Understanding Linkages between the Power Sector, Air Quality, and Human Health.

By

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Abstract

The tools, policies and strategies used to address air quality, climate, and energy have often been developed without consideration of interdependencies, thus limiting opportunities to assess multiple objectives. In this dissertation, interdisciplinary methods and tools from energy science, atmospheric science, and public health are utilized to answer cross-cutting questions regarding the co-management of air and climate through energy decision-making.

The first section of this dissertation examines the link between rising temperatures and power-sector emissions. Electricity demand rises with temperature, driven by increased cooling demand. We quantify the historical relationship between ambient temperature and power sector emissions in the Eastern U.S., finding approximately 3.5%/°C increases in emissions of carbon dioxide (CO_2), nitrogen oxides (NO_X), and sulfur dioxide (SO_2). Then we perform an interdisciplinary modeling assessment of the impact of rising temperatures on mid-century air conditioning, electricity demand, air pollution, and associated health impacts. We find nearly 1,000 deaths annually in the Eastern U.S. by mid-century associated with pollution driven by increased air conditioning.

The second section of this dissertation examines clean energy solutions to both the air and climate. Solar energy and energy efficiency are considered as potential strategies for the U.S. An integrated assessment of energy policy options is analyzed for the Republic of South Africa. In these studies, we find 17% solar energy in the Eastern U.S. can reduce fine particulate ($PM_{2.5}$) concentrations by nearly 5%. We find 15% energy efficiency can reduce ozone (O_3) and $PM_{2.5}$ concentrations by approximately 1% nationwide while significantly improving efforts to meet ambient air standards in many U.S. counties. In a comparative analysis for South Africa, we find end-of-pipe controls are cost-effective at limiting pollution and greenhouse gas emissions, and some renewable energy subsidies are also cost-effective.

This work highlights the importance of considering air quality and climate co-benefits in solutions-oriented energy research.

Introduction

Problem Statement

While it is well known that clean energy will have positive impacts on air pollution and climate mitigation efforts, the impacts have not been effectively quantified using detailed methods applicable to the regulatory and advanced scientific communities. Clean energy efforts at the intersection of energy, air, climate, and health are still predominantly addressed separately in both policy and science.

The U.S. currently spends approximately $50 billion per year to achieve the clean air standards required by the U.S. Environmental Protection Agency (EPA) under the Clean Air Act. These investments yield a remarkably high return on investment in public health—between $10 and $30 in benefits for every dollar spent;[1] https://www.epa.gov/clean-air-act-overview/progress-cleaning-air-and-improving-peoples-health).

For the power sector, the relationship between technologies and emissions is well known. Technologies without combustion like solar, wind and nuclear energy have far lower emissions than fossil-fuel power plants like coal, petroleum, and natural gas. However, the effects of temperature on this anthropogenic emissions source and subsequent air quality exposure are not well understood and often disregarded in analyses. As temperatures fluctuate throughout a year, and as climate continues to change on a longer scale, patterns of energy use and emissions also change. This has profound consequences for air quality and health. As power sector emissions can be controlled, understanding these consequences and interactions is critical for managing air pollution and public health.

To date, investments in clean air have been directed towards expensive technological controls, especially for large power plants. Expanding clean energy programs is an under-utilized method for states and utilities to meet clean air and health targets. Energy solutions reduce carbon dioxide (CO_2) along with health-damaging pollutants like NO_X, SO_2, ozone (O_3), and fine particulate matter ($PM_{2.5}$), whereas control technologies capture health-damaging pollutants, but reduce plant efficiency, subsequently increasing CO_2 emissions. Therefore, incorporating renewable energy and energy efficiency (RE/EE) into air management represents a huge step forward for co-management of air pollution and climate change mitigation. By reducing multiple pollutants and associated health impacts at a cost lower than standard technological fixes, clean energy strategies offer a potential win-win-win opportunity for states, ratepayers, and utilities.

Despite the air quality benefits of clean energy strategies, air emissions and health impacts are rarely included in energy analyses, and RE/EE are rarely utilized in air quality management and planning even though the EPA has advanced guidance on using renewable energy and energy efficiency to achieve clean air standards.[2,3] This disconnect arises in part from the difficulty in linking interdisciplinary models and methods to one another. To account for the air quality and health impacts of an energy policy, one would need to integrate the following:

- an electricity dispatch model to calculate which units will respond to a policy or technology change.
- an emissions model to calculate how generation changes will affect air emissions.
- atmospheric models to calculate how emissions will react and disperse in the atmosphere.
- a health impacts model to calculate the changes in mortality and morbidity associated with changes in air pollution exposure.

In this dissertation, I propose to answer the following questions using interdisciplinary modeling frameworks that utilize the most advanced tools from existing regulatory and scientific communities.

1. How do changes in ambient temperature affect power-sector emissions in the Eastern United States?
2. Given a relationship between ambient temperature and power-sector emissions driven by changes in electricity demand, what impact will climate change have on future U.S. air quality and air quality-related health?
3. What would be the air quality impacts of a realistic solar energy future for the Eastern United States?
4. What would be the air quality impacts of realistic increases in energy efficiency throughout the United States?
5. How do renewable energy policy interventions compare to end-of-pipe technology requirements in co-mitigating greenhouse gas emissions and air pollution in a developing country like South Africa? And can the relationships defined in a data-rich region like the U.S. with sophisticated models be replicated in a less data-rich region with integrated assessment models?

Motivation

Air pollution is the fourth highest risk factor in the Global Burden of Disease, and causes approximately 7 million premature deaths annually.[4] In the U.S., $PM_{2.5}$ and O_3 cause approximately 100,000 premature deaths annually (https://vizhub.healthdata.org/gbd-compare/). The health benefits of emissions reductions from the U.S. electricity sector were calculated to be \$130,000 per ton of directly emitted (primary) $PM_{2.5}$, \$28,000 to \$35,000 per ton of SO_2 precursor emissions (via the formation of secondary $PM_{2.5}$) and \$5,200 to \$16,000 per ton of NO_X precursor emissions (via the formation of secondary $PM_{2.5}$).[5,6] The high value of health benefits due to emission reduction is consistent with EPA benefit-cost analyses (https://www.epa.gov/clean-air-act-overview/benefits-and-costs-cleanair-act), and provide the basis for extensive emissions controls on power plants that have been implemented over the past few decades. However, renewable energy and energy efficiency offer a method of co-managing both health-damaging air pollutants and greenhouse gas emissions potentially more cost-effectively than with technological controls. While this dissertation in focused on the power sector and changes in $PM_{2.5}$ and O_3, changes in other sectors and to other pollutants are also important. For example, additional work considers the prevalence and impacts of polycyclic aromatic hydrocarbons in ethanol and other transportation fuels.[7]

The methods used in this analysis provide a framework for U.S. states to include clean energy in their health and air quality planning. Within the U.S. and globally, many regions are considering RE/EE as part of climate change mitigation plans or as a cost-competitive component of electricity systems planning, but the direct impacts of RE/EE are rarely considered for air quality alone, nor are the myriad of benefits considered wholly in most commercial, regulatory, or scientific contexts. In 2014, 92% of the world's population lived in places where World Health Organization guidelines for air quality were not met (http://www.who.int/mediacentre/factsheets/fs313/en/). Countries should begin to consider the benefits of RE/EE directly in energy and air planning, and the methods and findings of the research proposed here are designed to establish a framework for the broader adoption of RE/EE for public health. In the following, we provide the motivation behind each individual project and research question.

Historical Power Sector Emissions and Temperature

Chapter 1 is designed to answer research question 1: how do changes in ambient temperature affect power-sector emissions in the Eastern United States?[8,9]

Past studies have established strong connections between meteorology and air quality, via chemistry, transport, and natural emissions. A less understood linkage between weather and air quality is the temperature-dependence of emissions from electricity generating units (EGUs), associated with high electricity demand to support building cooling on hot days. This study quantifies the relationship between ambient surface temperatures and EGU air emissions (CO_2, SO_2, and NO_X) using historical data.

Meteorology plays a critical role in air quality and atmospheric chemical processes, including emissions.[10] Ambient temperature, humidity, wind and pressure drive changes in chemical activity, transport and emissions.[11] A large body of research has evaluated the climate sensitivity of biogenic emissions, especially biogenic volatile organic compound (VOCs),[12–14] as well as wildfires,[15–17] soil NO_X,[18] and lightning NO_X.[19–21] However, this study extends our understanding of temperature-dependent air emissions by quantifying the historical response of electricity generation-based emissions to ambient temperature.

Previous studies have looked at components of this relationship for specific pollutants in single states or small regions of the U.S.[22–24] Other studies have also examined the role of peaking power plants on hot days and peak air pollution days.[25–27] This study builds on this line of inquiry, with a focus on temporal and spatial patterns in the response of EGU emissions to ambient temperature. We would expect a relationship between ambient temperature and power-sector emissions as temperature is the dominant meteorological variable affecting electricity generation in developed economies.[28,29] In addition to demand increasing on hot days, the distribution of generation will also change for "peak" generation days, where older, less controlled and less efficient marginal plants may be activated to meet high levels of demand.[25]

Results from this analysis quantify an important and often overlooked feedback between temperature and air emissions. We discuss how electricity fuel mix affects emissions on hot days, and we report sensitivity factors to support improved modeling of U.S. air quality under current and future conditions.

Air Quality and Health under a Warmer Climate

Chapter 2 is designed to address research question 2: given a relationship between ambient temperature and power-sector emissions driven by changes in electricity demand, what impact will climate change have on future U.S. air quality and air quality-related health?[8,9,30,31]

Climate change negatively impacts human health through heat stress and exposure to worsened air pollution, amongst other pathways. Indoor use of air conditioning can be an effective strategy to reduce heat exposure. However, air conditioning in buildings is a form of adaptation to warmer temperatures that could increase population health risks, by increasing power plant emissions on hot days. As air conditioning use increases to cool buildings, the increased demand for electricity is supplied by a mix of generation sources including fossil fuels, thus increasing harmful emissions. We used an interdisciplinary linked model system to quantify the impacts of heat-driven adaptation through building demand on air quality-related health outcomes in a representative, mid-century climate scenario.

Quantifying the role of air conditioning adaptation in future air quality bears relevance to decision-making, as power-sector emissions are controllable by technology and policy, in a way that other climate-driven air quality mechanisms are not (i.e. chemical reaction rates, biogenic emissions, NO_X from lightning, and wildfire emissions). The scenario chosen here highlights the role of interactive effects amongst climate, energy and air quality. Interventions would, and likely will, reduce the damages calculated here. Control options include stack-level technological controls, which have been the traditional approach employed by U.S. air quality management agencies to meet health-based standards, or clean energy strategies such as RE/EE.

This work advances the line of research characterizing health co-benefits from mitigation strategies,[32–45] and the direct quantification of health damages from air pollution in a future climate.[46–55] This study builds upon a large body of epidemiological work relating air pollution and human health, including the studies utilized in EPA's Benefits Mapping and Analysis Program (BenMAP).[56]

This study explores power plants and heat-driven electricity demand in buildings as an insufficiently understood mechanism to future air quality-related health damages in a warmer climate. It is the first study to compare the impact of mid-century climate change on air quality and air quality-related health with and without associated heat-driven changes in emissions from the electricity sector.

Solar Energy and Air Quality

Chapter 3 is designed to answer research question 3: What would be the air quality impacts of a realistic solar energy future for the Eastern United States? [32]

Renewable energy and energy efficiency (RE/EE) strategies have very rarely been incorporated into the state implementation plan (SIP) process for air quality management. This is surprising given that a wide range of RE/EE strategies offer the potential to reduce NO_X from all fossil fuels and SO_2 from coal and oil, as well as other regulated pollutants. Other pollutants analyzed during graduate studies but not included in this dissertation include an assessment of polycyclic aromatic hydrocarbons in the context of ethanol combustion.[7] A historical disconnect between RE/EE planning and air quality assessment arises in part from the difficulty in quantifying emissions (which depend on EGU-specific fuel, technology, and generation) and air quality impacts (which depend on atmospheric chemistry, weather, and other emission sources). Thus, efforts to incorporate solar energy into air planning have been extremely limited and scientific methods and findings have been effective in showing the benefits of solar, but often only as a co-benefit to climate and energy planning.

Solar PV contributed less than 1% to U.S. electricity production in 2015 [57], but decreases in cost and high potential resources contribute to projections that solar energy production will continue to grow.[28,58] Studies suggest that solar could contribute ~15% of U.S. electricity generation by 2030 and nearly 30% by 2050.[59,60] As the U.S. generates more electricity from solar PV, the rate of air emissions from the electricity sector per megawatt-hour (MWh) produced will decrease. Thus, as the U.S. energy system incorporates more solar PV, we expect to see direct benefits to health-relevant air pollution, especially $PM_{2.5}$.

Reductions in $PM_{2.5}$ between 1980 and 2000 in the U.S. have been associated with an increase in life expectancy with substantial value to human health,[5,6,61–63] and past studies have applied similar analyses to RE/EE investments, though often with simplified models and integrated assessment methodologies that avoid the sophisticated energy dispatch and chemical transport modeling necessary for regulatory and planning purposes.[33,37,64–76]

While previous studies have addressed the air quality co-benefits of carbon reduction in the electricity sector, they use a vast array of different methodologies, and this work is the first to utilize a security-constrained electricity dispatch model with a best-available, regulatory standard emissions inventory, a detailed, regulatory standard chemical transport model, and a regulatory standard health impacts and valuation tool.

Using a robust approach with regulatory-standard tools, this study quantifies the impact of solar energy on air quality in the Eastern U.S. using novel methods replicable in future air and energy planning.

Energy Efficiency and Air Quality

Chapter 4 is designed to answer research question 4: What would be the air quality impacts of realistic increases in energy efficiency throughout the United States? [77]

Only a few research studies have directly addressed the air quality benefits of energy efficiency,[78–81] even though a large and growing body of work addressing the air quality and health co-benefits of climate change mitigation strategies exists.[66,82–84] As with previously discussed clean energy strategies, energy efficiency has rarely been considered in regulatory air planning. Texas once included energy efficiency in a state implementation plan in the early 2000s, and the Northeast States for Coordinated Air Use Management (NESCAUM) once ran a pilot program, but both have since been unsuccessful in integrating energy efficiency within air planning. This project will quantify the air quality and health benefits of a 15% energy efficiency scenario developed in collaboration with the American Council for an Energy Efficient Economy (ACEEE).

Energy efficiency is a particularly useful strategy to consider for air management as many energy efficiency measures are cost-negative, meaning any air quality and health benefits could actually also save ratepayers money. Therefore, states have an opportunity to simultaneously reduce energy costs, achieve air standards, and benefit public health. However, it can be difficult to quantify the effectiveness of energy efficiency programs and air planning typically does not include the type of analysis necessary to quantify the air pollution benefits of these programs. This creates a disconnect, similar to study 3 that is addressed by this study.

This research uses regulatory-standard tools, and it fills a need for studies addressing the potential benefits of energy efficiency for mitigating air pollution exposure and addressing adverse health outcomes.

Coordinated Air and Climate Management in South African Energy Scenarios

Chapter 5 is designed to answer research question 5: how do renewable energy policy interventions compare to end-of-pipe technology requirements in co-mitigating greenhouse gas emissions and air pollution in a developing country like South Africa? And can the relationships defined in a data-rich region like the U.S. with sophisticated models be replicated in a less data-rich region with integrated assessment models? [85]

The Republic of South Africa is facing an uncertain energy future defined by multiple, often competing objectives. The nation has clear, and long-term development goals outlined prominently in the National Development Plan (NDP) 2030,[86] as well as environmental goals including limiting greenhouse gas emissions consistent with contributions to the Paris Climate Agreement and local air pollution. These goals are not at odds with one another, and in fact chapter 5 of the NDP explicitly pertains to environmental sustainability. However, in a cost-limited world, investment across multiple objectives necessitates trade-offs, and creates opportunity for coordinated benefits. In this analysis, we consider the impact of energy scenarios consistent with future goals, but varying cost and technology structures on climate change mitigation, local air quality and ambient $PM_{2.5}$-related mortality.

The Republic of South Africa is facing an uncertain energy future defined by multiple, often competing, objectives. The current energy system in South Africa is dominated by coal and is characterized by high CO_2 and pollutant emissions, expected to further increase given projected growth. In general, previous work finds that energy, air pollution, and climate policies are often addressed separately in South Africa, and the nation could benefit from a framework that accounts for interacting environmental, economic, social and political factors.[87,88] The Republic of South Africa should design energy policies around multiple objectives.

In this study, we show the climate and air quality benefits of air controls and power-sector subsidies and the benefit to balancing both strategies. This behavior is important given current and pending policies such as the Integrated Energy Plan, National Development Plan, and Renewable Energy Independent Power Producers Procurement Plan.

Cross-Cutting Insights

This dissertation highlights the importance of considering health and policy implications at the intersection of energy, air quality, and climate solutions using interdisciplinary modeling methods.

The strength of this work especially lies in addressing specific scientific and policy objectives while also considering cross-cutting issues. This dissertation explores several of these cross-cutting questions throughout its chapters, and within the conclusion, explicitly addresses each of the following.

1. What is the relevance or importance of modeling for environmental policy and science?
2. How are energy science, climate science, and air quality analysis relevant to practical environmental management, public health, and policy?
3. What is the importance of framing issues and solutions in considering air quality and climate co-management?
4. Is there a shared role for climate mitigation and adaptation that is relevant to coordinated energy and air quality planning in a changing climate?
5. How do perspectives differ in considering energy, air quality, and climate across population demographics, scientific disciplines, and regions of the world?

These questions are valuable to consider across the chapters of this dissertation. The demonstrate the importance of integrated analysis across energy, air quality, and climate focused on practical solutions with multiple local and global benefits. In addition, the discussion of these insights in the conclusion emphasizes the practical applications of findings from this dissertation.

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Chapter 1: Historical Power Sector Emissions and Temperature

This manuscript was the second initially prepared, but the first published, over the course of my graduate studies. This paper built on work that was in progress at the time culminating in the study Abel et al., (2018) included here as chapter 2 and also including contributions to work modeling power sector emissions under a future climate included in Meier et al., (2017) [1,2]. This study was designed to support and extend ongoing work by comparing measured historical emissions and temperature data. This study quantifies the link between ambient temperatures and increasing power plant emissions due to changes in electricity demand. The paper was published in Environmental Science & Technology as given by the citation below. The work here has been slightly modified from the published version only to conform with formatting for the purposes of this dissertation.

Citation

Abel, D.; Holloway, T.; Kladar, R.; Meier, P.; Ahl, D.; Harkey, M.; Patz, J. Response of Power Plant Emissions to Ambient Temperature in the Eastern United States. *Environ. Sci. Technol.* **2017**, *51* (10), 5838–5846. https://doi.org/10.1021/acs.est.6b06201.

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Abstract

Past studies have established strong connections between meteorology and air quality, via chemistry, transport, and natural emissions. A less understood linkage between weather and air quality is the temperature-dependence of emissions from electricity generating units (EGUs), associated with high electricity demand to support building cooling on hot days. This study quantifies the relationship between ambient surface temperatures and EGU air emissions (CO_2, SO_2, and NO_X) using historical data. We find that EGUs in the Eastern U.S. region from 2007 to 2012 exhibited a 3.87%±0.41% increase in electricity generation per °C increase during summer months. This is associated with a 3.35%/°C±0.50%/°C increase in SO_2 emissions, a 3.60%/°C±0.49%/°C increase in NO_X emissions, and a 3.32%/°C±0.36 %/°C increase in CO_2 emissions. Sensitivities vary by year and by pollutant, with SO_2 both the highest sensitivity (5.04% in 2012) and lowest sensitivity (2.19% in 2007) in terms of a regional average. Texas displays 2007-2012 sensitivities of 2.34%/°C ± 0.28%/°C for generation, 0.91%/°C ± 0.25%/°C for SO_2 emissions, 2.15%/°C ± 0.29%/°C for NO_X emissions, and 1.78%/°C ± 0.22%/°C for CO_2 emissions. These results suggest demand-side and supply-side technological improvements and fuel choice could play an important role in cost-effective reduction of carbon emissions and air pollution.

Introduction

Meteorology plays a critical role in air quality and atmospheric chemical processes, including emissions.[3] Ambient temperature, humidity, wind and pressure drive changes in chemical activity, transport and emissions.[4] A large body of research has evaluated the climate sensitivity of biogenic emissions, especially biogenic volatile organic compound (VOCs),[5–7] as well as wildfires,[8–10] soil NO_X,[11] and lightning NO_X.[12–14] This study extends the understanding of temperature-dependent air emissions by quantifying the historical response of electricity generation-based emissions to ambient temperature.

Previous studies have looked at components of this relationship, including *Pusede et al.,* whom identified the relationship between electricity generating unit (EGU) NO_X emissions and temperature as a contributor to trends in ozone (O_3).[15] More directly, *He et al.* used similar methodology to this study to quantify the dependence of EGU NO_X emissions on temperature in the context of the climate penalty factor for O_3 production,[16] and found a 2.5-4.0 %/°C dependence of NO_X emissions from 1997 to 2011 for five Eastern U.S. states. [17] found that power plant NO_X emissions in California increase approximately 5.8% per °C.[17] *Farkas et al.*, find that controlled and monitored peaking plants can be responsible for up to 87% of local fine particulate matter ($PM_{2.5}$) in the Pennsylvania-New Jersey-Maryland (PJM) interconnect during July 2006 heat wave conditions.[18,19] *McDonald-Buller et al.* consider managing EGU emissions to control O_3 on peak pollution days by differentiated pricing schemes to reduce emissions from the electricity sector.[20] This study builds on this line of inquiry, with a focus on temporal and spatial patterns in the response of EGU emissions to ambient temperature.

Ambient temperature is the dominant meteorological variable affecting electricity generation in developed economies.[21] [22]) According to *Sailor*, states in the Eastern U.S. see residential electricity consumption increases of 0.4% (New York) to 5.3% (Florida) from a 1 °C increase in temperature, and commercially, this ranges from 0.8% to 2.4%.[23] [24] summarize the impacts of a warmer future climate on heating and cooling energy demand, and an increase in cooling degree-days and cooling energy demand is projected.[24] *Dirks et al.* project up to a three-fold increase in cooling demand by the end of the 21st century in the Northeast.[25] In addition to demand increasing on hot days, the distribution of generation will also change for "peak" generation days, where older, less controlled and less efficient marginal plants may be activated to meet high levels of demand.[19]

In addition to increased electricity demand and changes in generation fuel mix, hot days also decrease power plant efficiency and transmission efficiency. According to [26], a nearly 12% (75 MW) drop in output from a combined cycle, natural gas power plant is observed from a large increase (35°C) increase in ambient temperature (scenarios were tested from 0°C to 35°C).[26] Similarly, [27] find a 0.1% decrease in thermal efficiency of a gas turbine per Celsius increase in ambient temperature.[27] The coupling of a unit production cost and commitment model with temperature models has been used to demonstrate vulnerabilities of the system to future climate.[28]

While the interaction between climate and emissions associated with electricity generation is not a standard component of climate-air quality analyses, past studies have analyzed energy systems and air quality in other contexts.[29,30] [31]examined how temperature impacts O_3 production efficiency (OPE) from power-plant NO_X emissions, and find O_3 mortality and morbidity associated with NO_X emissions doubles under warm temperature conditions (28.9 ± 3.5°C) compared to cool temperature conditions (22.9 ± 4.3°C).[31] The OPE of NO_X emissions is also enhanced by tropospheric mixing and dilution, associated with summertime convective processes.[32] These results suggest the higher NO_X emissions expected on hot summer days may play a major role in ground-level O_3 production and public health.

This study examines temperature-dependence of electricity demand to EGU emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_X), and carbon dioxide (CO_2) using the Clean Air Markets Database (CAMD). Of these, SO_2 and NO_X are regulated in the U.S. for health implications.[33] CO_2 is a greenhouse gas that was regulated at EGUs for the first time in the U.S. by the 2015 Clean

Power Plan, although the plan is stayed as of early 2017. CAMD has been used in past studies for a range of analyses.[16, 34]

Here, historical CAMD data are analyzed for 2003-2014 to show spatial patterns in emissions sensitivity to temperature, and the change in these temperature sensitivities over time. Over the years from 2003 to 2014, emission controls and fuel switching to low-sulfur coal and natural gas were implemented at facilities in response to major federal initiatives from the U.S. Environmental Protection Agency, including the NO_X State Implementation Plans (SIP) call as part of the NO_X Budget Trading Program, New Source Performance Standards, the Clean Air Interstate Rule (CAIR), subsequent Cross-State Air Pollution Rule, and the Acid Rain Program.

Results from this analysis quantify an important and often overlooked feedback between temperature and air emissions. We discuss how electricity fuel mix affects emissions on hot days, and we report sensitivity factors to support improved modeling of U.S. air quality under current and future conditions.

Measurements and Methods

The Clean Air Markets (CAM) Program through the U.S. EPA collects continuous data from nearly every power generating facility in the United States. The largest fossil fuel power plants in the U.S. have provided continuous information on emissions, either directly from the exhaust stack or through emissions factor calculations based on energy output through various programs (https://www.epa.gov/airmarkets). We examined reported CAM gross electricity output, SO_2, NO_X and CO_2, on a daily basis, for all facilities in the database across the Eastern U.S. and Texas. The Eastern U.S. was chosen for higher prevalence of fossil-fuel electricity generation and more frequent exceedances of air quality standards. Daily data were aggregated at the state level across the Eastern U.S. for June 1 through August 31, 2003 to 2014. As a separate electric grid region that also experiences high air pollution events, Texas was examined as a case study to compare with the Eastern U.S., using facility-level fuel data from CAM for Texas.

Historical meteorological data are taken from the North Atlantic Regional Reanalysis (NARR) from the National Center for Environmental Prediction (NCEP).[35] NARR is a data assimilation product that combines observational data with model simulations to produce a temporally and spatially continuous meteorological dataset, with data available every three hours. In this study, daily average, two-meter-above-ground, temperature at each state's geographical center was compared with daily average CAM data from in-state EGUs. For Texas, additional temperature metrics were tested. This approach assumes in-state temperatures affect in-state generation, which is a simplifying assumption. In reality, EGU emissions are determined by demand across the multi-state electricity grid. Texas is used as a case study to look at the effects of fuel changes over time on an isolated grid.

We applied linear regression to daily emissions and temperature on a state-by-state basis for each year. Regional sensitivity is reported as the sum of absolute sensitivities for each state, as shown in Table 1, as opposed to a separate regional regression, as shown in Figure 1.1. To clarify, Figure 1.1 presents a regional regression using an average regional temperature, whereas Table 1 presents state-by-state regressions, such that results are dependent on each state's daily temperatures. The results presented in the abstract are the regional averages from Table 1. Standard error is reported for each state in Table 1, and all statistically insignificant results ($P > 0.05$) are removed before any averaging. Spatial or temporal averaging and aggregation can mask unique characteristics such as state fuel mix and demand profiles, and for this reason results are presented regionally over time, but also analyzed on a state-by-state basis to separately assess spatial and temporal behavior.

Future work could include multiple regression analysis to quantify the interdependency and influence of interacting variables.

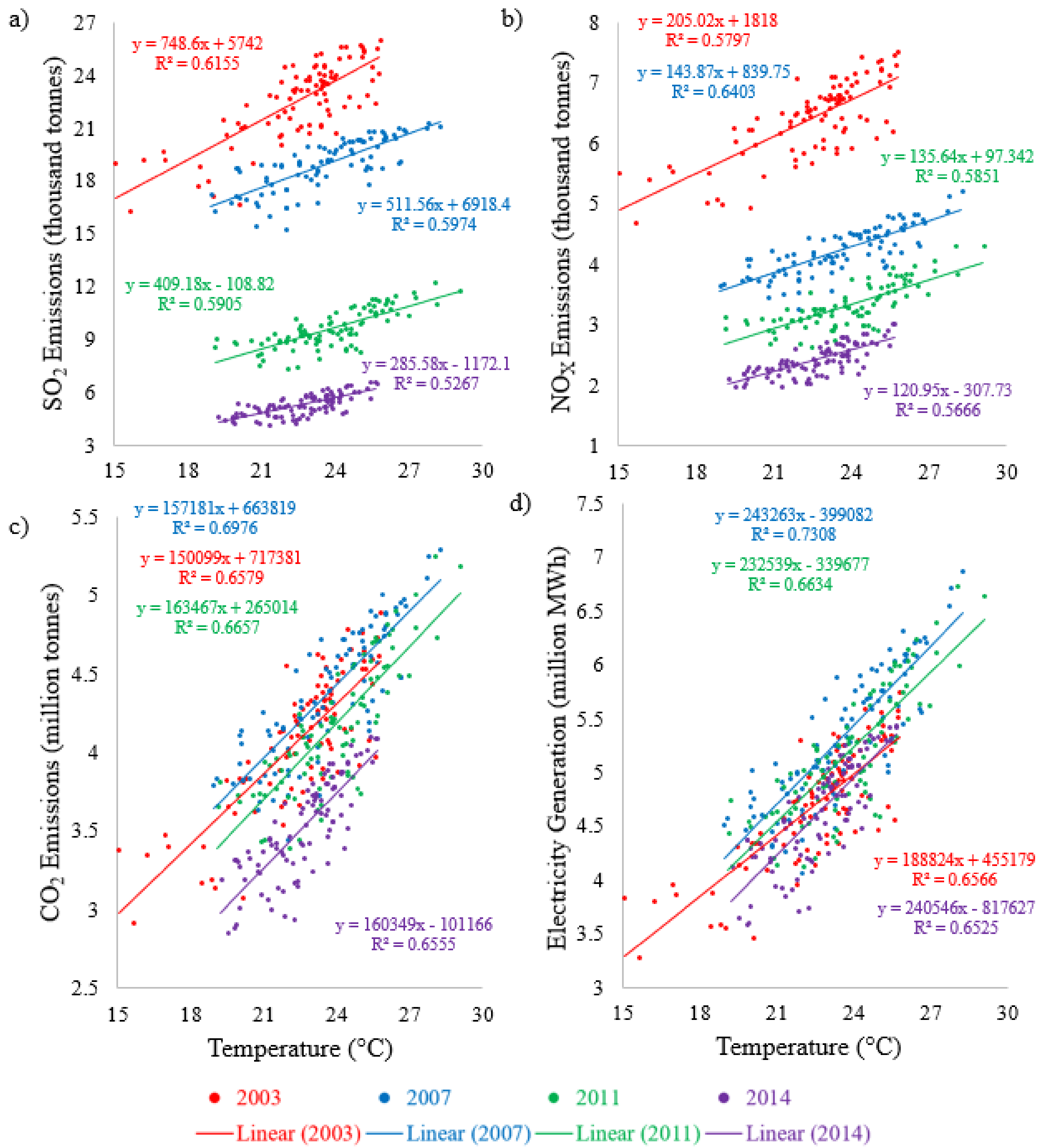

Figure 1.1: Emissions and Temperature Correlations. The total daily summer emissions of a) SO_2, b) NO_X, c) CO_2, and d) Generation summed for the 26 states that make the Eastern U.S. region are plotted against regional average temperature for that day. Historical emissions are plotted from 2003 to 2014. A linear model is overlaid for each scenario and species. These results differ from Supplemental Table 1 results as this is a linear regression on pre-aggregated regional emissions using a regional average temperature, whereas Supplemental Table 1 is a weighted average of state-by-state sensitivities.

Table 1.1: Historical Sensitivity Summary by State. A summary of state-by-state emissions sensitivity to temperature for SO_2, NO_X, CO_2 and generation historically as represented by a linear regression. This table differs from Figure 1.1 as the regional average here is a weighted average of individual states' sensitivities using state temperatures and state emissions, whereas Figure 1.1 is a regression on pre-aggregated emissions using a regional average temperature. The 2007-2012 %-sensitivities here are calculated as the average of annual proportional sensitivities rather than the average 2007-2012 slope divided by the average 2007-2012 emissions in order to provide even weight to every year since emissions have steadily decreased from 2007 to 2012.

	SO_2 - Historical (2007-2012)					**NO_X - Historical (2007-2012)**					**CO_2 - Historical (2007-2012)**					**Generation - Historical (2007-2012)**				
State	**Linear Slope (tonnes/°C)**	**Linear R^2**	**Average Summer Daily Emissions**	**SE in Slope (tonnes)**	**%-Sensitivity (%/°C)**	**Linear Slope (tonnes/°C)**	**Linear R^2**	**Average Summer Daily Emissions**	**SE in Slope (tonnes)**	**%-Sensitivity (%/°C)**	**Linear Slope (tonnes/°C)**	**Linear R^2**	**Average Summer Daily Emissions (tonnes)**	**SE in Slope (tonnes)**	**%-Sensitivity (%/°C)**	**Linear Slope (MWh/°C)**	**Linear R^2**	**Average Summer Daily Generation (MWh)**	**SE in Slope (tonnes)**	**%-Sensitivity (%/°C)**
AL	20.6	0.16	670	5.2	3.3%	4.7	0.16	180	1.2	2.7%	6400	0.42	250000	780	2.6%	12000	0.49	340000	1200	3.5%
CT	1.2	0.35	7	0.2	22.6%	1.2	0.39	9	0.2	13.7%	1700	0.56	22000	160	7.5%	2400	0.56	37000	230	6.8%
DE	4.8	0.49	53	0.5	10.8%	1.6	0.48	20	0.2	8.6%	1400	0.55	16000	130	9.6%	2100	0.57	21000	180	10.1%
FL	47.8	0.34	570	6.5	8.0%	19.8	0.37	320	2.7	6.4%	16000	0.47	380000	1800	4.1%	24000	0.46	550000	2800	4.4%
GA	26.6	0.34	820	4.0	4.5%	6.3	0.42	170	0.8	4.2%	8800	0.46	260000	1000	3.4%	13000	0.49	330000	1500	4.0%
IL	10.4	0.29	600	1.9	1.8%	4.2	0.34	190	0.7	2.2%	7100	0.42	290000	900	2.4%	9800	0.46	320000	1100	3.1%
IN	25.0	0.30	1300	4.3	2.1%	6.2	0.31	330	1.0	1.9%	7000	0.44	340000	850	2.1%	8800	0.48	380000	990	2.3%
KY	21.6	0.43	750	2.7	3.0%	5.5	0.32	240	0.9	2.3%	5500	0.42	270000	670	2.0%	6500	0.46	300000	750	2.2%
MA	6.8	0.36	84	1.0	10.0%	1.6	0.49	18	0.2	9.9%	3400	0.65	55000	260	6.4%	5700	0.66	95000	430	6.1%
MD	15.8	0.39	390	2.0	5.5%	4.3	0.55	69	0.4	6.6%	4800	0.65	82000	360	5.9%	6100	0.64	94000	470	6.6%
ME	0.7	0.17	2	0.2	32.7%	0.2	0.18	2	0.0	8.9%	530	0.42	9900	66	5.5%	1100	0.44	21000	130	5.3%
MI	14.0	0.30	760	2.4	1.9%	4.0	0.25	220	0.7	1.8%	4300	0.42	210000	540	2.1%	7000	0.47	230000	800	3.1%
MS	6.2	0.11	160	1.9	4.0%	3.7	0.26	110	0.7	3.6%	3900	0.39	92000	520	4.2%	7300	0.38	130000	980	5.8%
NC	24.1	0.49	470	2.7	6.1%	7.9	0.52	160	0.8	4.9%	9500	0.58	210000	840	4.5%	11000	0.59	210000	990	5.3%
NH	2.6	0.22	68	0.6	8.0%	0.5	0.29	11	0.1	6.0%	710	0.35	18000	110	4.1%	1100	0.38	26000	150	4.4%
NJ	4.9	0.40	60	0.6	11.2%	3.5	0.49	37	0.4	10.6%	4100	0.59	56000	350	7.3%	6400	0.61	90000	530	7.1%
NY	9.6	0.50	150	1.0	7.7%	8.0	0.53	120	0.8	7.2%	7400	0.59	130000	640	5.8%	13000	0.59	230000	1100	5.9%
OH	50.9	0.40	1700	6.9	3.1%	9.8	0.46	310	1.1	3.3%	9000	0.48	350000	1000	2.6%	11000	0.49	400000	1200	2.9%
PA	38.3	0.37	1600	5.5	2.8%	10.2	0.40	380	1.3	2.7%	9600	0.53	340000	950	2.9%	13000	0.53	420000	1300	3.1%
RI	0.0	0.35	0	0.0	4.5%	0.1	0.22	1	0.0	4.3%	420	0.35	10000	61	4.5%	910	0.35	22000	120	4.3%
SC	15.4	0.42	320	1.9	6.2%	4.2	0.57	92	0.4	4.8%	5500	0.65	130000	430	4.3%	7500	0.63	150000	620	4.9%
TN	10.4	0.27	410	1.9	3.1%	2.2	0.23	110	0.5	2.1%	3500	0.34	140000	520	2.5%	4200	0.33	160000	650	2.6%
VA	15.4	0.42	290	1.9	6.6%	7.5	0.54	120	0.7	6.4%	6700	0.58	100000	600	6.6%	10000	0.63	140000	830	7.3%
VT	0.0	0.16	0	0.0	5.4%	0.0	0.18	0	0.0	5.8%	57	0.18	1000	13	5.5%	44	0.17	760	11	5.8%
WI	7.6	0.45	280	0.9	2.8%	2.7	0.50	100	0.3	2.9%	3900	0.54	140000	380	2.9%	5600	0.57	150000	510	3.8%
WV	21.4	0.35	510	3.5	5.0%	4.7	0.24	150	0.9	3.4%	5700	0.30	220000	910	2.7%	6500	0.29	250000	1100	2.7%
Region (avg.)	402.2	0.34	12000	59.9	3.4%	124.7	0.37	3500	16.8	3.6%	140000	0.47	4100000	15000	3.3%	200000	0.49	5100000	21000	3.9%
TX	13.6	0.14	1500	3.7	0.9%	14.3	0.37	640	1.9	2.2%	13000	0.40	730000	1600	1.8%	23000	0.43	970000	2700	2.3%

Results for the Eastern U.S.

Eastern U.S. emissions show a positive relationship with temperature. Regionally, EGUs exhibit a 3.35% ± 0.50% increase in SO_2 emissions per °C increase for 2007-2012, calculated as the weighted average of linear regression for each state. The sensitivity is taken as the sum of regression slopes from each state in the region and taken as a proportion of regional emissions.

Emissions of NO_X and CO_2 show similar levels of sensitivity at 3.60% ± 0.49% and 3.32% ± 0.36% per °C respectively. All three emissions show 10-20% less sensitivity to ambient temperature compared to generation, which shows a 3.87% ± 0.41% increase per °C suggesting slightly cleaner plants meet increased demand on average. This is not completely unexpected, as new natural gas plants are required to have controls installed even as some peaking plants do not. Individual state sensitivities are shown in Table 1.

Figure 1.1 shows regional regressions using a regional average temperature to illustrate interannual changes in emissions. (For Texas, regressions are shown in the same format in Figure S1) There is no consistent year-to-year trend in the relationship between generation and temperature (Figure 1.1d) over the 2003-2014 period. Regression slopes for generation increase from 2003 to 2007, then decrease from 2007 to 2011, then increase again from 2011 to 2014. Proportional regional sensitivities of electricity generation to temperature range from ~4 – 5%/°C.

The relationship between CO_2 emissions and temperature in the Eastern U.S. (Figure 1.1c), shows a slight increase in sensitivity to temperature from 2003 to 2011, then a decrease in sensitivity from 2011 to 2014. These patterns differ from those seen for electricity generation overall, reflecting the influence of fuel mix and/or in power plant efficiencies. Although the proportional sensitivity of Eastern U.S. CO_2 emissions to temperature remains in the ~3.5 - 4.5%/°C range over all years, CO_2 emissions in 2014 are 14% lower than 2003 due to a reduction in electricity production from coal and increase in production from natural gas (http://www.eia.gov/electricity/data/browser/), which has a carbon intensity ~55% that of coal (https://www.eia.gov/tools/faqs/faq.cfm?id=73&t=11). The effects of changing fuel are explored further for Texas, discussed below.

Over this same 2003-2014 period, significant trends are seen in total emissions of SO_2 and NO_X. Both have decreased in the United States over the past decade due to mandatory caps on emissions through the EPA Clean Air Interstate Rule (CAIR) programs as well as a transition to cleaner fuels.[36] From 2003 to 2014, regional emissions from power plants have decreased by nearly 80% for SO_2 (Figure 1.1a) and 70% for NO_X (Figure 1.1b). We find that NO_X emissions decline most between 2003 to 2004 when NO_X decreases 28% while SO_2 decreases 4%. This timing corresponds with the implementation of NO_X controls in response to the 2002 NO_X SIP call as part of the NO_X Budget Trading Program. Emissions of SO_2 show the sharpest decline between 2007 to 2011, decreasing ~45% due to increased use of control technologies to comply with the Clean Air Interstate Rule.

Figure 1.1 shows decreasing absolute sensitivity from 2003 to 2014, where SO_2 sensitivity decreases from 749 to 286 tonnes per °C while NO_X sensitivity decreases from 205 to 121 tonnes per °C. Proportionally, sensitivities show a slight increase over time for both SO_2 (from 3.32%/°C to 5.40%/°C) and NO_X (from 3.19%/°C to 4.98%/°C). The increase in percentage sensitivities over time indicates that marginal electricity on hot days is being met by slightly dirtier (or less controlled) plants in relation to the average, even as total emissions decline due to emissions controls. These patterns suggest is that baseload and frequently used variable load plants are subject to increasing controls, relative to infrequently used peaking facilities.

Using 2007-2012 averages, we explore spatial trends in the relationships between emissions and temperature across the study domain. We find a high level of regional variability in electricity emissions and generation, shown in Figure 1.2 a-d. Figures 2e and 2f show the percent of electricity generation from coal-fired and gas-fired power plants respectively in each state. The highest emissions of SO_2 occur in Ohio, Pennsylvania, and Indiana, as well as Texas (over 1300 tonnes per day); The lowest emissions of SO_2 (near 0) occur in New Jersey, Connecticut, and Vermont. States with more coal power plants show higher SO_2 emissions, as coal combustion is the primary contributor to SO_2 emissions from the electricity sector. Because coal has higher NO_X emissions per unit generation relative to natural gas we find similar patterns in NO_X emissions (Figure 1.2b) with Ohio, Pennsylvania, and Indiana among the top emitters (all over 300 tonnes/day). In 2012, natural gas plants emitted approximately 7% of the NO_X emitted from coal plants per MWh.[37]

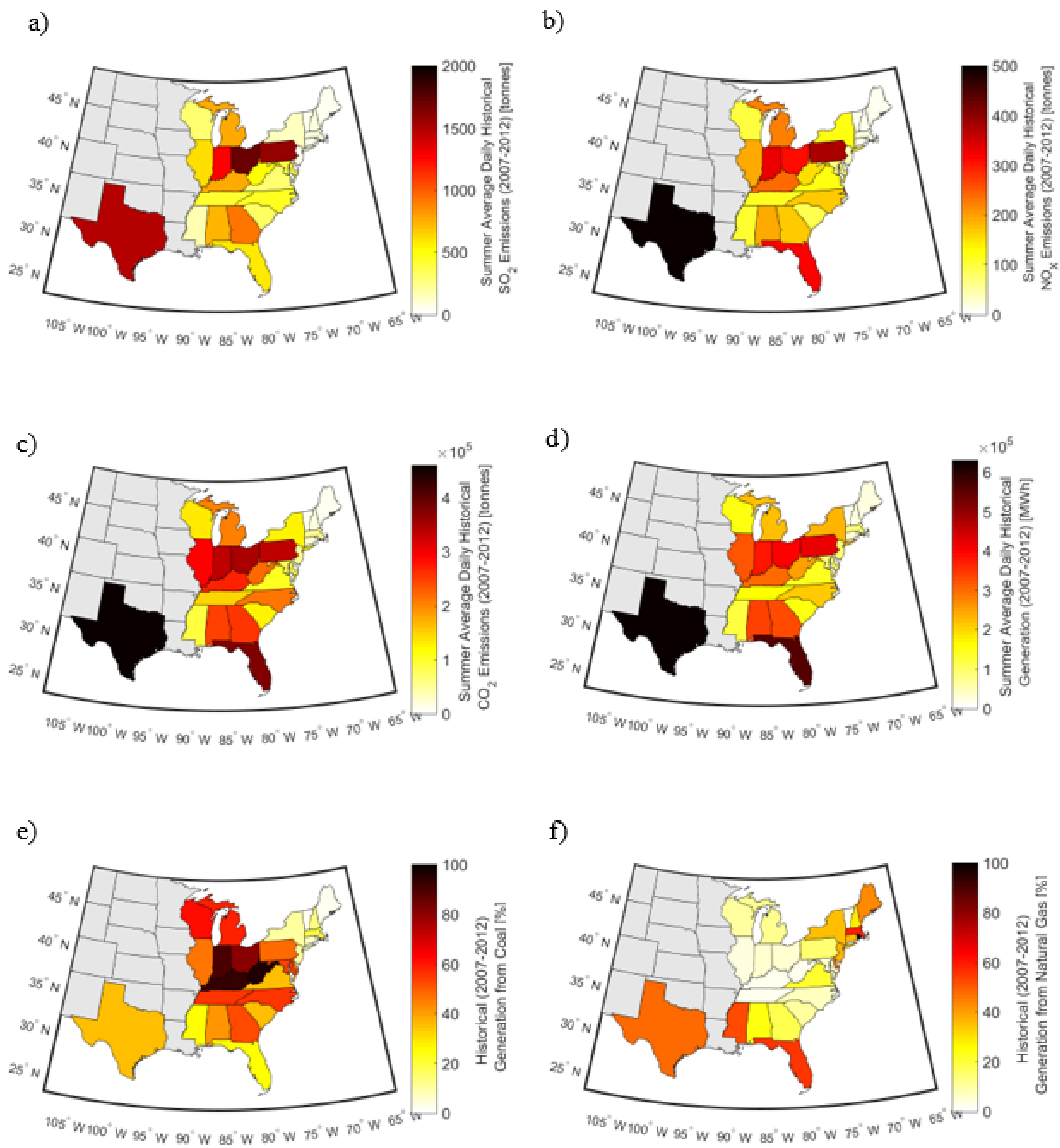

Figure 1.2: Historical Emissions by State. The state-by-state historical average daily emissions of a) SO_2, b) NO_X, and c) CO_2, as well as d) Electricity Generation (MWh) from power plants included in the Clean Air Markets Program over the summer (June, July and August) for years 2007 to 2012. Emissions are presented in tonnes. For context, the percent of generation produced from e) coal and f) natural gas from 2007 to 2012 is also included by state.

Patterns in CO_2 emissions (Figure 1.2c) generally follow generation (2d), with particularly high emissions in the states with higher coal fractions (Figure 1.2e). Some states like Illinois, West Virginia and North Carolina are relatively low in pollutant emissions (NO_X and SO_2), but high in CO_2 emissions indicating higher levels of SO_2 and NO_X controls on power plants in these states.

The spatial variability of power plant emissions sensitivity to temperature is shown in Figure 1.3 and described in Table 1. For SO_2 emissions, most states exhibit sensitivities in the range of a 1.8% increase per °C increase (e.g. Illinois) to 11.2% per °C (e.g. New Jersey), as shown in Figure 1.3a, with only Texas lower at 0.9% per °C (Table 1). However, some states with low SO_2 emissions see high proportional sensitivities to temperature greater than this range. These states include Maine with a 33 ± 8% per °C increase in SO_2 emissions and Connecticut, with a 23 ± 2% per °C sensitivity. They have very low SO_2 emissions, but both states use more petroleum for electricity generation than most states in the U.S., primarily as peaking plants deployed on the hottest days. Peaking plants in the Eastern U.S. are most commonly either gas- or petroleum-fired and have separate monitoring requirements under 40 CFR Part 75 monitoring rules which make them less well represented in the Clean Air Markets database.[19]

The temperature sensitivity of NO_X is shown in Figure 1.3b and exhibits many of the same patterns as in SO_2 (Figure 1.3a). Across the region, sensitivities range from 1.8% change in NO_X emissions per °C to 13.7% per °C. Generation and CO_2 emissions show less spatial variability than SO_2 and NO_X. Sensitivity ranges from a 1.8% to 9.6% increase in CO_2 emissions per °C increase and 2.2% to 10.2% increase in generation per °C. We expect to see less variability in the sensitivities as CO_2 emissions and generation are not greatly affected by control technologies, and they are less dependent on which plants are producing electricity at the margin.

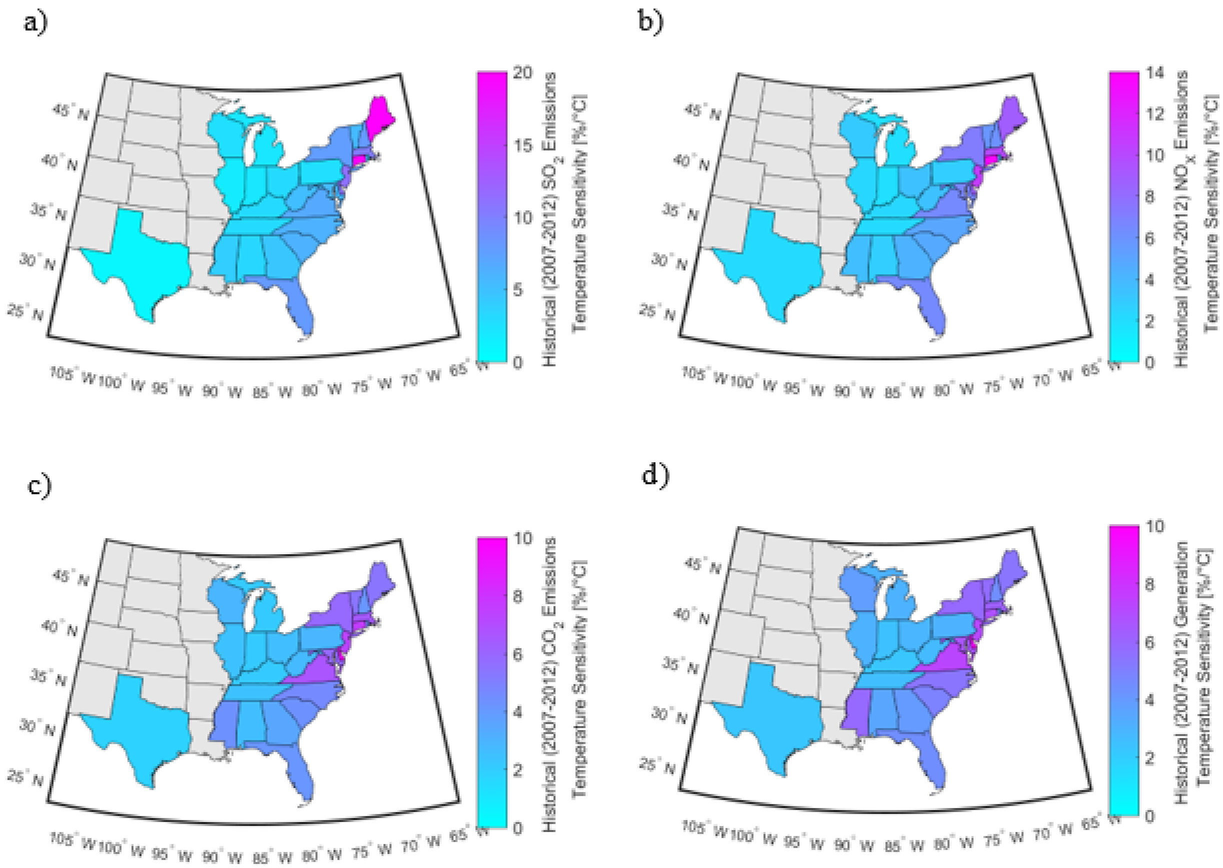

Figure 1.3: Historical Sensitivity by State. The state-by-state historical temperature sensitivity of average daily emissions of a) SO_2, b) NO_X, and c) CO_2, as well as d) Electricity Generation (MWh) from power plants included in the Clean Air Markets Program over the summer (June, July and August) for years 2007 to 2012. Sensitivity values reflect historical statewide daily emissions fit to a linear model annually from 2007 to 2012, with annual slopes averaged over the 6-year period. Percent sensitivity is calculated from daily average summer emissions from 2007 to 2012.

Results for Texas

In Texas, we test several of the study characteristics that are difficult across the Eastern U.S. and analyze different metrics for temperature. Based on the methods discussed above for the Eastern U.S., Texas shows a lower sensitivity of SO_2 emissions to temperature at 0.9% per °C (lower than any state in our Eastern U.S. domain). This increase in SO_2 emissions comes from a 2.3% increase in electricity generation per °C increase, and is also associated with a sensitivity of 2.2%/°C for NO_X emissions and 1.8%/°C for CO_2 emissions.

The results noted above, and shown in Figure 1.3, were calculated from the average temperature at the Texas centroid, as with other states in the study. The northernmost NARR grids in Texas average 4.4 °C colder than the centroid and southernmost NARR grids average 4.6 °C warmer than the centroid. To compare with the centroid approach, we also calculated the population weighted center for Texas, which averages 0.33% warmer than the centroid value. With most of the demand for electricity coming from buildings within cities, urban heat islands could have an impact on this analysis and temperatures taken at the centroid may underestimate temperatures where demand is changing most. When compared with CAM emissions, the population-weighted temperature showed a 48%-58% larger r-squared for a single 2011 test year relative to the centroid approach.

We also compared the impact of using maximum daily temperatures from NARR rather than daily mean values used throughout the study. Whereas the daily temperature showed a correlation with a significance of $P<0.05$ for all emissions, the maximum daily temperature does not correlate at the same level of significance.

Texas operates mostly as an independent electric grid, so the assumption that any increase in electricity demand within Texas will be met by power plants within Texas is more valid than in other parts of the U.S. As shown in Figure 1.4a, electricity production in Texas has increased by ~30% from 1997 to 2015, and the use of coal and petroleum for electricity in Texas has substantially decreased, by 12% and 84% respectively, while natural gas has increased by 57%. Interestingly, the proportion of NO_X emissions from gas has decreased, even as generation from gas has increased, as seen in Figure 1.4b. New Source Performance Standards requiring control technologies on new and modified natural gas plants lead to low NO_X/kW emission levels, while existing coal plants may be subject to fewer controls. Figure 1.4 also illustrates the decrease in NO_X emissions from EGUs in Texas throughout the last couple of decades even as electricity production has gone up.

