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

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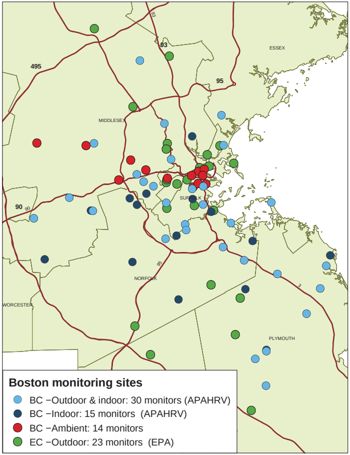
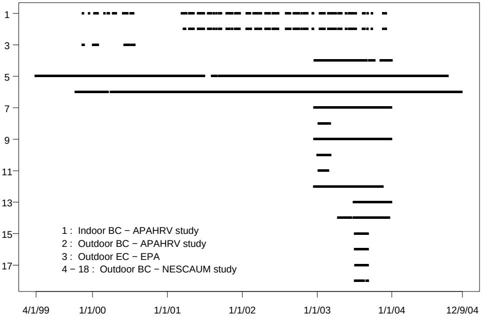
Eastern Massachusetts Daily Black Carbon





BC monitors in space (left) and time (right)

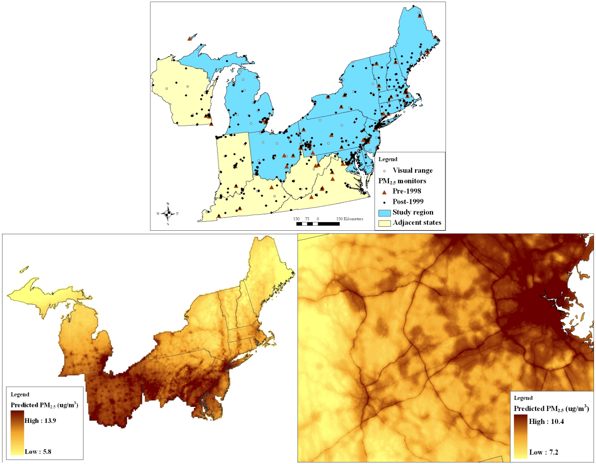
Model

- Published model (Gryparis et al. JRSSC 2007):
  - Contains a spatial term, temporal term, and spatial and temporal covariates

$$\log \mathrm{BC}_{it} = X_i\beta + Z_t\alpha + g(s_i) + h(t) + \epsilon_{it}$$

  - 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

Nationwide Monthly PM



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

Model

- Published model (Yanosky et al. Atm. Env't 2008, Paciorek et al. Annals Appl Stats in press):
  - 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

Prediction Uncertainty as Measurement Error

- 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:
    - Gryparis, Coull, Schwartz and Suh. 2007. Latent variable semiparametric regression models for spatio-temporal modeling of mobile source pollution in the greater Boston area. Journal of the Royal Statistical Society Series C 56:183.
    - Maynard, Coull, Gryparis, and Schwartz. 2007. Mortality risk associated with short-term exposure to traffic particles and sulfates. EHP 5:751.
- National PM modeling
    - Yanosky, Paciorek, Schwartz, Laden, Puett, and Suh. 2008. Spatio-temporal modeling of chronic PM_{10} exposure for the Nurses' Sealth Study. Atmospheric Environment 42:4047.
    - Paciorek, Yanosky, Puett, Laden, and Suh. 2008. Practical large-scale spatio-temporal modeling of particulate matter concentrations. Annals of Applied Statistics, in press (Harvard Biostatistics Technical Report 76).

- National PM modeling (cont'd)
  - Paciorek and Liu. 2008. Limitations of remotely-sensed aerosol as a proxy for fine marticulate matter. Harvard Biostatistics Technical Report 89; submitted.
  - Puett et al. 2008. Chronic particulate exposure, mortality and cardiovascular outcomes in the Nurses' Health Study. American Journal of Epidemiology in press.
- Measurement Error
  - Gryparis, Paciorek, Zeka, Schwartz, and Coull. 2008. Measurement error caused by spatial misalignment in environmental epidemiology. Biostatistics, in press (Harvard Biostatistics Technical Report 87).