Quantifying Air Quality and Health Impacts from Energy Systems: Electricity, Agriculture, Transportation

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Overarching goals of the research work

1. Quantify and evaluate metrics for greenhouse and noxious pollutants to estimate environmental consequences from interventions.

2. Develop metrics and tools to quantify air quality impacts of air emissions on human population from point, area, and mobile sources.

3. Quantify distribution of health impacts from air pollution by race, income, and geography.

4. Demonstrate the use a reduced-complexity air quality model (InMAP) to understand impacts from different energy systems.

Emissions from energy systems: Electricity, Agriculture and Transportation

Point sources

Image sources: Google images

Area sources

Line (Mobile) sources

Pollutants

Criteria (Common) Air Pollutants

- **Particulate matter**
- Ground-level ozone
- Carbon monoxide
- **Sulfur dioxide**
- **Nitrogen dioxide**
- Lead

Hazardous Air Pollutants

- Benzene
- Formaldehyde
- Asbestos
- Toluene
- Metals such as cadmium, mercury, chromium, etc.

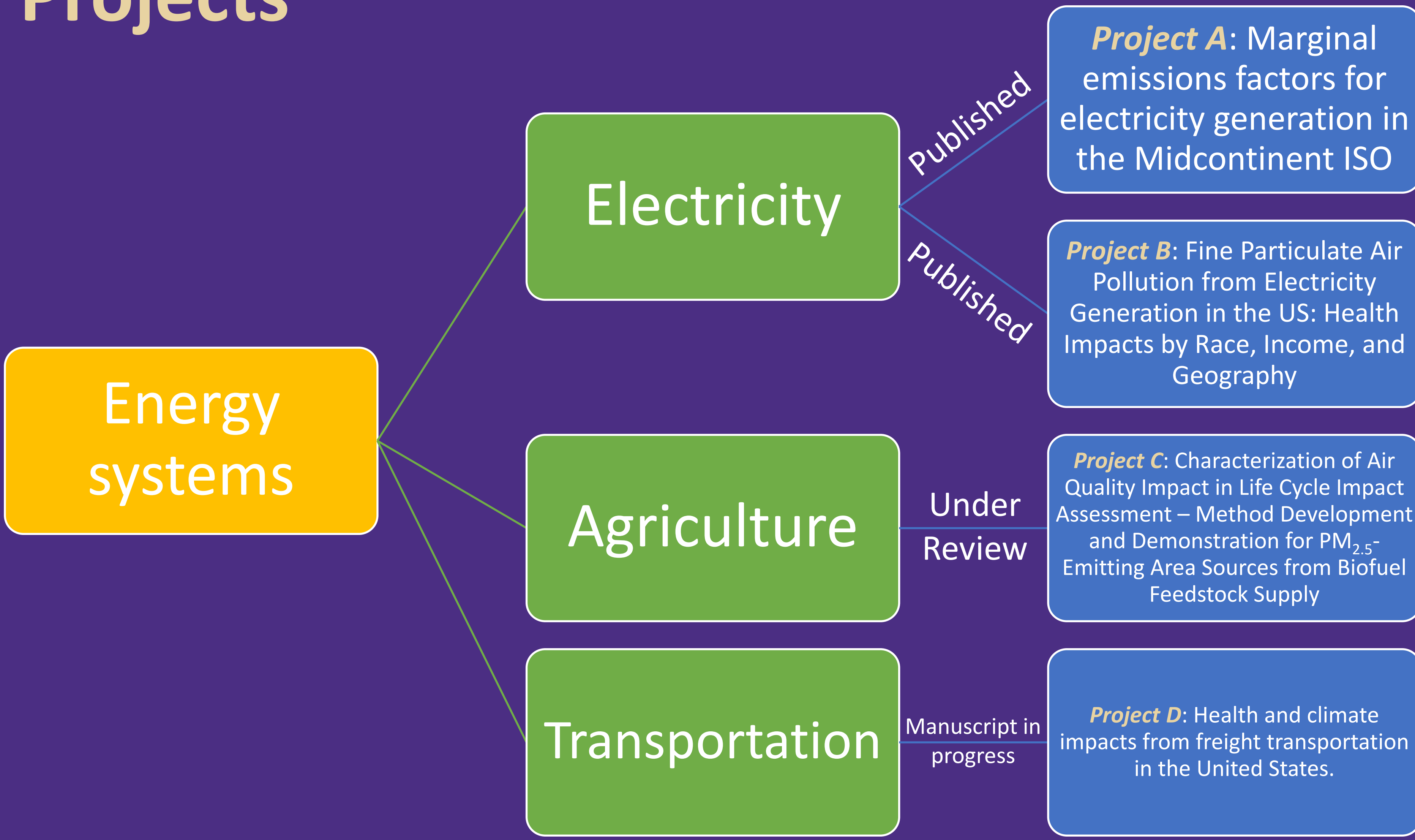
Greenhouse gases

- **Carbon dioxide**
- Methane
- Nitrous oxide
- Fluorinated gases

Other pollutants

- **Ammonia**
- **Volatile Organic Compounds (VOCs)**

Projects


Energy systems
Electricity
Agriculture
Transportation
Published
Published
Under Review
Manuscript in progress
Project A: Marginal emissions factors for electricity generation in the Midcontinent ISO
Project B: Fine Particulate Air Pollution from Electricity Generation in the US: Health Impacts by Race, Income, and Geography
Project C: Characterization of Air Quality Impact in Life Cycle Impact Assessment – Method Development and Demonstration for $PM_{2.5}$-Emitting Area Sources from Biofuel Feedstock Supply
Project D: Health and climate impacts from freight transportation in the United States.

Project A: Marginal emissions factors for electricity generation in the Midcontinent ISO

https://doi.org/10.1021/acs.est.7b03047

Environmental Science & Technology

Article

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Marginal Emissions Factors for Electricity Generation in the Midcontinent ISO

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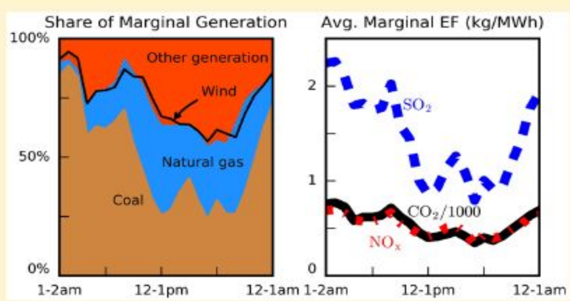
Supporting Information

ABSTRACT: Environmental consequences of electricity generation are often determined using average emission factors. However, as different interventions are incrementally pursued in electricity systems, the resulting marginal change in emissions may differ from what one would predict based on system-average conditions. Here, we estimate average emission factors and marginal emission factors for CO_2, SO_2, and NO_x from fossil and nonfossil generators in the Midcontinent Independent System Operator (MISO) region during years 2007–2016. We analyze multiple spatial scales (all MISO; each of the 11 MISO states; each utility; each generator) and use MISO data to characterize differences between the two emission factors (average; marginal). We also explore temporal trends in emissions factors by hour, day, month, and year, as well as the differences that arise from including only fossil generators versus total generation. We find, for example, that marginal emission factors are generally higher during late-night and early morning compared to afternoons. Overall, in MISO, average emission factors are generally higher than marginal estimates (typical difference: ~20%). This means that the true environmental benefit of an energy efficiency program may be ~20% smaller than anticipated if one were to use average emissions factors. Our analysis can usefully be extended to other regions to support effective near-term technical, policy and investment decisions based on marginal rather than only average emission factors.



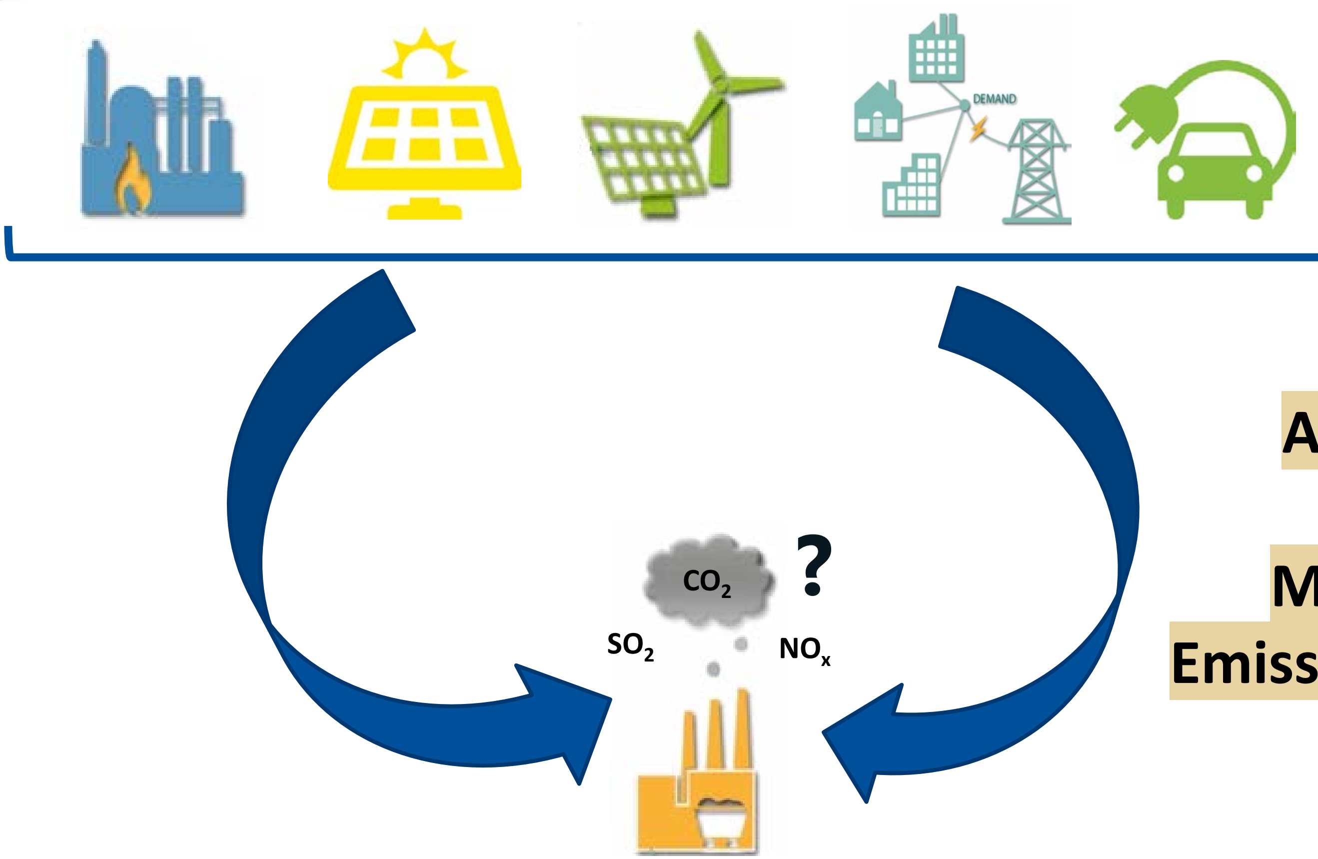
1. INTRODUCTION

In the United States, electricity generation is a major

marginal EFs based on bid-dispatch simulations of electricity generators;[6−11] such models use costs and engineering

Project A: Research question

Energy conservation interventions



Average

Vs

Marginal

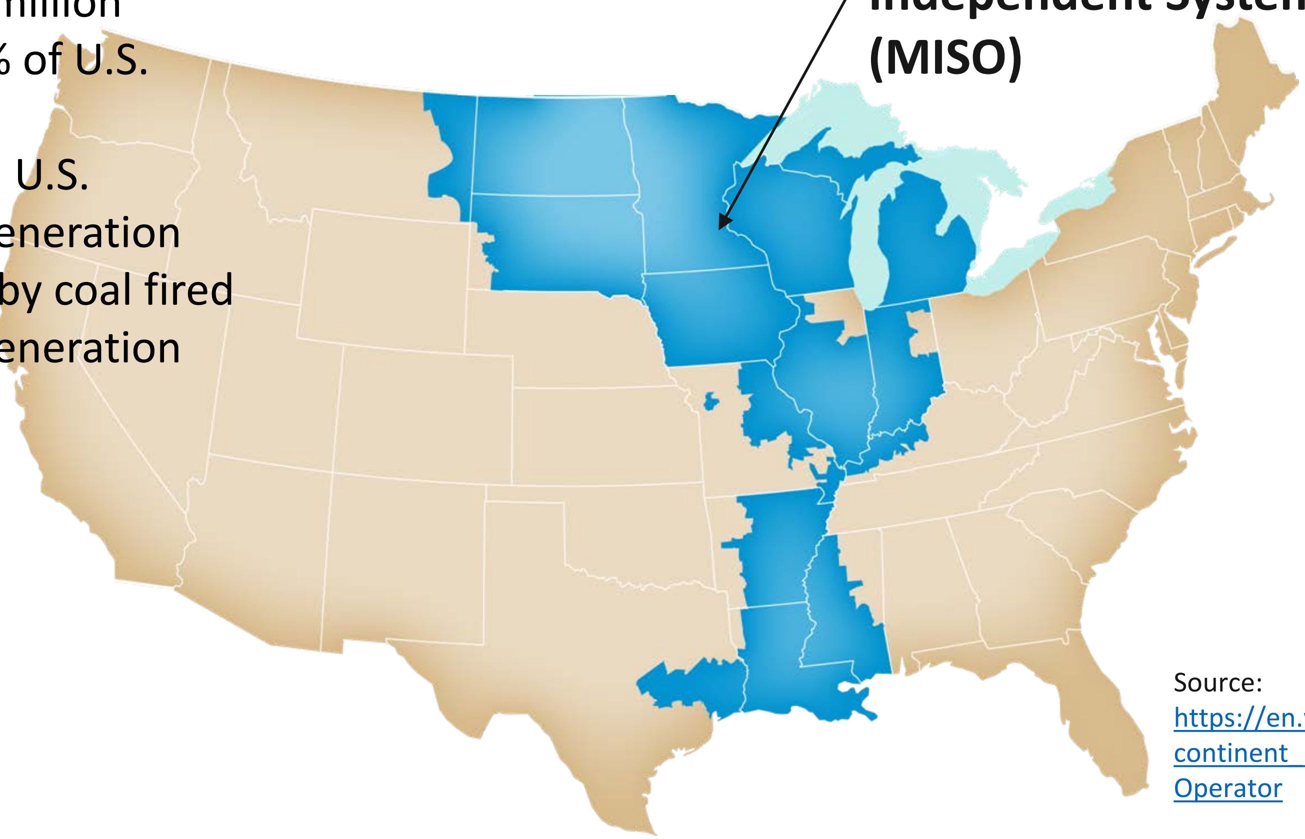
Emission Factors

Affecting/displacing MWhs

Project A: Case-study region - MISO

- 15 U.S. states
- Serves ~42 million people (13% of U.S. population)
- 16% of total U.S. electricity generation
- Dominated by coal fired electricity generation

Focus of study: Midcontinent Independent System Operator (MISO)