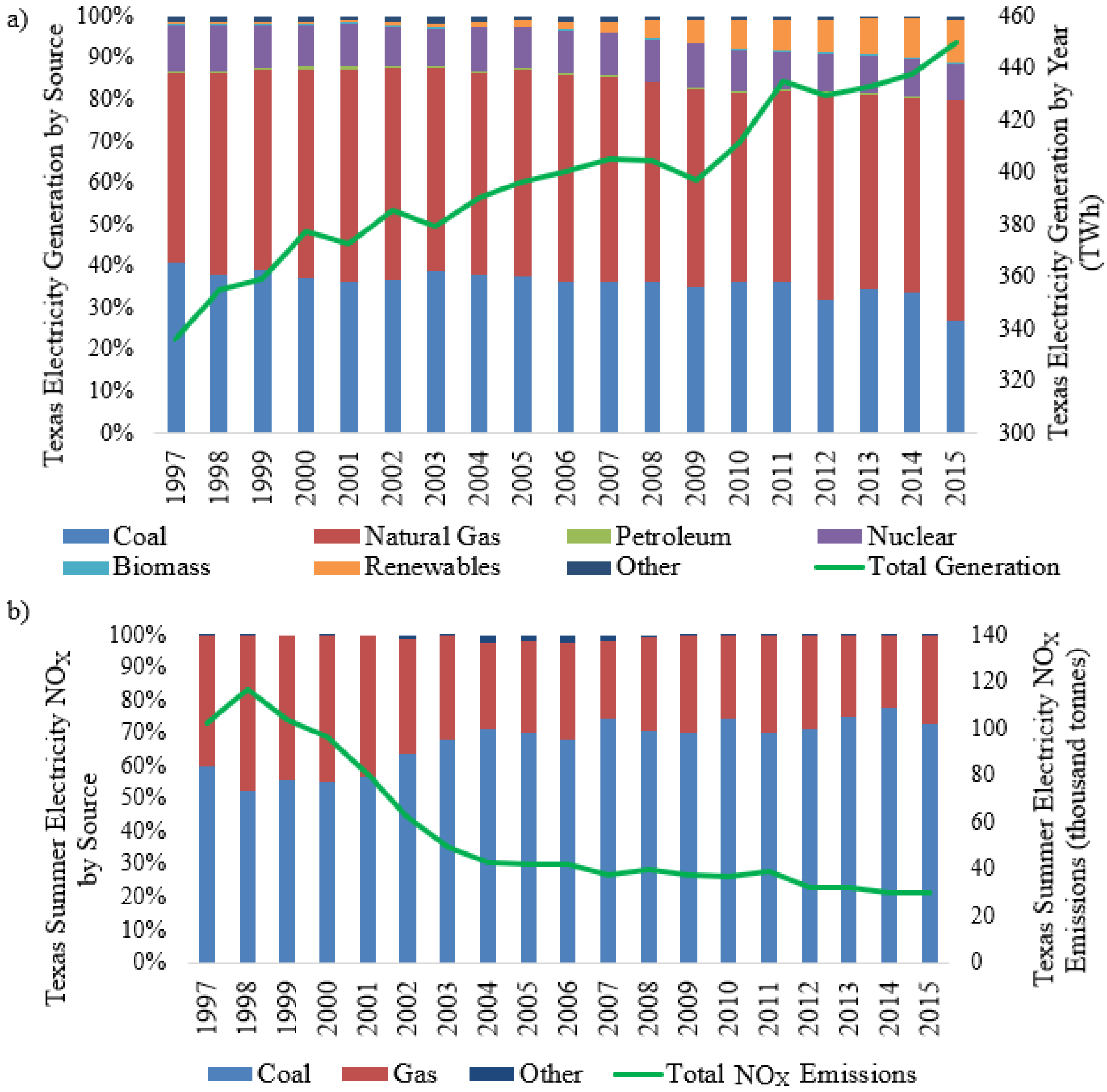

Figure 1.4: Texas NOx Emissions and Generation. a) shows the total summer (June, July and August) NOx emissions from electricity production in Texas by year and the percent of the total to come from coal, natural gas and other production sources as collected through the U.S. EPA's Clean Air Markets database. b) shows the total Texas electricity generation and the percent to come from different sources. The data for this portion is provided by the U.S. Energy Information Administration to include all sources

Texas proportional sensitivities show a slight upward tendency that is not corroborated with a statistically significant upward trend from 1997 to 2015. The results are less dependent on long-term trends in controls and electricity source fuel than interannual variation. Proportional sensitivities for 1997-2015 range from 1.23%-3.84% for electricity generation, leading to variability of 0.63%-2.76% for SO_2, 0.76%-4.03% for NO_X (the largest range), and 0.89%-3.19% for CO_2. This puts Texas sensitivities at the low end of those estimated for the Eastern U.S. However, this is not unexpected as Texas has a diverse electricity system with large demand. For direct comparison, 2007-2012 Texas sensitivities with error are 0.91%/°C ± 0.25%/°C for SO_2 emissions, 2.15%/°C ± 0.29%/°C for NO_X emissions, and 1.78%/°C ± 0.22%/°C for CO_2 emissions due to a sensitivity in electricity generation of 2.34%/°C ± 0.28%/°C. Additionally, as natural gas became more prevalent in the last decades, it replaced much of the petroleum that was previously used for this purpose. Overall, analysis of Texas provides valuable insight to trends in electricity sector emissions even as interannual sensitivity trends are not statistically significant.

Texas, like Florida, has a large proportion of natural gas with very high overall electricity demand, particularly due to being a hot climate. In Florida, natural gas accounts for over 60% of generation (Figure 1.2f, http://www.eia.gov/electricity/state/Florida/). This leads to both Florida and Texas being very high in NO_X emissions compared to other states, especially relative to their comparative SO_2 emissions. However, Florida and Texas differ in their NO_X sensitivities to temperature with Florida exhibiting a 2007-2012 average of 6.4%/°C while Texas is only 2.2%/°C. This is primarily because Florida produces nearly 9x more electricity from petroleum than Texas, predominantly as peaking power on hot days.

Discussion

This study examined the links between temperature and emissions in the Eastern U.S. and Texas during the summertime conditions over multiple years. Commercial and residential buildings are known to use more electricity on hotter days, [24,38] and our finding of a 3.9% increase in generation per ^{o}C is consistent with [23] 0.4% to 5.3% per °C sensitivity range.[23] Our finding of NO_X emissions sensitivity of 3.60 ± 0.49 %/°C is consistent with, He et al.'s range of 2.5-4.0 %/°C using similar methodology and region but a different range of years.[16]

CAM does not fully represent grandfathered peaking units that may play an important role in the sensitivity of emissions to temperature, as gas- and oil-fired peaking units (often with fewer emission controls) are allowed to use alternate methods for emissions calculations rather than direct measurements. Further, behind-the-meter generation, absent from the CAMD, has been found to contribute to EGU NO_X emissions.[39] Due to the exclusion of these peaking facilities, the emissions sensitivities presented here may underestimate the response of emissions to temperature, but captures the overall trend.

Process-based models of climate and air quality currently include the weather-dependent response of chemical emissions from biogenic sources, atmospheric chemical processes, and meteorological transport, all of which have a strong temperature component. However, such studies typically do not consider temperature impacts on electricity sector emissions.[40,41] This work quantifies the temperature response of electricity generation in a manner that may be well suited for integration into a modeling platform.

These results support the use of policy and technology interventions to lower demand at high temperatures and lower power plant emissions.

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Supporting Information

Supporting information can be found with the published version of this chapter.

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Chapter 2: Air Quality and Health under a Warmer Climate

This manuscript was the culmination of several previous studies (including others that I led and contributed to) during and before my graduate studies. These papers include Meier et al., (2018), Abel et al., (2017), and Schuetter et al., (2014). This study was published in a special issue of PLOS Medicine on Climate Change and Health. The completed work is cited below. The work here has been slightly modified from the published version only to conform with formatting for the purposes of this dissertation.

Citation

Abel DW, Holloway T, Harkey M, Meier P, Ahl D, Limaye VS, et al. Air-quality-related health impacts from climate change and from adaptation of cooling demand for buildings in the eastern United States: An interdisciplinary modeling study. PLOS Medicine. 2018;15: e1002599. doi:10.1371/journal.pmed.1002599

Abstract

Background

Climate change negatively impacts human health through heat stress and exposure to worsened air pollution, amongst other pathways. Indoor use of air conditioning can be an effective strategy to reduce heat exposure. However, increased air conditioning use increases emissions of air pollutants from power plants, in turn worsening air quality and human health impacts. We used an interdisciplinary linked model system to quantify the impacts of heat-driven adaptation through building demand on air quality-related health outcomes in a representative, mid-century climate scenario.

Methods and Findings

We used a modeling system that includes downscaling historical and future climate data with the Weather Research and Forecasting (WRF) model, simulating building electricity demand using the Regional Building Energy Simulation System (RBESS), simulating power sector dispatch and emissions using MyPower, simulating ambient air quality using the Community Multiscale Air Quality (CMAQ) model, and calculating incidence of adverse health outcomes using the Environmental Benefits Mapping and Analysis Program (BenMAP). We performed simulations for a representative present-day climate scenario and two representative mid-century climate scenarios, with and without exacerbated power sector emissions from adaptation in building energy use. We find that by mid-century, climate change alone can increase fine particulate matter ($PM_{2.5}$) concentrations by 58.6% (2.50 $\mu g/m^3$) and ozone (O_3) by 14.9% (8.06 ppbv) for the month of July. A larger change is found when comparing the present day to the combined impact of climate change and increased building energy use, where $PM_{2.5}$ increases 61.1% (2.60 $\mu g/m^3$) and

O_3 increases 15.9% (8.64 ppbv). Therefore, 3.8% of the total increase in $PM_{2.5}$ and 6.7% of the total increase in O_3 is attributable to adaptive behavior (extra air conditioning use). Health impacts assessment finds that for a mid-century climate change scenario (with adaptation), annual $PM_{2.5}$-related adult mortality increases by 13,547 (fourteen concentration-response functions with mean incidence range of 1,320 to 26,481, ~$126 billion cost) and annual O_3 mortality increases by 3,514 (three functions with mean incidence range of 2,175 to 4,920, ~$32.5 billion cost), calculated as a 3-month summer estimate based on July modeling. Air conditioning adaptation accounts for 654 (range of 87 to 1,245) of the $PM_{2.5}$-related deaths (~$6 billion cost, a 4.8% increase above climate change impacts alone) and 315 (range of 198 to 438) of the O_3-related deaths (~$3 billion cost, an 8.7% increase above climate change impacts alone). Limitations of this study include modeling only a single month, based on one model-year of future climate simulations. As a result, we do not project the future, but rather describe the potential damages from interactions arising between climate, energy, and air quality.

Conclusions

This study examines the contribution of future air pollution-related health damages that are caused by the power sector through heat-driven, air conditioning adaptation in buildings. Results show that without intervention, ~5-9% of exacerbated air pollution-related mortality will be due to increases in power sector emissions from heat-driven building electricity demand. This analysis highlights the need for cleaner energy sources, energy efficiency and energy conservation to meet our growing dependence on building cooling systems and simultaneously mitigate climate change.

Introduction

Climate change poses many health risks from elevated risk of heat stroke to broadening reach of vector-borne disease, food insecurity and air pollution [1]. According to the Lancet Countdown on health and climate change, climate change "is affecting the health of populations around the world, today [2]." Climate change has direct impacts on health and wellbeing from exacerbated extreme weather, extremes of the hydrologic cycle, and heat waves, as well as indirect effects such as increases in the burden of infectious disease, sea-level rise, ocean acidification, and climate-induced population displacement or conflict. Ultimately, these changes threaten access to clean air, water, and food, while potentially creating and exacerbating existing health disparities. However, climate mitigation and adaptation strategies have the potential to address these issues and improve public health broadly. This study focuses on ambient air pollution, and the potential increase in adverse air pollution-related health impacts associated with building air conditioning use, in response to warmer temperatures, highlighting the need for clean energy solutions as tools for improving public health.

Relationships between meteorological conditions and air quality have been established in past literature. For example, warmer temperatures and sunlight enhance production of biogenic, or natural, volatile organic carbons (VOCs), from certain plant species, which are precursors to both ozone and fine particulate matter [3,4]. Warm temperatures and sunlight also enhance ozone-forming reactions [5,6]. Pollutant concentrations decrease with increased air mixing [7,8], as well as precipitation [9,10], while increased humidity can increase formation of particulate matter [7,9]. Additional work has explored the impact of a warming climate on wildfire emissions [11–14], soil emissions of nitrogen oxides (NO_X) [15], and NO_X from lightning [16–18]. Using these relationships, a number of studies have investigated the potential impact of climate change on air quality, particularly the response of ozone and particulate matter concentrations to warming temperatures [7,19–21]. Past studies assessing climate change impacts on air pollution often focus on the impact of climate change and meteorological variables (as well as biogenic, natural emissions) [7,19–21], the impact of future anthropogenic emission scenarios [22], or the combined impact of climate change and anthropogenic emissions scenarios [10,22–27].

Air conditioning in buildings is a form of adaptation to warmer temperatures that could increase population health risks, by increasing power plant emissions on hot days. As air conditioning use increases to cool buildings, the increased demand for electricity is supplied by a mix of generation sources including fossil fuels, thus increasing harmful emissions. In this work, we deploy a novel interdisciplinary modeling effort to quantify the air pollution and health impacts of this climate change adaptation mechanism.

Few studies have explored the impact of climate change on health-damaging emissions from electricity generating units (EGUs), specifically emissions of nitrogen dioxide (NO_2) and sulfur dioxide (SO_2), but we know there is a relationship between power plant emissions and temperature through electricity demand in buildings. Buildings are the largest source of U.S. electricity demand, responsible for more than 60% of demand in most states in the Eastern U.S. (https://www.eia.gov/electricity/data/state/). Electricity for cooling is a large component of this demand with direct correlation to rising temperatures. Abel et al., (2017) showed that historical Eastern U.S. EGU emissions of NO_X, SO_2 and carbon dioxide (CO_2) increase 3.3-3.6% per °C change in daily temperature regionally over the summer [28], consistent with He et al., (2013) who find a range from 2.5-4.0% per °C in Eastern U.S. states and Dreschler et al., (2005) who found a 5.8% per °C increase in California [28–30].

Additional emissions from increased air conditioning demand have been shown to have a significant impact on fine particulate matter ($PM_{2.5}$), responsible for up to 87% of concentrations in the Pennsylvania-New Jersey-Maryland (PJM) electricity grid interconnection during July 2006 heat wave conditions [31]. The hourly variability of EGU emissions due to temperature can increase $PM_{2.5}$ mass, sulfate, and elemental carbon concentrations by 83%, 103%, and 310%, but this increase in emissions from anticipated heat-driven adaptation response is typically not included in air quality modeling studies [32]. Power plants have been extensively evaluated as a controllable source of pollution [33–35]. However without action, residential and commercial buildings are expected to see an increase in cooling load and subsequent emissions [36,37]. Recent research has demonstrated the air quality-related health benefit of the green building movement and thus reducing energy demand in buildings. MacNaughton et al., (2018) quantify the health benefits of U.S. Leadership in Energy Efficient Design (LEED) certified buildings built from 2000-2016 as 172 to 405 avoided premature mortalities [38].

This is the first study to compare the impact of mid-century climate change on air quality with and without associated heat-driven changes in emissions from the electricity sector. This work advances the line of research characterizing health co-benefits from mitigation strategies [39–52] and the direct quantification of health damages from air pollution in a future climate [1,2,30,53–59]. This study builds upon a large body of epidemiological work relating air pollution and human health, including the studies utilized in EPA’s BenMAP [60].

Methods

Overview

We apply a system of linked numerical models to assess changes in building energy demand, electricity production, power sector emissions, air quality and human health outcomes based on meteorology consistent with present-day conditions and a warm mid-century summer climate. We focus on the Eastern U.S. where electricity production and use are connected through a regional power grid. This region also experiences levels of ground level O_3 and $PM_{2.5}$ in exceedance of EPA health-based standards [61]and demographic trends in this area suggest continuing and increasing vulnerabilities to air pollution exposures [62–65].

Figure 2.1 provides a visual representation of the modeling system, which includes simulating present and future meteorology, electricity demand in buildings, electricity production and EGU emissions, air quality, and health impacts. For information on how to access the software used please see Supporting Information. We performed simulations for three scenarios using this linked model system and a fourth simulation is used for validation of results, following standard practice for chemical transport modeling for which uncertainty estimates are ill-suited and model evaluation is preferred (see Supporting Information) [66–68]. Satellite-derived NO_2 and previous studies are also used to validate results. Scenarios are shown below and outlined in Figure 2.1. Additionally, Table 2.1 shows the major data inputs for each model in the system.

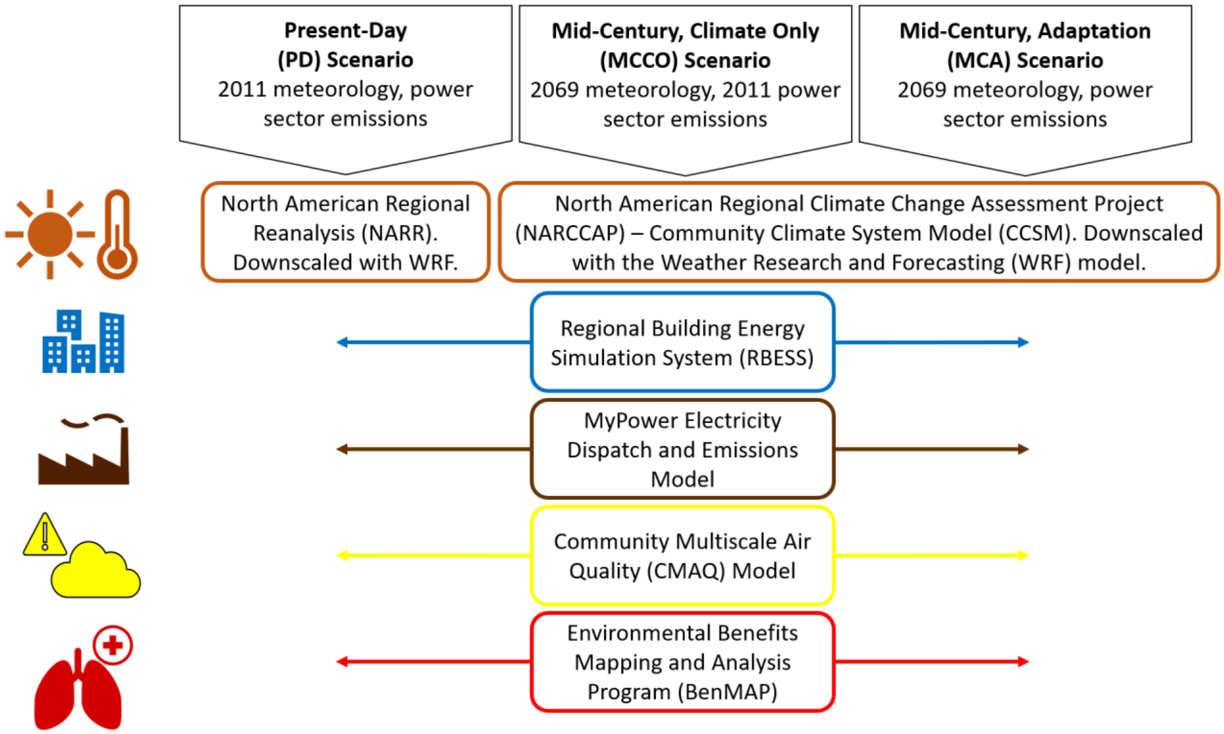


Figure 2.1. A visual representation of the methods used in this study.

Table 2.1. Major data inputs and sources for each step of the modeling framework.

MODEL	**INPUT DATA NEEDED**	**INPUT DATA SOURCE**
WRF	Present-day meteorology	NARR: Meteorological dataset (includes assimilated observations)
	Future meteorology	NARCCAP (CCSM): Meteorological dataset selected from a suite of climate models
RBESS	Meteorology	WRF
	Representative Building Types	Built for this study based on DOE-2 platform
	Building Stock	U.S. EIA Commercial Building Energy Consumption Survey (CBECS), Residential Energy Consumption Survey (RECS), Manufacturing Energy Consumption Survey (MECS)
MyPower	Electricity Demand	RBESS
	Power Plants and Characteristics	EPA's National Electric Energy Data System (NEEDS), EPA's Clean Air Markets Database
CMAQ	Power Plant Emissions	MyPower
	Other Anthropogenic Emissions	EPA's National Emissions Inventory (NEI)
	Biogenic Emissions	Model for Emissions of Gases and Aerosols from Nature (MEGAN)
	Meteorology	WRF
BenMAP	Population	U.S. Census
	Baseline Incidence	Many data sources, see [69]
	Concentration-Response Functions	Many studies. See health impacts tables and or BenMAP documentation for references [60,69].
	Air Quality Data	CMAQ

Three scenarios are simulated for present-day, a mid-century climate with present-day emissions, and a mid-century climate with emissions from adaptation. Each of these scenarios utilize meteorology from the WRF model for present-day and NARCCAP CCSM version 3 for mid-century. The RBESS is used to assess building energy demand and MyPower is used to simulate electricity dispatch and associated power-sector emissions. CMAQ is used to simulate air quality and BenMAP assesses the health outcomes from air quality changes.

Scenario 1 (PD). Present-day conditions for climate. Building energy demand and power-sector (EGU) emissions are simulated for present-day conditions. This scenario will be referred to as the present-day (PD) scenario.

Scenario 2 (MCCO). Warm, mid-century conditions for climate selected as described in detail below. Building energy demand and power-sector (EGU) emissions remain constant as simulated for present-day conditions. This scenario represents the impact of climate change alone on air quality and health. There is no change in building activity or associated anthropogenic emissions from electricity demand. This scenario will be referred to as the mid-century, climate-only (MCCO) scenario.

Scenario 3 (MCA). Warm, mid-century conditions for climate. Building energy demand and power-sector emissions are simulated using mid-century representative meteorology with inventory and performance held constant; (modern natural gas power plants are assumed to provide the additional capacity needed to meet increased electricity demand). This scenario is the impact of climate change and increased EGU emissions due to greater building air conditioning demand in response to warmer temperatures. This scenario will be referred to as the mid-century, adaptation scenario (MCA).

Climate and Meteorological Modeling

Warm-climate simulations of air quality use meteorology downscaled from the North American Regional Climate Change Assessment Project (NARCCAP, [70]) archive per Harkey and Holloway (2013) [71]. NARCCAP is a suite of climate data from several Global Climate Model –

Regional Climate Model pairs built on the A2 emissions scenario of the Intergovernmental Panel on Climate Change (IPCC), a trajectory which most closely mirrors current global greenhouse gas emissions trends [72,73]. This emissions scenario assumes little or no action is taken to mitigate climate change, consistent with the goals of this study, to isolate the potential impact of increased power sector emissions on air quality. Thus, any successful future action to mitigate climate change would alleviate some of the damages calculated here.

Due to the computationally demanding simulations of this study, it is not feasible to consider a 30-year subset of mid-century years, as is recommended for climate impacts study. Rather, July of a single year from a single model in NARCCAP was selected to represent a warm, realistic mid-century summer, as discussed in detail in Harkey and Holloway (2013) [71]. We selected 2069 from the Community Climate System Model version 3 (CCSM, [74]) downscaled with the Weather Research and Forecasting (WRF) model in NARCCAP, and further downscaled with WRF for this study to our 12 km by 12 km study domain. This year was chosen as the warmest year from the mean model in the suite, as shown in S1 Fig adapted from Meier et al., (2017) [36]. To isolate the impact of climate change on air quality, we used the same 2011 emissions data and lateral boundary conditions for all simulations. Climate processes are considered to affect biogenic, plant emissions and the transport of point-source, anthropogenic emissions.

Present-day meteorology is downscaled in WRF from the North American Regional Reanalysis (NARR) for 2011 conditions also as described in Harkey and Holloway (2013) [71]. The NARR model assimilates measured meteorological data to produce a gridded, continuous dataset [75]. We focus on July 2011 as representative of peak summertime electricity demand, the summer high O_3 season, and consistent with the latest National Emissions Inventory at the time of modeling.

Therefore, findings are separated into the impacts of meteorology representative of two summer climate scenarios, the present-day climate and a warm, mid-century climate representative of inaction (July 2011 and July 2069). Meteorological conditions for July in the warm, mid-century climate used in the MCCO and MCA scenarios are on average ~3.5°C (29.1°C versus 25.6°C, 13.7%) warmer in the Eastern U.S. region than in the present-day.

Building Energy Demand Modeling

Present-day and warm, mid-century meteorology is input to the Regional Building Energy Simulation System (RBESS), a modeling process developed following Schuetter et al., (2014) and used here to determine the response of building energy demand to meteorology [76]. This process merges industry-standard building energy modeling techniques using the DOE-2 software (developed by James J. Hirsch & Associates and Lawrence Berkeley National Laboratory) and regional building stock data with the meteorology discussed above following Meier et al., (2017), which describes the methodology used here in detail [36]. Building stock data was provided by the U.S. Energy Information Administration (EIA) through the Commercial Buildings Energy Consumption Survey (CBECS), the Manufacturing Energy Consumption Survey (MECS), and the Residential Energy Consumption Survey (RECS). The building stock is held static under both the present and warm-climate scenarios. The simulation was calibrated using historical, 2007 electricity data from a U.S. EPA compilation of Federal Energy Regulatory Commission (FERC) data. Use of the present-day building stock is not meant to be predictive but is chosen to bound the potential damages of inaction.

Electricity Sector Dispatch Modeling

Building energy demand is input to the MyPower model, a load duration curve (LDC) electricity dispatch model, used to simulate plant-level electricity production and emissions of NO_X, SO_2, and CO_2. Detailed methodology for MyPower is described in Meier et al., (2017) [36]. Data for power plant characteristics including heat rates and emissions rates are derived from the National Electric Energy Data System (NEEDS), a part of the U.S. Environmental Protection Agency's (EPA) Power Sector Modeling Platform and modified to reflect data reported in the U.S. EPA's Clean Air Markets Database through 2013. Present-day conditions reflect electricity-sector characteristics through 2011. Warm-climate conditions reflect planned changes to the electricity grid. Existing renewable portfolio standards are met through a combination of technologies reported in the Database of State Incentives for Renewables and Efficiency (DSIRE) database [77]. Nuclear power plants are retired given existing operating licenses with new constructions for applications at the Nuclear Regulatory Commission [78]. The warm-climate case is assumed to maintain "resource adequacy" such that the highest single hour of demand is exceeded by 15% in generating capacity. The additional required power is supplied through new construction of natural-gas power plants (70% combined-cycle, 30% single-cycle) with characteristics based on the Annual Energy Outlook from the U.S. Energy Information Administration [79]. All existing plants not retired are not modified.

Scenario selection, specifically using the present-day building stock and power plants, is not meant to be predictive, but to quantify the portion of future damages that could be alleviated by changes to the building sector and electricity sector. The scenario was chosen to describe the potential damages of interactions between climate, energy and air quality through this previously unstudied mechanism.

Air Quality Modeling

Air quality simulations are performed using the Community Multiscale Air Quality (CMAQ) model version 5.0.1 [67,80]. Anthropogenic emissions are input from the EPA 2011 National Emissions Inventory (NEI, [81]) and biogenic emissions are simulated using the Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN, [82]). We focus on July 2011 conditions for the present-day as representative of peak summertime electricity demand and production within O_3 season consistent with past literature and the latest available NEI emissions at the time of modeling [31]. Supporting Information includes validation of results and discussion of model performance.

EGU emissions from MyPower were gridded for use in CMAQ and substituted for NO_X and SO_2 emissions in the NEI. Emissions of NO_X were assigned constant partitioning of 85% NO and 15% NO_2. Chemical species that are contained in the NEI, but not directly calculated by MyPower are listed in Supporting Information, Table S2.1 with associated discussion.

All CMAQ simulations were configured with "AERO6" aerosol chemistry [67], in-line photolysis, and the Carbon Bond 5 (CB05) chemical mechanism with updated toluene and chlorine chemistry [83,84]. Simulations do not include estimates of emissions from fires but do include in-line estimates of lightning-generated NO_X. CMAQ was run with 25 vertical layers, a 12 km by 12 km horizontal resolution over the eastern U.S., and boundary conditions taken from a month-averaged run of present-day conditions with NEI emissions over the continental U.S., which in turn used boundary conditions from the Model for Ozone and Related Chemical Tracers, version 4 [85].

We chose to run simulations through CMAQ for only July as the most computationally expensive part of our linked model system. As results represent estimates based on only a single year of climate simulations, findings are meant as exploratory and illustrative, and as such the marginal limitation of extrapolating July results as representative of summer (and summer as representative of annual impacts) is small. Future research could utilize less computationally expensive methods to run more scenarios over longer and more representative time scales, but the complex mechanisms included in CMAQ are necessary to explore the impacts of power sector emissions on air quality in a changing climate through the new relationship described here. We also chose July as three additional simulations were run (baseline, baseline with fires, mid-century baseline), and two others were prepared, but not run (present and future emissions approximated through temperature vs. emissions relationships defined in Abel et al., 2017) [28]. These additional simulations influenced the decision to simulate July only, but did not contribute to the objectives of this manuscript and were therefore disregarded.

Health Impacts Assessment

We assess increased incidence of premature mortality and morbidity associated with exposure to higher daily mean $PM_{2.5}$, daily maximum 8-hour average (MDA8) O_3, and 1-hr maximum daily O_3 using EPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE v1.3) [60]. BenMAP calculates incidence of adverse health outcomes given a change in air quality. Expert-derived $PM_{2.5}$ exposure-response (or concentration-response, C-R) functions and pooling methods used for the U.S. EPA 2012 Regulatory Impact Analysis and O_3 C-R functions for 2008 National Ambient Air Quality Standards (NAAQS) evaluations are applied in this analysis [86–88]. These standard EPA configurations are available with the BenMAP software. Population is held constant for 2011 in all scenarios. Comparative analysis of the benefits of air conditioning in buildings for direct heat-related mortality versus air pollution effects from air conditioning-related electricity demand is beyond the scope of this study.

BenMAP combines population from U.S. Census data, baseline incidence data provided from several sources, but primarily the Centers for Disease Control (CDC) (outlined in Appendix D of

[69]), and an effect estimate from the chosen C-R function with specified changes in gridded air quality data to quantify health impacts. Each exposure-response function and pooling of incidence and valuation was run in a 5,000-member Monte Carlo ensemble to calculate mean impacts and associated uncertainty. Pooling methods are used to combine results for similar health endpoints across C-R functions as an alternative to meta-analysis. Techniques used here follow standard EPA methods including user-assigned weighting, random effects, fixed effects, addition, and subtraction to combine results of studies as described in Appendix K of [69]. Here we focus on mortality, which is not pooled as standard practice by EPA. Amongst mortality results, the American Cancer Society's Cancer Prevention Study-II, used for $PM_{2.5}$ mortality estimates is especially relevant because the study data include the most representative exposure sites in the US and a follow-up period of 18 years [89]. Health impacts based on maximum daily 1-hour O_3 are simulated but not pooled, as there is no standard EPA methodology based on maximum, daily 1-hour metrics, and these results are used primarily for comparison. Valuation to monetize the costs of exacerbated air pollution is performed according to standard EPA configurations by assigning a value to each health effect through a combination of willingness to pay and cost of illness (e.g., value of a statistical life) methods then applying that to calculated incidences [60].

Impact estimates are based on exacerbated pollution in July alone. Annual impacts are calculated as a three-month summer average based on July modeling. Thus, we take July as representative of the entire summer and triple our calculated results to arrive at a summer estimate. This is a reasonable assumption for the changes in air pollution and health impacts analyzed here, especially given the focus on the incremental impact of adaptation. Values presented in tables are for July exposure alone and have not been tripled. Average baseline scenario concentrations of $PM_{2.5}$ and O_3 from July modeling are applied outside of July in all calculations to isolate changes. Summer results are a good estimate for annual impacts although they are likely conservative as we would also expect spring and fall to exhibit some increased air pollution and adverse health outcomes. Winter air quality conditions are less influenced by the electricity sector. Estimated annual impacts are provided in the text while July impacts are presented in the tables.

All health impact functions for $PM_{2.5}$ mortality apply an annual average air pollution metric, calculated from daily-mean values with changes only in July. The daily-mean is used directly for many morbidity functions. All impacts calculated by BenMAP at any time-scale are summed and reported annually by the model as standard practice. Therefore, values provided in the table are annual impacts based on July exposure, while values provided in the text are annual impacts based on estimated annual exposure calculated as a 3-month summer average based on July modeling, as discussed above. O_3 premature mortality functions are based on metrics of MDA8 or daily 1-hr max O_3 with Jerrett et al. (2009) the only study based on an annual average metric [90]. Justification for modeling only July is discussed in detail in the methods for air quality modeling, but centers on balancing computational demands with the exploratory and representative (rather than predictive) nature of this study. We present in the main text primarily the results for mortality, which by standard methods are not pooled. Please see Table S2.2, Table S2.3, and Table S2.4 for morbidity results.

Results

Emissions and Air Quality

Changes in energy demand associated with warmer temperatures are driven by the distribution of temperatures at hourly or even sub-hourly scales. Figure 2.2 shows a histogram of regional-average (Eastern U.S.) hourly temperatures over the month of July for current and mid-century conditions. Results show a shift in the maximum ambient temperature from 32.4°C (present) to 38.5°C (future), an 18.8% increase. The mid-century scenario exhibits a decrease in the frequency of colder temperatures and increase in the frequency of warmer temperatures.

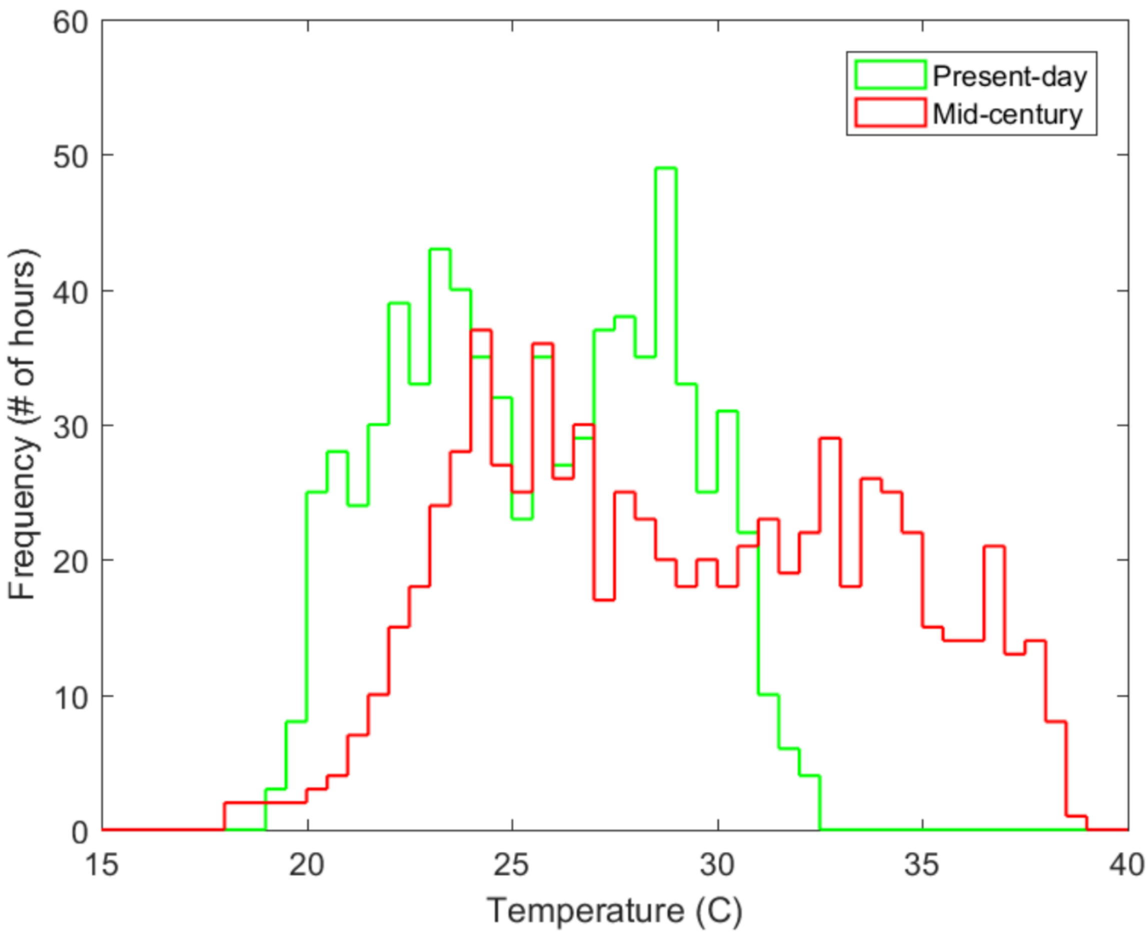


Figure 2.2. A histogram of hourly regional-average temperatures. A histogram of hourly, regional-average temperatures is presented for July in the present-day and in the mid-century, warm climate. Present-Day Mean: 25.6 °C, Min: 19.1 °C, Max: 32.4 °C; Mid-Century Mean: 29.1 °C, Min: 18.3 °C, Max: 38.5 °C.

The higher temperatures seen in the mid-century scenarios drive changes in electricity demand, production, and associated emissions. Figure 2.3 shows the hourly distribution of electricity production and emissions for current and future climates. These results show the response of electricity production to ambient temperature through demand for air conditioning. Under the future climate assumptions, average hourly regional electricity demand increases from 213 to 274 GWh (28.6%) and average hourly Eastern U.S. CO_2 emissions increase from 169 to 200 thousand metric tonnes (18.3%). Thus, adaptation through air conditioning use also constitutes a positive climate feedback.

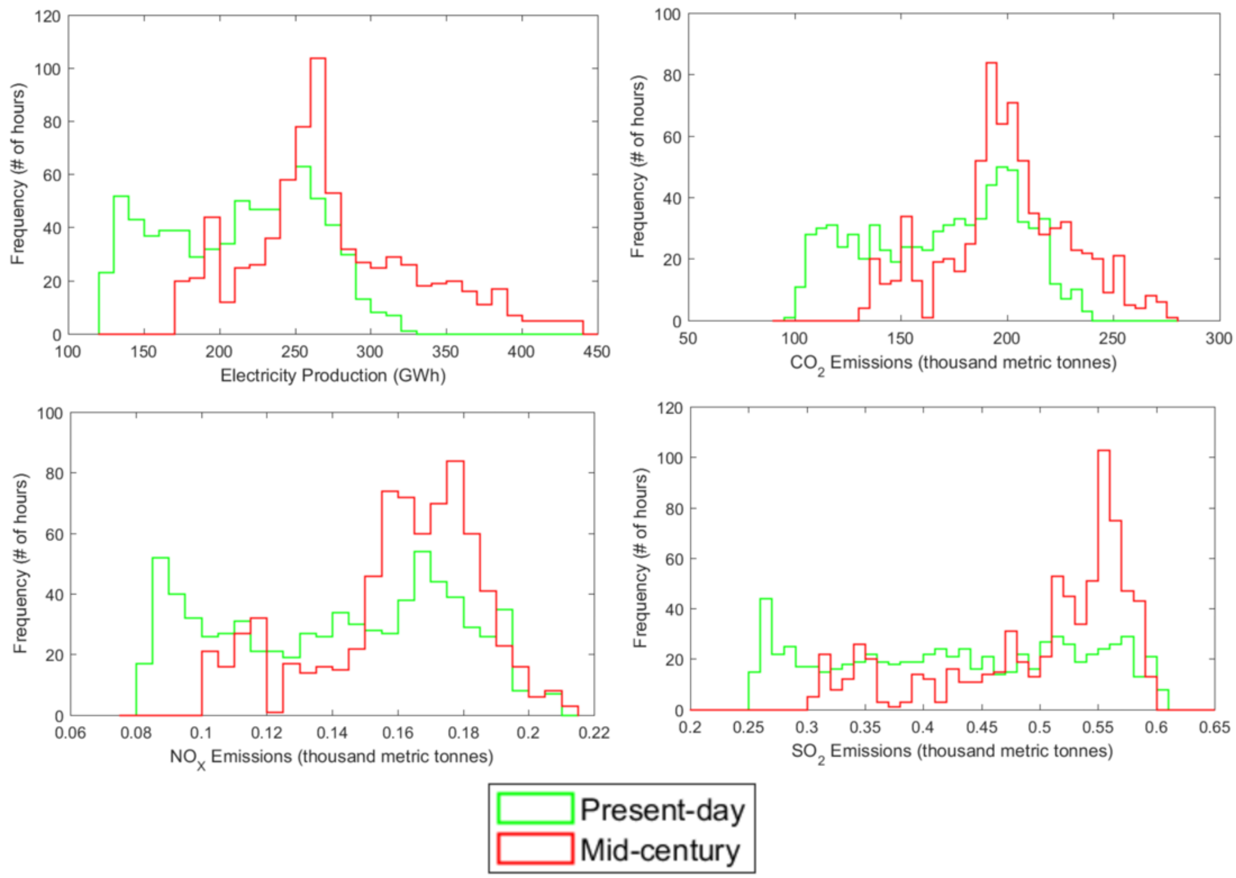


Figure 2.3. Histograms of hourly emissions and generation. Histograms are provided for hourly, regionally-summed a) electricity production, b) CO_2 emissions, c) NO_X emissions, and d) SO_2 emissions for July in the present-day and mid-century, warm climate. a) For electricity production: Present-Day Mean: 212.9 GWh, Min: 120.4, Max: 320.3; Mid-Century Mean: 274.2 GWh, Min: 172.0, Max: 438.0. b) For CO_2 emissions: Present-Day Mean: 168.8 thousand tonnes, Min: 99.8, Max: 238.8; Mid-Century Mean: 200.1 thousand tonnes, Min: 132.7, Max: 276.5. c) For NO_X emissions: Present-Day Mean: 140 tonnes, Min: 80, Max: 210; Mid-Century Mean: 160 tonnes, Min: 100, Max: 210. d) For SO_2 emissions: Present-Day Mean: 430 tonnes, Min: 250, Max: 610; Mid-Century Mean: 500 tonnes, Min: 300, Max: 590.

The change in maximum CO_2 is not as large as for electricity production because additional capacity in mid-century (necessary to meet increased demand) is generated by natural gas power plants based on the U.S. EIA's Annual Energy Outlook, which emit less carbon than the current mix of generation sources [36]. We find that electricity production and emissions in the present-day exhibit a more uniform distribution than do temperatures (Figure 2.2). This difference is due to the changing sensitivity of electricity generation as a function of temperature, with responsiveness increasing at higher temperature and decreasing at cooler temperatures when building cooling is less important. The distribution becomes less uniform in the mid-century climate as temperature-dependence plays a greater role compared to other end-uses of electricity.

Trends in the distribution of hourly electricity production and CO_2 emissions more closely follow changes in temperature than do emissions of NO_X and SO_2 shown in Figure 2.3c and 2.3d. Overall, emissions in the future climate scenario increase 13.7% for NO_X and 17.2% for SO_2, but the maximum hourly emissions rate does not increase for either NO_X or SO_2. Rather, the increase in average hourly emissions of NO_X and SO_2 occurs from greater frequency of emissions on the higher end of the present-day emissions distribution. Even as electricity demand increases, new peak electricity demand in the model is met by natural gas power plants that have little impact on NO_X and SO_2 emissions during peak conditions. Simulating likely retirements of coal-fired power plants and market-driven renewable energy investments would also result in lower emissions than found here where we maintain the existing power plant inventory to explore the arising interactions between climate, energy, and air quality without being predictive. This highlights the importance of considering cleaner energy sources in reducing future harmful emissions.

Overall, a 3.5 °C warmer summer is responsible for an increase in hourly average building energy demand of 28.6%. The air conditioning adaptation response to climate change in the Eastern U.S. is thus responsible for hourly average emissions increases of 13.7% for NO_X 17.2% for SO_2 and 18.5% for CO_2.

We analyze air quality in the PD (present-day climate, present-day EGU emissions), MCCO (mid-century climate only), and MCA (mid-century adaptation) scenarios as described in the methods. On a regional average, we find that climate change alone (MCCO vs. PD) increases $PM_{2.5}$ by 58.6% (2.50 μg/m^3) and O_3 by 14.9% (8.06 ppbv). A larger change is found when comparing the present day to the mid-century adaptation case, which includes building air conditioning (MCA vs. PD). In that case, $PM_{2.5}$ increases 61.1% (2.60 μg/m^3) and O_3 increases 15.9% (8.64 ppbv). Overall, 2.5% of the 61.1% increase in $PM_{2.5}$ and 1.0% of the 15.9% increase in O_3 is attributable to adaptive behavior (extra air conditioning use).

The July average change in each pollutant due to building energy use is shown in Figure 2.4 for $PM_{2.5}$ (2.4a) and July average MDA8 O_3 (2.4b). Increases in $PM_{2.5}$ from the MCCO to MCA scenario (Figure 2.4a) are highest (as high as >5%) in and downwind of the Ohio River Valley coincident with the highest concentration of fossil-fuel, especially coal-fired, power plants and the greatest increase in EGU emissions. A small decrease (<2.5%) in concentrations is observed in the southeast centered over South Carolina and the Chesapeake Bay. This is primarily due to a decrease in emissions in these regions (as seen in Figure 2.5) associated with power plant dispatch changes, see Meier et al., (2017) [36].

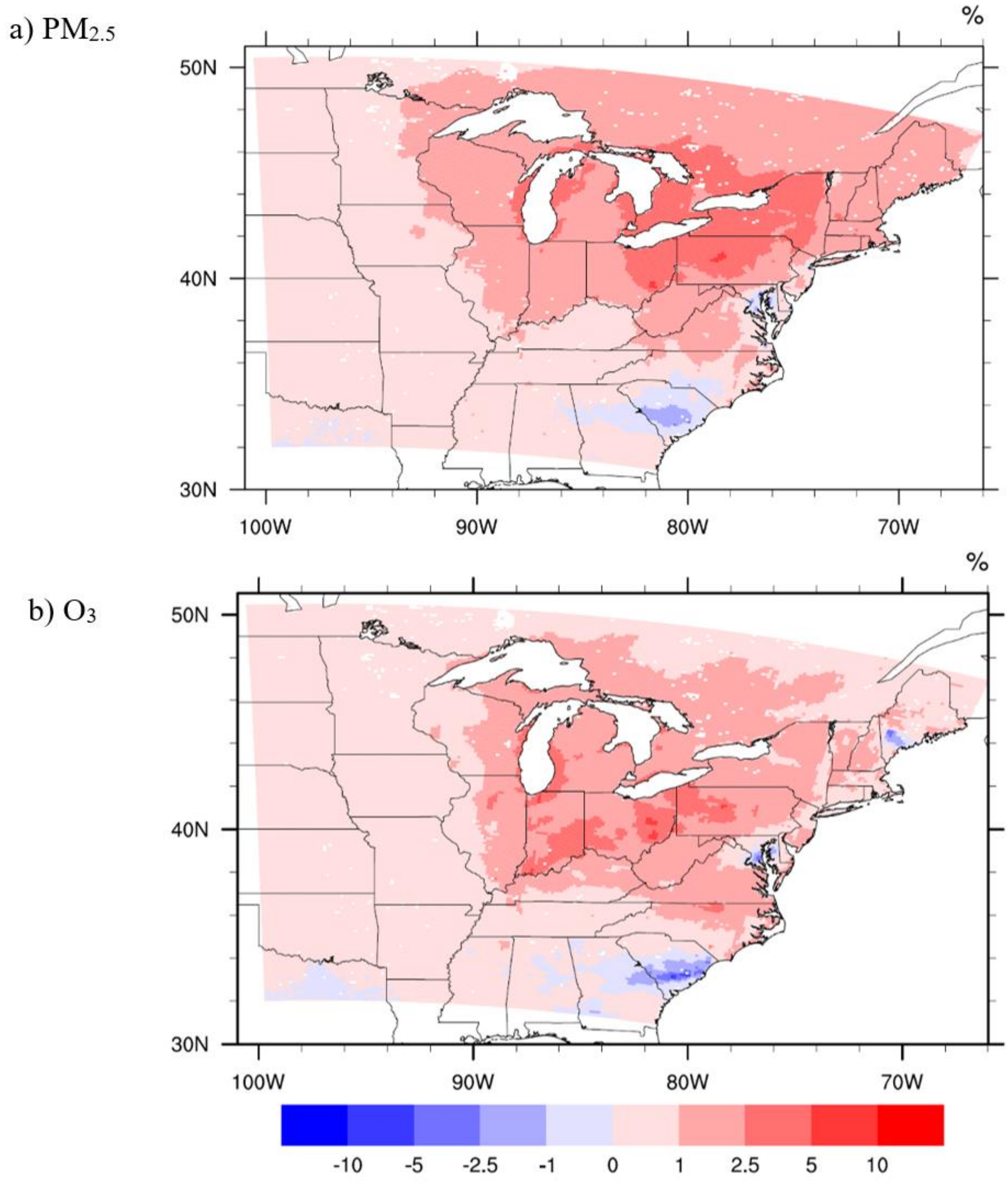
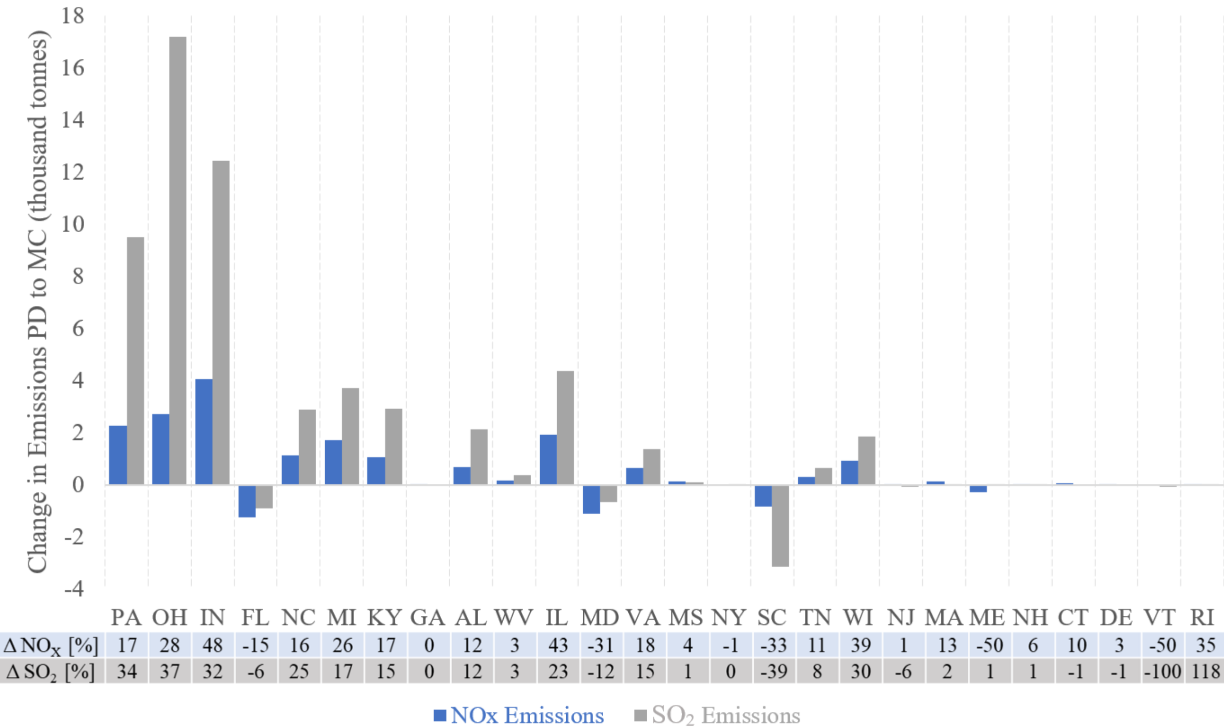


Figure 2.4. Change in ambient pollution concentrations. Maps of the percentage change in a) $PM_{2.5}$ and b) O_3 from the mid-century, warm-climate only (MCCO) scenario to the mid-century, warm-climate with adaptation (MCA) scenario. Red shows concentrations that are greater in the MCA scenario compared to MCCO while blue shows a decrease in concentrations compared to MCCO.



	PA	OH	IN	FL	NC	MI	KY	GA	AL	WV	IL	MD	VA	MS	NY	SC	TN	WI	NJ	MA	ME	NH	CT	DE	VT	RI
ΔNO_X [%]	17	28	48	-15	16	26	17	0	12	3	43	-31	18	4	-1	-33	11	39	1	13	-50	6	10	3	-50	35
ΔSO_2 [%]	34	37	32	-6	25	17	15	0	12	3	23	-12	15	1	0	-39	8	30	-6	2	1	1	-1	-1	-100	118

Figure 2.5. Change in emissions by state. The state by state changes in NO_X and SO_2 emissions from the present-day to mid-century as an absolute value (designated by the bars) and as a percentage (as listed).

We examine the distribution of regional average concentrations as a function of air pollution level in Figure 2.6. The number of hours with pollution at the highest levels increases due to climate change alone, and further rises given greater emissions of NO_X and SO_2 associated with higher climate-induced electricity demand. For $PM_{2.5}$, the minimum regional average concentration simulated under a future climate (4.37 μg/m^3 for climate-only) is above the average value for present-day $PM_{2.5}$ (4.26 μg/m^3). Current day values range from a minimum of 2.91 μg/m^3 to a maximum 5.98 μg/m^3. The highest regional average concentrations modeled under a future climate (8.75 μg/m^3 for climate-only) are higher than we see at any time in the present-day simulation. The additional consideration of adaptation through air conditioning use further increases the minimum and maximum values to 4.48 μg/m^3 and 8.87 μg/m^3, respectively.

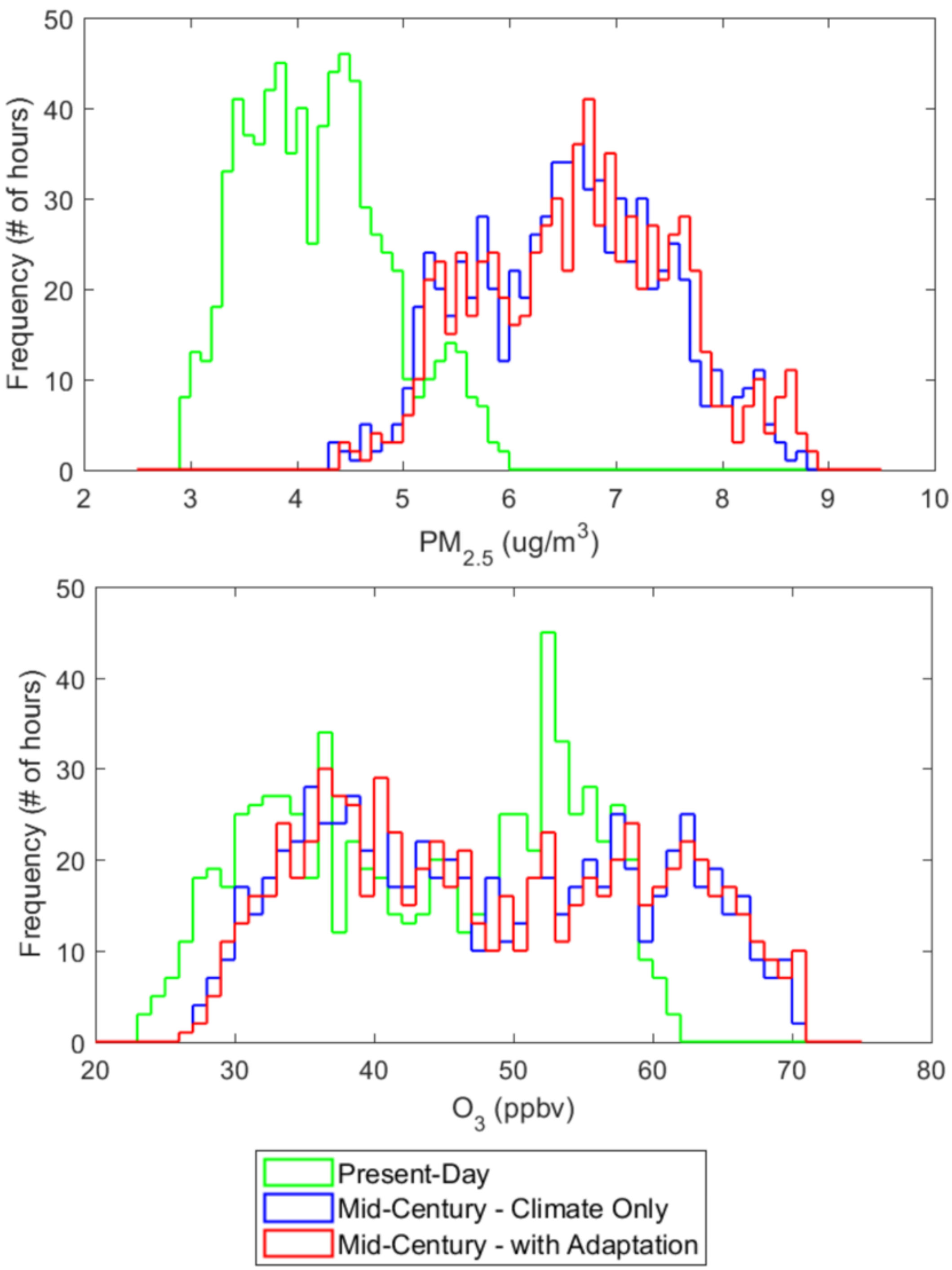


Figure 2.6: Histograms of ambient pollutant concentrations. Histograms of hourly, regional-average concentrations of a) $PM_{2.5}$ and b) O_3 for July in the present-day (PD) scenario, mid-century, warm climate only (MCCO) scenario, and mid-century, warm climate with adaptation (MCA) scenario. a) For $PM_{2.5}$ concentrations: PD Mean: 4.19 μg/m^3, Min: 2.91, Max: 5.98; MCCO Mean: 6.57 μg/m^3, Min: 4.37, Max: 8.75; MCA Mean: 6.67 μg/m^3, Min: 4.48, Max: 8.87. b) For O_3 concentrations: PD Mean: 43.4 ppb, Min: 23.6, Max: 61.7; MCCO Mean: 48.0 ppb, Min: 26.4, Max: 70.2; MCA Mean: 48.4 ppb, Min: 26.6, Max: 70.9.

Biogenic emissions, enhanced under a warmer climate, are the dominant contributor to the climate-only increase in $PM_{2.5}$. This impact is sensitive to the choice of chemical mechanism in the atmospheric model and details regarding the formation of secondary organic aerosol as a function of volatile organic compounds. Past studies have suggested that the CB05 mechanism in CMAQ may have errors in the representation of this atmospheric chemical process [91–93]. Thus, while the direct impact of climate on $PM_{2.5}$ is notable, we focus our discussion on the changes due to building energy use (i.e. MCCO vs. MCA).

Modeled EGU emissions of SO_2 increase by 17.2%, and NO_X by 13.7% due to building energy use in the future climate (state-by-state variation shown in Figure 2.5). This increase in EGU emissions results in increases in sulfate PM (SO_4^{2-}, 5.8% as compared to MCCO or 0.09 $\mu g/m^3$) and nitrate PM (NO_3^-, 3.1% as compared to MCCO or $0.7x10^{-3}$ $\mu g/m^3$).

