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RESEARCH REPORT

Estimating Model-Based Marginal Societal Health Benefits of Air Pollution Emission Reductions in the United States and Canada

Amir Hakami, Shunliu Zhao, Marjan Soltanzadeh, Petros Vasilakos, Anas Alhusban, Burak Oztaner, Neal Fann, Howard Chang, Alan Krupnick, and Ted Russell

INCLUDES A COMMENTARY BY THE INSTITUTE'S REVIEW COMMITTEE

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with a Commentary by the HEI Review Committee

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ABOUT HEI

The Health Effects Institute is a nonprofit corporation chartered in 1980 as an independent research organization to provide high-quality, impartial, and relevant science on the effects of air pollution on health. To accomplish its mission, the Institute

- identifies the highest-priority areas for health effects research
- competitively funds and oversees research projects
- provides an intensive independent review of HEI-supported studies and related research
- integrates HEI's research results with those of other institutions into broader evaluations
- communicates the results of HEI's research and analyses to public and private decision-makers.

HEI typically receives balanced funding from the US Environmental Protection Agency and the worldwide motor vehicle industry. Frequently, other public and private organizations in the United States and around the world also support major projects or research programs. HEI has funded more than 380 research projects in North America, Europe, Asia, and Latin America, the results of which have informed decisions regarding carbon monoxide, air toxics, nitrogen oxides, diesel exhaust, ozone, particulate matter, and other pollutants. These results have appeared in more than 260 comprehensive reports published by HEI, as well as in more than 2,500 articles in the peer-reviewed literature.

HEI's independent Board of Directors consists of leaders in science and policy who are committed to fostering the public–private partnership that is central to the organization. The Research Committee solicits input from HEI sponsors and other stakeholders and works with scientific staff to develop a Five-Year Strategic Plan, select research projects for funding, and oversee their conduct. The Review Committee, which has no role in selecting or overseeing studies, works with staff to evaluate and interpret the results of funded studies and related research.

All project results and accompanying comments by the Review Committee are widely disseminated through HEI's website (*www.healtheffects.org*), reports, newsletters, annual conferences, and presentations to legislative bodies and public agencies.

ABOUT THIS REPORT

Research Report 218, *Estimating Model-Based Marginal Societal Health Benefits of Air Pollution Emission Reductions in the United States and Canada*, presents a research project funded by the Health Effects Institute and conducted by Dr. Amir Hakami of Carleton University, Ottawa, Ontario, Canada, and his colleagues. The report contains three main sections:

The **HEI Statement**, prepared by staff at HEI, is a brief, nontechnical summary of the study and its findings; it also briefly describes the Review Committee's comments on the study.

The **Investigators' Report**, prepared by Hakami and colleagues, describes the scientific background, aims, methods, results, and conclusions of the study.

The **Commentary**, prepared by members of the Review Committee with the assistance of HEI staff, places the study in a broader scientific context, points out its strengths and limitations, and discusses the remaining uncertainties and implications of the study's findings for public health and future research.

This report has gone through HEI's rigorous review process. When an HEI-funded study is completed, the investigators submit a draft final report presenting the background and results of the study. Outside technical reviewers and a biostatistician first examine the draft report. The report and the reviewers' comments are then evaluated by members of the Review Committee, an independent panel of distinguished scientists who are not involved in selecting or overseeing HEI studies. During the review process, the investigators have an opportunity to exchange comments with the Review Committee and, as necessary, to revise their report. The Commentary reflects the information provided in the final version of the report.

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PREFACE

HEI's Accountability Research Program

INTRODUCTION

The goal of most air quality regulations is to protect the public's health by implementing regulatory actions or providing economic incentives that help to reduce the public's exposure to air pollutants. If that goal is met and air pollution is reduced, indicators of public health should improve or at least not deteriorate. Evaluating the extent to which air quality regulations succeed in protecting public health is part of a broader effort — variously termed *accountability research, outcomes research, or research on regulatory effectiveness* — designed to assess the performance of environmental regulatory policies in general. In recent decades, air quality in the United States and Western Europe has improved substantially, and this improvement is attributable to several factors, including increasingly stringent air quality regulations. However, the cost of the pollution-control technologies and mechanisms needed to implement and enforce these regulations is often high. It is, therefore, prudent to ask whether the regulations have in fact yielded demonstrable improvements in public health; results from such investigations can inform future efforts.

In 2003, the Health Effects Institute published Communication 11, a monograph on accountability research, titled *Assessing Health Impact of Air Quality Regulations: Concepts and Methods for Accountability Research* (HEI Accountability Working Group 2003). This monograph was written by the members of HEI's multidisciplinary Accountability Working Group after a 2001 workshop on the topic. Communication 11 set out a conceptual framework for accountability research and identified the types of evidence required and the methods by which the evidence should be obtained. It has also guided the development of the HEI Accountability Research program, which is discussed below.

Between 2002 and 2004, HEI issued four requests for applications (RFAs), under which eight studies were funded (see **Preface Table**). A ninth study was funded later, under Request for Preliminary Applications (RFPA) 05-3, "Health Effects of Air Pollution." Following this first wave of research, HEI held further workshops to discuss lessons learned, identify key remaining questions, and plan a second wave of research. Those efforts led to further assessments of progress in 2009 and 2010 (HEI 2010b; van Erp and Cohen 2009) and the issuance of RFA 11-1, "Health Outcomes Research — Assessing the Health Outcomes of Air Quality Actions." The first wave of research primarily consisted of studies evaluating relatively short-term, local-scale, and sometimes temporary interventions; RFA 11-1 solicited additional studies with a focus on longer-term, regional- and national-scale regulations, including programs targeted at improving air quality surrounding major ports, as well as further methods development.

This preface describes both the framework of accountability research as it relates to air quality regulations and HEI's Accountability Research program.

BACKGROUND

The first step in assessing the effectiveness of air quality regulations is to measure emissions of the targeted pollutants to see whether they have in fact decreased as intended. A series of intermediate assessments, described in detail below, is needed to measure the adverse health effects associated with air pollution accurately to see whether their incidence or severity decreased relative to emissions. To quantify past effects on health and to predict future effects (US EPA 1999), some accountability studies have used hypothetical scenarios (comparing estimated outcomes under existing and more stringent regulations) and risk estimates obtained from epidemiological studies. However, more extensive validation of those estimates with data on actual outcomes would be helpful.

The long-term improvements in US air quality have been associated with improved health in retrospective epidemiological studies (Chay and Greenstone 2003; Laden et al. 2006; Pope et al. 2009). Considerable challenges, however, are inherent in the assessment of the health effects of air quality regulations. Different regulations go into effect at different times, for example, and may be implemented at different levels of government (e.g., national, regional, or local). Therefore, their effectiveness needs to be assessed in ways that take into account the varying times of implementation and levels of regulation. In addition, other changes at the same time and place might confound an apparent association between pollution reduction and improved health, such as economic trends (e.g., changes in employment), healthcare improvements, and behavioral changes (e.g., staying indoors when government warnings indicate pollution concentrations are high). Moreover, adverse health effects that might have been caused by exposure to air pollution can also be caused by other environmental risk factors (some of which might have changed over the same time periods as the air pollution concentrations). These challenges become more pronounced when regulations are implemented over long periods and when changes in air quality and health outcomes are not seen immediately, thus increasing the chance of confounding by other factors. For these reasons, scenarios in which regulations are expected to have resulted in rapid changes in air quality tend to be among the first, and most likely, targets for investigation, rather than evaluations of complex regulatory programs implemented over multiple years. Studies in Ireland by Clancy and colleagues (2002) and in Hong Kong by Hedley and colleagues (2002) are examples of such scenarios.

These inherent challenges are well documented in Communication 11 (HEI Accountability Working Group 2003), which was intended to advance the concept of accountability research and to foster the development of methods and studies throughout the relevant scientific and policy communities. In addition, recent advances in data collection and analytic techniques provide an unprecedented opportunity to improve assessments of the effects of air quality interventions.

THE ACCOUNTABILITY EVALUATION CYCLE

The National Research Council (NRC) Committee on Research Priorities for Airborne Particulate Matter set out a conceptual framework for linking air pollution sources to adverse health effects (NRC 1998). This framework, which is still relevant today, can be used to identify factors along an "accountability evaluation cycle" (see **Preface Figure**), each stage of which affords its own opportunities for making quantitative measurements of the intended improvements.

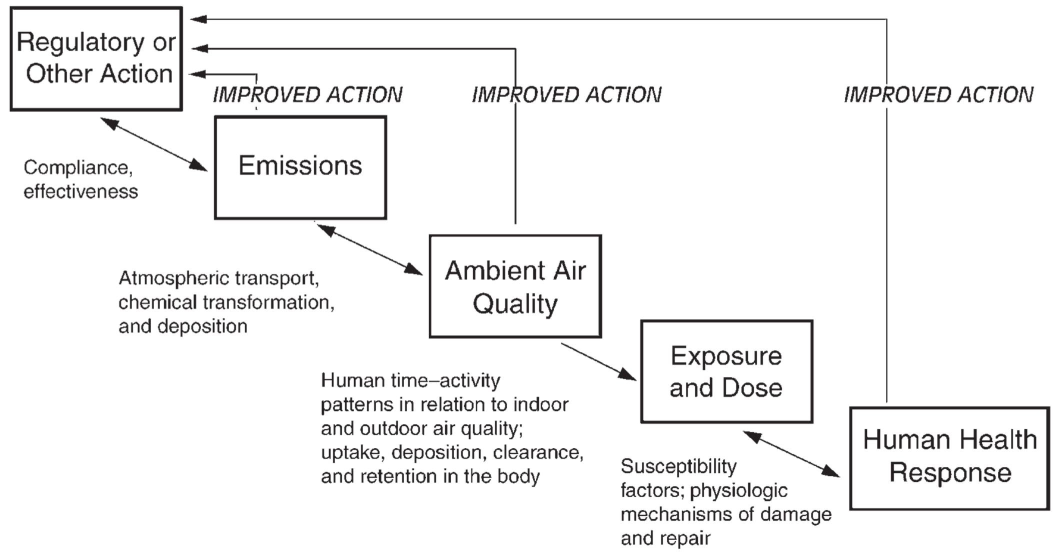
At the first stage (regulatory action), one can assess whether controls on source emissions have in fact been put into place. At the second stage (emissions), one can determine whether those controls have indeed reduced emissions, whether emitters have changed their practices, and whether there have been unintended consequences. At the third stage (ambient air quality), one can assess whether reductions in emissions have resulted in improved air quality. At the fourth stage (personal or population exposure), one can assess whether the improvement in air quality has reduced people's actual exposure and whether there has been a benefit for susceptible subpopulations (those most likely to experience adverse health effects). At this stage, it is important to consider changes in time–activity patterns that could either increase or reduce exposure. The actual dose that an individual's organs are exposed to should also be considered (i.e., whether reductions in exposure have led to reductions in concentrations in body tissues such as the lung). Finally, at the fifth stage (human health response), one can assess whether risks to health have declined, given the evidence about changes in health outcomes such as morbidity and mortality that have resulted from changes in exposure. The challenge at this stage is to investigate the health outcomes that are most directly related to exposure to air pollution.

At each stage in the accountability evaluation cycle, the opportunity exists to collect evidence that either validates the assumptions that motivated the intervention or points to ways in which the assumptions were incorrect. The collection of such evidence can thus ensure that future interventions are maximally effective.

Ultimately, the framework for accountability research will need to encompass investigations of the broader consequences of regulations, not just the intended consequences. Unintended consequences should also be investigated, along with the possibility that risks to public health in fact increased, as discussed by Wiener (1998) and others who have advanced the concept of a portfolio of effects of a regulation.

HEI'S ACCOUNTABILITY RESEARCH PROGRAM

The first wave of HEI's Accountability Research program included nine studies (see Preface Table). These studies involved the measurement of indicators along the entire accountability evaluation cycle, from regulatory or other interventions to human health outcomes.



Preface Figure. Accountability evaluation cycle. Each box represents a stage in the process between regulatory action and human health responses to air pollution. Arrows connecting the stages indicate possible directions of influence. The text below the arrows identifies factors affecting the effectiveness of regulatory actions at each stage. At several of the stages, knowledge gained from studies on outcomes can provide valuable feedback for improving regulatory or other actions.

Many of the studies focused on interventions that were implemented over relatively short periods of time, such as a ban on the sale of coal, reductions in the sulfur content of fuels, measures to reduce traffic, and the replacement of old wood stoves with more efficient, cleaner ones. Other studies focused on longer-term, wider-ranging interventions or events; for instance, one study assessed complex changes associated with the reunification of the former East and West Germany, including a switch from brown coal to natural gas for fueling power plants and home-heating systems and an increase in the number of modern diesel-powered vehicles in eastern Germany. HEI also supported research, including the development of methods, in an especially challenging area: assessment of the effects of regulations implemented incrementally over extended periods of time. In one such study, Morgenstern and colleagues (2012) examined changes that resulted from Title IV of the 1990 Clean Air Act Amendments (US EPA 1990), which aimed at reducing sulfur dioxide emissions from power plants by requiring compliance with prescribed emission limitations.

HEI later funded four studies as part of the second wave of its Accountability program (see **Preface Table**). Two studies evaluated regulatory and other actions at the national or regional level implemented over multiple years (Gilliland et al. 2017, Russell et al. 2018); a third study evaluated complex sets of actions targeted at improving air quality in large urban areas and major ports with well-documented air quality problems and programs to address them (Meng et al. 2021); and a fourth study developed methods to support such accountability research (Zigler et al. 2016).

HEI funded a third wave of accountability studies that are currently underway or in review (see Preface Table), which address an array of regional and national regulatory programs. Adar and colleagues are evaluating the National Clean Diesel Rebate Program that ran from 2012 to 2017. The available funding was allocated by lottery to school districts across the United States to replace or retrofit old-technology diesel-powered school buses. They compared student health and educational performance in districts with and without such funding. Hystad and colleagues assessed whether air pollution decreases related to cumulative long-term national and local traffic emission-control programs improved birth outcomes among a diverse population of 7.6 million births in Texas between 1996 and 2016. Harper and Baumgartner and their colleagues examined the impact of a coal heating ban and heat pump subsidy program in villages surrounding Beijing, China, on air quality, air pollutant exposure, and markers of respiratory and cardiovascular health among 1,000 participants from an existing cohort. This study seeks to identify specific mechanisms by which the coal ban might have improved health by investigating physical, social, and behavioral influences as mediating factors. Kinney and colleagues investigated sweeping air pollution control policies that began in 2013 across multiple regions of China. They seek to show a causal link between regulations, emissions, ambient air pollution, and mortality over a 10-year period.

Preface Table. HEI's Accountability Research Program

Investigator (Institution)	Intervention	Study or Report Title
First-Wave Studies		
RFA 02-1		
Douglas Dockery (Harvard T.H. Chan School of Public Health, Boston, MA)	Coal ban in Irish cities	Effect of Air Pollution Control on Mortality and Hospital Admissions in Ireland (Research Report 176; 2013)
Annette Peters (Helmholtz Zentrum München–German Research Center for Environment and Health, Neuherberg, Germany)	Switch from brown coal to natural gas for home heating and power plants, changes in motor vehicle fleet after reunification of Germany	The Influence of Improved Air Quality on Mortality Risks in Erfurt, Germany (Research Report 137; 2009)
RFA 04-1		
Frank Kelly (King's College, London, UK)	Measures to reduce traffic congestion in the inner city of London	The Impact of the Congestion Charging Scheme on Air Quality in London: Part 1. Emissions Modeling and Analysis of Air Pollution Measurements. Part 2. Analysis of the Oxidative Potential of Particulate Matter (Research Report 155; 2011)
RFA 04-4		
Frank Kelly (King's College, London, UK)	Measures to exclude most polluting vehicles from entering greater London	The London Low Emission Zone Baseline Study (Research Report 163; 2011)
Richard Morgenstern (Resources for the Future, Washington, DC)	Measures to reduce sulfur emissions from power plants east of the Mississippi River	Accountability Analysis of Title IV Phase 2 of the 1990 Clean Air Act Amendments (Research Report 168; 2012)
Curtis Noonan (University of Montana, Missoula, MT)	Wood stove change-out program	Assessing the Impact of a Wood Stove Replacement Program on Air Quality and Children's Health (Research Report 162; 2011)
Jennifer Peel (Colorado State University, Fort Collins, CO)	Measures to reduce traffic congestion during the Atlanta Olympics	Impact of Improved Air Quality During the 1996 Summer Olympic Games in Atlanta on Multiple Cardiovascular and Respiratory Outcomes (Research Report 148; 2010)
Chit-Ming Wong (University of Hong Kong)	Measures to reduce sulfur content in fuel for motor vehicles and power plants	Impact of the 1990 Hong Kong Legislation for Restriction on Sulfur Content in Fuel (Research Report 170; 2012)
RFPA 05-3		
Junfeng (Jim) Zhang (University of Medicine and Dentistry of New Jersey, Piscataway, NJ)	Measures to improve air quality during the Beijing Olympics	Cardiorespiratory Biomarker Responses in Healthy Young Adults to Drastic Air Quality Changes Surrounding the 2008 Beijing Olympics (Research Report 174; 2013)
Second-Wave Studies		
RFA 11-1		
Frank Gilliland (University of Southern California)	California and federal programs to improve air quality, including control of emissions from diesel engines and other sources targeted at freight transport and ports, as well as stationary sources	The Effects of Policy-Driven Air Quality Improvements on Children's Respiratory Health (Research Report 190; 2017)
Ying-Ying Meng (University of California–Los Angeles)	2006 California Emissions Reduction Plan for Ports and Goods Movement to control emissions from road, rail, and marine transportation, focusing on the ports of Los Angeles and Long Beach	Improvements in Air Quality and Health Outcomes Among California Medicaid Enrollees Due to Goods Movements (Research Report 205; 2021)

Continues next page

Preface Table. HEI's Accountability Research Program (*Continued*)

Investigator (Institution)	Intervention	Study or Report Title
Armistead Russell (Georgia Institute of Technology)	Programs to control emissions from major stationary sources and mobile sources in the Southeast United States	Impacts of Emission Changes on Air Quality and Acute Health Effects in the Southeast, 1993–2012 (Research Report 195; 2018)
Corwin Zigler (Harvard T.H. Chan School of Public Health)	National regulations to improve air quality focusing on State Implementation Plans for particulate matter	Causal Inference Methods for Estimating Long-Term Health Effects of Air Quality Regulations (Research Report 187; 2016)
Third-Wave Studies		
RFA 18-1		
Sara D Adar (University of Michigan)	National Clean Diesel Rebate Program in United States	Assessing the national health and educational benefits of the US EPA's school bus retrofit and replacement program: A randomized controlled trial design (In Review)
Sam Harper and Jill Baumgartner (McGill University, Canada)	Coal ban and heat pump subsidy program in the Beijing, China, region	How do household energy interventions work? (In Review)
Perry Hystad (Oregon State University)	National and local traffic emissions control measures in Texas	The TRANSIT Accountability Study: Assessing impacts of vehicle emission regulations and local congestion policies on birth outcomes associated with traffic air pollution (In Review)
Patrick L Kinney (Boston University)	Major national air pollution control regulations in China	Accounting for the health benefits of air pollution regulations in China, 2008–2020 (In Review)
RFA 17-2		
Amir Hakami (Carleton University, Canada)	Transportation emission reductions in the United States and Canada	Estimating Model-Based Marginal Societal Health Benefits of Air Pollution Emission Reductions in the United States and Canada (Current Report)
RFA 20-1A		
Stefanie Ebelt (Emory University) and David Rich (University of Rochester Medical Center)	Transportation and electricity generation emissions reductions in three US cities	Environmental and Health Benefits of Mobile Source and Electricity Generating Unit Policies to Reduce Particulate Pollution (Ongoing)
RFA 20-1B		
Kai Chen (Yale University)	COVID-19 pandemic lockdown in China, Germany, Italy, and the United States	Effect of air pollution reductions on mortality during the COVID-19 lockdown: A natural experiment study (In Review)
Walter A. Rosenblith New Investigator Award		
Lucas Henneman (George Mason University)	Source-specific emission reductions in the United States	Air pollution source impacts at fine scales for long-term regulatory accountability and environmental justice (Ongoing)
Rachel Nethery (Harvard University)	Health inequity policy design in the United States	Designing optimal policies for reducing air pollution-related health inequities (Ongoing)

RFA = request for application; RFPA = request for preliminary application

HEI also continues to fund accountability studies under various other RFAs. As described in their Investigators' Report, the current study by Amir Hakami and colleagues was funded under RFA 17-2, *Health Effects of Air Pollution*. They created a source- and location-specific database of mortality benefits per ton of primary $PM_{2.5}$, NO_x, SO_2, and ammonia emissions reductions. They showed that emissions reductions in larger cities, particularly primary $PM_{2.5}$, could elicit health benefits nationwide. A study by Stefanie Ebelt, David Rich, and colleagues was funded under RFA 20-1A *Health Effects of Air Pollution* and is evaluating the effect of selected policies that targeted emissions from motor vehicles and electricity generating units on air quality in Atlanta, New York City, and Los Angeles. Under RFA 20-1B *Air Pollution, COVID-19, and Human Health*, Kai Chen of Yale University and colleagues are conducting a multicountry study to evaluate whether changes in mortality are associated with changes in ambient NO_2 and $PM_{2.5}$ levels before, during, and after the COVID-19 lockdown in China, Germany, Italy, and the United States.

Two other accountability-focused studies were recently funded under the *Walter A. Rosenblith New Investigator Award*. In 2022, Lucas Henneman of George Mason University was funded to estimate the impacts of different emissions sources on daily patterns and concentrations of $PM_{2.5}$ at a fine spatial resolution in the United States. He will perform an environmental justice accountability analysis of source-related exposure reductions to determine how such reductions have been distributed across population groups. In 2023, a study by Rachel Nethery of Harvard University was funded to develop statistical methods for characterizing spatial and racial and ethnic variation in health effects associated with exposure to $PM_{2.5}$ across the United States and to design potential policies for reducing $PM_{2.5}$-attributable health inequities.

A complete list of accountability studies funded by HEI to date is summarized in the Preface Table. The first-wave studies are described in more detail in an interim evaluation of the HEI Accountability Research program (van Erp and Cohen 2009; van Erp et al. 2012). An updated interim discussion of HEI's recent experiences in accountability research is also available (Boogaard et al. 2017).

FUTURE DIRECTIONS

The second and third waves of accountability research were conceived and prioritized during HEI's Strategic Plans for 2010–2015 (HEI 2010a) and 2015–2020 (HEI 2015). In its current Strategic Plan for 2020–2025 (HEI 2020a), HEI seeks to continue its leadership role in accountability research by prioritizing opportunities for studies that evaluate what methods are best suited to assess the effectiveness of further air-quality improvements. We envision that future studies will again focus on large-scale, complex regulations to improve air quality. We will continue to develop and implement statistical methods, particularly those within a causal inference framework, to tackle these complicated questions. In 2023, HEI issued RFA 23-2, *Assessing Changes in Exposures and Health Outcomes in Historically Marginalized and Environmentally Overburdened Communities from Air Quality Actions, Programs, or Other Interventions*, which seeks to fund studies that focus on actions to improve air quality targeted at historically marginalized communities in the United States. The selected studies are expected to start in mid-2024.

Throughout its portfolio, HEI emphasizes the importance of data access and transparency because they underpin high-quality research that is used in policy settings. Thus, HEI continues to provide other researchers with access to extensive data and software from HEI-funded studies (see *https://www.healtheffects.org/research/databases*). In the same spirit, the State of Global Air website (HEI 2020b) makes available data on air quality and health outcomes for countries around the world. The interactive site allows exploration of the data and comparisons among countries. The data currently cover 1990–2020 and are updated as new data become available.

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HEI STATEMENT

Synopsis of Research Report 218

Health Benefits of Location-Specific Emissions Reductions in North America

BACKGROUND

Air pollution from particulate matter, a complex mixture of microscopic particles and liquid droplets, is a leading risk factor of morbidity and mortality. Particulate matter can be emitted directly from pollutant sources such as smokestacks and vehicle exhaust, in which case it is referred to as a primary particulate matter emission. Particulate matter can also form in the atmosphere by gas-to-particle conversion of other pollutants, including ammonia, nitrogen oxides, and sulfur dioxide, and is referred to as secondary particulate matter. Carbon dioxide, a potential driver of climate change, is often co-emitted with particulate matter and its chemical precursors. Research demonstrates that the social and economic costs of air pollution include increased health-care expenditures and reduced productivity. Research also suggests that society can benefit from air pollution reductions. Quantifying the relative costs and benefits of air pollution regulations is important for informing policy. For example, the United States Environmental Protection Agency (US EPA) estimated that the net benefit of lowering the annual fine particulate matter National Ambient Air Quality Standard from 12 to 9 $\mu g/m^3$ would be $22 billion. However, evaluating the costs and benefits of air pollution emissions reductions is complicated because standard modeling approaches have certain limitations in accuracy and difficulty estimating uncertainty.

To estimate the monetary health benefits associated with reducing emissions from transportation and other selected sources, HEI funded a study by Dr. Amir Hakami of Carleton University, titled "Quantifying marginal societal health benefits of transportation emission reductions in the United States and Canada" in response to HEI's Request for Applications 17-2, Health Effects of Air Pollution. Dr. Hakami and colleagues proposed to apply a novel extension to the widely used US EPA's Community Multiscale Air Quality Model (CMAQ) that they had developed to improve how health benefits are estimated. He would then estimate these benefits for specific locations and emissions sources in the United States and Canada. They also proposed to estimate the climate change cobenefit of reduced emissions of carbon dioxide.

What This Study Adds

- This study estimated potential health benefits associated with reducing emissions from transportation and other sources at specific locations across the United States and Canada.
- The investigators quantified the annual monetary benefit of averted premature mortality associated with long-term fine particulate matter exposure linked to primary emissions of fine particulate matter, ammonia, nitrogen oxides, and sulfur dioxide. They also quantified climate cobenefits linked to reductions in carbon dioxide emissions.
- The greatest estimated benefit came from reducing primary fine particulate matter emissions, and the combined health burden of all domestic emissions totaled $805 billion US dollars in the United States and $77 billion Canadian dollars in Canada in 2016.
- Climate cobenefits were higher for reducing emissions from diesel compared with gasoline vehicles, and highest for off-road vehicles or engines.
- Targeted reductions of emissions from a relatively small proportion of sources could yield substantial health benefits. Future studies should evaluate other key pollutants and other health outcomes.

APPROACH

Hakami and colleagues created a database of the health benefits associated with reduced emissions from transportation and other sectors in the United States and Canada that could be used by decision-makers to develop air pollution control policies that would result in the greatest health benefits to society. To achieve this goal, the investigators further developed a novel extension to CMAQ that enabled them to estimate the monetary benefit-per-ton (hereafter, benefits) of reduced emissions

This Statement, prepared by the Health Effects Institute, summarizes a research project funded by HEI and conducted by Dr. Amir Hakami at Carleton University and colleagues. Research Report 218 contains the detailed Investigators' Report and a Commentary on the study prepared by the Institute's Review Committee.

by seamlessly linking data from recent large-scale epidemiological studies back to the original pollutant emissions. The CMAQ model accounted for complex atmospheric processes and transport of air pollutants over time and incorporated detailed information on emissions and meteorology. The novel extension to the model also allowed for detailed sensitivity analyses to assess how the results changed with different model inputs.

The investigators calculated health benefits using the estimated annual monetary cost of mortality associated with long-term fine particulate matter exposure. For the monetary cost of averted mortality, they applied values published by the US EPA and the Canadian government of $10.2 million US dollars and $7.5 million Canadian dollars, respectively. To estimate the association between fine particulate matter and mortality, the investigators chose the widely cited concentration–response function estimated by the Global Exposure Mortality Model (GEMM) because it incorporated 41 cohorts from 16 countries and a range of fine particulate matter exposures. To evaluate how this choice might affect benefit-per-ton estimates, Hakami and colleagues compared the US results from GEMM to four alternative concentration–response functions reported by more recent high-quality epidemiological studies with large cohorts.

Hakami and colleagues calculated benefits of reduced emissions of ammonia and criteria pollutants fine particulate matter, nitrogen oxides, and sulfur dioxide for the years 2001, 2016, and 2028 projections because those were the years when national emissions inventories were available. The authors also estimated the cobenefit of carbon dioxide reductions because regulations targeting combustion-related pollutant emissions typically reduce carbon dioxide emissions.

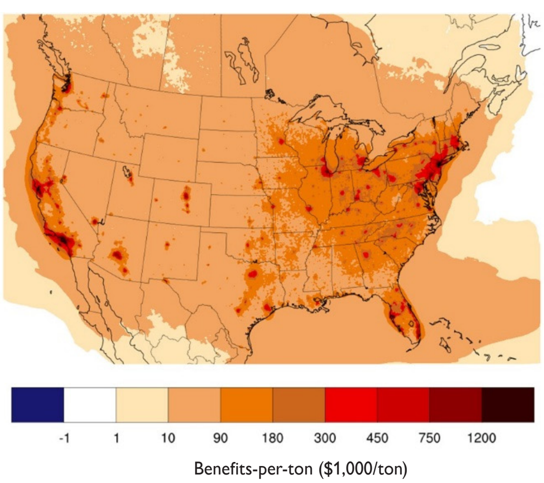
KEY RESULTS

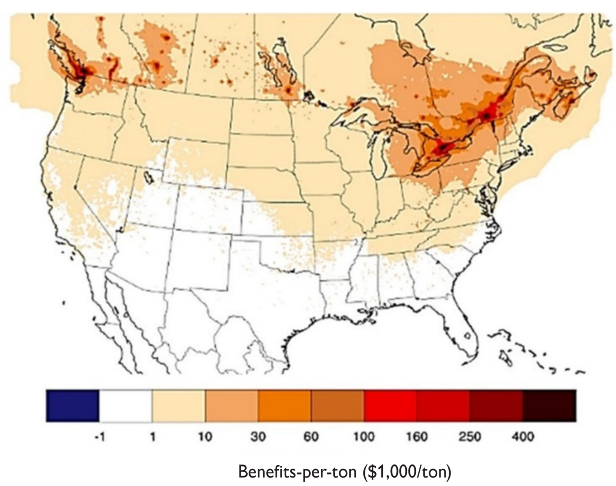
The benefits of reduced emissions were generally higher in the eastern half of the United States, with the greatest benefits near large cities, particularly in the northeast and California (**Statement Figure**). Compared with primary fine particulate matter, benefits were lower for fine particulate matter formed as a result of emissions of ammonia and lowest for fine particulate matter formed from sulfur dioxide and nitrogen oxide emissions.

Hakami and colleagues estimated that the total burden of all primary domestic emissions combined was $805 billion US dollars in the United States and $77 billion Canadian dollars in Canada. They reported that 10% of primary fine particulate matter emissions associated with the highest benefits were responsible for 35% and 60% of the health burden in the United States and Canada, respectively.

Estimated benefits were consistent across different concentration–response functions in locations where benefits were largest, but were variable in locations with smaller benefits. Differences in emissions among the years evaluated (2001, 2016, and 2028 projections) led to variations in benefits estimates, but the investigators reported that these variations were expected to decrease in the future.

