PGE 338 Data Analytics and Geostatistics

Lecture 16: Cosimulation

Lecture outline . . .

- Cosimulation
- Full Cokriging
- Collocated Cokriging
- P-field Simulation

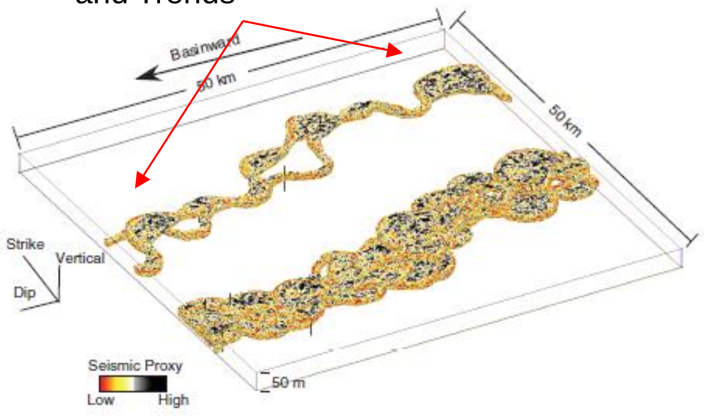
Michael Pyrcz, The University of Texas at Austin

Motivation

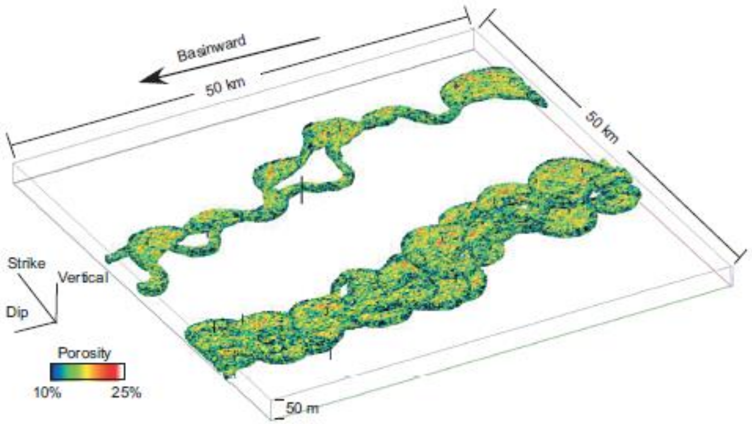
We need subsurface modeling methods that:

- Account for the relationships between multiple correlated variables, e.g., seismic acoustic impedance and porosity.

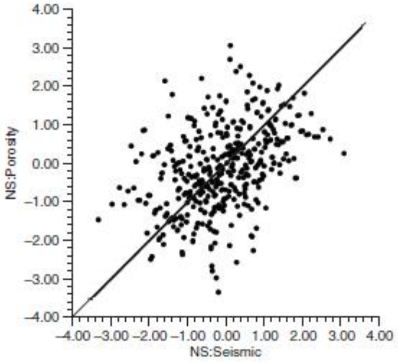
Secondary Data and Trends



Associated Seismic Secondary Variable Realization



Porosity Primary Variable Realization Conditioned by Secondary Variable



Bivariate Relationship Between Primary and Secondary Variables

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Flashback: A Common Modeling Workflow

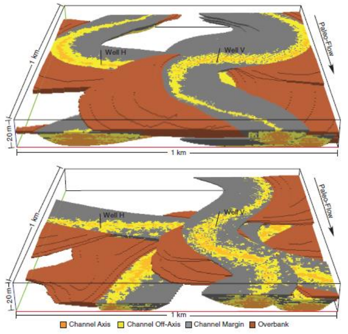
The common bivariate subsurface modeling workflow:

Categorical Simulation

Facies Realizations honoring PDF, Trends and Spatial Continuity

→

Multiple Facies Realizations



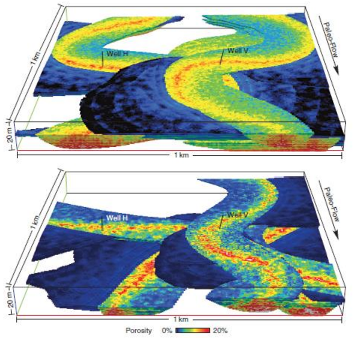
→

Continuous Simulation

Porosity Realizations honoring PDF, Trends and Spatial Continuity within each facies

→

Multiple Porosity By-facies Realizations

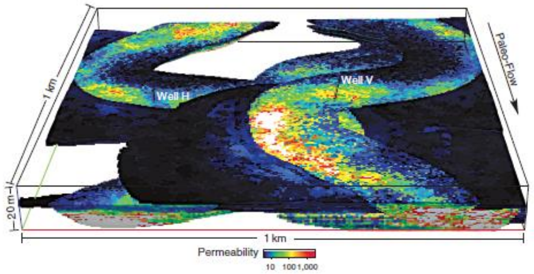


Continuous Cosimulation

Models Permeability honoring PDF, Trends and Spatial Continuity, Correlated with Porosity within each facies

←

Multiple Permeability By-facies Realizations Correlated with Porosity



Note: only had 1 realization image available (should be two in figure).

The standard bivariate subsurface modeling workflow.

Motivation for Cosimulation

We typically need to build reservoir models of more than one property of interest.

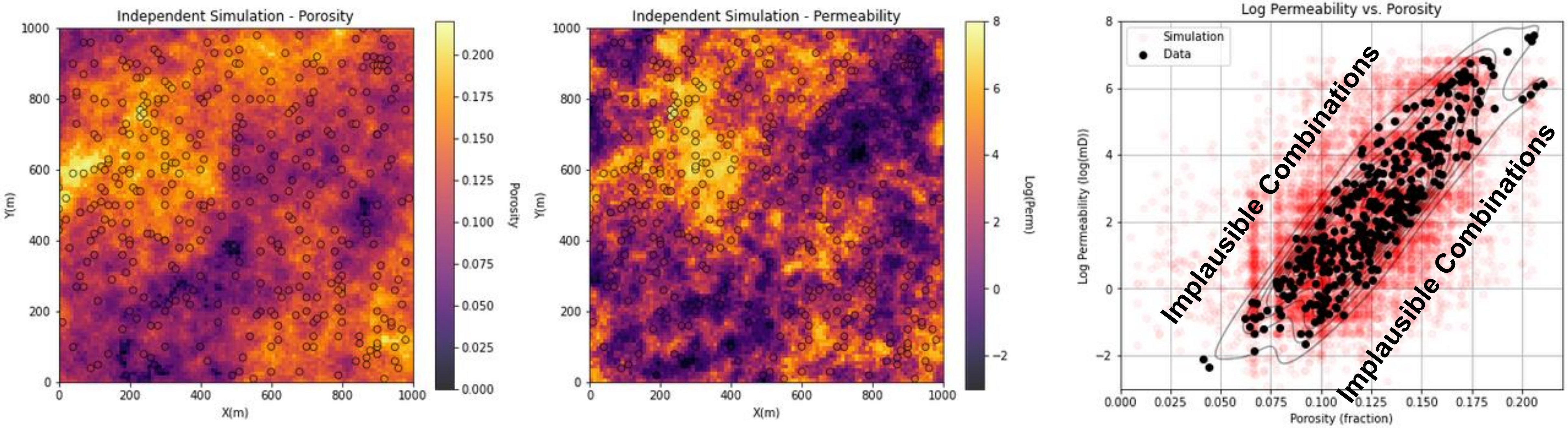
- our models must be beyond univariate
- one feature at a time models will have non-physical feature combinations! e.g., high porosity with low permeability

We will only cover the commonly applied cosimulation methods

- collocated cokriging, cloud transform, and p-field simulation
- we limit ourselves to simulating one property correlated to one other (bivariate)

Motivation for Cosimulation

Cosimulation is not perfect, but the alternative is to simulate each property independently