Ozone exhibits many of the same trends as exhibited by $PM_{2.5}$. However, the increase in hourly O_3 is not as pronounced from the present-day to mid-century scenarios as seen for $PM_{2.5}$. In the case of O_3, adaptive behavior is responsible for an ~1% increase in O_3. Like $PM_{2.5}$, O_3 increases across most of the region (Figure 2.4) with the greatest increases in and downwind of the Ohio River Valley (as high as >5%) due to increases in EGU NO_X emissions. Small decreases due to localized emissions increases from changes in electricity dispatch are also evident over South Carolina and Chesapeake Bay, as well as a highly localized decrease in Maine and very small decrease along the Texas domain boundary.

Building energy use also results in a greater frequency of high O_3 days (Figure 2.6b). Note that the highest regional (Eastern U.S.) average hourly concentrations exceed the current NAAQS for MDA8 O_3 of 70 ppb [87]. These metrics are not directly comparable as standards are met or achieved at the county or state level and based on the fourth highest annual maximum, daily 8-

hour average (MDA8), whereas we present hourly, regional average concentrations. Additionally, the standards may be lowered by mid-century, but this comparison highlights the relevance of results to attainment of regulatory standards. Overall, adaptation causes a 4.5% increase in high O_3 days (defined as when regionally averaged hourly O_3 exceeds 60 ppb) and a 22% increase in high $PM_{2.5}$ days (defined as when regionally averaged hourly $PM_{2.5}$ exceeds 8 μg/m^3). Note the NAAQS for $PM_{2.5}$ is an annual average concentration of 12 μg/m^3. However, this analysis is limited to a sample size of the 744 hours of July and not directly comparable to the NAAQS.

Health Impacts

Increased exposure to $PM_{2.5}$ and O_3 increases risk of premature mortality, which we quantify using BenMAP. Health impact functions are based on EPA-selected epidemiological studies and expert-elicitation used in the U.S. EPA 2012 Regulatory Impact Analysis for revisions to the National Ambient Air Quality Standards for particulate matter. Tables 2.2 and 2.3 summarize the changes to premature mortality from increased July exposure to $PM_{2.5}$ and O_3 under each scenario (negative numbers indicate adverse health outcomes and monetary costs). Morbidity impacts are summarized in Tables S2.2-S2.4.

As discussed in the methods we present annual impacts (estimated as a 3-month summer average based on July modeling) in the text, while results in tables are based on July only. We include fourteen C-R functions for $PM_{2.5}$-related adult mortality, with each function reported separately. The change to mortality incidence and economic valuation of this loss of life is shown in Table 2.2 with 95% confidence intervals based on the reported uncertainty underlying each relative risk point estimate simulated in 5,000-member Monte Carlo ensembles. Morbidity impacts are reported in Table S2.2 and validation of air quality results is provided in the Supporting Information text. For O_3, we calculate mortality based on maximum, daily 8-hour mean (MDA8) concentrations as well as daily, maximum 1-hour concentrations as shown in Table 2.3 (morbidity impacts are reported in Table S2.3 and S2.4).

* Lepeule et al. is based on an age range of 25-99 while all others are based on 30-99.

$PM_{2.5}$ (24-hr mean)	MCA-MCCO		MCCO-PD		MCA-PD	
C-R Function Authors	Mortality Incidence (95% CI)	Valuation [billion $]	Mortality Incidence (95% CI)	Valuation [billion $]	Mortality Incidence (95% CI)	Valuation [billion $]
Krewski et al. [89]	-122 (-83, -162)	-1 (-3, 0)	-2476 (-1673, -3279)	-23 (-62, -2)	-2599 (-1755, -3442)	-24 (-65, -2)
*Lepeule et al. [94]	-280 (-140, -420)	-3 (-7, 0)	-5682 (-2828, -8537)	-52 (-150, -5)	-5962 (-2968, -8959)	-55 (-157, -5)
Expert B	-261 (-17, -561)	-2 (-9, 0)	-4956 (-115, -10980)	-46 (-184, -1)	-5201 (-122, -11522)	-48 (-193, -1)
Expert F	-239 (-107, -353)	-2 (-6, 0)	-4281 (-2027, -6660)	-40 (-114, -3)	-4497 (-2128, -6992)	-42 (-120, -4)
Expert K	-29 (-135, 0)	0 (-2, 0)	-418 (-2394, 14)	-4 (-29, 0)	-440 (-2513, 13)	-4 (-31, 0)
Expert L	-183 (-1, -433)	-2 (-6, 0)	-3121 (-2, -8218)	-29 (-119, 0)	-3276 (-2, -8625)	-30 (-125, 0)
Expert A	-319 (-37, -657)	-3 (-10, 0)	-6459 (-749, -13348)	-60 (-202, -3)	-6779 (-786, -14010)	-63 (-212, -3)
Expert C	-251 (-61, -446)	-2 (-7, 0)	-5073 (-1223, -9037)	-47 (-146, -3)	-5325 (-1284, -9486)	-49 (-153, -4)
Expert D	-176 (0, -302)	-2 (-5, 0)	-3565 (0, -6117)	-33 (-104, 0)	-3742 (0, -6420)	-35 (-109, 0)
Expert E	-415 (-149, -658)	-4 (-11, 0)	-8409 (-3020, -13373)	-78 (-229, -6)	-8827 (-3169, -14037)	-82 (-240, -7)
Expert G	-147 (0, -278)	-1 (-5, 0)	-2966 (0, -5622)	-27 (-100, 0)	-3113 (0, -5901)	-29 (-105, 0)
Expert H	-183 (0, -521)	-2 (-7, 0)	-3707 (0, -10562)	-34 (-142, 0)	-3891 (0, -11086)	-36 (-149, 0)
Expert I	-248 (0, -442)	-2 (-7, 0)	-5028 (0, -8954)	-46 (-149, 0)	-5277 (0, -9398)	-49 (-156, 0)
Expert J	-202 (-16, -468)	-2 (-7, 0)	-4085 (-314, -9485)	-38 (-136, -2)	-4288 (-330, -9956)	-40 (-143, -2)

Table 2.2. $PM_{2.5}$ mortality results summed regionally for July exposure and displayed for each scenario comparison. Expert functions are used for EPA 2012 Regulatory Impact Analysis [69,88]. Elicitation was performed to help characterize uncertainty of $PM_{2.5}$ mortality estimates.

[a] These functions are based on daily maximum 1-hr O_3 concentrations.
[b] These functions have age ranges other than 0-99 years. Jerrett et al. is 30-99, Ito and Thurston is 18-99.

O_3		MCA-MCCO		MCCO-PD		MCA-PD	
Health Outcome	C-R Function Authors	Incidence (95% CI)	Valuation [million $]	Incidence (95% CI)	Valuation [million $]	Incidence (95% CI)	Valuation [million $]
Mortality Cardio-pulmonary	Huang et al. [95]	-38 (-14, -62)	-353 (-1045, -29)	-407 (-149, -672)	-3760 (-11203, -309)	-440 (-161, -727)	-4060 (-12111, -334)
Mortality All Cause	Bell et al. [96]	-103 (-49, -158)	-955 (-2752, -84)	-1057 (-493, -1634)	-9760 (-28323, -848)	-1149 (-536, -1775)	-10600 (-30775, -922)
Mortality All Cause	Levy et al. [97]	-146 (-100, -192)	-1350 (-3678, -126)	-1509 (-1019, -2010)	-14000 (-37984, -1297)	-1640 (-1107, -2182)	-15200 (-41264, -1410)
Mortality All Cause	Zanobetti & Schwartz [98]	-66 (-35, -97)	-609 (-1730, -54)	-667 (-353, -984)	-6160 (-17474, -546)	-725 (-385, -1069)	-6690 (-18999, -593)
Mortality Non-Accidental	Bell et al. [99]	-29 (-10, -49)	-270 (-813, -22)	-300 (-99, -502)	-2770 (-8353, -223)	-325 (-107, -545)	-3000 (-9054, -242)
Mortality Non-Accidental	Ito et al. [100]	-132 (-79, -184)	-1220 (-3392, -112)	-1398 (-820, -1992)	-12900 (-36202, -1174)	-1513 (-888, -2155)	-14000 (-39190, -1272)
Mortality Non-Accidental	Schwartz [101]	-44 (-14, -75)	-411 (-1248, -33)	-458 (-140, -780)	-4230 (-12914, -335)	-496 (-152, -845)	-4580 (-13996, -364)
Mortality Non-Accidental	Smith et al. [102]	-29 (8, -66)	-266 (-978, 63)	-296 (79, -679)	-2730 (-10097, 640)	-321 (86, -736)	-2960 (-10942, 695)
Mortality Non-Accidental	Smith et al. (2) [102]	-36 (-18, -55)	-333 (-956, -30)	-370 (-179, -563)	-3420 (-9833, -304)	-401 (-194, -610)	-3710 (-10658, -330)
Mortality All Cause	[a] Levy et al. [97]	-123 (-85, -162)	-886 (-1576, -308)	-1477 (-998, -1965)	-10600 (-18985, -3653)	-1603 (-1084, -2132)	-11507 (-20605, -3966)
Mortality Respiratory	[a,b] Jerrett et al. [90]	-55 (-19, -92)	-397 (-830, -104)	-623 (-209, -1039)	-4473 (-9360, -1165)	-679 (-228, -1131)	-4872 (-10196, -1269)
Mortality Non-Accidental	[a,b] Ito & Thurston [103]	-87 (-19, -154)	-623 (-1369, -125)	-1037 (-224, -1879)	-7440 (-16571, -1455)	-1125 (-243, -2039)	-8075 (-17976, -1580)
Mortality Non-Accidental	[a] Ito et al. [100]	-55 (-37, -73)	-395 (-706, -136)	-647 (-434, -863)	-4645 (-8334, -1598)	-703 (-471, -937)	-5044 (-9049, -1735)
Mortality Non-Accidental	[a] Schwartz [101]	-47 (-15, -80)	-341 (-721, -85)	-557 (-170, -950)	-3999 (-8507, -987)	-605 (-185, -1032)	-4342 (-9236, -1073)

Table 2.3. O_3 mortality results summed regionally for July exposure and displayed for each scenario comparison.

For the impact of adaptation alone, (MCA-MCCO), the fourteen functions for $PM_{2.5}$ exhibit a range of mean increases in mortality from 87 to 1245 ($0 to $12 billion in costs) annually and an average of 654 deaths ($6 billion), see Table 2.2 for individual study confidence intervals. Adapting to climate change as calculated here accounts for a 4.8% increase over the impacts from climate change alone (MCCO-PD) which on average causes 12,906 additional premature deaths (average study 95% CI: 1,254-25,227) with costs of $120 billion ($12-234 billion). The total impact of climate and adaptation (MCA-PD) causes a mean of 13,548 premature deaths (3,226-25,681) based on the average of all functions (roughly the sum of climate alone and adaptation alone).

Considering the health impact of projected mid-century building energy use on $PM_{2.5}$ (MCA-MCCO), we find a range of mean estimates of 87 to 1245 excess deaths annually ($1 to $12 billion in costs) with an average of 654 deaths ($6 billion). For comparison, application of the concentration-response function from the most representative epidemiological study, the American Cancer Society's Cancer Prevention Study-II finds a mean estimate of 366 (95% CI: 249 to 486) deaths annually, slightly on the lower end of all study estimates [89].

For O_3, the results are similar to findings for $PM_{2.5}$, but additional functions address mortality from specific causes. The health impacts of projected mid-century building energy use on O_3 (MCA-MCCO) include an average of 315 deaths ($3 billion) based on three standard configuration studies with a range of 198 to 438 ($2 to $4 billion). Using daily, 1-hr maximum O_3 concentrations to assess this same scenario (MCA-MCCO), one study calculates mortality from all causes finding 369 additional deaths. Analyzing the studies with common health endpoints, we find that using daily, 1-hr maximum O_3 rather than MDA8 O_3 concentrations results in higher mortality from all causes (369 versus 315) and higher non-accidental deaths (189 versus 162).

For comparison of these building-related impacts with the health impacts associated with climate change alone (MCCO-PD), we calculate premature mortality from all causes and MDA8 O_3 exposure as 3234 (range of 2001 to 4527) and non-accidental mortality from MDA8 exposure as 1692 (888 to 4194). Using daily, 1-hr maximum concentrations, we find 4431 deaths (2994 to 5895) and 2241 (1671 to 3111) non-accidental deaths. Using MDA8 O_3, premature mortality from all causes, we find 8.0% of additional deaths in the MCA scenario are from adaptation and 92.0% are from climate alone, or an 8.7% increase above climate change impacts alone.

Morbidity impacts are summarized in Table S2.2-S2.4. Health impacts are assessed for endpoints including hospital admissions, respiratory symptoms (including asthma), minor restricted activity days, work loss days, and school loss days. Mean estimates of the costs of morbidity impacts vary from \$0 to \$45 million annually for $PM_{2.5}$, \$0 to \$39 million annually for MDA8 O_3 and \$6 to \$18 million for 1-hr O_3.

The independent health impact estimates from exposure to $PM_{2.5}$ and O_3 cannot be directly summed because BenMAP does not account for interaction effects between the two pollutants, and exposures often occur in the same location at the same time. The spatial distributions of mortality are shown by county in Figure 2.7 for $PM_{2.5}$, and O_3 (1-hr and MDA8). The spatial distribution of impacts follows the patterns seen for air pollution in Figure 2.5. Regions near the Ohio River Valley and urban areas see the greatest mortality damages. In South Carolina, the Chesapeake Bay, and small portions of Maine and Texas there is a slight decrease in mortality associated with a small, localized decrease in modeled emissions associated with modeled building energy demand and electricity dispatch.

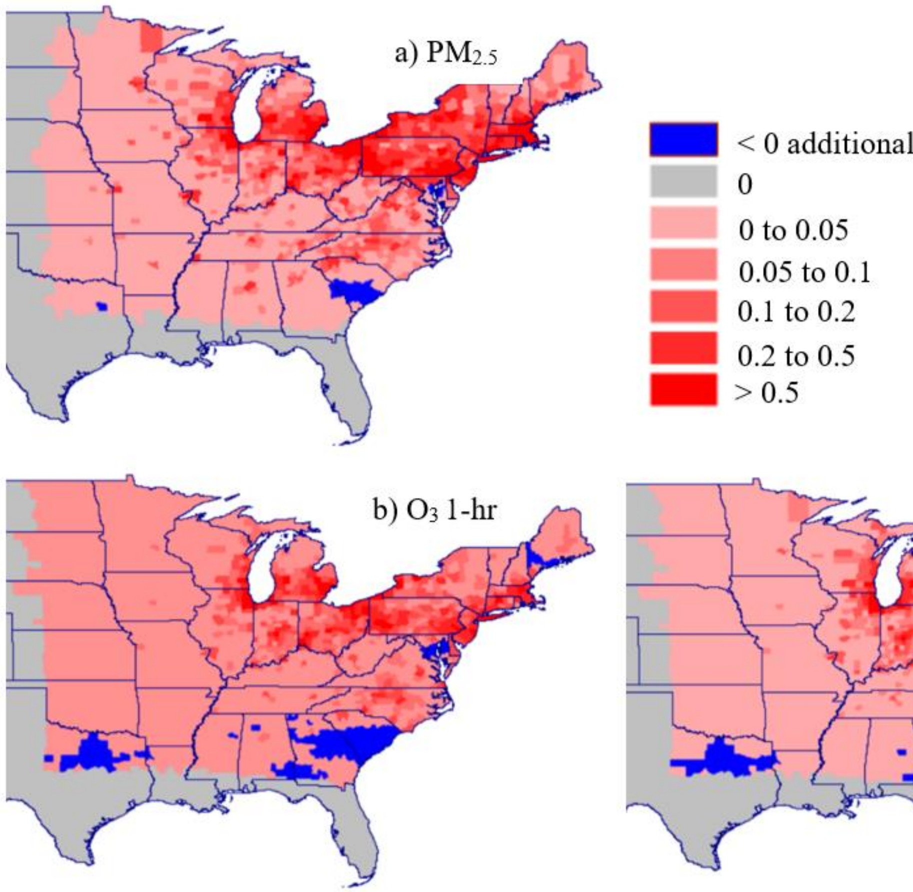


Figure 2.7. The mortality impacts of adaptation due to air pollution. Shown is the air pollution-related mortality increase due to adaptation (the MCA scenario minus the MCCO scenario) for a) $PM_{2.5}$ as taken from Expert F C-R function (the median function), b) O_3 based on Levy et al. using maximum daily 1-hr concentrations, c) O_3 based on Levy et al. using maximum daily 8-hr average concentrations.

Discussion

Simulating adaptive behavior to a warmer, mid-century climate shows that increased air conditioning use leads to higher emissions, degraded air quality, and adverse health outcomes. We find the increase in air pollution-related health outcomes attributable to climate change alone is 92-95% of the overall health burden (depending on air pollutant), while changes in human behavior to adapt to climate change through increased air conditioning in buildings comprises 5-8% of the health burden.

While our adaptation-related results are novel, our climate-only results are comparable to existing findings. Weaver et al. (2009) find substantial regions of the U.S. show increases in MDA8 O_3 of 2-8 ppbv in a future climate [21], and Jacob and Winner (2009) find 1-10 ppbv increases in O_3 [20]. Fiore et al., (2015) find previous studies show O_3 increases of up to 9 ppbv [19]. For $PM_{2.5}$, Jacob and Winner find an increase of 0.1 to 1 $\mu g/m^3$ [20], and Fiore et al. (2015) find a greater variability of results across studies dependent upon meteorology ranging from -2 to +3 $\mu g/m^3$ [19]. Tai et al. (2012) find that $PM_{2.5}$ likely will not increase greater than 0.5 $\mu g/m^3$ [104]. Our findings fit within the high end of previous estimates, and this is expected as we consider a particularly warm July, when large increases would be expected.

Quantifying the role of air conditioning adaptation in future air quality bears relevance to decision-making, as power-sector emissions are controllable by technology and policy, in a way that other climate-driven air quality mechanisms are not (i.e. chemical reaction rates, biogenic emissions, NO_X from lightning, and wildfire emissions). The scenario chosen here highlights the role of interactive effects amongst climate, energy and air quality. Interventions would, and likely will, reduce the damages calculated here. Control options include stack-level technological controls, such as SO_2 scrubbers and NO_X selective catalytic reduction, which have been the traditional approach employed by U.S. air quality management agencies to meet health-based standard. Although this technological approach would serve to reduce pollution exposure, such strategies do not modulate cost, energy use, or carbon emissions. In fact, end-of-pipe controls increase energy requirements to balance the decrease in plant efficiency associated with effluent treatment methods, this is often called the capacity and/or heat rate penalty.

An alternative to end-of-pipe controls is building energy efficiency measures (e.g. increasing insulation or installing more efficient cooling equipment [105,106]) that would reduce building energy demand in a manner that directly responds to the increased utilization of air conditioning. Efficiency measures would reduce demand on the electricity system, as well as associated carbon emissions, air quality impacts, and adverse health outcomes. Another option to reduce both carbon emissions and air-related health impacts would be to increase the portion of electricity generated by renewable sources like solar and wind. Studies show that solar energy would reduce and has reduced fine particulates in the Eastern U.S., especially on the highest concentration days [39,107]. Other options include demand response programs, building codes and standards, and conservation education. All of these alternatives would mitigate climate change and reduce the air-pollution related health burden from adaptation measures.

This study explores power plants and heat-driven electricity demand in buildings as an insufficiently understood mechanism to future air quality-related health damages in a warmer climate. Here we parse the contribution of this adaptation, but the study limitations include modeling only a single representative month, from one year in future climate projections. Typically, studies of climate would be based on a thirty-year average of results, which is not computationally feasible for this type of study. Additionally, results do not project future changes to population, air pollution exposure patterns in humans, building stock, and the electric power sector, but rather highlight the interactions amongst climate, electricity, air quality, and health. With less computationally demanding methods, more simulations could be run over longer timeframes to test the sensitivity of results to potential changes. Future directions could also include assessing the impact of interventions through climate change mitigation and air pollution control. Lastly, health impacts assessment relies on C-R functions for O_3 and $PM_{2.5}$, and these relationships continue to be improved through epidemiological and toxicological research.

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Supporting Information

Supporting information can be found with the published version of this chapter.

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Chapter 3: Solar Energy and Air Quality

This was the first manuscript prepared during my graduate studies and was published in the journal Atmospheric Environment early 2018. This paper began my personal exploration of the impact of renewable energy and energy efficiency on air quality. This study built on work from the National Renewable Energy Laboratory in assessing grid integration of solar energy. The completed work is cited below. The work here has been slightly modified from the published version only to conform with formatting for the purposes of this dissertation.

Citation

Abel, D., Holloway, T., Harkey, M., Rrushaj, A., Brinkman, G., Duran, P., Janssen, M., Denholm, P., 2018. Potential air quality benefits from increased solar photovoltaic electricity generation in the Eastern United States. Atmospheric Environment 175, 65–74. https://doi.org/10.1016/j.atmosenv.2017.11.049

Abstract

We evaluate how fine particulate matter ($PM_{2.5}$) and precursor emissions could be reduced if 17% of electricity generation was replaced with solar photovoltaics (PV) in the Eastern United States. Electricity generation is simulated using GridView, then used to scale electricity-sector emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_X) from an existing gridded inventory of air emissions. This approach offers a novel method to leverage advanced electricity simulations with state-of-the-art emissions inventories, without necessitating recalculation of emissions for each facility. The baseline and perturbed emissions are input to the Community Multiscale Air Quality Model (CMAQ version 4.7.1) for a full accounting of time- and space-varying air quality changes associated with the 17% PV scenario. These results offer a high-value opportunity to evaluate the reduced-form AVoided Emissions and geneRation Tool (AVERT), while using AVERT to test the sensitivity of results to changing base-years and levels of solar integration. We find that average NO_X and SO_2 emissions across the region decrease 20% and 15%, respectively. $PM_{2.5}$ concentrations decreased on average 4.7% across the Eastern U.S., with nitrate (NO_3^-) $PM_{2.5}$ decreasing 3.7% and sulfate (SO_4^{2-}) $PM_{2.5}$ decreasing 9.1%. In the five largest cities in the region, we find that the most polluted days show the most significant $PM_{2.5}$ decrease under the 17% PV generation scenario, and that the greatest benefits are accrued to cities in or near the Ohio River Valley. We find summer health benefits from reduced PM2.5 exposure estimated as 1,424 avoided premature deaths (95% Confidence Interval (CI): 284 deaths, 2732 deaths) or a health savings of \$13.1 billion (95% CI: \$0.6 billion, \$43.9 billion) These results highlight the potential for renewable energy as a tool for air quality managers to support current and future health-based air quality regulations.

Introduction

Renewable energy and energy efficiency (RE/EE) strategies have very rarely been incorporated into the state implementation plan (SIP) process for air quality management. This is surprising given that a wide range of RE/EE strategies offer the potential to reduce nitrogen oxides (NO_X = $NO + NO_2$) from all fossil fuels and sulfur dioxide (SO_2) from coal and oil, as well as other regulated pollutants. Both NO_2 and SO_2 are criteria pollutants, and both contribute to the formation of fine particulate matter ($PM_{2.5}$, or particulates less than 2.5 microns in aerodynamic diameter) via the production of secondary nitrate (NO_3^-) and sulfate (SO_4^{2-}). A historical disconnect between RE/EE planning and air quality assessment arises in part from the difficulty in quantifying emissions (which depend on EGU-specific fuel, technology, and generation) and air quality impacts (which depend on atmospheric chemistry, weather, and other emission sources). Any accounting for the air quality impacts of an energy policy requires the integration of an electricity dispatch model (to calculate which units will respond to a policy or technology change), an emissions model (to calculate how generation changes will affect air emissions), an atmospheric chemistry model (to calculate how emissions will react and disperse in the atmosphere), and for some studies a health impacts model (to calculate the changes in mortality and morbidity associated with changes in air pollution exposure).

Solar PV contributed less than 1% to U.S. electricity production in 2015 (U.S. Energy Information Administration, 2016), but decreases in cost and high potential resources contribute to projections that solar energy production will continue to grow (Nemet et al., 2016; U.S. Energy Information Administration, 2015). Studies suggest that solar could contribute ~15% of U.S. electricity generation by 2030 and nearly 30% by 2050 (Denholm et al., 2013; U.S. Department of Energy, 2012). As the U.S. generates more electricity from solar PV, the rate of air emissions from the electricity sector per megawatt-hour (MWh) produced will decrease. Thus, as the U.S. energy system incorporates more solar PV, we expect to see direct benefits to health-relevant air pollution, especially $PM_{2.5}$.

This work builds on previous work by the U.S. Department of Energy (DOE) and National Renewable Energy Laboratory (NREL), (Brinkman et al., 2011; Denholm et al., 2013; U.S. Department of Energy, 2012) which explores the benefits and challenges to solar energy integration, including changes in consumption, costs, rates, infrastructure, and operations. These and related studies primarily use the Regional Energy Deployment System (ReEDS), a capacity planning model, and GridView, a security-constrained, electricity dispatch model, to identify important considerations in feasibly incorporating high penetrations of solar generation (Feng et al., 2002; Short et al., 2011; U.S. Department of Energy, 2012). Here we utilize those findings in assessment of the air quality (particularly $PM_{2.5}$) impacts of solar integration using retrospective techniques consistent with SIP analysis.

Reductions in $PM_{2.5}$ between 1980 and 2000 in the U.S. have been associated with an increase in life expectancy. A 10 $\mu g/m^3$ decrease in annual exposure to $PM_{2.5}$ is associated with an increase in mean life expectancy of about 7 months (Pope et al., 2009). The health damages caused by $PM_{2.5}$ and $PM_{2.5}$ precursors from the electricity sector have been estimated to be 0.14-0.35 \$/kWh on a U.S. national average (Machol and Rizk, 2013). Similarly, the health benefits of emissions reductions from the U.S. electricity sector were calculated to be \$130,00/ton of directly emitted (primary) $PM_{2.5}$, \$35,000/ton of SO_2 precursor emissions (via the formation of secondary $PM_{2.5}$) and \$5,200/ton of NO_X precursor emissions (via the formation of secondary $PM_{2.5}$) (Fann et al., 2012). A related study at the individual plant level for Electricity Generating Units (EGUs) in the lower Great Lakes region and Mid-Atlantic found similar results, with health benefits per ton of emissions valued to be $130,000/ton of primary $PM_{2.5}$, $28,000/ton of SO_2 precursor emissions, and $16,000/ton of NO_X precursor emissions (Buonocore et al., 2014). In 2005, the electricity sector was the largest contributor to $PM_{2.5}$-related health impacts, including up to 48,000 premature deaths, but it drops to third largest by 2016 primarily due to increased controls (Fann et al., 2013). The high value of health benefits from emission reductions is consistent with EPA benefit-cost analyses (https://www.epa.gov/clean-air-act-overview/benefits-and-costs-clean-air-act), and provide the basis for extensive emissions controls on power plants that have been implemented over the past few decades in the U.S.

Like NO_X and SO_2, carbon dioxide (CO_2) is emitted from power plants. CO_2 is a pollutant of concern for climate change, due to its infrared absorption characteristics, but we do not analyze CO_2 in this study as it is not reactive in the atmosphere and thus the regional impacts are not incorporated into the SIP planning process. It is notable, however, that the incorporation of air quality "co-benefits" (the air pollution and health benefits from low-carbon energy) into climate policy assessments has been shown to estimate a mean benefit of $49/t$CO_2$ in health savings (Nemet et al., 2010). Additionally, the air pollution health benefits of a U.S. Clean Energy Standard that costs $208 billion were found to be $247 billion (Thompson et al., 2014). As such, this methodology bears relevance to CO_2 emissions reduction planning and the accounting for air quality co-benefits associated with RE/EE, as evidenced by the growth in interest around RE/EE accounting with the 2015 implementation of the U.S. Clean Power Plan. Although the future of the Clean Power Plan is uncertain, the potential cost savings of RE/EE to control reactive air pollutants (relative to expensive control technologies) is expected to increase interest in RE/EE accounting independent of direct U.S. policies for carbon reduction.

Past studies have applied a similar coupled-model analysis to air quality and RE/EE investments. For example, (Wiser et al., 2016)) use ReEDS and an integrated assessment model, the Air Pollution Emission Experiments and Policy Analysis model (AP2, formerly APEEP) to show when solar supplies 14% of U.S. electricity in 2030 and 27% in 2050, GHG and air pollutants drop 10% amounting to \$56-\$789 billion in climate benefits and \$77-\$298 billion in air quality and public health benefits. (Millstein et al., 2017) find a \$29.7-\$112.8 billion benefit to public health (3,000-12,700 avoided deaths) from 2007 to 2015 solar and wind development using EPA's AVoided Emissions and geneRation Tool (AVERT) and a suite of simplified air quality and health models. The tools and models used in previous studies as well as this study are summarized in Table 1 for comparison.

Among previous studies is a similar analysis assessing the benefits of low-carbon electricity production in Wisconsin using the MyPower least-cost dispatch model for generation change and emissions and the Community Multiscale Air Quality (CMAQ) model for air quality (Plachinski et al., 2014). Similarly, (Driscoll et al., 2015) calculated the health impacts of the Clean Power Plan using the Integrated Planning Model (IPM) for generation change and emissions, CMAQ for air quality, and the EPA Benefits Mapping and Analysis Program (BenMAP) for health. (Trail et al., 2015) and (Brown et al., 2013) predicted future air quality under CO_2 emissions reduction policies using emissions growth factors projected using the EPA U.S. 9-region national database with MARKet Allocation (EPAUS9r MARKAL) model, though (Trail et al., 2015) use CMAQ and (Brown et al., 2013) use APEEP to assess damages. (Hu and Hobbs, 2010) also use MARKAL to assess the impact of multi-pollutant policies. (Zapata et al., 2013) and (Carreras-Sospedra et al., 2010) use similar methodologies to assess the benefits of air quality co-benefits of California Assembly Bill 32 (AB32) and distributed generation, using estimates from environmental reports and emissions inventories with University of California, Davis and Irvine atmospheric models. The Tracking and Analysis Framework (TAF), U.S. Regional Energy Policy Model (USREP) and study-specific analysis models have also been utilized (Buonocore et al., 2016; Burtraw et al., 2003; Kerl et al., 2015; Saari et al., 2015). While previous studies have addressed the air quality co-benefits of carbon reduction in the electricity sector, they use a vast array of different methodologies, and this work is the first to utilize a security-constrained electricity dispatch model with a best-available, regulatory standard emissions inventory, a detailed, regulatory standard chemical transport model, and a regulatory standard health impacts and valuation tool.

Methodology

Figure 3.1 shows a flowchart detailing the methods for this study. We simulate two electricity scenarios using ABB's GridView model. These scenarios are used to scale SO_2 and NO_X power plant emissions from a state-of-the-art emissions inventory from the Lake Michigan Air Directors Consortium (LADCO) on a 12 km x 12 km grid of the Eastern U.S. for summer (June, July and August) 2006. Perturbed emissions are then used to calculate associated air quality changes using the U.S. EPA's Community Multiscale Air Quality (CMAQ) model. Finally, the U.S. EPA's Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE v.1.3) is used to assess the public health impacts of these air quality changes. EPA's AVoided Emissions and geneRation Tool (AVERT) is used for sensitivity testing and to apply results to different base-years and levels of solar integration. The models and tools used within this study are all summarized and compared with tools from related literature in Table 3.1.

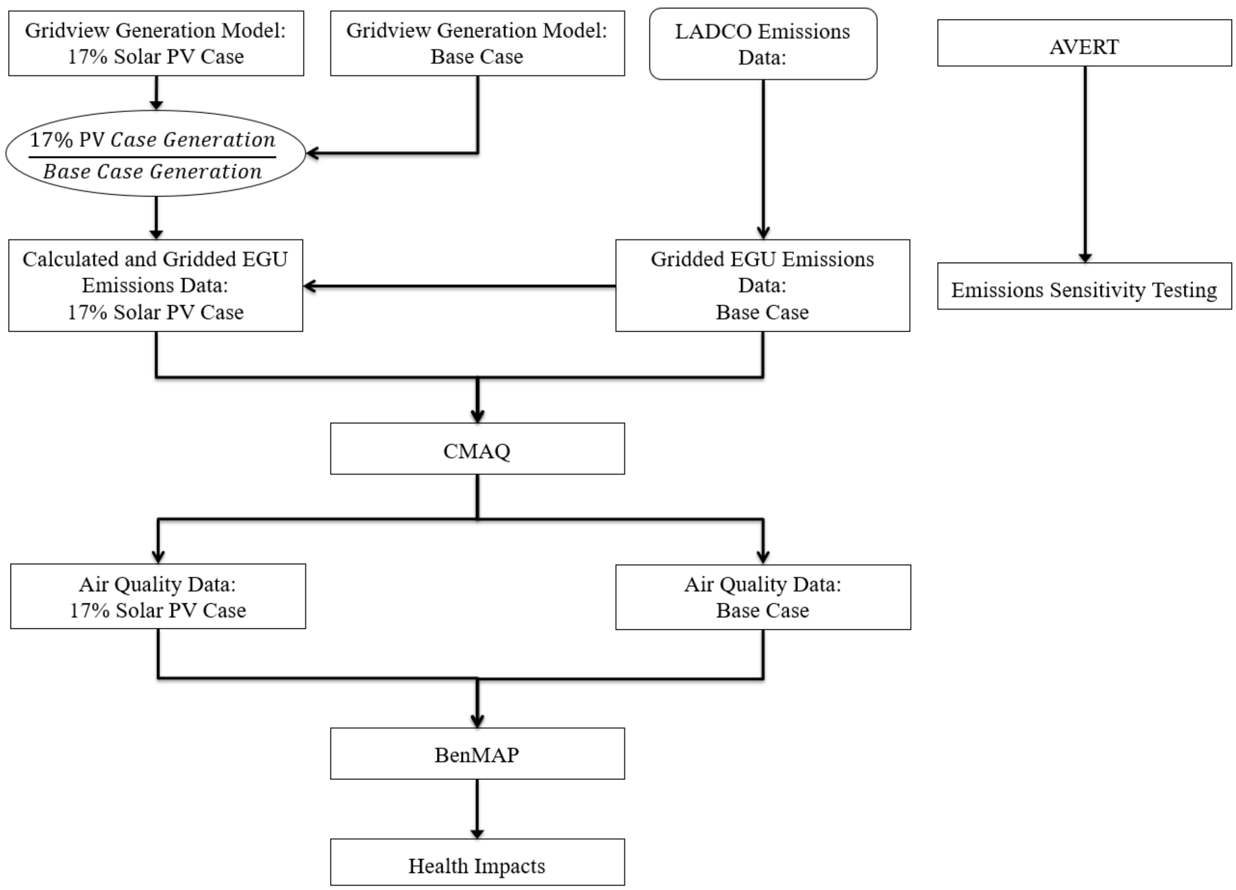

Figure 3.1: Flow diagram depicting analysis incorporating the GridView security constrained, electricity dispatch model, the Lake Michigan Air Directors Consortium (LADCO) emissions inventory, CMAQ, and BenMAP to determine electrical generation emissions, air quality, and health impacts under a base case scenario and a scenario replacing 17% of conventional electricity generation with solar photovoltaic electricity generation.

Table 3.1: A summary of the primary models and tools used in this study with a brief description of alternative tools and products and key differences between the models used in this study and alternative tools.

Models and Tools	Similar Models	Key Differences
ABB's GridView	Meier Engineering Research's MyPower, the National Renewable Energy Laboratory's Regional Energy Deployment System (ReEDS), ICF's Integrated Planning Model (IPM), and the International Energy Agency's MARKet ALlocation Tool (MARKAL).	GridView includes detailed security constraints provided by DC power flow calculations that other similar models lack.
Lake Michigan Air Directors Consortium's Emissions Inventory	U.S. EPA's National Emissions Inventory and Continuous Emissions Monitoring System (CEMS) data.	The LADCO inventory has the support of the Lake Michigan Air Directors Consortium and has been utilized for similar past studies.
U.S. EPA's AVoided Emissions and geneRation Tool (AVERT)	Other energy models as described above for GridView. No appropriate direct comparison.	AVERT is a reduced-form model specifically designed to calculate avoided emissions due to the addition of renewable energy and energy efficiency.
U.S. EPA's Community Multiscale Air Quality (CMAQ) Model	Environ's Comprehensive Air Quality Model with Extensions (CAMx), the National Oceanic and Atmospheric Administration's WRF-Chem, and other Chemical Transport Models (CTMs).	CMAQ is consistent with regulatory applications. The Air Pollution Emission Experiments and Policy Analysis model (AP2) is an integrated assessment model that does not use chemical transport methods
U.S. EPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE)	Health impact functions (i.e. concentration-response functions) can be directly applied without the use of a tool like BenMAP.	We follow EPA default, regulatory methods in using BenMAP to assess health impacts.

All weather-dependent aspects of our study are calculated for 2006, including the solar PV generation in GridView, and the meteorological inputs to CMAQ. 2006 was chosen as the base-year to coordinate with previous NREL work, however the most recent available emissions inventory was for 2007. Thus, our study year is considered 2006, with the assumption that technology change between 2006 and 2007 (the year of the LADCO inventory) will not significantly affect study results. A retrospective analysis was chosen to isolate the introduction of solar energy from other changes to the electricity grid and reduce the barriers to regulatory integration by following standard approaches to SIP analysis. Analysis is limited to summer months to represent peak electricity demand and associated emissions.

The GridView model is a security constrained, unit commitment and electricity dispatch model simulating power generation across the Eastern U.S. grid, using generation cost, transmission capacity, and demand assumptions, including time-varying weather conditions affecting the availability of renewables (Feng et al., 2002). Like other unit commitment and economic dispatch models, GridView commits and dispatches EGUs to minimize total production cost constrained by demand and reliability requirements including representing part-load operation. However, GridView additionally uses DC power flow calculations for detailed constraining of the transmission grid, which is fundamentally different than other models that have been used for air quality analysis; MyPower, ReEDS, IPM and MARKAL. GridView is an industry-grade model that was previously used to study the integration of renewable energy systems (Varadan et al., 2012), as well as the specific case of high-penetration solar energy validated through NREL applications (Arent et al., 2014; Brinkman et al., 2011; Denholm et al., 2013; Mai et al., 2014).

Two electricity scenarios are simulated with GridView: 1) a “base case” representation of 2006 generation (“noPV case”); 2) a simulation wherein PV supplies approximately 17% of total regional electricity demand (“PV17 case”) Locations of added PV in the PV17 scenario follow the scenarios derived in the U.S. DOE SunShot Vision study for 2050 (U.S. Department of Energy, 2012). The state distribution of solar capacity is reproduced here in Figure S3.1 in Supporting Information. Further discussion is provided in the supplementary methods. Detailed analysis of economic impacts and other benefits and challenges of increasing solar penetration are addressed by prior work(U.S. Department of Energy, 2012).

For this study, GridView provides hourly generation March 15 to October 1, 2006 for all power plants in the Eastern U.S. In examination of the hourly results, the study team found a two-hour shift in demand profiles (to earlier in the day). However, this two-hour shift occurs only in the electricity demand input for electricity modeling; this error does not affect the timing of solar availability to the grid, or any other aspect of the modeling system. Given that the electricity model is used to scale emissions, and that scaling factors follow expected trends, this offset is not expected to significantly impact results.

We used hourly GridView generation to scale hourly power plant emissions from an existing emissions inventory produced by LADCO for the Eastern U.S. at 12 km x 12 km for 2007 technology conditions yielding two EGU emissions inventories; one representing the noPV case (the original LADCO inventory) and one representing the PV17 case (calculated from grid-by-grid, hour-by-hour ratio of generation in the PV17:noPV GridView simulations). For detailed methods of this process as well as the advantages and disadvantages see the supplementary methods. The LADCO inventory was developed for regulatory air quality modeling and has been used for similar analysis (Lake Michigan Air Directors Consortium, 2011, 2003; Stanier et al., 2012). The inventory includes all major sectors of anthropogenic emissions allocated on a temporal and hourly basis. For the power sector this includes the emissions controls and fuel characteristics for fossil-fuel plants. The development and testing of emissions inventories is a high-priority activity for the air quality management community, as these inventories are used to support decision-making and planning (e.g. State Implementation Plans, SIPs). While a bottom-up, sector-specific inventory is common to include in research studies, it is rare for regulatory applications to replace ("swap out") a large section of an emissions inventory. In the case of swapping out an EGU inventory, the definition of an EGU, relative to industrial electricity generation, and stack characteristics can cause significant problems with integration into an existing inventory. Our approach avoids this swapping out in a manner that reduces the barriers to regulatory integration.

It is important to note that recent changes to the electricity grid have resulted in lower electricity emissions of NO_X and SO_2, primarily through changes in generation mix and emissions control technologies. Lag time required for solar energy penetration would further change the grid. Sensitivity analysis is useful to predicting future impacts of solar energy penetration, however the detailed integrated modeling methodology used here is cost- and time-prohibitive to multiple simulations. To compare multiple years and levels of solar integration, we use a simplified model developed by the U.S. EPA, the AVoided Emissions and geneRation Tool (AVERT). AVERT uses a method of intermediate complexity in which historical hourly emissions and generation from the EPA's Acid Rain program are used in conjunction with hourly RE/EE profiles to predict emissions reductions due to the introduction of RE/EE. However, since it used historical data, this does not consider future economic behavior. We run AVERT under various base-year and solar integration conditions, ranging from base-year 2007-2015 and 2%-17% solar integration, for the Northeast, Mid-Atlantic/Great-Lakes and Southeast regions, which best approximate the Eastern U.S. domain used here.

To calculate the impact of emissions changes on regional air quality requires a three-dimensional model of atmospheric chemistry and transport. The Community Multiscale Air Quality (CMAQ) model is a three-dimensional Eulerian air-chemistry transport model that brings together meteorology and emissions to calculate air quality data, namely pollutant concentrations. Two simulations are performed in CMAQ v4.7.1 using identical 2006 WRF meteorology pre-processed for CMAQ with the Meteorology-Chemistry Interface Processor (MCIP). The LADCO inventory is used for all anthropogenic emission sources with the EGU emissions calculated as described. Biogenic emissions are calculated with the Model of Emissions of Gases and Aerosols from Nature (MEGAN) for 2006 (Guenther et al., 2012). Other natural emissions sources, especially lightning and biomass burning, are not included in the simulation. Given the focus on change under an energy scenario, the exclusion of these sources is not expected to significantly affect results. Therefore, the difference between the two CMAQ simulations reflects changes in primary (directly emitted) and secondary (chemically formed) pollutants associated with the PV17 scenario. We use CMAQ version 4.7.1 (Byun and Schere, 2006), run with 27 vertical layers to cover the Eastern Continental U.S. on a grid with 12 km x12 km resolution with 172 rows and 216 columns. Model performance is evaluated against ground measurements in supplementary material (see Table S3.1).

Finally, BenMAP-CE v1.3 is used to calculate the reduced mortality incidence and associated monetary savings from reduced $PM_{2.5}$ exposure in the Eastern U.S. Default EPA configurations for PM are utilized for health impact function selection, pooling, aggregation, and valuation using 2005 mortality incidence (the closest available to 2006) and 2006 county-level population (U.S EPA, 2017). EPA standard methodology does not pool mortality outcomes and here we present results from various functions as a full representation of potential impacts and uncertainties. Health impact estimates assume average base-case $PM_{2.5}$ for non-summer months such that results are based exclusively on $PM_{2.5}$ reductions during June, July and August. This is likely conservative as solar energy would continue to reduce emissions from the power sector throughout the year.

Results and Discussion

Generation Analysis

Electricity modeling was conducted to assess how existing fossil fuel generation would be affected by increasing solar PV generation. Both the baseline (noPV) and the test case (PV17) scenarios are simulated in GridView for March 15 – October 1, during which time about 1,860 Terawatt-hours (TWh) of generation are simulated in the modeled region. The PV17 scenario simulates just under 0.4% more total electricity production. We focus our analysis here on June, July, and August, over a sub-region of the modeled region enveloping the majority of the Eastern U.S. limited by the domain covered by the LADCO inventory (extending from the northern U.S. border south to ~32^o N, hence omitting all of Florida and parts of Texas, Louisiana, Mississippi, Alabama, and Georgia). While over the entire region for the entire time frame 20% of generation is met with PV, within the Eastern U.S. emissions domain for only the summer (June, July and August), only 17% of generation is met with PV. 704 TWh is generated conventionally in the baseline case and 586 TWh in the solar-case. Conventional generation throughout is defined as any generation occurring at all facilities other than the newly introduced solar photovoltaics.

The differences in conventional generation between scenarios are used to scale gridded emissions of SO_2 and NO_X. Figure 3.2 shows the temporal variation in conventional electric generation summed over all units in the study domain under the baseline case (noPV, blue) and in conventional generation under the solar scenario (PV17, red). Conventional generation is lower in the PV17 scenario throughout the season, with the greatest difference during daytime hours as expected. Overall, generation increases through June into July and decreases into August with summer average NoPV output of 319 GW; and PV17 output of 268 GW.

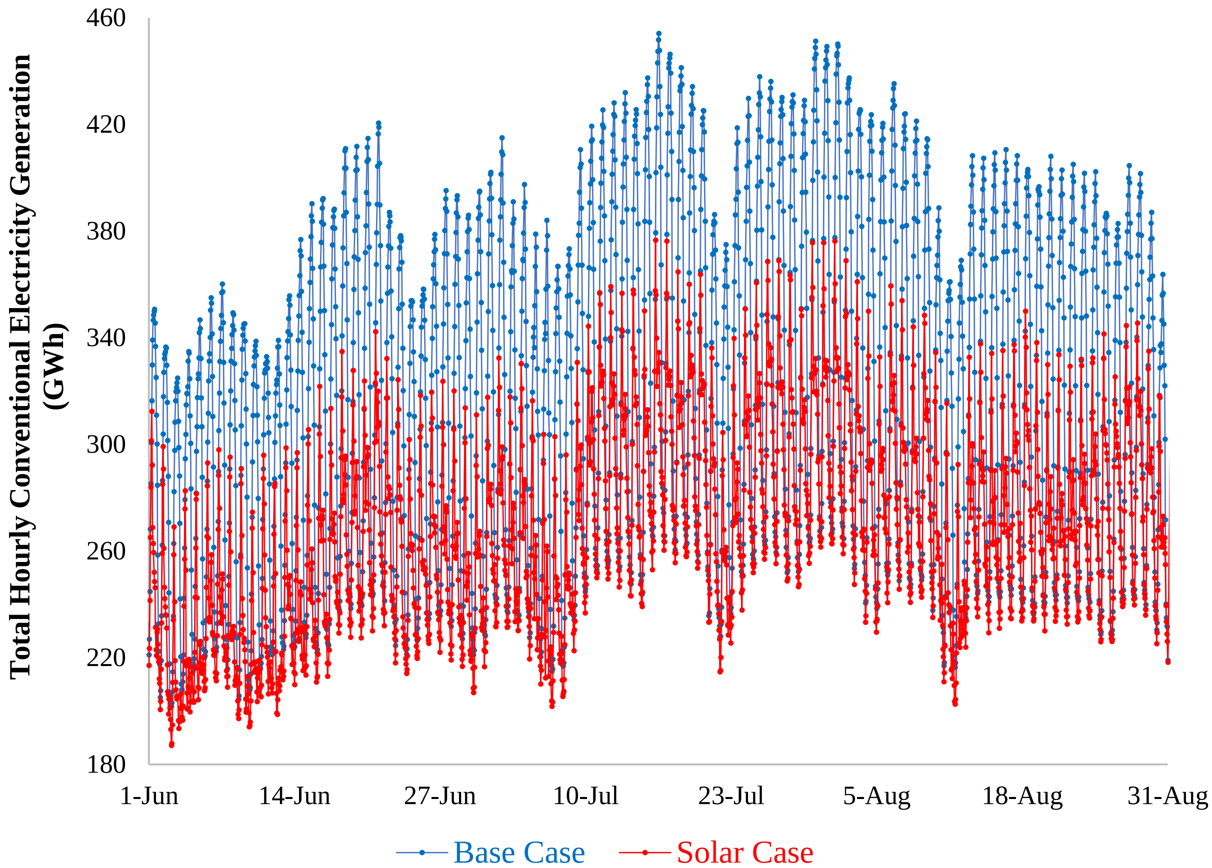

Figure 3.2: The total hourly conventional generation over the summer months for both the base-case and the solar-case for all power plants in the Eastern U.S. region.

Figure 3.3 shows the ratio of conventional generation between the PV17/noPV (red line) averaged across all facilities in the domain and June/July/August days, showing the average diurnal change in generation response. The hourly changes in generation follow expected behavior as conventional generation remains approximately constant throughout the night before dropping during the day as solar energy becomes available with increasing insolation. The overall generation decreases slightly even at night when no solar energy is available; this is likely due to a shift in some generation to outside the gridded domain.

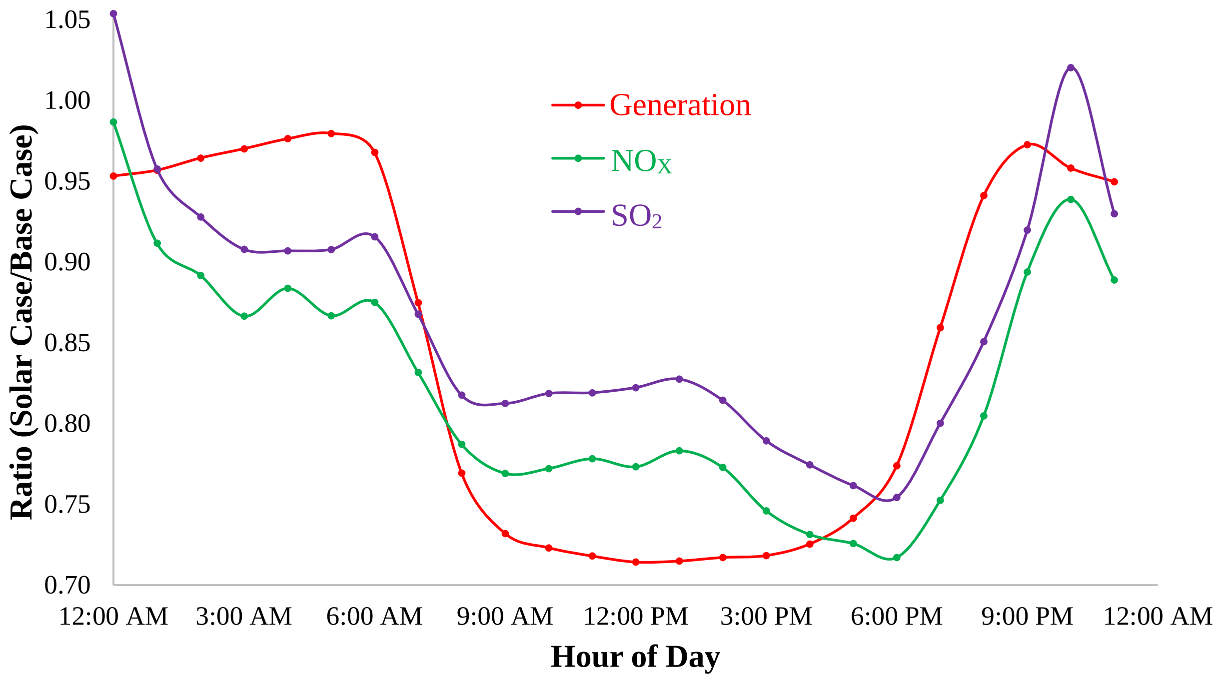

Figure 3.3: The ratio of SO_2 and NO_X emissions and generation in the solar-case as compared to the base-case for each hour of the day on average for the summer (June, July and August).

Figure 3.4 examines the hourly, diurnal change in conventional generation summed over the entire summer from the base-case to the solar-case by fuel-type. Figure 3.4a shows the absolute change in generation from the base-case to the solar-case in TWh (negative is a decrease in generation of that type), and Figure 3.4b shows the percentage change. Clearly evident in both plots, coal and natural gas generation decreases substantially during the day and remains slightly lower during the night (~5% for coal and ~10% for natural gas). This sustained decrease in fossil-fuel generation overnight is slightly offset by an increase in generation from other sources, but results in a decrease in overall generation of up to 5% as shown in Figure 3.3. The overall decrease is accounted for by a shift in generation to locations outside of the emissions domain, which is only a subset of the modeled region. Nuclear remains approximately the same throughout with a maximum decrease of only 1.8%.

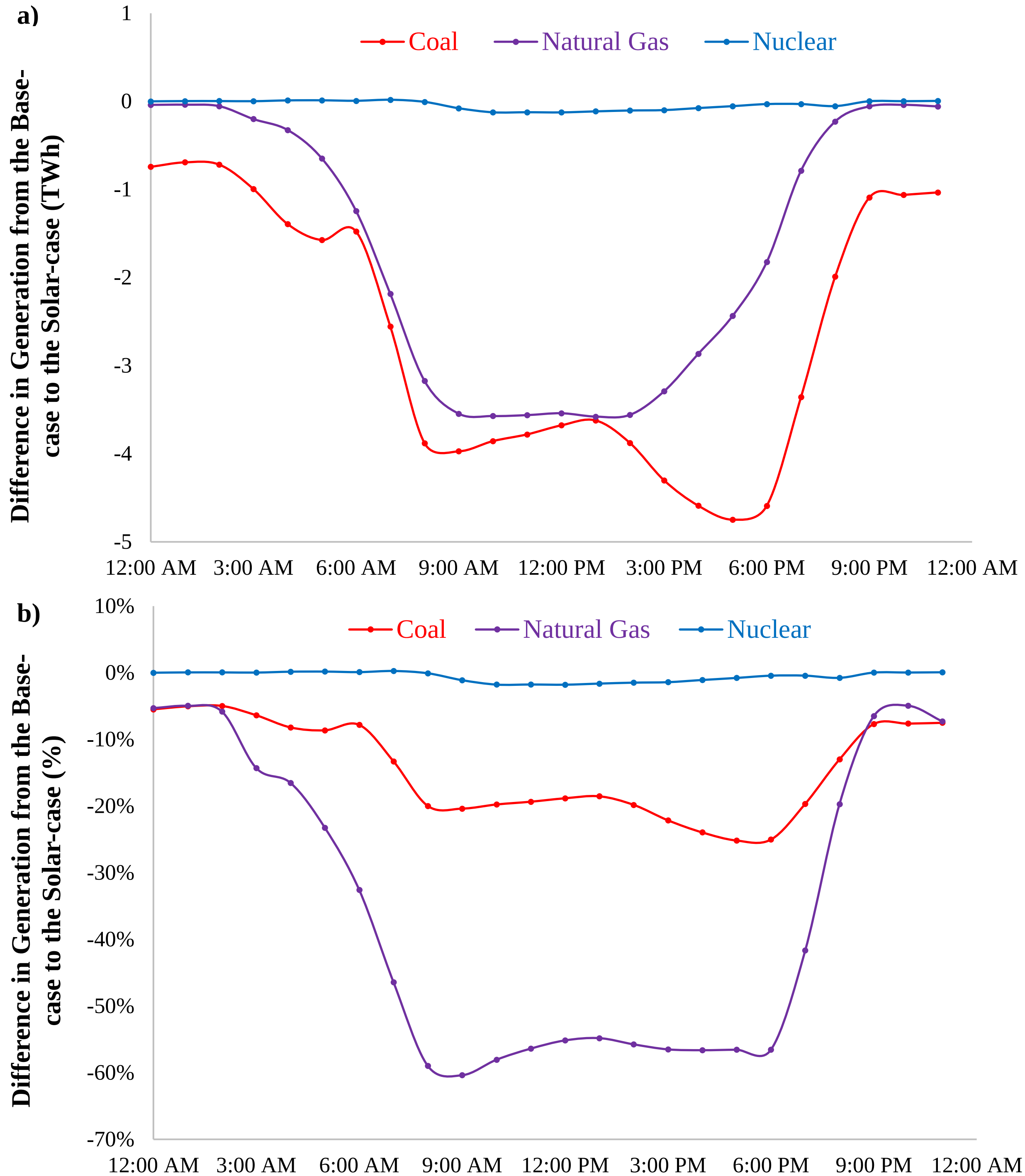

Figure 3.4: The hourly change in generation from the base-case to the solar-case by time-of-day summed over the entire summer (June, July and August) by a) absolute change and b) percent change in terawatt-hours based on fuel type. Petroleum, biomass, default and "other" designations in GridView are not shown for clarity due to their lower contributions.

availability. Most of the displaced generation is coming from coal and natural gas plants with almost none from nuclear. During times of solar availability, coal generation decreases approximately 18-25% which translates to up to 4.75 TWh throughout the summer while natural gas decreases up to 60% or 3.5 TWh. On average throughout the day, coal decreases 15% and natural gas decreases 49%. Other fuel types not shown in Figure 3.4 for clarity see decreases similar to coal and natural gas during times of solar availability. However, default designated plants (a designation for plants without a technically-defined fuel such as hydroelectric plants) see an increase in generation during the morning and evening hours of 1-2 TWh indicating re-dispatch of hydroelectric generation. Overall, coal see the most modest proportional generation decrease with the greatest coming from natural gas plants. This ordering of dispatch may change under differing price climates. Expected emissions changes based on more recent years and levels of solar integration are assessed in the Sensitivity Testing section.

