

Geostatistical representation of multiscale heterogeneity of porous media through a Generalized Sub-Gaussian model



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 EGU General Assembly 2020
Sharing Geoscience Online

Key Observations

Many earth, environmental, physical, bio / ecological, financial, & other variables show

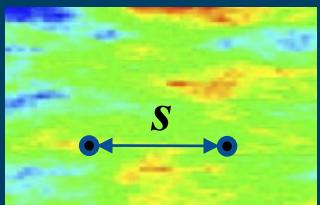
- 1. Power-law scaling in midrange of separation scales (lags).
Breakdown in power-law scaling at small and large lags.
Power-Law scaling extended to virtually all lags (ESS).**

- 2. Heavy-tailed frequency distributions of increments**

A variable Y can be Gaussian or non-Gaussian

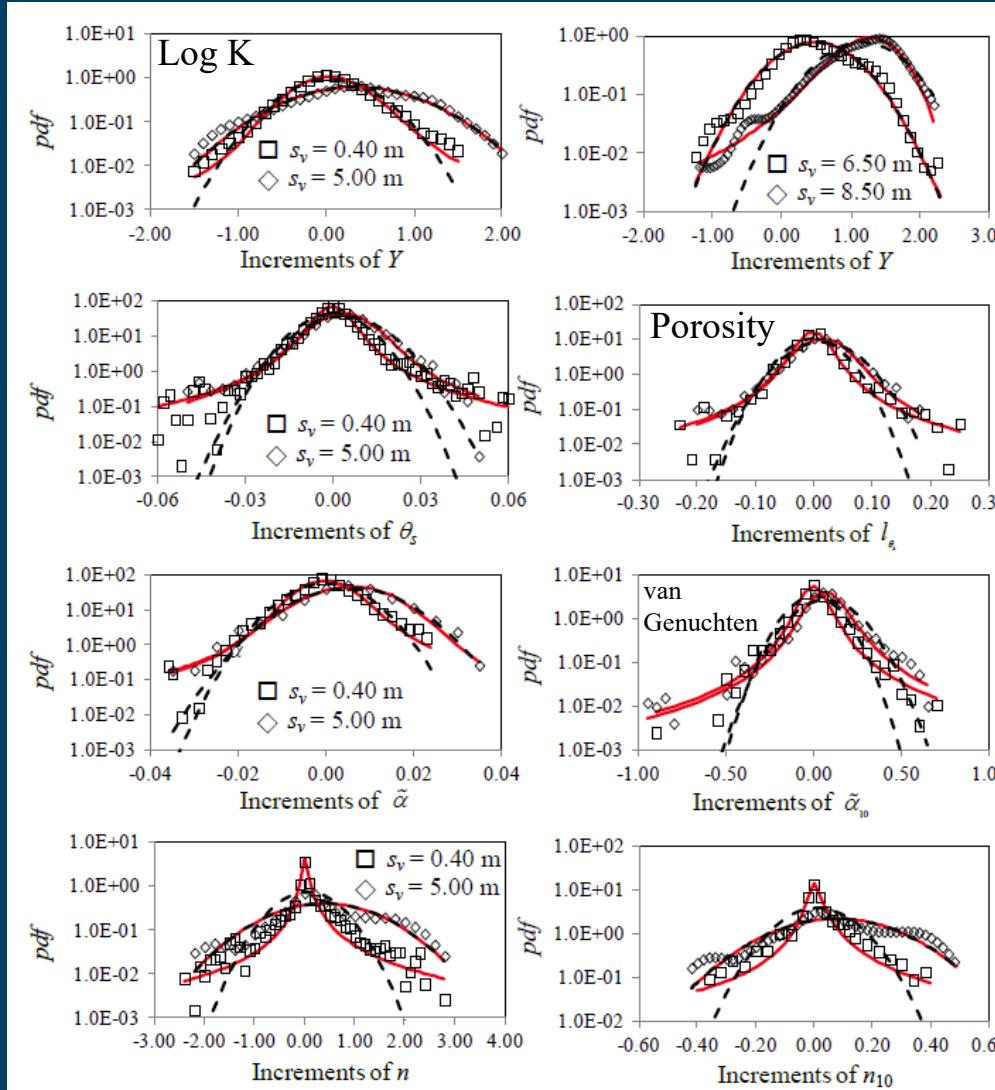
Pdfs of spatial increments ΔY scale with lag

Sharp peaks and heavy tails of pdf decaying with lag



$$\Delta Y(s) = Y(x + s) - Y(x)$$

Observations



WATER RESOURCES RESEARCH, VOL. 49, 1–17, doi:10.1002/2013WR014286, 2013

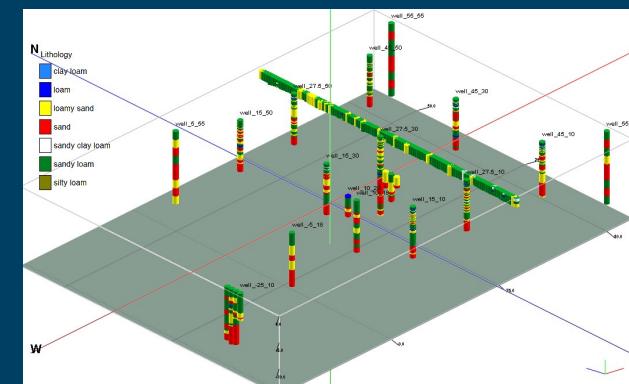
Anisotropic statistical scaling of vadose zone hydraulic property estimates near Maricopa, Arizona

