ML-based Dimension Reduction Strategies

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AI-Powered Carbon Capture and Storage

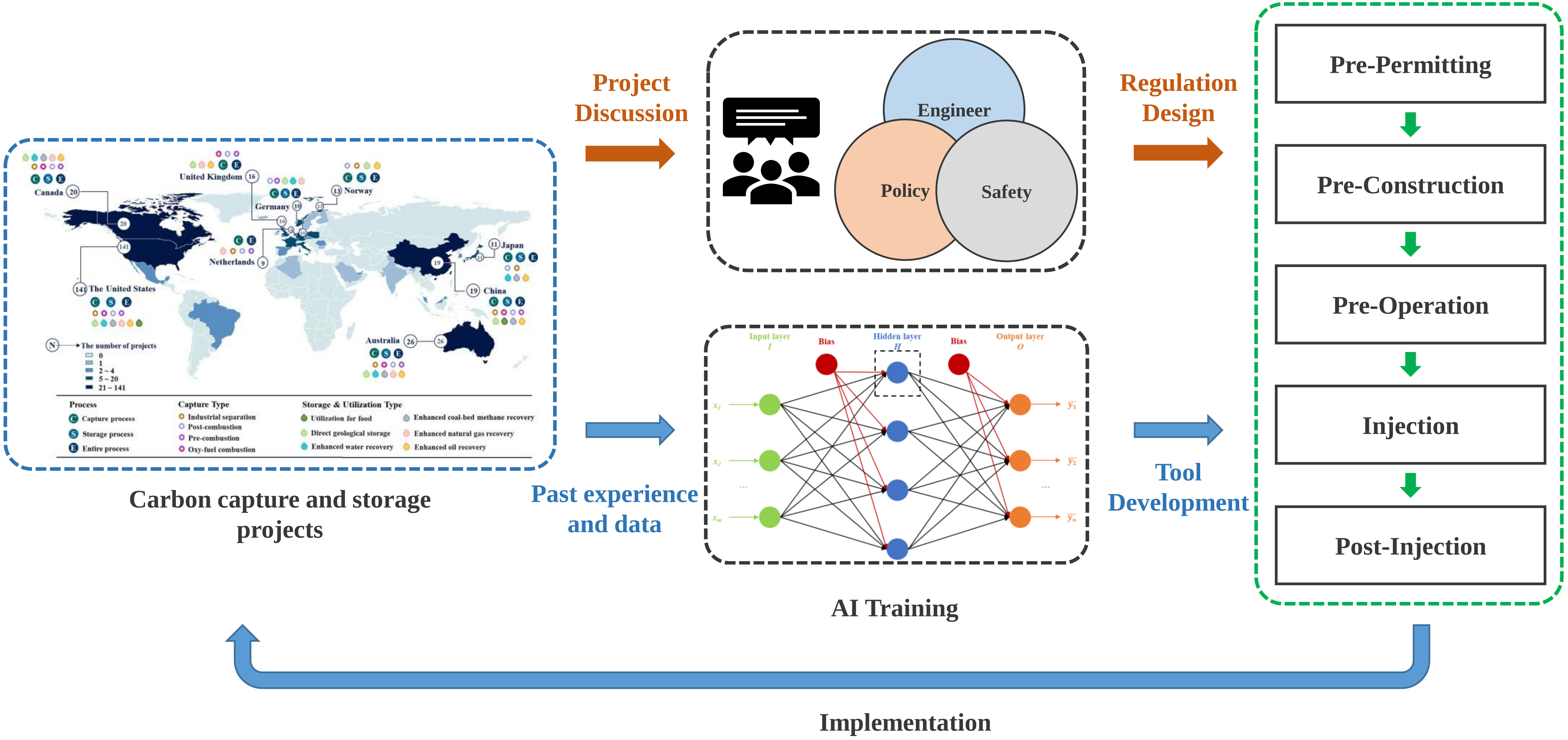
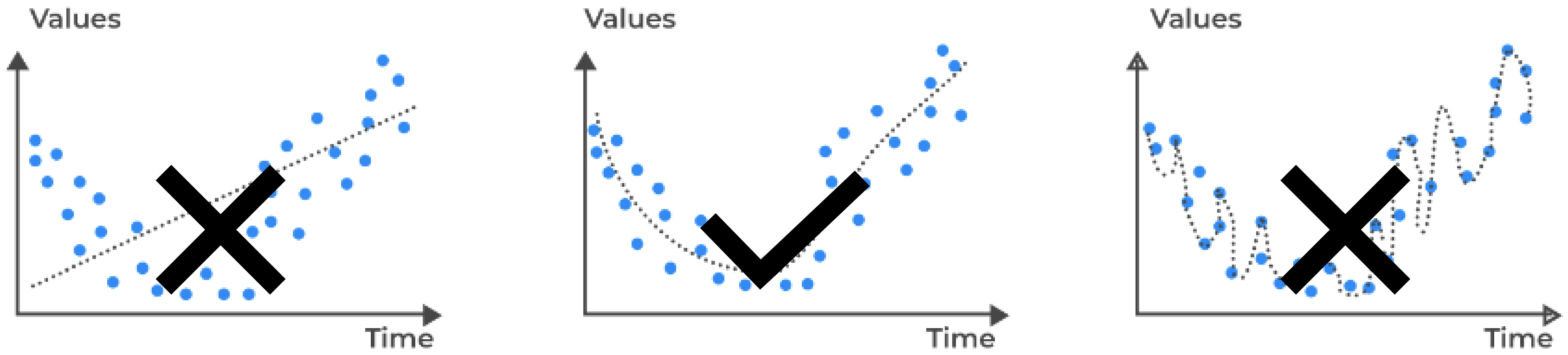


Figure reference: [Kang et al., 2021]

Challenges and motivations: Part 1

- Supervised learning achieved successes in subsurface applications.

