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Digital Twins in the era of generative AI — Application to Geological CO_2 Storage

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Haliburton – HCMF Seminar

Tuesday, February 13, 2024

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[5] now at Devito Codes

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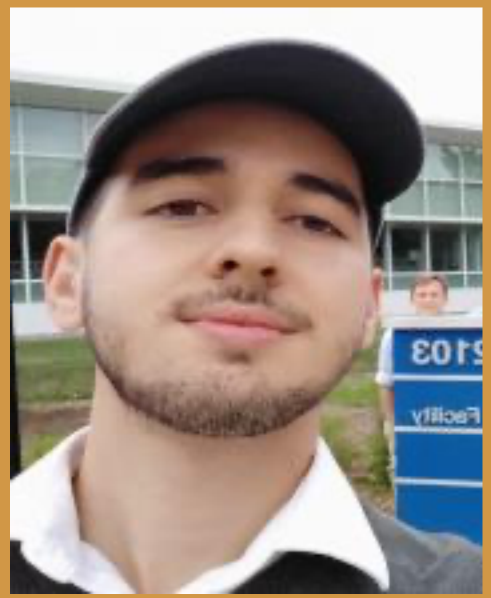
Digital Twins in the era of generative AI — Application to Geological CO_2 Storage



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Why Geological Carbon Storage?

Wood et. al, Locked away – geological carbon storage, The Royal Society, October 2022

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Drivers

geological CO_2 storage

To keep temperatures *below* the 1.5-1.7°C rise, we need to *safely* store

- 7 – 8 GtCO_2/ yr by 2050
- *cumulatively* 350 – 1200 GtCO_2 by 2100

Requires *commissioning* of 7000 – 8000 offshore “Sleipners”, @1 Mt/yr by 2050

- *deployment* of *300 – 400 wells* per year
- *monitoring* of CO_2 migration to *control* subsurface distribution & verification
- *assurance* of *safe* operations
- *transfer of liability* to national governments at *end of life cycle*

UK Government publication "Deep Geological Storage of CO2 on the UK Continental Shelf: Containment Certainty"

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Risk profiles

Uncertainties & risk *storage* model

- *highest* at *start*
- diminish when *more* time-lapse data is *collected*

***Containment* risk increases**

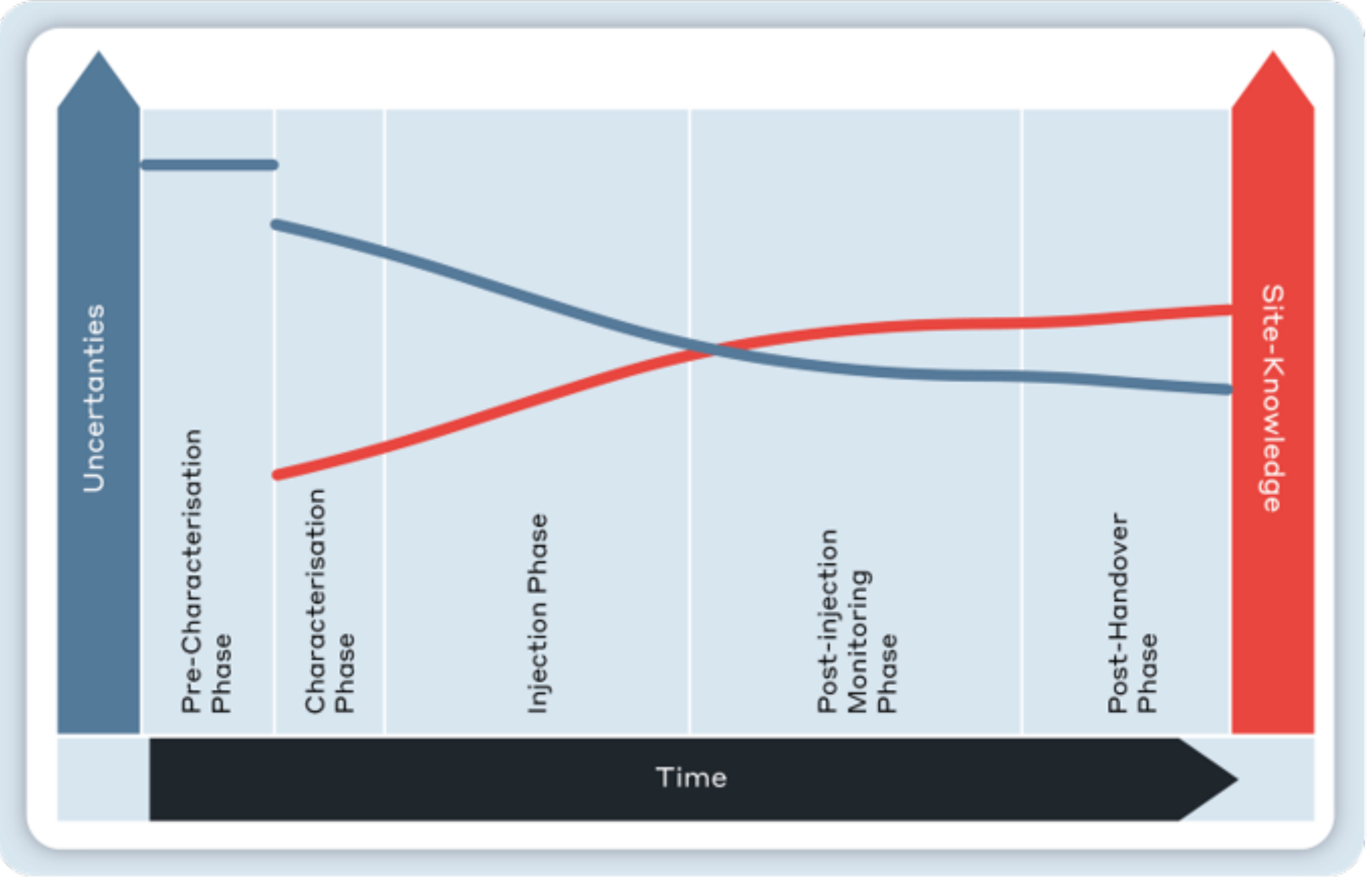
- w/ *amount* of CO_2 stored
- w/ size *area* undergoing *pressure* changes

There can be ***NO*** *lapse* in *monitoring* because

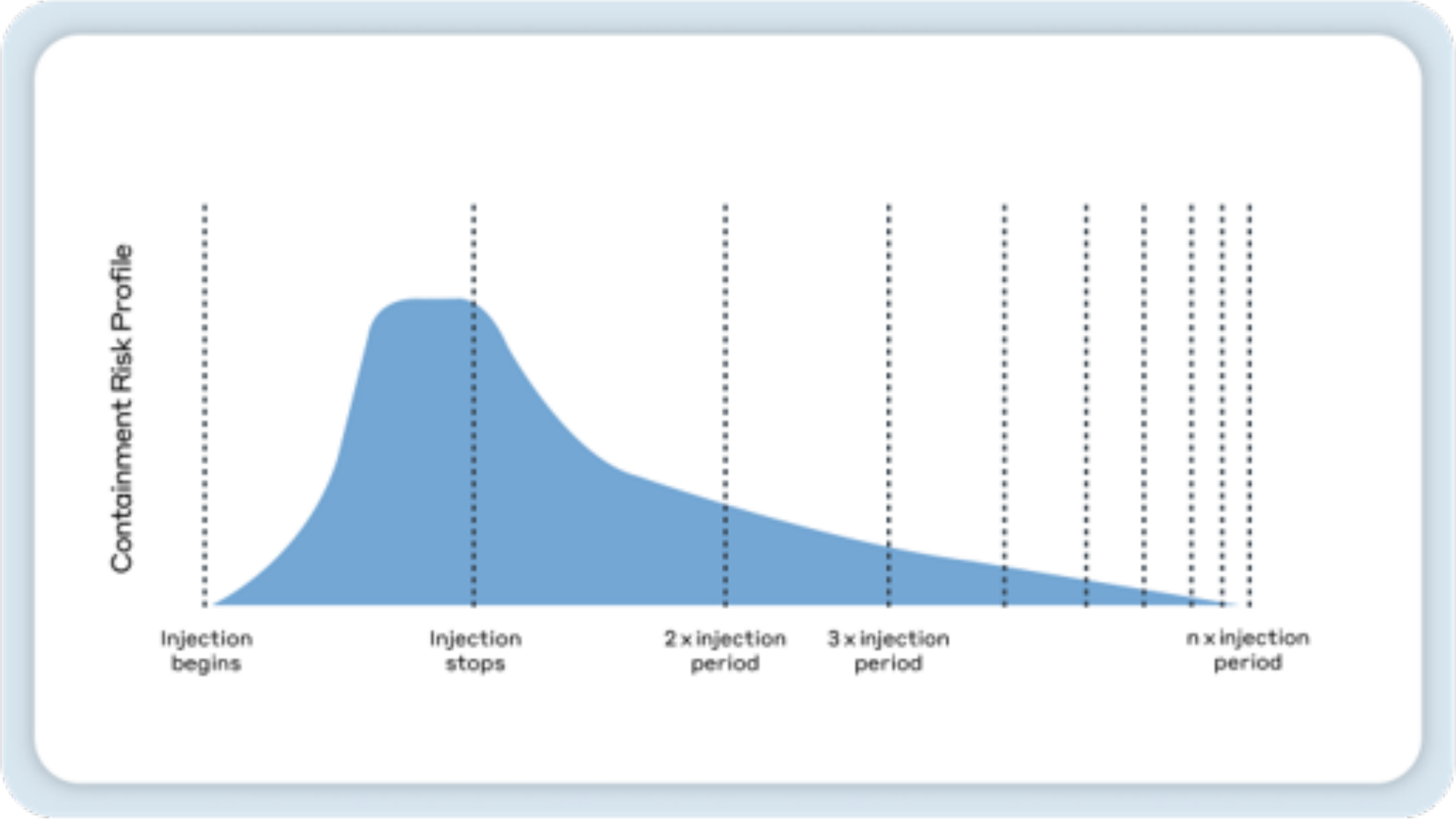
- any lack of *transparency* conformance
- will lead in loss in *confidence* by the *general* public

High-fidelity time-lapse information needs to be collected regularly over long periods of time!

uncertainty profile



containment risk profile



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.

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Challenges

monitoring Geological CO_2 Storage in Saline Aquifers

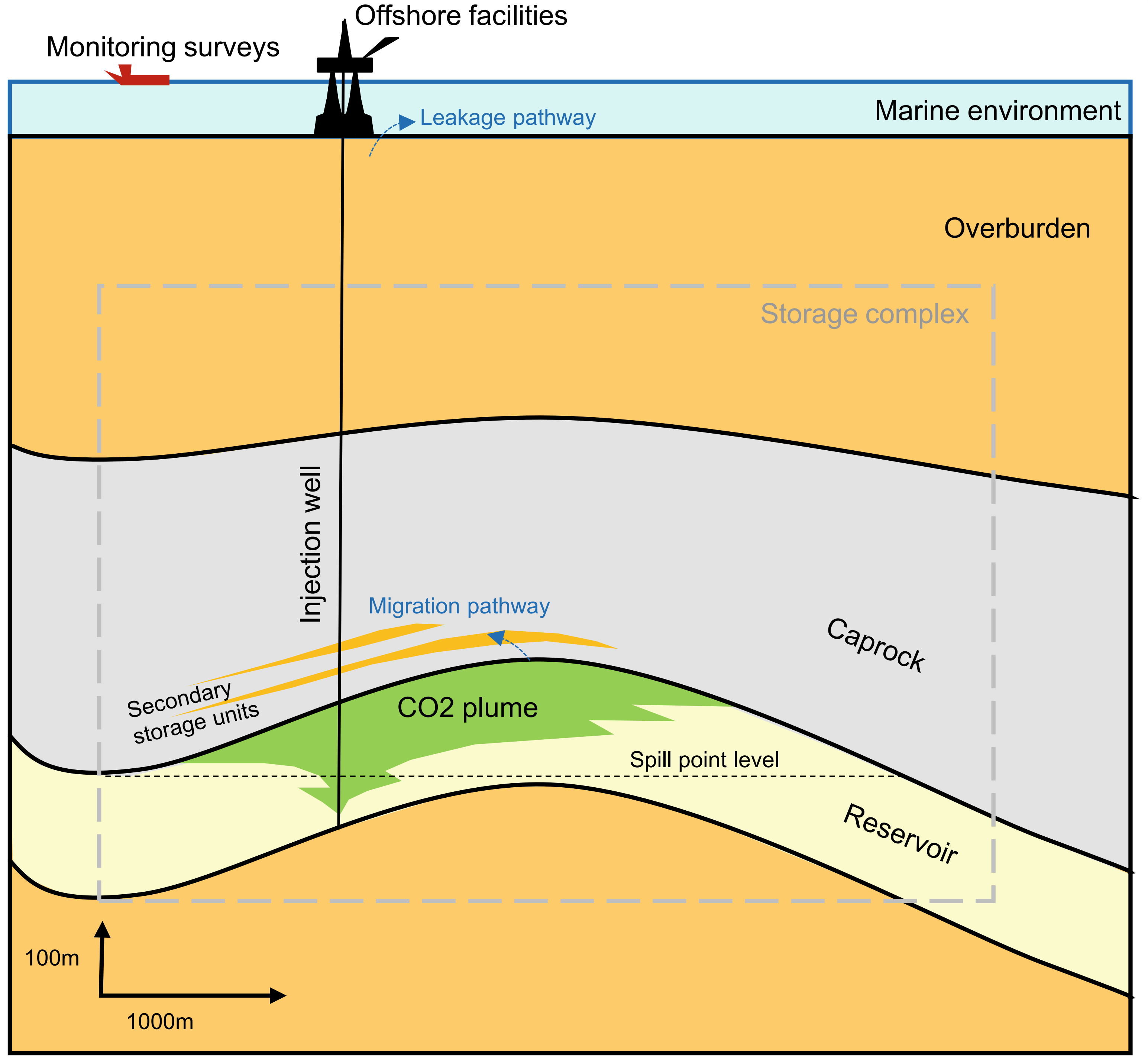
Regulators & general public require transparency & assurances that *supercritical* CO_2 stays put in the *storage complex*

- *reservoir* simulations alone are *uncertain* due to large *variability* permeability
- risk profile storage & containment highest at start & at end
- there is a need for *reproducibility* for *transparency*

Develop low-cost monitoring & control system for CO_2 plumes

- that is uncertainty aware
- maximally captures information collected over many decades
- attains accuracy needed to detect early onset leakage
- capable of risk mitigation via control

Systematic assessment of risks using techniques from uncertainty quantification.



from Ringrose

Digital Twins

from concept to reality

According to IBM, *"A digital twin is a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making."*

Innovation *accelerating* **open-source software platform** that

- makes *data-informed predictions* on *future* CO_2 plume *behavior*
- produces time-lapse data-*consistent* CO_2 *predictions*
- is *uncertainty aware* & allows for *scenario* testing & control
- informs on how much & where to *collect data*, thus *reducing* CCS monitoring *costs*

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

Open source

scalable 2/3D code

Flow simulations:

- Jutul.jl
- JutulDarcy.jl

Wave simulations & imaging:

- Devito
- JUDI.jl

Machine learning:

- InvertibleNetworks.jl
- Flux.jl

Digital Twin
enabling technologies

Key innovations:

- Learned *leakage* detection*
- Generative Geostatistical Modeling (GGM)*
- Learned FWI w/ WISE: Full-waveform *Inference* w/ Subsurface Extensions*
- Learned flow *imaging* via *coupled* flow-seismic*
- Uncertainty-aware Digital Twin that allows for
  - controlled CO_2 injectivity rate
  - optimized CO_2 monitor well placement

*will be integrated into the Digital Twin for Underground CO_2 Storage

Learned leakage detection

Explainable Leakage Detection

simulation-based training deep neural classifier

Huseyin Tuna Erdinc, Abhinav P. Gahlot, Ziyi Yin, Mathias Louboutin, and Felix J. Herrmann, **"De-risking Carbon Capture and Sequestration with Explainable CO2 Leakage Detection in Time-lapse Seismic Monitoring Images"**, in AAAI 2022 Fall Symposium: The Role of AI in Responding to Climate Challenges, 2022

Ziyi Yin, Huseyin Tuna Erdinc, Abhinav Prakash Gahlot, Mathias Louboutin, and Felix J. Herrmann, **"De-risking geological carbon storage from high resolution time-lapse seismic to explainable leakage detection"**, 2022

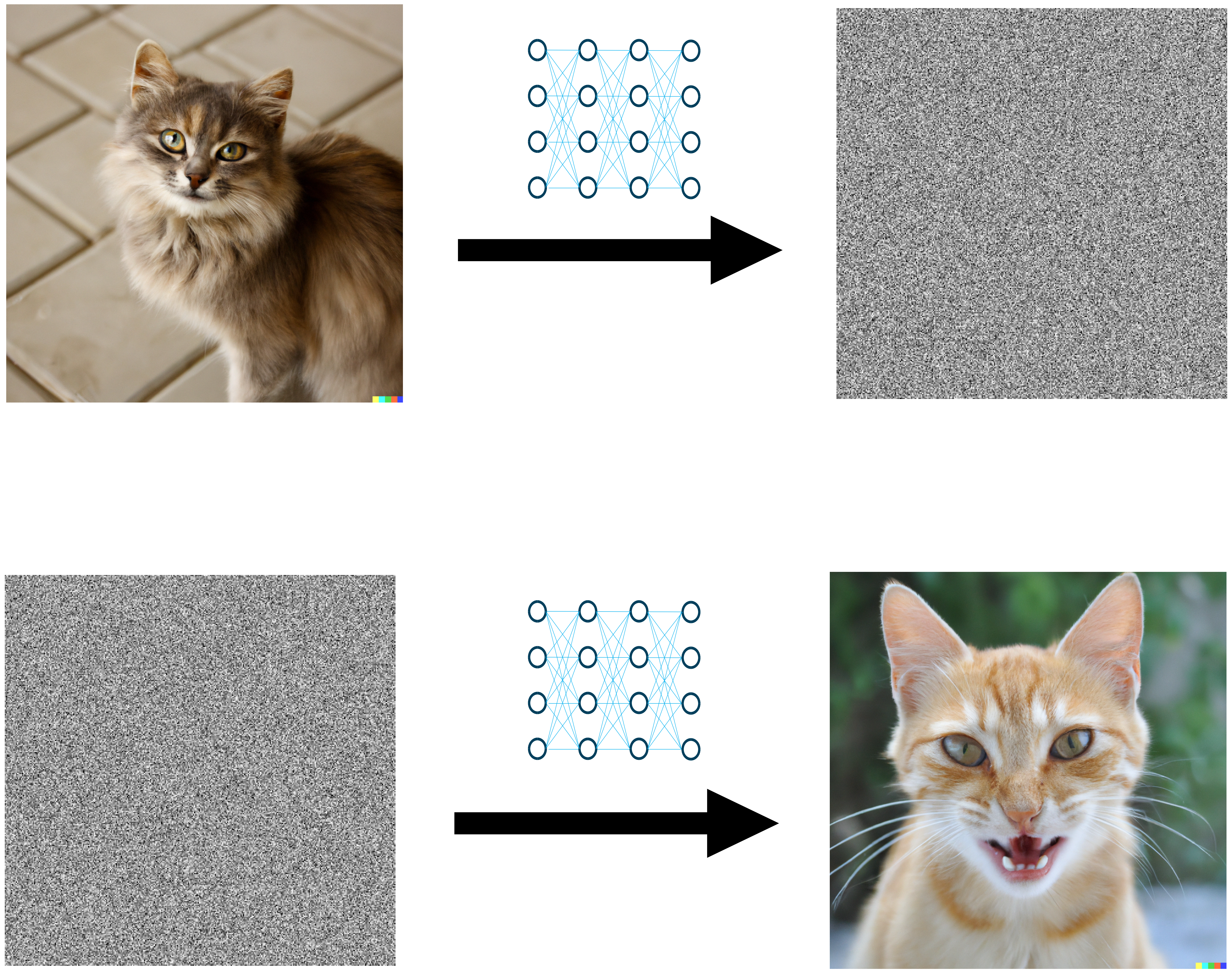
https://github.com/slimgroup/GCS-CAM

Generative Geostatistical Modeling (GGM)

Learning from examples
w/ Generative AI

Training:

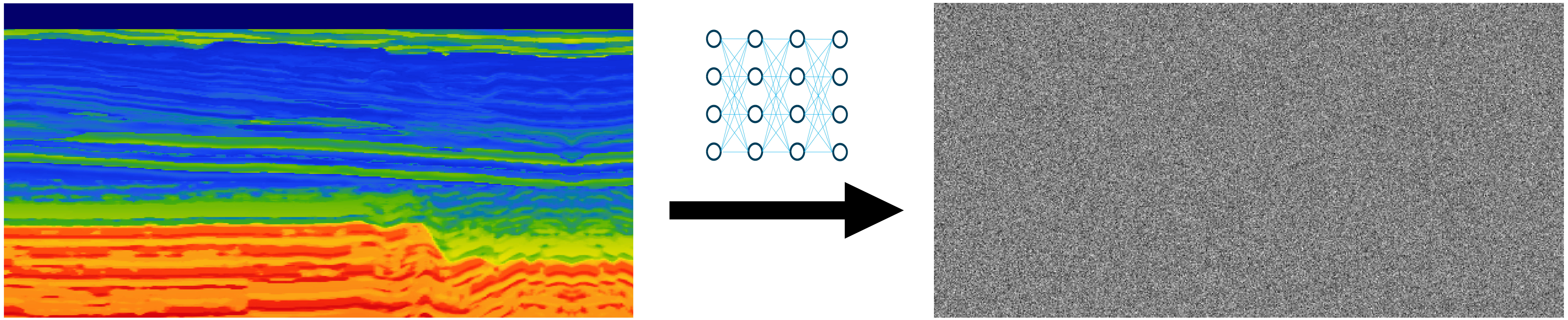
Sampling:



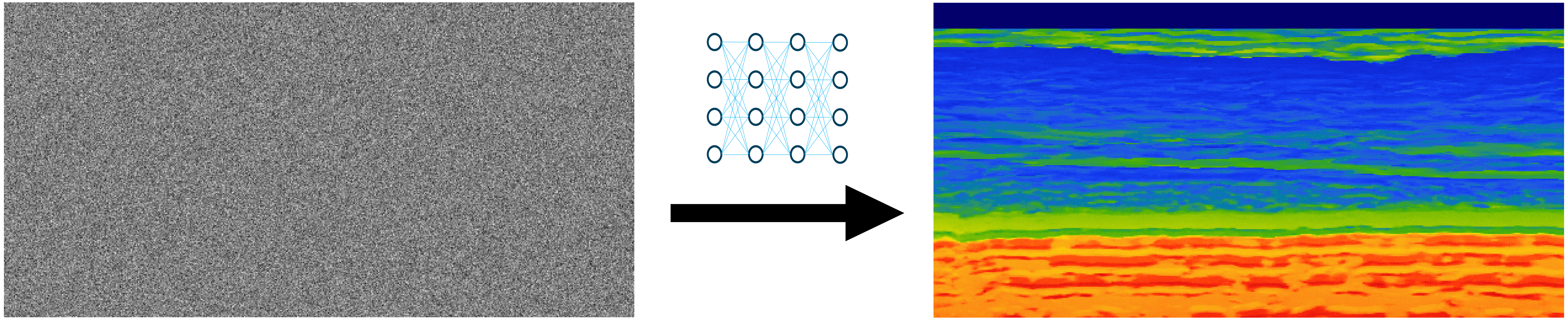
Learned Geology

from proxy Earth models

Training:



Sampling:



Generative Geostatistical Modeling
training data augmentation

Rafael Orozco, Mathias Louboutin, and Felix J. Herrmann, "**Towards generative seismic kriging with normalizing flows**", ML4SEISMIC Partners Meeting. 2023.

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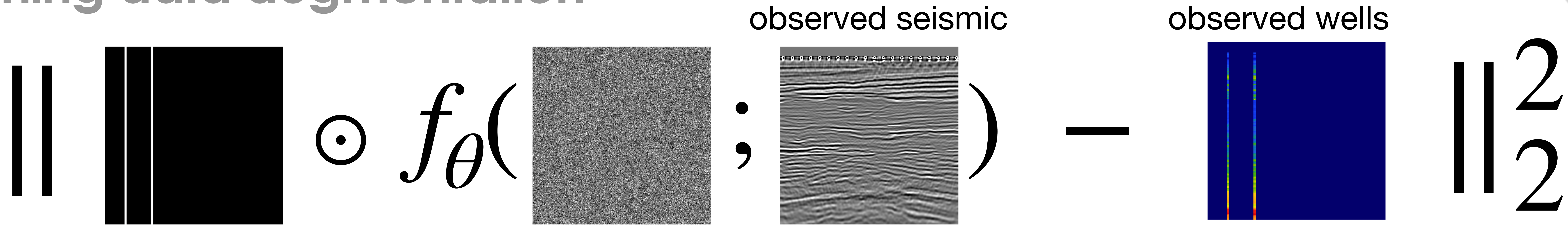
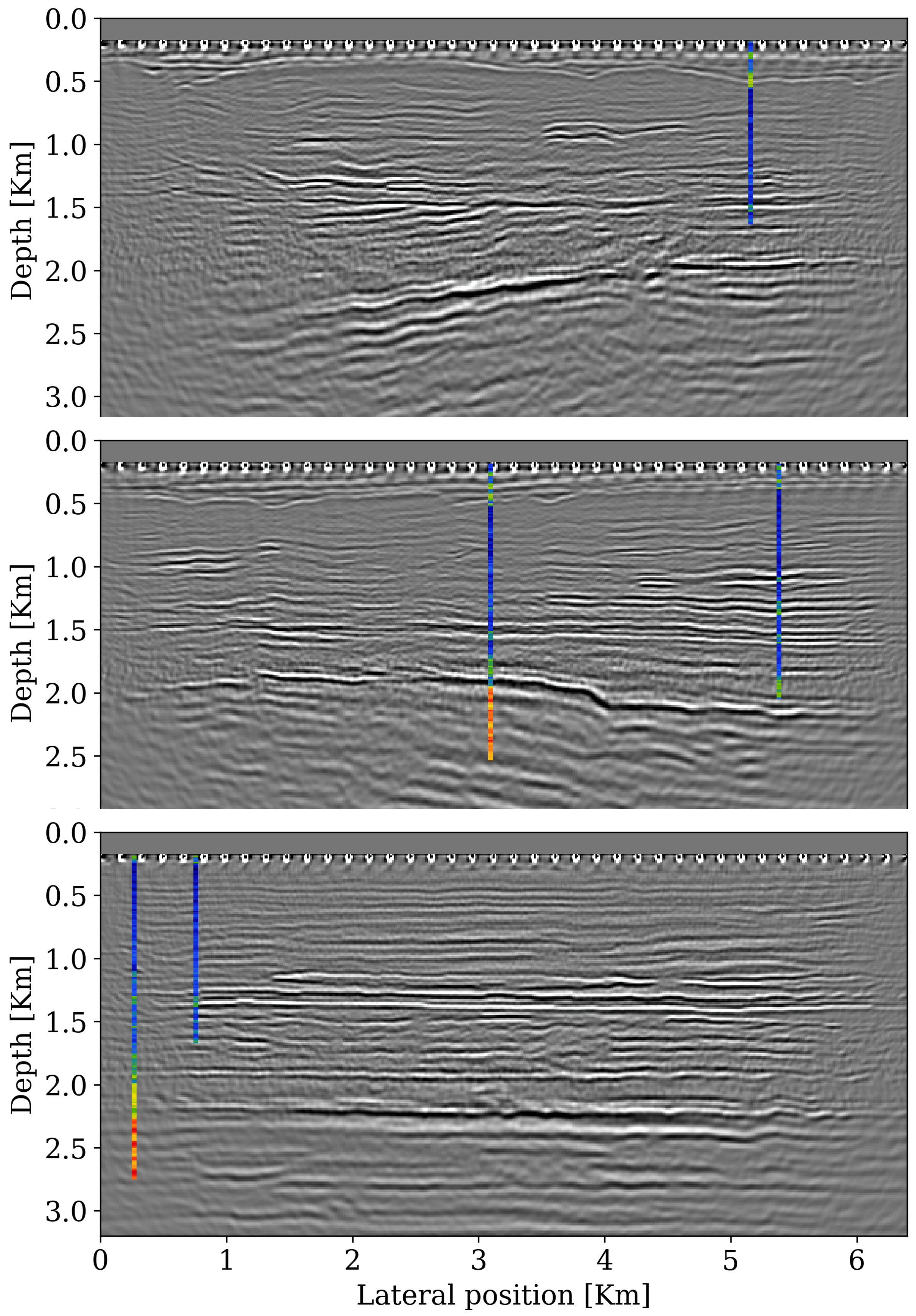
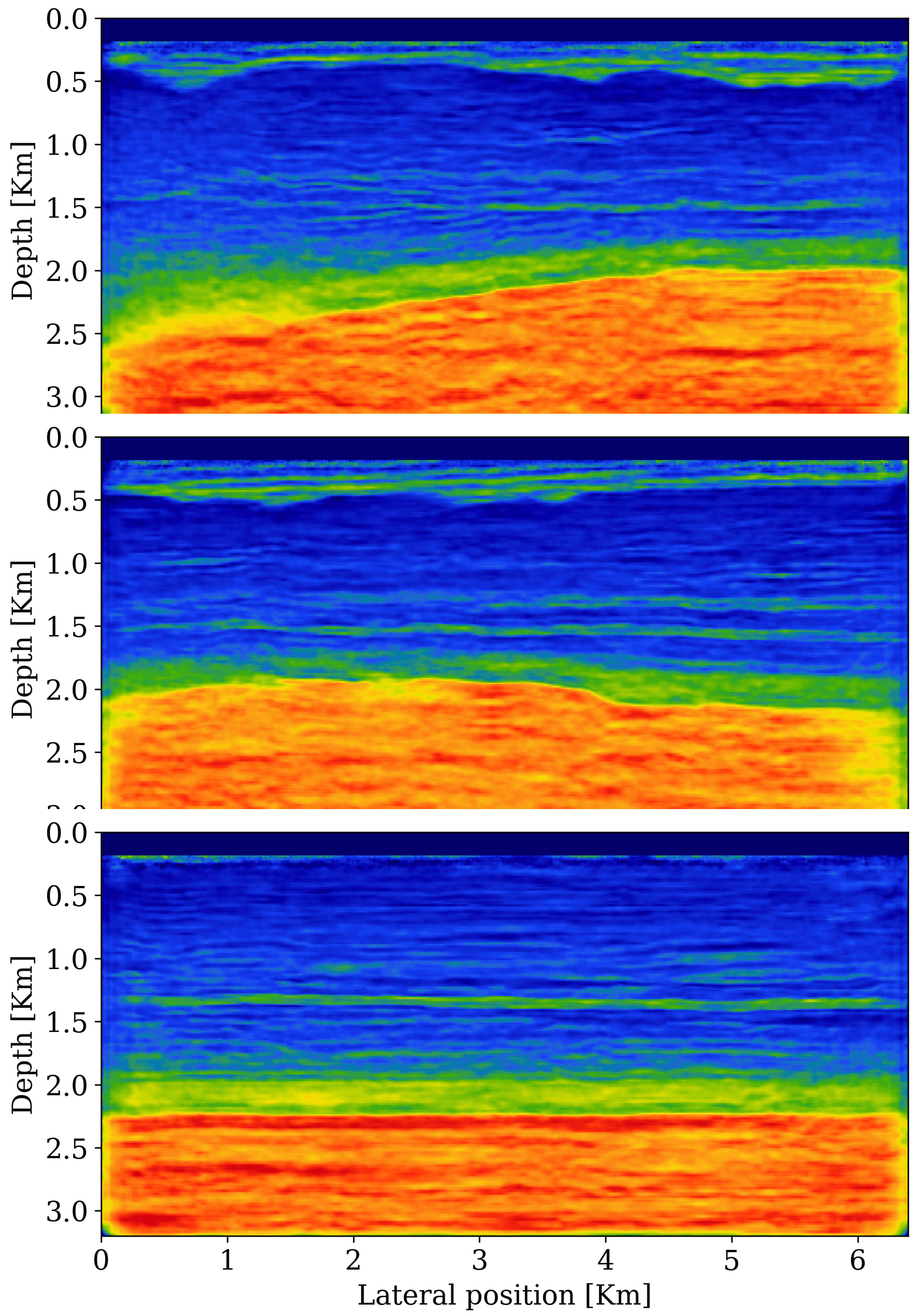




after training



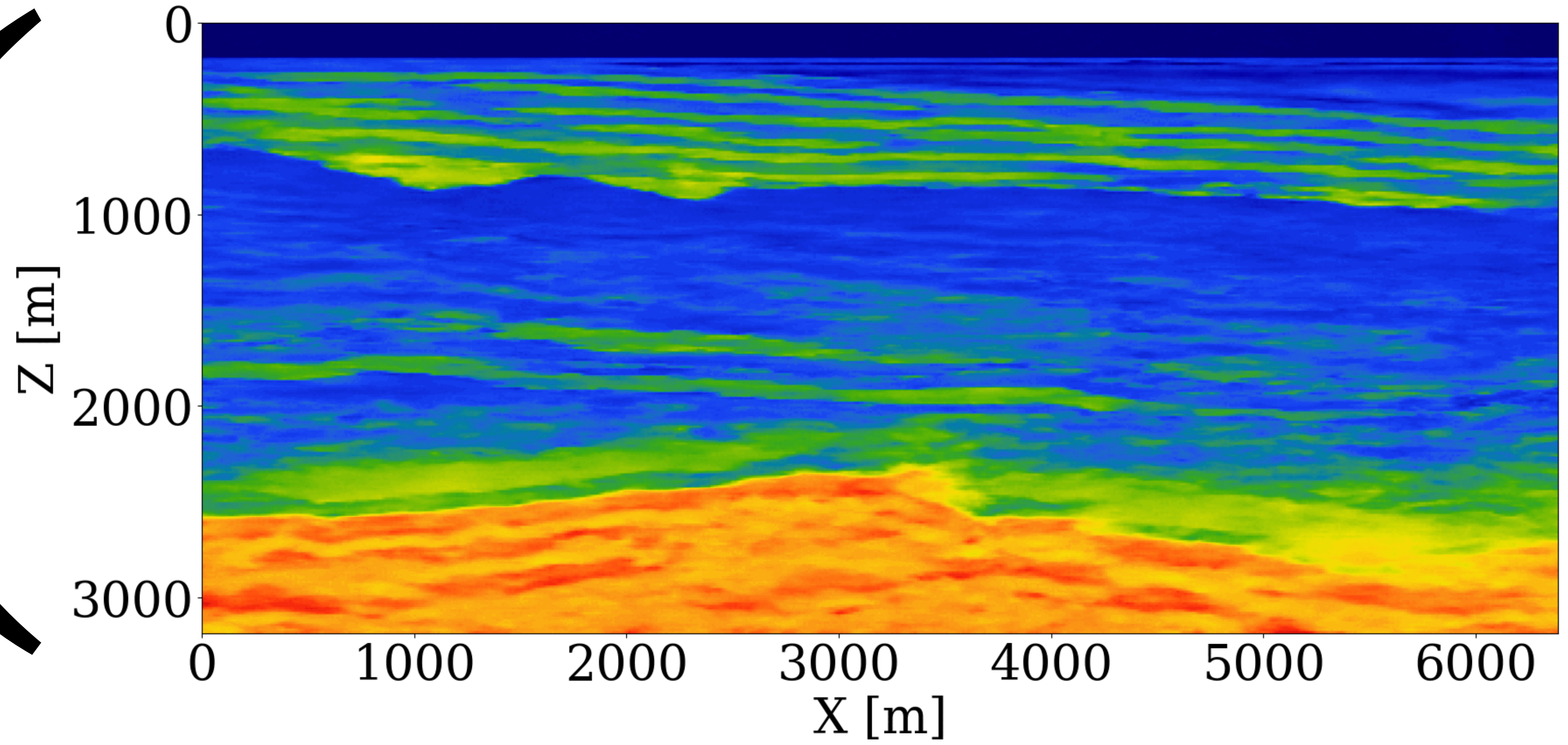
Learned FWI w/ WISE

Full-waveform inference
posterior distribution

Ziyi Yin, Rafael Orozco, Mathias Louboutin, and Felix J. Herrmann, "**WISE: Full-waveform Inference with Subsurface Extensions**", ML4SEISMIC Partners Meeting. 2023.

