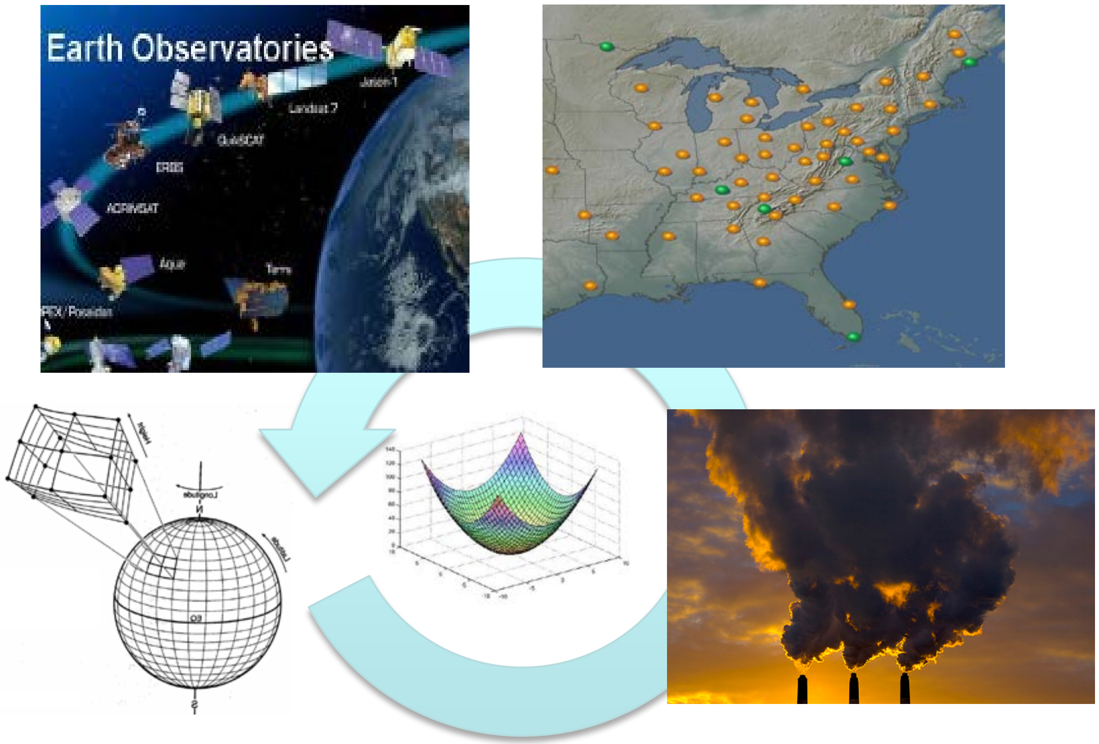
How scientific and technical air quality modeling tools interact with policy



Daven K. Henze
University of Colorado, Boulder

Outline

1. Brief history of AQ policy and AQ models
2. Roles of AQ models in policy
3. AQ model output for policy applications
4. Source attribution and receptor modeling

The first air quality regulation?

www.bbc.co.uk

King Edward I (1239-1307)

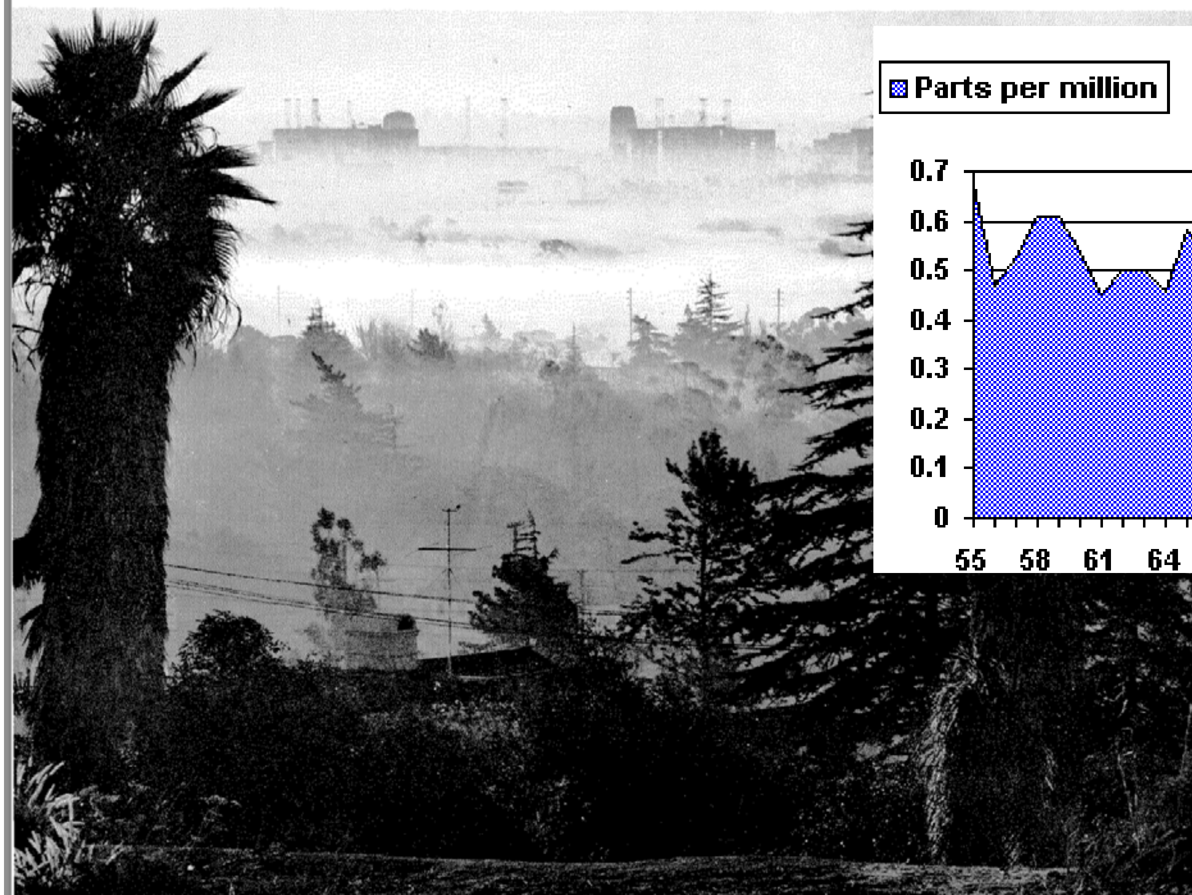
Monet, 1904

1273: Ordinance prohibited the use of coal in London as being prejudicial to health

1306: Royal Proclamation forbade the use of (sea) coal (Marsh, 1957)

Contemporary air quality

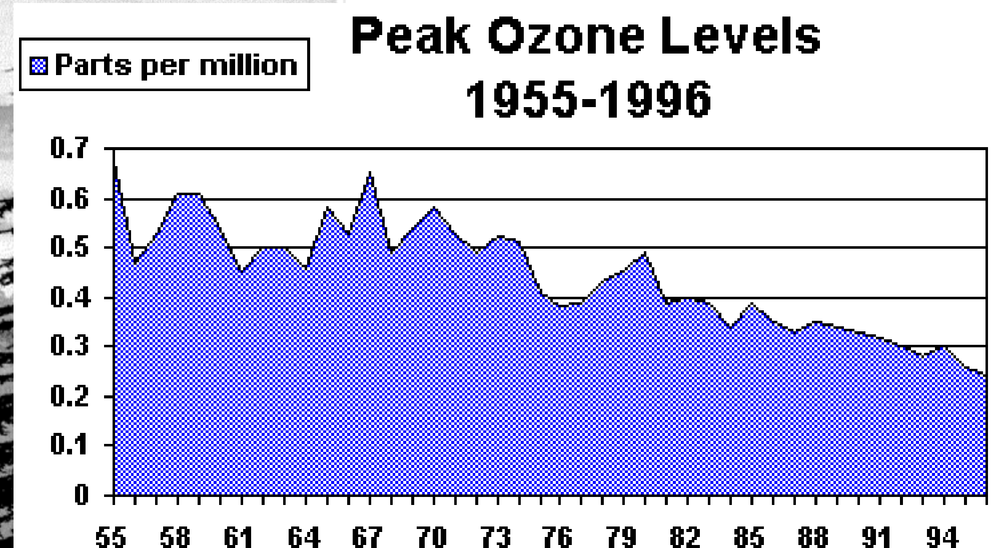
Volume XIV ENGINEERING AND SCIENCE December, 1950



Max Yavno photograph from The Los Angeles Book

THE AIR POLLUTION PROBLEM IN LOS ANGELES

by A. J. Haagen-Smit



AQ models

Plume / Dispersion:

- describe transport and diffusion of pollutants

newsblogs.chicagotribune.com

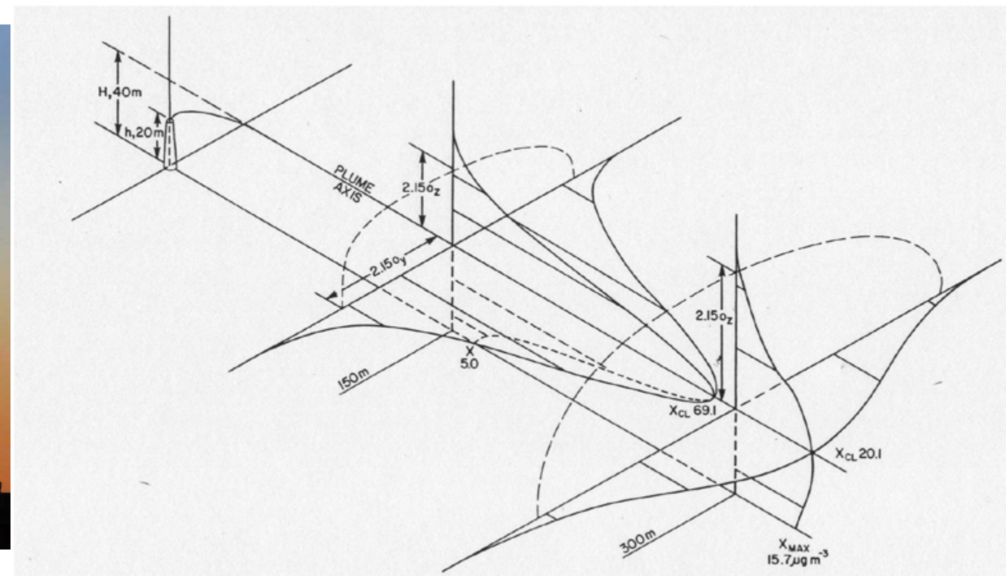


Fig. 19-5. Two cross sections through a Gaussian plume (total mass under curves conserved).

Boubel et al., 1994

- used to estimate pollution from point sources (Sutton et al., 1932), in cities (Lettau, 1931) and even throughout the globe (Machata, 1958)

AQ models – brief history

Persistence model: today's AQ is going to be just like yesterday's

Statistical models (e.g., McCollister and Wilson, 1975):

- based on timeseries, temperature, insolation, wind…
- hard to make predictions beyond range of existing data

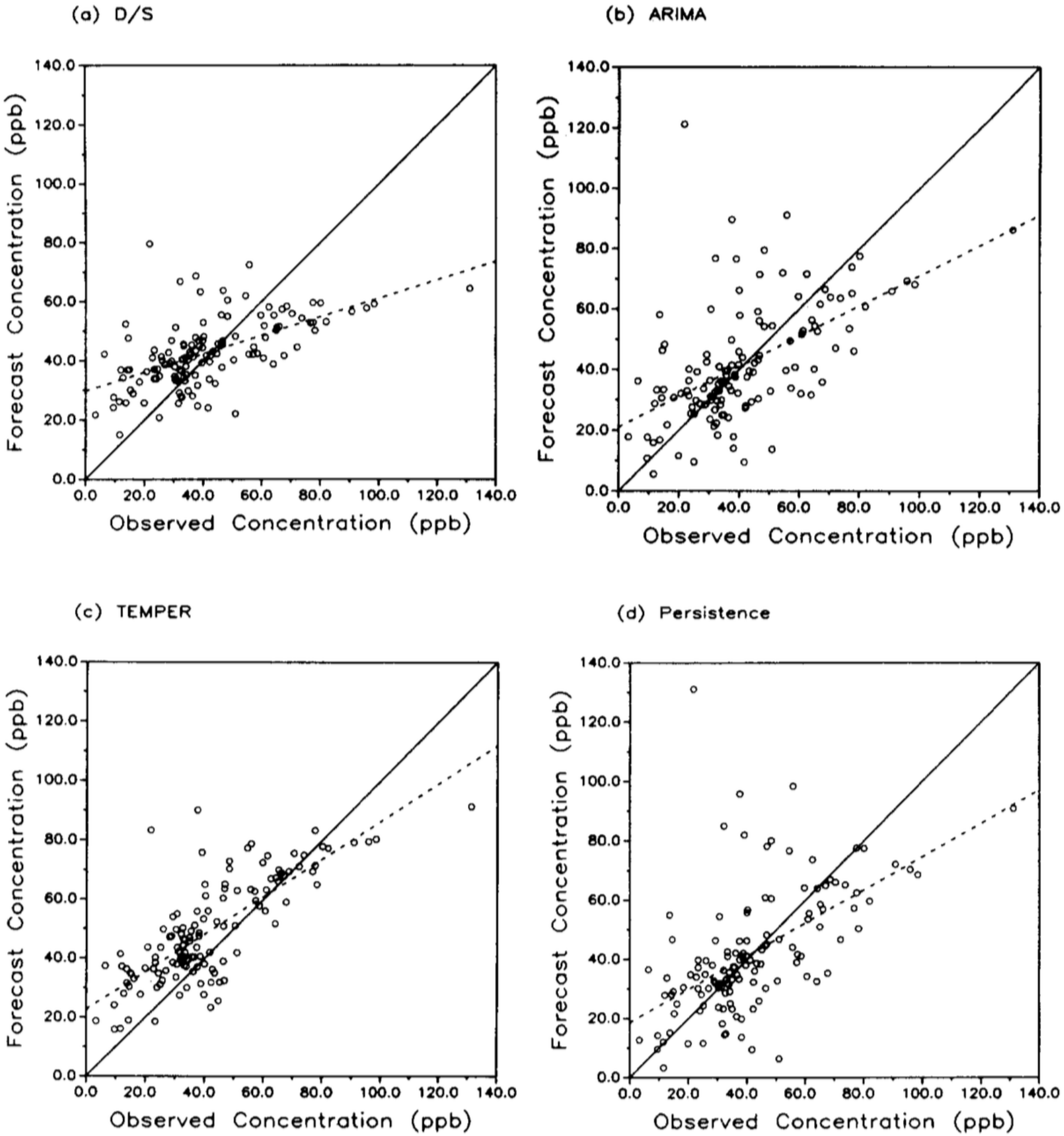


Fig. 2. Scatterplots of forecast vs observed daily maximum ozone concentrations for the summer of 1986 at station T9 using: (a) D/S, (b) ARIMA (1, 1, 0), (c) TEMPER and (d) persistence models. Solid line indicates perfect prediction while the dashed line is an ordinary least squares regression estimate.

(a) and (b) Timeseries+stochastic
(c) including T
(d) persistence

Robeson and Steyn, 1990

AQ models

Photochemical air quality models / chemical transport models (CTMs) developed >40 years ago (e.g., Friedlander and Seinfeld, 1969)

- 1st generation: simple chemistry at local scales
- 2nd generation: local, urban, regional addressing each scale with a separate model and often focusing on a single pollutant.
- 3rd generation: multiple pollutants simultaneously up to continental scales and incorporate feedbacks between chemical and meteorological components.
- 4th generation: extend linkages and process feedback to include air, water, land, and biota to simulate the transport and fate of chemical and nutrients throughout an ecosystem.

AQ models

Current advances in AQ models:

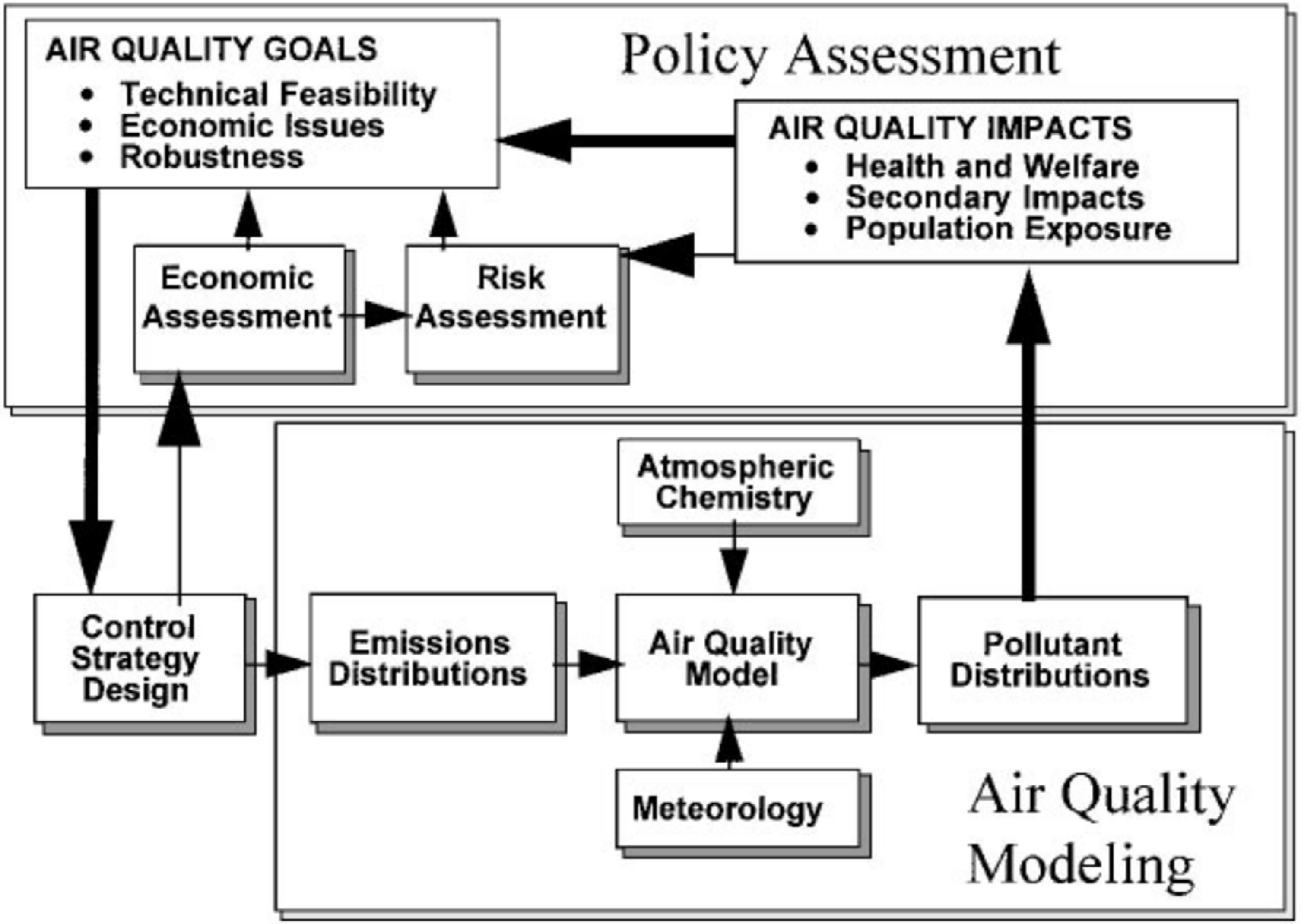
- online / coupled simulations of chemistry and meteorology (Baklanov et al., 2014)

- Large Eddy Simulations with chemistry (LES)

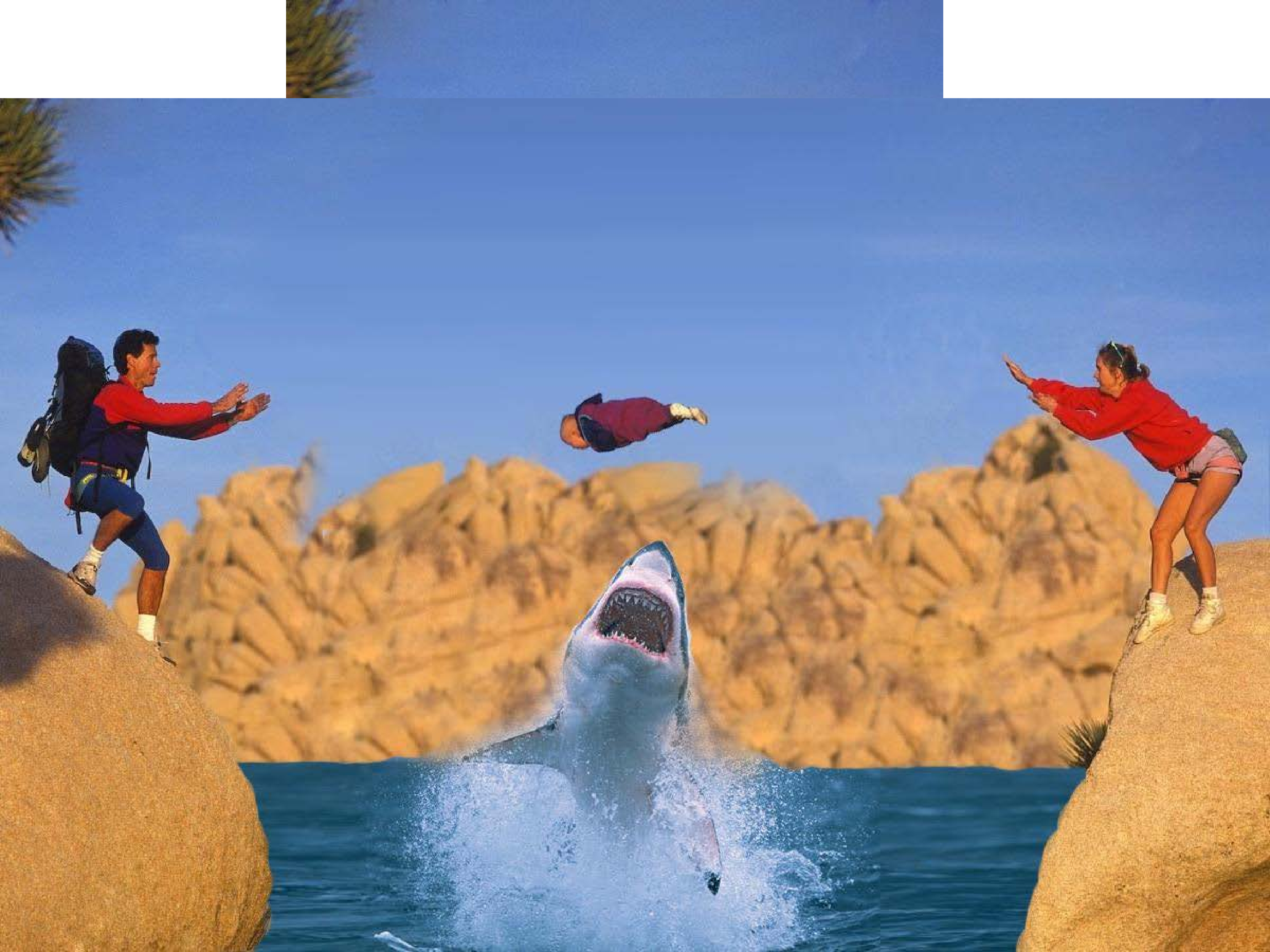
- ensembles / probabilistic

- self correcting / data assimilation (Bocquet et al., 2015)

Air quality modeling for policy assessment



Russell, 1997

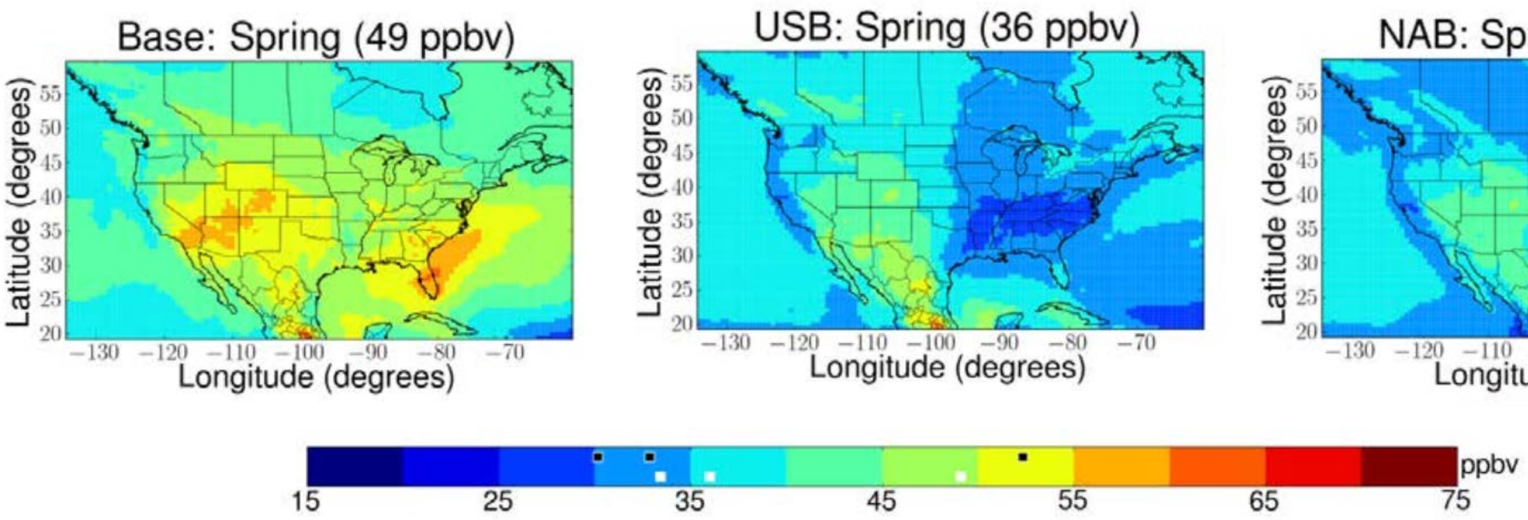


Roles of AQ models in policy

Setting standards

- developing concentration-response relationships
- exposure assessment / evaluating risk
- determining background / natural pollution levels

Background O_3



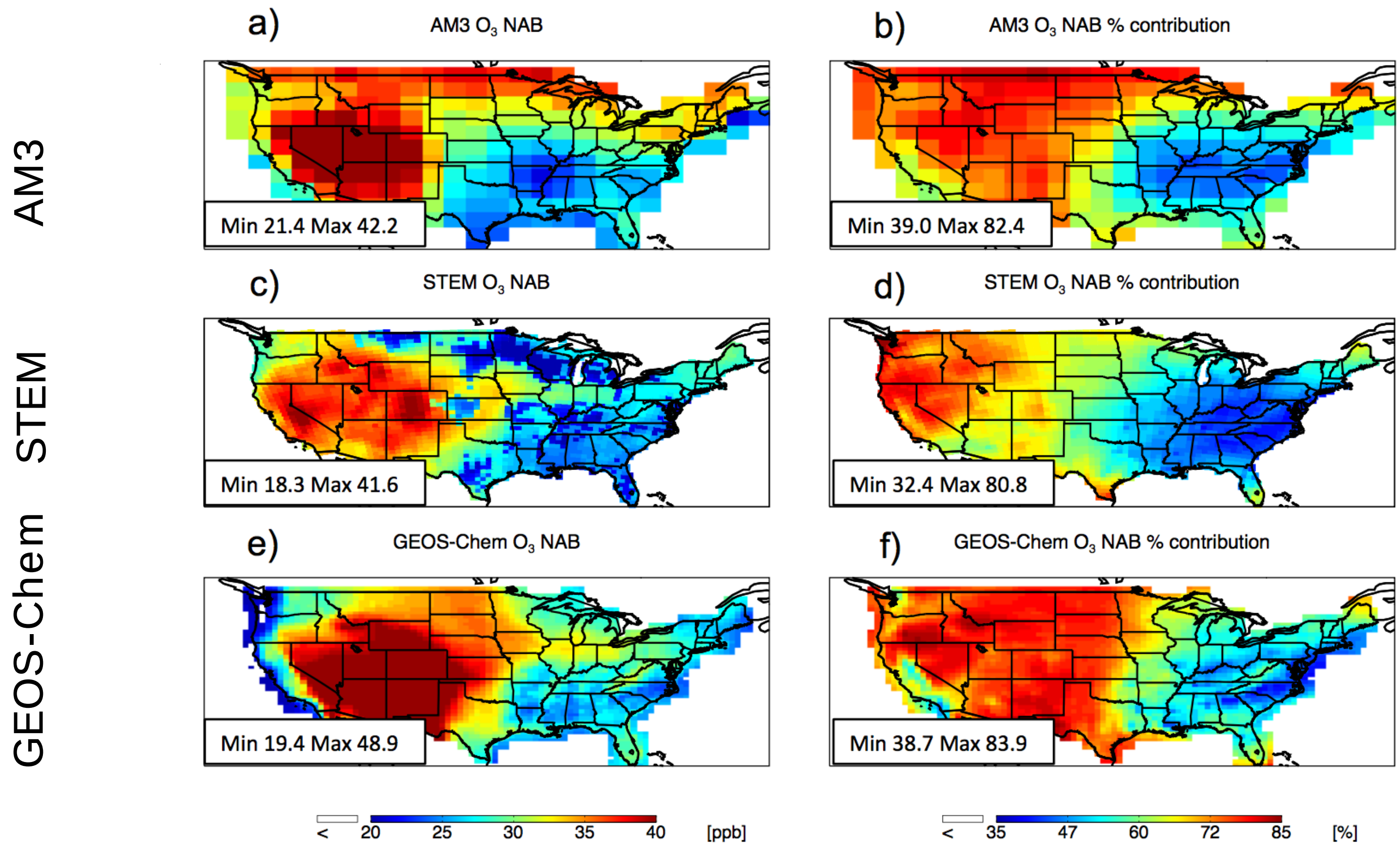
EPA, ISA, 2013
Adapted from Zhang et al,. 2011

USB = O_3 in the absence of anthropogenic emissions from the U.S.

NAB = O_3 in the absence of anthropogenic emissions from the U.S., Canada and Mexico

Background O_3

NAB O_3 from multi-model study (Lapina et al., 2014):



Background MDA8 O_3:

- Correlated with MDA8 O3 (Zhang et al., 2011)
- Relative background amount fairly consistent across models (56-67% of total daytime O_3 across entire US).

