

# Block Referenced Spatial Models

Acknowledgement: Many slides based on / borrowed from Sudipto Banerjee

# Block referenced data

- Data has an location, an attribute and an AREA
- Areas are usually contiguous
- Data often conceived of as being area integrals of some underlying continuous surface

$$z(B_i) = \frac{1}{|B_i|} \int_{B_i} z(s) ds$$

- Goals
  - Estimate surface  $z(s)$  or new blocks
  - Account for non-independence of adjacent blocks

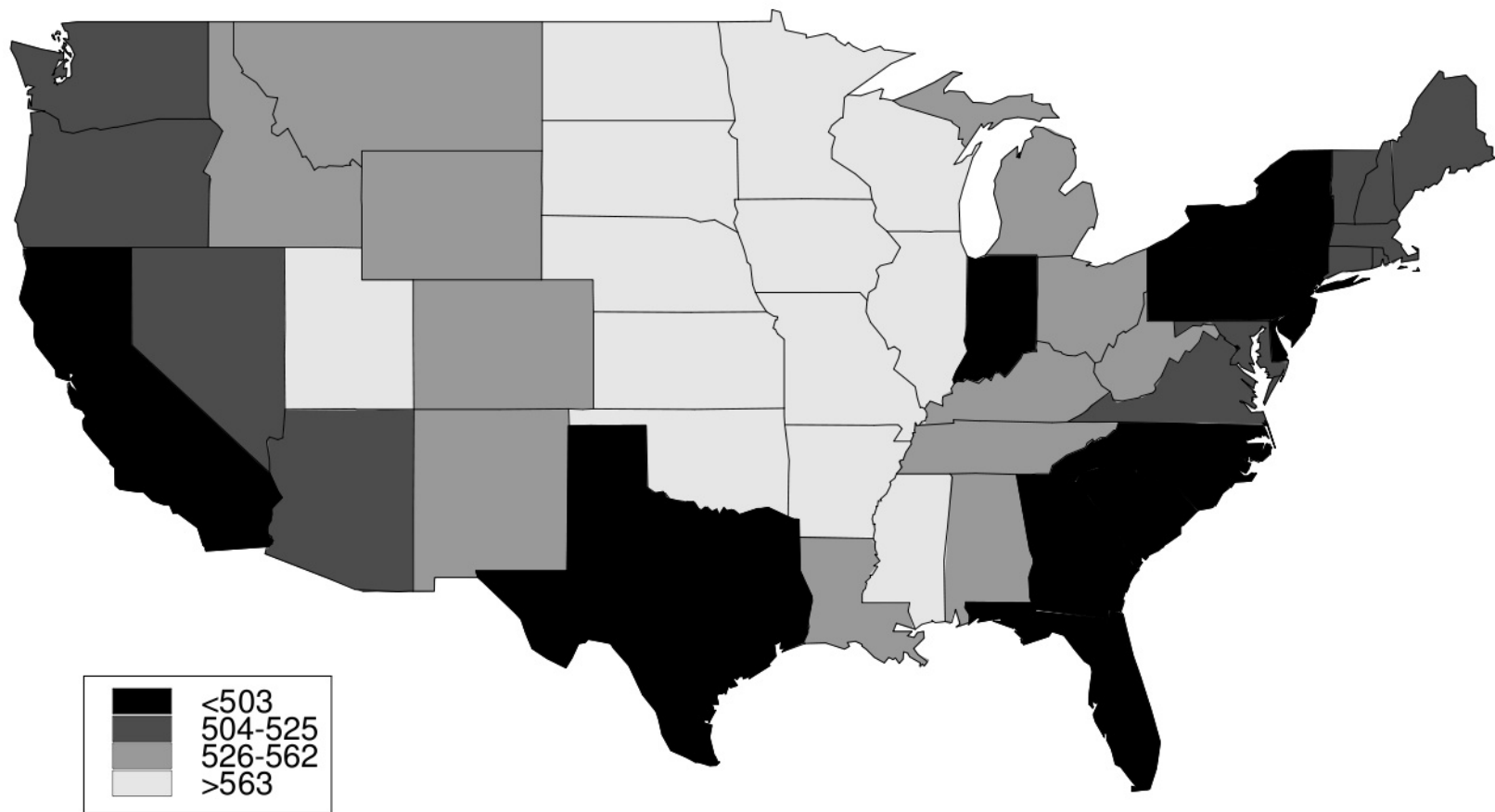


Figure 1: Choropleth map of 1999 average verbal SAT scores, lower 48 U.S. states.

