Capturing velocity-model uncertainty and two-phase flow with Fourier Neural Operators

Ali Siahkoohi, Thomas Grady, Abhinav P Gahlot, Hüseyin Tuna Erdinc, and Felix J. Herrmann

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Motivation

increasing complexity

Geophysical challenges such as *geological carbon storage* call for

- high-*resolution* & highly *sensitive* imaging of *weak* time-lapse signals
- *complex* multi-phase *flow* simulations
- *coupling* of wave & fluid-flow physics
- approaches that are *uncertainty* aware

Results in a need for *surrogate* models to make simulations computationally *feasible*

Today’s focus is on recent developments enabled by neural operators

What are neural operators?

Neural operators

Conventional Neural Networks:

- learn *discretized* image-to-image mappings
- generalize poorly to different discretization & sources (e.g. well locations)

Neural Operators:

- learn mappings between function spaces (e.g. PDE solution operators)
- finite-dimensional (fixed grid) $\Longrightarrow$ infinite-dimensional (gridless)

Learning neural operators

Given $\{a^{(i)}(\mathbf{x}), u^{(i)}(\mathbf{x})\}_{i=1}^{N}$ from nonlinear map between function spaces $\mathcal{A}, \mathcal{U}$:

$$\mathcal{G}: \mathcal{A} \mapsto \mathcal{U}$$

taking values on $\mathbb{R}^{d_a}$ and $\mathbb{R}^{d_u}$, operator learning entails minimizing

$$\mathbf{w}^* = \underset{\mathbf{w}}{\mathrm{arg}min} \frac{1}{N} \sum_{i=1}^{N} \| \mathcal{G}_{\mathbf{w}}(a^{(i)}) - u^{(i)} \|_2^2$$

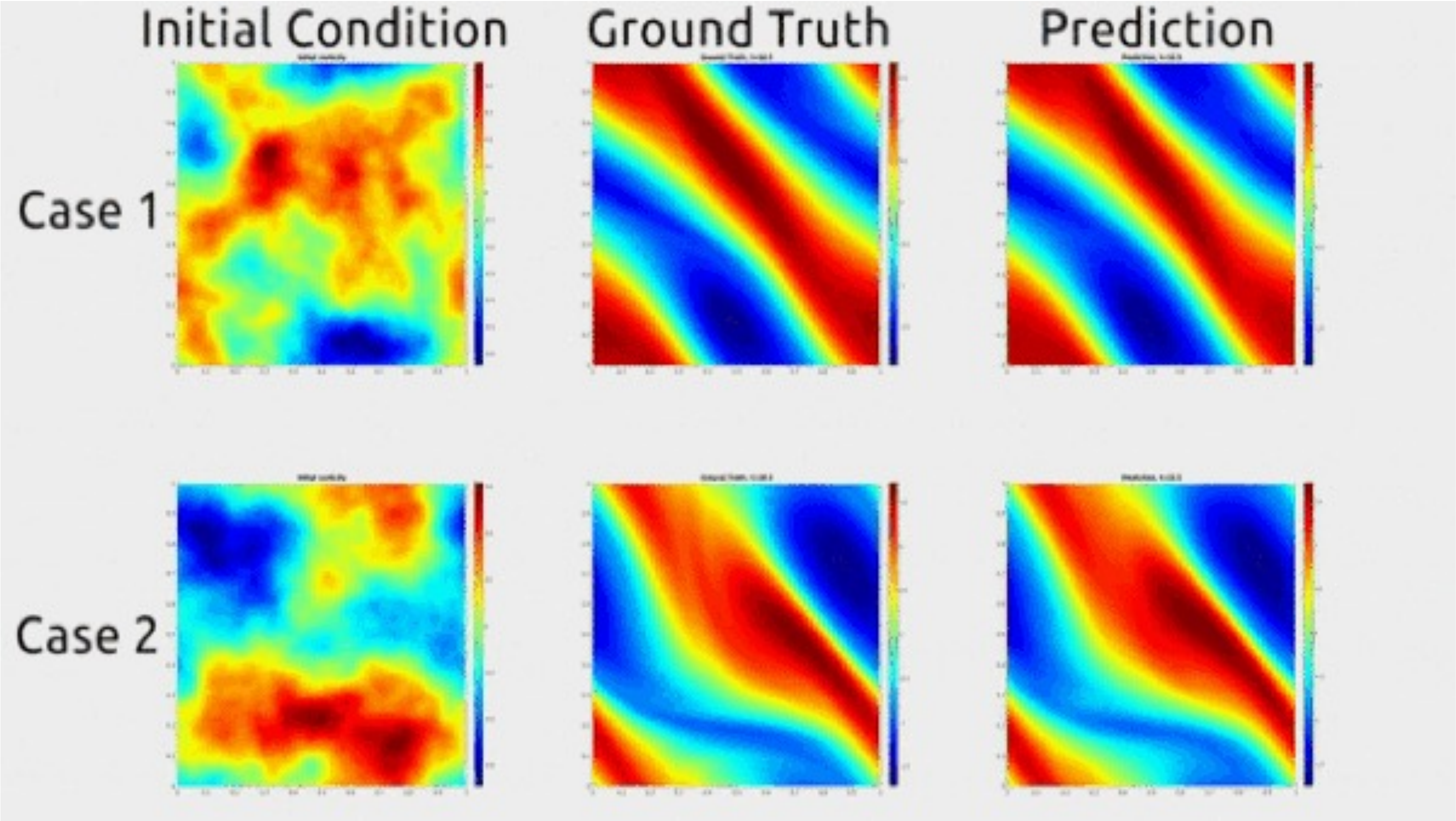
yielding the approximate mapping

$$\mathcal{G}_{\mathbf{w}^*}: \mathcal{A} \mapsto \mathcal{U}$$

https://zongyi-li.github.io/neural-operator/

Applications

Fourier Neural Operators



So what?

Surrogate model

two-phase flow equations

mass balance equation $\frac{\partial}{\partial t}(\phi S_i \rho_i) + \nabla \cdot (\rho_i \mathbf{v}_i) = \rho_i q_i, i = 1,2$

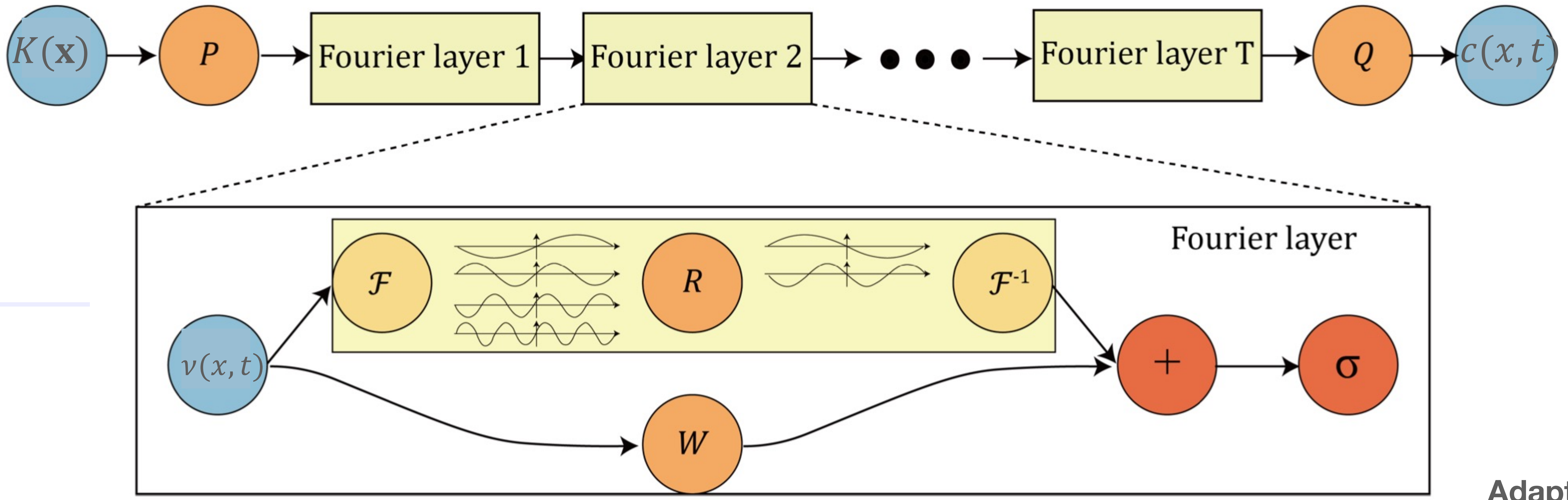
inject CO_2 to replace water $S_1 + S_2 = 1$

Darcy's law $\mathbf{v}_i = -\frac{K k_{ri}}{\tilde{\mu}_i}(\nabla P_i - g\rho_i \nabla Z), i = 1,2$

Corey model $k_{ri}(S_i) = S_i^2$

fluid pressure $P_2 = P_1 - P_c(S_2)$

Fourier Neural Operators



Adapted from Li

Maps permeability K in $(\mathbf{x}, K(\mathbf{x}))$ and outputs $c(\mathbf{x}, t)$

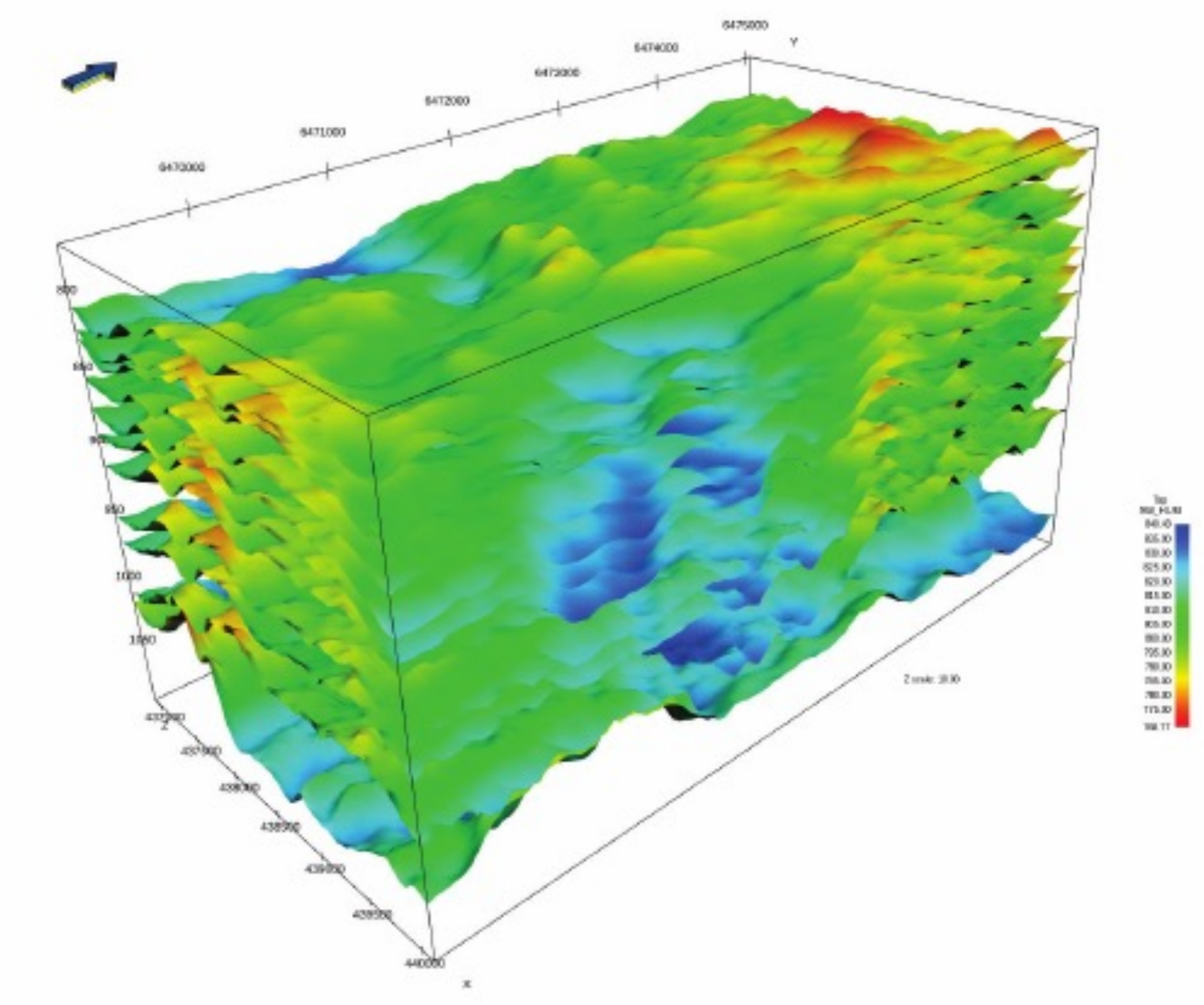
P lifts to higher latent dimension and Q projects back to target dimension

Fourier layer: $v_{j+1} = \sigma\left(W v_j + \mathcal{F}^{-1}\left(R_\phi \cdot (\mathcal{F} v_j)\right)\right)$