Roles of AQ models in policy

Setting standards

- developing concentration-response relationships
- exposure assessment / evaluating risk
- determining background / natural pollution levels

AQ management

- Development of control strategies (e.g., SIP)
- Permitting
- Determining exceptional events and long-range transport
- Forecasting

Evaluating impacts of emissions regulations

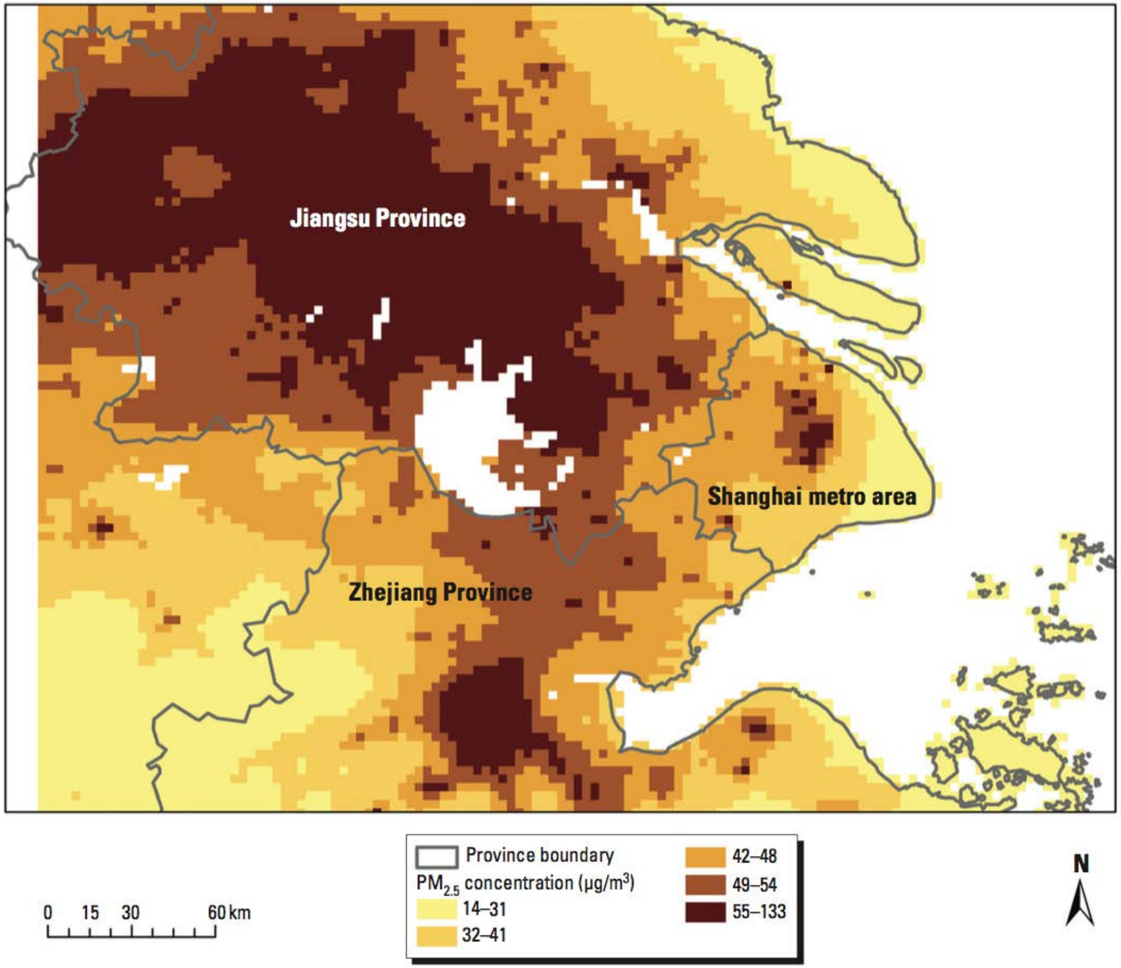


Figure 1. Estimated annual average $PM_{2.5}$ concentration (μg/m^3) in the YRD domain in the base–case scenario.

Zhou et al., 2011

Evaluating impacts of emissions regulations

ΔEmissions → Air quality model → ΔConcentrations

Evaluating impacts of emissions regulations

Table 1. CMAQ simulation scenarios targeting NO_x and other pollutant emission reductions in different sectors.

Scenario	Sector	Pollutants reduced	Reduction
1	Power	NO_x alone (SCR alone)	85%
2	Power	$NO_x + SO_2$ (SCR + FGD)	85% for NO_x + 90% for SO_2
3	Mobile	NO_x alone	20%
4	Mobile	VOC alone	20%
5	Mobile	NO_x + VOC + PM	20%
6	Mobile	NO_x + VOC + PM	50%
7	Industry	NO_x alone	20%
8	Industry	VOC alone	20%
9	Industry	NO_x + VOC + PM	20%
10	Domestic	NO_x alone	20%

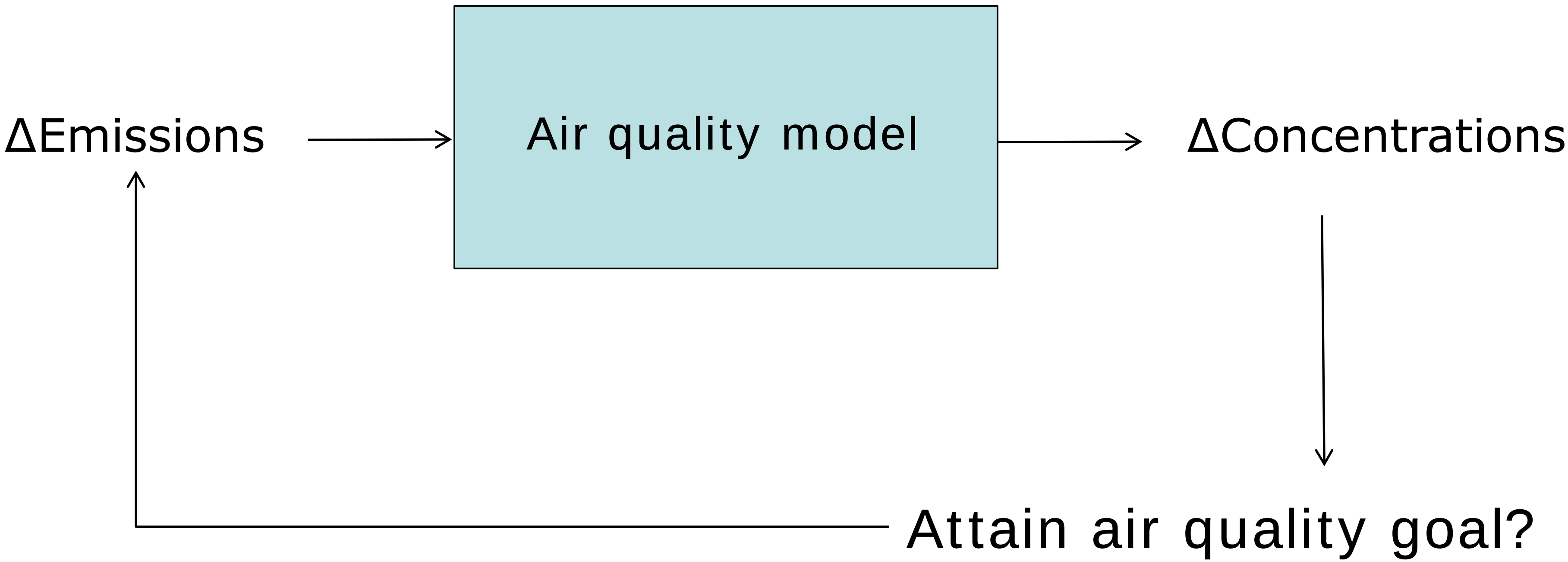
Abbreviations: FGD, fluidized gas desulfurization; SCR, selective catalytic reduction.

Table 4. Mortality change estimates for control scenarios by sector and pollutant.

Scenario	Sector	Pollutant controlled	Emission reductions from base–case (1,000 tons/year)	PM-related mortality change per year
1	Power	NO_x	610	2,000 (200, 4,000)
2	Power	SO_2	1,300	12,000 (1,200, 24,000)
3	Mobile	NO_x	83	260 (26, 520)
4	Mobile	VOC	200	380 (38, 750)
5	Mobile	Primary PM	6	620 (62, 1,200)
7	Industry	NO_x	96	300 (30, 610)
8	Industry	VOC	300	310 (31, 610)
9	Industry	Primary PM	110	12,000 (1,200, 24,000)
10	Domestic	NO_x	15	–21 (–2, –42)

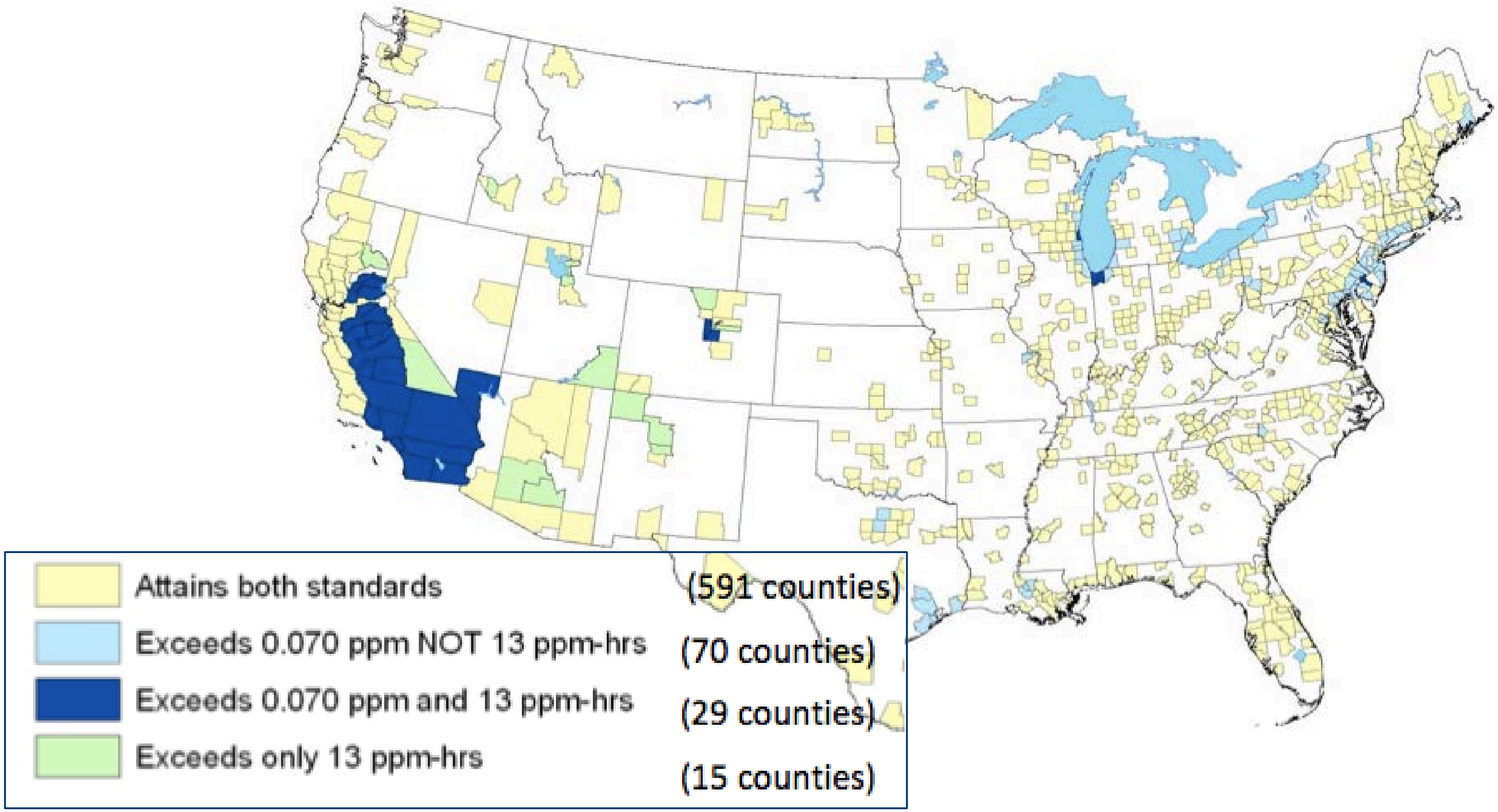
Zhou et al., 2011

Evaluating impacts of emissions regulations



Designing emissions strategies to meet a particular attainment goal

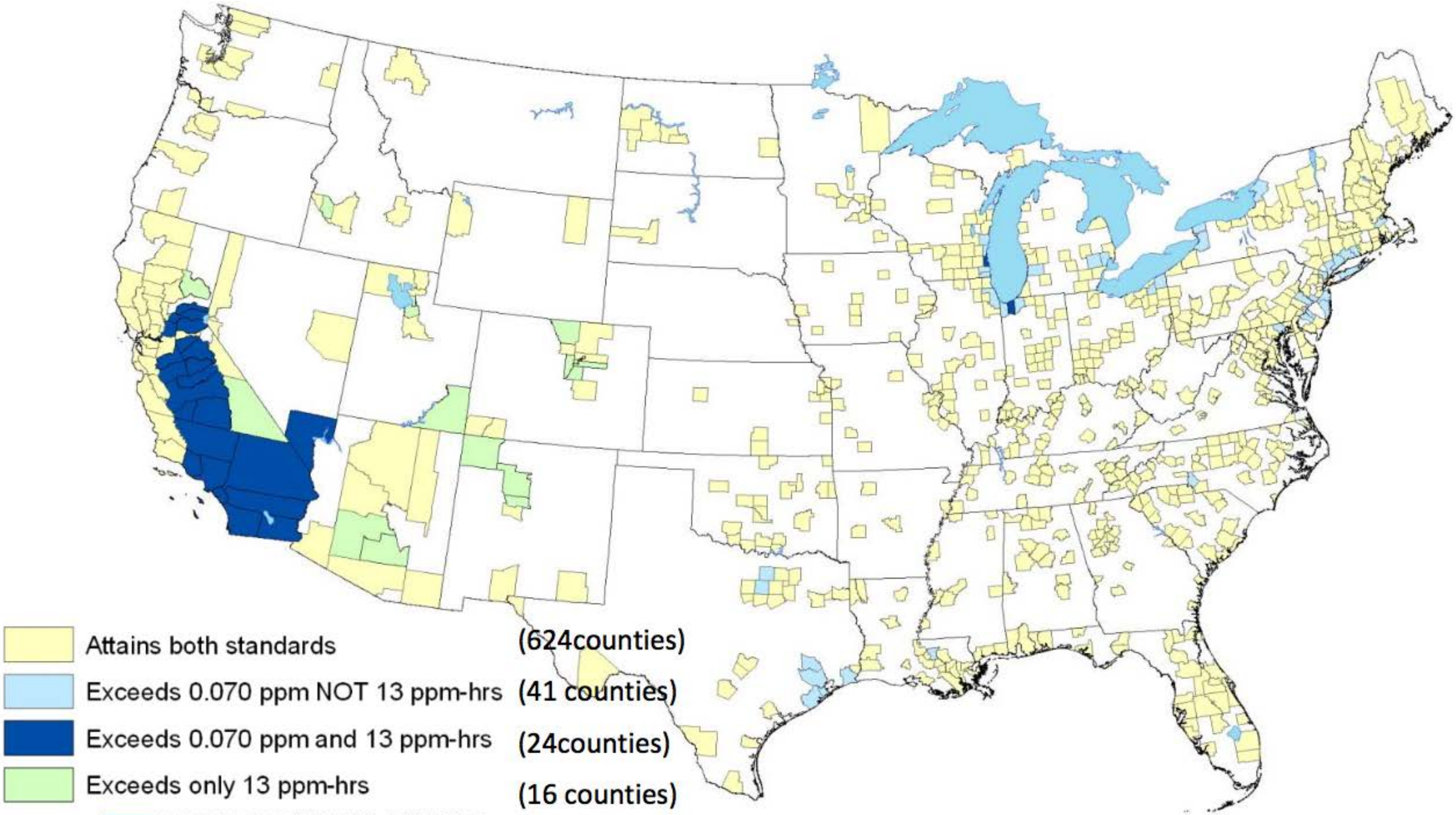
Counties projected to exceed 1st (70 ppb) and 2nd (13 ppm-hrs) NAAQS standards in Baseline 2020



US EPA, 2011

Designing emissions strategies to meet a particular attainment goal

Counties projected to exceed 1st (70 ppb) and 2nd (13 ppm-hrs) NAAQS standards in Projected 2020



US EPA, 2011

Exceptional events

Criteria To Be an Exceptional Event

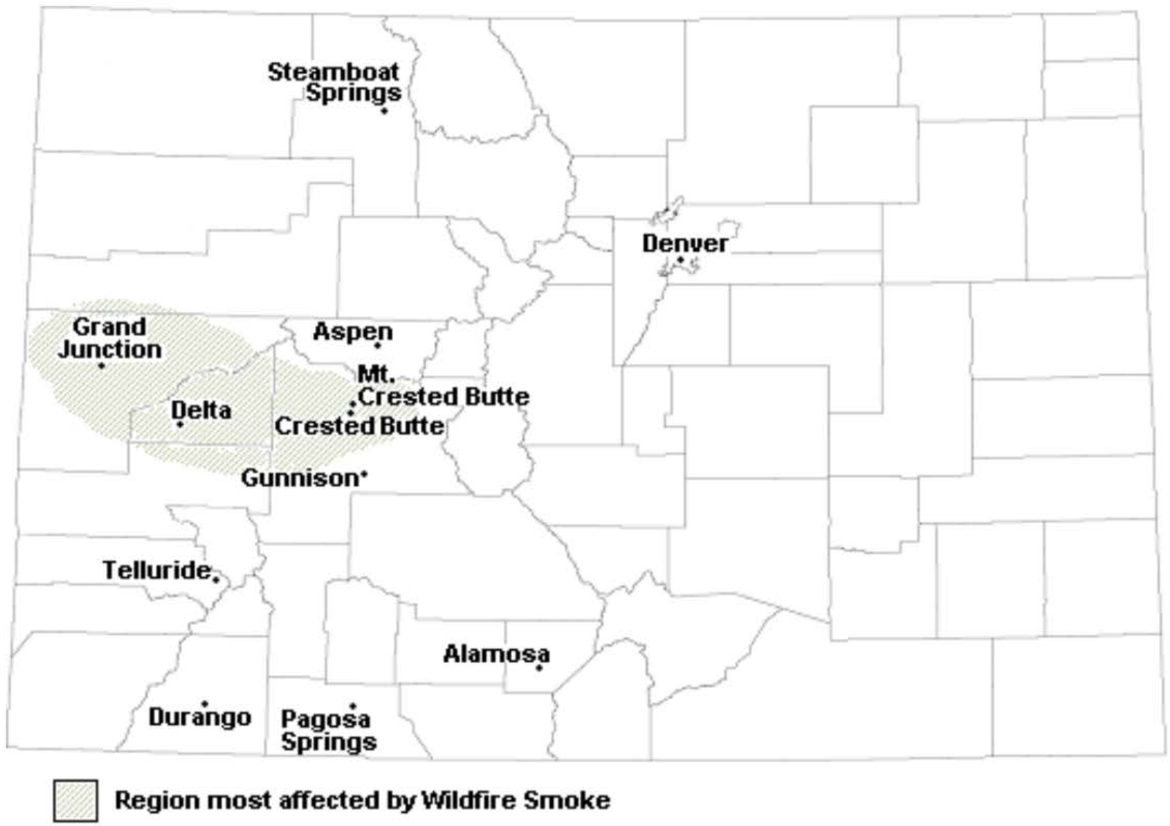
- The event is not reasonably controllable or preventable
- The event is caused by human activity that is unlikely to recur at that location or is a natural event
- There is a clear causal relationship between the event and the monitored concentration
- The event is associated with a measured concentration in excess of normal historical fluctuations
- There would have been no exceedance or violation but for the event

Examples of Exceptional Events

- High Wind Dust Events
- Wildfire Events
- Volcanic and Seismic Activities

Exceptional events

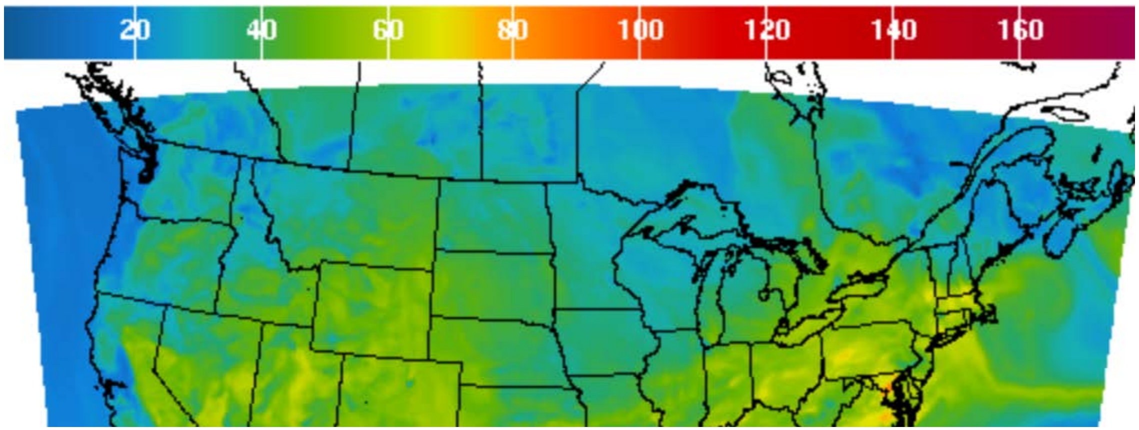
FIGURE 1 – COLORADO COMMUNITIES AFFECTED BY THE OCTOBER 2003 EVENT



CDPHE, 2006

Forecasting

http://airquality.weather.gov



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Review

Real-time air quality forecasting, part I: History, techniques, and current status

Yang Zhang [a,b,*], Marc Bocquet [c,d], Vivien Mallet [c,d], Christian Seigneur [d], Alexander Baklanov [e]

Roles of AQ models in policy

Setting standards

- developing concentration-response relationships
- exposure assessment / evaluating risk
- determining background / natural pollution levels

AQ management

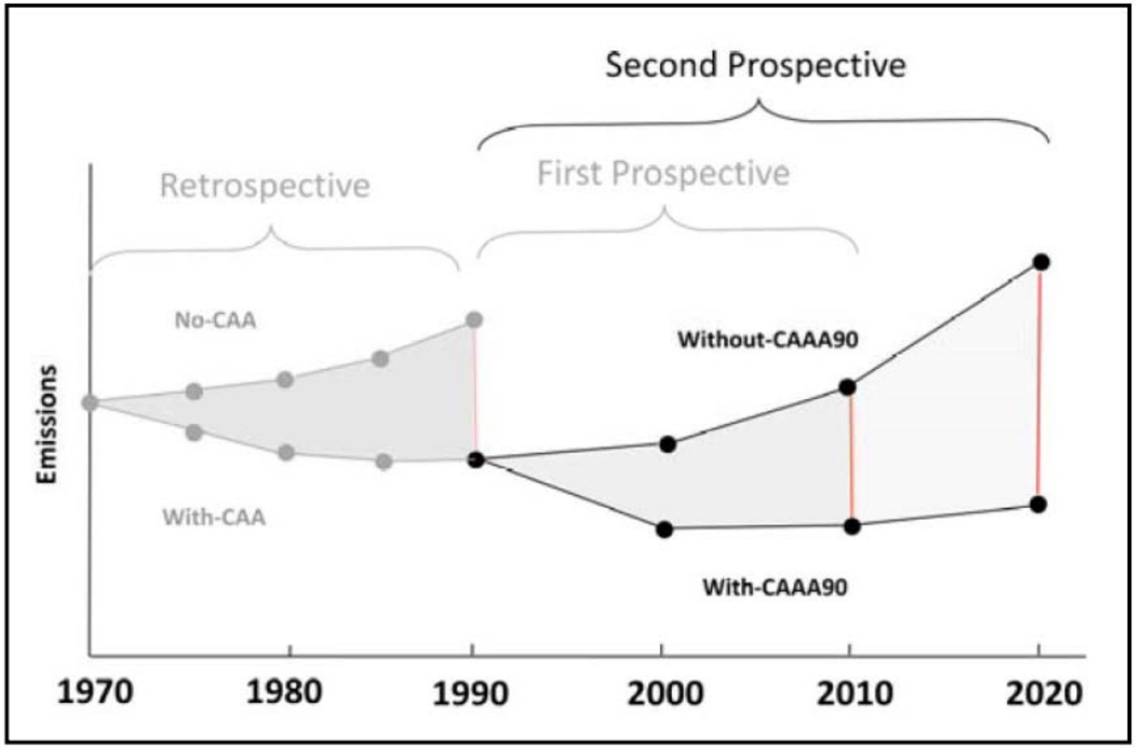
- Development of control strategies (e.g., SIP)
- Permitting
- Determining exceptional events and long-range transport
- Forecasting

Assessment

- Reanalysis
- co-benefits

Assessment of air quality regulations

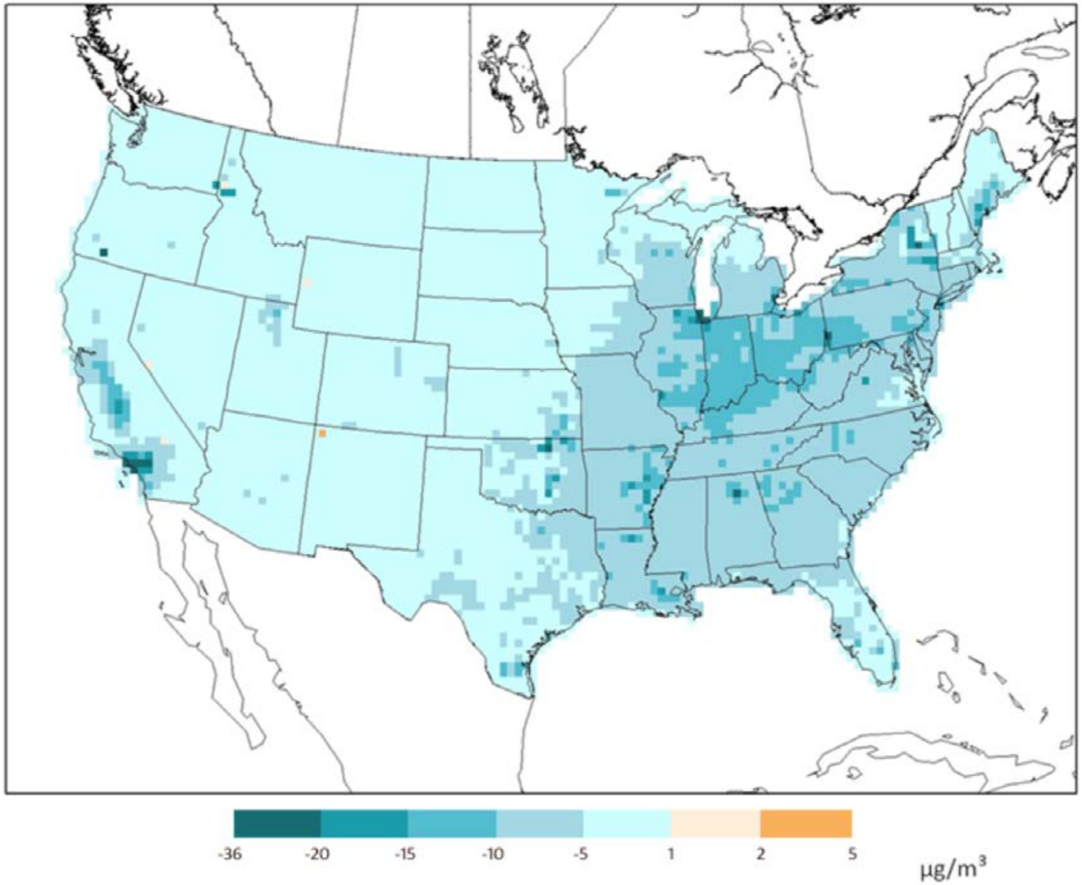
Impacts of CAA, 2020 - 1990



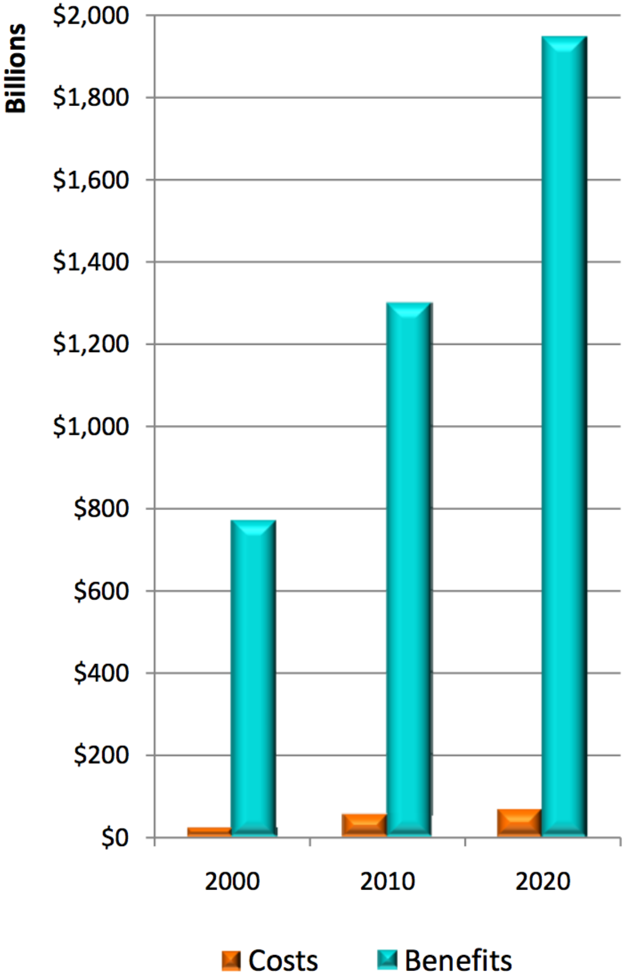
EPA, 2011

Assessment of air quality regulations

Impacts of CAA, 2020 - 1990



Change in surface annual ave $PM_{2.5}$



EPA, 2011

Outline

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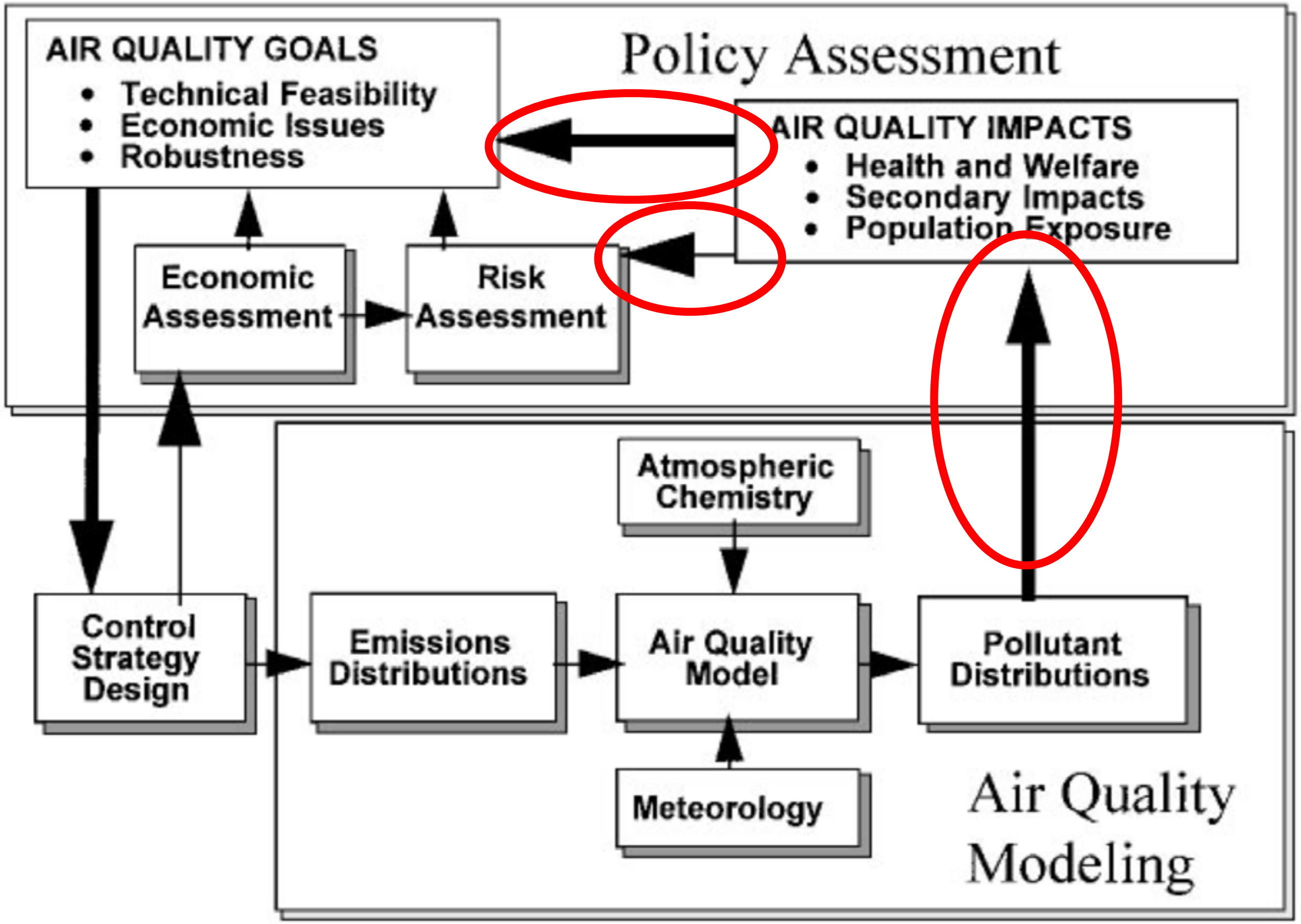
AQ output for policy applications

What output do air quality models generate that policy actually uses?



