Addressing Uncertainty in Health Impacts of Air Pollution under Climate Change Mitigation

by

Punith Dev Nallathamby

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Civil and Environmental Engineering

Waterloo, Ontario, Canada, 2021

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.
I understand that my thesis may be made electronically available to the public

Statement of Contributions

This research was conducted at the University of Waterloo by Punith Dev Nallathamby under the supervision of Dr. Rebecca Saari, with the assistance of post-doctoral fellow Dr. Ushnik Mukherjee. The analysis builds on work by undergraduate co-op students, including Yufei Mei (who developed the initial BenMAP-CE runs, analysis scrips and averaging procedure) and Maria Vasquez-Romero (who ran the additional BenMAP-CE runs within the reference case, and developed some initial scripts to process the outputs). The novel contributions of this thesis, including regional analysis, estimation of signal-to-noise ratios, noise reduction and minimum simulation lengths, and thesis drafting were performed solely by the author. This work is part of manuscript in preparation and was presented at American Geophysical Union conference in December, 2020. Dr. Rebecca Saari and Dr. Ushnik Mukherjee provided guidance during each step of the research, and also gave feedback and edited the manuscript and this thesis.

Abstract

Simulations to evaluate climate policy take a lot of time, but little evidence exists to say how long is enough, especially for policy impacts related to air pollution. Air pollution and climate change are the two leading global environmental issues affecting human health. Climate change can increase air pollution, an effect called the “climate penalty”. Climate policy can thus reduce air pollution, offering “co-benefits” for human health and the economy. However, climate policy makers lack robust information on these air pollution related co-benefits. This is due partly to uncertainty in these co-benefits. One such uncertainty is due to the natural variability in the climate system. Another is the response of the human system – including human health and the economy – to changes in air pollution. Natural variability obscures the effects of climate policy on air pollution and its associated health impacts. However, the computational cost of modelling health responses under many future climate scenarios means little is known about the size of this effect, or its implications for policy evaluation. This study seeks to address these gaps by determining minimum simulation lengths needed to address natural variability. It employs a novel analysis of results from a previously developed integrated modelling framework. This framework implemented global climate policies consistent with the Paris Agreement on Climate Change. It captured resulting changes to illness and premature death in the United States associated with outdoor concentrations of air pollutants including ozone and fine particulate matter, and resulting economic damages. Five initializations of the climate system and 30-year modelling periods resulted in 150 annual simulations for each pollutant (ozone and fine particulate matter), policy scenario (reference, a policy that meets a 2 degree warming target, and a policy meeting 2.5 degrees), and time period (2050 and 2100). In this new analysis of these results, climate policies were found to produce large co-benefits that were highest in the Eastern US and increased from 2050 to 2100. These co-benefits also had significant uncertainty related to both natural variability and uncertainty in health and economic responses (“health-related uncertainty”). Uncertainty due to natural variability was reduced by sampling within the annual simulations and averaging their results together. This process was continued until all initializations fall within the 95% confidence interval of health-related uncertainty. At this point, the simulation length was deemed sufficient to filter out natural variability. The simulation length required was found to vary depending on the signal-to-noise ratio (SNR), where co-benefits are the signal and the spread due to natural variability is the noise. SNR values increased over time from 2050 to 2100. In 2050, some regions, like the Midwest, showed a lower SNR and greater influence of natural variability. For these cases, eight years or more of simulation were needed to address natural variability. For cases with high SNR, as in 2100, less than three years were needed for all regions in the US. This work demonstrates the effect of natural variability on air quality co-benefits, and provides insights to inform simulation lengths to address it.

Acknowledgements

I would like to acknowledge my supervisor and advisor Dr. Rebecca Saari, the collaborators at NC State University, my Colleagues at Saari lab, Civil and Environmental Engineering Department for their funding.

Table of Contents

List of Figures

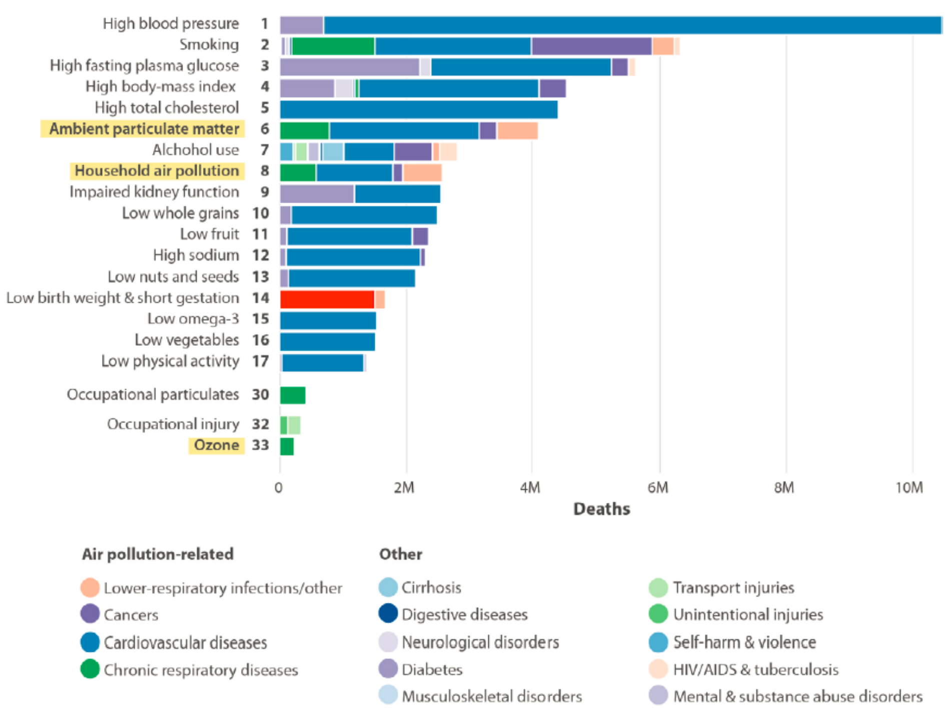
List of Tables

Chapter 1
Introduction

1.1 Problem

The Climate Penalty on Air Pollution

Air pollution is the release or presence of harmful substances in the air. Two air pollutants are thought to have the greatest effect on human health. These are fine particulate matter (particulate matter with aerodynamic diameter less than 2.5 µm, or $PM_{2.5}$) and ozone (O_3). Together, these pollutants are estimated to be responsible for millions of premature deaths worldwide (Vohra et al. 2021), and are among the top risk factors leading to premature death in the world (Cohen et al. 2017). The Institute for Health Metrics and Evaluation (IHME)'s Global Burden of Disease Study has ranked outdoor (or "ambient") $PM_{2.5}$ alone in the top 10 risk factors contributing to premature death, with ozone in the top 40, per **Figure 1-1Error! Reference source not found.**. These increased health risks are associated with economic impacts caused by, for example, medical expenses, lost wages, reduced worker productivity, and pain and suffering (U.S. Environmental Protection Agency 2011).



Climate change can make air pollution worse, an effect known as the "climate penalty" (Wu et al. 2008). The formation of ozone and $PM_{2.5}$ can be greatly affected by climate change (Fiore, Naik, and Leibensperger 2015). For example, future climate change can lead to more hot days with calm winds, conditions that boost the chemical reactions that produce ozone (Wu et al. 2008). With anthropogenic climate change, air pollution related illness and death have increased (Silva et al. 2013).

Since climate change can make air quality worse via the climate penalty, climate policy can improve air quality, yielding "co-benefits". Climate policy typically focusing on reduces the main anthropogenic source of climate change: greenhouse gas (GHG) emissions. GHGs are gases that absorb outgoing terrestrial infrared radiation that would otherwise escape to space. That radiation is transformed into heat (IPCC 2013). Policies that reduce GHGs can provide two types of "air quality co-benefits": the "co-emissions co-benefit", and the "climate co-benefit", shown in Figure 1-2. This study considers the Climate Penalty Pathway, which yields "climate co-benefits" by reducing the direct effect of climate change on pollutant formation.

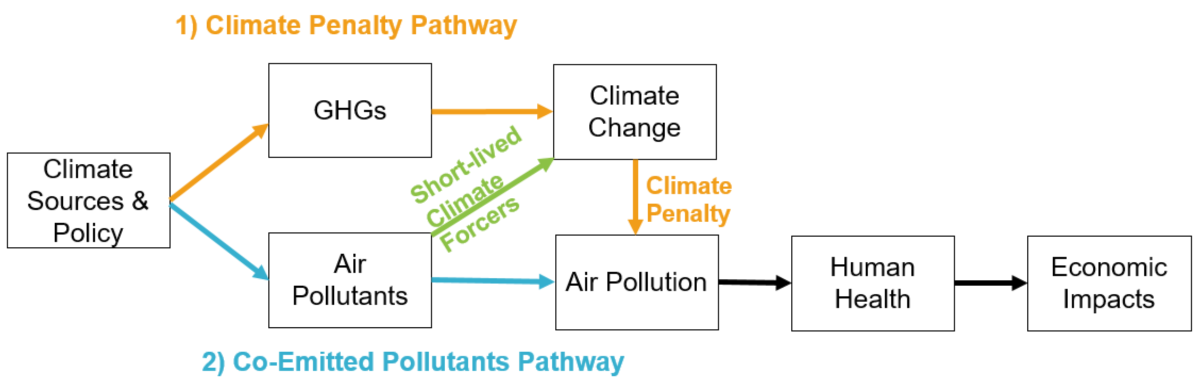


Figure 1-2: Air Quality Co-Benefits of Climate Policy.

The Co-Emitted Pollutants Pathway refers to air pollutant emissions reduced by controlling common emission sources. The co-emission co-benefit arises because many sources of GHG emissions also emit air pollutants. For example, burning coal to produce electricity releases carbon dioxide – a greenhouse gas – as well as $PM_{2.5}$ and other air pollutants. Most climate change policies are focused on addressing greenhouse gases at their source. As an ancillary effect, air pollutants from the same sources are curbed as well. This leads to a co-emission co-benefit, which can be large enough to exceed climate policy costs (Thompson et al. 2014; Saari et al. 2015). Air pollutants can also act as Short-lived Climate Forcers (SLCFs), affecting climate change on relatively short time-scales (typically less than a decade).

This requires coordinated efforts to reduce air pollutant and GHG emissions to meet climate goals (Shindell et al. 2017).

Studies of air quality co-benefits rarely include the Climate Penalty Pathway, which is the focus of this thesis (Saari et al. 2019). This is partly due to the complexity of modelling the climate response, and the uncertainty associated with it due to natural variability. Natural variability refers to the "unforced" changes of the climate system caused by its chaotic nature (Deser et al. 2012). Natural variability acts as random "noise", obscuring the effect of the "forced signal" of anthropogenic climate change or climate policy. If sufficient caution is not taken to address this natural variability, it will yield large differences in climate projections, which may be erroneously accredited to policies (Deser et al. 2020).

The effect of natural variability due to climate change can be filtered out by averaging many different future climate simulations (Milinski, Maher, and Olonscheck 2019). To filter out natural variability, the future climate simulations need a sufficient simulation length and ensemble size. Simulation length is the number of modelled years in a row to represent a given time period (e.g., in this study's case, 30-year simulations from 1981-2010 for start-of-century, 2036-2065 for mid-century, and 2086-2115 for end-of-century). An ensemble size is the number of different "members" of a group of simulations. To filter out natural variability, an "initial condition ensemble" is needed. Each "member" of an initial condition ensemble is a set of different potential climate futures, which differ only due to their starting conditions. For example, one member may start with a best estimate of climate conditions for the start-of-century, and model the climate from 1986-2115. Another may start with a slight random variation on those initial climate conditions, modelling another realistic potential future climate that can vary significantly from the first climate by 2115 due to the climate systems' chaotic nature. Long simulations (e.g., 30 years) represent year-to-year variability, while using different initial conditions helps to capture multi-decadal variability (e.g., natural responses that occur over longer than 30-year periods).

Application-specific metrics can be used to develop a robust analysis (Milinski, Maher, and Olonscheck 2019). This involves sampling across ensemble members to determine a minimum simulation length. This minimum length will depend on geographic location, spatial and temporal scales, and time outlook (Deser et al. 2020). Previous studies have suggested minimum lengths of 10 years or more for modelling the climate penalty on air pollution (Fiore, Naik, and Leibensperger 2015; Brown-Steiner et al. 2018; Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019). However, the computational cost of modelling health responses under many climate futures means that natural variability has not been well characterized or addressed for air quality co-benefits (Deser et al. 2020). Thus, little is known about the size of this effect, or its implications for policy evaluation.

1.2 Research Questions

This thesis seeks to address these gaps by answering three associated research questions:

1. How do air quality co-benefits vary regionally within the United States of America (US), by time period and climate policy?
2. How large is the “noise” in the signal of air quality co-benefits due to natural variability?
3. What is the minimum simulation length required to address natural variability in air quality co-benefits, and how does this vary with geographic location, spatial scale, and time period?

1.3 Scope

These questions are applied to the United States, the second-largest emitter of greenhouse gases in the world (Climate Watch 2018). The two most harmful air pollutants, $PM_{2.5}$ and ozone, are included, along with their effects on illness, premature death, and associated economic impacts. Three future emissions scenarios are considered, which are discussed in detail under Section 3 and shown in Table 3-2. The analysis includes two time periods (2050 and 2100). Impacts are evaluated for the contiguous United States, and for six regions in USA. These regions are defined in the U.S. National Climate Assessment reports (USGCRP 2018), as the Northwest, Southwest, Great Plains, Midwest, Southeast (excluding the Caribbean), and Northeast, as shown in **Figure 1-3**.

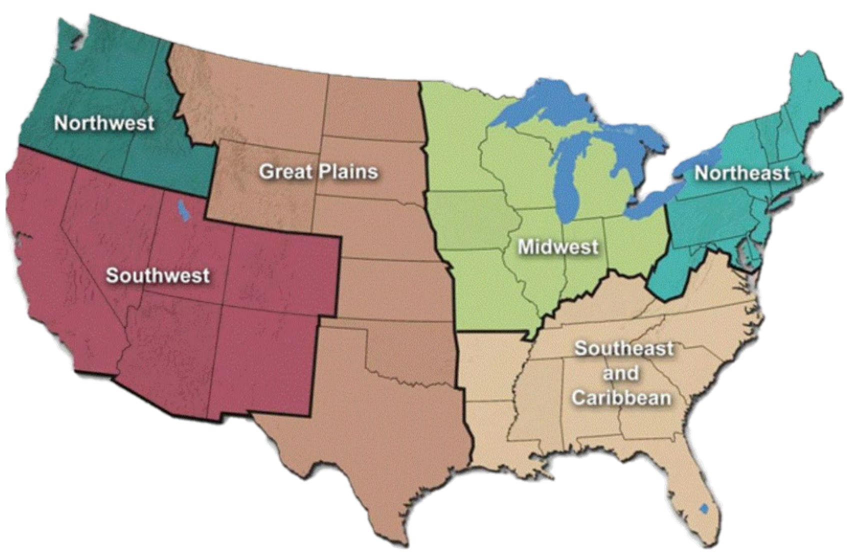


Figure 1-3: US regions.

Northwest – Idaho, Oregon, Washington; Southwest – Arizona, California, Colorado, Nevada, New Mexico, Utah; Great Plains – Kansas, Montana, Nebraska, North Dakota, Oklahoma, South Dakota, Texas, Wyoming; Midwest – Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, Wisconsin; Southeast – Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia; Northeast – Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia.

1.4 Thesis Structure

This chapter introduced the research problem and questions that, when answered, will advance understanding of how to address uncertainty in health impacts of air pollution under climate change mitigation. The remainder of this thesis is structured as follows: Chapter 2 presents background on air pollution, climate change, the interactions between them, and the uncertainties explored in this study. It also situates this work in the literature on air quality co-benefits of climate policy. Chapter 3 describes the modeling framework, data, and analysis approach to quantify impacts and uncertainty by region, policy, and time period. Chapter 4 presents the results that inform the research questions, including quantified uncertainty estimates and uncertainty-driven metrics. Chapter 5 concludes with key findings and insights for policy evaluation of air quality co-benefits. Works cited and supporting appendices follow.

Chapter 2
Literature Review

2.1 Ozone and $PM_{2.5}$ pollution

$PM_{2.5}$ is made of aerosols or particles suspended in air. These particles can be solid, liquid, or mixtures thereof. Some $PM_{2.5}$ is primary (emitted directly) and some is secondary (formed in the atmosphere through processes like nucleation, condensation and coagulation). In the world, most $PM_{2.5}$ is due to primary emissions from natural sources; of the anthropogenic sources, most $PM_{2.5}$ is secondary (Hinds 1998). $PM_{2.5}$ can last for days or weeks in the air. It leaves the atmosphere through a process called deposition, which can be wet (e.g., rainout) or dry (e.g., settling to the ground) (Jacob 1999).

$PM_{2.5}$ has significant effects on human health. It can deposit deep into the lungs and even enter the blood stream, given its small size. Among other things, it is associated with increased risk of death due to lung cancer, heart disease, and respiratory infection (Burnett et al. 2018). It also raises the risk of heart attacks and hospital admissions, and decreases worker productivity (U.S. Environmental Protection Agency 2011).

Ozone is a gaseous molecule composed of three oxygen atoms. It is a secondary pollutant. Ozone is typically formed in the lower atmosphere through photochemical oxidation of volatile organic compounds (VOC) and oxides of nitrogen (NOx). Both VOC and NOx (precursors) are produced by fossil fuel combustion, and found commonly in densely populated regions. Ozone's formation process is non-linear, and depends on the amount of NOx and VOCs present in the air. Ozone forms in the atmosphere through photo-chemical reactions; usually contaminants generated by vehicles, power plants, industrial boilers, refineries, chemical plants, and other sources react in the presence of sunlight to form ozone. In urban areas, ozone is more likely to reach harmful levels on hot, sunny days. It can also reach high levels during colder months in stagnant (i.e., still) air. It is also possible to transport ozone over long distances by wind, so that even rural areas can experience high levels of ozone. It is removed from the air by reaction with sunlight, and dry deposition (Jacob 1999).

Ozone, though the second most harmful pollutant, does far less harm overall than $PM_{2.5}$ (ranked in the 30s for global risk factors, as opposed to the top 10 in the Global Burden of Disease). Ozone is an irritant to eyes and lungs and can be harmful to health when exposed to high concentrations. People with asthma, infants, older adults, and people who are active outdoors, including outdoor workers are susceptible to ozone exposure. Furthermore, individuals with certain genetic features and individuals with decreased intake of certain nutrients, such as vitamins C and E, are at higher risk from exposure to ozone (Moreno-Macías et al. 2013). It is associated with premature death caused by chronic respiratory diseases. It is also linked to increased hospital and emergency room visits, respiratory symptoms (including asthma attacks), missed school days and lost productivity (U.S. Environmental Protection Agency 2011).

2.2 Health and Economic Impacts of Air Pollution

The health effects of air pollution are estimated using results from epidemiologic studies. Epidemiology seeks to identify the determinants of disease frequency in human populations. In particular, this work uses studies that assess the extent to which exposure to outdoor air pollution causes a change in the risk of disease or death.

Epidemiologic studies have developed concentration response functions (CRFs) to quantify the link between outdoor air pollution and human health risks (Fann et al. (2012)). CRFs are functions that can be applied to estimate the resulting outcomes due to changes in pollutant concentrations, such as premature deaths, symptoms, or hospitalizations. These outcomes can be estimated using equations (Fann et al. 2012) of the following form:

$$\Delta outcomes = y_0 \times pop \times \left(1 - e^{(-\beta \times \Delta x)}\right)$$

Equation 2-1

Where,

y_0	-	Baseline cause-specific incidence rate
pop	-	Population size
β	-	Risk coefficient for health end point of interest
Δx	-	Change in pollutant concentration

Health outcomes like premature deaths and hospitalizations have economic impacts. These impacts are estimated using economic studies. Ideally, these studies try to estimate the full economic value of an outcome, including non-market effects like pain and suffering. For example, avoided premature deaths are valued using the Value of a Statistical Life (VSL). VSL is defined as "the monetary value that a group of people are willing to pay to slightly reduce the risk of premature death in the population" (U.S. Environmental Protection Agency 2017). The VSL therefore is not the value of a life, nor the value of avoiding certain death, but the average value people are willing to pay to avoid small changes in their risk of death (Cameron 2010). The value of reducing premature death is typically over 90% of the economic impact of improving air quality (Saari et al. 2015). The remainder of the value comes from avoiding increased rates of illness and associated effects including hospitalizations, medical expenses, unpleasant symptoms, lost wages, and reduced worker productivity (U.S. Environmental Protection Agency 2011).

2.3 Health-Related Uncertainty

To put the effects of natural variability in context, this study compares it to "health-related uncertainty". Here, health-related uncertainty is defined as including the uncertainty associated with the CRF relating health risks to outcomes, and with economic valuation of those outcomes.

The uncertainty associated with the CRF is represented both as the choice of the CRF, and the uncertainty in the CRF parameters. This approach follows US air quality policy analysis. US air quality policy analysis typically presents results separately for the two main North American epidemiologic studies linking $PM_{2.5}$ to premature death. These are the American Cancer Society study (Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope, Thurston, Calle, Thun, et al. 2009) and the Harvard Six Cities study (Lepeule et al. 2012). Presenting results using CRFs from both studies is used to estimate the uncertainty introduced by the choice of CRF Both studies are widely used and accepted. They each have known advantages and disadvantages (Fann et al. 2012). On average, the Harvard Six Cities study estimates an increase in mortality risk that is twice as big as the American Cancer Society study.

Each CRF itself also contains parameter uncertainty. Sampling the uncertainty in these parameters via Monte Carlo simulation allows the creation of a 95th percentile confidence interval in the resulting outcomes using each CRF. The confidence interval in the CRF associated with individual studies is the most commonly quantified health-related uncertainty in US air quality policy analysis (Fraas 2011). The same approach can be applied across multiple health outcomes (illness and death) and distributions of uncertainty in their economic valuations to derive overall confidence intervals in the total air quality co-benefits.

2.4 Climate System, Natural Variability, and Climate Change

Weather is the state of the atmosphere, which is constantly changing. Climate is defined by the World Meteorological Organization as the average weather over 30 years, reflecting both the mean and variability of weather variables such as temperature, wind, precipitation, clouds and other weather elements (IPCC 2018). The atmosphere is the most variable part of the climate system. The climate system is an interactive coupled system consisting of components including land, ocean, atmosphere, biosphere, and cryosphere. Variations from natural processes in these components result in "internal variability" or natural variability within the climate system.

Climate change is a statistically significant shift in the mean state of the climate or of its variability, typically persisting for decades or longer (IPCC 2018). Detecting these shifts is made difficult by the natural variability in the climate (Brown-Steiner et al. 2018).

Climate change occurs when the climate system is influenced, or "forced", by so-called "external forcing mechanisms". "Radiative forcing" is used to compare the relative importance of different forcing mechanisms on the climate system. Radiative forcing is a first-order measure of the relative climatic importance of different forcing mechanisms, with units of W/m^2. Since the industrial revolution, total radiative forcing is positive, primarily driven by emissions of greenhouse gases, especially of carbon dioxide (CO_2) and methane (CH_4) (see Figure 2-1). A measure used to compare the relative importance of different greenhouse gas emissions is "CO_2 equivalent", a unit written as CO_2eq or CO_2e. CO_2e estimates the total climate effect relative to emissions of CO_2.

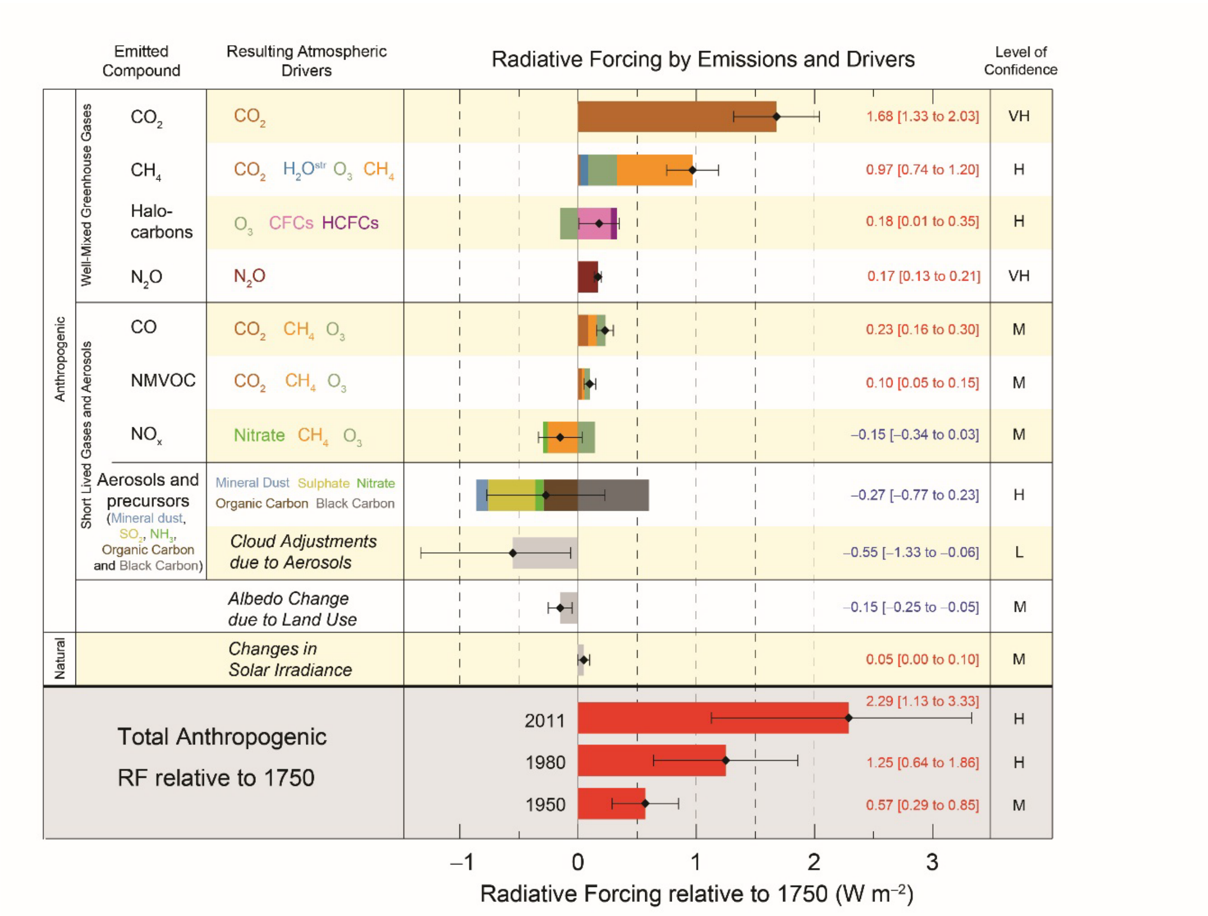


Figure 2-1: Radiative forcing since the Industrial Revolution (IPCC 2013)

2.5 Climate Change and Air Quality

The formation and loss of ozone and $PM_{2.5}$ depend on the weather, and thus can be affected by climate change and climate policy. Figure 2-2 shows the main influence of climate change on these pollutants. The effects of climate change can either increase or decrease pollutant levels by affecting their sources (e.g., emission rates, stratosphere-troposphere exchange, chemical formation) and sinks (e.g., chemical loss and deposition). For example, the figure below shows that atmospheric water vapor could increase with climate change, and that this is likely to substantially decrease ozone but increase $PM_{2.5}$ concentrations as seen by a black arrow next to water vapor, when (--) and (+) indicating the change in ozone and $PM_{2.5}$, respectively.

Given these complex processes, and the fact that $PM_{2.5}$ is more harmful to human health than ozone, models are needed to understand the balance of these effects for humans. While there is still uncertainty in terms of how climate change will affect air pollution, especially for $PM_{2.5}$, many recent reviews show that climate change will increase health risks due to air pollution (Sujaritpong et al. 2014; Madaniyazi et al. 2015; Orru, Ebi, and Forsberg 2017).

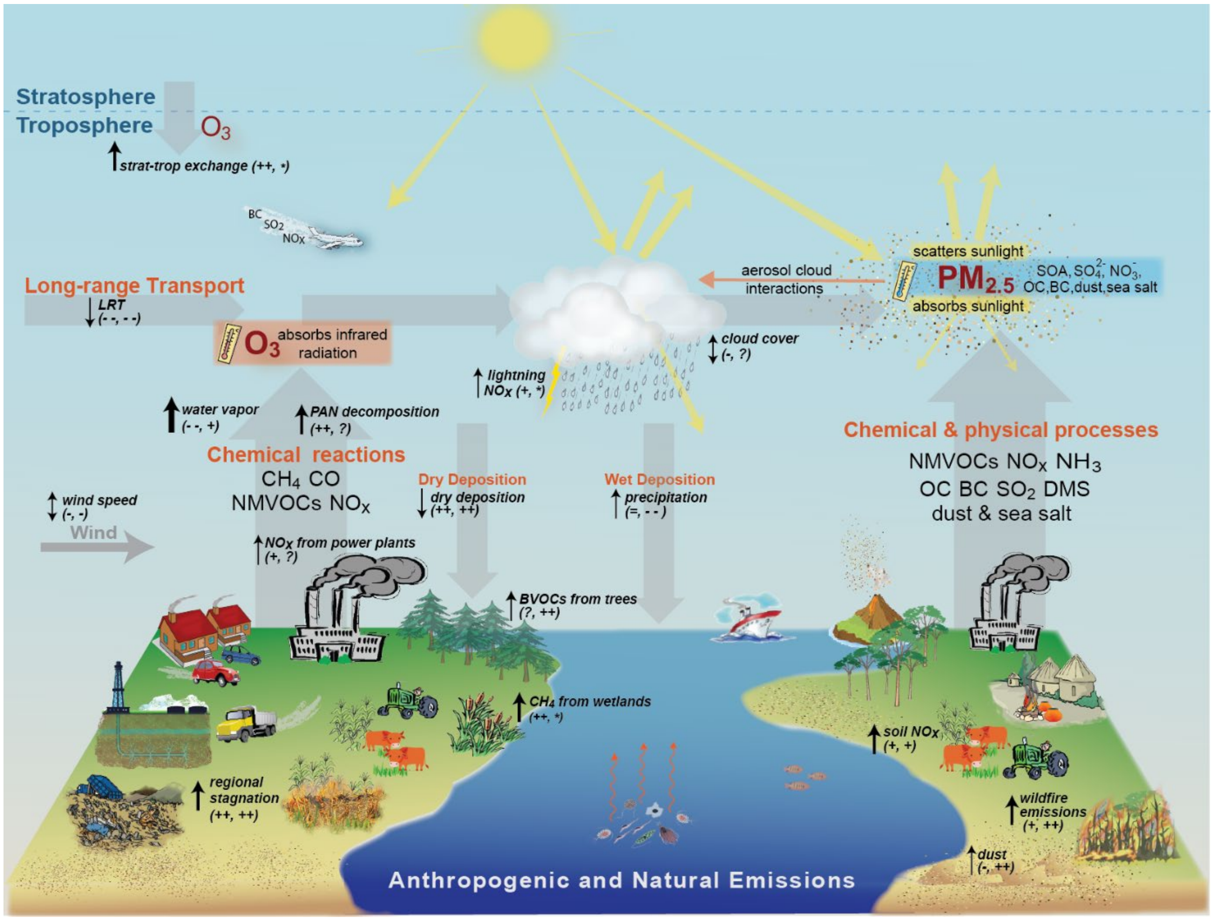


Figure 2-2: Air Quality and Climate Connections **(Fiore, Naik, and Leibensperger 2015)**.

