# Characterization and reproduction of the aperture distribution patterns in a basaltic fracture plane by Multi-point Geostatistics algorithms

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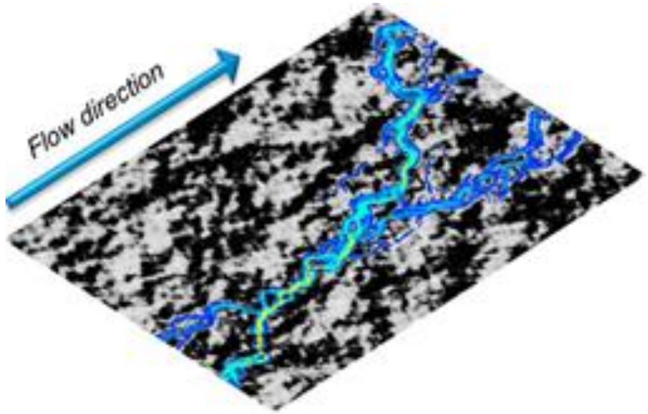
**Session HS3.7** – Advanced Geostatistics for Water, Earth and Environmental Sciences

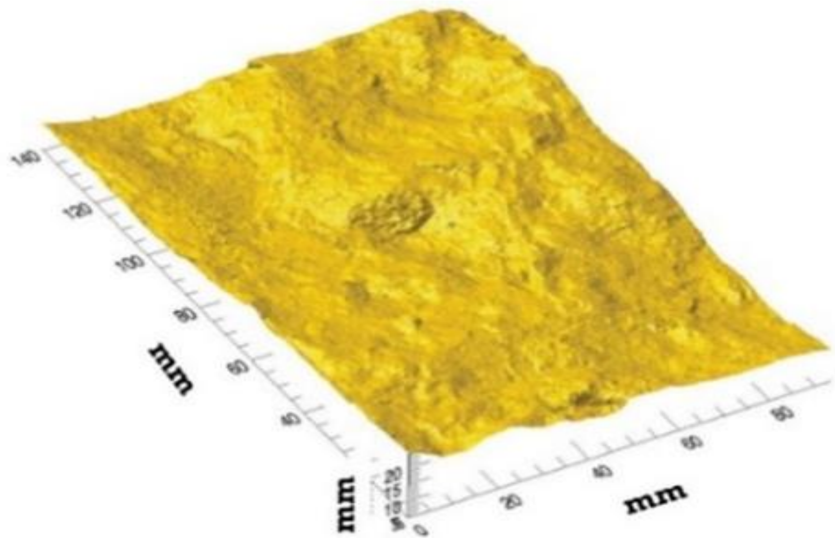
# ❖ Motivation

The knowledge of flow in fractured aquifers is fundamental to a better exploration of water, petroleum, and use as storage to high intensity radioactive wastes. Also, to preview the preferential way of contaminants. Numerical models can assist in predicting, using fracture aperture values as input.

X-ray microtomography (micro-CT) is a non-intrusive technique that provides 3D interior images of solid objects with spatial resolution of a dozen microns. However, the size of a fractured basaltic rock sample that can be analyzed is around 2 inches.

The use of Multi-point Geostatistics methods (MPS) can increase the representativeness of a data obtained by micro-CT through characterization and reproduction of random distribution patterns, as the aperture values.



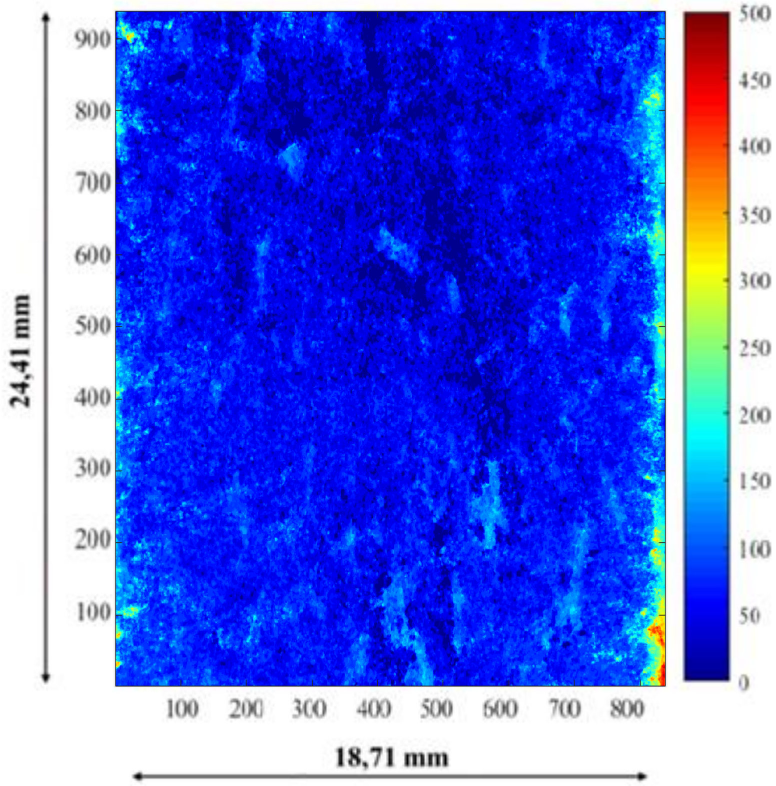



# ❖ Materials and Methods

Here, we use two MPS algorithms to reproduce random patterns of distribution of aperture values using a training image (TI) of a fracture plane obtained from a 3D micro-CT. The image referee to a cylindrical sample with circa 28 mm of length and 24 mm in diameter built as a 938×838 pixel matrix size with voxel dimension of 13.01µm. The aperture values ranging from 0 and 500µm (Lucas et al., 2019).

The Direct Sampling-DS (Pixel-Based) was adapted from Mariethoz et al. (2010), and the Multi-Scale Cross Correlation-based Simulation-MS CCSIM (Pattern-Based) was adapted from Tahmasebi et al. (2014), both in Python v 3.6.7. The PC configuration was Intel Core i7-7700HQ, 2.8 GHz, 16 GB RAM and 1 TB HD.

