A Brief History of Air Pollution and Health

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Atmospheric and Climate Science for PH

October 22, 2019

Overview

- Background and Introduction
- Methods for Air Pollution Epidemiology
- Landmark Cohort Studies
- Exposure Assessment
- Health Impact Assessment

THE LANCET

The Global Burden of Disease 2015

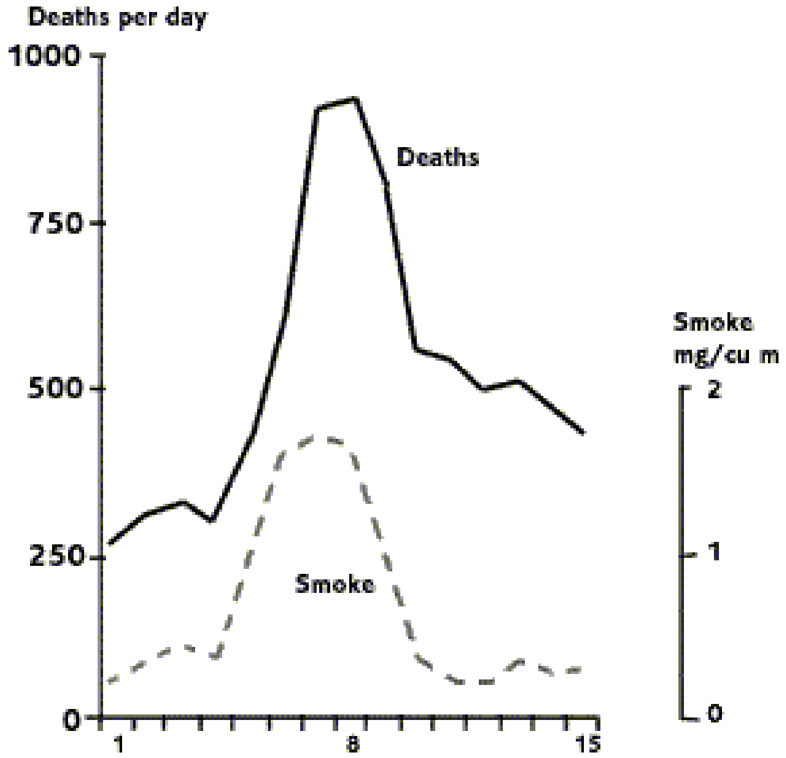
Breathing contaminates contributes to global burden of disease (GBD)

	Number of attributable deaths	
Tobacco Smoking	6.4 mil.	
Second Hand Smoke	0.9 mil.	
$PM_{2.5}$ air pollution	4.2 mil.	
Household air pollution from solid fuels	2.9 mil.	
Ambient Ozone	0.2 mil.	

Is this even believable??

Donora Smog (1948)

London Smog (1952)



NYC Smog (1966)

Examples of Catastrophic Air Pollution

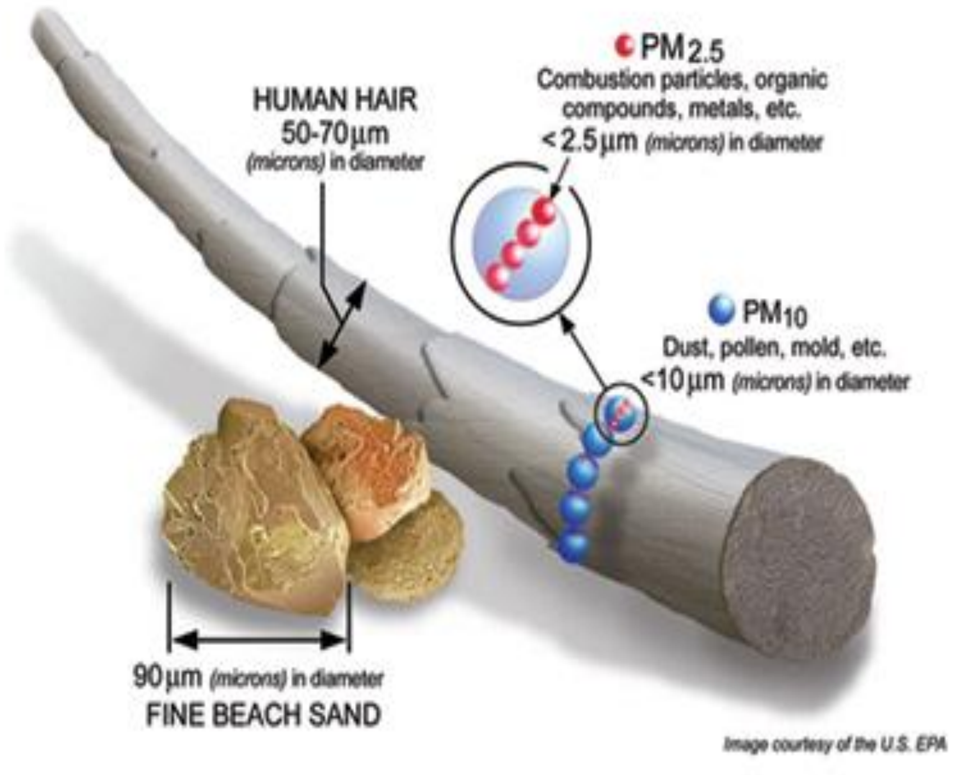
- **1911** in London – 1,150 died from effects of coal smoke. The term “smog” was coined to describe the mix of smoke and fog that hung over London at the time
- **1948** in Donora, Pennsylvania – 20 died and over 6,000 were ill from smog emitted from community’s steel mill, zinc smelter, and sulfuric acid plant
- **1952** in London – Caused by a severe air inversion resulting in a build up of SO_2 and PM. Over 4,000 deaths
- **1966** in New York City – 168 people died from air pollution

Clean Air Act

- Signed into law in 1963, amendments in in the 70s and 90s
- One of the most comprehensive air quality laws in the world
- Established the HAPs and CAPs
  - HAPs: **H**azardous **A**ir **P**ollutants: a list of 170+ chemicals considered harmful to human health
  - CAPs: **C**riteria **A**ir **P**ollutant: six high priority air pollutants with common point sources (ozone, **particulate matter**, lead, carbon monoxide, sulfur oxides, and nitrogen oxides)

Particulate Matter (PM)

- A complex air mixture of solid particles and liquid droplets. Components include:
  - Acids (nitrates, sulfates)
  - Organic chemicals
  - Metals
  - Soil, dust particles
- Common sources:
  - Primary emissions: dust, fuel combustion, motor vehicles, industrial processes, fires
  - Secondary formation in the atmosphere (chemistry!)
- PM is grouped into size-dependent categories:
  - Inhalable coarse particles (PM_{10})
  - Fine particles ($PM_{2.5}$)



Adapted from Kioumourtzoglou (2019)

Air Pollution Epidemiology

- Associations between exposures of air pollution and health endpoints
- Methods are somewhat complex, but can be roughly divided into two categories:
  - Short-term (acute) effects
  - Long-term (chronic) effects

Methods for Air Pollution Epidemiology

- Studies of short-term exposure (hours-days)
  - Episode
  - Population-based daily time-series
  - Panel-based acute exposure
  - Case-crossover
- Studies of long-term exposure (years-decades)
  - Population-based cross-sectional
  - Cohort-based mortality
  - Cohort- and panel-based morbidity
  - Case-control studies
  - (Population based monthly/annual time-series)
- Intervention/natural experiment (months-years)
- Controlled experimental human and animal

Adapted from C. Arden Pope III (2016)

Time-Series Epidemiology

- Usually addresses short-term, acute effects of air pollution
- Involves analysis of a series of daily observations of air pollution and health data
- Widely used and economical approach, often utilizing readily-available data
- Most air pollution epidemiology studies have followed this design

Daily Time-Series Studies

Environmental Science & Technology

Article

Cite This: *Environ. Sci. Technol.* 2018, 52, 11378–11386

pubs.acs.org/est

Fine Particle Constituents and Mortality: A Time-Series Study in Beijing, China

Chen Chen,[†] Dandan Xu,[†] Mike Z. He,[‡] Yanwen Wang,[†] Zonghao Du,[†] Yanjun Du,[†] Yan Qian,[§] Dongsheng Ji,[||] and Tiantian Li[*,†]

JIM Original Article

doi: 10.1111/joim.12724

Acute effect of multiple ozone metrics on mortality by season in 34 Chinese counties in 2013–2015

Q. Sun[1], W. Wang[1], C. Chen[1], J. Ban[1], D. Xu[1], P. Zhu[1], M. Z. He[2] & T. Li[1]

From the [1]Chinese Center for Disease Control and Prevention, National Institute of Environmental Health Sciences, Beijing, China; and [2]Department of Environmental Health Sciences, Columbia University Mailman School of Public Health, New York, NY, USA

Poisson Regression

- Counts of independent and random occurrences classically modeled as being generated by a Poisson distribution:

$$\text{Prob}\,(Y = r) \;=\; e^{(-\lambda)}\,\frac{\lambda^r}{r!}$$

- One form of a log-linear model

$$\ln \lambda_t \;=\; \alpha + \beta(w_0P_t + w_1P_{t-1} + w_2P_{t-2} + \ldots) + s^1(t) + s^2(\text{temp}_t) + \ldots$$

Modeling controversies

How to construct the lag structure? (MA, PDL, etc.)

How aggressive do you fit time? (harmonics vs GAMs, df, span, loess, cubic spline, etc.)

How to control for weather? (smooths of temp & RH, synoptic weather, etc.)

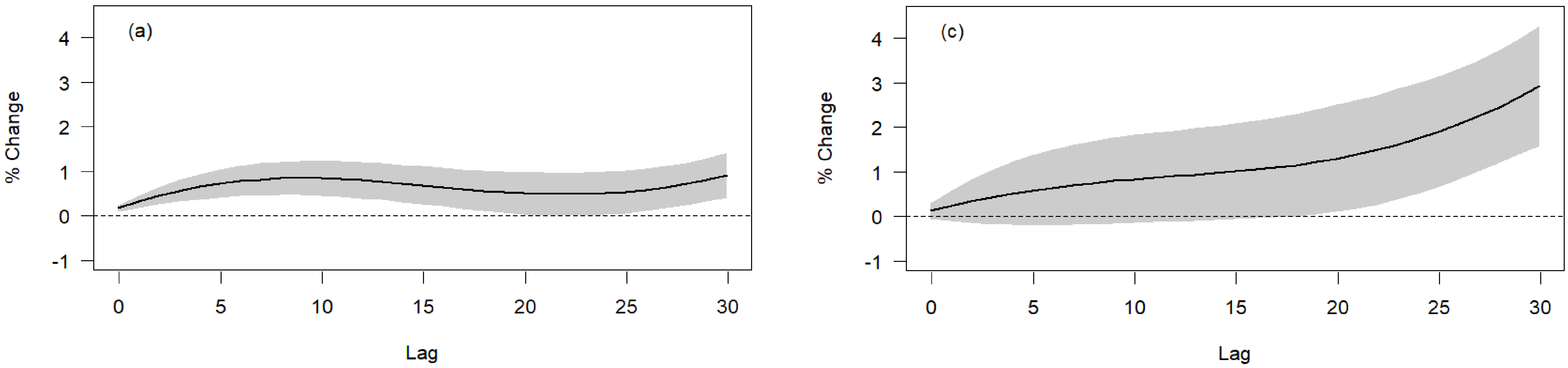
Also: How to combine or integrate information from multiple cities

Adapted from C. Arden Pope III (2016)

Studies are not just daily!

