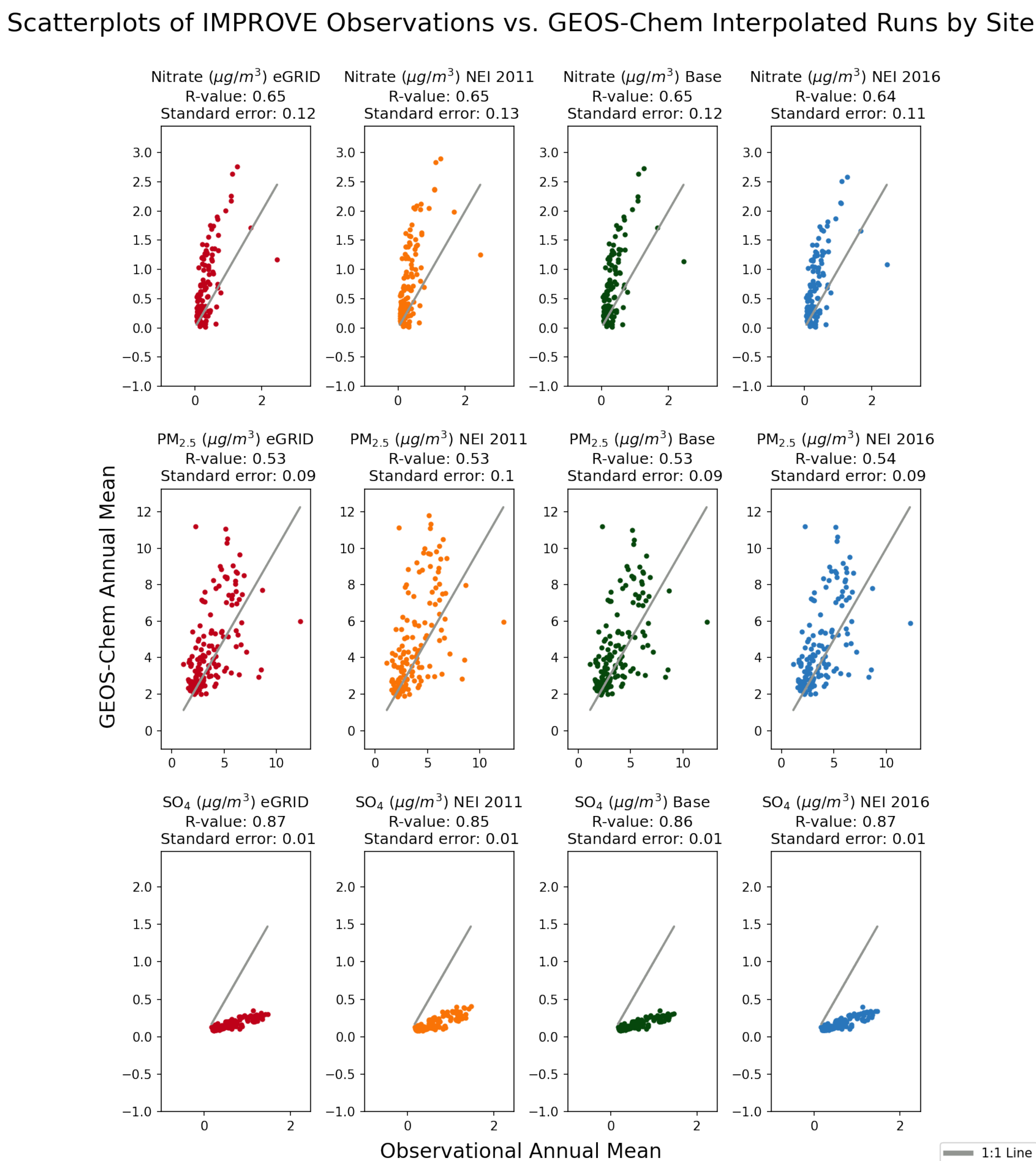

Fig. S10. Scatter plot of the interpolated annual mean GEOS-Chem data as compared to the IMPROVE observational annual mean for the *eGRID*, *NEI 2016*, *Base*, and *NEI 2011*.

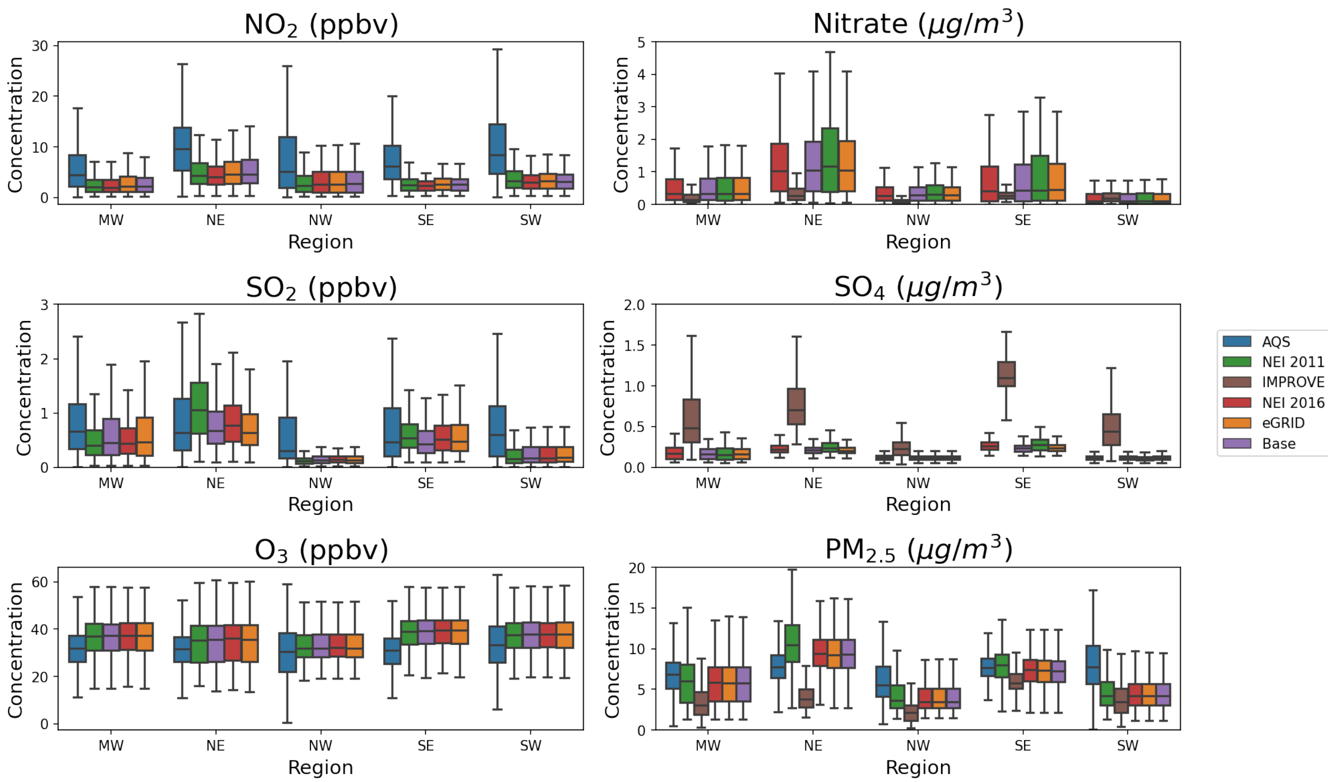

Fig. S11. Boxplots of the observational data from IMPROVE and AQS as compared to the eGRID, NEI 2016, NEI 2011, and normal model data. We split each pollutant into five regions for comparison.

