SMART-Phase 2

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

ML-based Data Assimilation and History Matching: Application to the IBDP CCS Project

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U.S. DEPARTMENT OF ENERGY

NATIONAL ENERGY TECHNOLOGY LABORATORY

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Objective and Challenges

- Development and application of ML-assisted tools and workflows for **field-scale application and validation** of geologic carbon storage
  - Rapid forecasting of CO_2 plume evolution and field pressure constrained to observed data while accounting for data sparsity and geologic uncertainties
- Current Challenges
  - Expensive forward simulation: multiphase, compositional and coupled flow
  - Repeated simulations for model calibration and uncertainty analysis
  - Traditional history matching is time consuming -- often takes weeks/months and is not amenable to real time decision-making

Proposed Workflow: Outline of Steps

- **Dimensionality and computational time reduction for training data generation**
  - Diffusive time of flight (DTOF) map representing pressure front propagation
- Neural Network Training
  - Variational autoencoder (VAE) for DTOF image compression using latent variables
  - Regression model to estimate autoencoder latent variables based on the monitoring data
- Prediction of CO_2 plume images
  - Estimate DTOF image from monitoring data (pressure and temperature at the injection and monitoring wells)
  - Predict CO_2 plume images

Data Dimensionality and Computational Time Reduction:
Single DTOF Map Representing Pressure Propagation

Radius of Investigation (ROI)
for homogeneous reservoir

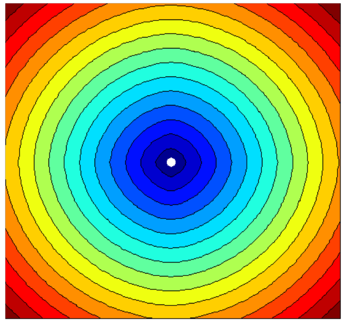
$$r = \sqrt{\frac{4kt}{\phi \mu c_t}}$$

Generalization of ROI
for heterogeneous reservoir

Eikonal eq.: $$\sqrt{\frac{k(\mathbf{x})}{\underline{\phi(\mathbf{x})\mu c_t}}}\left|\nabla \tau\right| = 1$$

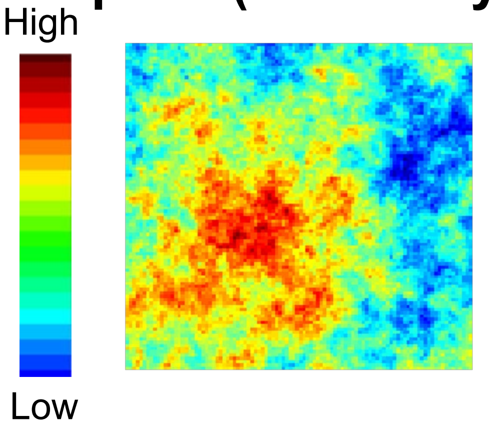
Fast Marching Method (FMM)

'Peak' arrival time

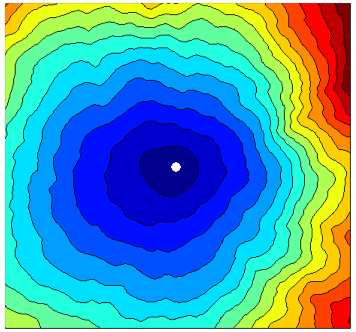


(Lee, 1982)

Speed (diffusivity)



Diffusive Time-of-Flight (DTOF)



(Datta-Gupta,et al., 2011)

Eikonal solution takes only a few seconds for multi-million cell models

Proposed Workflow: Outline of Steps

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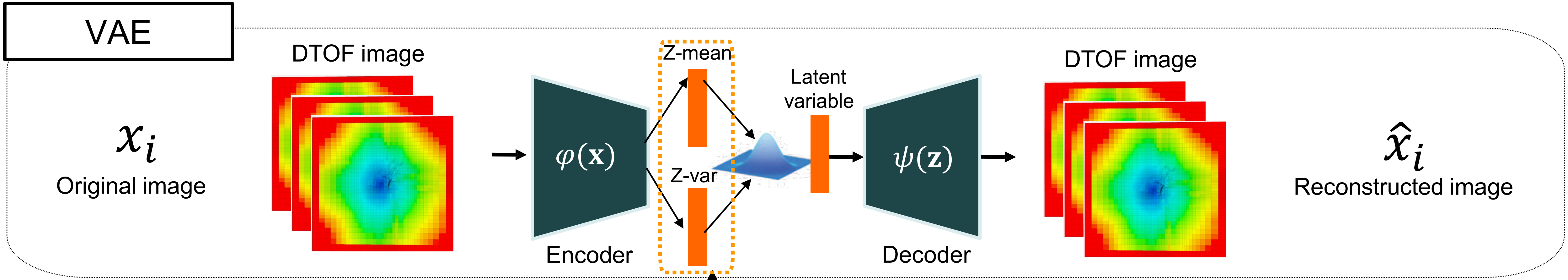
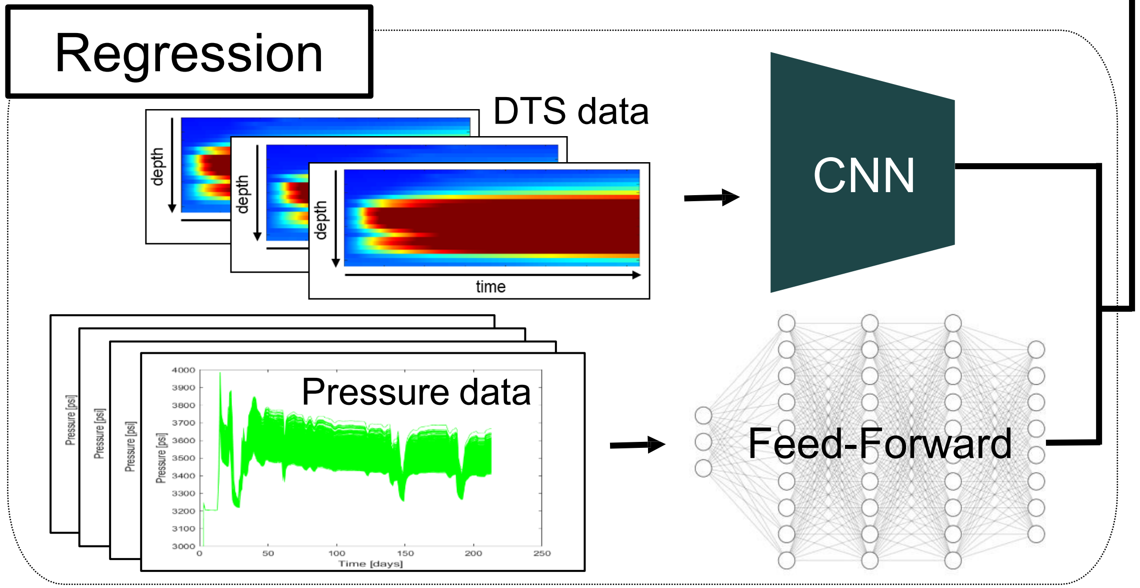
Neural Network Training





Loss function:

$$L = \underbrace{L_{VAE}}_{\text{Image reconstruction loss}} + \underbrace{\frac{1}{Nz}\sum_{j=1}^{Nz}\left|\sigma_j^2 - \hat{\sigma}_j^2\right|^2 + \frac{1}{Nz}\sum_{j=1}^{Nz}\left|\mu_j - \hat{\mu}_j\right|^2}_{\text{Bottleneck loss}}$$