velocity model **observed data**

$p($



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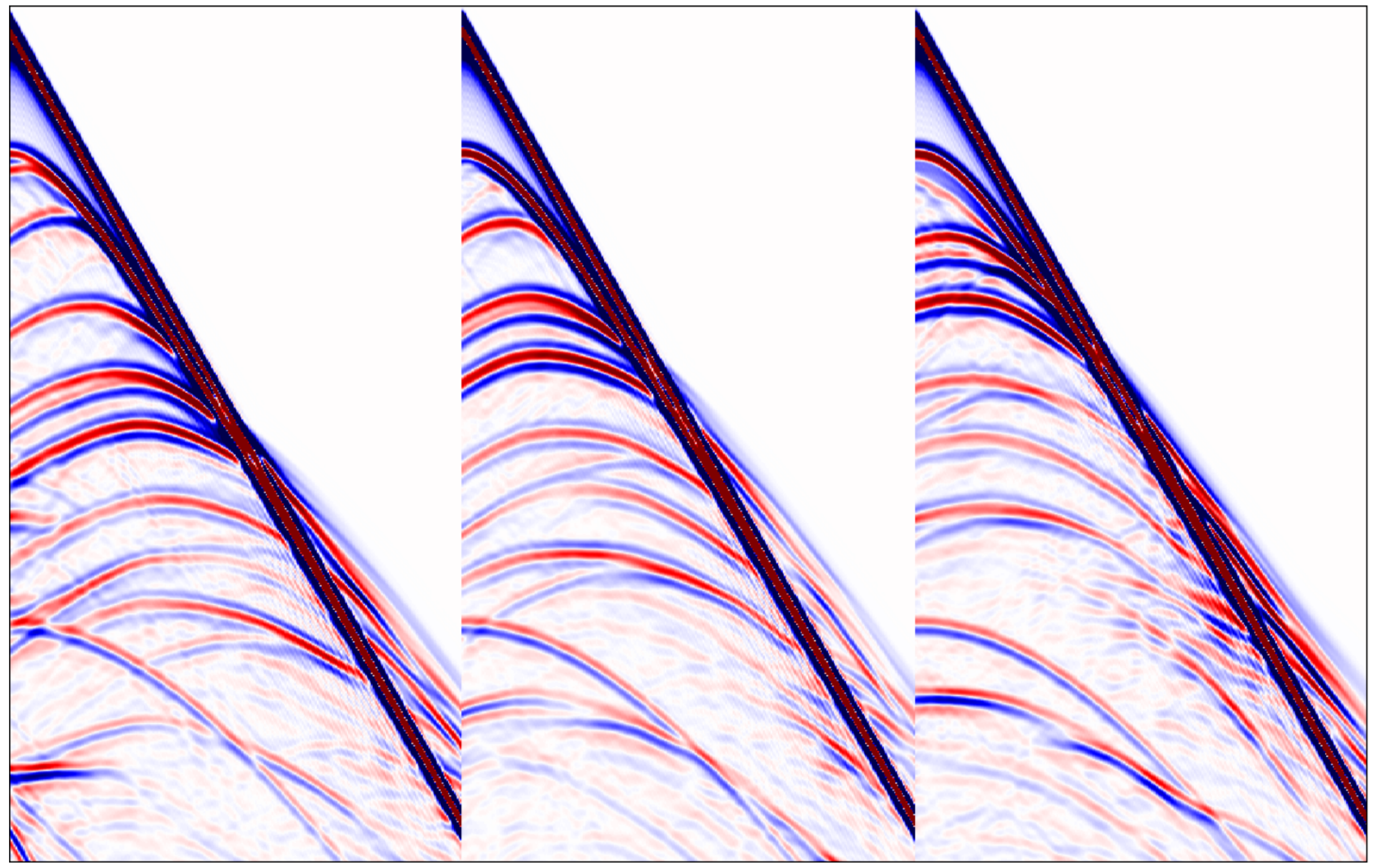


$)$

- fails because mapping is too complex

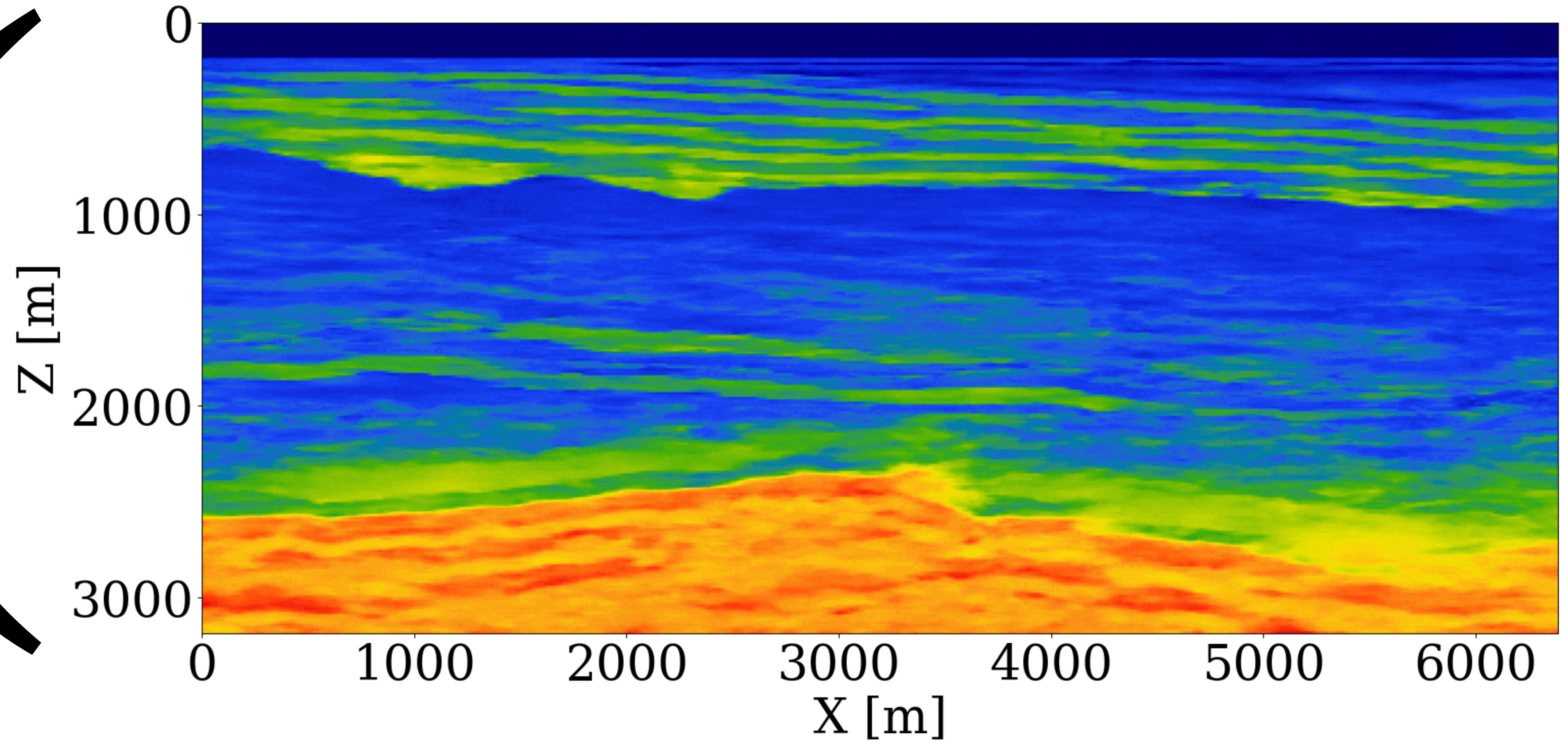
Full-waveform inference

posterior w/ physics-based *summary* statistic

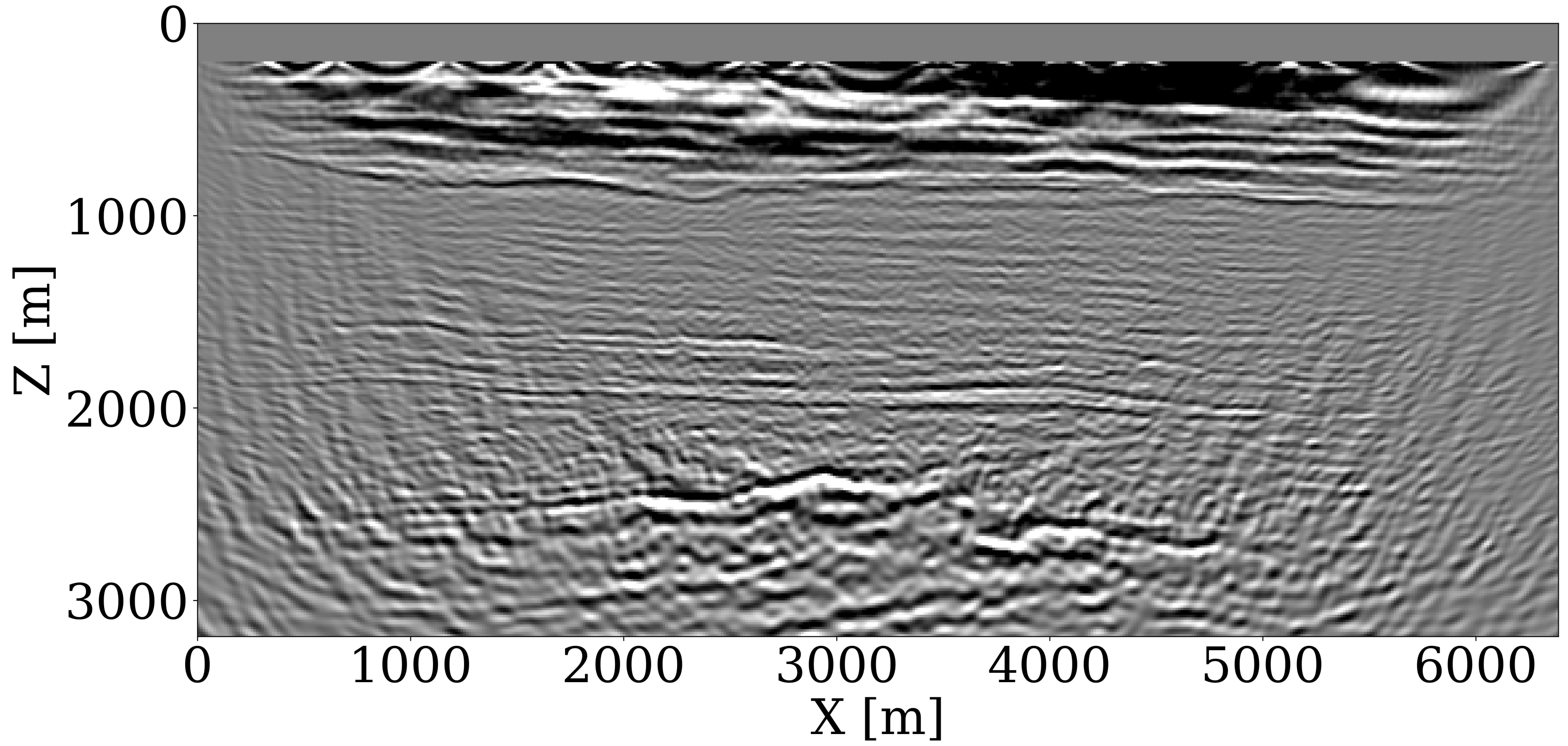
Rafael Orozco, Ali Siahkoohi, Gabrio Rizzuti, Tristan van Leeuwen, and Felix J. Herrmann, "**Adjoint operators enable fast and amortized machine learning based Bayesian uncertainty quantification**", in SPIE Medical Imaging Conference, 2023.

$p($ **velocity model** $|$ **RTM** $)$

velocity model



RTM



- migration preserves information as long as migration-velocity model is sufficiently accurate

Full-waveform inference

“approximate” posterior

velocity model **RTM**

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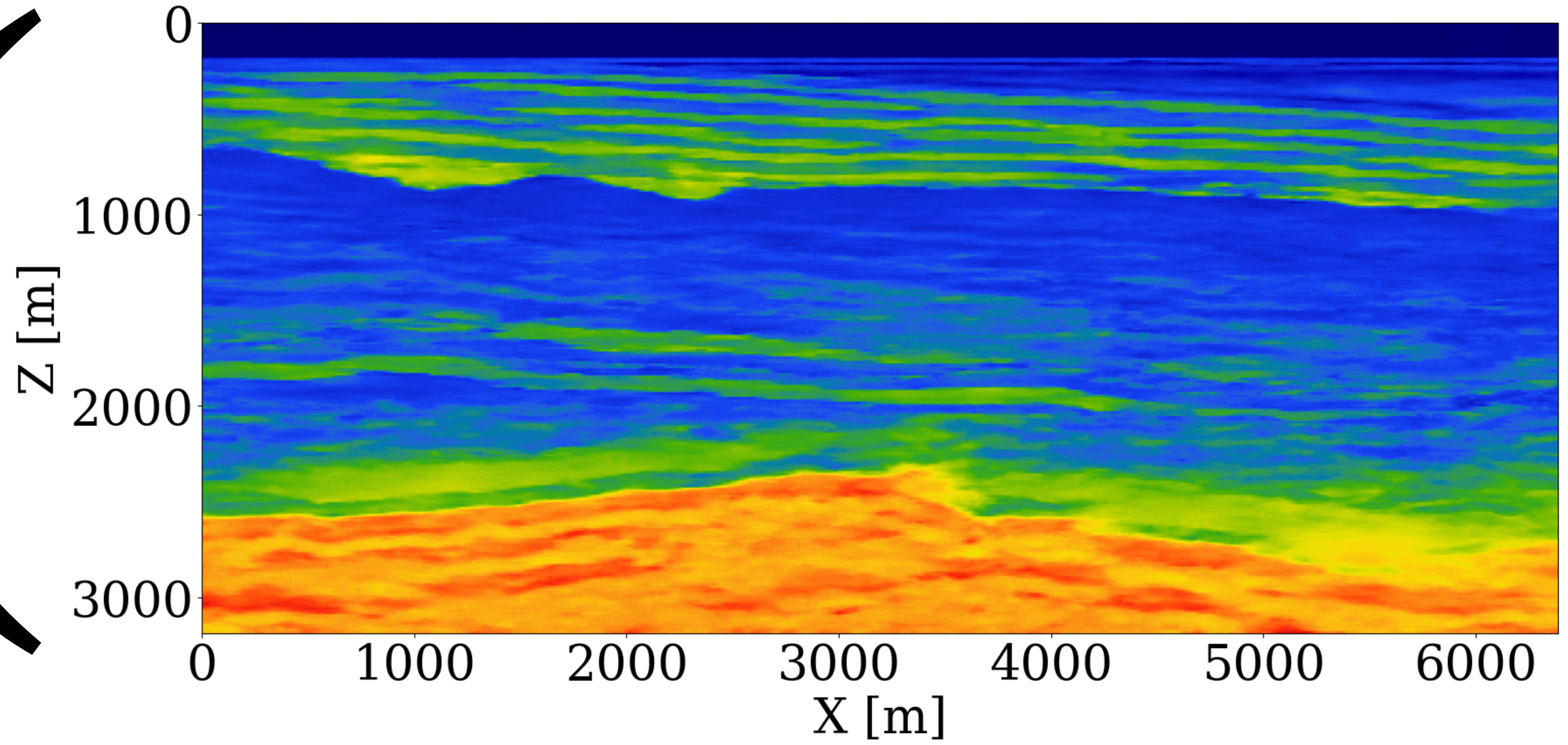

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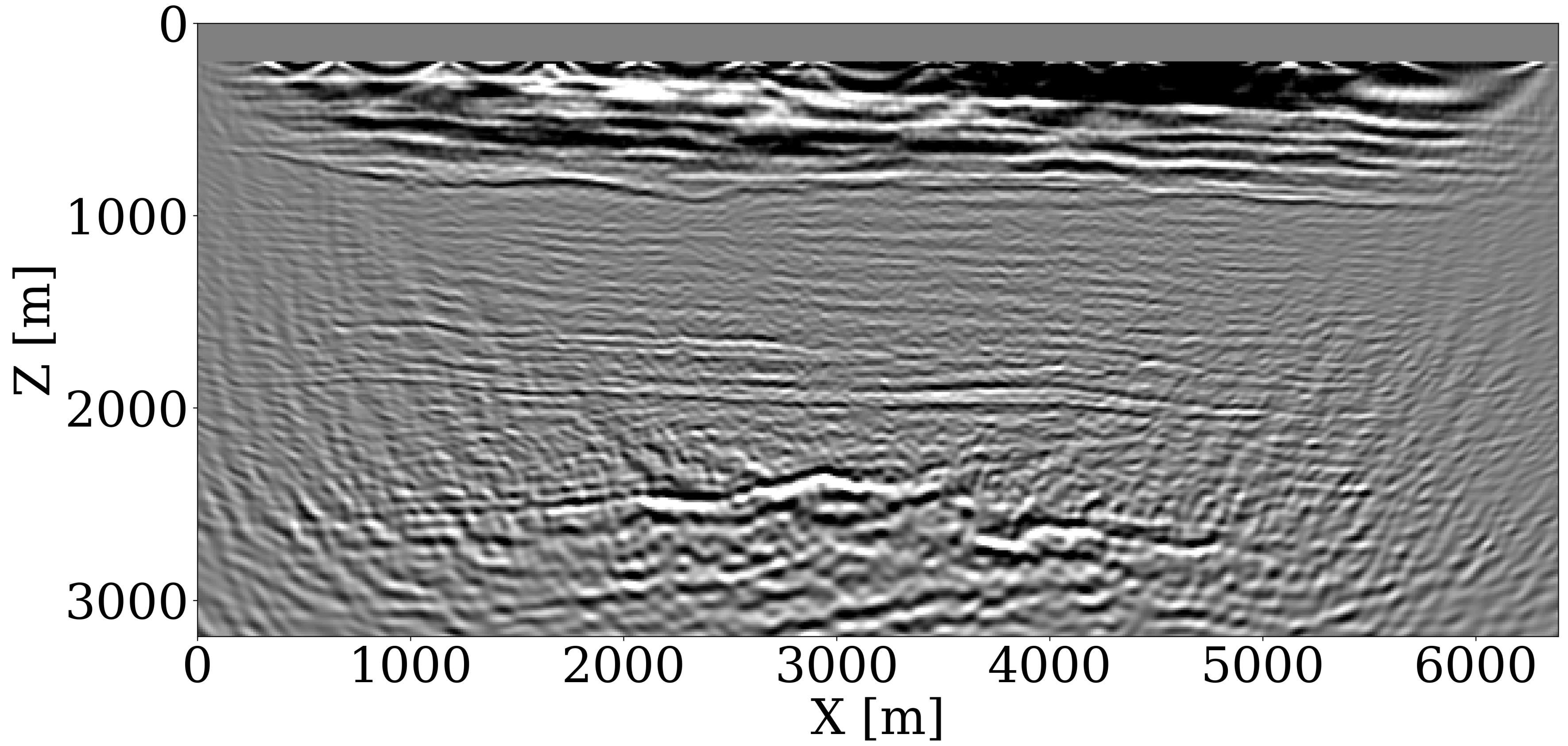

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Fails when migration-velocity model is poor!

Full-waveform inference

summary statistics = RTM + subsurface offset

sample velocity model | **subsurface offset gathers**

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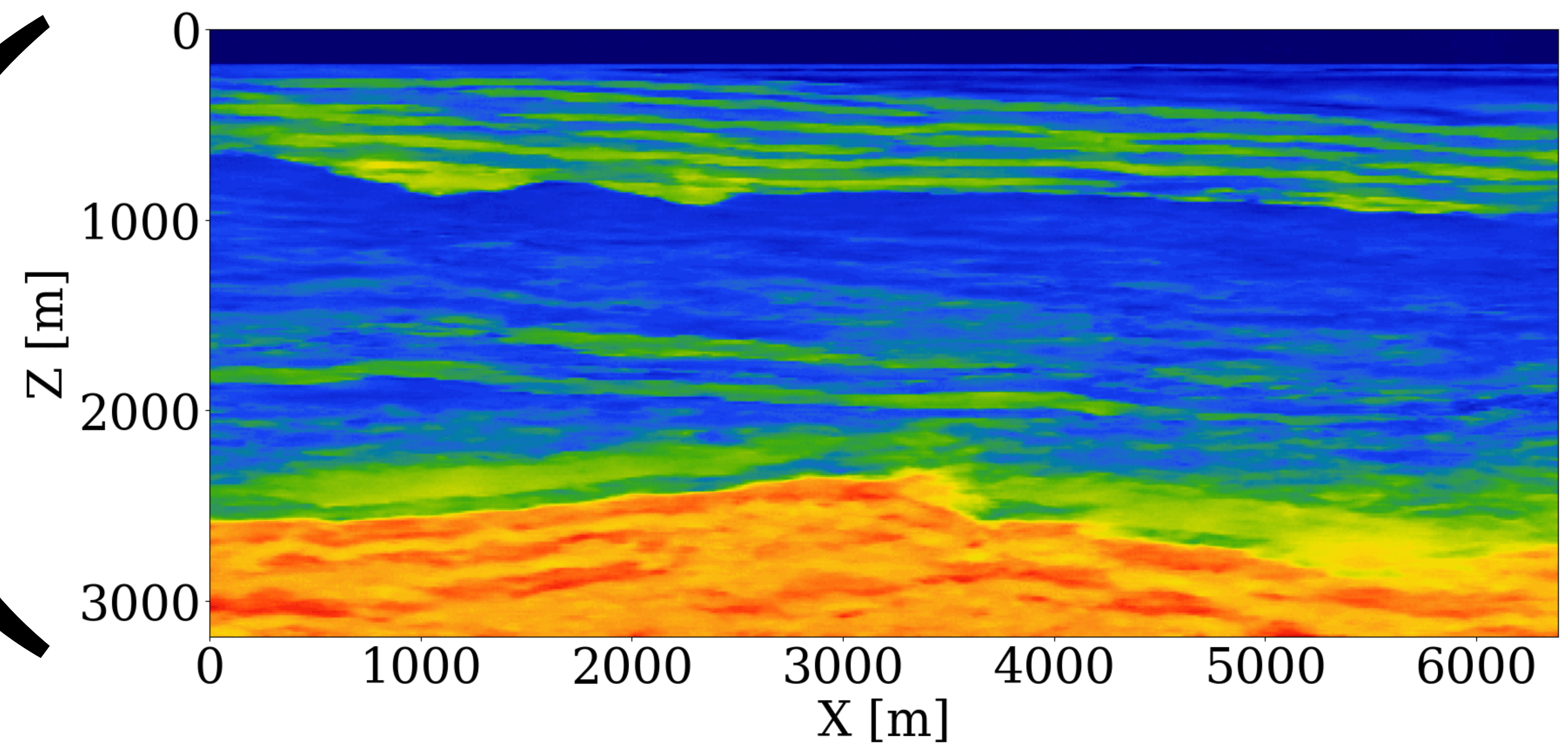

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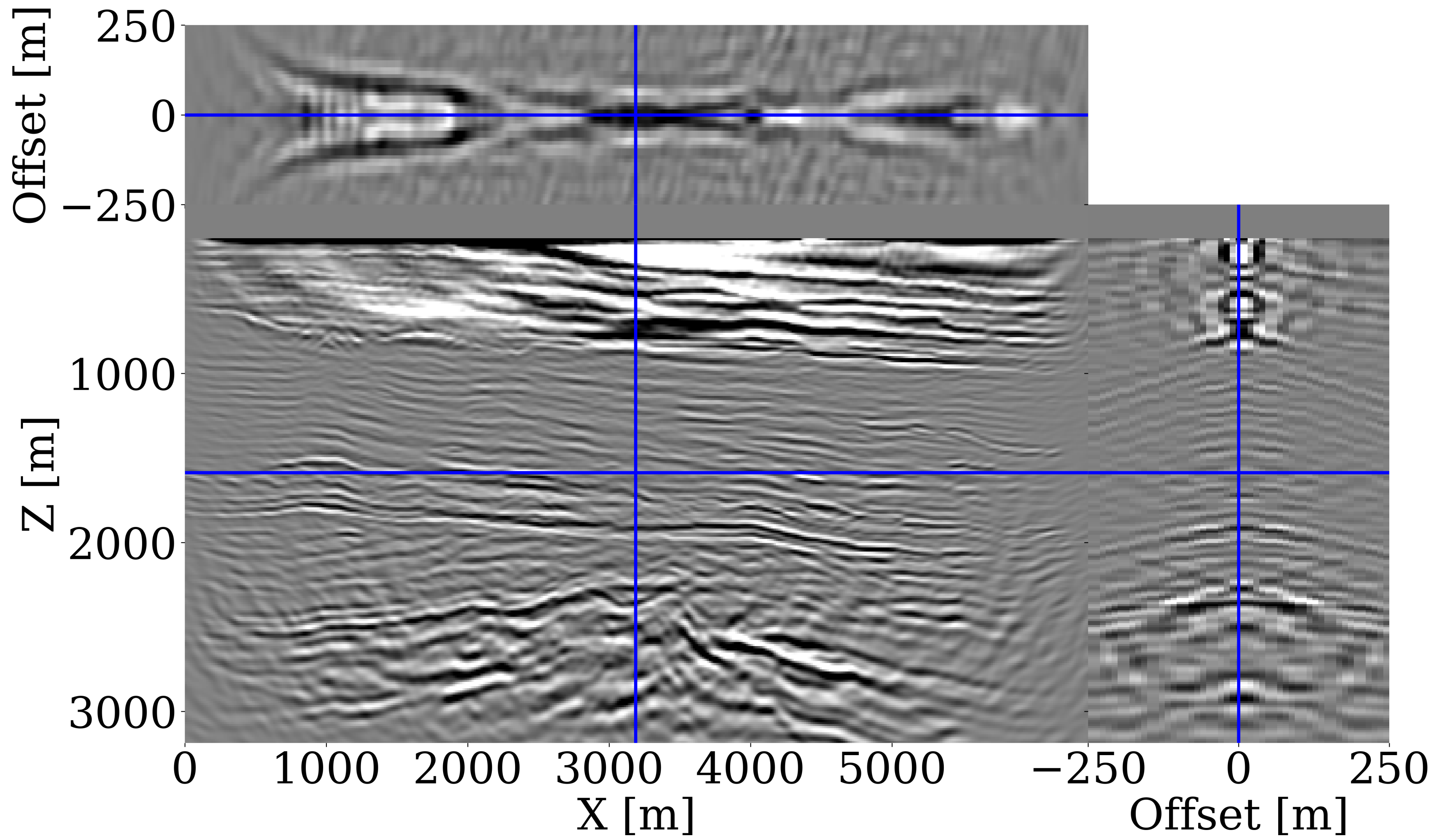

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Information resides in $\neq 0$ offsets!

Training
conditional Normalizing Flow (CNF)

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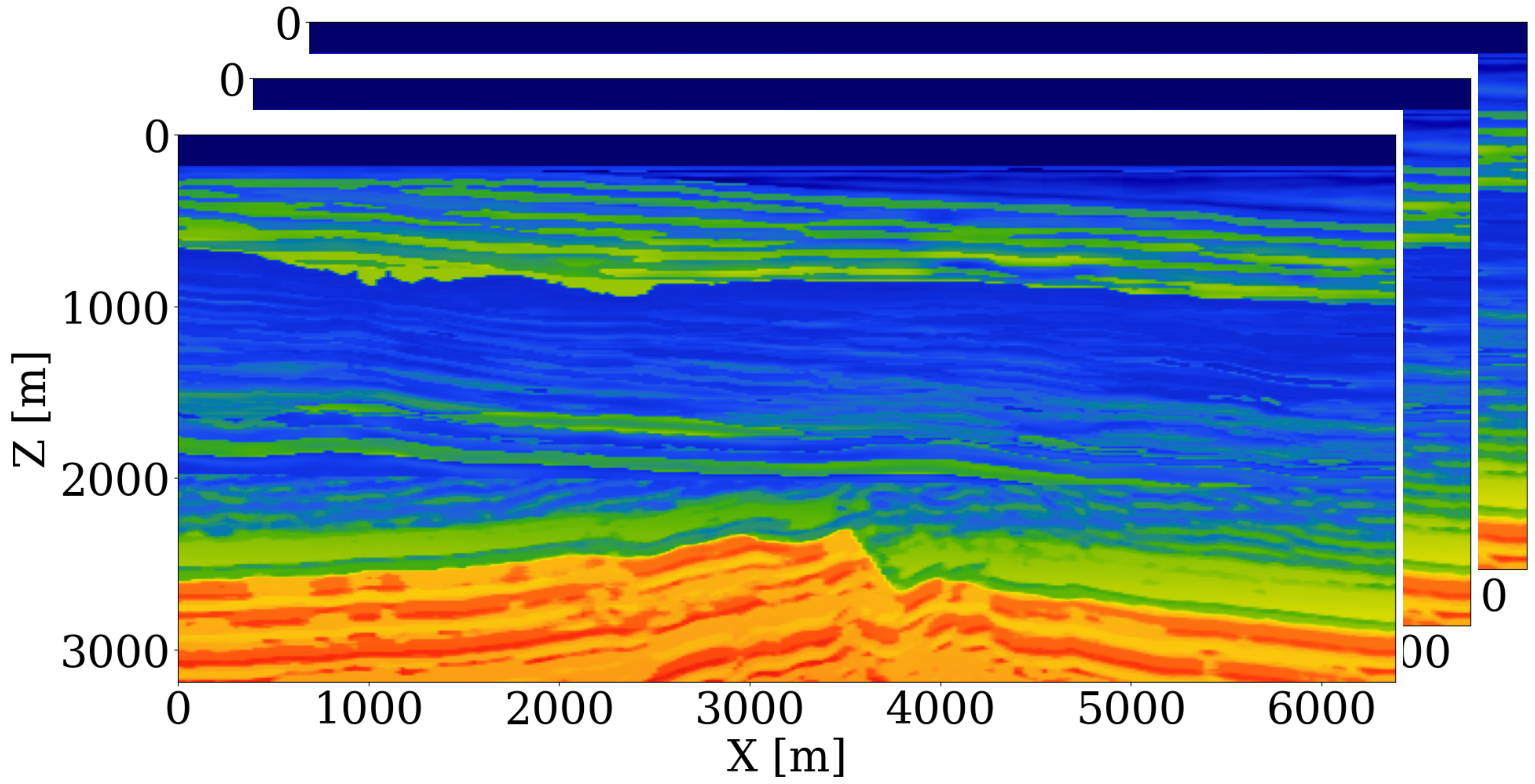
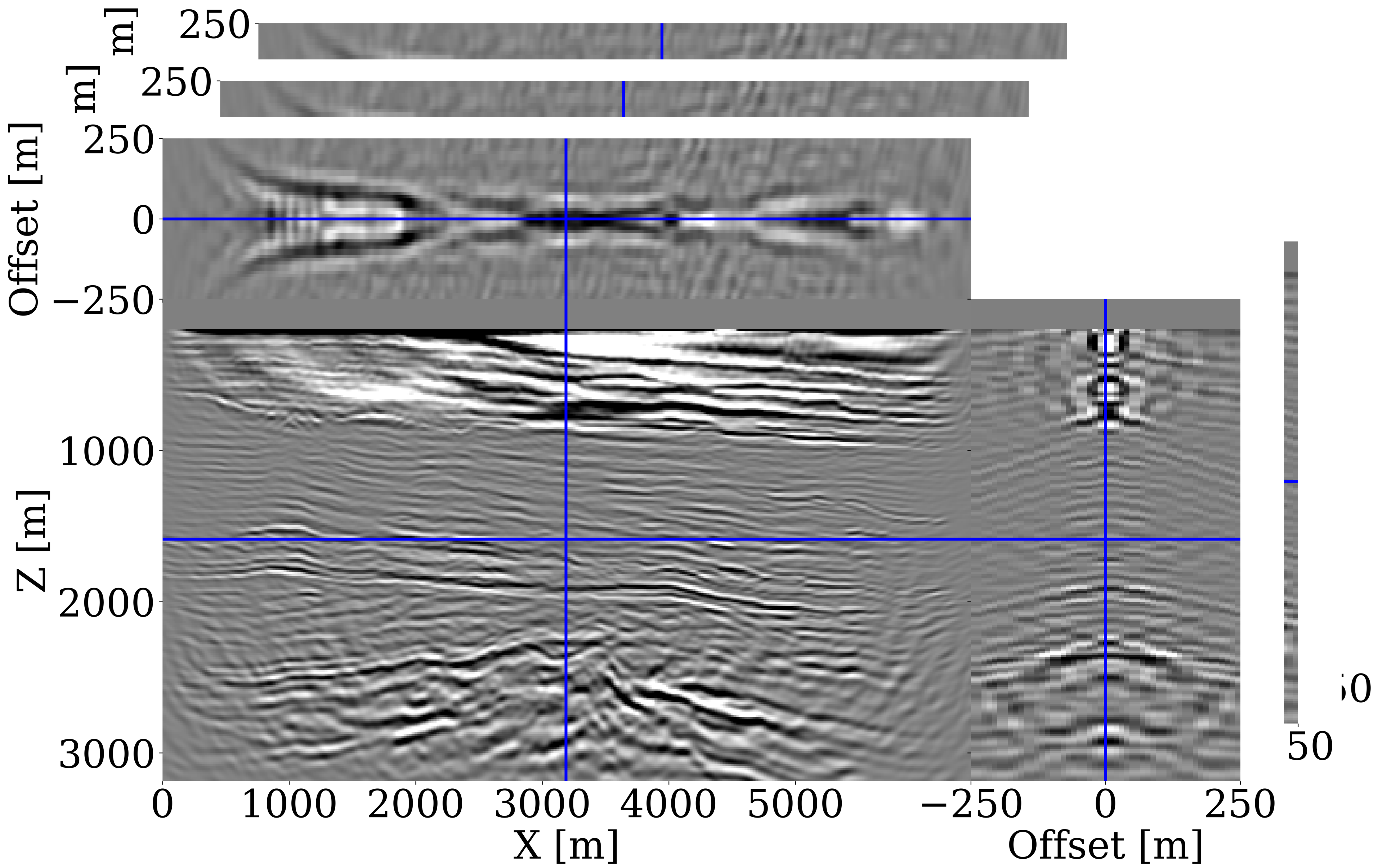


