Data-space Inversion for Prediction of Fault Slip Tendency in CO_2 Storage

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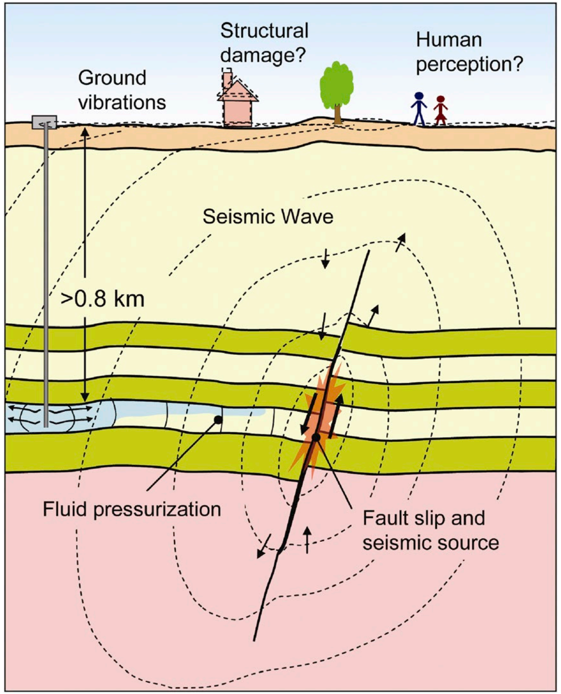
Motivation



Rutqvist et al., 2014

Challenges:

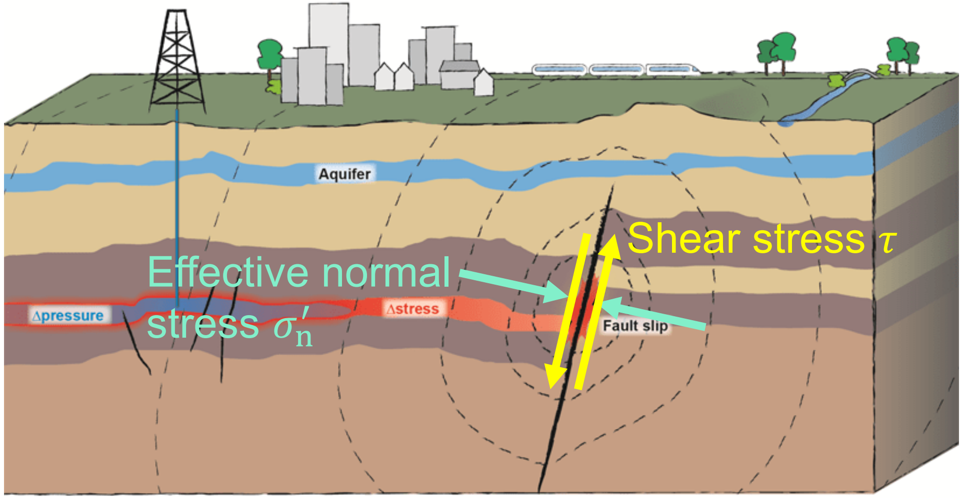
- Pressure build-up due to CO_2 injection can lead to fault slip and induced seismicity
- Significant uncertainty exists in flow and geomechanical properties
- History matching with coupled flow-geomechanics simulations is challenging

Goal in this work:

- Apply data-space inversion (**DSI**) history matching to predict key quantities of interest (QoI)

Fault Slip Tendency

- Fault slip tendency $T_s = \left|\frac{\tau}{\sigma_n'}\right|$, τ: shear stress, σ_n': effective normal stress
- Fault may slip when $T_s \geq \mu$, where μ is fault friction coefficient (~0.6)



