Data Integration Model for Air Quality: A Hierarchical Approach to the Global Estimation of Exposures to Ambient Air Pollution

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Outline

- Introduction
- DIMAQ
- Results
- Conclusions

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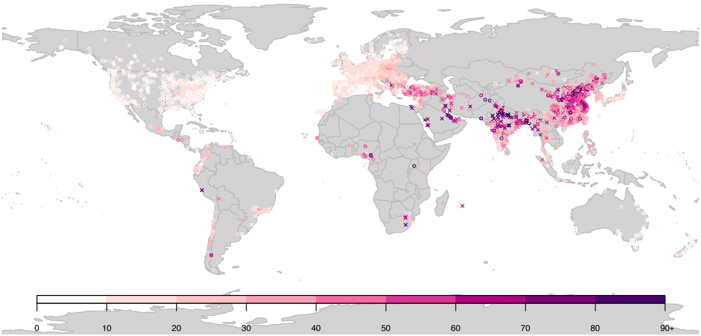
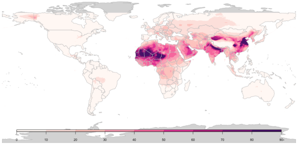
- In 2016, the World Health Organisation (WHO) estimated that over 3 million deaths can be attributed to ambient air pollution.
- The Global Burden of Disease (GBD) project estimate that in 2015 ambient air pollution was in the top ten leading risks to global health.
- Burden of disease calculations require accurate estimates of population exposure for each country.

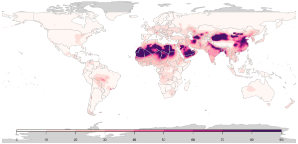
Estimating $PM_{2.5}$

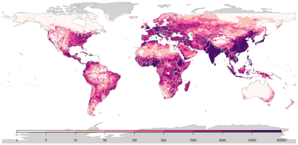


ESTIMATING $PM_{2.5}$

- Can utilise information from other sources
  - satellite remote sensing
  - atmospheric models
  - population estimates
  - land use
  - local network characteristics.
- Result of modelling and will be subject to uncertainties and biases.







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- Exploits a geographical nested hierarchy.
- Achieved using hierarchical random effects.

Regions

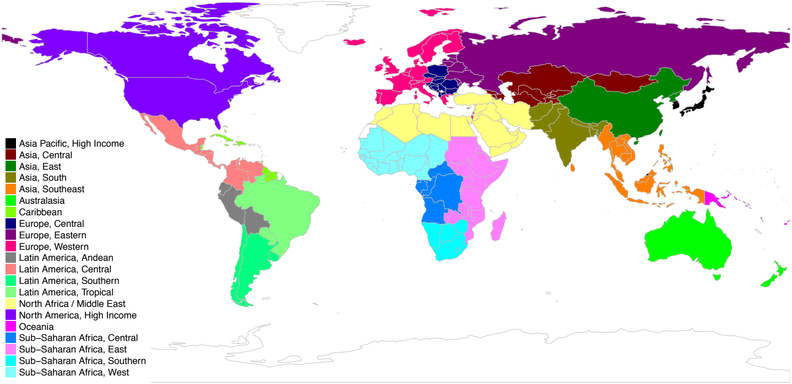

Figure: Map of regions.

SUPER-REGIONS

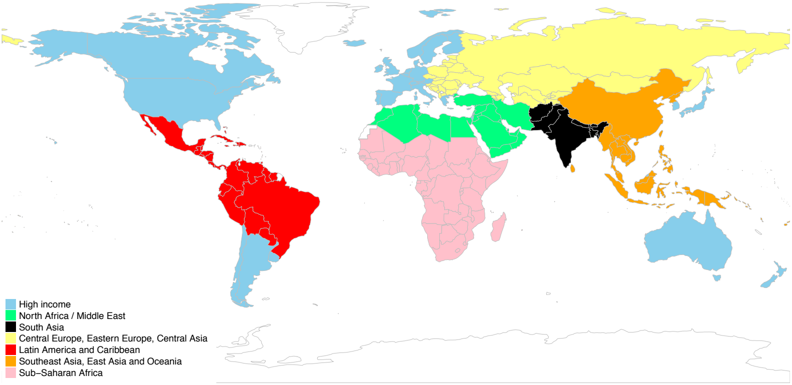

Figure: Map of super-regions.

