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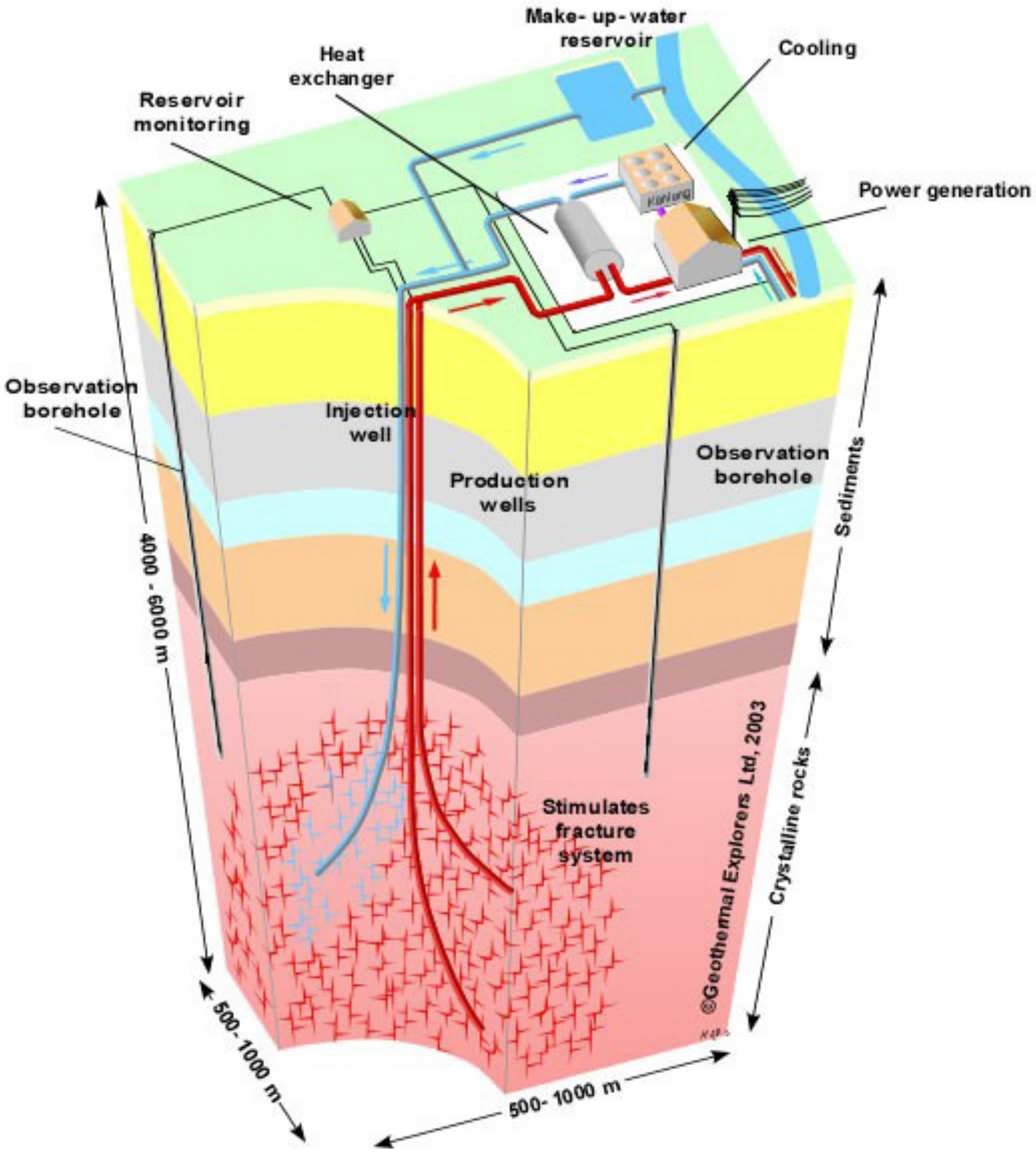
High Performance Computing Based Assessment of Hydraulic Stimulation

Nestola Maria, Karvounis Dimitrios, Patrick Zulian, Krause Rolf

Presented by Maria Nestola

ETH zürich

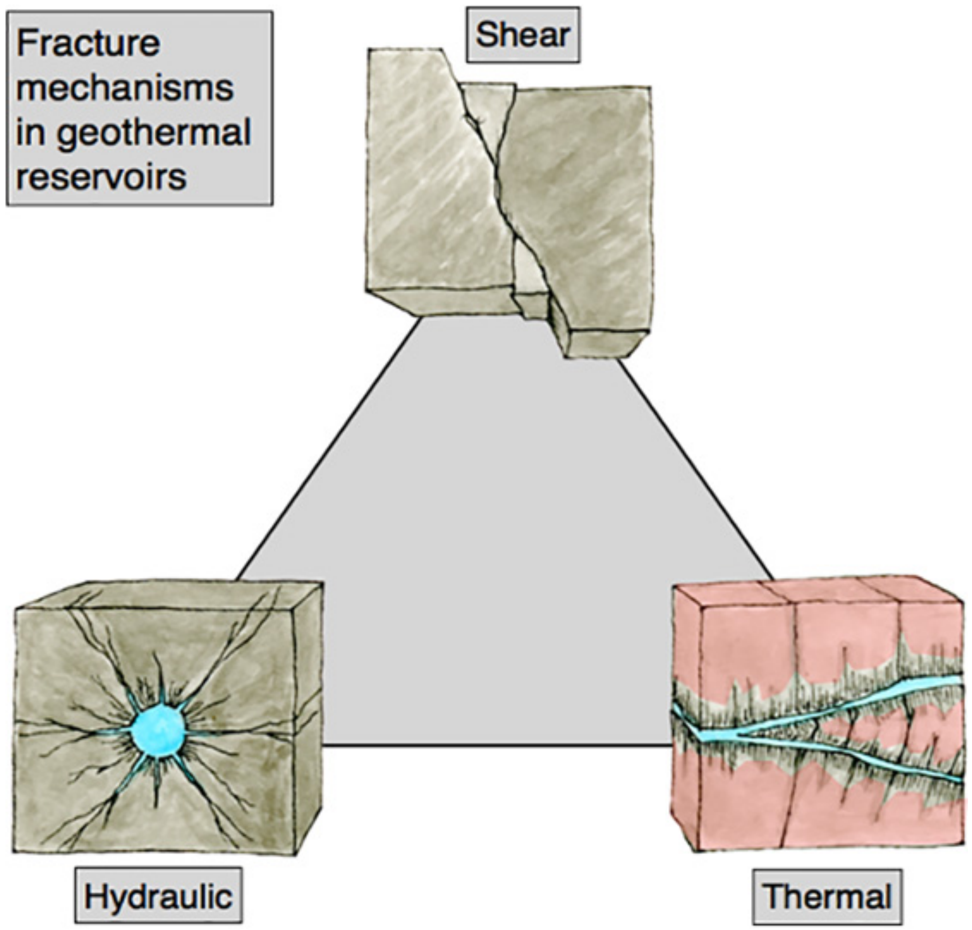
Motivations



An **enhanced geothermal system** (**EGS**) generates **geothermal electricity** without the need for natural **convective** hydrothermal resources.

EGS technologies **enhance** and/or create **geothermal resources** in hot dry rock (HDR) through *hydraulic stimulations*.

Motivations



Enhance permeability by pumping water down an **injection well**.

Water injection ⟶ **shear events.**

Lack of **adequate** modelling tools.

Long term performance is **poorly understood**.

Hydraulic stimulation can result in uncontrolled induced **seismicity**.

EGS Mathematical Model

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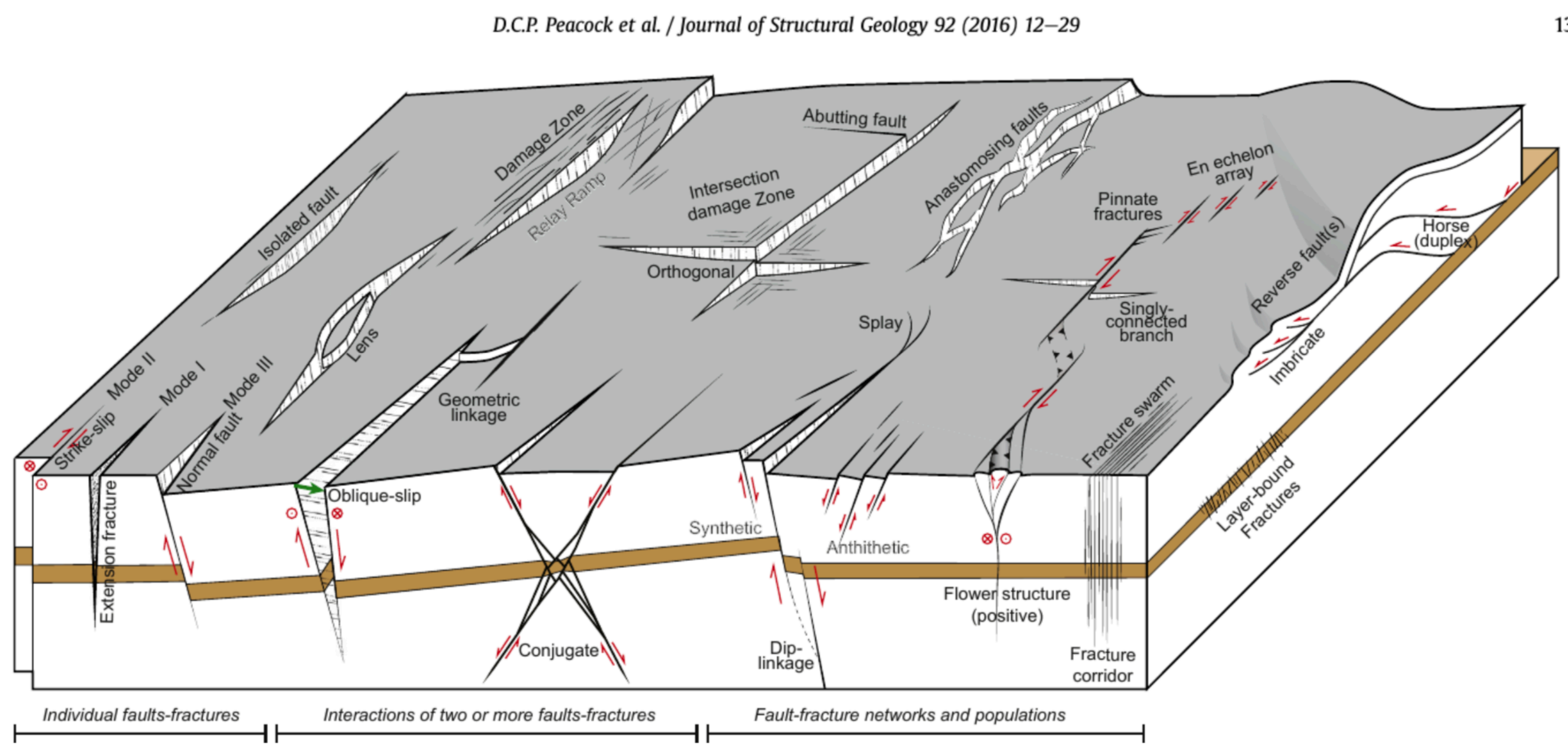
Main ingredients:

1. Background matrix

2. Well injection

3. Fracture Network

4. Fracture triggering



EGS Mathematical Model

Background matrix and well injection

Permeability

$$s_b \frac{\partial p}{\partial t} = \nabla \cdot \left(\frac{K_b}{\mu_b} \nabla p \right) + q_{ib} + w \quad \text{in } \Omega \times (\mathrm{T_i}, \mathrm{T_{fin}})$$

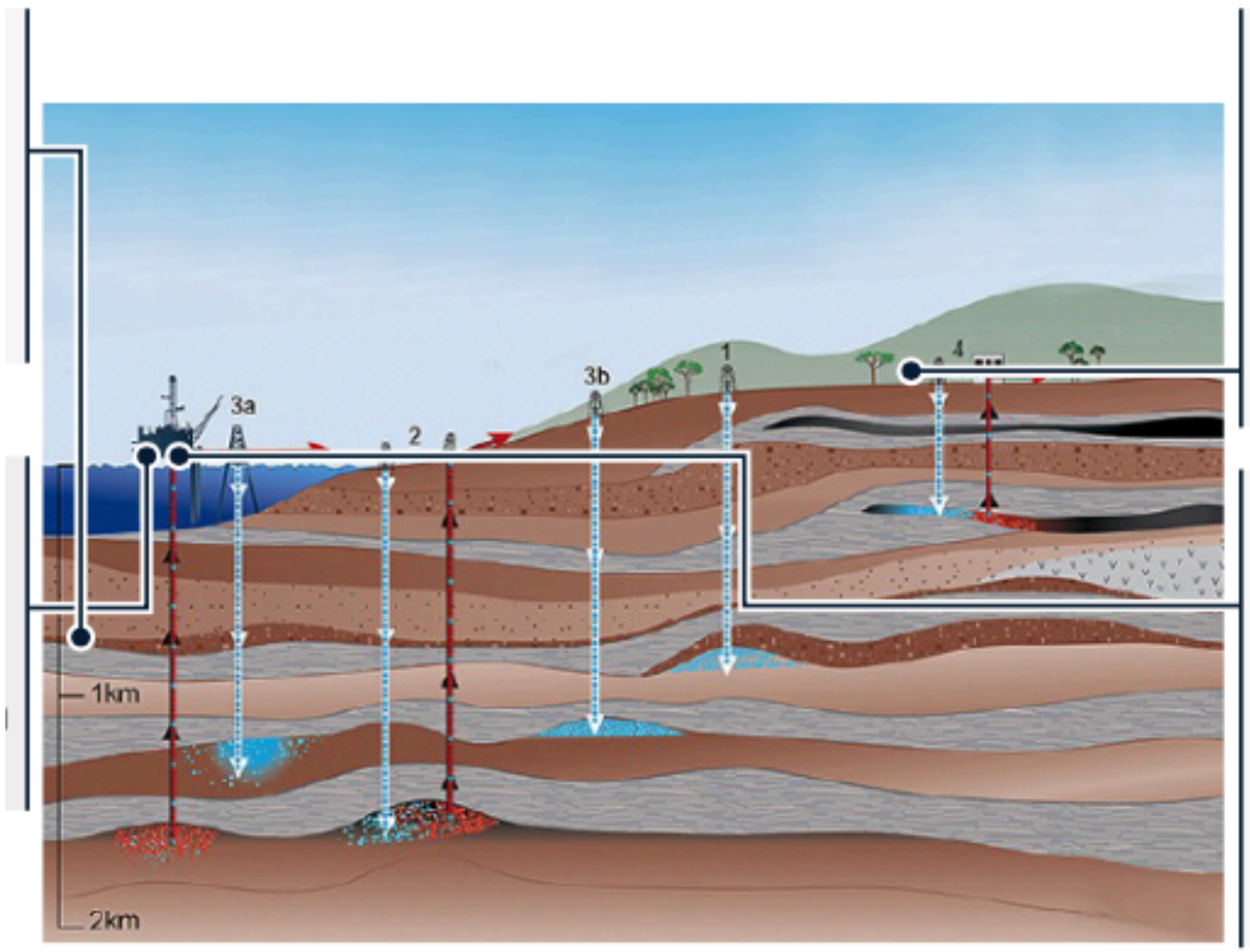
Storativity

Viscosity

w accounts for the **well** modelled **as a cylinder** penetrating the **background matrix**.

Permeability can be a **function of pressure**.

q_{bi} is the **coupling term** between **background matrix** and **fractures**.



EGS Mathematical Model

Fracture Network

Permeability

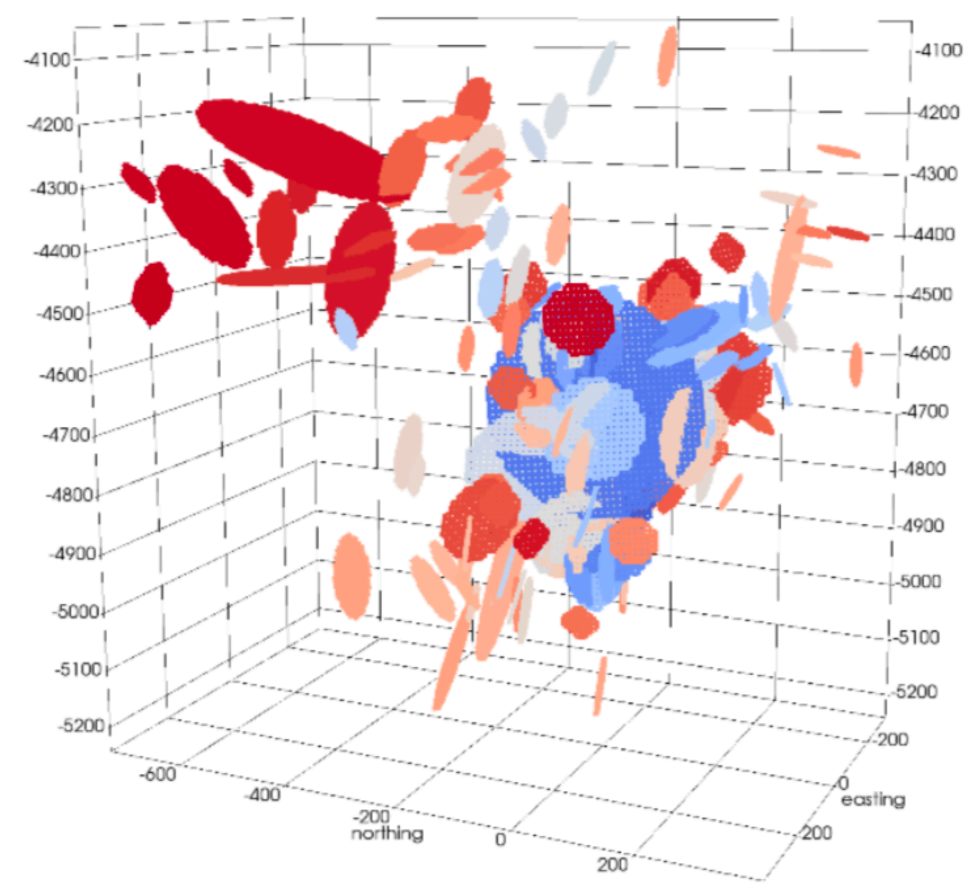
$$s_f \frac{\partial p_i}{\partial t} = \nabla \cdot \left(\frac{K_f}{\mu_f} \nabla p_i \right) + q_{ib} + q_{ij} \quad \text{in } \Omega_\text{i} \times (\text{T}_\text{i}, \text{T}_\text{fin})$$

Storativity

Viscosity

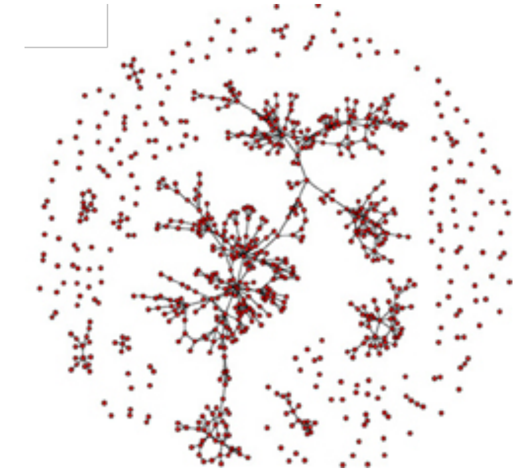
q_{ib} is the **coupling term** between **background matrix** and **fractures**.

q_{ij} is the **coupling term** among **fractures**.



Fractures are represented as **disks** with hypocenter x_i, and radius r_i.