Title: Short- and intermediate- term exposure to NO_2 and mortality: a multi-county analysis in China

Authors: Mike Z. He[a], Patrick L. Kinney[b], Tiantian Li[c*], Chen Chen[c], Qinghua Sun[c], Jie Ban[c], Jiaonan Wang[c], Siliang Liu[a], Jeff Goldsmith[d], Marianthi-Anna Kioumourtzoglou[a]



Panel-Based Acute Exposure

- Panel study: a longitudinal study of a cohort of people with multiple measures over time
- Different from a normal cohort study:
  - Limited sampling with respect to exposure
  - No guarantee of specific outcome (or lack of outcome)
  - In fact, disease/outcome of interest are not specified
  - They are just a group of people progressing through time towards undetermined outcomes...
- Statistical analysis: mixed effect models

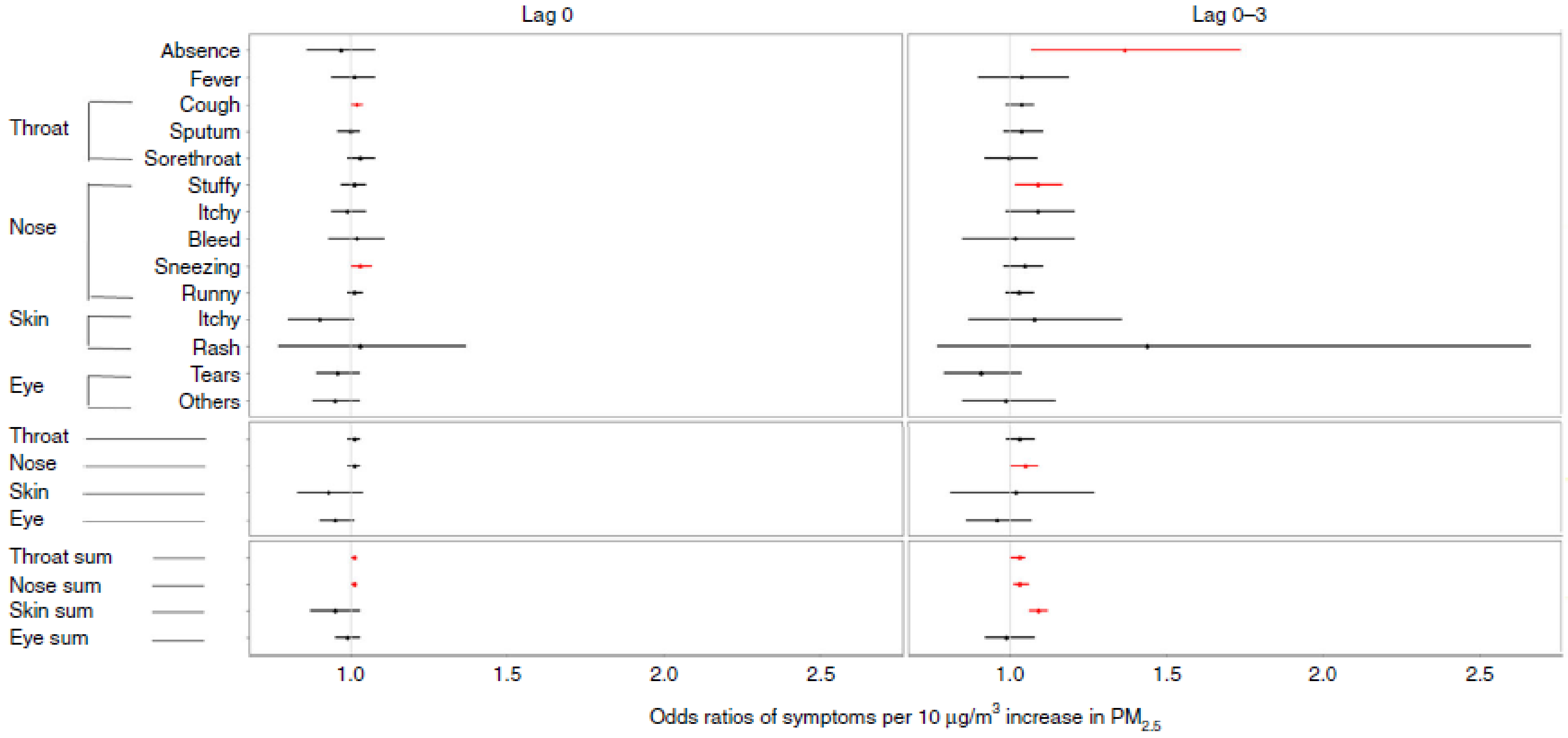
www.nature.com/pr

Pediatric RESEARCH

POPULATION STUDY ARTICLE

The association of ambient $PM_{2.5}$ with school absence and symptoms in schoolchildren: a panel study

Yi Zhang[1], Liangliang Cui[2], Dandan Xu[1], Mike Z. He[3], Jingwen Zhou[2], Lianyu Han[4], Xinwei Li[2] and Tiantian Li[1]



Cohort-Based Mortality

- Address longer-term, more chronic effects
- Approach:
  - Large populations in multiple cities enrolled and then followed for many years to determine disease or mortality experience
  - Must control for potential "spatial" confounders, e.g., smoking, income, race, diet, occupation
  - Assessment of confounders at individual level is an advantage over cross-sectional, "ecologic" studies
- $$$

Cox Proportional Hazards Survival Model

- Cohort studies of ambient air pollution have commonly used a Cox model to relate survival experience to exposure while simultaneously controlling for other well known mortality risk factors.
- The model has the form:

$$\lambda_i^{(l)}(t) = \lambda_0^{(l)}(t)\, exp\left(\beta^T x_i^{(l)}(t)\right)$$

Hazard function or instantaneous probability of death for the *i*th subject in the *l*th strata.

Baseline hazard function, common to all subjects within a strata.

Regression equation that modulates the baseline hazard. The vector $X_i^{(l)}$ contains the risk factor information related to the hazard function by the regression vector β which can vary in time.

The New England
Journal of Medicine

Volume 329 DECEMBER 9, 1993 Number 24

AN ASSOCIATION BETWEEN AIR POLLUTION AND MORTALITY IN SIX U.S. CITIES

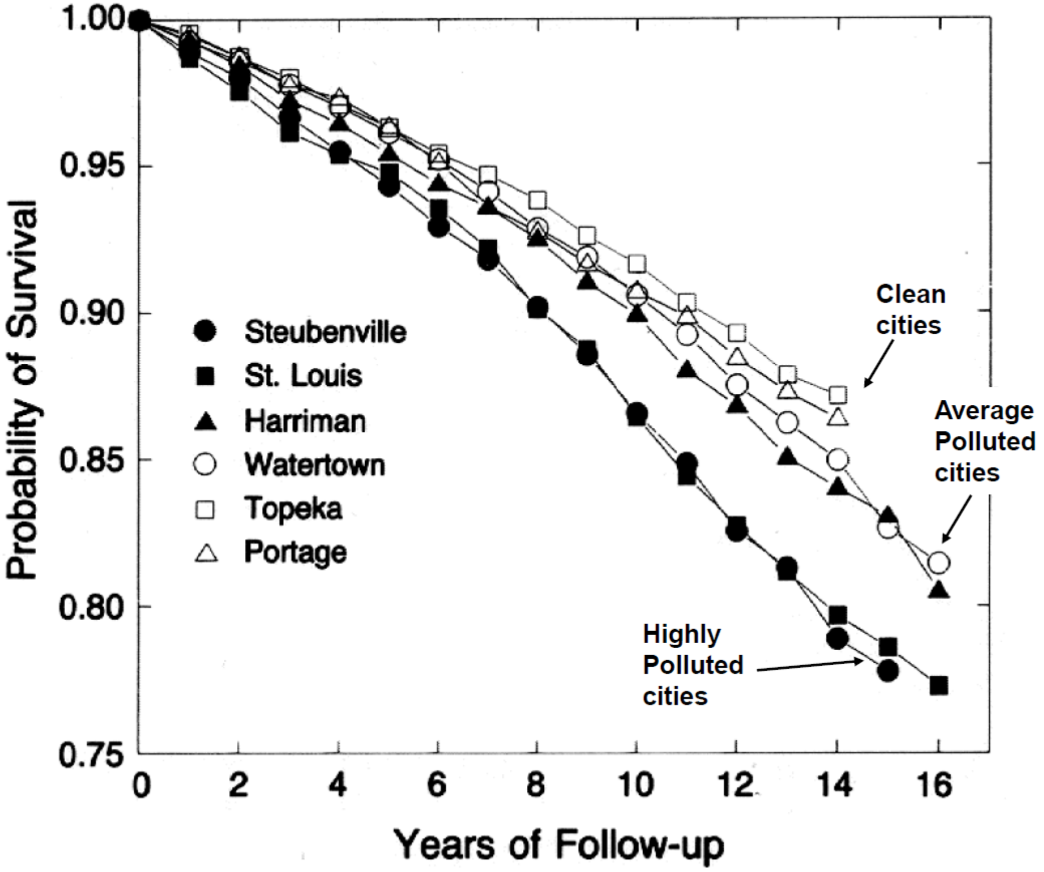
DOUGLAS W. DOCKERY, SC.D., C. ARDEN POPE III, PH.D., XIPING XU, M.D., PH.D.,
JOHN D. SPENGLER, PH.D., JAMES H. WARE, PH.D., MARTHA E. FAY, M.P.H.,
BENJAMIN G. FERRIS, JR., M.D., AND FRANK E. SPEIZER, M.D.