Müller et al., 2021

➢ $\sigma_n' = \sigma_n - \alpha P$

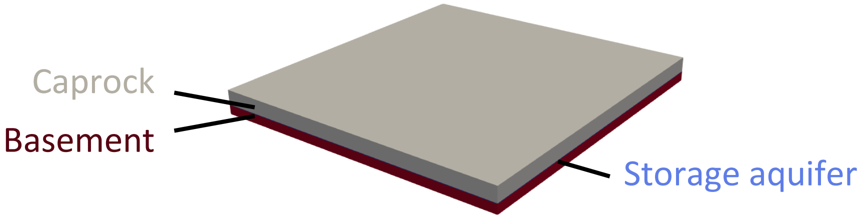
σ_n: normal stress

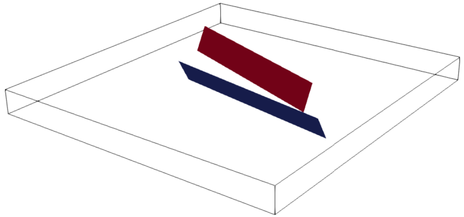
α: Biot's coefficient

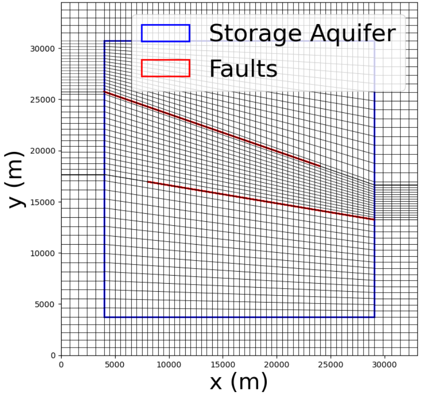
P: pore pressure

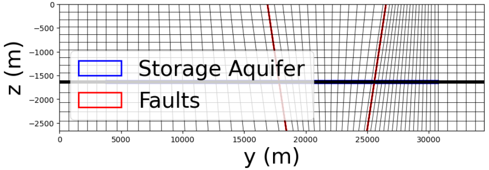
Geomodel Setup: 3D Faulted System

- Setup partially based on Silva et al. (IJGGC 2023) Gulf of Mexico model
- Storage aquifer: 25 km × 27 km × 60 m, 50 × 50 × 20 cells (50,000 total)
- Entire domain: 33.5 km × 34.5 km × 2660 m, 60 × 60 × 35 cells (126,000 total)

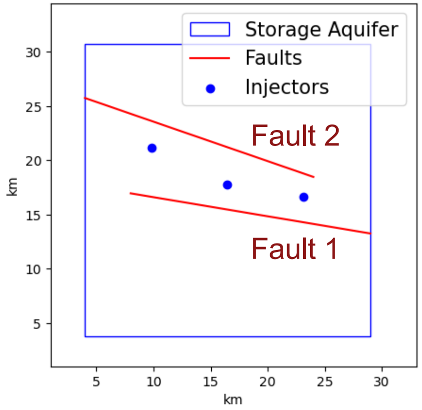


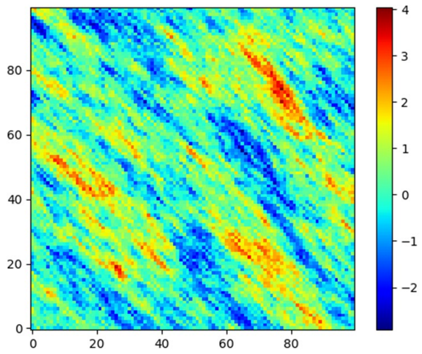






3D Faulted System Simulated in GEOS





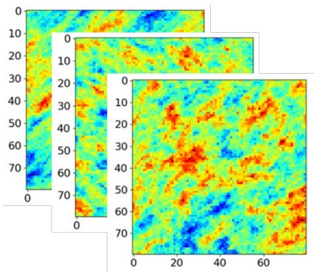
- 3 vertical wells, 3 Mt/year CO_2 (total) for 50 years
- Single geological scenario, randomly sampled realizations, 800 prior simulations used to train DSI
- Poisson's ratio: $\nu \in [0.25, 0.30]$
- Young's modulus: $E \in [10, 20]\ \mathrm{GPa}$
- Biot's coefficient: $\alpha \in [0.8, 1.0]$
- Fault permeability multipliers:

$$\log_{10} \eta_{\mathrm{fault1}} \in [-3,0),\ \log_{10} \eta_{\mathrm{fault2}} \in [-3,0)$$

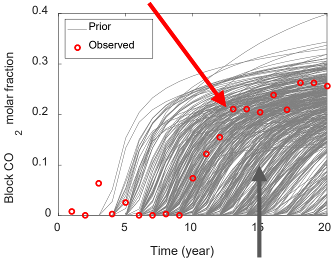
Data-space Inversion (DSI)