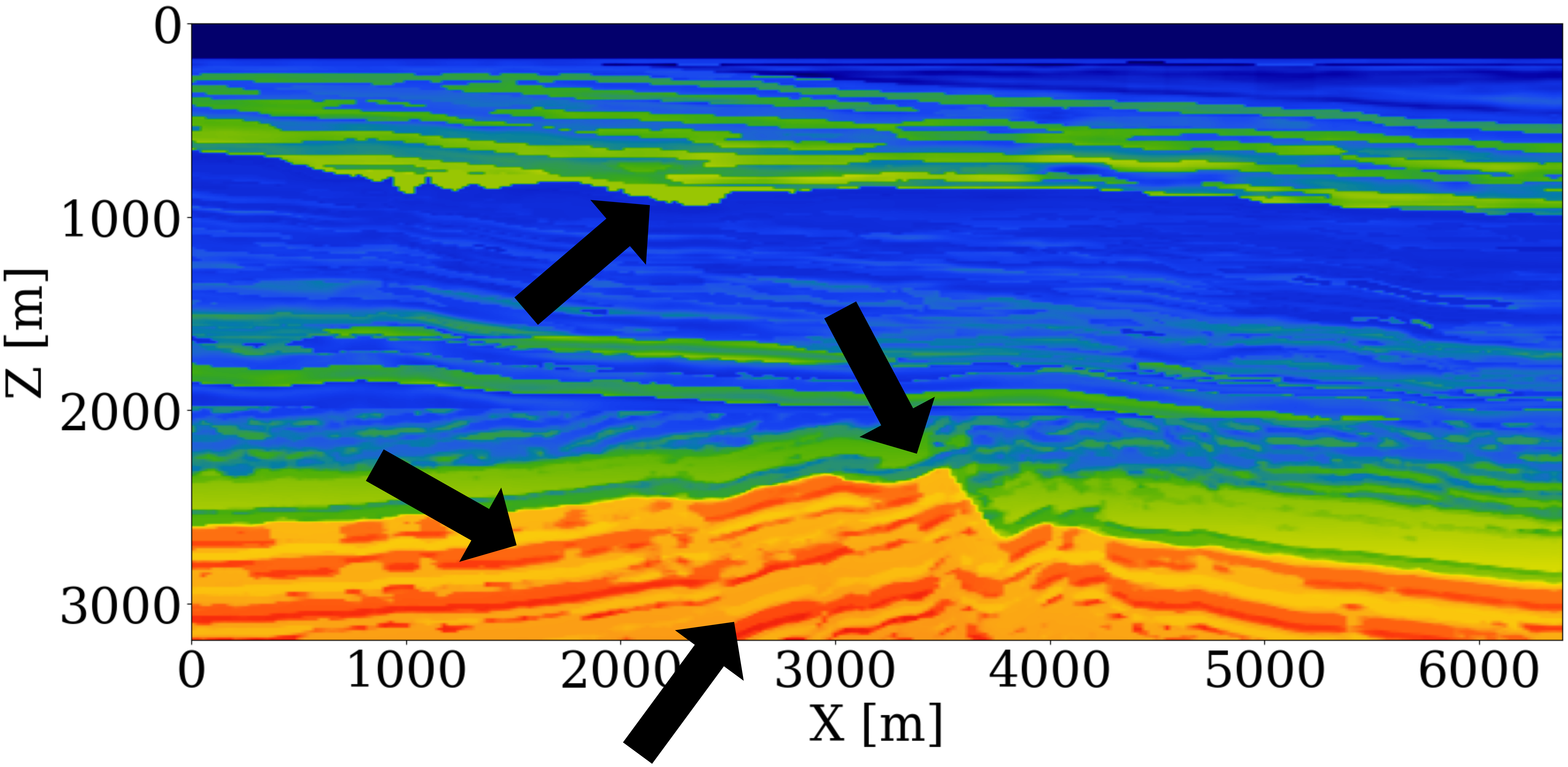


Train *amortized* CNF on N training pairs $\{\mathbf{x}^{(n)}, \mathbf{y}^{(n)}\}_{n=1}^{N}$ with

$$\hat{\theta} = \underset{\theta}{\arg\min} \frac{1}{N} \sum_{n=1}^{N} \left(\|f_\theta(\mathbf{x}^{(n)}; \mathbf{y}^{(n)})\|_2^2 - \log \left| \det \mathbf{J}_{f_\theta} \right| \right)$$

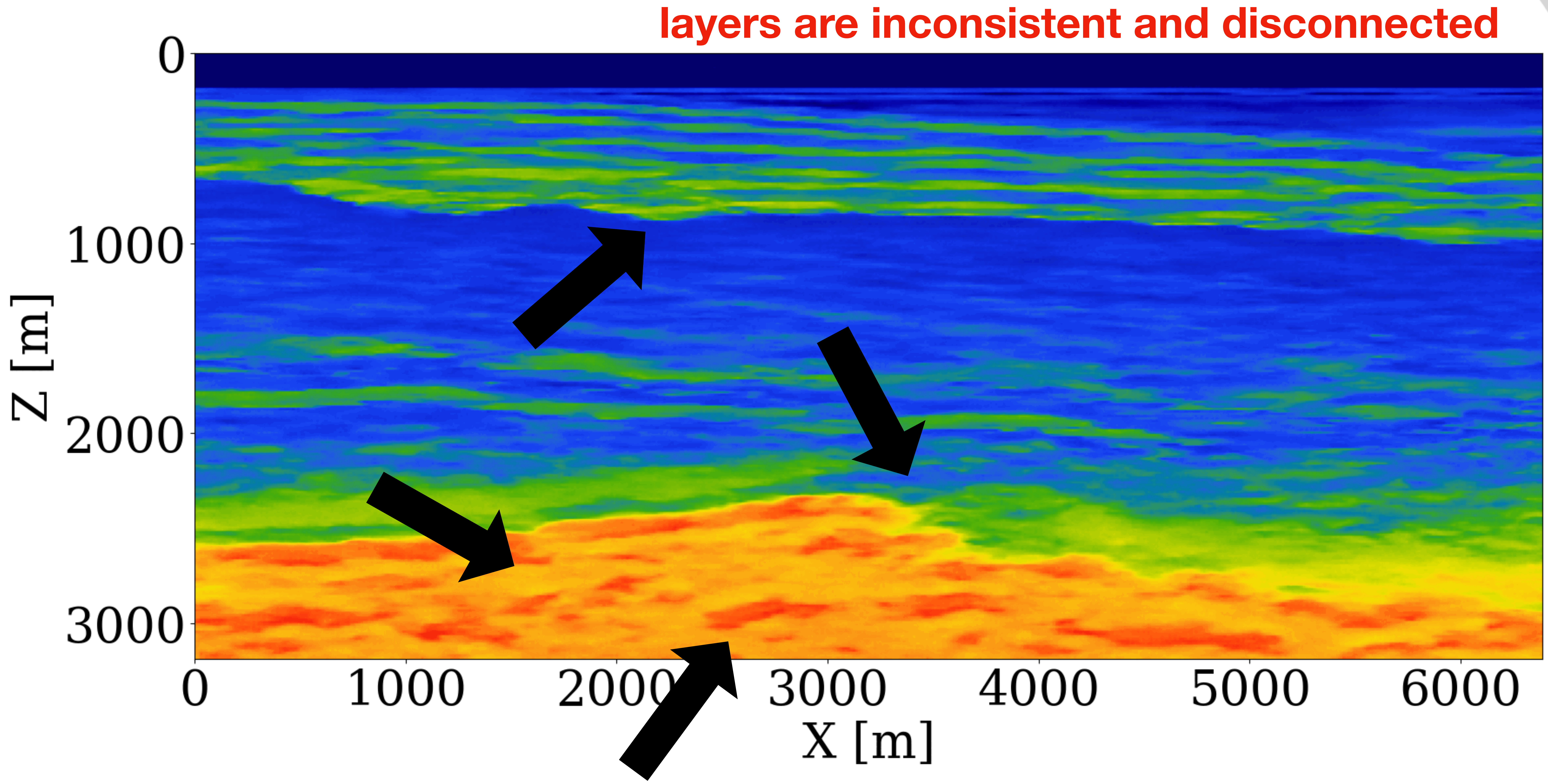
Ground-truth velocity model

SLIM ML4Seismic



Posterior samples

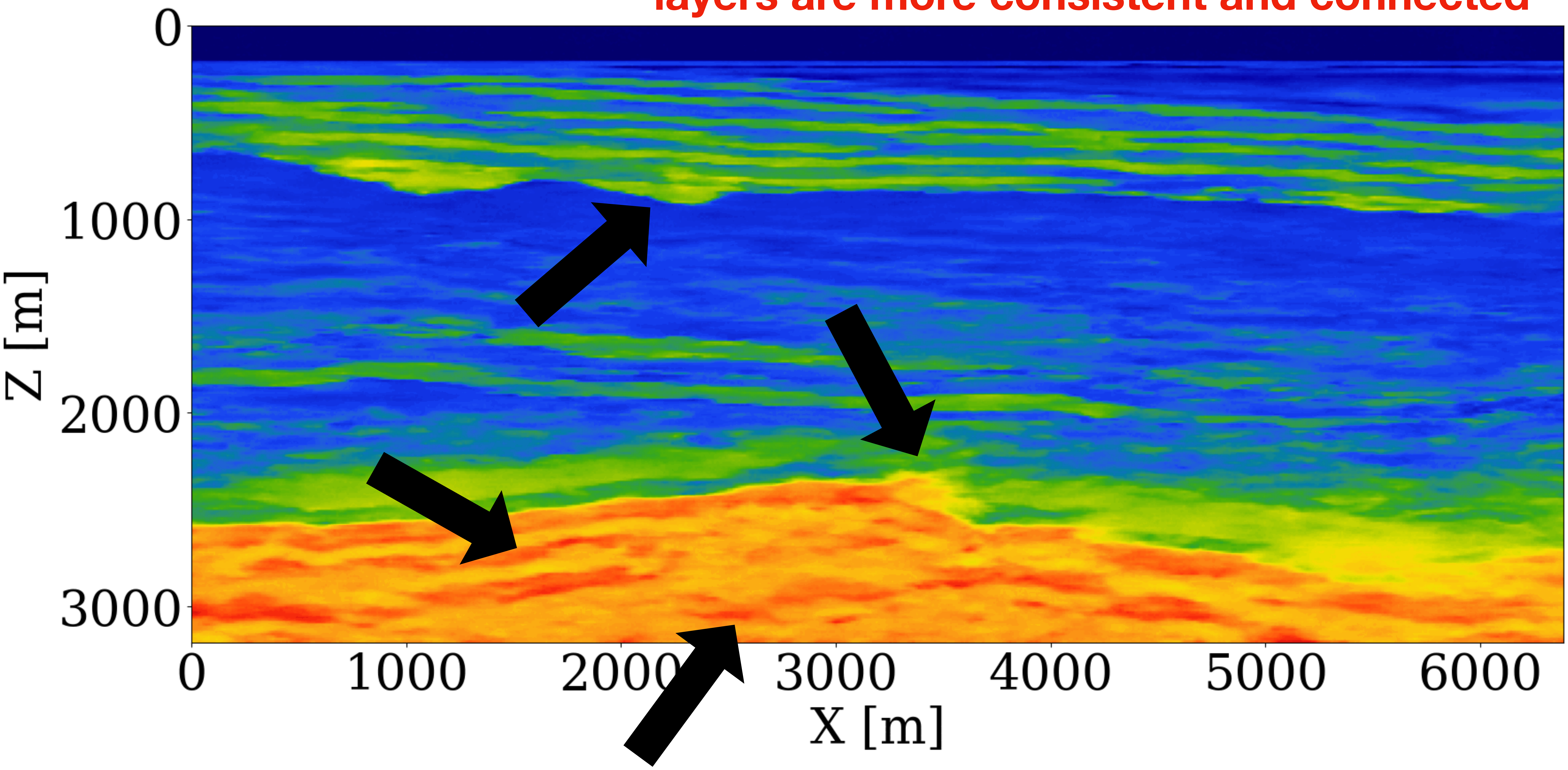
summary statistics = RTM



Posterior samples

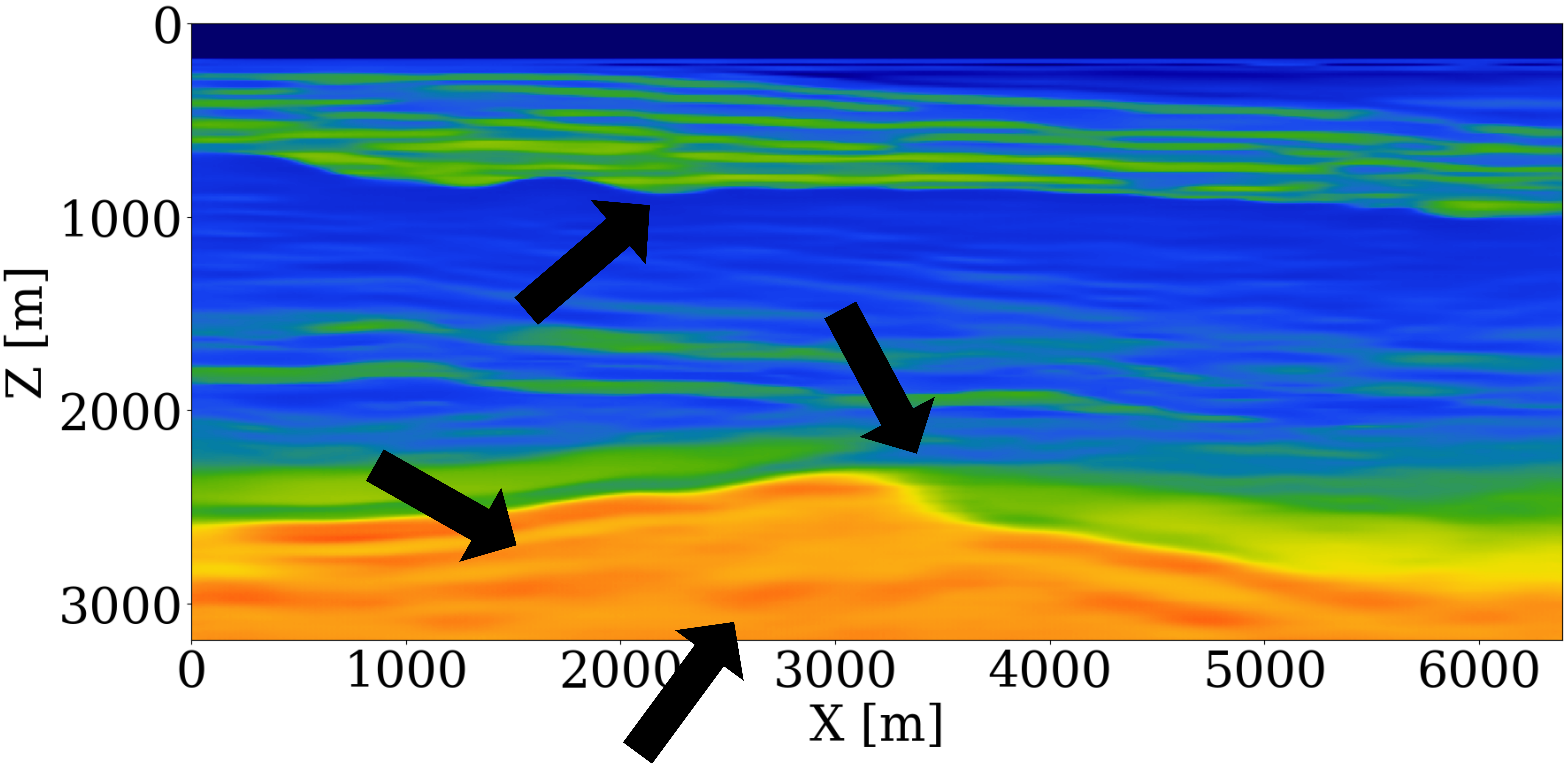
summary statistics = *extended* RTM w/ 50 offsets

layers are more consistent and connected



Conditional mean

summary statistics = RTM



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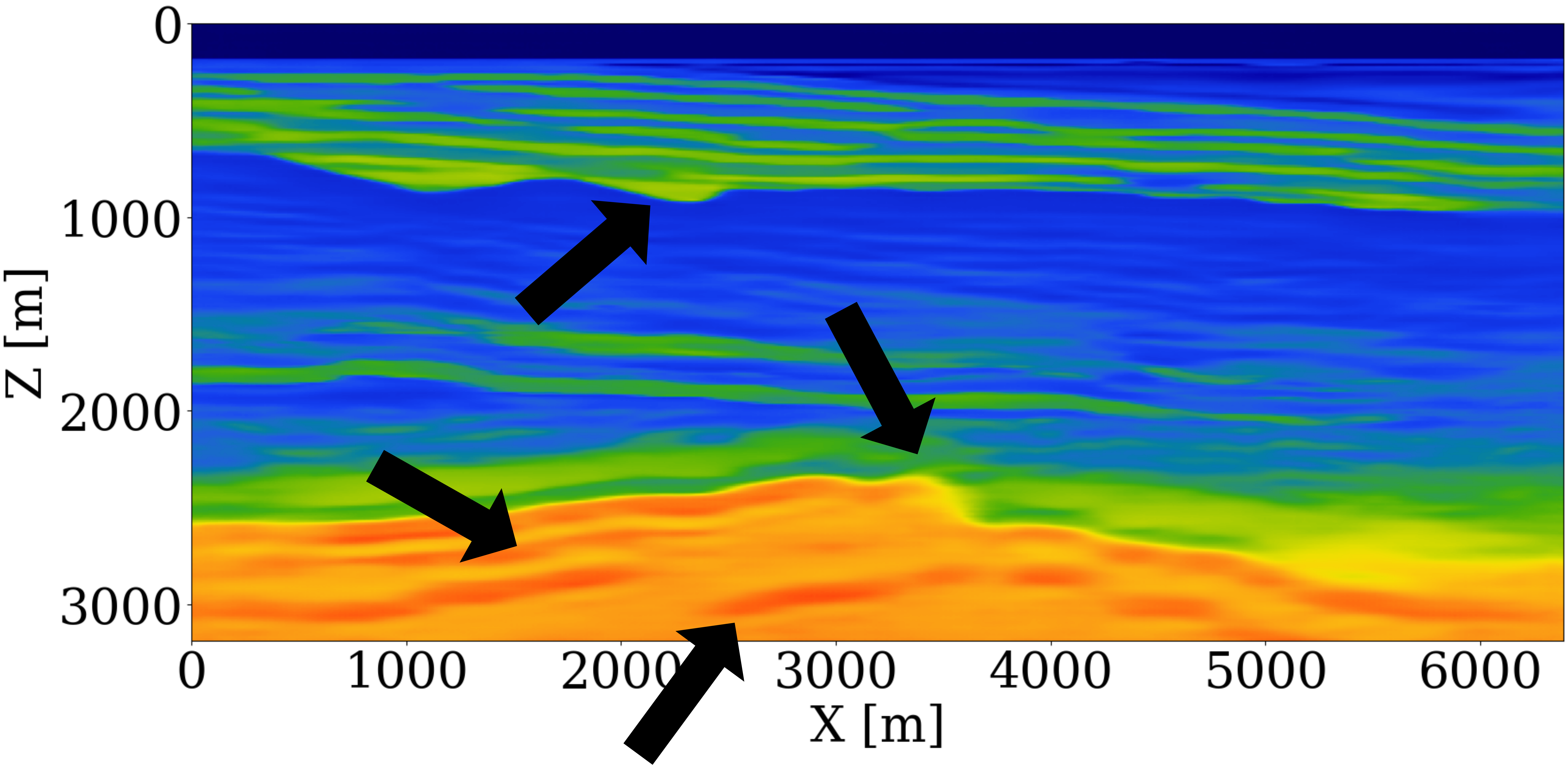
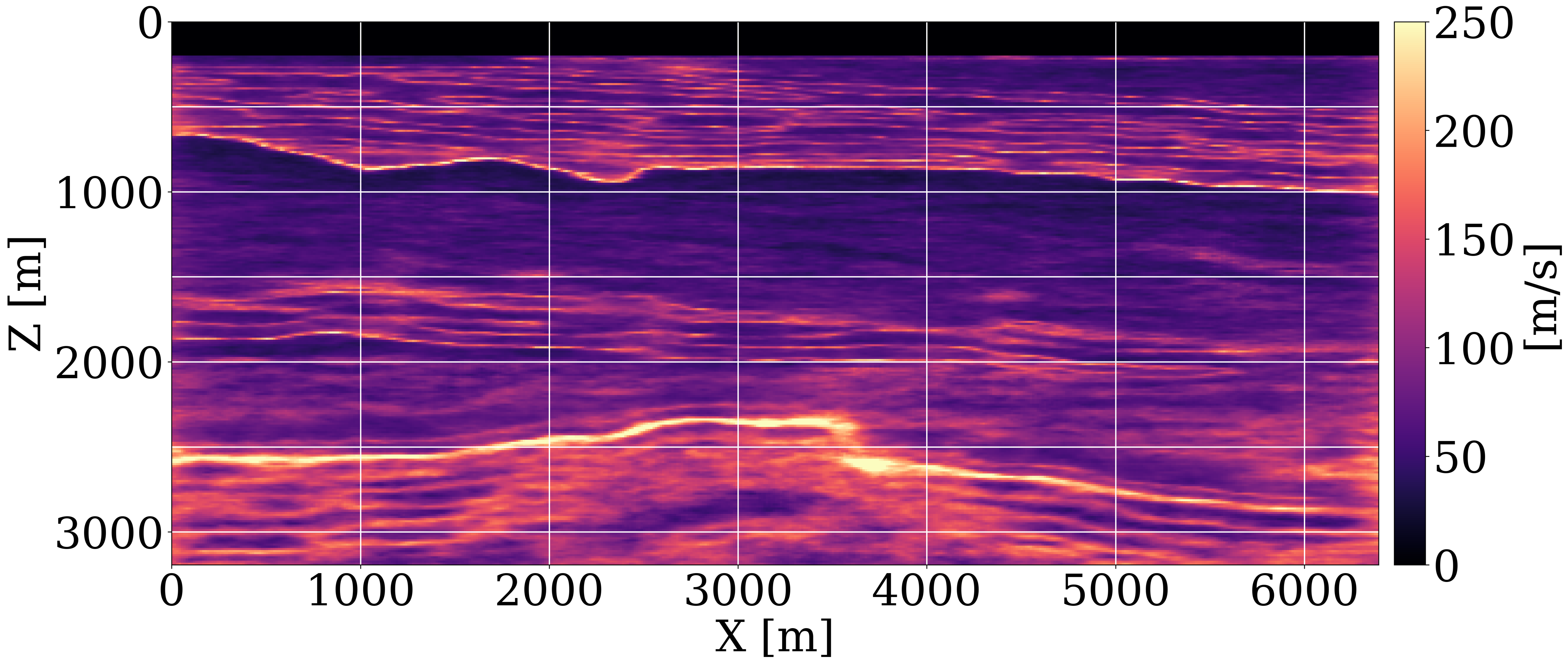
Conditional mean

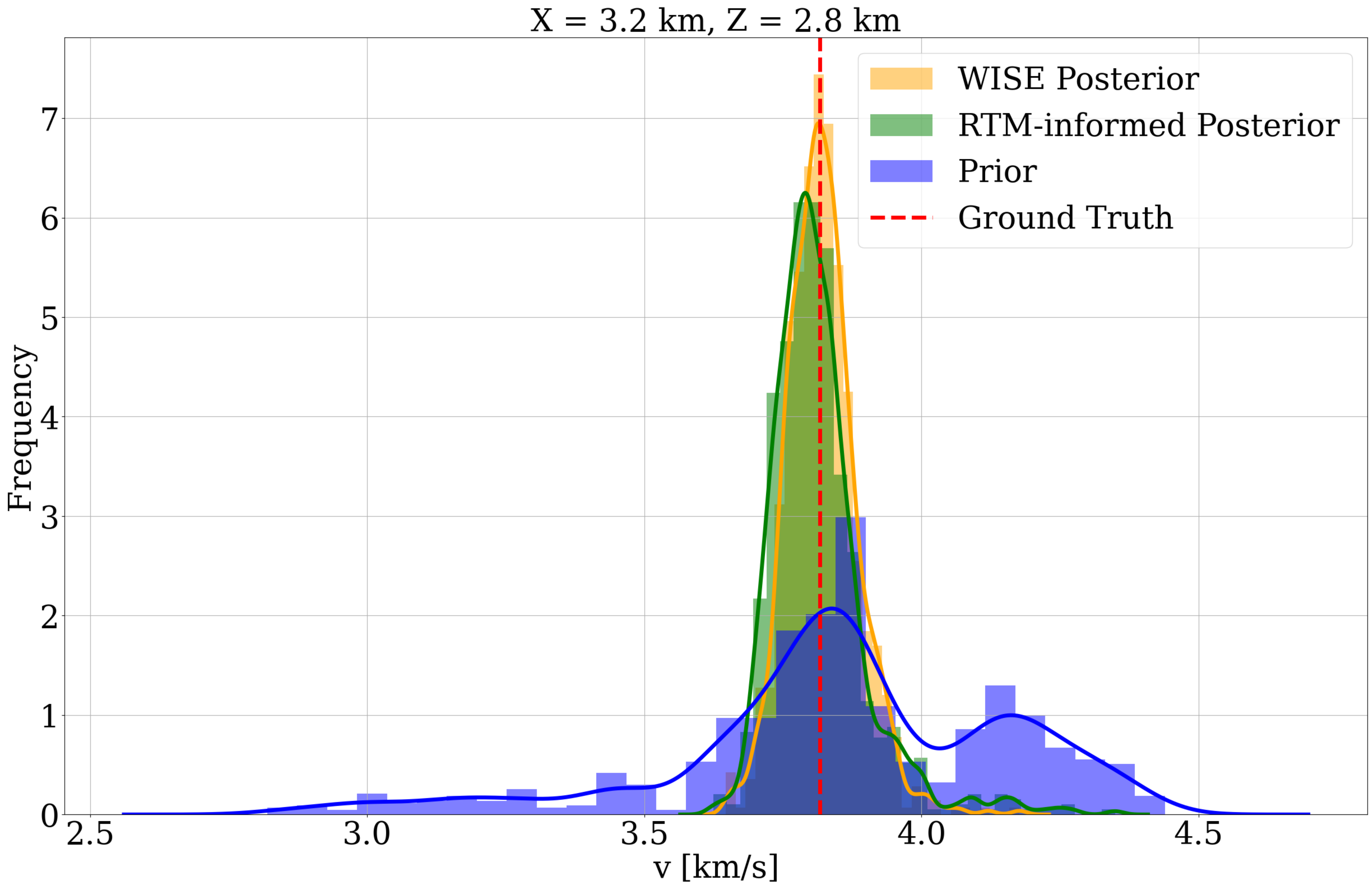
summary statistics = *extended* RTM w/ 50 offsets



Uncertainty Quantification
standard deviation



Histogram


X = 3.2 km, Z = 2.8 km
WISE Posterior
RTM-informed Posterior
Prior
Ground Truth
Frequency
0
1
2
3
4
5
6
7
2.5
3.0
3.5
4.0
4.5
v [km/s]

Forward UQ

RTMs from posterior samples migration-velocity models

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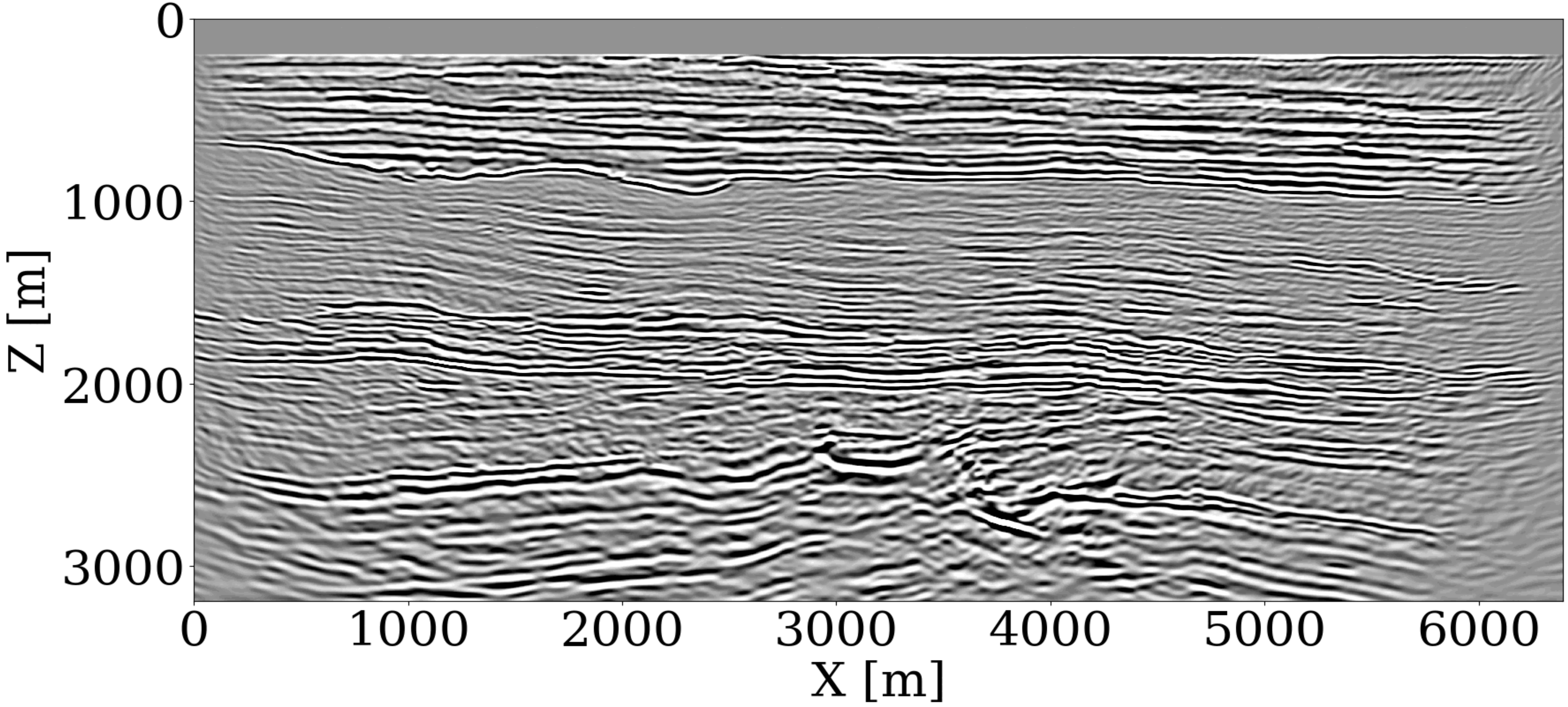


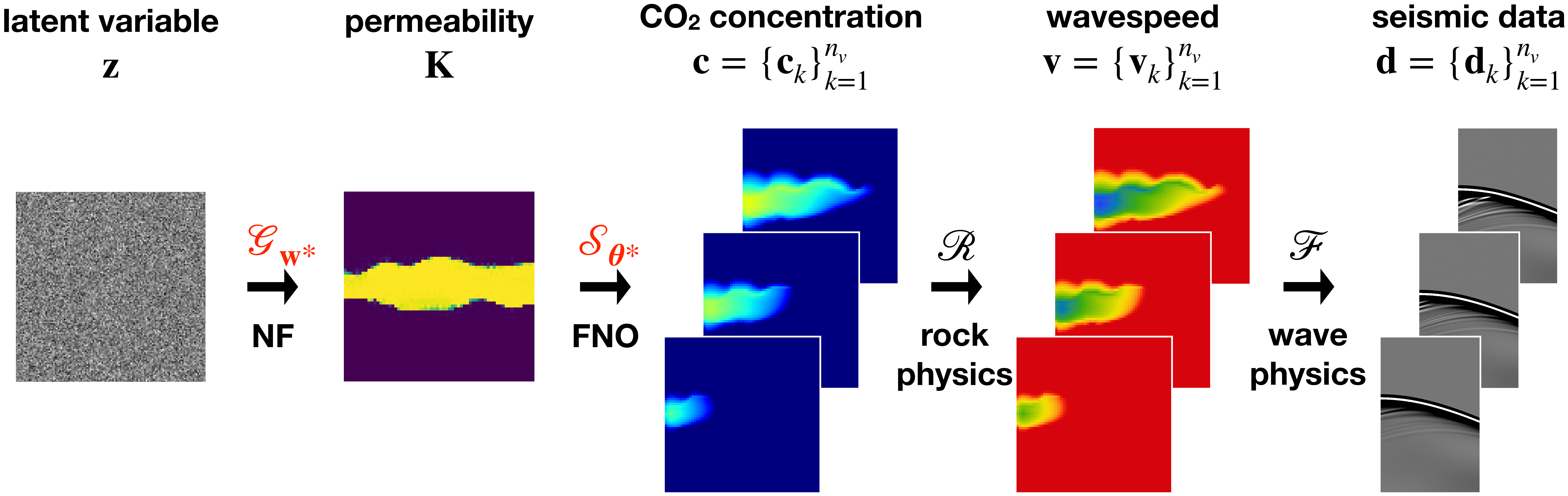
Learned flow imaging via *coupled* two-phase flow-seismic

Permeability inversion from time-lapse seismic data

Li, D., Xu, K., Harris, J. M., & Darve, E. (2020). Coupled time-lapse full-waveform inversion for subsurface flow problems using intrusive automatic differentiation. Water Resources Research, 56, e2019WR027032.
Mathias Louboutin, Ziyi Yin, Rafael Orozco, Thomas J. Grady II, Ali Siahkoohi, Gabrio Rizzuti, Philipp A. Witte, Olav Møyner, Gerard J. Gorman, and Felix J. Herrmann, "**Learned multiphysics inversion with differentiable programming and machine learning**", The Leading Edge, vol. 42, pp. 452-516, 2023.
Ziyi Yin, Rafael Orozco, Mathias Louboutin, and Felix J. Herrmann, "**Solving multiphysics-based inverse problems with learned surrogates and constraints**", Advanced Modeling and Simulation in Engineering Sciences, vol. 10, 2023.
Møyner, Olav, Martin Johnsrud, Halvor Møll Nilsen, Xavier Raynaud, Kjetil Olsen Lye, and Ziyi Yin. 2023. Sintefmath/Jutul.jl: V0.2.5 (version v0.2.5). Zenodo. https://doi.org/10.5281/zenodo.7775759.