A sensibility analyzes of parameters/factors that govern the performance of both algorithms were made. The number of simulations was 10 for each combination of parameters, with histogram analysis (absolute aperture values).



# Results

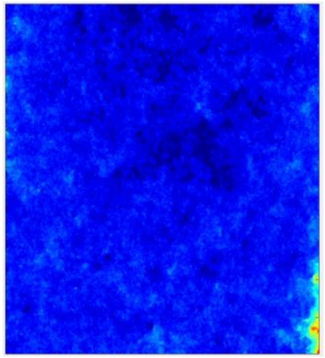
## DS parameter:

Number of closest neighbors *n*

## Other parameters:

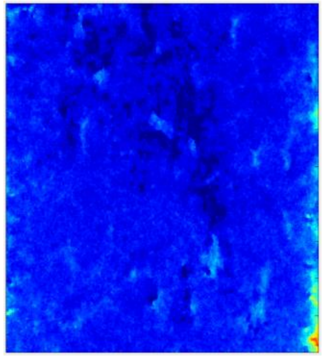
Maximum fraction of TI to scan $f = 0.1$
Distance threshold $t = 0.1$

$n = 20$



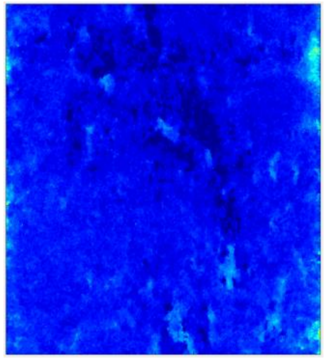
time* = 6 hours

$n = 40$



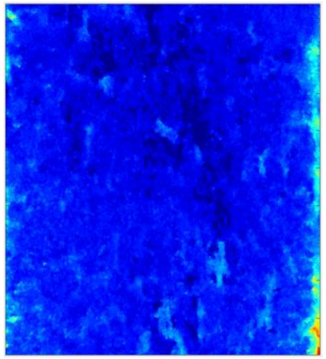
time* = 13 hours

$n = 60$

