

# Simulation of Gaussian random fields

May 28, 2019

## Definition

$\{Z(x)\}_{x \in \mathbb{R}^d}$  is called a (real) Gaussian random field if  $\forall n \in \mathbb{N} \setminus \{0\}, \forall x_1, \dots, x_n \in \mathbb{R}^d$ , the random vector  $(Z(x_1), \dots, Z(x_n))$  is Gaussian.

## Definition

**(Second order stationarity: usual definition)**

A random field  $Z(\cdot)$  on  $\mathbb{R}^d$  is second order stationary if the first two moments exist and verify:

$$E(Z(x)) = \mu \quad (1)$$

$$\text{Cov}(Z(x), Z(x+h)) = C(h), \quad (2)$$

for any  $x$  and  $h \in \mathbb{R}^d$ .

## Remark

*A 2nd order stationary Gaussian field  $Z$  is entirely determined by its mean and its covariance function  $C(h)$ .*

## Definition

Let  $Z(x)$  a second order stationary random field on  $\mathbb{R}^d$ . The variogram of  $Z(x)$  is the function

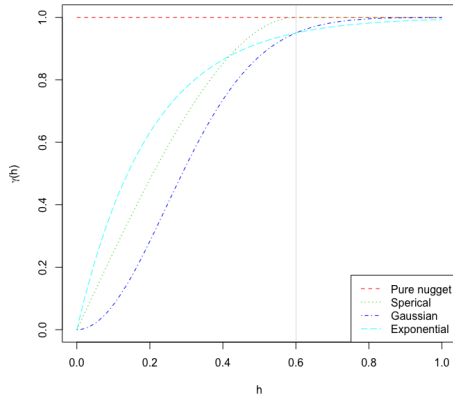
$$\gamma(h) = \frac{1}{2}E[(Z(x+h) - Z(x))^2] = C(0) - C(h) \quad (3)$$

## Definition (Isotropy)

A covariance function  $C(h)$  is said isotrope if it depends only on the distance  $r = \|h\|$  and not the direction of the vector  $h$ . We will therefore note  $C(h) = C(\|h\|) = C(r)$ .

Table: Examples of covariance functions

Name	Function
Pure nugget	$\gamma(h; \sigma^2) = \begin{cases} \sigma^2 & , \text{if } h > 0 \\ 0 & , \text{if } h = 0 \end{cases}$
Exponential	$\gamma(h; a, \sigma^2) = \sigma^2(1 - \exp(-\ h\ /a))$
Spherical	$\gamma(h; a, \sigma^2) = \begin{cases} \sigma^2(\frac{3\ h\ }{2a} - (\frac{\ h\ }{2a})^3) & , \text{if } \ h\  \leq a \\ \sigma^2 & , \text{if } \ h\  > a \end{cases}$
Gaussian	$\gamma(h; a, \sigma^2) = \sigma^2(1 - \exp(-(\ h\ /a)^2))$



**Figure:** Theoretical variograms for the real range of the spherical variogram and the practical range of the exponential and gaussian variograms; with nugget = 0, sill = 1 and range = 0.6.

# Simulation methods

## The Lower-Upper (LU) decomposition

Suppose we have  $n$  points to simulate with mean 0 and covariance  $C(r)$ . Let  $K$  be the covariance matrix. We decompose this matrix as  $K = LU$ , with  $L = {}^tU$  (Cholesky decomposition). We draw  $n$  independent random values  $y_i, i = 1 \dots n$  with distribution  $\mathcal{N}(0, 1)$ . Set  $z = Ly$ ;  $z$  is then a realization of  $Z$  having the right distribution law.

Proof.

$$\text{Cov}[LY, LY] = \mathbb{E}[LY^t Y^t L] = L \mathbb{E}[Y^t Y]^t L = L^t L = LU = K_{n \times n}$$



# Simulation methods

## The Turning Bands method

We choose an arbitrary origin  $0$  in  $\mathbb{R}^3$  and generate  $L$  lines  $i$  such that the corresponding direction vectors  $u_i$  are uniformly distributed on the unit sphere.

Let  $x_k$  be the points to be simulated where  $k \in \{1, \dots, n\}$ . We denote  $x_{ki} = x_k \cdot u_i$  the projection of the point  $x_k$  on the line  $i$ . Along each line  $i$ , we generate a second-order stationary unidimensional process having a covariance function

$$C_1(r) = \frac{d}{dr} rC(r).$$

Finally we assign to the point  $x_k$  the value  $z_s(x_k)$  given by

$$z_s(x_k) = \frac{1}{\sqrt{L}} \sum_{i=1}^L z_i(x_{ki})$$

as the realization of the three-dimensional random field.

# Simulations

## Distribution of $Z(\cdot)$

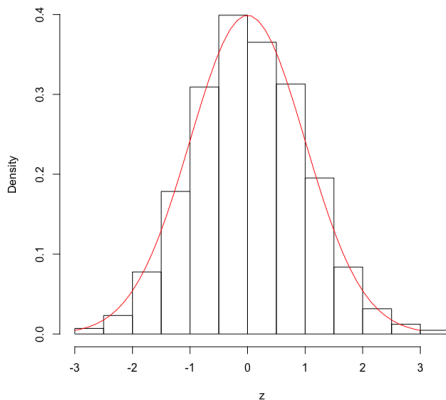
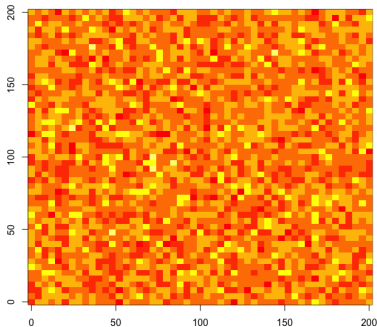


