

Dimension Reduction and Alleviation of Spatial Confounding for Spatial Generalized Linear Mixed Models

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What This Talk is About

- ▶ Modeling spatial data on a lattice is challenging.
- ▶ Spatial generalized linear mixed models (SGLMMs) provide a general framework. They are widely used.
- ▶ Shortcomings of SGLMMs: (1) Inference presents difficult computational issues. (2) Parameter interpretation is generally misleading.
- ▶ I will describe an approach that simultaneously resolves both these issues.

Non-Gaussian Spatial Data Example #1

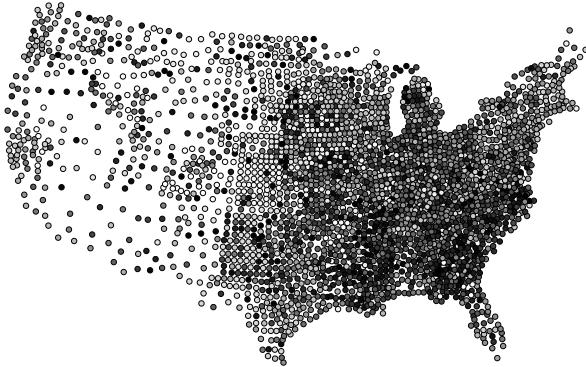
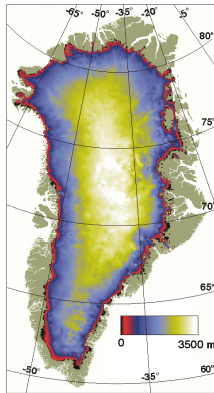


Figure: U.S. infant mortality data by county. $n = 3071$
Ratio of deaths to births, each averaged over 2002-2004.
Darker indicates higher rate.

Non-Gaussian Spatial Data Example #2



Greenland ice sheet thickness (Bamber et al., 2001)

Spatial Data on a Lattice

- ▶ Gaussian and non-Gaussian spatial data are very common and appear in a large number of disciplines.
- ▶ Common lattice data: binary, count, zero-inflated
- ▶ Purpose of the model
 1. regression while adjusting for residual spatial dependence
 2. smoothing the spatial field and “borrowing strength”
- ▶ These models are used widely and have become particularly important in disease epidemiology and ecology.

Spatial Linear Models

- ▶ Spatial process at location \mathbf{s} is $Z(\mathbf{s}) = X(\mathbf{s})\beta + W(\mathbf{s})$.
 - ▶ $X(\mathbf{s})$ are covariates at \mathbf{s} and β is a vector of coefficients.
 - ▶ Model dependence among spatial random variables by imposing it on the errors (the $W(\mathbf{s})$'s).
- ▶ Gaussian Markov Random field (GMRF): Let Θ be the parameters for precision matrix $Q(\Theta)$. Then:

$$\mathbf{z}_{n \times 1} | \Theta, \beta \sim N(\mathbf{X}_{n \times p} \beta_{p \times 1}, Q^{-1}(\Theta))$$

Spatial Linear Models: Dependence

- ▶ $Q = \text{diag}(A\mathbf{1}) - A$ where adjacency matrix A is such that $A_{ij} = 1$ if locations i and j are neighbors, 0 else
- ▶ Implications:
 - ▶ $W(\mathbf{s})$ is conditionally independent of all other W s given its neighbors
 - ▶ uncertainty about $W(\mathbf{s})$ is inversely proportional to its number of neighbors.

Spatial Generalized Linear Mixed Models

Model for Z at location \mathbf{s}_i

1. $Z(\mathbf{s}_i) | \beta, \Theta, W(\mathbf{s}_i), i = 1, \dots, n$, conditionally independent

E.g. $Z(\mathbf{s}_i) | \beta, W(\mathbf{s}_i) \sim \text{Poisson}(\mu(\mathbf{s}_i))$

