Inference of CO_2 flow patterns - a feasibility study

Abhinav P Gahlot[2] Huseyin Tuna Erdinc[1] Rafael Orozco[1] Ziyi Yin[1] Mathias Louboutin[2,4] Felix J. Herrmann[1,2,3]

Thursday, November 9, 2023

[1] Georgia Tech College of Computing School of Computational Science and Engineering
[2] Georgia Tech College of Sciences School of Earth and Atmospheric Sciences
[3] Georgia Tech College of Engineering School of Electrical and Computer Engineering
[4]now at Devito Codes

SLIM
Georgia Institute of Technology

NeurIPS'23

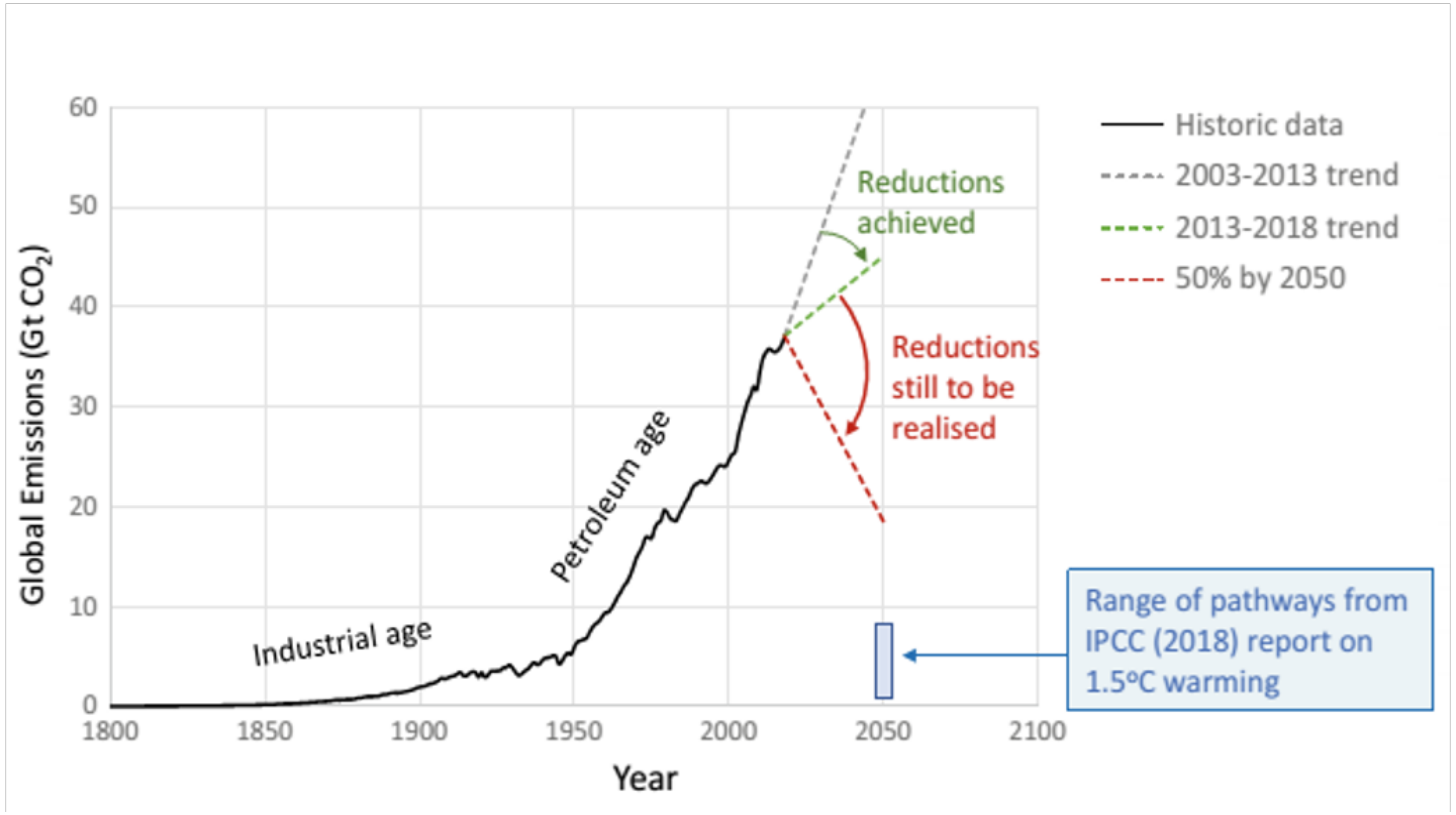
SLIM

Background

Geological Carbon Storage (GCS): What is it?

Involves capturing, transporting, and storing greenhouse gas emissions in the ground

50% reduction of greenhouse gas emissions required by 2050 to avoid 1.5 ˚C (IPCC 2018).

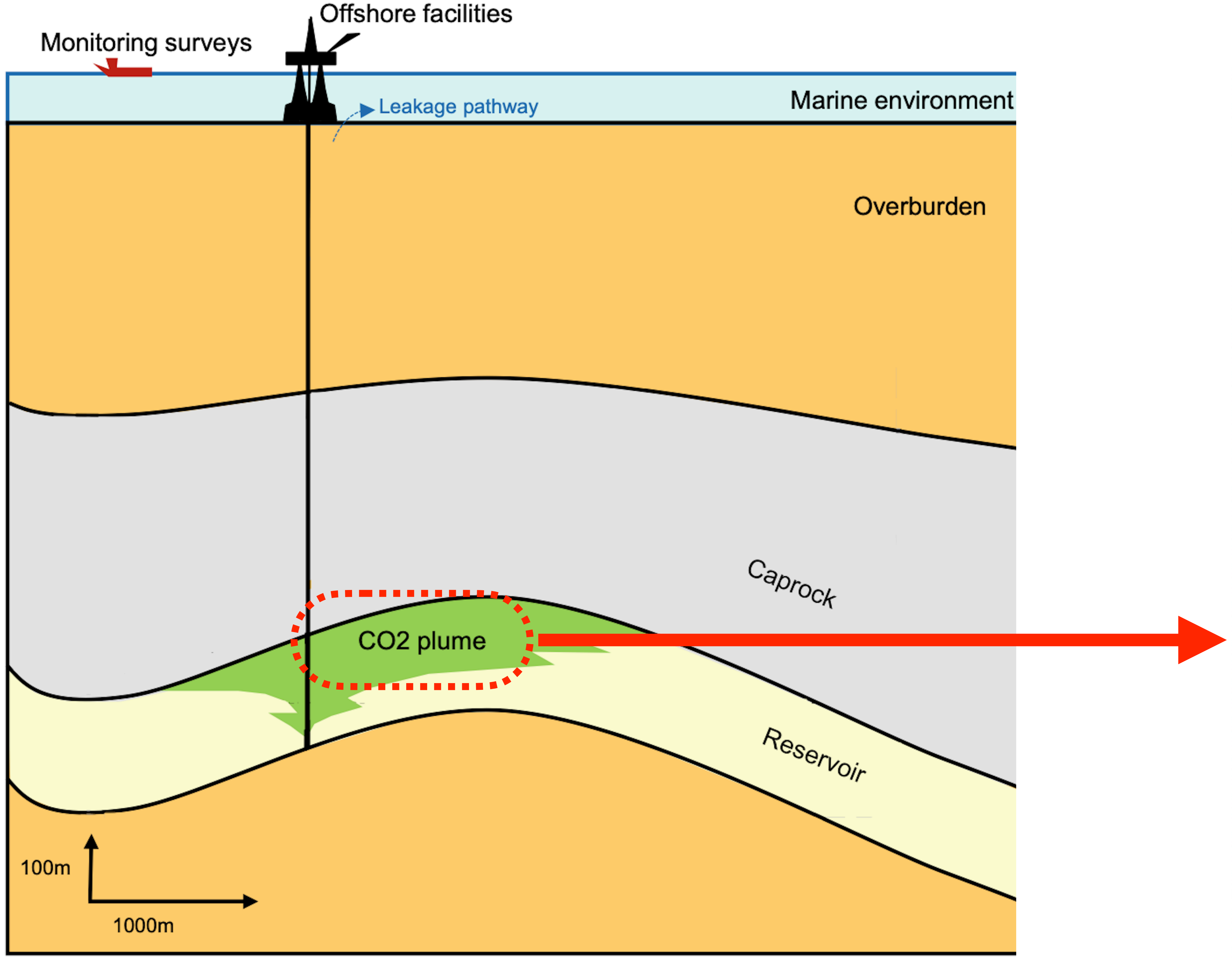


Ringrose, P. (2020)