Orange text shows atmospheric processes. Black arrows show sensitivity of processes to warming (increase is up; decrease is down; double-headed arrow is unknown). In parentheses is how O3 and PM2.5 respond, respectively (For double-headed arrows, the O3 and PM2.5 response denoted is for an increase in the process): ++ consistently positive, + generally positive, = weak or variable; - generally negative, -- consistently negative, ? uncertainty in the sign of the response, and * the response depends on changing oxidant levels.

The increase in air pollution under climate change is termed the "climate penalty" (Wu et al. 2008). Wu et al. (2008) in their paper discussed how projected population growth coupled with conducive climates such as increased temperatures and stagnant zones can cause an increase in the formation of ozone. That increased formation meant that an additional 10% reduction in NOx emissions would be needed to meet air quality targets in 2050.

2.6 Simulation Length

One reason that most studies of air quality co-benefits do not include the effect of climate penalty has to do with the computational cost. It takes many calculations to solve the systems of nonlinear equations that represent the chemical reactions that form ozone and $PM_{2.5}$ (Jacobson 2005). Thus, adding air quality to a typical climate simulation increases the computational time substantially, typically by a factor of five in the modelling system used here. As a result, most studies only simulate a few years of future air quality with one climate initialization (Pienkosz et al. 2019; Fu and Tian 2019; Fiore, Naik, and Leibensperger 2015; Garcia-Menendez, Monier, and Selin 2017).

In other words, most studies use a short simulation length, and an ensemble size of one. The simulation length refers to the number of consecutive annual simulations used to represent impacts in a given period (e.g., in this study's case, 30 year simulations from 1981-2010 for start-of-century, 2036-2065 for mid-century, and 2086-2115 for end-of-century). The ensemble size refers to the number "members" of an ensemble. "Members" can refer to different simulations of the same future conditions estimated either with different models or the same model with different initial conditions.

The typical approach in the literature, i.e., a single ensemble member with a few years of simulation, is probably not enough to filter out the forced signal (i.e., the effect of climate policy) from natural variability (Fiore, Naik, and Leibensperger 2015; Deser et al. 2020). Typically, when modelling the atmosphere, the desired forced signal is detected from noisy data by temporal and/or spatial averaging (Brown-Steiner et al. 2018). Temporal averaging involves increasing simulation lengths, and spatial averaging means calculating results over a larger area. Spatial averaging can be limited by the size of the desired study area (e.g., for local or national studies). Temporal averaging, for air quality modelling, is typically limited by computational cost restricting simulation lengths.

Fiore, Naik, and Leibensperger (2015a) pointed out multiple cases in which a larger ensemble size and/or longer simulation length are needed. They occur whenever the forced signal (i.e., the effect of climate policy) is expected to be small compared to natural variability, i.e., the signal-to-noise ratio is low. This is expected especially for modest policies, shorter time scales, and smaller geographic scales. In other words, near-term, local impacts most relevant for climate action can be the hardest to evaluate.

Deser et al. (2020) described one way to isolate the forced signal (i.e., the effect of climate policy) from the noise of natural variability by averaging both temporally and across an ensemble of model simulations. The general approach is to create an ensemble of future climates with a single model, then average the results across a “sufficient” number of “initial condition ensemble members”. Each initial condition ensemble member is created by randomly changing climate variables at the start of the simulation (also called “perturbed initial conditions”). Each member, from slightly different starting conditions, can produce very different future climates. The difference between these future climates is due only to natural variability, and thus can be used to quantify its effect. Finding the average between these many future climates can filter out natural variability.

An ensemble can also then be used to determine the minimum simulation length. Milinski, Maher and Olonscheck (2019) described how to assess the minimum simulation length using initial condition ensembles. Their approach involves averaging results between ensemble members until some application-specific metric is reached. However, they did not describe how to apply this approach to assessing air quality co-benefits. Large initial condition ensembles have been recently developed for climate change applications, involving 10-100 members - e.g., (Kay et al. 2015). For air quality under future climates, however, only small ensembles exist. These ensembles have demonstrated the importance of accounting for natural variability (Deser et al. 2020), but have not informed minimum simulation lengths.

Multiple studies have suggested that more than 10 years of simulation might be needed to assess future air pollution levels under a changing climate (Fiore, Naik, and Leibensperger 2015a; Brown-Steiner et al. 2018; Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019; Lacressonnière et al. 2016; Fu and Tian 2019). This thesis builds on that prior work, using air pollutant concentrations developed with 30-year simulations and the largest ensemble to date (Garcia-Menendez et al. 2015; Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019). That work proposes a margin of error in pollutant concentrations to determine minimum simulation lengths. Table 2-1 and Table 2-2 provide the number of simulation years required for different regions and metrics for 2100 for ozone, and $PM_{2.5}$, respectively. Using a 95% confidence level, these margins of error require simulation lengths that exceed a decade in most cases.

Table 2-1: Simulation lengths for ozone based on margin of error in concentrations **(Garcia-Menendez, Monier, and Selin 2017)**).

		National	Population-weighted	Southwest	Great Plains	Midwest	Northeast	Northwest	Southeast
Ensemble-mean climate impact (ppb_v):		-0.1	+3.2	+0.1	-1.7	+0.3	+2.4	-3.6	+2.6
Ensemble-mean temp. change (K):		+5.4	+4.9	+6.1	+5.1	+5.4	+5.4	+6.7	+4.3
Margin of error	**Confidence Level**	***Simulation years required***							
±1.0 ppb_v	90%	5	8	4	6	14	11	5	10
±1.0 ppb_v	95%	7	11	5	9	19	15	7	14
±0.5 ppb_v	90%	18	30	14	24	53	42	19	39
±0.5 ppb_v	95%	26	42	20	34	74	59	26	55

Note. Simulation years required to achieve ±1.0 or ± 0.5 ppbv margin of error at 90% and 95% confidence levels for the 2100 reference scenario climate impact on annual-average ground-level 8-h-max O3 for national, population-weighted and regional estimates"

Table 2-2: Simulation lengths for $PM_{2.5}$ based on margin of error in concentrations **(Pienkosz et al. 2019)**.

	Ensemble-mean climate penalty	Margin of error	Simulation years required
U.S. population-weighted	1.5 μg/m³	±0.5 μg/m³	8
		±0.25 μg/m³	29
Northeast	1.9 μg/m³	±0.5 μg/m³	23
Midwest	1.1 μg/m³	±0.5 μg/m³	16
Southeast	1.0 μg/m³	±0.5 μg/m³	9

Note. Simulation years required to achieve a ±0.5- or ±0.25-μg/m³ margin of error at 95% confidence in 2100 REF-scenario climate change impacts estimated from this ensemble. Ensemble-mean $PM_{2.5}$ impacts are also listed. Regions included correspond to those defined in the 2018 U.S. National Climate Assessment (Reidmiller et al., 2018).

However, air quality co-benefits are different from air pollution levels, involving uncertain health and economic responses that might inform the minimum simulation length in an approach more relevant for policy evaluation. Saari et al. (2019) demonstrated that just 5 years of simulation can reduce natural variability to within health-related uncertainty by the end of the century, much less than the 10 years at least for 2100 recommended by authors of the work in Table 2-1 and Table 2-2. Saari et al. (2019), however, did not identify minimum simulation lengths, nor did it consider subnational impacts. This thesis extends that analysis by informing minimum simulation lengths across time periods and locations within the US.

2.7 Summary

Most studies of the climate penalty do not sufficiently address natural variability because they only simulate 5 years or less of future air quality in one future climate (Pienkosz et al. 2019; Fu and Tian

2019; Garcia-Menendez, Monier, and Selin 2017; Fiore, Naik, and Leibensperger 2015). Saari et al. (2019) found that ignoring natural variability when assessing co-benefits can mean preferring the wrong policy 47% of the time; but this study did not explain how to address natural variability. Studies on how to address natural variability recommend using multiple future climates (i.e., a “multiple IC ensemble”) and 10 years or more of simulation (Deser et al. 2020; Fiore, Naik, and Leibensperger 2015; Brown-Steiner et al. 2018; Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019; Lacressonnière et al. 2016; Fu and Tian 2019). However, this is very computationally costly for evaluating air quality co-benefits. Others recommend estimating the minimum ensemble length by choosing a relevant metric and then finding the simulation length that meets it (Milinski, Maher, and Olonscheck 2019). Saari et al (2019) looked at co-benefits associated with reducing the climate penalty, but this was a national study, and it did not look at results within the country, or estimate minimum simulation lengths for such studies to address natural variability.

Most studies of the climate penalty do not account for natural variability well. Some suggest that this will take many simulations of future air quality under different climates. However, it takes about 5 times as long to estimate future air quality as it does to simulate future climate change, thanks to all the non-linear chemical reactions that take place. Current literature does not address how short our simulations can be and still address natural variability.

Chapter 3
Methods

3.1 Integrated Modelling System

This thesis further investigated the country wide data that was presented in Saari et al. (2019) to quantify the effect of natural variability, inform simulation lengths, and examine regional variation. A brief summary of how that data was generated is shown in Table 3-1 and discussed here.

Table 3-1: Experimental Design to Isolate the Effect of Natural Variability on Climate Co-Benefits (from Saari et al. (2019))

Framework	Variables	Simulations	Output
Policy (EPPA) ↓ Climate (MESM- CAM) ↓ Air Quality (CAM-Chem) ↓ Health & Valuation (BenMAP)	**Constant** Anthropogenic pollutant emissions Population age/spatial distribution **Varying** Population growth Economic growth Baseline mortality incidence rates GHG emissions Climatic conditions Pollution concentrations	**Scenarios** Reference, Policy 4.5, Policy 3.7 **Years of Interest** 2000, 2050, 2100 **Annual simulations** 30-year periods: 1986-2015; 2036-2065; 2086-2115 5 initializations 150 annual simulations per scenario and year of interest	**Impacts due to fine particulate matter and ozone exposure (multiple CRFs)** - All-cause mortality - Morbidity including: - acute myocardial infarction, - hospital admissions (respiratory, cardiovascular, emergency), - respiratory symptoms (upper respiratory symptoms, asthma exacerbation, acute bronchitis), - lost productivity (work loss days, school loss days, minor restricted activity days) - Economic valuation of benefits

EPPA =MIT Economic Projection & Policy Analysis; MESM = MIT Earth System Model; CAM-Chem = Community Atmosphere Model with Chemistry; BenMAP = environmental Benefits Mapping and Analysis Program; CRF = concentration-response function

Saari et al. (2019) used a multi-decadal, multiple initial condition ensemble to estimate mortality, morbidity, and economic impacts of air pollution under future climate and two global climate policies. The pollutants considered were $PM_{2.5}$ and ozone. Data were generated with a set of coupled models of the global economy, earth system, air quality, and human health. The coupling of those models is shown in Figure 3-1, including key output variables that served as inputs to this analysis, and sample visualizations of these outputs. Note that the economy and Earth system models are shown as the single MIT Integrated System Model, which includes the economic model (EPPA) and climate model (MIT-ESM) from Table 3-1. Two policies and a reference case were considered, as described in Table 3-2.

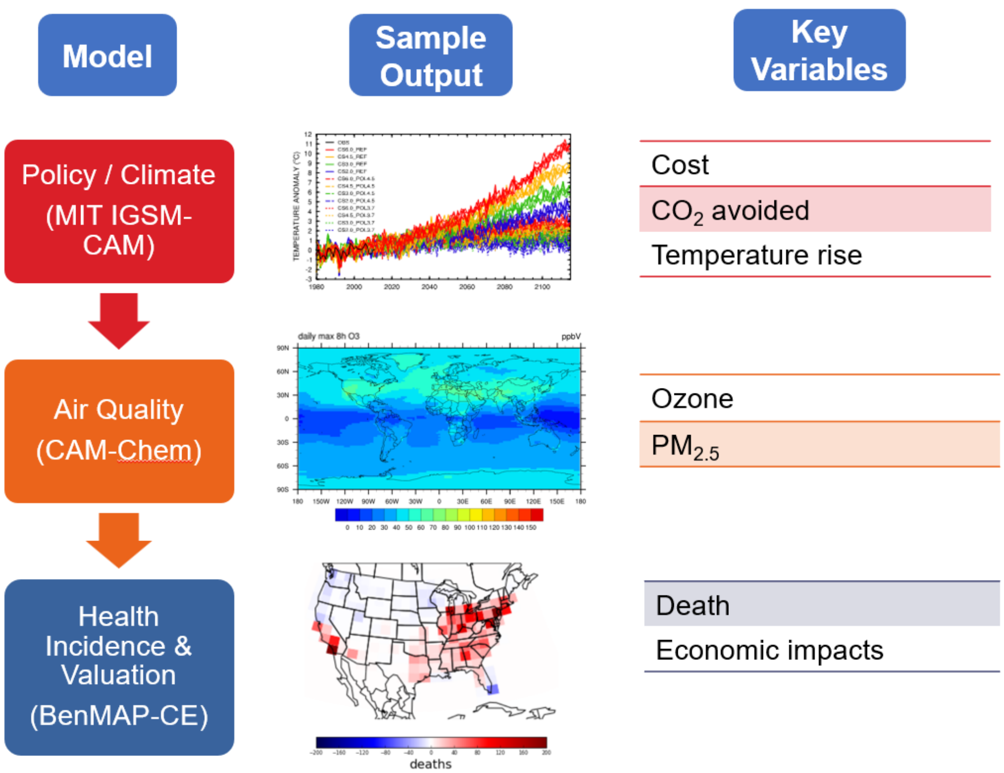


Figure 3-1: Coupled Models of the Economy, Climate, Air Quality, and Health.

Table 3-2: End-of-Century Conditions for Climate Change Reference and Mitigation Scenarios (as per Paltsev et al. **(2015)**)

Scenario	CO_2 (ppm)	Total Radiative Forcing (W/m^2)	Global Mean Surface Temperature Rise (°C)
Reference (REF)	830	10	6
Policy 4.5 (P45)	500	4.5	2.5
Policy 3.7 (P37)	460	3.7	2.0

The MIT Integrated Global System Model (IGSM) was used to implement climate policies and assess their costs, effects on greenhouse gas emission, and compliance with climate goals (i.e., rise in global mean surface temperature compared to pre-industrial conditions). The MIT-IGSM includes a global economic model, the Economic Projection & Policy Analysis (EPPA) and the MIT Earth System Model (MESM). EPPA is a computable general equilibrium (CGE) economic model with multiple economic sectors and regions.

To implement the climate policy scenarios, a carbon tax was imposed in the economic model EPPA to reduce greenhouse gas emissions. EPPA then solved for prices in the economy to balance supply and demand while considering exports, imports, government expenditures, household demand for final products, labor, capital, and natural resources. Rents on capital, labor, and resources are specified in EPPA in billions of dollars, while outputs are specified similarly or in relevant physical units (e.g., energy (exajoules), emissions (tonnes), land use (hectares), population (billions of people) etc). Emissions from EPPA then drove the Earth system model, which in this case was the MESM-CAM.

The MESM-CAM couples MIT's Earth System model with the Community Atmosphere Model (CAM) developed by the National Center for Atmospheric Research (NCAR). The MESM-CAM includes models of the land, atmosphere, and ocean. It was used to produce three-dimensional climate variables such as temperature and precipitation which were input to the air quality model, the Community Atmosphere Model with Chemistry (CAM-Chem).

CAM-Chem produced ground-level concentrations of O_3 and $PM_{2.5}$ at a horizontal resolution of 1.9° x 2.5°. Once ground level concentrations of the key pollutants were simulated, this information was fed into the Benefits Mapping and Analysis Program − Community Edition (BenMAP-CE v1.0814) to estimate health and economic impacts.

3.2 Ensemble Simulations

In order to weed out the noise from natural variability, many simulations of future health responses were produced. To achieve this, the approach recommended by Deser et al. (2020), to use an initial condition ensemble was adopted. Details on the development of the five sets of initial conditions used can be found in (Monier et al. 2013). For each of the five members in the ensemble, and for each of the three emission scenarios described in Table 3-2, three target years of interest were set, namely 2000, 2050, and 2100. For each of these target years, each ensemble member was run for thirty-year periods, specifically 1981-2010 for 2000, 2036-2065 for 2050, and 2086-2115 for 2100. With a total of five ensemble members, this means that one hundred and fifty annual simulations were run for each emission scenario and future target year.

3.3 Regional Analysis

The original analysis in Saari et al. (2019) only considered national total air quality co-benefits. One of the main contributions of this thesis, addressing research question number 1, was to examine the regional variation in co-benefits from the data developed in Saari et al. (2019). To our knowledge, this is the first presentation of regional air quality co-benefits due to reducing the climate penalty in the US.

3.3.1 Regions of Interest

A regional analysis was performed using similar regions to Pienkosz et al. (2019), which first presented the particulate matter concentrations used herein. There were six regions of interest covering the contiguous USA, namely Northwest, Southwest, Greatplains, Midwest, Southeast, and Northeast. The states within each region were as follows:

Northwest	-	Idaho, Oregon, Washington
Southwest	-	Arizona, California, Colorado, Nevada, New Mexico, Utah
Greatplains	-	Kansas, Montana, Nebraska, North Dakota, Oklahoma, South Dakota, Texas, Wyoming
Midwest	-	Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, Wisconsin
Southeast	-	Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia
Northeast	-	Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia

3.3.2 Regional Data Sorting

The health and economic output data from Saari et al. (2019) was available in grid cells sized 1.9° x 2.5°. The modelling domain was 15 rows by 25 columns. In total there were two hundred and twenty cells covering the contiguous US. Non-contiguous states such as Alaska and Hawaii were not covered by these grid cells. The task was to sort the gridded information using political boundaries. The state boundaries of the United States were overlayed on these two hundred and twenty cell grids using QGIS. The information from the grid cells was split among the states. Using QGIS, it was determined what percentage overland area of each grid cell fell within each state boundary. No impacts were assigned over water. The totals for each state were calculated based on the area-weighted sums of the impacts in the relevant grid cells. Once the information for each state was determined, it was then represented regionally by summing the values of the states within each region.

3.4 Air Quality Co-Benefits of Climate Policies

Climate policy can be used to mitigate climate change. For example, the Global Paris Agreement on Climate Change from December 2015 commits Members to the agreement to limit global warming to well below 2°C, preferably to 1.5°C, above preindustrial levels by reducing greenhouse gas emissions (Dimitrov 2016).

Many studies have shown that climate policies have significant air quality co-benefits (Chang et al. 2017; Nemet, Holloway, and Meier 2010) that can exceed climate policy costs (Saari et al. 2015; Thompson et al. 2014; Li et al. 2018). Most of these studies, however, do not include the climate penalty, thereby underestimating air quality co-benefits. Studies that do include it find large impacts, including thousands of premature deaths avoided and trillions of benefits amounting to one quarter of climate policy costs (Saari et al. 2019; Garcia-Menendez et al. 2015; Fann et al. 2015; Zhang et al. 2017).

3.4.1 Health and Economic Uncertainty

As recommended by Milinski et al. (2019), a metric was used to determine the minimum acceptable ensemble size. Here, that metric was set via the "health-related uncertainty". Health-related uncertainty was defined as the combined effect of uncertainty in health responses to concentrations, and uncertainty in the economic valuation of those responses, as defined in detail in this section. The 95th confidence interval of health-related uncertainty was used as the metric to determine how many years of averaging were needed to filter out natural variability.

Health-related uncertainty was measured as the 95th confidence interval in economic impacts based on a variety of health responses to both ozone and fine particulate matter, shown in Table 3-3. The data were derived from Saari et al. (2019) using the methods discussed in Section 2.2 and implemented in BenMAP-CE v1.0814).

The BenMAP model configuration was based on the "U.S. EPA approach for quantifying and valuing PM effects (1 pg, 4 MB, July 11, 2017)" and "U.S. EPA approach for quantifying and valuing ozone effects (1 pg, 4 MB, July 11, 2017)" (available at: https://www.epa.gov/benmap/benmap-community-edition).

Table 3-3: Outcomes, epidemiologic studies, and valuation methods (from Saari et al. (2019))

Outcome / Outcome Group	Pollutant	Ages (yrs)	Individual Epidemiological Studies	Valuation Method
All-cause Adult Mortality (AM)	$PM_{2.5}$	30-99 25-99	Krewski et al. (2009 Lepeule et al. (2012)	Weibull distribution based on 26 Value of Statistical Life estimates from peer-reviewed literature.
	Ozone	0-99	Smith et al. (2009)(Smith, Xu, and Switzer 2009) Zanobetti and Schwartz (2008)(Zanobetti and Schwartz 2008)	
Respiratory Hospital Admissions (RHA)	$PM_{2.5}$	>65 >65 0-17 0-64 18-64	Kloog et al. (2012) ICD 460-519 (All respiratory) Zanobetti et al. (2009) ICD 460-519 (All respiratory) Babin et al. (2007) ICD 493 (asthma) Sheppard (2003) ICD 493 (asthma) Moolgavkar (2000) ICD 490–492, 494-496 (COPD, less asthma)	Cost of illness estimates, including lost wages and medical expenses, based on ICD 9 code level information from Agency for Healthcare Research and Quality. Medical costs and wage loss.
	Ozone	>65	Katsouyanni et al. (2009)(Katsouyanni et al. 2009)	
Cardiovascular Hospital Admissions (CHA)	$PM_{2.5}$	18-64 65-99	Moolgavkar (2000) ICD 390–429 (all cardiovascular) Zanobetti et al. (2009) ICD 390-459 (all cardiovascular) Peng et al. (2008) ICD 426-427; 428; 430-438; 410-414; 429; 440-449 (Cardio-, cerebro- and peripheral vascular disease) Peng et al. (2009) ICD 426-427; 428; 430-438; 410-414; 429; 440-449 (Cardio-, cerebro- and peripheral vascular disease) Bell et al. (2008) ICD 426-427; 428; 430-438; 410-414; 429; 440-449 (Cardio-, cerebro- and peripheral vascular disease Moolgavkar (2003)	
Asthma-related Emergency Room Visits (ERA)	$PM_{2.5}$	0-99	Glad et al. (2012) Slaughter et al. (2005) Mar et al (2010)(Mar, Koenig, and Primomo 2010)	Average of cost of illness estimates from Smith et al. (1997) and Stanford et al. (1999).
	Ozone	0-99 0-17 18-99	Peel et al (2005)(Peel et al. 2005) Wilson et al (2005)(Wilson et al. 2005) Sarnat et al. (2013) Glad et al. (2012) Ito et al. (2007) Mar and Koenig (2009) Mar and Koenig (2009)	

Outcome / Outcome Group	Pollutant	Ages (yrs)	Individual Epidemiological Studies	Valuation Method
Work Loss Day (WLD)	$PM_{2.5}$	18-64	Ostro (1987)	Median daily wage, county-specific
Acute Bronchitis (AB)	$PM_{2.5}$	8-12	Dockery et al. (1996)	Willingness to pay for one symptom day based on contingent valuation studies for the relevant symptoms (IEc, 1994)
Upper Respiratory Symptoms (URS)		9-11	Pope et al. (1991)	
Asthma Exacerbation (AE)	$PM_{2.5}$ Ozone	6-18 6-18	Ostro et al. (2001) (cough, wheeze, shortness of breath) Mar et al. (2004) (cough, shortness of breath) Mortimer et al. (2002) Schildcrout et al. (2006)	Mean of four severity levels in Rowe and Chestnut (1986)
Acute Myocardial Infarction, nonfatal (NFMI)	$PM_{2.5}$	18-99	Sullivan et al. (2005) Pope et al. (2006) Zanobetti and Schwartz (2006) Zanobetti et al. (2009)	Lost income based on Cropper and Krupnick (1990), and medical expenses based on Russell et al. (1998) and Wittels et al. (1990).
Minor Restricted-Activity Days	Ozone	18–64	Ostro and Rothschild (1989)(Ostro and Rothschild 1989)	Median WTP estimate to avoid one MRAD from Tolley et al. (1986), with a triangular distribution ranging between a single mild symptom and a WLD.
School Loss Days	Ozone	5-17	Chen et al. (2000)(Chen et al. 2000) Gilliland et al. (2001)(Gilliland et al. 2001)	Based on lost wages given the probability that a parent stays home with the child.

ICD = International Classification of Disease

Many of the above health outcomes were estimated using multiple individual epidemiological studies. Those studies were combined (using a technique known as "pooling") following the recommended BenMAP configuration described above. Similarly, results from economic studies were also combined for some outcomes (e.g., using a 50% weighting of results from Smith et al. (1997) and Stanford et al. (1999) for asthma-related emergency room visits). The steps to combine evidence from multiple studies were performed following the aforementioned U.S. EPA approaches.

BenMAP population, baseline incidence, and currency rates were all set to reflect the year 2000. Incidence rates and damages were then projected for future years 2050 and 2100 based on the conditions in the integrated modelling framework used, to be consistent with the climate policy conditions. For example, early deaths were projected from the base year of 2000, using the following equation:

$$y_f = y_{2000} * \frac{pop_f}{pop_{2000}} * \frac{y_{o,f}}{y_{o,2000}} = y_{2000} * \gamma_{\text{pop}} * \gamma_o$$

Equation 3-1

Where:

y_f is the incidences of excess premature mortality in the future, in units of incidence per year

y_{2000} is the base year incidences of excess premature mortality from BenMAP, in units of incidence per year

pop_f is the future year population, in units of persons

pop_{2000} is the base year population, in units of persons

$y_{o,f}$ is the future baseline mortality incidence rate, in units of incidence per year

$y_{o,2000}$ is the base year baseline mortality incidence rate, in units of incidence per year,

The ratios of present values to future values are indicated by γ for population (pop) and mortality incidence rate (o), respectively.

Projections were completed as detailed in (Garcia-Menendez et al. 2015; Saari et al. 2019), with projection factors summarized in Table 3-4.

Table 3-4: Mortality Incidence Projection Factors and Data Sources (adapted from **(Shim 2021)**)

Category	Description	Year	Value	Source
Population Projection	Population Ratio of Year vs. Base Year of 2005	2050	1.48	EPPA modelled population growth based on long-term trends of United Nations Data provided in Paltsev et al. (2015)
		2100	1.73	
Mortality Projection	Baseline Mortality Ratio of Year vs. Base Year of 2008 (Ozone)	2050	1.24	Respiratory Mortality Incidence Rates from International Futures as provided in West et al. (2013)
		2100	1.64	
	Baseline Mortality Ratio of Year vs. Base Year of 2008 ($PM_{2.5}$)	2050	1.12	Cardiovascular Mortality Incidence Rates from International Futures as provided in West et al. (2013)

		2100	0.92	

The resulting projection factors, $\frac{pop_f}{pop_{2000}} * \frac{y_{o,f}}{y_{o,2000}}$, were summarized in Table 3-5.

Table 3-5: Overall Mortality Projection Factors

	Pollutant	
Year	**Ozone**	**$PM_{2.5}$**
2050	1.83	1.66
2100	2.84	1.59

To assess health-related uncertainty, the 95th confidence interval in the above impacts was determined using BenMAP-CE. First, the number of outcomes from different endpoints was determined by pooling the results from different studies. That pooling depended on the particular set of studies, what they estimated, and their uncertainty.

The pooling determined the combined risk coefficient (β) from the studies, and a combined (or pooled) variance in that β. The pooled risk coefficient was determined automatically in BenMAP-CE once the pooling method was specified. BenMAP-CE achieved this by assigning different weights to each estimate from each study, as:

$$\beta_{pooled} = \sum w_i \times \beta_i$$

Equation 3-2

Where:

β_{pooled} is the pooled estimate of the risk coefficient

β_i is the risk coefficient from an individual study, i

w is the weight assigned by the pooling method.

Similarly, the variance was determined in BenMAP-CE by:

$$v_{pooled} = \frac{1}{\sum 1/v_i}$$

Equation 3-3

For example, estimates of Acute Myocardial Infarction, nonfatal (NFMI) were estimated using Random / Fixed effects pooling of all four listed studies. This type of pooling accounts for potential between-study variability, as well as the sampling error associated with each study. Details are described in the BenMAP-CE Manual appendices sections K2.1.3 and K.2.1.4 (U.S. Environmental Protection Agency 2017).

The pooled health outcomes were then valued in BenMAP-CE by multiplying the economic value times the number of each outcome. The valuation of each endpoint had some variance or uncertainty distribution as detailed in Table 3-3.

To determine the overall 95th confidence interval, or "health-related uncertainty", BenMAP-CE was used to run 5000 Monte Carlo simulations, sampling within the uncertainty of all parameters. The mean and 95th confidence interval for any given year of interest (2050, 2100) and scenario (P3.7, P4.5) was determined by using the mean concentrations from the entire ensemble. This full ensemble mean, using 150 annual simulations for a given estimate, was assumed to filter out natural variability and be the 'true' impact without the effect of the noise from natural variability. Thus, the only uncertainty contributing to this metric (the 95th CI) was due to health and economic uncertainty.

In addition to the 95%CI, health-related uncertainty was also presented in terms of the CRF selection. As discussed in Section 2.3, a typical approach used in US regulatory air quality analysis was used to show the effect of CRF selection. Specifically, results were presented separately using CRFs from the two major studies linking fine particulate matter and mortality, namely the Harvard Six Cities study (Laden et al. 2006; Lepeule et al. 2012) and the American Cancer Society study (Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope, Thurston, Calle, and Thun 2009; Pope et al. 2002; Nasari et al. 2016). For simplicity, these two studies were labeled by the lead authors of the study from which the CRF was used, namely "Lepeule" for (Lepeule et al. 2012) and "Krewski" for (Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope III, et al. 2009).

