

# STATISTICAL AND MACHINE LEARNING FOR BIG GEOSPATIAL DATA: Part I

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# Course outline

Part I: Introduction to geostatistics and spatial linear models

Part II: Random forests for geospatial data

Part III: Neural networks for geospatial data

Part IV: Software demonstration

# Course outline

Part I: Introduction to geostatistics and spatial linear models

Part II: Random forests for geospatial data

    Part IV a: Software demonstration of random forests for spatial analysis in R

Part III: Neural networks for geospatial data

    Part IV b: Software demonstration of neural nets for spatial analysis in Python

Course materials available at ...

# Overview of Part I

Introduction to geostatistics

Exploratory data analysis  
Maps and variograms

Gaussian Processes (GP) and spatial linear regression  
Estimation and prediction (kriging)  
Spatial linear mixed effect models

Big spatial data  
Computing challenges  
Fast alternatives (Nearest Neighbor Gaussian Process)

# What is spatial data

Any data with some geographical information

Common sources of spatial data:

climatology, forestry, ecology, environmental health, disease epidemiology,  
real estate marketing

Other examples where spatial need not refer to space on earth:

Neuroimaging (data for each voxel in the brain)

Genetics (position along a chromosome)

Spatial transcriptomics (gene expression on slides)

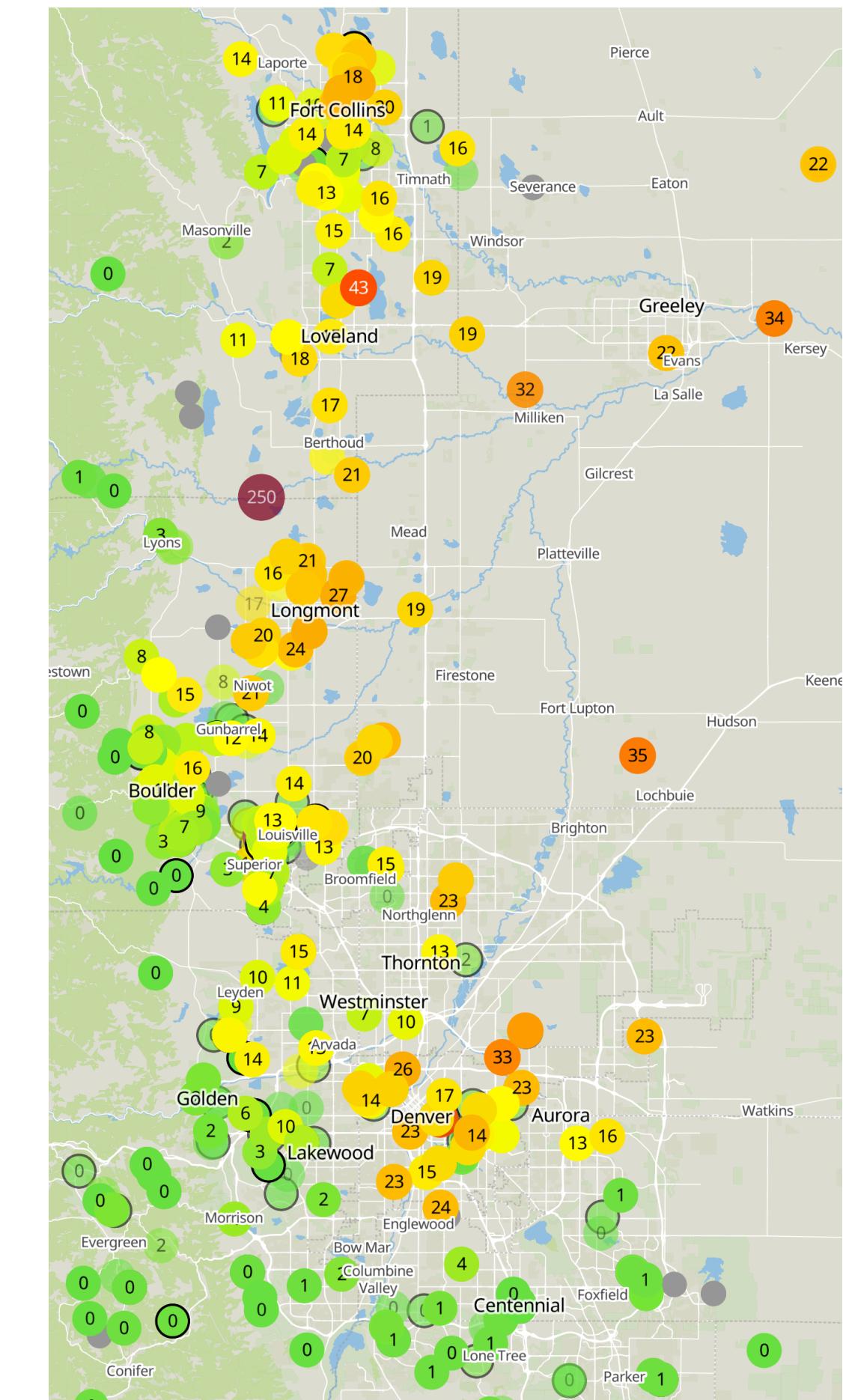
# Geostatistics

Each observation (data unit) is associated with a geographical location (latitude-longitude)

Data represents a sample from a continuous spatial domain

# Often displayed on a map

Referred to as geocoded/ geostatistical/ point referenced data



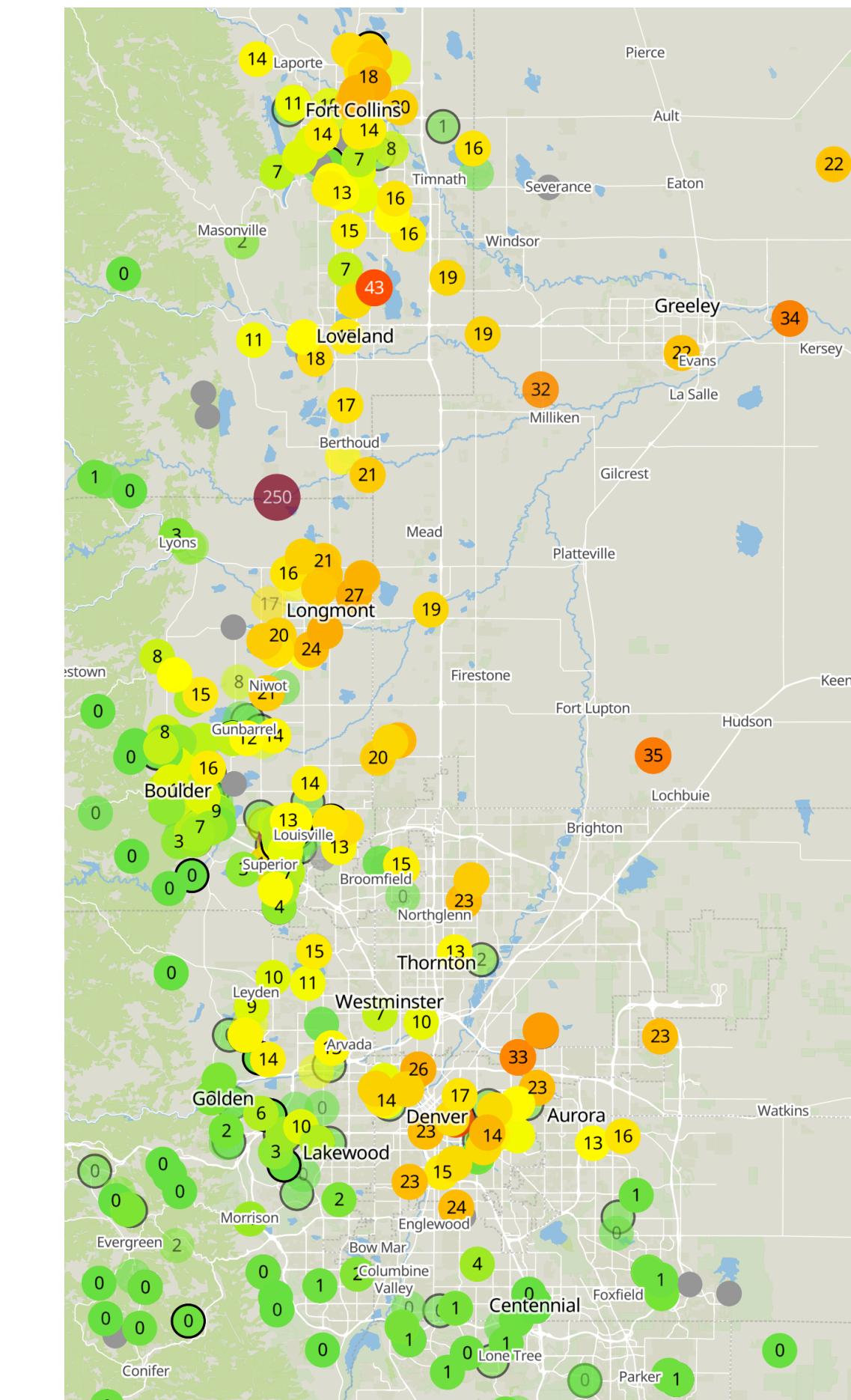
# PM<sub>2.5</sub> ( $\mu\text{g}/\text{m}^3$ ) in Colorado on Nov 12, 2024 from PurpleAir.com

# Geostatistics

Point reference data:

Data collected at locations  $s_1, \dots, s_n$

$Y_i = Y(s_i)$  : scalar response at location  $s_i$



PM<sub>2.5</sub> ( $\mu\text{g}/\text{m}^3$ ) in Colorado  
on Nov 12, 2024 from PurpleAir.com

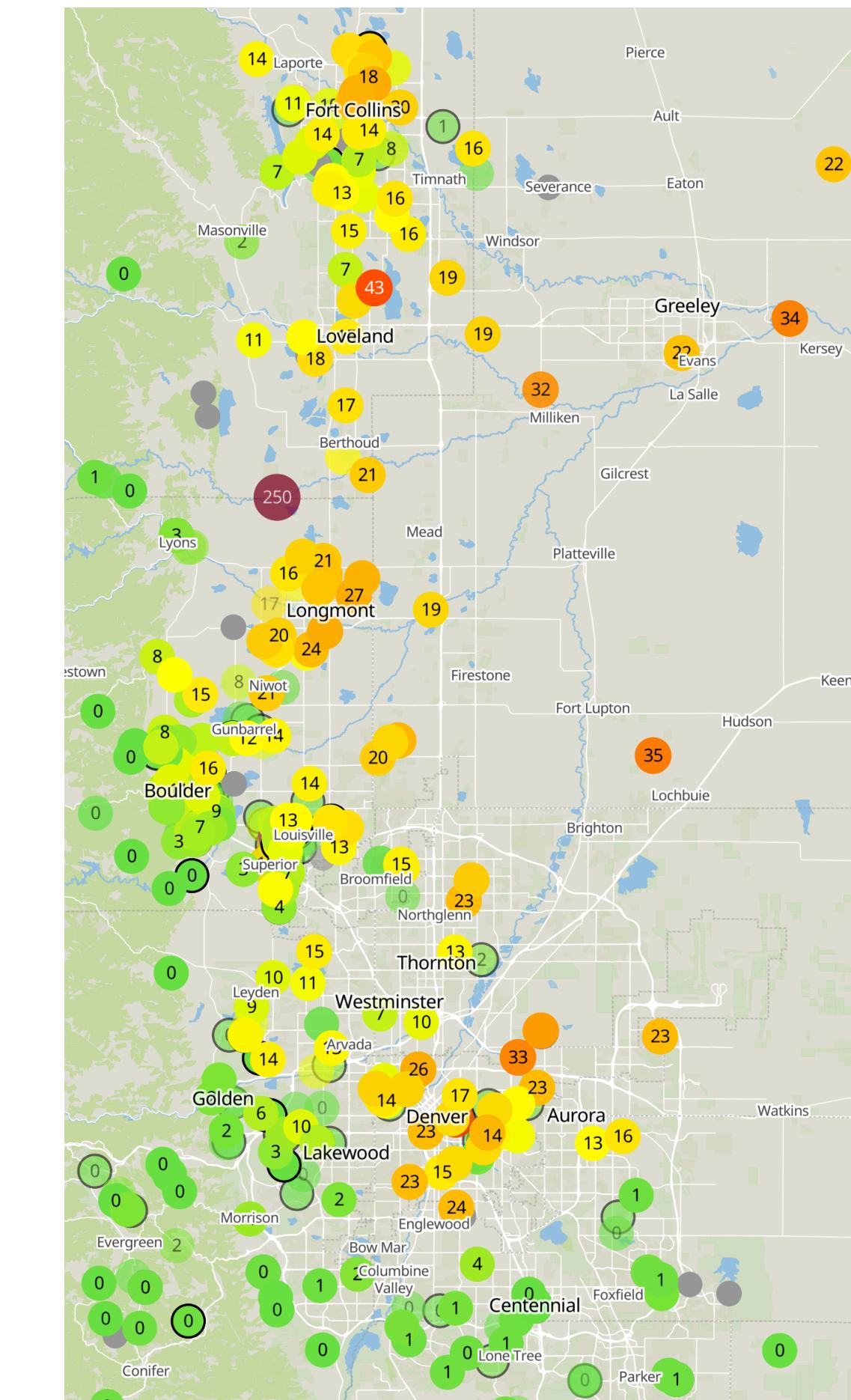
# Geostatistics

Point reference data:

Data collected at locations  $s_1, \dots, s_n$

$Y_i = Y(s_i)$ : scalar response at location  $s_i$

$X_i = X(s_i)$ :  $d \times 1$  vector of covariates (explanatory variables)



$\text{PM}_{2.5} (\mu\text{g}/\text{m}^3)$  in Colorado  
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# Geostatistics

Point reference data:

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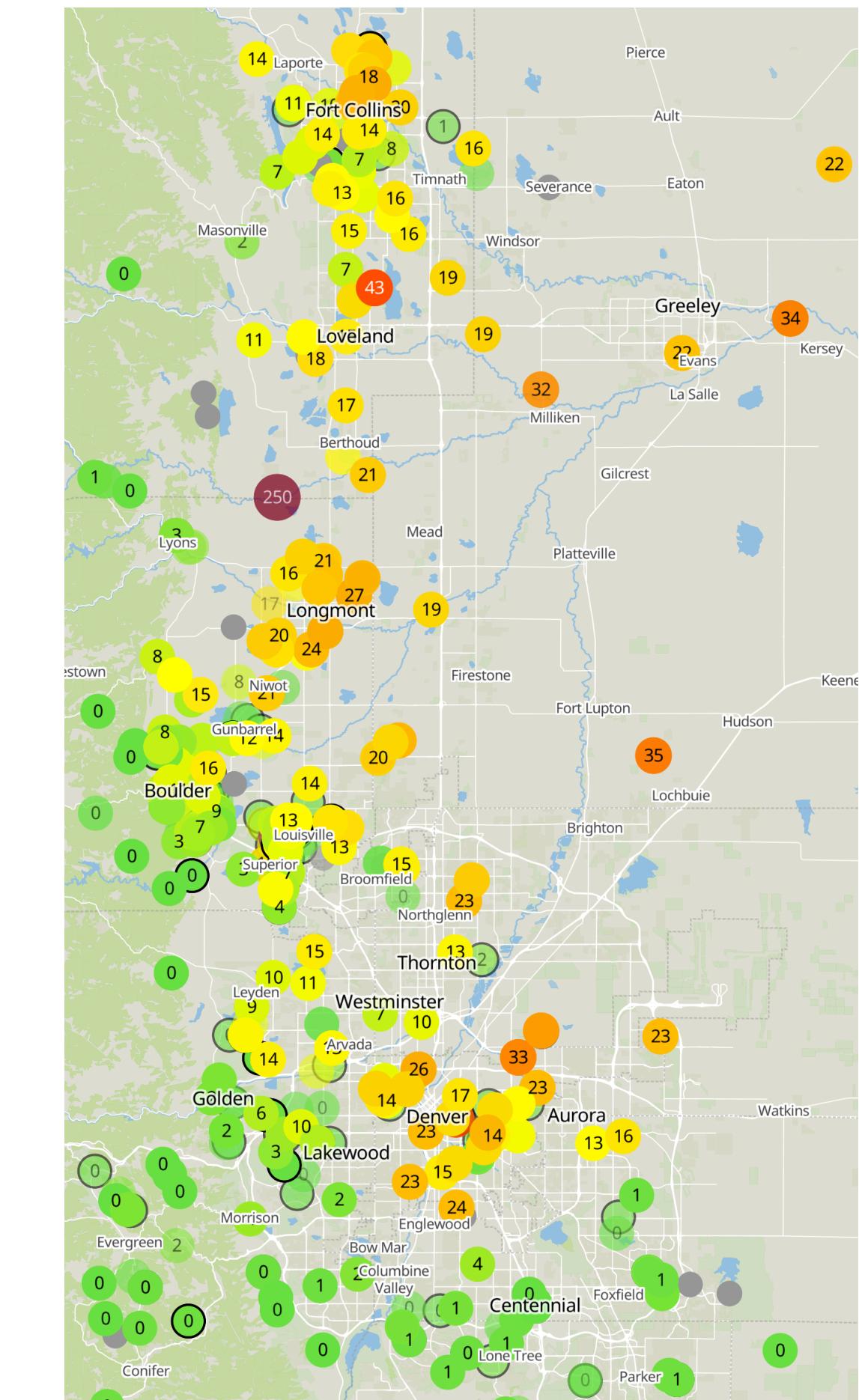
$X_i = X(s_i)$ :  $d \times 1$  vector of covariates (explanatory variables)

Objectives:

Predict  $Y$  at any location without data

Understand spatial patterns in  $Y$

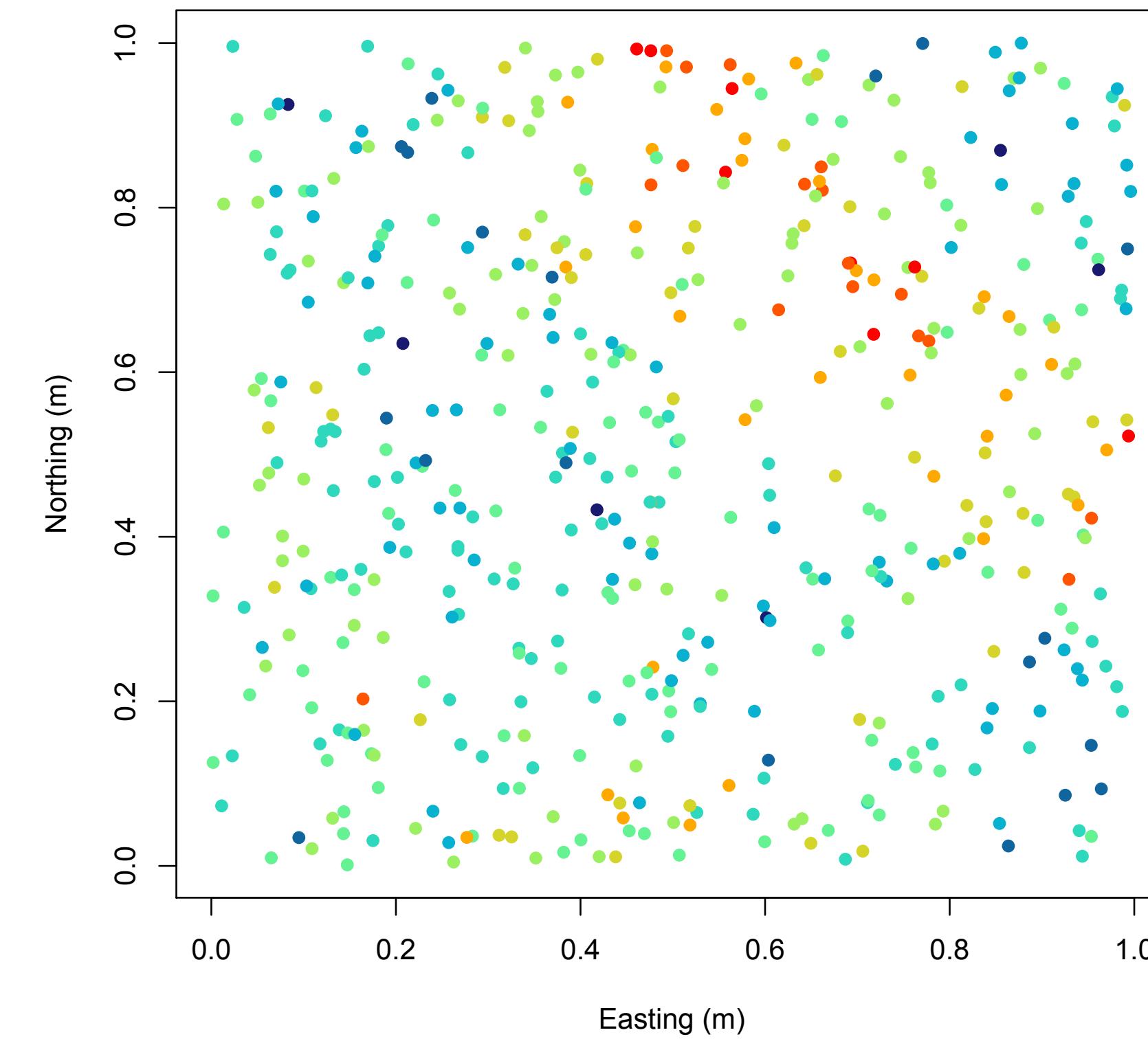
Understand relationship between  $X$  and  $Y$



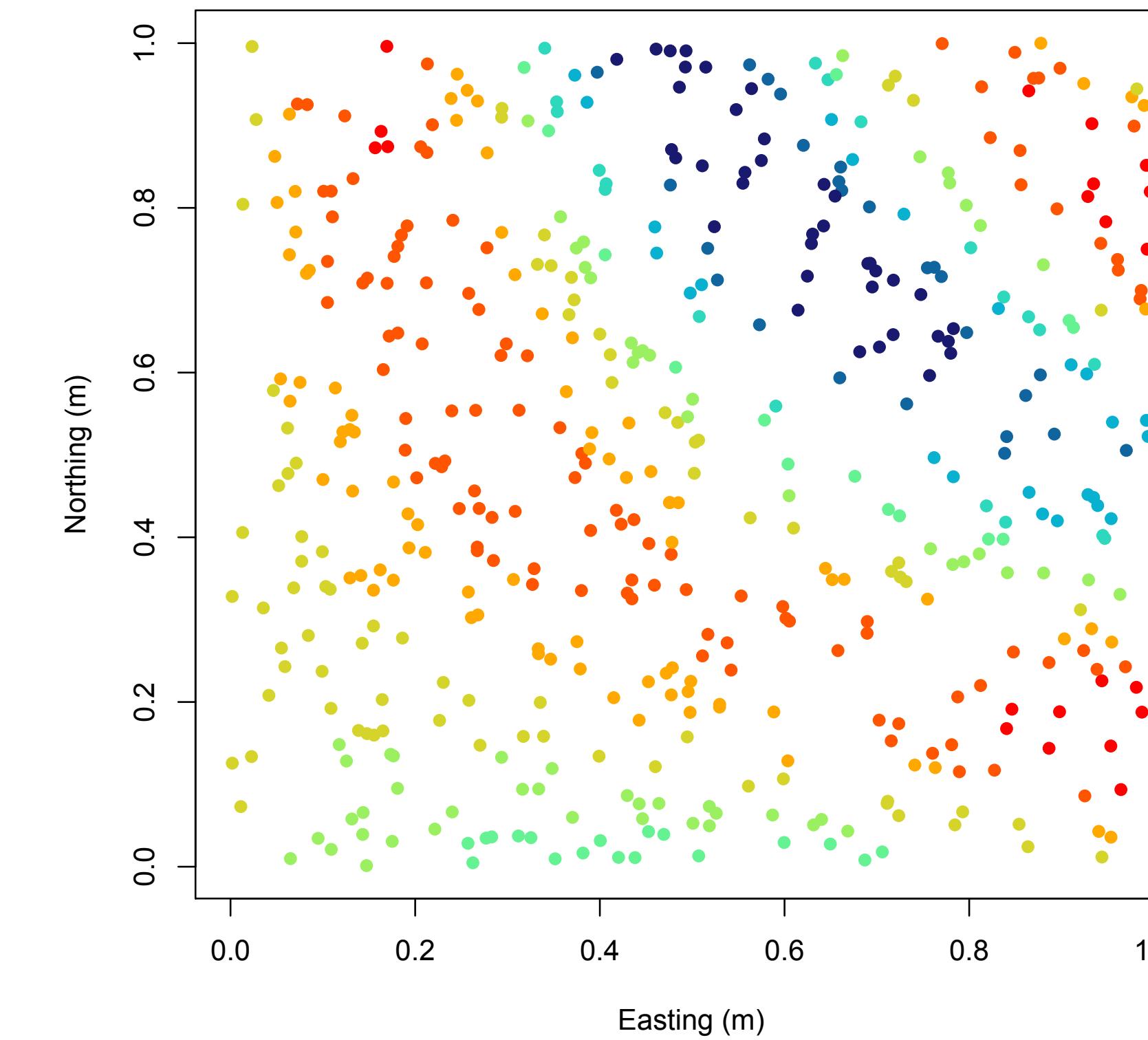
PM<sub>2.5</sub> ( $\mu\text{g}/\text{m}^3$ ) in Colorado  
on Nov 12, 2024 from PurpleAir.com

# Exploratory data analysis (EDA): Plotting the data

Point plots help to visualize the exact data where they are observed



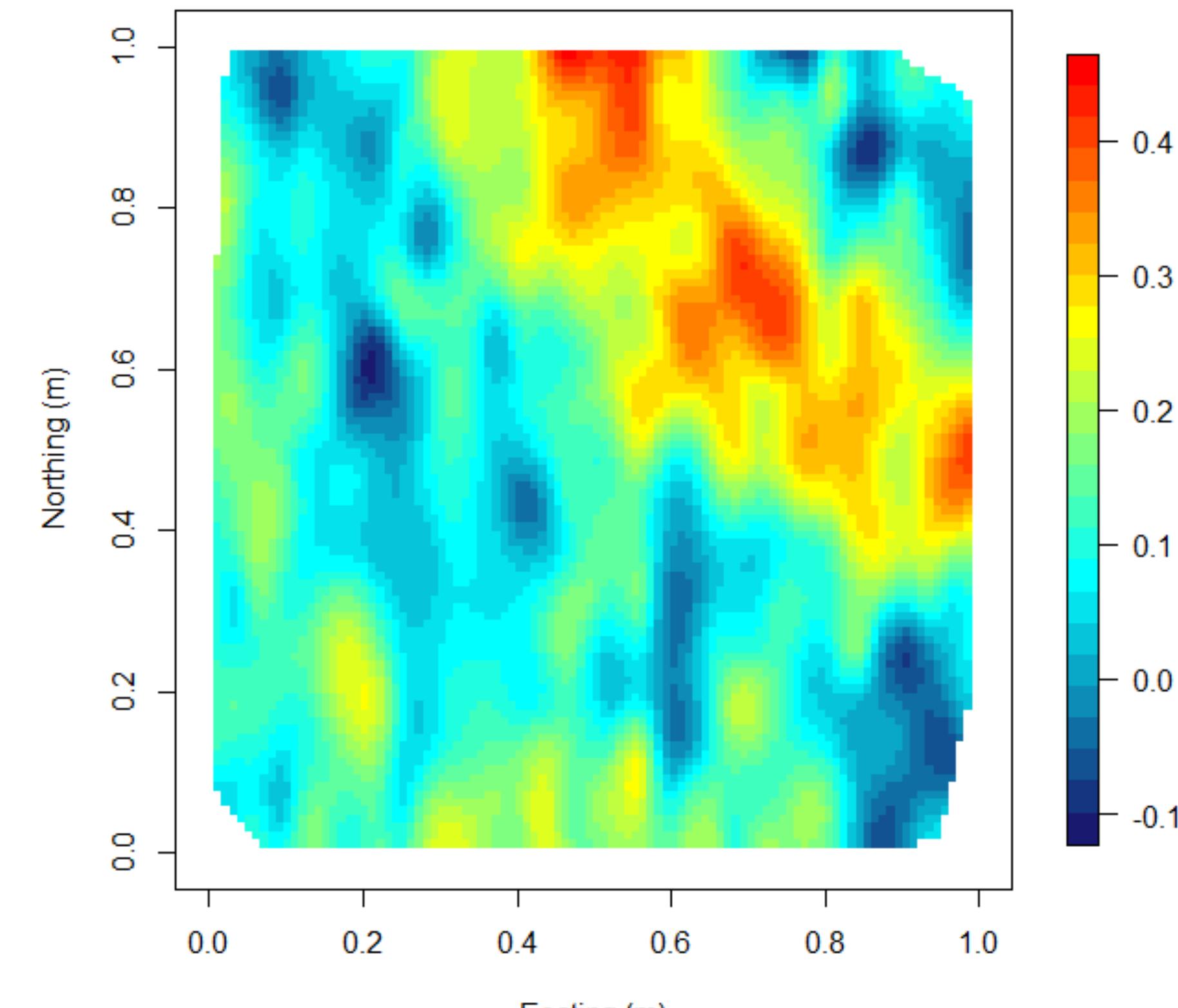
$$Y(s_i)$$



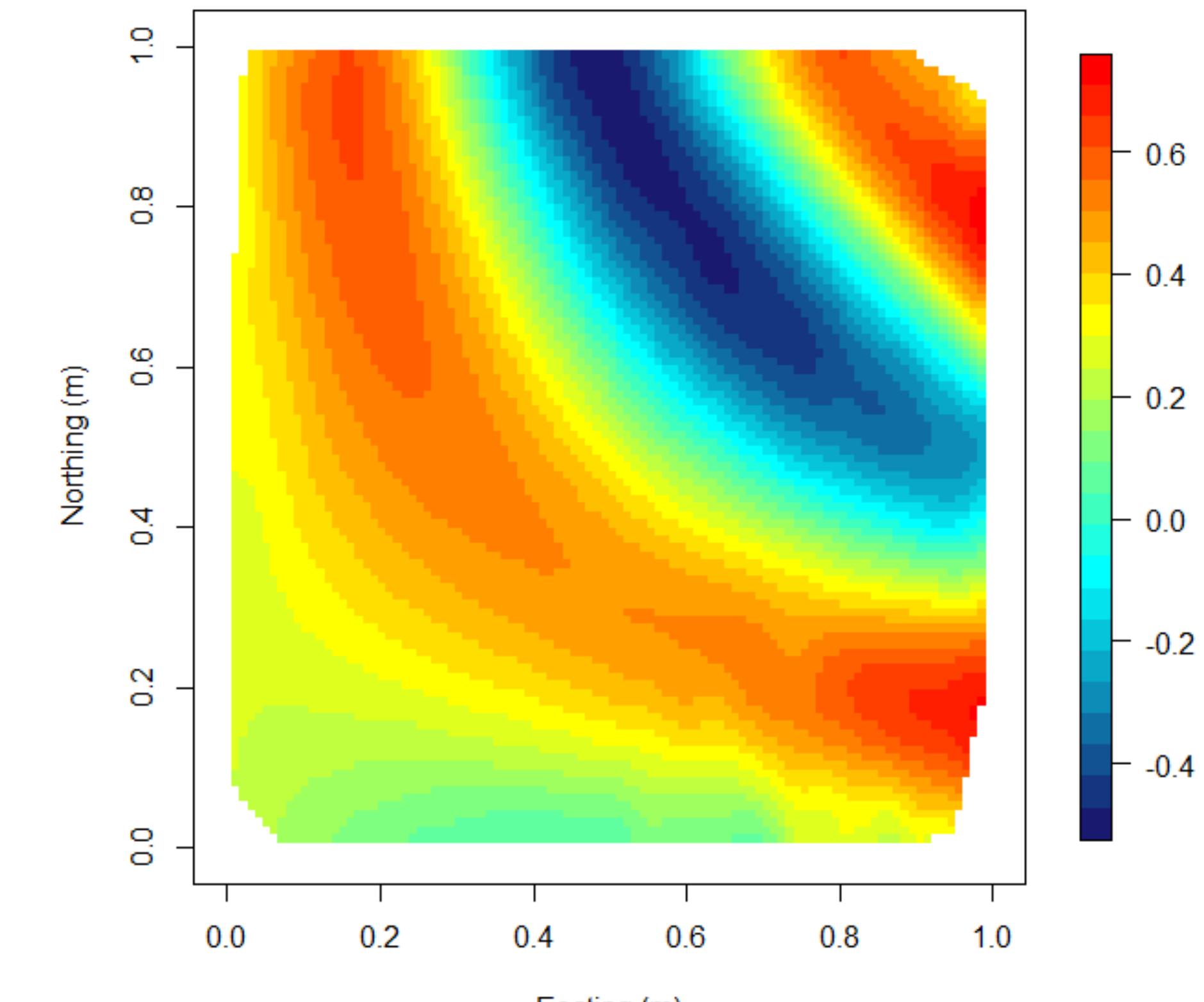
$$X(s_i)$$

# Exploratory data analysis (EDA): Plotting the data

Surface plots (interpolated data) are often better help understand spatial patterns