Figure: Histogram of  $Z(\cdot)$

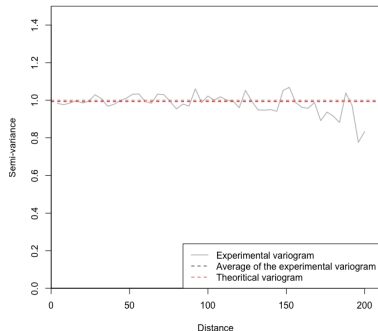


# Simulations

## Pure nugget effect



(a)

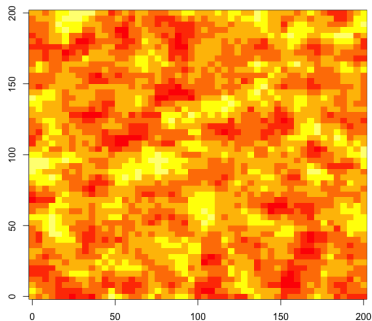


(b)

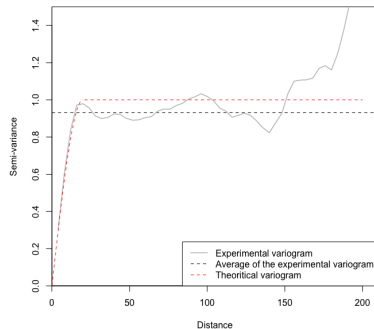
**Figure:** Pure nugget effect (a) gaussian random field and (b) variogram with sill = 1.

# Simulations

## Spherical



(a)

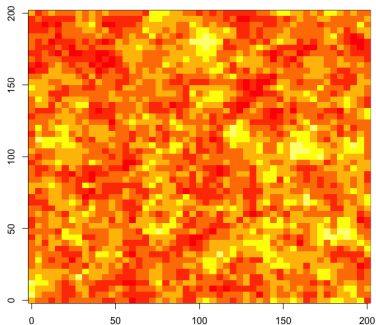


(b)

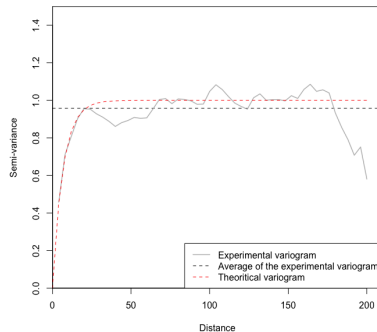
**Figure:** (a) Gaussian random field and (b) variogram of spherical covariance with nugget = 0, sill = 1 and range = 20.

# Simulations

## Exponential



(a)

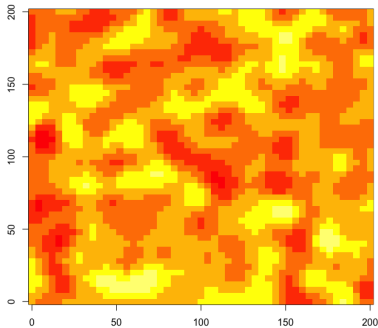


(b)

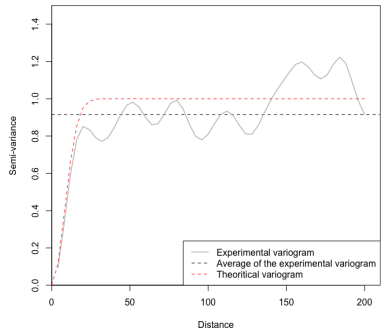
**Figure:** (a) Gaussian random field and (b) variogram of exponential covariance with nugget = 0, sill = 1 and range = 20.

# Simulations

## Gaussian



(a)

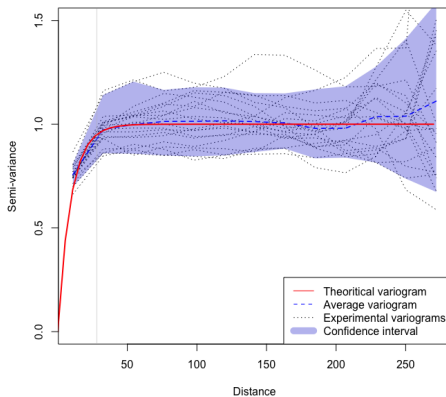


(b)

**Figure:** (a) Gaussian random field and (b) variogram of gaussian covariance with nugget = 0, sill = 1 and range = 20.

# Simulations

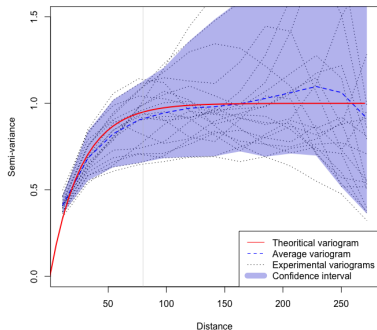
## Empirical convergence



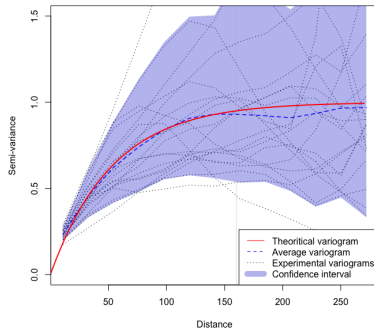
**Figure:** Averages of 20 exponential variograms with a practical ranges of 28.

# Simulations

## Empirical convergence



(b)



(c)

**Figure:** Averages of 20 exponential variograms with a practical range of (a) 80 and (b) 160.

Thank you for your attention

Q/A