

Lecture notes part 2: Point referenced data modeling / Geostatistics

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Aim. To introduce point referenced data modeling (geostatistics) with particular focus on concepts spatial variables, random fields, semi-variogram, kriging, change of support, multivariate geostatistics, for Bayesian and classical inference.

Reading list & references:

- [1] Cressie, N. (2015; Part I). Statistics for spatial data. John Wiley & Sons.
- [2] Kent, J. T., & Mardia, K. V. (2022). Spatial analysis (Vol. 72). John Wiley & Sons.
- [3] Chiles, J. P., & Delfiner, P. (2012). Geostatistics: modeling spatial uncertainty (Vol. 713). John Wiley & Sons.
- [4] Wackernagel, H. (2003). Multivariate geostatistics: an introduction with applications. Springer Science & Business Media.
- [5] Gaetan, C., & Guyon, X. (2010; Ch 2 & 5.1). Spatial statistics and modeling (Vol. 90). New York: Springer.

Part 1. Basic stochastic models & related concepts for model building

Note 1. We discuss basic stochastic models and concepts for modeling point referenced data in the Geostatistics framework.

1. RANDOM FIELDS (OR STOCHASTIC PROCESSES)

Definition 2. A random field (or stochastic process, or random function) $Z = (Z(s); s \in \mathcal{S})$ taking values in $\mathcal{Z} \subseteq \mathbb{R}^q$, $q \geq 1$ is a family of random variables $\{Z(s) := Z(s; \omega); s \in \mathcal{S}, \omega \in \Omega\}$ defined on the same probability space $(\Omega, \mathfrak{F}, \text{pr})$ and taking values in \mathcal{Z} . The label $s \in \mathcal{S}$ is called site, the set $\mathcal{S} \subseteq \mathbb{R}^d$ is called the (spatial) set of sites at which the random field is defined, and \mathcal{Z} is called the state space of the field.

Note 3. Given a set of sites $\{s_1, \dots, s_n\}$, with $s_i \in \mathcal{S}$ and $n \in \mathbb{N}$, the random vector $(Z(s_1), \dots, Z(s_n))^T$ has a well-defined probability distribution that is completely determined by its joint CDF

$$F_{s_1, \dots, s_n}(z_1, \dots, z_n) := \text{pr}(Z(s_1) \leq z_1, \dots, Z(s_n) \leq z_n)$$

The family of all finite-dimensional distributions (or fidi's) of Z is called the spatial distribution of the process .

Note 4. According to Kolmogorov Theorem 5, to define a random field model, one must specify the joint distribution of $(Z(s_1), \dots, Z(s_n))^T$ for all of n and all $\{s_i \in S; i = 1, \dots, n\}$ in a consistent way.

Proposition 5. (*Kolmogorov consistency theorem*) Let pr_{s_1, \dots, s_n} be a probability on \mathbb{R}^n with joint CDF F_{s_1, \dots, s_n} for every finite collection of points s_1, \dots, s_n . If F_{s_1, \dots, s_n} is symmetric w.r.t. any permutation \mathbf{p}

$$F_{\mathbf{p}(s_1), \dots, \mathbf{p}(s_n)}(z_{\mathbf{p}(1)}, \dots, z_{\mathbf{p}(n)}) = F_{s_1, \dots, s_n}(z_1, \dots, z_n)$$

for all $n \in \mathbb{N}$, $\{s_i \in S\}$, and $\{z \in \mathbb{R}\}$, and all if all permutations \mathbf{p} are consistent in the sense

$$\lim_{z_n \rightarrow \infty} F_{s_1, \dots, s_n}(z_1, \dots, z_n) = F_{s_1, \dots, s_{n-1}}(z_1, \dots, z_{n-1})$$

or all $n \in \mathbb{N}$, $\{s_i \in S\}$, and $\{z_i \in \mathbb{R}\}$, then there exists a random field Z whose fidi's coincide with those in F .

Example 6. Let $n \in \mathbb{N}$, let $\{X_i : \mathcal{S} \rightarrow \mathbb{R}; i = 1, \dots, n\}$ be a set of constant functions, and let $\{Z_i \sim N(0, 1)\}_{i=1}^n$ be a set of independent random variables. Then

$$(1.1) \quad \tilde{Z}(s) = \sum_{i=1}^n Z_i X_i(s), \quad s \in S$$

is a well defined random field as it satisfies Theorem 5.

1.1. Mean and covariance functions.

Definition 7. The mean function $\mu(\cdot)$ and covariance function $c(\cdot, \cdot)$ of a random field $(Z(s); s \in \mathcal{S})$ are defined as

$$(1.2) \quad \mu(s) = E(Z(s)), \quad \forall s \in \mathcal{S}$$

$$(1.3) \quad c(s, s') = \text{Cov}(Z(s), Z(s')) = E\left((Z(s) - \mu(s))(Z(s') - \mu(s'))^T\right), \quad \forall s, s' \in \mathcal{S}$$

Example 8. For (1.1), the mean function is $\mu(s) = E(\tilde{Z}_s) = 0$ and covariance function is

$$\begin{aligned} c(s, s') &= \text{Cov}(Z(s), Z(s')) = \text{Cov}\left(\sum_{i=1}^n Z_i X_i(s), \sum_{j=1}^n Z_j X_j(s')\right) \\ &= \sum_{i=1}^n X_i(s) \sum_{j=1}^n X_j(s') \text{Cov}(Z_i, Z_j) = \sum_{i=1}^n X_i(s) X_i(s') \end{aligned}$$

1.1.1. Construction of covariance functions.

Note 9. What follows provides the means for checking and constructing covariance functions.

Proposition 10. The function $c : \mathcal{S} \times \mathcal{S} \rightarrow \mathbb{R}$, $\mathcal{S} \subseteq \mathbb{R}^d$ is a covariance function iff $c(\cdot, \cdot)$ is semi-positive definite; i.e.

$$\forall n \in \mathbb{N} - \{0\}, \forall (a_1, \dots, a_n) \in \mathbb{R}^n \text{ and } \forall (s_1, \dots, s_n) \in \mathcal{S}^n : \sum_{i=1}^n \sum_{j=1}^n a_i a_j c(s_i, s_j) \geq 0$$

or in other words, the Gram matrix $(c(s_i, s_j))_{i,j=1}^n$ is non-negative definite for any $\{s_i\}_{i=1}^n$, $n \in \mathbb{N} - \{0\}$.

Example 11. $c(s, s') = 1(\{s = s'\})$ is a proper covariance function because

$$\sum_i \sum_j a_i a_j c(s_i, s_j) = \sum_i a_i^2 \geq 0, \quad \forall a$$

Note 12. One way to construct a c.f c is to set $c(s, s') = \psi(s)^\top \psi(s')$, for a given vector of basis functions $\psi(\cdot) = (\psi_1(\cdot), \dots, \psi_n(\cdot))$.

Proof. From Proposition 10, as

$$\sum_i \sum_j a_i a_j c(s_i, s_j) = (\psi a)^\top (\psi a) \geq 0, \quad \forall a \in \mathbb{R}^n$$

□

2. SECOND ORDER RANDOM FIELDS (OR SECOND ORDER PROCESSES)

Note 13. We introduce a particular class of random fields whose mean and covariance functions exist and which can be used for spatial data modeling.

Definition 14. Second order random field (or second order process) $(Z(s); s \in \mathcal{S})$ is called the random field where $E((Z(s))^2) < \infty$ for all $s \in \mathcal{S}$.

Example 15. In second order random field $(Z(s); s \in \mathcal{S})$ the associated mean function $\mu(\cdot)$ and covariance function $c(\cdot, \cdot)$ exist, because $c(s, t) = E(Z(s)Z(t)) - E(Z(s))E(Z(t))$ for $s, t \in \mathcal{S}$.

3. GAUSSIAN RANDOM FIELD (OR GAUSSIAN PROCESS)

Note 16. Gaussian random field (GRF) is a particular class of second order random field which is widely used in spatial data modeling due to its computational tractability.

Definition 17. $(Z(s); s \in \mathcal{S})$ is a Gaussian random field (GRF) or Gaussian process (GP) on \mathcal{S} if for any $n \in \mathbb{N}$ and for any finite set $\{s_1, \dots, s_n; s_i \in \mathcal{S}\}$, the random vector $(Z(s_1), \dots, Z(s_n))^\top$ follows a multivariate normal distribution. Also Example Proposition

Proposition 18. A GP $(Z(s); s \in \mathcal{S})$ is fully characterized by its mean function $\mu : \mathcal{S} \rightarrow \mathbb{R}$ with $\mu(s) = E(Z(s))$, and its covariance function with $c(s, s') = \text{Cov}(Z(s), Z(s'))$.

Notation 19. Hence, we denote the GP as $Z(\cdot) \sim \mathcal{GP}(\mu(\cdot), c(\cdot, \cdot))$.

Note 20. When using GP for spatial modeling we just need to specify its functional parameters i.e. the mean and covariance functions.

Note 21. Popular forms of mean functions are polynomial expansions, such as $\mu(s) = \sum_{j=0}^{p-1} \beta_j s^j$ for tunable unknown parameter β . A popular form of covariance functions (c.f.), for tunable unknown parameters $\phi > 0$, and $\sigma^2 > 0$, are

- (1) Exponential c.f. $c(s, s') = \sigma^2 \exp(-\phi \|s - s'\|_1)$
- (2) Gaussian c.f. $c(s, s') = \sigma^2 \exp(-\phi \|s - s'\|_2^2)$
- (3) Nugget c.f. $c(s, s') = \sigma^2 1(s = s')$

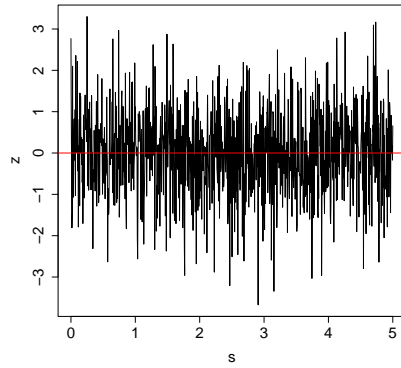
Example 22. Recall your linear regression lessons where you specified the sampling distribution to be $y_x | \beta, \sigma^2 \stackrel{\text{ind}}{\sim} \mathcal{N}(x^\top \beta, \sigma^2)$, $\forall x \in \mathbb{R}^d$. Well that can be considered as a GP $Z(\cdot) \sim \mathcal{GP}(\mu(\cdot), c(\cdot, \cdot))$ with $\mu(x) = x^\top \beta$ and $c(x, x') = \sigma^2 1(x = x')$ in (3).

Example 23. Figures 3.1 & 3.2 presents realizations of GRF $Z(\cdot) \sim \mathcal{GP}(\mu(\cdot), c(\cdot, \cdot))$ with $\mu(s) = 0$ and differently parameterized covariance functions in 1D and 2D. In 1D the code to simulate the GP is given in Algorithm 1. Note that we actually discretize it and simulate it from the fidi.

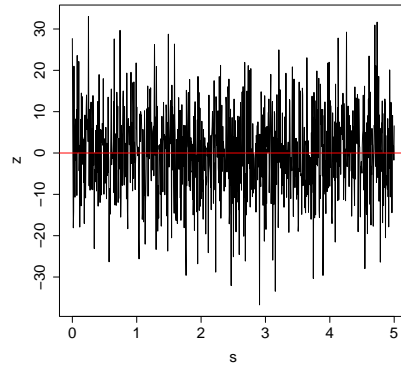
Algorithm 1 R script for simulating from a GP ($Z(s); s \in \mathbb{R}^1$) with $\mu(s) = 0$ and $c(s, t) = \sigma^2 \exp(-\phi \|s - t\|_2^2)$

```
# set the GP parameterized mean and covariance function
mu_fun <- function(s) { return (0) }
cov_fun_gauss <- function(s,t,sig2,phi) {
  return ( sig2*exp(-phi*norm(c(s-t),type="2")**2) )
}
# discretize the problem in n = 100 spatial points
n <- 100
s_vec <- seq(from = 0, to = 5, length = n)
mu_vec <- matrix(nrow = n, ncol = 1)
Cov_mat <- matrix(nrow = n, ncol = n)
# compute the associated mean vector and covariance matrix of the n=100 dimensional
Normal r.v.
sig2_val <- 1.0 ;
phi_val <- 5
for (i in 1:n) {
  mu_vec[i] <- mu_fun(s_vec[i])
  for (j in 1:n) {
    Cov_mat[i,j] <- cov_fun_gauss(s_vec[i],s_vec[j],sig2_val,phi_val)
  }
}
# simulate from the associated distribution
z_vec <- mu_vec + t(chol(Cov_mat))%*%rnorm(n, mean=0, sd=1)
# plot the path (R produces a line plot)
plot(s_vec, z_vec, type="l")
abline(h=0,col="red")
```

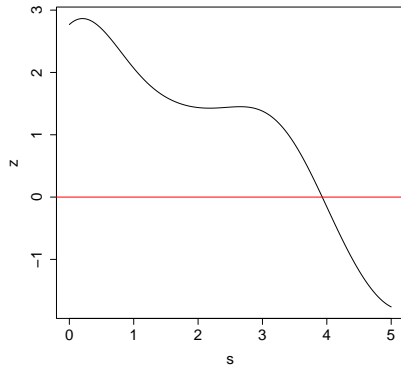
Nugget c.f. is the usual noise where the height of ups and downs are random and controlled by σ^2 (Figures 3.1a & 3.1b ; Figures 3.2a & 3.2b). In Gaussian c.f. the height of ups and downs are random and controlled by σ^2 (Fig.3.1c & 3.1d ; Figures 3.2c & 3.2d), and the spatial dependence / frequency of the ups and downs is controlled by β (Figures 3.1d & 3.1e ; Figures 3.2d & 3.2e). Realizations with different c.f. have different behavior (Figures 3.1a, 3.1d & 3.1e ; Figures 3.2a, 3.2d & 3.2e)



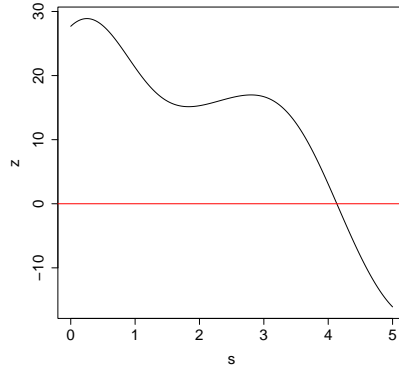
(A) Nugget c.f
($\sigma^2 = 1$)



