Seismic Laboratory for Imaging and Modeling (SLIM)

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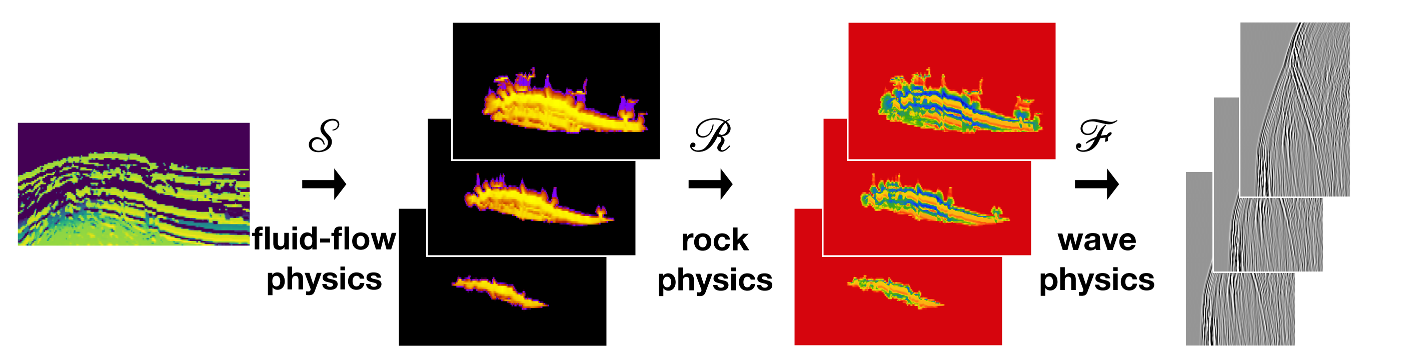
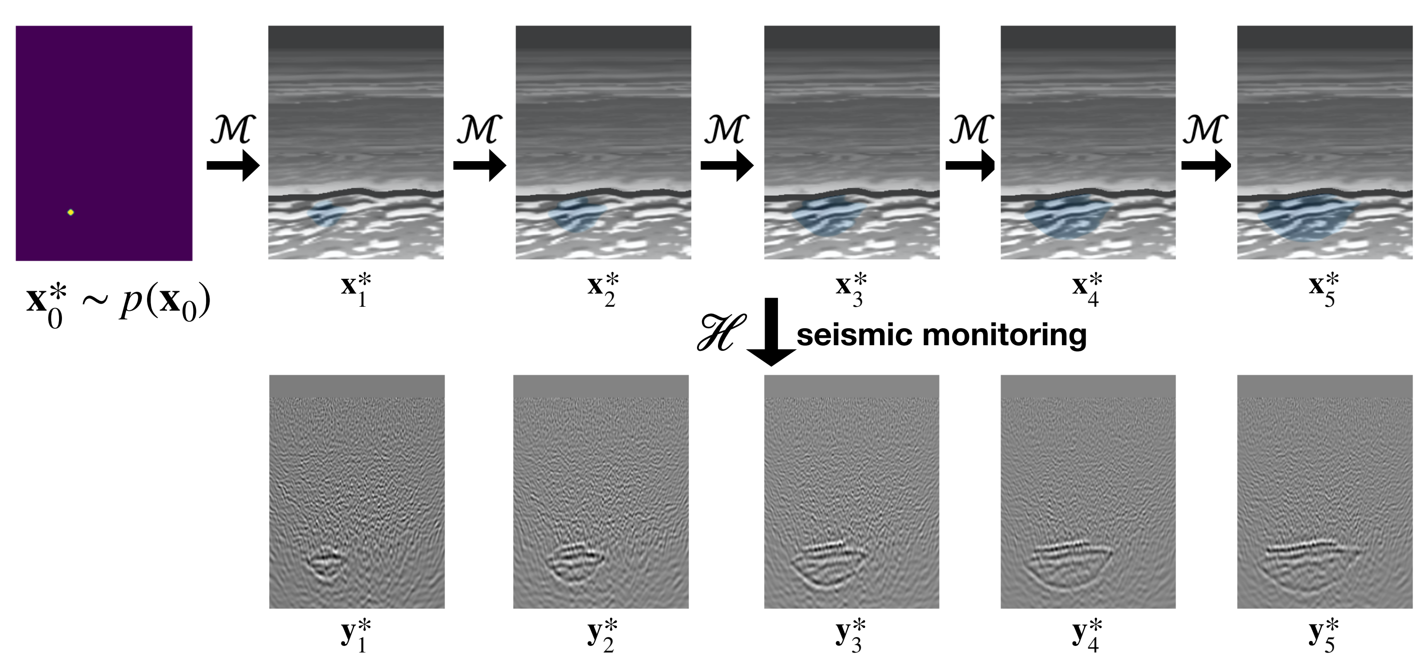
geological carbon storage monitoring