Russell, 1997

AQ output for policy applications

$[O_3]$, $[PM_{2.5}]$, $[Pb]$, $[CO_2]$,...

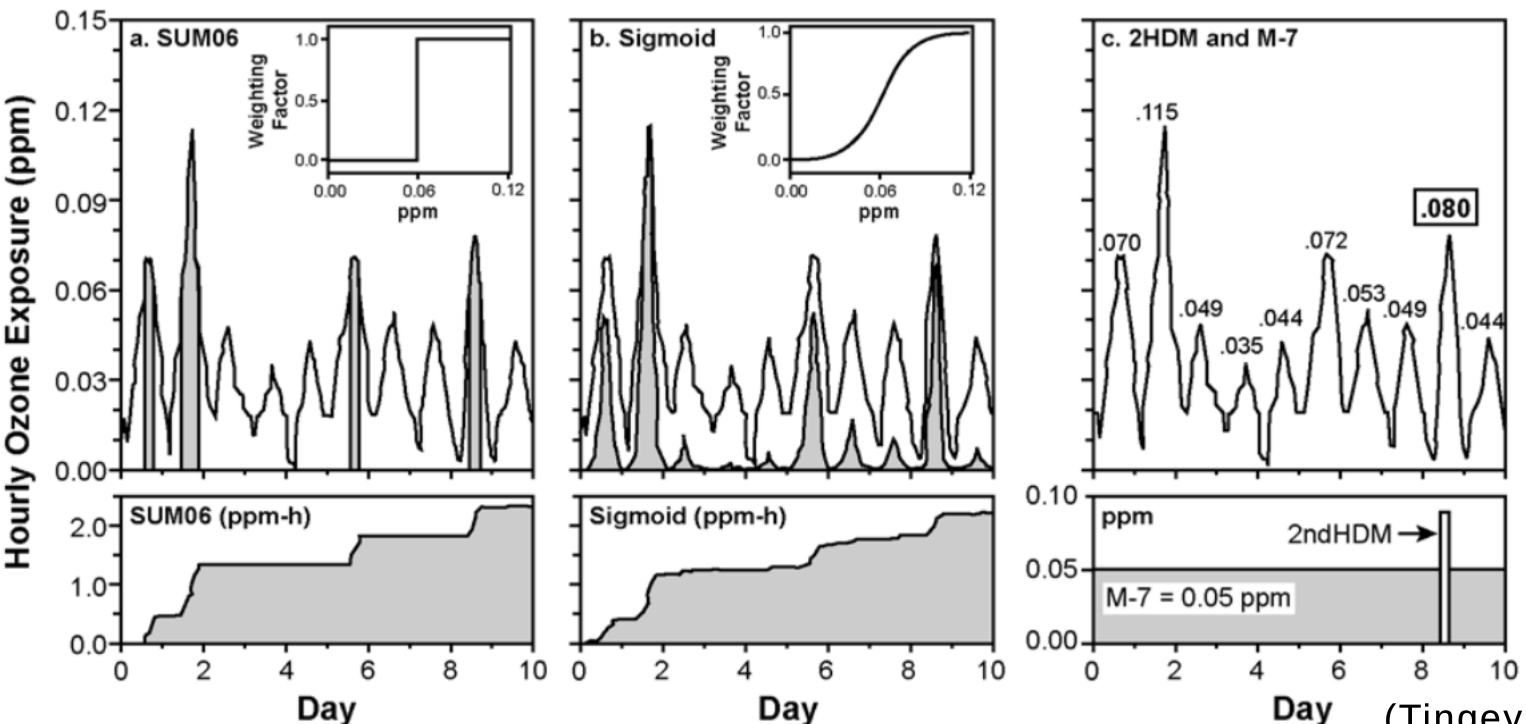
AQ output for policy applications: O_3 metrics

Primary:

- MDA8 = maximum daily 8-hr average
- Jerrett09 = maximum 6 month mean of daily 1-hr max

Secondary:

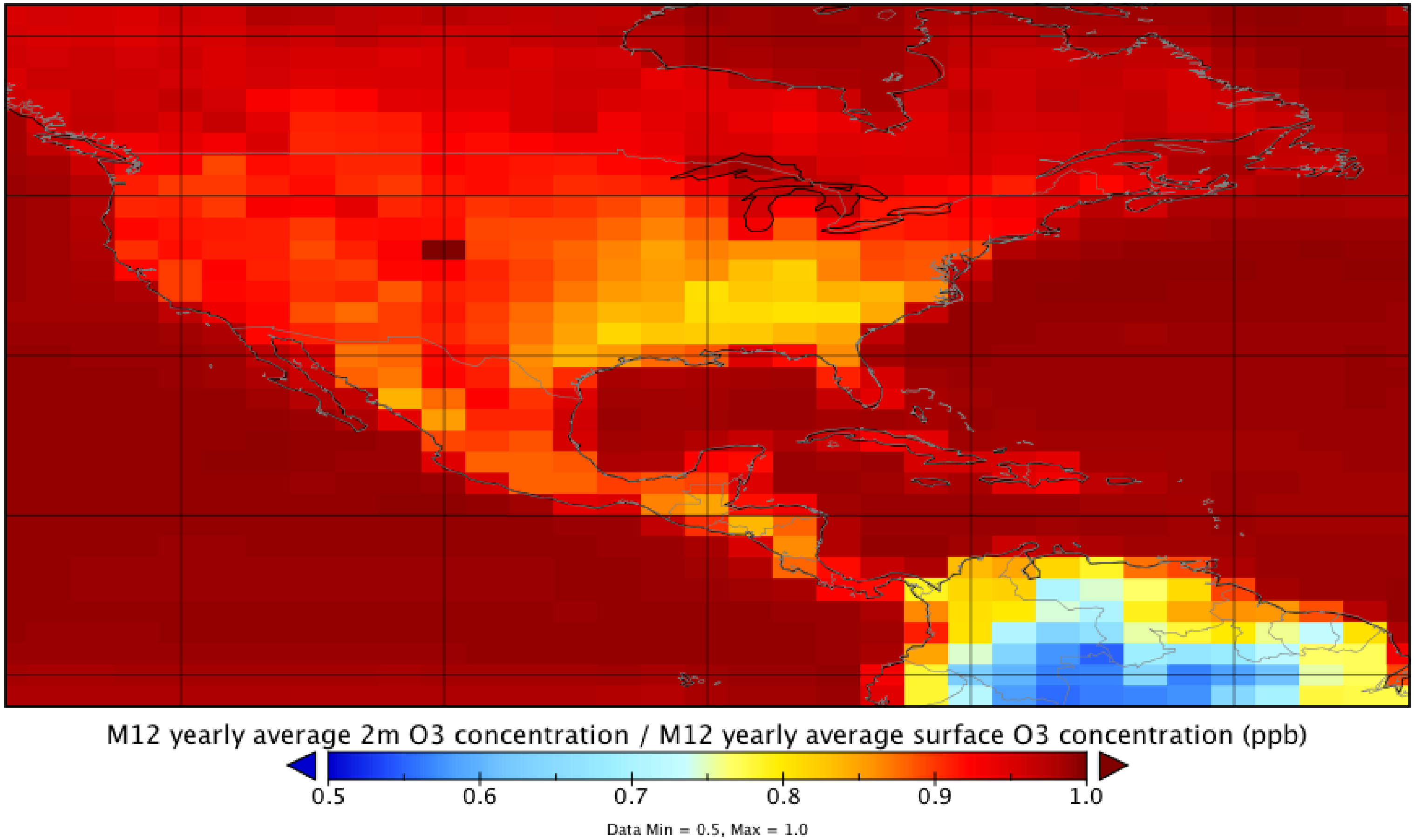
Threshold (SUM06) Weighted (W126) Daylight (M7) / peak (2HDM)



(Tingey et al., 1991)

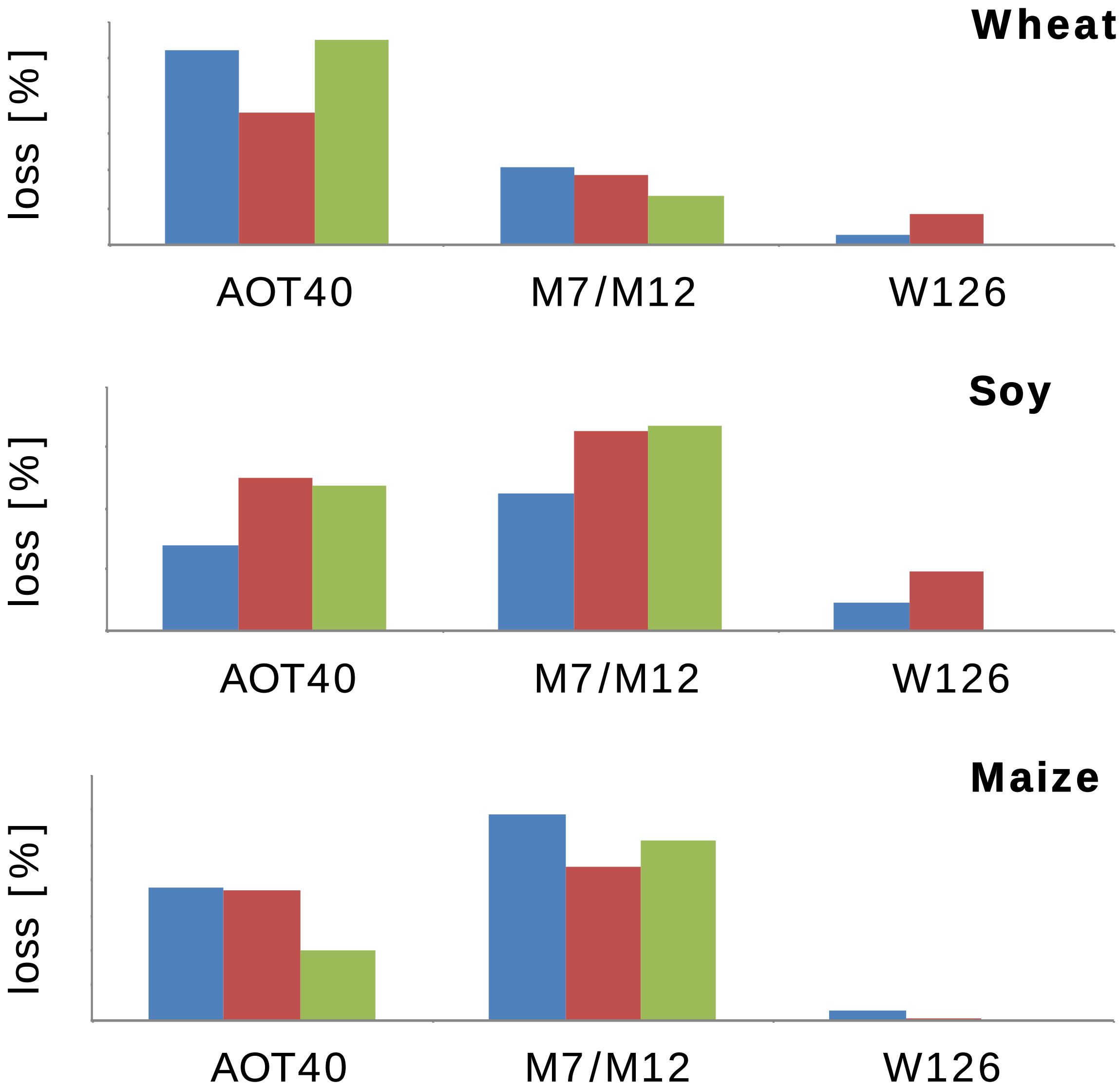
O_3 gradients near the surface

Model "surface" of GEOS-Chem actually at ~60m. Values should be reduced at canopy height (2m).



Estimated crop losses from O_3: differences across models and metrics

Lapina et al., 2016



0.5° x 0.667° GEOS-Chem (Lapina)

2.8° x 2.8° TOMCAT (Hollaway et al., 2012)

2.8° x 2.8° MOZART-2 (Avnery et al., 2011)

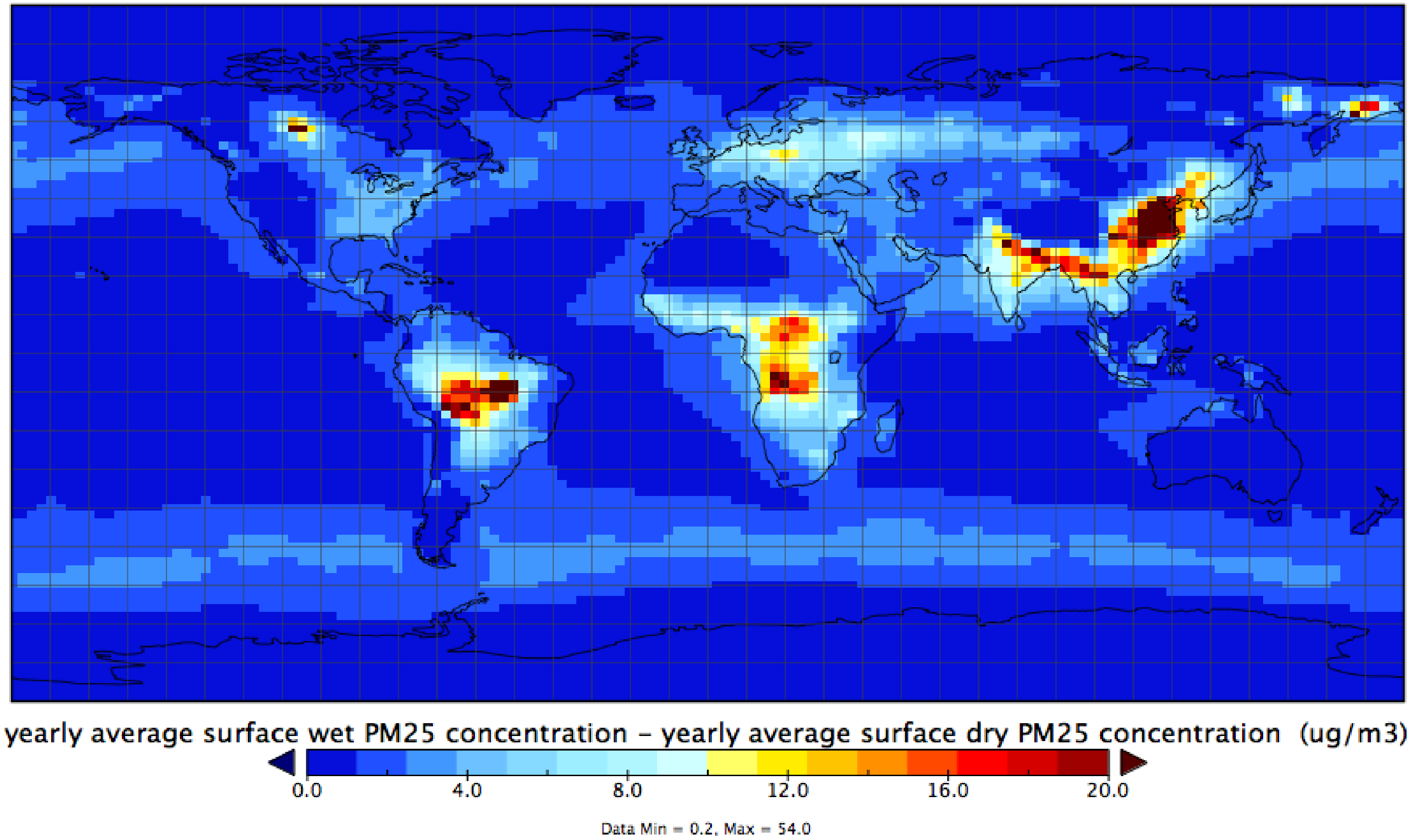
Cross-metric differences larger than cross-model differences

Notes:
- Hollaway and Avnery for NA, Lapina just for US
- Hollaway and Lapina bias corrected
- All: adjust model estimates for canopy height

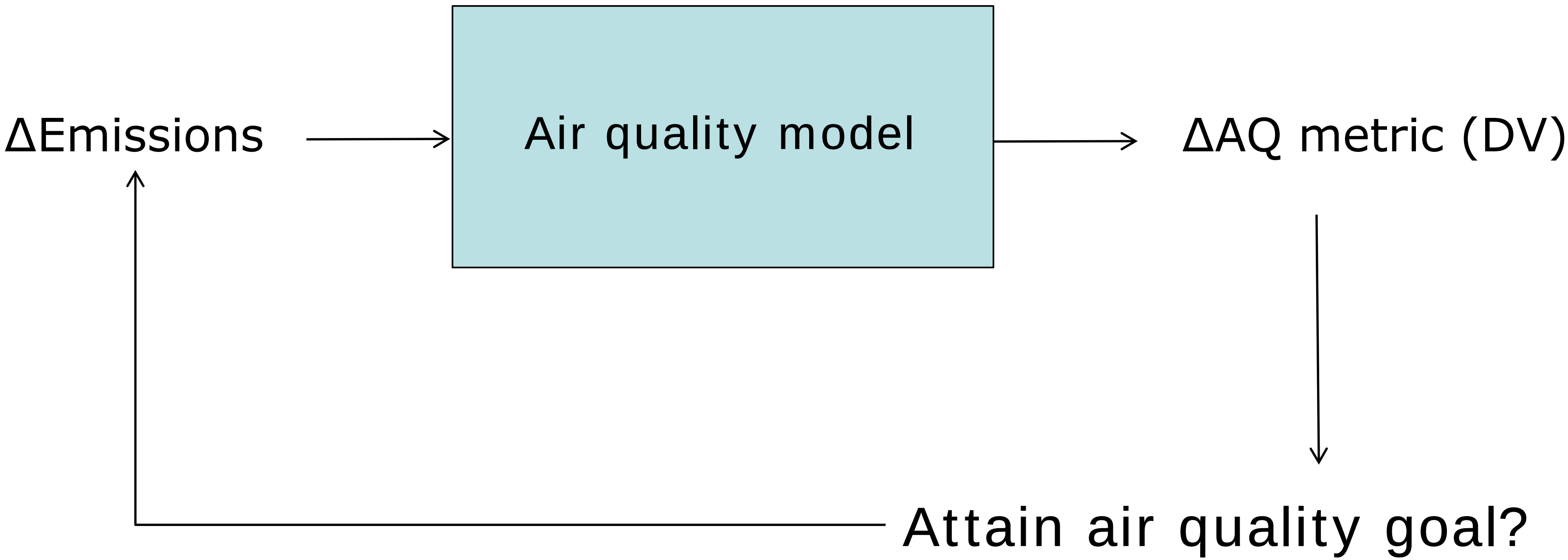
AQ output for policy applications: $PM_{2.5}$

Many models (e.g., GEOS-Chem) don't even report $PM_{2.5}$

- requires assumptions about size that may not be rigorously treated
- for comparison to monitors, requires equilibration to monitor RH



Evaluating impacts of emissions regulations



Estimating future concentrations

Model estimates may be not be correct.

Use models in a relative fashion to minimize systematic model bias.

EPA recommended approach:

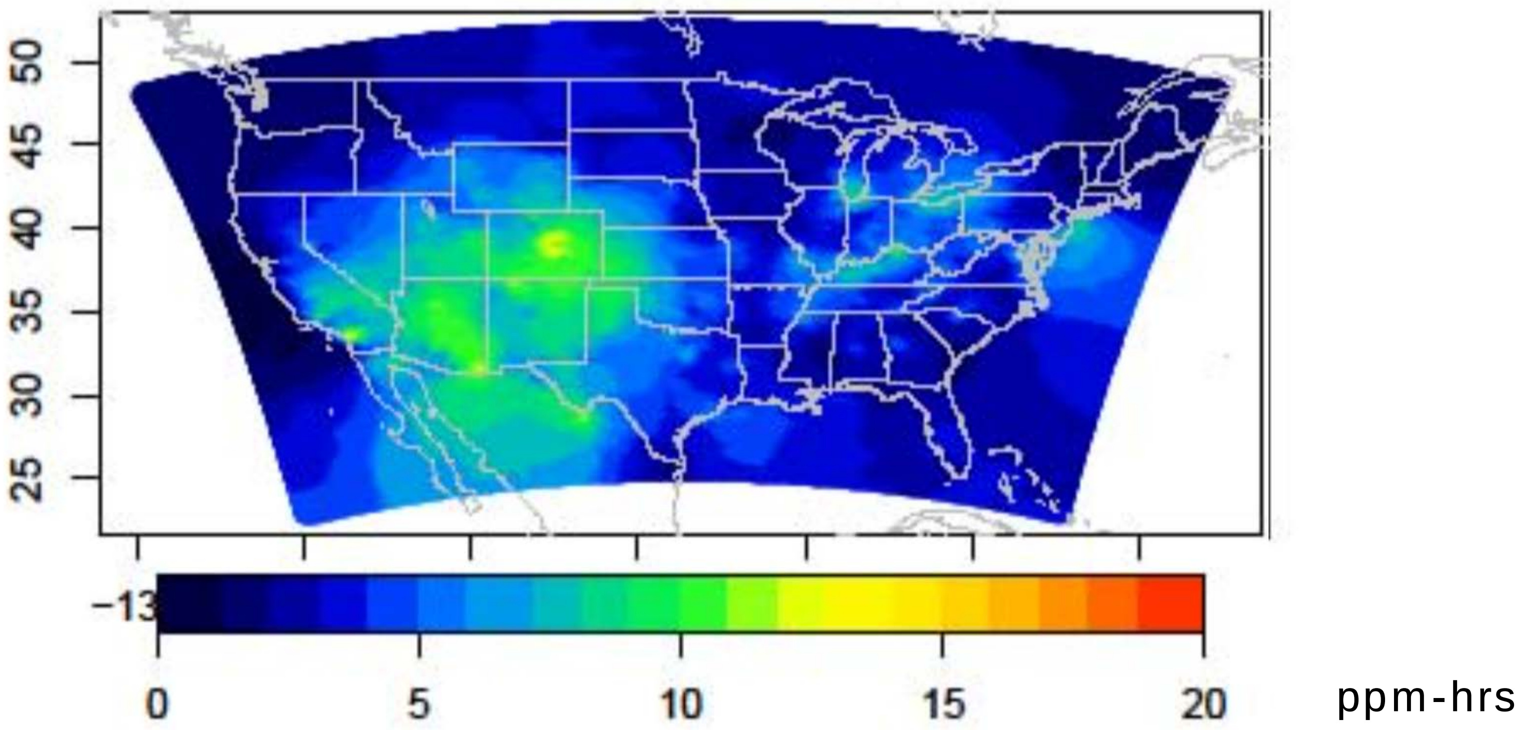
DV_i = Design Value upon which a standard is based at location i (e.g., monitored 3 yr average of annual 4th highest daily maximum 8-hr O_3)

RRF_i = Relative Response Factor from sensitivity modeling (fractional change in simulated DV)

DV_i (future) = DV_i (baseline) x RRF_i

Estimating future concentrations

CAMx simulations of O_3 W126 in 2025: 70 ppb primary



Attainment of a primary standard of 70 ppb would ensure attainment of a secondary stand of 17 ppm-hrs

→ secondary standard = primary standard

EPA, draft RIA, 2014

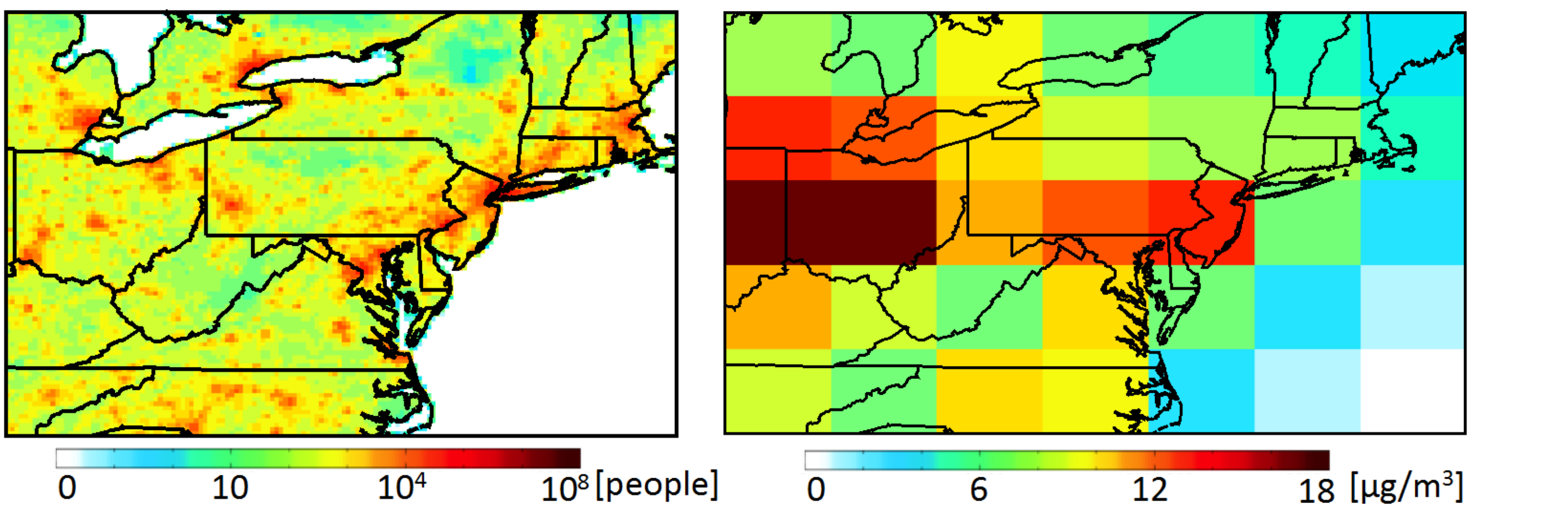
AQ output for policy applications: resolution

Previous works have investigated large-scale impacts:

- global reductions to fossil and biofuel (Jacobson, 2010)
- global BC and CH_4 measures (Anenberg et al., 2011; 2012)
- widespread adoption of vehicle standards (Shindell, 2011)

However, coarse models have trouble estimating exposure:

(a) population (b) 2° x 2.5° model $PM_{2.5}$



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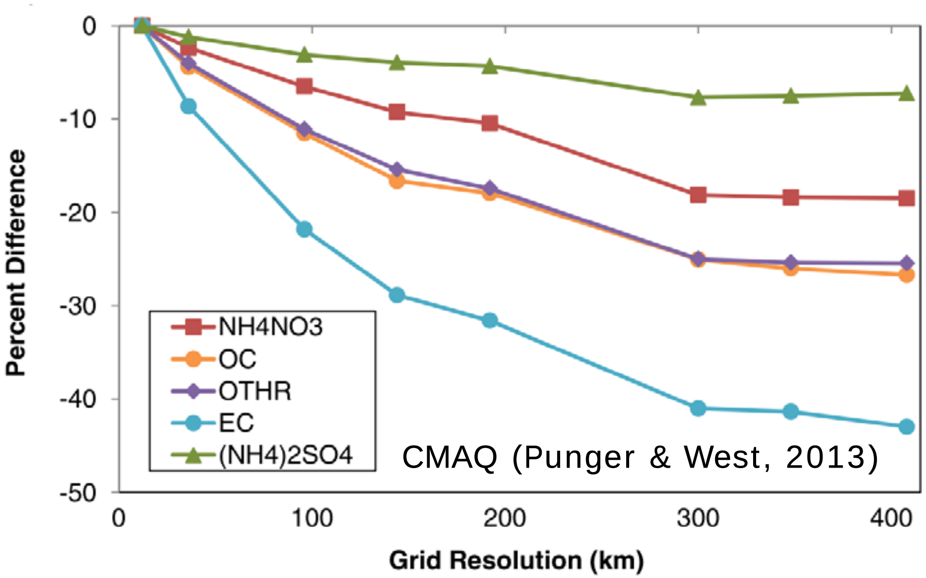
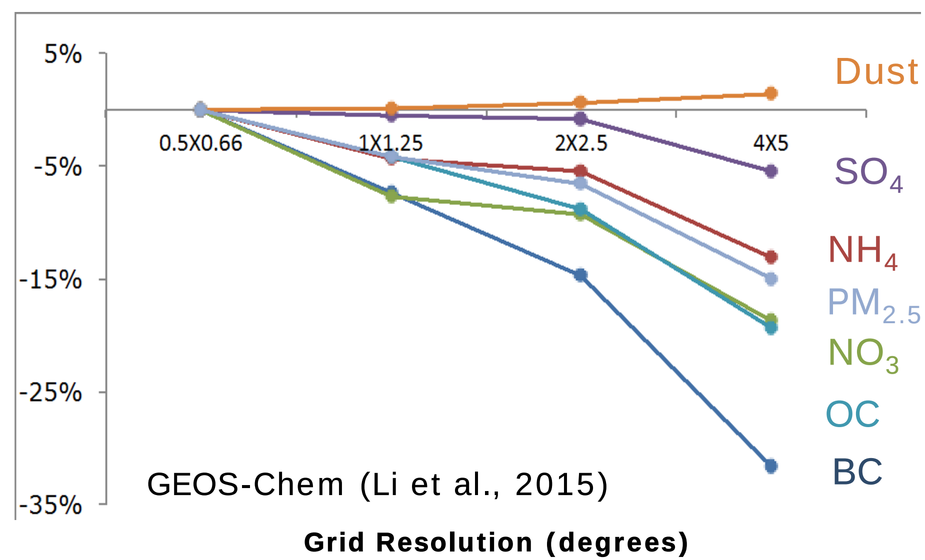
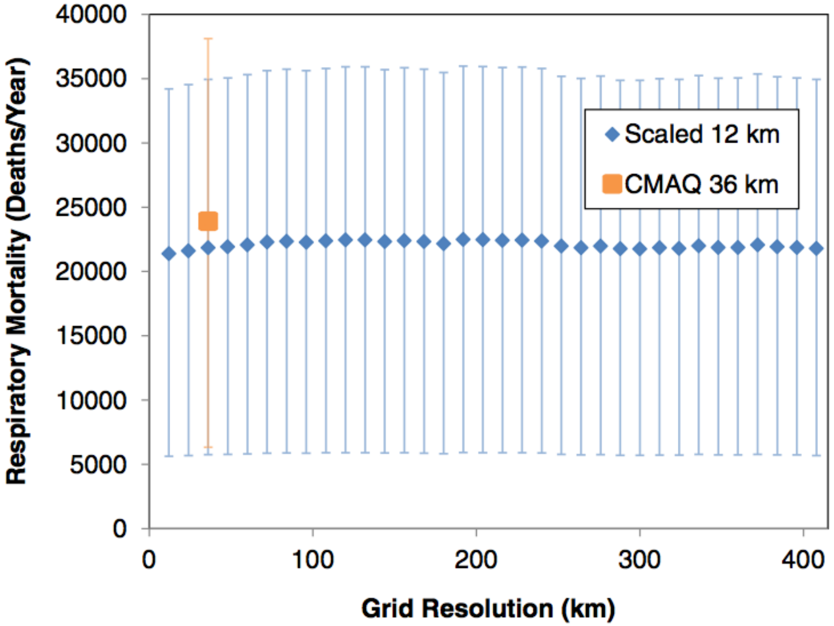




Individual components of $PM_{2.5}$ underestimated by 5-40% in a 2°x2.5° simulation over the US. Impacts of resolution ***not*** globally heterogeneous.

