Nantes, France, May 19-22, 2026

Uncertainty Quantification of Fluid Migration in Fault Zones for Geologic CO_2 Sequestration

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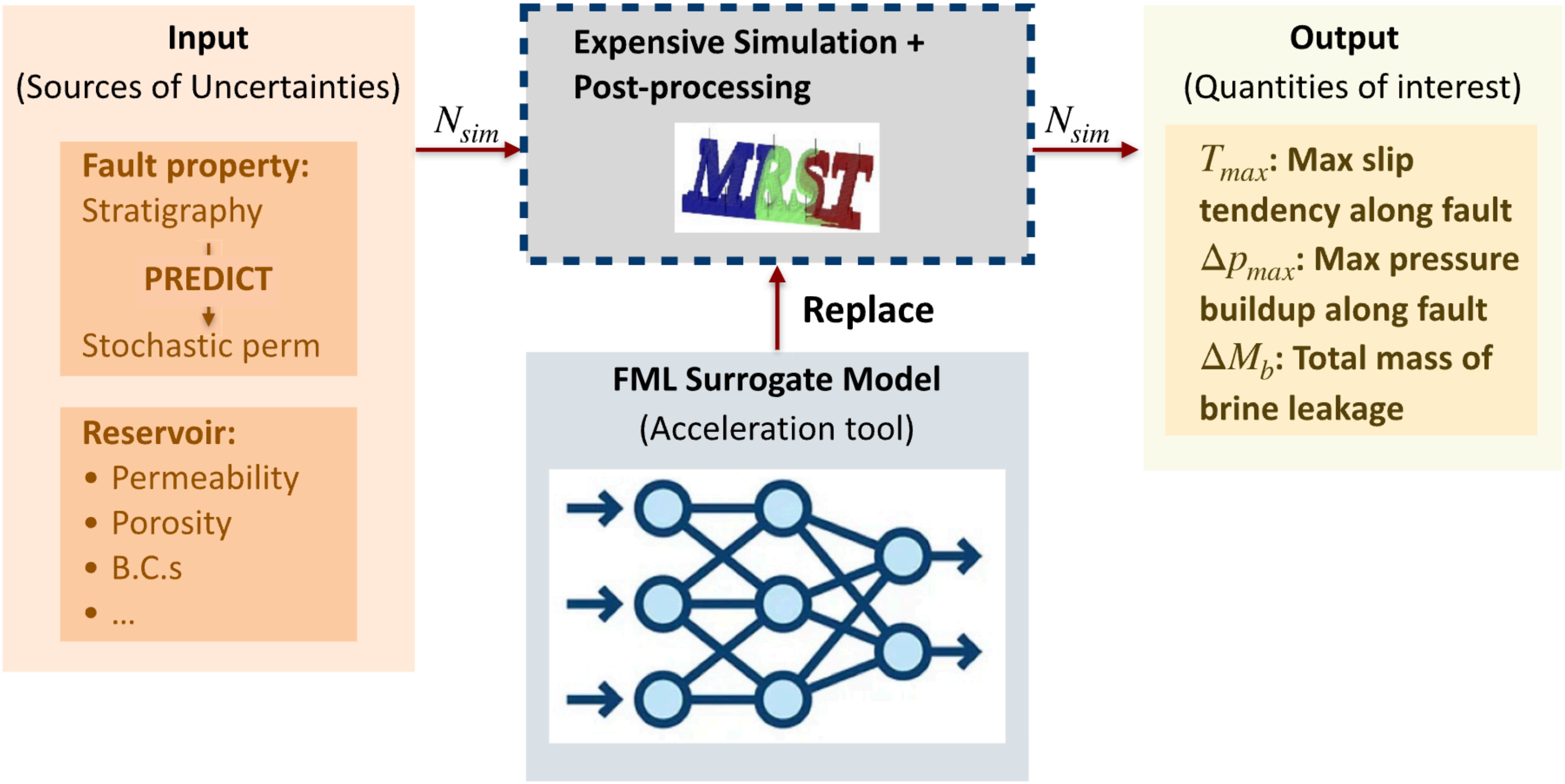
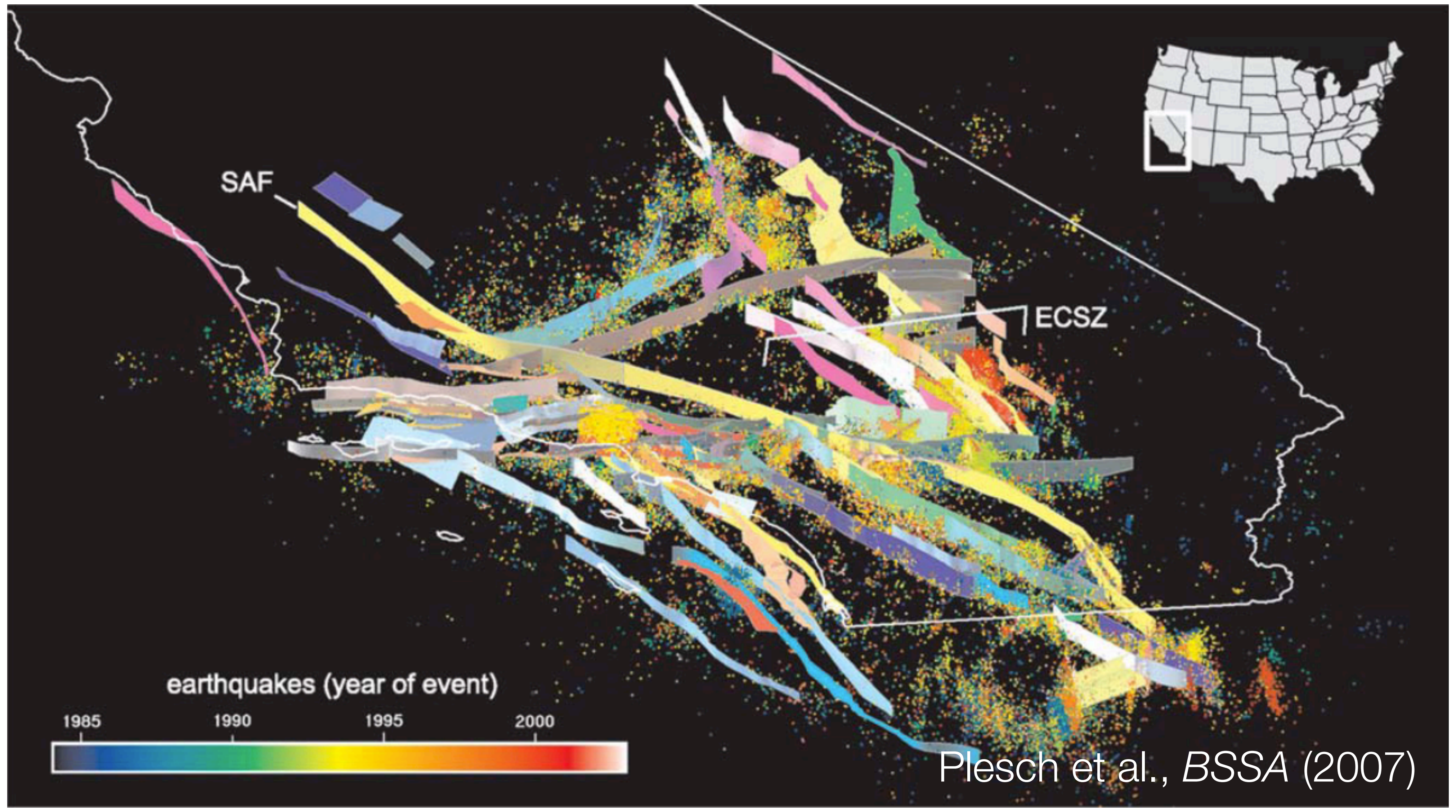
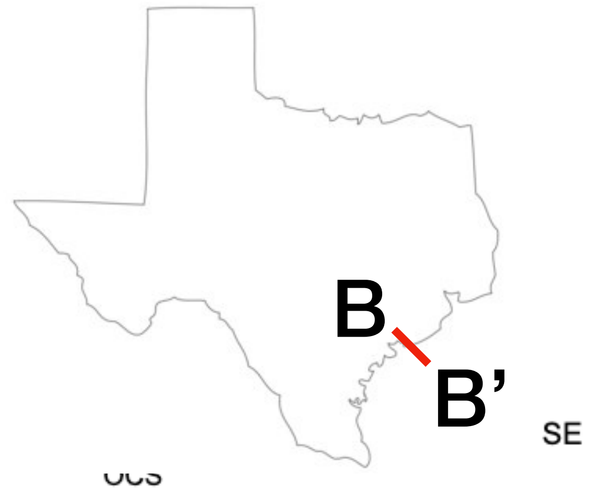
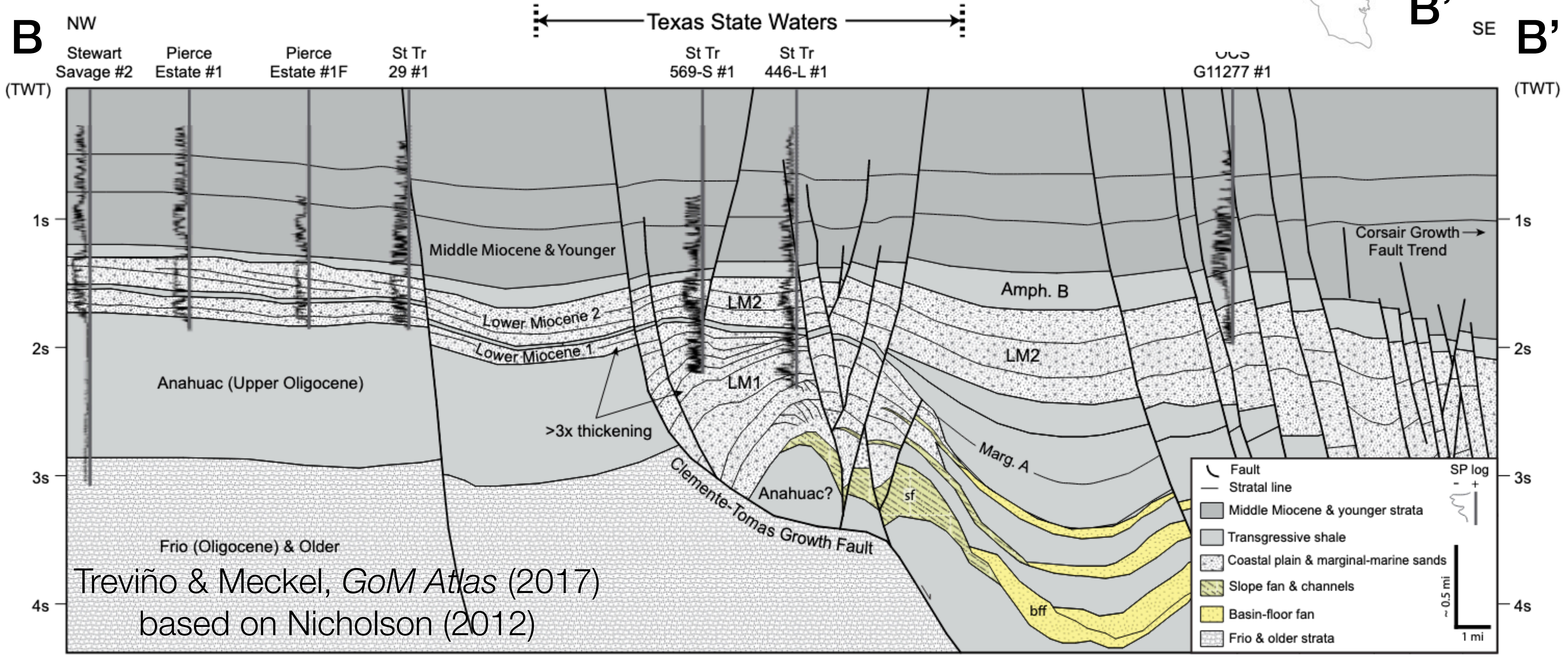