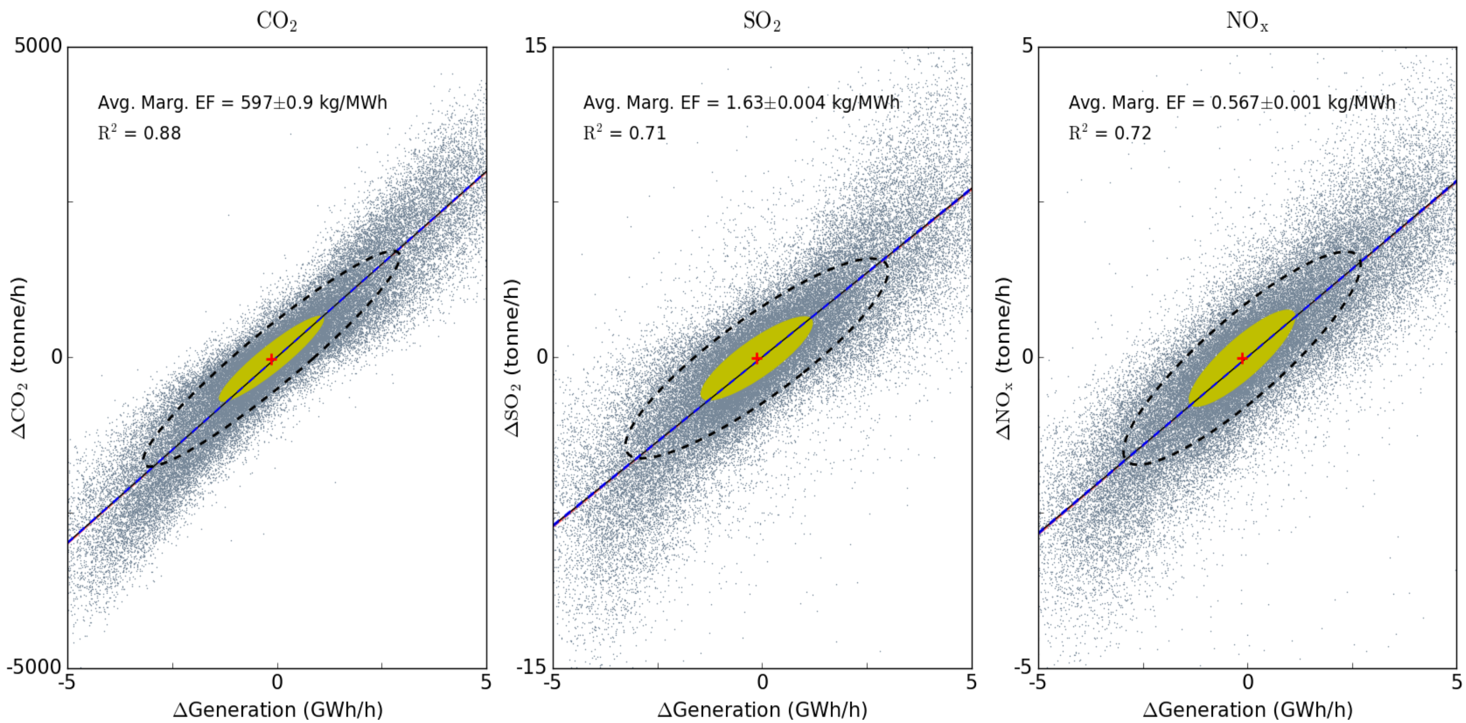


Source: https://en.wikipedia.org/wiki/Midcontinent_Independent_System_Operator

RTOs match **power generation** instantaneously with **demand** to keep the lights on

Project A: Methodology

- AEF = Total emissions/Total generation
- AMEF: Linear regression of hourly changes in generation and pollutant emissions (U.S. EPA's CEMS data)



$$\Delta G_h = G_{h+1} - G_h \qquad \text{Fit: } \Delta E = \beta_0 \Delta G$$

$$\Delta E_h = E_{h+1} - E_h \qquad \beta_0 = \text{AMEF}$$

Siler-Evans, K.; Azevedo, I.L.; Morgan, M.G. Marginal Emissions Factors for the U.S. Electricity System. *Environ. Sci. Technol.* **2012**, 46, 4742–4748.

Project A: Key findings – Differences between AEF and AMEF

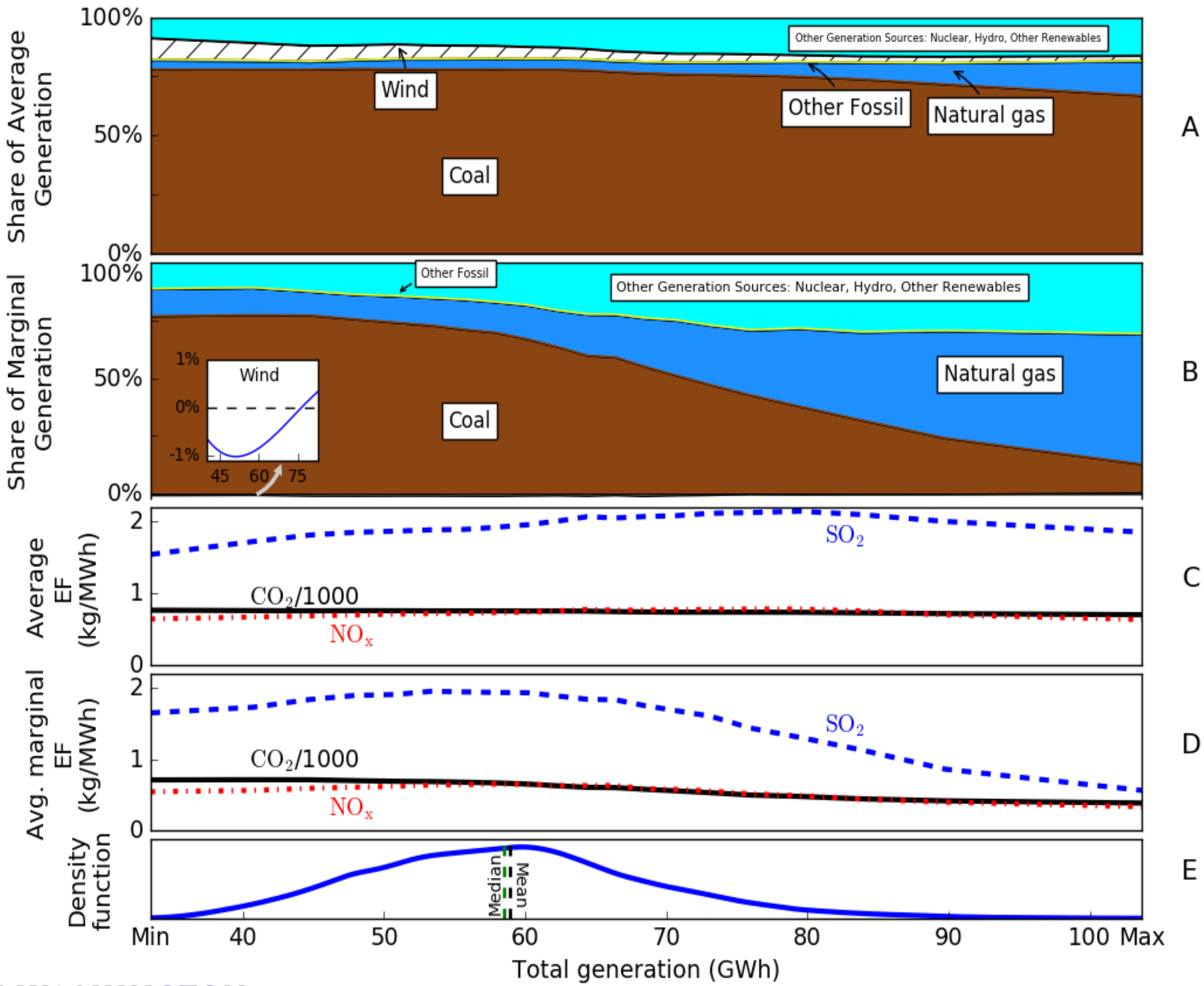
- Overall, in MISO, average emission factors are generally higher than marginal estimates (typical difference: ~20%)

Table: AEF and AMEF at MISO regional scale

Pollutant	AEF (Kg/MWh)	AMEF (Kg/MWh)	EFs % Difference
CO_2	739	597	-19%
SO_2	1.97	1.63	-17%
NO_x	0.727	0.567	-22%

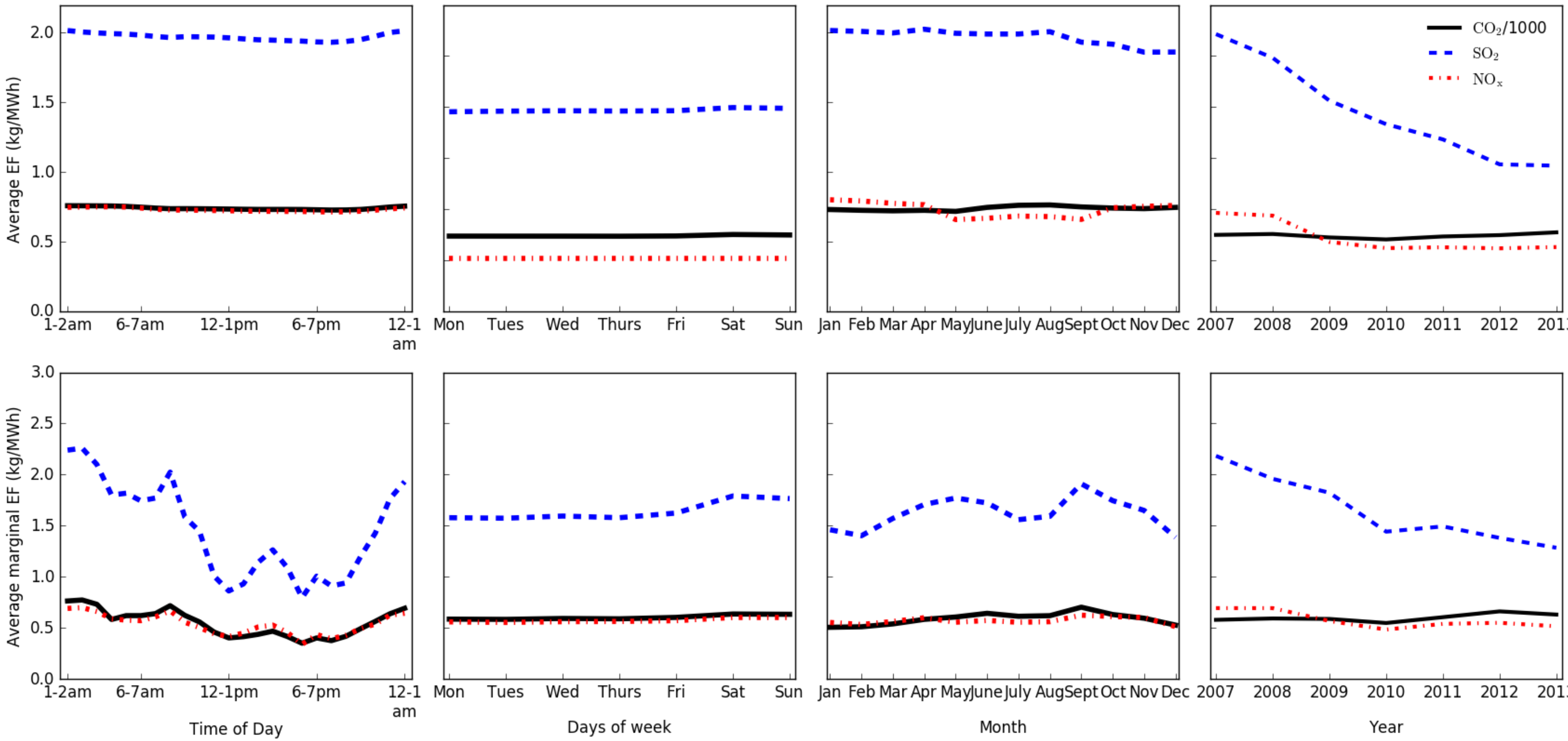
Project A: Key findings – Average EFs and Average Marginal EFs by system demand

- Coal is the dominant marginal fuel at low demand hours; natural gas is the dominant marginal fuel at high demand hours.



Project A: Key findings – Temporal analysis at regional MISO

- Marginal emission factors are generally higher during late-night and early morning compared to afternoons.



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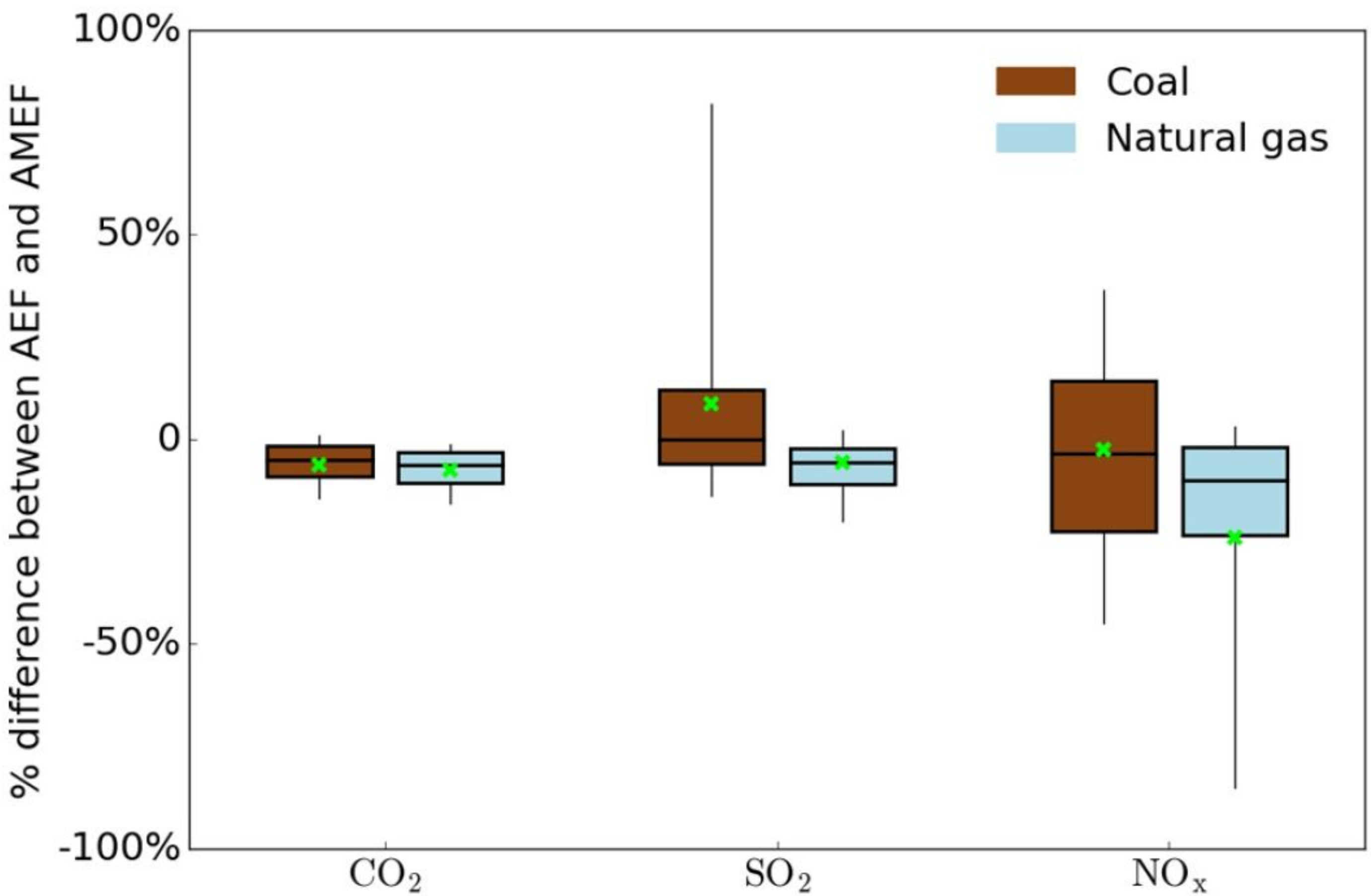
Project A: Key findings – AMEFs for individual generator

- There are noteworthy differences between AEF and AMEF estimates when applied at the generator level.



Boxplot showing distribution of EF differences among coal units and natural gas units

Intellectual significance

- First study to develop and compare Average Emission Factor (AEF) and Avg. Marginal Emission Factor (AMEF) metrics for a **U.S. power market (Regional transmission organization)** at different spatial scales: national, state, utility, and each generator.

- These metrics are useful to evaluate emission benefits from energy **efficiency interventions acting on the margin.**

- Interesting implications for **EV charging** and other time-flexible and potentially controllable loads in the Midwest.

