Air Pollution and Reproductive Outcomes: Opportunities for Increased Research and Translation

J. Warren, M. Fuentes, A.H. Herring, P. Langlois

October 12, 2010

We are grateful for the support of SAMSI, NIEHS, CDC, EPA, NCSU, UNC, and the TX Department of State Health Services

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- Areas with particularly strong needs: environmental, social, and infectious disease epidemiology

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  - (Seriously in soft money environments, those with spatial expertise are quickly overfunded)

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- Educational opportunities for epidemiologists even more limited

Epidemiology grad student on challenges in using spatial statistics

- "It's not included in our training, at all. Not even mentioned. So, in trying to learn it on my own, I'm starting at a baseline of 0. This translates to taking lots of time and requiring lots of motivation to learn the methods."

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- "The available resources to learn these methods aren't usually targeted at epidemiologists. So, you have to search in other fields' literature to find resources that include enough detail to learn the methods, but aren't too theoretically focused and complex."

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Epidemiology grad student on challenges in using spatial statistics

- "Mostly, we can't use standard software."
- "I'm not sure that the standard statistical training that we get in epi provides enough background to understand and implement these methods ... for example, standard epi training doesn't include much discussion of probability distribution functions. It makes it more difficult to use Bayesian methods to analyze spatial data if you never learned how to specify the different distributions or you don't know why a Poisson distribution is good for count data."

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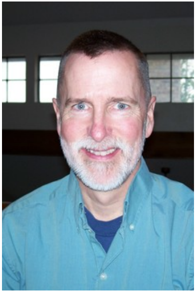
- In these rich data studies, confidentiality a **major** concern (latitude and longitude are personal identifiers)
- What is balance between protecting personal information and allowing sophisticated analysis?

My work in spatial epidemiology

"I know nothing about the subject,
but I'm happy to give you my expert opinion."

Excellent collaborators: Fuentes, Warren, Langlois



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  - geo-coded birth outcome data from Harris County, Texas (2000-2004)
  - two sources of daily pollution data

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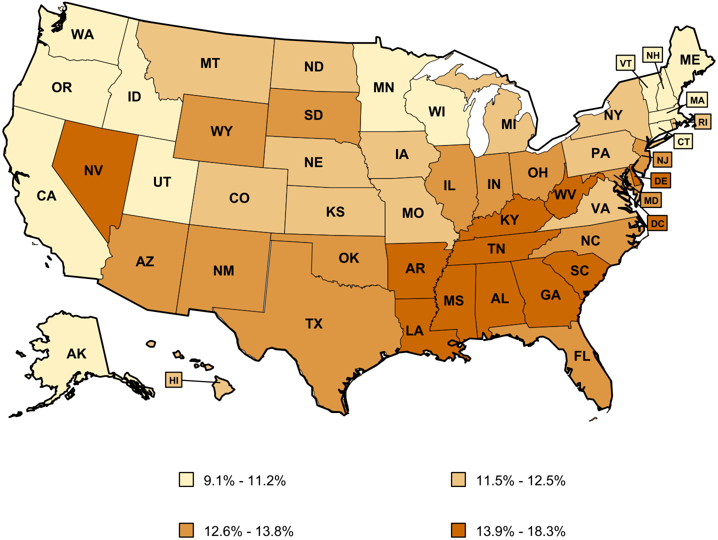
- US national incidence around 13%; around 1.8 times higher in African-American than in white and/or Hispanic women; rates increasing worldwide

Preterm birth prevalence



Harris County, TX

Figure: Harris County, TX

- Third largest county in the US as of July, 2009
- Includes Houston, TX – provides a large amount of heterogeneity to our study population

Why Harris County?