○ **High model training cost: computation burden and training dataset.**



Underfitting **Good fit** **Overfitting**

✓ **Train model on latent spaces: Dimension Reduction.**

- ✓ Keep data variance.
- ✓ Reduce feature number.

Figure reference: Google search

Methodology

- **Step 1: Dimension reduction models for Geological Parameters and State Variables.**
- **Step 2: Construct mapping function in latent spaces with less features.**
- **Step 3: Apply to new realizations or new datasets.**

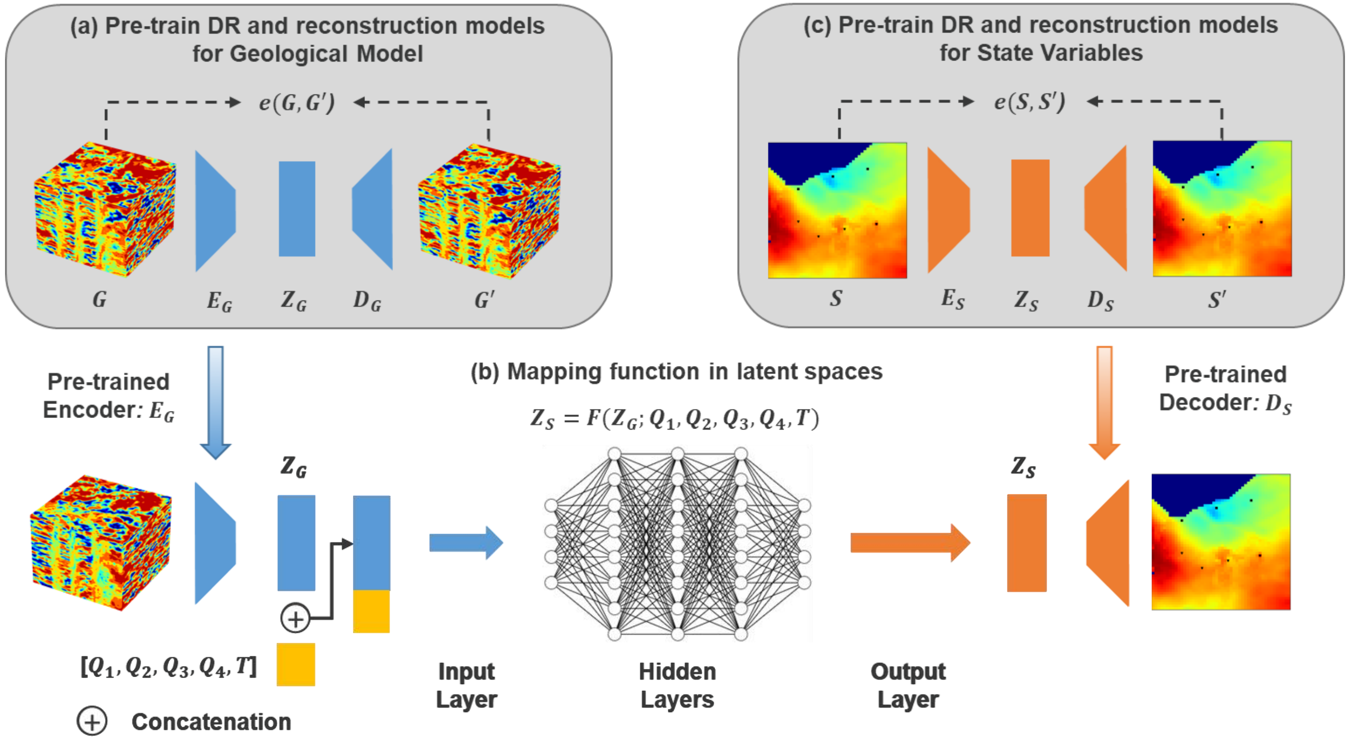
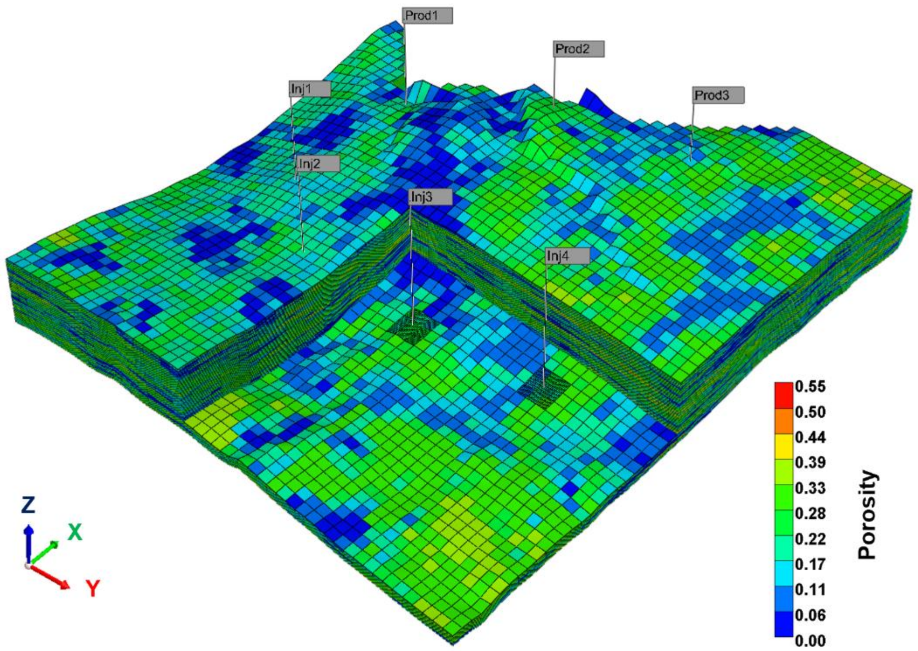
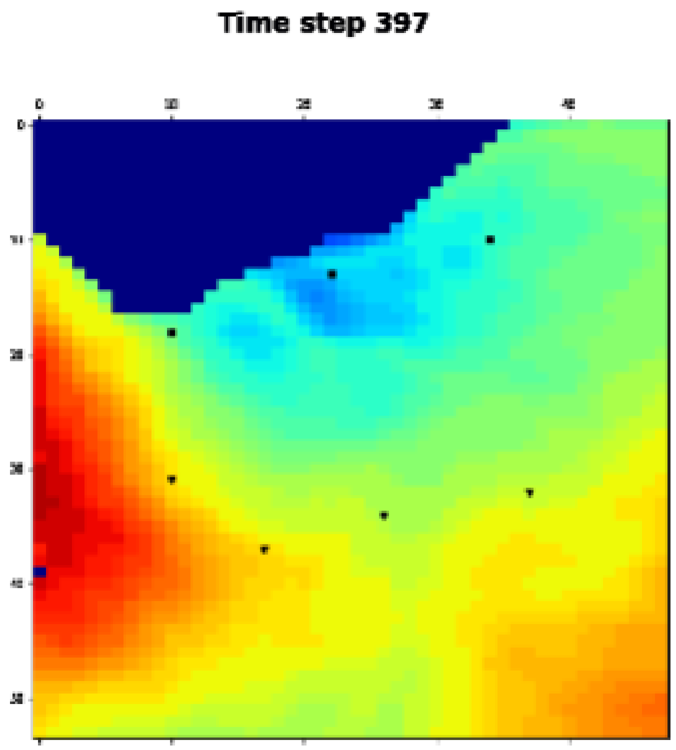


