Quantification of Heterogeneity of Spatially Averaged Generalized sub-Gaussian Random Fields

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Outline

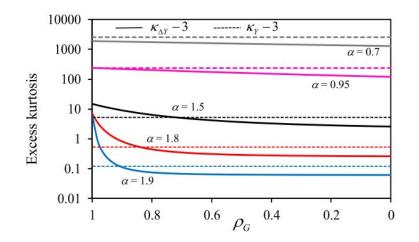
- Generalized sub-Gaussian (GSG) random fields
- > Spatially averaging random fields
- > Spatially averaged GSG variance model
- Model Verification: MC Results
- Application to data

Generalized sub-Gaussian Random Fields



- *U* Log-normal subordinator ($\mu_U = 0$, $\sigma_U = (2-\alpha)$)
- G Gaussian Random Field (μ_{G} = 0, σ_{G} , ρ_{G})

- $\Delta Y = Y(x) Y(x+h)$
- x Spatial Coordinate
- *h* Separation distance



"No statistical model known to us captures these behaviors of Y and ΔY in a unified and consistent manner."

1. Riva, M., Neuman, S. P., & Guadagnini, A. (2015). New scaling model for variables and increments with heavy-tailed distributions. *Water Resources Research*, *51*(6), 4623-4634.

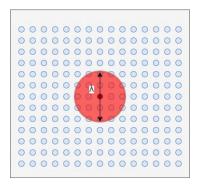
Spatially Averaging Random Fields

Weighted Spatial Average Definition

$$\langle Y(x) \rangle_{\lambda} = \int_{\mathbb{R}^d} w_{\lambda}(x+x')Y(x+x')dx$$

$$w_{\lambda}(x) = \frac{1}{\lambda^d} w_1\left(\frac{x}{\lambda}\right)$$

- Uniform weights: Moving Frame Window
 - Circle of radius, λ, centered on each data point. All data points within the circle are arithmetically averaged.



Spatially Averaged GSG Variance Model

General Model:

- Inner integral is the convolution of 2 weight functions - simple to evaluate for specific choices of weights

$$\mathbb{E}\left[\langle Y(x) \rangle_{\lambda}^{2}\right] = \mathbb{E}[U]^{2} \int_{\mathbb{R}^{d}} c_{G}(|u|) \int_{\mathbb{R}^{d}} w_{\lambda 1}(y'+u) w_{\lambda 2}(y') \, dy \, du$$

Model Specialisation

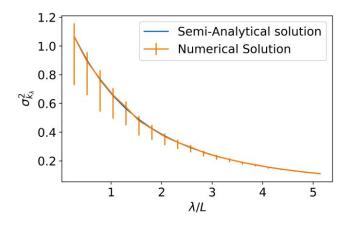
- 2D uniform weights, exponential covariance form.

$$\mathbb{E}\Big[\langle Y(x)\rangle_{\lambda}^2\Big] = \frac{4\exp((2-\alpha)^2)\sigma_G^2}{\lambda^2\pi} \int_0^{2\lambda} \exp(-\frac{r}{l}) \left(\arccos\left(\frac{r}{2\lambda}\right) - \frac{r}{2\lambda}\sqrt{1 - \frac{r^2}{4\lambda^2}}\right) r \, dr$$

Model Verification: Monte Carlo Results

- MC Results Vs Analytical Solution: Highly leptokurtic test case
 - GSG fields generated using Scipy and Numpy in Python.
 - Spatially averaged using uniform weights and a moving frame window average.
 - Largest error <2%.

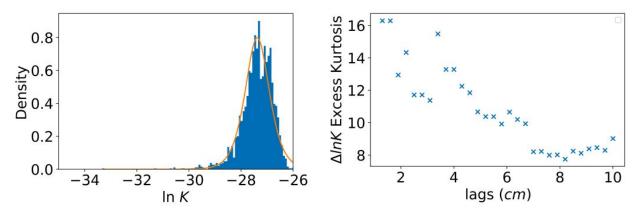
Parameter	Value
α	1.5
σ _G	1
Integral Length Scale (L)	1
MC simulations	5000
Domain Size	10x10
Grid Size	50x50
λ Range	0.21 - 4



Application to Data

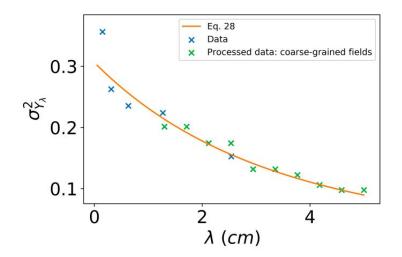
- Maximum Likelihood
 - Massillon Sandstone block (0.94x0.96x1.01m) from Briar Hill Stone Company, Ohio USA.
 - Uniform grid sampling on 6 sides of the block. 75000 Measurements in total.
 - Multi Measurement Scale dataset varying tip seal radius of permeameter (0.15, 0.31, 0.63, 1.27, 2.54 cm).
 - Parameters for analytical solution obtained via Maximum Likelihood.

Parameter	ML estimate (95% Confidence interval)
α	1.681 (±0.040)
σ _G	0.525 (±0.019)



Application to Data

- Comparison of Hard Data with Variance Model
 - 2D Analytical solution (orange) aligns well with multi-scale data (blue).
 - Data manually spatially averaged with uniform weights to obtain a larger range of λ
 - Excluding anomalous first data point (λ =0.15cm); max error <5%.



Conclusions

> Measurement scales of datasets should always be considered as it affects single- and multi- point statistics.

> Data collected at larger measurement scales is less heterogeneous as it is an average over the entire volume - high frequency fluctuations are smoothed.

> Our model allows a practitioner to determine the level of heterogeneity in their dataset in the context of the measurement length scale *and* allows estimations of heterogeneity at alternative length scales.

