Robust data assimilation/history matching applications for the IBDP with generative priors

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

Objectives: Accurate history matching of CO_2 operations and real-time forecasting CO_2 and pressure plume development at the Illinois Basin-Decatur Project (IBDP) site by
(1) developing a generative model (i.e., variational autoencoder, VAE) for parameter (3D permeability, porosity, and fault multipliers) generation,
(2) learning low dimensional representations in latent space to parameterize for data assimilation,
(3) utilizing machine learning driven surrogate models for fast and accurate forward prediction

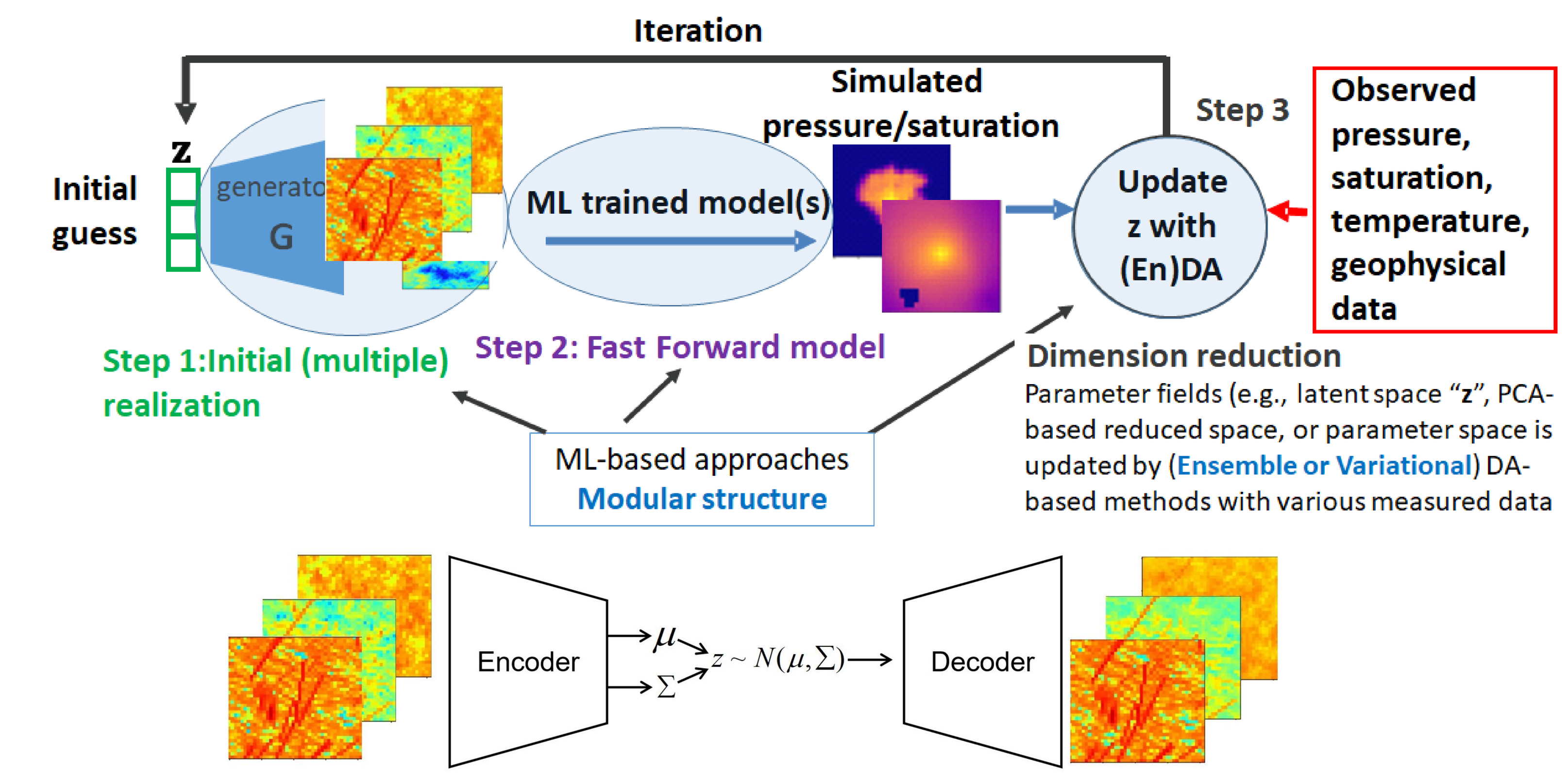

Figure 1. (top) A schematic of latent space-based data assimilation (LSDA) with ML forward models and (bottom) variational autoencoder for 3D permeability, porosity, and fault transmissivity multipliers.