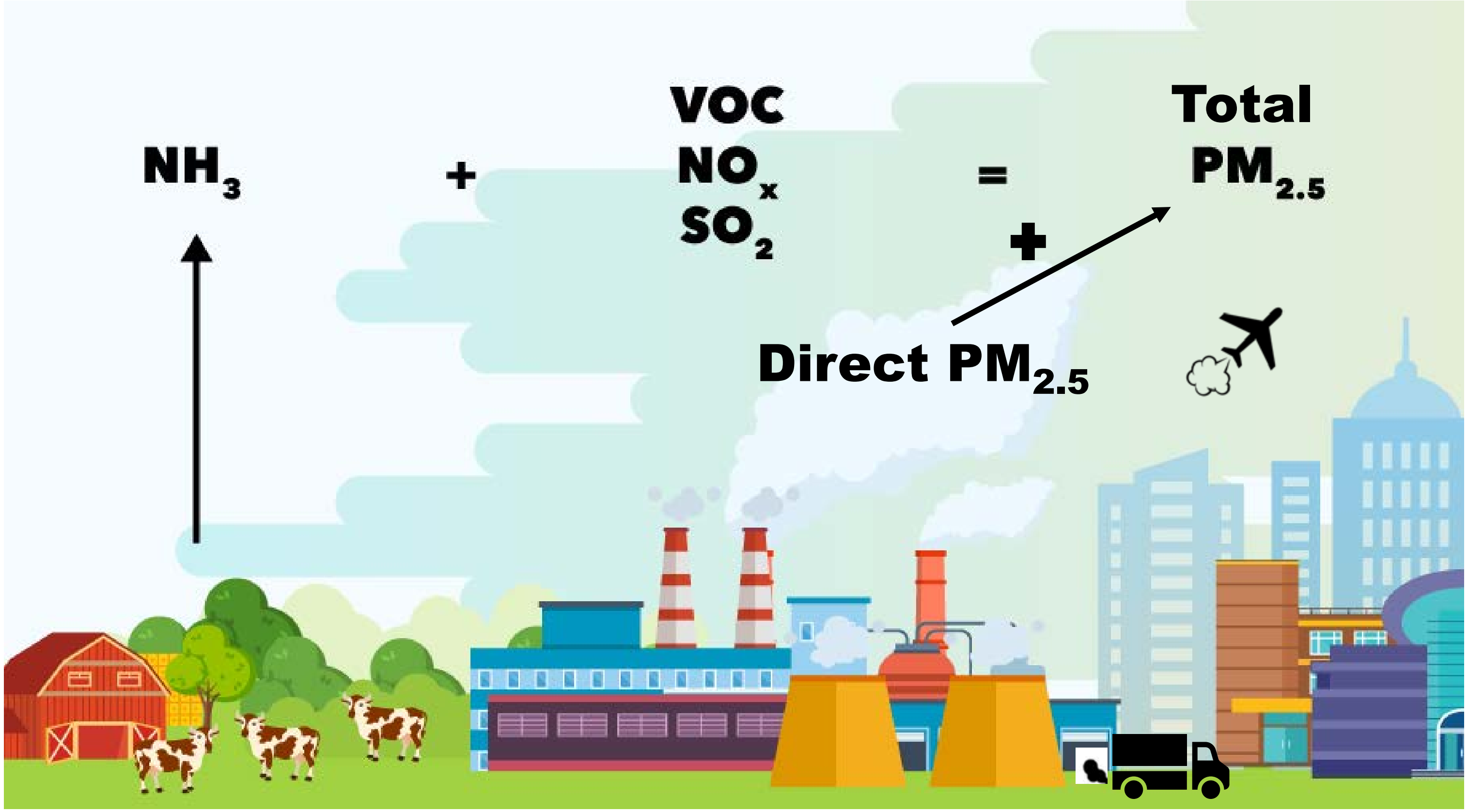
- This analysis can be usefully extended to other regions to support effective near-term technical, policy and investment decisions based on marginal rather than only average emission factors.

Overarching goals of the doctoral work

1. Quantify and evaluate metrics for greenhouse and noxious pollutants to estimate environmental consequences from interventions.
2. Develop metrics and tools to quantify air quality impacts of air emissions on human population from point, area, and mobile sources.
3. Quantify distribution of health impacts from air pollution by race, income, and geography.
4. Demonstrate the use a reduced-complexity air quality model (InMAP) to understand impacts from different energy systems.

Particulate Matter less than 2.5 µm ($PM_{2.5}$)

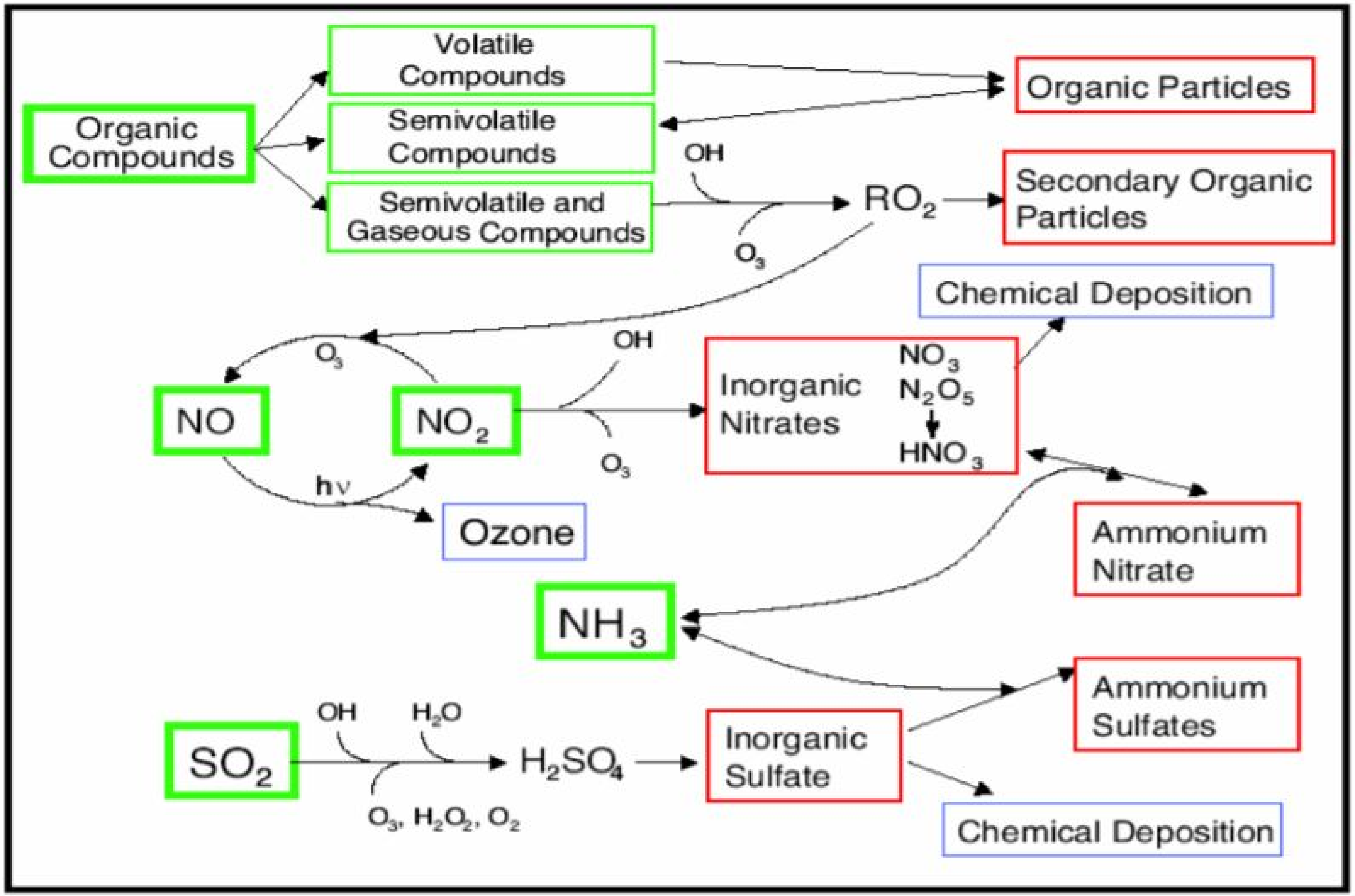
Sources of total fine particulate matter ($PM_{2.5}$)



$PM_{2.5}$ consists of particles and liquid droplets, which forms from gaseous precursor emissions of nitrogen oxides (NO_x), sulfur oxides (SO_x), ammonia (NH_3), and VOCs. $PM_{2.5}$ can also be emitted directly (Primary $PM_{2.5}$), as in the case of black carbon.

Source: Adapted from https://ensia.com/features/ammonia/

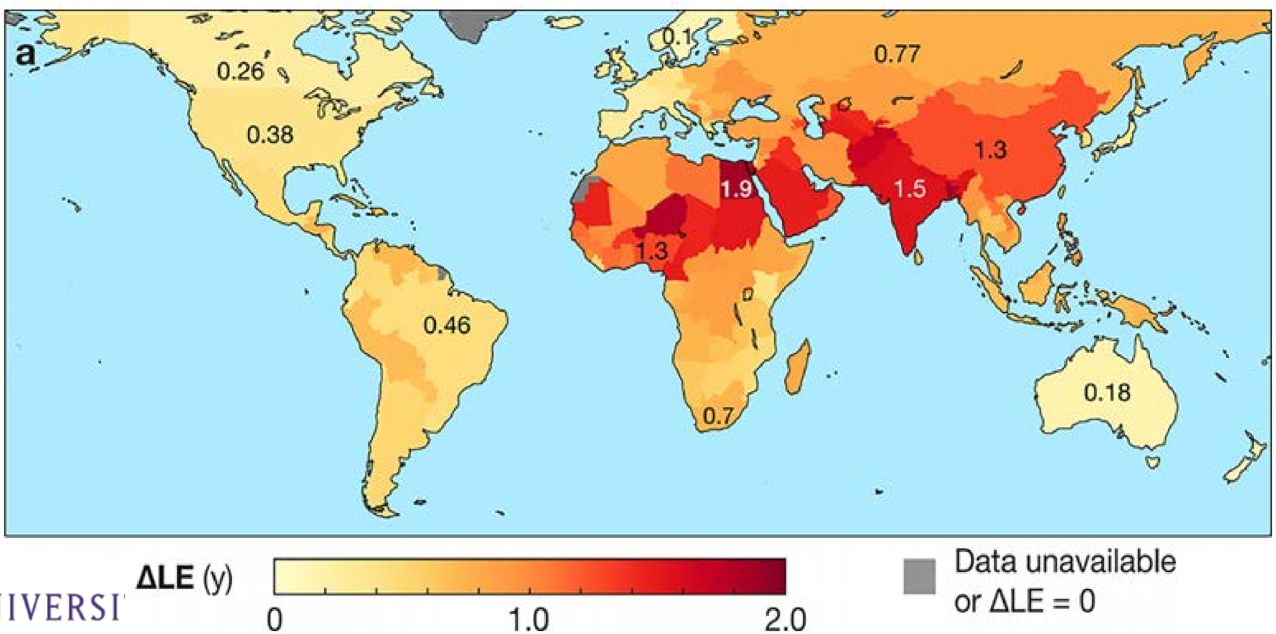
$PM_{2.5}$ formation processes in the atmosphere



Source: U.S. EPA https://www3.epa.gov/ttnchie1/conference/ei13/mobile/hodan.pdf

$PM_{2.5}$ health impacts

- Fine particles less than or equal to 2.5 µm ($PM_{2.5}$) aerodynamic diameter are small enough to penetrate deeply into the lung, irritate and corrode the alveolar wall
- Long-term exposure to $PM_{2.5}$ leads to an increased risk of premature death. $PM_{2.5}$ is associated with increased mortality rates from, e.g., cardiovascular disease (ischemic heart disease and stroke), chronic obstructive pulmonary disease, and lung cancer
- WHO estimates that in the year 2016, ambient air pollution was responsible for **4.2 million** deaths. (~100,000 deaths each year in the United States)



Global map of the life expectancy decrement ΔLE from $PM_{2.5}$: baseline ΔLE for year-2016 concentrations

Source: Apte et al. (2018), Ambient $PM_{2.5}$ Reduces Global and Regional Life Expectancy

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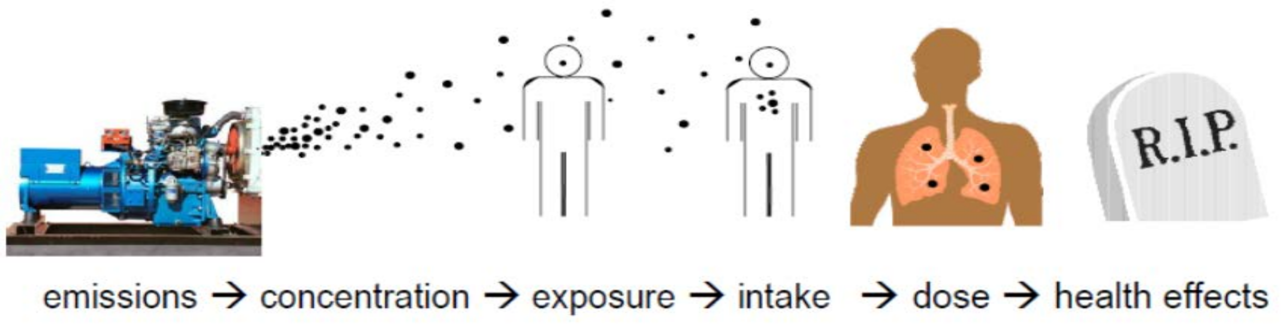
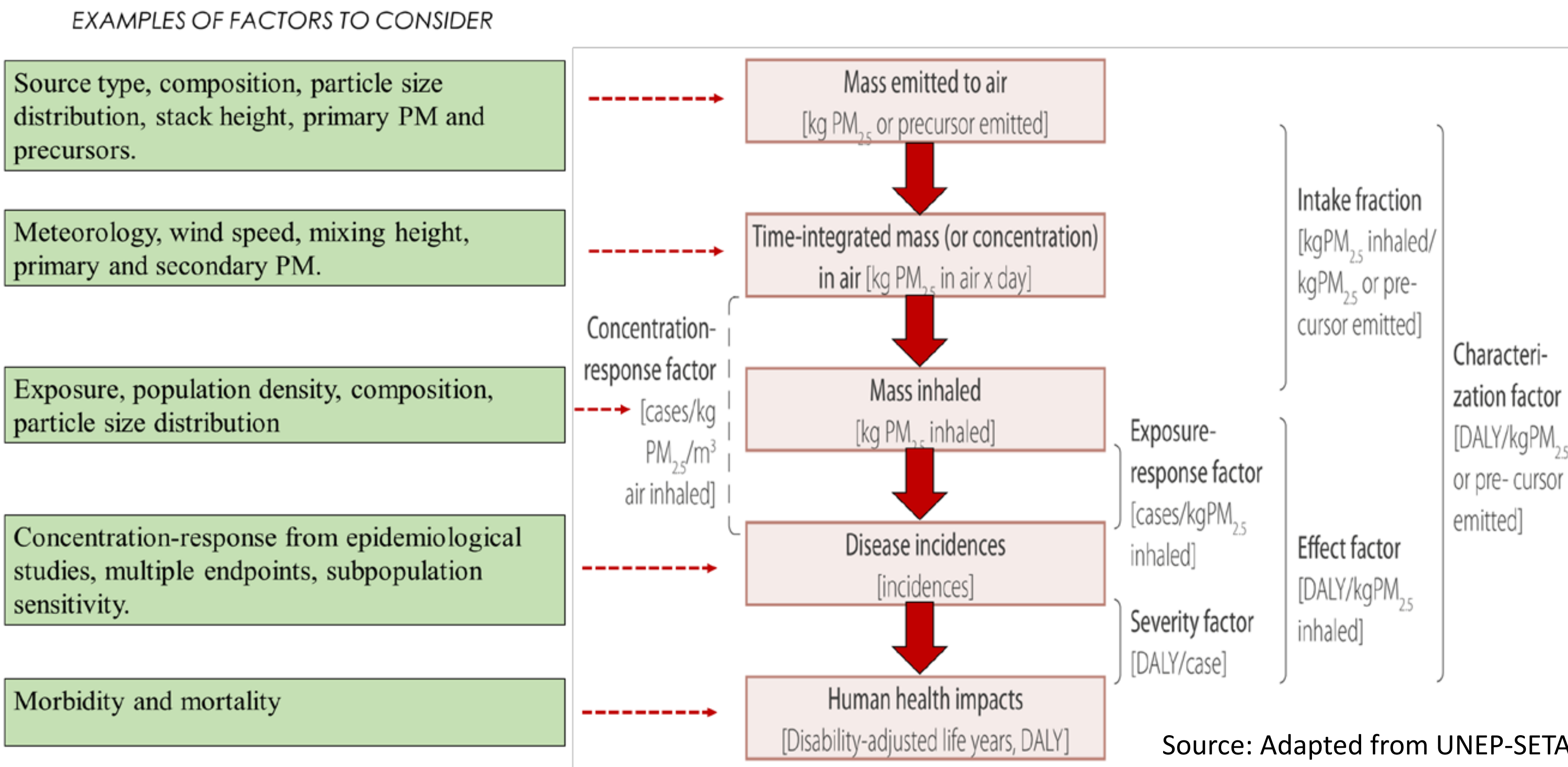
Impacts from PM emissions



Source: Smith et al. (1993)



Source: Adapted from UNEP-SETAC report, Humbert et al. (2011)

Complex chemical transport models

- **Deterministic Eulerian models**: powerful tools that can simulate atmospheric chemistry using meteorology to provide the effectiveness of emission reductions at reducing air quality-related health impact. (Eulerian refers to use of a fixed grid, with mass balance, chemical reactions and transportation in each cell.)

