

# Spatial Linear Models

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## Goal:

- Which connectivity model (IBD or IBR) better explains genetic diversity?
- Can the same pattern be explained by patch size as a proxy for population size?
- Do the same factors explain genetic diversity across the study area?

## Methodological Challenges:

### Video 1: Neighbourhood-level analysis

- Define connectivity hypotheses as distance matrices
- Neighborhood approach: connectivity index SI
- Explain genetic diversity by patch connectivity Si

### Video 2: Autocorrelation in linear models

- Generalized Least Squares regression (GLS)
- Spatial Regression with SAR
- Spatial Filtering with MEM
- Model selection (see also Week 12)
- Geographically-weighted Regression with SVC



Dianthus carthusianorum  
([www.schmetterlingswiesen.de](http://www.schmetterlingswiesen.de))

Refreshers: regression (Week 4), spatial statistics (Week 5), linear mixed models (Week 6)

# Dianthus Dataset

Rico et al. 2013, Molecular Ecology. See dataset video by Yessica Rico!

## Basic Dataset

Patches: 106  
Populations: 65  
Individuals: 1602  
Microsatellites: 11

Population size:  
 $< 4$ ,  $< 40$ ,  $< 100$ ,  $100+$

Patch size: ha

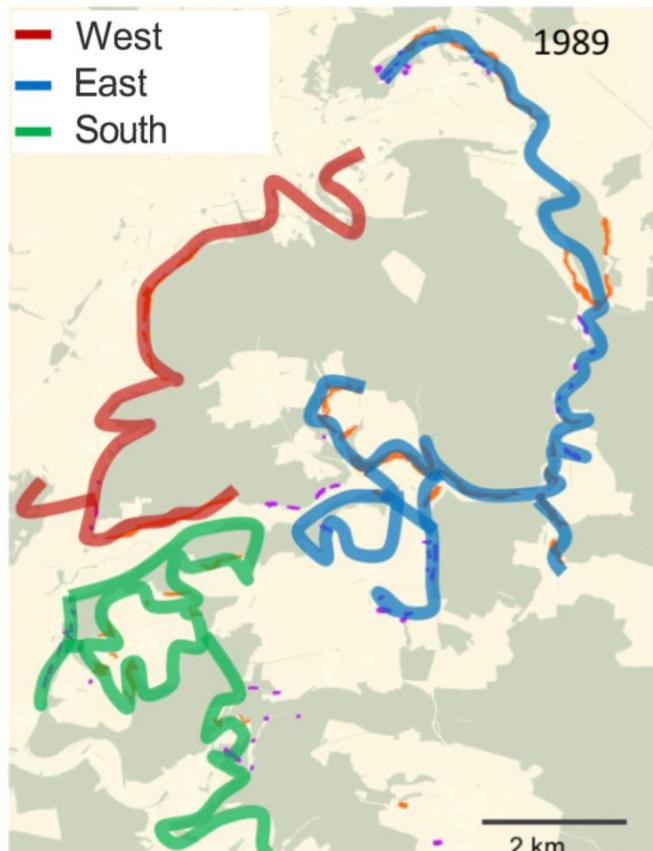
Grazing intensity:

- ungrazed
- intermittently
- consistently



[www.neuburg-schrobenhausen.de](http://www.neuburg-schrobenhausen.de)

## Connectivity by Shepherding



## Figures and map: Y. Rico

## Alternative Hypotheses

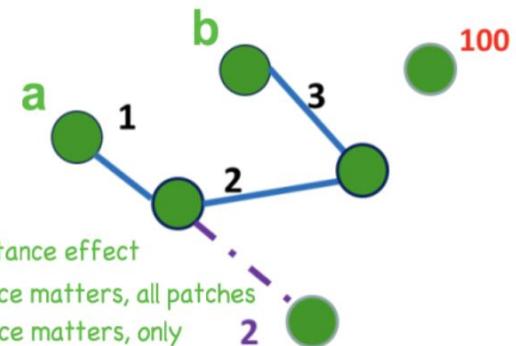
## Geographic distance (IBD)