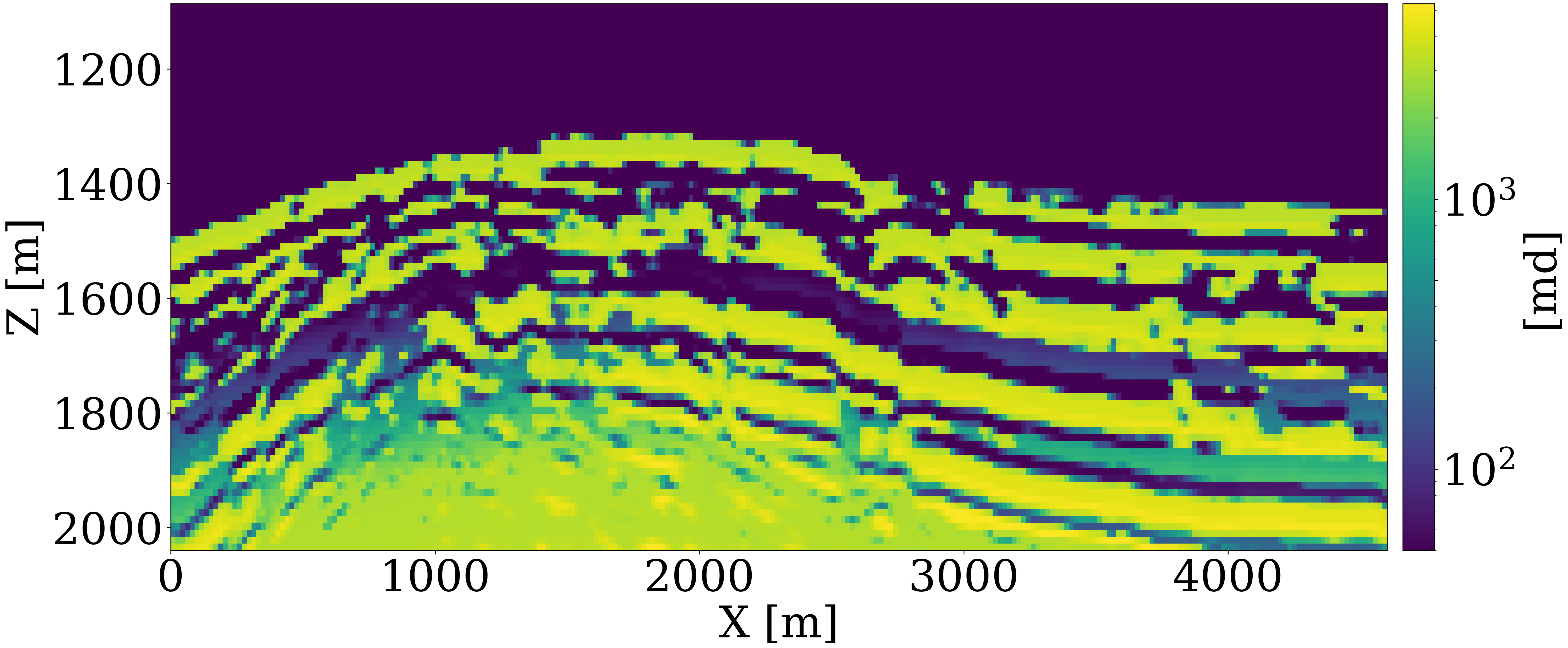
SLIM ML4Seismic

$$\underset{\mathbf{z}}{\text{minimize}} \quad \|\mathcal{F} \circ \mathcal{R} \circ \mathcal{S}_{\boldsymbol{\theta}^*} \circ \mathcal{G}_{\mathbf{w}^*}(\mathbf{z}) - \mathbf{d}\|_2^2$$

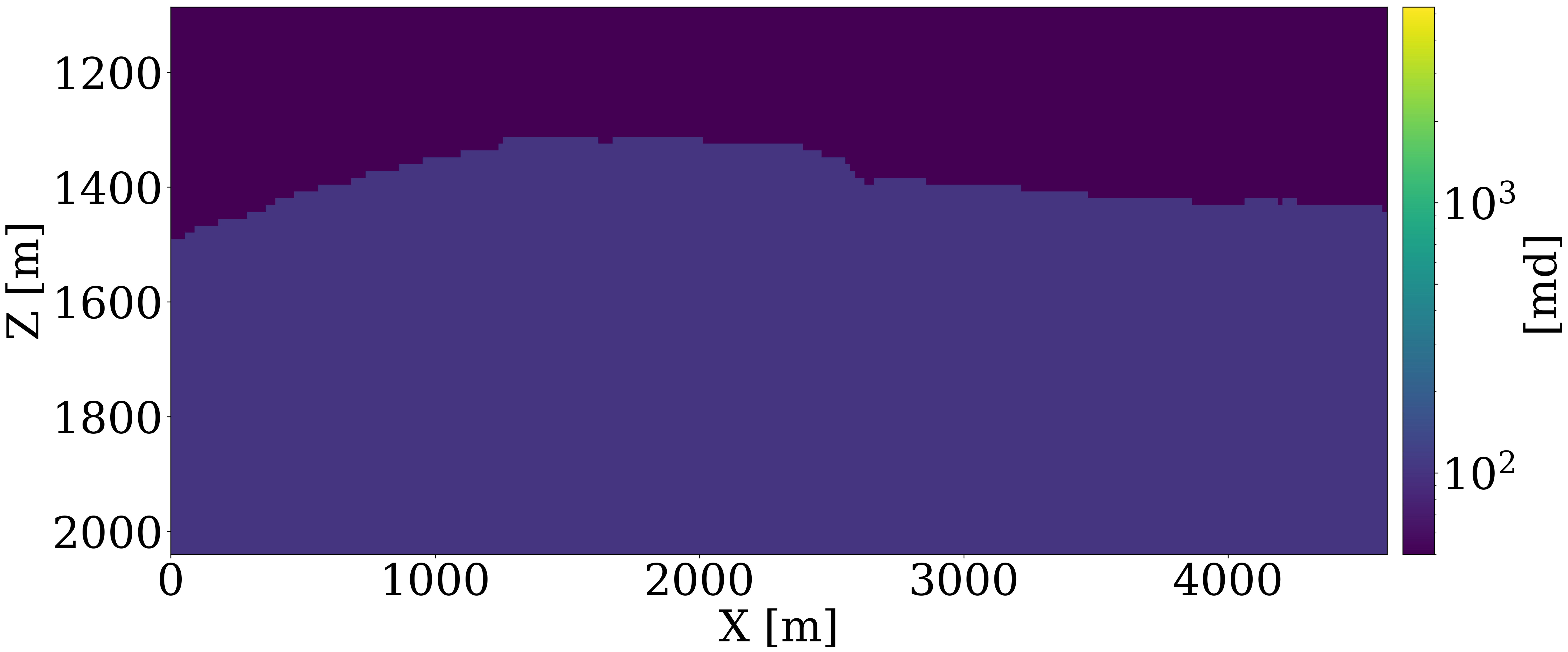


[InvertibleNetworks.jl] [FNO4CO2.jl] [Seis4CCS.jl] [JUDI.jl]

Unseen ground-truth permeability

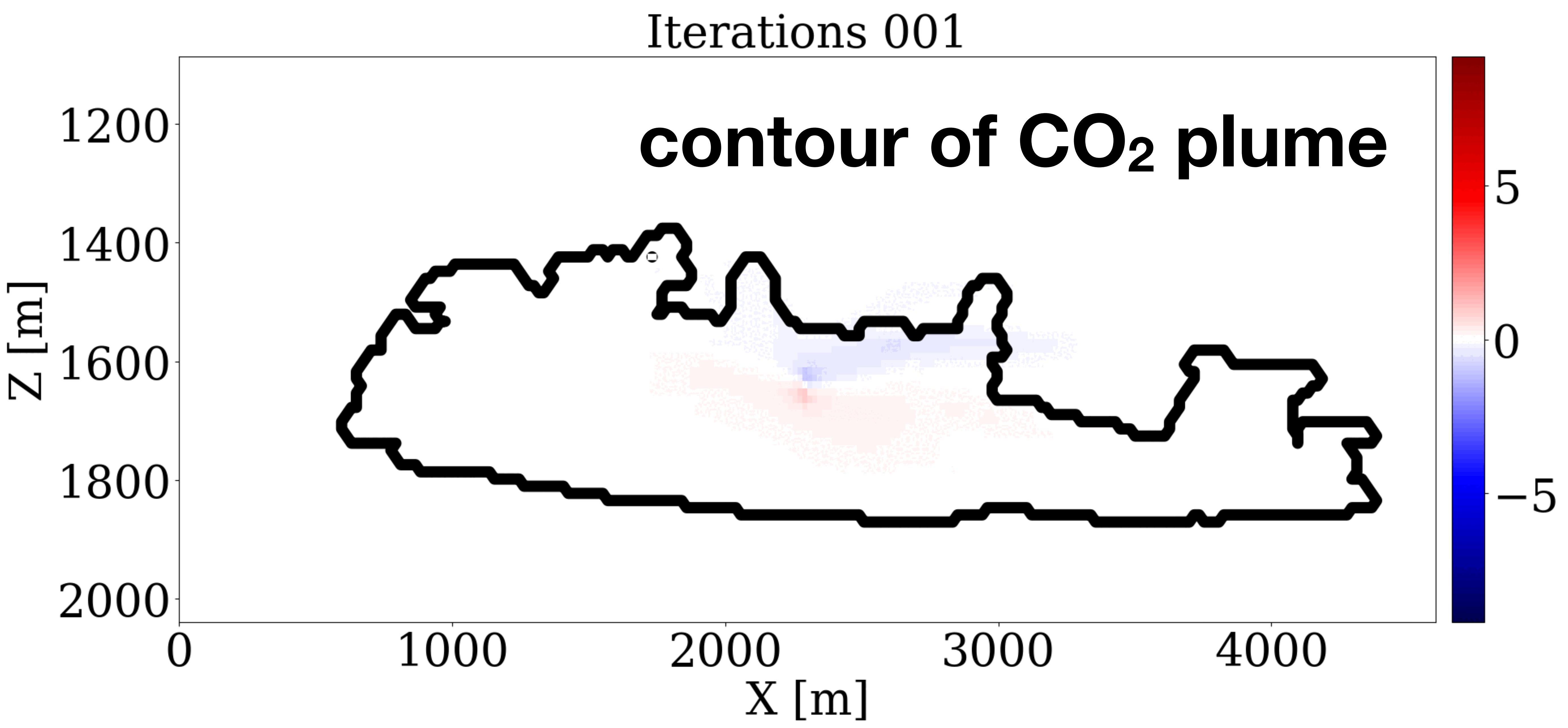


Initial permeability
case 1

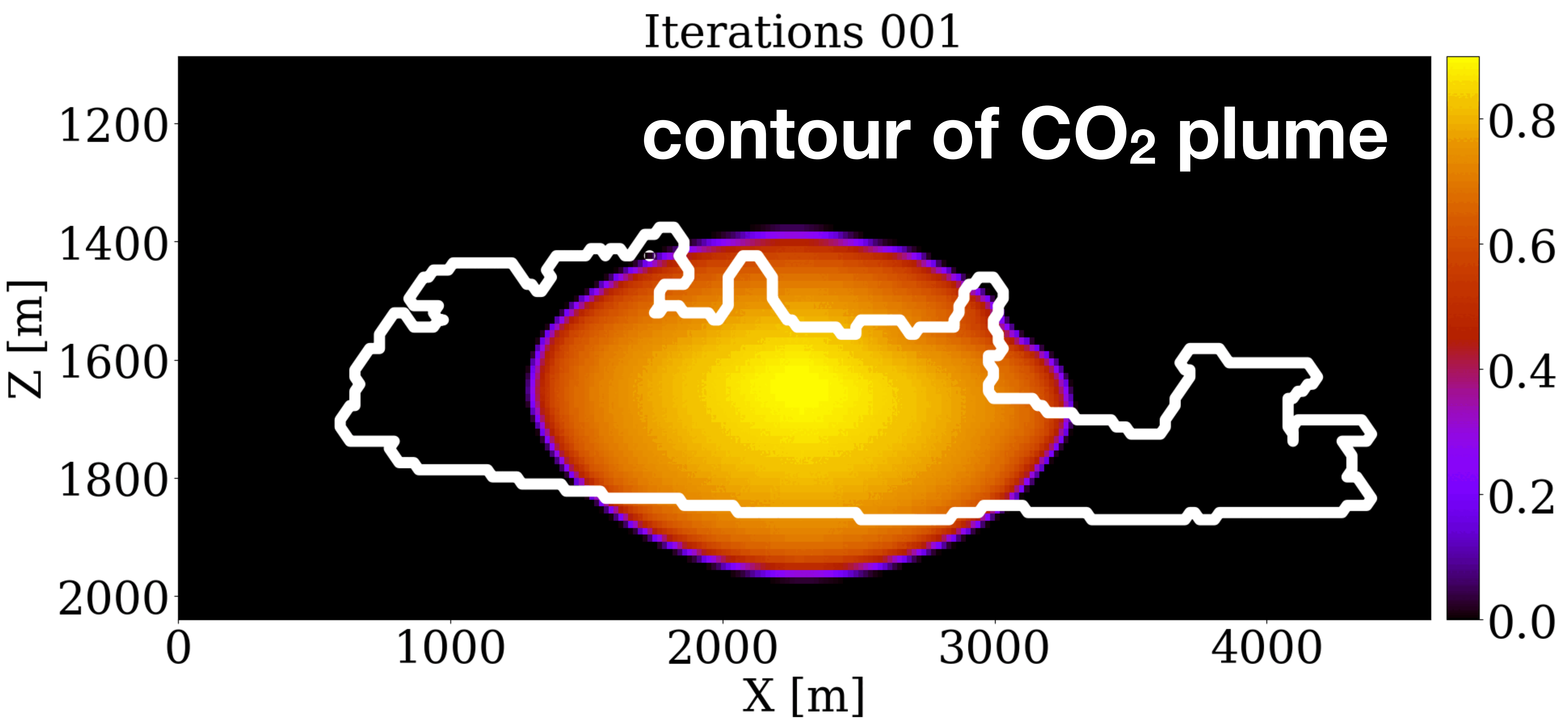


Inversion progress

permeability update



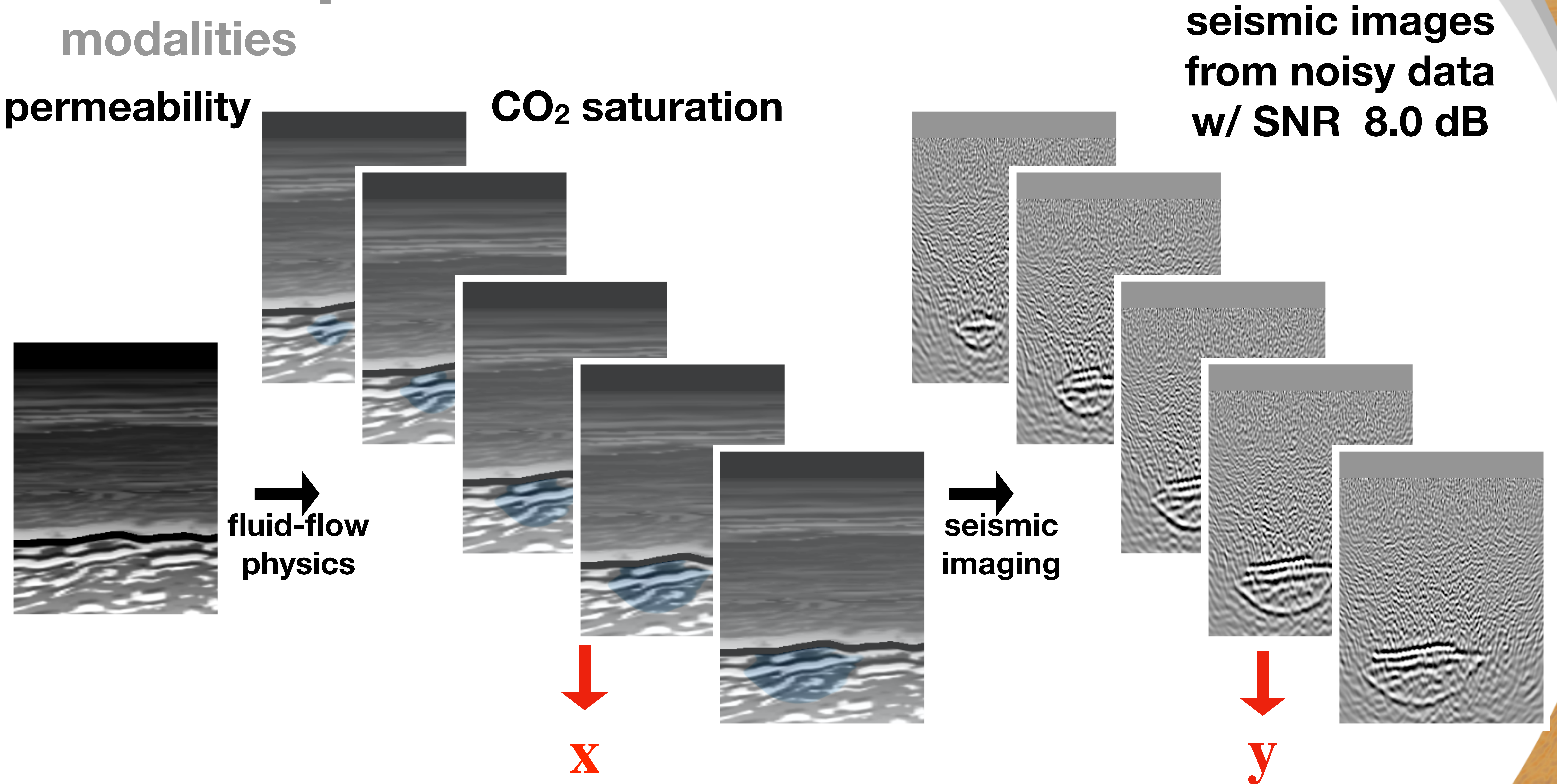
saturation update



Digital Twin w/ *generative* AI

Time-lapse data

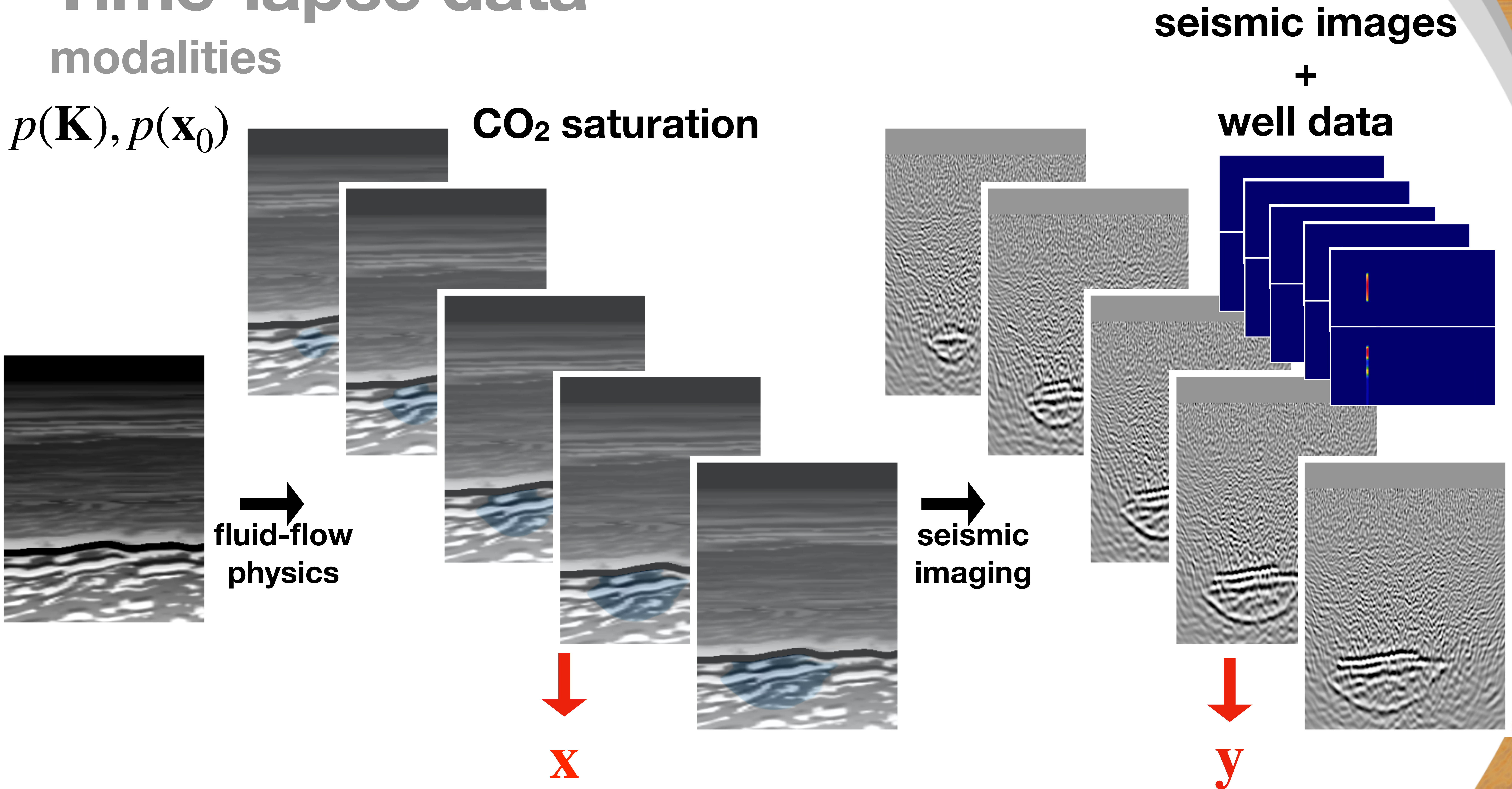
modalities



Møyner, Olav, Martin Johnsrud, Halvor Møll Nilsen, Xavier Raynaud, Kjetil Olsen Lye, and Ziyi Yin. 2023. *Sintefmath/Jutul.jl: V0.2.5* (version v0.2.5). Zenodo. https://doi.org/10.5281/zenodo.7775759.

Time-lapse data

modalities



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)

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

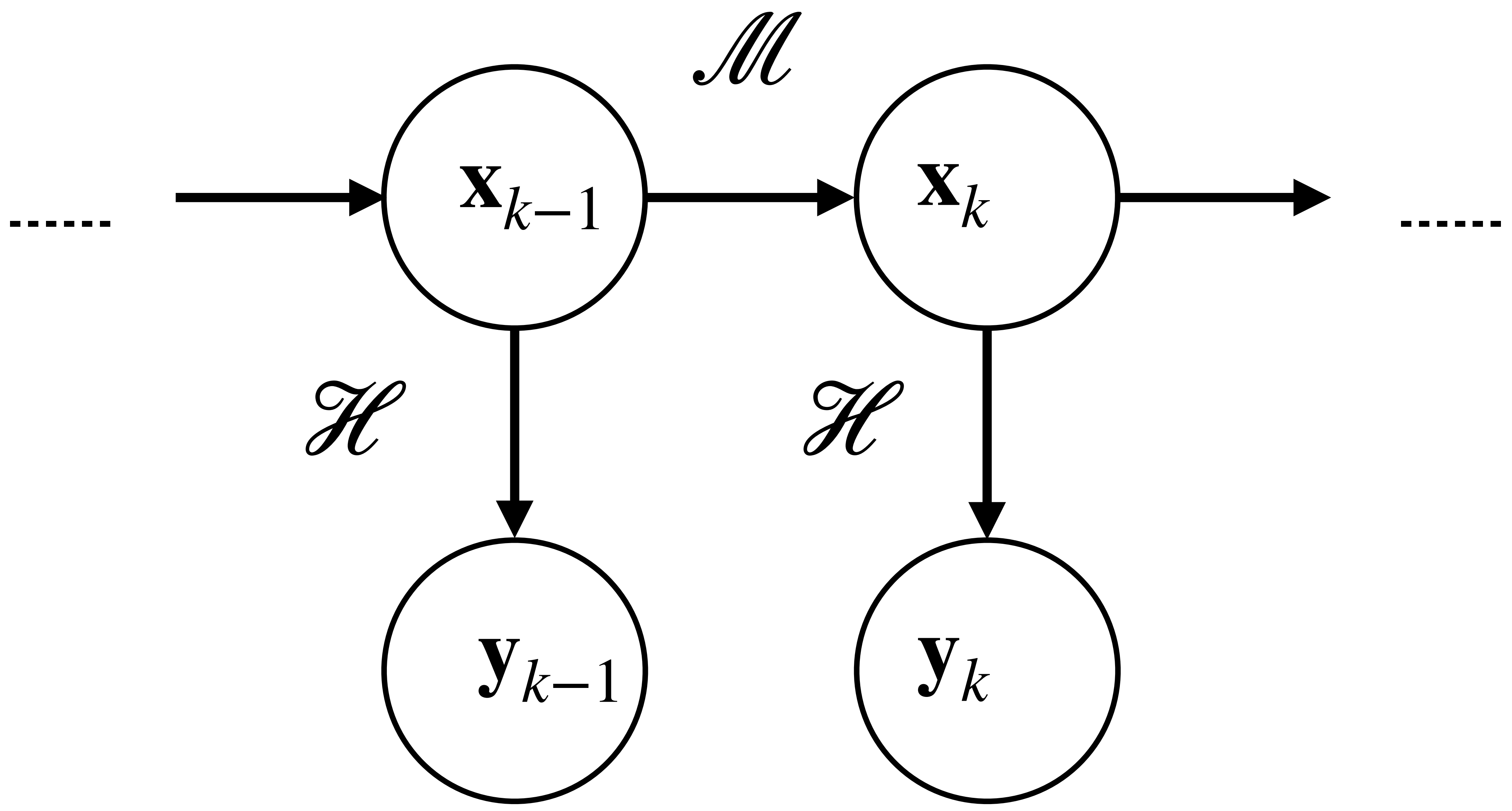
Given *simulated* training pairs $(\mathbf{x}, \mathbf{y})$

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

Dynamic simulation-based inference

Sequential Bayesian Inference

dynamical model for CO_2 plumes



At time index $k-1$

- $\mathbf{x}_{k-1}$ state (CO_2 saturation)
- $\mathbf{y}_{k-1}$ observed time-lapse data

$\mathscr{M}$ dynamics operator

$\mathscr{H}$ observation operator

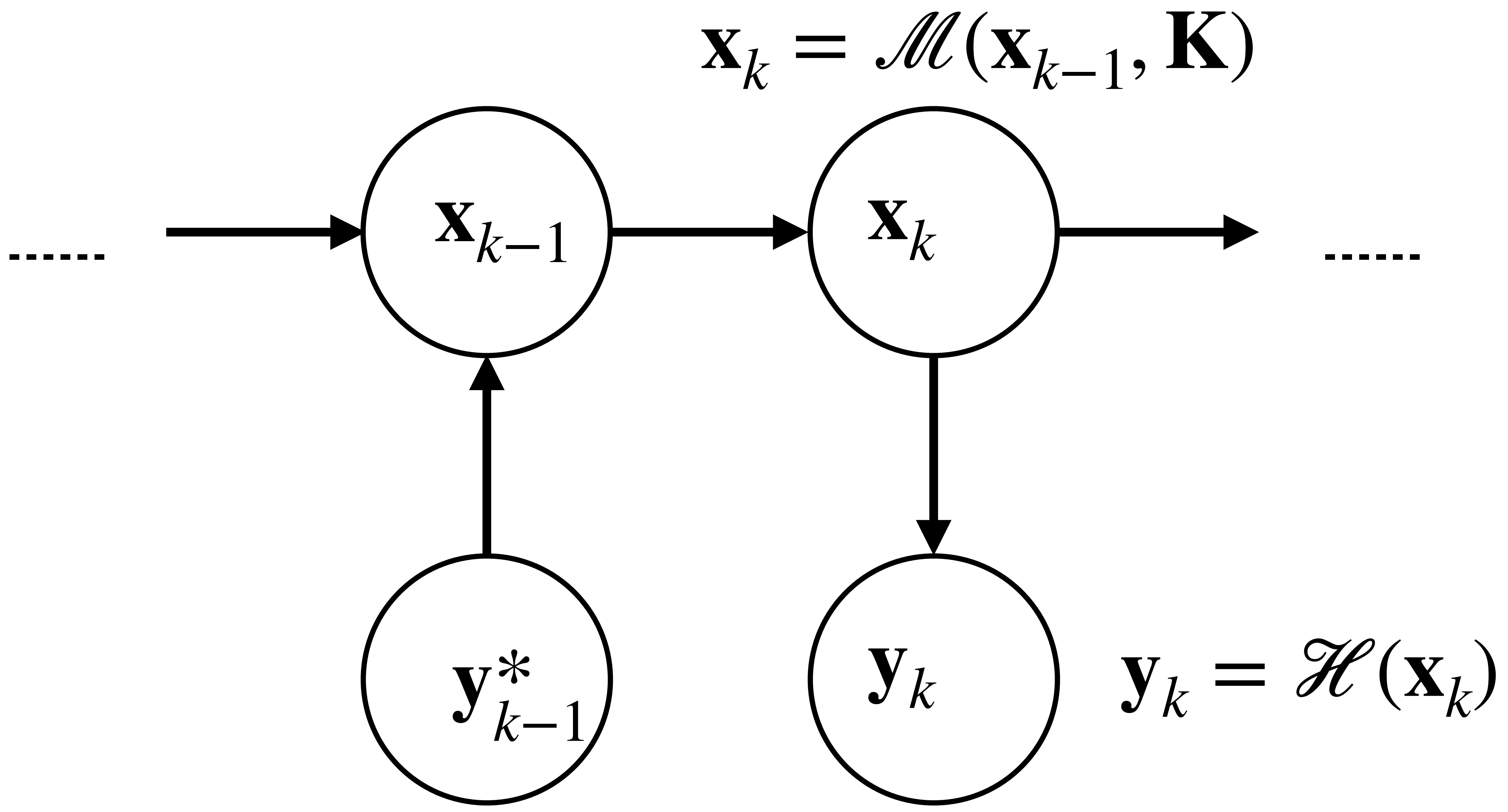
Approach: *sample* from *posterior* at *previous* time step, $k-1$, and use it as a *prior* for the *current* time step, k.

Tatsis, Konstantinos E., Vasilis K. Dertimanis, and Eleni N. Chatzi. "Sequential bayesian inference for uncertain nonlinear dynamic systems: A tutorial." arXiv preprint arXiv:2201.08180 (2022).

Kruse, Jakob, et al. "HINT: Hierarchical invertible neural transport for density estimation and Bayesian inference." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 35. No. 9. 2021

Learned Sequential Bayesian Inference

given $\mathbf{y}_{k-1}^{*}$ generate training samples $(\mathbf{x}_k, \mathbf{y}_k) \sim p(\mathbf{x}_k, \mathbf{y}_k)$



Create training ensemble by sampling

- prev. state $\mathbf{x}_{k-1} \sim p(\mathbf{x}_{k-1} \mid \mathbf{y}_{k-1}^{*})$
- permeability $\mathbf{K} \sim p(\mathbf{K})$

Applying dynamics $\mathbf{x}_k = \mathscr{M}(\mathbf{x}_{k-1}, \mathbf{K})$

Simulating data $\mathbf{y}_k = \mathscr{H}(\mathbf{x}_k)$

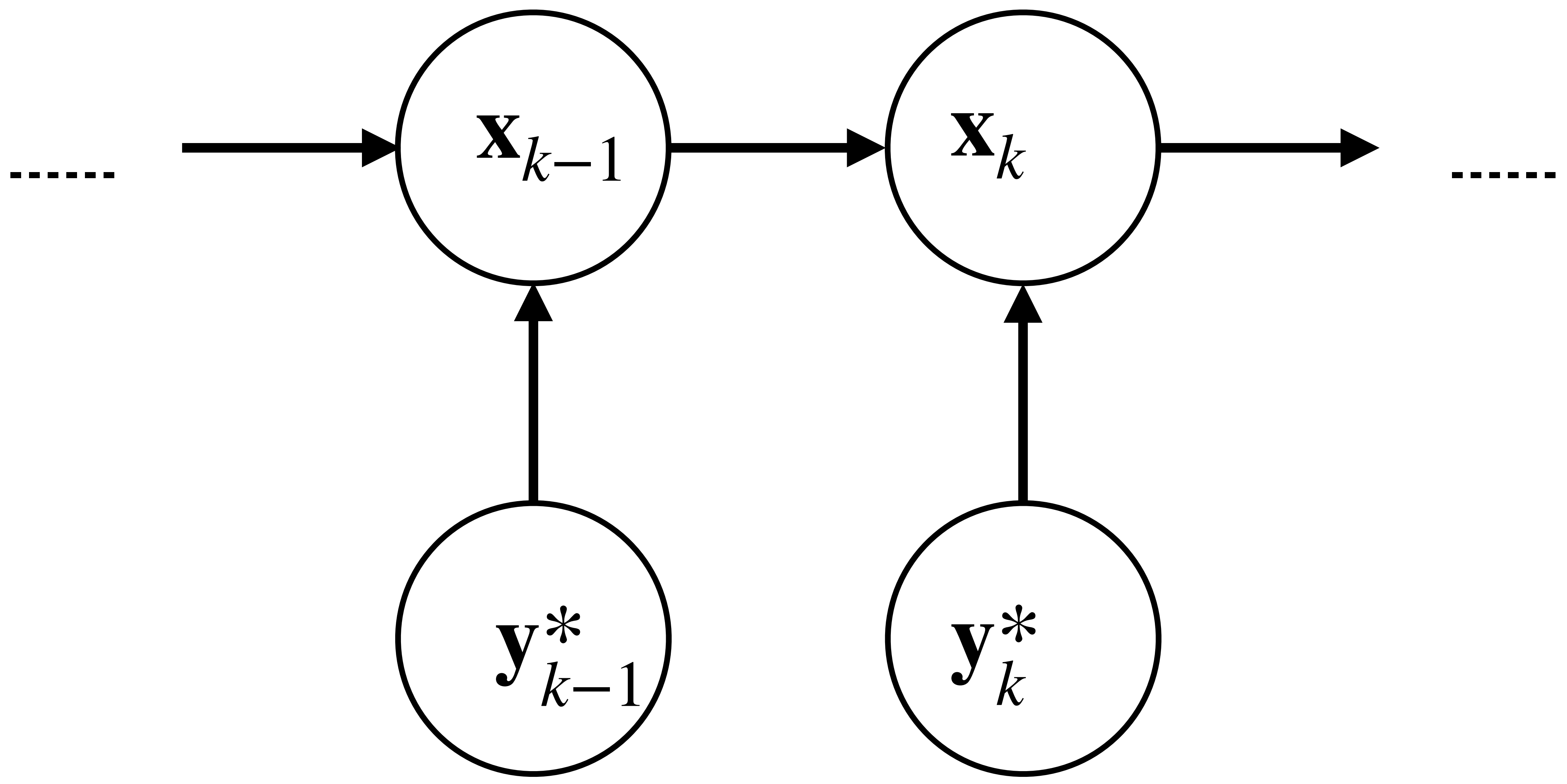
Train conditional NF on samples $(\mathbf{x}_k, \mathbf{y}_k) \sim p(\mathbf{x}_k, \mathbf{y}_k)$ via

$$\hat{\theta} = \underset{\theta}{\arg\min} \frac{1}{N} \sum_{n=1}^{N} \left(\|f_\theta(\mathbf{x}_k^{(n)}; \mathbf{y}_k^{(n)})\|_2^2 - \log \left| \det \mathbf{J}_{f_\theta} \right| \right)$$

Learned Sequential Bayesian Inference

sample from posterior $\mathbf{x}_k \sim p(\mathbf{x}_k \mid \mathbf{y}_k^*)$

$$\mathbf{x}_k \sim p(\mathbf{x}_k \mid \mathbf{y}_k^*)$$



Note: implicitly sampled from

$$p(\mathbf{x}_k \mid \mathbf{y}_k, \mathbf{y}_{1:k-1}) = \frac{p(\mathbf{y}_k \mid \mathbf{x}_k) p(\mathbf{x}_k \mid \mathbf{y}_{1:k-1})}{p(\mathbf{y}_k \mid \mathbf{y}_{1:k-1})}$$

$$p(\mathbf{x}_k \mid \mathbf{y}_{1:k-1}) = \mathbb{E}_{\mathbf{x}_{k-1} \sim p\left(\mathbf{x}_{k-1} \mid \mathbf{y}_{1:k-1}\right)} \left[p\left(\mathbf{x}_k \mid \mathbf{x}_{k-1}\right) \right]$$

Marginalizes over

- previous state $\mathbf{x}_{k-1}$
- permeability $\mathbf{K}$

Sample from posterior $\mathbf{x}_k \sim p(\mathbf{x}_k \mid \mathbf{y}_k^*)$ via $\mathbf{x}_k = f_{\hat{\theta}}^{-1}(\mathbf{z}; \mathbf{y}_k{}^*)$ with $\mathbf{z} \sim N(0, I)$.