# Proximity matrices

(block analog to distance matrix)

- $W$ , entries  $w_{ij}$  (with  $w_{ii} = 0$ ). Choices for  $w_{ij}$ :
  - $w_{ij} = 1$  if  $i, j$  share a common boundary (possibly a common vertex)
  - $w_{ij}$  is an *inverse* distance between units
  - $w_{ij} = 1$  if distance between units is  $\leq K$
  - $w_{ij} = 1$  for  $m$  nearest neighbors.
- $W$  is typically symmetric, but need not be
- $\widetilde{W}$ : standardize row  $i$  by  $w_{i+} = \sum_j w_{ij}$
- $W$  elements often called “weights”; interpretation
- Could also define *first-order* neighbors  $W^{(1)}$ , *second-order* neighbors  $W^{(2)}$ , etc.

# Measures of spatial association

- Moran's  $I$ : essentially an “areal covariogram”

$$I = \frac{n \sum_i \sum_j w_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{(\sum_{i \neq j} w_{ij}) \sum_i (Y_i - \bar{Y})^2}$$

- Geary's  $C$ : essentially an “areal variogram”

$$C = \frac{(n - 1) \sum_i \sum_j w_{ij} (Y_i - Y_j)^2}{(\sum_{i \neq j} w_{ij}) \sum_i (Y_i - \bar{Y})^2}$$

- Both are **asymptotically normal** if  $Y_i$  are i.i.d.;  
Moran has mean  $-1/(n - 1) \approx 0$ , Geary has mean 1
- Significance testing by comparing to a collection of say 1000 random permutations of the  $Y_i$

# Measures of spatial association (cont'd)

- For these data, the Moran's  $I$  is computed as 0.5833, with associated standard error estimate 0.0920  $\Rightarrow$  **very strong evidence against**  $H_0$  : no spatial correlation
- We obtain a Geary's  $C$  of 0.3775, with associated standard error estimate 0.1008  $\Rightarrow$  again, **very strong evidence against**  $H_0$  (departure from 1)
- **Warning:** These data have **not** been adjusted for covariates, such as the **proportion of students who take the exam** (Midwestern colleges have historically relied on the ACT, not the SAT; only the best and brightest students in these states would bother taking the SAT)
- $\Rightarrow$  the map,  $I$ , and  $C$  all motivate the **search for spatial covariates!**



# Spatial smoothers

- To smooth  $Y_i$ , replace with  $\hat{Y}_i = \frac{\sum_j w_{ij} Y_j}{w_{i+}}$
- More generally, we could include the value actually observed for unit  $i$ , and revise our smoother to

$$(1 - \alpha)Y_i + \alpha\hat{Y}_i$$

For  $0 < \alpha < 1$ , this is a linear (convex) combination in “shrinkage” form

Finally, we could try **model-based** smoothing, i.e., based on  $E(Y_i|Data)$ , i.e., the mean of the predictive distribution. Smoothers then emerge as byproducts of the hierarchical spatial models we use to explain the  $Y_i$ ’s

# Conditional Autoregressive (CAR) Model

$$y_i = \underbrace{\mu_i}_{\text{process model}} + \underbrace{\frac{1}{w_i} \sum_{j \neq i} w_{ij} (y_j - \mu_j)}_{\text{spatial autocorrelation}} + \underbrace{\epsilon_i}_{\text{error}}$$

- If raster, equivalent to Markov Random Field
- Analogous to AR(1) or our general model for spatial point data

$$Z(s) = \underbrace{\mu(s|\beta)}_{\text{trend}} + \underbrace{w(s|\phi)}_{\text{spatial error}} + \underbrace{\epsilon(s)}_{\text{residual error}}$$



