

# Introduction to Geostatistics

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- Course materials available at  
<https://doserjef.github.io/CASANR23-Spatial-Modeling/>

## What is spatial data?

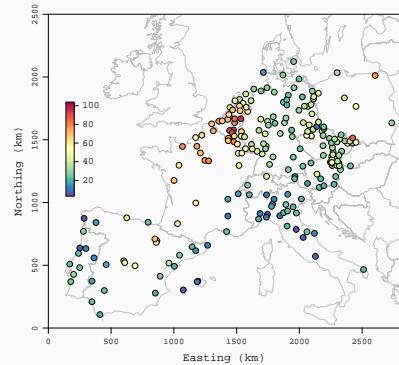
- Any data with some geographical information (i.e., spatially indexed)
- Common sources of spatial data: agricultural, climatology, forestry, ecology, environmental health, disease epidemiology, product marketing, etc.
  - have many important predictors and response variables
  - are often presented as maps

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  - have many important predictors and response variables
  - are often presented as maps
- Other examples where spatial need not refer to space on earth:
  - Genetics (position along a chromosome)
  - Neuroimaging (data for each voxel in the brain)

## Point-referenced spatial data

- Each observation is associated with a location (point)
- Data represents a sample from a continuous spatial domain
- Also referred to as **geocoded** or **geostatistical** data



**Figure:** Pollutant levels in Europe in March, 2009

## Point level modeling

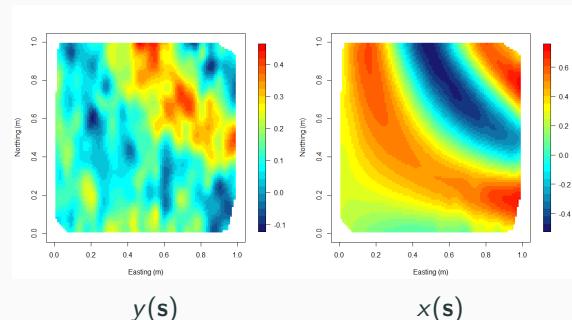
- **Point-level modeling** refers to modeling of point-referenced data collected at locations referenced by **coordinates** (e.g., lat-long, Easting-Northing).
- Data from a spatial process  $\{Y(\mathbf{s}) : \mathbf{s} \in \mathcal{D}\}$ ,  $\mathcal{D}$  is a subset in Euclidean space.
- **Example:**  $Y(\mathbf{s})$  is a **pollutant level** at site  $\mathbf{s}$
- **Conceptually:** Pollutant level exists at all possible sites
- **Practically:** Data will be a partial realization of a spatial process – observed at  $\{\mathbf{s}_1, \dots, \mathbf{s}_n\}$
- **Statistical objectives:** **Inference** about the process  $Y(\mathbf{s})$ ; **predict** at new locations.
- **Remarkable:** Can learn about entire  $Y(\mathbf{s})$  surface. The **key**: Structured dependence

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## Exploratory data analysis (EDA): Plotting the data

- A typical setup: Data observed at  $n$  locations  $\{\mathbf{s}_1, \dots, \mathbf{s}_n\}$
- At each  $\mathbf{s}_i$  we observe the response  $y(\mathbf{s}_i)$  and a  $p \times 1$  vector of covariates  $\mathbf{x}(\mathbf{s}_i)$
- **Surface plots** of the data often helps to understand spatial patterns



**Figure:** Response and covariate surface plots for Dataset 1

## What's so special about spatial?

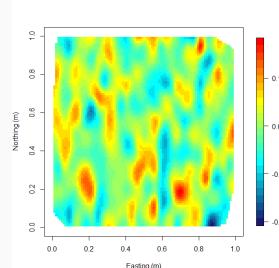
- Linear regression model:  $y(\mathbf{s}_i) = \mathbf{x}(\mathbf{s}_i)^T \boldsymbol{\beta} + \epsilon(\mathbf{s}_i)$
- $\epsilon(\mathbf{s}_i)$  are iid  $N(0, \tau^2)$  errors
- $\mathbf{y} = (y(\mathbf{s}_1), \dots, y(\mathbf{s}_n))^T$ ;  $\mathbf{X} = (\mathbf{x}(\mathbf{s}_1)^T, \dots, \mathbf{x}(\mathbf{s}_n)^T)^T$
- **Inference:**  $\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \sim N(\boldsymbol{\beta}, \tau^2 (\mathbf{X}^T \mathbf{X})^{-1})$
- **Prediction** at new location  $\mathbf{s}_0$ :  $\widehat{y(\mathbf{s}_0)} = \mathbf{x}(\mathbf{s}_0)^T \hat{\boldsymbol{\beta}}$
- Although the data is spatial, this is an **ordinary linear regression** model

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## Residual plots

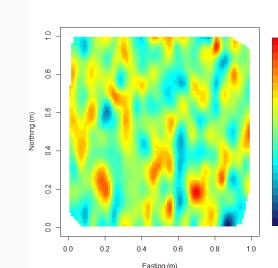
- Surface plots of the residuals ( $y(\mathbf{s}) - \hat{y}(\mathbf{s})$ ) help to identify any spatial patterns left unexplained by the covariates



**Figure:** Residual plot for Dataset 1 after linear regression on  $x(\mathbf{s})$

## Residual plots

- Surface plots of the residuals ( $y(\mathbf{s}) - \hat{y}(\mathbf{s})$ ) help to identify any spatial patterns left unexplained by the covariates



**Figure:** Residual plot for Dataset 1 after linear regression on  $x(\mathbf{s})$

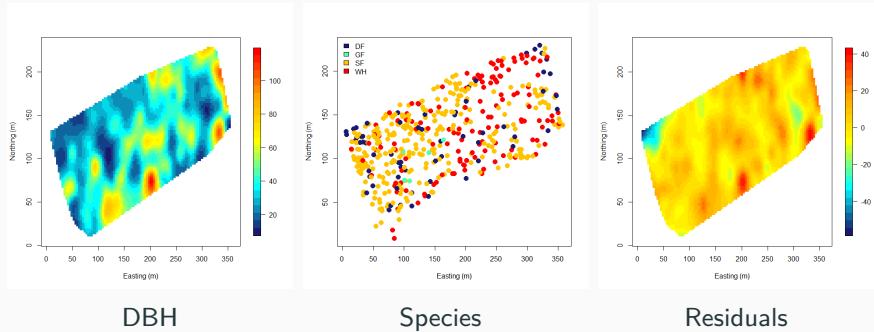
- No evident spatial pattern in plot of the residuals
- The covariate  $x(\mathbf{s})$  seem to explain all spatial variation in  $y(\mathbf{s})$
- Does a non-spatial regression model always suffice?

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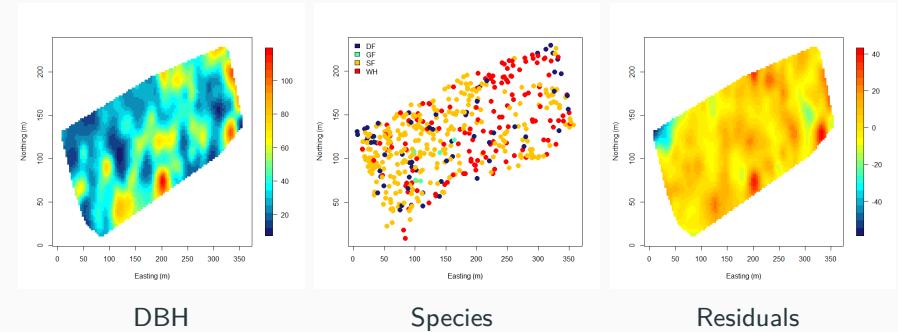
## Western Experimental Forestry (WEF) data

- Data consist of a census of all trees in a 10 ha. stand in Oregon
- Response of interest: Diameter at breast height (DBH)
- Covariate: Tree species (Categorical variable)



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- Data consist of a census of all trees in a 10 ha. stand in Oregon
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- Local spatial patterns in the residual plot
- Simple regression on species seems to be not sufficient

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- Besides eyeballing residual surfaces, how to do more formal EDA to identify spatial pattern?

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### First law of geography

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### First law of geography

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- In general  $(Y(\mathbf{s} + \mathbf{h}) - Y(\mathbf{s}))^2$  roughly increasing with  $\|\mathbf{h}\|$  will imply a spatial correlation
- Can this be formalized to identify spatial pattern?

- **Binning:** Make intervals  $I_1 = (0, m_1)$ ,  $I_2 = (m_1, m_2)$ , and so forth, up to  $I_K = (m_{K-1}, m_K)$ . Representing each interval by its midpoint  $t_k$ , we define:

$$N(t_k) = \{(\mathbf{s}_i, \mathbf{s}_j) : \|\mathbf{s}_i - \mathbf{s}_j\| \in I_k\}, k = 1, \dots, K.$$

- **Empirical semivariogram:**

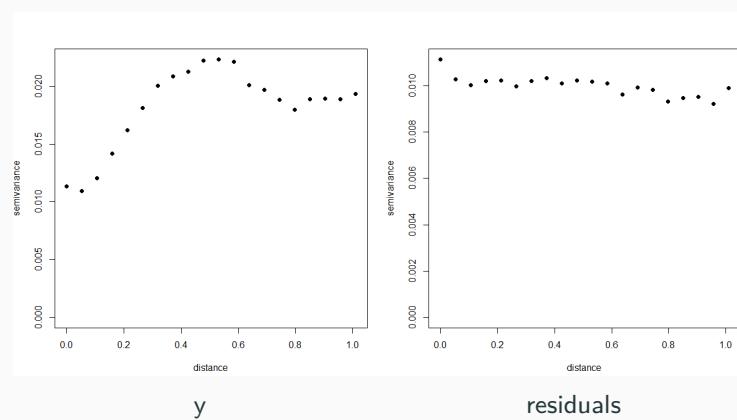
$$\gamma(t_k) = \frac{1}{2|N(t_k)|} \sum_{\mathbf{s}_i, \mathbf{s}_j \in N(t_k)} (Y(\mathbf{s}_i) - Y(\mathbf{s}_j))^2$$

- For spatial data, the  $\gamma(t_k)$  is expected to roughly increase with  $t_k$
- A flat semivariogram would suggest little spatial variation

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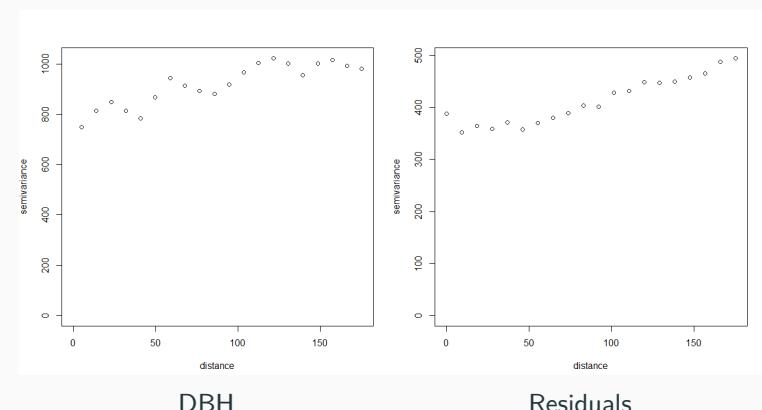
## Empirical variogram: Data 1



- Residuals display little spatial variation

## Empirical variograms: WEF data

- Regression model: DBH ~ Species



- Variogram of the residuals confirm unexplained spatial variation

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## Modeling with the locations

- When purely covariate based models does not suffice, one needs to leverage the information from locations
- General model using the locations:  
 $y(\mathbf{s}) = \mathbf{x}(\mathbf{s})^\top \boldsymbol{\beta} + w(\mathbf{s}) + \epsilon(\mathbf{s})$  for all  $\mathbf{s} \in \mathcal{D}$
- How to choose the function  $w(\cdot)$ ?
- Since we want to predict at any location over the entire domain  $\mathcal{D}$ , this choice will amount to choosing a surface  $w(\mathbf{s})$
- How should such a surface be chosen?

## Gaussian Processes (GPs)

- One popular approach to model  $w(\mathbf{s})$  is via Gaussian Processes (GP)
- The collection of random variables  $\{w(\mathbf{s}) \mid \mathbf{s} \in \mathcal{D}\}$  is a GP if
  - it is a valid stochastic process
  - all finite dimensional densities  $\{w(\mathbf{s}_1), \dots, w(\mathbf{s}_n)\}$  follow multivariate Gaussian distribution
- A GP is completely characterized by a mean function  $m(\mathbf{s})$  and a covariance function  $C(\cdot, \cdot)$
- Advantage:** Likelihood based inference.  
 $w = (w(\mathbf{s}_1), \dots, w(\mathbf{s}_n))^\top \sim N(\mathbf{m}, \mathbf{C})$  where  
 $\mathbf{m} = (m(\mathbf{s}_1), \dots, m(\mathbf{s}_n))^\top$  and  $\mathbf{C} = C(\mathbf{s}_i, \mathbf{s}_j)$

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- $C(\cdot, \cdot)$  needs to be **valid**. For all  $n$  and all  $\{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_n\}$ , the resulting covariance matrix  $C(\mathbf{s}_i, \mathbf{s}_j)$  for  $(w(\mathbf{s}_1), w(\mathbf{s}_2), \dots, w(\mathbf{s}_n))$  must be positive definite
- So,  $C(\cdot, \cdot)$  needs to be a **positive definite** function
- Simplifying assumptions:
  - Stationarity:**  $C(\mathbf{s}_1, \mathbf{s}_2)$  only depends on  $\mathbf{h} = \mathbf{s}_1 - \mathbf{s}_2$  (and is denoted by  $C(\mathbf{h})$ )
  - Isotropic:**  $C(\mathbf{h}) = C(||\mathbf{h}||)$
  - Anisotropic:** Stationary but not isotropic
- Isotropic models are popular because of their **simplicity**, **interpretability**, and because a number of relatively **simple parametric forms** are available as candidates for  $C$ .

Model	Covariance function, $C(t) = C(  \mathbf{h}  )$
Spherical	$C(t) = \begin{cases} 0 & \text{if } t \geq 1/\phi \\ \sigma^2 \left[ 1 - \frac{3}{2}\phi t + \frac{1}{2}(\phi t)^3 \right] & \text{if } 0 < t \leq 1/\phi \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$
Exponential	$C(t) = \begin{cases} \sigma^2 \exp(-\phi t) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$
Powered exponential	$C(t) = \begin{cases} \sigma^2 \exp(- \phi t ^p) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$
Matérn at $\nu = 3/2$	$C(t) = \begin{cases} \sigma^2 (1 + \phi t) \exp(-\phi t) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$

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## Notes on exponential model

$$C(t) = \begin{cases} \tau^2 + \sigma^2 & \text{if } t = 0 \\ \sigma^2 \exp(-\phi t) & \text{if } t > 0 \end{cases}.$$

- We define the **effective range**,  $t_0$ , as the distance at which this correlation has dropped to only 0.05. Setting  $\exp(-\phi t_0)$  equal to this value we obtain  $t_0 \approx 3/\phi$ , since  $\log(0.05) \approx -3$ .
- The **nugget**  $\tau^2$  is often viewed as a “**nonspatial effect variance**,”
- The **partial sill** ( $\sigma^2$ ) is viewed as a “**spatial effect variance**.”
- $\sigma^2 + \tau^2$  gives the maximum total variance often referred to as the **sill**
- Note **discontinuity** at 0 due to the nugget. **Intentional!** To account for measurement error or micro-scale variability.