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- Ground measurements at point locations, s, within grid cell, l, country, i, region, j, and super–region, k are denoted by Y_{slijk}.
- The model consists of a set of fixed and random effects, for both intercepts and covariates, and is given as follows,

$$\begin{aligned}\log(Y_{slijk}) = \tilde{\beta}_{0,lijk} \quad &+ \quad \sum_{p \in P} \beta_p X_{p,slijk} \\ &+ \quad \sum_{q \in Q} \tilde{\beta}_{q,lijk} X_{slijk} \\ &+ \quad \epsilon_{slijk} \ .\end{aligned}$$

Hierarchical Random Effects

- The random effect terms have contributions from the country, the region and the super–region.

$$\tilde{\beta}_{q,ijk} = \beta_q + \beta^{C}_{q,ijk} + \beta^{R}_{q,jk} + \beta^{SR}_{q,k}$$

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- The intercept also having a random effect for the cell representing within-cell variation in ground measurements.

$$\tilde{\beta}_{0,lijk} = \beta_0 + \beta^{G}_{0,lijk} + \beta^{C}_{0,ijk} + \beta^{R}_{0,jk} + \beta^{SR}_{0,k}$$

Random Effects Structure

- The coefficients for super-regions are distributed with mean equal to the overall mean (β_0, the fixed effect) and variance representing the between super–region variation,

$$\beta_k^{SR} \sim N(\beta, \sigma_{SR}^2)$$

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- The coefficients for regions are distributed with mean equal to the coefficient for the super–region with variance representing the between region variation,

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$$\beta_{jk}^{R} \sim N(\beta_k^{SR}, \sigma_{R,k}^2)$$

- The coefficients for a country is distributed with mean equal to the coefficient for the region with variance representing the between country variation,

$$\beta_{ijk}^{C} \sim N(\beta_{jk}^{R}, \sigma_{C,jk}^2)$$

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- Latent Gaussian models allows for sparse matrices, and therefore efficient computation.

Computation

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- Unable to run this model on standard computers (4-8GB RAM).
- Required the use of a High-Performance Computing (HPC) service.
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- Took an iterative approach to prediction.

Evaluation: Crossvalidation

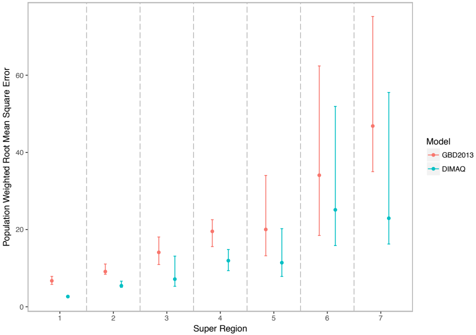

Figure: Summaries of predictive ability of the GBD2013 model and DIMAQ, for each of seven super–regions: 1, High income; 2, Central Europe, Eastern Europe, Central Asia; 3, Latin America and Caribbean; 4, Southeast Asia, East Asia and Oceania; 5, North Africa / Middle East; 6, Sub-Saharan Africa; 7, South Asia. For each model, population weighted root mean squared errors (μgm^{-3}) are given with dots denoting the median of the distribution from 25 training/evaluation sets and the vertical lines the range of values.

PREDICTIONS

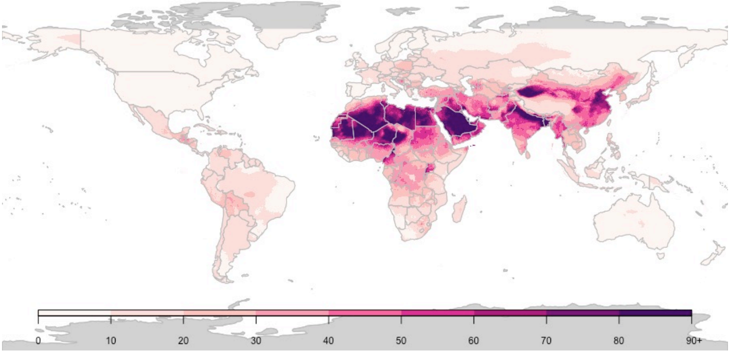

Figure: Median estimates of annual averages of $PM_{2.5}$ (μgm^{-3}) for 2014 for each grid cell ($0.1^o \times 0.1^o$ resolution) using DIMAQ.

UNCERTAINTY

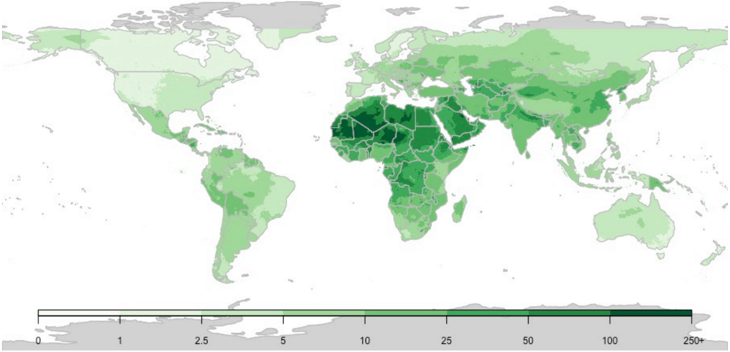

Figure: Half the width of 95% posterior credible intervals for 2014 for each grid cell ($0.1^o \times 0.1^o$ resolution) using DIMAQ.