ML training data generation at IBDP

- The IBDP site consists of a single injection well, a verification well, and a geophysical monitoring well.
- Only bottom hole pressure data at the injection and monitoring wells are used for current DA.
- ECLIPSE Compositional Model (E300) for reservoir simulations:
  - Grid: 126 * 125 * 110 (1.73 Million Cells)
  - Simulation Period: 11/02/2011-12/31/2015
  - 3D pressure and saturation (monthly, 50 time steps)
  - Pressure/CO_2 saturation at wells (daily)

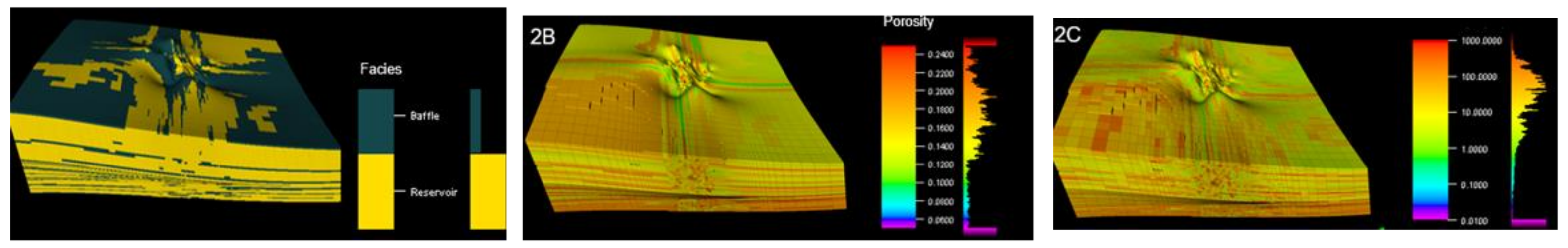

Figure 2. 3D distribution of low permeable baffles (left), porosity (middle), and permeability distribution (right).

Two ML forward models

(1) CNN-LSTM model for bottom hole pressures at injection (CCS1) and monitoring wells (VW1, WB1-6) with input of static parameters (3D x,y,z permeabilities, porosity, and x,y,z transmissivity multipliers), and injection data (CO2 injection rates, cumulative volume, and time)
(2) Improved neural operator (INO) for 3D pressure and saturation prediction (monthly) using updated model parameters from LSDA

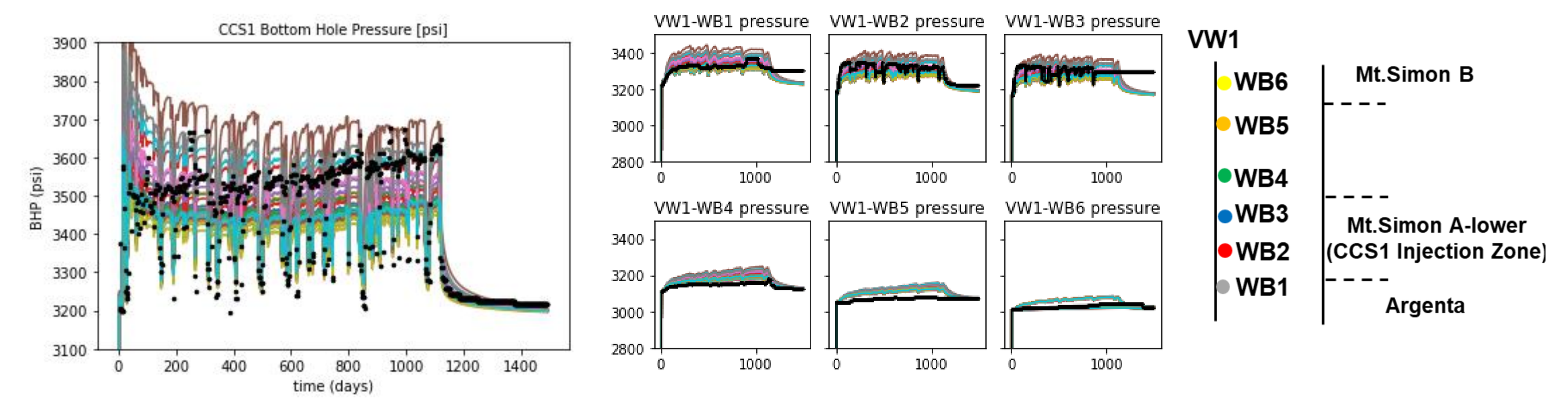

Figure 3. Observed (black) and Eclipse simulations-based (color) daily bottom hole pressure data at the CCS1 injection well (left) and multi-depth sensors at a verification well (VW1).