Example – inference w/ time-lapse seismic images & pressure data

CNF training block k=1

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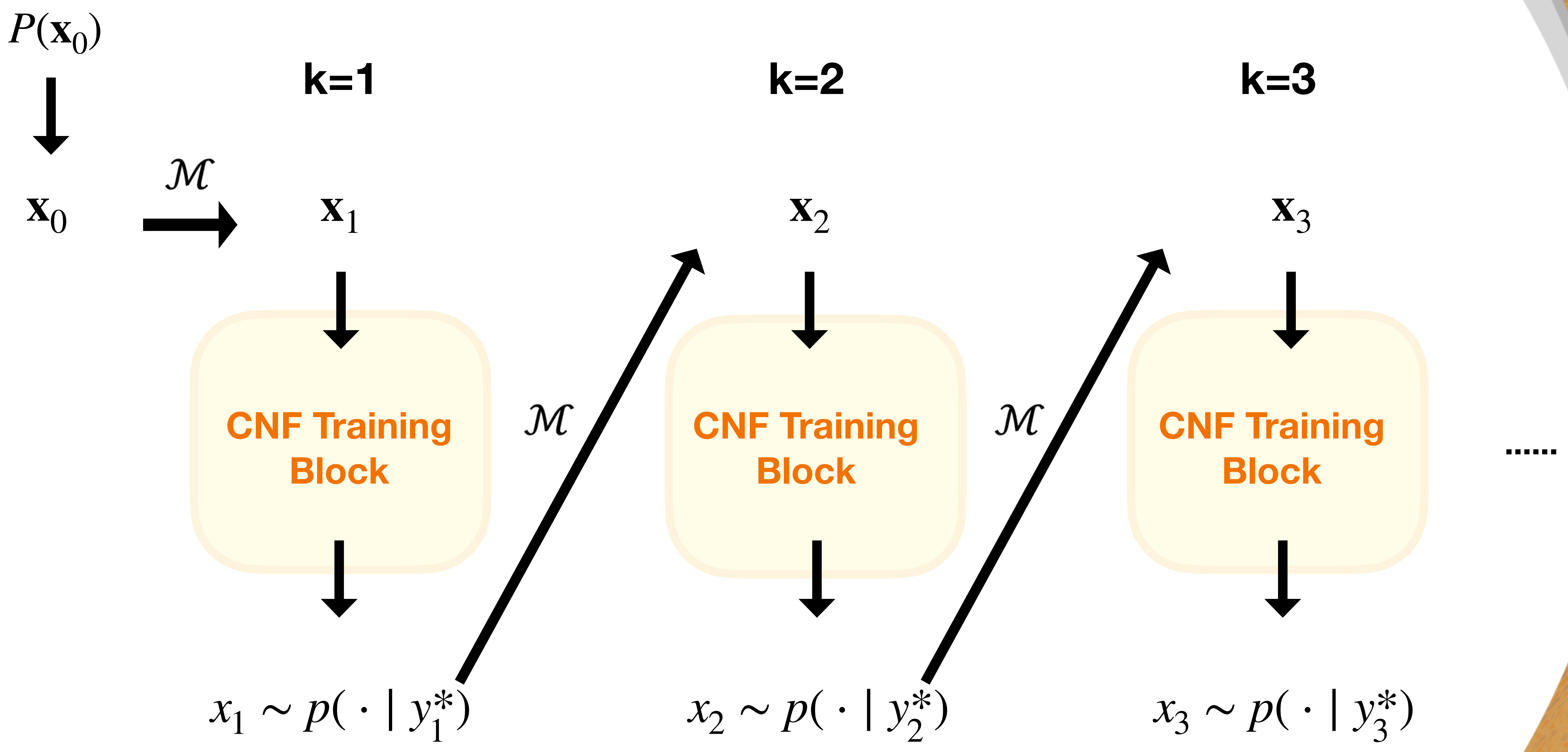
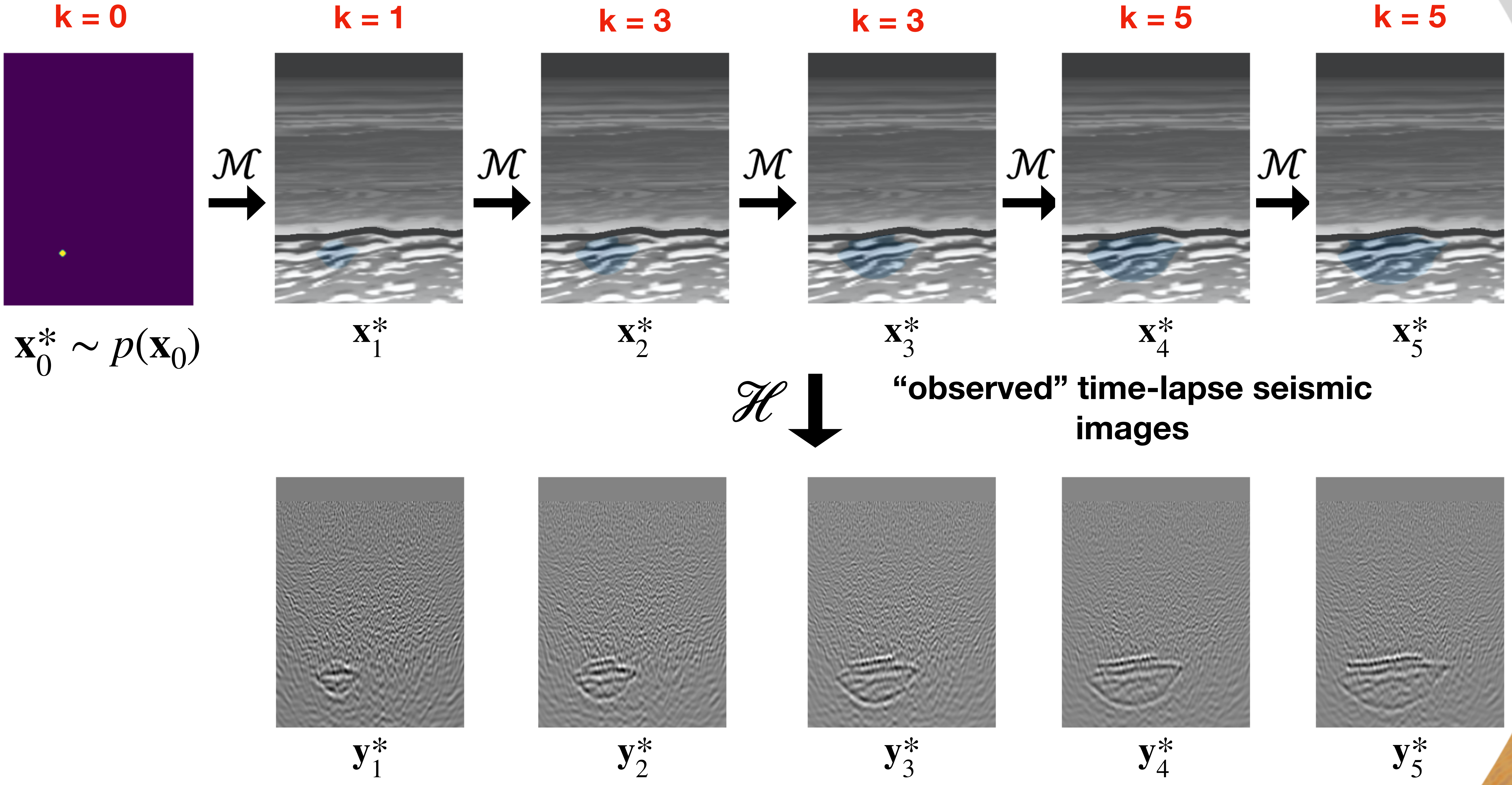
Kruse, Jakob, et al. "HINT: Hierarchical invertible neural transport for density estimation and Bayesian inference." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 35. No. 9. 2021.

Conditioned – sequential Bayesian



Generating ground-truth data

for single fixed $\mathbf{K}^* \sim p(\mathbf{K}), \mathbf{x}_0^* \sim p(\mathbf{x}_0)$



Conditioned on wells & seismic data

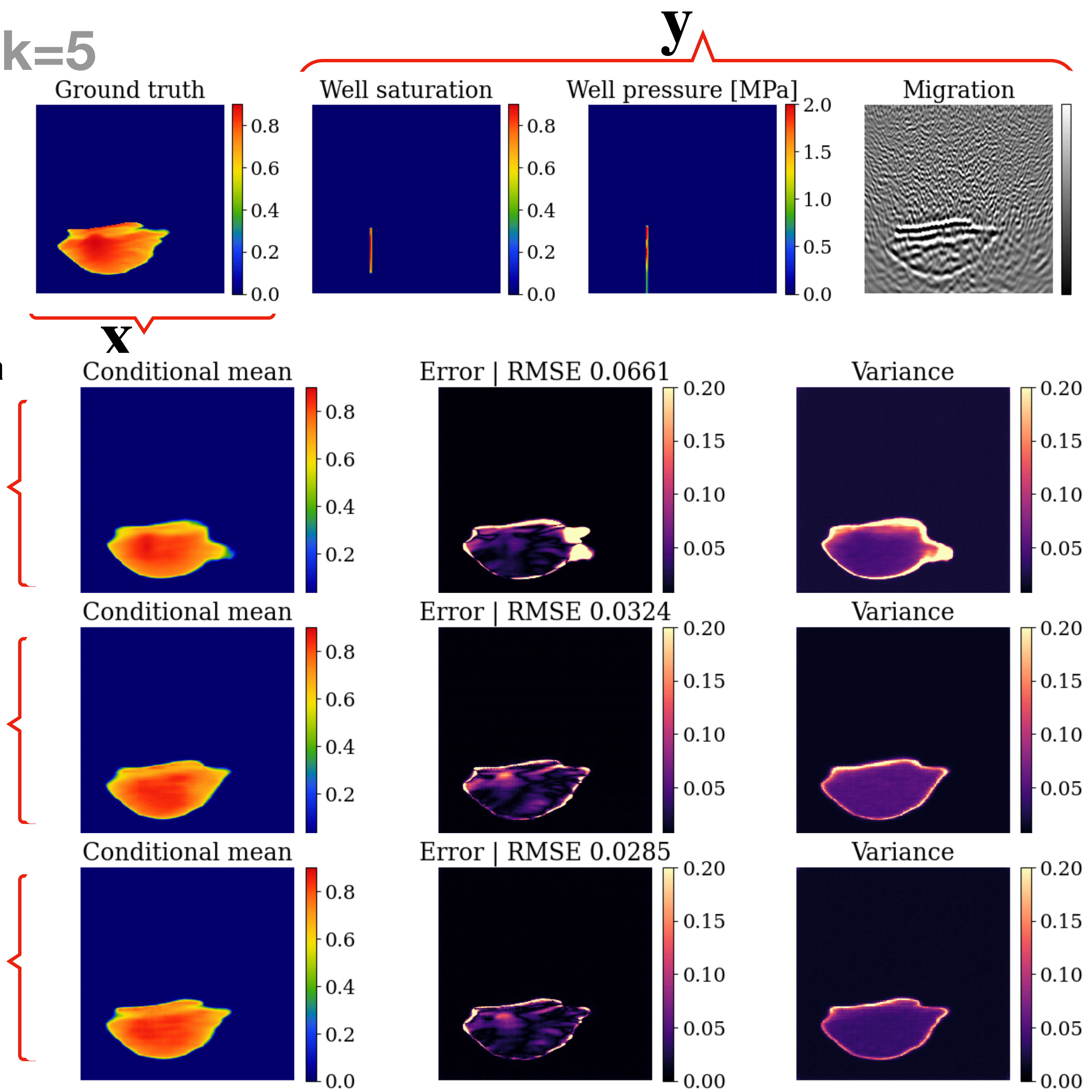
predict CO_2 plume k=5

Time-lapse data

Wells

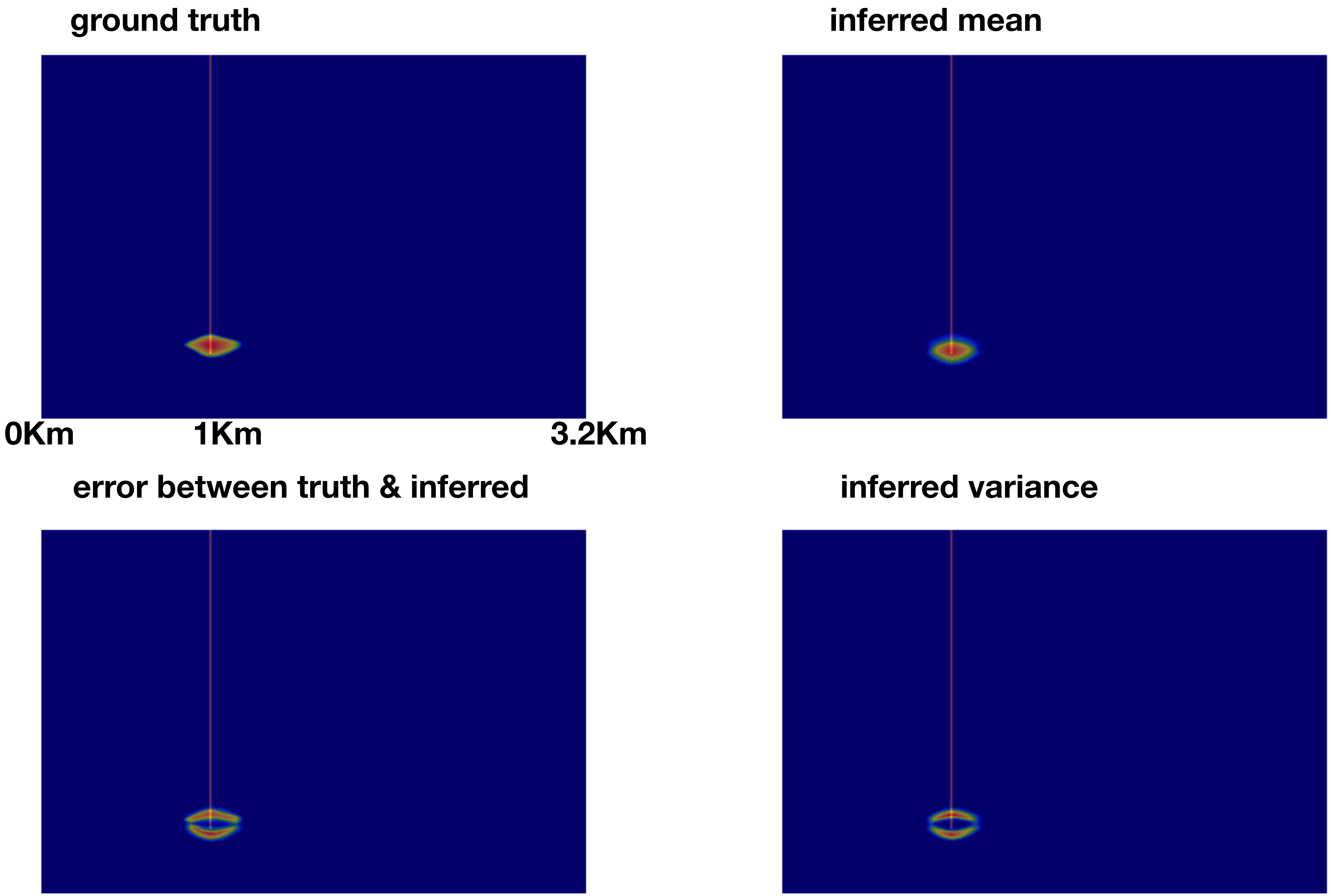
RTM

Wells & RTM



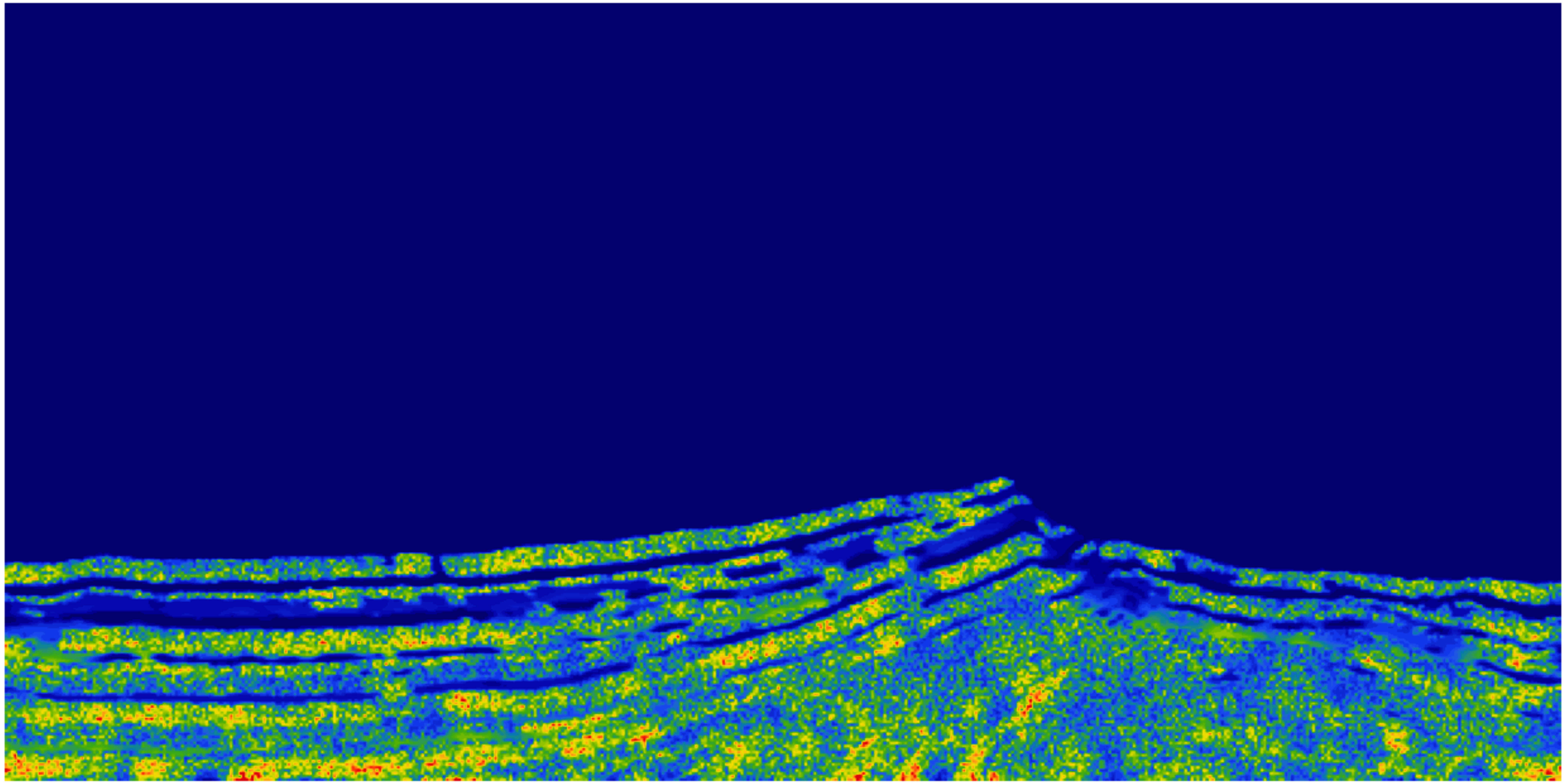
Digital Twin

inferred CO_2 saturations conditioned on time-lapse well & seismic data



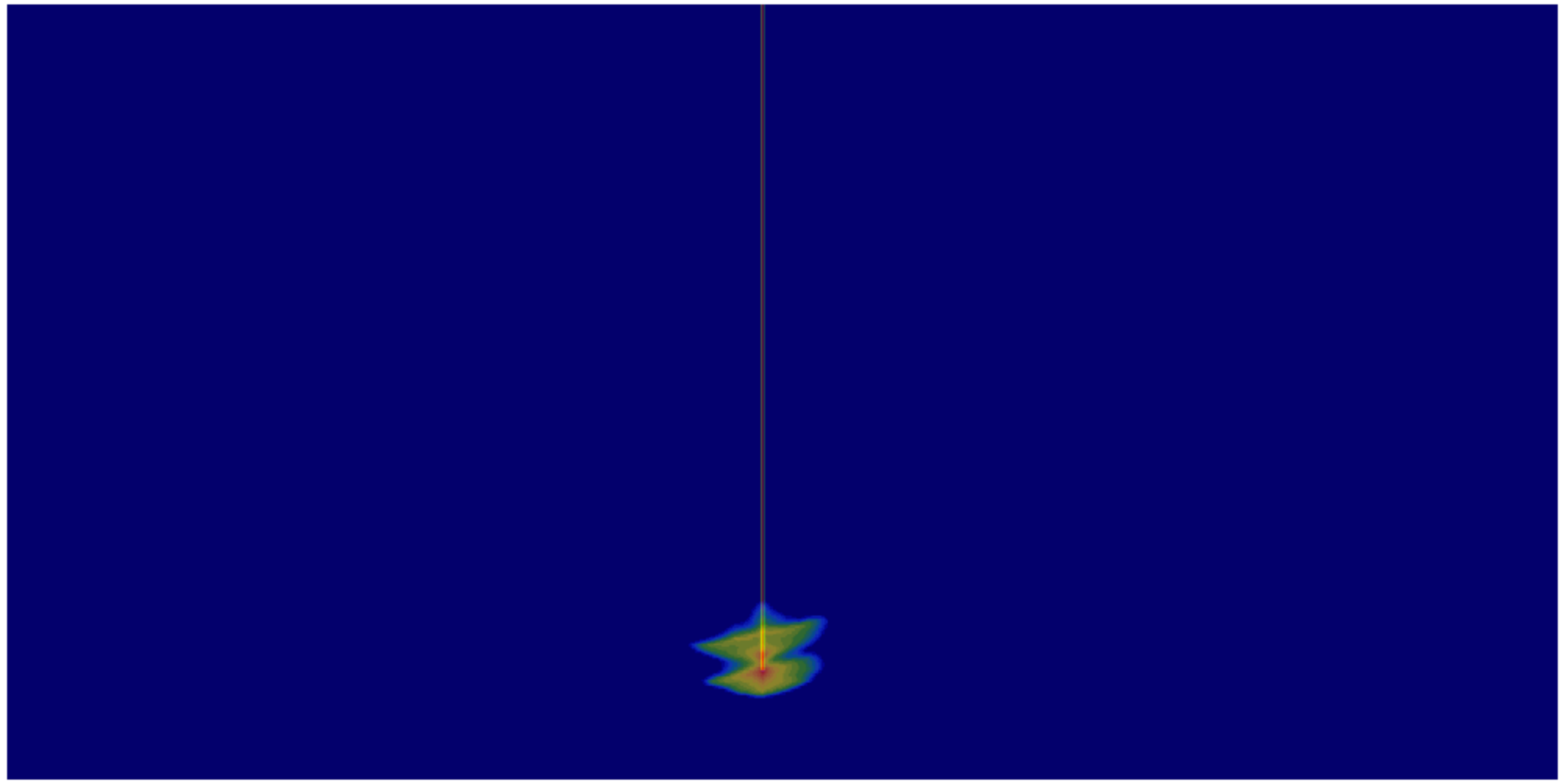
More realistic example

Samples
permeability distribution

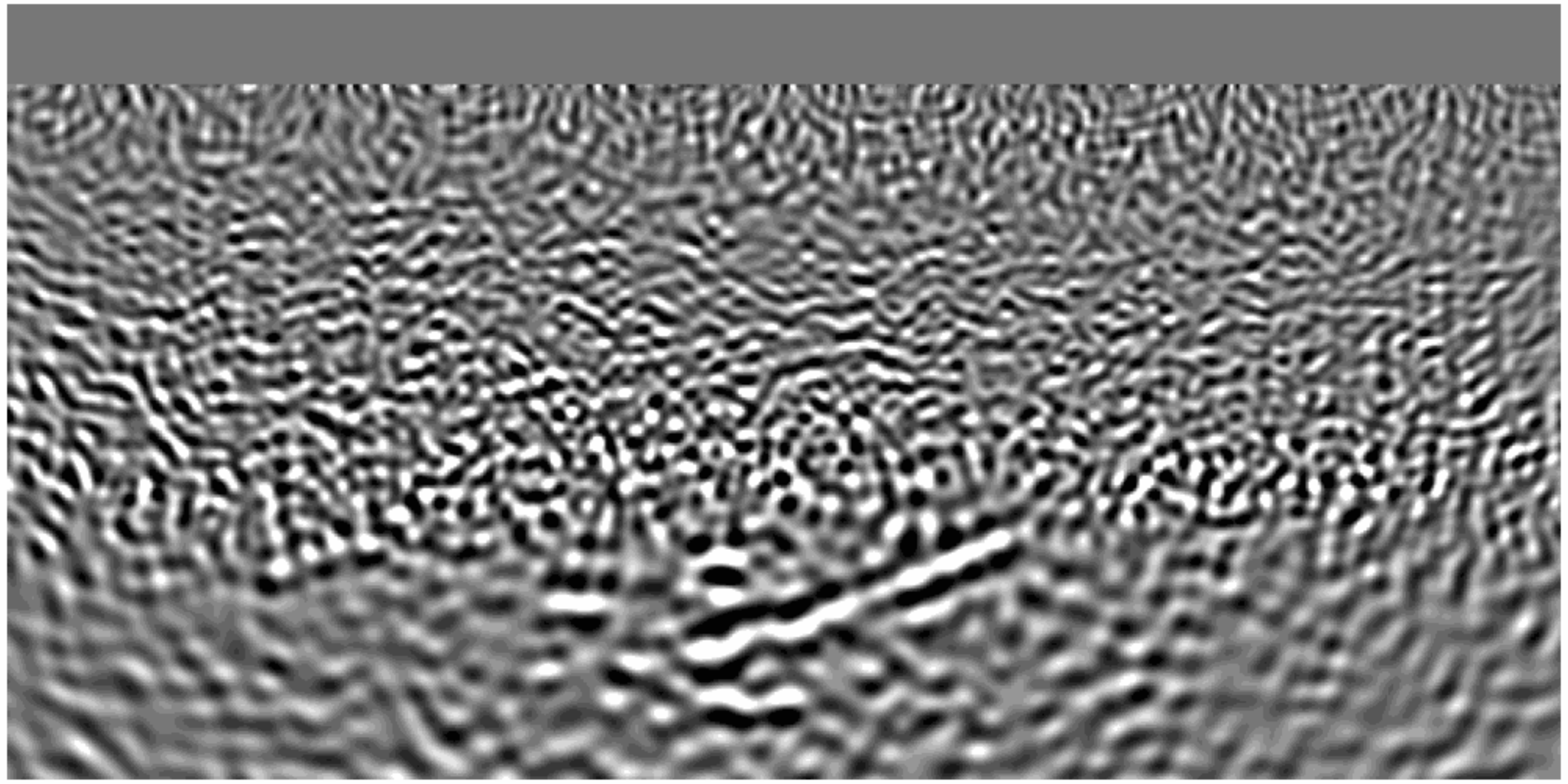


Ground-truth & observations
plumes & imaged seismic

ground-truth CO_2 plume

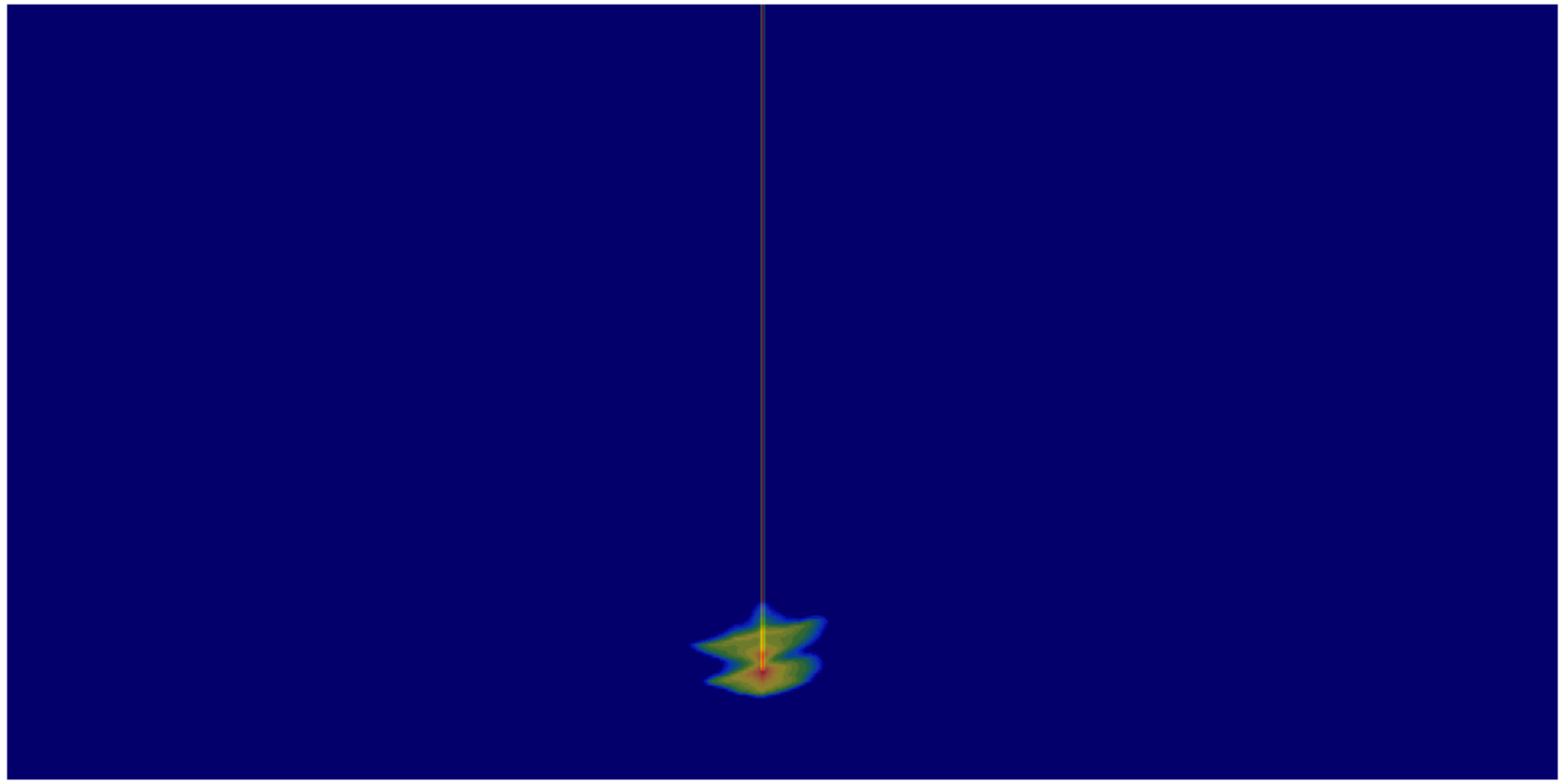


observed seismic



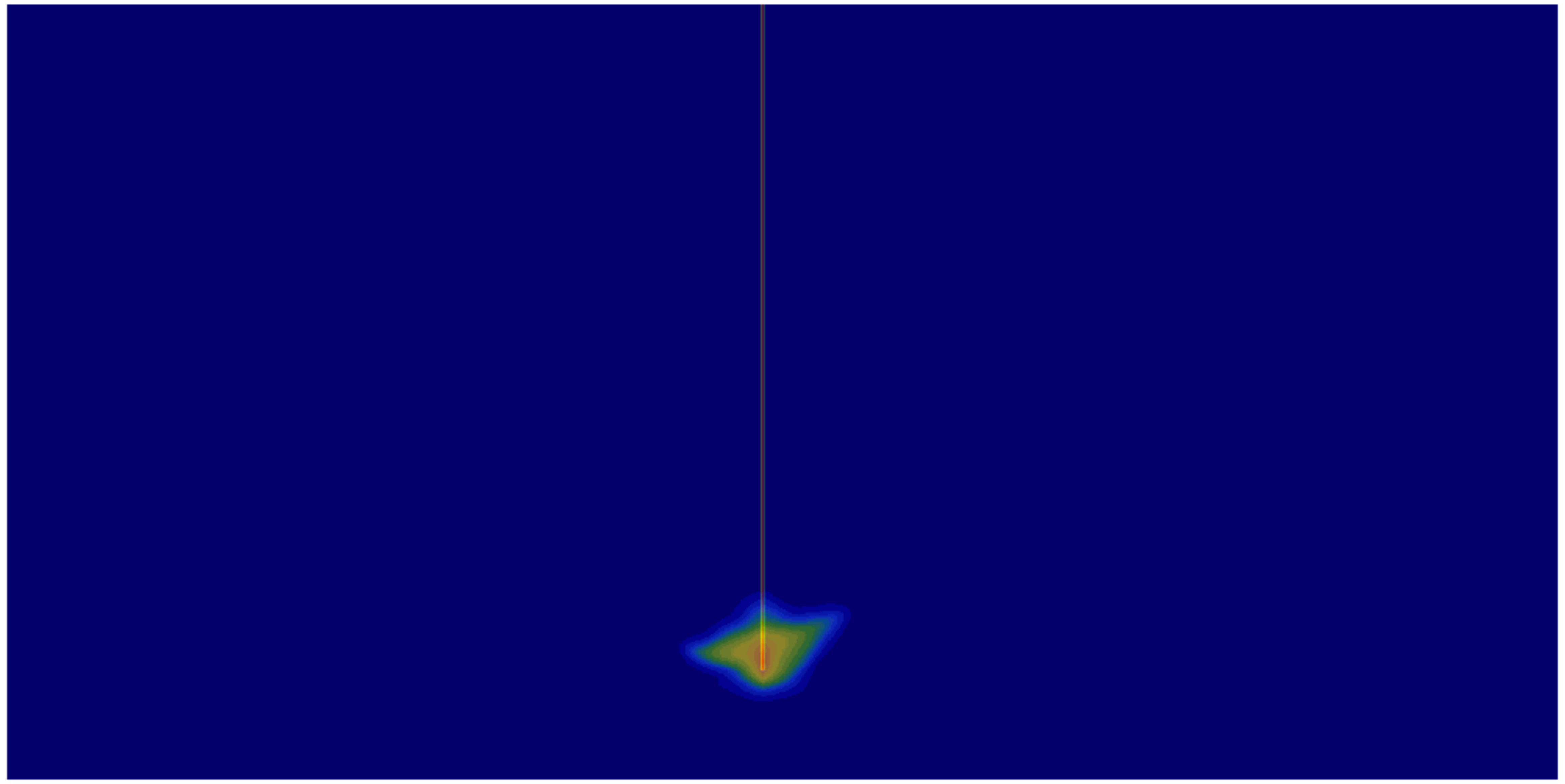
Assimilated plumes
ground-truth vs. inferred CO_2 plumes