$Y(s)$



$X(s)$

# What's so special about spatial?

Linear regression model:  $Y(s_i) = X(s_i)'\beta + \epsilon(s_i)$

$\epsilon(s_i)$  are iid  $N(0, \tau^2)$  errors

$$Y = (Y(s_1), Y(s_2), \dots, Y(s_n))'; X = (X(s_1)', X(s_2)', \dots, X(s_n)')'$$

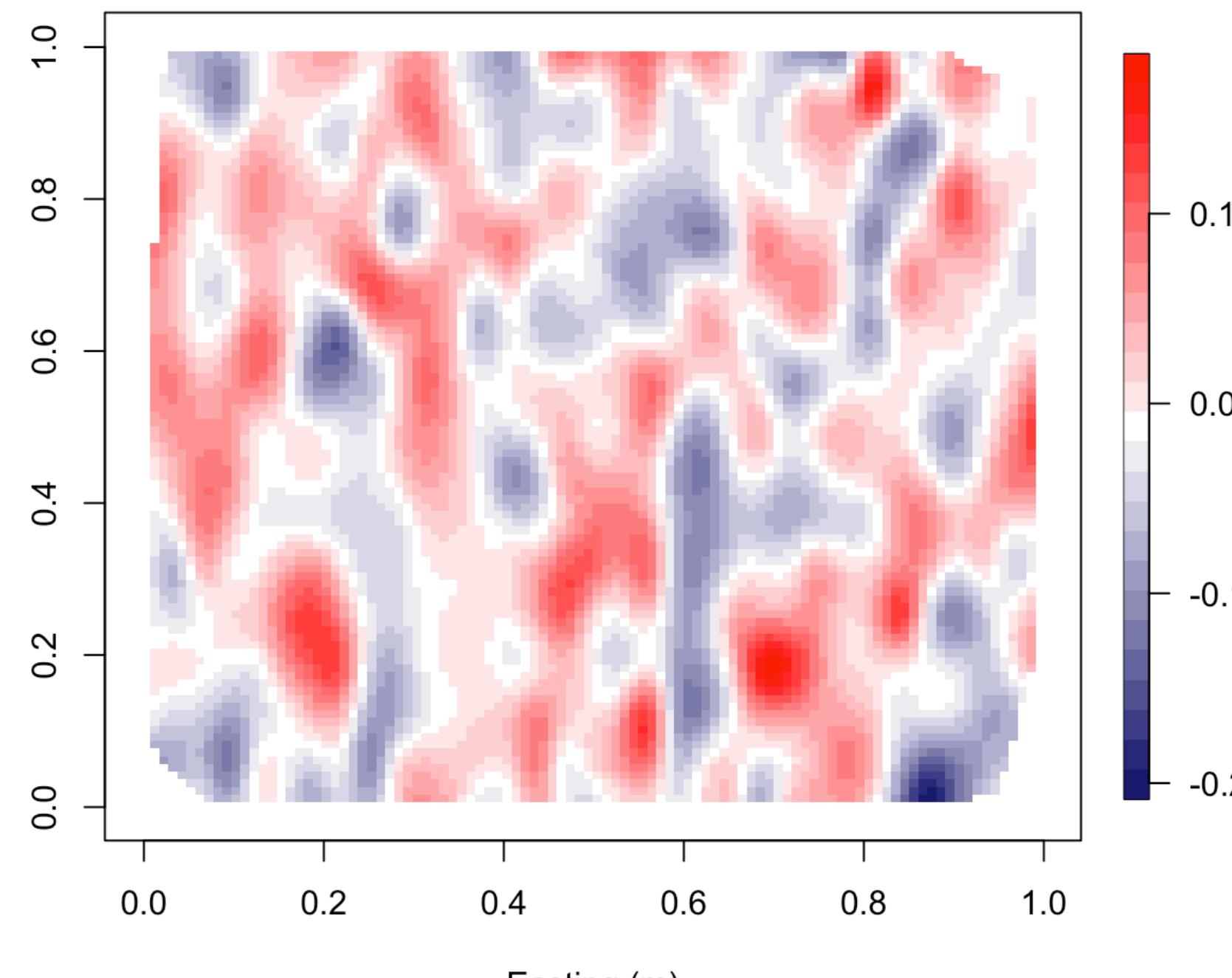
Inference:  $\hat{\beta} = (X'X)^{-1}X'Y \sim N(\beta, \tau^2(X'X)^{-1})$

Prediction at new location  $s_0$ :  $\widehat{Y(s_0)} = X(s_0)'\hat{\beta}$

Although the data is spatial, this is an ordinary linear regression model

# Residual plots

Surface plots of residuals  $y(s) - \hat{y}(s)$  help identify residual spatial patterns not explained by the covariates



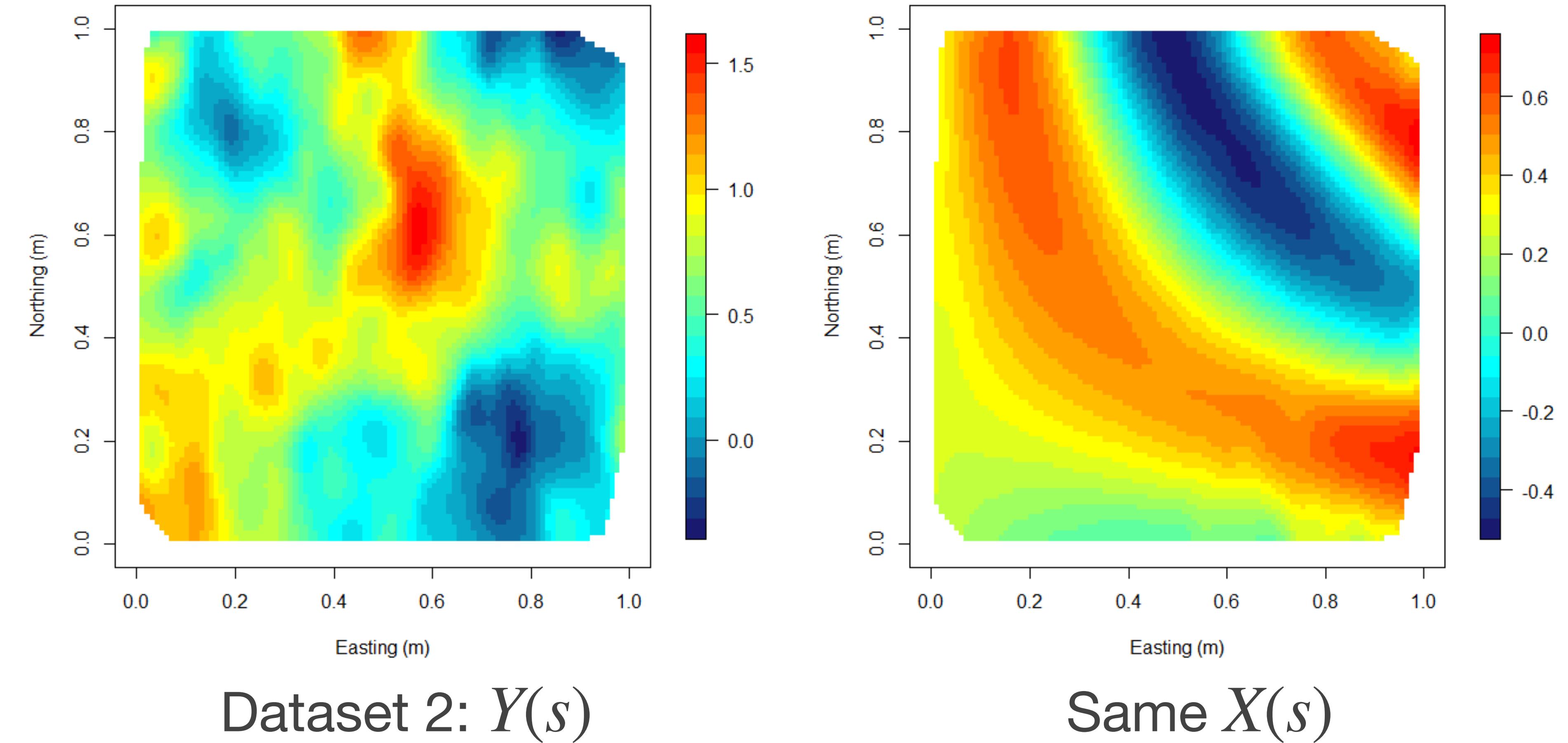
Surface plot of residuals

Surface plot of residuals not showing any large scale spatial patterns

The covariate  $X(s)$  seems to explain all spatial variation in the response  $Y(s)$

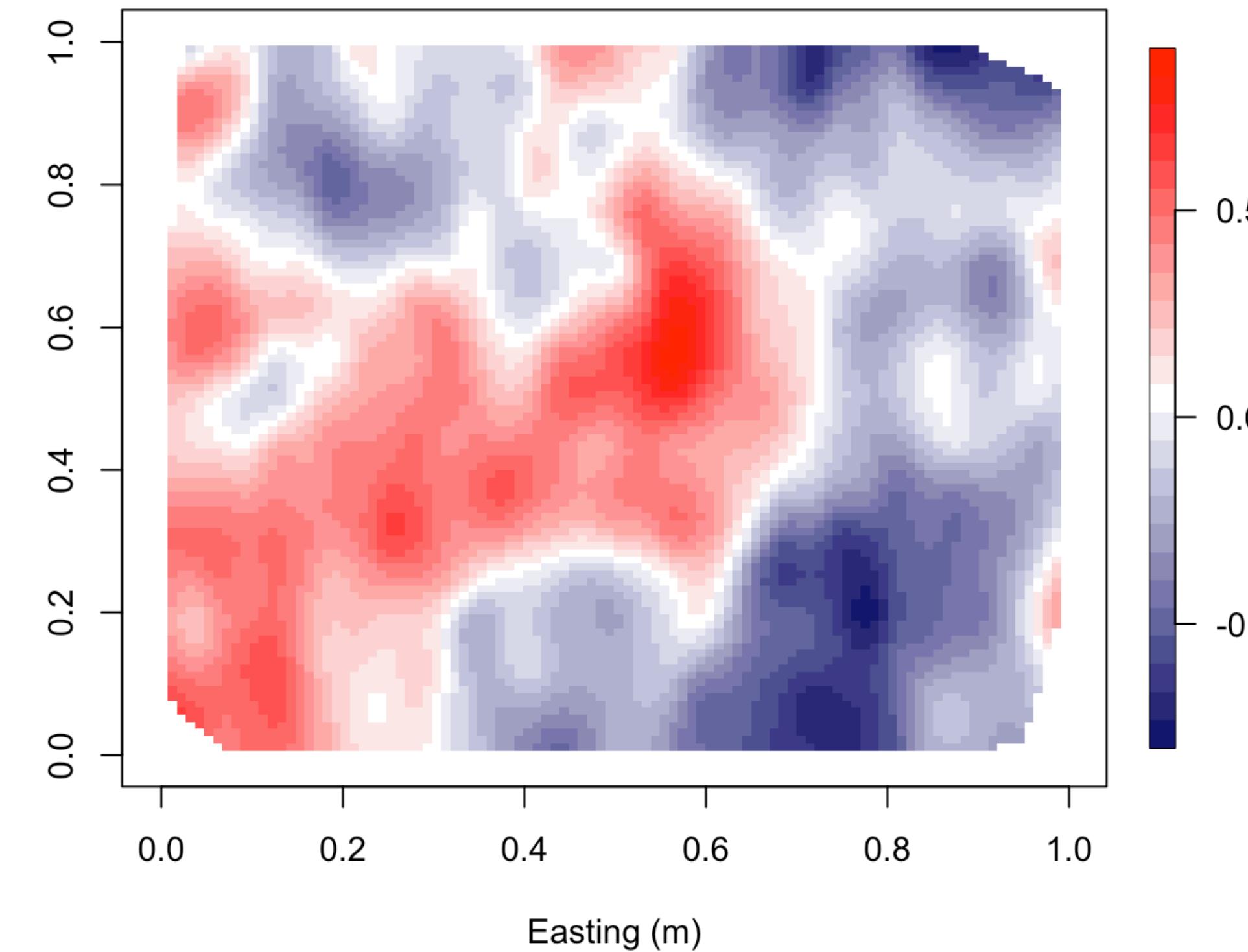
When does such a non-spatial analysis suffice?

# Another dataset

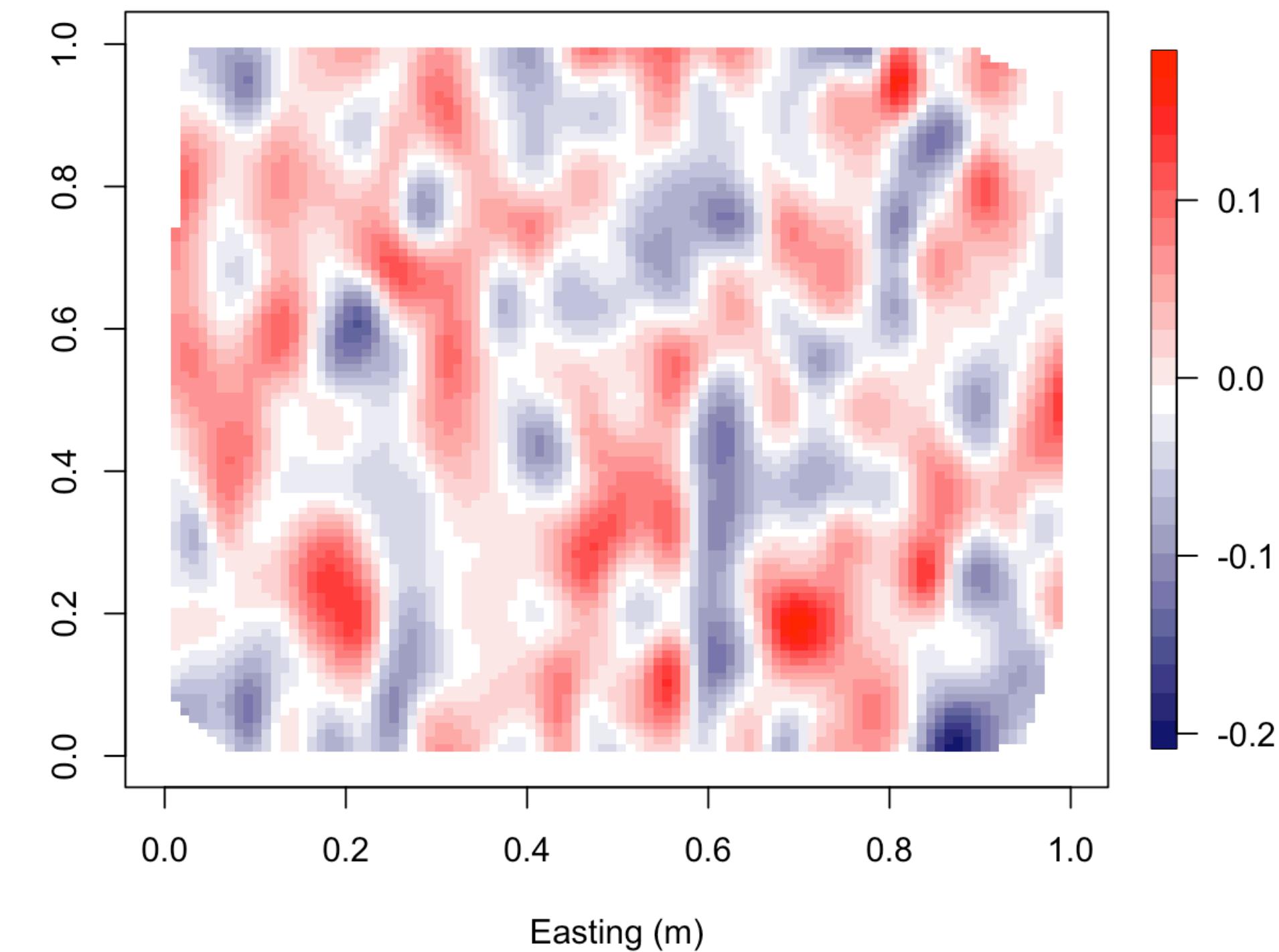


# Another dataset

Linear regression:  $y(s_i) = \beta_0 + x(s_i)\beta_1 + \epsilon(s_i)$



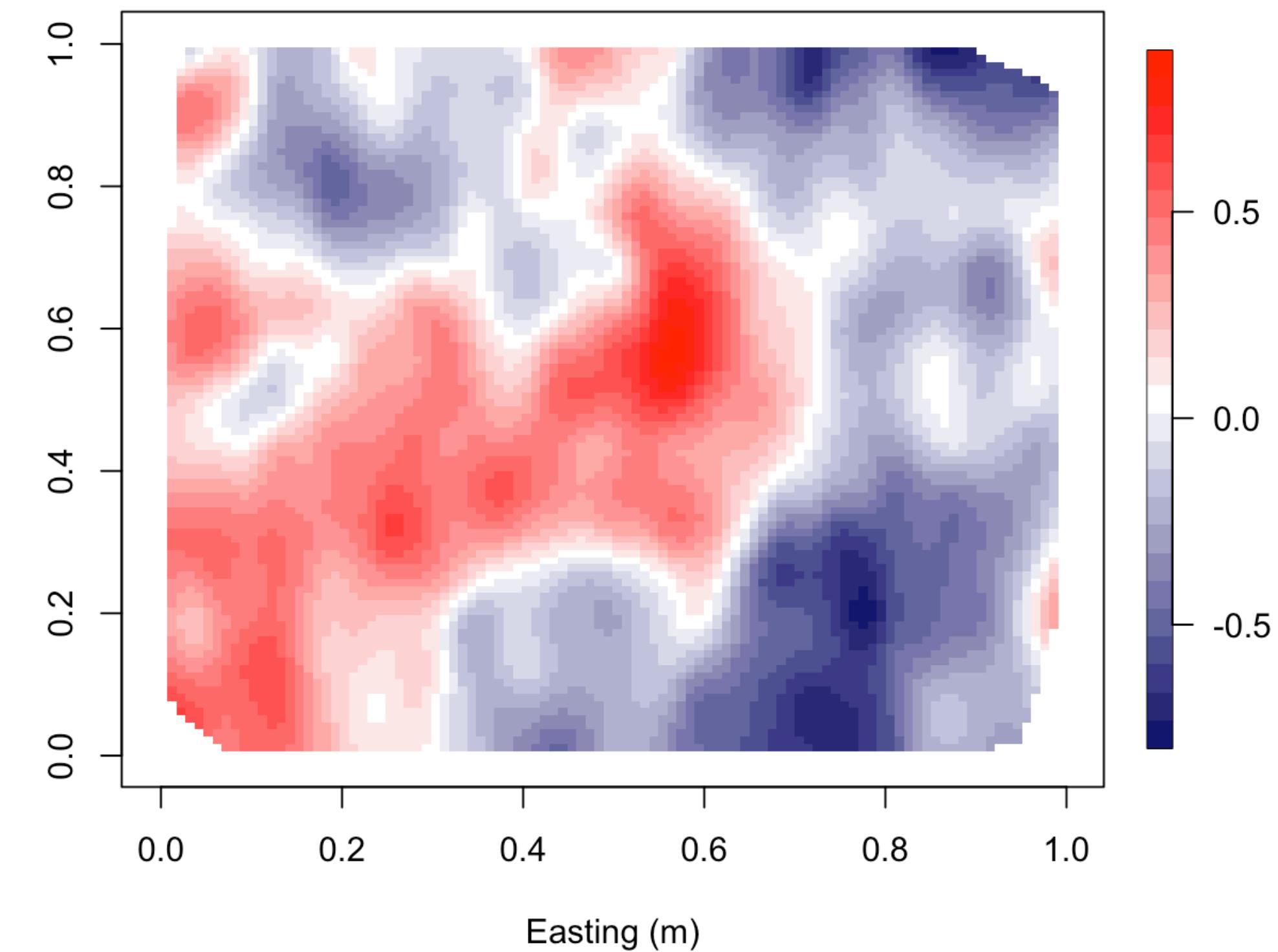
Dataset 2: Residual plot



Dataset 1: Residual plot

# Another dataset

Linear regression:  $y(s_i) = \beta_0 + x(s_i)\beta_1 + \epsilon(s_i)$



Dataset 2: Residual plot

Strong residual spatial pattern

The covariate  $X(s)$  does not explain all spatial variation in the response  $Y(s)$

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

# Semi-Variogram

**First Law of Geography:** “*Everything is related to everything else, but near things are more related than distant things.*” – Waldo Tobler

$Y(s_1)$  and  $Y(s_2)$  should be more similar if  $s_1$  is near  $s_2$

$(Y(s_1) - Y(s_2))^2$  should be small when  $\|s_1 - s_2\|$  is small and increase as  $\|s_1 - s_2\|$  increases

Can this be formalized to identify spatial pattern in data?

# Semi-Variogram

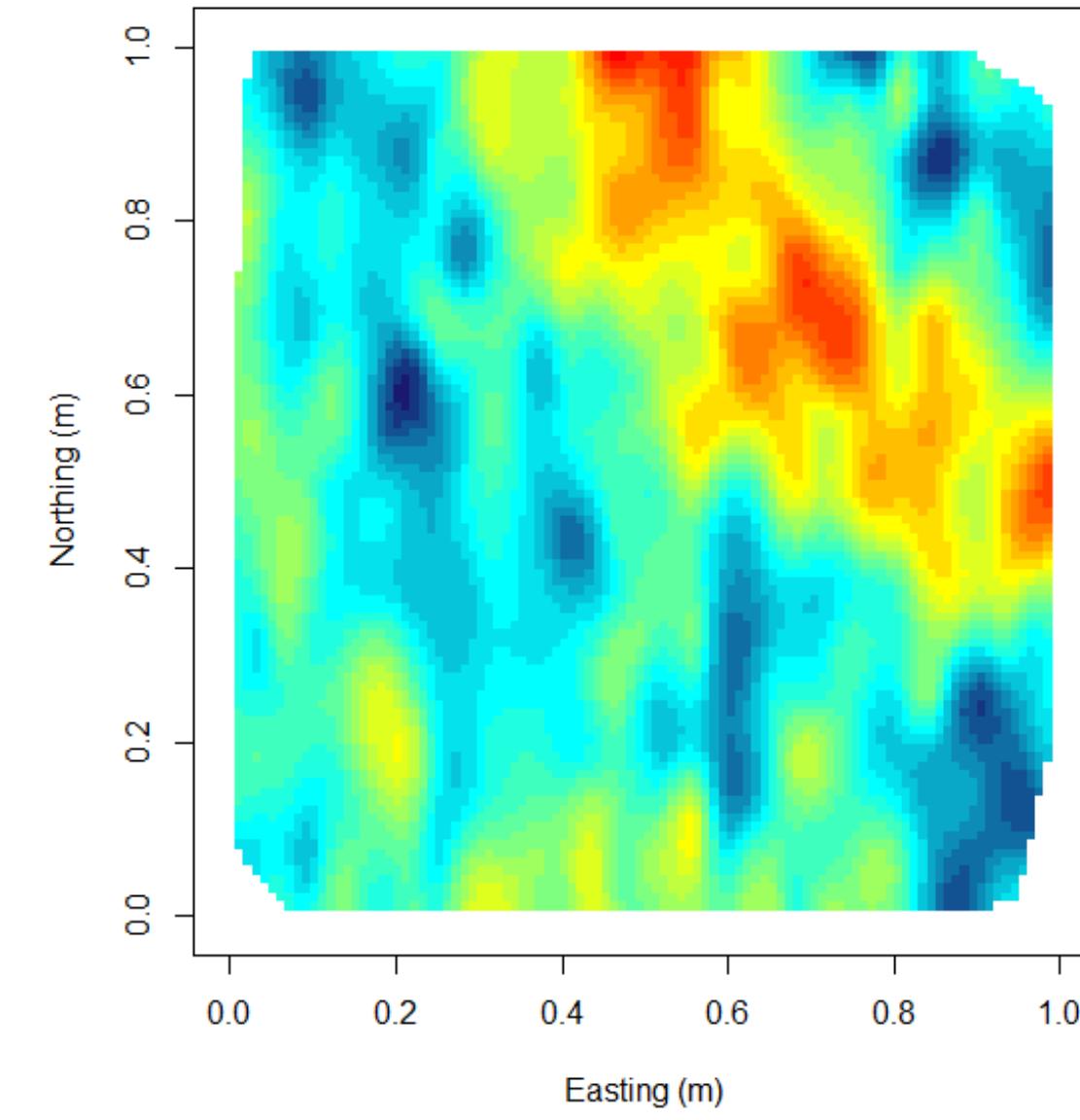
Empirical semi-variogram:

$\gamma(h)$  = Average of  $(Y(s_1) - Y(s_2))^2$  for all pairs  $s_1, s_2$  such that  $s_1 - s_2 \approx h$

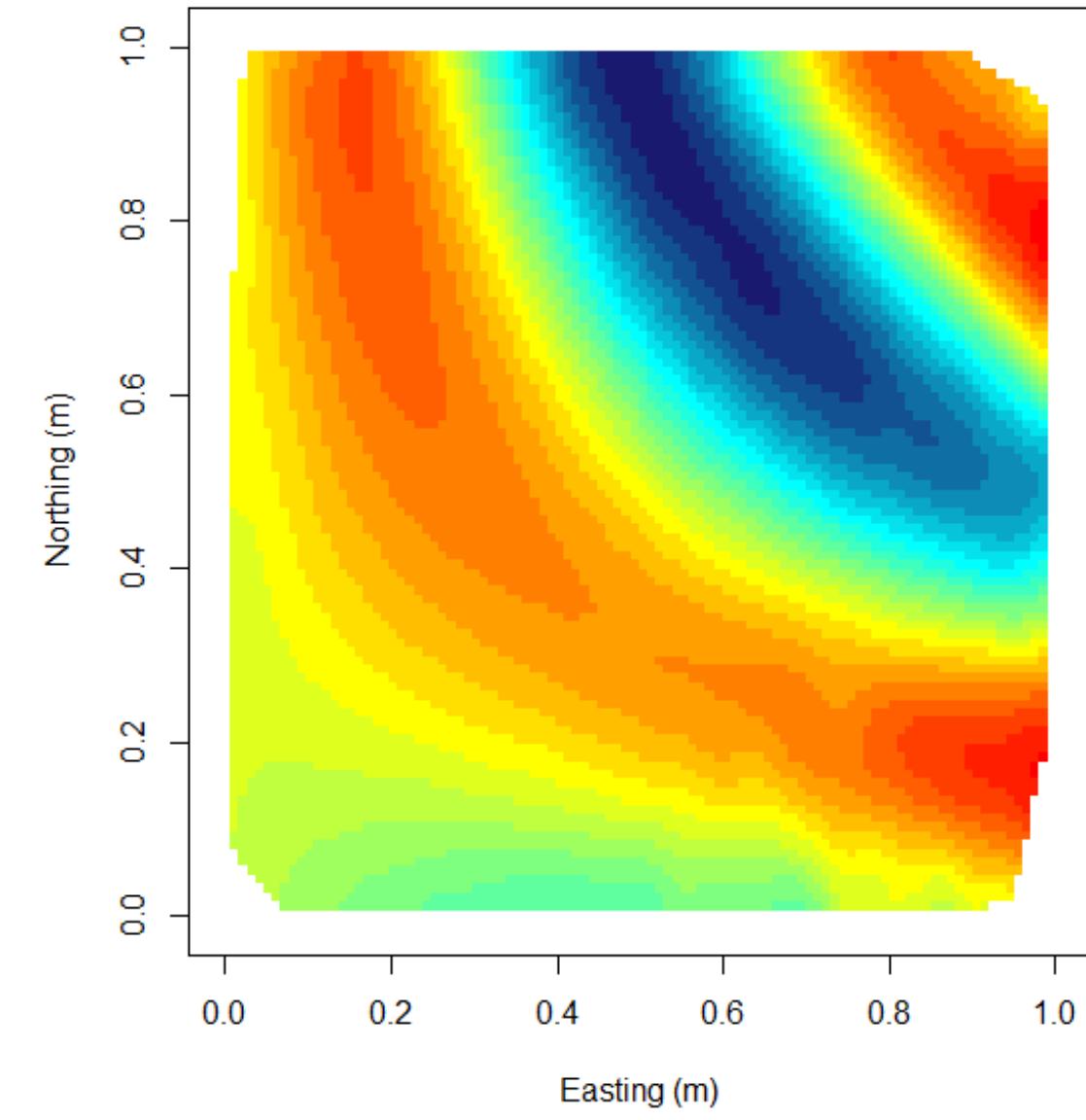
For spatial data, the  $\gamma(h)$  is expected to roughly increase with the distance  $h$   
A flat semivariogram would suggest little spatial variation