2. Link function $g(\mu(\mathbf{s}_i)) = X(\mathbf{s}_i)\beta + W(\mathbf{s}_i)$

E.g. $\log(\mu_i) = X(\mathbf{s}_i)\beta + W(\mathbf{s}_i)$

3. Impose dependence: $\mathbf{W} = (W(\mathbf{s}_1), \dots, W(\mathbf{s}_n))^T$

$$p(\mathbf{W} | \tau) \propto \tau^{(n-1)/2} \exp\left(-\frac{\tau}{2} \mathbf{W}' Q \mathbf{W}\right)$$

4. Priors for Θ, β

Inference based on $\pi(\Theta, \beta, \mathbf{W} | \mathbf{Z})$

(Besag et al. (1991), Diggle et al. (1998))

SGLMMs: Challenges

SGLMMs have become very popular even outside mainstream statistics. Flexible models but some drawbacks:

- (1) Confounding between spatial random effects and fixed effects (covariates)
- (2) Computational challenges

Spatial Confounding in SGLMMs

- ▶ $\mathbf{P} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$, orthogonal projection onto $C(\mathbf{X})$
- ▶ $\mathbf{P}^\perp = \mathbf{I} - \mathbf{P}$, orthogonal projection onto $C(\mathbf{X})$'s orthogonal complement
- ▶ Spectral decomposition to acquire orthogonal bases, $\mathbf{K}_{n \times p}$ and $\mathbf{L}_{n \times (n-p)}$, for $C(\mathbf{X})$ and $C(\mathbf{X})^\perp$. Rewrite:

$$g(\mathbb{E}(Z_i | \beta, W_i)) = \mathbf{X}_i\beta + W_i = \mathbf{X}_i\beta + \mathbf{K}_i\gamma + \mathbf{L}_i\delta.$$

\mathbf{K} is collinear with \mathbf{X} .

This is the source of confounding. Appears to cause variance inflation.

Computing for SGLMMs

MCMC algorithms for SGLMMs are challenging to construct:

- ▶ Spatial random effects: one random effect for each data point. $n + p + 1$ dimensions where n =size of data, p =number of predictors. MCMC is slow per iteration due to high dimensionality
- ▶ Markov chain is slow mixing due to strong cross-correlations among the spatial random effects.

Several attempts to address these issues: Rue and Held (2005), Haran et al. (2003), Haran and Tierney (2010)

Observations

- ▶ Spatial random effects **W** are the cause of confounding issues as well as computational challenges.
- ▶ **W** are just a device to induce dependence. Not intrinsically important.
- ▶ Idea: reparameterize and reduce dimensions of **W**.

Spatial Confounding: Reparameterization Solution

- ▶ Reich, Hodges and Zadnik (2006) propose solution: since \mathbf{K} have no scientific meaning, delete them from the model.
- ▶ $g(\mathbb{E}(Z_i | \beta, \delta)) = \mathbf{X}_i\beta + \mathbf{L}_i\delta$. Prior for random effects δ now

$$p(\delta | \tau) \propto \tau^{(n-p)/2} \exp\left(-\frac{\tau}{2}\delta'\mathbf{Q}^*\delta\right),$$

where $\mathbf{Q}^* = \mathbf{L}'\mathbf{Q}\mathbf{L}$.

- ▶ Corrects issues due to confounding
- ▶ # of parameters reduced (only slightly) from $n + p + 1$ to $n + 1$. Computational challenge remains.
- ▶ RHZ approach does not fully account for underlying graph

Our Sparse Reparameterization

- ▶ Represent graph $G = (V, E)$ using \mathbf{A} , $n \times n$ adjacency matrix with entries $\text{diag}(\mathbf{A}) = \mathbf{0}$ and $\mathbf{A}_{ij} = 1\{(i, j) \in E, i \neq j\}$, with $1\{\cdot\}$ an indicator function
- ▶ Basic idea inspired by Griffith (2003): augment a generalized linear model with selected eigenvectors of $(\mathbf{I} - \mathbf{1}\mathbf{1}'/n)\mathbf{A}(\mathbf{I} - \mathbf{1}\mathbf{1}'/n)$. This appears in Moran's I statistic (nonparametric measure of spatial dependence),

$$I(\mathbf{A}) \propto \frac{\mathbf{Z}'(\mathbf{I} - \mathbf{1}\mathbf{1}'/n)\mathbf{A}(\mathbf{I} - \mathbf{1}\mathbf{1}'/n)\mathbf{Z}}{\mathbf{Z}'(\mathbf{I} - \mathbf{1}\mathbf{1}'/n)\mathbf{Z}},$$