3.4.2 Signal and Noise due to Natural Variability

Another main contribution of this thesis, addressing research question number 2, was to quantify the effect of natural variability in evaluating air quality co-benefits. The noise due to natural variability was determined by using measures of spread across the economic impacts from O_3 and $PM_{2.5}$ as estimated using the five different climate condition initializations, Initial Condition (IC) IC1, IC2, IC3, IC4, and IC5. This noise was quantified by examining the co-benefits of different policies, and by examining the reference scenario itself.

First, the noise due to natural variability was quantified as the standard deviation in co-benefits across 150 annual simulations, i.e., 30 annual simulations for five different initializations to the climate model. This approach was used in order to compare the "signal" of air quality co-benefits for different policies to the "noise" of natural variability.

The mean co-benefits estimate was also calculated. This mean was calculated based on the average concentrations for all 150 simulations, and also the mean estimate of the distribution in health and economic uncertainty. This mean was the considered the desired "signal".

This signal was compared to the "noise" of natural variability (as estimated by the standard deviation across the 150 annual simulations). Signal-to-noise (SNR) ratios were presented for all cases. These cases included two different policies (P3.7, P4.5) and target years (2050, 2100). This analysis was repeated and presented separately for six different U.S. regions and for each $PM_{2.5}$ mortality CRF, "Krewski" and "Lepeule".

The noise due to natural variability was also quantified for the end of the century over the contiguous US using the reference scenario. This approach was used to attempt to remove any "signal". It was quantified by randomly sampling and comparing pairs of the 150 annual simulations for the reference case for 2100. Those 150 simulations were all based on the same GHG emissions scenario, and any trend in climate change over 2086-2115 was removed using linear regression (Garcia-Menendez et al. 2015). Therefore, the "forced signal" was zero in all 150 annual simulations. For any two pairs of simulations within the reference scenario, the only difference between them was due to natural variability.

Quantifying natural variability using the reference case involved new runs of BenMAP-CE that were performed by undergraduate co-op student Maria Vasquez-Romero. Within the 150 annual simulations in the reference case for the year 2100, 150 random pairs of annual simulations were selected. The differences in concentrations of ozone and $PM_{2.5}$ between these pairs were analysed in BenMAP-CE, and the resulting health and economic impacts were calculated. The data were then loaded and analysed in Python using scripts developed by this thesis' author. The noise due to natural variability was then quantified with measures of spread across these 150 pairs, namely the 95th CI and the standard deviation.

3.4.3 Noise Reduction and Minimum Simulation Lengths

Per (Milinski, Maher, and Olonscheck 2020), simulations were averaged together to reduce the "noise" due to natural variability. This averaging was implemented in Python with relevant scripts included in Appendix A. The general procedure is described below:

Each ensemble member (IC1, IC2, IC3, IC4, IC5) was first considered separately. For each CRF (Krewski or Lepeule), policy, target year, and IC, there were 30 annual simulations. Multiple annual simulations were averaged together until the entire set had been used.

The total air quality co-benefit across all health outcomes for a given case was defined as η. The cases varied by policy, target year, and IC, for which a set of 30 annual simulations were available. The average of two annual simulations, for example, for the policy P3.7, year 2050 and IC1 using Lepeule, was calculated using simulations for the year 2050 and 2051 as:

$$\eta_{LEPEULE,2050,P3.7,IC1,2,2050} = \frac{\eta_{LEPEULE,2050,P3.7,IC1,2050} + \eta_{LEPEULE,2050,P3.7,IC1,2051}}{2}$$

Equation 3-4

One pair is shown above, but there were 15 unique pairs available in the 30-year period around 2050 for this case. Thus, 15 pairs of two year averages were found, and this comprised a set of estimates of co-benefits using an averaging period of two years. The general form of the set for a generic averaging period (AP) between 1 and 30 years follows for the case example above and is provided in Appendix A as part of the analysis scripts . In the scripts, error checking was included to deal with the limits of the period.

This averaging process was used to demonstrate the value of increasing the simulation length within a single-member ensemble. This question is of interest because most studies of the climate penalty only use a single-member ensemble and a small averaging period, which may still be subject to considerable noise from natural variability (Fiore, Naik, and Leibensperger 2015). For each IC, the maximum averaging period is 30 years. Even after this, there remains some spread between the 5 ensemble members, indicating a contribution of multi-decadal variability (and the value of a large multi-member ensemble). The full range of co-benefits across the five ensemble members (IC1, IC2, IC3, IC4, and IC5) after 30 years of averaging is deemed the "noise" after 30 years of averaging within a single-member ensemble. A relative estimate of the benefit of averaging multiple years in a single-member ensemble is estimated as the “percent error reduction”. Then, for a given averaging period, the full range of co-benefits across the ensemble members is deemed the “noise” for that averaging period. The “percent error reduction” uses the “noise” at that averaging period compared to the “noise” at the 30-year period, as per the following equation:

$$\%\ Noise\ Reduction_{AP} = \frac{\eta_{max,AP} - \eta_{min,AP}}{\eta_{max,30} - \eta_{min,30}} \times 100\%$$

Equation 3-5

The averaging process was also used to estimate the minimum simulation length. This length was determined as the point at which the “noise” due to natural variability, as determined in Section Signal and Noise due to Natural Variability 3.4.2., was less than the established metric. In this case, the metric was that all estimated co-benefits estimates fell completely within the 95th confidence interval of health-related uncertainty. Additional metrics were considered, such as only requiring 90% of the estimated co-benefits to fall within the 95th CI of health-related uncertainty. This process was repeated for the two different policies (P3.7, P4.5) and target years (2050, 2100), as well as geographic locations (over the whole contiguous US, and for six US regions).

Chapter 4
Results and Discussion

4.1 Total Premature Deaths Avoided by Region

As discussed earlier, previous work focused on the health and economic impacts for the US as a whole (Saari et al., 2019). The two key pollutants considered were ozone and $PM_{2.5}$. In this thesis, those impacts are analysed on a regional level to determine the effect of policies ($P_{3.7}$ & $P_{4.5}$) for those two target years (2050, 2100). Table 4-1 gives an overall summary of the premature deaths avoided in each region, based on pollutant, policy, and target year. Results are presented with the CRF from (Lepeule et al. 2012). If the deaths avoided are negative, this indicates an increase in premature deaths associated with an increase in pollution (namely, ozone).

Table 4-1: Annual premature deaths avoided in each region (using **(Lepeule et al. 2012)**).

	2050				2100			
	P3.7		P4.5		P3.7		P4.5	
	$PM_{2.5}$	O_3	$PM_{2.5}$	O_3	$PM_{2.5}$	O_3	$PM_{2.5}$	O_3
Northwest	170	-55	81	-46	650	-91	560	-91
Southwest	280	182	410	104	2,700	1,690	2,400	1,570
Great Plains	1,120	-14	790	-36	3,000	350	2,500	510
Midwest	1,700	250	1,420	290	16,300	1,700	12,700	2,150
Southeast	3,400	178	2,400	256	10,900	1,890	9,400	2,130
Northeast	7,400	440	6,500	490	24,600	3,200	22,700	3,400
Total	14,100	980	11,600	1,058	58,000	8,700	50,000	9,700

4.1.1 $PM_{2.5}$

$PM_{2.5}$ was associated with the most cases of annual premature deaths avoided. This is because it has a much higher health impact than ozone. Figure 4-1 shows the distribution of the annual premature deaths avoided due to $PM_{2.5}$ on a regional basis over the US using (Lepeule et al. 2012). They reveal that, with the implementation of the policies, there is a direct reduction of $PM_{2.5}$ and corresponding reduction in human health impacts. The data shown on the maps have been rounded to the nearest 100th value. In general, irrespective of the scenario (Policy or Target Year), there is an increasing trend as we move from West to East; i.e., the amount of annual premature deaths avoided is higher in the Eastern US than the Western US. The Eastern US is more industrialized and has a belt of coal fired power plants. It also has a substantial population. The relative importance of these factors (pollutant concentrations and population) is explored further in section 4.2.

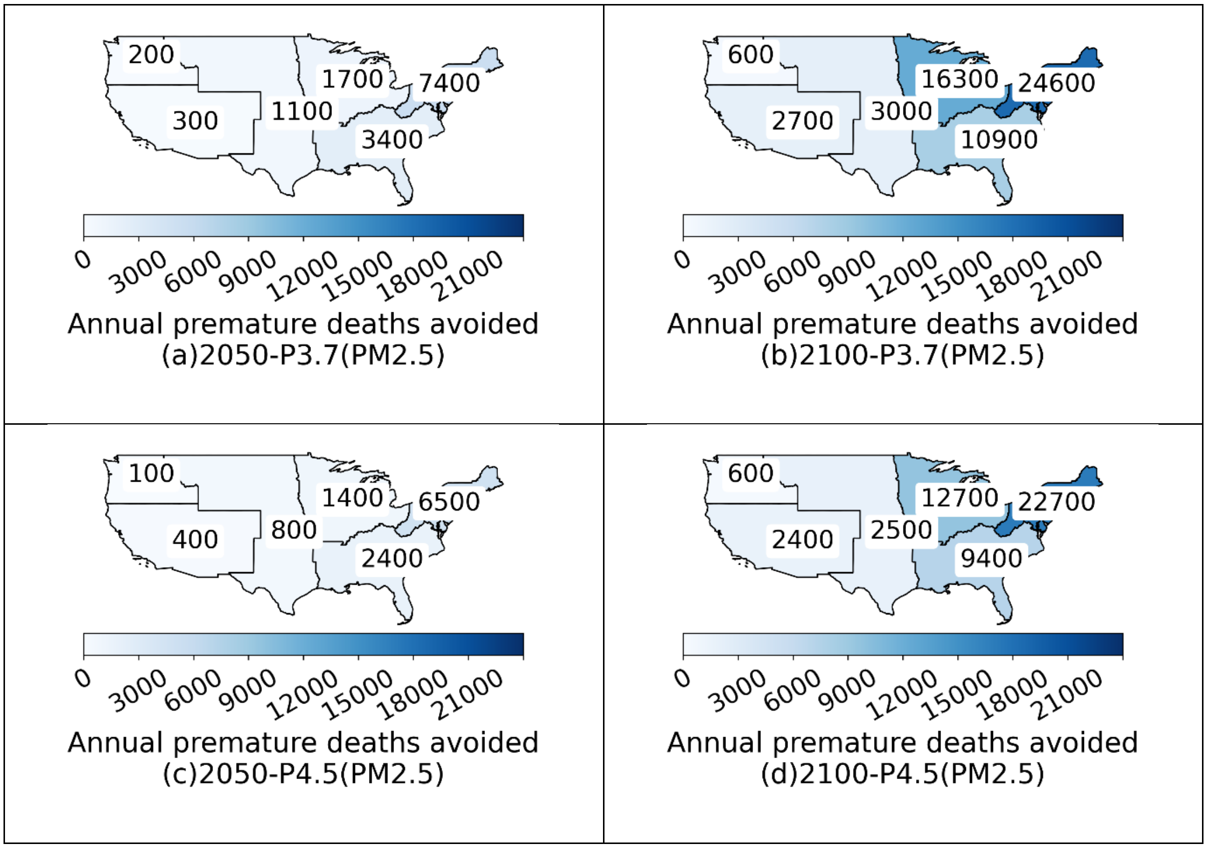


Figure 4-1: The annual premature deaths avoided in the six regions of the US, for $PM_{2.5}$ in the target years (2050, 2100) and under policies ($P_{3.7}$, $P_{4.5}$) (using **(Lepeule et al. 2012)**).

4.1.2 Ozone

Figure 4-2 show the distribution of annual premature deaths avoided due to O_3 on a regional basis over the continental US. The data shown on the maps have been rounded to the nearest 100th value. O_3 had an interesting outcome when compared to $PM_{2.5}$ for annual premature deaths avoided. For the year 2050 ($P_{4.5}$ & $P_{3.7}$), the most deaths avoided were in the Northeast region; the Northwest and Great Plains regions were unaffected with nearly zero deaths avoided. For the year 2100 (P4.5 & P3.7), the most deaths avoided was again in the Northeast region; but the Northwest region saw more premature deaths occur due to O_3.

This increase in premature deaths due to O_3 exposure is due to increasing O_3. Figure 4-3 (which is extracted from (Garcia-Menendez et al. 2015)) shows the simulated change in concentrations of O_3

from year 2000 to year 2100 for three cases of REF, $P_{4.5}$, and $P_{3.7}$. In the reference (REF) case it can be seen there is an increase in O_3 towards the east coast, and a decrease in the Mid-north and Northwest. In the other two cases where the policy has been applied, the extent of the decrease in O_3 in the Northwest and Mid-North is lessened. In other words, through the implications of the policy ($P_{4.5}$ or $P_{3.7}$), there is more O_3 exposure in the Northwest and Mid-North regions. As discussed earlier, O_3 is formed in the lower atmosphere through several mechanisms. This thesis does not explore these mechanisms, or their interaction with climate change. However, based on (Fiore, Naik, and Leibensperger 2015), the decreases in ozone under climate change might be due to increases in humidity.

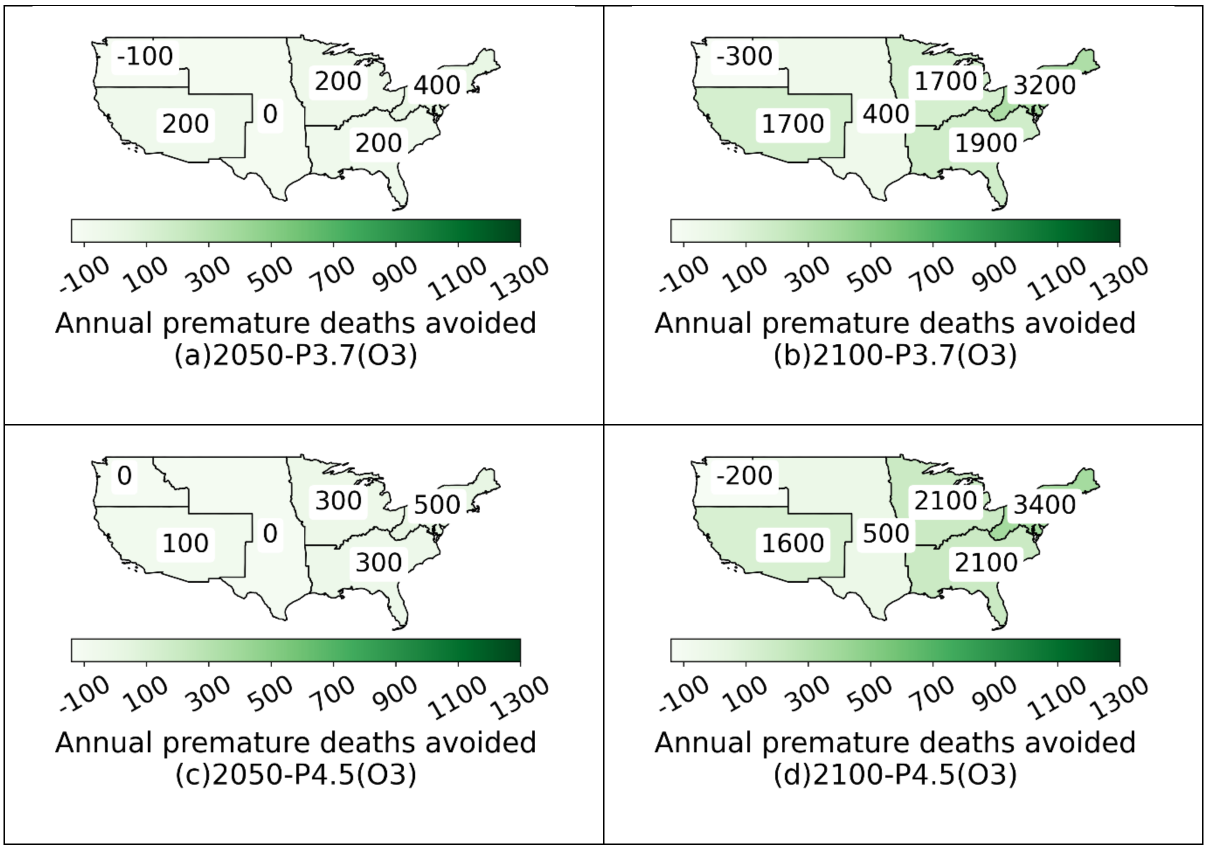


Figure 4-2: The annual premature deaths avoided (rounded to nearest hundreds) in the six regions of the US, for O_3 in the target years (2050, 2100) and under policies (P3.7, P4.5).

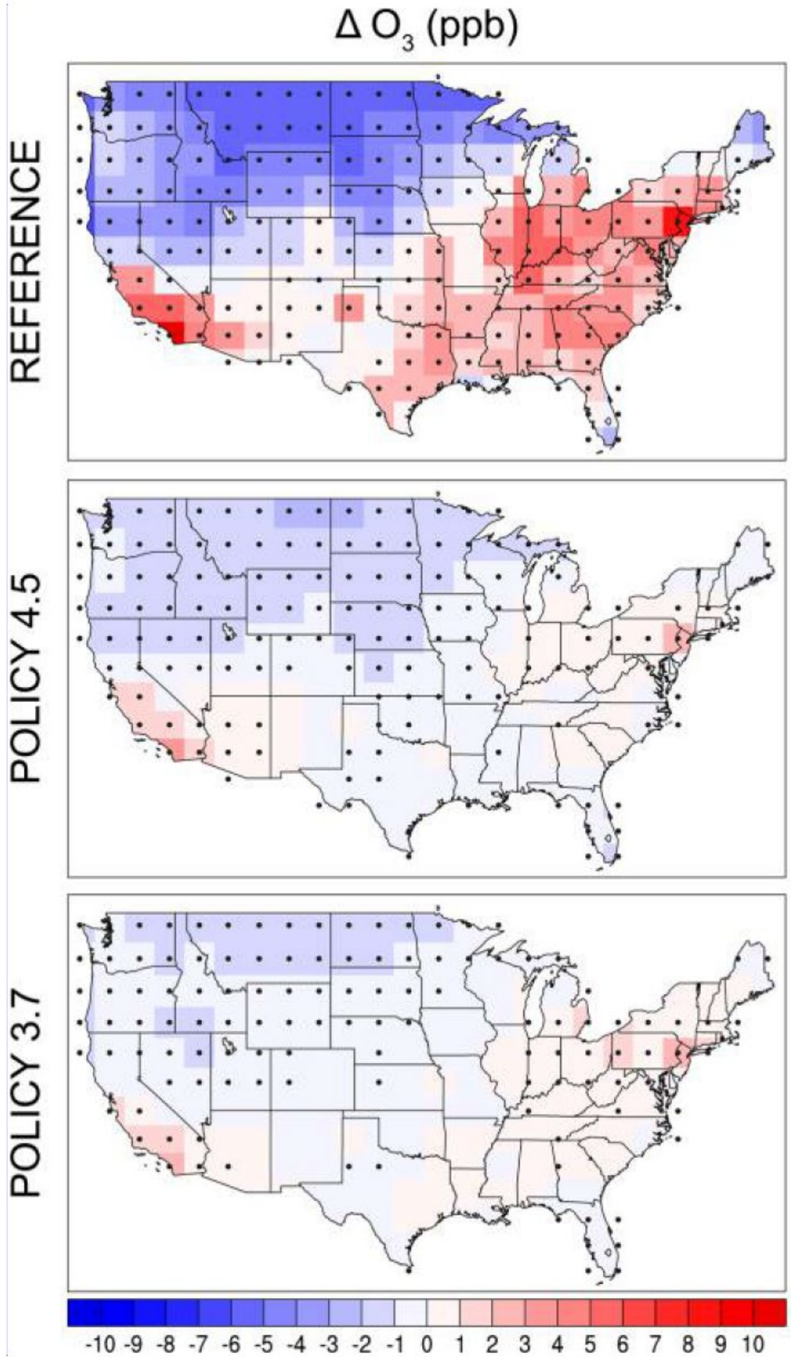


Figure 4-3: "Ensemble-mean climate-induced change in annual-average ground-level 8-h-max O3 from 2000 to 2100 under the REF, $P_{4.5}$, and $P_{3.7}$ scenarios. Changes identified as statistically significant are indicated by black dots". Figure extracted as is from Garcia Menendez et al. 2015.

There is a lack of other studies with which to compare total premature deaths avoided under these policies. This is because most studies do not model climate change itself, and thus do not include the climate penalty pathway, which is what we study here. If they do include the climate penalty pathway, they do not present those results spatially. Saari et al. (2019) previously compared our national total premature deaths avoided to other relevant work, finding that they agreed within errors and given differences in study designs.

We found no work, however, that spatially presented health impacts resulting from the effect of climate policy on the climate penalty alone. We examined literature within multiple recent systematic reviews of health co-benefits of climate policy (Chang et al. 2017; Gao et al. 2018; Karlsson, Alfredsson, and Westling 2020; Harper et al. 2021; Bikomeye, Rublee, and Beyer 2021) and more recent articles that cite them (e.g., (Hamilton et al. 2021)). No study we reviewed included spatial U.S. results on premature mortality due to reducing the climate penalty alone.

The closest studies provided avoided premature mortality based on the combined effects of co-emitted pollutans and the climate penalty pathway (see Figure 1-2). One study examined changes in premature mortaliy and morbidity under $P_{4.5}$ over the US in 2050, but only due to changes in extreme weather events (Yang Zhang et al. 2020).

The closest study examined premature deaths due to total change in air quality under $P_{4.5}$ (Zhang et al. 2017). Their results are provided as Figure 4-4. Figure 4-4(a) is closest to our Figure 4-1 for the case of $P_{4.5}$ and 2050 (bottom left panel). Similarly, Figure 4-4(b) is closest to our Figure 4-2 for case of $P_{4.5}$ and 2050 (bottom left panel). The differences in the presentation of the figures make them difficult to compare direcly. Figure 4-4 is shown at the model grid scale, whereas we aggregated to six regions and rounded to the nearest 100 deaths.

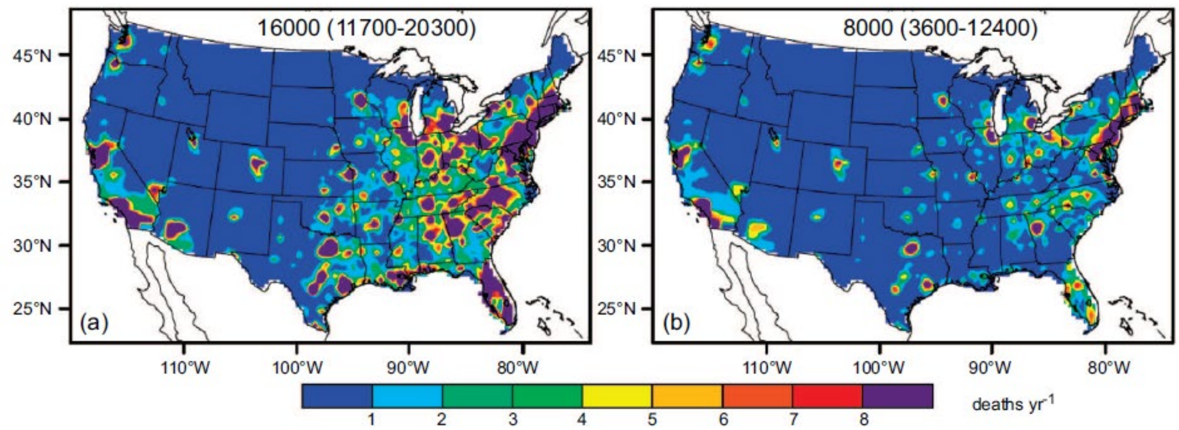


Figure 4-4: Total avoided premature mortality (due to effects of co-emitted pollutants and the climate penalty) in 2050 from **(Zhang et al. 2017)**.
"Total co-benefits (S RCP45-S REF) for avoided premature mortality (deaths yr−1) in the US in 2050, for (a) PM2.5 (all-cause mortality), and (b) ozone (respiratory mortality). Total avoided deaths and 90% confidence intervals are shown at the top of each panel. Positive values indicate fewer deaths."

Given this, we noticed common patterns between the two studies, with most impacts in the eastern US, especially the Northeast. We also noticed that the magntiude of avoided mortality for $PM_{2.5}$ was much greater than for ozone in both studies. This level of agreement was encouraging given the differences between their study and ours. In particular, Figure 4-4 includes the effect of reduced co-emitted air pollutants (the co-emissions co-benefit from Figure 1-2) and the climate penalty co-benefits studied here. The authors of that study found the contribution of the climate penalty to total co-benefits was small, contributing only 300 $PM_{2.5}$–related and 500 ozone-related deaths, respectively (Zhang et al. 2016). Thus, the total premature mortality avoided in Figure 4-4 mostly reflect co-emission co-benefits, which we did not include. This partly explains why they estimated a higher total number of deaths avoided. Other differences are explained by differences in the study designs, with details in Saari et al. (2019).

4.2 Incidence Rates of Premature Deaths Avoided by Region

The data generated in Section 4.1 was normalised with respect to the population in each region to find the incidence rates of premature deaths avoided. These results are presented in Figure 4-5 for $PM_{2.5}$ and Figure 4-6 for ozone, respectively. Incidence rates are a common public health metric that indicate the rate of occurrence of a health outcome in a population. When discussing mortality, it is commonly presented in deaths per 100,000 per year. Here, it is premature deaths avoided per 100,000 people per year. Normalising the data with respect to the population in the region isolates the contribution of pollutant exposure to the total regional mortality (presented in Section 4.1).

Similar trends were observed for both incidences (premature deaths avoided) and incidence rates (premature deaths avoided per 100,000 people). This indicates that the pattern in the effect of the policy across regions was mostly explained by differences in pollutant concentrations, rather than population differences. The incidence rate of premature deaths avoided was higher along the east coast than the west. This was the case for both $PM_{2.5}$ and O_3. In the case of O_3 for the year 2050, there were some increases in incidence rates of premature deaths observed in the Northeast and Great Plains; there were also some increases observed in the Northeast for the year 2100. This behavior was also observed in incidences of premature deaths and was explained under Section 4.1.2.

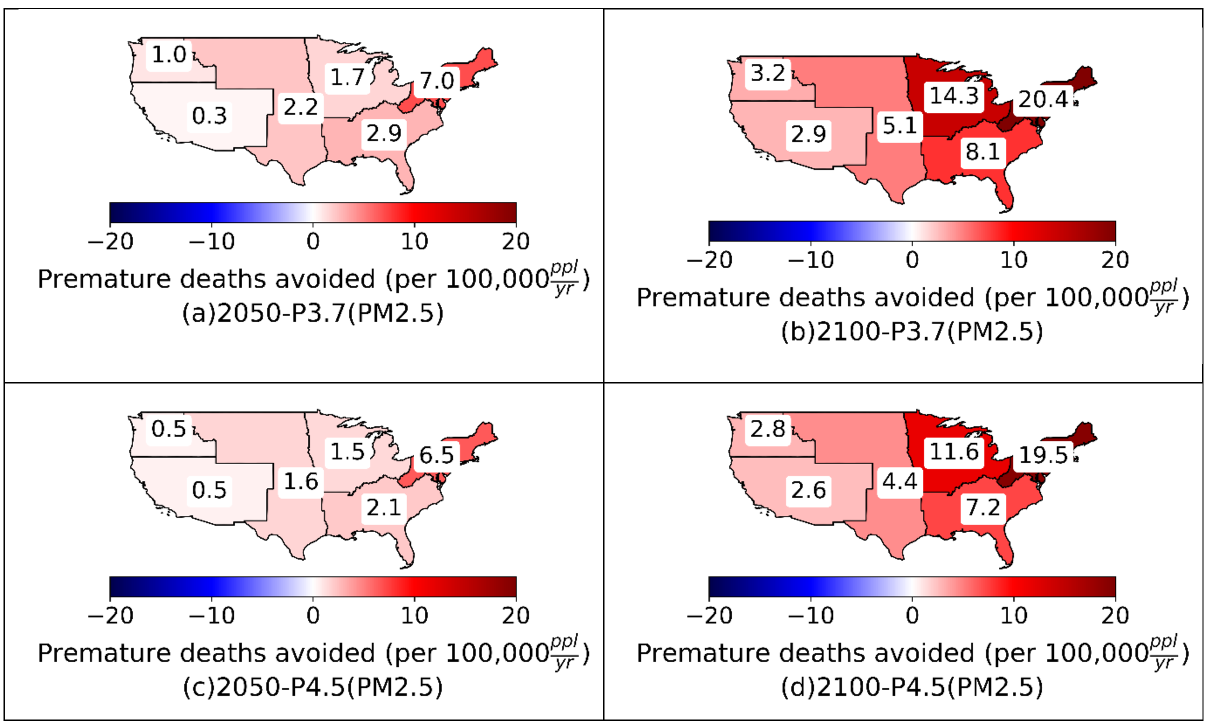


Figure 4-5: Incidence rates of premature deaths avoided (deaths avoided per 100,000 people per year) in the six regions of the US, for $PM_{2.5}$ in the target years (2050, 2100) and under policies ($P_{3.7}$, $P_{4.5}$) (using **(Lepeule et al. 2012)**).