The subsurface is complex, with faults as key structural component



Plesch et al., *BSSA* (2007)

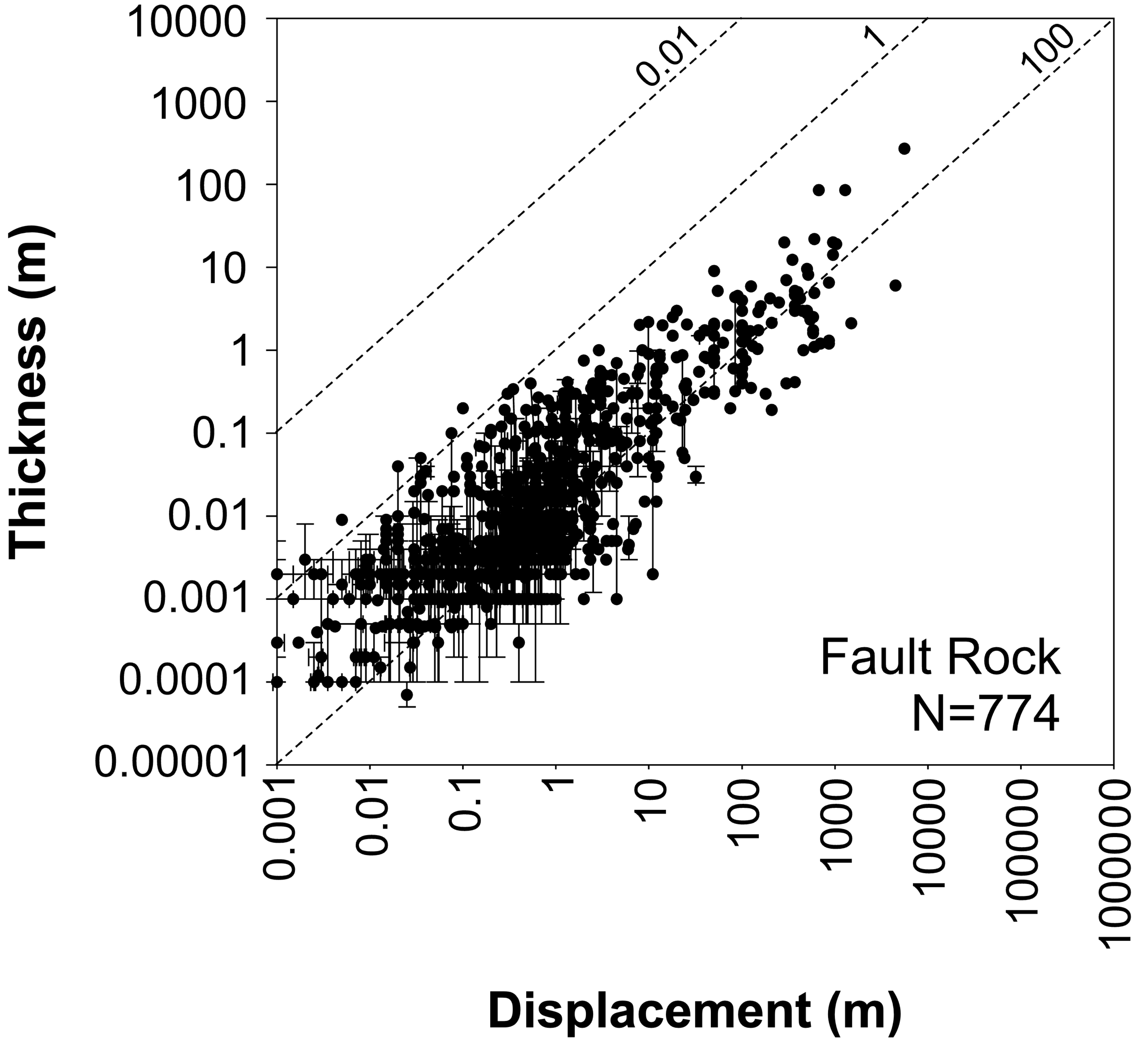




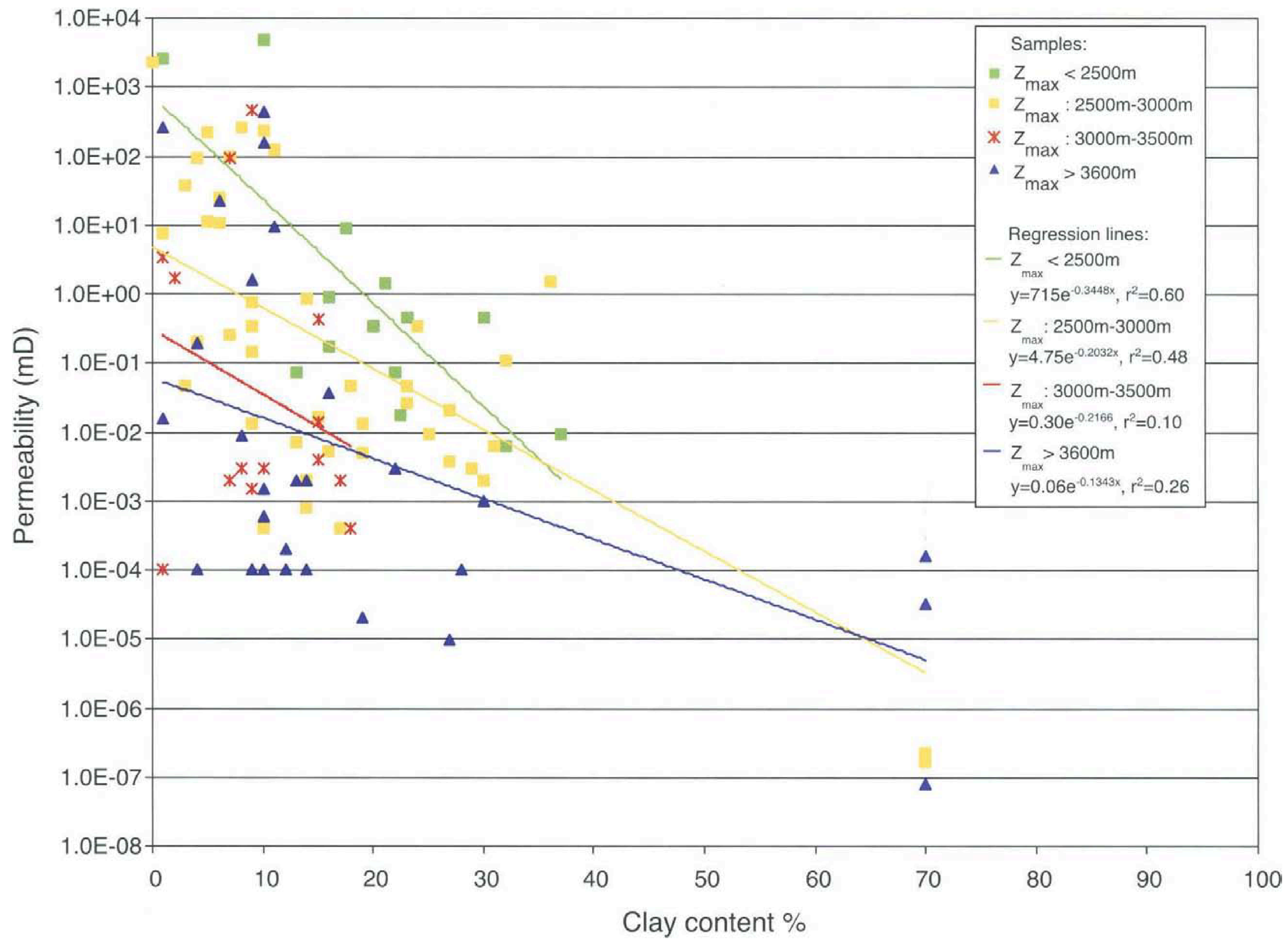
Treviño & Meckel, *GoM Atlas* (2017)
based on Nicholson (2012)

- Faults control geologic hazards in geothermal energy, CO_2 sequestration & H_2 storage
- Scaling-up these technologies is not possible if the guidelines require “avoiding faults”

Fault properties in sedimentary rocks are typically uncertain (by multiple orders of magnitude)

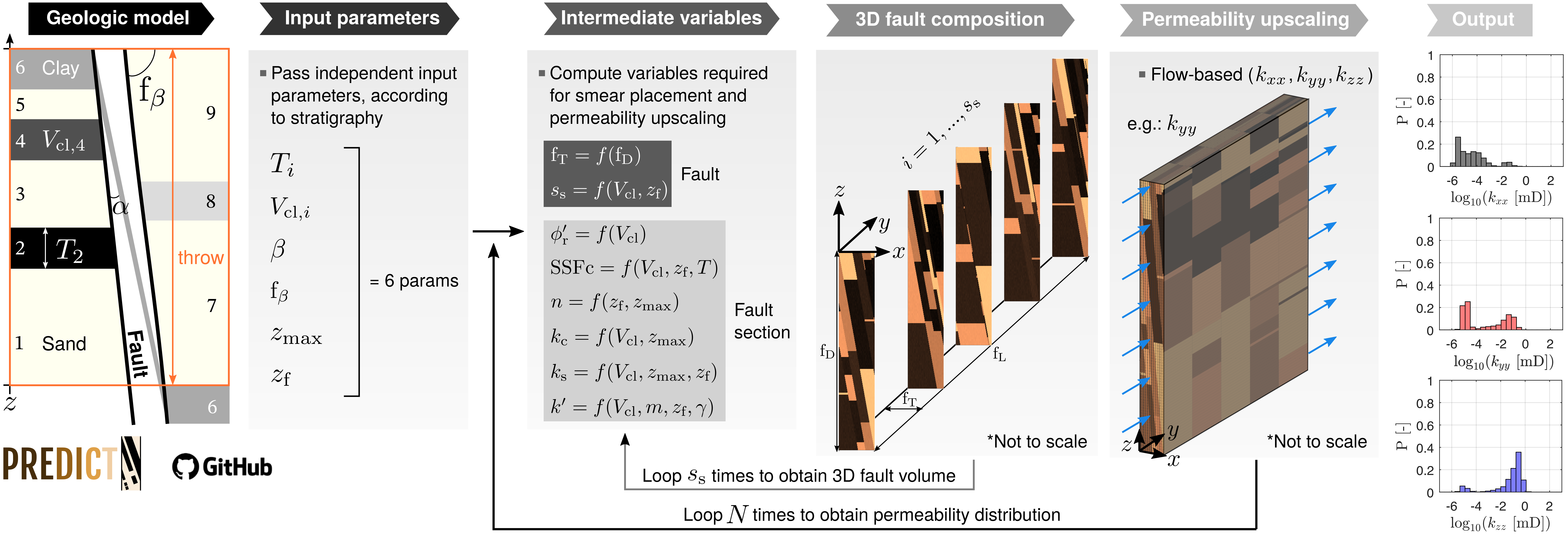


Childs et al., *JSG* (2009)



