

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 S_i
- Explain genetic diversity by patch connectivity S_i

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



Dianthus carthusianorum
(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

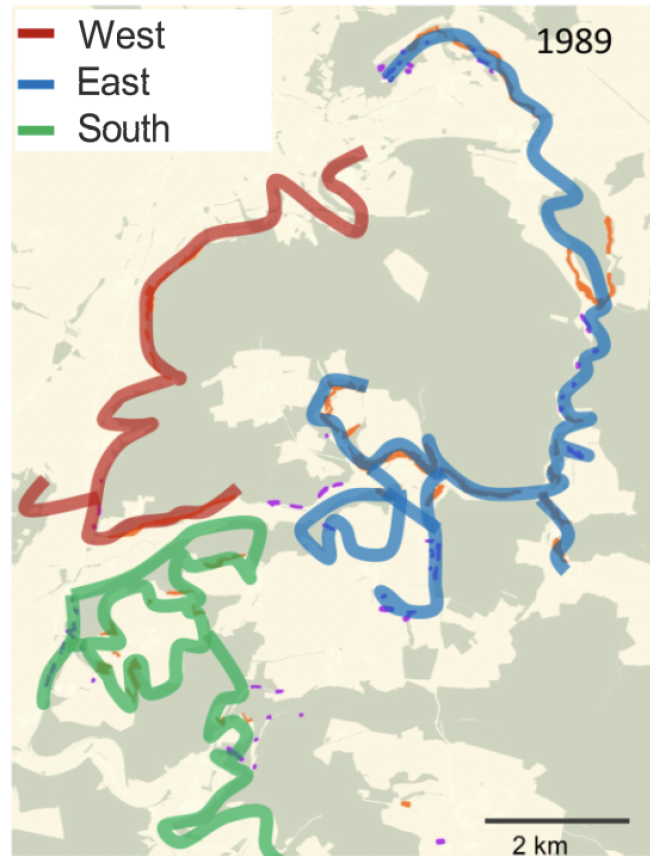
Grazing intensity:

- ungrazed
- intermittently
- consistently



www.neuburg-schrobenhausen.de

Connectivity by Shepherding



Figures and map: Y. Rico

Alternative Hypotheses

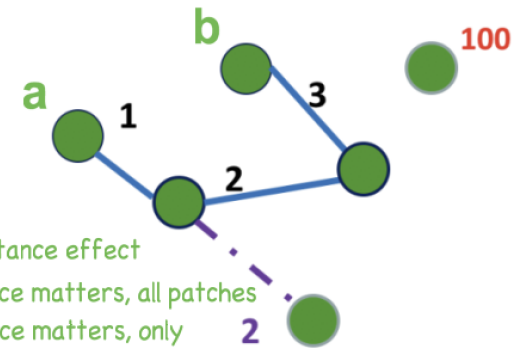
Geographic distance (IBD)



Forest as barrier (IBB)



Connectivity by shepherding (IBR)



- No distance effect
- Distance matters, all patches
- Distance matters, only consistently grazed patches

Connectivity Index S_i

See Week 7 Bonus Material

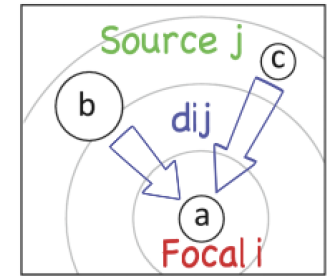
Sum over all neighbours j

Connectivity S_i
of focal patch i

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

Source patch:
 p_j, A_j, N_j

C Neighborhood level



$$Y \sim \sum_j X_j$$

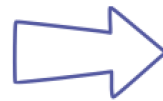
Connectivity model:

- ecological distance d_{ij}
- dispersal parameter α

Correlation with Allelic Richness

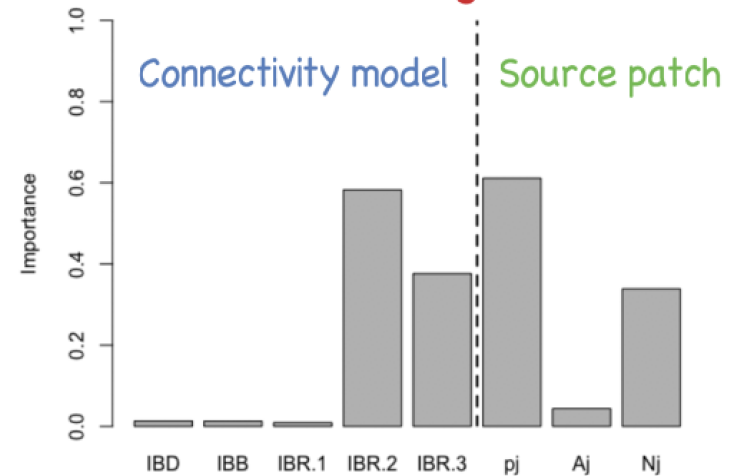
	p_j	A_j	N_j
IBD	0.02	0.21	0.10
IBB	0.14	0.17	0.14
IBR.1	0.13	-0.05	0.11
IBR.2	0.40	0.20	0.37
IBR.3	0.37	0.27	0.37