Climate cobenefits vary widely across different transportation sectors and vehicle types. Cobenefits were higher for the reduction of emissions from diesel compared with gasoline vehicles, and highest for off-road vehicles and vehicles of the oldest vintages. Regarding electricity generation, the cobenefits were higher for reducing emissions from coal-powered compared with natural gas-powered plants.





Statement Figure. Benefits-per-ton for reduction of primary fine particulate matter emissions in 2016 show that larger benefits could be obtained by reducing emissions in the United States (left) than in Canada (right) and in large cities.

INTERPRETATION AND CONCLUSIONS

In its independent review of the study, the HEI Review Committee thought that the study was methodologically rigorous, thorough, and policy-relevant, and agreed that the authors' interpretations and conclusions were supported by the results. The use of a high spatial resolution adjoint air quality model was a key advance in evaluating the effect of location-specific sources of air pollutants and the benefits of mitigating those sources, including cross-border effects between the United States and Canada. Indicating the areas and sectors with the highest emissions reduction benefits can support targeted and efficient air quality and decarbonization policies that reduce the emissions of relevant air pollutants. The Committee appreciated that Hakami and colleagues evaluated the carbon dioxide cobenefits for a multitude of policy-relevant transportation sectors that were representative of the sectors that are expected to change over the next 10 years as newer energy technologies increase market share, older vehicle fleets are replaced, and electrification makes greater inroads.

The Committee also appreciated Hakami's efforts to conduct comprehensive sensitivity analyses to evaluate how benefits estimates might change, including the spatial resolution of the model, the shape of the concentration–response function, and changes between past, current, and projected future emissions. In general, there was less variability in benefits estimates in locations where the benefits were largest. That result illustrates the importance of concentration–response function selection in health impact studies and the need for high-quality, population-representative epidemiological studies with relevant exposure ranges.

The Committee noted that health benefits were likely underestimated in this study because it focused on emissions that contributed to long-term fine particulate matter exposure but did not evaluate the direct and indirect effects of reducing other air pollutants, such as nitrogen oxides and ozone. It would be important to consider those pollutants in future studies and to broaden the estimates beyond mortality to include other important health and economic indicators such as chronic diseases, disability, and lost workdays.

In conclusion, this health impact study evaluated the benefits of decreased 2001, 2016, and projected 2028 air pollutant emissions that contribute to mortality from long-term ambient fine particulate matter exposure across the United States and Canada. Hakami and colleagues used a novel extension of the CMAQ model at high spatial resolution to produce a database of source- and location-specific benefits useful to policymakers. Their results suggest that reductions in a relatively small proportion of emissions could yield a large societal health benefit. In addition, focused emissions reductions in certain transportation sectors, including off-road engines and diesel vehicles, could yield important climate and health cobenefits. Future studies are recommended to evaluate the effect of additional pollutants, such as nitrogen oxides and ozone, which have both health and climate importance.

INVESTIGATORS' REPORT

Estimating Model-Based Marginal Societal Health Benefits of Air Pollution Emission Reductions in the United States and Canada

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ABSTRACT

We developed spatially detailed source-impact estimates of population health burden measures of air pollution for the United States and Canada by quantifying sources–receptor relationships using the benefit-per-ton (BPT*) metric. We calculated BPTs as the valuations of premature mortality counts due to fine particulate matter ($PM_{2.5}$; particulate matter ≤2.5 µm in aerodynamic diameter) exposure resulting from emissions of one ton of a given pollutant. Our BPT estimates, while accounting for a large portion of societal impact, do not include morbidity, acute exposure mortality, or chronic exposure mortality due to exposure to other pollutants such as ozone.

The *adjoint* version of a widely used chemical transport model (CTM) allowed us to calculate location-specific BPTs at a high level of granularity for source-impact characterization. Location-specific BPTs provides a means for exploiting the disparities in source impact of emissions at different locations. For instance, estimated BPTs show that 20% of primary $PM_{2.5}$ and ammonia emissions in the United States account for approximately 50% and 60% of the burden of each species, respectively, for an estimated burden of $370B USD. Similarly, 10% of the most harmful emissions of primary $PM_{2.5}$ and ammonia emissions in Canada account for approximately 60% and 50% of their burden, respectively. By delineating differences and disparities in source impacts, adjoint-based BPT provides a direct means for prioritizing and targeting emissions that are most damaging.

Sensitivity analyses evaluated the impact of our assumptions and study design on the estimated BPTs. The choice of concentration–response function had a substantial impact on the estimated BPTs and is likely to constitute the largest source of uncertainty in those estimates. Our method for constructing annual BPT estimates based on episodic simulations introduces low uncertainty, while uncertainties associated with the spatial resolution of the CTM were evaluated to be of medium importance. Finally, while recognizing that the use of BPTs entails an implied assumption of linearity, we show that BPTs for primary $PM_{2.5}$ emissions are stable across different emission levels in North America. While BPTs for precursors of secondary inorganic aerosols showed sensitivity to emission levels in the past, we found that those have stabilized with lower emissions and pollutant concentrations in the North American atmosphere.

We used BPTs to provide location-specific and sectoral estimates for the cobenefits of reducing carbon dioxide emissions from a range of combustion sources. Cobenefit estimates rely heavily on the emission characteristics of the sector and therefore exhibit more pronounced sectoral fingerprints than do BPTs. We provide cobenefit estimates for various subsectors of on-road transportation, thermal electricity generation, and off-road engines. Off-road engines and various heavy-duty diesel vehicles had the largest cobenefits, which in most urban locations far exceeded estimates of the social cost of carbon. Based on our cobenefit estimations, we also provide per-vehicle burden estimates for different vintages of vehicle subsectors such as transit buses and short-haul trucks in major US cities.

INTRODUCTION

Atmospheric CTMs are routinely used to inform air pollution policies. In that capacity, these models provide a basis to distinguish among policy options and offer priorities and decision metrics to decision-makers and regulators. One of the decision metrics that can be estimated using CTMs is BPT, also referred to as marginal benefit (MB) in environmental

This Investigators' Report is one part of Health Effects Institute Research Report 218, which also includes a Commentary by the Review Committee and an HEI Statement about the research project. Correspondence concerning the Investigators' Report may be addressed to Dr. Amir Hakami, 3432 C.J. Mackenzie Building, Carleton University, 1125 Colonel By Drive, Ottawa, ON K1S 5B6 Canada; email: *amir.hakami@carleton.ca*. No potential conflict of interest was reported by the authors.

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* A list of abbreviations and other terms appears at the end of this volume.

economics. BPT is the monetized societal benefit associated with reducing emissions of a specific pollutant by 1 metric ton. While the societal benefits of improved air quality span a range of outcomes and impacts, valuation of these benefits is often dominated by the reduced risk of premature mortality in the population (Health Canada 2021; Hubbell et al. 2005). Within this context, BPTs provide a quantitative measure that links the impact on population health (and welfare, if included) to sources of pollution. In this sense, BPTs provide information that differ from models and tools such as the United States Environmental Protection Agency (US EPA) Environmental Benefits Mapping and Analysis Program (BenMAP) (Sacks et al. 2018) or the Health Canada Air Quality Benefits Assessment Tool (AQBAT) (Judek et al. 2019) that link concentrations to population health impacts.

The conventional approach to estimating BPTs is to conduct CTM simulations for a baseline and a perturbed scenario, where the perturbed simulation includes an incremental change (as small as possible) to the source and pollutant of concern. This approach, known as brute-force, is straightforward and can be implemented easily for a limited number of sources (Mauzerall et al. 2005). However, given the large number of polluting sources in the atmosphere, estimating BPTs for all pollutants and from all sources through this approach becomes computationally infeasible. To address this challenge, two general approaches exist in the literature. In the first approach pollution sources are grouped together based on type and sector (Fann et al. 2009), region, or both (Fann et al. 2012). By reducing the number of sources, calculation of BPTs using the brute-force approach becomes possible; however, estimated BPTs do not account for spatial variability in source impacts beyond regional groupings. In the second approach, a simplified or reduced-form representation of a CTM is used to estimate source impacts. As the reduced-form models are inexpensive to run, BPTs for many sources can be estimated through a brute-force approach (Heo et al. 2016a,b; Muller 2014; Muller et al. 2011; Tessum et al. 2017). The drawback for this approach is in the simplification of the models that may compromise accuracy, reliability and consistency of the results (Baker et al. 2020; Gilmore et al. 2019; IEc 2019).

We introduce and use a third approach, named adjoint or reverse influence modeling, to estimate BPTs in Canada and the United States. The adjoint approach is distinct from other methods in the existing literature as it employs a full-form model with no simplification and describes how emissions from any location impacts air quality endpoints at all times, allowing for estimation of BPTs for all sources and pollutants. Unlike the conventional CTM that follows the evolution of pollutants from the point of release (source) to the point of impact (receptor), an adjoint model traces impacts on receptors back in time to pollution emission locations. To estimate monetized societal benefits, our study focuses on reduced mortality from long-term exposure to $PM_{2.5}$ in Canada and the United States.

Greenhouse gas (GHG) mitigation cobenefits associated with improved air quality can also be considered one form of BPT — one that is expressed per ton of carbon dioxide (CO_2). GHG emission reductions entail two forms of benefits: (1) reduced climate penalty (Bloomer et al. 2009), which can occur from climate change, leading to increased air pollution even when emissions are unchanged, and (2) the benefits realized when co-emitted pollutants are reduced (Markandya et al. 2018; Nemet et al. 2010), for example, the reduction of traditional air pollutant emissions when CO_2 emissions are reduced by using electric vehicles (Nopmongcol et al. 2017; Peters et al. 2020). Adjoint-based BPTs for these co-emitted pollutants can be used to estimate the second type of cobenefits — those associated with emissions of co-emitted pollutants of CO_2 in combustion processes. We use adjoint-based BPTs in combination with emission profiles from various sources to provide sectoral and location-specific cobenefits associated with the removal of combustion sources.

STUDY OBJECTIVES

The overarching objective of the study is to produce a database of *decision metrics* in BPTs that would help decision-makers devise air pollution control policies that deliver greater societal benefits. Specific objectives of the study are the following:

- Creating a database of sectoral and location-specific BPT estimates for Canada and the United States, as a measure of the societal benefits associated with reducing emissions from transportation and other select sources
- Conducting sensitivity analyses with respect to various assumptions in the study to evaluate the robustness of BPT estimates. These include sensitivity analysis with respect to (1) the shape of the epidemiological concentration–response functions (CRFs), (2) inventory levels in Canada and the United States as affected by past and future controls, (3) the spatial resolution of the adjoint simulations, and (4) construction of annual BPT estimates based on episodic simulations
- Estimating cobenefits of reduced combustion-based CO_2 emissions for transportation and other select sectors

METHODS

The central tool used in this study is the adjoint-enabled version of the US EPA's Community Multiscale Air Quality (CMAQ) model (Hakami et al. 2007; Zhao et al. 2020), one of the most widely used CTMs globally. CMAQ is a state-of-the-art and comprehensive photochemical CTM that accounts for transport and transformation of gas, particle, and aqueous-phase pollutants in the atmosphere (Byun and Schere 2006). Like the underlying CTMs, the adjoint model follows the atmospheric transformation of an emitted pollutant (e.g., nitrogen oxides [NO_x] emissions) between the release at the source and impact at receptors (e.g., mortality associated with ozone or particulate matter exposure).

CTMs are considered source-based models as they are designed to simulate the journey of pollutants from the point of release to the atmosphere (i.e., sources) to the point of impact (receptor) as they go through transport and transformation processes. The adjoint model is designed to do the opposite; it starts at the receptors and traces impacts back in time and through all the atmospheric processes to the sources at various locations and times. To do so, the adjoint model *advances* backward in time, in other words, an adjoint simulation starts at the end and ends at the beginning. As the model marches backward in time, it solves and integrates a system of equations that are distinct but related to the governing equations of the underlying CTM (in this case, CMAQ). The backward evolution of the adjoint model in time, and tracing back source impacts, are conceptually similar to that of a back-trajectory model. In line with that analogy, the adjoint model can be considered as an ensemble of all possible back trajectories that, unlike back-trajectory models, interact with each other and include all atmospheric processes. The adjoint method provides far more details about individual source impacts than do traditional approaches; however, the method requires development of an adjoint version of the CTM, which is a significant undertaking.

ADJOINT MODEL

We developed an adjoint version of the CTM based on the science processes in CMAQ v5.0. These processes include advection and diffusion in horizontal and vertical directions, gas-phase chemistry, cloud processes and aqueous chemistry, aerosol thermodynamics, aerosol growth and aging, secondary organic aerosol formation, and dry and wet deposition. Here we provide a qualitative description of the adjoint method. More formal and detailed descriptions of the adjoint model, or its application in health-impact assessment are available elsewhere (Hakami et al. 2007; Henze et al. 2007; Pappin and Hakami 2013; Pappin et al. 2015, 2016; Sandu et al. 2005; Zhao et al. 2020).

Adjoint-based source impacts are model constructs and are difficult (and for most practical purposes impossible) to directly measure. This is not a shortcoming of the adjoint method, but an inherent limitation of model-based estimations of source–receptor relationships. Source impacts are estimates of the atmospheric response to changes in emissions, and for all practical purposes, atmospheric response to a modest change in emissions cannot be isolated and measured. As such, evaluation or *validation* of BPTs generated by the adjoint model relies on a two-step process. First, the underlying (forward, in this case CMAQ) model is evaluated against observations to ensure that the model adequately reproduces the composition of the atmosphere. Second, sample results from the adjoint model are evaluated against comparable estimates from the original CTM to establish the consistency between the adjoint results and the underlying model. CMAQ has been widely used and evaluated in various applications in North America and across the globe. The adjoint version of CMAQ, hereafter referred to as CMAQ-ADJ, has also undergone extensive testing and evaluation and has been shown to produce estimates consistent with the original CMAQ model (Zhao et al. 2020).

To apply the adjoint method to a policy-relevant problem such as health-impact studies, two conditions need to be met. First, it should be possible to condense the policy question for which source impacts are sought into a single (or a few) number(s). For example, and as is the case for this study, one suitable policy question is the impact of air quality on population health, as represented by premature deaths due to long-term exposure to $PM_{2.5}$. In this study, this policy question is reduced to a single number — the total counts or monetary valuation of premature deaths attributed to air pollution in Canada or the United States. This single number is referred to as the adjoint cost function or adjoint objective function. Note that in our example, generating estimates for Canada and the United States constitutes two different adjoint cost functions and two sets of adjoint simulations. The second condition requires that the relationship between the adjoint cost function and concentrations of pollutants are known quantitatively. In this case, the relationship between premature mortality (and its valuation) is known through epidemiological models (and valuation estimates) for each country.

EPISODE SELECTION

As mentioned before, adjoint simulations are conducted backward in time. CMAQ-ADJ starts at the end of the simulation period and marches backward in time to the beginning of the period. During the backward simulation, CMAQ-ADJ requires concentrations of all pollutants at all times. Therefore, the adjoint or backward simulation has to follow a *forward* simulation by the original CMAQ model, during which all concentrations are saved (or checkpointed) for use by CMAQ-ADJ. This requires significant storage capacity. This storage requirement rapidly becomes more significant at higher resolutions, which renders long simulation periods (e.g., year-long) at fine resolutions infeasible. Additionally, adjoint simulations also require significant computational power. For instance, year-long North American simulations at 12-km resolution, as conducted for this study, require about 1,000 terabytes of storage and 128 core years (i.e., 1-year simulation time on 128 computational cores) on a modern and powerful cluster. For this reason, adjoint simulations at finer resolutions are often conducted for shorter periods than regular CMAQ simulations to address such computational limitations.

Our base BPT simulations were conducted for the contiguous United States and the more populous parts of Canada at a 12-km horizontal resolution. For this study we used 2-week episodes to represent BPT estimates for each season. In other words, annual estimates of source impacts were constructed from four seasonal estimates, each of which was based on simulating a 2-week representative period. We chose seasonal episodes based on an anomaly analysis of the entire year (by season). To conduct our anomaly analysis, we generated adjoint-based BPTs for the entire year at a coarser resolution (36-km) where year-long simulations were possible. We then formed normalized bias functions defined as the domain-wide bias for a 2-week representation of the season for each possible 2-week period in the season. We used two of such functions, one for domainwide bias in seasonal BPTs and one for bias in burden, as defined as the product of seasonal BPT and emissions for each grid cell in the model:

$$f_{BPT,t} = \frac{100}{N_{grids} \times N_{spc}} \sum_{spc} \sum_{grids} \frac{(BPT_{grid,spc,t} - BPT_{grid,spc,season})}{BPT_{grid,spc,season}},$$

and

$$f_{burden,t} = \frac{100}{N_{grids} N_{spc}} \sum_{grids} \frac{(\sum_{spc} BPT_{grid,spc,t} E_{grid,spc,t} - \sum_{spc} BPT_{grid,spc,season} E_{grid,spc,season})}{\sum_{spc} BPT_{grid,season} \times E_{grid,season}},$$

where $BPT_{grid,spc,t}$ is the BPT estimate for a specific grid cell and emitted species and for the episode starting on day t of the season, while $BPT_{grid,season}$ is the same estimate when all days of the season are included in the estimate, and E_{grid} values are the daily or seasonal average emission rates of an emitted species. Normalized bias functions $f_{BPT,t}$ and $f_{burden,t}$ are calculated for each day and are expressed as percentages. Primary $PM_{2.5}$, sulfur dioxide (SO_2), NO_x, and ammonia (NH_3) are the species that are included in constructing bias functions. As transportation was the primary focus of this study, only surface BPT and burden estimates were used in constructing bias functions.

The episode that minimizes the summation of these two bias functions is then chosen as the representative episode for the season:

$$min\ \left(\frac{f_{BPT,t} - f_{BPT,t,min}}{f_{BPT,t,min}} + \frac{f_{burden,t} - f_{burden,t,min}}{f_{burden,t,min}}\right),$$

where $f_{BPT,t,min}$ and $f_{burden,t,min}$ are the minimum daily BPT and burden biases for the season. These bias functions were chosen for spatiotemporal anomaly analysis based on trial and error of various measures of deviation, as well as different weights for the two bias functions. While our choice of bias function weighting was arbitrary, in our trial and error we found that selected episodes were not overly sensitive to that choice. Note that our anomaly analysis was based on 36-km BPTs, and therefore, our episodic representation of seasonal BPTs entailed three assumptions that: (1) the chosen episode was representative of the season, and (2) temporal patterns of 12-km BPTs were consistent with those of 36-km estimates, and selected episodes could be applied nationally without significant loss of regional representativeness. We conducted sensitivity analyses to evaluate errors associated with these assumptions and episodic representation of seasons.

The episodes were independently selected for Canada and the United States. Based on bias functions derived above (**Figure 1**), the episodes for the two countries were:

Canada

Winter: January 30, 2016 – February 12, 2016

Spring: May 4, 2016 – May 17, 2016

Summer: August 3, 2016 – August 16, 2016

Fall: November 18, 2016 – December 1, 2016

United States

Winter: February 12, 2016 – February 25, 2016

Spring: May 4, 2016 – May 17, 2016

Summer: August 2, 2016 – August 15, 2016

Fall: November 16, 2016 – November 29, 2016

CMAQ AND CMAQ-ADJ INPUTS AND SIMULATIONS

Conducting adjoint simulations relies on model inputs that are similar to those of regular CTM simulations. For modeling with CMAQ and CMAQ-ADJ, these inputs include gridded time series of emissions for the model's computational domain at the appropriate resolution, meteorological parameters used in CMAQ (e.g., wind, temperature, precipitation), and pollutant concentrations for model initialization and at the lateral boundaries (initial and boundary conditions).

Emission inventories used in this study were taken or derived from the 2016 Emission Inventory Platform (beta version) prepared by the US National Emissions Inventory Collaborative (NEIC). NEIC is a partnership of the US EPA, other federal agencies, and various state agencies responsible for air quality management in the United States. The partnership was established to provide consistent, reliable, and accessible data for photochemical air quality modeling in the United States. In this study we used the beta version as that was the version available at the time of our study implementation period. The 2016 platform emissions were derived from the 2014 version of the National Emission Inventory by applying significant adjustments and methodological modifications for various emission sectors (US EPA 2019b). These modifications included any additional state and local information that was available for the year 2016. In addition to using emissions from the 2016 platform, the MOtor Vehicle Emission Simulation–version 3 (MOVES3) (US EPA 2016) was run for all counties in the United States to generate the data required for estimating cobenefits of CO_2 reduction for on-road and nonroad engines.

The platform provides emissions for the chemical mechanism carbon bond 6 with aerosol speciation version AE7; however, the CMAQ-ADJ uses older versions of the

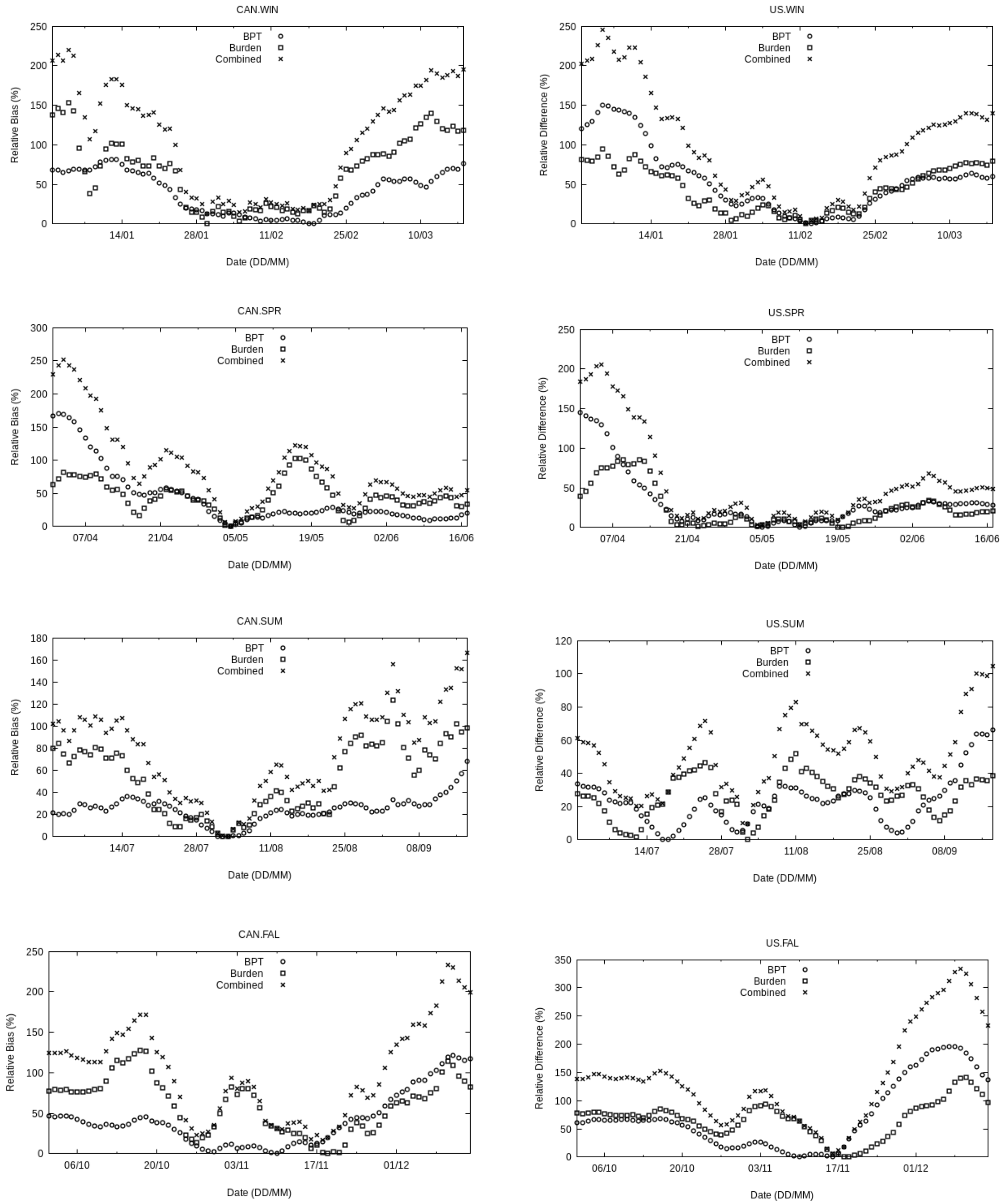


Figure 1. Summary of seasonal bias functions for episode selection in Canada (left) and the United States (right). Each point on the plot indicates normalized bias (BPT, burden, or combined) for a 2-week period starting with the date. (Zhao et al. [In press])

chemical mechanism (i.e., carbon bond 5) and aerosol speciation version AE5. Therefore, using the 2016 platform in this study required mapping between these versions of gas-phase mechanisms and aerosol speciation. The platform provides emissions at 12- and 36-km horizontal resolution. Additionally we conducted 4-km and 1-km simulations over New York City and Los Angeles. These four horizontal model resolutions were used in our study for sensitivity analyses (see the discussion section).

CMAQ simulations also require boundary conditions or concentrations at the lateral boundaries of the domain for the simulation period. Boundary conditions are provided from simulations by the Hemispheric version of CMAQ (H-CMAQ). As the name suggests, H-CMAQ is a version of the CMAQ model that is configured to conduct air quality simulation at a coarse resolution of 108-km for each hemisphere. H-CMAQ is built upon the 2016 Global Hemispheric Emission Inventory Platform (US EPA 2019a) that uses regional updates and improvements (particularly over North America and China) to the Hemispheric Transport of Air Pollution version 2 emission inventory.

The meteorological data needed for emission processing and air quality modeling are also available on the 2016 v7.2 platform. The input data needed by the Meteorology-Chemistry Interface Processor to produce the gridded meteorology that can later be used in emission processing and CMAQ were prepared using the Weather Research and Forecasting model (WRF) version 3.8 (Skamarock et al. 2008) at 12- and 36-km resolutions and with 35 vertical layers. The WRF configurations were chosen for higher resolutions (4-km and 1-km) based on a series of sensitivity-analysis runs using different available configurations, parameterizations, and physics options. The appropriate meteorological model resolution was applied at each CMAQ resolution.

CMAQ simulations are conducted over a continental domain that covers the contiguous United States and most of Canada. While the domain does not include all of Canada, 12- and 36-km domains cover 97.3% and 99.7% of the Canadian population. Our primary BPT estimates were based on simulations at 12-km horizontal resolution but for various purposes (e.g., sensitivity analyses, see Results and Discussions) we conducted simulations at 36-km, 4-km, and 1-km resolutions over larger or smaller domains. As is the practice in multiscale air quality simulations, domains of various resolutions are successively nested within each other to provide boundary conditions. In other words, H-CMAQ provides boundary values for 36-km simulations, while the results from the 36-km domain would inform 12-km simulations at the boundary, and 12-km results are used as boundary conditions for 4-km simulations. As a result, the 12-km domain was a subset of the 36-km domain, and the two 4-km domains centered around New York City and Los Angeles were smaller portions of the 12-km domain. All domains consisted of 35 vertical layers that extended well into the stratosphere. The vertical structure of the model was nonuniform and had a significantly higher resolution (i.e., shallower layer depths) closer to the surface where emissions and impacts were more significant than aloft.

All simulations were conducted using 2016 meteorology. Due to the computational cost of adjoint simulations, multiyear simulations were not feasible. Generally the $PM_{2.5}$ burden remains fairly stable despite natural interannual variability in pollutant concentrations (Zhang et al. 2018). For the 36-km domain, annual adjoint simulations were performed to provide a basis for episode selection as described above. Episodic 12-km simulations had ramp-up periods or added days to ensure that the simulation period started with representative concentrations and was free from the impact of initialization. Ramp-up periods applied to both forward and adjoint runs; adjoint simulations started for a period after the end of the episode. For the 36-km annual simulations, 10-day and 4-day ramp-up periods were used for forward and adjoint simulations, respectively. For 12-km, 4-km, and 1-km simulations shorter ramp-up periods (one day for both forward and adjoint simulations) were used, as both forward and adjoint simulations started with interpolated 36-km (or 12-km for 4-km domains, and 4-km for 1-km domains) concentrations that already included ramp-up periods. In addition to 2016 simulations, we also conducted simulations for summer and winter episodes using older or projected emissions (years 2001 and 2028) to evaluate the impact of large-scale changes in the inventory on BPT estimates.

HEALTH-IMPACT ESTIMATION

As mentioned before, information provided by adjoint simulations depends on the adjoint cost function. For the health-impact assessment studies here, this cost function describes the societal impact, or in this case monetization of premature mortality associated with chronic exposure to $PM_{2.5}$. When the adjoint cost function is constructed as the societal burden due to $PM_{2.5}$ mortality, then adjoint simulations provide derivatives of this cost function with respect to emissions. These derivatives are by definition BPTs. Therefore, the adjoint cost function combines information from $PM_{2.5}$ epidemiology with valuation economics and source–receptor relationships from CTMs. In conceptual and qualitative terms:

$$BPT\left(\frac{\$}{ton}\right) \approx \frac{\$}{(Health\ Outcome)} \times \frac{(Health\ Outcome)}{\Delta(Concentrations)} \times \frac{\Delta(Concentrations)}{\Delta(Emissions - ton)}$$

where the terms \$/(Health Outcome), (Health Outcome/ Δ(Concentrations), and Δ(Concentrations)/Δ(Emissions – tons) reflect, in order, the reliance of the adjoint cost function on the fields of economic valuation, epidemiology, and atmospheric modeling. The first two terms are valuation and concentration–response designations. They are often considered to be static in space in health-benefit assessments, that is, changes in concentrations at a (modeled) location would only affect health outcomes and their valuation at that location. The third term is a representation of quantitative relationships between emission strength at source locations and concentrations at exposure points that span over space. The role of CTMs (CMAQ-ADJ) in BPT estimations were discussed earlier; here we describe the details of epidemiological models and valuation as applied to the construction of the adjoint cost function.

Epidemiological Models

In the last 15 years a number of studies have provided effect estimates for $PM_{2.5}$ in Canada and the United States using various cohorts in these two countries (Burnett et al. 2018; Chen and Hoek 2020; Crouse et al. 2012, 2015; Di et al. 2017; Krewski et al. 2009; Nasari et al. 2016; Pinault et al. 2016, 2017; Pope et al. 2019; Turner et al. 2016; Wu et al. 2020). While in our sensitivity analysis we examine the impact of the choice of CRF, for baseline BPT estimations we have chosen to use the Global Exposure Mortality Model (GEMM) (Burnett et al. 2018). For our sensitivity analysis, we compare results from GEMM in the United States with two analyses from the American Cancer Society–Cancer Prevention Studies-II cohort (ACS-CPS-II) (Krewski et al. 2009; Turner et al. 2016), the National Health Interview Survey (NHIS) (Pope et al. 2019), and a meta-analysis of Chen and Hoek (2020). For Canada we compare GEMM results with one set of estimates from the Canadian Census Health and Environment Cohort (CANCHEC) (Crouse et al. 2012) that is officially used by Health Canada (Health Canada 2021). Adjoint simulations are driven by adjoint forcing terms that correspond to the slope of the hazard ratio (HR) curve with respect to concentrations (**Figure 2**). As these CRFs have different shapes and curvature forms, as well as different magnitudes of HR and effect estimates, simulations with adjoint-cost functions built upon them will result in concentration-dependent differences.