## Covariance functions and semivariograms

- Recall:** Empirical semivariogram:  

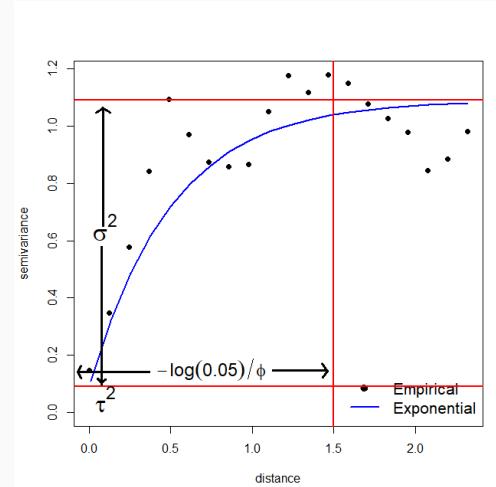
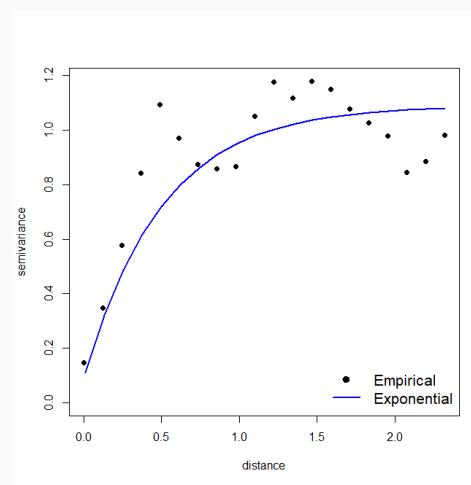
$$\gamma(t_k) = \frac{1}{2|N(t_k)|} \sum_{\mathbf{s}_i, \mathbf{s}_j \in N(t_k)} (Y(\mathbf{s}_i) - Y(\mathbf{s}_j))^2$$
- For any stationary GP,  

$$E(Y(\mathbf{s} + \mathbf{h}) - Y(\mathbf{s}))^2/2 = C(\mathbf{0}) - C(\mathbf{h}) = \gamma(\mathbf{h})$$
- $\gamma(\mathbf{h})$  is the **semivariogram** corresponding to the covariance function  $C(\mathbf{h})$
- Example:** For exponential GP,  

$$\gamma(t) = \begin{cases} \tau^2 + \sigma^2(1 - \exp(-\phi t)) & \text{if } t > 0 \\ 0 & \text{if } t = 0 \end{cases}$$
, where  $t = ||\mathbf{h}||$

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## The Matérn covariance function

- The Matérn is a very versatile family:

$$C(t) = \begin{cases} \frac{\sigma^2}{2^{\nu-1}\Gamma(\nu)}(2\sqrt{\nu}t\phi)^\nu K_\nu(2\sqrt{\nu}t\phi) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{if } t = 0 \end{cases}$$

$K_\nu$  is the modified Bessel function of order  $\nu$  (computationally tractable)

- $\nu$  is a smoothness parameter controlling process smoothness.  
**Remarkable!**
- $\nu = 1/2$  gives the exponential covariance function

## Kriging: Spatial prediction at new locations

- Goal:** Given observations  $\mathbf{w} = (w(\mathbf{s}_1), w(\mathbf{s}_2), \dots, w(\mathbf{s}_n))^\top$ , predict  $w(\mathbf{s}_0)$  for a new location  $\mathbf{s}_0$
- If  $w(\mathbf{s})$  is modeled as a GP, then  $(w(\mathbf{s}_0), w(\mathbf{s}_1), \dots, w(\mathbf{s}_n))^\top$  jointly follow multivariate normal distribution
- $w(\mathbf{s}_0) | \mathbf{w}$  follows a normal distribution with
  - Mean (**kriging estimator**):  $m(\mathbf{s}_0) + \mathbf{c}^\top \mathbf{C}^{-1}(\mathbf{w} - \mathbf{m})$
  - where  $\mathbf{m} = E(\mathbf{w})$ ,  $\mathbf{C} = Cov(\mathbf{w})$ ,  $\mathbf{c} = Cov(\mathbf{w}, w(\mathbf{s}_0))$
  - Variance:  $\mathbf{C}(\mathbf{s}_0, \mathbf{s}_0) - \mathbf{c}^\top \mathbf{C}^{-1} \mathbf{c}$
- The GP formulation gives the **full predictive distribution** of  $w(\mathbf{s}_0) | \mathbf{w}$

## Spatial linear model

$$y(\mathbf{s}) = \mathbf{x}(\mathbf{s})^\top \boldsymbol{\beta} + w(\mathbf{s}) + \epsilon(\mathbf{s})$$

- $w(\mathbf{s})$  modeled as  $GP(0, C(\cdot | \theta))$  (usually without a nugget)
- $\epsilon(\mathbf{s}) \stackrel{iid}{\sim} N(0, \tau^2)$  contributes to the nugget
- Under isotropy:  $C(\mathbf{s} + \mathbf{h}, \mathbf{s}) = \sigma^2 R(||\mathbf{h}||; \phi)$
- $\mathbf{w} = (w(\mathbf{s}_1), \dots, w(\mathbf{s}_n))^\top \sim N(\mathbf{0}, \sigma^2 \mathbf{R}(\phi))$  where  $\mathbf{R}(\phi) = \sigma^2 (R(||\mathbf{s}_i - \mathbf{s}_j||; \phi))$
- $\mathbf{y} = (y(\mathbf{s}_1), \dots, y(\mathbf{s}_n))^\top \sim N(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{R}(\phi) + \tau^2 \mathbf{I})$

- $\mathbf{y} = (y(\mathbf{s}_1), \dots, y(\mathbf{s}_n))^\top \sim N(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{R}(\phi) + \tau^2 \mathbf{I})$
- We can obtain MLEs of parameters  $\boldsymbol{\beta}, \tau^2, \sigma^2, \phi$  based on the above model and use the estimates to krig at new locations
- In practice, the likelihood is often very flat with respect to the spatial covariance parameters and choice of initial values is important
- Initial values can be eyeballed from empirical semivariogram of the residuals from ordinary linear regression
- Estimated parameter values can be used for kriging

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## Model comparison

## Back to WEF data

- For  $k$  total parameters and sample size  $n$ :
  - AIC:  $2k - 2 \log(I(\mathbf{y} | \hat{\boldsymbol{\beta}}, \hat{\theta}, \hat{\tau}^2))$
  - BIC:  $\log(n)k - 2 \log(I(\mathbf{y} | \hat{\boldsymbol{\beta}}, \hat{\theta}, \hat{\tau}^2))$
- Prediction based approaches using holdout data:
  - Root Mean Square Predictive Error (RMSPE):  

$$\sqrt{\frac{1}{n_{out}} \sum_{i=1}^{n_{out}} (y_i - \hat{y}_i)^2}$$
  - Coverage probability (CP):  $\frac{1}{n_{out}} \sum_{i=1}^{n_{out}} I(y_i \in (\hat{y}_{i,0.025}, \hat{y}_{i,0.975}))$
  - Width of 95% confidence interval (CIW):  

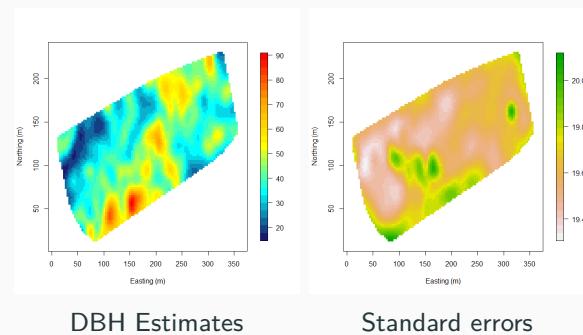
$$\frac{1}{n_{out}} \sum_{i=1}^{n_{out}} (\hat{y}_{i,0.975} - \hat{y}_{i,0.025})$$
  - The last two approaches compares the distribution of  $y_i$  instead of comparing just their point predictions

Table: Model comparison

	Spatial	Non-spatial
AIC	4419	4465
BIC	4448	4486
RMSPE	18	21
CP	93	93
CIW	77	82

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- Geostatistics – Analysis of point-referenced spatial data
- Surface plots of data and residuals
- EDA with empirical semivariograms
- Modeling unknown surfaces with Gaussian Processes
- Kriging: Predictions at new locations
- Spatial linear regression using Gaussian Processes

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## Bayesian Linear Models

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## Linear Regression

- Linear regression is, perhaps, *the* most widely used statistical modeling tool.
- It addresses the following question: How does a quantity of primary interest,  $y$ , vary as (depend upon) another quantity, or set of quantities,  $x$ ?
- The quantity  $y$  is called the *response* or *outcome variable*. Some people simply refer to it as the *dependent variable*.
- The variable(s)  $x$  are called *explanatory variables*, *covariates* or simply *independent variables*.
- In general, we are interested in the conditional distribution of  $y$ , given  $x$ , parametrized as  $p(y | \theta, x)$ .

- Typically, we have a set of *units* or *experimental subjects*  
 $i = 1, 2, \dots, n$ .
- For each of these units we have measured an outcome  $y_i$  and a set of explanatory variables  $\mathbf{x}_i^\top = (1, x_{i1}, x_{i2}, \dots, x_{ip})$ .
- The first element of  $\mathbf{x}_i^\top$  is often taken as 1 to signify the presence of an “intercept”.
- We collect the outcome and explanatory variables into an  $n \times 1$  vector and an  $n \times (p + 1)$  matrix:

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}; \quad \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1p} \\ 1 & x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix} = \begin{pmatrix} \mathbf{x}_1^\top \\ \mathbf{x}_2^\top \\ \vdots \\ \mathbf{x}_n^\top \end{pmatrix}.$$

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- The linear model is the most fundamental of all serious statistical models underpinning:
  - ANOVA:  $y_i$  is continuous,  $x_{ij}$ 's are *all* categorical
  - REGRESSION:  $y_i$  is continuous,  $x_{ij}$ 's are continuous
  - ANCOVA:  $y_i$  is continuous,  $x_{ij}$ 's are continuous for some  $j$  and categorical for others.

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## Conjugate Bayesian Linear Regression

- A conjugate Bayesian linear model is given by:
 
$$y_i | \beta, \sigma^2, \mathbf{x}_i \stackrel{\text{ind}}{\sim} N(\mu_i, \sigma^2); \quad i = 1, 2, \dots, n;$$

$$\mu_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip} = \mathbf{x}_i^\top \beta; \quad \beta = (\beta_0, \beta_1, \dots, \beta_p)^\top;$$

$$\beta | \sigma^2 \sim N(\boldsymbol{\mu}_\beta, \sigma^2 \mathbf{V}_\beta); \quad \sigma^2 \sim IG(a, b).$$
- Unknown parameters include the regression parameters and the variance, i.e.  $\theta = \{\beta, \sigma^2\}$ .
- We assume  $\mathbf{X}$  is observed without error and all inference is conditional on  $\mathbf{X}$ .
- The above model is often written in terms of the posterior density  $p(\theta | \mathbf{y}) \propto p(\theta, \mathbf{y})$ :

$$IG(\sigma^2 | a, b) \times N(\beta | \boldsymbol{\mu}_\beta, \sigma^2 \mathbf{V}_\beta) \times \prod_{i=1}^n N(y_i | \mathbf{x}_i^\top \beta, \sigma^2).$$

## Conjugate Bayesian (General) Linear Regression

- A more general conjugate Bayesian linear model is given by:
 
$$\mathbf{y} | \beta, \sigma^2, \mathbf{X} \sim N(\mathbf{X}\beta, \sigma^2 \mathbf{V}_y)$$

$$\beta | \sigma^2 \sim N(\boldsymbol{\mu}_\beta, \sigma^2 \mathbf{V}_\beta);$$

$$\sigma^2 \sim IG(a, b).$$
- $\mathbf{V}_y$ ,  $\mathbf{V}_\beta$  and  $\boldsymbol{\mu}_\beta$  are assumed fixed.
- Unknown parameters include the regression parameters and the variance, i.e.  $\theta = \{\beta, \sigma^2\}$ .
- We assume  $\mathbf{X}$  is observed without error and all inference is conditional on  $\mathbf{X}$ .
- The posterior density  $p(\theta | \mathbf{y}) \propto p(\theta, \mathbf{y})$ :
 
$$IG(\sigma^2 | a, b) \times N(\beta | \boldsymbol{\mu}_\beta, \sigma^2 \mathbf{V}_\beta) \times N(\mathbf{y} | \mathbf{X}\beta, \sigma^2 \mathbf{V}_y)$$
- The model on the previous slide is a special case with  $\mathbf{V}_y = \mathbf{I}_n$  ( $n \times n$  identity matrix).

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## Conjugate Bayesian (General) Linear Regression

- The joint posterior density can be written as

$$p(\beta, \sigma^2 | \mathbf{y}) \propto \underbrace{IG(\sigma^2 | a^*, b^*)}_{p(\sigma^2 | \mathbf{y})} \times \underbrace{N(\beta | \mathbf{Mm}, \sigma^2 \mathbf{M})}_{p(\beta | \sigma^2, \mathbf{y})},$$

where

$$a^* = a + \frac{n}{2}; \quad b^* = b + \frac{1}{2} (\boldsymbol{\mu}_\beta^\top \mathbf{V}_\beta^{-1} \boldsymbol{\mu}_\beta + \mathbf{y}^\top \mathbf{V}_y^{-1} \mathbf{y} - \mathbf{m}^\top \mathbf{Mm});$$

$$\mathbf{m} = \mathbf{V}_\beta^{-1} \boldsymbol{\mu}_\beta + \mathbf{X}^\top \mathbf{V}_y^{-1} \mathbf{y}; \quad \mathbf{M}^{-1} = \mathbf{V}_\beta^{-1} + \mathbf{X}^\top \mathbf{V}_y^{-1} \mathbf{X}.$$

- Exact posterior sampling from  $p(\beta, \sigma^2 | \mathbf{y})$  will automatically yield samples from  $p(\beta | \mathbf{y})$  and  $p(\sigma^2 | \mathbf{y})$ .
- For each  $j = 1, 2, \dots, N$  do the following:
  - Draw  $\sigma_{(j)}^2 \sim IG(a^*, b^*)$
  - Draw  $\beta_{(j)} \sim N(\mathbf{Mm}, \sigma_{(j)}^2 \mathbf{M})$
- The above is sometimes referred to as *composition sampling*.

## Exact sampling from joint posterior distributions

- Suppose we wish to draw samples from a joint posterior:

$$p(\theta_1, \theta_2 | \mathbf{y}) = p(\theta_1 | \mathbf{y}) \times p(\theta_2 | \theta_1, \mathbf{y}).$$

- In conjugate models, it is often easy to draw samples from  $p(\theta_1 | \mathbf{y})$  and from  $p(\theta_2 | \theta_1, \mathbf{y})$ .
- We can draw  $N$  samples from  $p(\theta_1, \theta_2 | \mathbf{y})$  as follows.
- For each  $j = 1, 2, \dots, N$  do the following:
  - Draw  $\theta_{1(j)} \sim p(\theta_1 | \mathbf{y})$
  - Draw  $\theta_{2(j)} \sim p(\theta_2 | \theta_{1(j)}, \mathbf{y})$
- Remarkably, the  $\theta_{2(j)}$ 's drawn above have marginal distribution  $p(\theta_2 | \mathbf{y})$  (see, Gelfand and Smith 1990).
- “Automatic Marginalization” we draw samples  $p(\theta_1, \theta_2 | \mathbf{y})$  and automatically get samples from  $p(\theta_1 | \mathbf{y})$  and  $p(\theta_2 | \mathbf{y})$ .