*variog* command in the *geoR* R-package calculates empirical semivariograms

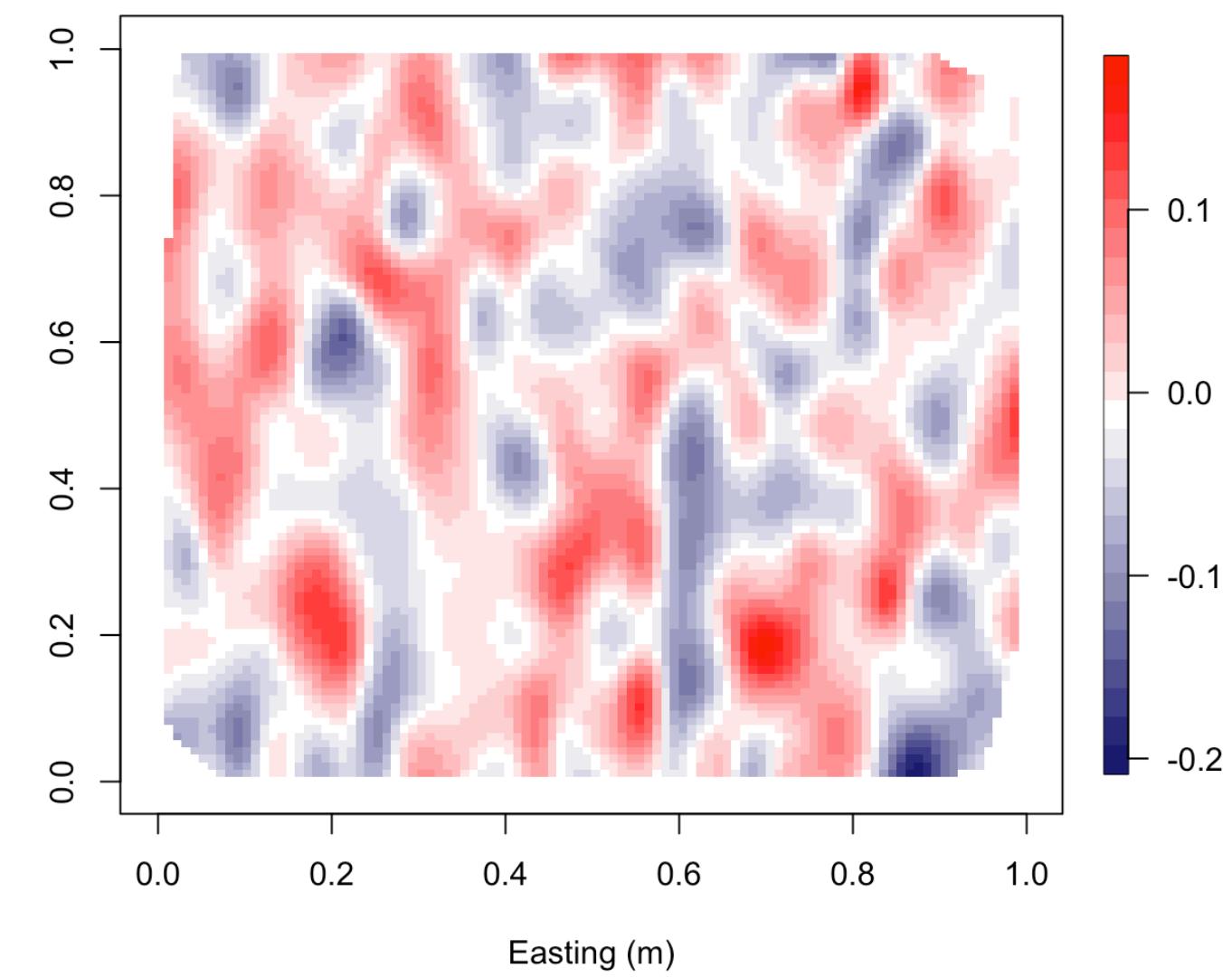
# Dataset 1



$Y(s)$

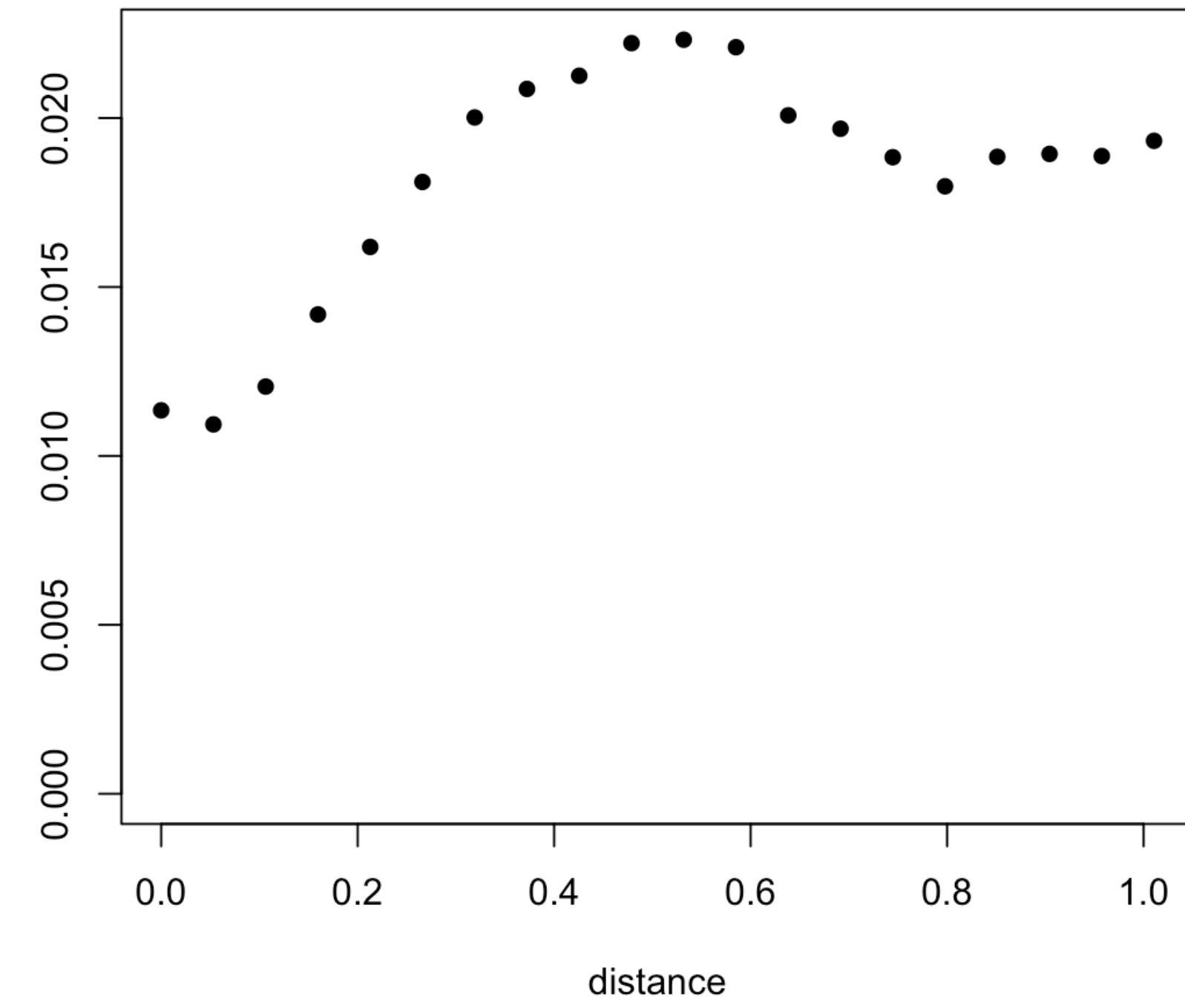


$X(s)$

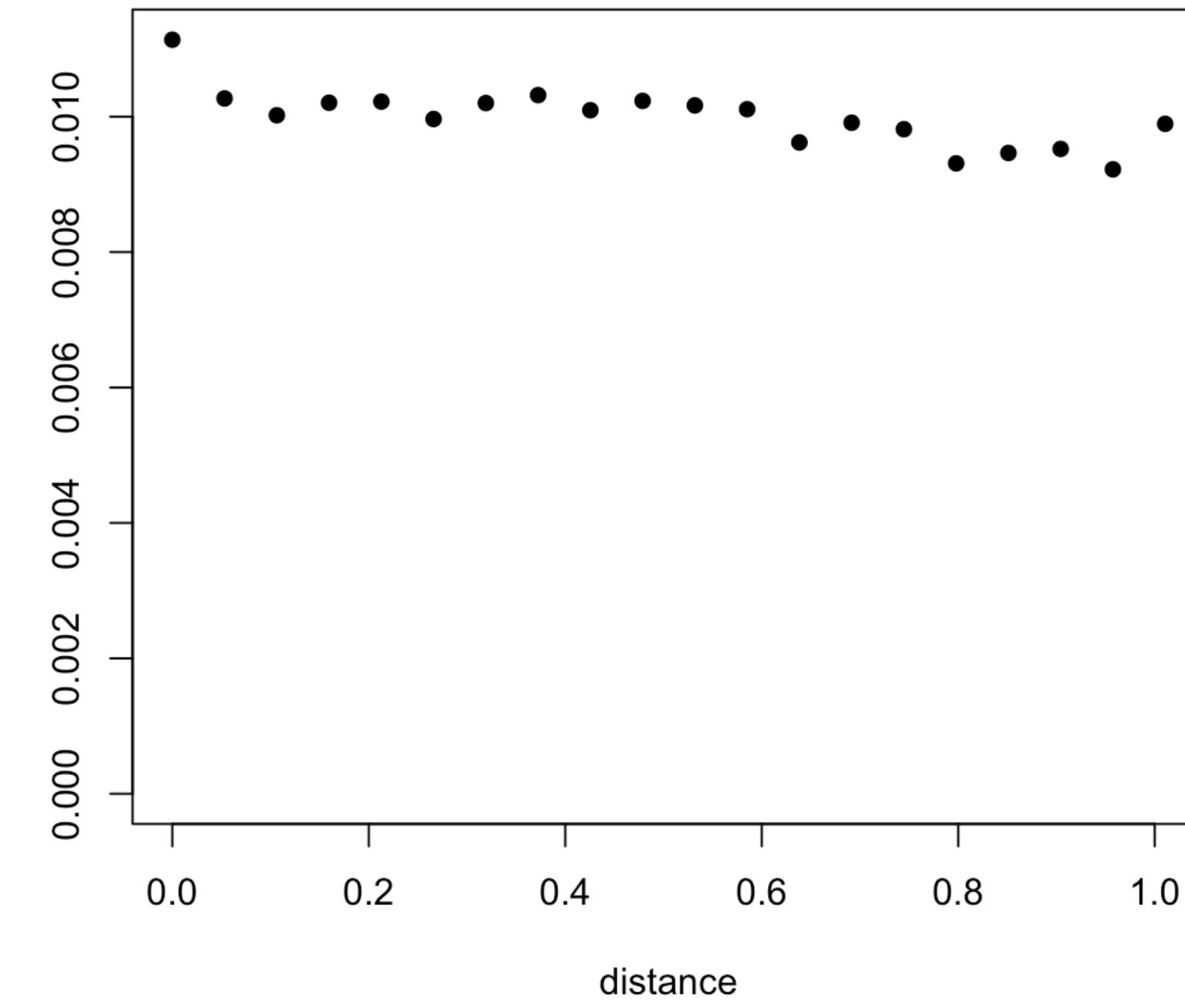


Residuals  $Y(s) - \hat{\beta}X(s)$

# Dataset 1



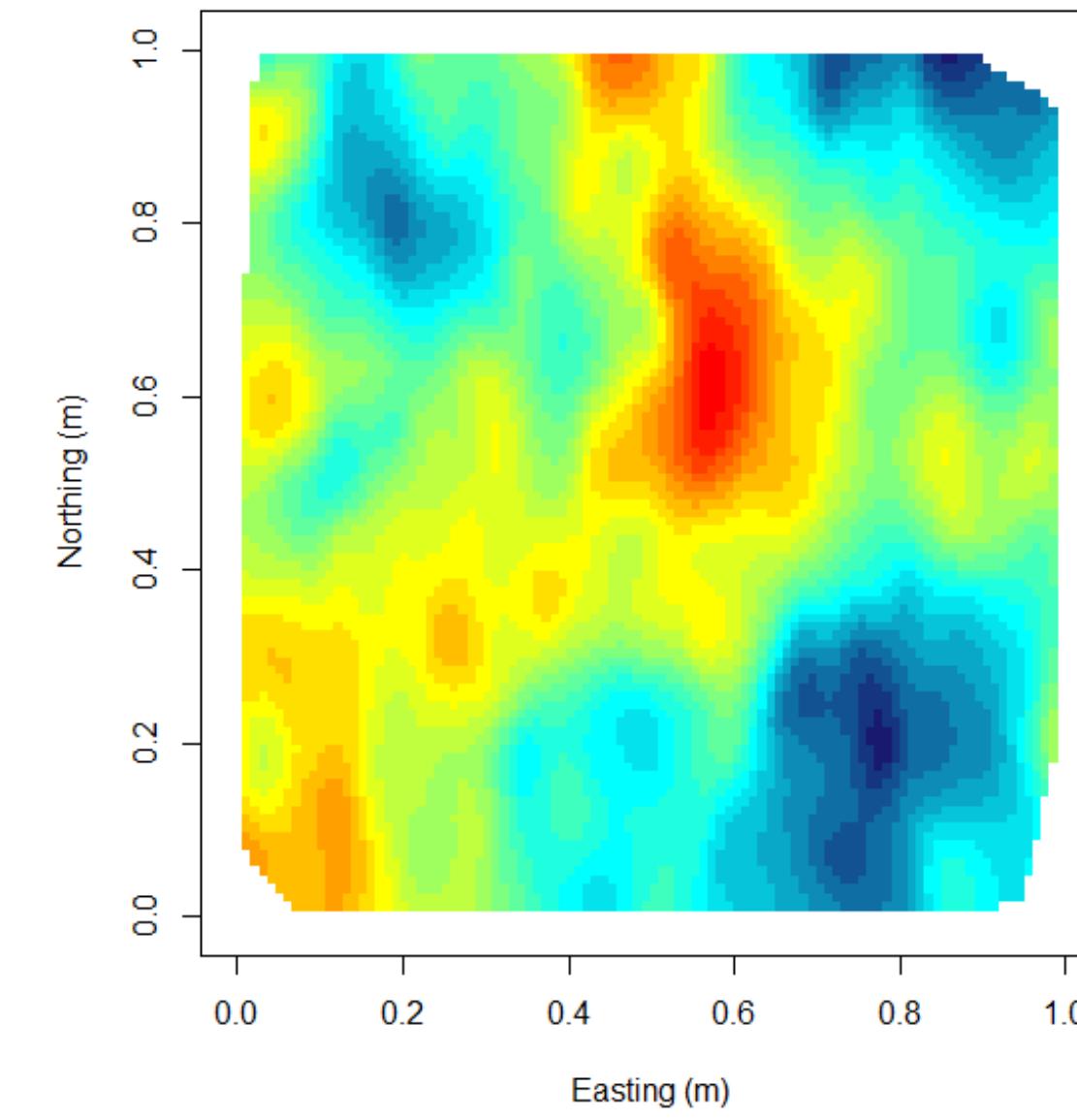
Variogram of  $Y(s)$



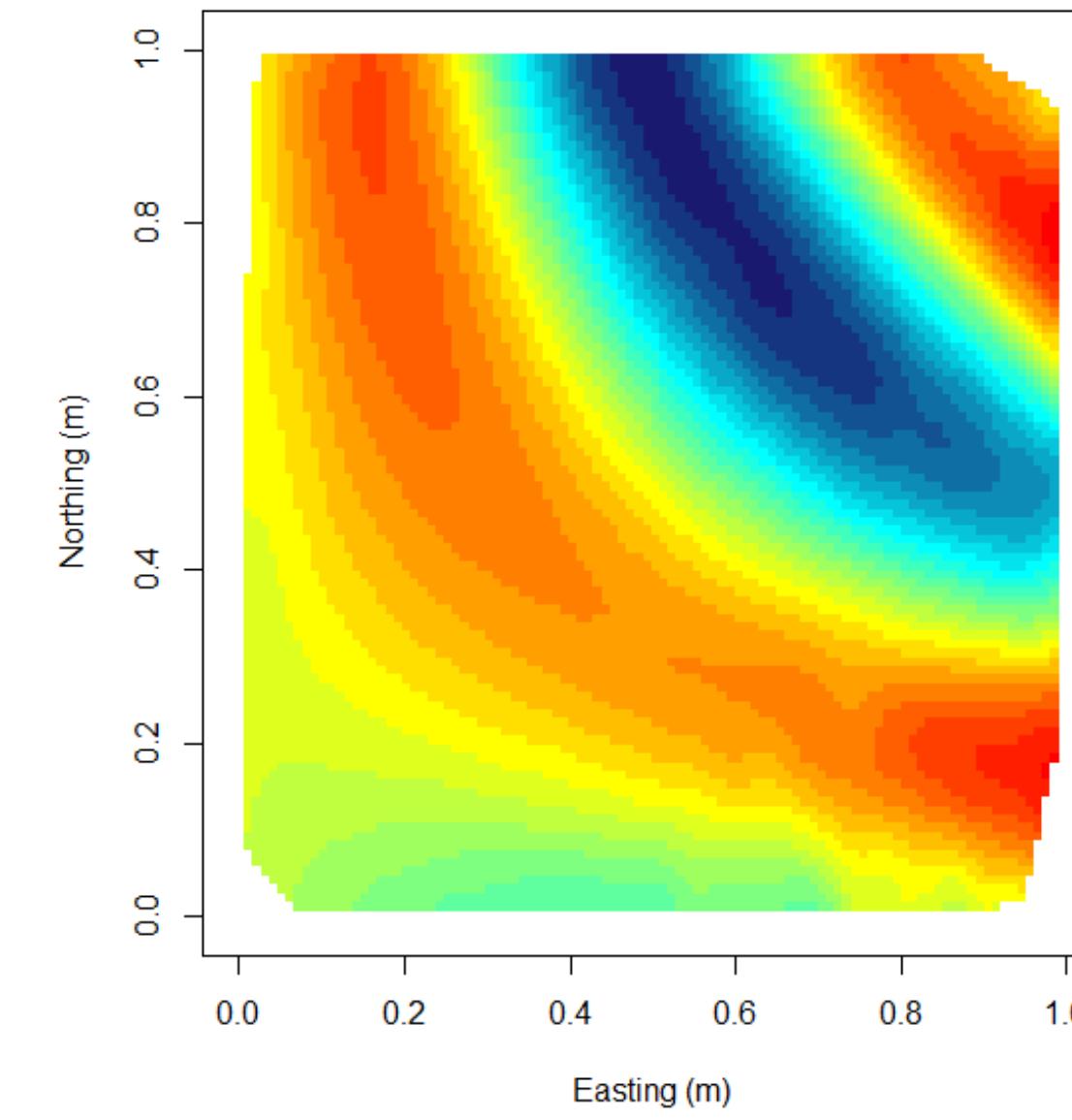
Variogram of residuals  
 $Y(s) - \hat{\beta}X(s)$

Variogram of residuals suggests very little spatial variation

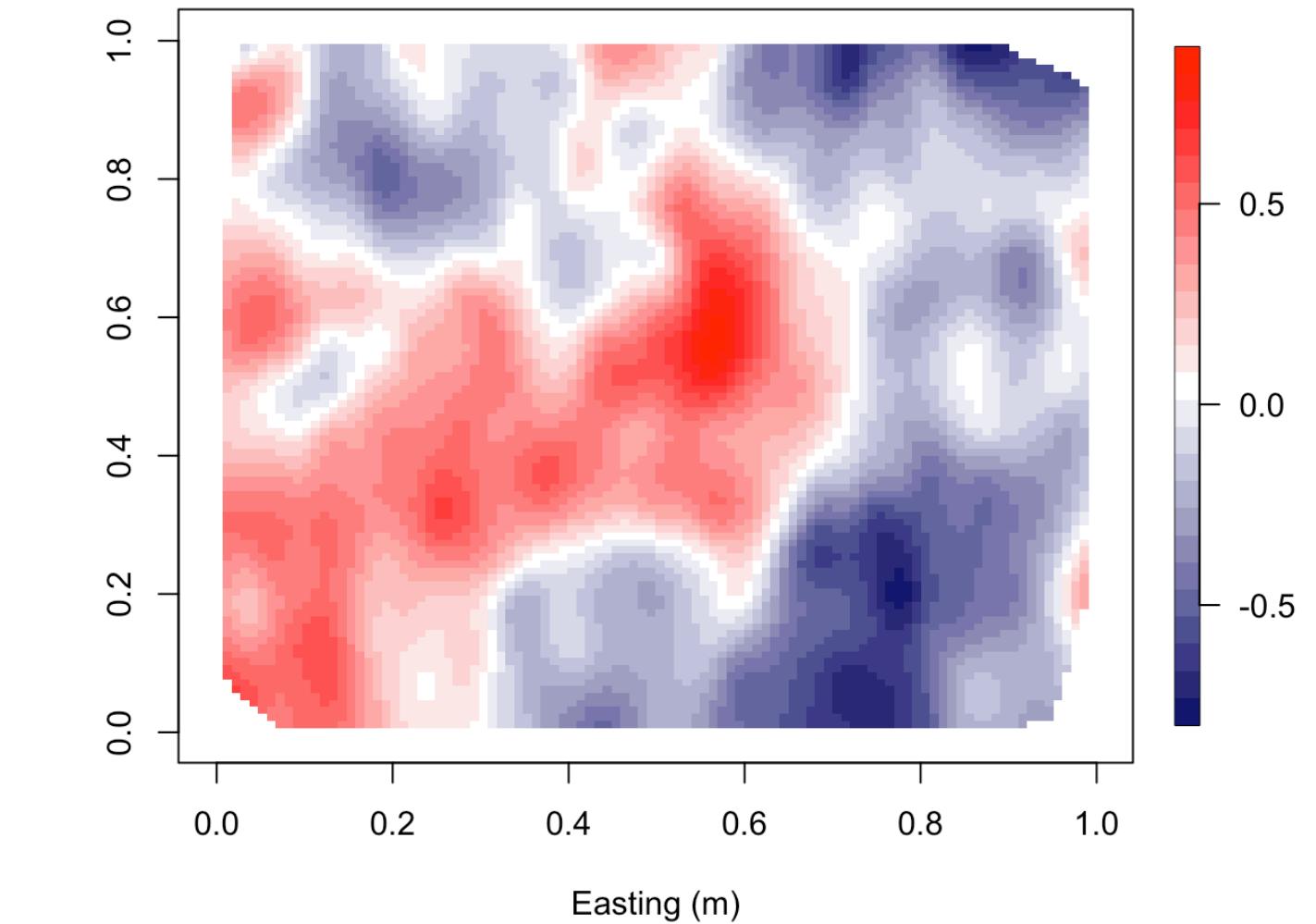
# Dataset 2



$Y(s)$

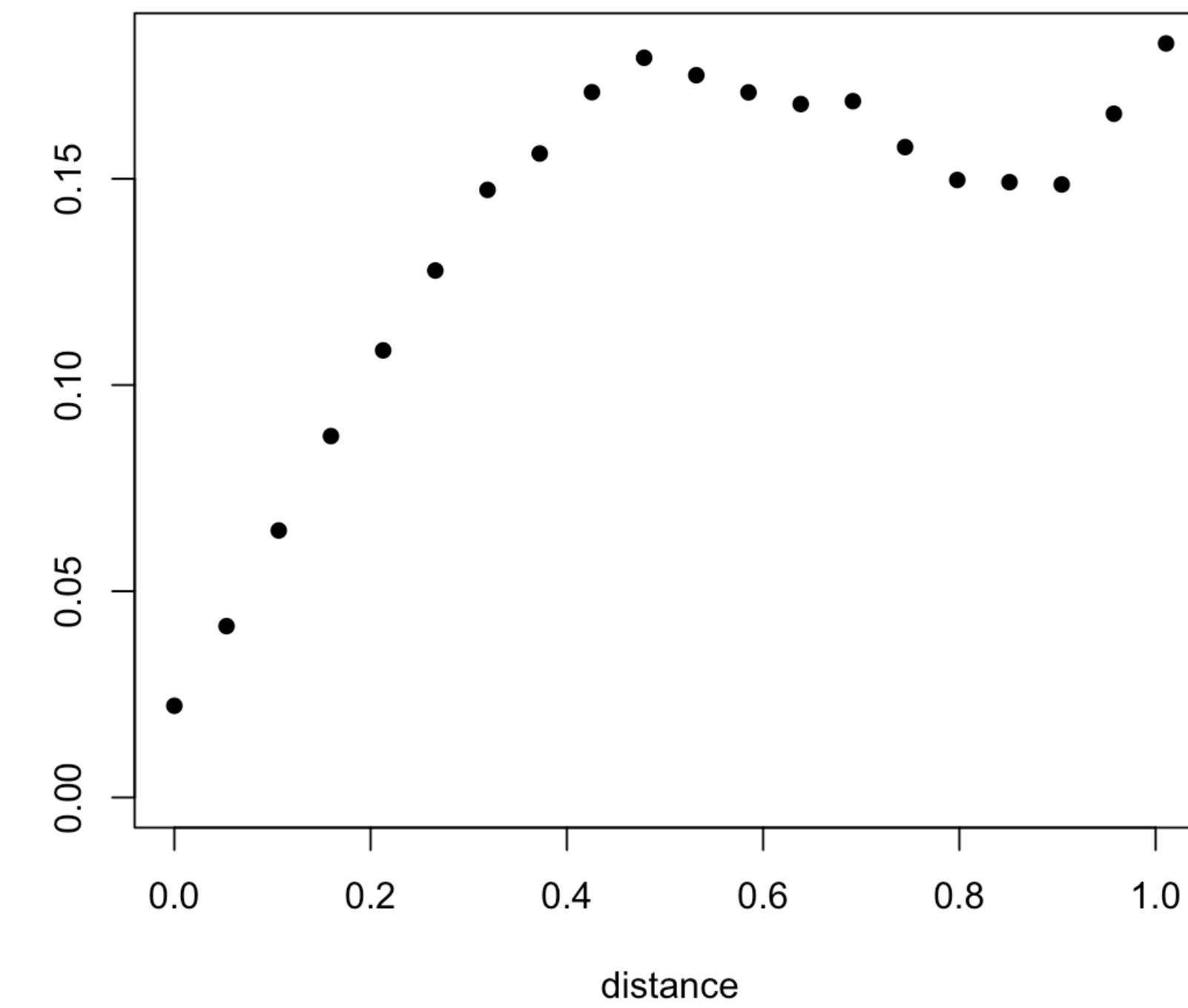


$X(s)$

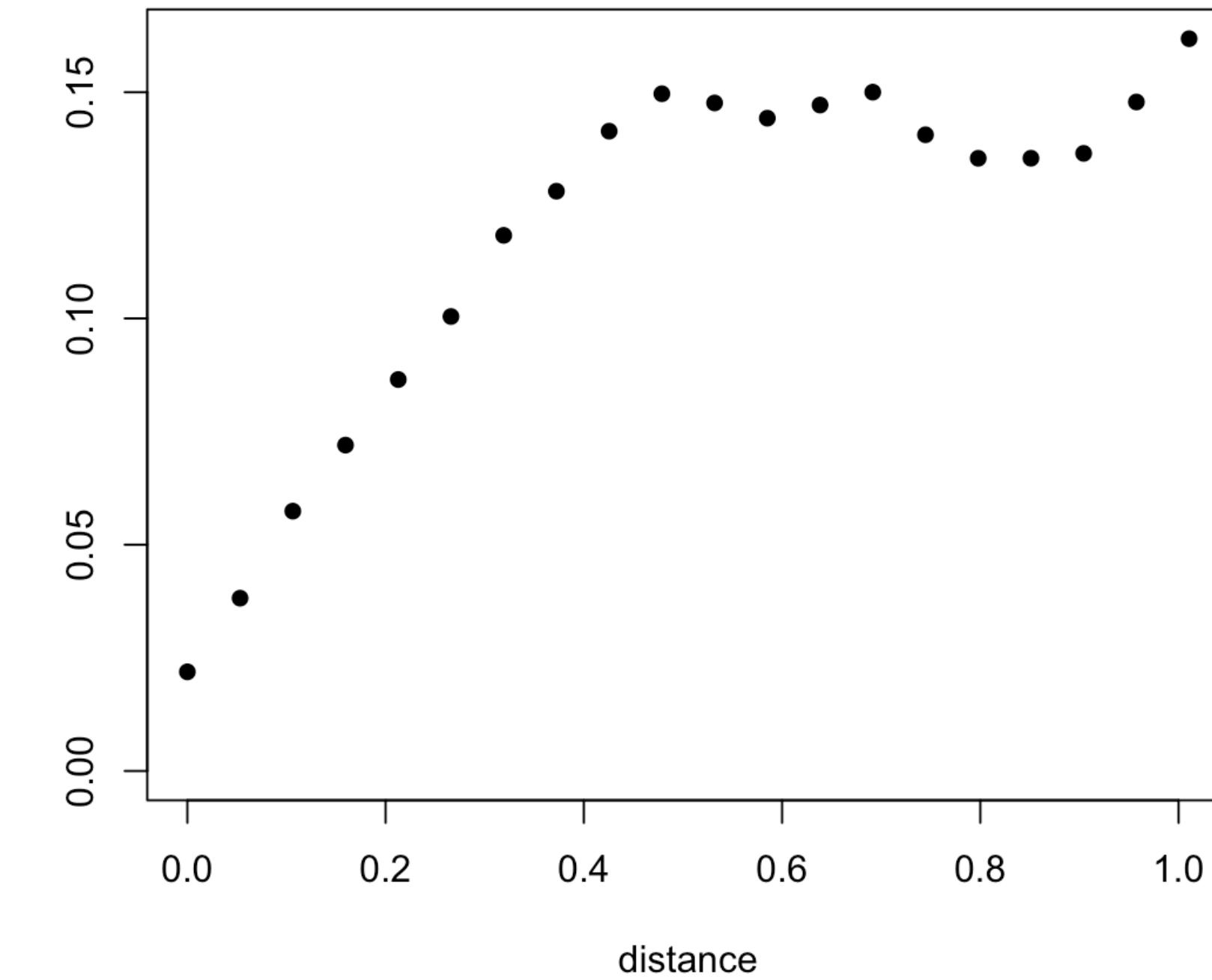


Residuals  $Y(s) - \hat{\beta}X(s)$

# Dataset 2



Variogram of  $Y(s)$



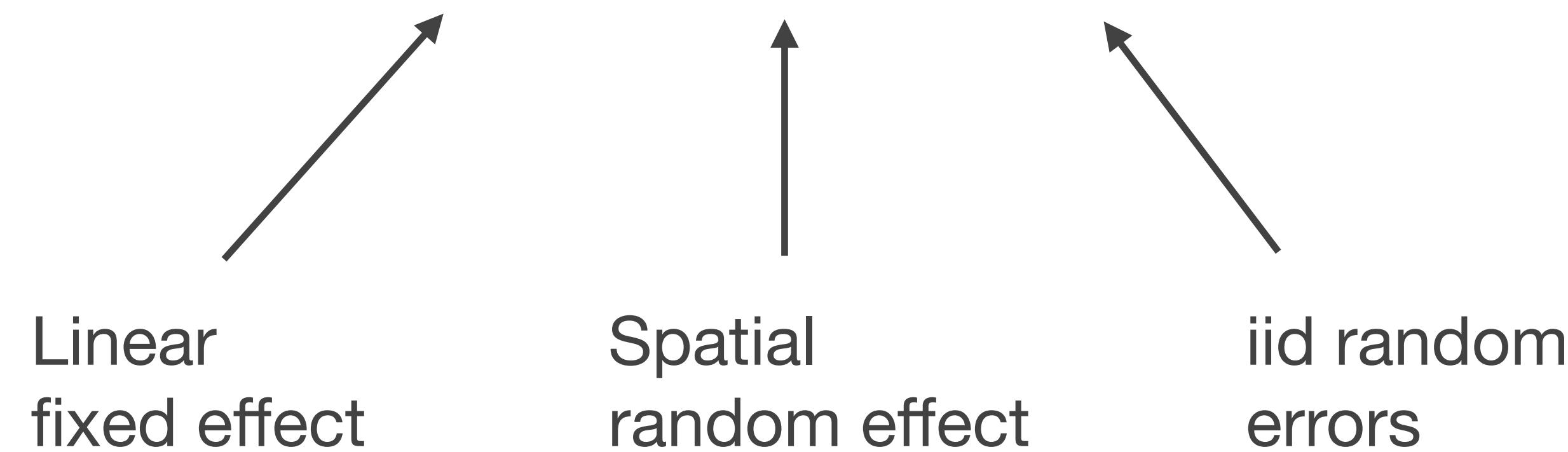
Variogram of residuals  
 $Y(s) - \hat{\beta}X(s)$

Variogram of residuals suggests residual spatial variation

# Spatial linear mixed effect models (SLMM)

When purely covariate based models does not suffice, one needs to leverage the information from locations

**SLMM:**  $Y(s_i) = X(s_i)'\beta + w(s_i) + \epsilon(s_i)$



$w(s_i)$  is introduced to model spatial patterns in  $Y(s_i)$  that is not explained by  $X(s_i)$

# Process-level model

Usually goal is predicting  $Y(s)$  at any location  $s$  in the domain  $D$

E.g., Conceptually pollutant level exists at all possible sites

**SLMM:**  $Y(s) = X(s)'\beta + w(s) + \epsilon(s)$  for any location  $s \in D$

Need to model  $w(s)$  as a smooth function or **stochastic process** over  $D$

Many approaches to model and estimate  $w(s)$ : basis function expansions, penalized regression splines, Gaussian Processes

# Gaussian processes

$w(s)$  is often modeled as a Gaussian Process (GP)

$$w(\cdot) \sim GP(0, C(\cdot, \cdot))$$

$$w = w(S) = (w(s_1), \dots, w(s_n))' \sim N(0, C)$$

$$C_{ij} = Cov(w(s_i), w(s_j)) = C(s_i, s_j)$$

# Gaussian processes

$$w(\cdot) \sim GP(0, C(\cdot, \cdot)),$$

$$w = w(S) = (w(s_1), \dots, w(s_n))' \sim N(0, C)$$

The covariance function models the spatial dependence

**Stationarity and Isotropy:**  $C(s_i, s_j) = C(\|h\|)$  where  $h = s_i - s_j$

# Gaussian processes

$$w(\cdot) \sim GP(0, C(\cdot, \cdot)),$$

$$w = w(S) = (w(s_1), \dots, w(s_n))' \sim N(0, C)$$

**Matérn covariance function:** A common, flexible family of covariances  $C$  specified using a spatial variance  $\sigma^2$ , spatial decay  $\phi$ , and smoothness  $\nu$