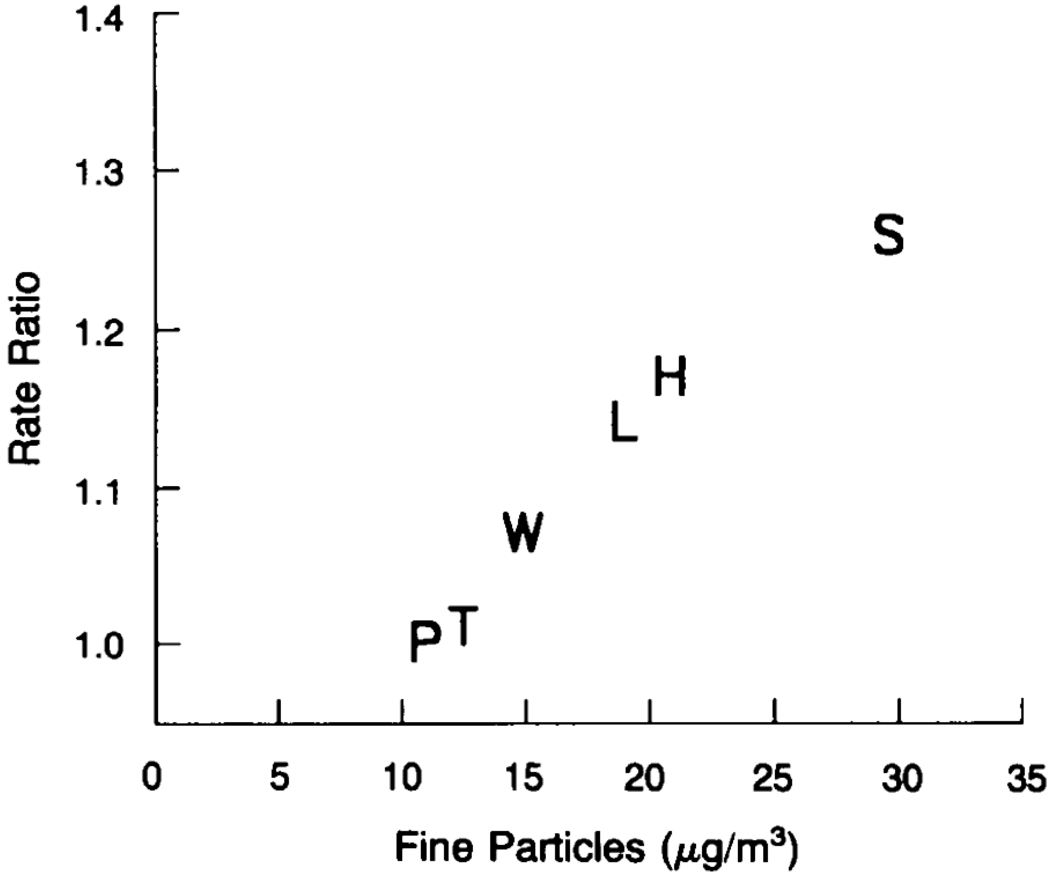
Harvard Six Cities Study

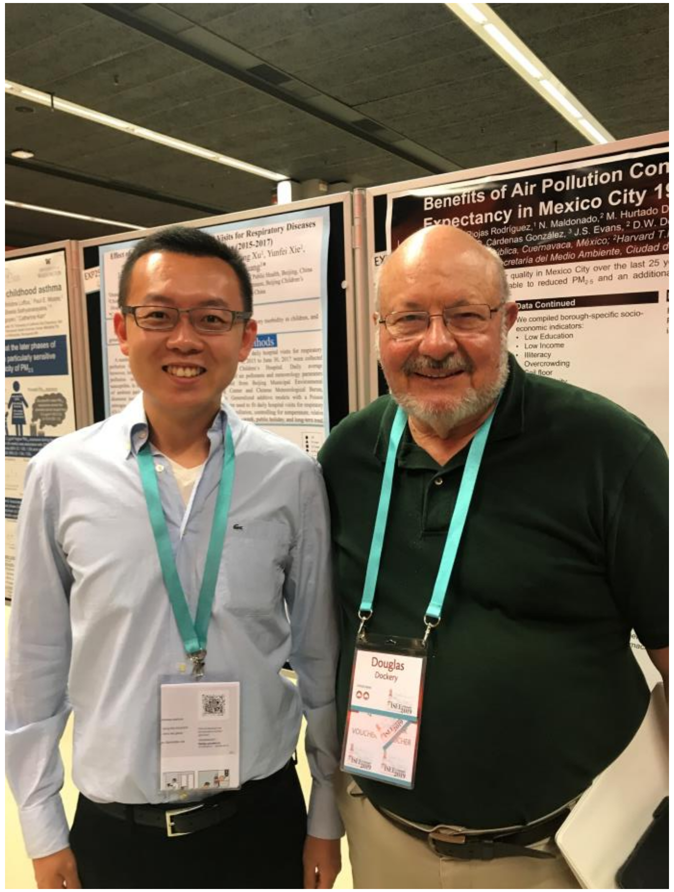
- 14-16 year prospective follow-up of 8,111 adults living in six U.S. cities
- Monitoring of TSP PM_{10}, $PM_{2.5}$, SO_4, H^+, SO_2, NO_2, O_3
- Data analyzed using survival analysis, including Cox Proportional Hazards Models
- Controlled for individual differences in: age, sex, smoking, BMI, education, occupational exposure.

Adapted from C. Arden Pope III (2016)

Harvard Six Cities Study






Data Continued
We compiled borough-specific socio-economic indicators:
Low Education
Low Income
Illiteracy
Overcrowding
Douglas
Dockery


gettyimages
Chris Jackson
83237993

JAMA®
The Journal of the American Medical Association
March 6, 2002—Vol 287, No. 9

Lung Cancer, Cardiopulmonary Mortality, and Long-term Exposure to Fine Particulate Air Pollution

C. Arden Pope III, PhD
Richard T. Burnett, PhD
Michael J. Thun, MD
Eugenia E. Calle, PhD
Daniel Krewski, PhD
Kazuhiko Ito, PhD
George D. Thurston, ScD

Context Associations have been found between day-to-day particulate ai and increased risk of various adverse health outcomes, including cardiopulmc tality. However, studies of health effects of long-term particulate air pollu been less conclusive.

Objective To assess the relationship between long-term exposure to fir late air pollution and all-cause, lung cancer, and cardiopulmonary mortalit

Design, Setting, and Participants Vital status and cause of death data lected by the American Cancer Society as part of the Cancer Prevention II stu going prospective mortality study, which enrolled approximately 1.2 million adu



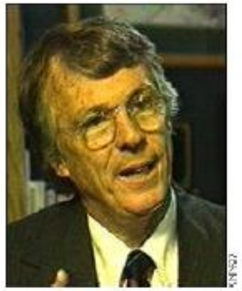




Table 2. Adjusted Mortality Relative Risk (RR) Associated With a 10-μg/m³ Change in Fine Particles Measuring Less Than 2.5 μm in Diameter

	Adjusted RR (95% CI)*		
Cause of Mortality	**1979-1983**	**1999-2000**	**Average**
All-cause	1.04 (1.01-1.08)	1.06 (1.02-1.10)	1.06 (1.02-1.11)
Cardiopulmonary	1.06 (1.02-1.10)	1.08 (1.02-1.14)	1.09 (1.03-1.16)
Lung cancer	1.08 (1.01-1.16)	1.13 (1.04-1.22)	1.14 (1.04-1.23)
All other cause	1.01 (0.97-1.05)	1.01 (0.97-1.06)	1.01 (0.95-1.06)

*Estimated and adjusted based on the baseline random-effects Cox proportional hazards model, controlling for age, sex, race, smoking, education, marital status, body mass, alcohol consumption, occupational exposure, and diet. CI indicates confidence interval.

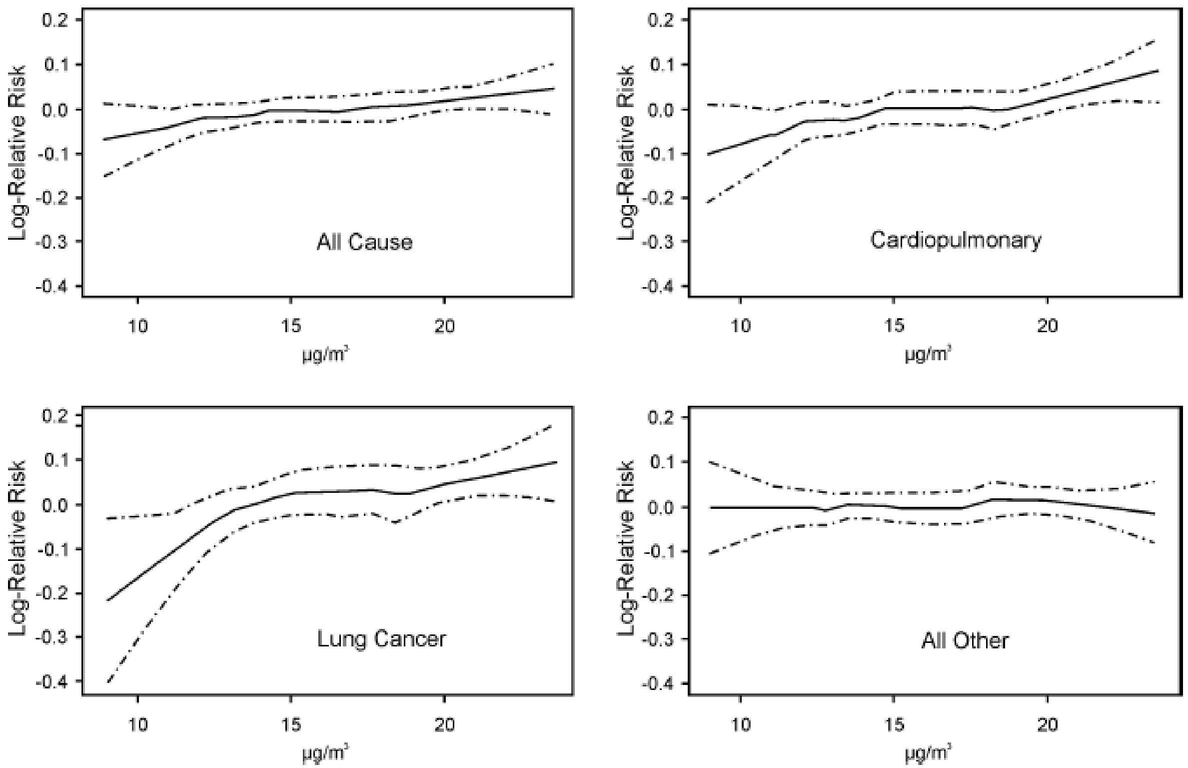


Figure 8-9. Natural logarithm of relative risk for total and cause-specific mortality per 10 μg/m³ $PM_{2.5}$ (approximately the excess relative risk as a fraction), with smoothed concentration-response functions. Based on Pope et al. (2002) mean curve (solid line) with pointwise 95% confidence intervals (dashed lines).