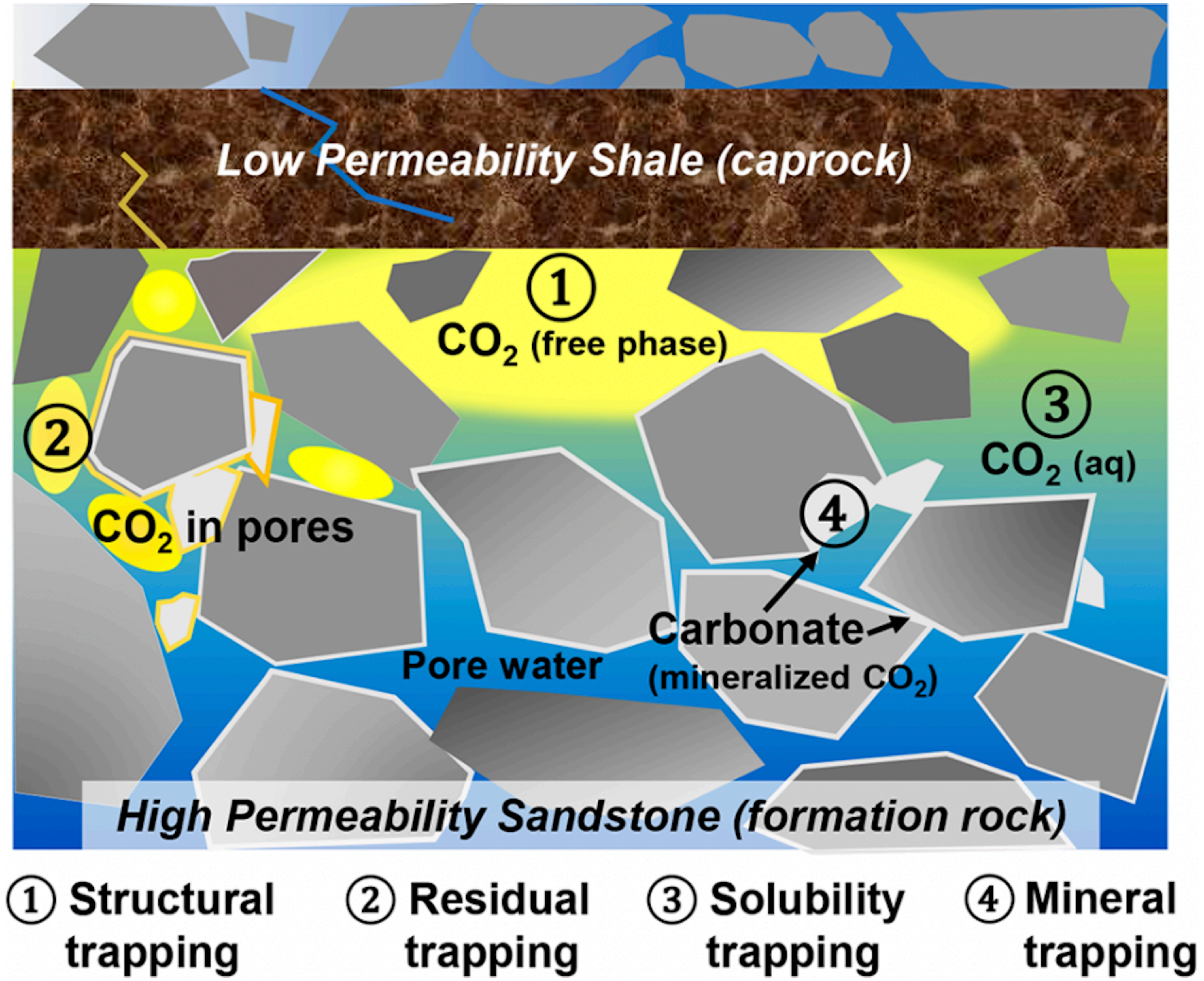
Ringrose, P. 2020. How to store CO_2 underground: Insights from early-mover CCS Projects, volume 129. Springer.
Jun, Y.-S.; Zhang, L.; Min, Y.; and Li, Q. 2017. Nanoscale Chemical Processes Affecting Storage Capacities and Seals during Geologic CO_2 Sequestration. Accounts of Chemical Research, 50(7): 1521–1529. PMID: 28686035.

Background

Geological Carbon Storage (GCS): How is it stored?



Adapted from Ringrose (2020)



Jun et al (2017)

Jun, Y.-S.; Zhang, L.; Min, Y.; and Li, Q. 2017. Nanoscale Chemical Processes Affecting Storage Capacities and Seals during Geologic CO_2 Sequestration. Accounts of Chemical Research, 50(7): 1521–1529. PMID: 28686035.