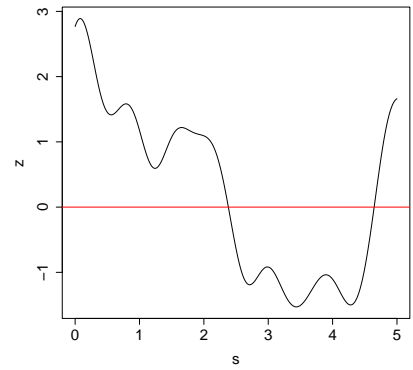
(B) Nugget c.f
($\sigma^2 = 100$)



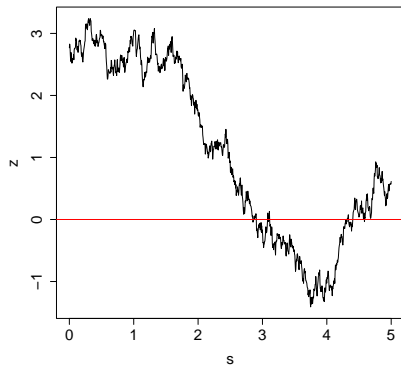
(C) Gauss c.f
($\sigma^2 = 1, \phi = 0.5$)



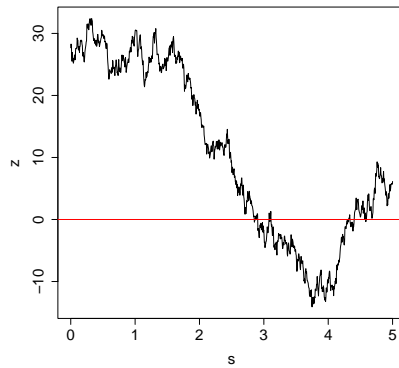
(D) Gauss c.f
($\sigma^2 = 100, \phi = 0.5$)



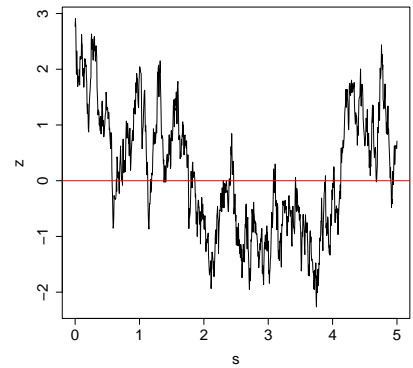
(E) Gauss c.f
($\sigma^2 = 1, \phi = 5$)



(F) Exp c.f
($\sigma^2 = 1, \phi = 0.5$)



(G) Exp c.f
($\sigma^2 = 100, \phi = 0.5$)



(H) Exp c.f
($\sigma^2 = 1, \phi = 5$)

FIGURE 3.1. Realizations of GRF $Z(\cdot) \sim \mathcal{GP}(\mu(\cdot), c(\cdot, \cdot))$ when $s \in [0, 5]$ (using same seed)

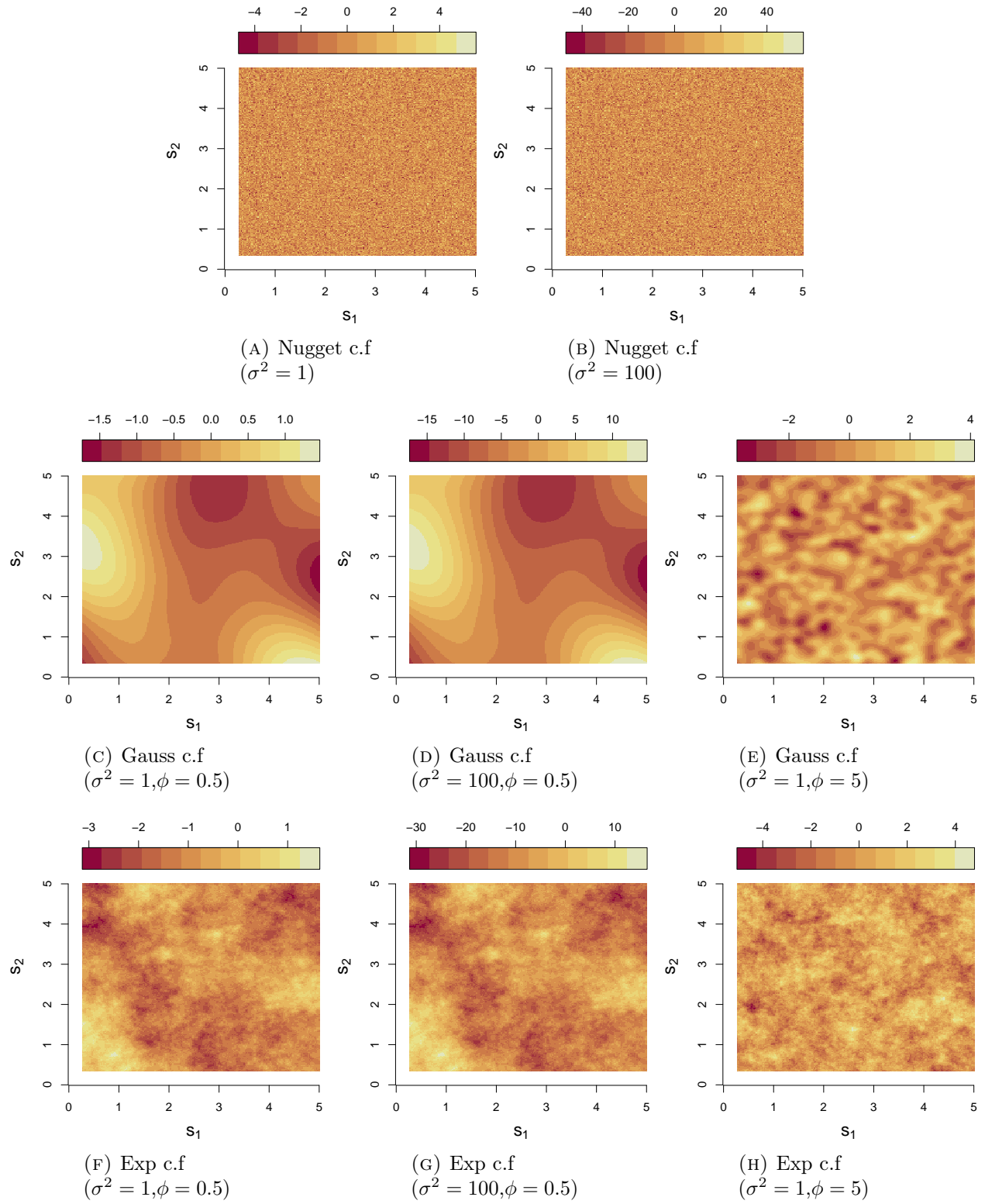


FIGURE 3.2. Realizations of GRF $Z(\cdot) \sim \mathcal{GP}(\mu(\cdot), c(\cdot, \cdot))$ when $s \in [0, 5]^2$ (using same seed)

4. STRONG STATIONARITY

Note 24. We introduce a specific behavior of random field to build our models.

Notation 25. Formally, we define the separation (or lag) set as $\mathcal{H} = \{h \in \mathbb{R}^d : s \in \mathcal{S}, s + h \in \mathcal{S}\}$ where $\mathcal{S} \subseteq \mathbb{R}^d$ is the spatial domain for $d = 1, 2, 3, \dots$. However, we will consider cases where $\mathcal{S} = \mathbb{R}^d$ and $\mathcal{H} = \mathbb{R}^d$ for $d = 1, 2, 3, \dots$ in Euclidean spaces.

Definition 26. A random field $(Z(s); s \in \mathcal{S})$ is strongly stationary on \mathcal{S} if for all finite sets consisting of $s_1, \dots, s_n \in \mathcal{S}$, $n \in \mathbb{N}$, for all $k_1, \dots, k_n \in \mathbb{R}$, and for all $h \in \mathcal{H}$

$$\text{pr}(Z(s_1 + h) \leq k_1, \dots, Z(s_n + h) \leq k_n) = \text{pr}(Z(s_1) \leq k_1, \dots, Z(s_n) \leq k_n)$$

Note 27. Yuh... strong stationary may represent a behavior being too “restrictive” to be used for spatial data modeling as it is able to represent only limiting number of spatial dependencies.

5. WEAK STATIONARITY (OR SECOND ORDER STATIONARITY)

Note 28. We introduce another weaker behavior of random field able to represent a larger class of spatial dependencies.

Note 29. Instead of working with the “restrictive” strong stationarity, we could just properly specify the behavior of the first two moments only; notice that Definition 26 implies that, given $E((Z(s))^2) < \infty$, it is $E(Z(s)) = E(Z(s+h)) = \text{const}$... and $\text{Cov}(Z(s), Z(s')) = \text{Cov}(Z(s+h), Z(s'+h)) \stackrel{h=s'-s}{=} \text{Cov}(Z(s-s'), Z(0)) = \text{funct of lag}$...

Definition 30. A random field $(Z(s); s \in \mathcal{S})$ is called stationary random field (s.r.f.) (or weakly stationary or second order stationary) if it has constant mean and translation invariant covariance; i.e. for all $s, s' \in \mathbb{R}^d$,

- (1) $E((Z(s))^2) < \infty$ (finite)
- (2) $E(Z(s)) = \mu$ (constant)
- (3) $\text{Cov}(Z(s), Z(s')) = c(s' - s)$ for some even function $c : \mathcal{S} \rightarrow \mathbb{R}$ (lag dependency)

Definition 31. Stationary (or weakly or second order stationary) covariance function is called the c.f. of a stationary random field.

6. COVARIOGRAM

Note 32. We introduce the covariogram function able to express many aspects of the behavior of a (weakly) stationary random field and hence be used as statistical descriptive tool.

Definition 33. The covariogram function of a weakly stationary random field $(Z(s); s \in \mathcal{S})$ is defined by $c : \mathcal{H} \rightarrow \mathbb{R}$ with

$$c(h) = \text{Cov}(Z(s), Z(s+h)), \forall s \in \mathcal{S}, \forall h \in \mathcal{H}.$$

Example 34. For the Gaussian c.f. $c(s, t) = \sigma^2 \exp(-\phi \|s - t\|_2^2)$ in (Ex. 20(2)), we may denote just

$$(6.1) \quad c(h) = c(s, s+h) = \sigma^2 \exp(-\phi \|h\|_2^2)$$

Observe that, in Figures 3.1 & 3.2, the smaller the ϕ , the smoother the realization (aka slower changes). One way to justify this observation is to think that smaller values of ϕ essentially bring the points closer by re-scaling spatial lags h in the c.f.

Proposition 35. If $c : \mathcal{H} \rightarrow \mathbb{R}$ is the covariogram of a weakly stationary random field $(Z(s); s \in \mathcal{S})$ then:

- (1) $c(h) = c(-h)$ for all $h \in \mathcal{H}$
- (2) $|c(h)| \leq c(0) = \text{Var}(Z(s))$ for all $h \in \mathcal{H}$
- (3) $c(\cdot)$ is semi-positive definite; i.e. for all $n \in \mathbb{N} - \{0\}$, $(a_1, \dots, a_n) \in \mathbb{R}^n$, and $(s_1, \dots, s_n) \subseteq \mathcal{S}^n$

$$\sum_{i=1}^n \sum_{j=1}^n a_i a_j c(s_i - s_j) \geq 0$$

Note 36. Given there is some knowledge of the characteristic functions of a suitable distribution, the following spectral representation theorem helps in the specification of a suitable covariogram.

Theorem 37. (Bochner's theorem) Let $c : \mathbb{R}^d \rightarrow \mathbb{R}$ be a continuous even real-valued function for $d \geq 1$. Then $c(\cdot)$ is positive semidefinite (hence a covariogram of a stationary random field) if and only if it can be represented as

$$c(h) = \int_{\mathbb{R}^d} \exp(i\omega^\top h) dF(\omega)$$

where F is a symmetric positive finite measure on \mathbb{R}^d called spectral measure.

Note 38. In our course, we focus on cases where F has a density $f(\cdot)$ i.e. $dF(\omega) = f(\omega) d\omega$. $f(\cdot)$ is called spectral density of $c(\cdot)$, it is

$$c(h) = \int_{\mathbb{R}^d} \exp(i\omega^\top h) f(\omega) d\omega,$$

and it dies as $\lim_{|h| \rightarrow \infty} c(h) = 0$

Theorem 39. If $c(\cdot)$ is integrable, the spectral density $f(\cdot)$ can be computed by inverse Fast Fourier transformation

$$f(\omega) = \left(\frac{1}{2\pi}\right)^d \int_{\mathbb{R}^d} \exp(-i\omega^\top h) c(h) dh$$

Example 40. Consider the Gaussian c.f. $c(h) = \sigma^2 \exp(-\phi \|h\|_2^2)$ for $\sigma^2, \phi > 0$ and $h \in \mathbb{R}^d$. Then, by using Theorem 37, the spectral density is

$$\begin{aligned} f(\omega) &= \left(\frac{1}{2\pi}\right)^d \int_{\mathbb{R}^d} \exp(-i\omega^\top h) \sigma^2 \exp(-\phi \|h\|_2^2) dh \\ &= \sigma^2 \left(\frac{1}{2\pi}\right)^d \prod_{j=1}^d \int_{\mathbb{R}} \exp(-i\omega_j h_j - \phi h_j^2) dh_j \\ &= \sigma^2 \left(\frac{1}{2\pi}\right)^d \prod_{j=1}^d \int_{\mathbb{R}} \exp(-\phi (h_j - (-i\omega_j / (2\phi)))^2) \exp(-\omega_j^2 / (4\phi)) dh_j \\ &= \sigma^2 \left(\frac{1}{4\pi\phi}\right)^{d/2} \exp(-\|\omega\|_2^2 / (4\phi)) \end{aligned}$$

i.e. it has a Gaussian form.

