Employing the State of Science

in Optimal Policy Decision-Making

for Air Quality, Energy, and Climate Change

Jinhyok Heo

November 2017

Acknowledgments

- Postdoc research (Cornell):

  ⇒ Lloyd's Register Foundation and New York Metropolitan Transportation Council (NYMTC).

- PhD research (Carnegie Mellon):

  ⇒ Center for Atmospheric Particle Studies (CAPS).

  ⇒ Center for Climate and Energy Decision Making (CEDM).

  ⇒ Department of Engineering and Public Policy (EPP).

  ⇒ Peter J. Adams (advisor) and many people at Carnegie Mellon.

Outline

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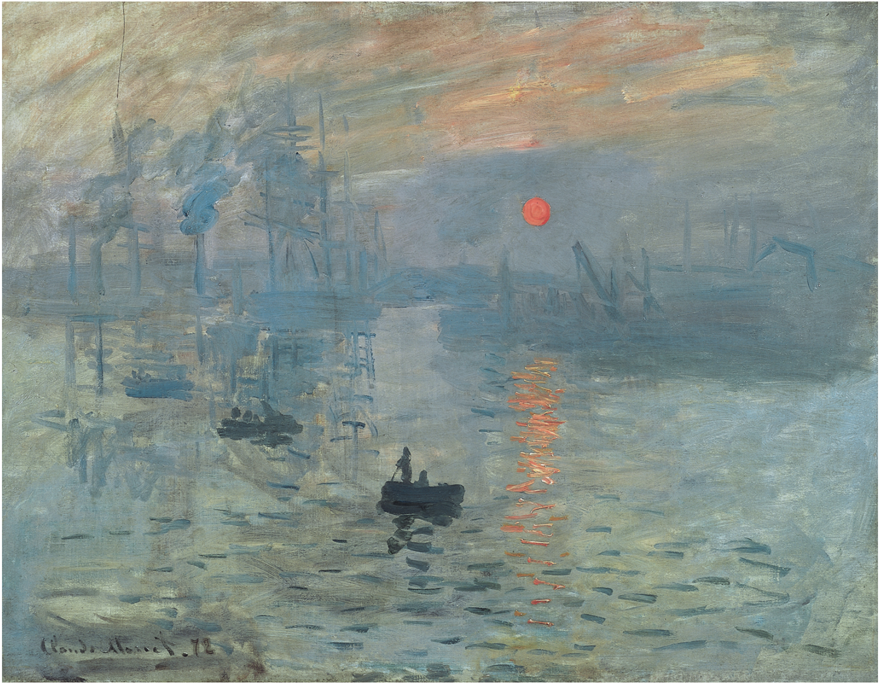
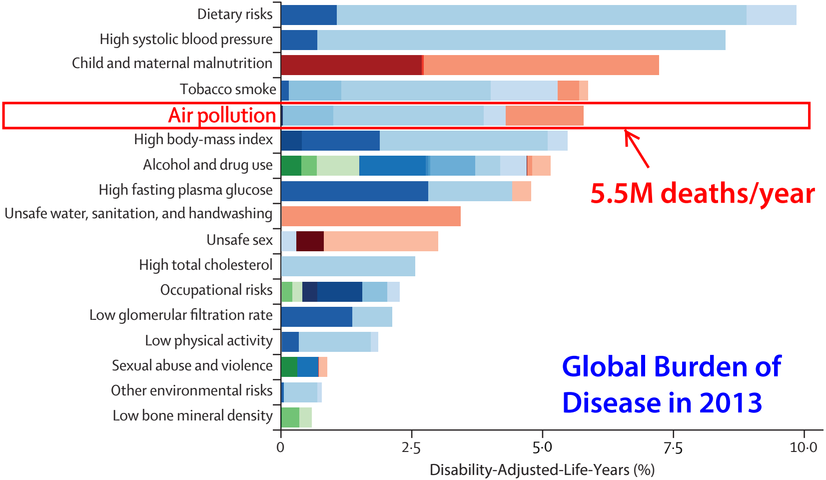


Claude Monet (1872), *"Impression, Sunrise"*, from Wikimedia Commons

Air Pollution Imposes Substantial External Costs

- One of the top global risk factors (Forouzanfar et al., *Lancet* 2015).



(adapted from Forouzanfar et al., *Lancet* 2015)

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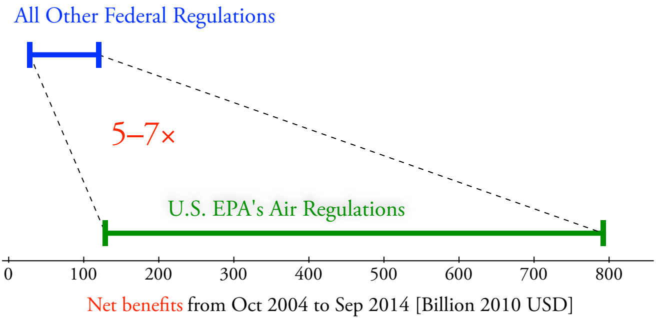

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Social Costs of Air Pollution

- Damages imposed by air pollution on human and the natural environment:
  - Human health: Mortality (premature death), morbidity (illness)
  - Natural environment: eutrophication, soil and water acidification, reduced tree growth, reduced agricultural yields, impaired visibility, and decreased worker productivity
- When monetized, the effects of fine particulate matter ($PM_{2.5}$) on mortality account for >95% of the social costs. (U.S. EPA, 2011; U.S. EPA, 1999).
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Fine Particulate Matter, $PM_{2.5}$

- Primary PM (10–20%): directly emitted as PM
  ⇒ Elemental Carbon (EC), dust, and other inert PM
- Secondary PM (80–90%): chemically produced in the atmosphere
  ⇒ Inorganic PM: SO_2, NO_x, and NH_3 gases
  ⇒ Secondary Organic Aerosol (SOA): certain Volatile Organic Compounds (VOCs)

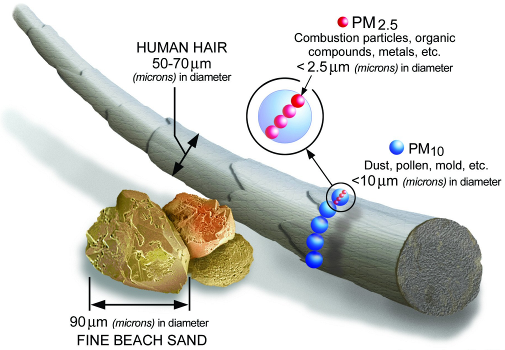

Image courtesy of the U.S. EPA

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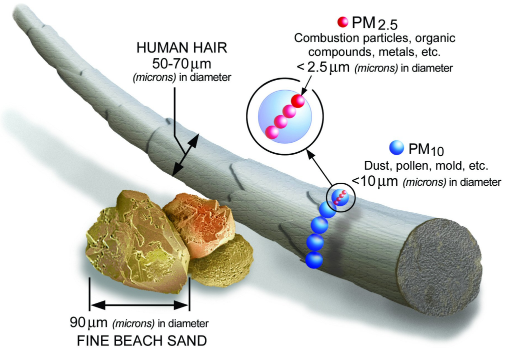

Image courtesy of the U.S. EPA

Important Secondary $PM_{2.5}$ species

- Inorganic PM ($\sim$50%)
  $\Rightarrow$ Only three species: sulfate (SO_4^{2-}), nitrate (NO_3^-), and ammonium (NH_4^+)
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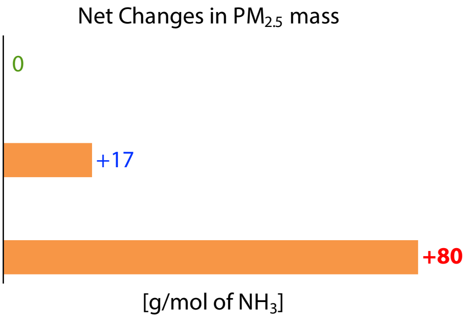
Inorganic Chemistry, well-understood but complex

For example, ammonia (NH_3) can produce three different amounts of $PM_{2.5}$:

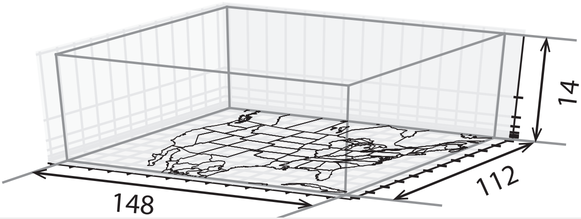
1. NH_3 remains as Gas:
   If there are no SO_2 and NO_x.
2. NH_3 forms Ammonium Sulfate PM:
   Sulfate is already PM.
3. NH_3 forms Ammonium Nitrate PM:
   More under cold temperature.



These reactions occur over hundreds of kilometers or more downwind!