A. Guadagnini,^{1,2} S. P. Neuman,¹ M. G. Schaap,³ and M. Riva^{1,2}



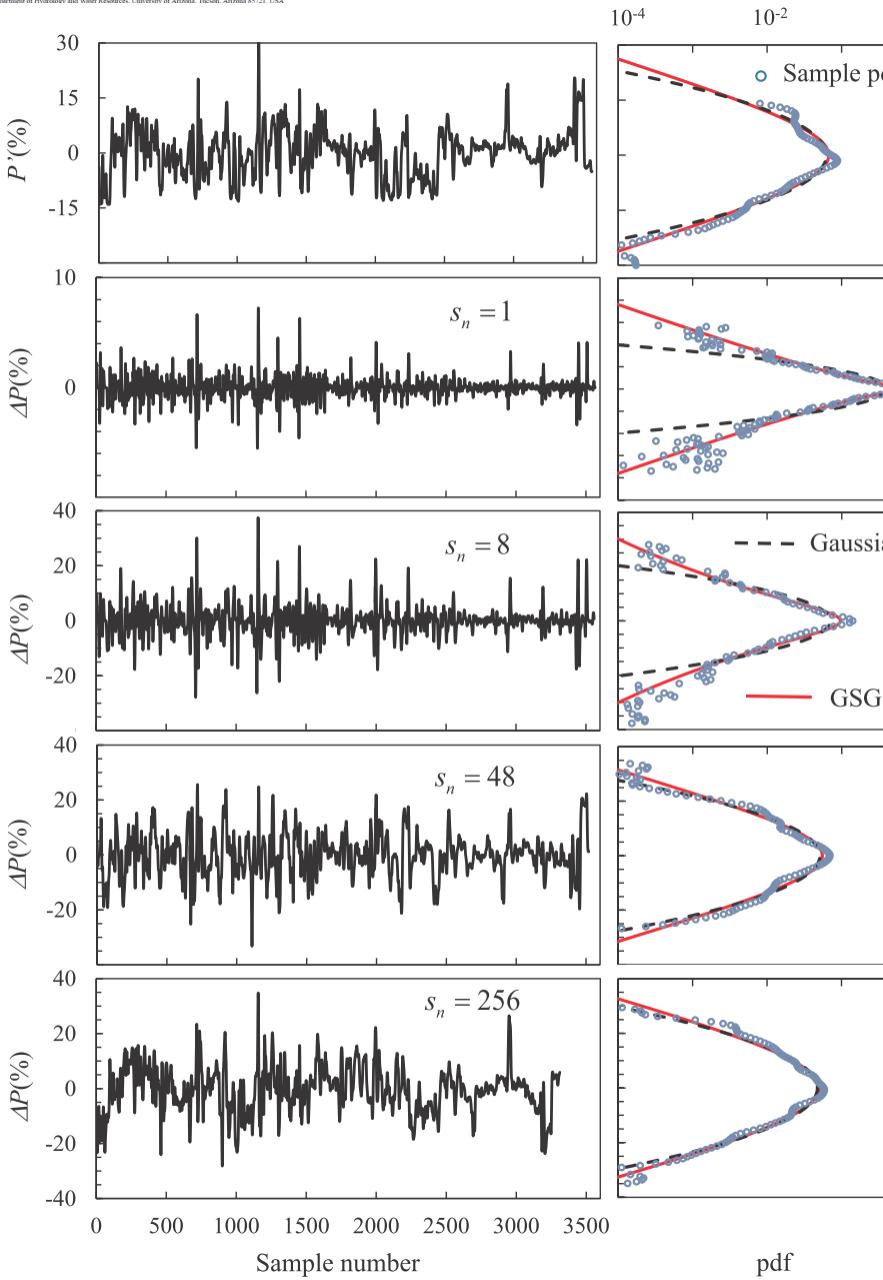
Sharp Peaks and Heavy Tails of Increment Frequency Distributions Decaying with Lag

Neural network hydraulic property estimates of borehole samples at UA Maricopa Agricultural Station





Scalable statistics of correlated random variables and extremes applied to deep borehole porosities
 A. Guadagnini^{1,2}, S. P. Neuman⁴, T. Nasu¹, M. Riva³, and C. L. Winter²
¹Department of Hydrology and Water Resources, University of Arizona, Tucson, Arizona 85721, USA



Model parameters and observation scale


Water Resources Research
 RESEARCH ARTICLE New scaling model for variables and increments with heavy-tailed distributions
 10.1002/2015WR016998
 Key Points:
 • A new statistical scaling model is

Monica Riva^{1,2}, Shlomo P. Neuman², and Alberto Guadagnini^{1,2}

GSG-Generalized Sub-Gaussian Model

Consider

$$Y'(x; \lambda_l, \lambda_u) = U(x) G(x; \lambda_l, \lambda_u)$$

tfBm

$$Y(x) = Y(x) - \langle Y \rangle$$

where $U(x) > 0$ is iid subordinator

N = 3567 Neutron Porosity data along a deep borehole

Mean = 14%; SD = 6.4%
 Sampling interval: 0.15 m

data courtesy of Prof. Sahimi

- Several models for U (lognormal, Exponential, Gamma, ...)
- Subordinator U renders Y' a scale mixture of Gaussian RFs
- The scale mixture is non-Gaussian (distribution depends on U)

GSG Model

Consider $Y'(x; \lambda_l, \lambda_u) = U(x)G(x; \lambda_l, \lambda_u)$ $Y'(x) = Y(x) - \langle Y \rangle$

where $U(x) > 0$ **is iid subordinator.**

It renders Y

- Subordinated to G
- Scale mixture of G with random variances $\propto U(x)$

To start, lognormal (LN) subordinator

$$U = e^V \quad V = \mathcal{N}\left\{0, (2-\alpha)^2\right\} \quad \alpha < 2$$

It renders Y' normal-lognormal (NLN)

$$f_{Y'}(y') = \frac{1}{2\pi(2-\alpha)} \int_0^\infty \frac{1}{u^2} e^{-\frac{1}{2}\left(\frac{1}{(2-\alpha)^2} \ln^2 \frac{u}{\sigma_G} + \frac{y'^2}{u^2}\right)} du$$

GSG Model

$$f_Y(y) = \frac{1}{2\pi(2-\alpha)} \int_0^\infty \frac{1}{u^2} e^{-\frac{1}{2}\left(\frac{1}{(2-\alpha)^2} \ln^2 \frac{u}{\sigma_G} + \frac{y^2}{u^2}\right)} du$$

Y increments are not NLN:

$$f_{\Delta Y}(\Delta y) = \frac{1}{2\sqrt{2}\pi^{3/2}(2-\alpha)^2} \int_0^\infty \int_0^\infty \frac{e^{-\frac{1}{2}\left[\frac{1}{(2-\alpha)^2}\left(\ln^2 \frac{u_1}{\sigma_G} + \ln^2 \frac{u_2}{\sigma_G}\right) + \frac{(\Delta y)^2}{u_1^2 + u_2^2 - 2u_1 u_2 \rho_G}\right]}}}{u_2 u_1 \sqrt{u_1^2 + u_2^2 - 2u_1 u_2 \rho_G}} du_2 du_1$$

**Scales with lag through $\rho_G(s)$
(coefficient of correlation of G)**

GSG Model

➤ ***Variogram of Y***

$$\gamma_Y = \sigma_G^2 e^{(2-\alpha)^2} \left(e^{(2-\alpha)^2} - 1 \right) + e^{(2-\alpha)^2} \gamma_G$$

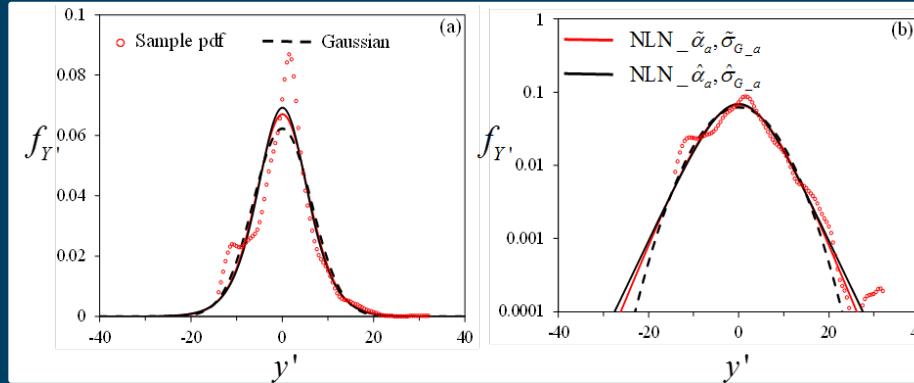
Observed nugget effects, attributed in the literature to variability of Y at scales smaller than the sampling interval and/or to measurement errors, may in fact be (at least in part) a symptom of non-Gaussianity.