## Forest as barrier (IBB)



## Connectivity by shepherding (IBR)



# Connectivity Index Si

See Week 7 Bonus Material

Connectivity Si  
of focal patch i

Sum over all neighbours j

$$Si = \sum_{j \neq i} \exp(-\alpha d_{ij}) p_j$$

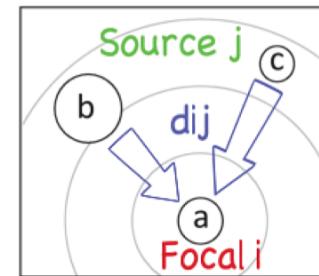
Source patch:  
 $p_j, A_j, N_j$

Connectivity model:  

- ecological distance  $d_{ij}$
- dispersal parameter alpha

$$Y \sim \sum_j X_j$$

C Neighborhood level



Wagner and Fortin 2013

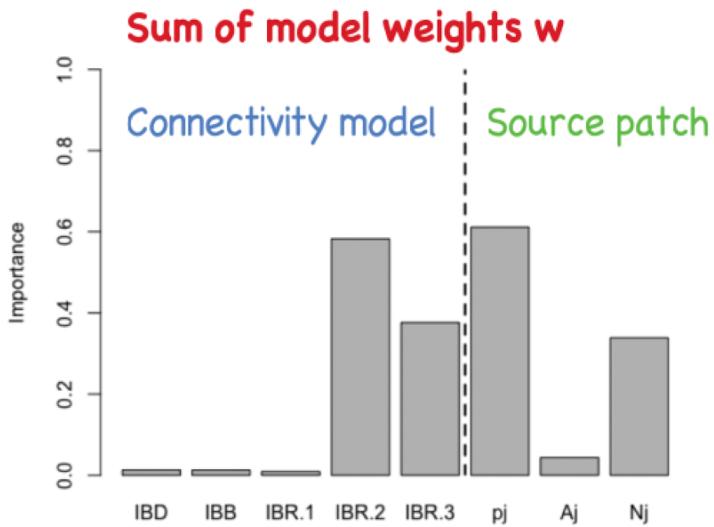
## Correlation with Allelic Richness

	$p_j$	$A_j$	$N_j$
IBD	0.02	0.21	0.10
IBB	0.14	0.17	0.14