- **Examples**
  - Community Multiscale Air Quality (CMAQ) (EPA)
  - Comprehensive Air Quality Model with Extensions (CAMx) (Environ)
  - Weather Research and Forecasting Model coupled with Chemistry (WRF-Chem);
  - Gas, aerosol, transport, radiation, general circulation, mesoscale, and ocean model (GATOR-GCMOM);
  - Goddard Earth Observing System with (GEOS-Chem)

- **Desirable traits**: Many pollutants modeled, many emission sources modeled, high accuracy

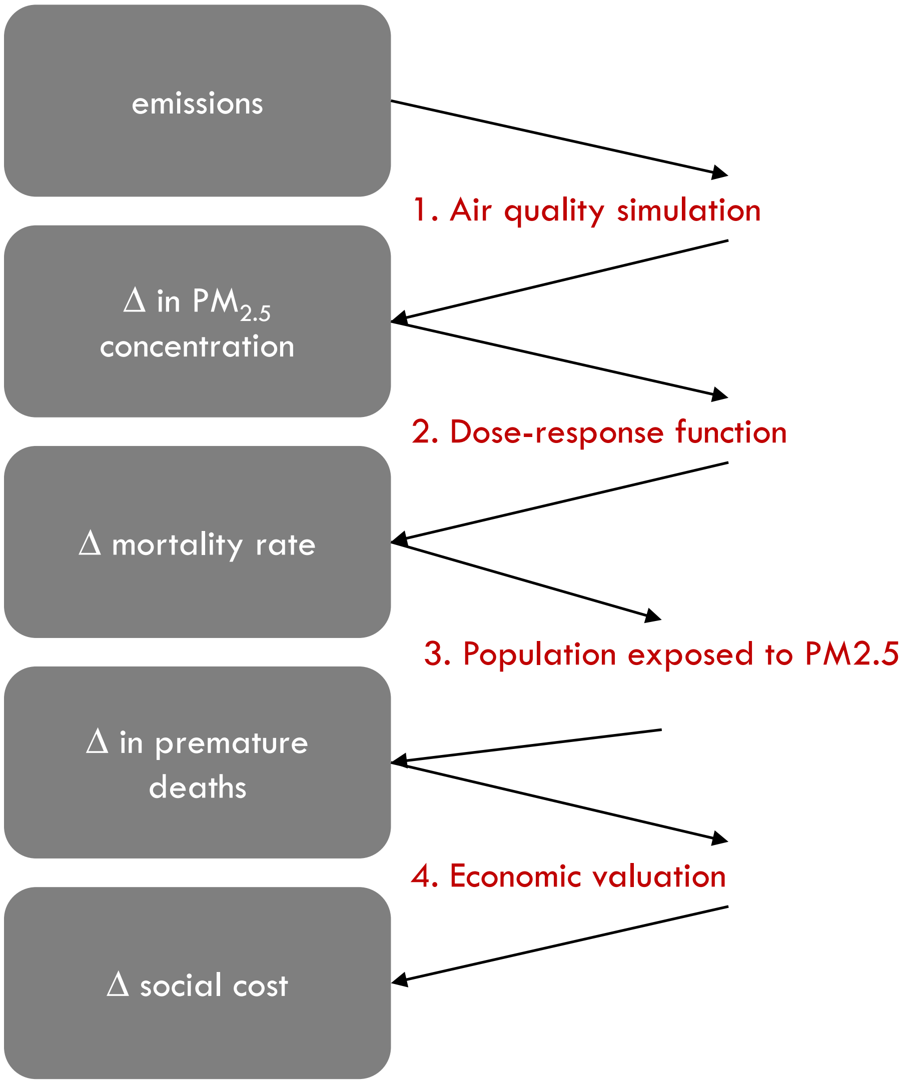
- **Undesirable traits**: Spatial resolution, spatial extent, and temporal resolution are limited by high computational cost

Reduced-complexity air quality models

- CTMs are time- and resource-intensive. **Reduced-complexity models (RCMs)** are a less-intensive alternative.
- RCMs are potentially less accurate than CTMs, but their reduced complexity allows for a far greater number of runs, thereby opening the door to sensitivity analyses, Monte Carlo approaches, longer simulation duration, and new understandings of source–receptor relationships.

	APEEP (AP2)	**EASIER**	**COBRA**	**InMAP**
Spatial resolution	County-level	36 km × 36 km grid	County-level	Neighborhood -scale
Pollutants modeled	All $PM_{2.5}$ precursors + O_3	$PM_{2.5}$ (P & S, no VOCs)	All $PM_{2.5}$ precursors	All $PM_{2.5}$ precursors
Spatial variation in secondary $PM_{2.5}$ formation	Yes	Yes	No	Yes
Computational cost	Low	Medium	Low	Low

How we determine the impacts of source emissions in this research?



Source: Slide modified from Prof. Ines Azevedo, with permission

A **reduced form air quality model** (InMAP) is used which requires three main inputs:

(1) Annual emissions of VOC, NO_x, NH_3, SO_2, and primary $PM_{2.5}$ for each electricity generating units (NEI 2014) or corn-stover producing counties (2016 Billion Ton study data) or freight modes (FAF data for Truck/Rail/Barge/Aircraft)

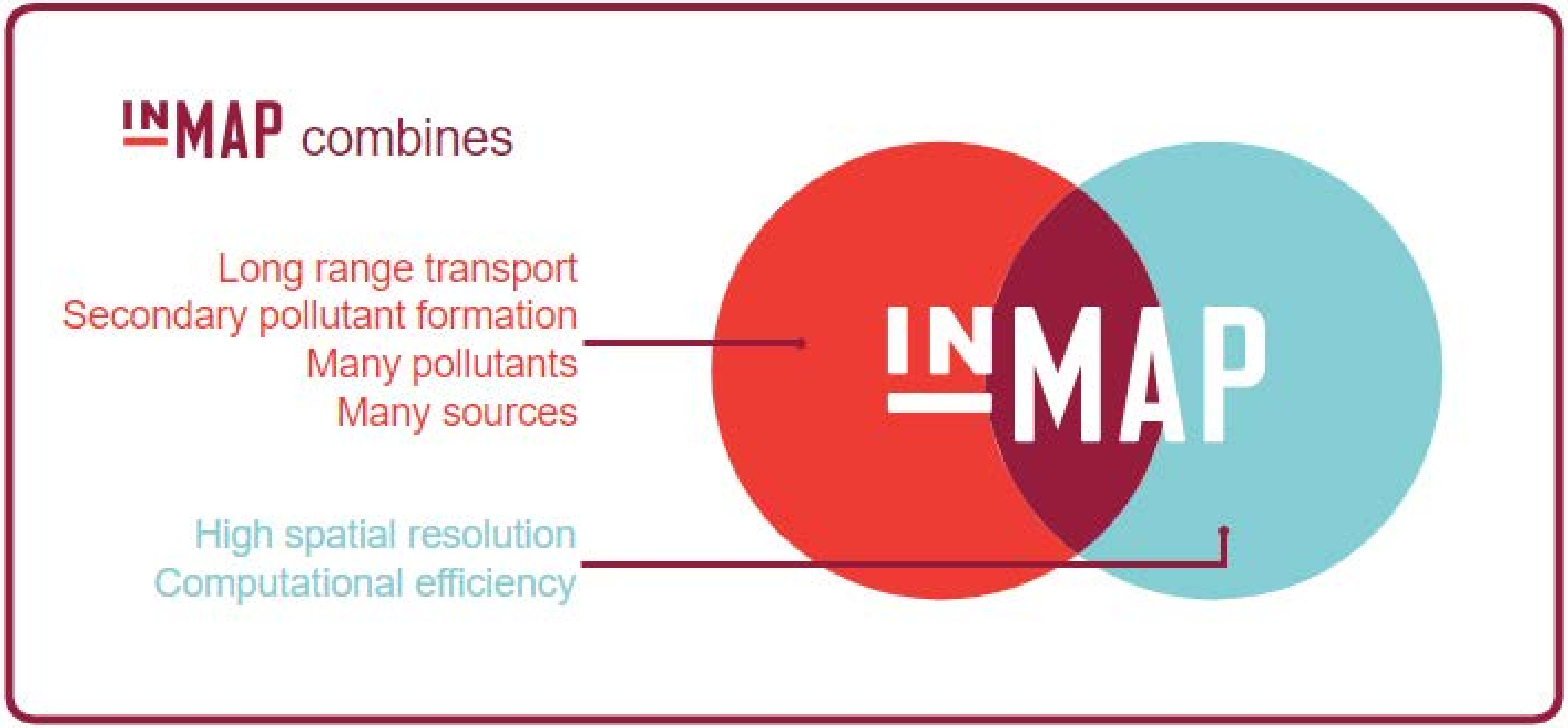
(2) Census data on self-reported race/ethnicity population (by block group) and household income (tract) from ACS 2014.

(3) CDC baseline all-cause mortality data (county level)

(4) We use the ACS dose-response function: Linear, non-threshold, and hazard ratio of 1.078

Interventional Model for Air Pollution (InMAP)

Tessum, C. W.; Hill, J. D.; Marshall, J. D. InMAP: A model for air pollution interventions. PLoS ONE 2017, 12 (4)



http://spatialmodel.com/inmap/

Source: http://spatialmodel.com/inmap/

InMAP model formulation

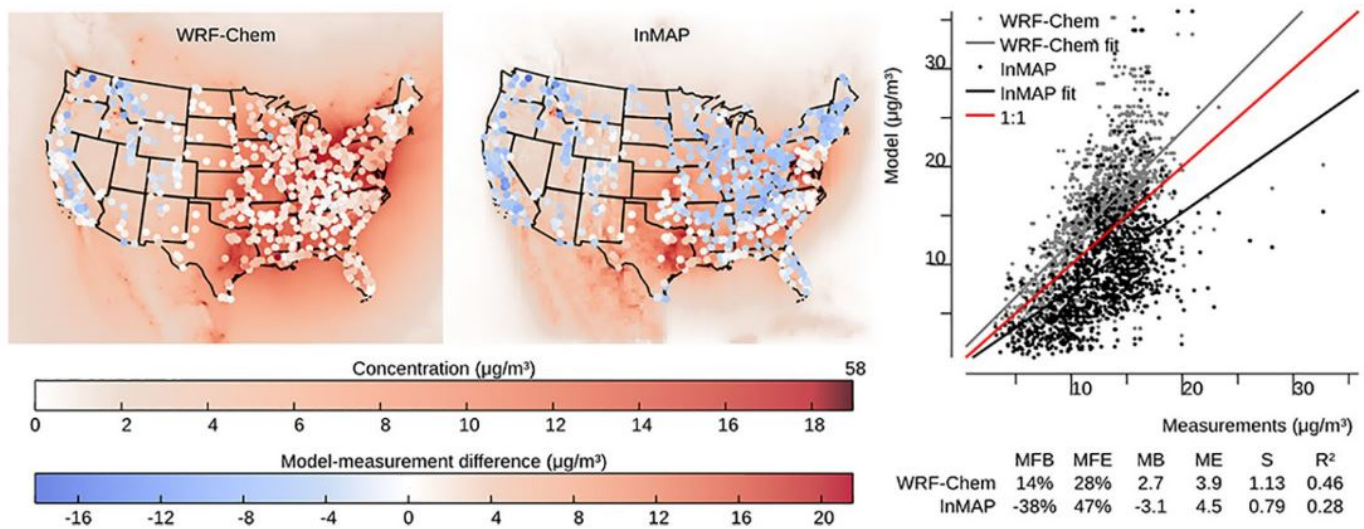
- The fate and transport of pollution in the atmosphere can be represented by a reaction-advection-diffusion equation:

$$\frac{\partial C_i}{\partial t} = \nabla \cdot (D \nabla C_i) - \nabla \cdot (\vec{v} C_i) + \sum_{j=1}^{n} R_{i,j} + E_i - d_i$$

- InMAP estimates pollutant concentrations by estimating a steady-state solution above equation yielding annual average pollutant concentration results.
- Grid cell size varies dynamically while the simulation is running based on gradients in population density and pollutant concentration.
- Grid cells smaller (larger) in high (low) population density areas: varies between 1×1 km to 48×48 km.

InMAP to model/measurement comparison

- InMAP recreates **comprehensive model** (WRF-Chem) predictions of changes in total $PM_{2.5}$ concentrations with population-weighted mean fractional bias (MFB) of −17% and population-weighted R^2 = 0.90.
- In general, InMAP tends to underpredict **observed** total $PM_{2.5}$ concentrations (MFB = −38%; WRF-Chem MFB = 14%).

