Assessing Uncertainties in Modeling Aerosol Health Impacts

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ABSTRACT: Atmospheric fine particulate matter <2.5 μm (PM2.5) can cause health impacts such as cardiovasculatory and respiratory damages as well as mortalities. Assessing population exposure to and potential damages from PM2.5 is a critical first step in designing policies to mitigate damages. However, measurement networks for PM2.5 are available only in a few developed regions such as the United States, Canada, Japan and Europe. Atmospheric models and/or satellite data can be used to assess concentrations outside these regions, but these models and estimates are not well-constrained. Here, we assess the uncertainties in using atmospheric models and satellite information to constrain population exposure to PM2.5, and compare the magnitude of this atmospheric concentration uncertainty to uncertainties in epidemiological exposure-response functions and in economic valuation of health impacts. We compare results from two atmospheric models, the MIT/NCAR CAM3 aerosol-climate model, and the GEOS-Chem atmospheric chemistry model, and satellite-derived PM2.5, based on their projections of regionally-averaged population-weighted concentrations. We then use the MIT Emissions Prediction and Policy Analysis Health Effects model (EPPA-HE) to assess global health impacts and related economic costs, and conduct uncertainty analysis of the exposure-response functions and economic costs using a probabilistic approach. We use these combined approaches to project uncertainty ranges for present-day health impacts and related economic costs due to PM2.5 concentrations.

1. INPUTS AND MODEL DESCRIPTION

ATMOSPHERIC CONCENTRATIONS: We compare PM2.5 estimates from three different sources at two different resolutions:
1) GEOS-Chem model v. 8-01-04, 2°x2.5° [1]
2) MIT/NCAR CAM3, 2°x2.5° [2,3]
3) Satellite PM2.5, 0.1°x0.1° [4].
We focus here on the concentrations in populated regions.

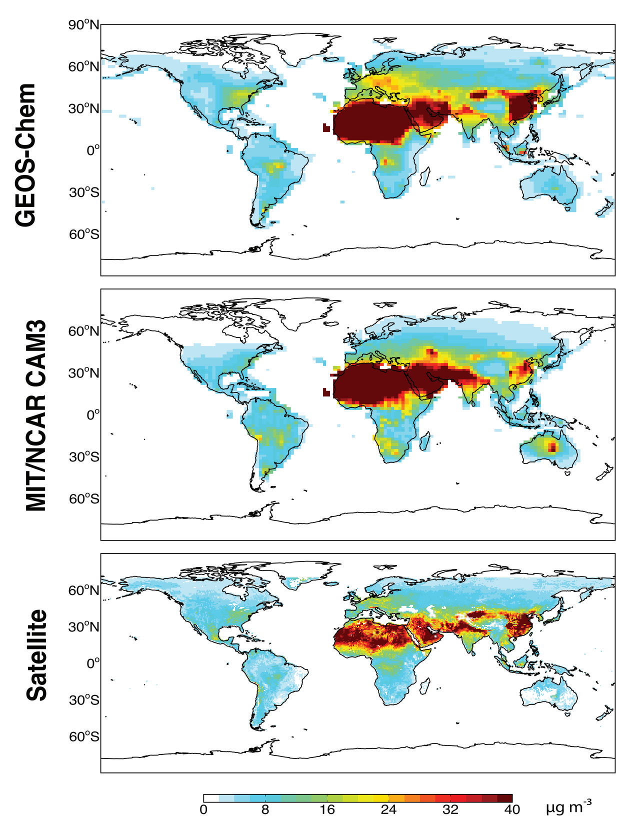

Figure 1: PM2.5 concentrations

HEALTH IMPACTS: We use the MIT Emissions Prediction and Policy Analysis Health Effects (EPPA-HE) model [5-7] to calculate global health impacts and related costs of PM2.5 exposure. EPPA takes as input population-weighted concentrations in 16 global regions, and calculates health outcomes and economic costs in a computable general equilibrium model.