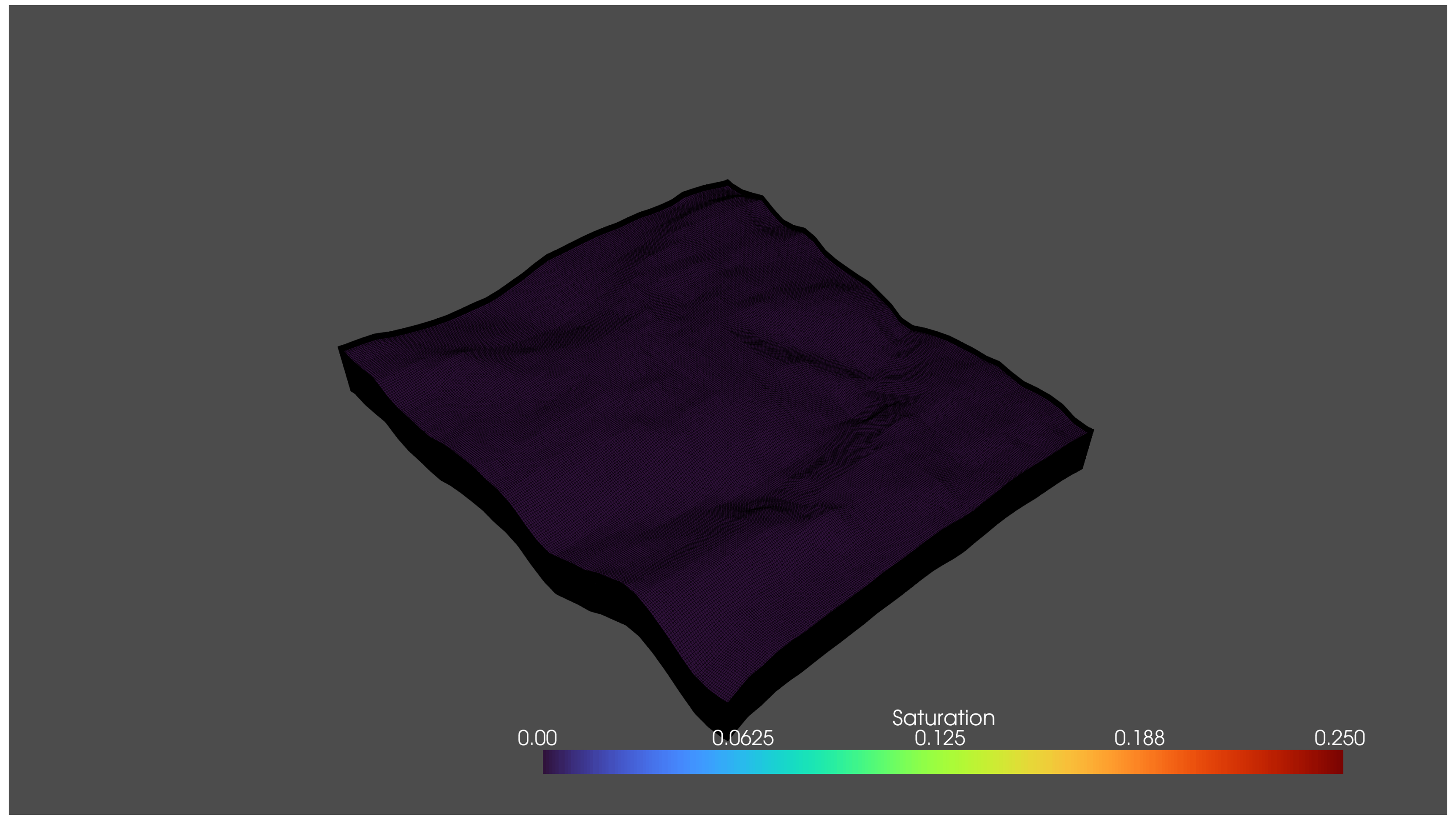
R_ϕ selects a subset of the modes, usually a low-pass filter https://co2datashare.org/dataset/sleipner-2019-benchmark-model#orgf2c5747

Challenges

Scaling FNOs to realistic problems is challenging

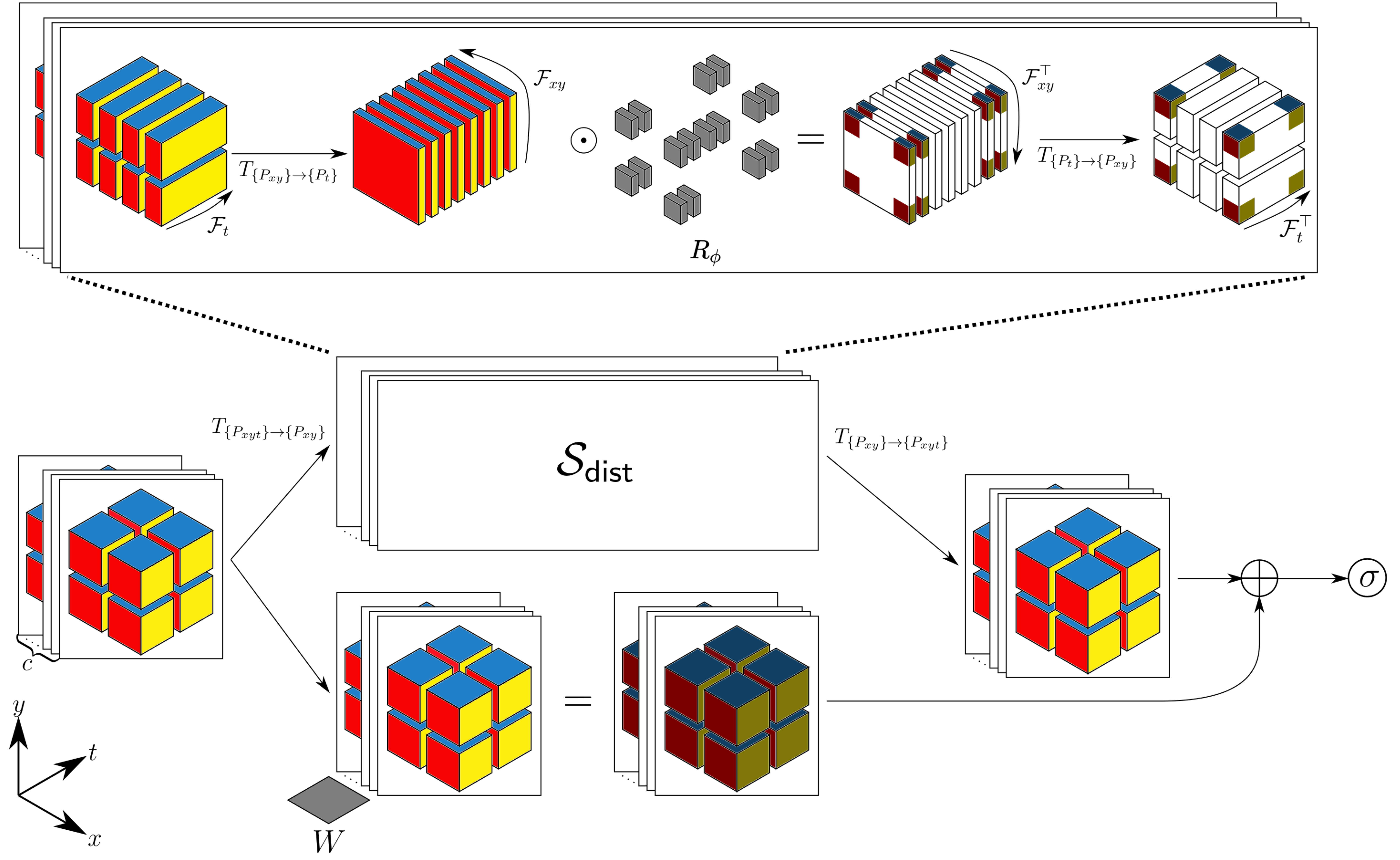


- 3D permeability $(x, y, z) \rightarrow$ 4D CO_2 evolution (x, y, z, t)
- problems beyond $64^3 (x, y, z)$ do not fit w/i GPUs
- real problems are often much larger, e.g. Sleipner (low-resolution) is $64 \times 118 \times 263$
- need high-dimensional model-parallelism on distributed-memory systems



FNO Block w/ domain decomposition

Implemented w/ DistDL



Grady et. al. Model-Parallel Fourier Neural Operators as Learned Surrogates for Large-Scale Parametric PDEs, 2022

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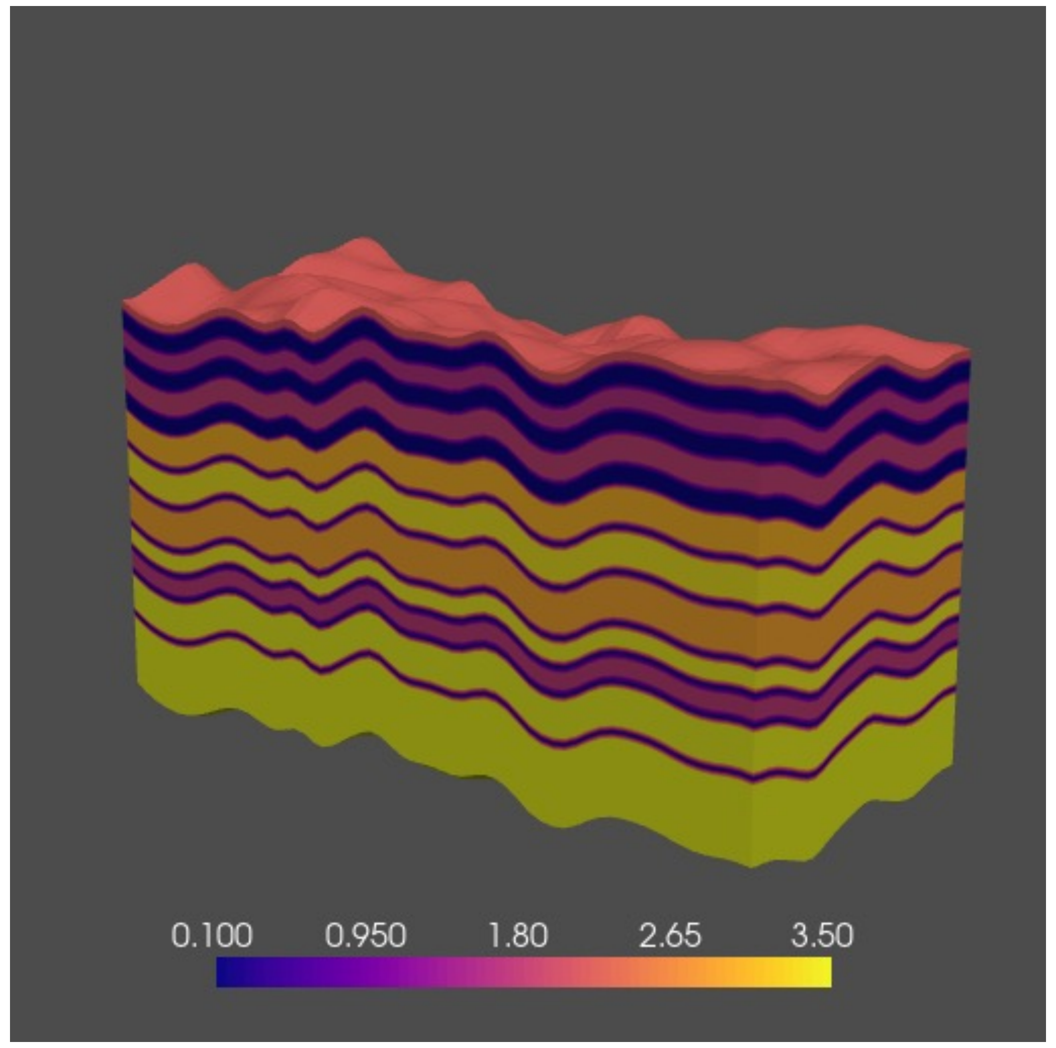
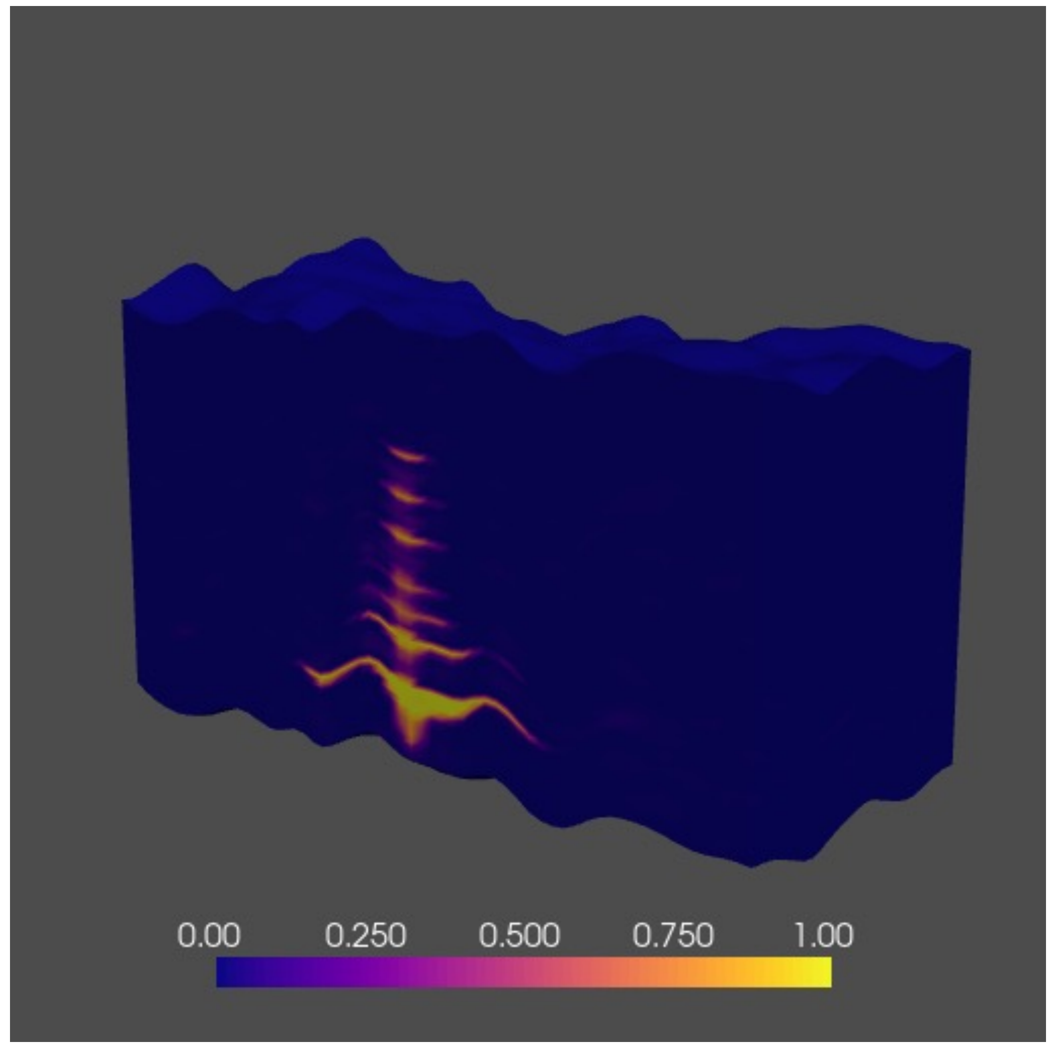
Results

