

# A Review of Spatial (and Spatio-Temporal) Autoregressive Models

Jay Ver Hoef

Marine Mammal Laboratory  
NOAA-NMFS Alaska Fisheries Science Center  
Seattle, WA and Fairbanks, AK, USA

## Collaborators

- ▶ Erin Peterson, ARC Centre of Excellence for Mathematical & Statistical Frontiers (ACEMS) and Institute for Future Environments, Queensland University of Technology
- ▶ Mevin Hooten, U.S. Geological Survey, Colorado Cooperative Fish and Wildlife Research Unit, Department of Fish, Wildlife, and Conservation Biology, Department of Statistics, Colorado State University
- ▶ Ephraim Hanks, Department of Statistics, Penn State University
- ▶ Marie-Josée Fortin, Department of Ecology and Evolutionary Biology, University of Toronto



# Goals

Talk based on:

- ▶ Ver Hoef, J.M., Peterson, E. E., Hooten, M. B., Hanks, E. M., and Fortin, M.-J. 2018. Spatial Autoregressive Models for Statistical Inference from Ecological Data. *Ecological Monographs*, **88**: 36–59. DOI:10.1002/ecm.1283
- ▶ Ver Hoef, J.M., Hanks, E.M., and Hooten, M.B. On the relationship between conditional (CAR) and simultaneous (SAR) autoregressive models. arXiv:1710.07000[math.ST] and in revision to *Spatial Statistics*.
- ▶ Spatio-temporal is new, but partly based on Brown, D.A. and McMahan, C.S. Sampling Strategies for Fast Updating of Gaussian Markov Random Fields. arXiv:1702.05518[stat.CO]

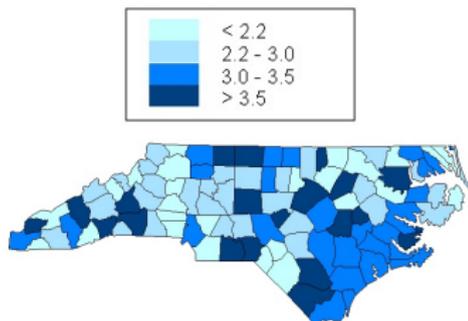
# Typical Inferences

- ▶ Model Comparison and Selection (Averaging)
- ▶ Regression (Effect of Explanatory Variables)
- ▶ Estimation of Autocorrelation Parameters
- ▶ Estimation of Other Network Parameters
- ▶ Prediction of Unsampled Locations
- ▶ Smoothing over Sampled and Unsampled Locations

# Autoregressive Models vs. Geostatistics

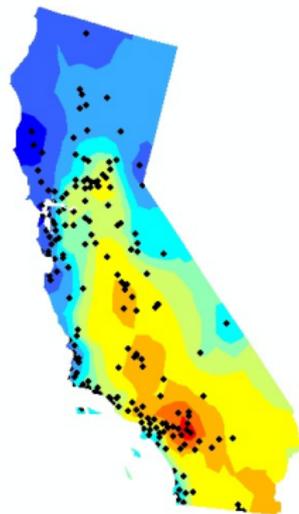
## Autoregressive Models

Sudden Infant Death Syndrome



## Geostatistics

Ozone



# CAR and SAR defined

## SAR

$$\mathbf{z} = \mathbf{B}\mathbf{z} + \boldsymbol{\nu}$$

$$\mathbf{z} - \mathbf{B}\mathbf{z} = \boldsymbol{\nu}$$

$$\mathbf{z} = (\mathbf{I} - \mathbf{B})^{-1}\boldsymbol{\nu}$$

## CAR

$$Z_i | \mathbf{z}_{-i} \sim N\left(\sum_{j=1}^n c_{ij} z_j, m_{ii}\right)$$

# CAR and SAR in Linear Model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{z} + \boldsymbol{\varepsilon}; \quad E(\boldsymbol{\varepsilon}) = 0, \text{var}(\boldsymbol{\varepsilon}) = \sigma_{\boldsymbol{\varepsilon}}^2 \mathbf{I}$$

## SAR

$$\begin{aligned} \text{var}(\mathbf{z}) &= \boldsymbol{\Sigma} \equiv \sigma_Z^2 ((\mathbf{I} - \mathbf{B})\boldsymbol{\Lambda}(\mathbf{I} - \mathbf{B}'))^{-1} \\ \boldsymbol{\Sigma} &= \sigma_Z^2 ((\mathbf{I} - \rho\mathbf{W})(\mathbf{I} - \rho\mathbf{W}'))^{-1} \\ \boldsymbol{\Sigma}^{-1} &= ((\mathbf{I} - \rho\mathbf{W})(\mathbf{I} - \rho\mathbf{W}'))/\sigma_Z^2 \end{aligned}$$

## Geostatistics

$$\begin{aligned} \text{var}(\mathbf{z}) &= \boldsymbol{\Sigma}_{i,j} = \sigma_Z^2 \exp(-d_{i,j}/\rho) \\ \boldsymbol{\Sigma} &= \sigma_Z^2 \exp(-\mathbf{D}/\rho) \end{aligned}$$

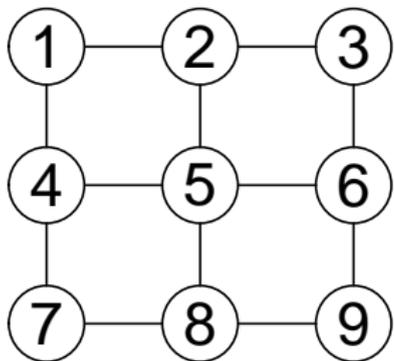
## CAR

$$\begin{aligned} \text{var}(\mathbf{z}) &= \boldsymbol{\Sigma} \equiv \sigma_Z^2 (\mathbf{I} - \mathbf{C})^{-1} \mathbf{M} \\ \boldsymbol{\Sigma} &= \sigma_Z^2 (\mathbf{M}^{-1} - \rho\mathbf{W})^{-1} \\ \boldsymbol{\Sigma}^{-1} &= (\mathbf{M}^{-1} - \rho\mathbf{W})/\sigma_Z^2 \end{aligned}$$

## Partial Correlation

$$\rho(Z_i, Z_j) = \frac{-\boldsymbol{\Sigma}^{-1}[i,j]}{\sqrt{\boldsymbol{\Sigma}^{-1}[i,i]\boldsymbol{\Sigma}^{-1}[j,j]}}$$

# Simple Example



$$\mathbf{W} = \begin{pmatrix} 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \end{pmatrix}$$