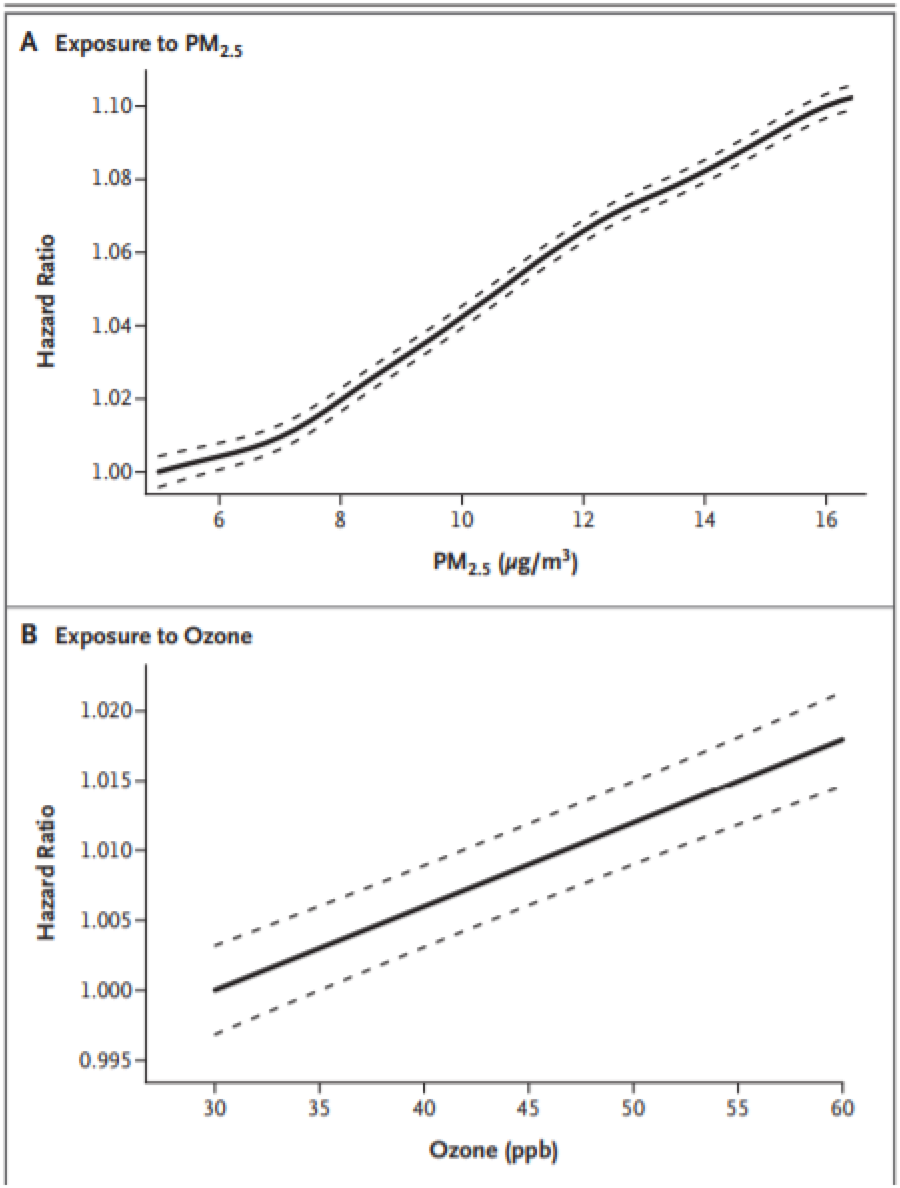
The NEW ENGLAND JOURNAL of MEDICINE

ESTABLISHED IN 1812 JUNE 29, 2017 VOL. 376 NO. 26

Air Pollution and Mortality in the Medicare Population

Qian Di, M.S., Yan Wang, M.S., Antonella Zanobetti, Ph.D., Yun Wang, Ph.D., Petros Koutrakis, Ph.D., Christine Choirat, Ph.D., Francesca Dominici, Ph.D., and Joel D. Schwartz, Ph.D.

- All of Medicare from 2000-2012
- 60,925,443 Medicare beneficiaries
- 460,310,521 person-years of follow-up
- HR = 1.08



Adapted from C. Arden Pope III (2016)

Harvard Six-Cities Study
Dockery et al. *New England Journal of Medicine (NEJM)*, **1993**

ACS CPS-II Cohort Study
Pope, et al. *Am J Respir Crit Care Med (AJRCCM)*, **1995**

Independent Re-analyses of Harvard Six-Cities and ACS CPS-II Studies
Krewski et al. HEI Special Report , **2000**; *J Tox Enviro Health*, Special Issue, **2003**

- 3-yr reanalysis by a team of 31 independent researchers with oversight from a 9-member expert panel and peer review by a special panel of the HEI Health Review Committee.
- Included full data access that insured the privacy and confidentiality of research participants.
- Re-analyses include data audits, full replication and validation, and extensive sensitivity analyses.

Extended analyses of Harvard Six-Cities study
Laden et al. *AJRCCM*, **2006**
Schwartz et al. *EHP*, **2008**
Lepeule et al. *EHP*, **2012**

Extended analyses of ACS CPS-II study
Pope et al. *JAMA*, **2002**; Pope et al. *Circulation*, **2004**; Jerrett et al. *Epidemiology*, **2005**; Krewski et al. HEI Rep. **2009**; Jerrett et al. *NEJM*, **2009**; Smith et al. *Lancet*, **2009**; Turner et al. *AJRCCM*, **2011**; Jerrett et al. *AJRCCM*, **2013**; Turner et al. AJE **2014**; Pope et al. *Circ. Res*, **2015**; Thurston et al. EHP 2016; Jerrett et al. EHP, **2017**

Replicative studies in many other cohorts:
German Women: Gehring et al. Epi, 2006
Women's Health Initiative: Miller et al. *NEJM*, 2007
Netherlands: Beelen et al. *EHP,* 2008
U.S. Medicare: Zeger et al. *EHP*, 2008
Nurses Health Study: Puett et al. *EHP*, 2009
Health Professionals: Puett et al. *EHP*, 2011
U.S. Truckers: Hart et al. *AJRCCM*, 2011
California Teachers: Lipsett et al. *AJRCCM*, 2011
Vancouver: Gan et al. EHP, 2011
China: Cao et al. J Hazard Mater. 2011
China: Zhang et al. PLoS One, 2012
Canadian: Crouse et al. *EHP*, 2012
New Zealand: Hales et al. J Epi Com Health, 2012
Rome: Cesaroni et al. *EHP*, 2013
National English: Carey et al. AJRCCM, 2013
22 European: Beelen et al Lancet, 2014
Ag. Health Study: Weichenthal et al. EHP 2014
Canadian Women : Villeneuve et al. Epi. 2015
CanCHEC (Canadian): Crouse et al. EHP 2015
Nurses Health: Hart et al. Environ Health 2015
Elderly Hong Kong: Wong et al. EHP 2015
Taiwan: Tseng et al. BMC Public Health 2015
Dutch (DUELS): Fischer et al. EHP 2015
France: Bentayeb et al. Environ Int. 2015
Canadian Com. Health: Pinault et al. EH 2016
U.S. Medicare: Kioumourtzoglou et al. *EHP*, 2016
NIH-AARP Diet and Health: Thurston et al. EHP, 2016
U.S. Medicare: Di et al. *NEJM*, 2017
Chinese Male: Yin et al. EHP, 2017
U.S. NHIS: Pope et al. AQ&AH 2017
U.S. NHIS: Parker et al. Circulation 2018 . . . .

The NEW ENGLAND JOURNAL of MEDICINE

ESTABLISHED IN 1812 AUGUST 22, 2019 VOL. 381 NO. 8

Ambient Particulate Air Pollution and Daily Mortality in 652 Cities

C. Liu, R. Chen, F. Sera, A.M. Vicedo-Cabrera, Y. Guo, S. Tong, M.S.Z.S. Coelho, P.H.N. Saldiva, E. Lavigne, P. Matus, N. Valdes Ortega, S. Osorio Garcia, M. Pascal, M. Stafoggia, M. Scortichini, M. Hashizume, Y. Honda, M. Hurtado-Díaz, J. Cruz, B. Nunes, J.P. Teixeira, H. Kim, A. Tobias, C. Íñiguez, B. Forsberg, C. Åström, M.S. Ragettli, Y.-L. Guo, B.-Y. Chen, M.L. Bell, C.Y. Wright, N. Scovronick, R.M. Garland, A. Milojevic, J. Kyselý, A. Urban, H. Orru, E. Indermitte, J.J.K. Jaakkola, N.R.I. Ryti, K. Katsouyanni, A. Analitis, A. Zanobetti, J. Schwartz, J. Chen, T. Wu, A. Cohen, A. Gasparrini, and H. Kan

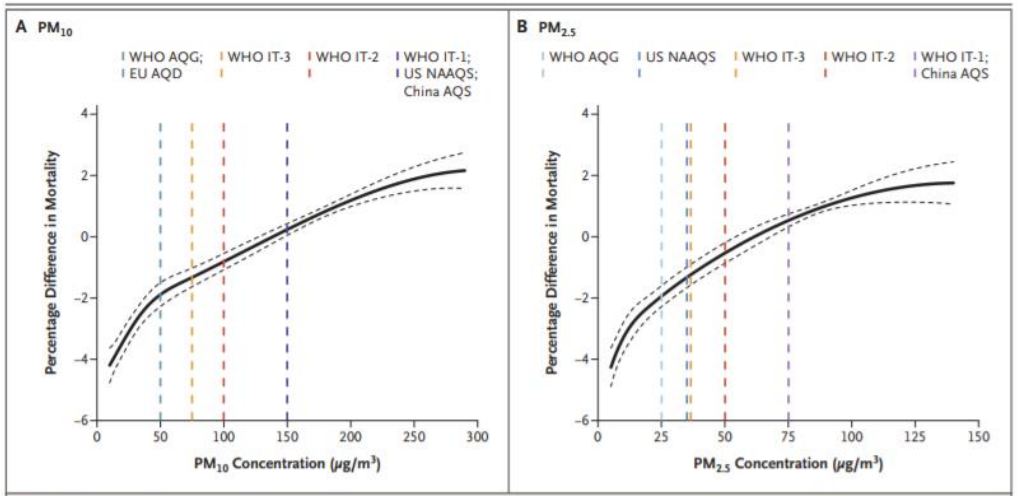


Figure 3. Pooled Concentration–Response Curves.