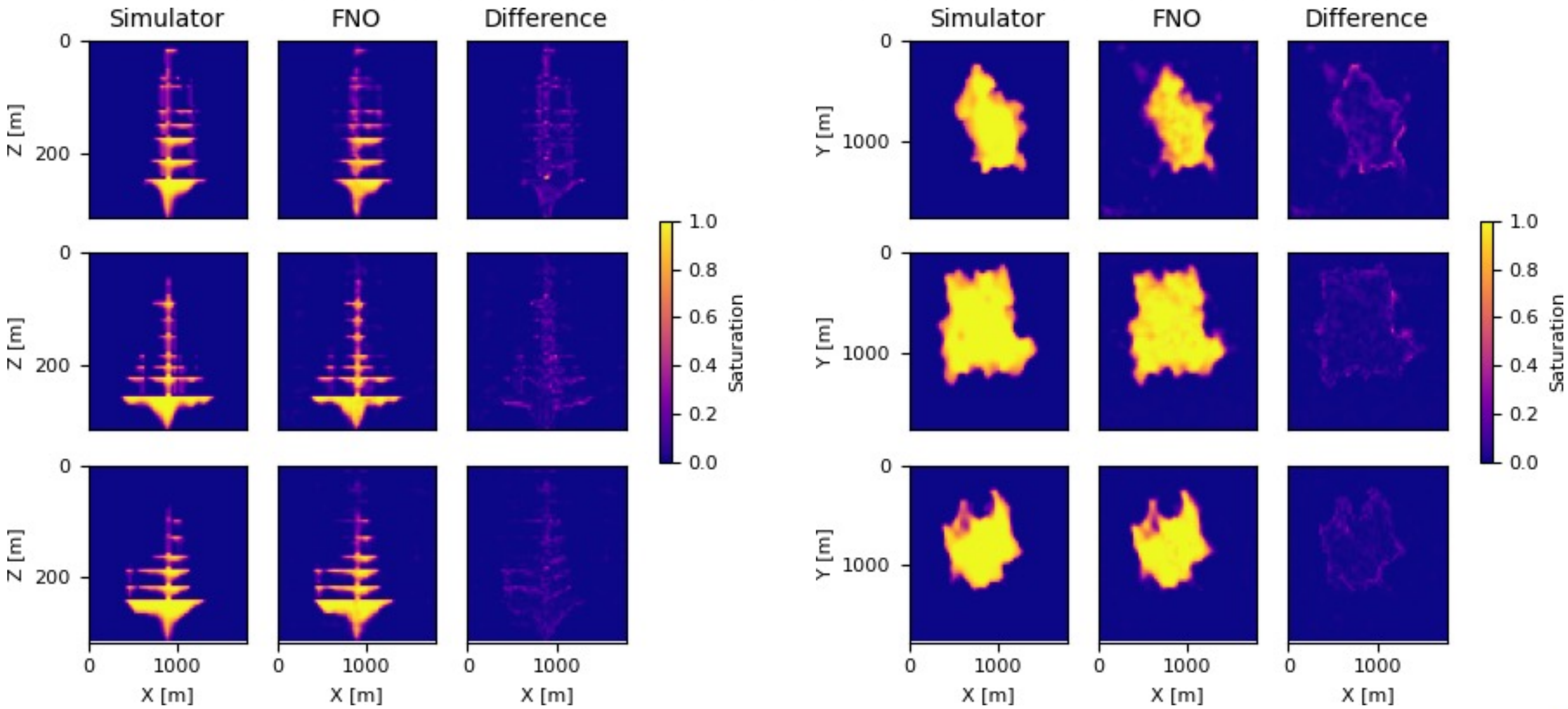
3D two-phase flow for CCS





$1386\times$speedup on Sleipner-size model

Problem Size	OPM Time (s)	FNO Time (s)	Speedup
$60 \times 60 \times 64 \times 30$	312	1.15	271x
$68 \times 118 \times 263 \times 16$	8291	5.98	1386x



Leakage detection

Jones,C. E., Building Complex Synthetic Models to Evaluate Acquisition Geometries and Velocity Inversion Technologies, 74th EAGE Conference and Exhibition incorporating EUROPEC 2012.

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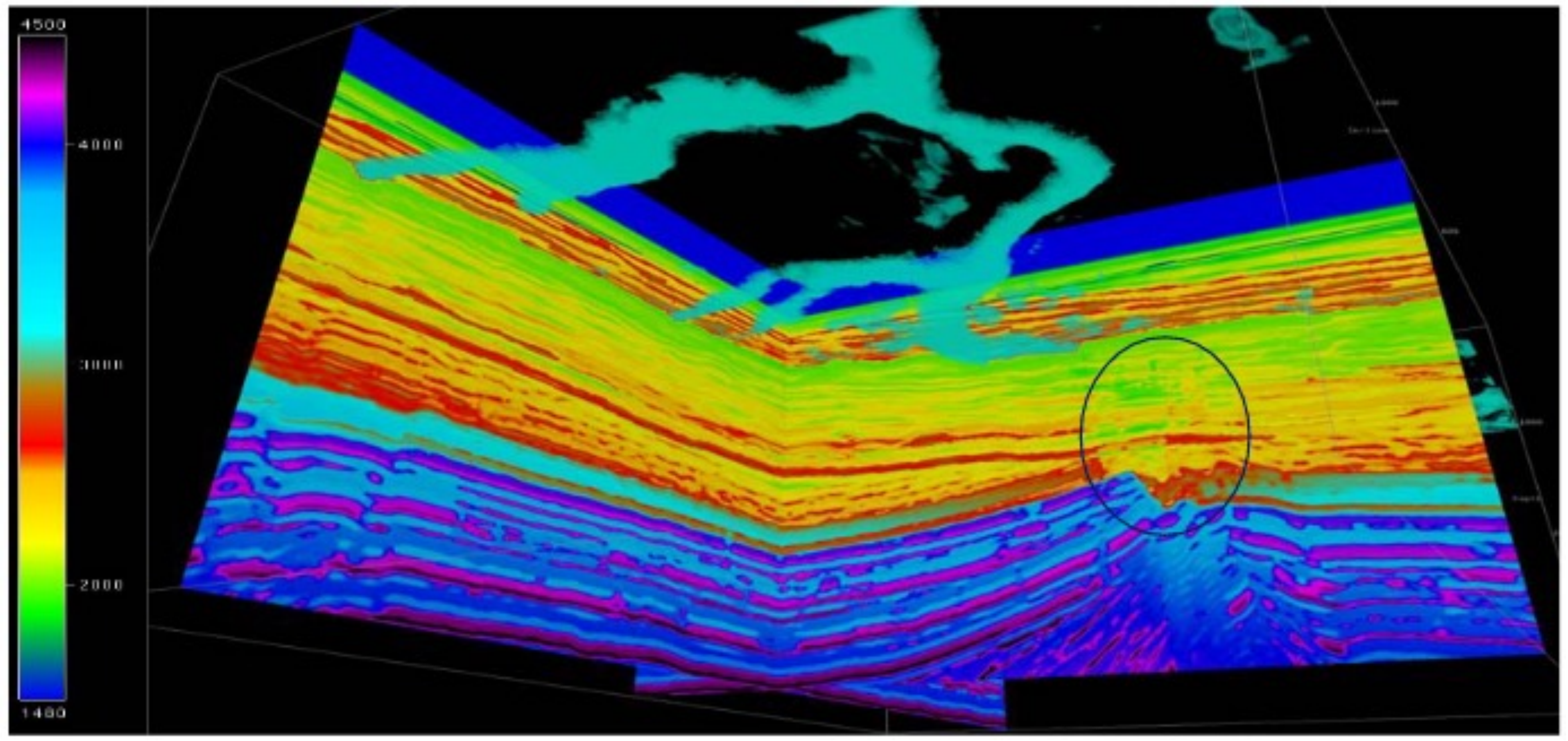
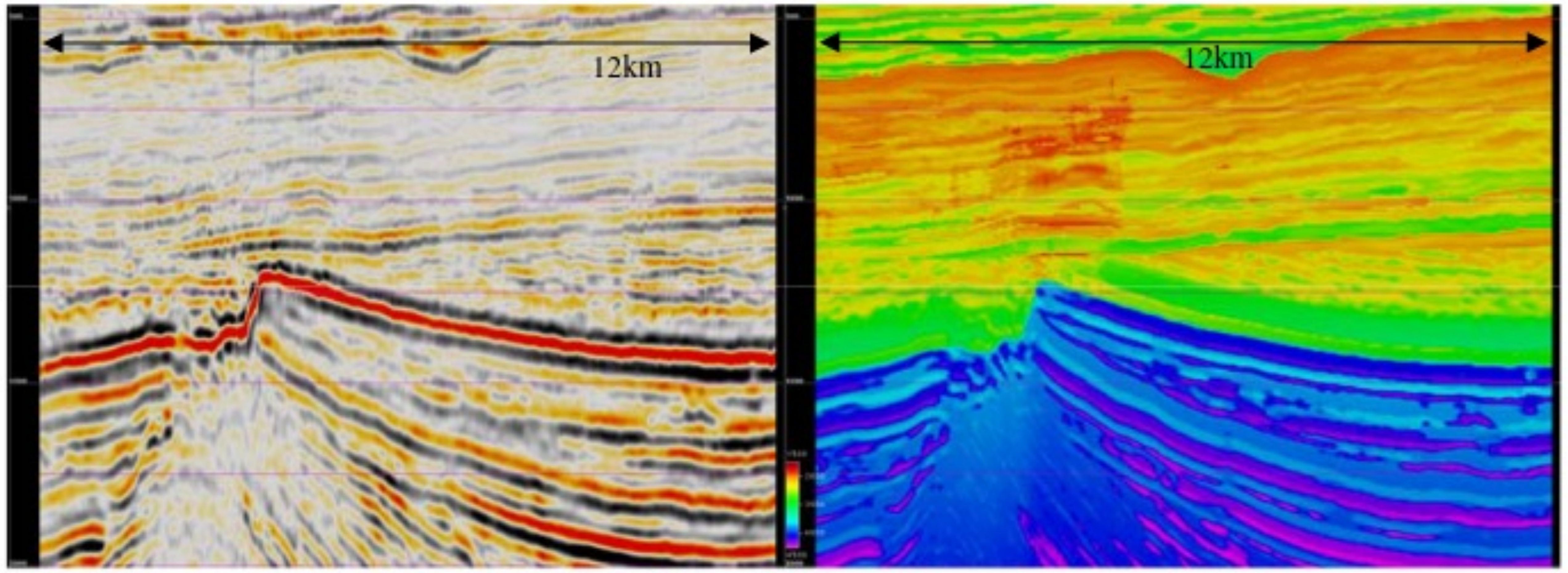
Proxy model