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## Bayesian predictions from linear regression

- Let  $\tilde{\mathbf{y}}$  denote an  $m \times 1$  vector of outcomes we seek to predict based upon predictors  $\tilde{\mathbf{X}}$ .

- We seek the posterior predictive density:

$$p(\tilde{\mathbf{y}} | \mathbf{y}) = \int p(\tilde{\mathbf{y}} | \theta, \mathbf{y}) p(\theta | \mathbf{y}) d\theta.$$

- Posterior predictive inference: sample from  $p(\tilde{\mathbf{y}} | \mathbf{y})$ .

- For each  $j = 1, 2, \dots, N$  do the following:

- Draw  $\theta_{(j)} \sim p(\theta | \mathbf{y})$
- Draw  $\tilde{\mathbf{y}}_{(j)} \sim p(\tilde{\mathbf{y}} | \theta_{(j)}, \mathbf{y})$

## Bayesian predictions from linear regression (cont'd)

- For legitimate probabilistic predictions (forecasting), the conditional distribution  $p(\tilde{\mathbf{y}} | \theta, \mathbf{y})$  must be well-defined.
- For example, consider the case with  $\mathbf{V}_y = \mathbf{I}_n$ . Specify the linear model:

$$\begin{bmatrix} \mathbf{y} \\ \tilde{\mathbf{y}} \end{bmatrix} = \begin{bmatrix} \mathbf{X} \\ \tilde{\mathbf{X}} \end{bmatrix} \boldsymbol{\beta} + \begin{bmatrix} \boldsymbol{\epsilon} \\ \tilde{\boldsymbol{\epsilon}} \end{bmatrix}; \quad \begin{bmatrix} \boldsymbol{\epsilon} \\ \tilde{\boldsymbol{\epsilon}} \end{bmatrix} \sim N \left( \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \sigma^2 \begin{bmatrix} \mathbf{I}_n & \mathbf{O} \\ \mathbf{O} & \mathbf{I}_m \end{bmatrix} \right).$$

- Easy to derive the conditional density:

$$p(\tilde{\mathbf{y}} | \theta, \mathbf{y}) = p(\tilde{\mathbf{y}} | \theta) = N(\tilde{\mathbf{y}} | \tilde{\mathbf{X}}\boldsymbol{\beta}, \sigma^2 \mathbf{I}_m)$$

- Posterior predictive density:

$$p(\tilde{\mathbf{y}} | \mathbf{y}) = \int N(\tilde{\mathbf{y}} | \tilde{\mathbf{X}}\boldsymbol{\beta}, \sigma^2 \mathbf{I}_m) p(\boldsymbol{\beta}, \sigma^2 | \mathbf{y}) d\boldsymbol{\beta} d\sigma^2.$$

- For each  $j = 1, 2, \dots, N$  do the following:

- Draw  $\{\beta_{(j)}, \sigma_{(j)}^2\} \sim p(\boldsymbol{\beta}, \sigma^2 | \mathbf{y})$
- Draw  $\tilde{\mathbf{y}}_{(j)} \sim N(\tilde{\mathbf{X}}\boldsymbol{\beta}_{(j)}, \sigma_{(j)}^2 \mathbf{I}_m)$

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- For example, consider the case with general  $\mathbf{V}_y$ . Specify:

$$\begin{bmatrix} \mathbf{y} \\ \tilde{\mathbf{y}} \end{bmatrix} = \begin{bmatrix} \mathbf{X} \\ \tilde{\mathbf{X}} \end{bmatrix} \beta + \begin{bmatrix} \epsilon \\ \tilde{\epsilon} \end{bmatrix}; \quad \begin{bmatrix} \epsilon \\ \tilde{\epsilon} \end{bmatrix} \sim N\left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \sigma^2 \begin{bmatrix} \mathbf{V}_y & \mathbf{V}_{y\tilde{y}} \\ \mathbf{V}_{y\tilde{y}}^\top & \mathbf{V}_{\tilde{y}} \end{bmatrix}\right).$$

- Derive the conditional density

$$p(\tilde{\mathbf{y}} | \theta, \mathbf{y}) = N(\tilde{\mathbf{y}} | \mu_{\tilde{y}|y}, \sigma^2 \mathbf{V}_{\tilde{y}|y}):$$

$$\mu_{\tilde{y}|y} = \tilde{\mathbf{X}}\beta + \mathbf{V}_{y\tilde{y}}^\top \mathbf{V}_y^{-1}(\mathbf{y} - \mathbf{X}\beta); \quad \mathbf{V}_{\tilde{y}|y} = \mathbf{V}_{\tilde{y}} - \mathbf{V}_{y\tilde{y}}^\top \mathbf{V}_y^{-1} \mathbf{V}_{y\tilde{y}}.$$

- Posterior predictive density:

$$p(\tilde{\mathbf{y}} | \mathbf{y}) = \int N(\tilde{\mathbf{y}} | \mu_{\tilde{y}|y}, \sigma^2 \mathbf{V}_{\tilde{y}|y}) p(\beta, \sigma^2 | \mathbf{y}) d\beta d\sigma^2.$$

- For each  $j = 1, 2, \dots, N$  do the following:

- Draw  $\{\beta_{(j)}, \sigma_{(j)}^2\} \sim p(\beta, \sigma^2 | \mathbf{y})$
- Compute  $\mu_{\tilde{y}|y}$  using  $\beta_{(j)}$  and draw  $\tilde{\mathbf{y}}_{(j)} \sim N(\mu_{\tilde{y}|y}, \sigma_{(j)}^2 \mathbf{V}_{\tilde{y}})$

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- Consider the spatial regression model

$$y(s_i) = \mathbf{x}^\top(\mathbf{s}_i)\beta + w(\mathbf{s}_i) + \epsilon(\mathbf{s}_i),$$

where  $w(\mathbf{s}_i)$ 's are spatial random effects and  $\epsilon(\mathbf{s}_i)$ 's are unstructured errors ("white noise").

- $\mathbf{w} = (w(\mathbf{s}_1), w(\mathbf{s}_2), \dots, w(\mathbf{s}_n))^\top \sim N(\mathbf{0}, \sigma^2 \mathbf{R}(\phi))$
- $\epsilon = (\epsilon(\mathbf{s}_1), \epsilon(\mathbf{s}_2), \dots, \epsilon(\mathbf{s}_n))^\top \sim N(\mathbf{0}, \tau^2 \mathbf{I}_n)$
- Integrating out random effects leads to a Bayesian model:

$$IG(\sigma^2 | a, b) \times N(\beta | \mu_\beta, \sigma^2 \mathbf{V}_\beta) \times N(\mathbf{y} | \mathbf{X}\beta, \sigma^2 \mathbf{V}_y)$$

where  $\mathbf{V}_y = \mathbf{R}(\phi) + \alpha \mathbf{I}_n$  and  $\alpha = \tau^2 / \sigma^2$ .

- Fixing  $\phi$  and  $\alpha$  (e.g., from variogram or other EDA) yields a conjugate Bayesian model (see `bayesGeostatExact()` in `spBayes` package).
- Exact posterior sampling is easily achieved as before!

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## Inference on spatial random effects

- Rewrite the model in terms of  $\mathbf{w}$  as:

$$IG(\sigma^2 | a, b) \times N(\beta | \mu_\beta, \sigma^2 \mathbf{V}_\beta) \times N(\mathbf{w} | \mathbf{0}, \sigma^2 \mathbf{R}(\phi)) \\ \times N(\mathbf{y} | \mathbf{X}\beta + \mathbf{w}, \tau^2 \mathbf{I}_n).$$

- Posterior distribution of spatial random effects  $\mathbf{w}$ :

$$p(\mathbf{w} | \mathbf{y}) = \int N(\mathbf{w} | \mathbf{Mm}, \sigma^2 \mathbf{M}) \times p(\beta, \sigma^2 | \mathbf{y}) d\beta d\sigma^2,$$

where  $\mathbf{m} = (1/\alpha)(\mathbf{y} - \mathbf{X}\beta)$  and  $\mathbf{M}^{-1} = \mathbf{R}^{-1}(\phi) + (1/\alpha)\mathbf{I}_n$ .

- For each  $j = 1, 2, \dots, N$  do the following:

- Draw  $\{\beta_{(j)}, \sigma_{(j)}^2\} \sim p(\beta, \sigma^2 | \mathbf{y})$
- Compute  $\mathbf{m}$  from  $\beta_{(j)}$  and draw  $\mathbf{w}_{(j)} \sim N(\mathbf{Mm}, \sigma_{(j)}^2 \mathbf{M})$

## Inference on the process

- Posterior distribution of  $w(\mathbf{s}_0)$  at new location  $\mathbf{s}_0$ :

$$p(w(\mathbf{s}_0) | \mathbf{y}) = \int N(w(\mathbf{s}_0) | \mu_{w(\mathbf{s}_0)|w}, \sigma_{w(\mathbf{s}_0)|w}^2) \times p(\sigma^2, \mathbf{w} | \mathbf{y}) d\sigma^2 d\mathbf{w},$$

where

$$\mu_{w(\mathbf{s}_0)|w} = \mathbf{r}^\top(\mathbf{s}_0; \phi) \mathbf{R}^{-1}(\phi) \mathbf{w}; \\ \sigma_{w(\mathbf{s}_0)|w}^2 = \sigma^2 \{1 - \mathbf{r}^\top(\mathbf{s}_0; \phi) \mathbf{R}^{-1}(\phi) \mathbf{r}(\mathbf{s}_0, \phi)\}$$

- For each  $j = 1, 2, \dots, N$  do the following:

- Compute  $\mu_{w(\mathbf{s}_0)|w}$  and  $\sigma_{w(\mathbf{s}_0)|w}^2$  from  $\mathbf{w}_{(j)}$  and  $\sigma_{(j)}^2$ .
- Draw  $w_{(j)}(\mathbf{s}_0) \sim N(\mu_{w(\mathbf{s}_0)|w}, \sigma_{w(\mathbf{s}_0)|w}^2)$ .

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- Posterior predictive distribution at new location  $s_0$  is  $p(y(s_0) | \mathbf{y})$ :

$$\int N(y(s_0) | \mathbf{x}^\top(s_0)\beta + w(s_0), \alpha\sigma^2) \times p(\beta, \sigma^2, \mathbf{w} | \mathbf{y}) d\beta d\sigma^2 d\mathbf{w},$$

- For each  $j = 1, 2, \dots, N$  do the following:

- Draw  $y_{(j)}(s_0) \sim N(\mathbf{x}^\top(s_0)\beta_{(j)} + w_{(j)}(s_0), \alpha\sigma_{(j)}^2)$ .

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- In principle, the Gibbs sampler will work for extremely complex hierarchical models. The only issue is sampling from the full conditionals. They may not be amenable to easy sampling – when these are not in closed form. A more general and extremely powerful - and often easier to code - algorithm is the Metropolis-Hastings (MH) algorithm.
- This algorithm also constructs a Markov chain, but does not necessarily care about full conditionals.
- Popular approach: Embed Metropolis steps within Gibbs to draw from full conditionals that are not accessible to directly generate from.

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- Let  $\theta = (\theta_1, \dots, \theta_p)$  be the parameters in our model.
- Initialize with starting values  $\theta^{(0)} = (\theta_1^{(0)}, \dots, \theta_p^{(0)})$
- For  $j = 1, \dots, N$ , update successively using the *full conditional* distributions:
 
$$\begin{aligned}\theta_1^{(j)} &\sim p(\theta_1^{(j)} | \theta_2^{(j-1)}, \dots, \theta_p^{(j-1)}, \mathbf{y}) \\ \theta_2^{(j)} &\sim p(\theta_2 | \theta_1^{(j)}, \theta_3^{(j-1)}, \dots, \theta_p^{(j-1)}, \mathbf{y}) \\ &\vdots \\ &\text{(the generic } k^{\text{th}} \text{ element)} \\ \theta_k^{(j)} &\sim p(\theta_k | \theta_1^{(j)}, \dots, \theta_{k-1}^{(j)}, \theta_{k+1}^{(j-1)}, \dots, \theta_p^{(j-1)}, \mathbf{y}) \\ &\vdots \\ \theta_p^{(j)} &\sim p(\theta_p | \theta_1^{(j)}, \dots, \theta_{p-1}^{(j)}, \mathbf{y})\end{aligned}$$

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## When we don't want to fix $\phi$ and $\alpha = \tau^2/\sigma^2$

### Latent Bayesian Model

$$\begin{aligned}N(\mathbf{y} | \mathbf{X}\beta + \mathbf{w}, \tau^2 \mathbf{I}) \times N(\mathbf{w} | \mathbf{0}, \sigma^2 \mathbf{R}(\phi)) \times N(\beta | \mu_\beta, \mathbf{V}_\beta) \\ \times IG(\tau^2 | a_\tau, b_\tau) \times IG(\sigma^2 | a_\sigma, b_\sigma) \times Unif(\phi | a_\phi, b_\phi)\end{aligned}$$

Sampler:

- Full conditionals for  $\beta$ ,  $\tau^2$ ,  $\sigma^2$  and  $w(s_i)$ 's
- Metropolis step for updating  $\phi$
- Pros:** Full conditional distributions for all parameters except  $\phi$ , easy to code up
- Cons:** High-dimensional parameter space can mean slow convergence

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### Collapsed Bayesian Model

$$\begin{aligned} N(\mathbf{y} | \mathbf{X}\beta, \sigma^2 \mathbf{R}(\phi) + \tau^2 \mathbf{I}) \times N(\beta | \mu_\beta, \mathbf{V}_\beta) \\ \times IG(\tau^2 | a_\tau, b_\tau) \times IG(\sigma^2 | a_\sigma, b_\sigma) \times Unif(\phi | a_\phi, b_\phi) \end{aligned}$$

Sampler:

- Full conditional for  $\beta$
- Metropolis step for updating  $\tau^2, \sigma^2, \phi$
- Pros: Low-dimensional parameter space
- “Recover”  $w(\mathbf{s}_i)$ ’s in a posterior predictive fashion

We can also integrate out  $\beta$ ! See Finley et al. (2015) for details  
<https://www.jstatsoft.org/article/view/v063i13> and implementation in the spBayes package.

- The Metropolis-Hastings algorithm: Start with a initial value for  $\theta = \theta^{(0)}$ . Select a *candidate* or *proposal* distribution from which to propose a value of  $\theta$  at the  $j$ -th iteration:  $\theta^{(j)} \sim q(\theta^{(j-1)}, \nu)$ . For example,  $q(\theta^{(j-1)}, \nu) = N(\theta^{(j-1)}, \nu)$  with  $\nu$  fixed.

- Compute

$$r = \frac{p(\theta^* | y)q(\theta^{(j-1)} | \theta^*, \nu)}{p(\theta^{(j-1)} | y)q(\theta^* | \theta^{(j-1)}, \nu)}$$

- If  $r \geq 1$  then set  $\theta^{(j)} = \theta^*$ . If  $r \leq 1$  then draw  $U \sim (0, 1)$ . If  $U \leq r$  then  $\theta^{(j)} = \theta^*$ . Otherwise,  $\theta^{(j)} = \theta^{(j-1)}$ .
- Repeat for  $j = 1, \dots, N$ . This yields  $\theta^{(1)}, \dots, \theta^{(N)}$ , which, after a burn-in period, will be samples from the true posterior distribution. It is important to monitor the acceptance ratio  $r$  of the sampler through the iterations. Rough recommendations: for vector updates  $r \approx 20\%$ ., for scalar updates  $r \approx 40\%$ . This can be controlled by “tuning”  $\nu$ .
- Popular approach: Embed Metropolis steps within Gibbs to draw from full conditionals that are not accessible to directly generate from.

