A Transfer Learning-Based Surrogate Model for Geological Carbon Storage with Multi-Fidelity Training Data

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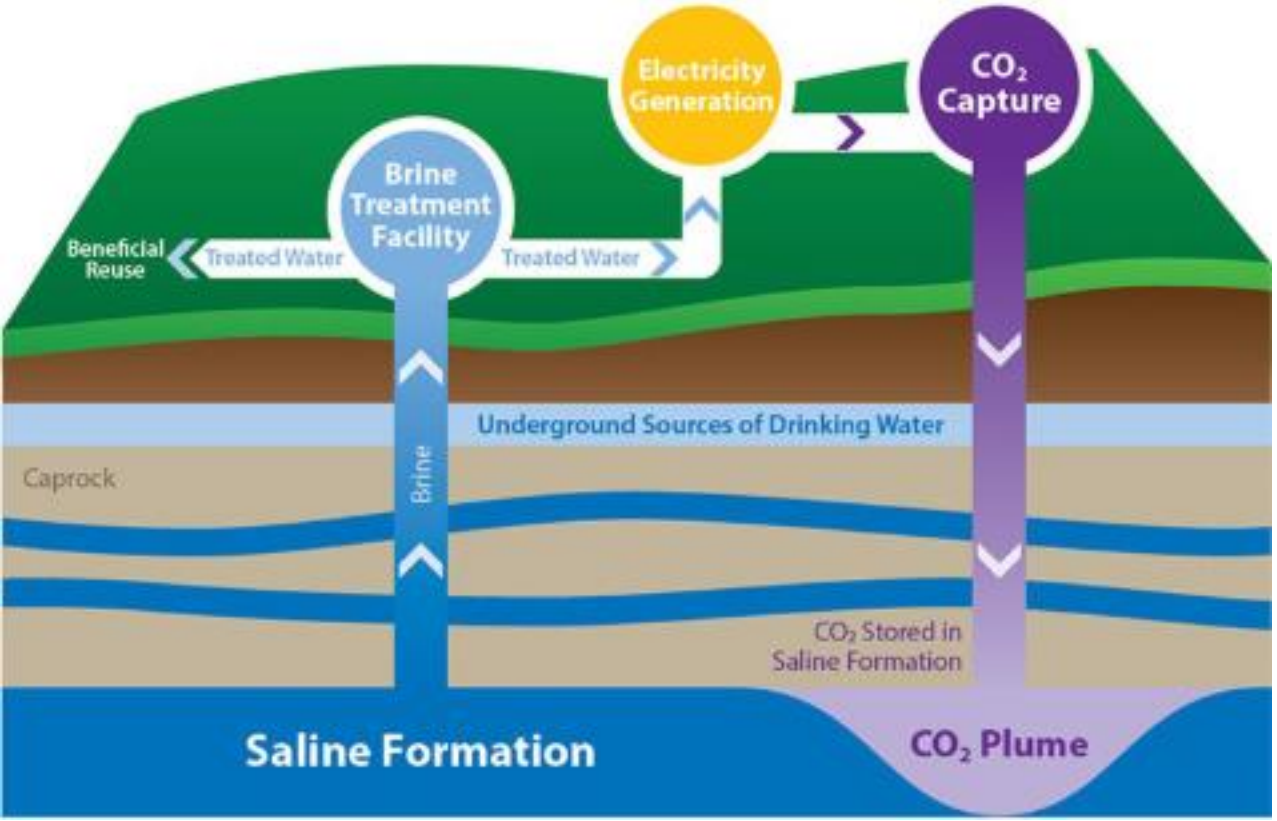
Motivation