derived from imaged 3D seismic & well data

convert velocity model into

- permeability
- porosity

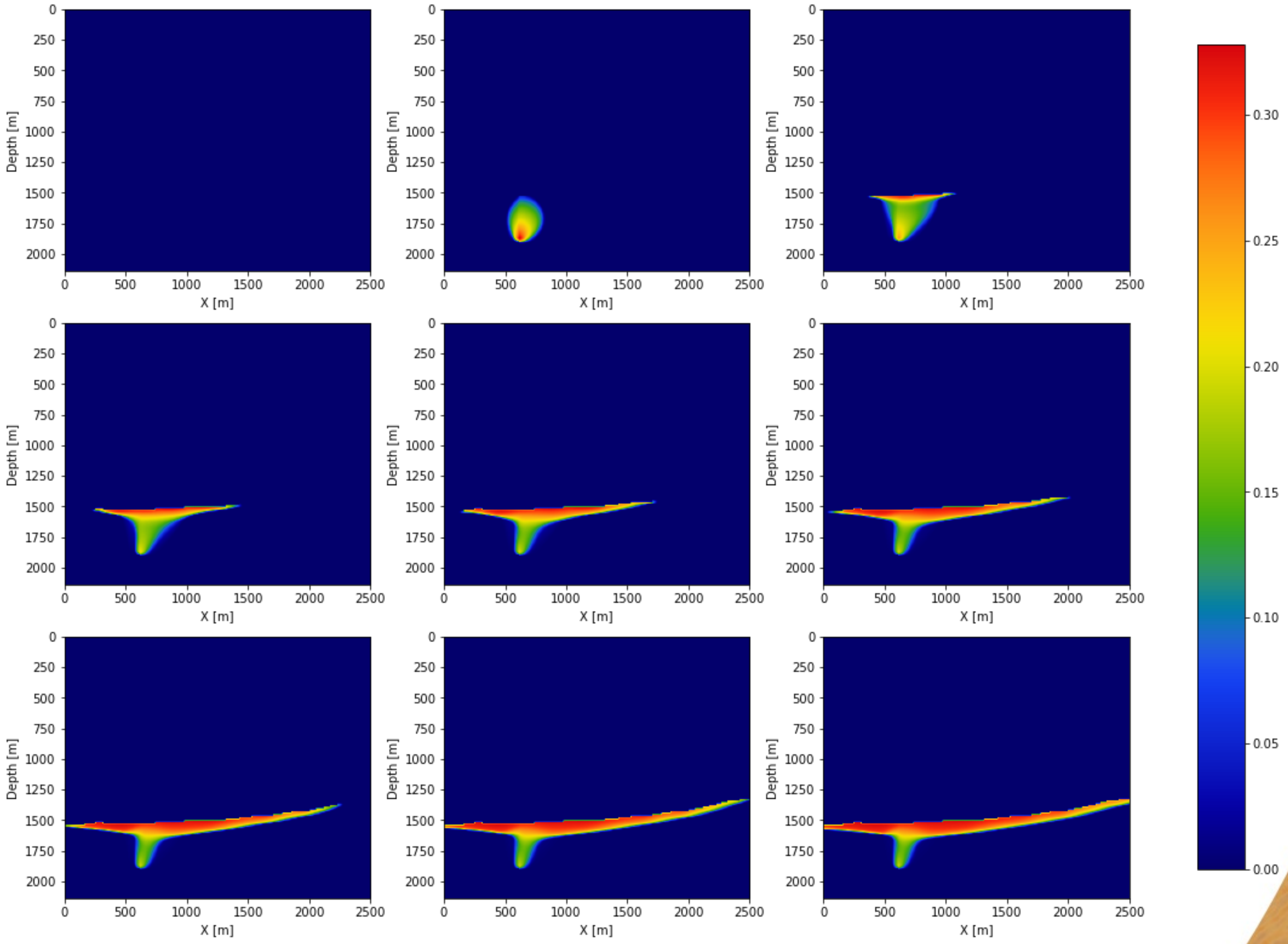




Dongzhuo Li, Kailai Xu, Jerry M Harris, and Eric Darve. Coupled time-lapse full-waveform inversion for subsurface flow problems using intrusive automatic differentiation. Water Resources Research, 56(8):e2019WR027032, 2020.

Simulations

regular CO2 plume



Dongzhuo Li, Kailai Xu, Jerry M Harris, and Eric Darve. Coupled time-lapse full-waveform inversion for subsurface flow problems using intrusive automatic differentiation. Water Resources Research, 56(8):e2019WR027032, 2020.

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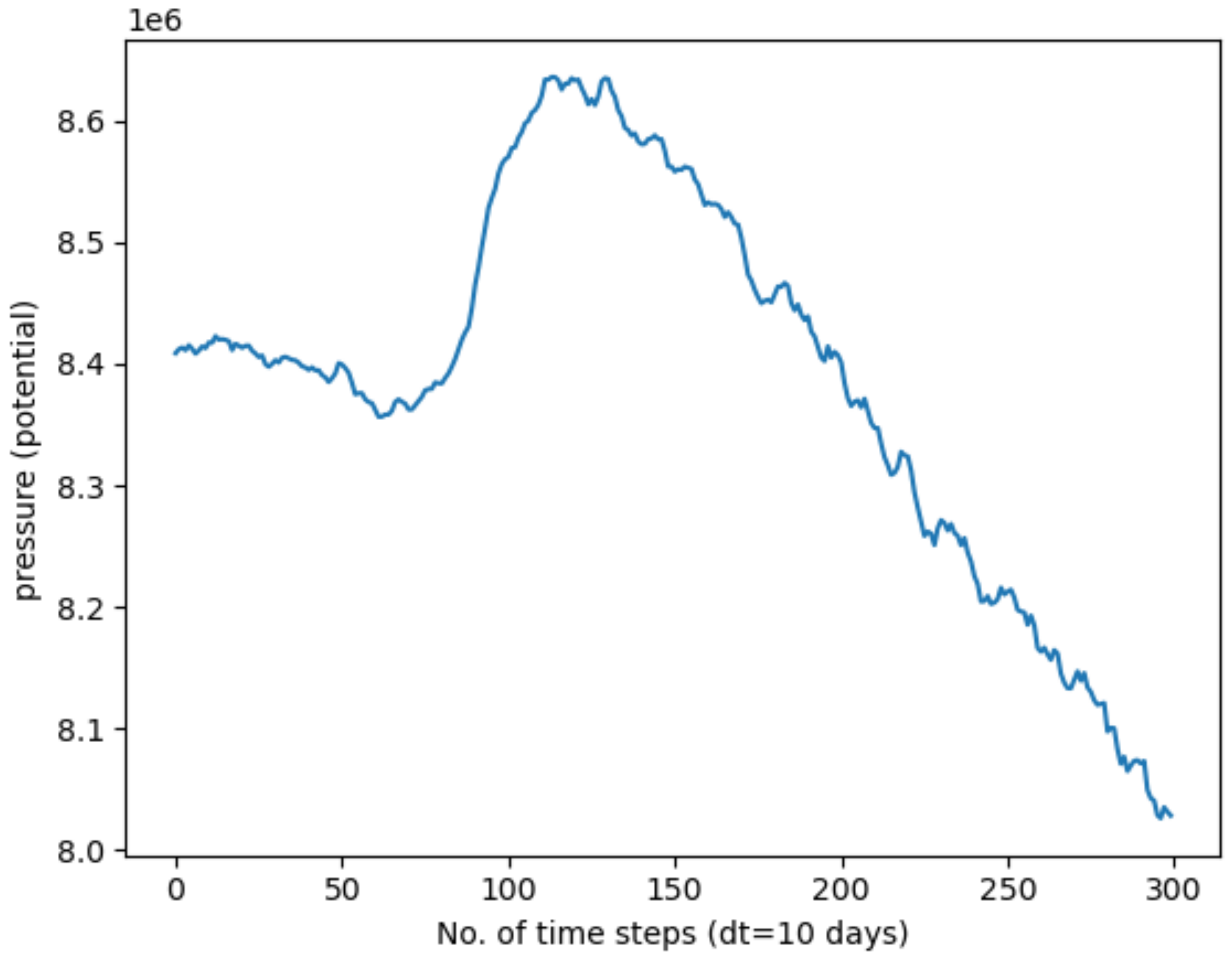
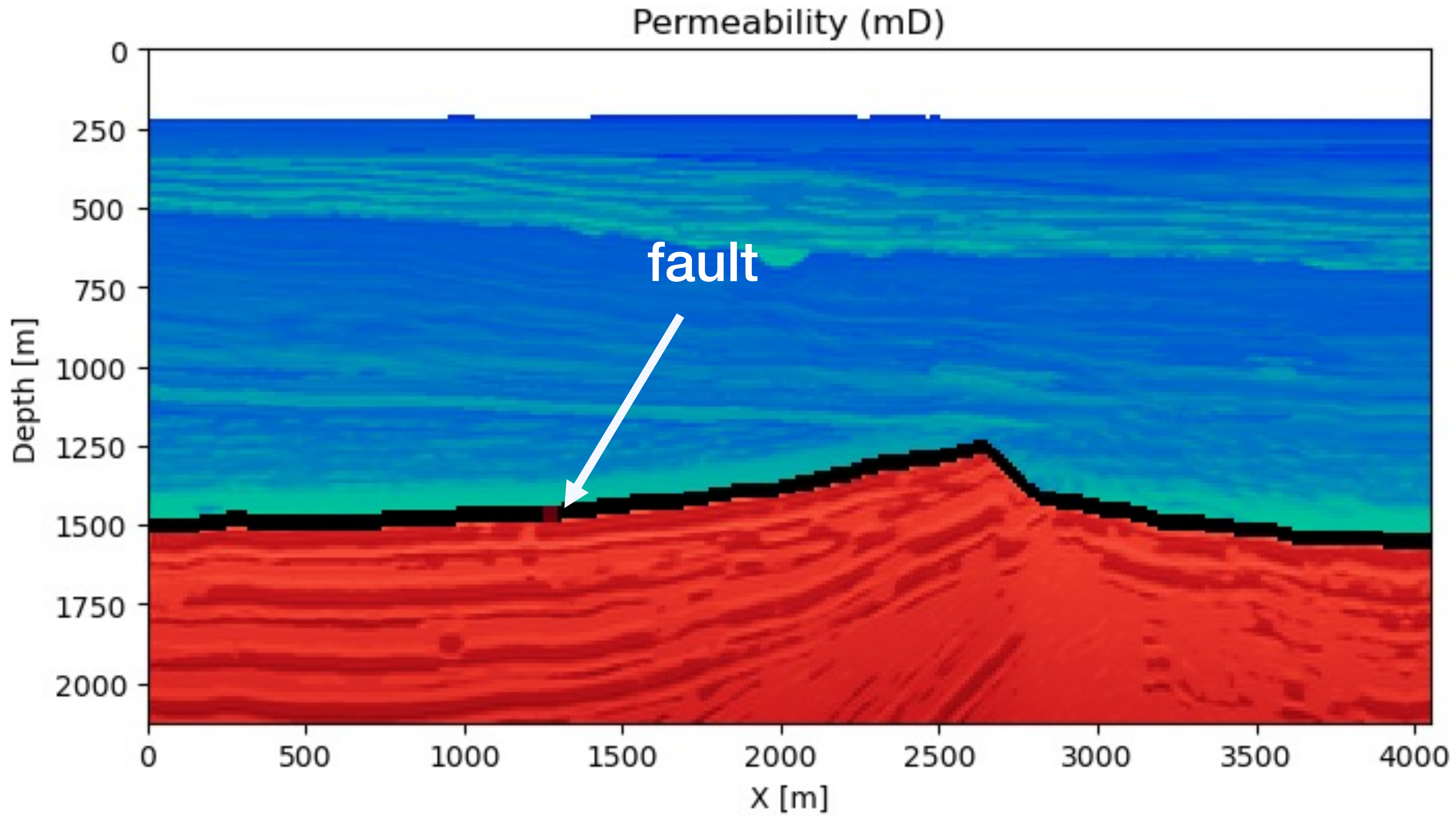
Leakage scenario