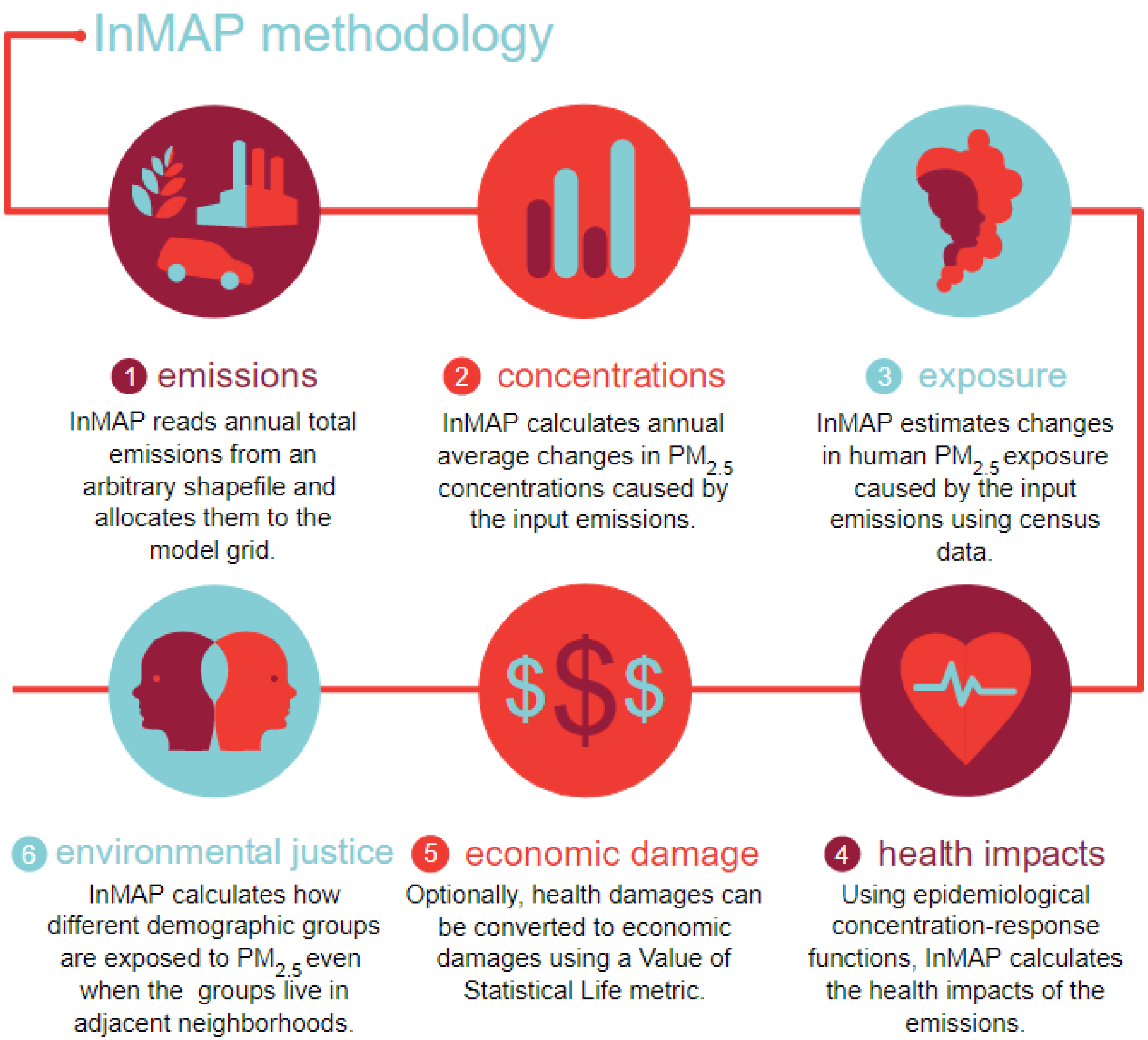


	MFB	MFE	MB	ME	S	R^2
WRF-Chem	14%	28%	2.7	3.9	1.13	0.46
InMAP	-38%	47%	-3.1	4.5	0.79	0.28

Fig 6. Comparison of WRF-Chem and InMAP performance in predicting annual average observed total $PM_{2.5}$ concentrations. The background colors in the maps represent predicted concentrations, and the colors of the circles on the maps represent the difference between modeled and measured values at measurement locations. For the comparison shown here, on average WRF-Chem overpredicts and InMAP underpredicts as compared to observations. Abbrevations: MFB = mean fractional bias; MFE = mean fractional error; MB = mean bias; ME = mean error; MR = model ratio; *S* = slope of regression line; R^2 = squared Pearson correlation coefficient.

Source: [Tessum et al. 2017]

InMAP methodology



Source: http://spatialmodel.com/inmap/

$PM_{2.5}$-related health impacts: C-R function from the American Cancer Society Re-analysis study

- We used the linear concentration-response (C-R) function with no threshold derived from the ACS reanalysis study representative of US concentrations and population.
- Employed an expression derived from Krewski et al. (2009) for the $PM_{2.5}$ C-R function (default in InMAP), which is used to estimate $PM_{2.5}$-related health impacts:

No. of premature deaths =

$$\left(e^{(PM_{2.5}\ Linear\ Coefficient \times [PM_{2.5}])} - 1\right) \times P \times \frac{All - Cause\ Mortality\ Rate}{100{,}000}$$

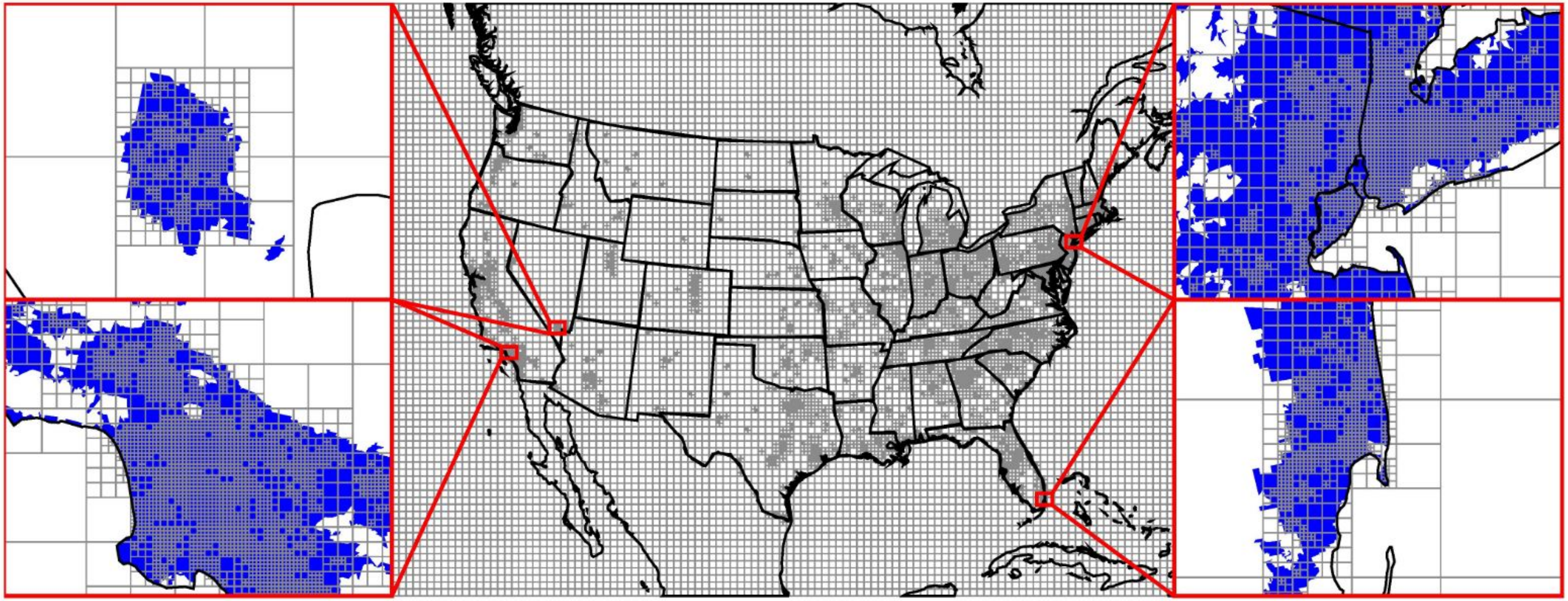
Here, $PM_{2.5}$ Linear Coefficient = ln(1.078)/10 = 0.007510747, i.e., a 7.8% increase in the number of premature deaths for every 10 ug/m^3 increase in the concentration of $PM_{2.5}$. [$PM_{2.5}$] is the concentration of $PM_{2.5}$; P is total population.

- This C-R function is standard and most widely used in the literature.

https://www.edockets.state.mn.us/EFiling/edockets/searchDocuments.do?method=showPoup&documentId=%7BE58591A3-0229-4192-B45E-5875C0F3F552%7D&documentTitle=201510-115285-04

InMAP grid

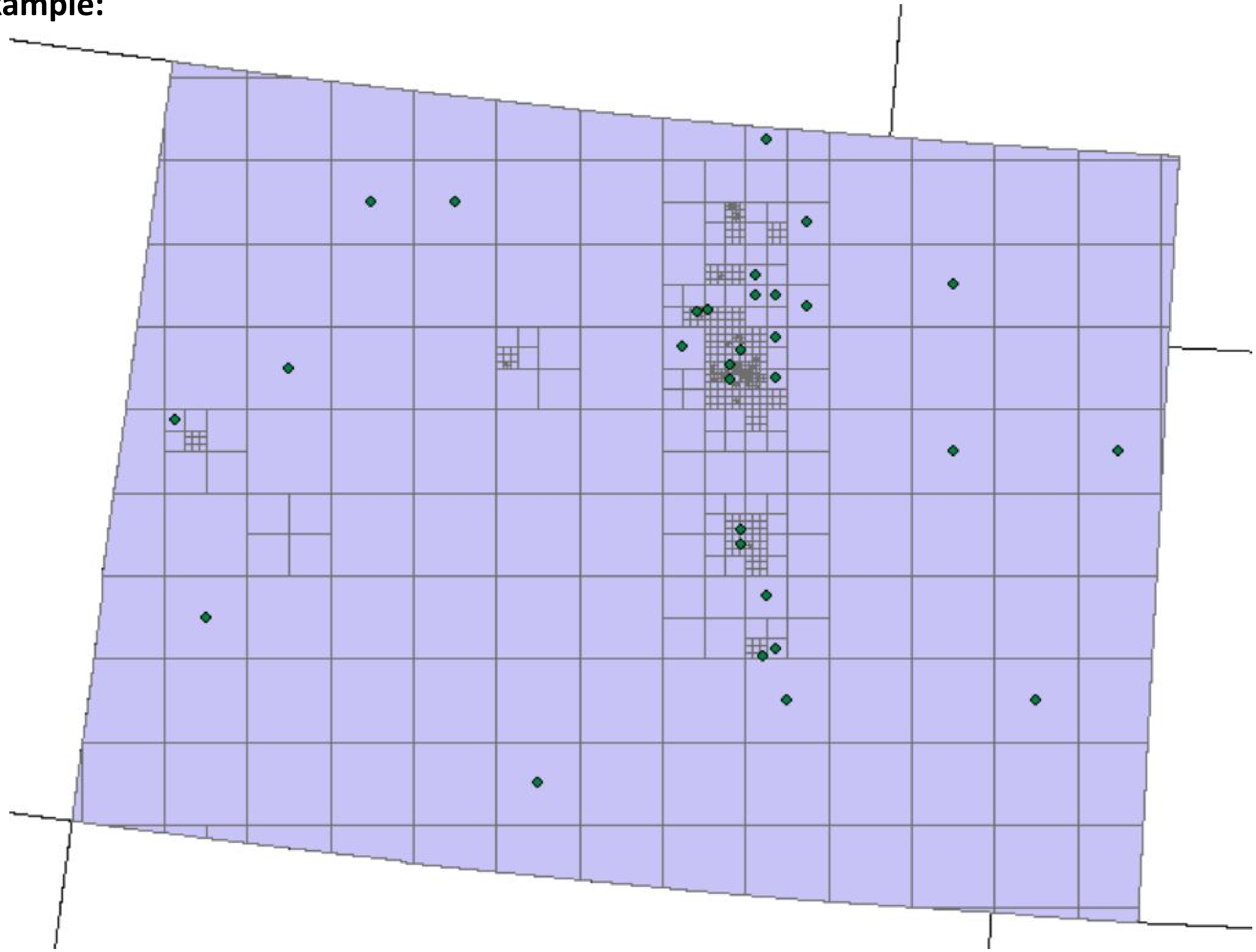
Spatial discretization of the model domain into variable resolution grid cells

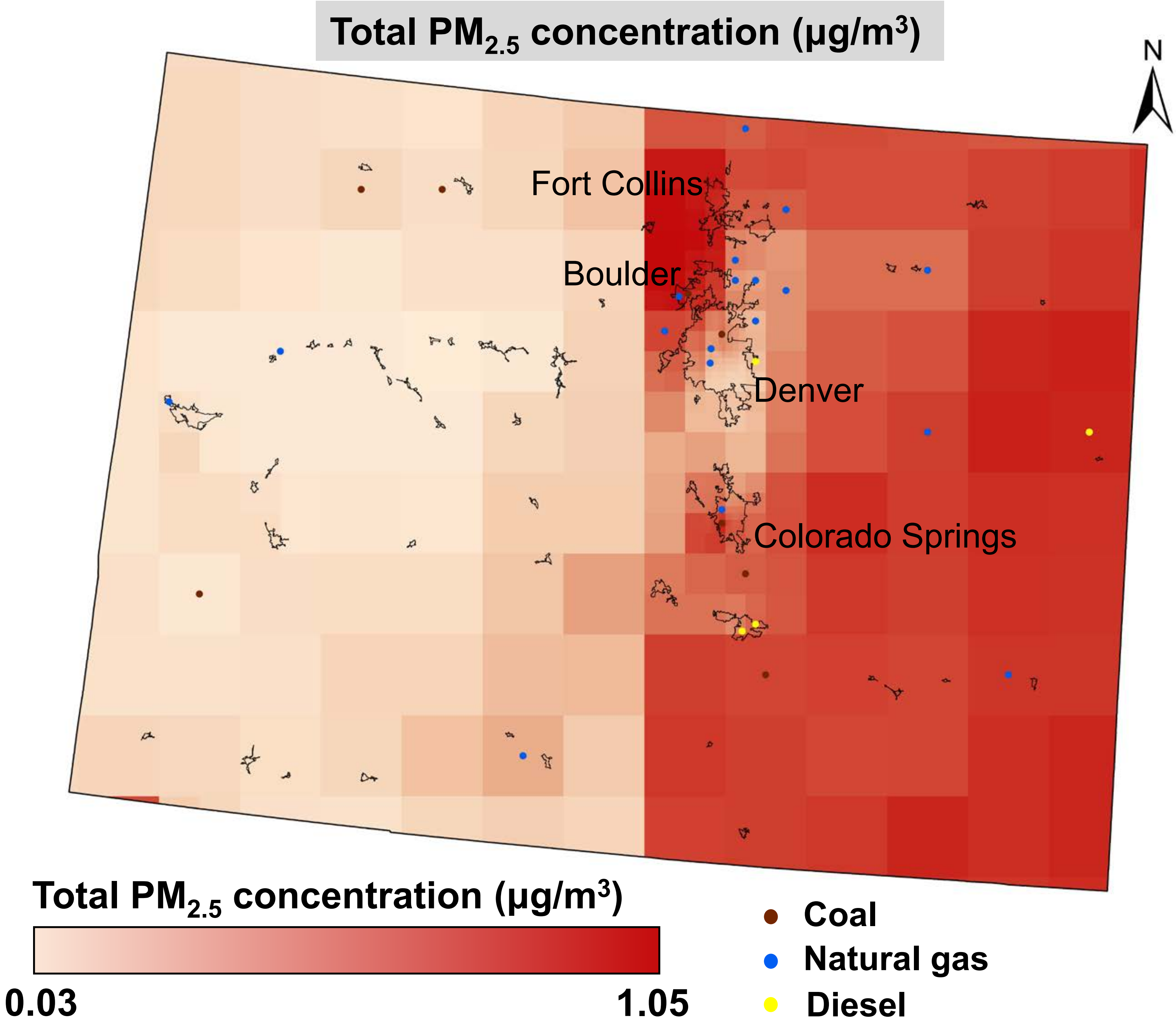


Source: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0176131

Total $PM_{2.5}$ concentration ($\mu g/m^3$)