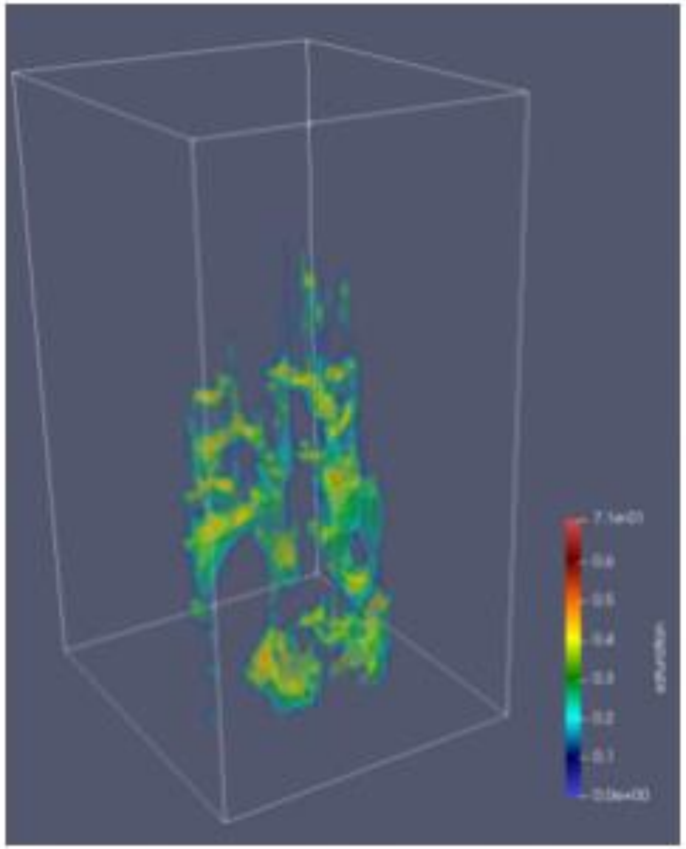
Figure reference: [Wang et al., 2024]

