SMART-CS Initiative

Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

Task 5: Active Reservoir Management in CO_2 Storage

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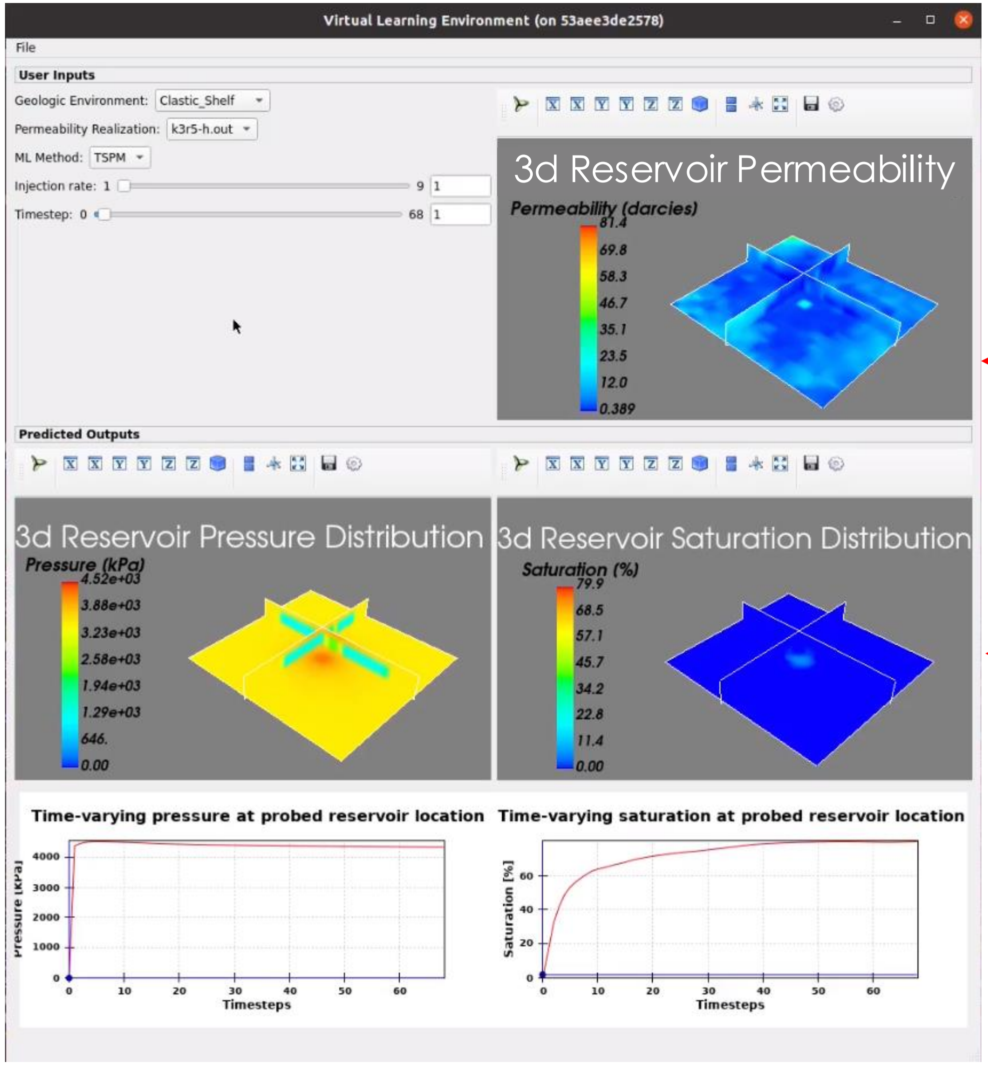
Motivation

Can we rapidly develop experience among CCS stakeholders to facilitate rapid & safe deployment of large-scale geologic CO_2 storage?

<u>Vision:</u> Enable a Virtual Learning Environment (VLE) for exploring and testing strategies to optimize reservoir development, management & monitoring prior to field activities