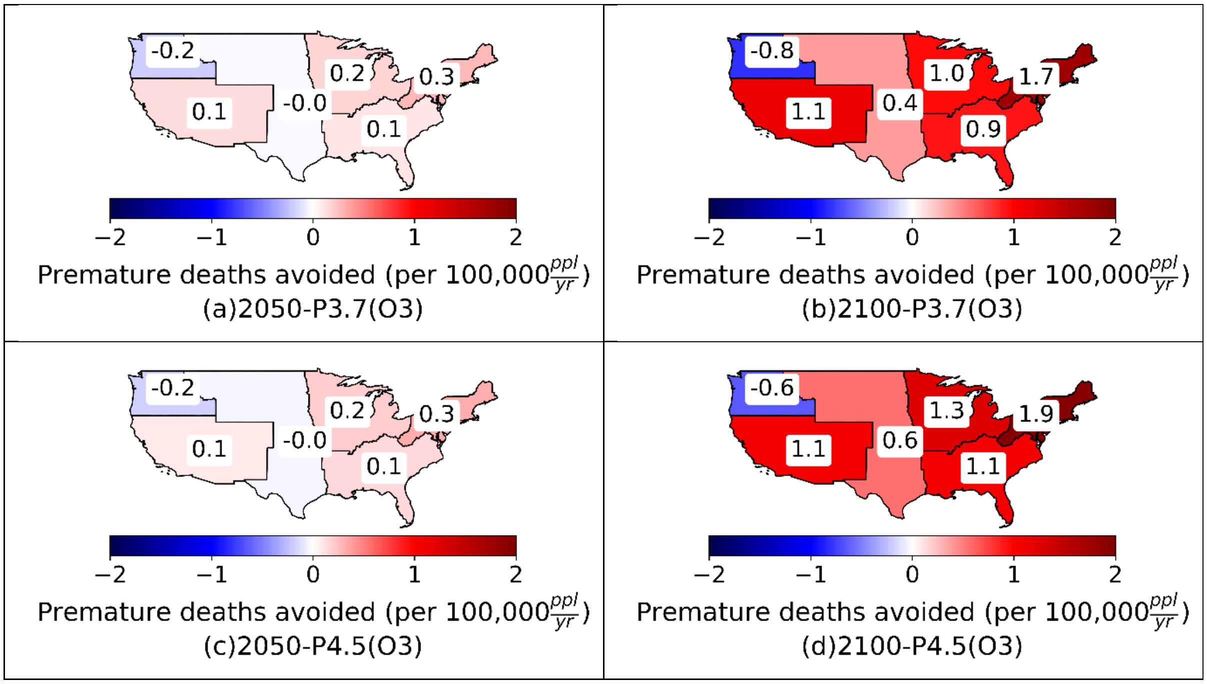


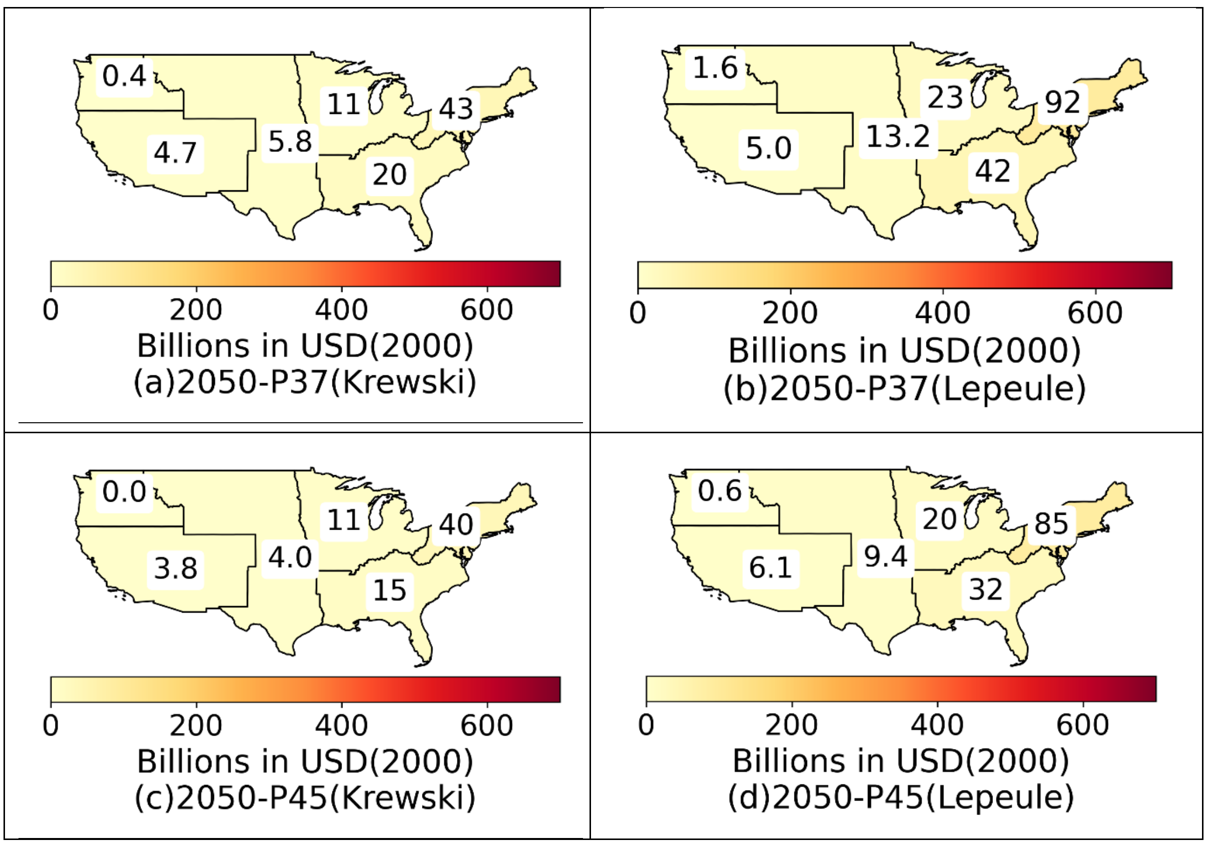
Figure 4-6: The annual premature deaths avoided per capita in the six regions of the US, for the pollutant O_3 in the target years (2050, 2100) and under policies ($P_{3.7}$, $P_{4.5}$).

4.3 Total Benefits by Region

Policies avoided adverse health outcomes and premature mortality. Subsequently, some economic benefits were accrued. These benefits were estimated from the health outcomes averted due to reductions in the pollutants $PM_{2.5}$ and O_3 (discussed in detail in Chapter 3), and presented in billions of USD (year 2000 currency). Most benefits were from premature deaths avoided from $PM_{2.5}$ exposure than from illness or exposure to O_3.

Benefits are shown separately using the CRFs from Krewski and Lepeule for $PM_{2.5}$-related premature deaths, respectively. On average, the benefits obtained using Lepeule were nearly twice that of Krewski. This result was expected and has been found in previous studies and US regulatory impact assessments, for example, (U.S. Environmental Protection Agency 2012; Saari et al. 2019). As previously mentioned in Section 2.3, the Harvard Six Cities Study that produced the Lepeule CRF found a premature-mortality risk increase that was approximately double that of the American Cancer Society study from which the Krewski CRF was produced (with a risk increase of 12% compared to 6%, or a relative risk of 1.12 compared to 1.06) (Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope, Thurston, Calle, Thun, et al. 2009; Lepeule et al. 2012). Since the majority of the value of air quality-related damages derives from $PM_{2.5}$-related premature mortality, the resulting co-benefits also differed by a factor of approximately two.

In general, total benefits increased from West to East, with maximum benefits realised in the Northeast region by target year 2100 and policy $P_{3.7}$ using Lepeule. The maximum benefit occurred in 2100 because this was the end of the analysis period, and the policy had more time to effect the climate. $P_{3.7}$, as the most stringent policy, had better outcomes in terms of co-benefits. Following similar logic, the minimum benefit was seen in the Northwest in 2050 under policy $P_{4.5}$ using Krewski. Typically, the Midwest had lower co-benefits when compared to the Southeast in the target year 2050; but by the target year 2100, the Midwest seemed to have more co-benefits than the Southeast.



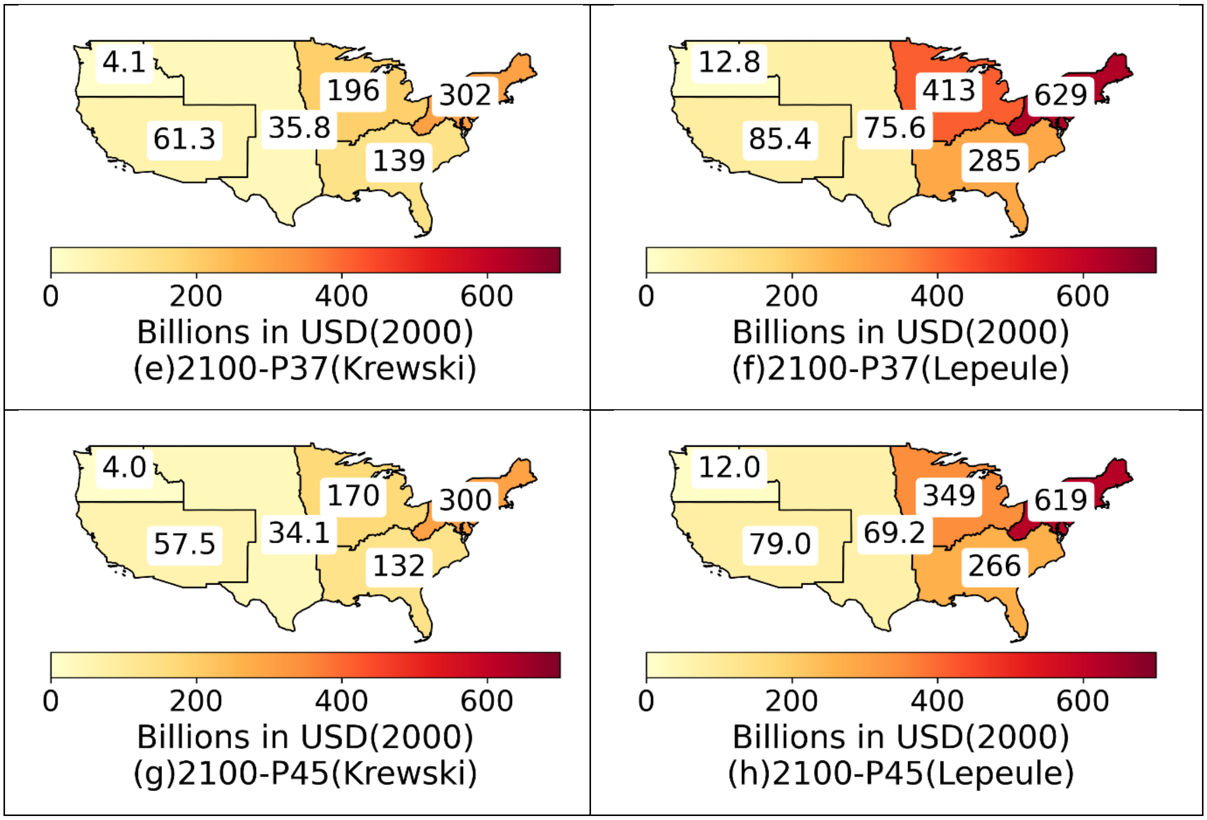
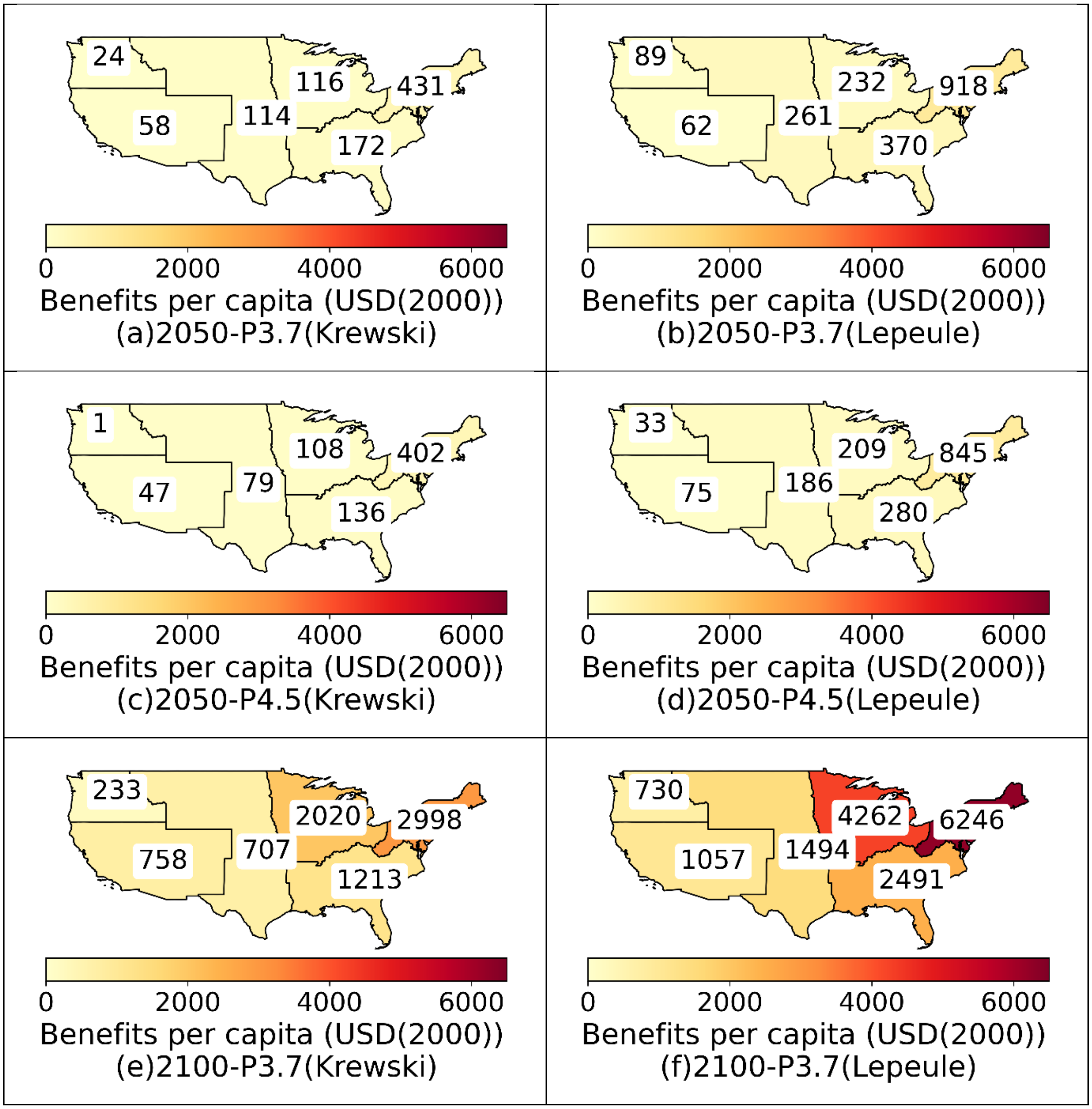


Figure 4-7: Annual air quality co-benefits of climate policy due to reducing the climate penalty for six different U.S. regions (billions USD2000). Values are shown for target years (2050, 2100) and policies ($P_{4.5}$, $P_{3.7}$). Adult premature mortality associated with $PM_{2.5}$ is based on the CRFs provided by **(Lepeule et al. 2012; Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope III, et al. 2009)**.

In attempting to compare our co-benefits with our studies, we lacked relevant sources beyond those on which we build directly (Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019; Saari et al. 2019). (Saari et al. 2019) did not identify any other studies that provided estimates of co-benefits due to the climate penalty pathway. The most recent literature review of climate policy co-benefits (Karlsson, Alfredsson, and Westling 2020) did not include any new studies not already considered in Saari et al. (2019). Studies published since (Karlsson, Alfredsson, and Westling 2020)'s review that include co-benefits (e.g., (Vandyck et al. 2020)) do not include the climate penalty pathway. Thus, we cannot compare our results directly to other work. However, we can note that, per ton of greenhouse gas emissions avoided, co-benefits from the climate penalty pathways are generally smaller than those from the co-emissions pathway.

4.4 Total Benefits per Capita by Region

Similar to Section 4.2, the total co-benefits per capita were estimated for each of the six regions. As with total benefits, the co-benefits per capita were highest in the Northeast for the target year 2100 under policy $P_{3.7}$. The general trend was to see an increase in co-benefits per capita from West to East.



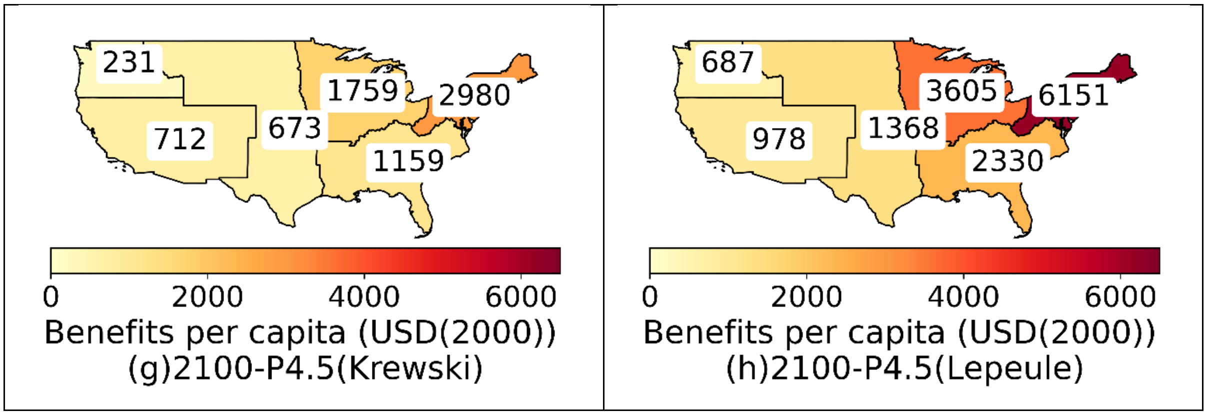
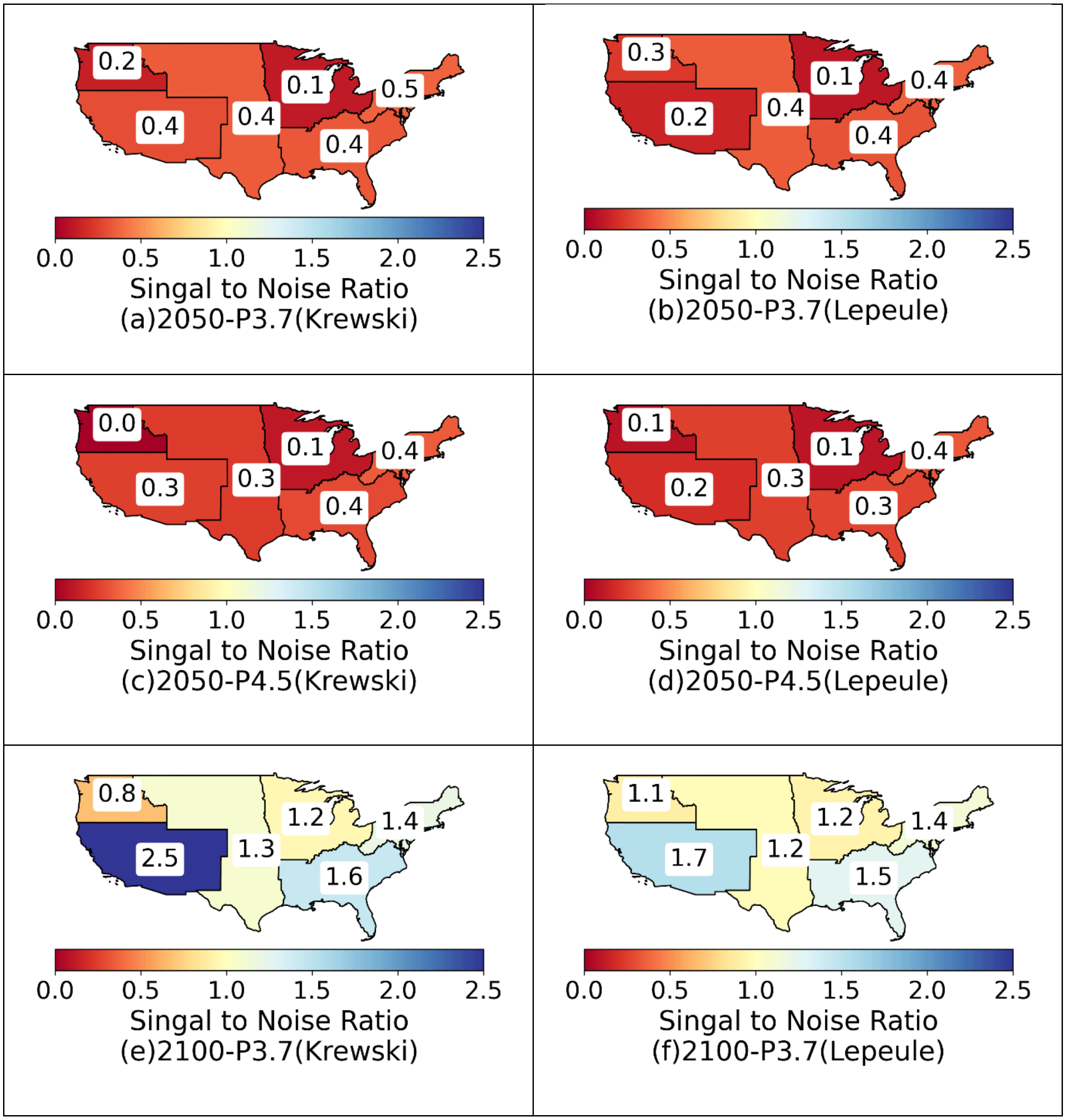


Figure 4-8: Total annual air quality co-benefits per capita of climate policy (USD2000) for six U.S. regions. Values are shown for target years (2050, 2100) and policies (P4.5, P3.7) using CRFs from **(Lepeule et al. 2012; Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope III, et al. 2009)**.

4.5 Signal-to-Noise Ratios

The Signal to Noise Ratio (SNR) was calculated to quantify the effect of natural variability on the ability to distinguish the impacts of policy from natural variations in the climate. The SNR was calculated as in Section 3.4.2. A SNR greater than one signified that the co-benefits due to applied policies emerged from the noise of natural variability. Typically, by the target year 2050, the SNR values were less than 0.5, indicating that some averaging would be needed to filter out this noise. The SNRs closely followed the patterns of the signal itself, i.e., co-benefits and co-benefits per capita in Figure 4-7 and Figure 4-8. SNRs, too, increased from West to East, following the co-benefits pattern, except for the Midwest. Although the Midwest had a higher signal (co-benefit), the lower SNR showed that there was more noise in this region due to natural variability. By the end of the century, the SNR was generally near or above one everywhere. Signals were usually stronger towards the Northeast and Midwest. However, the SNR was highest in the Southwest region for both policies. This implies that, although the Southwest had a smaller signal, its noise due to natural variability must be weaker in order to create a higher SNR. This finding is in line with a previous study that compared the effects of natural variability on temperature and precipitation. It found that Southwest (exemplified by Phoenix, Arizona) had relatively low natural variability compared to the US as a whole (Deser et al. 2012).


0.2
0.1
0.5
0.4
0.4
0.4
0.0 0.5 1.0 1.5 2.0 2.5
Singal to Noise Ratio
(a)2050-P3.7(Krewski)
0.3
0.1
0.4
0.2
0.4
0.4
0.0 0.5 1.0 1.5 2.0 2.5
Singal to Noise Ratio
(b)2050-P3.7(Lepeule)
0.0
0.1
0.4
0.3
0.3
0.4
0.0 0.5 1.0 1.5 2.0 2.5
Singal to Noise Ratio
(c)2050-P4.5(Krewski)
0.1
0.1
0.4
0.2
0.3
0.3
0.0 0.5 1.0 1.5 2.0 2.5
Singal to Noise Ratio
(d)2050-P4.5(Lepeule)
0.8
1.2
1.4
2.5
1.3
1.6
0.0 0.5 1.0 1.5 2.0 2.5
Singal to Noise Ratio
(e)2100-P3.7(Krewski)
1.1
1.2
1.4
1.7
1.2
1.5
0.0 0.5 1.0 1.5 2.0 2.5
Singal to Noise Ratio
(f)2100-P3.7(Lepeule)

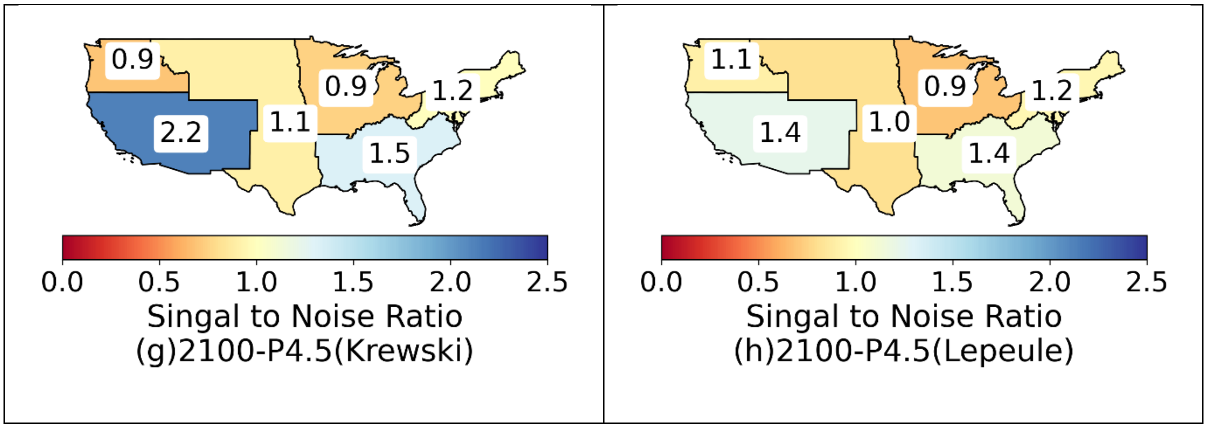


Figure 4-9: The signal to noise ratio represented by the mean co-benefits from O_3 and $PM_{2.5}$ changes over the standard deviation in co-benefits across 150 annual simulations for six different U.S. regions. Using CRFs from **(Lepeule et al. 2012; Krewski, Jerrett, Burnett, Ma, Hughes, Shi, Turner, Pope III, et al. 2009)**.

Having reviewed the literature, there were no studies that similarly examined signal-to-noise ratios in air quality co-benefits due to natural variability. In climate science, there are studies that examined the relationship of simulation length and signal-to-noise for temperature (Santer et al. 2011). For air quality, there have been global studies determining the 'time of emergence' of the signal of climate change on air quality from the noise of natural variability (Barnes, Fiore, and Horowitz 2016). For air quality-related mortality, there was a global study using 20-year simulations that estimated the mean and standard deviation of premature mortality due to ozone and $PM_{2.5}$ in 2100 under the IPCC-A1B "business-as-usual" scenario. They did not fully report these results, however, stating only that the global signal-to-noise ratio was greater than one, but that some regions (such as the Middle East and Rest of Asia) had a signal-to-noise ratio less than one (Fang et al. 2013).

In the US, there are a handful of studies that examined the effect of natural variability on air pollution spatially. All of these studies used the same air pollution levels as us, first presented in (Garcia-Menendez et al. 2015). The work on which we build most directly will be discussed in detail in Section 4.6 (Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019; Saari et al. 2019). One additional study used these air pollution levels along with observations and additional simulations to examine variability in ozone levels in the present and future (Brown-Steiner et al. 2018). For their future simulations, they used ozone levels similar to the ones we used. For the start-of-century values, they used the same air quality model, but with a different set-up (including a different model version and emission inventory). Their present-day results were thus developed with methods slightly different from our own, and provided a source of comparison data.

(Brown-Steiner et al. 2018) presented the effects of both spatial and temporal averaging on the error in present-day ozone, reproduced in Figure 4-10. The simulation length increased from left to right along the columns (from 1 to 20 years), and each row increased the spatial averaging to give results over an area around 200 km^2 to about 2000 km^2. The value of spatial averaging shown by the reduction in error (increasing blue shading) moving from the top to bottom row helps to explain why we aggregated (taking a sum of benefits, as opposed to an average of concentrations) to US regions for our results. The bottom row is closest in spatial scale to the results we presented. Moving from left to right in the bottom row shows which regions were most affected by natural variability for ozone in this study. They found that signals of ozone trends were hardest to detect in the Midwest region, as seen in the figure by the persistent orange region there in the bottom right figure. We also found that the Midwest had a low signal-to-noise in 2050 despite a relatively high signal, reflecting higher natural variability. This applied to effects of both ozone and fine particulate matter, but results from this study and ours can be considered to be aligned.

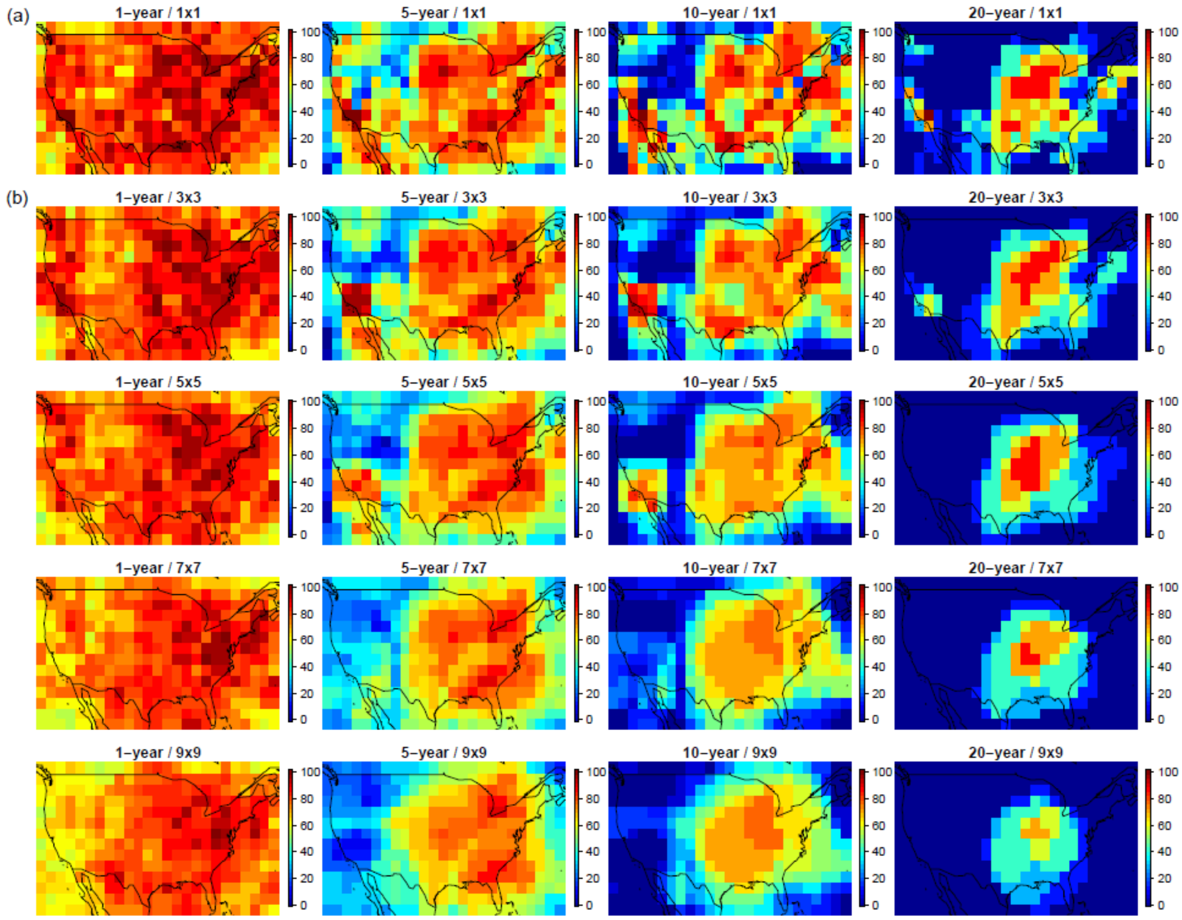


Figure 4-10: Effect of Temporal and Spatial Averaging on Natural Variability in Ozone **(Brown-Steiner et al. 2018)**

Note: Combined impact of temporal and spatial averaging on reducing ozone variability on the likelihood (%) of exceeding the 0.5 ppbv threshold for the present-day (year 2000) simulation. Each column increases the simulation length from left to right (from 1 to 20 years), and each row increases the spatial averaging (from model resolution (about 200 km) to averaging 9 by 9 grid cells (about 1800 km))

When moving beyond pollutant concentrations and considering air quality co-benefits spatially in the US, we found only one study. We discuss it with caution, and with the caveat that the uncertainties being compared were entirely different. The closest study found examined the effect of uncertainty in meteorological variables on premature deaths associated with ozone (O_3) and $PM_{2.5}$ in 2050 (Tagaris et al. 2009). The authors used climate fields (temperature and absolute humidity) from an earlier version of the same Earth System Model used here (the MIT-IGSM). They made use of a sensitivity analysis of the MIT-IGSM that produced probability distributions for its outputs. The authors chose the 0.5th, 50th, and 99.5th percentiles of temperature and absolute humidity with which to assess the effect of uncertainty in future meteorology.