MuMIn:
Multi-Model Inference

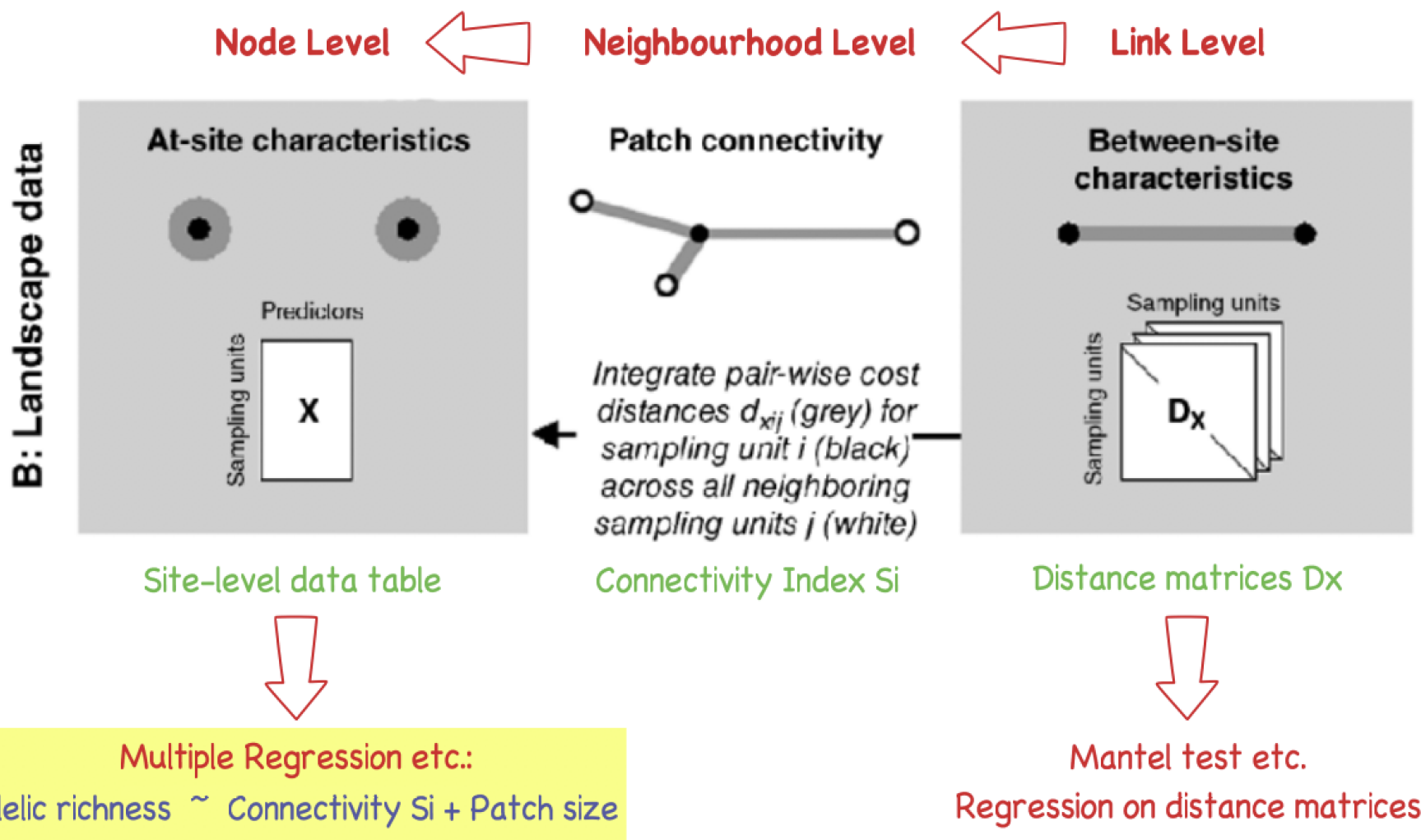


Calculate AIC
Compare models

Sum of model weights w



Back to Regression



Generalized Least Squares (GLS)

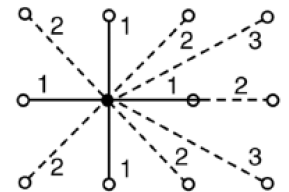
$$Y = \text{intercept} + b * X + \text{residuals}$$

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

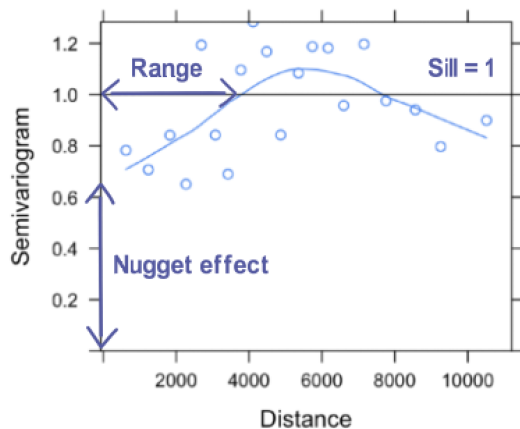
Direction: Sign of Moran's I?
 Size: Value of Moran's I?
 Significance: P-value of Moran's I?



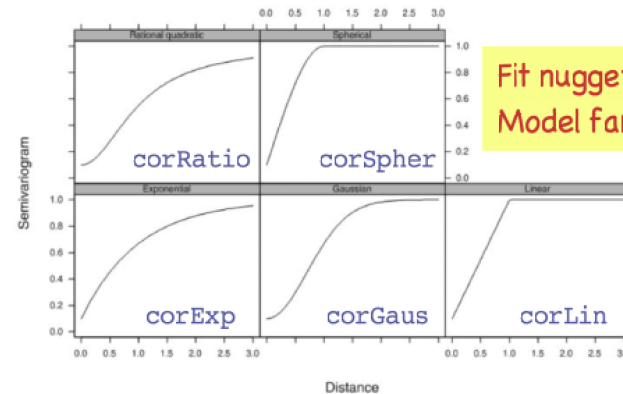
Geostatistical model



Empirical Variogram



Fit Theoretical Variogram



Fit nugget effect?
 Model family?