Definition 41. Let $(Z(s) : s \in \mathcal{S})$ be a weakly stationary random field with covariogram function $c : \mathcal{H} \rightarrow \mathbb{R}$ and $c(h) = \text{Cov}(Z(s), Z(s+h))$. The correlogram function $\rho : \mathcal{H} \rightarrow [-1, 1]$ is defined as

$$\rho(h) = \frac{c(h)}{c(0)}.$$

7. INTRINSIC STATIONARITY (OF ORDER ZERO)

Note 42. The class of (weakly) stationary random fields may not be sufficiently general enough to model a large number of important applications. E.g., in certain applications, it has been noticed that the “underline process” we wish to model presents increments whose variance

$$\text{Var}(Z(s+h) - Z(s)) = \text{Var}(Z(s+h)) + \text{Var}(Z(s)) - 2\text{Cov}(Z(s+h), Z(s))$$

increases indefinitely with $|h|$; this “process” cannot be modeled within the class of (weakly) stationary random fields whose increments have bounded variance $\text{Var}(Z(s+h) - Z(s)) = 2(c(0) - c(h)) < 2c(0)$. Intrinsic stationary is a weaker assumption extending the class of models we can use.

Definition 43. A random field $(Z(s) : s \in \mathcal{S})$ is called intrinsic random field (i.r.f.) (or intrinsic stationary r.f.) if, for all $h \in \mathcal{H}$,

- (1) $E(Z(s+h) - Z(s))^2 < \infty$
- (2) $E(Z(s+h) - Z(s)) = \mu(h)$ for some function $\mu : \mathcal{H} \rightarrow \mathbb{R}$ (lag dependent)
- (3) $\text{Var}(Z(s+h) - Z(s)) = 2\gamma(h)$ for some function $\gamma : \mathcal{H} \rightarrow \mathbb{R}$ (lag dependent)

Example 44. The random field with covariance function

$$c(s, t) = \frac{1}{2} \left(\|s\|^{2H} + \|t\|^{2H} - \|t - s\|^{2H} \right), \quad H \in (0, 1)$$

is not stationary r.f. because

$$c(s, s+h) = \frac{1}{2} \left(\|s\|^{2H} + \|s+h\|^{2H} - \|h\|^{2H} \right)$$

for $h \in \mathcal{H}$ but it intrinsic r.f. because

$$\frac{1}{2} \text{Var}(Z(s+h) - Z(s)) = \frac{1}{2} (\text{Var}(Z(s)) + \text{Var}(Z(s+h)) - 2\text{Cov}(Z(s), Z(s+h))) = \frac{1}{2} \|h\|^{2H}$$

Example 45. For an i.r.f. $(Z(s) : s \in \mathcal{S})$ with $\mu(h) = 0$, it can be shown that

$$(7.1) \quad \text{Cov}(Z(t) - Z(s), Z(v) - Z(u)) = \gamma(t-u) + \gamma(s-v) - \gamma(s-u) - \gamma(t-v)$$

by taking expectations from

$$2(a-b)(c-e) = (a-e)^2 + (a-b)^2 - (b-c)^2 - (a-c)^2$$

Note 46. The price to be paid for i.r.f. offering a larger class of models by setting the assumptions on the increments only, is involve an indeterminacy regarding the actual r.f. $Z(s)$; E.g. i.r.f. $(Z(s) : s \in \mathcal{S})$ and $(Z(s) + U : s \in \mathcal{S})$ where U a single variable leave (2) and (3) in Def 43 unchanged. When this causes problems, usual trick are: (a) “registration” (Example 47), i.e. consider an additional non-used specific site $s_0 \in \mathcal{S}$ (called origin) at which a value is known $Z(s_0) = z_0$ and try to work out (b) impose restrictions int eh increments.

Example 47. To specify the moments of an i.r.f. $Z(s)$. Consider an origin $s_0 \in \mathcal{S}$ with known $Z(s_0) = z_0$, and specify the “registered” r.f. $\tilde{Z}(s) = z_0 + (Z(s) - Z(s_0))$. Then $E(\tilde{Z}(s)) = z_0 + \mu(s - s_0)$ and $\text{Cov}(\tilde{Z}(s), \tilde{Z}(t))$ computed from (7.1).

Example 48. Only the covariance of allowed linear combinations can be represented w.r.t. $\gamma(\cdot)$. I.e.

$$\text{Cov} \left(\sum_{i=1}^n a_i Z(s_i), \sum_{j=1}^n b_j Z(s_j) \right) = \sum_{i=1}^n a_i \sum_{j=1}^n b_j \text{Cov}(Z(s_i), Z(s_j))$$

assuming Z is i.r.f. hence covariogram may not be defined, we consider origin $s_0 \in \mathcal{S}$ with $Z(s_0)$ and we restrict to the sum-to-zero linear combinations. Hence, by (7.1)

$$\begin{aligned} \text{Cov} \left(\sum_{i=1}^n a_i Z(s_i), \sum_{j=1}^n b_j Z(s_j) \right) &= \sum_{i=1}^n a_i \sum_{j=1}^n b_j \text{Cov}(Z(s_i) - Z(s_0), Z(s_j) - Z(s_0)) \\ &= \sum_{i=1}^n a_i \sum_{j=1}^n b_j (\gamma(s_i - s_0) + \gamma(s_j - s_0) - \gamma(s_j - s_i)) \\ &= - \sum_{i=1}^n \sum_{j=1}^n a_i b_j \gamma(s_j - s_i) \end{aligned}$$

8. INCREMENTAL MEAN FUNCTION

Definition 49. Incremental mean function (or drift) of the intrinsic random field $(Z(s) : s \in \mathcal{S})$ is defined as $\mu : \mathcal{H} \rightarrow \mathbb{R}$ with $\mu(h) = \mathbb{E}(Z(s+h) - Z(s))$.

Example 50. Let $(Z(s) : s \in \mathcal{S})$ be an intrinsic random field, the incremental drift is linear

$$(8.1) \quad \mu(h) = h^\top \beta$$

for some $\beta \in \mathbb{R}^d$. Indeed, it is

$$\begin{aligned} \mu(h+h') &= \mathbb{E}(Z(s+h+h') - Z(s)) = \mathbb{E}(Z(s+h) - Z(s)) + \mathbb{E}(Z(s+h+h') - Z(s+h)) \\ &= \mu(h) + \mu(h'), \quad \forall h, h'. \end{aligned}$$

Since, $\mu(\cdot)$ is continuous and $\mu(0) = 0$, then $\mu(h)$ is linear wrt h .

9. SEMIVARIOGRAM

Note 51. A very informative tool about the behavior of the intrinsic random field is the semivariogram function defined below.

Definition 52. The semivariogram of an intrinsic random field $(Z(s) : s \in \mathcal{S})$ is defined as $\gamma : \mathcal{H} \rightarrow \mathbb{R}$, with

$$\gamma(h) = \frac{1}{2} \text{Var}(Z(s+h) - Z(s))$$

Definition 53. Variogram of an intrinsic random field $(Z(s) : s \in \mathcal{S})$ is called the quantity $2\gamma(h)$.

Note 54. A stationary random field with covariogram $c(\cdot)$ and mean μ is intrinsic stationary as well with semivariogram

$$(9.1) \quad \gamma(h) = c(0) - c(h),$$

and constant incremental mean $\mu(h) = \mu$.

Example 55. For the Gaussian covariance function (Ex. 34) the semivariogram is

$$\gamma(h) = c(0) - c(h) = \sigma^2 (1 - \exp(-\beta \|h\|_2^2))$$

Proposition 56. *Properties of semivariogram. Let $(Z(s) : s \in \mathcal{S})$ be an intrinsic random field, then*

- (1) *It is $\gamma(h) = \gamma(-h)$, $\gamma(h) \geq 0$, and $\gamma(0) = 0$*
- (2) *Semivariogram is conditionally negative definite (c.n.d.): if for all $n \in \mathbb{N}$, $(a_1, \dots, a_n) \subseteq \mathbb{R}^n$ s.t. $\sum_{i=1}^n a_i = 0$, and for all $(s_1, \dots, s_n) \subseteq S^n$, it is*

$$\sum_{i=1}^n \sum_{j=1}^n a_i a_j \gamma(s_i - s_j) \leq 0$$

10. BEHAVIOR OF SEMIVARIOGRAM OF INTRINSIC RANDOM FIELDS

Note 57. The semivariogram $\gamma(h)$ is very informative when plotted against the lag h . Below we discuss some of the characteristics of it, using Figure 10.1

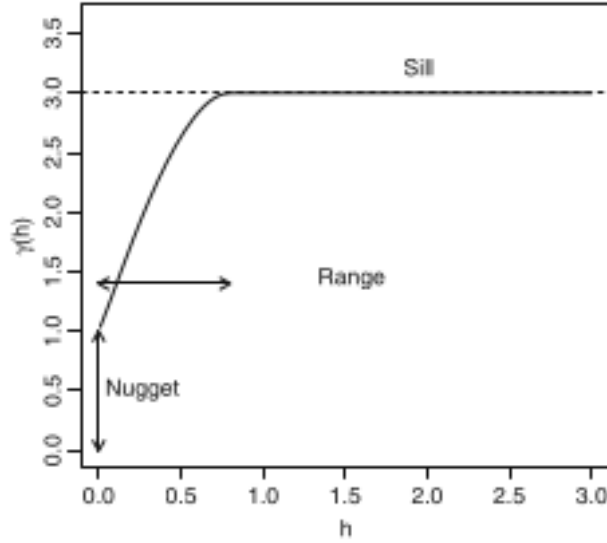


FIGURE 10.1. Semi Variogram's characteristics

Note 58. A semivariogram tends to be an increasing function of the lag $\|h\|$. Recall that for weakly stationary random fields with c.f. $c(\cdot)$, it is $\gamma(h) = c(0) - c(h)$ where common logic suggests that $c(h)$ is decreases with $\|h\|$.

Note 59. If $\gamma(h)$ is a positive constant for all non-zero lags $h \neq 0$, then $Z(s_1)$ and $Z(s_2)$ are uncorrelated regardless of how close s_1 and s_2 are. Then $Z(\cdot)$ is called white noise.

Note 60. Conversely, a non zero slope of the variogram indicates some structure.

Nugget Effect.

Note 61. Nugget effect is the semivariogram limiting value

$$\sigma_\varepsilon^2 = \lim_{\|h\| \rightarrow 0} \gamma(h)$$

when $\sigma_\varepsilon^2 \neq 0$.

Note 62. When used for modeling, nugget effect $\sigma_\varepsilon^2 \neq 0$ may express (1) measurement errors (e.g., if we collect repeated measurements at the same location s) or (2) some microscale variation causing discontinuity in the origin that cannot be detected from the data i.e. the spatial gaps because we collect a finite set of measurements at spatial locations. Ideally, a more detailed decomposition $\sigma_\varepsilon^2 = \sigma_{\text{MS}}^2 + \sigma_{\text{MS}}^2$ can be considered where σ_{MS}^2 refers to the microscale and σ_{MS}^2 refers to the measurement error. However this may lead to non-identifiability, without any obvious tweak to address it.

Sill.

Definition 63. Sill is the semivariogram limiting value $\lim_{\|h\| \rightarrow \infty} \gamma(h)$.

Note 64. For intrinsic processes, the sill may be infinite or finite. For weakly random field, the sill is always finite.

Partial sill .

Definition 65. Partial sill is $\lim_{\|h\| \rightarrow \infty} \gamma(h) - \lim_{\|h\| \rightarrow 0} \gamma(h)$ which takes into account the nugget.

Range .

Note 66. Range is the distance at which the semivariogram reaches the Sill. It can be infinite or finite.

Other.

Note 67. An abrupt change in slope indicates the passage to a different structuration of the values in space. This is often modeled via decomposition of processes with different semivariograms. E.g., let independent random fields $Y(\cdot)$ and $X(\cdot)$ with different semivariograms γ_Y and γ_X , then random field $Z(\cdot)$ with $Z(s) = Y(s) + X(s)$ has semivariogram $\gamma_Z(h) = \gamma_Y(h) + \gamma_X(h)$ which may present such a behavior.

11. ISOTROPY

Note 68. Isotropy introduces the assumption of “rotation invariance”.

Note 69. Isotropy applies to both intrinsic and (weakly) stationary random fields.

Definition 70. An intrinsic random field $(Z(s) : s \in \mathcal{S})$ is isotropic iff

$$(11.1) \quad \forall s, t \in \mathcal{S}, \frac{1}{2} \text{Var}(Z(s) - Z(t)) = \gamma(\|t - s\|), \text{ for some function } \gamma: \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}.$$

Definition 71. Isotropic semivariogram $\gamma : \mathcal{H} \rightarrow \mathbb{R}$ is the semivariogram of the isotropic random field (sometimes for simplicity of notation we use $\gamma : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$ with $\gamma(\|h\|) = \frac{1}{2} \text{Var}(Z(s) - Z(s - h))$).

Definition 72. Isotropic covariance function $C : \mathcal{S} \times \mathcal{S} \rightarrow \mathbb{R}$ is called the covariance function satisfying (11.1).

Definition 73. Isotropic covariogram $c : \mathcal{H} \rightarrow \mathbb{R}$ of a weakly stationary process is the covariogram associated to an isotropic semivariogram. Sometimes for simplicity of notation we use $c : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$ with $c(\|h\|)$ from (11.1).

11.1. Popular isotropic covariance functions.

Note 74. Isotropic semivariograms can be computed from $\gamma(h) = c(0) - c(h)$ given covariogram $c(\cdot)$ for any h .

11.1.1. Nugget-effect.

Note 75. Nugget-effect covariogram takes the form

$$c(h) = \sigma^2 1_{\{0\}}(\|h\|)$$

for $\sigma^2 > 0$. It is associate to white noise. It is used to model a discontinuity in the origin of the covariogram / sem-variogram.

11.1.2. Matern c.f.

Note 76. Matern covariogram takes the form

$$(11.2) \quad c(h) = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\|h\|}{\phi} \right)^\nu K_\nu \left(\frac{\|h\|}{\phi} \right)$$

for $\sigma^2 > 0$, $\phi > 0$, and $\nu \geq 0$. Parameter ν controls the variogram's regularity at 0 which in turn controls the quadratic mean (q.m.) regularity of the associated process. For $\nu = 1/2$, we get the exponential c.f.,

$$c(h) = \sigma^2 \exp \left(-\frac{1}{\phi} \|h\|_1 \right)$$

which is not differentiable at $h = 0$, while for $\nu \rightarrow \infty$, we get the Gaussian c.f.

$$c(h) = \sigma^2 \exp \left(-\frac{1}{\phi} \|h\|_2^2 \right)$$

which is infinite differentiable. ϕ is a range parameter, and σ^2 is the (partial) sill parameter.