Results: Part 1 – GoM Dataset



Geological Model



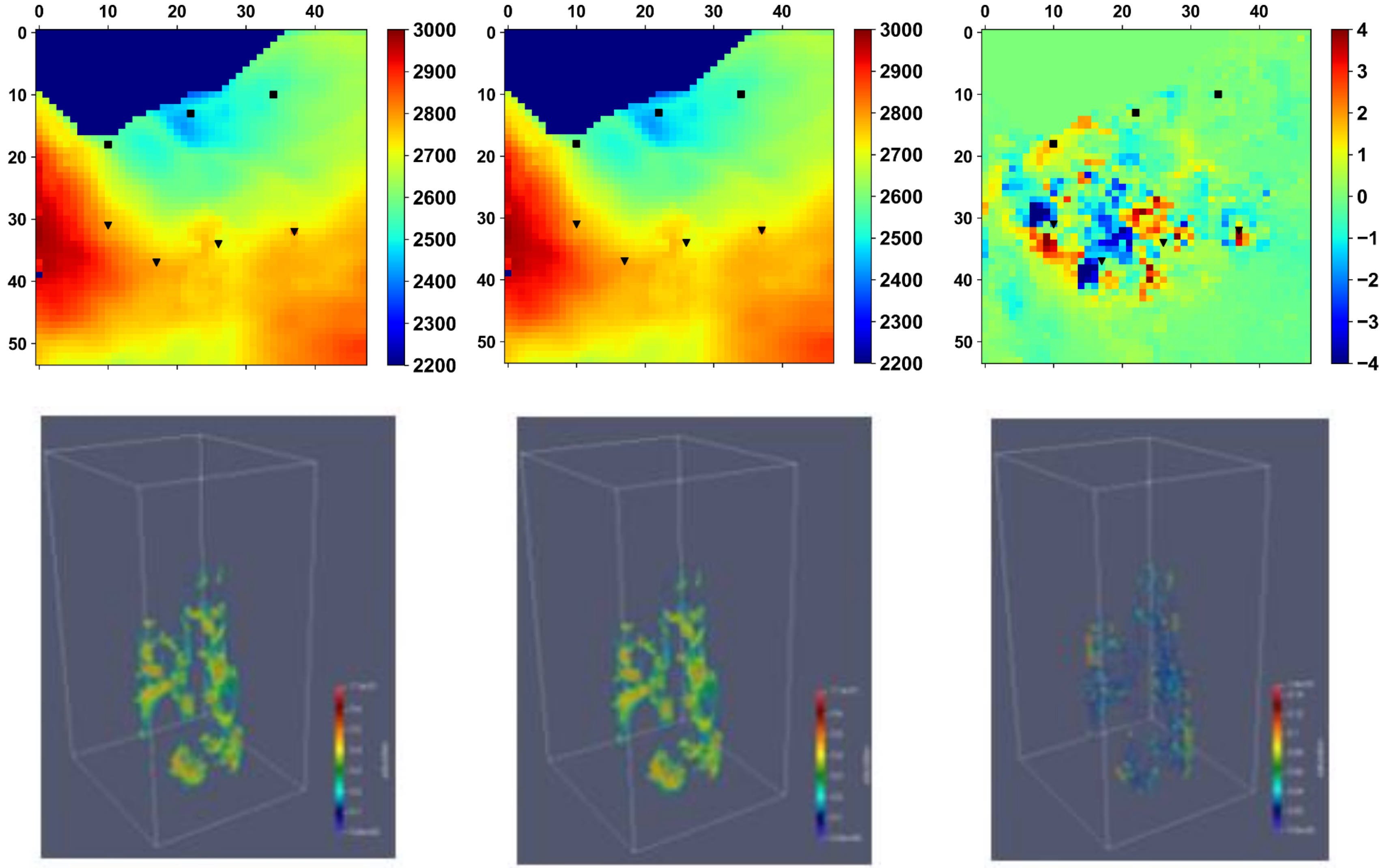


State variables
(Left: 2D slice of pressure; Right: CO2 saturation)