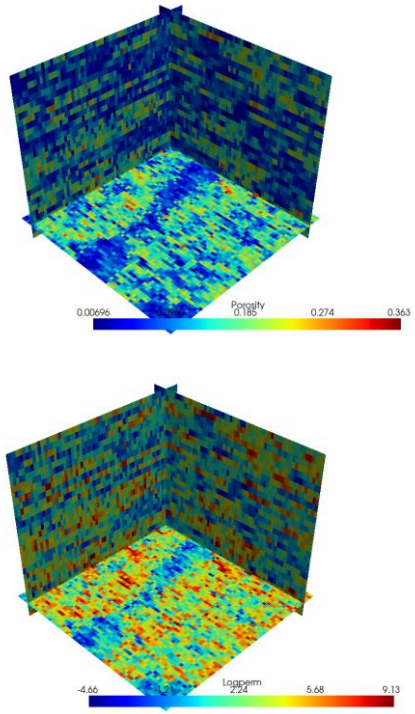


- Geological carbon storage can prevent 90% of industry emissions from atmosphere
- Time-consuming reservoir simulations are required to predict the subsurface responses
- Develop deep-learning-based surrogate models for efficient alternative
  - Thousands of high-fidelity simulation runs (~100,000 cells) still needed for training
- Transfer learning to accelerate training

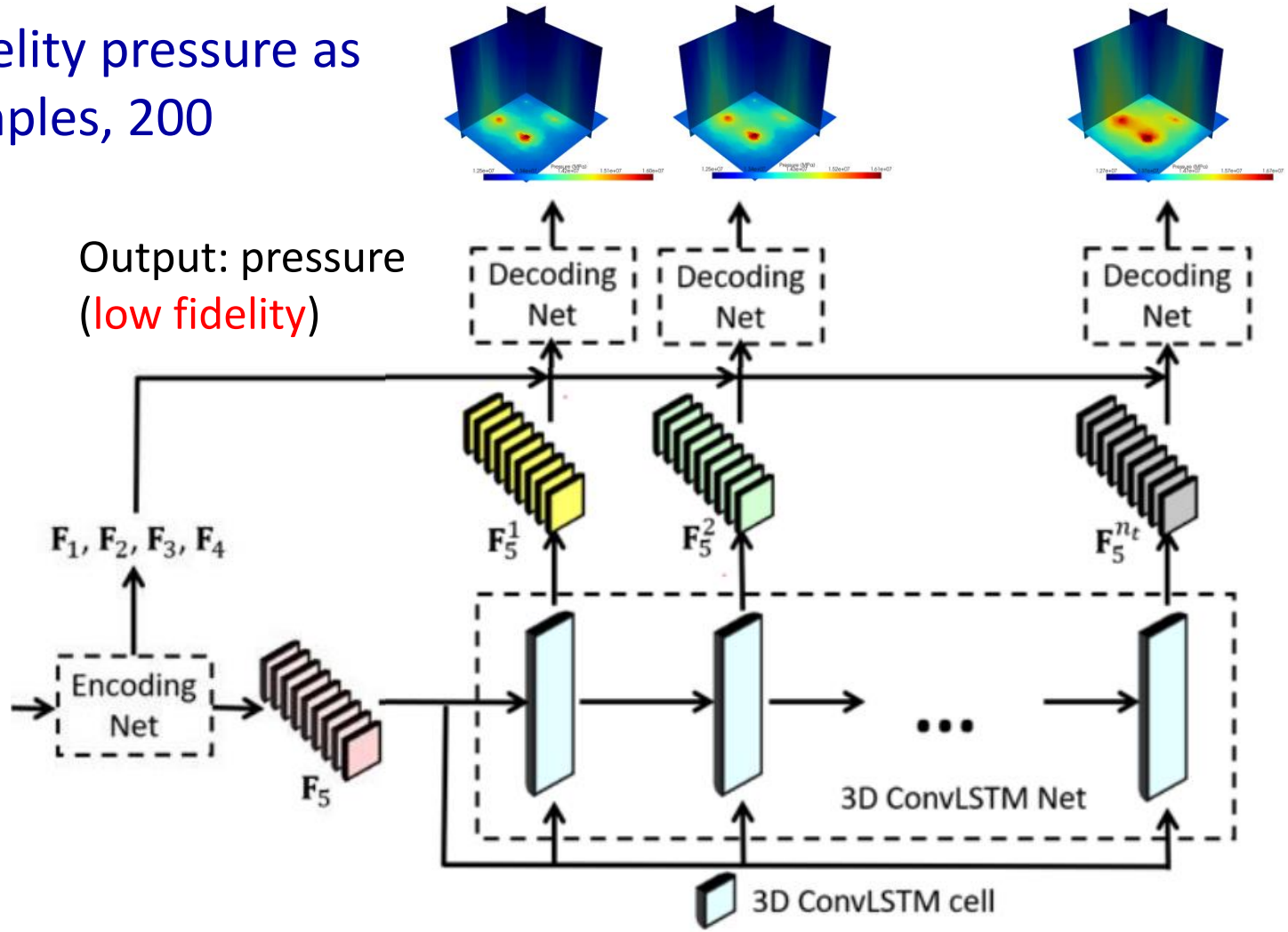
Multi-Fidelity Recurrent R-U-Net – Step 1