➤ **Integral scale of Y (subordination dampens and does not destroy covariance structure)**

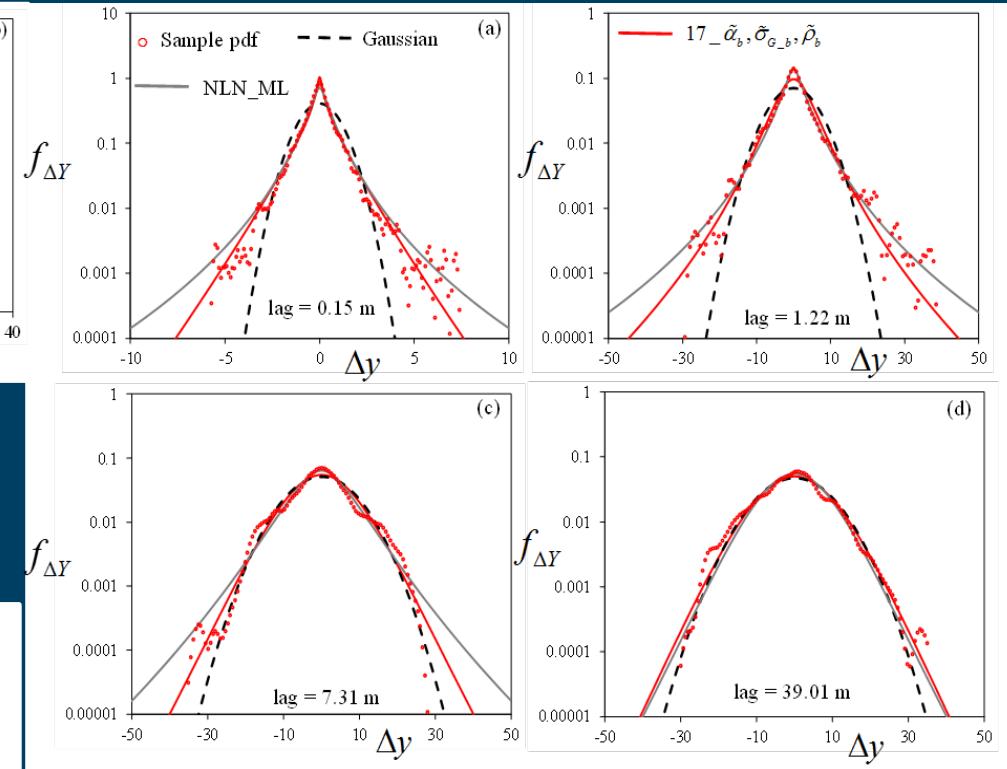
$$I_Y = e^{-(2-\alpha)^2} I_G$$

Deep Borehole Neutron Porosity data

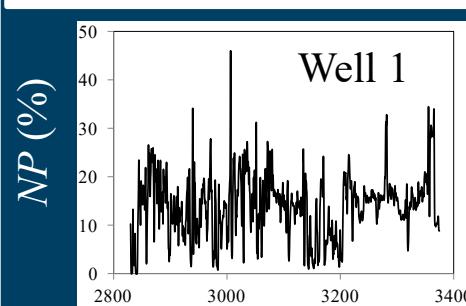
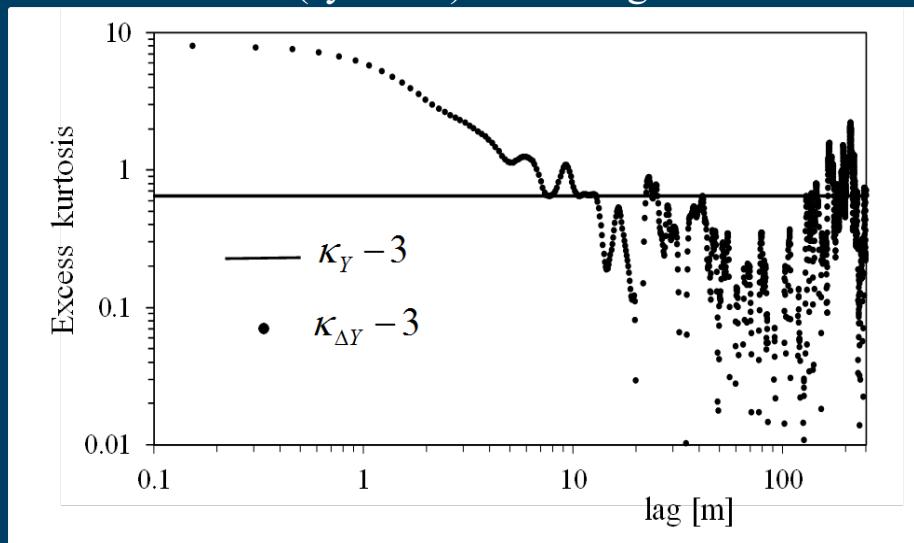
Sample pdf of neutron porosity data Y'



Sample pdf of increments of neutron porosity data



Excess kurtosis of mean-removed porosity data (continuous curve) and of porosity increments (symbols) versus lag



Dashian et al. [2011]

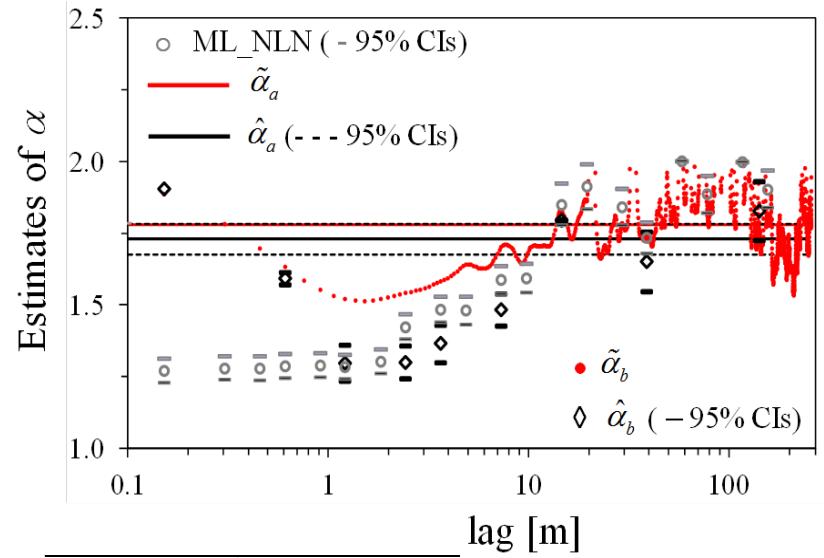
Southwest Iran
3,567 data
Minimum lag: 15 cm
Total depth: 543 m