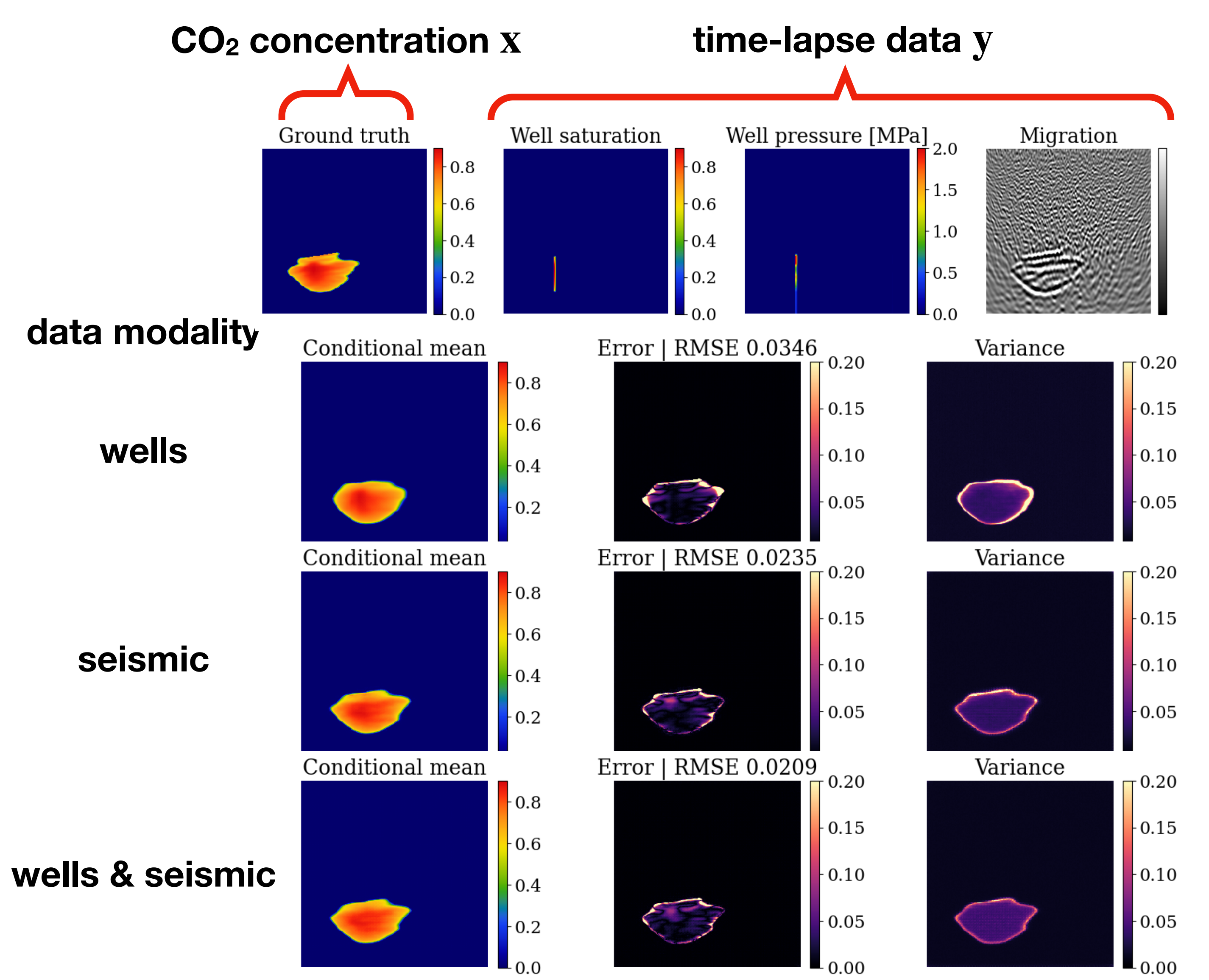
Geological carbon storage, as one of the few scalable technologies offering net-negative CO_2 emissions, aims to inject CO_2 into suitable underground geological formations for long-term storage. At SLIM, we drive innovations in subsurface time-lapse monitoring by developing low-cost and robust algorithms to monitor CO_2 movement and mitigate its potential risks.