Shown are the pooled concentration–response curves for the associations of 2-day moving average concentrations of PM_{10} (Panel A) and $PM_{2.5}$ (Panel B) with daily all-cause mortality. The y axis represents the percentage difference from the pooled mean effect (as derived from the entire range of PM concentrations at each location) on mortality. Zero on the y axis represents the pooled mean effect, and the portion of the curve below zero denotes a smaller estimate than the mean effect. The dashed lines represent the air-quality guidelines or standards for 24-hour average concentrations of PM_{10} or $PM_{2.5}$ according to the World Health Organization Air Quality Guidelines (WHO AQG), WHO Interim Target 1 (IT-1), WHO Interim Target 2 (IT-2), WHO Interim Target 3 (IT-3), European Union Air Quality Directive (EU AQD), U.S. National Ambient Air Quality Standard (NAAQS), and China Air Quality Standard (AQS).

Table 1. Percentage Change in All-Cause Mortality per 10-μg-per-Cubic-Meter Increase in 2-Day Moving Average Concentrations of Inhalable Particulate Matter (PM_{10}) and Fine Particulate Matter ($PM_{2.5}$).*

Country or Region	PM_{10}		$PM_{2.5}$	
	Cities with Available Data	Pooled Estimate	Cities with Available Data	Pooled Estimate
	no.	*% (95% CI)*	*no.*	*% (95% CI)*
Australia	3	1.32 (0.22 to 2.44)	3	1.42 (−0.12 to 2.99)
Brazil	1	1.22 (0.97 to 1.47)	0	NA
Canada	13	0.76 (0.25 to 1.27)	25	1.70 (1.17 to 2.23)
Chile	4	0.33 (0.14 to 0.53)	4	0.27 (−0.68 to 1.23)
China	272	0.28 (0.22 to 0.34)	272	0.41 (0.32 to 0.50)
Colombia	1	0.03 (−0.34 to 0.39)	0	NA
Czech Republic	1	0.40 (−0.02 to 0.82)	0	NA
Estonia	4	0.46 (−0.69 to 1.63)	3	0.23 (−4.24 to 4.90)
Finland	1	0.07 (−0.51 to 0.65)	1	0.14 (−0.55 to 0.83)
France	18	0.46 (−0.15 to 1.07)	0	NA
Greece	1	0.53 (0.17 to 0.90)	1	2.54 (1.28 to 3.83)
Italy	18	0.65 (0.26 to 1.04)	0	NA
Japan	47	1.05 (0.78 to 1.31)	47	1.42 (1.05 to 1.81)
Mexico	8	0.67 (0.48 to 0.86)	3	1.29 (0.21 to 2.39)
Portugal	2	0.11 (−0.27 to 0.49)	1	0.03 (−1.14 to 1.21)
South Africa	6	0.41 (0.14 to 0.68)	5	0.80 (0.16 to 1.44)
South Korea	7	0.42 (0.27 to 0.58)	0	NA
Spain	45	0.87 (0.60 to 1.15)	19	1.96 (1.18 to 2.75)
Sweden	1	0.20 (−1.03 to 1.44)	1	0.08 (−1.44 to 1.62)
Switzerland	8	0.47 (−0.36 to 1.31)	4	0.79 (−0.96 to 2.58)
Taiwan	3	0.25 (−0.03 to 0.53)	3	0.62 (−0.39 to 1.64)
Thailand	19	0.61 (0.24 to 0.99)	0	NA
United Kingdom	15	0.06 (−0.36 to 0.48)	0	NA
United States	100	0.79 (0.60 to 0.98)	107	1.58 (1.28 to 1.88)
Total	598	0.44 (0.39 to 0.50)	499	0.68 (0.59 to 0.77)

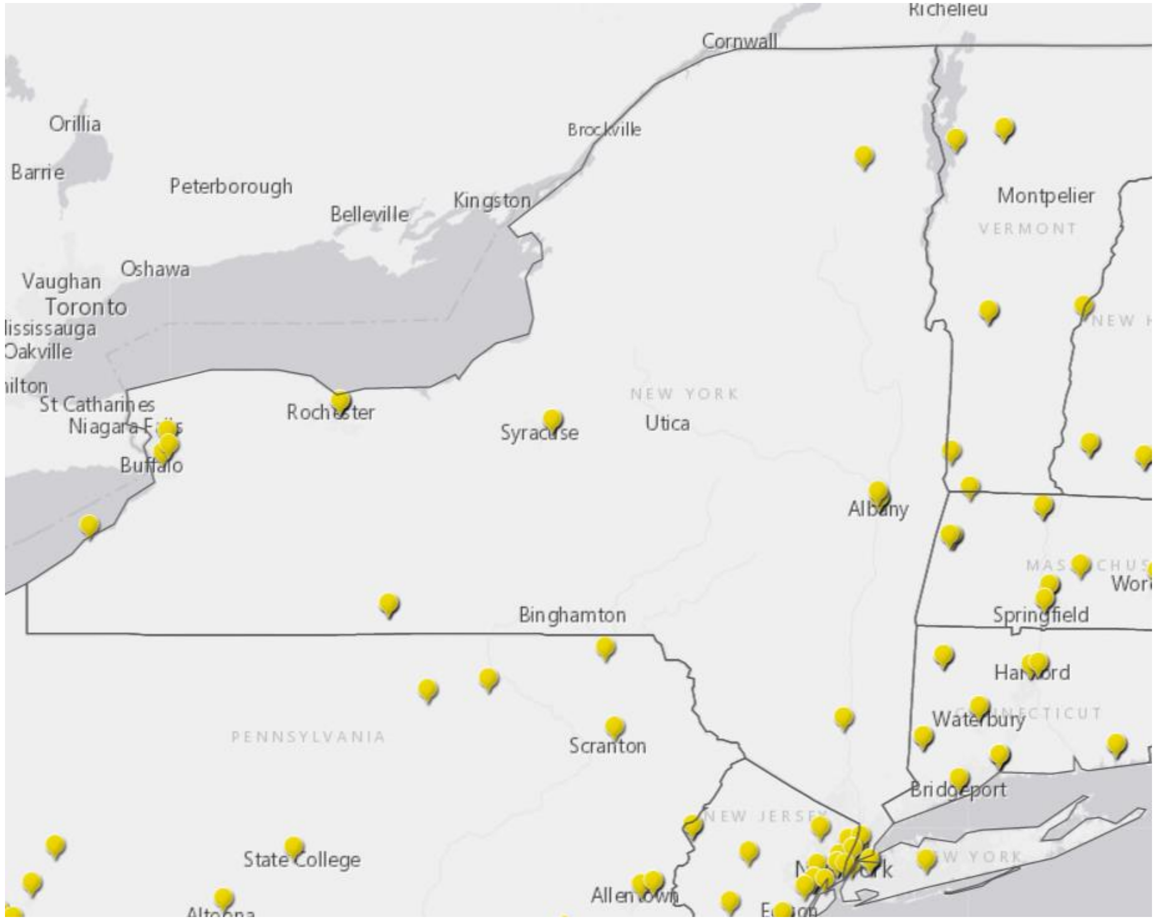
Exposure Assessment

- We need air pollution measurements for air pollution epi
- How do we measure air pollutant concentrations?
- Historically, we used monitoring data

AQS Monitors in the United States ($PM_{2.5}$)

https://www.epa.gov/outdoor-air-quality-data/interactive-map-air-quality-monitors

AQS Monitors in New York State ($PM_{2.5}$)



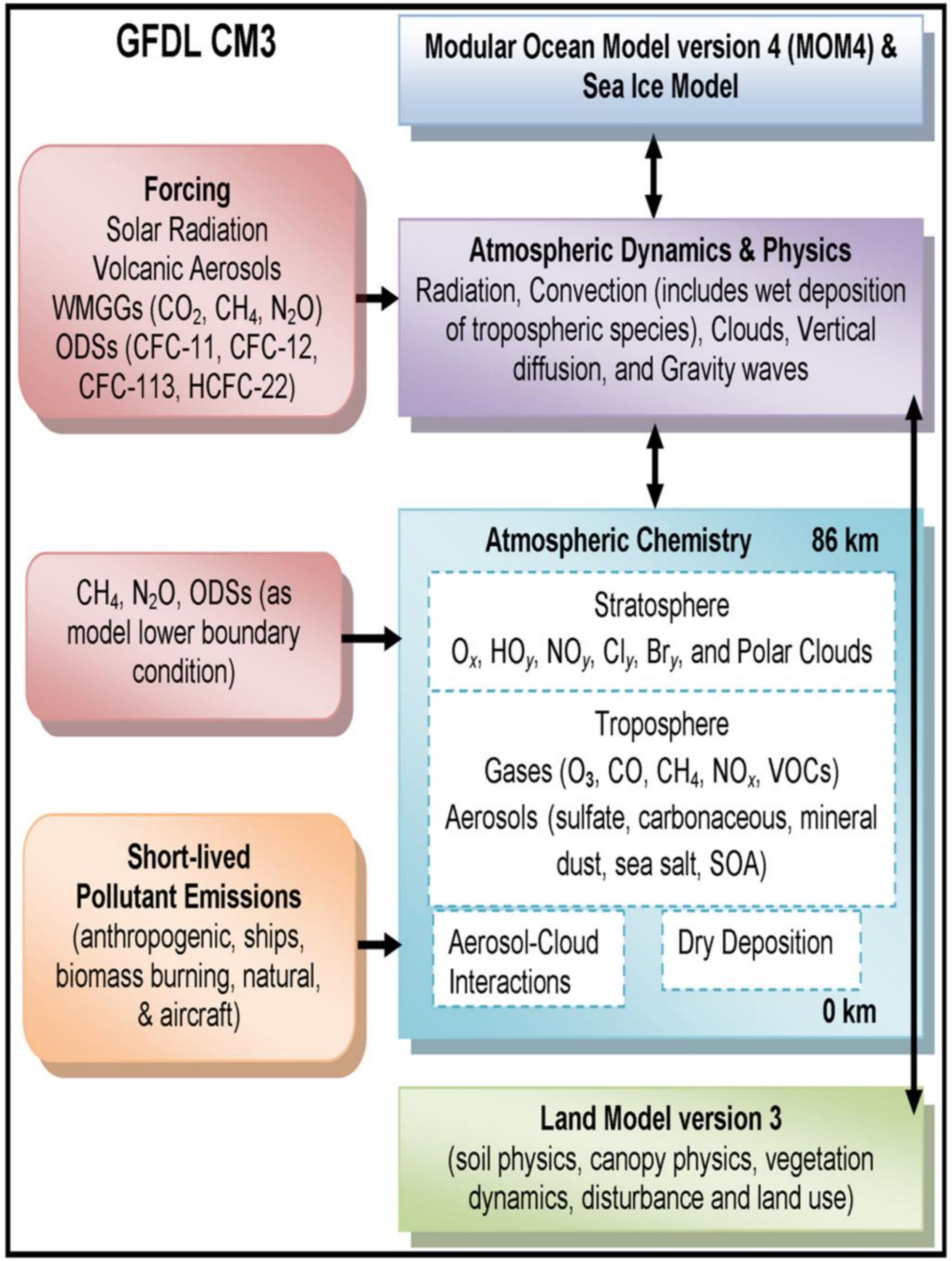
https://www.epa.gov/outdoor-air-quality-data/interactive-map-air-quality-monitors

Prediction Models

- Increasing use of prediction models to reduce exposure measurement error and include populations in areas without monitors
- Models predict both spatial and temporal changes in air pollution
- Initially, models were “simple”
  - Land use regression models
  - Generalized additive mixed models
- More recently, more sophisticated models
  - Fuse remote sensing data, predictions from chemical transport models, etc.
  - More robust methods for higher predictive accuracy (e.g. random forests, neural networks, ensembles)
  - Higher spatial and temporal resolution

How do these models work?