IBR.1	0.13	-0.05	0.11
IBR.2	0.40	0.20	0.37
IBR.3	0.37	0.27	0.37

MuMIn:  
Multi-Model Inference

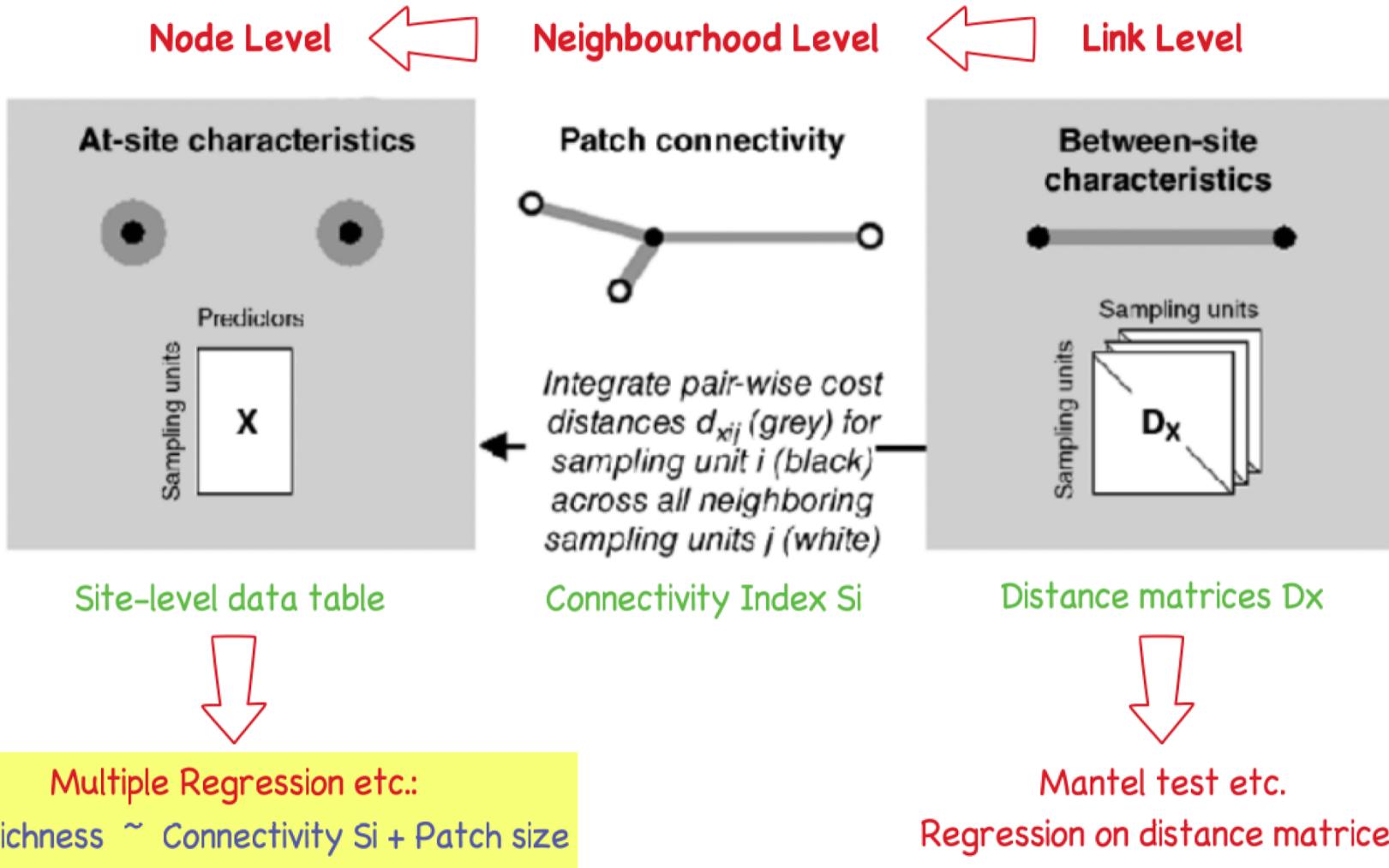


Calculate AIC  
Compare models



# Back to Regression

## B: Landscape data



# Generalized Least Squares (GLS)

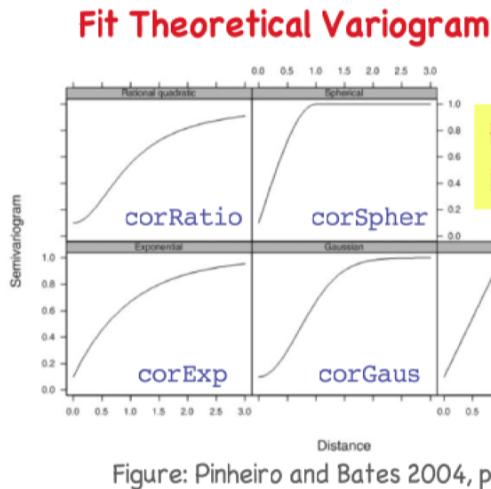
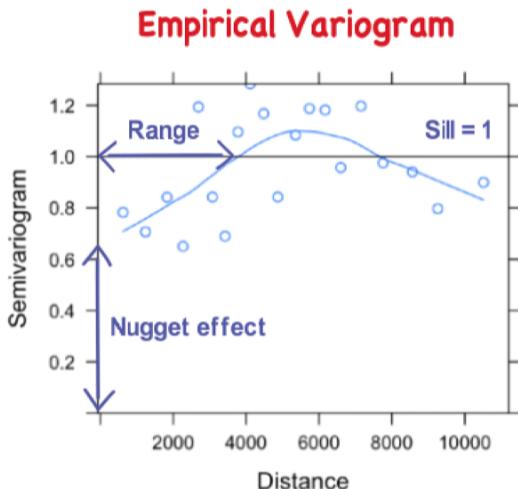
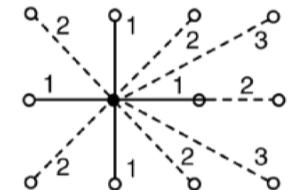
$$Y = \text{intercept} + b * X + \text{residuals}$$

```
model.lm = lm ( Y ~ X, data)
```

```
lm.morantest ( residuals ( model.lm ) )
```

Direction: Sign of Moran's I?  
Size: Value of Moran's I?  
Significance: P-value of Moran's I?