- Example: For the linear model, our parameters are  $(\beta, \sigma^2)$ . We write  $\theta = (\beta, \log(\sigma^2))$  and, at the  $j$ -th iteration, propose  $\theta^* \sim N(\theta^{(j-1)}, \Sigma)$ . The log transformation on  $\sigma^2$  ensures that all components of  $\theta$  have support on the entire real line and can have meaningful proposed values from the multivariate normal. But we need to transform our prior to  $p(\beta, \log(\sigma^2))$ .
- Let  $z = \log(\sigma^2)$  and assume  $p(\beta, z) = p(\beta)p(z)$ . Let us derive  $p(z)$ .  
**REMEMBER:** we need to adjust for the jacobian. Then  $p(z) = p(\sigma^2)|d\sigma^2/dz| = p(e^z)e^z$ . The jacobian here is  $e^z = \sigma^2$ .
- Let  $p(\beta) = 1$  and an  $p(\sigma^2) = IG(\sigma^2 | a, b)$ . Then log-posterior is:

$$-(a + n/2 + 1)z + z - \frac{1}{e^z} \{b + \frac{1}{2}(Y - X\beta)^T(Y - X\beta)\}.$$

- A symmetric proposal distribution, say  $q(\theta^* | \theta^{(j-1)}, \Sigma) = N(\theta^{(j-1)}, \Sigma)$ , cancels out in  $r$ . In practice it is better to compute  $\log(r)$ :  $\log(r) = \log(p(\theta^* | y) - \log(p(\theta^{(j-1)} | y)))$ . For the proposal,  $N(\theta^{(j-1)}, \Sigma)$ ,  $\Sigma$  is a  $d \times d$  variance-covariance matrix, and  $d = \dim(\theta) = p + 1$ .
- If  $\log r \geq 0$  then set  $\theta^{(j)} = \theta^*$ . If  $\log r \leq 0$  then draw  $U \sim (0, 1)$ . If  $U \leq r$  (or  $\log U \leq \log r$ ) then  $\theta^{(j)} = \theta^*$ . Otherwise,  $\theta^{(j)} = \theta^{(j-1)}$ .
- Repeat the above procedure for  $j = 1, \dots, N$  to obtain samples  $\theta^{(1)}, \dots, \theta^{(N)}$ .

### Nearest Neighbor Gaussian Processes for Large Spatial Data

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Consider again the spatially-varying intercept model for generic location  $\mathbf{s}$

$$y(\mathbf{s}) = \mathbf{x}(\mathbf{s})^\top \boldsymbol{\beta} + w(\mathbf{s}) + \epsilon(\mathbf{s}), \quad \mathbf{s} \in \mathcal{D} \subseteq \mathbb{R}^d,$$

where

$y(\mathbf{s})$  is the outcome,

$\mathbf{x}(\mathbf{s})$  is  $p \times 1$  set of predictors including an intercept,

$\boldsymbol{\beta}$  is a vector of  $p$  regression parameters,

$w(\mathbf{s})$  is a spatial random effect,

$\epsilon(\mathbf{s})$  is the independent noise process with variance  $\tau^2$ .

## Likelihood from (full rank) GP models

- Assuming  $w(\mathbf{s}) \sim GP(0, K_\theta(\cdot, \cdot))$  implies that for a set of  $n$  locations<sup>1</sup>

$$\mathbf{w} = (w(\mathbf{s}_1), w(\mathbf{s}_2), \dots, w(\mathbf{s}_n))^\top \sim MVN(\mathbf{0}, \mathbf{K}_\theta)$$

- Estimating process parameters from the likelihood involves:

$$p(\mathbf{w}) \propto -\frac{1}{2} \log(\det(\mathbf{K}_\theta)) - \frac{1}{2} \mathbf{w}^\top \mathbf{K}_\theta^{-1} \mathbf{w}$$

- Bayesian inference: priors on  $\boldsymbol{\theta}$  and many Markov chain Monte Carlo (MCMC) iterations

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<sup>1</sup> $K_\theta(\cdot, \cdot)$  is any valid spatial covariance function, e.g.,  $\sigma^2 R(\cdot, \cdot; \phi)$ , with  $\boldsymbol{\theta} = (\sigma^2, \phi)$ .

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## Burgeoning literature on spatial big data

### Computation issues

- Storage:  $n^2$  pairwise distances to compute  $\mathbf{K}_\theta$
- $\mathbf{K}_\theta$  is dense; Need to solve  $\mathbf{K}_\theta \mathbf{x} = \mathbf{b}$  and need  $\det(\mathbf{K}_\theta)$
- This is best achieved using  $\text{chol}(\mathbf{K}_\theta) = \mathbf{LDL}^\top$
- Complexity: roughly  $O(n^3)$  flops

### Computationally infeasible for large datasets

- Low-rank models:** (Wahba, 1990; Higdon, 2002; Rasmussen and Williams, 2006; Cressie and Johannesson, 2008; Banerjee et al., 2008, 2010; Gramacy and Lee, 2008; Finley et al., 2009; Lemos and Sansó, 2009; Sang et al., 2011; Sang and Huang, 2012; Guhaniyogi et al., 2011; Katzfuss and Hammerling, 2017)
- Spectral approximations and composite likelihoods:** (Fuentes, 2007; Paciorek, 2007; Eidsvik et al., 2014)
- Multi-resolution approaches:** (Nychka et al., 2015; Johannesson et al., 2007; Katzfuss, 2017; Guhaniyogi and Sanso, 2020)
- Sparsity:** (Solve  $\mathbf{A}\mathbf{x} = \mathbf{b}$  by (i) sparse  $\mathbf{A}$ , or (ii) sparse  $\mathbf{A}^{-1}$ )
  - Covariance tapering (Furrer et al., 2006; Du et al., 2009; Kaufman et al., 2008; Stein, 2013; Shaby and Ruppert, 2012)
  - GMRFs to GPs: INLA (Rue et al., 2009; Lindgren et al., 2011)
  - LAGP Gramacy et al., 2014; Gramacy and Apley, 2015)
  - Nearest-neighbor Gaussian Process (NNGP) models** (Datta et al., 2016a,c,b; Finley et al., 2019a) builds on Vecchia (1988).

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- $\mathbf{K}_\theta \approx \mathbf{J}_\theta \mathbf{K}_\theta^* \mathbf{J}_\theta^\top + \mathbf{D}_\theta$
- $\mathbf{J}_\theta$  is  $n \times r$  matrix of spatial basis functions,  $r \ll n$
- $\mathbf{K}_\theta^*$  is  $r \times r$  spatial covariance matrix
- $\mathbf{D}_\theta$  is either diagonal or sparse
- Examples: Kernel projections, Splines, Predictive process, FRK, spectral basis ...
- Computations exploit above structure: roughly  $O(nr^2) \ll O(n^3)$  flops

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**Low-rank models: hierarchical approach**

$$N(\mathbf{w}^* | \mathbf{0}, \mathbf{K}_\theta^*) \times N(\mathbf{w} | \mathbf{J}_\theta \mathbf{w}^*, \mathbf{D})$$

- $\mathbf{w}$  is  $n \times 1$  and  $n$  is large
- $\mathbf{w}^*$  is  $r \times 1$ , where  $r \ll n$ , defined over a user-defined set of locations, or knots,  $\mathcal{S}^* = \{\mathbf{s}_1^*, \mathbf{s}_2^*, \dots, \mathbf{s}_r^*\}$ .
- $\mathbf{J}_\theta$  is  $n \times r$  is a matrix of “basis” functions
- $\mathbf{D}$  is  $n \times n$ , but easy to invert (e.g., diagonal)
- Derive  $\text{var}(\mathbf{w})$  (or  $\text{var}(\mathbf{w}^* | \mathbf{y})$ ) in alternate ways to obtain

$$(\mathbf{J}_\theta \mathbf{K}_\theta^* \mathbf{J}_\theta^\top + \mathbf{D})^{-1} = \mathbf{D}^{-1} - \mathbf{D}^{-1} \mathbf{J}_\theta (\mathbf{K}_\theta^{*-1} + \mathbf{J}_\theta^\top \mathbf{D}^{-1} \mathbf{J}_\theta)^{-1} \mathbf{J}_\theta^\top \mathbf{D}^{-1}.$$

This is the famous Sherman-Woodbury-Morrison formula.

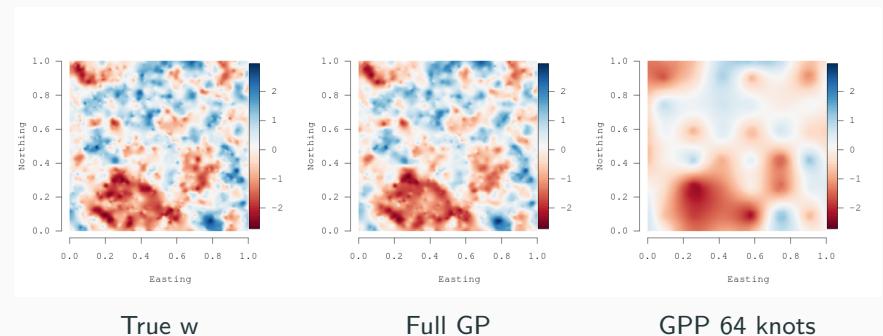
See, e.g., Finley et al. (2017) for implantation details and software for the Gaussian predictive process (GPP) model.

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**Simulation experiment**

- 2500 locations on a unit square
- $y(\mathbf{s}) = \beta_0 + \beta_1 x(\mathbf{s}) + w(\mathbf{s}) + \epsilon(\mathbf{s})$
- Single covariate  $x(\mathbf{s})$  generated as iid  $N(0, 1)$
- Spatial effects generated from  $GP(0, \sigma^2 R(\cdot, \cdot | \phi))$
- $R(\cdot, \cdot | \phi)$  is exponential correlation function with decay  $\phi$
- Candidate models: Full GP and Gaussian Predictive Process (GPP) with 64 knots

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**Oversmoothing due to reduced-rank models**

**Figure:** Comparing full GP vs low-rank GPP with 2500 locations. Figure (c) exhibits oversmoothing by a low-rank process (predictive process with 64 knots)

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See Stein (2014) for very good reasons NOT to use reduced-rank spatial models.

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## Low rank Gaussian Predictive Process

### Pros

- Proper Gaussian process
- Allows for coherent spatial interpolation at arbitrary resolution
- Can be used as prior for spatial random effects in any hierarchical setup for spatial data
- Computationally tractable

## Low rank Gaussian Predictive Process

### Cons

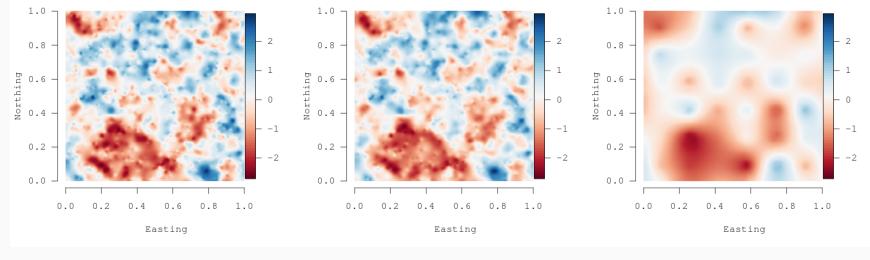


Figure: Comparing full GP vs low-rank GP with 2500 locations

- Low rank models, like the GPP, tend to oversmooth
- Increasing the number of knots can fix this but will lead to heavy computation

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## Sparse matrices

- **Idea:** Use a **sparse** matrix instead of a low rank matrix to approximate the dense full GP covariance matrix
- **Goals:**
  - Scalability: Both in terms of **storage** and computing **inverse** and **determinant**
  - Closely approximate full GP inference
  - Proper Gaussian process model like the GPP

## Cholesky factors

- Write a joint density  $p(\mathbf{w}) = p(w_1, w_2, \dots, w_n)$  as:
$$p(w_1)p(w_2 | w_1)p(w_3 | w_1, w_2) \cdots p(w_n | w_1, w_2, \dots, w_{n-1})$$
- For Gaussian distribution  $\mathbf{w} \sim N(\mathbf{0}, \mathbf{K}_\theta)$  this  $\Rightarrow$ 
$$w_1 = 0 + \eta_1;$$
$$w_2 = a_{21}w_1 + \eta_2;$$
$$\dots \quad \dots \quad \dots$$
$$w_n = a_{n1}w_1 + a_{n2}w_2 + \cdots + a_{n,n-1}w_{n-1} + \eta_n;$$

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## Cholesky factors

- Write a joint density  $p(\mathbf{w}) = p(w_1, w_2, \dots, w_n)$  as:

$$p(w_1)p(w_2 | w_1)p(w_3 | w_1, w_2) \cdots p(w_n | w_1, w_2, \dots, w_{n-1})$$

- For Gaussian distribution  $\mathbf{w} \sim N(\mathbf{0}, \mathbf{K}_\theta)$  this  $\Rightarrow$

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 \\ a_{21} & 0 & 0 & \dots & 0 & 0 \\ a_{31} & a_{32} & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{n,n-1} & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_n \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \vdots \\ \eta_n \end{bmatrix}$$

$$\Rightarrow \mathbf{w} = \mathbf{Aw} + \boldsymbol{\eta}; \quad \boldsymbol{\eta} \sim N(\mathbf{0}, \mathbf{D}).$$

## Cholesky factors

- Write a joint density  $p(\mathbf{w}) = p(w_1, w_2, \dots, w_n)$  as:

$$p(w_1)p(w_2 | w_1)p(w_3 | w_1, w_2) \cdots p(w_n | w_1, w_2, \dots, w_{n-1})$$

- For Gaussian distribution  $\mathbf{w} \sim N(\mathbf{0}, \mathbf{K}_\theta)$  this  $\Rightarrow$

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 \\ a_{21} & 0 & 0 & \dots & 0 & 0 \\ a_{31} & a_{32} & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{n,n-1} & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_n \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \vdots \\ \eta_n \end{bmatrix}$$

$$\Rightarrow \mathbf{w} = \mathbf{Aw} + \boldsymbol{\eta}; \quad \boldsymbol{\eta} \sim N(\mathbf{0}, \mathbf{D}).$$

- Cholesky factorization:

$$\mathbf{K}_\theta = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{D} (\mathbf{I} - \mathbf{A})^{-\top}, \text{ where } \mathbf{D} = \text{diag}(\text{var}\{w_i | w_{\{j < i\}}\})$$

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## Cholesky factors

- For Gaussian distribution  $N(\mathbf{w} | \mathbf{0}, \mathbf{K}_\theta)$ ,

$$\mathbf{K}_\theta = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{D} (\mathbf{I} - \mathbf{A})^{-\top}; \quad \mathbf{D} = \text{diag}(\text{var}\{w_i | w_{\{j < i\}}\})$$

- If  $\mathbf{L}$  is from  $\text{chol}(\mathbf{K}_\theta) = \mathbf{LDL}^\top$ , then  $\mathbf{L}^{-1} = \mathbf{I} - \mathbf{A}$ .