pressure-induced fault activation

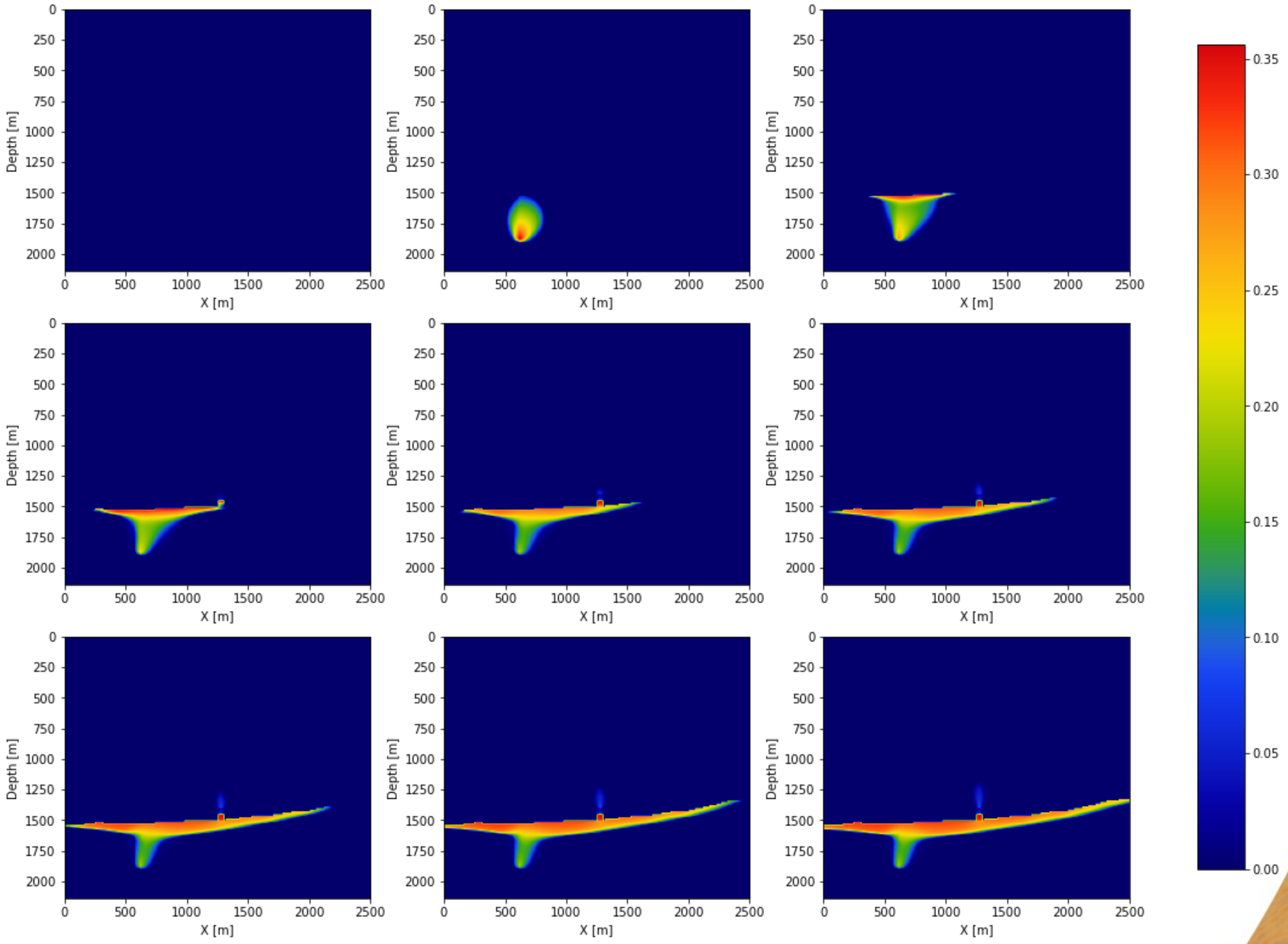
- two-phase-flow simulations
- pressure $\geq 15\text{MPa}$ induces a fault in the seal
- increase in permeability leads to leakage through seal
- leak location in seal selected at random w/ random widths





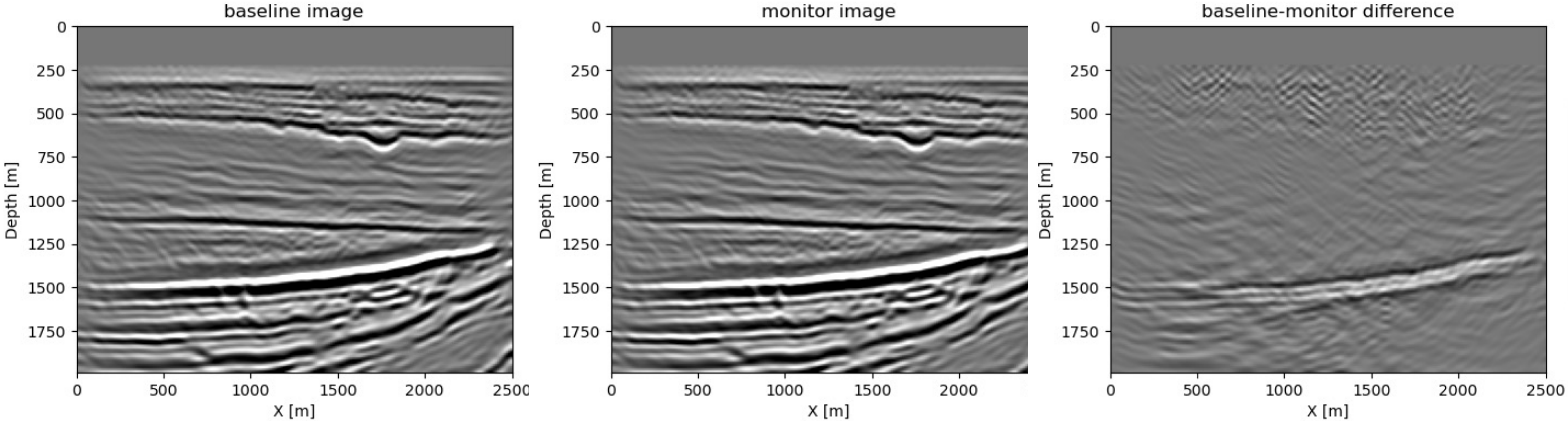
Simulations

irregular CO2 plume



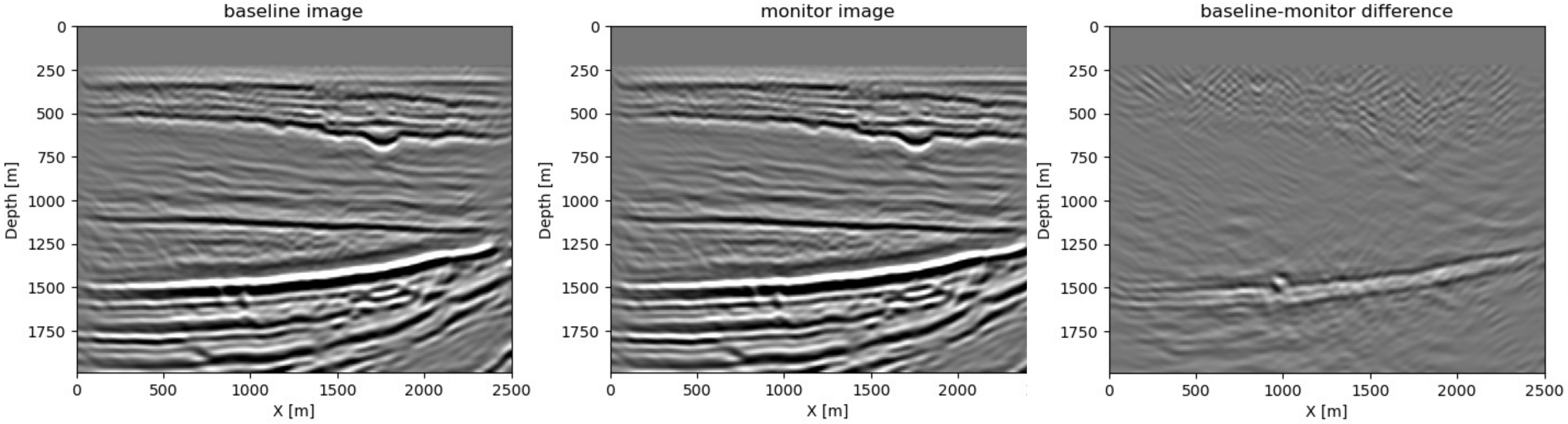
Time-lapse images

regular flow – no replication acquisition



Time-lapse images

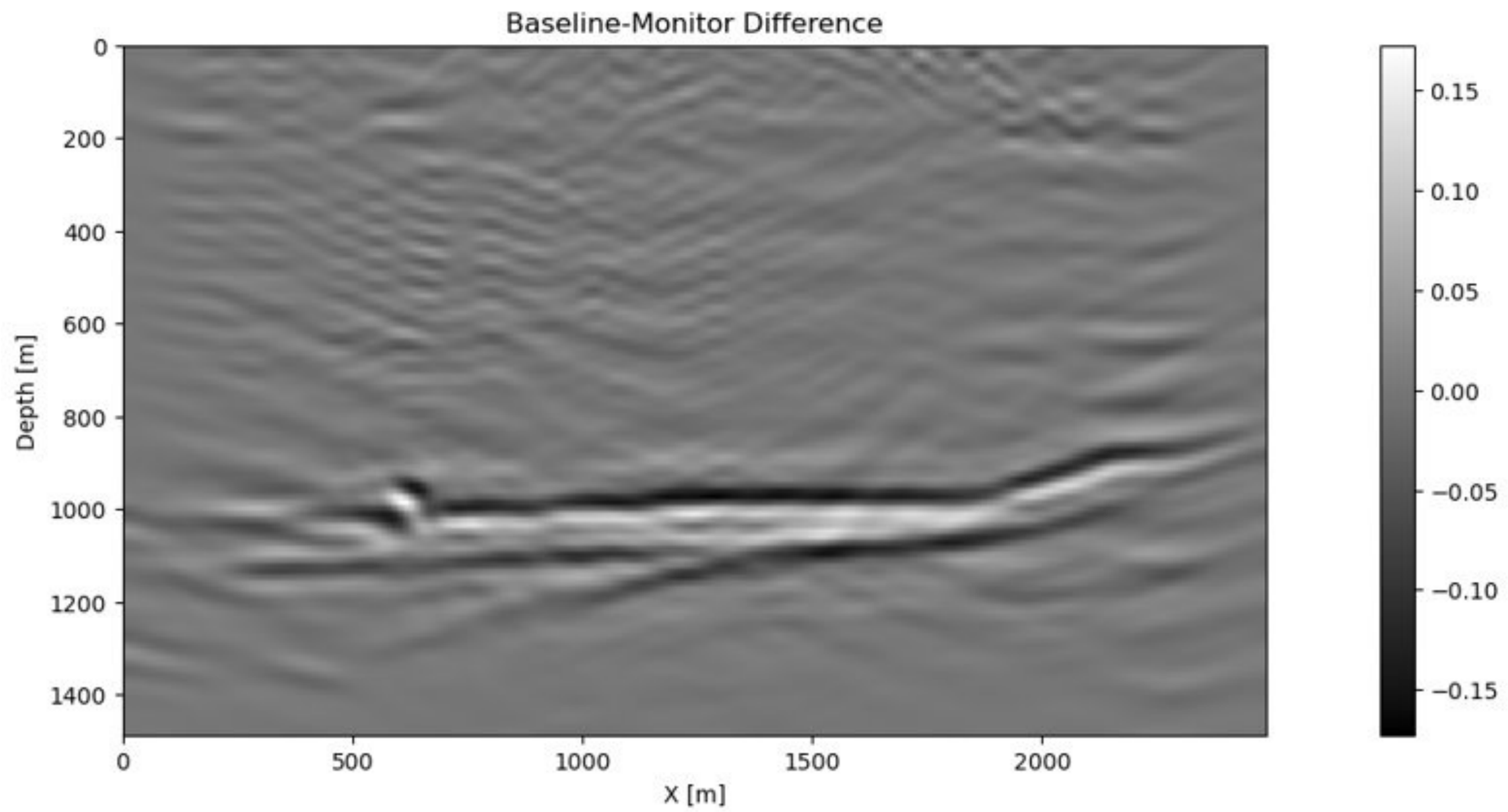
irregular flow – no replication acquisition



