

Geostatistics

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Mines ParisTech

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Geostatistics team – Centre de Géosciences

- 5 scholars, 3 Ph.D. students, 2 post-docs
- Main research themes : geostatistics (models, methods, applications), data assimilation, deep generative models
- Research axis :
 - models development
 - research with partners (public institutes, private companies)
 - Software development gstatlearn

[https:](https://www.geosciences.minesparis.psl.eu/en/presentation/geostatistique/)

//www.geosciences.minesparis.psl.eu/en/presentation/geostatistique/

Athens week: Geostatistics

- Objectives
master the theoretical and practical basis of the mathematical modeling of regionalized phenomena by probabilistic methods
- Prerequisites
basic probability and statistics courses
- Teachers
NICOLAS DESASSIS, MIKE PEREIRA, THOMAS ROMARY

History

- Origin 1950's : Mining applications (D. Krige, South Africa)
- Geostatistics (french school) : G. Matheron, from the 1960's
- Based on the random functions formalism (Lévy, Kolmogorov)

What goals ?

- Describe, model the behaviour of a variable in space (and/or in time)
Ex: depth variation of a geological horizon
⇒ spatial variability, spatial structure, stationarity or not
- Understand and predict the support effects
Ex: log porosity vs block porosity
⇒ dispersion variances, support effect, information effect
- Estimate, map the variable
Ex: estimate the atmospheric pollution at different scales
⇒ stationary/nonstationary kriging, estimation variance

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What goals ?

- Study jointly several variables
Ex: topography and pluviometry
⇒ multivariate geostatistics
- Estimate, map the variable and transformed versions of that variable
Ex: estimate the probability of an atmospheric pollution to exceed a given threshold at different scales
⇒ non-linear Geostatistics
- Simulate the variable to estimate complex quantities
Ex: confidence intervals on a reservoir volume
⇒ geostatistical simulations

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Some examples

Mine : gisements de diamants

Modélisation de dépôts de diamants alluvionnaires

- Estimation du nombre de pierres à partir de données de supports différents (2 à 10000 m²)
- Echantillonnage
- Distribution de la taille des pierres (des microdiamants aux macrodiamants)



Exemple d'irrégularités dans la roche mère

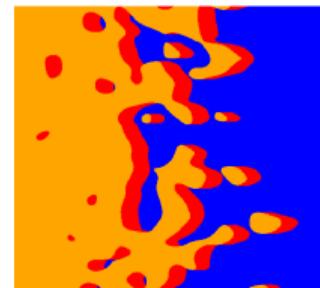
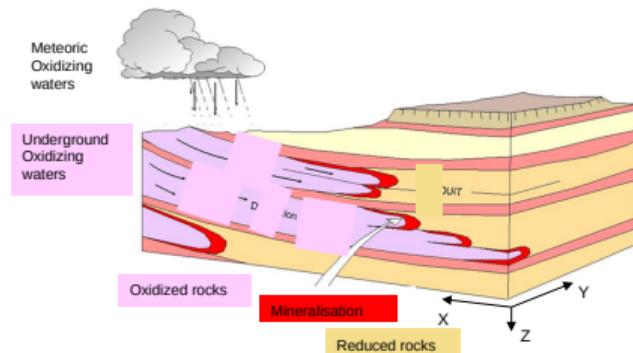
Christian Lantuéjoul,
Collaboration avec De Beers

Some examples

Mine : gisements d'Uranium

Modélisation de gisements de type roll front

- Simulation d'exploitation par lixiviation
- Géologie- Chimie - hydrogéologie
- Modèles géostatistiques ad hoc

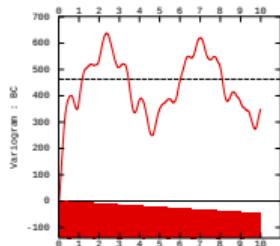


Some examples

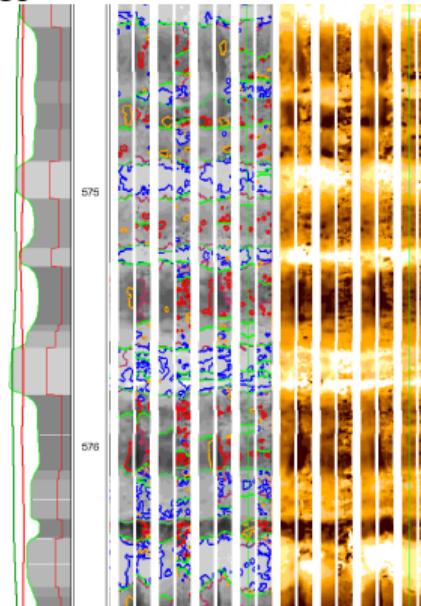
Stockage de déchets radioactifs

Variabilité des caractéristiques des argilites

- ❑ analyse de diaglyphies haute résolution et passage en repère chronostratigraphique