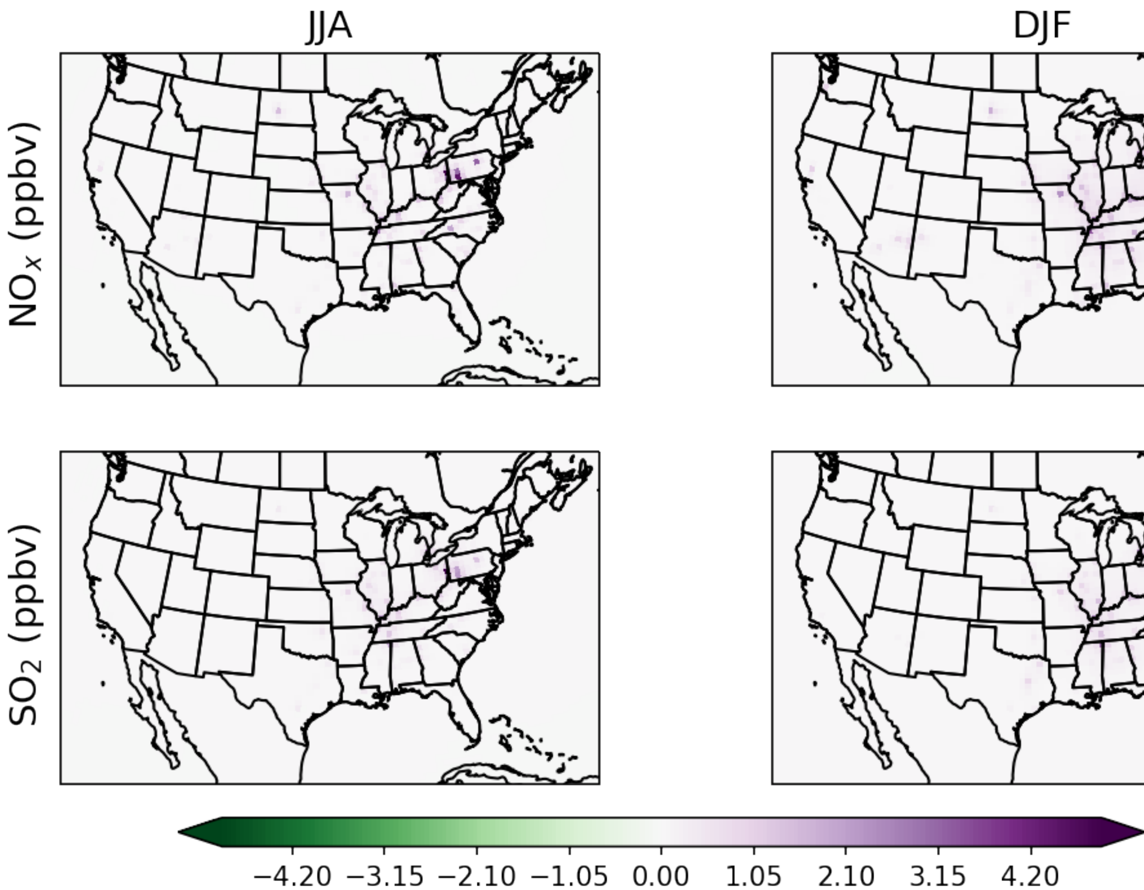

Fig. S12. NO_x and SO_2 concentrations in summer and winter for *No Nuclear* compared to the *Base*

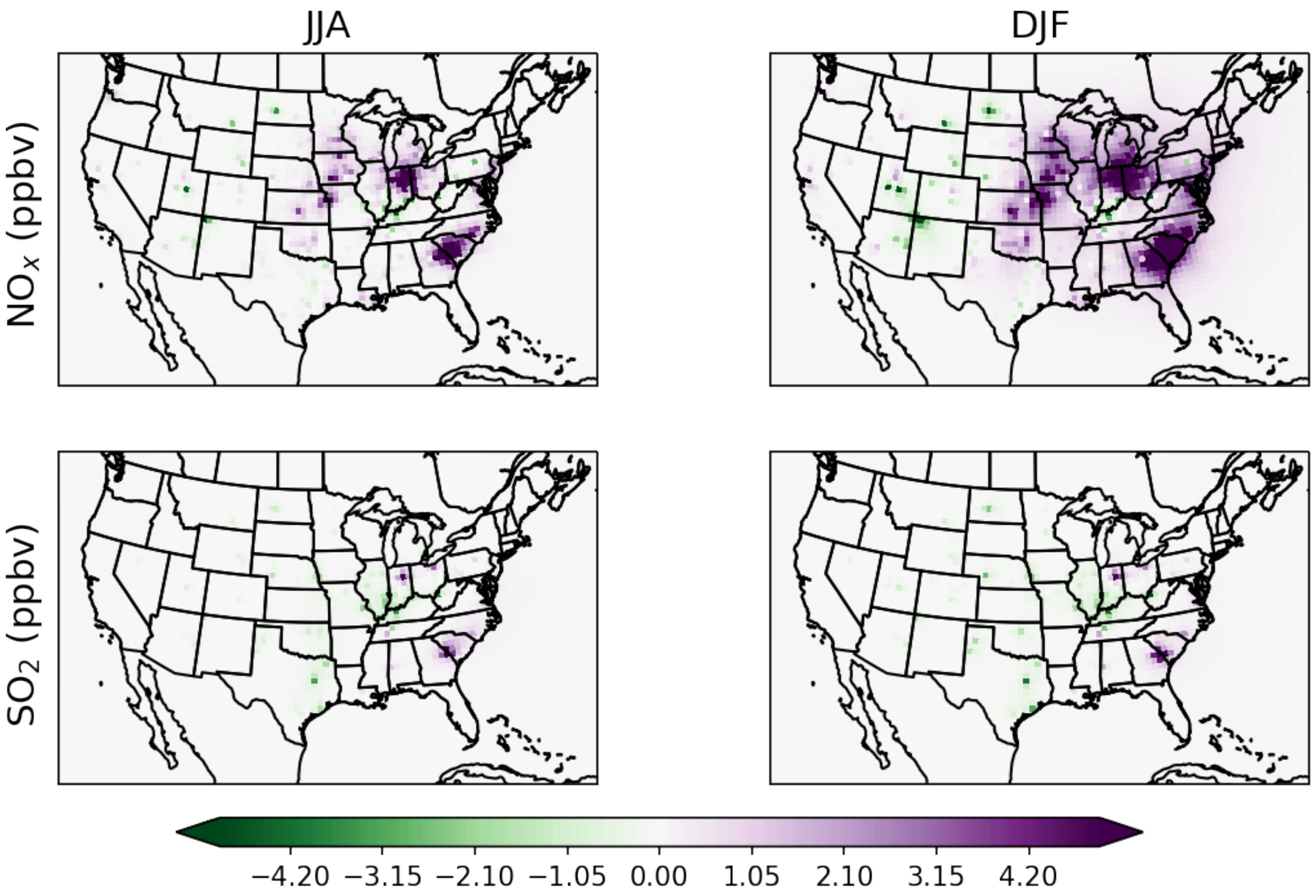

Fig. S13. NO_x and SO_2 concentrations in summer and winter for *No Nuclear-No Coal* compared to the *Base*.

