

# Spatial autocorrelation in ecological modelling

Workshop: Symposium for European Freshwater Sciences 2015

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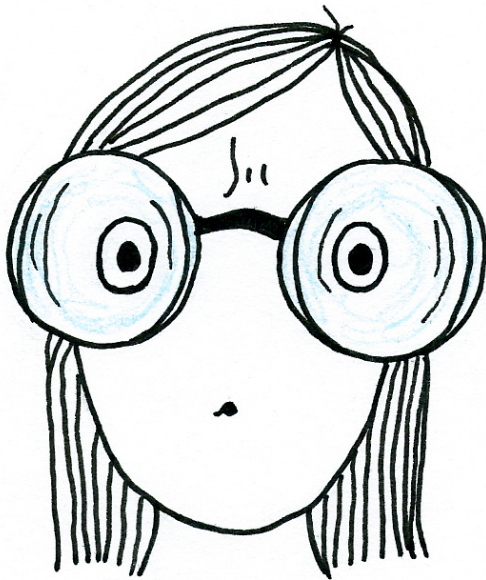
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# We need spatially explicit models. Why?



# Wear the GI glasses



# World is spatially autocorrelated

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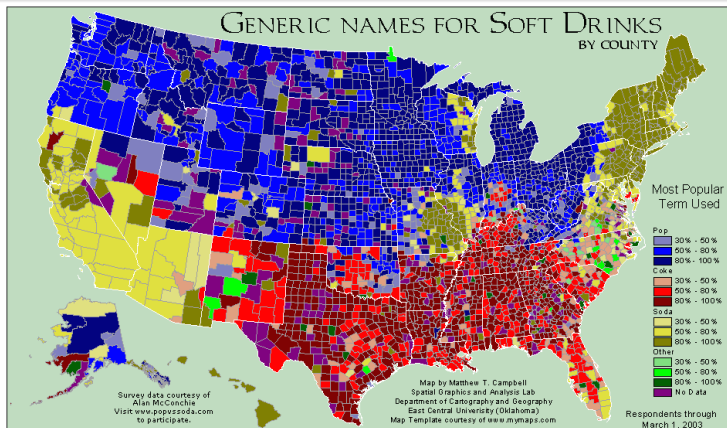
Tobler's first law of geography (Tobler, 1970. Eco.Geo)

“Everything is related to everything else, but near things are more related than distant things”

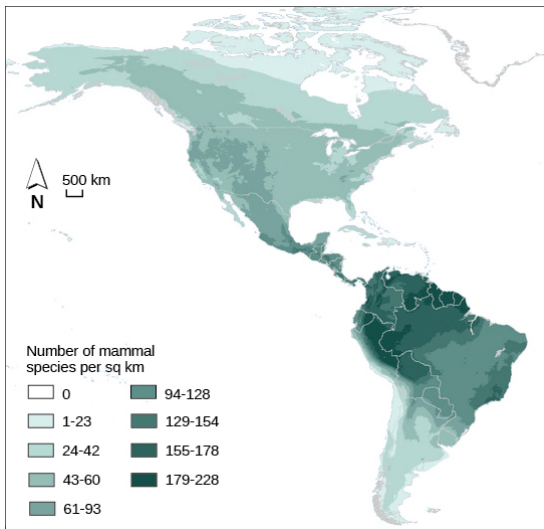
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(NASA, CIESIN, Columbia University, 2010)

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## Definition (Legendre, 1993. Ecology)

“...the property of random variables taking values, at pairs of locations a certain distance apart, that are more similar (positive autocorrelation) or less similar (negative autocorrelation) than expected for randomly associated pairs of observations”



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## Fact (Fortin and Dale, 2005. Spatial Analysis)

“natural systems almost always have autocorrelation in the form of patchiness or gradients...over a wide range of spatial and temporal scales”

# Two types of spatial autocorrelation

## 1 Endogenous

- caused by biotic processes, e.g. dispersal

## 2 Exogenous

- caused by functional dependence on spatially autocorrelated drivers, e.g. climate

- Spatial autocorrelation is a nuisance that complicates statistical hypothesis testing