<u>Goal:</u> Demonstrate the proof-of-concept with a prototype

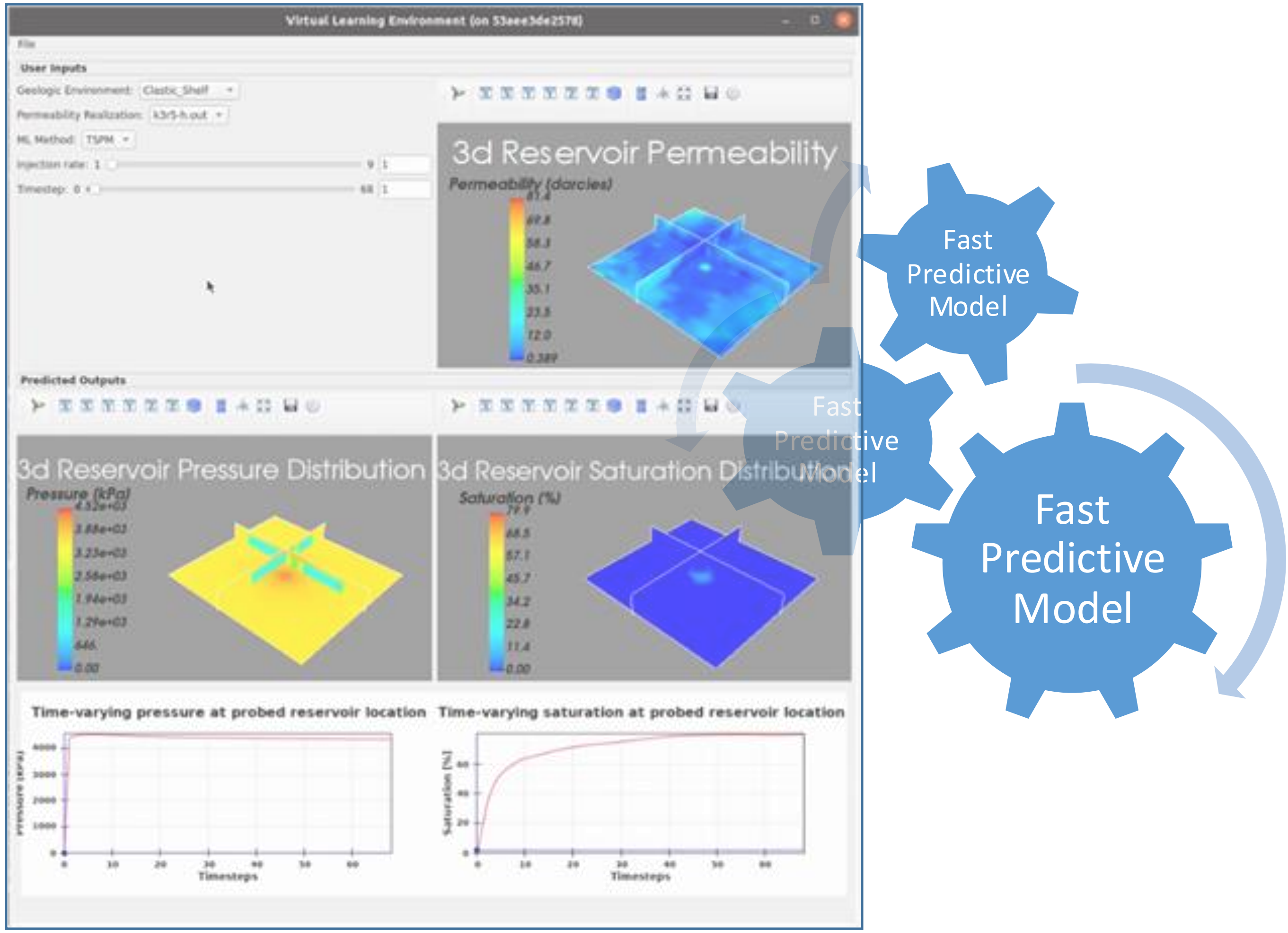


Interactively gain intuitive understanding of CO_2 storage site behavior by:

Manipulating Inputs

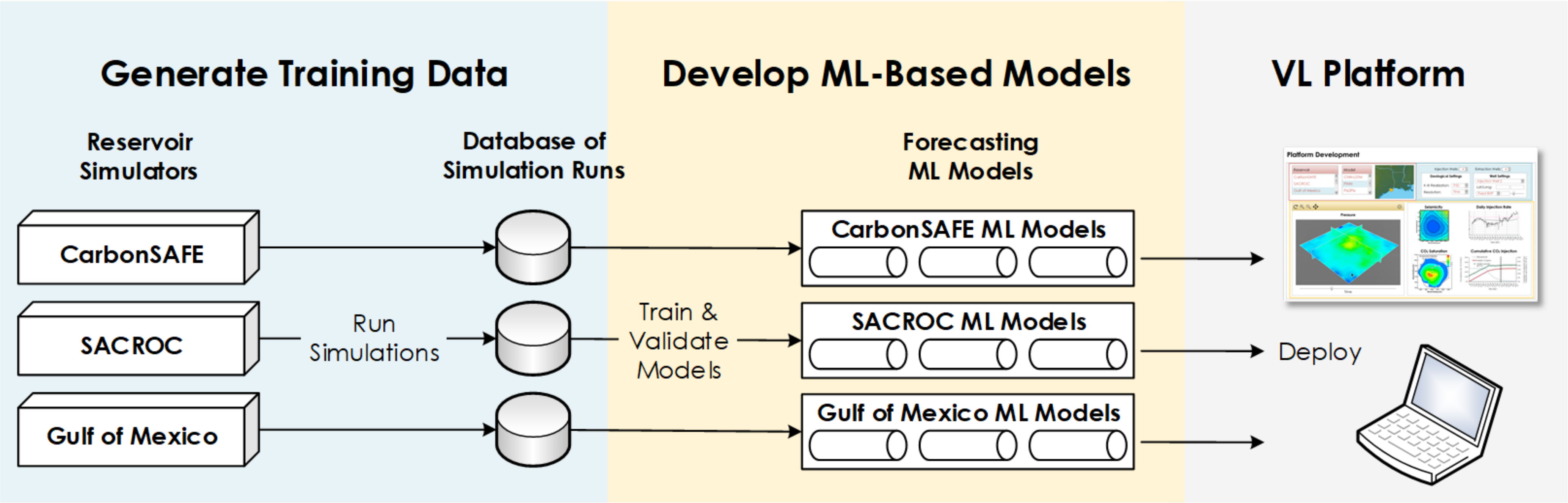
Exploring Outputs

Interactive Virtual Learning Platforms Need Accurate, Fast Predictive Models

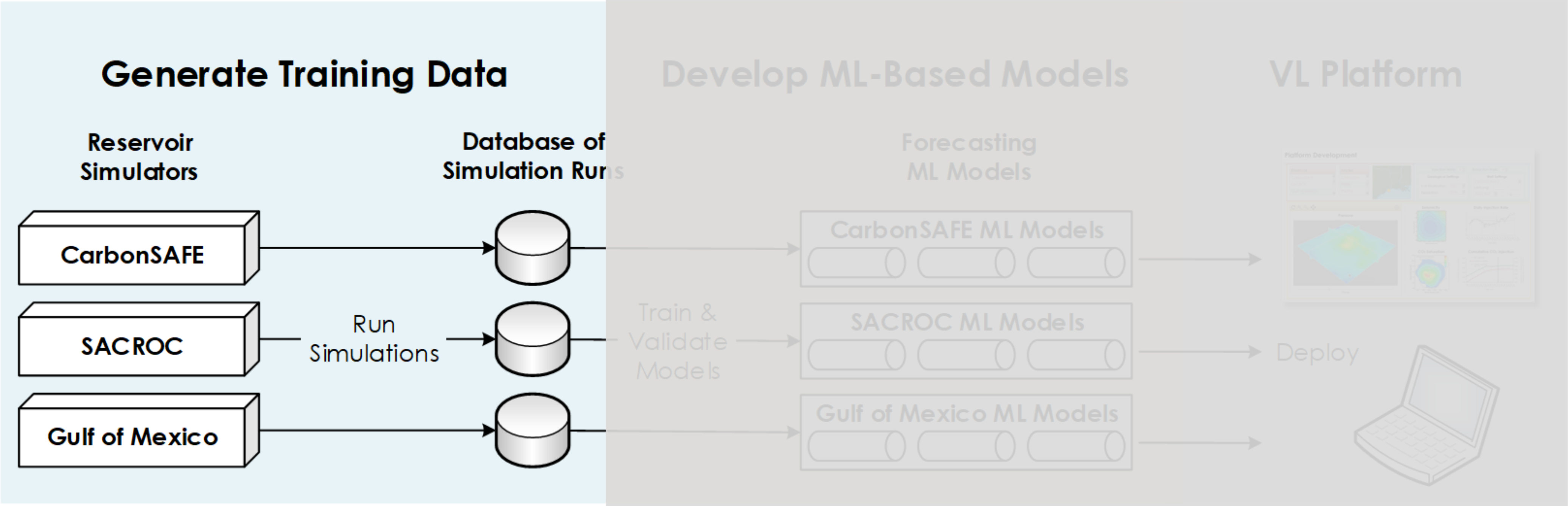


Fast predictive models can be developed using novel machine-learning based methods

Our Overall Approach



Part 1 – Generate Training Data



Task 5: Active Carbon Storage Management

Overview of Field Sites

Criteria for reservoir model selection

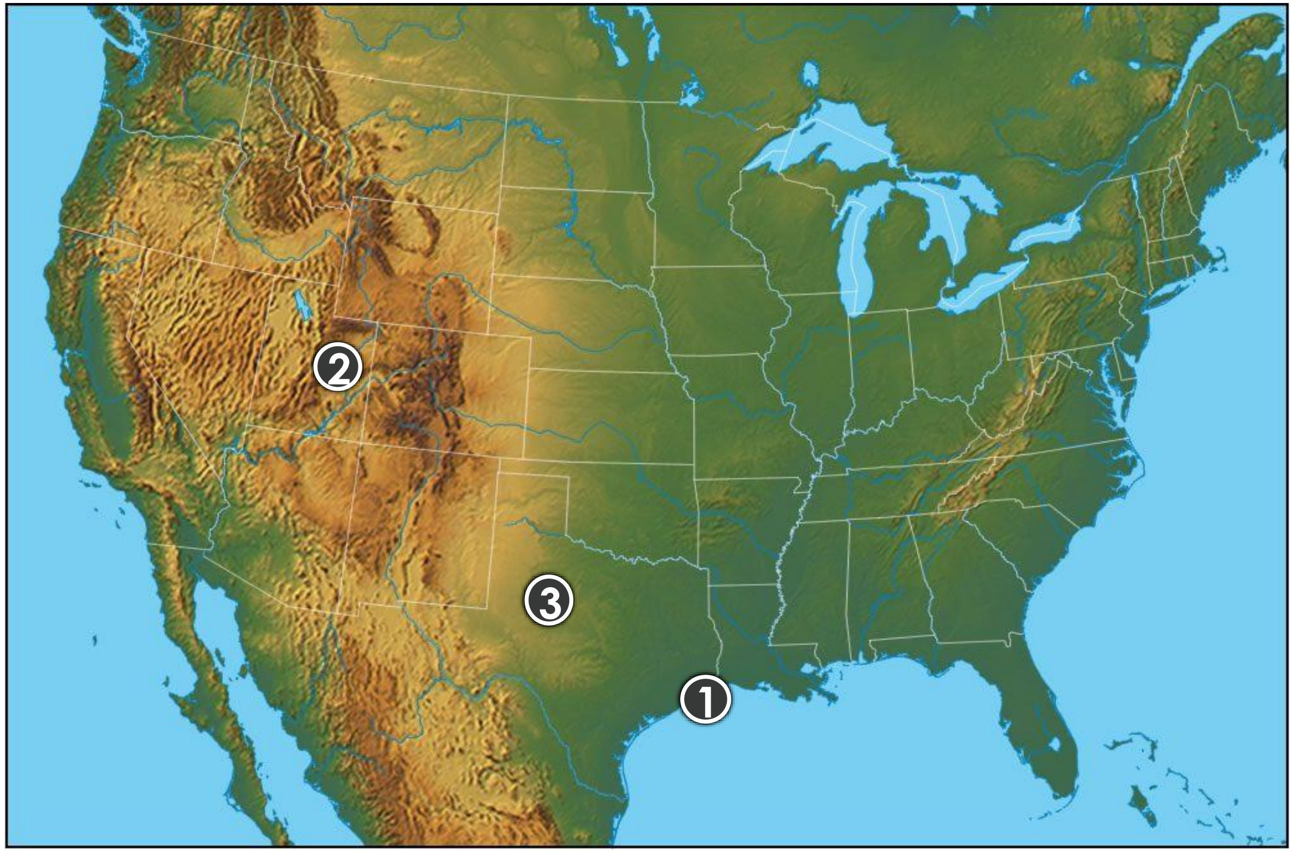
1. Capability to store up to 50 million tons of CO_2 over 50 years (injection + post injection periods)
2. Variety of geological depositional settings
3. Public availability and accessibility of multiple geological realizations to capture uncertainty
4. Preference to models created in previous DOE funded projects