Observed data

Posterior predictions

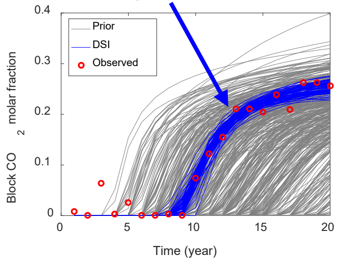


Prior models



Prior simulation results

Data-space inversion



- Under Bayesian framework, $P(\boldsymbol{d}_{\text{full}}|\boldsymbol{d}_{\text{obs}}) = \text{const} \times P(\boldsymbol{d}_{\text{obs}}|\boldsymbol{d}_{\text{full}})P(\boldsymbol{d}_{\text{full}})$

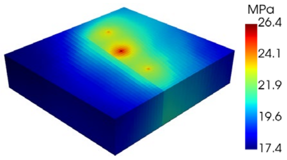
$$\boldsymbol{d}_{\text{full}} = \begin{bmatrix} \boldsymbol{d}_{\text{HM}} \\ \boldsymbol{d}_{\text{F}} \end{bmatrix}$$

Monitoring (pressure, strain)

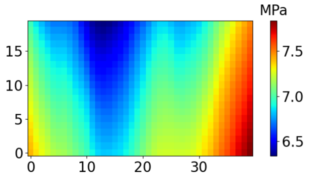
Forecast (pressure, strain, stress) at a few time steps

DSI Setup: Observations and Predictions

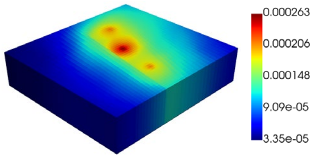
- **Observed data**: pressure and strain data (with noise) in the storage aquifer at 2, 4, 6, and 8 years from 4 monitoring wells, $N_{\mathrm{obs}} = 640$
- **Prediction**: pressure, strain, shear stress (τ), effective normal stress (σ_{n}') at 50 years $\longrightarrow$ $T_{\mathrm{s}} = \left|\frac{\tau}{\sigma_{\mathrm{n}}'}\right|$