σ_j^2: z-variance
μ_j: z-mean

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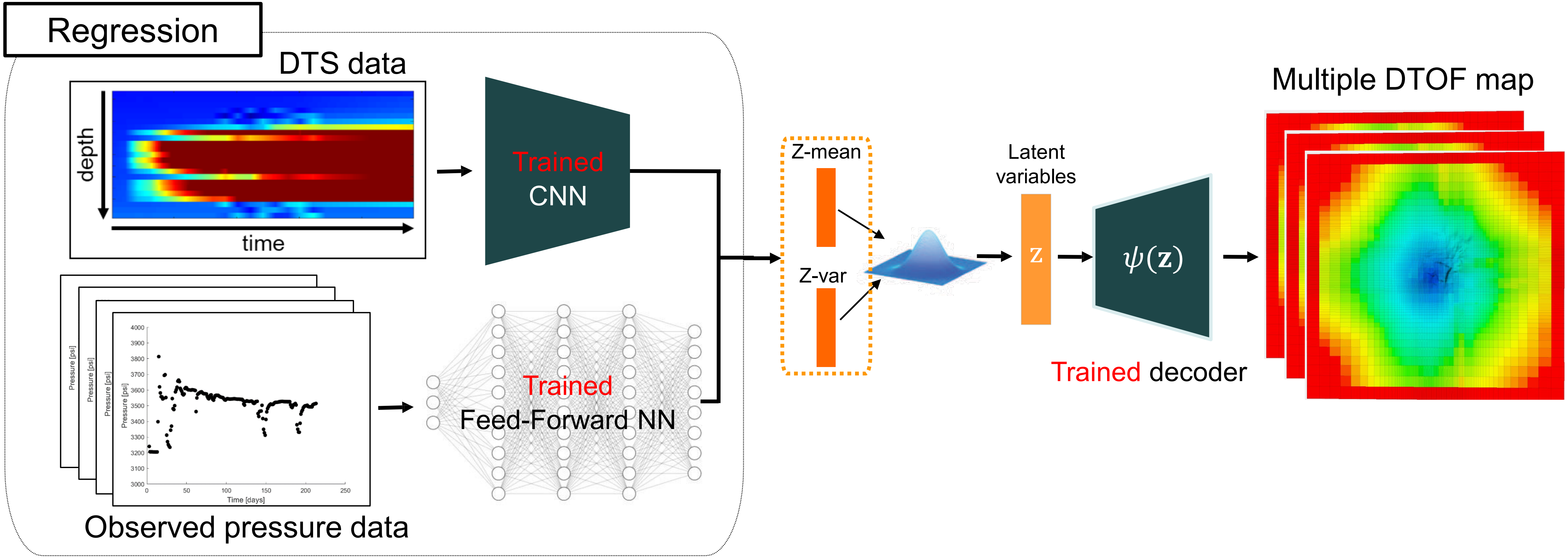
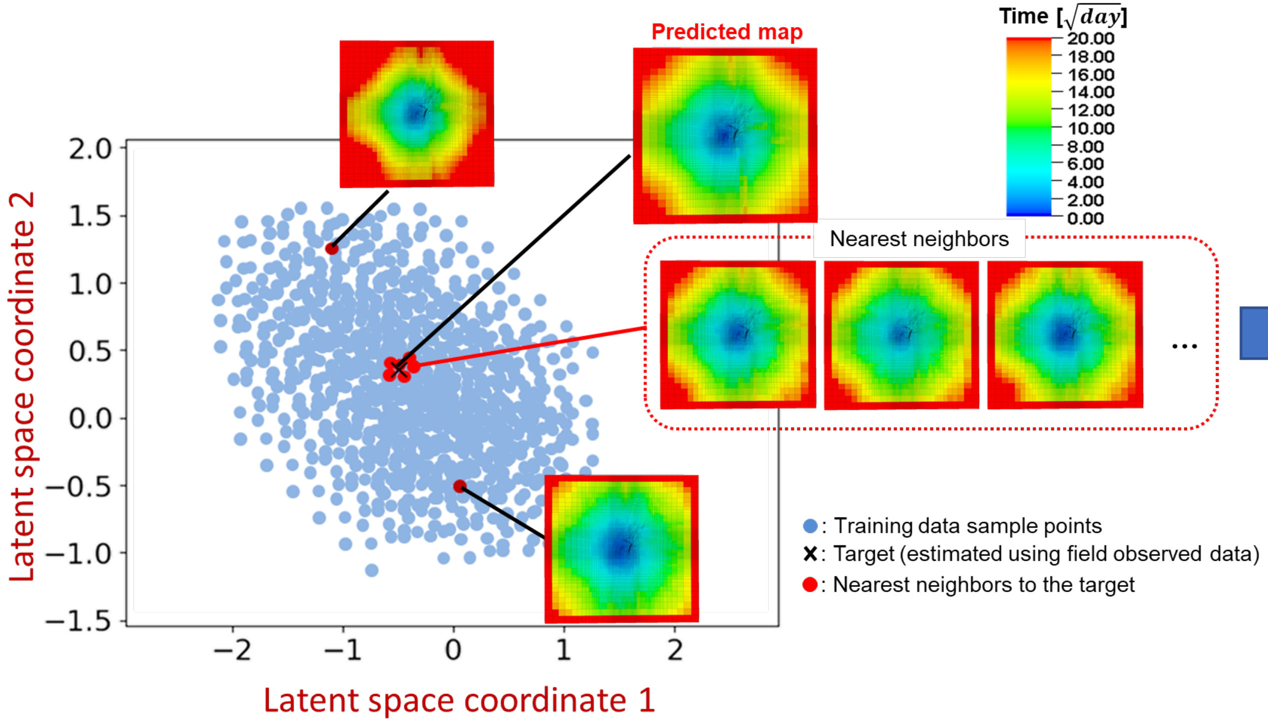
Estimation of Diffusive Time of Flight (DTOF) Map

Estimate the DTOF map based on the field monitoring measurements

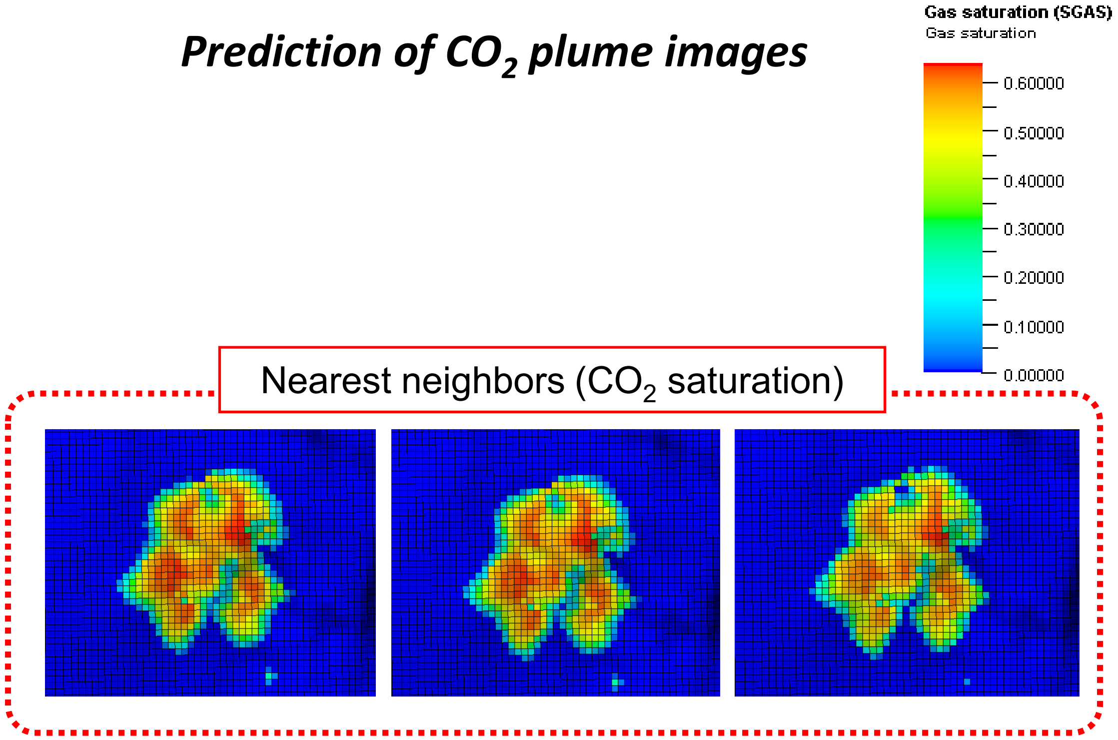


Prediction of CO_2 Plume Images

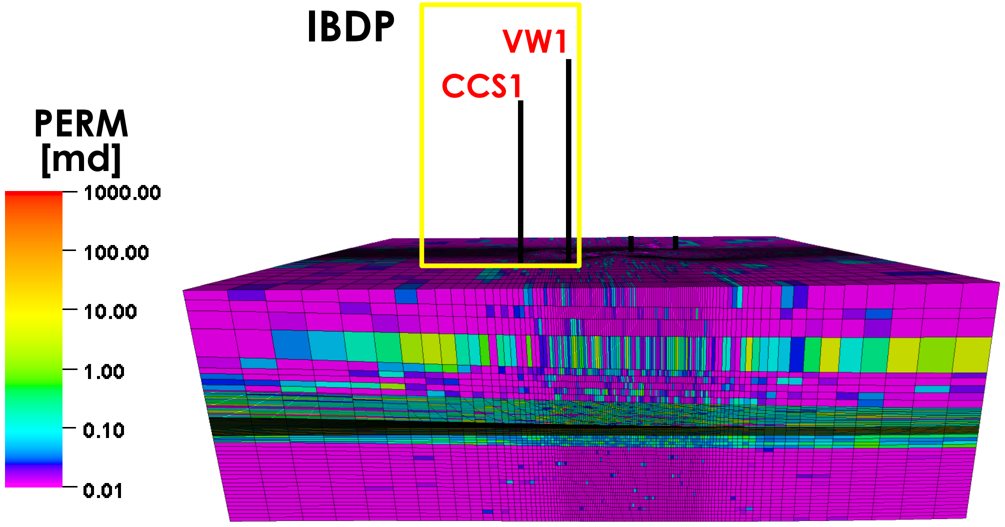
Model identification using DTOF map (History Matching)