- Texas an interesting state with diverse population and some areas out of compliance with air pollution standards

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- 64K eligible births in Harris County during that time (much more feasible)

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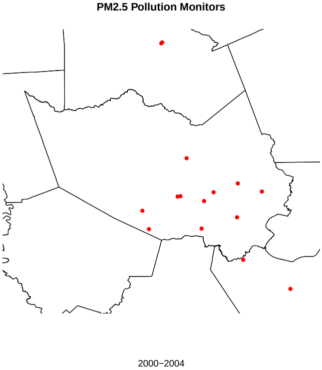
Pollution monitors



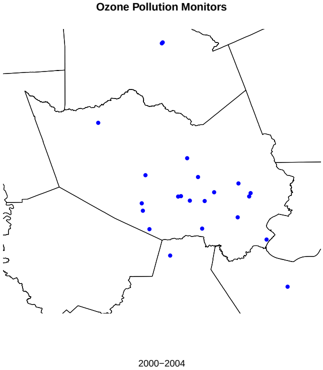


Figure: *Harris County $PM_{2.5}$ (left) and Ozone (right) Monitors, 2000-2004. Note Sudipto will talk about preferential sampling issues tomorrow.*

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Typical models for pollution and weather data

- Directional Bayesian approach of Fuentes and Raftery (2005); multi-stage model with estimates obtained separately at each stage and uncertainty captured in final stage

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- Stage 0 weather model:

$$\mathbf{W}(s,t) \quad = \quad \mu(s,t) + \varepsilon_1(s,t) + \varepsilon_2$$

Typical models for pollution and weather data

- Stage 1 AQS pollution monitor data $\tilde{\mathbf{Z}}_1$:

$$\begin{aligned} \mathbf{Z}_1(s,t) &= \mathbf{W}(s,t)'\delta + \varepsilon_3(s,t) \\ \tilde{\mathbf{Z}}_1(s,t) &= \mathbf{Z}_1(s,t) + \varepsilon_4 \end{aligned}$$

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- Values of $\mathbf{Z}_1(s,t)$ simulated from posterior predictive distribution at each woman's location on relevant day and used in next stage as input to PTB model

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- Will concentrate on **time** component of *space-time* epidemiology
- Exposures calculated by assignment to nearest monitor
- Will implement **space-time** model when examining birth defects outcomes (much smaller *n*; can take a subset of controls for analysis and examine entire state of TX and later a 10-state region)

Observed birth weight and gestational age for births

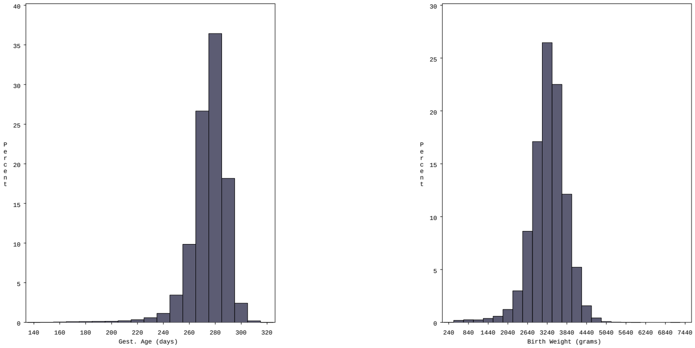

Figure: *Gestational age (left) and birth weight (right) histograms for the births included in the analysis.*

Preterm birth model

$$Y_i|\boldsymbol{\beta},\boldsymbol{\theta} \overset{ind}{\sim} Bern(p_i(\boldsymbol{\beta},\boldsymbol{\theta})),$$

$$p_i(\boldsymbol{\beta},\boldsymbol{\theta}) = \text{probability pregnancy } i \text{ results in preterm birth},$$

$$\Phi^{-1}(p_i(\boldsymbol{\beta},\boldsymbol{\theta})) = \mathbf{x}_i{}^T\boldsymbol{\beta} + \sum_{j=1}^{2} \sum_{w=1}^{min(ga_i,36)} \theta(j,w) Z_j(t_i(w), s_i),$$

- $\Phi^{-1}(.)$ is the inverse cumulative distribution function of the standard normal distribution
- 'ga_i' is the gestational age (weeks) for birth i
- $\theta(j,w)$ are temporally-varying coefficients for pollutant j at pregnancy week w (calendar week $t_i(w)$)

Modeling the Pollution Coefficients

The $\theta(j, w)$ parameters are temporally-varying coefficients that represent the effects of the concentration of air pollutant j at pregnancy week w (corresponding to calendar week $t_i(w)$) on the probability of PTB for woman i.