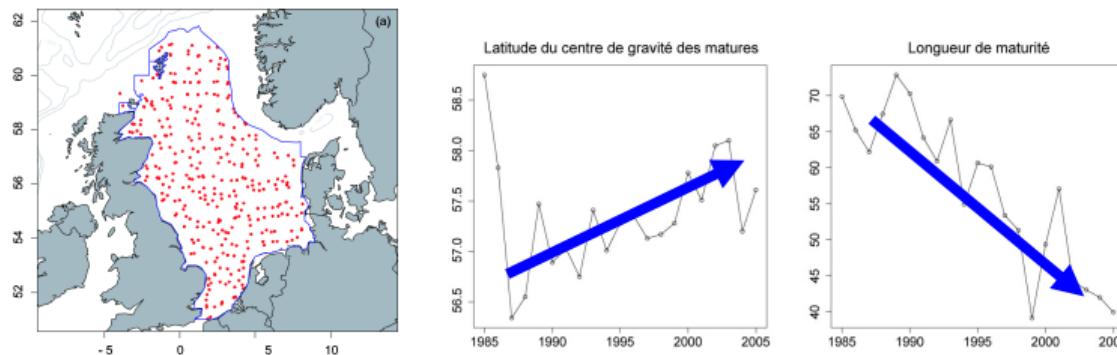
Thèse Marie Lefranc 2007



Some examples

Halieutique

Mise au point de méthodes d'évaluation des stocks à partir de campagnes scientifiques (acoustique / coups de chalut) et/ou des captures commerciales



Thèses M. Faraj et E. Walker Coll. Ifremer, IRD, instituts européens d'halieutique

Some examples

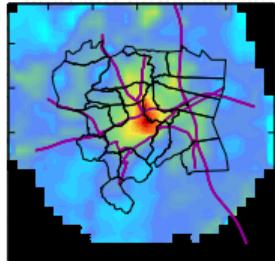
○ Qualité de l'air

○ Etude du NO₂ annuel

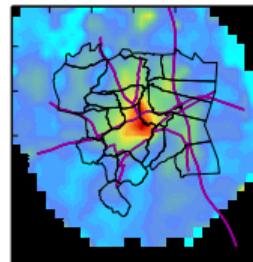
Mulhouse

Carte estimée

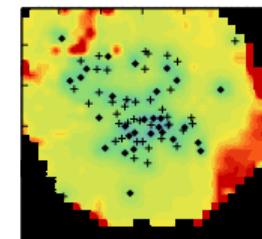
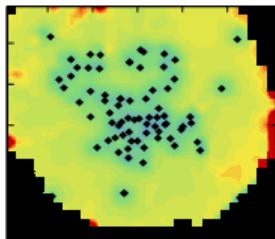
Mesures et information
auxiliaire