ground-truth CO_2 plumes



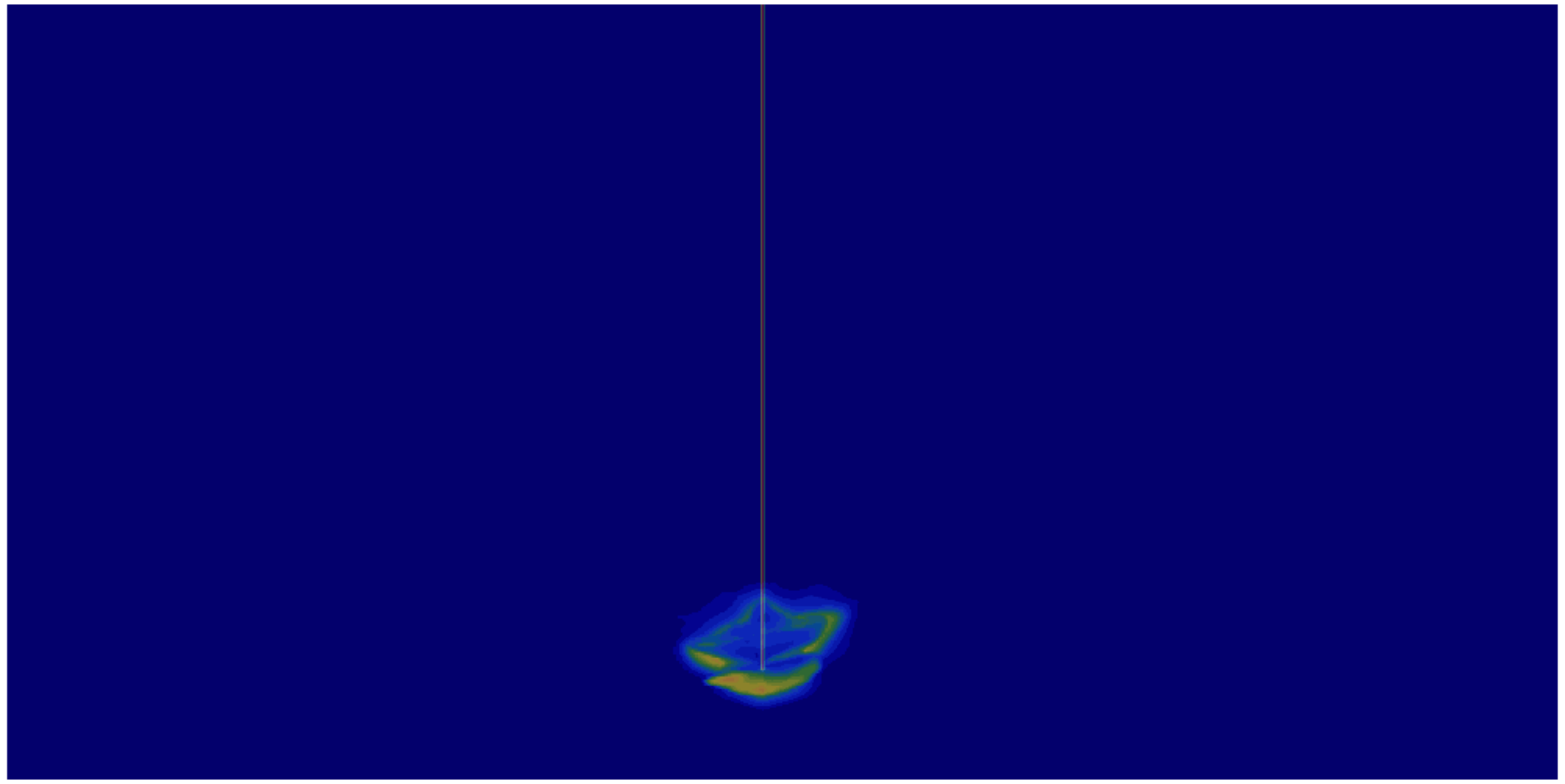
0Km 1.5Km 3.2Km

inferred w/ seismic CO_2 plumes

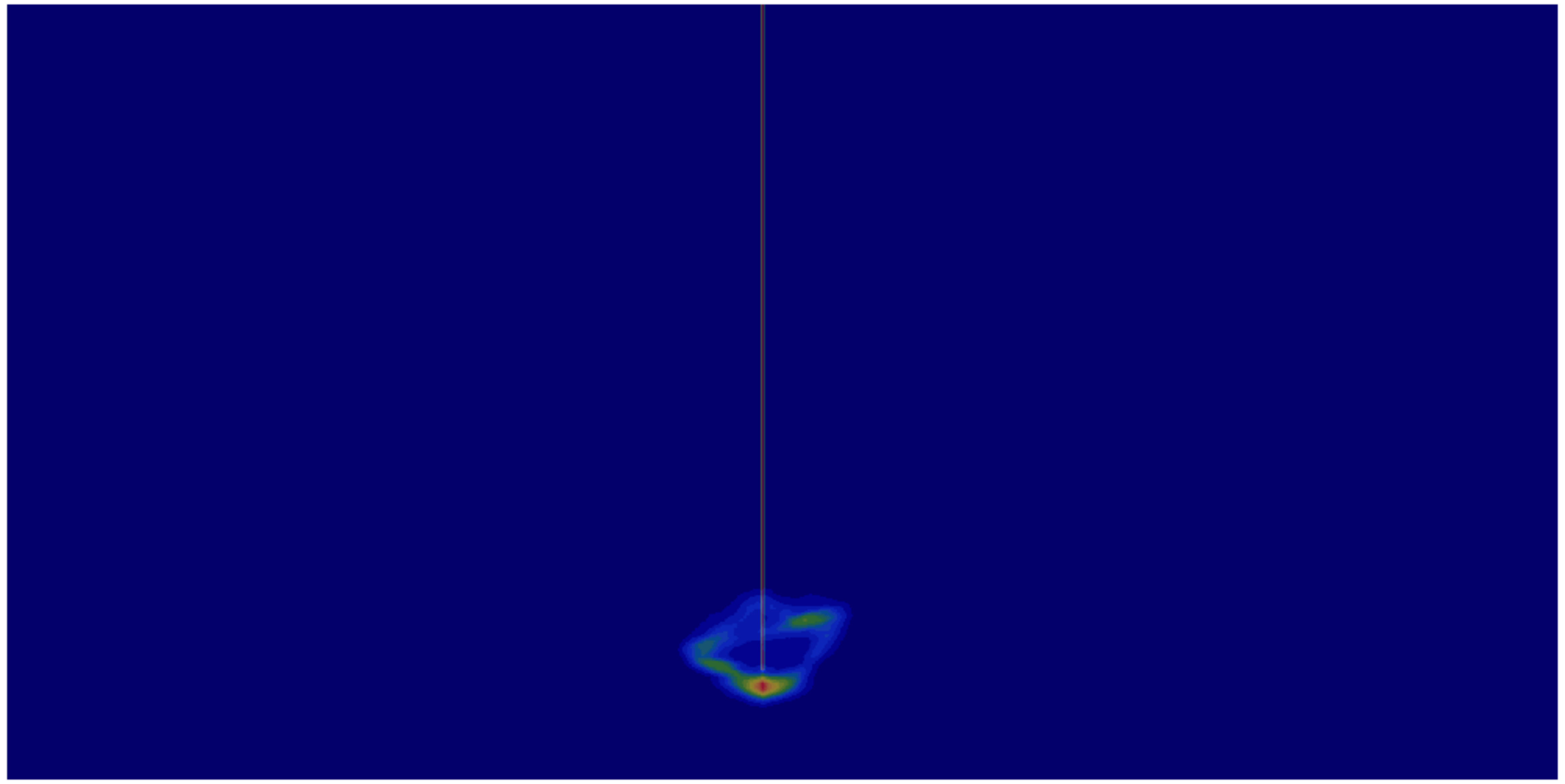


UQ
errors & inferred standard deviation

errors w.r.t. ground-truth

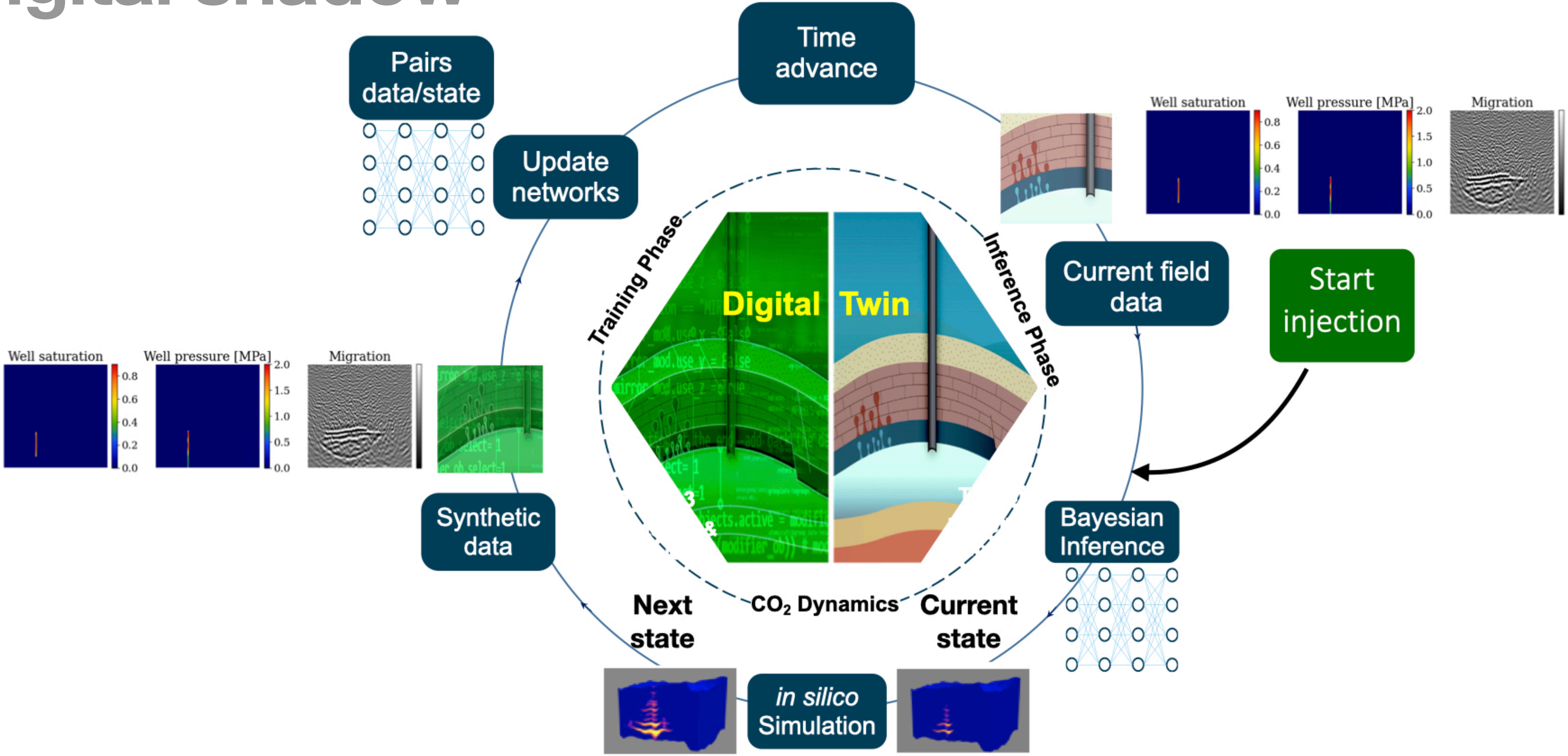


inferred standard deviations



0Km 1.5Km 3.2Km

Digital shadow

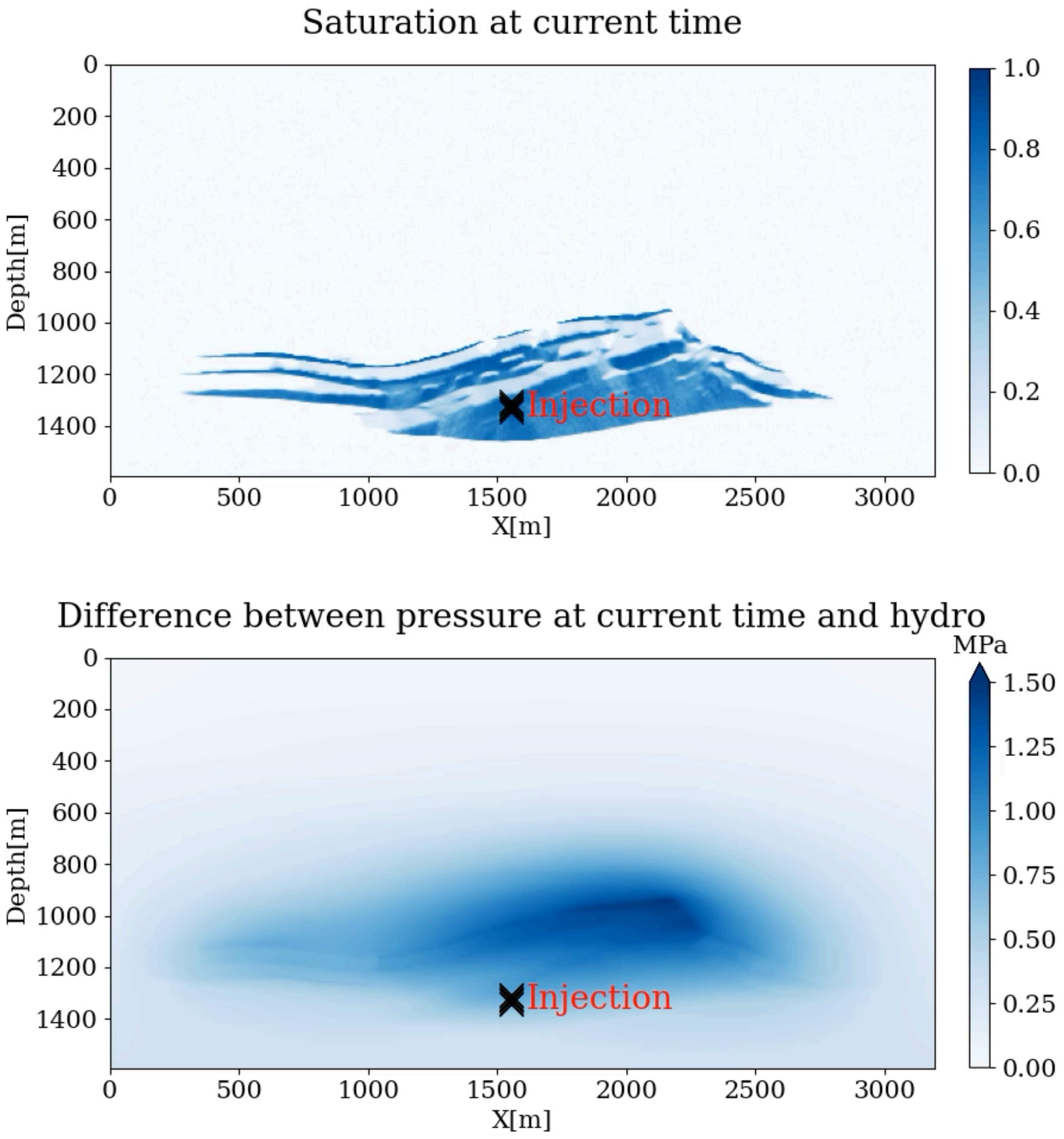


Check also president's column in the Leading Edge, November 2023

Digital Twin w/ *controlled* injectivity

Fracture risk

- **Initial state:** DT of $0.05 \pm 0.01\mathrm{m}^3/\mathrm{s}$ injectivity
- leads to *over* pressure after 1920 days of injection
- rock fractures due to over pressure denoted by red areas
- unacceptable risk



Ringrose, Philip. "How to store CO2 underground: Insights from early-mover CCS projects." (2020): 978-3.
Møyner, Olav, Martin Johnsrud, Halvor Møll Nilsen, Xavier Raynaud, Kjetil Olsen Lye, and Ziyi Yin. 2023. Sintefmath/Jutul.jl: V0.2.5 (version v0.2.5). Zenodo. https://doi.org/10.5281/zenodo.7775759.

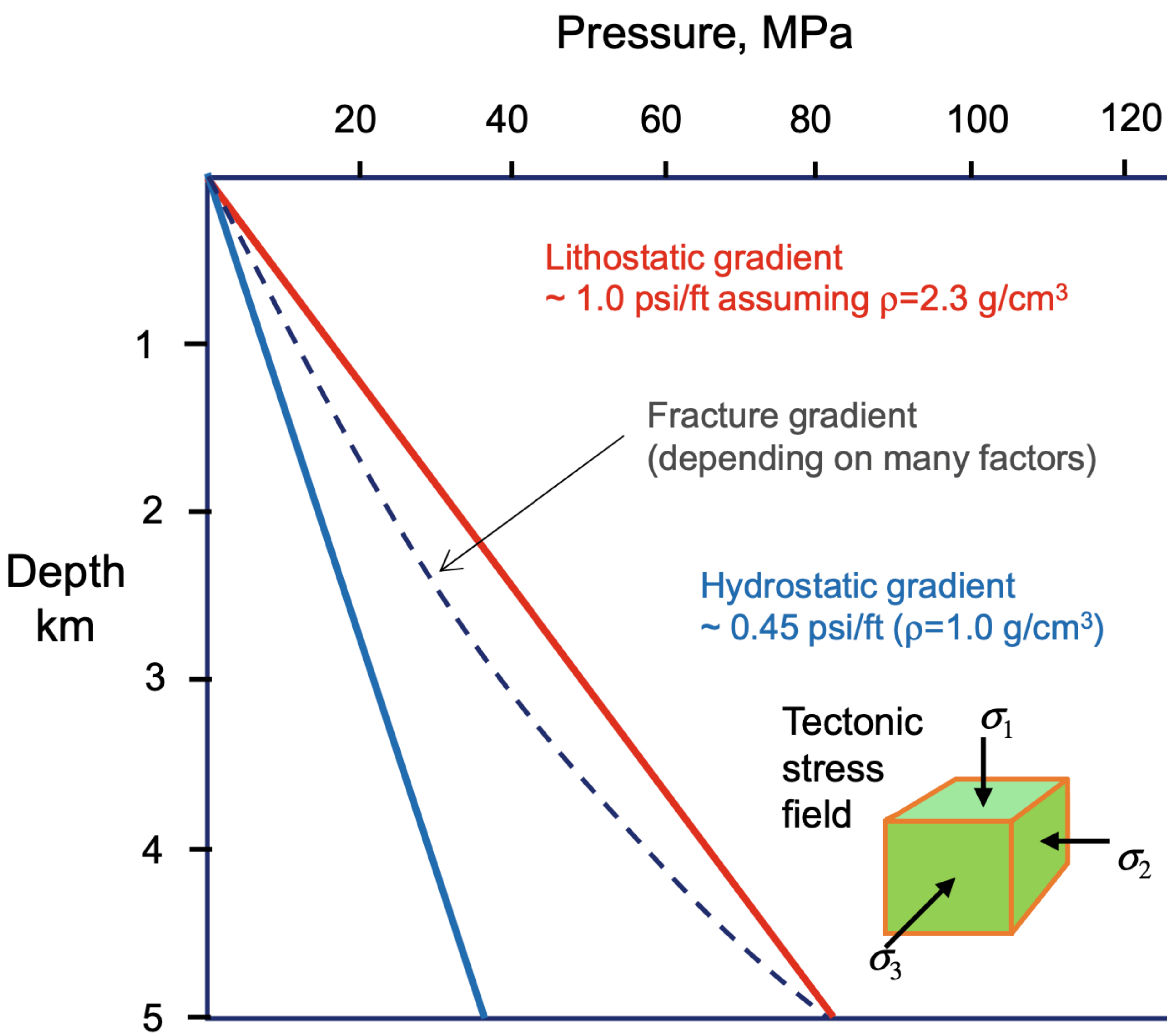
Approach

Develop a numerical scheme to

- ensure *induced* reservoir *pressure* remains below the fracture *pressure* with *high* probability
- *adapt* the *injection* rate

Make use of

- Jutul.jl's numerical reservoir simulations
- modern non-convex constrained optimization techniques
- numerical approximation of the gradient



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Reservoir simulations

control at timestep $k = 3$

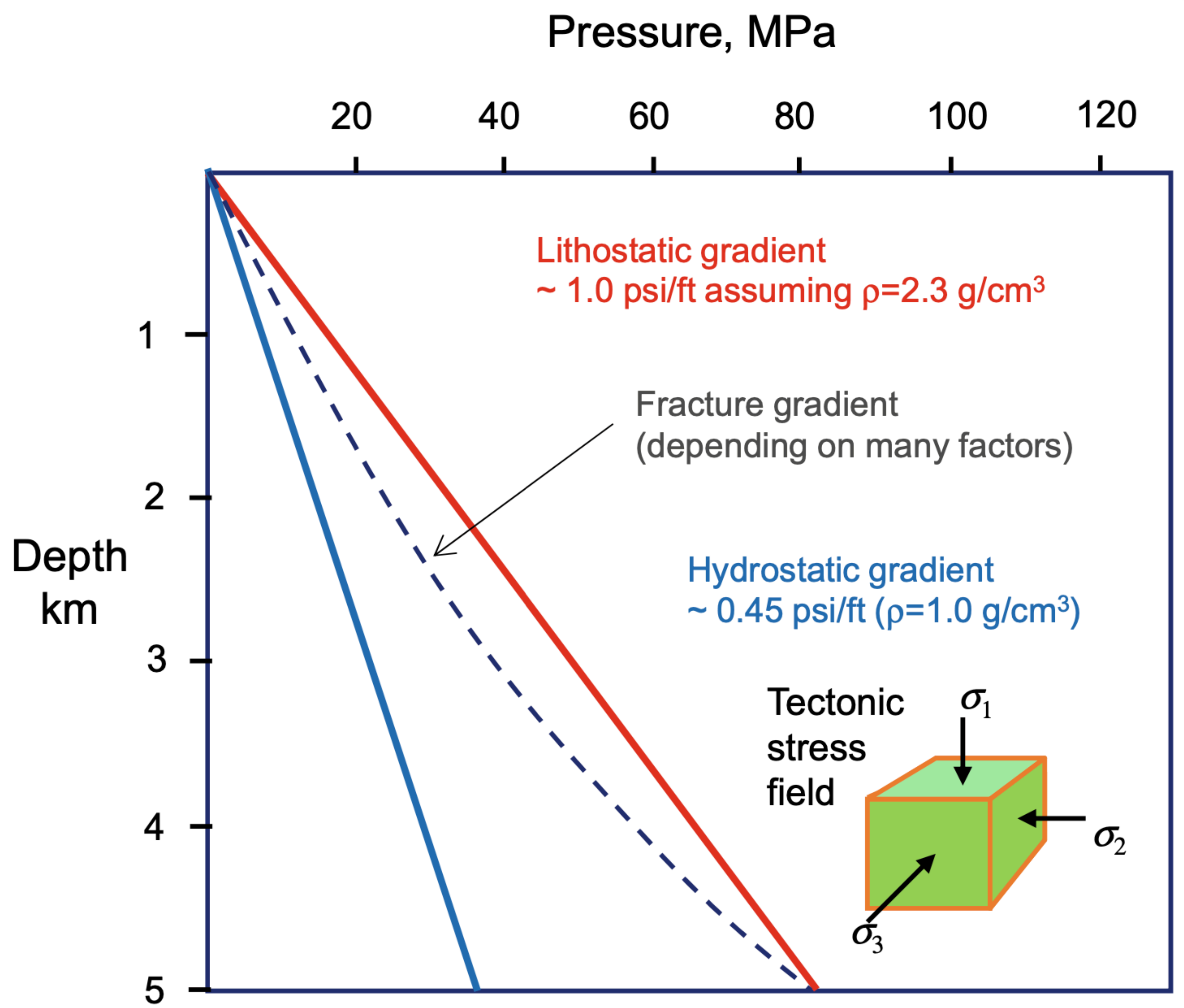
Add pressure to state $\mathbf{x}_k = \begin{bmatrix} \mathbf{c}_k \\ \mathbf{p}_k \end{bmatrix}$

Given injectivity, q_k ,simulate state, $\mathbf{x}_{k+1}$, via

$$\mathbf{x}_{k+1} = \mathscr{M}(\mathbf{x}_k, \mathbf{K}; q_k)$$

for $\mathbf{K} \sim p(\mathbf{K})$

- exceeds fracture pressure regularly at timestep $k = 4$
- need to control injectivity, q_k



Numerical Optimization (Jorge Nocedal and Stephen J. Wright), Springer, 2006.

Optimized
injection rates

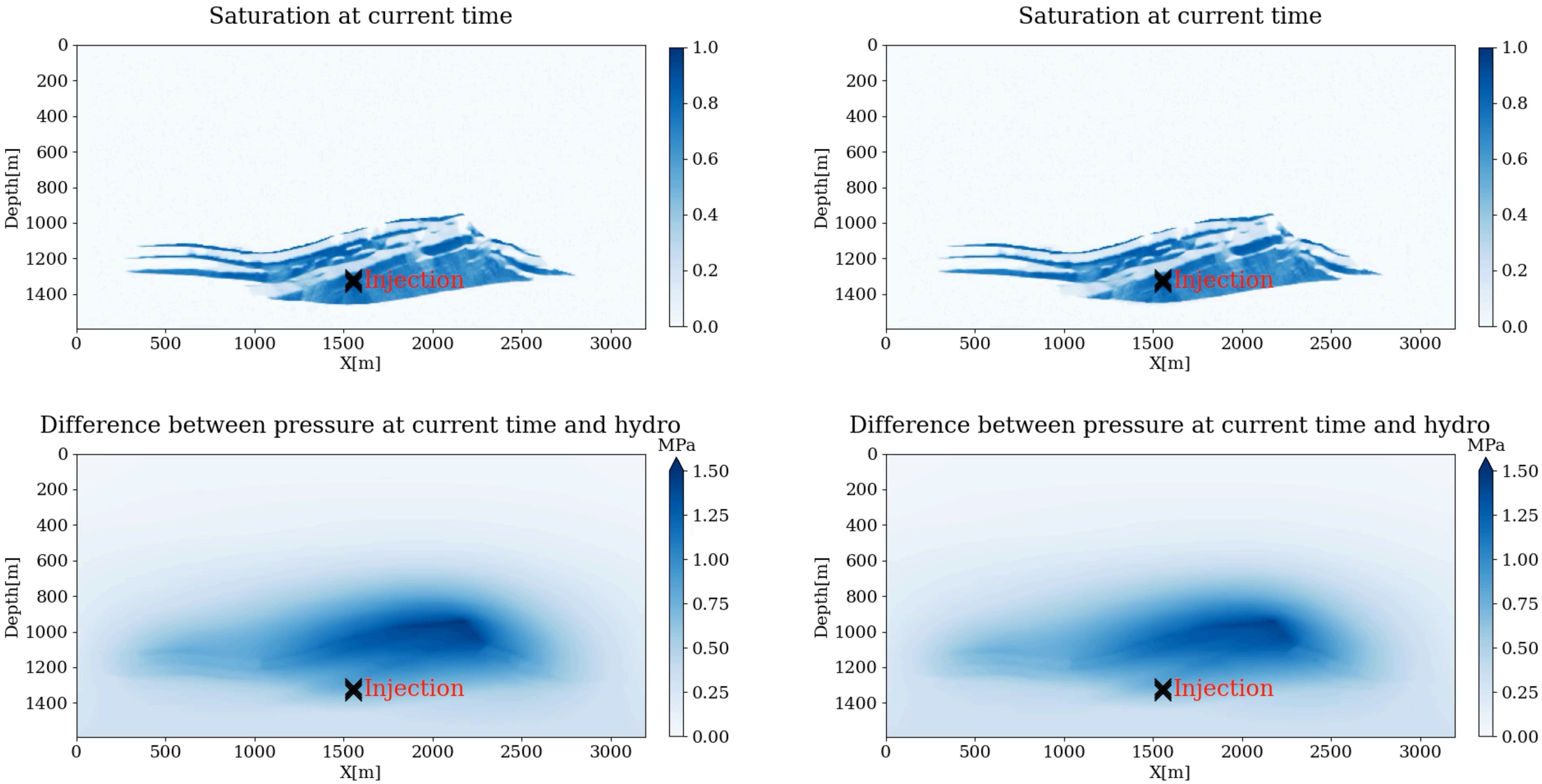
Solve

$$\max_{q_k} q_k \Delta t \quad \text{subject to} \quad \mathbf{x}_{k+1}['p'] < \mathbf{p}_{\max} \quad \text{where} \quad \mathbf{x}_{k+1} = \mathscr{M}(\mathbf{x}_k, \mathbf{K}; q_k)$$

with reservoir simulations over time interval $t = k\Delta t$ to $t = (k+1)\Delta t$

- use finite-differences to approximate $\dfrac{\partial \mathbf{x}_{k+1}}{\partial q_k}$
- impose constraint for fracture pressure, $\mathbf{p}_{\max}$, via log-barrier method
- use Armijo linesearch
- solve w/ until tolerance $\epsilon < 10^{-3}$
- requires on average 30 reservoir simulations

Optimized
w/o vs. w/ control



Is the control beneficial?

Without controlled injection rate:

- 44.3% of the samples during the next time step *fracture*

With controlled injection rate:

- 2.34% of the samples during the next time step *fracture*

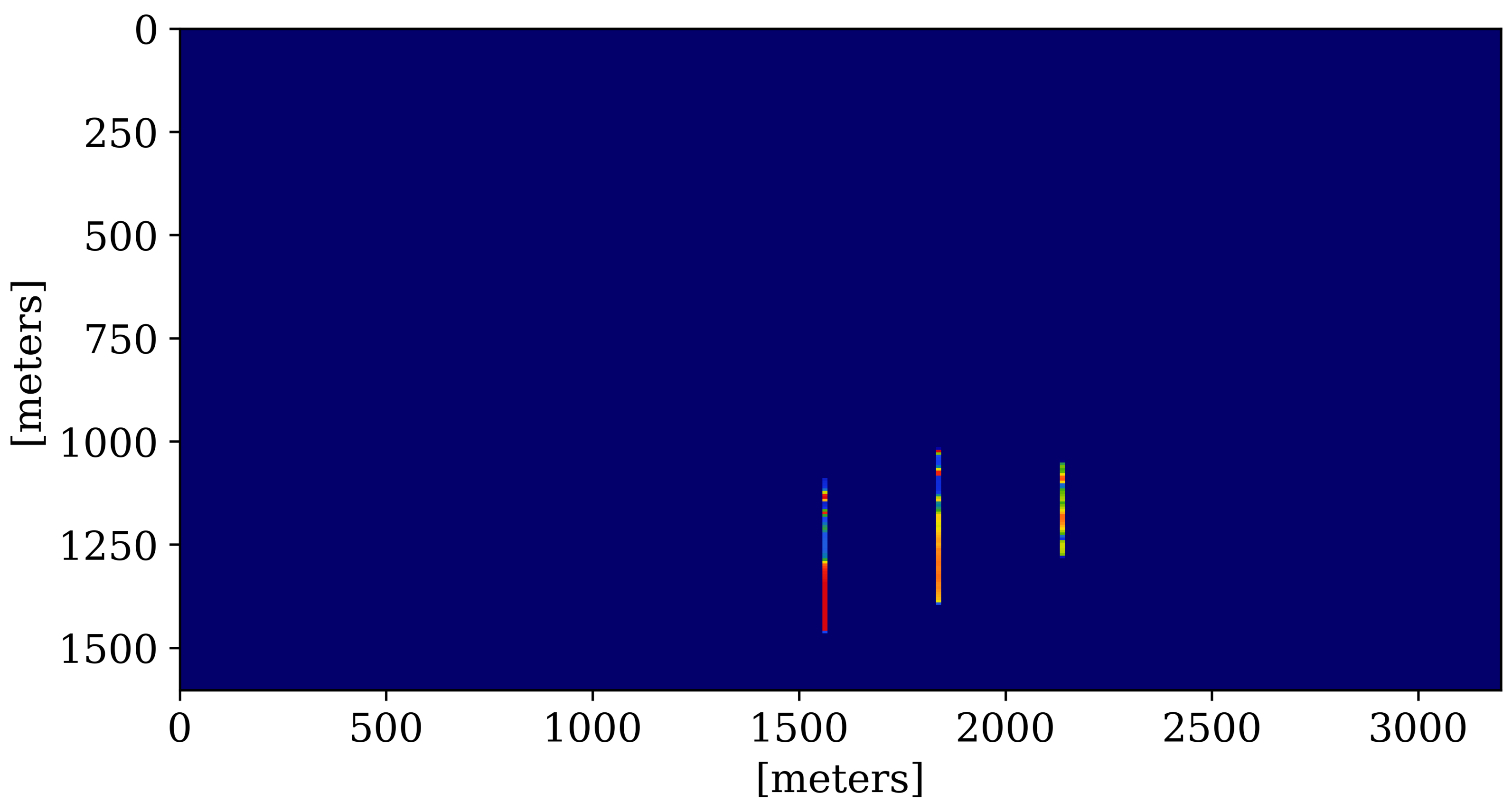
Conclusion: Controlling injection decreases risk of fracture.

Digital Twin w/ *optimized* well locations

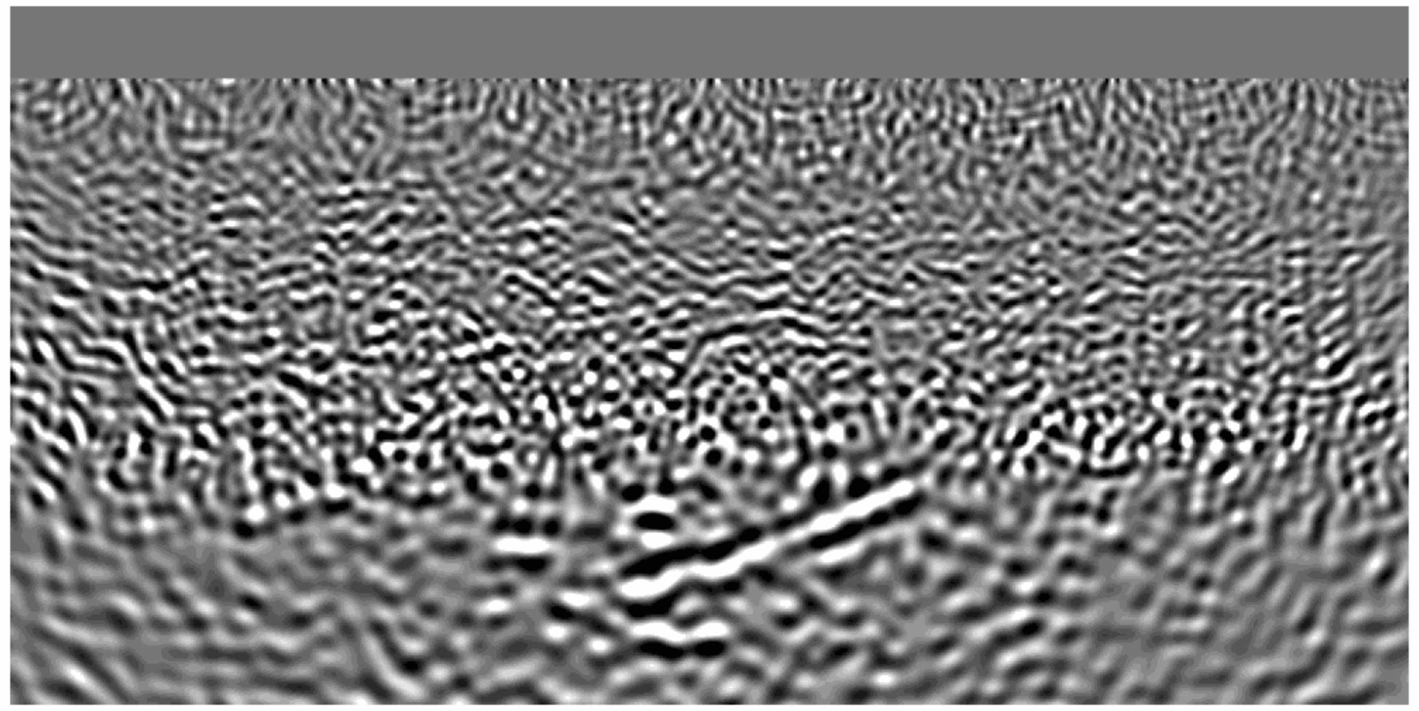
Situation

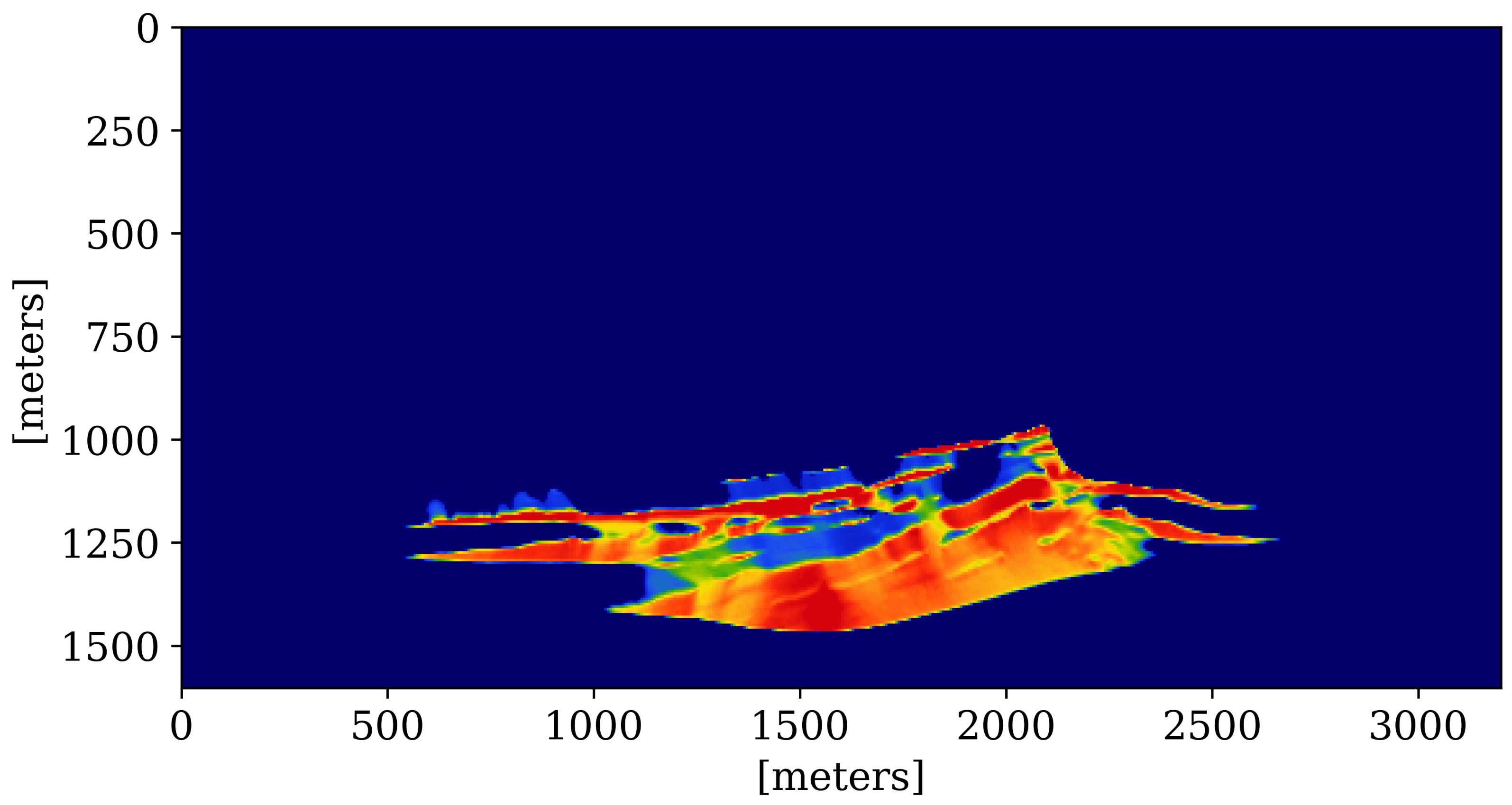
Two types of time-lapse CO_2 plume observations

- ► direct but local – borehole(s)



- ► indirect but global – seismic





Problem

CO_2 project lasts years thus can drill more wells but:

- many location options
- expensive

Operators deciding well locations should be informed by

- current knowledge of the CO_2 plumes
- physics simulations of plume forecasts

Solution: Bayesian experimental design

Chose experiment design $\mathbf{W}$ that allows for **maximal** information gain

$$\mathbf{y} = \mathbf{W}(\mathbf{u})$$

quantified by the Kullback-Leibler divergence:

$$D_{KL}(p(\mathbf{x}\,|\,\mathbf{y})\,||\,p(\mathbf{x}))\,.$$

Expected information gain **(EIG)** ***averages*** **over** ***all*** **possible designs**

$$EIG(\mathbf{W}) = \mathbb{E}_{p(\mathbf{y}|\mathbf{W})}\left[D_{KL}(p(\mathbf{x}\,|\,\mathbf{y})\,||\,p(\mathbf{x}))\right].$$

Go, Jinwoo, and Tobin Isaac. "Robust expected information gain for optimal Bayesian experimental design using ambiguity sets." *Uncertainty in Artificial Intelligence*. PMLR, 2022.

