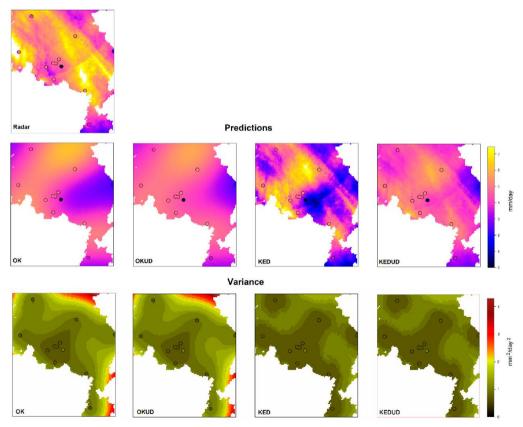


Statistical Methods

- Kriging (Simple, Ordinary, Universal)
- Conditional Simulation

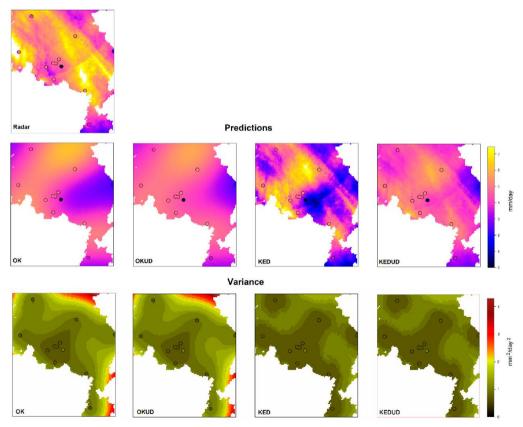


Cecinati et al.: Considering Rain Gauge Uncertainty Using Kriging for Uncertain Data, Atmosphere (2018)



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The measurement Z_i at location $x_i \in \mathbb{R}^n$ is interpreted as a **random variable** with **expected value**

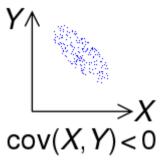
$$E[Z_i] = \int_{\Omega} z \, d\mu_{Z_i}(z)$$

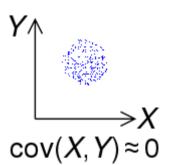
and variance

$$Var(Z_i) = E[(Z_i - E[Z_i])^2].$$

The covariance of two random variables is given by

$$Cov(Z_i, Z_j) = E[(Z_i - E[Z_i])(Z_j - E[Z_j])].$$





$$Y \wedge \longrightarrow X$$

 $cov(X, Y) > 0$



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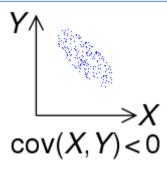
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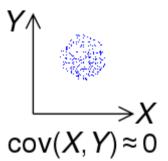
$$Cov(Z_i, Z_j) = E[(Z_i - E[Z_i])(Z_j - E[Z_j])].$$

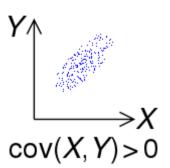
A crucial assumption in geostatistics is that of **stationarity**:

$$E[Z(x)] = m$$
, $Cov(Z(x+h), Z(x)) = C(h)$.

The covariance depends only on the increment $x - x_i$ between to locations, not the location itself!









An approximation Z^* of Z is given by

$$Z^*(x) = \lambda_0 + \sum_{i=1}^N \lambda_i(x) Z_i,$$

with unknown weights $\lambda_i(x)$ such that

$$Z^*(x_i) = z_i, \quad i = 1, \dots, N.$$



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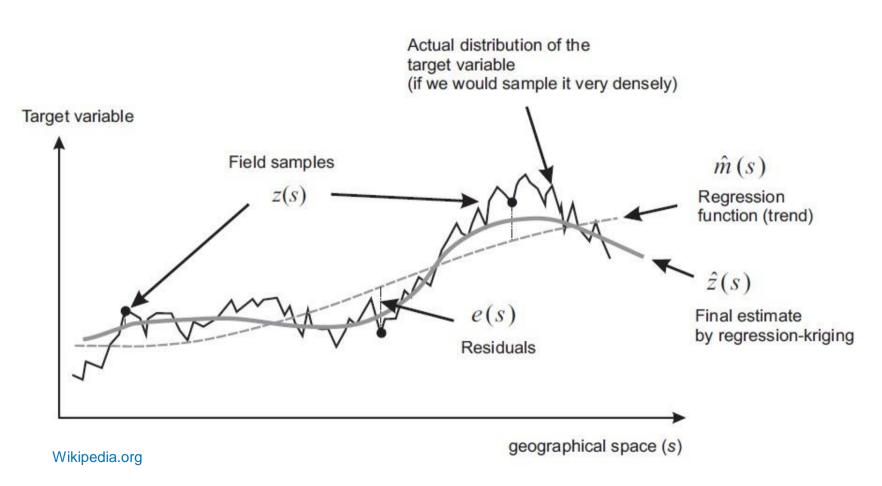
How to find the weights $\lambda_i(x)$? **Unbiasedness**

