Rapid forecasting of pressure and saturation for IBDP site and practical implementation issues

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SMART

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

Motivation

- ❑ Traditional full-physics reservoir simulations are computationally intensive, making real-time forecasting for forward and inverse modeling impractical. Machine learning (ML)-based surrogate models offer the potential for rapid predictions while maintaining reasonable accuracy.
- ❑ The SMART project has generated a rich database from ensembles of reservoir properties. Leveraging this database with ML algorithms can lead to powerful predictive tools that can efficiently capture complex reservoir dynamics.
- ❑ The goal is tailored to the Illinois Basin Decatur Project (IBDP) site, ensuring that the developed models are specific, relevant, and capable of accurately predicting the evolution of CO_2 and pressure plumes for this particular reservoir.

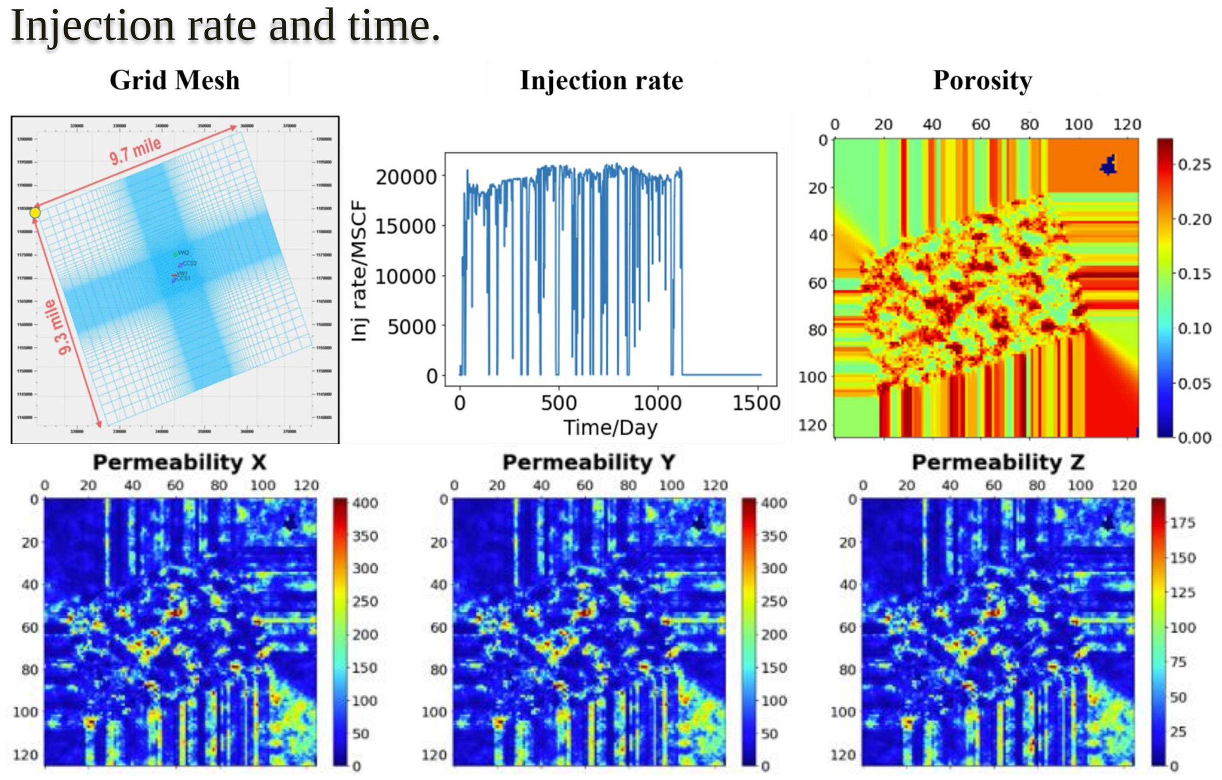
Research Objectives

- ❑ Adapt the previously developed CNN-MLP model from SMART Phase I to ensure compatibility and optimal performance with the IBDP dataset.
- ❑ Develop the UNet models for predicting the dynamic evolution of CO_2 and pressure plumes.
- ❑ Apply both the adapted CNN-MLP and the newly developed U-Net models to the IBDP dataset, aiming for real-time forecasting of reservoir performance with improved accuracy.

