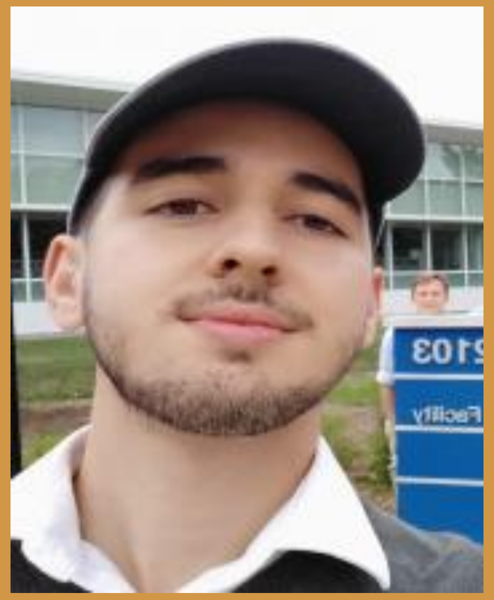
Uncertainty-aware time-lapse monitoring of geological carbon storage with learned surrogates

Ziyi Yin, Rafael Orozco, Mathias Louboutin, Ali Siahkoohi, Felix J. Herrmann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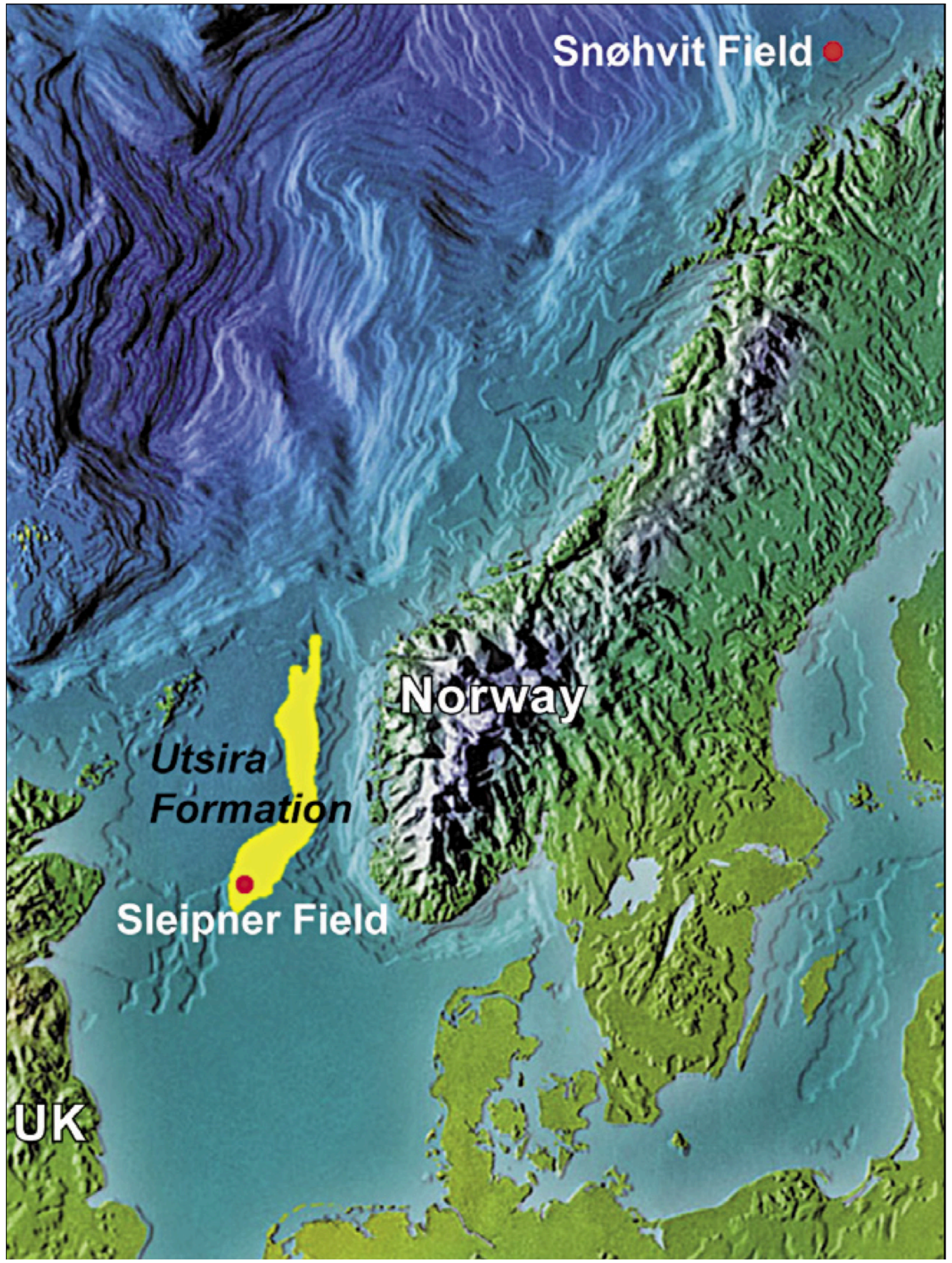
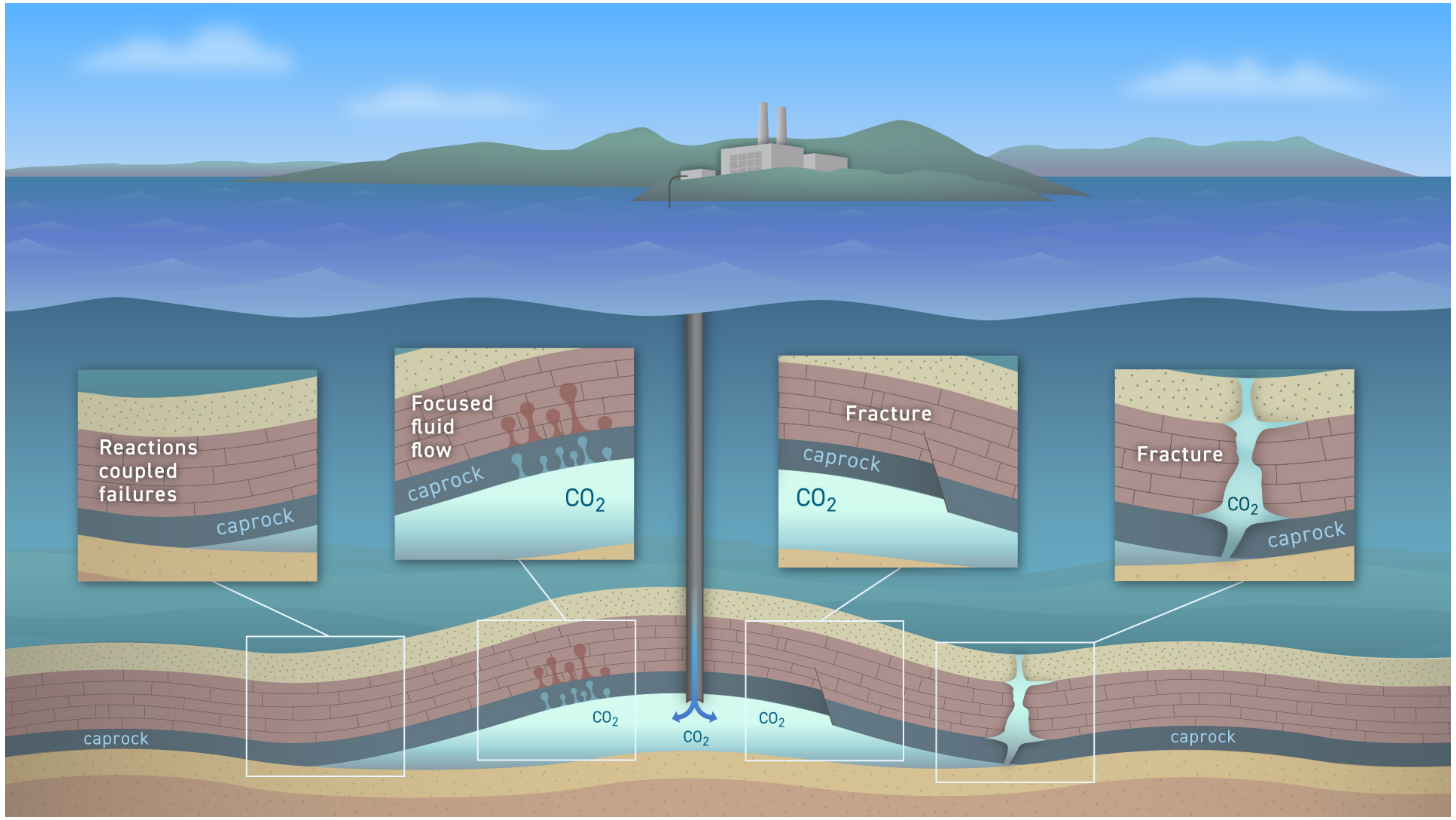
Engineering Mechanics Institute Conference 2023
June 7, 2023
Atlanta, Georgia

Seismic monitoring of geological carbon storage

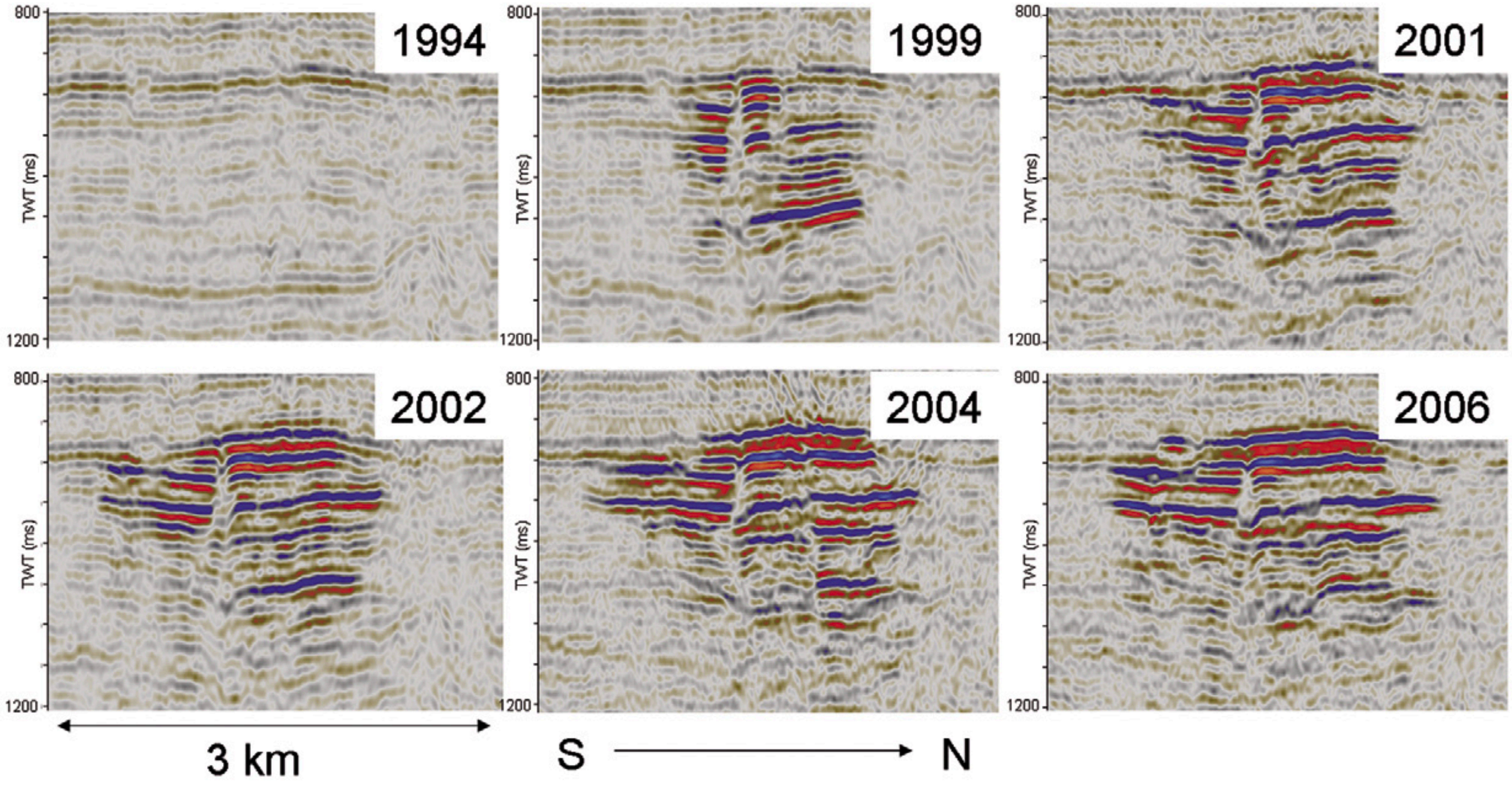
Geological carbon storage (GCS)
Sleipner project



Arts, R. J., et al. "Ten years' experience of monitoring CO2 injection in the Utsira Sand at Sleipner, offshore Norway." *First break* 26.1 (2008).