Figure: Pinheiro and Bates 2004, p. 233

```
Variogram( model.lm, form = ~ x + y )
gls( formula, data, correlation = corExp( form = ~ x + y, nugget=T ))
model.sel ( model.lm, mod.corRatio, mod.corSpher, 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)

	(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?

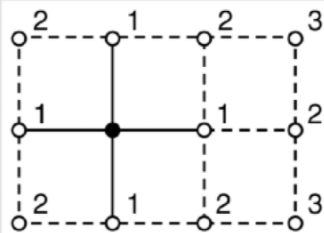
Model weight:
Support, given
all models in set

Spatial Regression with SAR

Simultaneous
Auto-
Regressive

SAR

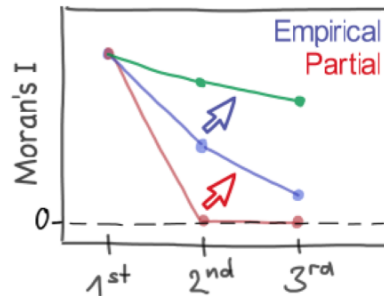
Weight w_{ij}



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)

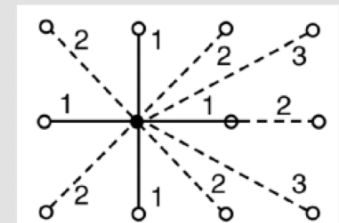


Weights reflect partial ACF

Variogram models empirical ACF

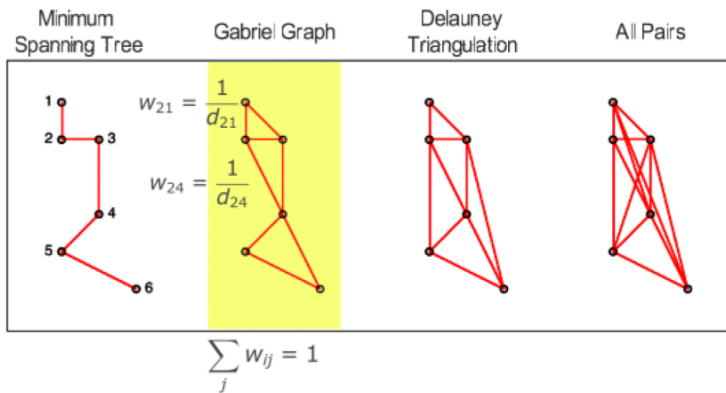
GLS

Distance d_{ij}



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

How to Choose Neighbours and Weights?



	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

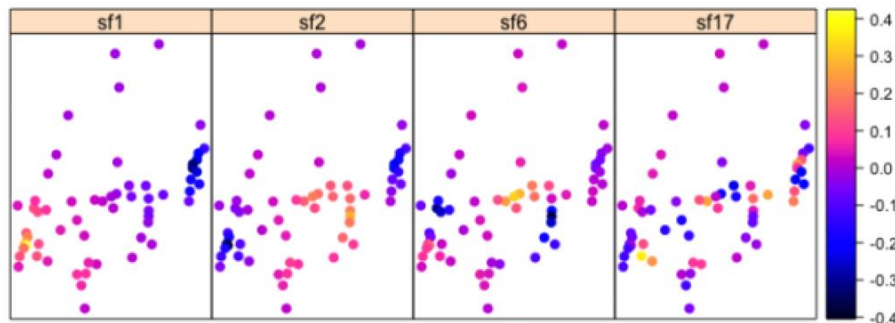
```
errorsarlm ( formula, data, listw )
model.sel ( model.lm, sar.Bin, sar.Inv.d1, sar.Inv.d2 )
```

Spatial Filtering with MEM

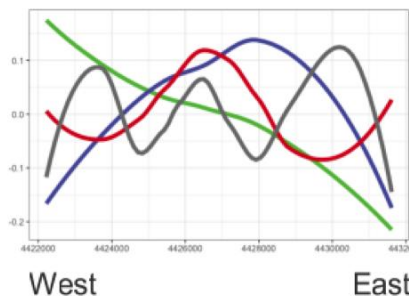