Sperrevik et al., *NPFSP* (2002)

New methodology: PREDICT, a stochastic approach to model the fault permeability tensor with uncertainty



- Provides a geologically-realistic link between the stratigraphy, the fault zone materials, and flow properties
- Flow-based upscaling to determine the main directional components of the fault perm tensor

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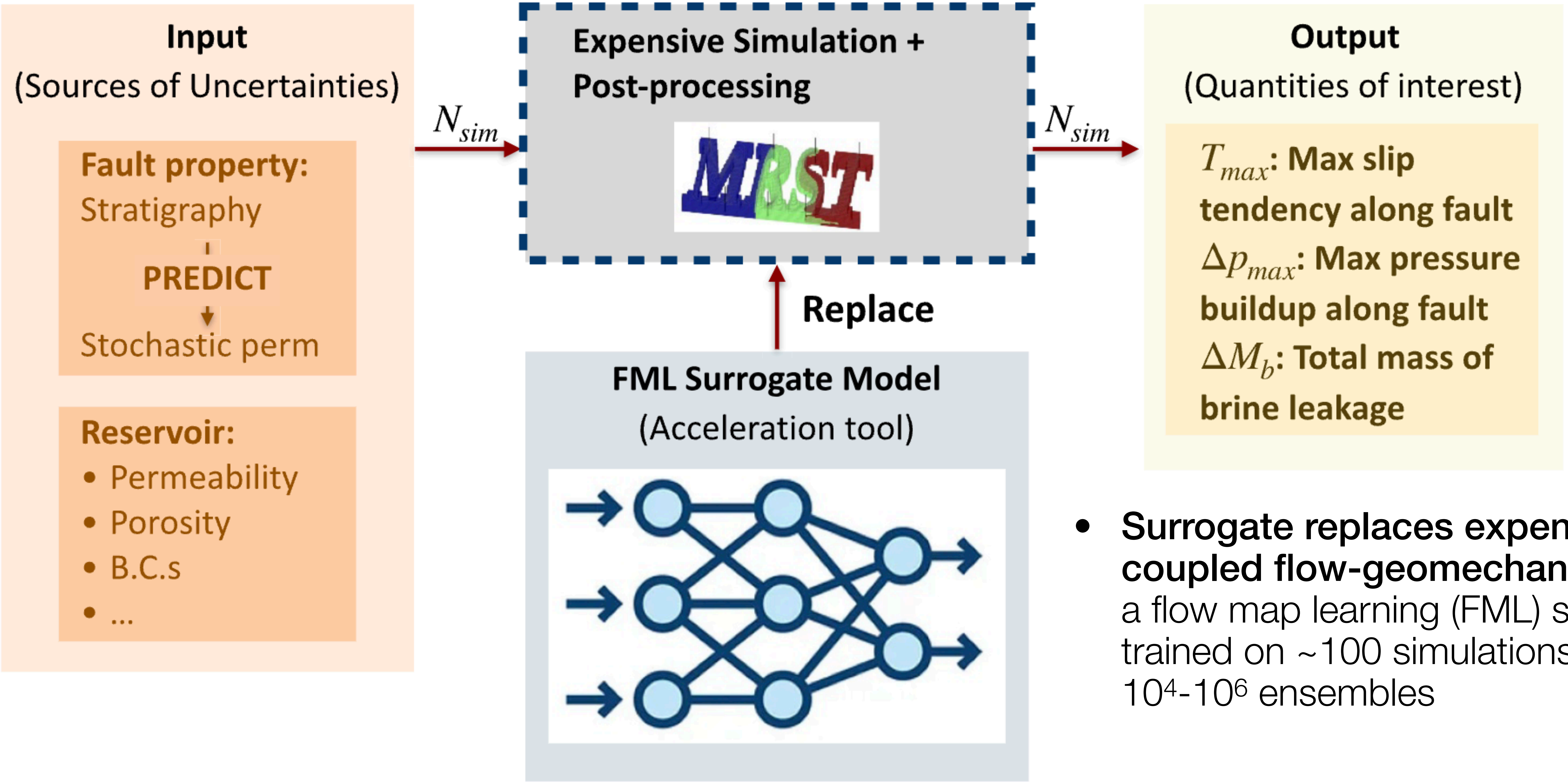
Saló-Salgado et al., *Geology* (2023)

Coupling PREDICT with a deep-learning surrogate enables UQ



- **Surrogate replaces expensive coupled flow-geomechanics models**: a flow map learning (FML) surrogate trained on ~100 simulations enables 10^4-10^6 ensembles

Problem setup: CO_2 injection in a faulted aquifer with uncertain properties

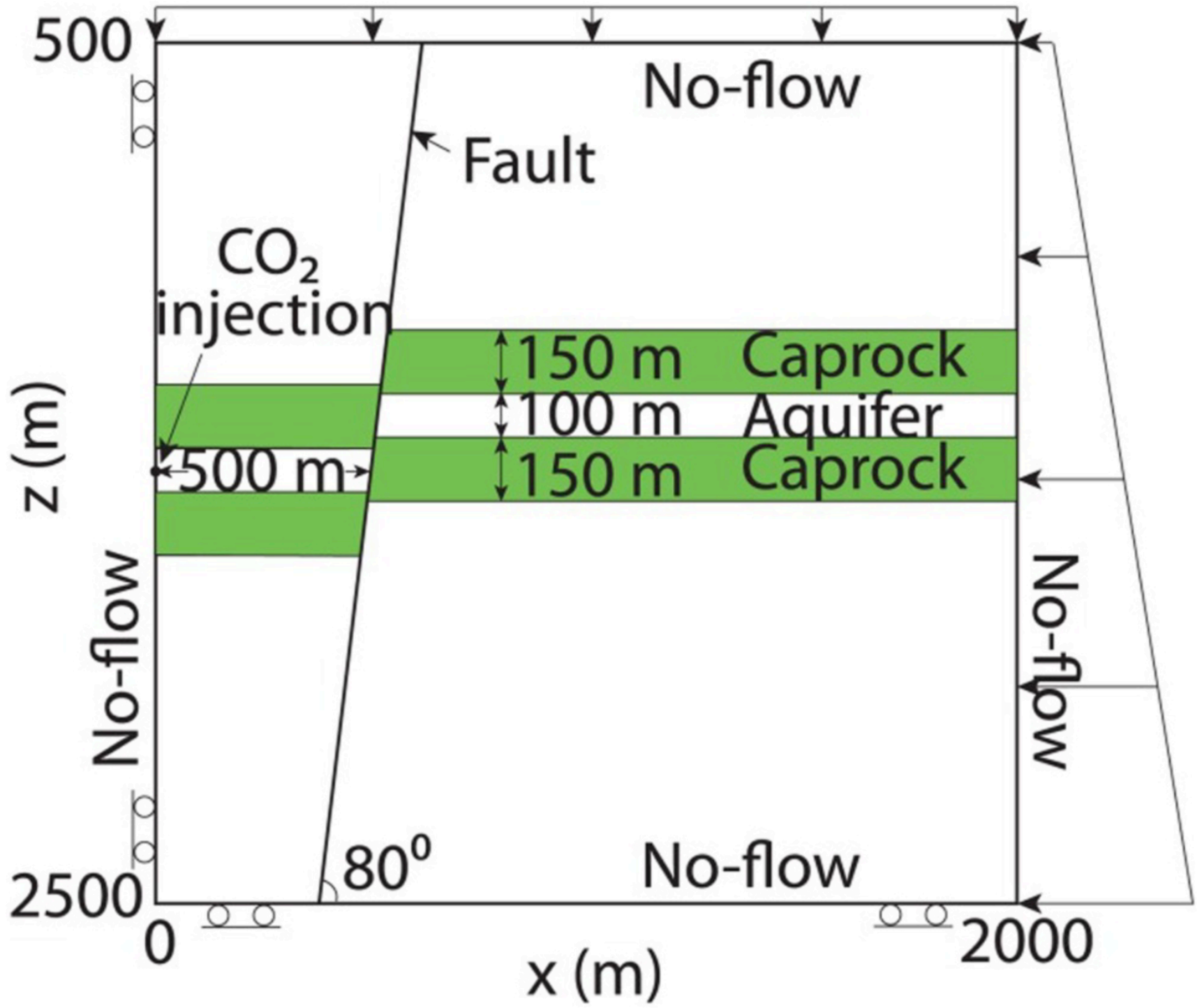
- **Physics**: coupled multiphase flow + geomechanics
- **Setup**: CO2 injection at 1500 m, normal fault dipping 80°, simulate until slip ($T_{s,\max} = \mu_s = 0.6$)
- **Uncertain parameters (14)**: fault perm tensor (10 from PREDICT, corr.) + reservoir properties (λ, k_s, φ_s, c_r).