Fracture triggering & Upscaling model



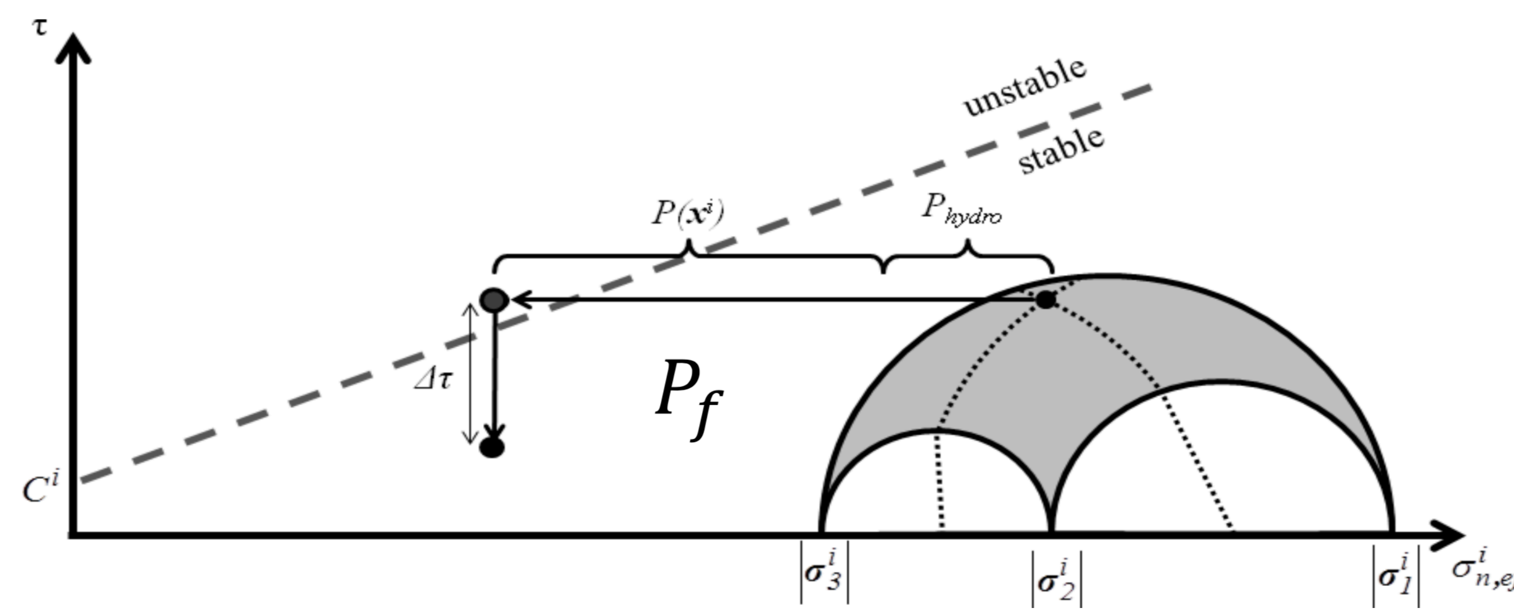
Stochastic seeds are generated:

1. **Geometry** (hypocenter x_i, inclination, radius r_i of the disk)
2. **Material properties** (compressive stress vectors, $\boldsymbol{\sigma}_1, \boldsymbol{\sigma}_2, \boldsymbol{\sigma}_3$, cohesion coefficient $C(x_i)$, friction coefficient $\mu(x_i)$, earthquake magnitude $M(x_i)$)

For each seed normal $\sigma_n(x_i)$ and shear stresses $\tau(x_i)$ are computed.

Mohr-Coulomb failure criterion:

$$P_f(x_i) = \sigma_n(x_i) - \frac{\tau(x_i) - C(x_i)}{\mu(x_i)}$$



Fracture triggering & Upscaling model

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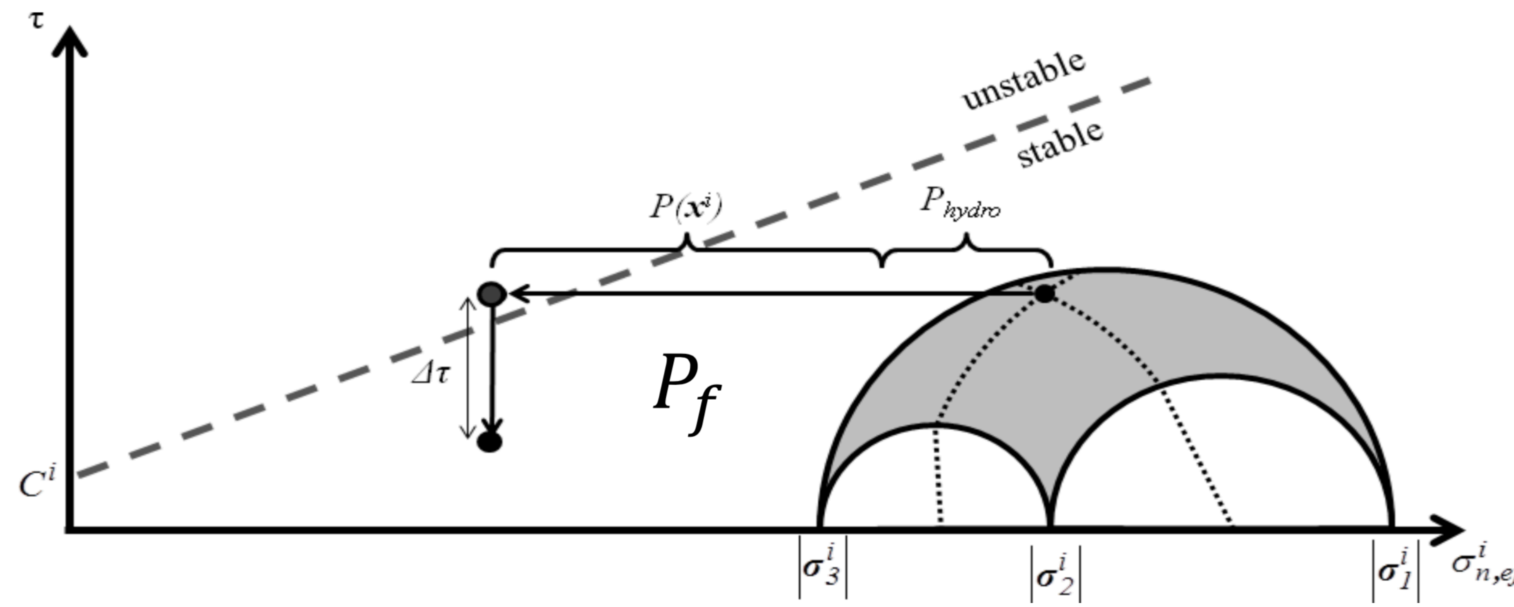


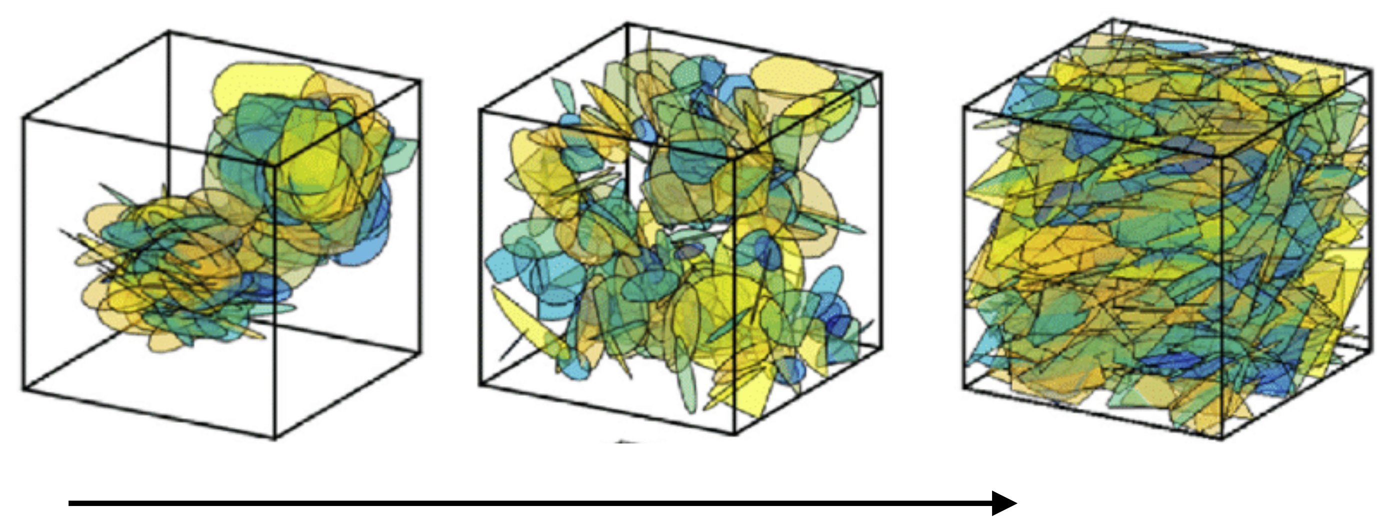
If $(p(x_i) > P_f(x_i))$

an earthquake **is triggered** with **magnitude**

$$m_r(x_i) = f_{rand}(s_i),$$

If $(m_r(x_i) > M(x_i))$

a **new fracture** is **added** to the original network



Simulation time

Fracture triggering & Upscaling model

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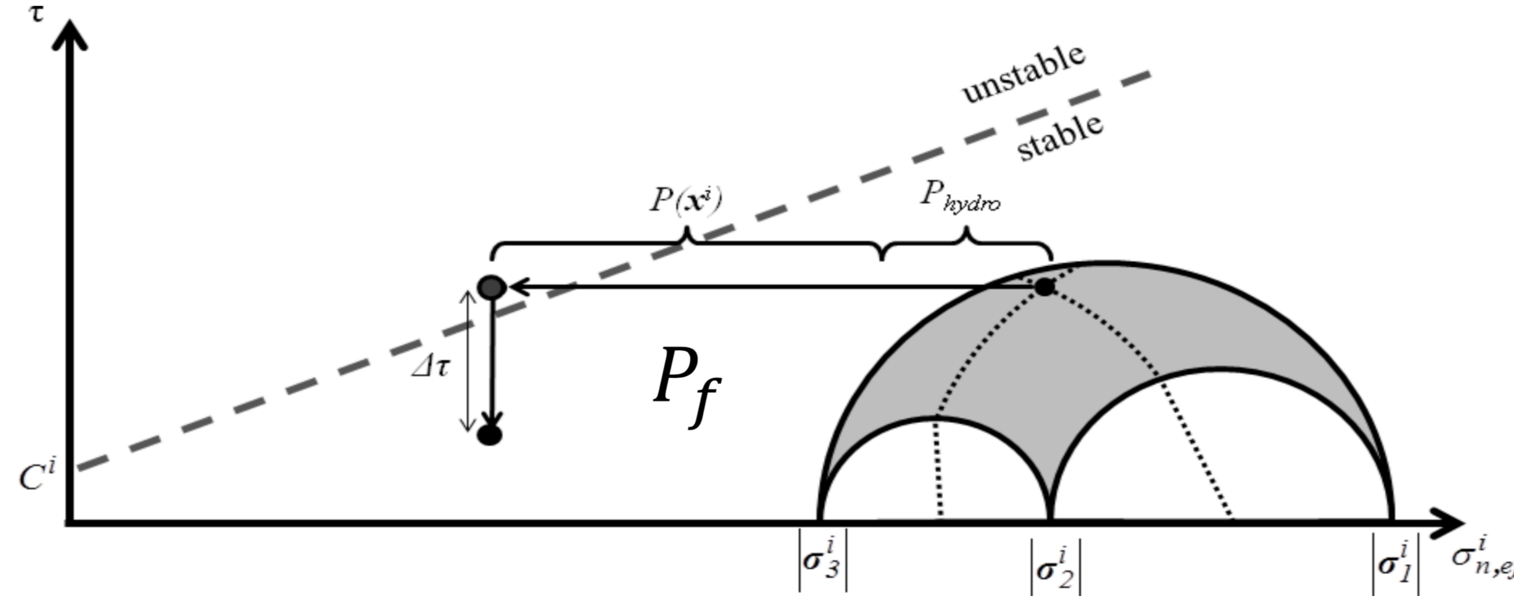