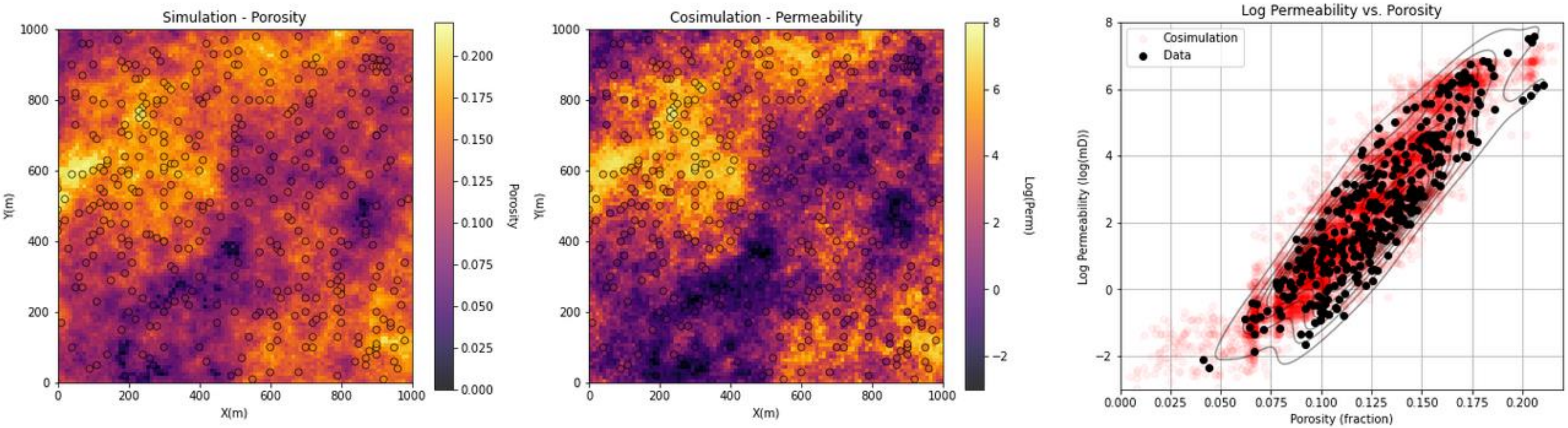
Independent simulation of porosity (left) and permeability (center) and cross plot data and simulated values (right), file is GeostatsPy_cosimulation.ipynb.

- no correlation or some minor degree correlation due to data conditioning (correlation at the data locations gets propagated away from the data in each feature).

This results in implausible combinations away from data and too high uncertainty, because we ignore information between the features.

Motivation for Cosimulation

Now we repeat the previous example with cosimulation.



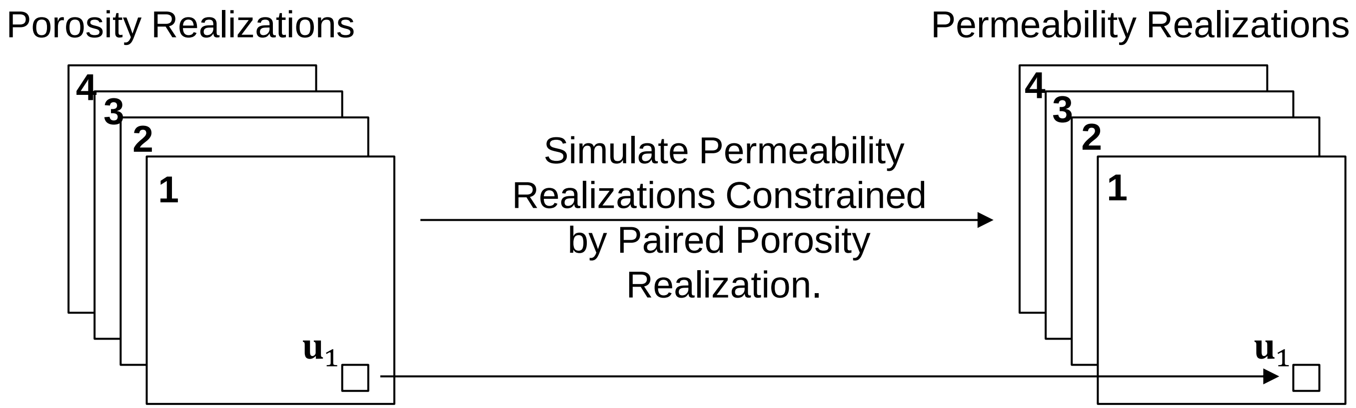
Cosimulation of permeability (center) given porosity (left) and cross plot data and simulated values (right), file is GeostatsPy_cosimulation.ipynb.

- an example with good reproduction of bivariate features, correlation based on collocated cokriging

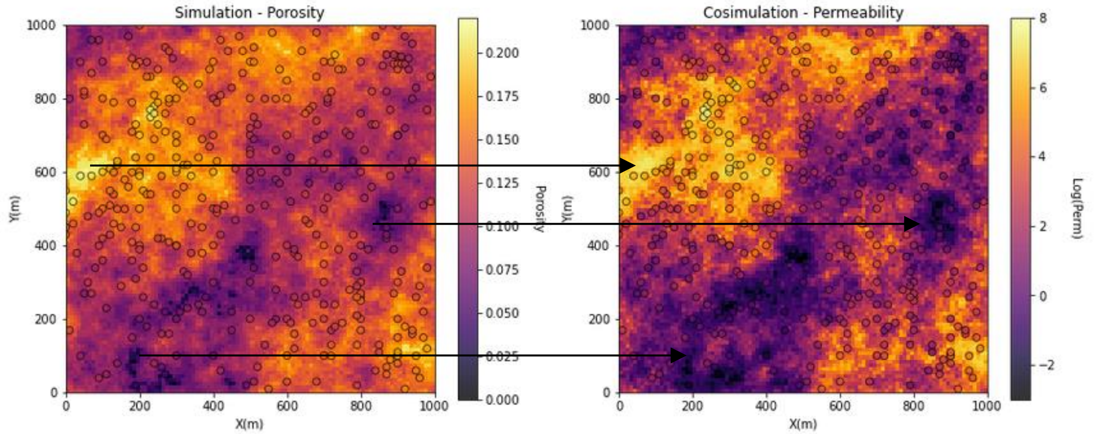
Capture the general correlation structure with some tail extrapolation.

Cosimulation

- Cosimulation is a simulation method that imposes correlation with a previously simulated property.
  - The realizations are paired.



Honor the bivariate relationship between pair values at the same locations, $\mathbf{u}_\alpha$



Cosimulation of permeability (center) given porosity (left) and cross plot data.

Limitations of Cosimulation

Each cosimulation method will have a ‘**conditioning**’ priority:

- **Collocated Cokriging** prioritizes the histogram and variogram and may honor the correlation coefficient between the two variables

- **Cloud transform** will honor the specific form of the bivariate relationship (cloud) between the two features but may not honor the histogram nor the variogram.

These methods start with a completed realization of the secondary feature

- e.g., porosity secondary feature, if we are cosimulated permeability primary feature constrained by porosity

Multiple information sources may be contradictory, in this cases lower priority information is preferentially sacrificed

Recall: Data Conditioning

Commonly used term in geostatistics for constraining a geostatistical model to honor / reproduce data, statistics and interpretations (trends, stationary domains) derived from data and / or expert knowledge.