# Covariance Matrix of Simple Example

$$\Sigma = (\mathbf{I} - 0.2\mathbf{W})^{-1} = \begin{pmatrix} 1.10 & 0.26 & 0.06 & 0.26 & 0.12 & 0.04 & 0.06 & 0.04 & 0.02 \\ 0.26 & 1.16 & 0.26 & 0.12 & 0.29 & 0.12 & 0.04 & 0.07 & 0.04 \\ 0.06 & 0.26 & 1.10 & 0.04 & 0.12 & 0.26 & 0.02 & 0.04 & 0.06 \\ 0.26 & 0.12 & 0.04 & 1.16 & 0.29 & 0.07 & 0.26 & 0.12 & 0.04 \\ 0.12 & 0.29 & 0.12 & 0.29 & 1.24 & 0.29 & 0.12 & 0.29 & 0.12 \\ 0.04 & 0.12 & 0.26 & 0.07 & 0.29 & 1.16 & 0.04 & 0.12 & 0.26 \\ 0.06 & 0.04 & 0.02 & 0.26 & 0.12 & 0.04 & 1.10 & 0.26 & 0.06 \\ 0.04 & 0.07 & 0.04 & 0.12 & 0.29 & 0.12 & 0.26 & 1.16 & 0.26 \\ 0.02 & 0.04 & 0.06 & 0.04 & 0.12 & 0.26 & 0.06 & 0.26 & 1.10 \end{pmatrix},$$

## Neighborhood Matrix

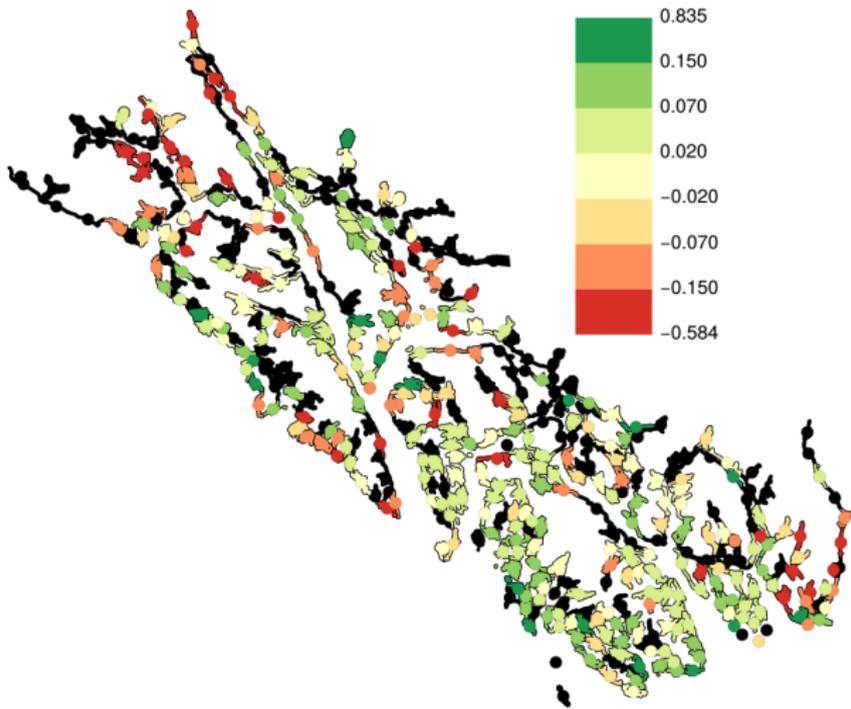


often  $\rightarrow$  
$$\mathbf{W} = \begin{pmatrix} 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 1 \\ \vdots & & & & & \end{pmatrix}$$

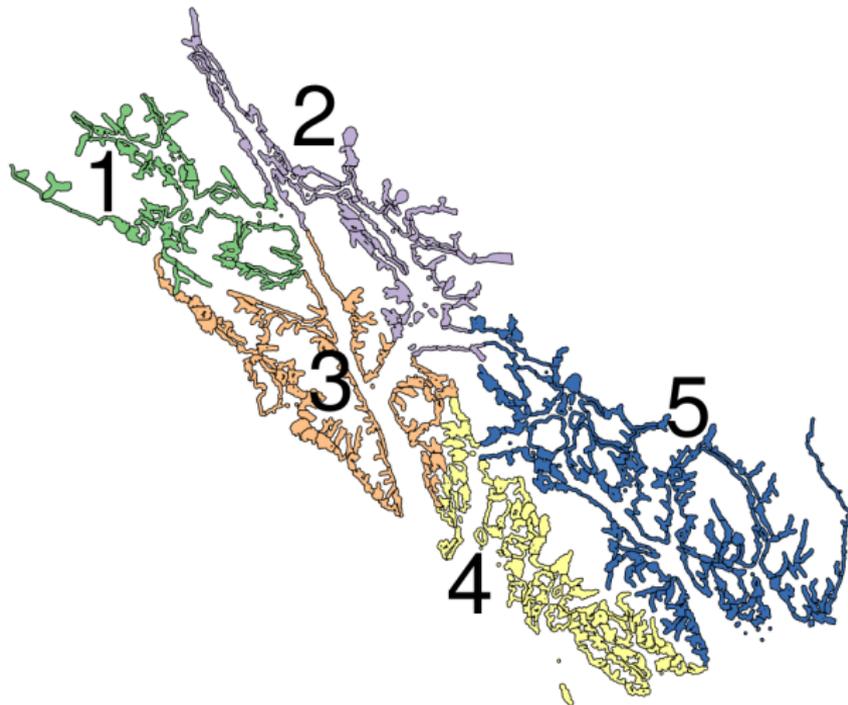
Row Standardization: 
$$\mathbf{W}_+ = \begin{pmatrix} 0 & 0 & 1/\mathbf{W}_{1,+} & 0 & \dots & 0 \\ 0 & 0 & 1/\mathbf{W}_{2,+} & 0 & \dots & 1/\mathbf{W}_{2,+} \\ \vdots & & & & & \end{pmatrix}$$

- ▶ For Row Standardization, need to fix up  $\mathbf{M}$  for CAR models
- ▶  $\mathbf{W}$ :  $1/\lambda_{[1]} < \rho < 1/\lambda_{[M]}$ ,  $\mathbf{W}_+$ :  $-1 < \rho < 1$
- ▶ More complex structures for  $\mathbf{W}$  (distance, connectivity,...)
- ▶ IAR special case of CAR using  $\mathbf{W}_+$  and  $\rho = 1$
- ▶ Estimation: MLE, Bayes MCMC, etc.