Seismic response
Sleipner project



4 Arts, R. J., et al. "Ten years' experience of monitoring CO2 injection in the Utsira Sand at Sleipner, offshore Norway." *First break* 26.1 (2008).

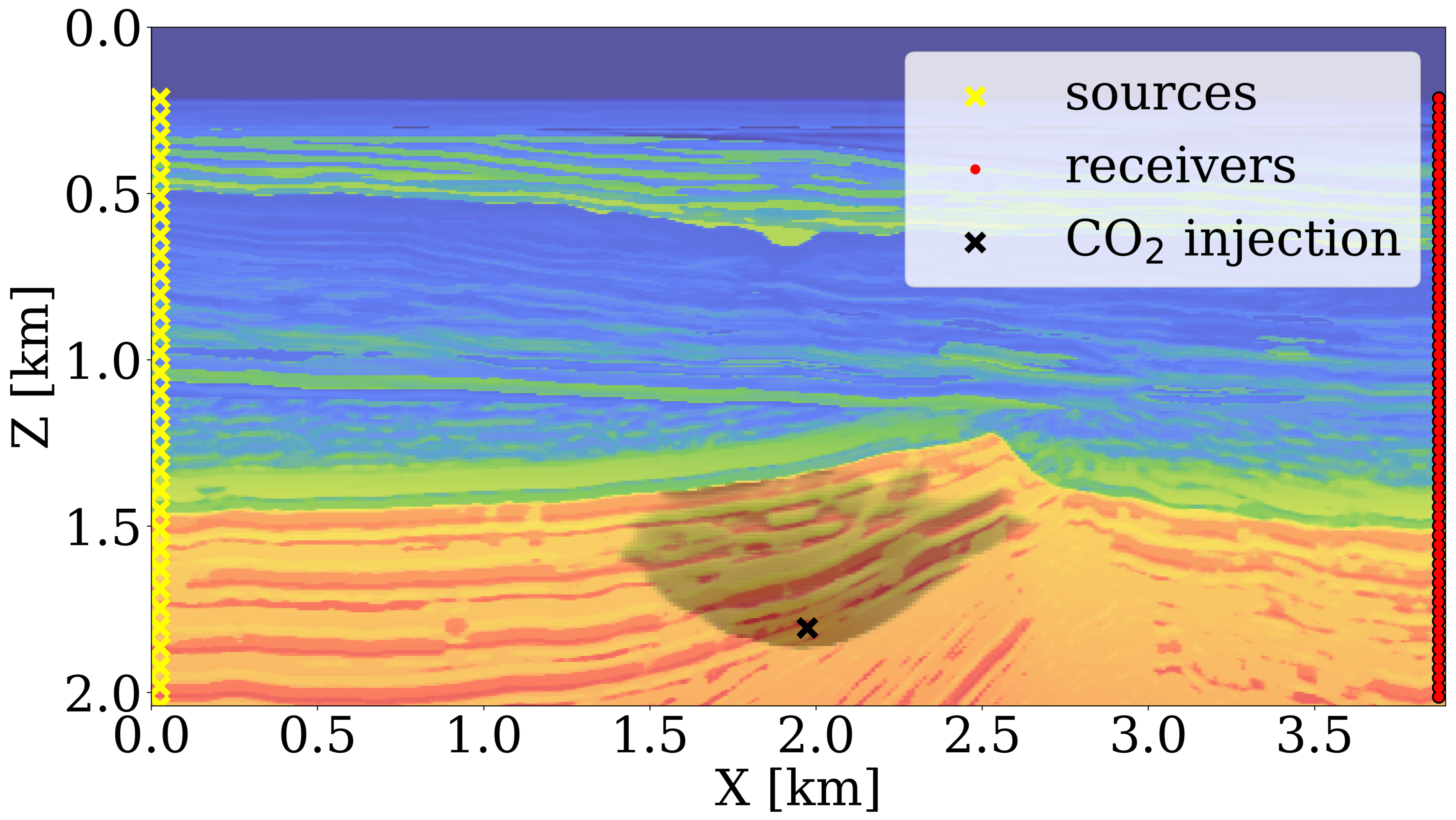
Motivation

time-lapse monitoring

Estimate permeability given time-lapse seismic data

- end-to-end inversion
- Fourier neural operator as cheap surrogate for physics
- **cheap & reliable uncertainty quantification**
- **uncertainty-aware CO_2 plume forecast**

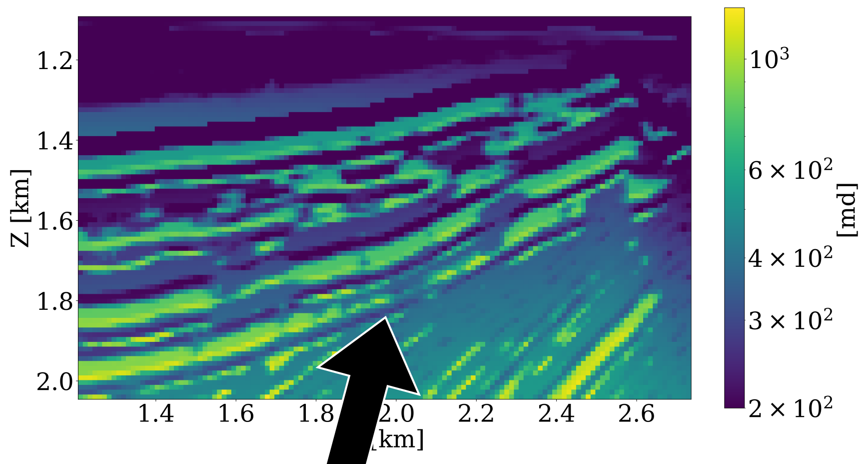
CO_2 plume prediction



CO_2 prediction (correct permeability)

permeability

$\mathbf{K}$



injection well

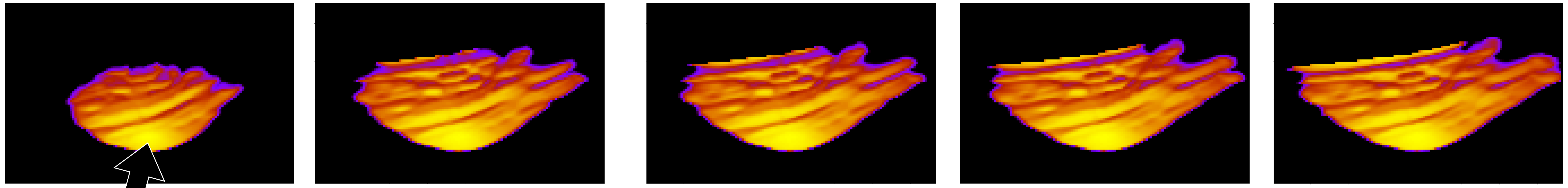
$\mathcal{S}$

fluid-flow physics

CO_2 concentration

$\mathbf{c}$

time



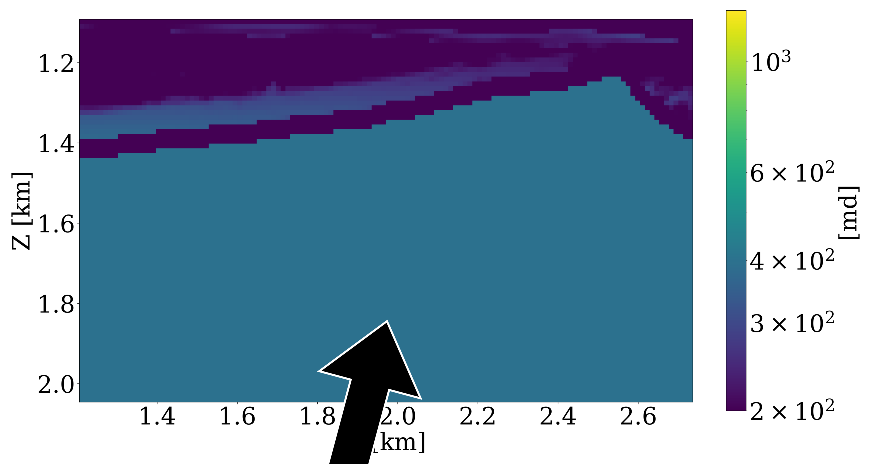
injection well

CO_2 flows due to high permeability channels & buoyancy

CO_2 prediction (wrong permeability)

