

ACCEPTED MANUSCRIPT • OPEN ACCESS

An inter-comparison of air quality social cost estimates from reduced-complexity models

To cite this article before publication: Elisabeth A Gilmore *et al* 2019 *Environ. Res. Lett.* in press <https://doi.org/10.1088/1748-9326/ab1ab5>

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2018 The Author(s). Published by IOP Publishing Ltd.

As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 3.0 licence, this Accepted Manuscript is available for reuse under a CC BY 3.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by/3.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

An Inter-Comparison of Air Quality Social Cost Estimates from Reduced-Complexity Models

Elisabeth A. Gilmore^{1,*}, Jinhyok Heo², Nicholas Z. Muller³, Christopher W. Tessum⁴, Jason D. Hill⁵, Julian D. Marshall⁴, Peter J. Adams⁶

1. Department of International Development, Community, and Environment. Clark University, Worcester, MA., USA. gilmore@clarku.edu, 1-508-793-7292
2. Center for Atmospheric Particle Studies, Carnegie Mellon University, Pittsburgh, PA, USA
3. Tepper School of Business / Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, USA & National Bureau of Economic Research, Cambridge, MA, USA
4. Department of Civil and Environmental Engineering, University of Washington, Seattle, WA, USA
5. Department of Bioproducts and Biosystems Engineering, University of Minnesota, St. Paul, MN, USA
6. Department of Civil and Environmental Engineering / Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, USA

Abstract

Reliable estimates of externality costs—such as the costs from premature mortality from exposure to fine particulate matter (PM_{2.5})—are critical for policy analysis. To facilitate broader analysis, several datasets of social costs of air quality have been produced by a set of reduced complexity models (RCMs). Using the tabulated marginal costs derived from RCMs is much easier than running the ‘state of the science’ chemical transport models (CTMs). However, the differences between these datasets have not been systematically examined, leaving analysts without guidance on how and when these differences matter. Here, we compare per-tonne marginal costs from ground-level and elevated emission sources for each county in the United States (U.S.) for sulfur dioxide (SO₂), nitrogen oxides (NO_x), ammonia (NH₃), and inert primary PM_{2.5} from three RCMs: Air Pollution Emission Experiments and Policy (AP2), Estimating Air pollution Social Impacts Using Regression (EASIUR), and the Intervention Model for Air Pollution (InMAP). National emission-weighted average damages vary among models by approximately 21%, 31%, 28% and 12% for inert primary PM_{2.5}, SO₂, NO_x, and NH₃ emissions, respectively, for ground-level sources. For elevated sources, emission-weighted damages vary by approximately 42%, 26%, 42% and 20% for inert primary PM_{2.5}, SO₂, NO_x, and NH₃ emissions, respectively. Despite fundamental structural differences, the three models predict marginal costs that are within the same order of magnitude. That different and independent methods have converged on similar results bolsters confidence in the RCMs. Policy analyses of national-level air quality policies that sum over pollutants and geographical locations are often robust to these differences, although the differences may matter for more source- or location-specific analyses. Overall, the loss of fidelity caused by using RCMs and their social cost datasets in place of CTMs is modest.

Keywords: Model Inter-Comparison, Air Quality, Externality Costs, Policy Analysis

1. Introduction

When analyzing policies, products, or processes, it is critical to account for costs that are observed in the market as well as non-market costs, known as externalities (Baumol & Oates, 1988). For air pollution, adverse human health effects – especially premature mortality from exposure to ambient concentrations of fine particulate matter (PM_{2.5}) – result in large costs to society (United States Environmental Protection Agency (U.S. EPA), 2009). To estimate these costs, the U.S. EPA has generally employed an impact pathway assessment. This multi-step approach is as follows: first, Chemical Transport Models (CTMs) are used to estimate the impact of emissions on ambient concentrations; second, the health effects from exposure to these concentrations are quantified using concentration – response (C-R) functions; and finally, the health impacts are monetized. For premature mortality, an estimate of the willingness-to-pay to avoid this impact, known as the value of a statistical life (VSL), is used to monetize these impacts. Presently, the U.S. EPA employs a central estimate of 7.4 million in 2006 USD (U.S. EPA, 2010).

The first step, modeling the relationship between pollutant emission and ambient PM_{2.5} concentrations, is especially challenging. PM_{2.5} consists of a complex mixture of chemical species, both inorganic and organic, from diverse sources. Some PM_{2.5} is directly emitted to the atmosphere and is known as primary particulate matter. Primary PM_{2.5} is dominated by particulate elemental carbon (PEC) and organic carbon (POC) (Hand et al., 2012). However, most PM_{2.5} is secondary, meaning that it originates from gaseous emissions that react in the atmosphere to form products that condense into the particle phase. PM_{2.5} is also separated into its inorganic and organic components. Inorganic PM_{2.5} mostly results from emissions of sulfur dioxide (SO₂), nitrogen oxides (NO_x), and ammonia (NH₃). These gaseous precursors are converted into sulphate (SO₄²⁻), nitrate (NO₃⁻) and ammonium (NH₄⁺) and form particulate matter through relatively well understood chemistry. This chemistry, however, is highly non-linear. The marginal sensitivities in PM_{2.5} concentrations to the precursor emissions depend on the initial concentrations and will change as the relative amounts of emissions of all three precursors change (Ansari and Pandis, 1998). For example, recent trends in emissions have decreased the marginal effect of NH₃ emissions and increased that of NO_x emissions (Pinder et al., 2008; Holt et al., 2015). Organic PM_{2.5} consists of primary and secondary organic aerosol (POA and SOA) depending on whether it is emitted already in the particulate phase or whether it forms from gases in the atmosphere. SOA is formed from the oxidation of volatile organic compounds (VOCs), but the yield of organic

1
2
3 PM_{2.5} varies substantially among VOC precursors. By contrast to the inorganic components, the
4 sources and behavior of both POA and SOA are less well understood (Robinson et al., 2007).
5 While scientific understanding of organic PM_{2.5} formation is advancing rapidly, this updated
6 understanding is still being incorporated into the CTMs and thus, into the resulting social costs.
7 The major removal mechanism for PM_{2.5} is via precipitation. Hence, PM_{2.5} can be transported for
8 several days downwind, affecting populations up to approximately 1,000 km away from the point
9 of emission (e.g., Evans et al., 2002). On the other hand, primary PM_{2.5} emitted in urban areas will
10 have a large impact in the immediate vicinity. As a result, models of PM_{2.5} must reproduce the
11 behavior of a complex physical and chemical system, and they require both sufficiently high
12 resolution near sources as well as a long-range spatial extent to capture all the health impacts of a
13 single source.
14
15
16
17
18
19
20
21

22 CTMs are the ‘state-of-the-science’ tool for predicting how much PM_{2.5} is formed from a given
23 set of emissions, but the complexity of these models limits their applicability. To improve the
24 availability and accessibility of air quality modeling and cost estimates, the air quality research
25 community has produced a set of new models, known as reduced-complexity air quality models
26 (RCMs) and associated sets of marginal social costs, i.e., monetized damages per pollutant (in
27 USD per tonne of emission). In this paper, we compare three RCMs and their datasets that provide
28 estimates of externality costs from air pollution: the Air Pollution Emission Experiments and
29 Policy (APEEP) model (Muller & Mendelsohn, 2007) updated to AP2 (Muller et al., 2011), the
30 Estimating Air pollution Social Impacts Using Regression (EASIUR) model (Heo et al., 2016a;
31 2016b), and the Intervention Model for Air Pollution (InMAP) (Tessum et al., 2017). We select
32 these three RCMs as they provide comprehensive estimates covering the entire continental United
33 States (U.S.) at relatively high spatial resolution (county level or finer).
34
35
36
37
38
39
40
41
42

43 In this inter-comparison, we have three main aims:

- 44 i. Provide guidance on how and when the differences matter between these three
45 RCMs. While these RCMs are documented in the peer-reviewed literature, the differences in the
46 social cost datasets have not been systematically examined.
47
48
- 49 ii. Compare the results from the RCMs to the CTMs. Since the RCMs are, by
50 definition, less physically detailed than the CTMs, there is also a potential loss of fidelity. This
51 type of comparison can help justify their use for certain applications and allow users to judge the
52 robustness of the results from the RCMs.
53
54
55
56
57
58
59
60

1
2
3 iii. Evaluate the uncertainty in the air quality models. While it is recognized that
4 evaluating the uncertainty in the air quality benefits is critical as the effects of changing PM_{2.5}
5 levels on mortality constitute a key component of the U.S. EPA's approach for assessing potential
6 health benefits for air quality regulations (National Research Council, 2002), characterizing the
7 full uncertainty in the air quality model is especially challenging (e.g., Fraas & Lutter, 2013). As
8 the three RCMs take fundamentally different approaches to the air quality modeling, they may be
9 understood to produce largely independent estimates. Hence, comparing and quantifying the
10 differences between the independently derived estimates of social costs from the RCMs also
11 provides an indication of the uncertainty of how emissions are transformed into ambient
12 concentrations.
13
14
15
16
17
18
19
20
21