Chemical Transport Model (CTM)

- The most rigorous method to simulate air quality.
- tries to simulate all the relevant processes:
  - ⇒ divides the atmosphere into a 3D grid
  - ⇒ emissions, transport, chemical reactions, and removal processes
- A collaborative work among a large community of scientists and engineers.
- used for U.S. EPA's Regulatory Impact Analyses and State Implementation Plans.
- I ran CAMx
  - ⇒ Horizontal resolution: 148 × 112 grid (1 cell = 36 km × 36 km)
  - ⇒ Vertical resolution: 14 layers for 16 km
  - ⇒ Temporal resolution: 15 minutes or less



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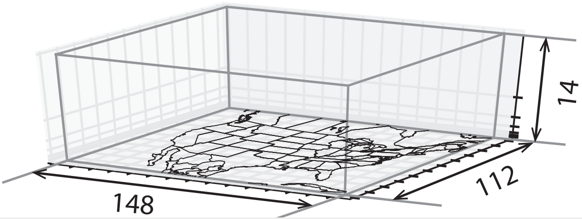


How to Estimate the Social Cost of Emissions

Emissions

1. Run Air Quality Simulations

Changes in $PM_{2.5}$

2. Use Epidemiological Studies

Changes in Mortality Rate

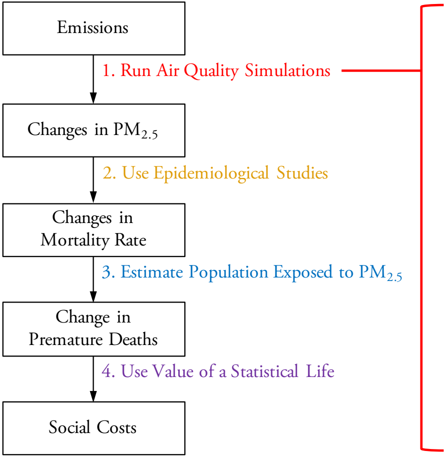
3. Estimate Population Exposed to $PM_{2.5}$

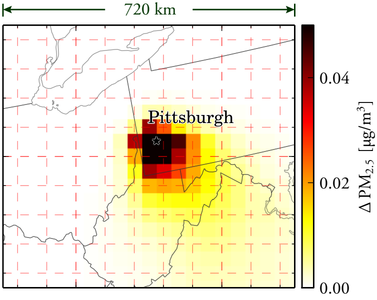
Change in Premature Deaths

4. Use Value of a Statistical Life

Social Costs

How to Estimate the Social Cost of Emissions





$\Delta PM_{2.5}$ by EC emissions in Pittsburgh

- $PM_{2.5}$ formation varies by:
  - Air pollutant
  - Atmospheric conditions

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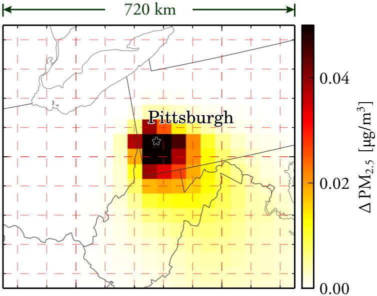

$\Delta PM_{2.5}$ by EC emissions in Pittsburgh

- Epidemiology:
  $+1\ \mu g/m^3 \longrightarrow +1\%$ mortality
  (Krewski et al., 2009; Lepeule et al., 2012)

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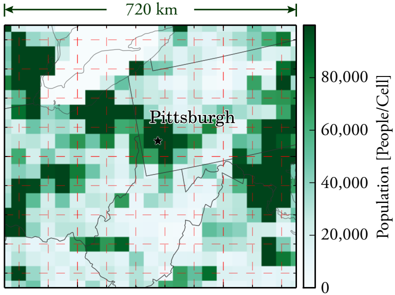

Population around Pittsburgh

- $PM_{2.5}$ concentrations:
  $\Rightarrow$ High near the source
  $\Rightarrow$ Low far from the source

How to Estimate the Social Cost of Emissions

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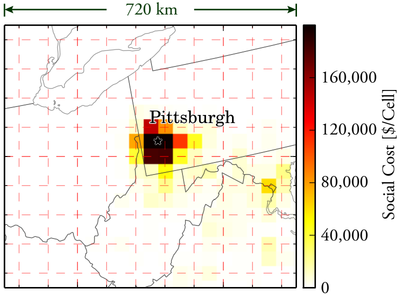

Social Cost of EC from Pittsburgh

- U.S. EPA's Value of a Statistical Life (VSL):
  $\Rightarrow$ $8M (in 2010 USD)

Marginal Social Cost, a Useful Metric

Policy interventions usually result in marginal changes in emissions.

$$\frac{\text{Social Cost [\$]}}{\text{Emissions [t]}} = \text{Marginal Social Cost [\$/t]}$$

Carbon Capture and Storage (CCS) Technology: Air Quality?

(Heo et al., *Environ. Sci. Technol.* 2015)

Environmental Science & Technology

Article

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Implications of Ammonia Emissions from Post-Combustion Carbon Capture for Airborne Particulate Matter

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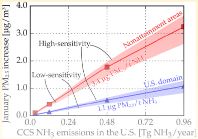
‡Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, United States

Ⓢ *Supporting Information*

ABSTRACT: Amine scrubbing, a mature post-combustion carbon capture and storage (CCS) technology, could increase ambient concentrations of fine particulate matter ($PM_{2.5}$) due to its ammonia emissions. To capture 2.0 Gt CO_2/year, for example, it could emit 32 Gg NH_3/year in the United States given current design targets or 15 times higher (480 Gg NH_3/year) at rates typical of current pilot plants. Employing a chemical transport model, we found that the latter emission rate would cause an increase of 2.0 μg $PM_{2.5}/m^3$ in nonattainment areas during wintertime, which would be troublesome for $PM_{2.5}$-burdened areas, and much lower increases during other seasons. Wintertime $PM_{2.5}$ increases in nonattainment areas were fairly linear at a rate of 3.4 μg $PM_{2.5}/m^3$ per 1 Tg NH_3, allowing these results to be applied to other CCS emissions scenarios. The $PM_{2.5}$ impacts are modestly uncertain (±20%) depending on future emissions of SO_2, NO_x, and NH_3. The public health costs of CCS NH_3 emissions were valued at \$31−68 per tonne CO_2 captured, comparable to the social cost of carbon itself. Because the costs of solvent loss to CCS operators are lower than the social costs of CCS ammonia, there is a regulatory interest to limit ammonia emissions from CCS.



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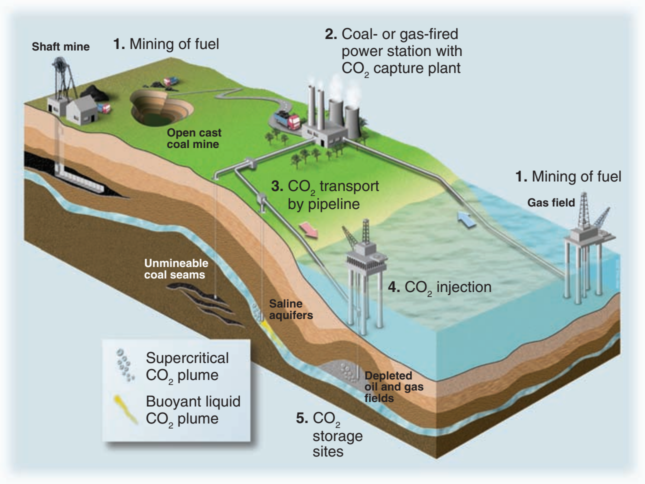


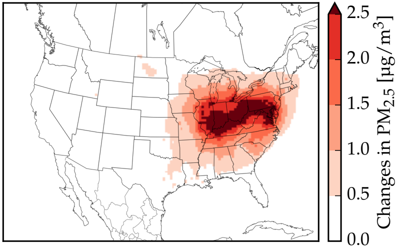
Fig. 1. Diagrammatic representation of the life-cycle chain of fossil fuel use. CO_2 separation and capture at power plants enables storage of CO_2 in porous rocks deep below ground.

(Haszeldine, *Science* 2009)

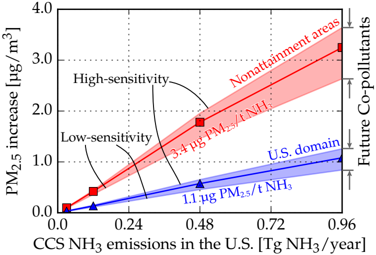
CCS Ammonia May Seriously Compromise Climate Benefits!

Main Scenario: capturing 2 Gt CO_2 ($\sim$ current CO_2 from coal generation) in 2050

(Heo et al., *Environ. Sci. Technol.* 2015)



(a) $PM_{2.5}$ increase in Winter 2050



(b) Two major uncertainties

Policy Implications:

- The social cost of CCS ammonia: \$31-68/t CO_2 captured by CCS.
  $\Rightarrow$ comparable to the social cost of carbon (U.S. IAWG, 2013): \$28-100/t CO_2
  $\Rightarrow$ CCS ammonia may seriously compromise the climate benefits from CCS.
- Our results provide a policy guide for the appropriate level of CCS ammonia control for a wide range of future CCS scenarios.