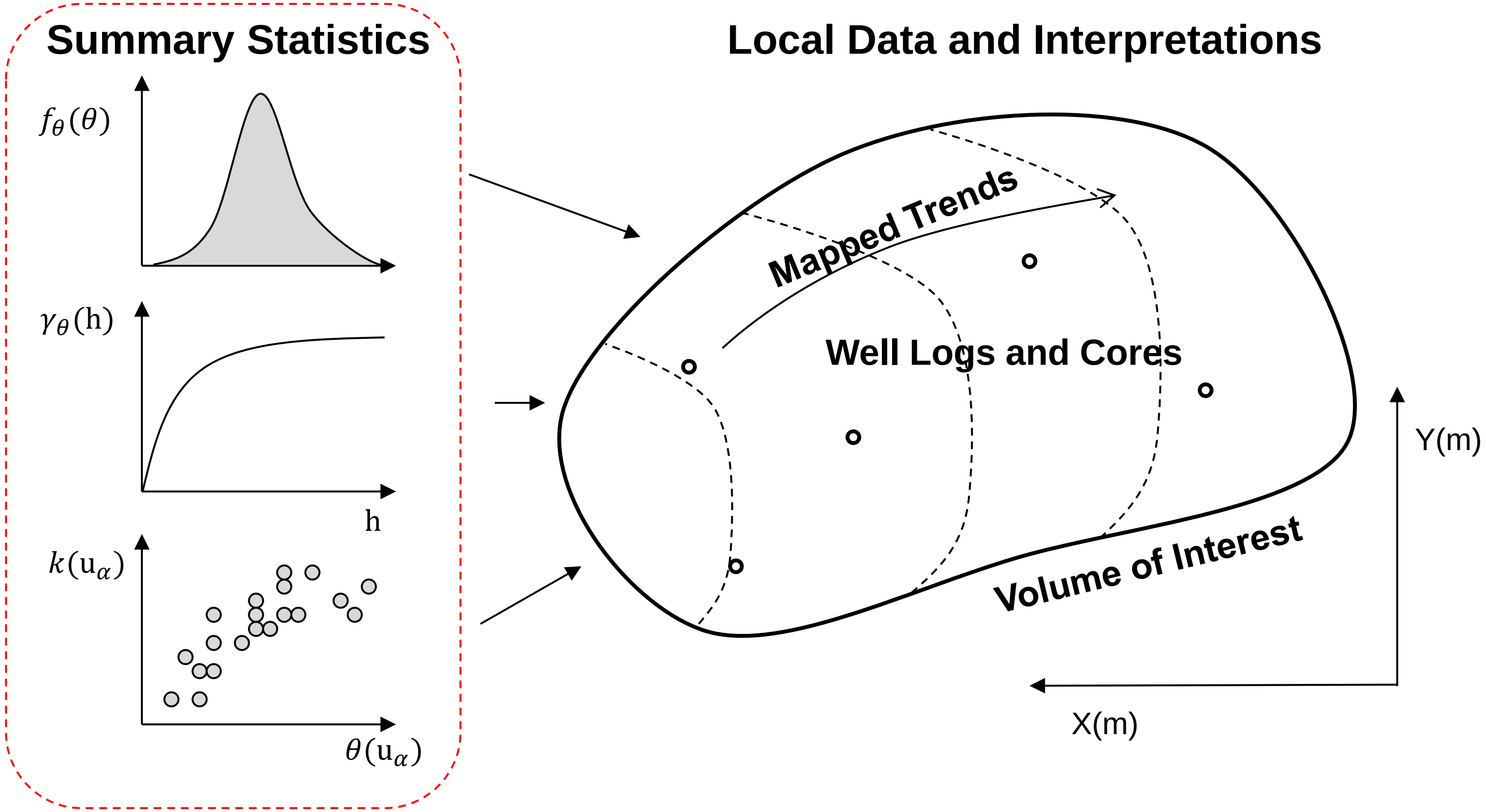


Illustration of various types of constraints to condition a geostatistical model.

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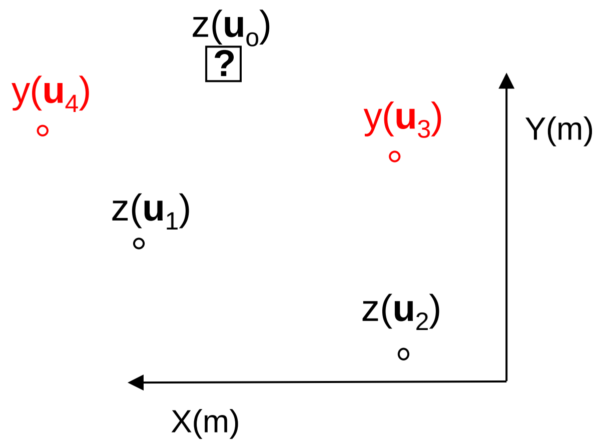
Full Cokriging

We can extend the simple kriging system to integrate other features.

For example, see this data (right) and the cokriging system (below):

- primary feature at $\mathbf{u}_1$ and $\mathbf{u}_2$
- secondary feature at $\mathbf{u}_3$ and $\mathbf{u}_4$
- to estimate primary feature at $\mathbf{u}_0$



Data (8) and estimate (?) locations.

Redundancy | **Weights** | **Closeness**

Direct (Primary, Primary) | **Cross** (Primary, Secondary) | Primary | **Direct** (Primary)

$$
\begin{bmatrix}
C_z(\mathbf{u}_1,\mathbf{u}_1) & C_z(\mathbf{u}_1,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_3) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_4) \\
C_z(\mathbf{u}_2,\mathbf{u}_1) & C_z(\mathbf{u}_2,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_2,\mathbf{u}_3) & C_{z,y}(\mathbf{u}_2,\mathbf{u}_4) \\
C_{z,y}(\mathbf{u}_3,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_3,\mathbf{u}_2) & C_{y,y}(\mathbf{u}_3,\mathbf{u}_3) & C_y(\mathbf{u}_3,\mathbf{u}_4) \\
C_{z,y}(\mathbf{u}_4,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_4,\mathbf{u}_2) & C_{y,y}(\mathbf{u}_4,\mathbf{u}_3) & C_y(\mathbf{u}_4,\mathbf{u}_4)
\end{bmatrix}
\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix}
=
\begin{bmatrix}
C_z(\mathbf{u}_o,\mathbf{u}_1) \\
C_z(\mathbf{u}_o,\mathbf{u}_2) \\
C_{z,y}(\mathbf{u}_o,\mathbf{u}_3) \\
C_{z,y}(\mathbf{u}_o,\mathbf{u}_4)
\end{bmatrix}
$$

Secondary, Primary **Cross** | Secondary, Secondary **Direct** | Secondary | Secondary **Direct**

Full cokriging system to 2 primary data and 2 secondary data.

Cross Variogram and Cross Covariance Definitions

Cross Variogram, measure of how two variables differ together over distance.

$$\gamma_{z,y}(\mathbf{h}) = \frac{1}{2}E\{[Z(\mathbf{u}) - Z(\mathbf{u}+\mathbf{h})][Y(\mathbf{u}) - Y(\mathbf{u}+\mathbf{h})]\} \ \forall\, \mathbf{u}$$

Cross Covariance, measure of how two variables vary together over distance.

$$C_{z,y}(\mathbf{h}) = E\{[Z(\mathbf{u}) - m_z][Y(\mathbf{u}+\mathbf{h}) - m_y]\}$$

$$= E\{[Z(\mathbf{u})][Y(\mathbf{u}+\mathbf{h})]\} - m_z \cdot m_y \qquad \forall\, \mathbf{u}$$

above can be shown with expectation.

Cross Correlogram is the standardized cross covariance. Correlation coefficient vs. lag distance!

$$\rho_{z,y}(\mathbf{h}) = \frac{C_{z,y}(\mathbf{h})}{\sigma_z \cdot \sigma_y} \qquad \rho_{z,y}(\mathbf{h}) = C_{z,y}(\mathbf{h}), \text{ if } \sigma_z = \sigma_y = 1.0$$

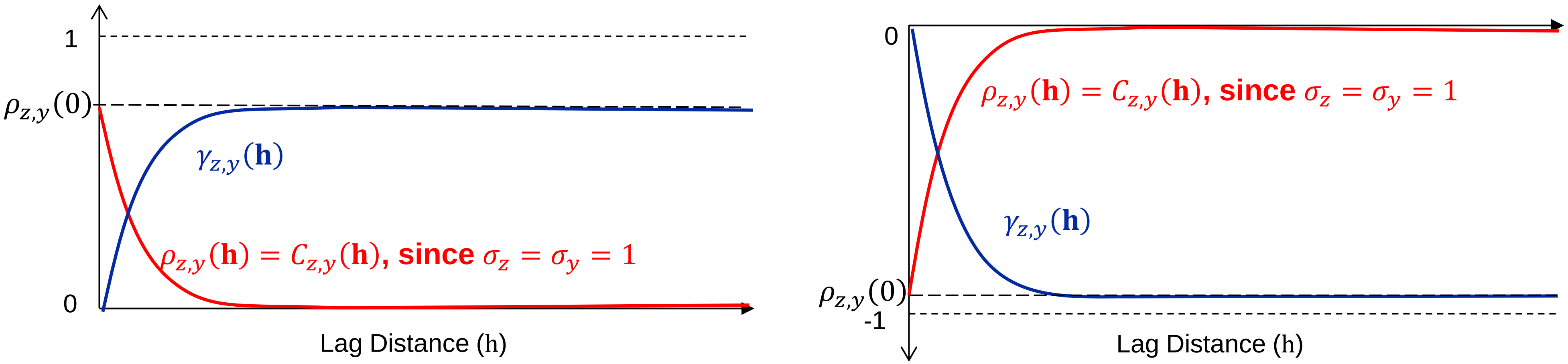
Cross Variogram and Cross Covariance Definitions

Cross variogram starts at 0.0, $\gamma_{z,y}(\mathbf{0}) = \mathbf{0}$, and then at the range reaches the correlation coefficient, $\gamma_{z,y}(\mathbf{h}) \rightarrow \rho_{z,y}(0)$, as $\mathbf{h} \rightarrow$ range.