$$M_1^Y = 14\%$$

Sample standard deviation = 6.4%

Deep Borehole Neutron Porosity data

Riva et al. (2015) WRR



$$\tilde{\alpha}_a \quad 1.78$$

$$\hat{\alpha}_a \quad 1.73 \pm 0.05$$

$$\text{Mean of } \tilde{\alpha}_b \quad 1.75$$

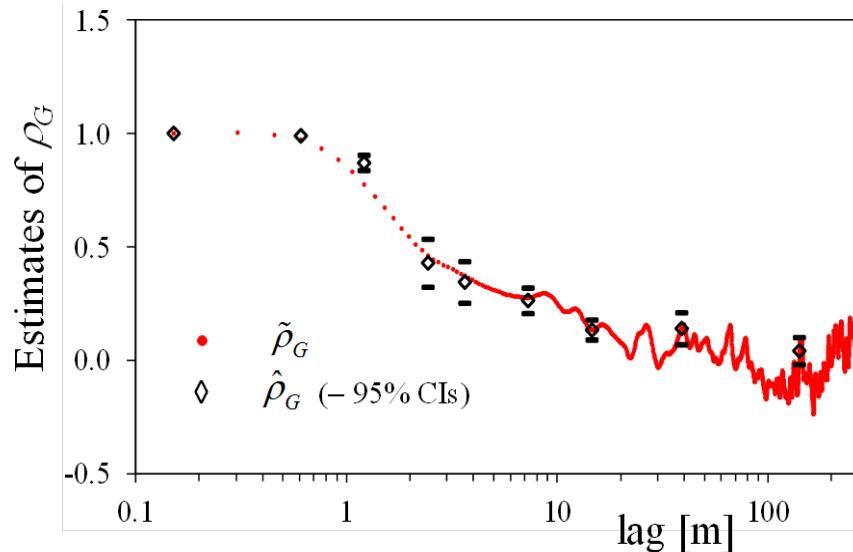
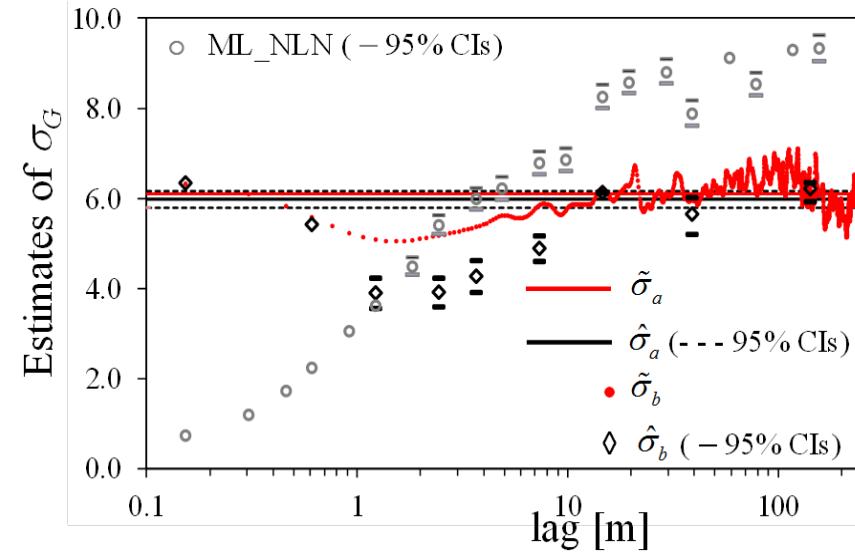
$$\text{CV of } \tilde{\alpha}_b \quad 0.05$$

$$\tilde{\sigma}_a \quad 6.1$$

$$\hat{\sigma}_a \quad 5.98 \pm 0.19$$

$$\text{Mean of } \tilde{\sigma}_b \quad 6.15$$

$$\text{CV of } \tilde{\sigma}_b \quad 0.07$$

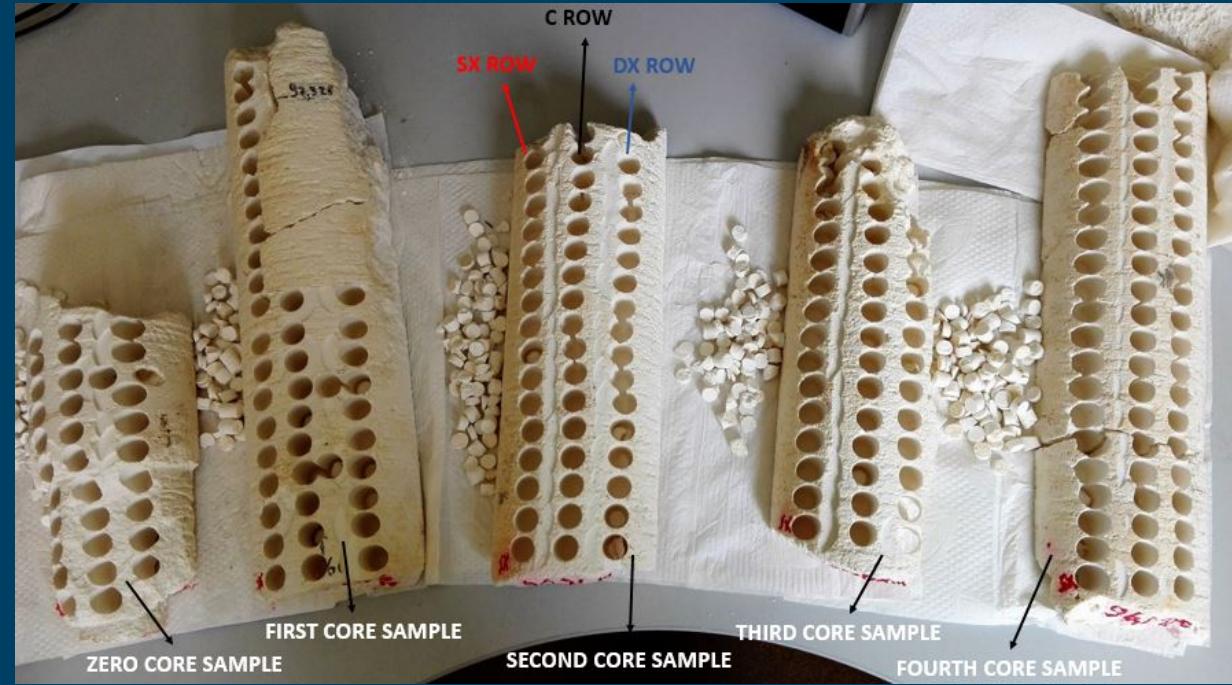
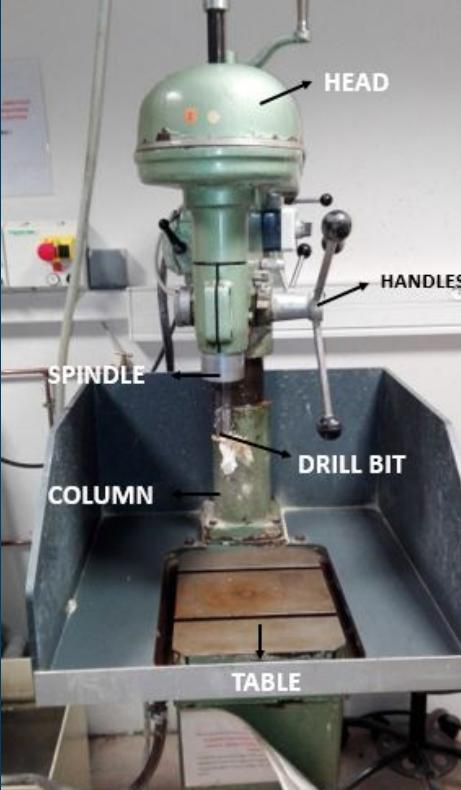




Statistical modeling of gas-permeability spatial variability along a limestone core

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A. Guadagnini ^{a,b}^a Dipartimento di Ingegneria Civile e Ambientale, Politecnico di Milano, Piazza L. Da Vinci 32, 20133 Milano, Italy^b Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ 85721, USA^c Géosciences Montpellier, CNRS-Université de Montpellier, Place Eugène Bataillon, 34095 Montpellier, France

- ❖ Drilling operation, using a drill press: multiple subsamples are obtained along three lines parallel to the core axis (left, central and right).