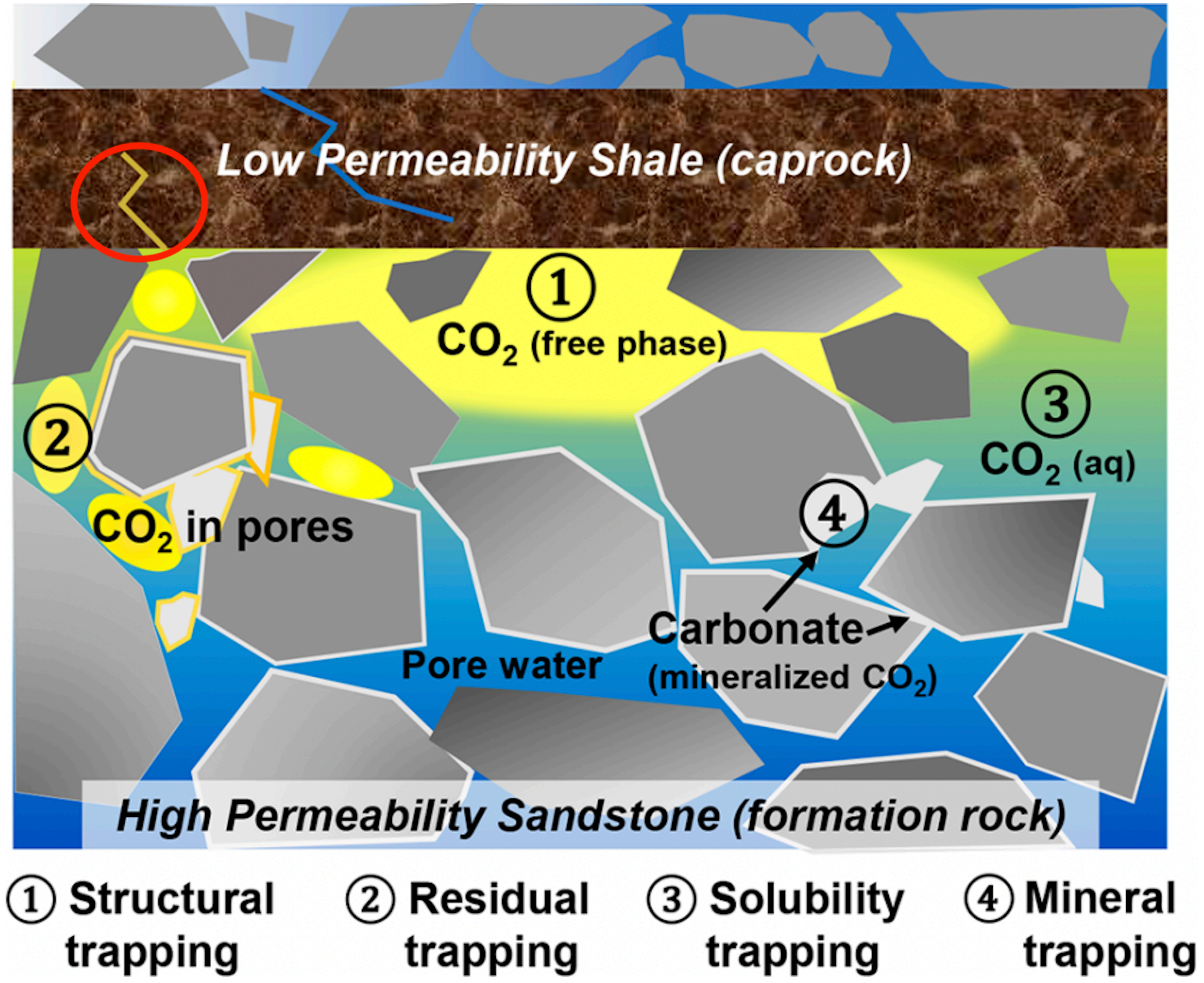
SLIM

Background

Geological Carbon Storage (GCS): Is there a risk?

Leakage

- Exceeding fracture pressure due to injection
- Pre-existing faults
- Imperfect storage sealing
- Abandoned wells

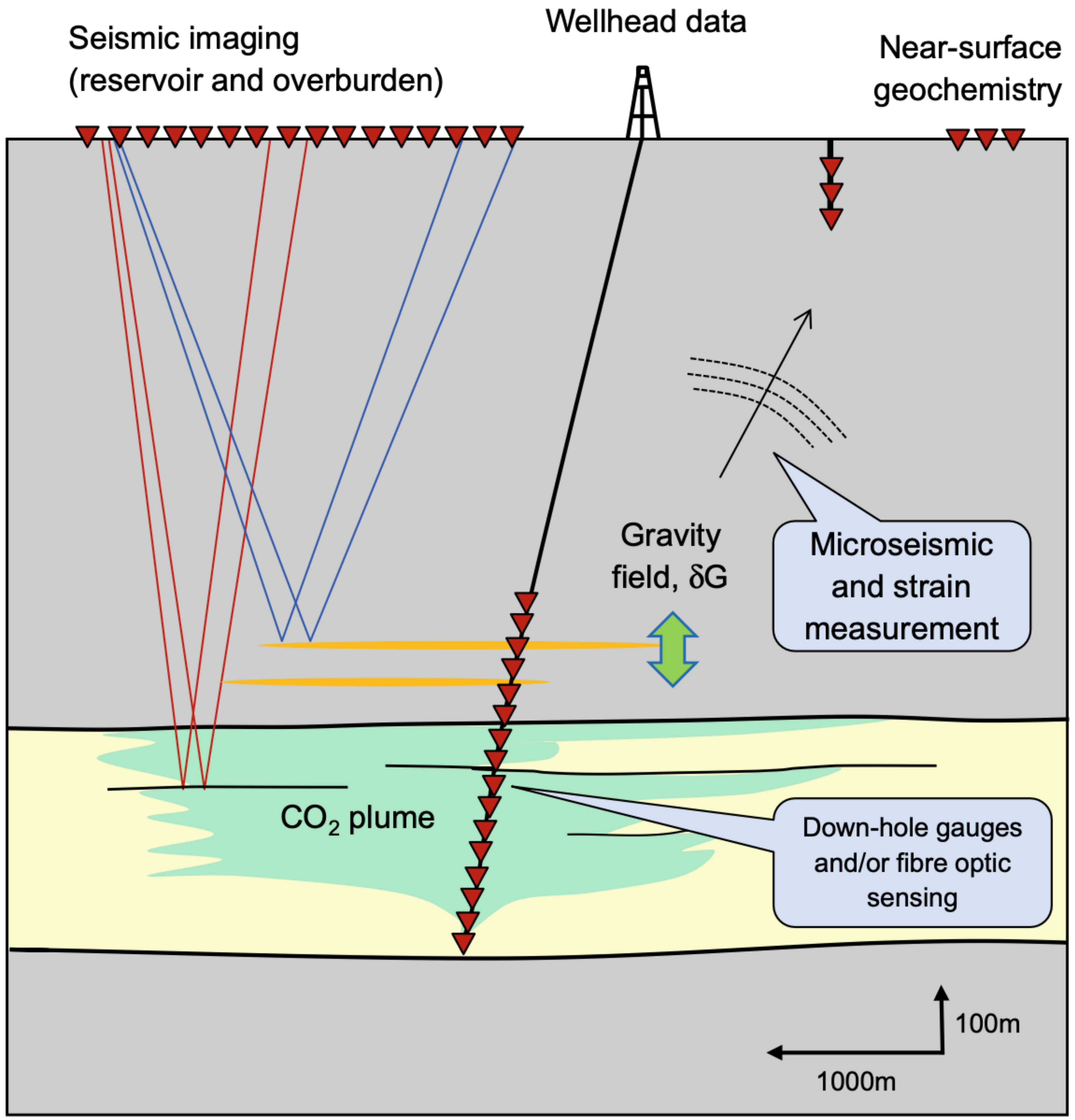


Jun et al (2017)