# Study Area - Harbor Seal Trends

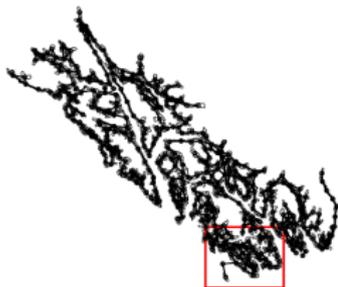


# Harbor Seal Stocks



# Neighbors

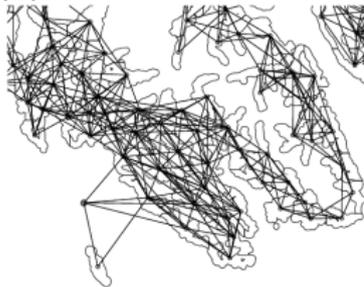
(a)



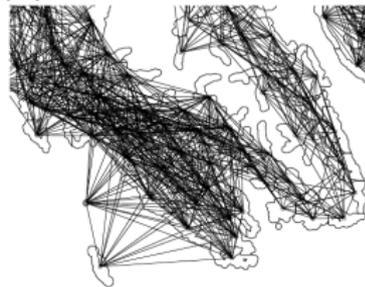
(b)



(c)



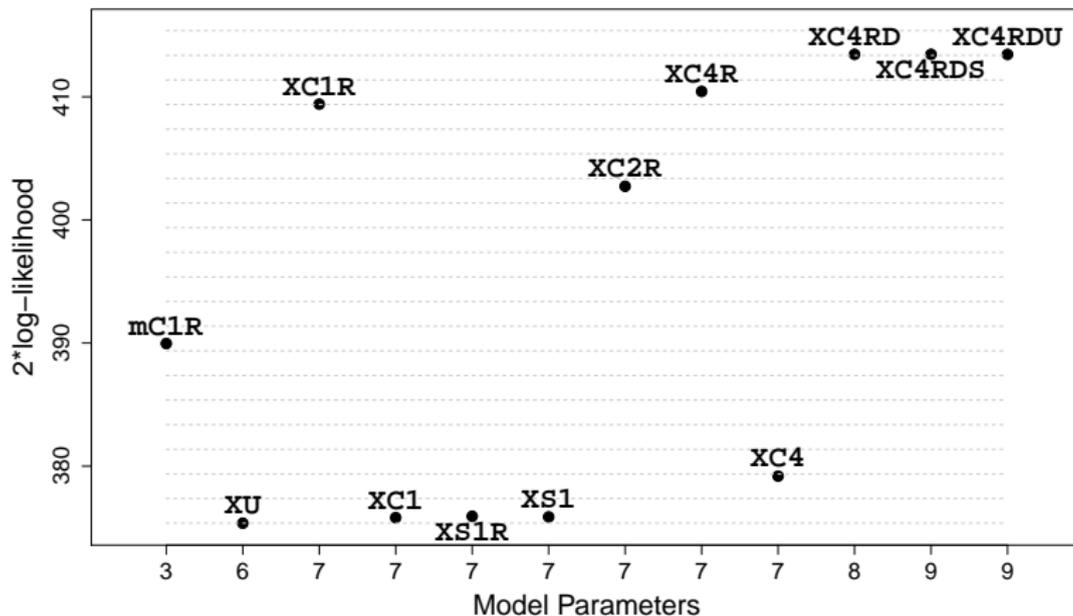
(d)



# Models

Model Code	Fixed Effects	Covariance Model	No. Parns
mU	<b>1</b>	$\sigma_{\varepsilon}^2 \mathbf{I}$	2
mC1R	<b>1</b>	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_1]_+)^{-1} [\mathbf{M}]_+$	3
XU	$\mathbf{X}_{\text{stock}}$	$\sigma_{\varepsilon}^2 \mathbf{I}$	6
XC1R	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_1]_+)^{-1} [\mathbf{M}]_+$	7
XC1	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho \mathbf{W}_1)^{-1}$	7
XS1R	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 [(\mathbf{I} - \rho[\mathbf{W}]_+)(\mathbf{I} - \rho[\mathbf{W}]_+)]^{-1}$	7
XS1	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 [(\mathbf{I} - \rho \mathbf{W}_1)(\mathbf{I} - \rho \mathbf{W}_1)]^{-1}$	7
XC2R	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_2]_+)^{-1} [\mathbf{M}]_+$	7
XC4R	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_4]_+)^{-1} [\mathbf{M}]_+$	7
XC4	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho \mathbf{W}_4)^{-1}$	7
XI4RU	$\mathbf{X}_{\text{stock}}$	(NA, ??) + $\varepsilon^2 \mathbf{I}$	7
XC4RD	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_4 \odot \exp(-\mathbf{D}/\theta_2)]_+)^{-1} [\mathbf{M}]_+$	8
XC4RDS	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_4 \odot \exp(-\mathbf{D}/\theta_2) \odot \exp(-\mathbf{S}/\theta_1)]_+)^{-1} [\mathbf{M}]_+$	9
XC4RDU	$\mathbf{X}_{\text{stock}}$	$\sigma_Z^2 (\mathbf{I} - \rho[\mathbf{W}_4 \odot \exp(-\mathbf{D}/\theta_2)]_+)^{-1} [\mathbf{M}]_+ + \sigma_{\varepsilon}^2 \mathbf{I}$	9

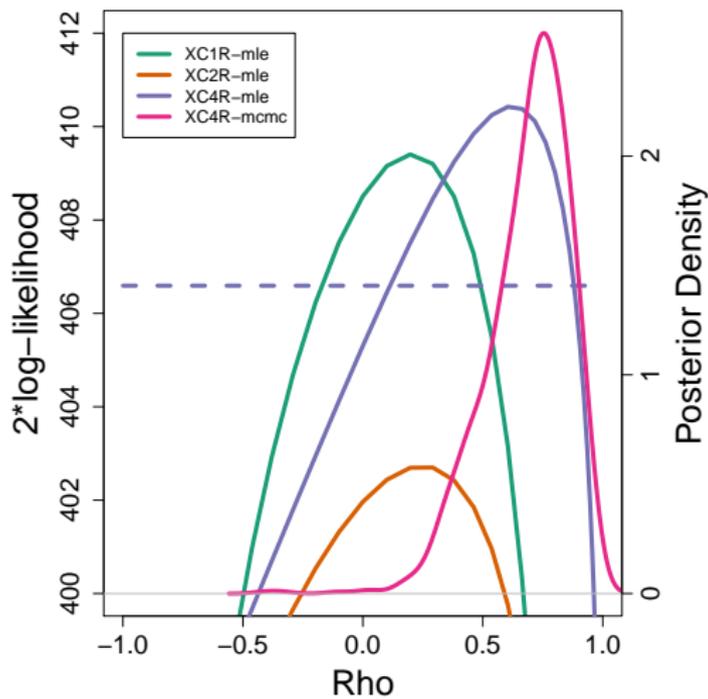
# Model Comparison and Selection



# Regression

Parameter	XU		XC4R-mle		XC4R-mcmc		XC4RD	
	Est.	Std.Err	Est.	Std.Err	Est.	Std.Err.	Est.	Std.Err
$\mu$	-0.079	0.0225	-0.080	0.0288	-0.082	0.0330	-0.077	0.0290
$\beta_{\text{stock 2}}$	0.048	0.0298	0.063	0.0379	0.063	0.0429	0.058	0.0386
$\beta_{\text{stock 3}}$	0.093	0.0281	0.095	0.0355	0.097	0.0386	0.092	0.0356
$\beta_{\text{stock 4}}$	0.132	0.0279	0.135	0.0346	0.138	0.0406	0.132	0.0346
$\beta_{\text{stock 5}}$	0.084	0.0259	0.093	0.0327	0.096	0.0378	0.089	0.0330