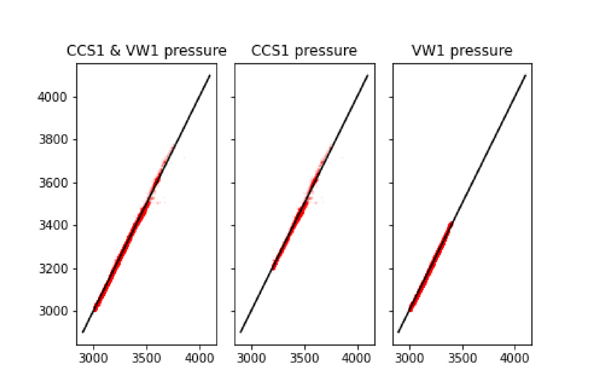

Figure 4. CNN-LSTM model for BHP prediction at CCS1 and VW1 wells.

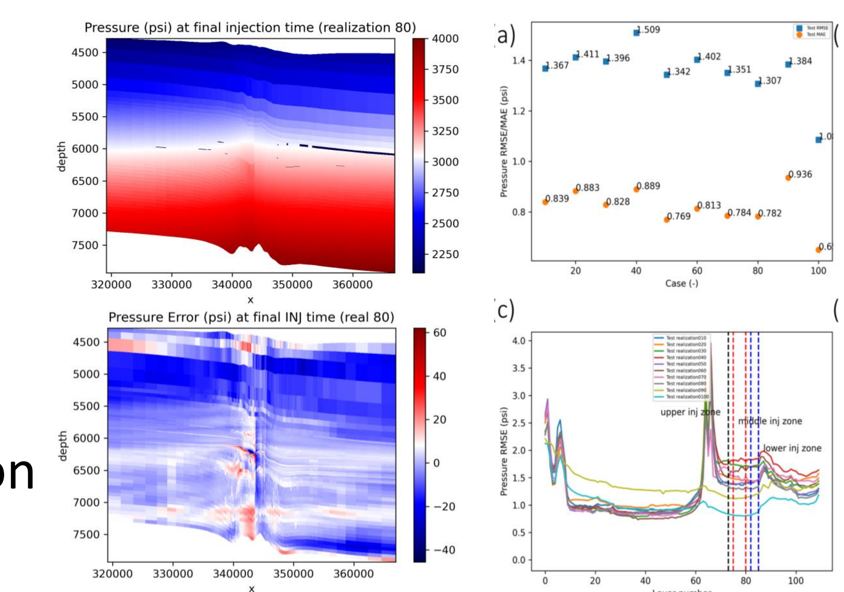

Figure 5. A snapshot of vertical cross-sectional pressure distribution at the end of CO_2 injection (3 years), ML-prediction error, and root mean square error (RMSE) and mean absolute error (MAE) changes over time and over layer.