❖ One-dimensional variability

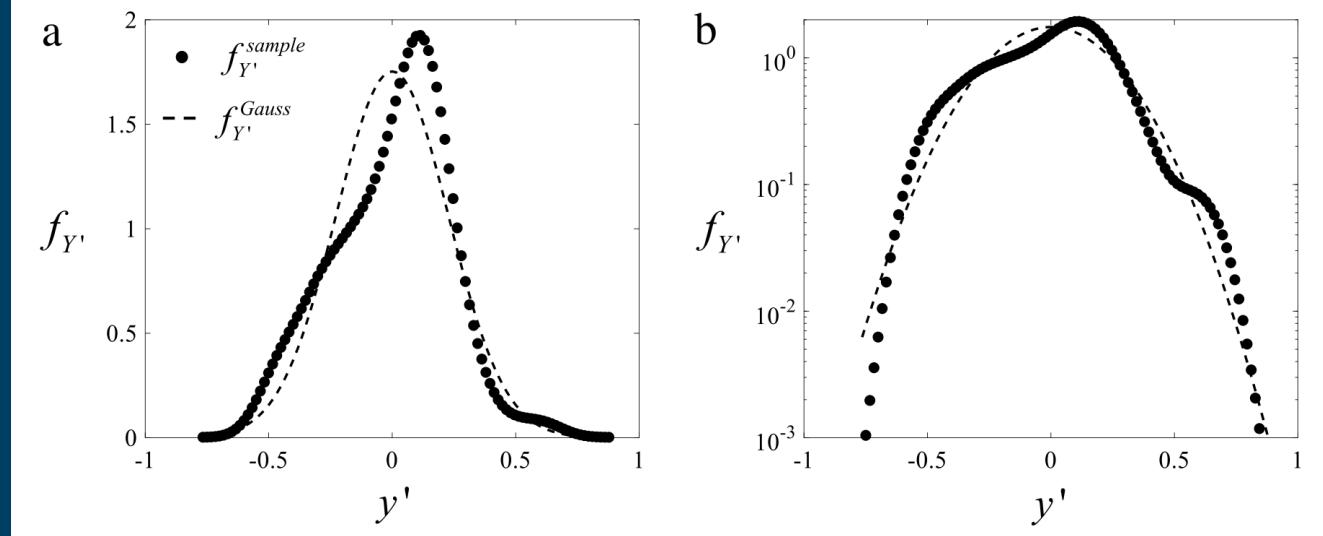
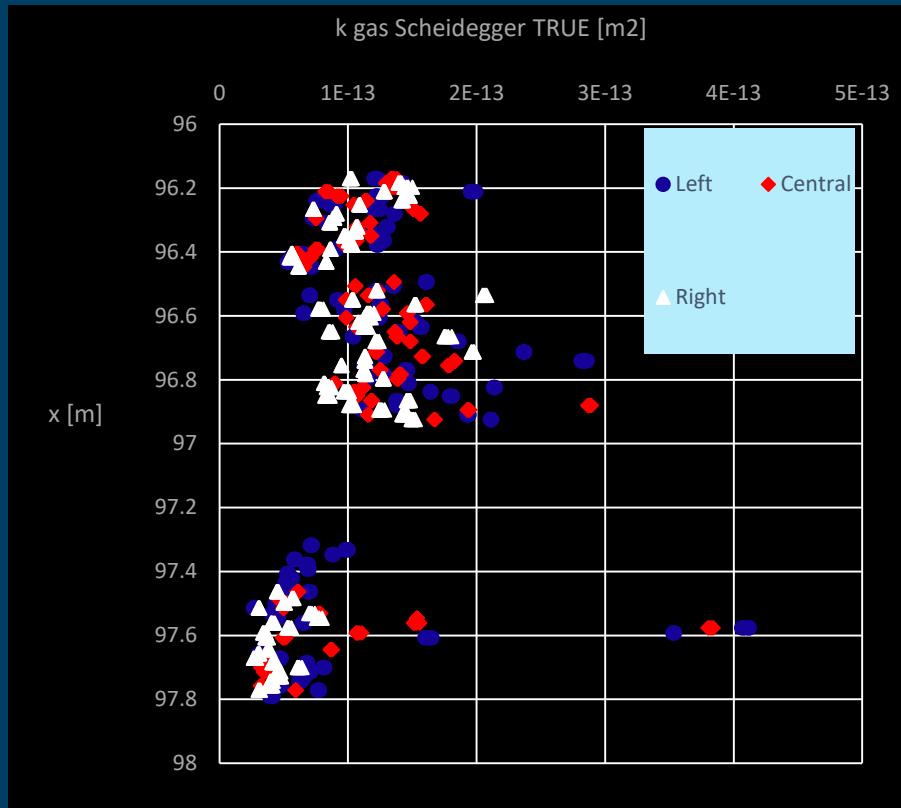


Fig. 3. Sample pdf of Y' data, $f_{Y'}^{sample}$ (symbols) on (a) arithmetic and (b) semi-logarithmic scale. A Gaussian pdf with variance equal to that of the Y' data, $f_{Y'}^{Gauss}$, is shown for comparison (dashed curve).