permeability

$\mathbf{K}$



injection well

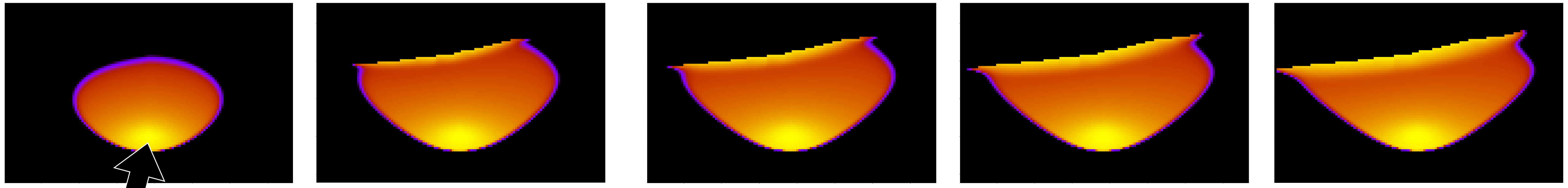
$\mathcal{S}$

fluid-flow physics

CO_2 concentration

$\mathbf{c}$

time

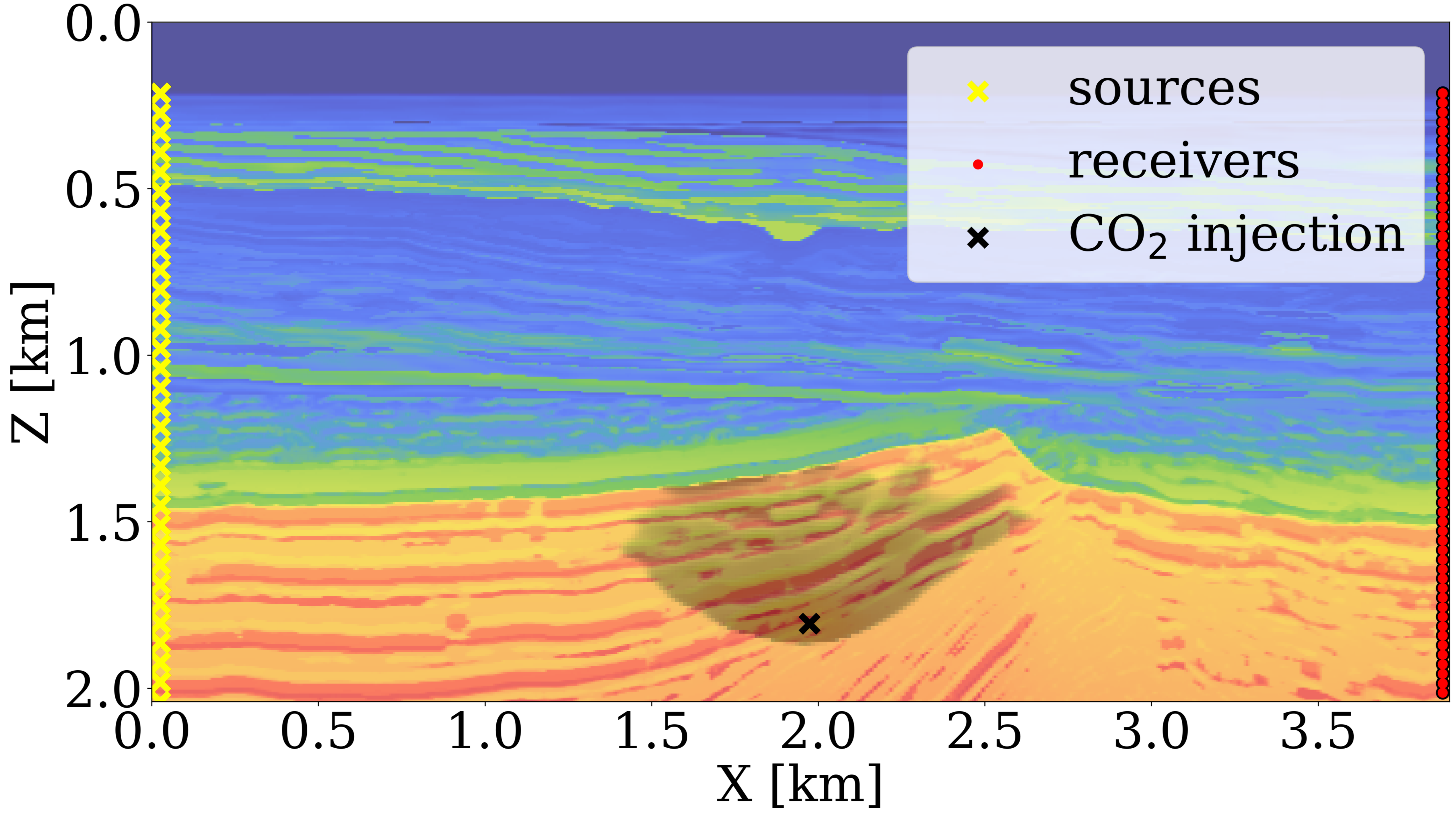


injection well

wrong CO_2 plume — wrong lateral extent

Time-lapse seismic monitoring

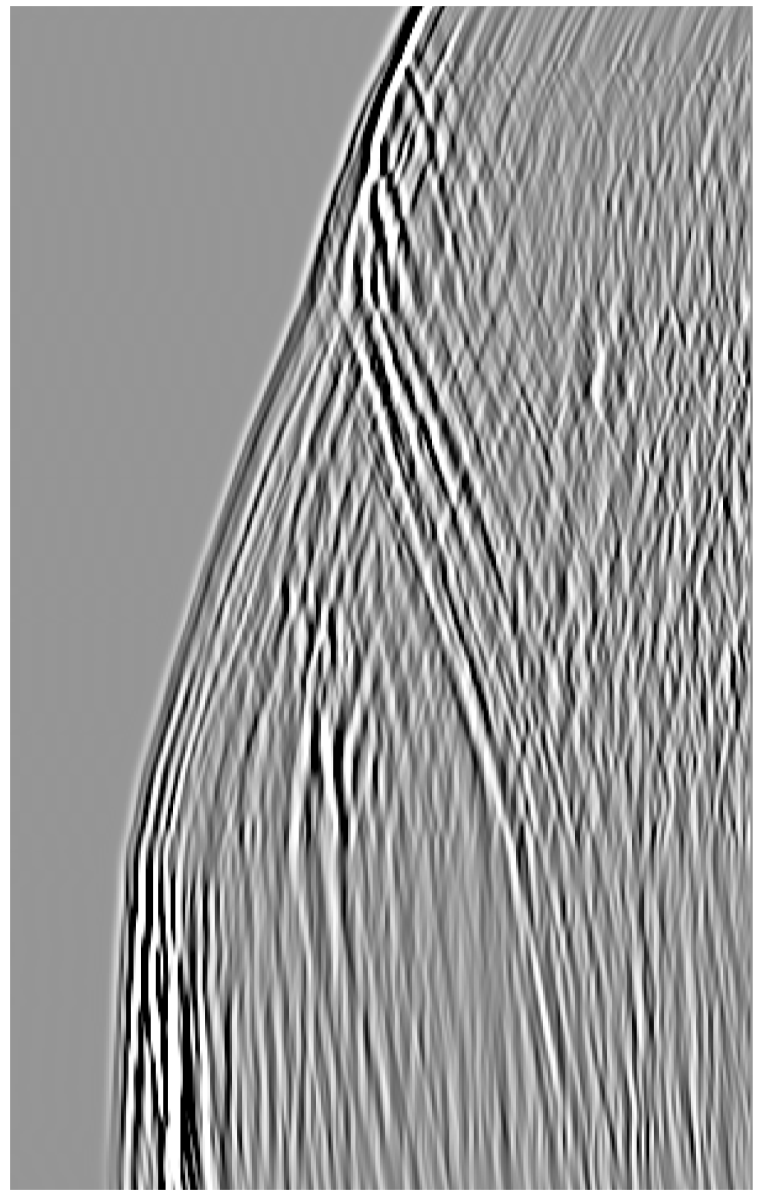
wavespeed $\mathbf{v}$



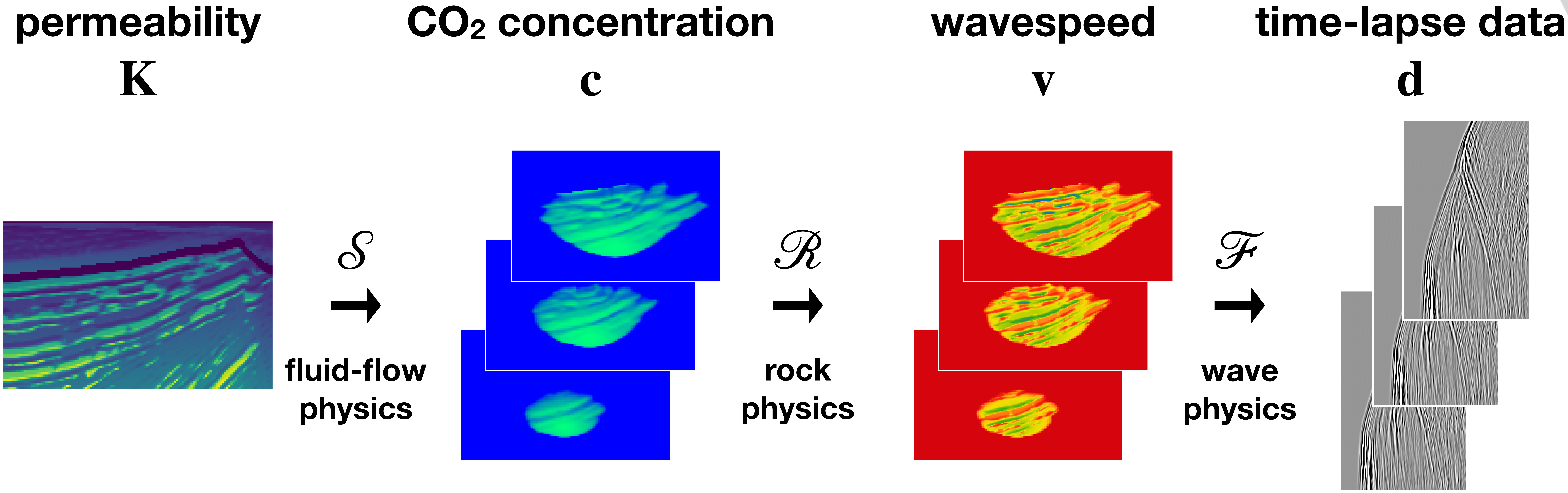
$\mathscr{F}$

wave physics

seismic data $\mathbf{d}$



Time-lapse monitoring of carbon storage
Multiphysics modeling



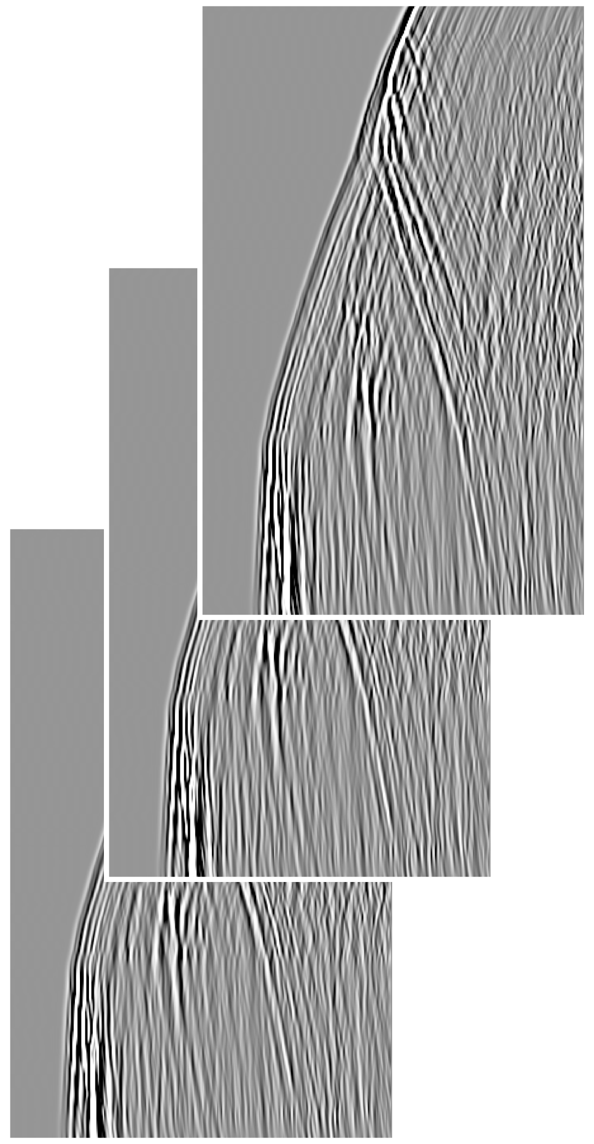
End-to-end inversion framework

permeability	CO_2 concentration	wavespeed	time-lapse data
$\mathbf{K}$	$\mathbf{c}$	$\mathbf{v}$	$\mathbf{d}$

?

$$\mathscr{F} \circ \mathscr{R} \circ \mathscr{S}$$

coupled physics



$$\underset{\mathbf{K}}{\text{minimize}} \quad \| \mathscr{F} \circ \mathscr{R} \circ \mathscr{S}(\mathbf{K}) - \mathbf{d} \|_2^2$$

End-to-end: "find permeability that matches seismic data"

Li D, Xu K, Harris JM, Darve E. Coupled time-lapse full-waveform inversion for subsurface flow problems using intrusive automatic differentiation. Water Resources Research. 2020 Aug;56(8):e2019WR027032.

Permeability inversion

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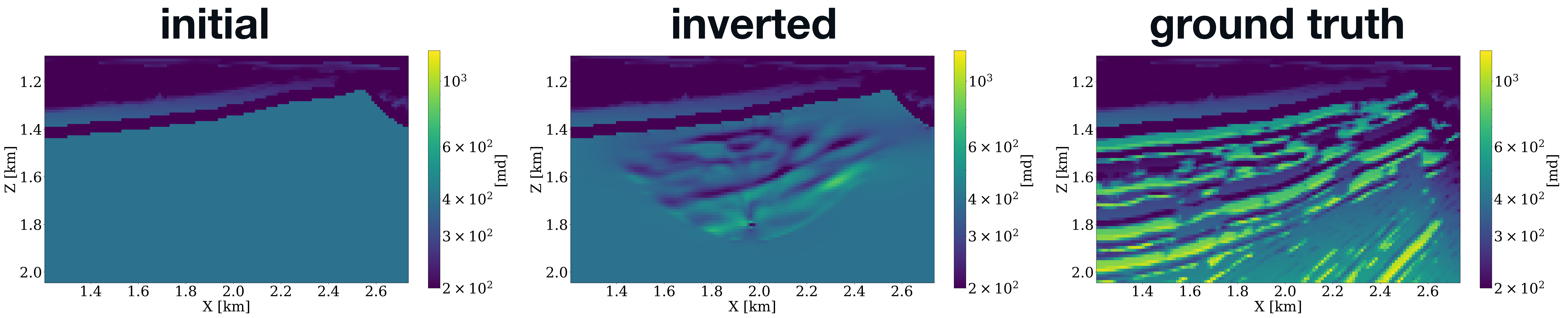