Emissions Analysis

Table 3.2 provides a summary of emissions from electricity generating units (EGUs) for NO, NO_2 and SO_2 as well as generation. The percentage changes in NO and NO_2 are exactly the same, as expected from an emissions inventory that assumes a constant NO:NO_2 partitioning ratio for all EGU NO_X emissions; NO, NO_2 and total NO_X all change 20% under the 17% PV scenario. Emissions of SO_2 decrease by 15%. NO_X is reduced more than SO_2 suggesting that a higher proportion of generation is being displaced by solar at natural gas plants (with no associated SO_2 emissions) than at coal plants (with high associated SO_2 emissions). This can be seen in Figure 3.4b as coal generation decreases around 20% during the day, while natural gas decreases by around 60%. Additionally, average decreases in coal generation (15%) and natural gas generation (49%) support the observed emissions reductions. A 15% reduction in SO_2 emissions is to be expected as SO_2 is only emitted at coal power plants, with a small contribution from petroleum plants. Similarly, natural gas plants emit far less NO_X per MWh, approximately 7% that of coal in 2012 (Gouw et al., 2014), but do have an impact on total emissions. Therefore, NO_X emissions reductions would be expected to be slightly higher than 15% supporting the 20% observed reduction. This result is also supported by expected dispatch as coal is lower on the dispatch stack due to lower variable costs.

Table 3.2: Total EGU emissions over the summer months from electricity generating units in the Eastern U.S. in the base case (NoPV) and in the proposed solar case (PV17) are shown for nitrogen oxide (NO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). Lastly, the decrease in emissions for each pollutant is shown as difference and this is also shown as a percentage decrease. Additionally, electrical generation is shown for each case.

Emissions Reductions	**NoPV (tonnes)**	**PV17 (tonnes)**	**Difference (tonnes)**	**Difference (%)**
Generation	704 TWh	586 TWh	119 TWh	17%
NO Emissions	250,000	200,000	50,000	20%
NO_2 Emissions	42,000	34,000	8,000	20%
SO_2 Emissions	1,890,000	1,600,000	290,000	15%

The emissions decreases seen from our multi-model approach are used to evaluate the reduced-form model, AVERT. AVERT data is not available for 2006, but is provided for years 2007 onward. With the addition of 17% solar, AVERT calculates displaced SO_2 emissions to be 15%, and 16% for NO_X emissions. This agrees well with results from the detailed approach discussed above, where SO_2 decreases 15% and NO_X decreases 20%. The effects of a changing base-year or level of solar integration are discussed in section 3.5.

Figure 3.3 shows the average ratio of NO_X and SO_2 emissions from our multi-model approach based on the hour of day. Both NO_X and SO_2 show large decreases in emissions (represented by a ratio of less than one) during the day, with slightly lower decreases at night. As electricity demand falls at night, changes at individual power plants become more pronounced proportionally, as is the case for the 12:00am hour and 10:00pm hour where SO_2 emissions actually see a slight increase. During these hours, a couple of large emitters see increases in production of up to 10x accounting for a proportionally large increase in overall emissions.

Overall, the reductions in emissions in Figure 3.3 match expected behavior based on changes in generation observed in Figure 3.4. Coal would be expected to have the greatest impact on changes in emissions, and this is clearly the case when Figure 3.3 and Figure 3.4a are compared together. Coal generation and emissions of NO_X and SO_2 follow the same trend. For example, at 6:00am, a spike in average emissions of SO_2 and NO_X is observed, and corresponds with an increase in coal power.

At the individual plant level, the trends are complicated by localized impacts, emissions control technology, and dispatch patterns. On a region-wide basis, the introduction of solar causes a shift to cleaner forms of electricity production at night and directly displaces conventional generation at all types of power plants (with nuclear the only exception) during times of solar availability resulting in a decrease in NO_X and SO_2 emissions similar to the percent introduction of solar PV.

Air Quality Analysis

Figures 3.5a and 3.5b show the base-case ambient ground-level concentration of $PM_{2.5}$ across the Eastern U.S. and the percent decrease from noPV to PV17. (Figure 3.5a also locates the five largest cities in the region for comparison with Figure 3.6.)

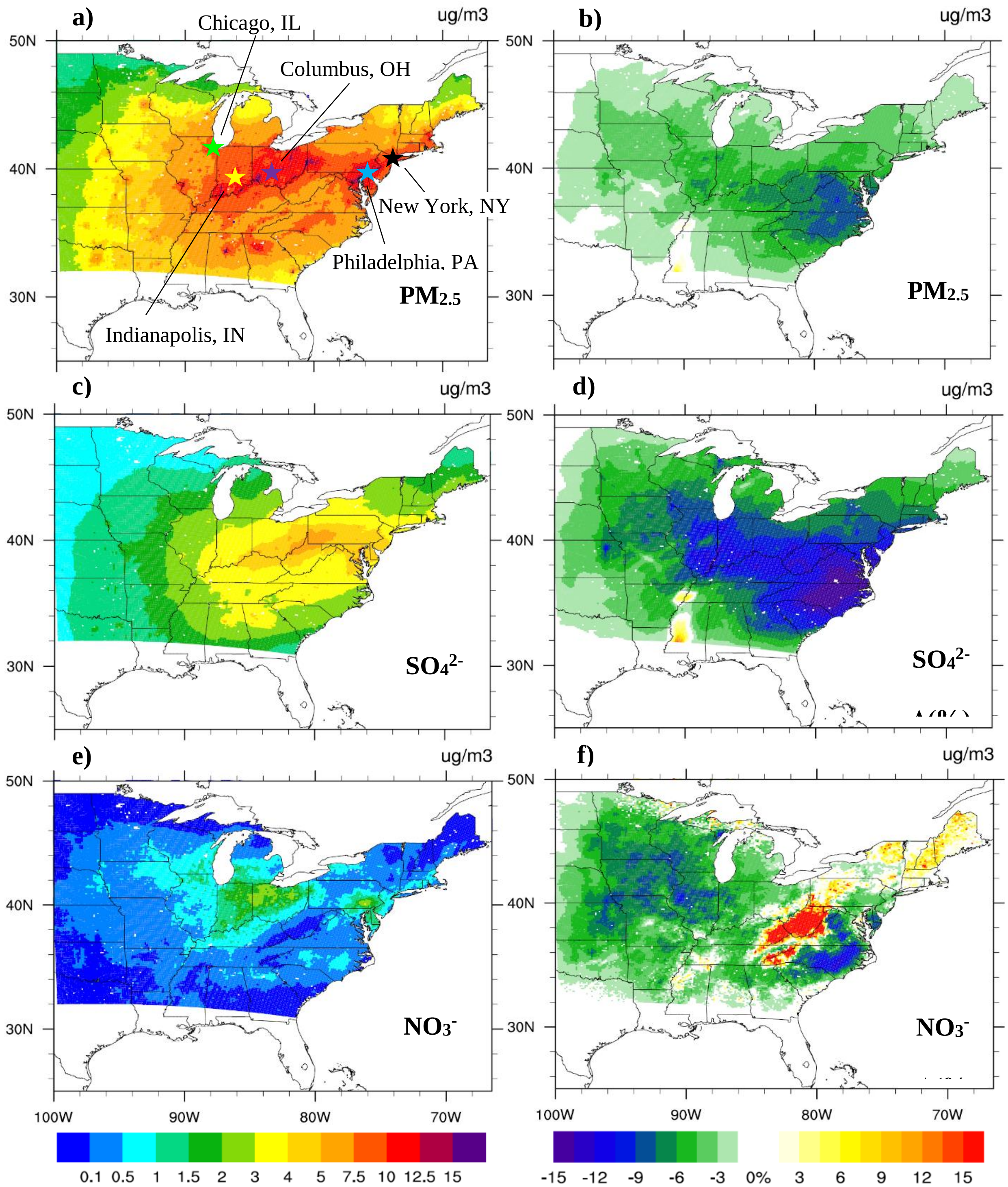

Figure 3.5: The spatially distributed concentrations of $PM_{2.5}$, SO_4^- and NO_3^-. The left-hand plots show the concentration of $PM_{2.5}$, SO_4^- or NO_3^- in the atmosphere averaged over each 12x12km grid for the entire summer (June 1 – August 31) for the base-case. The right-hand plots are the percent change in concentration from the base-case to the proposed case such that a negative number represents a decrease in concentration over that respective 12x12km grid.

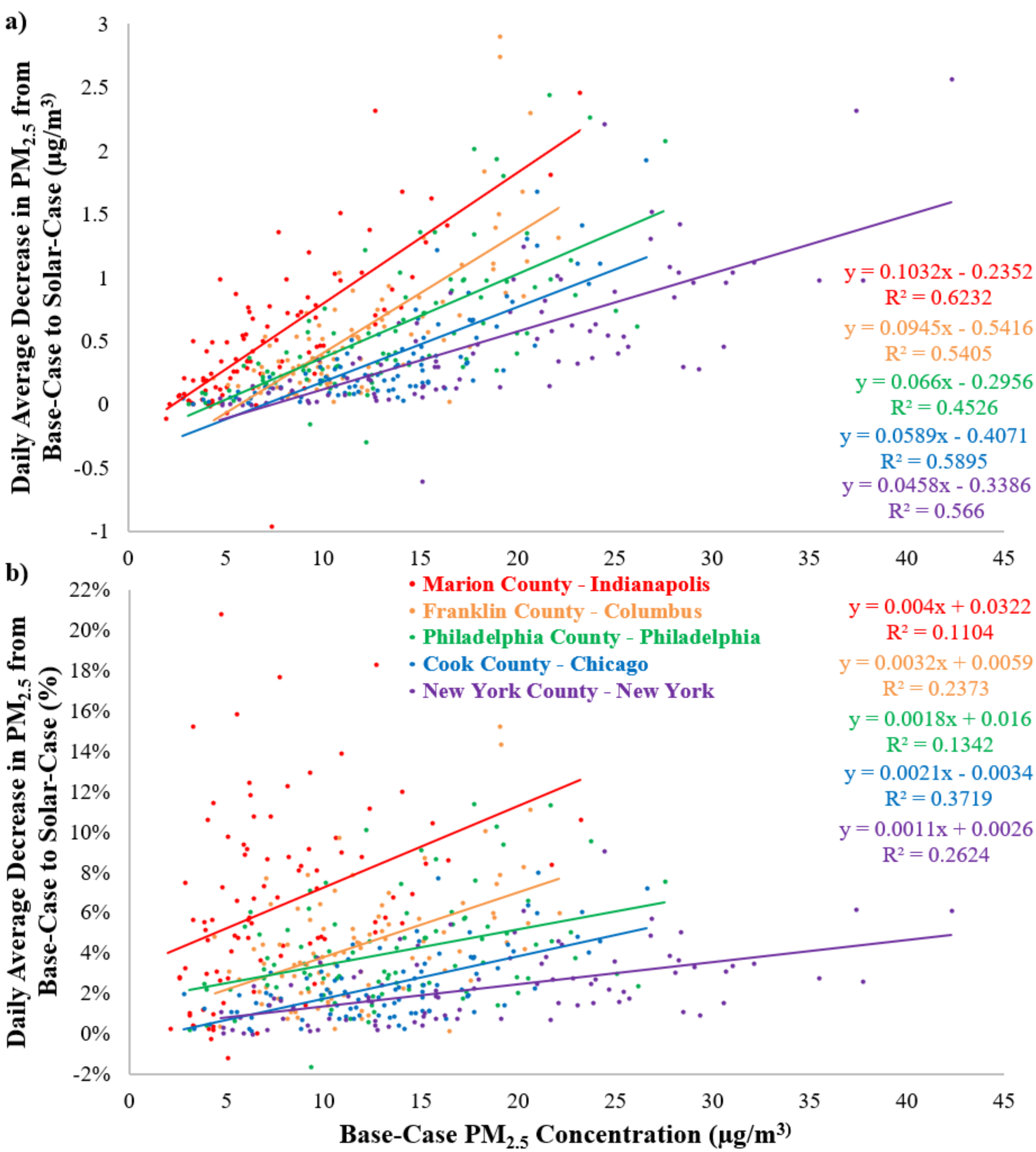

Figure 3.6: The distribution of the change in $PM_{2.5}$ from the base-case to the proposed solar-case is represented as a function of the base-case $PM_{2.5}$ concentrations. Each point represents daily average base-case $PM_{2.5}$ concentrations in one of the counties containing the five largest cities in the Eastern U.S. by population along the X-axis and the decreases in the daily average concentration from the base-case to the solar-case as: a) an absolute decrease in µg/m^3 or b) a percent along the Y-axis such that positive numbers correspond to a decrease from the base-case to the solar-case. A linear line of best fit is applied to each city's individual data points. Each city is shown on the map in Figure 5.

The average concentration of $PM_{2.5}$ in the base case (3.5a) is highest through the Ohio River Valley and across Pennsylvania to the East Coast. On average across the region, the base-case concentration is just under 4.7 $\mu g/m^3$. At its highest, base-case $PM_{2.5}$ reaches just under 28.5 $\mu g/m^3$ in New York City (blue star) on average over the summer. For comparison, the annual average $PM_{2.5}$ NAAQS is 12 $\mu g/m^3$ and daily maximum is 35 $\mu g/m^3$ (https://www.epa.gov/criteria-air-pollutants/naaqs-table), so this baseline summer value is above the annual allowable limit. Although power plant emissions are spread over the region, large cities often exhibit higher concentrations of $PM_{2.5}$ due to local emissions sources including transportation, construction, and industry.

Concentrations of $PM_{2.5}$ across the Eastern U.S. decrease under the PV17 scenario. The average concentration across the region decreased 4.7%, with a maximum decrease of 9.3% in central Virginia. A slight increase in $PM_{2.5}$ (3.5b) and SO_4^{2-} (3.5d) over Mississippi is considered a model artifact attributable to a slight increase in SO_4^{2-} concentrations due to interactions at the boundary edge. We find that grid cells with higher $PM_{2.5}$ concentrations in the base case decrease by a greater percentage than those with lower concentrations suggesting that renewable energy holds the greatest air quality benefit for the regions with the highest air pollution levels.

$PM_{2.5}$ is made up of different chemical species, including SO_4^{2-} and NO_3^-, formed through the heterogeneous atmospheric reactions involving SO_2 and NO_X. As a result, changes in EGU emissions and $PM_{2.5}$ are primarily tied to these secondary aerosol components.

Figures 3.5c and 3.5d show SO_4^{2-} in the noPV case, and the percent change associated with the PV17 scenario. The entire Eastern U.S. sees a substantial decrease in SO_4^{2-} with a decrease in the average concentration of 9.1%. Overall, SO_4^{2-} makes up 40-41% of the total average $PM_{2.5}$ concentration in both cases.

Figures 3.5e and 3.5f show NO_3^- base-case concentrations and the change under the PV17 scenario. Like SO_4^{2-} and total $PM_{2.5}$, NO_3^- decreases under the PV17 scenario over much of the region. However, NO_3^- exhibits regions of increase over the Appalachian region and to a lesser extent most of New England. This effect is overwhelmed by decreases in SO_4^{2-} in aggregate. The Appalachian region sees a decrease in NO_X emissions of 38% while the New England region sees a decrease of 24%. Thus the increase in NO_3^- is attributed to non-linear chemical processes, such as an increase in OH due to the SO_2 reduction promoting increased NO_2 oxidation to HNO_3 (Alexander et al., 2009). On average across the region, NO_3^- exhibits a decrease of 3.70%, and contributes just over 6% (in both noPV and PV17) to total $PM_{2.5}$, compared to 40% for SO_4^{2-}. The larger role of SO_4^{2-} relative to NO_3^- is expected for the summertime conditions simulated here. However, this biases the analysis against potential benefits of reduced NO_3^-, which would play a larger role for wintertime conditions in much of the region (Spak and Holloway, 2009). However, summer was chosen for analysis as representative of peak electricity demand and SO_4^{2-}, and this bias is likely to have a small impact on findings.

The health and regulatory impact of the solar scenario depends not just on average change in $PM_{2.5}$ exposure, but on the change on the most polluted days. Figures 3.6a and 3.6b show the absolute and percentage reductions in $PM_{2.5}$ as a function of daily average total $PM_{2.5}$ for the counties containing the most populous five cities in the study region: New York City, Chicago, Philadelphia, Indianapolis, and Columbus (Locations of each city are shown in Figure 3.5a.) Model performance and bias in these cities is presented in Table S3.1 and the model performance section of Supporting Information as an assessment of uncertainty from model simulation. For complex modeling studies incorporating several models with many complex interactions and built-in assumptions, the uncertainty is an inaccurate representation of performance and extremely difficult to quantify. For this reason, ground-based measurements are used to assess the accuracy of model simulations and performance is presented in Table S3.1.

Across all five cities, the decrease in $PM_{2.5}$ occurs on the most polluted days, with Indianapolis and Columbus showing the highest sensitivity to the solar energy scenario. In Indianapolis, for example, we find a 0.1 µg/m^3 (or 0.4%) decrease for every 1 µg/m^3 change in $PM_{2.5}$ concentration with an R^2 of 0.62 (0.11 proportionally). In cities proximate to a higher density of coal-fired power plants, the scenario of increased solar generation has the highest impact. New York City shows the lowest slope with 0.05 µg/m^3 (or 0.1%) decrease for each 1 µg/m^3 change in base-case concentration with an R^2 of 0.57 (0.26 proportionally). This lower response is due to the distance between New York City and upwind coal-fired power plants, as well as the higher contribution of non-EGU emissions sources in the New York region.

Health Impacts

Exposure to $PM_{2.5}$ leads to adverse health outcomes including mortality. We use the Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE v1.3), produced by the U.S. EPA, to assess the reduction in mortality associated with reduced $PM_{2.5}$ exposure over only the summer of 2006 given a reduction in EGU emissions from achieving 17% penetration of solar energy. Table 3.3 displays the full range of mortality incidence reduction and savings associated with a range of health-impact functions used in standard EPA analysis. Averaging across functions estimates an avoided 1,424 premature deaths with a 95% confidence-interval of 284 to 2,732 deaths. This results in savings of $13.1 billion (95% CI: $0.6 billion, $43.9 billion) in 2015 $. These estimates only assume a reduction in $PM_{2.5}$ during the summer, but we would expect to see year-round emissions reductions from the addition of solar energy, such that actual annual avoided mortality would be greater. However, emissions from the power sector have decreased since 2006 such that a present-day addition of solar energy would see lower health benefits. This impact is discussed in the Sensitivity Testing section.

Table 3.3: The reduction in mortality incidence and associated savings from reduced $PM_{2.5}$ exposure due to 17% solar penetration in the Eastern U.S. over the summer.

Health Impact Function	Mortality Incidence Reduction (95% CI)	Mortality Savings [Billions in 2015 $] (95% CI)
Expert B	1787 (85, 3887)	16.5 (0.4, 64.9)
Expert C	1774 (429, 3155)	16.4 (1.2, 50.9)
Expert D	1248 (0, 2139)	11.5 (0, 36.5)
Expert E	2935 (1058, 4655)	27.1 (2.2, 79.7)
Expert F	1613 (738, 2422)	14.9 (1.3, 42.9)
Expert G	1038 (0, 1967)	9.6 (0, 35)
Expert H	1297 (0, 3683)	11.9 (0, 49.5)
Expert I	1758 (0, 3126)	16.2 (0, 52.1)
Expert J	1429 (110, 3310)	13.2 (0.5, 47.5)
Expert K	188 (0, 916)	1.7 (0, 11.8)
Expert L	1203 (3, 2967)	11.1 (0, 43.2)
Krewski et al.	868 (587, 1149)	8 (0.7, 21.9)
[1]Lepeule et al.	1967 (981, 2950)	18.2 (1.6, 51.9)
Average	**1424** **(284, 2732)**	**13.1** **(0.6, 43.9)**

[1]Impact based on an age range of 25-99, all others based on 30-99.

Figure S3.2a shows the mortality incidence reduction aggregated to the state level showing region-wide decreases in mortality associated with reduced $PM_{2.5}$ exposure consistent with air quality findings. Several of the states at the perimeter of the figure are only partially included in the modeling domain as specified in the caption. Figure S3.2b shows the value of avoided mortality aggregated to the state level. Every state in the Eastern U.S. exhibits a state-averaged decrease in mortality and thus associated savings, but savings are greatest east of the Ohio River Valley (Ohio, Pennsylvania, and New York) with the next highest savings encompassing the entire Ohio River Valley and Mid-Atlantic states. These areas are consistent with high levels of pollution from fossil fuel electricity production, and the greatest decreases in $PM_{2.5}$ in the PV17 scenario.

Sensitivity Testing

The GridView analysis discussed above was conducted for a single summer, 2006 to utilize DOE findings from that year (U.S. Department of Energy, 2012). SIP procedures typically include performing a retrospective analysis with data four to five years out of date. While the multi-model approach is time- and cost-prohibitive to many simulations, our results compared well with the reduced-form, AVERT model as discussed in the Emissions Analysis section. Here we use AVERT to contextualize the GridView-derived emissions changes for alternate years and energy scenarios.

Figure 3.7 shows the proportional change in emissions of SO_2, NO_X and CO_2 given the introductions of 17% solar energy, as in the integrated modeling methodology, across years 2007-2015. It is evident that over time, the proportional reduction in emissions due to the addition of 17% solar by generation increases. The proportional reduction is SO_2 increases from 15% to 20% from 2007 to 2015, and linear regression shows the pattern continues during intermediate years as well as for NO_X and CO_2 emissions. However, from 2007-2015 absolute emissions reductions of

NO_X and SO_2 decrease over time, particularly for SO_2. This is primarily due to a shift from coal-fired power plants to natural gas power plants and increased use of control technology. As applied to scaled GridView results, reductions in emissions would be lower today for SO_2 (~75% lower) and NO_X (~50% lower) than as simulated for 2007, but would be greater proportional to total EGU emissions.

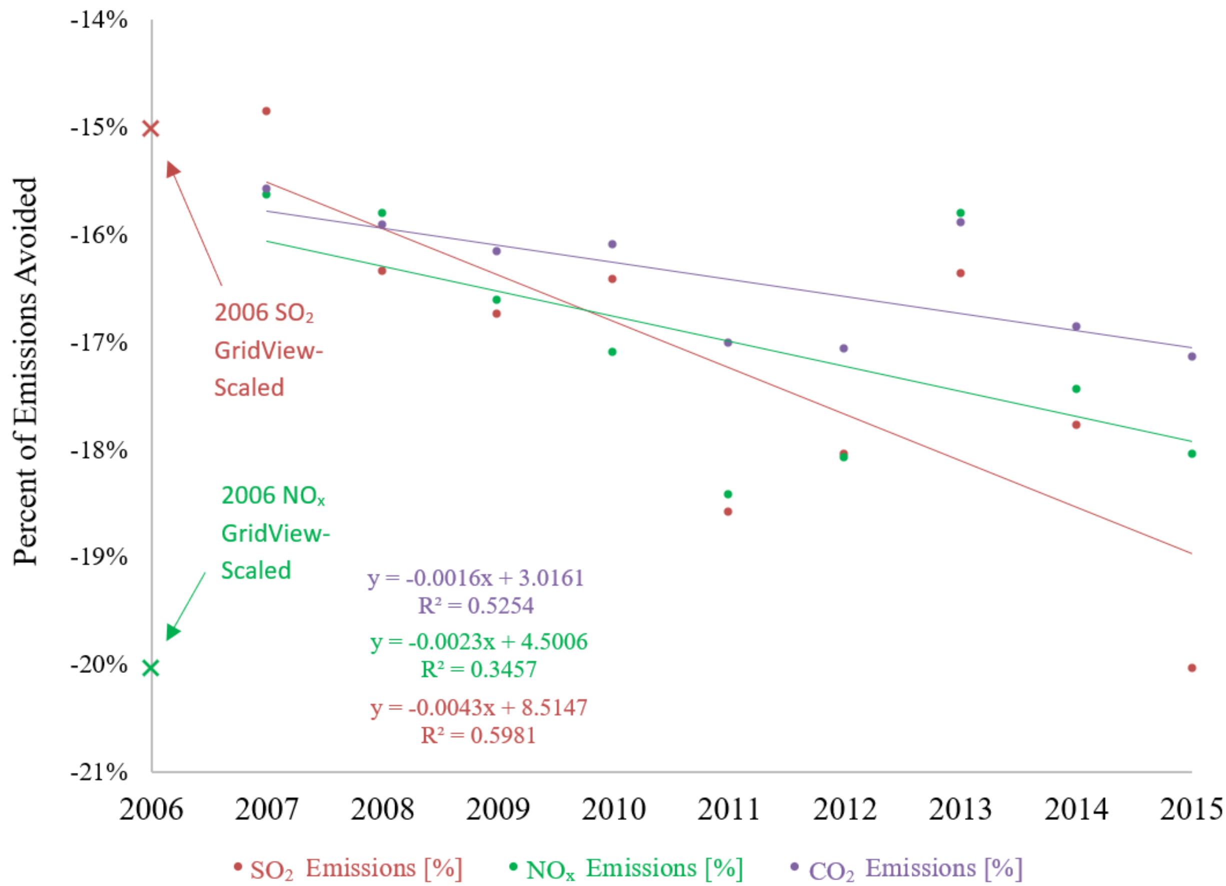

Figure 3.7: The annual avoided emissions, proportionally, as calculated with the AVoided Emissions and geneRation Tool (AVERT) from the addition of 17% solar by generation with varying base year from 2007 to 2015. The avoided emissions are calculated across the Northeast, Great Lakes/Mid-Atlantic, and Southeast regions as defined by AVERT. Linear trends are displayed with corresponding equations and R^2 values. Additionally, results from our multi-model approach using GridView are displayed as Xs.

Figure 3.8 shows the changes in emissions reductions due to changing levels of solar integration. Results show emissions reductions approximately scale linearly with solar integration. Essentially, early solar investment can be expected to have a similar effect on emissions as larger solar investment with all else constant contextualizing the GridView results for lower levels of solar integration.

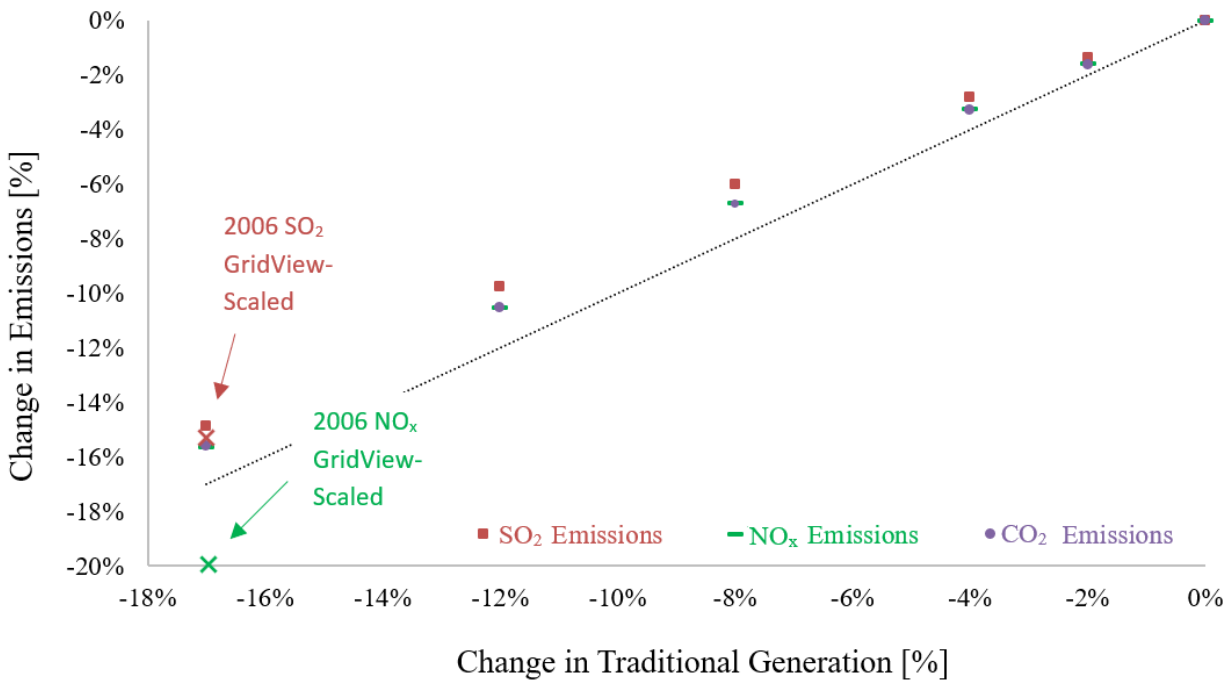

Figure 3.8: The avoided emissions, proportionally as calculated with the AVoided Emissions and geneRation Tool (AVERT) from the addition of a varying amount of solar by generation with base year 2007. The avoided emissions are calculated across the Northeast, Great Lakes/Mid-Atlantic, and Southeast regions as defined by AVERT. A baseline of equal change in emissions per change in generation is displayed. Additionally, the results from our multi-model approach using GridView are shown as Xs.

Conclusion

Here we evaluate the potential air quality benefits of an ambitious, but not unrealistic, increase in solar energy across the Eastern U.S., where 17% of electricity is supplied by solar. Quantifying the air quality benefits associated with this change provides a framework to integrate proposed energy changes within the existing pollution control frameworks of the Clean Air Act (CAA). Evaluation of AVERT with our detailed GridView methodology furthers the utility of AVERT for air quality management purposes while contextualizing results to show that present-day emissions reductions would be lower for this scenario in absolute terms, but larger proportionally.

NO_X emissions are reduced by 20%, while SO_2 is reduced by 15%, suggesting that natural gas facilities are more responsive to the introduction of solar onto the grid. This result is not surprising, given that coal-powered generation is more often used to meet baseload electricity demand and cheaper to dispatch. More surprising is the reduction in NO_X (20%) to a greater level than the change in regional generation (17%). This is explained by substantial displacement of both coal and natural gas plants during hours of solar availability, as well as a shift in generation mix overnight to more non-emitting sources and less coal and natural gas.

Given the spatial and temporal changes in emissions across our domain, we calculate an average decrease in $PM_{2.5}$ of 4.7%. SO_4^{2-} and NO_3^-, the PM species most closely linked to power plant NO_X and SO_2 emissions, decrease 9.1% and 3.7% on average. These results are impressive, given that many regions in the U.S. struggle to meet $PM_{2.5}$ limits set by EPA. The average change found here, while only for summer, is most relevant to attainment of the 12 μg/m^3 annual standard for $PM_{2.5}$ set by the NAAQS. Although some studies suggest a rebound effect, or backsliding, in electricity-sector air regulation (Groosman et al., 2009), this study does not include this possible mechanism. The assumption here is that power plants maintain a constant emission rate per MWh produced.

The NAAQS also set a daily maximum limit of 35 μg/m^3 for $PM_{2.5}$. This limit regulates the “dirty” air pollution days, to ensure that days with hot temperatures and stagnant air (or other weather conditions that promote localized by air quality) still maintain reasonably healthy air. With this daily maximum limit in mind, we evaluated how the solar energy scenario would change PM levels at the five most populated cities in our domain. These cities see the greatest absolute and relative change in $PM_{2.5}$ at higher base-case $PM_{2.5}$ concentrations. This outcome highlights the potential of energy systems changes, especially solar energy, as a measure for compliance with both annual and daily $PM_{2.5}$ NAAQS. In turn, by reducing air pollution on average and on the high-PM days, direct health benefits are expected across the region, especially in areas proximate to large power plants.

The U.S. currently spends about $50 billion per year to achieve clean air standards, which yields a remarkably high return on investment in public health – averaging $10-$30 in benefits for each dollar spent (Office of Management and Budget, 2015; U.S. EPA, 2011). Here we calculate $13.1 billion in health benefits form an avoided 1,424 premature deaths from one summer of 17% solar generation. Investments in clean air are primarily technological, including expensive air systems on large power plants. The potential for utilities to expand solar energy and other renewable energy and energy efficiency initiatives offers an under-explored opportunity to meet clean air targets, and concurrently reduce CO_2 therefore co-managing air pollution and climate change. The Clean Power Plan is an example of pending policy that requires states to create implementation plans for CO_2 reduction, and this study highlights the associated air quality benefits of solar energy, which would be a crucial component of the implementation plans.

Despite the air quality benefits of renewable energy, and the potential for them to meet clean air targets, they are rarely included in energy analyses, and renewable energy is rarely included with air quality planning such as State Implementation Plans (SIPs). In recent years, the EPA has advanced guidance to states on the potential role of renewable energy and energy efficiency (RE/EE) into state implementation plans (SIPs) (U.S. Environmental Protection Agency (EPA), 2012), but it is still very difficult and rarely done. The disconnect between energy and air quality planning most likely arises from the difficulty in quantifying emissions and air quality impacts. Additionally, the scale of electric power creates complex cross-state interactions such that regional planning and coordination would be required to achieve desired results. Evaluation of AVERT with results from our detailed approach addresses the utility of the model toward incorporating renewable energy and energy efficiency into SIPs.

Although solar and other renewable energy technologies offer a powerful means to comply with the NAAQS, the integration of energy modeling with SIP modeling for air quality (including with CMAQ) is a costly and unfamiliar activity to most states. Our approach of scaling an existing emissions inventory based on generation offers a replicable and consistent method to support states in the evaluation of renewable energy and energy efficiency measures. As such, our findings bear relevance not just for solar generation and air quality in the Eastern U.S., but as a potential methodology for any air quality management organization to quantify energy system impacts.

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Supporting Information

Supporting information can be found with the published version of this chapter.

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Chapter 4: Energy Efficiency and Air Quality

This manuscript is the second culmination of graduate work regarding the impacts of renewable energy and energy efficiency on air quality. This paper built on personal experience working in the building energy efficiency industry. The study was designed to support and extend ongoing work by the American Council for an Energy-Efficient Economy. The paper was submitted to Environmental Science & Technology in November 2018 as given by the citation below. The work here has been slightly modified from the submitted version only to conform with formatting for the purposes of this dissertation.

Citation

Abel, D. W.; Holloway, T.; Martinez-Santos, J.; Harkey, M.; Tao, M.; Kubes, C.; Hayes, S. The Air Quality-Related Health Benefits of Energy Efficiency in the United States. *Submitted to Environmental Science & Technology* **2018**.

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Abstract

While it is known energy efficiency (EE) lowers power sector demand and emissions, study of the air quality and public health impacts of EE has been limited. Here we quantify the air quality and mortality impacts of a 12% summertime (June, July, and August) reduction in baseload electricity demand. We use the AVoided Emissions and geneRation Tool (AVERT) to simulate plant-level generation and emissions, the Community Multiscale Air Quality (CMAQ) model to simulate air quality, and the Environmental Benefits Mapping and Analysis Program (BenMAP) to quantify mortality impacts. We find EE reduces emissions of NO_X by 13.2%, SO_2 by 12.6%, and CO_2 by 11.6%. On a nationwide, summer average basis, ambient $PM_{2.5}$ is reduced 0.55% and O_3 is reduced 0.45%. Reduced exposure to $PM_{2.5}$ avoids 300 premature deaths annually (95% CI: 60 to 580) valued at $2.8 billion ($0.13 billion to $9.3 billion), and reduced exposure to O_3 averts 175 deaths (101 to 244) valued at $1.6 billion ($0.15 billion to $4.5 billion). This translates into a health savings rate of $0.031/kWh for $PM_{2.5}$ and $0.018/kWh for O_3. These results illustrate the importance of capturing the health benefits of EE, and its potential as a strategy to achieve air standards.

Introduction

In the U.S., over 40% of the population lives in counties violating one or more of the health-based air quality limits known as the National Ambient Air Quality Standards (NAAQS) (https://www3.epa.gov/airquality/greenbook/popexp.html). Controls on power plant emissions have been a significant driver of emissions reductions since the passage of the Clean Air Act in 1970. NO_X emissions from electricity generating units (EGUs) have decreased 76% since 1970, peaking around 1980 at over six times current levels (https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data). SO_2 emissions have seen an even more dramatic 92% decrease since 1970. Historically, power-sector controls have been primarily end-of-pipe technologies to limit emissions of pollutants such as nitrogen oxides (NO_X), sulfur dioxide (SO_2) and particulates. However, these technologies are expensive, with capital costs for NO_X and SO_2 controls in the tens of millions of dollars for small power plants and hundreds of millions for large power plants, plus considerable operation and maintenance costs [1].

A 2013 study by Fann et al. found that EGUs were the leading contributor to deaths from exposure to ozone (O_3) and fine particulate matter ($PM_{2.5}$) in 2000 (approximately 38,000 deaths). By 2016, however, EGUs dropped to 4th highest contributor to death from O_3 and $PM_{2.5}$ (approximately 17,000 deaths)[2]. While reductions so far are impressive, EGUs remain a major source of health-damaging emissions. Power plant emissions are sensitive to ambient temperature (through demand for building cooling) [3], and may play a larger role in public health as air conditioning demand increases [4].

Although end-of-pipe controls have been effective at removing reactive pollutants from the waste stream of EGUs, there are no analogous technologies for limiting carbon dioxide emissions (CO_2). In fact, traditional controls effectively decrease the efficiency of a power plant through a heat rate penalty and increase CO_2 emissions [1]. Clean energy production has been identified as an alternative to traditional controls that would offer similar air quality benefits by displacing emissions from traditional power plants, while also decreasing emissions of CO_2 [5–9]. This area of research also includes a large body of literature devoted to the air quality co-benefits of climate change mitigation policy and interventions [10–19].

Many energy efficiency measures are cost-effective or cost-negative greenhouse gas mitigation strategies, and as such are often preferable to alternatives [20]. Further, the benefits of energy efficiency extend beyond energy cost savings to include energy security, job creation, reduced water use, consumer comfort, and improved fire safety [21,22]. These additional benefits are often described as non-energy benefits (NEB). While these NEB have been demonstrated, many states do not include NEB in cost-benefit analyses [21]. The air quality and health benefits of energy efficiency are likely to be the most high-value NEB [15].

A large body of research has explored the complex relationship between energy efficiency and indoor air quality [23–25]. Likewise, a large body of research has characterized the health impacts of ambient air quality [2,26–29]. However, only a few studies have quantified parts of the health impacts of ambient air quality changes attributable to energy efficiency [7,30–35]. By supporting clean air, energy efficiency could also help U.S. states and counties meet air quality standards set by the U.S. Environmental Protection Agency (EPA) under the U.S. Clean Air Act. The EPA has provided guidance to states on incorporating renewable energy and energy efficiency (RE/EE) into State Implementation Plans (SIPS) for air quality management [36,37]. States create SIPS when they are in violation of standards for one or more of the six criteria pollutants regulated under the NAAQS, also known as being in non-attainment. To date, RE/EE strategies have rarely been included in SIPS. A major barrier to the integration of energy and air quality planning is the difficulty in quantifying the benefits of RE/EE strategies.

Only a few studies have examined the air quality impact of demand-side measures. These have focused on the benefits of residential insulation [32,35], LEED buildings [33], cool roofs [31], and an empirical study of early demand-side management [30]. *Buonocore et al.* demonstrate the air quality-related public health and climate-related benefits of energy efficiency and renewable energy scenarios ranging from $14 to $170 per MWh by linking detailed electricity dispatch with a statistical representation of air quality impacts based on six locations in the Pennsylvania-New Jersey-Maryland interconnection and four different renewable energy and energy efficiency installations [7].

The potential benefits of energy efficiency to carbon mitigation, air quality and public health are understood in concept, but advanced modeling is required to quantify these benefits. This study is the first to quantify the ambient air quality and health benefits of a realistic and general U.S. energy efficiency scenario. This study builds on analysis of the benefits of energy efficiency for achieving air quality standards from the American Council for an Energy-Efficient Economy (ACEEE) [38].

Here we consider energy efficiency resulting in a constant load reduction throughout the year. Such measures could include more energy efficient appliances, electronics, and lighting, as well as energy storage combined with efficiency measures to reduce building cooling, such that the net reduction in demand were distributed evenly over time. This approach represents a reasonable first look at energy efficiency benefits, recognizing that additional efficiency measures targeting cooling loads could target peak generation as well as baseload. The methods are described in detail in the following section. Results are included separately for emissions analysis, air quality simulations, and health outcomes, and the discussion contextualizes results within ongoing efforts across energy efficiency, air quality management, and public health.

Methods

To analyze the impact of energy efficiency on EGU emissions, air quality and health, we follow an analysis structure shown graphically in Figure 4.1. Two scenarios are compared using a linked system of interdisciplinary models. The first scenario represents the current (2016) U.S. power system, without additional energy efficiency (NoEE). The second scenario includes energy savings of 12% over the summertime from energy efficiency, applied as a constant energy demand reduction over the continental U.S. study region. The 12% scenario is chosen because that is the summertime (June, July, and August) demand reduction of a 15% annual reduction in energy demand, where 15% is the maximum change within which AVERT is recommended for use [39]. As summer months exhibit higher demand than the annual average, a 15% annual reduction applied as a constant hourly reduction results in 11.9% average electricity demand reductions over the summer. This scenario is referred to as the energy efficiency scenario (EE); reductions on an annual basis by region are given in the caption of Figure S4.1. We focus on the summer, when electricity demand and O_3 are typically highest across the U.S. and sulfate contributes a greater fraction to $PM_{2.5}$ [40]. Thus, the impact of electricity measures is likely to be greatest during the summer.

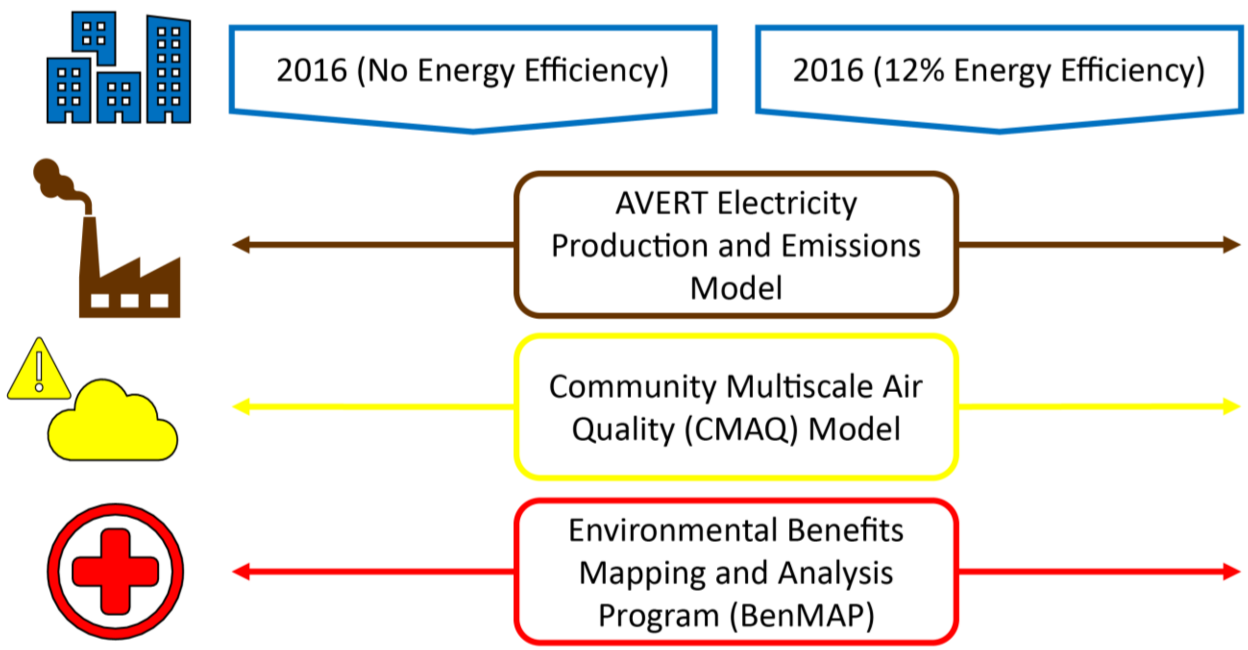


Figure 4.1: The methodological framework used in this study to analyze the air quality and health impacts of a 12% summertime energy efficiency scenario (15% energy efficiency on an annual basis). AVERT is the AVoided Emissions and geneRation Tool.

To simulate electricity grid behavior and associated EGU emissions we use the U.S. EPA's AVoided Emissions and geneRation Tool (AVERT) for 2016.[39] AVERT uses a statistical representation of emissions monitoring data from the Clean Air Markets Database to simulate displacements in generation and emissions under proposed scenarios. This statistical representation of historical emissions simulates power plant dispatch but does not explicitly represent least-cost dispatch nor transmission. AVERT divides the U.S. into ten regions simulated separately, (as shown in Figure S4.1), based on sub-regions from EPA's Emissions & Generation Resource Integrated Database (eGRID). We run AVERT for all ten regions for the year 2016, the most up-to-date year available at the time of the study. As described above, we apply a constant reduction in energy demand to represent an increase in baseload energy efficiency. AVERT then calculates hourly generation and emissions of NO_X, SO_2, CO_2, and primary $PM_{2.5}$ with and without energy efficiency. This approach has been shown to be appropriate for modest changes in demand as applied here and has been used in related work [39].

EGU emissions of NO_X and SO_2 from AVERT for the base-case and energy efficiency scenarios are input to the EPA's Community Multiscale Air Quality (CMAQ) model v5.0.1 run with the carbon bond 05 (CB05) chemical mechanism and "AERO6" aerosol chemistry to simulate ambient air quality on a 12 x 12 km grid of the continental U.S. with 25 vertical layers of the atmosphere. Meteorology is supplied for 2011 conditions as simulated with the Weather Research and Forecasting (WRF) model prepared for CMAQ with the Meteorology Control Interface Processor (MCIP). Non-EGU emissions are provided by the 2011 National Emissions Inventory (NEI), the most recent available emissions at the time of analysis. Biogenic emissions are provided by the Model of Emissions of Gases and Aerosols from Nature (MEGAN) version 2.1 for 2011 conditions. EGU locations and NO_X and SO_2 emissions are provided by AVERT and represent 2016 conditions. Emissions of NO_X are assigned constant partitioning of 85% NO and 15% NO_2. Boundary conditions are provided by monthly averages of simulations from the Model for Ozone and Related chemical Tracers (MOZART) [41].

Emissions of EGU pollutants not provided by AVERT are taken as a national average from the 2011 NEI and distributed evenly amongst AVERT power plants. While AVERT calculates primary $PM_{2.5}$ emissions, this information lacks the chemical partitioning needed as input to CMAQ. Therefore, calculated impacts are changes to secondary $PM_{2.5}$, not including changes to primary $PM_{2.5}$ emissions. EGUs in 2017 emitted only 3% of U.S. primary $PM_{2.5}$ which in turn only makes up a fraction of total, ambient $PM_{2.5}$ (https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data). CMAQ performance is within expectations and is evaluated in the supplementary material.

Simulated surface-level ambient concentrations of MDA8 O_3 and daily average $PM_{2.5}$ from CMAQ are used as input to the U.S. EPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE v1.3) to calculate mortality and morbidity benefits [42]. BenMAP is a GIS-based tool to combine gridded air pollution data with health outcome incidence data, population, and health impact functions. Population data is based on U.S. census data. Baseline incidence data comes from a variety of sources, but predominantly from the Centers for Disease Control and Prevention (CDC), as outlined in Appendix D of the BenMAP user manual [43]. We use standard EPA configurations for mortality based on O_3 and $PM_{2.5}$ exposure available with the BenMAP software. Each impact function is run in a 5,000-member Monte-Carlo ensemble to quantify uncertainty of mortality outcomes and valuation. Here we present results from each individual function and discuss the average of results with equal weighting across fourteen functions for mortality from all causes for $PM_{2.5}$ and three functions for O_3 [44–46]. Of particular interest are results for $PM_{2.5}$-related mortality based on the American Cancer Society's Cancer Prevention Study II as the study uses the most representative U.S. exposure sites and has a follow-up period of 18 years [26]. For O_3, we give extra focus to Levy et al's empiric Bayes metaregression designed to parse the effect of hypothesized confounders and effect modifiers [47].

We take a conservative approach to analyzing the annual impacts of air quality changes based on summer modeling results. Therefore, air pollution exposure is assumed to only change during the three summer months simulation, and nine months are assumed to have no change in air quality or health. This assumption offers a lower bound to potential benefits, given that any investment in energy efficiency would be expected to lower pollutant concentrations year-round. BenMAP results presented here are annual $PM_{2.5}$- and O_3-related mortality changes from energy efficiency based on reduced exposure in the summer months of June, July, and August only. Valuation of mortality results follows standard EPA methods using a combination of willingness to pay and cost of illness, (or value of statistical life), methods based on 23 studies. All costs are given as 2015 US dollars.

Results and Discussion

Emissions

We find that an annual 15% reduction in electricity demand (348 TWh annually), distributed evenly across the year, results in summertime (June, July and August) decrease in generation of 91 TWh or 12%. This is because summer shows higher electricity demand and, thus a constant hourly energy reduction has a lower percentage reduction over times of high demand (summertime). This reduction in summertime electricity production yields a nationwide 13.2% (44.8 thousand tonnes) decrease in NO_X emissions from the power sector and 12.6% (56.2 thousand tonnes) decrease in SO_2 emissions over the summer. CO_2 emissions are reduced by 64.5 Mt (11.6%). On a per energy basis, efficiency has an emissions savings rate of 0.49 kg/MWh for NO_X, 0.58 kg/MWh for SO_2, and 0.72 tonnes/MWh for CO_2. These metrics are displayed by state for the contiguous U.S. in Table 4.1 and graphically in Figures S4.2-S4.4.

State	**Displaced Generation**	**Displaced NO_X Emissions**	**Displaced NO_X Rate (Base Rate)**	**Displaced SO_2 Emissions**	**Displaced SO_2 Rate (Base Rate)**	**Displaced CO_2 Emissions**	**Displaced CO_2 Rate (Base Rate)**
	TWh (%)	tonnes (%)	kg/MWh	tonnes (%)	kg/MWh	ktonnes (%)	tonnes/MWh
AL	2.8 (10.4)	2000 (18.4)	0.7 (0.4)	1400 (16.7)	0.5 (0.31)	1800 (10.1)	0.63 (0.65)
AR	1.7 (13.1)	1200 (14.7)	0.7 (0.63)	2100 (14.7)	1.23 (1.09)	1300 (12.6)	0.73 (0.75)
AZ	3 (13.4)	1100 (10.6)	0.36 (0.45)	300 (8.8)	0.11 (0.16)	1700 (11.2)	0.57 (0.68)
CA	3 (12.6)	300 (10.3)	0.1 (0.13)	0 (11.4)	0 (0)	1300 (12.6)	0.44 (0.44)
CO	1.8 (14)	800 (9.9)	0.44 (0.63)	500 (10.3)	0.3 (0.41)	1300 (12.2)	0.73 (0.84)
CT	0.3 (6.7)	100 (16.4)	0.51 (0.21)	0 (26.4)	0.16 (0.04)	200 (7.4)	0.53 (0.48)
DE	0.4 (20.7)	100 (23.5)	0.23 (0.2)	0 (26.2)	0.11 (0.09)	300 (21.4)	0.64 (0.62)
FL	7 (12)	2600 (16.9)	0.38 (0.27)	6200 (24.1)	0.88 (0.44)	4100 (12.2)	0.58 (0.57)
GA	4.1 (14)	1000 (18)	0.24 (0.19)	1000 (18.5)	0.25 (0.19)	3100 (15.1)	0.75 (0.7)
IA	1.4 (15.7)	1000 (15.8)	0.72 (0.72)	1200 (13.7)	0.85 (0.97)	1200 (14.8)	0.88 (0.93)
ID	0.2 (20.3)	0 (31.8)	0.11 (0.07)	0 (22.6)	0 (0)	100 (25.4)	0.46 (0.37)
IL	4 (16.1)	1800 (17.8)	0.46 (0.42)	2700 (13.7)	0.69 (0.81)	3100 (14.4)	0.8 (0.89)
IN	2.7 (10)	2600 (11.3)	0.95 (0.85)	2800 (10.4)	1.03 (0.99)	2400 (9.9)	0.89 (0.91)

KS	1.1 (12.6)	700 (14.8)	0.67 (0.57)	300 (11.2)	0.23 (0.26)	1000 (11.6)	0.92 (0.99)
KY	2.2 (9.7)	1400 (9.5)	0.65 (0.67)	1900 (9.1)	0.85 (0.91)	1900 (9.1)	0.86 (0.93)
LA	1.9 (8.9)	2200 (18.9)	1.13 (0.54)	1600 (12)	0.82 (0.61)	1300 (10.3)	0.69 (0.6)
MA	0.7 (10.9)	100 (14)	0.15 (0.12)	100 (12.5)	0.09 (0.08)	400 (11.2)	0.52 (0.51)
MD	1.5 (20.9)	800 (26)	0.52 (0.41)	1100 (19.5)	0.75 (0.8)	1200 (19.4)	0.79 (0.85)
ME	0.2 (16.9)	0 (17.4)	0.08 (0.08)	0 (26.1)	0.18 (0.12)	100 (18.4)	0.45 (0.42)
MI	2.1 (10.8)	800 (9.3)	0.4 (0.46)	1700 (9.1)	0.82 (0.98)	1500 (10.2)	0.74 (0.79)
MN	1.4 (13.8)	500 (10.5)	0.35 (0.46)	300 (6.7)	0.2 (0.42)	1000 (11.2)	0.68 (0.84)
MO	2 (10.2)	1400 (9.2)	0.69 (0.77)	2500 (9)	1.24 (1.4)	1700 (9.2)	0.82 (0.91)
MS	1.6 (10.9)	1000 (26)	0.63 (0.26)	0 (25.4)	0.02 (0.01)	900 (13)	0.59 (0.49)
MT	0.3 (8.3)	300 (8.1)	0.89 (0.9)	300 (11.3)	0.79 (0.58)	400 (8.1)	1.02 (1.05)
NC	3.1 (14)	1300 (16.4)	0.42 (0.36)	900 (13.5)	0.28 (0.29)	2300 (15.5)	0.76 (0.68)
ND	0.4 (5.9)	400 (4.9)	0.98 (1.17)	700 (5.9)	1.56 (1.57)	400 (5.6)	1.02 (1.08)
NE	0.7 (10.1)	600 (11.8)	0.95 (0.81)	1200 (8.9)	1.8 (2.04)	600 (9.5)	0.89 (0.94)
NH	0.2 (13.3)	100 (14.8)	0.31 (0.28)	100 (23.1)	0.23 (0.13)	100 (10.3)	0.57 (0.73)
NJ	1.7 (13.1)	400 (29.3)	0.23 (0.1)	0 (22.5)	0.01 (0.01)	800 (14.6)	0.51 (0.46)
NM	0.6 (6.8)	600 (5.7)	1.05 (1.24)	100 (5.9)	0.22 (0.25)	400 (5.8)	0.71 (0.83)
NV	0.9 (10.9)	400 (25.2)	0.42 (0.18)	300 (33.7)	0.35 (0.11)	600 (14)	0.61 (0.48)
NY	2.3 (12.2)	800 (19.2)	0.35 (0.23)	400 (21.5)	0.19 (0.11)	1200 (12.8)	0.52 (0.5)
OH	3.5 (11.6)	2000 (13.2)	0.58 (0.51)	6200 (15.4)	1.79 (1.35)	2700 (11.6)	0.79 (0.78)
OK	2.3 (13.6)	1500 (17.8)	0.63 (0.48)	1600 (10.8)	0.69 (0.87)	1500 (12.8)	0.62 (0.66)
OR	0.7 (14.6)	200 (25.5)	0.29 (0.17)	400 (28.3)	0.49 (0.25)	400 (17)	0.54 (0.47)
PA	3.6 (10.9)	2200 (12.4)	0.63 (0.55)	3800 (15.6)	1.05 (0.73)	2700 (11.7)	0.75 (0.7)
RI	0.3 (13.4)	0 (9.3)	0.05 (0.08)	0 (13.5)	0 (0)	100 (14)	0.5 (0.48)
SC	1.5 (14)	500 (14.3)	0.32 (0.31)	400 (15.9)	0.26 (0.23)	1200 (13.9)	0.8 (0.81)
SD	0.2 (19.1)	100 (21)	0.42 (0.38)	0 (10.9)	0.13 (0.23)	100 (16.3)	0.74 (0.87)
TN	1.8 (13.3)	700 (12.5)	0.39 (0.41)	1000 (11.9)	0.54 (0.6)	1500 (13.1)	0.84 (0.85)
TX	11.1 (10.9)	4400 (13.4)	0.4 (0.32)	7700 (10.6)	0.7 (0.72)	7300 (10.5)	0.66 (0.69)
UT	0.9 (9.3)	800 (9.4)	0.86 (0.86)	200 (9.6)	0.28 (0.27)	700 (8.6)	0.74 (0.81)
VA	2.5 (14.7)	900 (17.6)	0.38 (0.31)	500 (20.3)	0.21 (0.15)	1500 (15.7)	0.6 (0.56)
VT	0 (4)	0 (4)	0.45 (0.45)	0 (6.8)	0.01 (0)	0 (3.9)	1.31 (1.33)
WA	1.1 (22.6)	500 (28.2)	0.46 (0.37)	200 (24)	0.14 (0.13)	800 (24.2)	0.7 (0.66)
WI	2 (13.7)	700 (15.8)	0.36 (0.31)	500 (14.6)	0.23 (0.21)	1600 (13)	0.8 (0.85)
WV	1.8 (8.8)	800 (6.8)	0.46 (0.59)	1200 (9.9)	0.67 (0.6)	1700 (8.5)	0.91 (0.94)
WY	0.9 (8.2)	800 (8.4)	0.85 (0.83)	700 (8)	0.76 (0.78)	900 (7.9)	1.01 (1.06)
Total	**91.7 (11.9)**	**44800 (13.2)**	**0.49 (0.44)**	**56200 (12.6)**	**0.61 (0.58)**	**64500 (11.6)**	**0.7 (0.72)**

Table 4.1: Displaced generation and emissions of NO_X, SO_2, and CO_2 from energy efficiency by state and total throughout the contiguous U.S. and includes the emissions rates of displaced emissions and the base emissions rates prior to energy efficiency.