Echantillonnage
réduit de 30%



Ecart type
d'estimation

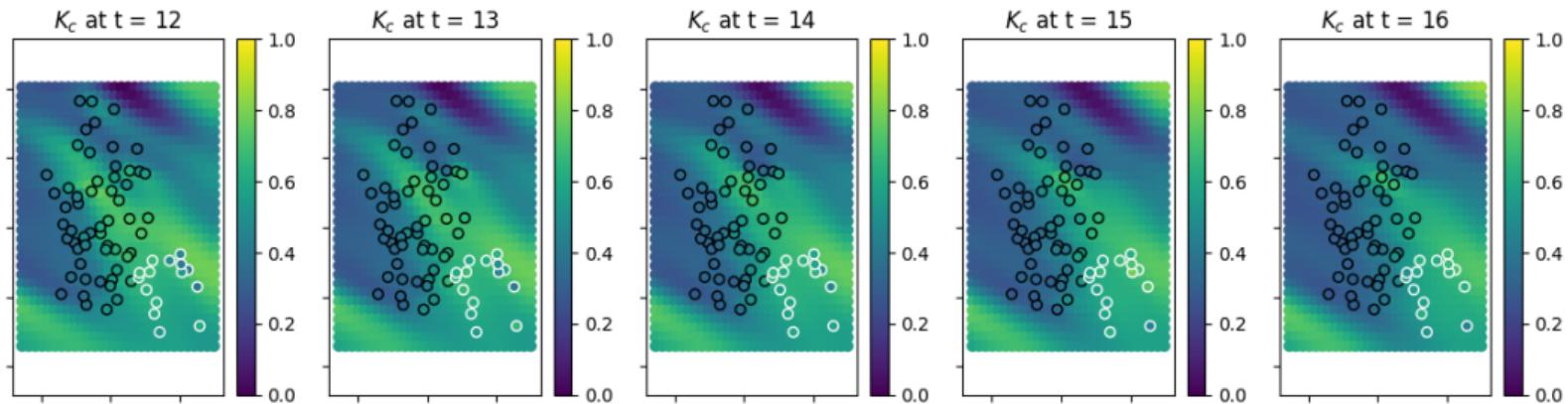


D. Gallois, Ch. de Fouquet Partenaires INERIS, ASQUA

Some examples

Spatio-temporal SPDE

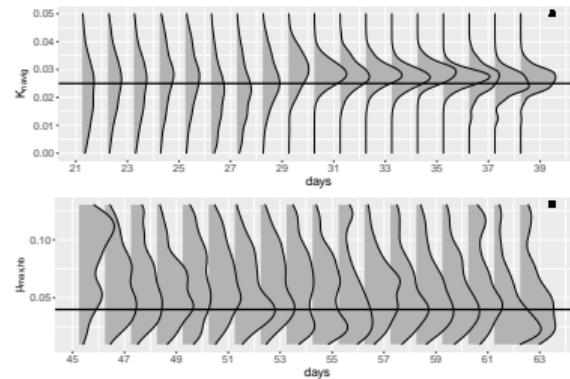
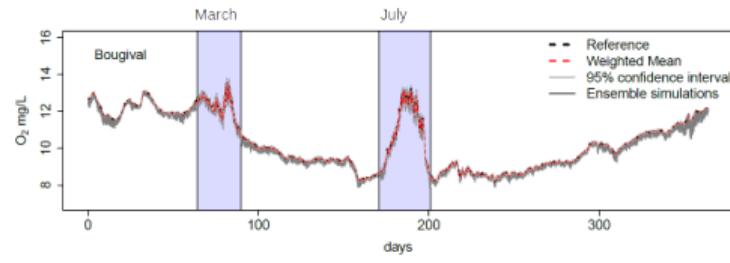
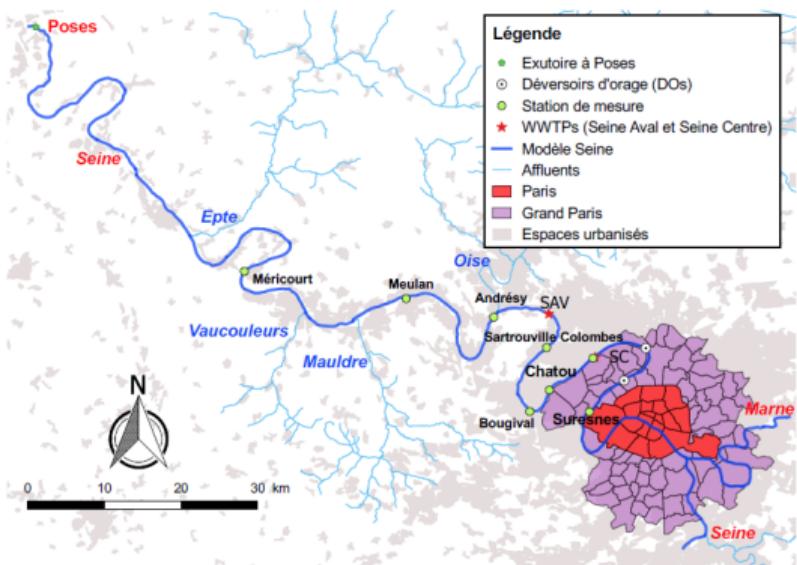
$$\left[\frac{\partial}{\partial t} + \frac{1}{c} (\kappa^2 - \nabla \cdot \mathbf{H} \nabla)^\alpha + \frac{1}{c} \boldsymbol{\gamma} \cdot \nabla \right] X(\mathbf{s}, t) = \frac{\tau}{\sqrt{c}} Z(\mathbf{s}, t)$$