Fourier neural operator surrogate
cheap alternative to numerical simulation

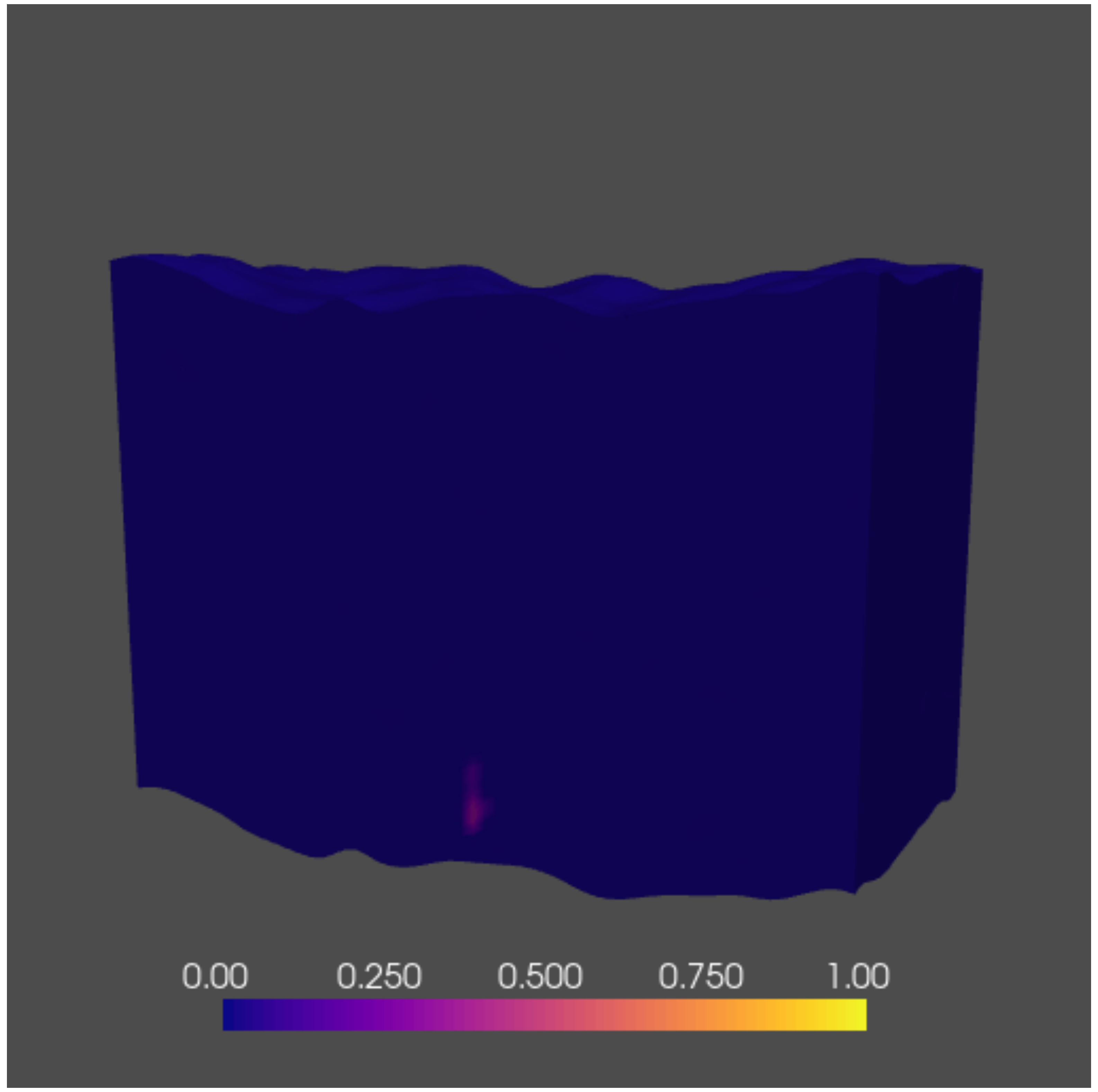
orders of magnitude faster

support surrogate inversion w/ automatic differentiation (AD)

scalable to large-scale 4D via domain decomposition

benefits:

- reduce computational cost
- enable uncertainty quantification



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

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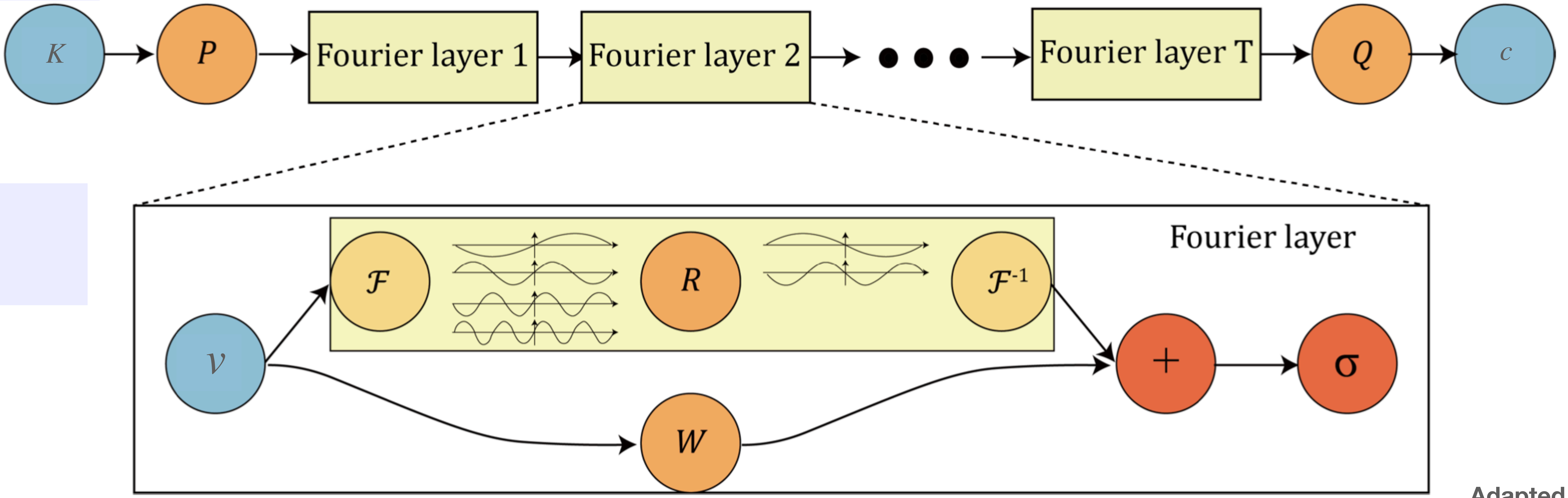
Surrogate Modeling

Fourier neural operators – FNOs

FNO learns mappings on low-frequency modes in Fourier space via



Adapted from Li

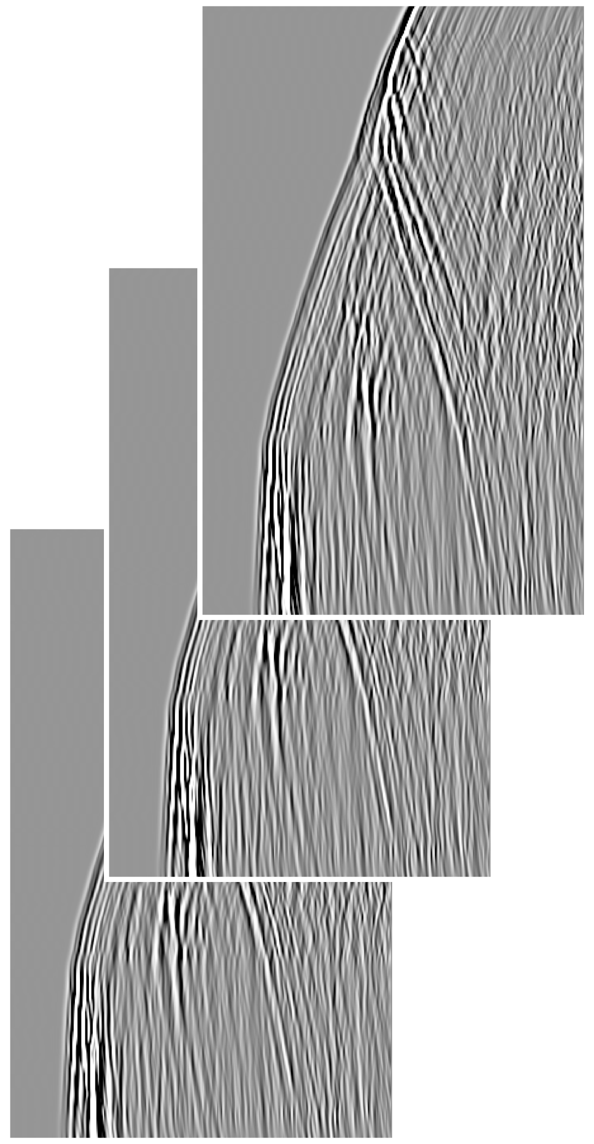
Learned end-to-end inversion

permeability	CO_2 concentration	wavespeed	time-lapse data
$\mathbf{K}$	$\mathbf{c}$	$\mathbf{v}$	$\mathbf{d}$

?

$$\mathscr{F} \circ \mathscr{R} \circ \mathscr{S}_{\boldsymbol{\theta}}$$

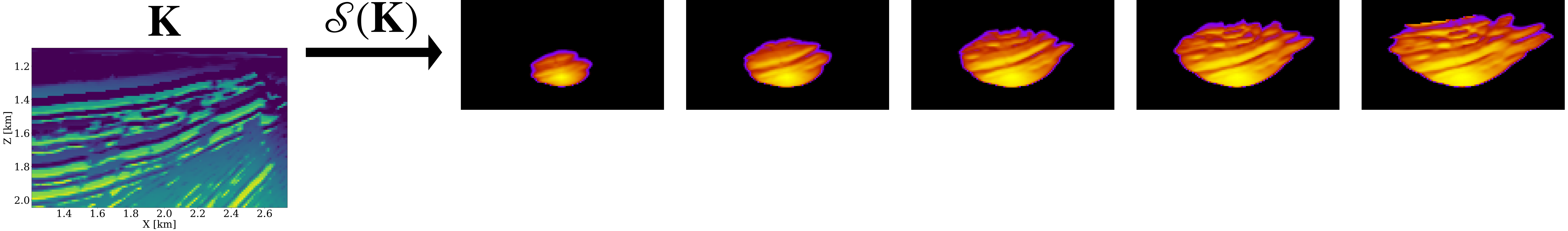
coupled physics



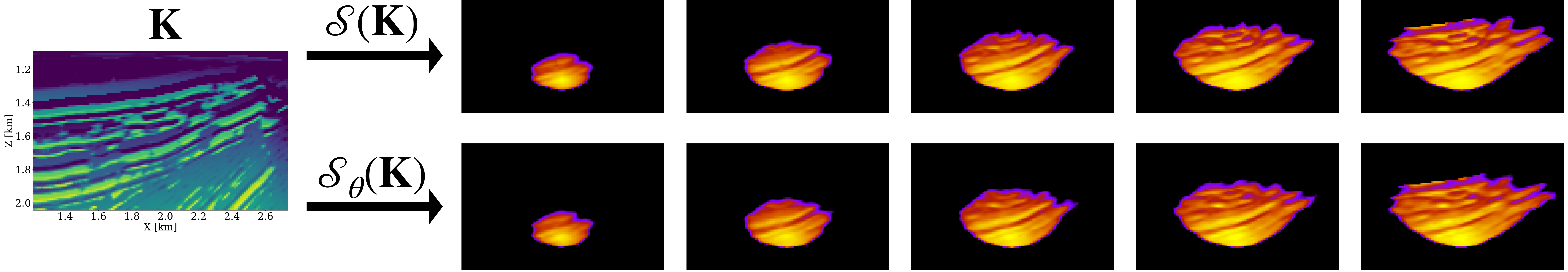
$$\underset{\mathbf{K}}{\text{minimize}} \quad \|\mathscr{F} \circ \mathscr{R} \circ \mathscr{S}_{\boldsymbol{\theta}}(\mathbf{K}) - \mathbf{d}\|_2^2$$

$\mathscr{S}_{\boldsymbol{\theta}}$ **pre-trained FNO: drastically reduce computational cost**