- $a_{ij}$ 's obtained from  $n - 1$  linear systems by comparing coefficients of  $w_j$ 's in

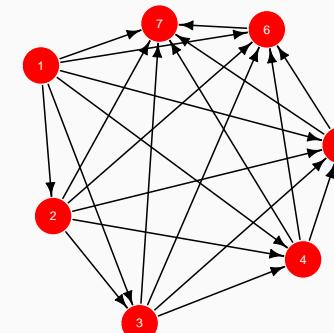
$$\sum_{j < i} a_{ij} w_j = E[w_i | w_{\{j < i\}}] \quad i = 2, \dots, n$$

- Non-zero elements of  $\mathbf{A}$  and  $\mathbf{D}$  are computed:

$\mathbf{D}[1,1] = \mathbf{K}[1,1]$  and first row of  $\mathbf{A}$  is zero.

```
for(i in 1:(n-1)) {
  A[i+1,1:i] = solve(K[1:i,1:i], K[1:i,i+1])
  D[i+1,i+1] = K[i+1,i+1] - dot(K[i+1,1:i], A[i+1,1:i])
}
```

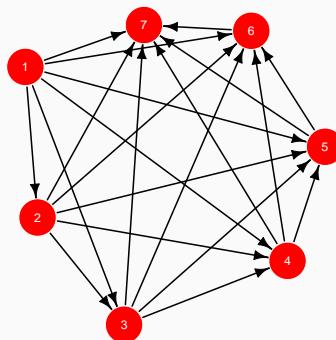
## Cholesky Factors and Directed Acyclic Graphs (DAGs)



- Number of non-zero entries (sparsity) of  $\mathbf{A}$  equals number of arrows in the graph
- In particular: Sparsity of the  $i^{\text{th}}$  row of  $\mathbf{A}$  is same as the number of arrows towards  $i$  in the DAG

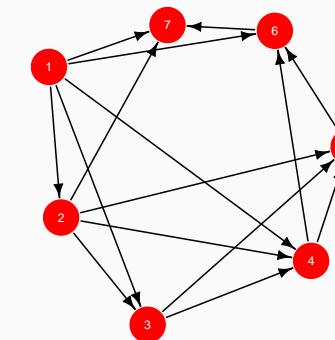
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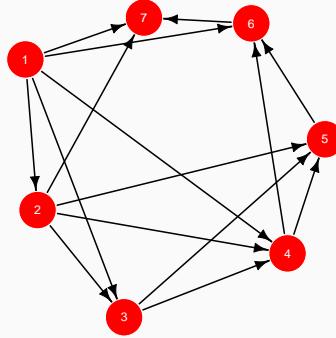
$$p(y_1)p(y_2 | y_1)p(y_3 | y_1, y_2)p(y_4 | y_1, y_2, y_3) \\ \times p(y_5 | y_1, y_2, y_3, y_4)p(y_6 | y_1, y_2, \dots, y_5)p(y_7 | y_1, y_2, \dots, y_6).$$

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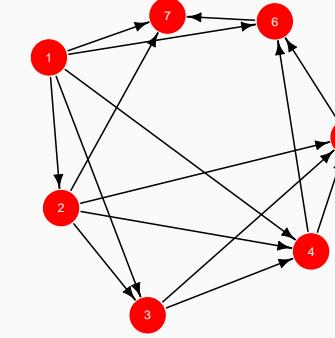
$$p(y_1)p(y_2 | y_1)p(y_3 | y_1, y_2)p(y_4 | y_1, y_2, y_3) \\ p(y_5 | \cancel{y_1}, y_2, y_3, y_4)p(y_6 | \cancel{y_1}, \cancel{y_2}, \cancel{y_3}, y_4, y_5)p(y_7 | y_1, y_2, \cancel{y_3}, \cancel{y_4}, \cancel{y_5}, y_6)$$

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- Create a **sparse** DAG by keeping **at most  $m$**  arrows pointing to each node
- Set  $a_{ij} = 0$  for all  $i, j$  which has no arrow between them
- Fixing  $a_{ij} = 0$  introduces **conditional independence** and  $w_j$  drops out from the conditional set in  $p(w_i | \{w_k : k < i\})$

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- $N(i)$  denote **neighbor set** of  $i$ , i.e., the set of nodes from which there are arrows to  $i$
- $a_{ij} = 0$  for  $j \notin N(i)$  and nonzero  $a_{ij}$ 's obtained by solving:

$$\mathbb{E}[w_i | w_{N(i)}] = \sum_{j \in N(i)} a_{ij} w_j$$

- The above linear system is only  **$m \times m$**

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## Choosing neighbor sets

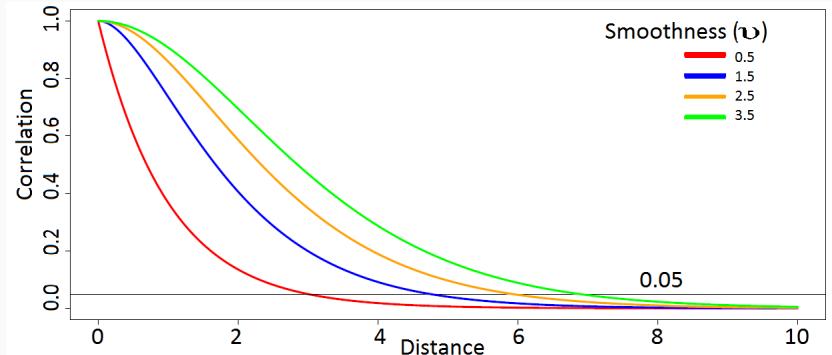
- Non-zero elements of sparse  $\mathbf{A}$  and  $\mathbf{D}$  are computed:

```
D[1,1] = K[1,1] and first row of A is zero.  
for(i in 1:(n-1)) {  
  Pa = N[i+1] # neighbors of i+1  
  A[i+1,Pa] = solve(K[Pa,Pa], K[i+1,Pa])  
  D[i+1,i+1] = K[i+1,i+1] - dot(K[i+1,Pa],A[i+1,Pa])  
}
```

- We need to solve  $n - 1$  linear systems of size at most  $m \times m$ .
- We effectively model a (sparse) Cholesky factor instead of computing it.

Matern Covariance Function:

$$K(\mathbf{s}_i, \mathbf{s}_j) = \frac{1}{2^{\nu-1}\Gamma(\nu)}(||\mathbf{s}_i - \mathbf{s}_j||\phi)^{\nu} \mathcal{K}_{\nu}(||\mathbf{s}_i - \mathbf{s}_j||\phi); \phi > 0, \nu > 0,$$



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## Choosing neighbor sets

## Nearest neighbors

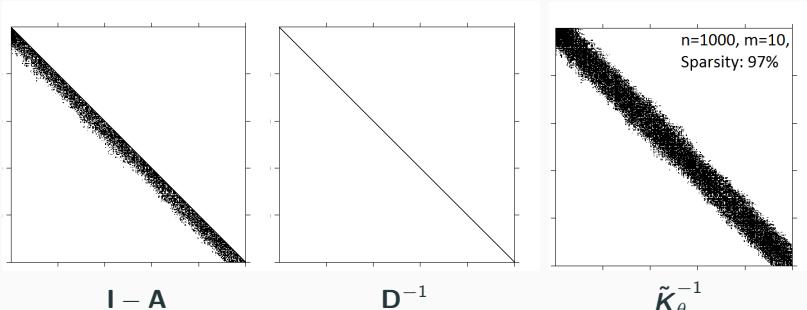
- Spatial covariance functions decay with distance
- Vecchia (1988):  $N(\mathbf{s}_i) = m$ -nearest neighbors of  $\mathbf{s}_i$  in  $\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_{i-1}$ 
  - Nearest points have highest correlations
  - Theory: "Screening effect" – Stein, 2002
- We use Vecchia's choice of  $m$ -nearest neighbor
- Other choices proposed in Stein et al. (2004); Gramacy and Apley (2015); Guinness (2018) can also be used, with additional discussion in Finley et al. (2019) and Katzfuzz and Guinness (2021)

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## Sparse precision matrices

- The neighbor sets and the covariance function  $K(\cdot, \cdot)$  define a sparse Cholesky factor  $\mathbf{A}$
- $N(\mathbf{w} | \mathbf{0}, \mathbf{K}_\theta) \approx N(\mathbf{w} | \mathbf{0}, \tilde{\mathbf{K}}_\theta)$ ;  $\tilde{\mathbf{K}}_\theta^{-1} = (\mathbf{I} - \mathbf{A})^\top \mathbf{D}^{-1} (\mathbf{I} - \mathbf{A})$



- $\det(\tilde{\mathbf{K}}_\theta) = \prod_{i=1}^n D_i$ ,
- $\tilde{\mathbf{K}}_\theta^{-1}$  is sparse with  $O(nm^2)$  entries

Explore some  $\mathbf{A}$  and  $\tilde{\mathbf{K}}_\theta^{-1}$  sparsity patterns [https://github.com/finleya/NNGP\\_LDL](https://github.com/finleya/NNGP_LDL)

## Extension to a Process

- We have defined  $\mathbf{w} \sim N(\mathbf{0}, \tilde{\mathbf{K}}_\theta)$  over the set of data locations  $S = \{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_n\}$
- For  $\mathbf{s} \notin S$ , define  $N(\mathbf{s})$  as set of  $m$ -nearest neighbors of  $\mathbf{s}$  in  $S$
- Define  $w(\mathbf{s}) = \sum_{i:\mathbf{s}_i \in N(\mathbf{s})} a_i(\mathbf{s}) w(\mathbf{s}_i) + \eta(\mathbf{s})$  where  $\eta(\mathbf{s}) \stackrel{iid}{\sim} N(0, d(\mathbf{s}))$ 
  - $a_i(\mathbf{s})$  and  $d(\mathbf{s})$  are once again obtained by solving  $m \times m$  system
- Well-defined GP over entire domain
  - Nearest Neighbor GP (NNGP) – Datta et al., JASA, (2016)

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## Hierarchical spatial regression with NNGP

### Spatial linear model

$$y(\mathbf{s}) = \mathbf{x}(\mathbf{s})^\top \boldsymbol{\beta} + w(\mathbf{s}) + \epsilon(\mathbf{s})$$

- $w(\mathbf{s})$  modeled as NNGP derived from a  $GP(0, (\cdot, \cdot, | \sigma^2, \phi))$
- $\epsilon(\mathbf{s}) \stackrel{iid}{\sim} N(0, \tau^2)$  contributes to the nugget
- Priors for the parameters  $\boldsymbol{\beta}$ ,  $\sigma^2$ ,  $\tau^2$  and  $\phi$
- Only difference from a full GP model is the NNGP prior  $w(\mathbf{s})$

## Hierarchical spatial regression with NNGP

### Full Bayesian Model

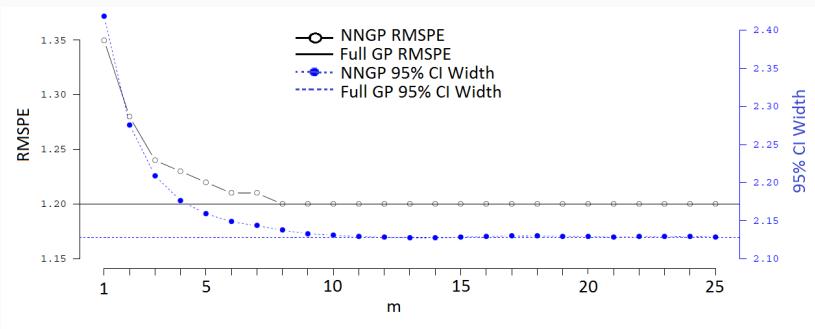
$$\begin{aligned} N(\mathbf{y} | \mathbf{X}\boldsymbol{\beta} + \mathbf{w}, \tau^2 \mathbf{I}) \times N(\mathbf{w} | \mathbf{0}, \tilde{\mathbf{K}}_\theta) \times N(\boldsymbol{\beta} | \boldsymbol{\mu}_\beta, \mathbf{V}_\beta) \\ \times IG(\tau^2 | a_\tau, b_\tau) \times IG(\sigma^2 | a_\sigma, b_\sigma) \times Unif(\phi | a_\phi, b_\phi) \end{aligned}$$

Gibbs sampler:

- Full conditionals for  $\boldsymbol{\beta}$ ,  $\tau^2$ ,  $\sigma^2$  and  $w(\mathbf{s}_i)$ 's
- Metropolis step for updating  $\phi$
- Posterior predictive distribution at any location using composition sampling

## Choosing $m$

## Storage and computation



- Run NNGP in parallel for few values of  $m$
- Choose  $m$  based on model evaluation metrics
- Our results suggested that typically  $m \approx 20$  yielded excellent approximations to the full GP

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### Storage:

- Never needs to store  $n \times n$  distance matrix
- Stores smaller  $m \times m$  matrices
- Total storage requirements  $O(nm^2)$

### Computation:

- Only involves inverting small  $m \times m$  matrices
- Total flop count per iteration of Gibbs sampler is  $O(nm^3)$
- Since  $m \ll n$ , NNGP offers great **scalability** for large datasets

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## Simulation experiment

## Fitted Surfaces

- 2500 locations on a unit square
- $y(\mathbf{s}) = \beta_0 + \beta_1 x(\mathbf{s}) + w(\mathbf{s}) + \epsilon(\mathbf{s})$
- Single covariate  $x(\mathbf{s})$  generated as iid  $N(0, 1)$
- Spatial effects generated from  $GP(0, \sigma^2 R(\cdot, \cdot | \phi))$
- $R(\cdot, \cdot | \phi)$  is exponential correlation function with decay  $\phi$
- Candidate models: Full GP, Gaussian Predictive Process (GPP) with 64 knots and NNGP

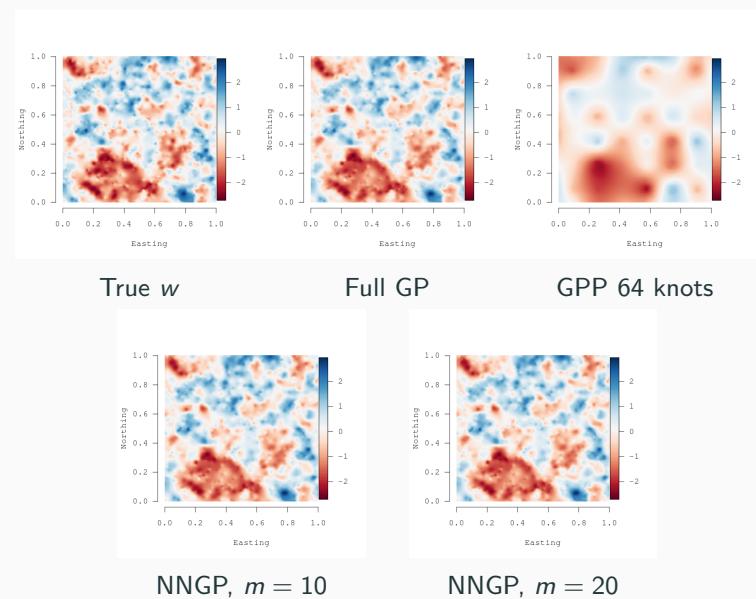


Figure: Univariate synthetic data analysis

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## Parameter estimates

	True	NNGP		Predictive Process	Full
		$m = 10$	$m = 20$	64 knots	Gaussian Process
$\beta_0$	1	1.00 (0.62, 1.31)	1.03 (0.65, 1.34)	1.30 (0.54, 2.03)	1.03 (0.69, 1.34)
$\beta_1$	5	5.01 (4.99, 5.03)	5.01 (4.99, 5.03)	5.03 (4.99, 5.06)	5.01 (4.99, 5.03)
$\sigma^2$	1	0.96 (0.78, 1.23)	0.94 (0.77, 1.20)	1.29 (0.96, 2.00)	0.94 (0.76, 1.23)
$\tau^2$	0.1	0.10 (0.08, 0.13)	0.10 (0.08, 0.13)	0.08 (0.04, 0.13)	0.10 (0.08, 0.12)
$\phi$	12	12.93 (9.70, 16.77)	13.36 (9.99, 17.15)	5.61 (3.48, 8.09)	13.52 (9.92, 17.50)