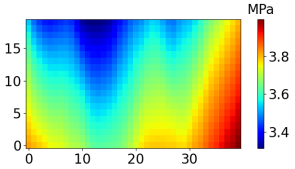
Pressure



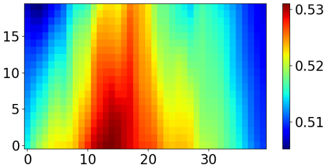
Effective normal stress



Strain



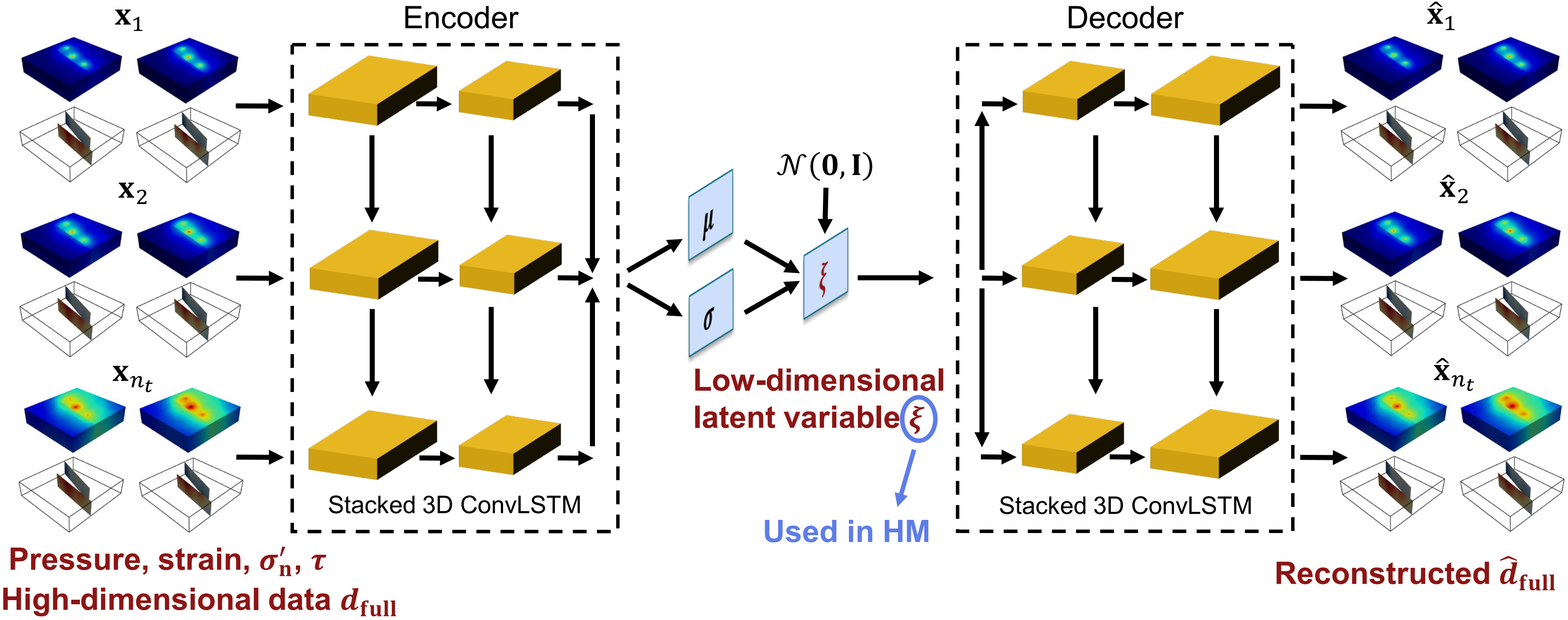
Shear stress



Fault slip tendency

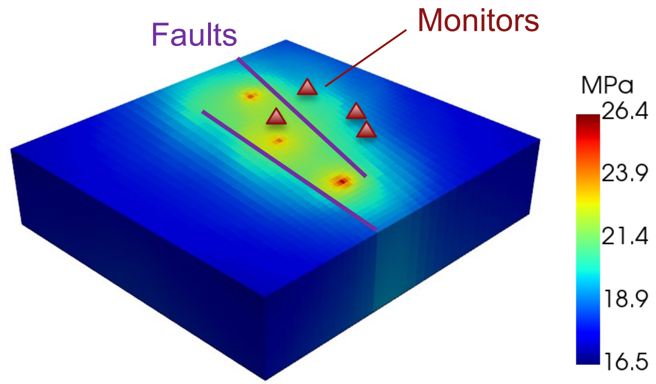
Data-space Inversion: VAE for Parameterization

- Variational autoencoder (VAE) for spatio-temporal data



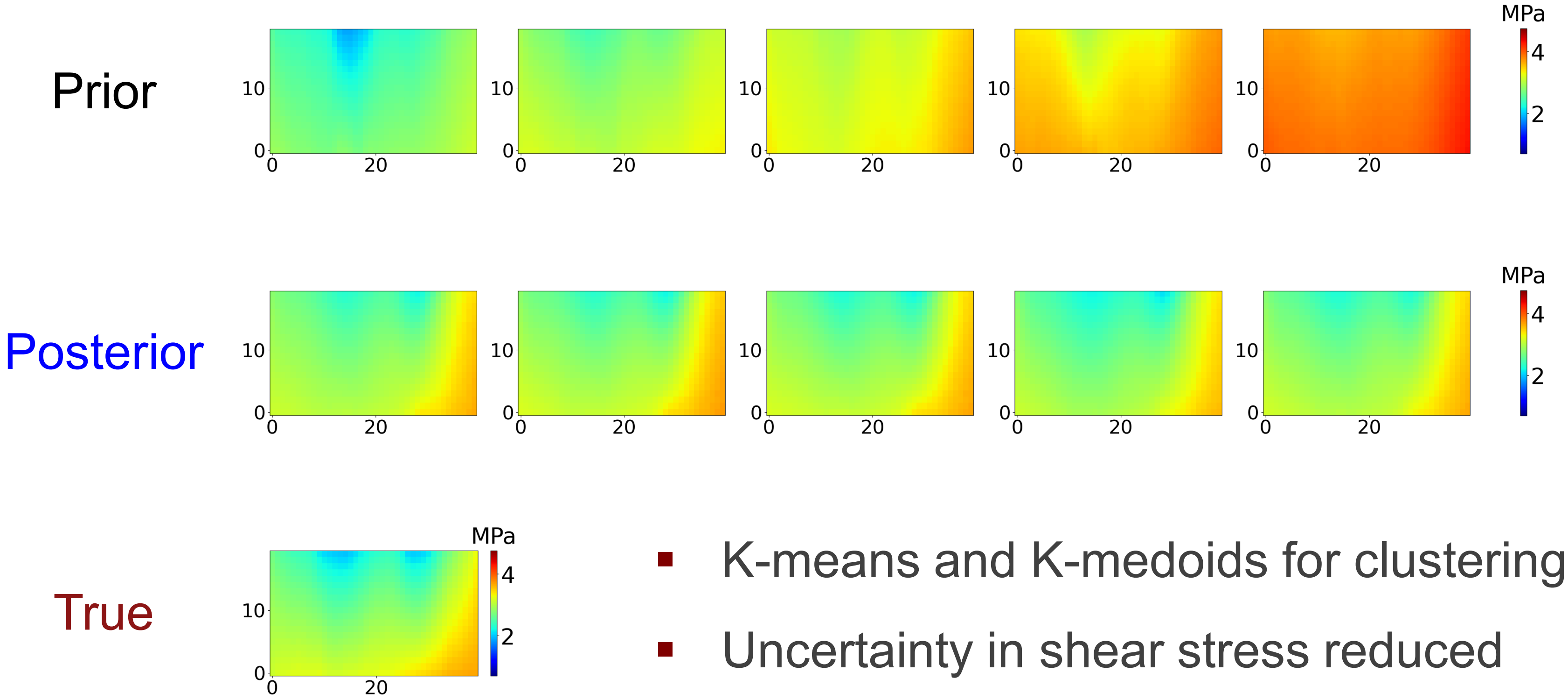
History Matching with Synthetic "True" Model