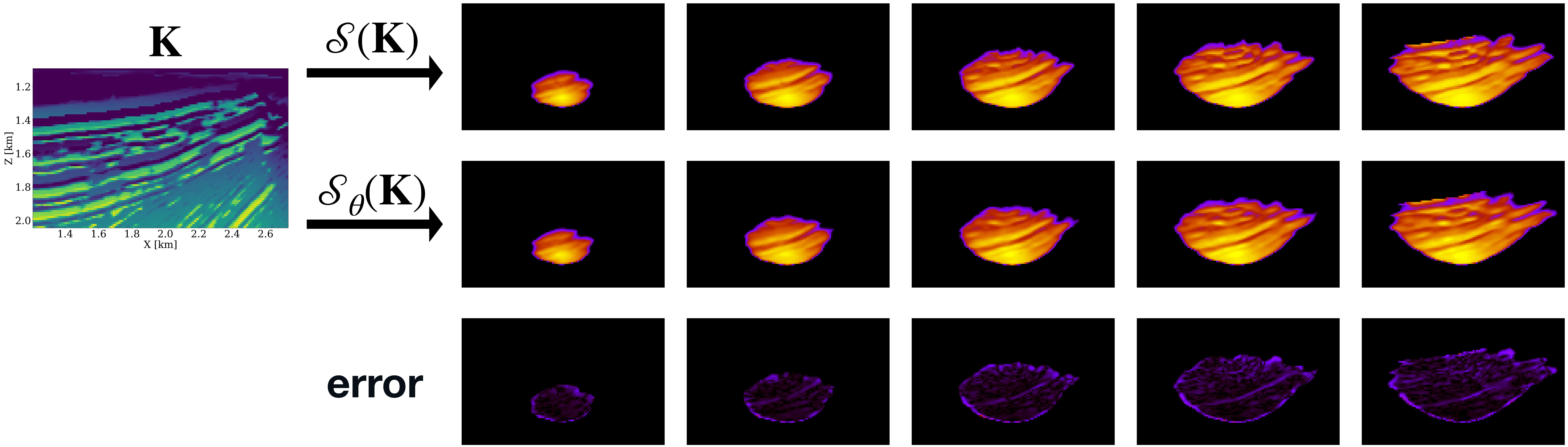
Fourier neural operators learns physics



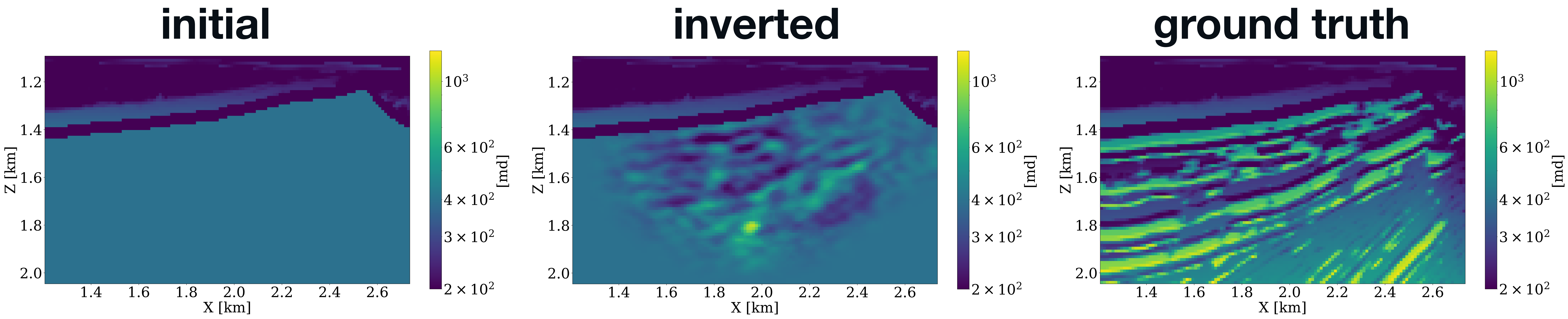
Fourier neural operators learns physics



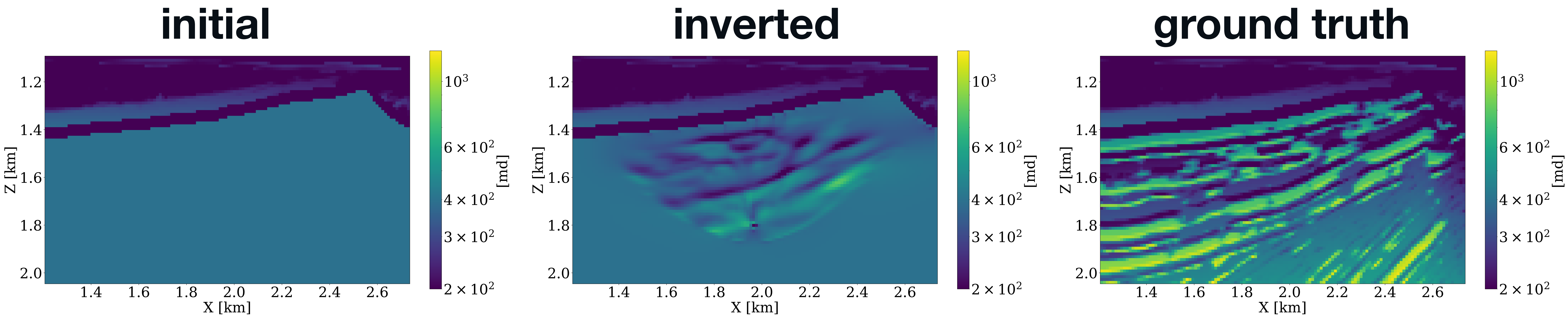
Fourier neural operators learns physics



Permeability inversion
FNO surrogate

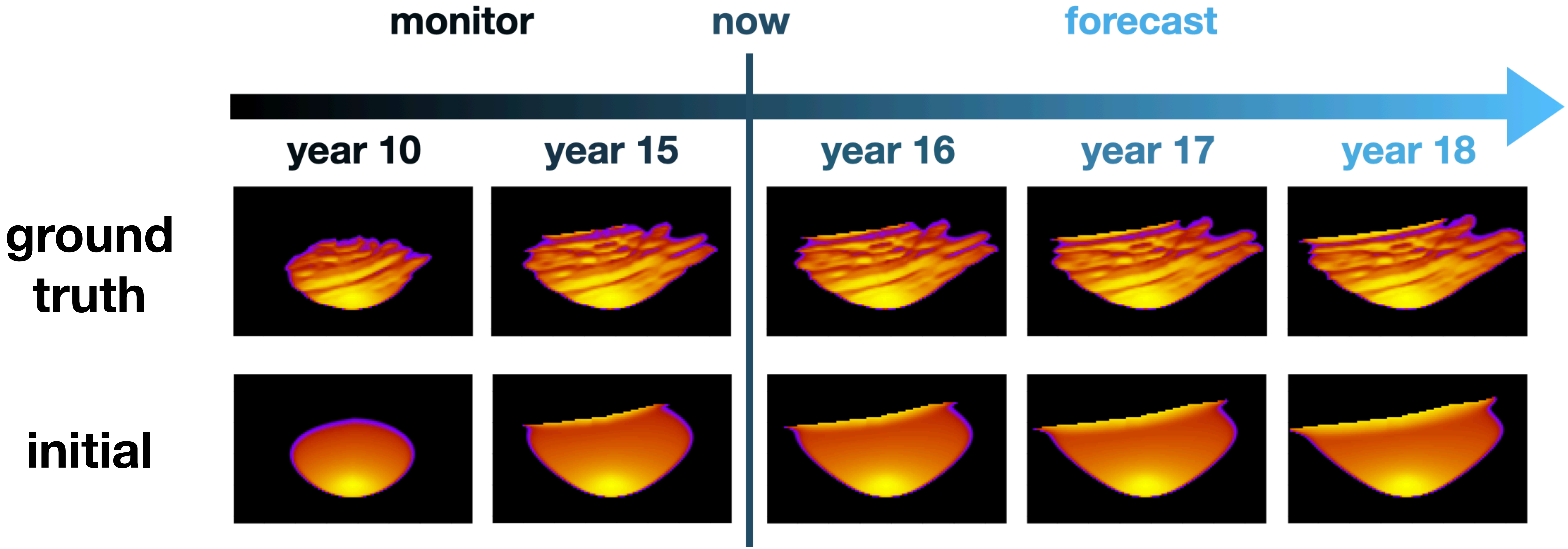


Permeability inversion
physics-based inversion

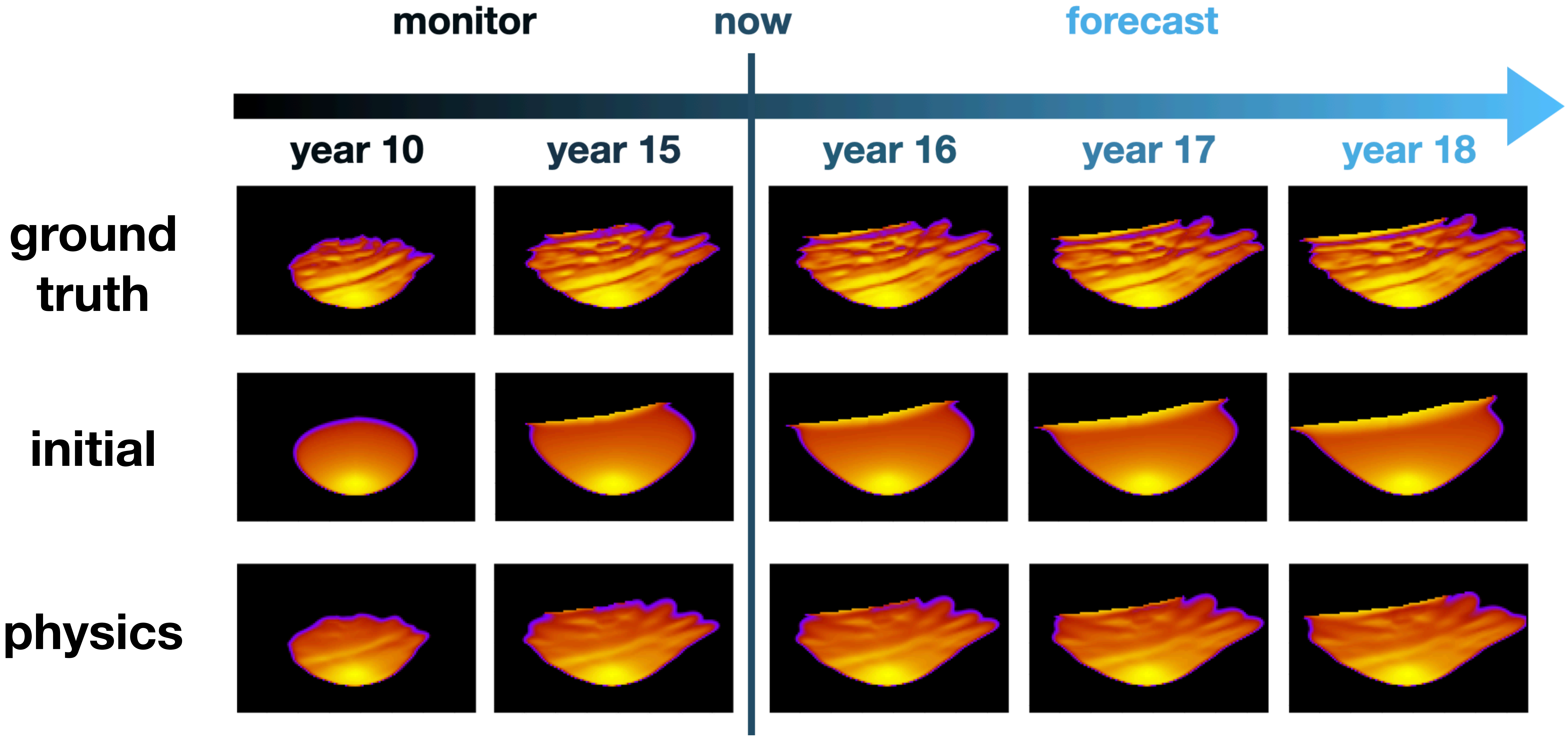


End-to-end inversion

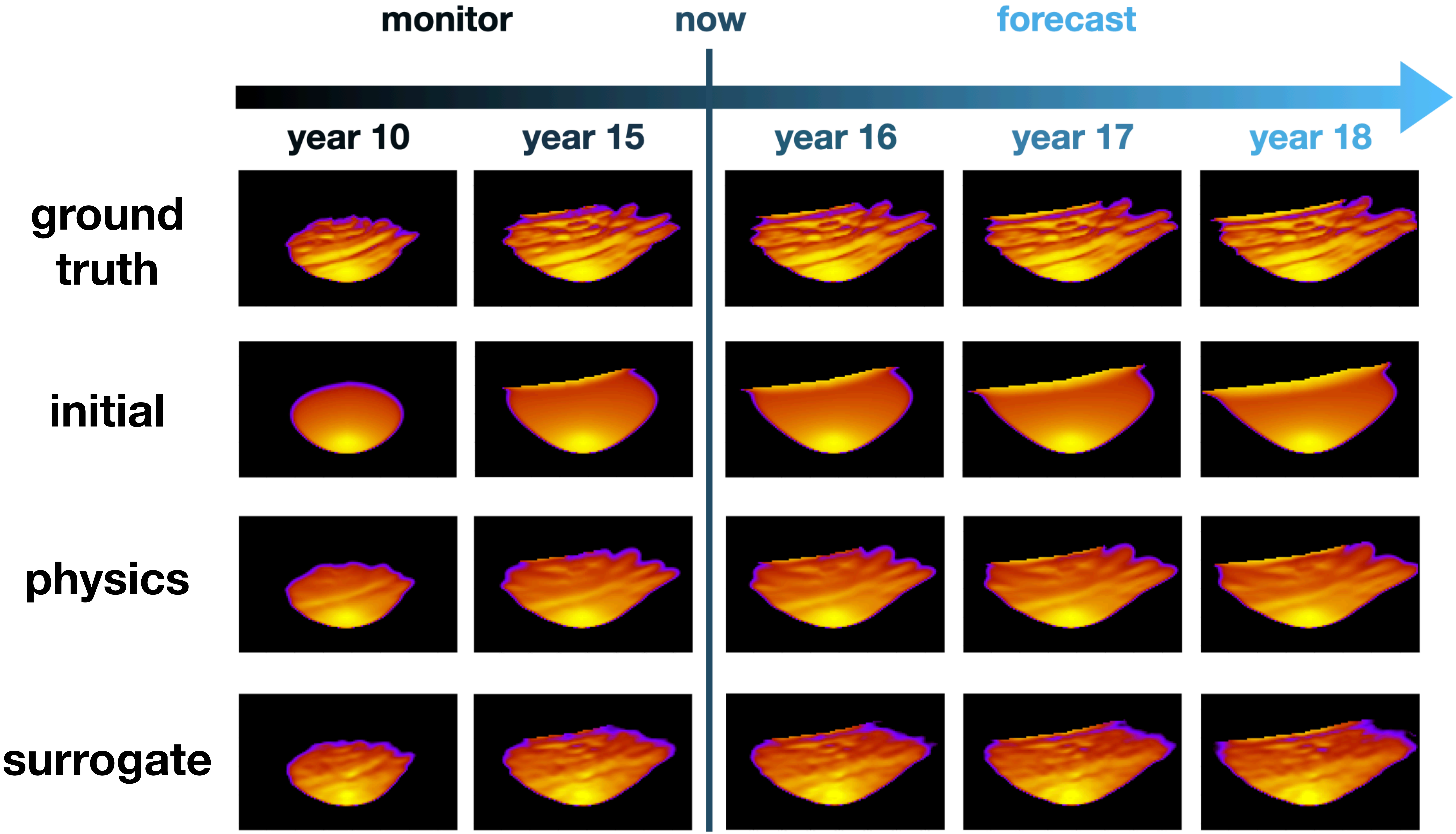
CO_2 plume



End-to-end inversion
CO_2 plume



End-to-end inversion
CO_2 plume



Uncertainty quantification

Bayesian Uncertainty Quantification

Bayesian posterior $p_{\text{post}}(\mathbf{K} \mid \mathbf{d}) \propto p_{\text{like}}(\mathbf{d} \mid \mathbf{K}) p_{\text{prior}}(\mathbf{K})$

$\mathbf{K}$	unknown model parameters (permeability)
$\mathbf{d}$	observed data
$p(\mathbf{d} \mid \mathbf{K})$	data likelihood
$p(\mathbf{K})$	prior

Bayesian Uncertainty Quantification

stochastic gradient Langevin dynamics (SGLD)

$$\mathbf{K}_{k+1} = \mathbf{K}_k - \frac{\alpha_k}{2} \nabla_{\mathbf{K}} \log p_{\text{post}}(\mathbf{K} \,|\, \mathbf{d}) + \boldsymbol{\eta}_k$$

- gradient-based MCMC
- α_k step size, $\boldsymbol{\eta}_k$ noise