Prediction of CO_2 plume images

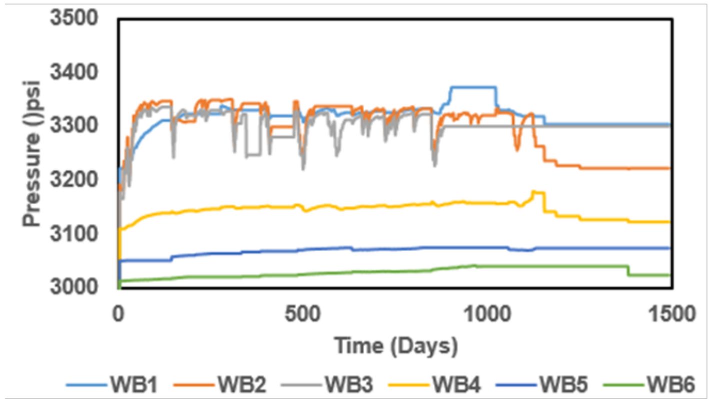


IBDP Model Description and Data Availability

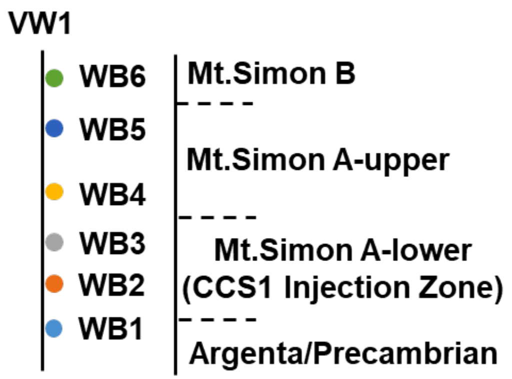


- Grid: 126 * 125 * 110 (1.73 Million Cells)
- ECLIPSE Compositional Model (E300)
- Thermal Option
- CO2STORE Module
- Simulation Period: 2011-2015
- Run Time: 12 hours with 32 Cores Parallel run

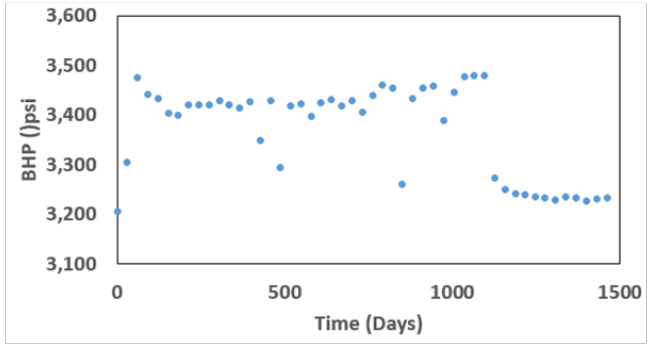
Observed data



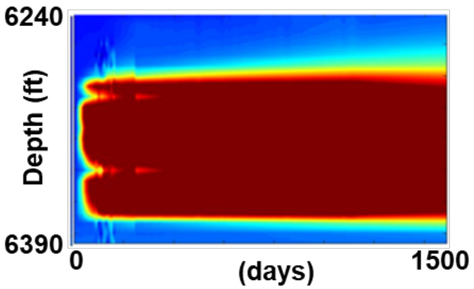
Behind-casing pressure (Monitoring Well)



Location of behind-casing sensors



Bottom hole pressure (Injector)



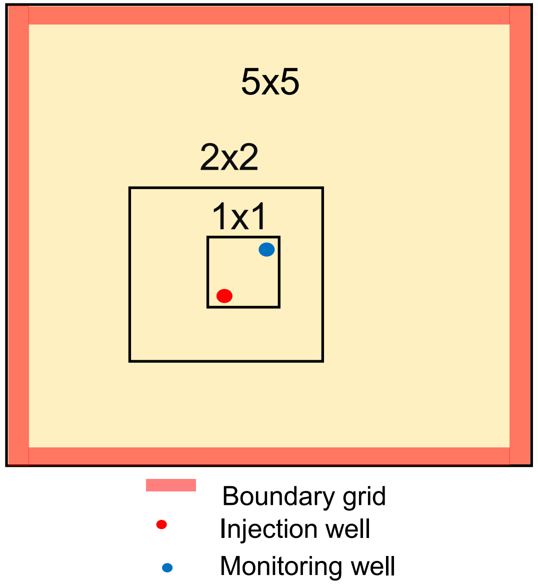
DTS data (Injector)

Acceleration of Training Data Generation

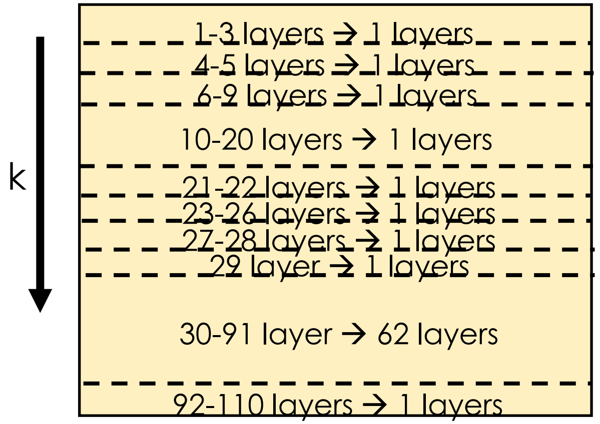
Challenge: Run time for an original simulation is too long (12 hrs with 32 core) and unfeasible for training data generation purpose (500 realizations)