To evaluate the skill of AVERT in capturing energy system change, we compare emissions simulations vs. measured emissions reported in the Air Markets Program database. Overall, AVERT captures measured emissions well, overestimating SO_2 emissions by 7.25% and underestimating NO_X emissions by 1.73% (Figure S4.5).

Emissions decreases, on a mass basis, remain approximately constant throughout the day, consistent with the study design, focused on baseload electricity demand. Displacement of NO_X emissions remain ~250 tonnes/hour, but percentage reductions on average throughout a day range from just under 12% to nearly 16.5%. Similarly, SO_2 displacement remains steady (~180 tonnes/hour) and ranges from 8% to 20%. The diurnal and summer profiles of emissions reductions are shown in Figures S4.6 and S4.7. The greater range in displaced SO_2 by percentage is emblematic of the role that individual power plants play in SO_2 emissions, especially large baseload coal plants that may be displaced at off-peak times of the day and peaking plants during peak hours. Emissions reductions exhibit expected behavior for the energy efficiency scenario applied.

Figure 4.2 shows electricity generation and emissions by power plant and fuel type. These figures are limited to power plants with measurable emissions (coal, gas, oil) and do not include production from solar, wind, and nuclear. Electricity generation in the base case is dominated by gas (50.1%) and coal (48.5%), while emissions are driven mostly by coal power plants (67.6% of CO_2, 80.4% of NO_X, and 98.7% of SO_2). Displaced emissions follow similar trends. 55.6% of generation is displaced at gas-fired plants while 42.5% is displaced at coal plants. 59.4% of CO_2, 65.7% of NO_X, and 96.9% of SO_2 is displaced at coal power plants.

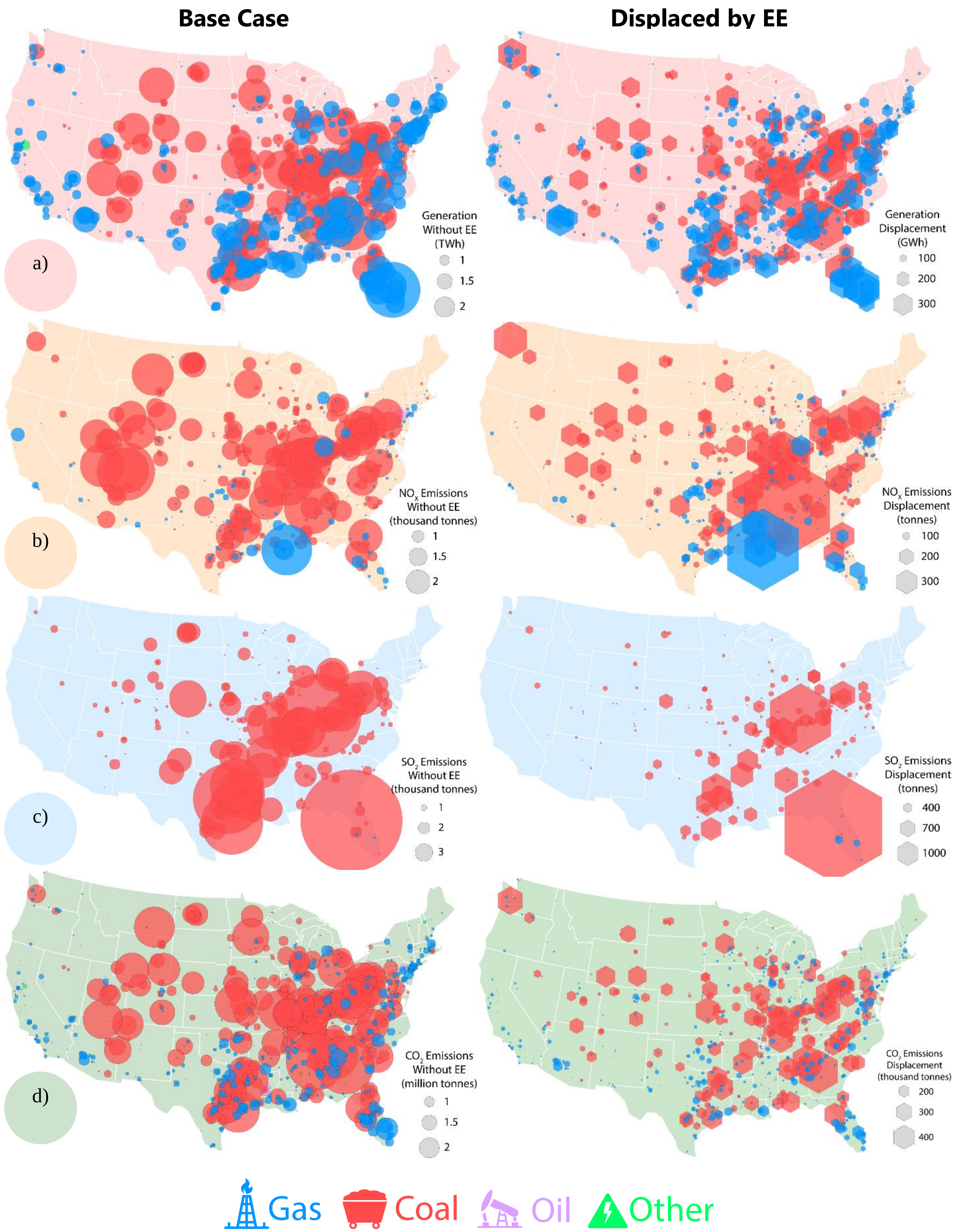


Figure 4.2: Base case (left) and displaced (right) a) generation and emissions of b) NO_X, c) SO_2, and d) CO_2 by power plant type and location summed over the summer.

State-level summer-total displacements range from 3.9 to 25.4% for CO_2, 4 to 31.8% for NO_X and 5.9 to 33.7% for SO_2. In all states, energy efficiency reduces emissions, although in some states these improvements round to zero absolute reduction. The largest savings accrue in Texas for all pollutants; while smaller states and states with fewer coal power plants tend to see the total smallest displacements (these small changes may still be high on a percentage basis).

Air Quality

On a summer and nationwide average, decreases in emissions of NO_X and SO_2 lower concentrations of O_3 and $PM_{2.5}$. Local and regional air impacts depend on meteorology and chemistry as calculated using CMAQ.

Figures 4.3 and 4.4 show the summer-average (June, July and August) concentrations of $PM_{2.5}$ and the 4th highest maximum daily 8-hr average (MDA8) O_3. On average, summer $PM_{2.5}$ concentrations over land decrease 0.55% (0.022 μg/m^3), relative to baseline summer-average $PM_{2.5}$ concentrations averaging 3.11 μg/m^3 (grid-average concentrations range from 0.787 to 38.08 μg/m^3). On average, MDA8 O_3 decreases 0.45% (0.313 ppbv) relative to the baseline average of 66.56 ppbv (grid-average concentrations range from 29.47 to 125.29 ppbv). The greatest pollutant reductions, up to 1.5% for both pollutants, accrue near and downwind from coal power plants in the mid-Atlantic states. CMAQ calculates potential O_3 increases in parts of the West Coast due to localized increases in NO_X emissions from some power plants as modeled by AVERT.

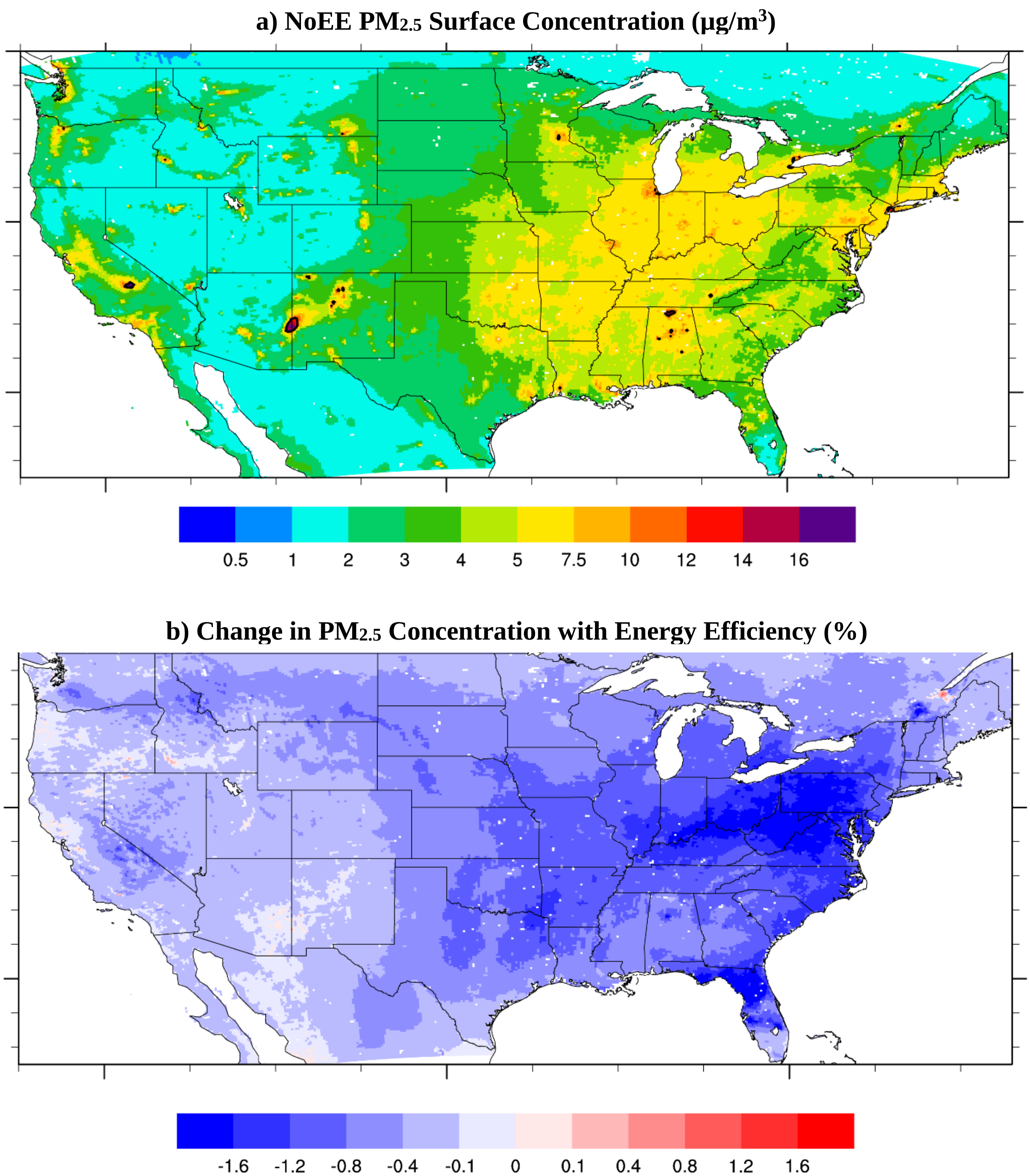


Figure 4.3: $PM_{2.5}$ surface concentrations in the a) NoEE scenario and the b) change in concentration from energy efficiency as a percentage.

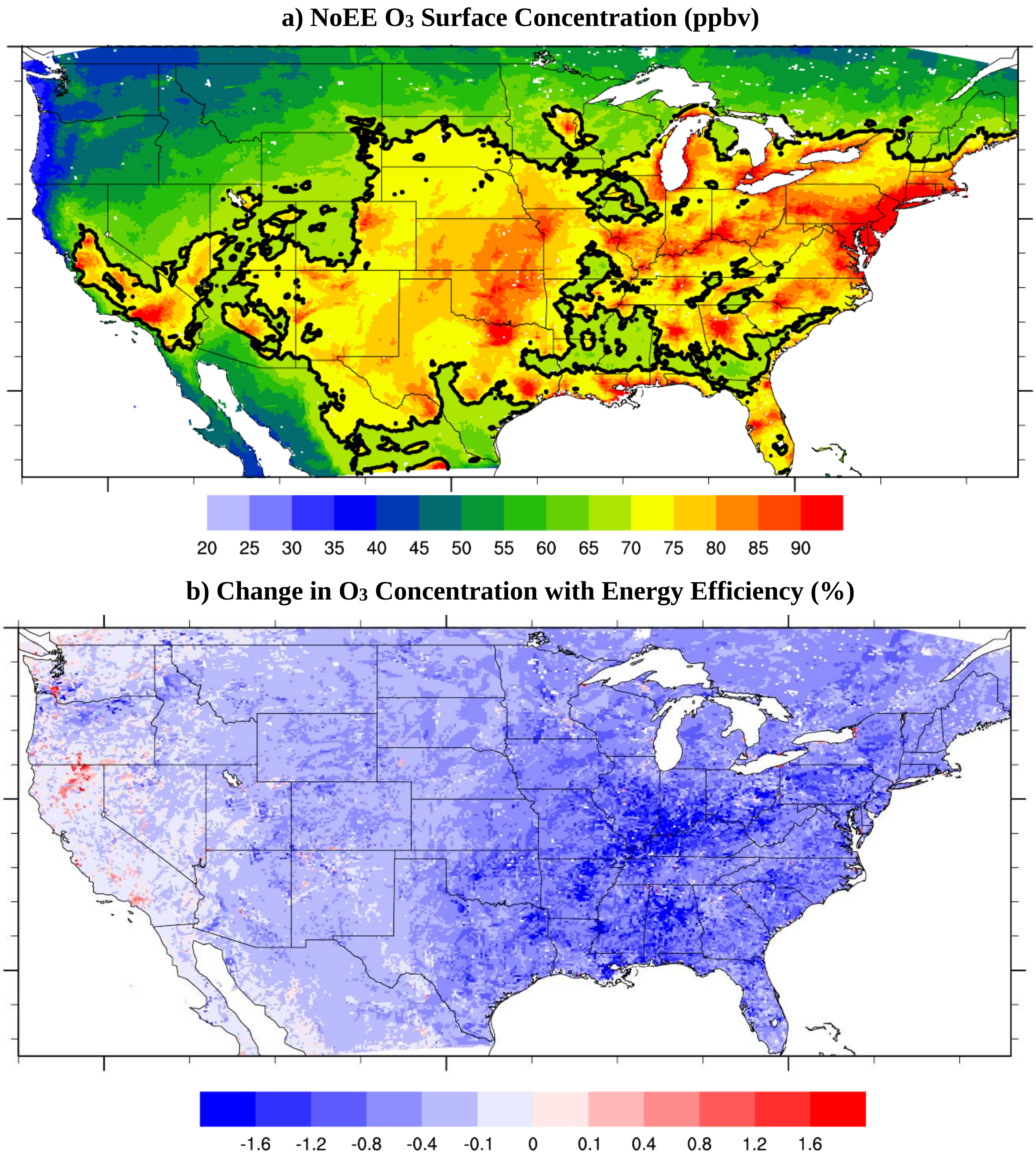


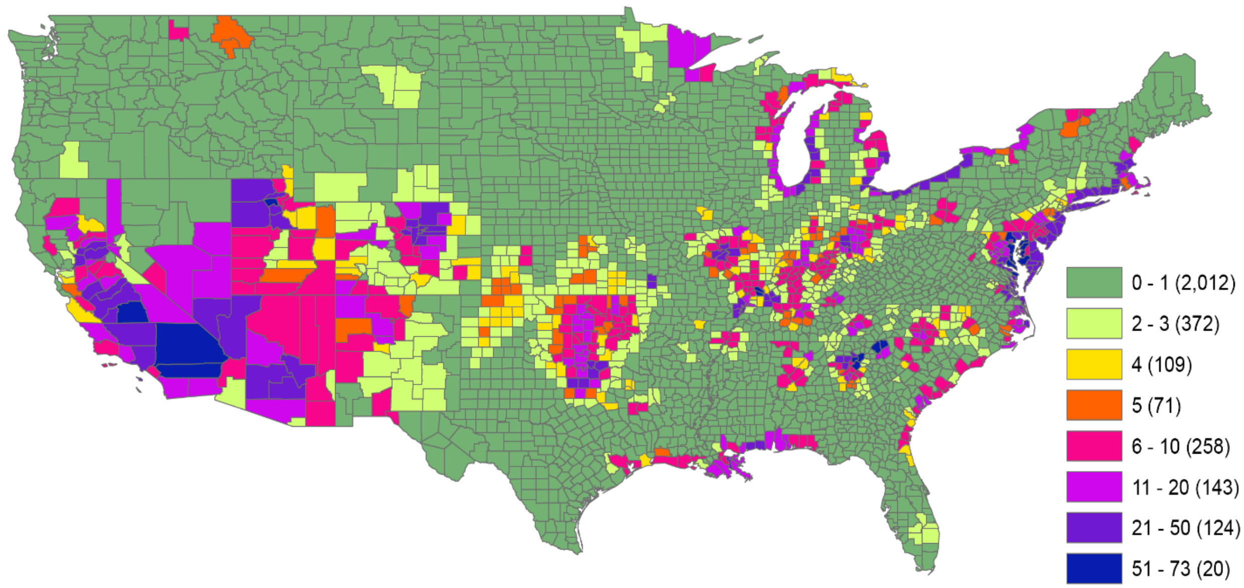
Figure 4.4: O_3 surface concentrations in the a) NoEE scenario and the b) change in concentration from energy efficiency as a percentage.

To assess the potential for energy efficiency to meet air quality standards, Figure 4.5 shows summer days above the 2015 NAAQS value of 70ppb mapped to county-level by selecting the grid with the maximum MDA8 O_3 in each county and correcting for model bias as described in the supplementary material. These values do not reflect formal EPA designations, which are based on three years of monitoring data. However, they are broadly consistent with 2018 final designations for counties under the 2015 O_3 standard (shown in Figure S8). Basing county-wide design values on the maximum grid concentration within that county as well as including counties without ground monitors explains the higher number of quasi-non-attainment counties measured by the model as compared to 2018 designations.

In our simulations for a three-month summer, 725 counties have four or more days with MDA8 O_3 above 70 ppb. We will refer to these here as quasi-non-attainment counties, recognizing the inconsistency between our model simulation and the actual regulatory metric. Of these quasi-non-attainment counties, 180 are within one or two days of achieving the standard and an additional 258 are within 7 days of achieving the standard. The energy efficiency scenario examined here lowers O_3 concentrations such that 45 quasi-non-attainment counties (6.2%) have fewer than four days above the 70 ppb MDA8 O_3 limit. These results suggest that 12% baseload energy efficiency measures could help actual non-attainment counties achieve attainment with the O_3 NAAQS. Table S4.1 shows the number of counties by state where model-based designations are flipped from quasi-non-attainment to quasi-attainment.

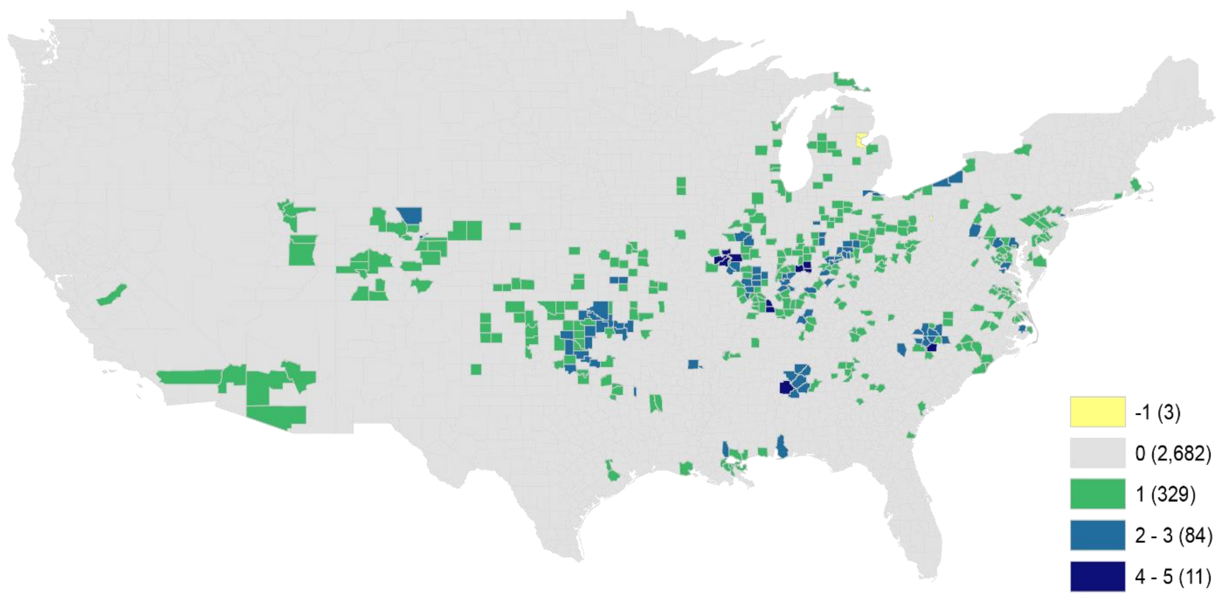
For $PM_{2.5}$, fewer counties are out of attainment with the NAAQS, and the benefits of energy efficiency are less pronounced. The potential health benefits of reduced $PM_{2.5}$, even in attainment counties, are discussed in the next section.

a) NoEE MDA8 O_3 Exceedance Days by County



 # days (# counties)

b) Reduction in MDA8 O_3 Exceedance Days by County with Energy Efficiency



 # days (# counties)

Figure 4.5: O_3 exceedance-days by county a) in the base case, and b) avoided through energy efficiency. Figures are adjusted for model bias based on measurements at AQS monitoring sites and interpolated between sites. Positive numbers in b) are number of exceedance days less with energy efficiency.

Health

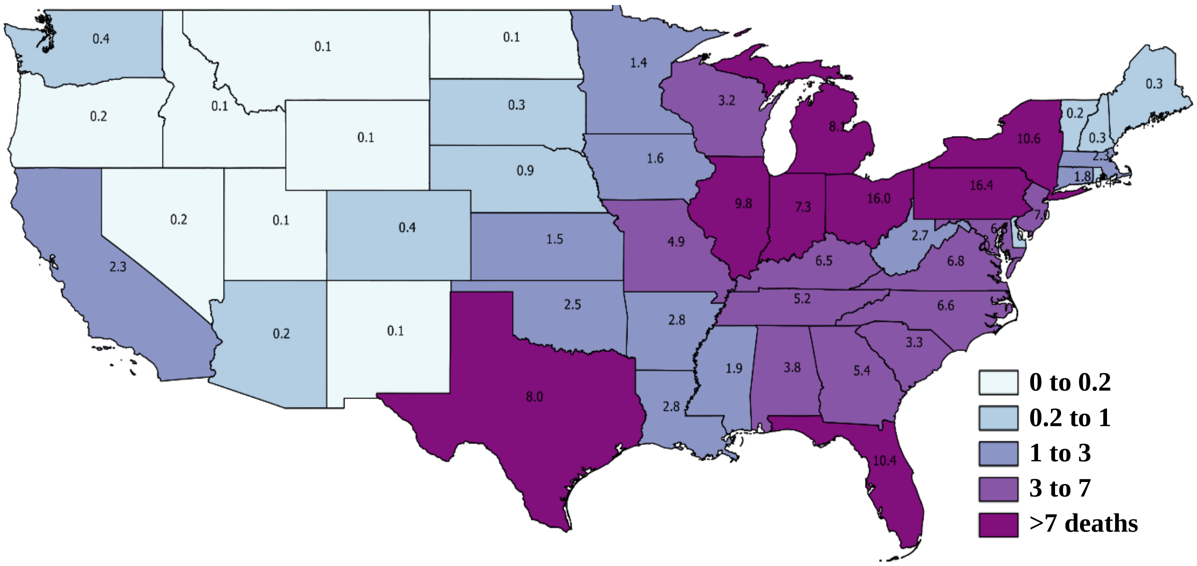
Reductions in concentrations of $PM_{2.5}$ and O_3 benefit public health by reducing premature mortality and other adverse health outcomes. Here we use BenMAP to quantify avoided premature mortality due to air quality improvements associated with energy efficiency. Benefits accrue most in states showing the greatest reductions in $PM_{2.5}$ and O_3 concentrations combined with high population exposure (compare with Figures 4.3 and 4.4). Figures 4.6 and 4.7 show graphically the state-level mortality benefits of energy efficiency based on the health-response functions from Krewski et al for $PM_{2.5}$ and Levy et al for O_3.[26,47]

Reduced exposure to $PM_{2.5}$, calculated as an average across the 14 health impact functions, reduces premature mortality by 300 deaths per year (95% CI: 60 to 580). The range of mean results from all studies is 27 to 593 deaths for $PM_{2.5}$. Reduced exposure to O_3, calculated as an average across the 3 health impact functions, reduces premature mortality by 173 deaths per year (95% CI: 101 to 244). The range of mean results from all studies is 109 to 240 deaths for O_3. These reductions are conservative, because only changes in exposure during the three summer months are considered. Mortality impacts from all causes are shown by study for all studies in standard EPA BenMAP configurations in Table S4.2.

Using a statistical value of life based on 23 studies BenMAP quantifies the monetary value of avoided premature mortality as \$2.8 billion (95% CI: \$0.13 to \$9.3 billion) based on $PM_{2.5}$ exposure and \$1.6 billion (95% CI: \$0.15 to \$4.5 billion) based on O_3 exposure. O_3 and $PM_{2.5}$ benefits cannot be directly summed due to interacting effects between the pollutants that are not captured by BenMAP. Given that the total summertime energy savings for this scenario is 91 TWh, the value of reduced $PM_{2.5}$-related mortality for is \$0.031/kWh and the value of reduced O_3-related mortality is \$0.018/kWh for O_3-related mortality. For context, electricity costs averaged

$0.110/kWh for all sectors in the U.S. in July 2018.[48] Therefore, the ambient air benefits of energy efficiency average 25% of the cost of electricity for $PM_{2.5}$ benefits, and 16% for O_3 benefits.

a) Annually Avoided $PM_{2.5}$-Related Premature Mortalities by State from Energy



b) Annual Savings from Avoided $PM_{2.5}$-Related Premature Mortalities by State ($

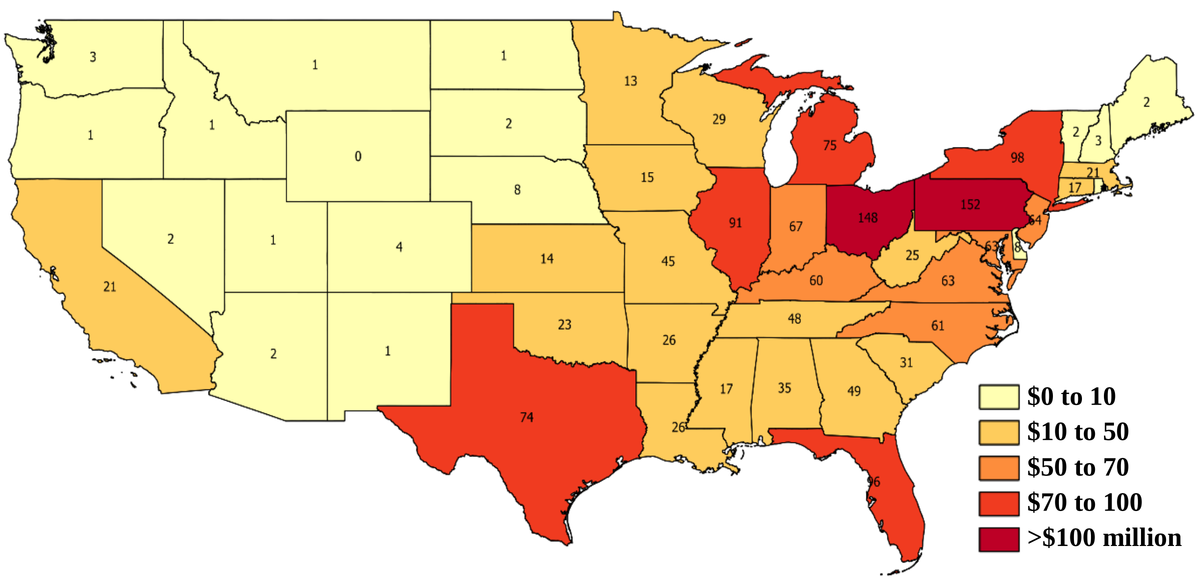


Figure 4.6: $PM_{2.5}$-related a) avoided premature mortality, b) mortality savings valuation by state based on the Harvard Six Cities study [26].

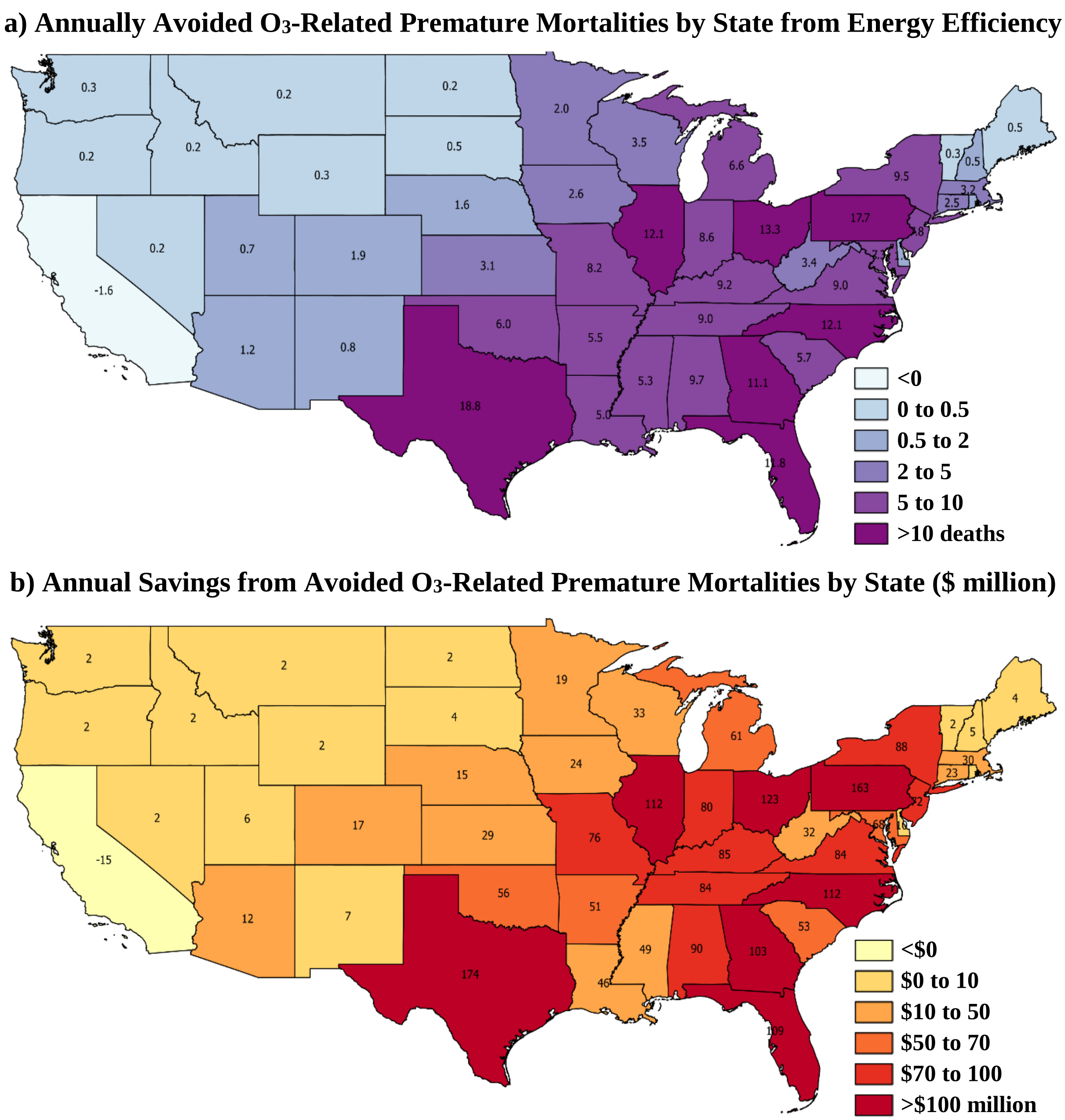


Figure 4.7: O_3-related a) avoided premature mortality and b) mortality savings valuation by state based on the Levy et al. health impact function [47].

Discussion

To date, air quality control strategies in the U.S. have relied most heavily on technological controls, such as desulfurization, electrostatic precipitators and selective catalytic reduction. The U.S. has invested greatly in these technologies in the past, with profound health benefits (estimated as 30:1 by EPA).[49] Although these technologies are highly effective at limiting pollutant emissions, they are both expensive and do not address CO_2 emissions. In fact, some controls can increase power plant CO_2 emissions by decreasing plants' efficiencies.

Energy efficiency and renewable energy offer great potential as complementary strategies to meet both climate and public health goals. Energy efficiency measures may offer a win-win-win strategy for environmental management and ratepayers with cost savings, air quality benefits, and climate mitigation benefits. We find that a 12% reduction in electricity demand would make a difference in the number of high-O_3 events experienced by U.S. counties in a 2011 summer. In our model results, over 6% of counties calculated as quasi-non-attainment would be brought into quasi-attainment through the implementation of efficiency measures considered here.

In the U.S., the design of State Implementation Plans (SIPs) to meet NAAQS standards offers a potential opportunity for the implementation of energy efficiency plans. This study aims to inform SIP development and state planning, as all models used here are freely available and developed for air quality planning by the EPA. Whatever a state's approach to energy efficiency, the modeling approach here could offer a framework for a wide range of policy options. Even for counties in attainment with federal air standards, significant health benefits may be realized by reduced electricity generation. These results bear direct relevance to public health planning and local decisions on energy infrastructure.

Energy efficiency programs are often evaluated for effectiveness to claim savings in cost-benefit analyses. However, the health benefits of avoided air pollution from energy efficiency are rarely included. We find \$0.031 in health benefits per kWh of energy saved for $PM_{2.5}$ alone, and \$0.018 in health benefits per kWh of energy saved for O_3 alone. While not directly additive, the total health benefit would be greater than either of these alone. The monetized value of health savings from energy efficiency offers a simple measure to integrate health benefits into energy decision-making. Both the air management and the public health communities stand to gain from incorporating the cost-effective benefits of energy efficiency. Such analyses would also ensure that full benefits of energy efficiency are accounted for when assessing energy investments, technologies, and programs.

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Supporting Information

Supporting information is included in Appendix 1 (S4) with text regarding CMAQ model performance and figures and tables to support the main text.

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Chapter 5: Coordinated Air and Climate Management in South African Energy Scenarios

This manuscript was prepared well in residence at the International Institute for Applied Systems Analysis (IIASA) in Vienna, Austria as a participant of the Young Scientists Summer Program (YSSP) sponsored by the U.S. National Academy of Sciences. This study was designed to support and extend ongoing work using new methods in a new region of the world. This study explores the impacts of energy scenarios and policies on air quality and climate goals. The work was completed and submitted as a final report for completion of IIASA's YSSP but has since been slightly modified for improvement and for the purposes of this dissertation. The improved paper is in preparation for submission to Energy Policy. The work here will likely be slightly modified before submission as this work has been formatted for the purposes of this dissertation.

Citation

Abel, D., Wagner, F., Gidden, M., In Preparation. Comparative Analysis of the Air Quality Impacts of Power Sector Control Strategies and Policies. Energy Policy.

Abstract

The Republic of South Africa faces an uncertain energy future in a policy sphere defined by many, often competing, objectives across social, economic, political, and environmental issues within a currently coal-dominated system characterized by high energy intensity. Here we link an energy systems model (MESSAGE) and greenhouse gas and air pollution integrated assessment model (GAINS) based on source-receptor modeling to analyze options for co-designing energy and air policy for the South African power sector to maximize climate, air quality, and mortality benefits. In linking these models, we add mechanisms to directly link end-of-pipe control strategies in GAINS to energy cost-optimization with an included heat-rate penalty and associated costs, and mechanistic improvements to facilitate rapid iteration. We show that this practice could be applied to other models and regions to better consider "blank-slate" policy options where existing air regulations may not be implemented or may not be the most effective strategy. We find that South Africa's current emissions controls legislation, rapid and complete investment in high efficiency dedusters, rapid and complete investment in flue-gas desulfurization, a $400/kW investment credit for wind, and a $400/kW investment credit for wind and solar photovoltaic systems all provide CO_2 reduction at less than $42/tonne and reduce fine particulate matter ($PM_{2.5}$) related mortality at less than $8 million/life. Results show that air legislation is cost-effective as a greenhouse gas mitigation strategy because the cost of end-of-pipe controls is sufficient to drive a transition away from direct, coal-fired power plants to other technologies, including integrated gasification combined-cycle power plants.

Integrating Power Sector Air Quality Control Strategies into Energy Integrated Assessment

Air quality policy is a central theme of environmentally-focused policy globally, and several policies are often referenced as highly successful interventions such as the United Nations Convention on Long-Range Transboundary Air Pollution and the United States Clean Air Act (U.S. EPA 2011, UN Economic Convention for Europe 1979). However, since the inception of these and other large legislative and technological actions against air pollution, global environmental change has risen as a universal and monumental challenge. The majority of air quality interventions exclusively target emissions of a single pollutant or category of pollutants, and greenhouse gas emissions are often unaffected or even exacerbated. In addition, many energy policies historically have been highly successful in promoting cheap and reliable access to greater populations, but rarely consider air and climate issues holistically. The development of integrated energy, air quality, and climate planning procedures and policies offers the potential for multiple benefits in a cost-effective and resource-effective structure.

In part, the disconnect between planning and policymaking across air, climate and energy issues is mirrored by a lack of interdisciplinary analysis methods. This is a problem that has spurred decades of development of integrated assessment models (IAMs) to look broadly at cross-cutting issues well into the future. These new tools have been highly successful at examining multi-objective policies and impacts across many disciplines. For example, the use of IAMs in climate policy analyses and global assessments including the International Energy Agency's World Energy Outlook and Intergovernmental Panel on Climate Change's assessment reports has been advanced substantially by integrated assessment models, including those used in this study (IEA 2015, IPCC 2014). However, for all of their benefits, IAMs remain developed around a specific area or sector. Typical analyses that wish to look at the interacting effects between sectors require linking or coupling the models or building new mechanisms into the existing models. For air quality assessment of energy sector changes, these linkages have been explored in many different contexts and have enabled highly influential research, but room for improvement remains. Often, energy-related IAMs or energy systems models (ESMs) run on cost-optimization, whereas air quality and climate mitigation assessment is primarily a linear, physically-based model procedure. This creates challenges in linking the models and selecting mechanisms for which to include feedbacks and interactions. For the MESSAGE ESM and the GAINS IAM, we examine this issue using national-level models for South Africa as a case study. We focus on the power sector to implement novel mechanisms to capture additional and consequential feedbacks and interactions relevant to co-management of climate and air pollution mitigation through power-sector policy. The new mechanisms include incorporating a power plant heat rate penalty for installing air controls, linking power plant costs directly to policy strategies derived from GAINS, and a procedural improvement to enable rapid iteration of energy and air scenarios.

The heat rate penalty is a measure of efficiency loss at a power plant based on the electricity required to run technological air controls. Capturing the heat rate penalty changes the price of emitting energy technologies relative to non-emitting technologies on top of the capital and O&M costs of air controls. Typically, these costs are associated with technologies under the assumption that these controls are package components. This, in practice, captures typical regulations requiring "best available control technologies" or a similar standard. However, in this manner, analyses fail to consider these policies as an option, but rather a foregone conclusion. While technological controls are highly effective in limiting pollution, they are expensive and in a world with growing priorities, investing in air controls may serve air quality needs, but at the cost of path dependence toward a high-carbon, water-intensive, potentially trade-dependent energy system. Therefore, in a holistic policy analysis, existing air regulations should be considered as a tool in overarching energy, climate, and air policy, rather than a base assumption.

In addition, capturing the heat rate penalty includes modifying the efficiency of the power plant as less power is delivered for final use per fuel input when running air controls. This in turn means a rise in the emissions rate per delivered energy of all uncontrolled chemicals (most prominently CO_2). Most IAMs, including GAINS, do not directly account for the increase in CO_2 and other pollutants incurred by installing air controls, and when it is captured it is tied to the energy technology rather than the strategy as a whole.

Deriving air pollution controls form GAINS and including the costs in MESSAGE captures the changing cost-optimal mix of energy sources in MESSAGE simulations while retaining a synchronization with GAINS in calculating air pollution and greenhouse gas emissions impacts. This allows the user to fully capture economically-driven energy sector transitions caused by air pollution control policies. This improvement necessitates the ability to quickly access and manipulate data, variables, and functions from both MESSAGE and GAINS. Therefore, we institute a procedural change to run GAINS equations in a programming environment and simultaneously utilize MESSAGE and GAINS data within the environment for rapid iteration of scenarios.

Including these additional links between energy and air IAMs for the power sector provides insights to future modeling activities and provides tangible policy implications. We show that modifications to costs and efficiencies in an energy systems model can be derived from a receptor-based air quality IAM and that control strategies can be rapidly considered simultaneously with typical energy and climate interventions like subsidies and emissions taxes. We also show that energy subsidies can be cost-effective policies for achieving both air and climate goals in lieu of technological controls while alleviating the problem of path dependence on carbon-intensive fuels in the power sector for South Africa.

Methods

We use an integrated assessment approach to analyze the impacts of future energy scenarios on South African air pollution and climate goals. We perform an energy systems analysis for South Africa using the MESSAGE ix model and ix platform. MESSAGE is an energy systems model (ESM) developed and maintained by the International Institute for Applied Systems Analysis (IIASA) since the 1980s (Huppmann *et al* 2018). Results from MESSAGE are supplied to the Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) model, also developed by IIASA to calculate climate and air pollution impacts (Klaassen *et al* 2005, Klaassen and Riahi 2007). In this analysis, we run a range of scenarios for South Africa to show the comparative greenhouse gas emission and air pollution impacts of potential energy and air policies (including the energy systems cost feedback of air policy implementation) across three SSPs. The scenarios considered are described below and in Table 1 and frameworks of analysis for MESSAGE and GAINS are shown in Appendix 2.B.

Energy Systems Analysis

The South Africa MESSAGE model was developed from the global MESSAGE framework. The model was first developed following (ORTHOFER *et al* 2017) and is adapted here for newer implementations of the model across multiple SSPs (Riahi *et al* 2017). The MESSAGE model uses an objective function that minimizes total discounted systems costs while satisfying given demand and considering technical and societal restrictions.

MESSAGE South Africa includes 80 technologies representing the extraction, transformation and use of energy across South Africa. These technologies are listed in Supplemental Table C1. The data for technologies is derived from the global MESSAGE model and some additional resources including underlying data from the International Energy Agency (IEA) and renewable resource characteristics from the U.S. National Renewable Energy Laboratory. Inputs for demand are derived from IEA data and the 2016 Integrated Energy Plan (IEP) for South Africa. We use validated, historical data from IEA and scale this data to match the future trends of the baseline scenario from the IEP to avoid discrepancies between historical data and sectoral partitioning of demand and technologies. This data is included in Supplemental Table C2. Constraints on the growth and potential of energy resources are supplied based on the global version of the MESSAGE model.

The costs of control technologies under policy scenarios are applied to investment and variable costs of technologies in MESSAGE to capture feedbacks between technological control decisions. These costs are derived as variable costs from the prices of control strategies implemented in GAINS to ensure consistency. The costs applied for each control scenario are summarized in Appendix 2.C Table S5.*C3.*

Emissions Analysis

Output from MESSAGE is mapped to activity sectors defined in GAINS according to technology following standard Integrated Assessment Modeling Consortium (IAMC) variables. This mapping assumes frozen distributions of sector and activity data captured within a single MESSAGE or IAMC variable. We validate this process using the most recent data from IEA and a validated GAINS scenario following the World Energy Outlook.

GAINS calculates emissions of many pollutants including nitrogen oxides (NO_X), (SO_2), (CO_2) and more based on activity data (mapped from MESSAGE), a control scenario (synchronized with costs in MESSAGE), emissions factors, unit costs, and activity/source factors. Here, activity data is mapped from MESSAGE using primarily IAMC standard variables. The current policy scenario (CLE, based on current legislation) was developed based on existing policies for South Africa under the assumption that regulations are followed and met on the timeframe designated. The "no further controls" (NFC) control scenario is defined by the current policy scenario, but frozen at 2015 levels of control. The 100% flue-gas desulfurization (100FGD) and 100% high efficiency de-dusters (100HED) scenarios are defined by implementing these single control technologies on 100% of power plants by the year 2020 in addition to NFC scenario.

Though here results are shown through 2050, GAINS baseline activity data is only projected to 2040 and then held constant to 2050. Therefore, expected changes outside of the energy sector are not considered between 2040 and 2050.

Fine Particulate Concentrations

We use a source-receptor matrix to calculate $PM_{2.5}$ concentrations for each scenario given emissions calculated by GAINS. The source-receptor model used here is derived from the global GAINS model for South Africa calculated for a range of 15% changes in emissions based on European Monitoring and Evaluation Programme (EMEP) simulations. Different procedures are discussed in Clappier *et al* 2015. We use emissions calculated from GAINS and the source-receptor matrix to calculate concentrations for South Africa on a 0.5° x 0.5° grid as shown in Appendix 2.A figures. This procedure assumes the source-receptor matrix remains accurate given changes through 2050 and at varying levels of emissions up to approximately 50% different for select pollutants. In addition, we assume a constant geographic downscaling of national-level emissions calculated by GAINS. These assumptions are reasonable given the changes simulated and the focus on national-level results rather than geographic distribution.

Health Impacts Assessment

We calculate $PM_{2.5}$-related mortality using a simplified, linear exposure-response function derived from analysis using GAINS-Europe shown in Equation (1) where RR is relative risk and $\beta=0.006/\mu gm^{-3}$ and similar to methods described in (Kiesewetter *et al* 2015). This β is chosen following recommendations of assessments by WHO-Europe (Henschel and Chan 2013, World Health Organization 2013) and under the reasonable assumption that $PM_{2.5}$ levels in South Africa are similar to those in $_{\text{Europe}}$. Population is assigned according to SSP scenario data and $PM_{2.5}$ concentrations are taken from previous calculations based on MESSAGE and GAINS data. Baseline mortality incidence is summed for all adults (>25 years) and across five health endpoints (acute lower respiratory infection, chronic obstructive pulmonary disorder, ischemic heart disease, lung cancer, and stroke) from 2013 Global Burden of Disease estimates (Brauer *et al* 2015, Burnett *et al* 2014). We assume constant geographic downscaling of population and a constant baseline mortality rate.

$$(1) \qquad RR = 1 + \beta * PM$$

Scenarios

We consider a range of scenarios for each SSP scenario that encompass subsidies for a range of emissions-free technologies under the no further controls air strategy and several air strategies in isolation. The subsidies are all applied as X$/kW investment cost reductions as shown in Table 5.1. The three power sector control scenarios include current legislation, immediate (by 2020) and complete (100% of plants) installation of high efficiency dedusters, and immediate and complete installation of flue gas desulfurization.

Table 5.1: The scenarios simulated and acronym used to refer to each scenario.

Scenario	Acronym
Baseline	
Business as Usual	BAU
Solar PV Subsidy	
$100/kW Subsidy	Solarpv-100
$200/kW Subsidy	Solarpv-200
$400/kW Subsidy	Solarpv-400
Zero-cost Subsidy	Solarpv0
Solar PV & CSP Subsidy	
$100/kW Subsidy	Solar-100
$200/kW Subsidy	Solar-200
$400/kW Subsidy	Solar-400
Zero-cost Subsidy	Solar0
Wind Subsidy	
$100/kW Subsidy	Wind-100
$200/kW Subsidy	Wind-200
$400/kW Subsidy	Wind-400
Zero-cost Subsidy	Wind0
Nuclear Subsidy	
$100/kW Subsidy	Nuclear-100
$200/kW Subsidy	Nuclear-200
$400/kW Subsidy	Nuclear-400
Zero-cost Subsidy	Nuclear0
Solar PV and Wind Subsidy	
$100/kW Subsidy	Solarwind-100
$200/kW Subsidy	Solarwind-200
$400/kW Subsidy	Solarwind-400
Zero-cost Subsidy	Solarwind0
Power Sector Controls	
Current Legislation	CLE
High Efficiency Dedusters	100HED
Flue Gas Desulfurization	100FGD

Case Study on South Africa

Introduction

The Republic of South Africa is facing an uncertain energy future defined by multiple, often competing, objectives. The nation has clear, and long-term development goals outlined prominently in the National Development Plan (NDP) 2030 (South Africa National Planning Commission 2012), as well as environmental goals including limiting greenhouse gas emissions consistent with contributions to the Paris Climate Agreement and local air pollution (UNFCCC 2015, Republic of South Africa 2015). These goals are not at odds with one another, and in fact chapter 5 of the NDP explicitly pertains to environmental sustainability. However, in a cost-limited world, investment across multiple objectives necessitates trade-offs, and creates opportunity for coordinated benefits. In this analysis, we consider the impact of energy scenarios consistent with future goals, but varying cost and technology structures on climate change mitigation, local air quality and ambient $PM_{2.5}$-related mortality.

The current energy system in South Africa is dominated by coal with a high level of CO_2 emissions, especially with projected growth. CO_2 emissions in 2015 were 427.6 Mt/year or 7.8 t/capita (http://energyatlas.iea.org/#!/profile/WORLD/ZAF). Coal production was 146.3 Mtoe in 2015 with 101.2 Mtoe consumed within the country. 2016 electricity generation totaled 237,006 GWh with 85.7% of electricity being produced from coal and 92.7% by fossil fuels. Nuclear is the second largest source behind coal at 5.2%, and solar and wind make up 0.9% of electricity supply each (Maluleke 2018). Overall, 43% of total final energy consumption goes to industry while 24% goes to transport and 22% to residential uses (http://energyatlas.iea.org/#!/profile/WORLD/ZAF).

While, the previous statistics outline the current state of the South African energy system, the future energy system is currently being considered by the Department of Energy. The 2016 Integrated Energy Plan (IEP) and Integrated Resource Plan (IRP) are yet to be finalized and consider four scenarios across eight main objectives. The scenarios include

1. Base case
2. Resource constrained

3. Environmental Awareness
4. Green shoots

and the objectives are:

1. Ensure security of the energy supply
2. Minimize the cost of energy
3. Promote job creation and localization potential
4. Minimize negative environmental impacts
5. Minimize water consumption
6. Diversify supply sources and primary energy carriers
7. Promote energy efficiency (reduce energy intensity of the economy)
8. Promote energy access

These eight objectives and four scenarios highlight the interdependencies of energy, air and climate decision-making. In this analysis, we use the base case scenario from South Africa's IEP to forecast demand, but choose to focus on Shared Socioeconomic Pathway (SSP) scenarios for alternatives to business as usual rather than the scenarios developed for the IEP. The SSP scenarios were developed to assess challenges facing adaptation to and mitigation of climate change (O'Neill *et al* 2017, Riahi *et al* 2017). We include in this analysis SSP1, SSP2 and SSP3, which are respectively the "Sustainability: Taking the Green Road" scenario with low socio-economic challenges to both mitigation and adaptation, the "Middle of the Road" scenario with intermediate challenges, and the "Regional Rivalry: A Rocky Road" scenario with high challenges. Previous work has considered future air pollution under the different SSP scenarios finding SSP3 pollutant emissions may be similar to current levels due to slower air quality improvements whereas SSP1 pollutant emissions fall to low levels due to technological advances and successful global action (Rao *et al* 2017).

Synergies and tradeoffs within climate, energy, and air policies have been considered by previous work. Henneman et al. use the GAINS model to compare energy transformations and controls costs in determining future air quality outcomes (Henneman *et al* 2016). Here we expand upon this approach by including an energy systems model to calculate least-cost energy systems changes and carry the analysis through to simulating ambient $PM_{2.5}$ concentration and related mortality. Henneman et al., find that eliminating coal power generation reduces CO_2 by 8%, but policy targeting the entire energy sector could reduce emissions by 40% by 2050. Results also show large benefits from investing in air controls, particularly for SO_2 emissions overall and NO_X emissions from the transport sector, and the domestic sector plays a key role in primary $PM_{2.5}$ emissions. Klausbruckner et al. contains a detailed analysis of the policy and legal framework surrounding climate change mitigation and air pollution strategies in South Africa (Klausbruckner *et al* 2016). In general, they find, air pollution and climate policies are addressed separately in South Africa, as with most nations, but could benefit from a framework that takes into account interacting environmental, economic, social and political factors.

Responsible energy policy in South Africa has the opportunity to promote sustainable development broadly. Winkler et al., characterize and identify key issues regarding energy and sustainable development within South Africa and build a profile of energy for South Africa (Winkler 2007). South Africa's energy sector, in particular, is characterized by high energy intensity which manifests in social, economic, and environmental implications. Specifically, Winkler et al,, highlight the high level of greenhouse gas emissions and local air pollution driven by South Africa's coal-based economy. Cairncross et al., in an analysis of climate change, air pollution,a and health in South Africa find that policy commitment in South Africa to address both climate change and air pollution is present, but implementation must be improved (Cairncross *et al* 2018). This fact supports the concept behind this analysis, that examining energy interventions assuming a blank-slate provides a great deal of added value, as policies on the books are not unchangeable and are often poorly implemented. Designing methods that include revisiting air controls in policy-focused analysis may identify better alternatives, and also shows the consequences of failing to follow through with proper implementation.

Emissions of greenhouse gases in South Africa are driven by many different sources with nearly 50% of CO_2, 70% of SO_2, and 40% of NO_X emissions coming from the power sector due to heavy reliance on coal power. Local air pollution in South Africa is responsible for approximately 27,000 premature deaths annually (~75% from ambient pollution exposure and 25% from household exposure, https://vizhub.healthdata.org/gbd-compare/). Note that in this analysis we use 2013 Global Burden of Disease data which estimates premature deaths at about half that of the 2017 numbers but is the most recently available data formatted for use with GAINS (Brauer *et al* 2015).

Under an uncertain future, South Africa will be making energy and power-sector decisions with implications for decades. While previous analyses have explored climate and air implications of some measures, this analysis provides a holistic view of re-examining existing air policy under climate and air pollution evaluation criteria, given a host of power sector intervention strategies available (examined here as subsidies for emissions-free technologies).

Procedure Validation

We validate the modeling procedure linking MESSAGE and GAINS using the most recent data from the International Energy Agency (IEA). We follow the same mapping procedure used to prepare MESSAGE output for use in GAINS with several small simplifications necessary to conform to IEA data as opposed to more detailed MESSAGE output. We compare the IEA-mapped emissions calculated by GAINS to emissions calculated by the validated GAINS scenario, WEO2017_NPS_CPS for 2010 and 2015. The results are shown in Table 5.2 below by pollutant. Overall, all pollutants are well represented by the mapping between MESSAGE and GAINS. SO_2

has the worst performance with a bias of -91 kt or -3.07% in 2015. All other pollutants and years are within 3% of base GAINS emissions in 2010 and 2015 with most within 1% except for NO_X which has a bias of -2.20% in 2010 and -1.05% in 2015. Regarding greenhouse gas emissions, CH_4 emissions are within 0.14% and 0.04% for 2010 and 2015 following the mapping procedure, and CO_2 emissions are 1.91% less in 2010 and -0.15% less in 2015. Following the standard procedure to calculate $PM_{2.5}$ concentrations and health impacts, we find the mapped IEA data is 0.71% lower in 2010 and 0.37% lower in 2015. This is a -0.076 and -0.042 μg/m^3 bias in $PM_{2.5}$ concentrations, and a -57.6 and -32.9 deaths bias in $PM_{2.5}$-related mortality.