Results: Part 1 – GoM Dataset

Pressure

Saturation

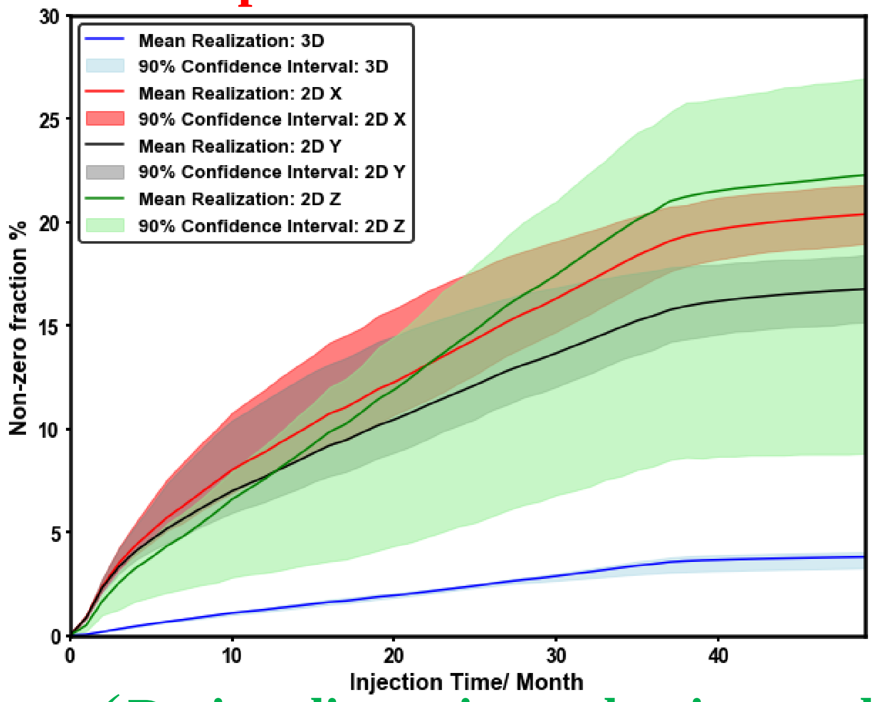


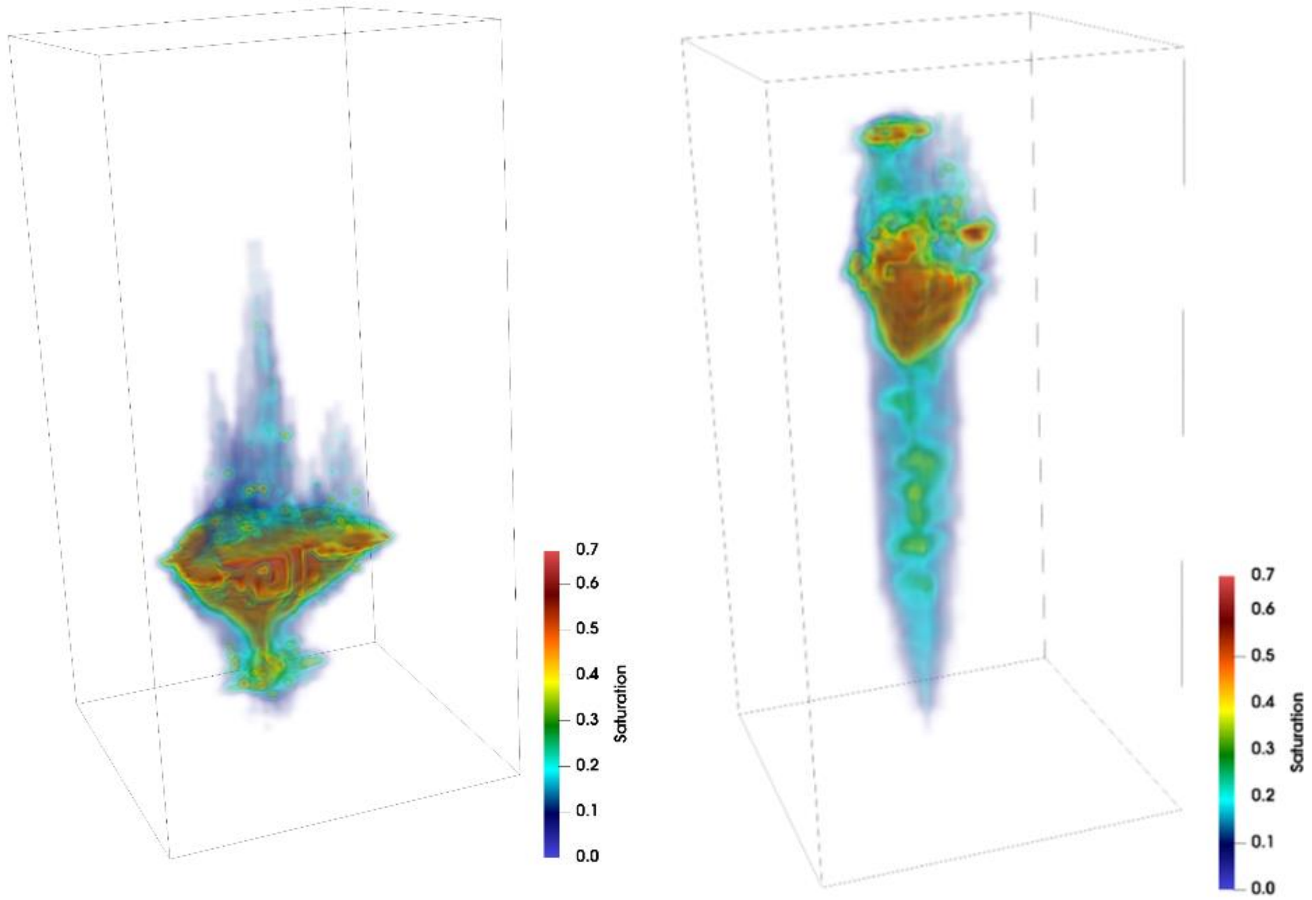
CMG simulation (4.5 h) DL results (1.7 mins) Difference

Challenges and motivations: Part 2

- **Workflow works!**

○ **Complex 3D saturation data**





More data variations with/without Baffle

✓ **Design dimension reduction model for saturation data.**

- ✓ New model.
- ✓ New loss function.