Outline

Wanted: A Better Tool for Policy Research

- Chemical Transport Models (CTMs) are too expensive.
  - Difficult to use: require expertise in atmospheric science and high-performance computing.
  - Often infeasible. For example,

    ⇒ 100s or more CTM runs for cost-benefit analysis with many policy options?

    ⇒ Monte Carlo simulation for uncertainty analysis?

- Current reduced-form models rely on overly simple or outdated air quality models.
  - Using a simple old air quality model (Latimer, 1996), APEEP (Muller and Mendelsohn, 2007; Muller et al., 2011) provides per-ton social costs of major pollutants for all U.S. counties (about 3,100).

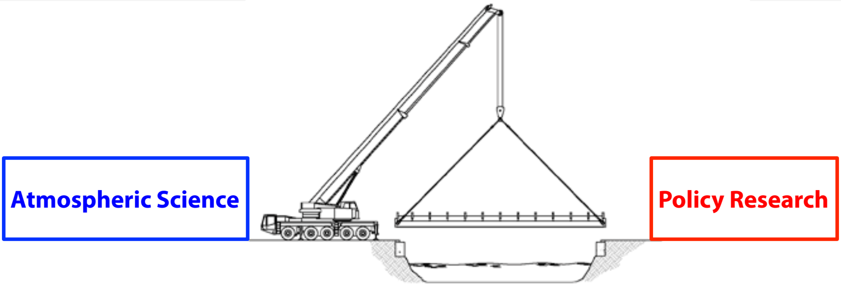
    ⇒ A CTM will require 6,000 CPU-years!

The Estimating Air pollution Social Impact Using Regression (EASIUR) Model

(Heo et al., *Atmos. Environ.* 2016; Heo et al., *Environ. Sci. Technol.* 2016)

Goal:

To build a *Per-tonne Social Cost* model that predicts like a state-of-the-art CTM without too much computation.



(Image credit: http://steel-bridges.com/tech-composite-beam-bridge.htm)

Research Design (1)

Our goal is to derive:

$$\boxed{\text{Per-tonne Social Cost } [\$/t] = f\ (\text{Exposed Population, Atmospheric Variables})}$$

1. Select 100 random CAMx cells based on population.

- 50 training samples:
  ⇒ Regression
- 50 test samples:
  ⇒ Out-of-sample evaluation

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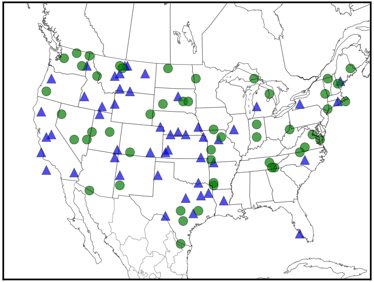

▲ : Training sample ● : Test sample

- 50 training samples:
  $\Rightarrow$ Regression
- 50 test samples:
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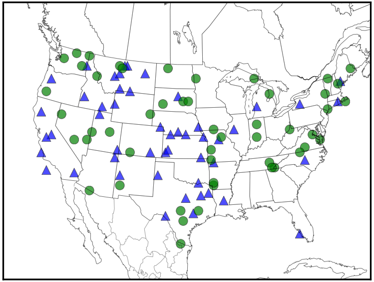
Research Design (2)

Our goal is to derive:

Per-tonne Social Cost [\$/t] = f (Exposed Population, Atmospheric Variables)

2. Run CAMx to estimate $PM_{2.5}$ increase from "marginal" emissions.



▲ : Training sample ● : Test sample

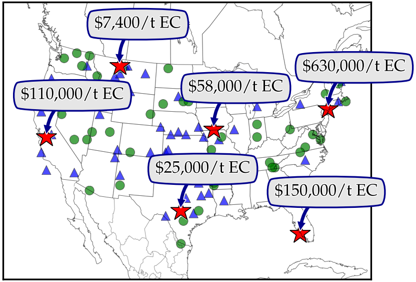
- For EC, SO_2, NO_x, and NH_3
- ∼30 TB data were generated although tagging (PSAT) reduced computations by 90%.

Research Design (3)

Our goal is to derive:

Per-tonne Social Cost [$/t] = *f* (Exposed Population, Atmospheric Variables)

3. Calculate per-tonne social costs for the 100 locations.



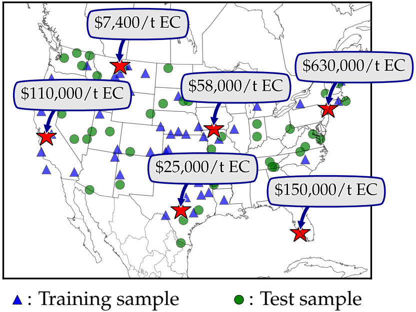
▲ : Training sample ● : Test sample

Research Design (4)

Our goal is to derive:

Per-tonne Social Cost [\$/t] = f (Exposed Population, Atmospheric Variables)

4. Run regressions to achieve our goal!



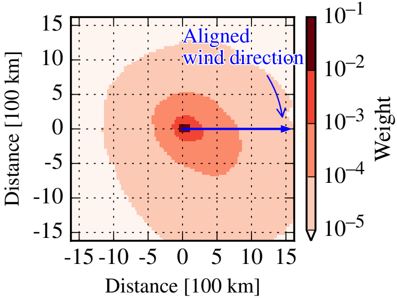
- Chose the best using Akaike Information Criterion (AIC) among many regression models.
- Out-of-sample test (Morris et al., 2005):

$$\text{Mean Fractional Bias} = \frac{2}{N}\sum_{i}^{N}\frac{P_i - O_i}{P_i + O_i}$$

$$\text{Mean Fractional Error} = \frac{2}{N}\sum_{i}^{N}\left|\frac{P_i - O_i}{P_i + O_i}\right|$$

Performance	MFB	MFE
"Excellent"	$\leq \pm 0.15$	≤ 0.35
"Good"	$\leq \pm 0.30$	≤ 0.50

Average Plumes for Quantifying Exposed Population



(a) EC Average Plume (Summer)

- averaged CTM results of 50 sample locations.
- normalized an average plume created from CTM results:
  $\sum_{x,y} \text{Weight}_{x,y} = 1.0$
- used as spatial weights in regression to express exposed population:
  $\text{Exposed Population} = \sum_{x,y} \left(\text{Wind-Direction-Adjusted Weight}_{x,y} \times \text{Population}_{x,y} \right)$

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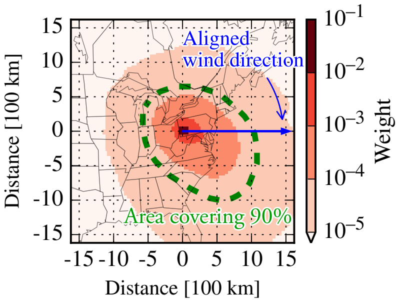

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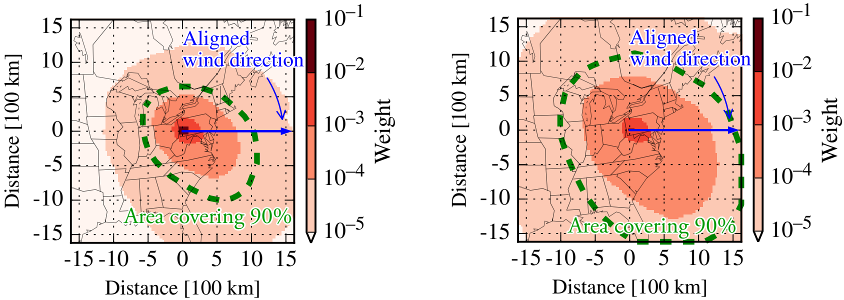

(a) EC Average Plume (Summer) (b) SO_2 Average Plume (Summer)

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EC: Marginal Social Cost (Summer)

$$\boxed{\text{Marginal Social Cost}\ [\$/\text{t EC}] = 1.1 \cdot 10^{36} \cdot P^{0.78} \cdot T^{-21} \cdot Pr^{5.6}}$$

P: Exposed Population [# of People], T: Temperature [K], Pr: Surface Atmopsheric Pressure [hPa]

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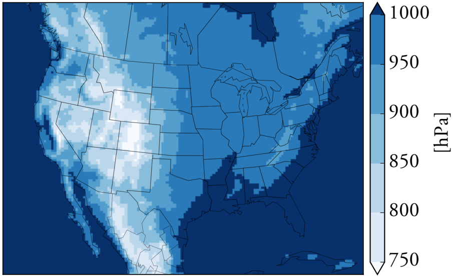

Average Surface Atmospheric Pressure (Summer)

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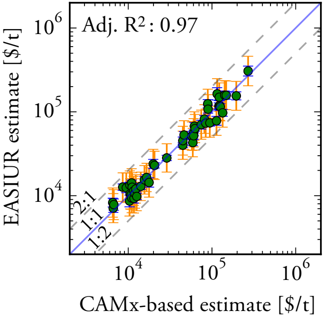

(a) Fitted values

Figure: EC model evaluation. Blue: 95% confidence intervals. Orange: 95% prediction intervals.