Table 5.2. Bias between GAINS base-case and mapped IEA data for historical years, 2010 and 2015.

Pollutant	**IEA-MAPPED**	**IEA-MAPPED**	**GAINS**	**GAINS**	**Bias**	**Bias**	**Percent Bias**	**Percent Bias**
	2010	**2015**	**2010**	**2015**	**2010**	**2015**	**2010**	**2015**
CH_4 (ktonnes)	2251	2391	2248	2390	3.1	1.0	0.14%	0.04%
CO_2 (Mtonnes)	458	462	466	462	-8.9	-0.7	-1.91%	-0.15%
NH_3 (ktonnes)	325	341	325	341	0.0	-0.1	0.00%	-0.03%
NO_X (ktonnes)	1353	1425	1384	1440	-31	-15	-2.20%	-1.05%
$PM_{2.5}$ (ktonnes)	491	531	493	531	-1.7	-0.4	-0.35%	-0.07%
SO_2 (ktonnes)	2935	2881	3010	2972	-75	-91	-2.49%	-3.07%
VOCs (ktonnes)	1066	1097	1057	1106	9.4	-8.8	0.89%	-0.80%

Baseline SSP Scenarios

Here we consider three SSP scenarios that address baseline (SSP2), low (SSP1), and high (SSP3) degrees of socioeconomic difficulty in adapting to and mitigating climate change (O'Neill *et al* 2017). By using energy trajectories derived from the South African IEP, we layer the SSP storylines on baseline energy planning. Results show that across SSPs air pollutant and CO_2

emissions tend to rise in all scenarios, though only modestly under SSP1, assuming no further controls across all scenarios. This is driven by the demand projections in the IEP, particularly large projected increases in industry demand. Plots for energy sector performance and emissions as well as maps of $PM_{2.5}$ concentrations for all three SSP scenarios are shown in Appendix 2.A.

In Figure 5.1, we see that there is a direct correlation between coal generation and resulting $PM_{2.5}$ concentrations in South Africa. Across all three SSP scenarios and all energy subsidy scenarios, as coal generation decreases, $PM_{2.5}$ concentrations decrease, by approximately the same rate 0.9 to 1.4 ng/m^3 for every PJ/yr of coal displaced. For SSP2, using our dose-response function for $PM_{2.5}$-related mortality and a population of 60 million, this is approximately 1 life saved annually from ambient $PM_{2.5}$ exposure for every PJ/yr of coal displaced or about 1,500 lives saved annually from eliminating coal power in the country.

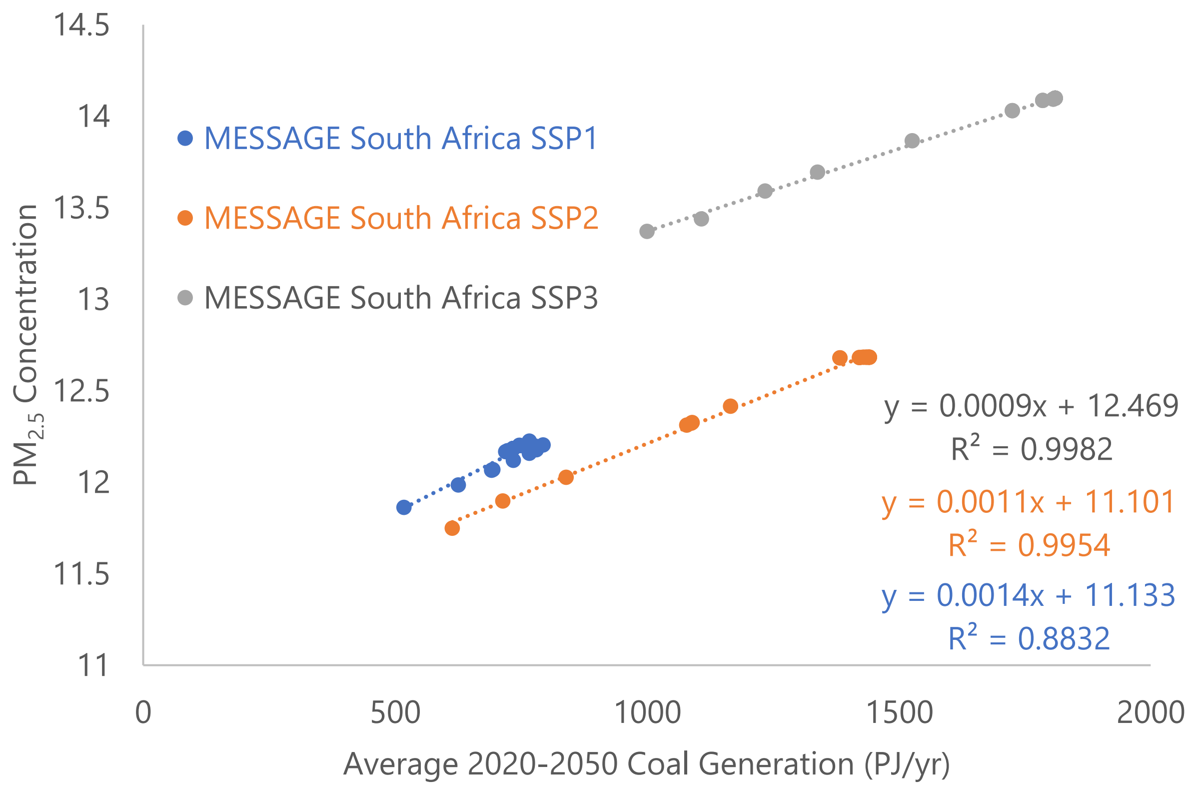

Figure 5.1: The correlation between coal power generation and $PM_{2.5}$ concentrations in South Africa.

One would expect socioeconomic scenarios related to the difficulty of adapting to and mitigating climate change, including technoeconomic assumptions and drivers, would have a large impact on resulting CO_2 emissions and $PM_{2.5}$ concentrations and health damages. In Figure 5.2, we show the difference in CO_2 emissions and $PM_{2.5}$-related deaths from SSP2 to SSP1 or SSP3 by year in deaths and as a percentage reduction. Our results follow expected trends as SSP1 saves nearly 1,500 lives and over 300 Mt of CO_2 each year by 2050 and SSP3 causes nearly 1,000 additional deaths and 200 Mt additional emissions of CO_2. As a percentage, the difference from BAU in SSP1 and SSP3 ranges from as much as 40% worse to 40% better for CO_2 and ±10% mortalities from $PM_{2.5}$. However, interestingly, SSP3 has a large proportional impact early (in 2020) and the impact lessens proportionally over time, whereas SSP1 becomes more and more impactful as time goes on and actually negates positive impacts early, resulting in an increase in CO_2 emissions and $PM_{2.5}$-related deaths in 2020, but 40% less emissions and 10% less deaths by 2050.

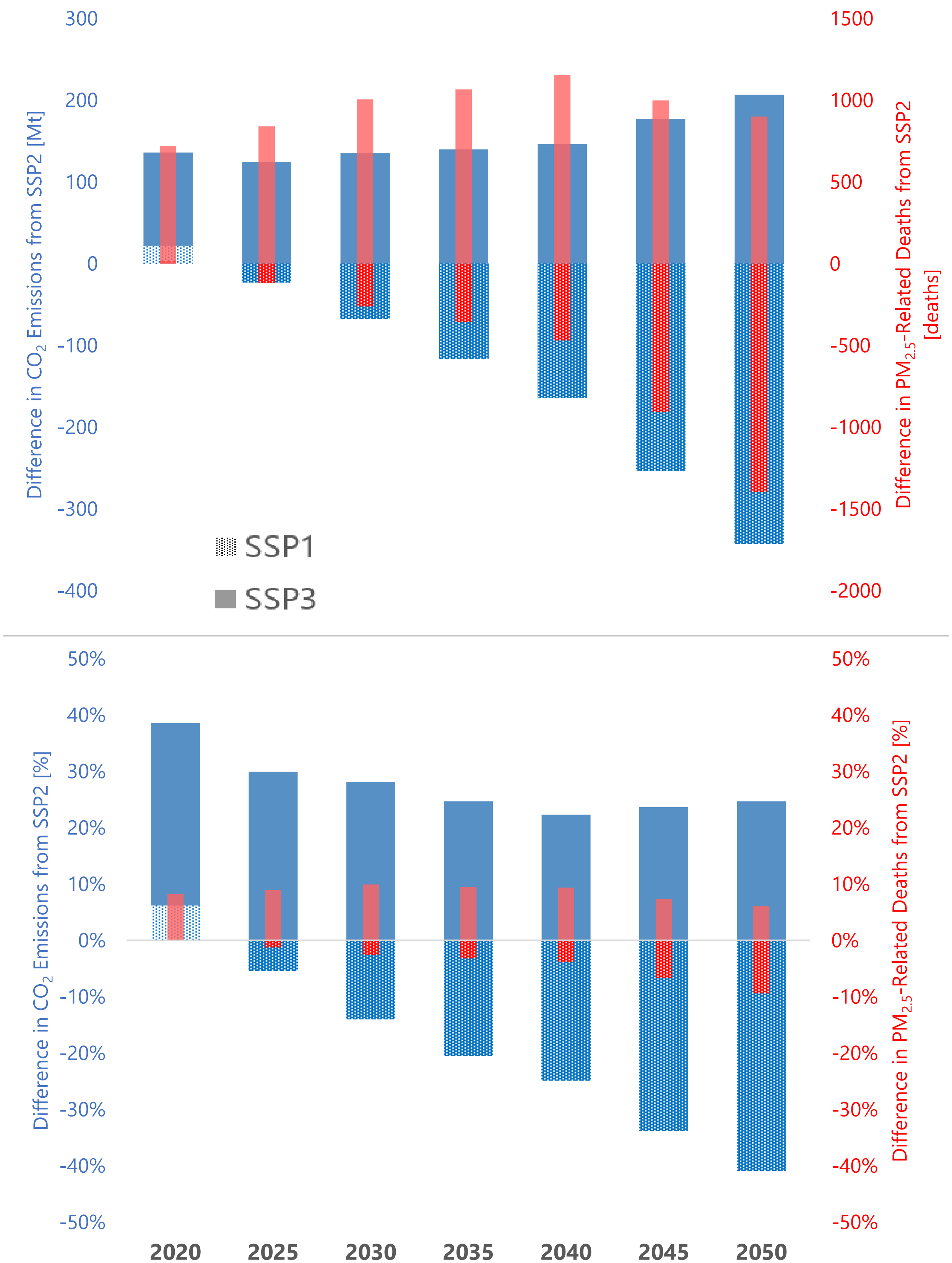

Figure 5.2: The difference in CO_2 emissions and $PM_{2.5}$-related deaths from SSP2 to SSP1/SSP3.

Comparative Benefits of Power Sector Controls and Strategies

The most important metrics considered here in comparing interventions in the power sector are cost, final $PM_{2.5}$ concentrations or related mortality, and CO_2 emissions. In Figure 5.3, we show the reduction in average CO_2 emissions from 2020 to 2050 vs. the reduction in average $PM_{2.5}$ concentrations from 2020 to 2050 for every scenario considered across all three SSPs. From Figure 5.3, one surprising result is that emissions control strategies can be highly effective at controlling CO_2 in addition to $PM_{2.5}$ and precursors. In fact, heavy investment in high efficiency dedusters is as effective as fully subsidizing emissions-free generation in many cases. The strategies that have the greatest influence on CO_2 emissions are those in the high-CO_2 SSP scenarios (SPP2 and SSP3) with the most effective strategy being full subsidy of nuclear with high efficiency dedusters as the second most effective. The strategies that have the greatest influence on $PM_{2.5}$ concentrations directly are the targeted, immediate controls of the power sector with HED causing the largest and

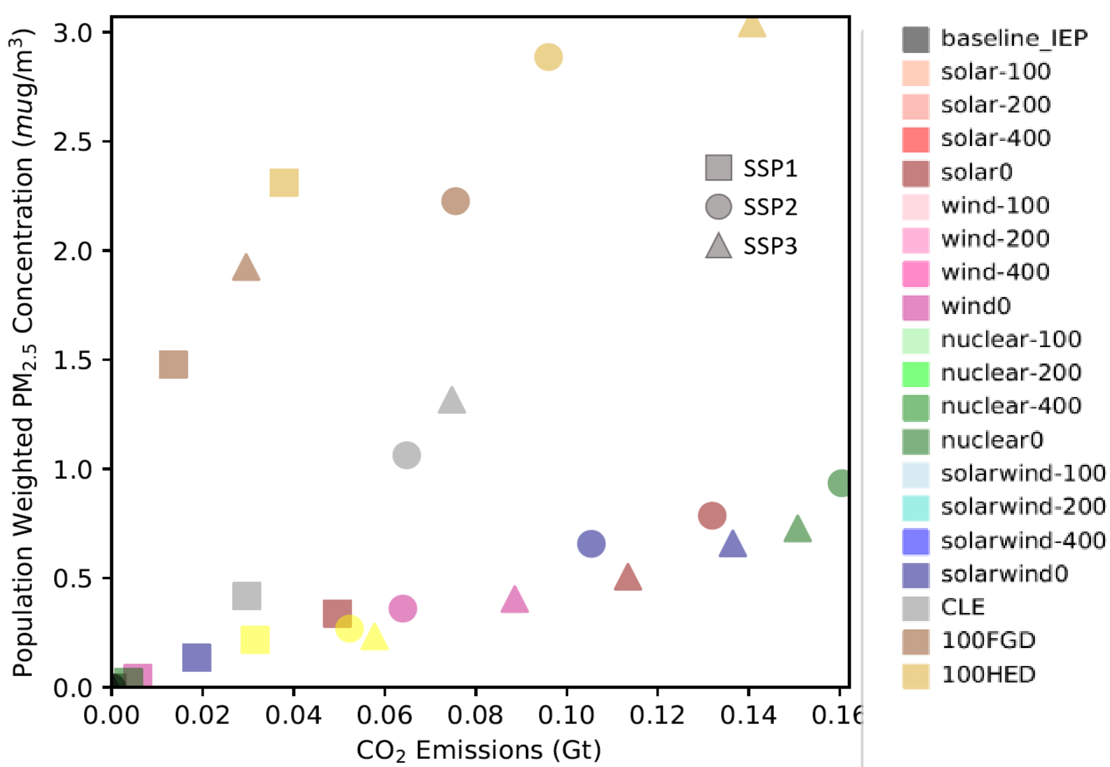

Figure 5.3: Avoided CO_2 Emissions and Reduction in $PM_{2.5}$ Concentrations

flue-gas desulfurization the second largest reductions in $PM_{2.5}$ concentrations. The dual-benefit of emissions controls may be counterintuitive but is caused by the cost of controls reaching a threshold at which simple coal power plants (coal_ppl) become too expensive. In the CLE scenario, these plants are substantially replaced by integrated gasification combined cycle (igcc) power plants. In addition, there is a decrease in exported electricity by 2050 compared to the baseline. Perhaps most importantly, this threshold exists across all SSP scenarios. Therefore, there exists a price of control at which coal becomes more expensive than other competitive technologies, and this price is consistent with the costs of current legislation regardless of socioeconomic barriers.

The trends seen in Figure 5.3 are driven by two mechanisms; 1) changes from high-emission to low-emission energy technologies and 2) changes of emissions factors of reactive pollutants within the use of a single energy technology. CO_2 emissions are only impacted by the first mechanism as there is no commercially-available ‘control technology’ effective in lowering the emissions factor of a particular activity through technological means. However, primary $PM_{2.5}$ and secondary $PM_{2.5}$ precursor emissions are impacted through both mechanisms, though more drastically by technological controls which immediately at the time of installation reduce emissions with efficiencies as high as 90%+. Emissions reductions through fuel or energy switching occurs more slowly, roughly proportionally to reductions in fossil fuel (primarily coal) production, as shown in Figure 5.1. Similarly, each intervention strategy (fuel switching and technological control) incentivizes one technology or disincentivizes another encouraging a switch to lower emissions options.

CO_2 emissions in Figure 5.3 are calculated as reductions from the respective SSP baseline. Baseline CO_2 emissions are in SSP1, SSP2 and SSP3, respectively. The large influence of SSP scenarios is expected as the SSP scenarios affect not only the electricity sector, but all energy sectors included in MESSAGE, and the narratives directly address climate change mitigation. SSP1 is few challenges in GHG mitigation and SSP3 is substantial challenges. Within SSP1, all scenarios exhibit lower CO_2 emissions than baseline except for wind and nuclear subsidies. In these scenarios, installed wind and nuclear offsets solar-CSP while gas and coal generation increases, resulting in higher emissions overall. The scenario with the lowest CO_2 emissions is the

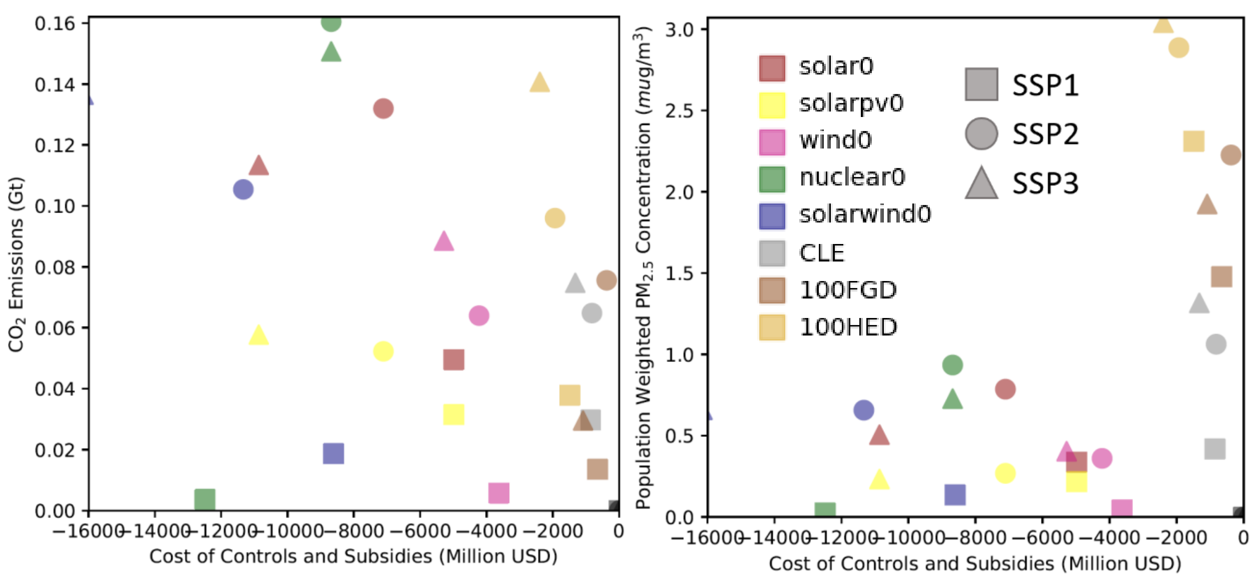

Figure 5.4: The cost of controls (negative numbers are costs) compared to avoided CO_2 emissions and $PM_{2.5}$ concentrations.

solar0 scenario followed by the CLE scenario and then the solarwind-400 scenario. The solar0 scenario sees a 5.16% (23 Mt) reduction in CO_2 emissions from the SSP1 baseline. For $PM_{2.5}$ results tend to reflect the same trends seen for CO_2 since the emissions are correlated. Within SSP2 and SSP3 we do not see the same exact behavior, in fact nuclear and wind subsidies are some of the most effective strategies, but this is driven by the fact that the transition to emissions-free technologies is not driven by socioeconomic factors and thus the changes in technologies are not displacing other clean resources to the same degree as is exhibited in the SSP1 scenarios. In considering the benefits of different scenarios, it is also important to consider the cost of avoided damages.

In Figure 5.4, negative numbers refer to costs and positive numbers are savings. In general, we see that controls tend to be much cheaper than wholly subsidizing emissions-free technologies. This is not unexpected as a full subsidy on any given energy technology would be an expensive affair and highly unlikely. However, here we see the potential for each strategy and the maximum, simulated cost of subsidizing certain technologies. If a policy could be designed to only pay the necessary additional cost of each project in order to maximize generation from emissions-free sources, costs would be greatly decreased.

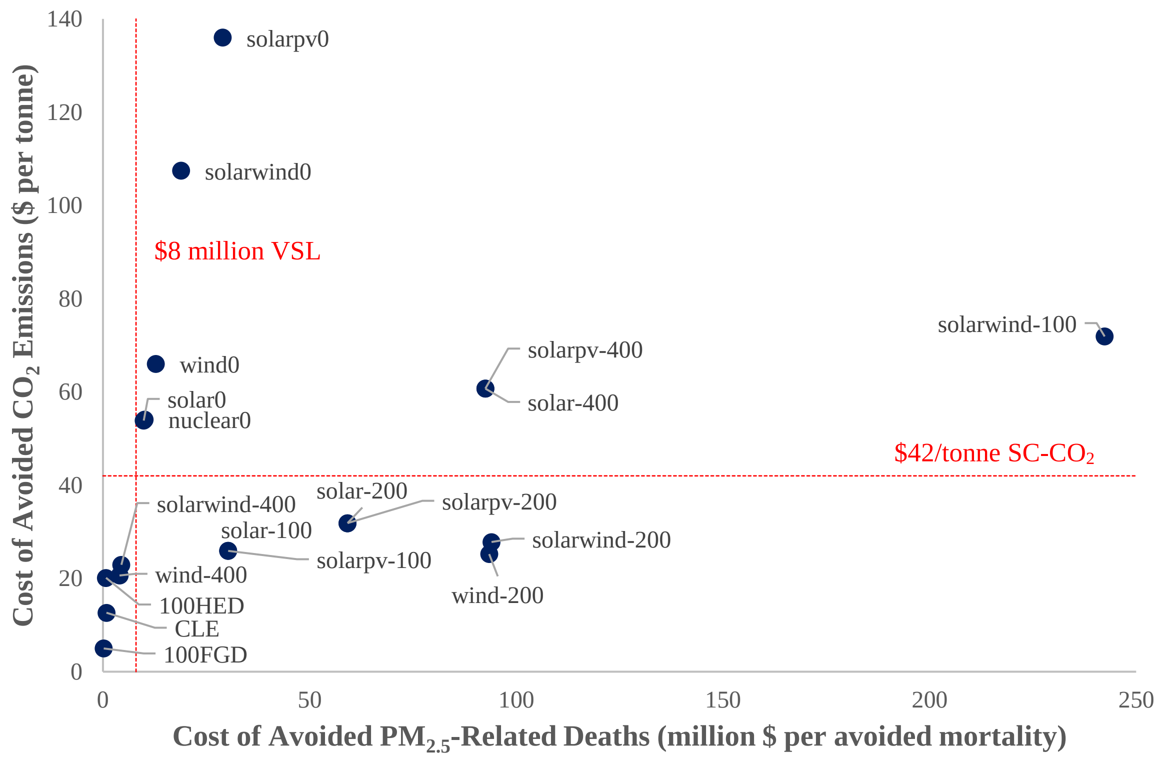

Figure 5.5: The cost of different control strategies per avoided CO_2 emissions and $PM_{2.5}$-related mortality averaged from 2020-2050. Shown for SSP2. $8 million per avoided mortality is shown as the value of statistical life (VSL) from the U.S. EPA (converted to 201 USD). $42/tonne is shown as the central estimate of the social cost of carbon (SC-CO_2) in 2020 from a U.S. interagency working group.

To compare the costs and benefits of each of these strategies more directly, Figure 5.5 shows the cost per avoided tonne of CO_2 emissions and cost per avoided $PM_{2.5}$-related death. Five scenarios: 100FGD, CLE, 100HED, wind-400, and solarwind-400 are both cheaper than \$42/tonne of avoided CO_2 and \$8 million per saved life. Using these metrics, these strategies would, on their own, be the most effective strategies for controlling climate and air pollution simultaneously. In addition, Table 5.3 shows that these strategies also rank toward the top of considered scenarios in avoided magnitude of CO_2 and $PM_{2.5}$ impacts. Therefore, we see the benefit of examining current air pollution strategies as an independent policy consideration. All of these scenarios would be cost-effective strategies with a range of associated, unaccounted for costs and benefits including path dependence, job creation, energy independence, land-use, and social and cultural considerations.

Table 5.3. The total change in CO_2 emissions and $PM_{2.5}$-related deaths from each control strategy averaged from 2020-2050. Shown for SSP2.

Change in CO_2 (kt)			**Change in $PM_{2.5}$-related Deaths**		
1.	nuclear0	-160000	1.	100HED	-2600
2.	solar0	-132000	2.	100FGD	-2039
3.	solarwind0	-105000	3.	CLE	-979
4.	100HED	-96000	4.	nuclear0	-860
5.	100FGD	-76000	5.	solar0	-721
6.	solarwind-400	-66000	6.	solarwind0	-600
7.	CLE	-65000	7.	solarwind-400	-341
8.	wind0	-64000	8.	wind0	-331
9.	wind-400	-64000	9.	wind-400	-329
10.	solarpv0	-52000	10.	solarpv0	-245
11.	solarwind-200	-14000	11.	solarwind-200	-4
12.	wind-200	-13000	12.	wind-200	-4
13.	solar-400	-3000	13.	solar-400	-2
14.	solarpv-400	-3000	14.	solarpv-400	-2
15.	solarwind-100	-2000	15.	solarwind-100	-1
16.	solar-200	-2000	16.	solar-200	-1
17.	solarpv-200	-2000	17.	solarpv-200	-1
18.	solarpv-100	-1000	18.	solarpv-100	-1
19.	solar-100	-1000	19.	solar-100	-1

Discussion

Overall, we demonstrate here the advantage of synchronizing control strategies across an energy systems model and source-receptor-based IAM. For South Africa, we identify policy strategies that would achieve similar, cost-effective benefits to climate change mitigation and local air pollution through alternative methods with differing advantages and disadvantages. To identify the ideal mix of policy measures, advanced analysis on a more local scale would be necessary leveraging unit-level power plant characteristics, gridded emissions, chemical transport modeling, and incorporating social, economic, political, and additional environmental factors. However, we provide a proof-of-concept for integrating more thorough and rapid analysis of technological air control regulations into energy systems cost-optimization for direct comparison of different energy and climate strategies for simultaneously controlling air pollution. In addition, we show the unexpected result that air controls themselves may be expensive enough in South Africa to drive a transition away from direct coal-fired power plants, resulting in CO_2 emissions reductions. Another advantage beyond the scope of this study is the water use required by energy technologies. South Africa has faced severe shortage of water supplies within the last decade. The benefit to climate and air quality of renewable energy preference in South Africa holds direct relevance to future energy planning such as through the Renewable Energy Independent Power Producers Procurement Program.

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Supporting Information

Supporting information for chapter 5 is listed in Appendix 2 (S5).

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Conclusion

There are many linkages between energy, air pollution, climate, and health. In my doctoral studies, I have chosen to focus on the relationship between the U.S. power sector and air pollution within various climate, policy, and health contexts. I have utilized a range of modeling techniques to build a comprehensive storyline surrounding the impacts of clean energy strategies on achieving air and climate goals. These results have thus far been published in high impact journals and have garnered general public interest while offering new scientific methodologies also applicable to regulatory purposes. The dissertation has provided novel answers to the questions posed by the problem statement and crosscutting questions posed across chapters.

Research Conclusions and Highlights

1. How do changes in ambient temperature affect power-sector emissions in the Eastern United States?

In the first chapter of this dissertation, we assess the relationship between power sector emissions and ambient temperatures across the Eastern United States in order to answer research question 1.[1] We hypothesize that power sector emissions are directly correlated to ambient temperature driven by temperature-dependent electricity demand, especially air conditioning. We use emissions data collected through the Clean Air Markets program and meteorological data from the North Atlantic Regional Reanalysis to establish a linear relationship between ambient temperature and power sector emissions over the summer from 2003 to 2014.

We find that EGUs in the Eastern U.S. region from 2007 to 2012 exhibited a 3.87%±0.41% increase in electricity generation per °C increase during summer months. This is associated with a 3.35%/°C±0.50%/°C increase in SO_2 emissions, a 3.60%/°C±0.49%/°C increase in NO_X

emissions, and a 3.32%/°C±0.36 %/°C increase in CO_2 emissions. Sensitivities vary by year and by pollutant, with SO_2 both the highest sensitivity (5.04% in 2012) and lowest sensitivity (2.19% in 2007) in terms of a regional average. Texas displays 2007-2012 sensitivities of 2.34%/°C ± 0.28%/°C for generation, 0.91%/°C ± 0.25%/°C for SO_2 emissions, 2.15%/°C ± 0.29%/°C for NO_X emissions, and 1.78%/°C ± 0.22%/°C for CO_2 emissions.

These results bear relevance to air quality management and energy planning under uncertain temperature and electricity demand patterns. The findings also highlight the importance of considering the impacts of climate change on power sector emissions and considering low-emission electricity production.

2. Given a relationship between ambient temperature and power-sector emissions driven by changes in electricity demand, what impact will climate change have on future U.S. air quality and air quality-related health?

The second chapter of this dissertation examines the contribution of future air pollution-related health damages that are caused by the power sector through heat-driven, air conditioning adaptation in buildings in order to answer research question 2. This analysis highlights the need for cleaner energy sources, energy efficiency and energy conservation to meet our growing dependence on building cooling systems and simultaneously mitigate climate change.

We find that by mid-century, climate change and increased building energy use increases $PM_{2.5}$ 61.1% (2.60 μg/m^3) and O_3 15.9% (8.64 ppbv). 3.8% of the total increase in $PM_{2.5}$ and 6.7% of the total increase in O_3 is attributable to adaptive behavior (extra air conditioning use). Health impacts assessment finds that air conditioning adaptation accounts for 654 (range of 87 to 1,245) of 13,547 $PM_{2.5}$-related deaths (~$6 billion cost, a 4.8% increase above climate change impacts alone) and 315 (range of 198 to 438) of 3,514 O_3-related deaths (~$3 billion cost, an 8.7% increase above climate change impacts alone).

These results bear relevance to considering heat adaptation measures and highlight the importance of low-emissions electricity production. As climate warms, air conditioning will become far more prevalent, and the increased cooling load will result in a greater number of air pollution-related deaths as long as the energy system relies on fossil fuels and combustion to produce electricity.

3. What would be the air quality impacts of a realistic solar energy future for the Eastern United States?

In the third chapter of this dissertation, we evaluate how fine particulate matter ($PM_{2.5}$) and precursor emissions could be reduced if 17% of electricity generation was replaced with solar photovoltaics (PV) in the Eastern United States. Electricity generation is simulated using GridView, then used to scale electricity-sector emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_X) from an existing gridded inventory of air emissions. CMAQ is used to cacluate air quality which offers a high-value opportunity to evaluate the reduced-form AVERT and test the sensitivity of results to changing base-years and levels of solar integration. BenMAP is used to calculate mortality outcomes.

We find that average NO_X and SO_2 emissions across the region decrease 20% and 15%, respectively. $PM_{2.5}$ concentrations decreased on average 4.7% across the Eastern U.S. In the five largest cities in the region, we find that the most polluted days show the most significant $PM_{2.5}$ decrease under the 17% PV generation scenario. Summer health benefits from reduced PM2.5 exposure estimated as 1,424 avoided premature deaths (95% Confidence Interval (CI): 284 deaths, 2732 deaths) or a health savings of $13.1 billion (95% CI: $0.6 billion, $43.9 billion).

These results highlight the potential for renewable energy as a tool for air quality managers to support current and future health-based air quality regulations. In addition, the combination of advanced and simplified models and methods demonstrates the utility of reduced-form calculations capable of being performed by stakeholders across energy planning and air quality management.

4. What would be the air quality impacts of realistic increases in energy efficiency throughout the United States?

In the fourth chapter of this dissertation, and second directly analyzing the air benefits of clean energy strategies, we use a system of linked models to quantify the air quality and health benefits of a 15% energy efficiency scenario in the continental United States. The project leverages expertise from the American Council for an Energy Efficient Economy (ACEEE) in scenario development and the promotion of its findings. We use AVERT to simulate changes in electricity demand and emissions and CMAQ and BenMAP to evaluate air quality and mortality outcomes.

Results show that a 15% energy efficiency scenario could save an average 175 and 300 hundred premature deaths annually from exposure to O_3 and $PM_{2.5}$ respectively. Emissions reductions accrue nationwide and total 13.2% for NO_X, 12.6% for SO_2, and 11.6% for CO_2 over the summer while generation decreases 12% over that same time period. Concentrations of O_3 and $PM_{2.5}$ decrease by 0.45% and 0.55% on average nationwide. In addition, it could be a useful strategy for counties out of attainment with the National Ambient Air Quality Standard (NAAQS) for O_3 as 6% of counties in non-attainment are able to achieve the standard in the EE scenario. These results, like those in chapter 4, demonstrate the importance of considering energy strategies like energy efficiency and renewable energy for air quality and public health management. In addition, chapter 4 highlights the utility of the reduced-form AVERT model and results offer an opportunity to also evaluate reduced-form health impact models like the Co-Benefits Risk Assessment (COBRA) model.

5. How do renewable energy policy interventions compare to end-of-pipe technology requirements in co-mitigating greenhouse gas emissions and air pollution in a developing country like South Africa? And can the relationships defined in a data-rich region like the U.S. with sophisticated models be replicated in a less data-rich region with integrated assessment models?

In the fifth and final chapter of this dissertation, we pursue a case study comparing clean energy and traditional, technological emissions control strategies for co-managing air pollution and climate mitigation efforts in South Africa using a linked system of integrated assessment models. This allows us to test hypotheses developed with advanced models in a data-rich, developed country like the U.S. in a less data rich, developing context. This analysis was performed in residency at the International Institute for Applied Systems Analysis under the supervision of Dr. Fabian Wagner and Dr. Matthew Gidden in completion of the Young Scientists Summer Program.

In comparing power sector interventions, we consider cost, final $PM_{2.5}$ concentrations (and related mortality), and CO_2 emissions. Results show that most control strategies target precursor $PM_{2.5}$ emissions and resulting concentrations, but also have a large impact on CO_2 emissions, while investment incentives tend to have a modest impact on $PM_{2.5}$ and greater impact on CO_2 emissions. The controls scenarios unexpectedly show benefits to both CO_2 and $PM_{2.5}$ because the costs of these end-of-pipe controls reach a price threshold for the cost of traditional, coal-fired power plants that causes a rapid decline of coal-fired power by the middle of the century. Therefore, current South African air legislation may drive a transition away from coal power regardless of socioeconomic pathway.

From this work, we show the ideal policy will be a mix of air policies to quickly reduce air pollution and clean energy subsidies to drive a transition away from CO_2-heavy power plants. We also present a novel method of combining an energy systems model and an air and climate integrated assessment model using a linked programming interface that includes the cost of controls in energy system optimization and a heat rate penalty from the installation of end-of-pipe controls in energy and emissions calculations. This type of configuration could be used in the future for planning and risk-assessment purposes.

Cross-Cutting Insights

Analyses at the intersection of energy, air quality, climate, and health have important implications for understanding actionable, practical solutions as well as scientific approaches to pressing world issues like air pollution and climate change. This work furthers our understanding of trends, impacts, and solutions to these problems through specific scientific investigation, i.e. the role of higher temperatures, solar energy, and energy efficiency in achieving air quality and climate goals. However, this work also offers insight to high-level, overarching questions regarding the value and interpretation of science and policy. Here we explore the cross-cutting questions posed in the introduction and addressed in part by each chapter of this dissertation.

1. What is the relevance or importance of modeling for environmental policy and science?

The value of models to science and decision-making is generally accepted across fields and disciplines. Economic models are used every day in business, policy analysis, and budgeting. Engineering computer models are used in architecture, design and construction. We all rely on meteorological forecasts to tell us whether to grab an umbrella in the morning. Models are common place in our lives whether accepted or not. However, the utility of models depends greatly on the design of the model and the application of the model. As stated by the former University of Wisconsin Professor George Box, “all models are wrong, but some are useful.” In even harsher tone, Vaclav Smil refers to long-range energy forecasts as “no more than fairy tales” in discussion of optimistic assumptions used by the Intergovernmental Panel on Climate Change for informing policy decision-making.[2]

This begs the question as presented above, are models useful for the type of energy, air quality, climate, and health analysis performed here? Power flow models, electricity dispatch models, capacity planning models, demand forecasting models, building energy models, energy systems models, and integrated assessment models are all used for energy planning and management. Air quality receptor models, dispersion models, chemical transport models, emissions models, weather models, climate models, integrated assessment models, and health impact models are all used for air quality planning and management. In this dissertation many of these models are used, often together. While these models are not perfect reflections of reality, they are robust and allow us to test the impacts of many scenarios across several sectors and impacts that would not be possible or practical to test through experimentation.

The results from studies performed as part of this dissertation demonstrate the particular value of not only models in general, but linking models to assess interdependencies across energy, air quality, and public health. The research questions addressed would not be possible to test without computer models. In addition, the models are all assessed in consideration of the underlying assumptions and evaluated against real data or provided with uncertainty. While the results here are not predictions, decisions are necessary under uncertainty and this information informs these decisions and reduces that uncertainty. In many cases, the information provided is robust enough to conclude expected outcomes regardless of many assumptions.

2. How are energy science, climate science, and air quality analysis relevant to practical environmental management, public health, and policy?

Solutions-oriented research has gained prevalence in the field of environmental science in large part because of the difficulty in communicating complex and significant hazards like climate change. The effort to produce practical use-inspired research is especially prevalent in sustainability science.[3] The intent to produce use-inspired research or policy-relevant research is applicable to the research in this dissertation. Each chapter is framed around answering a specific question that provides insight to policy and decision-making in energy, air, and climate management.

In general, science – energy, climate, air pollution, and health – is extremely applicable to practical environmental management, public health, and policy. The research here is designed to bridge scientific tools and insight with practical needs. The methods in many of the chapters utilize existing tools and knowledge in new combinations to connect practice across disciplines in order to capture win-win solutions. However, good science alone typically does not encourage action. Rather, these sciences can grow to incorporate efforts to translate policy-relevant results to actionable policies and guidelines that decision-makers and practitioners across the energy, air quality, climate, and health communities. In this work, efforts were made to involve these relevant stakeholders in design and implementation of each study.

3. What is the importance of framing issues and solutions in considering air quality and climate co-management?

The framing of problems and solutions can be extremely important in many issues, but especially contentious and interdisciplinary topics. For this work, the framing of every problem, solution, and finding was considered in two main contexts. First, the results must be communicated such that stakeholders from energy, atmospheric chemistry, and public health can understand, interpret, and utilize the results. Second, the interventions and benefits of interventions can be framed across these fields, as energy interventions, climate interventions, air quality interventions, or public health interventions. This framing and the idea of co-management, used in the question posed, is central to this dissertation.

There has been a great body of research considering the air quality "co-benefits" of climate mitigation strategies.[4] This has been one of the main connections between energy policy and air quality analysis in the last several decades. However, in this work, we choose to frame energy policies as air quality management strategies first and foremost. By assessing the potential for these strategies in air quality management, climate impacts become the co-benefit. This is especially relevant to the work of chapter 5, where air quality-focused emissions control strategies and energy subsidies are both considered without any predetermination of their impacts. In fact, results show that emissions controls are most cost-effective at not only controlling air quality, but also greenhouse gas emissions for South Africa.

4. Is there a shared role for climate mitigation and adaptation that is relevant to coordinated energy and air quality planning in a changing climate?

This research demonstrates the importance of considering the synergies and tradeoffs of climate mitigation and adaptation. Energy measures (i.e. solar and energy efficiency) considered here simultaneously lower greenhouse gas emissions and reactive pollutant emissions thus mitigating climate change while reducing the impacts of exacerbated air pollution exposure expected from climate change. In addition, we see that policies for air quality, that might be considered adaptation measures, such as requiring emissions controls, can also be highly cost-effective in lowering greenhouse gas emissions. However, some measures also exhibit counteracting effects. For example, increasing air conditioning to reduce heat exposure in a warmer climate will worsen air pollution outcomes if the power for air conditioning comes from emitting sources. In this case, adaptation to one aspect of climate change hinders the ability to adapt to another aspect and increases greenhouse gas emissions. This research emphasizes the takeaway that mitigation and adaptation strategies must both be considered in response to climate change, and it is extremely important to consider interacting effects across systems such as energy, air quality, and climate in order to identify win-win solutions and quantify the relative benefits of options with tradeoffs.

5. How do perspectives differ in considering energy, air quality, and climate across population demographics, scientific disciplines, and regions of the world?

Energy, air quality, climate, and public health offer many different perspectives in issues at the intersection of each of these disciplines like examined in this dissertation. In addition, demographics are important in determining the relative benefits and costs of interventions within these disciplines. Lastly, different regions within the U.S. and worldwide have different priorities and perspectives on these issues. For example, in the U.S. there is a higher prevalence of emissions controls on power plants than in other regions of the world like South Africa. Therefore, power sector interventions might be more effective in limiting pollution in regions like South Africa. This research demonstrates opportunities for win-win solutions that benefit people across demographics, regions, and industries. Solar energy and energy efficiency for example can offer energy cost reductions, emissions reductions, air quality improvements, and health benefits. This research also demonstrates the potential benefits of interdisciplinary research and integrated planning in identifying mutually beneficial solutions.

Research Directions

Future work that may begin before or shortly after the completion of doctoral work includes an air quality assessment of additional energy interventions such as an electric vehicle transition or load smoothing techniques. In addition, more sophisticated energy efficiency scenarios would be a helpful extension of the work in chapter 4. My doctoral work also frames the possibility of several broad research directions. For example, future work may involve diversifying methods, such as expanding modeling to more sophisticated combinations of models, developing new models, utilizing more long-term, integrated assessment models, and incorporating additional observational methods. Future directions may also involve more focused study of energy, atmospheric chemistry, climate, and health issues, or exploring other geographical regions and geographical scales, such as urban-scale impacts.

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2. Smil, V. Long-range energy forecasts are no more than fairy tales. *Nature* **453**, 154–154 (2008).
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4. Nemet, G. F., Holloway, T. & Meier, P. Implications of incorporating air-quality co-benefits into climate change policymaking. *Environ. Res. Lett.* **5**, 014007 (2010).

Appendix 1: Chapter 4 Supporting Information (S4)

A single supporting information file is included with text regarding CMAQ model performance and figures and tables to support the main text. The work here has been slightly modified from the published version only to conform with formatting for the purposes of this dissertation.

CMAQ Evaluation

CMAQ results are evaluated based on monitor data collected in the Air Quality System (AQS) for 2011. The baseline CMAQ scenario is biased high for O_3 and low for $PM_{2.5}$. The model exhibits a mean bias of 9.85 ppbv or fractional bias of 19.31% for maximum daily 8-hour average (MDA8) O_3 and mean bias of -4.57 $\mu g/m^3$ or -49.57% for $PM_{2.5}$ over the model domain. Our O_3 bias is consistent with past studies, which find CMAQ O_3 positive biases up to 10 ppbv. [1] Our $PM_{2.5}$ bias is higher than past studies, which find negative biases up to 3.6 $\mu g/m^3$ [1-2]; however, our utilization of 2016 EGU emissions would be expected to yield lower $PM_{2.5}$ values than were measured in 2011 due to emissions reductions over that time. Two methods are used to minimize the impact of model biases on our results. First, results focus primarily on the difference between NoEE and EE simulations, rather than absolute concentrations. Second, we adjust model results for analysis of O_3 NAAQS attainment, by a correction factor calculated as the difference between modeled MDA8 O_3 over land and interpolated AQS monitors MDA8 O_3, based on the Poisson equation solved through relaxation. County quasi-non-attainment designations before model correction are shown in Figure S4.9. Baseline model bias is shown at monitor locations in Figure S4.10 and interpolated bias is shown in Figure S4.11. Simulated ambient concentrations are shown in Figures S4.12 and S4.13 for the baseline, NoEE and EE scenarios. Performance metrics are described in Tables S4.3 and S4.4.

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(3) U.S. Environmental Protection Agency. *AVoided Emissions and GeneRation Tool (AVERT) User Manual*; 2014; pp 1–73.

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Supporting Tables and Figures

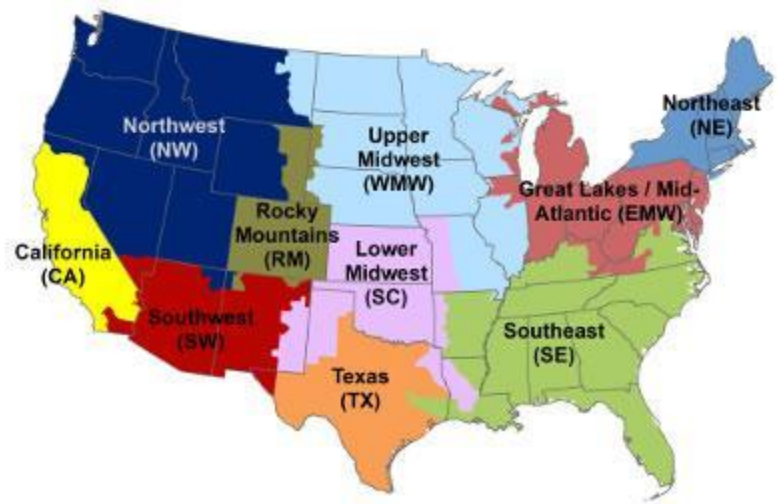


Figure S4.1: Map of AVERT regions. [3]. Generation reductions are 15% in each region. In GWh annually, reductions are: SE: 113,000; NE: 15,700; NW: 14,700; SW: 16,400; CA: 11,800; TX: 36,00; RM: 8,550; SC: 22,240; WMW: 31,600; EMW: 77,500; Total: 347,990.

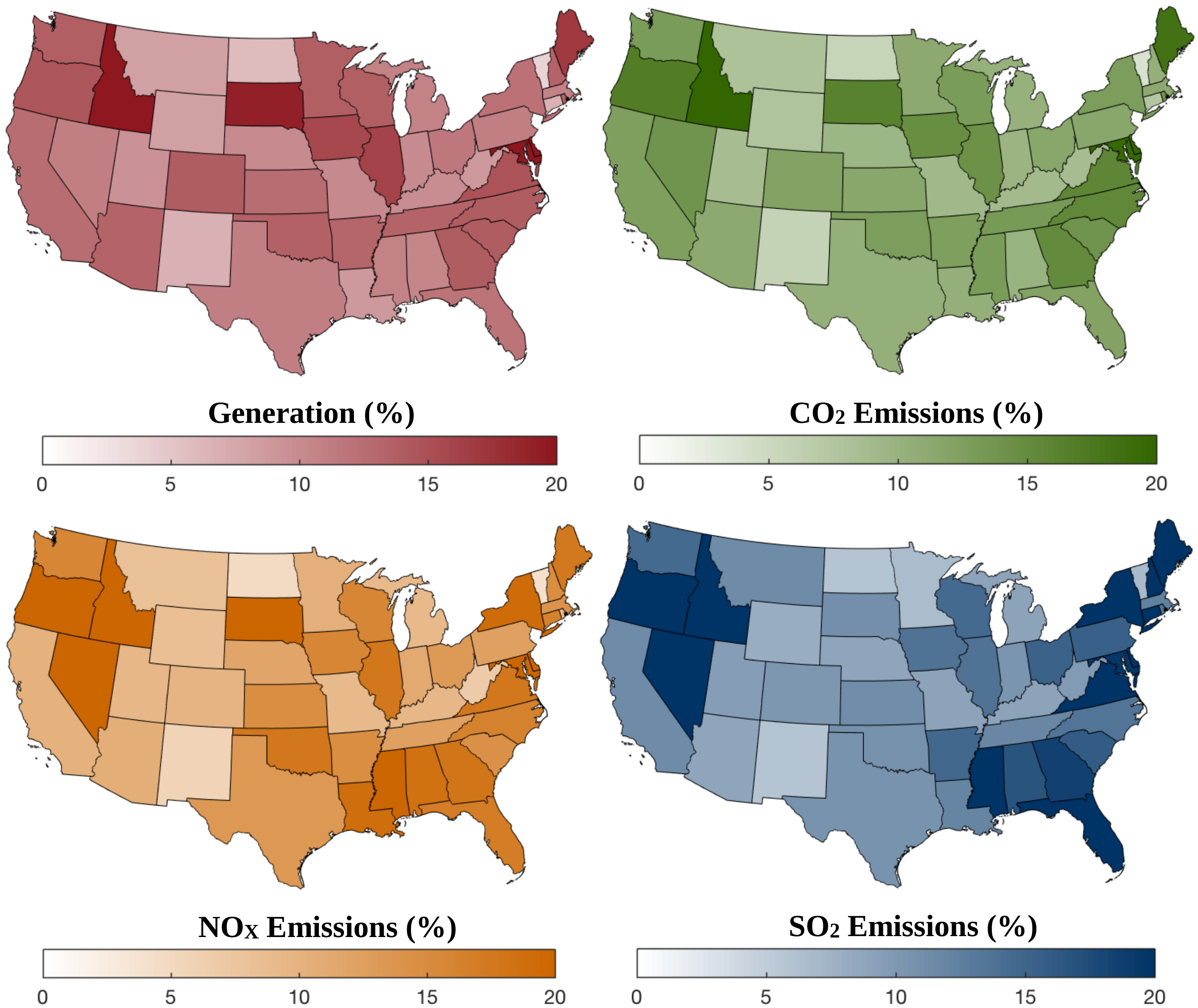


Figure S4.2: The percentage of displaced generation, CO_2 emissions, NO_X emissions, and SO_2 emissions in the EE scenario by state.

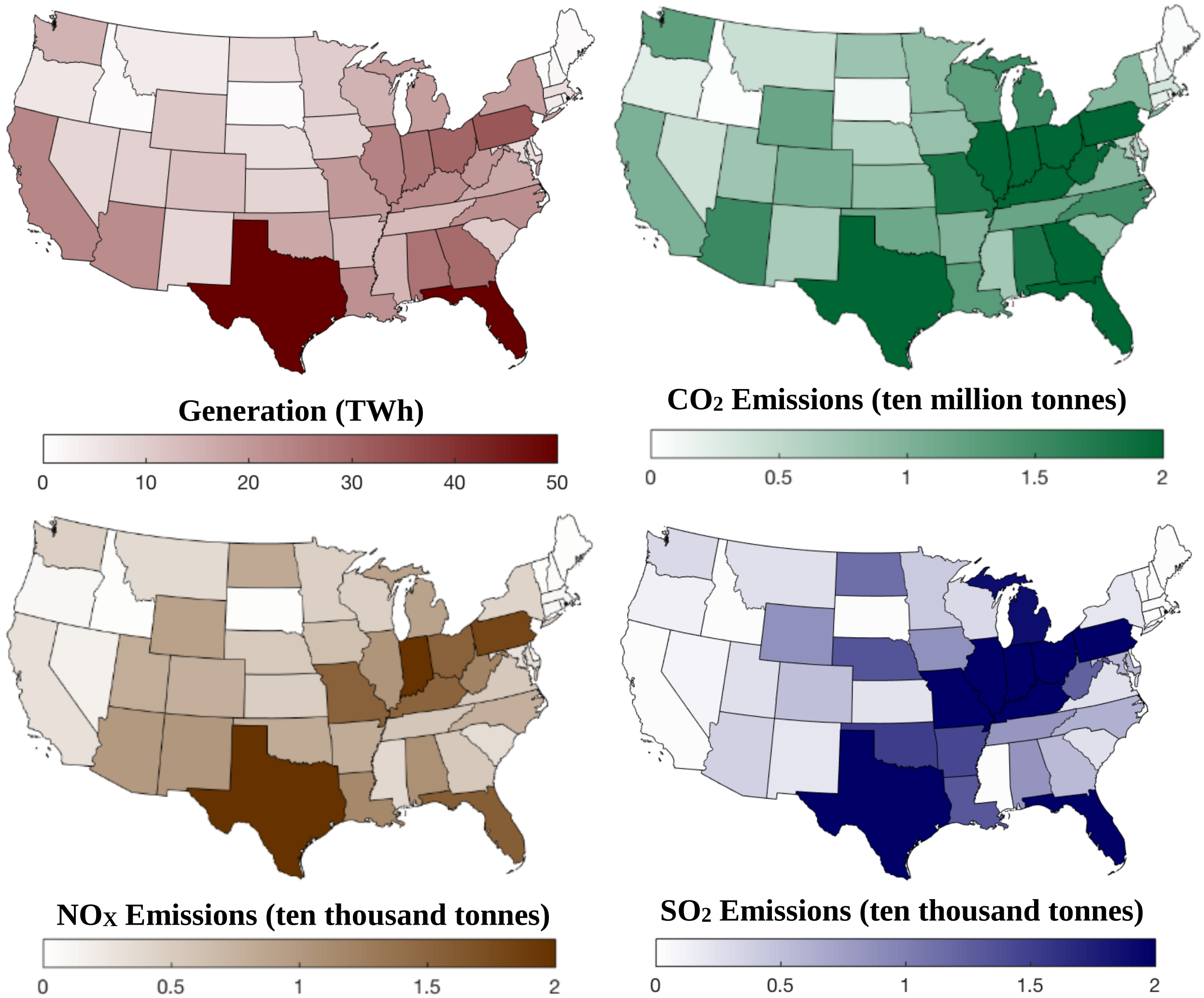


Figure S4.3: Generation and emissions of CO_2, NO_X, and SO_2 in the NoEE scenario by state.

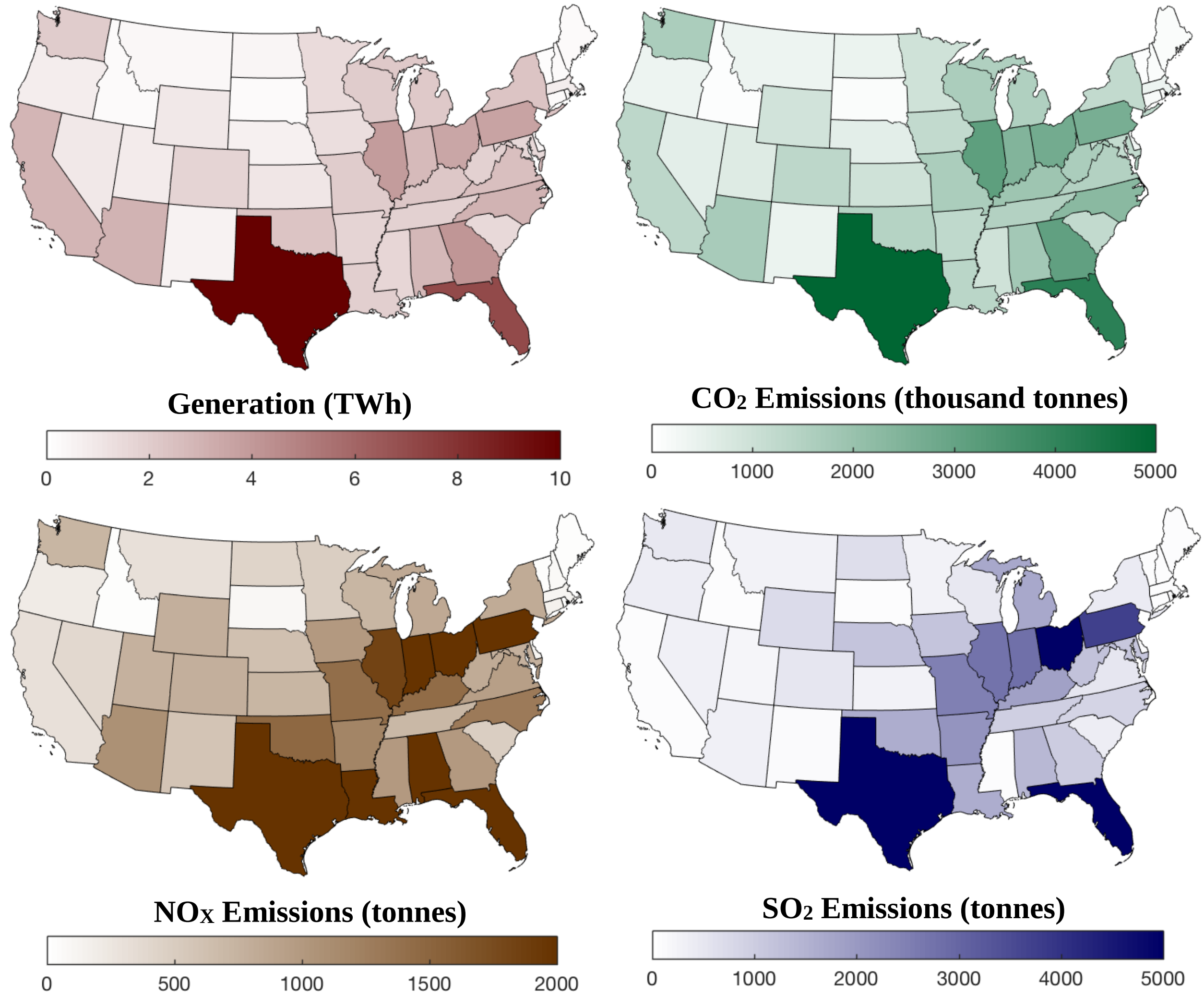


Figure S4.4: Displaced generation and emissions of CO_2, NO_X, and SO_2 from energy efficiency by state.