Dataset

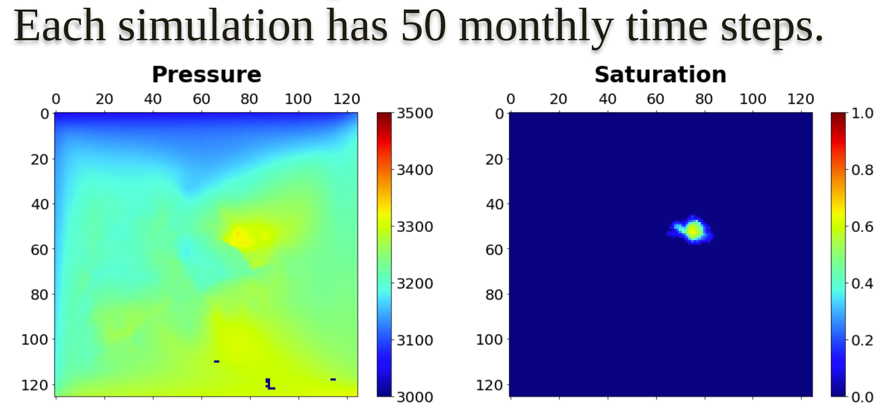
Input data: 100 realizations. Dimension (126, 125, 110).

- ❑ First 80 with modifiers and last 20 without modifier.
- ❑ Parameters:
  - ▪ Grid mesh: Coordinate x, y, and z; Grid volume.
  - ▪ Geological models: Permeability x, y, and z; Porosity.
  - ▪ Injection rate and time.

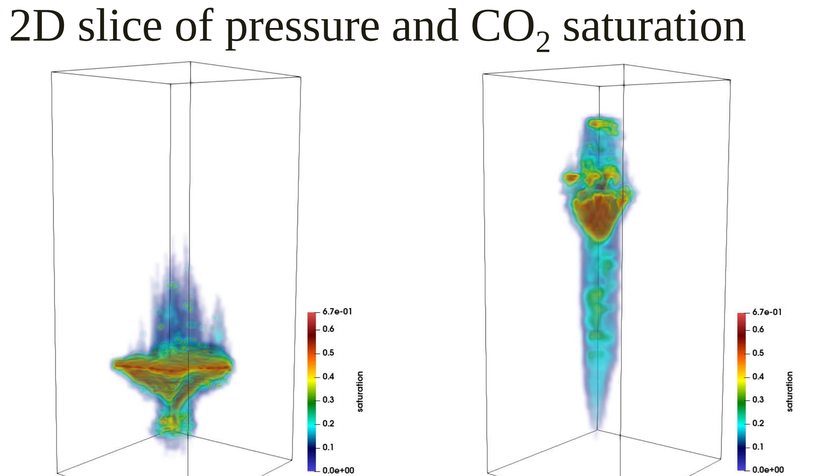


Output state variables: 100 realization.

- ❑ Pressure and CO_2 saturation.
- ❑ Each simulation has 50 monthly time steps.



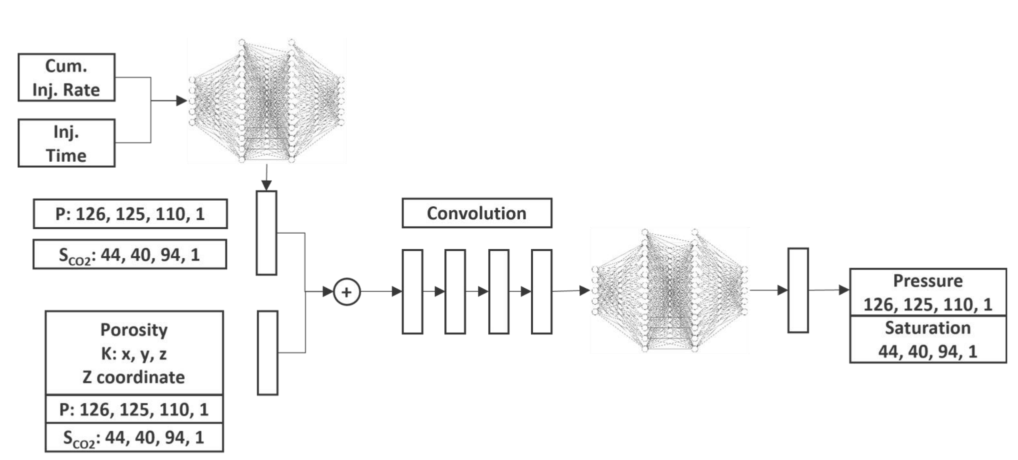
2D slice of pressure and CO_2 saturation