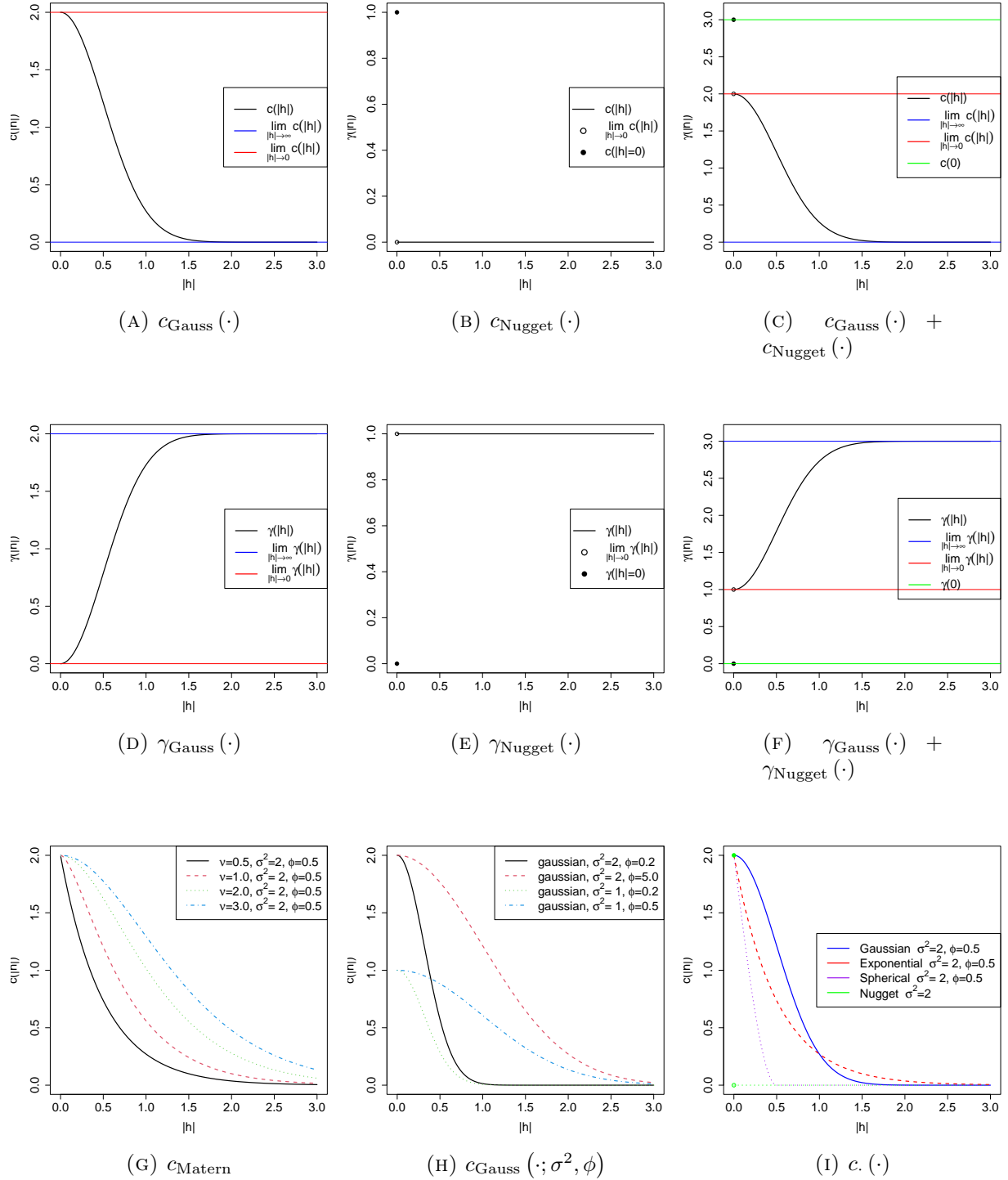


FIGURE 11.1. Covariograms $c(\cdot)$ and semivariograms $\gamma(\cdot)$

11.1.3. Spherical c.f.

Note 77. ¹Spherical covariogram takes the form

$$(11.3) \quad c(h) = \begin{cases} \sigma^2 \left(1 - \frac{3}{2} \frac{\|h\|_1}{\phi} + \frac{1}{2} \left(\frac{\|h\|_1}{\phi} \right)^3 \right) & \|h\|_1 \leq \phi \\ 0 & \|h\|_1 > \phi \end{cases}, \quad h \in \mathbb{R}^3.$$

No need to
memorize
(11.3)

for $\sigma^2 > 0$ and $\phi > 0$. The c.f. starts from its maximum value σ^2 at the origin, then steadily decreases, and finally vanishes when its range ϕ is reached. ϕ is a range parameter, and σ^2 is the (partial) sill parameter.

12. ANISOTROPY

Note 78. Dependence between $Z(s)$ and $Z(s+h)$ is a function of both the magnitude and the direction of separation h . This can be caused by the underlying physical process evolving differently in space (e.g., vertical and horizontal axes).

Definition 79. The semivariogram $\gamma : \mathcal{H} \rightarrow \mathbb{R}$ is anisotropic if there are h_1 and h_2 with same length $\|h_1\| = \|h_2\|$ but different direction $h_1/\|h_1\| \neq h_2/\|h_2\|$ that produce different semivariograms $\gamma(h_1) \neq \gamma(h_2)$.

Definition 80. The intrinsically random field $(Z(s) : s \in \mathcal{S})$ is anisotropic if its semivariogram is anisotropic.

Definition 81. The covariogram $c : \mathcal{H} \rightarrow \mathbb{R}$ is anisotropic if there are h_1 and h_2 with same length $\|h_1\| = \|h_2\|$ but different direction $h_1/\|h_1\| \neq h_2/\|h_2\|$ that produce different covariogram $c(h_1) \neq c(h_2)$.

Definition 82. The (weakly) stationary random field $(Z(s) : s \in \mathcal{S})$ is anisotropic if its covariogram is anisotropic.

Note 83. For brevity, below we discuss about intrinsic random fields and semivariograms, however the concepts/definitions apply to stationary random fields and covariograms when defined, as in Defs 79 & 81.

12.1. Geometric anisotropy.

Definition 84. The semivariogram $\gamma_{\text{g.a.}} : \mathcal{H} \rightarrow \mathbb{R}$ exhibits geometric anisotropy if it results from an A -linear deformation of an isotropic semivariogram with function $\gamma_{\text{iso}}(\cdot)$; i.e.

$$\gamma_{\text{g.a.}}(h) = \gamma_{\text{iso}}(\|Ah\|_2)$$

Note 85. Such semivariograms have the same sill in all directions but with ranges that vary depending on the direction. See Figure 12.1a.

¹For it's derivation see Ch 8 in [4]

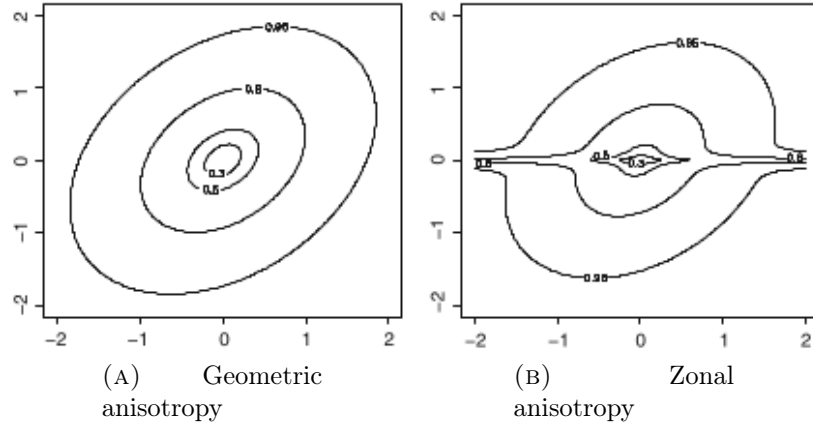


FIGURE 12.1. Isotropy vs Anisotropy

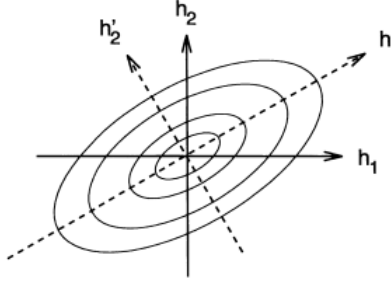


FIGURE 12.2. Rotation of the 2D coordinate system

Example 86. For instance, if $\gamma_{\text{g.a.}}(h) = \gamma_{\text{iso}}\left(\sqrt{h^\top Q h}\right)$, where $Q = A^\top A$.

Example 87. [Rotating and dilating an ellipsoid in 2D] Consider a coordinate system for $h = (h_1, \dots, h_n)^\top$. We wish to find a new coordinate system for h in which the iso-semivariogram lines are spherical.

(1) [Rotate] Apply rotation matrix R to h such as $h' = Rh$. In 2D, it is

$$R = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix}, \text{ for } \theta \in (0, 2\pi), \text{ is the rotation angle.}$$

(2) [Dilate] Apply a dilation of the principal axes of the ellipsoid using a diagonal matrix $\sqrt{\Lambda} = \text{diag}(\sqrt{\lambda_1}, \dots, \sqrt{\lambda_n})$, as $\tilde{h} = \sqrt{\Lambda}h'$.

Now the ellipsoids become spheres with radius $r = \|\tilde{h}\|_2 = \sqrt{\tilde{h}^\top \tilde{h}}$. This yields the equation of an ellipsoid in the h coordinate system

$$h^\top (R^\top \Lambda R) h = r^2$$

where the diameters d_j (principal axes) of the ellipsoid along the principal directions are

$$d_j = 2r / \sqrt{\lambda_j}$$

and the principal direction is the j -th column of the rotation matrix $R_{:,j}$.

Hence the anisotropic semivariogram is $\gamma_{\text{g.a.}}(h) = \gamma_{\text{iso}}\left(\sqrt{h^\top Q h}\right)$ with $Q = R^\top \Lambda R$. This derivation extends to d dimensions.

12.2. Zonal (or stratified) anisotropy.

Definition 88. Support anisotropy is called the type of anisotropy that the semivariogram $\gamma(h)$ depends only on certain coordinates of h .

Example 89. If it is $\gamma(h = (h_1, h_2)) = \gamma(h_1)$, then I've support anisotropy

Definition 90. Zonal anisotropy occurs when the semivariogram $\gamma(h)$ is the sum of several components each with a support anisotropy.

Example 91. Let γ' and γ'' be semivariogram with sills v' and v'' correspondingly. If it is $\gamma(h = (h_1, h_2)) = \gamma'(\|h_1\|) + \gamma''\left(\sqrt{\|h_1\| + \|h_2\|}\right)$, then I've Zonal anisotropy because γ has a sill $v' + v''$ in direction $(0, 1)$ and a sill v' in direction $(1, 0)$.

Note 92. We have Zonal anisotropy then the semivariogram calculated in different directions suggest a different value for the sill (and possibly the range).

Note 93. If in 2D case, the sill in h_1 is larger than that in h_2 , we can model zonal anisotropy of random field $(Z(s) : s \in \mathcal{S})$ by assuming $Z(s) = I(s) + A(s)$, where $I(s)$ is an isotropic random field with isotropic semivariogram γ_I along dimension of h_1 and $A(s)$ is a process with anisotropic semivariogram γ_I without effect on dimension h_1 ; i.e. $\gamma_Z(h) = \gamma_I(h) + \gamma_A(h)$.

12.3. Non-linear deformations.

Note 94. A (rather too general) non-stationary non-intrinsic random field model can be specified by considering semivariogram $2\text{Var}(Z(s) - Z(t)) = 2\gamma_o(\|G(s) - G(t)\|)$ such that a bijective non-linear (function) deformation $G(\cdot)$ of space \mathcal{S} has been applied on the isotropic semivariogram γ_o . For instance, $\gamma_o(h) = \sigma^2 \exp(-\|h\|/\phi)$ and $G(s) = s^2$ as a deterministic function. Now, if function $G(\cdot)$ is considered as unknown, one can model it as a random field $(G(s) : s \in \mathcal{S})$ with semivariogram $2\text{Var}(G(s) - G(t)) = 2\gamma'_o(\|G'(s) - G'(t)\|)$ and so on...; then we will be talking about deep learning.

13. GEOMETRICAL PROPERTIES OF RANDOM FIELDS

Note 95. We discuss basic geometric properties of random field we will use for modeling, as it can give us a deeper intuition on how to design appropriate spatial statistical models.

Definition 96. (Continuity in quadratic mean (q.m.)) Second-order random field $(Z(s) : s \in \mathcal{S})$ is q.m. continuous at $s \in \mathcal{S}$ if

$$\lim_{h \rightarrow 0} E(Z(s+h) - Z(s))^2 = 0.$$

Note 97. Consider random field $(Z(s) : s \in \mathcal{S})$. Then

$$E(Z(s+h) - Z(s))^2 = (E(Z(s+h)) - E(Z(s)))^2 + \text{Var}(Z(s+h) - Z(s))$$

- If Z is intrinsic r.f., then

$$E(Z(s+h) - Z(s))^2 = \frac{1}{2}\gamma(h)$$

and hence Z is q.m. continuous iff $\lim_{\|h\| \rightarrow 0} \gamma(h) = \gamma(0)$.

- If Z is stationary r.f., then

$$E(Z(s+h) - Z(s))^2 = \frac{1}{2}(c(0) - c(h))$$

and hence Z is q.m. continuous iff $\lim_{\|h\| \rightarrow 0} c(h) = c(0)$ (i.e. , c is continuous).