Governing equations

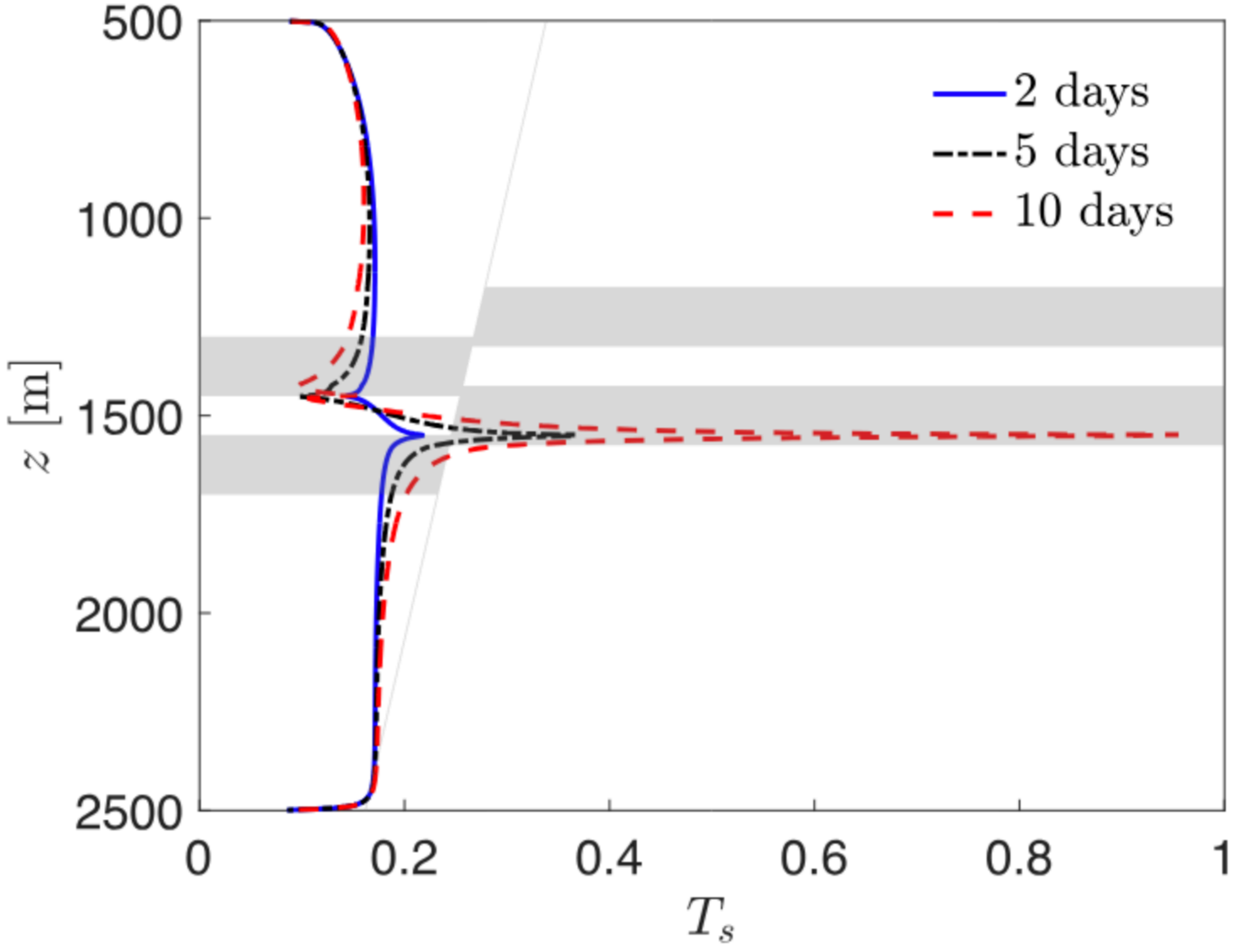
$$\frac{dm_\alpha}{dt} + \nabla \cdot \mathbf{w}_\alpha = \rho_\alpha f_\alpha$$