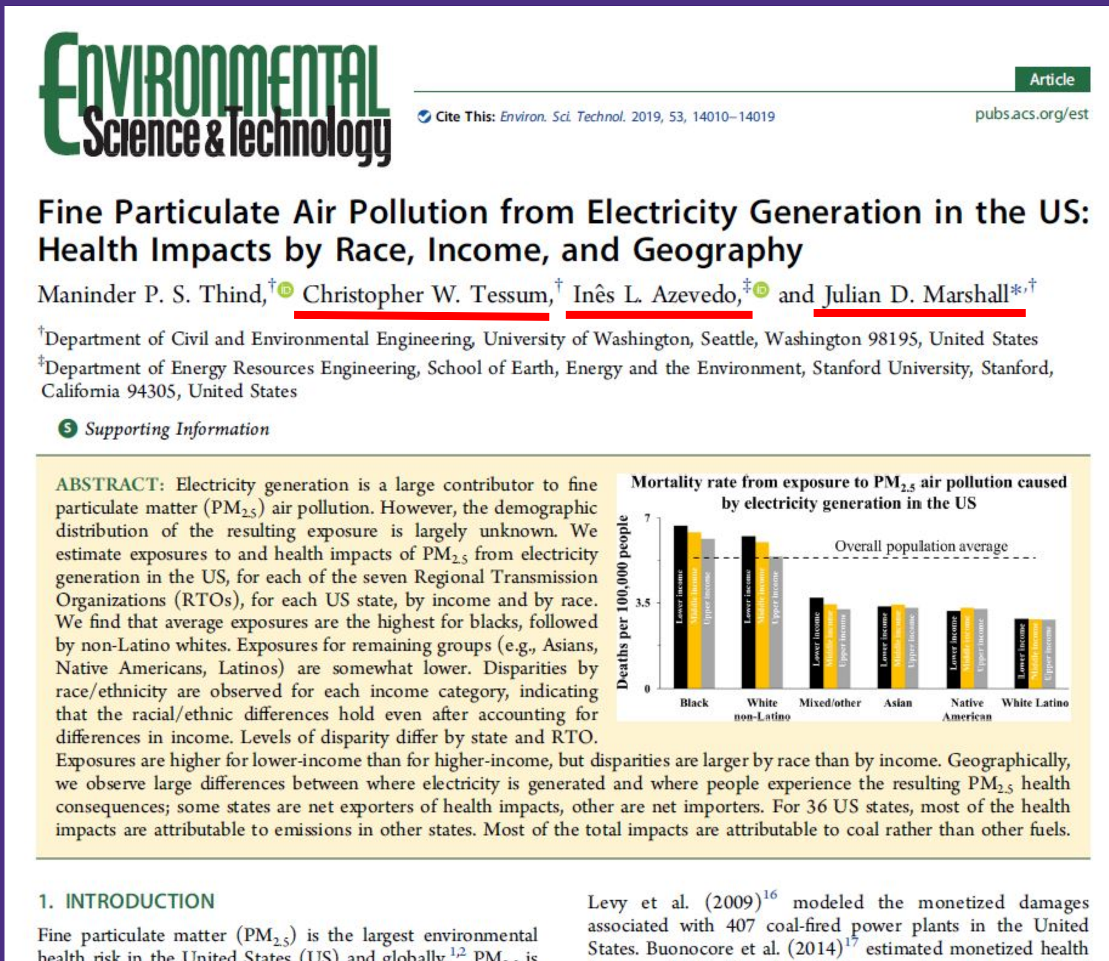
Example:




Total PM2.5 concentration (μg/m3)
N
Fort Collins
Boulder
Denver
Colorado Springs
Total PM2.5 concentration (μg/m3)
0.03
1.05
Coal
Natural gas
Diesel

Project B: Fine Particulate Air Pollution from Electricity Generation in the US: Health Impacts by Race, Income, and Geography

https://doi.org/10.1021/acs.est.9b02527



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Fine Particulate Air Pollution from Electricity Generation in the US: Health Impacts by Race, Income, and Geography

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Supporting Information

ABSTRACT: Electricity generation is a large contributor to fine particulate matter ($PM_{2.5}$) air pollution. However, the demographic distribution of the resulting exposure is largely unknown. We estimate exposures to and health impacts of $PM_{2.5}$ from electricity generation in the US, for each of the seven Regional Transmission Organizations (RTOs), for each US state, by income and by race. We find that average exposures are the highest for blacks, followed by non-Latino whites. Exposures for remaining groups (e.g., Asians, Native Americans, Latinos) are somewhat lower. Disparities by race/ethnicity are observed for each income category, indicating that the racial/ethnic differences hold even after accounting for differences in income. Levels of disparity differ by state and RTO. Exposures are higher for lower-income than for higher-income, but disparities are larger by race than by income. Geographically, we observe large differences between where electricity is generated and where people experience the resulting $PM_{2.5}$ health consequences; some states are net exporters of health impacts, other are net importers. For 36 US states, most of the health impacts are attributable to emissions in other states. Most of the total impacts are attributable to coal rather than other fuels.

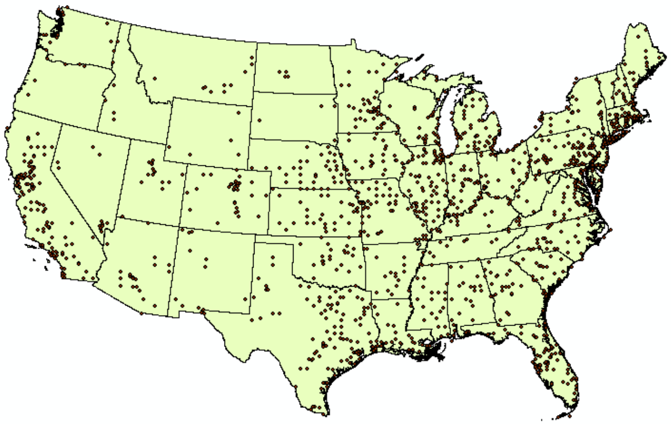
1. INTRODUCTION

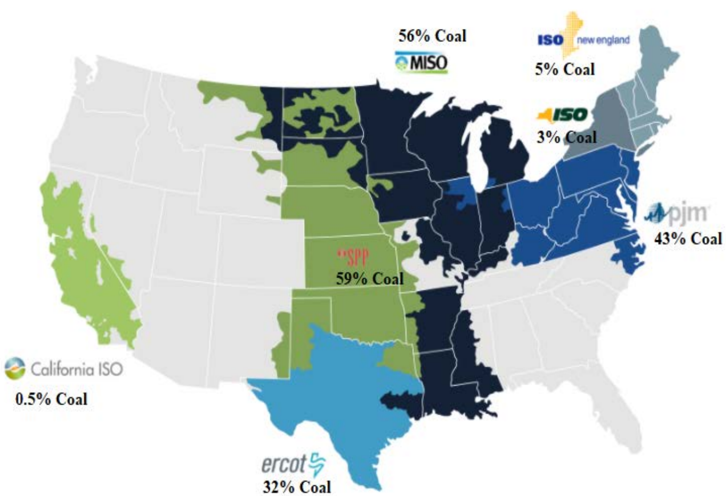
Fine particulate matter ($PM_{2.5}$) is the largest environmental health risk in the United States (US) and globally.[1,2] $PM_{2.5}$ is

Levy et al. (2009)[16] modeled the monetized damages associated with 407 coal-fired power plants in the United States. Buonocore et al. (2014)[17] estimated monetized health

Project B: Research question

- **What are the distributional effects from air pollution from electricity?**
  - ➢ How $PM_{2.5}$ health impacts vary among race groups (Whites, Black Americans, Asians, and Native Americans), income groups and geographically (National, Regional Transmission Organizations (RTOs), States)?





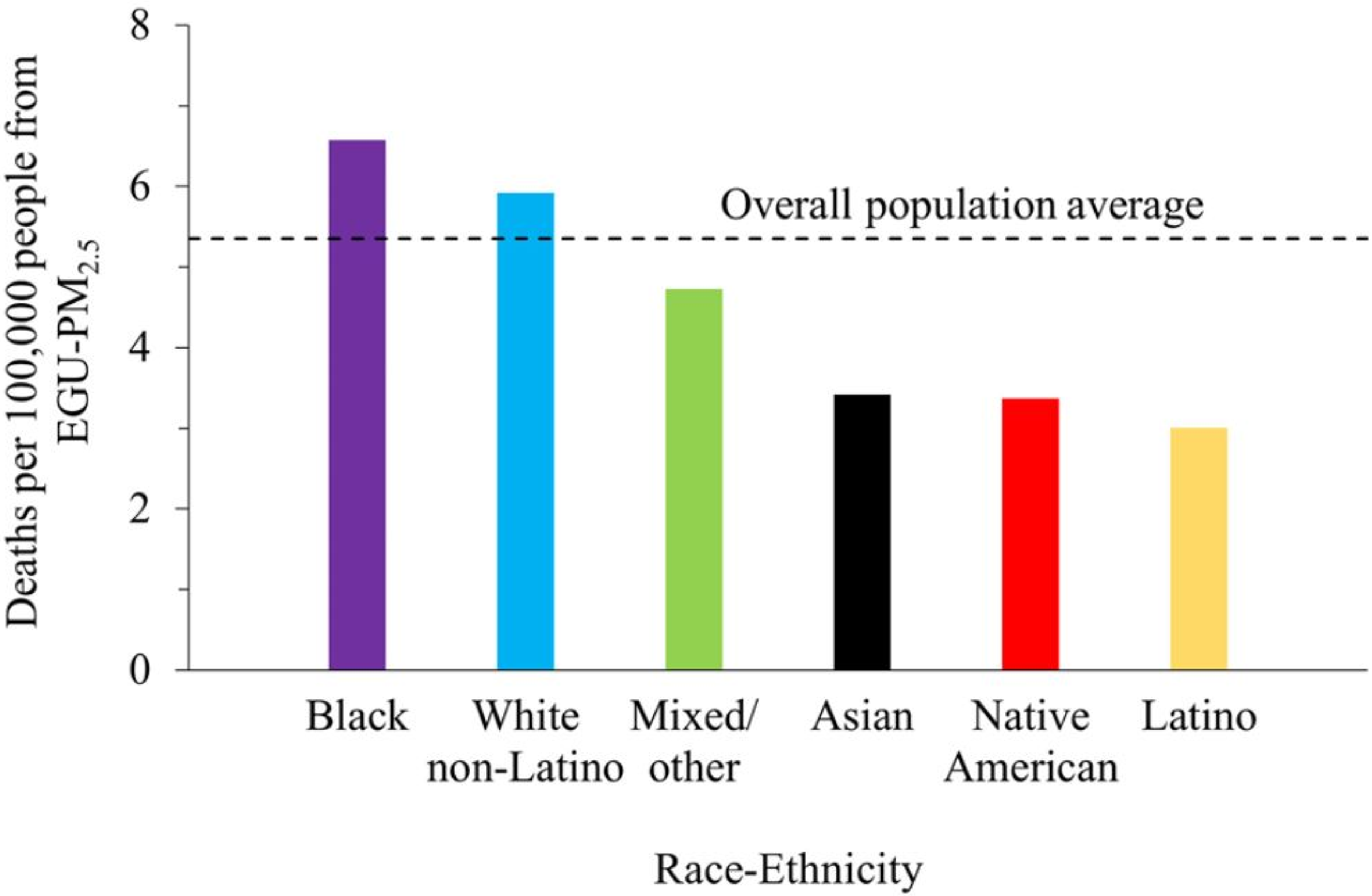
Project B: Key findings – Deaths at national and RTO scale

- National scale: We find that the operation of EGUs in 2014 is associated with **~16,400** $PM_{2.5}$-related premature deaths per year (~4 deaths/TWh).
- ~ **85%** are attributable to EGUs that are in an RTO.

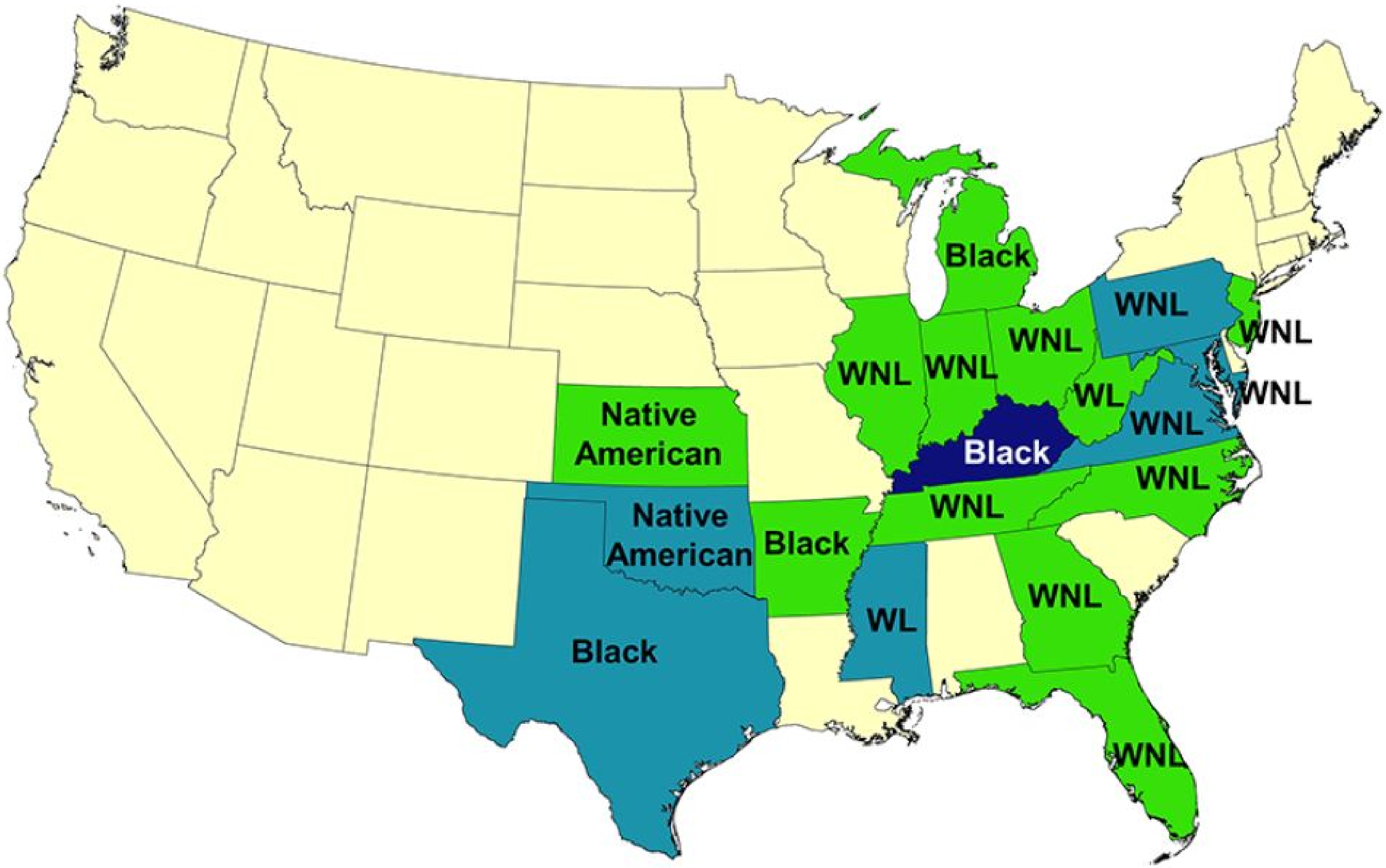
		total deaths attributable to RTO's emissions		percent of generation by fuel[a]		
RTO	annual net generation (TWh)[a]	total deaths	deaths per TWh	coal (%)	natural gas (%)	oil, biomass, and other fossil fuels (%)
CAISO	170	45	0.3	0.5	59	4
ERCOT	365	1788	4.9	32	46	0.7
MISO	691	5649	8.2	56	19	4
NEISO	110	48	0.4	5	43	10
NYISO	140	162	1.2	3	42	4
PJM	809	4868	6.0	43	17	2
SPP	238	1599	6.7	59	19	0.8

[a]From year 2014 in eGRID.[29]