AQ output for policy applications: resolution

Coarse models are better at estimating long-term O_3 exposure:



CMAQ (Punger & West, 2013)

At some scale, uncertainty dominated by other factors (Thompson and Selin, 2012)

AQ models still have other difficulties related to exposure, e.g.:

- resolving response in high-NOx or low-NOx environments
- near roadway PM exposure
- indoor / outdoor exposure

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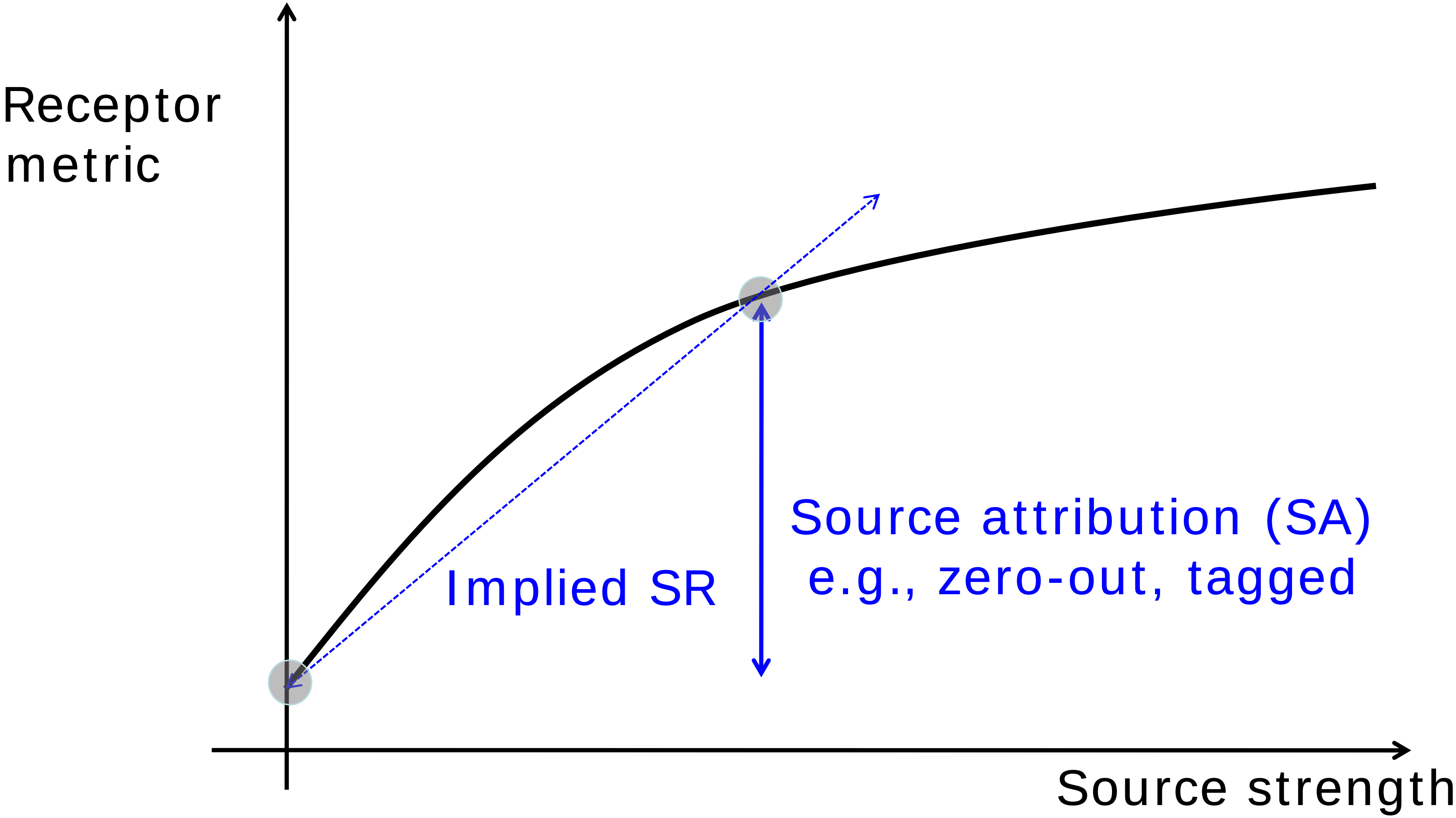
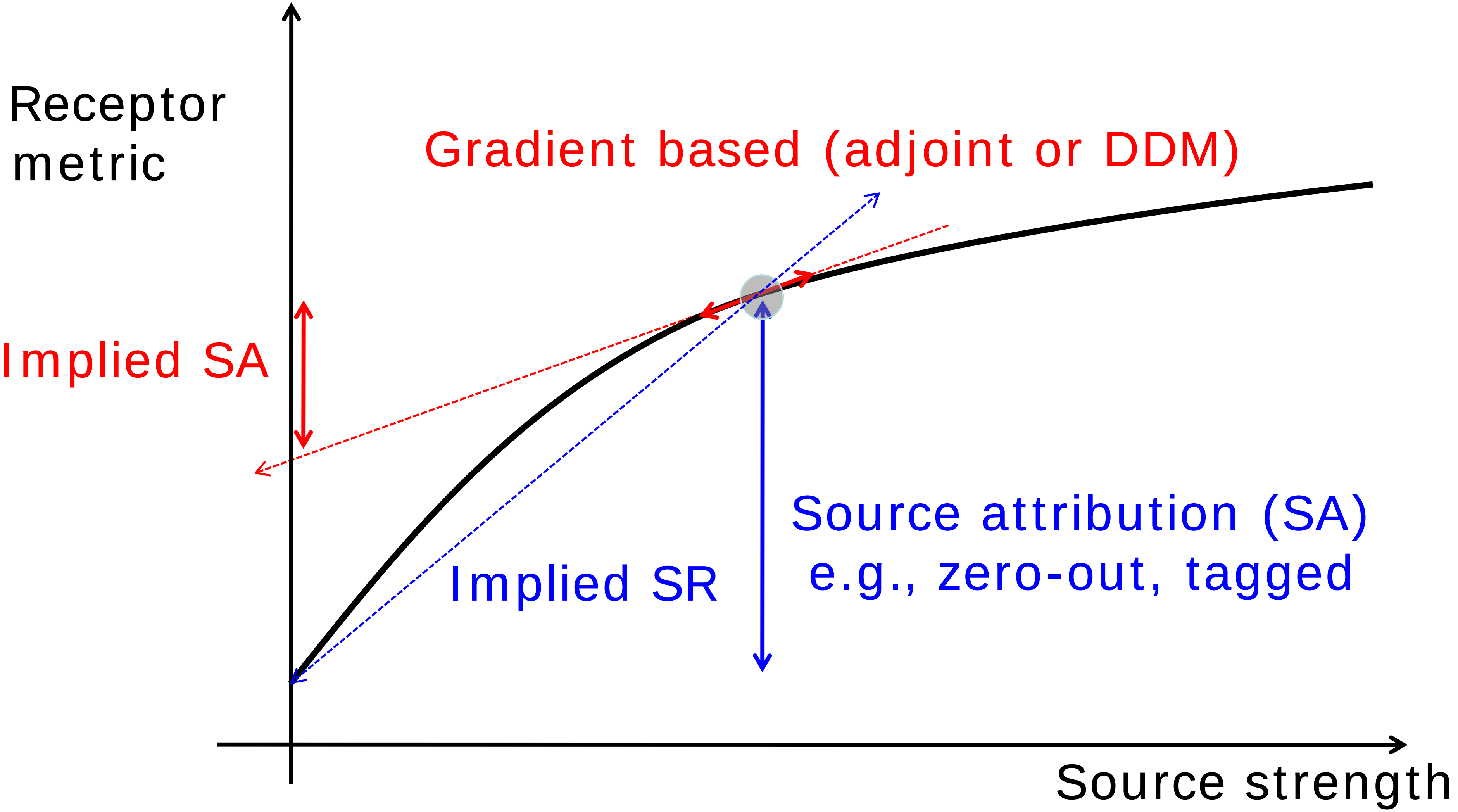
4. Source apportionment and receptor modeling

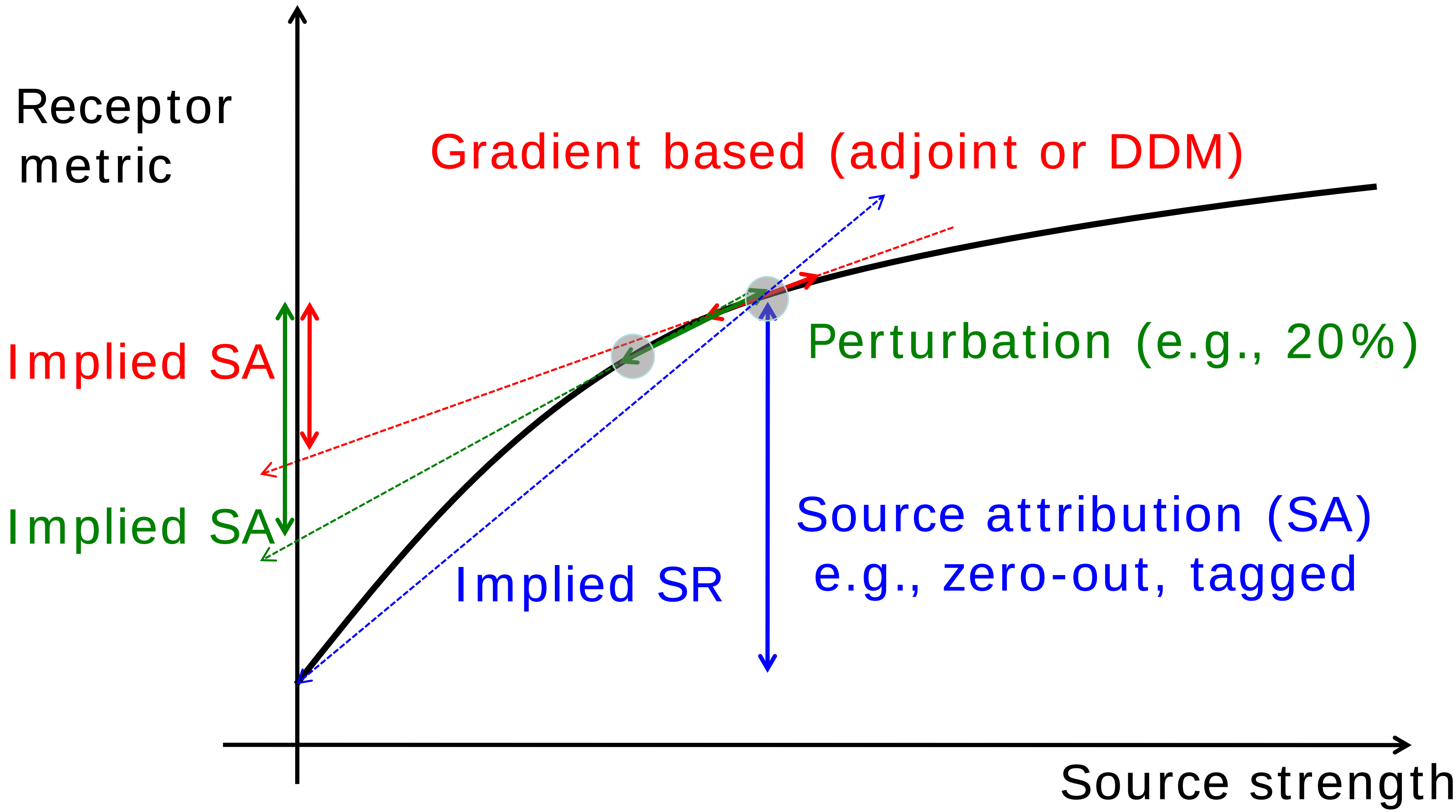
Source Apportionment (SA) vs Source Receptor (SR)



Source Apportionment (SA) vs Source Receptor (SR)



Source Apportionment (SA) vs Source Receptor (SR)



Source apportionment methods

Methods implemented in common US models:

Model	Methods			
CMAQ	DDM	HDDM	Adjoint	Tagging (TSSA)
CAMx	DDM	HDDM	Tagging (OSAT, APCA, PSAT, OPSA)	
WRF-Chem	Lagrangian (WRF-STILT)		Tagging	
GEOS-Chem	Tagging	Adjoint		
AM3	Tagging			

Acronym	Definition
DDM	Decoupled Direct Method
HDDM	High-order Decoupled Direct Method
TTSA	Tagged Species Source Apportionment
OSAT	Ozone Source Apportionment Tool
PSAT	Particulate Source Apportionment Technology
APCA	Anthropogenic Precursor Culpability Assessment
OPSA	Online Particulate Source Apportionment

Source apportionment uses for policy

http://preview.wiscwebcms.wisc.edu/aqast/source-apportionment-methods.htm

UNIVERSITY OF WISCONSIN – MADISON

AQAST

Using Satellite Data for Air Quality Management

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Source-apportionment methods

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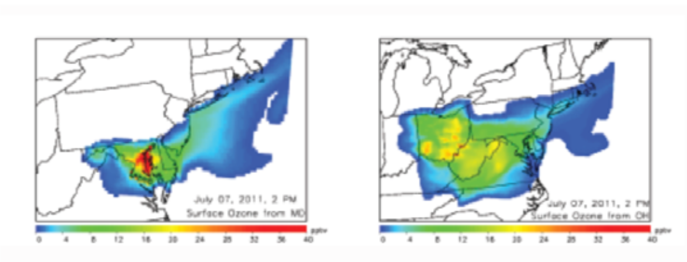


An example of surface ozone attributed to the emissions from Maryland (left) and Ohio (right) at 2 p.m. on 7 July 2011 using CAMx v6.10.

Source apportionment uses for policy

What is the spatio-temporal distribution of pollution owing to a few broadly defined or aggregated source sectors or species, such as all transportation versus power plant emissions?

What is the origin of air pollution occurring in a particular location?

What would be the impact of implementing control strategies in a different order, or the co-benefits of implementing them together over each implemented in isolation?

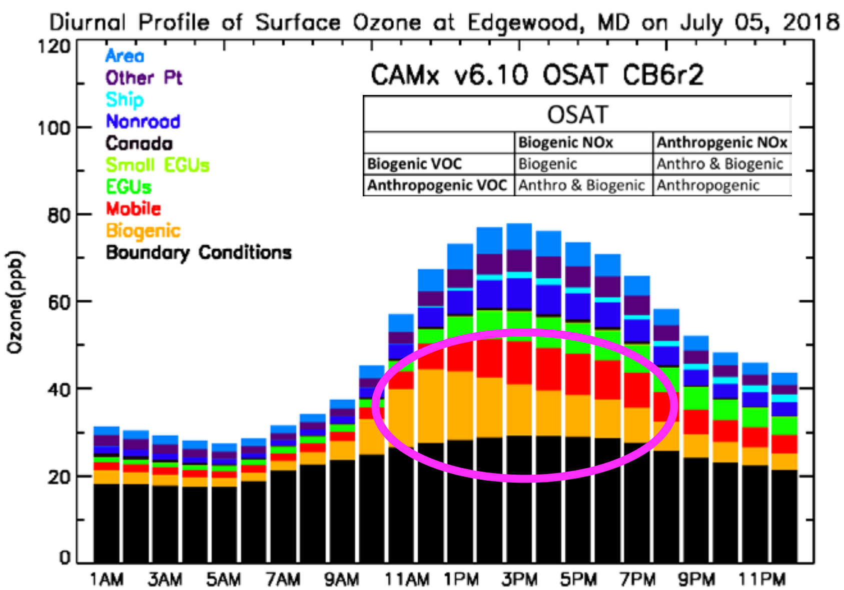
What are the marginal pollution responses to changes in emission (e.g., ppb per amount emitted)?

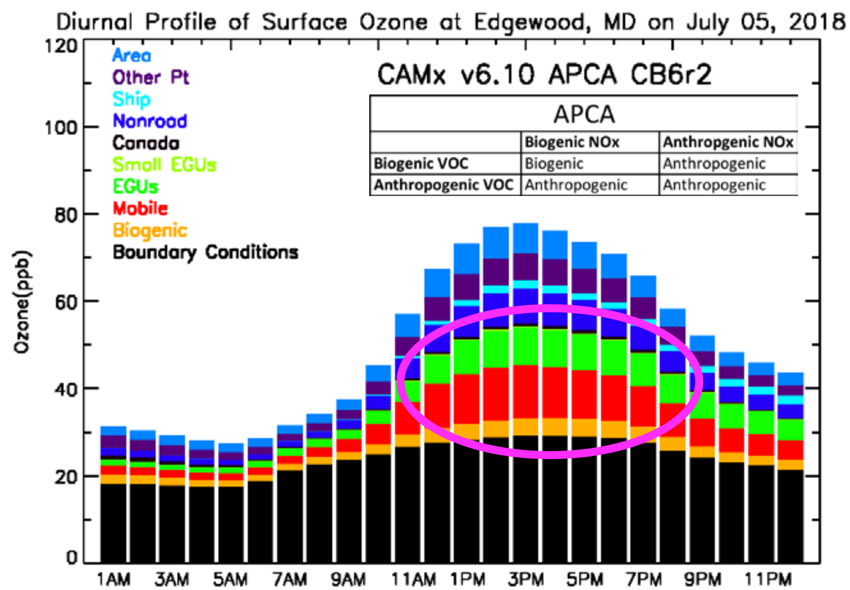
What is the complete breakdown of pollutant sources contributing to total concentration levels?

Concerns for nonlinear systems

When biogenic VOCs react with anthropogenic NOx, who is to blame for the resulting ozone?

Consider example (Dan Goldberg) of O_3 in Maryland:





Concerns for nonlinear & discontinuous systems: discontinuities

Consider metrics:

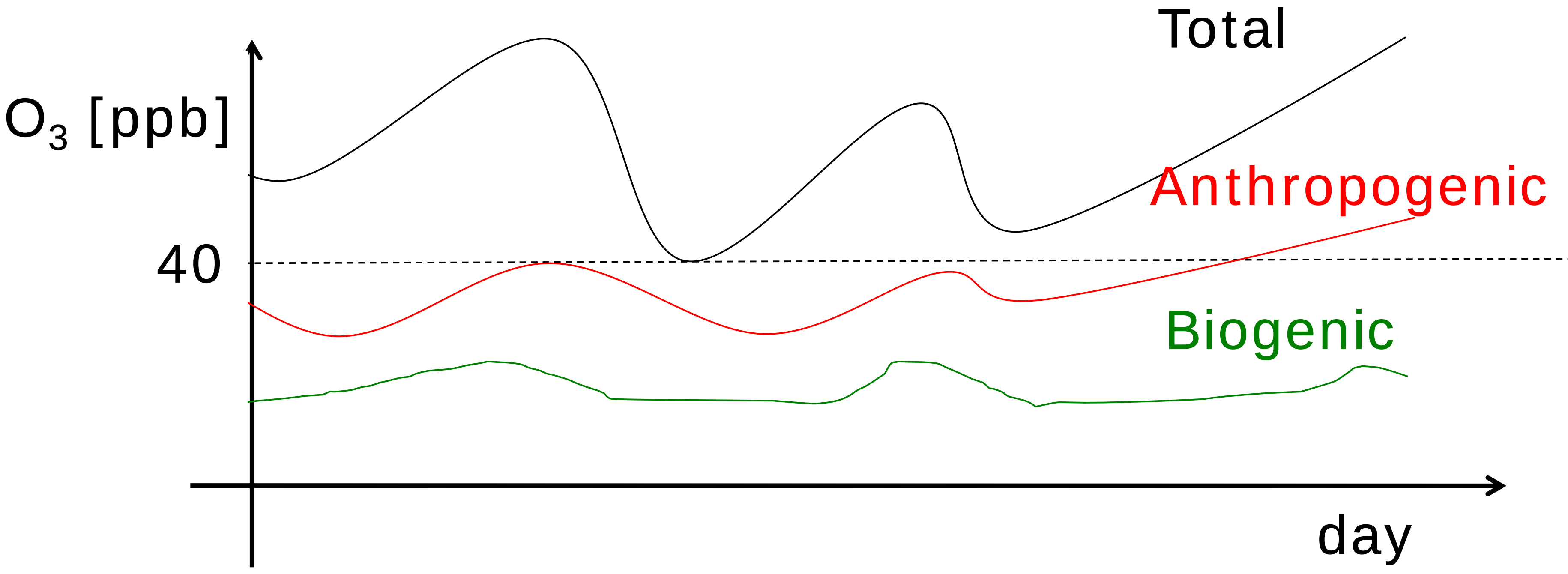
$$\mathrm{AOT40} = \sum_{i=1}^{n} [\mathrm{C}_{\mathrm{O}_3} - 40]_i \quad \text{for} \quad \mathrm{C}_{\mathrm{O}_3} \geq 0.04 \text{ ppm}$$

“critical” value after 3 months = 3,000 ppb h
(Karenlampi and Skarby, 1996)

Concerns for nonlinear & discontinuous systems: discontinuities

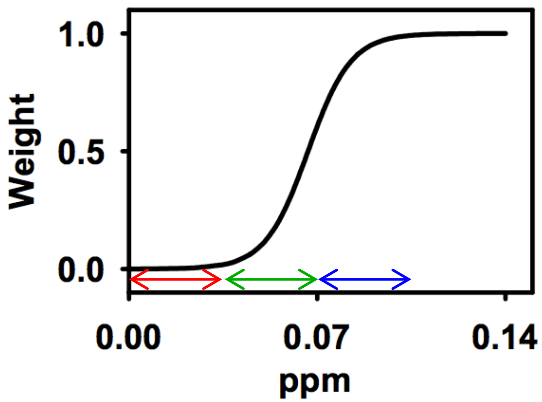
Consider metrics:

$$\mathrm{AOT40} = \sum_{i=1}^{n} [C_{O_3} - 40]_i \quad \text{for} \quad C_{O_3} \geq 0.04 \text{ ppm}$$



Concerns for nonlinear & discontinuous systems: nonlinearities

$$W126 = \sum_{i=1}^{n} \left[\frac{C_{O_3}}{1 + 4403 \exp(-0.126 \times C_{O_3})} \right]$$



Consider 3 policies, that target 3 different sources, each with equal impacts on O_3.

What are their impacts on W126?

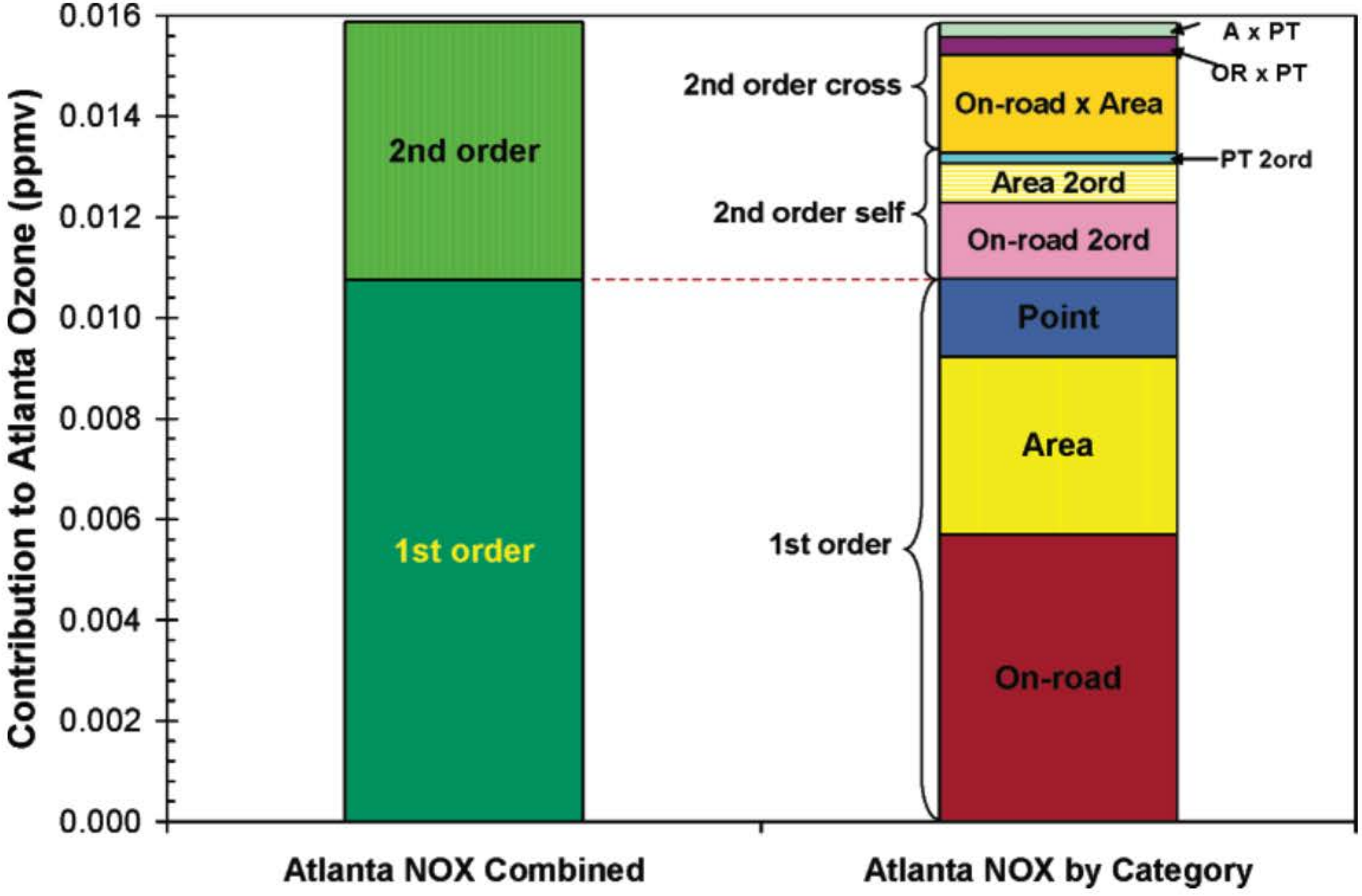
- Depends on the order in which you consider them

What are their contributions to W126?