$$\nabla \cdot \boldsymbol{\sigma} + \rho_b \mathbf{g} = \mathbf{0}$$

$$T_{s,\max} = \frac{\tau}{\sigma'_n}$$



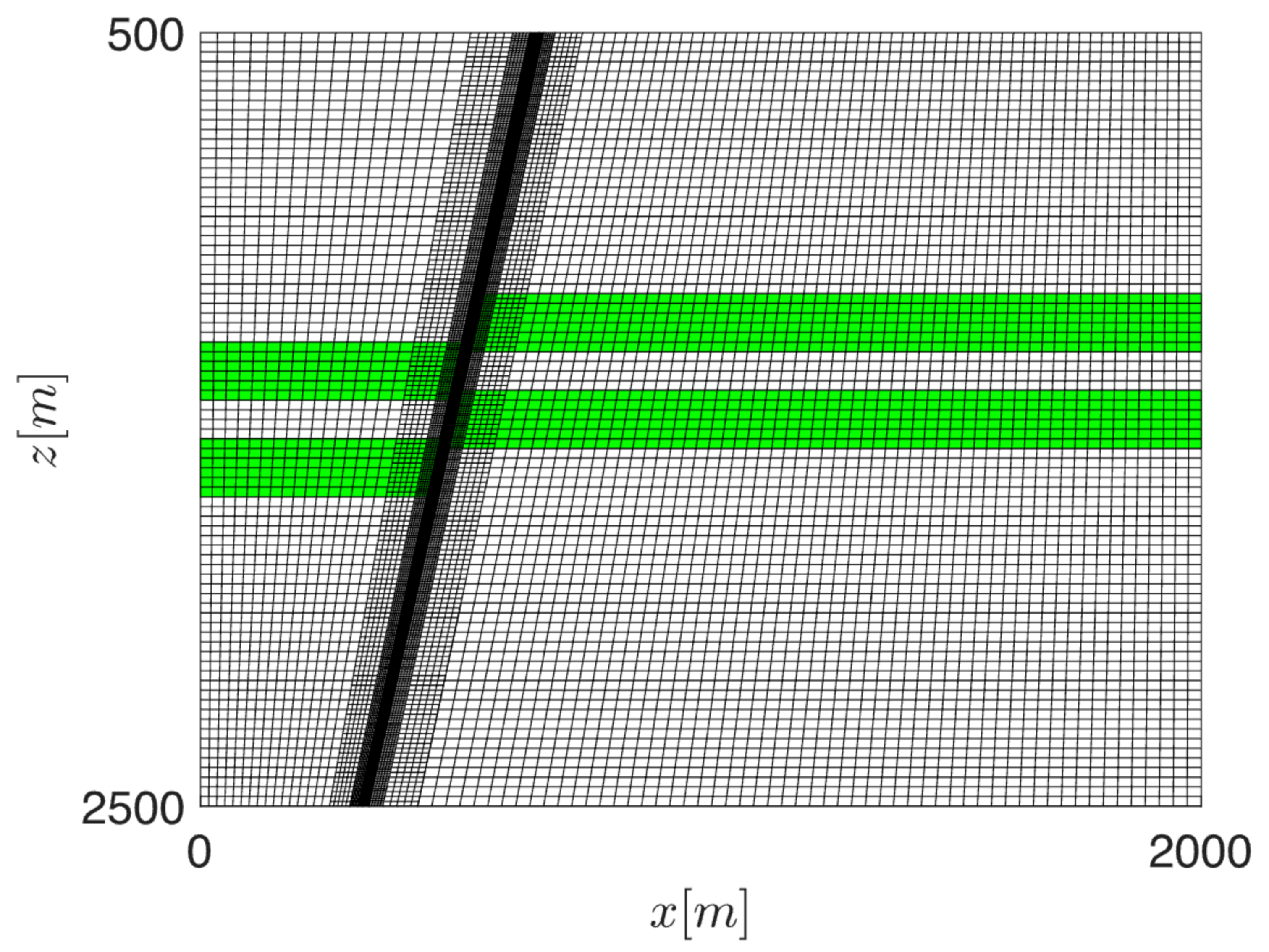
Cappa & Rutqvist, *GRL* (2011)