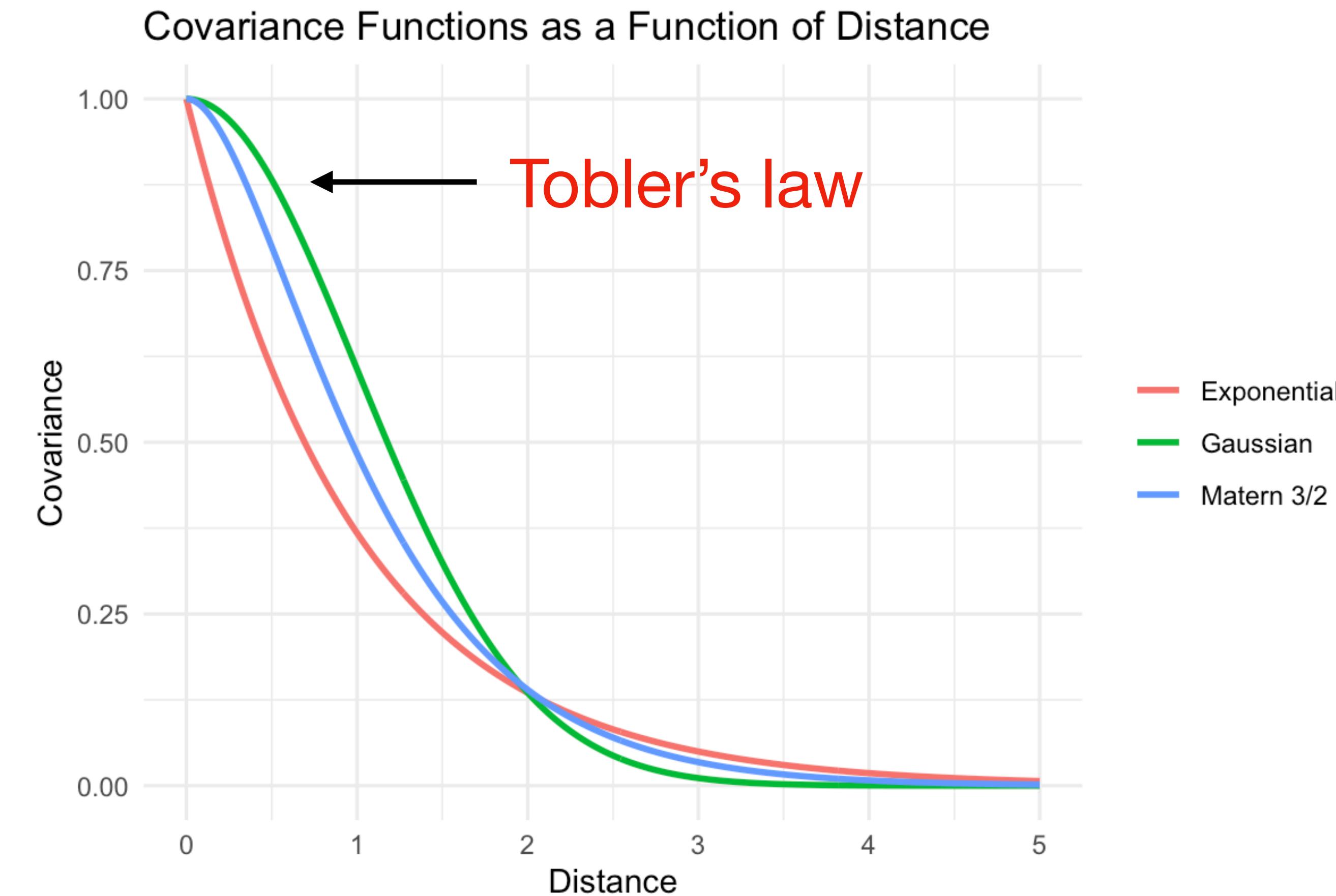
$$\nu = 1/2 \text{ (Exponential covariance): } C(\|h\|) = \sigma^2 \exp(-\phi \|h\|)$$

$$\nu = 3/2: C(\|h\|) = \sigma^2 (1 + \phi \|h\|) \exp(-\phi \|h\|)$$

$$\nu = \infty \text{ (Gaussian covariance): } C(\|h\|) = \sigma^2 \exp(-\phi \|h\|^2)$$

# Gaussian processes

Matérn covariance function:



# Gaussian processes

$$w(\cdot) \sim GP(0, C(\cdot, \cdot)),$$

$$w = w(S) = (w(s_1), \dots, w(s_n))' \sim N(0, C)$$

Estimation of covariance parameters using Gaussian likelihood maximization

**Process-level modeling:**  $w(s)$  is defined for any  $s$  in a region  $R$

Allow predictions at any location  $s_0$  via *kriging*

$$\begin{pmatrix} w(s_0) \\ w \end{pmatrix} \sim N\left(0, \begin{bmatrix} C(s_0, s_0) & C(s_0, S) \\ C(S, s_0) & C \end{bmatrix}\right)$$

$$w(s_0) \mid w \sim N(\mu(s_0), \nu(s_0))$$

# Gaussian processes

$$w(\cdot) \sim GP(0, C(\cdot, \cdot)),$$

$$w = w(S) = (w(s_1), \dots, w(s_n))' \sim N(0, C)$$

**Flexibility and robustness:**  $w(s)$  for suitable covariance functions  $C$  can non-parametrically model any smooth fixed function  $f(s)$  (van der Vaart 2008, 2011)

# Spatial linear mixed effect models (SLMM)

**SLMM:**  $Y(s_i) = X(s_i)'\beta + w(s_i) + \epsilon(s_i), i = 1, \dots, n$

$w(\cdot) \sim GP(0, C(\cdot, \cdot))$ ,  $C$  is Matérn covariance with parameters  $\sigma^2, \phi, \nu$

$w = w(S) = (w(s_1), \dots, w(s_n))' \sim N(0, C)$

$\epsilon(s_i) \sim_{\text{iid}} N(0, \tau^2)$ ,  $\tau^2$  is often called the *nugget*

# Spatial linear mixed effect models (SLMM)

Marginal model:  $Y \sim N(X\beta, C + \tau^2 I)$

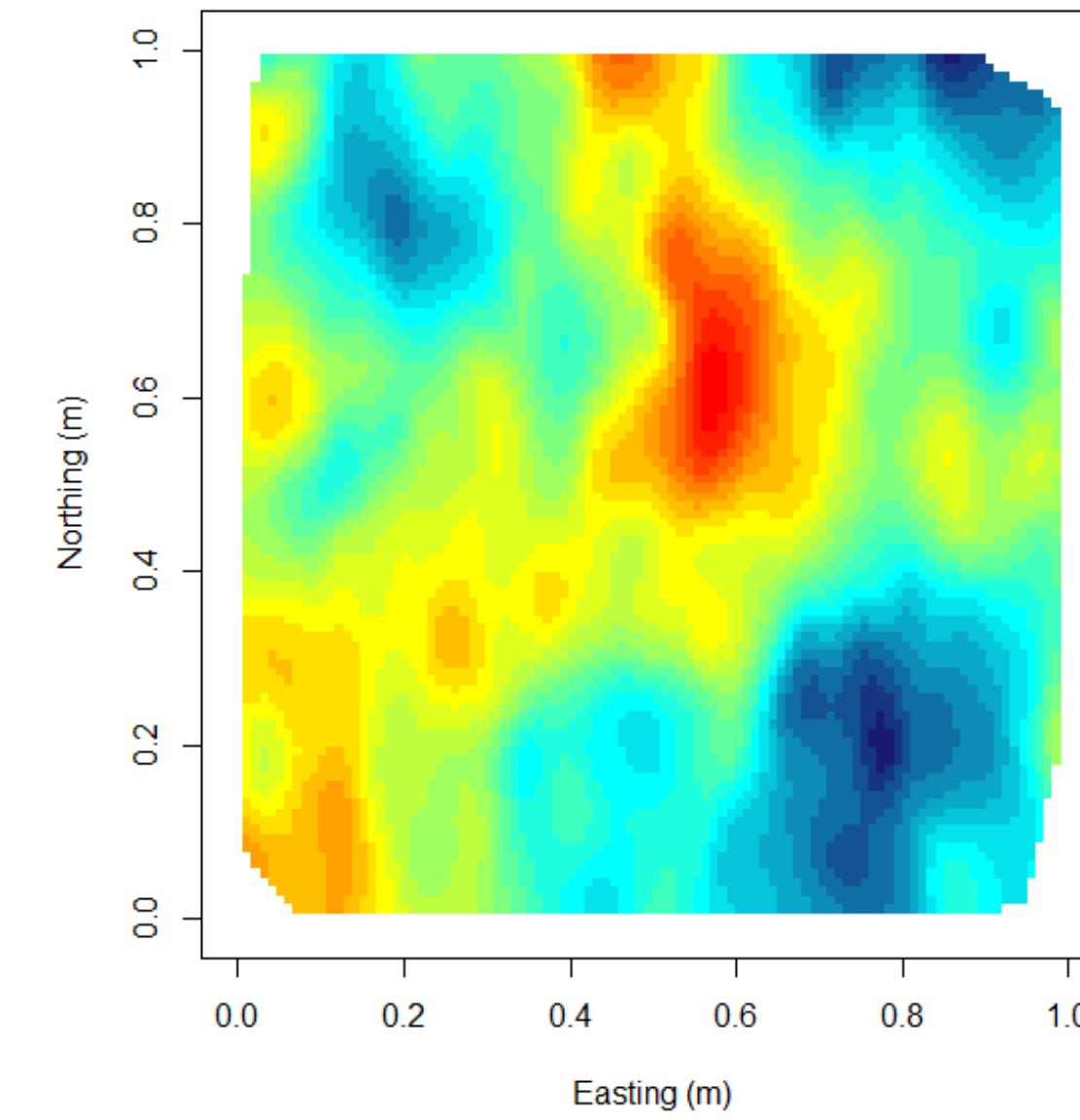
Parameters: Regression coefficient  $\beta$  and covariance parameters  $\theta = (\tau^2, \sigma^2, \phi, \nu)$

Estimates using maximum likelihood estimation (MLE)

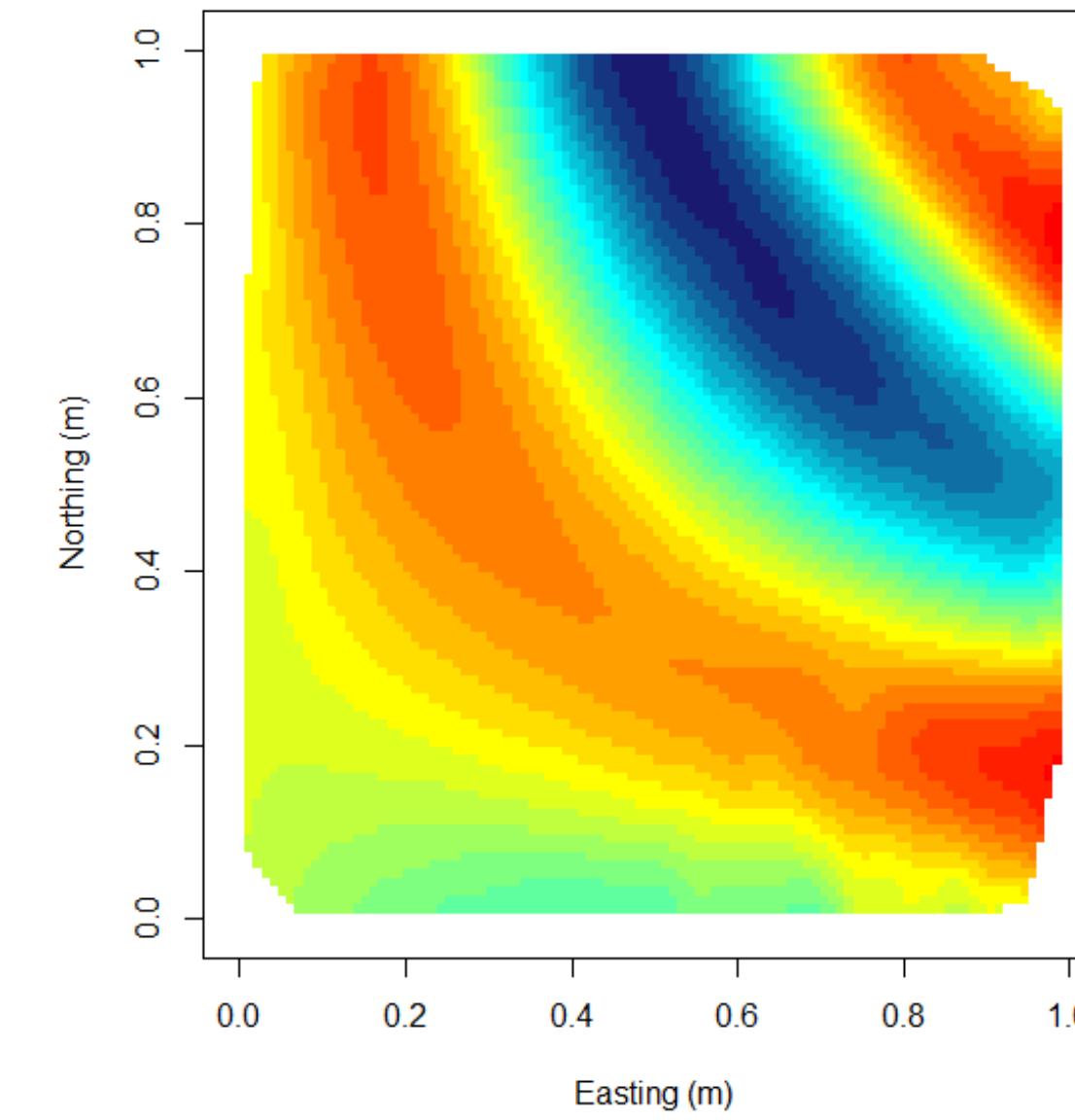
Predictions at a new location using kriging

Based on the conditional normal distribution of  $Y(s_0) | Y$

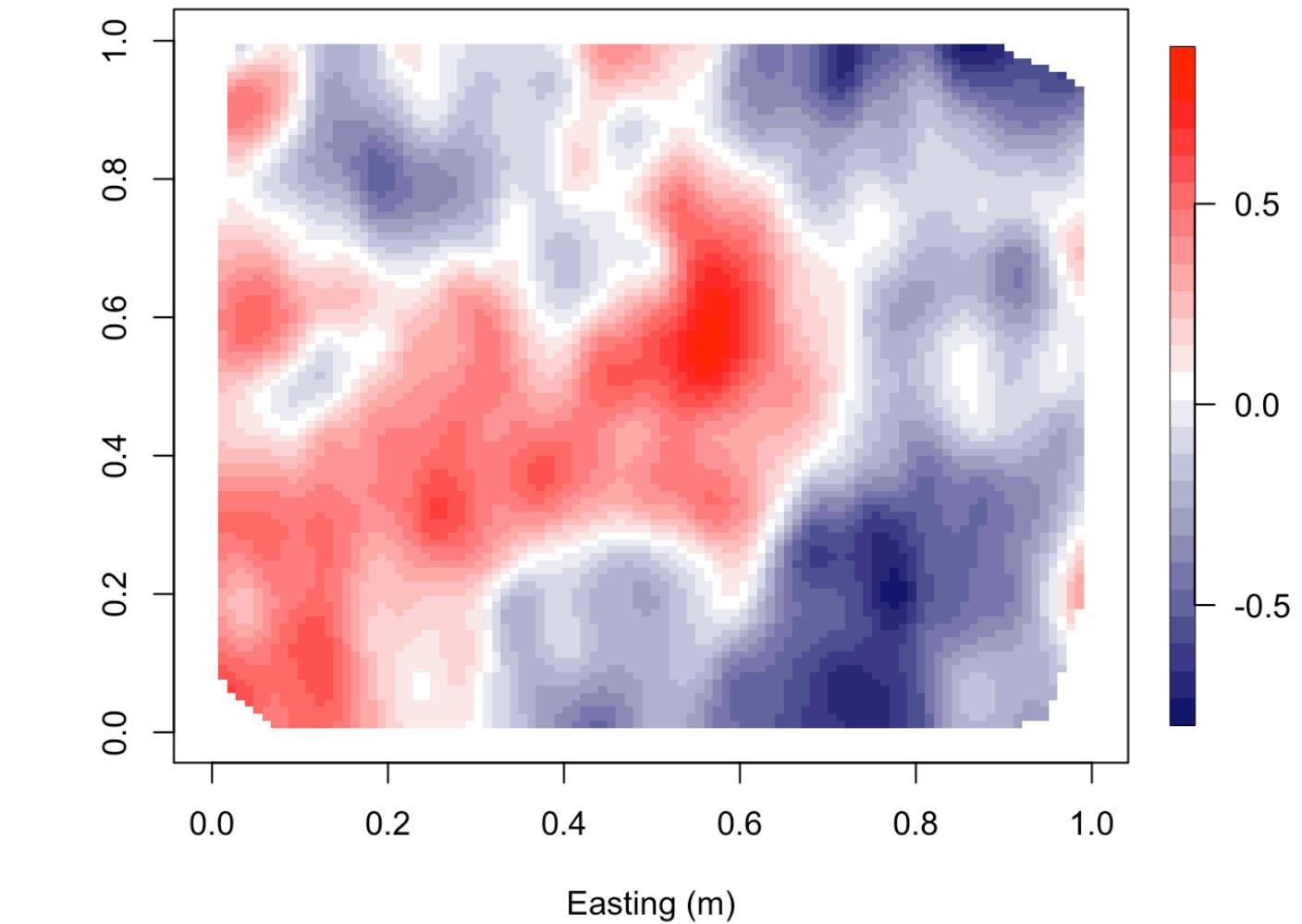
# Dataset 2



$Y(s)$



$X(s)$



Residuals  $Y(s) - \hat{\beta}X(s)$

# Dataset 2

**Model:**  $Y \sim N(X^* \beta^*, C + \tau^2 I)$ ,  $X^* = [1 : X]$ ,  $\beta^* = (\beta'_0, \beta'_1)'$

Parameters estimated using *likfit* function of geoR package

Parameter	Value
$\beta_0$	0.68
$\beta_1$	-0.50
$\tau^2$	0.01
$\sigma^2$	0.14
$\phi^{[1]}$	0.26
$\nu^{[2]}$	0.5

<sup>[1]</sup> In geoR,  $\phi$  is the inverse of our definition of  $\phi$

<sup>[2]</sup> Fixed at 0.5, i.e., using the exponential covariance

# Dataset 2

**Model comparison** metrics: Akaike Information Criterion (**AIC**) and Bayes Information Criterion (**BIC**)

Lower values better

AIC and BIC values are available from the output of `likfit`

	<b>AIC</b>	<b>BIC</b>
<b>Model with Spatial</b>	-146.1	-126.1
<b>Model without Spatial</b>	324.1	336.1

Spatial model is clearly favored

# Dataset 2

**Prediction:** Available from `krige.conv` function of geoR

Data split:

80% for estimation of parameters (`train`),  
20% for validation of predictions (`test`)

# Dataset 2

## Prediction metrics:

Root mean square prediction error (**RMSPE**)

$$= \sqrt{\frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (y_i - \hat{y}_i)^2}$$

Compares the point predictions  $\hat{y}_i$

Lower values is better

# Dataset 2

## Prediction metrics:

Mean coverage probability (**CP**) of 95% prediction intervals

$$= \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} I(y_i \in (\hat{y}_{i,0.025}, \hat{y}_{i,0.975}))$$

Evaluates the coverage of the interval predictions  $(\hat{y}_{i,0.025}, \hat{y}_{i,0.975})$

Ideally should be close to 95%

Otherwise we will have under or over coverage

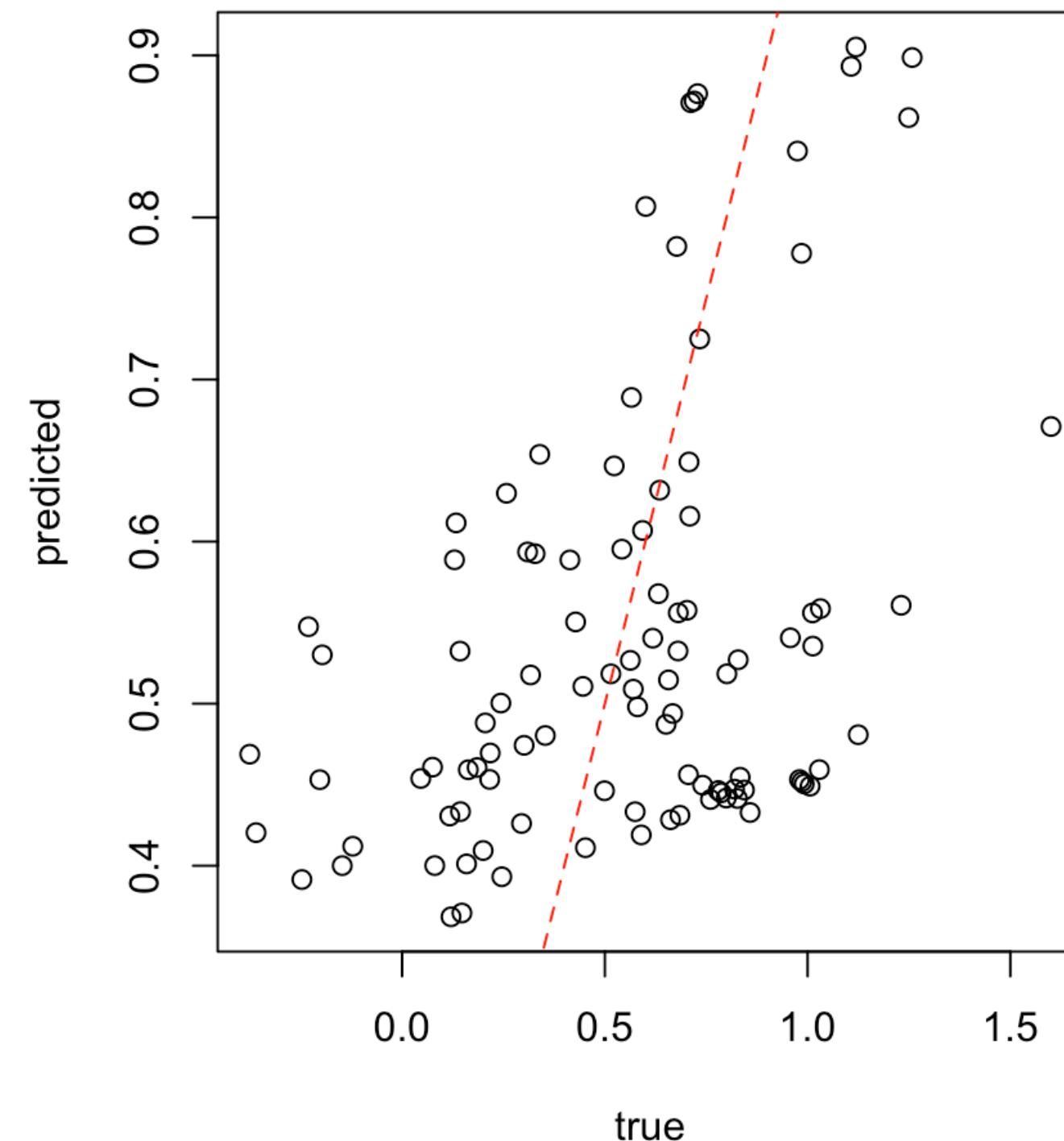
$$\text{Mean prediction interval width (**PIW**)} = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (\hat{y}_{i,0.975} - \hat{y}_{i,0.025})$$

If  $\text{CP} \approx 0.95$ , then smaller PIW is better

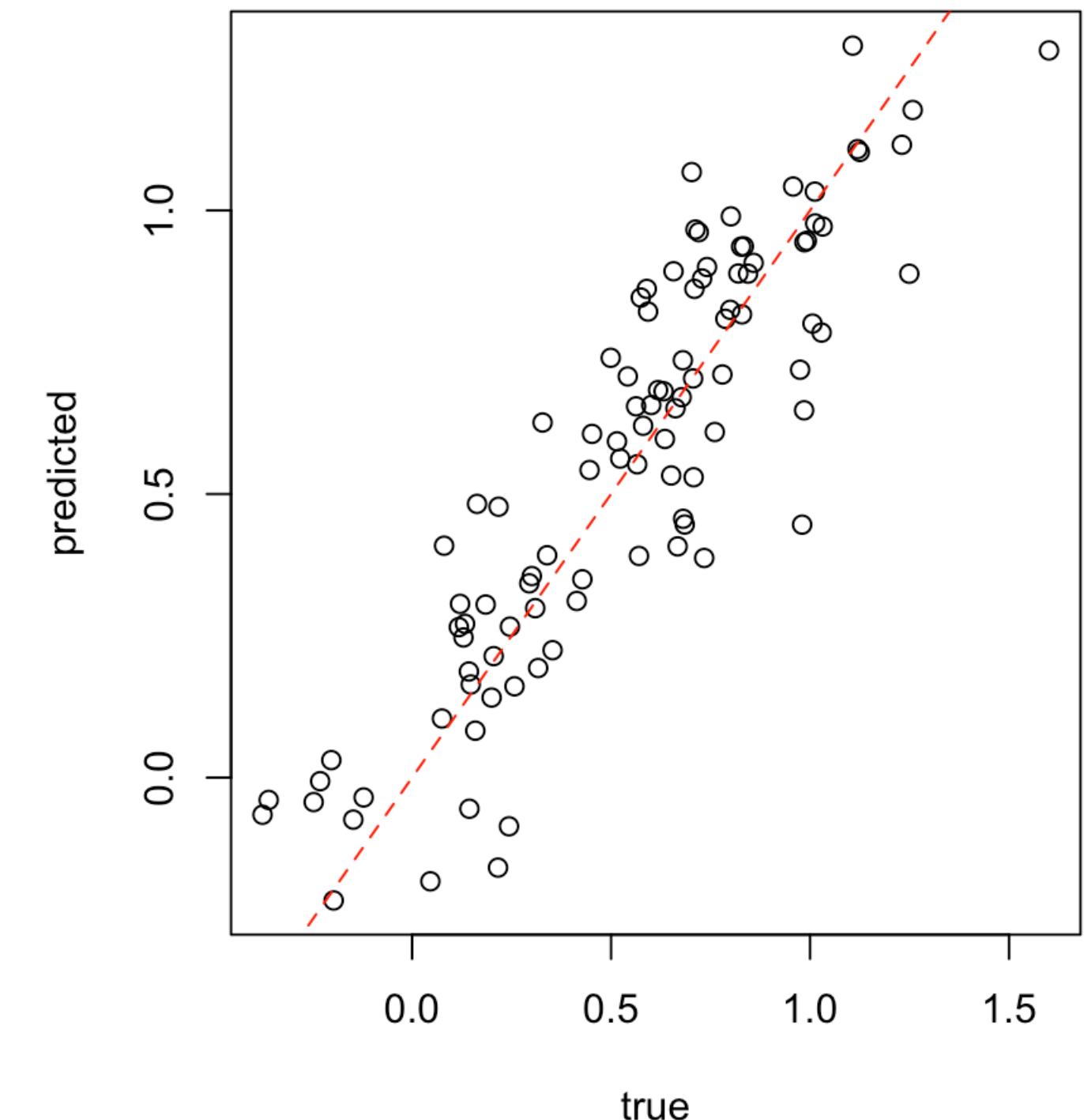
# Dataset 2

## Prediction:

Metric	Spatial	Non-Spatial
RMSPE	0.18	0.36
CP	0.95	0.95
PIW	0.68	1.42



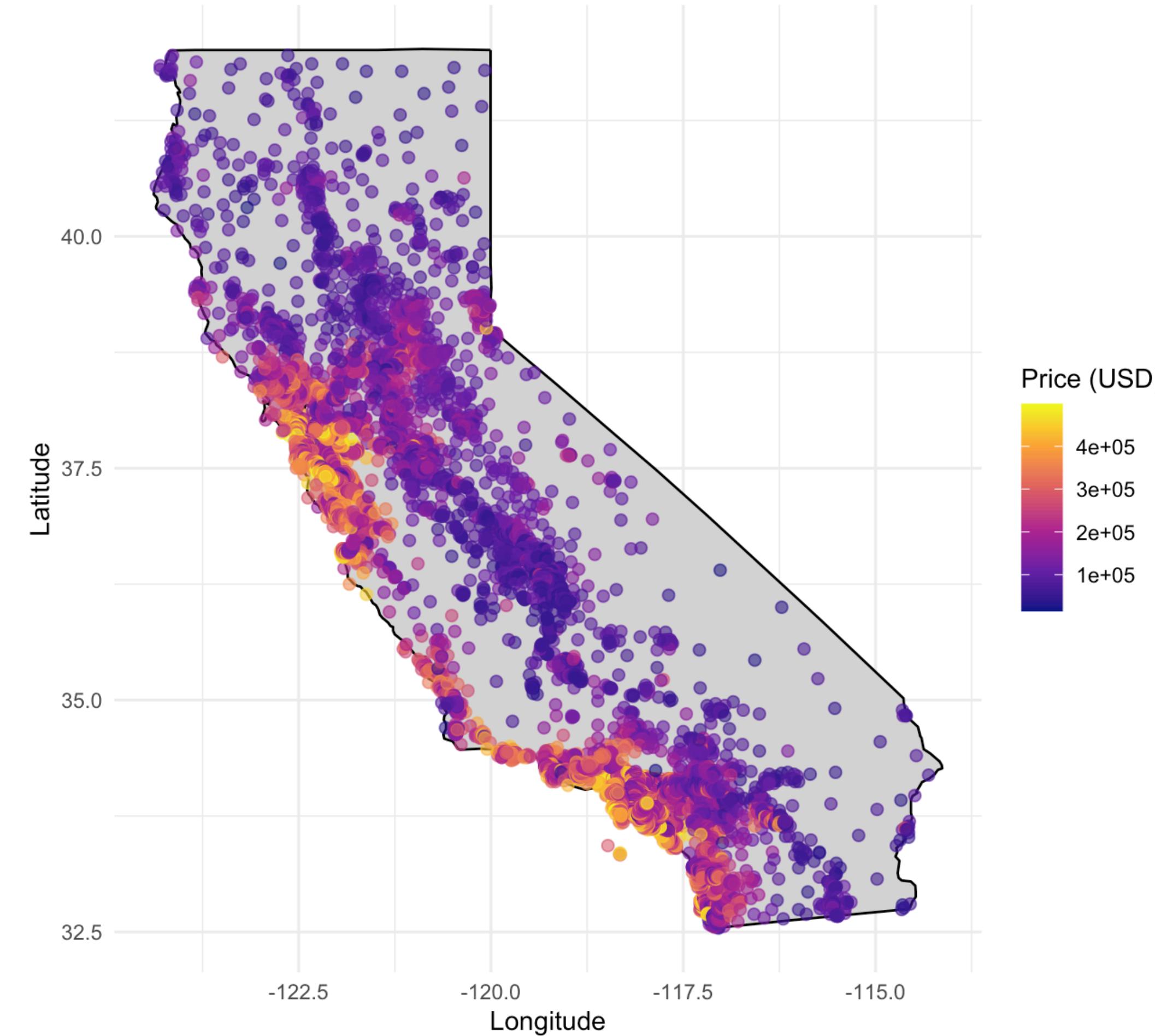
Non-spatial model fit  
on test data



Spatial model fit  
on test data

# House prices in California

Housing Data in California



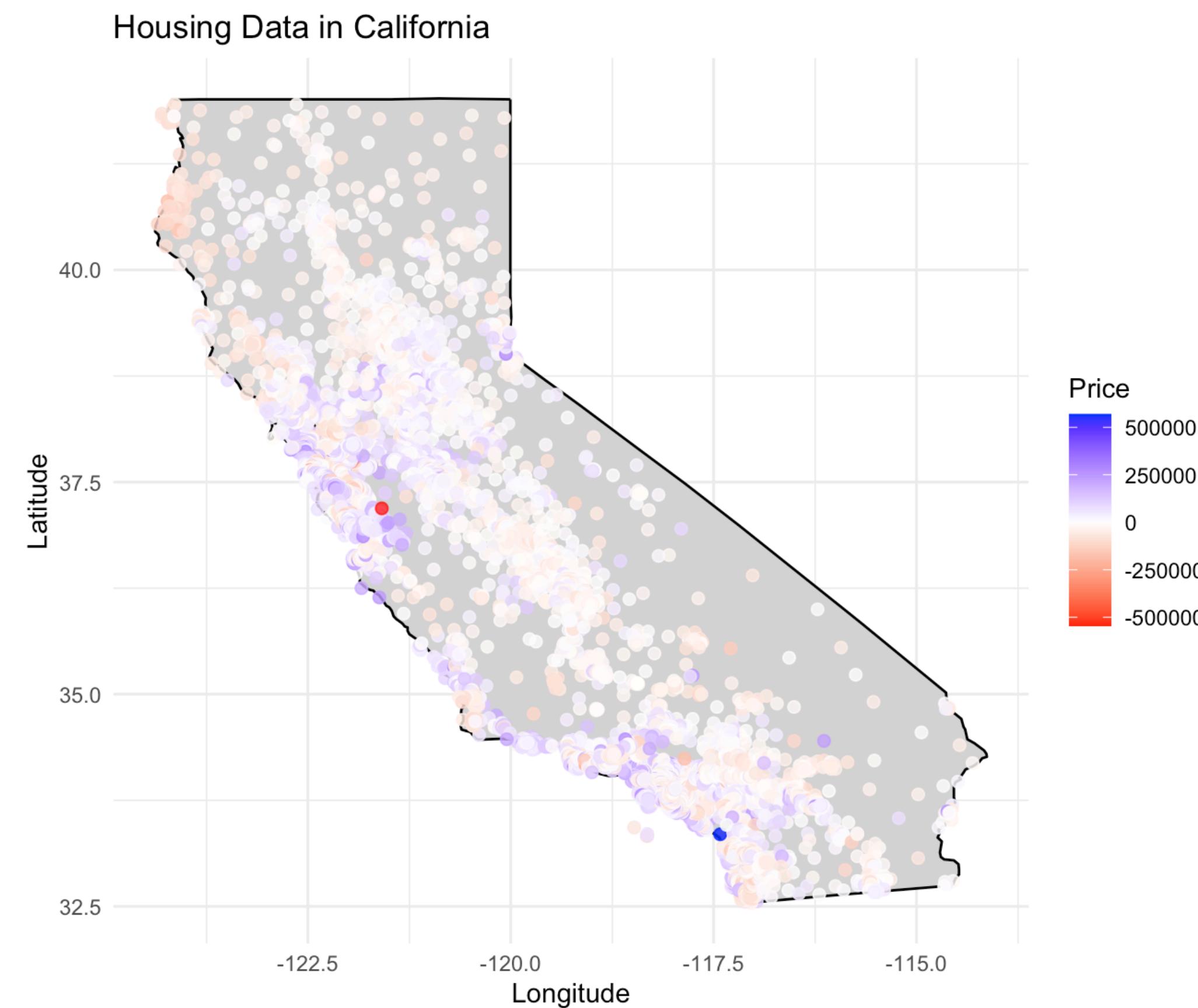
Covariates:

- Median income
- Median house age
- Total rooms
- Total bedrooms
- Population
- Number of Households
- Ocean proximity

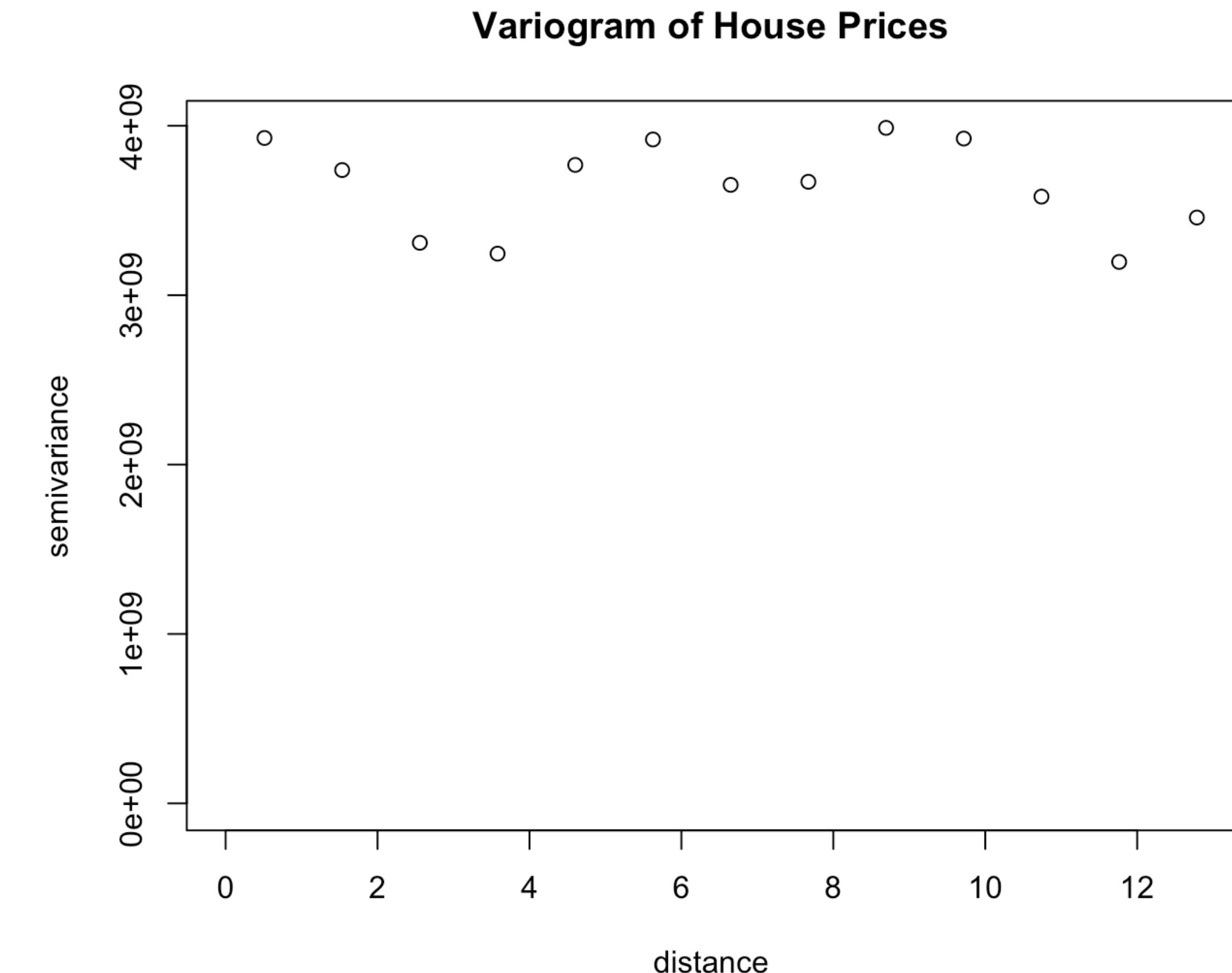
Data available on [Kaggle.com](https://www.kaggle.com)

# House prices in California

## Linear model analysis



Map of residuals



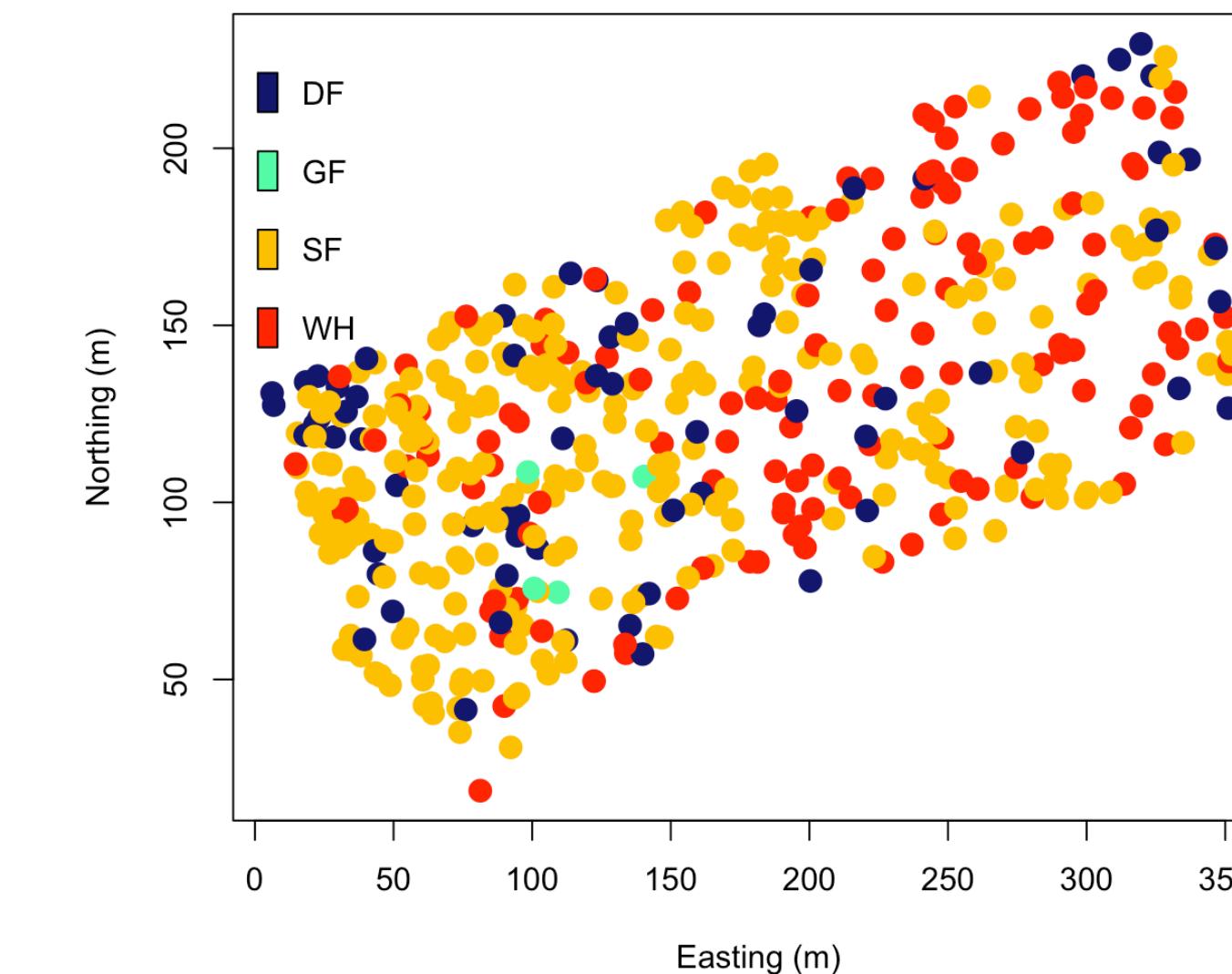
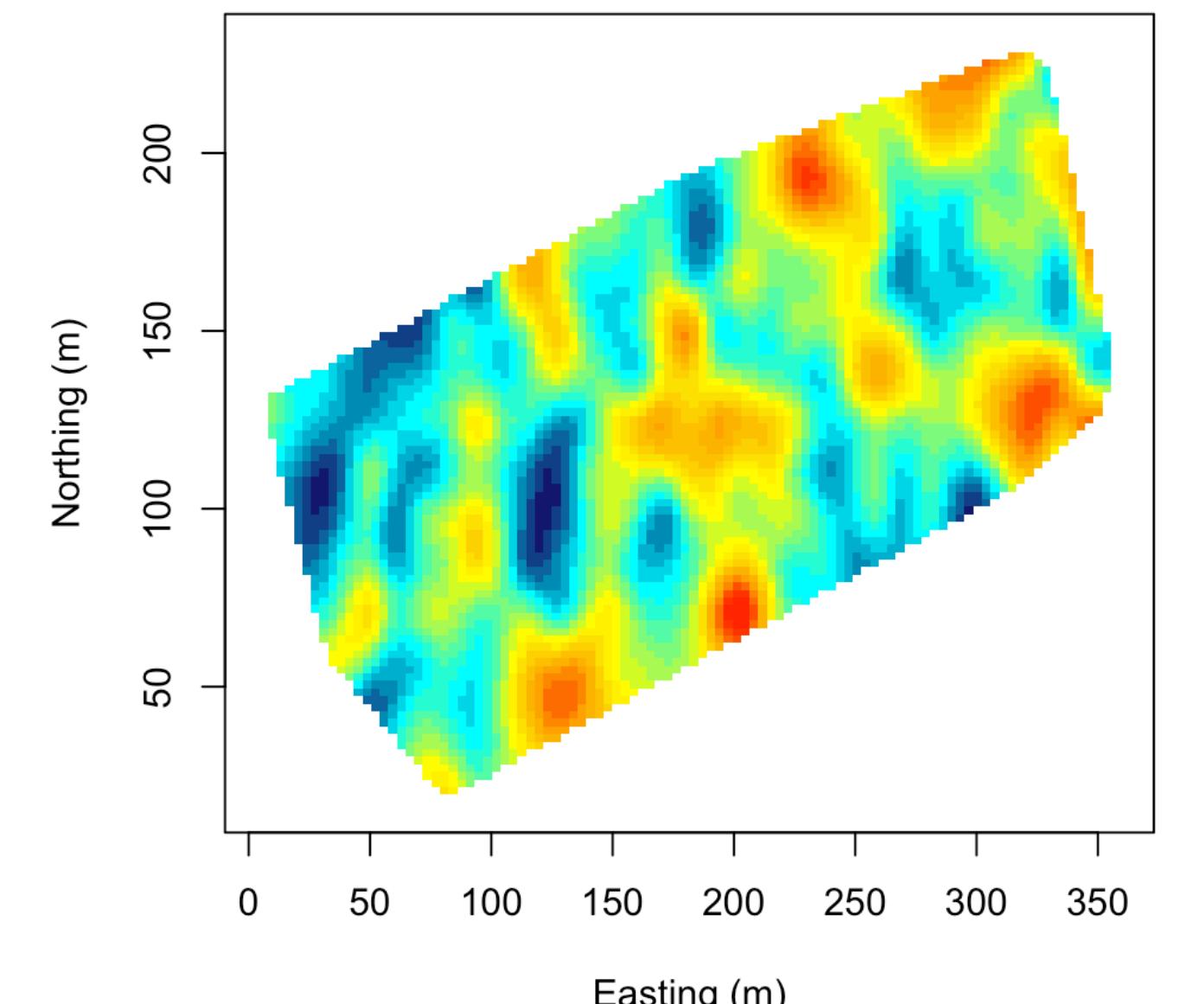
Variogram of residuals

# Western Experimental Forestry (WEF) data

Data from *spBayes* package on census of all trees in a 10 ha. stand in Oregon

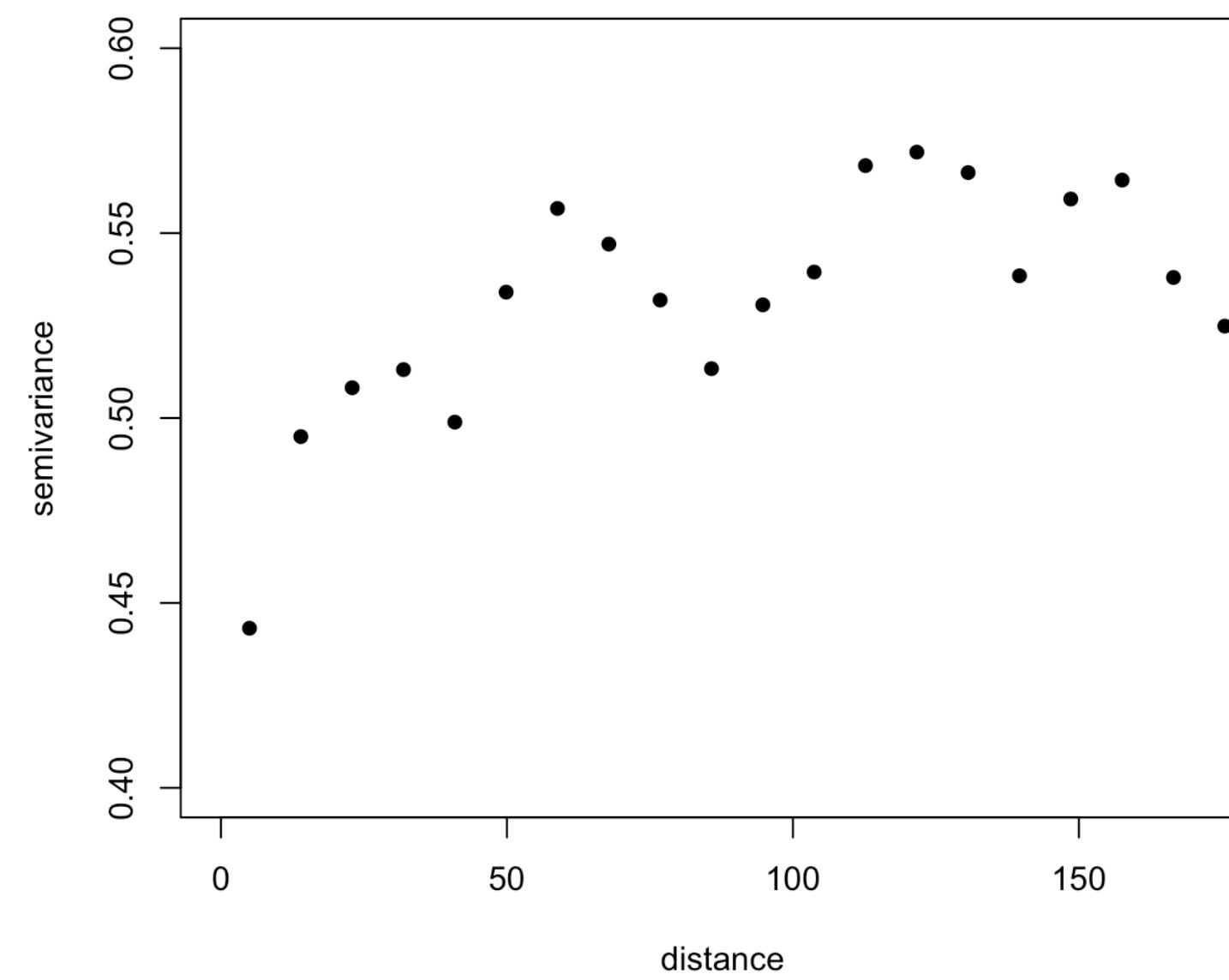
Response of interest: log(Diameter at breast height), i.e., log(DBH)

Covariate: Tree species (Categorical variable based on 4 species)

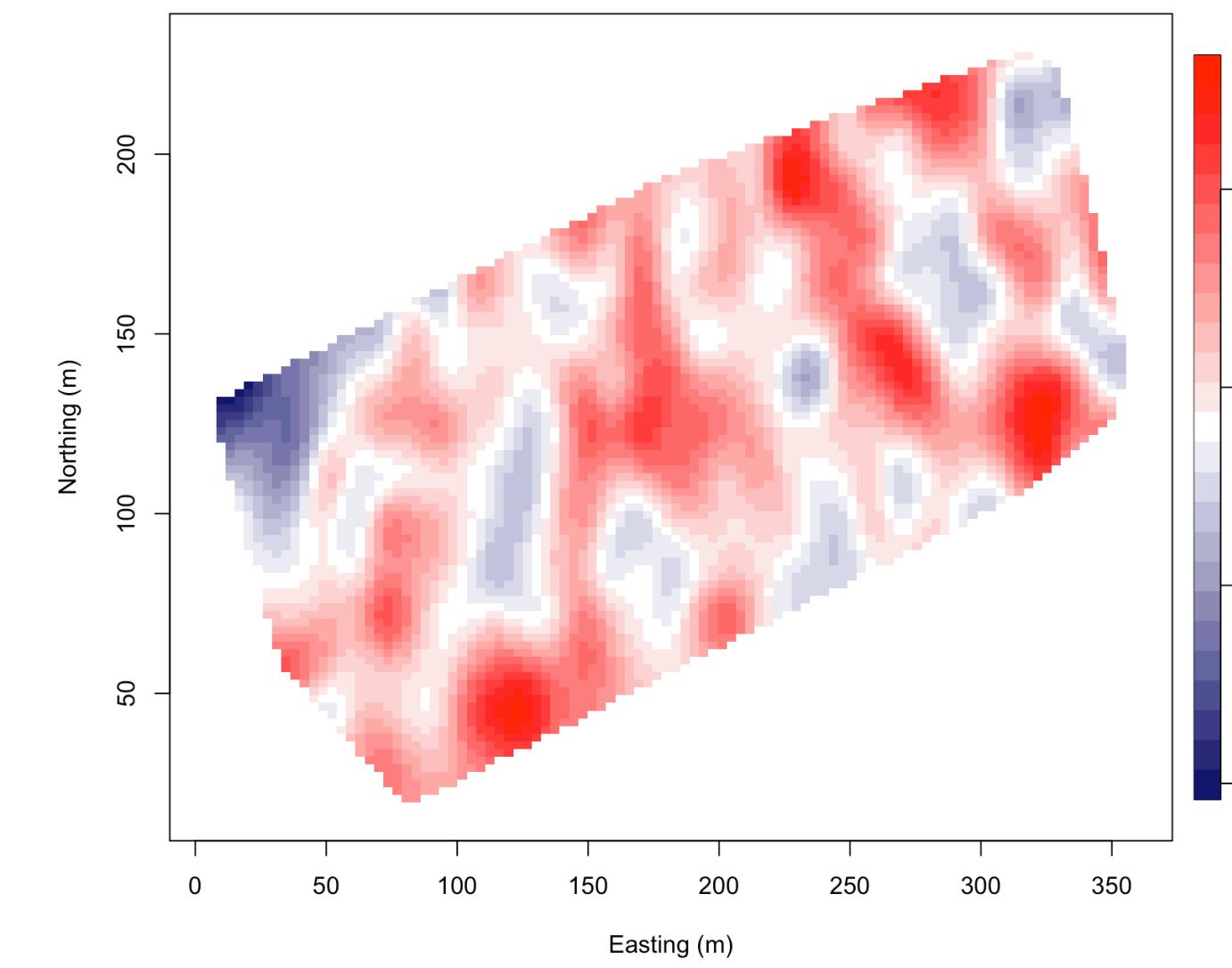


# Western Experimental Forestry (WEF) data

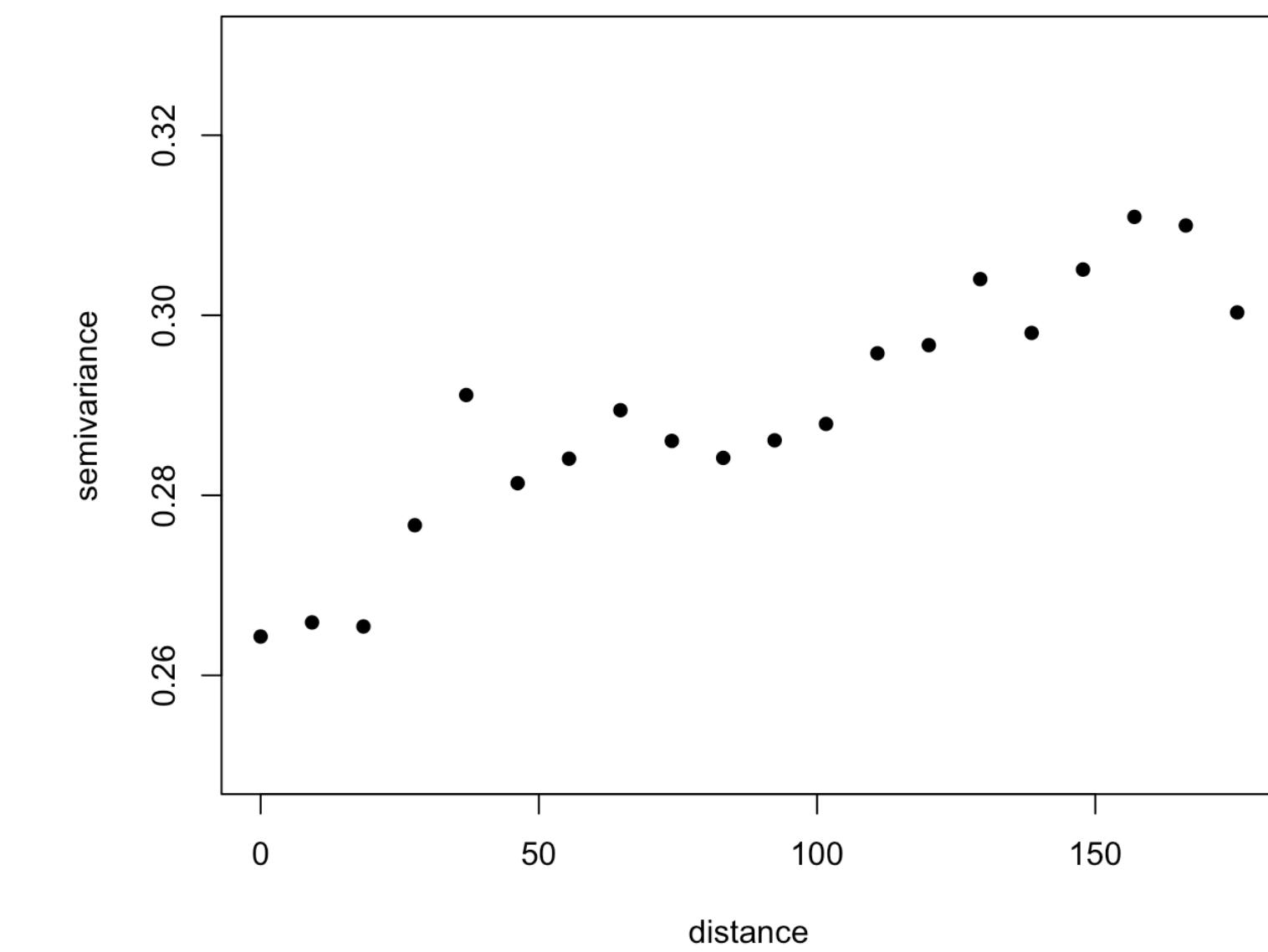
Linear model analysis:



Variogram of log(DBH)



Map of residuals

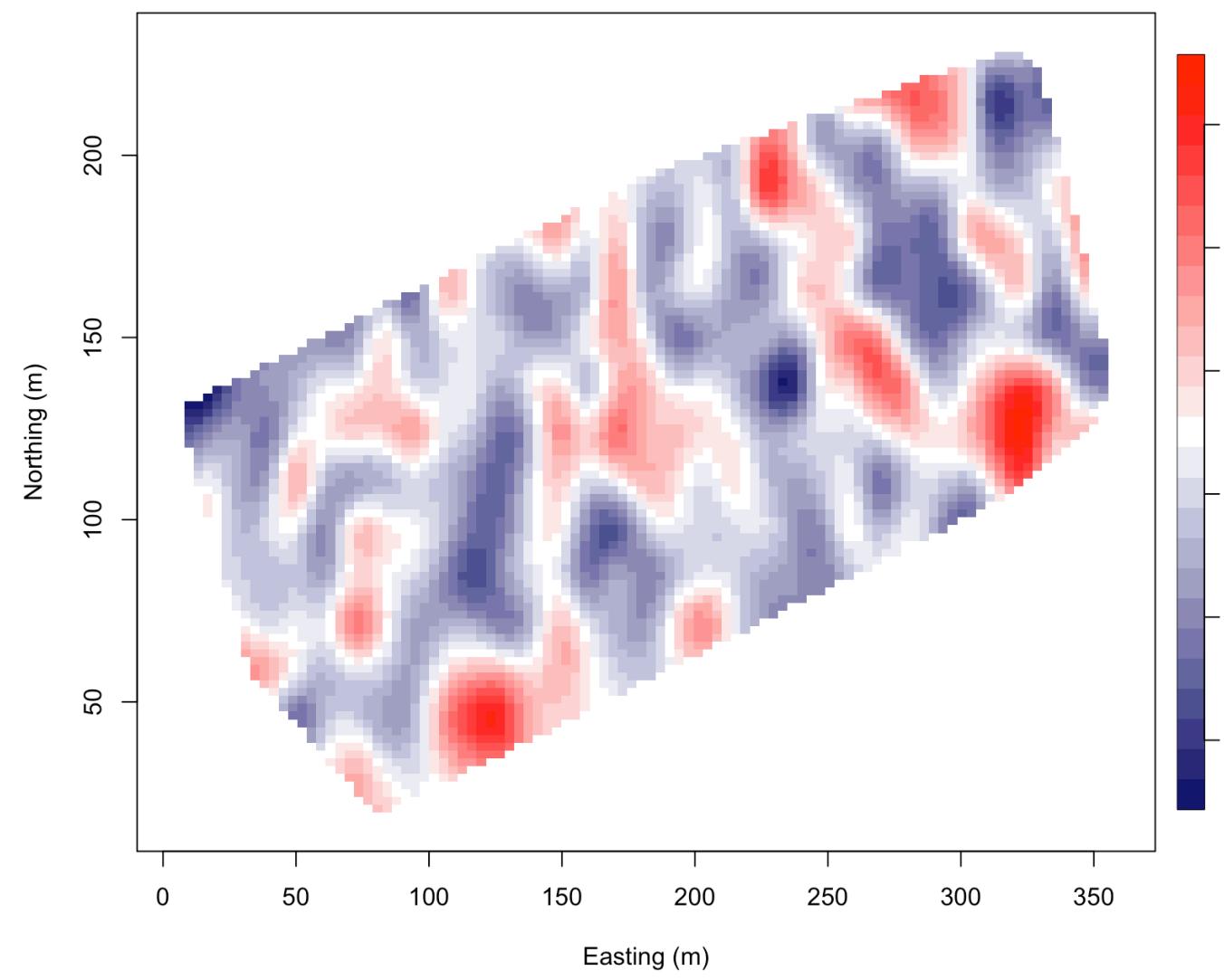


Variogram of residuals

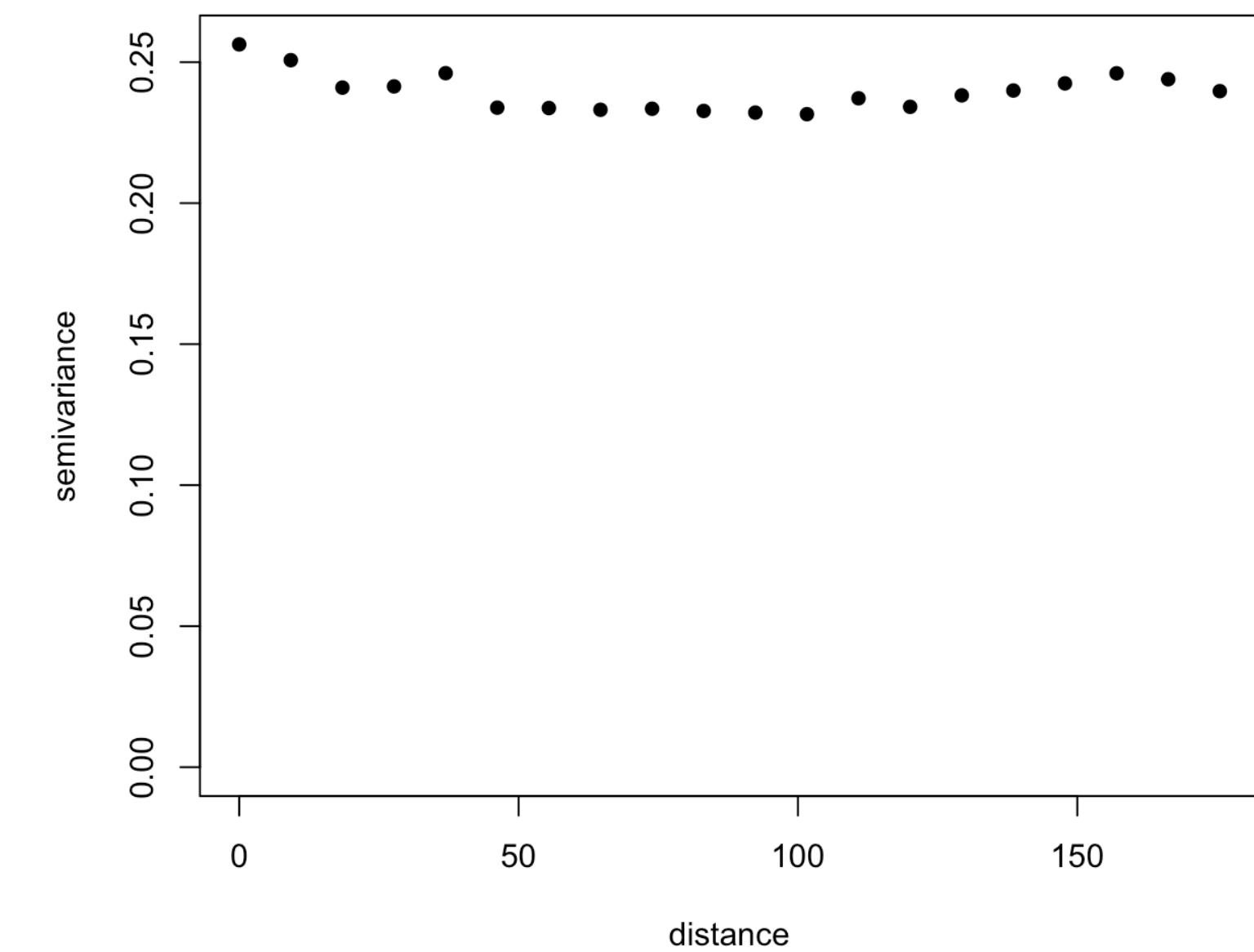
# Western Experimental Forestry (WEF) data

