A Brief History of Air Pollution and Health

Mike He
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
**Breathing contaminates** contributes to global burden of disease (GBD)

<table>
<thead>
<tr>
<th></th>
<th>Number of attributable deaths</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tobacco Smoking</td>
<td>6.4 mil.</td>
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<td>PM$_{2.5}$ air pollution</td>
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<td>2.9 mil.</td>
</tr>
<tr>
<td>Ambient Ozone</td>
<td>0.2 mil.</td>
</tr>
</tbody>
</table>

*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 SO₂ 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 the 70s and 90s
• One of the most comprehensive air quality laws in the world
• Established the HAPs and CAPs
  • HAPs: Hazardous Air Pollutants: a list of 170+ chemicals considered harmful to human health
  • CAPs: Criteria Air Pollutant: 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

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

Acute effect of multiple ozone metrics on mortality by season in 34 Chinese counties in 2013–2015
Q. Sun, W. Wang, C. Chen, J. Ban, D. Xu, P. Zhu, M. Z. He, & T. Li

From the 1Chinese Center for Disease Control and Prevention, National Institute of Environmental Health Sciences, Beijing, China; and 2Department 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

\[
\ln \lambda_t = \alpha + \beta (w_0 P_t + w_1 P_{t-1} + w_2 P_{t-2} + \ldots) + s^1(t) + s^2(\text{temp}_t) + \ldots
\]

**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 NO2 and mortality: a multi-county analysis in China

Authors: Mike Z. He\textsuperscript{a}, Patrick L. Kinney\textsuperscript{b}, Tiantian Li\textsuperscript{c}, Chen Chen\textsuperscript{c}, Qinghua Sun\textsuperscript{c}, Jie Ban\textsuperscript{c}, Jiaonan Wang\textsuperscript{c}, Siliang Liu\textsuperscript{a}, Jeff Goldsmith\textsuperscript{d}, Marianthi-Anna Kloumourtzoglou\textsuperscript{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
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$^3$, Mike Z. He$^4$, Jingwen Zhou$^5$, Lianyu Han$^6$, Xinwei Li$^7$ and Tianlan Li$^8$
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:

\[ \lambda_i^{(l)}(t) = \lambda_0^{(l)}(t) \exp(\beta^T x_i^{(l)}(t)) \]

Adapted from C. Arden Pope III (2016)
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
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 air pollution and increased risk of various adverse health outcomes, including cardiopulmonary mortality. However, studies of health effects of long-term particulate air pollution have been less conclusive.

Objective  To assess the relationship between long-term exposure to fine particulate air pollution and all-cause, lung cancer, and cardiopulmonary mortality.

Design, Setting, and Participants  Vital status and cause of death data were collected by the American Cancer Society as part of the Cancer Prevention II Study, a long-term ongoing prospective mortality study, which enrolled approximately 1.2 million adults...
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

<table>
<thead>
<tr>
<th>Cause of Mortality</th>
<th>1979-1983</th>
<th>1999-2000</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>All-cause</td>
<td>1.04 (1.01-1.08)</td>
<td>1.06 (1.02-1.10)</td>
<td>1.06 (1.02-1.11)</td>
</tr>
<tr>
<td>Cardiopulmonary</td>
<td>1.06 (1.02-1.10)</td>
<td>1.06 (1.02-1.14)</td>
<td>1.09 (1.03-1.16)</td>
</tr>
<tr>
<td>Lung cancer</td>
<td>1.08 (1.01-1.16)</td>
<td>1.13 (1.04-1.22)</td>
<td>1.14 (1.04-1.23)</td>
</tr>
<tr>
<td>All other cause</td>
<td>1.01 (0.97-1.05)</td>
<td>1.01 (0.97-1.06)</td>
<td>1.01 (0.95-1.06)</td>
</tr>
</tbody>
</table>

*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 PM₂.₅ (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).
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 Choiot, 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

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
> 3-yr reanalysis by a team of 31 independent researchers with oversight from a 9-member expert panel
> 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 ACS CPS-II study

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

Replicative studies in many other cohorts:
- German Women: Gehring et al. Epi, 2006
- Nurses Health Study: Puett et al. *EHP*, 2009
- Health Professionals: Puett et al. *EHP*, 2011
- California Teachers: Lipsett et al. *AJRCCM*, 2011
- Vancouver: Gan et al. *EHP*, 2011
- Canadian: Crouse et al. *EHP*, 2012
- National English: Carey et al. *AJRCCM*, 2013

- Ag. Health Study: Weichenthal et al. *EHP* 2014
- CanCHEC (Canadian): Crouse et al. *EHP* 2015
- Nurses Health: Hart et al. Environ Health 2015
- Elderly Hong Kong: Wong et al. 2015
- France: Bentayeb et al. Environ Int. 2015
- Canadian Com. Health: Pinault et al. EH 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...
Ambient Particulate Air Pollution and Daily Mortality in 652 Cities


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}).