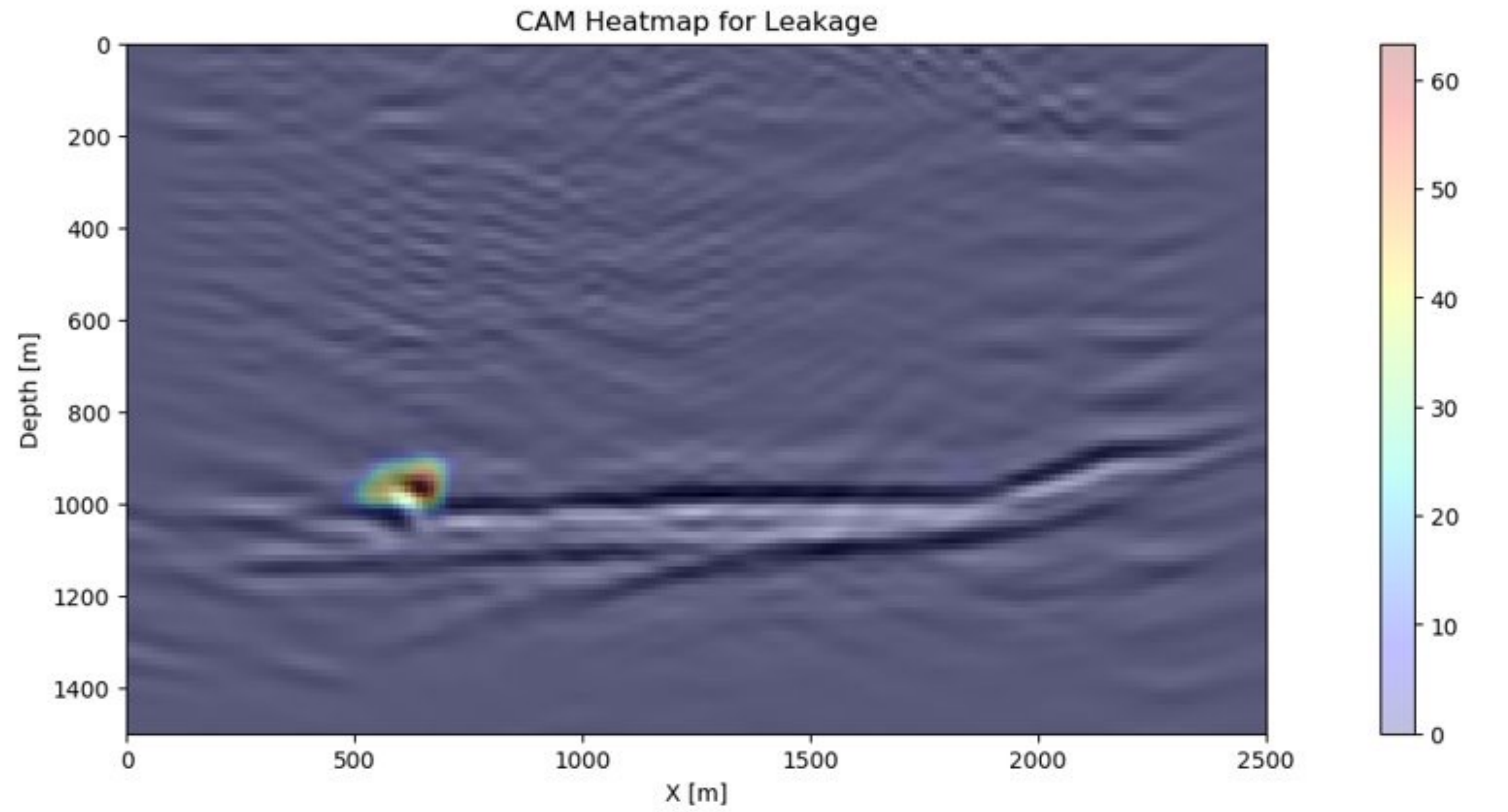
Leak / no leak classification

TABLE I
Performance Metric Comparison

Metrics	Mean Deviation
Accuracy	0.797 ± 0.066
Precision	0.711 ± 0.105
Recall	0.954 ± 0.023
F1 Score	0.818 ± 0.068



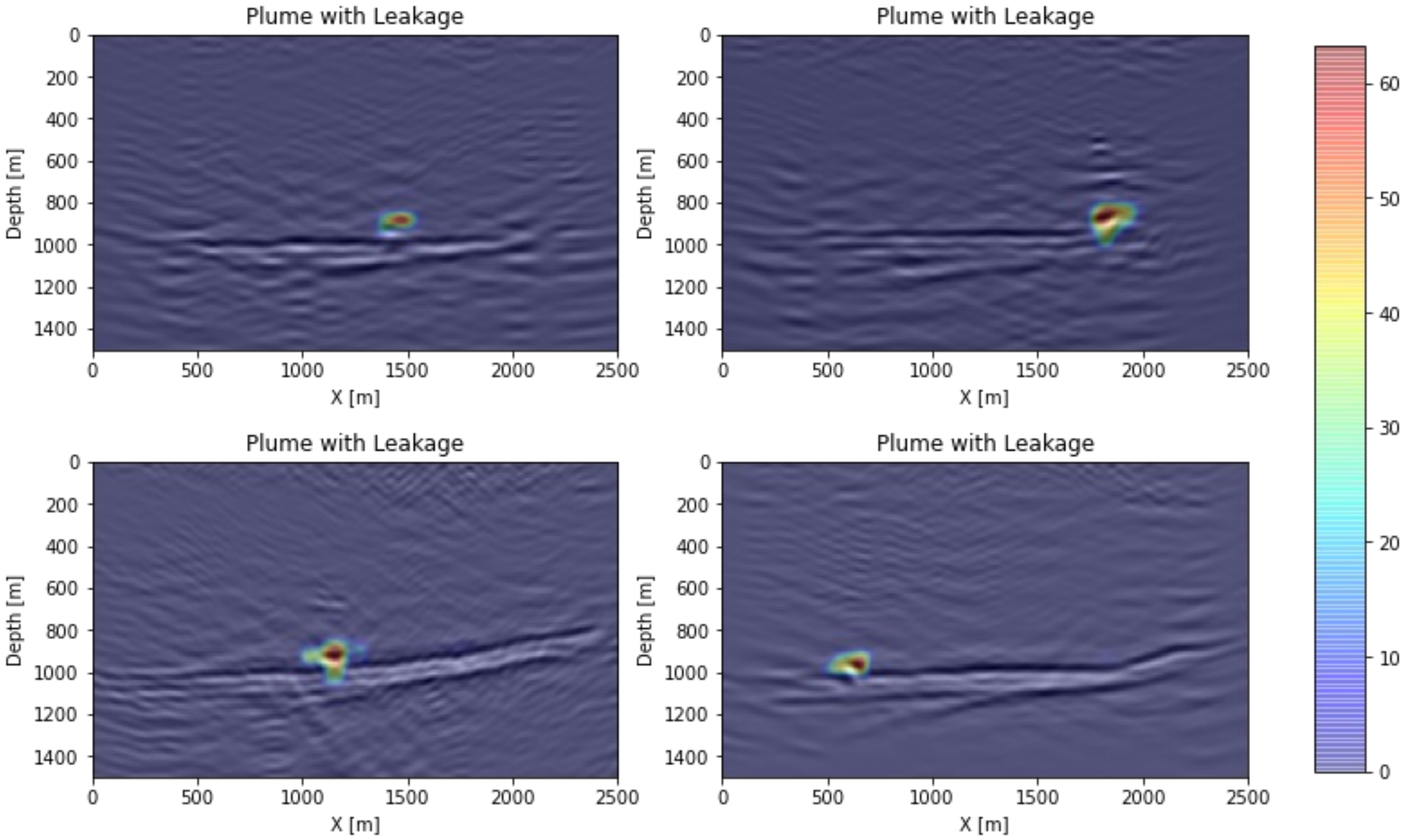
Precision: measures how many leakages model predicted correctly, out of all predicted leakages



Recall: measures how many leakages model predicted correctly, out of all actual leakages

Leakage detection

examples

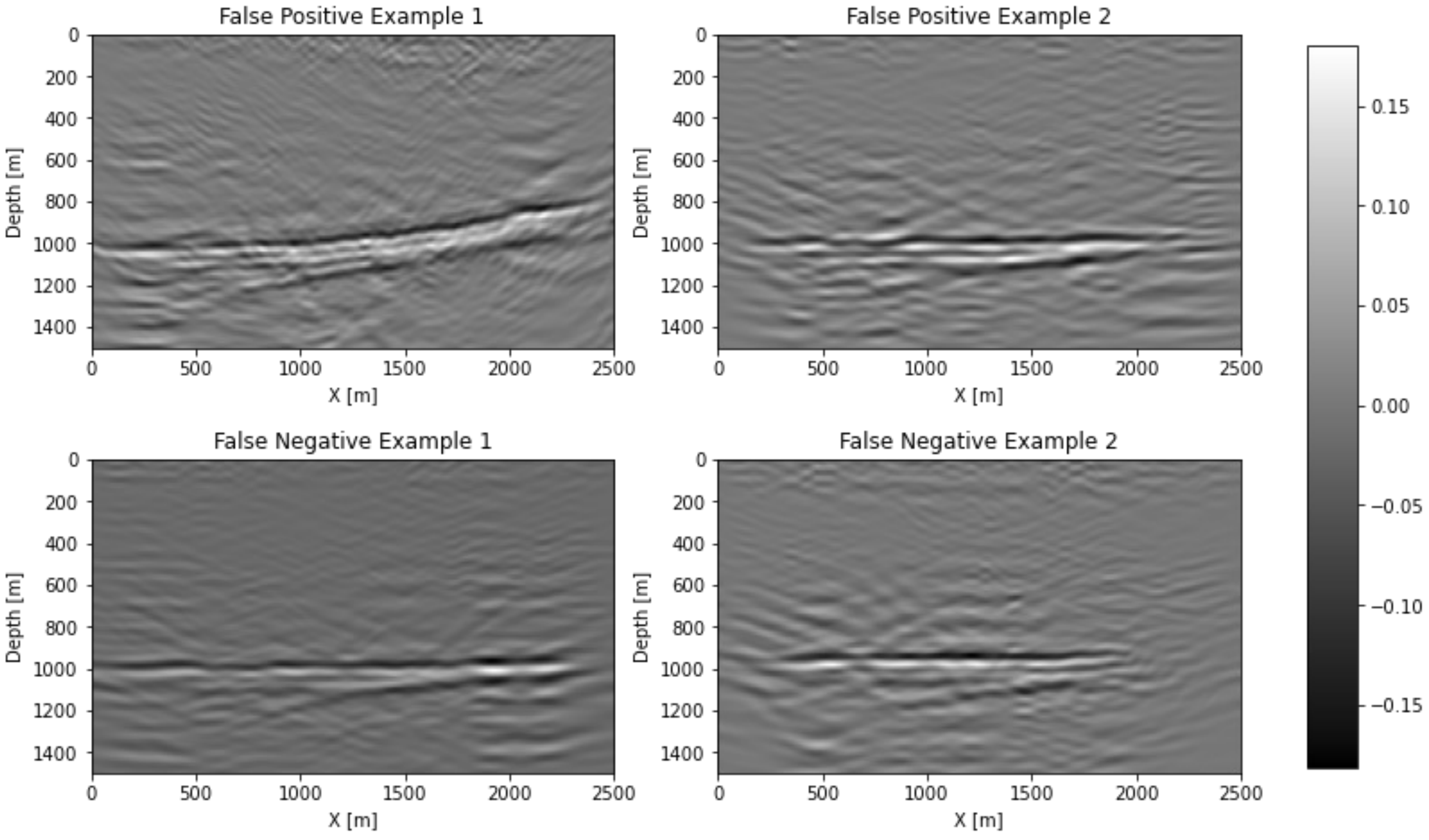


False positives/negatives

examples

false positives

false negatives



What about uncertainty?

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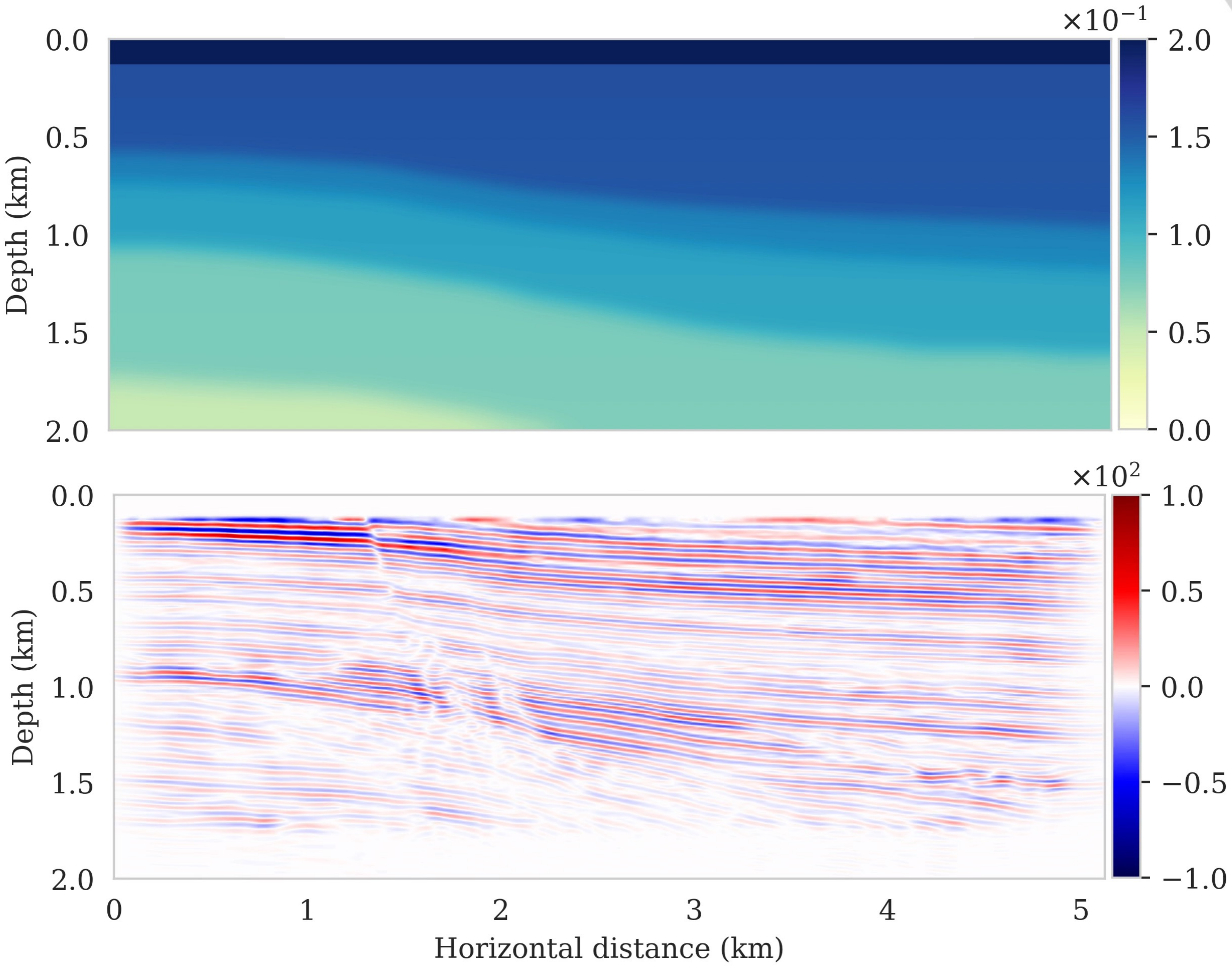
e.g. w.r.t. background velocity models…