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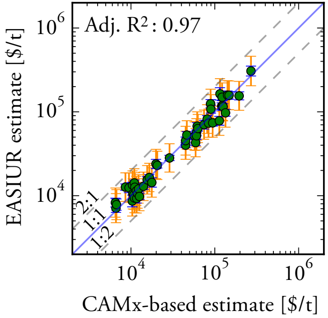
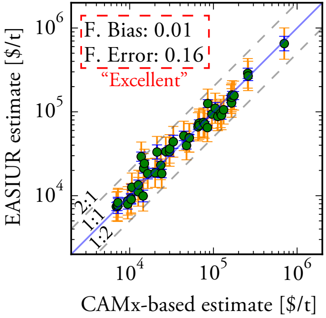




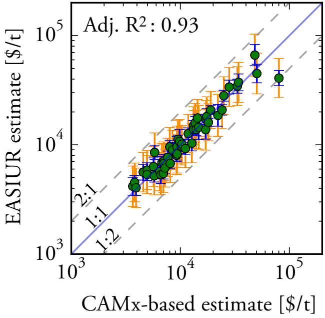
(a) Fitted values (b) Out-of-sample evaluation

Figure: EC model evaluation. Blue: 95% confidence intervals. Orange: 95% prediction intervals.

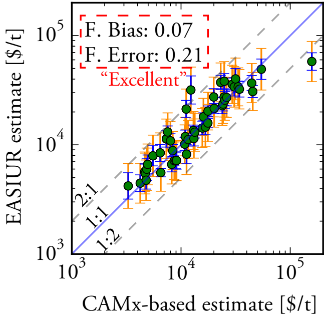
SO_2: Marginal Social Cost (Summer)

$$\text{MSC}\ [\$/\text{t}\ SO_2] = 1.4 \cdot 10^{32} \cdot P^{0.56} \cdot T^{-20} \cdot Pr^{7.3} \cdot Hu^{-0.74} \cdot TS^{0.23} \cdot TA^{-0.15}$$

P: Exposed Population [# of People], *T*: Temperature [K], *Pr*: Surface Atmopsheric Pressure [hPa], *Hu*: Absolute Humidity [ppm], *TS*: Total Sulfate [μmol/m^3], *TA*: Total Ammonia [μmol/m^3]



(a) Fitted values

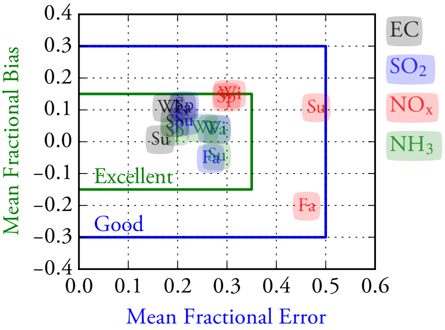


(b) Out-of-sample evaluation

Figure: SO_2 model evaluation. Blue: 95% confidence intervals. Orange: 95% prediction intervals.

Success! Most regression models meet the "Excellent" criteria.

Wi: Winter, Sp: Spring, Su: Summer, Fa: Fall



- "Excellent" and "Good":
  ⇒ "the best a model can be expected to achieve" (Boylan and Russell, 2006).
- Small additional uncertainty for air quality modeling.

$$\text{Mean Fractional Bias} = \frac{2}{N}\sum_{i}^{N}\frac{P_i - O_i}{P_i + O_i}$$

$$\text{Mean Fractional Error} = \frac{2}{N}\sum_{i}^{N}\left|\frac{P_i - O_i}{P_i + O_i}\right|$$

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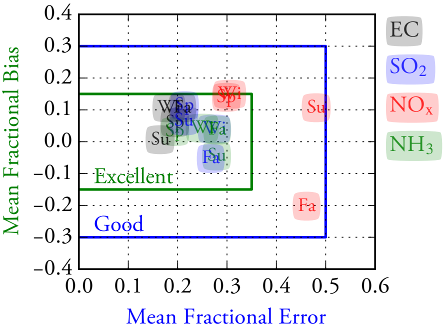

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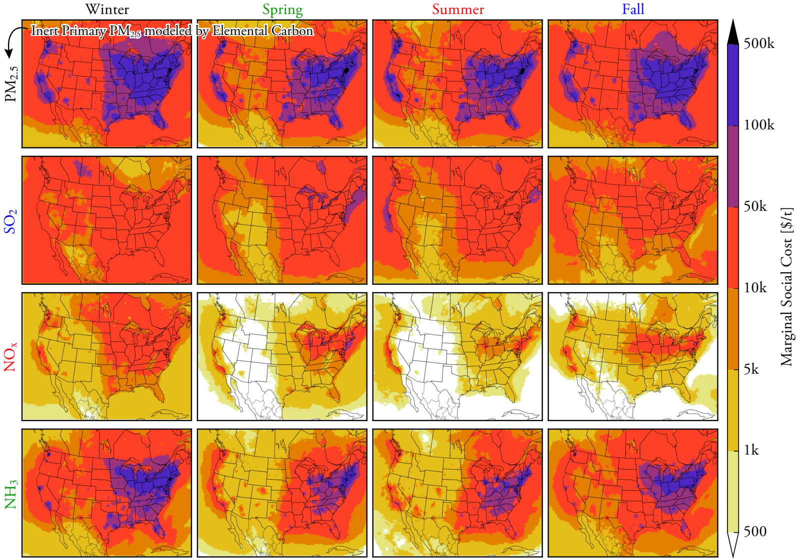
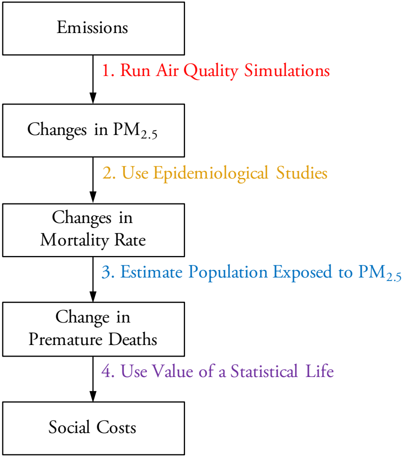
EASIUR's Marginal Social Costs [$/t] at the Point of Emissions



This is for ground-level emissions. There are two more for 150 m and 300 m emission elevations.

Summary: Why EASIUR?

Current Method



EASIUR Method

- Accurate
- Fast
- Easy-to-use
- Can be updated

To get EASIUR, google EASIUR!

Outline

Very hard to find the sources of $PM_{2.5}$ that you are exposed to!

- Because innumerable emission sources and air pollutants travel long distances while they undergo complex chemical reactions.
- Current methods:
  - Receptor Models: Chemical Mass Balance (CMB), Positive Matrix Factorization (PMF)
    $\Rightarrow$ limited spatial/sectoral/temporal resolutions
    $\Rightarrow$ suitable for descriptions, but not for predictions.
  - Chemical Transport Models: Brute-force, tagging, DDM, and adjoint methods
    $\Rightarrow$ computationally very expensive

New: The Air Pollution Social Cost Accounting (APSCA) Model

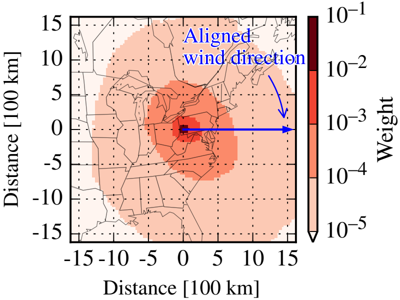
(Heo et al., *Environ. Int.* 2017)

- quantifies sources of $PM_{2.5}$ social costs and their contributions
  $\Rightarrow$ spatially resolved for the entire U.S. domain,
  $\Rightarrow$ temporally resolved for four seasons,
  $\Rightarrow$ sectorally resolved for emission inventory's resolution.
- estimates who are affected and who are affecting.

The Air Pollution Social Cost Accounting (APSCA) Model

- Key idea: spatially distribute EASIUR's social costs with population-weighted average plumes.