Hoffmann, Till, and Jukka-Pekka Onnela. "Minimizing the Expected Posterior Entropy Yields Optimal Summary Statistics." arXiv preprint arXiv:2206.02340 (2022).

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Relation

conditional neural density & EIG

Maximizing the expected *posterior density* is equivalent to maximizing the expected *information gain*

$$\max_{\mathbf{W}} \; EIG(\mathbf{W}) = \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} \left[D_{KL}(p_\theta(\mathbf{x} \mid \mathbf{y}, \mathbf{W}) \,||\, p(\mathbf{x}))\right] = \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} \left[\mathbb{E}_{p(\mathbf{x}|\mathbf{y})} \left[\log p_\theta(\mathbf{x} \mid \mathbf{y}) - \log p(\mathbf{x})\right]\right]$$

$$= \mathbb{E}_{p(\mathbf{y}|\mathbf{W})} \left[\mathbb{E}_{p(\mathbf{x}|\mathbf{y})} \left[\log p_\theta(\mathbf{x} \mid \mathbf{y})\right]\right]$$ law of total expectation

$$= \mathbb{E}_{p(\mathbf{x},\mathbf{y}|\mathbf{W})} \left[\log p_\theta(\mathbf{x} \mid \mathbf{y})\right]$$ same as neural posterior objective!

Thus optimizing under the posterior density objective will increase the EIG!

Proposed method

As usual, prepare posterior learning algorithm: $\{\mathbf{x}^{(n)}, \mathbf{y}^{(n)}\}_{i=1}^{N}$

Instead of optimizing only network parameters:

$$\hat{\theta} \; = \underset{\theta}{\arg\max} \; \frac{1}{N}\sum_{n=1}^{N}\left(-\|f_{\theta}(\mathbf{x}^{(n)};\mathbf{y}^{(n)})\|_2^2 + \log\left|\det \mathbf{J}_{f_{\theta}}\right|\right).$$

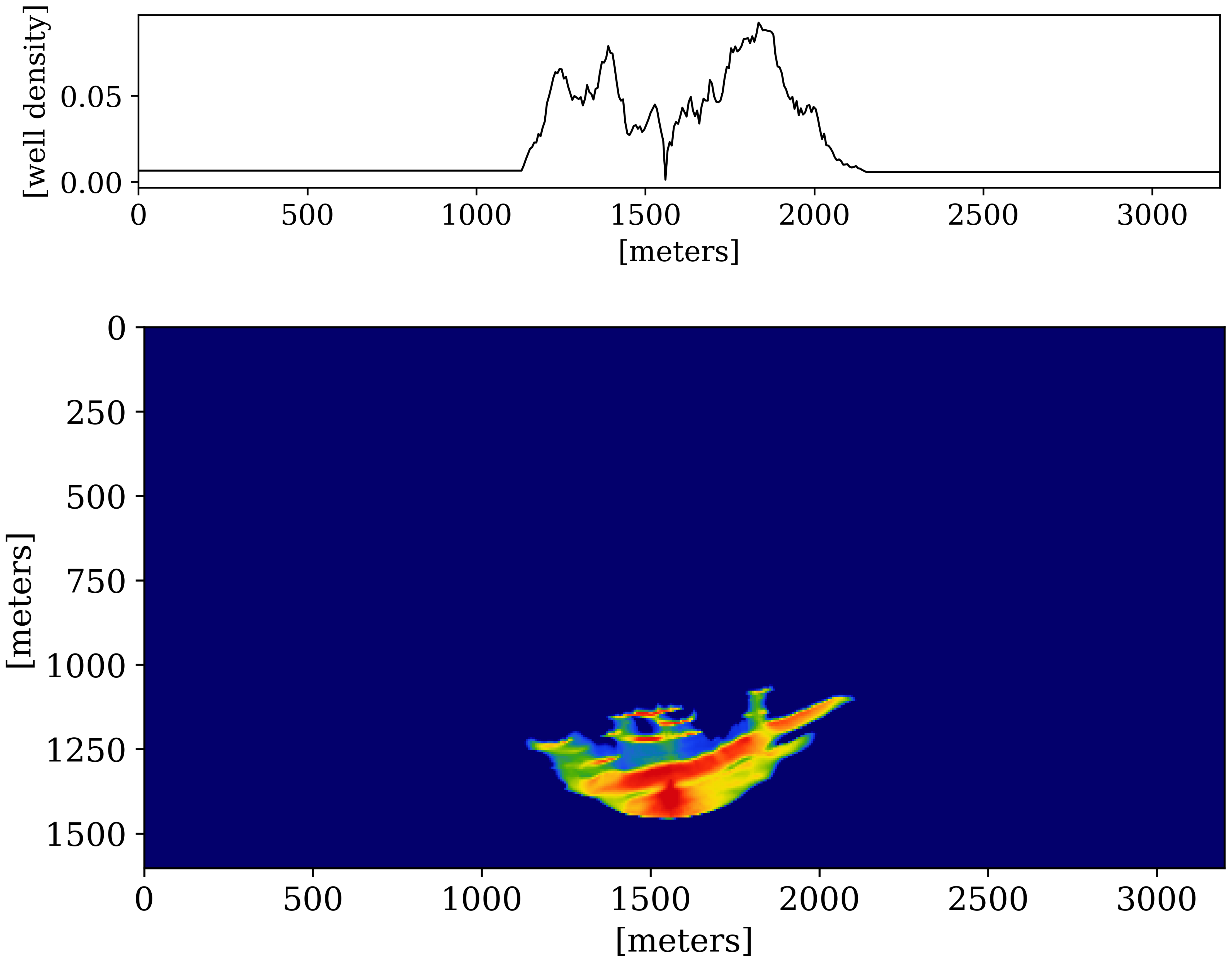
Jointly optimize experiment design, $\mathbf{W}$, –i.e., by

$$\hat{\theta},\,\hat{\mathbf{W}} = \underset{\theta,\,\mathbf{W}}{\arg\max} \; \frac{1}{N}\sum_{i=1}^{N}\left(-\|f_{\theta}(\mathbf{x}^{(n)};\mathbf{W}\odot\mathbf{y}^{(n)})\|_2^2 + \log\left|\det \mathbf{J}_{f_{\theta}}\right|\right).$$

Proposed method

Optimize for probability *density* of well placement

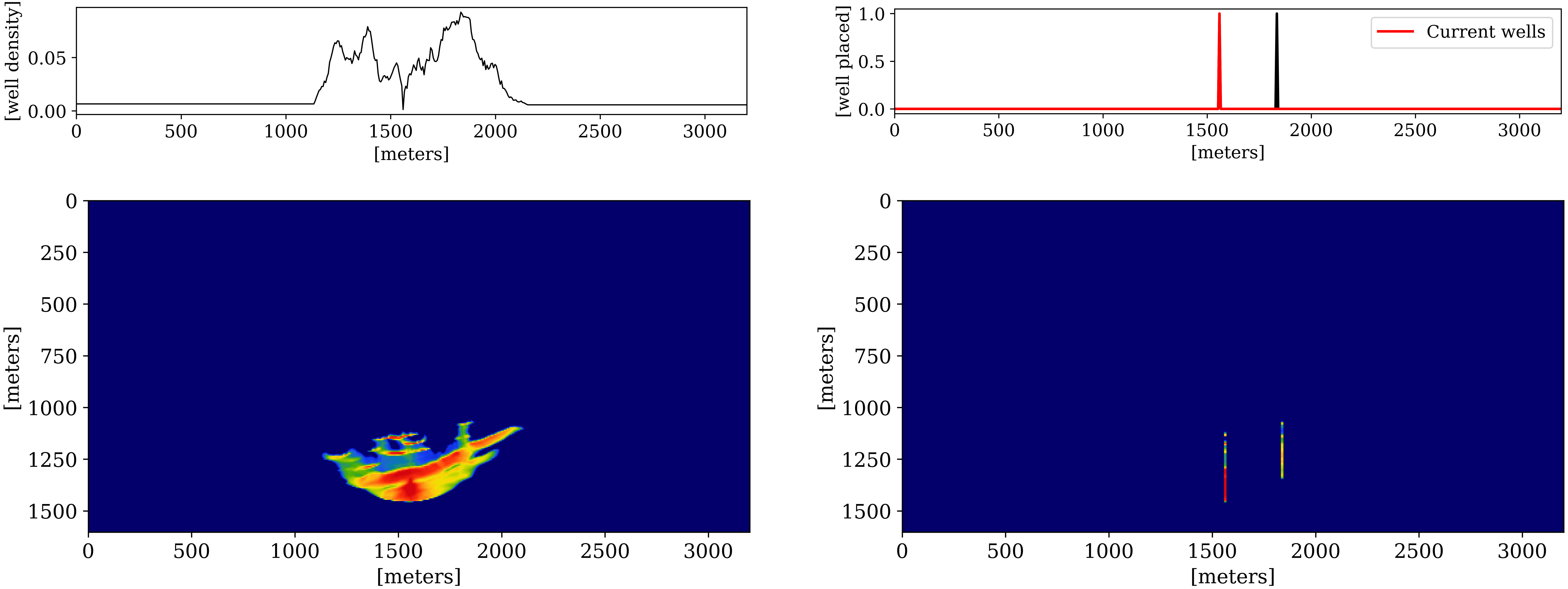
- well budget agnostic
- decide number of wells post-hoc
- easier optimization
- stochastic sampling during training avoids local minima



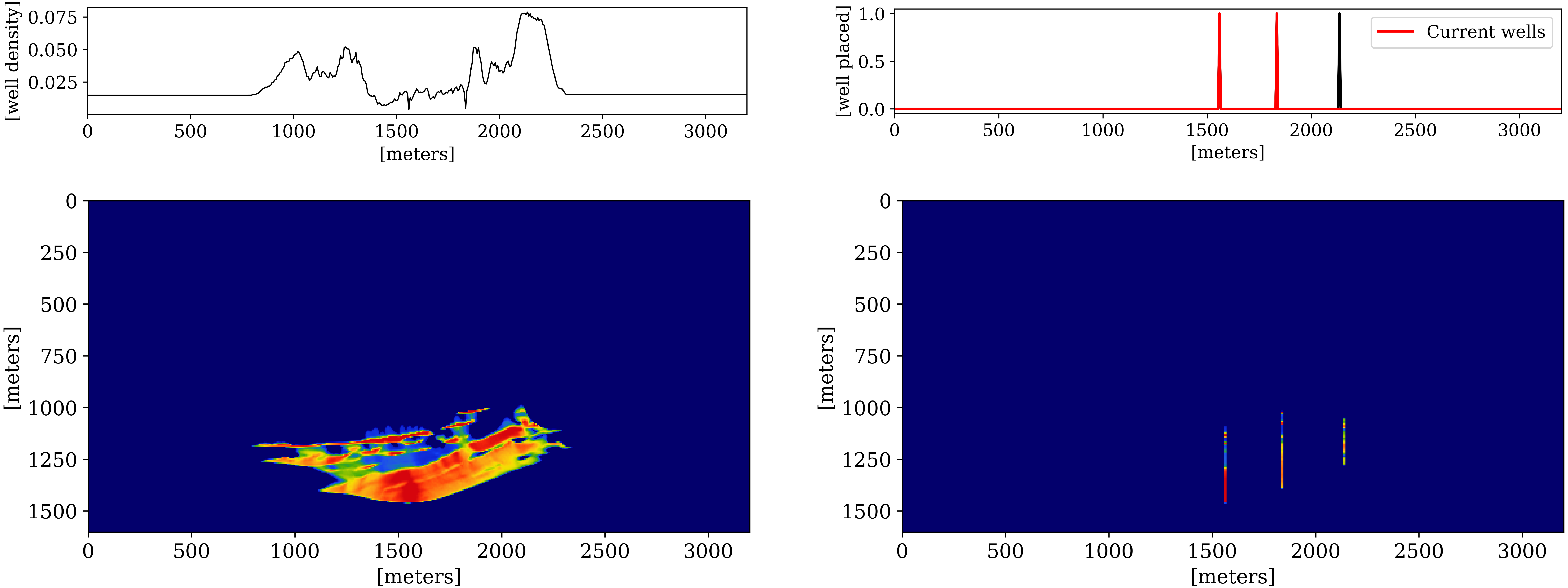
Wu, Sixue, Dirk J. Verschuur, and Gerrit Blacquière. "Automated seismic acquisition geometry design for optimized illumination at the target: A linearized approach." *IEEE Transactions on Geoscience and Remote Sensing* 60 (2021)

Bengio, Yoshua, Nicholas Léonard, and Aaron Courville. "Estimating or propagating gradients through stochastic neurons for conditional computation." *arXiv:1308.3432* (2013).

Monitor 1

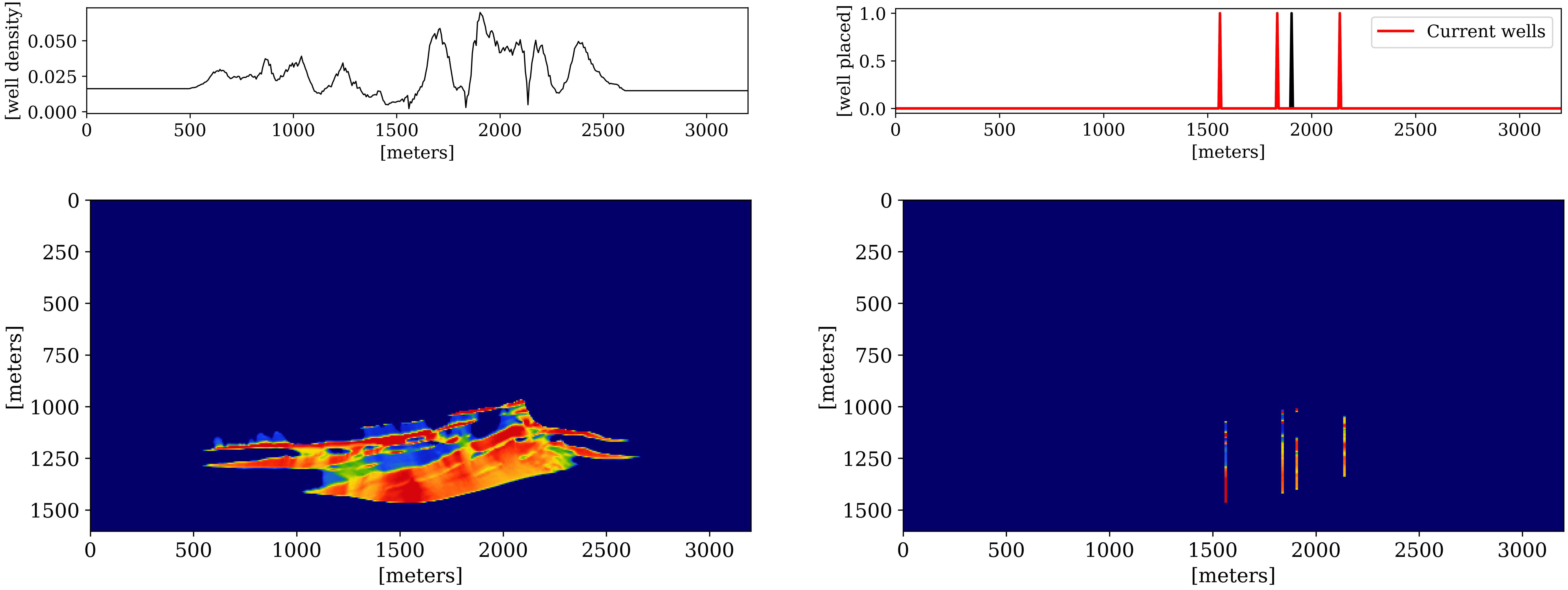

[well density]
0.05
0.00
0
500
1000
1500
2000
2500
3000
[meters]
[well placed]
1.0
0.5
0.0
Current wells
[meters]
0
250
500
750
1000
1250
1500

Monitor 2



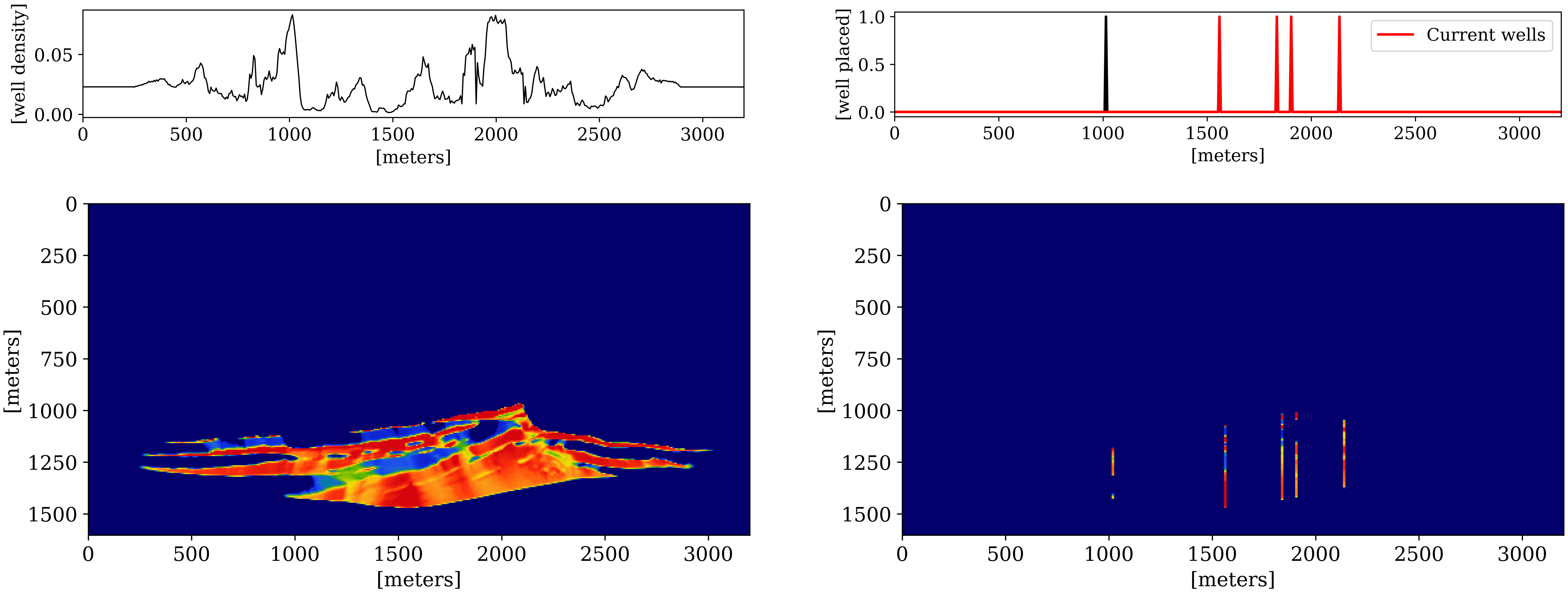
[well density]
0.075
0.050
0.025
0
500
1000
1500
2000
2500
3000
[meters]
[well placed]
1.0
0.5
0.0
Current wells
0
500
1000
1500
2000
2500
3000
[meters]
0
250
500
750
1000
1250
1500
[meters]
0
500
1000
1500
2000
2500
3000
[meters]
0
250
500
750
1000
1250
1500
[meters]
0
500
1000
1500
2000
2500
3000
[meters]

Monitor 3

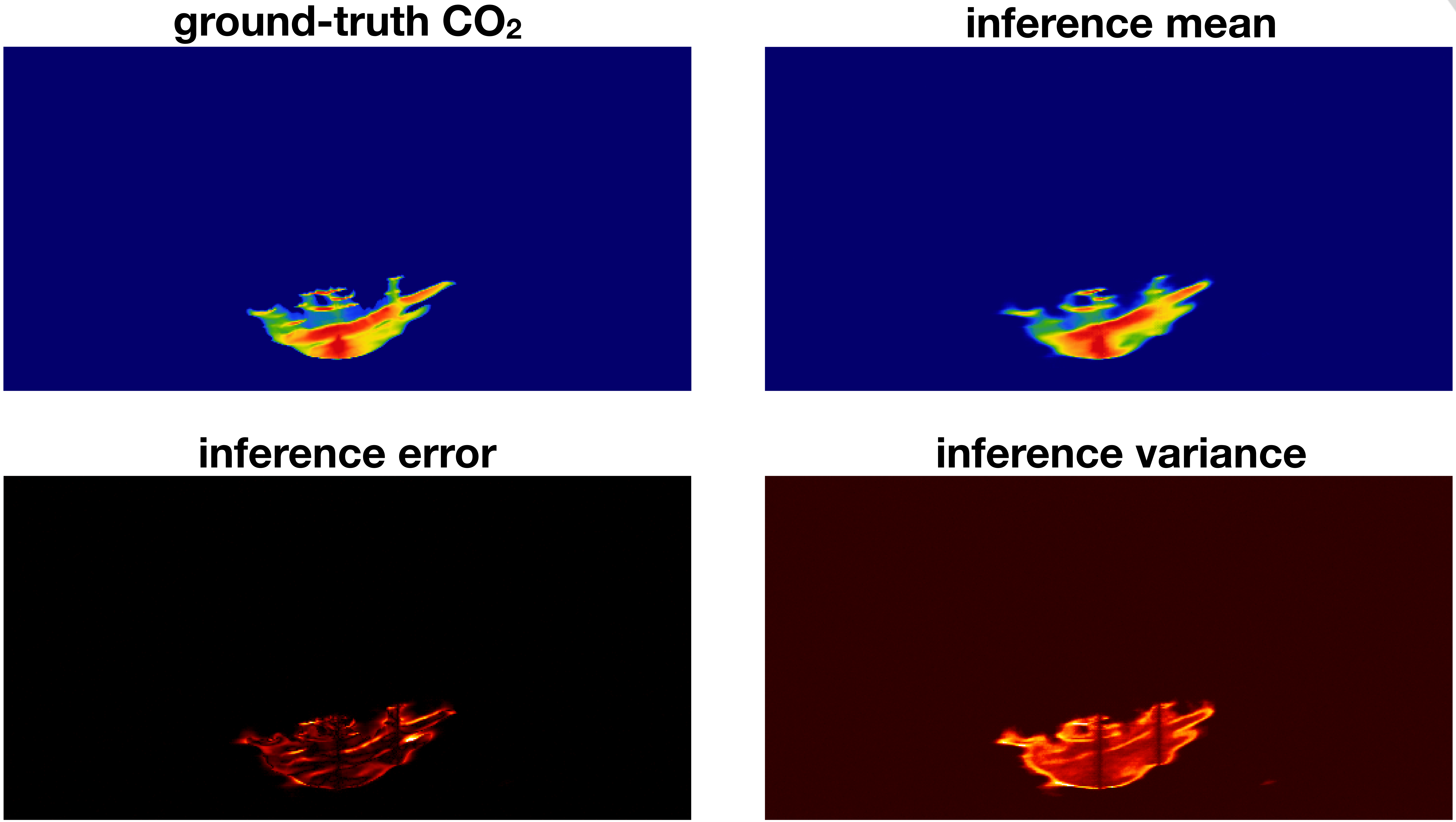


[well density]
0.050
0.025
0.000
0
500
1000
1500
2000
2500
3000
[meters]
[well placed]
1.0
0.5
0.0
Current wells
[meters]
[meters]
[meters]
[meters]
[meters]

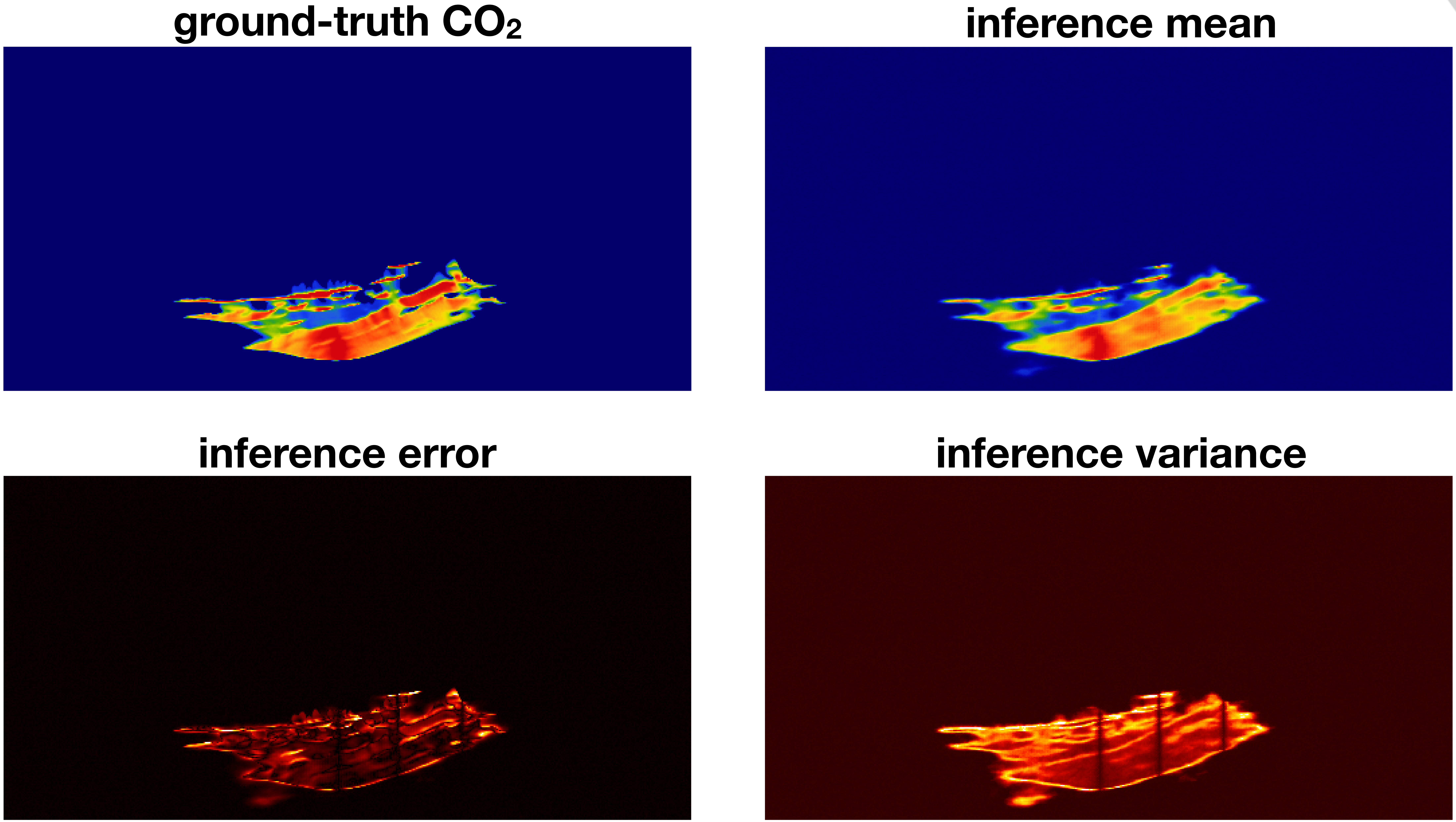
Monitor 4


[well density]
0.05
0.00
0
500
1000
1500
2000
2500
3000
[meters]
[well placed]
1.0
0.5
0.0
Current wells
[meters]
0
250
500
750
1000
1250
1500

Monitor 1


ground-truth CO_2
inference mean
inference error
inference variance

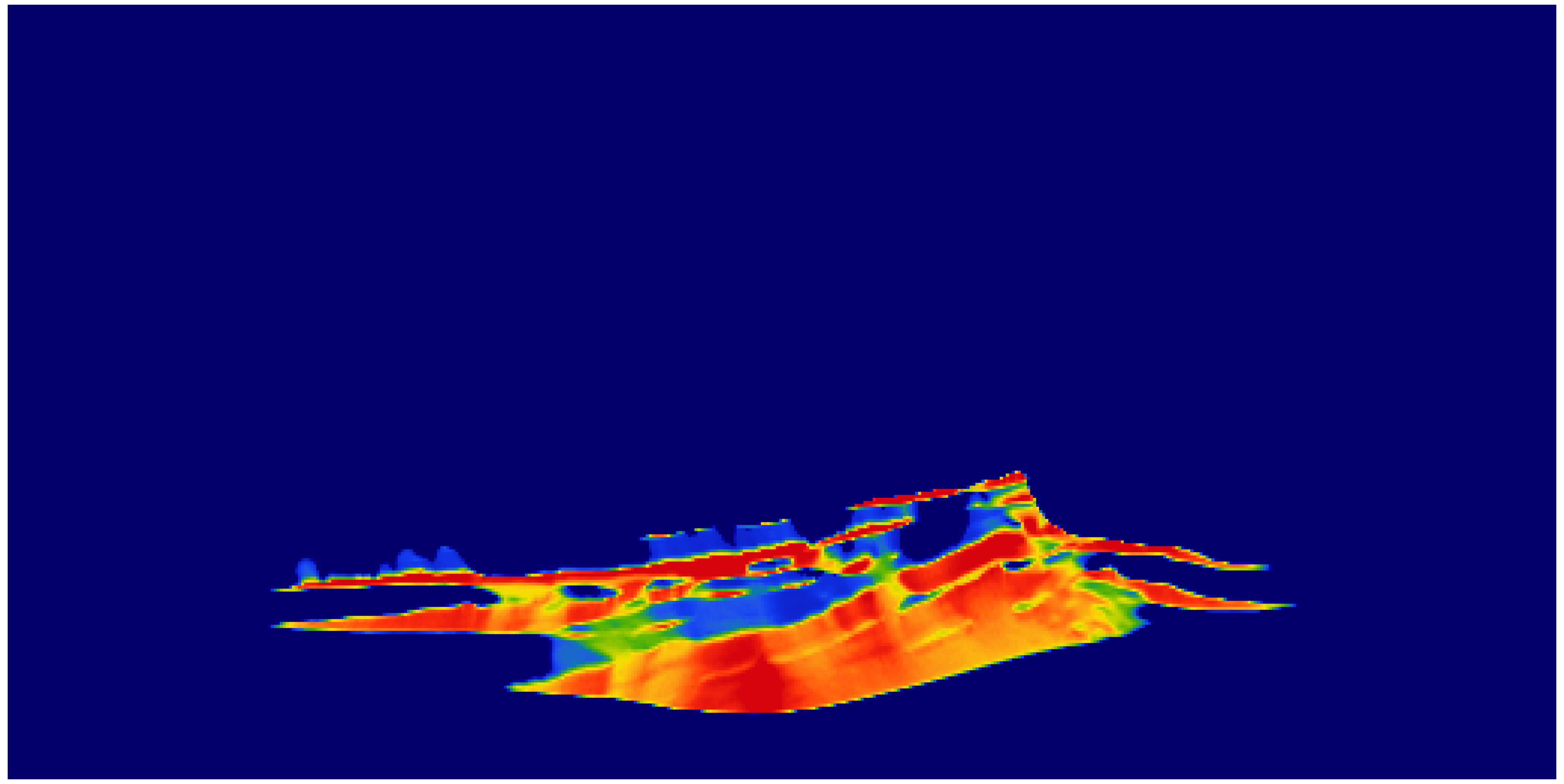
Monitor 2



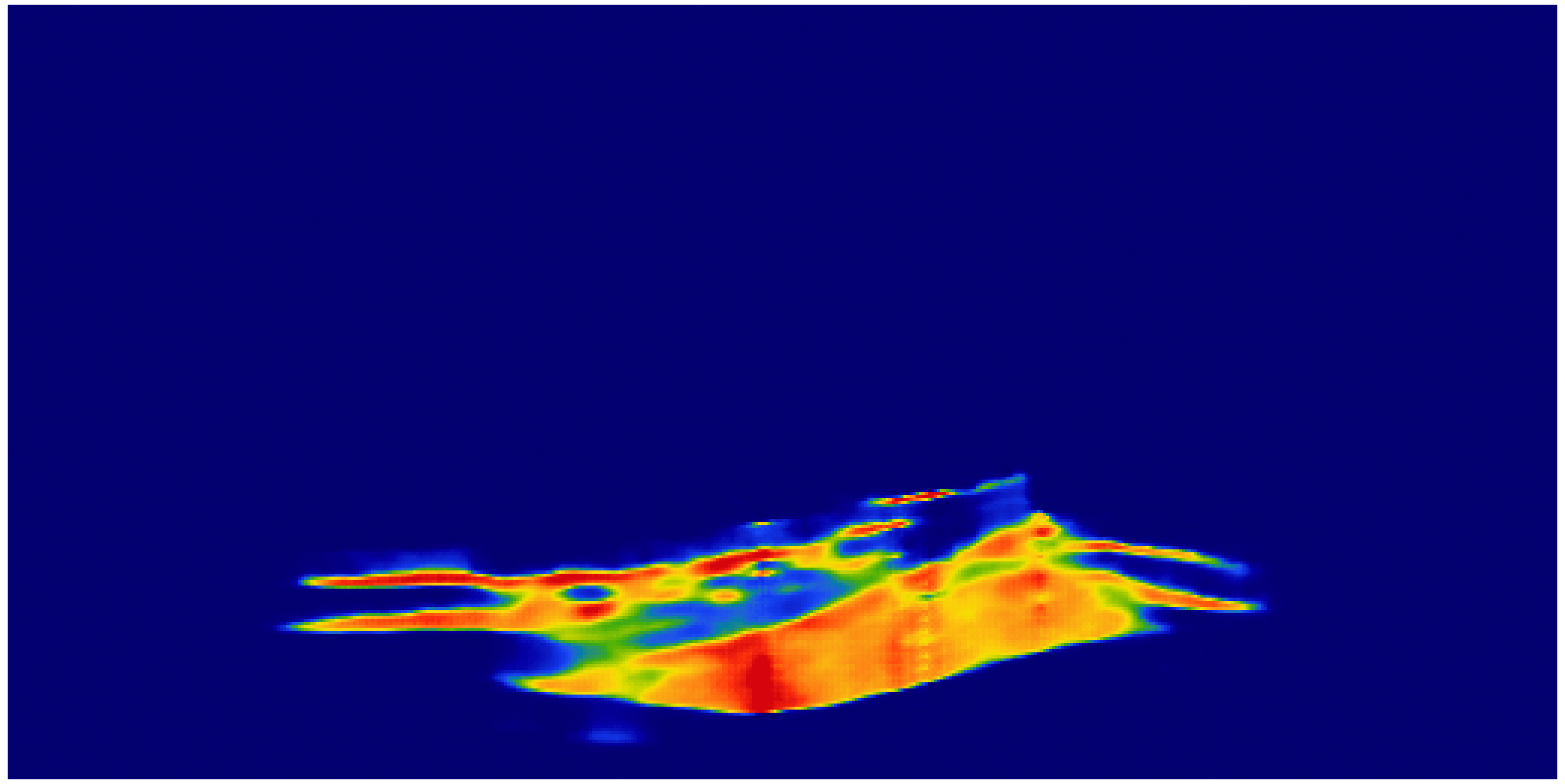
ground-truth CO_2
inference mean
inference error
inference variance