Training set

RTMs for different background velocity models

Samples from $p(\mathbf{m}_0 \mid \mathbf{d})$ for the background velocity model

Corresponding RTMs
$\delta \mathbf{m}_{RTM} = \sum_{i=1}^{n_s} \mathbf{J}(\mathbf{m}_0, \mathbf{q}_i)^\top \delta \mathbf{d}_i$



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Velocity continuation

w/ FNOs

Learn mapping $\mathcal{T}_{(\mathbf{m}_{\text{init}},\mathbf{m}_{\text{target}})}: \delta\mathcal{M} \rightarrow \delta\mathcal{M}$ from training pairs

$$\{((\mathbf{m}_0^{(i)}, \delta\mathbf{m}_{\text{init}}), \delta\mathbf{m}_{\text{RTM}}^{(i)}) | i = 1, \ldots, N\}$$

- $(\mathbf{m}_0^{(i)}, \delta\mathbf{m}_{\text{init}})$ input target background and initial seismic image training pair
- $\delta\mathbf{m}_{\text{RTM}}^{(i)}$ target seismic image

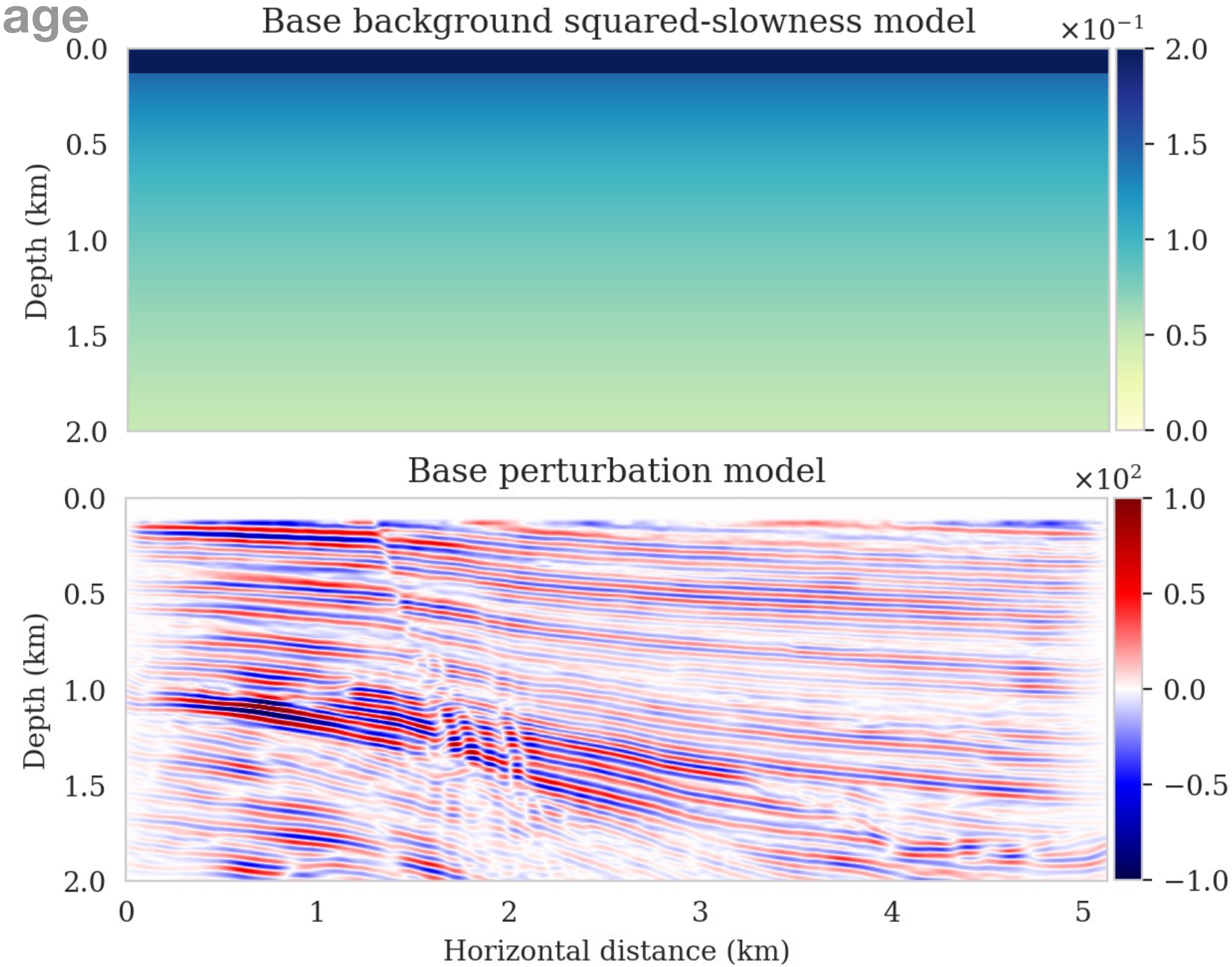
by minimizing

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} \frac{1}{N} \sum_{i=1} \| \mathcal{G}_{\mathbf{w}}(\mathbf{m}_0^{(i)}, \delta\mathbf{m}_{\text{init}}) - \delta\mathbf{m}_{\text{RTM}}^{(i)} \|_2^2$$

yielding the learned FNO $\mathcal{G}_{\mathbf{w}^*}: \mathcal{M} \times \delta\mathcal{M} \rightarrow \delta\mathcal{M}$.

Reference

velocity & image



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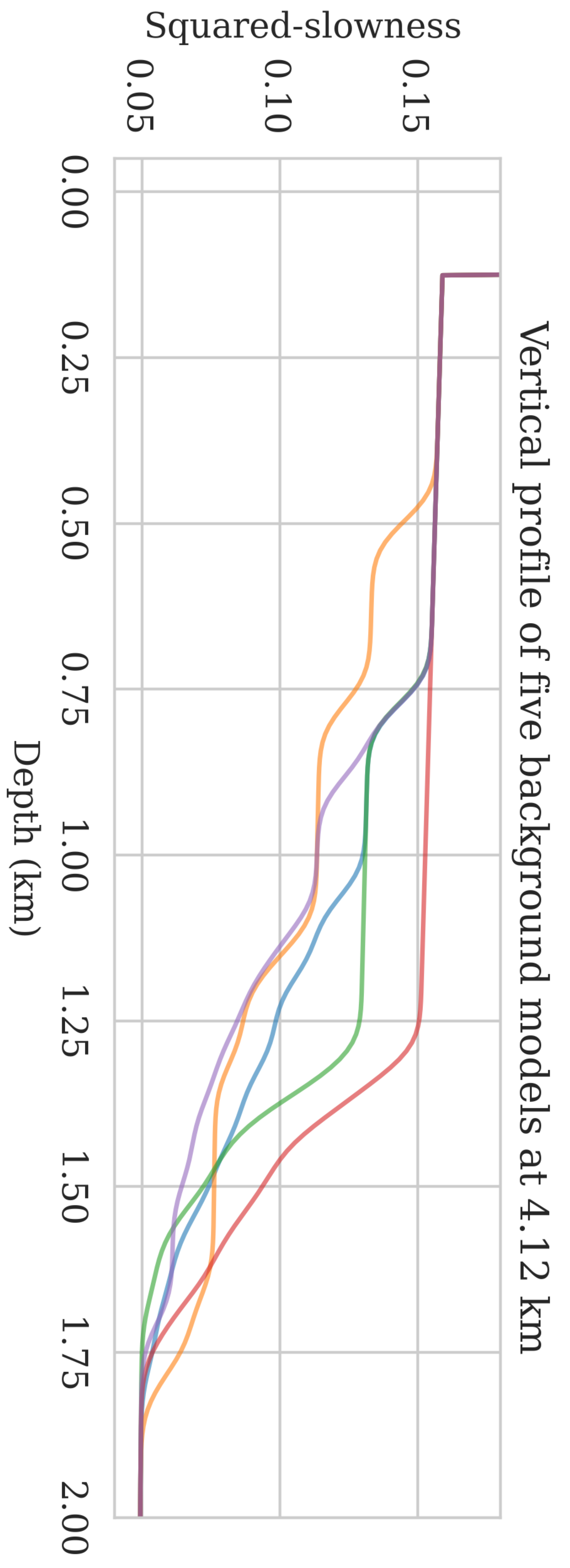
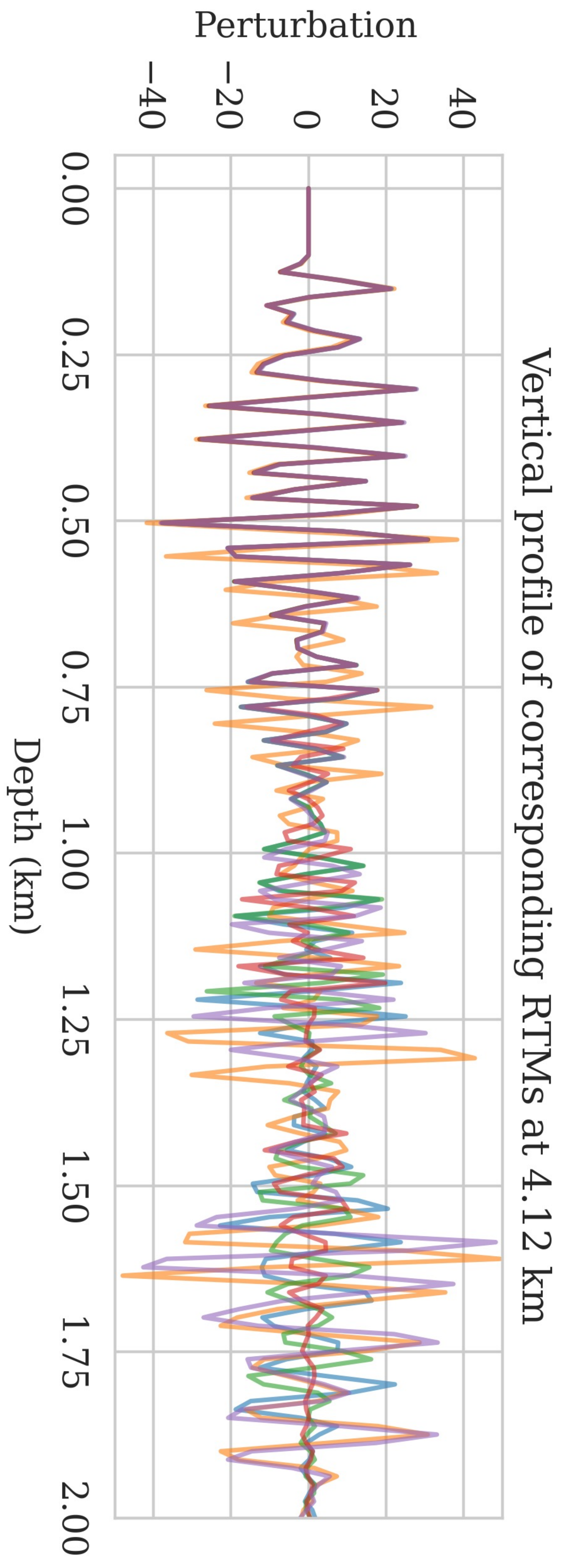
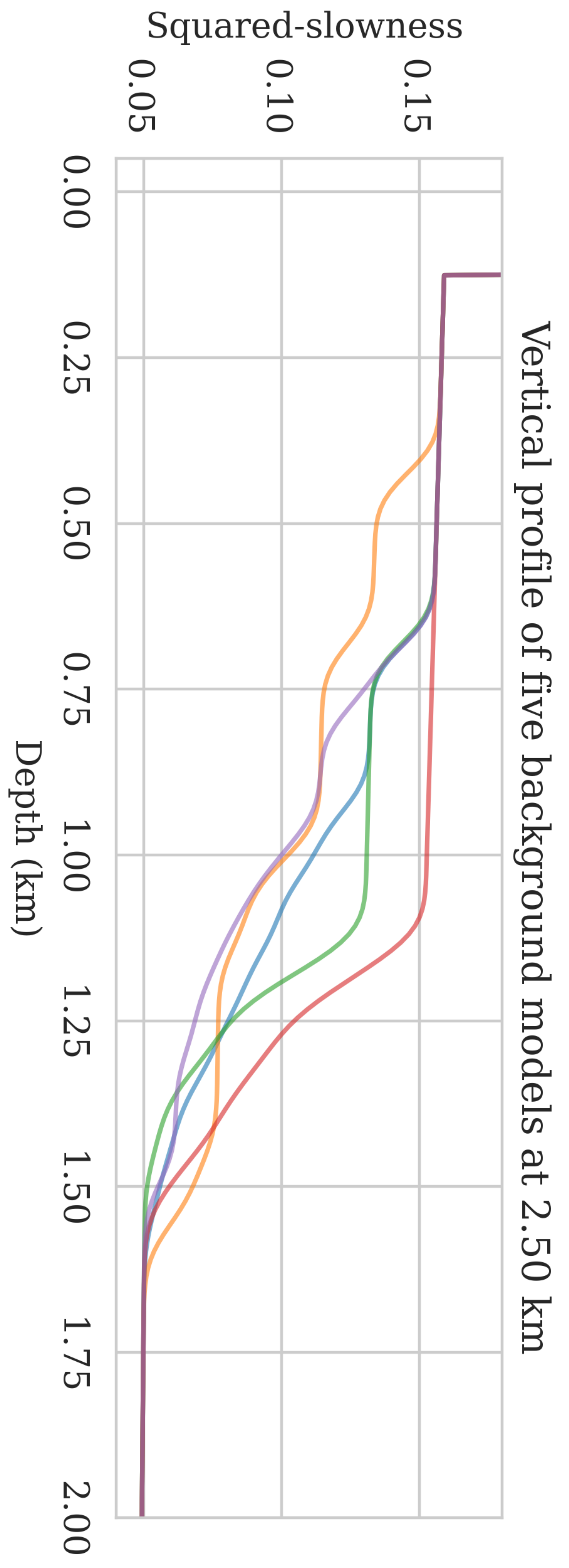
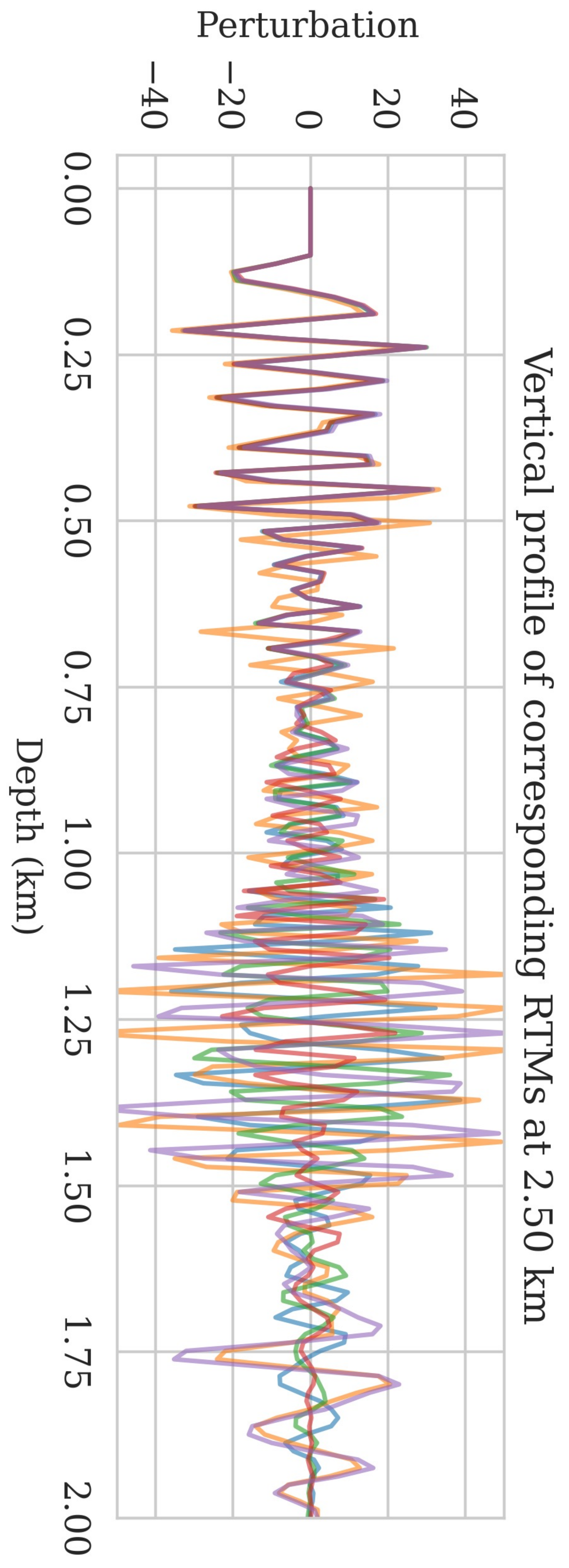
Differences