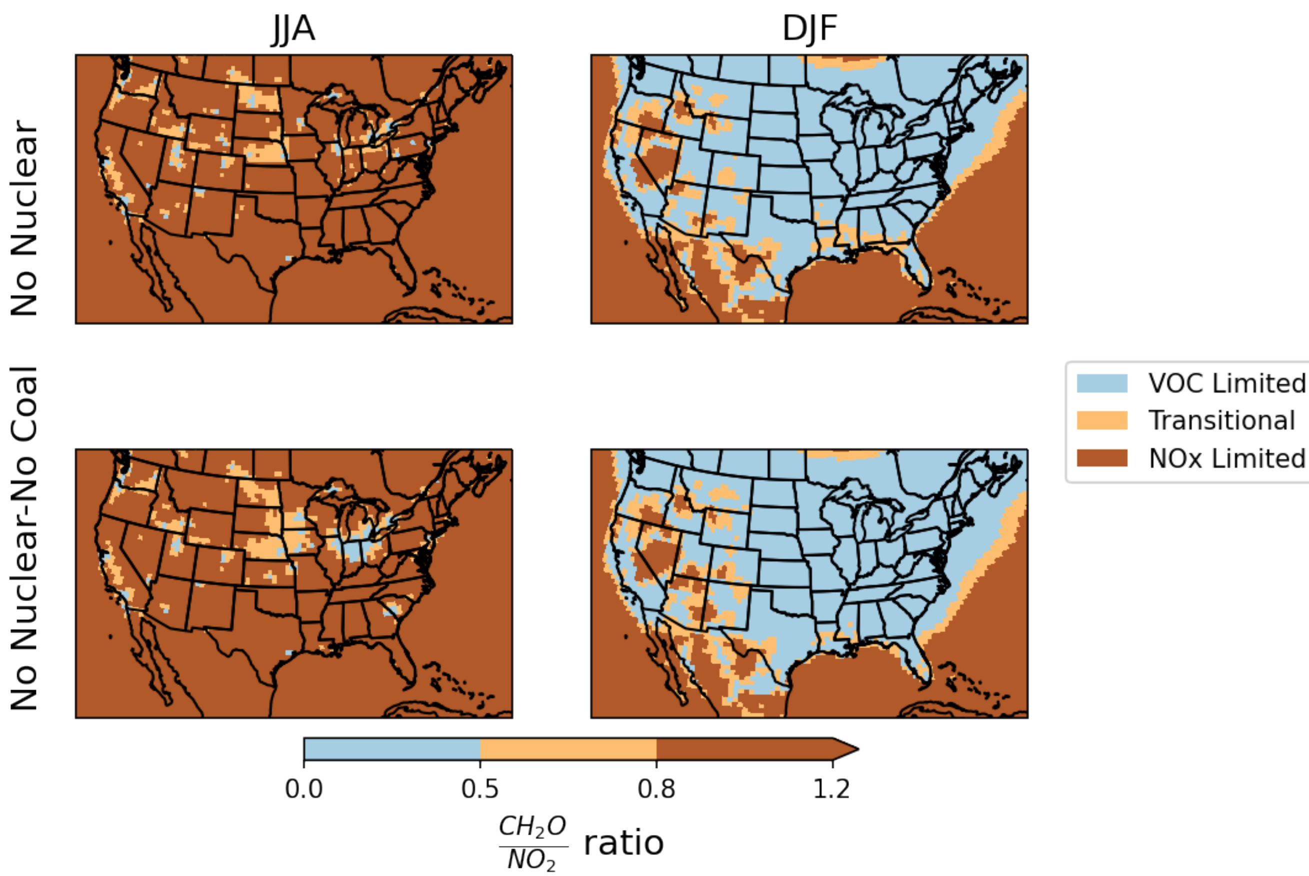

Fig. S14. Summertime and wintertime CH_2O/NO_2 regimes.

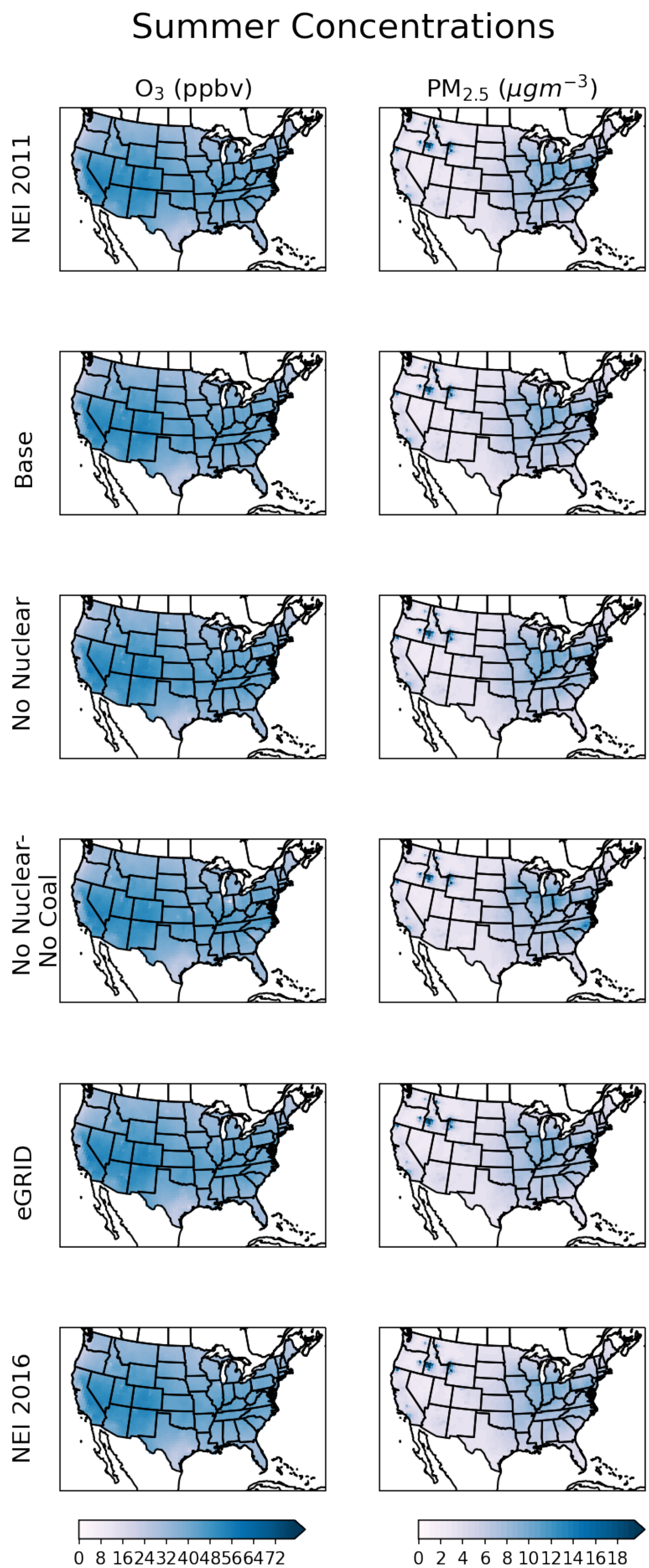

Fig. S15. Mean summer (JJA 24-hour) concentrations of ozone and $PM_{2.5}$ for all six scenarios.

