Analyzing Health and Environmental Data: Statistical Methods and Inferential Considerations

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EPA and CDC Symposium on Air Pollution Exposure and Health
September 19, 2006

Acknowledgements

- **Many ideas are based on joint work with:**

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Combining incompatible spatial data. *Journal of the American Statistical Association,* 2002.

Linking spatial data from different sources: The effects of change of support. *Stochastic Environmental Research and Risk Assessment*, 2006.

Very Low Birth Weight Study

Assess the association between:

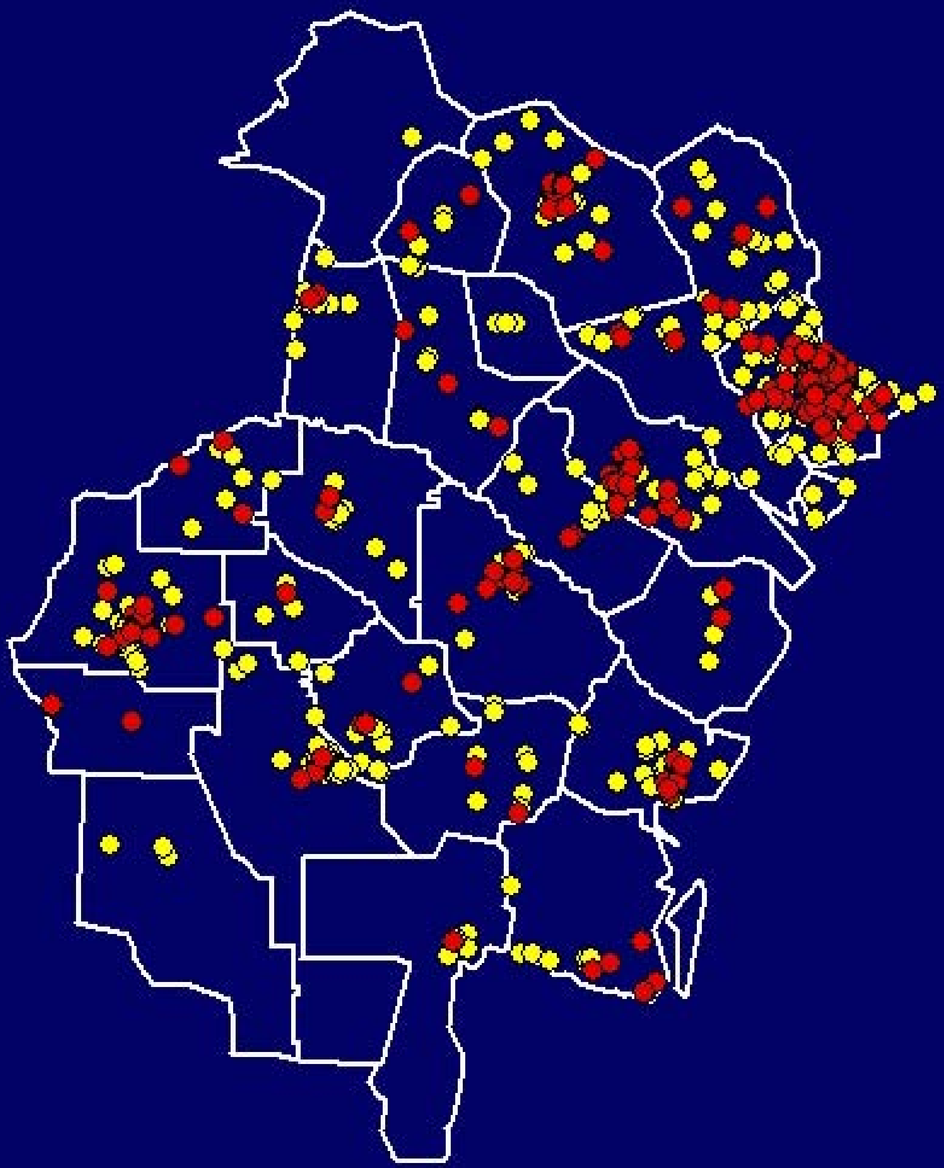
maternal exposure to air pollution
(here Total Suspended Particulates (TSP))

and

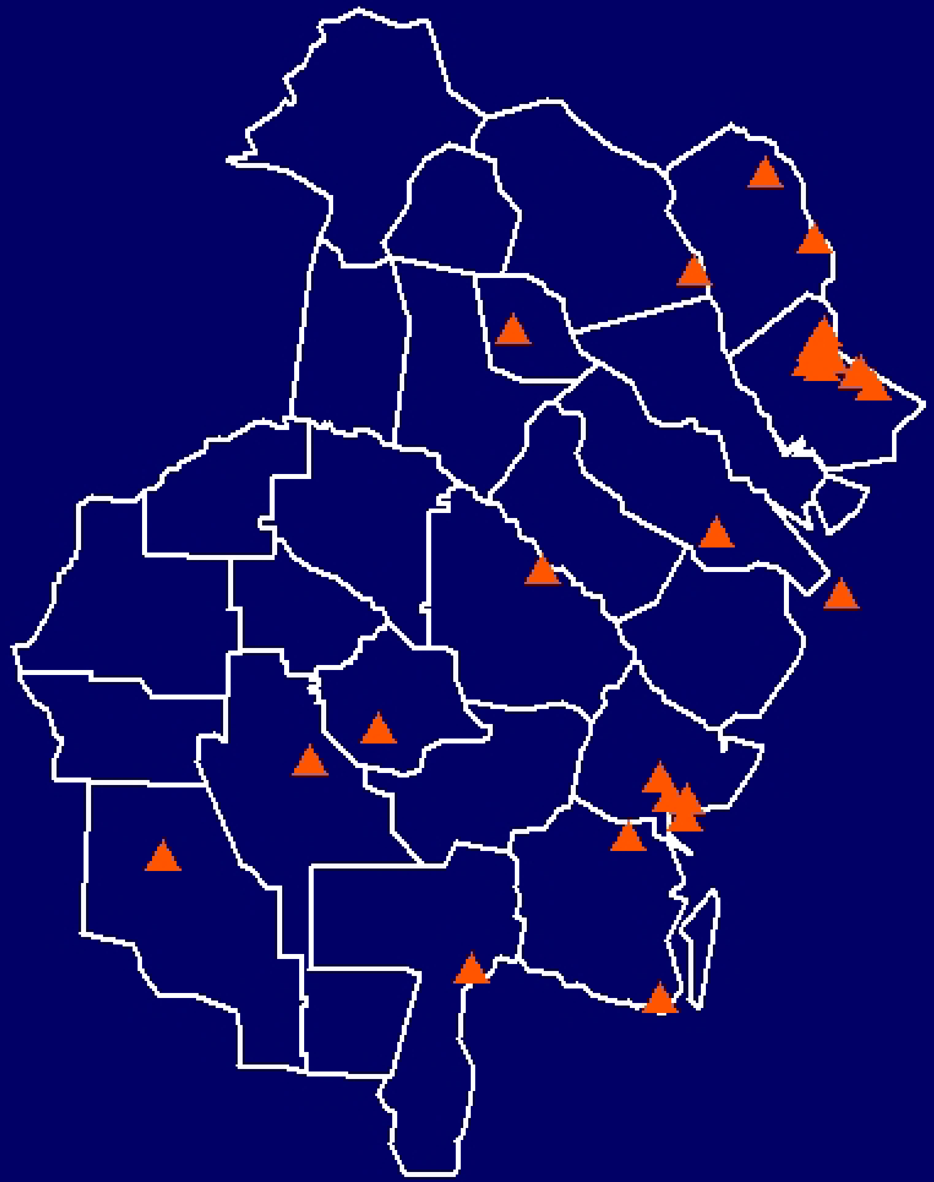
the risk of a very low birth weight baby
(weighs less than 1500 grams at birth)