22 **2. Review of CTMs and RCMs for Assessing Air Quality Social Costs**

23 Predicting the impacts of emissions on ambient concentrations is usually done using a
24 comprehensive CTMs. CTMs are three-dimensional mechanistic models that predict ambient
25 concentrations of pollutants using mass balance principles and accounting for emissions, transport,
26 and dispersion by winds, chemical transformations, and atmospheric removal processes. CTMs
27 are the most scientifically detailed and rigorous tools available for linking emissions to ambient
28 concentrations. Examples of CTMs include the Comprehensive Air Quality Model with
29 Extensions – CAMx (ENVIRON, 2016), Community Multi-scale Air Quality Model – CMAQ
30 (Appel et al., 2017), and Weather Research and Forecasting model coupled with Chemistry –
31 WRF-Chem (Powers et al., 2017). Running full CTMs is intensive enough in terms of expertise,
32 time, and resources that their usage is generally limited to air quality researchers and regulatory
33 authorities, such as the U.S. EPA's regulatory impact assessment for revisions to the National
34 Ambient Air Quality Standards (NAAQS) and state agencies as part of the accompanying State
35 Implementation Plans (SIPs). Even then, many states do not have in-house capabilities to run
36 CTMs, relying on consultants or regional associations for their modeling needs. Despite the
37 availability of RCMs, however, it is prudent to use a full CTM to assess the likely impact of major
38 air quality policies before their implementation to ensure the best estimates of benefits for
39 comparison to costs. Additionally, the comprehensive CTMs constitute the benchmark against
40 which simpler models can be judged.
41
42
43
44
45
46
47
48
49
50
51
52
53

54 To address the challenges with running CTMs, a number of RCMs have been developed. The
55
56
57
58
59
60

1
2
3 magnitude of the social costs of air pollution suggests that it would be useful to have models like
4 RCMs that facilitate the quantification of the costs and their uncertainty as part of routine policy
5 analysis. Further, the availability of simpler and more accessible models would greatly expand the
6 community of people who could quantify the public health costs of air pollution, including city
7 planners, affected industries, and citizen groups. Those who run CTMs can find RCMs useful
8 when they want to explore quickly a broad range of emissions scenarios. In this paper, we describe
9 and compare results from three such models, which are described in detail below: AP2, EASIUR,
10 and InMAP. We also briefly describe other RCM efforts.

11
12 APEEP and its updated version, AP2, employs a source-receptor (S-R) matrix framework to
13 map emissions to ambient concentrations at the county-level (Muller & Mendelson, 2007, Muller
14 et al., 2011). The contribution of emissions in a source county (S) to the ambient concentration in
15 a receptor county (R) is represented as the (S, R) element in a matrix. In the module for PM_{2.5}
16 formation, the model contains S-R matrices that govern how PEC, SO₂, NO_x, NH₃, and VOC map
17 to PM_{2.5}. Each of these matrices accepts annual (U.S. short tons per year) emission vectors to
18 produces predictions of annual means. For each of these matrices, the model distinguishes among
19 emissions released at four different effective height categories: ground-level emissions, point
20 sources under 250 meters, point sources between 250 meters and 500 meters, and point sources
21 over 500 meters. AP2 employs the approach to estimating the NH₄⁺, SO₄²⁻ and NO₃⁻ equilibrium
22 embodied in the Climatological Regional Dispersion Model (CRDM), a national-scale Gaussian
23 dispersion model (Latimer, 1996). In the equilibrium computations, ambient NH₄⁺ reacts
24 preferentially with SO₄²⁻. Second, ammonium nitrate (NH₄NO₃) is only able to form if there is
25 excess NH₄⁺. To translate VOC emissions into secondary organic particulates, AP2 employs the
26 fractional aerosol yield coefficients estimated by Grosjean and Seinfeld (1989). While APEEP was
27 evaluated against a 2002 annual average baseline run produced by CMAQ, AP2 predictions are
28 tested against Air Quality System (AQS) monitoring data. Calibration coefficients are used to
29 adjust AP2 predictions to jointly minimize mean fractional error and mean fractional bias. We use
30 AP2 in the text to clarify that we are comparing the results from the updated version of the original
31 APEEP.

32
33 The EASIUR model (Heo et al. 2016a; 2016b) estimates marginal social costs for four
34 species—inert primary PM_{2.5}, SO₂, NO_x, and NH₃—in a 36 km × 36 km grid covering the
35 continental U.S. The social costs are provided for four seasons and for three emissions elevations
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 (ground-level, 150 m, and 300 m). The EASIUR model was derived by running regressions on a
4 CTM data set consisting of small emissions perturbations occurring at 100 sample locations.
5
6 CAMx was run to calculate social costs of the four species at the sample locations (randomly
7 chosen based on population size) across the nation. Then, the resulting per-tonne social costs were
8 regressed as a function of exposed population and atmospheric variables such as temperature and
9 atmospheric pressures using half of the sample locations as training for the regression and half as
10 out-of-sample evaluations. Finally, using the regression models, per tonne social costs were
11 estimated at all the cells in the 36 km × 36 km grid. In addition, an EASIUR-based source-receptor
12 model was developed from the regression results (Heo et al., 2017). The source-receptor version
13 was used to estimate concentrations for comparisons made in this study.
14
15

16
17
18
19
20 InMAP (Tessum et al., 2017) combines simplified representations of atmospheric chemistry
21 and physics with output from WRF-Chem to calculate annual-average marginal changes in
22 concentrations of PM_{2.5} caused by marginal changes in emissions of SO₂, NO_x, NH₃, VOCs, and
23 inert primary PM_{2.5} using a three-dimensional spatial grid with horizontal resolution ranging
24 between 1 km × 1 km in highly populated areas to 48 km × 48 km in unpopulated areas and over
25 the ocean. InMAP operates independently of the underlying CTM, and InMAP users would only
26 need to also use a CTM or access the raw CTM output data if they were interested in applying
27 InMAP to a new spatial or temporal domain (e.g., outside of the continental U.S.). We used an
28 InMAP-based source-receptor matrix (ISRM; Goodkind et al., 2019) to predict the health impacts
29 and to calculate social costs of emissions in every InMAP grid cell at three emission heights
30 (ground level, low stack height point sources, and high stack height point sources) and used the
31 social cost of emissions from each county centroid in comparisons here.
32
33
34
35
36
37
38
39
40

41
42 There are other RCMs that we review here, but do not include in our inter-comparison. The
43 Co-Benefits Risk Assessment (COBRA) screening model is another RCM, developed by the U.S.
44 EPA, which provides marginal social costs at county-level resolution (U.S. EPA, 2018). COBRA
45 and AP2 share the core framework for modeling the air quality impacts of a unit of emission. Both
46 models are built around the CRDM (Latimer, 1996) and then calibrated to existing air quality
47 modeling and measurements. There are minor differences in the treatment of the elevated sources,
48 the approach to the simplified chemistry and the calibration approach. Because COBRA and AP2
49 are built on the same core air quality modeling, marginal social costs from COBRA are typically
50 very similar to those from AP2. We only review AP2 in this paper.
51
52
53
54
55
56
57
58
59
60

U.S. EPA's Response Surface Model (RSM), with its benefit per ton values, is another similar tool (Fann et al., 2009; Fann et al., 2012; U.S. EPA, 2015). Compared to the RCMs evaluated here, RSM has lower spatial resolution, only providing average impacts for nine urban areas plus the U.S. overall average. An advantage of RSM, however, is that it can capture some of the nonlinear responses in the PM_{2.5} chemistry, which can occur with larger changes in inorganic PM_{2.5} levels (e.g., Holt et al., 2015). We also do not review related tools such as Environmental Benefits Mapping and Analysis Program (BenMAP), which is focused on estimating health outcomes and does not include any air quality modeling. Rather, it requires ambient concentrations as inputs rather than emissions (U.S. EPA, 2017). The RCMs evaluated in this manuscript use a similar approach to health effect and economic valuation as employed in BenMAP. Other studies also have provided marginal social cost values but for limited regions of the US or limited emissions sectors, including the Direct Decoupled Method (DDM) of Bergin et al. (2008), regression-based approaches developed by Buonocore et al. (2014) and Levy et al. (2009), and source-based estimates from Goddard Earth Observing System with Chemistry model (GEOS-Chem) (Caiazzo et al., 2013).

3. Methods and Models

Here, we evaluate the performance and the damage estimates from three RCMs. One of the first applications of the RCMs has been to develop marginal damage estimates, i.e., those that result from small perturbations of emissions. The results from the model, expressed in US dollars (USD) of damage per tonne of emissions, are specified at a minimum for a type of pollutant, a location, a population and at least implicitly, for a given time period (e.g., a year). All results in this manuscript are expressed in 2010 USD.