Among the CRFs used for our sensitivity analysis, ACS-09 (Krewski et al. 2009) is chosen as the basis for most of the BPT estimates in the literature. To provide source-impact estimates based on more recent linear CRFs we provide BPTs for an updated analysis of the ACS cohort (Turner et al. 2016) as well as a meta-analysis by Chen and Hoek (2020). We note that all the CRFs used in our sensitivity analysis apply the effect estimate to the entire $PM_{2.5}$ mass and do not distinguish among various particulate constituents. Finally, our burden estimate is based only on chronic-exposure mortality and does not include morbidity outcomes. In terms of valuation, mortality constitutes the largest valuated burden (Health Canada 2021; Hubbell et al. 2005). Therefore, our results account for the majority of the $PM_{2.5}$ population health burden, even if they do not include morbidity outcomes such as hospitalizations, asthma, or estimates of disabilities or deterioration of quality of life.

GEMM GEMM is a pooled cohort informed by 41 individual cohorts from 16 countries and covers the range of concentrations seen across the globe. The choice of GEMM allowed for the use of a single model in both Canada and the United States. GEMM predicts globally higher estimates of air pollution burden than do the global burden of disease studies (Burnett et al. 2018), but for North America the estimates are more in line with previous studies. For BPT estimations we used GEMM effect estimates for noncommunicable diseases and lower respiratory infections with population and baseline rates for adults 25 years and older. GEMM has a sublinear (concave) CRF, with an increasing rate of reduction in HR at lower concentrations (Figure 2).

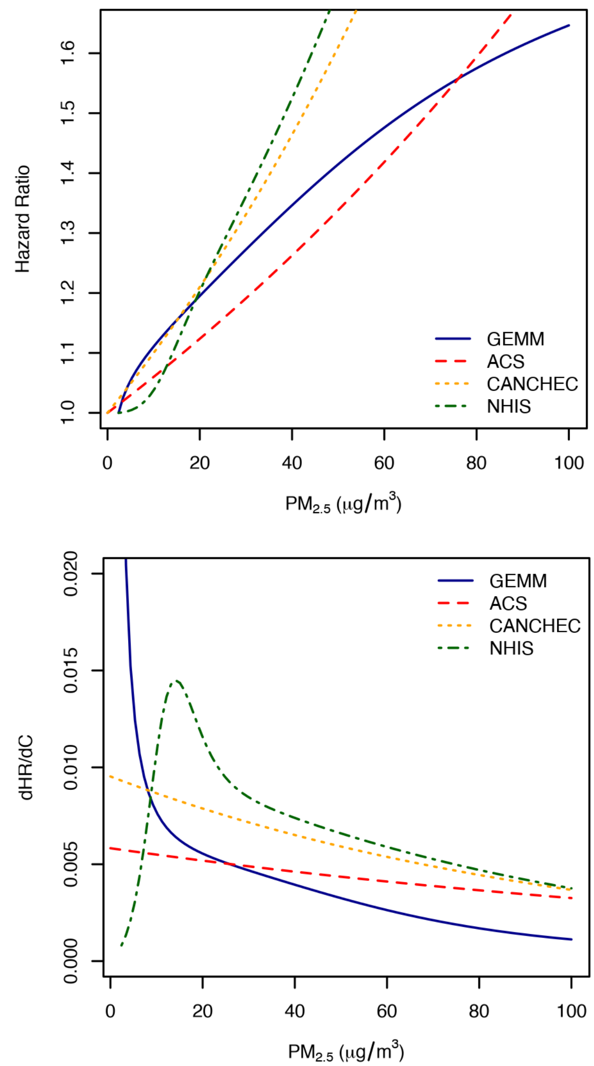


Figure 2. Hazard ratios (top) and their derivative (dHR/dC), bottom, where HR is the hazard ratio and C is the concentration, for GEMM, ACS-09, NHIS, and CANCHEC. The derivative of HR corresponds to the magnitude with which adjoint simulations are driven. (ACS-09 = CRF from Krewski et al. 2009; CANCHEC = Canadian Census Health and Environment Cohort; GEMM = Global Exposure Mortality Model; NHIS = National Health Interview Survey.) (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0)

GEMM is formulated into the adjoint cost function based on the following equations (Burnett et al. 2018):

$$J = V_{SL} \sum_i M_{0,i} \times P_i \left(1 - e^{-\theta T(z)}\right),$$

where

$$T(z) = \log\left(1 + \frac{z}{\alpha}\right) \omega(z),$$

$$\omega(z) = \frac{1}{1 + e^{-(z-\mu)/\nu}},$$

$$HR = e^{\theta T(z)},$$

and

$$z = MAX(0, \mathrm{PM}_{2.5} - cf).$$

V_{SL} is value of a statistical life, $M_{0,i}$ and P_i are baseline mortality rates and population (age > 25), respectively, *cf* indicates counterfactual concentration, and *HR* is the hazard ratio from the model. The coefficients in the above equations have the following values [Burnett et al. 2018]: $\theta = 0.1231$, $\alpha = 1.5$, $\mu = 10.4$, $\nu = 25.9$, and $cf = 2.4$ μg/m^3. Population data are generated using respective census information in Canada and the United States and are mapped to various grid resolutions. Similarly, baseline rates are taken from BenMAP and AQBAT for United States and Canada, respectively, and are mapped or aggregated onto the appropriate horizontal resolution in various simulations.

Linear CRFs Krewski and colleagues (2009) provided a reanalysis of the extended ACS-CPS cohort of approximately 360,000 adults 30 years and older. They used a standard Cox proportional hazard model and also the random effects Cox model and provided their respective effect estimates for the national cohort, as well as estimates for two urban areas. ACS-CPS-II CRF has been extensively used in health-impact assessment studies, including those estimating sectoral and regional BPTs (Fann et al. 2009, 2012). This CRF is linear and its adjoint cost function has the following formulation:

$$J = V_{SL} \sum_i M_{0,i} \times P_i (1 - e^{-\beta \bar{C}_i}),$$

where $\beta = 0.00583 \left(\frac{\mu g}{m^3}\right)^{-1}$ is the effect estimate from the random effects model and $\bar{C}_i$ is the average $\mathrm{PM}_{2.5}$ concentration. We refer to BPTs from this CRF as ACS-09.

In addition to the 2009 reanalysis of the ACS cohort, we also use the single-pollutant ($\mathrm{PM}_{2.5}$) model of the updated analysis (Turner et al. 2016) for our sensitivity analyses. For this updated study, an effect estimate of $\beta = 0.00677 \left(\frac{\mu g}{m^3}\right)^{-1}$ is used. Given the near-linear form of the CRF, BPTs for this updated analysis of the ACS cohort (referred to as ACS-16) is estimated using a simple scaling of BPTs from Krewski and colleagues (2009).

Similarly, we also provide BPTs for a linear CRF from the meta-analysis of Chen and Hoek (2020) (referred to as CHEN). We use the effect estimate of $\beta = 0.00862 \left(\frac{\mu g}{m^3}\right)^{-1}$ for the middle-age population of the cohorts used in the meta-analysis, as it more closely aligns with other cohorts used in our study.

NHIS The NHIS study is from a cohort of approximately 1.5 million individuals ages 18–84 that was surveyed between years 1986 and 2014. The size and longitudinal extent of the cohort allowed for a large number of deaths to be recorded in the cohort. The CRF for the NHIS cohort is superlinear (convex) unlike the GEMM model, indicating a lower rate of change in HR with decreasing concentrations. The adjoint cost function based on the NHIS CRF can be written as (Burnett RT, personal communication, 2020):

$$J = V_{SL} \sum_i M_{0,i} \times P_i \left(1 - e^{-\theta T_{NHIS}(z)}\right),$$

where

$$T_{NHIS}(z) = \frac{z}{1 + e^{-(z-\mu)/\nu}} = z\omega(z),$$

and $z = \mathrm{MAX}(0, \mathrm{PM}_{2.5} - cf)$, $cf = 2.5$ μg/m^3, $\theta = 0.011253$, $\mu = 8.330415$, $\nu = \tau \times \mathrm{RANGE}$, $\tau = 0.2$, RANGE = 16.7. Note, the form of $\omega(z)$ is identical to that of the GEMM model.

CanCHEC Crouse and colleagues (2012) developed a random effects Cox proportional hazard model based on a cohort of Canadians (approximately 3.6 million) who had completed the long-form census questionnaire in the 1991–2001 period. This cohort is the predecessor to the CanCHEC. Similar to ACS-CPS-II, CanCHEC CRF is linear with $\beta = 0.00953 \left(\frac{\mu g}{m^3}\right)^{-1}$.

Mortality Valuation

We used a United States and Canadian Value of a Statistical Life (VSL) for monetizing premature mortality counts, based on US EPA and Health Canada practices in benefit–cost analyses of proposed regulations, as embodied in the BENMAP model in the United States and AQBAT in Canada. In addition to being the standard valuation method of choice for American and Canadian governments, the VSL, either derived from surveys (termed *stated preference studies*) or from real world observations (termed *revealed preference studies*) is the recommended concept for valuing reductions in mortality risks from regulations (Chestnut and De Civita 2009; Krupnick 2007; OMB 2003; US EPA 2010, 2017).

We used VSLs of \$10.2M (2016 USD, with income adjustment) for the United States (US EPA 2010) and \$7.5M (2016 CAD) for Canada (Chestnut and De Civita 2009). We followed the US EPA's recommended approach to apply a cessation lag between the timing of reduction in $\mathrm{PM}_{2.5}$ exposure and the realization of mortality reductions. We applied the recommended 20-year distributed lag model with 30% of deaths occurring in the first year, 50% in years 2–5, and the remaining 20% in years 6–20 for $\mathrm{PM}_{2.5}$ (US EPA 2021), and a social discount rate of 3% per year (OMB 2003). This resulted in an overall discounting factor of 0.90606 for the United States (IEc 2019). For Canada, a cessation lag is not officially recommended and therefore was not applied. As mentioned before, our valuation is based solely on the VSL and does not account for morbidity, disability, and loss of quality of life.

Cobenefit Calculations

Location-specific BPTs can be used to estimate the sectoral and location-specific GHG reduction cobenefits associated removing combustion sources. To do so, BPTs of co-emitted pollutants of CO_2 are used in combination with relative emission profiles of the sector to estimate cobenefits:

$$CB_{grid,sector}\ \left(\frac{\$}{ton - CO_2}\right) = \sum_{spc} BPT_{grid,spc} \times \frac{E_{sector,grid,spc}}{E_{sector,grid,CO_2}},$$

where $CB_{grid,sector}$ is the cobenefit of combustion-based CO_2 reduction for a specific *sector* at a specific location (i.e., *grid*), $BPT_{grid,spc}$ are the adjoint-based BPTs for a specific emitted species (*spc*) and at a given location (*grid*), and $E_{sector,grid,spc}$ (or $E_{sector,grid,CO_2}$) are the sectoral emissions of that species (or CO_2) at that location. Cobenefits are estimated from BPTs for primary $PM_{2.5}$, SO_2, NH_3, and NO_x emissions, and are expressed in units of \$/ton-CO_2. Note that in the calculation above we assume that CO_2 emissions are fully removed from a source, that is, the combustion process for a given amount of CO_2 is eliminated. An example of a situation where this assumption is applicable is electrification of a source (e.g., transportation or residential heating) using a zero-pollution (renewable) source of energy. The limitations of such an assumption is discussed later when results are presented.

SUMMARY RESULTS

The main results of this study, including BPTs and cobenefits are presented in this section. Location-specific BPTs for the United States and Canada are presented as maps (**Figure 3**). Further discussion of the results, including sensitivity analyses is provided in the discussion section of the report. The results shown are GEMM BPTs for surface sources unless otherwise indicated. BPTs for other CRFs are presented in Appendix A (Figures A1–A7), available on the HEI website. Similarly, BPTs for elevated sources can be found in Appendix Figures A8 and A9. BPTs for elevated sources have patterns very similar to surface BPTs but decrease with altitude as expected; however, the rate of this reduction with altitude is very gradual. In other words, while surface and aloft BPTs are different, these differences are not very large, particularly for shorter stack heights.

For each species, a value on a map location indicates the monetized societal benefits of reducing emissions of that species by 1 metric ton. For example, a value of \$1M in New York City for $PM_{2.5}$ BPT implies that reducing primary $PM_{2.5}$ emissions at that location in the city leads to a \$1M population health benefit in the form of avoided mortality across the country. It is important to note that while adjoint-based BPTs are location-specific and provide granular information about source impacts at all locations, they do not contain any information about the location of impact, as the benefits are integrated across the domain. For the example above, the \$1M estimated benefit associated with a 1-ton $PM_{2.5}$ emission reduction pertains to reducing source emissions at that location. However, from adjoint simulations one cannot establish where those benefits would occur. In other words, the adjoint BPTs provide source location specificity but at the expense of receptor location specificity.

Adjoint-based BPTs represent source impacts, and although BPTs are defined as benefits of emission reductions, they can also be viewed as the damage or burden associated with increased emissions. As potential source impacts, BPTs can exist at any location, regardless of the level of emissions at that location. Therefore, sizeable BPTs may exist over the ocean or uninhabited areas. BPTs over regions without significant emissions indicate the impact on population centers if emissions were present at that location. In fact, for precursor species, BPTs may be larger in areas with insignificant emissions (i.e., clean areas), because for polluted areas the abundance of the pollutant may render insignificant the impact of any additional emissions. Conversely, in a clean area, molecules of precursor species are likely to be more efficient in generating secondary particles, as they face little to no competition for taking part in reactions. While such behavior is possible, depending on the lifetime of primary emissions, or conversion time to $PM_{2.5}$ for precursor emissions, BPTs will largely follow the spatial distribution of population. For example, BPTs for primary $PM_{2.5}$ emissions often closely follow the population centers, as emissions are expected to result in the largest exposure in the vicinity of surface sources. Note that values of US BPTs over Canada or estimates of Canadian BPTs at locations in the United States in Figure 3 indicate cross-border source impacts.

For both Canada and the United States, $PM_{2.5}$ and NH_3 have the largest BPTs. However, the total burden associated with the emissions of each species would also depend on the magnitude of emissions. Assuming a linear response (see Box 1), one can use BPTs to estimate, to a first-order approximation, the total burden associated with emissions of each species (**Figure 4**, total surface emissions burden). Note that while primary emission BPTs are almost invariably positive, BPTs of precursor emissions may be occasionally negative. For example, in NO_x-rich environments or plumes, the negative impact of NO_x on night-time ozone through titration can also reduce night-time nitrate formation that is facilitated by ozone, resulting in negative BPTs. Similarly, in NH_3-limited environments, a reduction in SO_2 emissions may, on rare occasions, result in increased particle mass through less favorable nitrate formation, again resulting in a negative BPT.

Location-specific cobenefits ($\$/ton - CO_2$) for sample on-road and nonroad sectors are shown in **Figures 5 and 6**. Cobenefits for all on-road, off-road, and electricity generation sectors and subsectors are provided in Appendix Tables B1–B5, available on the HEI website. Cobenefits (Figures 5 and 6, and Appendix Figures B1–B5) are fleet average values for the subsector; vintage-specific values are discussed later. Subsector trans-

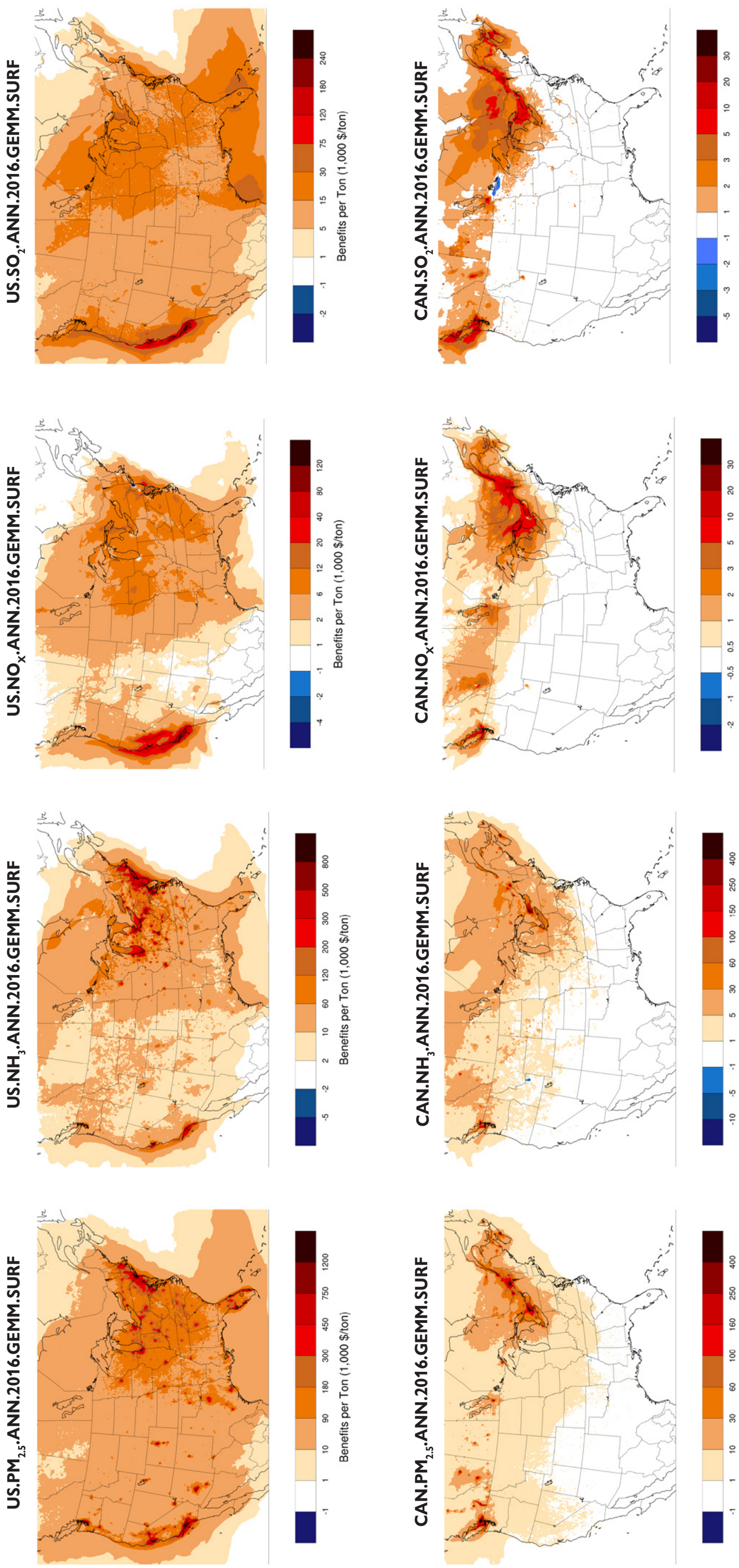
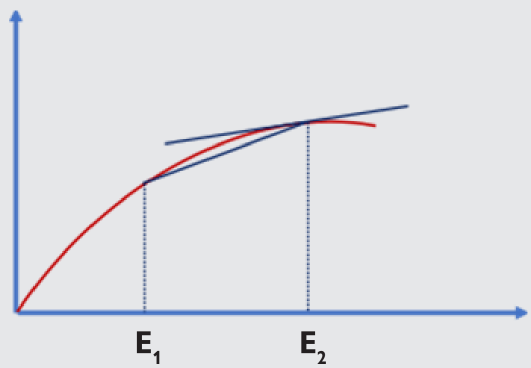


Figure 3. Surface (annual) United States and Canadian BPTs for various species and the GEMM model. Individual plot titles indicate the country and species for which the plot is generated. US and Canadian BPT estimates are for 2016 USD and CAD, respectively. (Adapted from Zhao et al. [In press])

Box 1. BPTs: Linear Approximation to Nonlinear Response

Regardless of the approach used in estimating BPTs, they are, by definition, the response to a small change in emissions. As measures of response at the margin, BPTs represent the slope or tangent to the model's response surface. This is by definition and not a shortcoming or limitation of BPTs. However, if for a nonlinear response surface, BPTs are used to characterize source impacts in presence of large-scale changes in emissions, their use can lead to errors due to nonlinearity. In the presence of significant nonlinearities (i.e., curvature in the response surface), or large-scale changes in emissions, or both, the BPT or tangent to the surface may deviate from change between the two emission points. Nonlinearity in the health response to an emissions change can stem from nonlinear atmospheric processes (e.g., gas-phase and aqueous chemistry and aerosol thermodynamics) or from a nonlinear CRF such as GEMM. We further explore the stability of adjoint-based BPTs in presence of large-scale changes in inventory as a sensitivity analysis.

BPTs represent marginal source impacts; however, to a first-order approximation the overall burden from emissions of a species can be estimated using BPTs. The burden can be approximated as a product of BPT and emissions for any given location. It is important to note that such estimate of the total burden (or damage) is approximate and assumes a linear response. In this study, we use this first-order approximation, while recognizing its inherent limitation.



Box 1 Figure. Schematic of a nonlinear response surface and differences between the tangent (BPT) and slope between two emission points.

portation cobenefits are only provided for the United States, as access to the data required for running MOVES3 and estimating sector-specific emission profiles was not available for Canada. Cobenefit and total burden estimates for thermal electricity generation in both Canada and the United States (coal and gas) are presented in **Figure 7**. For certain sectors, cobenefits may exhibit distinct patterns across county or state boundaries due to differing characteristics of emission inventories in those states or boundaries (e.g., recreational off-road vehicles in Figure 6).

GHG reduction cobenefits carry significant sectoral footprint information due to the use of sector-specific emission profiles in their calculation (see Equation 8 and Box 2). Cobenefit values differ significantly across sectors and are very substantial for subsectors such as different types of heavy-duty diesel vehicles, as well as two-stroke off-road engines used in a variety of off-road subsectors such as construction, lawn and garden, or recreational vehicles (also Appendix Figures B1, B3, and B4). In comparison, light-duty gasoline vehicles have smaller cobenefits across various subsectors because the emissions of NO_x and primary PM are lower per ton of CO_2 emitted (Appendix Figure B2). The value of cobenefits for off-road engines and heavy-duty diesel vehicles for many locations far exceeds the current recommended values (51 \$/ton-CO_2) for the social cost of carbon in the United States and is comparable to the higher values (190 \$/ton-CO_2) proposed by the US EPA (US EPA 2022).

Cobenefit values shown here represent the societal benefits associated with removing emissions of CO_2 and its co-emitted pollutants. The implied assumption in calculation of these cobenefits is the complete elimination of the combustion source in the subsector in question. As such, these cobenefits can be used to evaluate the population health impact of electrification or decarbonization policies that fully replace a combustion-based energy use with a noncombustion alternative (e.g., electrification with a renewable energy source or energy efficiency measures). Evaluation of air quality impacts of such measures is then straightforward using sectoral cobenefits; the impact is simply the product of the cobenefit and the amount of CO_2 removed. If the policy option does not fully eliminate the combustion process (e.g., improved fuel efficiency in passenger cars), or if the alternative energy source

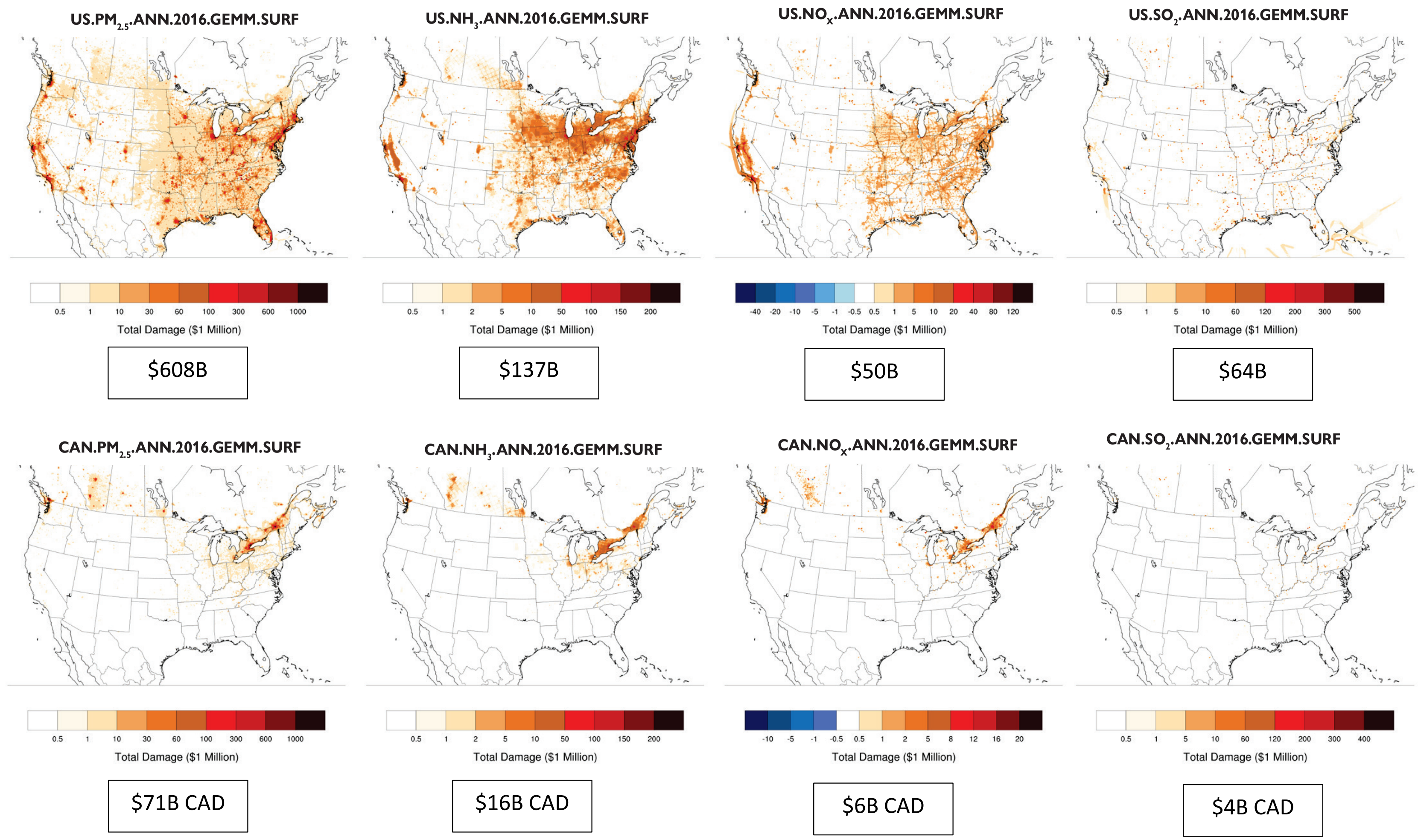


Figure 4. Total burden estimates for the United States (top row) and Canada (bottom row) based on estimated BPTs. Total nationwide burdens for each species are shown under individual plots. (Adapted from Zhao et al. [In press])

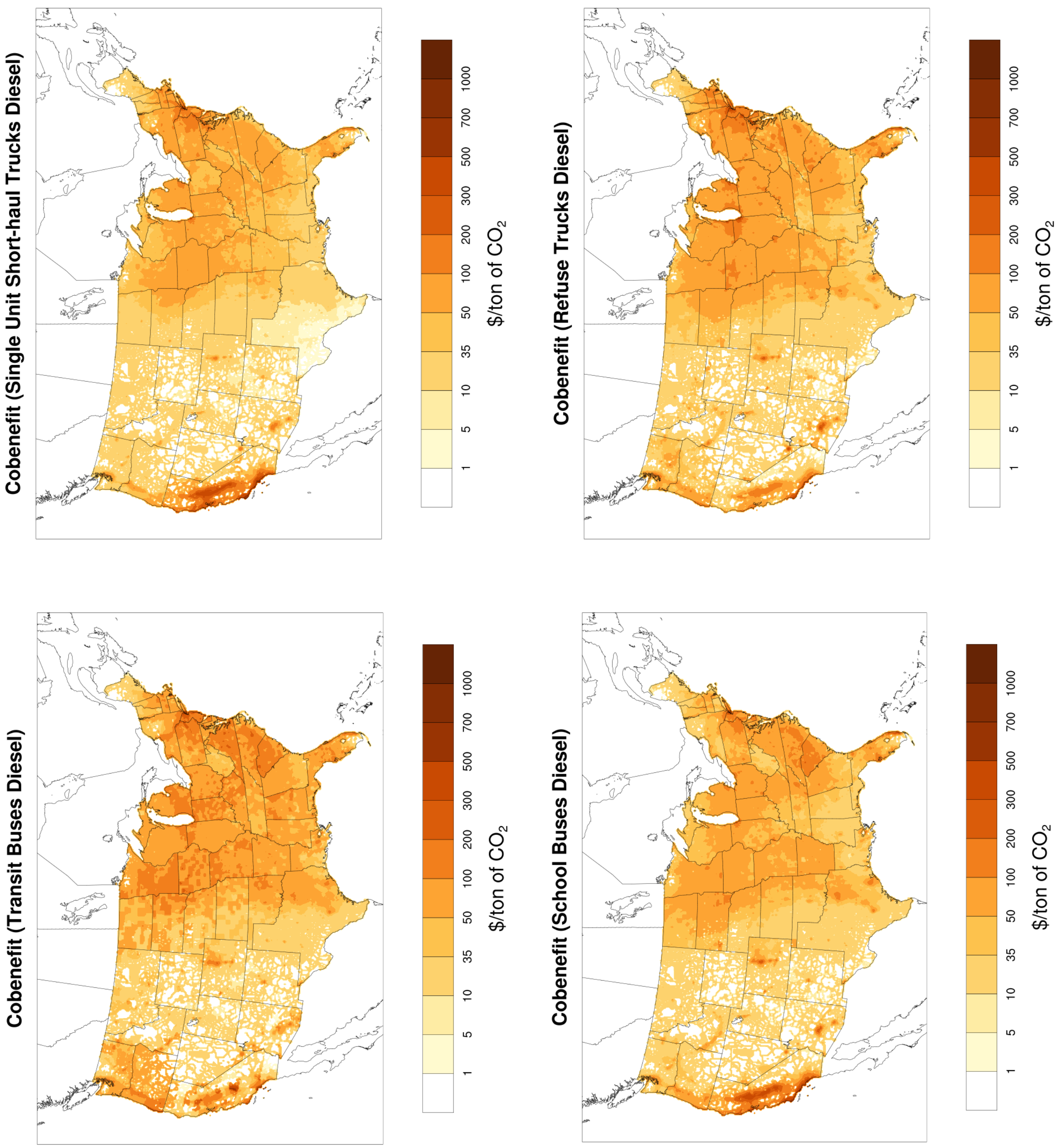


Figure 5. Location-specific cobenefits for sample subsectors of on-road diesel vehicles.