- Each may have relatively small contribution alone
- sum of source contributions ≠ 100%

Concerns for nonlinear & discontinuous systems: higher order sensitivity analysis (HDDM)

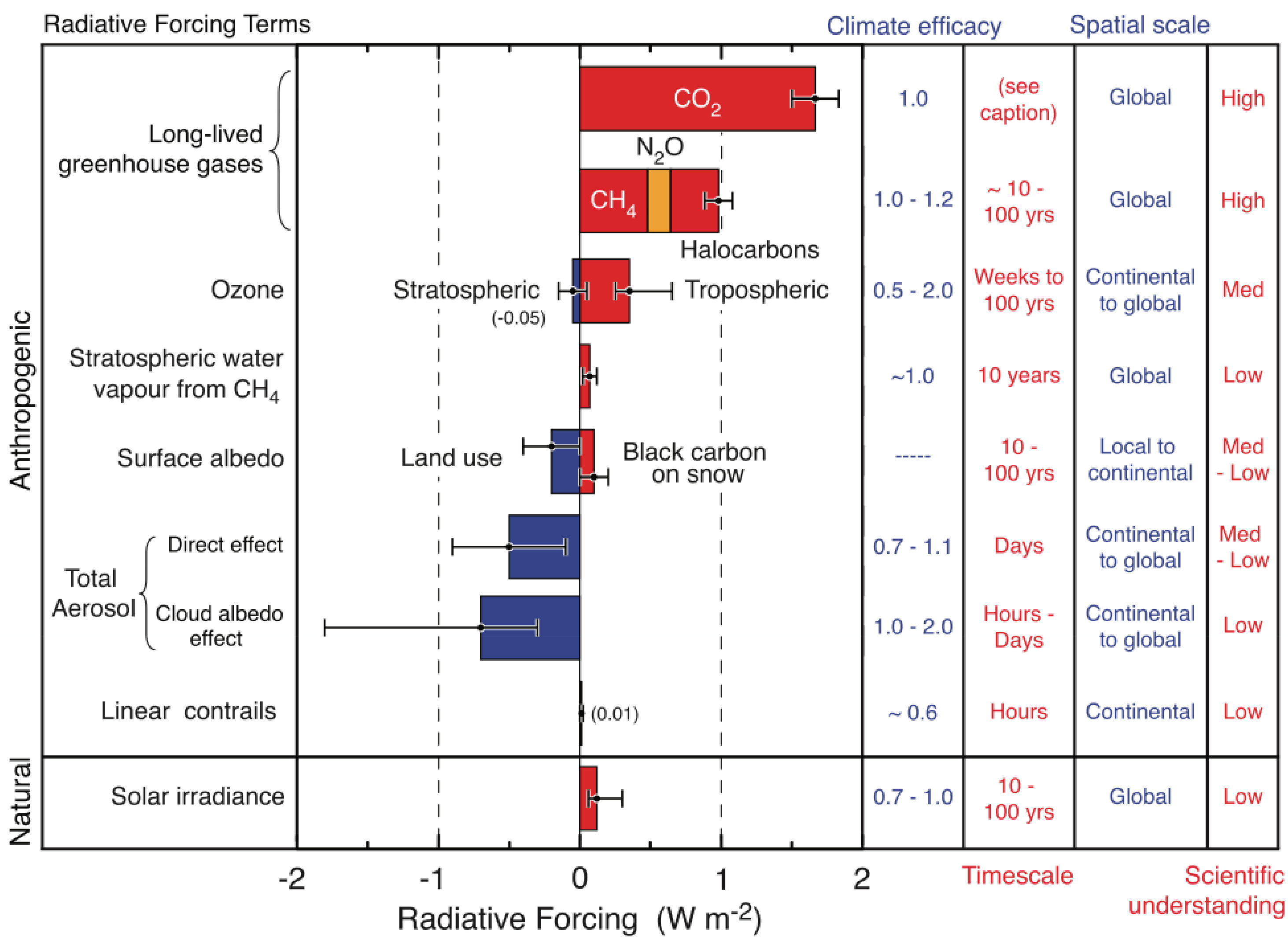
Contributions of NOx emissions to O_3 in Atlanta (Cohan et al., 2005)



Concerns for nonlinear & discontinuous systems: response surface modeling

Wang et al., 2011

Models are based on species, yet policies are based on sectors



Forster et al., 2007

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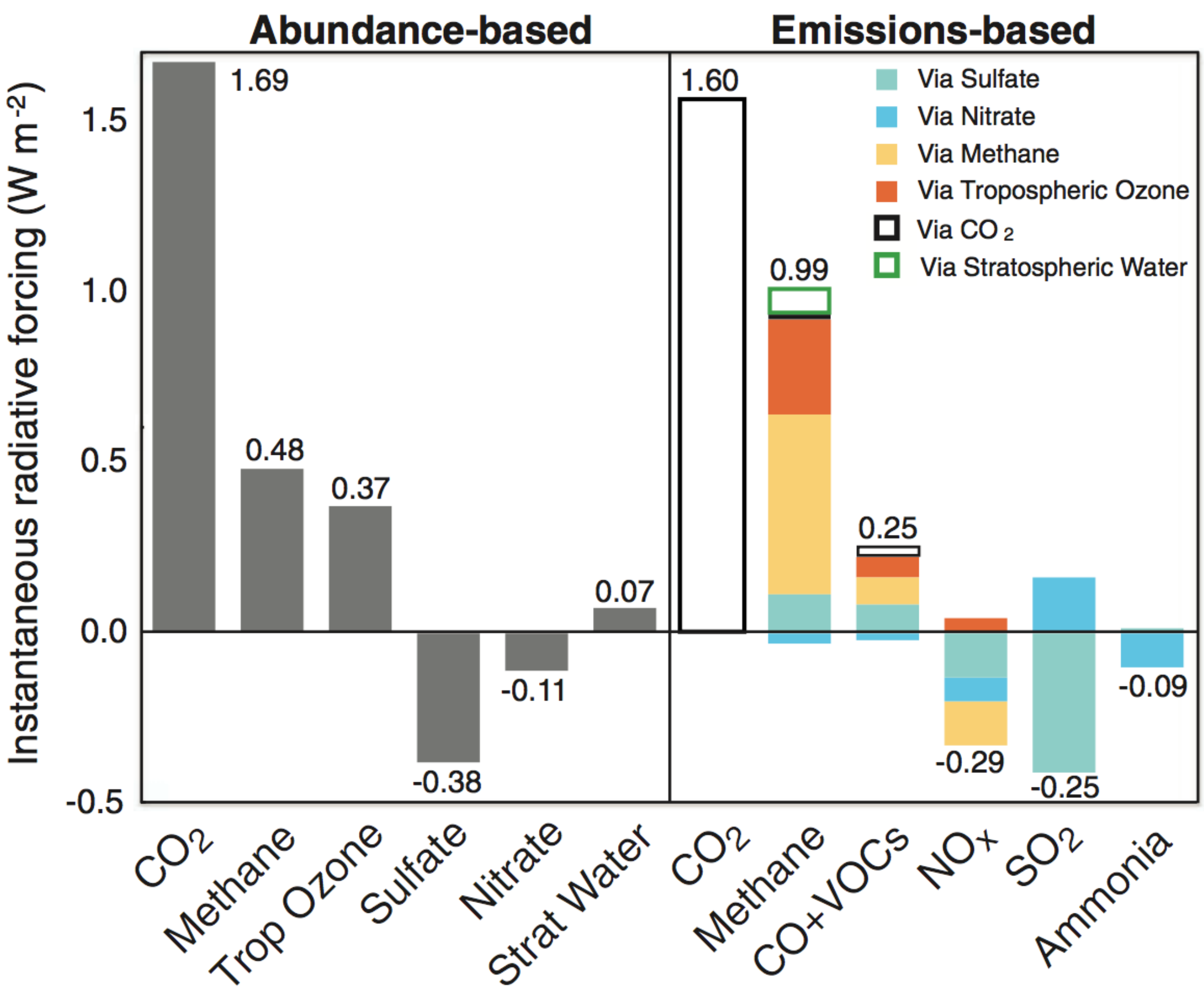
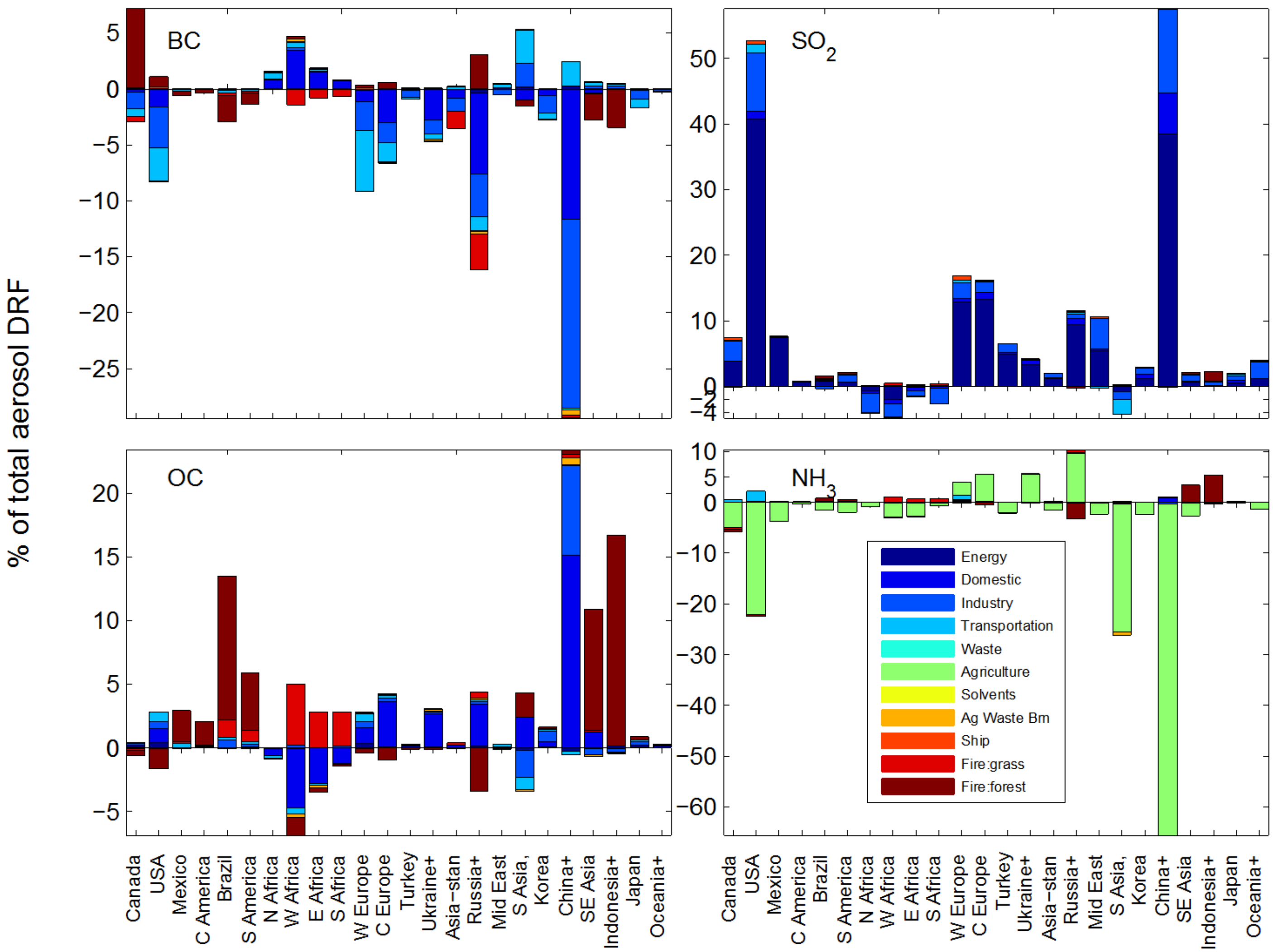


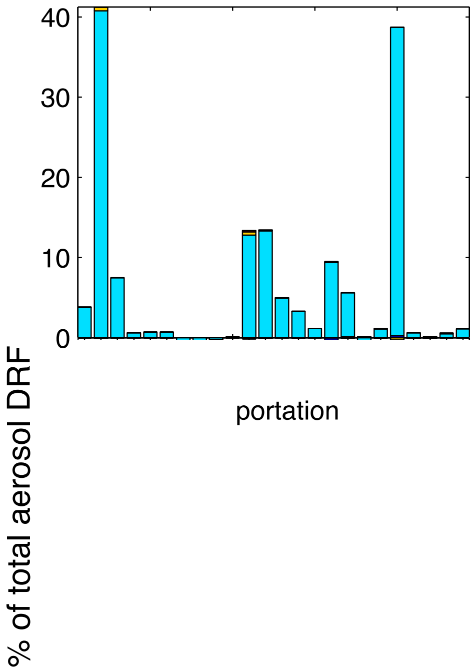
Shindell et al., 2009

Models are based on species, yet policies are based on sectors



Henze et al., 2012

Models are based on species, yet policies are based on sectors



portation

Ag Waste Brn

Agriculture

Ship

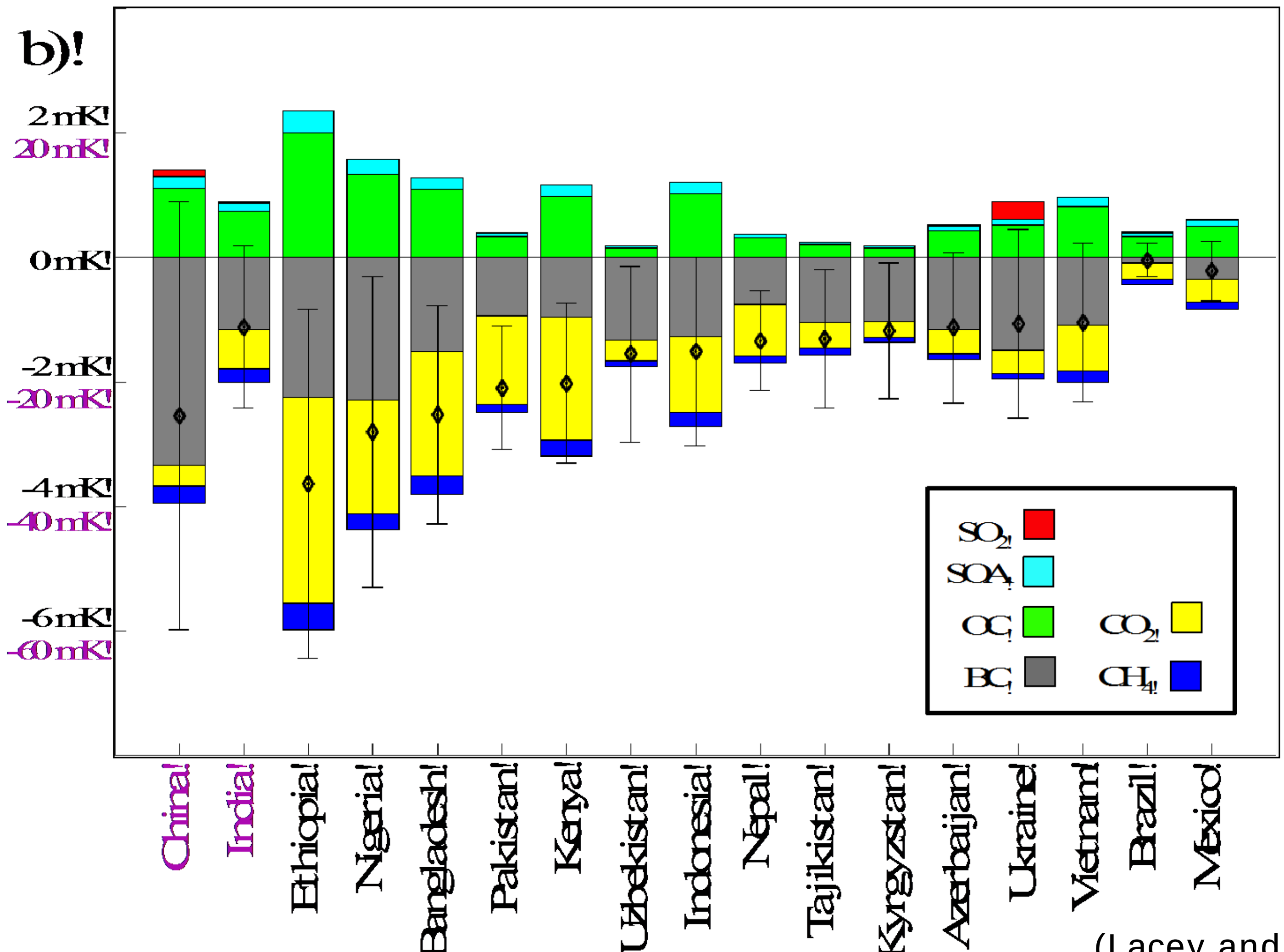
Fire:grass

Fire:forest

Henze et al., 2012

Speciated, country-specific contributions to global temperature change from cookstove emissions abatement

Countries with large populations using solid fuels tend to have larger OC and GHG impacts.



(Lacey and Henze, in prep)

Conclusions

• AQ models play an integral role in many stages of policy

• Thinking in advance about how AQ model results are to by used can help you tailor model output to match the policy need, for more effective transferal of information

• Many policy applications of models
 - relative changes
 - response of changes to emissions

• Care is warranted when considering source-receptor relationships and attribution for nonlinear response metrics

• Policy needs us to consider co-emitted species from controllable sectors.

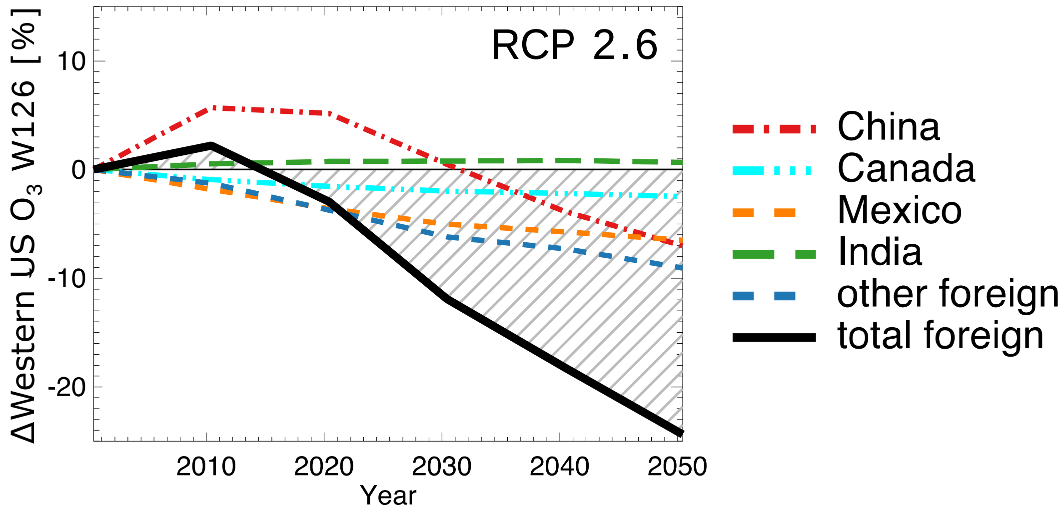
Questions?

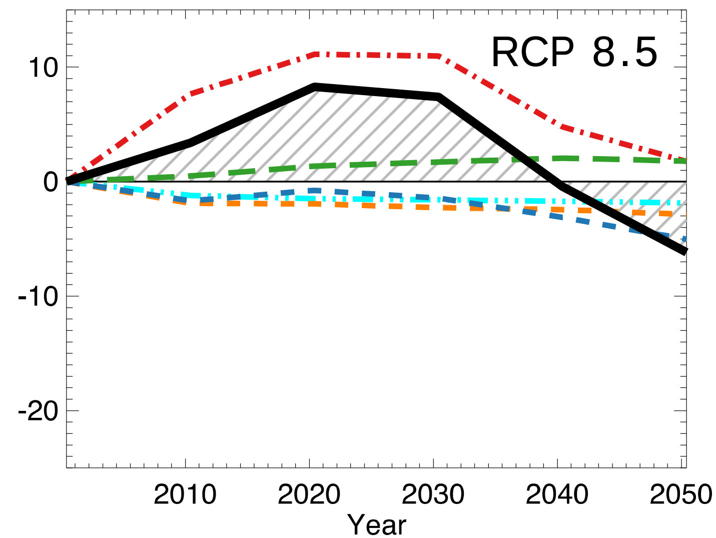
Balkanov, A., et al., Online coupled regional meteorology chemistry models in Eu- rope: current status and prospects, Atmos. Chem. Phys., 14, 317– 398, doi:10.5194/acp-14-317-2014, 2014.
Bocquet, M., et al., Data assimilation in atmospheric chemistry models: current status and future prospects for coupled chemistry meteorology models, Atmos. Chem. Phys., 15, 5325–5358, doi:10.5194/acp-15-5325- 2015, 2015.
Bosanquet, C.H. (1936) The Spread of Smoke and Gas from Chimmneys. Trans. Faraday Soc. 32:1249.
EPA, The benefits and costs of the clean air act from 1990 – 2020, Summary Report, 2011.
EPA, O3 NAAQS Regulatory Impact Analysis, 2011.
EPA, O3 NAAQS Integrated Science Assessment, 2013.
Forster, P., et al., Constituents and in Radiative Forcing, in: Climate Change 2007: The Physical Science Basis. Contributions of working group I to the fourth Assessment Report on the Intergovernmental Panel on Climate Change.
Friedlander and Seinfeld, A dynamic model of photochemical smog, ES&T, 3(11), 1175-1181, 1969.
Lapina, K., **D. K. Henze**, J. B. Milford, M. Huang, M. Lin, A. M. Fiore, G. Carmichael, G. G. Pfister, and K. W. Bowman (2014), Assessment of source contributions to seasonal vegetative exposure to ozone in the U.S., *J. Geophys. Res.*, 119, 324-340, doi:10.1002/2013JD020905.
Lapina, K., **D. K. Henze**, J. B. Milford and K. Travis (2016), Impacts of foreign, domestic and state-level emissions on ozone-induced vegetation loss in the U.S., *Environ. Sci. Technol.*, 50 (2), 806-813, doi:10.1021/acs.est.5b04887.
Lettau, H., Die wirksamkeit einer grosstadt als qulle von luftverschmutzung, Gerlands Beitr. Geophys., 31, 387-397, 1931.
Machata, L., Global scale dispersion of the atmosphere, Proc. U.N. Int. Conf. Peaceful Uses At. Energy, 2nd, 519-523, 1958.
Marsh, A., Air pollution legislation, Air Pollution, Ed. M. W. Thring, pp 239 – 45, 1957.
Robeson and Steyn, Evaluation and comparison of statistical forecast models for daily maximum ozone concentrations, Atmos. Environ., 24B(2), 303-312, 1990.
Russell, A., Regional photochemical air quality modeling: Model formulations, history, and state of the science, *Annu. Rev. Energy Environ. 1997. 22:537–88.*
Sutton O.G. (1932) A theory of Eddy Diffusion in the Atmosphere. Proc. Roy. Soc. A, 135:143.
Zhang, L., D. J. Jacob, N. V. Downey, D. A. Wood, D. Blewitt, C. C. Carouge, A. van Donkelaar, D. B. Jones, L. T. Murray, and Y. Wang (2011), Improved estimate of the policy-relevant background ozone in the United States using the GEOS-Chem global model with 1/2 x 2/3 horizontal resolution over North America, Atmos. Environ., 45(37), 6769 – 6776, doi:10.1016/j.atmosenv.2011.07.054.
Zhou, Y., J. S. Fu, G. Zhuang, and J. I. Levy, Risk-based prioritization among air pollution control strategies in the Yangtze River Delta, China, EHP, 118(9), 1204-1210, 2010.

Future vegetative O_3 exposure in ***Western US*** following changes in emissions...

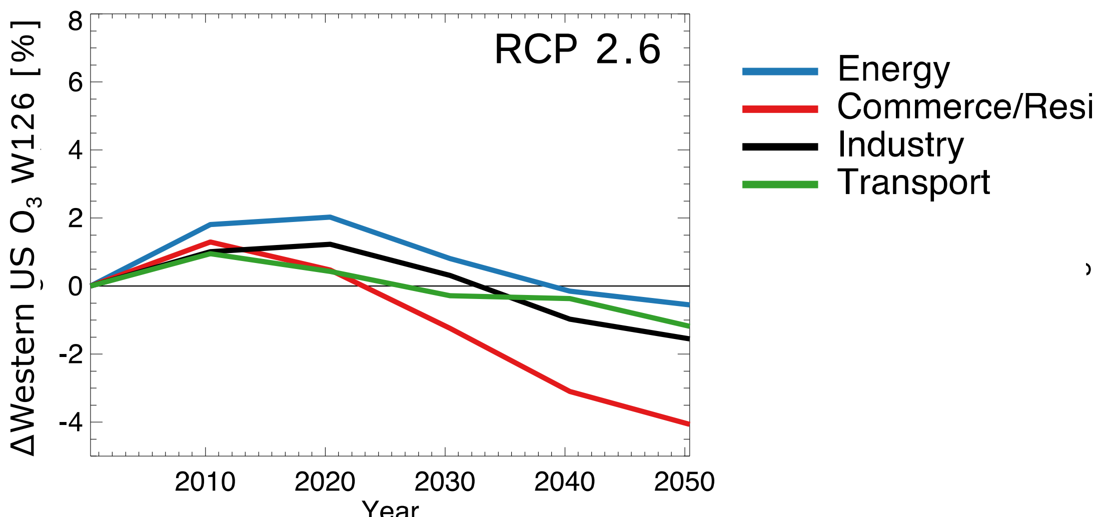
...from specific countries:

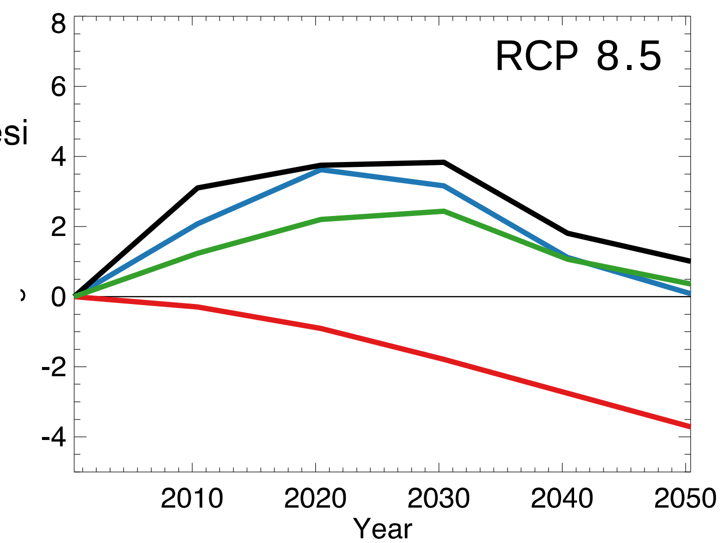
(Lapina et al., GRL, 2015)



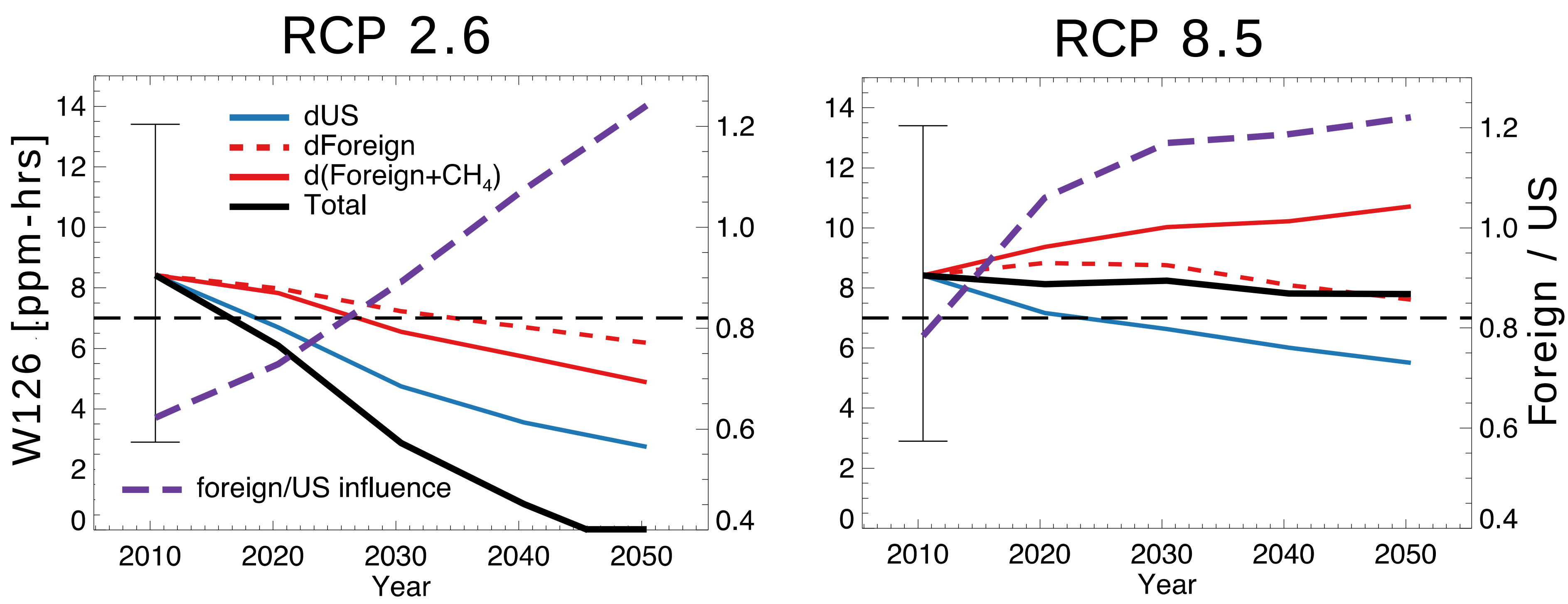


...from specific sectors in China:





Vegetative O_3 exposure in Western US following RCP emissions

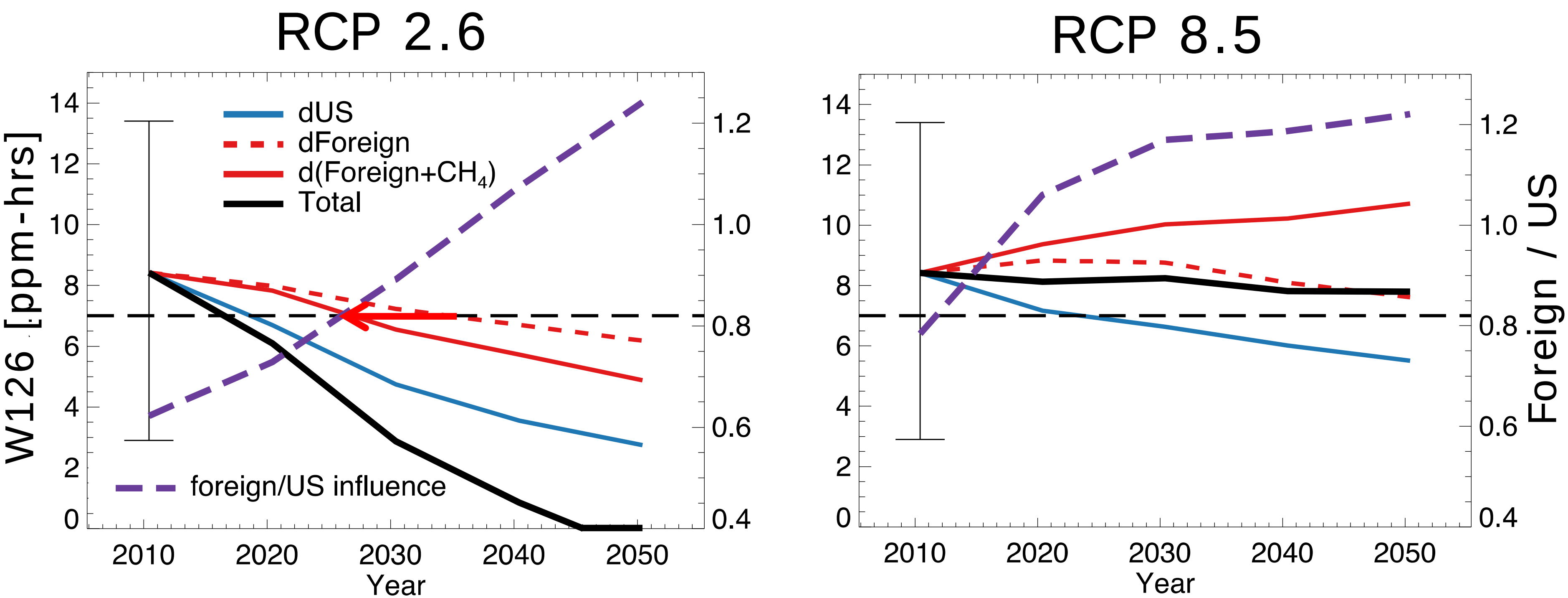


RCP 2.6: Domestic emission reductions drive attainment.

RCP 8.5: Background W126 O_3 overtakes domestic by 2020, driven largely by global CH_4 emissions.