## Model evaluation

	NNGP		Predictive Process	Full
	$m = 10$	$m = 20$	64 knots	Gaussian Process
DIC score		2390	2377	13678
RMSPE		1.2	1.2	1.68
Run time (Minutes)	14.40	46.47	43.36	560.31

- NNGP performs at par with Full GP
- GPP oversmooths and performs much worse both in terms of parameter estimation and model comparison
- NNGP yields huge computational gains

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## Multivariate spatial linear model

- Spatial linear model for  $q$ -variate spatial data:  
 $y_i(\mathbf{s}) = \mathbf{x}_i^\top(\mathbf{s})\boldsymbol{\beta}_i + w_i(s) + \epsilon_i(s)$  for  $i = 1, 2, \dots, q$
- $\epsilon(s) = (\epsilon_1(s), \epsilon_2(s), \dots, \epsilon_q(s))^\top \sim N(0, E)$  where  $E$  is the  $q \times q$  noise matrix
- $w(s) = (w_1(s), w_2(s), \dots, w_q(s))^\top$  is modeled as a  $q$ -variate Gaussian process

## Multivariate GPs

- $Cov(w(\mathbf{s}_i), w(\mathbf{s}_j)) = K(s_i, s_j | \theta)$  – a  $q \times q$  cross-covariance matrix
- Choices for the function  $K(\cdot, \cdot | \theta)$ 
  - Multivariate Matérn
  - Linear model of co-regionalization
- For data observed at  $n$  locations, all choices lead to a dense  $nq \times nq$  matrix  $\mathbf{K}_\theta = Cov(w(\mathbf{s}_1), w(\mathbf{s}_2), \dots, w(\mathbf{s}_n))$
- Not scalable when  $nq$  is large

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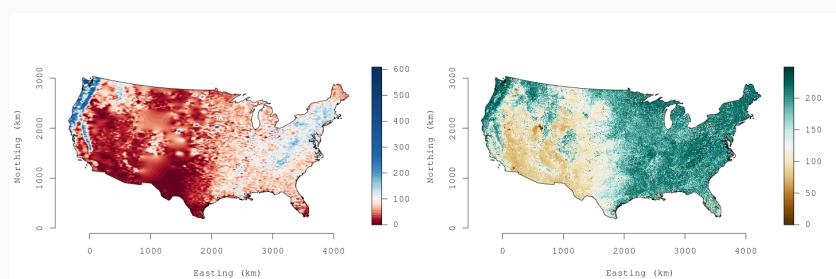
- Cholesky factor approach similar to the univariate case

$$\begin{bmatrix} \mathbf{w}(\mathbf{s}_1) \\ \mathbf{w}(\mathbf{s}_2) \\ \mathbf{w}(\mathbf{s}_3) \\ \vdots \\ \mathbf{w}(\mathbf{s}_n) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 \\ \mathbf{A}_{21} & 0 & 0 & \dots & 0 & 0 \\ \mathbf{A}_{31} & \mathbf{A}_{32} & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{A}_{n1} & \mathbf{A}_{n2} & \mathbf{A}_{n3} & \dots & \mathbf{A}_{n,n-1} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{w}(\mathbf{s}_1) \\ \mathbf{w}(\mathbf{s}_2) \\ \mathbf{w}(\mathbf{s}_3) \\ \vdots \\ \mathbf{w}(\mathbf{s}_n) \end{bmatrix} + \begin{bmatrix} \eta(\mathbf{s}_1) \\ \eta(\mathbf{s}_2) \\ \eta(\mathbf{s}_3) \\ \vdots \\ \eta(\mathbf{s}_n) \end{bmatrix}$$

$$\implies \mathbf{w} = \mathbf{Aw} + \eta; \quad \eta \sim N(\mathbf{0}, \mathbf{D}), \quad \mathbf{D} = diag(\mathbf{D}_1, \mathbf{D}_2, \dots, \mathbf{D}_n).$$

Only differences:

- $\mathbf{w}(\mathbf{s}_i)$  and  $\eta(\mathbf{s}_i)$ 's are  $q \times 1$  vectors and  $\mathbf{A}_{ij}$  and  $\mathbf{D}_i$ 's are  $q \times q$  matrix
  - we must solve  $n - 1$  at most  $mq \times mq$  linear systems  
(challenging when  $q$  gets large, e.g.,  $q > 5$ ).



## Observed biomass

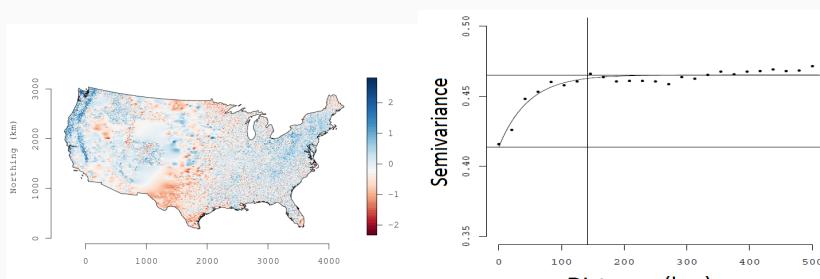
NDVI

- Forest biomass data from measurements at 114,371 plots
  - NDVI (greenness) is used to predict forest biomass

## **U.S. Forest biomass data**

## Non Spatial Model

$$\text{Biomass} = \beta_0 + \beta_1 NDVI + \text{error}, \quad \hat{\beta}_0 = 1.043, \quad \hat{\beta}_1 = 0.0093$$



## Residuals

### Variogram of residuals

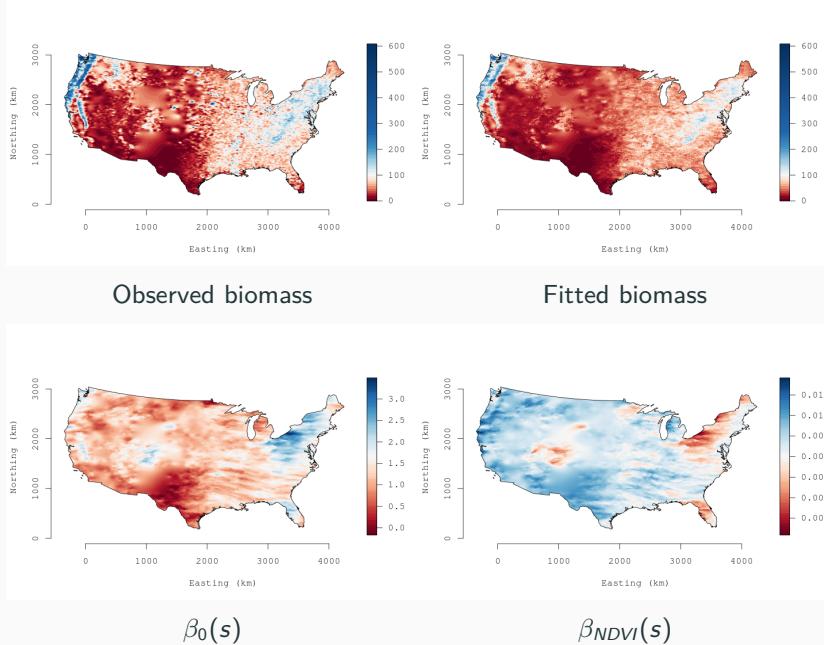
## Strong spatial pattern among residuals

## Forest biomass dataset

- $n \approx 10^5$  (Forest Biomass)  $\Rightarrow$  full GP requires storage  $\approx 40\text{Gb}$  and time  $\approx 140$  hrs per iteration.
  - We use a spatially varying coefficients NNGP model

## Model

- $Biomass(s) = \beta_0(s) + \beta_1(s)NDVI(s) + \epsilon(s)$
  - $\mathbf{w}(s) = (\beta_0(s), \beta_1(s))^\top \sim \text{Bivariate } NNGP(0, \tilde{K}(\cdot, \cdot | \theta)),$   
 $m = 5$
  - Time  $\approx 6$  seconds per iteration
  - Full inferential output: 41 hours (25000 MCMC iterations)



- The Gibbs sampler algorithm for the NNGP updates  $w(\mathbf{s}_1), w(\mathbf{s}_2), \dots, w(\mathbf{s}_n)$  sequentially
- Dimension of the MCMC for this **sequential** algorithm is  $O(n)$
- If the number of data locations  $n$  is very large, this **high-dimensional** MCMC can converge slowly
- Although each iteration for the NNGP model will be very fast, **many more MCMC iterations** may be required

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## Collapsed NNGP

## Collapsed NNGP

- Same model:

$$y(\mathbf{s}) = \mathbf{x}(\mathbf{s})^\top \boldsymbol{\beta} + w(\mathbf{s}) + \epsilon(\mathbf{s})$$

$$w(\mathbf{s}) \sim NNGP(0, K(\cdot, \cdot | \theta))$$

$$\epsilon(\mathbf{s}) \stackrel{iid}{\sim} N(0, \tau^2)$$

- **Latent** model:  $\mathbf{y} \sim N(\mathbf{X}\boldsymbol{\beta} + \mathbf{w}, \tau^2 \mathbf{I})$ ;  $\mathbf{w} \sim N(\mathbf{0}, \tilde{\mathbf{K}}_\theta)$

- **Collapsed** model: Marginalizing out  $\mathbf{w}$ ,  $\mathbf{y} \sim N(\mathbf{X}\boldsymbol{\beta}, \tau^2 \mathbf{I} + \tilde{\mathbf{K}}_\theta)$

$$\mathbf{y} \sim N(\mathbf{X}\boldsymbol{\beta}, \tau^2 \mathbf{I} + \tilde{\mathbf{K}}_\theta)$$

- Only involves few parameters  $\boldsymbol{\beta}$ ,  $\tau^2$  and  $\theta = (\sigma^2, \phi)$
- Drastically **reduces** the MCMC dimensionality
- Gibbs sampler updates are based on sparse linear systems using  $\tilde{\mathbf{K}}_\theta^{-1}$  (e.g., use CHOLMOD)
- **Improved** MCMC convergence
- Can **recover** posterior distribution of  $\mathbf{w} | \mathbf{y}$
- Complexity of the algorithm depends on the design of the data locations and is **not guaranteed to be  $O(n)$**

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## Response NNGP

- $w(\mathbf{s}) \sim GP(0, K(\cdot, \cdot | \theta)) \Rightarrow y(\mathbf{s}) \sim GP(\mathbf{x}(s)^\top \beta, \Sigma(\cdot, \cdot | \tau^2, \theta))$
- $\Sigma(\mathbf{s}_i, \mathbf{s}_j) = K(\mathbf{s}_i, \mathbf{s}_j | \theta) + \tau^2 \delta(\mathbf{s}_i = \mathbf{s}_j)$  ( $\delta$  is Kronecker delta)
- We can directly derive the NNGP covariance function corresponding to  $\Sigma(\cdot, \cdot)$
- $\tilde{\Sigma}$  is the NNGP covariance matrix for the  $n$  locations
- Response model:**  $\mathbf{y} \sim N(\mathbf{X}\beta, \tilde{\Sigma})$
- Storage and computations are guaranteed to be  $O(n)$
- Low dimensional MCMC  $\Rightarrow$  Improved convergence
- Cannot** coherently recover  $\mathbf{w} | \mathbf{y}$

## Conjugate NNGP

- Full GP model:  $\mathbf{y} \sim N(\mathbf{X}\beta, \Sigma)$  where  $\Sigma = \sigma^2 \mathbf{M}$
- $\mathbf{M} = \mathbf{R}(\phi) + \alpha \mathbf{I}$
- $\alpha = \tau^2 / \sigma^2$  is the ratio of the **noise to signal variance**
- Response NNGP model:  $\mathbf{y} \sim N(\mathbf{X}\beta, \tilde{\Sigma})$
- $\tilde{\Sigma} = \sigma^2 \tilde{\mathbf{M}}$  where  $\tilde{\mathbf{M}}$  is the NNGP approximation for  $\mathbf{M}$

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## Conjugate NNGP

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- $\mathbf{M} = \mathbf{R}(\phi) + \alpha \mathbf{I}$
- $\alpha = \tau^2 / \sigma^2$  is the ratio of the **noise to signal variance**
- Response NNGP model:  $\mathbf{y} \sim N(\mathbf{X}\beta, \tilde{\Sigma})$
- $\tilde{\Sigma} = \sigma^2 \tilde{\mathbf{M}}$  where  $\tilde{\mathbf{M}}$  is the NNGP approximation for  $\mathbf{M}$
- If  $\phi$  and  $\alpha$  are known,  $\mathbf{M}$ , and hence  $\tilde{\mathbf{M}}$ , are known matrices
- The model becomes a standard Bayesian linear model
- Assume a **Normal Inverse Gamma (NIG)** prior for  $(\beta, \sigma^2)^\top$
- $(\beta, \sigma^2)^\top \sim NIG(\mu_\beta, \mathbf{V}_\beta, a_\sigma, b_\sigma)$ , i.e.,  $\beta | \sigma^2 \sim N(\mu_\beta, \sigma^2 \mathbf{V}_\beta)$  and  $\sigma^2 \sim IG(a_\sigma, b_\sigma)$
- Exact posterior distributions** of  $\beta$  and  $\sigma^2$  are available

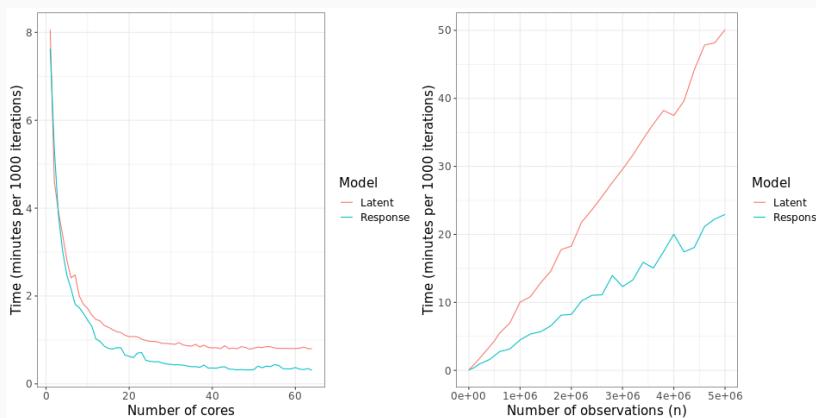
## Comparison of NNGP models

	Latent	Collapsed	Response	Conjugate
$O(n)$ time	Yes	No	Yes	Yes
Recovery of $\mathbf{w}   \mathbf{y}$	Yes	Yes	No	Yes
Parameter dimensionality	High	Low	Low	Low
Inference on $\theta$	Yes	Yes	Yes	Partially

Can handle  $n$  in the 100s of millions!