- Randomly sample flow and geomechanical parameters ($E = 12.6$ GPa, $\nu = 0.26, \ldots$)
- Generate corresponding realization ⟶ **true model**
- Run fully coupled flow-geomechanics simulation with 3 injectors, each injecting 1 Mt/year (as in training runs)
- Measure pressure and strain data at 2, 4, 6, & 8 years from 4 monitoring wells
- Apply ensemble smoother with multiple data assimilation (ESMDA) history matching on the latent variables ξ to provide posterior predictions



True model pressure response

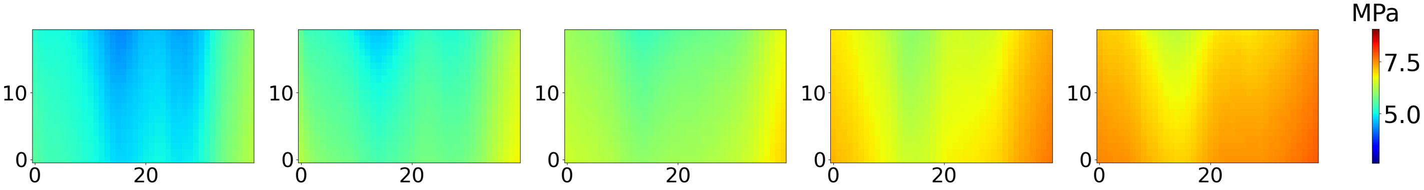
Prior and Posterior Shear Stress (Fault 1, 50 Years)



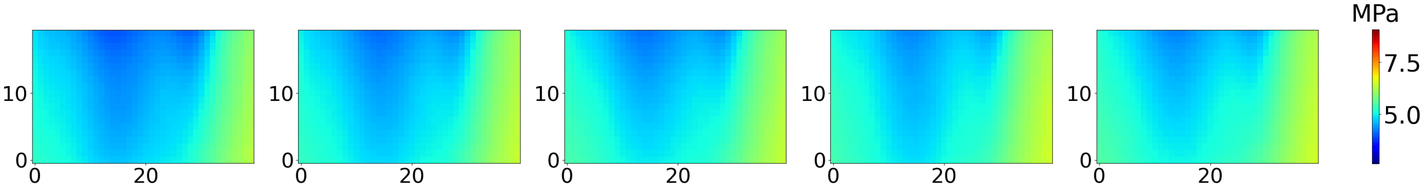
- K-means and K-medoids for clustering
- Uncertainty in shear stress reduced

Prior and Posterior Effective Normal Stress (Fault 1, 50 Years)

