

# Spatial Statistics

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Centre for Modern Beamer Themes

# Spatial Stochastic Process/ Spatial Random Field\*\*

A spatial stochastic process is a family of random variables

$$\{Z(s) : s \in D\}$$

indexed by spatial locations  $s \in D$ .

$D$ : Spatial domain (the geographical region in which observations could be made)

$Z(s)$ : Random variable representing the quantity that you measure at location  $s$

# Temporal Stochastic Process

A collection of random variables  $\{X_t : t \in T\}$  or  $\{X(t) : t \in T\}$  where  $T$  is an index set. For each  $t \in T$ ,  $X_t$  or  $X(t)$  is a random variable.

# Three types of spatial data

1. Geostatistical processes

Example: Maximum temperature in Colombo District

2. Areal processes

Example: Dengue cases in each district in Sri Lanka

3. Point processes

Example: Location of dengue patients household addresses

# Geostatistical processes

A geostatistical process is the stochastic process

$$\{Z(\mathbf{s}) : \mathbf{s} \in D\}$$

where  $D$  is a fixed subset of the  $p$ -dimensional space  $\mathbb{R}^p$ . The locations  $s$  at which data could occur vary **continuously** over  $D$ . In other words, it is possible to measure at infinitely many locations across the spatial domain  $D$ .

## Areal unit process/ Lattice process

The spatial domain  $D$  is partitioned into  $n$  disjoint areal units which are denoted by

$$D = \{B_1, B_2, \dots, B_n\}$$

The areal stochastic process is denoted by

$$Z = \{Z(B_1), Z(B_2), \dots, Z(B_n)\}$$

## Alternative formulation of areal unit processes

Let  $s_1, s_2, \dots, s_n$  be the centroids of  $B_1, B_2, \dots, B_n$ . Then the areal stochastic process is denoted by

$$Z = \{Z(s_1), Z(s_2), \dots, Z(s_n)\}.$$

# Point Stochastic Process

Let

$$D = \{A_1, A_2, \dots, A_n\}$$

, where  $n$  denotes the number of points in  $D$ . Then the stochastic process is

$$Z = \{Z(A_1), Z(A_2), \dots, Z(A_n)\}.$$



# Goals of spatial analysis

- To find a statistical model that adequately explains the spatial dependency structure and trends, etc.
- Interpolation
- To make inferences
- To model the relationship between covariates and response

# Geostatistical stochastic process

A geostatistical process is the stochastic process

$$\{Z(\mathbf{s}) : \mathbf{s} \in D\}$$

where  $D$  is a fixed subset of the  $p$ -dimensional space  $\mathbb{R}^p$ . The locations  $\mathbf{s}$  at which data could occur vary **continuously** over  $D$ . In other words, it is possible to measure at infinitely many locations across the spatial domain  $D$ .

In this course, we focus on  $p = 2$ . That is, a location  $\mathbf{s} = (s_1, s_2)$ . For example,  $s_1$  and  $s_2$  could be longitude and latitude.

## Meuse river data set

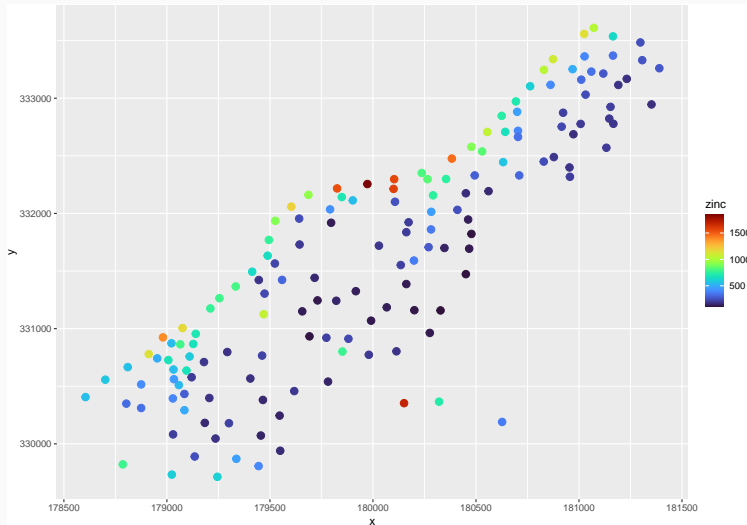
This data set gives locations and topsoil heavy metal concentrations, along with a number of soil and landscape variables at the observation locations, collected in a flood plain of the river Meuse, near the village of Stein (NL).

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x	y	cadmium	copper	lead	zinc	elev	dist
181072	333611	11.7	85	299	1022	7.909	0.00133
181025	333558	8.6	81	277	1141	6.983	0.01222
181165	333537	6.5	68	199	640	7.800	0.10300

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# EDA



# Mean function

The mean function of  $\{Z(\mathbf{s}) : \mathbf{s} \in D\}$  is

Continuous random variable

$$\mu(s) = E[Z(s)] = \int_{-\infty}^{\infty} z f_{ZZ}(s) dz$$

where  $f_{ZZ}(s)$  is the probability density function of  $Z(s)$ .

Discrete random variable

$$\mu(s) = E[Z(s)] = \sum_{z_i \in S} z_i f_{ZZ}(s)$$

where  $f_{ZZ}(s)$  is the probability mass function for  $Z(s)$ .

# Autocovariance function

$$C(\mathbf{s}, \mathbf{t}) = \text{Cov}[Z(\mathbf{s}), Z(\mathbf{t})]$$

Measures the linear dependence between  $Z(\mathbf{s})$  and  $Z(\mathbf{t})$ .