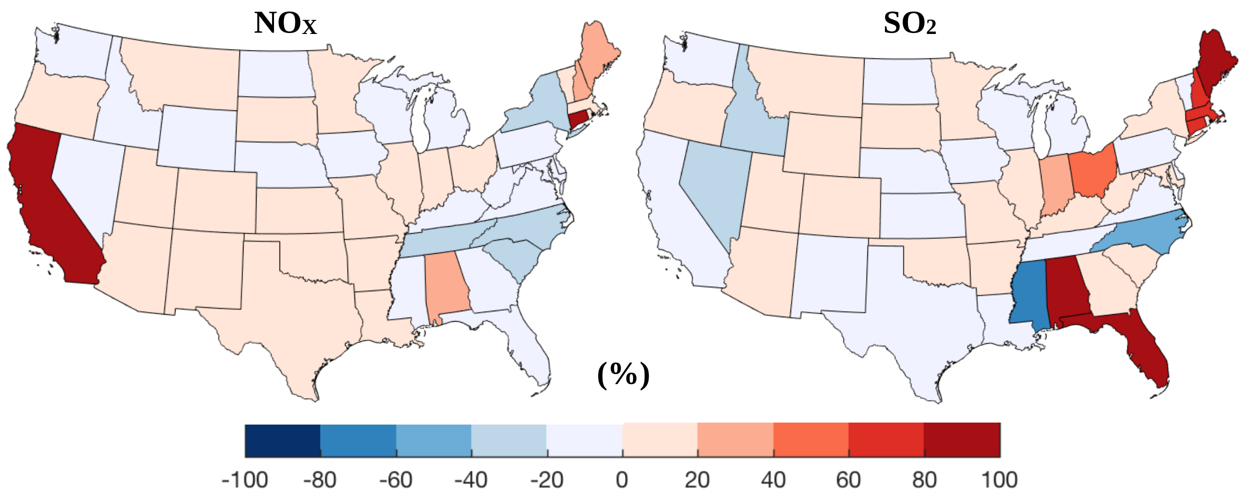


Figure S4.5: Comparison between 2016 measured power plant emissions reported in the EPA's Air Markets Program and modeled 2016 power plant emissions from AVERT.

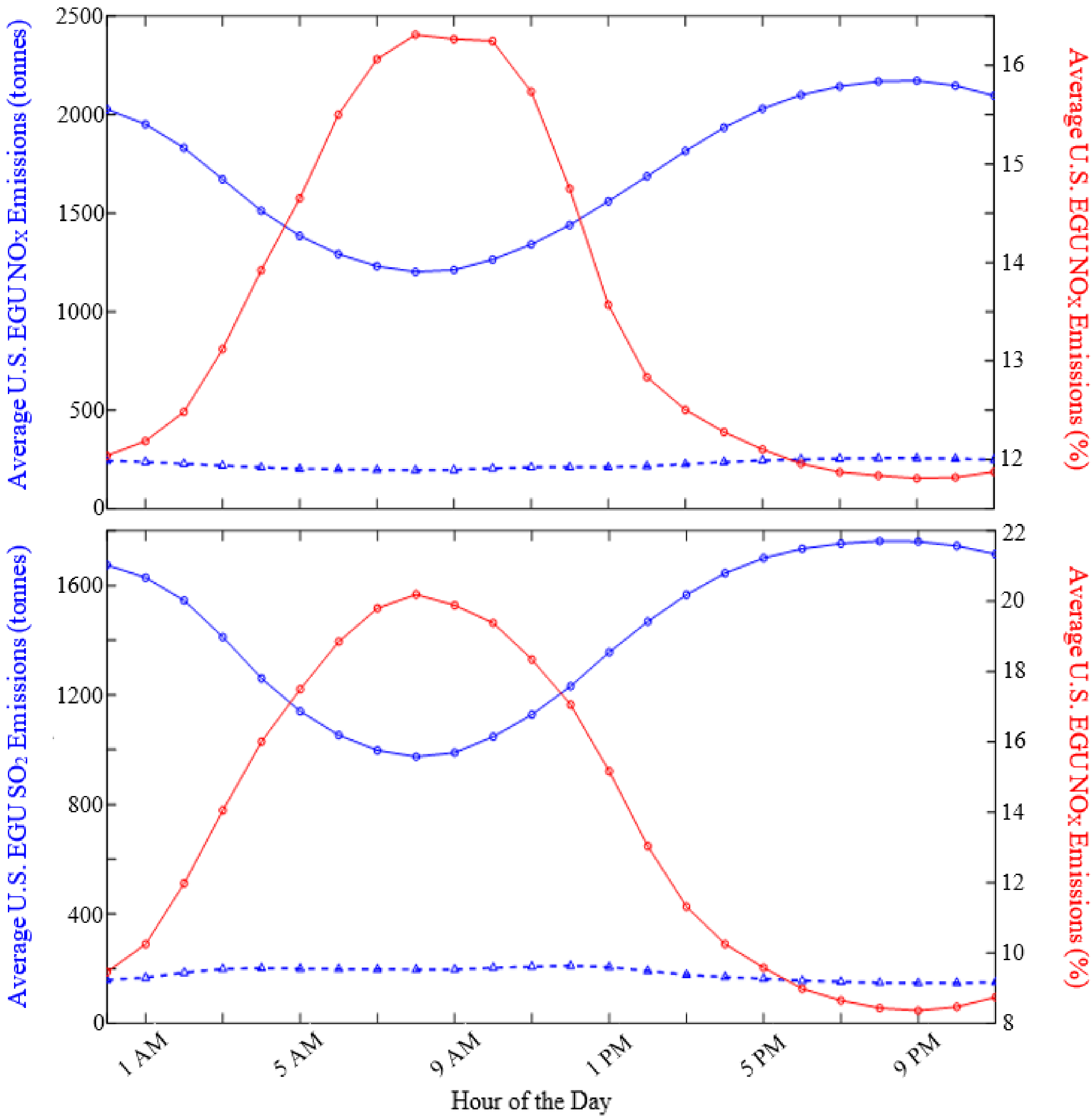
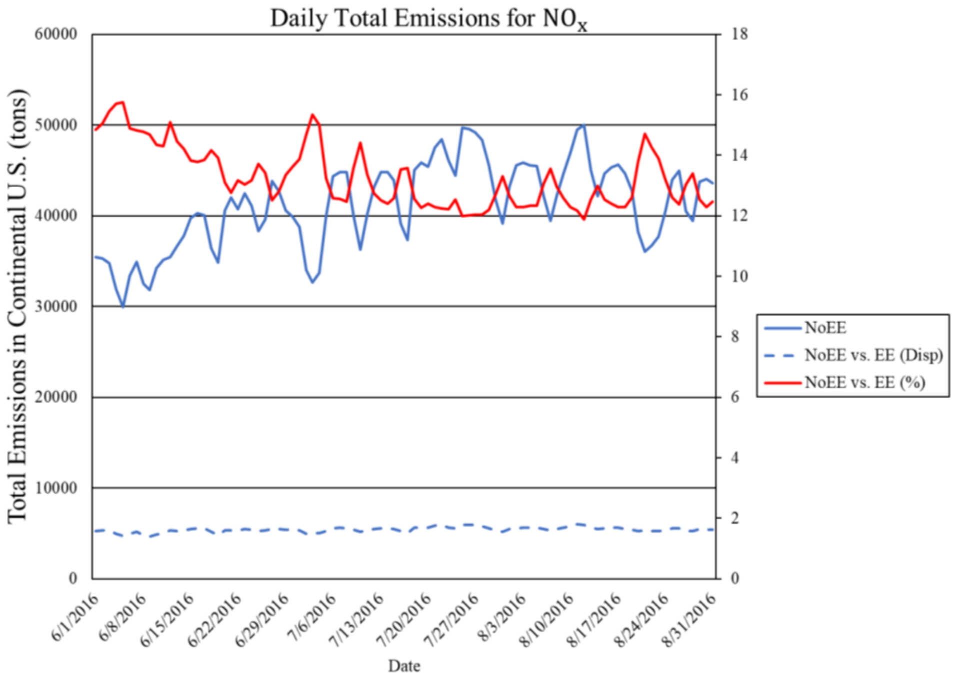


Figure S4.6: Diurnal profile of emissions of NO_X and SO_2 from U.S. power plants in June, July and August



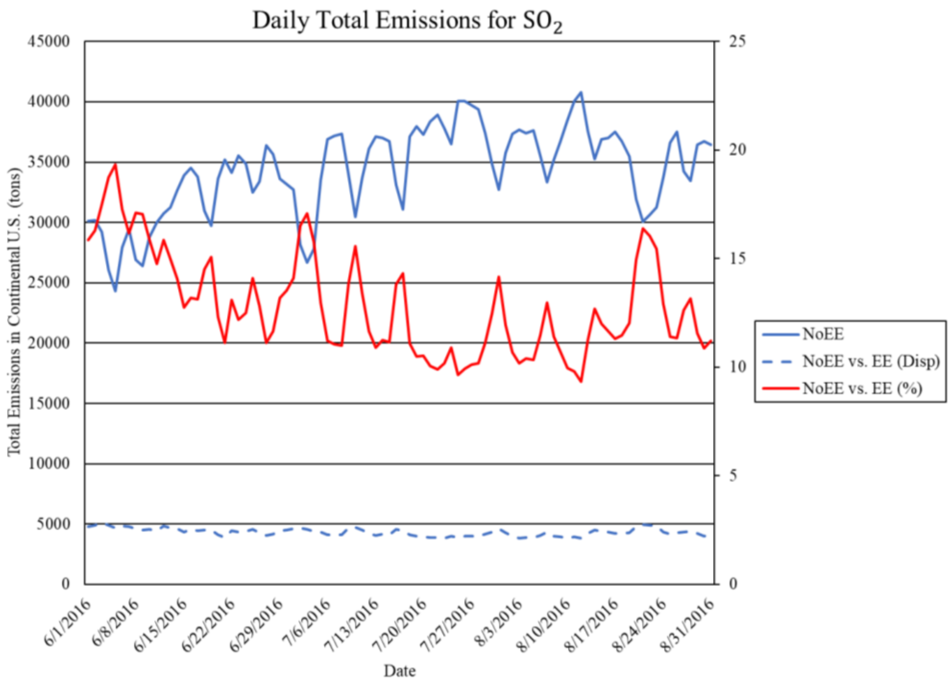


Figure S4.7: Total U.S. EGU emissions of NO_X and SO_2 by day over the summer in the NoEE case and the displaced emissions in the EE case on an absolute- and percentage-basis.

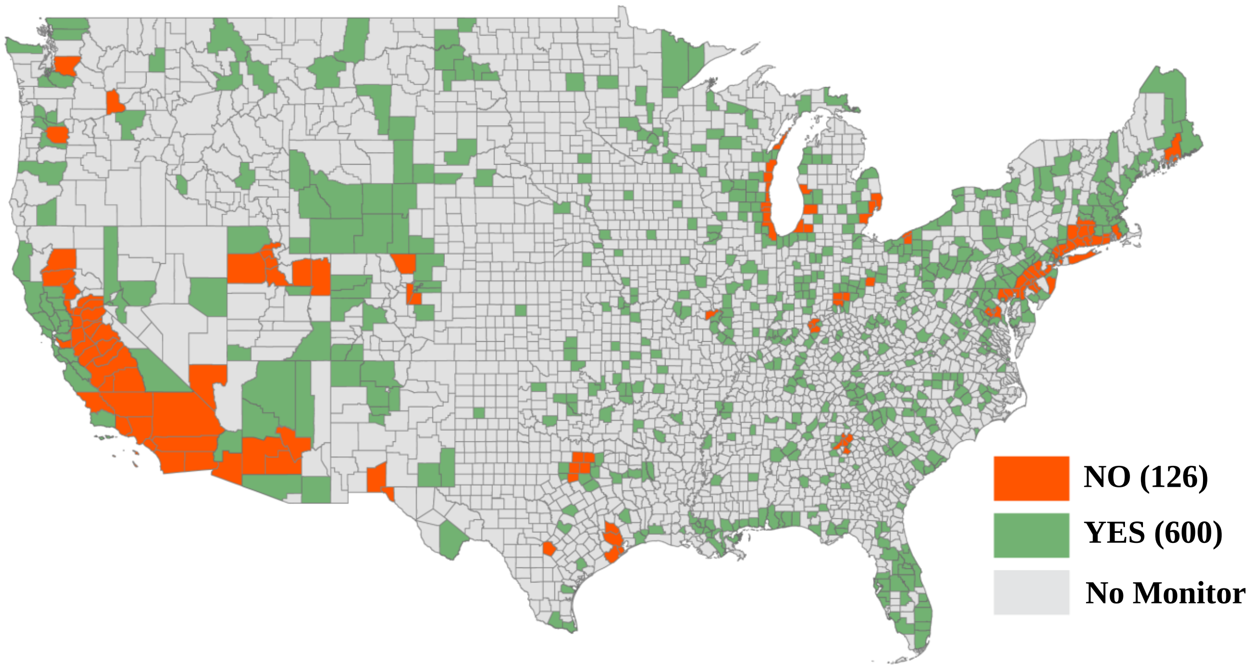


Figure S4.8: Attainment designations for the 2015 O3 NAAQS based on 2015-2017 design values. No is non-attainment, Yes is attainment, and grey counties have no designation because there is not a monitor within the county. Data from: https://www.epa.gov/air-trends/air-quality-design-values.

State	Counties Flipped from Non-Attainment to Attainment
Alabama	4
Colorado	3
Georgia	1
Illinois	5
Indiana	7
Kansas	4
Kentucky	4
Maryland	1
Michigan	1
Missouri	1
New Jersey	2
North Carolina	2
Ohio	3
Oklahoma	2
Pennsylvania	1
Texas	3
Utah	1

Table S4.1: Counties flipped from quasi-non-attainment to quasi-attainment through EE by state using model designations after being corrected for monitor bias. These designations are based on the 2015 MDA8 O_3 NAAQS and do not reflect actual EPA designations.

C-R Function Source	Health Endpoint	Metric	Age Range	Avoided Mortality incidence (95% CI)	Valuation (95% CI) [million $]
Expert B [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	333 (7, 738)	3100 (43, 12400)
Expert F [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	279 (135, 442)	2600 (228, 7500)
Expert K [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	27 (0, 162)	300 (0, 2000)
Expert L [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	209 (0, 552)	1900 (1, 8000)
Expert A [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	456 (53, 940)	4200 (212, 14300)
Expert C [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	359 (87, 638)	3300 (240, 10300)
Expert D [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	252 (0, 432)	2300 (0, 7400)
Expert E [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	593 (214, 942)	5500 (455, 16100)
Expert G [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	210 (0, 397)	1900 (0, 7100)
Expert H [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	262 (0, 745)	2400 (0, 10000)
Expert I [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	355 (0, 632)	3300 (0, 10500)
Expert J [4]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	289 (22, 669)	2700 (107, 9600)
Krewski et al. [5]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	30 to 99	175 (118, 232)	1600 (151, 4400)
Lepeule et al. [6]	Mortality, all causes	$PM_{2.5}$ (24-hour mean)	25 to 99	402 (200, 603)	3700 (330, 10600)
Bell et al. [7]	Mortality, all causes	O_3 (MDA8)	0 to 99	170 (81, 259)	1600 (139, 4500)
Levy et al. [8]	Mortality, all causes	O_3 (MDA8)	0 to 99	240 (164, 315)	2200 (208, 6000)
Zanobetti and Schwartz [9]	Mortality, all causes	O_3 (MDA8)	0 to 99	109 (58, 159)	1000 (89, 2800)
Average	**Mortality, all causes**	**$PM_{2.5}$ (24-hour mean)**	**30 to 99**	**300 (60, 580)**	**2800 (126, 9300)**
Average	**Mortality, all causes**	**O_3 (MDA8)**	**0 to 99**	**173 (101, 244)**	**1600 (145, 4500)**

Table S4.2: Reduction in mortality incidence and valuation based on summertime O_3 and $PM_{2.5}$ exposure summed across the contiguous U.S.

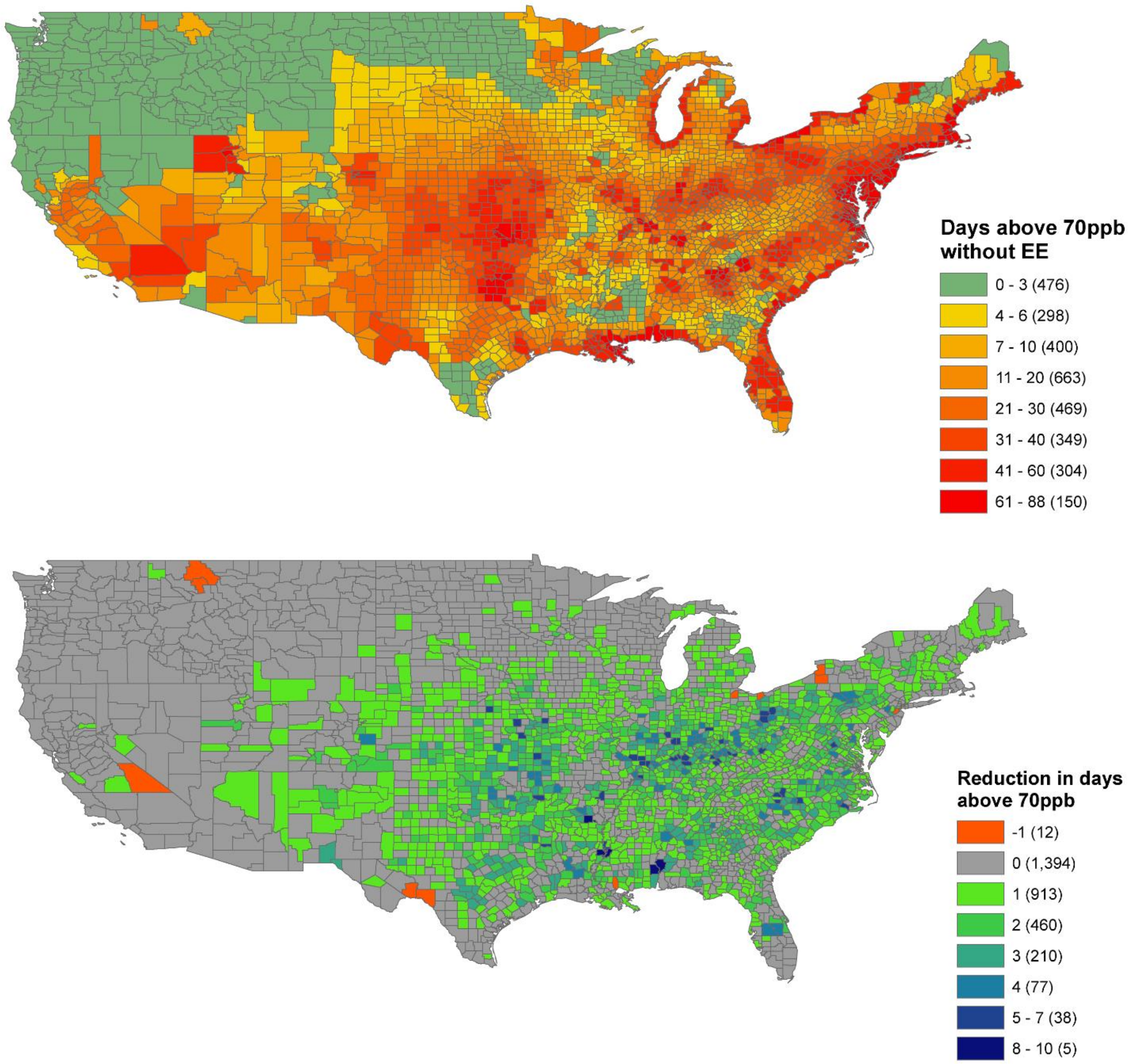


Figure S4.9: O_3 exceedance-days by county a) in the base case, and b) avoided through energy efficiency. Figures are NOT adjusted for model bias. Positive numbers in b) are number of exceedance days less with energy efficiency.

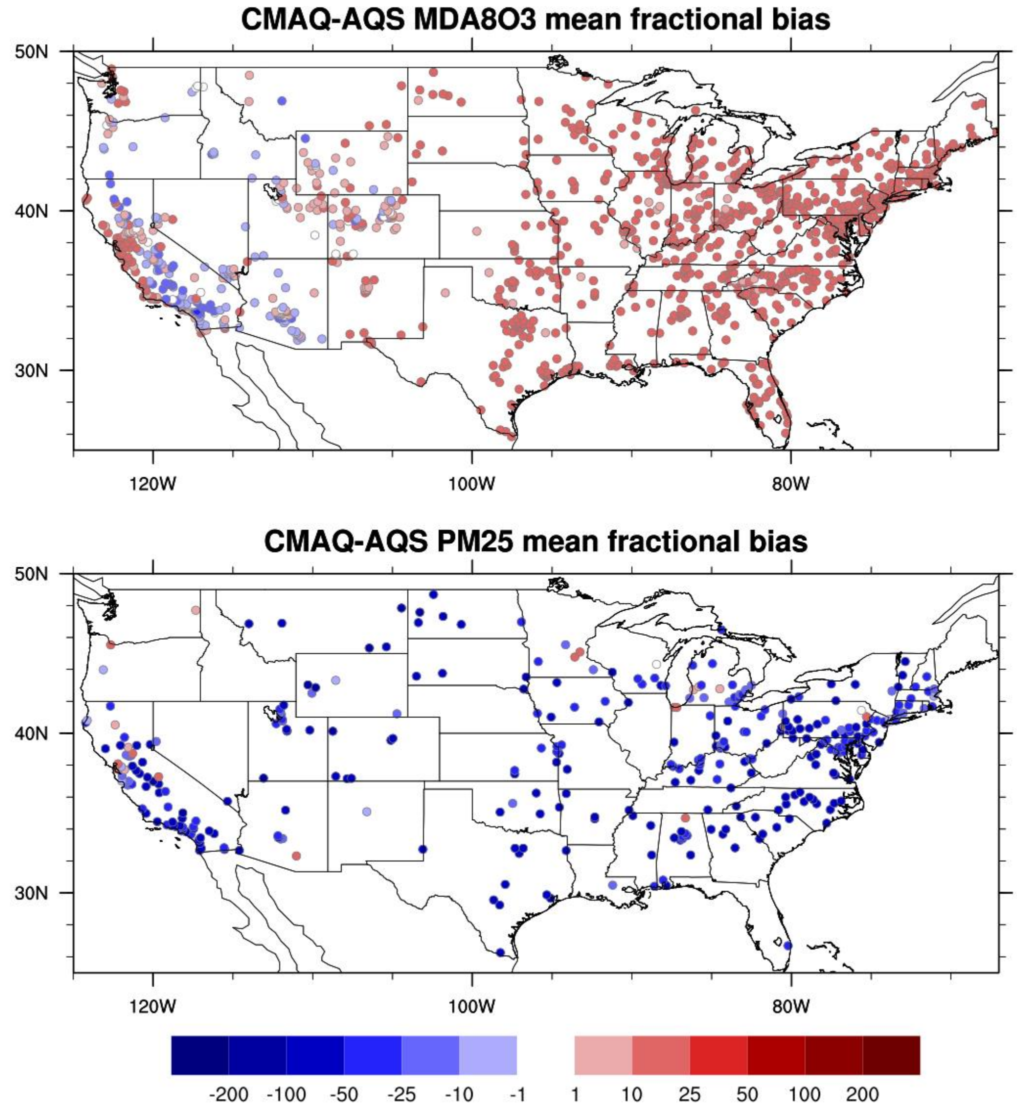


Figure S4.10: Mean fractional bias (%) between baseline CMAQ model simulated MDA8 O_3 and $PM_{2.5}$ compared with Air Quality System (AQS) monitors at monitor locations.

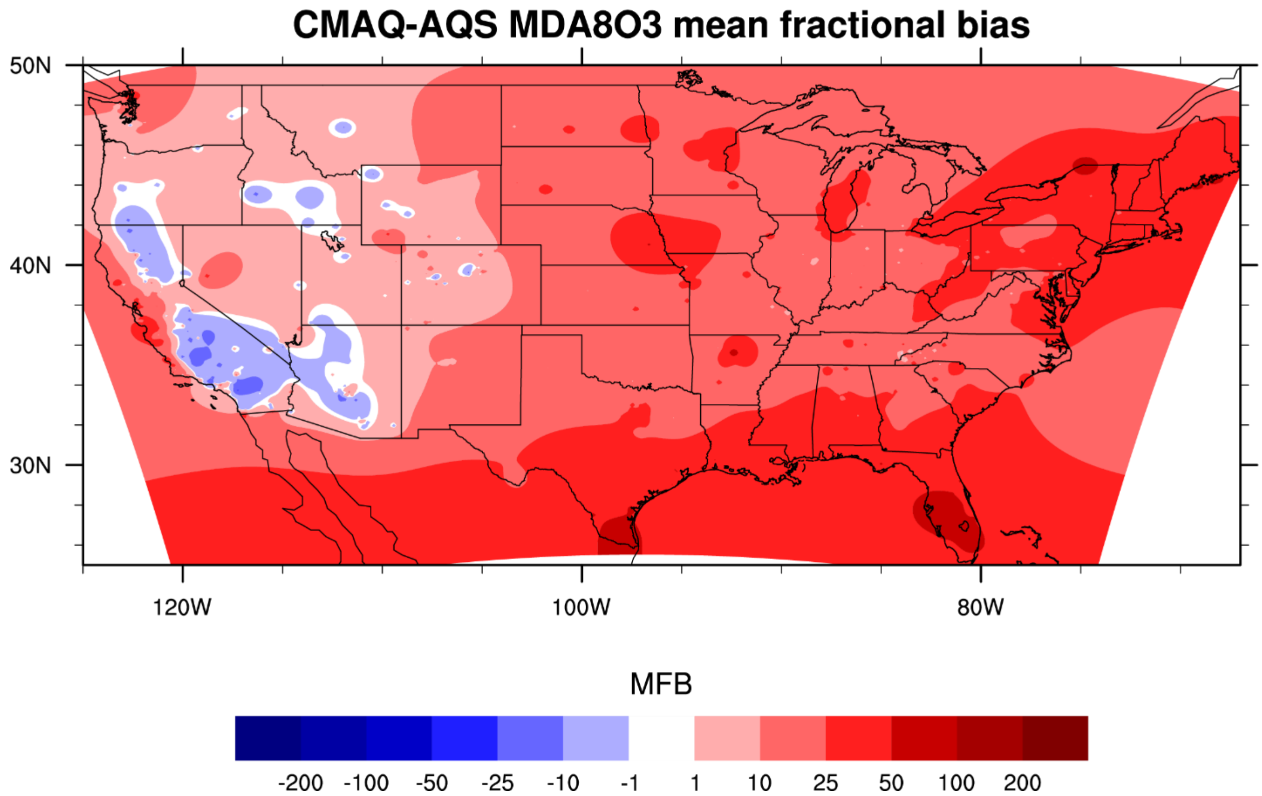


Figure S4.11: The mean fractional bias of baseline CMAQ performance (based on 2011 NEI) as compared to AQS monitors as a percentage interpolated solving the Poisson equation using relaxation.

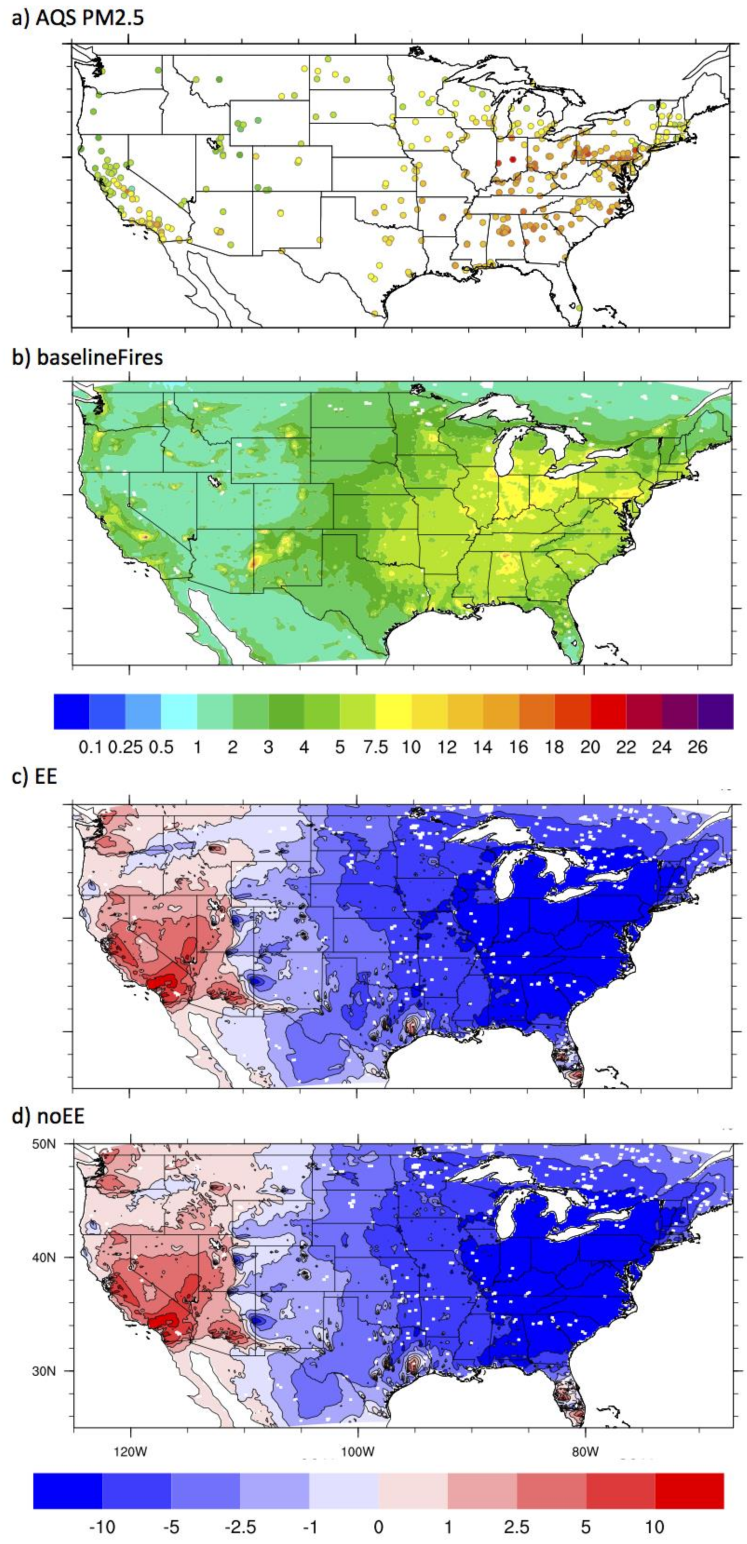


Figure S4.12: Summertime average $PM_{2.5}$ concentrations measured in µg/m^3 a) at AQS monitor sites and b) in the baseline CMAQ simulation with fires. The difference (%) in concentration is shown for c) EE against the baseline and d) NoEE against the baseline where positive is higher in the EE/NoEE simulations

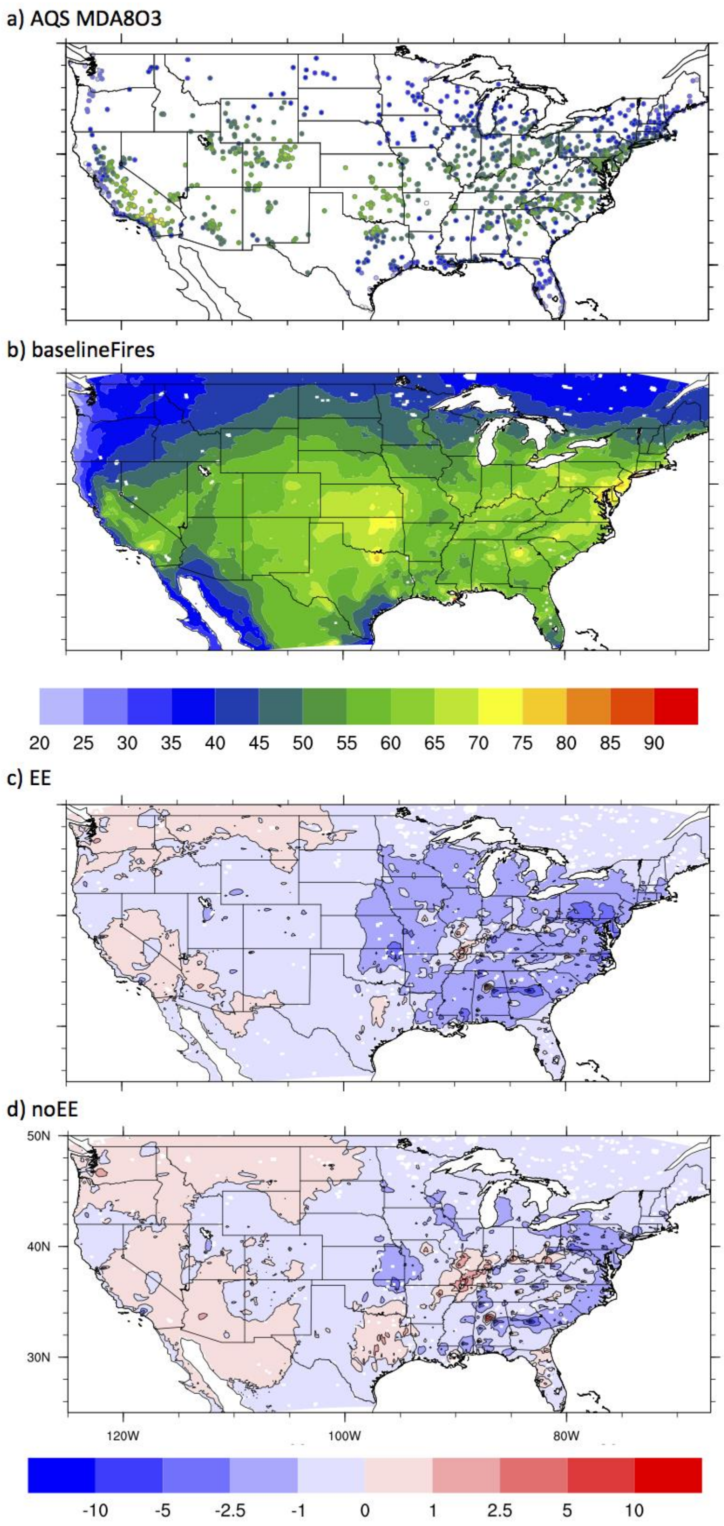


Figure S4.13: Summertime average MDA8 O_3 concentrations measured in ppbv a) at AQS monitor sites and b) in the baseline CMAQ simulation with fires. The difference (%) in concentration is shown for c) EE against the baseline and d) NoEE against the baseline where positive is higher in the EE/NoEE simulations

MDA8 ozone:

	average	RMSE	mean error	mean fractional error (%)	mean bias	mean fractional bias (%)	correlation
AQS	49.057						
CMAQ baselineFires	(52.106) 59.349	15.669	13.036	24.954	9.852	19.309	0.507
CMAQ EE	(51.773) 58.775	15.238	12.624	24.393	9.283	18.483	0.498
CMAQ noEE	(51.956) 59.055	15.454	12.829	24.685	9.561	18.899	0.499

Table S4.3: Model performance compared to AQS monitor data for MDA8 O_3 concentrations in each simulation. Averages in parentheses indicate domain-wide averages, excluding gridpoints over water. All units ppbv unless indicated otherwise.

$PM_{2.5}$:

	average	RMSE	mean error	mean fractional error (%)	mean bias	mean fractional bias (%)	correlation
AQS	10.759						
CMAQ baselineFires	(3.363) 6.331	6.457	5.157	58.814	-4.568	-49.570	0.461
CMAQ EE	(3.093) 5.733	6.979	5.669	65.087	-5.169	-56.731	0.440
CMAQ noEE	(3.115) 5.777	6.941	5.631	64.557	-5.125	-56.124	0.441

Table S4.4: Model performance compared to AQS monitor data for $PM_{2.5}$ concentrations in each simulation. Averages in parentheses indicate domain-wide averages, excluding gridpoints over water. All units µg/m^3 unless indicated otherwise.

Appendix 2: Chapter 5 Supporting Information (S5)

Supporting Information from Chapter 5 includes 4 added appendices with 23 added figures and tables. The work here will likely be modified for submission for publication in Energy Policy and has been slightly modified from the version submitted as the final report in completion of the International Institute for Applied Systems Analysis' Young Scientists Summer Program in order to conform to formatting for the purposes of this dissertation.

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Appendix 2.A: SSP Scenario Plots

