# Geostatistical models – Part II

**Applied Spatial Statistics** 

# Spatial linear models

Part I introduced the standard model

$$Y_i = \mu_i + Z_i + \varepsilon_i$$

The mean is the same as linear regression

$$\mu_i = \beta_0 + X_{i1}\beta_1 + \dots + X_{ip}\beta_p$$

- There are two error terms:
  - ► *Z<sub>i</sub>* is spatially-correlated
  - $\varepsilon_i$  are independent across *i*

In Part II we will discuss models for  $Z_i$ 

# Spatial covariance models

- The Z<sub>i</sub> capture spatial correlation not explained by the covariates
- Assume they are Gaussian with mean zero and variance  $\sigma^2$
- Define covariance function as

$$\operatorname{Cov}(Z_i, Z_j) = C(\mathbf{s}_i, \mathbf{s}_j) = \sigma^2 \rho(\mathbf{s}_i, \mathbf{s}_j)$$

- The spatial correlation function ρ is large when s<sub>i</sub> and s<sub>j</sub> are close and small when they are far apart
- In the extreme, assume that ρ(s, s) = 1 so that Z is a continuous function of s

# Spatial covariance models

Common sources of spatial variation:

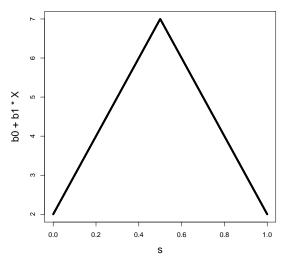
- Missing covariates that have spatial patterns
- Shared exposure to a common point sources (power plant)
- Share exposure to meteorological events
- Dispersion (e.g., pests, air, water)
- Measurement error, e.g., blurred satellite images

0.5 0.4 0.3  $\times$ 0.2 0.1 0.0 0.2 0.4 0.6 0.8 1.0 0.0 s

X = distance from edge

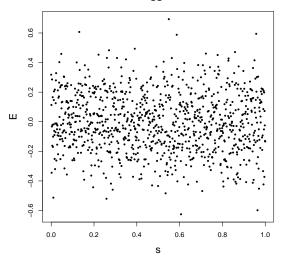
Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

b0+b1\*X = mean trend



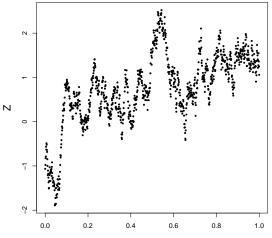
Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

E = nugget term



Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

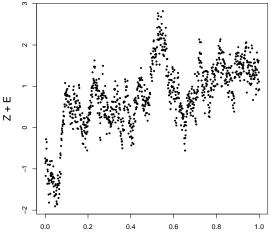
Z = spatial term



s

Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

Z+E = residuals term

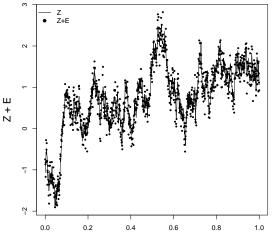


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Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

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Z+E = residuals term

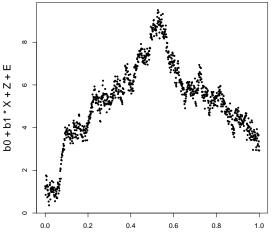


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Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

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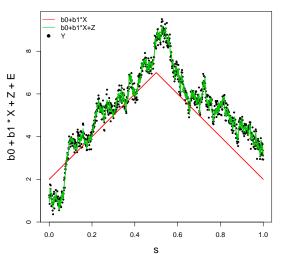
Y = observed data



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Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

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Y = observed data

Model:  $Y_i = \beta_0 + \beta_1 X_i + Z_i + E_i$ 

# Spatial covariance models

Which factors might contribute each type of variation in the air pollution example?