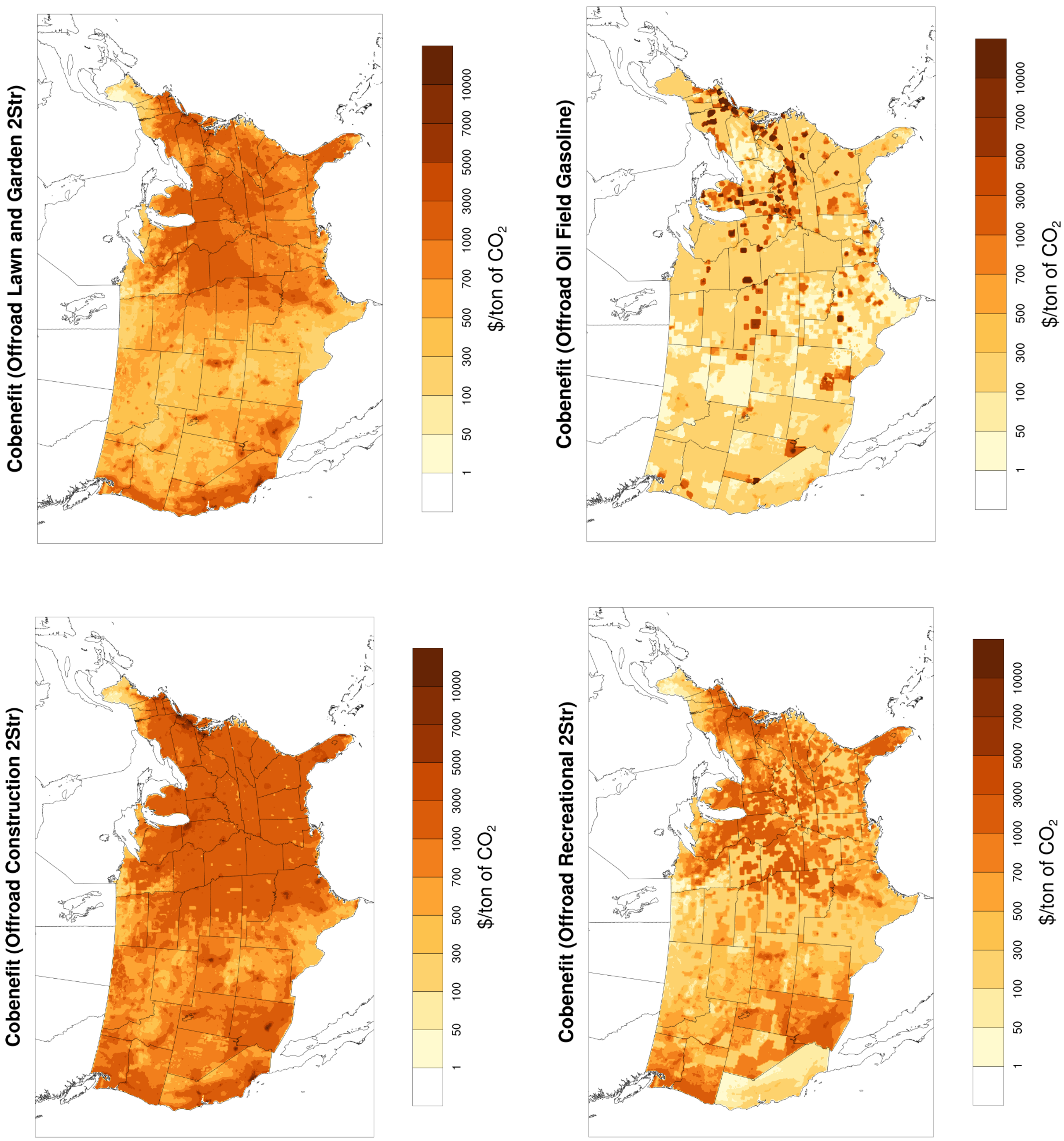


Figure 6. Examples of cobenefits for two-stroke off-road engines in various sectors.

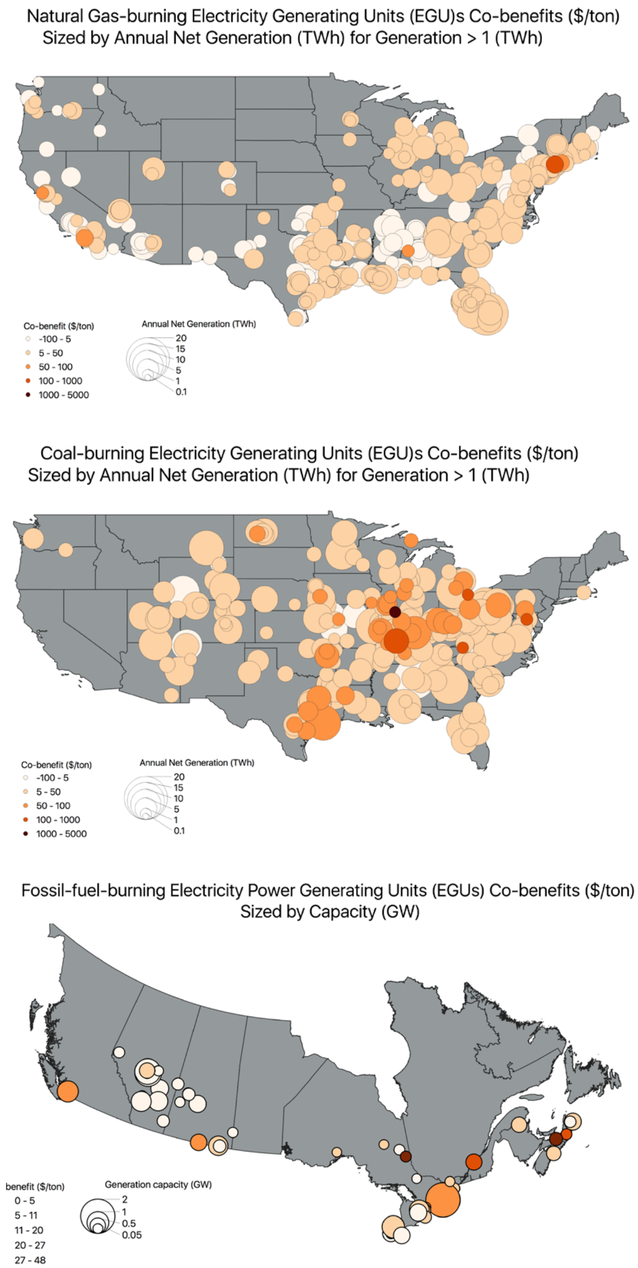


Figure 7. Cobenefits for thermal electricity generation in the United States and Canada. Note that the United States and Canada maps are presented separately with different units and scales due to large differences between the two countries.

has an associated air pollution footprint (e.g., electrification using electricity generated from coal or natural gas), then the use of cobenefits for policy evaluation should include further consideration and additional information. For instance, if at a certain location, the fleet of diesel transit buses are being replaced with electric buses that run on electricity from coal and natural gas, then the population health impact from this measure can be readily assessed using cobenefits, so long as the energy mix (coal vs. natural gas) of the electricity usage is known. In this case, the impact is simply the difference between full removal of diesel fleet (as discussed above) and the impact from the added electricity generation from coal and/or natural gas. The latter can be calculated from electricity sector cobenefits (Figure 7, Appendix Figures B5 and B6) if the amount of generated CO_2 and its location (i.e., the power plant) can be identified. If a policy proposition does not eliminate combustion, but instead alters the emission profile of the sector, then the best approach for a location-specific population health-impact assessment would be the direct use of BPTs in combination with the emission changes from the measure. It is important to note that cobenefits are not separate simulated values, but direct derivatives of BPT estimates. Therefore, if emission profiles of existing sources change, or if new source sectors or subsectors emerge, cobenefits for those sectors can be updated by using the existing BPTs, as long as new source emission profiles for CO_2 and co-emitted pollutants are known.

On-road cobenefit values (Figure 5) are fleet-averaged estimates. However, there is a great deal of variability within each sector due to different vehicle vintages. Cobenefits can also be estimated for each specific model year and vintage, for example, for diesel transit buses and gasoline passenger cars in major US cities as shown in **Tables 1 and 2**. Also shown in the tables are the yearly per-vehicle burden estimates, based on the cobenefit and the expected vehicle miles traveled (VMT) for the vintages and counties in question. Tables of cobenefits and per-vehicle burdens of different vintages are also provided for diesel school buses, diesel combination short-haul trucks, diesel single-unit short-haul trucks, diesel refuse trucks, and gasoline passenger trucks in Appendix Tables B1–B5.

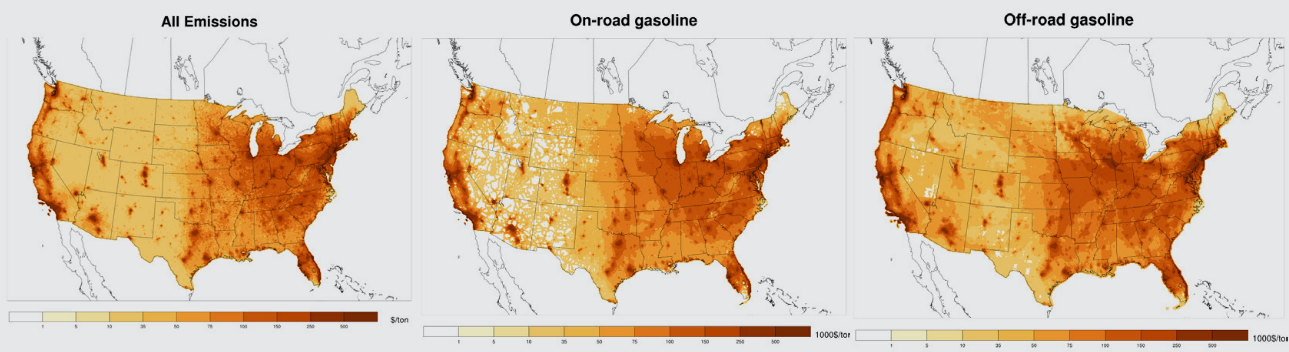
Cobenefits are substantial for older heavy-duty diesel vehicles, including transit buses, reflecting old standards and comparatively higher emission rates relative to fuel usage (and CO_2 emissions) in those vintages. Per-vehicle burden estimates depend on vintage-specific cobenefits and VMTs; older vintages have higher cobenefits but tend to have lower VMTs. Similar to cobenefit estimates, per-vehicle burden estimates can be used directly in evaluating policies that aim to renew and/or decarbonize the fleet in specific subsectors. Comparing values in Tables 1 and 2 (and those in Appendix Tables B1–B5) suggests that per unit of CO_2 removed, electrification of heavy-duty diesel vehicles may provide larger and more immediate population health benefits than electrification of passenger cars. Of course, the costs associated with the electrification of different vehicle types can differ significantly, as does the number of those vehicles on the road.

DISCUSSION

The summary results for location-specific BPTs and cobenefits, as well as per-vehicle burden estimates were presented earlier. Here we discuss further details about the presented

Box 2. Sectors, BPTs, and Cobenefits

BPT values have often been estimated for emissions of various sectors (Fann et al. 2009 and 2012). However, at any given time and location (including altitude), source impacts for an emitted pollutant are independent of the sector and type of the source as the atmosphere does not distinguish among the origins of the pollutant. What leads to sectoral differences are the different spatial and temporal emission patterns for sources that are grouped together. For example, while the impact of primary $PM_{2.5}$ emissions at a given location is the same for emissions from on-road transit buses or off-road construction equipment (assuming that the toxicity of the emissions is the same per mass), their collective sectoral impacts when grouped together are different because they follow different distributions in space and time. Adjoint-based BPTs are location-specific, and therefore sectoral differences in adjoint BPTs exist only due to sector-specific temporal patterns. Because temporal fingerprints of source sectors are less pronounced than spatial features and patterns, adjoint BPTs for various source sectors show only subtle differences (Box 2 Figure). Therefore, BPT results shown throughout this report are calculated and presented for all emissions regardless of the sector, as adjoint-based BPTs do not have strong sectoral features. However, unlike BPTs, adjoint-based cobenefit estimations rely on sectoral emission profiles of CO_2 and co-emitted criteria pollutants (see Equation 8) that can be vastly different across sectors and subsectors. Therefore, adjoint-based cobenefits carry a much more pronounced sectoral fingerprint than adjoint-based BPTs.



Box 2 Figure. Differences between sectoral emissions, when adjoint BPTs are estimated using temporal distribution of all surface emissions, on-road gasoline passenger cars, or off-road gasoline engines. (Adapted from Zhao et al. [In press])

results, as well as their implications and significance. We also discuss our sensitivity analyses to assess the robustness of BPT estimations against various assumptions made in the study and provide a qualitative assessment of the uncertainty level.

VARIABILITY IN BPTS

Location-specific BPTs provide more granular differentiation among source impacts. The level of detail and granularity offered by adjoint-based BPTs and cobenefits may or may not be applicable to regulatory or policy questions; however, when possible, these BPTs can provide valuable information for guiding air quality management decisions. This is particularly true as BPTs in both Canada and the United States exhibit significant spatial and seasonal variability. One way to depict differences and disparities among BPTs in various locations is to construct the Lorenz curve from the estimated BPTs. A Lorenz curve is often used to illustrate the income inequality in a society by visualizing the share of income or wealth by sorted fractions of population. Here we use Lorenz curves to demonstrate disparities among units of emissions of various species that are emitted in different locations (**Figure 8**, Appendix Figures A22 and A24). For example, our BPT results suggest that in the United States, the most damaging 20% of primary $PM_{2.5}$ and NH_3 emissions are responsible for 50% and 60% of the health burden of those species, respectively. Similarly in Canada, the most harmful 10% of $PM_{2.5}$ and NH_3 emissions account for approximately 60% and 50% of the total burden, respectively (Figure 8). In other words, targeting the most damaging emissions in each country can entail significantly larger benefits than indiscriminate reduction in emissions. Of course, targeted emission reductions may be challenging for certain sectors such as on-road passenger cars, but for certain sectors (e.g., point sources, transit buses), BPTs

Table 1. Cobenefits and Per-Vehicle Burden of Diesel Transit Buses in Major US Cities for Different Vintages[a]

	Cobenefit (\$/ton-CO_2)					Per-Vehicle Damage (\$/year)				
City	1998	2002	2008	2012	2016	1998	2002	2008	2012	2016
Baltimore	248	245	40	25	23	7690 (1)	10423 (3)	2029 (6)	1519 (6)	1369 (9)
Boston	262	285	24	12	10	8317 (1)	12374 (3)	1235 (6)	710 (6)	615 (9)
Buffalo	280	263	43	24	20	8344 (2)	10742 (6)	2081 (12)	1378 (12)	1205 (17)
Chicago	364	396	39	22	21	13337 (7)	15490 (27)	1858 (53)	1278 (52)	1242 (74)
Dallas - Forth Worth	120	120	15	8	6	4233 (6)	4528 (23)	667 (45)	403 (44)	343 (62)
Denver	153	162	16	8	7	7250 (1)	6308 (5)	722 (10)	423 (10)	379 (14)
Detroit	227	239	28	16	14	7212 (4)	9612 (13)	1269 (27)	899 (26)	852 (37)
Houston	96	95	13	7	6	3357 (10)	3667 (37)	577 (74)	368 (72)	320 (101)
Las Vegas	231	249	18	7	5	7628 (4)	9674 (14)	803 (28)	352 (27)	267 (38)
Los Angeles	1211	1078	188	96	73	42574 (20)	41595 (75)	8757 (148)	5537 (144)	4483 (204)
Memphis	220	191	39	22	18	8495 (4)	7606 (16)	1832 (32)	1279 (31)	1086 (44)
Miami	260	286	18	7	5	9828 (4)	11133 (16)	857 (31)	350 (31)	281 (43)
Minneapolis	328	317	48	26	22	11718 (5)	12281 (19)	2177 (38)	1457 (37)	1278 (53)
New York	612	695	39	14	12	16498 (1)	25680 (3)	1700 (6)	868 (5)	682 (8)
Orlando	305	303	38	18	15	8609 (1)	11723 (3)	1729 (6)	1002 (6)	809 (9)
Philadelphia	383	401	44	24	21	17093 (1)	14722 (5)	2114 (9)	1357 (9)	1224 (13)
Phoenix	167	183	12	4	3	6138 (8)	7126 (31)	538 (61)	207 (60)	150 (85)
Raleigh-Durham	171	151	30	17	14	7043 (2)	5700 (9)	1416 (17)	967 (17)	839 (24)
Salt Lake City	95	93	13	7	6	3610 (2)	3638 (8)	577 (16)	360 (16)	319 (22)
San Diego	316	275	54	29	22	11002 (14)	10381 (53)	2452 (105)	1589 (102)	1330 (144)
San Francisco	580	503	100	55	43	32501 (1)	38611 (3)	9130 (6)	6034 (6)	5342 (8)
Seattle	127	137	12	6	5	4475 (4)	5315 (15)	529 (30)	306 (29)	274 (41)
Washington	177	164	33	22	19	1994 (0)	7585 (1)	1797 (2)	1383 (2)	1209 (3)

[a]Numbers are based on 2016 national MOVES simulations. Number of vehicles in each vintage year in the county is shown parenthetically.

can provide invaluable guidance for prioritizing emission-reduction measures.

All the BPTs shown in this report have been averaged over four seasons to construct annual values. However, depending on the species, BPTs may also display significant seasonal variability (**Figure 9**, Appendix Figures A10 and A11). As expected, seasonal variability is more significant for precursors of secondary inorganic aerosols for which the efficacy in production of secondary particles is dependent on meteorological conditions such as temperature, humidity, and precipitation. Among these, NH_3 shows very significant seasonal trends with larger BPTs during the colder winter and fall seasons, where lower temperatures favor partitioning to particulate ammonium and also contributing to nitrate formation. In contrast, primary $PM_{2.5}$ emissions show little seasonality as their impact is affected not by the nonlinear chemical or thermodynamic transformations, but only through seasonal weather parameters and mixing patterns.

SENSITIVITY TO EPISODIC SIMULATIONS

As mentioned before, due to the computational challenges of long-term adjoint simulations, annual BPT estimates are constructed based on episodic (2-week) simulations for each season. Despite our efforts for selecting representative epi-

Table 2. Cobenefits and Per-Vehicle Burden of Gasoline Passenger Cars in Major US Cities for Different Vintages[a]

City	Cobenefit ($/ton-$CO_2$)					Per-Vehicle Damage ($/year)				
	1998	2002	2008	2012	2016	1998	2002	2008	2012	2016
Baltimore	179	60	42	39	45	540 (2932)	219 (5638)	190 (7130)	181 (7840)	198 (8567)
Boston	101	36	24	23	27	309 (2991)	133 (5751)	107 (7273)	107 (7997)	119 (8739)
Buffalo	109	39	22	21	25	327 (5484)	140 (10546)	99 (13336)	97 (14664)	107 (16023)
Chicago	198	67	47	43	51	592 (24229)	243 (46593)	207 (58921)	202 (64788)	222 (70795)
Dallas - Forth Worth	38	13	8	7	8	112 (20083)	46 (38619)	33 (48837)	32 (53701)	35 (58680)
Denver	54	19	12	11	14	156 (4493)	68 (8640)	50 (10926)	51 (12014)	56 (13128)
Detroit	122	43	29	27	32	365 (12000)	155 (23077)	126 (29183)	124 (32089)	137 (35064)
Houston	33	11	7	7	8	99 (32970)	41 (63402)	30 (80177)	29 (88162)	32 (96336)
Las Vegas	41	18	8	9	11	125 (12094)	66 (23257)	36 (29411)	41 (32340)	46 (35338)
Los Angeles	270	72	34	32	38	793 (65923)	258 (126769)	149 (160311)	145 (176275)	159 (192618)
Memphis	86	28	16	15	17	258 (14502)	103 (27887)	70 (35266)	66 (38778)	73 (42373)
Miami	45	18	9	9	11	141 (14233)	67 (27371)	42 (34613)	44 (38060)	48 (41588)
Minneapolis	157	53	32	30	35	457 (16876)	187 (32452)	139 (41039)	136 (45126)	149 (49310)
New York	178	66	41	40	48	532 (2543)	240 (4891)	181 (6185)	188 (6801)	209 (7432)
Orlando	88	32	18	17	20	248 (2420)	109 (4654)	73 (5885)	73 (6471)	81 (7071)
Philadelphia	159	55	37	34	41	478 (4208)	202 (8091)	163 (10232)	160 (11251)	177 (12294)
Phoenix	27	10	5	5	6	84 (27366)	37 (52625)	21 (66549)	22 (73176)	24 (79960)
Raleigh-Durham	67	23	14	12	14	199 (7776)	84 (14954)	59 (18910)	56 (20794)	61 (22722)
Salt Lake City	37	13	8	7	9	109 (7099)	46 (13652)	33 (17264)	33 (18983)	36 (20743)
San Diego	72	20	11	10	12	206 (45093)	68 (86714)	45 (109658)	43 (120578)	47 (131757)
San Francisco	169	46	25	23	27	1012 (2643)	335 (5082)	219 (6427)	211 (7067)	232 (7722)
Seattle	43	16	10	10	11	126 (13100)	55 (25191)	42 (31856)	43 (35028)	47 (38276)
Washington	119	40	27	24	28	377 (1059)	153 (2037)	126 (2576)	119 (2832)	129 (3095)

[a] Numbers are based on 2016 national MOVES simulations. Number of vehicles in each vintage year in the county is shown parenthetically.

sodes for Canada and the United States, using a short period in lieu of a full season would introduce errors and uncertainties in the estimated BPTs. We used 36-km adjoint simulations, for which year-long simulations are computationally feasible, to evaluate the representativeness of our episodic simulations.

Our 36-km resolution episodic simulations produced BPTs that are reasonably similar to full-year simulations for both Canada and the United States without any significant bias (**Figure 10**). BPTs for all species show good agreement between episodic and full-year simulations, but agreement is strongest for primary $PM_{2.5}$ emissions, and weaker for precursor species, particularly SO_2. Our episode-selection algorithm is closely linked to grid cells (surface or aloft) that have more significant burdens. Those grid cells are more likely to be at the surface, and therefore it is not surprising that the selected episodes are not as representative for SO_2, whose emissions are primarily from elevated sources. It is also important to note that our results suggest that primary $PM_{2.5}$ emissions account for 71% and 73% of the total burden in the United States and Canada, respectively, and therefore their strong representation through episodic simulations is reassuring. Seasonal BPTs show a lower degree of agreement between episodic and seasonal simulations (Figure 10, Appendix Figures A14–A21), particularly for SO_2 and NO_x. However, the annual BPTs being more consistent with year-long simulations reaffirms that there is

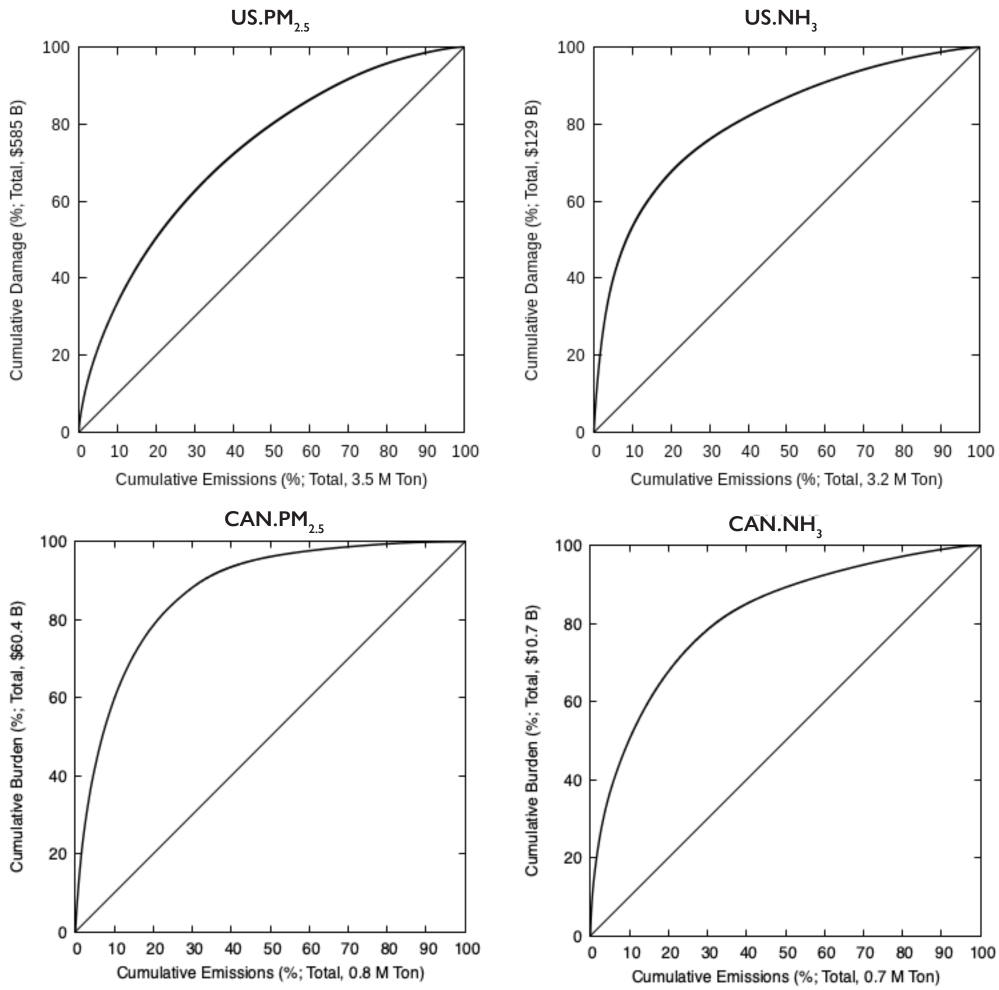


Figure 8. Lorenz curves for the United States (top row) and Canada (bottom row) display the extent differences and disparities in health burden of emissions across the two countries. The vertical and horizontal axes show cumulative burden and cumulative emission fractions, respectively. (Zhao et al. [In press])

no systemic bias across seasons in episodic representation of BPTs, as expected.

The implied assumption in our evaluation of errors from episodic simulations is that temporal trends and patterns at 36-km are similar to those of 12-km simulations that are the basis for our BPT evaluations. We will revisit this assumption in our sensitivity analysis of horizontal resolution but believe that this is a justifiable assumption.

While we did not quantify uncertainties, we attempted to assign a qualitative evaluation of uncertainty to the topics of our sensitivity analyses. In assigning a qualitative index of uncertainty, we assigned more importance to primary $PM_{2.5}$ BPTs, as those emissions constitute approximately 70% of the total burden in the United States. We assigned a grade of low, medium, or high uncertainty based on the normalized mean bias estimates shown on respective scatter plots (e.g., Figure 10) or other relevant measures of uncertainty such as coefficient of variation. We assigned low, medium, and high levels of uncertainty to normalized mean bias or coefficient of variation values of <15%, 15%–30%, and >30%, respectively.

The qualitative uncertainty grade for episodic simulations is *low uncertainty*.

SENSITIVITY TO THE CHOICE OF CRF

To examine the impact of the choice of CRF, we compared US BPTs from the GEMM epidemiological model with those from the two ACS-CPS-II cohorts (ACS-09 and ACS-16), NHIS, and CHEN as calculated through episodic simulations at 12-km. These comparisons are shown in **Figure 11**. Overall, GEMM BPTs are consistently larger than ACS-09 BPTs, with a fairly consistent ratio of approximately 1.1–1.2 for different species. However, GEMM BPTs show significantly better agreement with the updated ACS-16 BPTs. On the other hand, comparison of GEMM and NHIS BPTs show more spread and bifurcation. While in general, GEMM results in larger BPTs (overall slopes of less than one for all species), for some grid cells and species NHIS BPTs are larger.