- Train network with low-fidelity pressure as output (1800 upscaled samples, 200 epochs)

Input:
Porosity
Permeability
(high fidelity)



Output: pressure
(low fidelity)

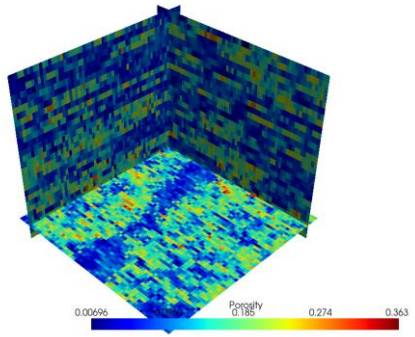


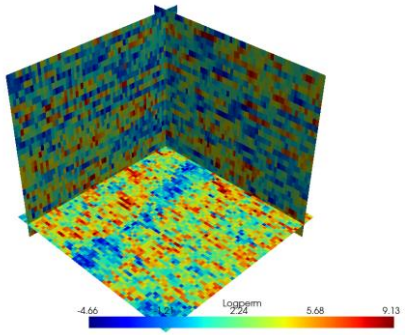
3D Recurrent R-U-Net (from Tang et al., 2021)

Multi-Fidelity Recurrent R-U-Net – Step 2

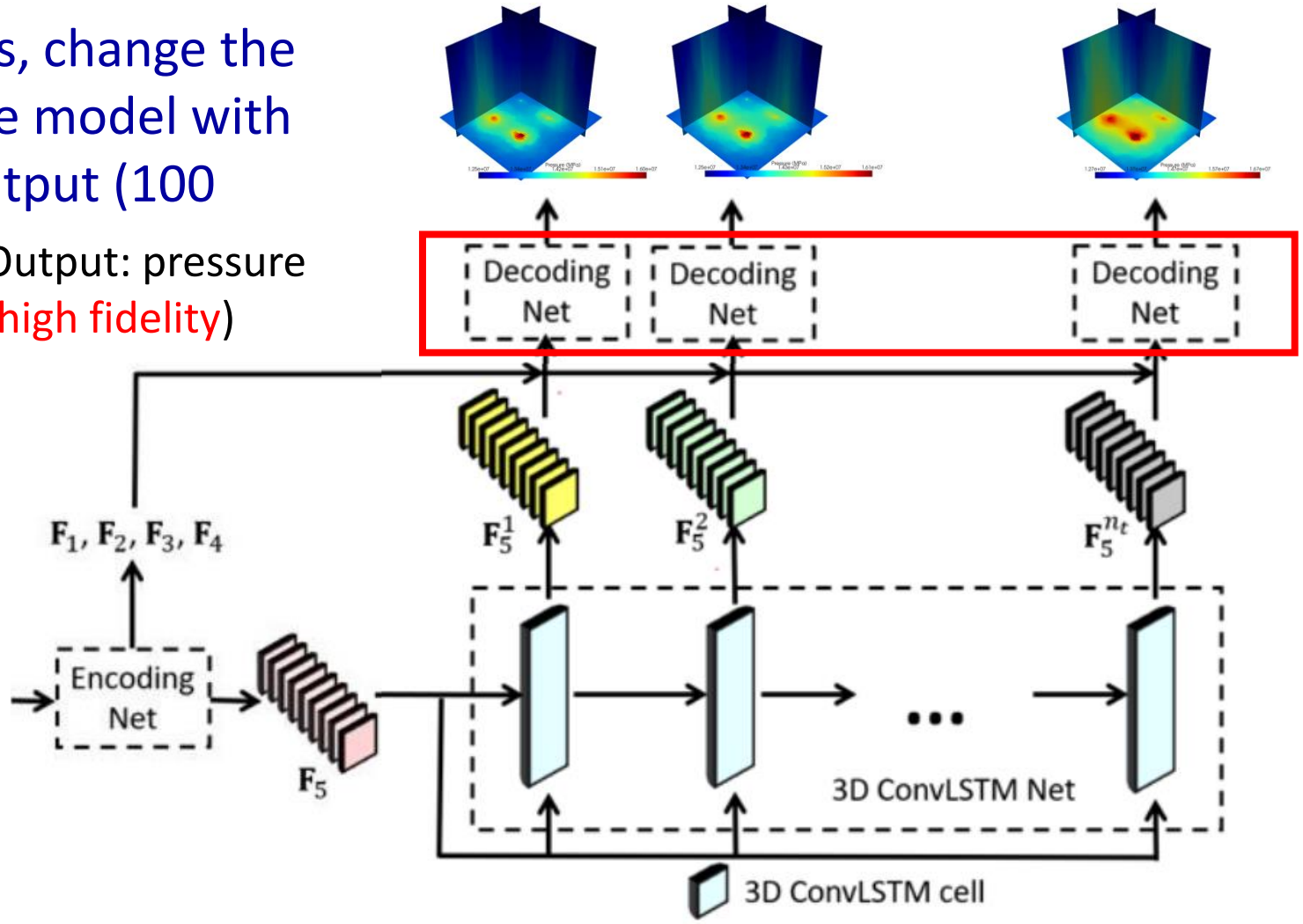
- Fix all the other parameters, change the output layer and retrain the model with high-fidelity pressure as output (100 samples, 100 epochs)