Project B: Key findings – Impacts by race at national scale



Project B: Key findings – Impacts by race in each state

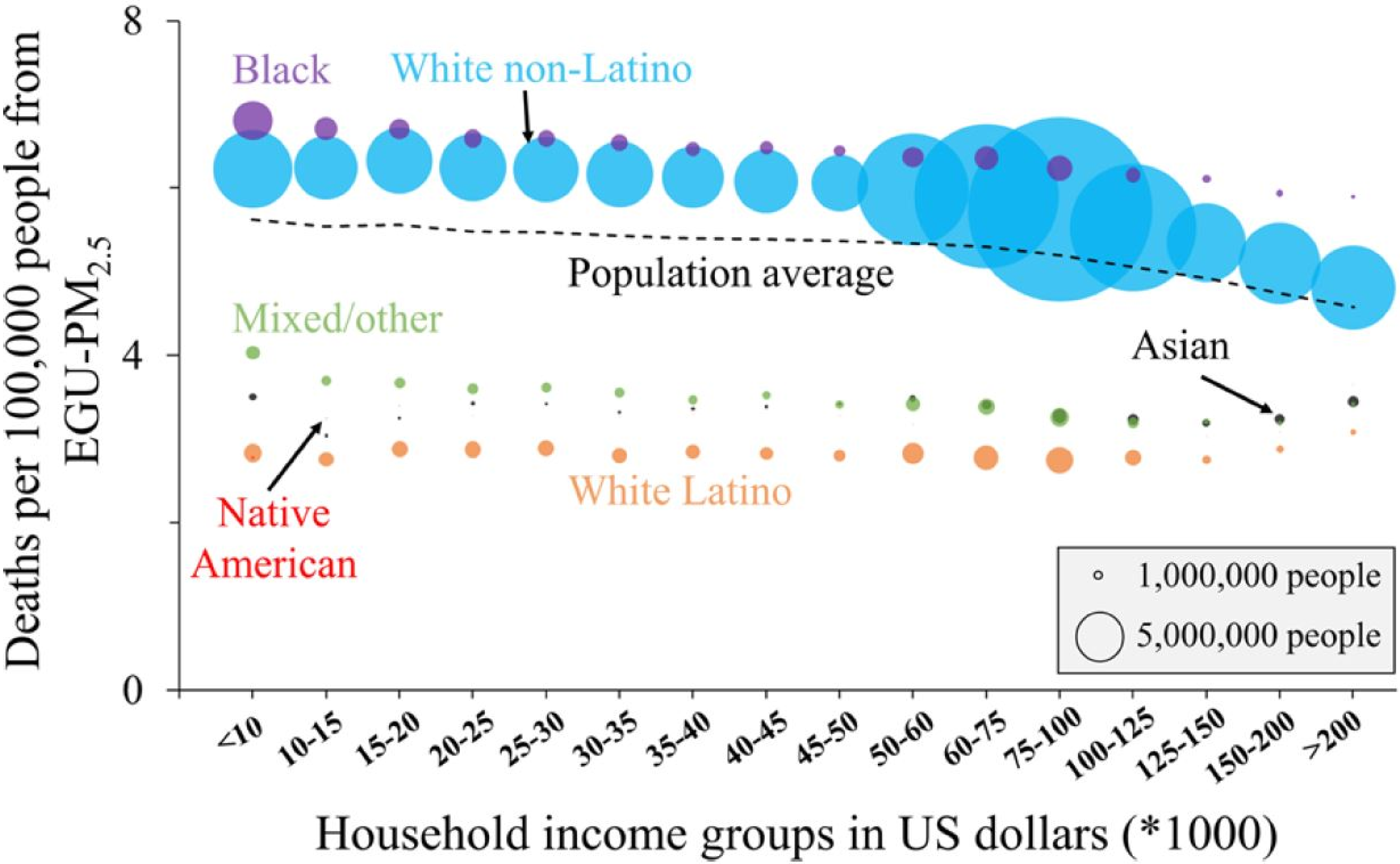


Risk gap (deaths per 100,000 people) between the most and least exposed race-ethnic group in each state from EGU-$PM_{2.5}$

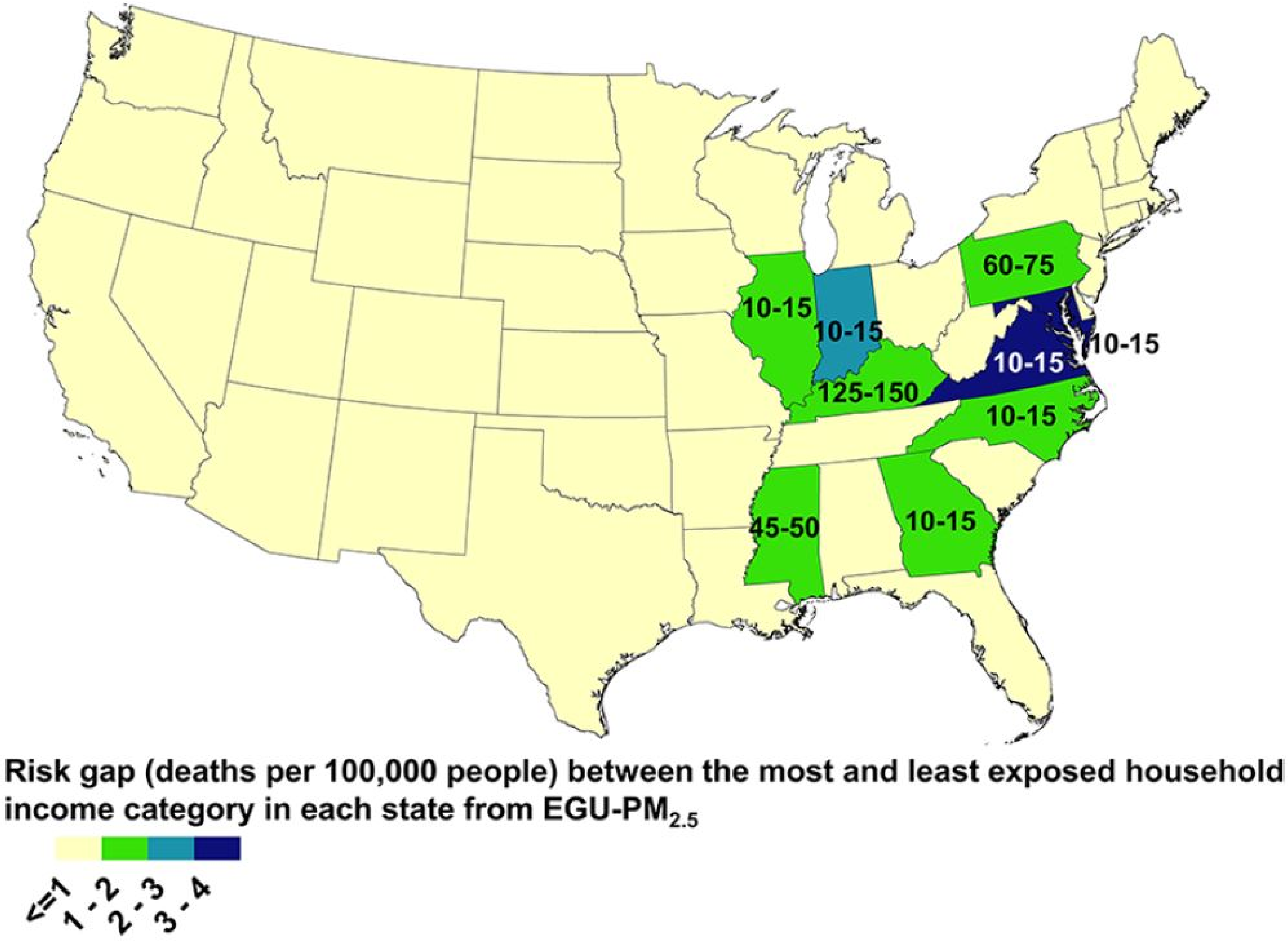
<=1 1-2 2-3 3-4

WL: White Latino
WNL: White Non-Latino

Project B: Key findings – Impacts by income at national scale



Project B: Key findings – Impacts by income in each state



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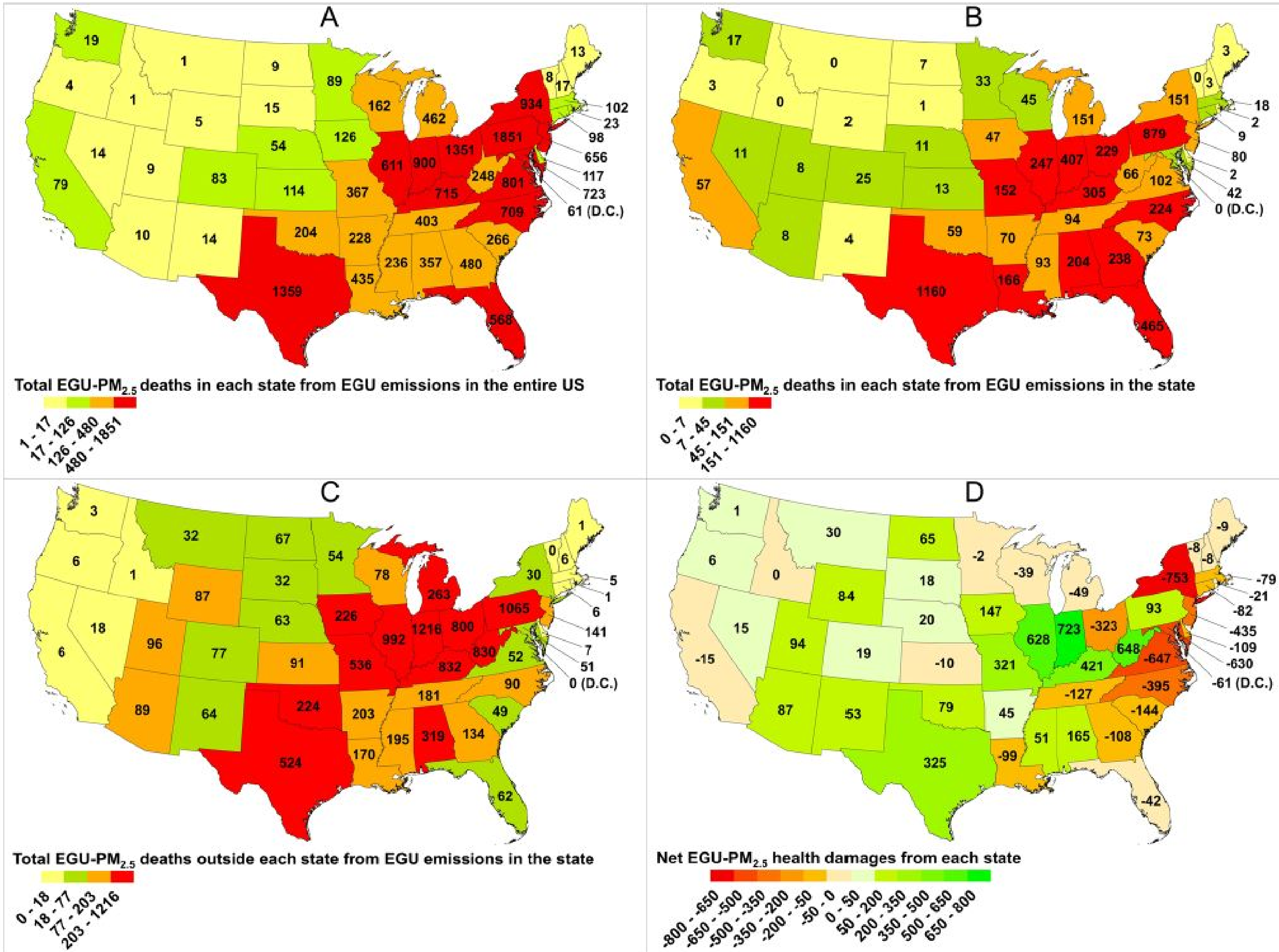
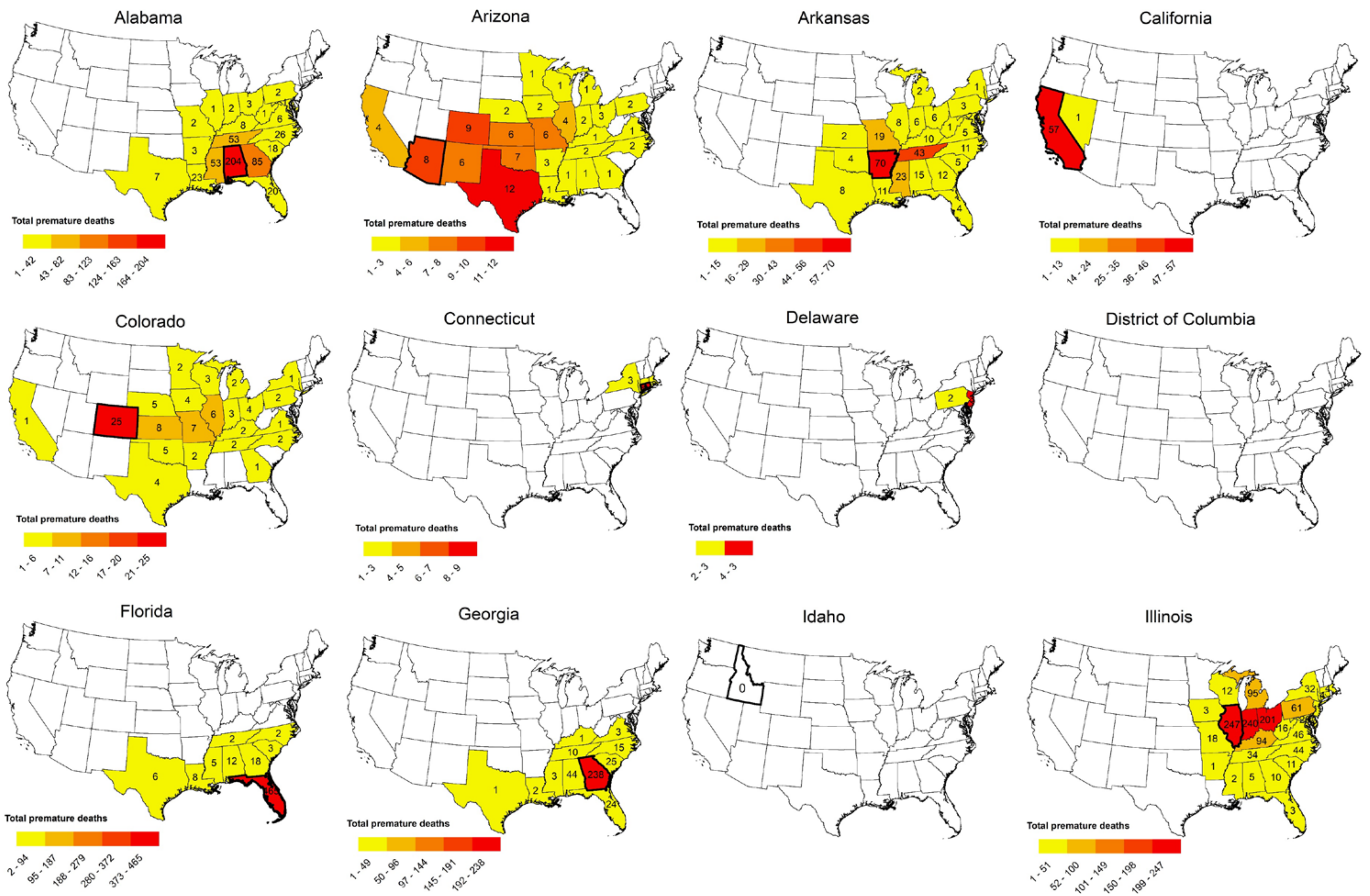
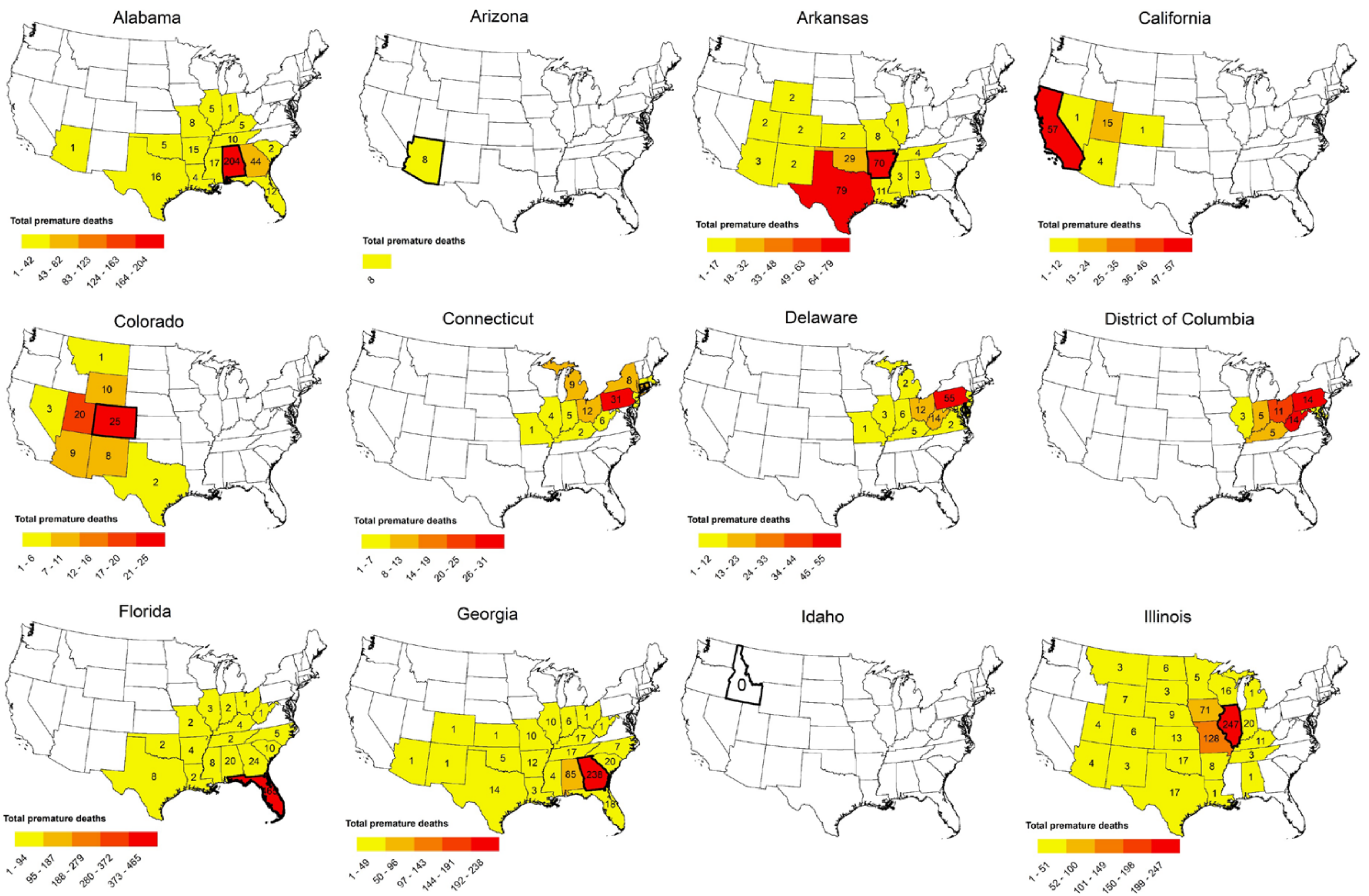
Project B: Key findings – Interstate damages



Project B: Key findings – Interstate damages



Project B: Key findings – Damages from other states



Project B: Intellectual significance

- This work is the **first national-scale investigation of environmental justice impacts** of $PM_{2.5}$ air pollution from electricity generation.