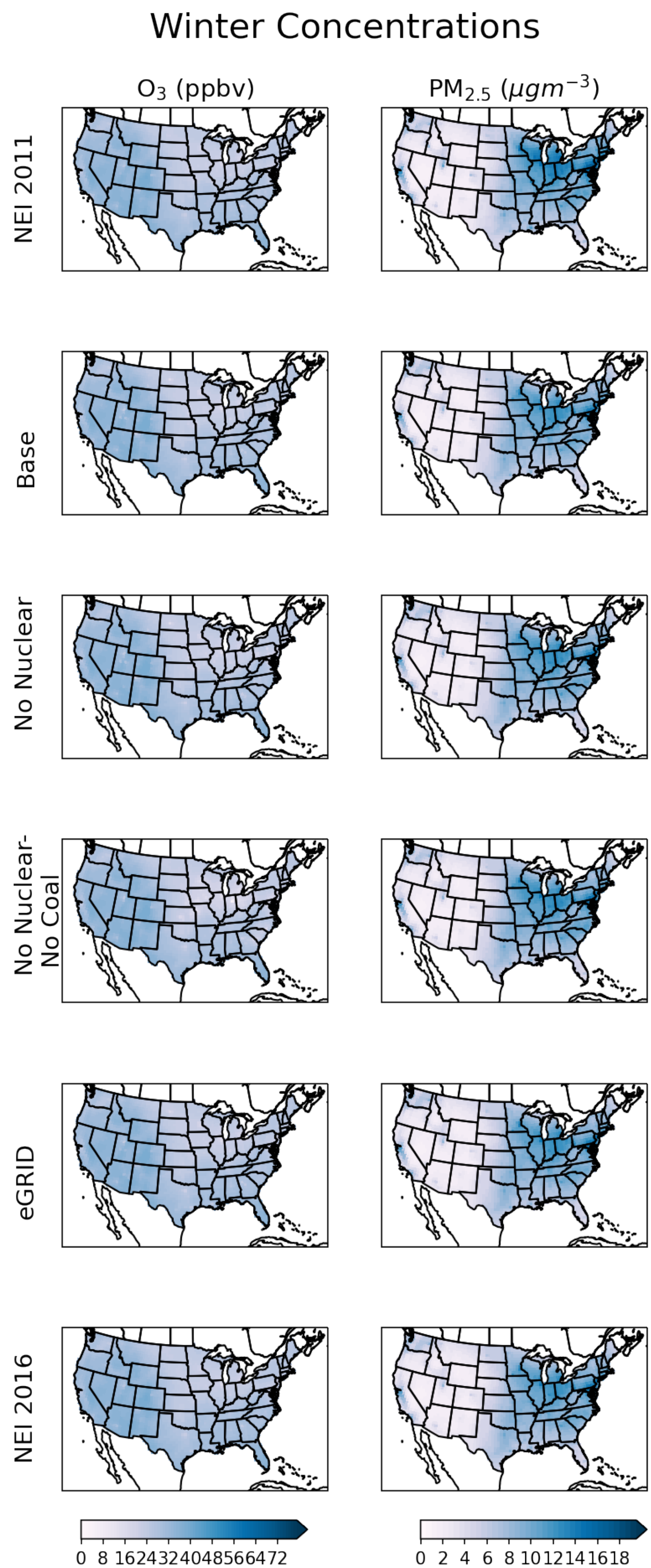

Fig. S16. Mean winter (DJF 24-hour) concentrations of ozone (top) and $PM_{2.5}$ (bottom) for all six scenarios.

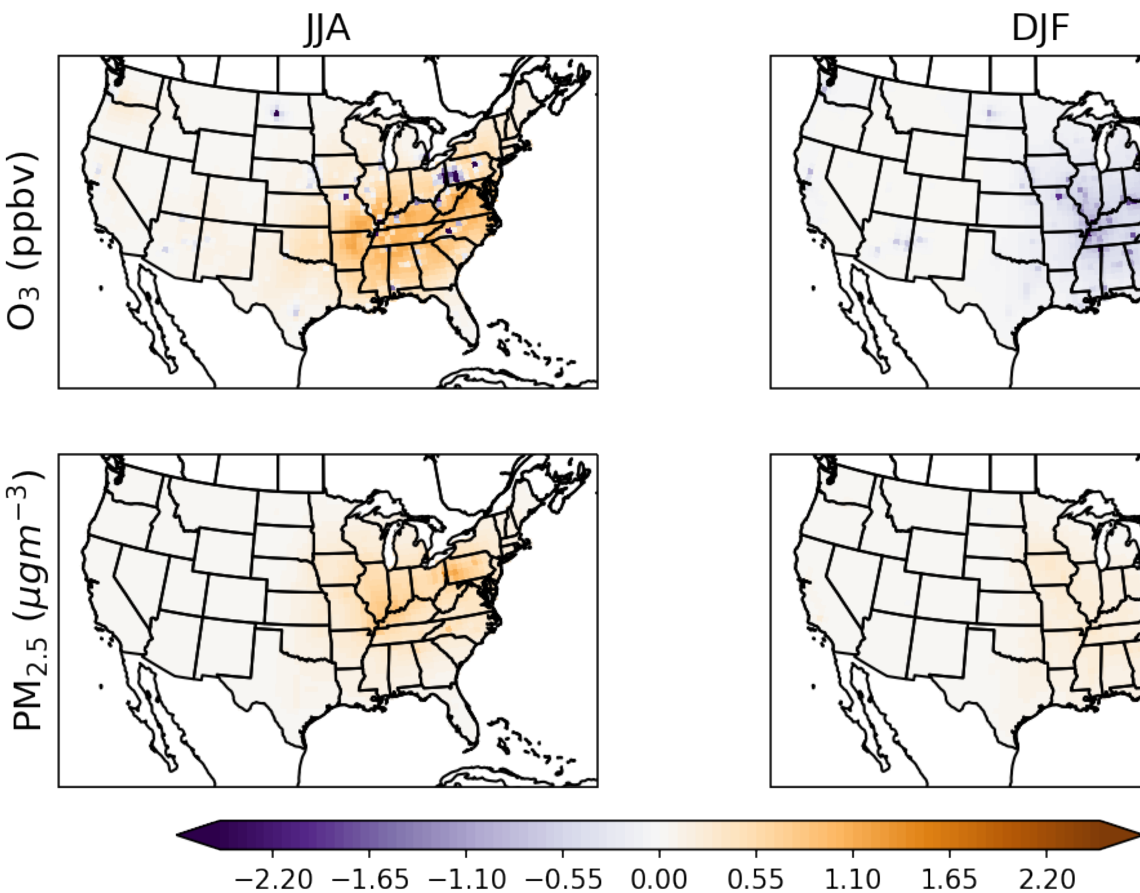

Fig. S17. Differences in summer (JJA) and winter (DJF) mean $PM_{2.5}$ and differences in summer afternoon (JJA 10 A.M.-6 P.M.) and winter (DJF) mean ozone between *No Nuclear* and the *Base*.