First, we assess the RCMs in terms of their ability to predict observed PM_{2.5} concentrations and their composition. We compared concentration estimates against annual average concentrations provided by U.S. EPA's Air Data (available at <https://www.epa.gov/outdoor-air-quality-data>). A caveat is that, given nonlinearities in PM_{2.5} formation discussed above, one does not necessarily expect that the marginal values from the RCMs will predict realistic PM_{2.5} concentrations. Using the 2005 National Emissions Inventory (NEI), AP2 estimated concentrations directly using its county-level source-receptor model. By contrast, EASIUR and InMAP combined the 2005 NEI with each RCM's marginal damage estimates in a spatially disaggregated way, i.e., the emissions of each species in each model source location make a linear

1
2
3 contribution to all model locations. These contributions are then summed at each downwind
4 “receptor” location to represent the RCM’s prediction of $PM_{2.5}$. The latter approach assumes that
5 the nonlinearities in the chemistry are not large. As a representative CTM, we also show the
6 performance for WRF-Chem (Grell et al., 2005, as configured in Tessum et al., 2015). See Table
7 S1 for information on the configuration of WRF-Chem.
8
9

10
11
12 Second, we conduct an inter-comparison of the social costs from three models, focusing on
13 four main categories of emissions that form ambient $PM_{2.5}$: inert primary $PM_{2.5}$, SO_2 , NO_x , and
14 NH_3 . To isolate the effect of the air quality modeling on the damage estimates, we harmonized the
15 main inputs: baseline emissions, population, C-R function, and VSL. We select the baseline
16 emission inventories and population for 2005. For the $PM_{2.5}$ C-R function, we use the results from
17 the American Cancer Society (ACS) epidemiological study for annual, all-cause mortality for
18 adults (Krewski et al., 2009); we do not quantify morbidity effects. We apply the U.S. EPA’s VSL
19 of 7.4 million in 2006 USD. We do not show results for VOCs because not all three models predict
20 impacts from VOCs due in part to the uncertainties described in the introduction. Additionally,
21 because neither AP2 nor InMAP accounts for the variability in SOA yield among individual VOC
22 species, we are less confident that the variability between the models is representative of overall
23 uncertainty in predictions of SOA impacts than we are for the inorganic species. We discuss the
24 implications of the uncertainty in the damage estimates and make recommendations for how to
25 approach these estimates in the results and discussion section.
26
27
28
29
30
31
32
33
34
35
36
37

38 **4. Results and Discussion: Comparison of Ambient Concentrations and Social Costs**

39
40 First, we compare the models to WRF-Chem and find that in general, they have similar
41 performance. These results show some important trends, with all models, including the CTM,
42 performing worse for NH_4^+ and NO_3^- predictions, illustrating that some $PM_{2.5}$ species are more
43 difficult to model and, by extension, the damage estimates for their precursors will be more
44 uncertain. At the same time, the relative success in reconstructing $PM_{2.5}$ concentrations from
45 marginal impact estimates suggests that differences between marginal and average changes are not
46 too large or mostly cancel out among different pollutants and locations. On balance, these
47 comparisons boost confidence in the use of RCMs and suggest that the necessary simplifications
48 inherent in them do not substantially degrade their performance compared to CTMs. EASIUR does
49 not estimate damages or SOA formation from VOC emissions; hence, an estimate of total $PM_{2.5}$
50
51
52
53
54
55
56
57
58
59
60

1
2
3 is not possible from EASIUR at the current time. Additionally, we do not include a comparison of
4 InMAP's predicted PEC concentrations against observations. In principle, InMAP can predict
5 PEC; however, the NEI reports only total primary PM_{2.5}. It is outside of the scope of this work to
6 conduct the additional processing to speciate these emission into InMAP format. We show the
7 results of this evaluation in Supplemental Information (Figure S1). In addition to this comparison
8 with WRF-Chem, each RCM has undergone substantial validation to both CTMs and in the case
9 of AP2, observed ambient concentrations. InMAP was compared against 14 separate runs from
10 WRF-Chem to show that it could predict concentration changes (Tessum et al., 2017). EASIUR
11 was directly derived from CAMx output with out-of-sample evaluations for independent testing
12 and is thus indirectly already validated against a CTM. Further, by comparing AP2 and InMAP to
13 EASIUR, they are also indirectly compared to CAMx.

14
15
16
17
18
19
20
21
22 Turning to social costs, we show the summary results for ground and elevated sources in the
23 US in Figure 1, respectively. For ground-level sources, emission-weighted damages for the US
24 varied by approximately 21%, 31%, 28% and 12% for inert primary PM_{2.5}, SO₂, NO_x, and NH₃
25 emissions, respectively with a range of 70,000–120,000 USD per tonne of PM_{2.5}, 21,000–45,000
26 USD per tonne of SO₂, 6,400–13,000 USD per tonne of NO_x, and 38,000–49,000 USD per tonne
27 of NH₃. For elevated sources, emission-weighted damages for the US varied by approximately
28 42%, 26%, 42% and 20% for inert primary PM_{2.5}, SO₂, NO_x, and NH₃ emissions, respectively with
29 a range of 36,000–110,000 USD per tonne of PM_{2.5}, 20,000–35,000 USD per tonne of SO₂, 6,300–
30 11,000 USD per tonne of NO_x, and 32,000–51,000 USD per tonne of NH₃. See Supplemental
31 Information (Table S2) for tabulated values and calculations of variance. We report emissions-
32 weighted averages because aggregate health damages from a set of emissions are the sum of
33 emissions rate and marginal social cost which is then summed across all source locations.
34 Therefore, aggregate damages are proportional to the emissions-weighted mean. Put another way,
35 if two models differ by 10% in their emissions-weighted mean, their assessment of aggregate
36 damages across the country for that species would also differ by 10%. Therefore, this metric is a
37 good indicator of how much two models would differ for a policy where emissions changes are
38 distributed similarly to current emissions. We also compare our national results to those produced
39 by Fann et al. (2009). We find that our values are within the same range with the exception of
40 primary PM_{2.5} where Fann et al. (2009) have much higher values than the three RCMs. We show
41 the tabulated comparison in Table S3.

1
2
3 Overall, these three sets of marginal costs show similar trends. First, as shown in Figure 1, for
4 any given emitted species by model, the marginal social cost varies by at least one order of
5 magnitude depending on the location of emissions for both ground and elevated sources.
6 Additionally, we conclude that the elevated and ground level sources generally behave the same
7 with most point sources having a similar or lower social cost than the ground level sources. While
8 the elevation allows the plume to span a greater area, the point sources are generally in rural areas.
9 There are isolated cases where the reverse is true. These exceptions occur where the point sources,
10 which are primarily in rural areas, have plumes that overlap with highly populated urban centers.
11 Furthermore, the difference between elevated and ground is largest for primary PM_{2.5} as expected.
12 For secondary PM_{2.5}, where chemical and/or physical transformation needs to take place, the social
13 costs are similar. By the time the PM_{2.5} is formed by chemical reactions, there has been enough
14 vertical mixing that the original release height has little influence. As the results are similar for the
15 ground and elevated sources, we focus the rest of the discussion on the ground sources for
16 simplicity.

17
18 In Figure 2, we show the estimates of social costs for ground-level sources from each model
19 for each county in the US. Figure 2 shows that social costs are consistently higher from emissions
20 in or near densely populated areas, especially the eastern U. S.. Much of the variability in impacts,
21 therefore, is a simple function of the number of people downwind exposed to the resulting PM_{2.5}.
22 Third, for each RCM, the rank order of species from most damaging to least damaging (per tonne)
23 is generally primary PM_{2.5}, NH₃, SO₂, and NO_x. Since current understanding treats all PM_{2.5}
24 components the same in terms of the health impacts, this rank order simply reflects the efficiency
25 with which a tonne of emitted species forms ambient PM_{2.5}. By definition, primary PM_{2.5}
26 emissions immediately form ambient PM_{2.5}; hence, they have the largest efficiency and highest
27 damages. For the secondary species, damages from NH₃ and SO₂ are moderate with NO_x having
28 the lowest damages. The relatively high social costs of NH₃ can be understood as follows. Both
29 NH₃ and NO_x emissions contribute to the formation of NH₄NO₃; but, depending on circumstances,
30 either one or the other emission can be limiting. However, since the molecular weight of NH₃ is
31 much lower than that of NO_x, a ton of NH₃ represents more molecules. All else being equal, it will
32 tend to have a higher marginal social cost on a per mass basis. Additionally, NH₃ emissions will
33 increase PM_{2.5} concentrations by neutralizing SO₄²⁻. For comparison, Holt et al. (2015) also shows
34 high sensitivity of PM_{2.5} to NH₃ emissions on a per tonne basis (Holt et al., 2015). Thus, all three
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

RCMs show similar and expected trends that are easily interpretable in terms of atmospheric behavior and population exposure, boosting confidence in these estimates.