Lapina et al., 2015

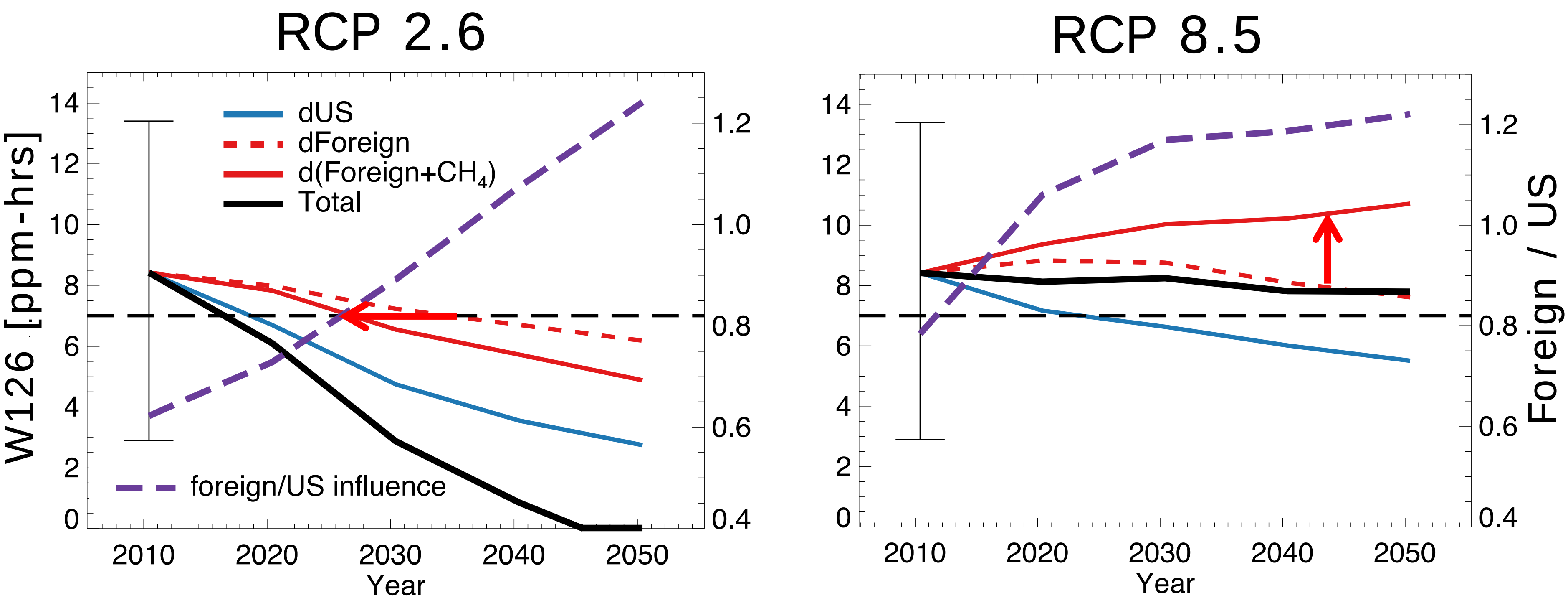
Vegetative O_3 exposure in Western US following RCP emissions



RCP 2.6: Global CH_4 emissions reductions shifts attainment forward by a decade.

Lapina et al., 2015

Vegetative O_3 exposure in Western US following RCP emissions



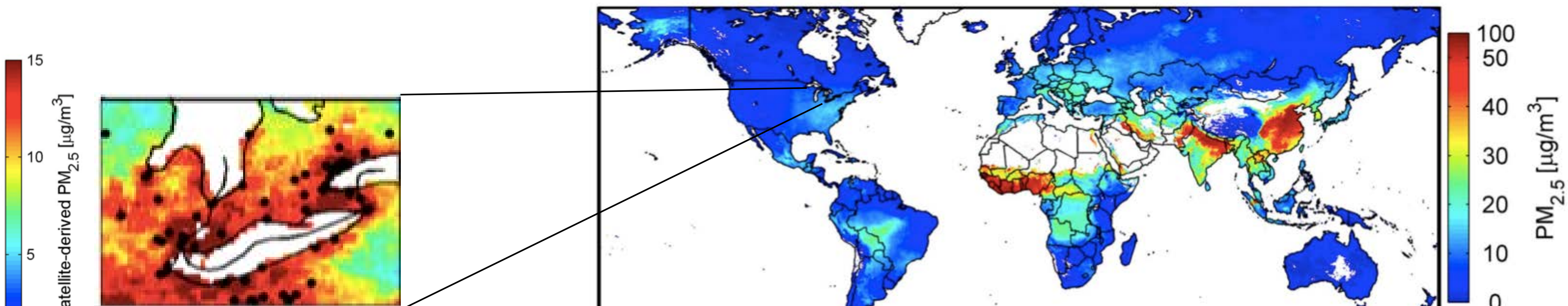
RCP 2.6: Global CH_4 emissions reductions shifts attainment forward by a decade.

RCP 8.5: Global CH_4 emissions increases more than counteract domestic O_3 controls.

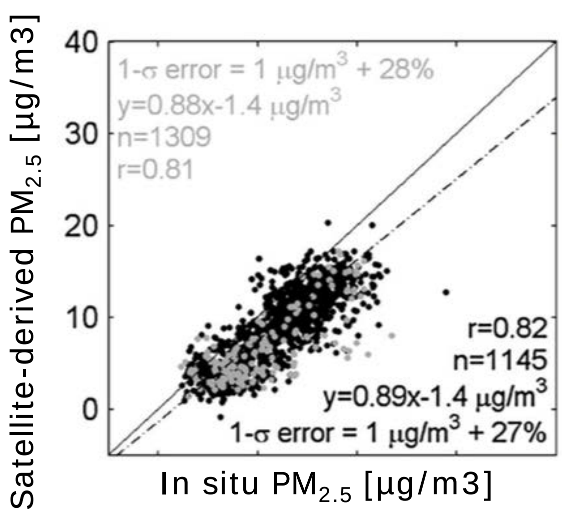
Lapina et al., 2015

Source attribution of $PM_{2.5}$ related global mortality

$PM_{2.5}$ subgrid variability (0.1° x 0.1°) resolved using MODIS, MISR, SeaWiFS AOD and CALIOP vertical profile (van Donkelaar et al., 2016):



2°x2.5° grid cell



Satellite-derived $PM_{2.5}$ shows good agreement with in situ total $PM_{2.5}$ and speciated $PM_{2.5}$ concentrations (Philip et al., 2014).

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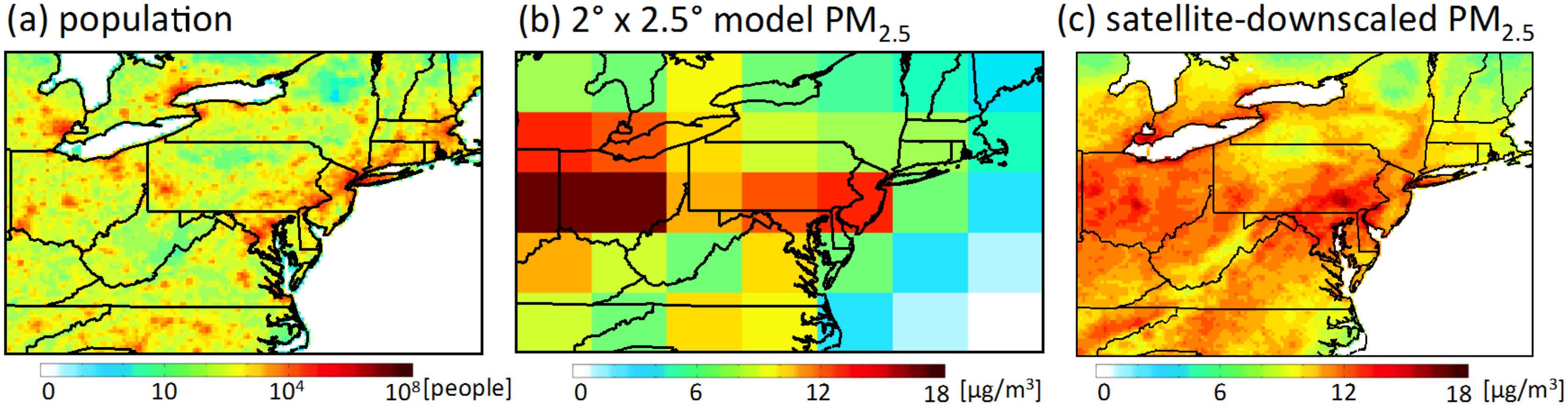
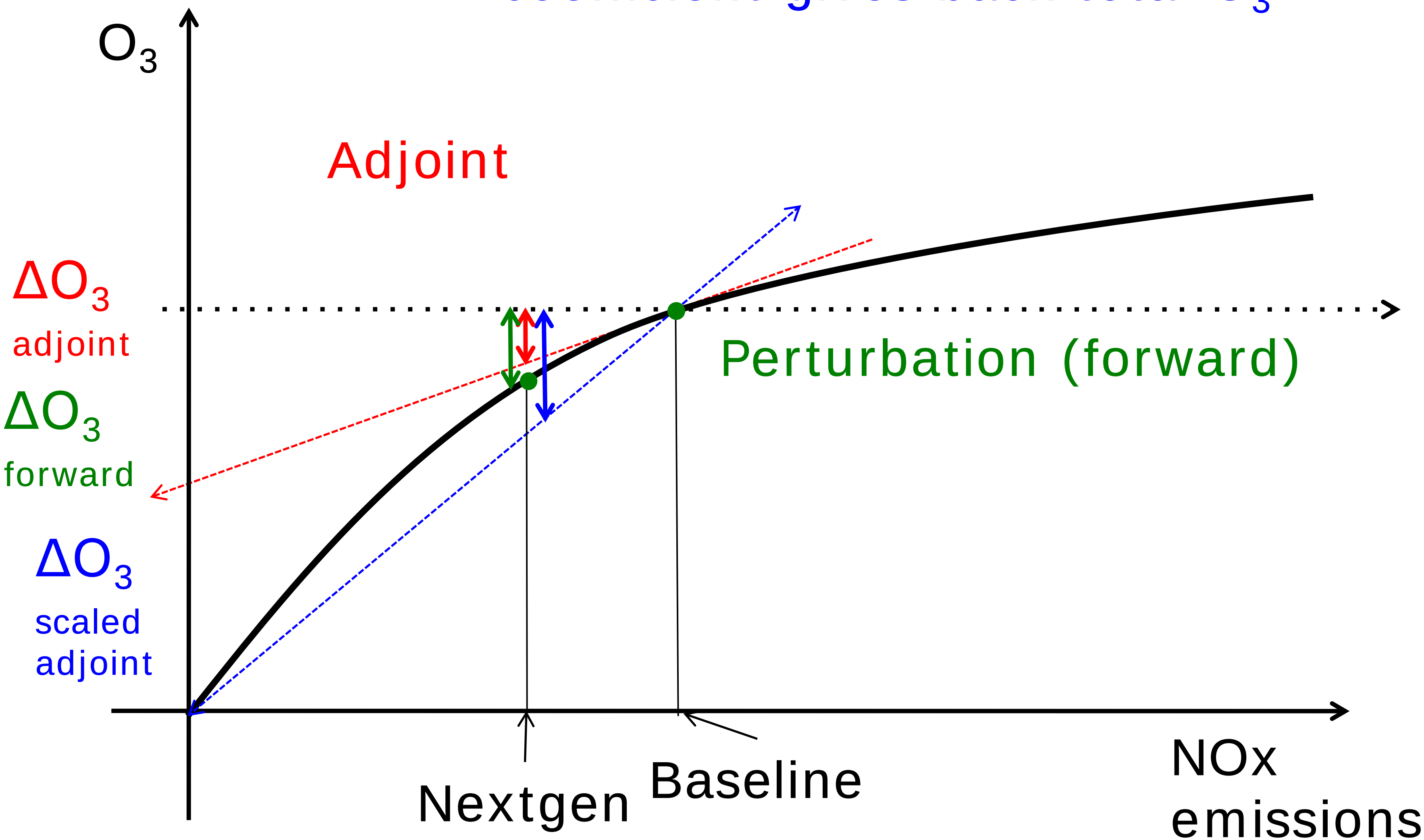


Combined high-resolution $PM_{2.5}$ data and adjoint modeling affords source attribution world-wide (Lee et al., 2015).

Adjoint results scaled for LEAP-IBC such that total emissions * coefficient gives back total O_3



Climate and Clean Air Coalition (CCAC)

CLIMATE AND CLEAN AIR COALITION
TO REDUCE SHORT-LIVED CLIMATE POLLUTANTS

www.unep.org/ccac

- Initiated Feb 2012
- Bangladesh, Colombia, Ghana, Mexico, Sweden, US, and UNEP
- now 109 members (50 countries, European Commission, multiple NGOs).
- US involvement through the State Department and EPA.
- SLCP Task Force Bill introduced to Congress (May 20, 2013).

Objectives

- Raising awareness of SLCP impacts and mitigation strategies
- Enhancing and developing new national and regional actions
- Promoting best practices and showcasing successful efforts
- Improving scientific understanding of SLCP impacts & mitigation strategies

Decision Support for Global Initiatives

Climate and Clean Air Coalition (UN)
- Reducing BC, CH_4 and other emissions from vehicles, brick production, oil & gas, solid waste

CLIMATE AND CLEAN AIR COALITION TO REDUCE SHORT-LIVED CLIMATE POLLUTANTS

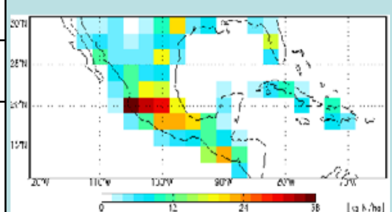
www.unep.org/ccac

Cross-cutting efforts:
- Financing SLCP mitigation
- **SLCP National Action Plans**

First action: rapid emission and scenario assessment toolkit

Mitigation

ΔEmissions



Response

ΔO_3,
$\Delta PM_{2.5}$
ΔCH_4

Impacts
- health
- climate
- ecosystem

Use country-specific responses for arbitrary Δemissions from adjoint calculations

Air quality modeling: chemical transport model

GEOS-Chem (*Bey et al.*, 2001; *Park et al.*, 2004)

emissions, assimilated meteorology, initial c_i's. → chemistry aerosol thermo, convection, advection, turbulent mixing → distributions of c_i

Reactive convection-diffusion:

$$\frac{\partial c_i}{\partial t} + \mathbf{u}\nabla c_i = \frac{1}{\rho}\nabla(\rho K \nabla c_i) + \frac{1}{\rho} f_i(\rho \mathbf{c}) + E_i$$

c_i = mixing ration of species *i*

f_i = mass action of species *i*

$\mathbf{u}$ = wind

E_i = emission of species *i*

Energy systems optimization with MARKAL

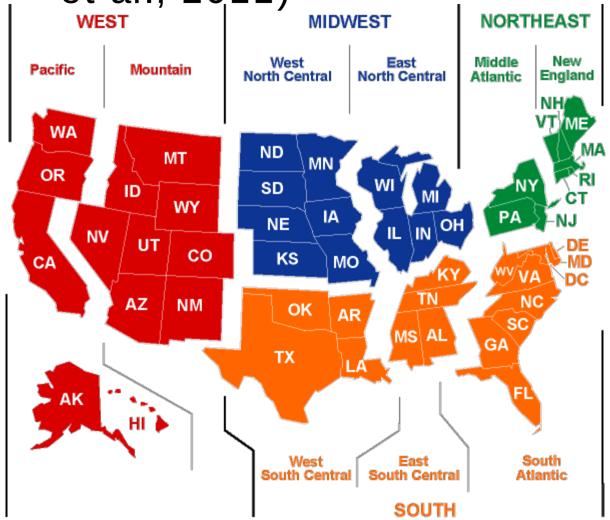
MARket ALocations (Loulou et al., 2004)

- Selects the **optimal mix of technologies and fuels** at each time step to minimize the net present value of energy system capital and O&M costs

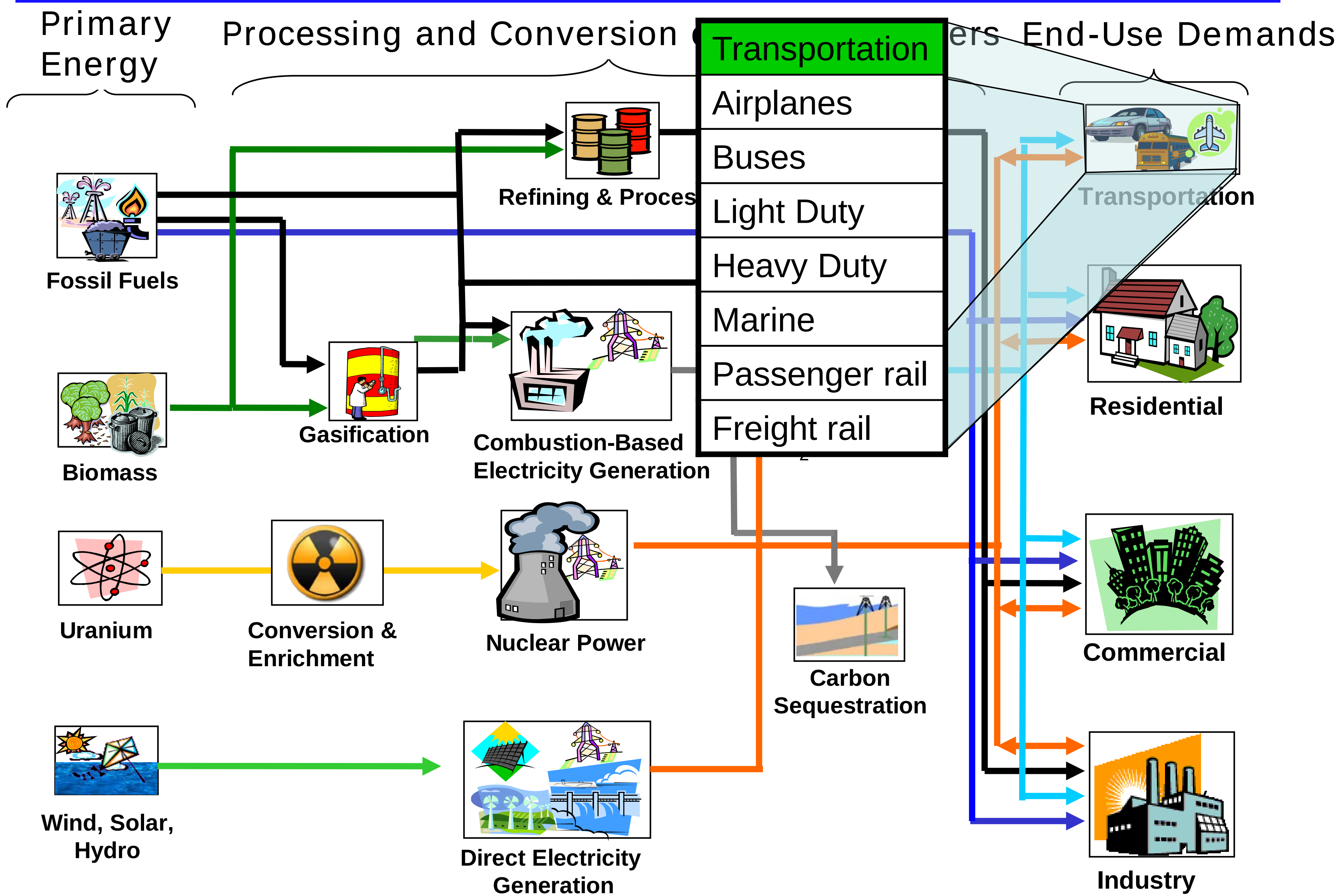
- Subject to:
  - Current and projected technology costs and efficiencies
  - Resource supply costs and competition for fuel across sectors
  - Resource supply constraints
  - Trade costs and constraints
  - Emission limits (e.g., policies)

EPA 9-region database

(Shay et al., 2008; Loughlin et al., 2011)

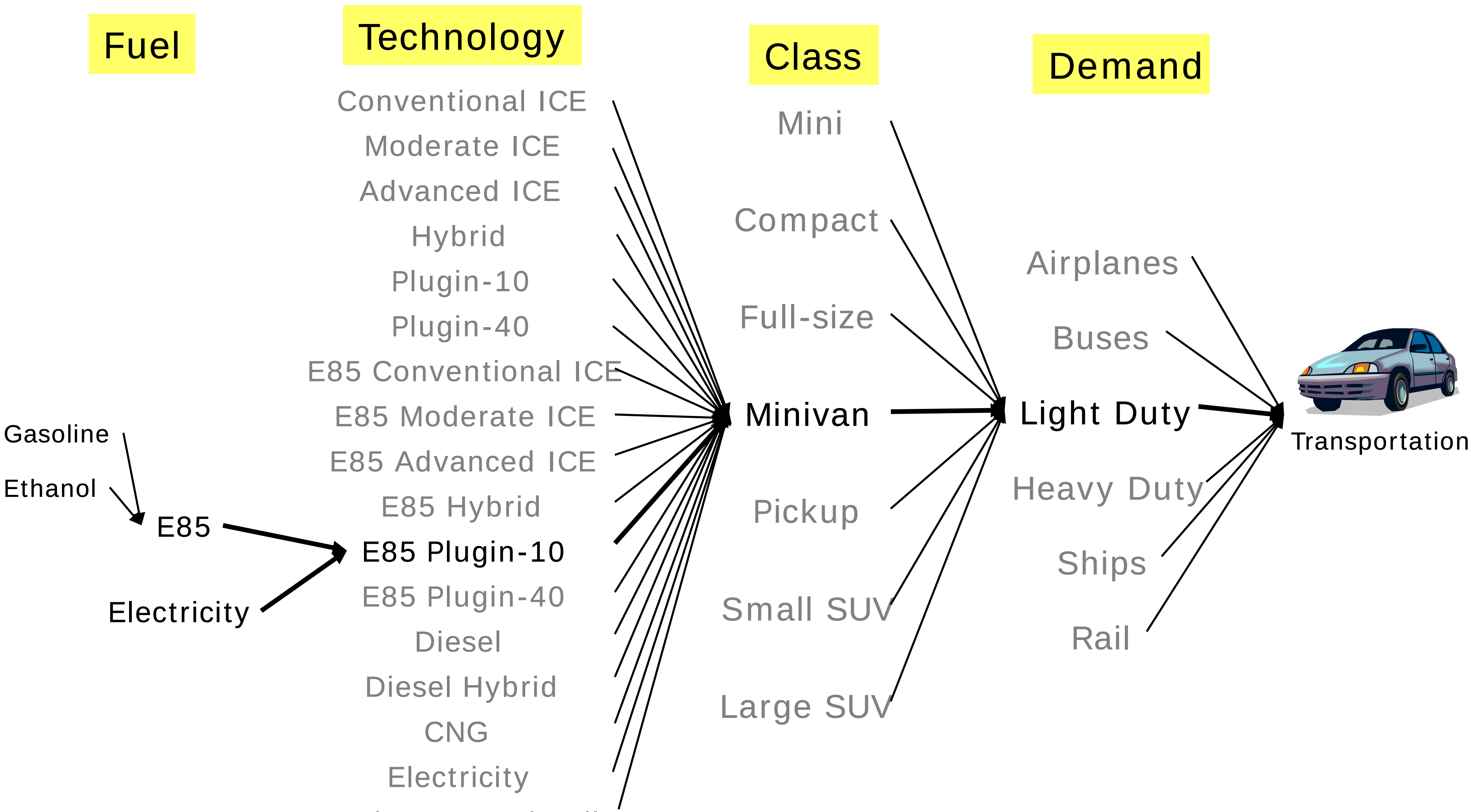


The Energy System



EPA Nine-Region MARKAL Database

Technology Detail: Light Duty Vehicles



(ICE = Internal combustion engine)

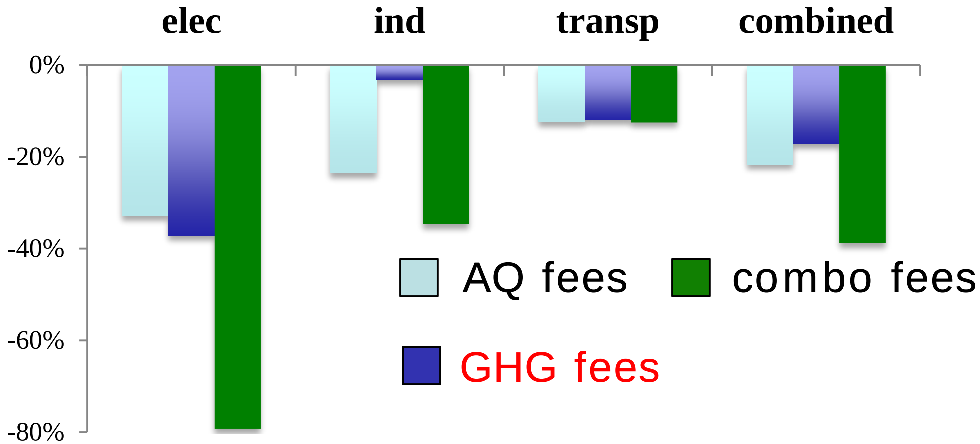
US climate and AQ co-benefits

Incorporate "fees" on emissions into MARKAL

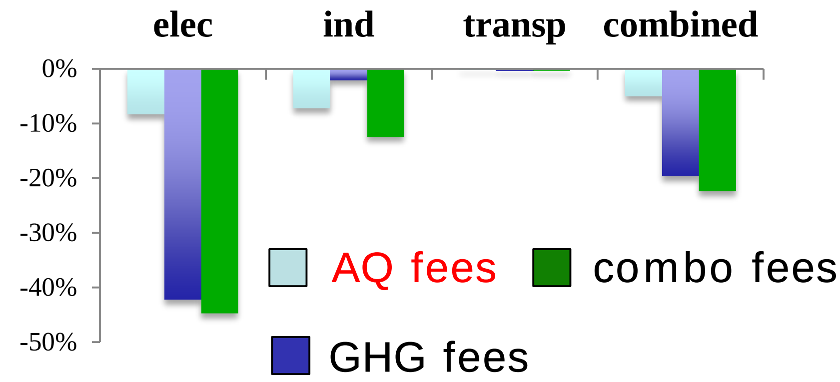
- criteria pollutant fees from Hidden Costs of Energy (NRC, 2010)
- CO2 fees from Social Cost of Carbon (SCC, 2013)

AQ and Climate fee-based **co-benefits** (Brown et al., 2013; in prep):

2045 NOx: (fees – BAU) /BAU



2045 CO_2: (fees – BAU) /BAU

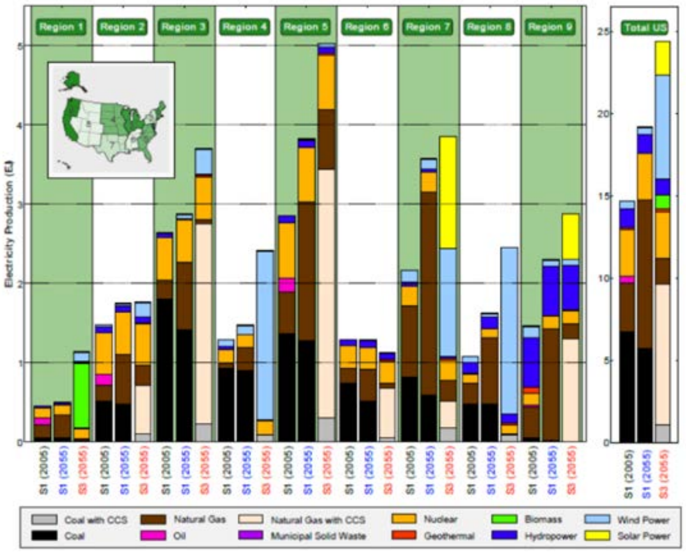


Air quality co-benefits of GHG policies are more prominent.

Have you considered the air quality impacts of your renewable energy source?

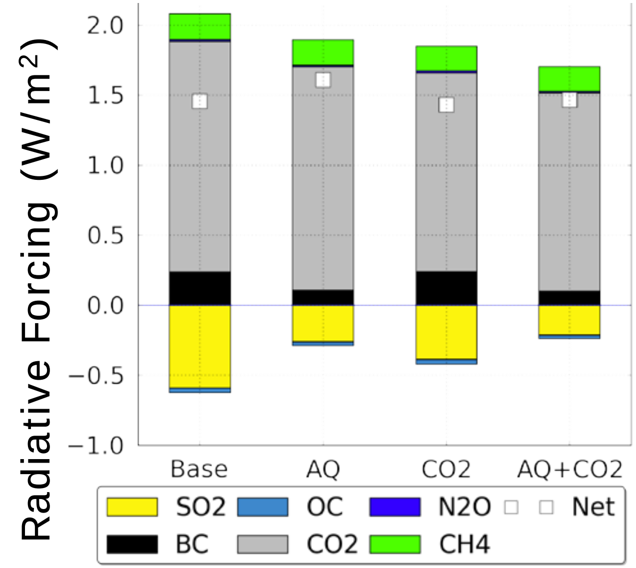
US climate and AQ co-benefits: GLIMPSE and MARKAL

AQ and RF diagnostics of emissions-cap scenarios (Akhtar et al., 2013):



Energy sources

$$\triangle E_{i,k} \times \frac{\partial \mathrm{RF}}{\partial E_{i,k}}$$



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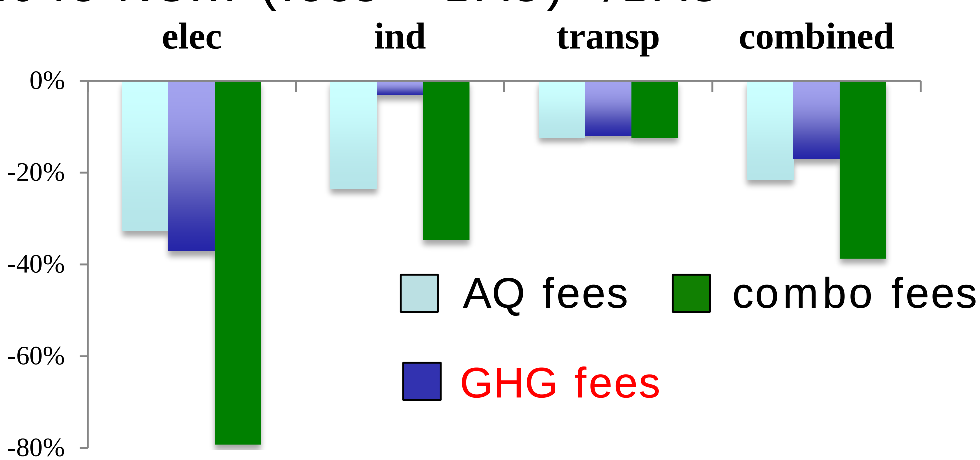