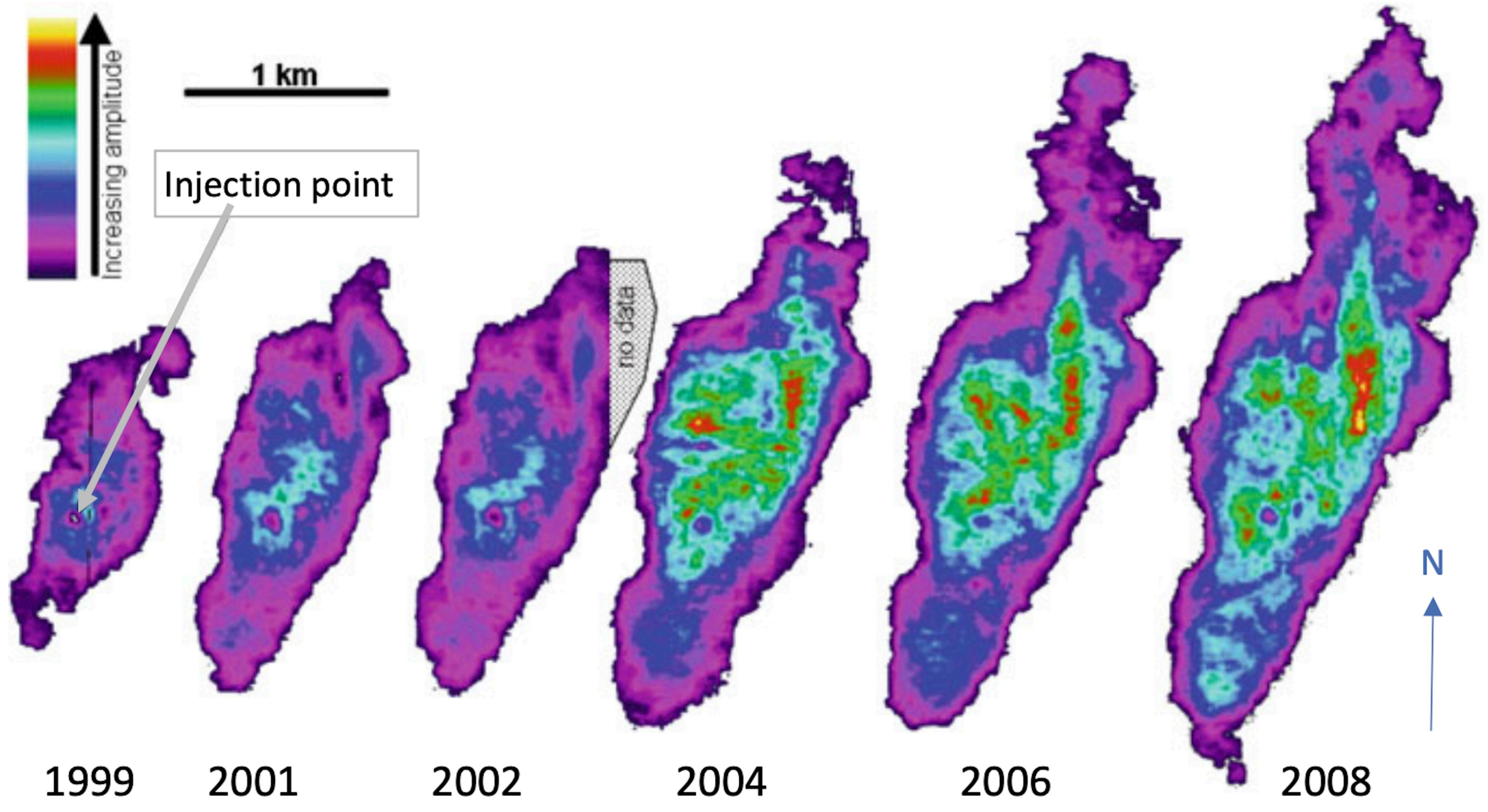
Eiken, O.; Ringrose, P.; Hermanrud, C.; Nazarian, B.; Torp, T. A.; and Høier, L. 2011. Lessons learned from 14 years of CCS operations: Sleipner, In Salah, and Snøhvit.
Ringrose, P. 2020. How to store CO_2 underground: Insights from early-mover CCS Projects, volume 129. Springer.

Background

geophysical time-lapse monitoring : GCS application

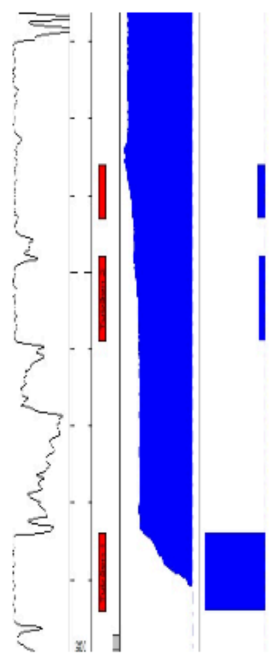


Adapted from Ringrose (2020)

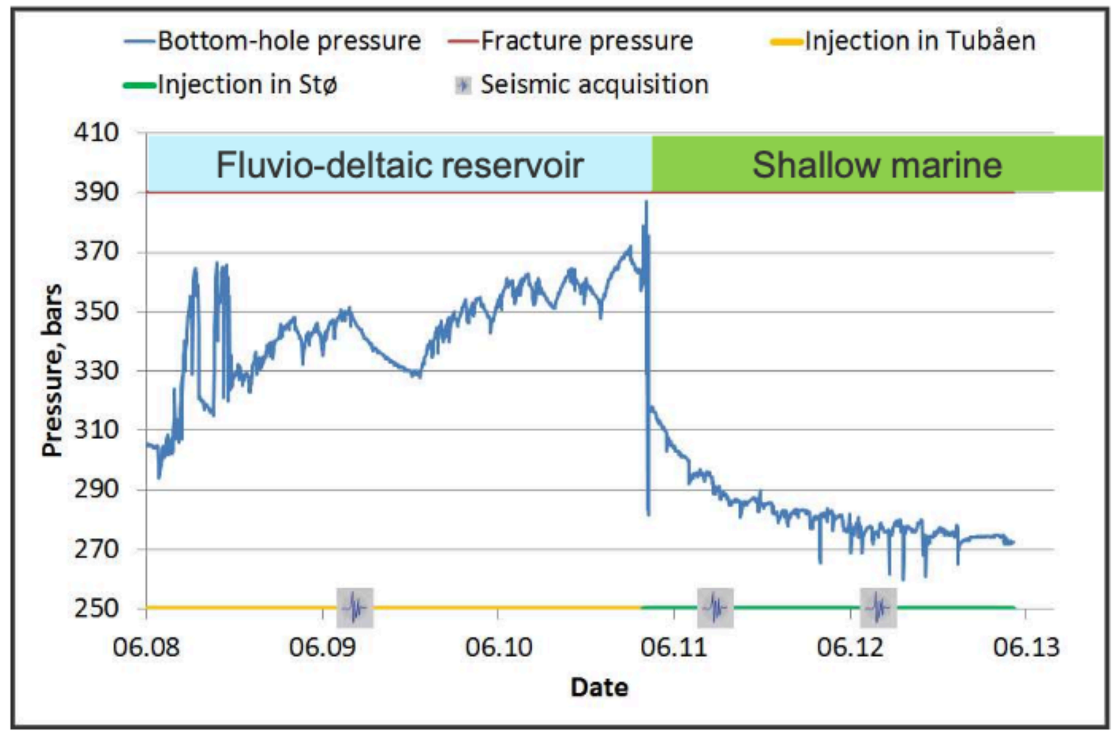


Eiken et al. 2011

Down-hole data:
PLT flow log



Down-hole pressure data



Hansen et al. 2013; Pawar et al., 2015

Wood et. al, Locked away – geological carbon storage, The Royal Society, October 2022
Ringrose, Philip. How to store CO2 underground: Insights from early-mover CCS Projects, 2020.

SLIM
ML4Seismic

Motivation

CO_2 plume *forecasts* based on fluid flow *simulations* alone are *uncertain*

- can ***not*** expect *precise* predictions of regular & irregular flow
- need to *constrain* CO_2 plumes by incorporating *monitoring* data

Calls for a *principled* approach using techniques from ML & data assimilation to

- incorporate time-lapse well & seismic data *jointly*
- assess *uncertainty* in CO_2 plumes to *inform* policy decisions

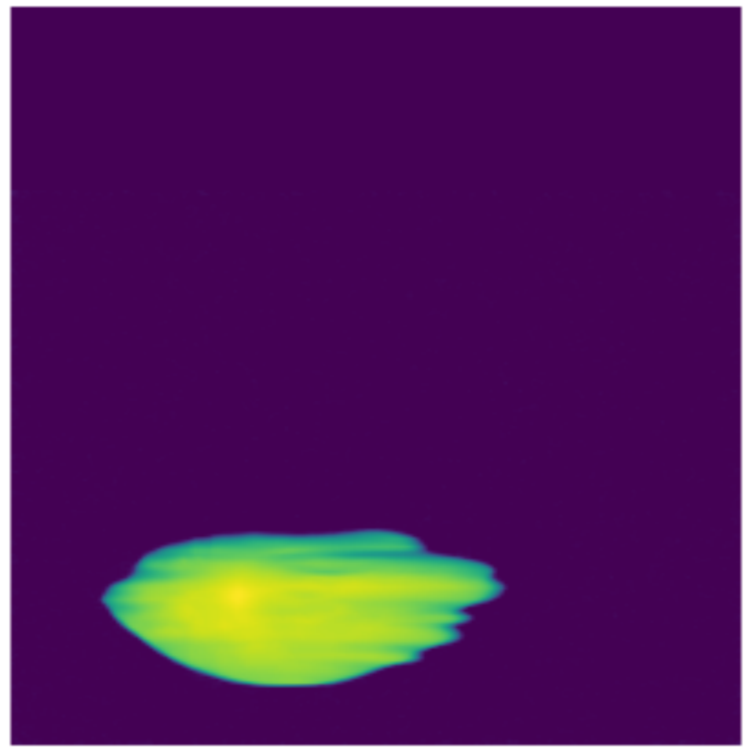
Methodology

Kobyzev, Ivan, Simon Prince, and Marcus Brubaker. "Normalizing flows: An introduction and review of current methods." IEEE Transactions on Pattern Analysis and Machine Intelligence (2020).