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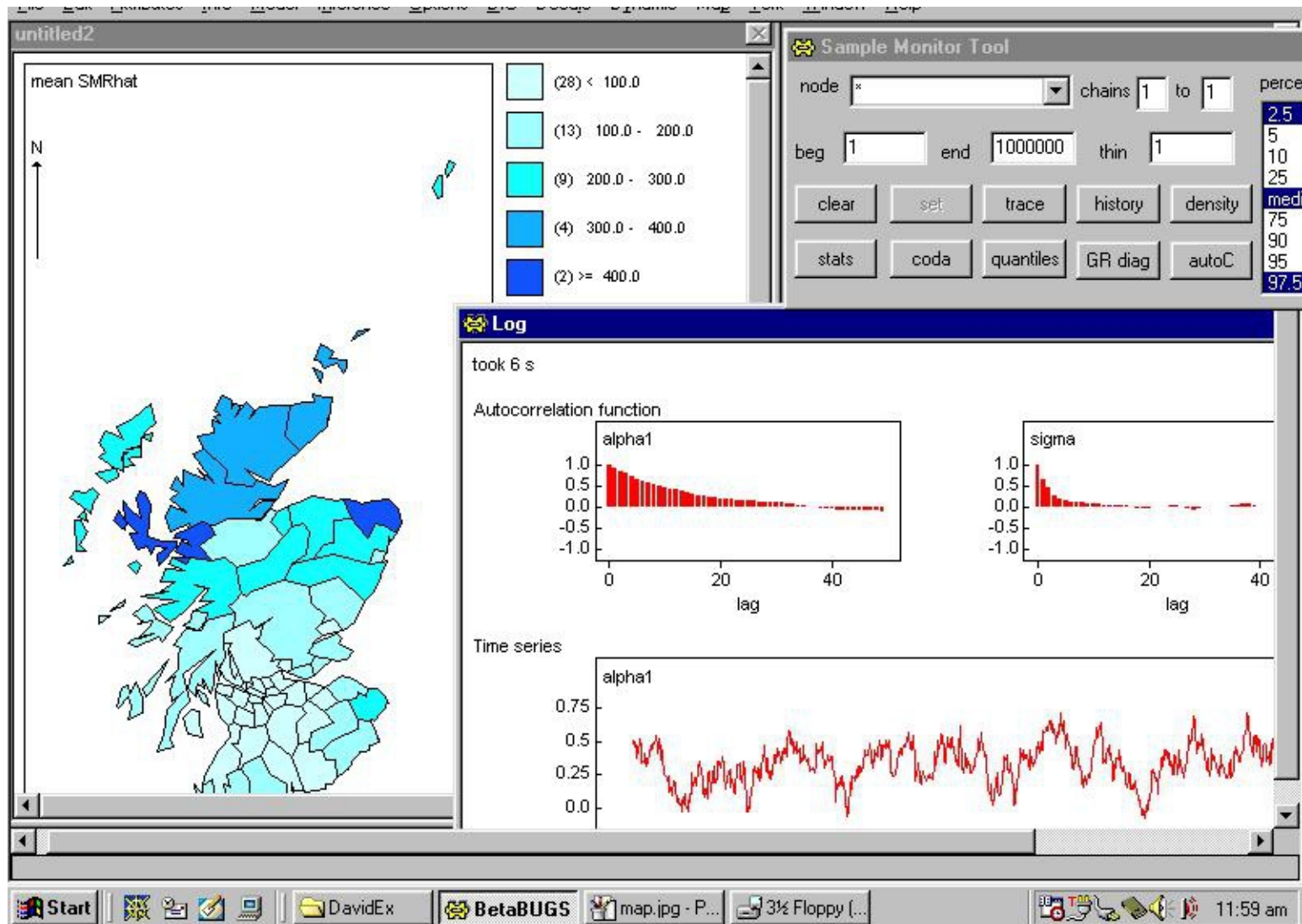
$$\vec{y} \sim N\left(\vec{\mu} | (I - \tilde{W})^{-1} \sigma^2 I\right)$$

**Analogous to time-series**

$$Y_t = \mu + \sum_{i=1}^p \rho_i Y_{t-i} + \epsilon_t \rightarrow Y \sim N\left(\mu, \frac{\sigma^2}{1 - \rho^2} R\right)$$

# Computation of CAR models

- “GeoBUGS” extension of WinBUGS



# Spatial Misalignment Problem

- “Change of support” problem
- Often need to compare / compute / infer spatial data of different types

Observe

Infer

- Point – Point (Kriging)
  - Point – Block
  - Block – Point
  - Block – Block
- **DON'T just interpolate/regrid**
  - Misrepresents sample size & uncertainty