Rogers, JF et al. (2000). *American Journal of Epidemiology*

VLBW Data Locations
Cases and **Controls**

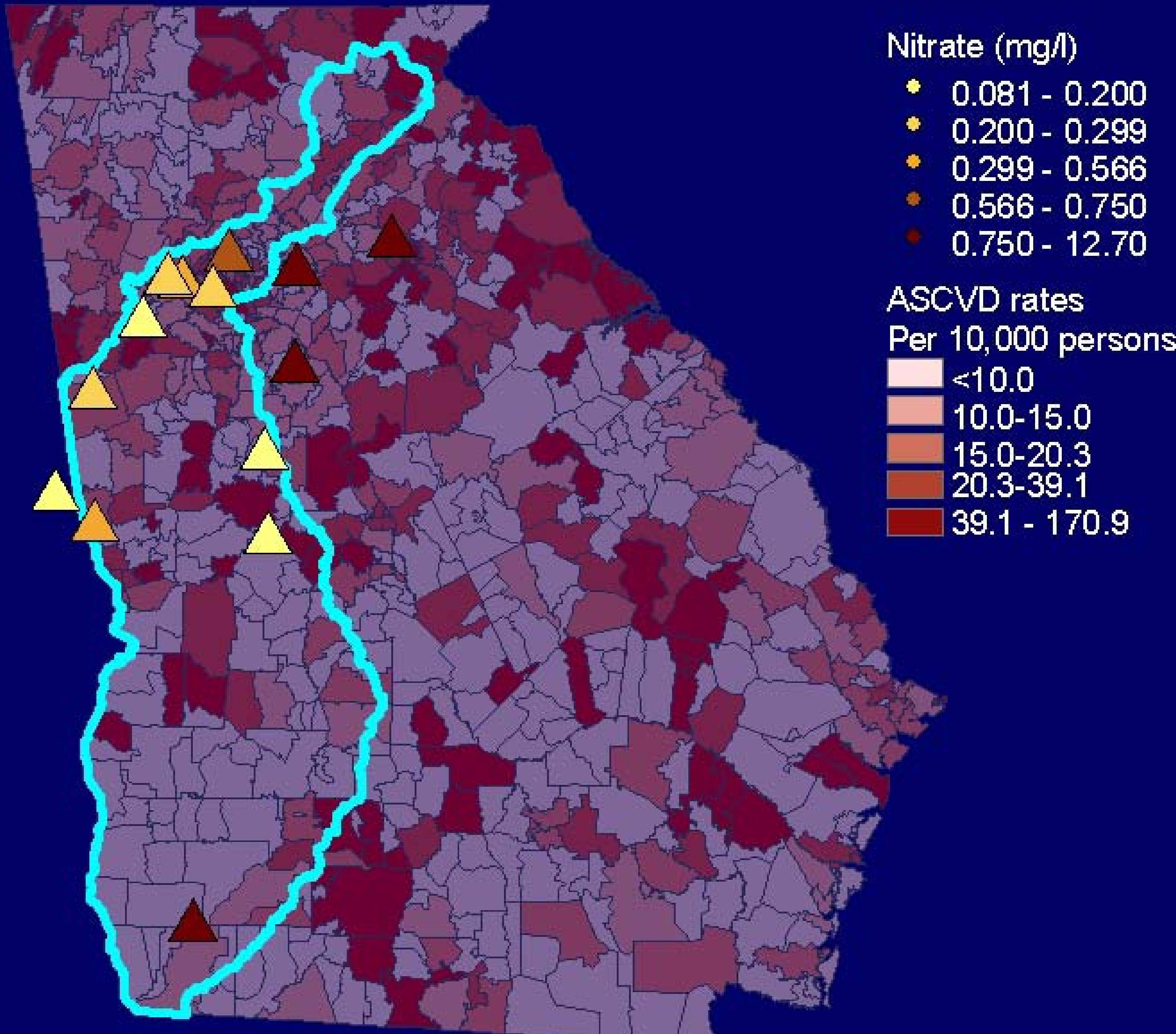


Emissions Data Locations

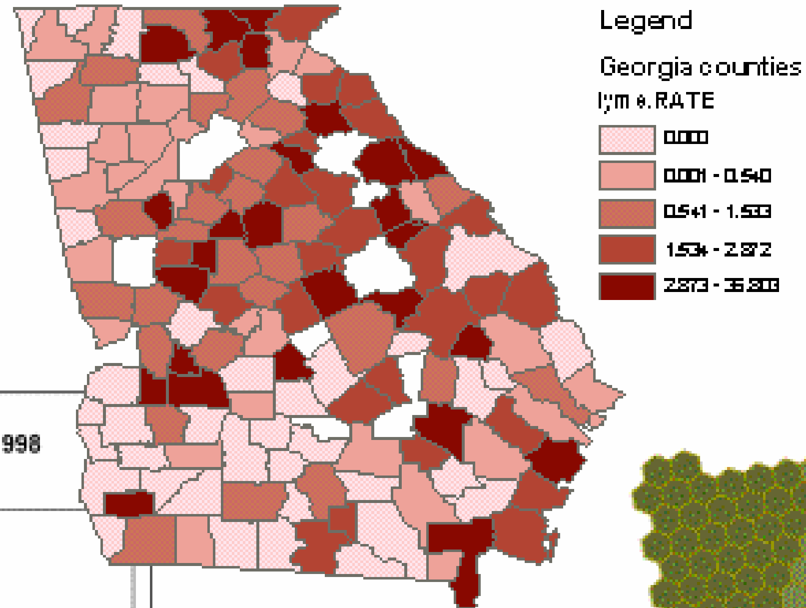


Linking Hospital Discharge and Water Quality Data

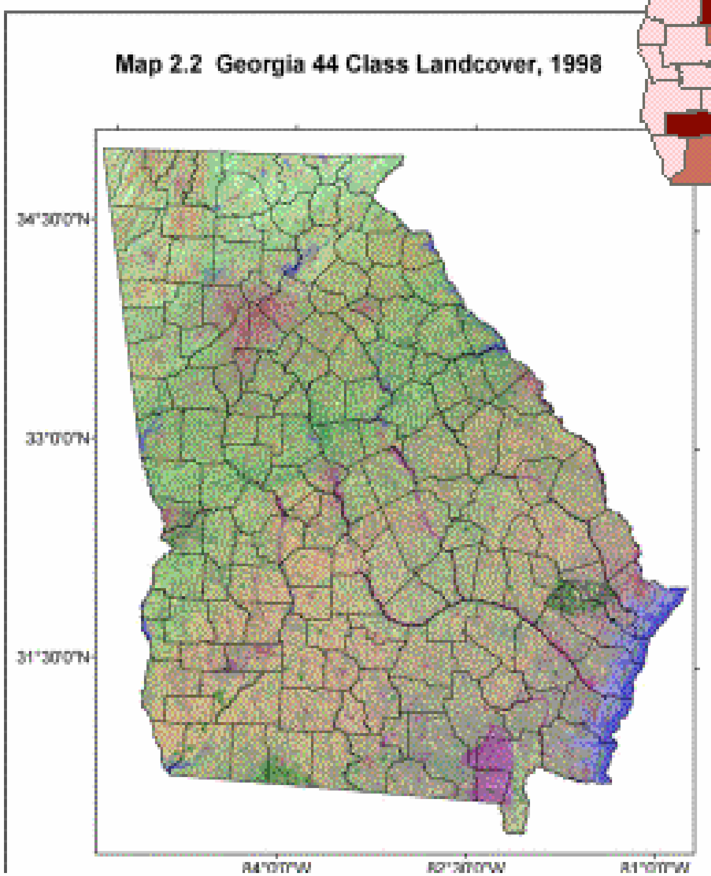
- Hospital discharge data: 1999-2003, GA, ZIP codes
- Environmental data from NAWQA
- Is there an association between **atherosclerotic cardiovascular disease** and **surface water nitrate concentration** in the Apalachicola-Chattahoochee-Flint river basin?
- How to monitor such potential associations?

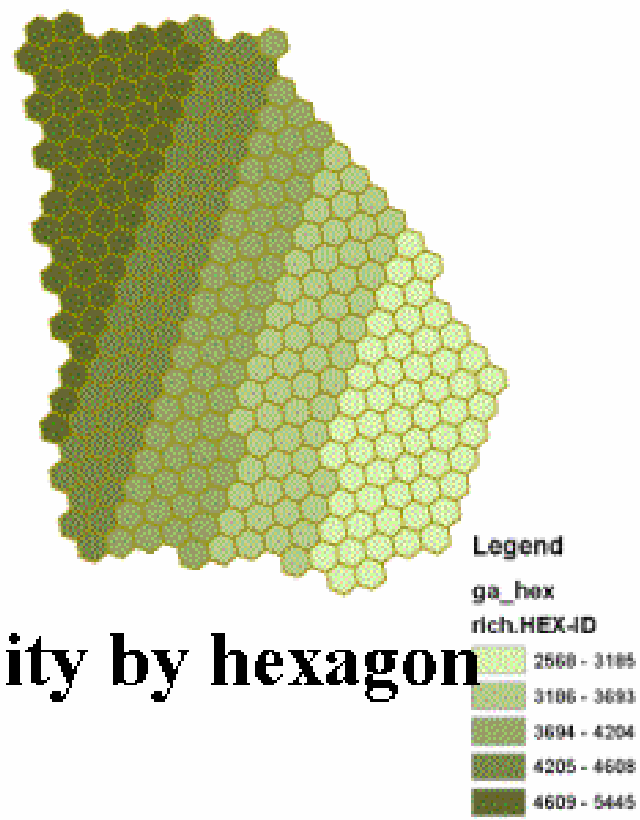

Nitrate (mg/l)
0.081 - 0.200
0.200 - 0.299
0.299 - 0.566
0.566 - 0.750
0.750 - 12.70
ASCVD rates
Per 10,000 persons
<10.0
10.0-15.0
15.0-20.3
20.3-39.1
39.1 - 170.9

Lyme disease rates by county



Landcover 30m





Species Diversity by hexagon

Key Features

- Data collected for different purposes
- Rarely recorded at the same time and place
- Many different spatial units involved:

Health Data:

- Census Units:
  - Tracts, counties, states
- ZIP code units
- Geocoded addresses

Environmental Data:

- Monitors
- Satellites
- Sampling Units

The Common Goal

- Use all the data to make inference about an outcome associated with one particular set of spatial units (e.g., health of individuals)
- Must involve upscaling (aggregation), downscaling (disaggregation), or side scaling (overlapping units or points)
- Statistically, this means making **predictions** of data associated with one set of spatial units from data associated with other sets of spatial units.

Main Statistical Issues

- Choice of geographic/spatial units
  - Modifiable Areal Unit Problem (MAUP)
  - Ecological Fallacy
- Spatial support
- Uncertainty

The Modifiable Areal Unit Problem

- Results from any statistical analysis depend on how the data are aggregated geographically.

- Openshaw and Taylor (1979):
  - Different geographical aggregations of the same data can produce ``**a million or so**'' correlation coefficients.
  - Could produce correlations ranging from -0.97 to +0.99!

- **The Ecological Fallacy:**
  - Analyses based on grouped data often lead to conclusions different from those based on individual data.

Spatial Support

- The size, shape and orientation of the spatial units.
- Measurements associated with areal units are inherently aggregates (totals, averages).
- The statistical and spatial properties of averages are different from those of the individual measurements (**Change of Support Problem**).
- Predicting at a point in the center of an areal unit is not the same as predicting an average value over that unit.