Selected Reservoir Models

❶ High Island 24L (offshore Gulf of Mexico)
Fluvial depositional environment

❷ CarbonSAFE Utah
Eolian depositional environment

❸ SACROC
Carbonate Reef depositional environment



Task 5: Active Carbon Storage Management

Simulation Runs at Field Sites

Numerical reservoir simulation of active reservoir management:

- 30 years of injection/extraction and up to 50 years of post-injection CS performance
- Fixed number of injection/extraction wells

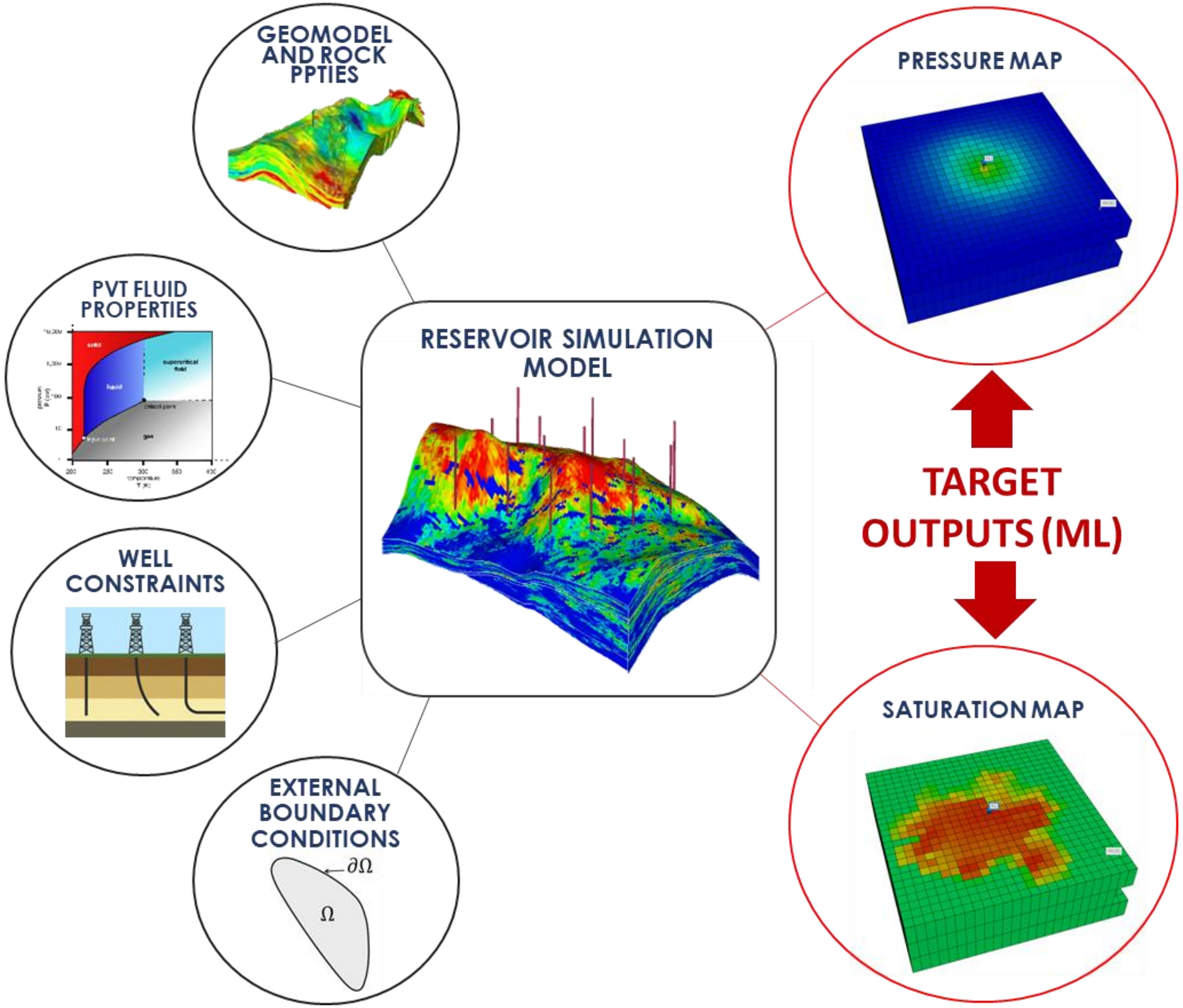
Geological uncertainty

- *Multiple Depositional Environments / Reservoir Sites*
- *Heterogeneous porosity/permeability*