Multiphysics inversion for CO_2 monitoring and forecasting. From: Louboutin et al, “Learned multiphysics inversion with differentiable programming and machine learning”. The Leading Edge, 2023.

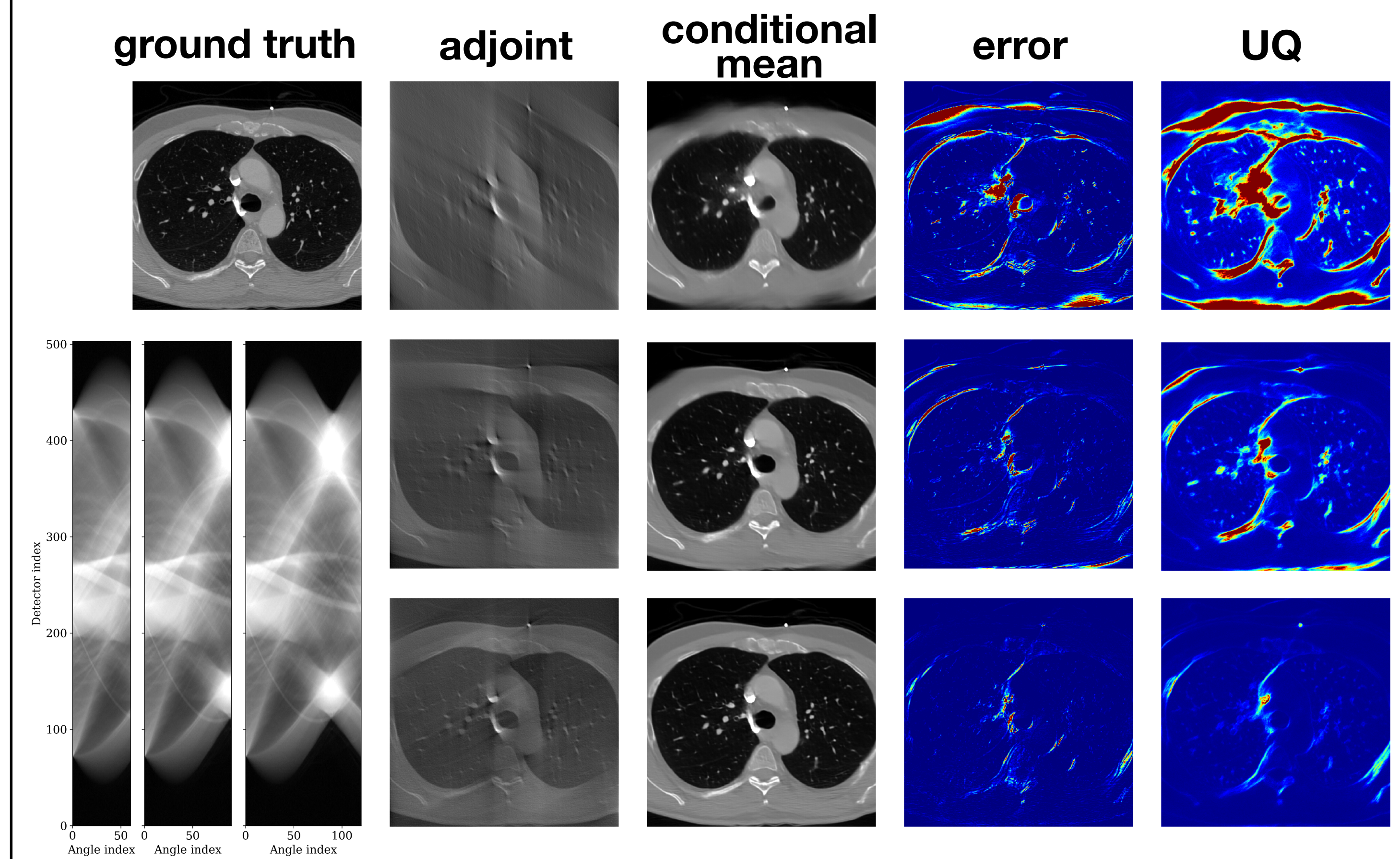


Learned sequential Bayes for subsurface CO_2 monitoring with conditional normalizing flows. From: Gahlot et al, “Monitoring subsurface CO_2 with sequential Bayesian inference”. International Meeting for Applied Geoscience & Energy, 2023.