Definition 98. Differentiable in quadratic mean (q.m.)) Second-order random field $(Z(s) : s \in \mathcal{S})$ is q.m. differentiable at $s \in \mathcal{S}$ there exist

$$(13.1) \quad \dot{Z}(s) = \lim_{h \rightarrow 0} \frac{Z(s+h) - Z(s)}{h} \text{ in q.m.}$$

Proposition 99. Let $c(s, t)$ be the covariance function of $Z = (Z(s) : s \in \mathcal{S})$. Then Z is everywhere differentiable if $\frac{\partial^2}{\partial s \partial t} c(s, t)$ exists and it is finite. Also, $\frac{\partial^2}{\partial s \partial t} c(s, t)$ is the covariance function of (13.1).

Example 100. The process with exponential c.f. $c(h) = \sigma^2 \exp(-|h|/\phi)$ is continuous because $\lim_{h \rightarrow 0} c(h) = \sigma^2 = c(0)$ but not differentiable because $\frac{\partial^2}{\partial h^2} c(h)$ does not exist at $h = 0$.

Part 2. Model building & related parametric inference

14. THE GEOSTATISTICAL MODEL (THE BIG PICTURE)

14.1. Linear Model of Regionalization.

Note 101. A spatial phenomenon can be thought as being the sum of several independent subphenomena acting at different characteristic scales. A linear model can be set up to split the stochastic process representing the phenomenon into several uncorrelated stochastic processes, each with a different variogram or covariance function and characterizing different aspect of the overall phenomenon under investigation.

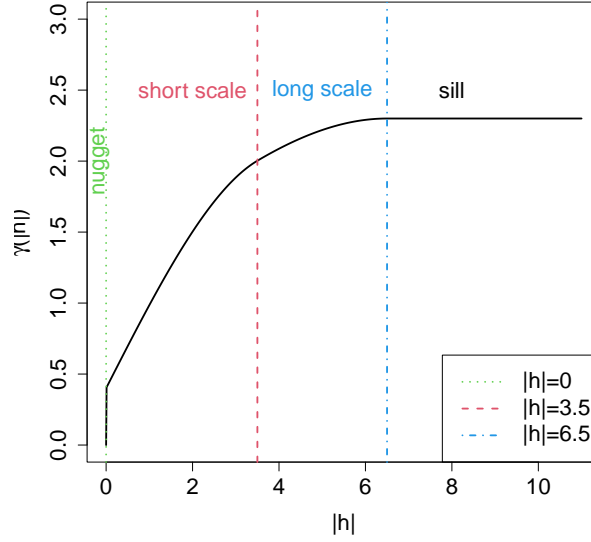


FIGURE 14.1. Variogram $\gamma(\cdot)$ of $Z(s) = Z_1(s) + Z_2(s) + Z_3(s)$ with spherical s.v. $\gamma_1(|h|; \sigma^2 = 0.8, \phi = 3.5)$, spherical s.v. $\gamma_1(|h|; \sigma^2 = 1.1, \phi = 6.5)$, and nugget $\gamma_3(|h|; \sigma^2 = 0.4)$.

14.1.1. Decomposition of the random field.

Note 102. The linear model of regionalization consider the decomposition of the random field of interest $Z(s)$ as a summation of m independent zero-mean random fields $\{Z_j(s); s \in \mathcal{S}\}_{j=0}^m$ each of them characterizing different spatial scales, as

$$(14.1) \quad Z(s) = \mu(s) + Z_1(s) + \dots + Z_m(s)$$

with $\mu(s) = E(Z(s))$ be a deterministic drift (or trend) function.

Remark 103. In (14.1), let $Z_j(\cdot)$ be intrinsic random field with semivariogram $\gamma_j(\cdot)$ and mutually independent, then the semivariogram of $Z(\cdot)$ is $\gamma(\cdot) = \sum_{j=1}^m \gamma_j(\cdot)$.

Example 104. For instance consider (14.1) with $\mu(s) = 0$, $m = 3$, $Z_1(s)$ with a spherical semivariogram (11.3) with range $\phi_1 = 3.5$, $Z_2(s)$ with a spherical semi-variogram (11.3) with range $\phi_2 = 6.5$, and $Z_3(s)$ with a nugget semi-variogram. See the “sudden” changes of the line in Figure 14.1 representing change of spatial behavior.

14.1.2. Scale of variation.

Note 105. Cressi [1] considers the following intuitive decomposition

$$(14.2) \quad Z(s) = \mu(s) + W(s) + \eta(s) + \varepsilon(s), \quad s \in S$$

where

$\mu(s) = \mathbf{E}(Z(s))$: is the deterministic mean (or drift) structure. It aims to represent the “large scale variation”.

$W(s)$: is a zero mean second order continuous intrinsic random field whose range is larger than gaps between the sites (sampling grid). It aims to represent “smooth small scale variation”.

$\eta(s)$: is a zero mean intrinsic random field whose variogram range exists and is smaller than the gaps between the sites. It aims to represent “microscale variation”

$\varepsilon(s)$: is a zero-mean white-noise process (modeled as nugget effect). It aims to represent “measurement error or noise”

$W(s), \eta(s), \varepsilon(s)$ are mutually independent.

Note 106. Reasonably, larger scale components, such as $\mu(s), W(s)$ can be represented in the variogram if the diameter of the sampling domain is large S is large enough.

Note 107. Clearly, smaller scale components, such as $\eta(s), \varepsilon(s)$ could be identified if the sampling grid is sufficiently fine.

Note 108. Decomposition (14.2) is not unique and the components are not clearly identifiable from the data when modeled; e.g. one may find two pairs of $\mu(s), W(s)$ doing the same thing; yet, separating $\eta(s)$ and $\varepsilon(s)$ is difficult as they often describe changes with range smaller than that of the sites (!)

Note 109. The geostatistical model is often presented (with reference to (14.2)) in a form

$$Z(s) = \mu(s) + w(s) + \varepsilon(s), \quad s \in S$$

where $w(s) = W(s) + \eta(s)$ contains all the spatial variation.

Note 110. Alternatively, the hierarchical statistical model (Handout 1, 3.5) is used

$$(14.3) \quad Z(s) = Y(s) + \varepsilon(s), \quad s \in S$$

where $Y(s) = \mu(s) + W(s) + \eta(s)$ is the spatial model, signal random field or noiseless random field.

Note 111. Another decomposition we will use

$$Z(s) = \mu(s) + \delta(s), \quad s \in S$$

where $\delta(s) = W(s) + \eta(s) + \varepsilon(s)$ is called the correlated process.

Note 112. In several problems, additional covariates may be considered. The available dataset is of the form $\{(x_i, s_i, Z_i)\}_{i \in S}$ where $Z_i := Z(s_i, x_i)$ is the observed response at

location s_i , associated with the p -dimensional covariate $x_i = (x_{i,1}, \dots, x_{i,p})^\top$ for $i \in \mathcal{S}$. Although not a necessity rule, the effect of the associated p -dimensional covariates is often expressed via the deterministic drift function $\mu(s, x) = E(Z(s, x))$. E.g. in decomposition in (14.2)

$$(14.4) \quad Z(s, x) = \mu(s, x) + W(s) + \eta(s) + \varepsilon(s), \quad s \in S, x \in \mathcal{X}.$$

Here, to simplify the presentation, we suppress dependence on possible covariates $x \in \mathcal{X}$.

15. LEARNING THE SEMIVARIOGRAM

Note 113. Consider a random field $(Z(s); s \in \mathcal{S})$, $\mathcal{S} \in \mathbb{R}^d$ observed at n sites $S = \{s_1, \dots, s_n\}$, and hence a dataset $\{(s_i, Z(s_i))\}_{i=1}^n$.

Note 114. Consider a decomposition

$$Z(s) = \mu(s) + \delta(s), \quad s \in S$$

where $\mu(\cdot)$ is an unknown deterministic drift and $\delta(\cdot)$ is a zero mean intrinsic random field.

Example 115. (Meuse river data set) The Meuse river dataset set, used as a running example 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). Here, we use the topsoil zinc concentration, mg kg⁻¹ soil ("ppm") as quantity of interest (Z). See Figure 15.1a. This is the R dataset `meuse{sp}`.

Example 116. (Wolfcamp-aquifer dataset) We also consider the Wolfcamp-aquifer dataset in Exercise 2 in the Exercise sheet. See Figure 15.2a

15.1. The semvariogram cloud.

Assumption 117. Assume that $(Z(s); s \in \mathcal{S})$ in an intrinsic random field with unknown constant mean; aka $Z(s) = \mu + \delta(s)$.

Definition 118. Dissimilarity between pairs of data values $Z(s_a)$ and $Z(s_b)$ is called the measure

$$(15.1) \quad \gamma^*(s_a, s_b) = \frac{1}{2} (Z(s_b) - Z(s_a))^2$$

Definition 119. If we let dissimilarity between pairs of data values $Z(s)$ and $Z(s_b)$ depend on the separation $h = s_b - s$ (lag or orientation) then we get

$$\gamma^*(h) = \frac{1}{2} (Z(s+h) - Z(s))^2.$$

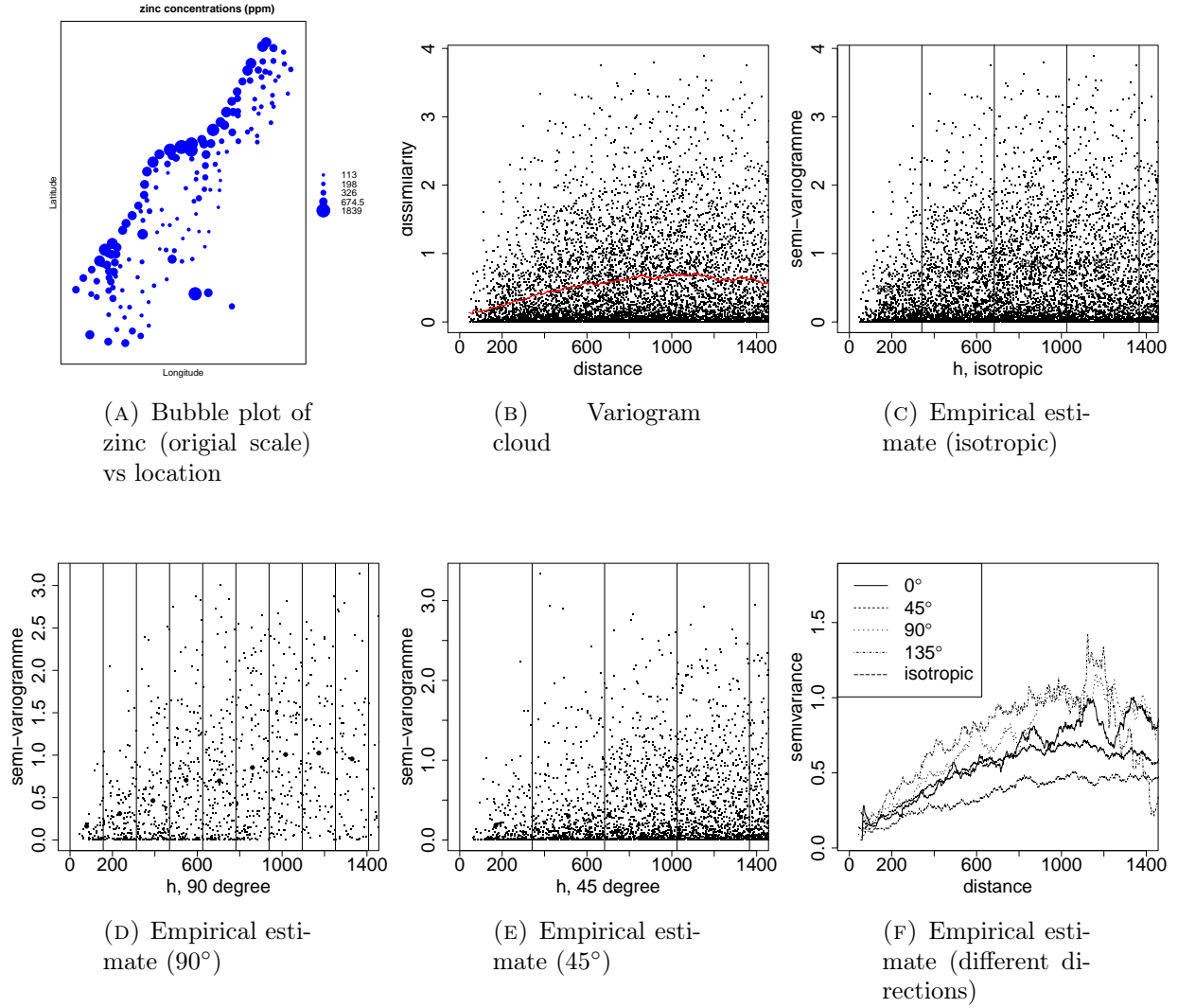


FIGURE 15.1. Meuse dataset variogram estimations (Zinc in log scale)

Definition 120. The semivariogram cloud is the set of $n(n-1)/2$ points

$$\mathfrak{C}_S = \{(\|s_i - s_j\|, \gamma^*(s_j, s_i)), i, j = 1, \dots, n, \text{ and } s_i \neq s_j\}$$

Note 121. Note that (15.1) is an unbiased estimator of the semivariogram and hence the semivariogram cloud is too.

Note 122. Often there is a smoothing of the cloud is superimposed onto the cloud itself to help us see semivariogram's characteristics (e.g., sill, nugget, range) which may be “hidden” due to potential outliers in the plot.