Monitor 3

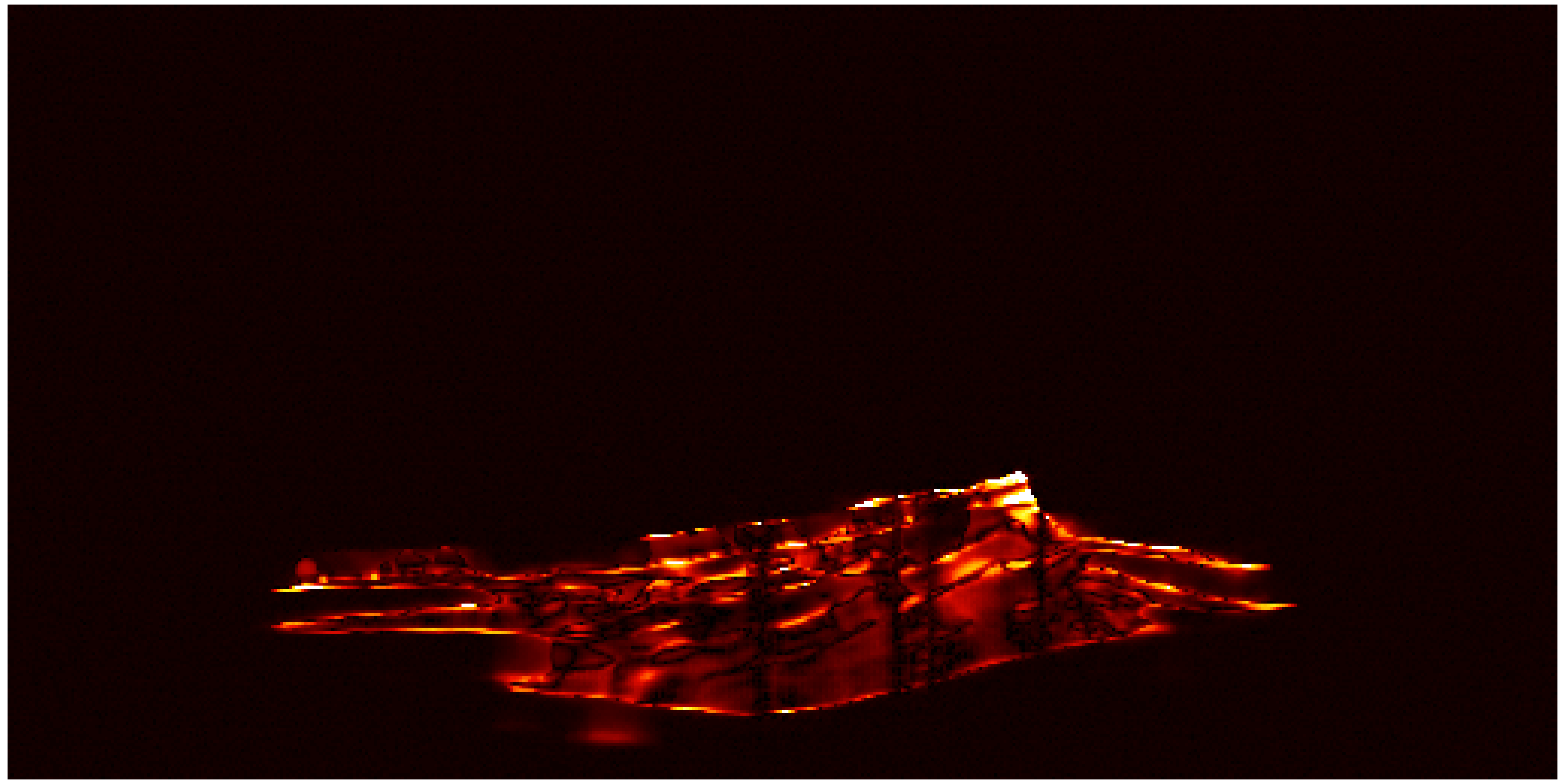
ground-truth CO_2



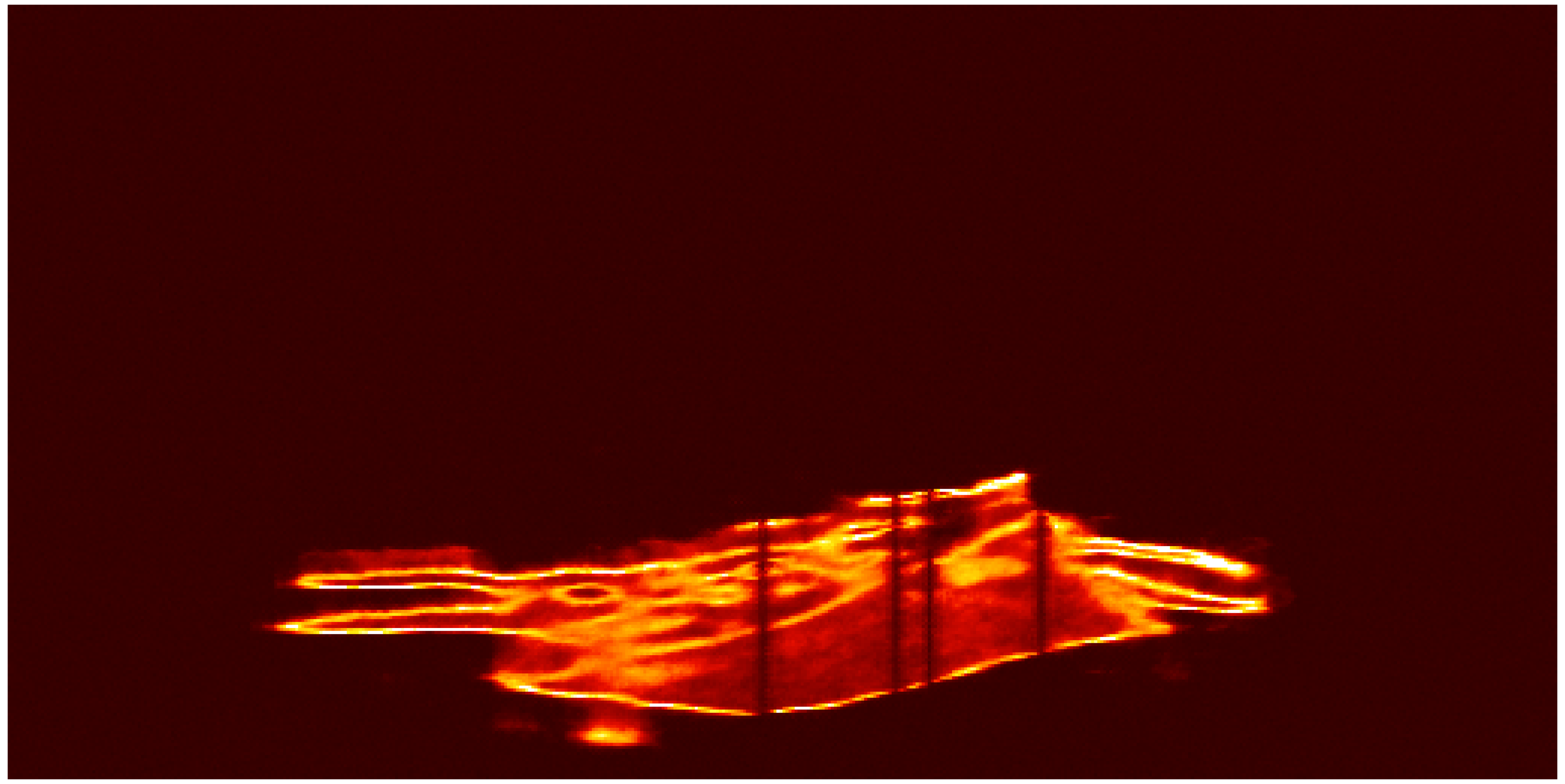
inference mean



inference error

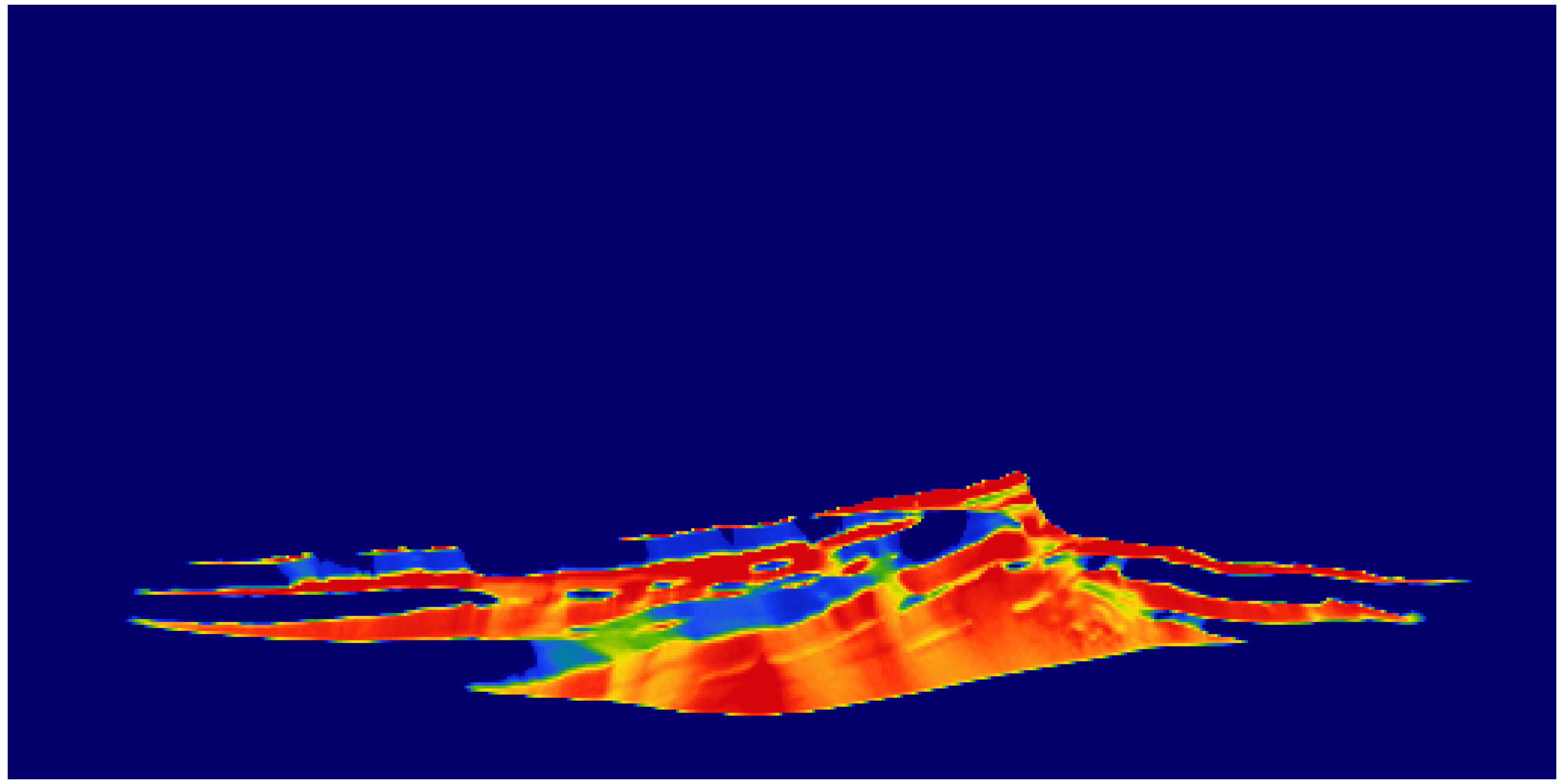


inference variance

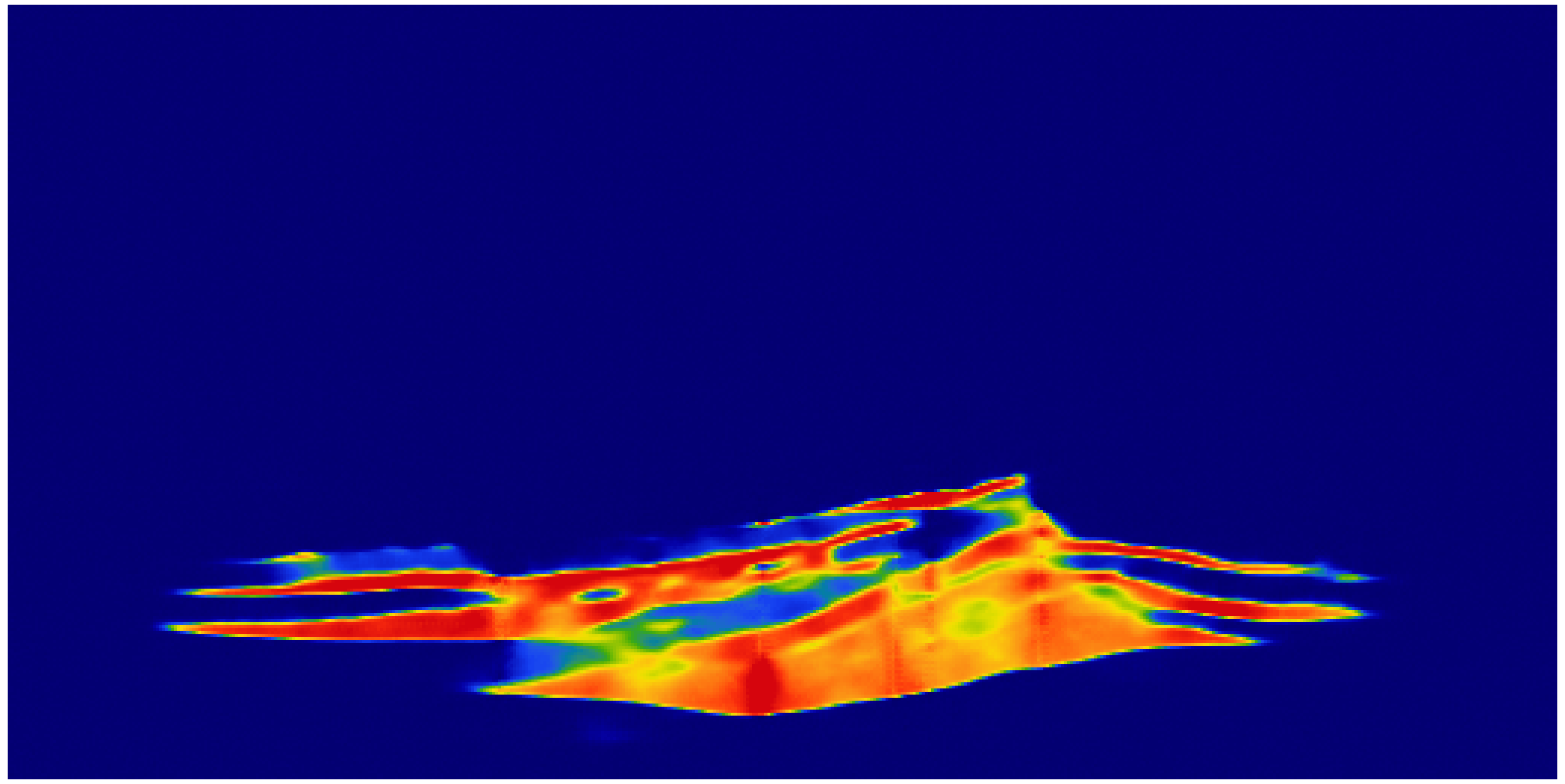


Monitor 4

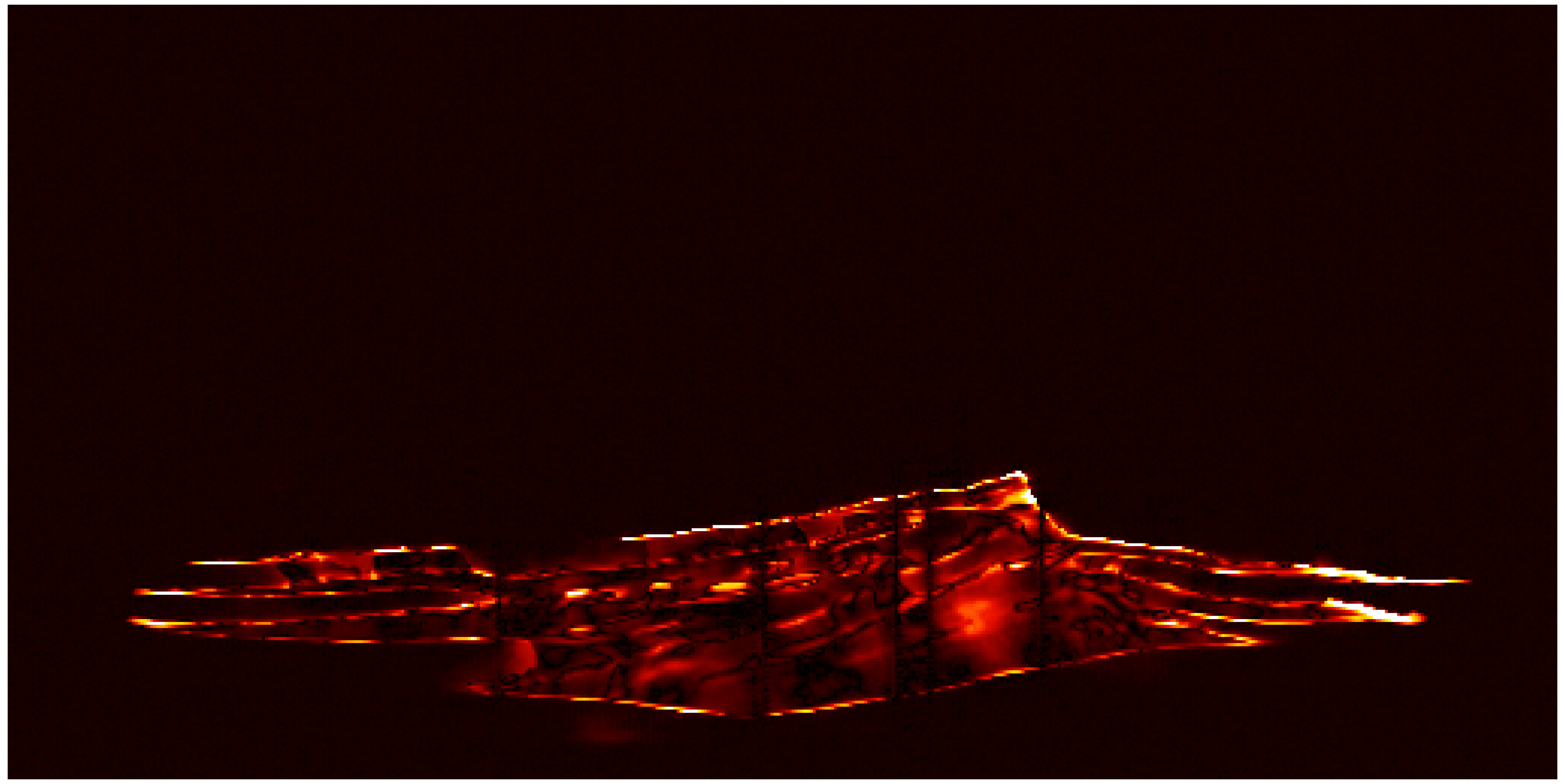
ground-truth CO_2



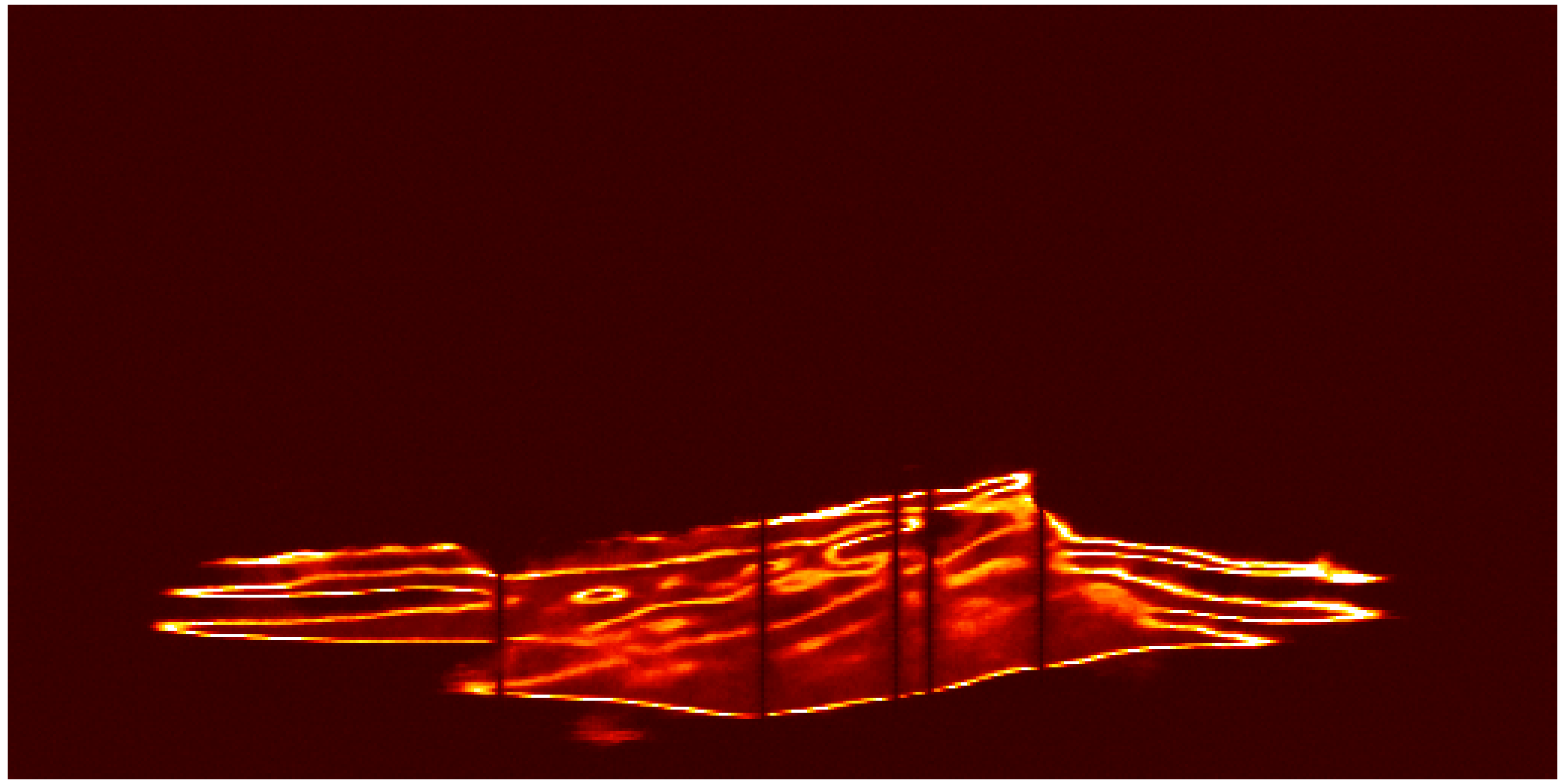
inference mean



inference error

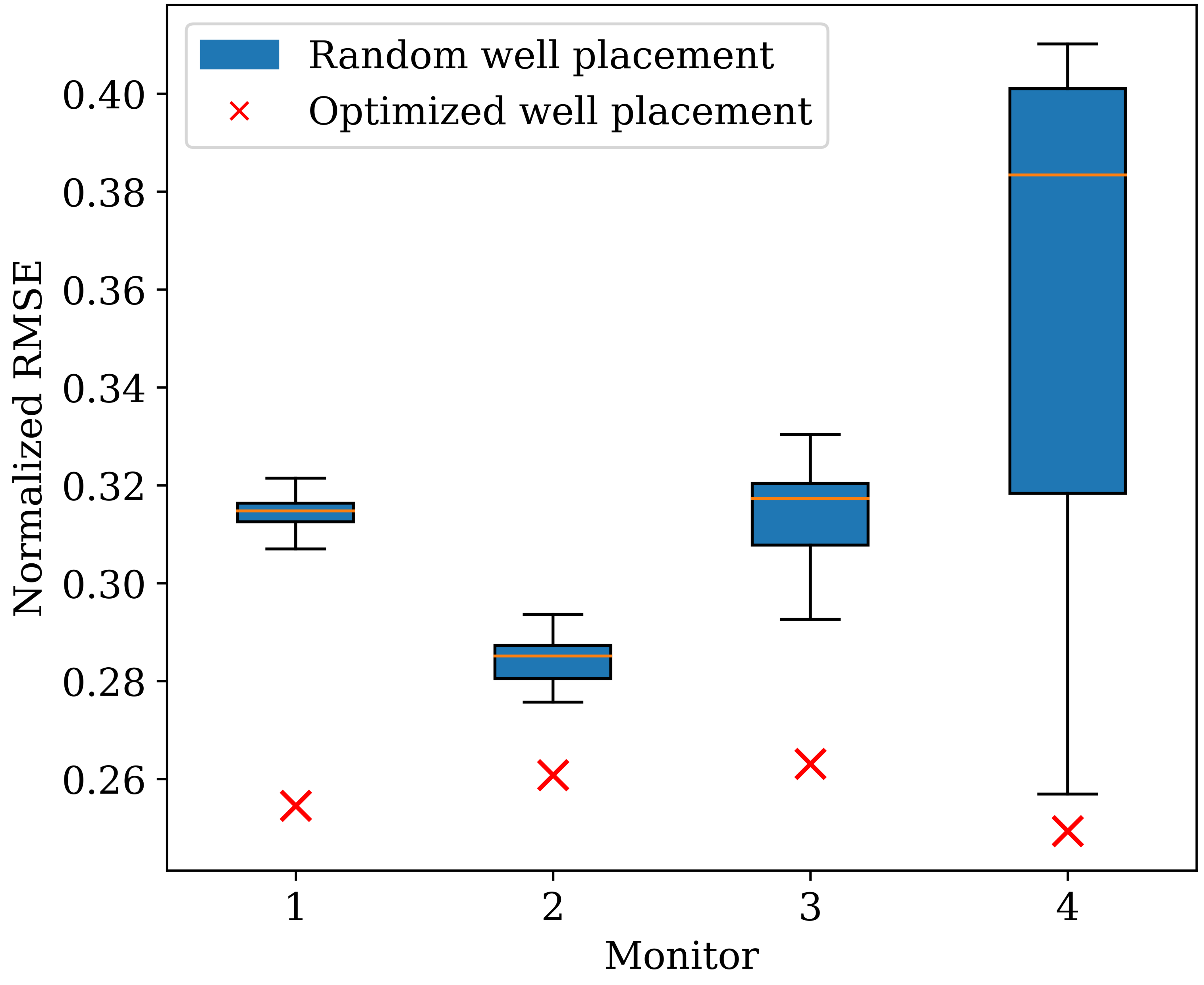


inference variance

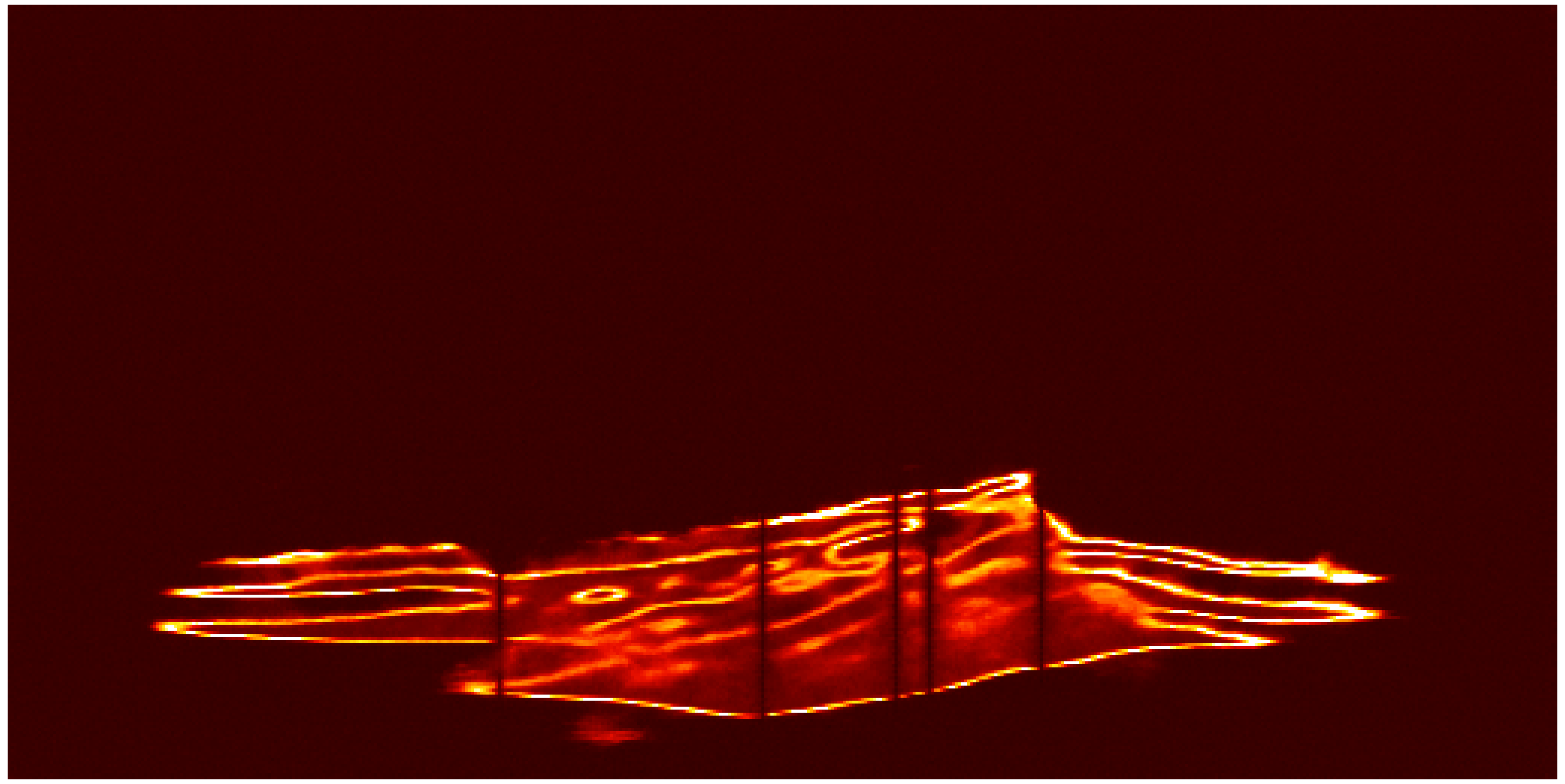


Improvement on baseline

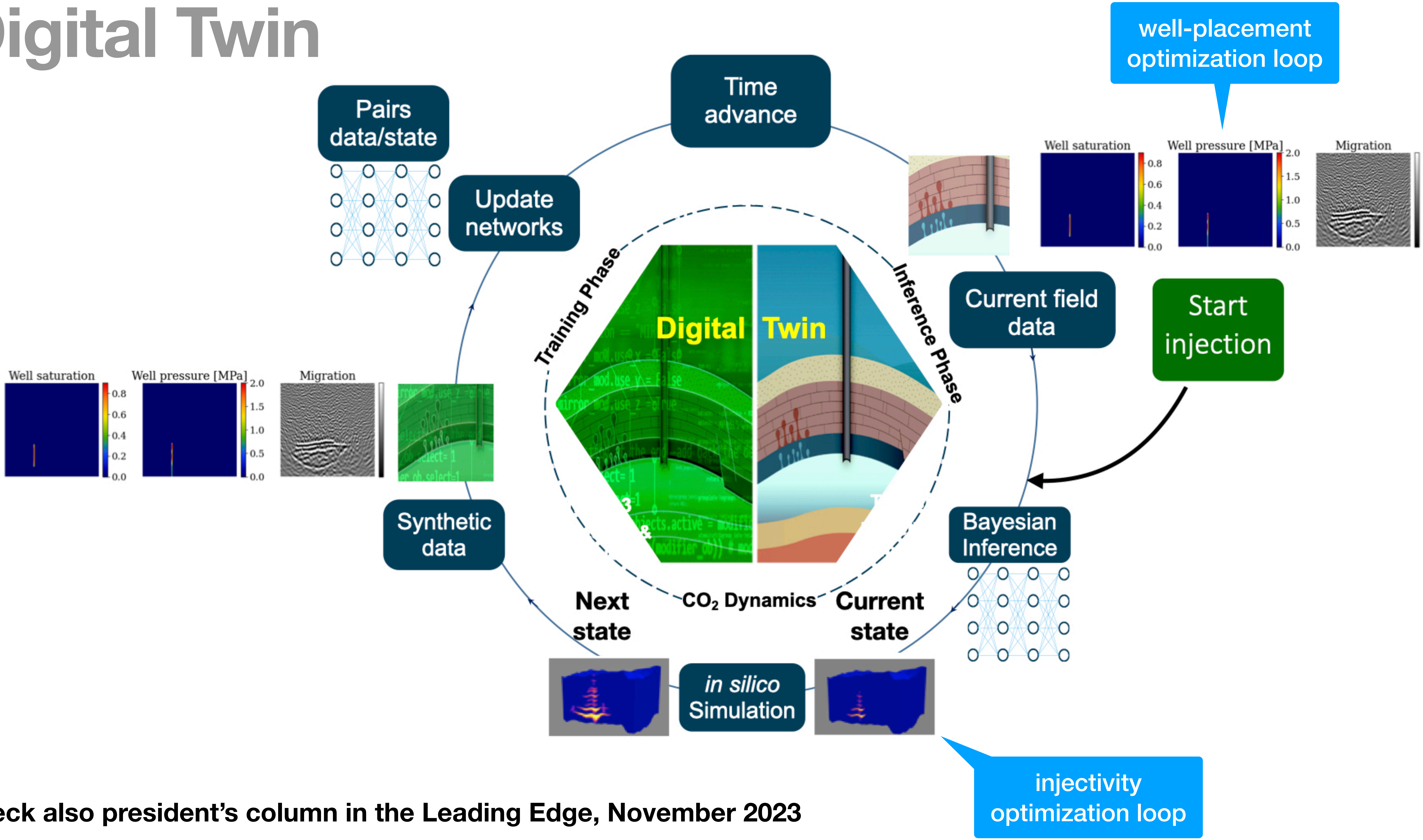
Our algorithm places wells near or at optimal locations as measured by error



inference variance



Digital Twin



Check also president's column in the Leading Edge, November 2023

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.