In GEMM, NHIS, and ACS-09/ACS-16/CHEN we have three different shapes of CRFs. GEMM is a sublinear (concave) CRF, while NHIS has a superlinear (convex) shape, and the

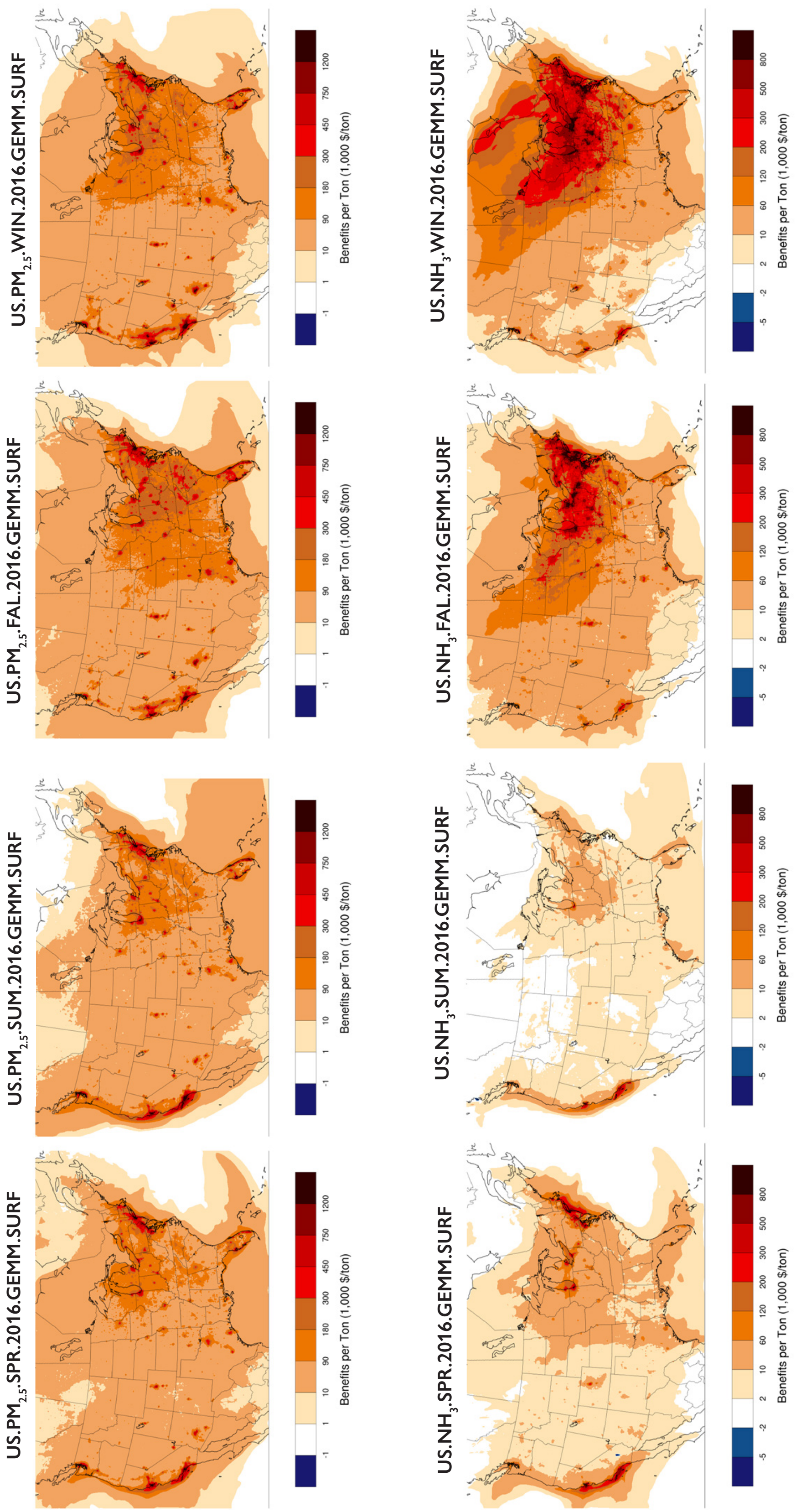


Figure 9. Seasonal variability in emissions of primary $PM_{2.5}$ and NH_3 emissions, surface emissions, GEMM. (Zhao et al. [In press])

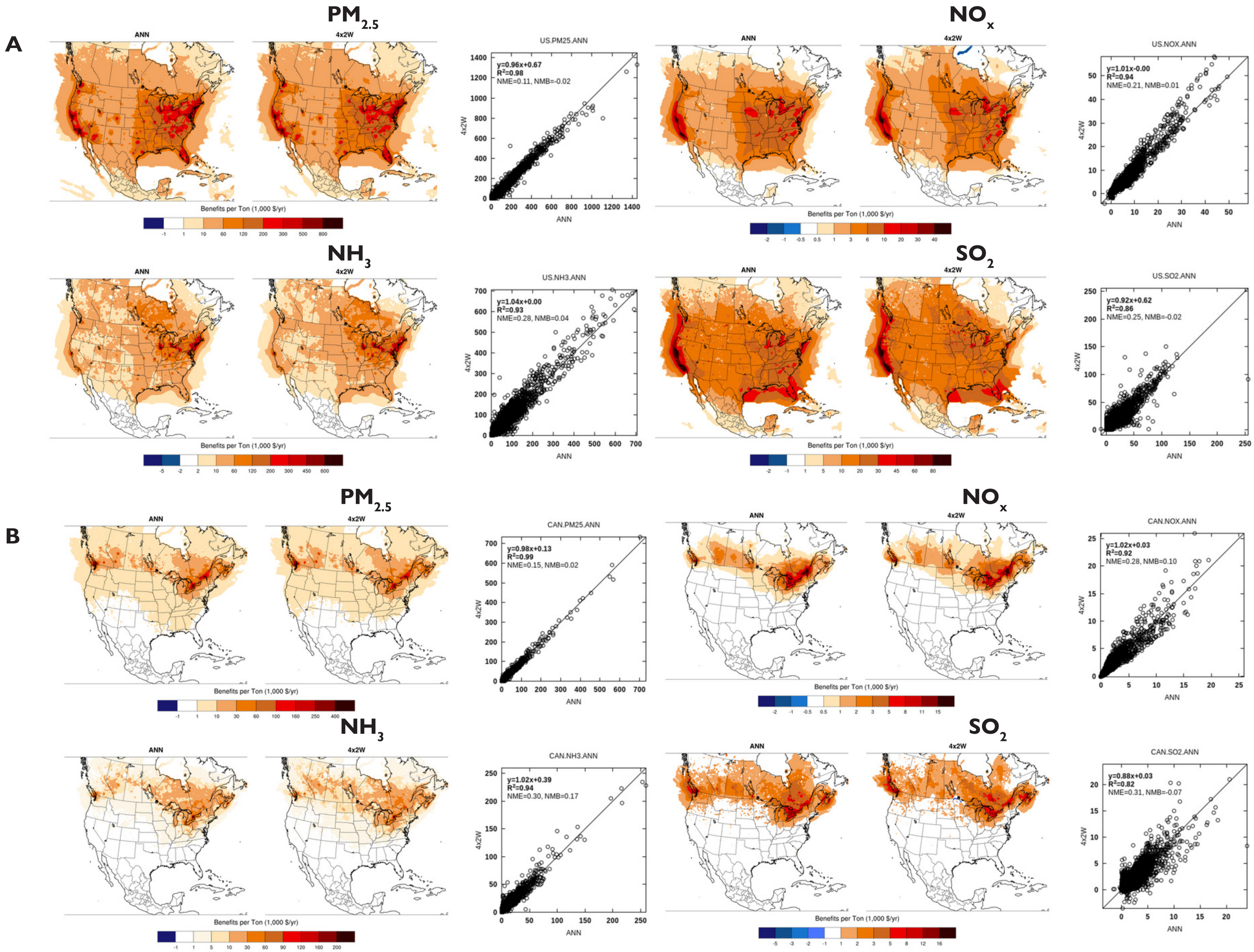


Figure 10. Comparison of BPTs from full year (left) and episodic (2 weeks per season) (right) and simulations at 36-km resolution, US, surface emissions, GEMM. Normalized mean bias (NMB) and errors (NME) associated with episodic representation are shown for each species. **A**. United States; **B**. Canada. (Figure 10A adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0)

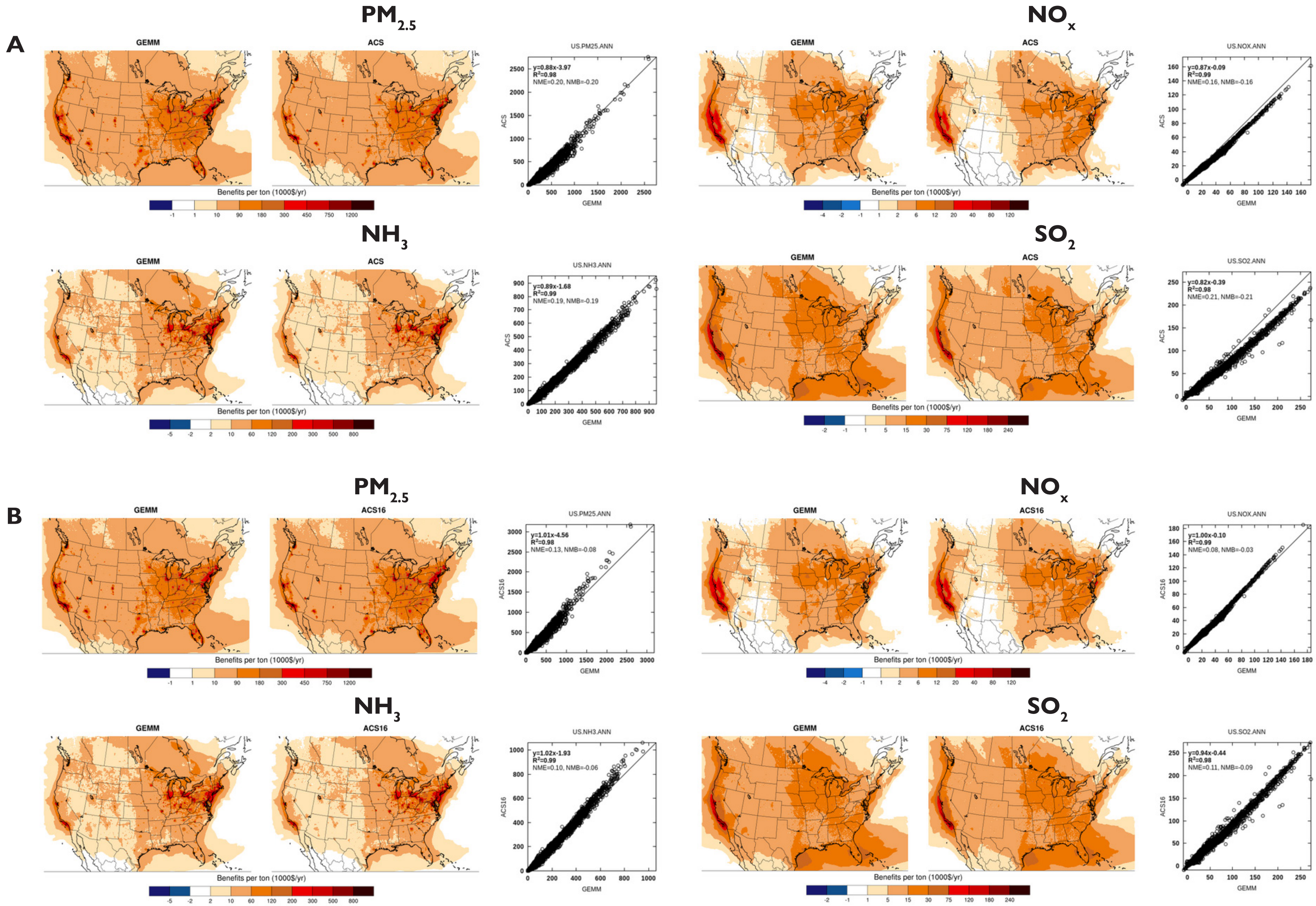


Figure 11. Comparisons between GEMM and (A) ACS-09, (B) updated ACS-16, (C) CHEN, and (D) NHIS BPTs for the US, surface emissions, annual BPTs. Normalized mean bias (NMB) and normalized mean errors (NME) for the comparison between BPTs are shown. (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0, and Zhao et al. [In press]) (*continues next page*)

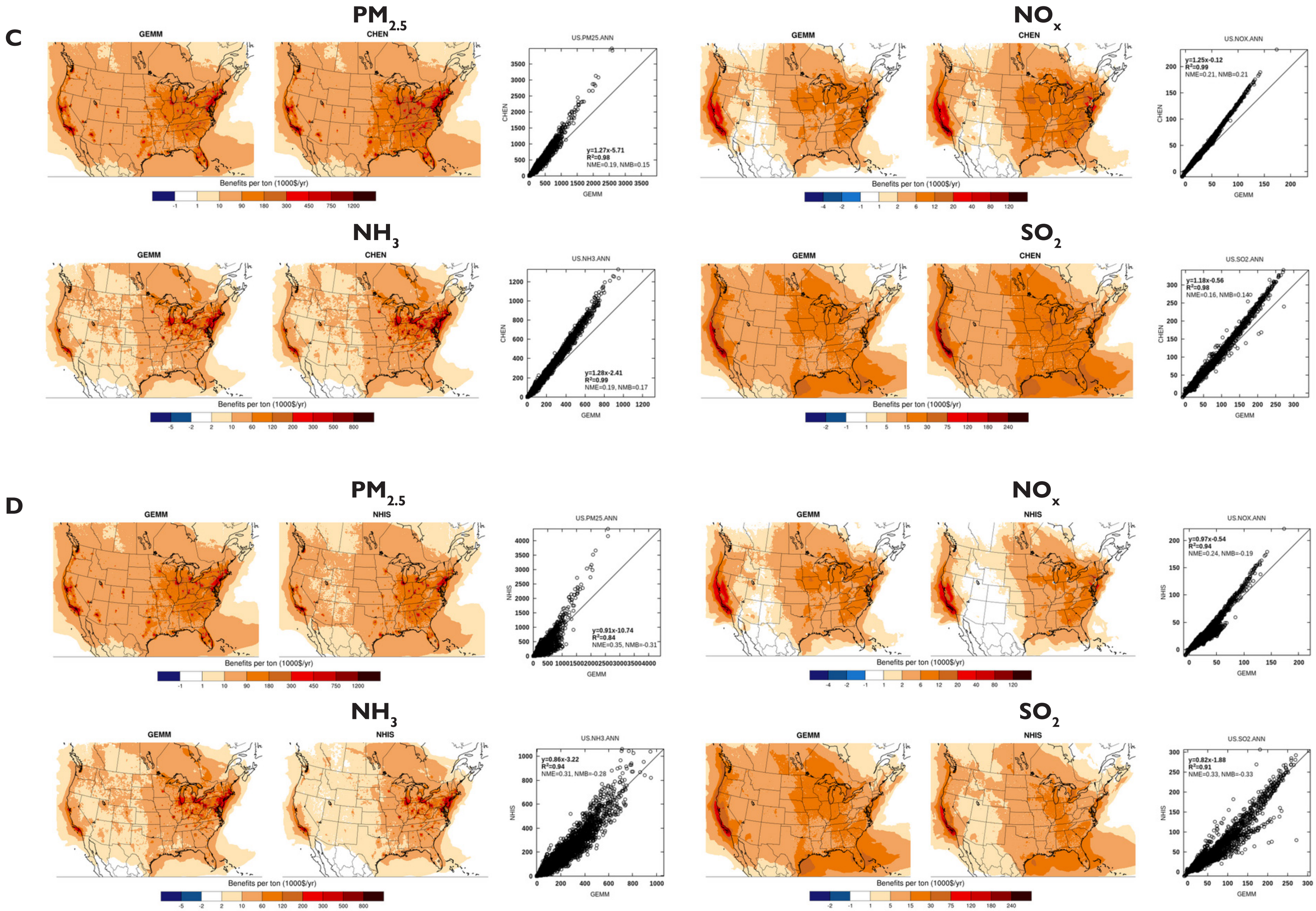


Figure 11 (*continued*). **Comparisons between GEMM and (A) ACS-09, (B) updated ACS-16, (C) CHEN, and (D) NHIS BPTs for the US, surface emissions, annual BPTs.** Normalized mean bias (NMB) and normalized mean errors (NME) for the comparison between BPTs are shown. (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0, and Zhao et al. [In press])

ACS/CHEN CRFs are linear. The adjoint system of equations is driven by the adjoint forcing terms, which are proportional to the slope of the HR curves for each CRF (Figure 2). The magnitude of the forcing term for nonlinear CRFs is a function of annual average concentrations of $PM_{2.5}$ at each location. As similar atmospheric conditions apply to simulations for all three CRFs, different forcing terms are the main source of discrepancy among the estimated BPTs.

For much of the lower range of concentrations (<10 μg/m^3), GEMM has a larger forcing term than ACS-09 and NHIS and is expected to produce the larger BPTs. At annual average concentrations above 10 μg/m^3, the NHIS forcing term exceeds that of the GEMM, resulting in larger NHIS BPT estimates. Therefore, within the practical range of 2016 $PM_{2.5}$ concentrations in the United States, forcing terms may be larger for either GEMM or NHIS CRFs at different locations, leading to a less consistent relationship between the two sets of BPTs. As a linear CRF, the ACS-09 forcing changes slightly with concentrations and only exceeds GEMM forcing at concentrations above approximately 25 μg/m^3. As annual average concentrations rarely exceeded that level for the United States in 2016, ACS-09 BPTs are consistently lower than GEMM. ACS-16 and CHEN have proportionally larger effect estimates than ACS-09, and therefore show similar behavior but at different thresholds. Finally, for each CRF the same forcing affects BPTs of all species; however, different species undergo different chemical or thermodynamic transformation pathways, resulting in further interspecies differences.

Variability across BPTs from different CRFs provides a measure of uncertainties associated with the choice of CRF. **Figure 12** shows the mean of the five BPTs for the United States, and the coefficient of variation (i.e., the standard deviation divided by the mean) among them. In general, coefficient of variation is smaller in areas with larger BPTs and ranges from 15% to 50% for different species. It is important to note that this uncertainty does not include, and is in addition to, the statistical model uncertainty in each individual CRF, expressed as standard errors and confidence intervals for parametric estimates within each model. Overall, the choice of CRF is an important factor that can greatly affect BPT simulations, and the uncertainty associated with epidemiological modeling is a significant source of the overall uncertainty in BPT estimates.

The qualitative uncertainty grade for choice of CRF is *medium-high uncertainty*.

SENSITIVITY TO CTM RESOLUTION

Our base (episodic) simulations for this study were conducted at 12-km horizontal resolution for CMAQ to cover a continental domain. We also conducted year-long 36-km simulations for the purpose of episode selection. To further examine the impact of CTM resolution, we conducted 4-km and 1-km simulations over two smaller domains centered around New York City and Los Angeles. Comparisons of primary $PM_{2.5}$ and precursor emission BPTs over these domains are shown in **Figure 13**. 4-km and 1-km simulations are conducted for the summer episode, and therefore, the comparisons presented here use that season for 12- and 36-km resolutions as well.

CTM resolution can affect BPT estimates in many ways. At a higher resolution, population distribution is captured at a more detailed and realistic level. As exposure is a prominent factor in driving adjoint simulations, the impact of a better-resolved population can be significant. CTM simulations are also affected by the resolution, primarily through emissions, meteorology, and numerical accuracy. Among these factors meteorology plays an important role, as higher-resolution meteorological simulations can reveal patterns that are absent in coarse simulations. CMAQ's treatment of clouds is also dependent on the grid resolution, which can greatly impact in-cloud processes and production of sulfate particles.

Although there is general consistency among the BPTs at different resolutions, there is a progression toward more detail and larger BPTs at higher resolutions (**Figure 14**). 36-km BPTs are consistent with 12-km results at the continental scale; however, 36-km results appear inadequate in resolving BPTs in urban settings such as Los Angeles and New York City. 12-km BPTs appear to be consistent with higher resolution results over these two domains, even though for most species they underestimate the BPTs at hot spots, particularly in Los Angeles, for precursors of inorganic $PM_{2.5}$, and in comparison with the 1-km domain. In both cities, there is very good consistency among all resolutions for primary $PM_{2.5}$ emissions that have the largest share of the health burden. As a result, 12-km BPTs show burden estimates that are generally consistent with 4-km and 1-km results (**Table 3**). As 4-km and 1-km simulations are not feasible at the continental scale, the consistency of the 4-km and 12-km simulations support that the 12-km results are adequate for national- and regional-level analysis. In Los Angeles there is a more pronounced difference between the spatial distribution of 12-km and 1-km BPTs, as well as the estimated burden for precursor emissions. For both Los Angeles and New York City, 1-km simulations can resolve areas of negative NO_x BPTs that do not appear at coarser resolutions. While 12-km BPTs appear to provide results that are generally consistent with higher resolution simulations, for more local applications, particularly for those considering environmental justice endpoints, the necessary level of detail can only be achieved through higher-resolution simulations.

The qualitative uncertainty grade for CMT resolution is *medium uncertainty*.

SENSITIVITY TO INVENTORY CHANGES AND VARIATION OF BPTS OVER TIME

As mentioned before, BPTs are tangents to the atmospheric response surface and are based on an implied assumption of linearity. In the presence of large-scale changes in emissions, or extremely nonlinear behavior, using BPTs would entail

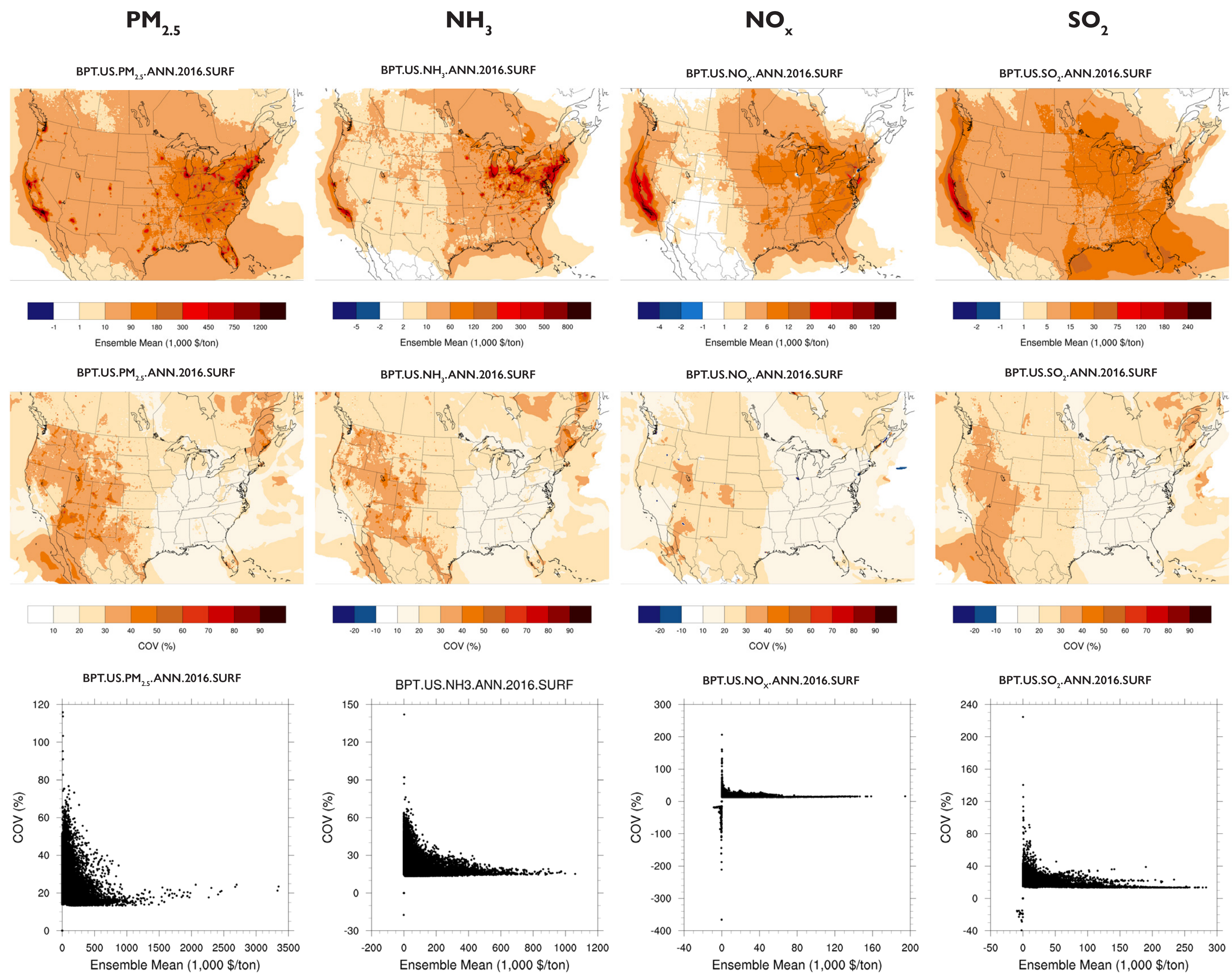


Figure 12. Mean (row 1) and coefficient of variation (%) (row 2) for the five BPT estimates. Scatter plots in row 3 show that coefficients of variation are smaller in areas with large BPTs. (Hakami et al. 2024; Creative Commons license CC BY 4.0)

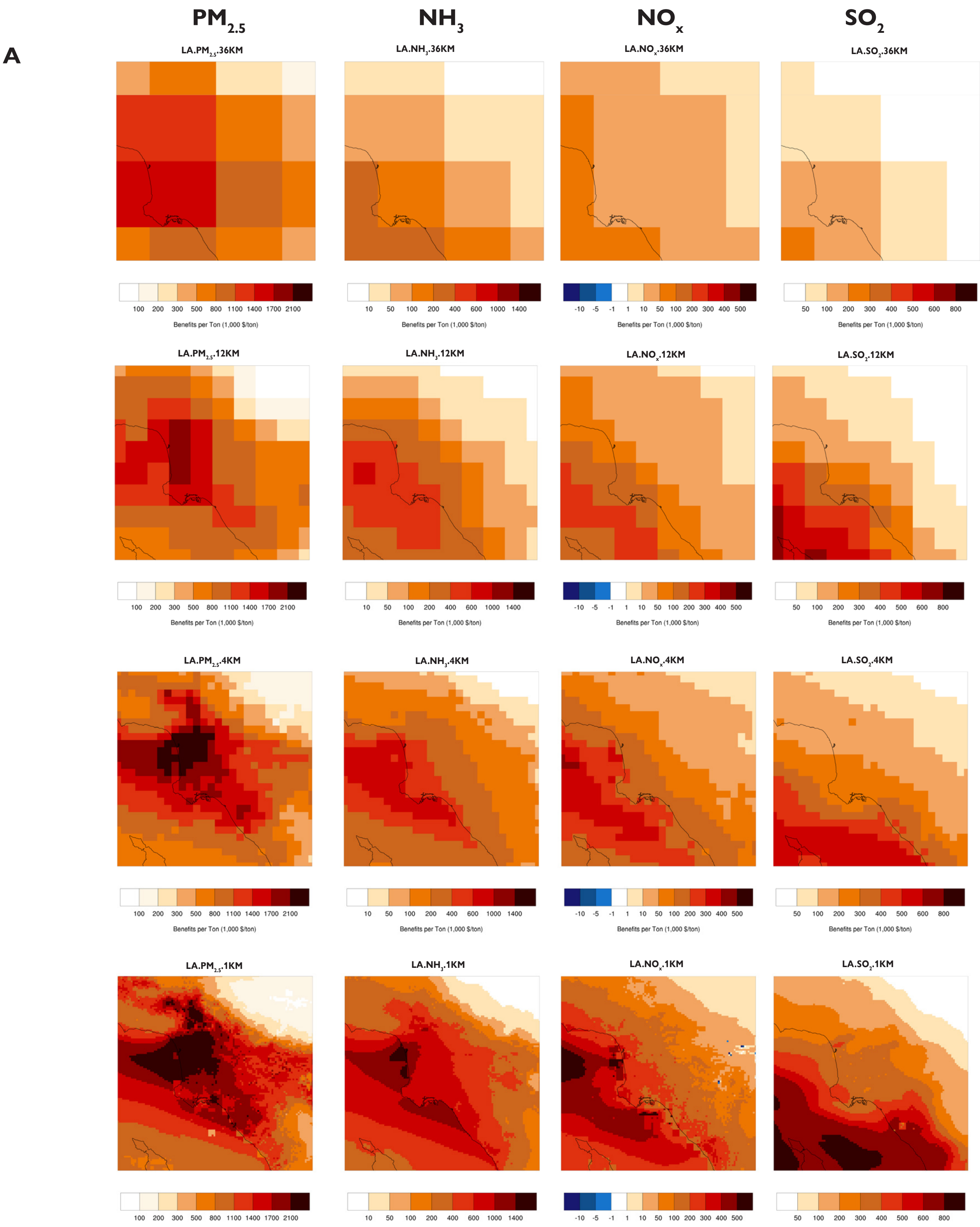


Figure 13. BPTs at 36-, 12-, 4-, and 1-km resolution, surface emissions, summer, GEMM, for (A) Los Angeles; (B) New York City. (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0) (*continues next page*)

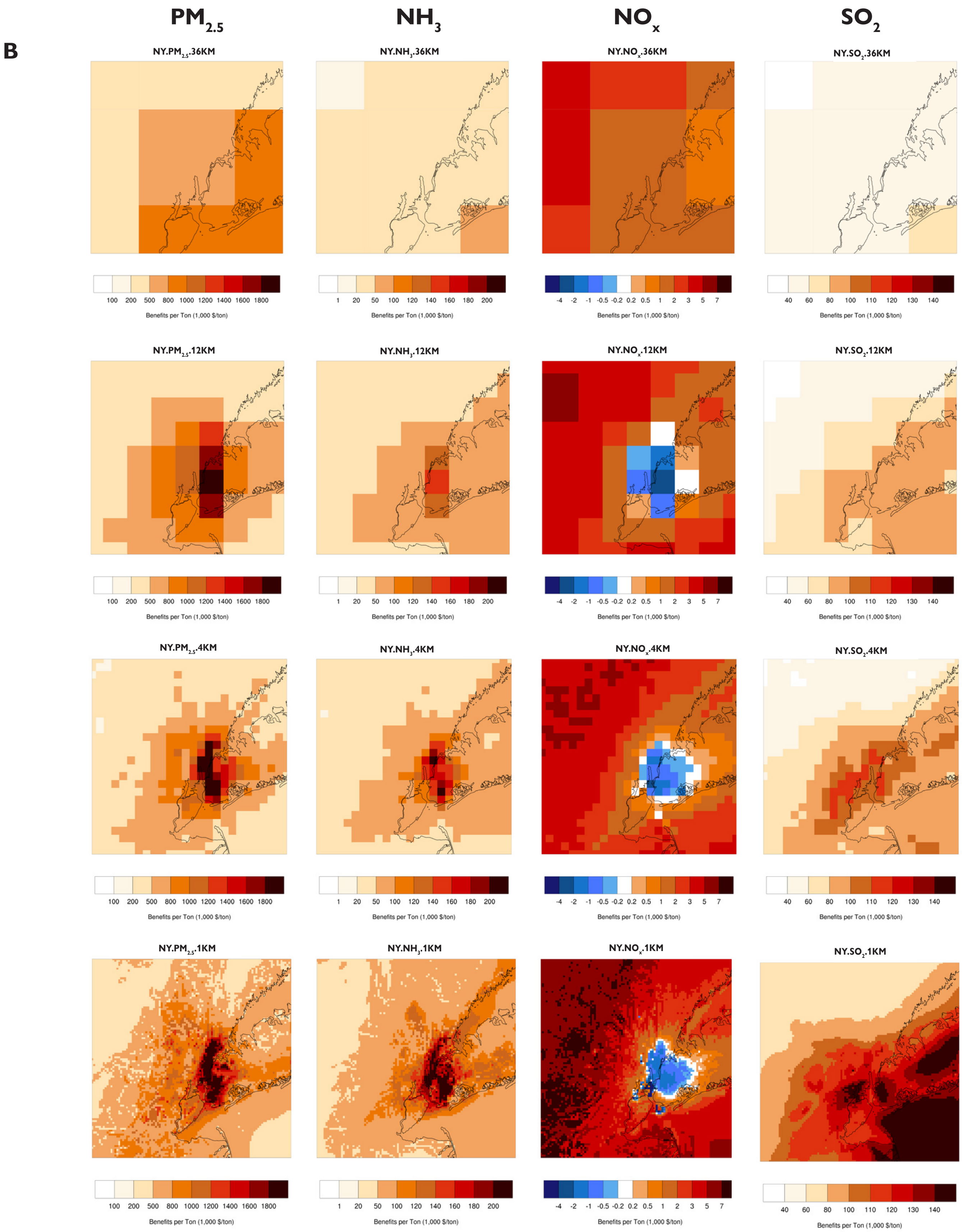


Figure 13 (*continued*). **BPTs at 36-, 12-, 4-, and 1-km resolution, surface emissions, summer, GEMM, for (A) Los Angeles; (B) New York City.** (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0)