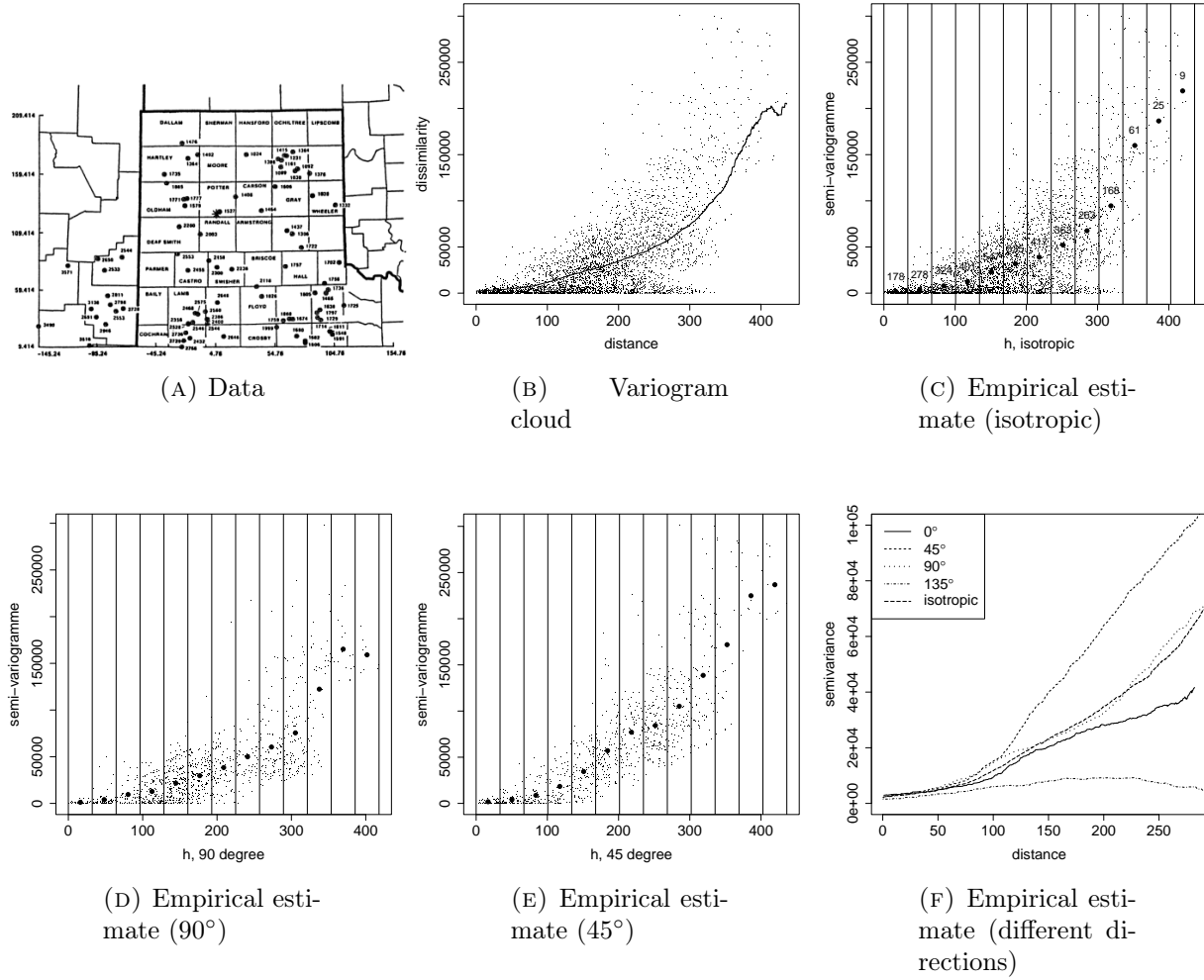


FIGURE 15.2. Wolfcamp-aquifer dataset variogram estimations

Example 123. Figure 15.1b and Figure 15.2b show the semivariogram cloud plots (that is a point plot of the dissimilarities vs the distances) for the datasets Meuse and Wolfcamp-aquifer dataset. The red line is a smoother line of the cloud.

15.2. Non-parametric semivariogram estimator of $\gamma(\cdot)$.

Assumption 124. Assume that $(Z(s); s \in \mathcal{S})$ in an intrinsic random field with unknown constant mean; aka $\mu(\cdot)$ is an unknown constant.

Proposition 125. The Smoothed Matheron estimator $\hat{\gamma}(\cdot)$ of semivariogram $\gamma(\cdot)$ of an unknown constant mean intrinsic random field $Z(\cdot)$ is

$$(15.2) \quad \hat{\gamma}_M(h) = \frac{1}{2|N_{r_1, r_2}(h)|} \sum_{\forall (s_i, s_j) \in N_{r_1, r_2}(h)} (Z(s_i) - Z(s_j))^2$$

where

$$N_{r_1, r_2}(h) = \{(s_i, s_j) \in \mathcal{S} : s_i - s_j \in B_{r_1, r_2}(h)\}$$

contains all the pairs of spatial points whose difference is in a ball

$$(15.3) \quad B_{r_1, r_2}(h) = \left\{ x : \left| \|x\| - \|h\| \right| < r_1, \text{ and } \left\| \frac{x}{\|x\|_2} - \frac{h}{\|h\|_2} \right\|_2 < r_2 \right\}$$

centered at h with radius $r_1 > 0$ and $r_2 > 0$.

Note 126. If we consider isotropic semivariogram $\gamma(\cdot)$ then the ball may just considerate only the length of the distance as

$$(15.4) \quad B_{r_1}(h) = \{x : \left| \|x\| - \|h\| \right| < r_1\}$$

because the direction does not have any effect.

Note 127. The choice of r_1 , r_2 is an art, and a trade-off between variance and bias, similar to the bin length in histograms.

Note 128. In practice, we consider a finite number of k separations $\mathcal{H} = \{h_1, \dots, h_k\}$, we estimate in such a way that each class contains at least 30 pairs of points. Then compute $\{\hat{\gamma}_M(h); h \in \mathcal{H}\}$, and plot $\{(h_j, \hat{\gamma}_M(h_j)); j = 1, \dots, k\}$.

Example 129. Figures 15.1c and 15.2c, show the nonparametric estimator ignoring the direction for the datasets Meuse and Wolfcamp-aquifer dataset. The estimator is calculated by using the ball in (15.4).

Example 130. Figures 15.2d and 15.1e show the nonparametric estimator considering directions 90° and 45° for the dataset Meuse. Figures 15.2d and 15.2e do the same for the Wolfcamp-aquifer dataset. The estimator is calculated by using the ball (15.3).

Note 131. In practice anisotropies are detected by inspecting experimental semivariograms in different directions and are induced into the model by tuning predefined anisotropy parameters.

Example 132. Figure 15.1f and 15.2a show the nonparametric semivariogram estimator for different directions for the two datasets. We observe possible anisotropy due to the differences in the lines.

15.3. Classic parametric estimator of $\gamma(\cdot)$.

Assumption 133. Consider (for now) the assumption that $(Z(s); s \in \mathcal{S})$ is an intrinsic random field with unknown constant mean; aka $\mu(\cdot)$ is an unknown constant.

Note 134. Smoothed Matheron estimator (15.2) does not necessarily satisfies semivariogram properties, such as negative definiteness. To address this we use a parametric family of appropriate semi-variogram functions and tune them against data.

Note 135. Popular parametrized isotopic semivariogrames are those Section 11.1. Anisotropic semi-variogrames/covariogrames can be specified by using isotropic ones and applying a rotation and dilation as in Example 86.

Note 136. Below are some properties that allow the specification of sophisticated semivariograms from simpler ones.

- (1) $\tilde{\gamma}(h) = \gamma(Ah)$ where $\gamma(\cdot)$ is a semivariogram and A constant matrix.
- (2) $\gamma(\cdot) = \sum_{i=1}^n a_i \gamma_i(\cdot)$, if $a_i \geq 0$, and $\{\gamma_i(\cdot)\}$ are semivariograms
- (3) $\gamma(\cdot) = \prod_{i=1}^n \gamma_i(\cdot)$, if $\{\gamma_i(\cdot)\}$ are semivariograms
- (4) $\gamma(\cdot) = \int \gamma_u(\cdot) dF(u)$, if $\gamma_u(\cdot)$ is a semivariogram parametrized by $u \sim F$
- (5) $\gamma(\cdot) = \lim_{n \rightarrow \infty} \gamma_n(\cdot)$ if $\gamma_n(\cdot)$ is semivariogram and the limit exists
- (6) $\gamma_Z(h) = \gamma_Y(h) + \gamma_X(h)$ corresponds to random field $Z(s) = Y(s) + X(s)$ if $(Y(s) : s \in \mathcal{S})$ and $(X(s) : s \in \mathcal{S})$ are independent intrinsic random fields with semivariograms $\gamma_Y(\cdot)$ and $\gamma_X(\cdot)$.
- (7) $\gamma(\cdot)$ is a semivariogram iff $\exp(-a\gamma(\cdot))$ is positive definite for any $a > 0$.

Example 137. $\gamma(h) = \|h\|^2$ is a semivariogram because $\exp(-a\|h\|_2^2)$ is a c.f. for any $a > 0$ and hence positive definite.

Note 138. For a q.m. continuous $(Z(s) : s \in \mathcal{S})$, it is $\lim_{\|h\| \rightarrow 0} \gamma(h) = 0$ because $\gamma(0) = 0$. However, when modeling a real problem we may need to consider (or it may appear from the data) that $\gamma(h)$ should have a discontinuity $\lim_{\|h\| \rightarrow 0} \gamma(h) = \sigma_\varepsilon^2 \neq 0$ aka a nugget. Nugget effect is often mathematically described by considering a decomposition ; [5; Ch 1.4.1]

$$Z(s) = Y(s) + \varepsilon(s)$$

where Y can be a continuous random field with $\gamma_Y(\cdot)$, and ε can be a random field (called errors-in-variables model) with (nugget) semivariogram $\gamma_\varepsilon(h) = \sigma_\varepsilon^2 1(h \neq 0)$. In this case,

$$\gamma_Z(h) = \gamma_Y(h) + \gamma_\varepsilon(h) \xrightarrow{\|h\| \rightarrow 0} \sigma_\varepsilon^2$$

Note 139. Let $\hat{\gamma}$ be the empirical semivariogram $\hat{\gamma}$ (e.g., Matheron (15.2)) computed at k classes, i.e. it is available $\{h_j, \hat{\gamma}(h_j)\}_{j=1}^k$. Let γ_θ be a parametrised semivariogram by the unknown θ . The Least Square Errors (LSE) estimator is $\hat{\gamma}_{\text{LSE}}(h) = \gamma(h; \hat{\theta}_{\text{LSE}})$ where

$$(15.5) \quad \hat{\theta}_{\text{LSE}} = \arg \min_{\theta} (\hat{\gamma} - \gamma(h; \theta))^T V(\theta) (\hat{\gamma} - \gamma(h; \theta)),$$

$V(\theta)$ is a user specific positive definite matrix $V(\theta)$ serving as a weight, $\hat{\gamma} = (\hat{\gamma}(h_1), \dots, \hat{\gamma}(h_k))^\top$, and $\gamma(h; \theta) = (\gamma(h_1; \theta), \dots, \gamma(h_k; \theta))^\top$.

Note 140. An example is OLS

$$(15.6) \quad \hat{\theta}_{\text{OLS}} = \arg \min_{\theta} \left(\sum_j (\hat{\gamma}(h_j) - \gamma(h; \theta))^2 \right)$$

Example 141. Figures 15.3a and 15.3b show the OLE and WLE estimates (15.6) and (7.5) of the exponential and spherical semivariogram for the Meuse dataset. Figure 15.3c shows the OLE and WLE estimates (15.6) and (7.5) of the exponential semi-variogram for the Wolfcamp dataset. The parametric semivariograms were tuned against the non-parametric estimator (15.2) presented in dots, as discussed in Proposition 139.

15.4. Parametric learning of nonzero $\mu(\cdot)$ and $\gamma(\cdot)$.

Note 142. Assume a random field model $(Z(s); s \in \mathcal{S})$ decomposed as

$$Z(s) = \mu(s) + \delta(s)$$

where the trend $\mu(s)$ is parameterized as $\mu(s) = \mu(s; \beta)$ with unknown β (e.g. $\mu(s; \beta) = \psi^\top(s) \beta$), and the zero mean intrinsic process $\delta(s)$ has a semivariogram $\gamma(h)$ parameterised as $\gamma(h) = \gamma(h; \theta)$ with unknown θ .

15.4.1. Non-parametric inference.

Note 143. Semi-parametric learning is as follows:

- (1) Compute estimate $\hat{\beta}$ via LSE (or equivalent)

$$\hat{\beta}_{\text{LSE}} = \arg \min_{\beta} \left(\sum_i (Z(s_i) - \mu(s_i; \beta))^2 \right)$$

- (2) Compute the residuals $\hat{\delta} := \hat{\delta}(s_i)$ from

$$\hat{\delta}(s_i) = Z(s_i) - \mu(s_i; \hat{\beta}_{\text{LSE}})$$

- (3) Compute empirical variogram against $\hat{\delta}$ on \mathcal{H} according to Proposition 125.
- (4) Compute estimates $\hat{\theta}_{\text{LSE}}$ and $\hat{\gamma}_{\text{LSE}}(h)$ according to Proposition 139.

Example 144. Figure 15.3a and 15.3b fit an exponential c.f. and a spherical c.f. in the data of Meuse dataset (assuming constant mean); we cannot eyeball any big difference. Figure 15.3c fit an exponential c.f. in the data of Wolfcamp dataset (assuming constant mean); the fit looks really bad, possibly we should consider a non-constant mean and remove the trend.