$$E[Z^*(x)] = E[Z(x)]$$

and variance minimizing

$$\min_{Z^*} Var(Z^*(x) - Z(x)).$$







Simple Kriging: Expectation $m_0 = E[Z(x)]$ is known: Unbiasedness yields

$$\lambda_0 = m_0 - \sum_{i=1}^n \lambda_i m_0.$$



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Variance minimization leads to

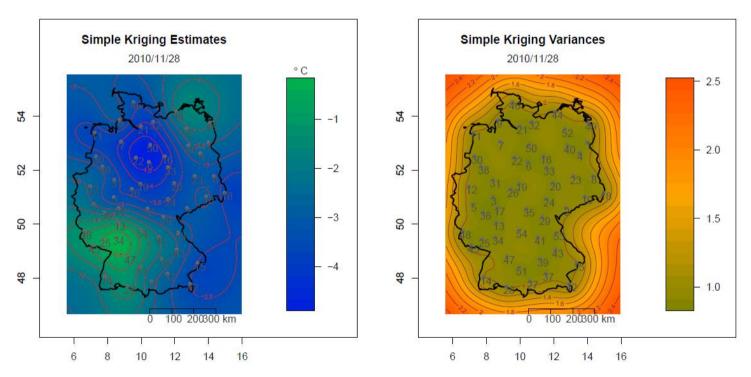
$$\sum_{i=1}^{n} \lambda_i(x) Cov(Z_i, Z_k) = Cov(Z_k, Z(x)), \quad k = 1, \dots, n.$$

Note that stationarity implies $Cov(Z_k,Z(x))=C(x_k-x)$ — Relation to radial basis functions.

$$\sigma_{SK}^2 = Var[Z^* - Z_0] = C(0) - \sum_{k=1}^n \lambda_k^{SK} C(x_k - x_0)$$



Simple Kriging: Expectation $m_0 = E[Z(x)]$ is known: Unbiasedness yields



Example from the Bachelor thesis "Kriging methods in spatial statistics", Andreas Lichtenstern, TU München



A crucial role is given to the **variogramm**

$$\gamma(h) = \frac{1}{2} Var(Z(x) - Z(x+h)) = C(0) - C(h).$$

It can be estimated from the data (under certain conditions).



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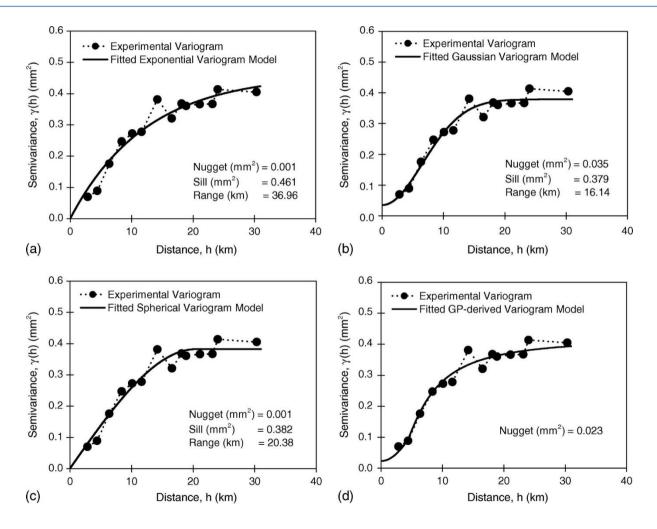
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Empirical variogram

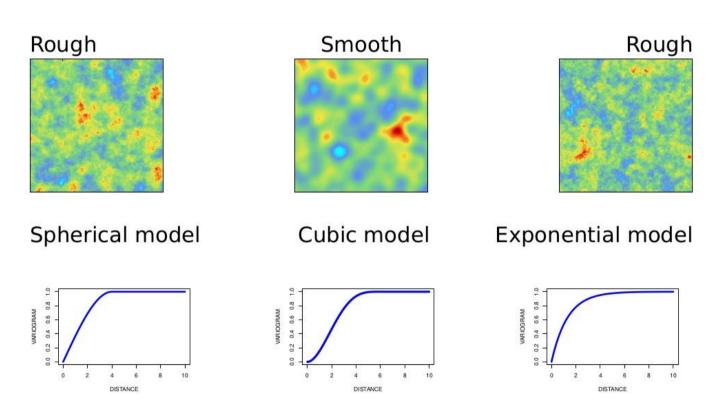
$$\hat{\gamma}(h) = \frac{1}{N_h} \sum_{x_i - x_j = h} (Z_i - Z_j)^2.$$

After the empirical variogram has been computed, a theoretical model needs to be fit to it. This model needs to satisfy certain properties, e.g. conditional negative definiteness.