N. of observations	Mean	Standard deviation	Skewness	Excess kurtosis
220	-13.03	0.228	-0.208	-0.161



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Spatial Statistics

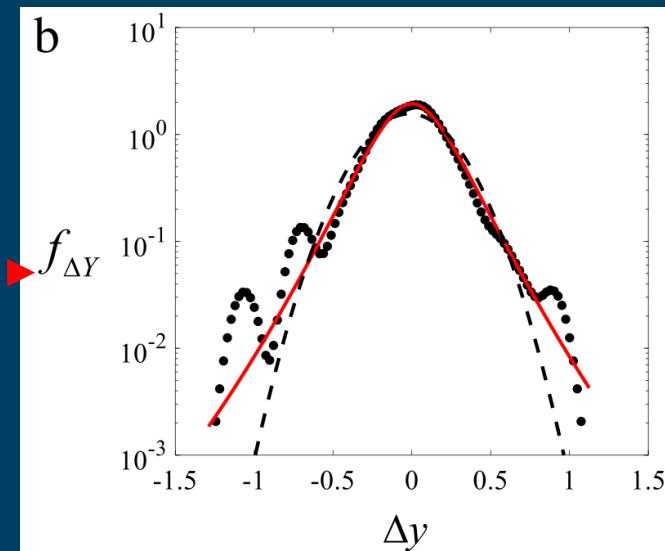
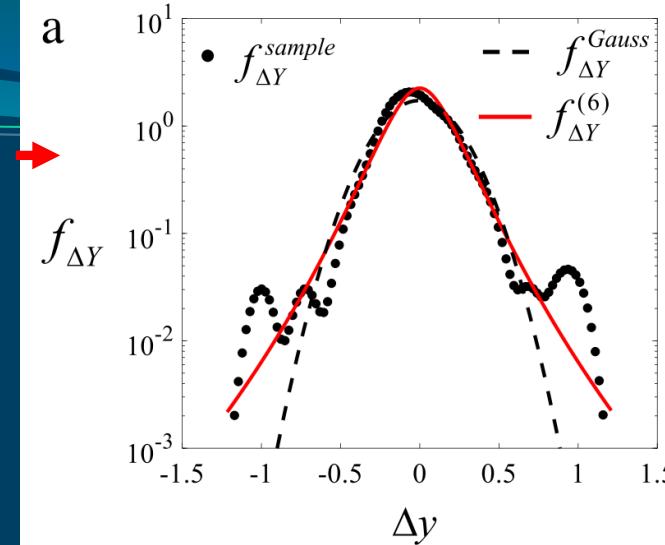
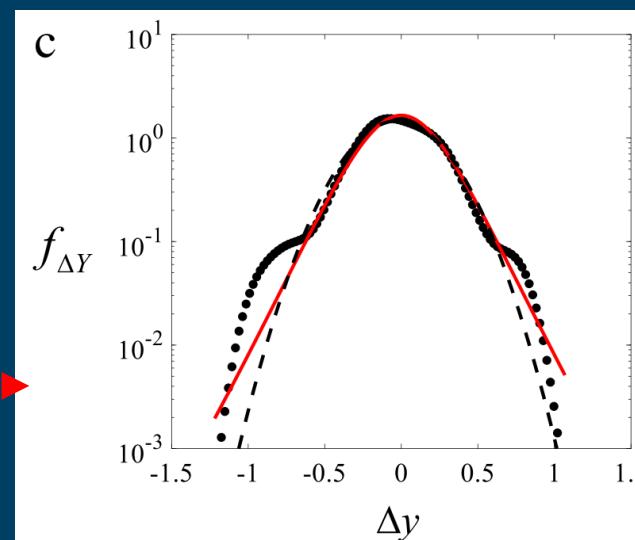
journal homepage: www.elsevier.com/locate/spasta

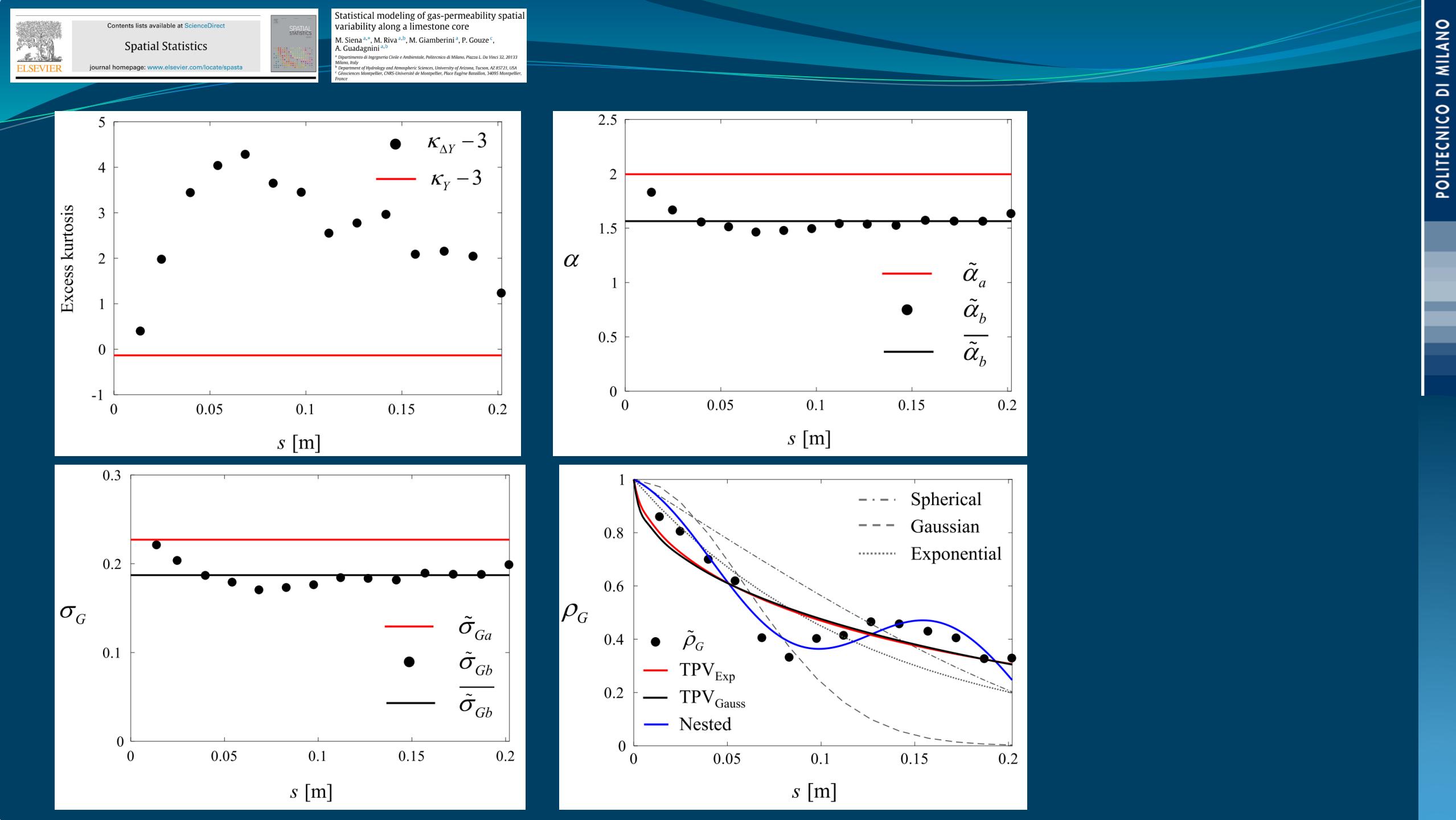


Statistical modeling of gas-permeability spatial variability along a limestone core
 M. Siena^{a,*}, M. Riva^{a,b}, M. Giamborini^b, P. Gouze^c,
 A. Guadagnini^{a,b}
^a Dipartimento di Ingegneria Civile e Ambientale, Politecnico di Milano, Piazza L. Da Vinci 32, 20133
 Milano, Italy
^b Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ 85721, USA
^c Géosciences Montpellier, CNRS-Université de Montpellier, Place Eugène Bataillon, 34095 Montpellier,
 France

Table 2Lead sample statistics of incremental data ΔY for the selected 14 classes of lags.