Training & sampling

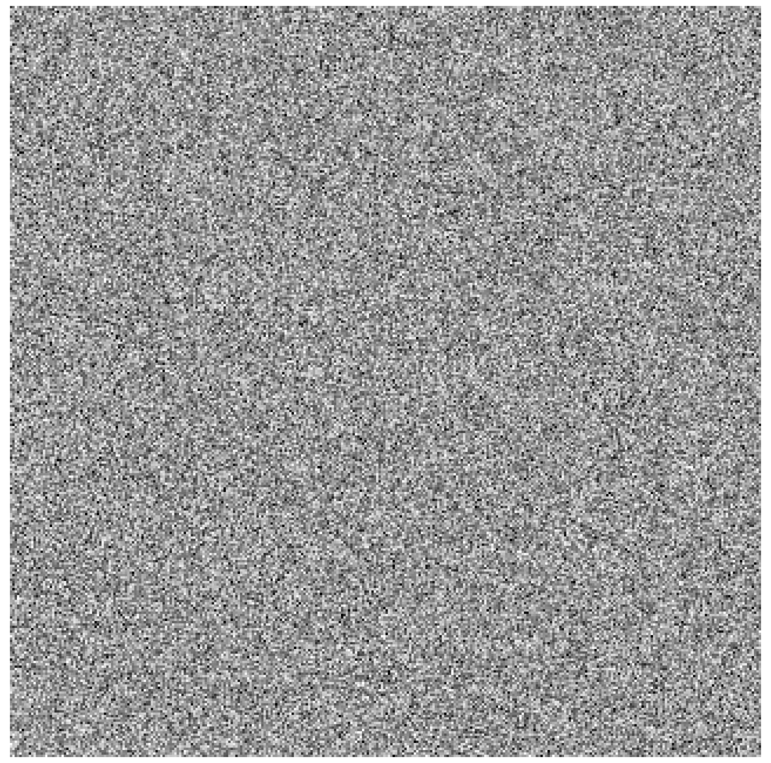
w/ Normalizing Flows (NFs)

Training:



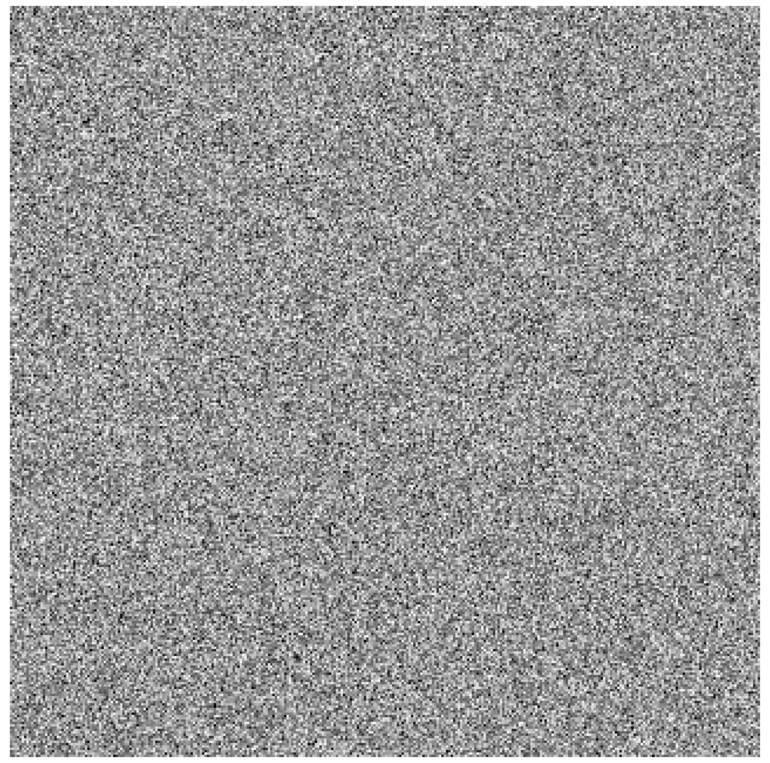
$\mathbf{x} \sim p_X(\mathbf{x})$

$\xrightarrow{\mathcal{G}_{\mathbf{w}}^{-1}(\mathbf{x})}$



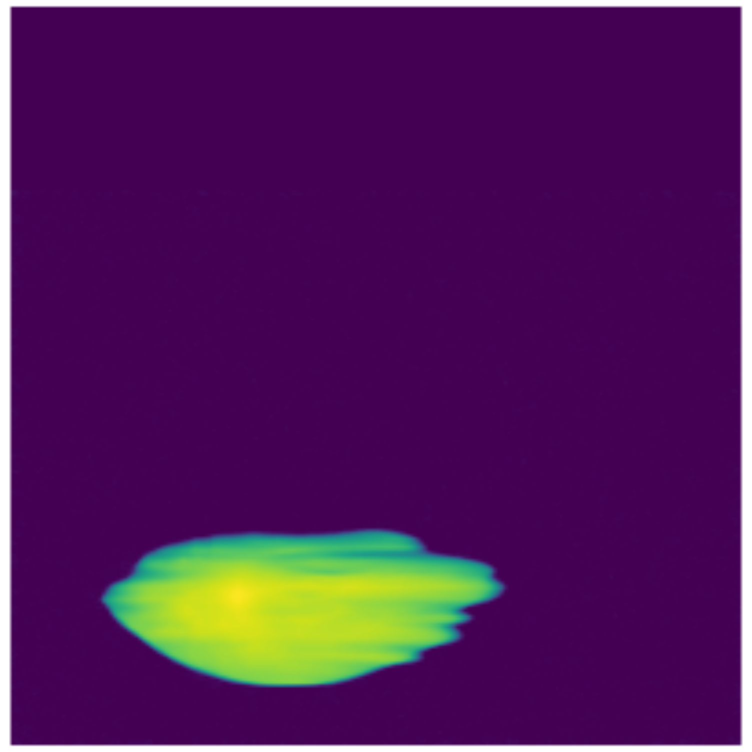
$\mathbf{z} \sim p_Z(\mathbf{z})$

Sampling:



$\mathbf{z} \sim p_Z(\mathbf{z})$

$\xrightarrow{\mathcal{G}_{\mathbf{w}}(\mathbf{z})}$



$\mathbf{x} \sim p_X(\mathbf{x})$

Ardizzone, Lynton, et al. "Conditional Invertible Neural Networks for Guided Image Generation." (2019).
Radev, Stefan T., et al. "BayesFlow: Learning complex stochastic models with invertible neural networks." IEEE transactions on neural networks and learning systems 33.4 (2020)
Cranmer, Kyle, Johann Brehmer, and Gilles Louppe. "The frontier of simulation-based inference." Proceedings of the National Academy of Sciences 117.48 (2020): 30055-30062

Simulation-based inference

w/ conditional Normalizing Flows (CNFs)