Output: pressure (high fidelity)





Input:
Porosity
Permeability
(high fidelity)

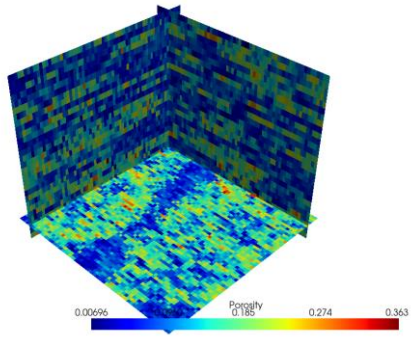


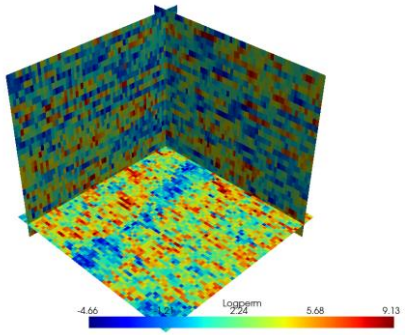
3D Recurrent R-U-Net (from Tang et al., 2021)

Multi-Fidelity Recurrent R-U-Net – Step 3

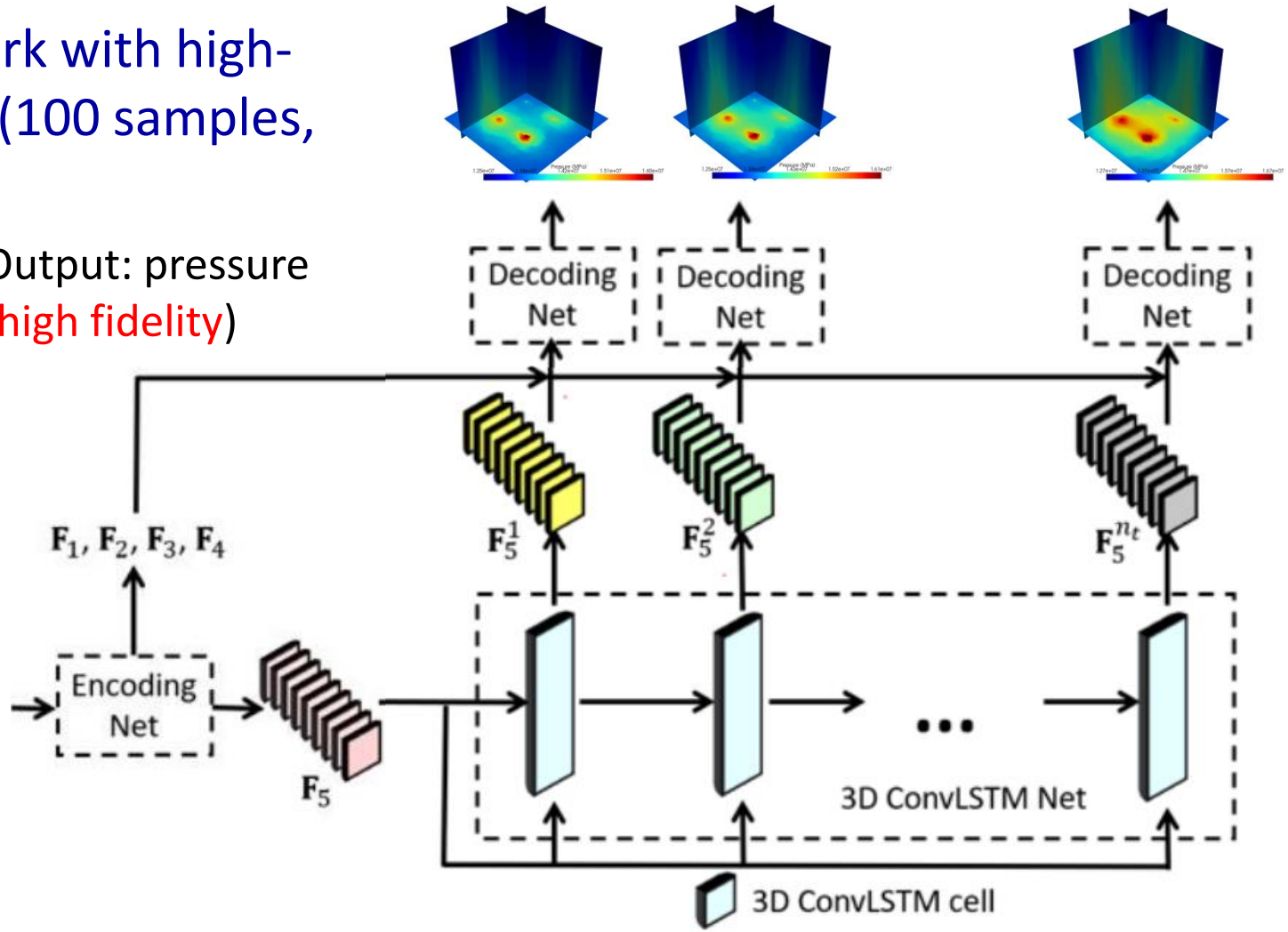