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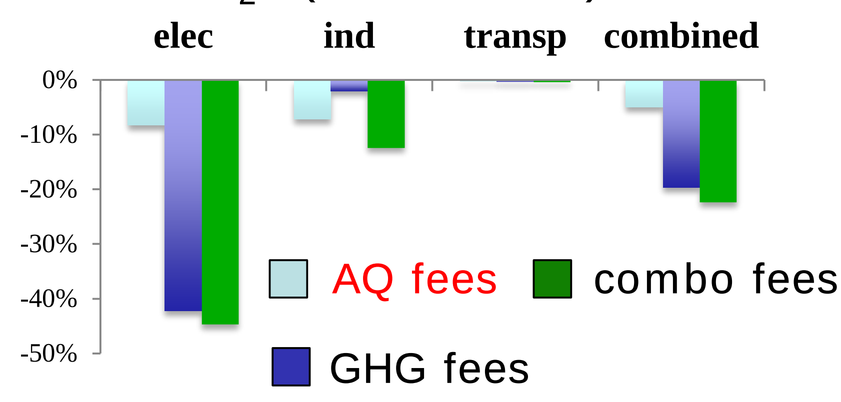
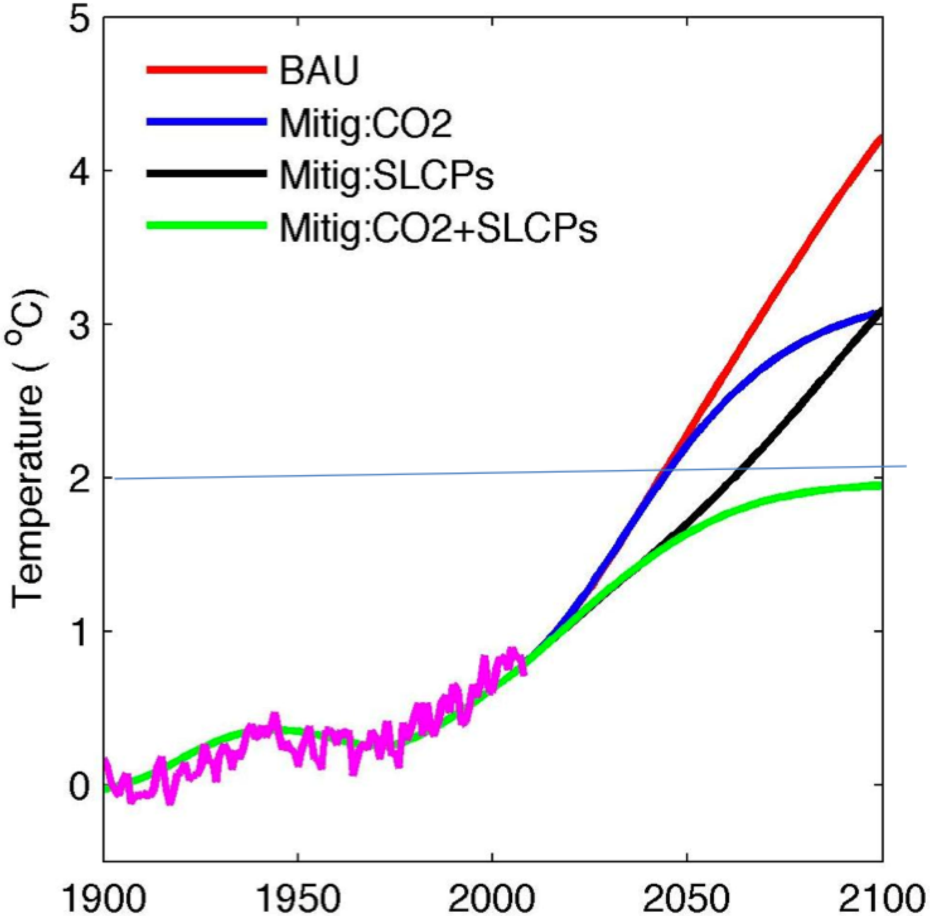
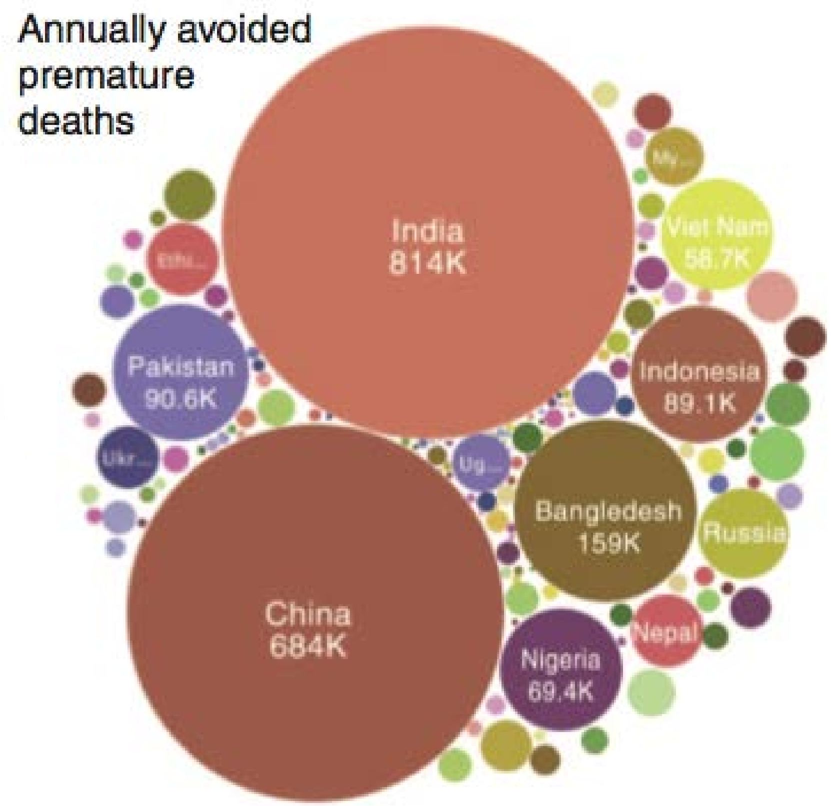


Climate and health impacts of Short Lived Climate Pollutants (SLCPs)

SLCPs = CH_4, **BC**, OC, CO, VOCs, NO_x, SO_2, NH_3, (HFCs)





Ramanathan and Xu, PNAS, 2010;
Hu et al., Nature CC, 2013
Ramanathan and Carmichael, Nature Geo, 2008

UNEP 2011;
Shindell et al., Science, 2012

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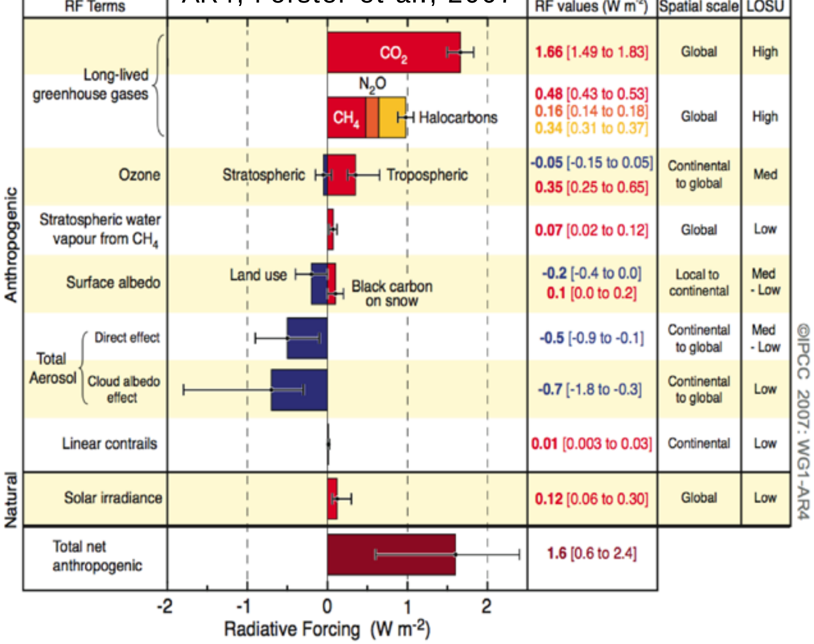
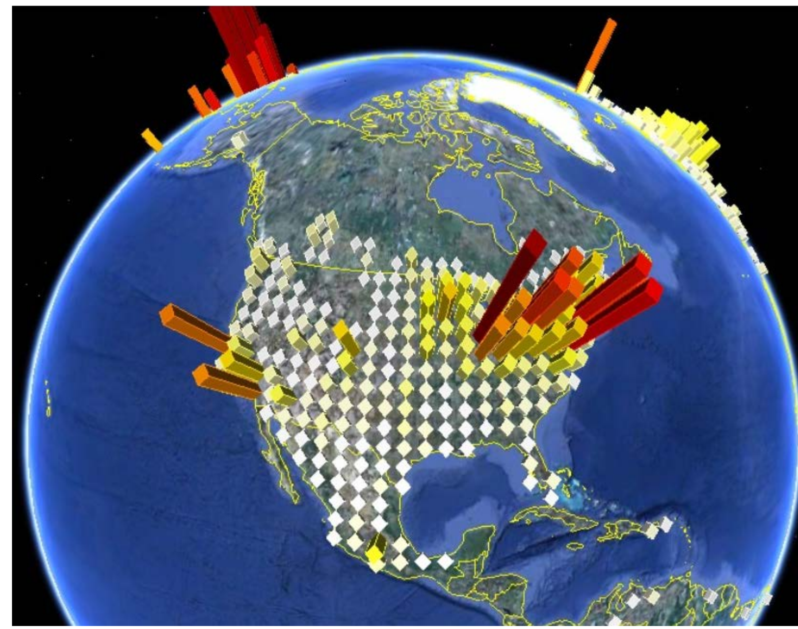
Integration of climate impacts into design of air quality control strategies

Abundance-based RF

AR4, Forster et al., 2007



Emissions-based ΔT



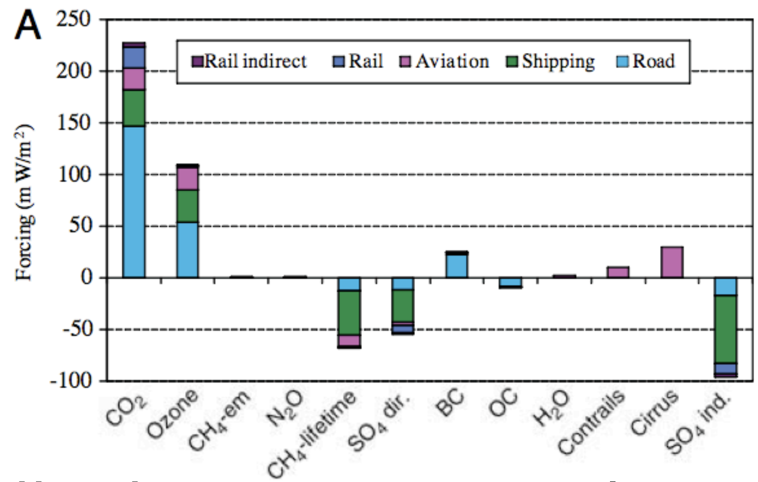
The traditional IPCC bar chart (abundance-based radiative forcing) has been invaluable for atmospheric scientists…

…yet disconnected from the needs of policy makers, who need to know the impacts of control strategies on co-emitted species.

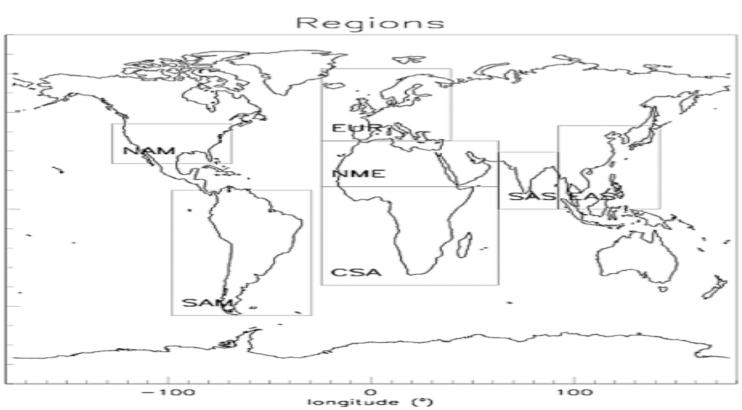
Refining the bar chart: from abundance-based to emissions-based RF

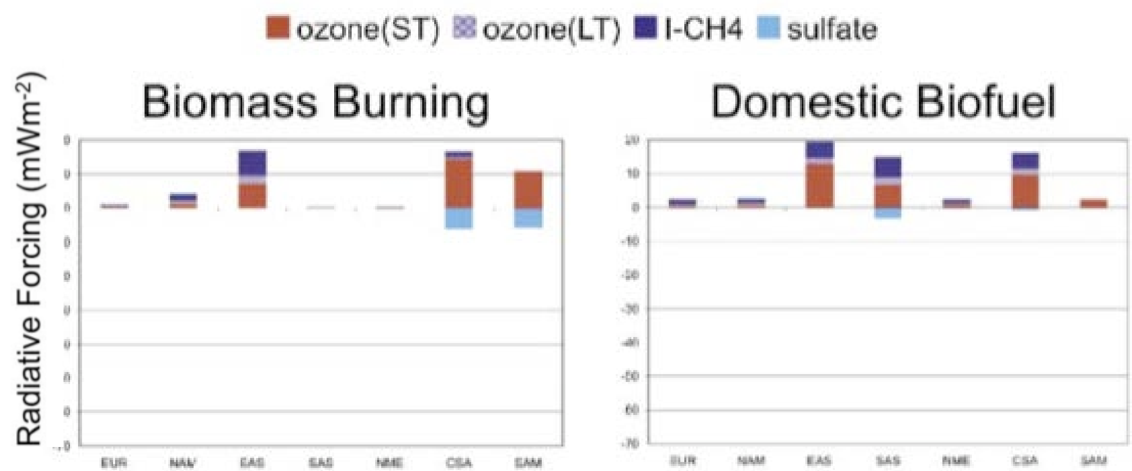
Perturbing emissions & recalculating RF:

- Sector specific contributions: Fuglestvedt et al., 2008;



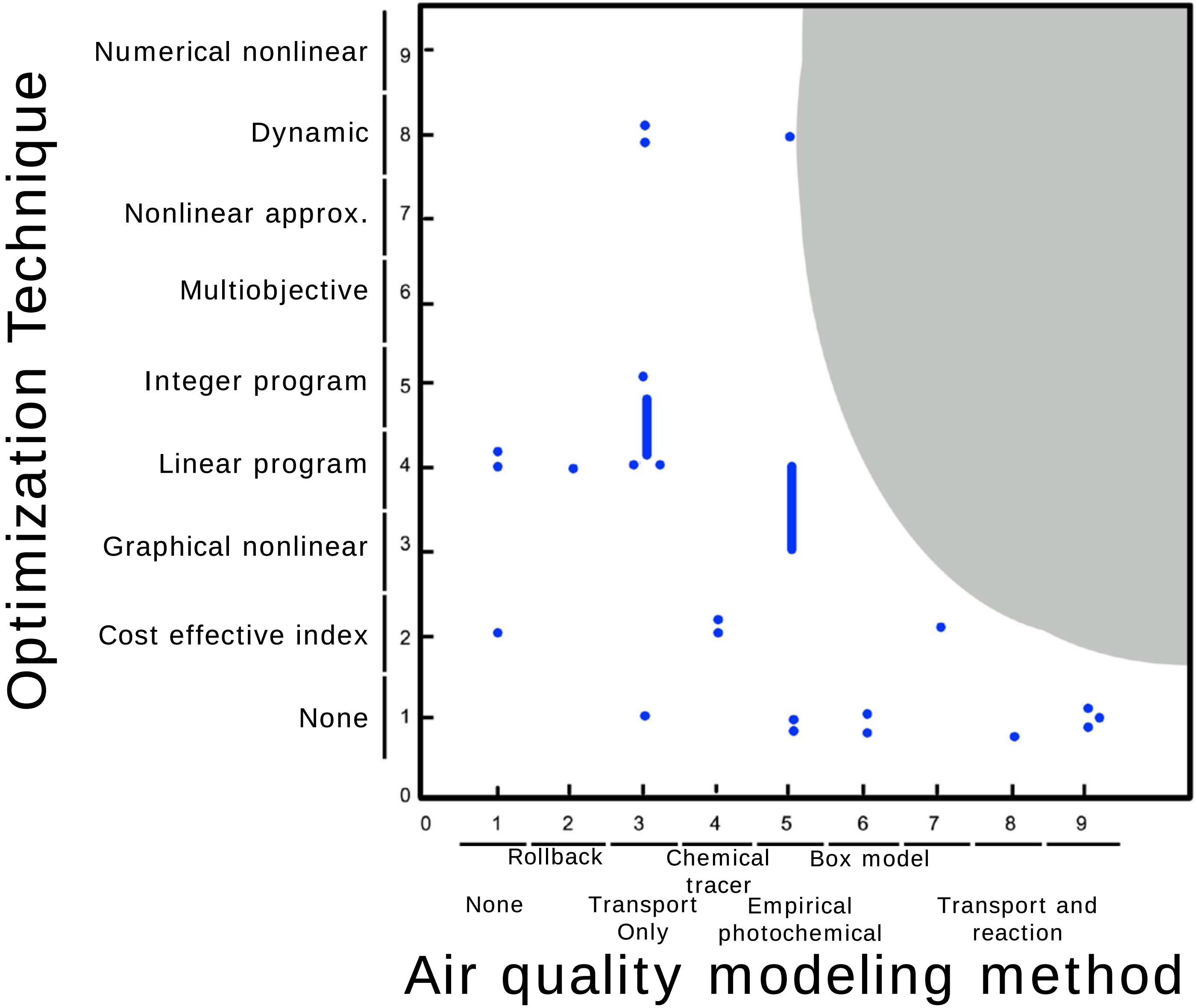
- Sector & regional specific contributions: Unger et al., 2008





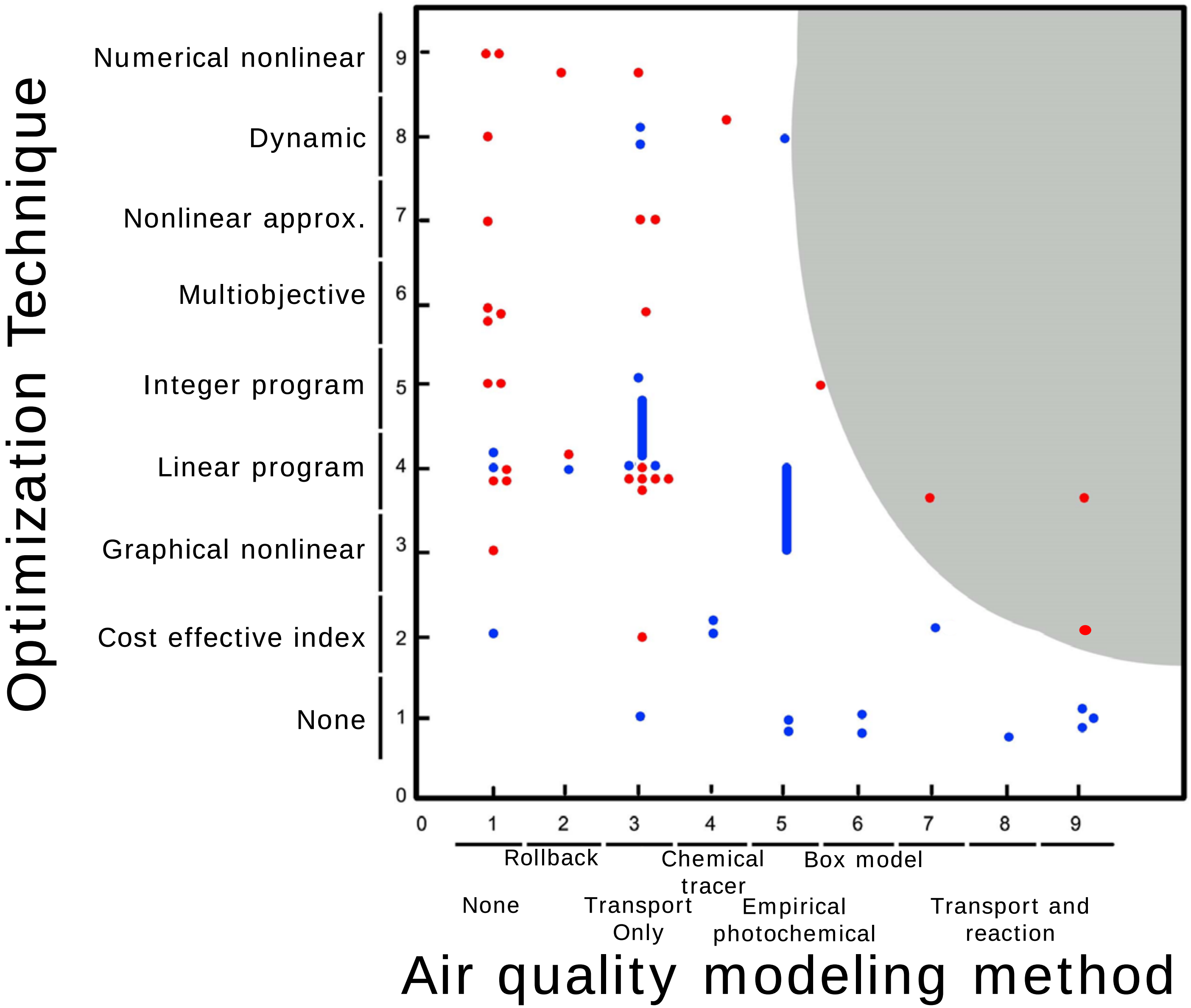
Koch et al., 2005; Unger et al., 2010; Shindell et al., 2011; 2012; Menon and Bauer, 2012

Optimal AQ control strategy design: past



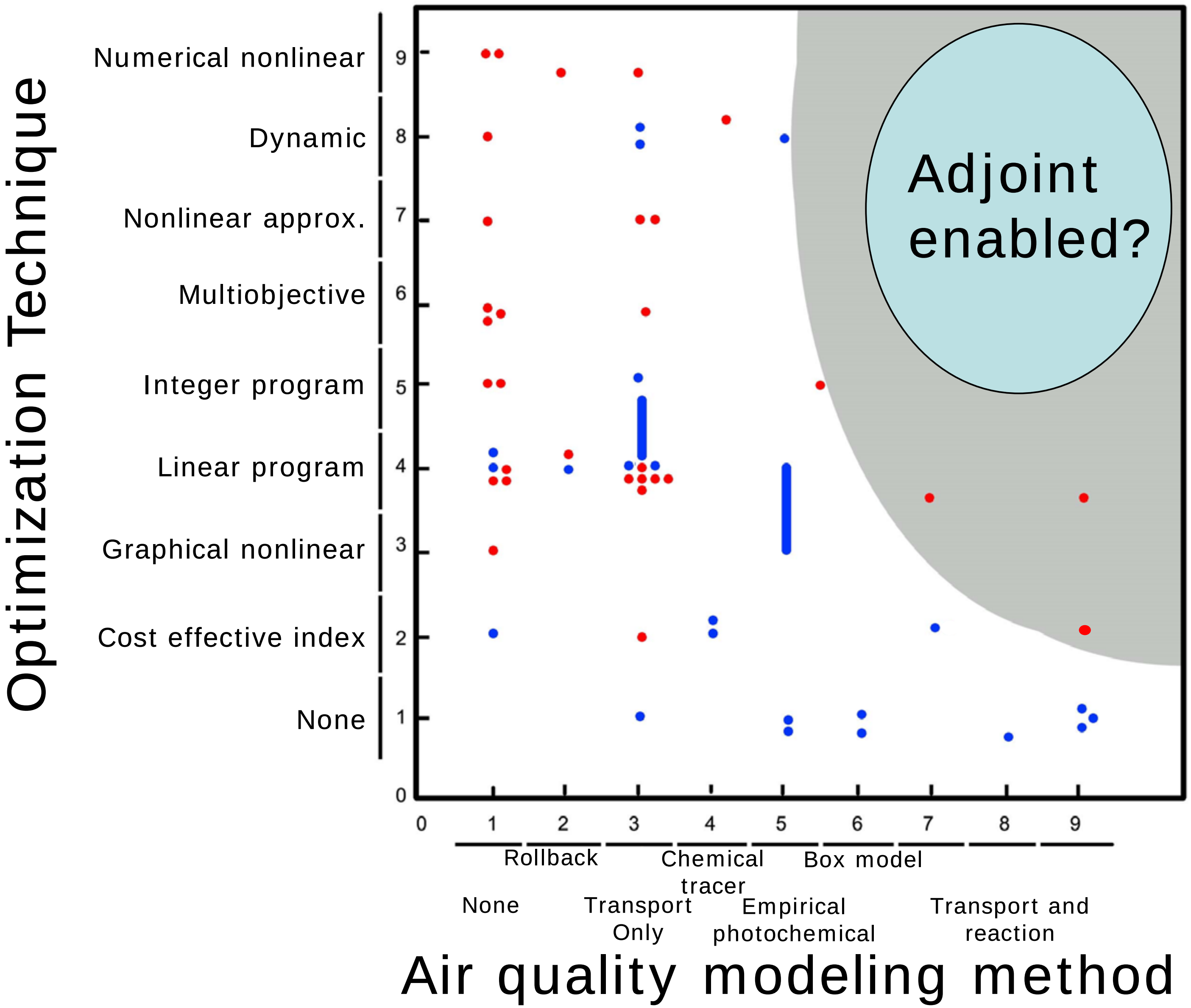
McRae and Cass (1981)

Optimal AQ control strategy design: present



Mesbah and Hakami (2011)

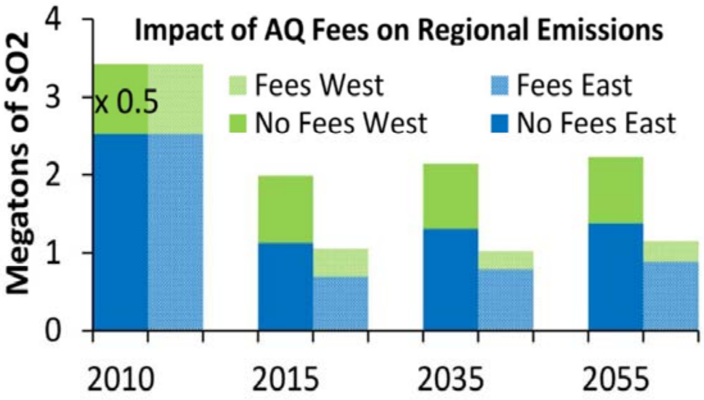
Optimal AQ control strategy design: future



Mesbah and Hakami (2011)

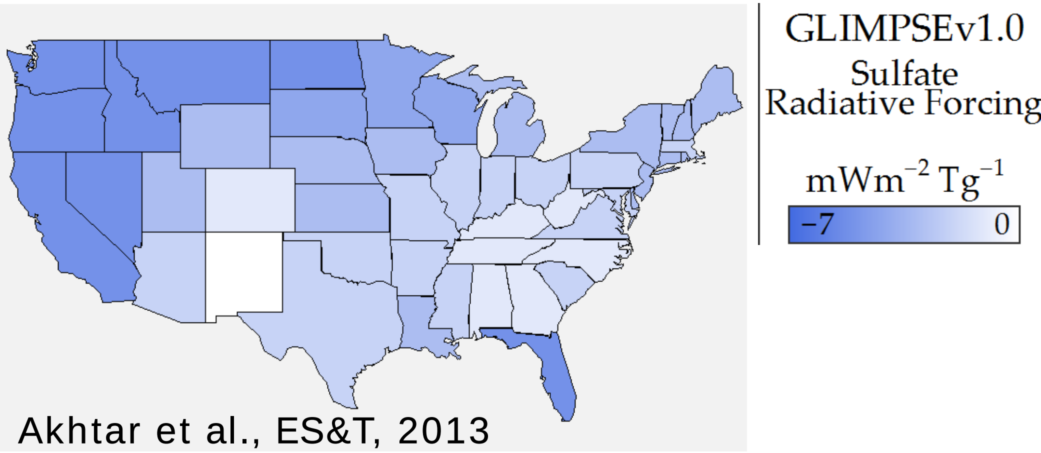
Integration of multiple damages for multi-objective optimization using adjoint modeling

Informing energy modeling



Brown et al., ES&T, 2013

Climate impacts of SO_2



Akhtar et al., ES&T, 2013

Additional impacts being explored with adjoint modeling:

- reactive nitrogen deposition (Paulot et al., ES&T, 2013)
- vegetative exposure to ozone (Lapina et al., 2014)
- cloud condensation nucleii (Karydis et al., GRL, 2012)

Iteratively minimize cost function analogous to 4D-VAR:

$$\min_{\mathbf{x}} \mathcal{J}(\mathbf{x}) = \underbrace{\sum_i d_i(\mathcal{M}(\mathbf{x}))}_{\textit{damages}} + \underbrace{(\mathbf{x} - \mathbf{x}_a)^T \mathbf{C}_{\mathbf{x}} (\mathbf{x} - \mathbf{x}_a)}_{\textit{abatement costs}}$$

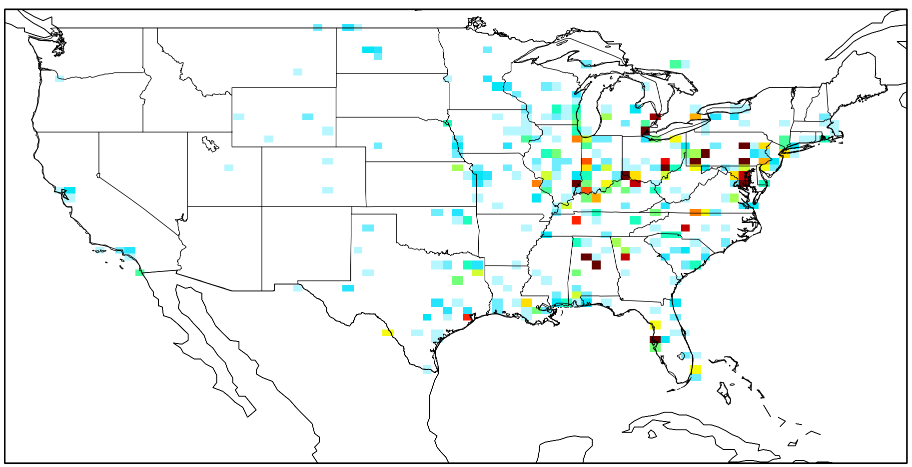
Source attribution of $PM_{2.5}$ related mortality

Source contributions to national mortality from $PM_{2.5}$
- total estimated to be 117,000 / yr

    compare to 130,000 / yr from Fann et al. (2012)

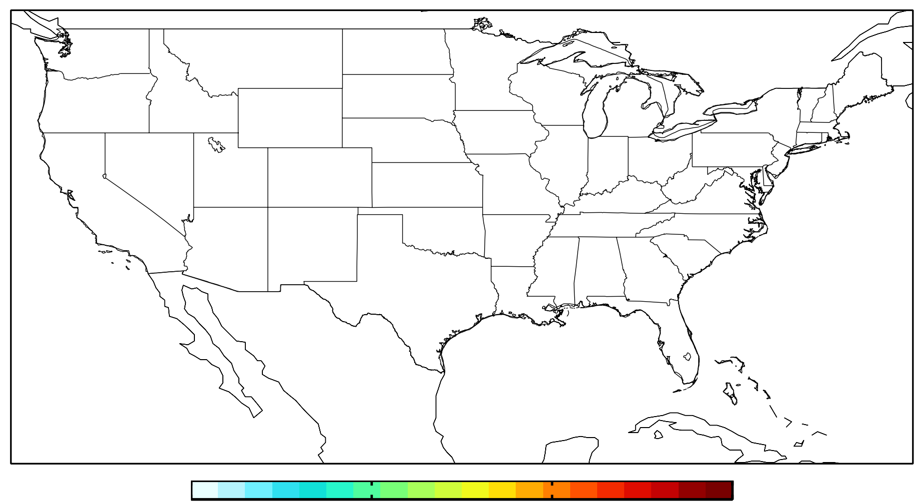
- contributions by location / sector / species:

From fossil fuel SO_2 (25,638)



[deaths]

From fossil fuel NO_x (19,816)