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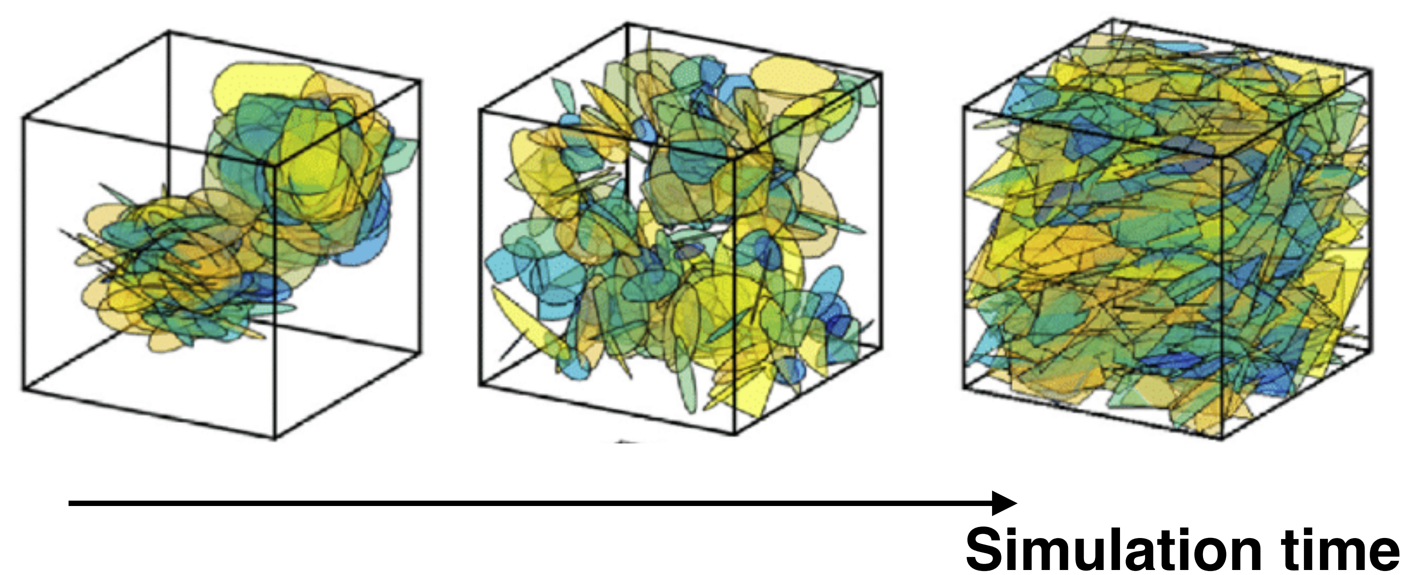

If $(m_r(x_i) < M(x_i))$

fractures are **upscaled**

$$K_b = K_b + \Delta K_b$$

Hydraulic FR-Simulations

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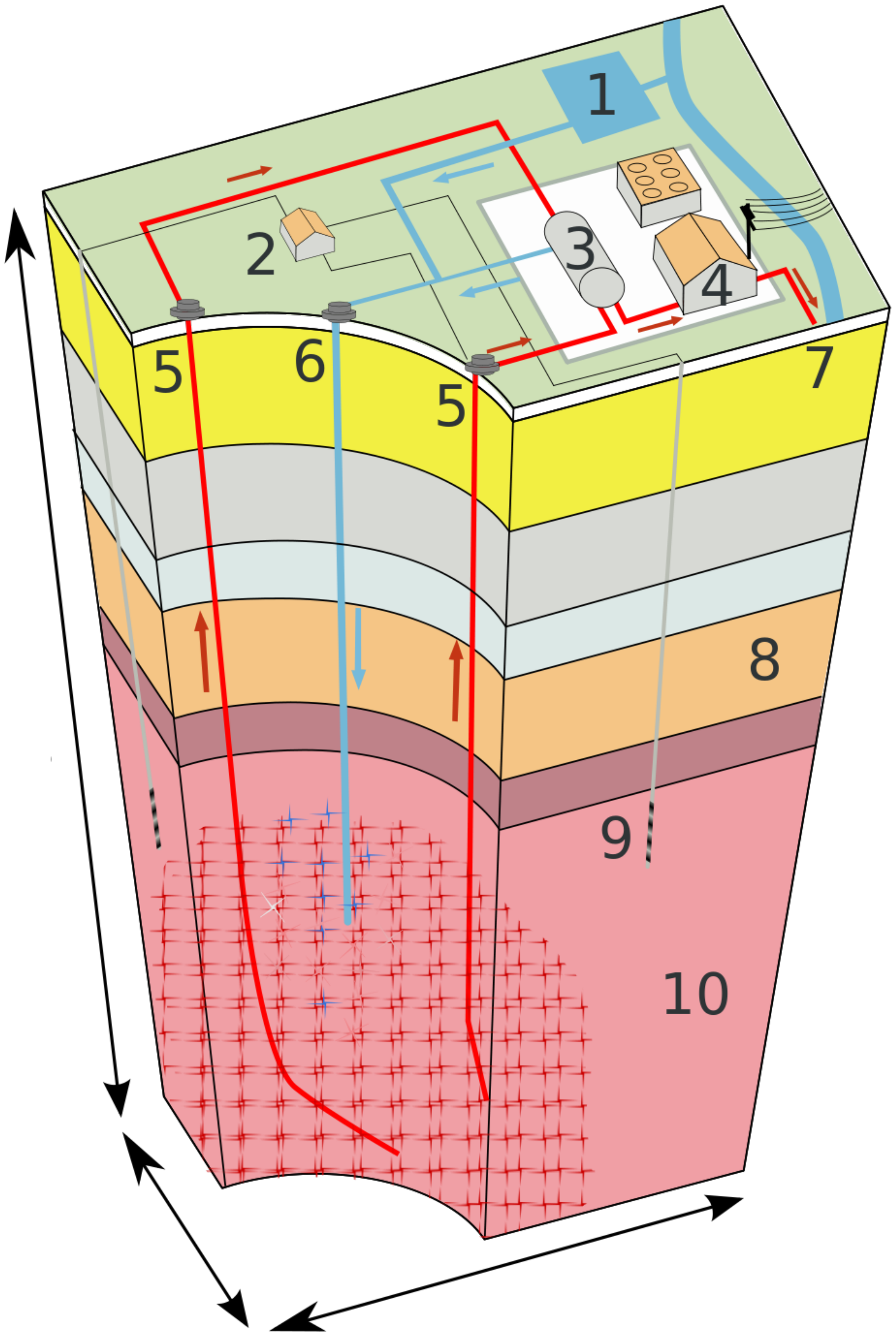

Material Properties:

$\mu_b = \mu_f = 1.0e^{-3}$ [Pa s]

$s_b = 7.2e^{-11}$

$s_f = 1.8e^{-10}$

$K_b = 2.0e^{-17}$ [m^2]

Matrix & Well:

$1300 \times 1000 \times 1500$ [m]

$x_s = [31, -33, -4632]$

$x_f = [0, 0, -5000]$

$r = 0.12$ [m]

$P_{w0} = 3176133$ [Pa]