Max Welling and Yee Whye Teh. "Bayesian Learning via Stochastic Gradient Langevin Dynamics". In: Proceedings of the 28th International Conference on International Conference on Machine Learning. ICML'11. 2011, pp. 681–688. doi: 10.5555/3104482.3104568

Fast Uncertainty Quantification

learned surrogate & prior

$$p_{\text{post}}(\mathbf{K} \mid \mathbf{d}) \propto p_{\text{like}}(\mathbf{d} \mid \mathbf{K}) p_{\text{prior}}(\mathbf{K})$$

Fast Uncertainty Quantification

learned surrogate & prior

$$p_{\text{post}}(\mathbf{K} \mid \mathbf{d}) \propto p_{\text{like}}(\mathbf{d} \mid \mathbf{K}) p_{\text{prior}}(\mathbf{K})$$

Fourier neural operators

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Fast Uncertainty Quantification

learned surrogate & prior

$$p_{\text{post}}(\mathbf{K} \mid \mathbf{d}) \propto p_{\text{like}}(\mathbf{d} \mid \mathbf{K}) p_{\text{prior}}(\mathbf{K})$$

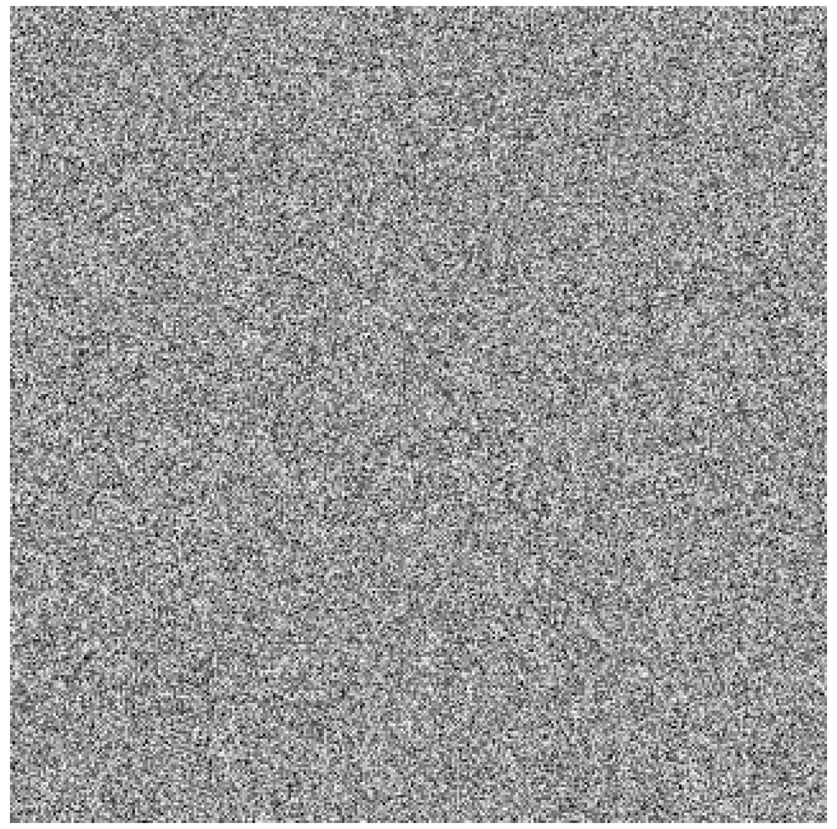
Fourier neural operators

normalizing flows

Normalizing flows (NFs)

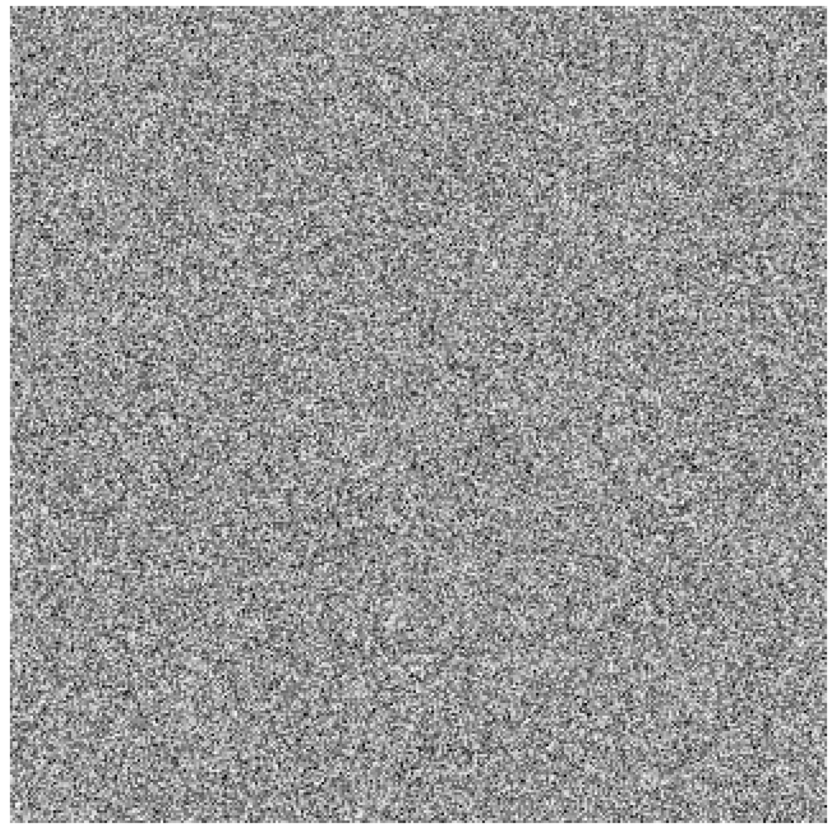
Training:

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



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

Sampling:



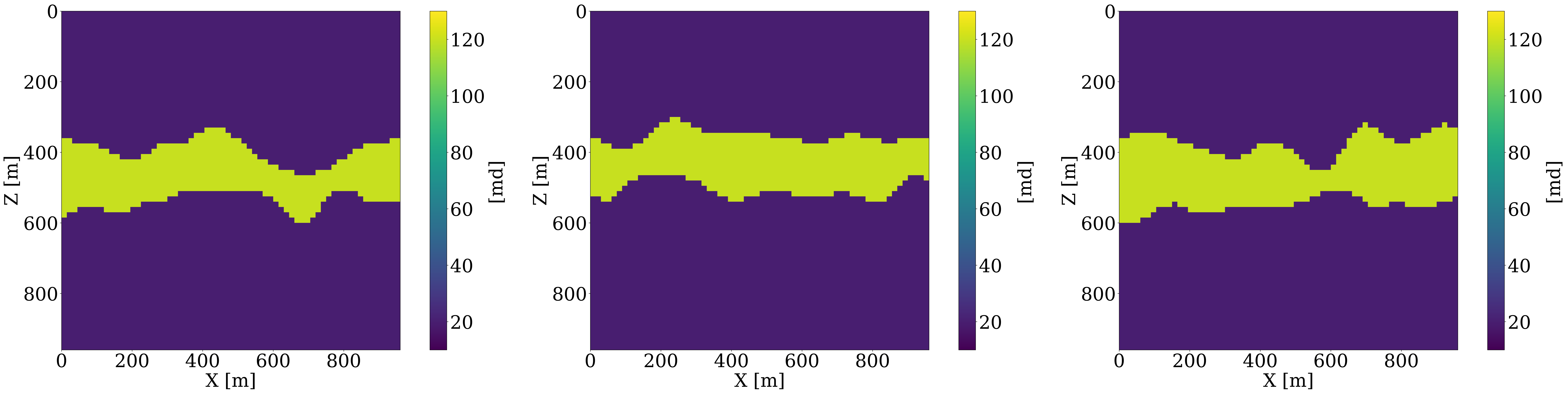
$$\xrightarrow{\mathscr{G}_{\mathbf{w}}(\mathbf{z})}$$

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

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).

