The Use of Spatial Exposure Predictions in Health Effects Models: An Application to PM Epidemiology

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Boston monitoring sites
- BC – Outdoor & indoor: 30 monitors (APAHRV)
- BC – Indoor: 15 monitors (APAHRV)
- BC – Ambient: 14 monitors
- EC – Outdoor: 23 monitors (EPA)

BC monitors in space (left) and time (right)
Published model (Gryparis et al. JRSSC 2007):
- Contains a spatial term, temporal term, and spatial and temporal covariates

\[
\log \text{BC}_{it} = X_i \beta + Z_t \alpha + g(s_i) + h(t) + \epsilon_{it}
\]
- Little space-time interaction except for stratification by summer/winter

Ongoing work:
- Build in space-time smoothing and effects of covariates that vary in space and time
- Additional data from rotating monitors and from 7-day integrated samples

Application
- Acute and chronic health studies in eastern Massachusetts: stroke, hypertension, intermediate cardiovascular markers, mortality, birthweight
Enhancing Exposure Assessment
Using Exposure Predictions in Health Models

Nationwide Monthly PM

PM$_{2.5}$ monitors (top) and predictions: northeast US (left) and greater Boston (right)

- Contains a spatio-temporal terms (one spatial term for each month) plus spatio-temporal covariates
- Combination of land-use regression and spatial smoothing

Ongoing work:

- Assessment of use of remotely-sensed AOD to improve spatial coverage (see poster)
- Consideration of new land use covariates and improved space-time characterization

Application

- Chronic health effects in the Nurses’ Health Study
Spatial smoothing exposure models (kriging, splines, additive modeling) produce a form of regression calibration

- Result is Berkson-type error in health models

Implication of limited bias in health models

- But, 1.) exposure away from home and 2.) ambient concentrations vs. personal exposure probably adds classical error
Accounting for Prediction Uncertainty

- Approaches that do not work:
  - Directly weighting by prediction uncertainty
  - Simulating exposures based on prediction uncertainty

- Approaches with more promise:
  - Bayesian models
  - Using held-out data to calibrate the predictions

- Application
  - Effect of BC on birthweight in eastern Massachusetts
  - Accounting for uncertainty in large cohort studies in survival analysis such as the Nurses’ Health Study is an open challenge.
References

- Eastern Massachusetts BC model:

- National PM modeling
National PM modeling (cont’d)


Measurement Error