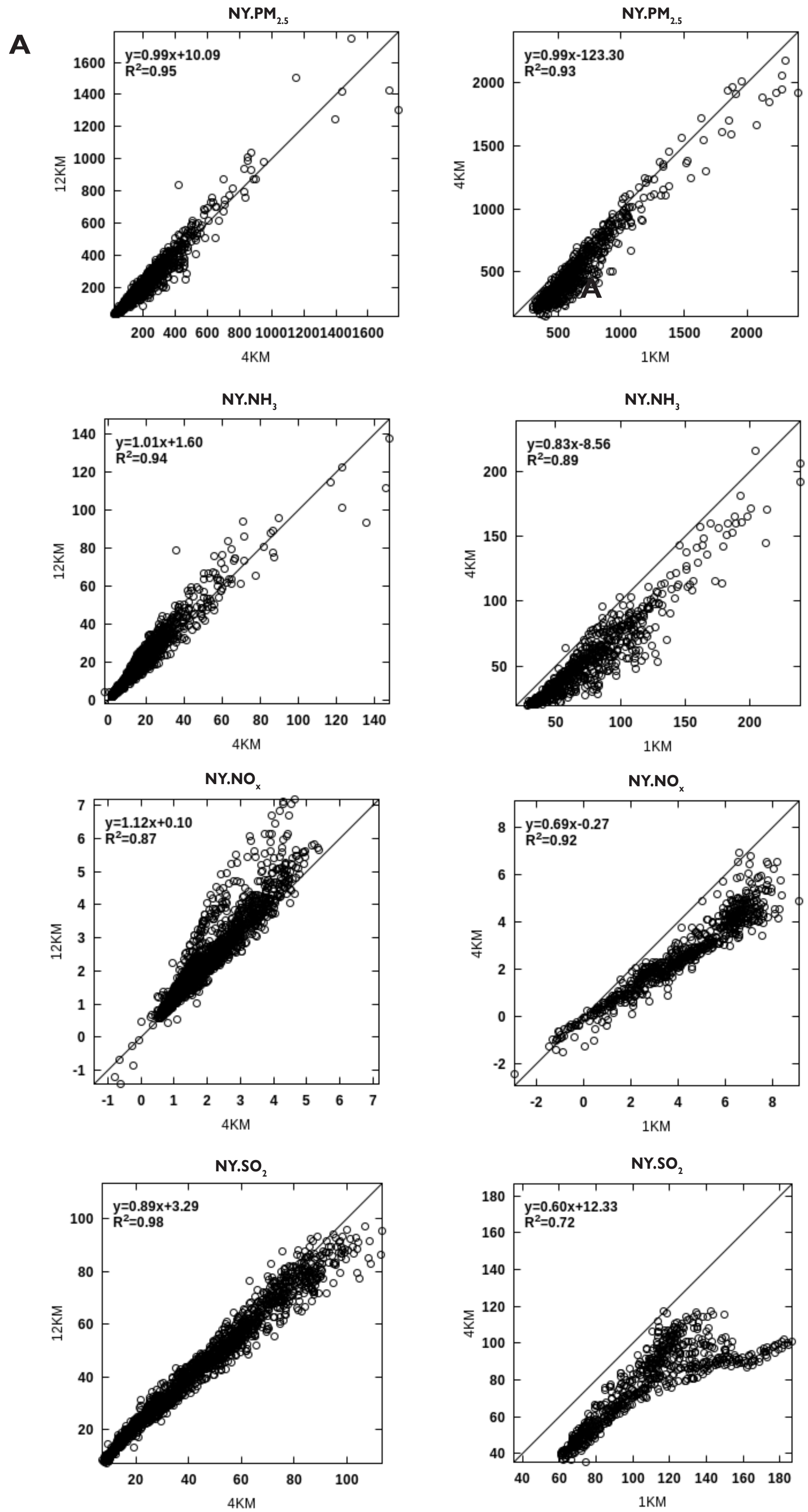


Figure 14. Comparison between 12- and 4-km (left panels) and 4- and 1-km (right panels) BPTs over (A) New York City; (B) Los Angeles. Comparisons are made between coarser resolution values (e.g., 4-km) and aggregated values from finer resolution (e.g., 1-km) into the coarser grid. (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0) (*continues next page*)

Figure 14 (*continued*). **Comparison between 12- and 4-km (left panels) and 4- and 1-km (right panels) BPTs over (A) New York City; (B) Los Angeles.** Comparisons are made between coarser resolution values (e.g., 4-km) and aggregated values from finer resolution (e.g., 1-km) into the coarser grid. (Adapted from Hakami et al. 2024; Creative Commons license CC BY 4.0)

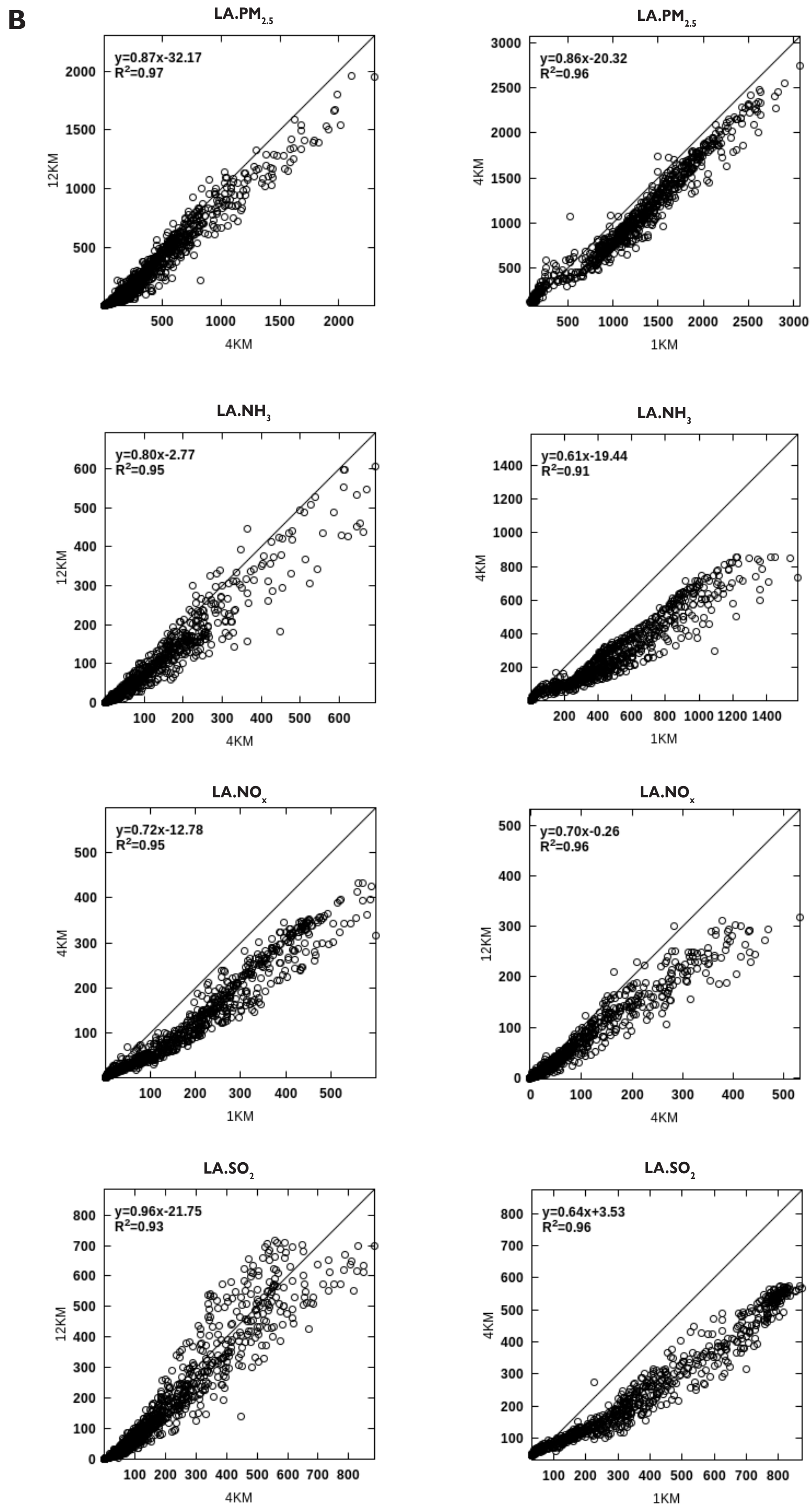


Table 3. Burden Estimates for the Los Angeles and New York City Domains at Various Resolutions (Hakami et al. 2024; Creative Commons license CC BY 4.0)

	Los Angeles ($ Billion)				New York City ($ Billion)			
Species	36 km	12 km	4 km	1 km	36 km	12 km	4 km	1 km
$PM_{2.5}$	21.6	21.1	25.3	29.6	12.1	18.4	17.3	19.3
NH_3	3.1	4.3	6.4	13.6	0.3	0.6	0.7	0.9
NO_x	2.7	5.1	8.3	13.7	0.2	0.1	0.1	0.2
SO_2	0.7	1.4	1.2	1.8	0.3	0.5	0.5	0.7
Total	28.0	31.9	41.2	58.7	12.9	19.6	18.7	21.1

increased errors. To evaluate the robustness of estimated BPTs across decadal changes in emissions and North American atmospheric composition, we estimated BPTs for past and future conditions. We conducted simulations for the years 2001 and 2028 for GEMM US BPTs and over two seasons (summer and winter). In these simulations, we use the same meteorology as 2016 to isolate the impact of changes in emission levels.

If the implied assumption of linearity in BPTs is justified, then BPTs should not change among different years. The nonlinearity in the response of population health to emissions (as captured by BPTs) stems from (1) nonlinearity in the CRF for GEMM, and (2) nonlinearity in atmospheric transformation processes. For primary pollutants such as primary $PM_{2.5}$ emissions, the main source of nonlinearity impacting its BPT is epidemiological nonlinearity. However, for inorganic aerosol precursors (SO_2, NH_3, NO_x), nonlinearity in chemistry and aerosol thermodynamic equilibrium is a much more significant source of nonlinearity. The nonlinearity in these transformation processes is largely caused by the change in the chemical state and composition of the atmosphere across North America from progressive changes in emissions.

Comparison of 2016 BPTs with those calculated with past and future inventories reveals interesting patterns (**Figure 15**, Appendix Figures A12, A13). Our findings are consistent with those from Holt and colleagues (2015) who found larger source impacts for SO_2 and NO_x, and a reduced source impact for NH_3 in lower emission cases. While there are notable differences between 2001 and 2016 BPTs, there is a much higher level of consistency between 2016 and 2028 estimates. This is expected as the change in North American emissions, and the resulting atmospheric composition, is larger in the 2001–2016 period than the modeled change during the 2016–2028 period. This is particularly true for changes in SO_2 emissions and concentrations that greatly affect the availability of NH_3 to combine with nitric acid to form aerosol nitrate. Of note, BPTs of primary $PM_{2.5}$ emissions and SO_2 (which typically has a near-linear oxidation pathway to sulfate) remained relatively stable among years 2001, 2016, and 2028, as they are mainly affected by the epidemiological nonlinearities. These BPTs increase with reducing $PM_{2.5}$ concentrations due to the sublinear or concave form of GEMM, resulting in increased BPTs in later years. In the case of SO_2, and particularly from 2001 to 2016, reduced SO_2 availability would also increase its conversion efficiency to sulfate due to reduced competition for oxidants (e.g., hydrogen peroxide in the aqueous phase). Reduced SO_2 availability greatly impacts nitrate formation, as NO_x becomes more likely to form nitrate in 2016 than 2001, resulting in larger NO_x BPTs. Overall, it appears that as the rate of change in atmospheric composition, and in particular SO_2 concentrations stabilizes into the future, BPTs would also become more robust estimates for future scenarios.

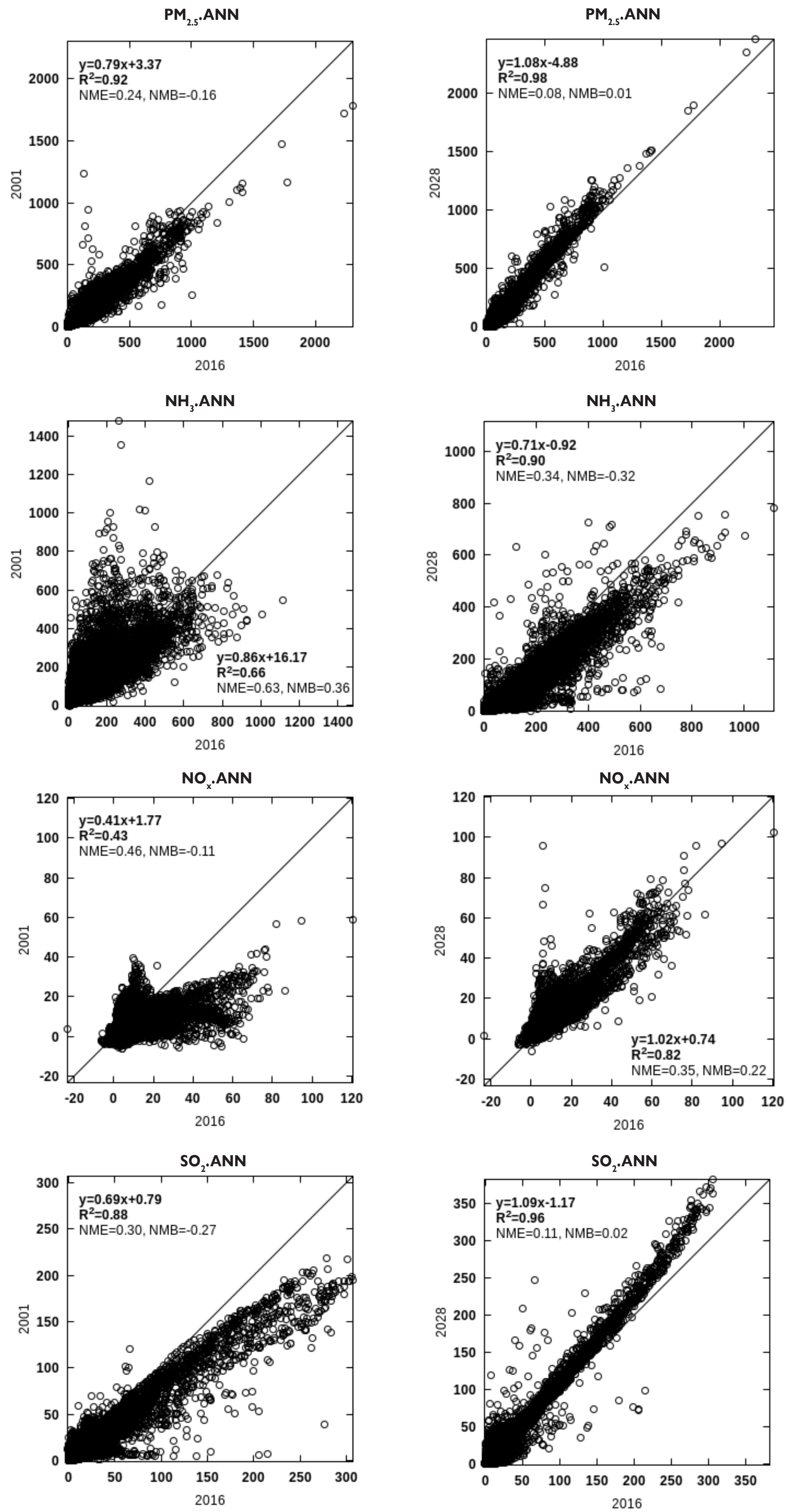
The qualitative uncertainty grade for inventory changes and variation of BPTs over time is *medium uncertainty, likely to diminish*.

COMPARISON WITH OTHER ESTIMATES

The most widely used estimates of BPTs for $PM_{2.5}$ chronic exposure mortality are from Fann and colleagues (2012). While our estimates appear to be consistent with the values reported therein, those nationwide and sectoral BPTs are not easily comparable to the location-specific BPTs calculated in this study. Instead we compared our BPT estimates to those generated by three reduced complexity models: Air Pollution Emission Experiments and Policy Analysis (APEEP, and its successor AP2) (Muller 2014), Estimating Air Pollution Social Impact Using Regression (EASIUR) (Heo et al. 2016a,b), and Intervention Model for Air Pollution (InMAP) (Tessum et al. 2017).

These three models take different approaches to reducing complexity and computational cost of source-impact estimations. APEEP/AP2 is the first model that has provided location-specific BPT estimations for the United States and draws its source–receptor relationship matrix from a dispersion model, augmented by additional linear terms for simplified particle chemistry. APEEP/AP2 provides BPTs at the county level for the contiguous United States. EASIUR is a regression-based model for location-specific source-impact estimation based on the Comprehensive Air quality Model with eXtensions (CAMx), a state-of-the-art air quality model equipped with various probing tools such as source apportionment. EASIUR uses CAMx simulations of source-apportioned contributions to $PM_{2.5}$ concentrations for a training

Figure 15. Comparison of 2016 BPTs with past (2001) and future (2028) simulations. (Hakami et al. 2024; Creative Commons license CC BY 4.0)



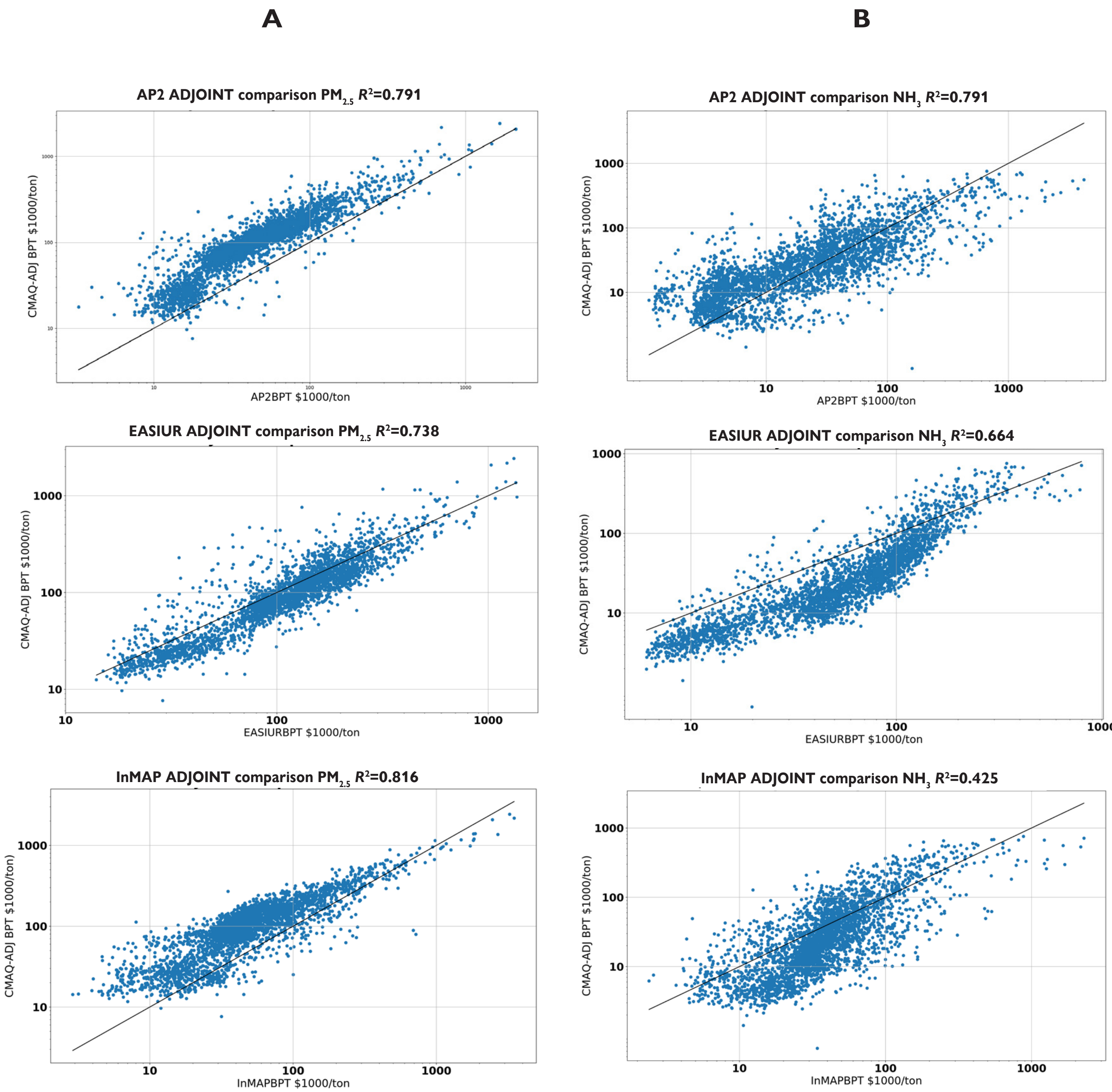


Figure 16. Comparisons between Adjoint and the AP2, EASIUR, and InMAP BPTs for emissions of (A) primary $PM_{2.5}$; (B) NH_3; (C) NO_x; and (D) SO_2. Note that plots are in log-scale (*continues next page*).

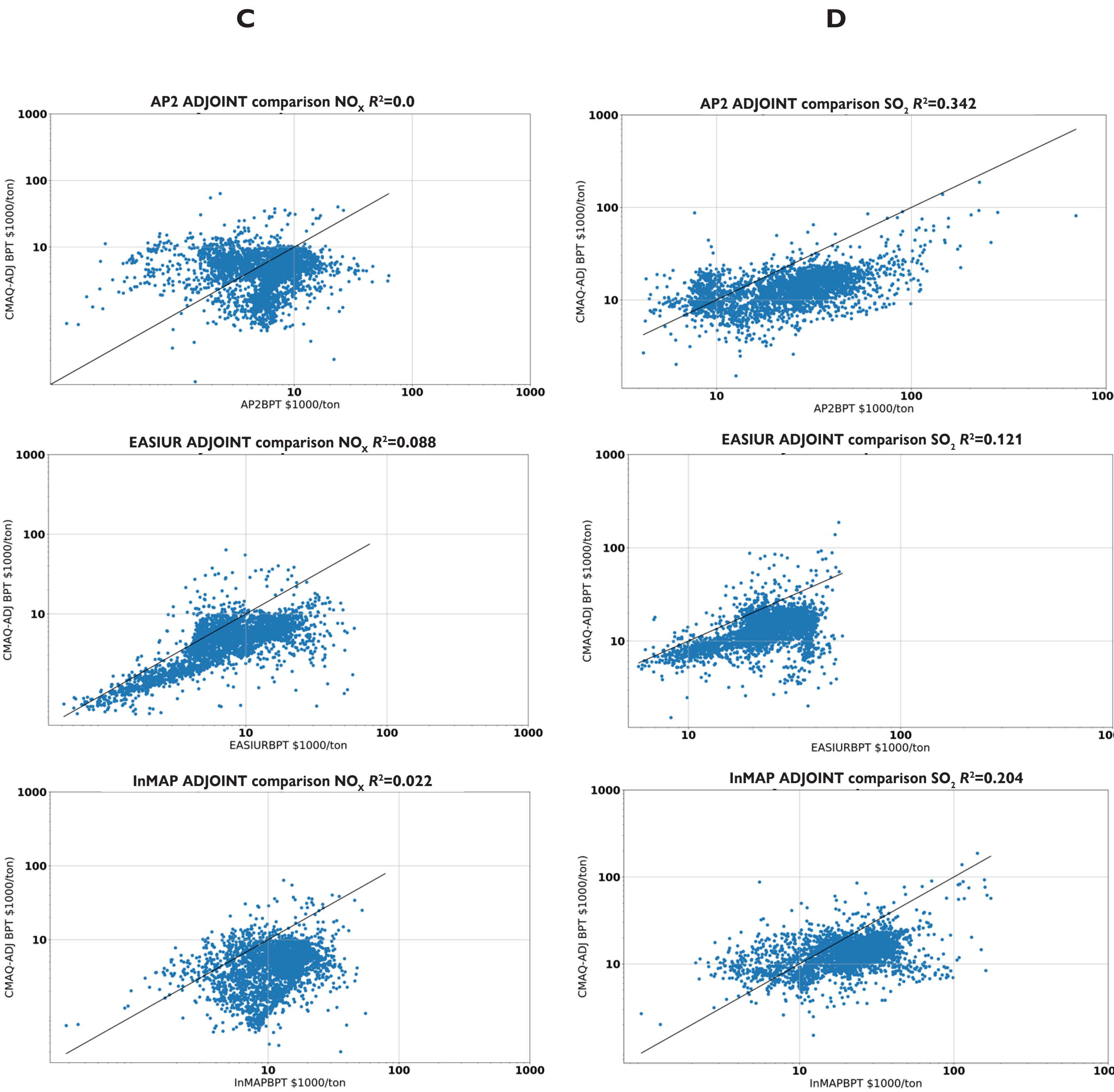


Figure 16 (*continued*). **Comparisons between Adjoint and the AP2, EASIUR, and InMAP BPTs for emissions of (A) primary $PM_{2.5}$; (B) NH_3; (C) NO_x; and (D) SO_2.** Note that plots are in log-scale.

Table 4. Comparison Statistics for BPT Estimates from the Adjoint and Reduced Complexity Models

Inter-model stats for $PM_{2.5}$					
R^2/RMSE	Adjoint	AP2	EASIUR	InMAP	AVG3
Adjoint		0.791	0.738	0.816	0.912
AP2	93.987		0.663	0.703	0.883
EASIUR	71.581	98.349		0.529	0.804
InMAP	84.467	100.475	125.390		0.890
AVG3	55.564	51.438	67.243	68.283	
Inter-model stats for NO_x					
R^2/RMSE	Adjoint	AP2	EASIUR	InMAP	AVG3
Adjoint		0	0.088	0.022	0.051
AP2	6.156		0.008	0.191	0.319
EASIUR	8.743	9.176		0.250	0.628
InMAP	10.269	8.653	7.828		0.747
AVG3	6.984	5.342	4.900	4.572	
Inter-model stats for SO_2					
R^2/RMSE	Adjoint	AP2	EASIUR	InMAP	AVG3
Adjoint		0.342	0.121	0.204	0.344
AP2	24.395		0.235	0.375	0.847
EASIUR	13.487	21.461		0.259	0.468
InMAP	16.354	19.351	12.943		0.707
AVG3	15.387	12.921	9.898	8.323	
Inter-model stats for NH_3					
R^2/RMSE	Adjoint	AP2	EASIUR	InMAP	AVG3
Adjoint		0.358	0.664	0.425	0.508
AP2	155.323		0.458	0.624	0.916
EASIUR	52.989	152.445		0.517	0.666
InMAP	81.951	123.971	76.139		0.834
AVG3	79.262	89.081	68.884	46.058	

[a]RMSE Values are in Thousand Dollars

dataset of 50 locations (tiered by population) at 36-km resolution — for the year 2005. InMAP uses a variable grid structure and generates annual average $PM_{2.5}$ concentrations for the contiguous United States by relying on a modified set of governing equations that are derived to simulate average conditions. In other words, InMAP does not follow evolution of pollutant concentrations in time; instead, it aims to simulate the average condition gathered from a CTM simulation for the year 2005.

BPTs from these three models are obtained for the year 2016 based on estimates developed by the Center for Air, Climate and Energy Solutions using AP2/EASIUR/InMAP models as described above. These estimates are provided at the county level, and for comparison, adjoint-based BPTs are also mapped to county-level estimates. All three reduced-complexity models use the CRF of Krewski and colleagues (2009), and therefore for this comparison we use the same CRF (ACS-09) for adjoint simulations rather than baseline GEMM estimates. Note that apart from methodology there are inherent differences among these models, such as the baseline simulation year, treatment of secondary inorganic species, and underlying meteorology and emissions.

For primary $PM_{2.5}$ emissions all models are in reasonable agreement, although the adjoint-based BPTs agree most with the EASIUR estimates (**Figure 16**). For precursor species the agreement between adjoint-based BPTs and the other models is poor, particularly for SO_2 and NO_x. In general, and apart from primary $PM_{2.5}$ BPTs, no two models show very strong correlation with each other (**Table 4**). This is in agreement with the findings of a previous scenario-based assessment of reduced complexity models (IEc 2019). Because InMAP provides BPTs at a variable grid resolution, we also compared adjoint-based BPTs with those of InMAP at 1-km resolution over Los Angeles for primary $PM_{2.5}$ emissions. While adjoint and InMAP BPTs show reasonable agreement for primary $PM_{2.5}$ BPTs at the county level, their BPT estimates at high resolution exhibit deteriorated agreement (**Figure 17**).

As discussed earlier, source-impact estimation is by definition a model construct that cannot be measured or observed, and therefore, relying on a clear benchmark for comparing different models is a challenging task. The relative agreement for primary $PM_{2.5}$ BPTs among all models suggests that they are equipped with tools to account for local impacts and near-source transport. However, longer-range transport and chemical/thermodynamic transformations appear to cause significant divergence among predictions of different models for precursor BPTs. Fully benchmarking and evaluating these estimates is beyond the scope of this study; however, it is reasonable to expect that as a

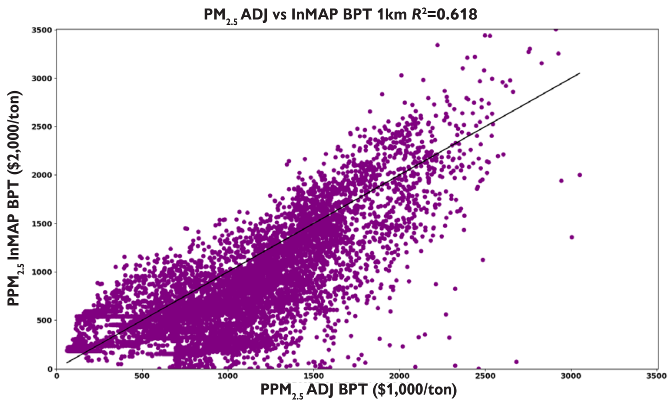


Figure 17. Comparison of InMAP and adjoint BPTs over the 1-km domain in Los Angeles.

full complexity model capable of accounting for nonlinear transformation processes, the adjoint model would be better equipped than the reduced-form models to delineate nonlinear responses to changes in emissions.

LIMITATIONS AND UNCERTAINTIES

In our sensitivity analyses we evaluated four potential sources of uncertainty. Among these sources, we found the epidemiological model uncertainty to be the most significant. The uncertainty in epidemiological modeling goes beyond the traditional statistical model uncertainty that is relatively well understood and characterized. We find large uncertainty exists due to the choice of epidemiological model and the inter-model and inter-cohort variability in the associated CRFs. Apart from the magnitude of the effect estimate, for the estimation of BPTs, the shape of CRF is also of significance. Linear, sublinear, and superlinear CRFs would result in different BPT estimates, even if they all provide the same HR for a certain concentration. Our BPT estimates were also based on a single-pollutant model. The use of a multipollutant CRF would add some complexity to BPT estimations, as similar precursors may affect various pollutants in the same multipollutant model. For example, NO_x BPTs, that are small for a single-pollutant $PM_{2.5}$ model, may become significantly larger for a multipollutant model that includes ozone and/or nitrogen dioxide (NO_2).

Our BPT and cobenefit estimates are based on chronic $PM_{2.5}$ exposure mortality, which is by far the most significant valuated population health burden of air pollution. Our analysis does not include ozone (and NO_2 for Canada). This would mainly affect BPTs of NO_x that can contribute to $PM_{2.5}$, and ozone (and NO_2) formation. Estimating ozone-based BPTs is a straightforward task but was not undertaken in this study due to the focus on $PM_{2.5}$, as well as computational limitations.

A significant but currently unavoidable limitation in our estimated BPTs is the use of mass-based CRFs that do not distinguish among the health impacts of different PM constituents. This implied assumption of equal toxicity for all $PM_{2.5}$ constituents can have important implications, as the epidemiological models and estimates may mischaracterize the population health burden and consequently result in placing the source impact in the wrong pollutant or sector. This limitation becomes more important if our policies and regulations continue to have a strong sectoral structure, as various source sectors are likely to have differing associated particle compositions.

Apart from epidemiological model uncertainty, we find that episodic simulations of BPTs are likely to introduce only low levels of uncertainty if the episodes are chosen carefully and in a data-driven manner. We also find that 12-km resolution, while not resolving neighborhood-level details, provides results that are consistent with those at higher (4-km) resolutions. Therefore, we believe that our estimated BPTs are useful for most applications at national, regional, or local scales. We also show that while BPTs have changed with progressive reduction in emissions, present-day BPTs are unlikely to change significantly in the near future (i.e., next decade) due to the changes in inventory level.