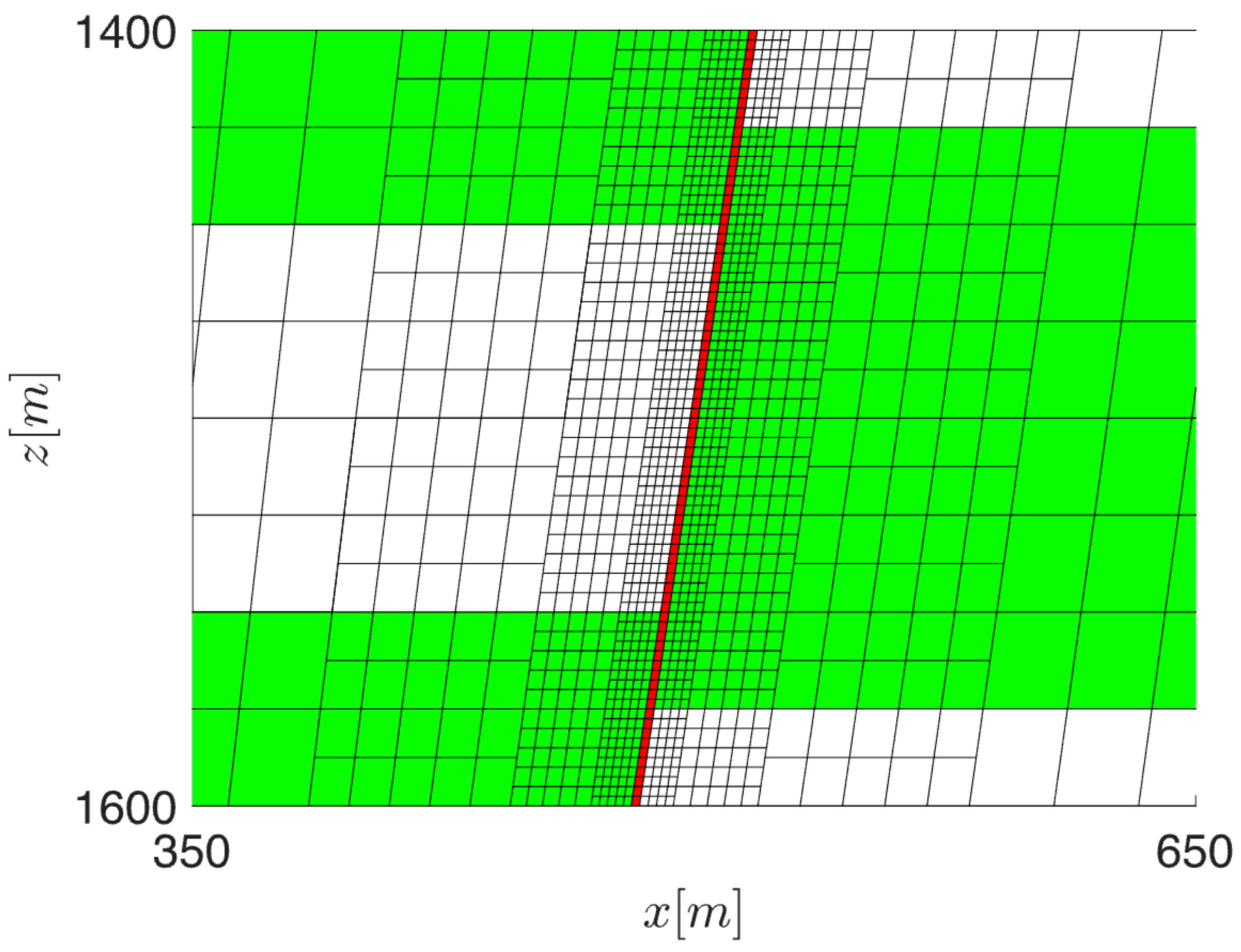


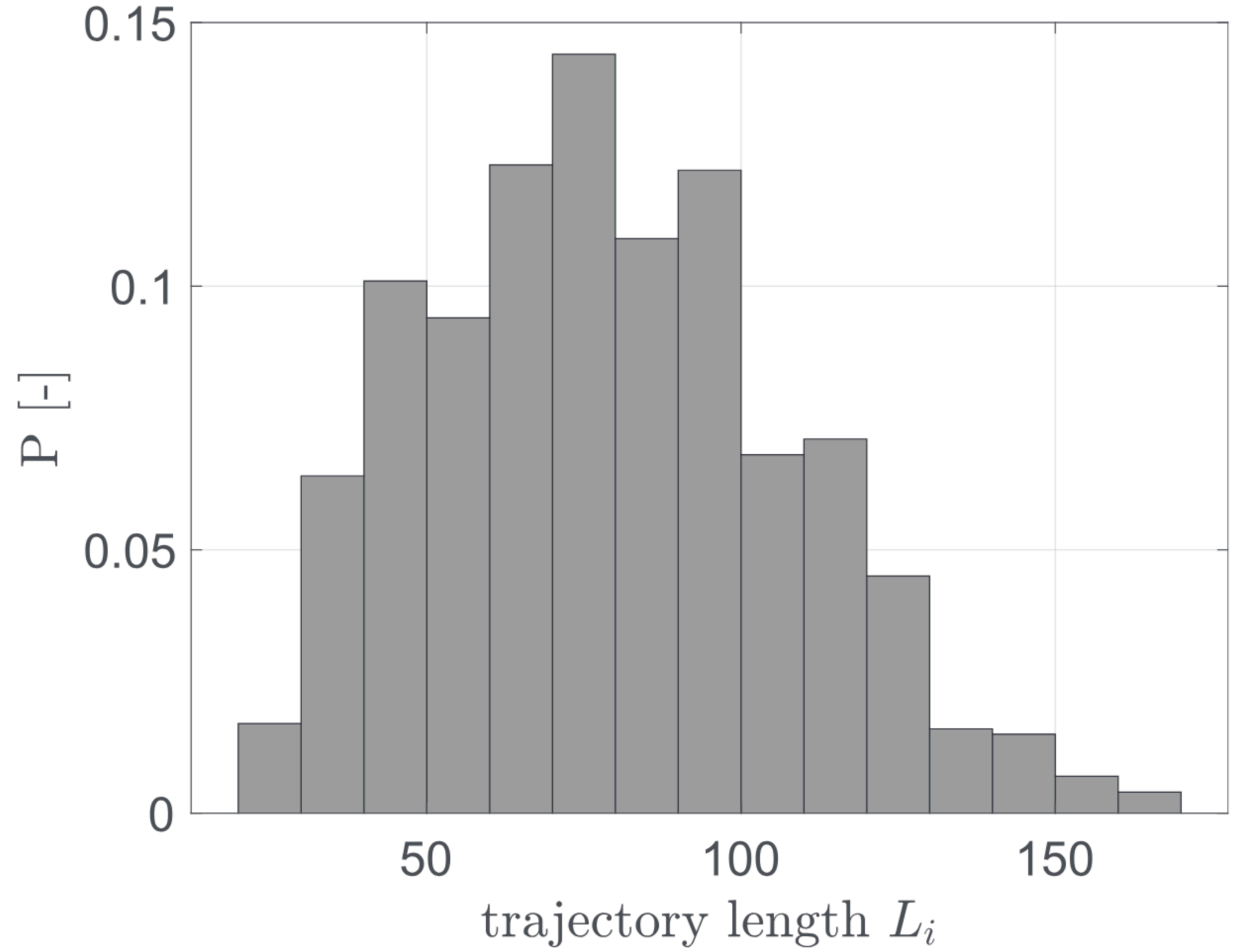
Lu et al., *WRR* (2025)

Training data: MRST simulations + space-filling design

- N_{budget}: 100 physics-based, coupled simulations with **`MRST`** (`ad-mechanics` module). ~5 CPU-hours each
- Space-filling design: Selects N_{budget} from a larger candidate space, maximizing coverage (modified from Johnson et al., *JSPI*,1990)
- Each trajectory runs until slip ($T_{s,\max} = \mu_s = 0.6$)







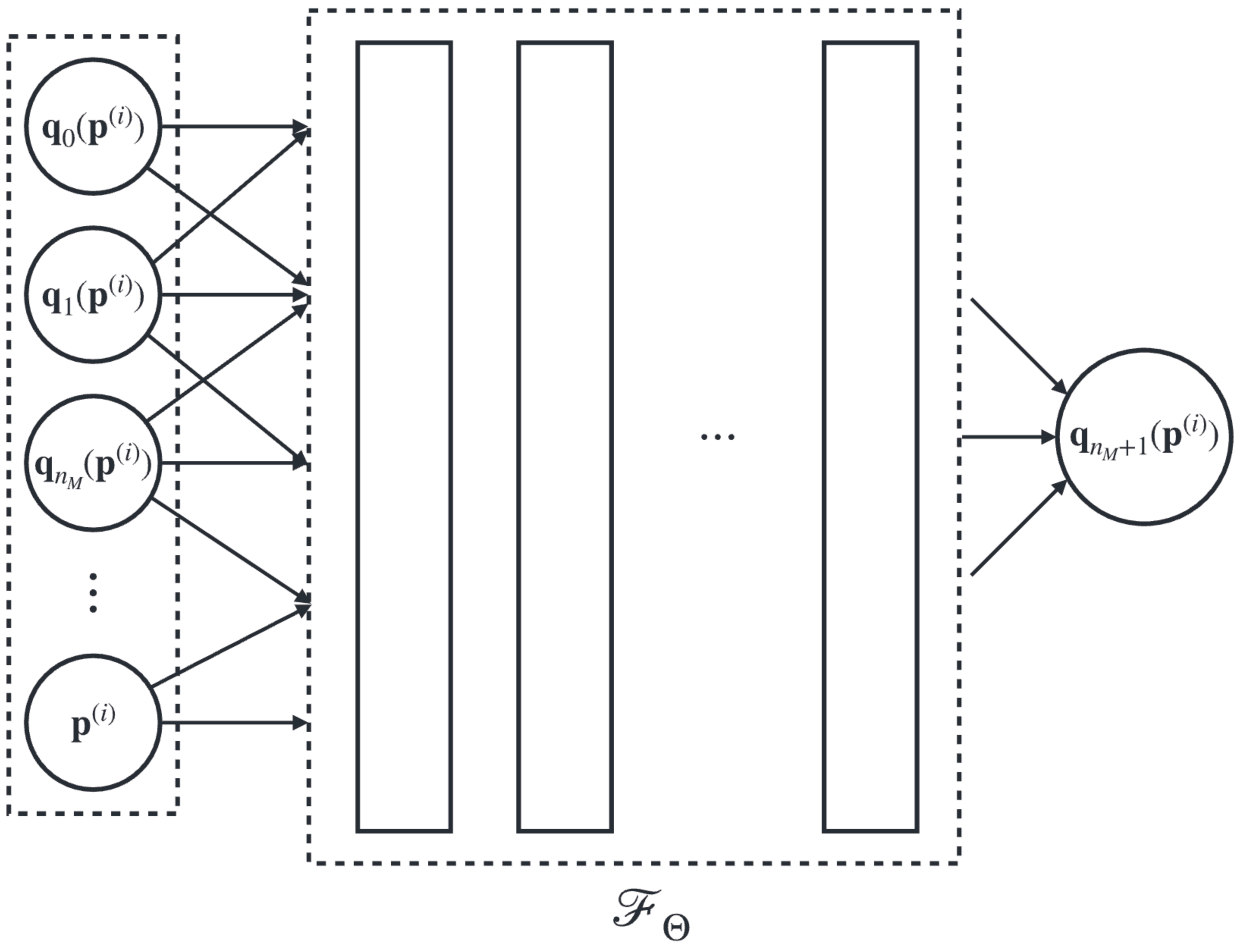
Flow map learning (FML): time-marching surrogate on the QoIs

- We learn a **time-marching map directly on QoIs** (not the full state field)

- **Memory terms** (n_M = 20 steps) compensate for the QoIs being a projection of the full state. Multi-step loss improves stability