- if the correlation coefficient is less than zero, $\rho_{z,y}(0) < 0$, then the cross variogram is negative!
- sill is the correlation coefficient

Cross correlogram (equal to cross covariance if $\sigma_z = \sigma_y = 1$), starts at the correlation coefficient, $\rho_{z,y}(\mathbf{0}) = \rho_{z,y}$, and then at the range reaches the 0, $\rho_{z,y}(\mathbf{h}) \rightarrow \mathbf{0}$, as $\mathbf{h} \rightarrow$ range.

- if the correlation coefficient is less than zero, $\rho_{z,y}(0) < 0$, then the cross correlogram is negative!



Cross variogram and cross correlograms for features Y and Z with positive correlation (left) and negative correlation (right).

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- Collocated Cokriging

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Collocated Cokriging Simulation

Collocated Cokriging makes two simplifications of full cokriging:

- Only one (the collocated) secondary variable is considered
- Cross covariance $C_{z,y}(\mathbf{h})$ is assumed to be a linear scaling of $C_z(\mathbf{h})$

The collocated secondary value is surely the most important and likely screens the influence of multiple secondary data

- Consider the implications for the cokriging system with only the collocated secondary data value included (below).

$$\begin{bmatrix} C_z(\mathbf{u}_1,\mathbf{u}_1) & C_z(\mathbf{u}_1,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_3) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_4) \\ C_z(\mathbf{u}_2,\mathbf{u}_1) & C_z(\mathbf{u}_2,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_2,\mathbf{u}_3) & C_{z,y}(\mathbf{u}_2,\mathbf{u}_4) \\ C_{z,y}(\mathbf{u}_3,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_3,\mathbf{u}_2) & C_{y,y}(\mathbf{u}_3,\mathbf{u}_3) & C_y(\mathbf{u}_3,\mathbf{u}_4) \\ C_{z,y}(\mathbf{u}_4,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_4,\mathbf{u}_2) & C_{y,y}(\mathbf{u}_4,\mathbf{u}_3) & C_y(\mathbf{u}_4,\mathbf{u}_4) \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix} = \begin{bmatrix} C_z(\mathbf{u}_o,\mathbf{u}_1) \\ C_z(\mathbf{u}_o,\mathbf{u}_2) \\ C_{z,y}(\mathbf{u}_o,\mathbf{u}_3) \\ C_{z,y}(\mathbf{u}_o,\mathbf{u}_4) \end{bmatrix}$$

$$\begin{bmatrix} C_z(\mathbf{u}_1,\mathbf{u}_1) & C_z(\mathbf{u}_1,\mathbf{u}_n) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_o) \\ C_z(\mathbf{u}_n,\mathbf{u}_1) & C_z(\mathbf{u}_n,\mathbf{u}_n) & C_{z,y}(\mathbf{u}_n,\mathbf{u}_o) \\ C_{z,y}(\mathbf{u}_0,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_0,\mathbf{u}_n) & C_y(\mathbf{u}_o,\mathbf{u}_o) \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_n \\ \lambda_y \end{bmatrix} = \begin{bmatrix} C_z(\mathbf{u}_o,\mathbf{u}_1) \\ C_z(\mathbf{u}_o,\mathbf{u}_n) \\ C_{z,y}(\mathbf{u}_o,\mathbf{u}_o) \end{bmatrix}$$

Full cokriging system (above) and collocated cokriging system (below) to 2 primary data and only the collocated secondary data.

Collocated Cokriging Simulation

The collocated value is surely the most important and likely screens the influence of multiple secondary data

- Therefore, secondary variogram is not needed, never need covariance between secondary data

$$\begin{bmatrix} C_z(\mathbf{u}_1,\mathbf{u}_1) & C_z(\mathbf{u}_1,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_o) \\ C_z(\mathbf{u}_2,\mathbf{u}_1) & C_z(\mathbf{u}_2,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_2,\mathbf{u}_o) \\ C_{z,y}(\mathbf{u}_0,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_0,\mathbf{u}_2) & \boxed{\sigma_y^2} \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_n \\ \lambda_y \end{bmatrix} = \begin{bmatrix} C_z(\mathbf{u}_o,\mathbf{u}_1) \\ C_z(\mathbf{u}_o,\mathbf{u}_2) \\ C_{z,y}(0\,) \end{bmatrix}$$

- No need for secondary variogram, $\gamma_y(\mathbf{h})$.

- For the secondary data on the left-hand redundancy size, we only need the sill, $C_y(0) = \sigma_y^2$

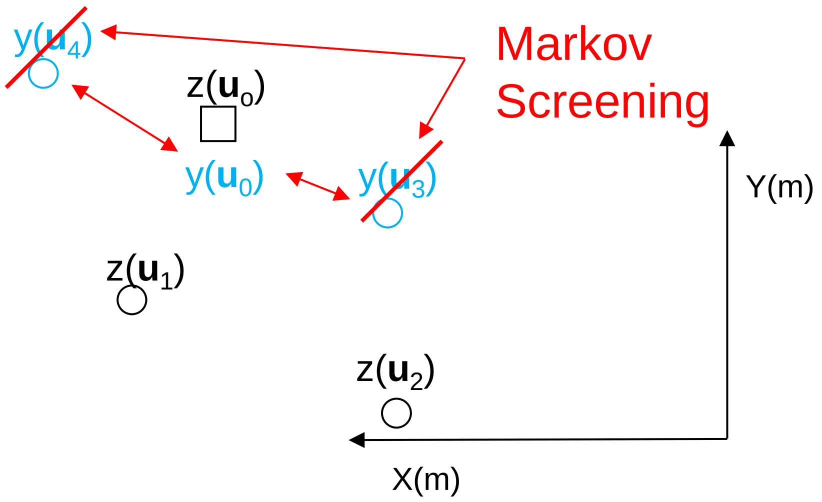


Illustration of the impact of Markov screening on the full cokriging system (above), non-collocated secondary data removed (below).

Collocated Cokriging Simulation

The collocated value is surely the most important and likely screens the influence of multiple secondary data

- The retained collocated secondary has a lag distance of 0, we just need the sill of the cross variogram, $\rho_{z,y}$.

$$\begin{bmatrix} C_z(\mathbf{u}_1,\mathbf{u}_1) & C_z(\mathbf{u}_1,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_1,\mathbf{u}_o) \\ C_z(\mathbf{u}_2,\mathbf{u}_1) & C_z(\mathbf{u}_2,\mathbf{u}_2) & C_{z,y}(\mathbf{u}_2,\mathbf{u}_o) \\ C_{z,y}(\mathbf{u}_0,\mathbf{u}_1) & C_{z,y}(\mathbf{u}_0,\mathbf{u}_2) & \sigma_y^2 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_n \\ \lambda_y \end{bmatrix} = \begin{bmatrix} C_z(\mathbf{u}_o,\mathbf{u}_1) \\ C_z(\mathbf{u}_o,\mathbf{u}_2) \\ \boxed{\rho_{z,y}} \end{bmatrix}$$

- No need for cross variogram, $\gamma_{z,y}(\mathbf{h})$ on closeness side, right-hand side of the kriging system.