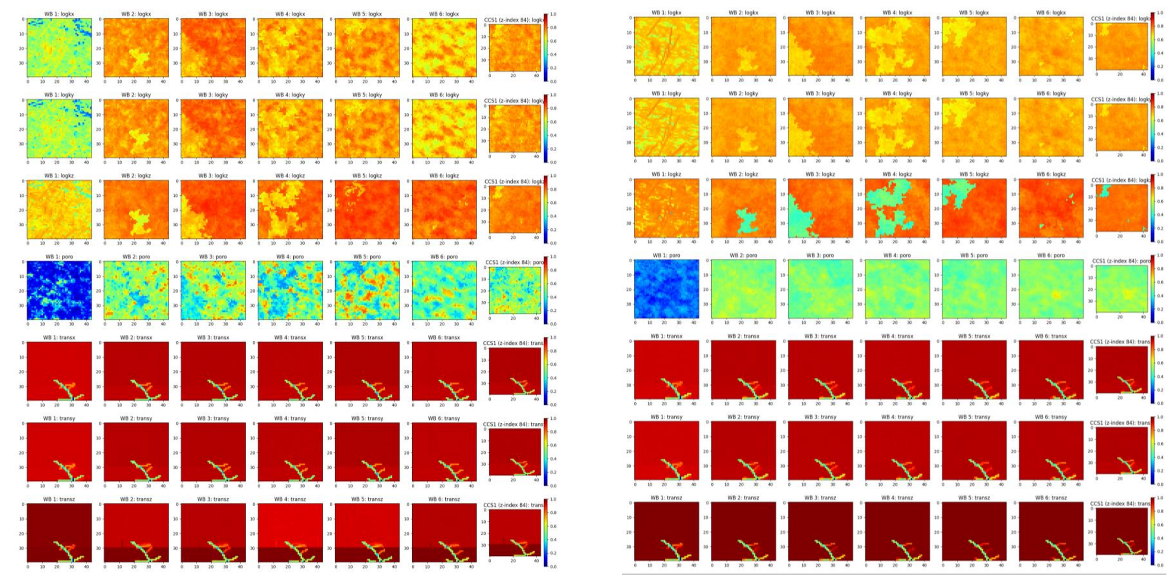

Figure 6. VAE prior (left) and LSDA (right) outcomes to show 3D x,y,z permeabilities, porosity, and x,y,z transmissivity multipliers at CCS1 and six sensor depths at VW1.

History matching results

➔ LSDA takes ~ 10min using a laptop computer.

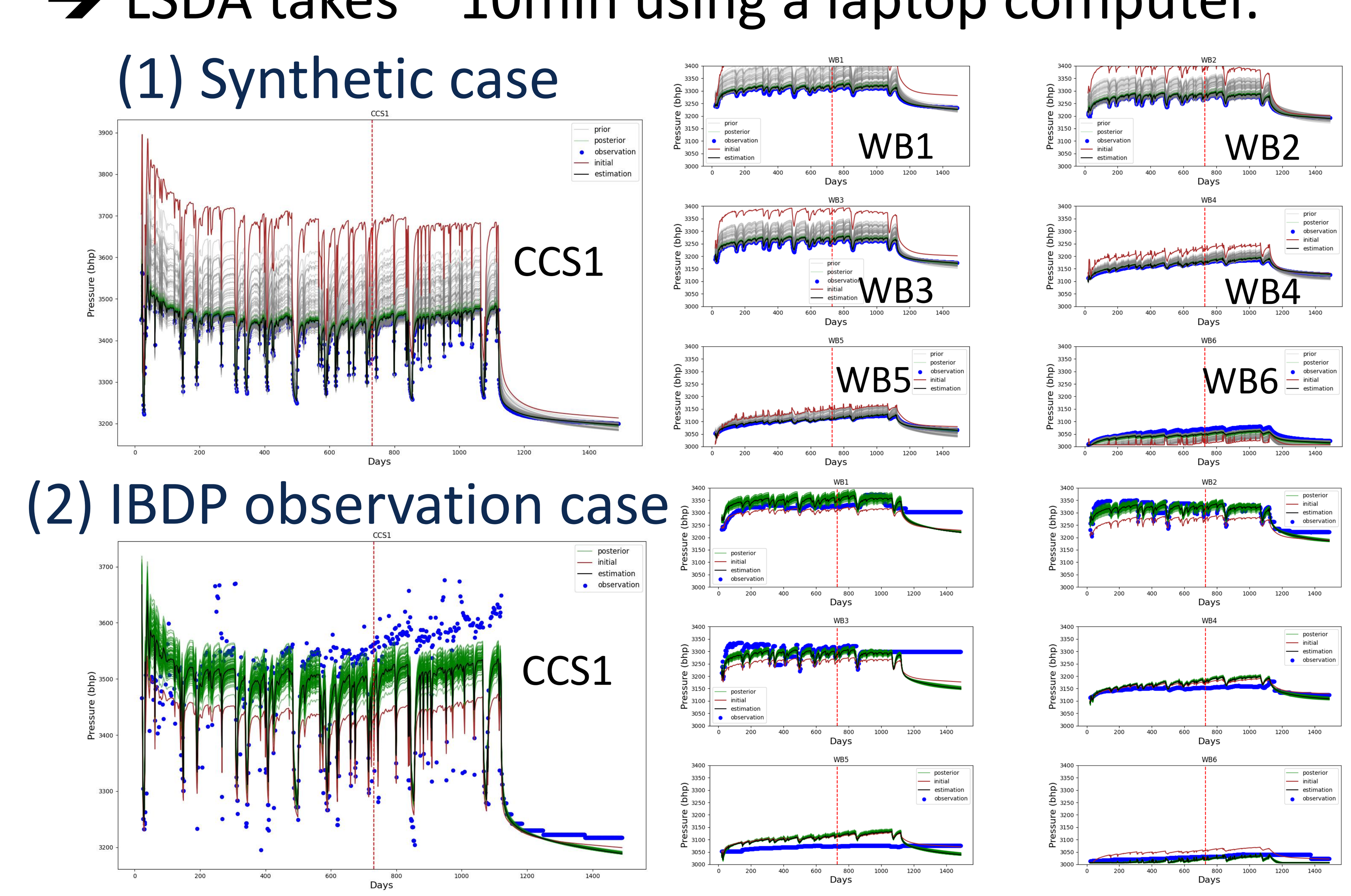

Figure 7. History matching results with bottom hole pressure data from (1) synthetic and (2) real IBDP cases. 2 years calibration & blind test for the rest of period.