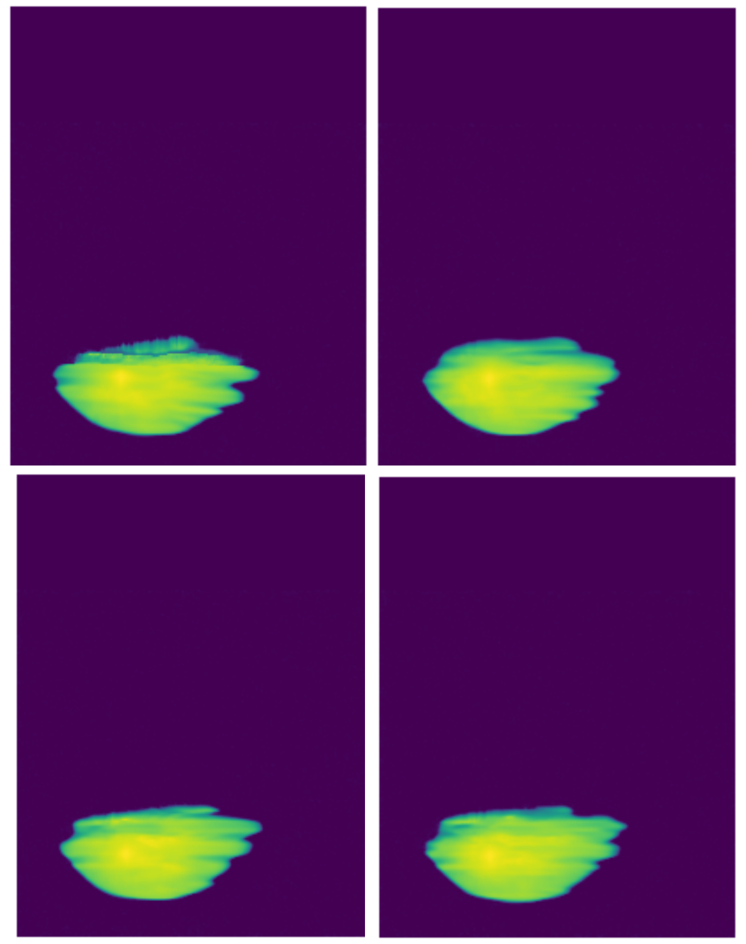
$$\mathbf{x} \sim p(\,\mathbf{x} \mid \mathbf{y}\,)$$

Given *simulated* training pairs $(\mathbf{x}, \mathbf{y})$

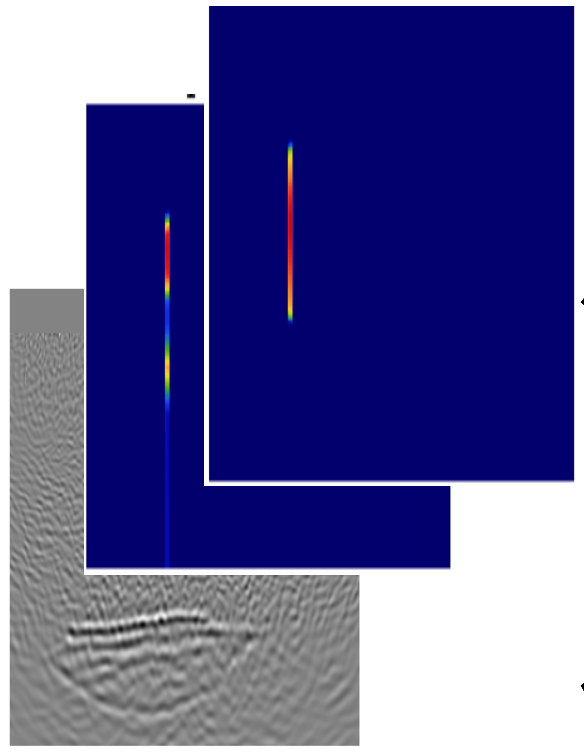
- *amortized* training of CNFs to sample from the posterior $p(\mathbf{x}\,|\,\mathbf{y})$ for any $\mathbf{y}$
- when trained, CNFs solve inference problems by generating samples $\mathbf{x} \sim p(\mathbf{x}\,|\,\mathbf{y}^*)$
- samples are conditioned on observed data, $\mathbf{y}^*$

Simulation-based inference

w/ CO_2 saturation/pressure at wells & imaged seismic



$$\sim p(\ \mathbf{x}\ |$$



$$)$$

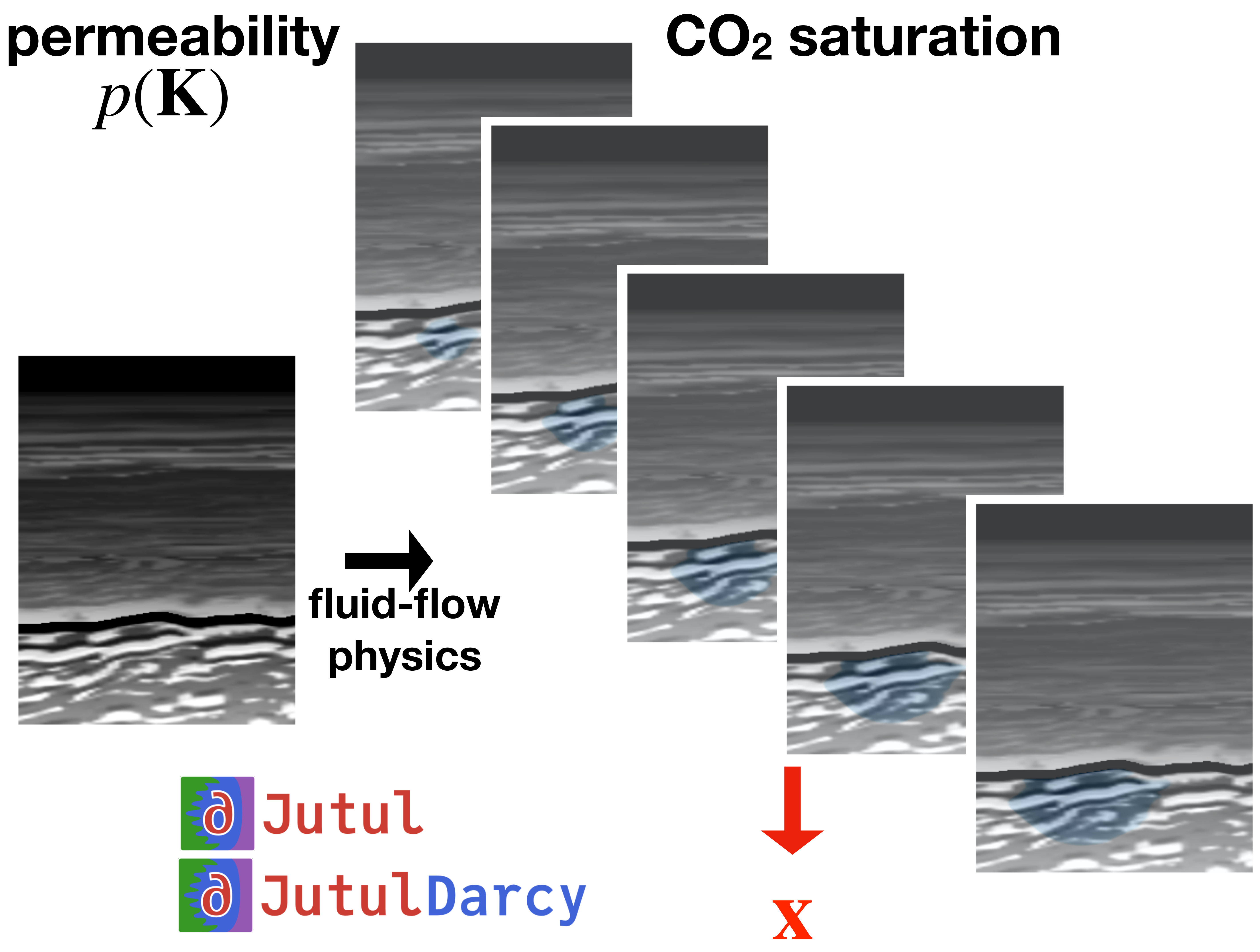
Given *simulated* training pairs $(\mathbf{x}, \mathbf{y})$ for the CO_2 saturation & saturation/pressure at wells