Geostatistical model



```
Variogram( model.lm, form = ~ x + y )
```

```
gls( formula, data, correlation = corExp( form = ~ x + y, nugget=T ) )
```

```
model.sel ( model.lm, mod.corRatio, mod.corSper, mod.corExp, mod.corGaus, mod.corLin )
```

# Which Model Fits Best?

See also Week 12

Ranked models  
(best to worst)

Models penalized  
for df used

Criterion  
used: AICc

delta =  
AICc - AICc(best)

mod.corExp  
mod.corRatio  
model.lm  
mod.corGaus  
mod.corSpher

	(Intrc)	IBR	PtchS	correlation	df	logLik	AICc	delta	weight
mod.corExp	4.044	0.08468	0.04269	n:::cE(x+y,T)	6	6.283	1.1	0.00	0.336
mod.corRatio	4.032	0.09704	0.04129	n:::cR(x+y,T)	6	6.229	1.2	0.11	0.319
model.lm	4.052	0.11340	0.04266		4	3.702	1.3	0.29	0.291
mod.corGaus	4.047	0.11840	0.04247	n:::cG(x+y,T)	6	3.763	6.1	5.04	0.027
mod.corSpher	4.048	0.11710	0.04242	n:::cS(x+y,T)	6	3.760	6.1	5.04	0.027

Do estimates vary  
between models?

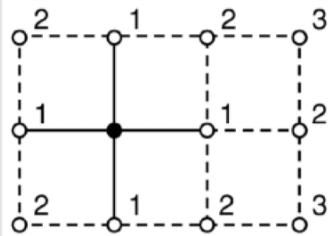
Model weight:  
Support, given  
all models in set

# Spatial Regression with SAR

Simultaneous  
Auto-  
Regressive

SAR

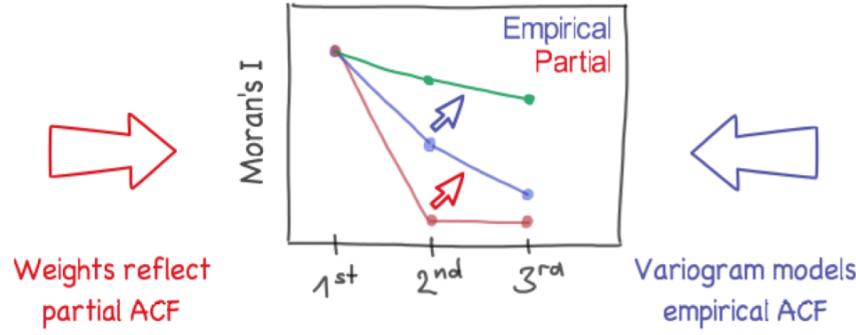
Weight  $w_{ij}$



Error covariance =  $f(w_{ij})$

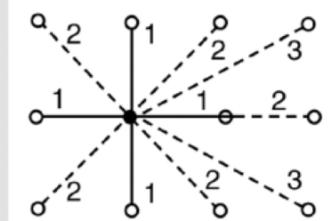
	Ind 1	Ind 2	Ind 3	Ind 4
Ind 1	1	0.7	0.2	0
Ind 2	0.7	1	0.3	0.1
Ind 3	0.2	0.3	1	0.8
Ind 4	0	0.1	0.8	1

Autocorrelation Function (ACF)