- Mathematical representations of the planet
- Starts with the basics:
  - Thermodynamics
  - Blackbody radiation
  - Atmospheric chemistry
  - Cloud microphysics
- Each adds his/her own “sophisticated” parts into the mix…


GFDL CM3
Modular Ocean Model version 4 (MOM4) & Sea Ice Model
Forcing
Solar Radiation
Volcanic Aerosols
WMGGs (CO_2, CH_4, N_2O)
ODSs (CFC-11, CFC-12, CFC-113, HCFC-22)
Atmospheric Dynamics & Physics
Radiation, Convection (includes wet deposition of tropospheric species), Clouds, Vertical diffusion, and Gravity waves
CH_4, N_2O, ODSs (as model lower boundary condition)
Atmospheric Chemistry
86 km
Stratosphere
O_x, HO_y, NO_y, Cl_y, Br_y, and Polar Clouds
Troposphere
Gases (O_3, CO, CH_4, NO_x, VOCs)
Aerosols (sulfate, carbonaceous, mineral dust, sea salt, SOA)
Short-lived Pollutant Emissions
(anthropogenic, ships, biomass burning, natural, & aircraft)
Aerosol-Cloud Interactions
Dry Deposition
0 km
Land Model version 3
(soil physics, canopy physics, vegetation dynamics, disturbance and land use)

The Community Multiscale Air Quality Model (CMAQ)

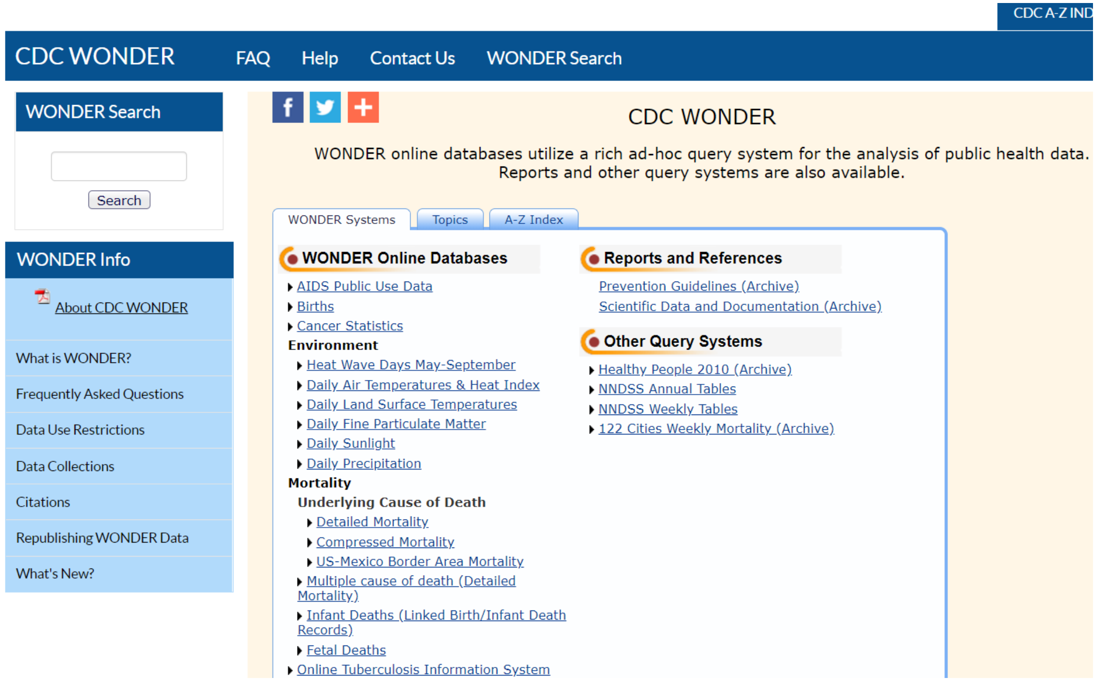
- Atmospheric dispersion model developed by US EPA
- Goal is to address regional air pollution problems
- 12x12 km^2 grids

Fused Air Quality Surface Using Downscaling (FAQSD)

- Combines AQS (monitor) and CMAQ (modeled) outputs
- Uses a Bayesian space-time downscaler model to “fuse” the two sets of data
- 12x12 km^2 grids

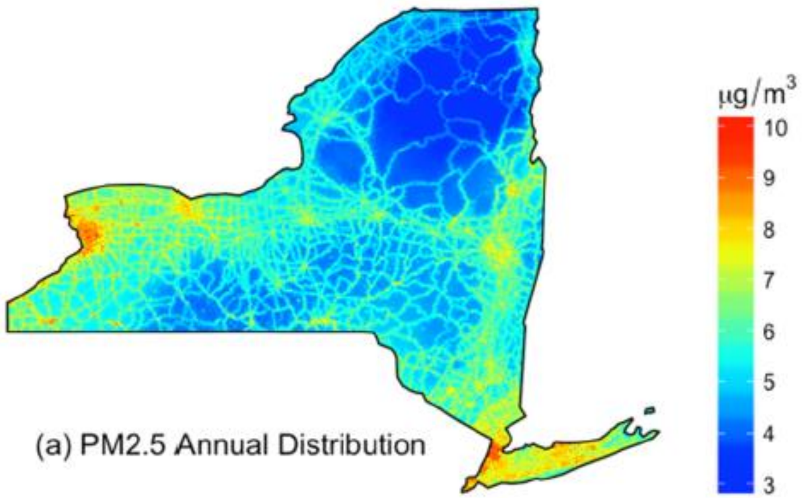
CDC Wide-ranging Online Data for Epidemiologic Research (CDC WONDER)

- Database of public health information provided by CDC
- Included are daily $PM_{2.5}$ predictions
- Links satellite-derived and spatially interpolated ground-based $PM_{2.5}$ using linear regression
- 10x10 km^2 grids
- Available from 2003-2011



Statistical Satellite-Based $PM_{2.5}$ (Emory)

- Model developed by Yang Liu's group at Emory University
- Statistical model that combines satellite aerosol optical depth (AOD), land use, traffic, and meteorological data using machine learning (random forest algorithm)
- 1x1 km^2 grids



Prediction Models in Health Studies

- Many groups are developing these models for exposure assessment in epidemiologic studies
- To date, most health studies use predictions from a single model to assign exposures
    - $PM_{2.5}$ and Mortality (Kloog, Epidemiology, 2013)
    - Long-Term Ozone and Mortality (Turner et al, AJRCCM, 2016)
    - Air Pollution and Mortality in the Medicare Population (Di et al, NEJM, 2018)

Prediction Models in Health Studies

- Results of these papers are used to inform regulations
- But…are these models telling the same story?
    - Exposure measurement error?
    - Are variations in space (e.g. urban vs. rural) different by prediction model?
    - How about in time (e.g. seasons?)

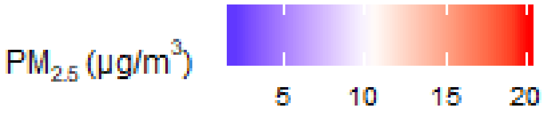
One Story, Five Ways

- $PM_{2.5}$ and cardiovascular admissions over NY State, 2002-2012
  - Five exposure datasets
  - **<u>Goal:</u> assess sensitivity of health effect estimates on the choice of different prediction models for exposure assessment**

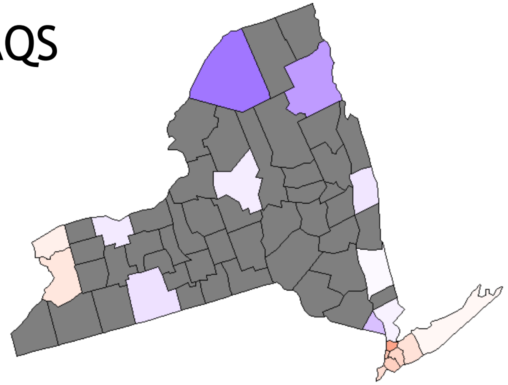
Methods

- Exposure assessment
  - Five daily county-average $PM_{2.5}$ datasets: AQS, CMAQ, AQS + CMAQ Fused, CDC WONDER, Emory model
  - Meteorological data from NASA
- Outcome assessment: daily inpatient cardiovascular admissions from NYS DOH
  - On average, 7 admissions per day per county
- Statistical analysis: Poisson regression models
  - Indicator variables for counties and day of week
  - Temperature (3 *df*), relative humidity (3 *df*), and long-term and seasonal trends (4 *df* per year)