Figure reference: Google search

Methodology

- **Step 1: Dimension reduction models for 2D saturation data.**
- **Step 2: Deep learning-based 3D reconstruction.**

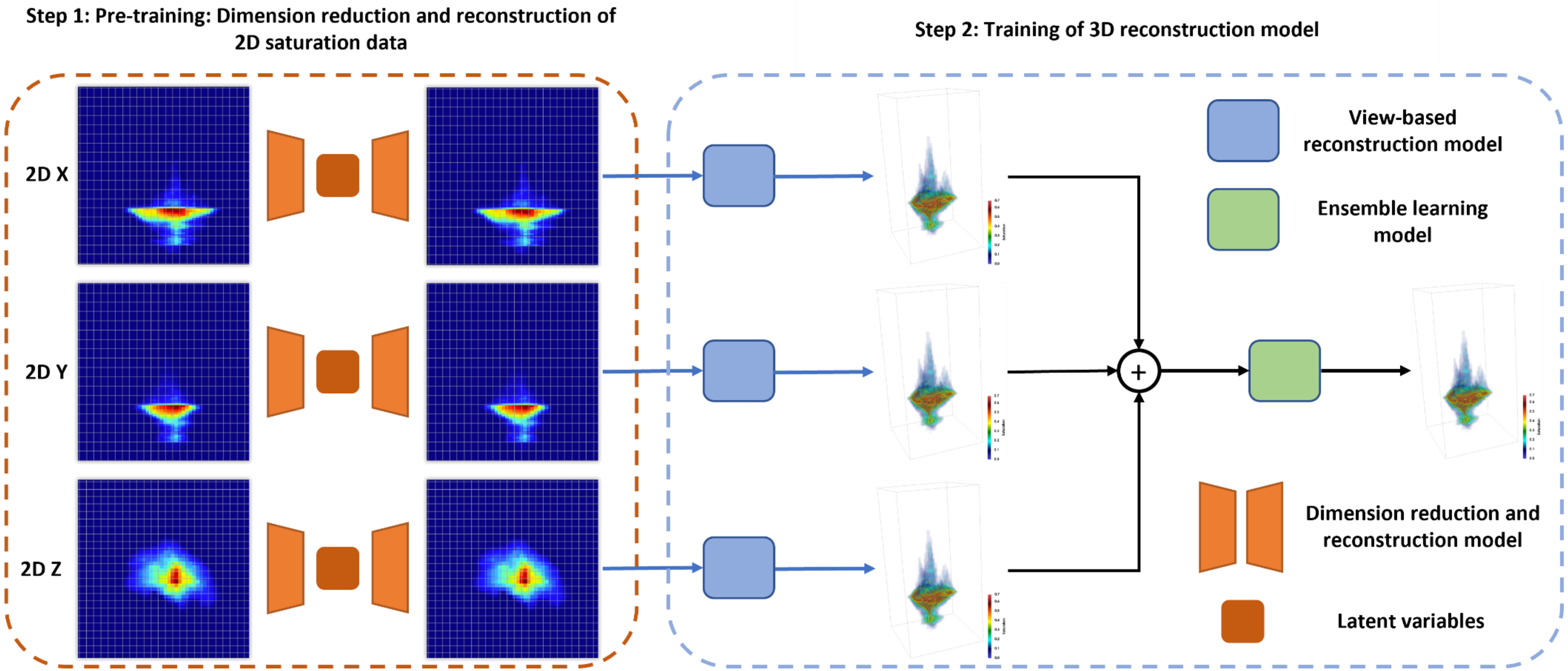
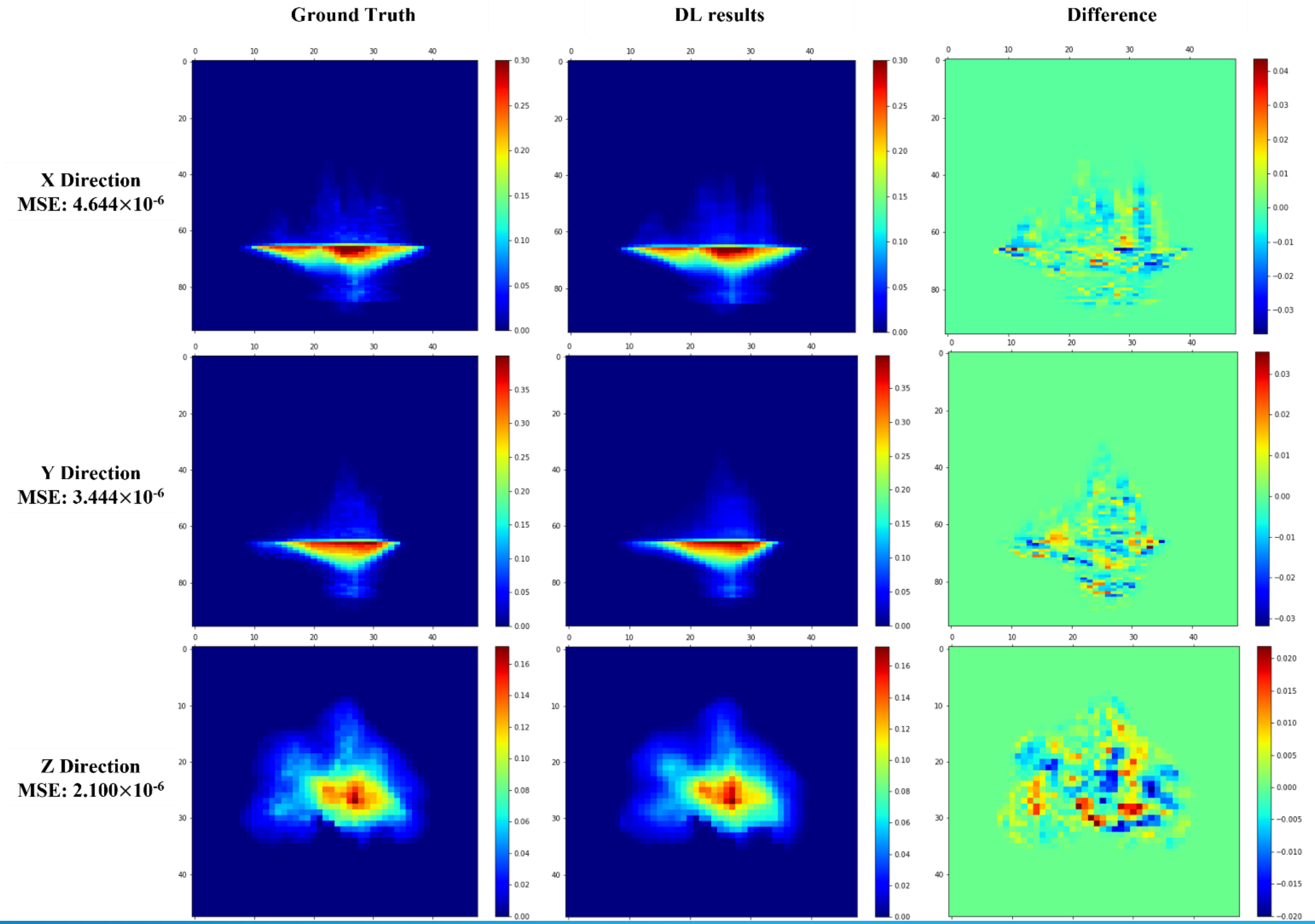