- Ozone and $PM_{2.5}$ are used in the analysis
- $Z_j(t_i(w), s_i)$ represents the pollution exposure for pollutant j on calendar week $t_i(w)$ at location s_i

Modeling the Pollution Coefficients

$$\boldsymbol{\theta} = (\theta(1,1), \ldots, \theta(1,36), \theta(2,1), \ldots, \theta(2,36))^T \sim MVN(0, \phi_0 \boldsymbol{\Sigma}),$$

where entries of $\phi_0 \boldsymbol{\Sigma}$ are given by,

$$\text{cov}(\theta(j,w), \theta(j^{'}, w^{'})) = \phi_0 \exp\left\{-\phi_1 |w - w^{'}| - \phi_2 I(j \neq j^{'})\right\}.$$

- This exponential covariance structure provides a relatively simple parameterization that still allows separate degrees of shrinkage across air pollutants j and pregnancy week w
- Appropriate prior distributions are chosen for the covariance hyper-parameters

Selected parental covariate results

		Percentiles		
Covariate	**Mean**	**0.025**	**0.50**	**0.975**
Maternal Race				
Black vs. White	0.2095	0.1224	0.2094	0.2971
Asian vs. White	0.1157	0.0148	0.1158	0.2159
Other vs. White	0.0793	-0.1925	0.0812	0.3406
Paternal Race				
Black vs. White	0.0061	-0.0797	0.0062	0.0909
Asian vs. White	-0.2086	-0.3151	-0.2086	-0.1017
Other vs. White	-0.0288	-0.2758	-0.0270	0.2087

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Covariate	**Mean**	**0.025**	**0.50**	**0.975**
Maternal Age				
$20-24$ vs. $10-19$	-0.0738	-0.1168	-0.0738	-0.0310
$25-29$ vs. $10-19$	-0.0236	-0.0714	-0.0236	0.0243
$30-34$ vs. $10-19$	0.0461	-0.0068	0.0462	0.0991
$35-39$ vs. $10-19$	0.1530	0.0846	0.1531	0.2211
≥ 40 vs. $10-19$	0.3235	0.2032	0.3238	0.4426

Selected parental covariate results

		Percentiles		
Covariate	**Mean**	**0.025**	**0.50**	**0.975**
Paternal Education: (Years Completed)				
12 vs. $<$ 12	-0.0250	-0.0666	-0.0249	0.0168
$>$ 12 vs. $<$ 12	-0.0848	-0.1327	-0.0847	-0.0369
Female vs. Male Baby	-0.0625	-0.0903	-0.0625	-0.0349

Diversion: gender effect

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- Secondary sex ratio (among live births) estimated as 105 males to 100 females
- Reaches 1:1 around age 30

Diversion: gender effect

Ratio is 82 males for 100 females at age

Diversion: gender effect

Ratio 44 males to 100 females at age

Diversion: gender effect

Ratio 26 males to 100 females at age

But I digress...

Estimated probabilities of preterm birth

		Percentiles		
Maternal Attributes	**Mean**	**0.025**	**0.50**	**0.975**
White, Age 20-24	0.1111	0.0943	0.1107	0.1297
White, Age $\geq$ 40	0.2053	0.1664	0.2047	0.2479
Black, Age $\geq$ 40	0.2699	0.2173	0.2691	0.3267

Table: *Estimated posterior probabilities of preterm birth for a boy's mother who had education beyond high school and whose partner was white, had a high school education, and who was under 50.*