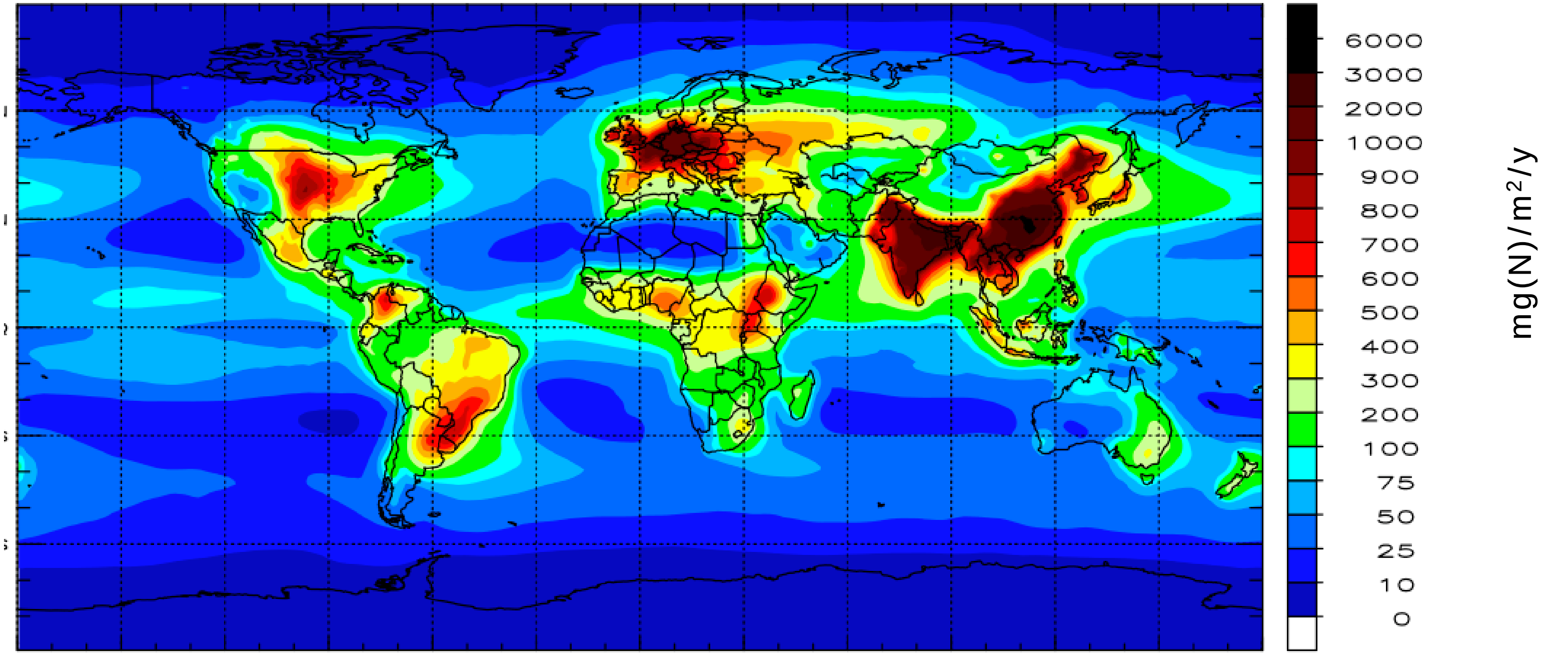
[deaths]

note: preliminary analysis, complete annual average results in progress

Analysis valuable for determining health impacts of future emissions control strategies, particularly jointly addressing $PM_{2.5}$ and O_3

Environmental impacts of NH_3

Estimated N deposition from NH_x, Dentener et al. (2006)

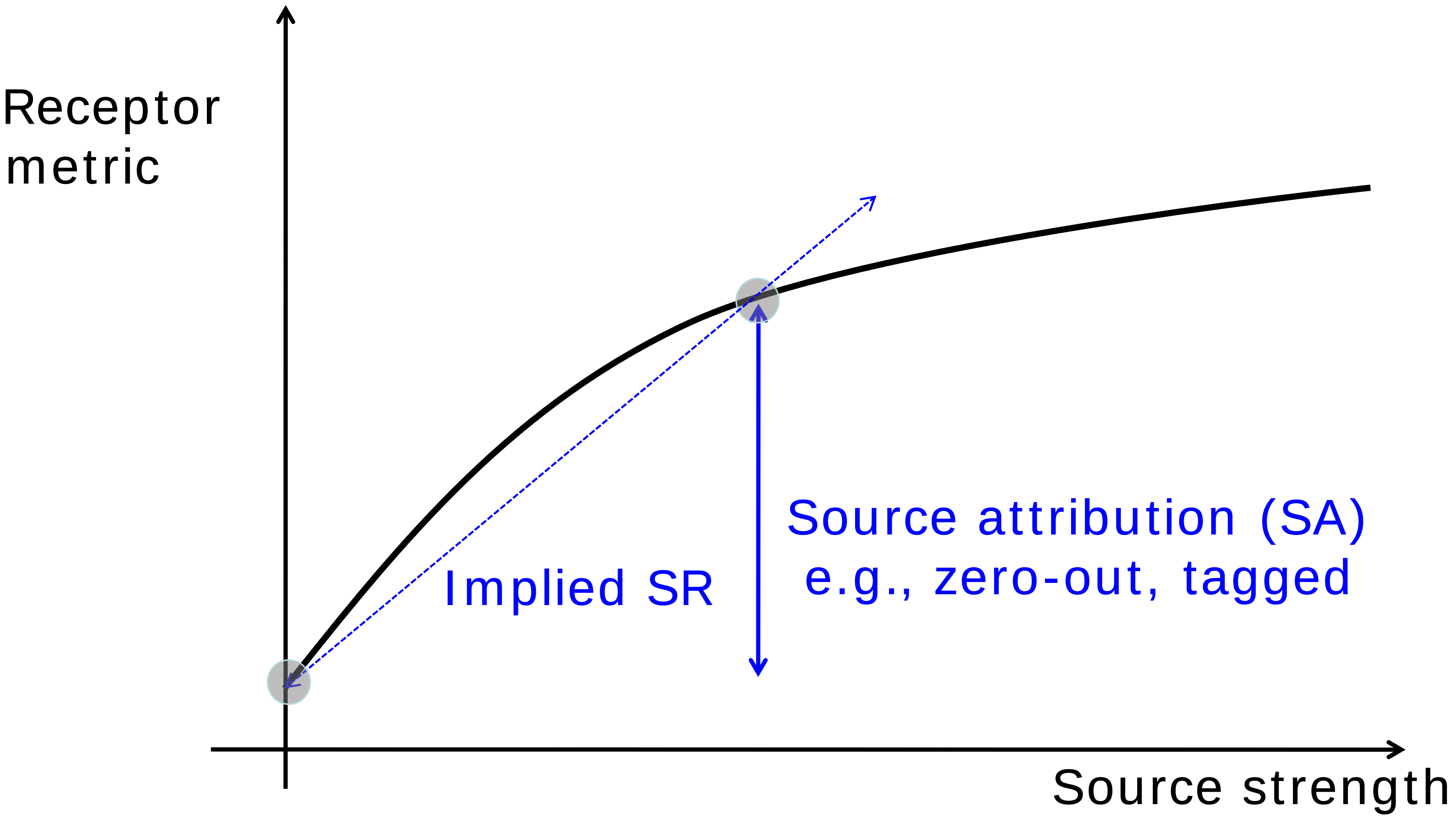


Areas where color approaches dark red --> deposited levels are hazardous to ecosystem.

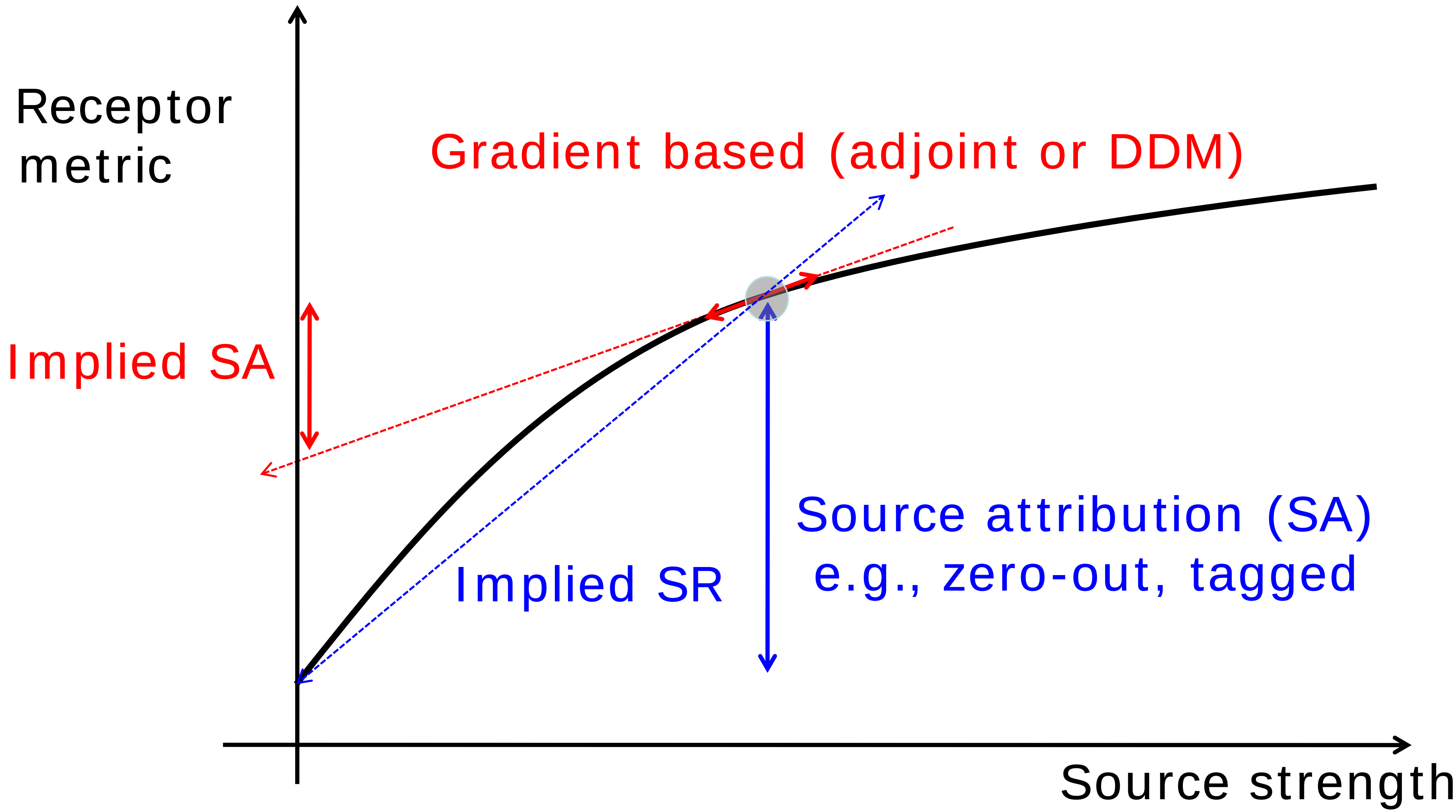
NH_3 emissions:

- increased by factor of 2 – 5 since preindustrial era.
- to double by 2050 (*IPCC*, Denman et al., 2007; Moss et al., 2010).
- contribute to 46 Tg gap in global N budget (Schlesinger, 2009)?

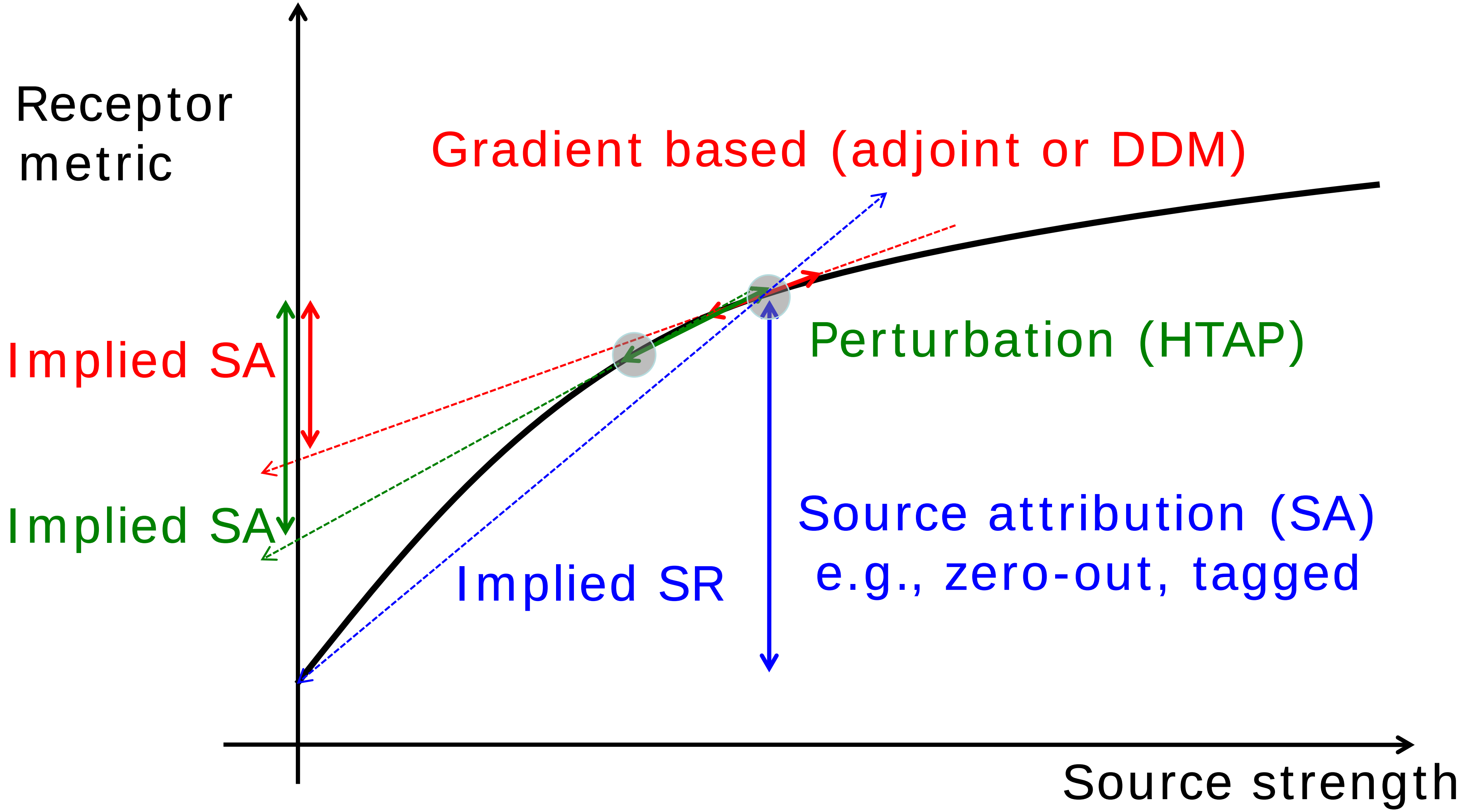
Concerns for nonlinear systems



Concerns for nonlinear systems

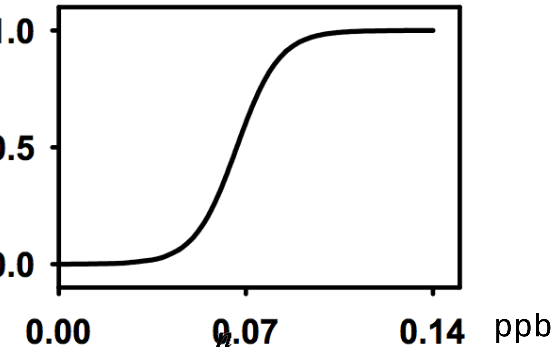


Concerns for nonlinear systems

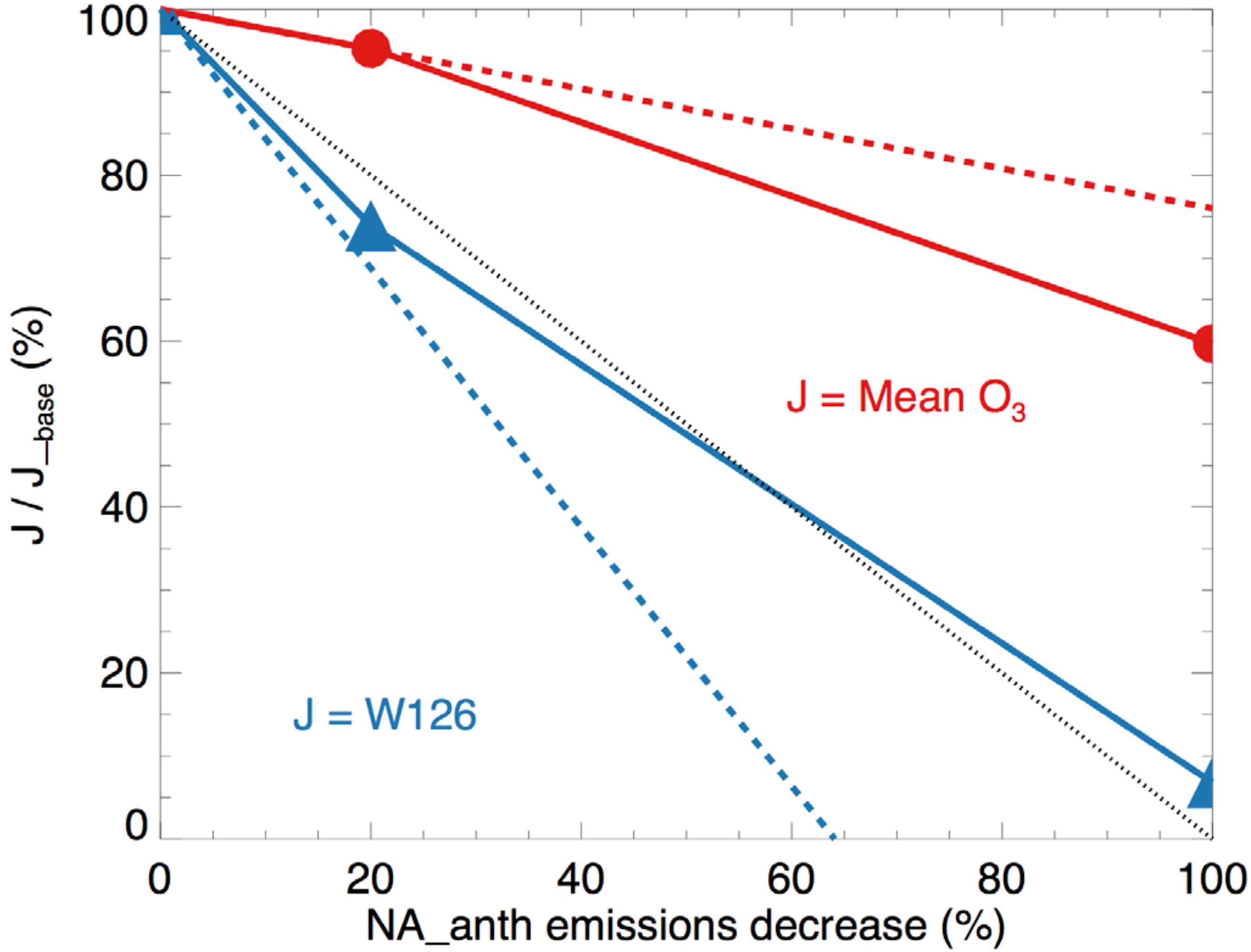


HTAP: we have multiple models capable of each

Variability across SA approaches

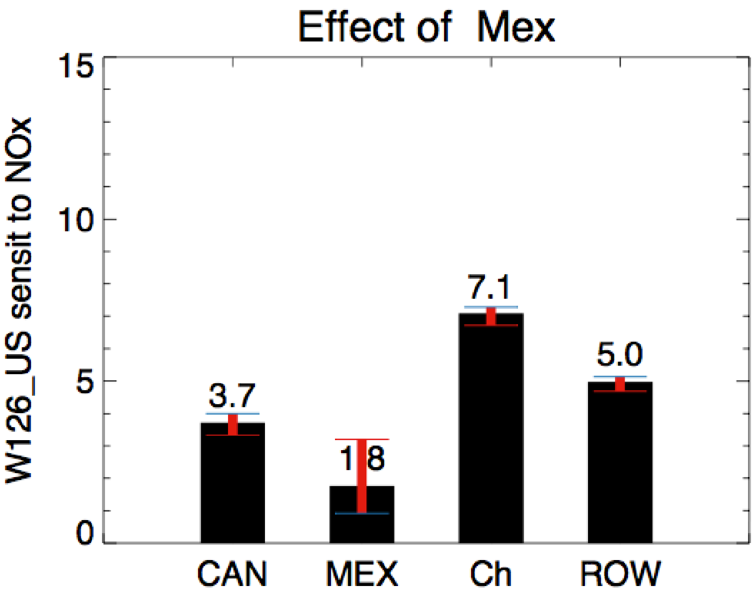


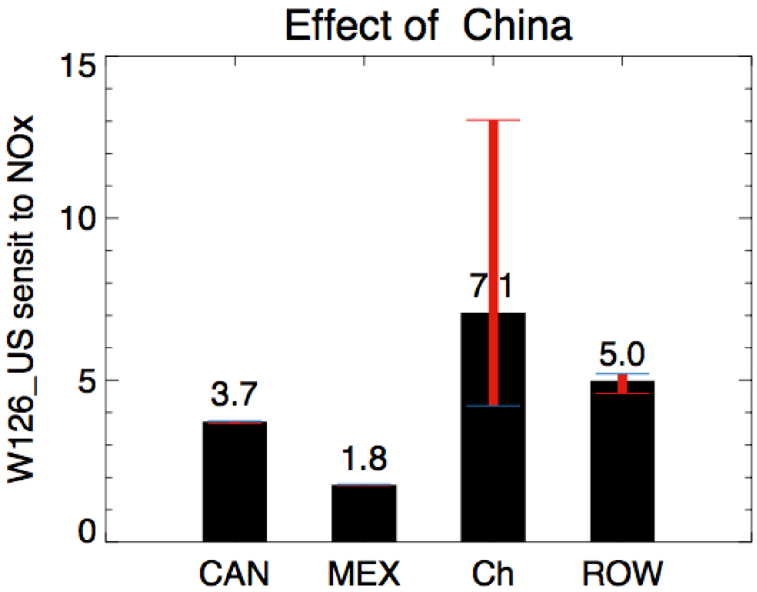
$$W126 = \sum_{i=1}^{n} w_i \times [C_{O3}]_i$$

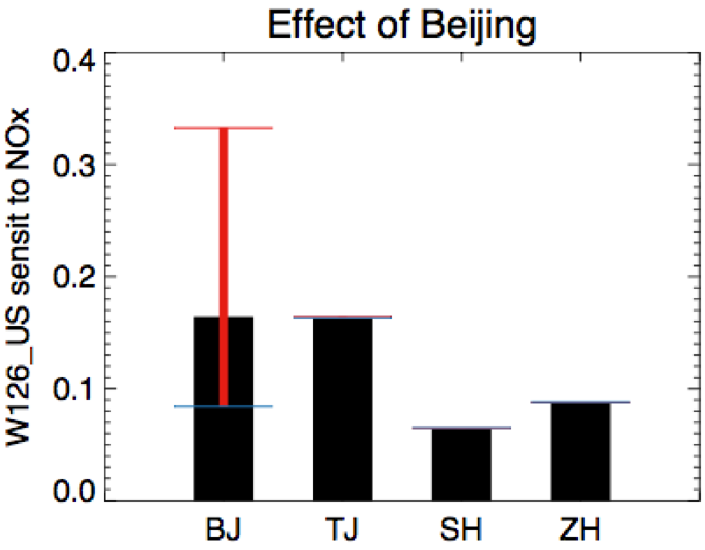


Variability across approaches depends upon response metric

Concerns for nonlinear systems: cross sensitivities by region and city area







Effect of emissions doubling/halving

- emissions x 2
- emissions x 0.5

- Cross sensitivities larger for regions
- Smaller for grid-scale perturbations

Constraining aerosol sources with 4D-Var approach

Model (GEOS-Chem, *www.geos-chem.org*) predicts 4D distributions:

meteorology & emissions: SO_2, NO_x, NH_3 dust, BC, OC → Gas-phase chemistry, Heterogeneous chem, Aerosol thermo, Deposition → NH_3, HNO_3, SO_4^{2-}, NO_3^-, NH_4^+ dust, BC, OC

4D-Var approach: constrain emissions through inverse modeling
- uses adjoint of GEOS-Chem (Henze et al., 2007)
- assimilates observations (from satellites)
- adjusts emissions (***x***) at the grid-scale to minimize *J*:

$$\min_{\mathbf{x}} \mathcal{J}(\mathbf{x}) = \underbrace{\sum_i (M(\mathbf{x})-\mathbf{y}_i)^T \mathbf{S}_y^{-1}(M(\mathbf{x})-\mathbf{y}_i)}_{\textit{model error}} + \underbrace{(\mathbf{x}-\mathbf{x}^a)^T \mathbf{S}_x^{-1}(\mathbf{x}-\mathbf{x}^a)}_{\textit{a priori constraint}}$$

x = emissions, *M* = model, **y** = observations, $\mathbf{S}_y$, $\mathbf{S}_x$ = error covariances

Model sensitivity relationships

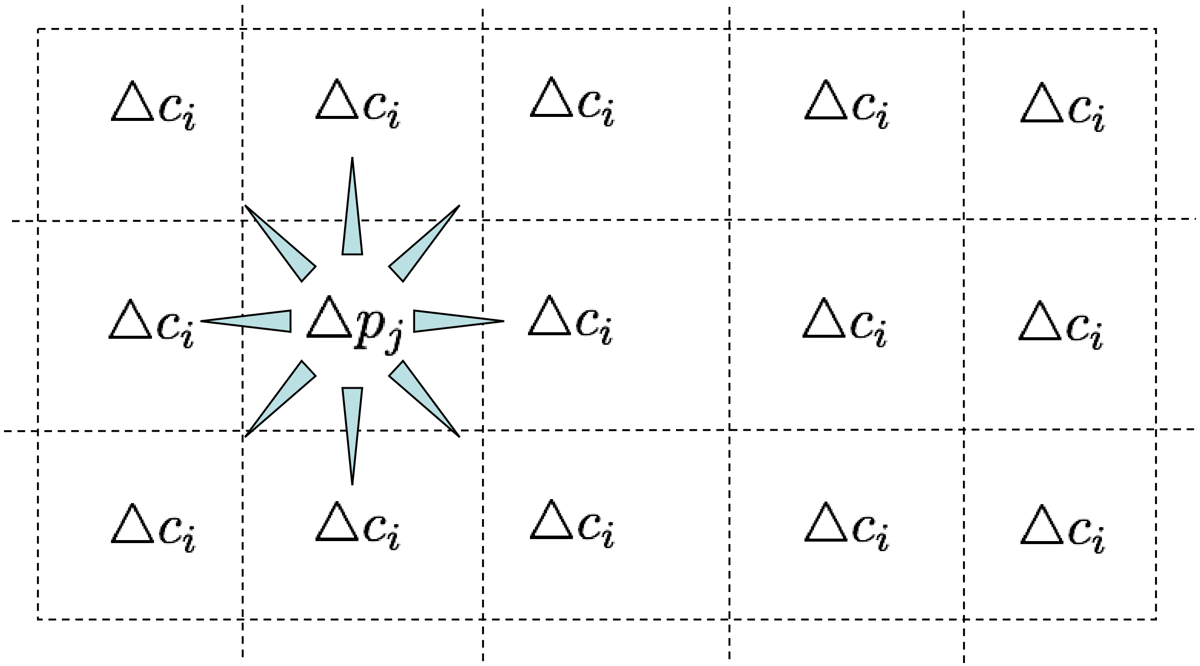
Model: estimates, c_i , and parameters, p_i

c_i, p_i	c_i, p_i	c_i, p_i	c_i, p_i	c_i, p_i
c_i, p_i	c_i, p_i	c_i, p_i	c_i, p_i	c_i, p_i
c_i, p_i	c_i, p_i	c_i, p_i	c_i, p_i	c_i, p_i

Ideally, want model Jacobian, $$\frac{\partial \mathbf{c}}{\partial \mathbf{p}} = \begin{bmatrix} \frac{\partial c_1}{\partial p_1} & \cdots & \frac{\partial c_1}{\partial p_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial c_I}{\partial p_1} & \cdots & \frac{\partial c_I}{\partial p_J} \end{bmatrix}$$

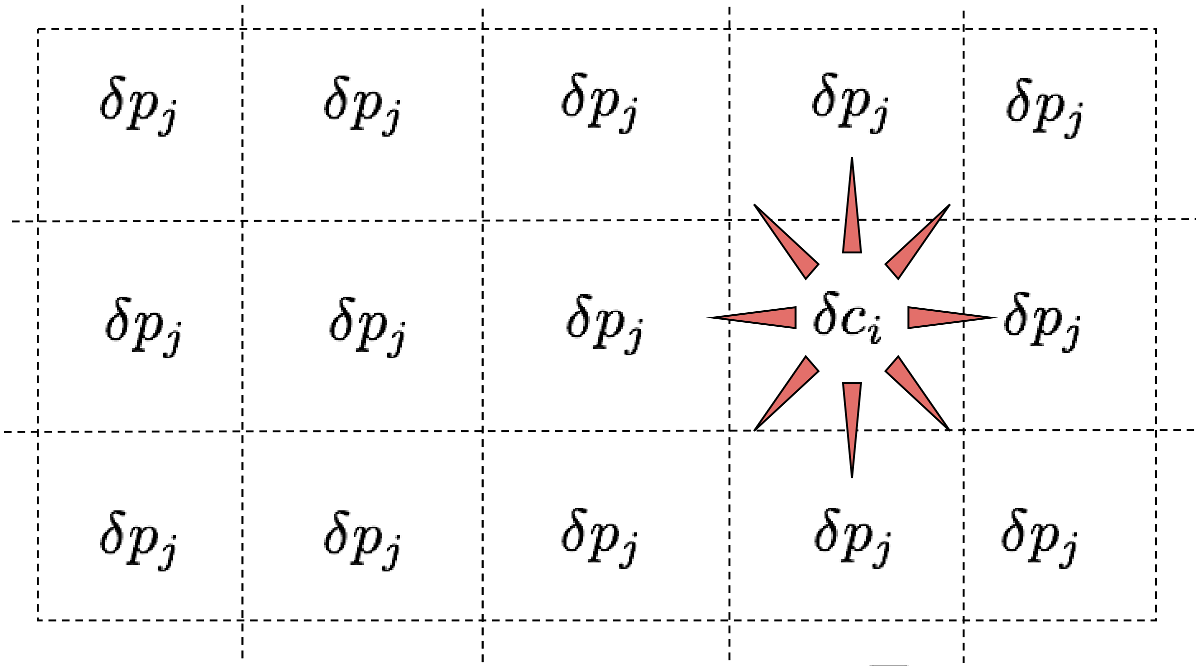
but it is generally much too large to calculate.

Forward sensitivity



$$\frac{\partial \mathbf{c}}{\partial p_j} = \begin{bmatrix} \frac{\partial c_1}{\partial p_1} & \cdots & \frac{\partial c_1}{\partial p_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial c_I}{\partial p_1} & \cdots & \frac{\partial c_I}{\partial p_J} \end{bmatrix} \mathbf{u_j}$$

Adjoint sensitivity



$$\begin{bmatrix} \frac{\partial c_1}{\partial p_1} & \cdots & \frac{\partial c_1}{\partial p_J} \\ \vdots & \ddots & \vdots \\ \frac{\partial c_I}{\partial p_1} & \cdots & \frac{\partial c_I}{\partial p_J} \end{bmatrix}^T \mathbf{u_i} = \frac{\partial c_i}{\partial \mathbf{p}}$$

Air pollution and visibility: urban scale

NYC

Pasadena, CA

(photo courtesy of M. Kleeman)

Mexico City

~3 Million premature deaths per year globally (GBD, 2012)

Air pollution and visibility: regional scale

SeaWiFS, May 4, 2001

Transcontinental health impacts (HTAP, 2010)
Aerosols interact with visible light.