Moran
Eigenvector
Maps

Goal: control for spatial variation when assessing 'lm (Y ~ X)'

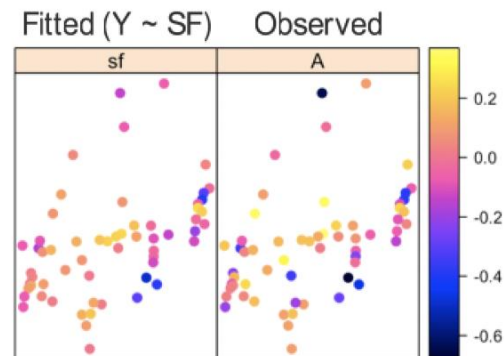
$$Y = \text{intercept} + b.x * X + \text{b.sf} * \text{SF} + \text{residuals}$$



Moving
average



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?

What to build into the null model?

Isolation by Distance
(IBD)

Any spatial structure
(IBD, IBB, IBR)

Gene flow model?

Spatially continuous

Stepping stone model

Generalized Least
Squares GLS

Spatial Regression
with SAR

Spatial Filtering
with MEM

E.g., individual sampling
in gradient landscape

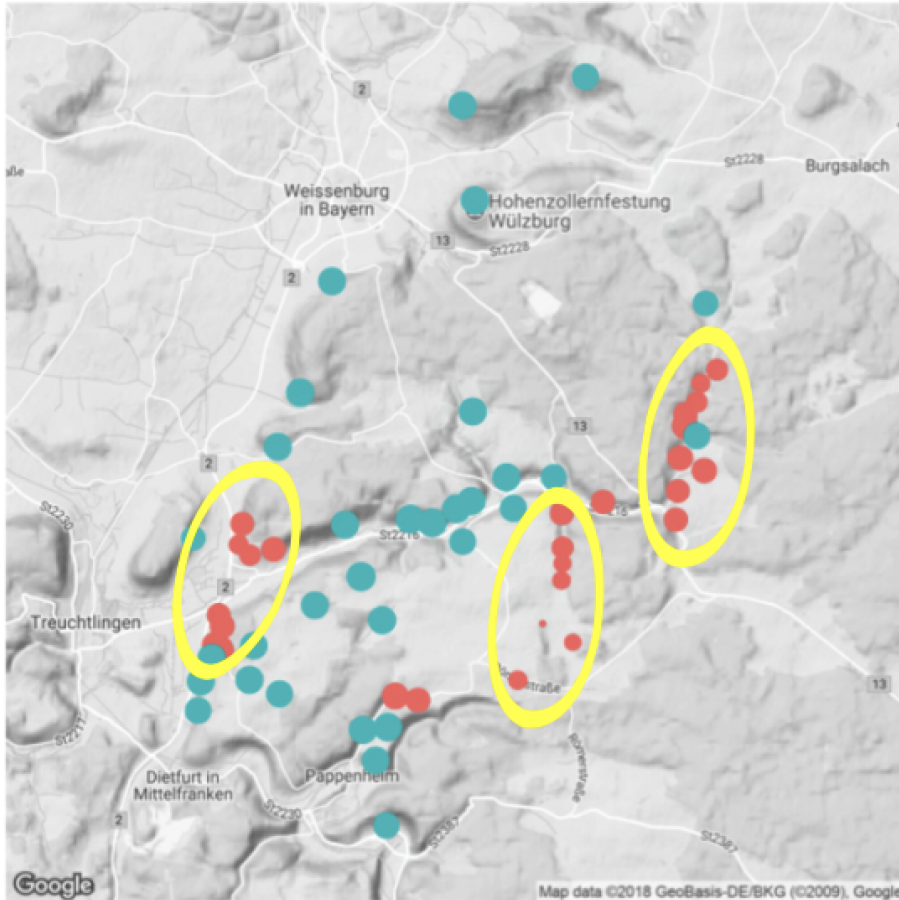
E.g., metapopulation

E.g., testing genotype -
environment association

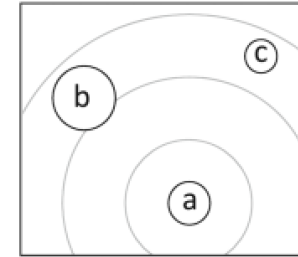
Spatially Varying Coefficients

Similar to Geographically Weighted Regression (GWR)

Does relationship hold across study area?

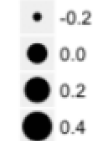


C Neighborhood level



$$Y \sim \sum_j X_j$$

b.V1



Slope estimate for Si.IBR varies across study area

p.V1 < 0.05



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" )
```