Investigating critical exposure windows

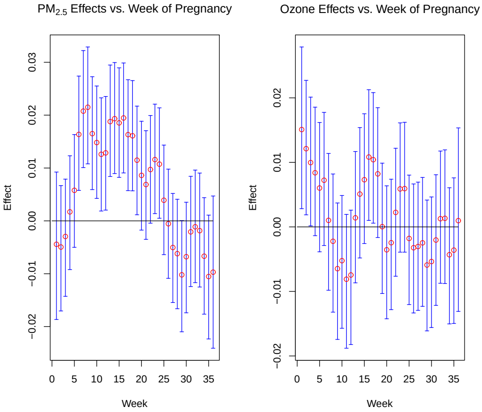

Figure: *Susceptible windows of exposure using AQS Data from Harris County, Texas, 2000-2004. Posterior means and 90% credible intervals are displayed.*

Results without smoothing time-varying coefficients

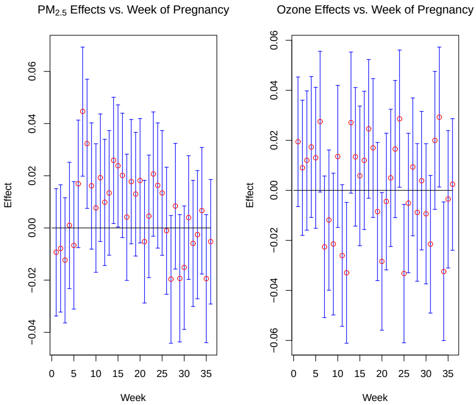

Figure: *Susceptible windows of exposure for the simplified analysis using AQS Data from Harris County, Texas, 2000-2004. Posterior means and 90% credible intervals are displayed.*

Ozone results using FSD data

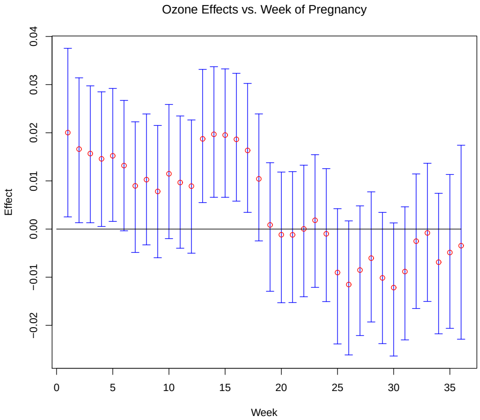

Figure: *Susceptible windows of exposure using FSD data for the ozone pollutant in Harris County, Texas, 2001-2004. Posterior means and 95% credible intervals are displayed.*

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- Data includes the entire state of Texas

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- Common challenges: confidentiality and reproducibility

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- How does one release code and data for reproducibility purposes (preserving information content) while protecting individual privacy?

Data confidentiality and reproducibility: possible approaches

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- How to do this, especially for rare outcomes related to spatial covariates?
- Perhaps build a flexible spatial model for the real data using nonparametric Bayes and then impute data under this flexible model

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  - Banerjee, A., Dunson, D.B. and Tokdar, S. (2010) propose using compressive sensing for fast computation in large spatial data sets involving Gaussian process models

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  - Zhao et al.: considering both in biosurveillance applications

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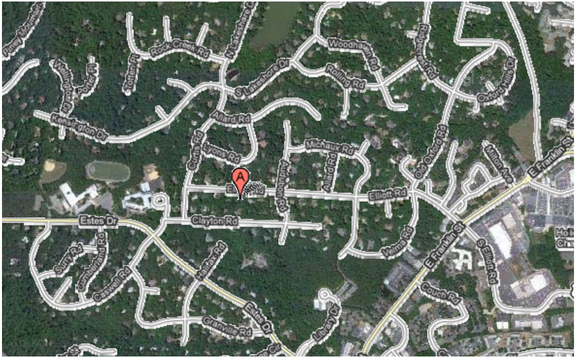
  - Even very definition of neighborhood is extremely difficult to characterize

Is Euclidean distance an appropriate metric?



- Reich et al. consider some of these issues in Biometrics paper examining neighborhood quality and multivariate physical activity outcomes

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- When preferential sampling designs used, appropriate methods to analyze data are needed

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- Need for new approaches

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- Literature in epidemiology and public health lags behind in use of spatial methods...rapid growth expected in next 5-10 years