Operational uncertainty

- *Variable cumulative CO_2 injection (up to 50 million tons)*
- *Variable injection allocation among injectors*

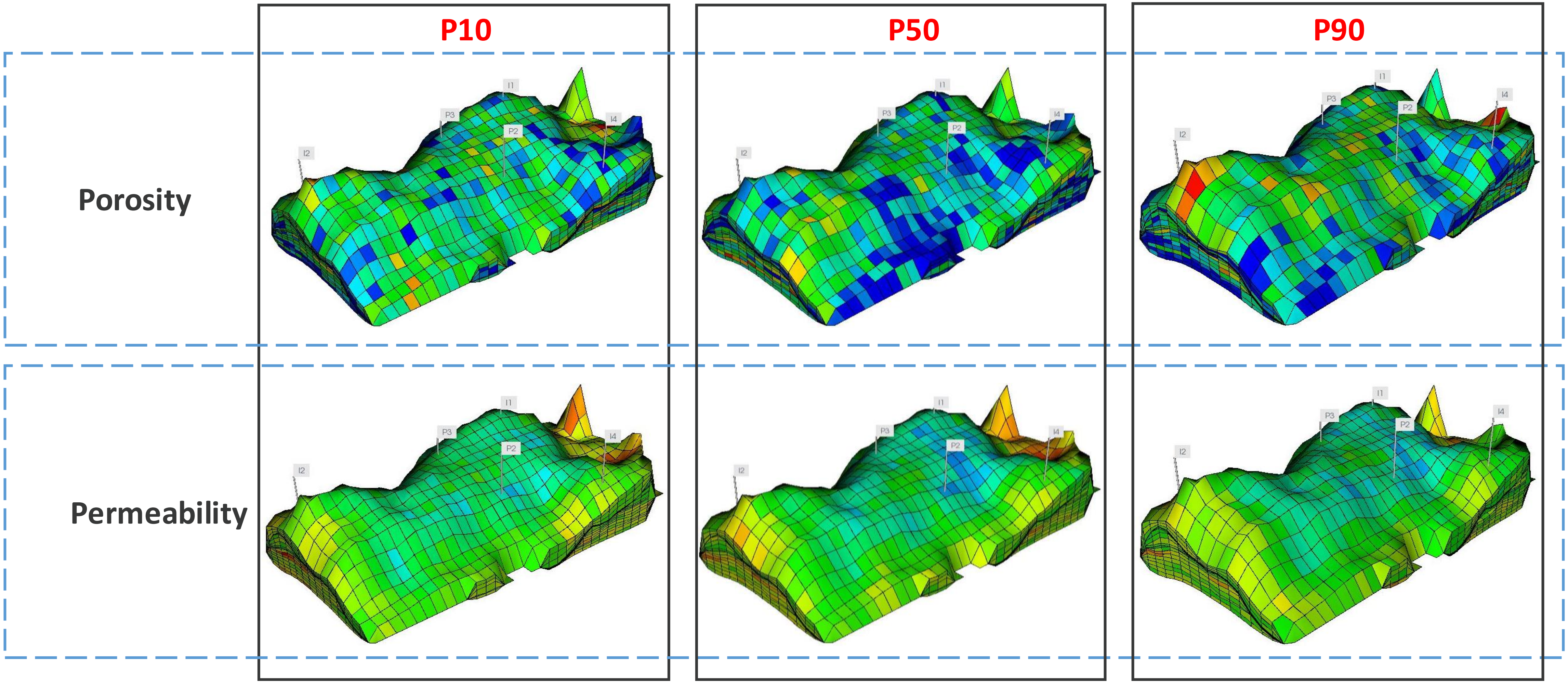
Use of high-fidelity reservoir simulators provides the needed science-basis