Left: With modifier; Right: Without modifier.

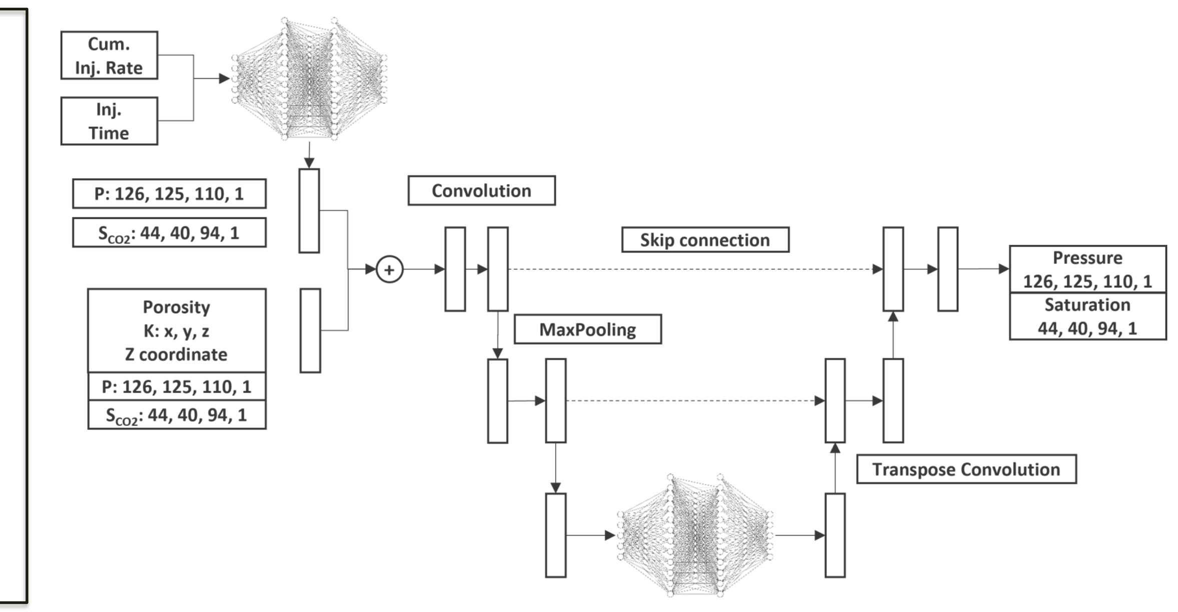
Models

- ❑ Model 1: convolution neural network (CNN)-multilayer perceptron (MLP)
- ❑ Developed in Phase I and adapted for IBDP dataset.
- ❑ Two separate models:
  - ▪ Pressure: Full domain (126, 125, 110).
  - ▪ CO_2 Saturation: Cropped domain (44, 40, 94).
- ❑ Train on 90 realizations and test on 10 realizations.