Mean trend:

Spatial error:

Nugget error:

# Spatial covariance models - isotropy

- The spatial correlation term ρ(s<sub>i</sub>, s<sub>j</sub>) is the novel term in a spatial analysis
- As illustrated from the plots above, it is challenging to estimate
- For example, how would you estimate  $\rho(0.2, 0.3)$ ?
- We will make several simplifying assumptions (isotropic, stationary, etc)
- We will then propose models for the correlation function that satisfy these assumptions

# Spatial covariance models - isotropy

- The simplest assumption is isotropy
- A covariance is isotropic if it depends only on the distance between locations
- Denoting the distance between  $\mathbf{s}_i$  and  $\mathbf{s}_j$  as  $d_{ij}$ , then

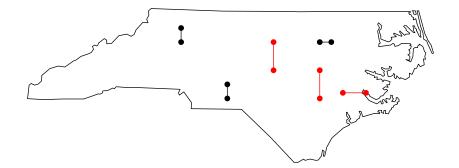
$$\operatorname{Cor}(Z_i, Z_j) = \rho(\mathbf{s}_i, \mathbf{s}_j) = \rho(d_{ij})$$

For example, the exponential correlation model is

$$\rho(d) = \exp(-d/\phi)$$

where  $\phi$  determines the range of correlation

# Spatial covariance models - isotropy



Pairs with the same color have the same correlation

### Spatial covariance models - stationary

- Stationarity is more general than isotropy
- A covariance is stationary if it depends only on the difference s<sub>i</sub> - s<sub>j</sub>

$$\operatorname{Cov}(Z_i, Z_j) = \rho(\mathbf{s}_i, \mathbf{s}_j) = \rho(\mathbf{s}_i - \mathbf{s}_j)$$

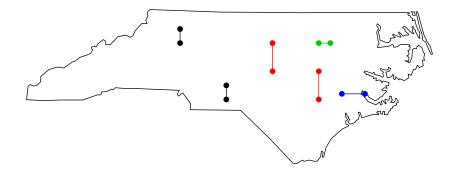
- Stationary means that the covariance is the same throughout the spatial domain
- For if two sites in the east have s<sub>1</sub> − s<sub>2</sub> = h and two sites in the west have s<sub>3</sub> − s<sub>4</sub> = h, then

$$\operatorname{Cor}(Z_1,Z_2)=\operatorname{Cor}(Z_3,Z_4)$$

# Spatial covariance models - anisotropy

- Stationary means that the covariance is the same throughout the spatial domain
- However, a stationary covariance can depend on both the distance between locations and the angle
- A covariance that is depends on the angle between location is called **anisotropic**
- For example, if the predominant wind pattern is east/west, then east/west pairs may have stronger correlation than north/south pairs

# Spatial covariance models - anisotropy



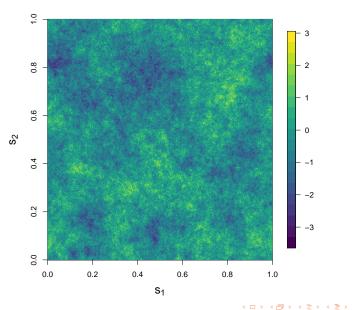
Pairs with the same color have the same correlation

# Spatial covariance models - nonstationary

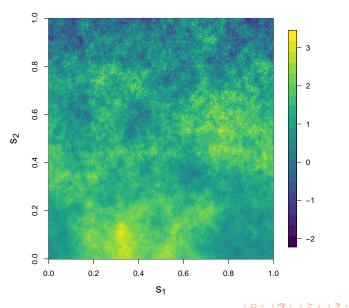
If the spatial covariance can change in different parts of the spatial domain, it is **nonstationary** 

- Stronger correlation in the east than the west
- Larger variance in the north than the south
- Stronger correlation between sites at the same elevation
- Larger variance in cities than rural areas

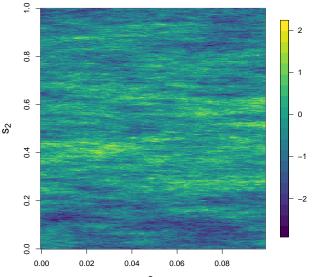
Nonstationary covariance are much harder to estimate



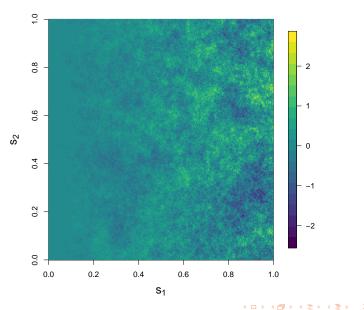
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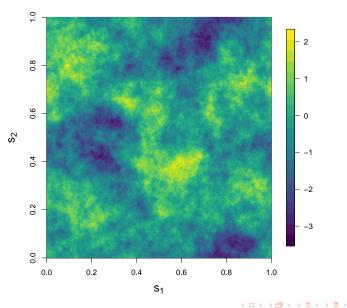
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Landsat data

Malaria data

Link to maps of the microbiome data