Upscaling of original model

- Areal Coarsening

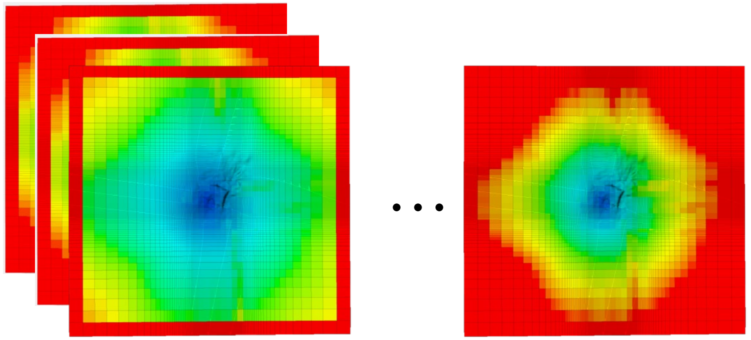


- Optimal Layering Scheme



Active cell: 1,732,292 → 229,693

DTOF map generation



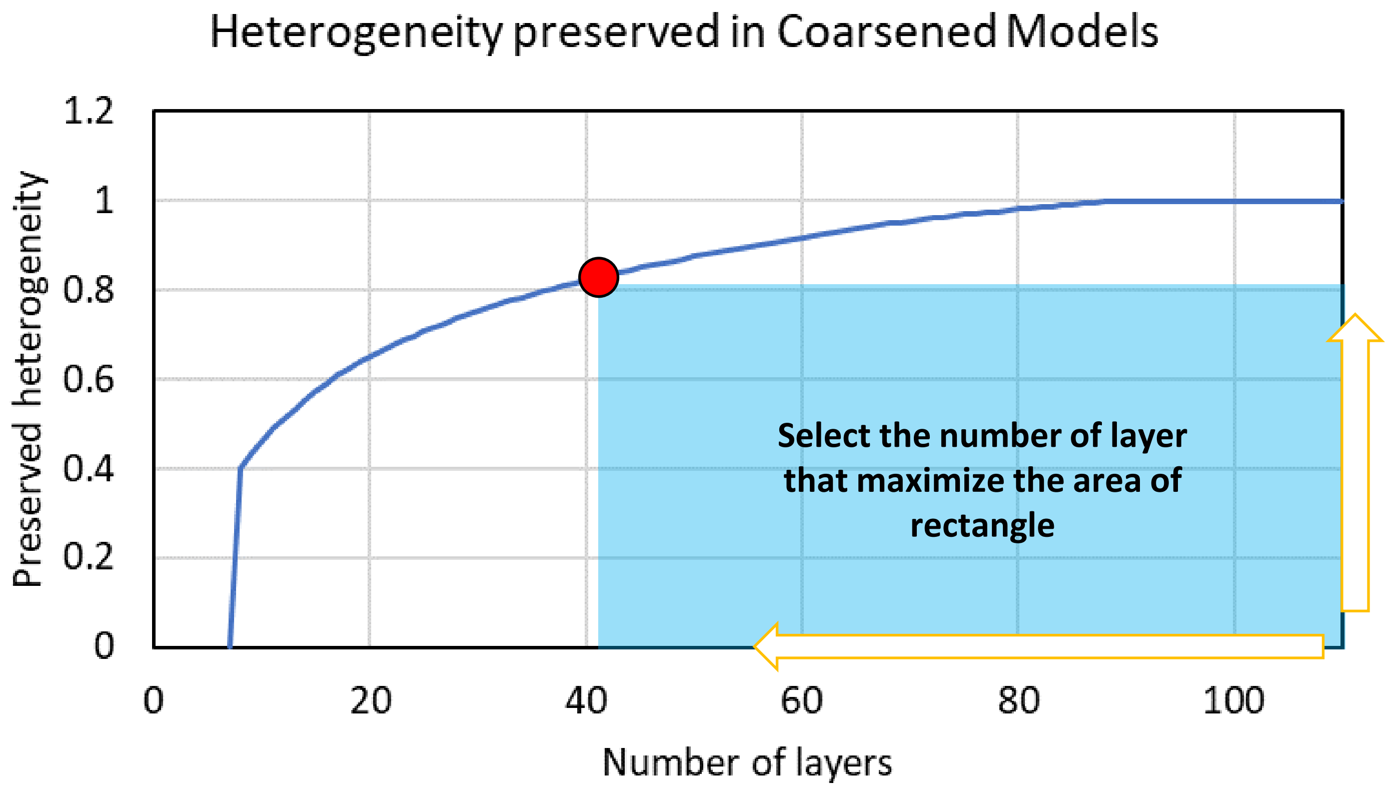
- Generate at initial timestep without reservoir simulations
- Few seconds

Run Time: 12 hrs → 15 mins (32 core)

Model Coarsening using Bias-Variance Trade-off

Optimal Layering Scheme Selection

Select the optimal number of layers based on bias-variance trade-off between preserved heterogeneity and number of layers (number of grid cells)



Well Response of Fine vs. Coarsened Model

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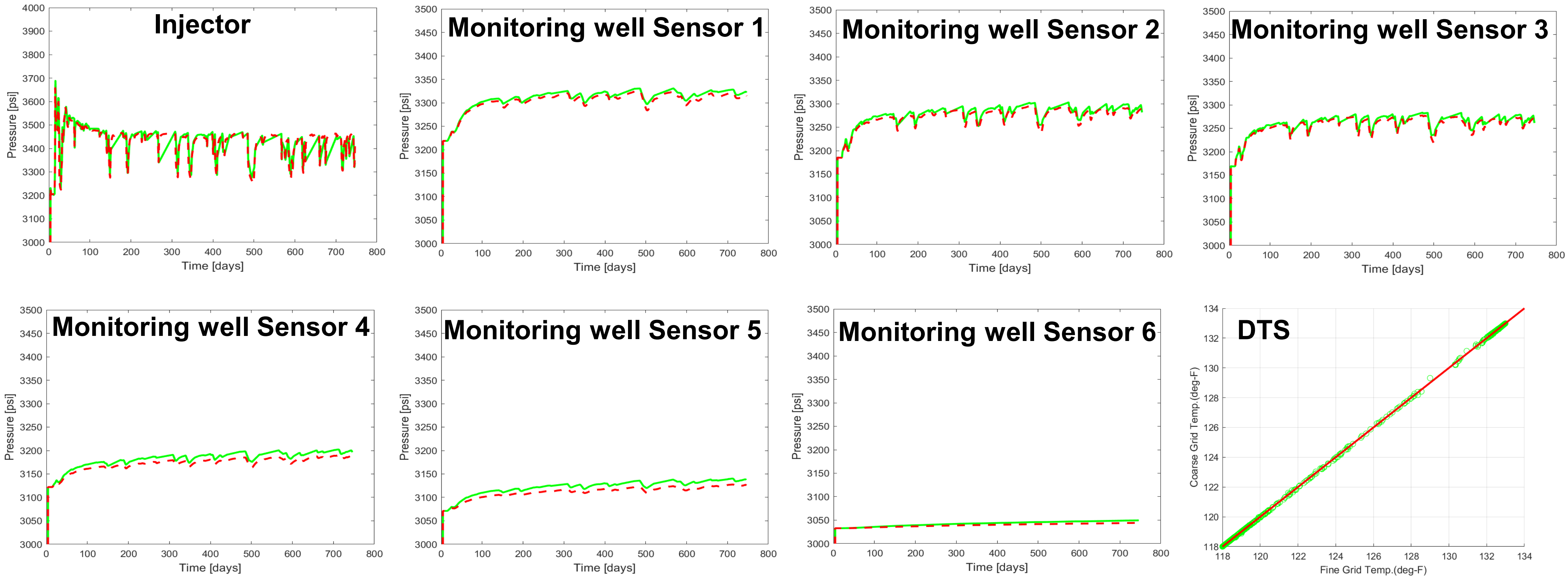
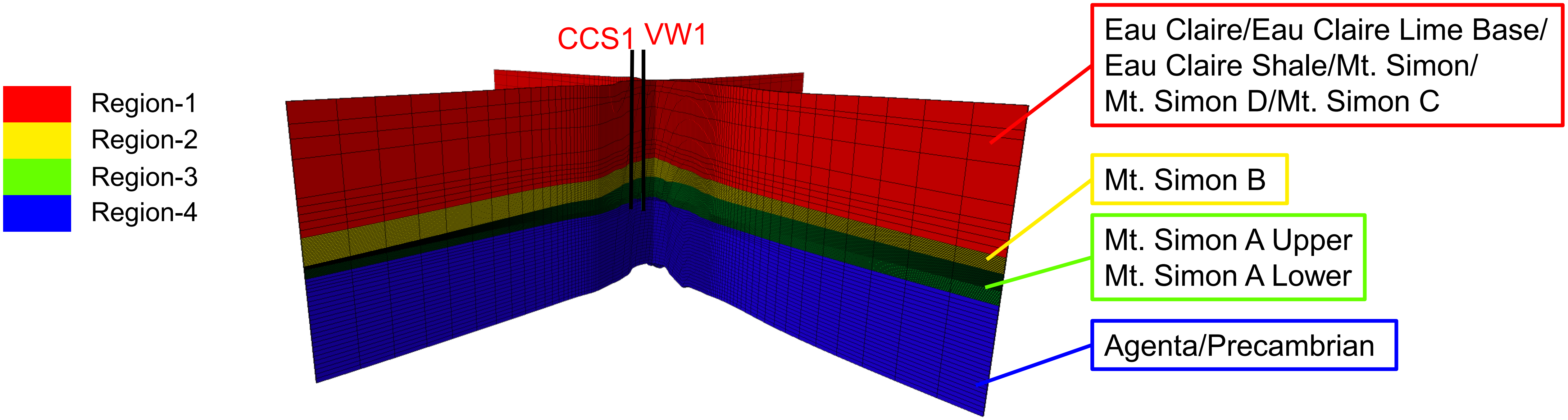
Runtime: 12 hrs → 15 min

Original Coarsened

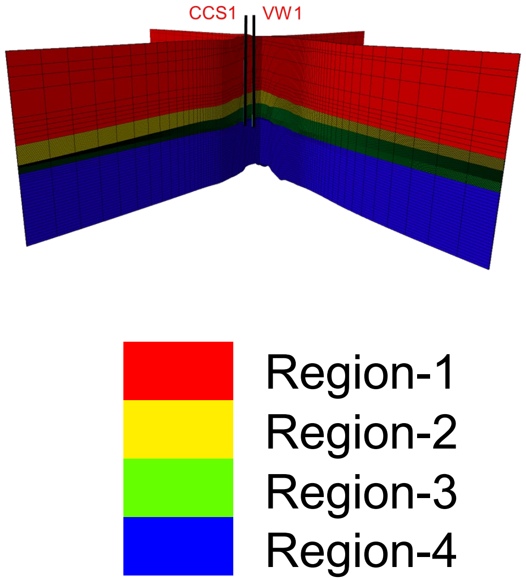


Parameterization for Training Data Generation



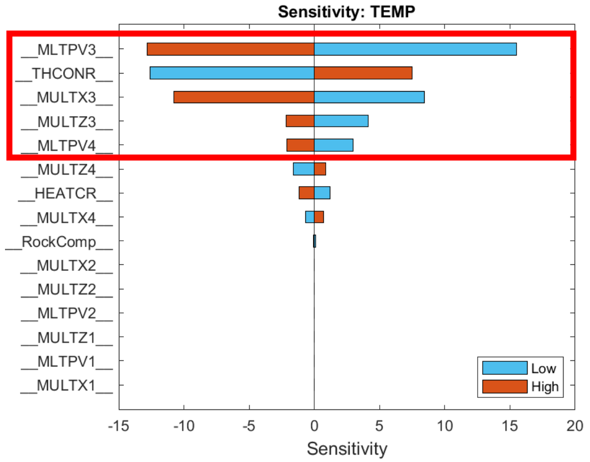
4 regions are identified based on geologic layers