This uncertainty, however, was not due to natural variability. It was due to uncertainty in inputs to the MIT-IGSM, of which "economic growth, technological change, deep oceanic circulation, aerosol radiative forcing, and cloud processes" were the most important influences (Prinn et al. 1999). Using this uncertainty, they determined which states had the highest uncertainty in premature mortality, based on the change over the 99th percentile weather conditions compared to the 50th percentile. They list states which were found to have the highest uncertainty (though the threshold used was not specified) as shown in Figure 4-11.

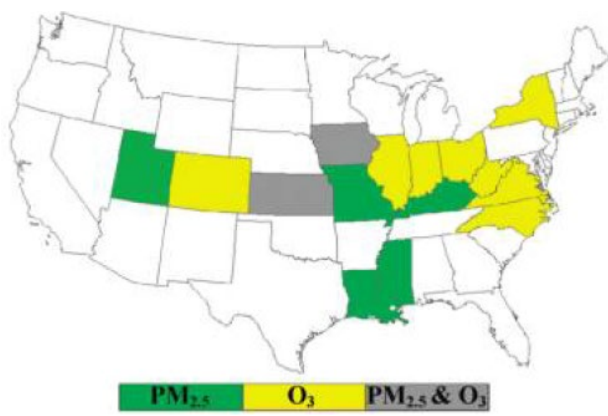


Figure 4-11: States with highest uncertainty in premature mortality in 2050 based on uncertainty in meteorological variables (adapted from **(Tagaris et al. 2009)**)

We note that several states appear in the Midwest, for which our signal-to-noise ratios were lowest in 2050, despite relatively high signals. However, our source of uncertainty in meteorological variables was different than used in (Tagaris et al. 2009), so it does not reflect on the accuracy of our findings. If anything, comparing these two studies served to remind us that certain US regions may be subject to greater uncertainty than others in estimating the benefits of future climate policy, including from natural variability and other factors.

4.6 Minimum Simulation Lengths for Addressing Natural Variability

Signal-to-noise ratios identified the cases and places for which averaging to reduce the effect of natural variability was most needed. However, they did not specify how much averaging is needed, i.e., the minimum simulation length for addressing natural variability. The minimum length matters because longer simulations take longer to run on high-performance computers. This extra computational costs takes time away from other useful activities like evaluating more potential emissions pathways or increasing the spatial resolution of the simulation. Thus, the costs of increasing simulation lengths should be balanced with the benefits it brings. In this case, we examined benefits in terms of reducing noise due to natural variability. As simulation length increased, we found that those benefits diminished.

Two approaches are presented in this section for evaluating minimum simulation lengths. The first approach analysed the diminishing returns of increasing simulation length, and the second used a metric to determine the minimum length (here, based on health-related uncertainty), following the advice of (Milinski, Maher, and Olonscheck 2020).

The first approach quantified the reduction in noise achieved by increasing simulation lengths. Reductions in both absolute and relative errors introduced by natural variability were calculated. Exponential decay curves were fit to characterize the diminishing returns of increasing simulation length.

To calculate the absolute error associated with natural variability, the Reference (REF) case was considered for the target year 2100. There were 150 simulations (30 years for 5 initializations) available. If there were no noise due to natural variability, the difference in co-benefits between any two random pairs of simulations should be zero. Instead, a distribution of non-zero differences was found, each representing natural variability between two random annual simulations. The noise due to natural variability was measured as the 95th Confidence Interval (95CI) in this distribution, which was \$1.2 Trillion for the CRF by Krewski and about \$1.5 Trillion for the CRF by Lepeule. By selecting multiple pairs to average together, the averaging period, and thus the minimum simulation length, increased. Averaging reduced the noise to ~\$0.2 Trillion, reducing it approximately by a factor of six. Figure 4-12 shows how the noise from natural variability (95CI) dropped by nearly a factor of six, for the two CRFs used.

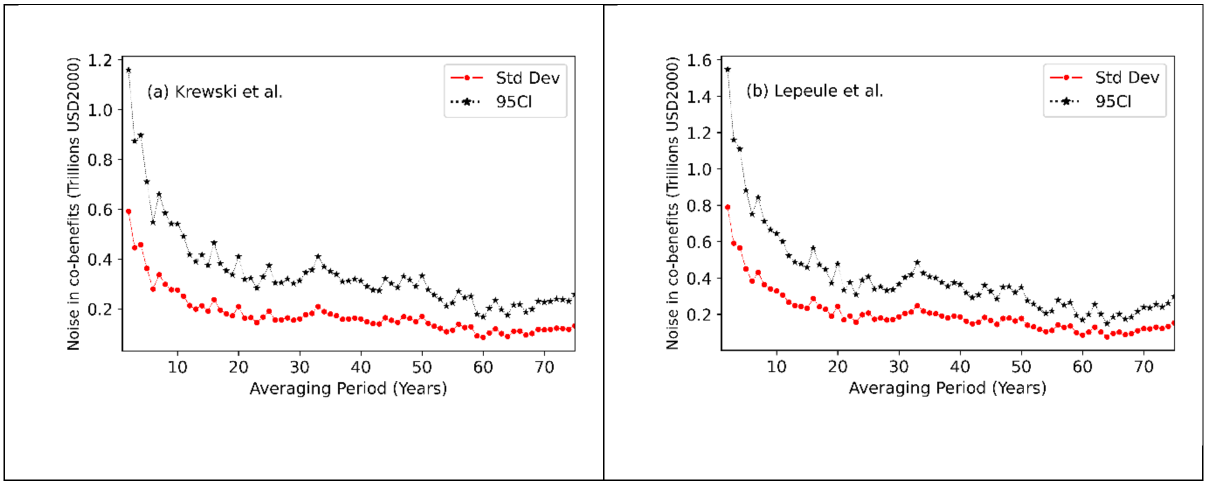


Figure 4-12: The reduction in noise in co-benefits due to natural variability with increasing averaging period (in years). Noise is measured by the standard deviation (Std Dev) and 95th Confidence Interval (95CI) estimating co-benefits within the Reference scenario at end-of-century for (a) Krewski and (b) Lepeule (in Trillions USD2000).

The noise reduction clearly showed diminishing returns as the averaging period increased in Figure 4-12. This was quantified by fitting an exponential decay curve to the relative error reduction achieved by averaging. This analysis was repeated for all co-benefits cases and regions. Since the absolute error varied by case and region, the relative error reduction was calculated per Section 3.4.3. The reduction in error was found to have an exponential decay trend. Fitting parameters and goodness of fit (R^2) for the eight cases at the national scale are presented in Equation 4-1

Table 4-2. The fitting parameters were based on representing the relative error reduction as (with code included in Appendix A):

$$y = Ae^{-Kt} + C$$

Equation 4-1

Table 4-2: Exponential decay fitting parameters and goodness-of-fit for relative noise reduction induced by increasing simulation lengths for national-scale analysis.

Policy	Year	CRF	A	K	1/K	C	R^2
P3.7	**2050**	Krewski et al.	1103	0.28	3.6	31	0.99
		Lepeule et al.	1223	0.30	3.4	40	0.99
	2100	Krewski et al.	1138	0.31	3.2	100	0.95

		Lepeule et al.	1119	0.31	3.2	98	0.96
P4.5	**2050**	Krewski et al.	1291	0.32	3.1	51	0.99
		Lepeule et al.	1289	0.33	3.0	49	0.99
	2100	Krewski et al.	1588	0.42	2.4	151	0.95
		Lepeule et al.	1553	0.38	2.6	142	0.94

At the national scale, the time constant for this exponential decay was about two to four years; hence by the fourth averaging period, the noise had dropped to approximately one third of its initial value (because $e^{-1} \approx 0.37$). This means that a few years of averaging decreased the noise due to natural variability by 63%, or nearly two-thirds.

Figure 4-13 shows the relative error reduction in the Northeast region, at the target year 2050, for the policy $P_{3.7}$. For the six different regions, plots similar to Figure 4-13 were generated for the two target years and two policies.

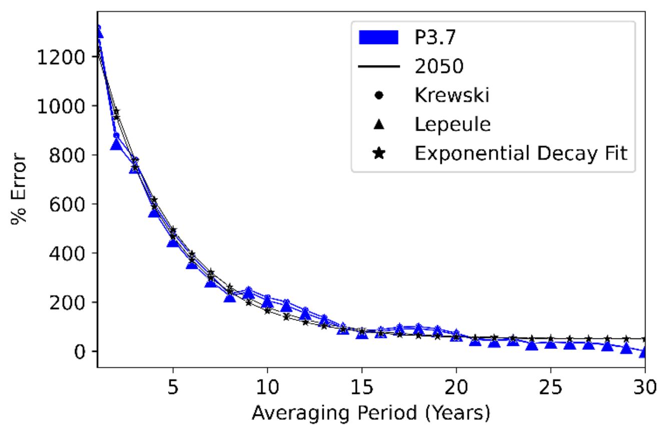


Figure 4-13: The decrease in spread (%Error) across ensemble members with increase in averaging period in the Northeast region, at the target year 2050, for the policy $P_{3.7}$.

An exponential decay curve was fit to the data, and the time constants for them were summarized in Table 4-3. The mean time constant was five years, with a range of 3-7 years. The table was colour-coded so that cases near the mean are white, cases below are blue, and above are red. Cases and regions with higher time constants are areas in which more averaging was needed to reduce the noise from natural variability by the same amount, while cases with blue colouring needed less averaging. Because these are relative errors, these results had a different meaning than the SNR analysis, which was affected by the magnitude of co-benefits; conversely, these findings focused only on how easy it was to reduce noise. The table revealed patterns by region and policy, with smaller changes by target year or CRF. For example, the Northwest required more averaging than the Northeast for all cases, and for the Midwest for all but two cases. The more stringent policy, $P_{3.7}$, required slightly less averaging, on average, than $P_{3.7}$; however, there were noticeable differences in this effect across regions, with most of the effect seen in the Great Plains and Southeast. Overall, this analysis suggests that diminishing returns were obtained by increasing simulation length, especially after 4-7 years of simulation.

Table 4-3: Summary of the time constant from the exponential decay fits, in other words, the simulation length needed to reduce the noise from natural variability by two-thirds.

			Northwest	Southwest	Great Plains	Midwest	Northeast	Southeast
Policy $P_{3.7}$	Year 2050	Krewski et al.	5.9	4.9	3.5	4.4	5.1	4.6
		Lepeule et al.	5.4	5.2	3.3	4.4	4.9	4.4
	Year 2100	Krewski et al.	4.8	5.1	3.5	5.4	3.9	4.6
		Lepeule et al.	5.5	5.6	3.6	5.2	4.0	4.5
Policy $P_{4.5}$	Year 2050	Krewski et al.	5.0	3.8	6.1	4.2	4.3	6.0
		Lepeule et al.	3.6	3.9	6.2	4.1	4.2	5.8
	Year 2100	Krewski et al.	6.1	5.0	5.9	3.8	4.1	6.9
		Lepeule et al.	6.7	4.9	5.8	4.0	4.1	7.3

While the previous analysis showed the benefits of a few years of averaging, and the diminishing returns of additional averaging, it still did not provide a recommended minimum simulation length that accounts for the magnitude of co-benefits. This is important, for example, to avoid using precious computational time reducing errors in very small co-benefits. To address this, we apply a metric to determine the minimum simulation length, as described in section 3.4.3.

Nationally and regionally, we used health-related uncertainty as the metric to determine minimum simulation length across all co-benefits cases. Specifically, we looked at the percentage of co-benefits estimates that fall within the 95th confidence interval (95CI) in health-related uncertainty as determined per Section 3.4. That 95CI is estimated based on the mean pollutant concentrations across the ensemble (all 150 annual simulations for each case), thus, it reflects only irreducible, epistemic uncertainty in health and economic responses that cannot be affected by increasing simulation lengths.

Figure 4-14 presents these results at the national scale. The percentage of co-benefits estimates that meet the metric are plotted for each averaging period. The minimum simulation length was determined by finding the averaging period for which 100% of the estimates met the metric. For comparison, a less stringent alternative, a metric of 90% of the estimates falling within the 95CI, was also shown with a grey horizontal line. For the target year 2100 (shown in blue), 90% of the co-benefits estimates met the metric (i.e., fell within the 95CI of health-related uncertainty) immediately, with a single year of simulation; 100% of the estimates met the metric with just three years of averaging. This suggests a minimum simulation length of just a few years for the end-of-century target year across policies and CRFs. Conversely, in the case of the target year 2050, it took about six to eight years of averaging to get at least 90% of the estimates to meet the metric, and about ten to fifteen years of averaging to get 100% to meet it.

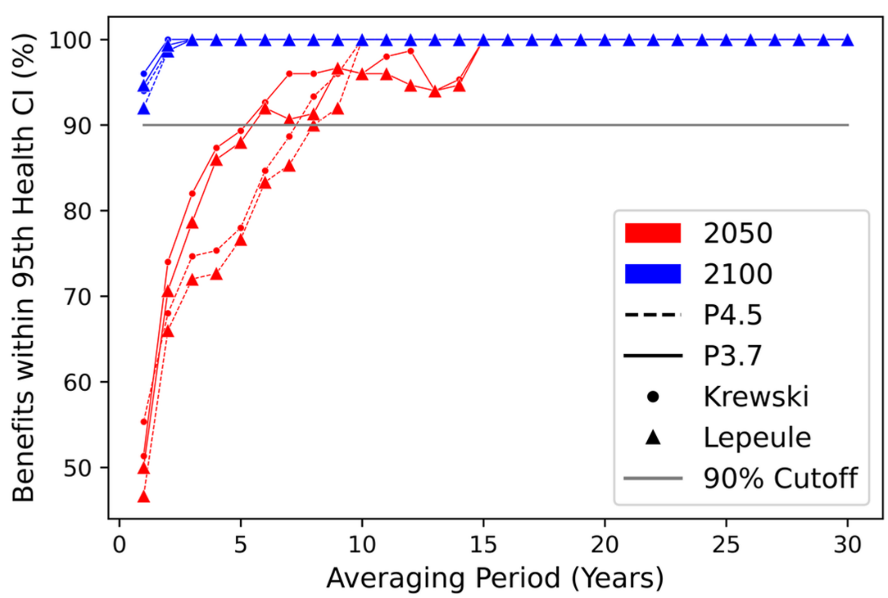


Figure 4-14: National-scale minimum simulation lengths. Minimum determined by finding the averaging period (in years) for which either 90% or 100% of co-benefits estimates fall within 95CI of health-related uncertainty.

The data presented in Figure 4-14 was split for the six regions, and represented in Figure 4-15 for target year 2100 and Figure 4-16 for target year 2050. The target year of 2100 is presented first because its interpretation is simpler. In 2100, a similar result was found for the regions as for the national scale, requiring minimum simulation lengths of only a few years. In the target year 2100, an averaging period of two years put 90% of estimates within health related uncertainty. Four years of averaging brought 95% of estimates within the metric. Eight years of averaging brought 100% of estimates within the metric.

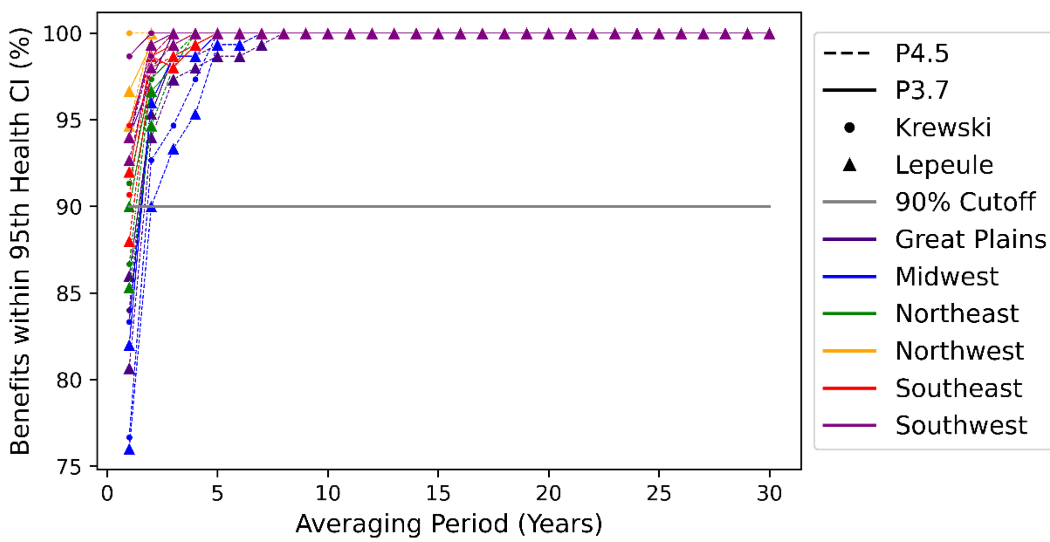


Figure 4-15: Regional-scale minimum simulation lengths for 2100. Minimum determined by finding the averaging period (in years) for which either 90% or 100% of co-benefits estimates fall within 95CI of health-related uncertainty.

In the case of the target year 2050, shown in Figure 4-16, results were more complicated. Regions which had the highest signal to noise ratios (e.g., Great Plains, Northeast, and Southeast, per Figure 4-9) needed a minimum simulation length of about eight years. Other regions with low signal to noise ratios needed more than eight years.

In fact, the maximum simulation length here (30 years) seemed insufficient for the Midwest region in 2050, which never met the metric for any policy or CRF. Even for the 30-year average values, one of the five ensemble members for $P_{3.7}$ did not meet the metric (i.e., only 4 out of 5 or 80% of estimates met the metric). In other words, one 30-year mean estimate fell outside of the 95CI of health-related uncertainty.

$P_{4.5}$ was even more troublesome. As the less stringent policy, it had a smaller effect on the climate and a smaller co-benefits signal. In the Midwest, which the SNR analysis showed had higher noise, two ensemble members gave estimates that failed to meet the metric even with 30 years of averaging.

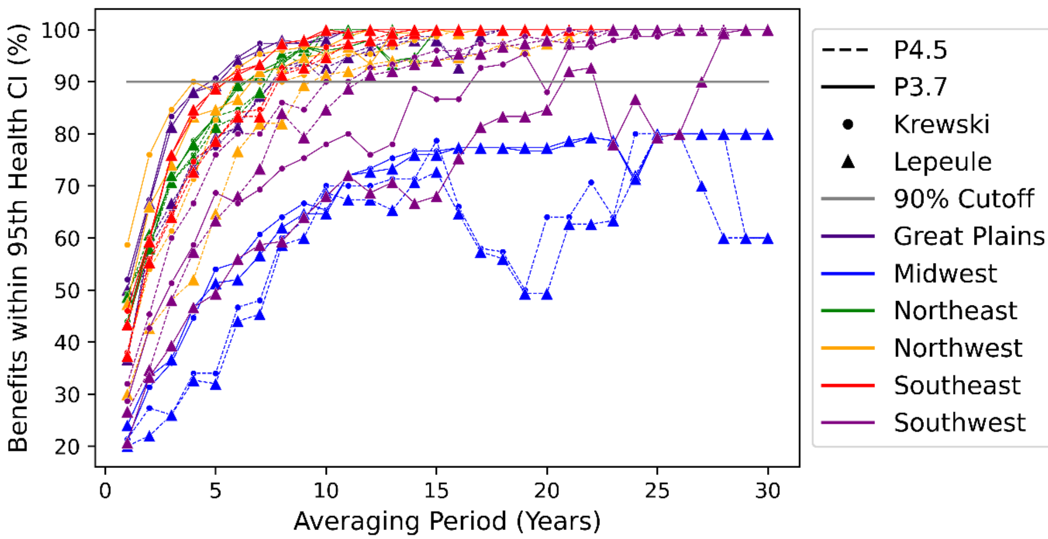


Figure 4-16: Regional-scale minimum simulation lengths for 2050. Minimum determined by finding the averaging period (in years) for which either 90% or 100% of co-benefits estimates fall within 95CI of health-related uncertainty.

The case of the Midwest at mid-century showed that increasing simulation length alone can be insufficient for filtering out natural variability in air quality co-benefits. For other cases, the five ensemble members converged enough that they agreed within our metric with less than 30 years of simulation. In the case of the Midwest at mid-century, however, one or two members did not converge enough to meet our metric.

This result shows the danger of the common practice in air quality co-benefits research of using a single climate model initialization instead of multiple initial conditions (in other words, using a single member instead of an ensemble of members). This result fits with findings from climate science, which has already shown the importance of long-run, large initial condition ensembles to address natural variability in climate variables like temperature or precipitation (Deser et al. 2020).

There are several possible explanations for this result in our case. First, as a reminder, our metric for the minimum simulation length was derived using the mean pollutant concentrations from our full ensemble, and then deriving a 95CI in so-called "health-related uncertainty" using 5000 Monte Carlo simulations based on uncertainty in health and economic responses. The full ensemble included 30-year simulations meant to represent year-to-year variability. Those 30-year simulations were repeated using five different sets of initial climate conditions, which produced five divergent climate futures. The different initial conditions helped to capture multi-decadal variability, e.g., natural variations in the climate system with periods of longer than 30 years. The difference in mean concentrations between policy and reference scenarios across the whole ensemble (150 annual simulations in total), was meant to be the "true" estimate of the policy impact without natural variability. However, while five members is large compared to previous air quality studies, it is a relatively small ensemble for climate studies, and might not be enough to capture the full range of multi-decadal variability (Deser et al. 2020). For most cases, the five ensemble members converged enough that they agreed within our metric with less than 30 years of simulation. In the case of the Midwest at mid-century, however, one or two members continued to stand out, which may be due to persistent multi-decadal variability. In such cases, therefore, multiple initial conditions were needed in addition to long simulation lengths to address natural variability in co-benefits.

Our results for the Midwest and other cases match well with results from climate studies. Such studies have not yet been performed for air quality co-benefits, but work on simulating future climate change has found similar patterns in natural variability. They find that addressing natural variability is more difficult when estimating climate change impacts for smaller regions, shorter time periods, and less ambitious policy (Fiore, Naik, and Leibensperger 2015). Logically, then, it would be simplest to address for long time periods, large regions and ambitious policies. This is in line with our finding that the shortest simulations were needed for our longest time period (2100), largest region (continental US), and strongest policy (P3.7).

By addressing this thesis' third research question and finding minimum simulation lengths in air quality co-benefits, we extend previous work which found minimum simulation lengths for air quality concentrations. We consider uncertainty in health and economic responses to develop a metric for minimum simulation lengths that recognises this irreducible uncertainty in policy co-benefits. Using this metric, we generally found that minimum simulation lengths could be reduced, saving computational time.

By 2100, we found that four years of simulation sufficed for 95% of all estimates in all cases to meet our metric. This is shorter than previous studies recommending minimum lengths of 10 years or more might be needed to assess future air pollution levels (Fiore, Naik, and Leibensperger 2015; Brown-Steiner et al. 2018; Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019; Lacressonnière et al. 2016; Fu and Tian 2019). While such longer simulations may be appropriate for studies of future air pollution for which such accuracy in concentrations might be needed (Brown-Steiner et al. 2018), our shorter lengths recognized additional uncertainties in evaluating policy benefits. This yielded minimum lengths which are more policy-relevant and realistic given computational limits of current studies (Fu and Tian 2019).

We specifically compared our recommendation (at 95% confidence level) for 2100 of four years of simulation length to those based on modelled ozone and $PM_{2.5}$ pollution. First, we considered recommendations from two studies which used the same modelled ozone and $PM_{2.5}$ as we did. Those studies recommended longer simulation lengths for 2100, provided in Table 2-1 and Table 2-2 (Garcia-Menendez et al. 2015; Garcia-Menendez, Monier, and Selin 2017; Pienkosz et al. 2019). Their minimum lengths were based on accuracy in pollutant concentrations. For $PM_{2.5}$, their length was 8 years for national estimates, and 9-23 years for subnational regions; for ozone, it was 11 for national estimates, and 5-19 for subnational regions (based on a 95% confidence level).

We also reviewed other advice on simulation lengths based on pollutant concentrations, including multiple literature review studies (Fiore, Naik, and Leibensperger 2015; Deser et al. 2020; Fu and Tian 2019). Two studies focused only on ozone (Fu and Tian 2019; Brown-Steiner et al. 2018) while others included both ozone and $PM_{2.5}$ (Fiore, Naik, and Leibensperger 2015; Lacressonnière et al. 2016; Deser et al. 2020). One recent review (Fu and Tian 2019) cites the other studies mentioned. It notes that older studies used 3-5 years but that, due to recent findings that at least 15 years of simulation may be needed, most, but not all, recent studies use 10-year to 30-year simulation lengths. However, individual studies giving these recommendations do point out that the appropriate context for decision-making is required. (Brown-Steiner et al. 2018) state, “Quantifying the signal-to-noise ratio at a variety of spatial scales, and determining an acceptable threshold of a particular signal, could be one accessible method for providing this context”. Here, we aimed to address this specific gap to offer more policy-relevant recommendations.

Chapter 5
Conclusion

5.1 Main Contributions and Implications

This thesis aimed to provide policy-relevant insight about how to evaluate the effects of climate policy on impacts associated with air pollution given uncertainty within the climate system. To do this, this thesis offered new analysis of results from a multiple initial condition ensemble of future climate scenarios previously used to evaluate the effects of natural variability on estimates of air quality co-benefits nationally in the US (Saari et al. 2019).

That previous study estimated the effects of different greenhouse gas emissions scenarios in 2050 and 2100. Specifically, it examined the effect of greenhouse gas emissions on a changing climate, and the changing climate's effect on outdoor air pollutants, a relationship known as the "climate penalty". It quantified the effect of the climate penalty on air pollutants including $PM_{2.5}$, ozone and their associated health and economic effects. Under two different climate policies consistent with the Paris Agreement on climate change, the air quality co-benefits associated with reducing the climate penalty on $PM_{2.5}$ and ozone were explicitly modelled and isolated.

This thesis offered new analysis of that ensemble to address three research questions:

1. How do air quality co-benefits vary regionally within the United States of America (US), by time period and climate policy?
2. How large is the "noise" in the signal of air quality co-benefits due to natural variability?
3. What is the minimum simulation length required to address natural variability in air quality co-benefits, and how does this vary with geographic location, spatial scale, and time period?

The conclusions and contributions of this thesis to each research question are summarized below:

1. The air quality co-benefits of climate policies were largest in the Eastern US and grew over time. This result was consistent with the closest existing study (Zhang et al. 2016). This thesis, however, was the first to present results that isolated the effect of the climate penalty spatially,

yielding climate co-benefits which were expectedly smaller than the total co-benefits (climate co-benefits and co-emissions co-benefits) in (Zhang et al. 2016).

2. The noise due to natural variability was large. In 2100, the spread in air quality impacts due only to natural variability exceeded \$1 trillion USD (year 2000 currency) measured as the 95th CI in estimates across the ensemble. To understand the importance of this noise in estimating co-benefits, signal-to-noise ratios (SNRs) were calculated for U.S. regions in 2050 and 2100. SNRs were below one across the U.S. in 2050, increasing to above one by 2100 in most regions as the climate policy had more time to affect the climate system. The magnitude of this noise, and its value relative to the signal, suggested that methods were needed to filter it out by increasing simulation length.

3. In 2100, despite the significant noise from natural variability found in response to question (2), minimum simulation lengths were relatively short when assessed using a metric based on health-related uncertainty. That metric required co-benefits estimates to fall within the 95CI of health-related uncertainty. Nationally, 95% of simulations met the metric with a minimum length of 2 years, and all regions met the metric with four years. In 2050, however, minimum simulation lengths of eight years were needed even in regions with high SNRs. In some regions, like the Midwest, even 30 years were not sufficient. This indicated that single simulations of the future climate might not be sufficient to filter out natural variability in cases where SNRs were expected to be low. In such cases, multiple initial condition ensembles would be needed, in addition to long simulation lengths.

Compared to previous studies, the simulation lengths recommended here are generally shorter. These shorter lengths are more reflective of recent practice, less resource-intensive, and help lower the bar for including co-benefits in the evaluation of climate policy. Shorter lengths were obtained by designing a more policy-relevant metric based on uncertainty in health and economics impacts. Previous studies used metrics based on accuracy in pollutant concentrations, recommending that at least 10-15 years of simulation be used in 2100 (Fiore, Naik, and Leibensperger 2015; Deser et al. 2020; Fu and Tian 2019; Deser et al. 2020; Lacressonnière et al. 2016; Brown-Steiner et al. 2018). As noted by those studies, the simulation length for a given policy evaluation will depend on the specific question; however, this thesis provided an approach for developing a more accessible, policy-relevant simulation length.

5.2 Summary of Comparison to Previous Work

This thesis built on simulations that were previously evaluated. Firstly, the modelled pollutant concentrations used for the start-of-century conditions compare reasonably well with measured pollutant concentrations, as detailed in previous work (Garcia-Menendez et al. 2015; Pienkosz et al. 2019). The economic projections and associated emissions have undergone intermodal comparisons (Fawcett et al. 2014; McFarland et al. 2018). National estimates of the future health burden of air pollution in 2050 and 2100 agreed with previous relevant studies, as detailed in (Saari et al. 2019).