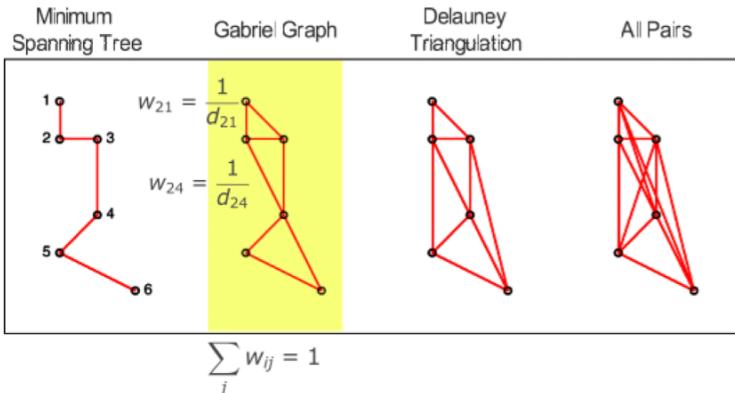
GLS

Distance  $d_{ij}$



Error covariance =  $f(d_{ij})$

How to Choose Neighbours and Weights?



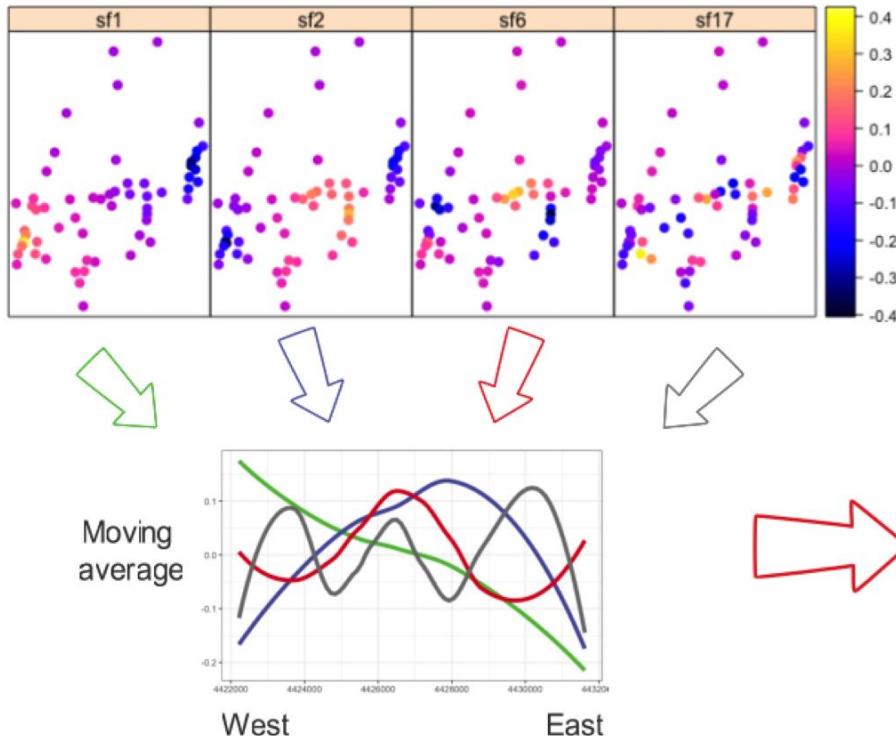
```
errorsarlm( formula, data, listw )
model.sel( model.lm, sar.Bin, sar.Inv.d1, sar.Inv.d2 )
```