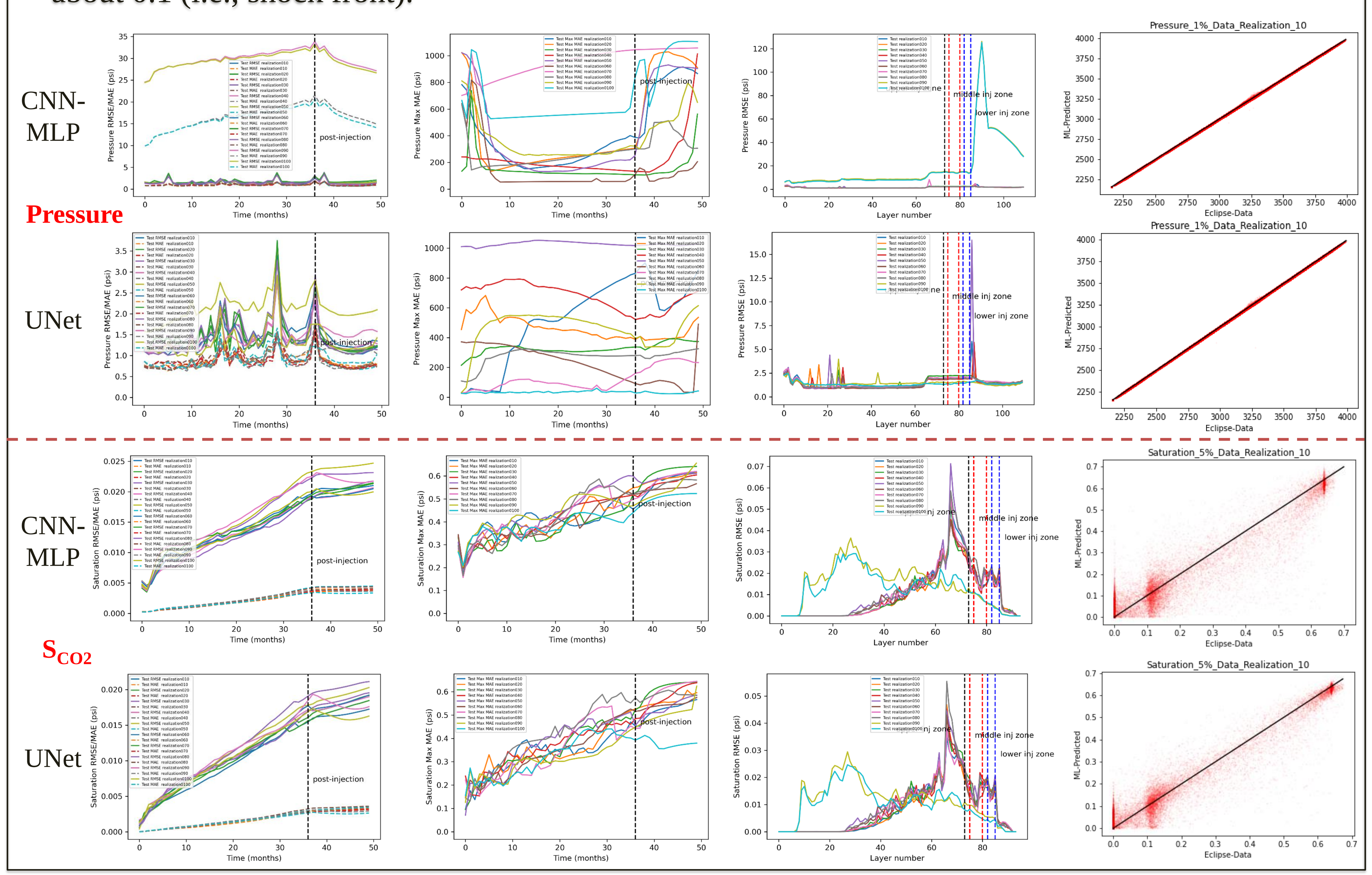
Models

- ❑ Model 2: convolution neural network (CNN)-multilayer perceptron (MLP) in UNet architecture
- ❑ Developed in Phase II for IBDP dataset.
- ❑ Two separate models:
  - ▪ Pressure: Full domain (126, 125, 110).
  - ▪ CO_2 Saturation: Cropped domain (44, 40, 94).
- ❑ Train on 90 realizations and test on 10 realizations.
- ❑ Input: Permeability x, y, and z; Porosity; z coordinate; Injection rates and time.
- ❑ Output: Spatial-temporal state variables.



Results and Summary

- ❑ The pressure prediction of both models are accurate. UNet model is better than CNN-MLP
- ❑ The saturation prediction of both models need to be improved. The main errors happen at the values about 0.1 (i.e., shock front).



Acknowledgment

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