- Only need $C_{z,y}(0) = \rho_{z,y}$, the correlation coefficient.

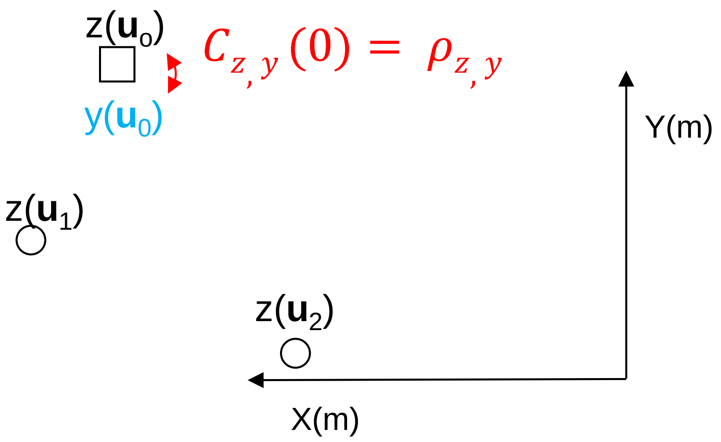
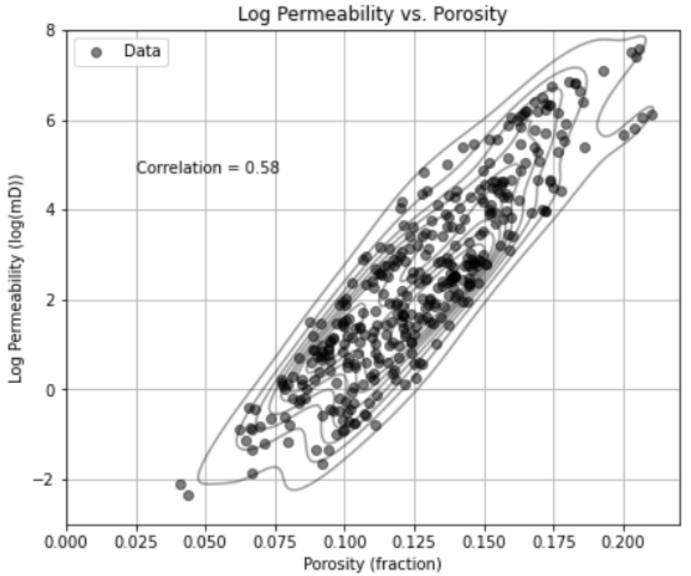


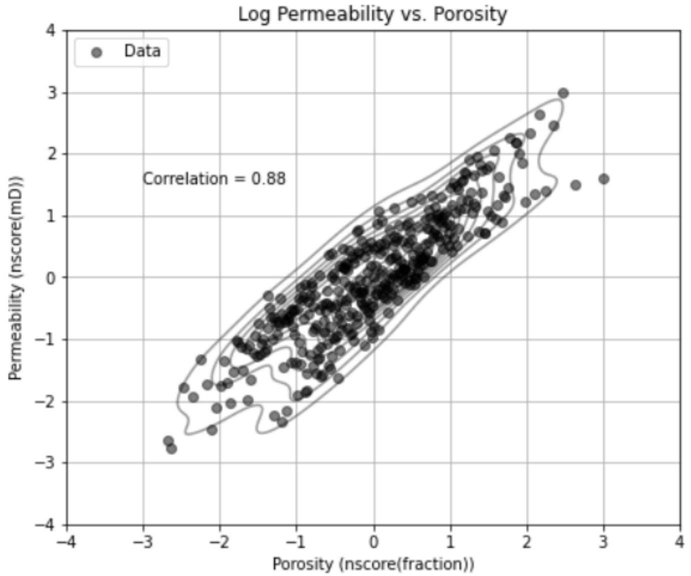
Illustration of the impact of Markov screening on the full cokriging system (above), non-collocated secondary data removed (below).

Collocated Cokriging Simulation

The correlation coefficient for collocated cokriging.

- kriging is applied in Gaussian space for the sequential Gaussian simulation paradigm.
- therefore, we require the correlation coefficient in Gaussian space.
- this is approximated by univariate transformations of both primary and secondary features.





Scatter plot and correlation coefficient for original (left) and Gaussian transformed features (right), non-collocated secondary data removed (below), file is GeostatsPy_cosimulation.ipynb.

- often assists with outliers and improves the inference of the correlation coefficient
- this is an approximation that could be, but is rarely ever, checked.

Collocated Cokriging Simulation

Bayesian updating to calculate the cross variogram from the primary variogram x correlation coefficient between primary and secondary features.

$$\gamma_{z,y}(\mathbf{h}) = \rho_{z,y}\gamma_z(\mathbf{h}) \qquad\qquad C_{z,y}(\mathbf{h}) = \rho_{z,y} - \gamma_{z,y}(\mathbf{h})$$

- Now the cross variogram is not needed on the left-hand side, redundancy of the kriging system either!

$$\begin{bmatrix} C_z(\mathbf{u}_1,\mathbf{u}_1) & C_z(\mathbf{u}_1,\mathbf{u}_2) & \rho_{z,y}C_z(\mathbf{u}_1,\mathbf{u}_o) \\ C_z(\mathbf{u}_2,\mathbf{u}_1) & C_z(\mathbf{u}_2,\mathbf{u}_2) & \rho_{z,y}C_z(\mathbf{u}_2,\mathbf{u}_o) \\ \rho_{z,y}C_z(\mathbf{u}_0,\mathbf{u}_1) & \rho_{z,y}C_z(\mathbf{u}_0,\mathbf{u}_2) & \sigma_y^2 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_n \\ \lambda_y \end{bmatrix} = \begin{bmatrix} C_z(\mathbf{u}_o,\mathbf{u}_1) \\ C_z(\mathbf{u}_o,\mathbf{u}_2) \\ \rho_{z,y} \end{bmatrix}$$

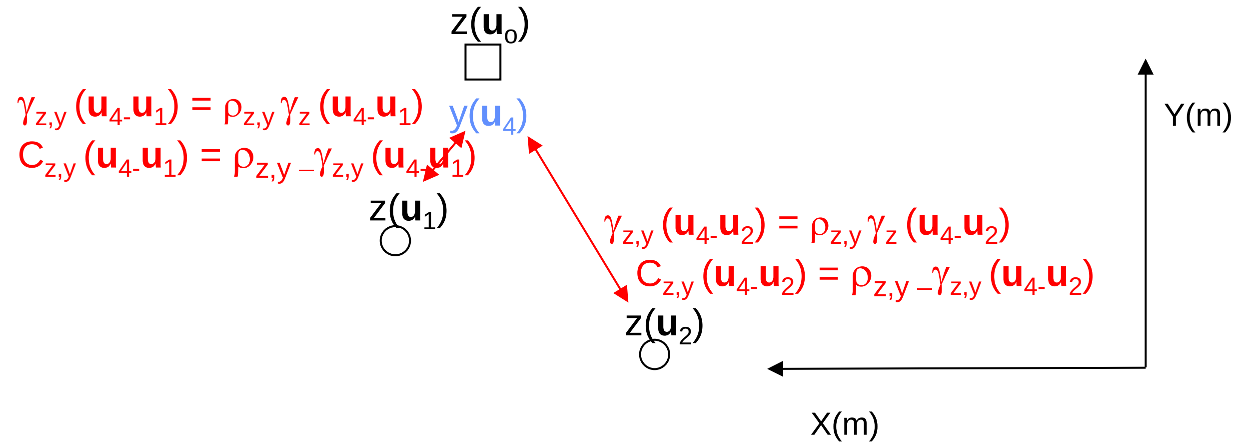


Illustration of the impact of Bayesian updating on the full cokriging system (above), and covariances between primary data and collocated secondary (below).