# Spatial Filtering with MEM

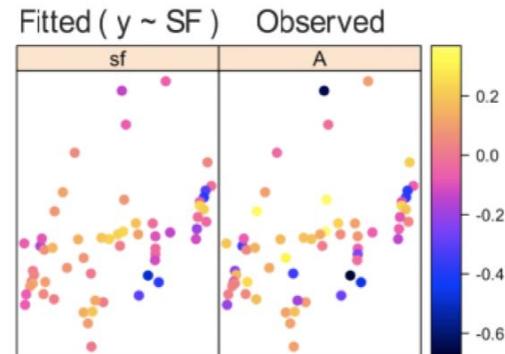
Moran  
Eigenvector  
Maps

Goal: control for spatial variation when assessing  $\text{Im}(y \sim X)$

$$y = \text{intercept} + b_X * X + b_{SF} * SF + \text{residual}$$



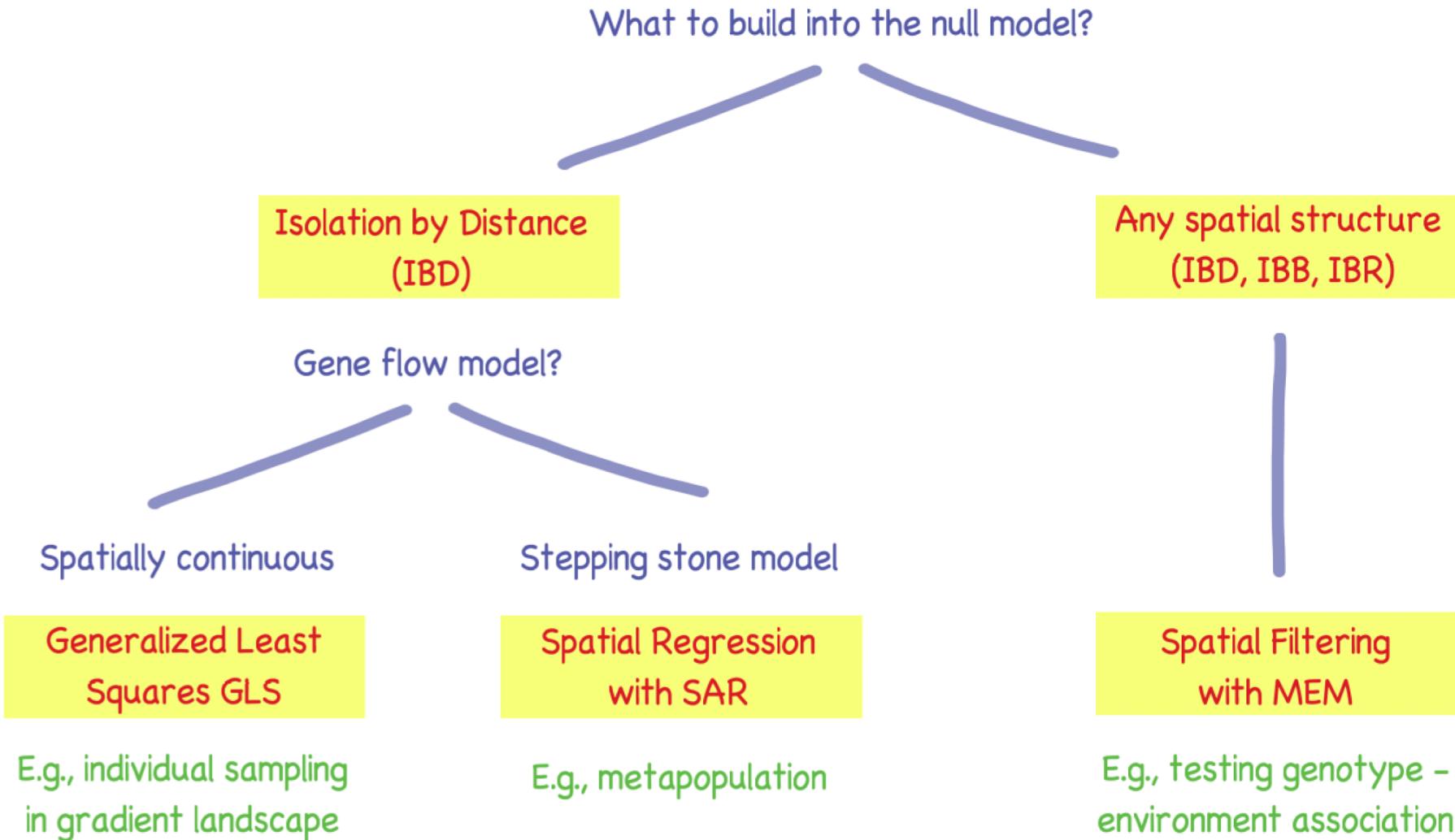
1. Define spatial weights matrix
2. Extract spatial eigenvectors (MEM)
3. Stepwise selection of significant MEM
4. Use as additional predictors SF
5. Effect of predictors X assessed from remaining non-spatial variation in y



```
meig <- spmoran :: meigen ( coords, cmat )
spmoran :: esf ( y, x, meig, fn = "r2" )
spmoran :: resf ( y, x, meig, fn = "r2" )
```

cmat: 'connectivity matrix' = spatial weights  
meig: spatial eigenvectors, eigenvalues  
fn: method for stepwise selection  
'esf': fixed effects, 'resf': random effects (REML)