# Variance function

$$V[Z(\mathbf{s})] = C(\mathbf{s}, \mathbf{s}) = \nu^2(s)$$

# Theorems

1. The autocovariance function is symmetric in its arguments. That is,  $C(\mathbf{s}, \mathbf{t}) = C(\mathbf{t}, \mathbf{s})$  for each  $\mathbf{s}, \mathbf{t} \in D$ .
2. The autocovariance function  $C(\mathbf{s}, \mathbf{t})$  is a nonnegative definite function.



# Autocovariance function

$$\rho(\mathbf{s}, \mathbf{t}) = \text{Corr}[Z(\mathbf{s}), Z(\mathbf{t})] = \frac{C(\mathbf{s}, \mathbf{t})}{\sqrt{C(\mathbf{s}, \mathbf{s})C(\mathbf{t}, \mathbf{t})}}$$

Properties of autocorrelation function: In class

# White noise process

1.  $\mu(\mathbf{s}) = \mu$  for all  $\mathbf{s} \in D$
- 2.

$$C(\mathbf{s}, \mathbf{t}) = \begin{cases} \tau^2, & \text{if } \mathbf{s} = \mathbf{t}. \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

# Strictly Stationary

A geostatistical process  $\{Z(\mathbf{s}) : \mathbf{s} \in D\}$  is strictly stationary if

$$f(Z(\mathbf{s}_1), \dots, Z(\mathbf{s}_n)) = f(Z(\mathbf{s}_1 + h), \dots, Z(\mathbf{s}_n + h))$$

for any displacement vector  $h$  and any set of  $n$  locations  $\{\mathbf{s}_1, \dots, \mathbf{s}_n\}$ . This means, the joint distribution of a set of random variables are unaffected by spatial shifts.

## Weakly stationarity

1.  $E[Z(\mathbf{s})] = \mu(\mathbf{s}) = \mu$  for some finite constant  $\mu$  which does not depend on  $\mathbf{s}$ .
2.  $\text{Cov}[Z(\mathbf{s}), Z(\mathbf{s}+\mathbf{h})] = C(\mathbf{s}, \mathbf{s}+\mathbf{h}) = C(h)$

Here  $h$  is called the spatial lag or displacement.

Note: Strictly stationary implies it is weakly stationary, but the converse is not true in general (unless  $Z(\mathbf{s})$  is a Gaussian process).

# Isotropic

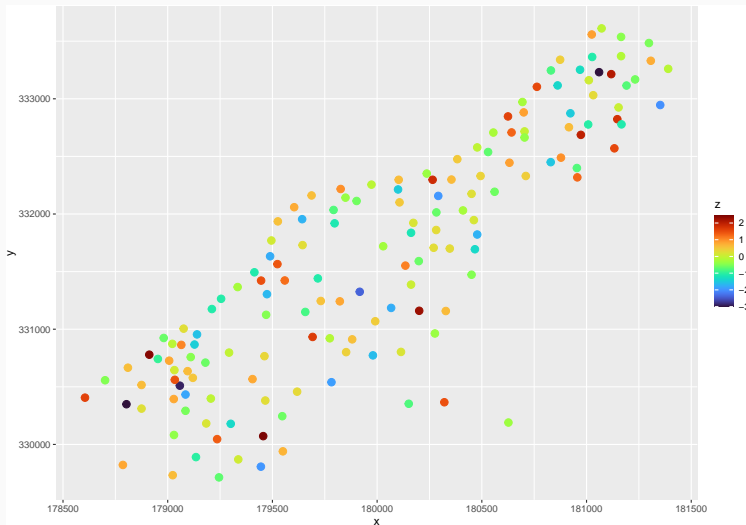
This means that the correlation between any two observations depends only on the distance between those locations and not on their relative orientation. There is no directional influence.

# Spatial Continuity

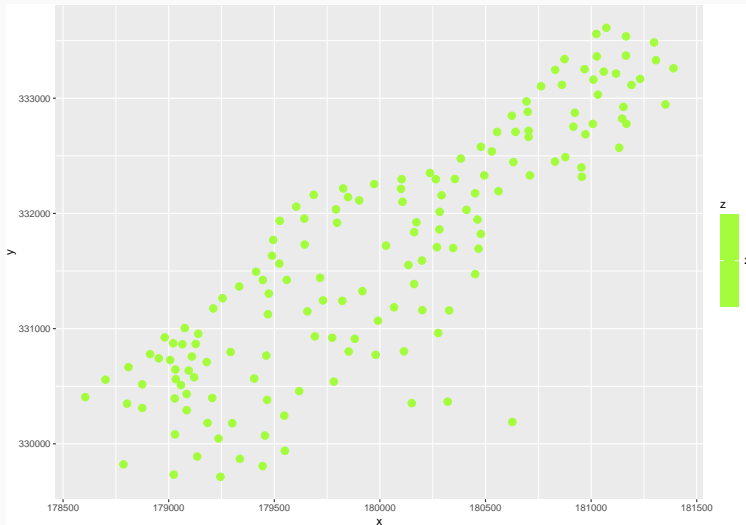
Spatial continuity: Correlation between values over distance

# No spatial continuity

Random values at each location



# Perfect spatial continuity





# Variogram

- Used to check if there is any spatial autocorrelation in the data.

# Semi-variogram

$$\gamma(\mathbf{s}, \mathbf{t}) = \frac{1}{2} \text{Var}[z(\mathbf{s}) - z(\mathbf{t})]$$

# Task

Show that, when the process has constant mean  $\mu(\mathbf{s}) = \mu$

$$\gamma(\mathbf{s}, \mathbf{t}) = \frac{1}{2} E[z(\mathbf{s}) - z(\mathbf{t})]^2$$

Proof: in-class

# Variogram calculation

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (Z(s_i) - Z(s_i + h))^2$$

# Important results

$$\gamma(\mathbf{h}) = \nu^2 - C(\mathbf{h})$$

Proof: In-class