Background for Sparse Reparameterization

- ▶ Griffith's goal: reveal the structure of missing spatial covariates. Our goal: smoothing orthogonal to \mathbf{X}
- ▶ Hence, we replace $\mathbf{I} - \mathbf{1}\mathbf{1}'/n$ with \mathbf{P}^\perp
- ▶ $\mathbf{M}_\mathbf{X}(\mathbf{A}) = \mathbf{P}^\perp \mathbf{A} \mathbf{P}^\perp$, Moran operator for \mathbf{X} with respect to the graph G , appears in numerator of generalized Moran's I :

$$I_\mathbf{X}(\mathbf{A}) \propto \frac{\mathbf{Z}' \mathbf{P}^\perp \mathbf{A} \mathbf{P}^\perp \mathbf{Z}}{\mathbf{Z}' \mathbf{P}^\perp \mathbf{Z}}.$$

Applying the Sparse Reparameterization

- Replacing \mathbf{L} with \mathbf{M} in the RHZ model gives

$$g(\mathbb{E}(Z_i | \beta, \delta)) = \mathbf{X}_i\beta + \mathbf{M}_i\delta.$$

And the prior for the random effects is now

$$p(\delta | \tau) \propto \tau^{q/2} \exp\left(-\frac{\tau}{2} \delta' \mathbf{Q}^{**} \delta\right),$$

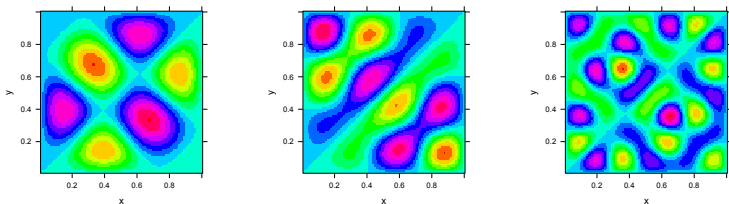
where $\mathbf{Q}^{**} = \mathbf{M}'\mathbf{Q}\mathbf{M}$.

- Corrects issues due to confounding
- Potential for dimension reduction: if we reduce dimensions of \mathbf{M}_i to q , the # parameters is reduced from $n + p + 1$ to $q + p + 1$ (q can be small)

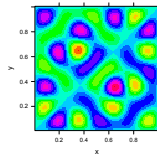
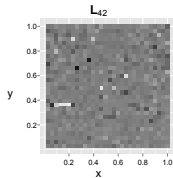
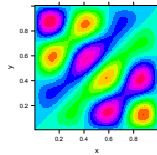
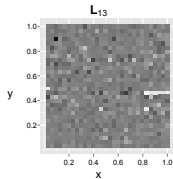
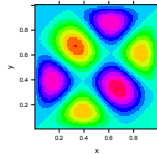
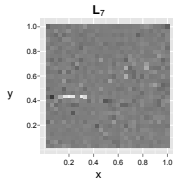
Interpreting the Resulting Reparameterization

- “Tailored” to \mathbf{X} and G : eigenvectors comprise all possible patterns of clustering residual to \mathbf{X} and accounting for G

Some selected basis vectors for the 30×30 lattice.



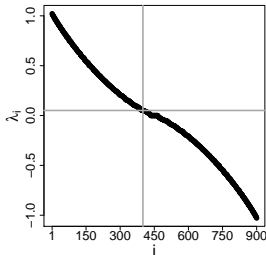
Eigenvectors 7, 13, 42 from RHZ and Moran bases



Interpreting the Resulting Reparameterization

- Positive (negative) eigenvalues correspond to varying degrees of positive (negative) spatial dependence (Boots and Tiefelsdorf, 2000)

The standardized eigenvalues for the 30×30 lattice.