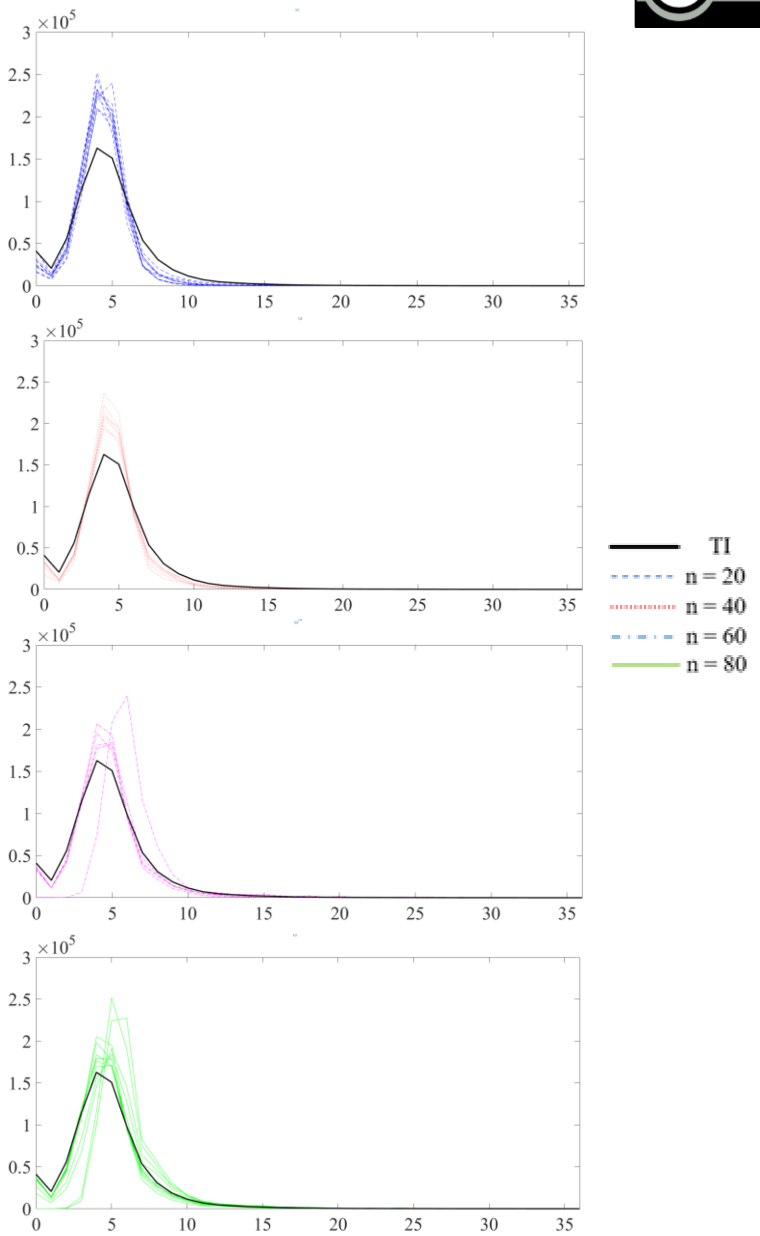


time* = 19 hours

$n = 80$



time* = 25 hours






* *average time in simulations*

## ❖ Results

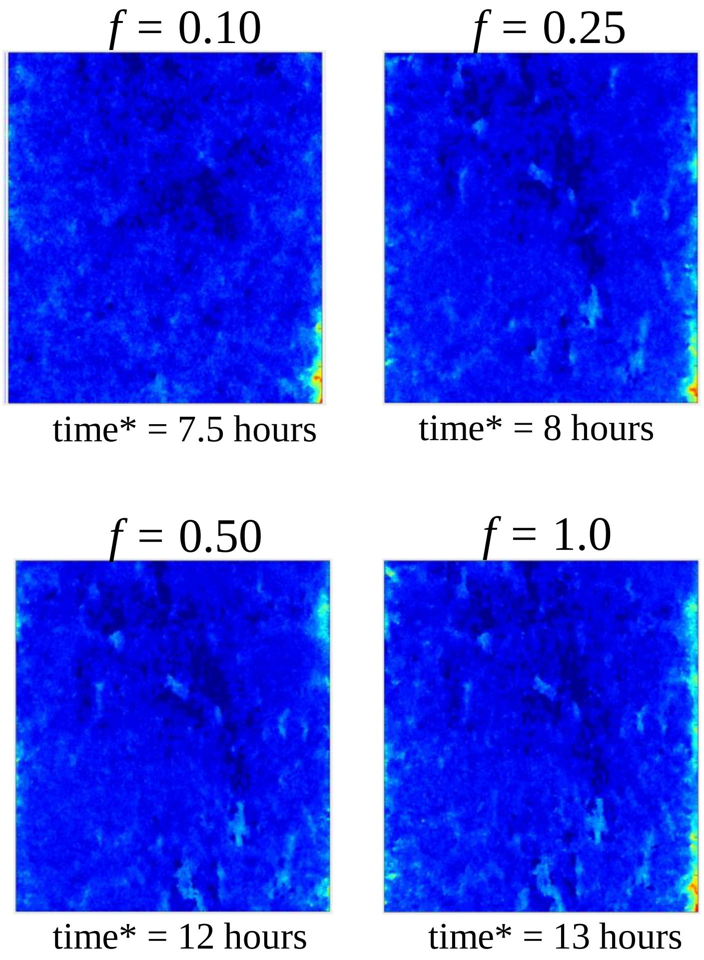
### DS parameter:

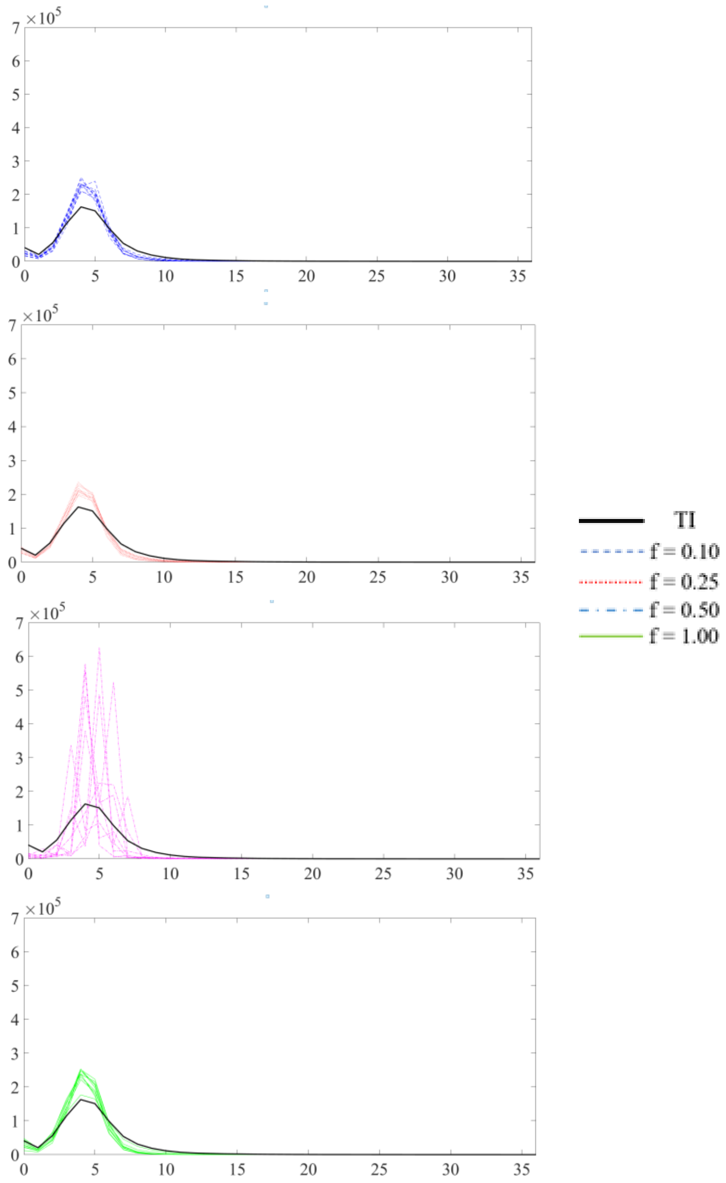
Maximum fraction of TI to scan *f*

### Other parameters:

Number of closest neighbors *n* = 20

Distance threshold *t* = 0.1




* *average time in simulations*

# Results

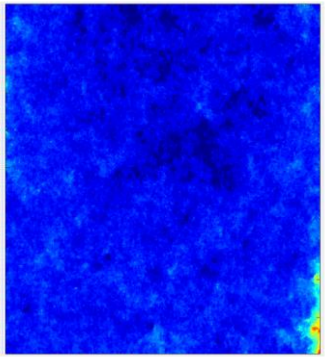
## DS parameter:

Distance threshold *t*

## Other parameters:

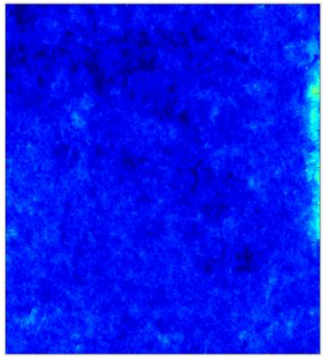
Number of closest neighbors *n* = 20
Maximum fraction of TI to scan *f* = 0.1