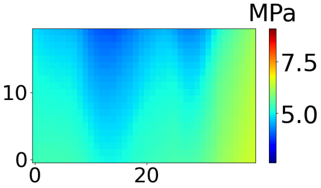
Prior



Posterior

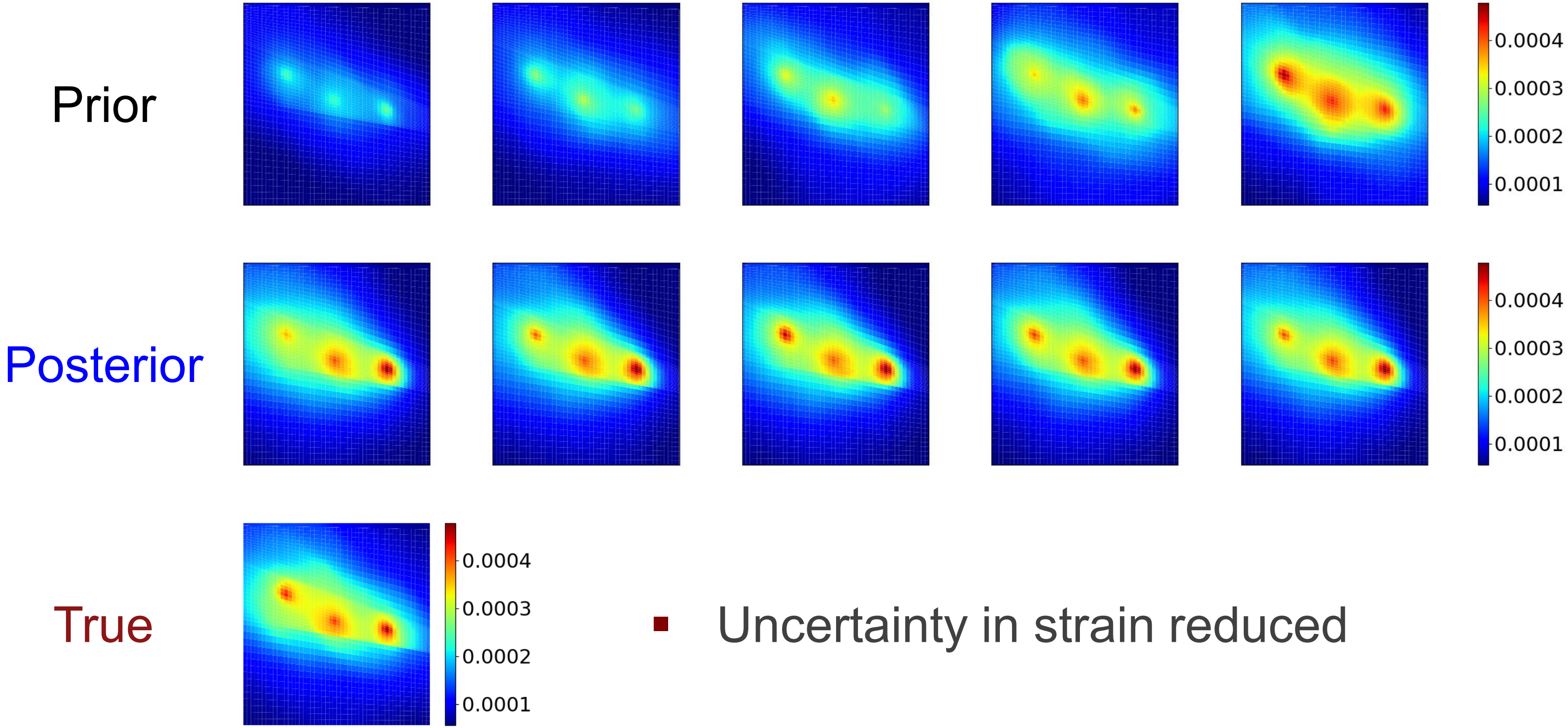


True



- Uncertainty in effective normal stress reduced

Prior and Posterior Strain (Top Layer, 50 Years)