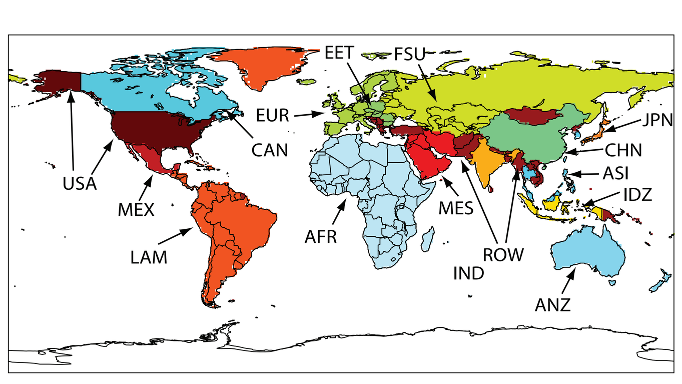

Figure 2. EPPA Regions

2. VARIATION IN CONCENTRATION ESTIMATES

We use population-weighted annual average PM2.5 as a proxy for exposure. This is an imperfect estimate of actual exposure, but approximates the large-scale monitoring data used to develop exposure-response functions. Population-weighted average concentrations have different characteristics than area-weighted averages. Our comparison shows:
1) Differences between estimates are large (up to an order of magnitude) especially outside developed regions
2) Much of the difference between estimates comes from dust, which is poorly constrained.

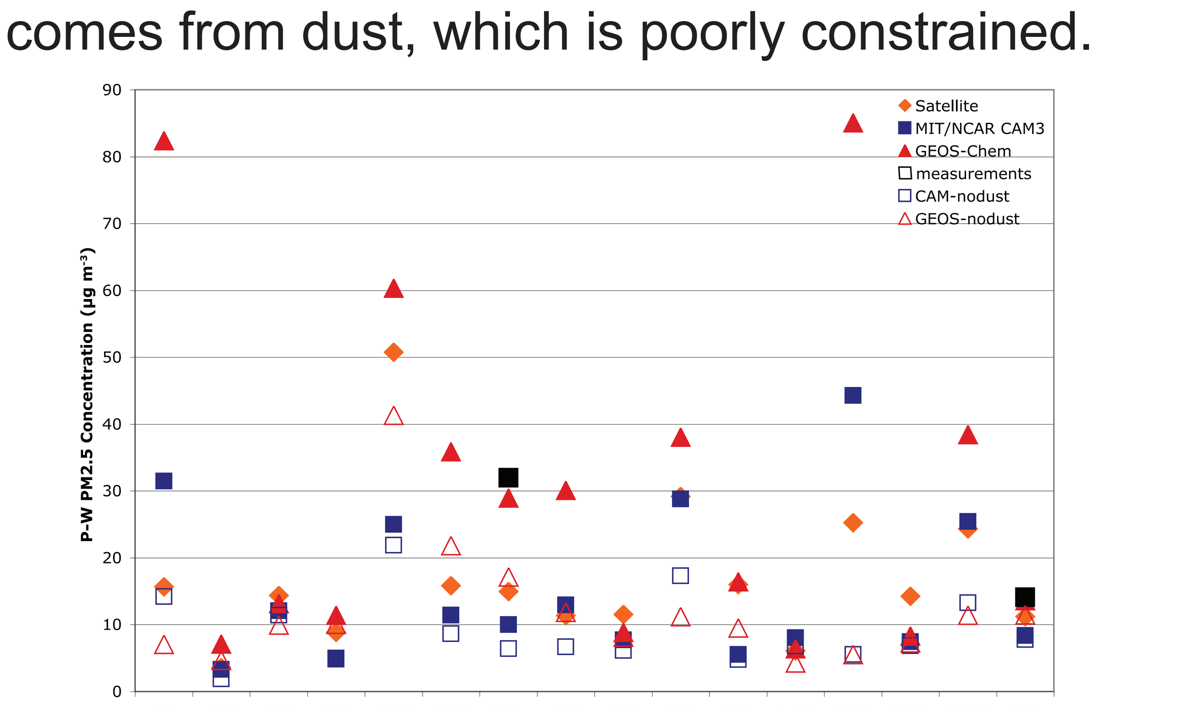

Figure 3: Annual population-weighted PM2.5 by region [8, 9]

2. SOURCES OF CONCENTRATION UNCERTAINTY

Sources of uncertainty in PM estimates include emissions, atmospheric processing including chemical components, spatial variability/resolution of model or data, and interannual variability.

Emissions: Differences between models (with different emissions) and the satellite product are large where emissions are poorly constrained; uncertainties in resolution are secondary.

Interannual Variability: GEOS-Chem results for 2001-2006 showed small (<10%) interannual differences for most regions, except for Indonesia, high-income Asia, and Australia/New Zealand (max of 40%, likely due to biomass burning).