EC Average Plume for Winter



The Air Pollution Social Cost Accounting (APSCA) Model

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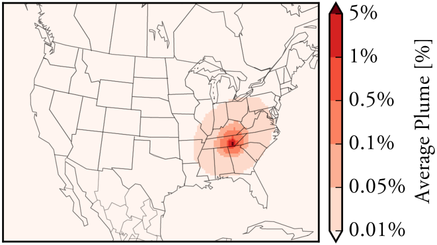
EC Average Plume for Winter at one out-of-sample location (Chattanooga, TN)



Average plume

The Air Pollution Social Cost Accounting (APSCA) Model

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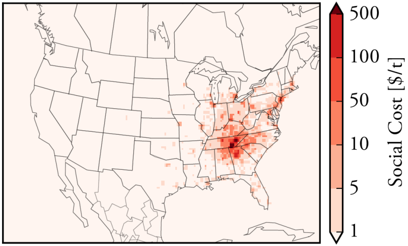
Social costs originated from EC at one out-of-sample location (Chattanooga, TN):



by population-weighted average plume

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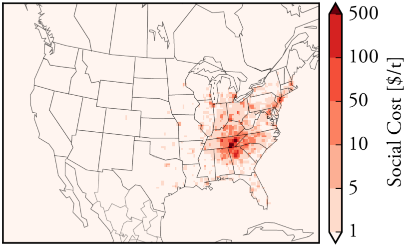
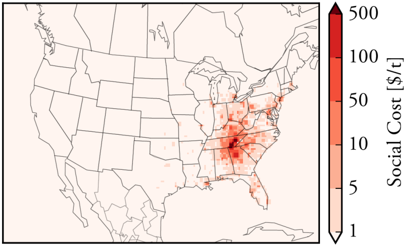


by population-weighted average plume

v.s.

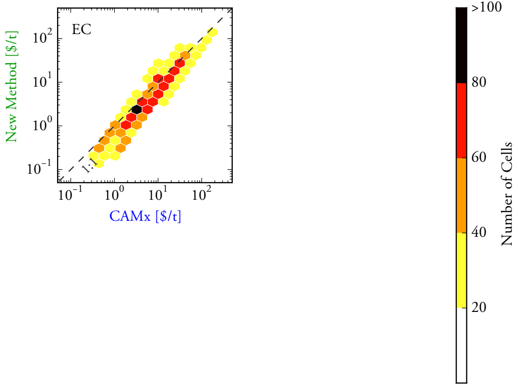


by CTM (CAMx)

Comparisons at all downwind locations: CTM v.s. New Method

- Key idea: spatially distribute EASIUR's social costs with population-weighted average plumes.

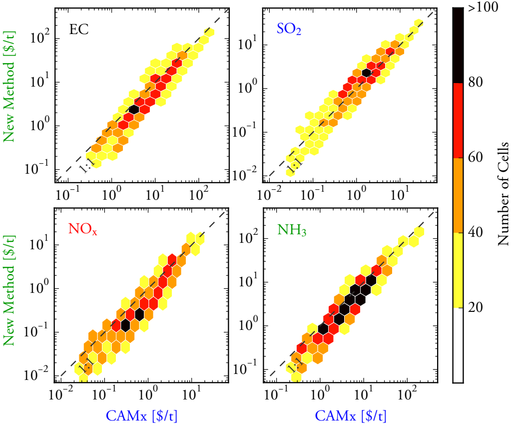
Social costs originated from EC at Chattanooga, TN:



Comparisons at all downwind locations: CTM v.s. New Method

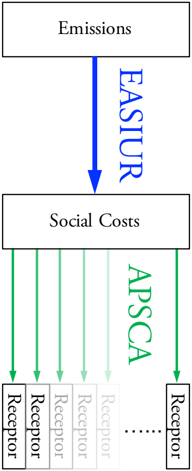
- Key idea: spatially distribute EASIUR's social costs with population-weighted average plumes.

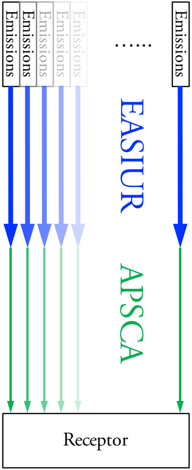
Social costs originated from EC, SO_2, NO_x, NH_3 at Chattanooga, TN:



Summary: Why APSCA (& EASIUR)?

For an emission source,
Who are affected?



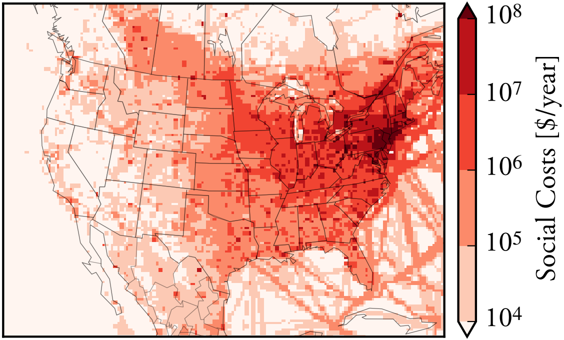


For a receptor,
Who are affecting?

- Accurate
- Fast
- Easy-to-use
- Can be updated

Emission Sources responsible for

Air Quality Social Cost in the New York Metropolitan Area



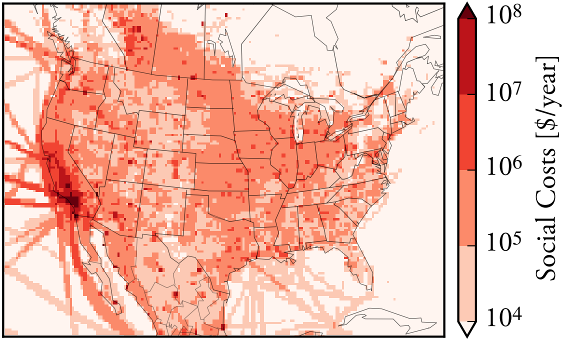
- The most comprehensive social cost accounting!
- Policy paradigm shift:

Emission Source oriented $\Longrightarrow$ Receptor oriented

What to reduce and how much *FOR YOU!*

Emission Sources responsible for

Air Quality Social Cost in the Los Angeles Metropolitan Area



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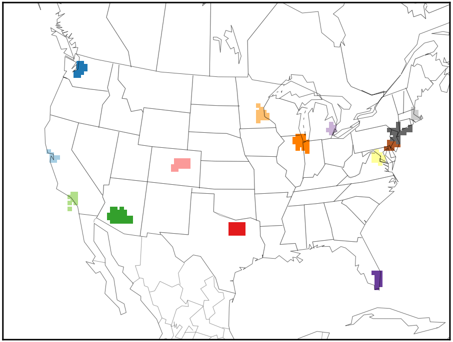
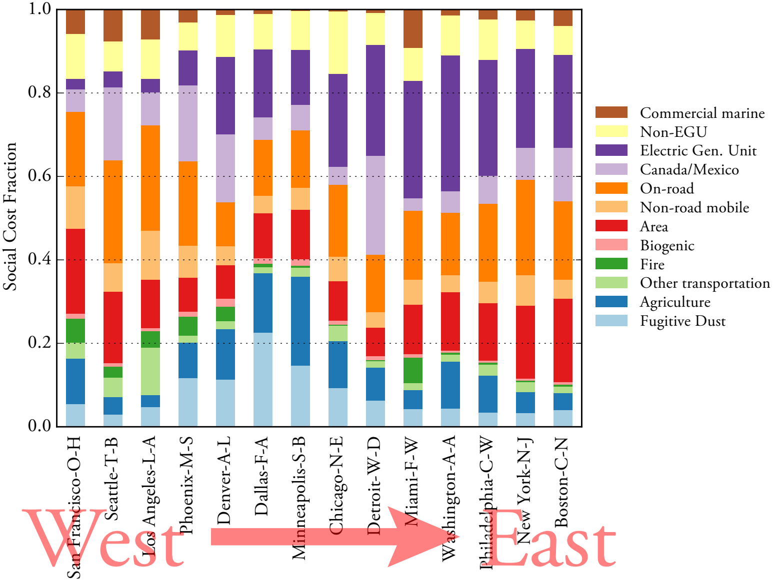
What to reduce and how much *FOR YOU!*

APSCA Application: 14 Metropolitan Areas in 2005



- **San Francisco**-Oakland-Hayward CA
- **Seattle**-Tacoma-Bellevue WA
- **Los Angeles**-Long Beach-Anaheim CA
- **Phoenix**-Mesa-Scottsdale AZ
- **Denver**-Aurora-Lakewood CO
- **Dallas**-Fort Worth-Arlington TX
- **Minneapolis**-St.Paul-Bloomington MN/WI
- **Chicago**-Naperville-Elgin IL/IN/WI
- **Detroit**-Warren-Dearborn MI
- **Miami**-Fort Lauderdale-West Palm Beach FL
- **Washington**-Arlington-Alexandria DC/VA/MD/WV
- **Philadelphia**-Camden-Wilmington PA/NJ/DE/MD
- **New York**-Newark-Jersey City NY/NJ/PA
- **Boston**-Cambridge-Nashua MA/NH