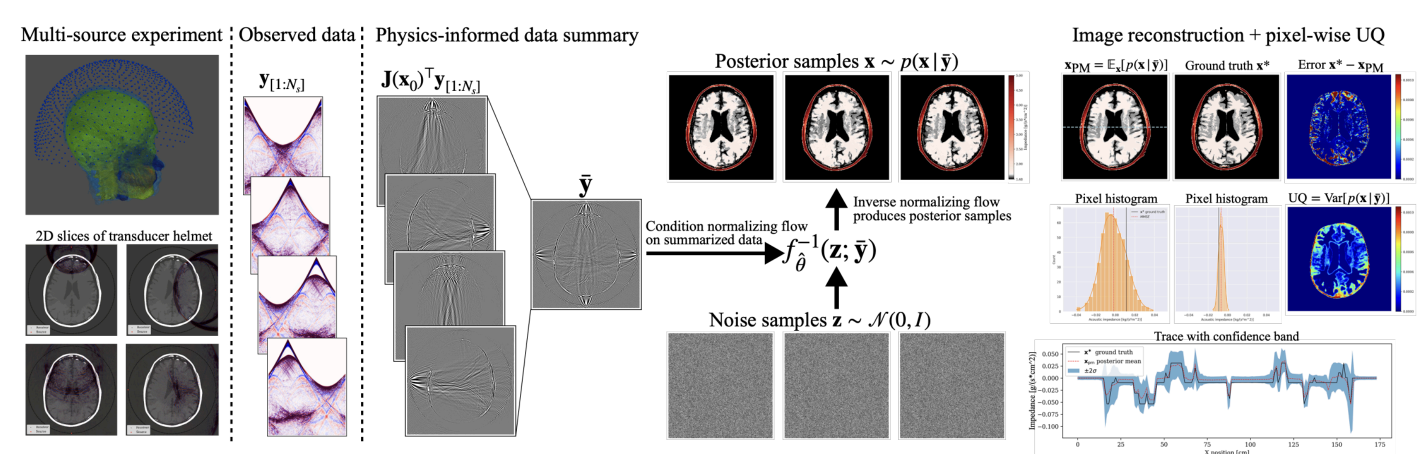


medical imaging and uncertainty quantification

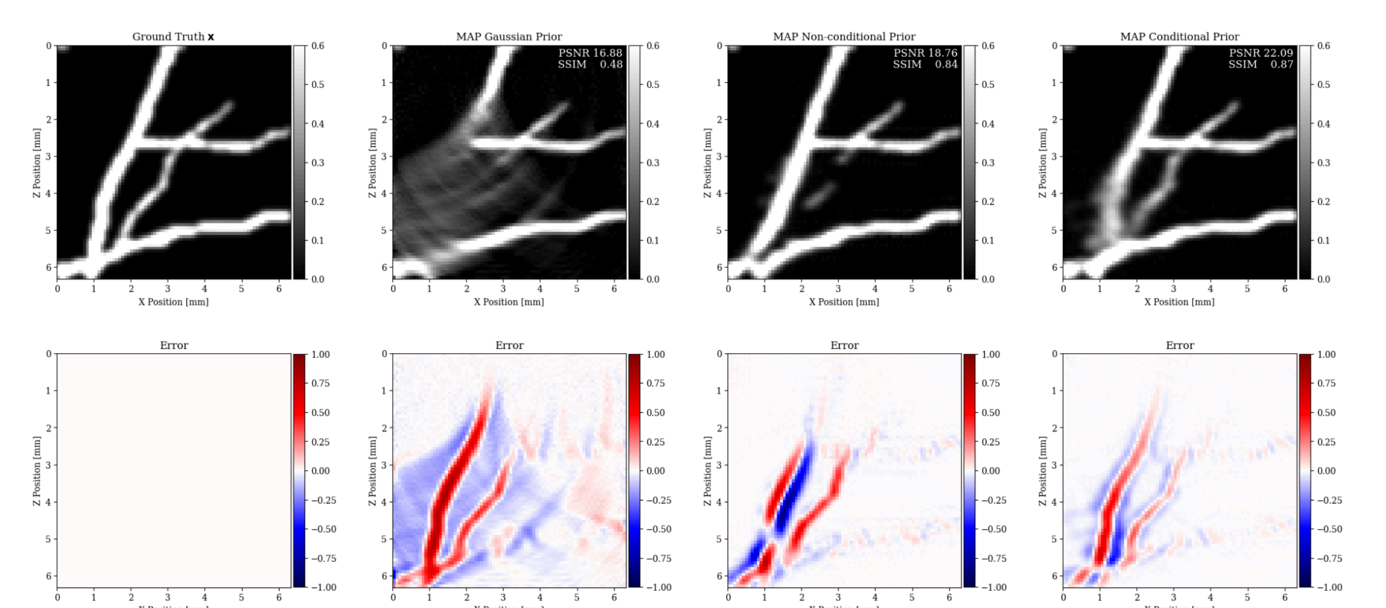
Learned uncertainty quantification methods that take raw data as input struggle to generalize to different imaging configurations. This is because data can be heterogeneous in dimensionality. At SLIM, we explore an adjoint physics-informed technique to standardize input data via normalizing flows. Our techniques are showcased on three medical imaging problems: X-ray tomography, photoacoustic imaging, and ultrasound imaging.



X-ray tomography with limited angles. From: Orozco et al, “Adjoint operators enable fast and amortized machine learning based Bayesian uncertainty quantification”. SPIE Medical Imaging Conference, 2023.