SACROC Field Site

Accounting for Geological Uncertainty

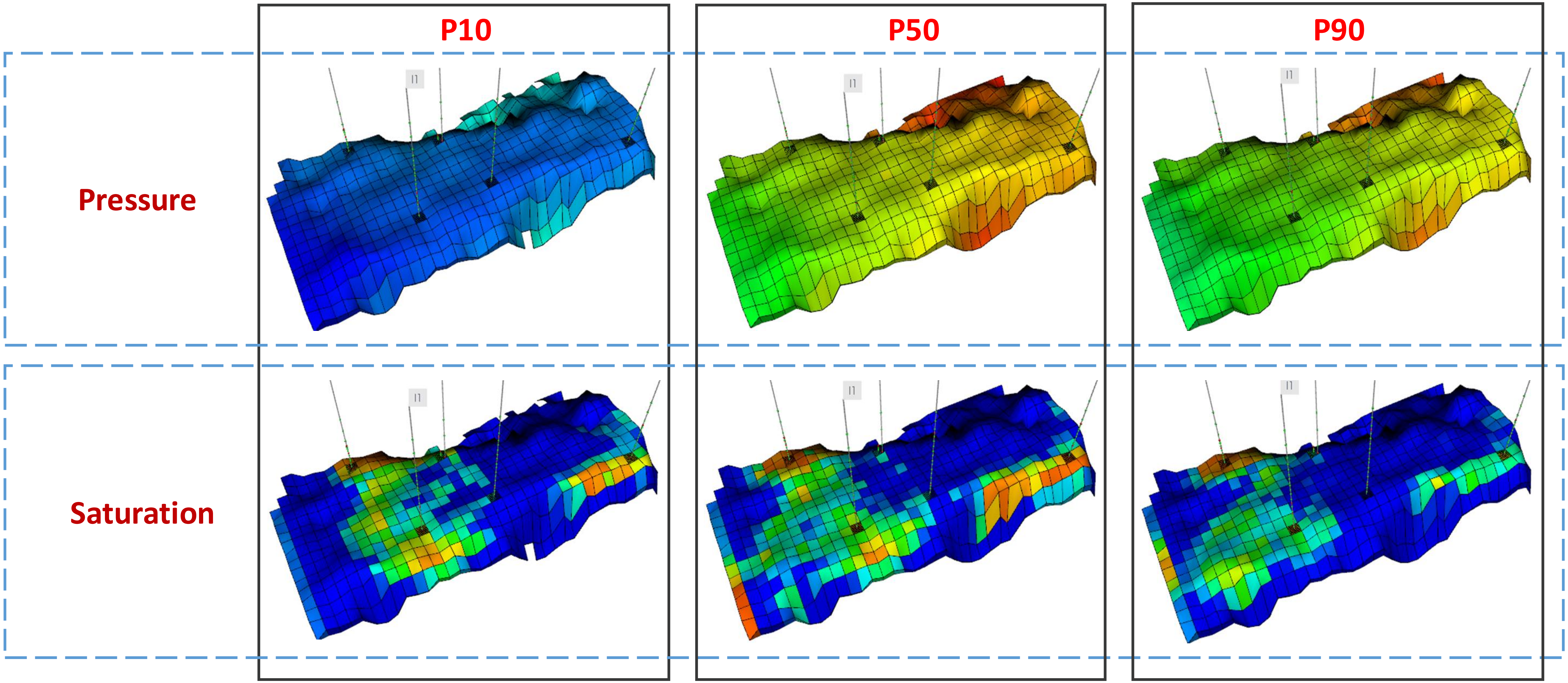
3 porosity-permeability realizations: P10, P50, P90