Implications for Data Linkage and Analysis

- Method of spatial prediction needed for linkage depends on the support of the data involved:
  - **Case 1:** VLBW: All data have point support.
  - **Case 2:** ACF Basin: Health data have supports defined by ZIP code units, environmental data have point support.
  - **Case 3:** Lyme Disease: Health data have county-level supports, land use data have areal support (30m pixels) and species diversity data have hexagonal support.

Spatial Prediction of Point-Support Data

Can obtain a predicted value at any point in space.

- **Deterministic:**
  - Given inputs get output
  - Does not use data to estimate parameters or determine form
  - No measure of uncertainty
- **Probabilistic:**
  - Based on a statistical model
  - Estimate unknown parameters and/or model using the data
  - Provide prediction standard errors.
- **Combination**

Prediction Methods

- **Deterministic interpolation methods**
  - Closest point/triangulation/Voronoi polygons
  - Inverse distance
- **Deterministic process models**
  - Gaussian plume models
  - Numerical methods
- **Statistical Methods**
  - Trend surface analysis
  - Regression
  - Kriging
  - Splines

Atmospheric Transport Model

$$\chi = \frac{Q\sqrt{2/\pi}\,f}{(2\pi x/16)\sigma_z u}\exp\left(-\frac{h_e^{\,2}}{2\sigma_z^{\,2}}\right)$$

u = wind speed (m s^{-1})

f = fraction of the time the wind blows into the receptor sector

x = distance (m) from the source to the receptor

σ_z = vertical dispersion coefficients (m) as a function of downwind distance from the source

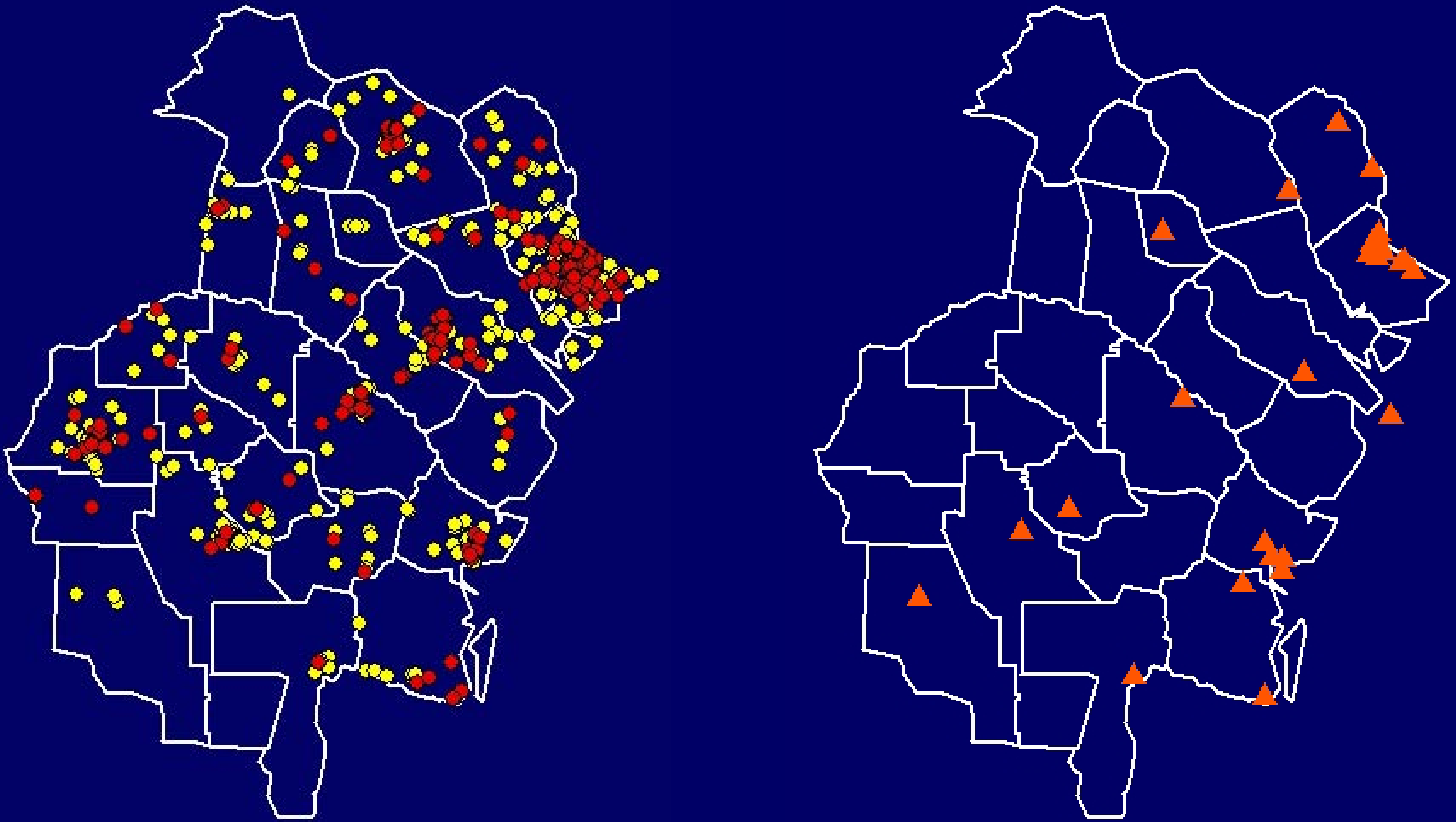
h_e = effective stack height of the source(m)

Q = release rate of TSP from the source (μg s^{-1})