Hydraulic FR-Simulations

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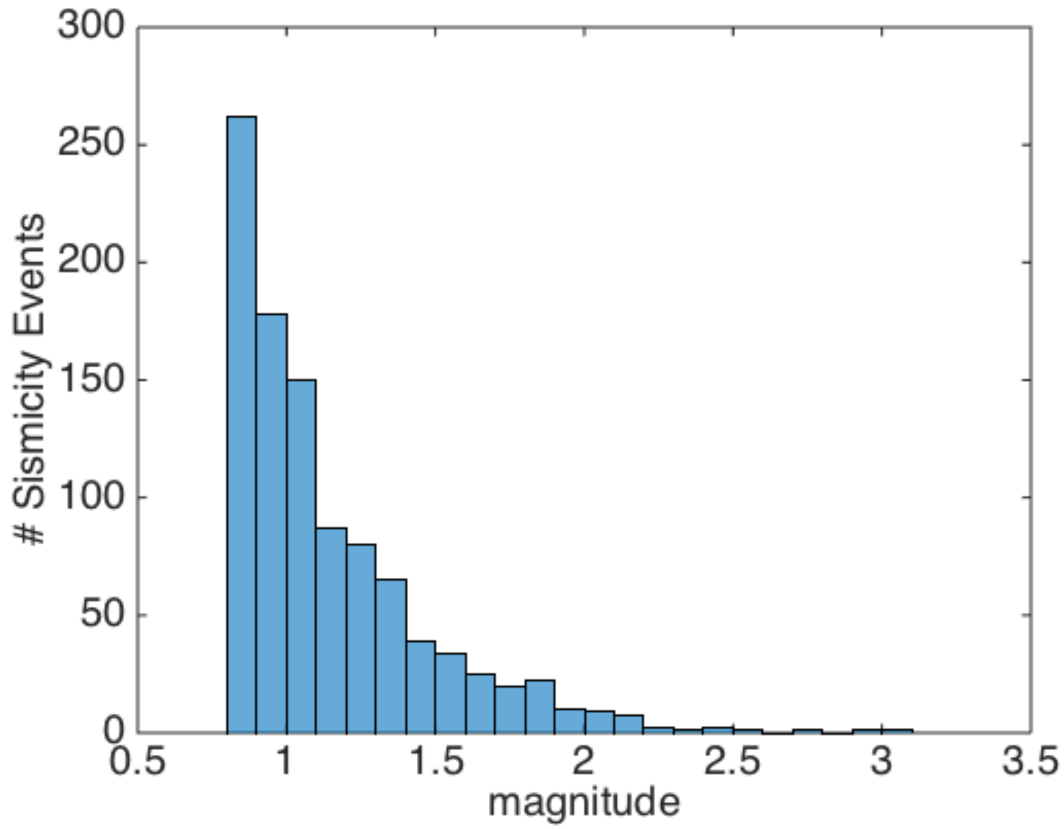
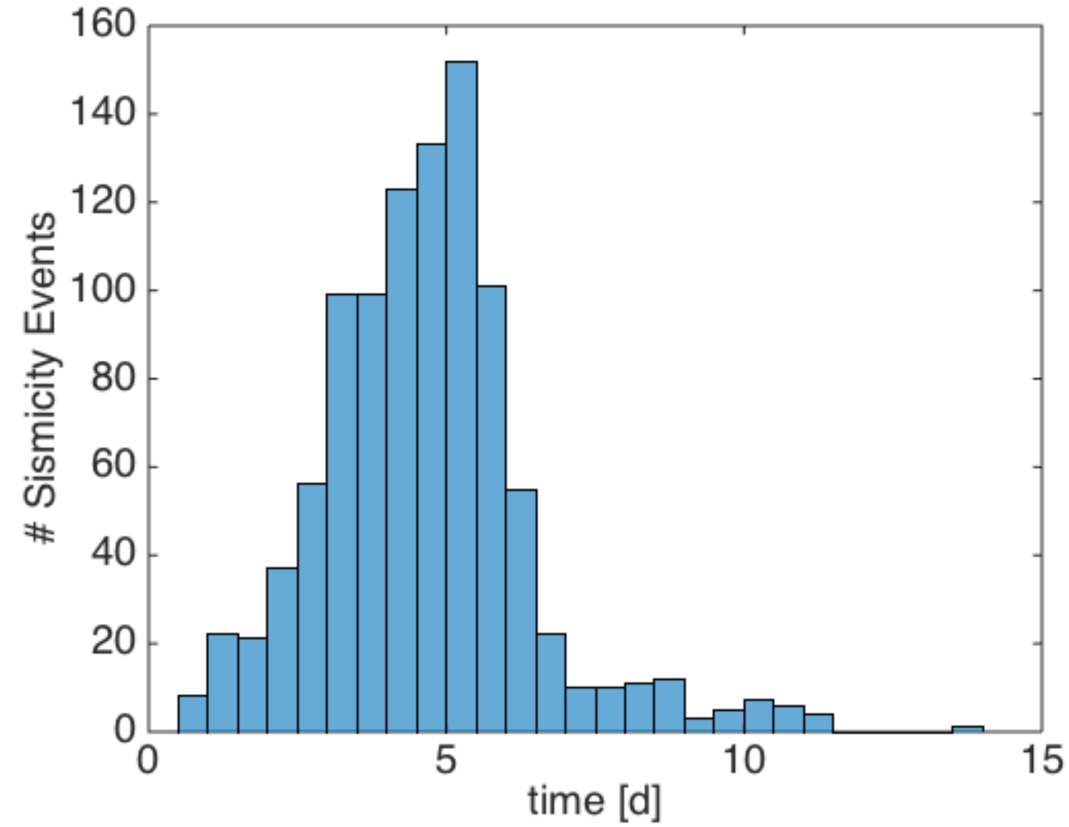
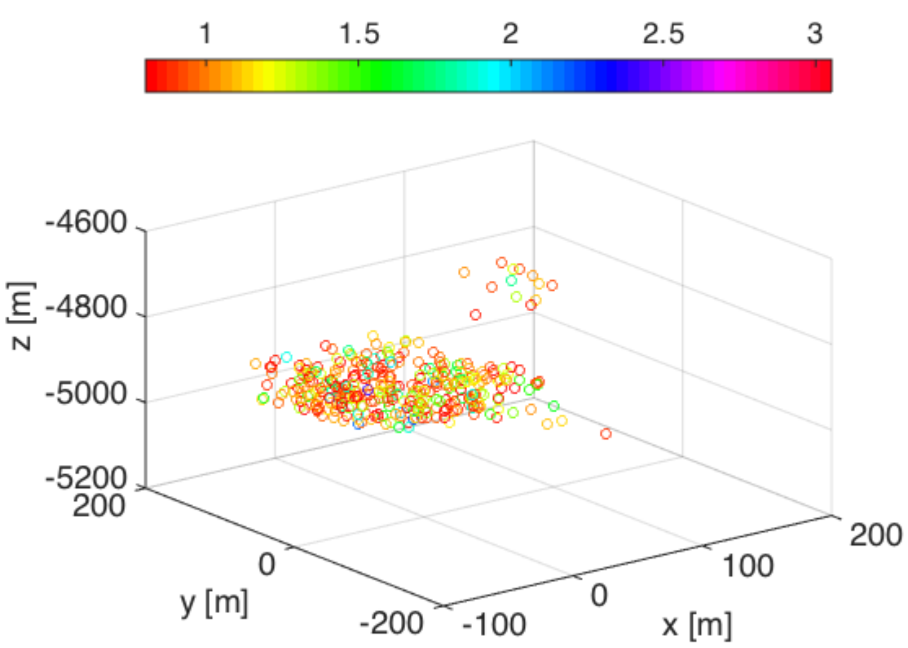
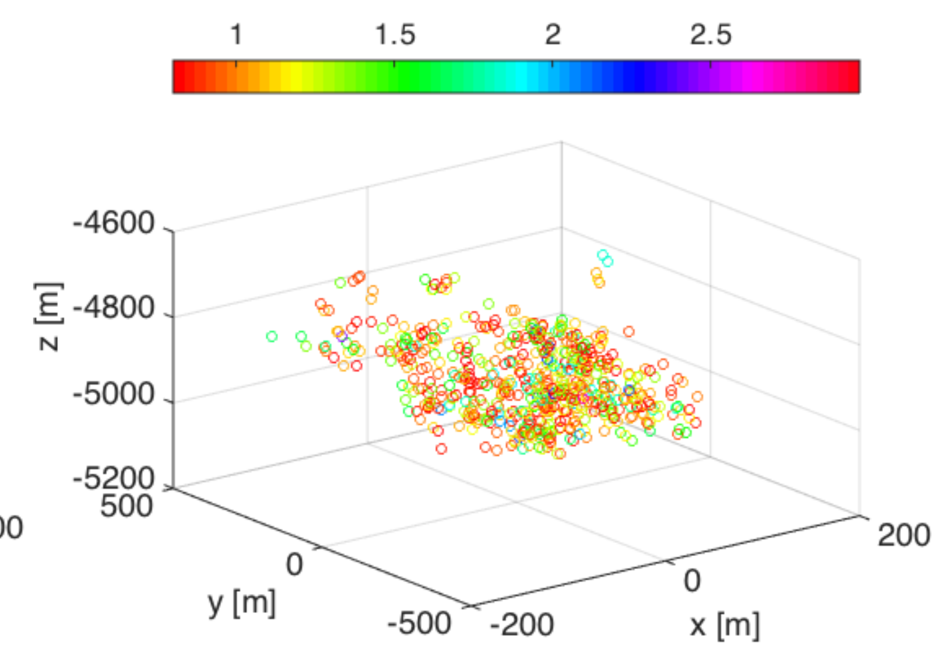




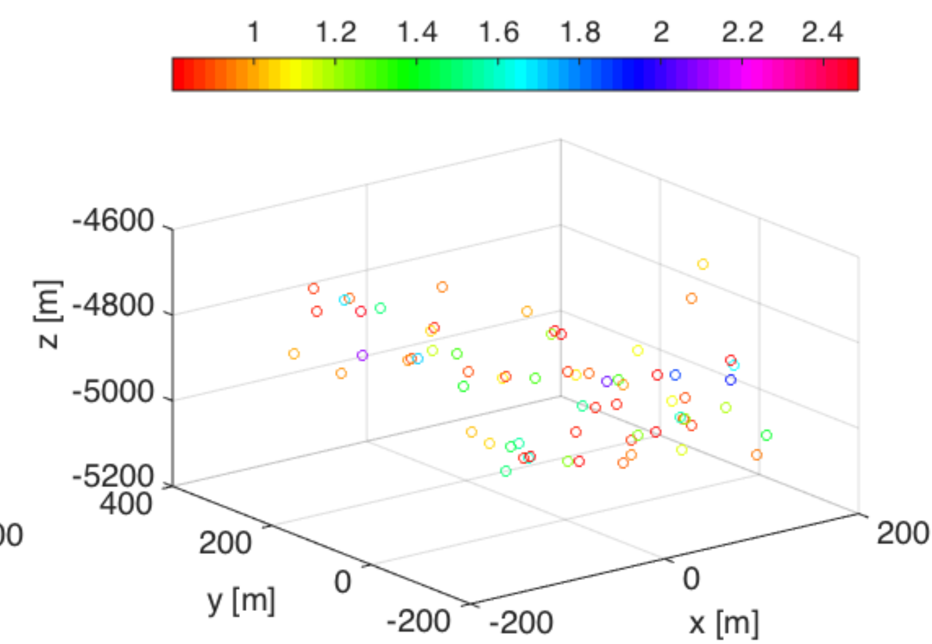
1-3 days



4-7 days



8-14 days



Probabilistic forecast

High uncertainty regarding the **in-situ conditions**.

High uncertainty regarding the **material properties**.

Monte Carlo (MC) simulations: allow for **probabilistic forecasts** for all possible in situ conditions and complicated scenarios.