In Figures 3 – 6, we show the model inter-comparisons for each species for ground level sources. Similar plots for elevated sources can be found in Supplemental Information (Figures S2 – S5). All three RCMs provide damage estimates that are highly spatially resolved with respect to emissions location. Whereas some application scenarios will involve nationwide emissions changes, others may be focused on damages from emissions in one region of the country, perhaps a single state or even a single county. Therefore, it is worthwhile evaluating to what extent the three RCMs agree in terms of spatial patterns and county-by-county damage estimates. Here, we find that the level of agreement varies considerably by species according to the complexity of the associated chemistry, mirroring how some species are inherently more difficult to model than others, even for a CTM (Figure S1). While all three RCMs estimate these social costs at high spatial resolution, the similarity of their answers depends on the species in question and the complexity of its atmospheric behavior. For ground-level primary PM_{2.5}, the models have very similar values across all counties with Pearson's correlation ranging from 0.73–0.81. For primary PM_{2.5}, which is an inert species emitted directly in particulate form, concentrations are influenced only by differences in atmospheric transport and dilution. This is noted because it has been suggested that Gaussian dispersion modeling is not applicable at distances that exceed 100 km, yet we do not observe systematic biases in the AP2 estimates compared to the CTM-derived models. Consistent with the more complex chemistry, results for cost estimates for secondary pollutants are more variable on average and spatially and the correlations are lower of the secondary pollutants: 0.54–0.73 for NH₃, 0.35–0.49 for SO₂, and 0.077–0.54 for NO_x. The formation of secondary PM_{2.5} depends on how efficiently precursors are converted to secondary species. In the atmosphere, this typically depends on chemistry, deposition rates, sunlight, and the availability of co-reactants especially atmospheric oxidants and thermodynamic interactions between inorganic ions (Ansari and Pandis 1998; West et al. 1999). Additionally, the impacts of secondary pollutants should also more dependent on accurately predicting transport as chemical reactions can occur over long distances and thus expose populations further from the source. Thus, the model selection has a larger role as the estimates of impacts depends on both the representation for long-range transport and chemical processes. Since NH₄⁺, SO₄²⁻ and NO₃⁻ concentrations depend on each other, differences in the model predictions for one species will influence the others.

1
2
3 Finally, in the case of SOA impacts, we are less confident that variability between current
4 RCM estimates represents true prediction uncertainty than we are for inorganic PM_{2.5} species. This
5 is because VOCs from different emissions sources can vary greatly in their SOA production
6 efficiencies and because the fundamental understanding of the formation of SOA from precursor
7 VOCs is still rapidly evolving (Robinson et al., 2007). Presently, marginal social costs for VOC
8 emissions are available from the InMAP and AP2 models, but the prediction of impacts from VOC
9 emissions in RCMs is an area for future development. Specifically, RCMs that account for the fact
10 that different sources have different mixes of VOCs and, therefore, different SOA/PM_{2.5} formation
11 and damage costs (Jathar et al., 2014) would be desirable. When using SOA estimates from current
12 RCMs, we recommend that users consider how the specific mix of VOC species that are relevant
13 to their own scenarios compared to the anthropogenic average mixes implied within the RCMs. In
14 cases where the VOC mixes are substantially different, chemical transport modeling with a more
15 detailed treatment of VOC composition may be warranted.
16
17
18
19
20
21
22
23
24
25
26

27 **5. Conclusion**

28
29 The public health impacts of air pollution, mostly due to premature mortality caused by PM_{2.5}
30 exposure, dominate the benefits analysis of most rules and regulations that target the energy and
31 transportation sectors. Because evaluating these impacts using a state-of-the-science CTM can be
32 challenging, several recent efforts have developed RCMs to provide estimates of the marginal
33 social costs stemming from a tonne of PM_{2.5} emissions and its precursors. In this paper, we
34 compare three datasets of air quality costs derived by RCMs: AP2, EASIUR, and InMAP. We
35 conclude that users can generally use marginal social costs reported by these models for decision
36 and policy analysis in lieu of chemical transport modeling with only a modest loss of fidelity.
37
38
39
40
41
42

43 We show that the RCMs evaluated here can predict the nationwide distribution of PM_{2.5}
44 concentrations with only a modest reduction in accuracy as compared to a CTM. Further, for
45 analyses at a national scale and over many sources, the differences in the air quality modeling
46 approaches reviewed in this paper are less important for the aggregate social costs. Generally, for
47 the evaluation of policies that are enacted at the national level, the total costs from all models are
48 within a factor of two or three. Further, the differences in the social costs as a function of species
49 emitted and source location are broadly similar between models and can be readily understood
50 based on the known atmospheric behavior of that species and the size of the downwind population
51
52
53
54
55
56
57
58
59
60

1
2
3 exposed to PM_{2.5}.

4
5 Additionally, the model estimates reviewed in this paper are derived from different air quality
6 modeling approaches but with harmonized assumptions for the C-R function and the VSL. Hence,
7 the range of the estimates presented here can be interpreted as a measure of the degree of
8 uncertainty inherent in the air quality modeling. Understanding why two CTMs produce different
9 results is challenging as it is difficult to isolate all the factors that drive the differences. We face
10 the same type of challenge when comparing the RCMs. Additionally, since each RCM takes a
11 different approach to abstracting the physical and chemical processes for PM_{2.5} and the
12 meteorology, it is even more challenging to isolate the factors. Thus, we focus on the substantive
13 differences – the social costs – that are affected by the modeling choices made by each RCM. In
14 general, the air quality modeling differences introduced by and between the RCMs shown here are
15 not large when viewed in the context of the other uncertainties in the damage estimates. These
16 differences are small in comparison with other uncertainties involved in air quality decision-
17 making such as the C-R function and VSL. The differences in the damages are comparable to
18 errors between CTMs as well as the errors between CTMs and observed ambient concentrations.
19

20
21 In some locations and for some pollutants, however, these differences can be more substantial;
22 for example, it would be appropriate to investigate the range of benefit estimates for applications
23 which are more geographically limited and especially where NO_x emissions are the dominant
24 concern, such as the Marcellus shale development (Roy et al., 2014) and replacing diesel engines
25 for port power for shipping (Vaishnav et al., 2016). Furthermore, there are cases where the RCM-
26 derived social cost estimates should be applied with more caution, including when changes in
27 emission occur for only a few days per year (e.g., Gilmore et al., 2010) and when there is the
28 potential for non-linearity or if the change in emissions is large enough to change the underlying
29 chemical regimes (see Holt et al., 2015).
30

31
32 While CTMs remain the gold standard for air quality simulation and should continue to be
33 used in many regulatory settings, e.g., SIPs and regulatory impact assessments (RIAs) of major
34 new rules, the ease-of-use of RCMs means that they can be used by a broad range of researchers
35 and analysts. This may include initial scoping of new rules or regulations as well as decision-
36 making in a large number of analyses where air pollution public health costs are not routinely
37 considered in a rigorous and explicit fashion. Because the social cost estimates from these RCMs
38 are sensible and generally consistent and because they are far simpler to use than a CTM, we
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 encourage researchers and analysts to use them in a broad range of applications when air pollution
4 public health impacts may be important. Additionally, RCMs may open up more opportunities for
5 assessing uncertainty. For example, in a CTM, it is impractical to conduct a Monte Carlo type
6 approach to capture the uncertainty in the emission inventories. As RCMs are computational less
7 expensive, these types of analyses could be implemented. Finally, the successful development of
8 RCMs for the U.S. suggests that they might be developed and applied to other regions of the globe
9 where air quality issues are more severe; however, this requires both suitable models and data.
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