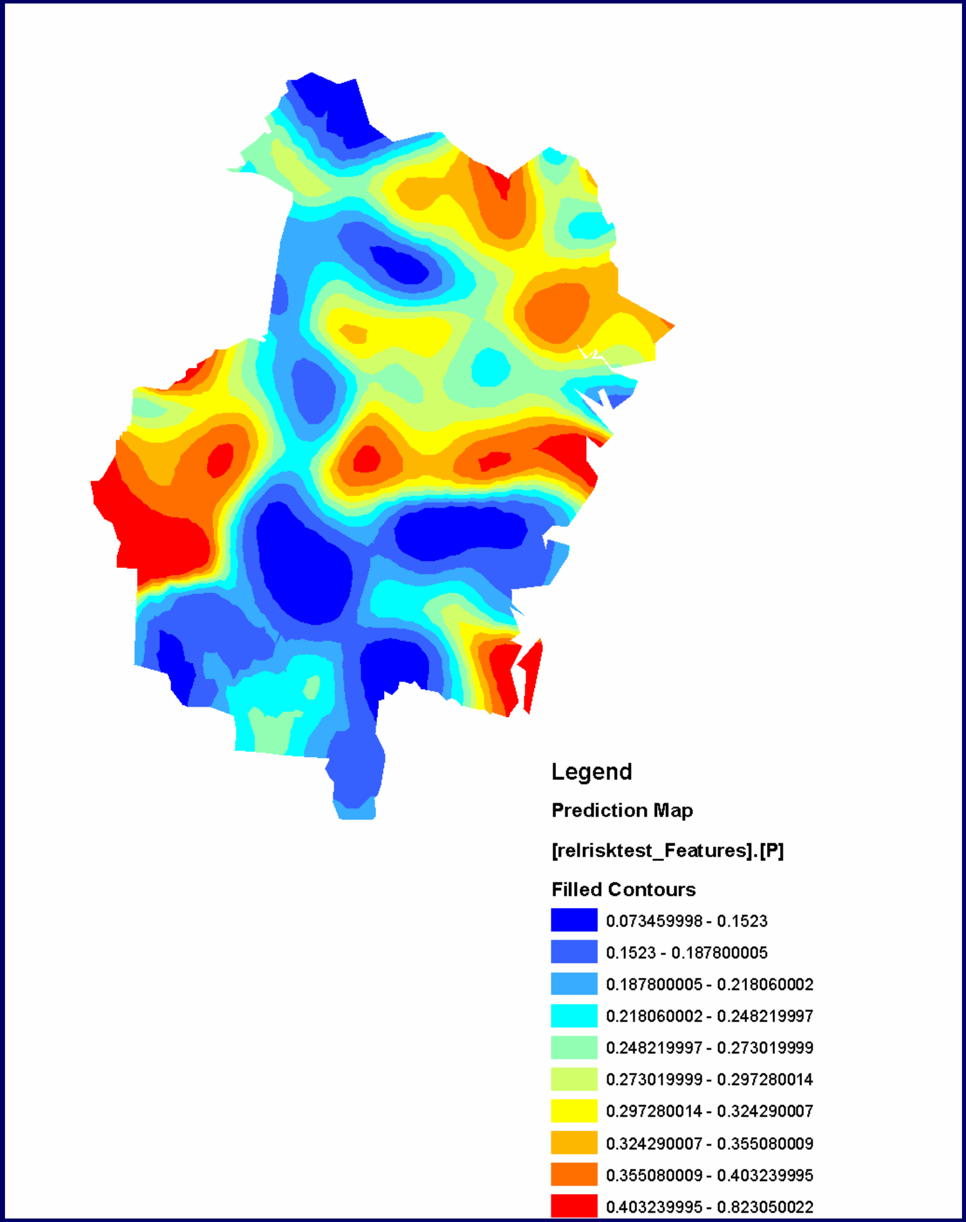
χ = average ground level concentration (μg m^{-3})

Case 1: Predict ground-level concentrations at each case and control location

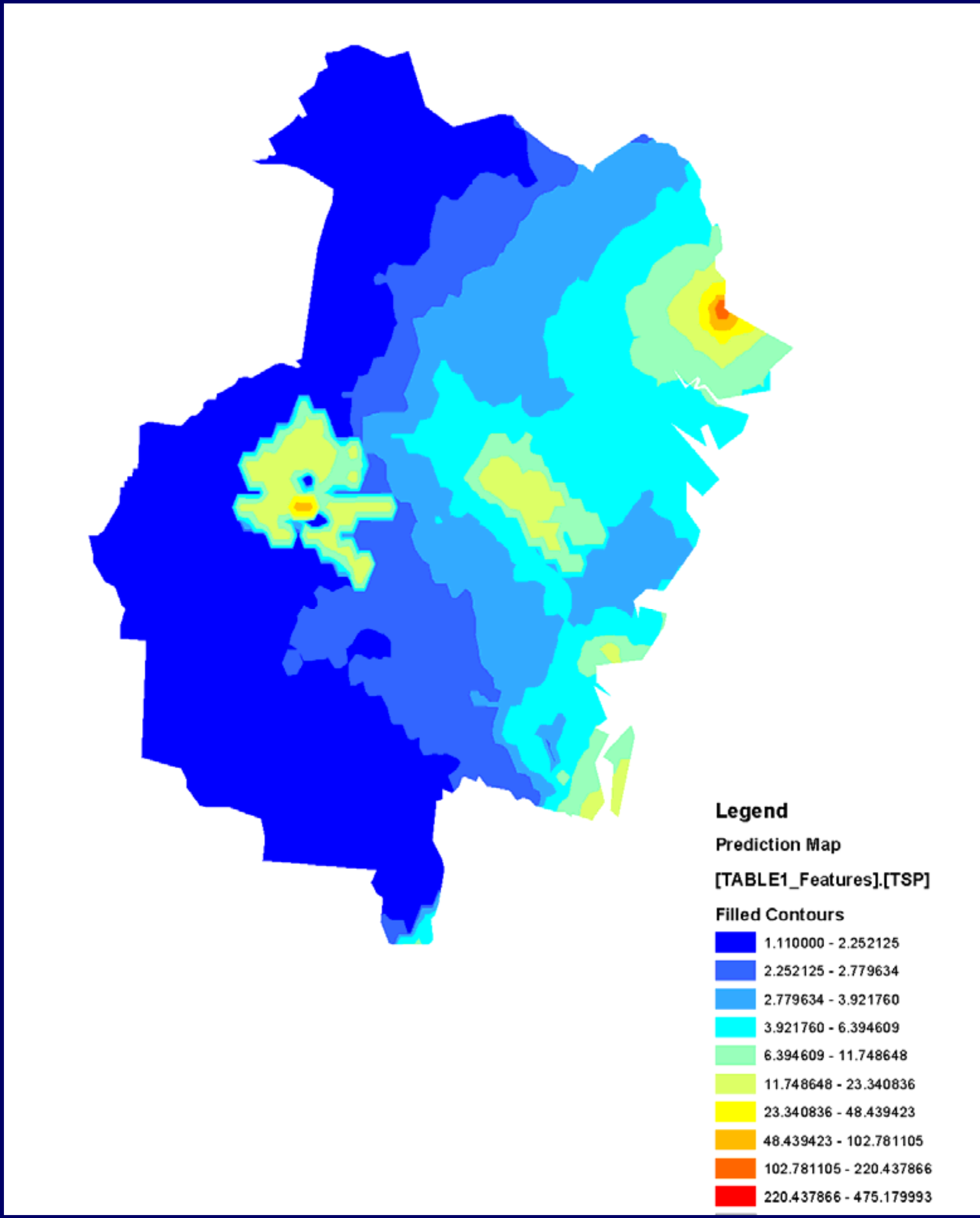
Can also predict the risk of having a VLBW birth at each industrial facility. Makes post-linkage analysis more difficult (?).