## Model comparisons:

Metric	Spatial	Non-Spatial
AIC	797	825
BIC	826	846



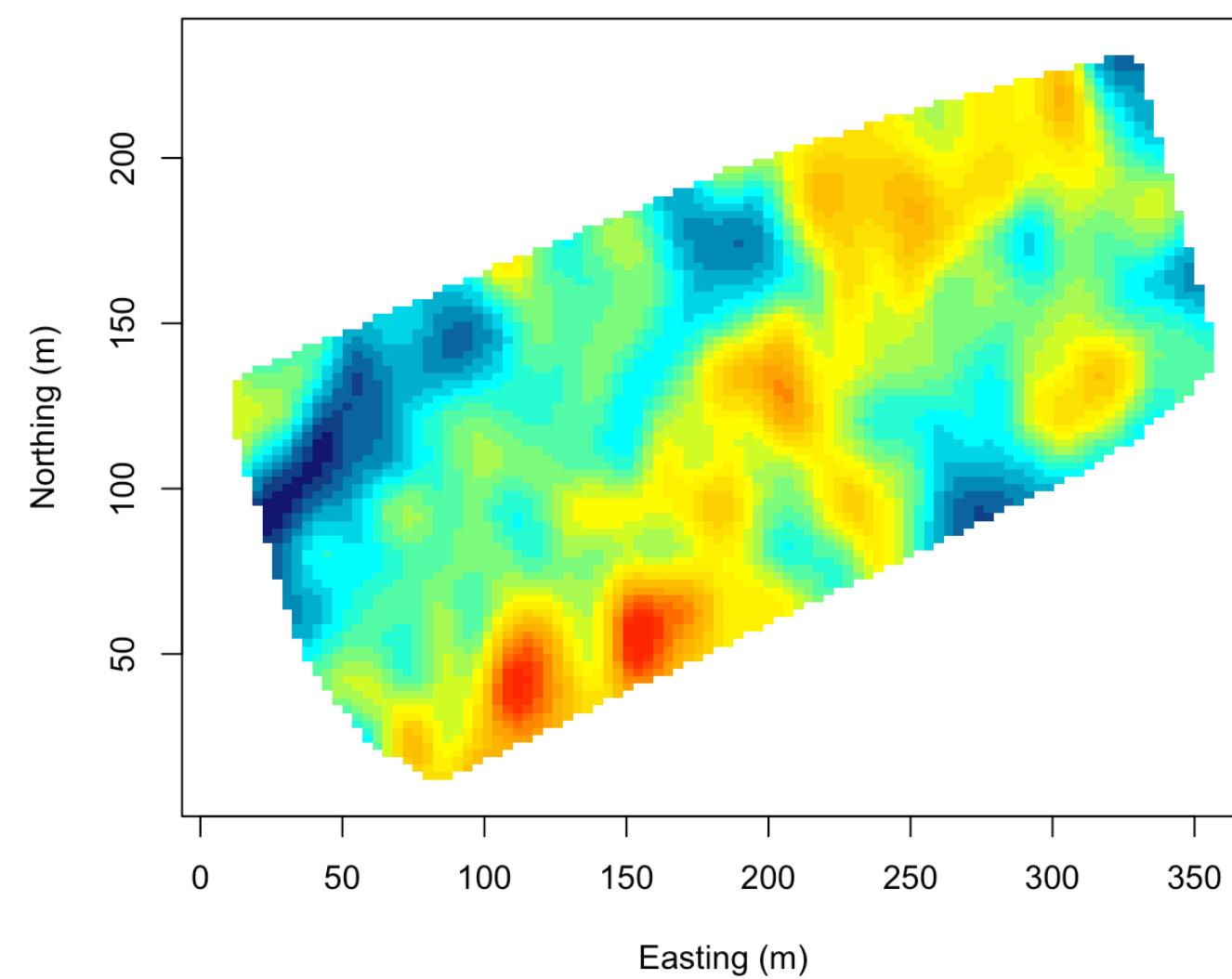
Map of residuals  
from the spatial model



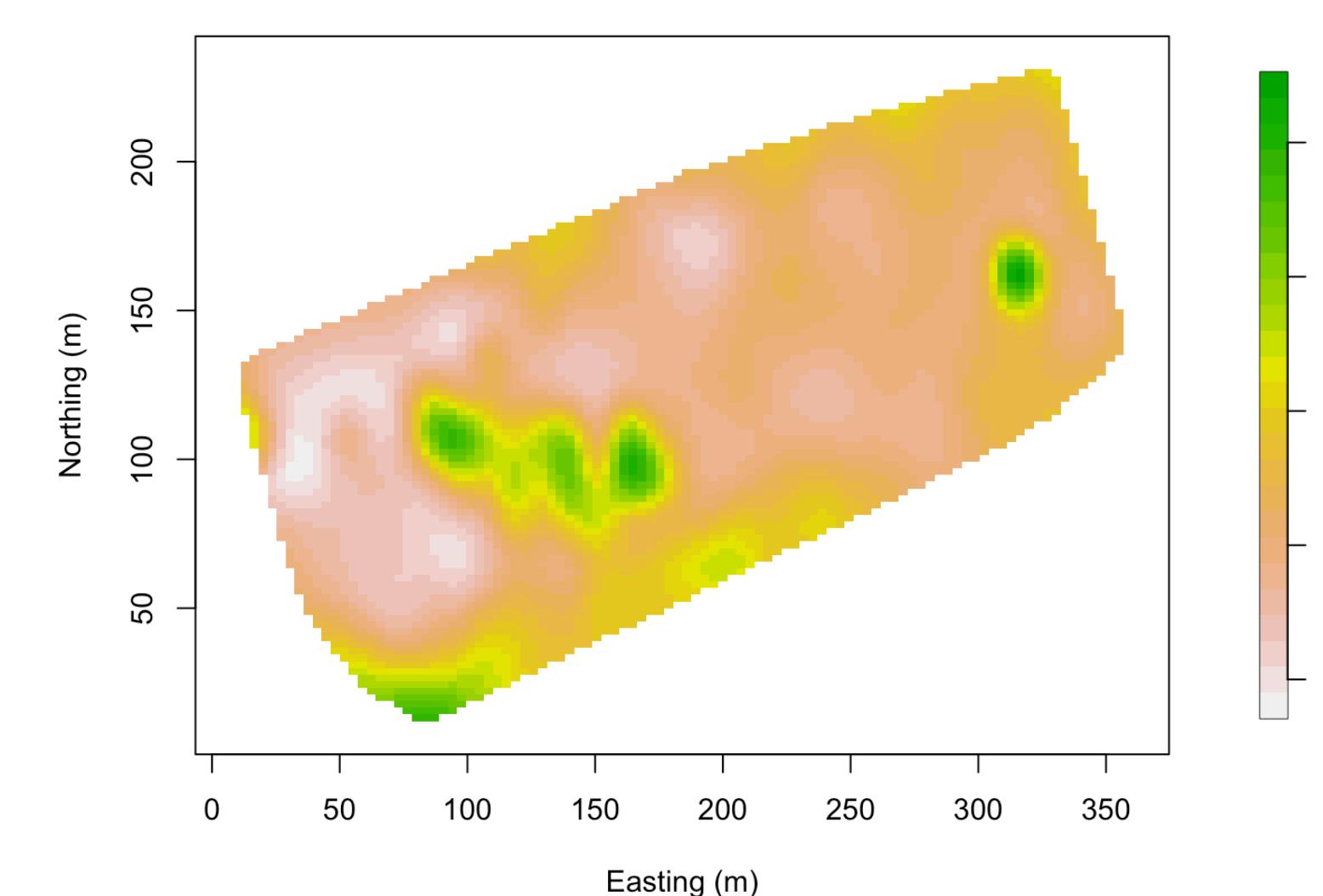
Variogram of residuals  
from the spatial model

# Western Experimental Forestry (WEF) data

## Predictions:



Map of predicted DBH

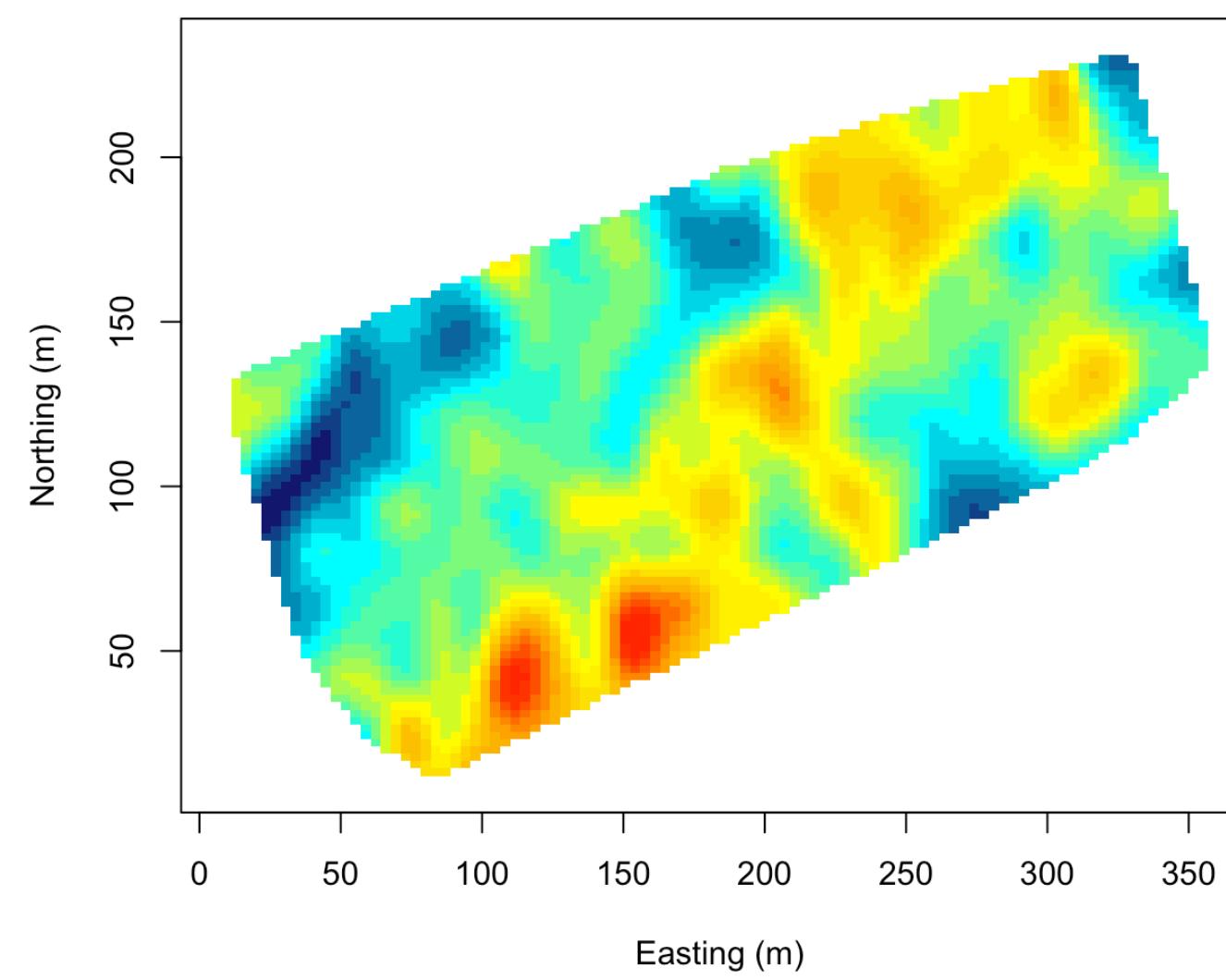


Map of standard deviation  
of predicted DBH

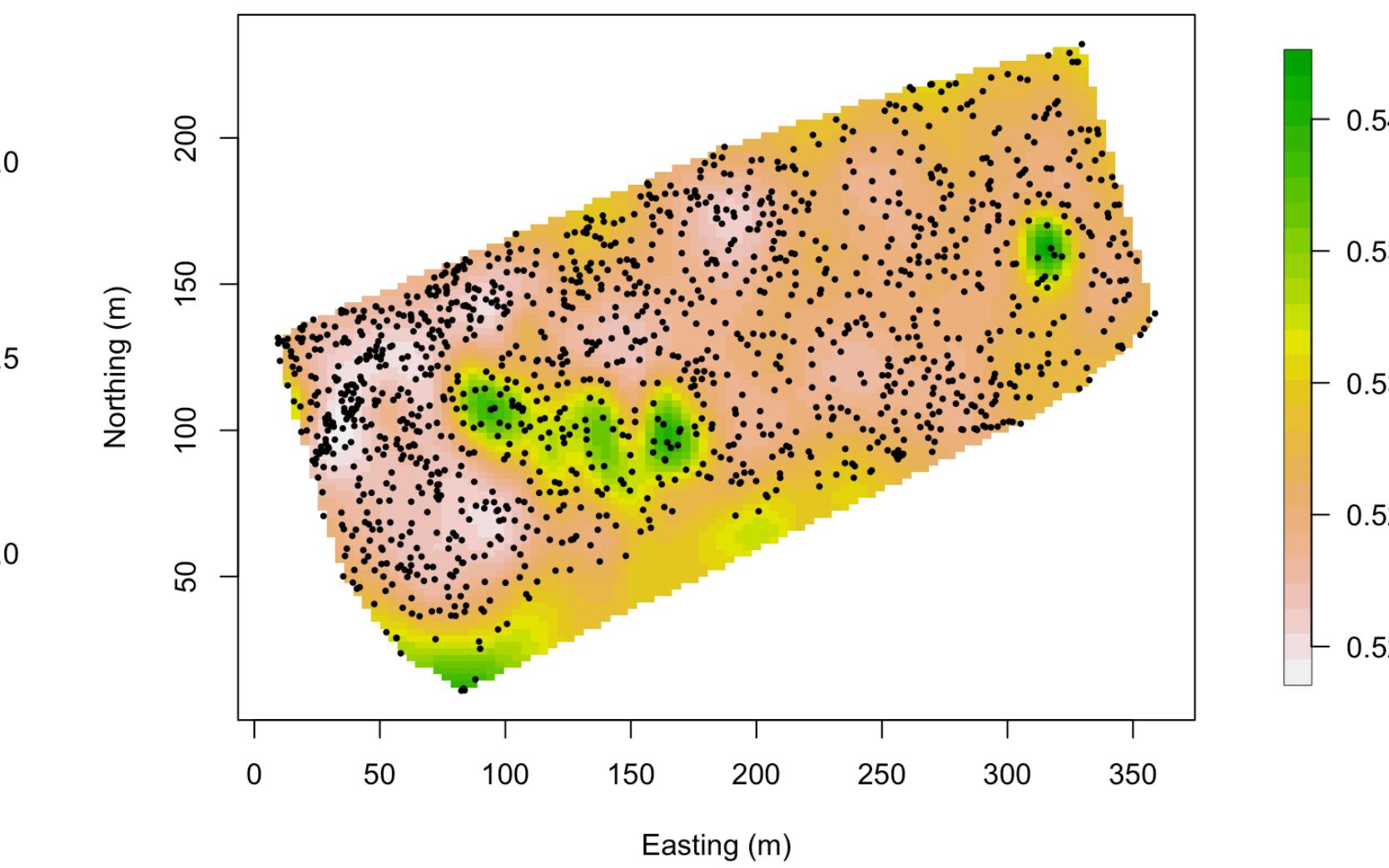
Metric	Spatial	Non-spatial
RMSPE	0.54	0.56
CP	0.96	0.98
PIW	2.1	2.2

# Western Experimental Forestry (WEF) data

Predictions:



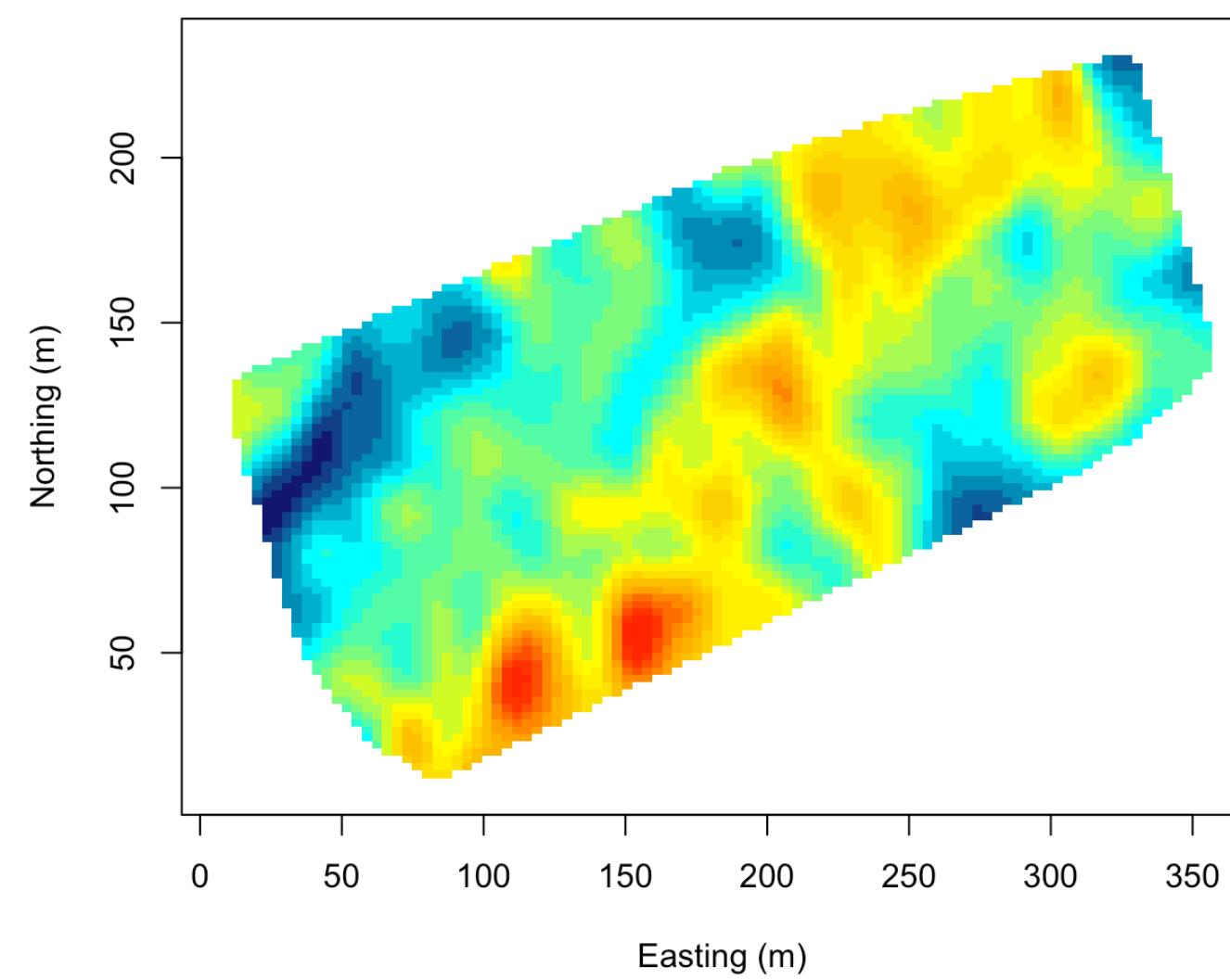
Map of predicted DBH



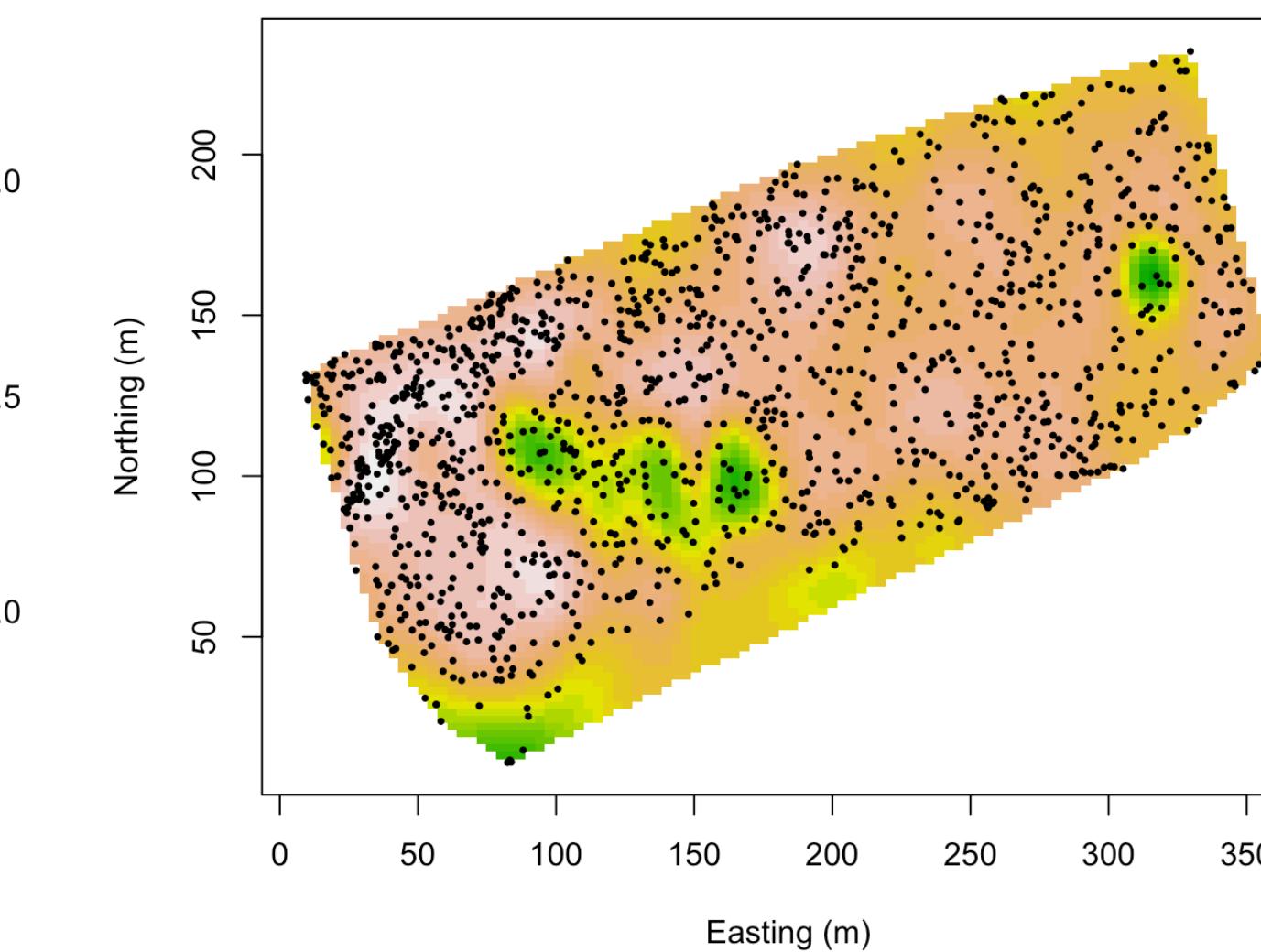
Map of standard deviation  
of predicted DBH

# Western Experimental Forestry (WEF) data

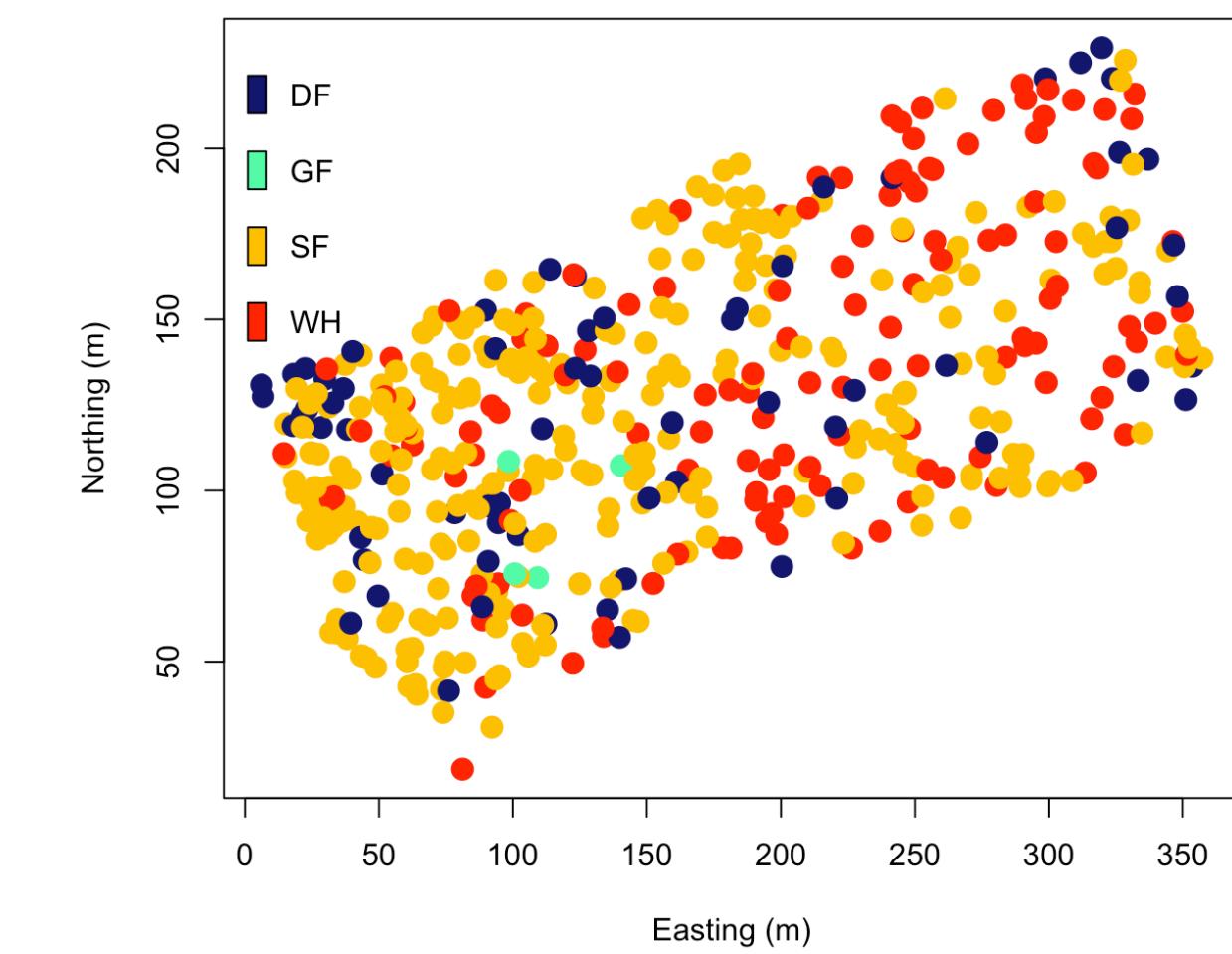
## Predictions:



Map of predicted DBH



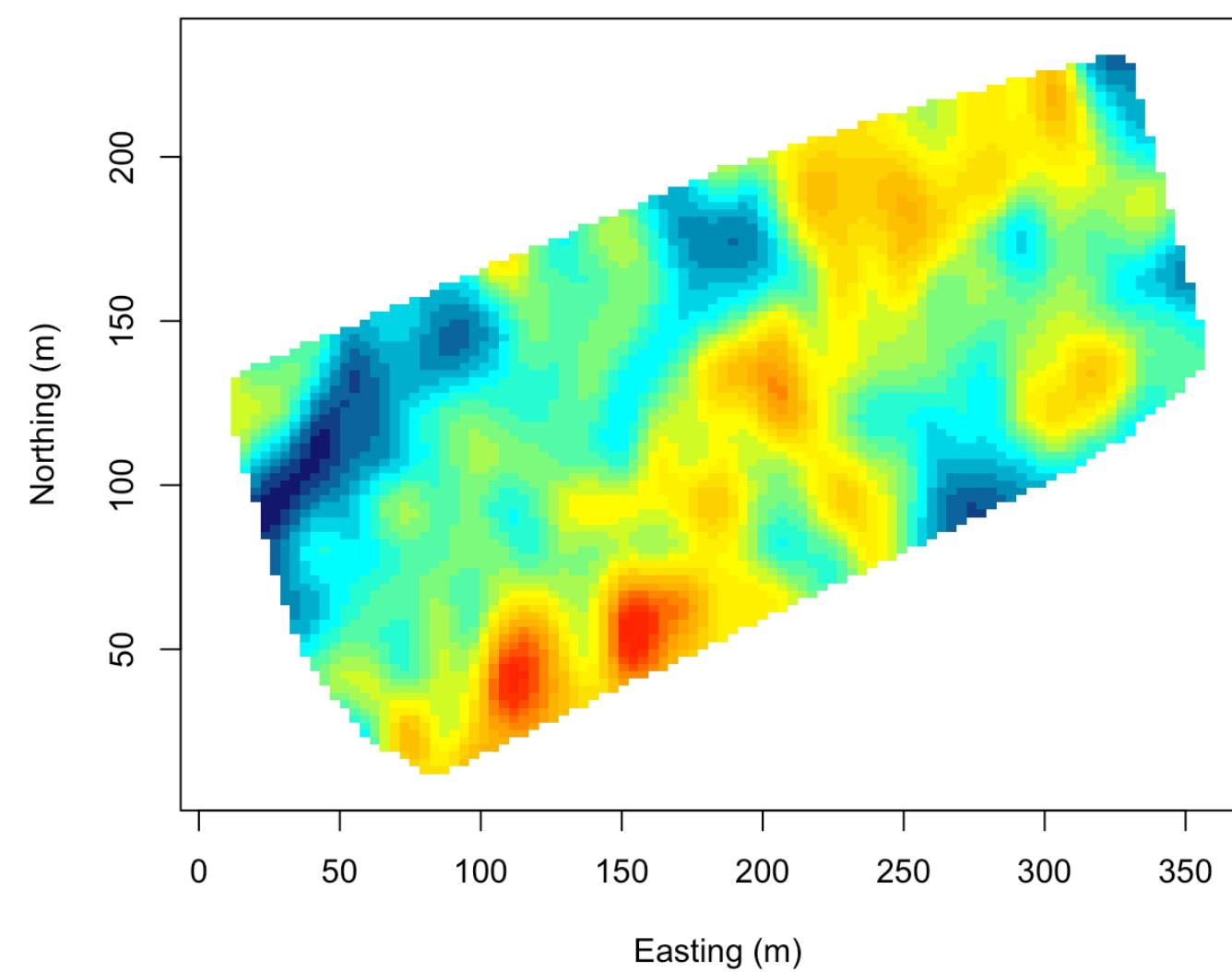
Map of standard deviation  
of predicted DBH  
with data locations