# Point to Block

- Collect point data, want to infer the integral of the surface (e.g. county level biomass)
- Traditional approach: sample mean, var
  - Ignores autocorrelation, covariates, etc.
- Recommended Alternative:
  - Bayesian Kriging -> project to a fine grid
  - From each grid, numerically integrate

# Block to Point

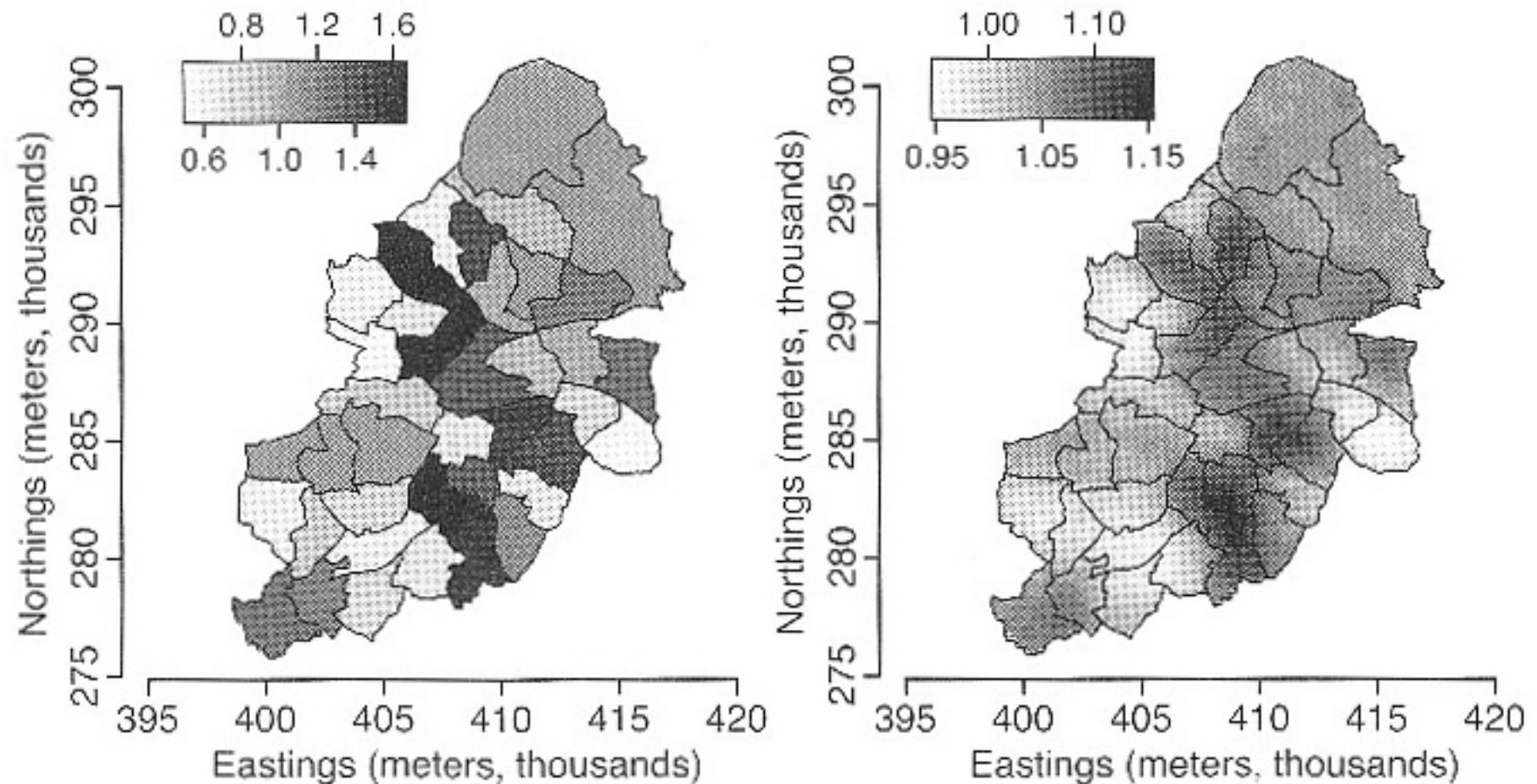
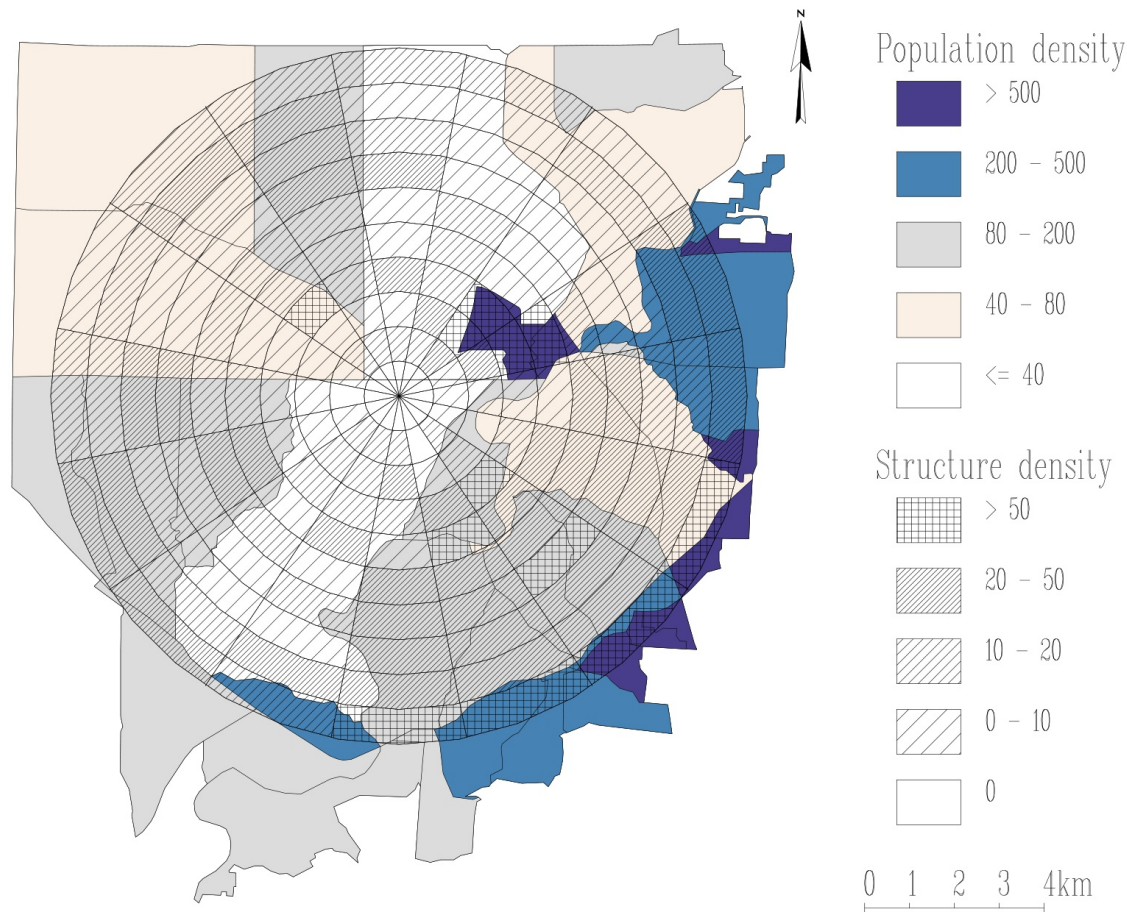