- *amortized* training of CNFs to sample from the posterior $p(\mathbf{x}\,|\,\mathbf{y})$ for any $\mathbf{y}$
- when trained, CNFs solve inference problems by generating samples $\mathbf{x} \sim p(\mathbf{x}\,|\,\mathbf{y}^*)$
- sampled CO_2 saturations are conditioned on observed CO_2 saturation/pressure & seismic data, $\mathbf{y}^*$

Møyner, O., et.al. 2023. Sintefmath/Jutul.jl: V0.2.5 (version v0.2.5). Zenodo. https://doi.org/10.5281/zenodo.7775759

Dataset Generation

fluid-flow simulations

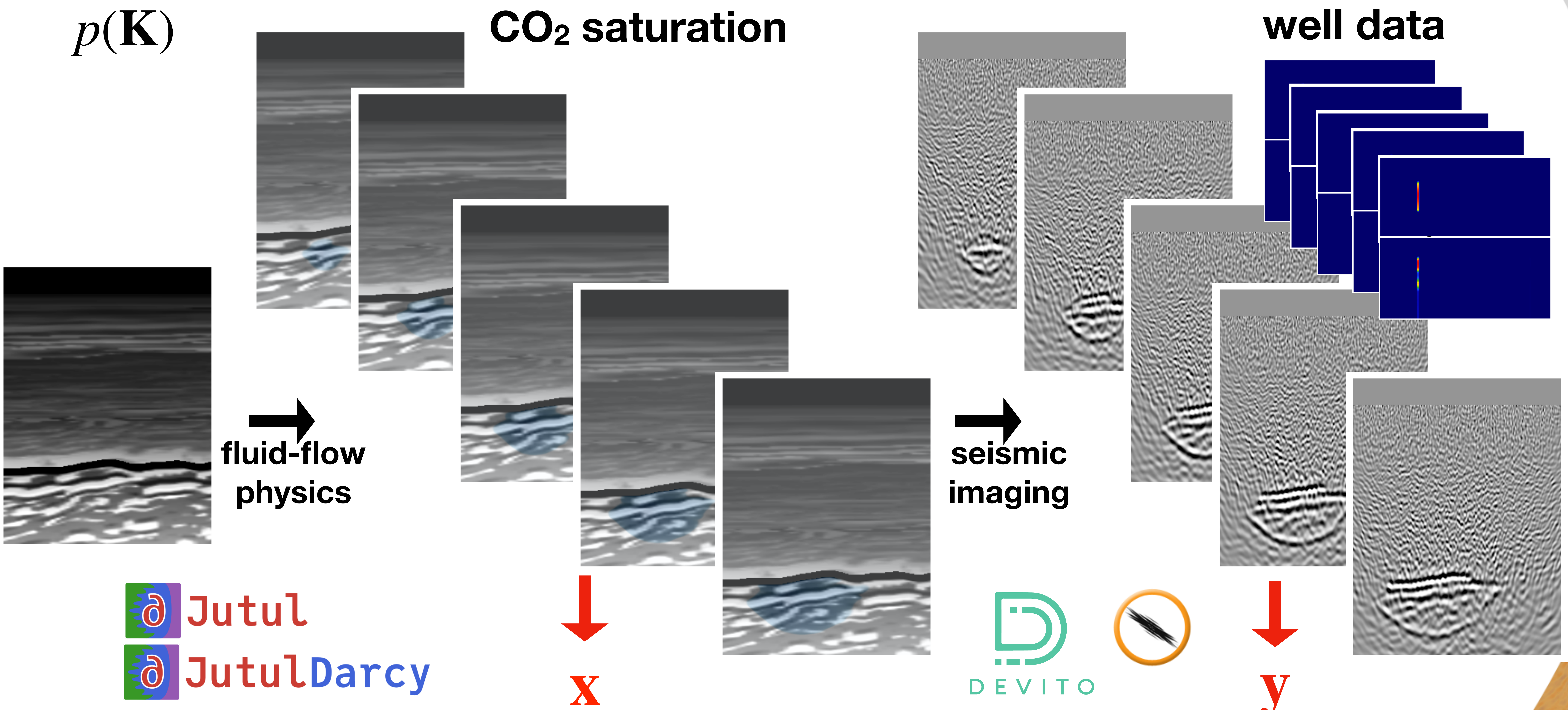


Møyner, O., et.al. 2023. Sintefmath/Jutul.jl: V0.2.5 (version v0.2.5). Zenodo. https://doi.org/10.5281/zenodo.7775759
Luporini, F., et. al. 2022. devitocodes/devito: v4.6.2 (v4.6.2). Zenodo. https://doi.org/10.5281/zenodo.6108644
Witte, P., et.al. 2020. slimgroup/JUDI.jl: DOI release (v2.0.2). Zenodo. https://doi.org/10.5281/zenodo.3878711