14 Metropolitan Areas: Social Cost Fractions by 12 Source Sectors



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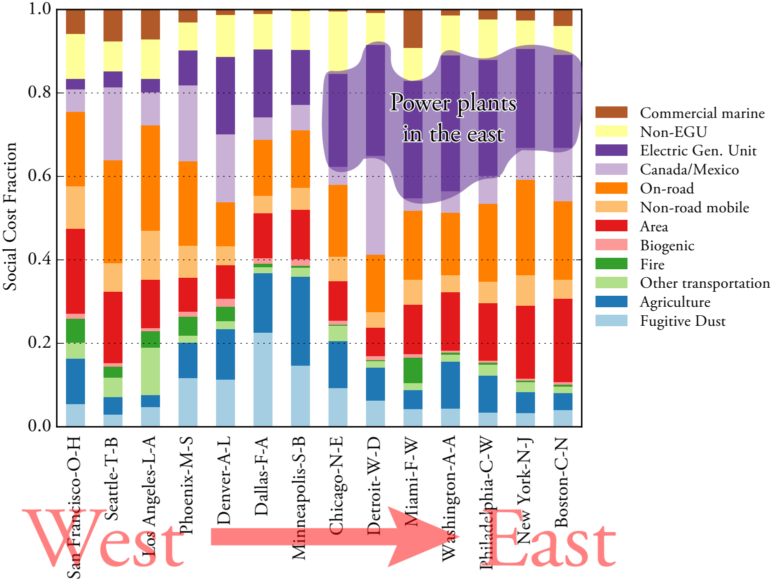

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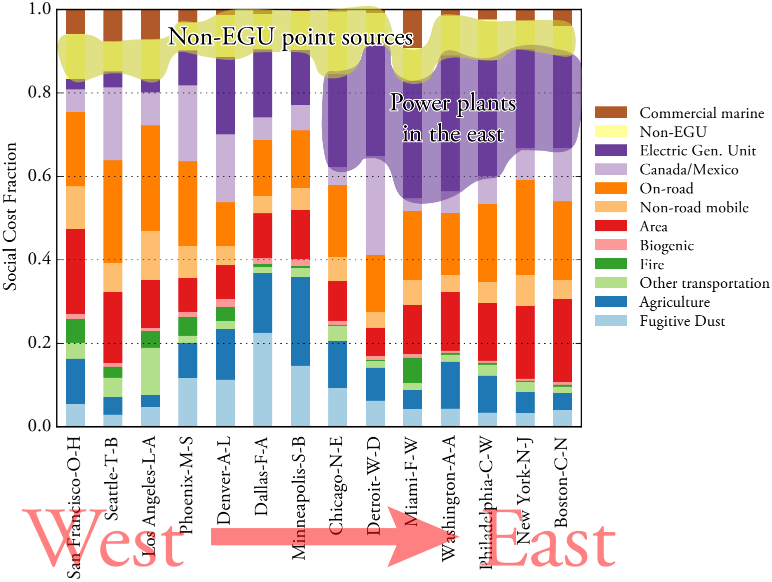

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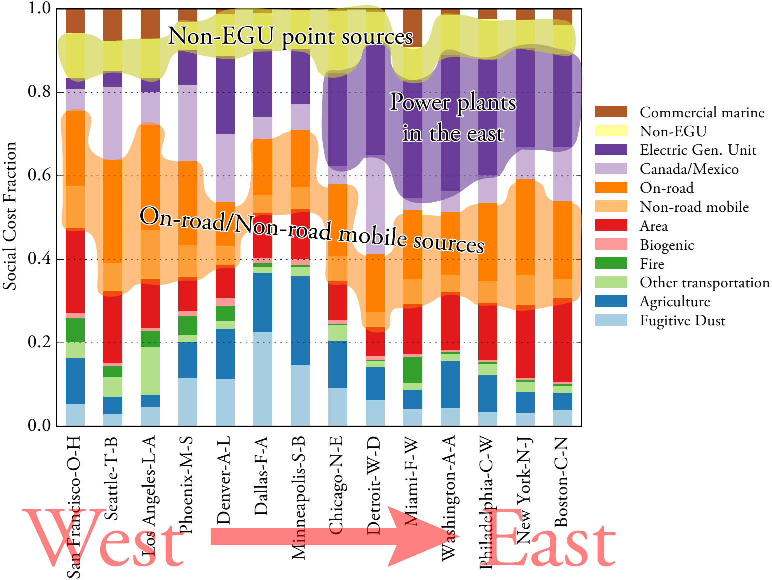

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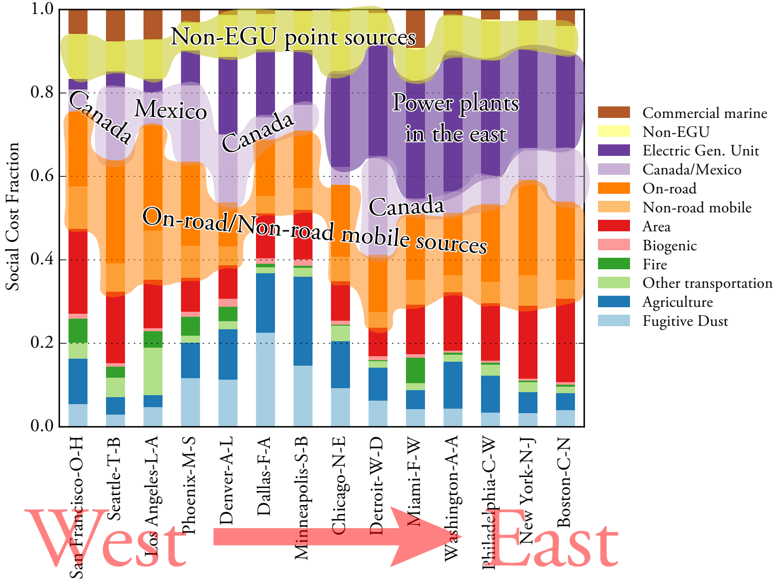
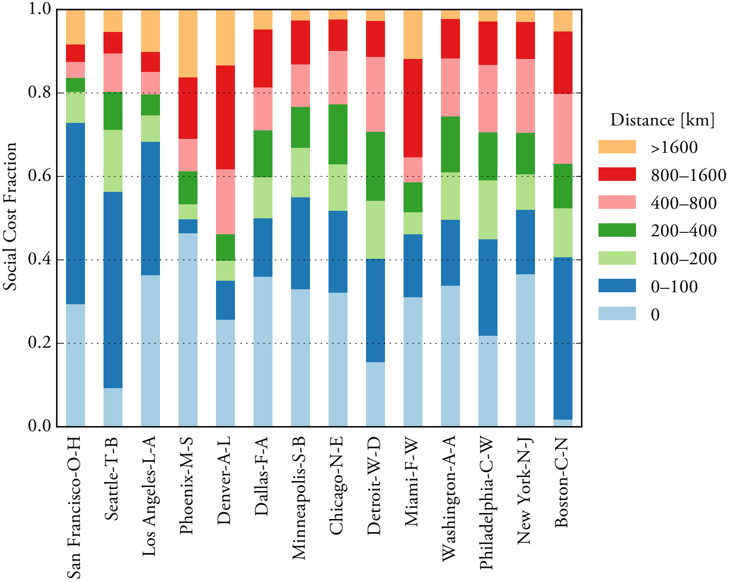


14 Metropolitan Areas: Social Cost Fractions by Source Distance



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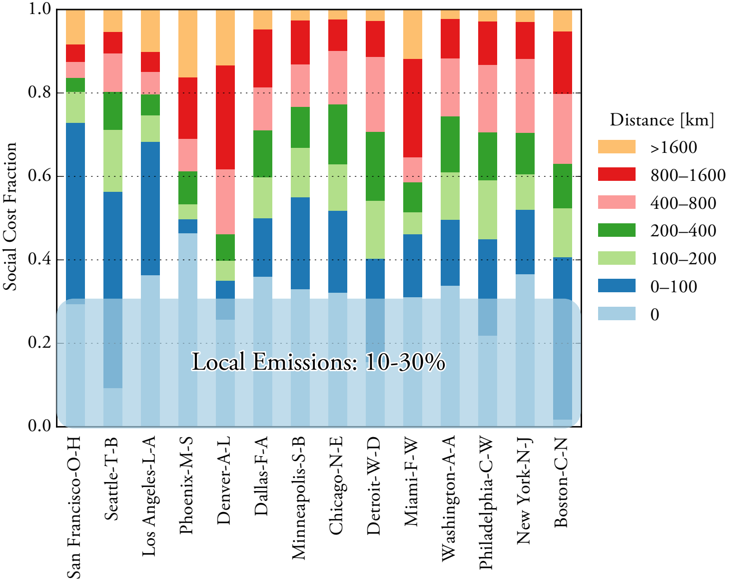