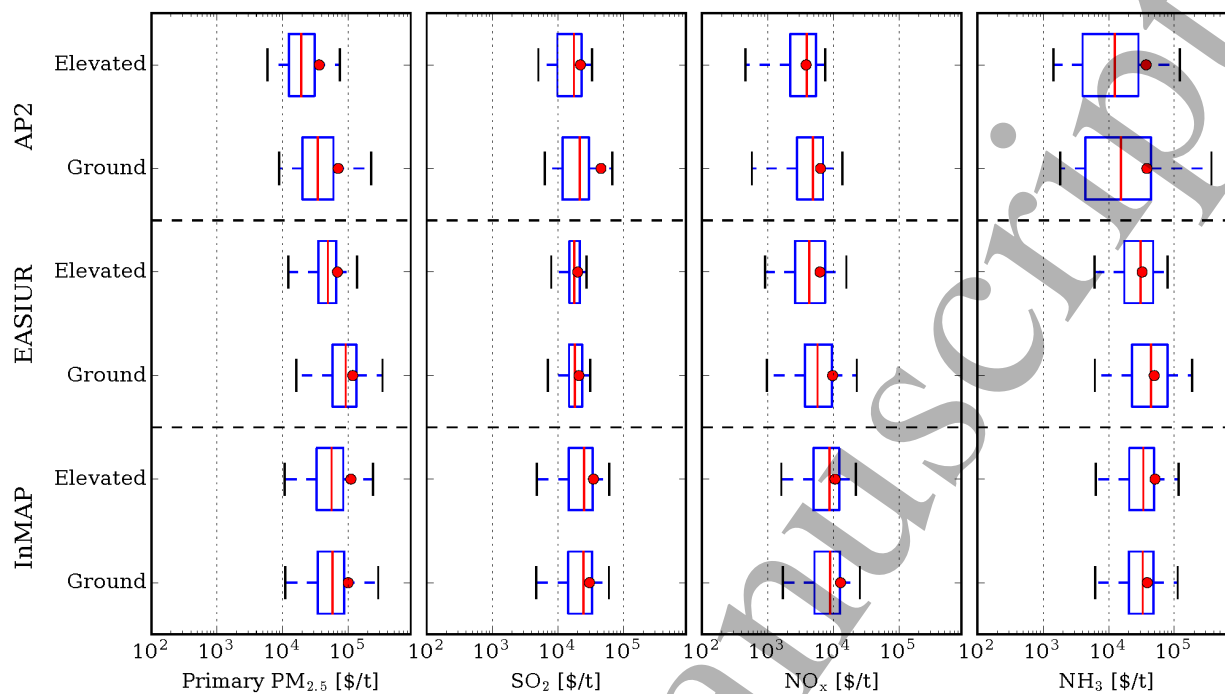


Figure 1: Box plot of the marginal social costs (in USD/tonne) for ground and elevated source emissions across all US counties by pollutant and by air quality model. Red dots and lines indicate emission-weighted mean and median, respectively. The left and right boxes are the 25th and 75th percentiles and the whiskers are the 2.5th and 97.5th percentiles. See Supplemental Information (Table S1) for tabulated values.

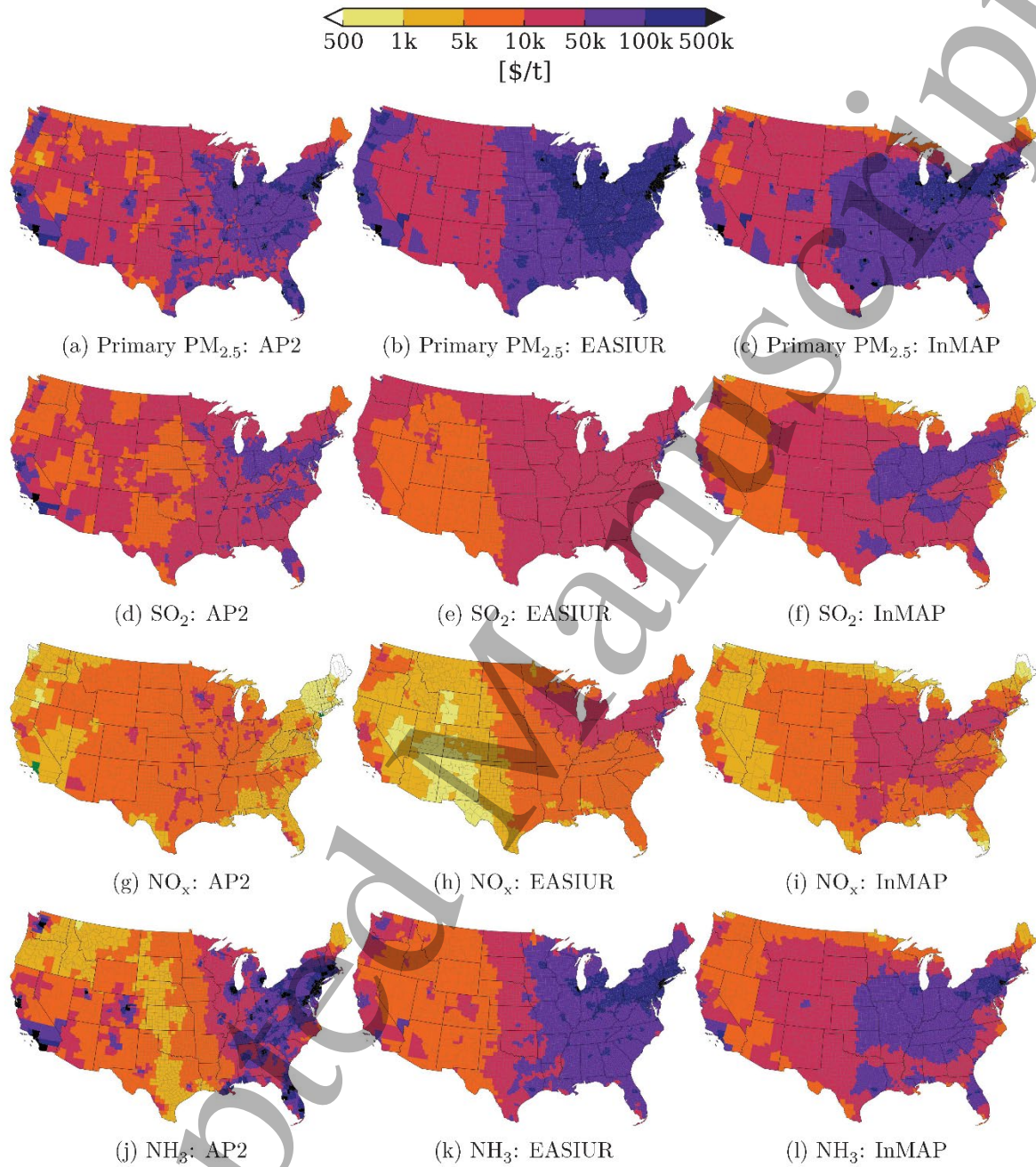


Figure 2: Marginal social costs for ground-level emissions for each US County by pollutant and by air quality model (in USD/tonne). Negative values are in shown in green.