Posterior Distributions

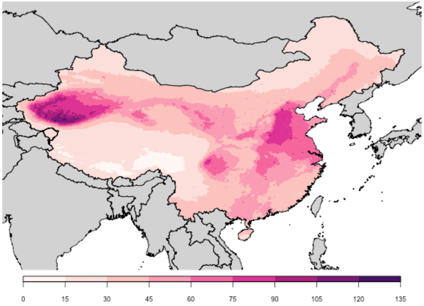

Figure: Medians of posterior distributions for estimates of annual mean $PM_{2.5}$ concentrations (μgm^{-3}) for 2014, in China.

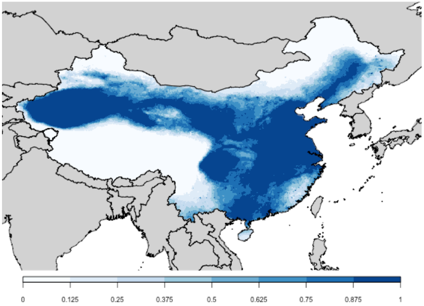

Figure: Probability of exceeding 35 μgm^{-3} using a Bayesian hierarchical model for each grid cell ($0.1^o \times 0.1^o$ resolution) for 2014, in China.

Population Exposures to $PM_{2.5}$

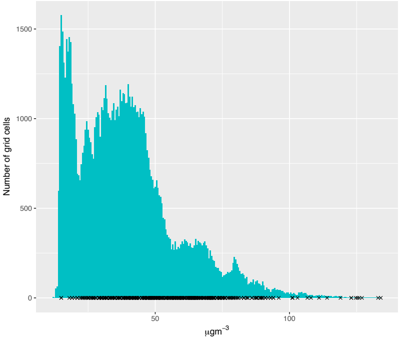

Figure: Estimated annual average concentrations of $PM_{2.5}$ by grid cell ($0.1^o \times 0.1^o$ resolution). Black crosses denote the annual averages recorded at ground monitors.

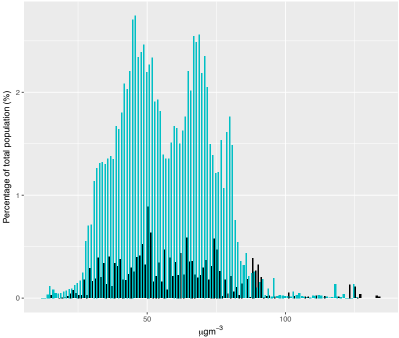

Figure: Estimated population level exposures (blue bars) and population weighted measurements from ground monitors (black bars).

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    - Within country variability
    - Allowing for errors and biases in covariates
    - Use data at native resolutions

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- Future Developments
  - Higher resolution estimates
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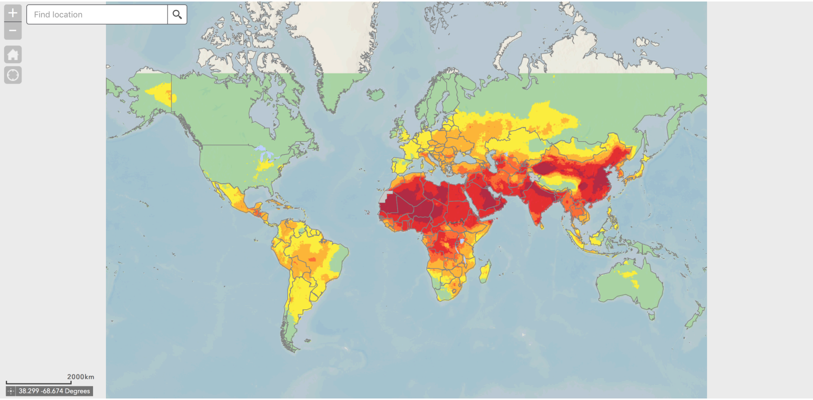
  - Use data at native resolutions
- Possible approaches to address these issues
  - Statistical downscaling
  - Bayesian melding.

Interactive Map



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- GBD Paper:
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- Interactive Map:
  http://maps.who.int/airpollution/

Any Questions?