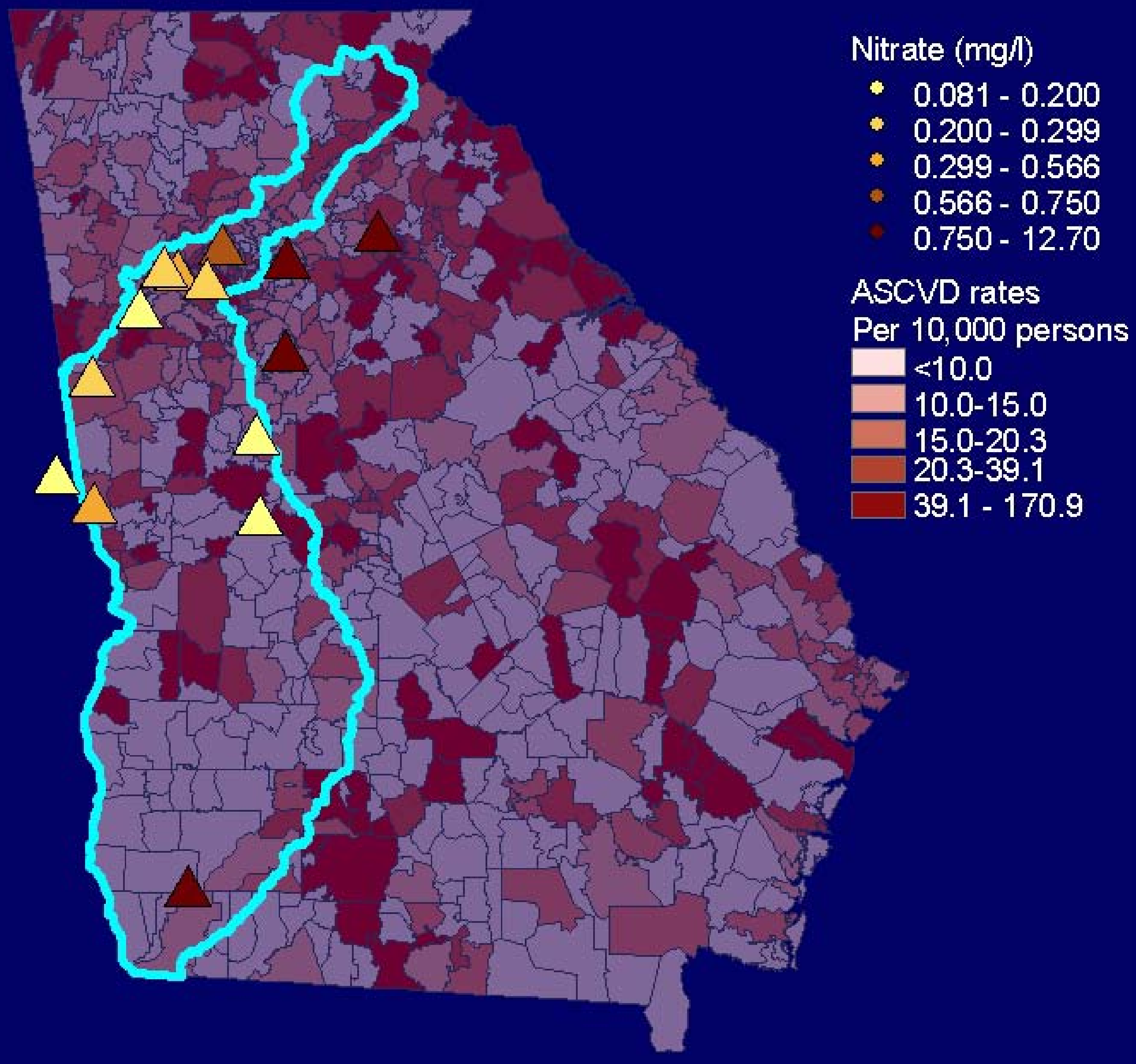
Relative Risk Map



Ground-level Exposure Estimates from Transport Model



Case 2: Nitrate data have point support, but health data are aggregated over ZIP code units (rates)



Options

- Predict a nitrate value at the “center” of each ZIP code unit (“traditional” approach)
- Support-adjusted prediction:
  - Predict many values in the ZIP code and then average the results
  - Need point-in-polygon codes or “zonal” analysis capabilities
  - Formal statistical technique is called “**block** kriging” and is used to get correct standard errors
- Can also “downscale” health data and predict the relative risk of ASCVD at any point.

Does Support Really Matter?

Poisson regression used after linkage:

Method	Rate Ratio	95% CI
Point Prediction at Centroids	0.85	(0.77, 0.94)
Support-adjusted Prediction	0.72	(0.58, 0.89)

Accounting for support effects may be even more important when we account for prediction uncertainty.

Case 3 and Beyond

- Many more sophisticated solutions
- Most are complex spatial and space-time models
- Many are situation specific
- Overview in Gotway and Young (2002)
- Area of current statistical research

Traditional Post-Linkage Analysis

- **Poisson/Logistic regression analysis**
  - Include variables for seasonal trends; can adjust for temporal autocorrelation
- **Non-/semi-parametric regression**
  - Allows more flexible models for seasonal variation in both health and environmental data
  - GAMs, Regression splines (B-splines, P-splines), GLASS (generalized linear additive smooth structures, Eilers and Marx, 2002)
- **Case-Crossover analysis**
  - Exposures of cases just prior to an event are compared to the exposures for the same cases from some separate time period.
  - Avoids geographic aggregation, but may introduce locational error.