FIGURE 10.20. Standardized mortality ratios for thirty-nine wards in Birmingham, England, calculated as observed versus expected cases (*left*), and posterior median relative risk  $\gamma(s)$  (*right*). From Kelsall and Wakefield (2002).

# Block-Block Misalignment

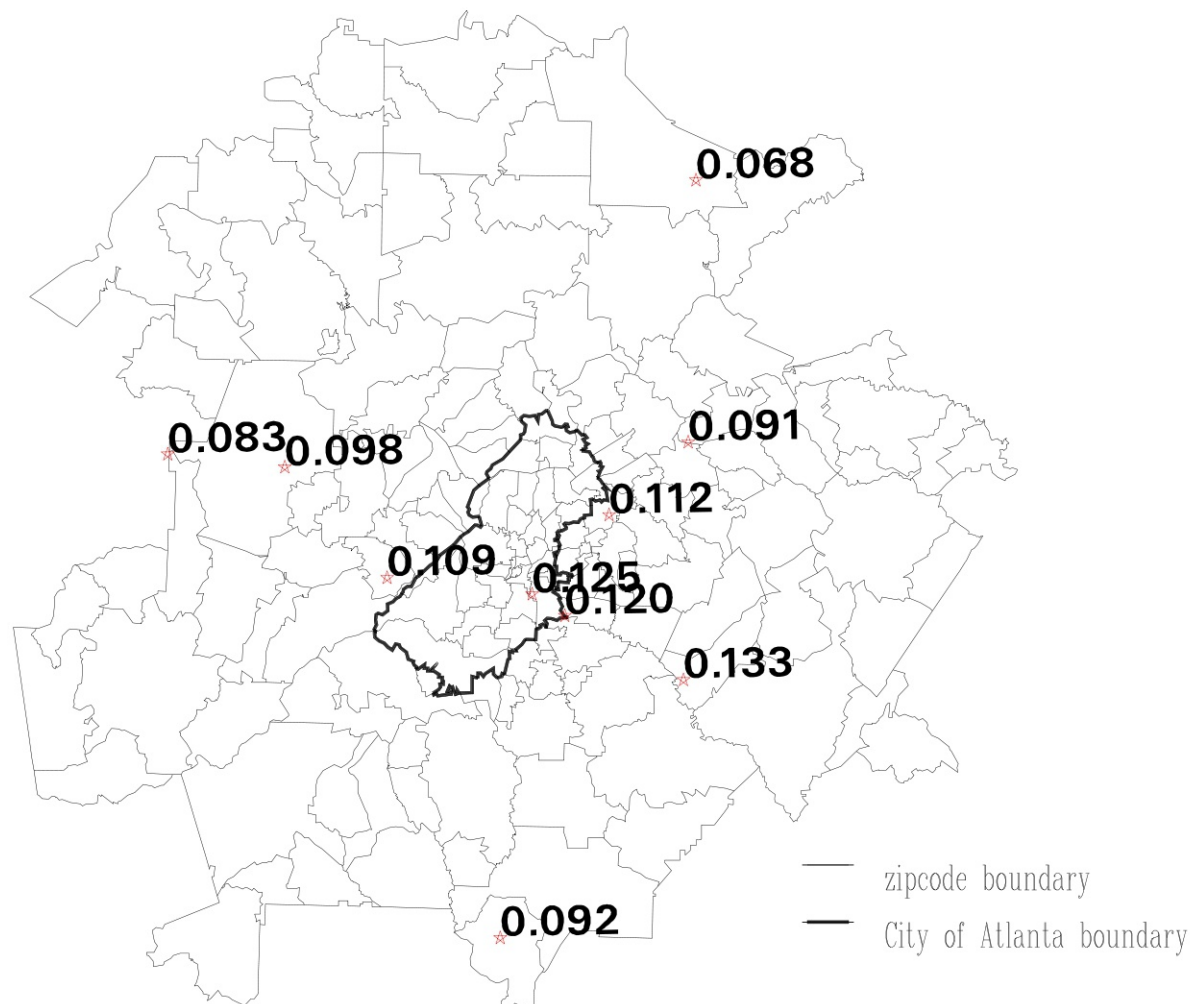
Population by census tract; residential structures by “cell”:



- “Areal Allocation”
- Hierarchical Modeling (e.g. CAR)

# Bivariate misalignment

Ozone measurements at fixed sites; counts of pediatric asthma cases by zip code in Atlanta, GA:





# Bivariate misalignment issues

- When we have two spatially referenced variables, interest often lies in **spatial regression**.
- But we cannot fit a regression if the two variables are **misaligned**:
  - X at point level, Y at other points
  - X at point level, Y at block level
  - X at block level, Y at point level
  - X at block level, Y at a different block level
- **Solution**: Bring the X's to the scale of the Y's, then fit the model (BCG, Sec 6.4)
- With more than two variables, bring **all** the variables to a common scale. Highest resolution is obviously preferred, but may be computationally infeasible!

# Next Steps

If you are interested in spatial modeling I recommend:  
“Hierarchical Modeling and Analysis for Spatial Data” 2003 by  
Sudipto Banerjee, Alan E. Gelfand, Bradley. P. Carlin

Cressie & Wikle 2011 “Statistics for Spatio-Temporal Data”

**Wikle, Zammit-Mangion, & Cressie. 2019. Spatio-Temporal  
Statistics with R, Chapman and Hall/CRC.**

<http://spacetimewithr.org/> (free pdf)