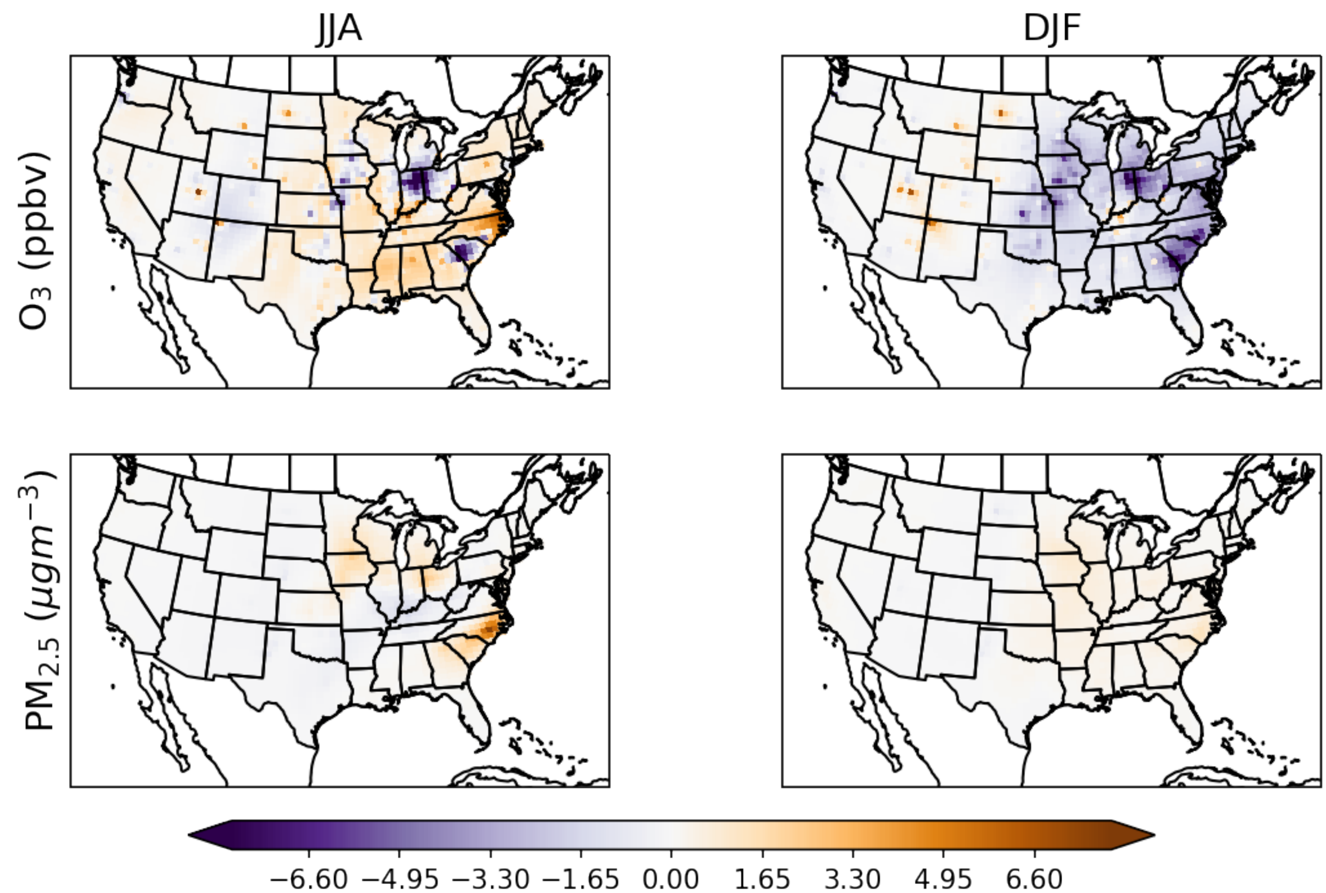

Fig. S18. Differences in summer (JJA) and winter (DJF) mean $PM_{2.5}$ and differences in summer afternoon (JJA 10 A.M.-6 P.M.) and winter (DJF) mean ozone between *No Nuclear-No Coal* and the *Base*.

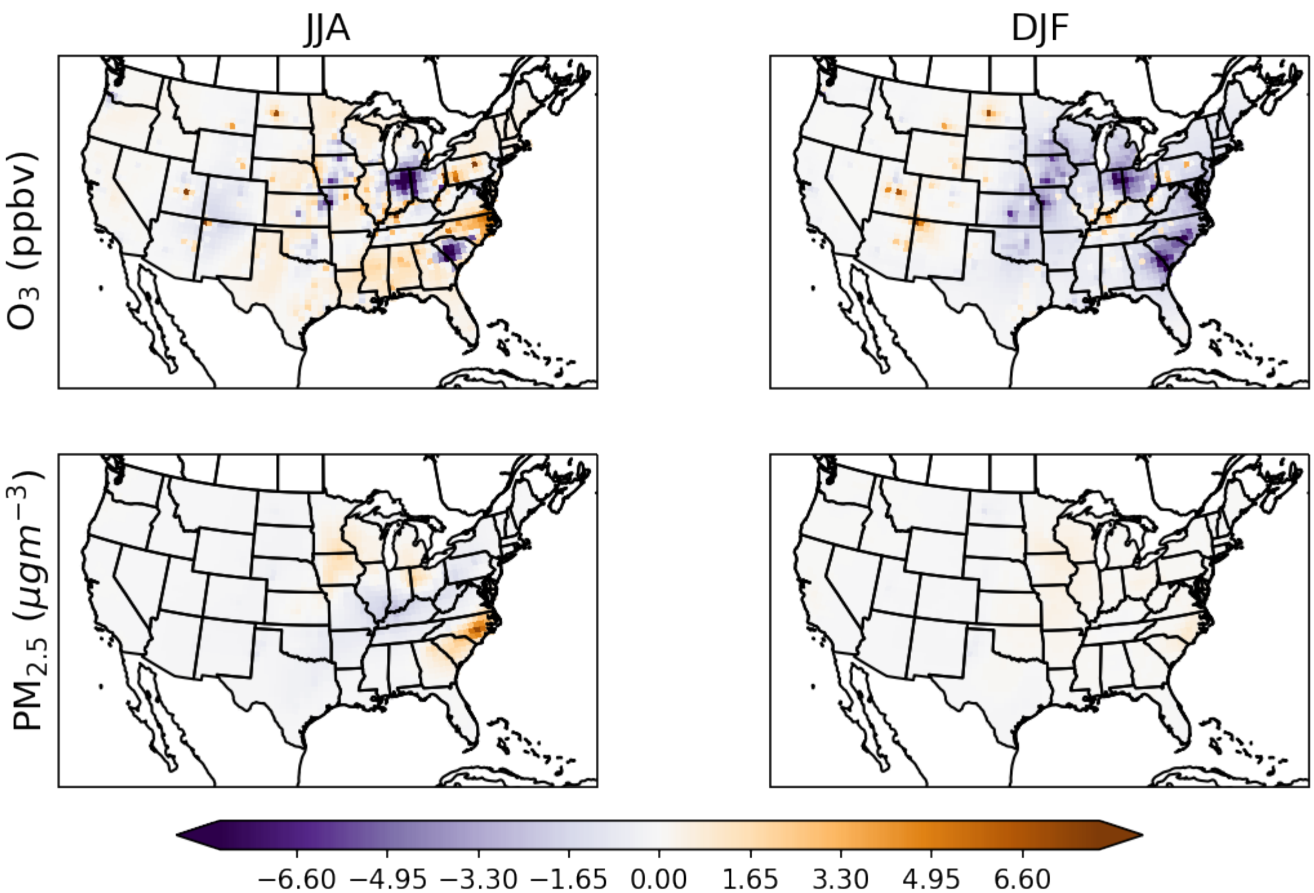

Fig. S19. Differences in summer (JJA) and winter (DJF) mean $PM_{2.5}$ and differences in summer afternoon (JJA 10 A.M.-6 P.M.) and winter (DJF) mean ozone between *No Nuclear-No Coal* and *No Nuclear*.