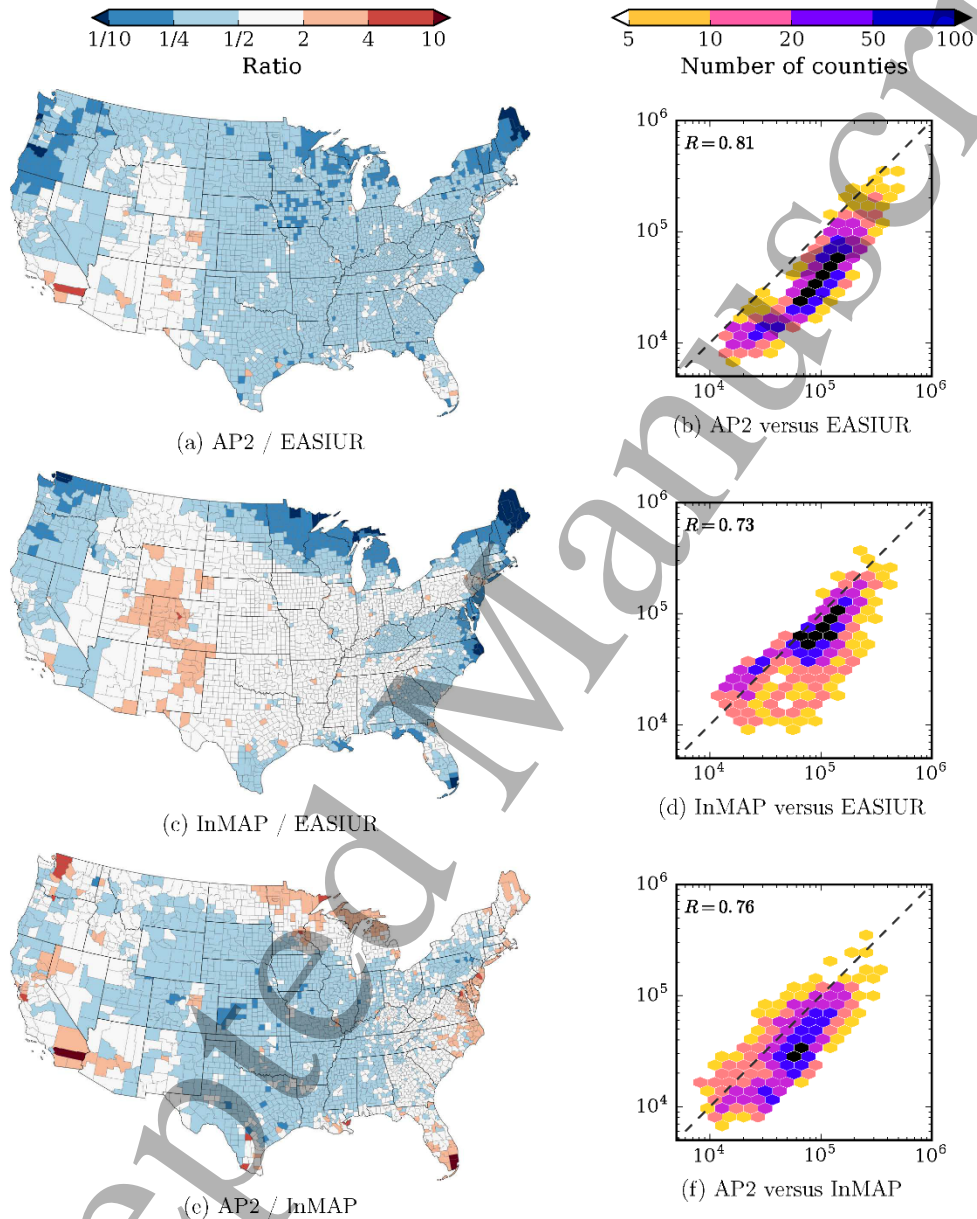


Figure 3: Comparison of marginal social costs from primary PM_{2.5} for ground-level emissions. Panels a, c, and e show the ratio of the social cost estimates for each county for each model pair. White counties indicate agreement within a factor of two. In panels b, d and f, the social costs of emissions (in USD/tonne) by county are plotted for each model pair to show the overall model agreement. R is the Pearson's correlation coefficient.

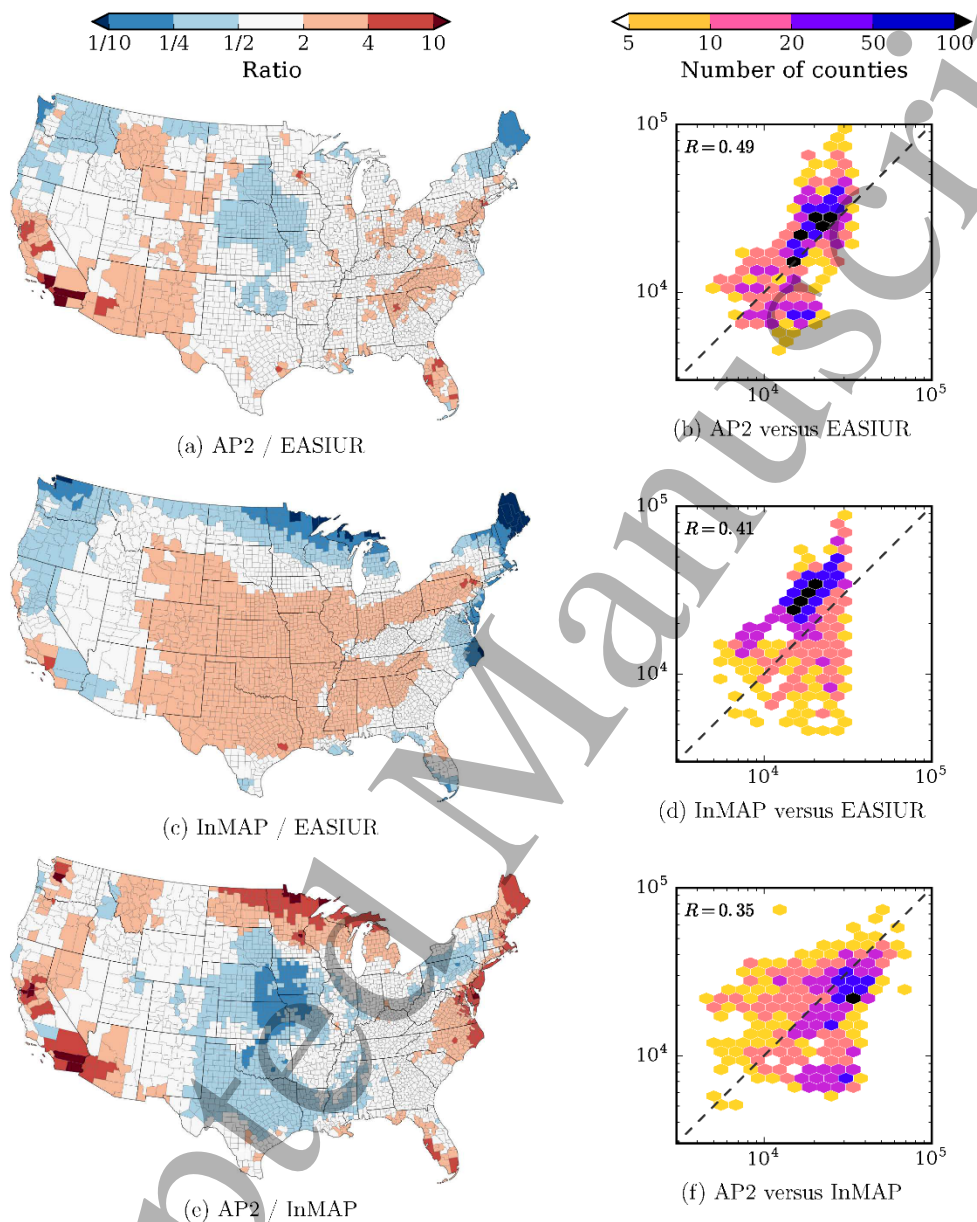


Figure 4: Comparison of marginal social costs of ground-level SO₂ emissions. Panels a, c, and e show the ratio of the social cost estimates for each county for each model pair. White counties indicate agreement within a factor of two. In panels b, d and f, the social costs of emissions (in USD/tonne) by county are plotted for each model pair to show the overall model agreement. R is the Pearson's correlation coefficient.

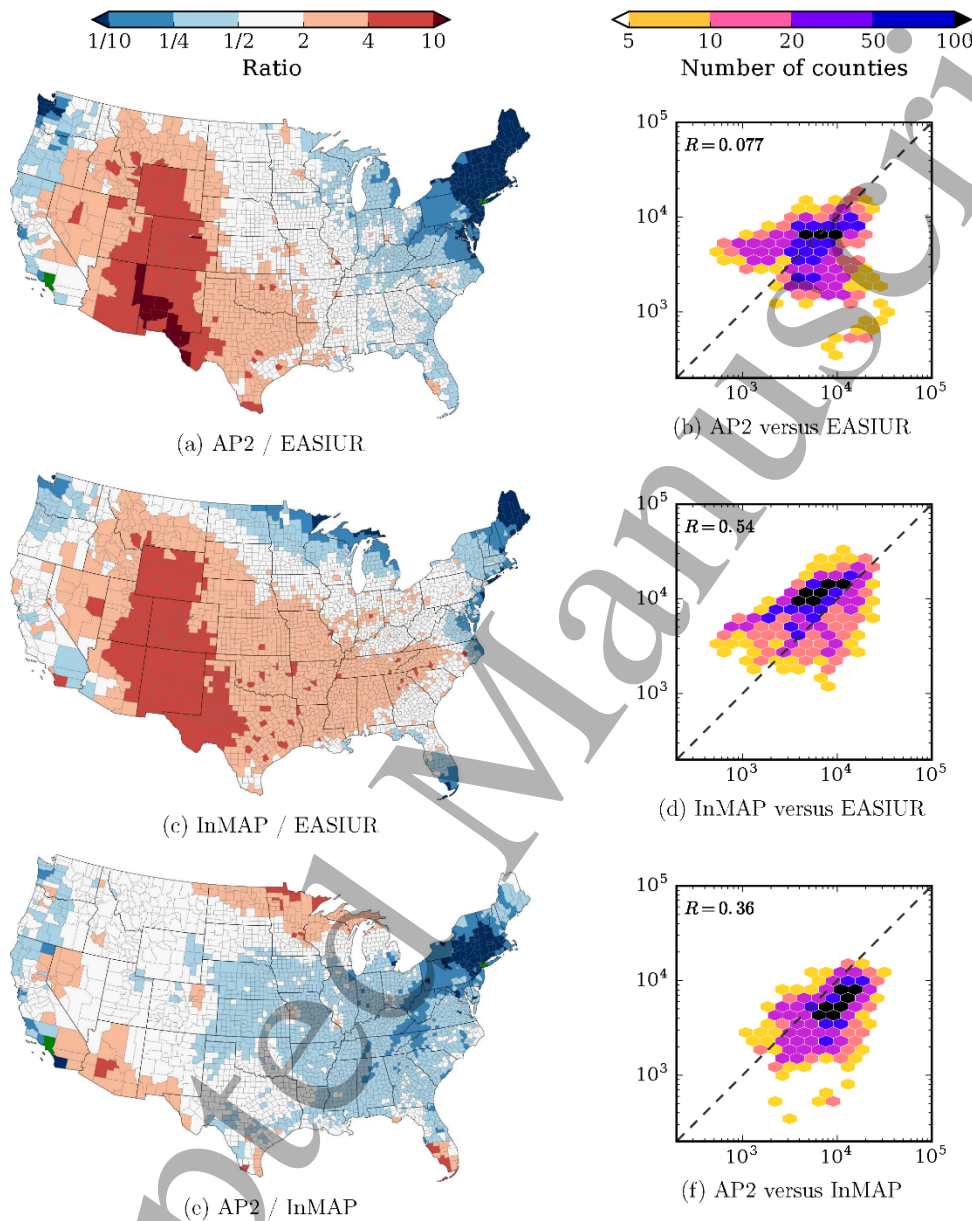


Figure 5: Comparison of marginal social costs of ground-level NO_x emissions. Panels a, c, and e show the ratio of the social cost estimates for each county for each model pair. White counties indicate agreement within a factor of two. In panels b, d and f, the social costs of emissions (in USD/tonne) by county are plotted for each model pair to show the overall model agreement. R is the Pearson's correlation coefficient.