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

Figure 3. Pooled Concentration–Response Curves. Shown are the pooled concentration–response curves for the associations of 2-day moving average concentrations of PM_{2.5} (Panel A) and PM_{10} (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 concentration at each location) on mortality. Bars on the x 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_{2.5} or PM_{10} according to the World Health Organization Air Quality Guidelines (WHO AQG), WHO Interim Target 1 (IT1), WHO Interim Target 2 (IT2), WHO Interim Target 3 (IT3), European Union Air Quality Directive (EU AQD), U.S. National Ambient Air Quality Standard (NAAQS), and China Air Quality Standard (AQS).
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...
The Community Multiscale Air Quality Model (CMAQ)

- Atmospheric dispersion model developed by US EPA
- Goal is to address regional air pollution problems
- 12x12 km² 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 km² 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
  • \( \text{PM}_{2.5} \) 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
  • **Goal:** 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

<table>
<thead>
<tr>
<th></th>
<th>AQS</th>
<th>CMAQ</th>
<th>Fused</th>
<th>CDC</th>
<th>Emory</th>
</tr>
</thead>
<tbody>
<tr>
<td>AQS</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CMAQ</td>
<td>0.52</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fused</td>
<td>0.89</td>
<td>0.61</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDC</td>
<td>0.83</td>
<td>0.49</td>
<td>0.86</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Emory</td>
<td>0.90</td>
<td>0.52</td>
<td>0.92</td>
<td>0.85</td>
<td>1.00</td>
</tr>
</tbody>
</table>

PM$_{2.5}$ (µg/m$^3$)

5  10  15  20
PM$_{2.5}$ and Cardiovascular Hospitalization

![Graph showing the percent increase (per 10 µg/m$^3$) for PM$_{2.5}$ data sources: AQS, CMAQ, Fused, CDC, and Emory. Analysis types include All Data, AQS Only, and Complete Case.](image)
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
Breathing contaminants contributes to global burden of disease (GBD)

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</tbody>
</table>

Is this even believable??
Health Impact Assessments

• Mortality estimate from the following equation:

\[ M = M_0 \times P \times (1 - e^{-CRF \times C}) \]

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
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:

\[ M = M_0 \times P \times (1 - e^{-CRF \times \Delta O_3}), \]  

(1)
Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter


Table 1. Population-weighted average 2015 PM₂.⁵ concentrations by country groupings, excess deaths (in thousands) for a 100% and 20% reduction in exposure based on GEMM NCD+LRI, GEMM S-COD, and IER

<table>
<thead>
<tr>
<th>Region</th>
<th>Rollback, %</th>
<th>PM₂.⁵ exposure, µg/m³</th>
<th>GEMM NCD+LRI</th>
<th>GEMM S-COD</th>
<th>IER</th>
<th>Ratio: IER to GEMM NCD+LRI</th>
<th>Ratio: GEMM S-COD to GEMM NCD+LRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada, USA</td>
<td>100</td>
<td>7.9</td>
<td>213</td>
<td>121</td>
<td>95</td>
<td>0.45</td>
<td>0.57</td>
</tr>
<tr>
<td>Caribbean</td>
<td>20</td>
<td>20.2</td>
<td>39</td>
<td>20</td>
<td>17</td>
<td>0.44</td>
<td>0.70</td>
</tr>
<tr>
<td>Latin America</td>
<td>20</td>
<td>17.5</td>
<td>365</td>
<td>228</td>
<td>152</td>
<td>0.42</td>
<td>0.63</td>
</tr>
<tr>
<td>Africa</td>
<td>20</td>
<td>36.1</td>
<td>691</td>
<td>517</td>
<td>280</td>
<td>0.41</td>
<td>0.75</td>
</tr>
<tr>
<td>Western Europe</td>
<td>20</td>
<td>13.4</td>
<td>439</td>
<td>245</td>
<td>176</td>
<td>0.40</td>
<td>0.56</td>
</tr>
<tr>
<td>Eastern Europe</td>
<td>20</td>
<td>23.2</td>
<td>208</td>
<td>154</td>
<td>99</td>
<td>0.48</td>
<td>0.74</td>
</tr>
<tr>
<td>Russia and Eil*</td>
<td>20</td>
<td>21.8</td>
<td>457</td>
<td>462</td>
<td>257</td>
<td>0.56</td>
<td>0.88</td>
</tr>
<tr>
<td>Middle East</td>
<td>20</td>
<td>62.0</td>
<td>428</td>
<td>318</td>
<td>166</td>
<td>0.59</td>
<td>0.74</td>
</tr>
<tr>
<td>China</td>
<td>20</td>
<td>57.5</td>
<td>2,470</td>
<td>1,946</td>
<td>1,110</td>
<td>0.45</td>
<td>0.79</td>
</tr>
<tr>
<td>India</td>
<td>20</td>
<td>74.0</td>
<td>2,219</td>
<td>1,867</td>
<td>1,022</td>
<td>0.46</td>
<td>0.84</td>
</tr>
<tr>
<td>Asia (other)</td>
<td>20</td>
<td>39.1</td>
<td>1,367</td>
<td>1,053</td>
<td>620</td>
<td>0.45</td>
<td>0.77</td>
</tr>
<tr>
<td>Oceania</td>
<td>20</td>
<td>8.0</td>
<td>18</td>
<td>11</td>
<td>7</td>
<td>0.41</td>
<td>0.60</td>
</tr>
<tr>
<td>Global</td>
<td>20</td>
<td>43.7</td>
<td>8,915</td>
<td>6,889</td>
<td>4,062</td>
<td>0.45</td>
<td>0.58</td>
</tr>
</tbody>
</table>
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?