Figure reference: [Wang et al., 2024]

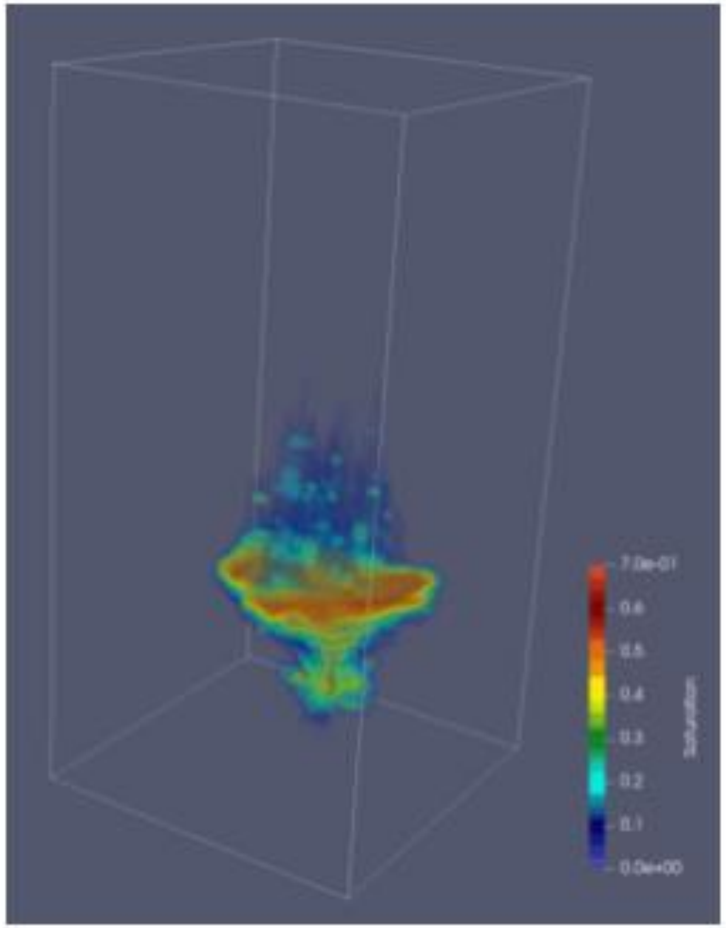
Results: Part 2 – IBDP Dataset

- **Dimension reduction is easier for 2D data.**
  - ❑ Low error observed.
  - ❑ Convolutional autoencoder models used.
  - ❑ 128 latent variables for 2D saturation data on each direction.