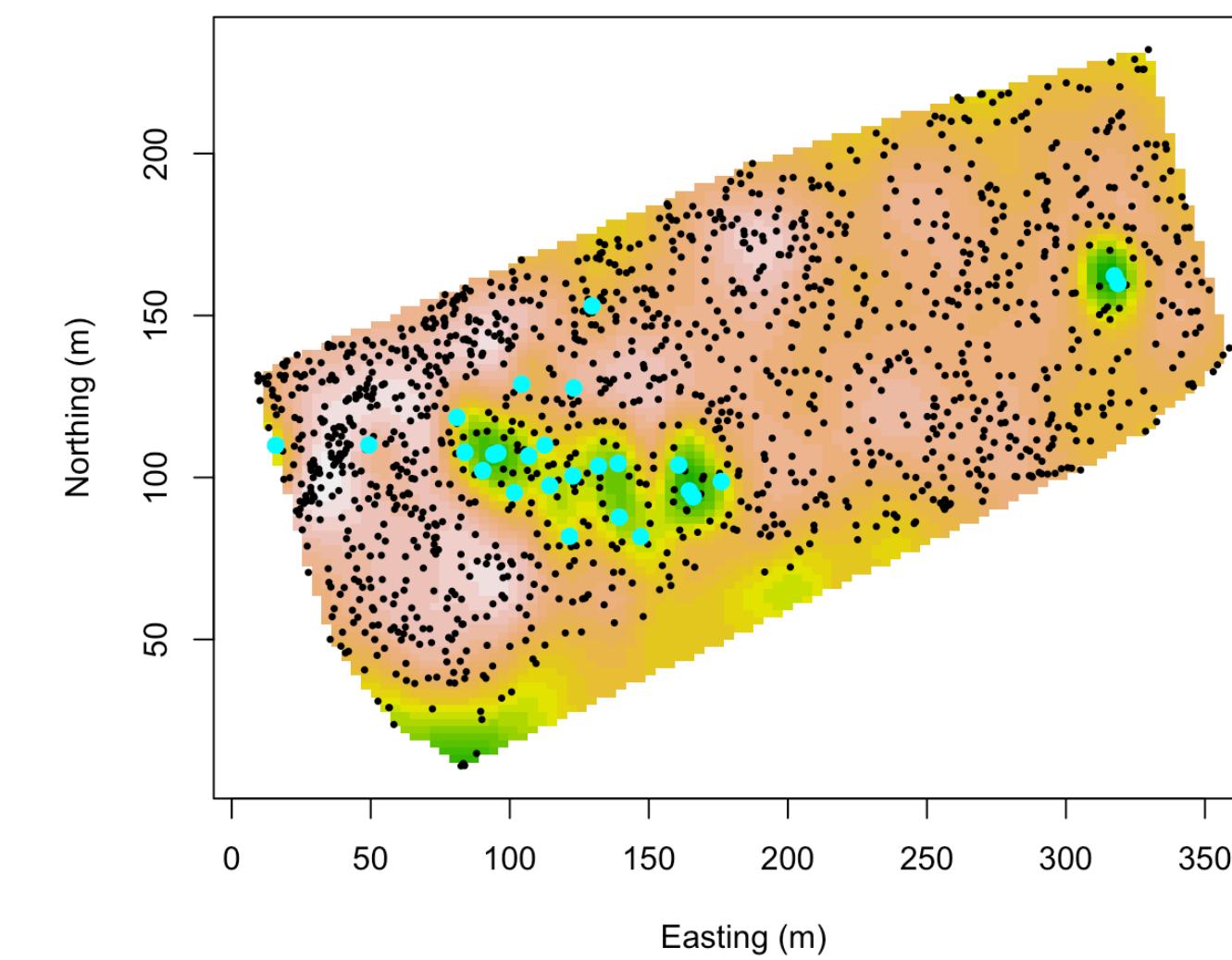
Map of species type  
for training data

# Western Experimental Forestry (WEF) data

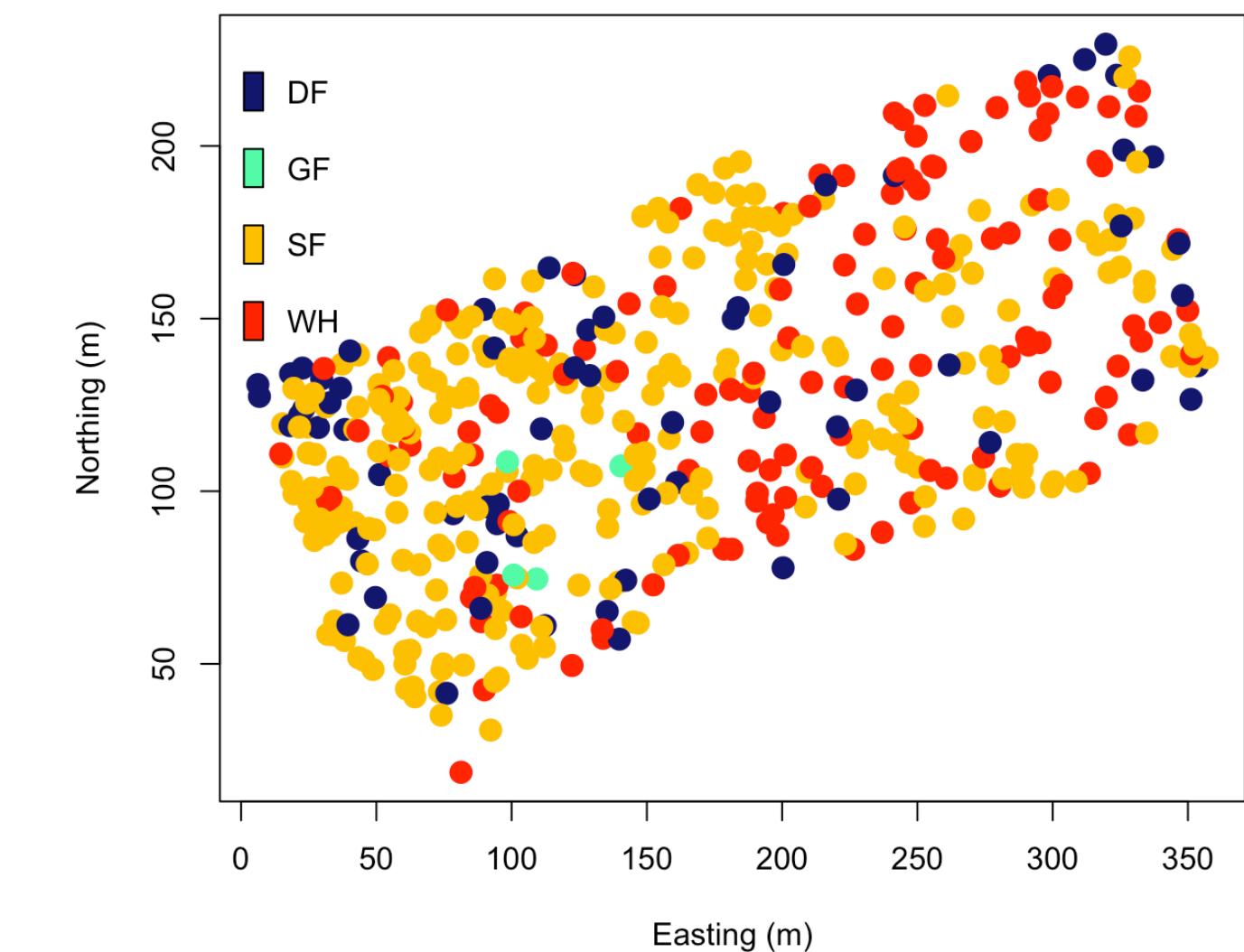
## Predictions:



Map of predicted DBH



Map of standard deviation  
of predicted DBH  
(highlighting locations  
of Species GF)



Map of species type  
for training data

# Big spatial data

Data at  $n$  locations:  $S = \{s_1, \dots, s_n\}$

Marginal model:  $Y \sim N(X\beta, \Sigma(\theta))$  where  $\Sigma(\theta) = C + \tau^2 I$

Parameter estimation using MLE

Log-likelihood:  $l(\beta, \theta | Y) = -\frac{1}{2} \log \det(\Sigma(\theta)) - \frac{1}{2}(Y - X\beta)^\top \Sigma(\theta)^{-1}(Y - X\beta)$

Needs evaluation of  $\det(\Sigma(\theta))$  and quadratic forms of  $\Sigma(\theta)^{-1}$

# Big spatial data

Prediction at a new location  $s_0$ :  $Y(s_0) \mid Y, \theta, \beta = N(\mu(s_0), \sigma^2(s_0))$

Conditional mean:  $\mu(s_0) = X'(s_0)\beta + C(s_0, S)\Sigma^{-1}(Y - X\beta)$

Conditional variance:  $\sigma^2(s_0) = C(s_0, s_0) + \tau^2 - C(s_0, S)\Sigma^{-1}C(S, s_0)$

Again needs evaluation of quadratic forms of  $\Sigma^{-1}$

# Computational details

$\Sigma$  is a **dense**  $n \times n$  matrix

Both  $\det(\Sigma)$  and  $\Sigma^{-1}$  are best computed via the **Cholesky decomposition**

Cholesky decomposition: Any symmetric matrix  $A$  can be factorized as  $A = LDL'$  where  $L$  is **lower triangular** and  $D$  is **diagonal**

Cholesky decomposition requires  $O(n^2)$  storage and  $O(n^3)$  memory

Not feasible for **large  $n$**

# Methods for spatial big data

Low-rank models

Spectral approximations

Lattice-based

Multi-resolution approaches

Covariance tapering

Stochastic Partial Differential Equations

Nearest-neighbor models

See Heaton et al. (2019) for a review

# Methods for spatial big data

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# Nearest Neighbor Gaussian Processes

GP regression model:  $Y \sim N(X\beta, \Sigma(\theta))$

Likelihood factorization:  $p(Y) = p(Y_1) \times \prod_{i=2}^n p(Y_i | Y_1, \dots, Y_{i-1})$

**Vecchia's GP likelihood approximation** (Vecchia, 1988, JRSSB):

$$p(Y) \approx p(Y_1) \times \prod_{i=2}^n p(Y_i | Y_{N(i)})$$

$N(i)$  = set of  $m$  **nearest neighbors** of location  $s_i$  among  $s_1, \dots, s_{i-1}$

Reduces computation time from  $O(n^3)$  to  $O(nm^3)$

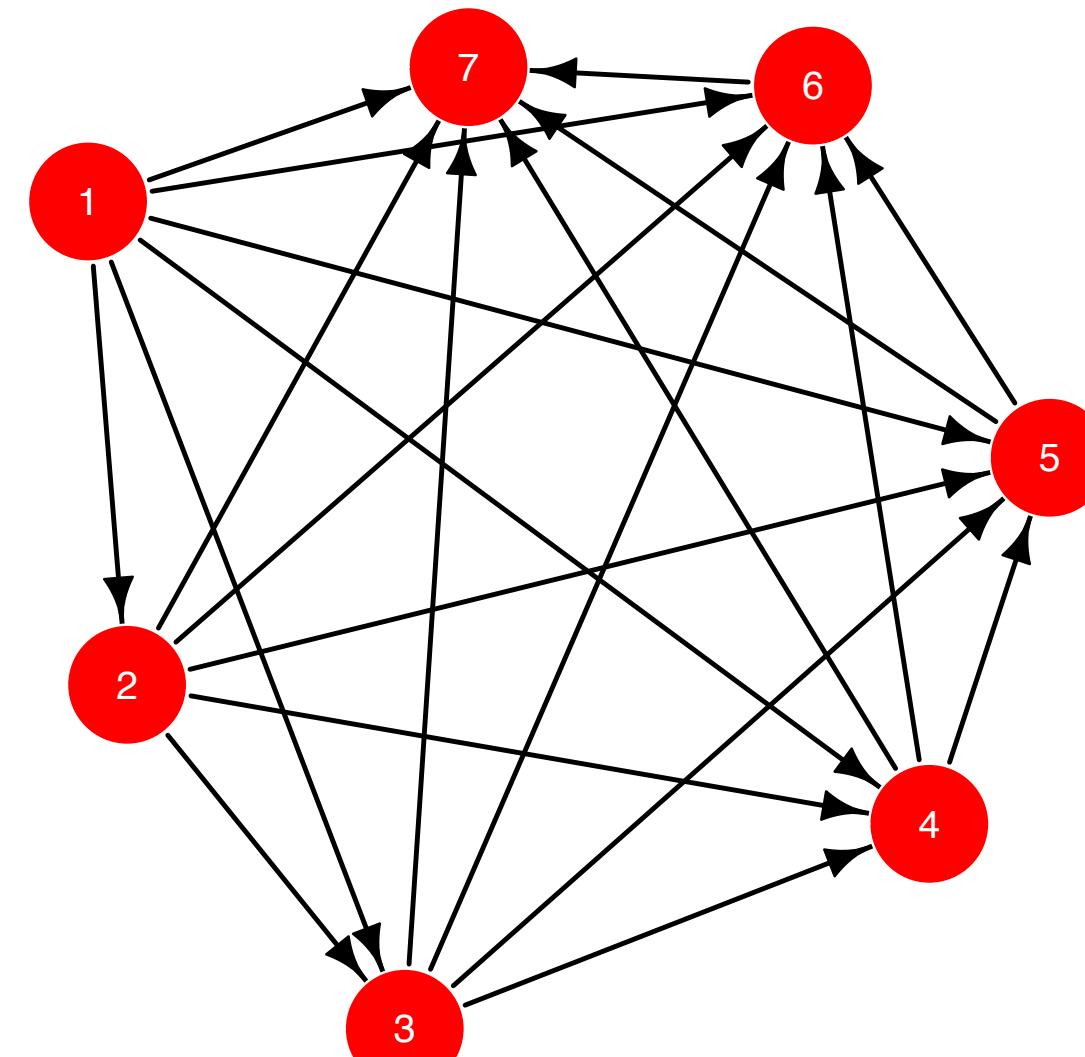
# Nearest Neighbor Gaussian Processes

NNGP (Datta et al, 2016, JASA): Vecchia's approximation corresponds to a distribution  $N(0, \tilde{\Sigma})$  and can be extended to a valid Gaussian process (NNGP)

# Nearest Neighbor Gaussian Processes

NNGP (Datta et al, 2016, JASA): Vecchia's approximation is the likelihood of a distribution  $N(0, \tilde{\Sigma})$  and can be extended to a valid Gaussian process (NNGP)

NNGP likelihood factorizes on a sparse **directed acyclic graph (DAG)**



Full GP likelihood

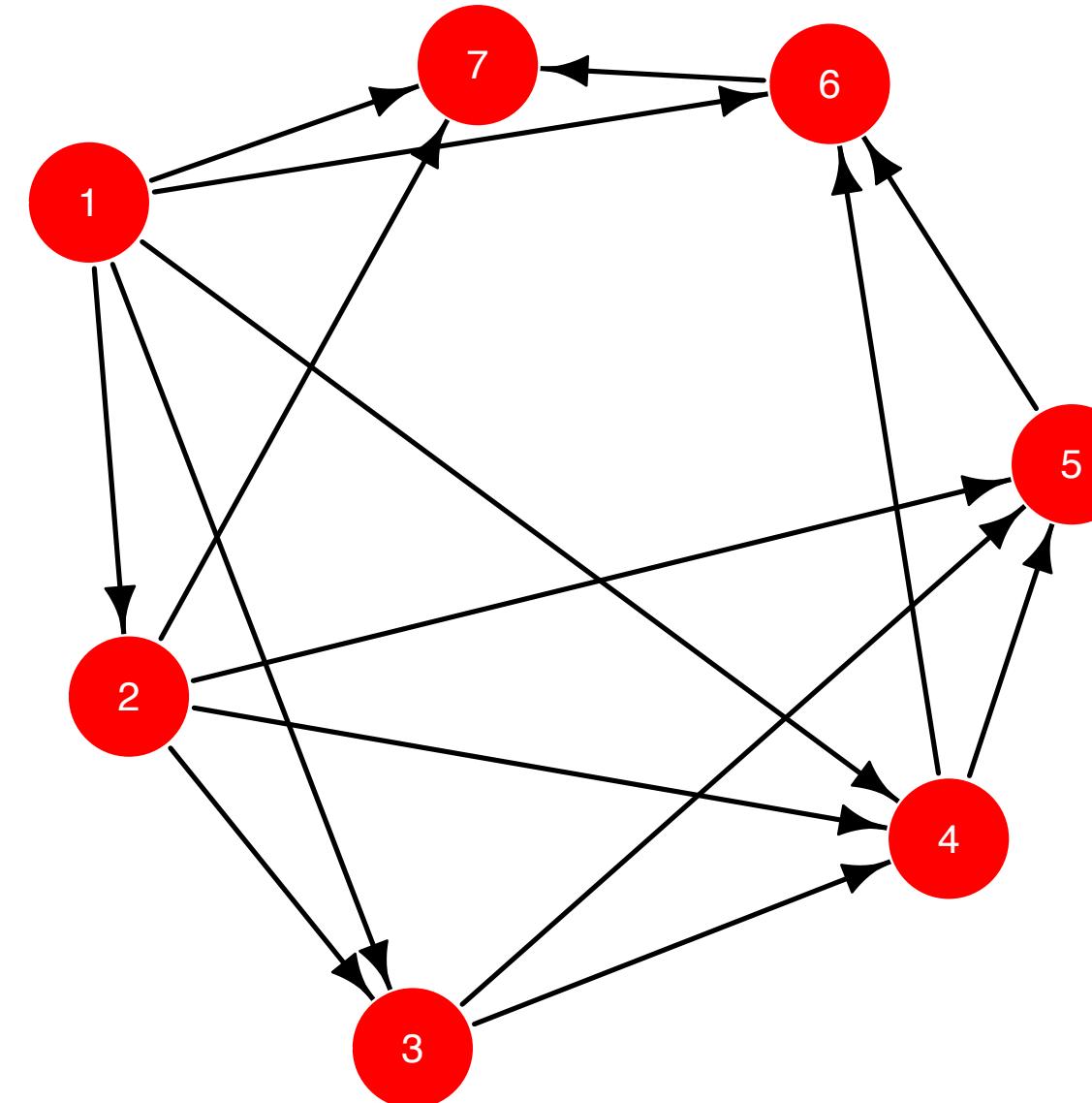
$$\begin{aligned} p(y) = & p(y_1)p(y_2 \mid y_1) \\ & \times p(y_3 \mid y_1, y_2)p(y_4 \mid y_1, y_2, y_3)p(y_5 \mid y_1, y_2, y_3, y_4) \\ & \times p(y_6 \mid y_1, y_2, y_3, y_4, y_5)p(y_7 \mid y_1, y_2, y_3, y_4, y_5, y_6) \end{aligned}$$

Complete DAG

# Nearest Neighbor Gaussian Processes

NNGP (Datta et al, 2016, JASA): Vecchia's approximation is the likelihood of a distribution  $N(0, \tilde{\Sigma})$  and can be extended to a valid Gaussian process (NNGP)

NNGP likelihood factorizes on a sparse **directed acyclic graph (DAG)**



3-NN DAG

NNGP likelihood

$$p(y) = p(y_1)p(y_2 | y_1)$$

$$\times p(y_3 | y_1, y_2)p(y_4 | y_1, y_2, y_3)p(y_5 | y_1, y_2, y_3, y_4)$$

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

# Nearest Neighbor Gaussian Processes

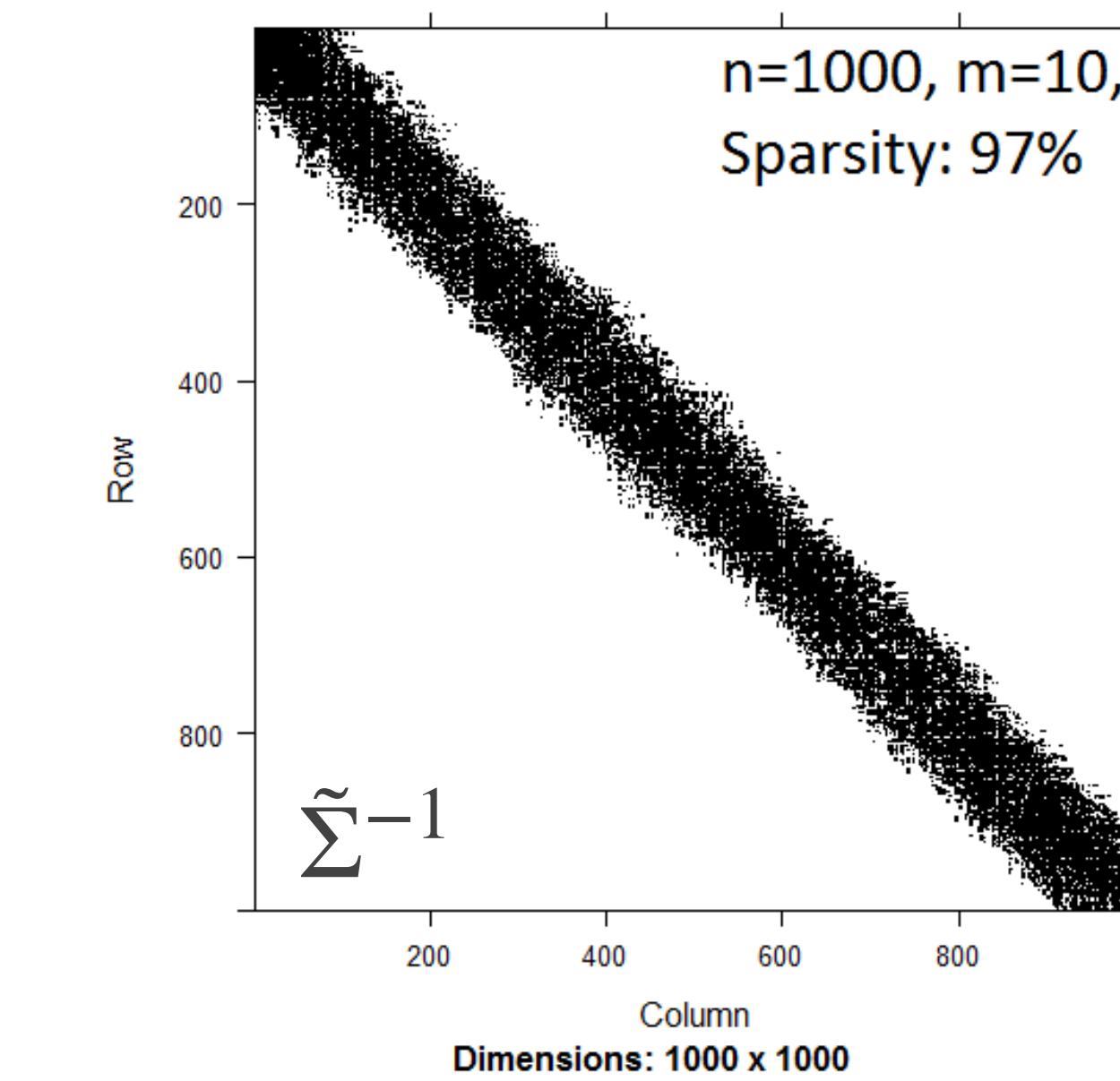
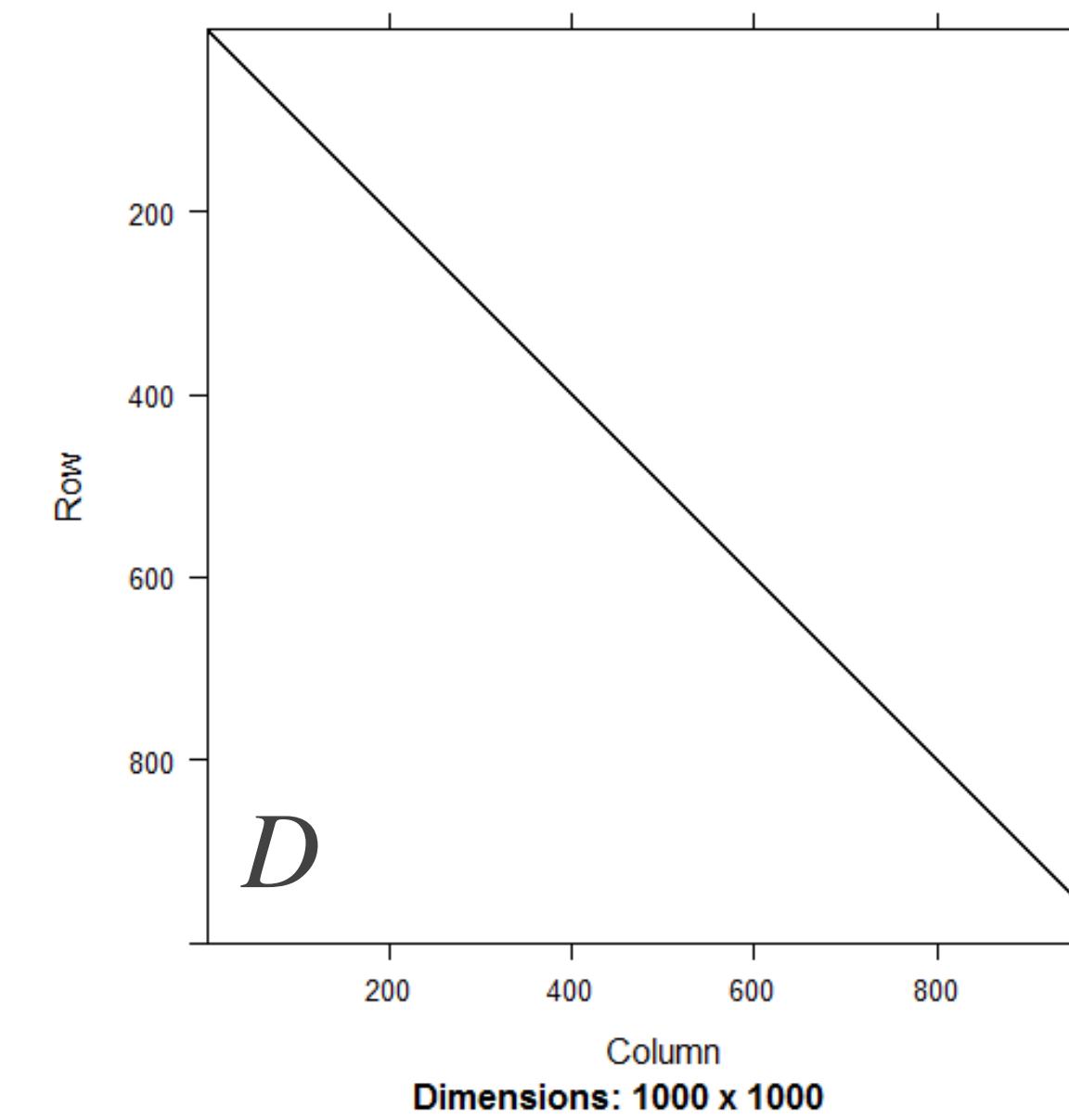
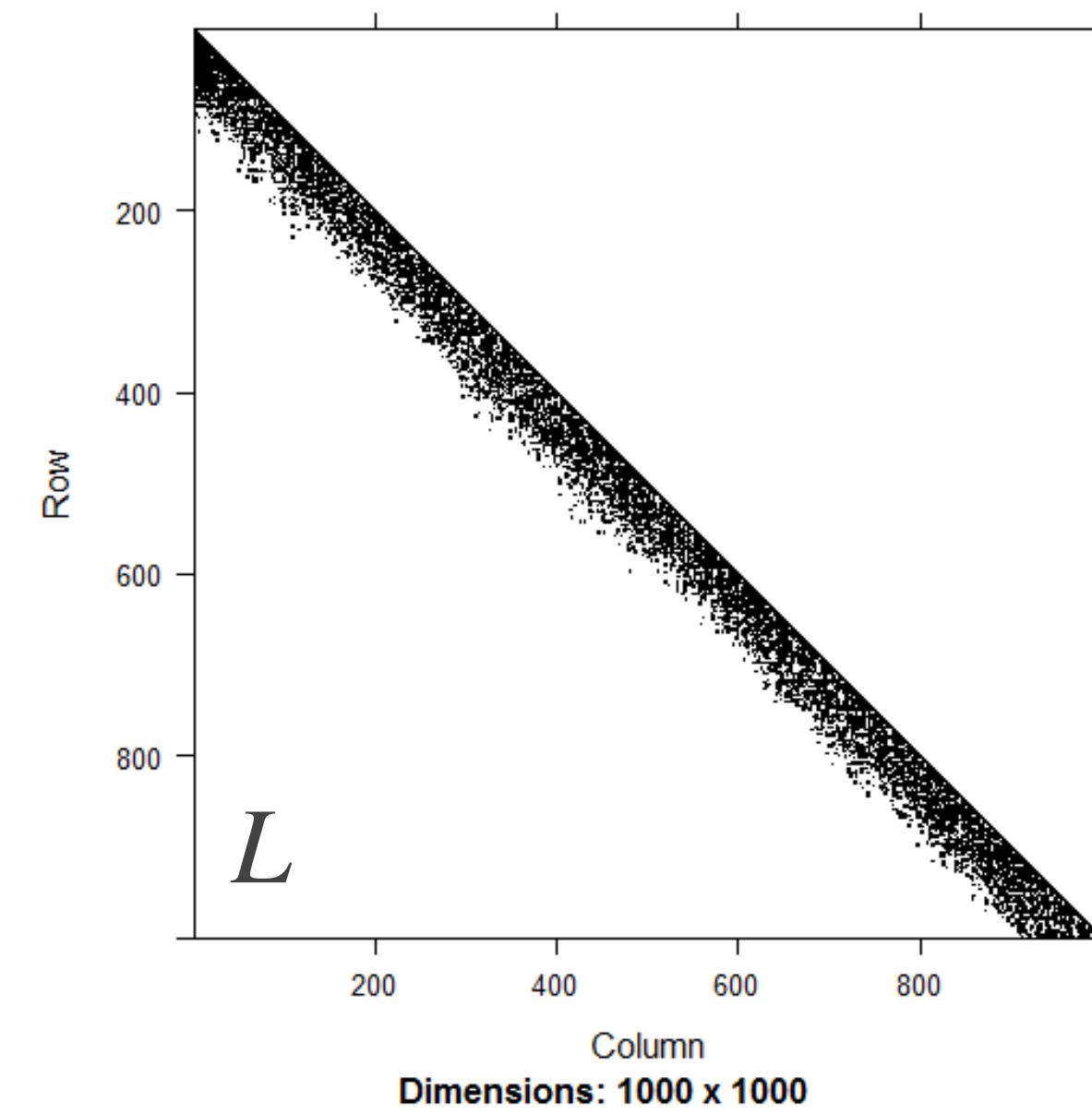
The NNGP **precision matrix** admits the factorization  $\tilde{\Sigma}^{-1} = L'DL$

$L$  is diagonal with entries  $d_i$

$L$  is lower triangular and row sparse

Sparsity determined by the nearest-neighbor DAG

$\tilde{\Sigma}^{-1}$  is also sparse



# Nearest Neighbor Gaussian Processes

## Estimation:

The NNGP **precision matrix**  $\tilde{\Sigma}^{-1} = L'DL$

$D$  is diagonal with entries  $d_i$

$L$  is lower triangular and row sparse

$L$  and  $D$  can be computed in  $O(nm^3)$  time

$$\det(\tilde{\Sigma}) = \frac{1}{\prod_i d_i}$$

$$x' \tilde{\Sigma}^{-1} x = (Lx)' D (Lx) = \sum_i v_i^2 d_i \text{ where } v = Lx$$

Total time to evaluate NNGP likelihood is  $O(nm^3)$

# Nearest Neighbor Gaussian Processes

## Predictions:

NNGP prediction at a new location  $s_0$ :

$$Y(s_0) \mid Y, \theta, \beta = Y(s_0) \mid Y_{N_0}, \theta, \beta = N(\tilde{\mu}(s_0), \tilde{\sigma}^2(s_0))$$

$N_0 = m$  nearest neighbors of  $s_0$  among  $s_1, \dots, s_n$

Conditional mean:  $\tilde{\mu}(s_0) = X'(s_0)\beta + C(s_0, N_0)\Sigma_{N_0, N_0}^{-1}(Y_{N_0} - X_{N_0}\beta)$

Conditional variance:  $\tilde{\sigma}^2(s_0) = C(s_0, s_0) + \tau^2 - C(s_0, N_0)\Sigma_{N_0, N_0}^{-1}C(N_0, s_0)$

# Nearest Neighbor Gaussian Processes

Software (R package):

*BRISC* (Saha and Datta)