- Fine tune the whole network with high-fidelity pressure as output (100 samples, 100 epochs)

Output: pressure (high fidelity)





Input:
Porosity
Permeability
(high fidelity)

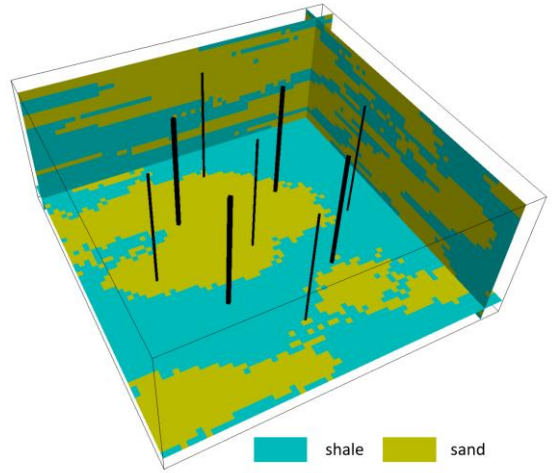


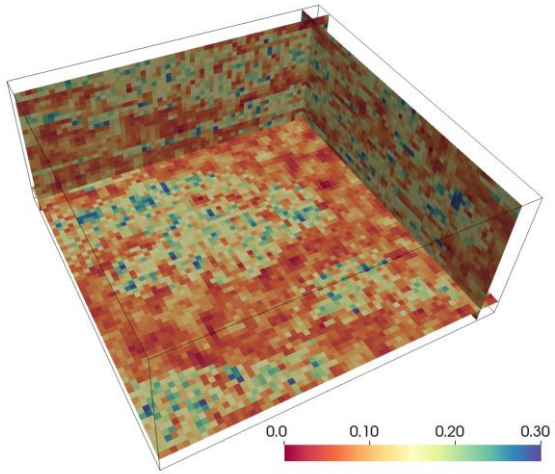
3D Recurrent R-U-Net (from Tang et al., 2021)