# Inference on Autocorrelation Parameter

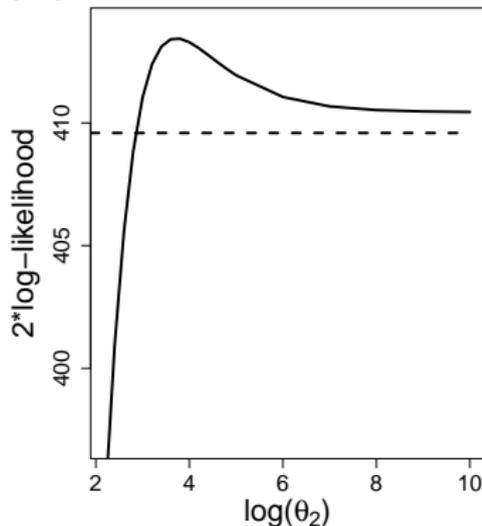


# Inference on Connectivity Parameters

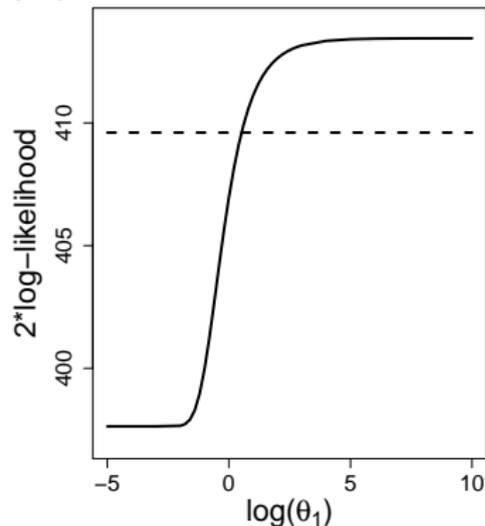
$$\mathbf{W} = \mathbf{N}_i \odot \exp(-\mathbf{S}/\theta_1) \odot \exp(-\mathbf{D}/\theta_2)$$

$$\mathbf{S}_{i,j} = 0 \text{ if } i, j \text{ in same stock, otherwise } 0$$

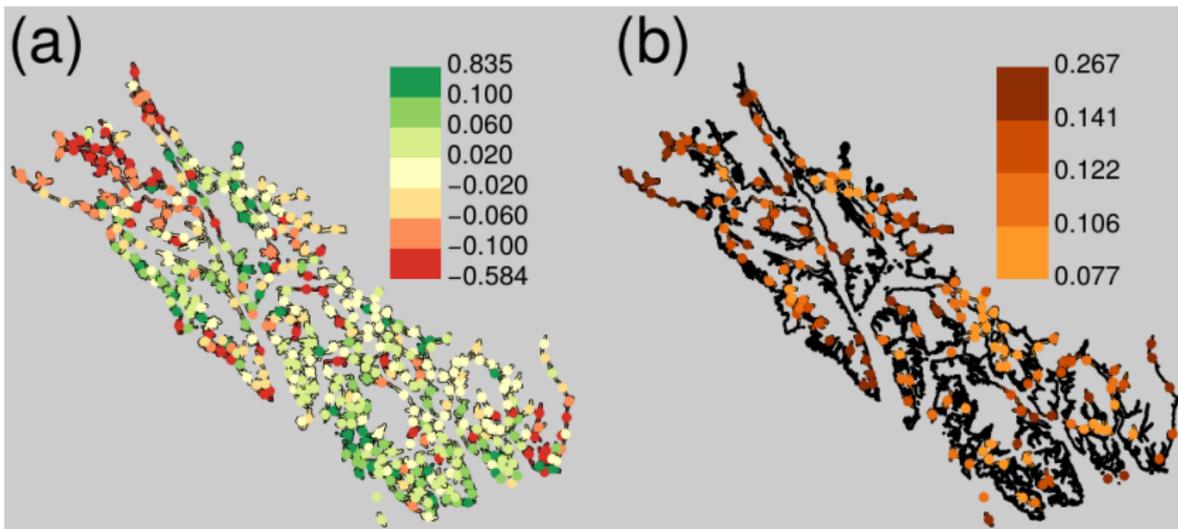
(a)



(b)