Collocated Cokriging Markov Screening

Simplification due to retaining the collocated secondary variable:

- no need for the variogram of the secondary variable
- no need for a cross variogram
- if the secondary data are smooth then considering more than the collocated variable *should* not help

There is a **potential problem** with excess variance of the results when used in simulation mode

- resulting kriging variance may be slightly biased too high since we remove non-collocated secondary data
- practical approach is to set a constant variance reduction factor (a global correction over all estimation locations) to correct this

Collocated Cokriging Bayesian Updating

Eliminate the need for calculating a cross variogram:

- no need for a cross variogram, i.e., the linear model of coregionalization

We are [Bayesian] updating the primary variogram with the primary to secondary correlation coefficient as the new sill.

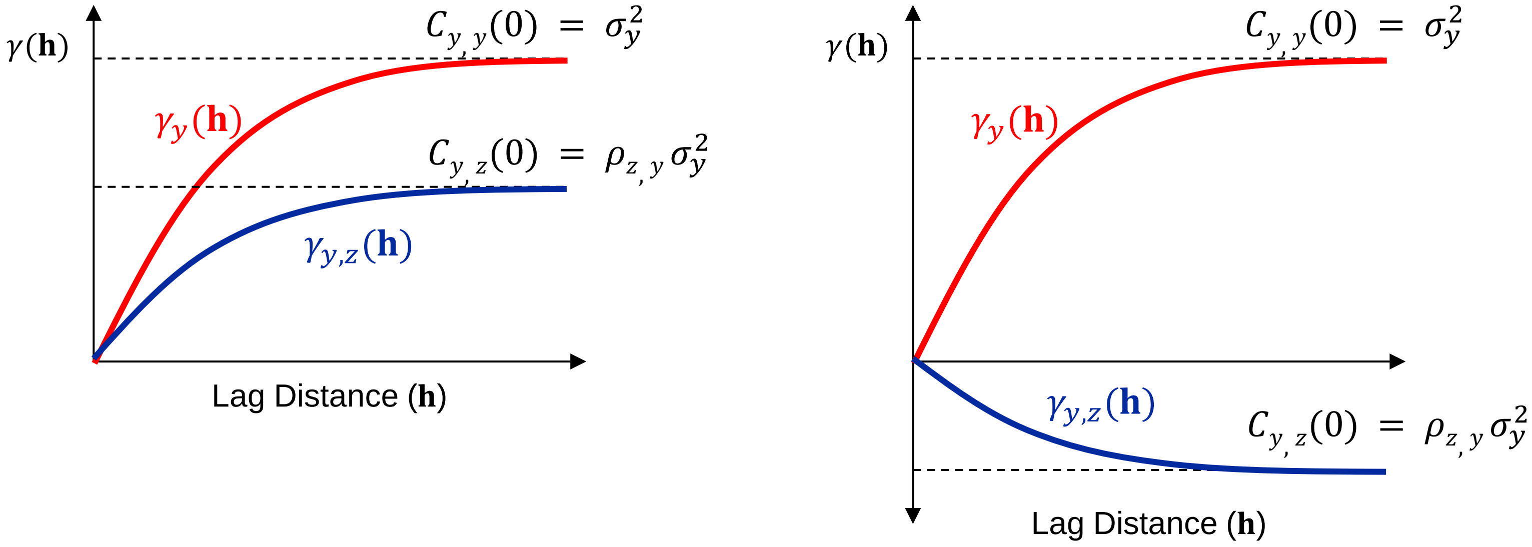
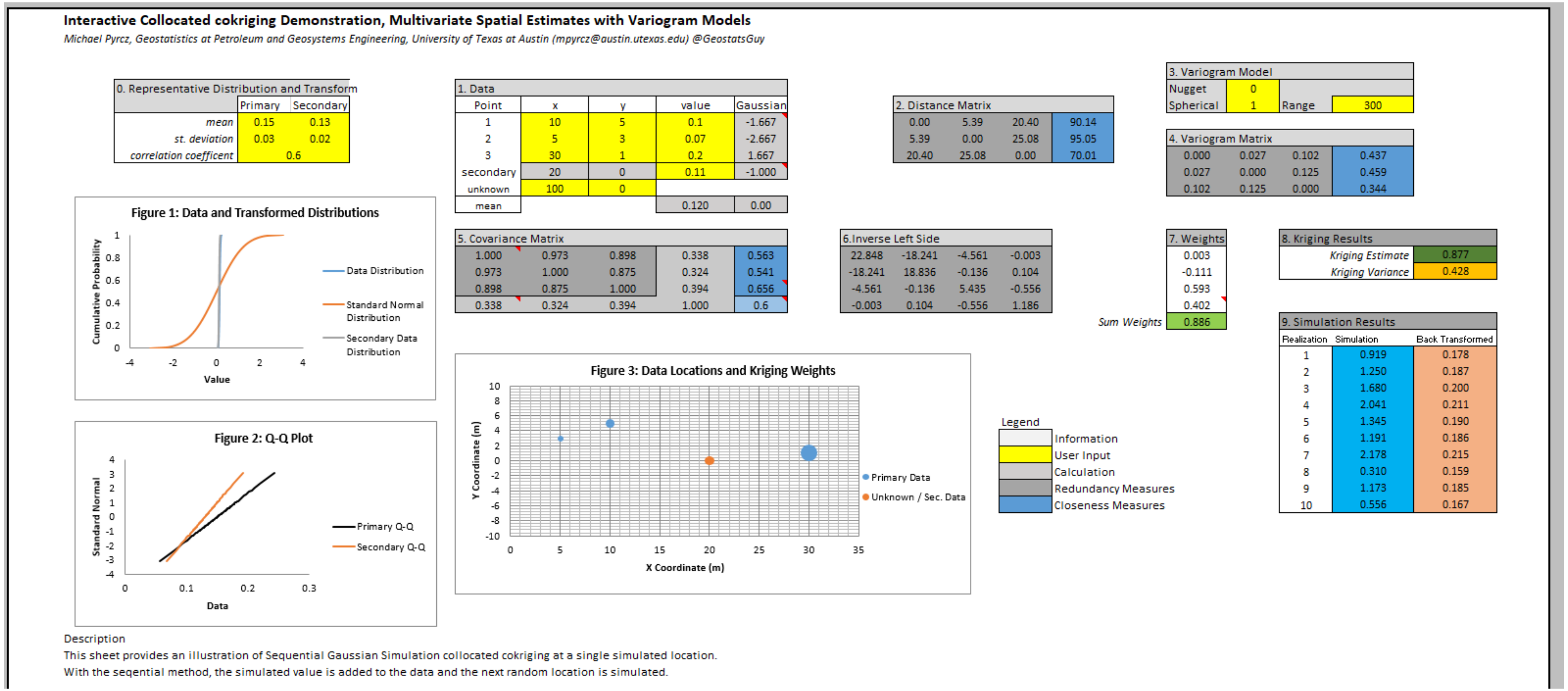


Illustration Bayesian updating the primary variogram to approximate the cross variogram for positive (left) and negative primary to secondary correlation coefficients.

Collocated Cokriging Demonstration in Excel

Hands-on example of collocated cokriging:



Interactive Collocated cokriging Demonstration, Multivariate Spatial Estimates with Variogram Models

Michael Pyrcz, Geostatistics at Petroleum and Geosystems Engineering, University of Texas at Austin (mpyrcz@austin.utexas.edu) @GeostatsGuy

0. Representative Distribution and Transform

	Primary	Secondary
mean	0.15	0.13
st. deviation	0.03	0.02
correlation coefficent	0.6	

1. Data

Point	x	y	value	Gaussian
1	10	5	0.1	-1.667
2	5	3	0.07	-2.667
3	30	1	0.2	1.667
secondary	20	0	0.11	-1.000
unknown	100	0		
mean			0.120	0.00

2. Distance Matrix

0.00	5.39	20.40	90.14
5.39	0.00	25.08	95.05
20.40	25.08	0.00	70.01

3. Variogram Model

Nugget	0		
Spherical	1	Range	300

4. Variogram Matrix

0.000	0.027	0.102	0.437
0.027	0.000	0.125	0.459
0.102	0.125	0.000	0.344

5. Covariance Matrix

1.000	0.973	0.898	0.338	0.563
0.973	1.000	0.875	0.324	0.541
0.898	0.875	1.000	0.394	0.656
0.338	0.324	0.394	1.000	0.6

6.Inverse Left Side

22.848	-18.241	-4.561	-0.003
-18.241	18.836	-0.136	0.104
-4.561	-0.136	5.435	-0.556
-0.003	0.104	-0.556	1.186

7. Weights

	0.003
	-0.111
	0.593
	0.402
Sum Weights	0.886

8. Kriging Results

Kriging Estimate	0.877
Kriging Variance	0.428

9. Simulation Results

Realization	Simulation	Back Transformed
1	0.919	0.178
2	1.250	0.187
3	1.680	0.200
4	2.041	0.211
5	1.345	0.190
6	1.191	0.186
7	2.178	0.215
8	0.310	0.159
9	1.173	0.185
10	0.556	0.167

Description
This sheet provides an illustration of Sequential Gaussian Simulation collocated cokriging at a single simulated location.
With the seqential method, the simulated value is added to the data and the next random location is simulated.