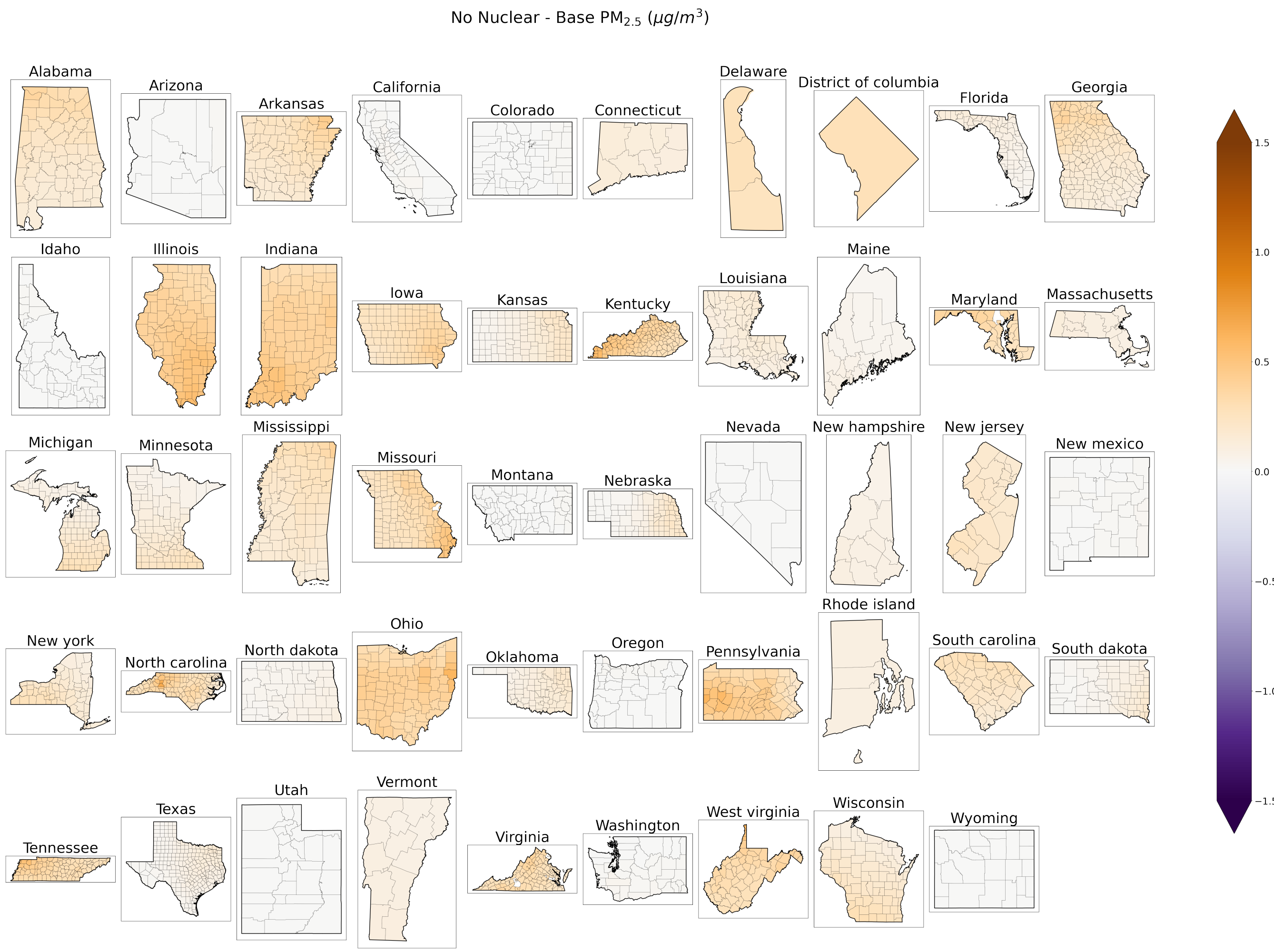

Fig. S20. State specific differences in $PM_{2.5}$ between *No Nuclear* and *Base*