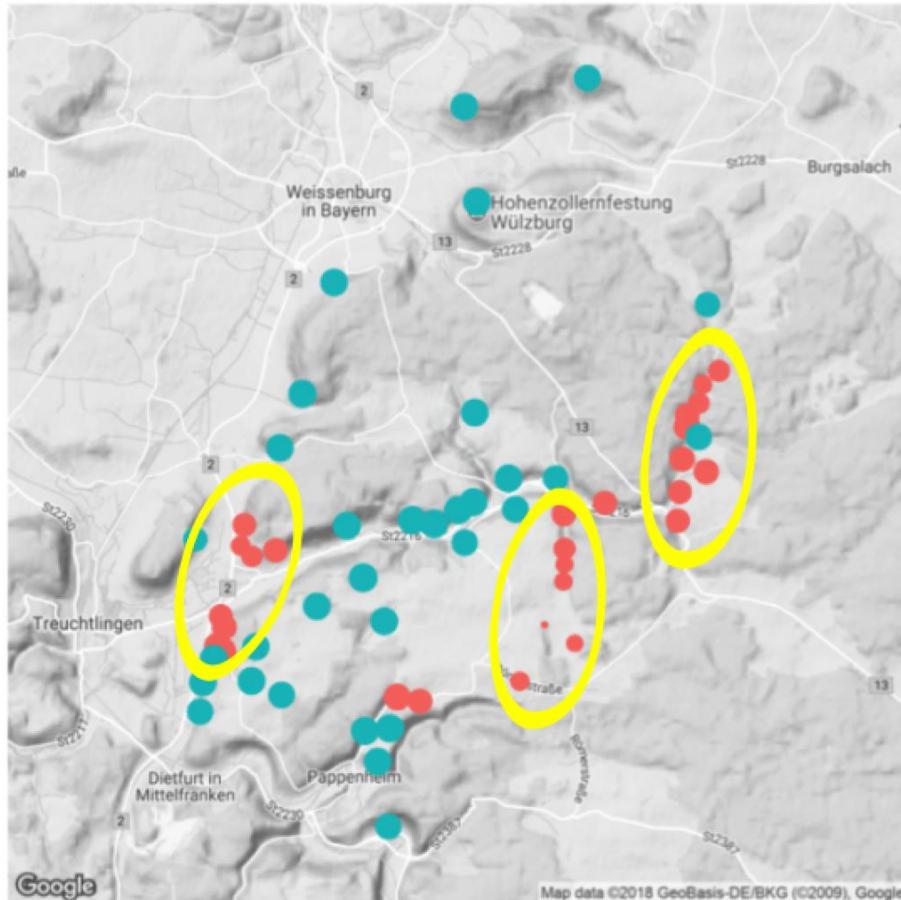
# Which Method to Choose?



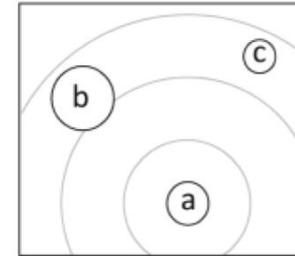
# Spatially Varying Coefficients

Similar to Geographically Weighted Regression (GWR)

Does relationship hold across study area?



C Neighborhood level



$$Y \sim \sum_j X_j$$

Slope estimate for Si.IBR varies across study area

Statistical significance varies across study area

(Intercept)	V1 = Si.IBR
Min. :3.801	Min. :-0.2020
1st Qu.:3.919	1st Qu.: 0.1545
Median :3.941	Median : 0.2549
Mean :3.941	Mean : 0.2101
3rd Qu.:3.969	3rd Qu.: 0.3113
Max. :4.060	Max. : 0.4180

```
spmoran :: resf_vc( y, x, xconst = NULL, meig, method = "reml" )
```