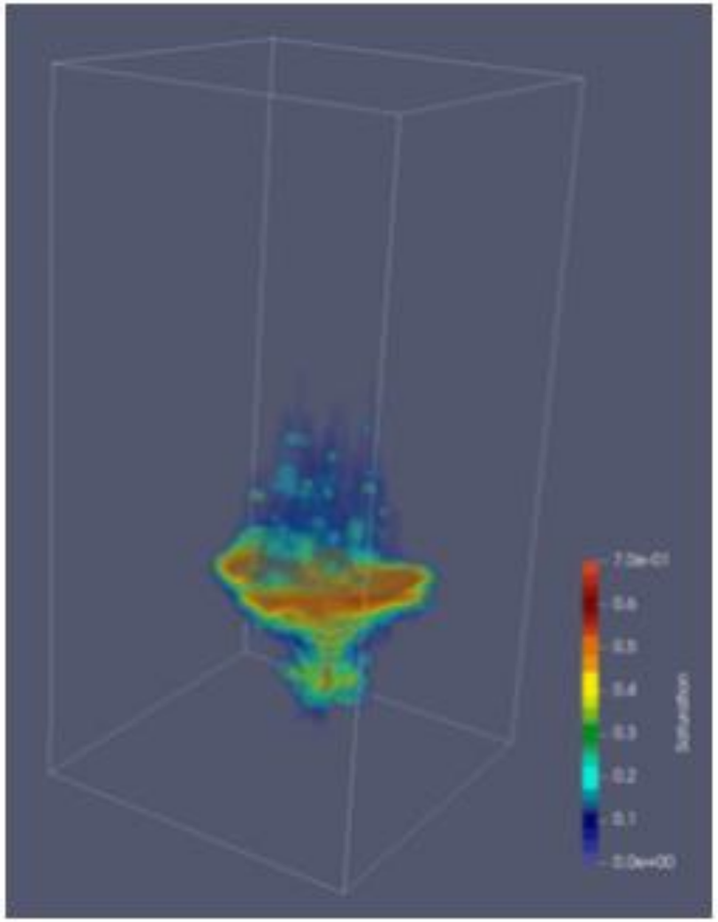


Results: Part 2 – IBDP Dataset

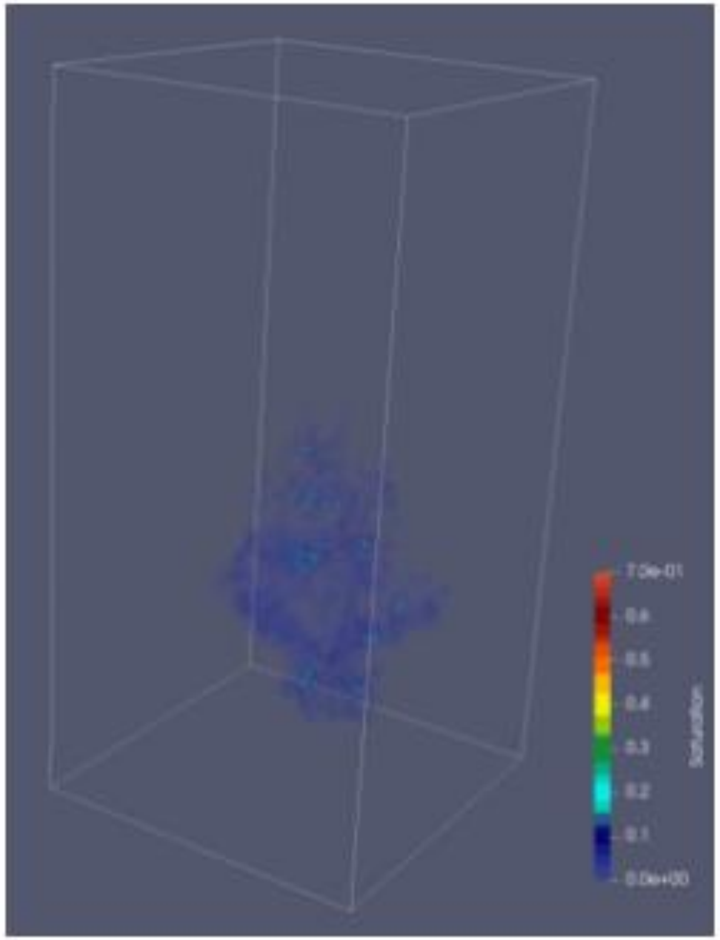
- **3D reconstruction model achieved good performance.**



Ground Truth



3D Reconstruction



Difference

Conclusions

- **Excellent Performance Achieved:** Integrated dimension reduction and deep learning models accurately predict state variables with short prediction time.
- **Flexible Model Selection:** Dimension reduction model selection is adaptable to specific dataset needs, enhancing performance.
- **Geological vs. Saturation Challenges:** Dimension reduction is straightforward for geological models like porosity and permeability but challenging for 3D saturation data.
- **Effective Multi-Step Approach:** A multi-step process involving dimension reduction of 2D data and 3D reconstruction shows promise for handling complex 3D saturation.

Thank you!

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