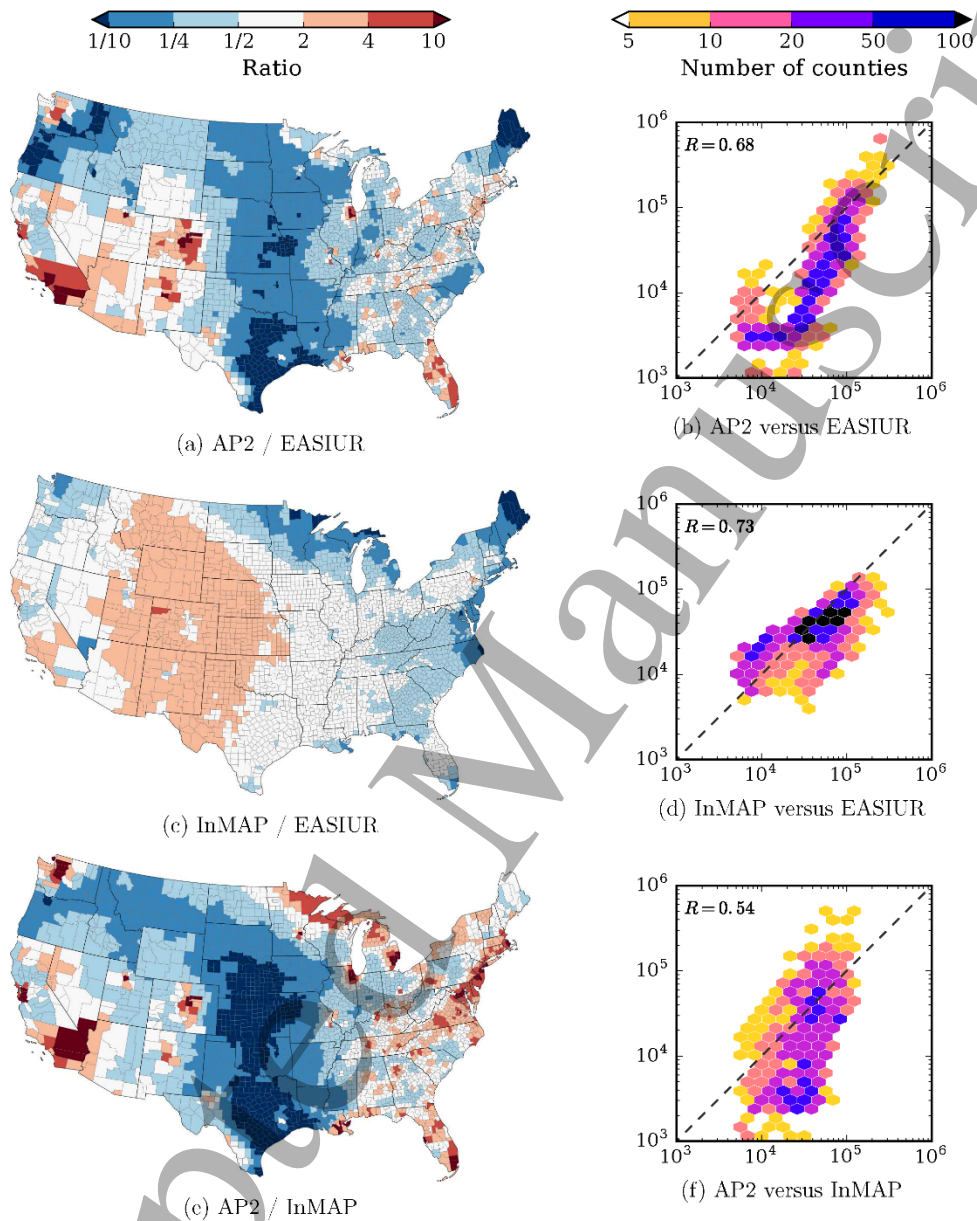


Figure 6: Comparison of marginal social costs of ground-level NH_3 emissions. Panels a, c, and e show the ratio of the social cost estimates for each county for each model pair. White counties indicate agreement within a factor of two. In panels b, d and f, the social costs of emissions (in USD/tonne) by county are plotted for each model pair to show the overall model agreement. R is the Pearson's correlation coefficient.

Funding Acknowledgement: This publication was developed by funding from the Center for Air, Climate and Energy Solutions under Assistance Agreement No. RD83587301 awarded by the U.S. Environmental Protection Agency. It has not been formally reviewed by the U.S. EPA. The views expressed in this document are solely those of the authors and do not necessarily reflect those of the Agency. U.S. EPA does not endorse any products or commercial services mentioned in this publication. Jason Hill acknowledges the US Department of Energy (Grant No. EE0004397) and the US Department of Agriculture (Grant Nos. 2011-68005-30411 and MIN-12-083).

References

- Ansari, A. S., & Pandis, S. N. (1998). Response of Inorganic PM to Precursor Concentrations. *Environmental Science & Technology*, 32(18), 2706–2714. doi:10.1021/es971130j
- Appel, K.W., Napelenok, S.L., Hogrefe, C., Foley, K.M., Pouliot, G.A., Murphy, B., Heath, N., Roselle, S., Pleim, J., Bash, J.O., Pye, H.O.T., Mathur, R. (2017). Overview and evaluation of the Community Multiscale Air Quality (CMAQ) modeling system version 5.2. *Air Pollution Modeling and its Application XXV*, 11:63–72. ITM 2016. Springer Proceedings in Complexity. Springer, Cham, doi: 10.1007/978-3-319-57645-9_11.
- Baumol, W.J. & W.E. Oates (1988). *The Theory of Environmental Policy*. 2nd Edition. Cambridge University Press.
- Bergin, M. S., Russell, A. G., Odman, M. T., Cohan, D. S., and Chameldes, W. L. (2008). Single-Source Impact Analysis Using Three Dimensional Air Quality Models, *J. Air Waste Manag. Assoc.*, 58, 1351–1359: <https://doi.org/10.3155/1047-3289.58.10.1351>
- Buonocore, JJ, Dong, X, Spengler, JD, Fu, JS, Levy JI (2014). Using the Community Multiscale Air Quality (CMAQ) model to estimate public health impacts of PM_{2.5} from individual power plants. *Environ Int.* 68:200-8. doi: 10.1016/j.envint.2014.03.031
- Caiazzo, F., Ashok, A., Waitz, I. A., Yim, S. H., & Barrett, S. R. (2013). Air pollution and early deaths in the United States. Part I: Quantifying the impact of major sectors in 2005. *Atmospheric Environment*, 79, 198-208. <https://doi.org/10.1016/j.atmosenv.2013.05.081>
- ENVIRON (2016). User's Guide Comprehensive Air Quality Model with Extensions version 6.40, ENVIRON International Corporation, Novato, http://www.camx.com/files/camxusersguide_v6-40.pdf
- Fraas A., Lutter R. (2013). Uncertain benefits estimates for reductions in fine particle concentrations. *Risk Anal.* 33(3):434-49. doi: 10.1111/j.1539-6924.2012.01883.x.
- Fann, N., Fulcher, C. M., & Hubbell, B. J. (2009). The influence of location, source, and emission type in estimates of the human health benefits of reducing a ton of air pollution. *Air Quality, Atmosphere, & Health*, 2(3), 169–176. doi:10.1007/s11869-009-0044-0
- Fann, N, Lamson, AD, Anenberg, S. C., Wesson, K, Risley, D, Hubbell BJ. (2012). Estimating the national public health burden associated with exposure to ambient PM_{2.5} and ozone. *Risk Anal.* 32(1):81-95. doi: 10.1111/j.1539-6924.2011.01630.x
- Gilmore, E. A., Apt, J., Walawalkar, R., Adams, P. J., Lave, L. B. (2010). The air quality and human health effects of integrating utility-scale batteries into the New York State electricity grid. *Journal of Power Sources*, 195(8), 2405–2413. doi:10.1016/j.jpowsour.2009.10.072