*t* = 0.10



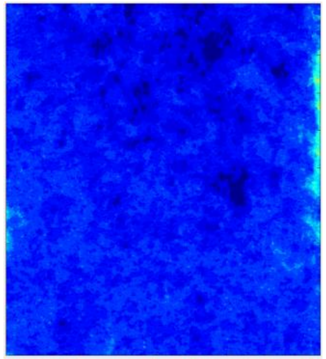
time* = 7.5 hours

*t* = 0.25



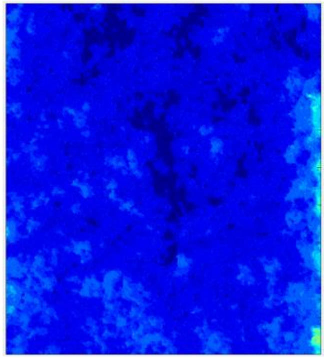
time* = 6.5 hours

*t* = 0.50

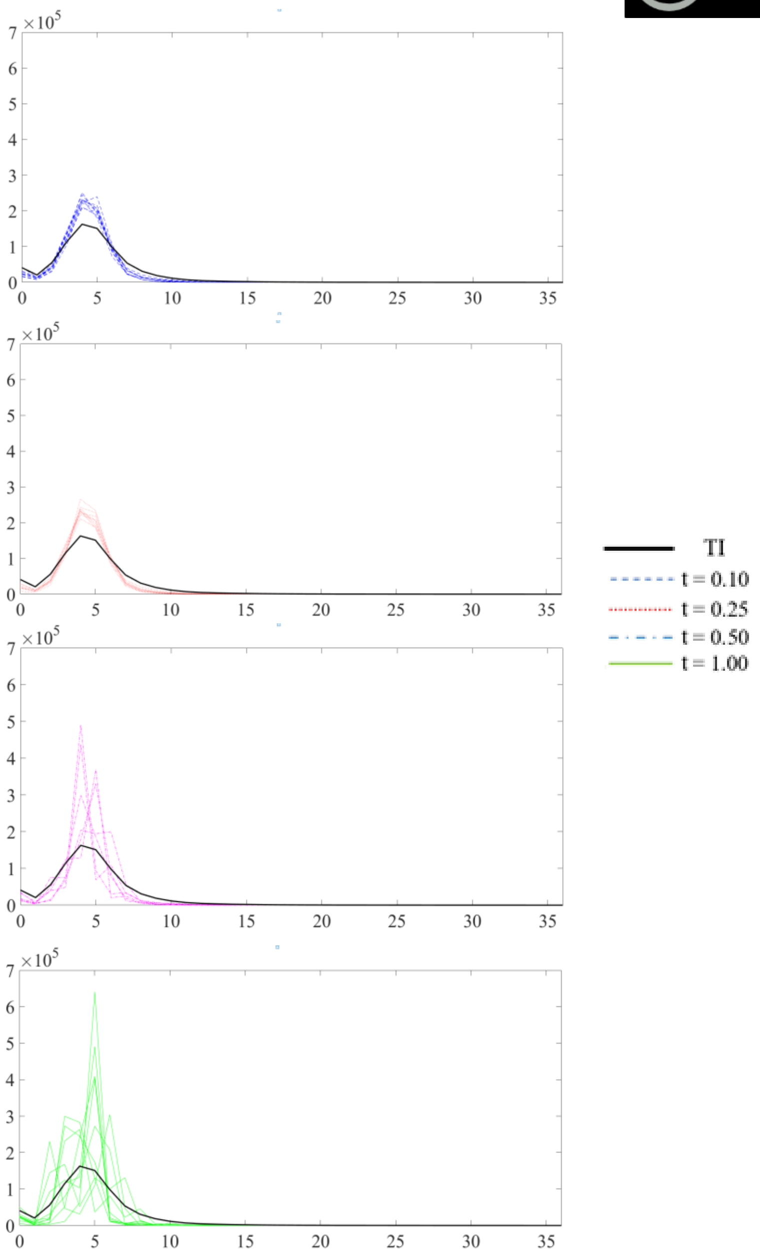


time* = 6 hours

*t* = 1.0



time* = 4 hours






* *average time in simulations*

## ❖ Results

### DS parameter:

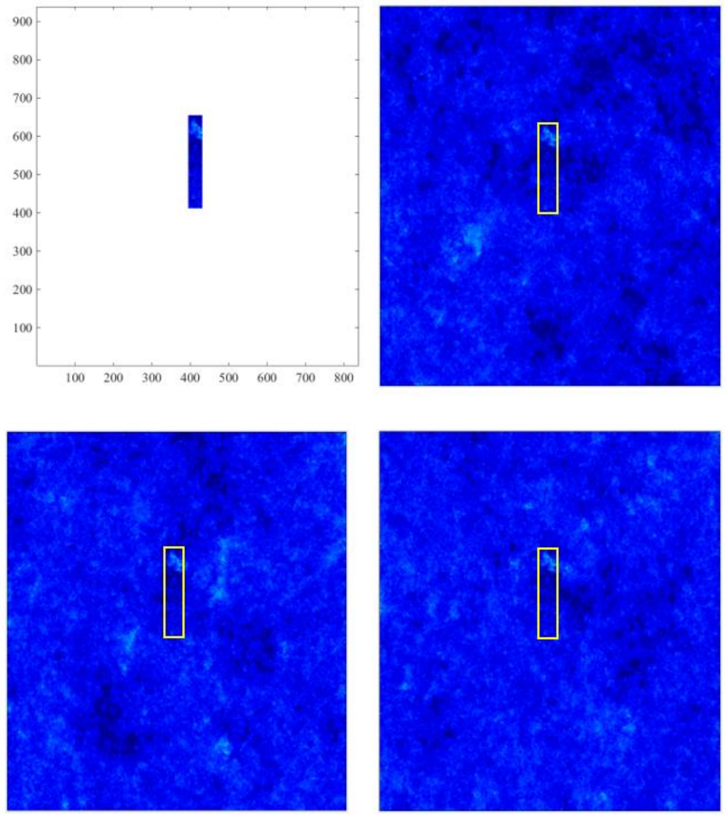
Conditional data

### Other parameters:

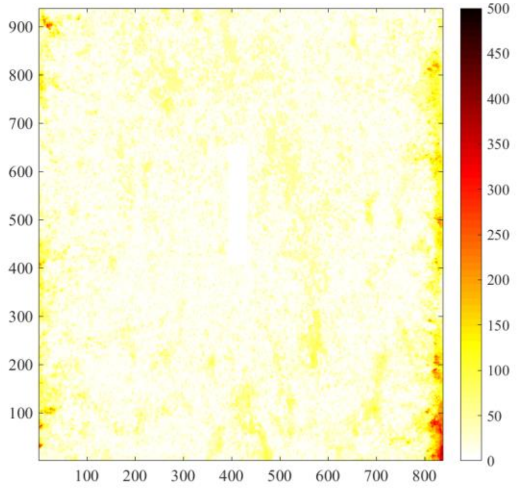
Number of closest neighbors $n = 20$

Maximum fraction of TI to scan $f = 0.1$

Distance threshold $t = 0.1$




Difference between mean values of simulations and TI



❖ # Results

## DS parameter:

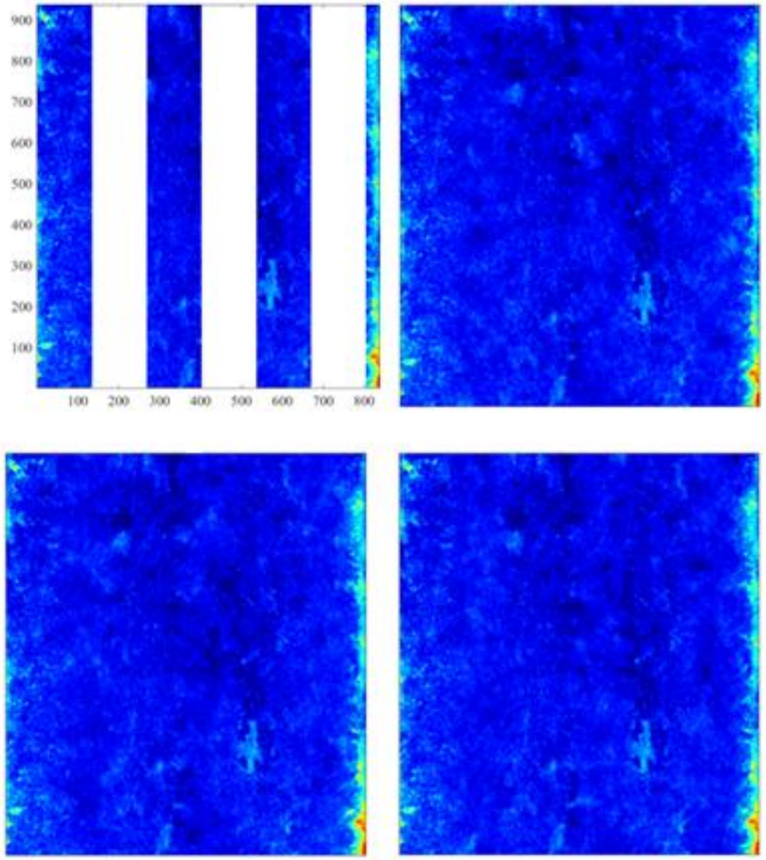
Conditional data