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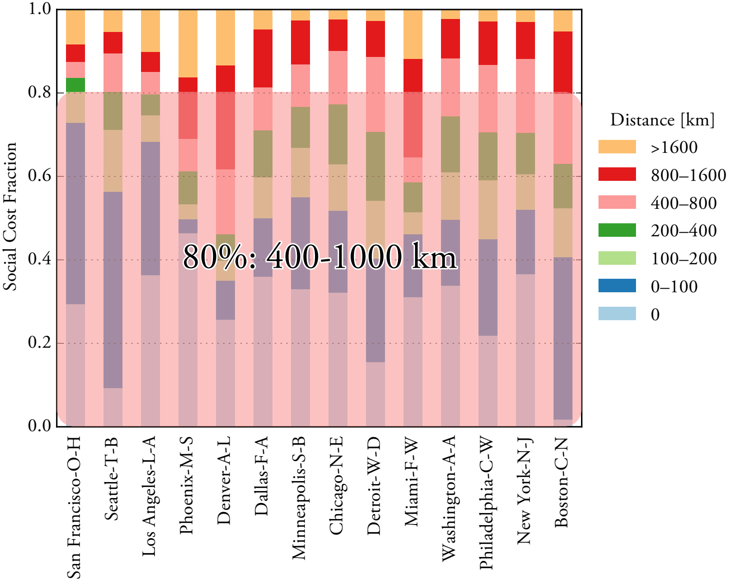
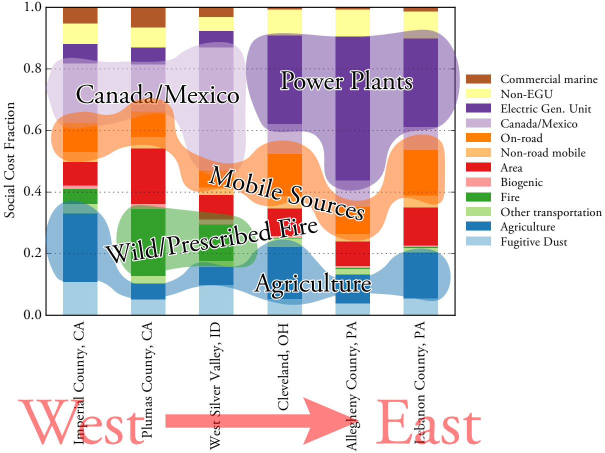


Outline

Local Policy: Improving State Implementation Plans (SIPs)?

- Background:
  ⇒ $PM_{2.5}$ nonattainment areas: state and local air quality management agencies have to show U.S. EPA how to meet the standards with SIPs.



⇐ Source breakdowns for some recently designated nonattainment areas estimated by APSCA.

Local Policy: Improving State Implementation Plans (SIPs)?

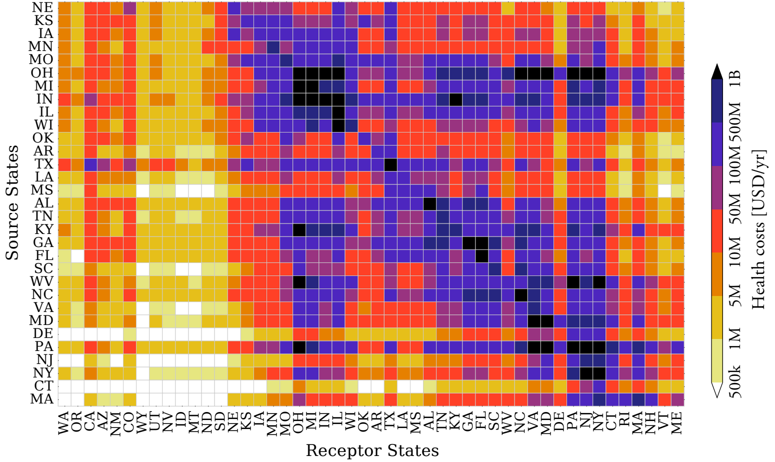
- Background:
  $\Rightarrow$ $PM_{2.5}$ nonattainment areas: state and local air quality management agencies have to show U.S. EPA how to meet the standards with SIPs.
- Goal:

Maximize (the social benefits of control measures (with EASIUR))
− (the costs of control measures)
subject to:
- Meet the $PM_{2.5}$ standard (with APSCA).
- Meet the budget constraints.
- Meet the technical constraints.

Federal Policy: Improving the Cross-State Air Pollution Rule (CSAPR)?

- Background: The Clean Air Act requires one state not to interfere with the maintenance of air quality in downwind states.

Source-Receptor Relationship from 4405 Power Plants in 2005



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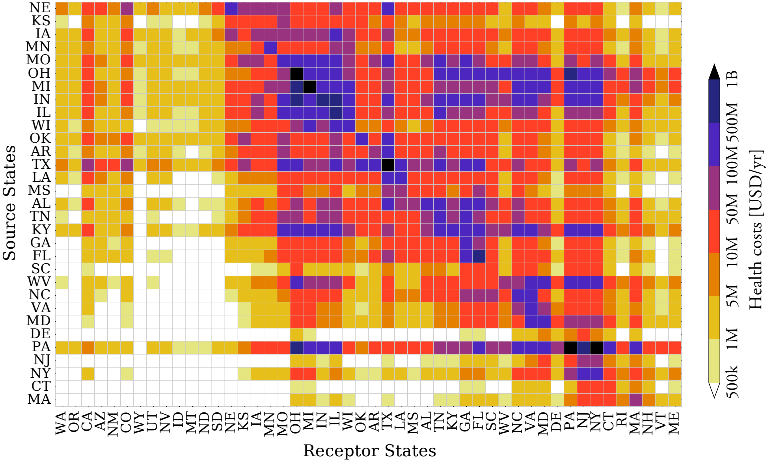


Federal Policy: Improving the Cross-State Air Pollution Rule (CSAPR)?

- Background: The Clean Air Act requires one state not to interfere with the maintenance of air quality in downwind states.

More benefits while controlling cross-state effects at a fair level?

Maximize (the social benefits of control measures (with EASIUR))
− (the costs of control measures)

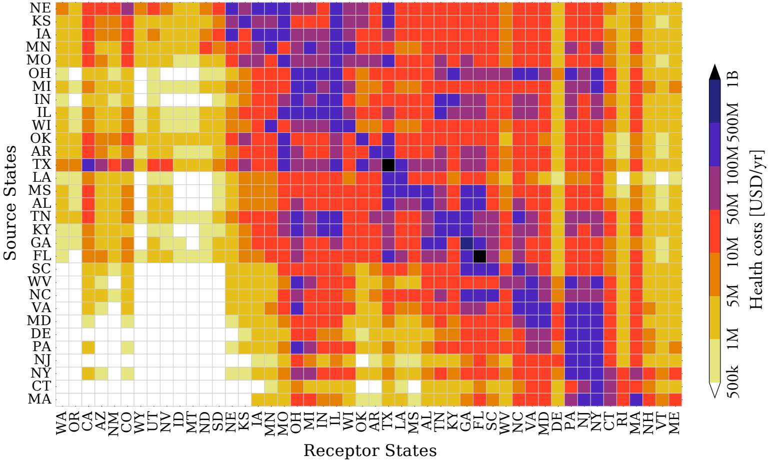
subject to:

- Limit cross-state interference at a desirable level (with APSCA).
- Meet the budget constraints.
- Meet the technical constraints.

Federal Policy: Improving the Cross-State Air Pollution Rule (CSAPR)?

- Background: The Clean Air Act requires one state not to interfere with the maintenance of air quality in downwind states.

10-30% more benefits with 7-17x less max cross-state interferences!



Energy/Climate: Optimal Plans for the Clean Power Plan Rule?

- Background:
  ⇒ In 2015, U.S. EPA promulgated the Clean Power Plan Rule that requires states to reduce CO_2 from power plants by 32% below 2005 levels by 2030.
  ⇒ Each state has different conditions (e.g. CO_2 reductions required by the rule, power mix, transmission capacity, and renewable resources).
- Goal: Design state-level strategies that maximize social net benefits.

Maximize (the co-benefits of control measures (with EASIUR))
− (the costs of control measures)

subject to:

- Meet the CO_2 reduction goals.
- Meet the renewable constraints.
- Meet the transmission constraints.

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Maximize (the state's co-benefits of control measures (with EASIUR & APSCA))
− (the costs of control measures)

subject to:

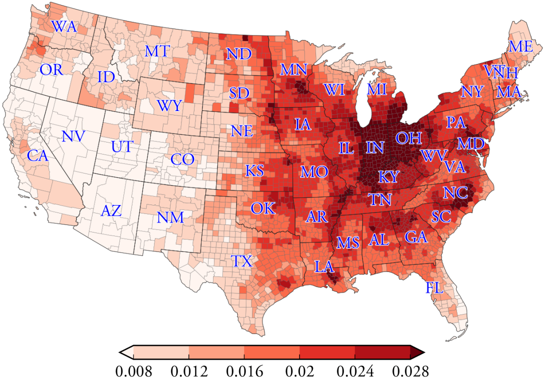
- Meet the CO_2 reduction goals.
- Meet the renewable constraints.
- Meet the transmission constraints.