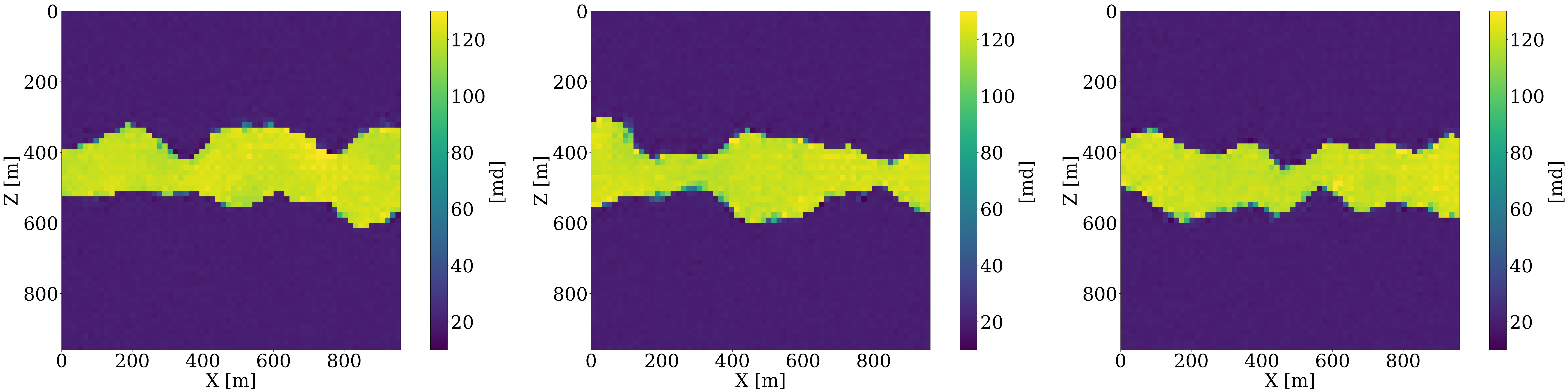
Training samples

permeability models



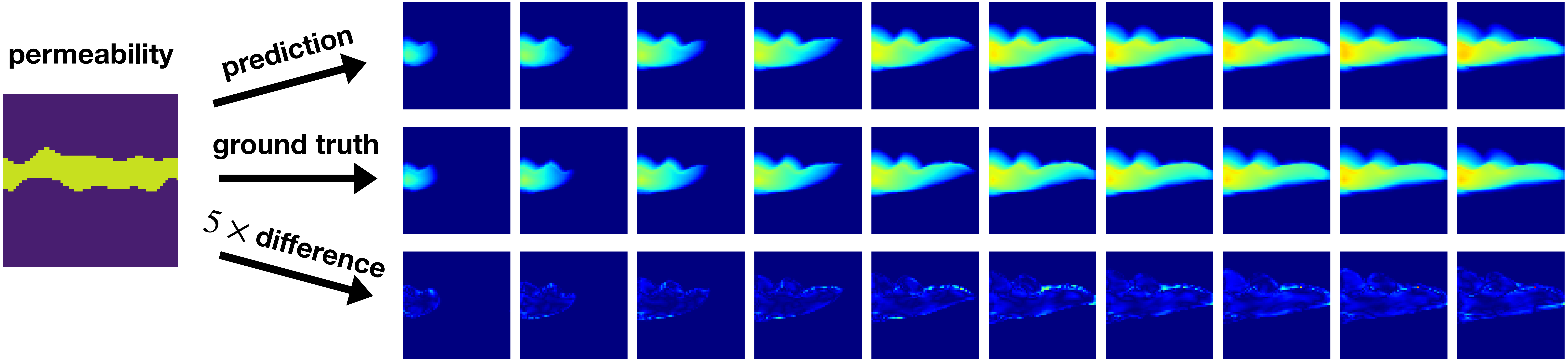
Generative samples

“fake” permeability models



Fourier neural operators

likelihood



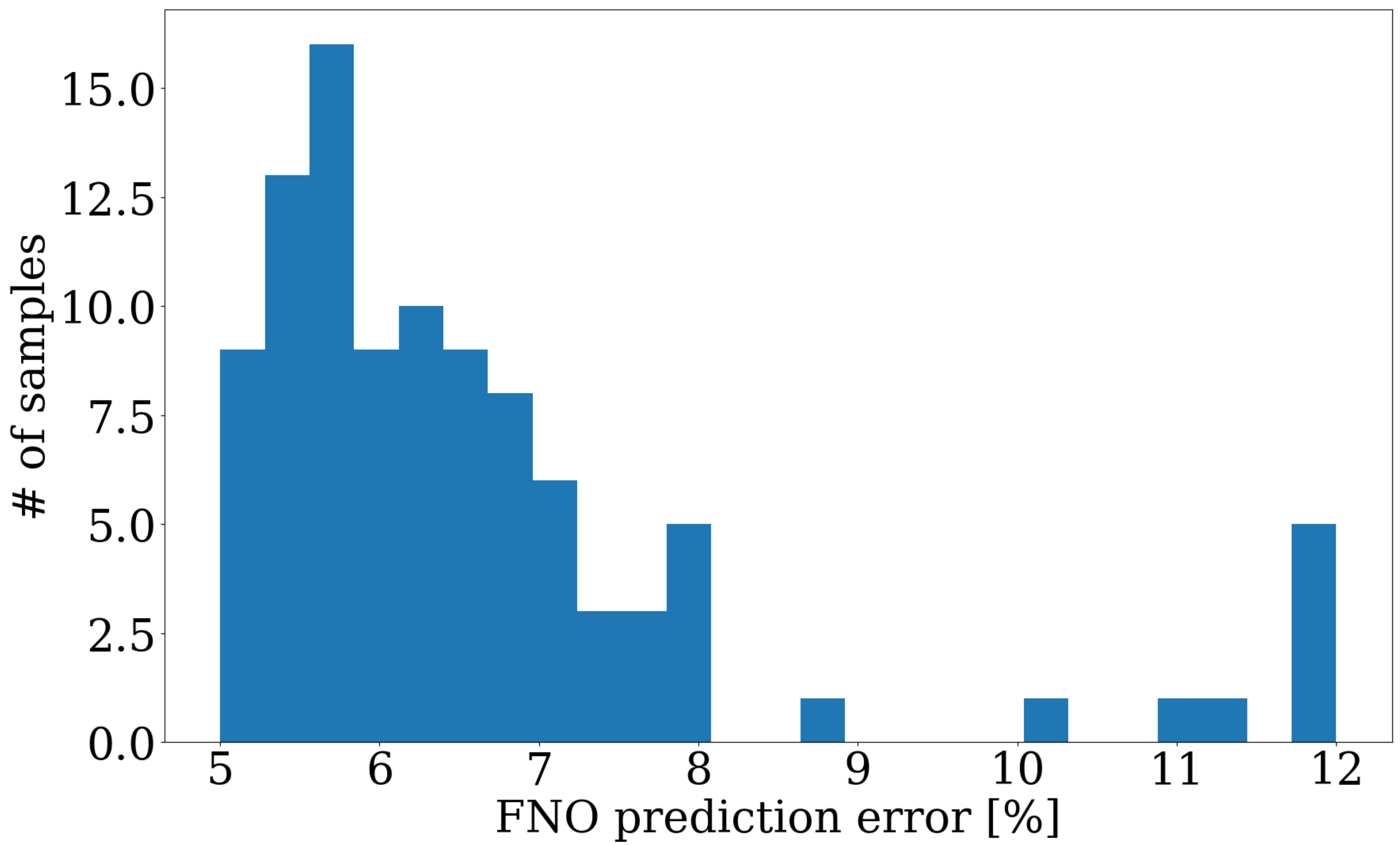
2000 random permeability channels

FNO & NF share the same training samples

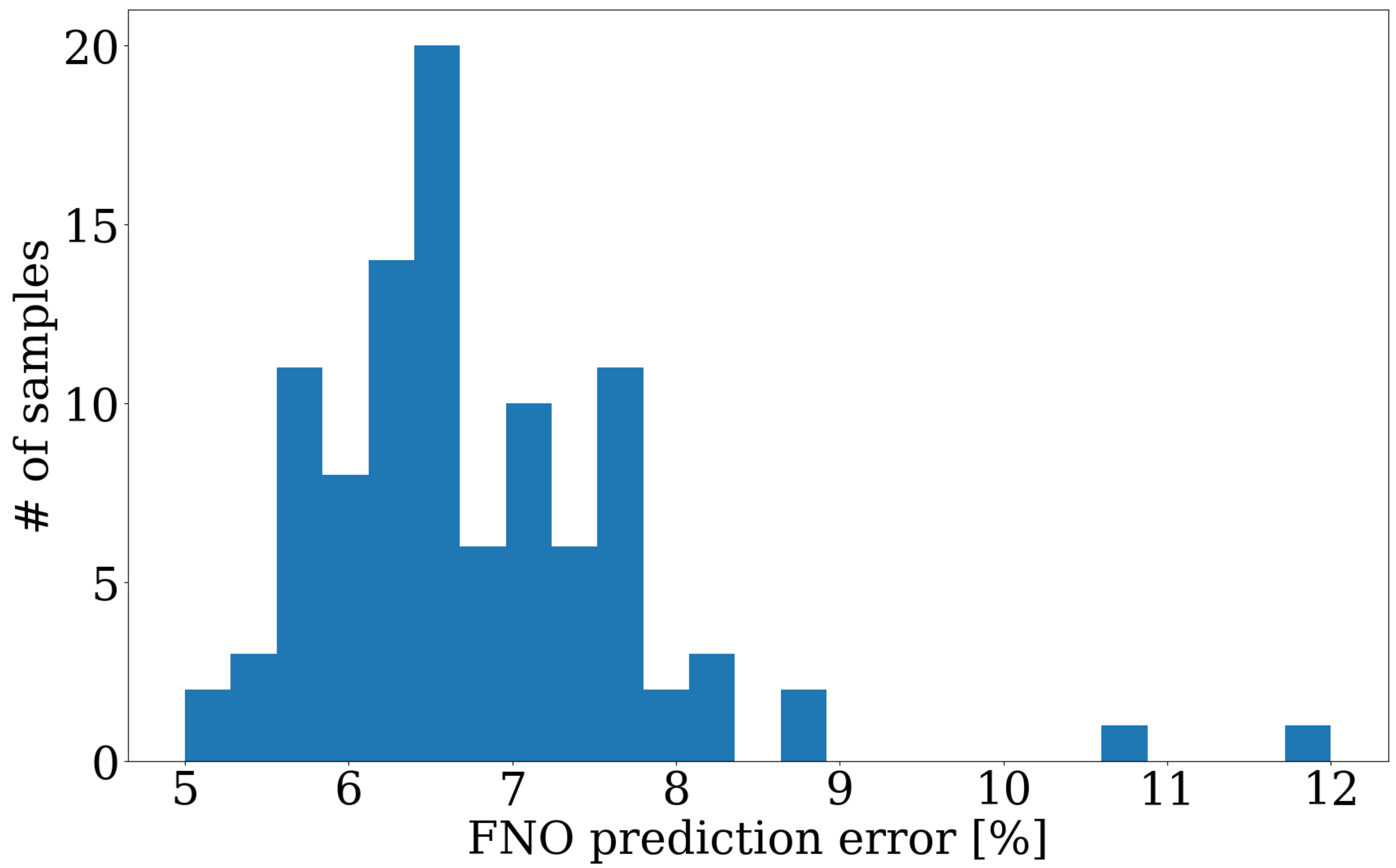
FNO prediction error

FNO gives low prediction error on generative samples from NF

real samples



generative samples



Bayesian Uncertainty Quantification

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- gradient-based MCMC
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Bayesian Uncertainty Quantification

stochastic gradient Langevin dynamics (SGLD)

$$\mathbf{z}_{k+1} = \mathbf{z}_k - \frac{\alpha_k}{2} \nabla_{\mathbf{z}_k} \log p_{\text{post}}(\mathbf{z} \mid \mathbf{d}) + \boldsymbol{\eta}_k$$

- gradient-based MCMC
- α_k step size, $\boldsymbol{\eta}_k$ noise
- $\mathscr{G}(\mathbf{z}) = \mathbf{K}$, $\mathscr{G}$ trained NF, $\mathbf{z}$ latent variable