There are other, potentially important sources of uncertainty that our study did not consider. We did not evaluate CTM simulation uncertainties. While the adjoint model is comprehensively evaluated and is shown to be consistent with its underlying model, the CMAQ model predictions are subject to various uncertainties. These uncertainties include those stemming from emission inventories, allocation of emissions in time and space, model representation of physical and chemical processes, meteorological modeling, and numerical inaccuracies. While all these uncertainties contribute to the overall uncertainty in the estimated BPTs, emission inventory and emission allocation uncertainty are likely to be chief among factors affecting model uncertainty. As detailed estimates of emission uncertainties are not available, formal and appropriate uncertainty analysis remains a challenge for air quality modelers. Furthermore, while our episodic simulations appear to provide representative BPTs, our study was conducted for a single year and does not capture interannual variability in atmospheric conditions. Zhang and colleagues (2018) estimate that interannual variability contributes only slightly to variation in $PM_{2.5}$ population health burden. However, the impact of interannual variability may be more pronounced at the regional levels. Finally, we did not consider uncertainties in economic valuation parameters such as VSL or discount rate used in cessation lag, nor did we employ nonfatal valuation metrics to account for these outcomes.

Better characterization of associated uncertainties should be considered a priority for future research. When expressed as cobenefits, BPTs provide a powerful tool for coordinating climate and population-health policies. An extension of source-impact estimation to environmental justice metrics is a logical future direction. While our BPT estimates appear to be robust with regard to the spatial resolution for the assessment of the aggregate burden, inclusion of environmental justice considerations would require higher-resolution simulations. Overall, while our BPT estimates are based on the state-of-the-science methodology and tools, they are estimated in the presence of a wide array of uncertainties, the quantification of which is a worthwhile undertaking for future studies.

CONCLUSIONS

The adjoint model provides a unique approach for the estimation of location-specific source impacts within a full-complexity modeling framework. Location-specific BPTs and cobenefits, as estimated by the adjoint model, show a great deal of spatial variability, and therefore can be used in guiding targeted emission-control policies. In particular, cobenefit estimates are substantial for sectors such as off-road engines and diesel heavy-duty vehicles, and in most urban locations far exceed estimates of the social cost of carbon. Within the decarbonization context, these cobenefits can offer valuable information for harvesting significant population health benefits from decarbonization policies.

We find that location-specific BPT estimates are consistent within our study design and across various model resolutions. While higher spatial resolutions provide locally larger BPTs, a high degree of consistency exists in the overall burden estimates. Among various sources of uncertainty, we find that epidemiological uncertainties, particularly those in the choice and form of the concentration–response functions, are likely to contribute most significantly to the overall uncertainty in BPT estimates. Our sensitivity analyses also suggests that BPT estimates are likely to become more stable over time as changes in emission levels and atmospheric composition in North America become less significant.

PROJECT ASSETS

The detailed data for BPT and cobenefits can be found at: *https://doi.org/10.5683/SP3/DTS44O*.

ACKNOWLEDGMENTS

The authors thank Dr. Daniel Tong for providing 1-km CMAQ-ready emissions for Los Angeles and New York.

All simulations for this study were conducted on computational resources of Compute Canada.

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HEI QUALITY ASSURANCE STATEMENT

The conduct of this study was subjected to an independent audit by Mr. David Bush and Dennis Mikel of Trinity Consultants, Inc. Mr. Bush and Mr. Mikel are experts in quality assurance for air quality monitoring studies and data management. The audit included a review of data quality for conformance to the study protocol as detailed in the final report and the study's quality assurance plan. The date of the audit is listed in the table below along with the phase of the study examined.

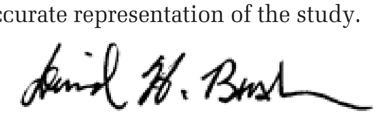
QUALITY ASSURANCE AUDITS

Date: October 2023

Phase of Study

The final report was reviewed, including verification of data quality for each of the study components. An off-site audit was conducted via a teleconferencing platform with primary study personnel. The audit concentrated on the study's data management activities and included a review of the overall process utilized to manage and combine the air quality, meteorology, emissions, and modeling data. Also evaluated were the procedures and measures undertaken to ensure quality and consistency in the processed databases and modeling results. Examples of data sets for the different types of data and modeling files were displayed by study personnel and reviewed for consistency, clarity, and completeness.

Written reports of the audit were provided to the HEI project manager, who transmitted the findings to the Principal Investigator. The quality assurance audit demonstrated that the study was conducted by an experienced team with a high concern for data quality. Study personnel were responsive to audit recommendations, providing formal responses that adequately addressed all issues. The report appears to be an accurate representation of the study.



David H. Bush, Quality Assurance Officer

SUPPLEMENTARY APPENDICES ON THE HEI WEBSITE

Appendices A and B contain figures not included in the main report. They are available on the HEI website at *www.healtheffects.org/publications*.

Appendix A: BPTs

Appendix B: Cobenefits

ABOUT THE AUTHORS

Amir Hakami is an associate professor in the department of civil and environmental engineering at Carleton University in Ottawa, Canada. His research focus is on the development of sensitivity analysis tools and models in CTMs, and the use of such tools and models in decision support for applications related to air pollution policy, population health, air pollution economics, and environmental justice. Dr. Hakami received his PhD from Georgia Institute of Technology and completed postdoctoral studies at Caltech before joining Carleton. He was the lead investigator for the development of an adjoint version for the US EPA's CMAQ model and is the principal investigator for this study.

Shunliu Zhao is a research associate at Carleton University's department of civil and environmental engineering. His research focuses on developing and using numerical tools for sensitivity analysis in air quality models. The results of his research have shed light on the impact of emissions on population health and environmental inequalities, as he aims to help policymakers make cost-effective control strategies. Dr. Zhao has a PhD in Mechanical Engineering from the University of Akron and is the lead developer for CMAQ v5.0 Adjoint.

Marjan Soltanzadeh is a PhD student in the environmental engineering program at Carleton University. Her research focuses on estimation of adjoint-based, location-specific cobenefits, and she contributed to this study with calculations of sectoral cobenefits and per-vehicle burden estimates.

Petros Vasilakos is a scientist at the Paul Scherrer Institute in Villigen, Switzerland. At the time of the project's completion, he was a postdoctoral scholar at the Georgia Institute of Technology. He has worked extensively with CTMs and advanced sensitivity tools, looking at the interactions between biogenic and anthropogenic emissions and how aerosol formed through these processes contributes to particulate matter. He has applied this expertise on a variety of first principle and policy-oriented projects, including aerosol formation under acidic conditions, future emission reduction scenarios, and prescribed burns. Dr. Vasilakos earned a PhD in chemical engineering from the Georgia Institute of Technology and a diploma in chemical engineering from the National Technical University of Athens.

Anas Alhusban is a PhD student in the environmental engineering program at Carleton University. His research interests include health impacts of air pollution, source attribution, high-resolution air pollution modeling and forecasting. He has worked on several air quality modeling projects. He graduated from Jordan University of Science and Technology with a BSc in civil engineering and a master's degree in environmental engineering from University of Putra Malaysia. He contributed to high-resolution modeling in this study.

Burak Oztaner is a PhD student in the environmental engineering program at Carleton University. His research focuses on quantification of source–receptor relationships at regional-to-hemispheric scales. He contributed to the study with emission modeling and postprocessing of simulation results.

Neal Fann serves in the Office of Air and Radiation of the US EPA, where he began working as a Presidential Management Fellow after graduating from the Sanford School of Public Policy in 2003. In the US EPA he has developed extensive experience in quantifying and characterizing the human health impacts, and monetized benefits, of changes in criteria and toxic air pollution. In this role, he has performed technically complicated and policy-relevant benefits assessments in support of major US EPA regulatory actions including the Cross-State Air Pollution Rule and the Mercury and Air Toxics Rule, among many others. His work informs US air quality management policy, most recently for a recent rule governing emissions from electrical generating units. Neal also makes contributions to the academic literature, recently publishing a national assessment of the public health burden of recent levels of fine particles and ground-level ozone in the United States and a proof-of-concept approach for maximizing the public health benefits of air quality improvements while achieving a more equitable distribution of risk.

Howard H. Chang is a professor of biostatistics and environmental health (secondary appointment) at Emory University Rollins School of Public Health. His research interests focus on the development and application of statistical and computational methods for analyzing complex spatial–temporal exposure and health data. Dr. Chang has led or co-led multiple NIH projects that utilize large health databases (e.g., birth and death certificates, hospital billing records, electronic health records and disease surveillance systems) to conduct population health studies. He also has collaborative experience in air quality modeling, environmental and social epidemiology, disease ecology, and climate science. He has served on the editorial board of the *Journal of the American Statistical Association*, the NIEHS-chartered grant proposal review panel, and the external advisory committees of environmental health research projects.

Alan Krupnick is a senior fellow at Resources for the Future and an expert on cost-benefit analysis of reducing GHG emissions from the oil and gas and other industrial sectors. Dr. Krupnick's recent research focuses on green public procurement, decarbonized hydrogen and tax credits, and developing markets for green natural gas. His portfolio also includes guiding the value-of-information agenda covered by our VALUABLES initiative with NASA, the valuation of reducing asthma risks, estimating the VSL, and issues of regulatory reform. He served as senior economist on the President's Council of Economic Advisers, advising the Clinton administration on environmental and natural resource policy issues. In 2011, he was elected President of the Association of Environmental and Resource Economists (AERE) and earlier that year was named an AERE Fellow.

Armistead (Ted) Russell is the Howard T. Tellepsen Chair and Regents' Professor of Civil and Environmental Engineering at Georgia Institute of Technology, where his research is aimed at better understanding the dynamics of air pollutants at urban and regional scales and assessing their impacts on health and the environment to develop approaches for design strategies that would effectively improve air quality. He earned his MS and PhD degrees at the California Institute of Technology, conducting his research at Caltech's Environmental Quality Laboratory; his BS is from Washington State University. Dr. Russell was a member of the US EPA's Clean Air Science Advisory Committee (CASAC) and a member of the National Research Council's Board on Environmental Studies and Toxicology. He has served on and chaired multiple National Academies of Sciences, Engineering, and Medicine committees, most recently the committee for Assessing Causality from a Multidisciplinary Evidence Base for National Ambient Air Quality Standards. He chaired the CASAC NO_x–SO_x, Secondary National Ambient Air Quality Standard review panel, the Ambient Air Monitoring Methods Subcommittee and the Council on Clean Air Compliance Analysis' Air Quality Modeling Subcommittee.

OTHER PUBLICATIONS RESULTING FROM THIS RESEARCH

Hakami A, Zhao S, Vasilakos P, Alhusban A, Oztaner YB, Krupnick A, etc. 2024. Spatiotemporally detailed quantification of air quality benefits of emissions reductions – part II: Sensitivity to study parameters and assumptions. Environ Sci Technol Air [ahead of print]; *https://pubs.acs.org/doi/10.1021/acsestair.4c00128*.

Zhao S, Vasilakos P, Alhusban A, Oztaner YB, Krupnick A, Chang H, et al. In press. Spatiotemporally detailed quantification of air quality benefits of emissions reductions – part I: Benefit-per-tonne estimates for Canada and the US. Environ Sci Technol Air.

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COMMENTARY
Review Committee

Research Report 218, *Estimating Model-Based Marginal Societal Health Benefits of Air Pollution Emission Reductions in the United States and Canada*, A. Hakami et al.

INTRODUCTION

Particulate matter (PM*) is an air pollutant that is a mixture of organic (e.g., carbon-containing) and inorganic microscopic particles and liquid droplets suspended in the air. Anthropogenic PM can be emitted directly from point (e.g., smokestacks) and mobile (e.g., vehicle exhaust) sources, in which case it is referred to as a primary PM emission. PM can also form by atmospheric gas-to-particle conversion of pollutants such as ammonia (NH_3), nitrogen oxides (NO_x), and sulfur dioxide (SO_2), and is referred to as a secondary PM. Due to its ubiquity and links to human health, PM is commonly used as a proxy for overall air quality (World Health Organization [WHO] 2022).

Size determines how far a particle can reach the respiratory tract and influences what health effects can result from exposure. Fine particles (PM ≤2.5 µm in aerodynamic diameter, or $PM_{2.5}$) and chemical compounds attached to the particle surface can deposit deep within the lungs and directly enter the bloodstream (Li et al. 2022). Even at relatively low exposure levels, PM is associated with a myriad of adverse health effects — including respiratory and cardiovascular diseases — and is recognized as a leading risk factor for morbidity and mortality worldwide (GBD 2020; IARC 2016; US EPA 2019). The substantial body of evidence has led the United States Environmental Protection Agency (US EPA) to conclude that the link between exposure to $PM_{2.5}$ and mortality is causal (US EPA 2019).

Beyond explicit health effects, air pollution has numerous social and economic costs to society, including increased healthcare expenditures and reduced productivity resulting from air pollution-induced chronic diseases, disability, and death (Alexeeff et al. 2022; Pandey et al. 2021; US EPA 2011). Air pollution also can decrease road and scenic visibility and decrease agricultural yields (US EPA 2011). Furthermore, carbon dioxide (CO_2), a potential driver of global climate change, is frequently co-emitted with anthropogenic air pollutants (Orru et al. 2017). Accordingly, research suggests that air pollution reductions can have a multitude of benefits to society, even in regions with air pollution levels below current regulatory standards (Meng et al. 2021; Schraufnagel et al. 2019; Tschofen et al. 2019; US EPA 2011). However, research evaluating the costs and benefits of air pollution emissions reductions has been limited by computational challenges associated with accurate modeling and characterization of uncertainty. Thus, prior studies often applied unrealistic assumptions and simplifications.

To estimate the monetary health benefits associated with reducing emissions from transportation and other selected sources, Dr. Amir Hakami of Carleton University submitted an application to HEI titled "Quantifying marginal societal health benefits of transportation emission reductions in the United States and Canada" in response to HEI's Request for Applications RFA 17-2, Health Effects of Air Pollution. This RFA provided a mechanism for investigators whose area of interest broadly centered on novel and important aspects of the health effects of air pollutants, particularly those derived from motor vehicle emissions. Dr. Hakami and colleagues proposed to apply a novel extension to the US EPA's Community Multiscale Air Quality model (CMAQ) that they had developed to improve the way health benefits were estimated and then create a database of these benefits for specific locations and emissions sources in the United States and Canada. The health benefits estimates would be based on a method of monetizing premature mortality from long-term $PM_{2.5}$ exposure. They also proposed to estimate the climate change cobenefit of reduced emissions by quantifying the reduction in co-emitted CO_2. HEI funded the study because it would improve upon a state-of-the-art air quality model and apply the most recent emissions inventories to estimate the benefit of cutting emissions for different geographic locations, while also addressing many modeling concerns with sensitivity analyses. The study also offered an approach that fits well under the broader umbrella of HEI's accountability research program, which evaluates the effectiveness of air pollution reduction policies aimed at improving air quality and public health.

This Commentary provides the HEI Review Committee's independent evaluation of the study. It is intended to aid the sponsors of HEI and the public by highlighting both the strengths and limitations of the study and by placing the Investigators' Report into scientific and regulatory perspective.

Dr. Amir Hakami's 3-year study, "Quantifying Marginal Societal Health Benefits of Transportation Emission Reductions in the United States and Canada," began in October 2018. Total expenditures were $399,417. The draft Investigators' Report from Hakami and colleagues was received for review in October 2022. A revised report, received in April 2023, was accepted for publication in June 2023. During the review process, the HEI Review Committee and the investigators had the opportunity to exchange comments and clarify issues in both the Investigators' Report and the Review Committee's Commentary.

* A list of abbreviations and other terms appears at the end of this volume.

SCIENTIFIC AND REGULATORY BACKGROUND

REGULATING AIR POLLUTION IN THE UNITED STATES AND CANADA

Air pollution in the United States is regulated by the Clean Air Act, which sets allowable concentrations, known as National Ambient Air Quality Standards (NAAQS), for major pollutants including PM, NO_x, and SO_2. To attain the NAAQS, federal- and state-level policies are adopted to control air pollutant emissions from large stationary sources like power plants or mobile sources like cars and trucks by mandating fuel changes, requiring installation of control technologies, or capping total or facility-specific emission rates. In Canada, air quality policy is broadly directed by the Canadian Environmental Protection Act of 1999. A multistakeholder council recommends nonlegally binding Canadian Ambient Air Quality Standards (CAAQS), which are voluntarily adopted by states and territories. Air quality is actively managed to achieve the CAAQS by individual air zones (Canadian Council of Ministers of the Environment [CCME]) 2021).

Although air pollution levels have declined in high-income countries over the past few decades, health impacts continue to be seen at levels at and below current air quality standards (Brauer et al. 2019, 2022; Brunekreef et al. 2021; Chen and Hoek 2020; Dominici et al. 2019, 2022). Accordingly, the WHO revised its air quality guidelines (WHO 2021), and some governmental agencies, such as the US EPA, have lowered the regulatory standard for $PM_{2.5}$ (US EPA 2024b). These agencies continue to review the scientific evidence to evaluate the need for even lower standards. Alternatively, future regulations could focus on specific sources of emissions or particular components or fractions of PM to optimize health benefits (Henneman et al. 2023; Kwon et al. 2020; McDuffie et al. 2021).

EVALUATING THE COSTS AND BENEFITS OF AIR POLLUTION REGULATIONS

The US EPA is mandated to evaluate the costs and benefits of the Clean Air Act and any regulation considered to be economically significant or innovative. To date, the US EPA has released one retrospective (US EPA 1997) and two prospective (US EPA 1999, 2011) studies of the benefits of the Clean Air Act relative to its costs. The US EPA has also released regulatory impact analyses (RIAs) that estimate the expected costs and benefits of numerous individual rules and their alternatives proposed under the Clean Air Act. RIAs generally compare expected future scenarios with and without regulation (or different versions of the regulation) to assess whether the proposed rules are likely to be cost effective and meet their stated goals. They consider such factors as implementation and compliance costs and the projected changes in air quality, health outcomes, and nonmonetary effects.

The US EPA uses estimates of avoided mortality, hospital admissions, and other outcomes — and economic assumptions about the value of those avoided outcomes — to characterize the monetary benefits of improved health from the regulation or intervention. The monetary benefits are calculated using a metric called benefits-per-ton (BPT, see Sidebar). As an illustration, the US EPA's recently completed RIA estimated the net benefit of lowering the $PM_{2.5}$ NAAQS from 12 to the current standard of 9 μg/m³ in 2032 to be $22 billion (US EPA 2024a). In response to climate change concerns, the US EPA may also examine the additional benefits of decreased CO_2 emissions that result from proposed controls on other pollutants that are emitted simultaneously (US EPA 2022). Canada also conducts similar analyses (Health Canada 2022).

BPT estimation has historically been conducted in a two-step process by first linking health benefits with changes in ambient air pollutant concentrations using such tools as the US EPA's Environmental Benefits Mapping and Analysis Program (BenMAP) or Health Canada's Air Quality Benefits Assessment Tool (AQBAT) and then linking the outputs to emissions grouped by source or location using separate air quality modeling (Judek et al. 2012; US EPA 2023). Although some advances in modeling approaches have been developed in recent years, they often rely on unrealistic modeling assumptions and simplifications such as ignoring secondary PM formation. Hakami and colleagues integrated BPT estimation by directly linking the health benefits to a wide array of individual source- and location-specific pollutant emissions using an adjoint extension of CMAQ (CMAQ-ADJ). The CMAQ model is among the most widely used computer models for simulating the quantity, chemical, and physical transformation, and the geographical transport of numerous pollutants in the atmosphere over time (US EPA 2012).

To what extent have regulations achieved their intended goals in reducing emissions, air pollution concentrations, and adverse health impacts? These are questions that accountability research attempts to answer. Over the past two decades, HEI has emerged as a leader in air pollution accountability research, contributing to research design, funding, and study oversight. In 2003, an HEI working group developed a conceptual framework for conducting air pollution accountability research and outlined methods and opportunities for future research (HEI Accountability Working Group 2003). See the Preface for more details about HEI's involvement in accountability research. Through a series of RFAs over the past two decades, HEI has now funded 23 studies that have assessed a wide variety of regulations targeting both point and mobile sources of air pollution, the indirect effects of the COVID-19 lockdowns on air quality, and the development of methods to assist in environmental justice policy. The study by Hakami and colleagues uniquely contributes to the accountability research program by analyzing economic factors and estimating BPTs using current data to shape future policy. Additionally, it examines past emissions data to estimate the observed benefit of the Clean Air Act over a 15-year period.

Estimating Societal Benefits

Hakami and colleagues evaluated the health benefits of reduced emissions using the **BPT** metric, which combines economic valuation, epidemiology, and pollutant information. In this study, the BPT metric specifically estimated the annual monetary cost of a reduced mortality risk from long-term $PM_{2.5}$ exposure in dollars for every 1 ton of emissions reduction (see equation).

$$BPT\left(\frac{\$}{1\ ton\ emissions}\right) = VSL\left(\frac{\$}{death}\right) \times CRF\left(\frac{deaths}{\Delta PM_{2.5}}\right) \times \frac{\Delta PM_{2.5}}{\Delta source\ emissions}$$

The monetary cost of a reduced mortality risk is known as the **value of a statistical life (VSL)** and is the first term on the right-hand side of the equation. Importantly, VSL is not the value placed on a person's life nor does it represent the loss in economic productivity associated with a premature death. VSL is a theoretical concept that measures the collective societal demand to forgo the consumption of goods and services to reduce associated health risks and is used by governments for cost-benefit analyses (Colmer 2020). For example, a policy might be expected to reduce the risk of death by 0.001%, or 1 averted death per 100,000 people. If people are willing to pay $10 on average for that risk reduction, then collectively, society would incur a cost of $1 million to save one statistical life.

The second term in the BPT equation, **concentration–response function (CRF)**, is the estimated association between $PM_{2.5}$ exposure and death derived from published epidemiological studies. The final term in the equation represents the relationship between the source emissions and the ultimate time- and location-specific $PM_{2.5}$ exposure reductions (Δ denotes the difference in $PM_{2.5}$ concentrations or source emissions over the study period) and is estimated by the adjoint CMAQ simulations.

SUMMARY OF APPROACH AND METHODS

STUDY AIMS AND APPROACH

To estimate the societal benefits associated with reducing emissions from transportation and other select sources, Dr. Hakami and colleagues aimed to accomplish the following:

- Estimate location-specific BPTs associated with certain emissions sectors throughout the United States and Canada and create a publicly available database of the location-specific BPTs.
- Evaluate the robustness of the BPT estimates using sensitivity analyses of
  - the spatial resolution of the adjoint model simulations
  - the effect of estimating annual BPT estimates based on selected representative time periods
  - the emissions levels in the United States as affected by past and future controls
  - the choice and form of the epidemiological CRFs.
- Estimate the cobenefits of reduced combustion-based CO_2 emitted from transportation sources and other select sectors.

Hakami and colleagues sought to create a BPT database that could be used by decision-makers to develop air pollution control policies that would result in the greatest health benefits to society. To achieve this goal, they further developed a novel extension to CMAQ. CMAQ-ADJ enabled the investigators to estimate BPTs by seamlessly linking data from recent large-scale epidemiological studies back to the original pollutant emissions in backward simulations. CMAQ-ADJ also allowed for detailed sensitivity analyses to assess the robustness of the results. BPTs of reduced 2016 emissions of NH_3 and criteria pollutants $PM_{2.5}$, NO_x, and SO_2 were calculated.

METHODS AND STUDY DESIGN

Hakami and colleagues developed the CMAQ-ADJ and have extensively validated and applied the model (Hakami et al. 2007; Zhao et al. 2020). CMAQ-ADJ accounts for complex atmospheric processes, including advection and diffusion in horizontal and vertical space; gas-phase chemistry; cloud processes; aerosol formation, growth, aging, and thermodynamics; and dry and wet deposition. Detailed information on pollutant emissions data came from the 2016 Emissions Inventory Platform, beta version (National Emissions Inventory Collaborative 2019) and the MOtor Vehicle Emission Simulation–version 3 (MOVES3) (US EPA 2021), which contains detailed inventories for emissions from point, nonpoint, and on-road sources. Model simulations were conducted for the contiguous United States and most of Canada (inclusive of ≥ 97.3% of the Canadian population) using 2016 meteorology, and they accounted for cross-border effects. The analysis included daily 2016 emissions of primary $PM_{2.5}$, NO_x, SO_2, and NH_3, and covered emissions from both ground-level and elevated sources.

Hakami and colleagues applied 2016 inflation-adjusted VSLs published by the Government of Canada and the US EPA of $7.5 million CAD and $10.2 million USD, respectively (Chestnut and De Civita 2009; US EPA 2010), with other recommended time-lag adjustments. Population data were linked at the census-tract level. The CRF selected for the primary analyses was derived from the Global Exposure Mortality Model (GEMM) because it incorporated 41 cohorts from 16 countries and a range of $PM_{2.5}$ exposures, and it could be applied to both the United States and Canada (Burnett et al. 2018). The BPTs along with the level of emissions were used to estimate the total burden of each pollutant. Because of their location specificity, adjoint-based BPTs do not have strong sectoral signatures, so BPTs were reported for different source elevations with no designation to any specific sector.

Because reducing combustion-related pollutant emissions can simultaneously reduce CO_2 emissions, the authors also estimated the cobenefit-per-ton of CO_2 using the relative emissions profiles of copollutants for each sector. Unlike the BPTs, cobenefits exhibit strong sectoral differences and were evaluated by 60 different sectors and vehicle or engine types (e.g., on-road, off-road, gasoline, diesel, passenger, industrial, construction, goods movement, agricultural, lawn and garden, and recreation). Because targeted replacement of certain gasoline or diesel vehicles with electric vehicles would require evaluation of local electricity production, the authors also evaluated cobenefits associated with natural gas and coal electricity-generating units.

Sensitivity Analyses of the Adjoint CMAQ Model

Spatial resolution and representative time periods The CMAQ-ADJ model is computationally demanding, even on powerful supercomputers, necessitating a trade-off between the length of the simulated time period and the spatial resolution. The investigators first simulated the annual BPTs at 36-km resolution using hourly emissions for the contiguous United States and most of Canada. To allow for a finer spatial scale, they then selected representative time periods. Two-week periods were simulated for each season at 12-km resolution, and thus annual estimates were derived from eight representative weeks. The periods were selected separately for the United States and Canada (**Commentary Figure 1**) by using bias functions to identify the two-week periods most representative of the seasonal average and most consistent with the 36-km modeling. To evaluate any differences at an even finer spatial scale, Hakami and colleagues simulated summertime BPTs for Los Angeles, California, and New York City, New York, using hourly emissions within the selected 2-week episode at 4-km and 1-km resolutions.

CRF selection The selected CRF is a key component of BPT calculations by providing information on estimated mortality for a given change in $PM_{2.5}$ exposure (see Sidebar). To evaluate how the selected CRF would affect BPT estimates, Hakami and colleagues compared the primary-selected CRF reported by the GEMM (Burnett et al. 2018) in the United States to four alternative CRFs reported by high-quality epidemiological studies with large cohorts — two from the American Cancer Society Cancer Prevention Study II (Krewski et al. 2009; Turner et al. 2016), one from the National Health Interview Survey (NHIS) (Pope et al. 2019), and one from a recent meta-analysis (Chen and Hoek 2020). Although the studies used the same cohort, Krewski and colleagues (2009) was included because it is widely used in health impact assessments, and Turner and colleagues (2016) was included because it applied improved methods for CRF estimation. For the United States, Hakami and colleagues calculated the mean BPTs from all five CRFs and estimated the variation.

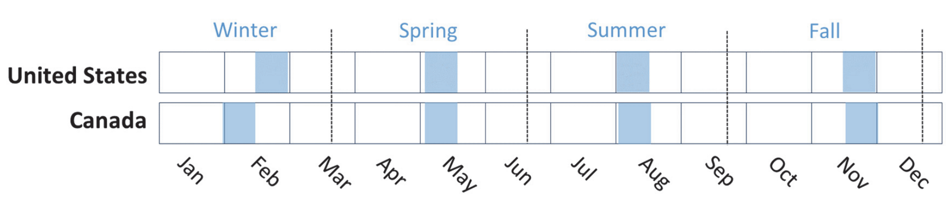
Emissions levels The primary analysis applied 2016 emissions data, which was the most recent data available at the time. To evaluate changes in the BPT estimates by large-scale changes in emissions, Hakami and colleagues also simulated the selected summer and winter time periods using available emissions data from 2001 and emissions projections for 2028. The selected years were chosen because that is when the national emissions inventories were available.

The authors conducted these sensitivity analyses and qualitatively rated the level of uncertainty from spatial resolution, time period selection, CRFs, and emissions levels as low, medium, and high. They also compared the BPT estimates to those of three other reduced complexity models (Muller 2014; Heo et al. 2016a,b; Tessum et al. 2017).

SUMMARY OF KEY FINDINGS

BENEFITS OF EMISSIONS REDUCTIONS

BPT estimates for the United States and Canada are mapped in **Commentary Figures 2** and **3**, respectively; note that BPT scales differ by pollutant and show cross-border effects. The BPTs represent the societal benefit of reducing emissions at a specific location and as such do not provide exact information on where the health benefits will be realized. For both countries, BPTs were largest for primary $PM_{2.5}$, followed by NH_3. SO_2 and NO_x were much smaller. BPTs were generally higher in the eastern half of the United States, with the highest levels near large cities, particularly in the northeast and California. However, BPTs were more uniform across the United States for SO_2 except for California where BPTs were highest. Note also that BPTs can be lower than expected in high pollution areas because the impact from incremental increases in emissions would be trivial, whereas BPTs can be elevated in low emission and uninhabited areas due to secondary $PM_{2.5}$ formation that can affect health elsewhere. Due to the complex atmospheric chemistry of PM precursors, BPTs can also be negative in exceptional circumstances where secondary PM formation dominates. The authors reported that



Commentary Figure 1. Two-week season- and country-specific time periods in 2016 selected for CMAQ-ADJ model simulation at 12-km resolution.

BPTs for primary $PM_{2.5}$ were relatively stable across seasons, whereas variability was observed across seasons for precursor emissions due to the influences of temperature and humidity.

Considering BPTs and cumulative domestic emissions, Hakami and colleagues estimated that the total burden of all primary $PM_{2.5}$ emissions was estimated at $585B USD and $60B CAD for the United States and Canada, respectively (**Commentary Table**). Including cross-border transport of pollution, the national burden in the United States and Canada increases to $608B USD and $71B CAD, respectively. Furthermore, primary $PM_{2.5}$ accounted for about 70% of the total burden of long-term exposure to $PM_{2.5}$ from all emissions evaluated (i.e., primary $PM_{2.5}$, NH_3, NO_x, and SO_2) in both countries. Taking advantage of the unequal distribution of BPTs across each country and using a graphing method called a Lorenz curve (see Investigators' Report Figure 8) to identify disparities in BPTs over the full range of emissions levels, the authors reported that just 10% of primary $PM_{2.5}$ emissions associated with the highest BPTs were responsible for 35% and 60% of the primary $PM_{2.5}$ attributed health burden in the United States and Canada, respectively. The total burden of domestic NH_3 emissions was estimated to be $129B USD in the United States and $11B CAD in Canada ($137B USD and $16B CAD when including cross-border transport of pollution) and accounted for about 16% of the total burden of long-term exposure to $PM_{2.5}$ in each country. 10% of NH_3 emissions could be attributed to about half of the NH_3-attributed health burden in both countries.