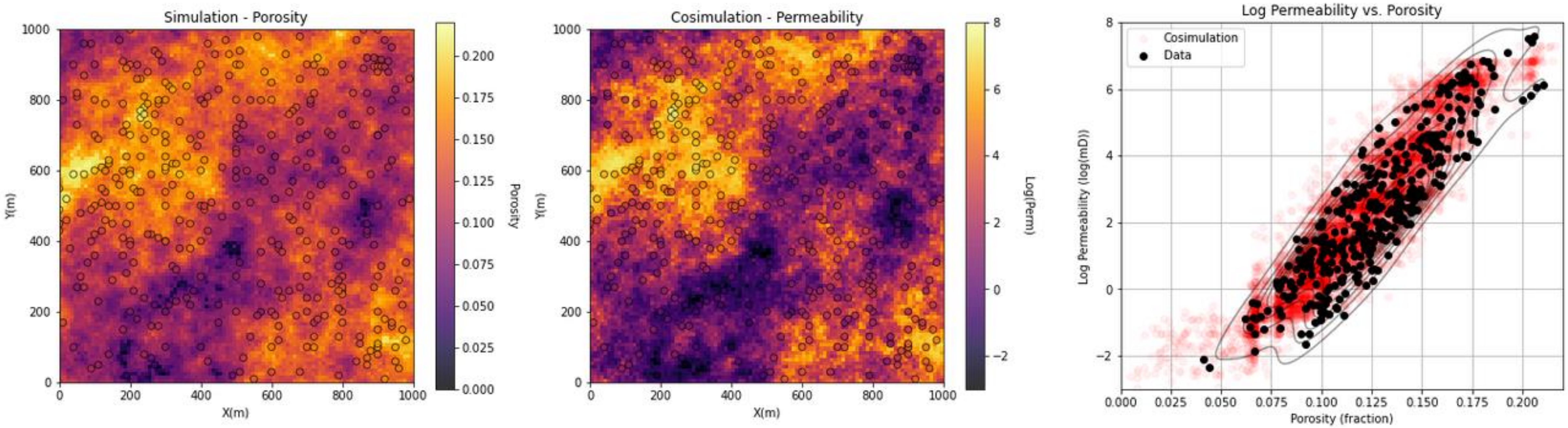
Kriging and simulation at a single location with collocated cokriging in Excel, file is Collocated_Cokriging_Demo.xlsx

Collocated Cokriging Demonstration in Python

(Co)simulation Workflow in Python

Walkthrough and try to:

- Change the correlation coefficient for cosimulation.
- Try changing the variogram range and check the scatter plot for independent simulation.



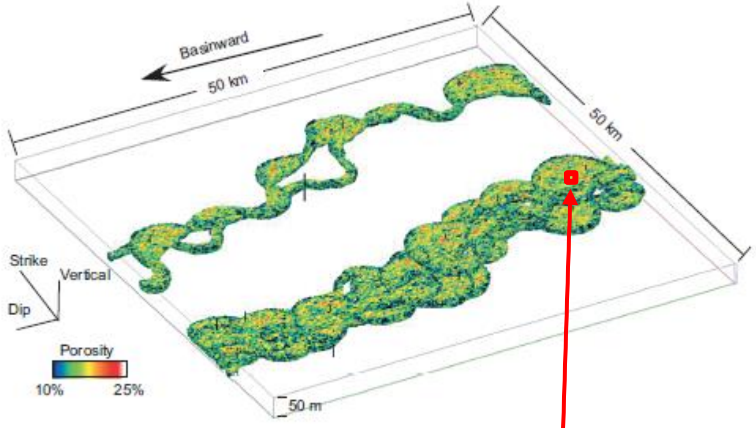
Cosimulation of permeability (center) given porosity (left) and cross plot data and simulated values (right), file is GeostatsPy_cosimulation.ipynb.

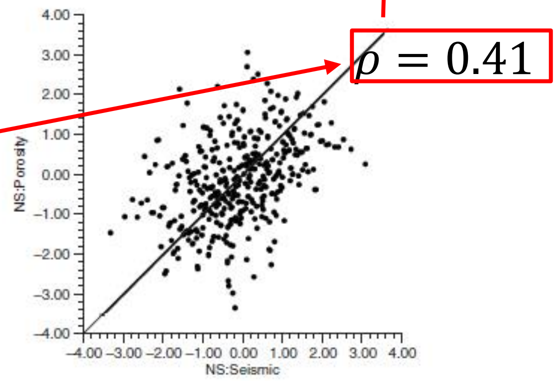
Collocated Cokriging Simulation Example

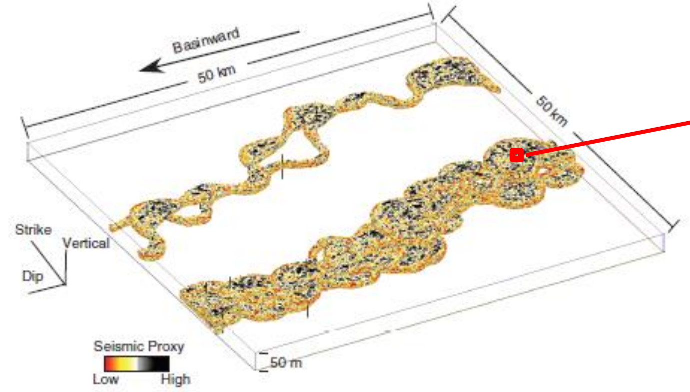
The Cosimulation Workflow:

1. Simulate realization of secondary variable (e.g., acoustic impedance)
2. Integrate the collocated secondary realization at each location with correlation coefficient.
3. Check simulation histogram, variogram and scatter plot.

3. Exhaustive Primary Cosimulation







1. Exhaustive Secondary Simulation

2. Correlation coefficient after Gaussian transform of primary and secondary variable

Cosimulation of porosity given a realization of acoustic impedance and Gaussian space correlation coefficient.

PGE 338 Data Analytics and Geostatistics

Lecture 16: Cosimulation

Lecture outline . . .

- P-field Simulation

Michael Pyrcz, The University of Texas at Austin

Introduction
General Concepts
Univariate
Bivariate
Spatial
Calculation
Variogram Modeling
Kriging
Simulation
Time Series
Machine Learning
Uncertainty Analysis

P-field and Cloud Transform

The key idea of p-field simulation is to perform the simulation in two separate steps:

- Construct local distributions of uncertainty
- Draw from those distributions simultaneously with correlated probabilities

Separating the two steps simulation has advantages:

1. the distributions of uncertainty can be constructed to honor all data and checked before any realizations are drawn, and
2. the simulations are consistent with the distributions of uncertainty

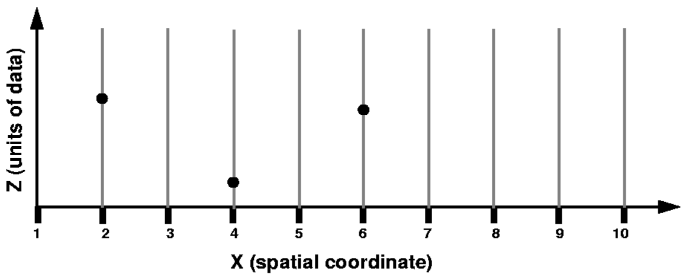
Also, good reproduction of the primary to secondary data scatter plot.