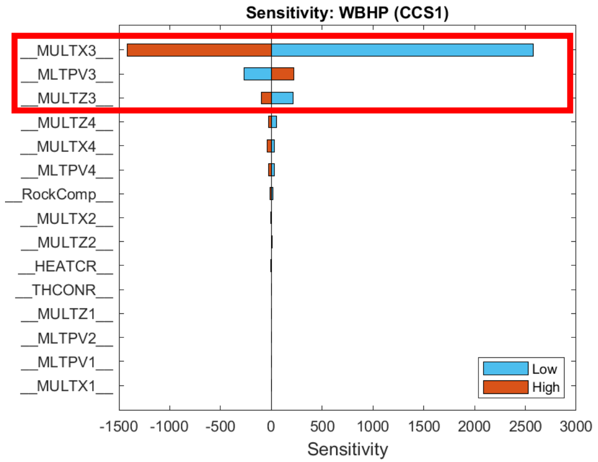
Sensitivity Analysis for Training Data Generation

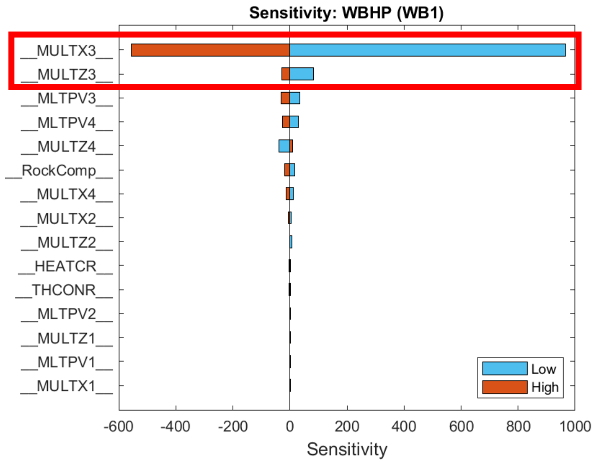


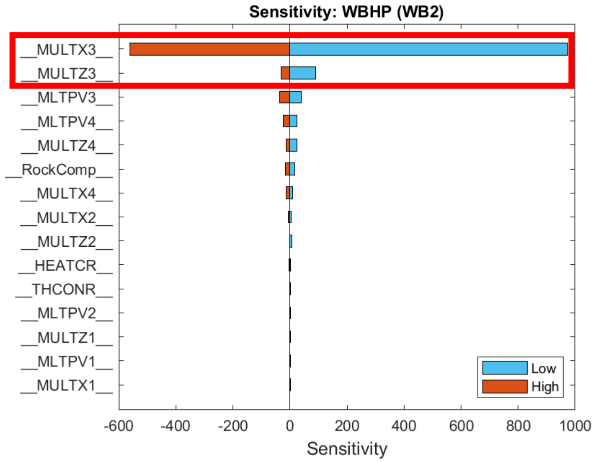
Properties	Parameters	Description	Low	Base	High
Region Pore Volume Multipliers	MLTPV1	Region 1 PV Multiplier	0.7	1.0	1.3
	MLTPV2	Region 2 PV Multiplier	0.7	1.0	1.3
	MLTPV3	Region 3 PV Multiplier	0.7	1.0	1.3
	MLTPV4	Region 4 PV Multiplier	0.7	1.0	1.3
Region TRANX Multipliers	MULTX1	Region 1 TRANX Multiplier	0.5	1.0	2.0
	MULTX2	Region 2 TRANX Multiplier	0.5	1.0	2.0
	MULTX3	Region 3 TRANX Multiplier	0.5	1.0	2.0
	MULTX4	Region 4 TRANX Multiplier	0.5	1.0	2.0
Region TRANZ Multipliers	MULTZ1	Region 1 TRANZ Multiplier	0.1	0.5	1.0
	MULTZ2	Region 2 TRANZ Multiplier	0.1	0.5	1.0
	MULTZ3	Region 3 TRANZ Multiplier	0.1	0.5	1.0
	MULTZ4	Region 4 TRANZ Multiplier	0.1	0.5	1.0
Rock Compressibility	ROCK	Rock Compressibility	2.7E-6	3.2E-6	3.7E-6
Rock Heat Capacity	HEATCR	Rock volumetric heat capacity	0.3	0.5	0.7
Thermal Conductivity	THCONR	Combined rock and fluid thermal conductivity	1.0	2.0	3.0

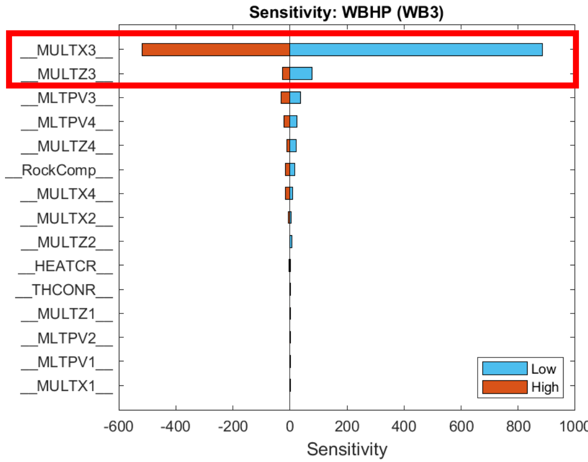
Sensitivity Analysis for Training Data Generation