Commentary Table. Total Burden and Disparity of Domestic Emissions Contributing to Long-term $PM_{2.5}$ Exposure

	United States		Canada	
	Total Burden (Billion USD)	%Burden of 10% of Emissions	Total Burden (Billion CAD)	%Burden of 10% of Emissions
Primary $PM_{2.5}$	$585	35%	$60	60%
NH_3	$129	50%	$11	50%
NO_x	$43	35%	$3	37%
SO_2	$48	20%	$2	30%
Total	**$805**		**$77**	

BPT SENSITIVITY TO DIFFERENT MODEL INPUTS

Choosing different seasonal time periods minimally affected BPTs. Agreement between annual BPTs estimated from daily 36-km resolution and 2-week seasonal time periods at 12-km resolution was high for primary $PM_{2.5}$. Specifically, the coefficients of determination (R^2) were high (0.98 and 0.99 for the United States and Canada, respectively) and measures of bias and random error were low. Agreement between the daily and 2-week time period estimated BPTs was slightly lower for precursor emissions. For example, in the United States, R^2 ranged between 0.86 for SO_2 and up to 0.94 for NO_x, and measures of random error were slightly higher than for primary $PM_{2.5}$. The authors rated the uncertainty in time period selection as low.

The spatial resolution of the CMAQ modeling affected BPTs. When comparing BPTs estimated at 36-, 12-, 4-, and 1-km resolution in Los Angeles and New York City, investigators found good agreement (moderate to high R^2) and a tendency toward higher BPTs at finer resolutions, particularly for precursor emissions. Dependence on model resolution was more pronounced in Los Angeles. The authors rated the uncertainty in spatial resolution as medium.

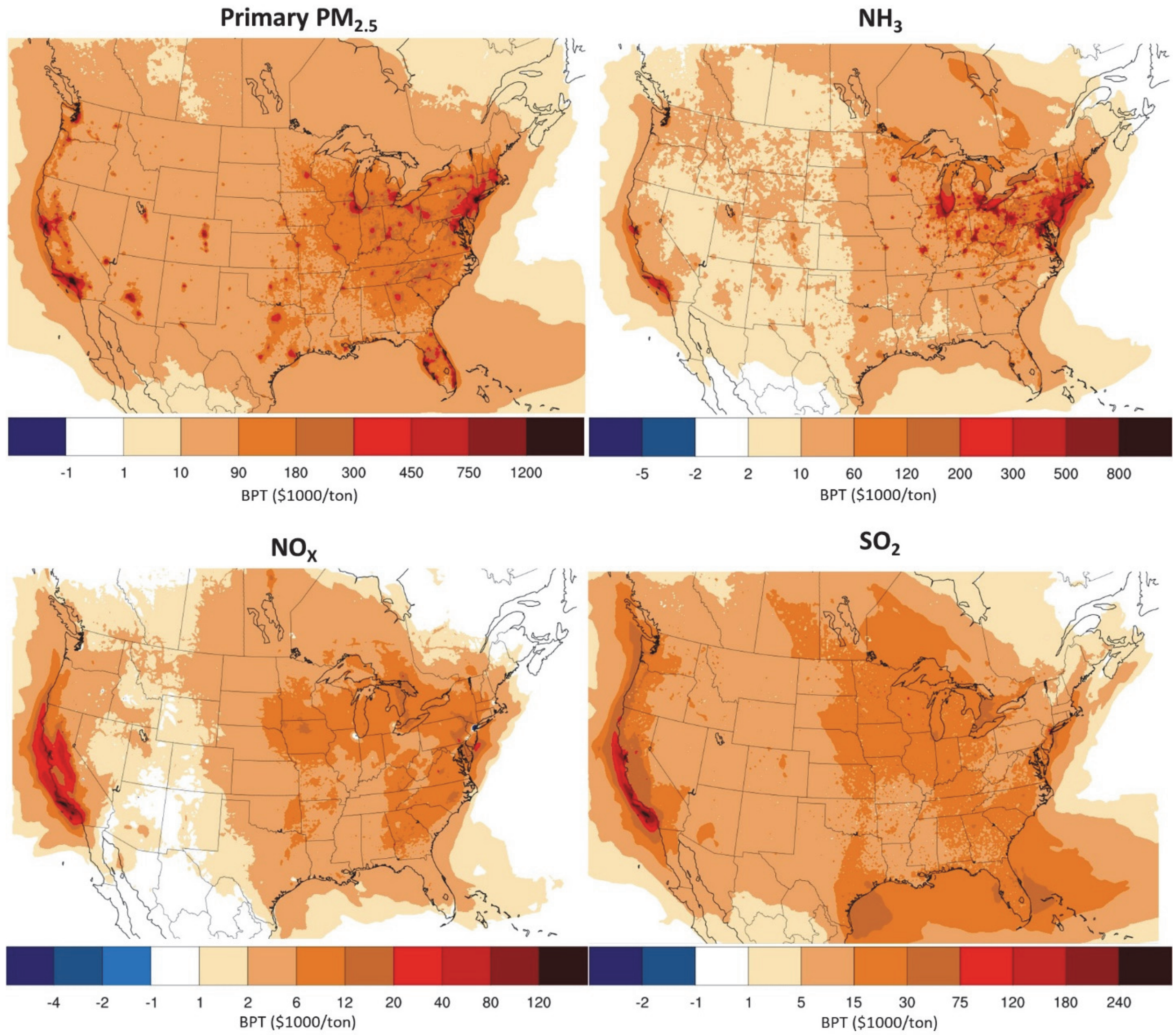
Choice of CRF also affected BPTs. Averaged across the United States, GEMM BPTs were most similar to BPTs derived from the American Cancer Society cohort ACS-16 (Turner et al. 2016) CRF, followed by the Chen and Hoek (2020) CRF, although there were some regional differences. GEMM BPTs were slightly higher than BPTs derived from CRFs of the American Cancer Society cohort ACS-09 (Krewski et al. 2009) and NHIS (Pope et al. 2019), but lower than the BPTs derived from the Chen and Hoek (2020) CRF. The authors reported that relative comparisons of BPTs varied by individual location based on the CRF shape and location-specific pollutant concentrations. Mean BPTs across all five CRFs and the coefficient of variation (COV) are reported in **Commentary Figure 4**. The COV was generally lower in areas with higher BPTs, such as much of the eastern United States, and ranged from 15% to 50% for different pollutants. The authors rated the uncertainty in CRF selection as medium-high.

Temporal changes in emissions from 2001, 2016, and 2028 projections led to some variation in BPTs estimates. The authors reported that the variation was due to nonlinearities in the GEMM CRF, which mostly affected primary $PM_{2.5}$ and SO_2, and atmospheric processes, which mostly affected precursors NH_3 and NO_x. BPTs were more consistent for the years 2016 and 2028 compared with 2001, which the authors interpreted to mean that BPTs would be more robust to future scenarios. They rated the uncertainty due to temporal changes in emissions as medium but stated that the uncertainty was likely to decrease in the future.

Compared with BPTs derived from the previously published reduced complexity models, the CMAQ-ADJ BPT estimates were in good agreement for primary $PM_{2.5}$ (R^2 0.738–0.816), low-moderate agreement for NH_3 (R^2 0.358–0.664), and low agreement for NO_x and SO_2 (R^2 0–0.342) emissions.

CLIMATE COBENEFITS OF EMISSIONS REDUCTIONS

Cobenefits varied widely across different sectors as shown for selected vehicle and engine types in **Commentary Figure 5**. These cobenefits represent the estimated health benefits of reduced $PM_{2.5}$ exposure following a reduction in combustion-related CO_2 emissions. Generally, cobenefits were higher for

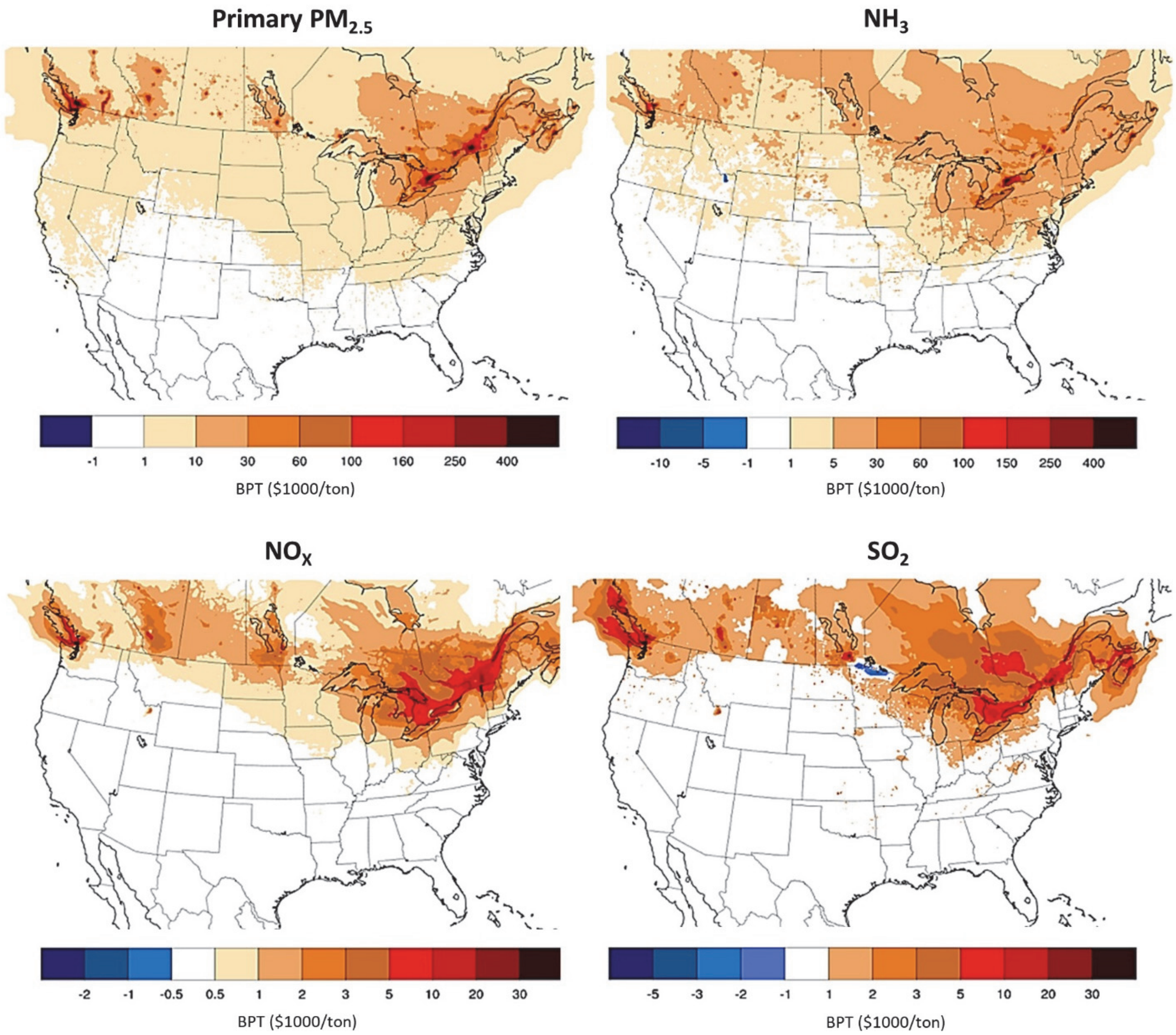


Commentary Figure 2. US 2016 surface BPTs by emitted pollutant. Note that BPT scales differ by pollutant.

diesel vehicles and engines compared with gasoline ones, and highest for off-road vehicles and engines, particularly those with 2-stroke engines. Evaluation by vintage within a specific vehicle sector revealed substantial cobenefit differences, with older vehicles showing higher cobenefits. For example, in Los Angeles, the cobenefit for diesel transit buses made in 2002 was 15 times higher than for buses made in 2016. Compared with the 2016 buses, the buses made in 2002 produced more than three times the total burden, even though their annual mileage was lower and only a third of them were still on the road. Such information would be useful for policymakers and planners in developing targeted climate action plans. National cobenefit maps and city-specific cobenefit data for other sectors are available in the Investigators' Report Appendix B (available on the *HEI website*). In terms of electricity generation, the cobenefits were higher for coal-powered compared with natural gas-powered electricity. The complete results for BPTs and cobenefits are available at *https://doi.org/10.5683/SP3/DTS44O*.

EVALUATION BY THE HEI REVIEW COMMITTEE

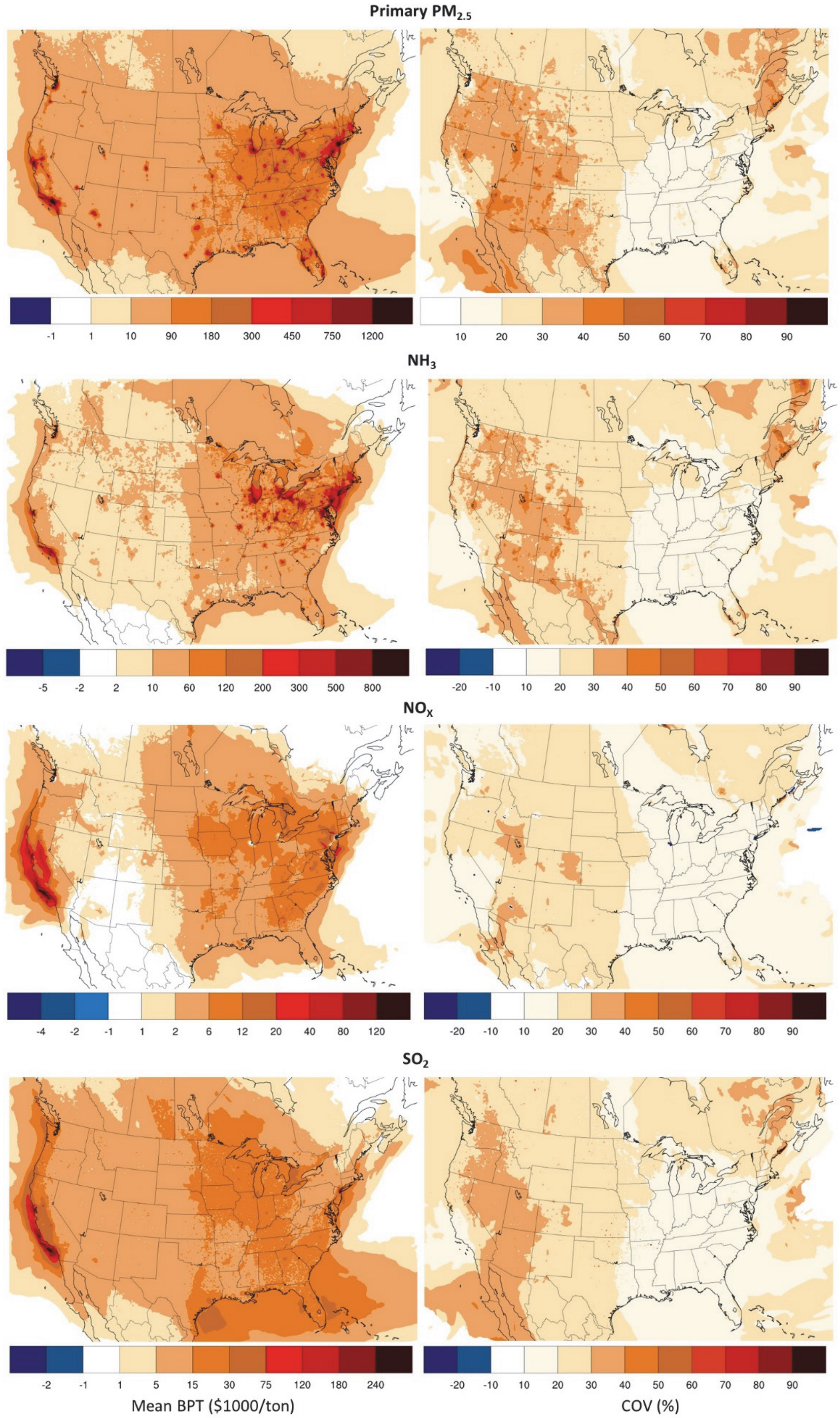
This health impact study evaluated the benefits of decreased air pollutant emissions from different classes of vehicles and major point sources that contribute to ambient $PM_{2.5}$ exposure across the United States and Canada. Hakami and colleagues simulated the effect of multipollutant emissions at 12-km resolution using a novel adjoint extension of the US EPA's CMAQ model. This state-of-the-art model enabled them to



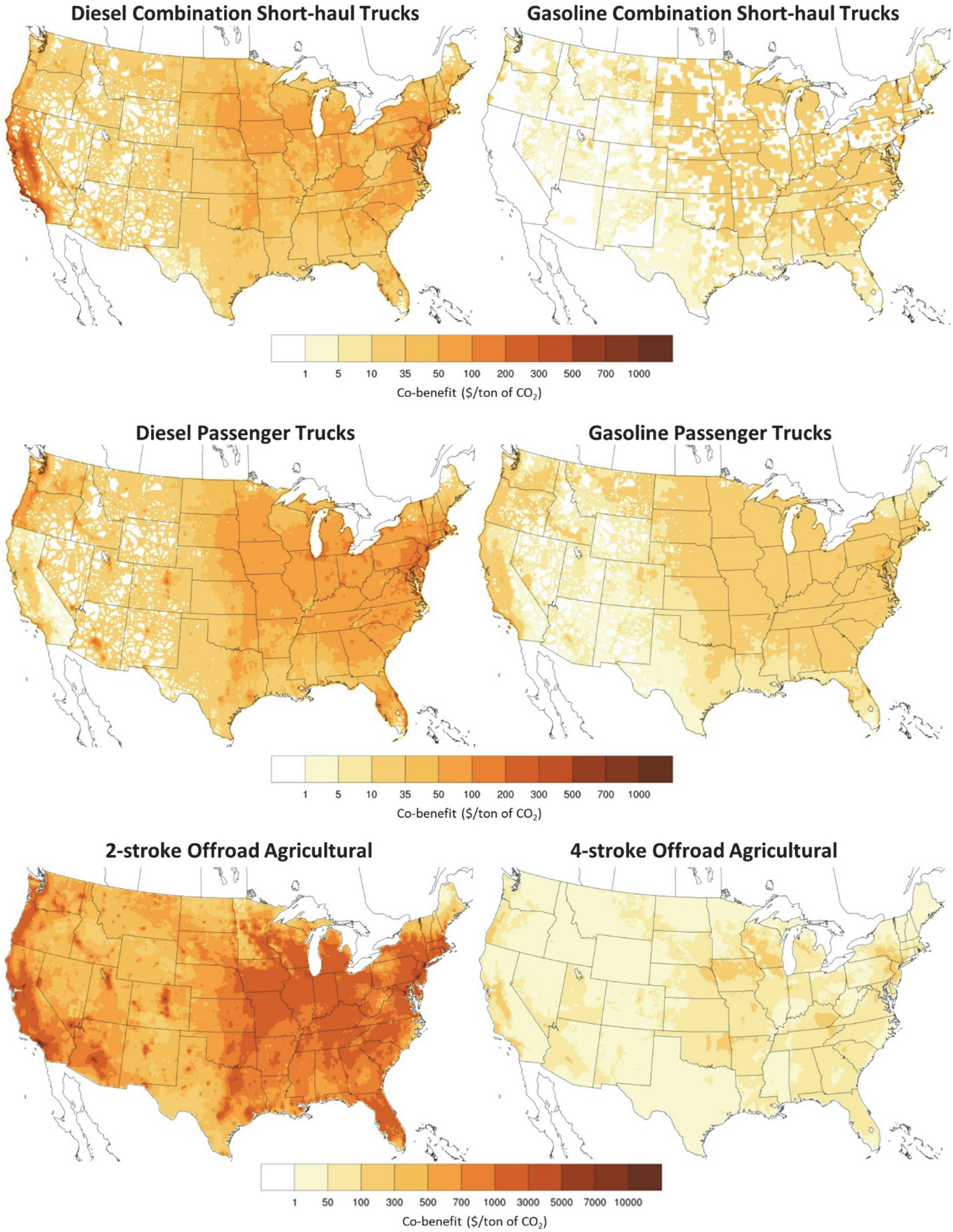
Commentary Figure 3. Canada 2016 surface BPTs by emitted pollutant. Note that BPT scales differ by pollutant.

create a database of source- and location-specific BPTs of reduced emissions. They also estimated the climate-change relevant cobenefit of the concomitant reduction in CO_2 associated with the same emissions sources. BPTs were largest for primary $PM_{2.5}$, followed by NH_3, and lowest for SO_2 and NO_x. BPTs were generally higher in the eastern half of the United States, with the highest levels near large cities, particularly in the northeast and California. The total burden of primary $PM_{2.5}$ was estimated at $585B USD and $60B CAD for the United States and Canada, respectively, and accounted for about 70% of the total burden of long-term exposure to $PM_{2.5}$ from all domestic emissions sources. The results suggested that a relatively small percentage of emissions accounted for most of the health burden.

In its independent review of the study, the HEI Review Committee thought that the report was methodologically rigorous, thorough, and policy-relevant and agreed that the authors' interpretations and conclusions were supported by the results. They considered a key strength of the study to be the use of a high spatial resolution adjoint air quality model to evaluate the effect of location-specific sources of air pollutants and the benefits of mitigating those sources, including cross-border effects between the United States and Canada. Indicating the areas and sectors with the highest emissions reduction benefits can support targeted and efficient air quality and decarbonization policies that reduce the emissions of relevant air pollutants. The Committee appreciated that Hakami and colleagues evaluated the CO_2 cobenefits for a multitude of policy-relevant transportation sectors, including various on- and off-road vehicles using gasoline- or diesel-powered engines and vehicles of different classes such as passenger, public transit buses, and construction, among



Commentary Figure 4. Mean and COV US 2016 surface BPTs from primary $PM_{2.5}$ emissions combined over five CRFs at 12-km resolution. Note that BPT and COV scales differ by pollutant.



Commentary Figure 5. Cobenefits of selected vehicle sectors. Note that cobenefit scales differ by sector.

others. These examples were considered representative of the sectors that are expected to change over the next 10 years as newer energy technologies increase market share, older vehicle fleets are replaced, and electrification makes greater inroads. In its evaluation, the Review Committee also identified some limitations and areas warranting further research as described below.

MODEL UNCERTAINTY

A weakness of health impact studies is that the models rely on numerous assumptions and uncertainties that can affect the results. Some assumptions, however, are required to make the analyses feasible in terms of computing resources. The Committee appreciated Hakami's efforts to conduct a comprehensive and thoughtful sensitivity analysis to evaluate the model assumptions and how that would change the BPT estimates. The investigators evaluated the effect of the shape of the CRF extracted from relevant published epidemiological studies; changes between past, current, and projected future emissions; the spatial resolution of the model; and the selection of time-period episodes for simulations.

Incorporation of different CRFs substantially influenced the estimated BPTs, and the authors considered this to be the largest source of uncertainty in the study. The CRF used for the primary analysis was a sublinear curve reported using the GEMM (Burnett et al. 2018) and was compared to a supralinear curve reported using a US nationally representative cohort (Pope et al. 2019), linear curves derived from the American Cancer Society — Cancer Prevention Studies-II cohort (Krewski et al. 2009; Turner et al. 2016), and a linear curve derived from a 107-study meta-analysis (Chen and Hoek 2020). BPTs estimated using the GEMM were similar to those estimated using Turner and colleagues (2016) and Chen and Hoek (2020) but were generally larger than BPTs estimated using Krewski and colleagues (2009) and Pope and colleagues (2019).

In general, the uncertainty in the BPT estimates due to the CRF was inversely proportional to the magnitude of the estimated BPTs across locations. For example, in the Midwest and East Coast regions of the United States, where the BPT estimates were generally higher, there was lower variation in estimated BPTs between the different input exposure–response functions. Hakami and colleagues explained that the differences in estimated BPTs by CRF were driven by changes in the hazard ratios across different $PM_{2.5}$ exposure concentrations, which were most dramatic for the sublinear and supralinear curves. The Committee noted that this explanation was reasonable but thought that the report could have been improved by further discussion of the differences. They noted that this sensitivity analysis illustrated the importance of CRF selection in health impact studies and the need for high-quality, population-representative epidemiological studies with relevant exposure ranges.

In contrast to the exposure–response function inputs, the BPT estimates were less sensitive to changes in the spatial resolution of the adjoint CMAQ model. Hakami and colleagues compared BPTs estimated from models with spatial resolutions of 1, 4, 12, and 36 km. Due to computational constraints, models with the 1- and 4-km resolution were evaluated only for two large metropolitan areas, Los Angeles and New York City. They found that in general, higher-resolution models estimated higher BPTs but that the results remained relatively consistent across the different spatial resolutions. The Committee noted that the results were not as sensitive to spatial resolution as one might expect and agreed with Hakami's conclusion that the coarser 12-km resolution used for the primary analysis was appropriate at a national level. Finally, the Committee appreciated the reported comparisons with other BPT estimates, which demonstrated consistency with less complex modeling methods.

OPPORTUNITIES FOR FUTURE RESEARCH

This study focused on emissions that contributed to chronic $PM_{2.5}$ exposure, including primary $PM_{2.5}$, NO_x, SO_2, and NH_3. Consequently, the study did not evaluate the direct and indirect effects of other air pollutants, likely leading to an underestimation of the health benefits reported. In particular, the Committee noted that NO_x can affect human health directly and through its contribution to ground-level ozone formation (Badida et al. 2023; Boogaard et al. 2023; Dominici et al. 2022; Yang et al. 2023). Ambient ozone is also an important greenhouse gas that is relevant to climate change, and its formation exhibits substantial spatial and temporal heterogeneity. Thus, location-specific benefit estimates of reduced ozone have the potential to inform air pollution and climate policy on both the national and local scale and should be investigated in future studies. It is also worth noting that the benefits in this study were evaluated based only on chronic exposure in relation to premature mortality. Although premature mortality accounts for 98% of the benefits associated with chronic $PM_{2.5}$ health effects (US EPA 2024a), it will also be useful for future health impact studies to consider acute exposures and other important health and economic indicators such as chronic diseases, disability, and lost workdays.

SUMMARY AND CONCLUSIONS

In summary, this health impact study evaluated the BPTs of decreased 2001, 2016, and projected 2028 air pollutant emissions from different sources that contribute to mortality from chronic ambient $PM_{2.5}$ exposure across the United States and Canada. Hakami and colleagues used a novel adjoint extension of the CMAQ model at high spatial resolution to produce a database of source- and location-specific BPTs. Their results suggest that reductions in a relatively small proportion of emissions could yield a large societal health benefit. In addition, focused emissions reductions in certain transportation sectors, including off-road engines and heavy-duty diesel vehicles, could yield climate and health cobenefits. The Committee noted that the study included rigorous sensitivity analyses to assess the uncertainties of BPT estimates and that the emissions sectors evaluated were policy-relevant. They recommended that future studies evaluate the effect of additional pollutants, such as NO_x and ozone, that have both health and climate importance.

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ABBREVIATIONS AND OTHER TERMS

ACS-09	CRF from Krewski et al. 2009
ACS-CPS-II	American Cancer Society–Cancer Prevention Studies-II
APEEP	Air Pollution Emission Experiments and Policy Analysis
AP2	successor to APEEP
AQBAT	Air Quality Benefits Assessment Tool
BenMAP	Environmental Benefits Mapping and Analysis Program
BPT	benefit-per-ton
CAAQS	Canadian Ambient Air Quality Standards
CanCHEC	Canadian Census Health and Environment Cohort
CCME	Canadian Council of Ministers of the Environment
CHEN	CRF from Chen and Hoek 2020
CMAQ	Community Multiscale Air Quality
CMAQ-ADJ	CMAQ-adjoint version
CO_2	carbon dioxide
COV	coefficient of variation
CRF	concentration–response function
CTM	chemical transport model
EASIUR	Estimating Air Pollution Social Impact Using Regression
GEMM	global exposure mortality model
GHG	greenhouse gas
H-CMAQ	hemispheric CMAQ
HR	hazard ratio
InMAP	Intervention Model for Air Pollution
MB	marginal benefit
MOVES3	MOtor Vehicle Emission Simulation–version 3
NAAQS	National Ambient Air Quality Standards
NEIC	National Emission Inventory Collaborative
NH_3	ammonia
NHIS	National Health Interview Survey
NO_2	nitrogen dioxide
NO_x	nitrogen oxides
PM	particulate matter
$PM_{2.5}$	particulate matter 2.5 µm in aerodynamic diameter
RIA	regulatory impact analysis
R^2	coefficient of determination
SO_2	sulfur dioxide
US EPA	United States Environmental Protection Agency
VMT	vehicle miles traveled
VSL	value of a statistical life
WHO	World Health Organization
WRF	weather research and forecast model

GLOSSARY

Adjoint Model: A model that traces population health burdens back to individual emission sources. Used for reverse influence modeling, an adjoint model employs a full-form representation of the atmosphere and describes how emissions from any location impact air quality endpoints.

Benefit-per-ton (BPT): Monetized societal benefits associated with reduced adverse health effects that are associated with emissions of a specific pollutant that had been reduced by one metric ton. BPTs are also referred to as marginal benefits (MB) in environmental economics. In the context of this report, BPTs reflect valuated societal benefits due to reduced premature mortality from chronic exposure to $PM_{2.5}$ and do not include morbidity health effects or mortality due to exposure to other pollutants. BPTs are expressed in units of $/ton-pollutant.

Burden: Total valuated societal impact of a pollutant or emissions from a sector. In the context of this report burden refers only to total valuated societal benefits due to reduced premature mortality from chronic exposure to $PM_{2.5}$. For a first-order approximation, burden can be estimated by multiplying emissions and BPTs.

Cobenefits: Ancillary benefits associated with reduced emissions of CO_2 or other greenhouse gases. In the context of this report, cobenefits refer to the population health benefits associated with reduced emissions of co-emitted pollutants. Cobenefits are expressed in units of $/ton-$CO_2$.

Fine particulate matter ($PM_{2.5}$): Atmospheric particles with aerodynamic diameters up to 2.5 microns.

Marginal benefits (MB): See benefit-per-ton.

Precursor species: Gaseous species that undergo transformations to produce secondary $PM_{2.5}$.

Primary and secondary $PM_{2.5}$: Primary $PM_{2.5}$ are particles or particle constituents that are emitted into the atmosphere in the particle phase. In contrast, secondary $PM_{2.5}$ particles or particle constituents are formed in the atmosphere from chemical or physical transformations. Secondary $PM_{2.5}$ can be organic or inorganic. Sulfate, nitrate, and ammonium are the main constituents of secondary inorganic $PM_{2.5}$.

Social cost of carbon: Monetized societal cost associated with each metric ton of emissions of CO_2 or CO_2-equivalent of other greenhouse gases.

Source–receptor relationship: Model-based estimates of how emissions at various sources impact concentrations of pollutants as they reach affected populations (i.e., at receptor locations). BPTs are one form of quantified source–receptor relationships.

Value of Statistical Life (VSL): Statistical willingness-to-pay measure in a society for a small reduction in the risk of mortality. VSL is used by governments in Canada and the United States to monetize mortality counts. VSL is applied to mortality counts regardless of age or socioeconomic status.

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