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**Figure:** (a) Runtime for 1000 MCMC iterations for  $n = 100000$  and different number of cores. (b) Runtime for 1000 MCMC iterations using 40 cores and  $n$  from 1000 to 5 million. Model type (latent and response) refers to different NNGP parameterizations, see Finley et al. 2022.

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- **Sparsity** inducing Gaussian process
- Constructed from sparse Cholesky factors based on  $m$  nearest neighbors
- **Scalability** in storage, inverse, and determinant of NNGP covariance matrix are all  $O(n)$
- **Proper Gaussian process**, allows for inference using hierarchical spatial models and predictions at arbitrary spatial resolution
- Closely approximates full GP inference, does not oversmooth like low rank models
- Extension to **multivariate NNGP**
- Collapsed and response NNGP models with improved MCMC convergence
- R packages `spNNGP` (Finley et al. 2022) and `spOccupancy` (Doser et al., 2022) on CRAN

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## Some notes on efficient computing and high performance computing environments

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May 15, 2023

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## Code implementation

Very useful libraries for efficient matrix computation:

1. Fortran BLAS (Basic Linear Algebra Subprograms, see Blackford et al. 2001). Started in late 70s at NASA JPL by Charles L. Lawson. See <http://www.netlib.orgblas>.
2. Fortran LAPACK (Linear Algebra Package, see Anderson et al. 1999). Started in mid 80s at Argonne and Oak Ridge National Laboratories. See <http://www.netlib.orglapack>.

Modern math software has a heavy reliance on these libraries, e.g., Matlab and *R*. Routines are also accessible via C, C++, Python, etc.

Many improvements on the standard BLAS and LAPACK functions, see, e.g.,

- Intel Math Kernel Library (MKL)
- AMD Core Math Library (ACML)
- Automatically Tuned Linear Algebra Software (ATLAS)
- Matrix Algebra on GPU and Multicore Architecture (MAGMA)
- OpenBLAS <http://www.openblas.net>
- vecLib (for Mac users only)

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Key BLAS and LAPACK functions used in our setting.

Function	Description
dpotrf	LAPACK routine to compute the Cholesky factorization of a real symmetric positive definite matrix.
dtrsv	Level 2 BLAS routine to solve the systems of equations $\mathbf{Ax} = \mathbf{b}$ , where $\mathbf{x}$ and $\mathbf{b}$ are vectors and $\mathbf{A}$ is a triangular matrix.
dtrsm	Level 3 BLAS routine to solve the matrix equations $\mathbf{AX} = \mathbf{B}$ , where $\mathbf{X}$ and $\mathbf{B}$ are matrices and $\mathbf{A}$ is a triangular matrix.
dgemv	Level 2 BLAS matrix-vector multiplication.
dgemm	Level 3 BLAS matrix-matrix multiplication.

## Computing environments

Consider different environments:

1. A **distributed system** consists of multiple autonomous computers (nodes) that communicate through a network. A computer program that runs in a distributed system is called a distributed program. Message Passing Interface (MPI) is a specification for an Application Programming Interface (API) that allows many computers to communicate.

Consider different environments:

1. A **distributed system** consists of multiple autonomous computers (nodes) that communicate through a network. A computer program that runs in a distributed system is called a distributed program. Message Passing Interface (MPI) is a specification for an Application Programming Interface (API) that allows many computers to communicate.
2. A **shared memory multiprocessing system** consists of a single computer with memory that may be simultaneously accessed by one or more programs running on multiple Central Processing Units (CPUs). OpenMP (Open Multi-Processing) is an API that supports shared memory multiprocessing programming.
3. A **heterogeneous system** uses more than one kind of processor, e.g., CPU & (Graphics Processing Unit) GPU or CPU & Intel's Xeon Phi Many Integrated Core (MIC).
  - My lab currently favors **shared memory multiprocessing** and **heterogeneous** systems.
  - Newest unit is a Dell Poweredge with 384 GB of RAM, 2 threaded 10-core Xeon CPUs, and 2 Intel Xeon Phi Coprocessor with 61-cores (244 threads) running a Linux operating systems.
  - Software includes OpenMP coupled with Intel MKL. MKL is a library of highly optimized, extensively threaded math routines designed for Xeon CPUs and Phi coprocessors (e.g., BLAS, LAPACK, ScaLAPACK, Sparse Solvers, Fast Fourier Transforms, and vector RNGs).

Which environments are right for large  $n$  settings?

- MCMC necessitates iterative evaluation of the likelihood which requires operations on large matrices.
- A specific hurdle is **factorization** to computing determinant and inverse of large dense covariance matrices.
- We try to model our way out and use computing tools to overcome the complexity (e.g., covariance tapering, Kaufman et al. 2008; low-rank methods, Cressie and Johannesson 2008; Banerjee et al. 2008, etc.).
- Due to **slow network communication** and transport of submatrices among nodes distributed systems are not ideal for these types of iterative large matrix operations.

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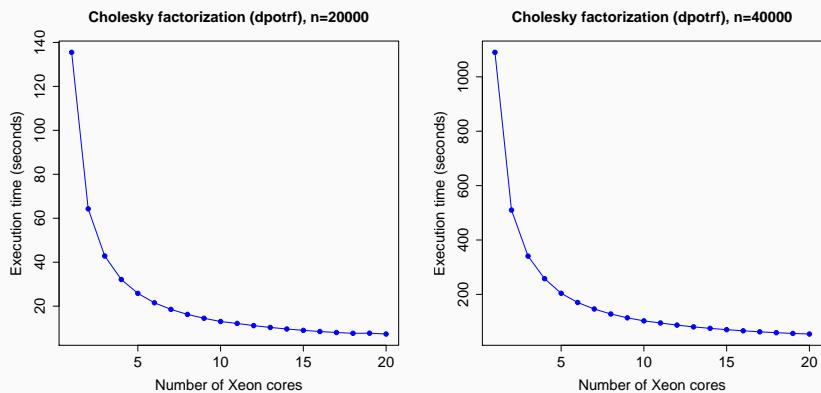
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So what kind of speed up to expect from threaded BLAS and LAPACK libraries.



The BLAS and LAPACK that “ships” with R is single-threaded, but these can be replaced with multi-threaded libraries.

### Windows

- Microsoft R Open: The Enhanced R Distribution  
<https://mran.microsoft.com/open> comes with MLK  
<https://software.intel.com/en-us/mkl>.
- Replace existing R's `libRblas.so` with OpenBLAS library `libopenblas.so`. OpenBLAS is available here  
<http://www.openblas.net>.

### Mac OS X

- Mac vecLib obtained via XCode. Use install notes [here](#).

### Linux/Unix

- MKL, OpenBLAS, ACML (compile R against MLK or post compile symbolic link of `libRblas.so` to `libopenblas.so`).
- Some additional gains using Intel icc and ifort compilers.

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## Non-Gaussian spatial data

# Modeling non-Gaussian spatial data

Jeffrey Doser<sup>1</sup> & Andrew Finley<sup>2</sup>

May 15, 2023

<sup>1</sup>Department of Integrative Biology, Michigan State University.

<sup>2</sup>Department of Forestry, Michigan State University.

- Often data sets preclude Gaussian modeling:  $y(\mathbf{s})$  may not even be continuous
- Examples:
  - Binary: presence or absence of a species at location  $\mathbf{s}$ .
  - Count: abundance of a species at location  $\mathbf{s}$ .
  - Categorical: counts of trees by size class at location  $\mathbf{s}$ .
- Replace Gaussian likelihood by exponential family member (Diggle, Tawn, and Moyeed (1998)).

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- **First stage:**  $y(\mathbf{s}_i)$  are conditionally independent given  $\beta$  and  $w(\mathbf{s}_i)$ . Here we use a canonical link function, say  $g(E[y(\mathbf{s}_i)]) = \eta(\mathbf{s}_i) = \mathbf{x}(\mathbf{s}_i)^\top \beta + w(\mathbf{s}_i)$ .

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- **Second stage:** Model  $w(\mathbf{s}_i)$  as a Gaussian process:

$$\mathbf{w} \sim N(\mathbf{0}, \sigma^2 \mathbf{R}(\phi))$$

- Additional GLMM flexibility comes at a computational cost: lose conjugacy of  $\beta, \mathbf{w}$
- Requires more Metropolis steps. Particularly costly for  $\mathbf{w}$
- Practical consequence: slower, less efficient algorithms
- Prediction and interpolation proceed as with the Gaussian case

- **Third stage:** Priors and hyperpriors.

- General approach for Bayesian (spatial) logistic regression that yields conjugate updates of  $\beta$  (and  $\mathbf{w}$ )

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- Introduce augmented data  $\omega(\mathbf{s}_i)$  for each  $i = 1, \dots, n$ , where  $\omega(\mathbf{s}_i) \sim \text{PG}(N(\mathbf{s}_i), 0)$ , with  $N(\mathbf{s}_i)$  the Binomial weights

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- Define  $\kappa(\mathbf{s}_i) = y(\mathbf{s}_i) - N(\mathbf{s}_i)/2$
- Resulting Gibbs sampler is remarkably similar to that of a Gaussian model with response  $y(\mathbf{s}_i)^* = \kappa(\mathbf{s}_i)/\omega(\mathbf{s}_i)$  and heteroskedastic variances  $\tau^2(\mathbf{s}_i) = 1/\omega(\mathbf{s}_i)$ .

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## Pólya-Gamma data augmentation

- Suppose  $y(\mathbf{s}_i) \sim \text{Bernoulli}(\psi(\mathbf{s}_i))$ .

$$\begin{aligned}\psi(\mathbf{s}_i)^{y(\mathbf{s}_i)}(1 - \psi(\mathbf{s}_i))^{1-y(\mathbf{s}_i)} &= \frac{\exp(\mathbf{x}(\mathbf{s}_i)^\top \boldsymbol{\beta} + \mathbf{w}(\mathbf{s}_i))^{y(\mathbf{s}_i)}}{1 + \exp(\mathbf{x}(\mathbf{s}_i)^\top \boldsymbol{\beta} + \mathbf{w}(\mathbf{s}_i))} \\ &= \exp(\kappa(\mathbf{s}_i)(\mathbf{x}(\mathbf{s}_i)^\top \boldsymbol{\beta} + \mathbf{w}(\mathbf{s}_i))) \times \\ &\quad \int \exp\left(-\frac{\omega(\mathbf{s}_i)}{2}(\mathbf{x}(\mathbf{s}_i)^\top \boldsymbol{\beta} + \mathbf{w}(\mathbf{s}_i))^2\right) \times \\ &\quad p(\omega(\mathbf{s}_i) | 1, 0) d\omega(\mathbf{s}_i),\end{aligned}$$

- $p(\omega(\mathbf{s}_i) | 1, 0)$  is the Pólya-Gamma PDF with parameters 1 and 0
- With Gaussian priors on  $\boldsymbol{\beta}$  and IG prior on  $\sigma^2$ , full conditionals for  $\boldsymbol{\beta}$ ,  $\sigma^2$ , and  $\mathbf{w}$  are available in closed form.  $\phi$  updated with MH.
- See Polson, Scott, Windle (2013) JASA

## Example: Binary spatial regression

- Objective: predict the distribution of Loggerhead Shrike across the US

$$\begin{aligned}y(\mathbf{s}_i) &\sim \text{Bernoulli}(\psi(\mathbf{s}_i)) \\ \text{logit}(\psi(\mathbf{s}_i)) &= \mathbf{x}(\mathbf{s}_i)^\top \boldsymbol{\beta} + \mathbf{w}(\mathbf{s}_i) \\ \mathbf{w} &\sim N(\mathbf{0}, \sigma^2 \mathbf{R}(\phi)) \\ \boldsymbol{\beta} &\sim N(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}_\beta) \\ \sigma^2 &\sim IG(a_\sigma, b_\sigma) \\ \phi &\sim \text{Uniform}(l, u) \\ \omega(\mathbf{s}_i) &\sim PG(1, 0)\end{aligned}$$

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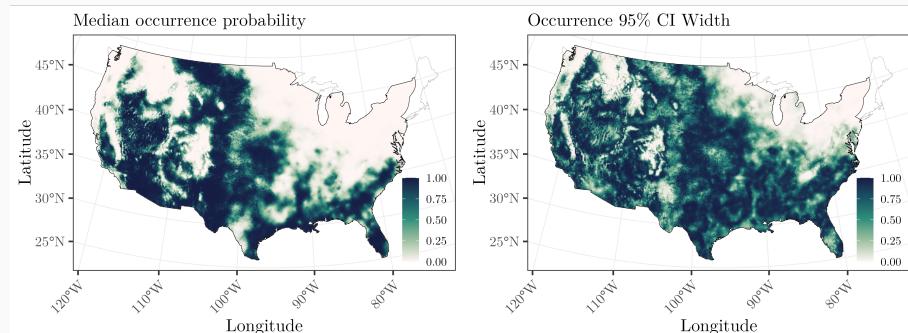
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## Example: Binary spatial regression

Posterior predictive inference proceeds as with the Gaussian case

## Some practical considerations

- Priors for  $\sigma^2$  and  $\phi$  may need to be more informative, particularly for binary data.



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- Priors for  $\sigma^2$  and  $\phi$  may need to be more informative, particularly for binary data.
- Be careful with non-identity link functions when thinking about priors.
- Pólya-Gamma data augmentation works really for binomial data. Computational cost increases as Binomial weights increases.
- Pólya-Gamma data augmentation also applicable for Negative Binomial count data, but slow for large counts and can be unstable.

- **spBayes**
  - Univariate and multivariate, full GPs or predictive processes
  - Gaussian, Binomial (no Pólya-Gamma data augmentation), Poisson
- **spNNGP**
  - Univariate, NNGPs
  - Gaussian, Binomial
- **spOccupancy**
  - Univariate and multivariate, focus on modeling wildlife distributions, full GPs or NNGPs
  - Bernoulli
- **spAbundance**  
[\(https://github.com/doserjef/spAbundance\)](https://github.com/doserjef/spAbundance)
  - Univariate and multivariate, focus on modeling wildlife/plant abundance, NNGPs
  - Gaussian, Poisson, Negative Binomial

# Spatial Factor Models for Multivariate Spatial Data

---

Jeffrey Doser<sup>1</sup> & Andrew Finley<sup>2</sup>

May 15, 2023

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<sup>2</sup>Department of Forestry, Michigan State University.

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  - **Atmospheric modeling:** at a given site we observe surface temperature, precipitation and wind speed
- We anticipate dependence between measurements
  - at a particular location
  - across locations

## Multivariate spatial generalized linear model

- Spatial generalized linear model for  $h$ -variate spatial data for  $j = 1, 2, \dots, h$  and  $i = 1, \dots, n$ :

$$y_j(\mathbf{s}_i) \sim f(\mu_j(\mathbf{s}_i), \tau_j)$$
$$\mu_j(\mathbf{s}_i) = g^{-1}(\eta_j(\mathbf{s}_i)) = \mathbf{x}(\mathbf{s}_i)^\top \boldsymbol{\beta}_j + \mathbf{w}_j^*(\mathbf{s}_i)$$

- We can imagine modeling  $\mathbf{w}^*(\mathbf{s}_i) = (w_1^*(\mathbf{s}_i), w_2^*(\mathbf{s}_i), \dots, w_h^*(\mathbf{s}_i))'$  as an  $h$ -variate Gaussian process

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- Could model using Multivariate NNGP as discussed previously with SVCs, works well when  $h < 5$ .
- But what about when  $h$  is large (e.g., 10, 100)?