RTM images









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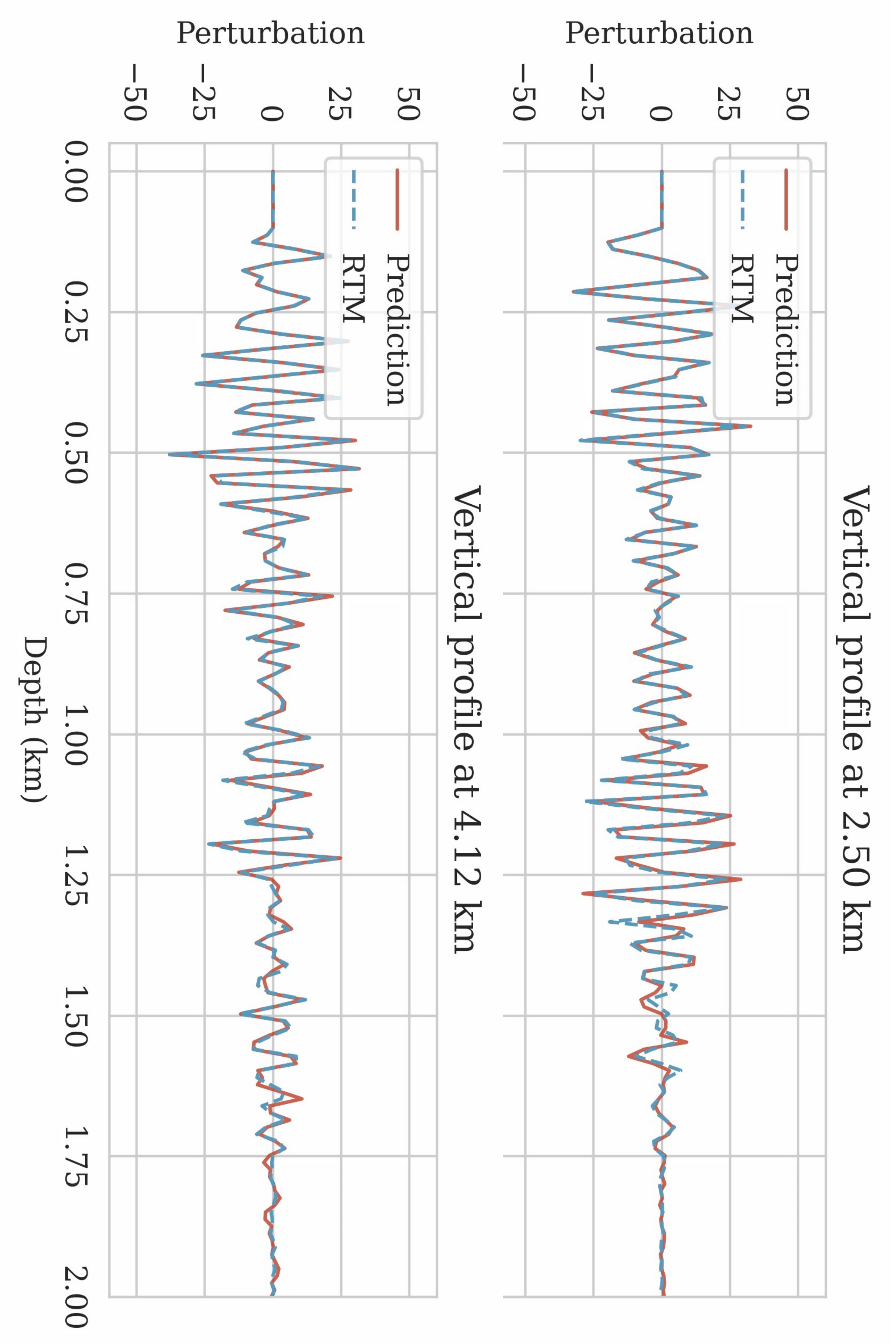
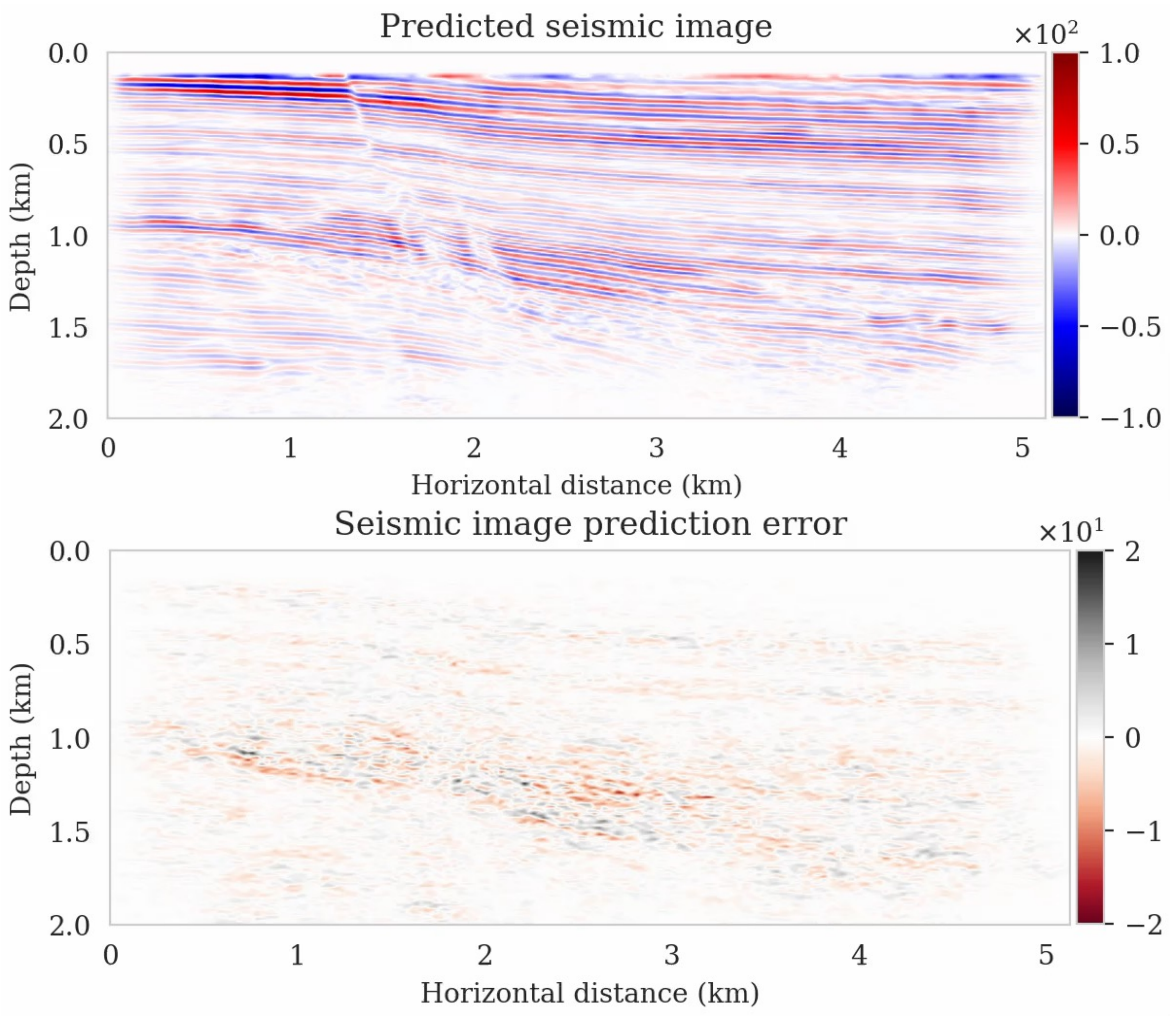
Predicted reflectivity models





Conclusions

Neural Networks and Neural Operators can act as surrogates to capture complicated physics:

- two-phase flow
- velocity continuations

Bayes Inference allows for risk analysis for geological carbon storage

FNO's opens to possibility to

- carry out inversions using AD
- conduct UQ

Acknowledgment

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