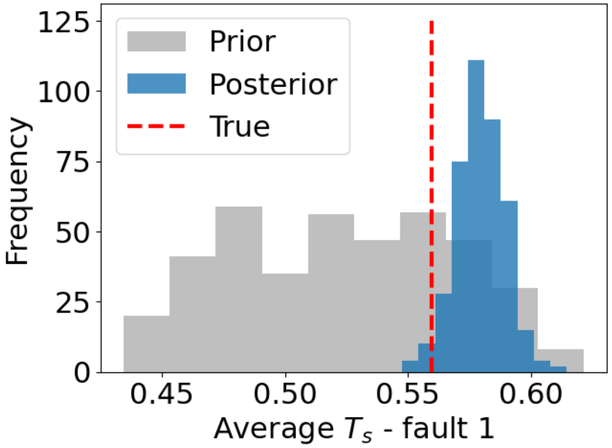


- Uncertainty in strain reduced

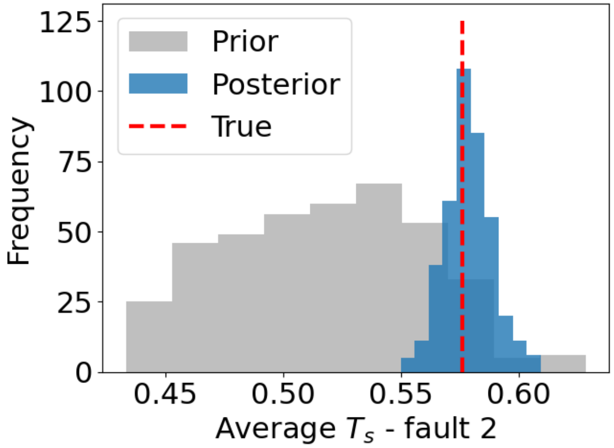
Prior and Posterior Fault Slip Tendency

- Fault slip tendency $T_s = \left|\frac{\tau}{\sigma'_\mathrm{n}}\right|$, τ: shear stress, σ'_n: effective normal stress
- Average fault slip tendency at 50 years:

Fault 1



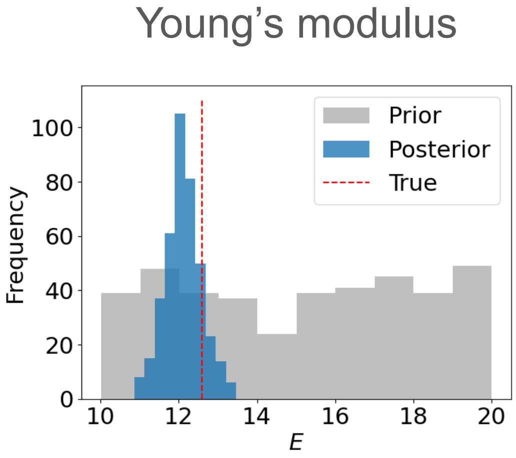
Fault 2

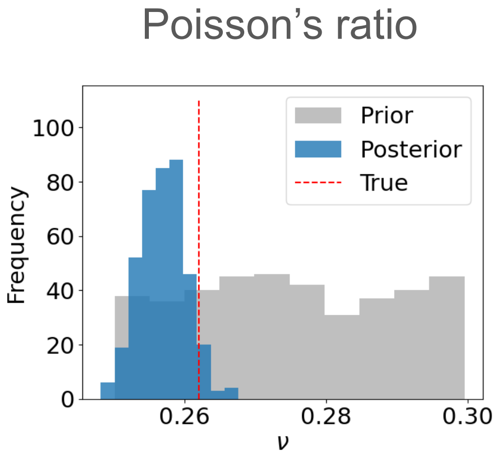


Prior and Posterior Geomechanical Parameters

- Joint DSI inversion of latent variables ξ and key geomechanical parameters $\boldsymbol{m}$

$$\boldsymbol{d}_{\mathrm{full}} = \begin{bmatrix} \boldsymbol{d}_{\mathrm{HM}} \\ \xi \\ \boldsymbol{m} \end{bmatrix}$$





Summary and Future Work

- Applied GEOS for coupled flow-geomechanics in 3D faulted model
- Extended DSI framework to predict pressure, strain, stress, and geomechanical parameters using pressure and strain observations
- Applied monitoring well optimization to achieve maximal uncertainty reduction in key quantities of interest (e.g., fault slip tendency)
- Future work – integrate geomechanical parameters into optimization objectives; evaluate the impact of different observation data types and errors; consider more realistic models

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Thank you!