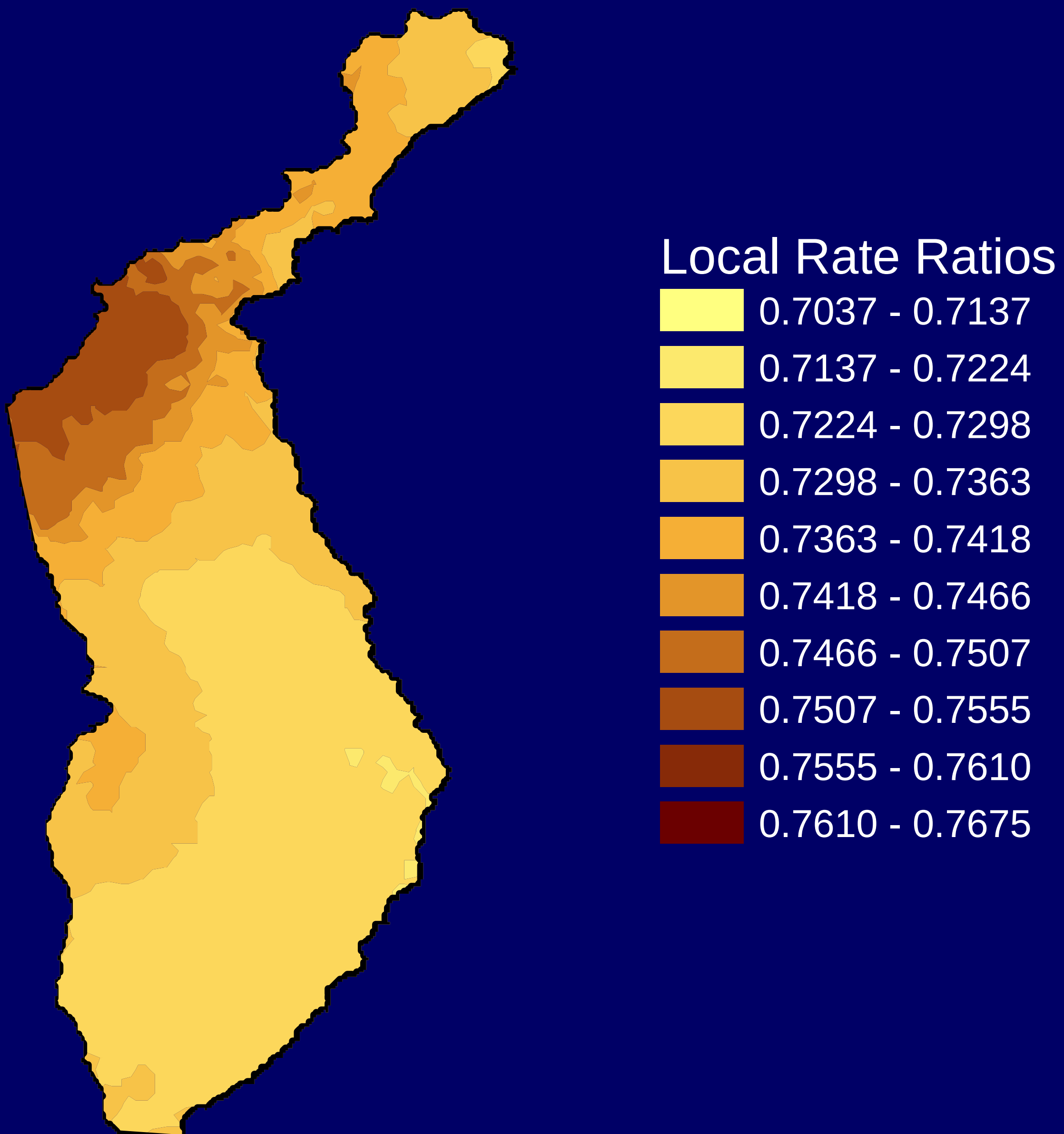
- Focus mostly on temporal variation in the data. Little focus on geographic variation.

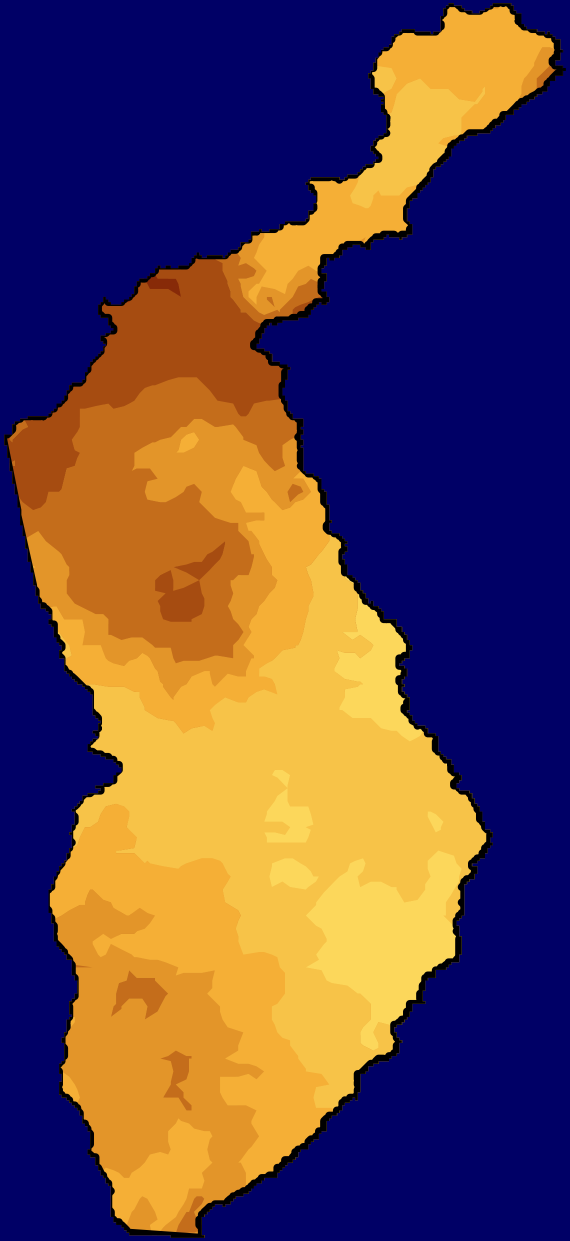
Beyond the Traditional

- **Quality control models**
  - Routinely used in health surveillance
    - EARS, Lori Hutwagner, NCID
  - Environmental monitoring, multivariate, regression, spatial, and space-time adaptations

- **Spatially-varying coefficient models**
  - Geographically weighted regression
    (Fotheringham et al 2002, Nakaya et al. 2005)
  - Random coefficient models
    (Gelfand et al. 2003; Congdon, 2003)

Map the association between the environmental hazard and the health outcome of concern
(Map the correlation, odds ratio, or risk)





Monitor through time

THE Most Important Issue: Uncertainty

- Post-linkage analysis must account for the uncertainties that arise from prediction during linkage, as well as any uncertainties in the initial data.
- Otherwise, confidence intervals are too narrow, p-values are too small, and conclusions are probably wrong.
- Probabilistic prediction methods provide a measure of prediction uncertainty (standard errors), but these cannot be easily used in subsequent analyses.