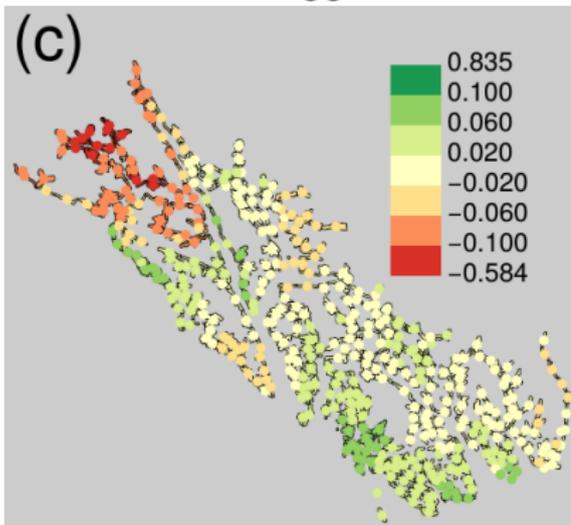


# Predictions

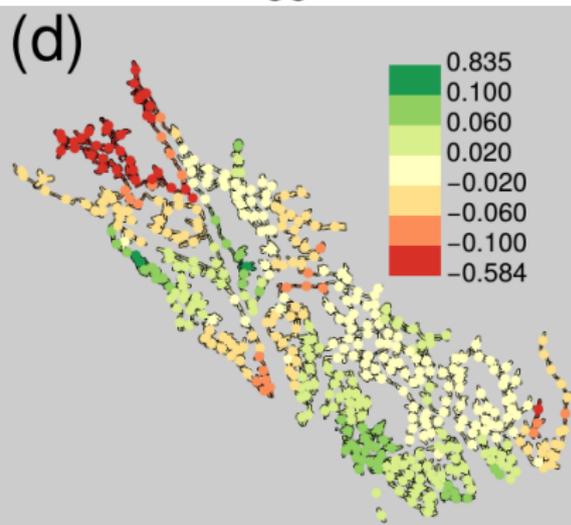


# Smoothing

CAR - no nugget

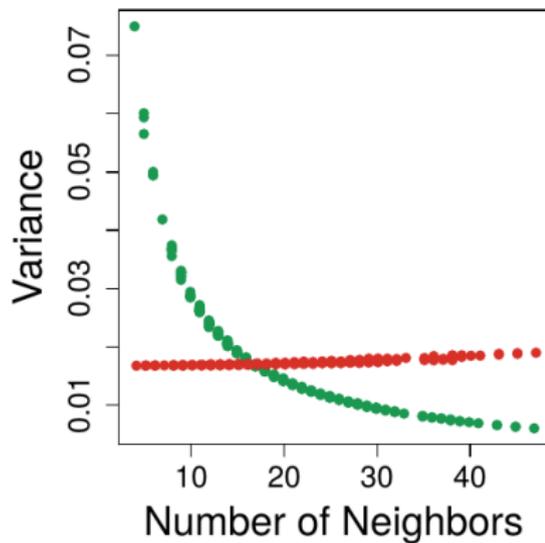


IAR + nugget

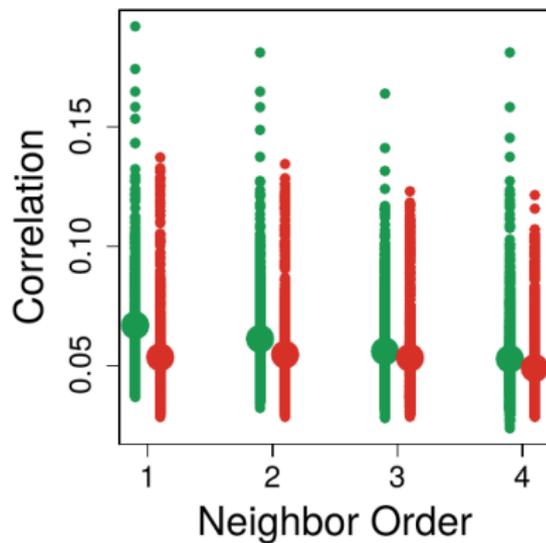


# Variances and Correlations

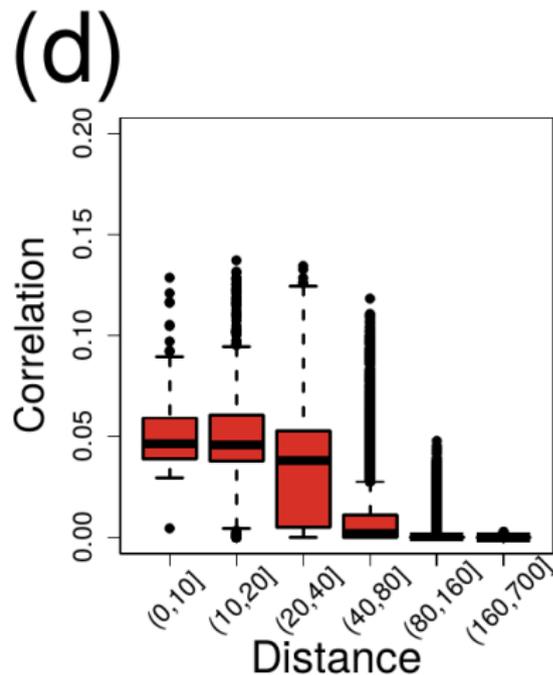
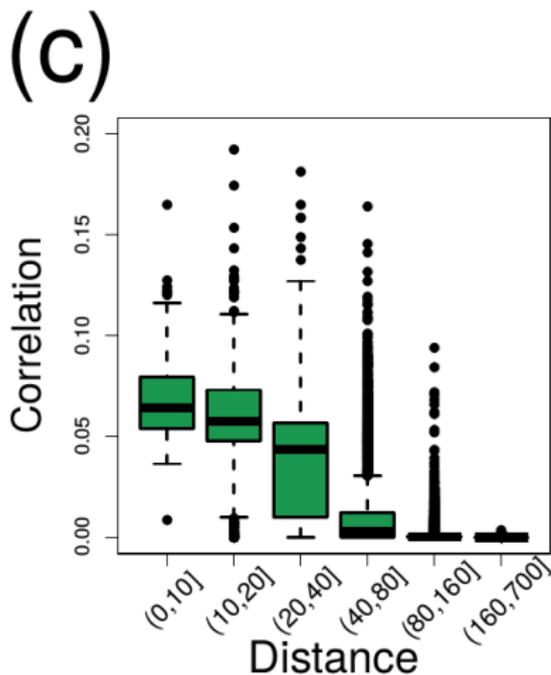
(a)



(b)



# Fitted Spatial Autocorrelations



## Practical Advice

- ▶ Models are harder to understand than geostatistical, but they can/should still be used. There many important objectives and applications.
- ▶ Important idea is that we are modeling the inverse covariance matrix (precision matrix), and it is essentially equivalent to partial correlations.
- ▶ Connectivity ideas can be explored by modeling in the covariance matrix, and inference on parameters obtained through profile likelihoods or posterior distributions. However, they may have large confidence/credibility regions, requiring large sample sizes.
- ▶ Row standardization and various neighborhood definitions should be explored.

## Practical Advice

- ▶ IAR vs. CAR when used hierarchically in generalized linear mixed models.  $\mathbf{y} \sim [\mathbf{y}|g(\boldsymbol{\mu}), \delta^2\mathbf{I}]$  and then  $\boldsymbol{\mu} = \mathbf{X}\boldsymbol{\beta} + \mathbf{z} + \boldsymbol{\varepsilon}$ . To use nugget,  $\boldsymbol{\varepsilon}$ , or not?
- ▶ Model diagnostics, especially for covariance parameters, are especially important for CAR/SAR models.
- ▶ Sites without neighbors:

$$\begin{pmatrix} \sigma_I^2 \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma} \end{pmatrix}$$

- ▶ Check software carefully!

## A Closer Look at Properties

### SAR

$$\Sigma_{\text{SAR}} = (\mathbf{I} - \mathbf{B})^{-1} \Lambda (\mathbf{I} - \mathbf{B}')^{-1}$$

- S1  $(\mathbf{I} - \mathbf{B})$  is nonsingular,
- S2  $\Lambda$  is diagonal with positive diagonal elements, and
- S3  $b_{i,j} = 0, \forall i$ .