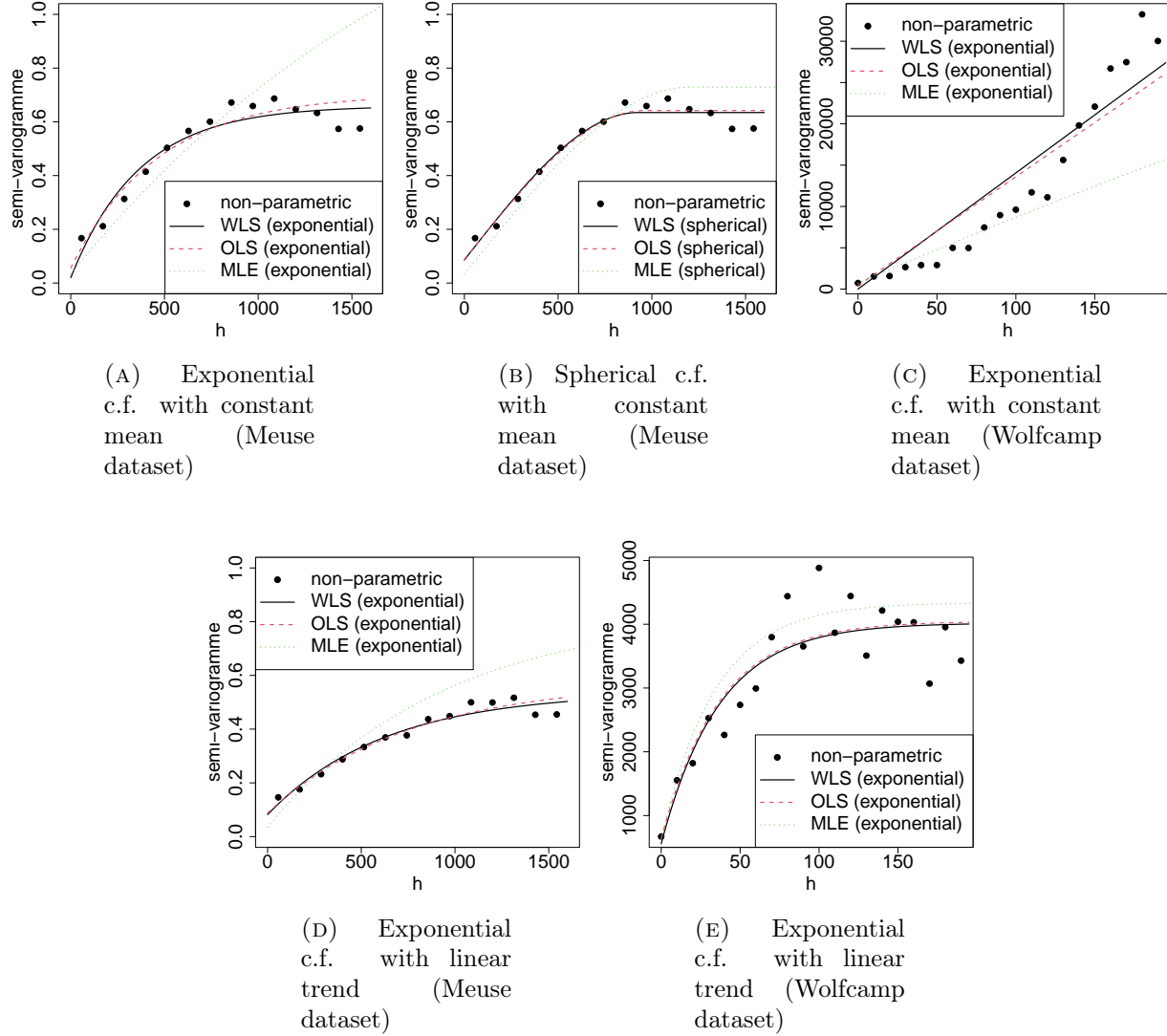


FIGURE 15.3. Parametric training

Example 145. Figure 15.3d fits an exponential c.f. in the residuals $\delta(s) = Z(s) - \mu(s)$ where $\mu(s) = \beta_0 + \beta_1 s_1 + \beta_2 s_2$ and $\hat{\beta}_{\text{OLS}} = (-42.8, -9.5 \cdot 10^{-4}, -6.6 \cdot 10^{-4})^\top$ in Meuse dataset. Possibly inference would suggest a constant mean function. Figure 15.3e fits an exponential c.f. in the residuals $\delta(s) = Z(s) - \mu(s)$ where $\mu(s) = \mu(s) = \beta_0 + \beta_1 s_1 + \beta_2 s_2$ and $\hat{\beta}_{\text{OLS}} = (-607, -1.12, -1.13)^\top$ in Wolfcamp dataset; we see an improvement in fit compared to Figure 15.3c.

15.4.2. Parametric inference via MLE.

Note 146. Assume that the probability distribution of the random field $(Z(s); s \in \mathcal{S})$ is known. The MLE estimates $(\hat{\beta}_{\text{MLE}}, \hat{\theta}_{\text{MLE}})$ of (β, θ) can be computed as

$$(\hat{\beta}_{\text{MLE}}, \hat{\theta}_{\text{MLE}}) = \arg \min_{(\beta, \theta)} (-2 \log (L(z_1, \dots, z_n | \beta, \theta)))$$

where $L(z_1, \dots, z_n | \beta, \theta)$ is the associated likelihood function given observed data $\{(s_i, Z_i)\}_{i=1}^n$.

Example 147. If $Z(\cdot) \sim \text{GP}(\mu(\cdot; \beta), c(\cdot, \cdot; \sigma^2, \phi))$, with $\mu(s; \beta) = \beta_0 + s_1\beta_1 + s_2\beta_2$ and $\gamma_{(\sigma^2, \phi)}(h) = \sigma^2(1 - \exp(-\phi h^2))$ then MLE of (β, σ^2, ϕ) is

$$(\hat{\beta}_{\text{MLE}}, \hat{\sigma}_{\text{MLE}}^2, \hat{\phi}_{\text{MLE}}) = \arg \min_{\beta, \sigma^2, \phi} (-2 \log (N(Z | \mu_\beta, C_{\sigma^2, \phi})))$$

where $N(Z | \mu_\beta, C_\theta)$ is the Gaussian pdf at $Z = (Z(s_1), \dots, Z(s_n))^\top$, with mean $[\mu_\beta]_i = \mu(s_i; \beta) = \beta_0 + s_{1,i}\beta_1 + s_{2,i}\beta_2$ and covariance matrix $[C_{\sigma^2, \phi}]_{i,j} = \sigma^2 \exp(-\phi(s_i - s_j)^2)$.

16. (CLASSICAL) KRIGING (FOR PREDICTION)

Note 148. “Kriging” is a general technique for deriving an estimator / predictor of $Z(\cdot)$ (or a function of it) at a location (such as a spatial point s_0 , or a block of points $\{s_j^*\}$ or a subregion v_0) of a spatial region \mathcal{S} by properly averaging out data in the neighborhood around the location of interest.

16.1. Universal Kriging.

Note 149. Consider we have specified the statistical model as a stochastic process $(Z(s); s \in \mathcal{S})$ with

$$(16.1) \quad Z(s) = \mu(s) + \delta(s)$$

where $\mu(s)$ is a deterministic linear expansion of known basis functions $\{\psi_j(\cdot)\}_{j=0}^p$ and unknown coefficients $\{\beta_j\}_{j=0}^p$ such as

$$\mu(s) = \sum_{j=0}^p \psi_j(s) \beta_j = (\psi(s))^\top \beta$$

with $\beta = (\beta_0, \dots, \beta_p)^\top$ and $\psi(s) = (\psi_0(s), \dots, \psi_p(s))^\top$. Also, $\delta(s)$ is a zero mean process, and for this derivation, assume that $\delta(s)$ is an intrinsic stationary process with a (presumably known) semi-variogram $\gamma(\cdot)^2$

Note 150. Consider there is available a dataset $\{(s_i, Z_i)\}_{i=1}^n$ with $Z_i := Z(s_i)$ being a realization of $(Z(s); s \in \mathcal{S})_{s \in \mathcal{S}}$ at site s_i . Then one can consider the matrix form for (16.1)

²As mentioned in Note 164, stationarity and hence existence of the semi-variogram are not necessary in general, but they are convenient for training via the semi-variogram estimation.

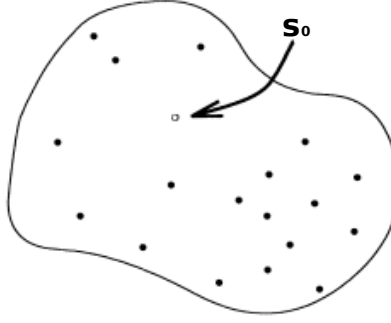


FIGURE 16.1. Kriging area

as

$$Z = \mu + \delta = \Psi\beta + \delta$$

with vector $Z = (Z(s_1), \dots, Z(s_n))^T$ vector $\delta = (\delta(s_1), \dots, \delta(s_n))^T$, vector $\mu = (\mu(s_1), \dots, \mu(s_n))^T$, and (design) matrix Ψ with $[\Psi]_{i,j} = \psi_j(s_i)$.

Note 151. We are interested in learning/predicting $Z(s_0)$ at an unseen spatial location s_0 (Figure 16.1).

Note 152. “Universal Kriging” (UK) is the technique for producing a Best Linear Unbiased Estimator (BLUE) predictor for $Z_0 := Z(s_0)$ at spatial location $s_0 \in \mathcal{S}$ by using data in the neighborhood of the location of interest.

Definition 153. The Universal Kriging (UK) predictor $Z_{UK}(s_0)$ of $Z(s_0)$ at location $s_0 \in \mathcal{S}$ is the Best Linear Unbiased Estimator (BLUE) of $Z(s_0)$ given the data $\{(s_i, Z_i)\}_{i=1}^n$.

Note 154. The UK predictor $Z_{UK}(s_0)$ of $Z(s_0)$ at s_0 has the following linear form weighted by a set of tunable unknown weights $\{w_i\}$

$$(16.2) \quad \begin{aligned} Z_{UK}(s_0) &= w_{n+1} + \sum_{i=1}^n w_i Z(s_i) \\ &= w_{n+1} + w^T Z \end{aligned}$$

where $Z = (Z_1, \dots, Z_n)^T$ and $w = (w_1, \dots, w_n)^T$.

Note 155. For (16.2), to satisfy unbiasedness (that is zero systematic error), we get

$$(16.3) \quad \begin{aligned} E(Z_{UK}(s_0)) &= E(Z(s_0)) \Leftrightarrow w_{n+1} + \sum_{i=1}^n w_i E(Z(s_i)) = \mu(s_0) \\ &\Leftrightarrow w_{n+1} + \sum_{i=1}^n w_i \mu(s_i) = \mu(s_0) \Leftrightarrow w_{n+1} + \sum_{i=1}^n w_i (\psi(s_i))^T \beta = (\psi(s_0))^T \beta \\ &\Leftrightarrow w_{n+1} + w^T \Psi \beta = \Psi_0 \beta \end{aligned}$$

where matrix Ψ with $[\Psi]_{i,j} = \psi_j(s_i)$ and (column) vector Ψ_0 with $[\Psi_0]_{1,j} = \psi_j(s_0)$. Because in (16.3) both sides are polynomial w.r.t β all coefficients must be equal; hence sufficient conditions for unbiasedness are $w_{n+1} = 0$ and

$$(16.4) \quad \text{ASSUMPTION: } (\psi(s_0))^\top = \sum_{i=1}^n w_i (\psi(s_i))^\top \Leftrightarrow \Psi_0 = w^\top \Psi$$

$$(16.5) \quad w_{n+1} = 0$$

Note 156. Without loss of generality, set $\psi_0(\cdot) = 1$; then (16.3) implies

$$(16.6) \quad \text{ASSUMPTION: } \sum_{i=1}^n w_i = 1$$

Note 157. The MSE of $Z_{\text{UK}}(s_0)$, given the Assumption (16.4) is

$$(16.7)$$

$$\begin{aligned} \text{MSE}(Z_{\text{UK}}(s_0)) &= \mathbb{E}(Z_{\text{UK}}(s_0) - Z(s_0))^2 \\ &= \mathbb{E}(\Psi\beta + \delta(s_0) - w^\top \Psi\beta - w^\top \delta)^2; \quad \left\{ \text{let } \delta = (\delta(s_1), \dots, \delta(s_n))^\top \right\} \\ (16.8) \quad &= \mathbb{E} \left(\sum_{i=1}^n w_i \delta(s_i) - \delta(s_0) \right)^2 \stackrel{\sum_{i=1}^n w_i = 1}{=} \mathbb{E} \left(\sum_{i=1}^n w_i (\delta(s_i) - \delta(s_0)) \right)^2 \end{aligned}$$

$$(16.9) \quad = -\mathbb{E} \left(\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n w_i w_j (\delta(s_i) - \delta(s_j))^2 - 2 \frac{1}{2} \sum_{i=1}^n w_i (\delta(s_i) - \delta(s_0))^2 \right)$$

$$(16.10) \quad = -\sum_{i=1}^n w_i \sum_{j=1}^n w_j \frac{1}{2} \mathbb{E}(\delta(s_i) - \delta(s_j))^2 + 2 \sum_{i=1}^n w_i \frac{1}{2} \mathbb{E}(\delta(s_i) - \delta(s_0))^2$$

Note 158. Since we have assumed that $(\delta(s); s \in \mathcal{S})$ is intrinsic stationary, its semivariogram exists, and allow $\text{MSE}(Z_{\text{UK}}(s_0))$ to be expressed w.r.t. that semivariogram as

$$\begin{aligned} (16.11) \quad \text{MSE}(Z_{\text{UK}}(s_0)) &= -\sum_{i=1}^n w_i \sum_{j=1}^n w_j \gamma(s_i - s_j) + 2 \sum_{i=1}^n w_i \gamma(s_i - s_0) \\ &= -w^\top \mathbf{\Gamma} w + 2w^\top \boldsymbol{\gamma}_0 \end{aligned}$$

where $w = (w_1, \dots, w_n)^\top$, $\boldsymbol{\gamma}_0 = (\gamma(s_0 - s_1), \dots, \gamma(s_0 - s_n))^\top$, and $[\mathbf{\Gamma}]_{i,j} = \gamma(s_i - s_j)$.