MC simulations useful for estimating **expectations** arising from stochastic simulations

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MC simulations useful for estimating **expectations** arising from stochastic simulations

Standard MC

1. Draw N samples ω_n of the uncertain parameters.
2. Run N simulations and compute $P(\omega_n)$ for each solution.

$$\mathbb{E}[P] = \frac{1}{N}\sum_{n=1}^{N} P(\omega_n)$$

Probabilistic forecast: MC

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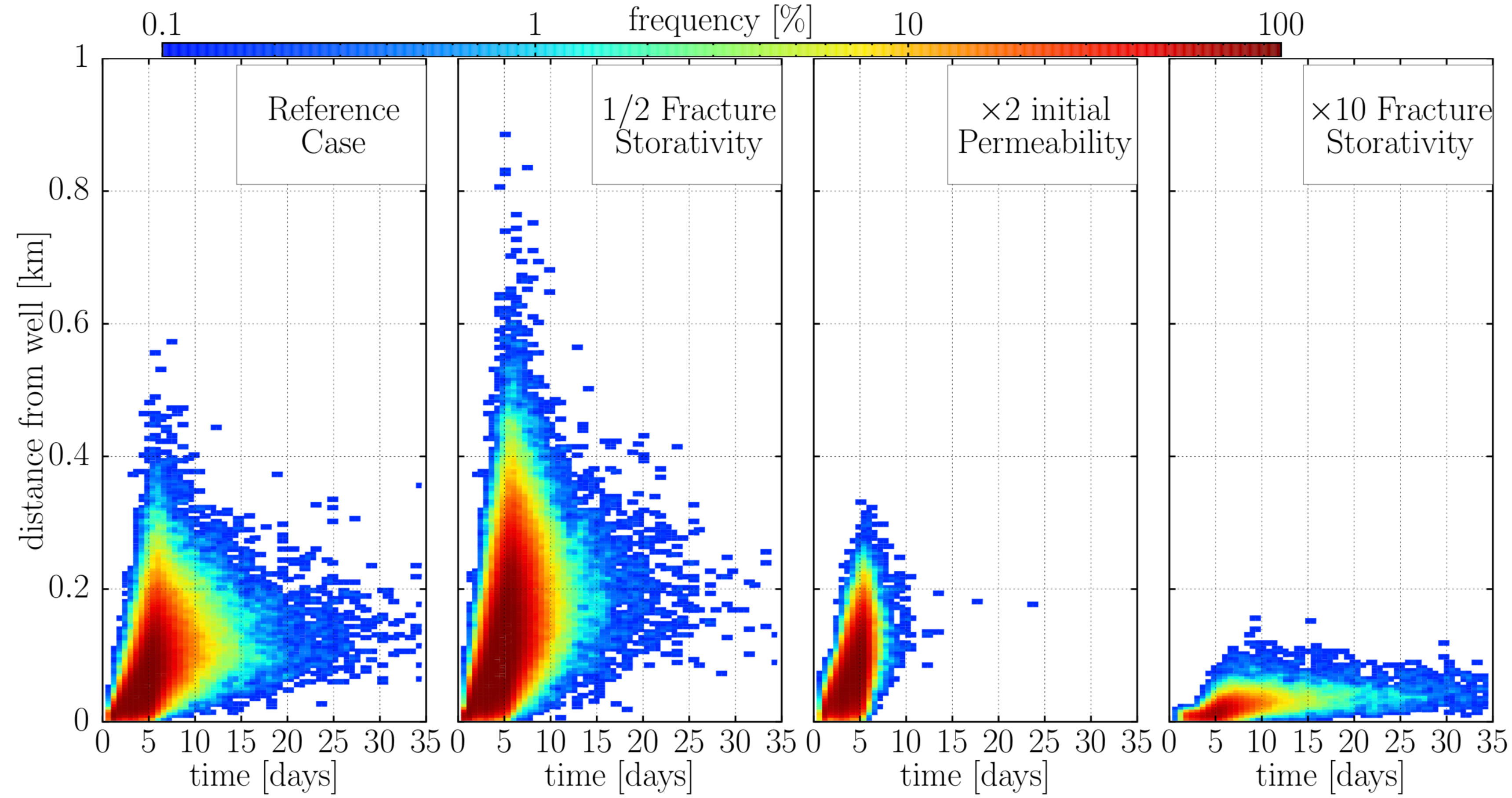
Sensitivity Analysis

$N = 250$



MC simulation (250 samples)	Mean seismicity ($M_w \geq 0.8$)	Difference from Reference	Furthest Hypocenter
Reference set of parameters	905	-	273 m
$1/4$ less fractures's density	1132	$+25\%$	312 m
$\times 2$ specific storativity (fractures)	536	-40.8%	179.1 m
$\times 10$ specific storativity (fractures)	71	-92.1%	64.7 m
$1/2$ specific storativity (fractures)	2126	$+134\%$	403 m
$\times 2$ permeability of fractures	863	-6.0%	277m
$\times 2$ initial permeability	530	-41.4%	218.1 m
$\times 4$ initial aperture	827	-8.7%	258 m
$\times 2$ post-shearing aperture	1201	$+32.7\%$	312 m
$\times 2$ stress drop	1156	$+27.7\%$	256 m

Dimitrios Karvounis, Schatzalp Workshop on Induced Seismicity, 5-8 March 2019, Davos, Switzerland

Standard MC

1. Draw N samples ω_n of the uncertain parameters.
2. Run N simulations and compute $P(\omega_n)$ for each solution.
3. **N needs to be $O(1/\epsilon^2)$ $\longrightarrow$ expensive.**

Multilevel MC

There is a sequence of approximations, $P_0, \ldots, P_{l-1}, P_l$, with increasing accuracy and computational cost.

$$E[P_L] = E[P_0] + \sum_{l=1}^{N_l} E[P_l - P_{l-1}],$$

with N_l being the number of samples on each level.

Probabilistic forecast

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The **MLMC** method **works** if:

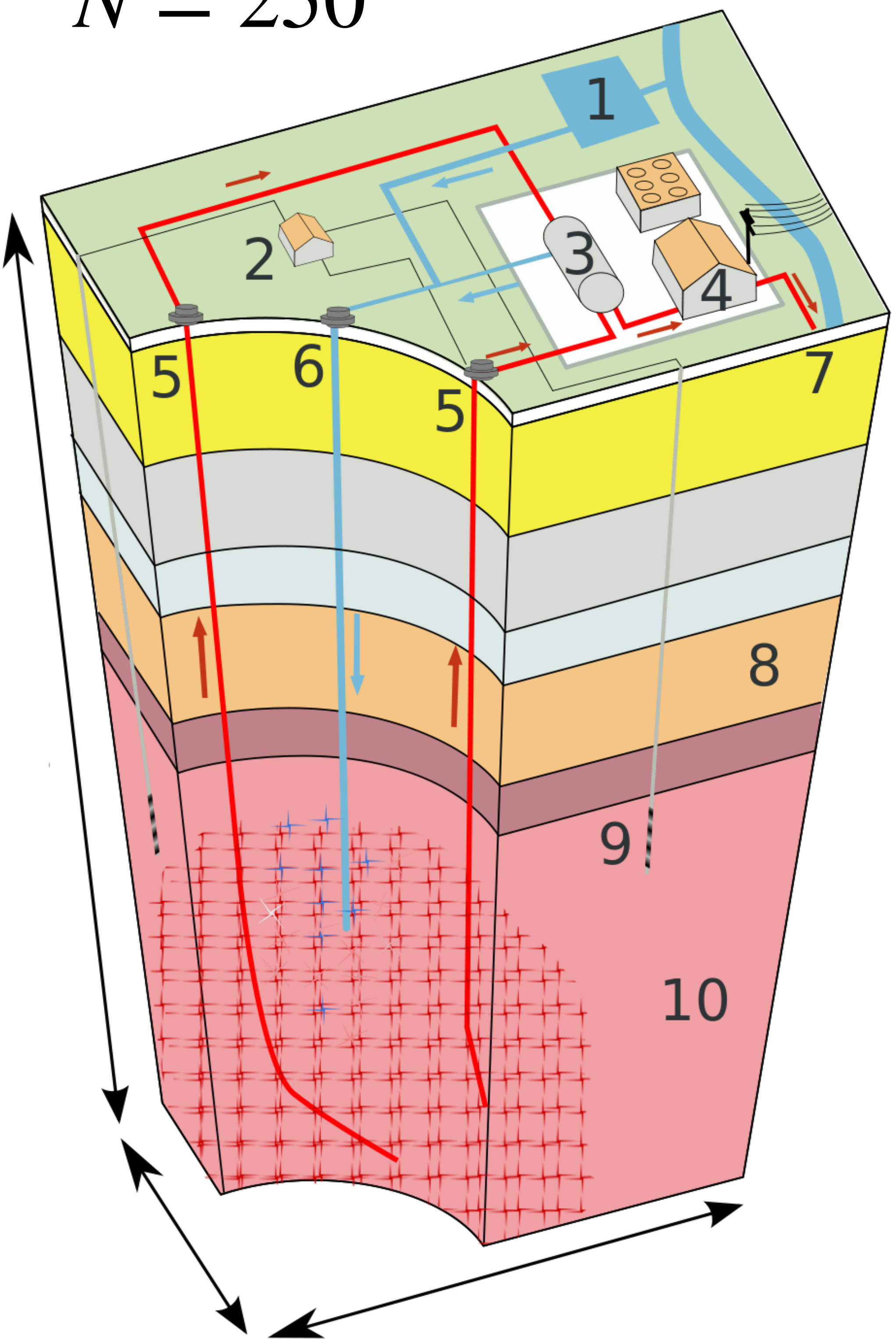
$$\mathbb{V}[P_l - P_{l-1}] \to 0 \text{ as } l \to \infty,$$

for the same underlying stochastic samples ω_n.