s_k	N	Mean	Standard deviation	Skewness	Excess kurtosis
1	154	-0.01	0.13	-0.18	0.39
2	211	-0.01	0.17	0.38	1.97
3	189	-0.01	0.21	0.27	3.44
4	182	-0.01	0.23	0.41	4.03
5	177	-0.01	0.27	0.24	4.28
6	176	0.00	0.28	0.11	3.64
7	165	-0.01	0.27	0.03	3.44
8	159	-0.02	0.26	-0.14	2.54
9	156	-0.01	0.26	-0.33	2.77
10	156	-0.02	0.26	-0.26	2.96
11	149	-0.03	0.26	-0.11	2.08
12	152	-0.04	0.26	-0.07	2.15
13	138	-0.03	0.28	-0.32	2.04
14	134	-0.02	0.27	-0.21	1.23

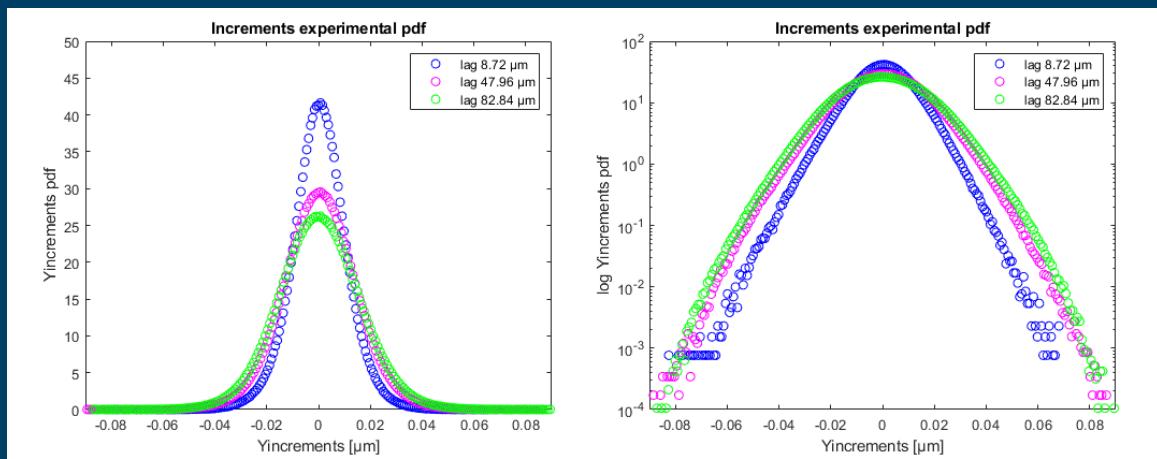
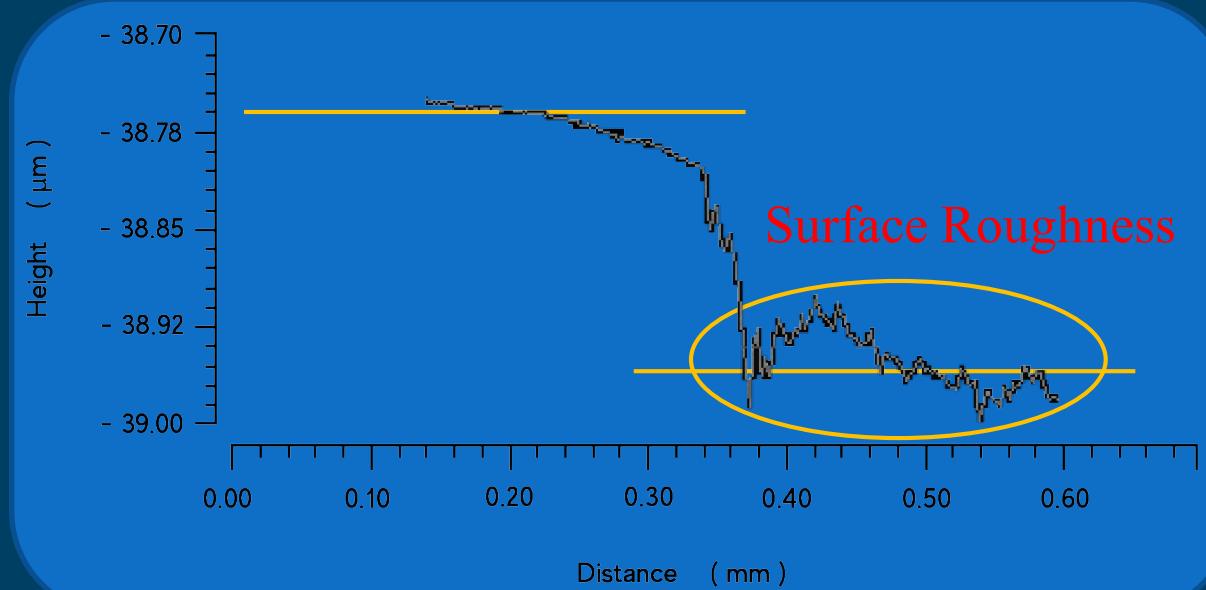
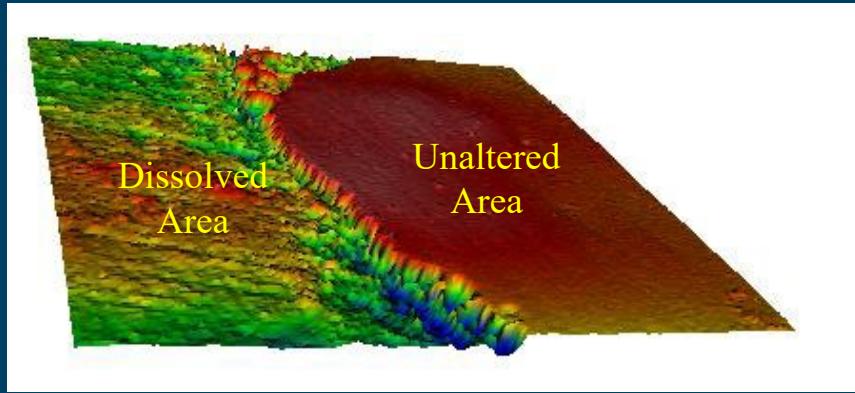




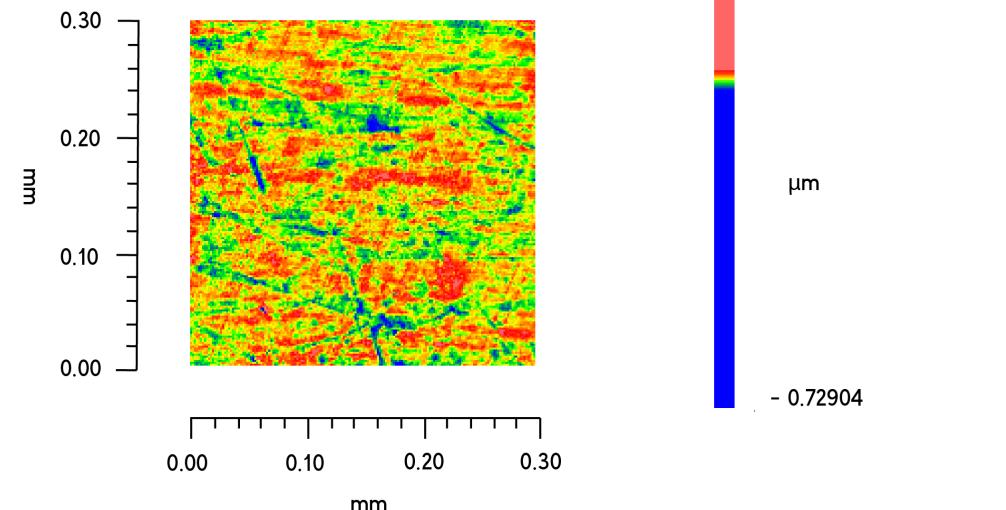
Application to geochemical data – assessment of calcite dissolution