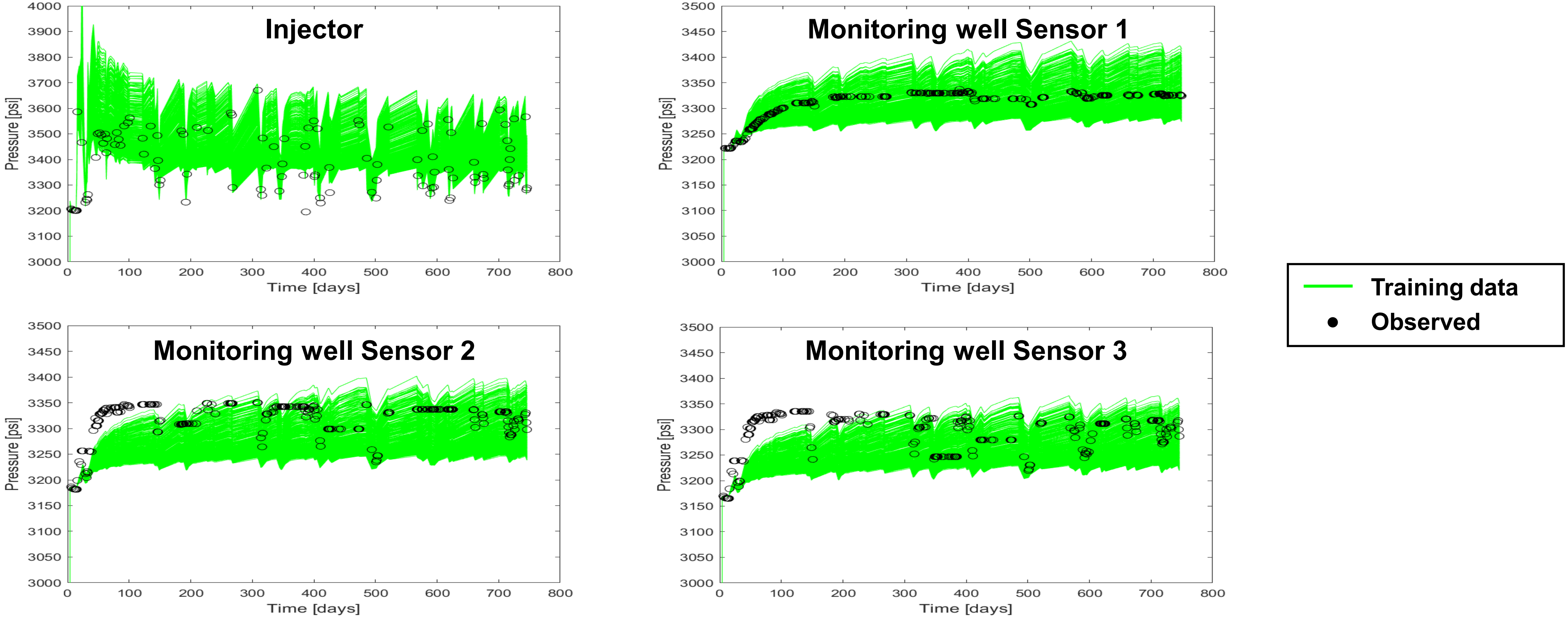




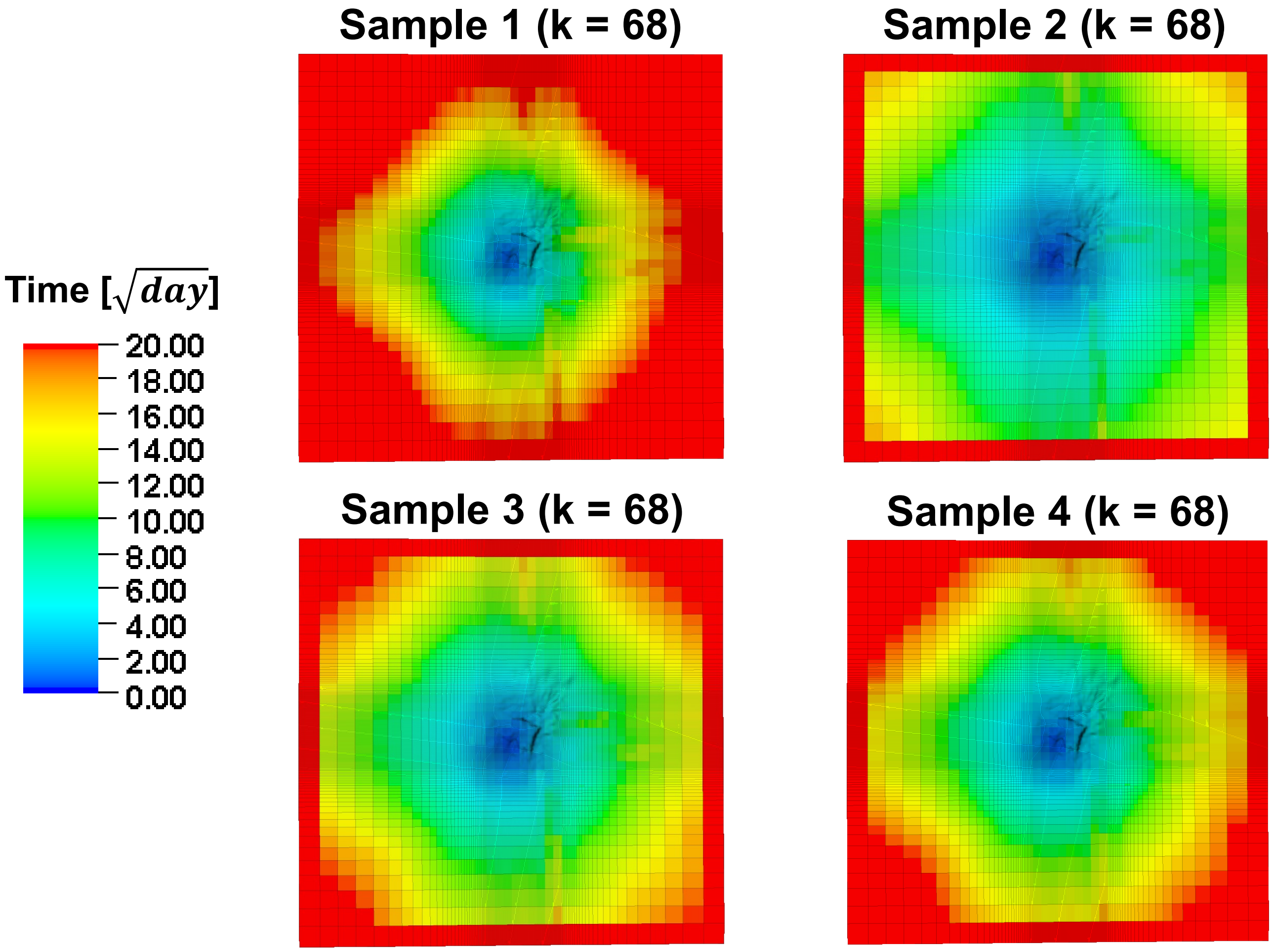


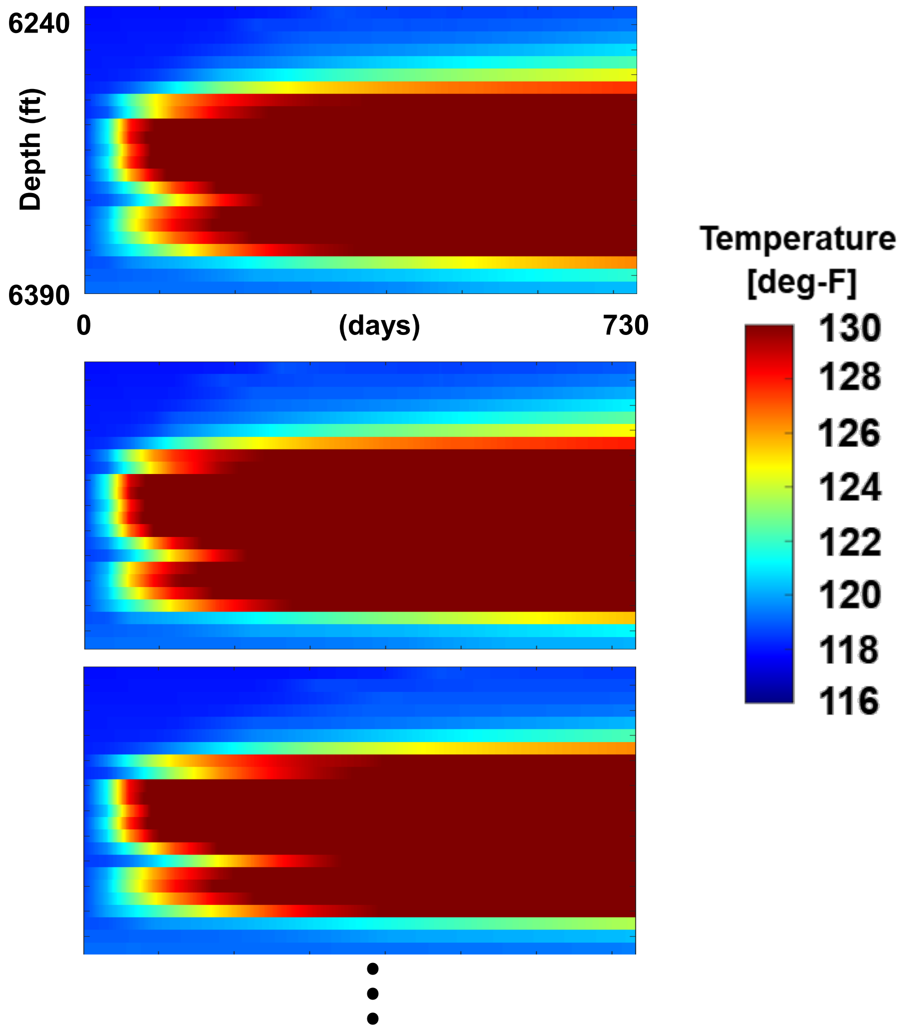
Selected Parameters: MLTPV3, MULTX3, MULTZ3, MLTPV4, THCON