SLIM

Dataset Generation

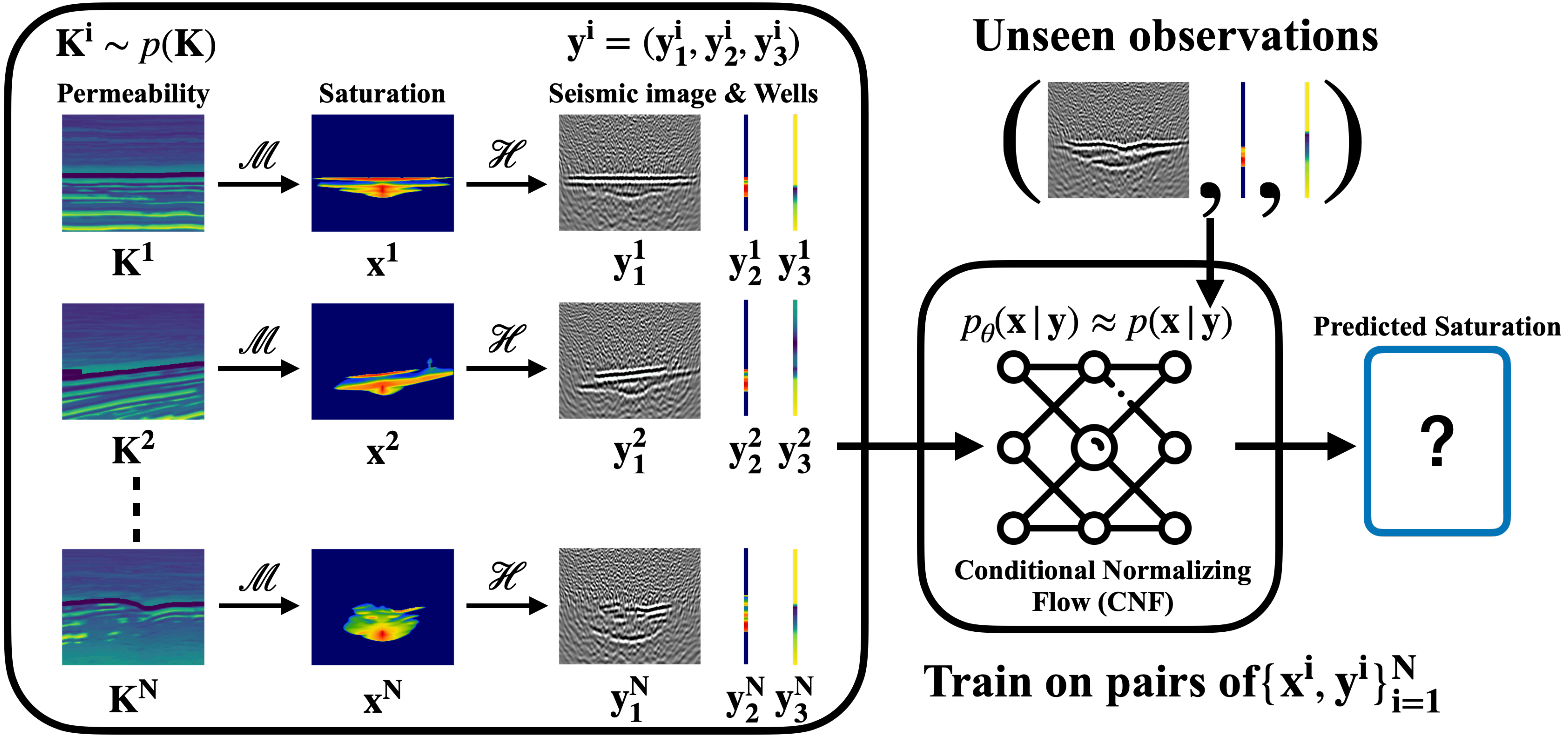
time-lapse observations



Training Configuration & Results

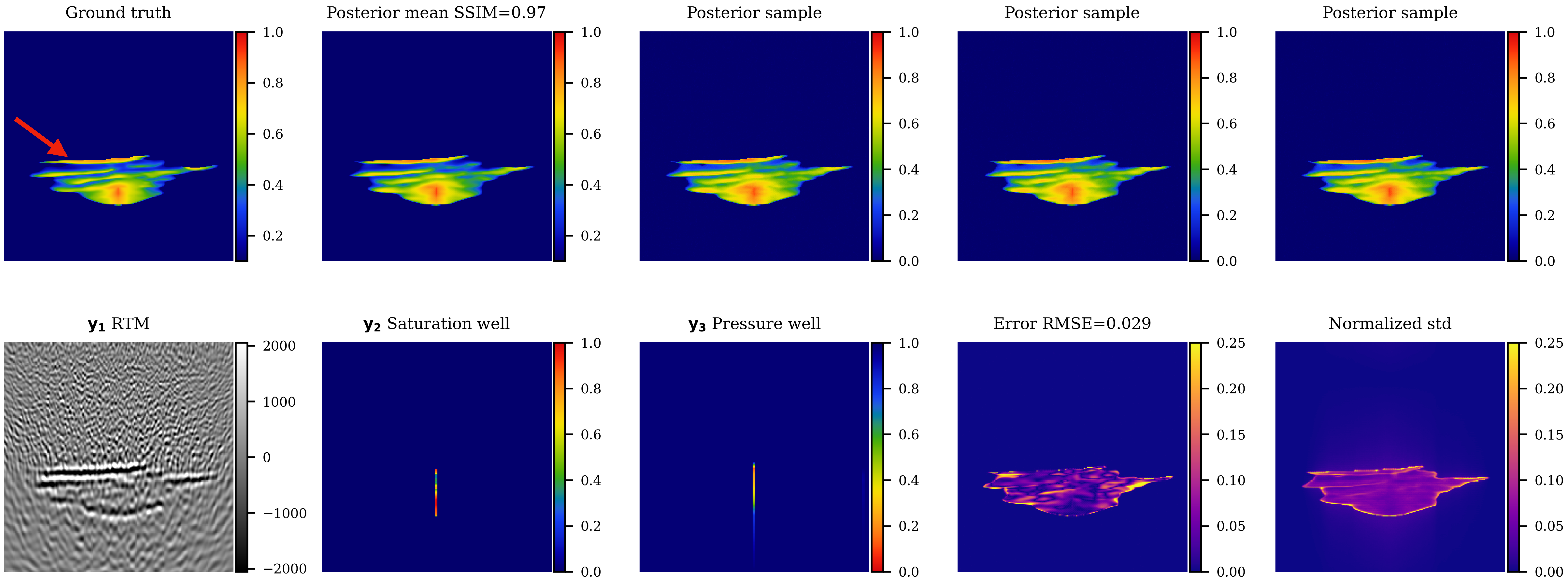
Witte, P., et.al. 2021. slimgroup/InvertibleNetworks.jl: v2.1.0 (v2.1.0). Zenodo. https://doi.org/10.5281/zenodo.5761654

Training & Testing Schematic



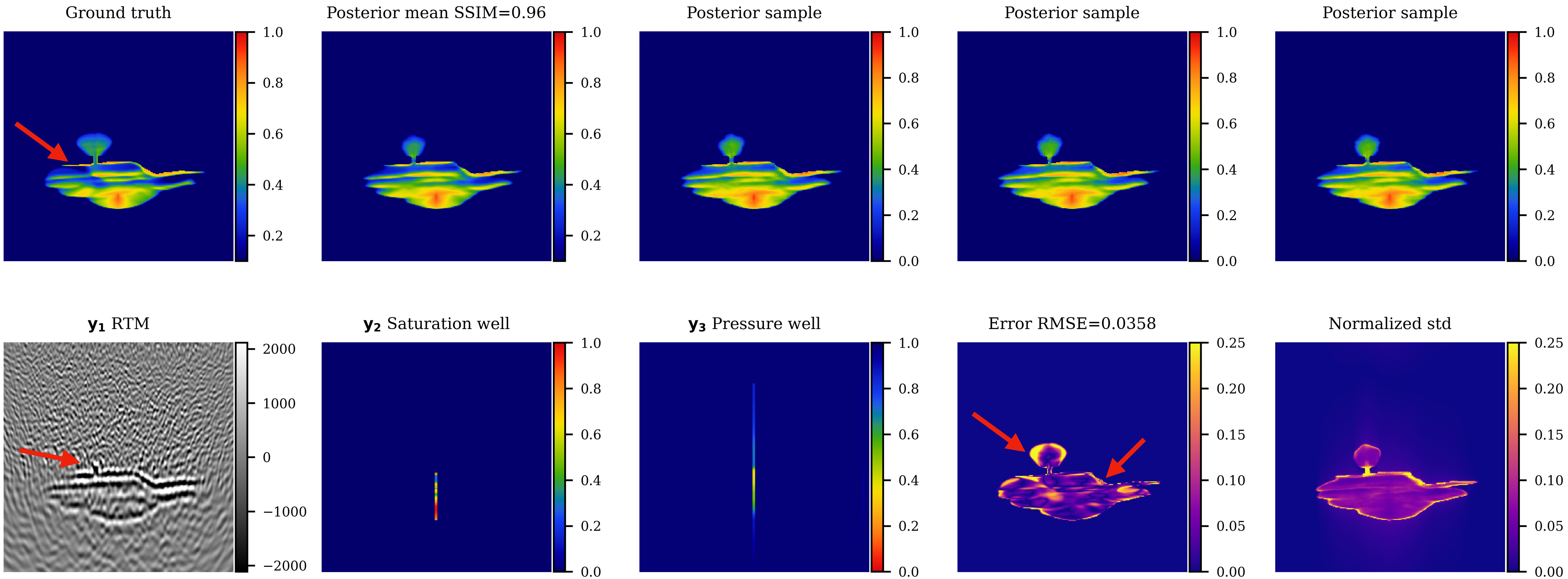
$\mathscr{M}$ dynamics operator $\mathscr{H}$ observation operator K permeability model

Results
no-leakage scenario



Results

leakage scenario



Acknowledgement

This research was carried out with the support of Georgia Research Alliance and partners of the ML4Seismic Center and in part by the US National Science Foundation grant OAC 220382.