### CAR

$$\Sigma_{\text{CAR}} = (\mathbf{I} - \mathbf{C})^{-1} \mathbf{M}$$

- C1  $(\mathbf{I} - \mathbf{C})$  has positive eigenvalues,
- C2  $\mathbf{M}$  is diagonal with positive diagonal elements,
- C3  $c_{i,j} = 0, \forall i$ , and
- C4  $c_{i,j}/m_{i,i} = c_{j,i}/m_{j,j}, \forall i, j$ .

# From SAR to CAR

The easy part, but still most get it wrong!

Let  $\mathbf{M} = \mathbf{I}$  and  $\mathbf{\Lambda} = \mathbf{I}$

$$(\mathbf{I} - \mathbf{C})^{-1} = [(\mathbf{I} - \mathbf{B})(\mathbf{I} - \mathbf{B}')]^{-1} = (\mathbf{I} - \mathbf{B} - \mathbf{B}' + \mathbf{B}\mathbf{B}')^{-1}$$

so, according to Haining (1990)

$$\mathbf{C} = \mathbf{B} + \mathbf{B}' - \mathbf{B}\mathbf{B}'$$

Repeated many times in textbooks and peer-reviewed papers,  
but **C3** is not satisfied because diagonal of  $\mathbf{B}\mathbf{B}'$  not  $\mathbf{0}$ .

$$\mathbf{C} \neq \mathbf{B} + \mathbf{B}' - \mathbf{B}\mathbf{B}'$$

# CAR Theorem

Any positive-definite covariance matrix  $\Sigma$  can be expressed as the covariance matrix of a CAR model  $(\mathbf{I} - \mathbf{C})^{-1}\mathbf{M}$ , for a unique pair of matrices  $\mathbf{C}$  and  $\mathbf{M}$ .

## *Outline of Proof*

Let  $\Sigma^{-1} = \mathbf{D} - \mathbf{R}$ , where  $\mathbf{D}$  is diagonal and  $\mathbf{R}$  has zeros on the diagonal.

Then  $\Sigma^{-1} = \mathbf{D} - \mathbf{R} = \mathbf{D}(\mathbf{I} - \mathbf{D}^{-1}\mathbf{R}) = \mathbf{M}^{-1}(\mathbf{I} - \mathbf{C})$ ,  
where  $\mathbf{C} = \mathbf{D}^{-1}\mathbf{R}$  and  $\mathbf{M} = \mathbf{D}^{-1}$ .

Then  $\Sigma$  can be expressed in CAR form.

## Corrected Result from Cressie, 1993, pg. 409

$$\mathbf{M}^{-1}(\mathbf{I} - \mathbf{C}) = \mathbf{I} - 2\mathbf{B} + \mathbf{B}^2$$

$$\begin{aligned}
 E(Z(u, v) | \{z(k, l) : (k, l) \neq (u, v)\}) \\
 &= (1 + 2\xi_1^2 + 2\xi_2^2)^{-1} \{2\xi_1 [z(u-1, v) + z(u+1, v)] \\
 &\quad + 2\xi_2 [z(u, v-1) + z(u, v+1)] \\
 &\quad - 2\xi_1\xi_2 [z(u-1, v-1) + z(u+1, v-1) \\
 &\quad\quad + z(u+1, v-1) + z(u+1, v+1)] \\
 &\quad - \xi_1^2 [z(u-2, v) + z(u+2, v)] \\
 &\quad - \xi_2^2 [z(u, v-2) + z(u, v+2)] \}.
 \end{aligned}$$

# SAR Theorem

Any positive definite covariance matrix  $\Sigma$  can be expressed as the covariance matrix of a SAR model  $(\mathbf{I} - \mathbf{B})^{-1}\Lambda(\mathbf{I} - \mathbf{B}^T)^{-1}$ , for a (non-unique) pair of matrices  $\mathbf{B}$  and  $\Lambda$ .

## Outline of Proof

Let  $\Sigma^{-1} = \mathbf{L}\mathbf{L}'$ , where  $\mathbf{L}$  is full rank with positive eigenvalues.

Note that  $\mathbf{L}$  is *not* unique. For example, a Cholesky or spectral decomposition can be used.

Now let  $\mathbf{L} = \mathbf{G} - \mathbf{P}$ , where  $\mathbf{G}$  is diagonal and  $\mathbf{P}$  has zeros on the diagonal.

Then  $\mathbf{L}\mathbf{L}' = (\mathbf{G} - \mathbf{P})(\mathbf{G}' - \mathbf{P}') = (\mathbf{I} - \mathbf{P}\mathbf{G}^{-1})\mathbf{G}\mathbf{G}(\mathbf{I} - \mathbf{G}^{-1}\mathbf{P}') = (\mathbf{I} - \mathbf{B}^T)\Lambda^{-1}(\mathbf{I} - \mathbf{B})$ .

where  $\Lambda^{-1} = \mathbf{G}\mathbf{G}$  and  $\mathbf{B}^T = \mathbf{P}\mathbf{G}^{-1}$

## Corollary

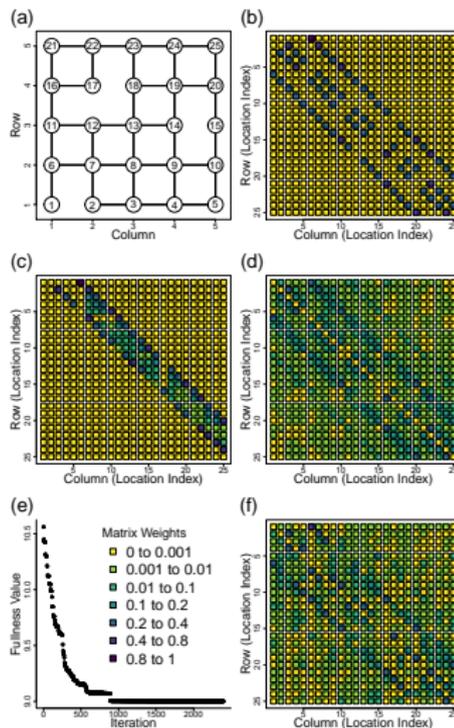
Any  $\Sigma$  can be expressed as one of an infinite number of  $\mathbf{B}$  matrices that define the SAR covariance matrix.

$$\mathbf{A}_{h,s}(\theta) = \begin{bmatrix} 1 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & \cos(\theta) & 0 & \dots & 0 & \sin(\theta) & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & 0 & 1 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & -\sin(\theta) & 0 & \dots & 0 & \cos(\theta) & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 1 \end{bmatrix}$$