Some disadvantages include potentially poor reproduction of the histogram and variogram.

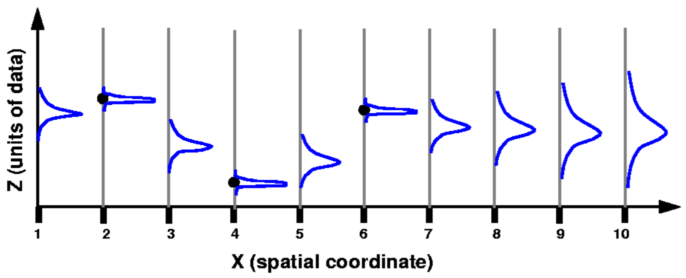
The most commonly used approach is known as cloud transform, often used to simulate permeability from porosity

p-field simulation Method

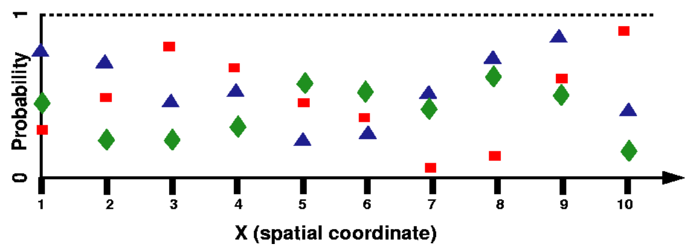
(a) Data values



(b) Distributions of uncertainty



(c) Probability values (unconditional simulations)



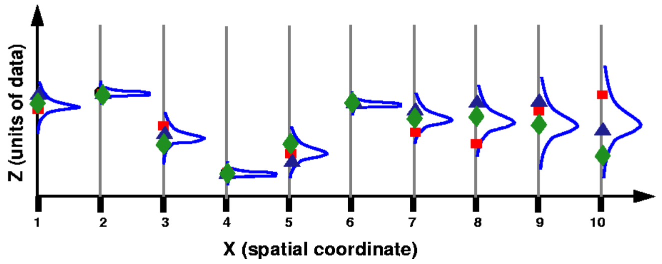
The p-field simulation method steps:

1. Construct local distributions of uncertainty with all available information sources

2. Generate spatially correlated probability values (p-values) (usual with Gaussian simulation) uniform [0,1] distributed to avoid bias.

3. Draw values simultaneously and retain together as a realization

(d) Simulated values drawn from conditional distributions

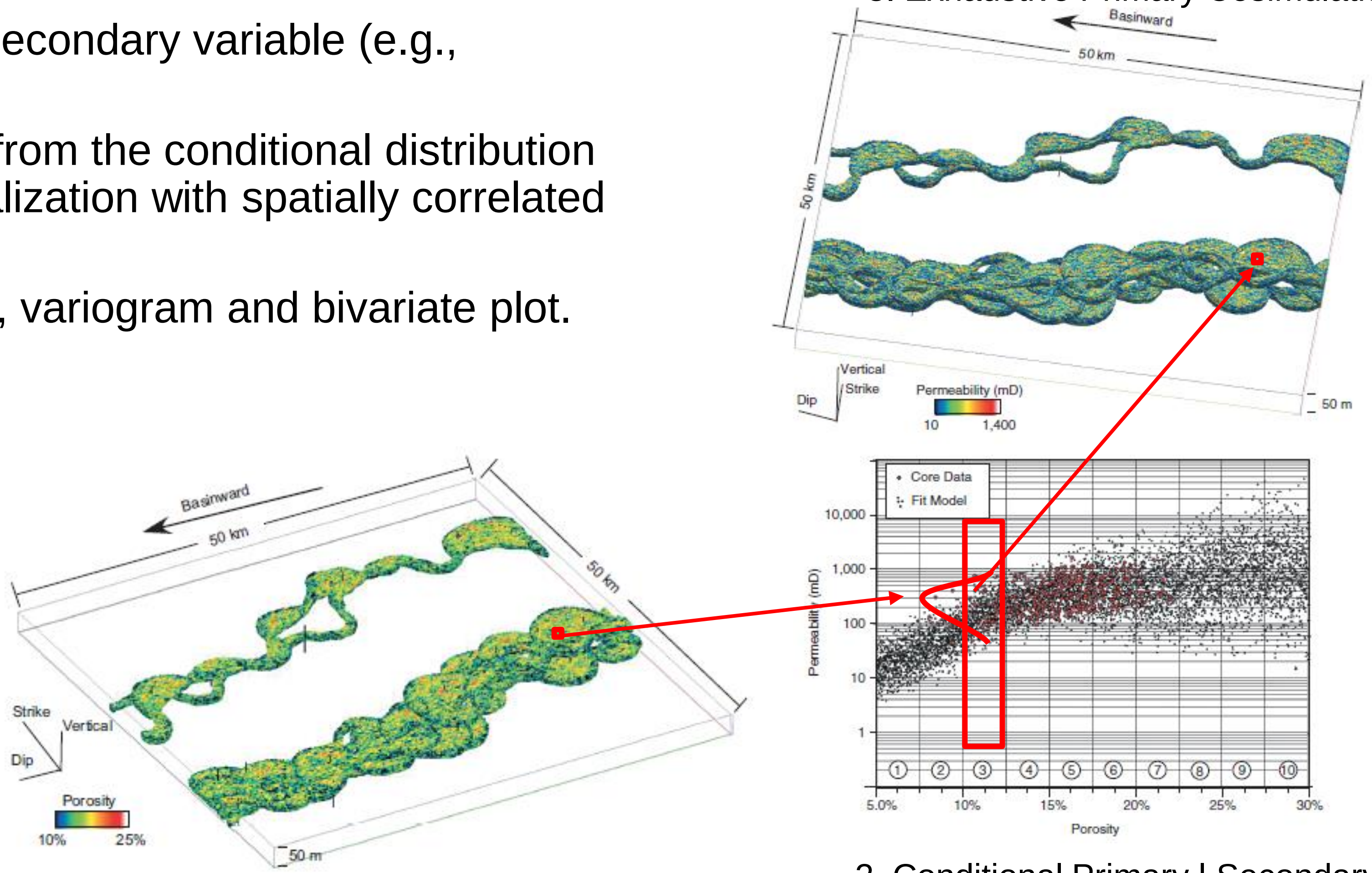


Cloud Transform Simulation

Cloud Transform Workflow

1. Simulate realization of secondary variable (e.g., porosity)
2. For each location draw from the conditional distribution given the secondary realization with spatially correlated p-values
3. Check model histogram, variogram and bivariate plot.

3. Exhaustive Primary Cosimulation



2. Conditional Primary | Secondary

1. Exhaustive Secondary Simulation

Cloud transform simulation of permeability given a realization of porosity and permeability | porosity conditional distributions.

Cosimulation Review

What should you have learned?

- Cosimulation includes methods that simulate a property realization (primary) conditional to a previously simulated property realization (secondary)
- Two independently simulated features [without cosimulation] will only have correlations imposed by data and outside spatial correlation, variogram range of data will be uncorrelated.
  - This leads to implausible combinations of the features and inflated spatial uncertainty.

Two methods are commonly applied for cosimulation:

1. Collocated Cokriging simplifies the full Cokriging system
   - Markov assumption – only need collocated secondary value
   - Bayesian updating – get the cross variogram by scaling the primary variogram with correlation coefficient
   - May not reproduce the cloud well (relationship between the 2 variables)
2. Cloud transform
   - Forces reproduction of the cloud
   - May not get the spatial continuity and distribution well

It is essential to know their assumptions and steps

PGE 338 Data Analytics and Geostatistics

Lecture 16: Cosimulation

Lecture outline . . .

- Cosimulation
- Full Cokriging
- Collocated Cokriging
- P-field Simulation

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