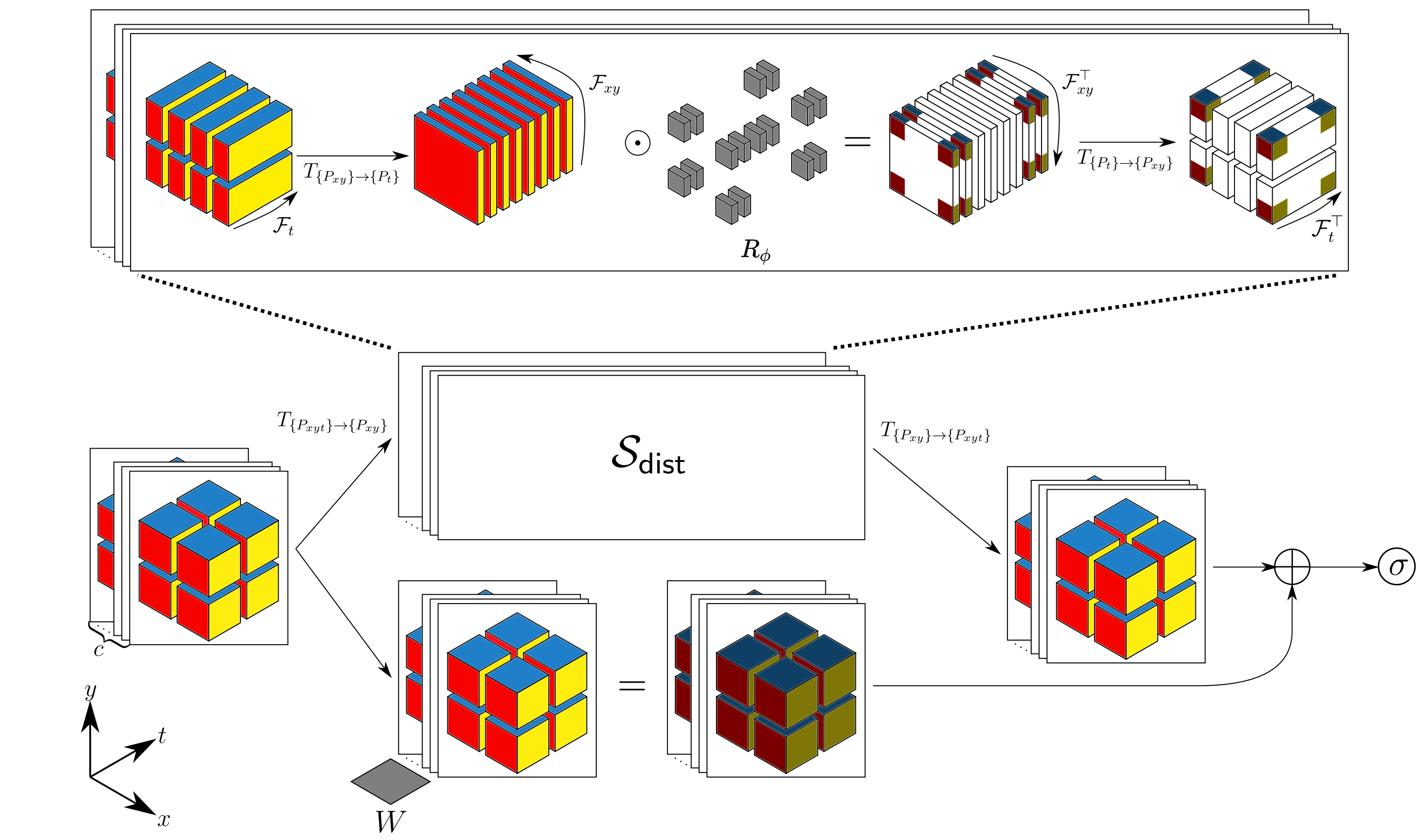
Amortized Bayesian inference for transcranial ultrasound imaging. From: Orozco et al, “Amortized normalizing flows for transcranial ultrasound with uncertainty quantification”. Medical Imaging with Deep Learning (MIDL) Conference, 2023.