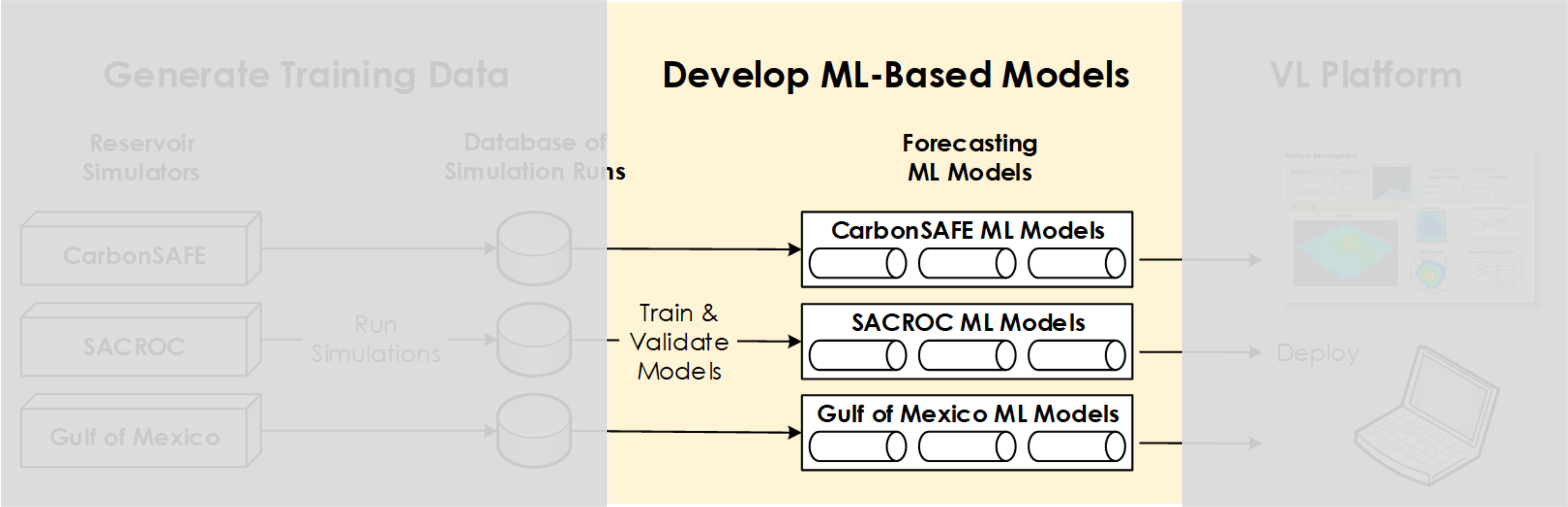
SACROC Field Site

Sample Results

3 porosity-permeability realizations: P10, P50, P90

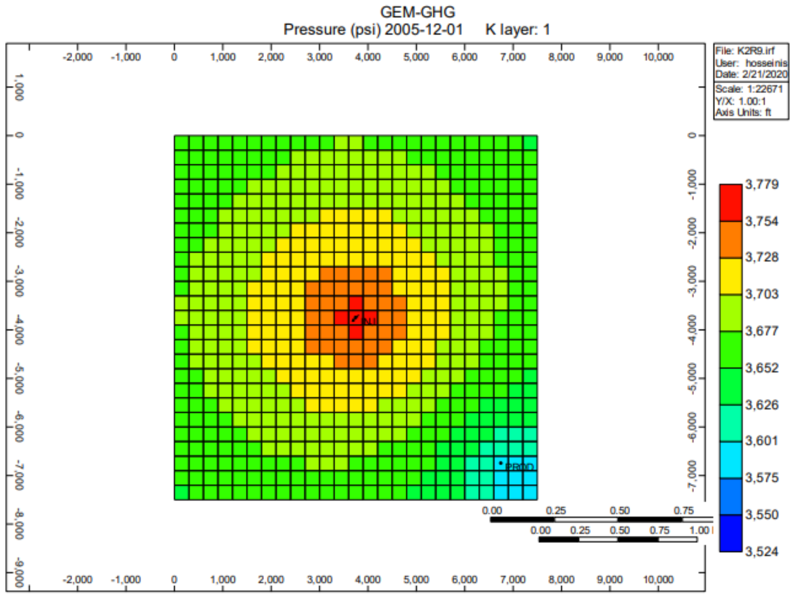


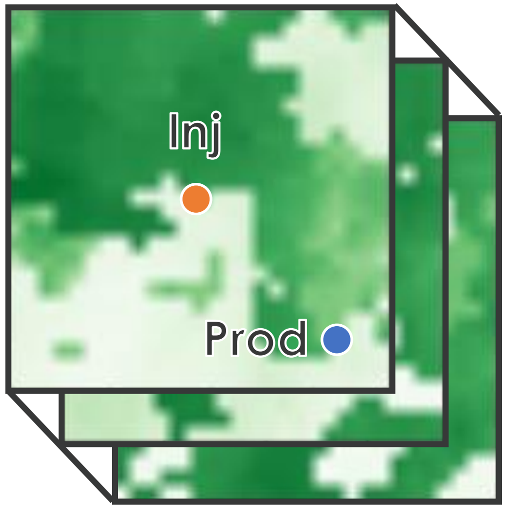
Part 2 – Develop ML-Based Models



Model Development on Toy Reservoirs

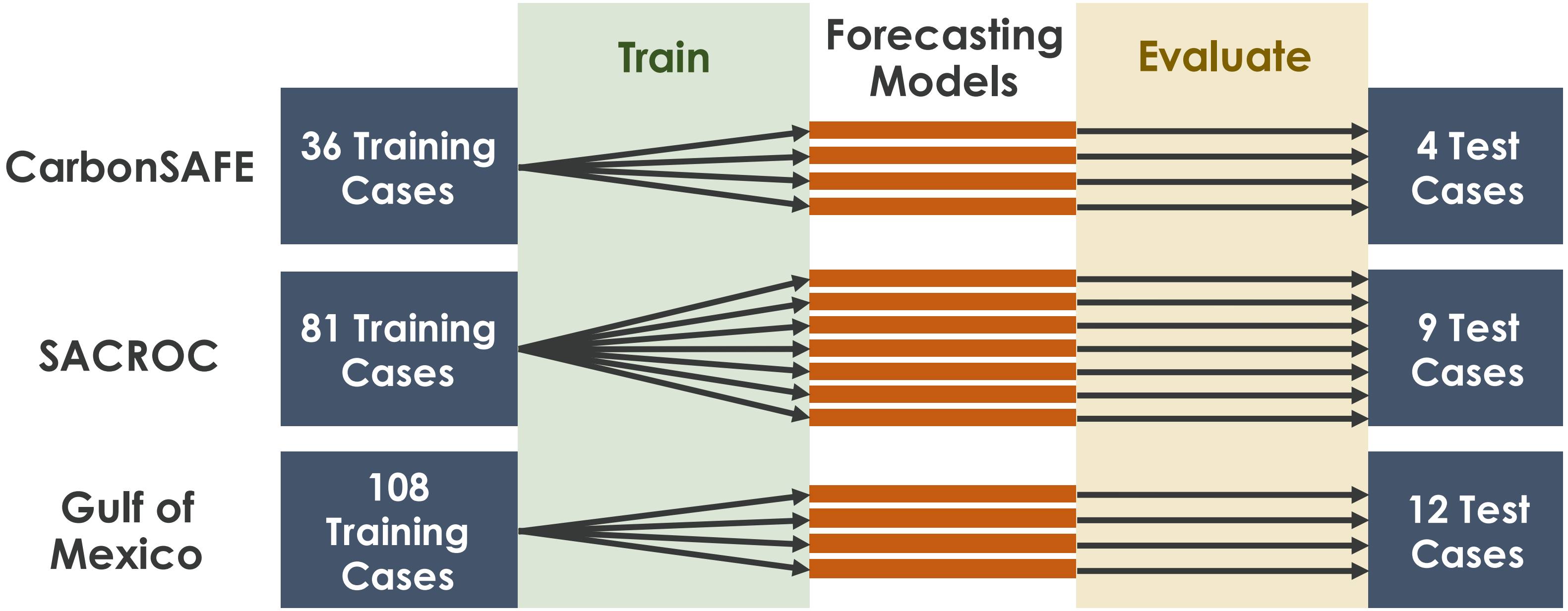
- Initial work focused on building models for two toy reservoirs
  - One 2D reservoir with homogeneous permeability and porosity
  - One 3D reservoir with heterogeneity for added complexity
- This provided early cases for modelers to work with while the simulation teams generated runs on the field-scale reservoirs
- Coming out of this effort, scripts had been written for training models on simulation output files and many implementation details had been worked out





Development on Field Scale Reservoirs

- Simulation cases for each reservoir were used to train rapid forecasting models, adapting toy model scripts as needed to handle the new size and complexity
- Additional cases were used to evaluate the models



Model Inputs

Por/Perm Realization
- P10/P50/P90 (categorical)
- 3D Porosity (i, j, k)
- 3D Permeability (i, j, k)