Kriging of clear sky index over 5 time steps

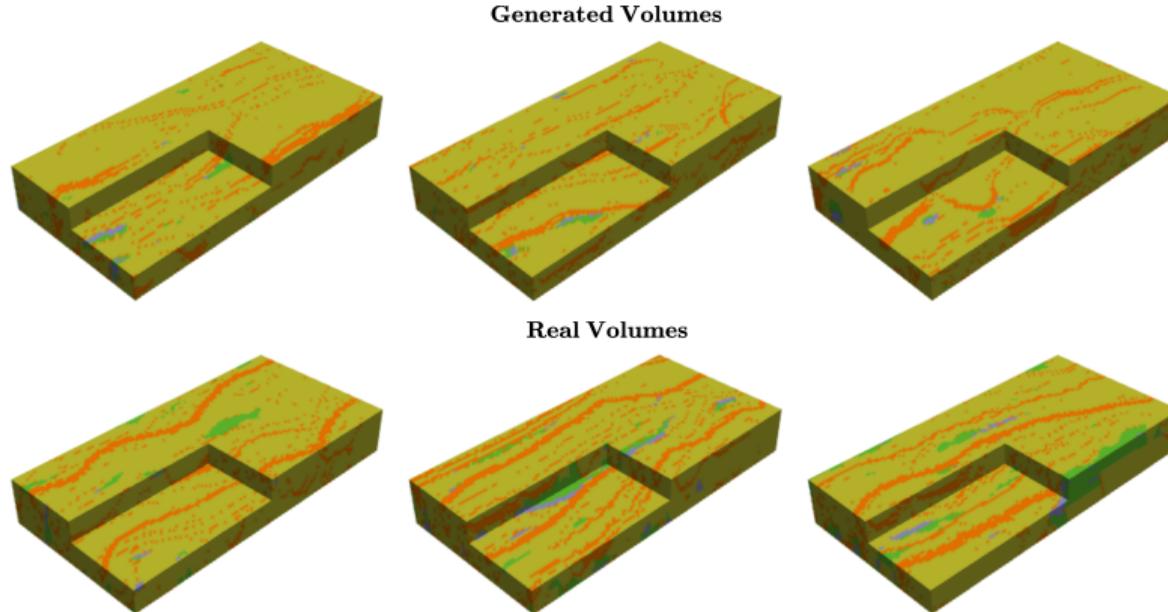
Some examples

Data assimilation in water quality



Some examples

Deep generative models



Visual comparison of 3D volumes generated with the Multi-Scale Wasserstein GAN (top) and the Flumy 3D volume (bottom)

Chaire geolearning

chaire-geolearning.org/en

Geostatistics, extreme events and Machine Learning for the climate transition

- 3 main research axis
 - Geostatistical methods for spatio-temporal data
 - Hybridize Machine Learning with geostatistics
 - Methods for extreme events
- 4 partners
 - Andra
 - BNP Paribas
 - CCR
 - Fondation SCOR

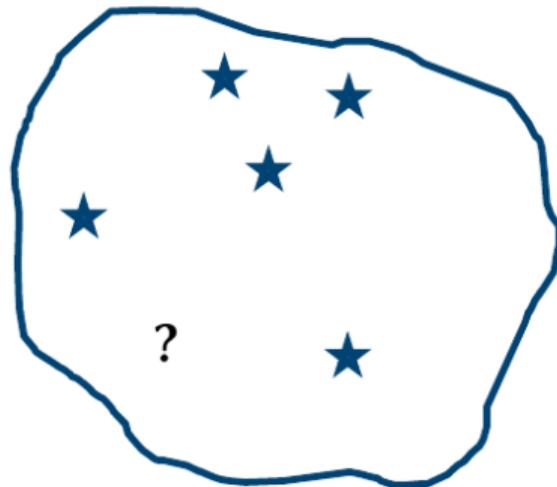
Why a probabilistic approach?

- It is generally impossible to
 - build a quantitative description based solely on physical laws
 - build a deterministic mathematical model due to the complexity of the problem
- The probabilistic approach allows to
 - integrate data from different sources to reduce the uncertainties
 - generate multiple realizations of the natural variable for the quantification of the uncertainties incertitudes

En résumé

★ On observe

- Valeurs ponctuelles
- Valeurs moyennes sur un support donné
- Valeurs transformées
- Informations qualitatives
- Modèles physiques
- ...



? On cherche

- Valeurs possibles?
- Valeur moyenne?
- Probabilité que la valeur soit supérieure à un seuil?

Program

Room L218

	Mon	Tue	Wed	Thu	Fri
Morning 9h - 12h15	General introduction Probability	Random Functions	Kriging	Maximum Likelihood Approach	Summary Project
After- noon 13h45-17h	Regression & Spatial Interpolation	Variography & parametric models	Multi- variate modelling	Simulations	Project

Evaluation

- Report on mini-project to be delivered on november 24th at 23:59
- Kaggle competition :
<https://www.kaggle.com/c/geostatistics-athens-week-2024>

References

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- Diggle P.J. and Ribeiro P.J. (2007) Model-based Geostatistics. Springer, New-York.
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- Lantuéjoul C. (2002) Geostatistical simulation ; models and algorithms. Springer, Berlin.
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- Stein M. L. (2005) Interpolation of Spatial Data: Some Theory for Kriging. Springer, New York.
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