High correlation $\rho_{l,l-1} = \dfrac{\mathrm{Cov}(P_l, P_{l-1})}{\mathbb{V}(P_l)\mathbb{V}(P_{l-1})}$ **!**

Probabilistic forecast: MLMC

$N = 250$



3 levels:

Level 1: $\Delta x = 40$

Level 2: $\Delta x = 20$

Level 3: $\Delta x = 10$

$$\Delta t \sim \frac{\Delta x^2}{D}$$

with

$$D = \frac{K_b}{\phi_b \mu_b}$$

Probabilistic forecast: MLMC

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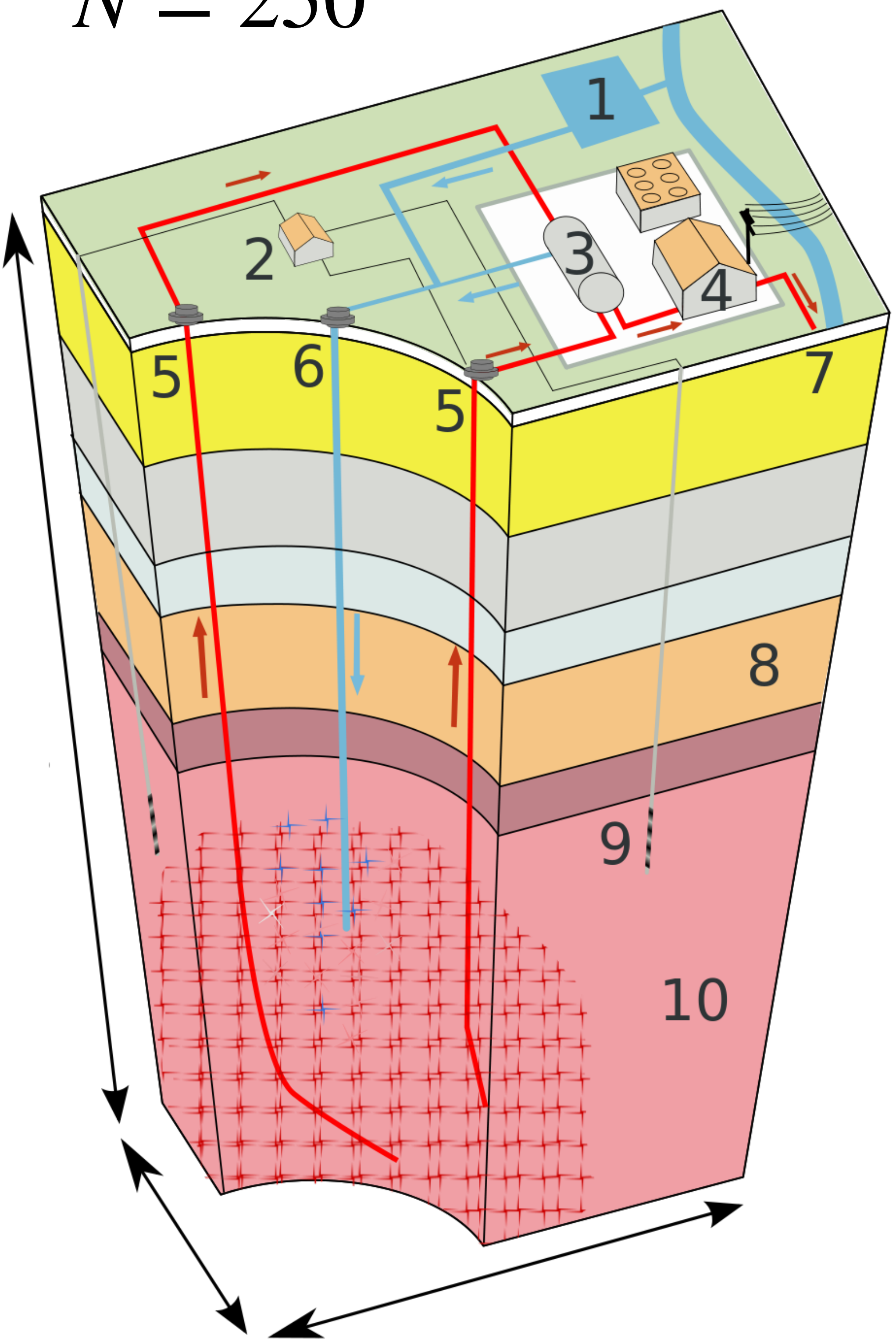

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$$\rho_{l,l-1} = \frac{\mathrm{Cov}(P_l, P_{l-1})}{\mathbb{V}(P_l)\mathbb{V}(P_{l-1})}$$

$$\rho_{12} = 0.75$$

$$\rho_{13} = 0.72$$

$$\rho_{23} = 0.77$$

Probabilistic forecast: MLMC

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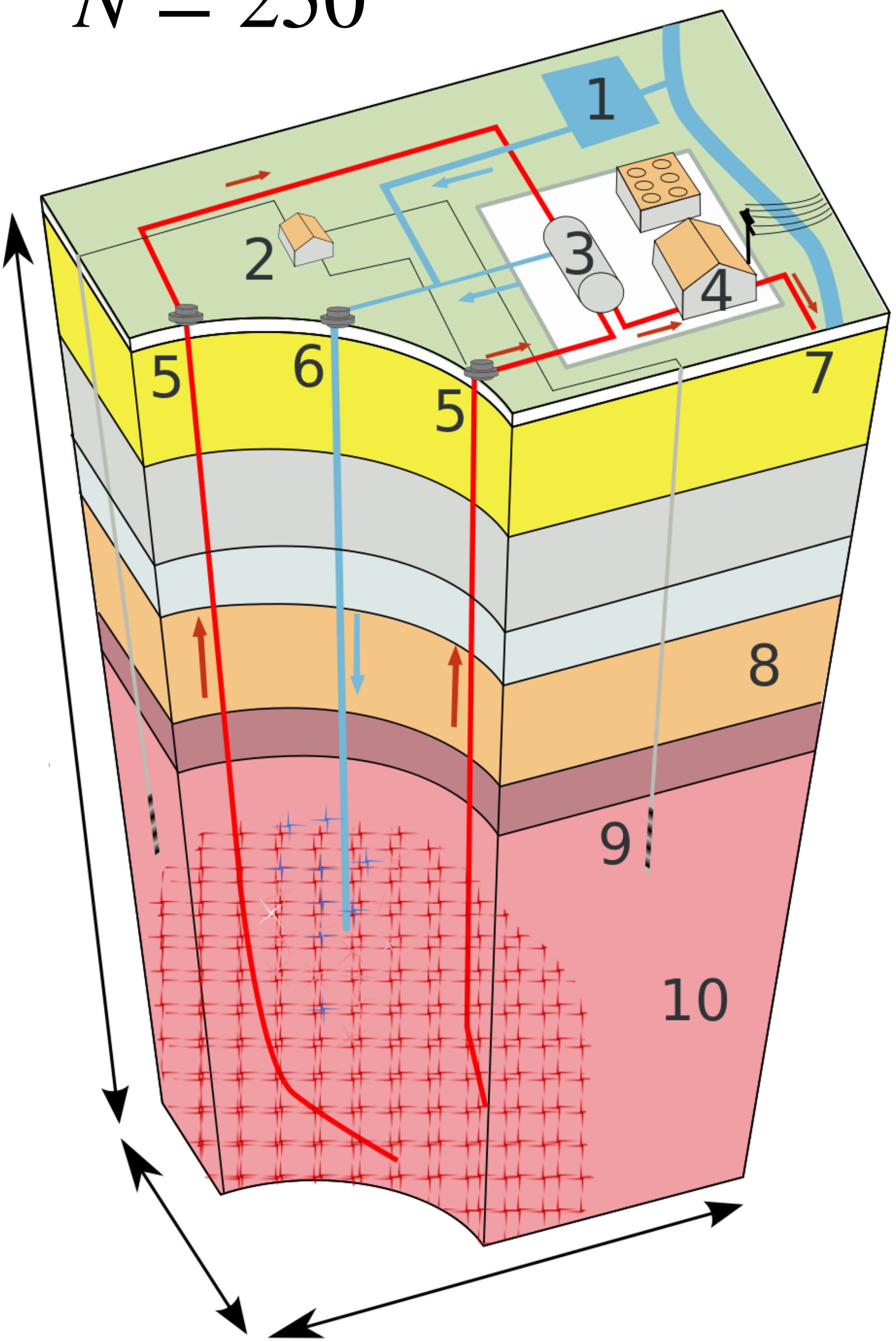
$N = 250$



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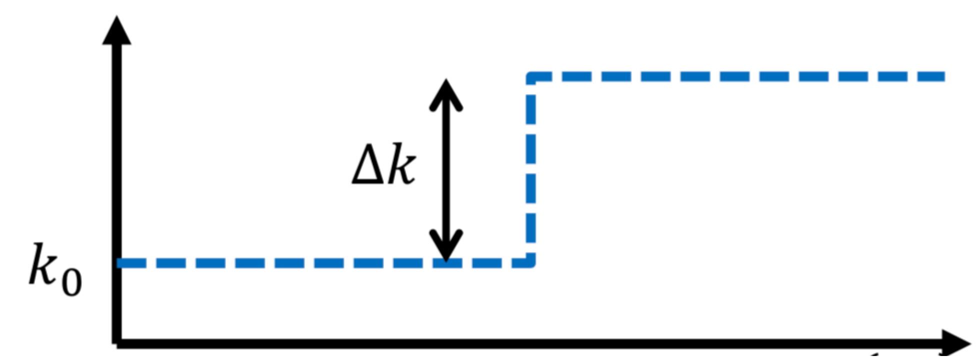
Discontinuities in the parameters!



Abrupt changes induced by **earthquakes**!

Conclusions

HM simulations may be used to

- **forecast seismicity** and reservoirs performance,
- **highlight** the **limitations** of the modelled processes.

MC Simulations ⟶ **high uncertainty** of the **parameters** and i**n-situ conditions**.

Future work: **MultiLevel MonteCarlo** methods.