Frequentist implementation

Estimation with bootstrapped uncertainty

Prediction with uncertainty

Simulation of large spatial data

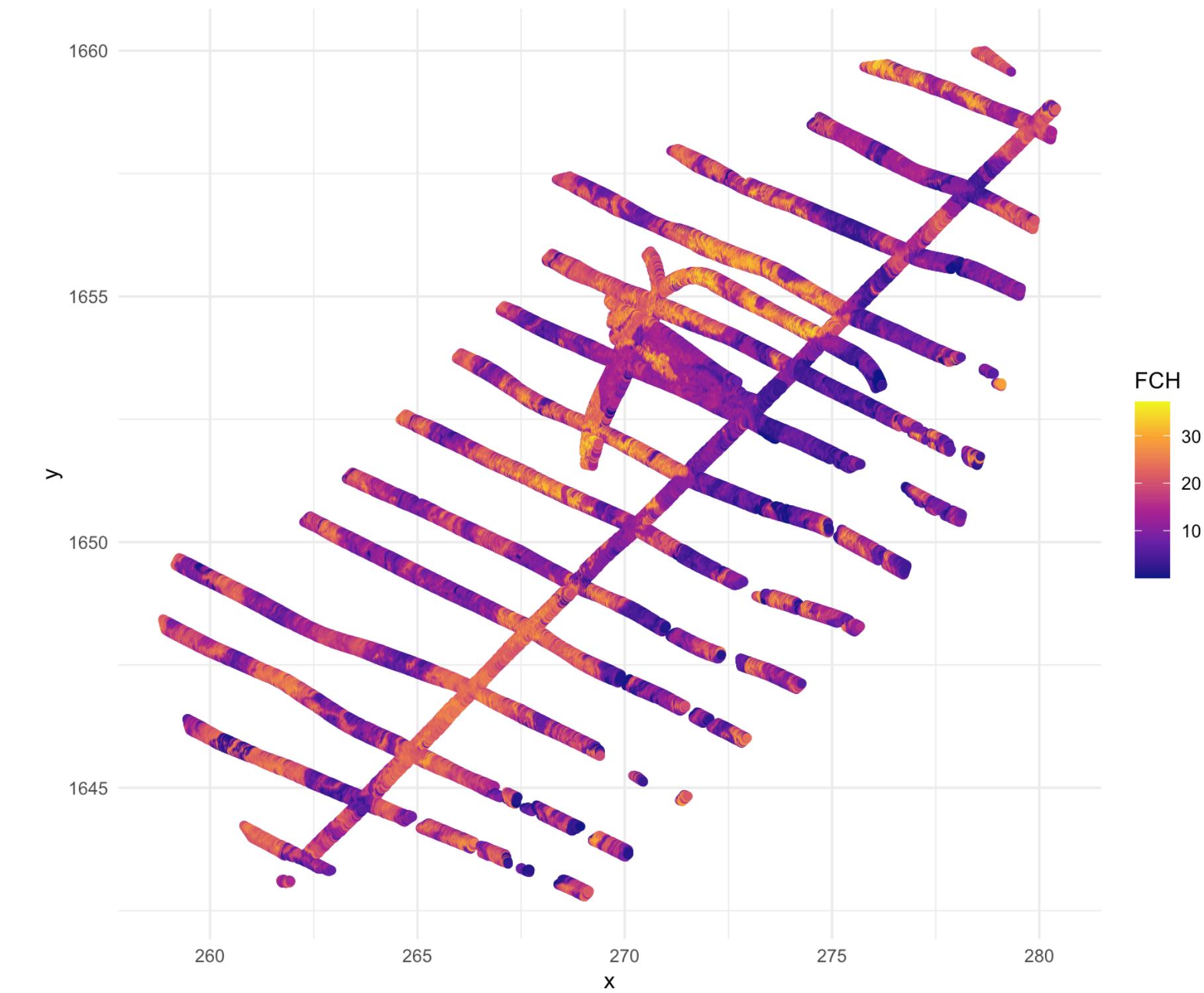
*spNNGP* (Finley, Datta, and Banerjee)

Bayesian implementation

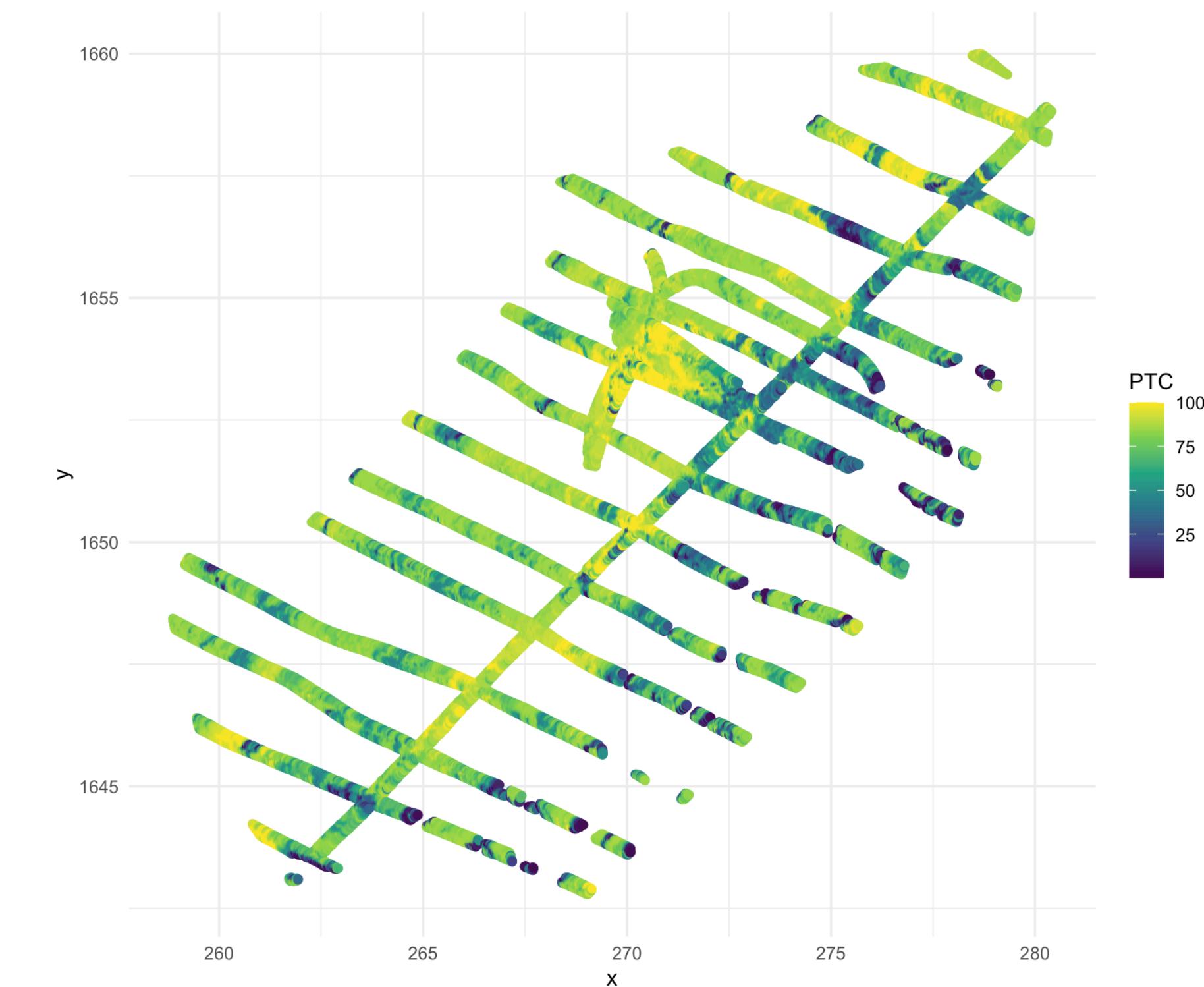
Full posterior distributions using MCMC

# Bonanza Creek Experimental Forest Data

Forest canopy height (FCH) estimates at 180,000 locations NASA Goddard's LiDAR in Bonanza Creek Experimental Forest, Alaska



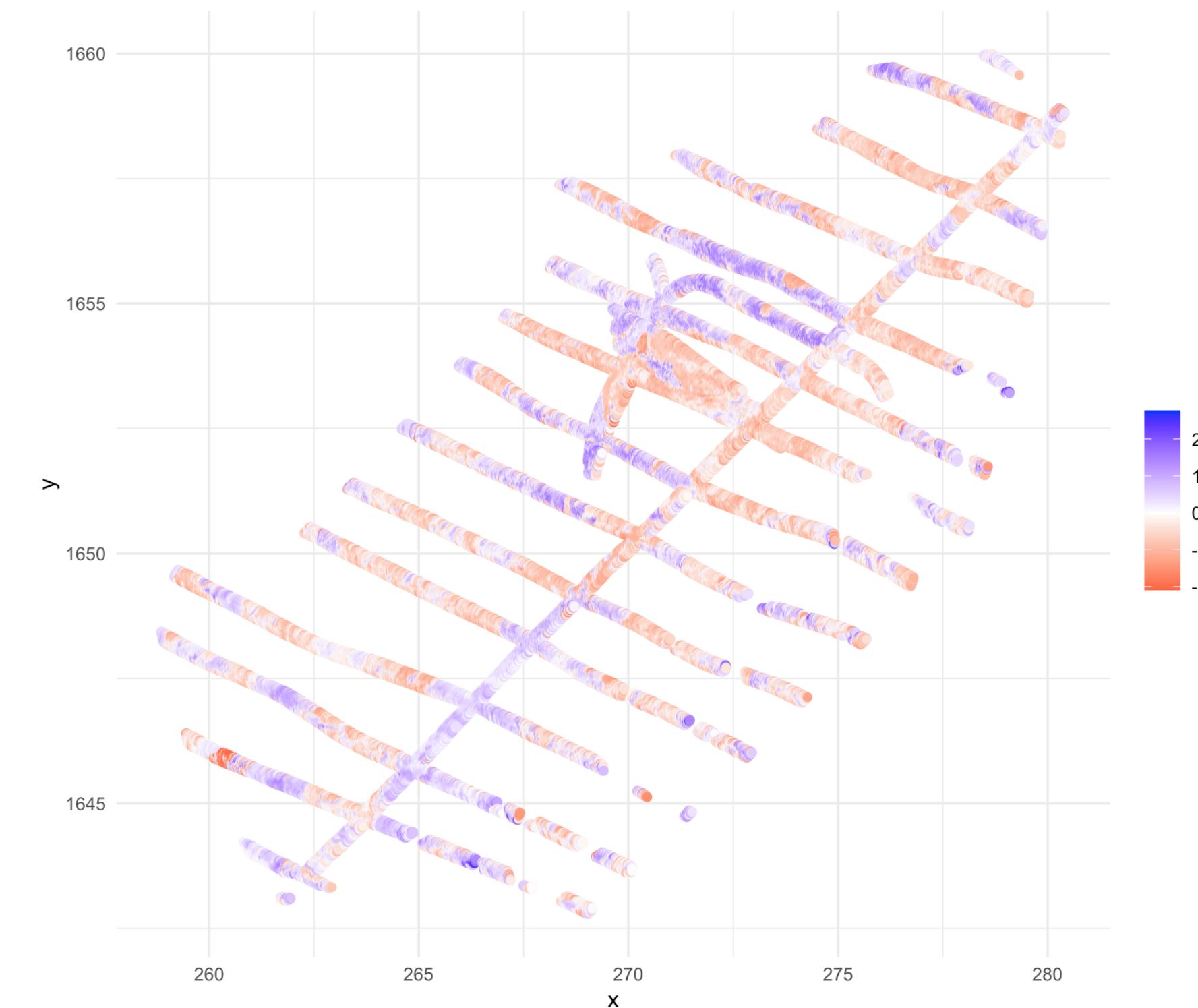
Forest canopy height (FCH)



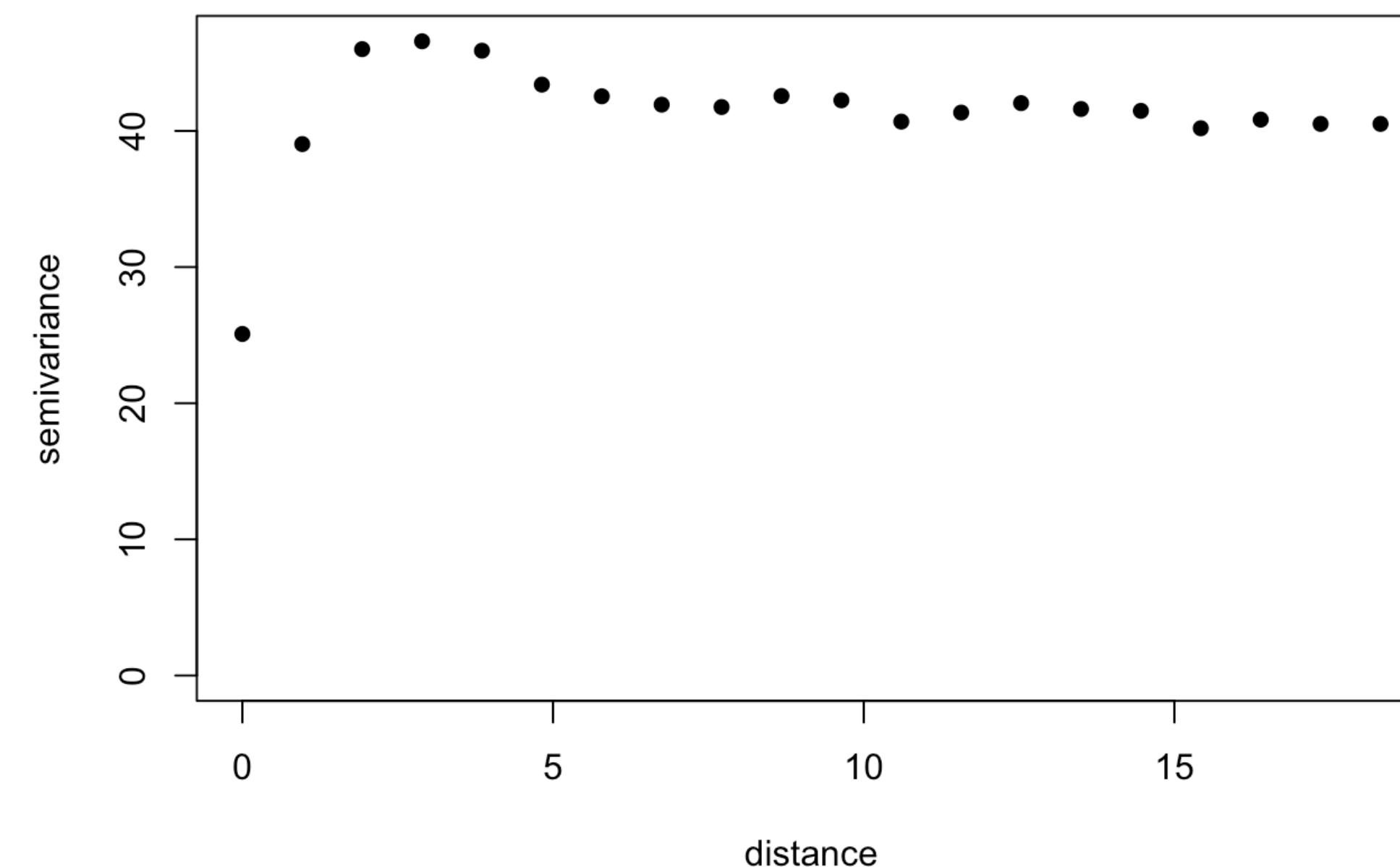
Covariate — Percent tree cover (PTC)

# Bonanza Creek Experimental Forest Data

Linear model:



Residuals

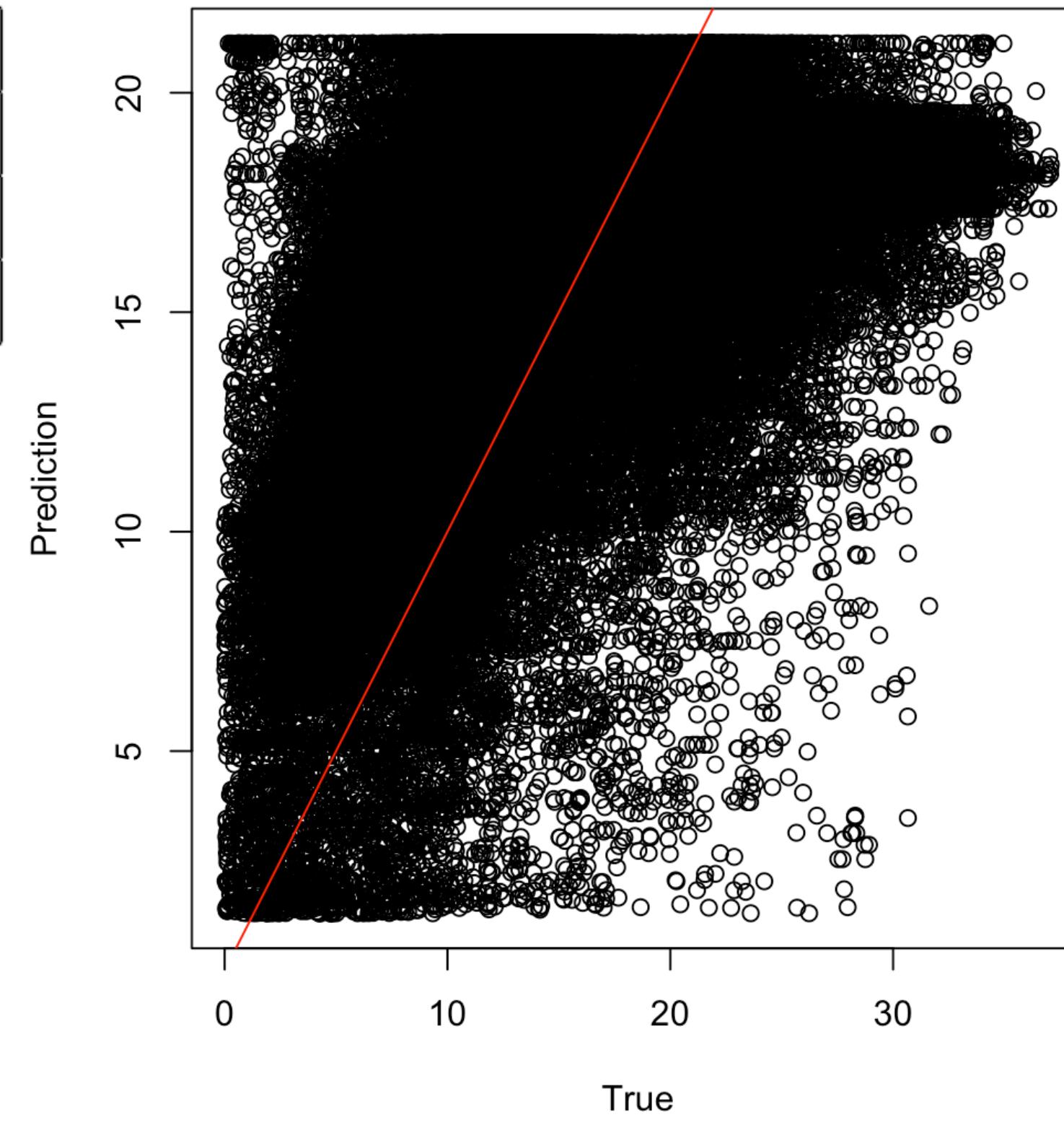


Variogram of a subset of residuals

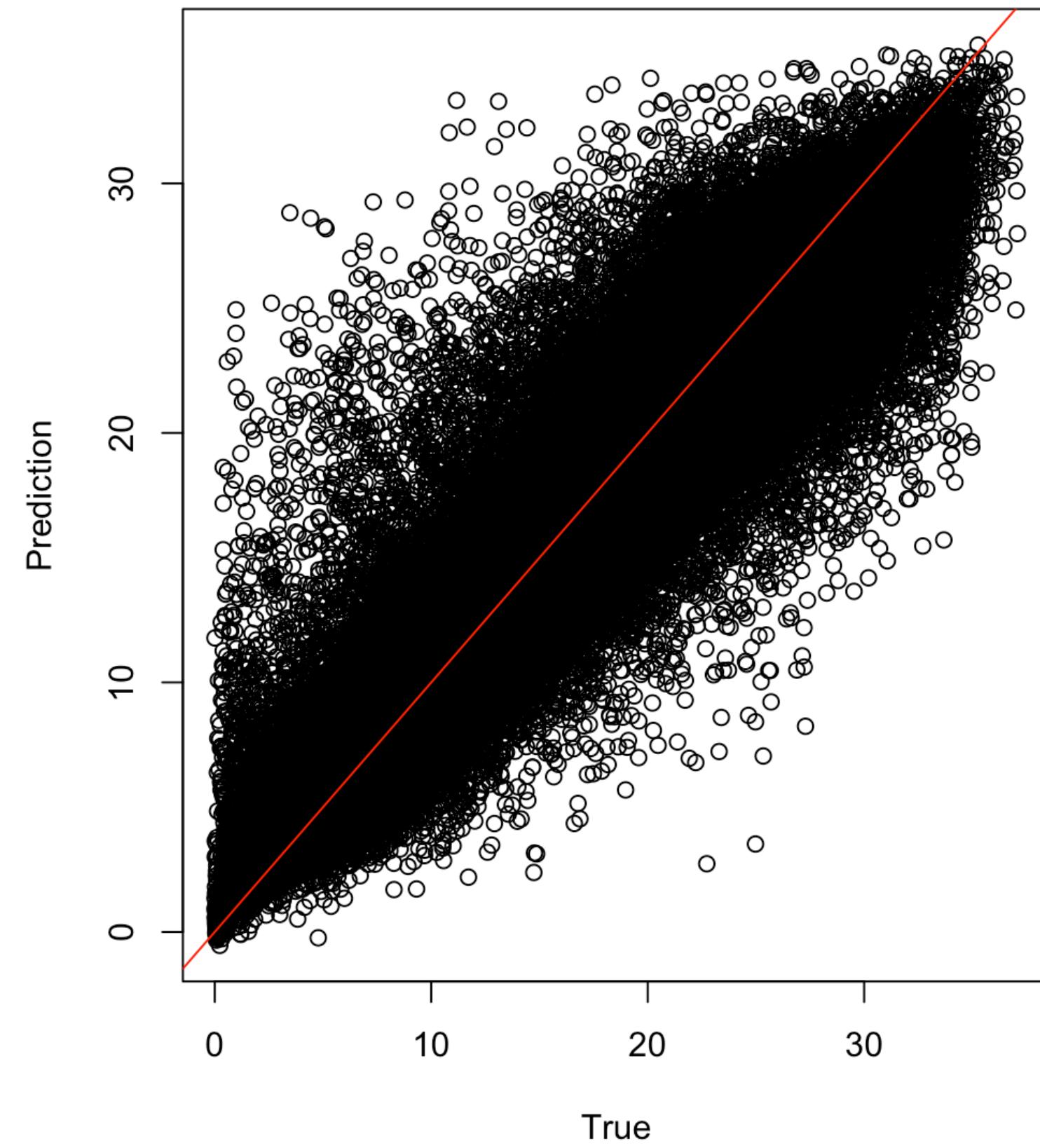
# Bonanza Creek Experimental Forest Data

Spatial model: Fitted using *BRISC\_estimation*, predictions using *BRISC\_prediction*

Metric	Spatial	Non-Spatial
RMSPE	2.92	6.59
CP	0.94	0.96
CIW	11.15	25.84



Non-spatial model

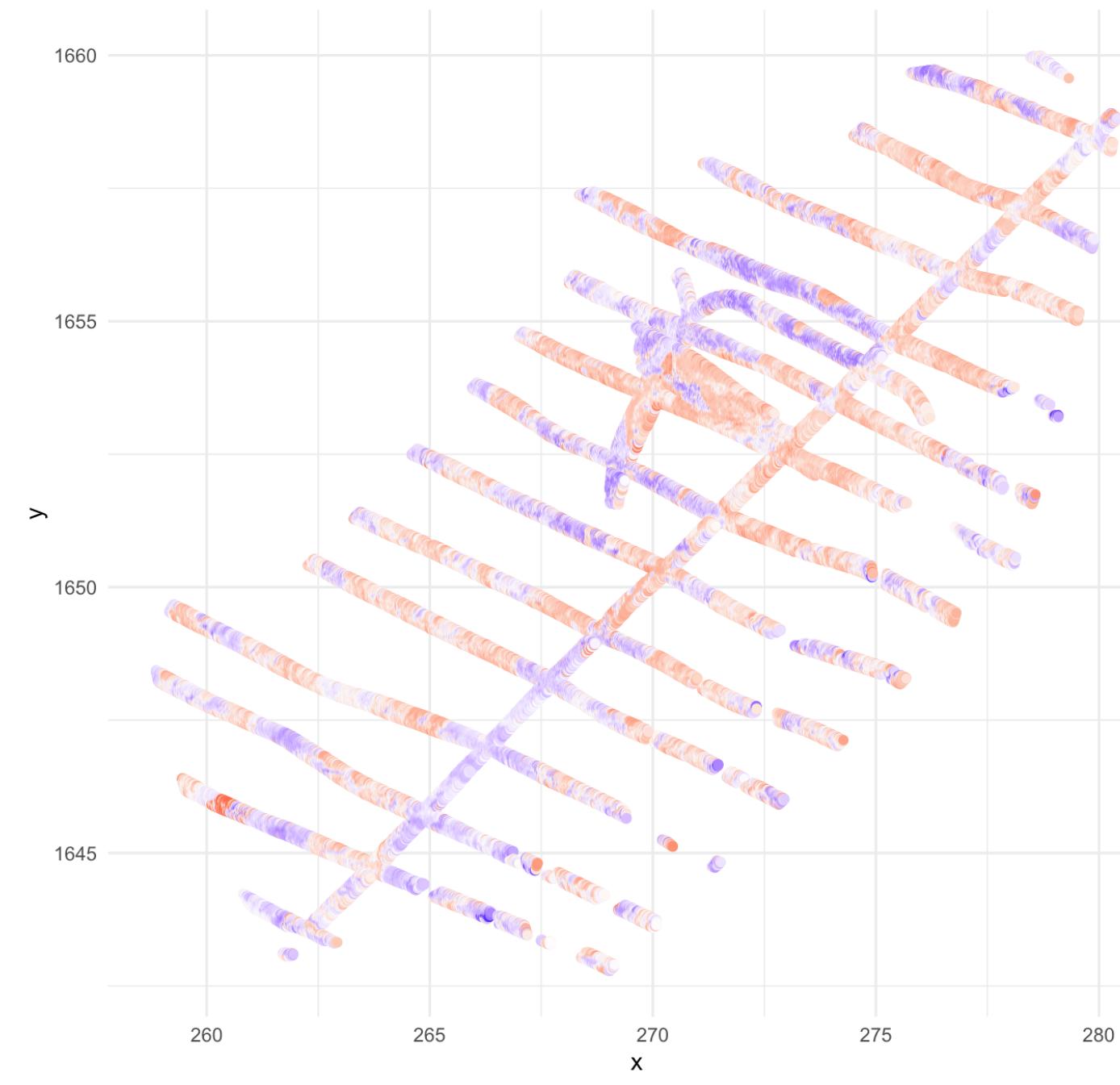


Spatial model

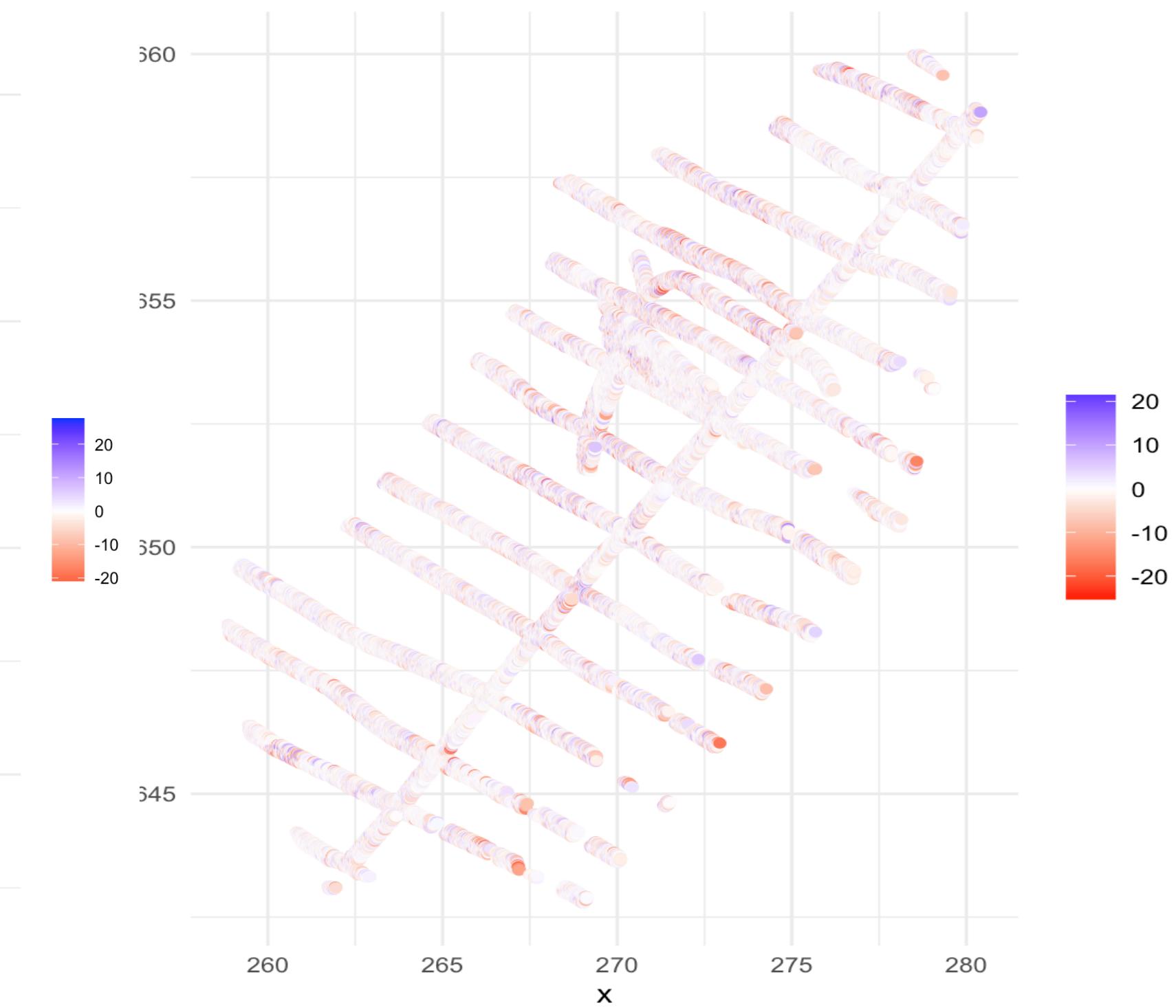
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Spatial  
model residuals



Non-spatial  
model residuals

# Summary

Introduction to geostatistics

  Data setup and analysis objectives

Exploratory data analysis to understand need for spatial modeling

  Maps and variograms of data and linear model residuals

Spatial linear mixed effect models

  Process level modeling and Gaussian processes

  Parameter estimation

  Prediction (kriging) with uncertainty quantification

# Summary

Model comparison

Estimation: AIC, BIC

Prediction: RMSPE, coverage probability and width of prediction intervals,

Big spatial data

Computing challenges

Fast alternatives (Nearest Neighbor Gaussian Process)

Spatial analysis using geoR and BRISC R-packages

# References

- Banerjee, S., Carlin, B. P., & Gelfand, A. E. (2003). *Hierarchical modeling and analysis for spatial data*. Chapman and Hall/CRC.
- Cressie, N., & Wikle, C. K. (2011). *Statistics for spatio-temporal data*. John Wiley & Sons.
- Stein, M. L. (2012). *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media.
- Van Der Vaart, A. W., & Van Zanten, J. H. (2008). *Rates of contraction of posterior distributions based on Gaussian process priors*.
- Van Der Vaart, A., & Van Zanten, H. (2011). *Information Rates of Nonparametric Gaussian Process Methods*. Journal of Machine Learning Research, 12(6).
- Heaton, M. J., Datta, A., Finley, A. O., Furrer, R., Guinness, J., Guhaniyogi, R., ... & Zammit-Mangion, A. (2019). A case study competition among methods for analyzing large spatial data. *Journal of Agricultural, Biological and Environmental Statistics*, 24, 398-425.
- Vecchia, A. V. (1988). *Estimation and model identification for continuous spatial processes*. *Journal of the Royal Statistical Society Series B: Statistical Methodology* , 50 (2), 297-312.
- Datta, A., Banerjee, S., Finley, A. O., & Gelfand, A. E. (2016). *Hierarchical nearest-neighbor Gaussian process models for large geostatistical datasets*. *Journal of the American Statistical Association*, 111(514), 800-812.