Exploiting the New Parameterization

- ▶ If we assume positive spatial dependence, eigenvectors corresponding to negative spatial dependence (negative eigenvalues) should be removed.
- ▶ Small eigenvalues may not be meaningful. Remove corresponding eigenvectors.
- ▶ Result: much reduced dimensions

Study: Inference for Spatial Binary

30×30 lattice simulated from RHZ model with $\beta_1 = \beta_2 = 1$.

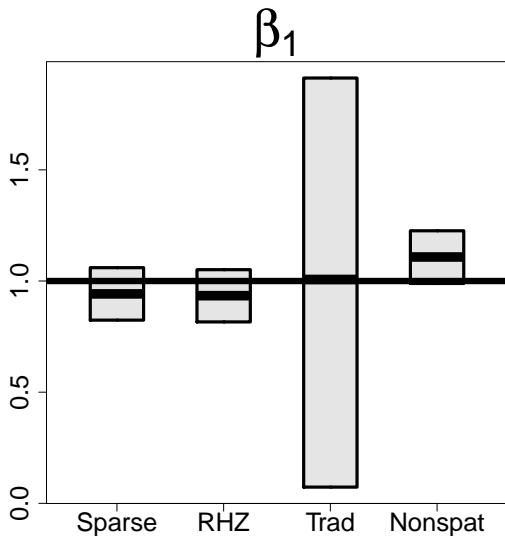
Predictors are the coordinates of unit square.

Model	$\hat{\beta}_1$ CI(β_1)	$\hat{\beta}_2$ CI(β_2)
Sparse	1.080 (0.613, 1.556)	1.130 (0.644, 1.635)
RHZ	1.120 (0.637, 1.606)	1.192 (0.679, 1.713)
Traditional	0.500 (-2.655, 3.616)	-0.605 (-3.698, 2.577)

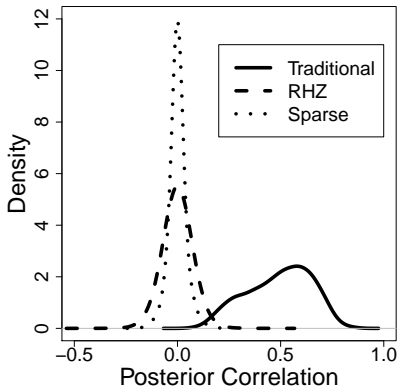
- Point and interval estimates for Traditional are very poor:
95% interval includes 0
- Sparse and RHZ produce similar (good) results

Similar results for Gaussian (linear) and Poisson

Spatial Count Data: Simulation Results



De-correlated Random Effects



Greatly improves efficiency of simple MCMC. No need for elaborate proposals (cf. Held and Rue (2005), Haran et al. (2003), Haran and Tierney (2010)).

Spatial Binary: Computational Efficiency

Model	Dimension	Running Time
Sparse	228	2.5 hours
RHZ	901	18.5 hours
Traditional	903	38.5 hours

- ▶ MCMC algorithm is
 - ▶ faster per iteration (far fewer random effects)
 - ▶ mixes faster (random effects are “decorrelated”)
 - ▶ Far greater speed-ups with much smaller q , e.g. 25-50 is adequate for our examples (we are also being *extremely* careful by running very long chains!)
- Real data example: 14 days (traditional) versus 2-8 hours

Summary

- ▶ SGLMMs provide a very general approach for modeling non-Gaussian spatial data
- ▶ Our sparse approach results in more interpretable regression coefficients
- ▶ We allow for only meaningful spatial dependence and a natural approach to dimension reduction
- ▶ Automated MCMC is computationally efficient, allowing for routine analysis of large data sets

References

- ▶ Besag, York, Mollie (1991) Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics*
- ▶ Griffith (2003) Spatial Autocorrelation and Spatial Filtering. *Springer*.
- ▶ Reich, Hodges and Zadnik (2006) Effects of residual smoothing on the posterior of the fixed effects in disease-mapping models. *Biometrics*

Hughes, J. and Haran, M. (2013) "Dimension Reduction and Alleviation of Confounding for Spatial Generalized Linear Mixed Models," *Journal of the Royal Statistical Society (B)*

Software: <http://www.biostat.umn.edu/~johnh/software.html>