# Relevance for ecological models

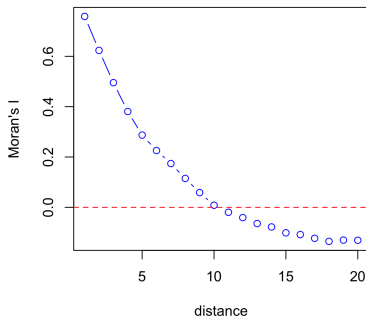
- Spatial autocorrelation is a nuisance that complicates statistical hypothesis testing
- Spatial autocorrelation is functionally important in many ecosystems, so we must revise our theories and models to incorporate spatial structure (Fortin and Dale, 2005. Spatial Analysis)

# Quantification and visualization of spatial autocorrelation

- **Morans I** , **Gearys c** correlation coefficients over multiple distances

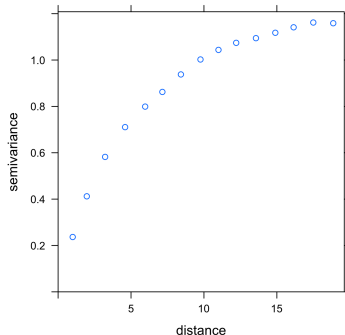
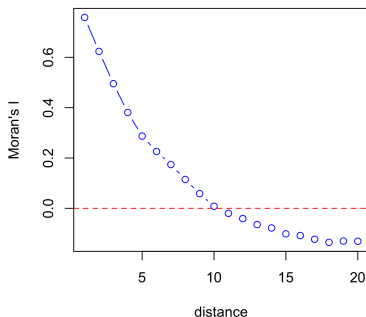
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- **Correlogram** plot distance on X-axis against correlation coefficient on Y-axis
  - **Mantel correlogram** for multivariate response
  - Observe distance decay!



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- **Semi-variogram** or **variogram**
  - Inverse correlogram!

# Introduce spatial autocorrelation structure to linear models

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- Incorporate a **variance-covariance matrix (C)** that is affected by a **proximity matrix (W)** of neighbor weights

$$y = X\beta + \epsilon$$

$$y = X\beta + \rho W(y - X\beta) + \epsilon$$

$$C = \sigma^2[(I - \rho W)^T(I - \rho W)]^{-1}$$

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- I will show you two models:  
**Generalized Least Squares (GLS) and Generalized Linear Mixed Models (GLMM)**

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## R package “nlme”

```
library(nlme)
?glms
?corClasses
```

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- Assumes non-normally distributed errors and **within-group errors may be spatially autocorrelated**
- Linear predictor is transformed by a **link function**
- Linear predictor may contain **random effects**

$$E[Y_{i,j}|\zeta_i] = g_{-1}(\eta_{i,j})$$

$$\eta_{i,j} = x_{i,j}\beta + z_{i,j}\zeta_i$$



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## R package “MASS” and “lme4”

```
library(MASS)
?glmmPQL
library(lme4)
?glmer()
```

# For more and on temporally autocorrelated data



Dormann et al. (2007)

Methods to account for spatial autocorrelation in the analysis of species distributional data: a review

*Ecography* 30, 609 – 628.

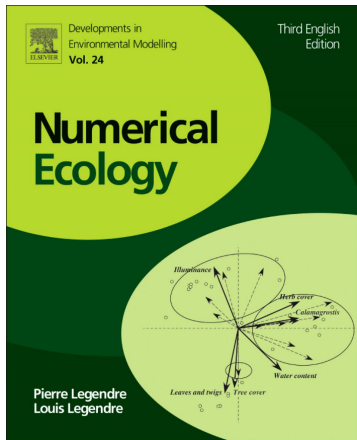
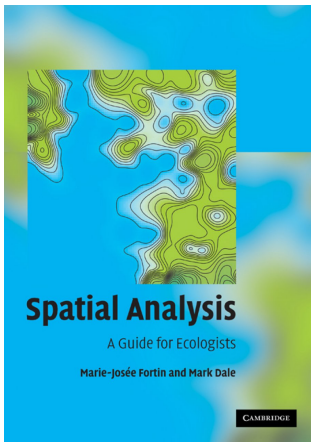
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<http://encyclopedia.thefreedictionary.com/Snouter>

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- We will use Snouter data from Dormann et al., 2007. Ecogra provided in the GItHub repo

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- We will use Snouter data from Dormann et al., 2007. Ecogra provided in the GItHub repo
- Questions
  - Do Snouter abundance and presence exhibit spatial autocorrelation?
  - What are the explained variances in Snouter abundance and presence by precipitation and distance to jungle?

# Let's do it together!