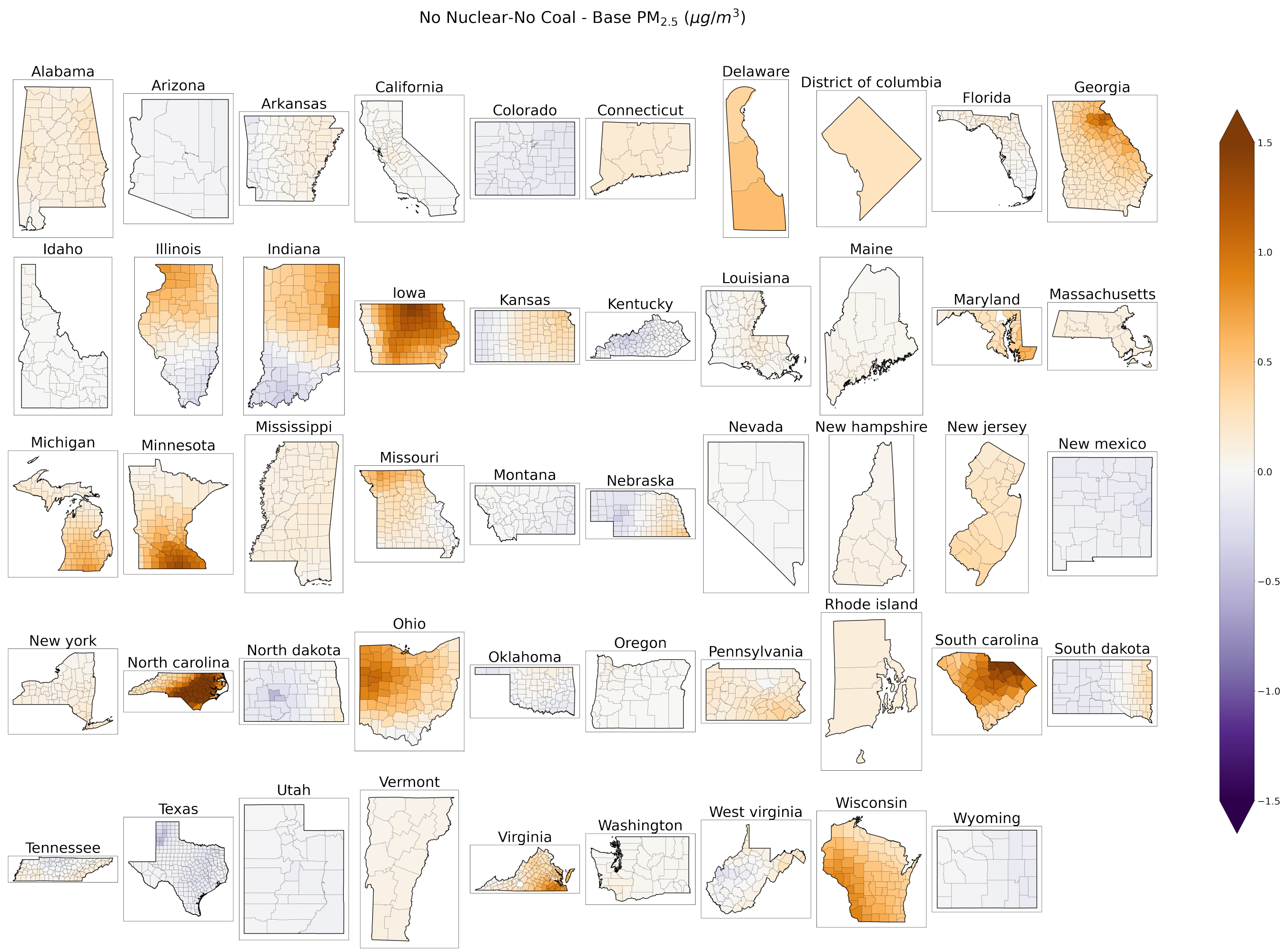

Fig. S21. State specific differences in $PM_{2.5}$ between *No Nuclear-No Coal* and *Base*

Fig. S22. State specific differences in $PM_{2.5}$ between *No Nuclear* and *Base*

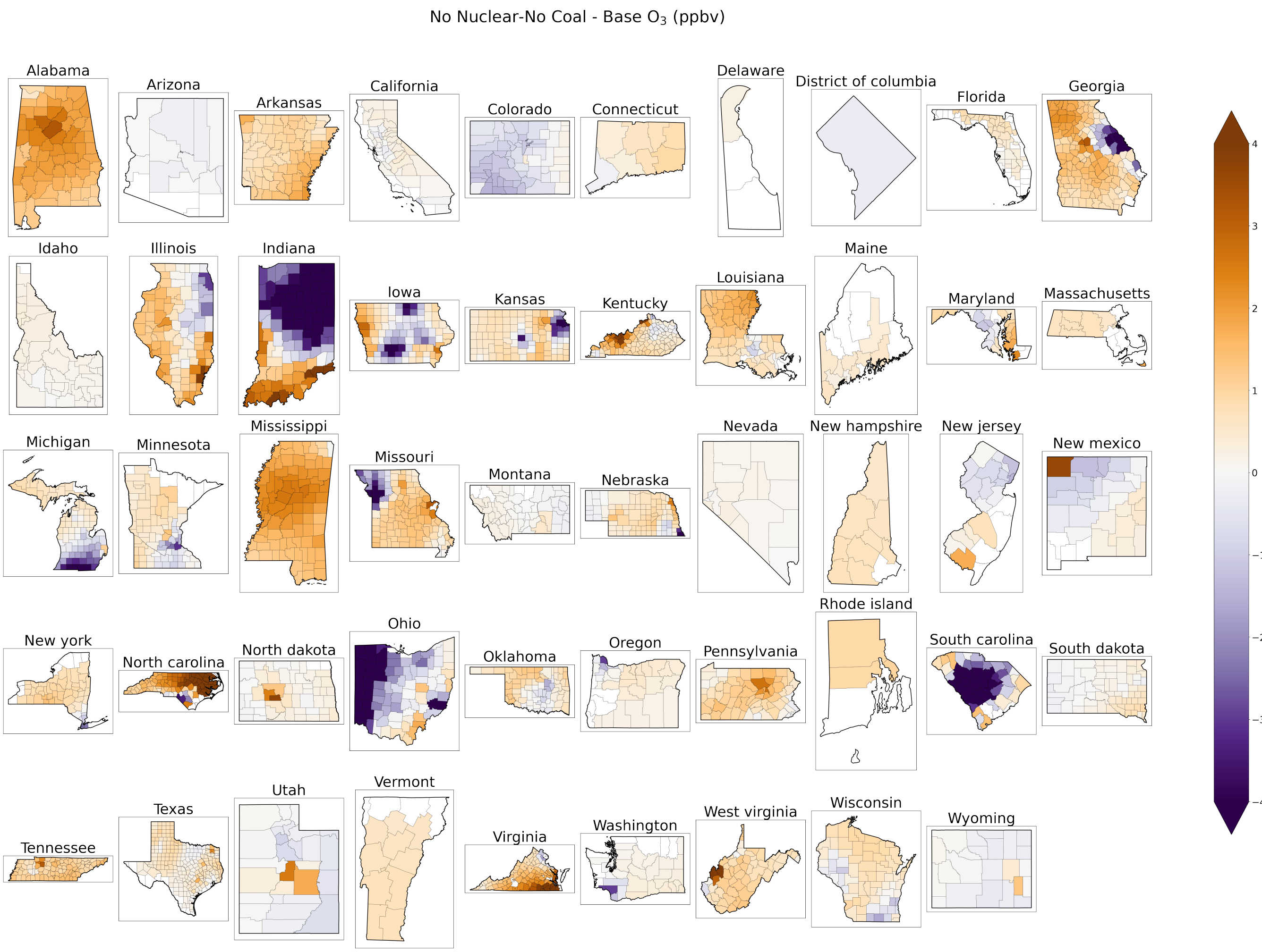

Fig. S23. State specific differences in $PM_{2.5}$ between *No Nuclear-No Coal* and *Base*

Table S4. $PM_{2.5}$ Population Weighted Exposure by Race and Ethnicity, Mean and 95% Confidence Interval

Race and Ethnicity	No Nuclear Change in Exposure WONDER data ($\mu g/m^3$)	No Nuclear-No Coal Change in Exposure WONDER data ($\mu g/m^3$)	No Nuclear Change in Exposure Census data ($\mu g/m^3$)	No Nuclear-No Coal Change in Exposure Census data ($\mu g/m^3$)
Black or African American	0.20	0.26	0.20	0.27
Asian or Pacific Islander	0.12	0.14	0.12	0.15
Hispanic or Latino	0.09	0.08	0.10	0.09
White	0.17	0.18	0.17	0.18
American Indian or Alaska Native	0.07	0.09	0.11	0.13

Table S5. $PM_{2.5}$ Mortality by Race and Ethnicity, Mean and 95% Confidence Interval