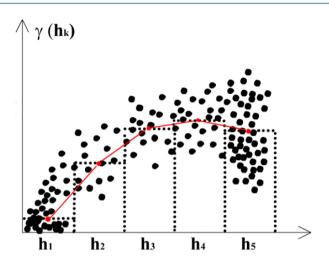


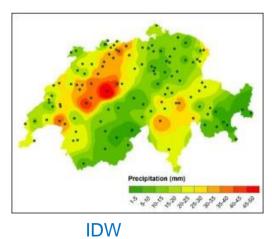


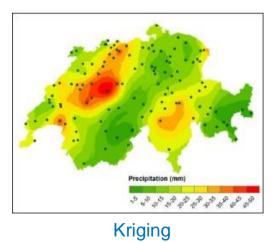
From a presentation by H. Wackernagel



Example IDW, Kriging

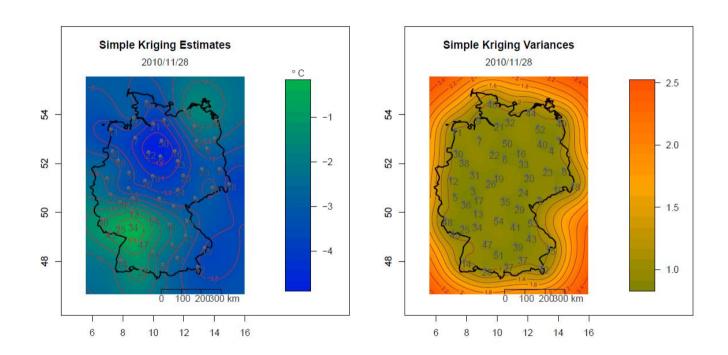






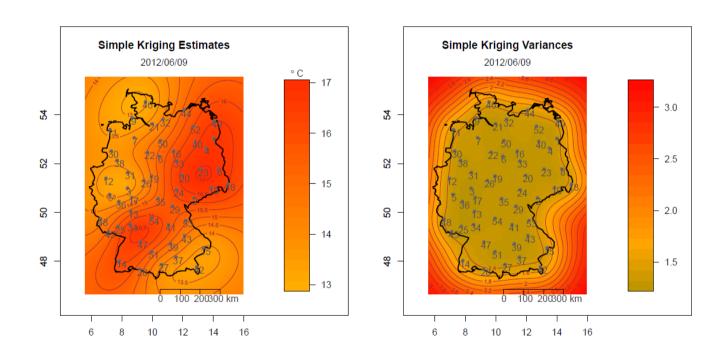
gitta.info





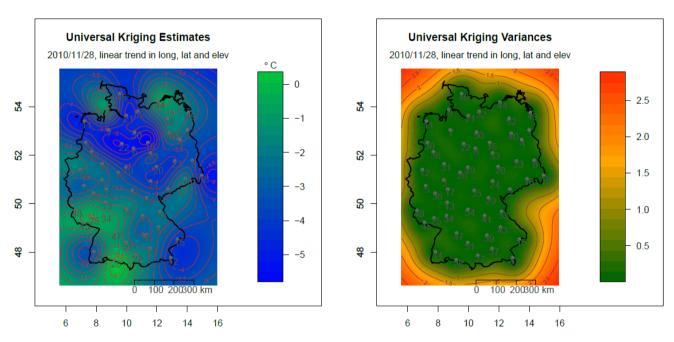
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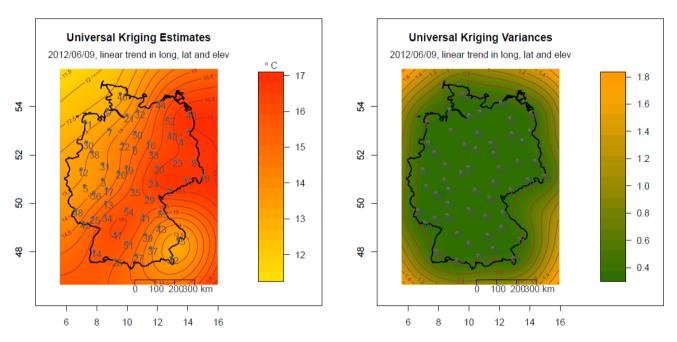
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