Software Libraries

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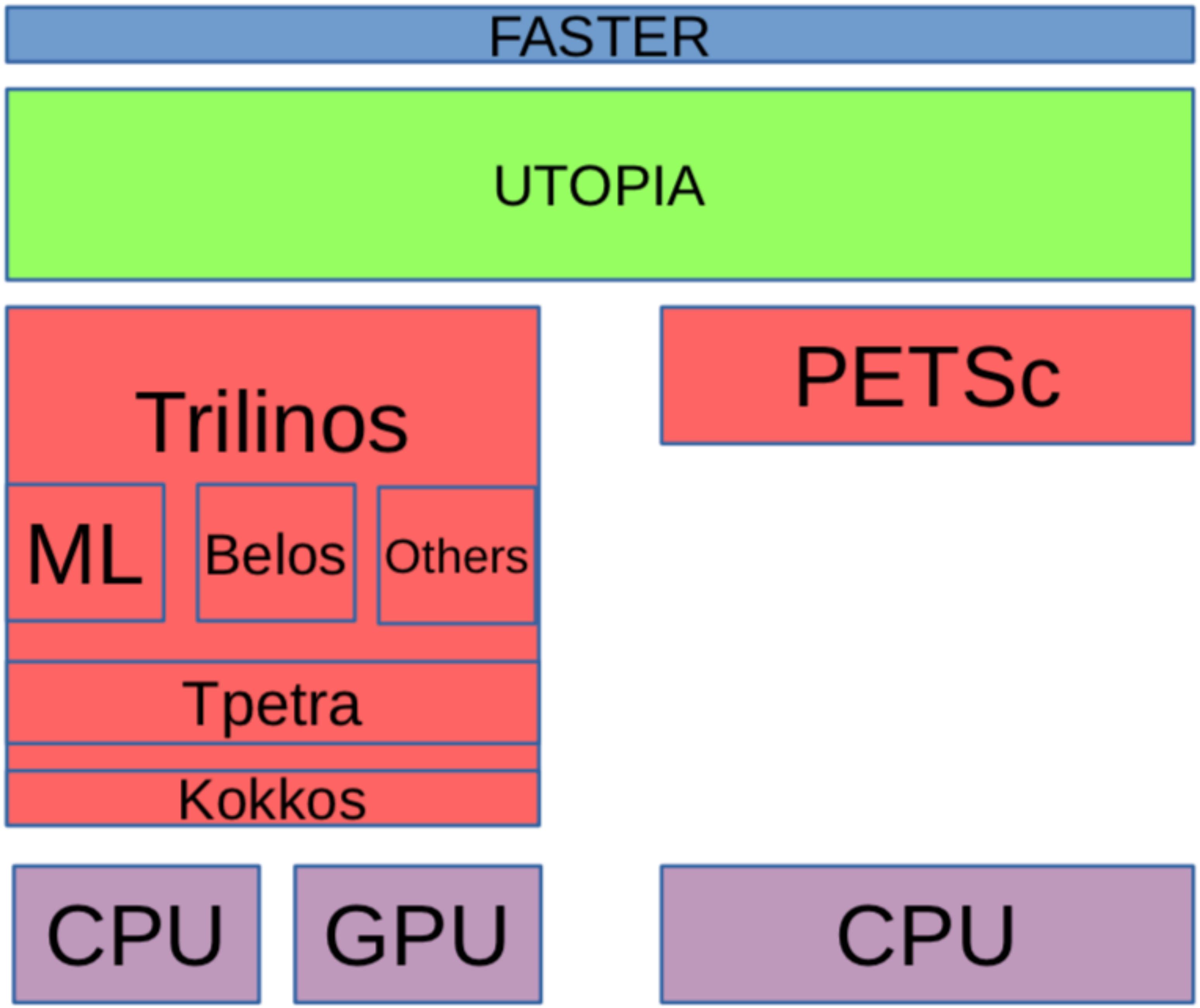

Discretization of the mathematical model (FV)

https://bitbucket.org/zulianp/utopia

Linear algebra library

References

Karvounis, PhD Thesis, ETH, 2013, https://doi.org/10.3929/ethz-a-009967366

Karvounis, Wiemer, Decision Making Software for Forecasting Induced Seismicity and Thermal Energy

Giles, Michael B. "Multilevel monte carlo path simulation." *Operations Research* 56.3 (2008): 607-617.

Thank you for your attention

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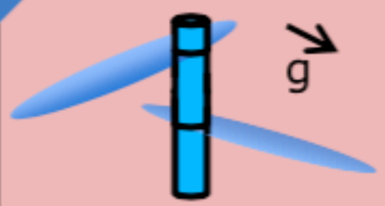
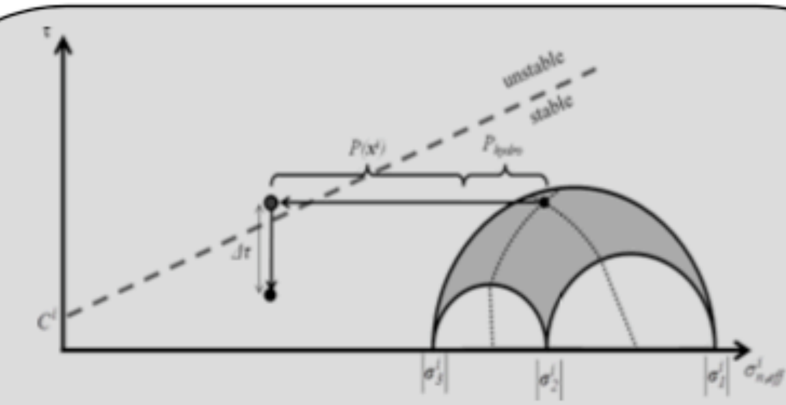
To summarise

Start

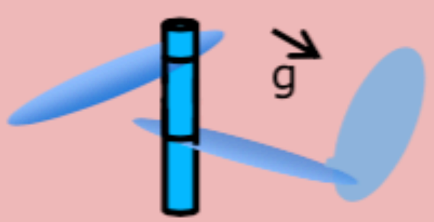


HFR-Sim approximates the pressure field inside the EGS reservoir at each time-step.

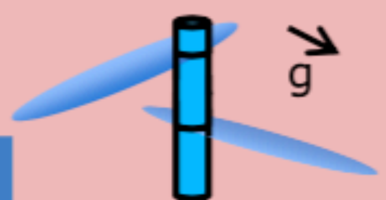


The Mohr-Coulomb failure criterion is applied at potential hypocenters. Observed statistics for the orientation, the stress conditions, the fracture density and the rate of seismicity are taken into account.

When the criterion is satisfied, a magnitude M of the corresponding earthquake is sampled according to the provided b-value. By sampling stress drop, the size of the ruptured area can be approximated.



If M is larger than the threshold value, then a discrete fracture with high permeability is added in the HFR-Sim flow model and with the corresponding orientation size.

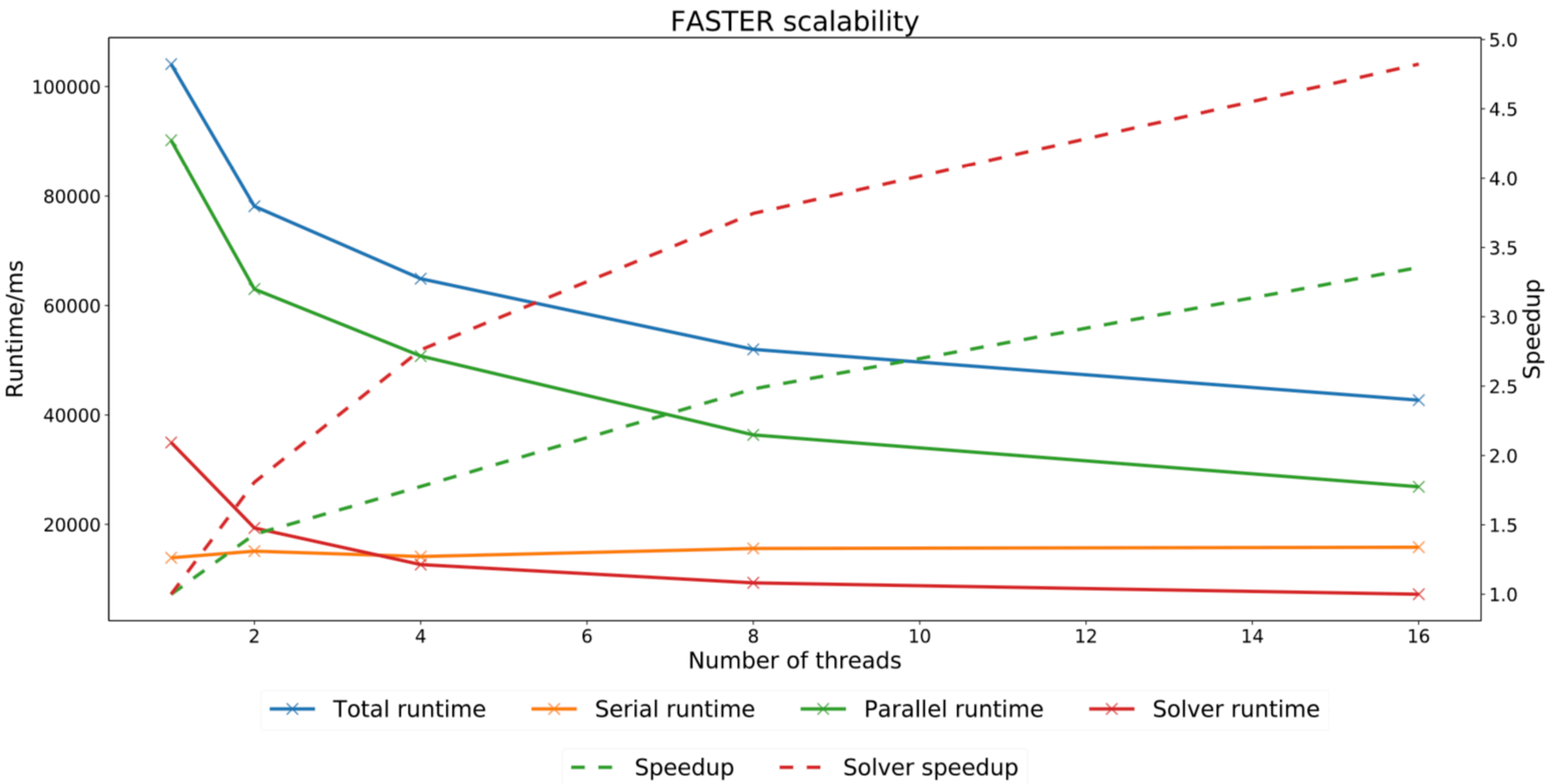


If M is smaller than a threshold value then the ruptured surface is not represented discretely but it is upscaled.

End

Dimitrios Karvounis

Scalability



CSCS

CSCS Nur Feidel, Andreas Fink, Patrick Zulian, PASC Conference 2018