The new results in this thesis, including regional co-benefits, SNRs, and simulation lengths, did not have any source of direct comparison to measurements or other modelling studies. However, certain components and insights appear aligned with other work. (Zhang et al. 2017) had total co-benefits (due to both co-emitted pollutants and the climate penalty) with a similar pattern to our co-benefits due to the climate penalty alone. Our findings about the effect of natural variability and resulting signal-to-noise ratios appeared aligned with other work, even if they only considered one pollutant (Brown-Steiner et al. 2018), had different sources of meteorological variability (Tagaris et al. 2009), or different geographic scope (Fang et al. 2013). We found that the shortest simulation lengths applied to our furthest time period (2100), largest region (continental US), and strongest policy (P3.7), which agreed with previous findings on the role of natural variability in isolating the climate penalty (Fiore, Naik, and Leibensperger 2015; Deser et al. 2020).

5.3 Limitations

This thesis aimed to represent and isolate the effect of natural variability on air pollution and its related health and economic outcomes. However, our approach may be inaccurate. First, our model's internal variability may not accurately represent natural variability in the real climate system. Nonetheless, comparisons between the CESM modelling system and ground-level observations of ozone showed they were largely consistent in their representation of variability (Brown-Steiner et al. 2018). Still, some natural climate processes that can affect air quality were not included, such as projected changes in wildfire emissions, as detailed in (Garcia-Menendez et al. 2015). Second, we may have misattributed some co-benefits to natural variability. We assumed that any difference in co-benefits between two random years in one emission scenario could be attributed only to natural variability. This assumed we completely removed the forced signal from climate change or climate policy, leaving only the noise due to natural variability. In the original model results, there was also an expected trend due to the climate change over each 30-year period. That was removed through linear regression per (Garcia-Menendez et al. 2015). Theoretically, any variation not caused by the forced signal would be due to natural variability. However, it is possible that some variation could have another explanation, such as non-linearity in the forced response, or numerical noise due to discretization in the computational modelling methods, for example.

Our metric for assessing the effect of natural variability was based on health-related uncertainty, which also had its limitations. There are other sources of health-related uncertainty that we did not quantify, such as the effect of thresholds, the shape of the CRF, or the selection of additional CRFs for mortality or additional health outcomes (Nasari et al. 2016; Burnett et al. 2018; Silva et al. 2017). Others include uncertainty in baseline health incidence rates (West et al. 2013; Silva et al. 2017) and population demographics (Dionisio et al. 2017). Further, there are additional health-related uncertainties which remain difficult to quantify, such as the effects of emission sources or particulate matter size and composition, to name a few (Bell and Ebisu 2012; Hime, Marks, and Cowie 2018). There is also the question of how health responses may change over time as populations and relevant factors evolve (e.g., characteristics of exposures and available prevention and treatment).

In addition to limitations affecting the main variables in this thesis – uncertainties due to health responses and natural variability – many other factors limit the accuracy or generalizability of its findings. The limitations of the modelling framework used here have been detailed at length in other studies (Garcia-Menendez et al. 2015; Garcia-Menendez, Monier, and Selin 2017; Paltsev et al. 2015; Monier et al. 2013). Previous work focusing the MIT-ISGM have quantified other sources of uncertainty (Prinn et al. 1999; Webster et al. 2003) and their effects on health impacts related to air pollution (Tagaris et al. 2009). Limitations of a specific modelling system can be addressed in part using multi-model ensembles (Lacressonnière et al. 2016). However, they cannot address sources of uncertainty which are not captured within these systems. Numerous studies have presented detailed critiques of integrated assessment models and their ability to represent natural and human systems (Asefi-Najafabady, Villegas-Ortiz, and Morgan 2020). Here, we used a relatively complex IAM coupled to an Earth System Model of intermediate complexity, and a full 3-D chemical transport model, which offers some advantages in representation. However, many gaps remain, including, for example, robust inclusion of social processes (Mathias et al. 2020). Sociocultural responses to emissions and their impacts at different scales of governance, by policy-makers, institutions, and individuals, for example, introduce significant uncertainties that are generally not well captured in integrated assessment models used to evaluate the effects of climate policy (Donges et al. 2020). Linking models of human behavioral change to systems models of climate policy have been shown to introduce behavioral uncertainty of a similar magnitude to physical uncertainty (Beckage et al. 2018).

5.4 Future Work

Future work could address several limitations to offer more accurate simulation lengths, and to better understand the role of natural variability in evaluating climate policy's effect on air quality co-benefits. Simulation lengths here were based on comparing noise due to natural variability and health-related uncertainty. Representations of natural variability could be improved by using more sophisticated Earth System Models (ESMs) that include other natural responses and feedbacks, especially those which affect air pollution. Using an ensemble of multiple ESMs with different internal variability could help account for uncertainty in model parameters and structure (Lacressonnière et al. 2016). Representations of health-related uncertainty could be expanded by including other relevant sources of uncertainty, such as the shape of the CRF. Finally, these techniques could be expanded to better represent behavioral responses. Behavioural change appeared most influenced by clear signals with clear responses in previous work (Beckage et al. 2018). Natural variability could obscure those signals, influencing adaptive responses and the resulting impacts of climate policy. Methods in this thesis could be paired with models of behavioral responses to poor air quality to understand how natural variability may mediate co-benefits, and how behavioral uncertainty may inform simulation lengths.

Bibliography

Asefi-Najafabady, Salvi, Laura Villegas-Ortiz, and Jamie Morgan. 2020. "The Failure of Integrated Assessment Models as a Response to 'Climate Emergency' and Ecological Breakdown: The Emperor Has No Clothes." *Globalizations* 0 (0): 1–11. https://doi.org/10.1080/14747731.2020.1853958.

Barnes, Elizabeth A., Arlene M. Fiore, and Larry W. Horowitz. 2016. "Detection of Trends in Surface Ozone in the Presence of Climate Variability." *Journal of Geophysical Research: Atmospheres* 121 (10): 6112–29. https://doi.org/10.1002/2015JD024397.

Beckage, Brian, Louis J. Gross, Katherine Lacasse, Eric Carr, Sara S. Metcalf, Jonathan M. Winter, Peter D. Howe, et al. 2018. "Linking Models of Human Behaviour and Climate Alters Projected Climate Change." *Nature Climate Change* 8 (1): 79–84. https://doi.org/10.1038/s41558-017-0031-7.

Bell, Michelle L., and K. Ebisu. 2012. "Environmental Inequality in Exposures to Airborne Particulate Matter Components in the United States." *Environ Health Perspect* 120 (12): 1699–1704. https://doi.org/10.1289/ehp.1205201.

Bikomeye, Jean C., Caitlin S. Rublee, and Kirsten M. M. Beyer. 2021. "Positive Externalities of Climate Change Mitigation and Adaptation for Human Health: A Review and Conceptual Framework for Public Health Research." *International Journal of Environmental Research and Public Health* 18 (5): 2481. https://doi.org/10.3390/ijerph18052481.

Brown-Steiner, B., N. E. Selin, R. G. Prinn, E. Monier, S. Tilmes, L. Emmons, and F. Garcia-Menendez. 2018. "Maximizing Ozone Signals among Chemical, Meteorological, and Climatological Variability." *Atmospheric Chemistry and Physics* 18 (11): 8373–88. https://doi.org/10.5194/acp-18-8373-2018.

Burnett, Richard, Hong Chen, Mieczysław Szyszkowicz, Neal Fann, Bryan Hubbell, C. Arden Pope, Joshua S. Apte, et al. 2018. "Global Estimates of Mortality Associated with Long-Term Exposure to Outdoor Fine Particulate Matter." *Proceedings of the National Academy of Sciences* 115 (38): 9592–97. https://doi.org/10.1073/pnas.1803222115.

Cameron, T. A. 2010. "Euthanizing the Value of a Statistical Life." *Review of Environmental Economics and Policy* 4 (2): 161–78. https://doi.org/10.1093/reep/req010.

Chang, Kelly M., Jeremy J. Hess, John M. Balbus, Jonathan J. Buonocore, David A. Cleveland, Maggie L. Grabow, Roni Neff, et al. 2017. "Ancillary Health Effects of Climate Mitigation Scenarios as Drivers of Policy Uptake: A Review of Air Quality, Transportation and Diet Co-Benefits Modeling Studies." *Environmental Research Letters* 12 (11): 113001. https://doi.org/10.1088/1748-9326/aa8f7b.

Chen, L., B. L. Jennison, W. Yang, and S. T. Omaye. 2000. "Elementary School Absenteeism and Air Pollution." *Inhalation Toxicology* 12 (11): 997–1016. https://doi.org/10.1080/08958370050164626.

Climate Watch. 2018. "Greenhouse Gas (GHG) Emissions." 2018. https://www.climatewatchdata.org/.

Cohen, Aaron J., Michael Brauer, Richard Burnett, H. Ross Anderson, Joseph Frostad, Kara Estep, Kalpana Balakrishnan, et al. 2017. "Estimates and 25-Year Trends of the Global Burden of Disease Attributable to Ambient Air Pollution: An Analysis of Data from the Global Burden of Diseases Study 2015." *The Lancet* 389 (10082): 1907–18. https://doi.org/10.1016/S0140-6736(17)30505-6.

Deser, Clara, Reto Knutti, Susan Solomon, and Adam S. Phillips. 2012. "Communication of the Role of Natural Variability in Future North American Climate." *Nature Climate Change* 2 (11): 775–79. https://doi.org/10.1038/nclimate1562.

Deser, Clara, F. Lehner, K. B. Rodgers, T. Ault, T. L. Delworth, P. N. DiNezio, A. Fiore, et al. 2020. "Insights from Earth System Model Initial-Condition Large Ensembles and Future Prospects." *Nature Climate Change* 10 (4): 277–86. https://doi.org/10.1038/s41558-020-0731-2.

Dimitrov, R. S. 2016. "The Paris Agreement on Climate Change: Behind Closed Doors." *Global Environmental Politics* 16 (3): 1–11. https://doi.org/10.1162/GLEP_a_00361.

Dionisio, Kathie L., Christopher G. Nolte, Kristen M. Foley, Kristin K. Isaacs, Nina Caraway, Stephen Graham, and Tanya L. Spero. 2017. "Characterizing the Impact of Projected Changes in Climate and Air Quality on Human Exposures to Ozone." *Journal of Exposure Science and Environmental Epidemiology* 27 (3): 260. https://doi.org/10.1038/jes.2016.81.

Donges, Jonathan F., Jobst Heitzig, Wolfram Barfuss, Marc Wiedermann, Johannes A. Kassel, Tim Kittel, Jakob J. Kolb, et al. 2020. "Earth System Modeling with Endogenous and Dynamic Human Societies: The Copan:CORE Open World–Earth Modeling Framework." *Earth System Dynamics* 11 (2): 395–413. https://doi.org/10.5194/esd-11-395-2020.

Fang, Yuanyuan, Denise L. Mauzerall, Junfeng Liu, Arlene M. Fiore, and Larry W. Horowitz. 2013. "Impacts of 21st Century Climate Change on Global Air Pollution-Related Premature Mortality." *Climatic Change* 121 (2): 239–53. https://doi.org/10.1007/s10584-013-0847-8.

Fann, Neal, Kirk R. Baker, and Charles M. Fulcher. 2012. "Characterizing the PM2.5-Related Health Benefits of Emission Reductions for 17 Industrial, Area and Mobile Emission Sectors across the U.S." *Environment International* 49 (November): 141–51. https://doi.org/10.1016/j.envint.2012.08.017.

Fann, Neal, Amy D. Lamson, Susan C. Anenberg, Karen Wesson, David Risley, and Bryan J. Hubbell. 2012. "Estimating the National Public Health Burden Associated with Exposure to Ambient PM2.5 and Ozone." *Risk Analysis* 32 (1): 81–95. https://doi.org/10.1111/j.1539-6924.2011.01630.x.

Fann, Neal, Christopher G. Nolte, Patrick Dolwick, Tanya L. Spero, Amanda Curry Brown, Sharon Phillips, and Susan Anenberg. 2015. "The Geographic Distribution and Economic Value of Climate Change-Related Ozone Health Impacts in the United States in 2030." *Journal of the Air & Waste Management Association* 65 (5): 570–80. https://doi.org/10.1080/10962247.2014.996270.

Fawcett, Allen A., Leon C. Clarke, Sebastian Rausch, and John P. Weyant. 2014. "Overview of EMF 24 Policy Scenarios." *The Energy Journal* 35 (01). https://doi.org/10.5547/01956574.35.SI1.3.

Fiore, Arlene M., Vaishali Naik, and Eric M. Leibensperger. 2015. "Air Quality and Climate Connections." *Journal of the Air & Waste Management Association* 65 (6): 645–85. https://doi.org/10.1080/10962247.2015.1040526.

Fraas, Arthur G. 2011. "The Treatment of Uncertainty in EPA's Analysis of Air Pollution Rules: A Status Report." *Journal of Benefit-Cost Analysis* 2 (2): 1–27.

Fu, Tzung-May, and Heng Tian. 2019. "Climate Change Penalty to Ozone Air Quality: Review of Current Understandings and Knowledge Gaps." *Current Pollution Reports* 5 (3): 159–71. https://doi.org/10.1007/s40726-019-00115-6.

Gao, Jinghong, Sari Kovats, Sotiris Vardoulakis, Paul Wilkinson, Alistair Woodward, Jing Li, Shaohua Gu, et al. 2018. "Public Health Co-Benefits of Greenhouse Gas Emissions Reduction: A Systematic Review." *Science of The Total Environment* 627 (June): 388–402. https://doi.org/10.1016/j.scitotenv.2018.01.193.

Garcia-Menendez, Fernando, Erwan Monier, and Noelle E. Selin. 2017. "The Role of Natural Variability in Projections of Climate Change Impacts on U.S. Ozone Pollution." *Geophysical Research Letters* 44 (6): 2911–21. https://doi.org/10.1002/2016GL071565.

Garcia-Menendez, Fernando, Erwan Monier, and Noelle E. Selin. 2017. "The Role of Natural Variability in Projections of Climate Change Impacts on U.S. Ozone Pollution: NATURAL VARIABILITY IN OZONE PROJECTIONS." *Geophysical Research Letters* 44 (6): 2911–21. https://doi.org/10.1002/2016GL071565.

Garcia-Menendez, Fernando, Rebecca K. Saari, Erwan Monier, and Noelle E. Selin. 2015. "U.S. Air Quality and Health Benefits from Avoided Climate Change under Greenhouse Gas Mitigation." *Environmental Science & Technology* 49 (13): 7580–88. https://doi.org/10.1021/acs.est.5b01324.

Gilliland, F. D., K. Berhane, E. B. Rappaport, D. C. Thomas, E. Avol, W. J. Gauderman, S. J. London, et al. 2001. "The Effects of Ambient Air Pollution on School Absenteeism Due to Respiratory Illnesses." *Epidemiology (Cambridge, Mass.)* 12 (1): 43–54.

Hamilton, Ian, Harry Kennard, Alice McGushin, Lena Höglund-Isaksson, Gregor Kiesewetter, Melissa Lott, James Milner, et al. 2021. "The Public Health Implications of the Paris Agreement: A Modelling Study." *The Lancet Planetary Health* 5 (2): e74–83. https://doi.org/10.1016/S2542-5196(20)30249-7.

Harper, S. L., A. Cunsolo, A. Babujee, S. Coggins, E. De Jongh, T. Rusnak, C. J. Wright, and M. Domínguez Aguilar. 2021. "Trends and Gaps in Climate Change and Health Research in North America." *Environmental Research*, May, 111205. https://doi.org/10.1016/j.envres.2021.111205.

Hime, Neil J., Guy B. Marks, and Christine T. Cowie. 2018. "A Comparison of the Health Effects of Ambient Particulate Matter Air Pollution from Five Emission Sources." *International Journal of Environmental Research and Public Health* 15 (6): 1206. https://doi.org/10.3390/ijerph15061206.

Hinds, William C. 1998. *Aerosol Technology: Properties, Behavior, and Measurement of Airborne Particles, 2nd Edition*. Wiley. https://www.wiley.com/en-ca/Aerosol+Technology%3A+Properties%2C+Behavior%2C+and+Measurement+of+Airborne+Particles%2C+2nd+Edition-p-9780471194101.

IPCC. 2013. “Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.” Doi:10.1017/CBO9781107415324. [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)] Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. doi:10.1017/CBO9781107415324. http://www.climatechange2013.org/report/full-report/.

———. 2018. “Annex I: Glossary [Matthews, J.B.R. (Ed.)]. In: Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (Eds.)].” In Press. https://www.ipcc.ch/sr15/chapter/glossary/.

Jacob, Daniel J. 1999. *Introduction to Atmospheric Chemistry*. Princeton, New Jersey: Princeton University Press.

Jacobson, Mark Z. 2005. *Fundamentals of Atmospheric Modeling*. 2 edition. Cambridge, UK ; New York: Cambridge University Press.

Karlsson, Mikael, Eva Alfredsson, and Nils Westling. 2020. “Climate Policy Co-Benefits: A Review.” *Climate Policy* 20 (3): 292–316. https://doi.org/10.1080/14693062.2020.1724070.

Katsouyanni, Klea, Jonathan M. Samet, H. Ross Anderson, Richard Atkinson, Alain Le Tertre, Sylvia Medina, Evangelia Samoli, et al. 2009. “Air Pollution and Health: A European and North American Approach (APHENA).” *Research Report (Health Effects Institute)*, no. 142 (October): 5–90.

Kay, J. E., C. Deser, A. Phillips, A. Mai, C. Hannay, G. Strand, J. M. Arblaster, et al. 2015. “The Community Earth System Model (CESM) Large Ensemble Project: A Community Resource for Studying Climate Change in the Presence of Internal Climate Variability.” *Bulletin of the American Meteorological Society* 96 (8): 1333–49. https://doi.org/10.1175/BAMS-D-13-00255.1.

Krewski, Daniel, Michael Jerrett, Richard T Burnett, Renjun Ma, Edward Hughes, Yuanli Shi, Michelle C Turner, C Arden Pope 3rd, George Thurston, Eugenia E Calle, Michael J Thun, et al. 2009. “Extended Follow-up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality.” *Research Report (Health Effects Institute)*, no. 140 (May): 5–114; discussion 115-136.

Lacressonnière, Gwendoline, Gilles Foret, Matthias Beekmann, Guillaume Siour, Magnuz Engardt, Michael Gauss, Laura Watson, et al. 2016. “Impacts of Regional Climate Change on Air Quality Projections and Associated Uncertainties.” *Climatic Change* 136 (2): 309–24.

Laden, Francine, Joel Schwartz, Frank E. Speizer, and Douglas W. Dockery. 2006. “Reduction in Fine Particulate Air Pollution and Mortality.” *American Journal of Respiratory and Critical Care Medicine* 173 (6): 667–72. https://doi.org/10.1164/rccm.200503-443OC.

Lepeule, Johanna, Francine Laden, Douglas Dockery, and Joel Schwartz. 2012. “Chronic Exposure to Fine Particles and Mortality: An Extended Follow-up of the Harvard Six Cities Study from 1974 to 2009.” *Environmental Health Perspectives* 120 (7): 965–70. https://doi.org/10.1289/ehp.1104660.

Li, Mingwei, Da Zhang, Chiao-Ting Li, Kathleen M. Mulvaney, Noelle E. Selin, and Valerie J. Karplus. 2018. “Air Quality Co-Benefits of Carbon Pricing in China.” *Nature Climate Change* 8 (5): 398–403. https://doi.org/10.1038/s41558-018-0139-4.

Madaniyazi, Lina, Yuming Guo, Weiwei Yu, and Shilu Tong. 2015. “Projecting Future Air Pollution-Related Mortality under a Changing Climate: Progress, Uncertainties and Research Needs.” *Environment International* 75 (Supplement C): 21–32. https://doi.org/10.1016/j.envint.2014.10.018.

Mar, Therese F., Jane Q. Koenig, and Janet Primomo. 2010. “Associations between Asthma Emergency Visits and Particulate Matter Sources, Including Diesel Emissions from Stationary Generators in Tacoma, Washington.” *Inhalation Toxicology* 22 (6): 445–48. https://doi.org/10.3109/08958370903575774.

Mathias, Jean-Denis, Marko Debeljak, Guillaume Deffuant, Arnaud Diemer, Florian Dierickx, Jonathan F. Donges, Ganna Gladkykh, et al. 2020. “Grounding Social Foundations for Integrated Assessment Models of Climate Change.” *Earth’s Future* 8 (7): e2020EF001573. https://doi.org/10.1029/2020EF001573.

McFarland, James, Allen A. Fawcett, Adele C. Morris, John M. Reilly, and Peter J. Wilcoxen. 2018. “Overview of the Emf 32 Study on u.s. Carbon Tax Scenarios.” *Climate Change Economics* 09 (01): 1840002. https://doi.org/10.1142/S201000781840002X.

Milinski, Sebastian, Nicola Maher, and Dirk Olonscheck. 2019. “How Large Does a Large Ensemble Need to Be?” *Earth System Dynamics Discussions*, November, 1–19. https://doi.org/10.5194/esd-2019-70.

———. 2020. “How Large Does a Large Ensemble Need to Be?” *Earth System Dynamics* 11 (4): 885–901. https://doi.org/10.5194/esd-11-885-2020.

Monier, E., J. R. Scott, A. P. Sokolov, C. E. Forest, and C. A. Schlosser. 2013. “An Integrated Assessment Modeling Framework for Uncertainty Studies in Global and Regional Climate Change: The MIT IGSM-CAM (Version 1.0).” *Geosci. Model Dev.* 6 (6): 2063–85. https://doi.org/10.5194/gmd-6-2063-2013.

Moreno-Macías, Hortensia, Douglas W. Dockery, Joel Schwartz, Diane R. Gold, Nan M. Laird, Juan J. Sienra-Monge, Blanca E. Del Río-Navarro, et al. 2013. “Ozone Exposure, Vitamin C Intake, and Genetic Susceptibility of Asthmatic Children in Mexico City: A Cohort Study.” *Respiratory Research* 14 (1): 14. https://doi.org/10.1186/1465-9921-14-14.

Nasari, Masoud M., Mieczysław Szyszkowicz, Hong Chen, Daniel Crouse, Michelle C. Turner, Michael Jerrett, C. Arden Pope, et al. 2016. “A Class of Non-Linear Exposure-Response Models Suitable for Health Impact Assessment Applicable to

Large Cohort Studies of Ambient Air Pollution." *Air Quality, Atmosphere & Health* 9 (8): 961–72. https://doi.org/10.1007/s11869-016-0398-z.
Nemet, G. F., T. Holloway, and P. Meier. 2010. "Implications of Incorporating Air-Quality Co-Benefits into Climate Change Policymaking." *Environmental Research Letters* 5 (1): 014007. https://doi.org/10.1088/1748-9326/5/1/014007.
Orru, H., K. L. Ebi, and B. Forsberg. 2017. "The Interplay of Climate Change and Air Pollution on Health." *Current Environmental Health Reports*, October, 1–10. https://doi.org/10.1007/s40572-017-0168-6.
Ostro, Bart D., and Susy Rothschild. 1989. "Air Pollution and Acute Respiratory Morbidity: An Observational Study of Multiple Pollutants." *Environmental Research* 50 (2): 238–47. https://doi.org/10.1016/S0013-9351(89)80004-0.
Paltsev, Sergey, Erwan Monier, Jeffery Scott, Andrei Sokolov, and John Reilly. 2015. "Integrated Economic and Climate Projections for Impact Assessment." *Climatic Change* 131 (1): 21–33. https://doi.org/10.1007/s10584-013-0892-3.
Peel, Jennifer L., Paige E. Tolbert, Mitchel Klein, Kristi Busico Metzger, W. Dana Flanders, Knox Todd, James A. Mulholland, P. Barry Ryan, and Howard Frumkin. 2005. "Ambient Air Pollution and Respiratory Emergency Department Visits." *Epidemiology* 16 (2): 164–74.
Pienkosz, Bret D., Rebecca K. Saari, Erwan Monier, and Fernando Garcia-Menendez. 2019. "Natural Variability in Projections of Climate Change Impacts on Fine Particulate Matter Pollution." *Earth's Future* 7 (7): 762–70. https://doi.org/10.1029/2019EF001195.
Pope, C. Arden, Richard T. Burnett, Michael J. Thun, Eugenia E. Calle, Daniel Krewski, Kazuhiko Ito, and George D. Thurston. 2002. "Lung Cancer, Cardiopulmonary Mortality, and Long-Term Exposure to Fine Particulate Air Pollution." *JAMA* 287 (9): 1132–41. https://doi.org/10.1001/jama.287.9.1132.
Prinn, R., H. Jacoby, A. Sokolov, C. Wang, X. Xiao, Z. Yang, R. Eckhaus, et al. 1999. "Integrated Global System Model for Climate Policy Assessment: Feedbacks and Sensitivity Studies." *Climatic Change* 41 (3): 469–546. https://doi.org/10.1023/A:1005326126726.
Saari, Rebecca K., Yufei Mei, Erwan Monier, and Fernando Garcia Menendez. 2019. "Effect of Health-Related Uncertainty and Natural Variability on Health Impacts and Co-Benefits of Climate Policy." *Environmental Science & Technology* 53 (3): 1098–1108. https://doi.org/10.1021/acs.est.8b05094.
Saari, Rebecca K., Noelle E. Selin, Sebastian Rausch, and Tammy M. Thompson. 2015. "A Self-Consistent Method to Assess Air Quality Co-Benefits from U.S. Climate Policies." *Journal of the Air & Waste Management Association* 65 (1): 74–89. https://doi.org/10.1080/10962247.2014.959139.
Santer, B. D., C. Mears, C. Doutriaux, P. Caldwell, P. J. Gleckler, T. M. L. Wigley, S. Solomon, et al. 2011. "Separating Signal and Noise in Atmospheric Temperature Changes: The Importance of Timescale." *Journal of Geophysical Research: Atmospheres* 116 (D22). https://doi.org/10.1029/2011JD016263.

Shim, Gene W. 2021. “Future of Canadian Air Quality and Related Health Benefits from Climate Change Mitigation.” MASc, Waterloo, Ontario: University of Waterloo. UWSpace. http://hdl.handle.net/10012/17011.
Shindell, D., N. Borgford-Parnell, M. Brauer, A. Haines, J. C. I. Kuylenstierna, S. A. Leonard, V. Ramanathan, A. Ravishankara, M. Amann, and L. Srivastava. 2017. “A Climate Policy Pathway for Near- and Long-Term Benefits.” *Science* 356 (6337): 493–94. https://doi.org/10.1126/science.aak9521.
Silva, Raquel A., J. Jason West, Jean-François Lamarque, Drew T. Shindell, William J. Collins, Greg Faluvegi, Gerd A. Folberth, et al. 2017. “Future Global Mortality from Changes in Air Pollution Attributable to Climate Change.” *Nature Climate Change* 7 (9): 647–51. https://doi.org/10.1038/nclimate3354.
Silva, Raquel A., J. Jason West, Yuqiang Zhang, Susan C. Anenberg, Jean-François Lamarque, Drew T. Shindell, William J. Collins, et al. 2013. “Global Premature Mortality Due to Anthropogenic Outdoor Air Pollution and the Contribution of Past Climate Change.” *Environmental Research Letters* 8 (3): 034005. https://doi.org/10.1088/1748-9326/8/3/034005.
Smith, Richard L., Baowei Xu, and Paul Switzer. 2009. “Reassessing the Relationship between Ozone and Short-Term Mortality in U.S. Urban Communities.” *Inhalation Toxicology* 21 (sup2): 37–61. https://doi.org/10.1080/08958370903161612.
Sujaritpong, Sarunya, Keith Dear, Martin Cope, Sean Walsh, and Tord Kjellstrom. 2014. “Quantifying the Health Impacts of Air Pollution under a Changing Climate—a Review of Approaches and Methodology.” *International Journal of Biometeorology* 58 (2): 149–60. https://doi.org/10.1007/s00484-012-0625-8.
Tagaris, Efthimios, Kuo-Jen Liao, Anthony J. DeLucia, Leland Deck, Praveen Amar, and Armistead G. Russell. 2009. “Potential Impact of Climate Change on Air Pollution-Related Human Health Effects.” *Environmental Science & Technology* 43 (13): 4979–88. https://doi.org/10.1021/es803650w.
Thompson, Tammy M., Sebastian Rausch, Rebecca K. Saari, and Noelle E. Selin. 2014. “A Systems Approach to Evaluating the Air Quality Co-Benefits of US Carbon Policies.” *Nature Climate Change* 4 (10): 917–23. https://doi.org/10.1038/nclimate2342.
U.S. Environmental Protection Agency. 2011. “The Benefits and Costs of the Clean Air Act from 1990 to 2020.” U.S. Environmental Protection Agency. https://www.epa.gov/sites/production/files/2015-07/documents/summaryreport.pdf.
———. 2012. “Regulatory Impact Analysis for the Final Revisions to the National 1 Ambient Air 2 Quality Standards for Particulate Matter, Office of Air Quality Planning and Standards.” EPA-452/R-12-005. Research Triangle Park, NC 27711. http://www.epa.gov/ttnecas1/regdata/RIAs/finalria.pdf.
———. 2017. “Environmental Benefits Mapping and Analysis Program: Community Edition (BenMAP-CE) User Manual and Appendices.” Research Triangle Park, NC, USA. https://www.epa.gov/benmap/manual-and-appendices-benmap-ce.
USGCRP. 2018. “Fourth National Climate Assessment.” U.S. Global Change Research Program, Washington, DC. https://nca2018.globalchange.gov.
Vandyck, Toon, Kimon Keramidas, Stéphane Tchung-Ming, Matthias Weitzel, and Rita Van Dingenen. 2020. “Quantifying Air Quality Co-Benefits of Climate Policy across

Sectors and Regions." *Climatic Change* 163 (3): 1501–17. https://doi.org/10.1007/s10584-020-02685-7.

Vohra, Karn, Alina Vodonos, Joel Schwartz, Eloise A. Marais, Melissa P. Sulprizio, and Loretta J. Mickley. 2021. "Global Mortality from Outdoor Fine Particle Pollution Generated by Fossil Fuel Combustion: Results from GEOS-Chem." *Environmental Research* 195 (April): 110754. https://doi.org/10.1016/j.envres.2021.110754.

Webster, Mort, Chris Forest, John Reilly, Mustafa Babiker, David Kicklighter, Monika Mayer, Ronald Prinn, et al. 2003. "Uncertainty Analysis of Climate Change and Policy Response." *Climatic Change* 61 (3): 295–320. https://doi.org/10.1023/B:CLIM.0000004564.09961.9f.

West, J. Jason, Steven J. Smith, Raquel A. Silva, Vaishali Naik, Yuqiang Zhang, Zachariah Adelman, Meridith M. Fry, Susan Anenberg, Larry W. Horowitz, and Jean-Francois Lamarque. 2013. "Co-Benefits of Mitigating Global Greenhouse Gas Emissions for Future Air Quality and Human Health." *Nature Climate Change* 3 (10): 885–89. https://doi.org/10.1038/nclimate2009.