Race and Ethnicity	No Nuclear Mortality Rate per 1 million people WONDER (95% CI)	No Nuclear-No Coal Mortality Rate per 1 million people WONDER (95% CI)	No Nuclear Mortality Rate per 1 million people Census Data (95% CI)	No Nuclear-No Coal Mortality Rate per 1 million people Census Data (95% CI)
Black or African American	28.8 (27.6, 29.9)	39.5 (37.9, 41.0)	12.3 (12.0, 12.7)	16.3 (15.9, 16.7)
Asian or Pacific Islander	2.8 (2.2, 3.4)	3.4 (2.7, 4.1)	7.6 (7.4, 7.8)	9.0 (8.8, 9.3)
Hispanic or Latino	2.9 (2.5, 3.3)	1.7 (1.5, 2.0)	6.1 (6.0, 6.3)	5.3 (5.1, 5.4)
White	10.3 (9.8, 10.6)	10.7 (10.2, 11.1)	10.5 (10.3, 10.8)	11.2 (11.0, 11.5)
American Indian or Alaska Native	3.8 (2.3, 0.52)	5.2 (3.2, 7.3)	6.5 (6.4, 6.7)	7.7 (7.5, 7.9)

Table S6. Ozone Population Weighted Exposure by Race and Ethnicity, Mean and 95% Confidence Interval

Race and Ethnicity	No Nuclear Change in Exposure WONDER data (ppb)	No Nuclear-No Coal Change in Exposure WONDER data (ppb)	No Nuclear Change in Exposure Census data (ppb)	No Nuclear-No Coal Change in Exposure Census data (ppb)
Black or African American	0.28	-0.12	0.29	-0.11
Asian or Pacific Islander	0.10	-0.38	0.11	-0.34
Hispanic or Latino	0.08	-0.24	0.09	-0.21
White	0.18	-0.12	0.18	-0.12
American Indian or Alaska Native	0.12	-0.15	0.15	-0.10

Table S7. Ozone Mortality by Race and Ethnicity, Mean and 95% Confidence Interval

Race and Ethnicity	No Nuclear Mortality Rate per 1 million people WONDER (95% CI)	No Nuclear-No Coal Mortality Rate per 1 million people WONDER (95% CI)	No Nuclear Mortality Rate per 1 million people Census data (95% CI)	No Nuclear-No Coal Mortality Rate per 1 million people Census data (95% CI)
Black or African American	2.0 (1.1, 2.6)	-0.8 (-0.5 -1.1)	5.0 (2.5, 9.8)	-1.9 (-1.0, -3.8)
Asian or Pacific Islander	-0.5 (-0.6, -0.3)	2.4 (3.4, 1.4)	1.9 (1.0, 3.8)	-6.0 (-3.0, -11.7)
Hispanic or Latino	-0.3 (-0.4, -0.2)	2.2 (2.8, 1.7)	1.5 (0.8, 3.1)	-3.7 (-1.8, -7.3)
White	2.3 (2.1, 2.4)	-0.7 (-0.6, -0.79)	3.1 (1.6, 6.2)	-2.0 (-1.0, -4.0)
American Indian or Alaska Native	-3.2 (-4.7, -1.8)	1.5 (2.2, 0.85)	2.7 (1.3, 5.3)	-1.7 (-0.9, -3.4)

Table S8. Change in $PM_{2.5}$ Population Weighted Exposure in Nuclear-adjacent and Non-adjacent Counties

Nuclear Adjacent or not	No Nuclear - Base $PM_{2.5}$ exposure WONDER	No Nuclear-No Coal - Base $PM_{2.5}$ exposure WONDER	No Nuclear - Base $PM_{2.5}$ exposure Census Data	No Nuclear-No Coal - Base $PM_{2.5}$ exposure Census Data
Nuclear-adjacent	0.21	0.31	0.21	0.31
Non-adjacent	0.001	0.31	0.14	0.09

Table S9. Change in $PM_{2.5}$ Mortality in Nuclear-adjacent and Non-adjacent Counties

Nuclear Adjacent or not	No Nuclear - Base $PM_{2.5}$ Mean Mortality Rate per 1 million people WONDER	No Nuclear-No Coal - Base $PM_{2.5}$ Mean Mortality Rate per 1 million people WONDER	No Nuclear - Base $PM_{2.5}$ Mean Mortality Rate per 1 million people Census Data	No Nuclear-No Coal - Base $PM_{2.5}$ Mean Mortality Rate per 1 million people Census Data
Nuclear-adjacent	8.2	11.9	13.1	18.9
Non-adjacent	5.1	3.5	8.3	5.7

Table S10. Change in Population Weighted Ozone Exposure in Nuclear-adjacent and Non-adjacent Counties

Nuclear Adjacent or not	No Nuclear - Base ozone exposure WONDER	No Nuclear-No Coal - Base ozone exposure WONDER	No Nuclear - Base ozone exposure census	No Nuclear-No Coal - Base ozone exposure census
Nuclear-adjacent	0.17	-0.29	0.17	-0.28
Non-adjacent	0.004	-0.006	0.21	0.002

Table S11. Change in Population Weighted Ozone Mortality in Nuclear-adjacent and Non-adjacent Counties

Nuclear Adjacent or not	No Nuclear - Base ozone Mean Mortality Rate per 1 million people WONDER	No Nuclear-No Coal - Base ozone Mean Mortality Rate per 1 million people WONDER	No Nuclear - Base ozone Mean Mortality Rate per 1 million people Census Data	No Nuclear-No Coal - Base ozone Mean Mortality Rate per 1 million people Census Data
Nuclear-adjacent	0.9	0.02	2.9	-4.9
Non-adjacent	1.2	0.4	3.6	0.04

References

1. U.S. electric system is made up of interconnections and balancing authorities - Today in Energy - U.S. Energy Information Administration (EIA) (2016).
2. R Uría-Martínez, et al., 2017 Hydropower Market Report, (Oak Ridge National Laboratory), Technical report (2018).
3. Refined coal has made up nearly one-fifth of coal-fired power generation so far in 2017 - Today in Energy - U.S. Energy Information Administration (EIA) (2017).
4. EPA, Power Sector Modeling Platform v.5.15 (2016).
5. WC Malm, JF Sisler, D Huffman, RA Eldred, TA Cahill, Spatial and seasonal trends in particle concentration and optical extinction in the United States. *J. Geophys. Res. Atmospheres* **99**, 1347–1370 (1994).
6. U EPA, Daily summary data for pollutants (2016) Library Catalog: aqs.epa.gov.
7. S Hoyer, J Hamman, xarray: N-D labeled Arrays and Datasets in Python. *J. Open Res. Softw.* **5**, 10 (2017) Number: 1 Publisher: Ubiquity Press.
8. H Simon, KR Baker, S Phillips, Compilation and interpretation of photochemical model performance statistics published between 2006 and 2012. *Atmospheric Environ.* **61**, 124–139 (2012).
9. J Holt, NE Selin, S Solomon, Changes in Inorganic Fine Particulate Matter Sensitivities to Precursors Due to Large-Scale US Emissions Reductions. *Environ. Sci. & Technol.* **49**, 4834–4841 (2015) Publisher: American Chemical Society.
10. JM Walker, S Philip, RV Martin, JH Seinfeld, Simulation of nitrate, sulfate, and ammonium aerosols over the United States. *Atmospheric Chem. Phys.* **12**, 11213–11227 (2012).
11. CL Heald, et al., Atmospheric ammonia and particulate inorganic nitrogen over the United States. *Atmospheric Chem. Phys.* **12**, 10295–10312 (2012).
12. X Jin, et al., Evaluating a Space-Based Indicator of Surface Ozone-NOx-VOC Sensitivity Over Midlatitude Source Regions and Application to Decadal Trends. *J. Geophys. Res. Atmospheres* **122**, 10,439–10,461 (2017).