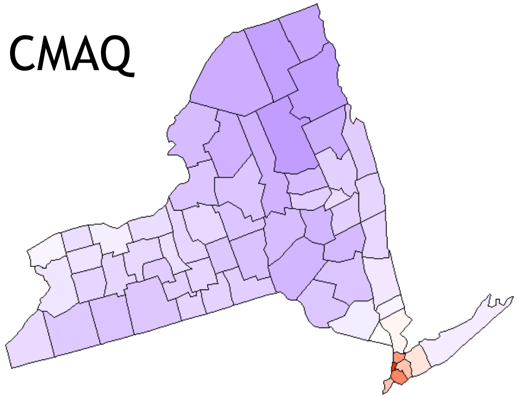
Results



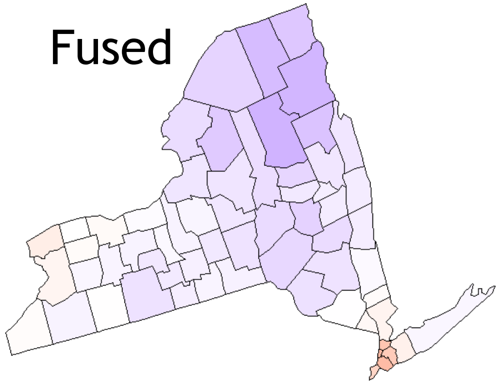
AQS



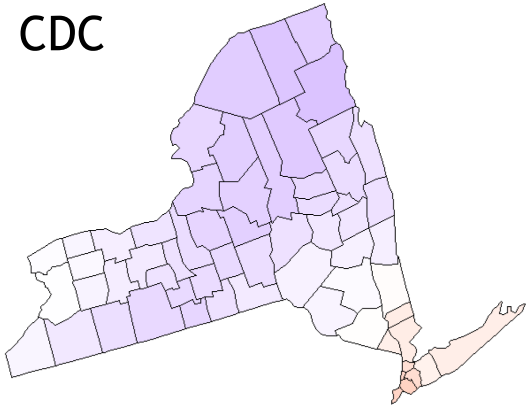
CMAQ



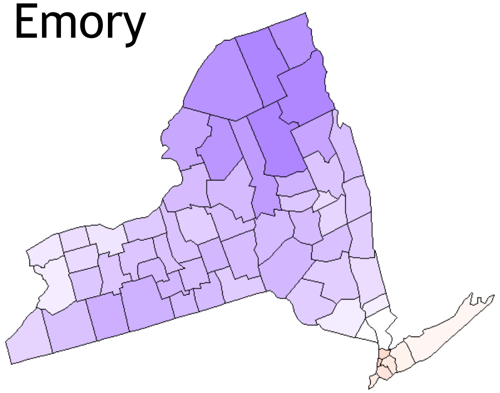
Fused



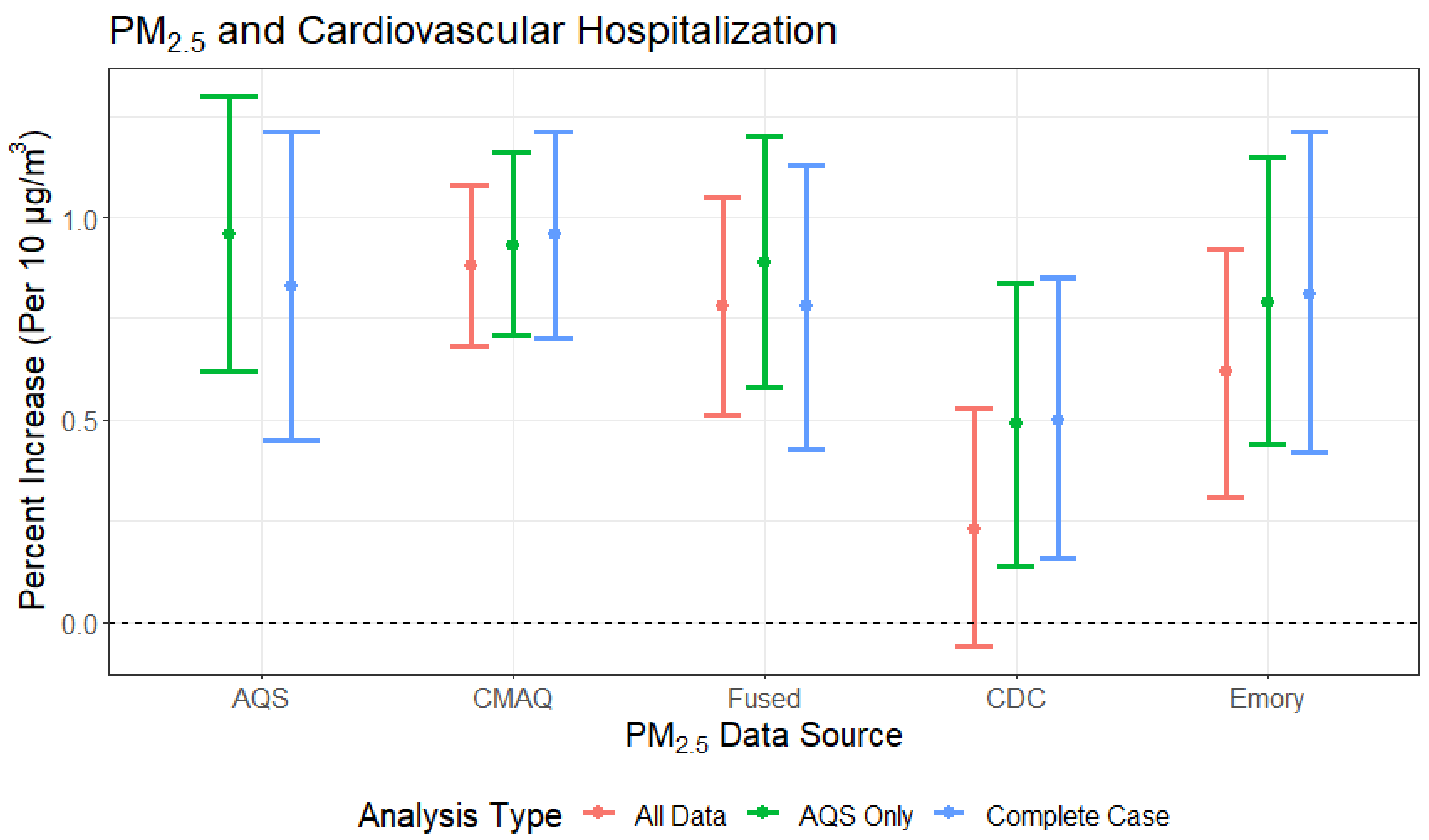
CDC

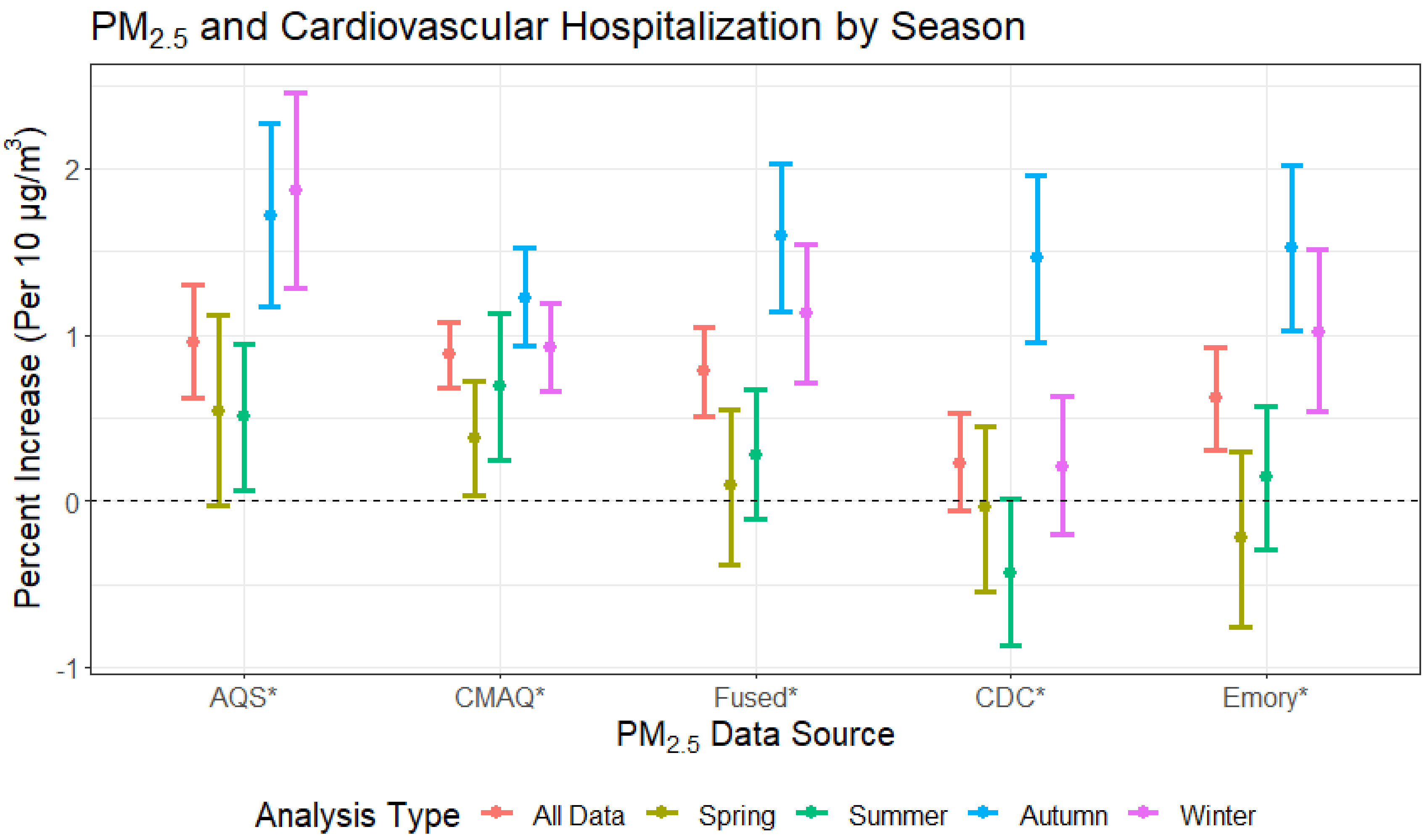


Emory



	AQS	CMAQ	Fused	CDC	Emory
AQS	1.00				
CMAQ	0.52	1.00			
Fused	0.89	0.61	1.00		
CDC	0.83	0.49	0.86	1.00	
Emory	0.90	0.52	0.92	0.85	1.00


PM2.5 and Cardiovascular Hospitalization
Percent Increase (Per 10 µg/m3)
1.0
0.5
0.0
AQS
CMAQ
Fused
CDC
Emory
PM2.5 Data Source
Analysis Type
All Data
AQS Only
Complete Case



PM2.5 and Cardiovascular Hospitalization by Season
Percent Increase (Per 10 µg/m3)
2
1
0
-1
AQS*
CMAQ*
Fused*
CDC*
Emory*
PM2.5 Data Source
Analysis Type
All Data
Spring
Summer
Autumn
Winter

Conclusions

- Significant, positive associations between $PM_{2.5}$ and cardiovascular admissions for all (but one) model
- Some fluctuation in effect estimates depending on analysis type
    - Differences could be due to measurement error
    - However, conclusion remains the same!
- Effect modification:
    - Spatial: higher estimates in more urban areas
    - Temporal: generally higher estimates in fall/winter, but some differences across models

THE LANCET

The Global Burden of Disease 2015

Breathing contaminates contributes to global burden of disease (GBD)

	Number of attributable deaths	
Tobacco Smoking	6.4 mil.	
Second Hand Smoke	0.9 mil.	
$PM_{2.5}$ air pollution	4.2 mil.	
Household air pollution from solid fuels	2.9 mil.	
Ambient Ozone	0.2 mil.	