Components: While contributions to global total population-weighted PM2.5 are very different from those in the US, contributions to anthropogenic (non-dust or sea salt) population-weighted PM are more similar to those in the US. The largest difference is for nitrate.

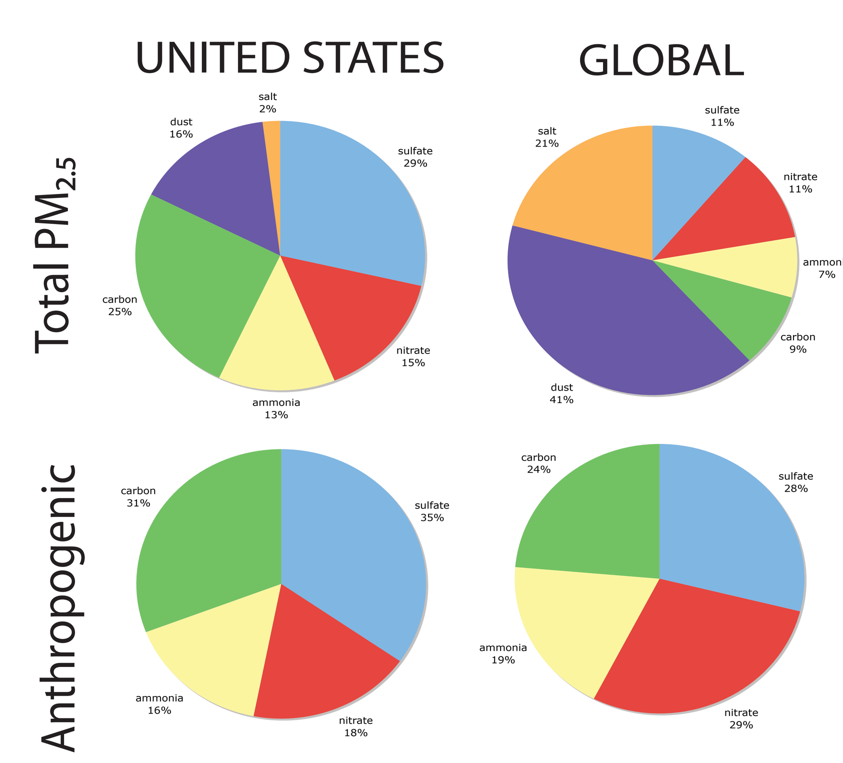

Figure 4: Population-weighted PM2.5 by component from GEOS-Chem

3. UNCERTAINTIES IN HEALTH IMPACTS AND VALUATION

For health outcomes and acute mortality, we take into account costs to labor and services and simulate their influence on the rest of the economy [5]. For chronic mortality, we assess the continuing impact of mortalities (2000-2005, with exposures assumed constant) on the 2005 economy. We assume linearity without threshold for E-R functions. Costs are adjusted by purchasing power parity for other regions [6].

	Exposure-Response Function	5%-95% Confidence Interval	Cost ($US y2000)	Standard Error Cost ($)
ENTIRE POPULATION				
Respiratory hospital admissions	7.03E-06	(3.83E-06, 1.03E-05)	2000	670
Cerebrovascular hospital admissions	5.04E-06	(3.88E-07, 9.69E-06)	2000	670
Cardiovascular hospital admissions	4.34E-06	(2.17E-06, 6.51E-06)	2000	670
Acute mortality	0.06%	(0.04%, 0.08%)	25000	1850
Chronic mortality	0.25%	(0.02%, 0.48%)	calculated	
CHILDREN				
Chronic bronchitis	1.61E-03	(1.24E-04, 3.10E-03)	360	123
Chronic cough	2.07E-03	(1.59E-04, 3.98E-03)	38	13
Respiratory symptoms days	1.86E-01	(9.20E-02, 2.77E-01)	38	13
Bronchodilator usage	1.80E-02	(-6.90E-02, 1.06E-01)	1	0.33
Cough	1.33E-01	(2.30E-02, 2.43E-01)	38	13
Lower respiratory symptoms (wheeze)	1.86E-01	(9.20E-02, 2.77E-01)	38	13
ADULTS				
Restricted activity day	5.41E-02	(4.75E-02, 6.08E-02)	82	27
Minor restricted activity days	3.46E-02	(2.81E-02, 4.12E-02)	38	13
Respiratory symptoms days	1.30E-01	(1.5E-02, 2.43E-01)	38	13
Chronic bronchitis	2.65E-05	(-1.90E-06, 5.41E-05)	190000	63000
Bronchodilator usage	9.12E-02	(-9.12E-02, 2.77E-01)	1	0.33
Cough	1.68E-01	(2.91E-02, 3.07E-01)	38	13
Lower respiratory symptoms (wheeze)	1.30E-01	(1.50E-02, 2.43E-01)	38	13
OVER AGE 65				
Congestive heart failure	1.85E-05	(1.42E-06, 3.56E-05)	12000	925
Ischaemic heart disease	1.75E-05	(1.35E-06, 3.37E-05)	12000	925