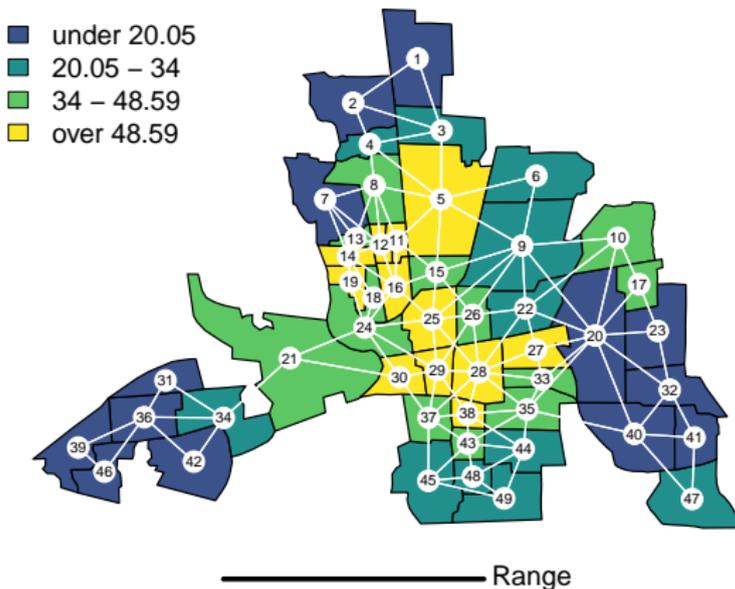
and  $\Sigma = \mathbf{L}\mathbf{L}' = \mathbf{L}\mathbf{A}'_{h,s}\mathbf{A}_{h,s}\mathbf{L}' = \mathbf{L}_*\mathbf{L}'_*$ .

## CAR to SAR

$$\text{fullness}(\mathbf{B}) = \frac{\sum_{i,j} |b_{i,j}|}{\sqrt{\sum_{i,j} b_{i,j}^2}}$$



# Columbus Crime Data



# Geostat to CAR

$$\Sigma_{CAR} = \sigma^2(\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{M} + \delta^2\mathbf{I}$$

$$\mathcal{L}_{un}(\theta; \mathbf{y}) = 388.83$$

$$\mathcal{L}_{rs}(\theta; \mathbf{y}) = 397.25$$

$$\Sigma_{geo} = \sigma^2\text{sph}(\mathbf{D}) + \delta^2\mathbf{I}$$

$$\mathcal{L}_{geo}(\theta; \mathbf{y}) = 374.61$$

$$\Sigma_{C|g} = \sigma^2(\mathbf{I} - \rho\mathbf{C}_{geo})^{-1}\mathbf{M}_{geo} + \delta^2\mathbf{I}$$

$$\sigma^2 > 0, -1.104 < \rho < 1.013, \delta^2 > 0$$

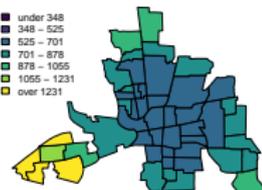
$$\mathcal{L}_{C|g}(\theta; \mathbf{y}) = 373.95$$

$$\hat{\sigma}_{C|g}^2 = 0.941, \hat{\rho}_{C|g} = 1.010$$

(a)



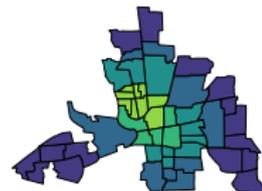
(b)



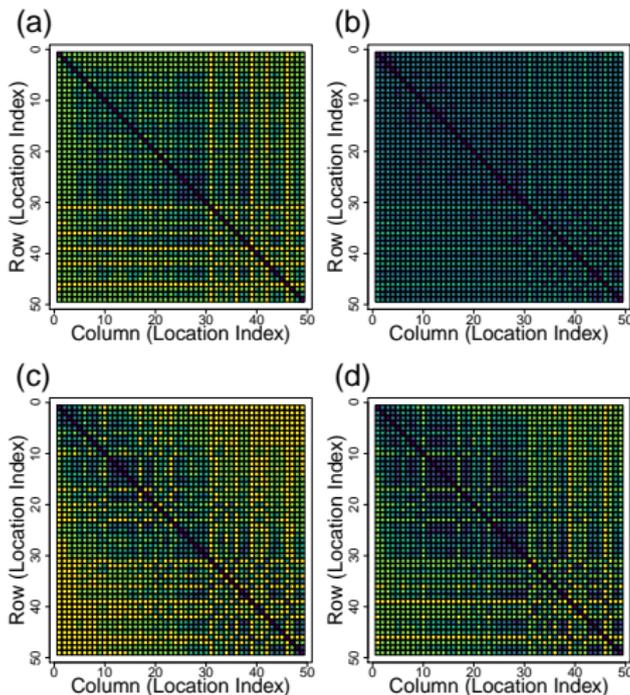
(c)



(d)



# Geostat to CAR



# Alaska Survey Polygons

1308 Polygons with Harbor Seal Counts over 20 Years



## STARMA (Cliff, 1975)

$$\mathbf{Z}(t) - \sum_{k=0}^p \mathbf{B}_k \mathbf{Z}(t-k) = \boldsymbol{\varepsilon}(t) - \sum_{\ell=0}^q \mathbf{E} \boldsymbol{\varepsilon}(t-1)$$

## Additive Model

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{V}_{t|z_i} + \mathbf{Z}_i + \boldsymbol{\varepsilon}_{i,t}$$

## Spatio-temporal CAR?

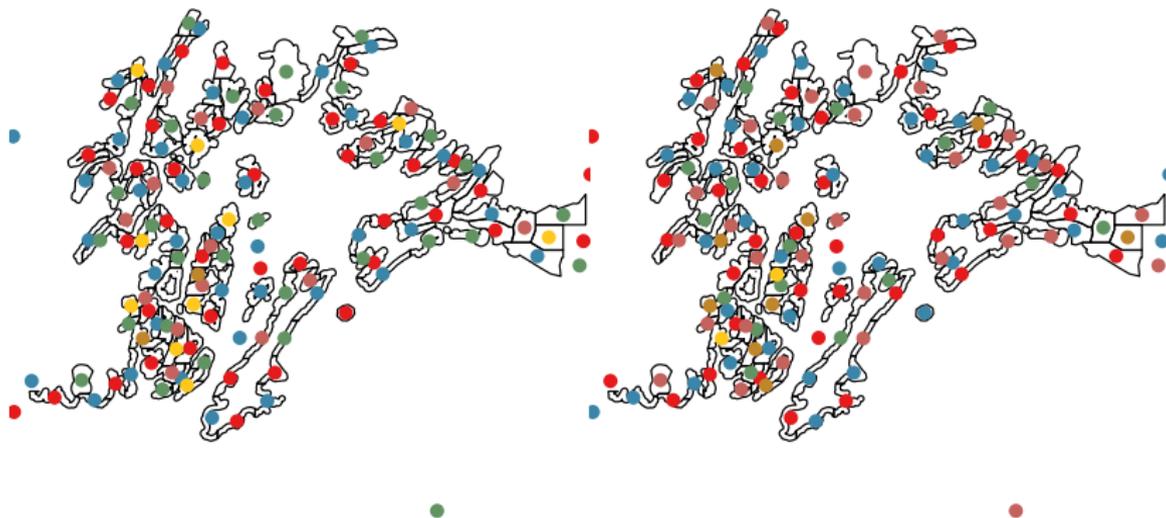
# Spatio-temporal CAR

$$\mathbf{z} = \begin{bmatrix} \mathbf{z}_{\text{yr1}} \\ \mathbf{z}_{\text{yr2}} \\ \vdots \\ \mathbf{z}_{\text{yr20}} \end{bmatrix}$$