Is this even believable??

Health Impact Assessments

- Mortality estimate from the following equation:
  - $\boldsymbol{M = M_o \times P \times (1 - e^{-CRF \times C})}$

Where

M = change in the number of deaths

M_0 = baseline mortality rate

P = population

CRF = concentration-response function (slope of the log-linear relationship between concentration and mortality)

C = change in air pollution concentration

Mid-21st century ozone air quality and health burden in China under emissions scenarios and climate change

D M Westervelt[1,2], C T Ma[3], M Z He[4], A M Fiore[1,5], P L Kinney[6], M-A Kioumourtzoglou[4], S Wang[7], J Xing[7], D Ding[7] and G Correa[1]

4. Ozone-related mortality over China

Using the difference in our model simulations for 2050 versus 2015 in the CLE, MFR, and CLIM scenario and concentration-response factors from a recent long-term ozone mortality study (Turner *et al* 2016), we calculate the change in annual premature mortality due to future ozone in China. Mortality calculations are completed using the equation below:

$$M = M_o \times P \times (1 - e^{-\mathrm{CRF} \times \Delta \mathrm{O_3}}), \qquad (1)$$

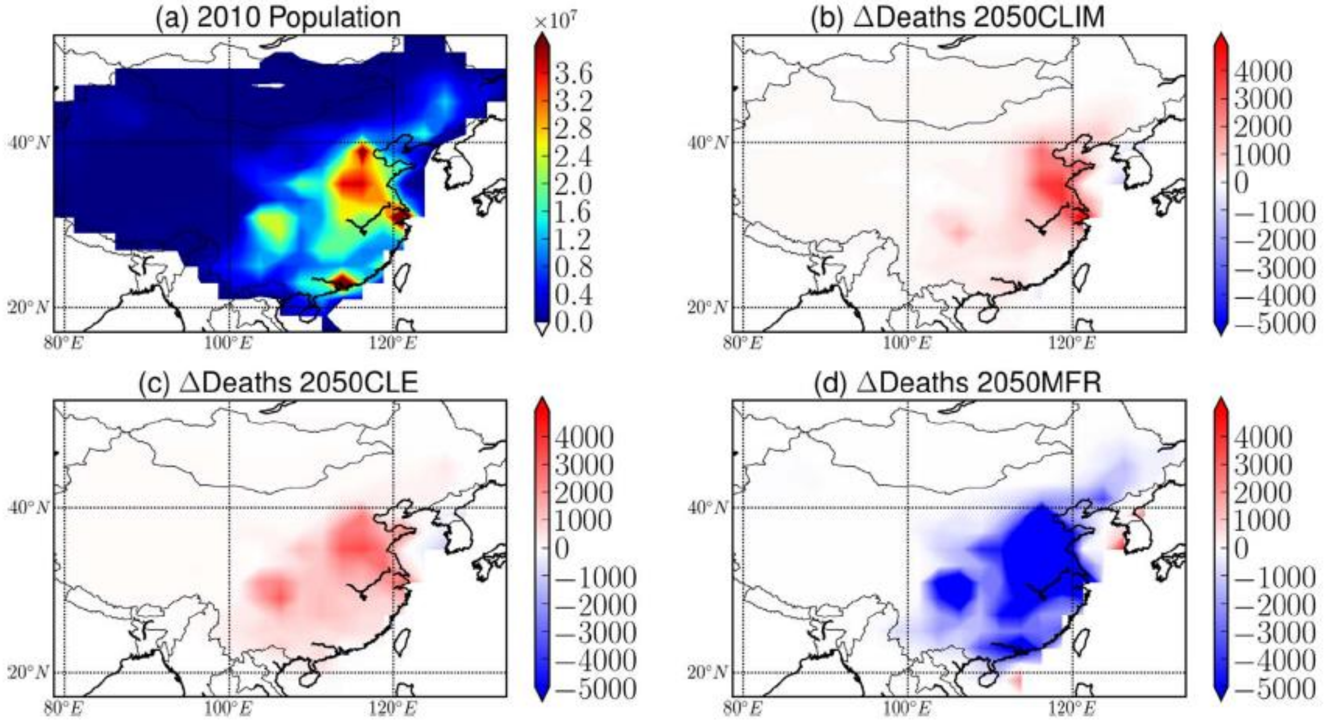


Figure 4. (a) 2010 baseline population in China, (b) change in premature deaths between 2015 and 2050 due to climate change alone (2050CLIM scenario) (c) change in premature deaths between 2015 and 2050 due to CLE scenario (2050CLE, includes climate change), and (d) change in premature deaths between 2015 and 2050 due to MFR scenario (2050MFR, includes climate change). Units are number of deaths.

Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter

Richard Burnett[a], Hong Chen[a,b], Mieczysław Szyszkowicz[a,1], Neal Fann[c], Bryan Hubbell[d], C. Arden Pope III[e], Joshua S. Apte[f], Michael Brauer[g], Aaron Cohen[h], Scott Weichenthal[i,j], Jay Coggins[k], Qian Di[l], Bert Brunekreef[m], Joseph Frostad[n], Stephen S. Lim[n], Haidong Kan[o], Katherine D. Walker[h], George D. Thurston[p], Richard B. Hayes[q], Chris C. Lim[r], Michelle C. Turner[s], Michael Jerrett[t], Daniel Krewski[u], Susan M. Gapstur[v], W. Ryan Diver[v], Bart Ostro[w], Debbie Goldberg[x], Daniel L. Crouse[y], Randall V. Martin[z], Paul Peters[aa,bb,cc], Lauren Pinault[dd], Michael Tjepkema[dd], Aaron van Donkelaar[z], Paul J. Villeneuve[aa], Anthony B. Miller[ee], Peng Yin[ff], Maigeng Zhou[ff], Lijun Wang[ff], Nicole A. H. Janssen[gg], Marten Marra[gg], Richard W. Atkinson[hh,ii], Hilda Tsang[jj], Thuan Quoc Thach[jj], John B. Cannon[e], Ryan T. Allen[e], Jaime E. Hart[kk], Francine Laden[kk], Giulia Cesaroni[ll], Francesco Forastiere[ll], Gudrun Weinmayr[mm], Andrea Jaensch[mm], Gabriele Nagel[mm], Hans Concin[nn], and Joseph V. Spadaro[oo]

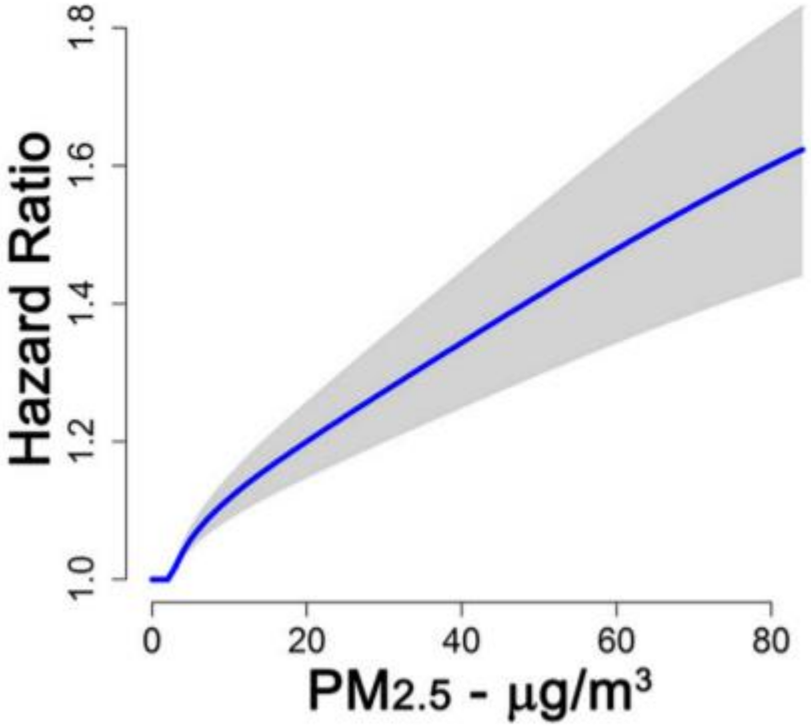


Table 1. Population-weighted average 2015 $PM_{2.5}$ concentrations by country groupings, excess deaths (in thousands) for a 100% and 20% reduction in exposure based on GEMM NCD+LRI, GEMM 5-COD, and IER

Region	Rollback, %	$PM_{2.5}$ exposure, µg/m^3	GEMM NCD+LRI	GEMM 5-COD	IER	Ratio: IER to GEMM NCD+LRI	Ratio: GEMM 5-COD to GEMM NCD+LRI
Canada, USA	100	7.9	213	121	95	0.45	0.57
	20		42	28	20	0.48	0.68
Caribbean	100	20.2	39	28	17	0.44	0.70
	20		6	5	2	0.32	0.91
Latin America	100	17.5	365	228	152	0.42	0.63
	20		58	47	19	0.33	0.81
Africa	100	36.1	691	517	280	0.41	0.75
	20		111	102	34	0.31	0.92
Western Europe	100	13.4	439	245	176	0.40	0.56
	20		70	50	34	0.34	0.71
Eastern Europe	100	23.2	208	154	99	0.48	0.74
	20		32	28	10	0.32	0.88
Russia and EIT*	100	21.8	457	402	257	0.56	0.88
	20		70	72	26	0.37	1.03
Middle East	100	62.0	428	318	166	0.39	0.74
	20		65	56	15	0.24	0.86
China	100	57.5	2,470	1,946	1,110	0.45	0.79
	20		409	368	122	0.30	0.90
India	100	74.0	2,219	1,867	1,022	0.46	0.84
	20		359	329	108	0.30	0.92
Asia (other)	100	39.1	1,367	1,053	620	0.45	0.77
	20		216	203	69	0.32	0.94
Oceania	100	8.0	18	11	7	0.41	0.60
	20		4	3	2	0.58	0.69
Global	100	43.7	8,915	6,889	4,002	0.45	0.58
	20		1,443	1,283	452	0.31	0.89

Take-Home Messages

- Air pollution remains a major problem today, in both developed and developing countries
- There are numerous methods in the air pollution epidemiologist's toolbox: key is to know when to use what
- The $PM_{2.5}$-health association is very robust, and likely causal
- Prediction models are being used as the exposure in air pollution epi studies to reduce exposure measurement error
- A strong health impact assessment relies on all of the above, and more

Questions?