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## Spatial Factor Model

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- Approximates the dependence between multivariate (spatially-dependent) outcomes through a linear combination of a (much) lower-dimensional set of spatial factors

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- We represent the  $h \times 1$  vector  $\mathbf{w}^*(\mathbf{s}_i)$  as a linear combination of latent spatial factors and factor loadings:

$$\mathbf{w}^*(\mathbf{s}_i) = \boldsymbol{\Lambda} \mathbf{w}(\mathbf{s}_i)$$

- $\boldsymbol{\Lambda}$  is an  $h \times q$  loadings matrix (tall and skinny) and  $\mathbf{w}(\mathbf{s}_i)$  is a  $q \times 1$  vector of realizations from  $q$  independent spatial GPs

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- In traditional factor analysis,  $\mathbf{w}(\mathbf{s}_i)$  are realizations from independent standard normal random variables.

- Choosing  $q \ll h$  leads to substantial computational reductions.
- Simple to code: just sample from  $q$  independent GPs as with basic univariate models.
- Yields a non-separable multivariate cross-covariance function between location  $\mathbf{s}_i$  and  $\mathbf{s}_{i'}$ :  

$$\text{cov}(\mathbf{w}^*(\mathbf{s}_i), \mathbf{w}^*(\mathbf{s}_{i'})) = \sum_{k=1}^q \rho_k(\mathbf{s}_i, \mathbf{s}_{i'}, \phi_k) \boldsymbol{\lambda}_k \boldsymbol{\lambda}_k^\top$$
- Can simply replace the  $q$  full GPs with their corresponding NNGPs to yield a spatial factor NNGP model
- Identifiability constraints on  $\boldsymbol{\Lambda}$ : fix upper triangle to 0 and diagonal to 1. See Ren and Banerjee (2013) *Biometrics*

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- Standard normal priors for the lower triangle of  $\boldsymbol{\Lambda}$
- We like to model response-specific regression coefficients  $\beta_j$  hierarchically. For each  $r = 1, \dots, p$  covariate, we model  $\beta_{j,r}$  following

$$\beta_{j,r} \sim N(\mu_{\beta_r}, \tau_{\beta_r}^2)$$

- Gaussian hyperpriors for  $\mu_{\beta_r}$  and IG or half-Cauchy priors for  $\tau_{\beta_r}^2$
- Independent uniform priors for spatial decay parameters  $\phi$

- Full conditionals are in closed form for all parameters except  $\phi$  for Gaussian and Binomial responses.
- Update  $\phi$  with an Adaptive Metropolis-within-Gibbs algorithm (Roberts and Rosenthal 2009)
- See Taylor-Rodriguez et al. 2019 for Gaussian sampler, spOccupancy website for Pólya-Gamma sampler

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- Simple to code (don't need to deal with cross-covariance matrices).
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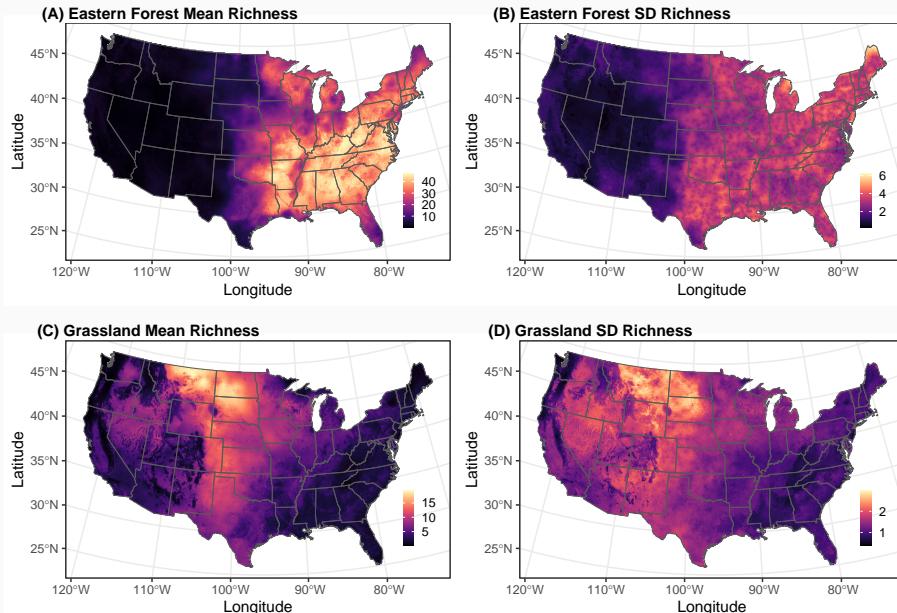
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- Simple to code (don't need to deal with cross-covariance matrices).
- Relatively fast and efficient (well, at least for Gaussian and Binomial).
- Factors and factor loadings can be used for model-based ordination.
- Straightforward extensions to spatially-varying coefficient models.

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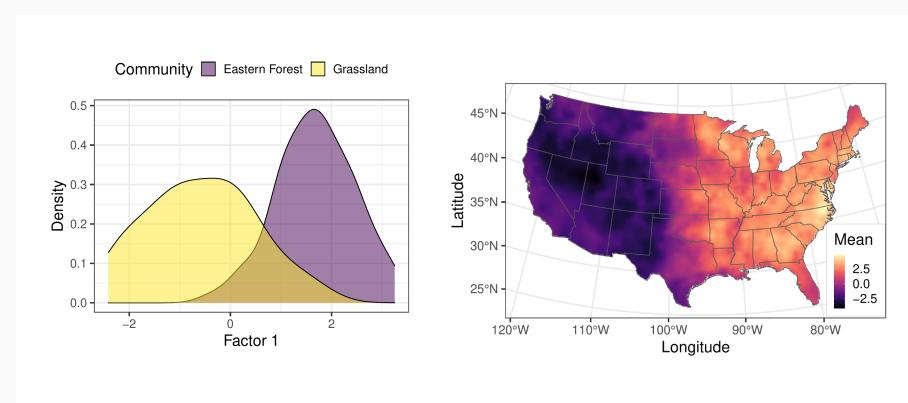
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## Example: bird communities across the continental US



## Example: bird communities across the continental US

Visualization of the first spatial factor and corresponding factor loadings



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## Some downsides to spatial factor models

- Convergence assessment is not always straightforward
- Sensitivity to initial values
- Order of the first  $q$  responses has important implications for convergence and mixing.
- Assume a multivariate stochastic process can be represented as a linear combination of independent univariate processes

## Software

- `spOccupancy`: spatial NNGP and non-spatial factor models for binary data
- `spAbundance`: Gaussian, Poisson, and NB spatial NNGP and non-spatial factor models.
- `boreal`: many distributions for non-spatial and spatial factor models (Hui 2015 *MEE*; spatial use full GPs fit in JAGS)
- `Hmsc`: spatial models using NNGPs (Tikhonov et al. 2019; *MEE*)
- `spBFA`: a variety of spatial models with some nifty priors (Berchuck et al. 2022 *Bayesian Analysis*)

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# Application of Spatially-Varying Coefficient Models

Modeling the distribution of 10 tree species across Vermont

Jeffrey Doser<sup>1</sup> & Andrew Finley<sup>2</sup>

May 15, 2023

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<sup>2</sup>Department of Forestry, Michigan State University.

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## Spatially-Varying Coefficient Models

## SVC GLMMs

- Extension of spatial regression approaches that allow regression coefficients to vary across space, and not just the intercept
- SVC models are random slopes models, with spatial structure given to the random slopes

$$y(\mathbf{s}_i) \sim f(\mu(\mathbf{s}_i), \tau)$$

$$\mu(\mathbf{s}_i) = g^{-1}(\eta(\mathbf{s}_i)) = \mathbf{x}(\mathbf{s}_i)^\top \tilde{\beta}(\mathbf{s}_i)$$

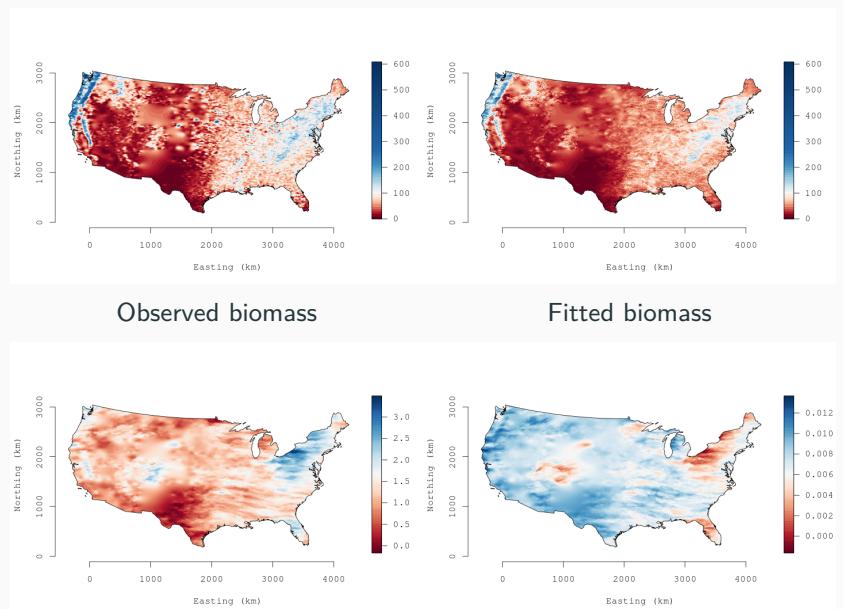
$$\tilde{\beta}_r(\mathbf{s}_i) = \beta_r + w_r(\mathbf{s}_i) \text{ for each } r = 1, \dots, p$$

- We can model  $w(\mathbf{s}_i)$  using a GP, predictive process, or **NNGP**
- We can envision modeling  $w(\mathbf{s}_i)$  in two ways:
  1. Multivariate NNGP (see previous forest biomass example)
  2. **Independent NNGPs**
- Here we focus on the latter
- Pros and cons to both approaches, similar to correlations between random slopes and intercepts in mixed models

## Potential benefits of SVC models

- Improved predictive performance
- Tremendous flexibility to accommodate spatial variability in effects
- Hypothesis testing and generation
- Accommodate highly non-linear relationships
- Model spatial variability in trends over time

## Improved predictive performance

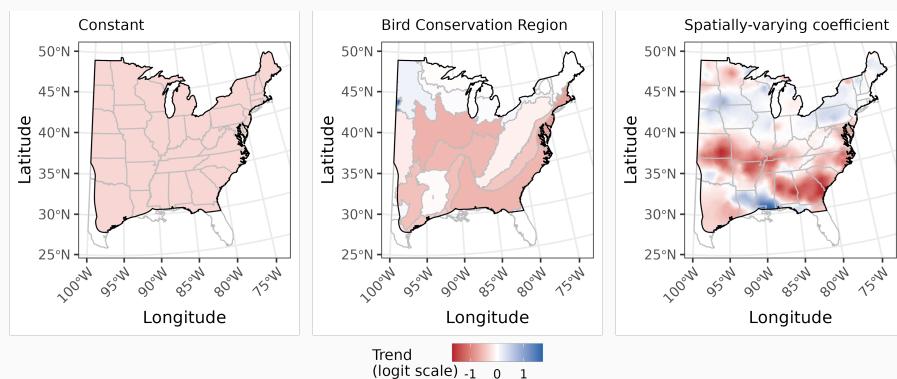


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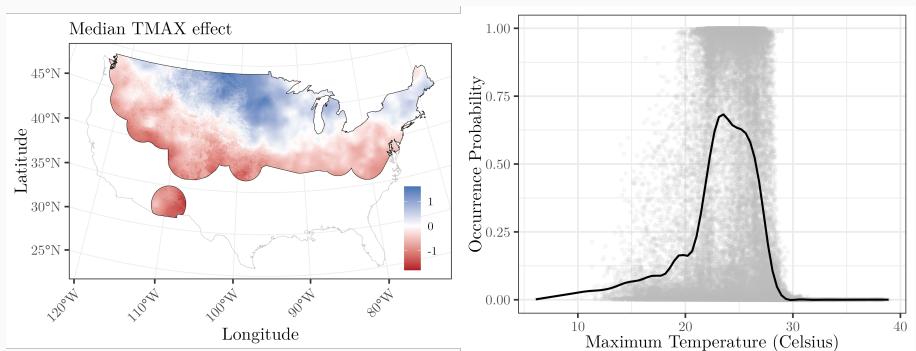
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## More flexibility to accommodate spatial variability in effects

Gray Catbird occurrence trend across the eastern US from 2000-2019



## Example: Effect of max temperature on Bobolink occurrence

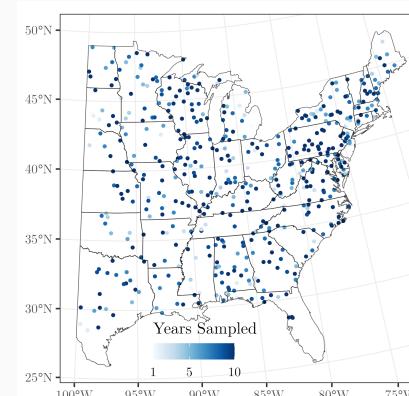


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- spBayes: univariate Gaussian SVC with full GPs
- spOccupancy: univariate Binomial SVC with NNGPs (multivariate on its way)
- varycoef: maximum likelihood Gaussian SVCs (Dambon et al. 2021 *Spatial Stats.*)
- sdmTMB: penalized likelihood and Bayesian SVC GLMMs (Anderson et al. 2022 *bioRxiv*)

- Data come from USGS North American Breeding Bird Survey
- We desire to account for observational biases in detection of the birds (i.e., false negatives).
- Add on an additional observational layer to our hierarchical model



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## Exercise: Process model

- Let  $z_t(\mathbf{s}_i)$  denote the true presence (1) or absence (0) of the species at site  $i = 1, \dots, 500$  during year  $t = 1, \dots, 10$ .

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- If the bird was detected at a site and year, we know  $z_t(\mathbf{s}_i) = 1$ . If not, it might be there and we just missed it during the surveys.
- We model  $z_t(\mathbf{s}_i)$  just as before with a Bernoulli GLM, with a SVC for trend

$$z_t(\mathbf{s}_i) \sim \text{Bernoulli}(\psi_t(\mathbf{s}_i))$$

$$\text{logit}(\psi_t(\mathbf{s}_i)) = \tilde{\beta}_0(\mathbf{s}_i) + \tilde{\beta}_1(\mathbf{s}_i) \cdot \text{YEAR}_t$$

- $\tilde{\beta}_0(\mathbf{s}_i)$  and  $\tilde{\beta}_1(\mathbf{s}_i)$  are modeled as independent SVCs with NNGPs

## Exercise: Observation model

- Let  $y_{t,k}(\mathbf{s}_i)$  denote the observed detection (1) or nondetection (0) of the bird at site  $i$  during year  $t$  and survey  $k = 1, \dots, 5$ .
- We model  $y_{t,k}(\mathbf{s}_i)$  conditional on the true presence/absence of the species  $z_t(\mathbf{s}_i)$

$$y_{t,k}(\mathbf{s}_i) \mid z_t(\mathbf{s}_i) \sim \text{Bernoulli}(p_{i,t,k} \cdot z_t(\mathbf{s}_i))$$

$$\text{logit}(p_{i,t,k}) = \alpha_{0,t} + \alpha_1 \cdot \text{DAY}_{i,t,k} + \alpha_2 \cdot \text{DAY}_{i,t,k}^2$$

- A key assumption for identifiability is that  $z_t(\mathbf{s}_i)$  does not change across the 5 replicate surveys at site  $i$  during year  $t$ .