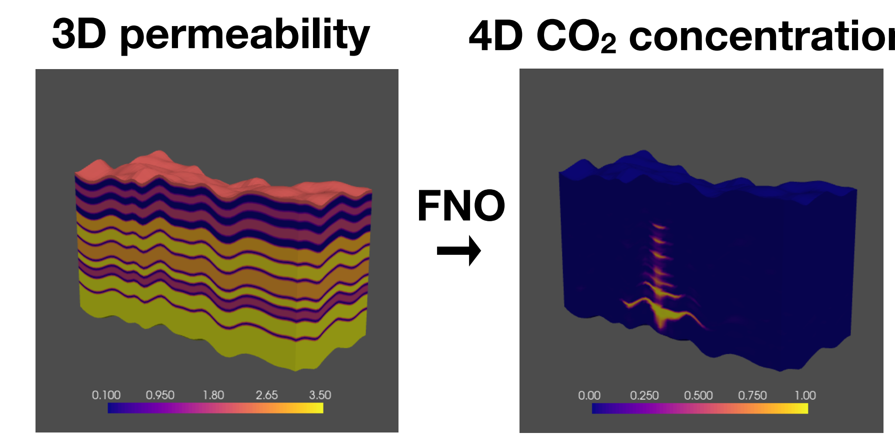
Photoacoustic imaging with (conditional) normalizing flow priors. From: Orozco et al, “Photoacoustic imaging with conditional priors from normalizing flows”. NeurIPS 2021 Deep Inverse Workshop.

scientific machine learning and high performance computing

SLIM group is a world leader in developing scalable algorithms for solving exascale inverse problems. Our expertise ranges from 4D model-parallel Fourier neural operators to math-inspired scientific machine learning algorithms.



Distributed Fourier neural operators based on model parallelism. All tensors (input, output, network weights, gradients) are partitioned to fit across multiple GPUs. We demonstrate that our model-parallel Fourier neural operators can predict 4D PDE solutions of over 2.6 billion variables on Perlmutter using up to 512 A100 GPUs. From: Grady et al, “Model-Parallel Fourier neural operators as learned surrogates for large-scale parametric PDEs”. Computers & Geosciences, 2023.



problem size (nx*ny*nz*nt)	PDE solver time	FNO time	speed up
60*60*64*30	312	1.15	271X
68*118*263*16 Sleipner	8291	5.98	1386X

Algorithm: reliable surrogate-assisted inversion with Fourier neural operators and normalizing flows. From: Yin et al, “Solving multiphysics-based inverse problems with learned surrogates and constraints”. Advanced Modeling and Simulation in Engineering Sciences, 2023.

Input: initial model parameter $\mathbf{K}_0 \in \mathbb{R}^N$, observed data $\mathbf{d}$, noise level σ
Input: trained FNO $\mathcal{S}_{\theta^*}$, trained NF $\mathcal{G}_{\mathbf{w}^*}$
Input: number of inner-loop iterations *maxiter*
Input: initial ℓ_2 ball size τ_{init}, multiplier $\beta > 1$, final ℓ_2 ball size τ_{final}
$\mathbf{z} = \mathcal{G}_{\mathbf{w}^*}^{-1}(\mathbf{K}_0)$
$\tau = \tau_{\text{init}}$
while $\|\mathbf{d} - \mathcal{H} \circ \mathcal{S}_{\theta^*} \circ \mathcal{G}_{\mathbf{w}^*}(\mathbf{z})\|_2 > \sigma \|\mathcal{N}(0, \mathbf{I})\|_2$ and $\tau \leq \tau_{\text{final}}$ **do**
  for $iter = 1 : maxiter$ **do**
    $\mathbf{g} = \nabla_{\mathbf{z}} \|\mathbf{d} - \mathcal{H} \circ \mathcal{S}_{\theta^*} \circ \mathcal{G}_{\mathbf{w}^*}(\mathbf{z})\|_2^2$
    $\mathbf{z} = \mathcal{P}_\tau(\mathbf{z} - \gamma \mathbf{g})$
  end
  $\tau = \beta\tau$
end
Output: inverted model parameter $\mathbf{K} = \mathcal{G}_{\mathbf{w}^*}(\mathbf{z})$