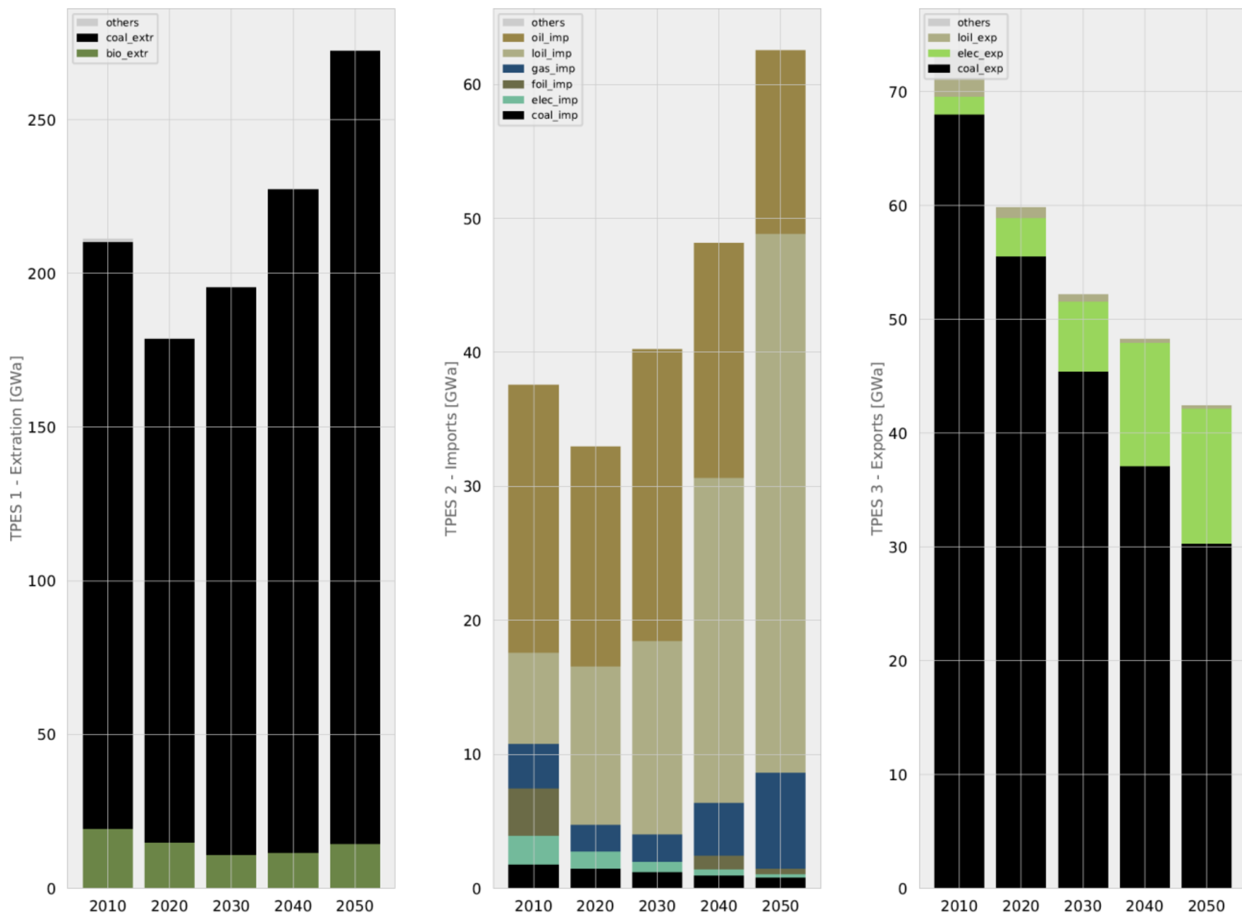

Figure S5.A1: SSP2 Total Primary Energy Supply

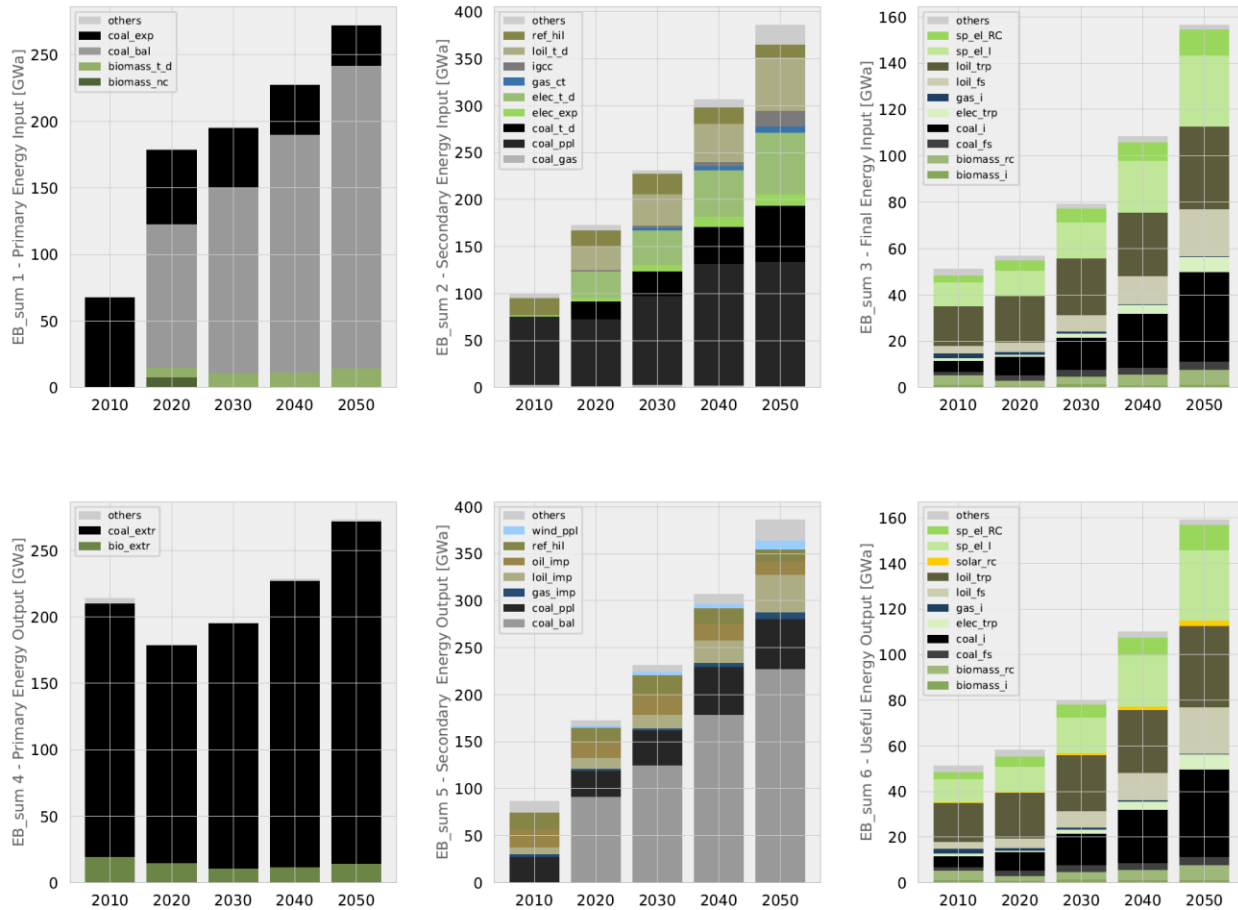

Figure S5.A2: SSP2 Energy Balance

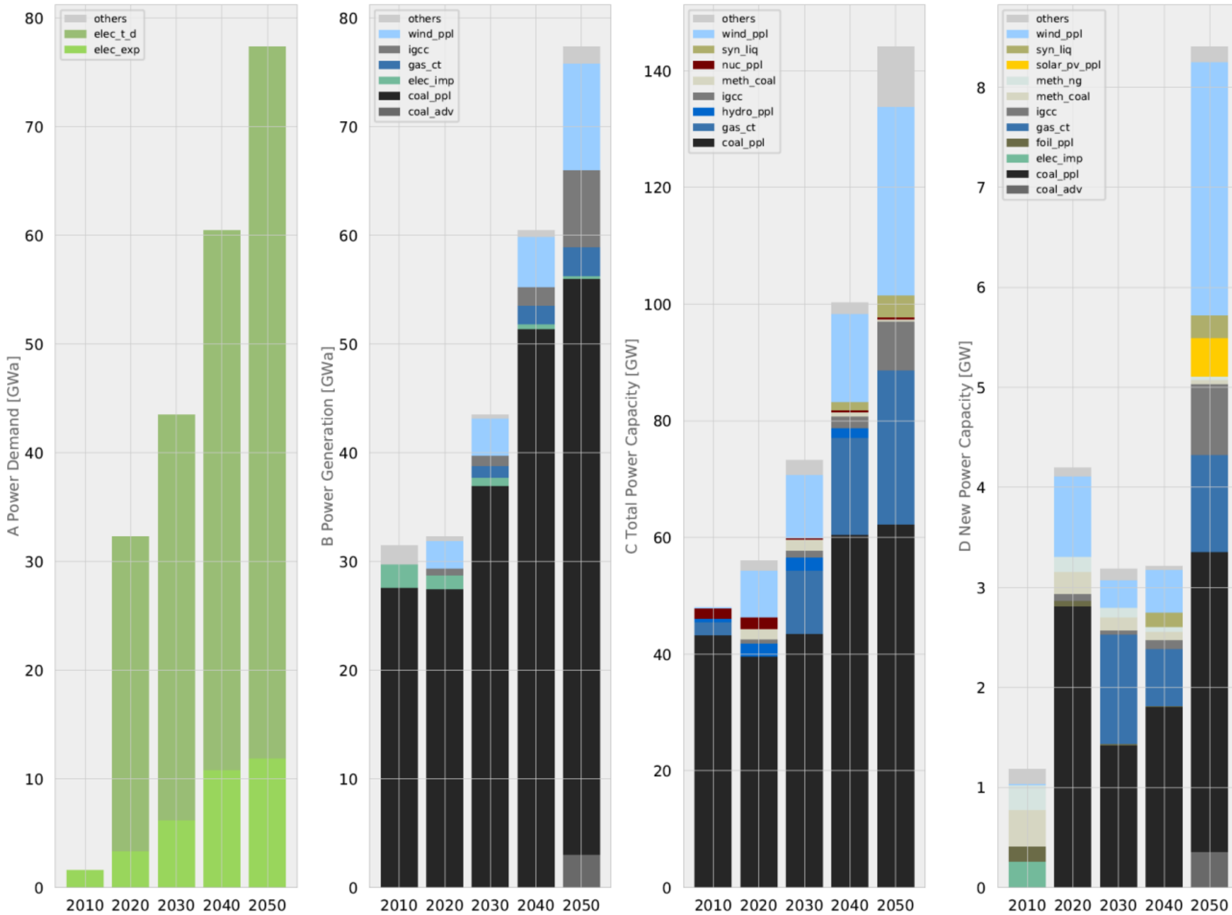

Figure S5.A3: SSP2 Power Sector

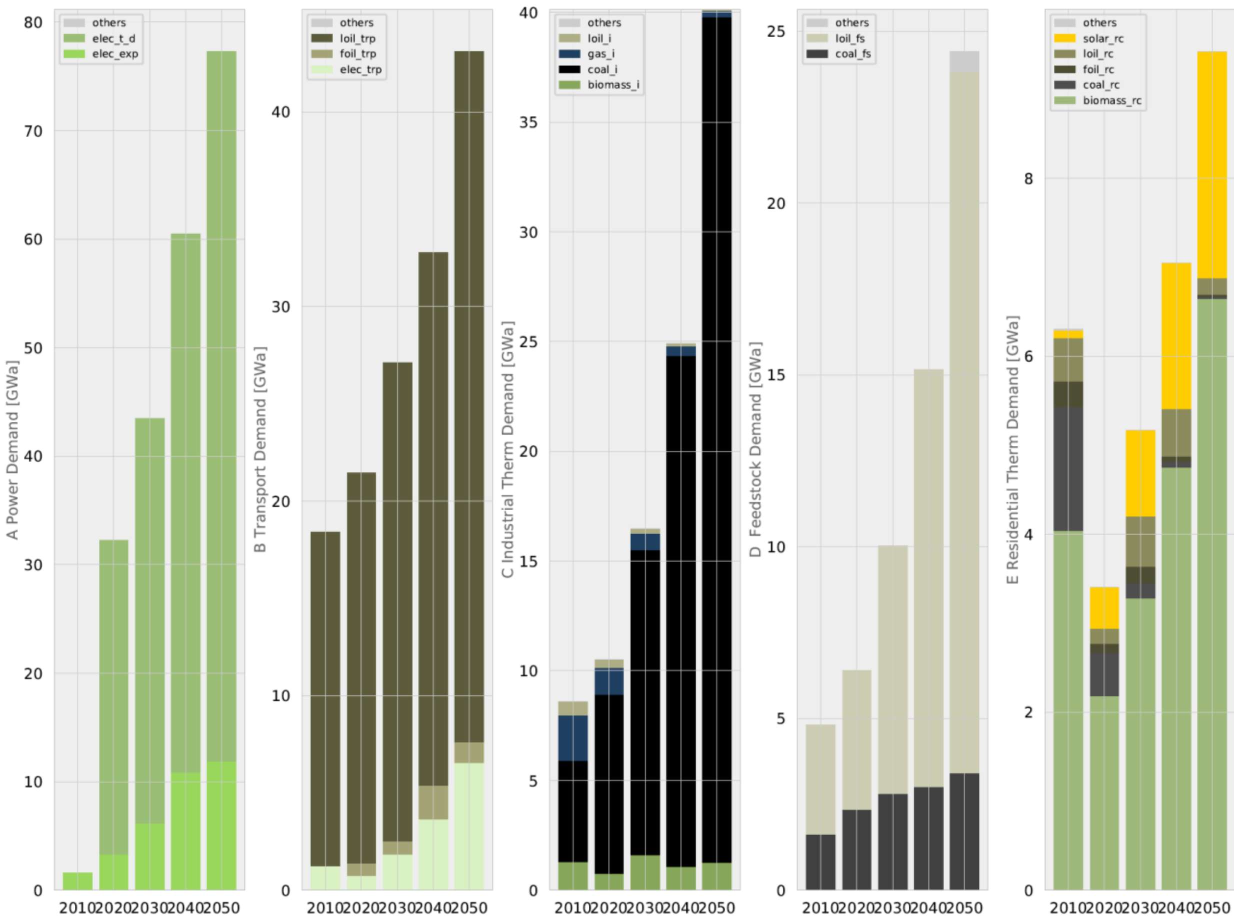

Figure S5.A4: SSP2 Demand

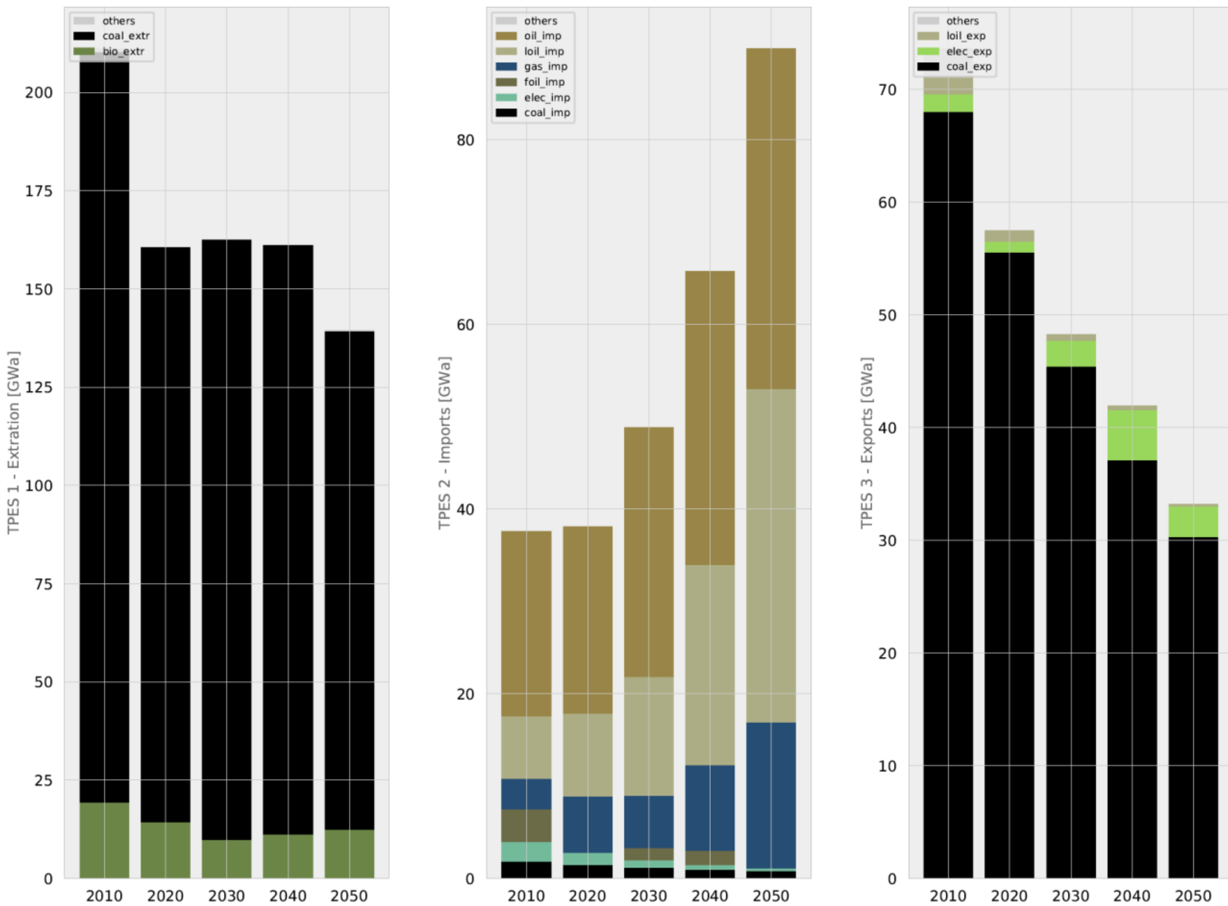

Figure S5.A5: SSP1 Total Primary Energy Supply

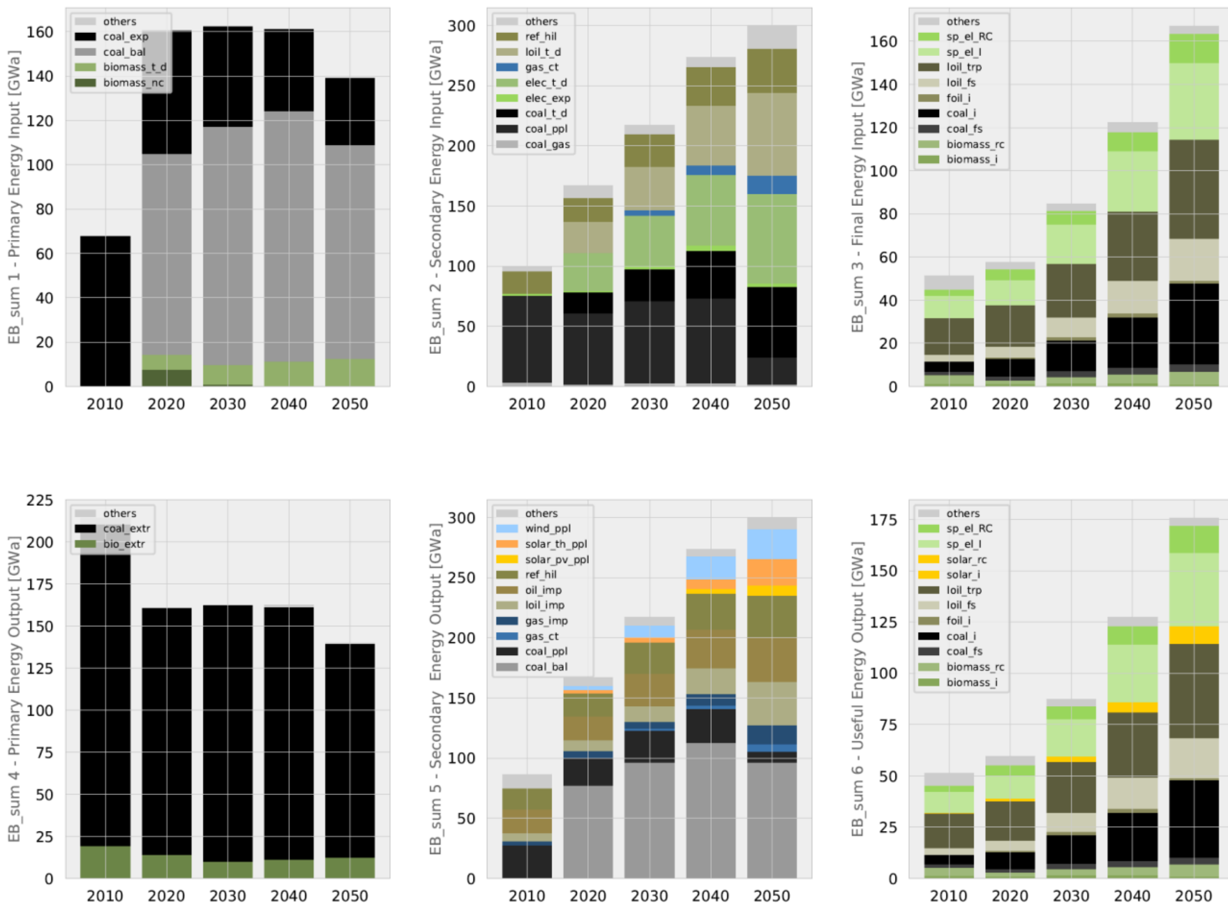

Figure S5.A6: SSP1 Energy Balance

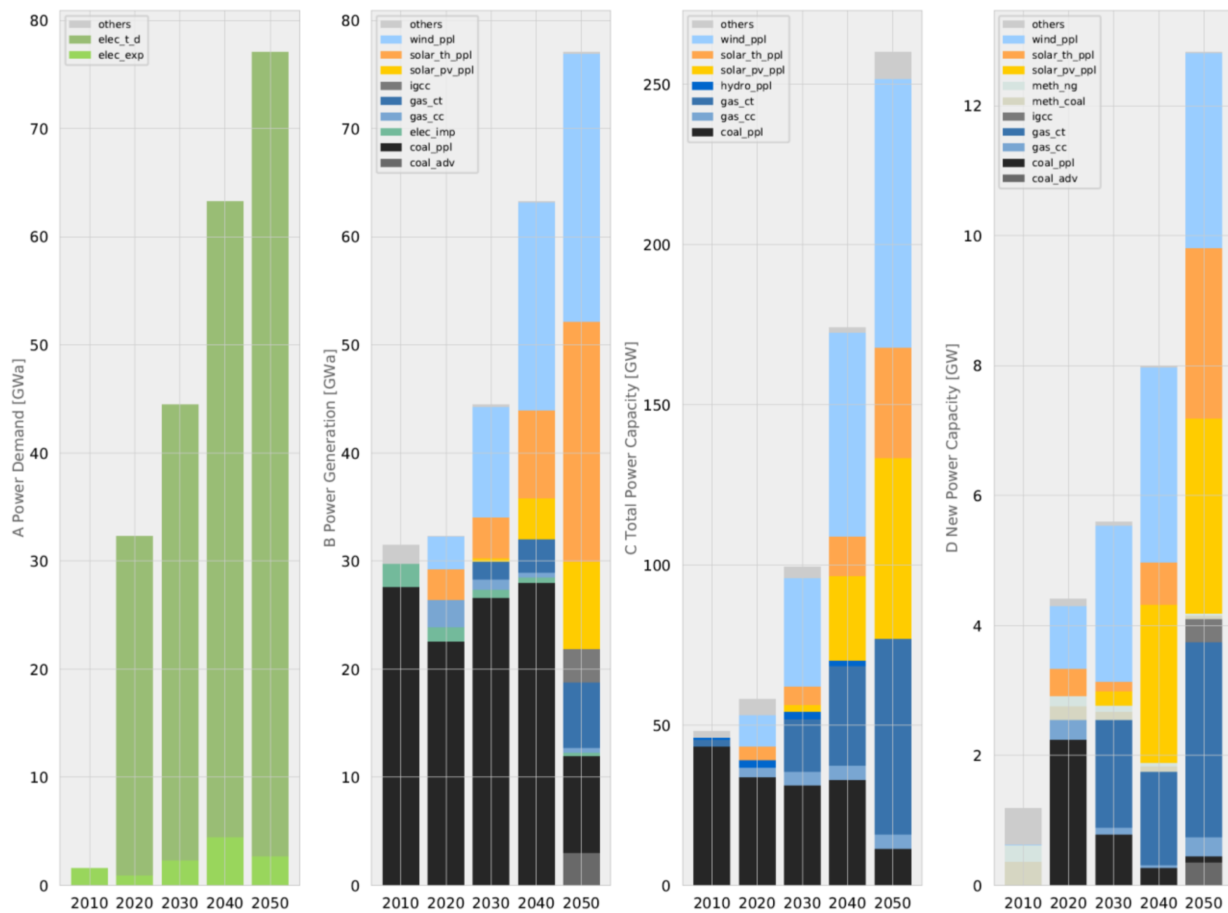

Figure S5.A7: SSP1 Power Sector

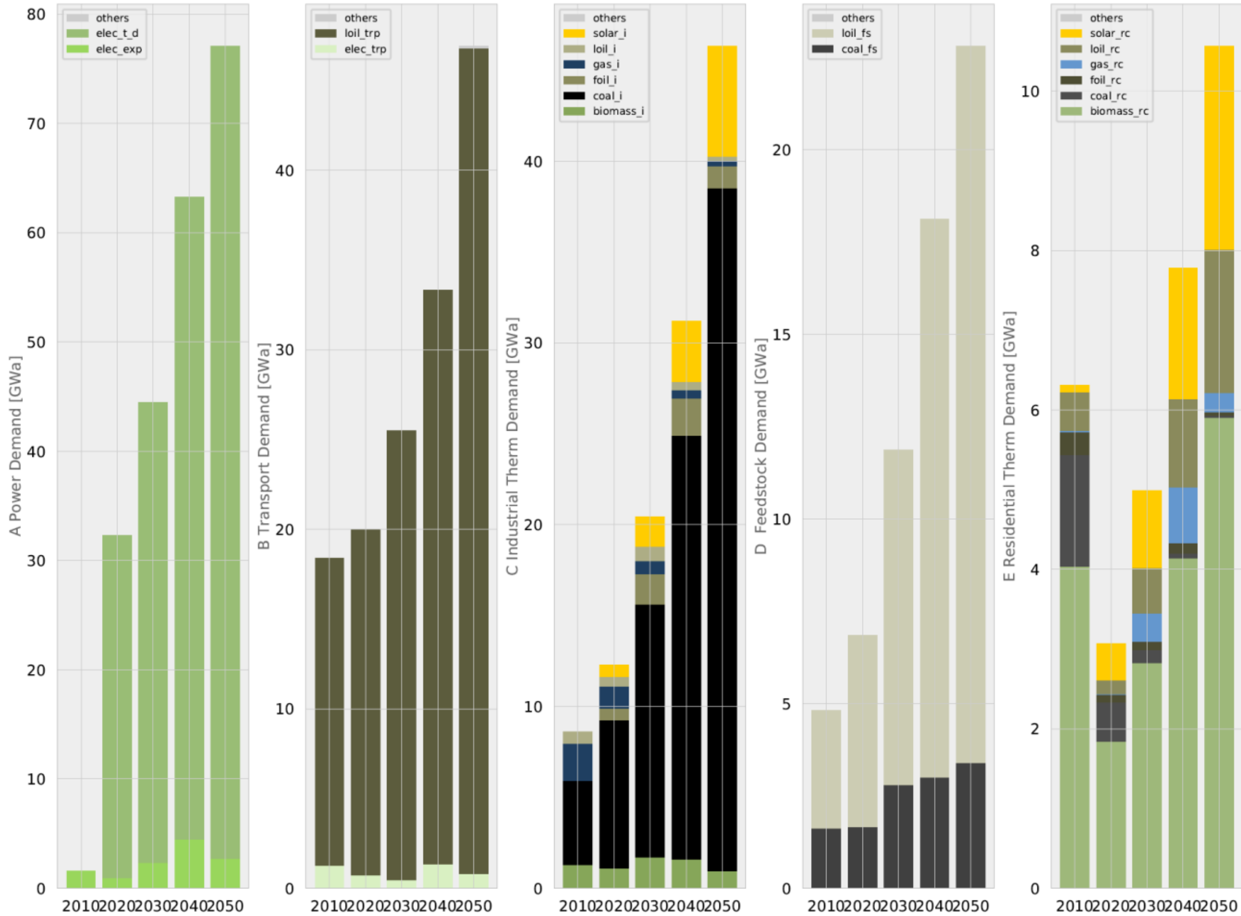

Figure S5.A8: SSP1 Demand

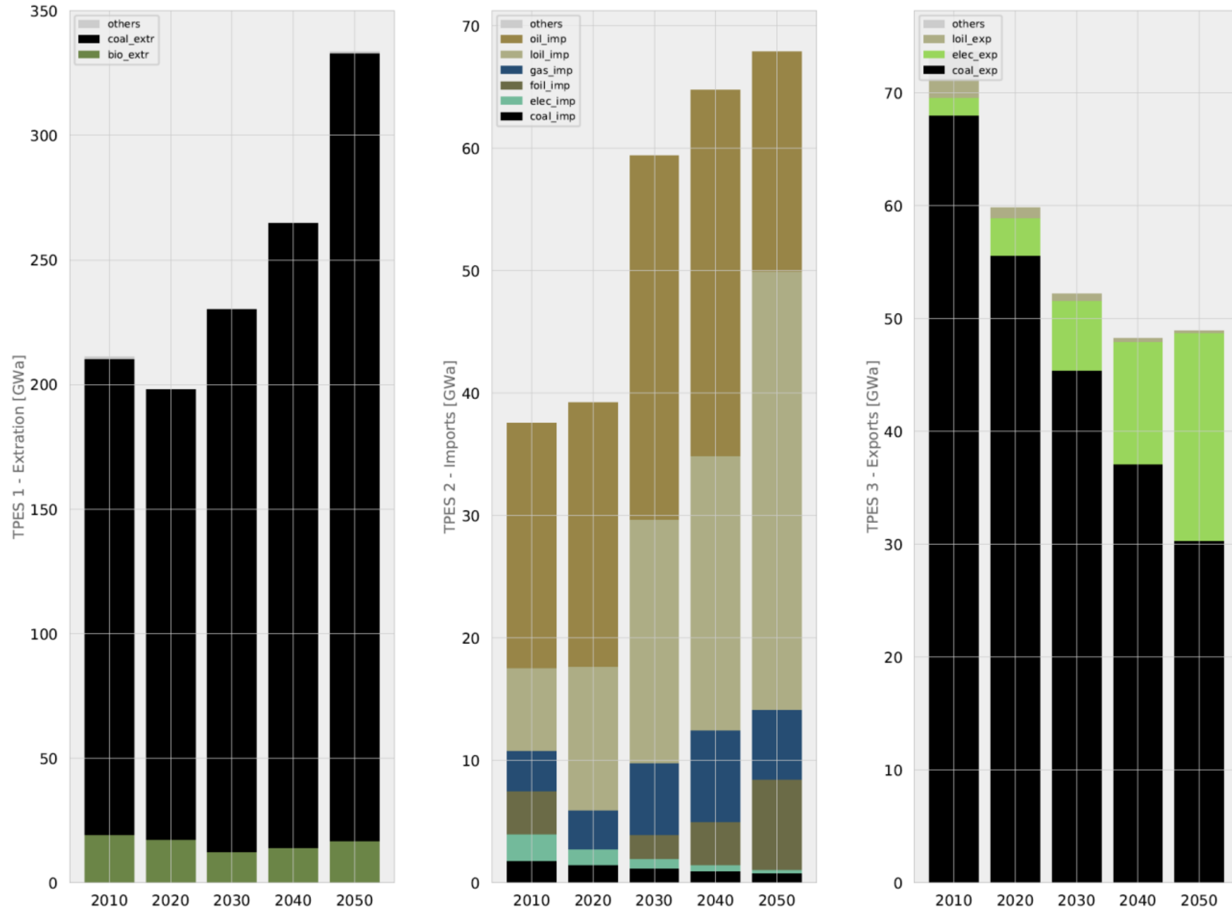

Figure S5.A9: SSP3 Total Primary Energy Supply

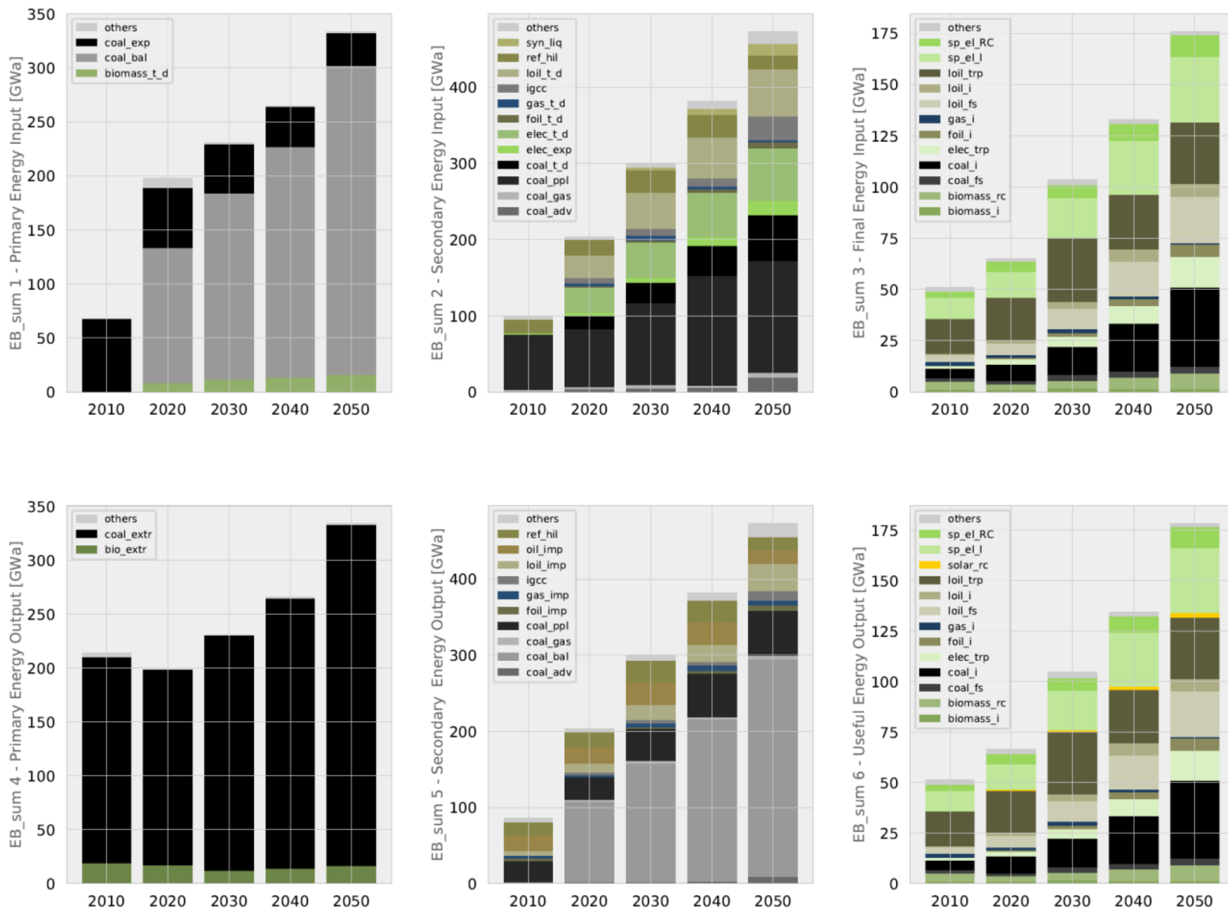

Figure S5.A10: SSP3 Energy Balance

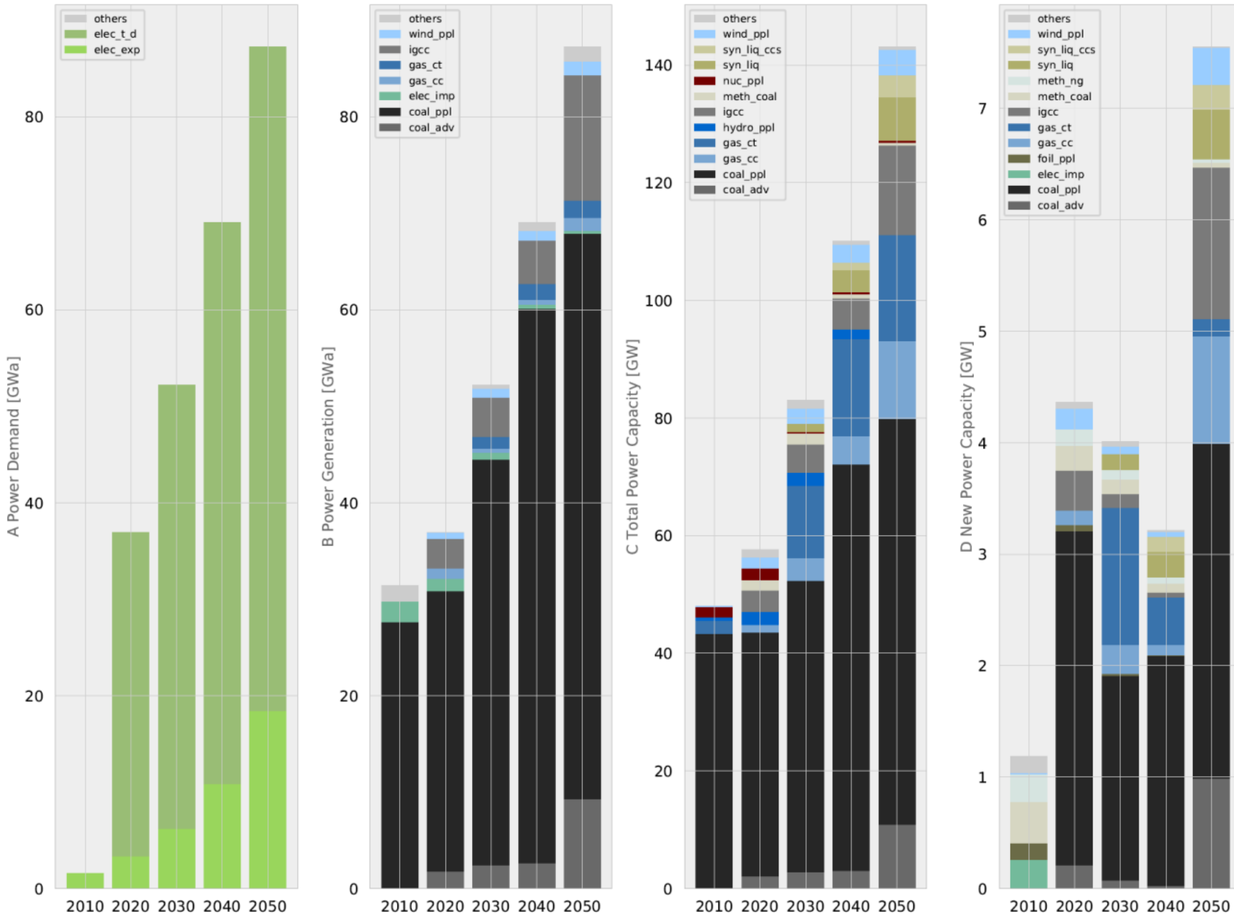

Figure S5.A11: SSP3 Power Sector

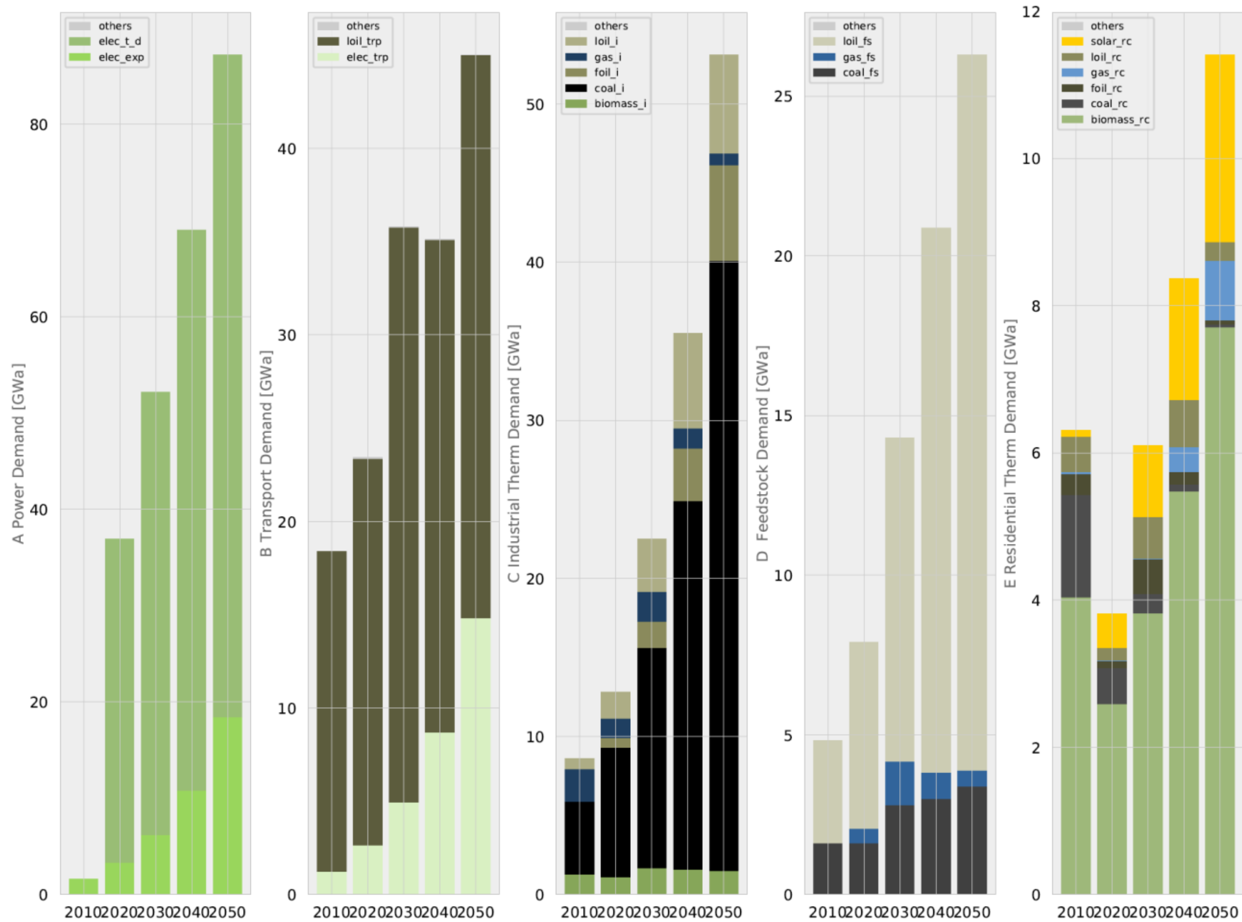

Figure S5.A12: SSP3 Demand

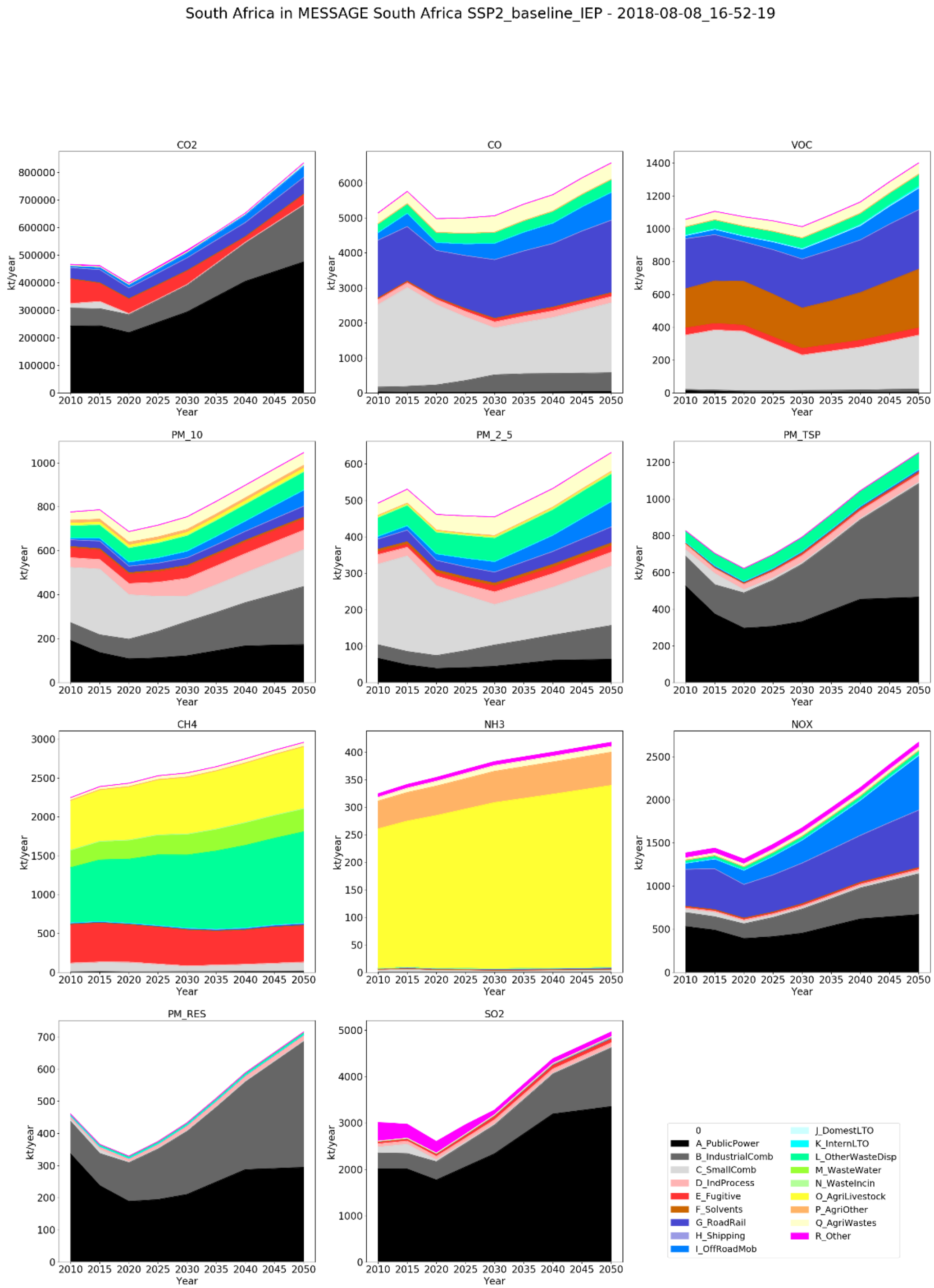

Figure S5.A13: SSP2 Emissions by Sector

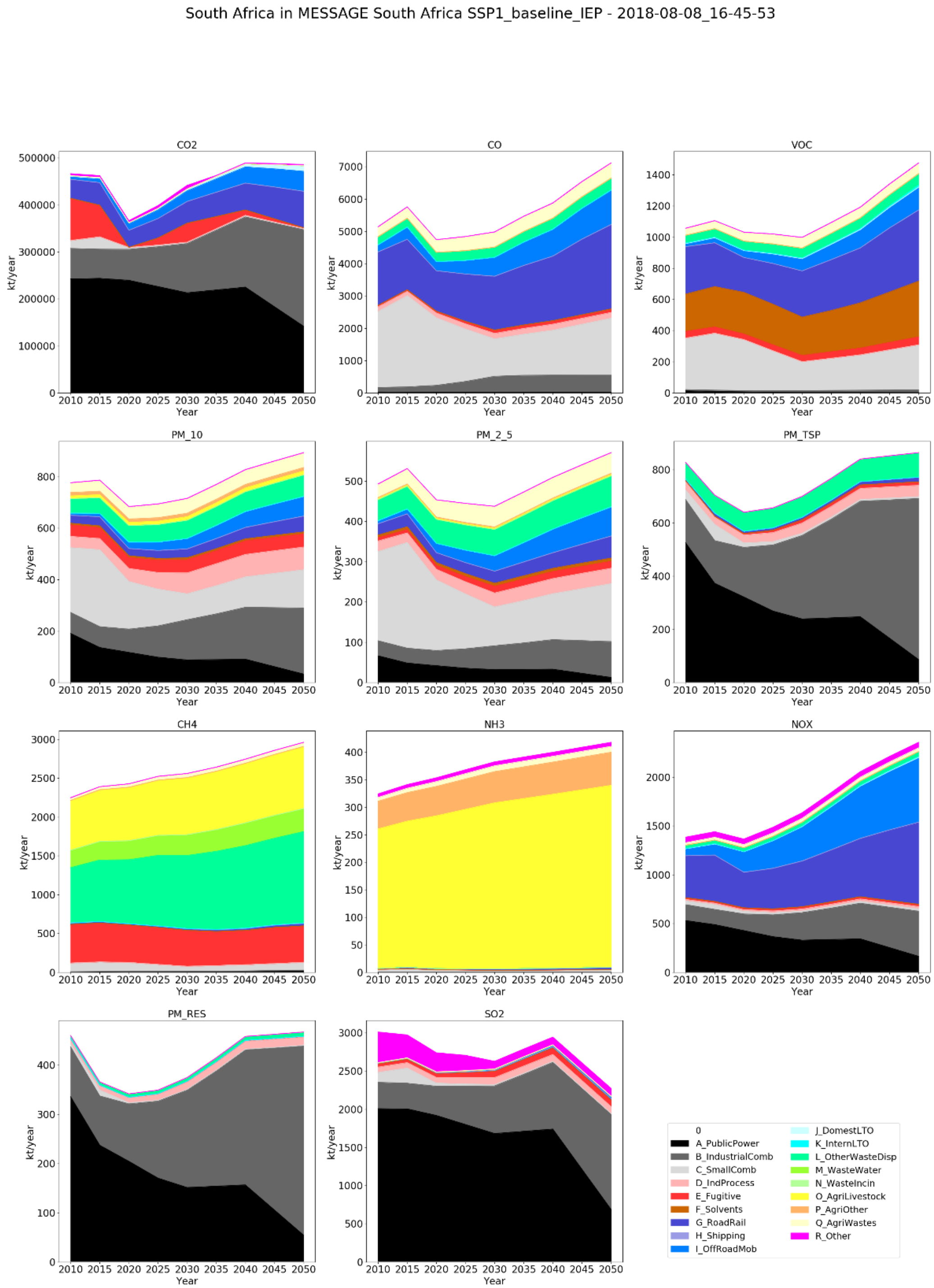

Figure S5.A14: SSP1 Emissions by Sector

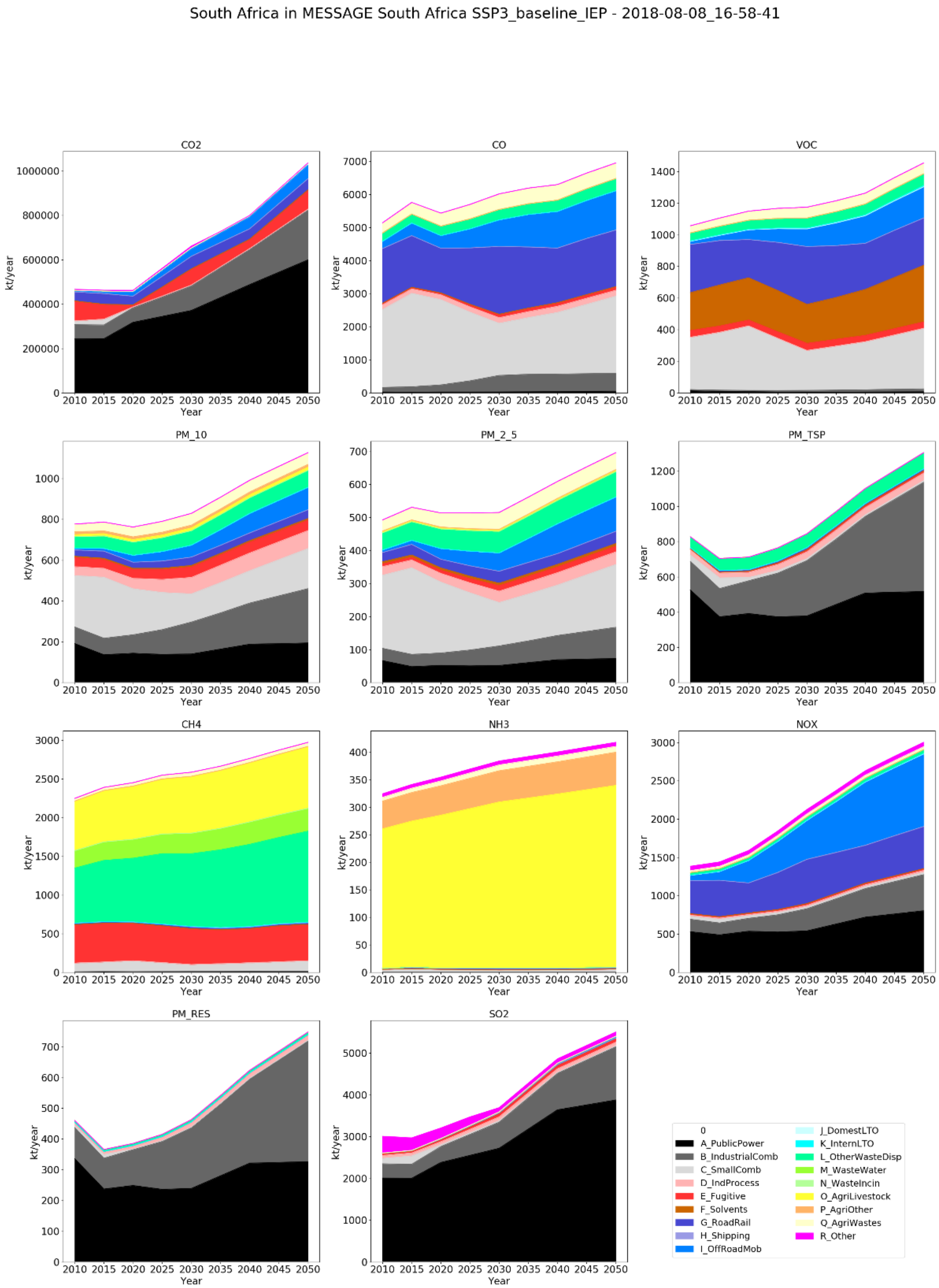

Figure S5.A15: SSP3 Emissions by Sector

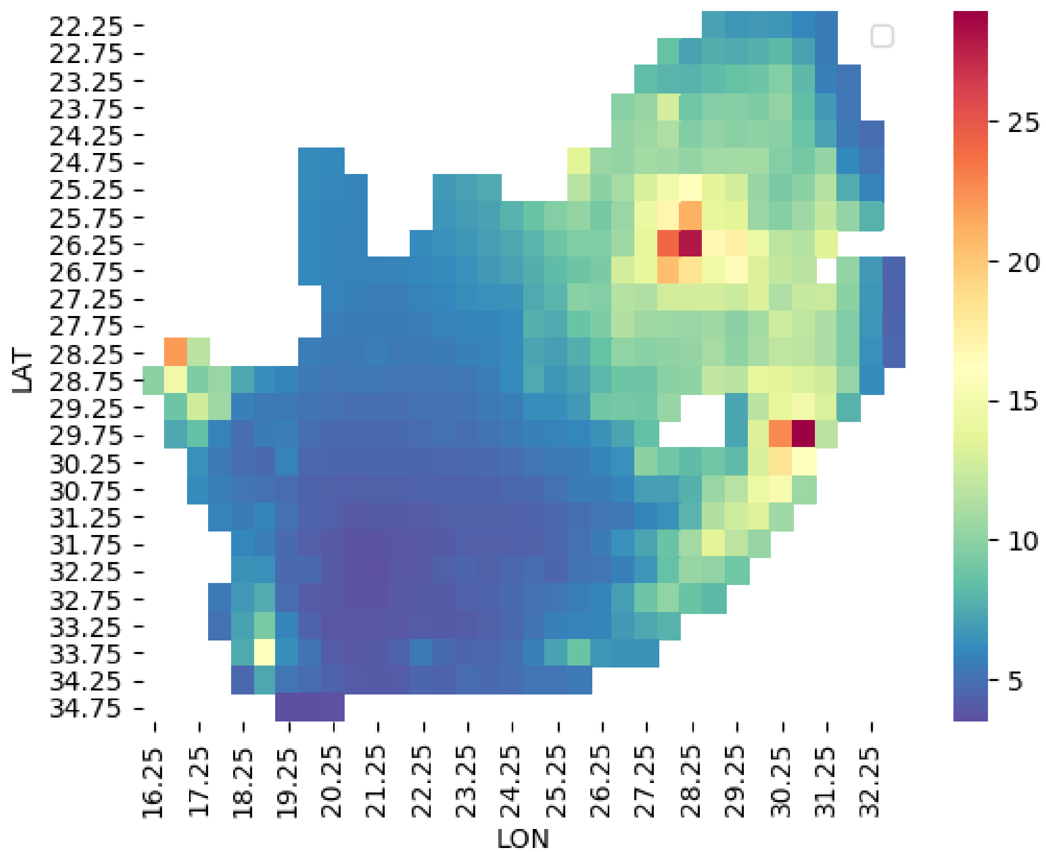

Figure S5.A16: SSP2 $PM_{2.5}$ Concentrations Map in 2050

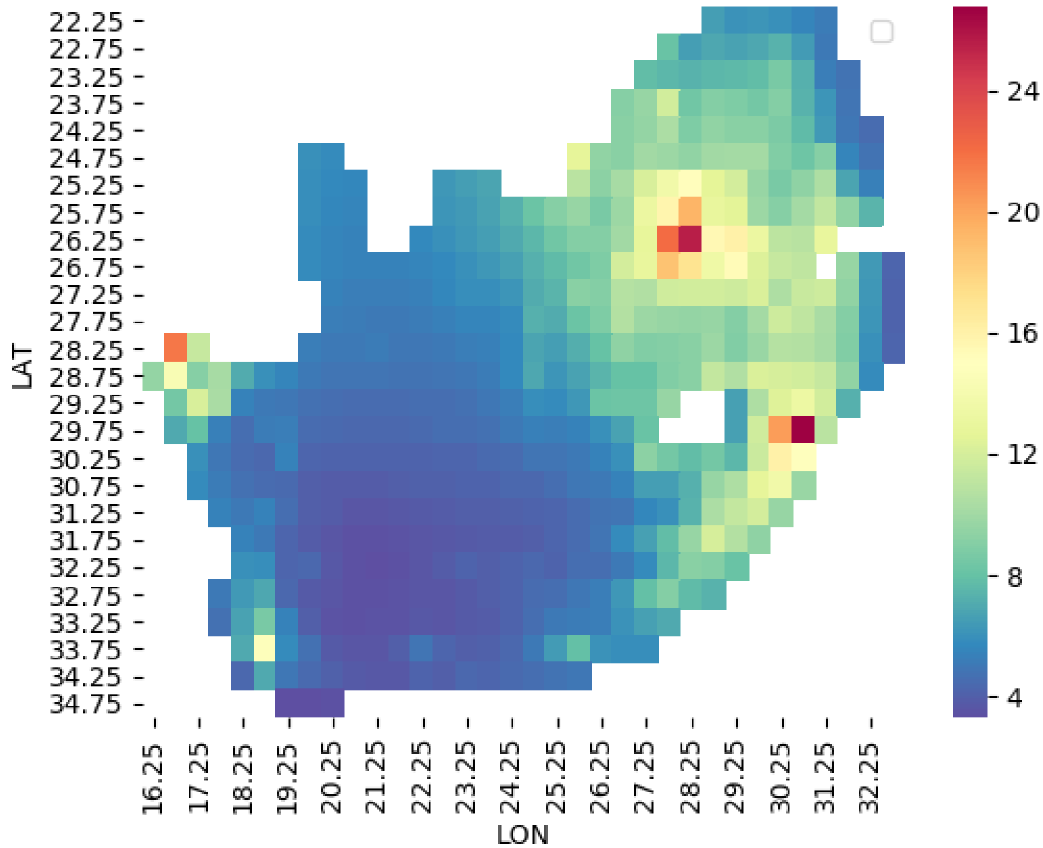

Figure S5.A17: SSP1 $PM_{2.5}$ Concentrations Map in 2050

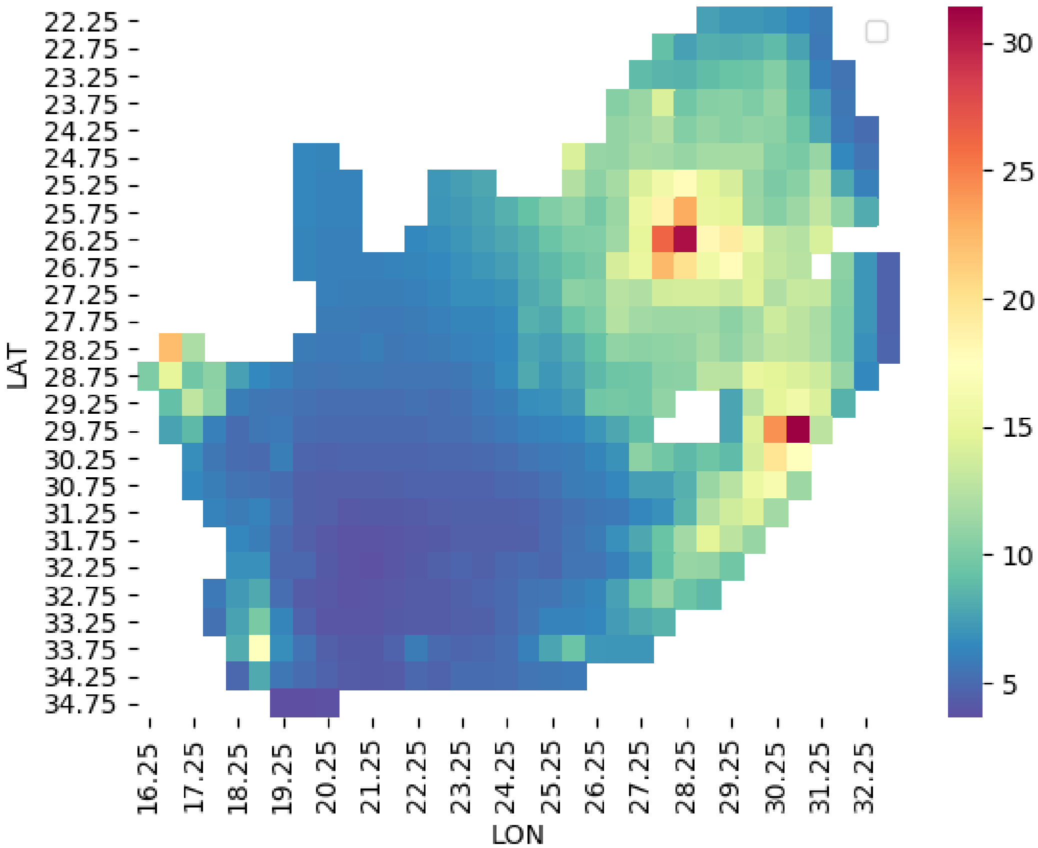

Figure S5.A18: SSP3 $PM_{2.5}$ Concentrations Map in 2050

Appendix 2.B: MESSAGE and GAINS Diagrams

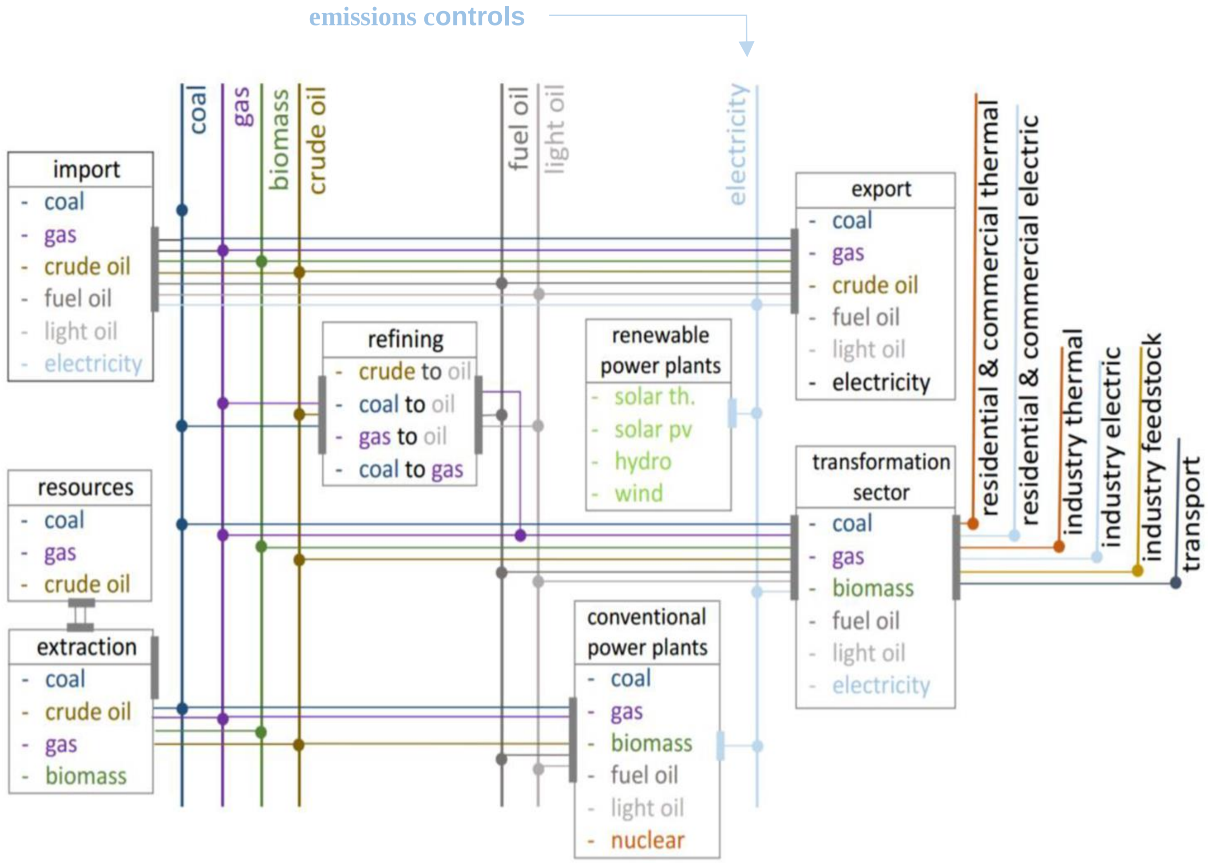

Figure S5.B1: MESSAGE South Africa Diagram. Adapted with permission from co-author Clara Orthofer.

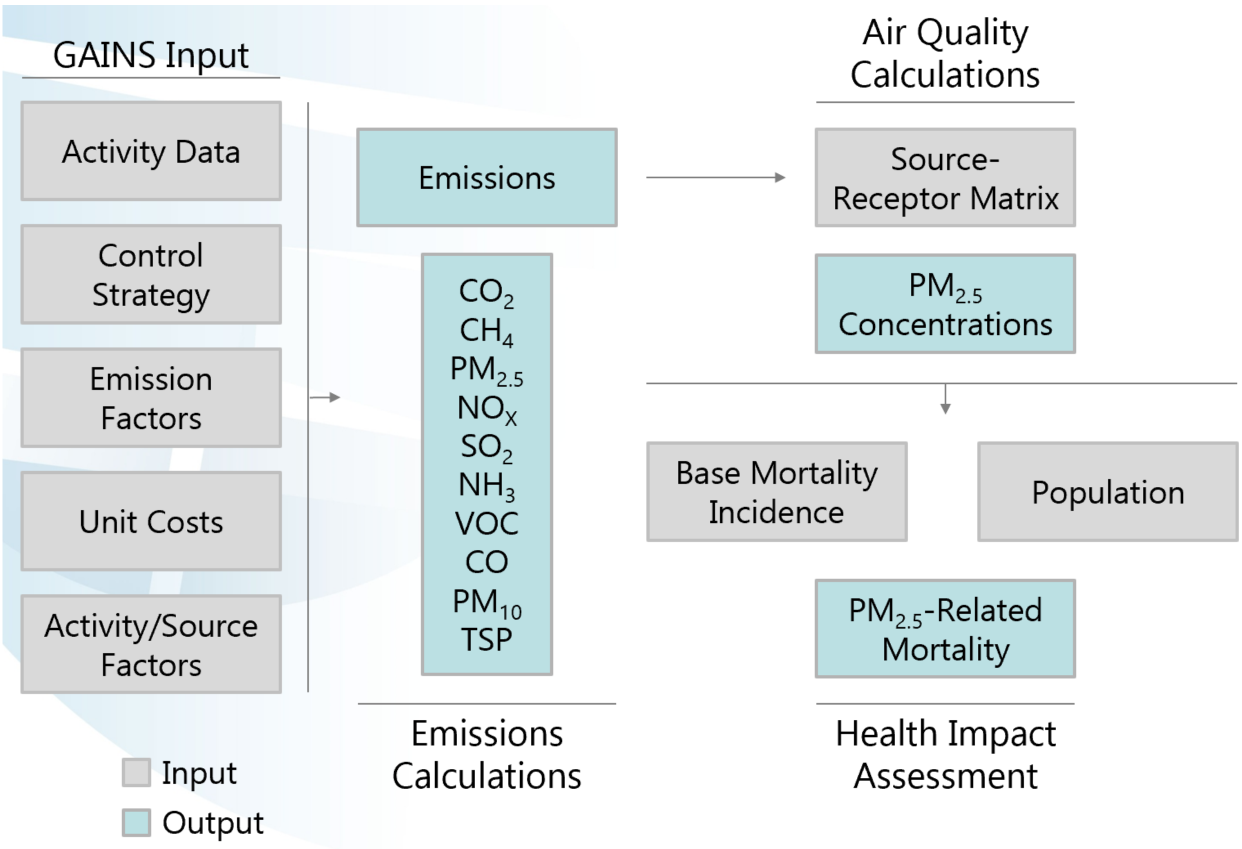

Figure S5.B2: GAINS South Africa Diagram

Appendix 2.C: MESSAGE Inputs and Configuration

Table S5.C1: MESSAGE South Africa Technologies

bio_extr	coal_ppl	foil_trp	hydro_ppl	oil_bal
bio_ind	coal_rc	gas_bal	igcc	oil_exp
bio_istig	coal_t_d	gas_bio	igcc_ccs	oil_extr
biomass_i	elec_exp	gas_cc	loil_exp	oil_imp
biomass_nc	elec_i	gas_cc_ccs	loil_fs	ref_hil
biomass_rc	elec_imp	gas_ct	loil_i	shale_extr
biomass_t_d	elec_rc	gas_exp	loil_imp	solar_i
coal_adv	elec_t_d	gas_extr	loil_ppl	solar_pv_ppl
coal_adv_ccs	elec_trp	gas_fs	loil_rc	solar_rc
coal_bal	foil_exp	gas_i	loil_t_d	solar_th_ppl
coal_exp	foil_fs	gas_imp	loil_trp	solar_th_ppl_base
coal_extr	foil_i	gas_ind	meth_coal	sp_el_I
coal_fs	foil_imp	gas_ppl	meth_coal_ccs	sp_el_RC
coal_gas	foil_ppl	gas_rc	meth_ng	syn_liq
coal_i	foil_rc	gas_t_d	meth_ng_ccs	syn_liq_ccs
coal_imp	foil_t_d	gas_trp	nuc_ppl	wind_ppl

Table S5.C2: MESSAGE South Africa Demand Inputs

node	**year**	**commodity**	**level**	**SSP1 Value**	**SSP2 Value**	**SSP3 Value**	**unit**	**time**
South Africa	2010	i_spec	useful	9.70	9.80	9.59	GWa	year
South Africa	2020	i_spec	useful	11.44	11.00	12.66	GWa	year
South Africa	2030	i_spec	useful	18.06	15.64	19.55	GWa	year
South Africa	2040	i_spec	useful	27.90	22.34	26.54	GWa	year
South Africa	2050	i_spec	useful	35.77	30.94	31.94	GWa	year
South Africa	2010	i_therm	useful	8.64	8.72	8.54	GWa	year
South Africa	2020	i_therm	useful	12.27	10.52	12.80	GWa	year
South Africa	2030	i_therm	useful	20.45	16.47	22.49	GWa	year
South Africa	2040	i_therm	useful	31.19	24.92	35.51	GWa	year
South Africa	2050	i_therm	useful	46.32	40.15	53.14	GWa	year
South Africa	2010	i_feed	useful	5.31	5.31	5.31	GWa	year
South Africa	2020	i_feed	useful	6.84	6.40	7.89	GWa	year
South Africa	2030	i_feed	useful	11.86	10.02	14.29	GWa	year
South Africa	2040	i_feed	useful	18.12	15.16	20.88	GWa	year
South Africa	2050	i_feed	useful	22.79	24.42	26.30	GWa	year
South Africa	2010	rc_spec	useful	3.82	3.80	3.83	GWa	year
South Africa	2020	rc_spec	useful	4.99	4.34	4.86	GWa	year
South Africa	2030	rc_spec	useful	6.43	5.64	6.38	GWa	year
South Africa	2040	rc_spec	useful	8.86	7.84	8.17	GWa	year
South Africa	2050	rc_spec	useful	13.37	10.99	10.41	GWa	year
South Africa	2010	rc_therm	useful	2.97	2.94	2.95	GWa	year
South Africa	2020	rc_therm	useful	3.07	3.41	3.81	GWa	year
South Africa	2030	rc_therm	useful	4.99	5.17	6.10	GWa	year
South Africa	2040	rc_therm	useful	7.78	7.05	8.37	GWa	year
South Africa	2050	rc_therm	useful	10.56	9.43	11.41	GWa	year
South Africa	2010	transport	useful	19.62	19.46	19.51	GWa	year
South Africa	2020	transport	useful	20.00	21.43	23.45	GWa	year
South Africa	2030	transport	useful	25.50	27.10	35.82	GWa	year
South Africa	2040	transport	useful	33.35	32.77	35.15	GWa	year
South Africa	2050	transport	useful	46.91	43.12	45.04	GWa	year
South Africa	2010	non-comm	useful	1.38	1.38	1.38	GWa	year
South Africa	2020	non-comm	useful	0.92	0.97	1.06	GWa	year
South Africa	2030	non-comm	useful	0.09	0.10	0.12	GWa	year
South Africa	2040	non-comm	useful	0.04	0.05	0.07	GWa	year
South Africa	2050	non-comm	useful	0.03	0.04	0.06	GWa	year

Table S5.C3: MESSAGE control cost inputs – derived from GAINS scenarios

UNITS of 2010 $ per kW-year				
NFC	**2020**	**2030**	**2040**	**2050**
coal_adv	0.00	0.00	0.00	0.00
coal_ppl	0.00	0.00	0.00	0.00
foil_ppl	0.00	0.00	0.00	0.00
loil_ppl	0.00	0.00	0.00	0.00
CLE				
coal_adv	4.88	47.40	1.28	5.53
coal_ppl	36.07	53.68	41.56	30.35
foil_ppl	16.96	35.80	30.63	0.00
loil_ppl	5.47	17.90	15.31	0.00
100% FGD				
coal_adv	11.30	11.30	11.30	11.30
coal_ppl	11.81	11.81	11.81	11.81
foil_ppl	0.00	0.00	0.00	0.00
loil_ppl	0.00	0.00	0.00	0.00
100% HED				
coal_adv	12.14	12.14	12.14	12.14
coal_ppl	11.63	11.63	11.63	11.63
foil_ppl	0.00	0.00	0.00	0.00
loil_ppl	0.00	0.00	0.00	0.00