Joint work with Philippe Ackerer and Damien Daval (Université de Strasbourg-CNRS ENGEES/EOST)

- Topography images of calcite crystals



Images from L. Stigliano (Msc Thesis, 2020)

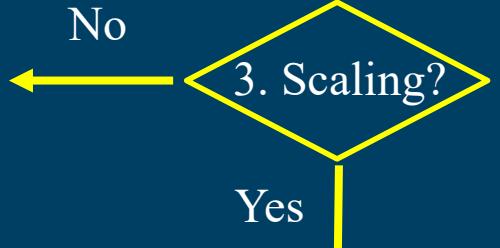


1. Data processing and analysis



2. Distributions of P' and ΔP

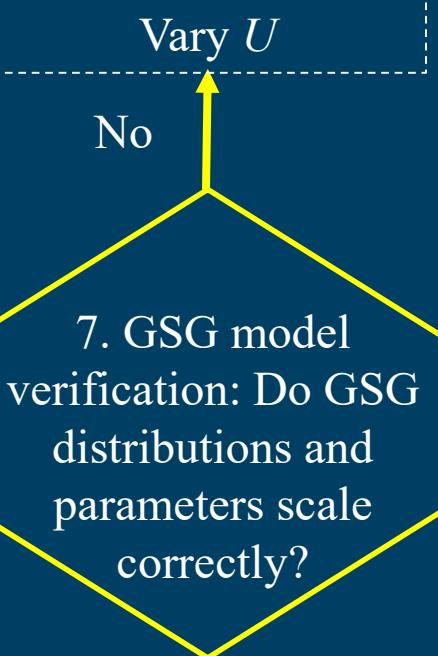
Classical geostatistical models



4. GSG (with given U)

5. Fitting GSG model to statistical moments and/or frequency distributions of P' and ΔP

6. Parameter estimation



9. State variables

Process Simulation

P'

8. Generation of GSG functions



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Review papers

Recent advances in scalable non-Gaussian geostatistics: The generalized sub-Gaussian model

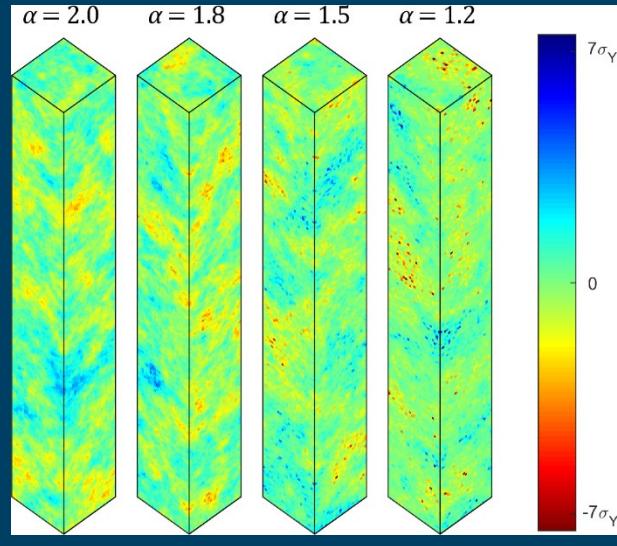
Alberto Guadagnini^{a,b,*}, Monica Riva^{a,b}, Shlomo P. Neuman^b

^a Dipartimento di Ingegneria Civile Ambientale, Politecnico di Milano, Piazza L. Da Vinci 32, 20133 Milano, Italy

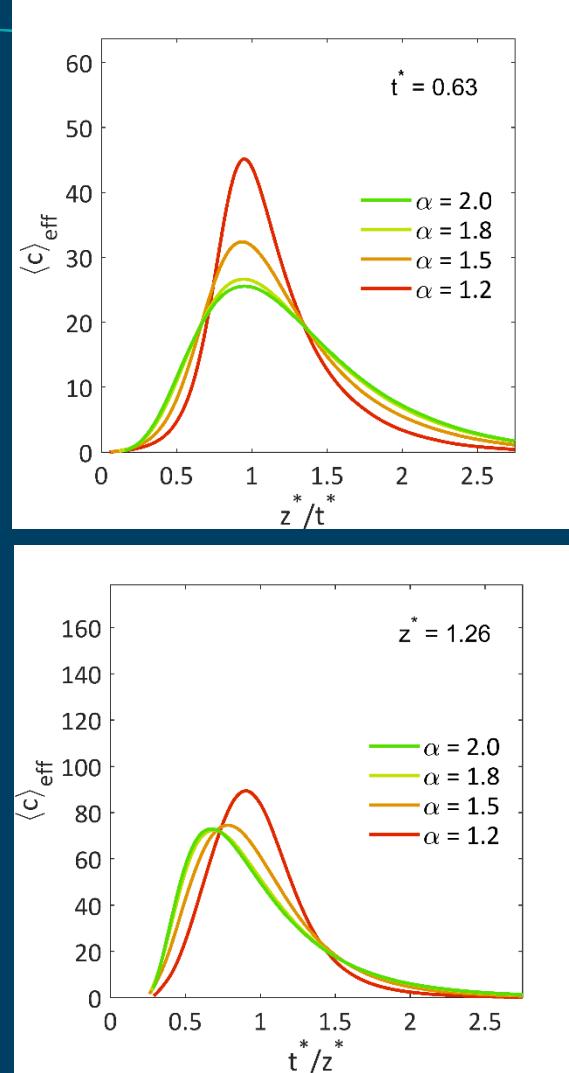
^b Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ 85721, USA

WORKFLOW FOR ANALYSIS

3D- flow/transport problems



8×10^6 cells



- Many variables with scalable statistics exhibit
 - Heavy-tailed increment frequency distributions with sharp peaks at small lags
 - Peak and tail decay with increasing lag
- These aspects are captured by a GSG model based on sub-Gaussian subordination
 - Simple ways to estimate parameters
- We developed a methodology to generate unconditional and conditional realizations of such random fields
 - Ready to be employed for Monte Carlo flow and transport simulations in randomly heterogeneous systems (see *Libera, A., F. de Barros, M. Riva, and A. Guadagnini, JCH, 2018*).
- Lead-order analytical solutions for a simple non-Gaussian case of flow and transport in an unbounded unimodal GSG log permeability field Y under mean uniform flow in two spatial dimensions

Summary

- **GSG model can reconcile several aspects exhibited by many (environmental and other) variables**

Power-law scaling of structure functions in midrange of lags

Breakdown in such scaling at small / large lags

Heavy-tailed increment frequency distributions with sharp peaks at small lags

Peak and tail decay with increasing lag

Extended power-law scaling or ESS

Linear / nonlinear scaling of power exponent

- **Simple ways to estimate model parameters**
- **Lead-order analytical solutions for simple flow/transport settings**
- **Numerical flow/transport solutions**
- **Conditional GSG**