Training Data Generation: Pressure Responses

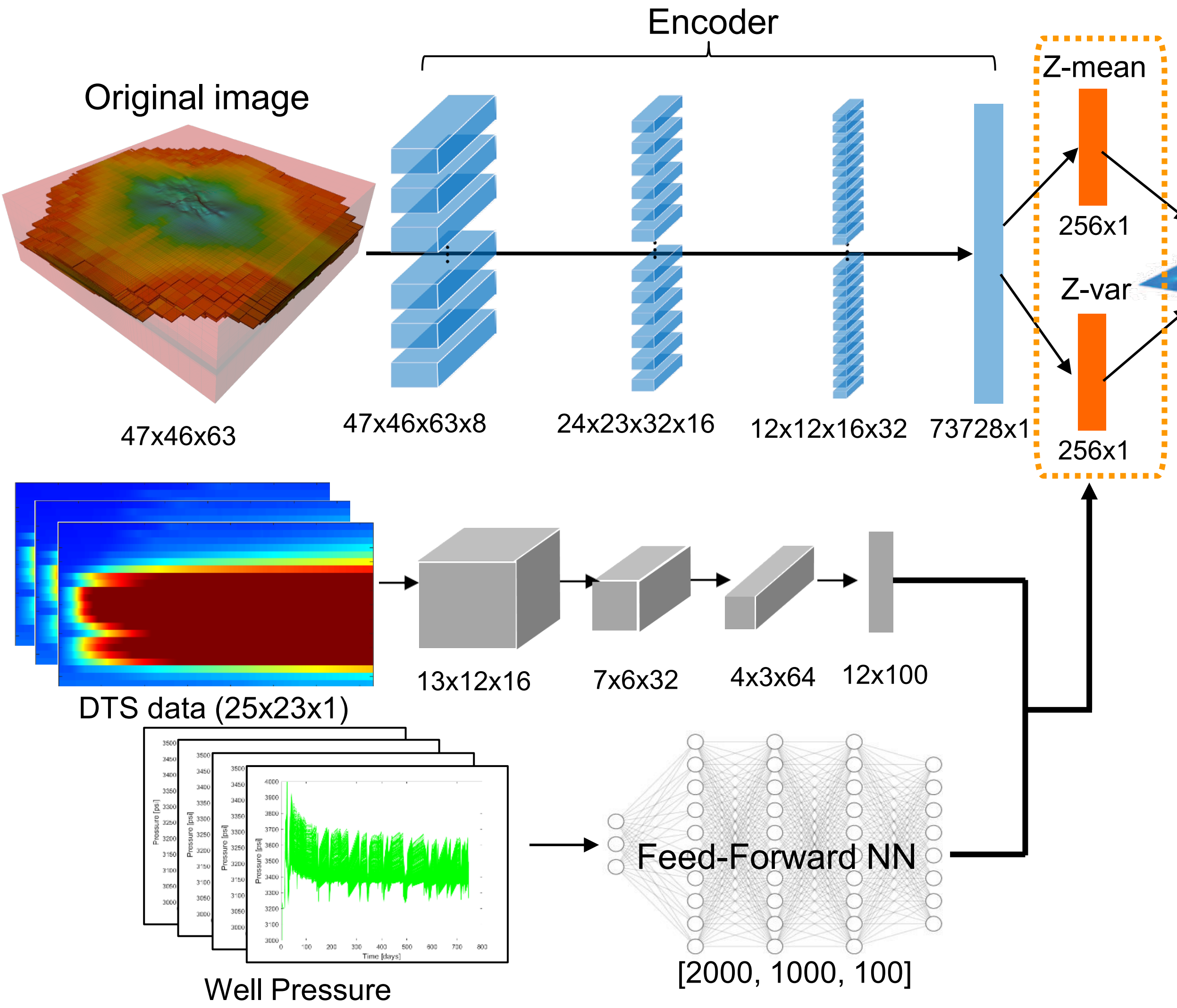


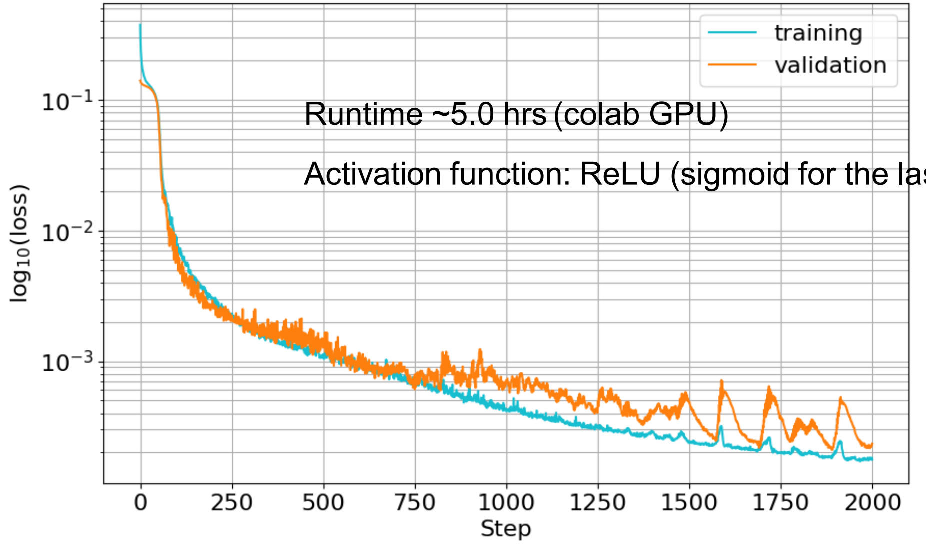
Training Data Generation: DTOF Images and DTS





Neural Network Architecture and Training



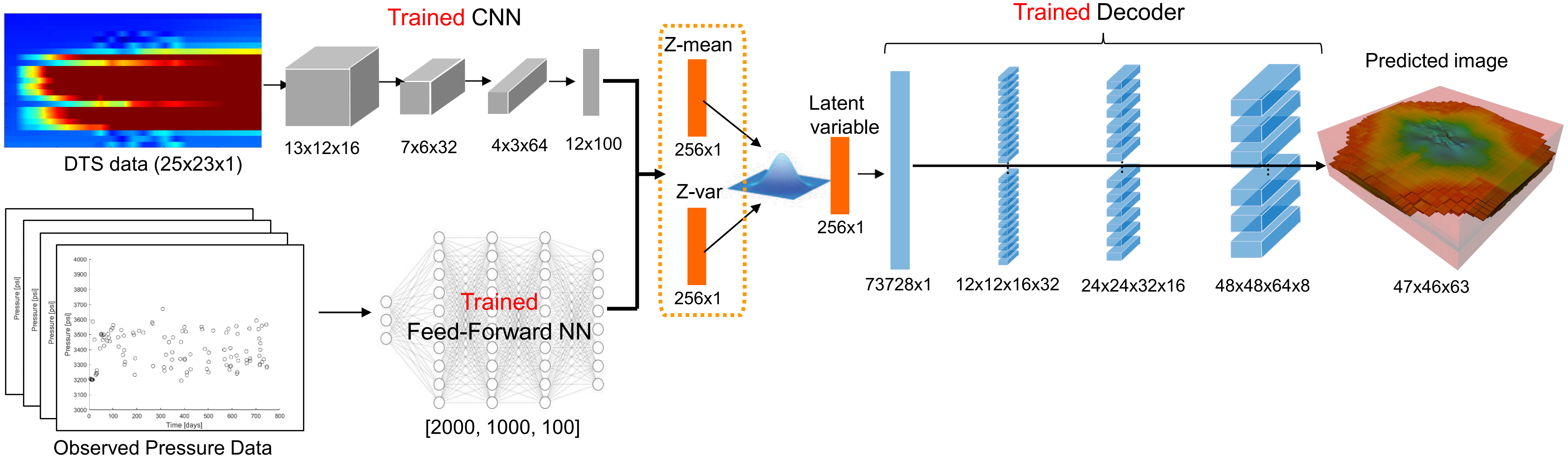


Runtime ~5.0 hrs (colab GPU)

Activation function: ReLU (sigmoid for the last layer)

Neural Network Architecture: Prediction

- Input the pressure responses of injection well/monitoring well and DTS at injector and predict the DTOF map