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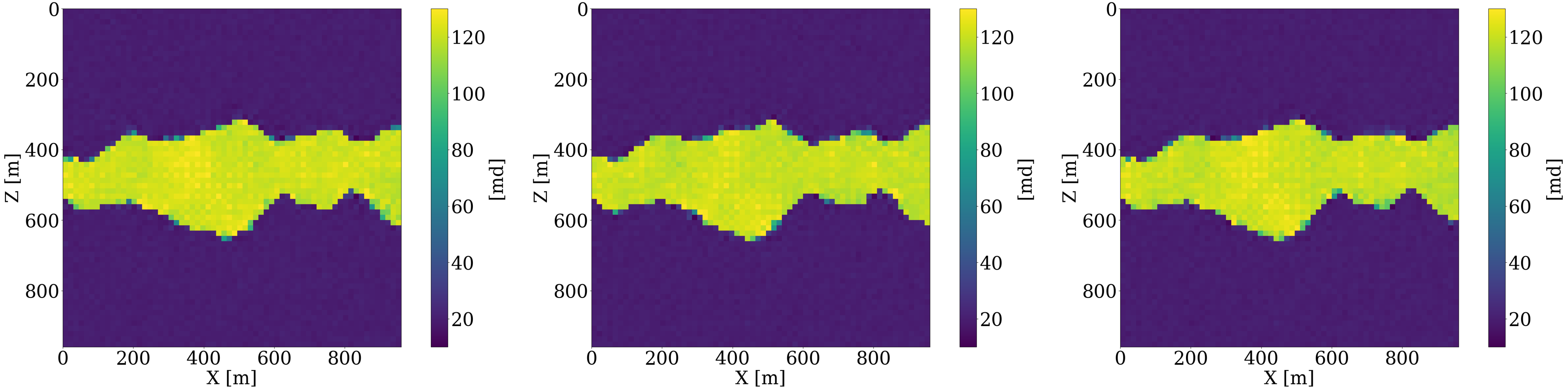
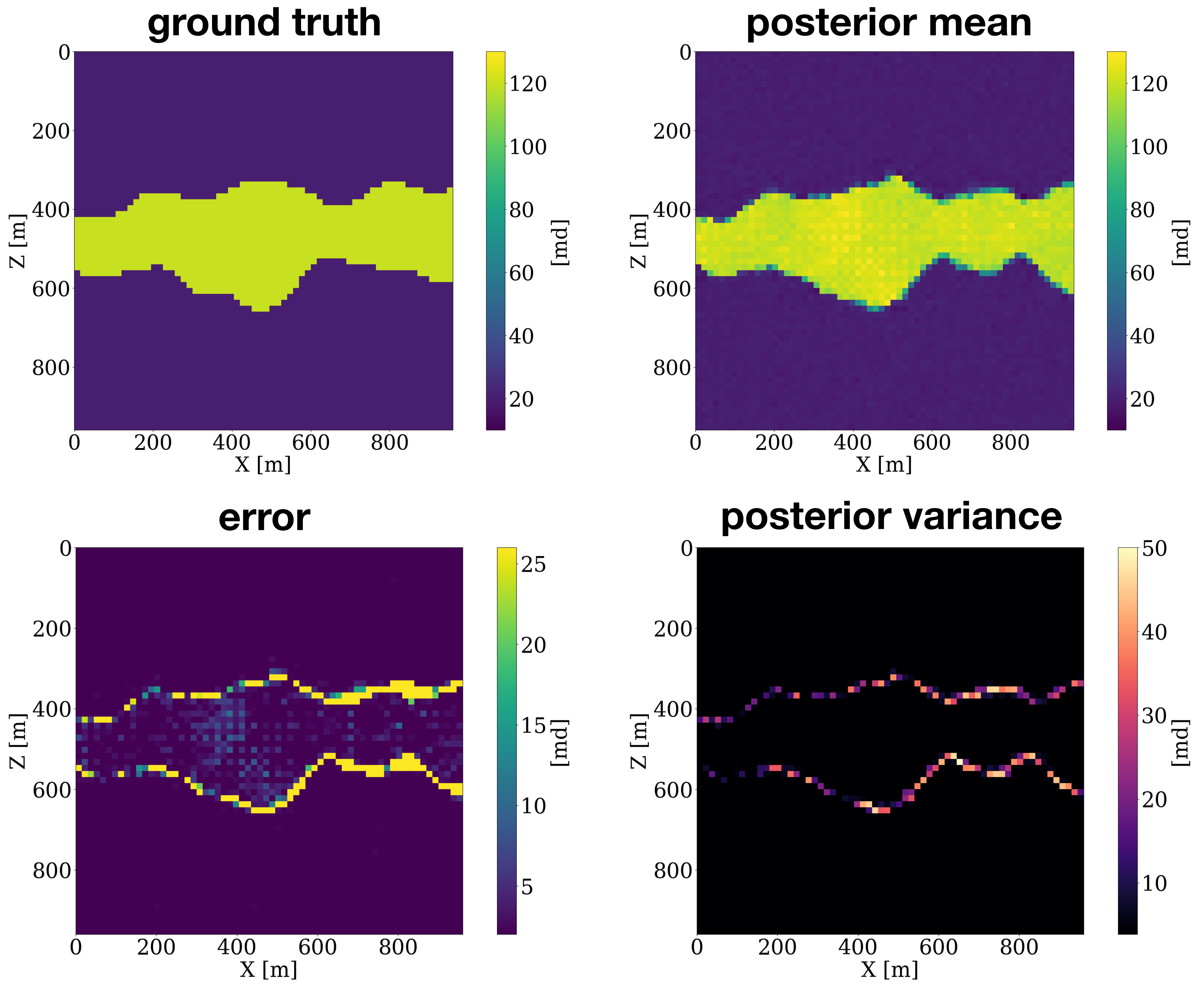
FNO + Normalizing Flow prior

Numerical experiment
posterior samples



Numerical experiment
UQ - permeability



well recovered channel

error & variance aligned

higher uncertainty on far end

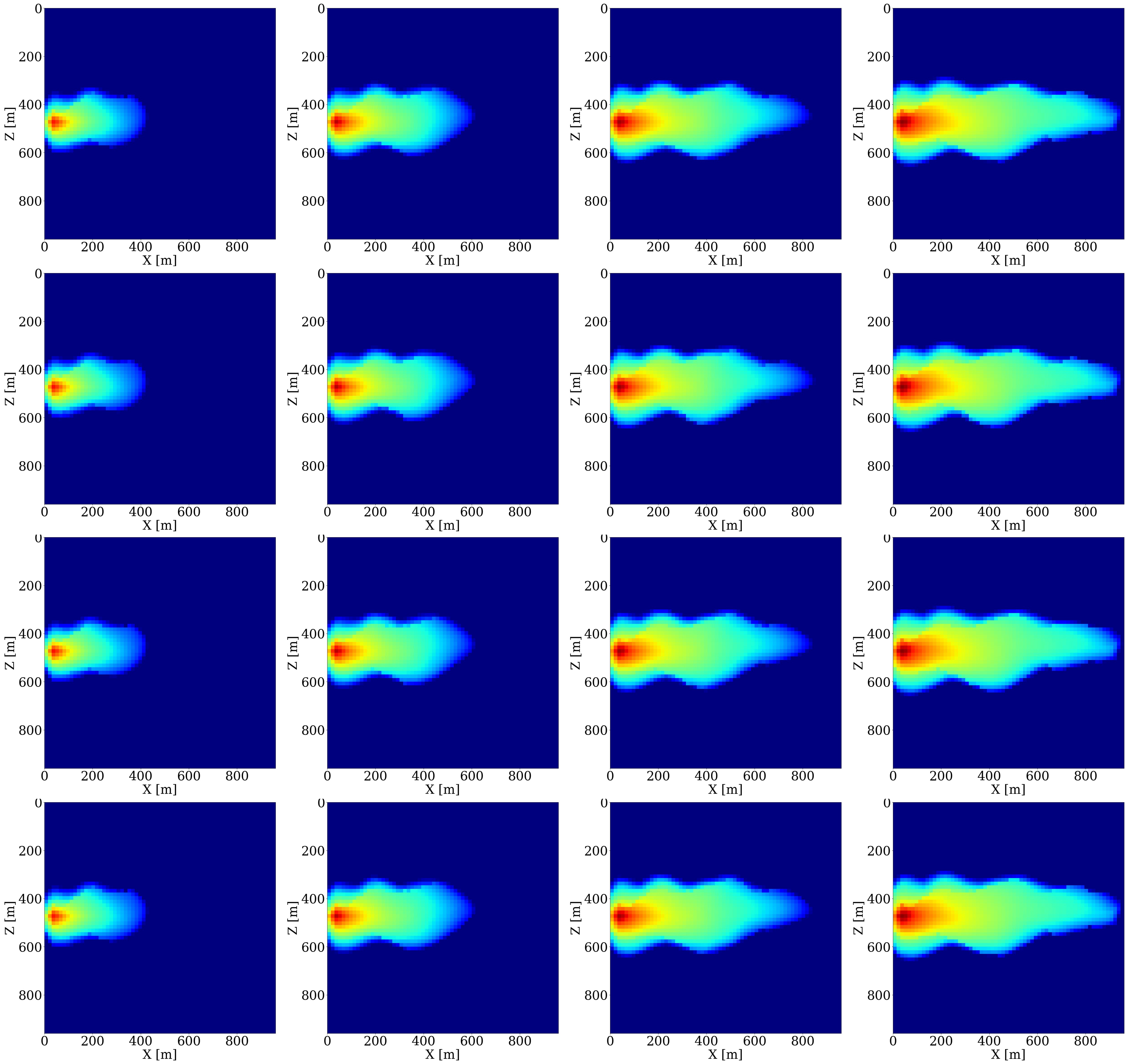
Numerical experiment
UQ - plume

ground truth

posterior sample 1

posterior sample 2

posterior sample 3



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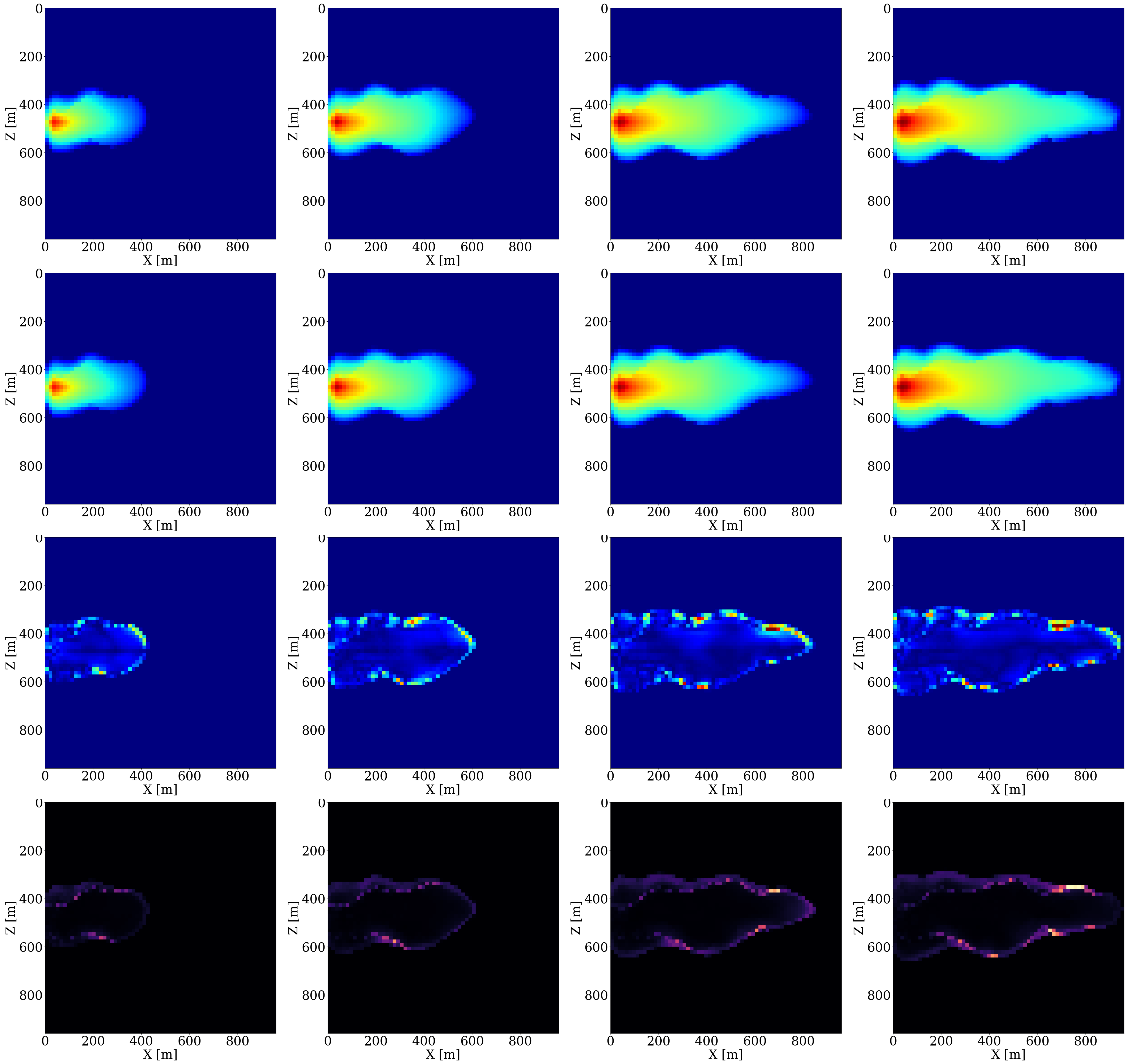
Numerical experiment
UQ - plume

ground truth

posterior mean

5X error

posterior variance



higher uncertainty

- edge
- far end of the plume
- later time steps
- aligned w/ error

Conclusions

End-to-end inversion

- estimate permeability
- predict & forecast CO_2 plume

Fast & reliable UQ

- Fourier neural operators — cheap likelihood
- normalizing flows — important prior
- FNO + normalizing flows — low FNO error enables fast & reliable UQ

Acknowledgement

We thank Olav Møyner (SINTEF) for constructive discussions.

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