Note 159. The Lagrange function for minimizing the MSE (16.11) under (16.3) is

$$\begin{aligned} \mathcal{L}(w, \lambda) &= -\sum_{i=1}^n \sum_{j=1}^n w_i w_j \gamma(s_i - s_j) + 2 \sum_{i=1}^n w_i \gamma(s_0 - s_i) - \sum_{j=0}^p \lambda_j \left(\sum_{i=1}^n w_i \psi_j(s_i) - \psi_j(s_0) \right) \\ &= -w^\top \mathbf{\Gamma} w + 2w^\top \boldsymbol{\gamma}_0 - (w^\top \Psi - \Psi_0) \lambda \end{aligned}$$

Note 160. The UK system of equations is

$$0 = \nabla_{(w,\lambda)} \mathfrak{L}(w, \lambda) \Big|_{(w_{\text{UK}}, \lambda_{\text{UK}})} \iff$$

(16.12)

$$\begin{cases} 0 = -2 \sum_{j=1}^n w_{\text{UK},j} \gamma(s_i - s_j) + 2\gamma(s_0 - s_i) - \sum_{j=0}^p \lambda_{\text{UK},j} \psi_j(s_i), & i = 1, \dots, n \\ \psi_j(s_0) = \sum_{i=1}^n w_{\text{UK},i} \psi_j(s_i), & j = 0, \dots, p \end{cases} \iff$$

(16.13)

$$\begin{cases} 0 = -2\Gamma w + 2\gamma_0 - \Psi \lambda_{\text{UK}} \\ \Psi_0 = w_{\text{UK}}^\top \Psi \end{cases}$$

Then by multiplying both sides by $\Psi^\top \Gamma^{-1}$ I get

$$0 = -2\Psi^\top \Gamma^{-1} \Gamma w_{\text{UK}} + 2\Psi^\top \Gamma^{-1} \gamma_0 - \Psi^\top \Gamma^{-1} \Psi \lambda_{\text{UK}} \iff$$

(16.14) $\lambda_{\text{UK}} = 2(\Psi^\top \Gamma^{-1} \Psi)^{-1} (\Psi^\top \Gamma^{-1} \gamma_0 - \Psi_0^\top)$

and then by substituting (16.14) in (16.13), I get the UK weights as

$$(16.15) \quad w_{\text{UK}} = \Gamma^{-1} \left(\gamma_0 - \Psi (\Psi^\top \Gamma^{-1} \Psi)^{-1} (\Psi^\top \Gamma^{-1} \gamma_0 - \Psi_0^\top) \right)$$

Note 161. Hence the UK predictor $Z_{\text{UK}}(s_0)$ at s_0 is

$$(16.16) \quad Z_{\text{UK}}(s_0) = \left(\gamma_0 - \Psi (\Psi^\top \Gamma^{-1} \Psi)^{-1} (\Psi^\top \Gamma^{-1} \gamma_0 - \Psi_0^\top) \right)^\top \Gamma^{-1} Z$$

with standard error

$$(16.17) \quad \sigma_{\text{UK}}(s_0) = \sqrt{-w_{\text{UK}}^\top \Gamma w_{\text{UK}} + 2w_{\text{UK}}^\top \gamma_0}$$

$$(16.18) \quad = \sqrt{\gamma_0^\top \Gamma^{-1} \gamma_0 - (\Psi^\top \Gamma^{-1} \gamma_0 - \Psi_0^\top)^\top (\Psi^\top \Gamma^{-1} \Psi)^{-1} (\Psi^\top \Gamma^{-1} \gamma_0 - \Psi_0^\top)}$$

Note 162. $(1 - \alpha)$ 100% Prediction interval of UK predictor $Z_{\text{UK}}(s_0)$ at s_0 is

$$(16.19) \quad \left(Z_{\text{UK}}(s_0) - q_{\alpha/2} \sqrt{\sigma_{\text{UK}}^2(s_0)}, Z_{\text{UK}}(s_0) + q_{1-\alpha/2} \sqrt{\sigma_{\text{UK}}^2(s_0)} \right)$$

where q_\cdot are suitable quantiles of the distribution of Z_s . E.g. if $Z_s \sim \text{GP}(\mu(\cdot), c(\cdot, \cdot))$ then $q_{0.05/2} = -1.96$ and $q_{0.95/2} = 1.96$ at $\alpha = 0.05$.

Note 163. Note that we have not assumed a particular distribution of Z_s or δ_s , but only stationarity assumptions.

Note 164. It was not necessary to consider the intrinsic stationarity assumption in Note 149 in order to derive the Universal Kriging predictor; we could have derived its formulas (16.16) & (16.17) with respect to the covariance function $c(\cdot, \cdot)$ of (Z_s) instead of its semivariogram $\gamma(\cdot)$. Here, intrinsic stationarity was assumed for practical reasons: it allowed us to express

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16.16 and (16.17) as functions of the semi-variogram which is discussed how to be estimated in Section 15.

Note 165. To use (16.16), (16.17), and (16.19), we need to learn the unknown coefficients $\{\beta_j\}$ and the semi-variogram $\gamma(\cdot)$, or “equivalently” the unknown hyper-parameter θ of the parametric semivariogram $\gamma_\theta(\cdot)$ used to cast $\gamma(\cdot)$. In practice, we use the same dataset used to compute (16.15), however in principle a fresh training dataset $\{(s'_i, Z'_i)\}_{i=1}^n$ is required (never use the same training data 2 times). A training procedure can be the following.

- (1) Compute estimates $\hat{\beta}$ via LSE (or equivalent)

$$(16.20) \quad \hat{\beta}_{\text{LSE}} = \arg \min_{\beta} \left(\sum_i \left(Z(s_i) - \underbrace{\psi(s_i)^\top \beta}_{=\mu(s_i)} \right)^2 \right)$$

- (2) Compute the residuals

$$(16.21) \quad \hat{\delta}_i := Z(s_i) - \psi(s_i)^\top \hat{\beta}_{\text{LSE}}$$

- (3) Compute the empirical variogram $\hat{\gamma}$ for $\hat{\delta}$ on \mathcal{H} according to Proposition 125,
- (4) Compute the estimate $\hat{\theta}$ of θ of the parameterized semivariogram γ_θ , according to Proposition 139, and hence compute $\gamma_{\hat{\theta}}(\cdot)$.

Example 166. ³ Consider the example with the Meuse dataset. Fig 16.2b presents the UK prediction $Z_{\text{UK}}(s_0)$ at any point $s_0 \in \mathcal{S}$ under model (16.1) for when the spatial mean has a linear form $\mu(s) = \beta_0 + \beta_1 s_1 + \beta_2 s_2$. Following Note 165, we computed the $\hat{\beta}_{\text{LSE}}$ of β by (16.20), then we removed the linear trend by (16.21) and computed the residual process $\{\hat{\delta}_i\}$, then we computed the semi-variogram $\hat{\gamma}$ (15.2) of δ as in Proposition 125; then we considered a (parametric) isotropic exponential semi-variogram $\gamma_{(\sigma^2, \phi)}$ of δ where we computed the OLS $\hat{\theta}_{\text{OLS}} = (\hat{\sigma}_{\text{OLS}}^2, \hat{\phi}_{\text{OLS}})$ of the hyperparameters (σ^2, ϕ) as in (15.6) (see Figure 15.3d); and then we plugged in the estimated $\gamma_{(\hat{\sigma}_{\text{OLS}}^2, \hat{\phi}_{\text{OLS}})}$ in (16.16) to compute the UK weights w_{UK} for the UK predictor $Z_{\text{UK}}(s_0) = w_{\text{UK}} Z$ for any $s_0 \in \mathcal{S}$. The reason that we do not see much difference between OK in Figure 16.2a and UK in Figure 16.2b is possibly because the slopes in the linear trend (mean) of UK are rather small and insignificant (See Example 145).

Example 167. (Cont. Examples 115, 132) Consider the example with the Meuse dataset. The dataset has another measurement (a potential regressor in the deterministic mean $\mu(s)$), the “distance to the Meuse river bed” $\{d_i\}$ at the associated locations $\{s_i\}$, let’s denote it by d . Figure 16.2c shows a rather linear relationship between Z and \sqrt{d} , hence we can consider

³https://github.com/georgios-stats/Spatio-Temporal_Statistics_Michaelmas_2023/blob/main/Lecture_handouts/R_scripts/03.Geostatistical_data_meuse_gstats.R

a UK predictor with deterministic mean $\mu(s, d) = \beta_0 + \beta_1 \sqrt{d_s}$. We follow the same procedure as in Example 166 and we get the UK predictor in Figure 16.2d.

16.2. Ordinary Kriging.

Note 168. Ordinary Kriging (OK) addresses spatial prediction in cases that the specified statistical model on $(Z(s); s \in \mathcal{S})$ has the form

$$(16.22) \quad Z(s) = \beta_0 + \delta(s)$$

with unknown $\beta_0 \neq 0$ and intrinsically stationary process $(\delta(s); s \in \mathcal{S})$.

Note 169. OK can be derived as a special case of the Universal Kriging by setting $p = 0$ and constant spatial mean $\mu(s) = \beta_0$.

Example 170. [The derivation is in (Exercise ?? Exercise sheet).] As a supplementary and for demonstration, we mention that the OK assumption is $\sum_{i=1}^n w_i = 1$; the OK system of equations is $0 = \nabla_{(\{w_i\}, \lambda)} L(w, \lambda)|_{(w, \lambda)}$ producing

$$(16.23) \quad \begin{cases} 0 = -2\Gamma w_{\text{OK}} + 2\gamma_0 - 1\lambda \\ w_{\text{OK}}^\top 1 = 1 \end{cases}$$

the weights are

$$(16.24) \quad w_{\text{OK}} = \Gamma^{-1} \left(\gamma_0 + \frac{1 - 1^\top \Gamma^{-1} \gamma_0}{1^\top \Gamma^{-1} 1} 1 \right)$$

the Kriging standard error of $Z_{\text{OK}}(s_0)$ at s_0 is

$$(16.25) \quad \sigma_{\text{OK}}^2(s_0) = \gamma_0^\top \Gamma^{-1} \gamma_0 - \frac{(1 - 1^\top \Gamma^{-1} \gamma_0)^2}{1^\top \Gamma^{-1} 1}.$$

16.3. Simple Kriging.

Note 171. Simple Kriging (SK) addresses spatial prediction in cases that the specified statistical model on $(Z(s); s \in \mathcal{S})$ has the form

$$(16.26) \quad Z(s) = \mu(s) + \delta(s)$$

where the deterministic mean $\mu(s)$ is known, and $(\delta(s); s \in \mathcal{S})$ is a weakly stationary process with covariogram $c(\cdot)$.

Example 172. [The derivation is in (Exercise ?? in the Exercise sheet).] It does not require any assumption in the weights such as (16.4) or (16.23). As a supplementary and

for demonstration, we mention the SK predictor at s_0 and standard error:

$$Z_{\text{SK}}(s_0) = \mu(s_0) + C_0^\top C^{-1} [Z - \mu]$$

$$\sigma_{\text{SK}} = \sqrt{c(s_0, s_0) - C_0^\top C^{-1} C_0}$$

with $\mu = (\mu(s_1), \dots, \mu(s_n))^\top$, $C_0 = (c(s_0 - s_1), \dots, c(s_0 - s_n))^\top$, and $[C]_{i,j} = c(s_i - s_j)$.

Example 173. Consider the example with the Meuse dataset. Fig 16.2a presents the OK prediction $Z_{\text{OK}}(s_0)$ at any point $s_0 \in \mathcal{S}$ under model (16.22) that is the UK case (16.1) for when $\mu(s) = \beta_0$. First we computed the non-parametric semivariogram $\hat{\gamma}$ (15.2) as in Proposition 125; then we considered a (parametric) isotropic exponential semi-variogram $\gamma_{(\sigma^2, \phi)}$ where we computed the OLS $\hat{\theta}_{\text{OLS}} = (\hat{\sigma}_{\text{OLS}}^2, \hat{\phi}_{\text{OLS}})$ of the hyperparameters (σ^2, ϕ) as in (15.6) (see Figure 15.3a); and then we plugged in the estimated $\gamma_{(\hat{\sigma}_{\text{OLS}}^2, \hat{\phi}_{\text{OLS}})}$ in (16.24) to compute the OK weights w_{OK} for the OK predictor $Z_{\text{OK}}(s_0) = w_{\text{OK}}Z$ for any $s_0 \in \mathcal{S}$.

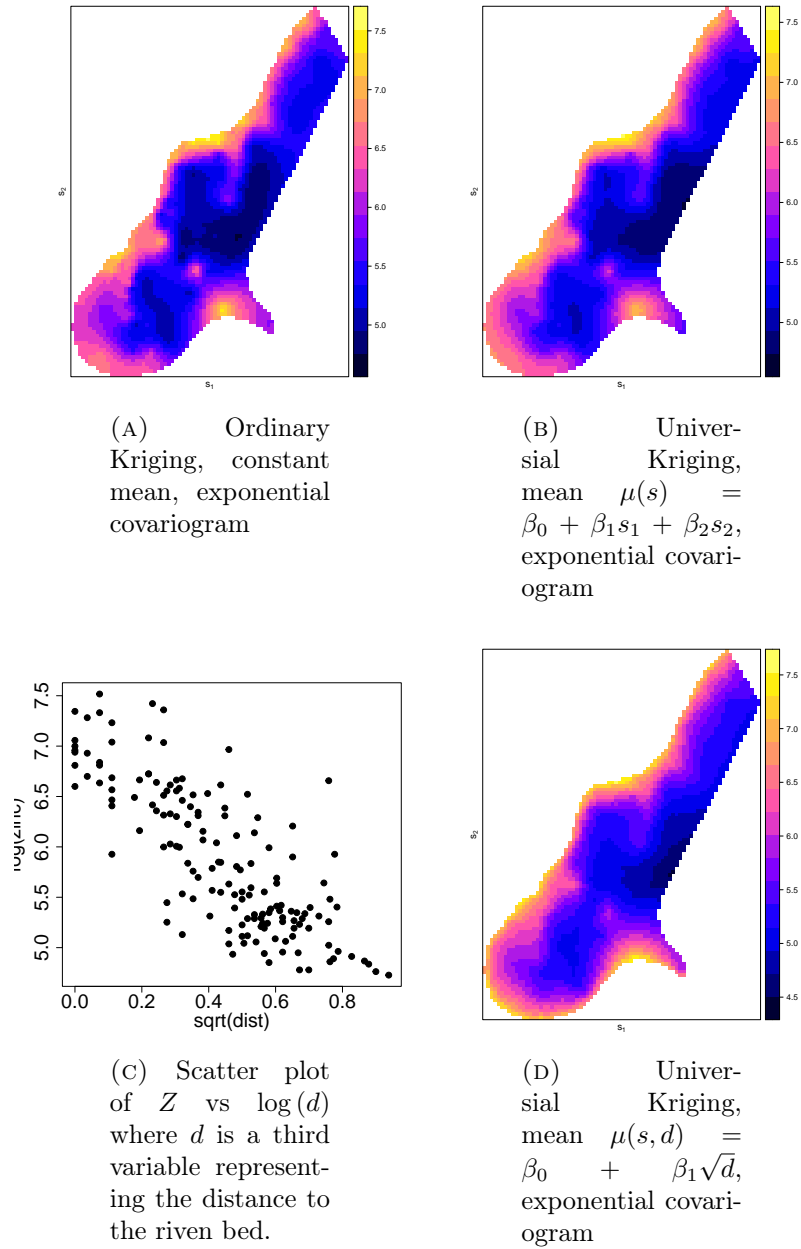


FIGURE 16.2. Kriging Meuse dataset.