Challenges in modelling air pollution and understanding its impact on human health

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Acknowledgements

Work in this talk part of a larger collaboration:

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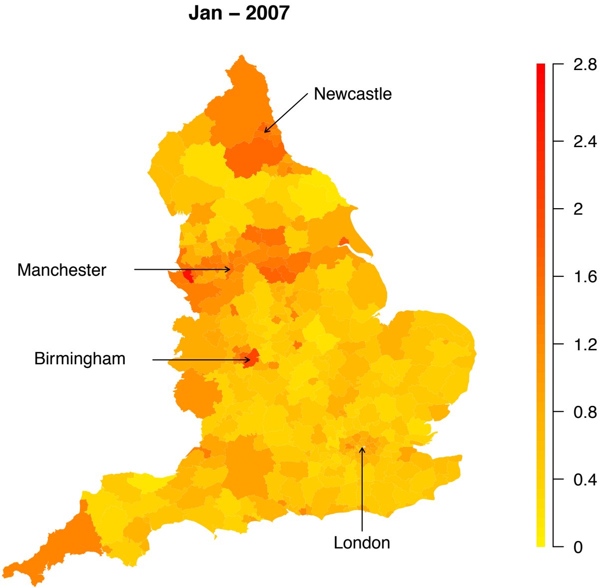
Goals

- Construct state-of-the-art spatio-temporal model for predicting air pollution at high spatial resolution across England.
  - $\mathrm{NO_2}$, $\mathrm{O_3}$, $\mathrm{PM_{10}}$ and $\mathrm{PM_{2.5}}$ monitored at 142 urban and rural locations
  - Output from computer model (AQUM) on 1km^2 grid.
  - Fusion of modelled and measured data sources achieved using anisotropic Gaussian predictive process model, where AQUM included as a regressor.
  - See technical report for details `www.southampton.ac.uk/~sks/research/papers/anisotropy4.pdf`
- Build better models for disease risk given an air pollution exposure, that can adequately represent the spatio-temporal pattern in disease risk.
- Utilising the new models above within a two-stage framework, estimate the health effects of air pollution across England.

England LHA respiratory admissions data



- Jan 2007 to Dec 2011 (60 months)
- 323 Local Health Authorities
- $N = 19380$

Typical model for spatial heath counts

$$
\begin{aligned}
Y_{kt}|E_{kt}, R_{kt} &\sim \text{Poisson}(E_{kt}R_{kt}) \\
\ln(R_{kt}) &= \beta_0 + x_{kt}\beta + \mathbf{z}_{kt}^\top \boldsymbol{\alpha} + \phi_{kt}, \\
t &= 1, \ldots, T \quad \text{time points} \\
k &= 1, \ldots, N \quad \text{regions}
\end{aligned}
$$

Where

Y_{kt}	health counts	E_{kt}	expected cases
R_{kt}	health risk	ϕ_{kt}	random effect
$\mathbf{z}_{kt}^\top \boldsymbol{\alpha}$	other covariate effects	β_0	intercept
x_{kt}	air pollution	β	pollution effect

Statistical considerations

Unmeasured confounding: Air pollution, and the other measured covariates do not account for all variation. Adding a set of spatio-temporal random effects, ϕ_{kt} can offer a solution.

How should ϕ_{kt} be structured in space and time?

Misalignment: The air pollution model estimates the true exposure surface $Z(s_{kj}, t)$, by a set of predictive distributions at grid locations, $\{s_{kj}\}$.

Health counts are regional totals. How can we reconcile these quantities? Could we simply average the air pollution?

Uncertainty: The posterior density of $Z(s_{kj}, t)$ is available via MCMC samples, and therefore uncertainty in air pollution is quantified.

How should this source of uncertainty be incorporated into the health model? What effect does this have on estimation?

Unmeasured confounding: An existing model for ϕ_{kt}

Rushworth et al. (2014) propose the 'global' model:

$$\ln(R_{kt}) \quad = \quad \beta_0 + x_{kt}\beta + \mathbf{z}_{kt}^\top \boldsymbol{\alpha} + \phi_{kt}$$

Letting $\boldsymbol{\phi}_t = (\phi_{1t}, \ldots, \phi_{Nt})$, where $t = 1, \ldots, T$, then:

$$\begin{aligned} \boldsymbol{\phi}_1 &\sim \mathrm{N}\left(\mathbf{0}, \sigma^2 \mathbf{Q}(\mathbf{W}, \rho)^{-1}\right) \\ \boldsymbol{\phi}_t | \boldsymbol{\phi}_{t-1} &\sim \mathrm{N}\left(\alpha \boldsymbol{\phi}_{t-1}, \sigma^2 \mathbf{Q}(\mathbf{W}, \rho)^{-1}\right) \quad \text{for } t \geq 2 \end{aligned}$$

$$\begin{aligned} \mathbf{Q} &= \rho\left[diag(\mathbf{W1}) - \mathbf{W}\right] + (1-\rho)\mathbf{I} \\ \mathbf{W} &= \text{spatial (binary) neighbours matrix.} \end{aligned}$$

Unmeasured confounding: a more flexible model for ϕ_{kt}

$\mathbf{Q}(\mathbf{W}, \rho)$ restricts the range of surfaces that can be fitted.

Solution: Treat non-zero elements of $\mathbf{W}$ as random variables $w_{ij}^{+} \in [0, 1]$.