- 1
2
3 Goodkind AL, Tessum CW, Coggins JS, Hill JD, Marshall JD. (2019) Fine-scale damage estimates
4 of particulate matter air pollution reveal opportunities for location-specific mitigation of
5 emissions. *Proceedings of the National Academy of Sciences*. Apr 3;201816102.
6 <https://doi.org/10.1073/pnas.1816102116>
7
- 8 Grosjean, D. and J. H. Seinfeld (1989), Parameterization of the Formation Potential of Secondary
9 Organic Aerosols, *Atmospheric Environment*, 23(8), 1733-1747:
10 [https://doi.org/10.1016/0004-6981\(89\)90058-9](https://doi.org/10.1016/0004-6981(89)90058-9)
11
- 12 Grell, G. A., Peckham, S. E., Schmitz, R., McKeen, S. A., Frost, G., Skamarock, W. C., Eder, B.
13 (2005). Fully coupled “online” chemistry within the WRF model. *Atmospheric Environment*,
14 39(37), 6957-6975. <https://doi.org/10.1016/j.atmosenv.2005.04.027>
15
- 16 Hand, J. L., Schichtel, B.A., Pitchford, M., Malm, W. C., Frank, N. H. (2012) “Seasonal
17 composition of remote and urban fine particulate matter in the United States,” *Journal of*
18 *Geophysical Research*, vol. 117, no. 5, Article ID D05209. doi/pdf/10.1029/2011JD017122
19
- 20 Heo, J., Adams, P. J., Gao, H. O. (2016a). Public Health Costs of Primary PM_{2.5} and Inorganic
21 PM_{2.5} Precursor Emissions in the United States. *Environmental Science & Technology*,
22 50(11), 6061–6070. doi:10.1021/acs.est.5b06125
23
- 24 Heo, J., Adams, P. J., Gao, H. O. (2016b). Reduced-form modeling of public health impacts of
25 inorganic PM_{2.5} and precursor emissions. *Atmospheric Environment*, 137, 80–89.
26 doi:10.1016/j.atmosenv.2016.04.026
27
- 28 Heo, J., Adams, P. J., Gao, H. O. (2017). Public health costs accounting of inorganic PM_{2.5}
29 pollution in metropolitan areas of the United States using a risk-based source-receptor model.
30 *Environment International*, 106, 119-126: doi: 10.1016/j.envint.2017.06.006.
31
- 32 Holt, J. Selin, N.E. Solomon, S. (2015) "Changes in Inorganic Fine Particulate Matter Sensitivities
33 to Precursors Due to Large-Scale US Emissions Reductions", *Environmental Science &*
34 *Technology* 49 (8), 4834-4841: doi: 10.1021/acs.est.5b00008
35
- 36 Jathar, S. H., Gordon, T. D., Hennigan, C. J., Pye, H. O. T., Pouliot, G.A., Adams, P. J., Donahue,
37 N. M., Robinson, A. L. (2014). Unspeciated organic emissions from combustion sources and
38 their influence on the secondary organic aerosol budget in the United States, *Proceedings of*
39 *the National Academy of Sciences*, 111 (29), 10473-10478:
40 <https://doi.org/10.1073/pnas.1323740111>
41
- 42 Krewski, D., Jerrett, M., Burnett, R.T., Ma, R., Hughes, E., Shi, Y., Turner, M.C., Pope III, C.A.,
43 Thurston, G., Calle, E.E., Thun, M.J. (2009). Extended follow-up and spatial analysis of the
44 American Cancer Society study linking particulate air pollution and mortality (No. 140).
45 Boston, MA: Health Effects Institute.
46
- 47 Latimer, D.A. (1996). Particulate matter source-receptor relationships between all point and area
48 sources in the United States and PSD class I area receptors. Prepared for Office of Air Quality
49 Planning and Standards, U.S. EPA. Research Triangle Park, NC. (September).
50
- 51 Muller, N. Z., Mendelsohn, R. (2007). Measuring the damages of air pollution in the United States.
52 *Journal of Environmental Economics and Management*, 54(1), 1–14.
53 <https://doi.org/10.1016/j.jeem.2006.12.002>
54
- 55 Muller, N. Z., Mendelsohn, R., & Nordhaus, W. (2011). Environmental accounting for pollution
56 in the United States economy. *American Economic Review*, 101(5), 1649-75. DOI:
57
58
59
60

1
2
3 10.1257/aer.101.5.1649

4
5 National Research Council (2002). Estimating the Public Health Benefits of Proposed Air
6 Pollution Regulations. Washington, DC: The National Academies Press.
7 doi:<https://doi.org/10.17226/10511>.

8
9 Pinder, R.W., Gilliland, A.B., Dennis, R.L. (2008), Environmental impact of atmospheric NH₃
10 emissions under present and future conditions in the eastern United States. Geophysical
11 Research Letters, 35(12), <https://doi.org/10.1029/2008GL033732>

12
13 Powers, J.G., Klemp, J.B., Skamarock, W.C., Davis, C.A., Dudhia, J., Gill, D.O., Coen, J.L.,
14 Gochis, D.J., Ahmadov, R., Peckham, S.E., and Grell, G.A. (2017). The Weather Research
15 and Forecasting Model: Overview, System Efforts, and Future Directions. Bulletin of the
16 American Meteorological Society, 98(8), 1717-1737: [https://doi.org/10.1175/BAMS-D-15-](https://doi.org/10.1175/BAMS-D-15-00308.1)
17 00308.1

18
19 Robinson, A.L., Donahue, N.M., Shrivastava, M.K., Weitkamp, E.M., Sage, A.M., Grieshop, A.P.,
20 Lane, T.E., Pierce, J.R., Pandis, S.N. (2007). Rethinking Organic Aerosols: Semivolatile
21 Emissions and Photochemical Aging. Science, Vol. 315, Issue 5816, pp. 1259-1262, doi:
22 10.1126/science.1133061

23
24 Roy, A.A., Adams, P. J., Robinson, A.L. (2014). Air pollutant emissions from the development,
25 production, and processing of Marcellus Shale natural gas. Journal of the Air & Waste
26 Management Association. 64(1): 19-37, doi:10.1080/10962247.2013.826151

27
28 Tessum CW, Hill JD, Marshall JD (2014) Life cycle air quality impacts of conventional and
29 alternative light-duty transportation in the United States. Proc Natl Acad Sci USA
30 111(52):18490–18495. doi: <https://doi.org/10.1073/pnas.1406853111>

31
32 Tessum CW, Hill JD, Marshall JD. (2015) Twelve-month, 12km resolution North American WRF-
33 Chem v3. 4 air quality simulation: performance evaluation. Geoscientific Model
34 Development. Apr 1;8(4).

35
36 Tessum CW, Hill JD, Marshall JD (2017) InMAP: A model for air pollution interventions. PLoS
37 ONE 12(4): e0176131. <https://doi.org/10.1371/journal.pone.0176131>

38
39 U.S. EPA (2006). Report of the EPA Work Group on VSL Meta-Analysis. Washington, DC:
40 National Center for Environmental Economics, Report NCEE-0494/.

41
42 U.S. EPA (2009). Integrated Science Assessment for Particulate Matter (Final Report). Research
43 Triangle Park, NC.

44
45 U.S. EPA (2010). Guidelines for Preparing Economic Analyses. National Center for
46 Environmental Economics, Office of Policy, U.S. Environmental Protection Agency.

47
48 U.S. EPA (2015). Regulatory Impact Analysis for the Clean Power Plan Final Rule (No. EPA-
49 452/R-15-003). U.S. Environmental Protection Agency. Office of Air and Radiation.
50 Office of Air Quality Planning and Standards, Research Triangle Park, NC

51
52 U.S. EPA (2017). Environmental Benefits Mapping and Analysis Program: Community Edition
53 (BenMAP-CE) User Manual and Appendices. Research Triangle Park, NC, USA. April,
54 2017

55
56 U.S. EPA (2018). User's Manual for the Co-Benefits Risk Assessment (COBRA) Screening
57 Model (version 3.1), 2018. <https://www.epa.gov/sites/production/files/2018->

[03/documents/cobra_user_manual_february_2018_508.pdf](#)

Vaishnav, P.; Fischbeck, P. S., Morgan, M. G., Corbett, J. J. (2016). Shore Power for Vessels Calling at US Ports: Benefits and Costs. *Environmental Science & Technology*, 50(3): 1102-1110: doi:10.1021/acs.est.5b04860

West, J. J., Ansari, A. S., Pandis, S. N. (1999). Marginal PM_{2.5}: Nonlinear aerosol mass response to sulfate reductions in the eastern United States. *Journal of the Air & Waste Management Association*, 49(12), 1415–1424: <https://doi.org/10.1080/10473289.1999.10463973>

Accepted Manuscript