Wilson, Adam M., Cameron P. Wake, Tom Kelly, and Jeffrey C. Salloway. 2005. "Air Pollution, Weather, and Respiratory Emergency Room Visits in Two Northern New England Cities: An Ecological Time-Series Study." *Environmental Research* 97 (3): 312–21. https://doi.org/10.1016/j.envres.2004.07.010.

Wu, Shiliang, Loretta J. Mickley, Eric M. Leibensperger, Daniel J. Jacob, David Rind, and David G. Streets. 2008. "Effects of 2000–2050 Global Change on Ozone Air Quality in the United States." *Journal of Geophysical Research* 113 (D6): D06302. https://doi.org/10.1029/2007JD008917.

Zanobetti, Antonella, and Joel Schwartz. 2008. "Temperature and Mortality in Nine US Cities." *Epidemiology (Cambridge, Mass.)* 19 (4): 563–70. https://doi.org/10.1097/EDE.0b013e31816d652d.

Zhang, Yang, Peilin Yang, Yang Gao, Ruby L. Leung, and Michelle L. Bell. 2020. "Health and Economic Impacts of Air Pollution Induced by Weather Extremes over the Continental U.S." *Environment International* 143 (October): 105921. https://doi.org/10.1016/j.envint.2020.105921.

Zhang, Yuqiang, Jared H. Bowden, Zachariah Adelman, Vaishali Naik, Larry W. Horowitz, Steven J. Smith, and J. Jason West. 2016. "Co-Benefits of Global and Regional Greenhouse Gas Mitigation for US Air Quality in 2050." *Atmospheric Chemistry and Physics* 16 (15): 9533–48. https://doi.org/10.5194/acp-16-9533-2016.

Zhang, Yuqiang, Steven J. Smith, Jared H. Bowden, Zachariah Adelman, and J. Jason West. 2017. "Co-Benefits of Global, Domestic, and Sectoral Greenhouse Gas Mitigation for US Air Quality and Human Health in 2050." *Environmental Research Letters* 12 (11): 114033. https://doi.org/10.1088/1748-9326/aa8f76.

Appendix A

Analysis Scripts

AGU2020-Fig1-DataSorting_20200819

```
# -*- coding: utf-8 -*-
"""
Created on Fri Aug 19 10:23:17 2020

@author: devpu
"""

import pickle as cp
import numpy as np
import os
import datetime
import pandas as pd
import geopandas as gpd
from osgeo import ogr
import csv
import gdal

indir = 'C:/Users/devpu/OneDrive - University of 
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-Fig1/RawData'
ExSHP = 'C:/Users/devpu/OneDrive - University of 
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/ExMapData'
outdir = 'C:/Users/devpu/OneDrive - University of 
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig1/ProcessedData/'
outdir1 = 'C:/Users/devpu/OneDrive - University of 
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig1/ProcessedData/ShapeFiles/'

USAGRIDCUT_DATA = pd.read_csv(os.path.join(indir,'USAGRIDCUT.csv'))

for Yr in [2050]:
    for Pol in ['P37']:
        for Poll in ['O3']:
            iden = 'BenMAP_' + 
str(Yr)+'_'+Pol+'vsREF_'+Poll+'_IncidenceMeanOutput.csv'
            DEATHS_PER_CELL = pd.read_csv(os.path.join(indir,iden))
            DEATHS_PER_CELL.columns = ["ROW", "COL", "MORT"]

            # The grid-state map
            gs_map = {}
            state_mort = {}

            for i, row in USAGRIDCUT_DATA.iterrows():
                r, c, st, pc = int(row["ROW"]), int(row["COL"]), 
row["STUSPS"], float(row["area_percent_grid"][:-1])
                if (r,c) in gs_map:
                    gs_map[(r,c)].append((st,pc))
```

```
                else:
                    gs_map[(r,c)] = [(st,pc)]

                # If we haven't seen this state before, add it to the
state_mortality dictionary
                if st not in state_mort:
                    state_mort[st] = 0

            # Check all the grid cells which don't add up to at least 99%
            # for k in gs_map.keys():
            #     states = gs_map[k]
            #     total_pc = sum([pair[1] for pair in states])
            # #    if total_pc < 99.0:
            #         print(k, total_pc)

            for i, row in DEATHS_PER_CELL.iterrows():
                 r, c, mort = int(row["ROW"]), int(row["COL"]),
float(row["MORT"])
                 if (r,c) in gs_map:
                     states = gs_map[(r,c)]
                     total_pc = sum([pair[1] for pair in states])
                     for pair in states:
                         state_mort[pair[0]] += (pair[1]/total_pc * mort)
                 else:
                     print("Couldn't find grid cell {} in USAGRIDCUT
data".format((r,c)))
            #print(state_mort)

            Northwest = state_mort['ID']+state_mort['OR']+state_mort['WA']
            Southwest =
state_mort['AZ']+state_mort['CA']+state_mort['CO']+state_mort['NV']+state_
mort['NM']+state_mort['UT']
            Greatplains =
state_mort['KS']+state_mort['MT']+state_mort['NE']+state_mort['ND']+state_
mort['OK']+state_mort['SD']+state_mort['TX']+state_mort['WY']
            Midwest =
state_mort['IL']+state_mort['IN']+state_mort['IA']+state_mort['MI']+state_
mort['MN']+state_mort['MO']+state_mort['OH']+state_mort['WI']
            Southeast =
state_mort['AL']+state_mort['AR']+state_mort['FL']+state_mort['GA']+state_
mort['KY']+state_mort['LA']+state_mort['MS']+state_mort['NC']+state_mort['
SC']+state_mort['TN']+state_mort['VA']
            Northeast =
state_mort['CT']+state_mort['DE']+state_mort['DC']+state_mort['ME']+state_
mort['MD']+state_mort['MA']+state_mort['NH']+state_mort['NJ']+state_mort['
NY']+state_mort['PA']+state_mort['RI']+state_mort['VT']+state_mort['WV']

            #region_mort = state_mort
            #region_mort.update([('NW',0), ('SW',0), ('GP',0), ('MW',0),
('SE',0), ('NE',0)])

            region_mort = {'State': 'Mortality','AK': 0,'HI': 0,'RNW':
0,'RSW': 0,'RGP': 0,'RMW': 0,'RSE': 0,'RNE': 0,}
```

```
region_mort.update(state_mort)

region_mort['Northwest'] = Northwest
region_mort['ID'] = Northwest
region_mort['OR'] = Northwest
region_mort['WA'] = Northwest

region_mort['Southwest'] = Southwest
region_mort['AZ'] = Southwest
region_mort['CA'] = Southwest
region_mort['CO'] = Southwest
region_mort['NV'] = Southwest
region_mort['NM'] = Southwest
region_mort['UT'] = Southwest

region_mort['Greatplains'] = Greatplains
region_mort['KS'] = Greatplains
region_mort['MT'] = Greatplains
region_mort['NE'] = Greatplains
region_mort['ND'] = Greatplains
region_mort['OK'] = Greatplains
region_mort['SD'] = Greatplains
region_mort['TX'] = Greatplains
region_mort['WY'] = Greatplains

region_mort['Midwest'] = Midwest
region_mort['IL'] = Midwest
region_mort['IN'] = Midwest
region_mort['IA'] = Midwest
region_mort['MI'] = Midwest
region_mort['MN'] = Midwest
region_mort['MO'] = Midwest
region_mort['OH'] = Midwest
region_mort['WI'] = Midwest

region_mort['Southeast'] = Southeast
region_mort['AL'] = Southeast
region_mort['AR'] = Southeast
region_mort['FL'] = Southeast
region_mort['GA'] = Southeast
region_mort['KY'] = Southeast
region_mort['LA'] = Southeast
region_mort['MS'] = Southeast
region_mort['NC'] = Southeast
region_mort['SC'] = Southeast
region_mort['TN'] = Southeast
region_mort['VA'] = Southeast

region_mort['Northeast'] = Northeast
region_mort['CT'] = Northeast
region_mort['DE'] = Northeast
region_mort['DC'] = Northeast
region_mort['ME'] = Northeast
```

```
            region_mort['MD'] = Northeast
            region_mort['MA'] = Northeast
            region_mort['NH'] = Northeast
            region_mort['NJ'] = Northeast
            region_mort['NY'] = Northeast
            region_mort['PA'] = Northeast
            region_mort['RI'] = Northeast
            region_mort['VT'] = Northeast
            region_mort['WV'] = Northeast

            with open(outdir +'/'+ 'BenMAP_' +
str(Yr)+'_'+Pol+'vsREF_'+Poll+'_IncidenceMeanOutput-
Regions_'+datetime.date.today().strftime("%Y%m%d")+'.csv', 'w') as f:
                for key in region_mort.keys():
                    f.write("%s,%s\n"%(key,region_mort[key]))

            exshpfile = gpd.read_file(os.path.join(ExSHP, 'USA-
Regions20191008.shp'))
            infile = ogr.Open(os.path.join(ExSHP, 'USA-
Regions20191008.shp'))
            layer = infile.GetLayer()
            spatialRef = layer.GetSpatialRef()
            epsg = spatialRef.ExportToWkt()
            exshpfile.insert(1, "Mortality", 0, True)

            # Creating blank shapefiles to copy the generated values into;
            shpMortality = exshpfile.copy()

            for i in range(len(shpMortality)):
                j = shpMortality.iloc[i,0]
                kk = region_mort[j]
                shpMortality.loc[(shpMortality["region"] == j),
"Mortality"] = kk

            shpfname= 'BenMAP_' +
str(Yr)+'_'+Pol+'vsREF_'+Poll+'_IncidenceMeanOutput-
Regions_'+datetime.date.today().strftime("%Y%m%d")+'.shp'
            shpfilename = outdir1 + shpfname
            shpMortality.to_file(shpfilename)
            prjfname= 'BenMAP_' +
str(Yr)+'_'+Pol+'vsREF_'+Poll+'_IncidenceMeanOutput-
Regions_'+datetime.date.today().strftime("%Y%m%d")+'.prj'
            prj = open(os.path.join(outdir1, prjfname), "w")
            prj.write(epsg)
```

AGU2020-Fig1-Plotting_20210928

```
# -*- coding: utf-8 -*-
"""
Created on Fri Aug 21 11:49:35 2020
edited September 28, 2021 by rks to add projection and change dir
@author: devpu
"""
import os
#os.environ["PROJ_LIB"] = "C:/Users/devpu/Anaconda3/pkgs/proj4-5.2.0-
ha925a31_1/Library/share"; #fixr
import geopandas as gpd
import matplotlib as mpl
import matplotlib.pyplot as plt
import datetime
import numpy as np
import matplotlib.ticker as ticker

def fmt(x, pos):
    a, b = '{:.2e}'.format(x).split('e')
    b = int(b)
    return r'${} \times 10^{{{}}}$'.format(a, b)

O3_2050 = 1.831321396
O3_2100 = 2.844556219
PM_2050 = 1.662276345
PM_2100 = 1.589653446
proj_factor = {'O3': {'2050': O3_2050, '2100': O3_2100}, 'PM2.5': {'2050':
PM_2050, '2100': PM_2100}}

indir = 'C:/Users/rsaari/OneDrive - University of
Waterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig1/ProcessedData/ShapeFiles/'
figdir = 'C:/Users/rsaari/OneDrive - University of
Waterloo/Dr.SaariLab/WorkingFolder/Figures/AGU2020-Fig1/'

myfontsize = 20
myfontsize_smaller = 18

for Poll in ['PM25','O3']:
    mysubno = 0
    for Pol in ['P37','P45']:
        for Yr in [2050,2100]:
            iden = 'BenMAP_' +
str(Yr)+'_'+Pol+'vsREF_'+Poll+'_IncidenceMeanOutput-Regions_20200821'

            strYr = str(Yr)

            if Poll == 'O3':
                mymax = 3500
                mymin = -100
                gap = 200
            else:
                mymax = 20000
```

```
                mymin = 0
                gap = 3000

            if Pol == 'P37':
                pol = 'P3.7'
            else:
                pol = 'P4.5'

            if Poll == 'PM25':
                poll = 'PM2.5'
                mycmap='Blues'
            else:
                poll = 'O3'
                mycmap='Greens'

            ticklabels =np.arange(mymin,mymax+gap,gap)
            norm = mpl.colors.Normalize(mymin, mymax) #play with these
numbers
            cbar = plt.cm.ScalarMappable(norm=norm, cmap=mycmap)

            shp_file = ''.join([indir,iden,'.shp'])

            shpfile = gpd.read_file(shp_file)
            mytitle = ''.join([r'Annual premature deaths
avoided','\n(',chr(mysubno+97),')',str(Yr),'-
',str(pol),'(',str(poll),')'])
            fig, ax = plt.subplots(1,1)
            fig, ax = plt.subplots(figsize=(5.7,4.7))
            mysubno+=1
            # ax  = fig.add_subplot(frameon=False)
            #ax.set_title(mytitle,  weight = 'bold',fontsize = myfontsize,
pad=0)
            #fig.set_dpi(600)

            # divider = make_axes_locatable(ax)

            # cax = divider.append_axes("bottom", size="5%", pad=0.1)

            shpfile.plot(column = 'Mortality', ax=ax, legend=False,
cmap=mycmap, edgecolor = "black", vmin=mymin, vmax=mymax)
            # shpfile.plot(column = 'D24HourMea', ax=ax, legend=True,
legend_kwds={'label': "Population by Country",'orientation':
"horizontal"})
            # shpfile.plot(column = 'D24HourMea', cmap = 'RdBu', edgecolor
= "black", ax=ax, cax = cax, legend=True, cbar_kwds={"orientation":
"horizontal"}, vmin=mymin, vmax=mymax)
            # shpfile.plot(column = 'D24HourMea', cmap = 'RdBu',
legend=True, ax=ax)

            # add colorbar
            ax_cbar = fig.colorbar(cbar, ax=ax, orientation='horizontal',
pad=0)
            # add label for the colorbar
```

```
            # ax_cbar.set_label('Annual premature deaths avoided')
            ax_cbar.set_label(mytitle,fontsize = myfontsize)

ax_cbar.ax.set_xticklabels(ticklabels[::1],rotation=30,fontsize=myfontsize
_smaller)#, format='%.0e')
            ax.set_axis_off()


            RNW=int(round(shpfile.iloc[3,1]*proj_factor[poll][strYr]/100,
ndigits=0))*100
            RSW=int(round(shpfile.iloc[5,1]*proj_factor[poll][strYr]/100,
ndigits=0))*100
            RGP=int(round(shpfile.iloc[0,1]*proj_factor[poll][strYr]/100,
ndigits=0))*100
            RMW=int(round(shpfile.iloc[1,1]*proj_factor[poll][strYr]/100,
ndigits=0))*100
            RNE=int(round(shpfile.iloc[2,1]*proj_factor[poll][strYr]/100,
ndigits=0))*100
            RSE=int(round(shpfile.iloc[4,1]*proj_factor[poll][strYr]/100,
ndigits=0))*100

            plt.annotate(RNW, xy=(0.1,0.8), xycoords='axes fraction',
bbox=dict(facecolor='white', edgecolor='none', boxstyle='round,pad=0.2'),
fontsize=myfontsize_smaller)
            plt.annotate(RSW, xy=(0.2,0.45), xycoords='axes fraction',
bbox=dict(facecolor='white', edgecolor='none', boxstyle='round,pad=0.2'),
fontsize=myfontsize_smaller)
            plt.annotate(RGP, xy=(0.425,0.5), xycoords='axes fraction',
bbox=dict(facecolor='white', edgecolor='none', boxstyle='round,pad=0.2'),
fontsize=myfontsize_smaller)
            plt.annotate(RMW, xy=(0.54,0.67), xycoords='axes fraction',
bbox=dict(facecolor='white', edgecolor='none', boxstyle='round,pad=0.2'),
fontsize=myfontsize_smaller)
            plt.annotate(RSE, xy=(0.63,0.35), xycoords='axes fraction',
bbox=dict(facecolor='white', edgecolor='none', boxstyle='round,pad=0.2'),
fontsize=myfontsize_smaller)
            plt.annotate(RNE, xy=(0.76,0.65), xycoords='axes fraction',
bbox=dict(facecolor='white', edgecolor='none', boxstyle='round,pad=0.2'),
fontsize=myfontsize_smaller)
            plt.show()

            fname =
''.join([iden,'_',datetime.date.today().strftime("%B_%d_%Y"),'.tiff'])
            figname = os.path.join(figdir,fname)
            fig.savefig(figname, dpi = 300,  bbox_inches = 'tight',
pad_inches = 0.2)
```

AGU2020-Fig2-ReadExtractPopulation_20200819.py

```
# -*- coding: utf-8 -*-
"""
Created on Fri Aug 19 14:12:43 2020

@author: devpu
"""

import numpy as np
import pickle as cp
import csv
import os

# SPECIFY DIRECTORY AND POLICY
indir = 'C:/Users/devpu/OneDrive - University of
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-Fig2/RawData'
outdir = 'C:/Users/devpu/OneDrive - University of
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig2/ProcessedData/'

# Projection
proj = -1 # Select Health Projection

if proj == 1:
    ##UNPROJ
    P45_2050 = 1
    P45_2100 = 1
    P37_2050 = 1
    P37_2100 = 1
    ProjStr = 'Unprojected'
elif proj == 0:
    # TOTAL PROJ
    P45_2050 = 3.136074168
    P45_2100 = 6.191667419
    P37_2050 = 3.0267895
    P37_2100 = 5.845025311
    REF_2100= 6.29375291
    ProjStr = 'Total Projection'
else:
    ##HEALTH PROJ
    P45_2050 = 1.681818182
    P45_2100 = 1.666666667
    P37_2050 = 1.770547945
    P37_2100 = 1.733944954
    ProjStr = 'Incidence Projection'
proj_factor = {'P45': {'2050': P45_2050, '2100': P45_2100}, 'P37':
{'2050': P37_2050, '2100': P37_2100}}


# LOAD THE FILE TO READ FOR

for Yr in [2050,2100]:
    for Pol in ['P37','P45']:
```

```
        for Poll in ['PM25','O3']:
            iden = 'BenMAP_' + str(Yr)+'_'+Pol+'vsREF_'+Poll+'_Incidence'
            with open (os.path.join(indir, iden), 'rb') as f:
                infile = (cp.load(f))

#CREATE NEW CSV FOR BENMAP
            output = open(outdir +'/'+ iden + 'PopulationOutput.csv', 'w')
#outputs are  empty csv files created to store the values for BenMAP
            newlinechar = '\n'
            output.write('Row,  Column,    Values'+newlinechar)

            for i in range(len(infile['Row'])): #doing this with arrays
bypasses the necessity to create a seperate agg dict
                output.write(str(infile['Row'][i]) + ' ,' +
str(infile['Col'][i]) + ' , ' + str(
float(infile['Population'][i])*proj_factor[Pol][str(Yr)]) +  newlinechar)
            output.close()
```