## Other parameters:

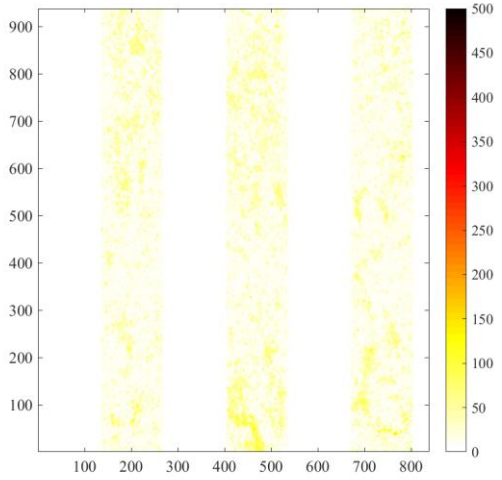
Number of closest neighbors $n = 20$

Maximum fraction of TI to scan $f = 0.1$

Distance threshold $t = 0.1$



Difference between mean values of simulations and TI



# Results

## DS parameter:

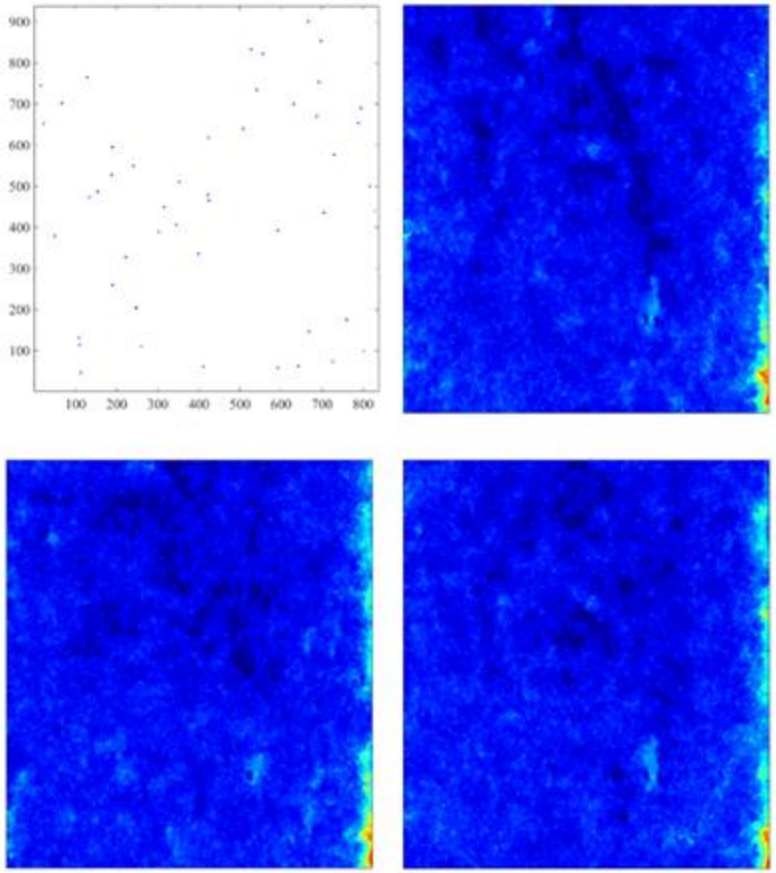
Conditional data

## Other parameters:

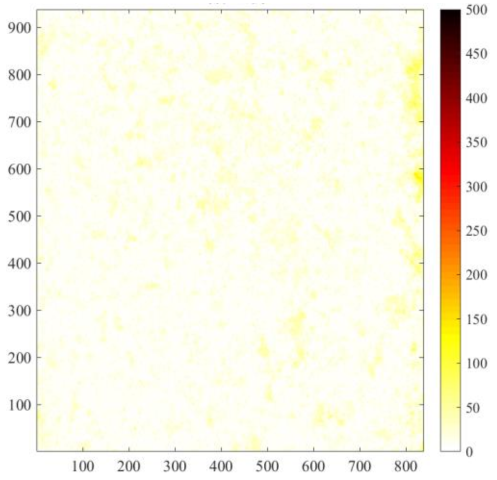
Number of closest neighbors $n = 20$

Maximum fraction of TI to scan $f = 0.1$

Distance threshold $t = 0.1$



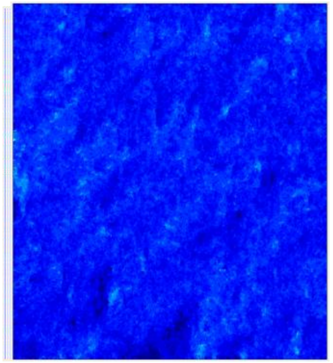
Difference between mean values of simulations and TI



## ❖ Results
## MS-CCSIM parameter:
## Template size *T*

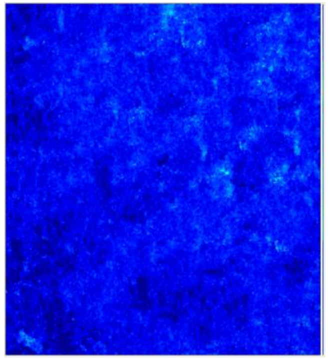
## Other parameters:
Overlap region *OL* = 12
Multi-scale factor *g* = 1