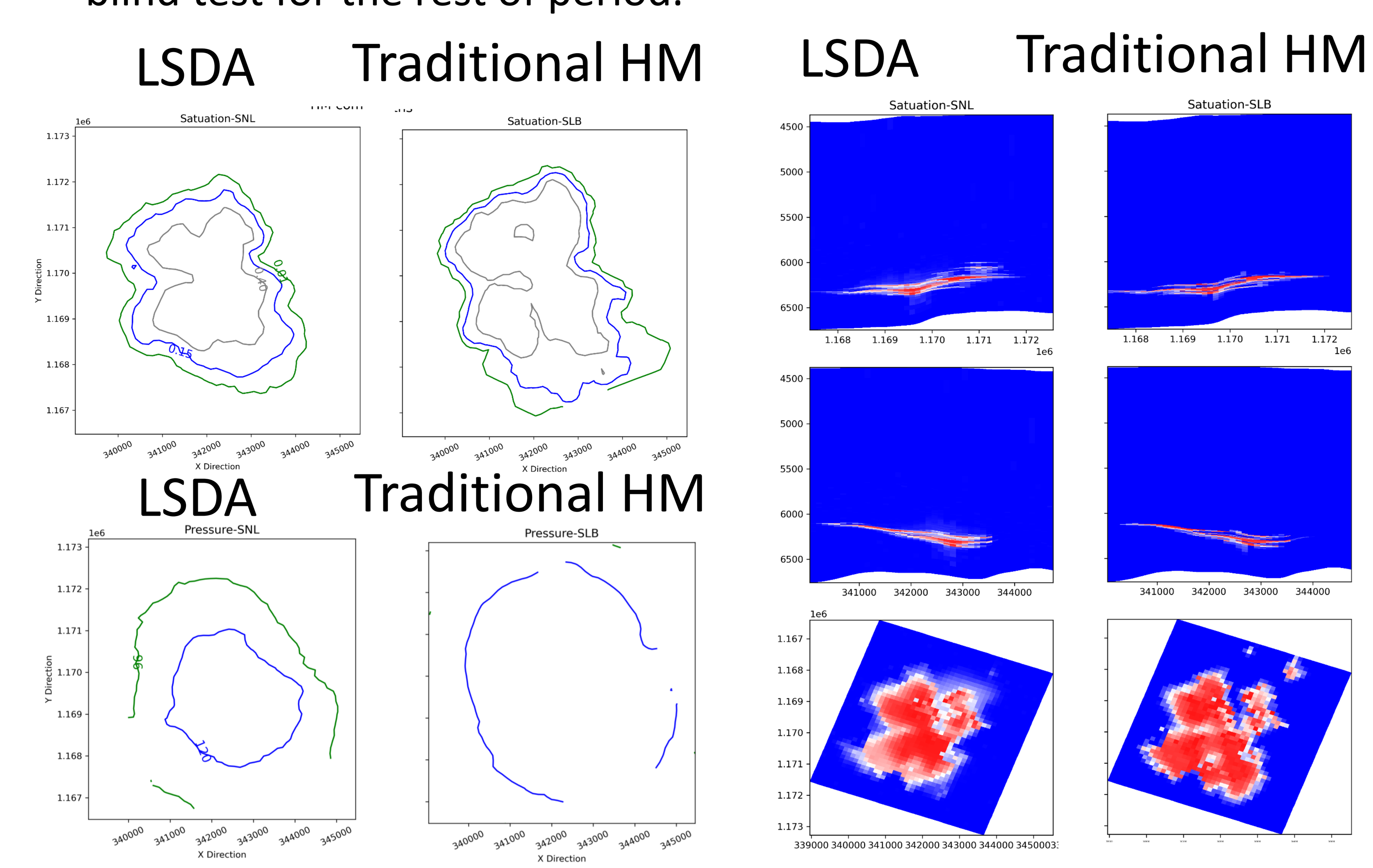

Figure 8. Area of review comparison for CO2 saturation (top) and pressure (bottom) as well as CO2 plume distribution (right)..

Future works

- HM workflow update with multiple data (BHP, CO2 saturation, and temperature at CCS1 and VW1 wells.
- A wider range of static parameter fields for ML training data

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