National optimal and state optimal are different?

Environmental Justice: Distributional Effects of Air Pollution

(Heo and Strauss, *in prep.*)

- U.S. EPA is working towards achieving environmental justice (EJ) in rule making (U.S. EPA, 2014), but has no established summary measures yet.
- introduce Berliant-Strauss Vertical and Horizontal Equity Indices (Berliant and Strauss, 1983; 1985; 1991).



Per-capita "Effective Air Pollution Tax Rate [%]" without CSAPR

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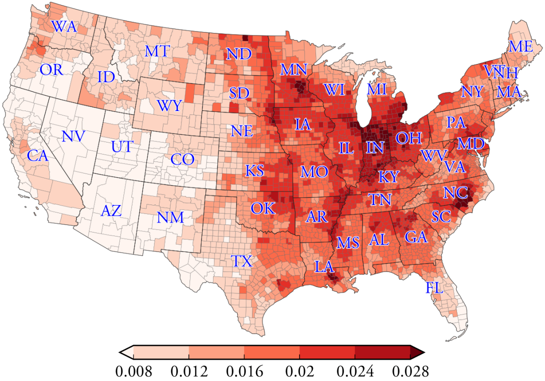

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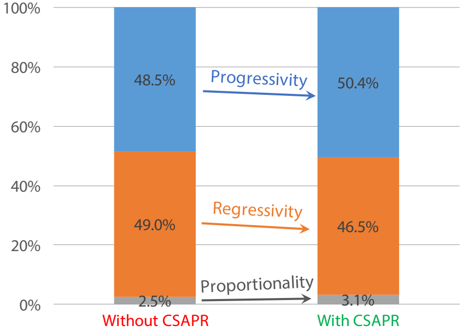

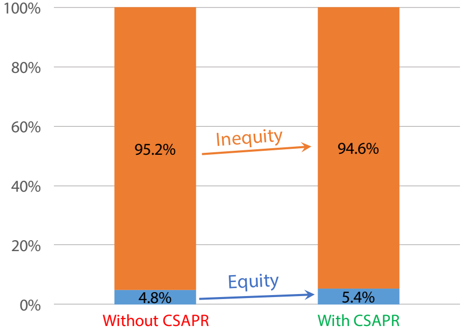

Vertical Equity:
Comparisons among people of different status

Horizontal Equity:
Comparisons among people of same status

Outline

Conclusions

- I successfully developed two models (EASIUR and APSCA) that predict like state-of-the-art air quality models but without high computational costs:
  $\Rightarrow$ EASIUR estimates the social costs of emissions.
  $\Rightarrow$ APSCA identifies all the sources of the social costs of emissions.
- The most comprehensive sets of marginal social costs (by EASIUR) and social cost accounting information (by APSCA) are provided.
- My methods will continue to link policy research associated with air quality, energy, and climate change with the latest atmospheric science because EASIUR and APSCA can be updated as CTMs and/or input data change.

Future Work 1: Addressing Organic $PM_{2.5}$

- EASIUR and APSCA for Organic $PM_{2.5}$, the single missing pollutant:
  ⇒ Science evolved substantially for the past 10 years.
  ⇒ to explore public health implications and to characterize remaining uncertainties.
  ⇒ Hugh policy implications related with gasoline and diesel emissions and biomass burning from new organic science as well as EASIUR's high resolutions.

Future Work 2: Integrating with Systems Approach

- Integrating EASIUR and APSCA with optimization methods:
  ⇒ Develop a SIP support tool.
  ⇒ Develop a Cross-State Air Pollution Transport support tool
- Combine with energy and climate models for air quality co-benefit analysis.
  ⇒ Economic dispatch models (for electricity), Vehicle emission models, Building energy models, Climate integrated assessment models.

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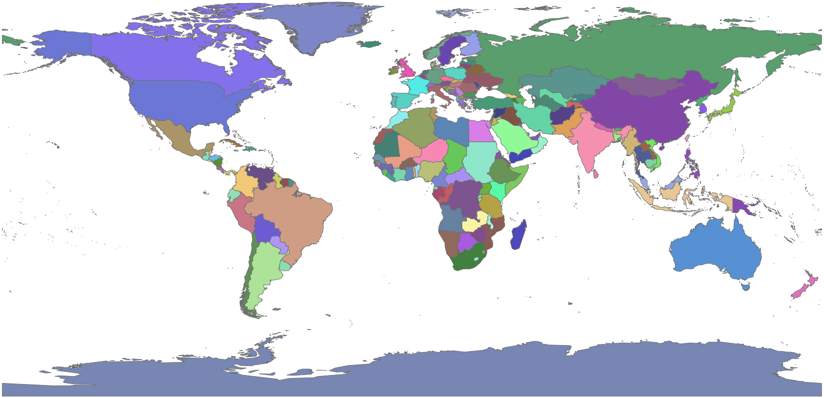
Future Work 3: EASIUR and APSCA to the World

- Model China (Korea & Japan), India, and EU.
- Finally, develop Global EASIUR and APSCA for regions where data are too limited to run advanced models.



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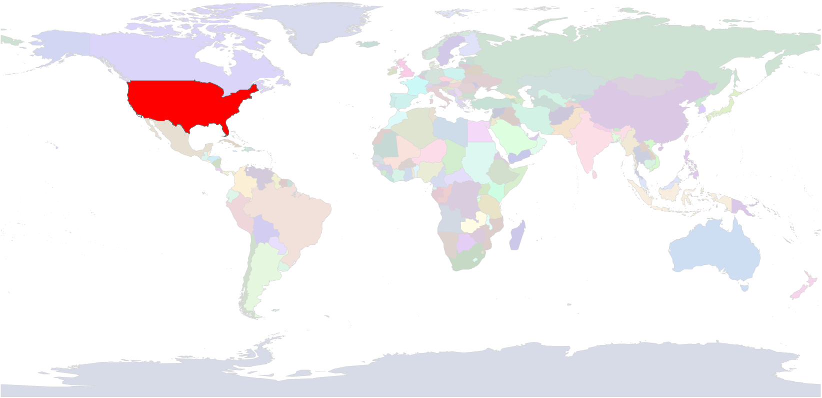

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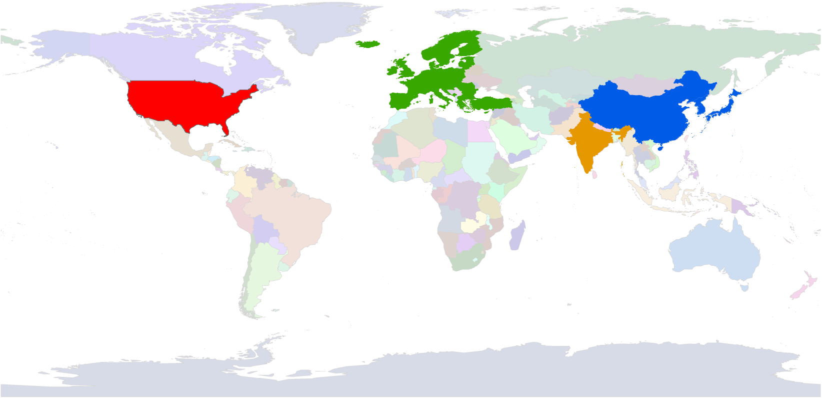

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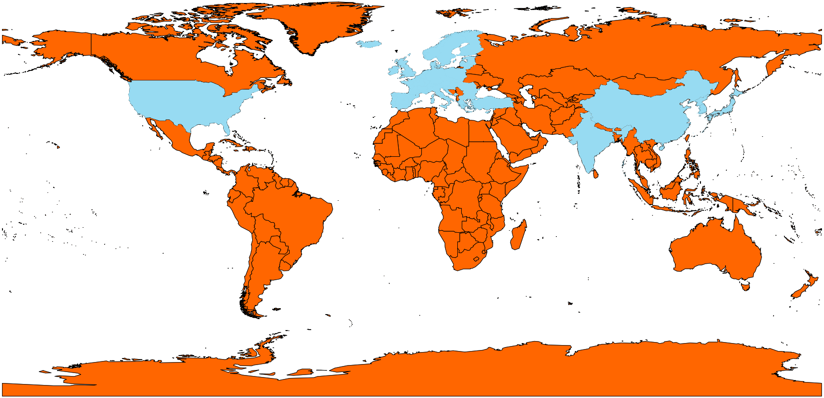

Thank you!

Employing the State of Science

in Optimal Policy Decision-Making

for Air Quality, Energy, and Climate Change

Jinhyok Heo

November 2017