AGU2020-Fig3-DataSorting_Krewski_20201117

```
# -*- coding: utf-8 -*-
"""
Created on Fri Sep 11 14:35:53 2020

@author: devpu
"""
# In this the mean of O3 and PM2.5 has been summed and then the  .shp
files generatd
# for policy and year.

import pickle as cp
import numpy as np
import os
import datetime
import pandas as pd
import geopandas as gpd
from osgeo import ogr
import csv
import copy


#DEFINE VARIABLES
mydir = 'C:/Users/devpu/OneDrive - University of
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig5/Pickles/CSV-Region'
ExSHP = 'C:/Users/devpu/OneDrive - University of
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/ExMapData'
outdir = 'C:/Users/devpu/OneDrive - University of
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-Fig3/'
outdir1 = 'C:/Users/devpu/OneDrive - University of
Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig3/ShapeFiles/'
Poll = ['PM25', 'O3']
Year = '2050'    # Year to Plot

if Year == '2050':
    Year_range = range(2036,2065+1)
    x_lim = [2034,2067]
    myticks = np.arange(2035,2070,5)
else:
    Year_range = range(2086,2115+1)
    x_lim = [2084,2117]
    myticks = np.arange(2085,2120,5)


# Projection
proj = 0 # Select Total Projection

if proj == -1:
    ##UNPROJ
    P45_2050 = 1
    P45_2100 = 1
```

```
    P37_2050 = 1
    P37_2100 = 1
    ProjStr = 'Unprojected'
elif proj == 0:
    # TOTAL PROJ
    P45_2050 = 3.136074168
    P45_2100 = 6.191667419
    P37_2050 = 3.0267895
    P37_2100 = 5.845025311
    ProjStr = 'Total Projection'
else:
    ##HEALTH PROJ
    P45_2050 = 1.681818182
    P45_2100 = 1.666666667
    P37_2050 = 1.770547945
    P37_2100 = 1.733944954
    ProjStr = 'Incidence Projection'
proj_factor = {'P45': {'2050': P45_2050, '2100': P45_2100}, 'P37':
{'2050': P37_2050, '2100': P37_2100}}

# The dictionaries for means calculated
meanP37PM25 = {}
meanP45PM25 = {}

meanP37O3 = {}
meanP45O3 = {}

# The dictionaris which will be later converted to dataframes
dfP37PM25 = {}
dfP37O3 = {}
dfP37Poll={}
dfP37PollMean = {}
dfP37PollStd = {}
dfP37PollSNR = {}

dfP45PM25 = {}
dfP45O3 = {}
dfP45Poll={}
dfP45PollMean = {}
dfP45PollStd = {}
dfP45PollSNR = {}

DFP37Mean = {}
DFP45Mean = {}

DFP37SNR = {}
DFP45SNR = {}
# Checking for inconsistancies in row and col numbers

for reg in ['GP','MW','NE','NW','SE','SW']:
    meanP37PM25[reg] = {}
    meanP45PM25[reg] = {}
```

```
    meanP37O3[reg] = {}
    meanP45O3[reg] = {}

    dfP37PM25[reg] = {}
    dfP37O3[reg] = {}
    dfP37Poll[reg]={}
    dfP37PollMean[reg] = 0
    dfP37PollStd[reg] = 0
    dfP37PollSNR[reg] = 0

    dfP45PM25[reg] = {}
    dfP45O3[reg] = {}
    dfP45Poll[reg]={}
    dfP45PollMean[reg] = 0
    dfP45PollStd[reg] = 0
    dfP45PollSNR[reg] = 0
    for ic in range (5):
        IC = 'IC'+str(ic+1)
        print (IC)

        #Dictionaries based on Pol and Poll
        meanP37PM25[reg][str(IC)] = {}
        meanP45PM25[reg][str(IC)] = {}

        meanP37O3[reg][str(IC)] = {}
        meanP45O3[reg][str(IC)] = {}

        # dfP37PM25[reg][str(IC)] = {}
        # dfP37O3[reg][str(IC)] = {}

        # dfP45PM25[reg][str(IC)] = {}
        # dfP45O3[reg][str(IC)] = {}

        year = [] ## x-axis
        Mean = []

        # year2 = [] ## x-axis
        # Mean2 = []

        Pol = 'P37'

        # LOAD DATA TO ARRAY
        for Yr in Year_range:

            year.append(Yr)

            idenPM25 = reg+'_BenMAP_' +
str(Yr)+'_'+IC+'_'+Pol+'vsREF_'+Poll[0]
            with open (os.path.join(mydir,idenPM25), 'rb') as f:
                    mydictP37PM25 = (cp.load(f))

            idenO3 = reg+'_BenMAP_' +
str(Yr)+'_'+IC+'_'+Pol+'vsREF_'+Poll[1]
```

```
            with open (os.path.join(mydir,idenO3), 'rb') as f:
                    mydictP37O3 = (cp.load(f))


            meanP37PM25[reg][str(IC)][str(Yr)] = 0
            meanP37O3[reg][str(IC)][str(Yr)] = 0

            # Over here I try to add up the values for each cell based on
the specific authors, and try to eliminate the author dicitionaries.
            for author in mydictP37PM25.keys():
                if author != 'Lepeule et al.'and author != 'Schwartz and
Neas' and author != 'Peters et al.':
                    meanP37PM25[reg][str(IC)][str(Yr)] +=
mydictP37PM25[author] * proj_factor[Pol][Year] /(10**12)

            for author in mydictP37O3.keys():
                if author in ['Zanobetti and Schwartz (b)','Smith et
al.','Schildcrout et al.','Mortimer et al.','Sarnat et al. Peel et al.
Wilson et al. Glad et al. Mar and Koenig Ito et al.']:
                    meanP37O3[reg][str(IC)][str(Yr)] +=
mydictP37O3[author] * proj_factor[Pol][Year] /(10**12)
                else:
                    meanP37O3[reg][str(IC)][str(Yr)] +=
mydictP37O3[author] * proj_factor[Pol][Year] /(10**12)


        Pol = 'P45'

        for Yr in Year_range:

            year.append(Yr)

            idenPM25 = reg+'_BenMAP_' +
str(Yr)+'_'+IC+'_'+Pol+'vsREF_'+Poll[0]
            with open (os.path.join(mydir,idenPM25), 'rb') as f:
                    mydictP45PM25 = (cp.load(f))

            idenO3 = reg+'_BenMAP_' +
str(Yr)+'_'+IC+'_'+Pol+'vsREF_'+Poll[1]
            with open (os.path.join(mydir,idenO3), 'rb') as f:
                    mydictP45O3 = (cp.load(f))


            meanP45PM25[reg][str(IC)][str(Yr)] = 0
            meanP45O3[reg][str(IC)][str(Yr)] = 0


            # Over here I try to add up the values for each cell based on
the specific authors, and try to eliminate the author dicitionaries.
            for author in mydictP45PM25.keys():
                if author != 'Lepeule et al.'and author != 'Schwartz and
Neas' and author != 'Peters et al.':
```

```
                    meanP45PM25[reg][str(IC)][str(Yr)] +=
mydictP45PM25[author] * proj_factor[Pol][Year] /(10**12)


            for author in mydictP45O3.keys():
                if author in ['Zanobetti and Schwartz (b)','Smith et
al.','Schildcrout et al.','Mortimer et al.','Sarnat et al. Peel et al.
Wilson et al. Glad et al. Mar and Koenig Ito et al.']:
                    meanP45O3[reg][str(IC)][str(Yr)] +=
mydictP45O3[author] * proj_factor[Pol][Year] /(10**12)
                else:
                    meanP45O3[reg][str(IC)][str(Yr)] +=
mydictP45O3[author] * proj_factor[Pol][Year] /(10**12)

    # Over here I am converting the dictionaries to dataframes, in order
to simplify the averaging within each cell based on Year and IC.
    dfP37PM25[reg] = pd.DataFrame.from_dict({(i,j): meanP37PM25[reg][i][j]
    for i in meanP37PM25[reg].keys()
    for j in
meanP37PM25[reg][i].keys()},orient='index')#.stack().reset_index()

    dfP37O3[reg] = pd.DataFrame.from_dict({(i,j): meanP37O3[reg][i][j]
    for i in meanP37O3[reg].keys()
    for j in
meanP37O3[reg][i].keys()},orient='index')#.stack().reset_index()

    for reg in dfP37Poll:
        dfP37Poll[reg] = dfP37PM25[reg]+dfP37O3[reg]
    dfP37PollMean[reg] = (dfP37Poll[reg].mean(axis =
0).to_frame()).iloc[0][0]
    dfP37PollStd[reg] = (dfP37Poll[reg].std(axis =
0).to_frame()).iloc[0][0]
    dfP37PollSNR[reg] = dfP37PollMean[reg]/dfP37PollStd[reg]

    dfP45PM25[reg] = pd.DataFrame.from_dict({(i,j): meanP45PM25[reg][i][j]
    for i in meanP45PM25[reg].keys()
    for j in
meanP45PM25[reg][i].keys()},orient='index')#.stack().reset_index()

    dfP45O3[reg] = pd.DataFrame.from_dict({(i,j): meanP45O3[reg][i][j]
    for i in meanP45O3[reg].keys()
    for j in
meanP45O3[reg][i].keys()},orient='index')#.stack().reset_index()

    for reg in dfP45Poll:
        dfP45Poll[reg] = dfP45PM25[reg]+dfP45O3[reg]
    dfP45PollMean[reg] = (dfP45Poll[reg].mean(axis =
0).to_frame()).iloc[0][0]
    dfP45PollStd[reg] = (dfP45Poll[reg].std(axis =
0).to_frame()).iloc[0][0]
    dfP45PollSNR[reg] = dfP45PollMean[reg]/dfP45PollStd[reg]
```

```python
    # Here i sum up PM25 and O3 dataframes for P37
    # for reg in dfP37PM25Mean.keys():
    #     DFP37Mean[reg] = dfP37PM25Mean[reg]+dfP37O3Mean[reg]

    # for reg in dfP37PM25SNR.keys():
    #     DFP37SNR[reg] = dfP37PM25SNR[reg]+dfP37O3SNR[reg] #total

    # # Here i sum up PM25 and O3 dataframes for P45
    # for reg in dfP45PM25Mean.keys():
    #     DFP45Mean[reg] = dfP45PM25Mean[reg]+dfP45O3Mean[reg]

    # for reg in dfP45PM25SNR.keys():
    #     DFP45SNR[reg] = dfP45PM25SNR[reg]+dfP45O3SNR[reg]


region_benP37 = {'State': 'Mortality','AK': 0,'HI': 0,'RNW': 0,'RSW':
0,'RGP': 0,'RMW': 0,'RSE': 0,'RNE': 0,}

region_benP37['Northwest'] = dfP37PollMean['NW']
region_benP37['ID'] = dfP37PollMean['NW']
region_benP37['OR'] = dfP37PollMean['NW']
region_benP37['WA'] = dfP37PollMean['NW']

region_benP37['Southwest'] = dfP37PollMean['SW']
region_benP37['AZ'] = dfP37PollMean['SW']
region_benP37['CA'] = dfP37PollMean['SW']
region_benP37['CO'] = dfP37PollMean['SW']
region_benP37['NV'] = dfP37PollMean['SW']
region_benP37['NM'] = dfP37PollMean['SW']
region_benP37['UT'] = dfP37PollMean['SW']

region_benP37['Greatplains'] = dfP37PollMean['GP']
region_benP37['KS'] = dfP37PollMean['GP']
region_benP37['MT'] = dfP37PollMean['GP']
region_benP37['NE'] = dfP37PollMean['GP']
region_benP37['ND'] = dfP37PollMean['GP']
region_benP37['OK'] = dfP37PollMean['GP']
region_benP37['SD'] = dfP37PollMean['GP']
region_benP37['TX'] = dfP37PollMean['GP']
region_benP37['WY'] = dfP37PollMean['GP']

region_benP37['Midwest'] = dfP37PollMean['MW']
region_benP37['IL'] = dfP37PollMean['MW']
region_benP37['IN'] = dfP37PollMean['MW']
region_benP37['IA'] = dfP37PollMean['MW']
region_benP37['MI'] = dfP37PollMean['MW']
region_benP37['MN'] = dfP37PollMean['MW']
region_benP37['MO'] = dfP37PollMean['MW']
region_benP37['OH'] = dfP37PollMean['MW']
region_benP37['WI'] = dfP37PollMean['MW']

region_benP37['Southeast'] = dfP37PollMean['SE']
region_benP37['AL'] = dfP37PollMean['SE']
```

```
region_benP37['AR'] = dfP37PollMean['SE']
region_benP37['FL'] = dfP37PollMean['SE']
region_benP37['GA'] = dfP37PollMean['SE']
region_benP37['KY'] = dfP37PollMean['SE']
region_benP37['LA'] = dfP37PollMean['SE']
region_benP37['MS'] = dfP37PollMean['SE']
region_benP37['NC'] = dfP37PollMean['SE']
region_benP37['SC'] = dfP37PollMean['SE']
region_benP37['TN'] = dfP37PollMean['SE']
region_benP37['VA'] = dfP37PollMean['SE']

region_benP37['Northeast'] = dfP37PollMean['NE']
region_benP37['CT'] = dfP37PollMean['NE']
region_benP37['DE'] = dfP37PollMean['NE']
region_benP37['DC'] = dfP37PollMean['NE']
region_benP37['ME'] = dfP37PollMean['NE']
region_benP37['MD'] = dfP37PollMean['NE']
region_benP37['MA'] = dfP37PollMean['NE']
region_benP37['NH'] = dfP37PollMean['NE']
region_benP37['NJ'] = dfP37PollMean['NE']
region_benP37['NY'] = dfP37PollMean['NE']
region_benP37['PA'] = dfP37PollMean['NE']
region_benP37['RI'] = dfP37PollMean['NE']
region_benP37['VT'] = dfP37PollMean['NE']
region_benP37['WV'] = dfP37PollMean['NE']

region_benP45 = {'State': 'Mortality','AK': 0,'HI': 0,'RNW': 0,'RSW':
0,'RGP': 0,'RMW': 0,'RSE': 0,'RNE': 0,}

region_benP45['Northwest'] = dfP45PollMean['NW']
region_benP45['ID'] = dfP45PollMean['NW']
region_benP45['OR'] = dfP45PollMean['NW']
region_benP45['WA'] = dfP45PollMean['NW']

region_benP45['Southwest'] = dfP45PollMean['SW']
region_benP45['AZ'] = dfP45PollMean['SW']
region_benP45['CA'] = dfP45PollMean['SW']
region_benP45['CO'] = dfP45PollMean['SW']
region_benP45['NV'] = dfP45PollMean['SW']
region_benP45['NM'] = dfP45PollMean['SW']
region_benP45['UT'] = dfP45PollMean['SW']

region_benP45['Greatplains'] = dfP45PollMean['GP']
region_benP45['KS'] = dfP45PollMean['GP']
region_benP45['MT'] = dfP45PollMean['GP']
region_benP45['NE'] = dfP45PollMean['GP']
region_benP45['ND'] = dfP45PollMean['GP']
region_benP45['OK'] = dfP45PollMean['GP']
region_benP45['SD'] = dfP45PollMean['GP']
region_benP45['TX'] = dfP45PollMean['GP']
region_benP45['WY'] = dfP45PollMean['GP']

region_benP45['Midwest'] = dfP45PollMean['MW']
```

```
region_benP45['IL'] = dfP45PollMean['MW']
region_benP45['IN'] = dfP45PollMean['MW']
region_benP45['IA'] = dfP45PollMean['MW']
region_benP45['MI'] = dfP45PollMean['MW']
region_benP45['MN'] = dfP45PollMean['MW']
region_benP45['MO'] = dfP45PollMean['MW']
region_benP45['OH'] = dfP45PollMean['MW']
region_benP45['WI'] = dfP45PollMean['MW']

region_benP45['Southeast'] = dfP45PollMean['SE']
region_benP45['AL'] = dfP45PollMean['SE']
region_benP45['AR'] = dfP45PollMean['SE']
region_benP45['FL'] = dfP45PollMean['SE']
region_benP45['GA'] = dfP45PollMean['SE']
region_benP45['KY'] = dfP45PollMean['SE']
region_benP45['LA'] = dfP45PollMean['SE']
region_benP45['MS'] = dfP45PollMean['SE']
region_benP45['NC'] = dfP45PollMean['SE']
region_benP45['SC'] = dfP45PollMean['SE']
region_benP45['TN'] = dfP45PollMean['SE']
region_benP45['VA'] = dfP45PollMean['SE']

region_benP45['Northeast'] = dfP45PollMean['NE']
region_benP45['CT'] = dfP45PollMean['NE']
region_benP45['DE'] = dfP45PollMean['NE']
region_benP45['DC'] = dfP45PollMean['NE']
region_benP45['ME'] = dfP45PollMean['NE']
region_benP45['MD'] = dfP45PollMean['NE']
region_benP45['MA'] = dfP45PollMean['NE']
region_benP45['NH'] = dfP45PollMean['NE']
region_benP45['NJ'] = dfP45PollMean['NE']
region_benP45['NY'] = dfP45PollMean['NE']
region_benP45['PA'] = dfP45PollMean['NE']
region_benP45['RI'] = dfP45PollMean['NE']
region_benP45['VT'] = dfP45PollMean['NE']
region_benP45['WV'] = dfP45PollMean['NE']

region_snrP37 = {'State': 'Mortality','AK': 0,'HI': 0,'RNW': 0,'RSW':
0,'RGP': 0,'RMW': 0,'RSE': 0,'RNE': 0,}

region_snrP37['Northwest'] = dfP37PollSNR['NW']
region_snrP37['ID'] = dfP37PollSNR['NW']
region_snrP37['OR'] = dfP37PollSNR['NW']
region_snrP37['WA'] = dfP37PollSNR['NW']

region_snrP37['Southwest'] = dfP37PollSNR['SW']
region_snrP37['AZ'] = dfP37PollSNR['SW']
region_snrP37['CA'] = dfP37PollSNR['SW']
region_snrP37['CO'] = dfP37PollSNR['SW']
region_snrP37['NV'] = dfP37PollSNR['SW']
region_snrP37['NM'] = dfP37PollSNR['SW']
region_snrP37['UT'] = dfP37PollSNR['SW']
```

```
region_snrP37['Greatplains'] = dfP37PollSNR['GP']
region_snrP37['KS'] = dfP37PollSNR['GP']
region_snrP37['MT'] = dfP37PollSNR['GP']
region_snrP37['NE'] = dfP37PollSNR['GP']
region_snrP37['ND'] = dfP37PollSNR['GP']
region_snrP37['OK'] = dfP37PollSNR['GP']
region_snrP37['SD'] = dfP37PollSNR['GP']
region_snrP37['TX'] = dfP37PollSNR['GP']
region_snrP37['WY'] = dfP37PollSNR['GP']

region_snrP37['Midwest'] = dfP37PollSNR['MW']
region_snrP37['IL'] = dfP37PollSNR['MW']
region_snrP37['IN'] = dfP37PollSNR['MW']
region_snrP37['IA'] = dfP37PollSNR['MW']
region_snrP37['MI'] = dfP37PollSNR['MW']
region_snrP37['MN'] = dfP37PollSNR['MW']
region_snrP37['MO'] = dfP37PollSNR['MW']
region_snrP37['OH'] = dfP37PollSNR['MW']
region_snrP37['WI'] = dfP37PollSNR['MW']

region_snrP37['Southeast'] = dfP37PollSNR['SE']
region_snrP37['AL'] = dfP37PollSNR['SE']
region_snrP37['AR'] = dfP37PollSNR['SE']
region_snrP37['FL'] = dfP37PollSNR['SE']
region_snrP37['GA'] = dfP37PollSNR['SE']
region_snrP37['KY'] = dfP37PollSNR['SE']
region_snrP37['LA'] = dfP37PollSNR['SE']
region_snrP37['MS'] = dfP37PollSNR['SE']
region_snrP37['NC'] = dfP37PollSNR['SE']
region_snrP37['SC'] = dfP37PollSNR['SE']
region_snrP37['TN'] = dfP37PollSNR['SE']
region_snrP37['VA'] = dfP37PollSNR['SE']

region_snrP37['Northeast'] = dfP37PollSNR['NE']
region_snrP37['CT'] = dfP37PollSNR['NE']
region_snrP37['DE'] = dfP37PollSNR['NE']
region_snrP37['DC'] = dfP37PollSNR['NE']
region_snrP37['ME'] = dfP37PollSNR['NE']
region_snrP37['MD'] = dfP37PollSNR['NE']
region_snrP37['MA'] = dfP37PollSNR['NE']
region_snrP37['NH'] = dfP37PollSNR['NE']
region_snrP37['NJ'] = dfP37PollSNR['NE']
region_snrP37['NY'] = dfP37PollSNR['NE']
region_snrP37['PA'] = dfP37PollSNR['NE']
region_snrP37['RI'] = dfP37PollSNR['NE']
region_snrP37['VT'] = dfP37PollSNR['NE']
region_snrP37['WV'] = dfP37PollSNR['NE']

region_snrP45 = {'State': 'Mortality','AK': 0,'HI': 0,'RNW': 0,'RSW':
0,'RGP': 0,'RMW': 0,'RSE': 0,'RNE': 0,}

region_snrP45['Northwest'] = dfP45PollSNR['NW']
region_snrP45['ID'] = dfP45PollSNR['NW']
```

```
region_snrP45['OR'] = dfP45PollSNR['NW']
region_snrP45['WA'] = dfP45PollSNR['NW']

region_snrP45['Southwest'] = dfP45PollSNR['SW']
region_snrP45['AZ'] = dfP45PollSNR['SW']
region_snrP45['CA'] = dfP45PollSNR['SW']
region_snrP45['CO'] = dfP45PollSNR['SW']
region_snrP45['NV'] = dfP45PollSNR['SW']
region_snrP45['NM'] = dfP45PollSNR['SW']
region_snrP45['UT'] = dfP45PollSNR['SW']

region_snrP45['Greatplains'] = dfP45PollSNR['GP']
region_snrP45['KS'] = dfP45PollSNR['GP']
region_snrP45['MT'] = dfP45PollSNR['GP']
region_snrP45['NE'] = dfP45PollSNR['GP']
region_snrP45['ND'] = dfP45PollSNR['GP']
region_snrP45['OK'] = dfP45PollSNR['GP']
region_snrP45['SD'] = dfP45PollSNR['GP']
region_snrP45['TX'] = dfP45PollSNR['GP']
region_snrP45['WY'] = dfP45PollSNR['GP']

region_snrP45['Midwest'] = dfP45PollSNR['MW']
region_snrP45['IL'] = dfP45PollSNR['MW']
region_snrP45['IN'] = dfP45PollSNR['MW']
region_snrP45['IA'] = dfP45PollSNR['MW']
region_snrP45['MI'] = dfP45PollSNR['MW']
region_snrP45['MN'] = dfP45PollSNR['MW']
region_snrP45['MO'] = dfP45PollSNR['MW']
region_snrP45['OH'] = dfP45PollSNR['MW']
region_snrP45['WI'] = dfP45PollSNR['MW']

region_snrP45['Southeast'] = dfP45PollSNR['SE']
region_snrP45['AL'] = dfP45PollSNR['SE']
region_snrP45['AR'] = dfP45PollSNR['SE']
region_snrP45['FL'] = dfP45PollSNR['SE']
region_snrP45['GA'] = dfP45PollSNR['SE']
region_snrP45['KY'] = dfP45PollSNR['SE']
region_snrP45['LA'] = dfP45PollSNR['SE']
region_snrP45['MS'] = dfP45PollSNR['SE']
region_snrP45['NC'] = dfP45PollSNR['SE']
region_snrP45['SC'] = dfP45PollSNR['SE']
region_snrP45['TN'] = dfP45PollSNR['SE']
region_snrP45['VA'] = dfP45PollSNR['SE']

region_snrP45['Northeast'] = dfP45PollSNR['NE']
region_snrP45['CT'] = dfP45PollSNR['NE']
region_snrP45['DE'] = dfP45PollSNR['NE']
region_snrP45['DC'] = dfP45PollSNR['NE']
region_snrP45['ME'] = dfP45PollSNR['NE']
region_snrP45['MD'] = dfP45PollSNR['NE']
region_snrP45['MA'] = dfP45PollSNR['NE']
region_snrP45['NH'] = dfP45PollSNR['NE']
region_snrP45['NJ'] = dfP45PollSNR['NE']
```

```
region_snrP45['NY'] = dfP45PollSNR['NE']
region_snrP45['PA'] = dfP45PollSNR['NE']
region_snrP45['RI'] = dfP45PollSNR['NE']
region_snrP45['VT'] = dfP45PollSNR['NE']
region_snrP45['WV'] = dfP45PollSNR['NE']

exshpfile = gpd.read_file(os.path.join(ExSHP, 'USA-Regions20191008.shp'))
infile = ogr.Open(os.path.join(ExSHP, 'USA-Regions20191008.shp'))
layer = infile.GetLayer()
spatialRef = layer.GetSpatialRef()
epsg = spatialRef.ExportToWkt()
# exshpfile["D24HourMean"] = 0
exshpfile.insert(1, "D24HourMean", 0, True)

# Creating blank shapefiles to copy the generated values into;
shpP37 = copy.deepcopy(exshpfile)
shpP45 = copy.deepcopy(exshpfile)
shpP37snr = copy.deepcopy(exshpfile)
shpP45snr = copy.deepcopy(exshpfile)

for i in range(len(shpP37)):
    j = shpP37.iloc[i,0]
    k = region_benP37[j]
    shpP37.loc[(shpP37["region"] == j), "D24HourMean"] = k

for i in range(len(shpP45)):
    j = shpP45.iloc[i,0]
    k = region_benP45[j]
    shpP45.loc[(shpP45["region"] == j), "D24HourMean"] = k

for i in range(len(shpP37snr)):
    j = shpP37snr.iloc[i,0]
    k = region_snrP37[j]
    shpP37snr.loc[(shpP37snr["region"] == j), "D24HourMean"] = k

for i in range(len(shpP45snr)):
    j = shpP45snr.iloc[i,0]
    k = region_snrP45[j]
    shpP45snr.loc[(shpP45snr["region"] == j), "D24HourMean"] = k

shpfname12=
'AGU2020Fig3_'+Year+'_P37'+'_Krewski_Valuations_'+datetime.date.today().st
rftime("%Y%m%d")+'.shp'
shpfilename12 = outdir1 + shpfname12
shpP37.to_file(shpfilename12)
prjfname12=
'AGU2020Fig3_'+Year+'_P37'+'_Krewski_Valuations_'+datetime.date.today().st
rftime("%Y%m%d")+'.prj'
prj = open(os.path.join(outdir1, prjfname12), "w")
prj.write(epsg)
prj.close()
```

```
shpfname34=
'AGU2020Fig3_'+Year+'_P45'+'_Krewski_Valuations_'+datetime.date.today().st
rftime("%Y%m%d")+'.shp'
shpfilename34 = outdir1 + shpfname34
shpP45.to_file(shpfilename34)
prjfname34=
'AGU2020Fig3_'+Year+'_P45'+'_Krewski_Valuations_'+datetime.date.today().st
rftime("%Y%m%d")+'.prj'
prj = open(os.path.join(outdir1, prjfname34), "w")
prj.write(epsg)
prj.close()

shpfname56= 'AGU2020Fig3_'+Year+'_P37'+'_Krewski_V-
SNR_'+datetime.date.today().strftime("%Y%m%d")+'.shp'
shpfilename56 = outdir1 + shpfname56
shpP37snr.to_file(shpfilename56)
prjfname56= 'AGU2020Fig3_'+Year+'_P37'+'_Krewski_V-
SNR_'+datetime.date.today().strftime("%Y%m%d")+'.prj'
prj = open(os.path.join(outdir1, prjfname56), "w")
prj.write(epsg)
prj.close()

shpfname78= 'AGU2020Fig3_'+Year+'_P45'+'_Krewski_V-
SNR_'+datetime.date.today().strftime("%Y%m%d")+'.shp'
shpfilename78 = outdir1 + shpfname78
shpP45snr.to_file(shpfilename78)
prjfname78= 'AGU2020Fig3_'+Year+'_P45'+'_Krewski_V-
SNR_'+datetime.date.today().strftime("%Y%m%d")+'.prj'
prj = open(os.path.join(outdir1, prjfname78), "w")
prj.write(epsg)
prj.close()
```

AGU2020_Fig6_Plotting_Region_20200301.py

Fits relative error reduction to exponential decay

```
# --- Import
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import matplotlib.lines as mlines
import pickle as cp
import numpy as np
import os
import datetime
import scipy as sp
import scipy.optimize
from sklearn.metrics import r2_score
import matplotlib as mpl
mpl.rc('font',size=12)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# -----------------------------------------------------------------
# --- Define Functions
def model_func(t, A, K, C):
    return A * np.exp(-K * t)+C

def fit_exp_nonlinear(t, y):
    opt_parms, parm_cov = sp.optimize.curve_fit(model_func, t, y, maxfev=10000)
    A, K, C = opt_parms
    return A, K, C

# def fit_exp_linear(t, y, C=0):
#     y = y - C
#     y = np.log(y)
#     K, A_log = np.polyfit(t, y, 1)
#     A = np.exp(A_log)
#     return A, K
# --- Define variables
data = {}

mydir = 'C:/Users/devpu/OneDrive - University of Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Data/AGU2020-
Fig6/Pickles/Region/'
outdir = 'C:/Users/devpu/OneDrive - University of Waterloo/UWaterloo/Dr.SaariLab/WorkingFolder/Figures/AGU2020-
Fig6/SouthWest/'

fig = plt.figure(figsize=(6,4))
ax1 = fig.add_subplot(111)
#ax2 = ax1.twinx()

# --- Load and store the CPickle File Data

data = {}
for pol in ['P45','P37']:
    data[pol] = {}
    for year in ['2050','2100']:
```

```
        data[pol][year] = {}
        iden = 'SW_All_150_Lines_data_' + year + '_' + pol #+ '_Unix'
        with open (os.path.join(mydir, iden), 'rb') as f:
            data[pol][year] = cp.load(f)

# for pol in ['P37','P45']:
#     data[pol] = {}
#     for year in ['2050', '2100']:
#         data[pol][year] = {}
#         iden = '150_Lines_data_' + year + '_' + pol + '_Unix'
#         with open (os.path.join(mydir, iden), 'rb') as f:
#             data[pol][year] = cp.load(f)


data1 = {}
for pol in ['P45','P37']:
    data1[pol] = {}
    for year in ['2050','2100']:
        data1[pol][year] = {}
        for auth in ['Krewski et al.', 'Lepeule et al.']:
            data1[pol][year][auth] = {}
            for maxmin in ['Max', 'Min']:
                data1[pol][year][auth][maxmin] = {}
                # for yr in range(int(year)-14,int(year)+15+1):
                #     data1[pol][year][auth]['Max'][yr] = max(max(data[pol][year][auth][yr]['IC5']),
max(data[pol][year][auth][yr]['IC4']), max(data[pol][year][auth][yr]['IC3']), max(data[pol][year][auth][yr]['IC2']),
max(data[pol][year][auth][yr]['IC1']))
                #     data1[pol][year][auth]['Min'][yr] = min(min(data[pol][year][auth][yr]['IC5']),
min(data[pol][year][auth][yr]['IC4']), min(data[pol][year][auth][yr]['IC3']), min(data[pol][year][auth][yr]['IC2']),
min(data[pol][year][auth][yr]['IC1']))

x_value=range(1,31)
MaxK = {}
MinK = {}
MaxL = {}
MinL = {}

for pol in ['P45','P37']:
    MaxK[pol] = {}
    MinK[pol] = {}
    for year in ['2050','2100']:
        MaxK[pol][year] = {}
        MinK[pol][year] = {}
        for auth in ['Krewski et al.']:
            MaxK[pol][year][auth] = []
            MinK[pol][year][auth] = []
            for i in x_value:
                buf150p = []                    # to store 150 points
                Yr1 = str(int(year)-14)
                Yr2 = str(int(year)+15)
                for start in range(int(Yr1),int(Yr2)+1):  # 30 starting yr
                    for ic in range(5):             # 5 ic
                        IC = 'IC' +str(ic+1)
                        buf150p.append(data[pol][year][auth][start][IC][i-1])
```

```
            MaxK[pol][year][auth].append(max(buf150p))
            MinK[pol][year][auth].append(min(buf150p))

for pol in ['P45','P37']:
   MaxL[pol] = {}
   MinL[pol] = {}
   for year in ['2050','2100']:
      MaxL[pol][year] = {}
      MinL[pol][year] = {}
      for auth in ['Lepeule et al.']:
         MaxL[pol][year][auth] = []
         MinL[pol][year][auth] = []
         for i in x_value:
            buf150p = []                    # to store 150 points
            Yr1 = str(int(year)-14)
            Yr2 = str(int(year)+15)
            for start in range(int(Yr1),int(Yr2)+1):  # 30 starting yr
               for ic in range(5):              # 5 ic
                  IC = 'IC' +str(ic+1)
                  buf150p.append(data[pol][year][auth][start][IC][i-1])

            MaxL[pol][year][auth].append(max(buf150p))
            MinL[pol][year][auth].append(min(buf150p))


for pol in ['P45','P37']:
   for year in ['2050','2100']:
      Yr1 = str(int(year)-14)
      Yr2 = str(int(year)+15)
      for auth in ['Krewski et al.']:
         for maxmin in ['Max', 'Min']:
            # for yr in range(int(year)-14,int(year)+15+1):
            for i in range(int(Yr1),int(Yr2)+1):
               data1[pol][year][auth]['Max'][str(i)] = MaxK[pol][year][auth][i-int(Yr1)]
               data1[pol][year][auth]['Min'][str(i)] = MinK[pol][year][auth][i-int(Yr1)]

for pol in ['P45','P37']:
   for year in ['2050','2100']:
      Yr1 = str(int(year)-14)
      Yr2 = str(int(year)+15)
      for auth in ['Lepeule et al.']:
         for maxmin in ['Max', 'Min']:
            # for yr in range(int(year)-14,int(year)+15+1):
            for i in range(int(Yr1),int(Yr2)+1):
               data1[pol][year][auth]['Max'][str(i)] = MaxL[pol][year][auth][i-int(Yr1)]
               data1[pol][year][auth]['Min'][str(i)] = MinL[pol][year][auth][i-int(Yr1)]

# --- Generate data for lines
# --- Calculate % error
x_val = range(1,30+1)
y_val = {}
for pol in ['P37','P45']:
   y_val[pol] = {}
   for year in ['2050', '2100']:
      y_val[pol][year] = {}
```

```
        for auth in ['Krewski et al.', 'Lepeule et al.']:
            y_val[pol][year][auth] = {}
            temp = []
            min_val = data1[pol][year][auth]['Min']
            max_val = data1[pol][year][auth]['Max']
            for i in range(int(year)-14,int(year)+15+1):
#                temp.append((max_val[str(i)] - min_val[str(i)])/(max_val[str(int(year)+15)] - min_val[str(int(year)+15)])*100)
                val_avgP = (max_val[str(i)] - min_val[str(i)])
                val_year = (max_val[str(int(year)+15)] - min_val[str(int(year)+15)])
                temp.append(((val_avgP-val_year)/val_year)*100)
            y_val[pol][year][auth] = temp

# Non-linear Fit
fit_y = {}
AA = {}
KK = {}
CC = {}
R2 = {}
for pol in ['P37','P45']:
    fit_y[pol] = {}
    AA[pol] = {}
    KK[pol] = {}
    CC[pol] = {}
    R2[pol] = {}
    for year in ['2050', '2100']:
        fit_y[pol][year] = {}
        AA[pol][year] = {}
        KK[pol][year] = {}
        CC[pol][year] = {}
        R2[pol][year] = {}
        for auth in ['Krewski et al.', 'Lepeule et al.']:
            fit_y[pol][year][auth] = {}
            AA[pol][year][auth] = {}
            KK[pol][year][auth] = {}
            CC[pol][year][auth] = {}
            R2[pol][year][auth] = {}
            A, K, C = fit_exp_nonlinear(x_val, y_val[pol][year][auth])
            AA[pol][year][auth] = A
            KK[pol][year][auth] = K
            CC[pol][year][auth] = C
            fit_y[pol][year][auth] = model_func(x_val, A, K, C)
            R2[pol][year][auth] = r2_score(y_val[pol][year][auth], fit_y[pol][year][auth])


# --- Plot the lines

# assign colours, set to P37 = blue and P45 = red (based on loop)
colour_vec = ['red','red','red','red','blue','blue','blue','blue']
bar_col = ['r','g','b','y','r','g','b','y']
# assign line styles, set to different line styles for P37 and P45
line_style = [':','--',':','--',':','--',':','--']
marker_style = ['.','^','.','^','.','^','.','^']
a = 0
legend_vec = ['P4.5', 'P3.7', '2050', '2100', 'Krewski', 'Lepeule']
```

```
P45_patch = mpatches.Patch(facecolor='red', label='P4.5')
P37_patch = mpatches.Patch(facecolor='blue', label='P3.7')
Y2050_patch = mlines.Line2D([], [], color='black', ls = '-', marker='', label='2050')
Y2100_patch = mlines.Line2D([], [], color='black', ls = ':', marker='', label='2100')
Krewski_patch = mlines.Line2D([], [], color='black', marker='.', lw = 0, markersize = 8, label='Krewski')
Lepuele_patch = mlines.Line2D([], [], color='black', marker='^', lw = 0, markersize = 5, label='Lepeule')
FitY_patch = mlines.Line2D([], [], color='black', ls = ':', marker='*', lw = 0, markersize = 8, label='Exponential Decay Fit')

# for loop structure determines the order of plotting

# For P37-2050
# for pol in ['P37']:
#     for year in ['2050']:
#         for auth in ['Krewski et al.', 'Lepeule et al.']:
#             if auth == 'Krewski et al.':
#                 size = 6.5
#             else:
#                 size = 4.5
#             ax1.plot(x_val, y_val[pol][year][auth], linewidth = 0.75, color = 'blue', ls = '-', marker = marker_style[a], ms = 8.5,
markeredgecolor='white', markeredgewidth=0.2)
#             ax1.plot(x_val, fit_y[pol][year][auth], linewidth = 0.5, color = 'black', ls = '-', marker = '*', ms = 6.5,
markeredgecolor='white', markeredgewidth=0.2)
#             a += 1
# ax1.legend(bbox_to_anchor=(1,1), handles=[P37_patch, Y2050_patch, Krewski_patch, Lepuele_patch, FitY_patch], loc =
1)

# # For P37-2100
# for pol in ['P37']:
#     for year in ['2100']:
#         for auth in ['Krewski et al.', 'Lepeule et al.']:
#             if auth == 'Krewski et al.':
#                 size = 6.5
#             else:
#                 size = 4.5
#             ax1.plot(x_val, y_val[pol][year][auth], linewidth = 0.75, color = 'blue', ls = ':', marker = marker_style[a], ms = 8.5,
markeredgecolor='white', markeredgewidth=0.2)
#             ax1.plot(x_val, fit_y[pol][year][auth], linewidth = 0.5, color = 'black', ls = '-', marker = '*', ms = 6.5,
markeredgecolor='white', markeredgewidth=0.2)
#             a += 1
# ax1.legend(bbox_to_anchor=(1,1), handles=[P37_patch, Y2100_patch, Krewski_patch, Lepuele_patch, FitY_patch], loc =
1)

# # For P45-2050
# for pol in ['P45']:
#     for year in ['2050']:
#         for auth in ['Krewski et al.', 'Lepeule et al.']:
#             if auth == 'Krewski et al.':
#                 size = 6.5
#             else:
#                 size = 4.5
#             ax1.plot(x_val, y_val[pol][year][auth], linewidth = 0.75, color = 'red', ls = '-', marker = marker_style[a], ms = 8.5,
markeredgecolor='white', markeredgewidth=0.2)
#             ax1.plot(x_val, fit_y[pol][year][auth], linewidth = 0.5, color = 'black', ls = '-', marker = '*', ms = 6.5,
markeredgecolor='white', markeredgewidth=0.2)
#             a += 1
```

```
# ax1.legend(bbox_to_anchor=(1,1), handles=[P45_patch, Y2050_patch, Krewski_patch, Lepuele_patch, FitY_patch], loc =
1)

# # For P45-2100
for pol in ['P45']:
   for year in ['2100']:
      for auth in ['Krewski et al.', 'Lepeule et al.']:
         if auth == 'Krewski et al.':
            size = 6.5
         else:
            size = 4.5
         ax1.plot(x_val, y_val[pol][year][auth], linewidth = 0.75, color = 'red', ls = ':', marker = marker_style[a], ms = 8.5,
markeredgecolor='white', markeredgewidth=0.2)
         ax1.plot(x_val, fit_y[pol][year][auth], linewidth = 0.5, color = 'black', ls = '-', marker = '*', ms = 6.5,
markeredgecolor='white', markeredgewidth=0.2)
         a += 1
ax1.legend(bbox_to_anchor=(1,1), handles=[P45_patch, Y2100_patch, Krewski_patch, Lepuele_patch, FitY_patch], loc = 1)

# for pol in ['P37','P45']:
#    for year in ['2050', '2100']:
#       for auth in ['Krewski et al.', 'Lepeule et al.']:
#          if auth == 'Krewski et al.':
#             size = 6.5
#          else:
#             size = 4.5
#          ax1.plot(x_val, y_val[pol][year][auth], linewidth = 0.5, color = colour_vec[a], ls = line_style[a], marker =
marker_style[a], ms = size,  markeredgecolor='white', markeredgewidth=0.2)
#          a += 1
#ax1.legend(bbox_to_anchor=(1,1), handles=[P45_patch, P37_patch, Y2050_patch, Y2100_patch, Krewski_patch,
Lepuele_patch], loc = 1)

# Figure formatting
ax1.set_xlabel('Averaging Period (Years)', size = 12)
ax1.set_ylabel('% Error', size = 12)
plt.xlim(1,30)

fname= 'Figure_'+pol+'_'+year+'_'+datetime.date.today().strftime("%B_%d_%Y")+'.png'
figname = outdir + fname

plt.savefig(figname,dpi = 800,bbox_inches = 'tight', pad_inches = 0.5)
```