Methods for Quantifying Uncertainty

- Model the variability in the input, simulate from this model, analyze the resulting variation in output.
  - Monte Carlo/Geostatistical simulation
  - EM algorithm with maximum likelihood
  - Bayesian hierarchical models
- Must account for differing supports.
- Accounting for temporal variation may require complex space-time models.
- Computationally challenging.

Case 1: VLBW Study Regression Results (adjusted for maternal covariates)

- **Original logistic regression:**

Exposure Categories	Odds Ratio	95% C.I.
High	2.88	(1.16, 7.13)
Medium	1.27	(0.68, 2.37)
Low	0.99	(0.99, 1.92)

- **Accounting for uncertainty in modeled TSPs:**

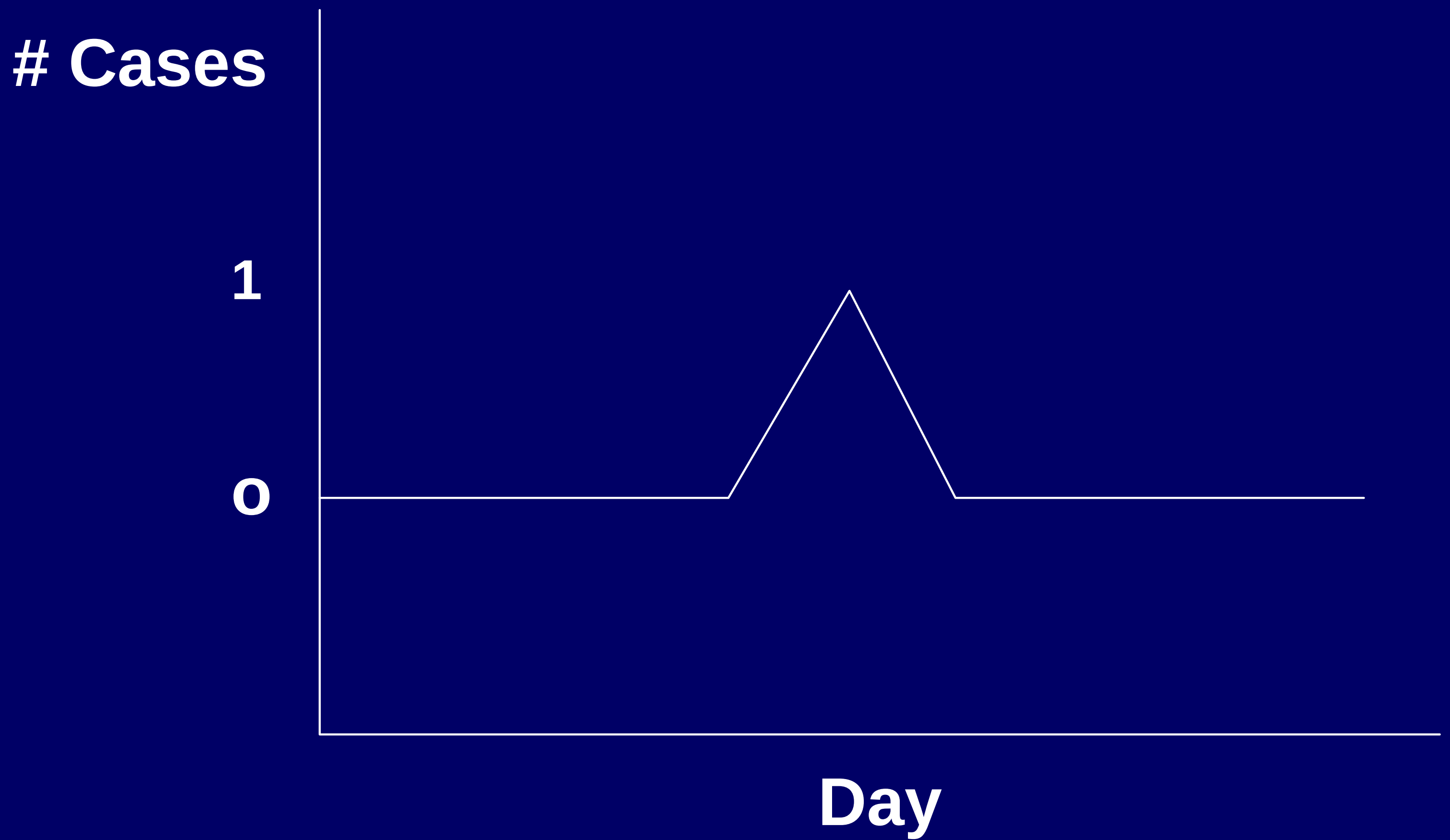
Exposure Categories	Odds Ratio	95% C.I.
High	4.18	(1.82, 9.08)
Medium	2.13	(1.09, 4.13)
Low	1.45	(0.72, 2.87)

Beyond The Three-Step Approach

- Link, Analyze, Uncertainty Assessment
- All-in one: Bayesian Hierarchical Models with Kalman Filtering. Theoretically, should be able to simultaneously:
  - take the data and models used in PHASE
  - combine them with health data
  - get a map of associations with estimated uncertainties
  - provide an algorithm for routine updating as new data become available
  - produce forecasts in space and time

Pre-Linkage Issues

- Data management
  - PHASE dataset has 6 million (**?!!!**) records
- Ensuring confidentiality of health data
  - Personal liability
  - Lack of secure infrastructure
- Controls (?)
- Other data (temperature, humidity)?
- Determination of meaningful temporal and spatial scales:
  - Fine stratification
  - Unstable rates (small number problem)
  - Lots of zeros



Is one case important if it is asthma in Atlanta in July?
If it is a rare birth defect?

If 95% of the values are 0, are the results from Poisson/Logistic regression valid? Meaningful?

Final Thoughts

- Just because we can does not mean we should:
  - Data not collected for this purpose; Spurious associations; Beyond usual observational study.
- Do we need to formally link the data?
  - What will we learn that we couldn't learn from monitoring each separately?
  - What will we learn that we don't already know?
- **Scale issues are extremely important:**
  - What temporal changes are important (Hourly? Daily? Yearly)?
  - Over what geographic extent are models valid?
  - How much geographic variability can we expect?

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