History Matching Results: Pressure and Temperature Response

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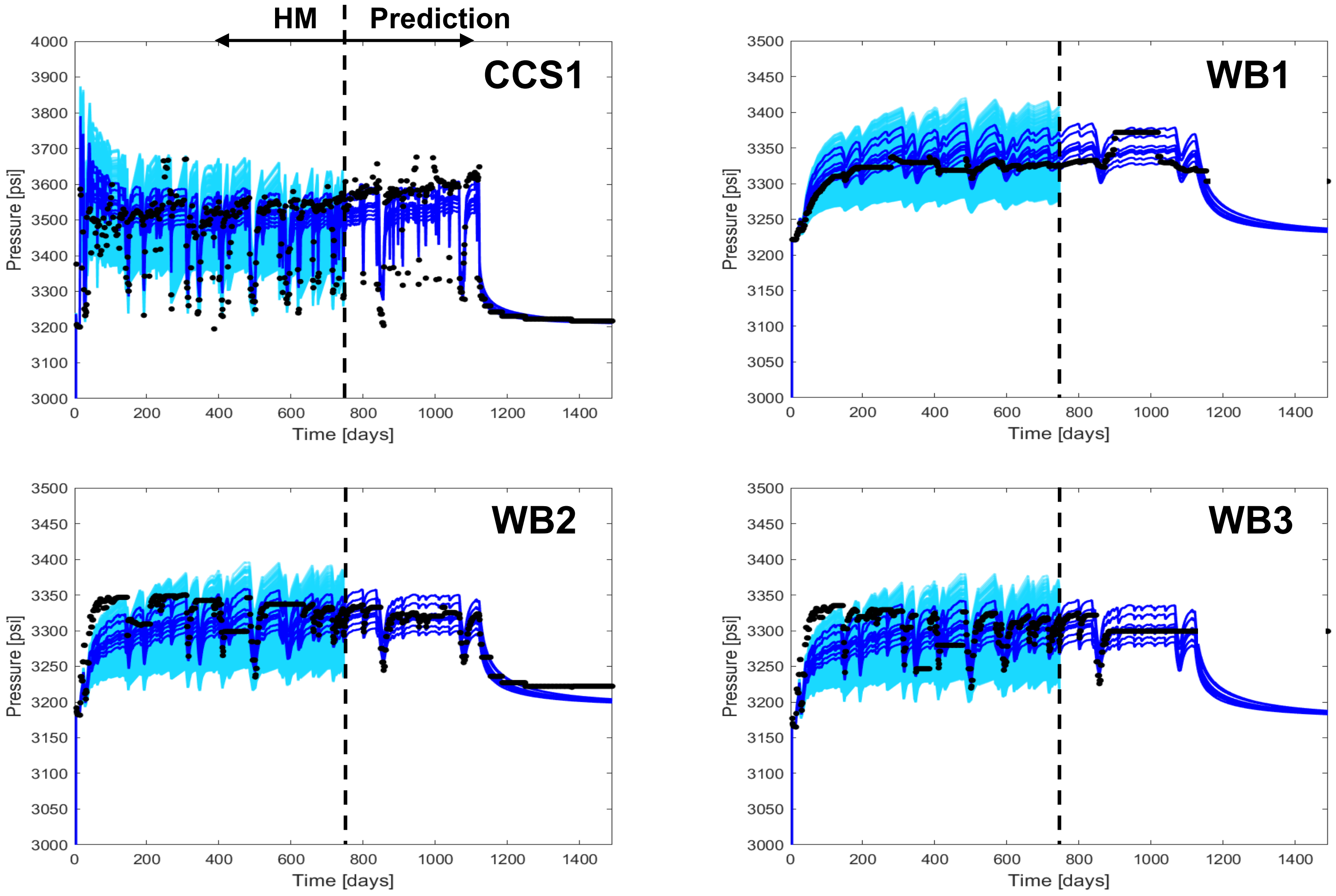
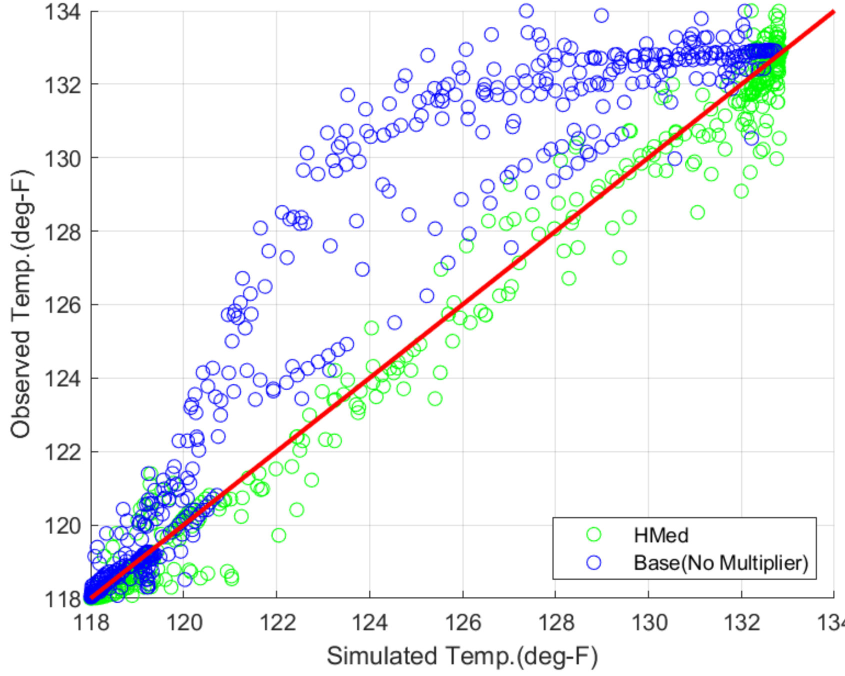
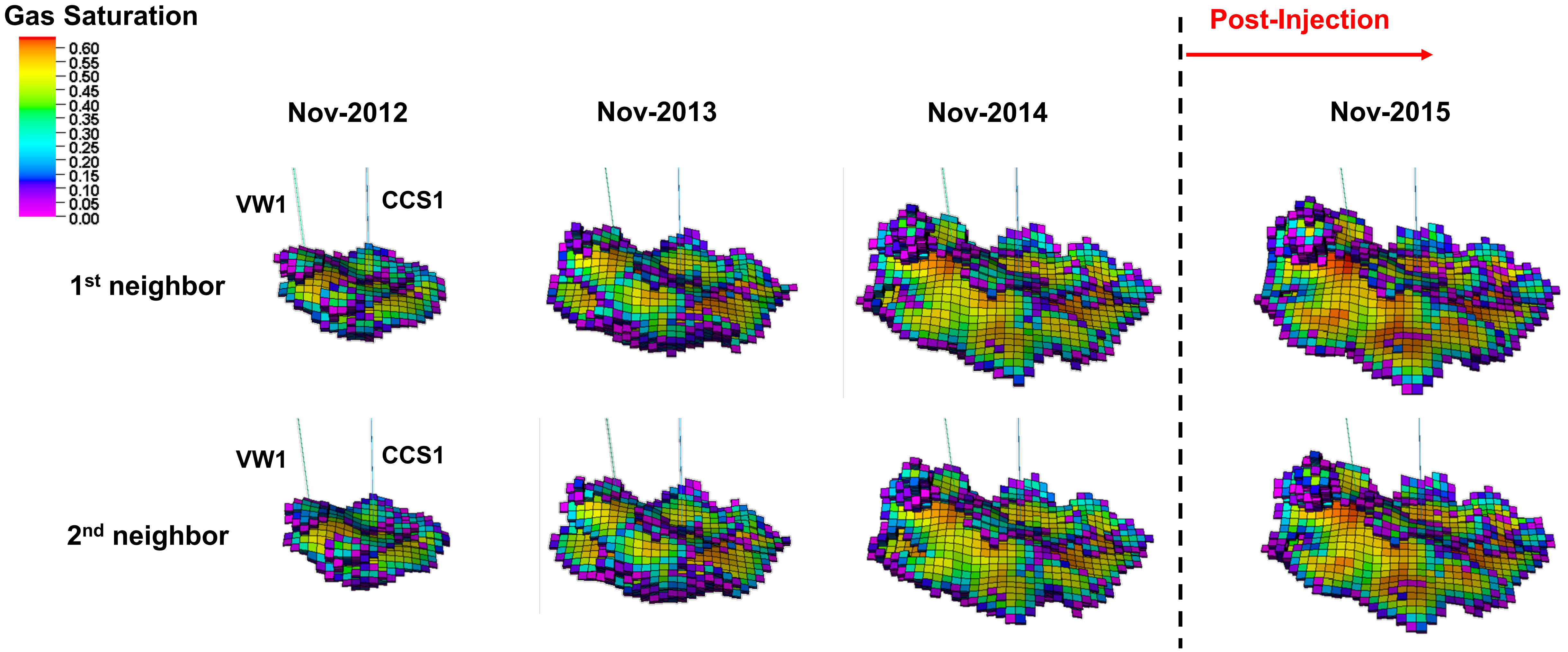


Prior
Posterior
(10 nearest neighbors)
● Observed



CO2 Plume Evolution of Calibrated Models



Summary: Challenges, Gaps and Opportunities

- Proposed ML assisted workflow and application to the IBDP site shows promising results with orders of magnitude speed up
- Incorporated thermal effects to integrate DTS data
- Utilized DTOF maps to further reduce computational time and facilitate real-time decision making
- Key Development Challenges and Gaps
  - Incorporation of additional physics: geo-mechanical effects to study potential induced seismicity
  - Use of reduced physics models to speed up training
- New Opportunities
  - Leverage Oil Industry Experience: Fast Marching Method for Coupled Flow, Streamlines for visualization, Storage/CO_2 Sweep Optimization via Rate control

Questions?

Acknowledgments

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