- Previous studies have estimated the total damages associated with $PM_{2.5}$ from the US electricity sector. This work complements those findings by systematically analyzing the damages for different **geographical boundaries (RTOs and states)** and for different **demographic groups (race and income).**

- We find that **blacks are disproportionately affected by EGU-$PM_{2.5}$ nationally**, but most-exposed race/ethnicity varies by state and by RTO.

- **Exposures are higher for lower-income** than for higher-income households, but differences by race/ethnicity are larger than differences by income.

- For **36 US states**, most of the health impacts are attributable to emissions in other states.

Project C: Characterization of Air Quality Impact in Life Cycle Impact Assessment – Method Development and Demonstration for $PM_{2.5}$-Emitting Area Sources from Biofuel Feedstock Supply

Paper “Under Review” in the Science of the Total Environment journal

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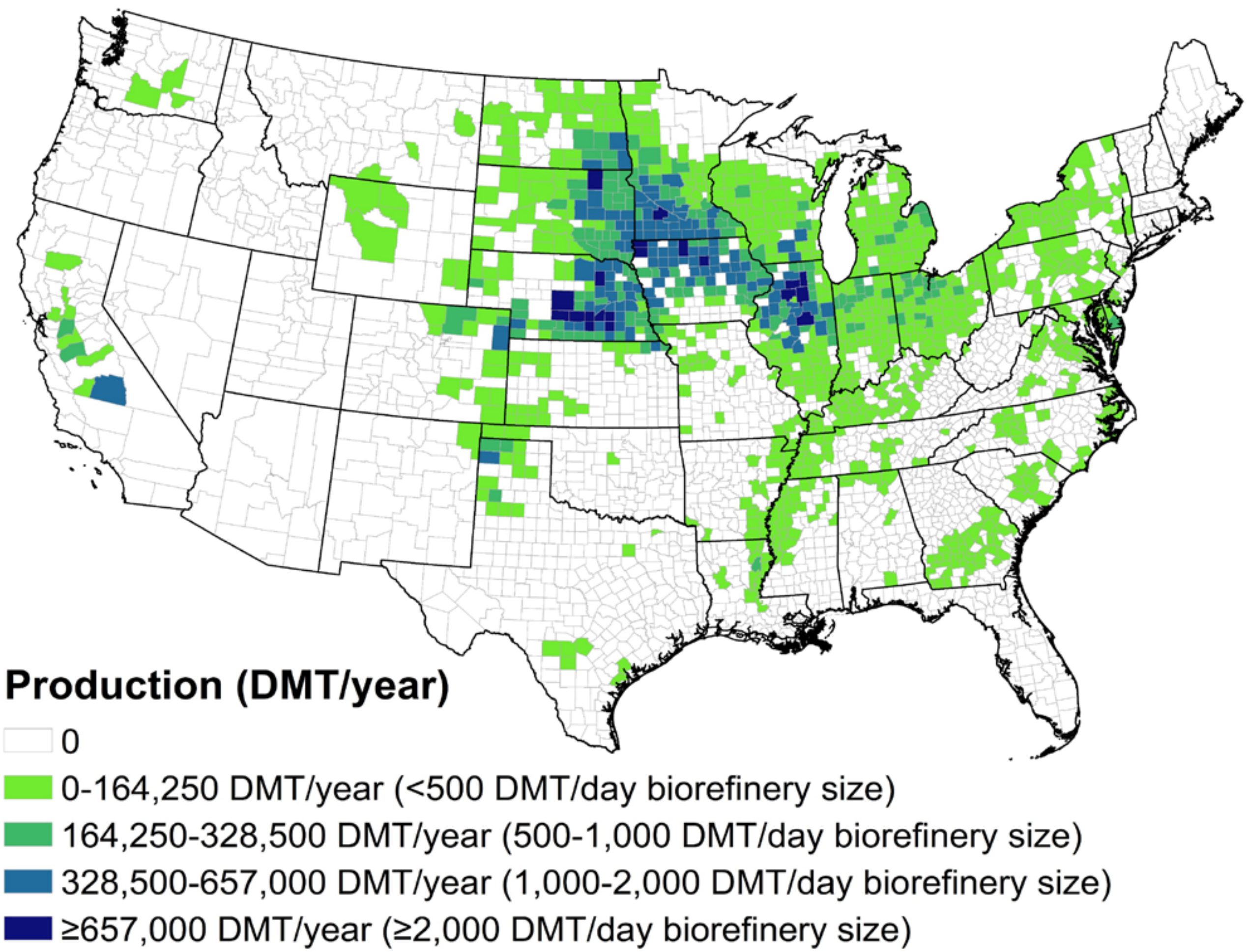
Project C: Research question

How to site new biorefineries in the regions with available biomass production to have least impact on the ambient air quality and health outcomes?

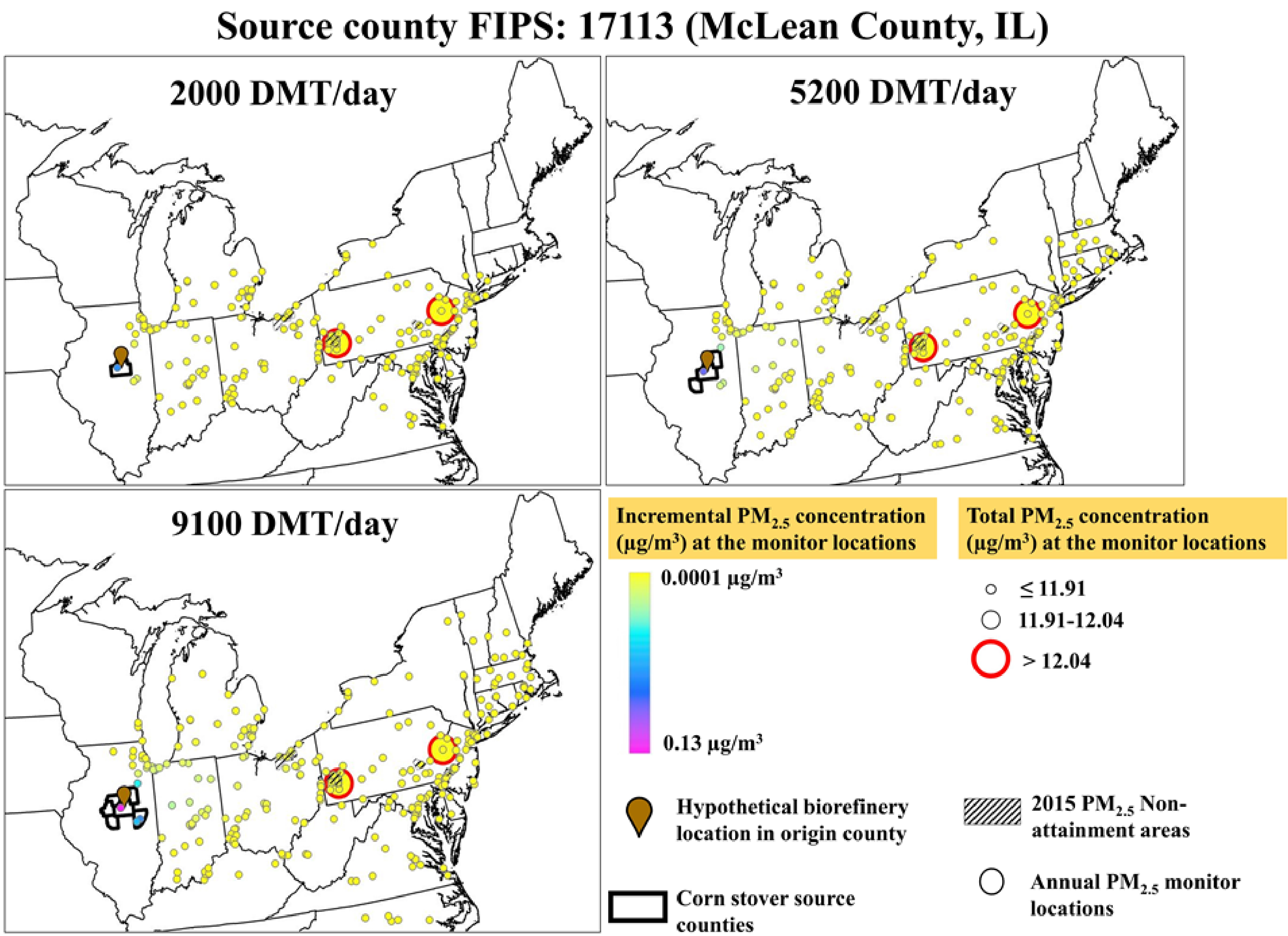
Project C: Data – BT16 study

- Production and emissions data from the U.S. Department of Energy's **Billion Ton Study Vol 1 and Vol 2**
- Emissions generated using **NREL's FPEAM Model**



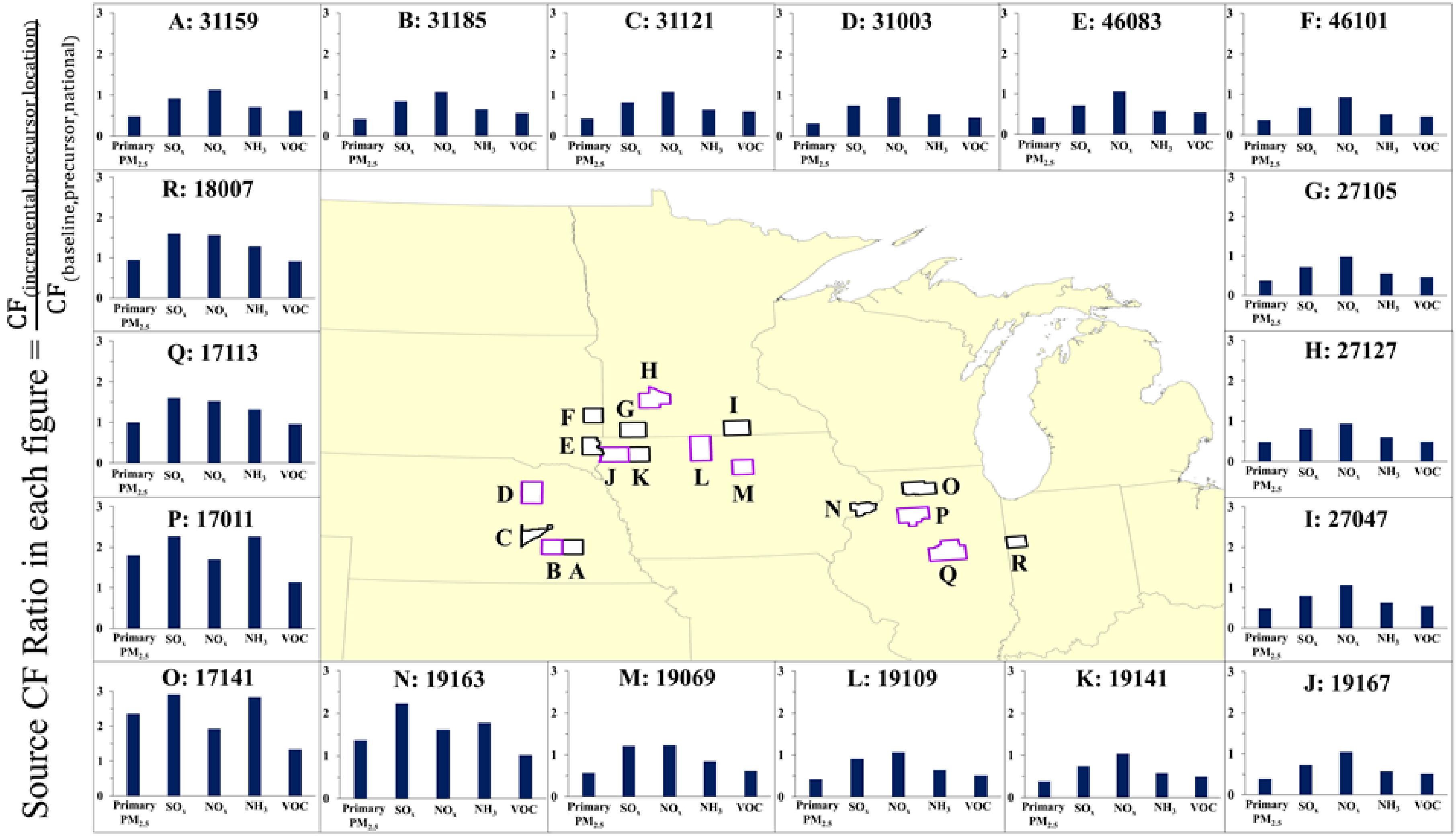
Project C: Key findings

Available Regulatory Capacity for Incremental Emissions (ARCIE) = $[PM_{2.5}]_{NAAQS} - [PM_{2.5}]_{receptor}$



Project C: Key findings

$$\text{Source CF Ratio} = \frac{CF_{(\text{incremental, pollutant, new-source location})}}{CF_{(\text{baseline, pollutant, spatial modeling domain})}}$$



Conclusions

1. Avg. marginal emissions factors provide a better metric to estimate benefits from energy efficiency interventions acting on margin: In MISO, generally avg. marg. EF < avg. EF

2. Air quality impacts of air emissions on human population are estimated for EGUs, corn-stover producing counties, and freight modes.

3. We find that average impacts from power plant pollution is highest for the Blacks, followed by Non-Latino Whites. Impacts for remaining groups (e.g., Asians, Native Americans, and Latinos) are somewhat lower.

4. InMAP is a novel spatial air quality modeling tool to understand impacts from different energy systems at very high resolution.

Limitations and filling remaining gaps

- Employing more updated alternative concentration–response functions (e.g., a supralinear C–R) or allowing the C–R to vary by source, geography, or chemical components
- Improvement in the chemistry of PM formation in InMAP
- Modeling impacts of ozone at high resolution
- Compare results with complex CTMs and other RCMs

Thank You!

Questions?