Control model complexity using normal prior on transformed w_{ij}^{+}:

$$\ln\left(\frac{w_{ij}^{+}}{1 - w_{ij}^{+}}\right) \sim N\left(\mu,\ \tau^2\right)$$

μ is chosen to be large and positive reflecting prior preference for spatial smoothness.

English respiratory data: random effects

We will compare the random effects models

Model type	Random effects	Adjacency model
GLM	NA	—
Non-adaptive	ϕ_{kt}	$w_{kt}^{+} = 1$
Adaptive	ϕ_{kt}	$\mathrm{logit}(w_{kt}^{+}) \sim N(\mu, \tau^2)$

Under the risk specification

$$\ln(R_{kt}) = \beta_0 + x_{kt}\beta + \texttt{jobseekers}_{kt}\alpha_1 + \texttt{houseprice}_{kt}\alpha_2 + \phi_{kt}$$

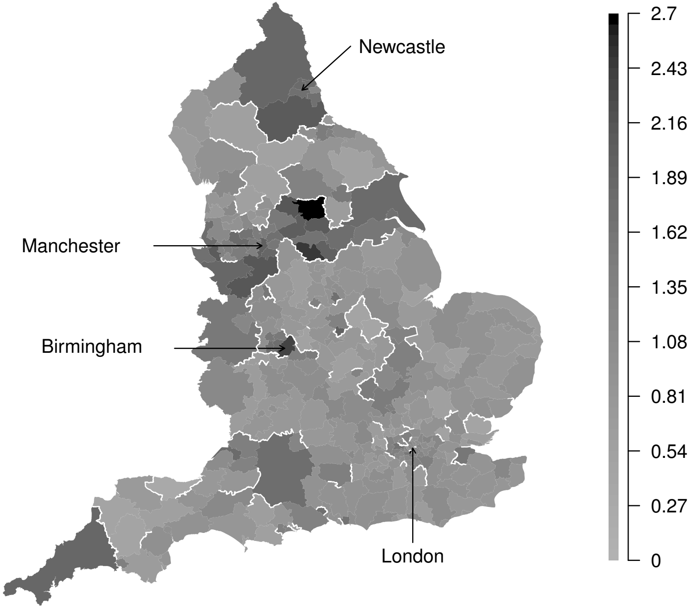
English respiratory data: random effects

Pollutant	No random effects (GLM)	Non-adaptive ϕ_{kt}	Adaptive ϕ_{kt}
NO_2	1.151 $(1.144, 1.158)$	1.057 $(1.045, 1.069)$	1.048 $(1.036, 1.060)$
PM_{10}	1.013 $(1.007, 1.020)$	1.007 $(0.998, 1.015)$	1.006 $(0.995, 1.015)$
$PM_{2.5}$	1.013 $(1.007, 1.019)$	1.006 $(0.997, 1.014)$	1.006 $(0.997, 1.016)$
O_3	0.981 $(0.974, 0.987)$	0.983 $(0.972, 0.995)$	0.980 $(0.965, 0.993)$

Table : Risks and 95% CIs for 1-standard deviation increases in pollutant

Simpler models have a tendency to overestimate air-pollution effects.

ϕ_{kt} estimates and adjacency model



Air pollution - uncertainty

1^{st} stage model yields predictive distributions for air pollution in space and time.

This uncertainty should be passed through the 2^{nd} stage health model so that resulting health estimates represent all available information.

Some possible strategies:

(1) Treat posterior mean pollution concentrations as true values (no uncertainty)

(2) Directly feed samples from the posterior air pollution density through the health model

(3) Treat the posterior pollution densities as prior distributions in the health model (e.g. using a Gaussian approximation)

Exploring the English respiratory data: uncertainty

Compare approaches to incorporating pollution uncertainty:

$$\begin{array}{lccl} \textbf{(1)} & x_{kt} & = & \bar{x}_{kt} \\ \textbf{(2)} & x_{kt} & \sim & DU \text{ over posterior air pollution samples} \\ \textbf{(3)} & x_{kt} & \sim & MVN \text{ estimated from posterior samples} \end{array}$$

Again, under the risk specification

$$\ln(R_{kt}) = \beta_0 + x_{kt}\beta + \texttt{jobseekers}_{kt}\alpha_1 + \texttt{houseprice}_{kt}\alpha_2 + \phi_{kt}$$

Results – uncertainty

Pollutant	**(1)** $x_{kt} = \bar{x}_{kt}$	**(2)** $x_{kt} \sim DU$	**(3)** $x_{kt} \sim MVN$
NO_2	1.048 (1.036, 1.060)	1.001 (0.999, 1.003)	1.035 (1.030, 1.041)
PM_{10}	1.006 (0.995, 1.015)	1.000 (0.998, 1.003)	1.025 (0.999, 1.043)
$PM_{2.5}$	1.006 (0.997, 1.016)	1.001 (0.997, 1.004)	1.008 (0.995, 1.062)
O_3	0.980 (0.965, 0.993)	1.000 (0.999, 1.001)	0.996 (0.967, 1.000)

Table : Risks and 95% CIs for 1-standard deviation increases in pollutant

Conclusions

- Choices for handling spatio-temporal autocorrelation have important consequences for the estimating the effects of air pollution.
- It is important to treat air pollution exposure as uncertain, as it is rarely realistic to assume exposure is observed (or predicted) without error.

Future work:

- Simulate to determine bias and coverage properties for β
- Improve on current Gaussian approximation to air pollution posterior
- Multivariate disease responses

Thank you very much for listening!