$$\mathbf{C} = \rho \begin{bmatrix} (1 - \phi)\mathbf{W}_+ & \phi\mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots \\ \frac{\phi}{2}\mathbf{I} & (1 - \phi)\mathbf{W}_+ & \frac{\phi}{2}\mathbf{I} & \mathbf{0} & \mathbf{0} & \cdots \\ \mathbf{0} & \frac{\phi}{2}\mathbf{I} & (1 - \phi)\mathbf{W}_+ & \frac{\phi}{2}\mathbf{I} & \mathbf{0} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \phi\mathbf{I} & (1 - \phi)\mathbf{W} \end{bmatrix}$$

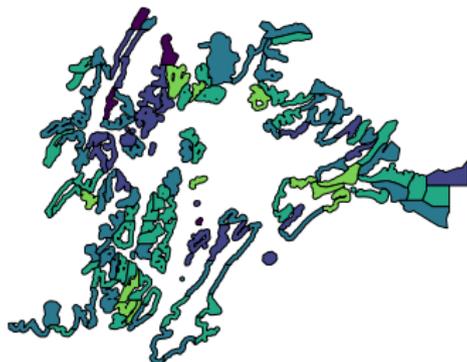
$$0 \leq \rho \leq 1 \text{ and } 0 \leq \phi \leq 1$$

# Spatio-temporal Chromatic Coloring

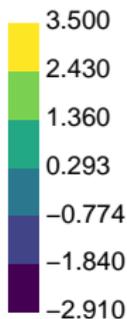
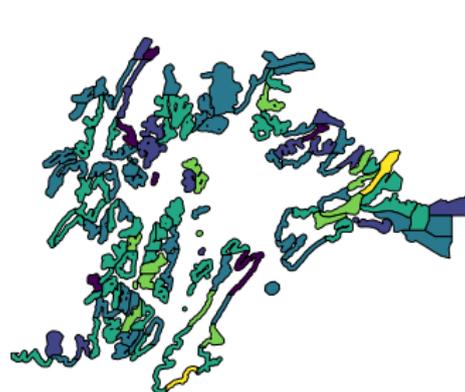


# Simulated Data

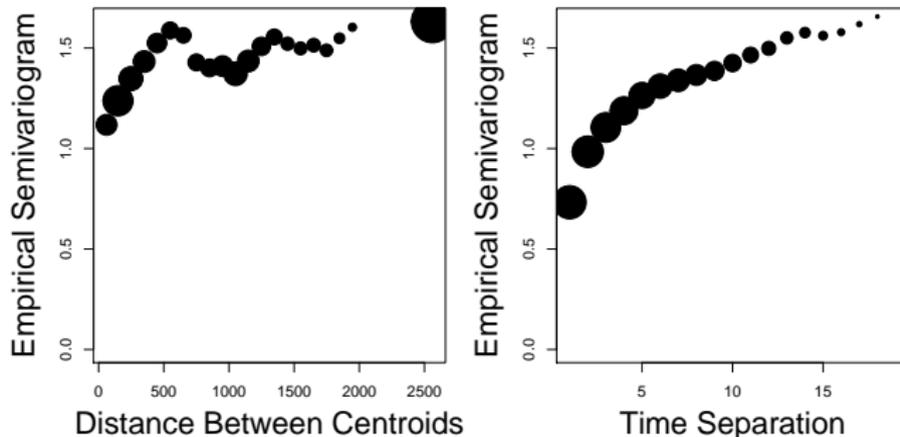
Year 10



Year 11



# Simulation Variograms



How to estimate model parameters?  
Especially for Poisson/Spatial hierarchical models?

What About Trend?

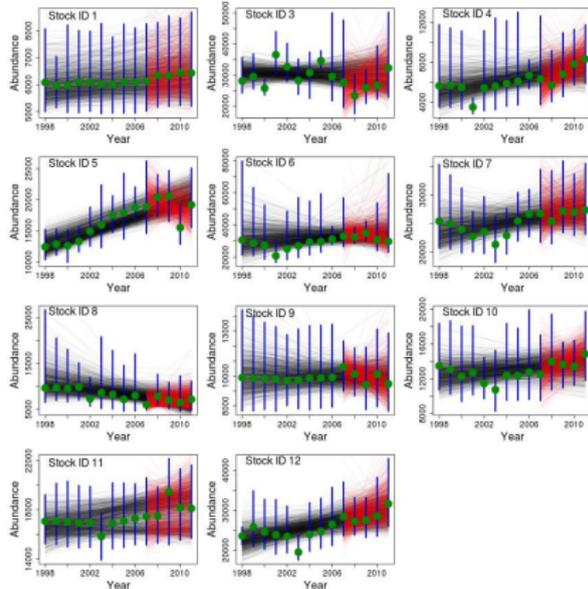
# What About Trend?

$\mathbf{f}(\mathbf{t})'\beta \in p(\hat{N}_t | \dots)$  NOT good

$N_t = \phi N_{t-1} \dots \in p(\hat{N}_t | \dots)$  Good

Compute Trend on posterior of

$$\hat{N}_t^{[k]}, \dots, \hat{N}_{t+I}^{[k]}$$



# Summary

- ▶ Review of CAR and SAR Models
  - ▶ Model Comparison and Selection (Averaging)
  - ▶ Regression (Effect of Explanatory Variables)
  - ▶ Estimation of Autocorrelation Parameters
  - ▶ Estimation of Other Network Parameters
  - ▶ Prediction of Unsampled Locations
  - ▶ Smoothing over Sampled and Unsampled Locations
- ▶ Relationships between CAR and SAR
  - ▶ Any pos. def.  $\Sigma$  can written as CAR or SAR
- ▶ Spatio-temporal CAR models?
  - ▶ What about trend?