3D Case Setup

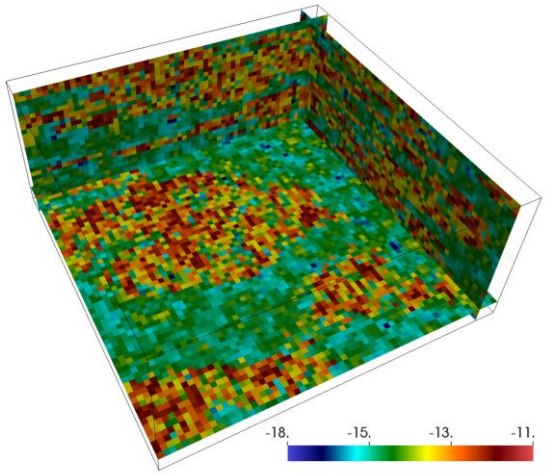
- ❑ 64 x 64 x 28 grid
- ❑ Upscale to 32 x 32 x 28 grid
- ❑ Condition to hard data at 9 wells
- ❑ Simulation time: 10 years
- ❑ 1800 for training and validation
- ❑ 100 for testing
- ❑ 100 high-fidelity samples for transfer learning

facies





porosity



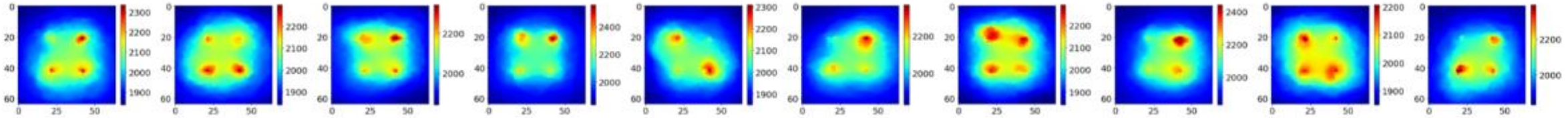
logperm

Pressure Prediction (t = 10, last layer, 10 cases, error increase)

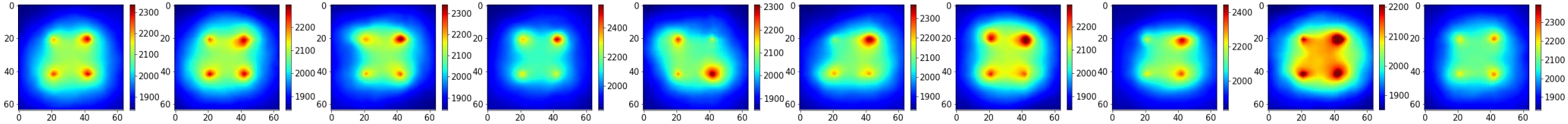
1.62% **Relative Error** **3.62%**

(1.50%) **(4.05%)**

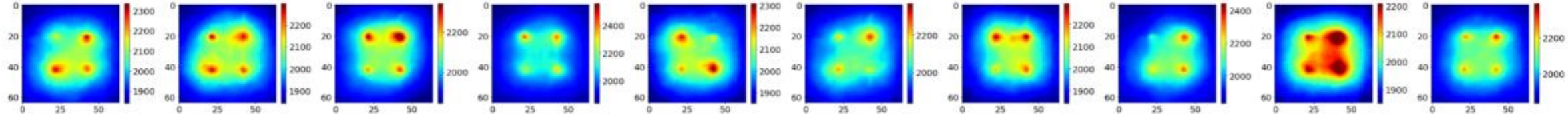
Simulation



Surrogate (reference from high-fidelity)



Surrogate (multi-fidelity training data)



Computational Time Summary

	High-fidelity training	Multi-fidelity training
GEOSX simulation (64x64x28)	~ 2 core hours x 1800 = 3600 core hours	~ 2 core hours x 100 = 200 core hours
GEOSX simulation (32x32x28)		~ 0.3 core hours x 1800 = 540 core hours
GPU training time	11.5 hours	Step 1: 9.3 hours Step 2: 0.1 hours Step 3: 0.3 hours = 9.7 hours

Conclusions

- ❑ Surrogate model with multi-fidelity training data provides accurate pressure prediction
- ❑ Multi-fidelity framework saves 80% simulation time