*T* = 20



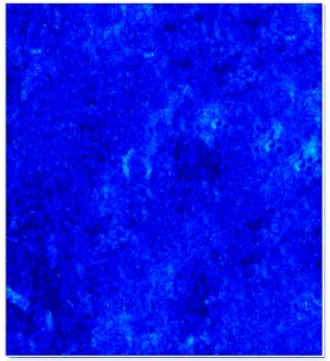
time* = 12 min

*T* = 40



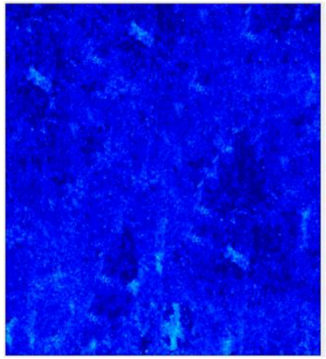
time* = 1 min

*T* = 60

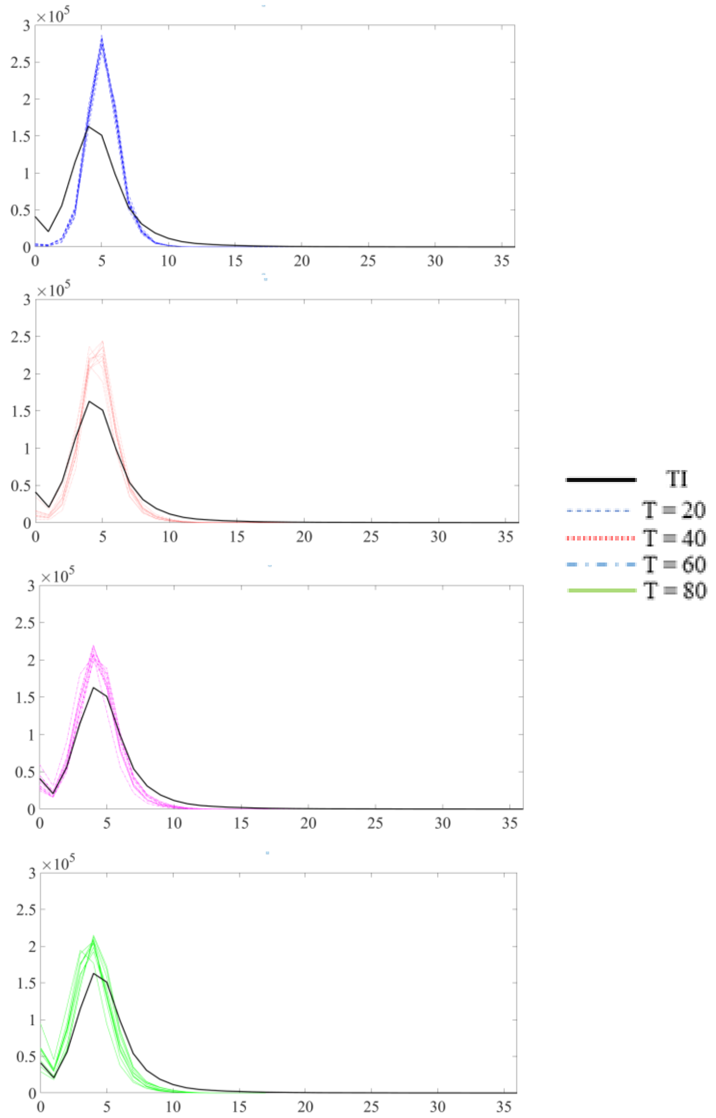


time* ≅ 1 min

*T* = 80



time* ≅ 1 min



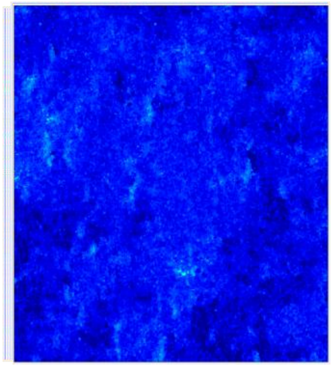



* *average time in simulations*

## ❖ Results
MS-CCSIM parameter:
Overlap region *OL*

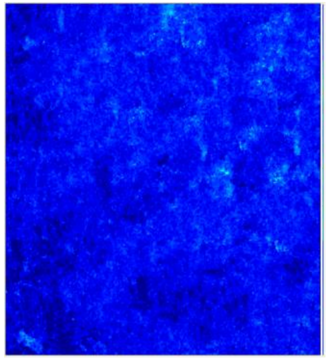
Other parameters:
Template size $T = 20$
Multi-scale factor $g = 1$

*OL* = 6



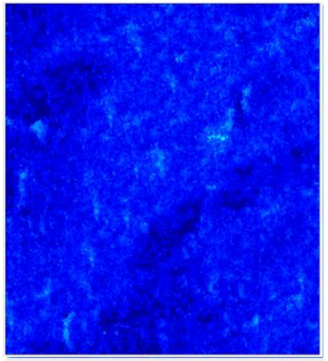
time* ≌ 1 min

*OL* = 12



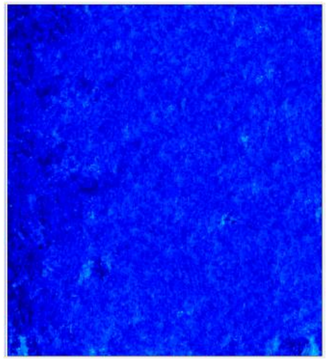
time* ≌ 1 min

*OL* = 24

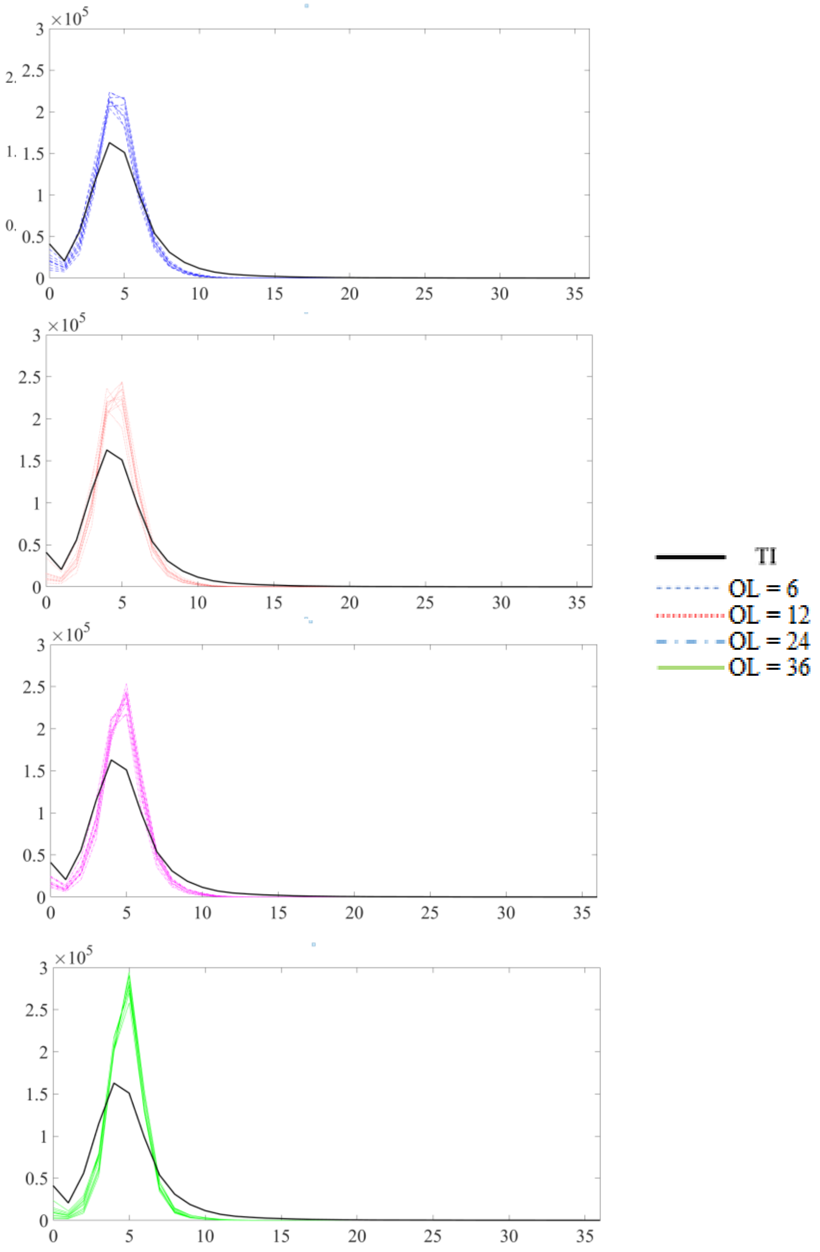


time* ≌ 7 min

*OL* = 36



time* = 120 min




* *average time in simulations*

## Results

MS-CCSIM parameter:

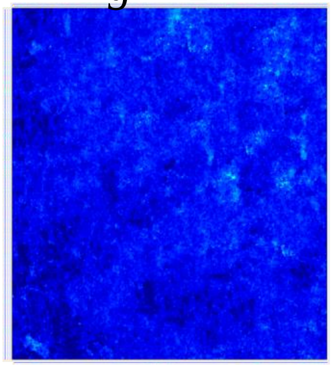
Multi-scale factor *g*

Other parameters:

Template size $T = 20$

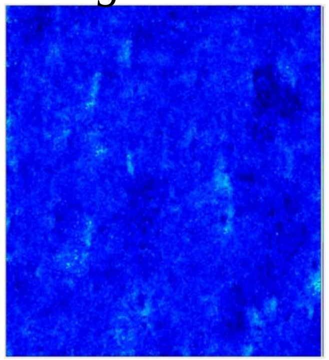
Overlap region $OL = 1$

$g = 1$



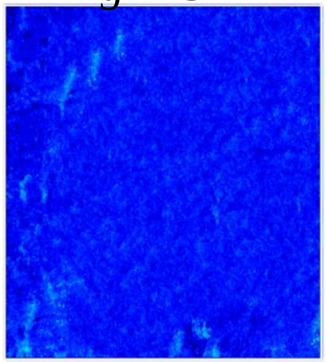
time* ≅ 1 min

$g = 2$

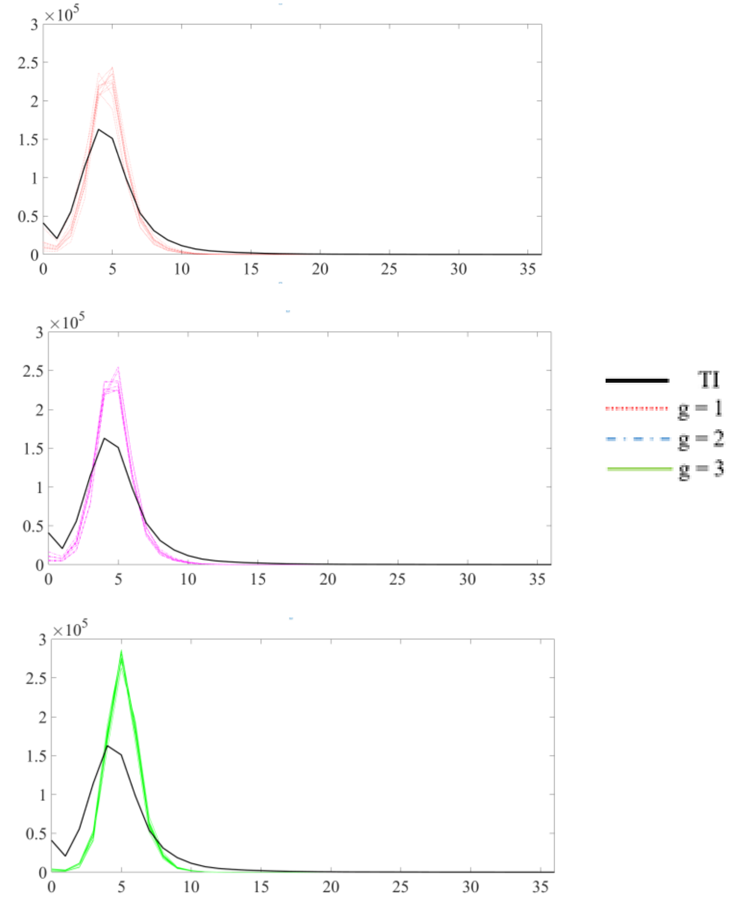


time* ≅ 20 sec

$g = 3$



time* ≅ 20 sec




* *average time in simulations*

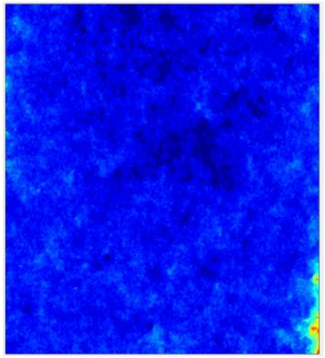
# ❖ Conclusions

- The histograms demonstrate witch configuration of parameters is optimized, where the combination between an image simulated visually similar to the TI, and a histogram that present the same behavior as the TI line, but not close to identical, show the expected reproduction.

❖DS

Parameter configuration assumed as the optimal:

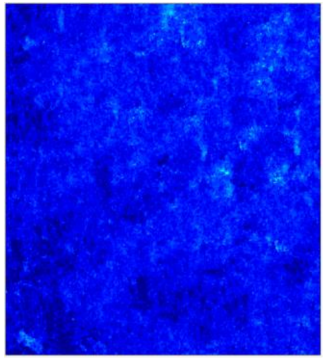
- $n$ = 20
- $f$ = 0.1
- $t$ = 0.1



❖MS-CCSIM

Parameter configuration assumed as the optimal:

- $T$ = 40
- $OL$ = 12
- $g$ = 1



# ❖ Conclusions

- The DS presented a great ability to reconstruct images from a conditional data, maintaining the randomness of aperture values, the connectivity of both global and local structures, without a tendency to copy the TI.
- The DS results presented a better spatial connectivity of the structures and channels existing in the fracture plane, regarding the randomness of the aperture values and the distribution pattern found in the TI. The images reproduced by MS-CCSIM, in contrast, tended to copy certain regions of TI to most of combinations of parameters used.
- On the other hand, in terms of computational effort required, the DS underperformed MS-CCIM.
- Comparing their global statistics with those of the TI, both presented similar representativeness of the aperture values.
- A preference for the DS algorithm is made and recommended for TI's with similar characteristics. However, for images with different features, a sensitivity analysis should be performed.

# ❖ References


- Lucas, M., Cantareira, G. D., & Wendland, E. (2019). Solute transport performance analysis of equivalent apertures in a single undisturbed basaltic fracture. *Hydrogeology Journal*, 27(6), 1999-2010.
- Mariethoz, G., Renard, P., & Straubhaar, J. (2010). The direct sampling method to perform multiple-point geostatistical simulations. *Water Resources Research*, 46(11).
- Tahmasebi, P., Sahimi, M., & Caers, J. (2014). MS-CCSIM: accelerating pattern-based geostatistical simulation of categorical variables using a multi-scale search in Fourier space. *Computers & Geosciences*, 67, 75-88.

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