Units for E-R factors: cases yr^{-1} person μg^{-1} m^3, except for acute mortality (Δ annual mortality rate μg^{-1} m^3). Costs are per case.

Table 1. E-R factors, Costs & Uncertainties [11,12]

4. COMPARING RELATIVE UNCERTAINTIES

We use a Monte Carlo approach [13] (n=400) to quantitatively assess uncertainties in E-R functions and economic valuation of health impacts. We assume that exposure-response functions and costs are normally distributed, taking into account correlations among E-R functions and costs.
We find that the variation in concentration estimates covers a similar sample space as variation in health impacts and valuation. The mean annual global welfare loss from PM2.5, calculated using satellite data is $US 300 billion.

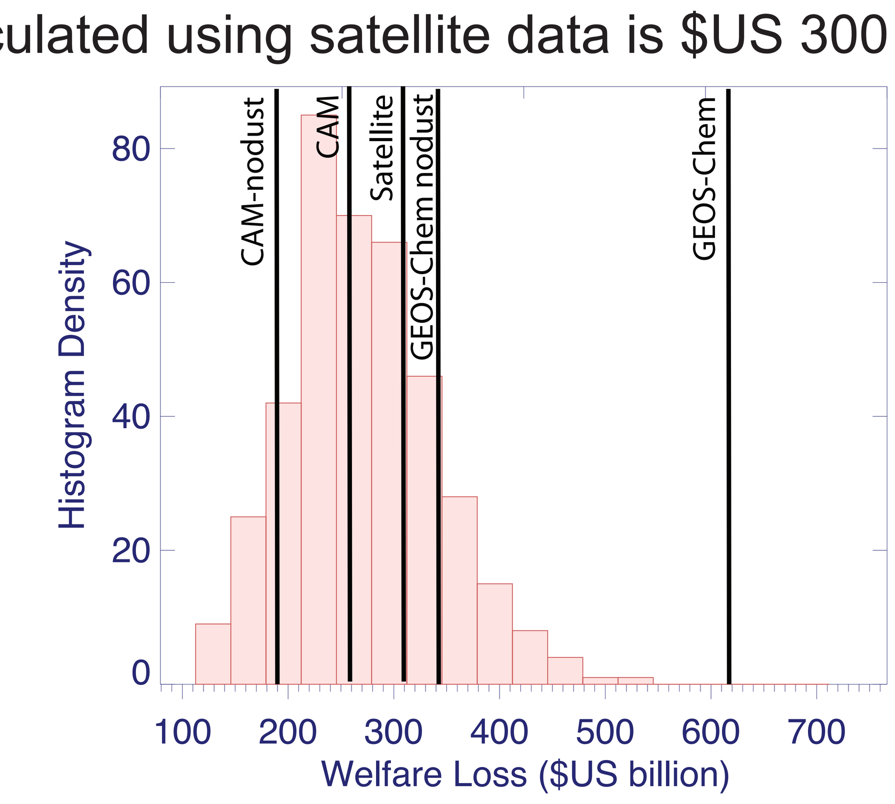

Figure 5: Uncertainty in welfare losses; histogram presents uncertainty results for satellite data

5. UNQUANTIFIABLE UNCERTAINTIES

We assess here the relative importance of errors from PM concentration estimates relative to those from exposure-response functions and the costs of health impacts. We do not account for other sources of uncertainty, such as the shape of the exposure-response function or errors in underlying data (such as mortality rates or population data). In addition, the damages from PM will continue to compound and affect the economy long into the future.
Many aspects of the uncertainty in PM health impacts cannot be quantified at this time:
--the error in using area concentrations as a proxy for exposure
--the errors in applying E-R functions from the US and Europe to other countries (particularly developing countries)
--the degree to which damages are modified by differential access to health care
--the unknown health impacts of aerosols such as dust and sea salt
These and other uncertainties should be addressed in future research.

6. REFERENCES

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