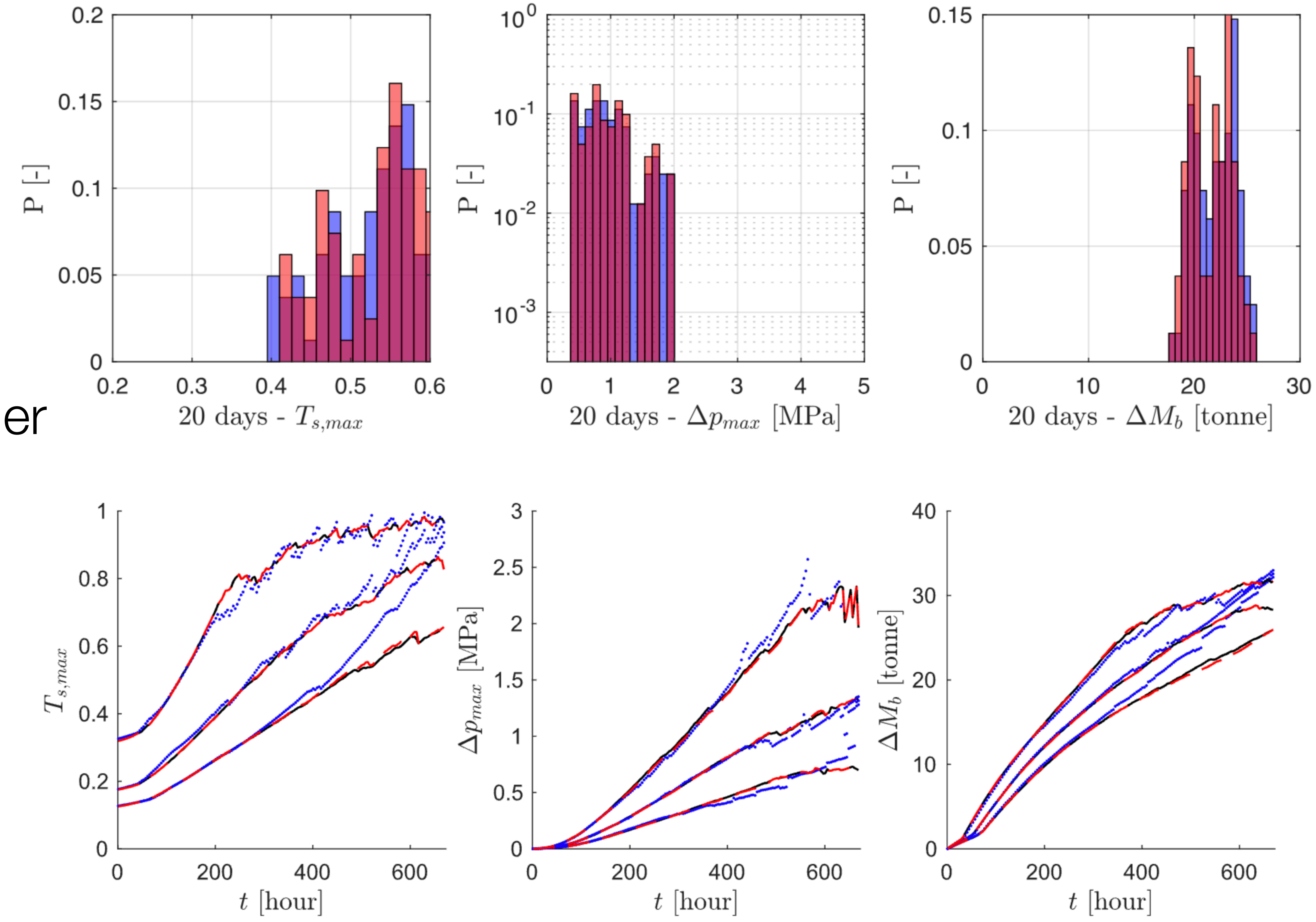
- DNN architecture: 10 neurons per layer (~580 parameters). **Ensemble** of 10 averaged at inference.

$$\mathbf{q}_{n+1}(\mathbf{p}) = \mathcal{F}_{\Theta}(\mathbf{q}_n, \ldots, \mathbf{q}_{n-n_M}; \mathbf{p})$$



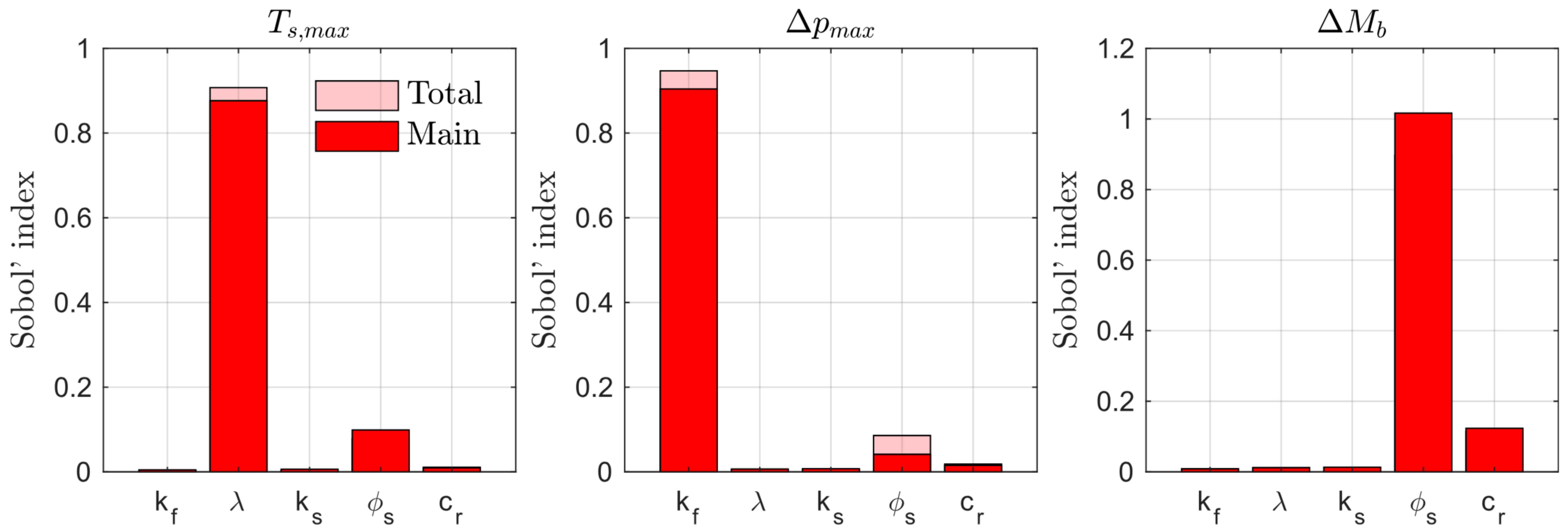
FML surrogate captures evolving, multi-modal QoI distributions

- Distributions and percentiles **match reference** MC across all 3 QoIs
- **10x reduction in cost** to produce ensemble statistics (including FML training)
- **FML enables MC sampling** in the order of millions of samples



Global sensitivity analysis: which uncertainties drive which QoIs?

- **Sobol' **variance-based **indices decompose output variance into contributions from each input** (main effect) **and its interactions** (total effect)
- $N_{\text{sim}} = 10{,}000$ (FML surrogate required)
- Negative indices are eliminated
- Geologically-grounded fault permeability (`PREDICT`) dominates the pressure response



Lu et al., *WRR* (2025)

Summary: Geologically-informed UQ for fault risk in CO_2 storage

- Geologically-grounded fault permeability (`PREDICT`) + FML surrogate enable tractable UQ of coupled flow-geomechanics in CO_2 storage
- ~10× reduction in cost vs. direct MC for the same task; 10^4–10^6 samples feasible once trained
- **Different parameters may control different risks**: stress ratio → fault slip; fault permeability → pressure buildup; aquifer porosity → brine leakage. Implications for monitoring and site characterization priorities

Limitations informing future work

- 2D, homogeneous aquifer, deterministic saturation functions

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Lu et al., *WRR* (2025)

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Odd Andersen & Olav Møyner (SINTEF)

Water Resources Research

Uncertainty Quantification of Fluid Leakage and Fault Instability in Geologic CO_2 Storage

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