Well Locations
- Injection Wells (i, j)
- Production Wells (i, j)

Injection Rates
- Per Injection Well (time)
- Cum. CO_2 Injected (time)

Model Outputs

4D Pressure (i, j, k, time)
4D Saturation (i, j, k, time)
Production Rates
- Per Production Well (time)

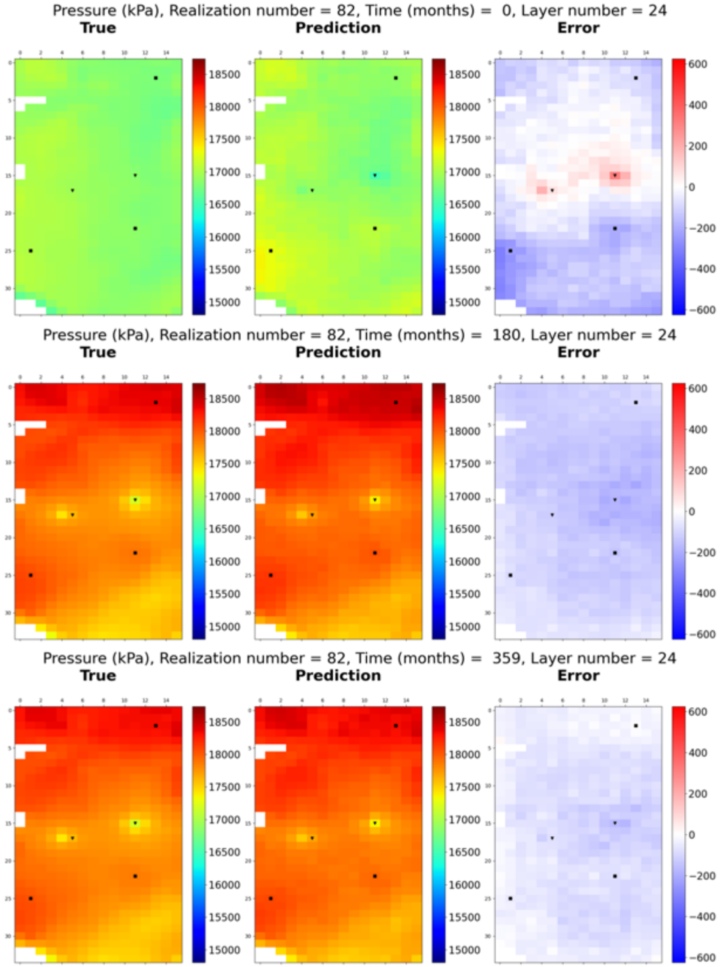
Development on Field Scale Reservoirs

- A total of 15 models were built across the three reservoirs
- Accuracy and forecast time were measured and converted to common units

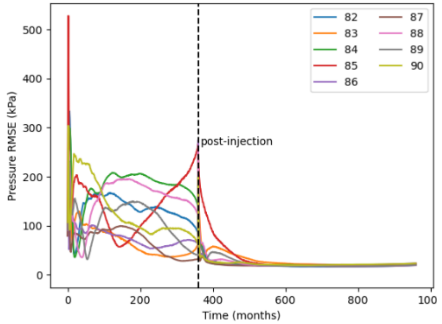
Model Type	Reservoir: CarbonSAFE	SACROC	Gulf of Mexico
Multi-layer Perceptron (MLP)	UU	NETL	PSU
Convolutional Neural Network (CNN)			UTBEG
CNN Autoencoder	LBNL		
Long Short Term Memory (LSTM)	NETL	NETL (x2)	PSU
CNN / LSTM	SNL	SNL	
U-Net		UTBEG	
Fourier Neuron Operator (FNO)		LANL	
Generative Adversarial Network (GAN)		PNNL	
Graph Neural Network (GNN)			Battelle

Development on Field Scale Reservoirs

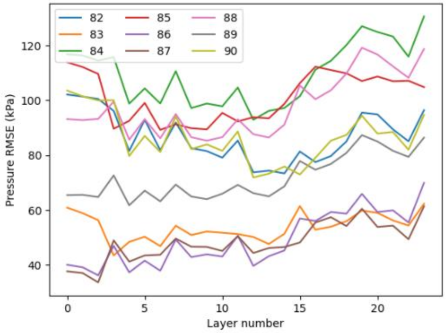
Pressure Truth, Prediction, and Error at Start of Injection, Middle Injection, and End of Injection



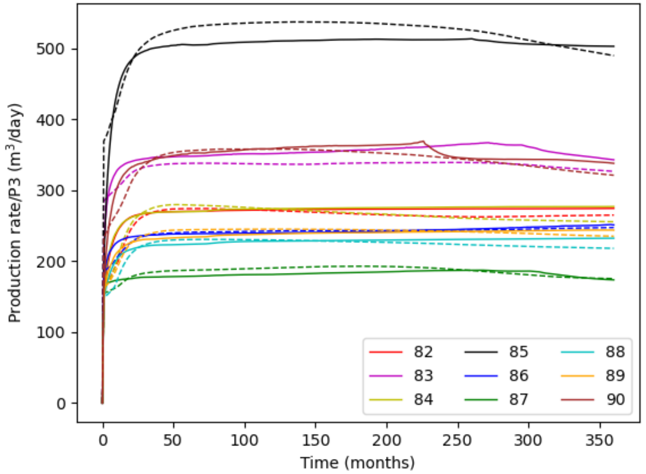
Pressure RMSE Over Time, by Test Case



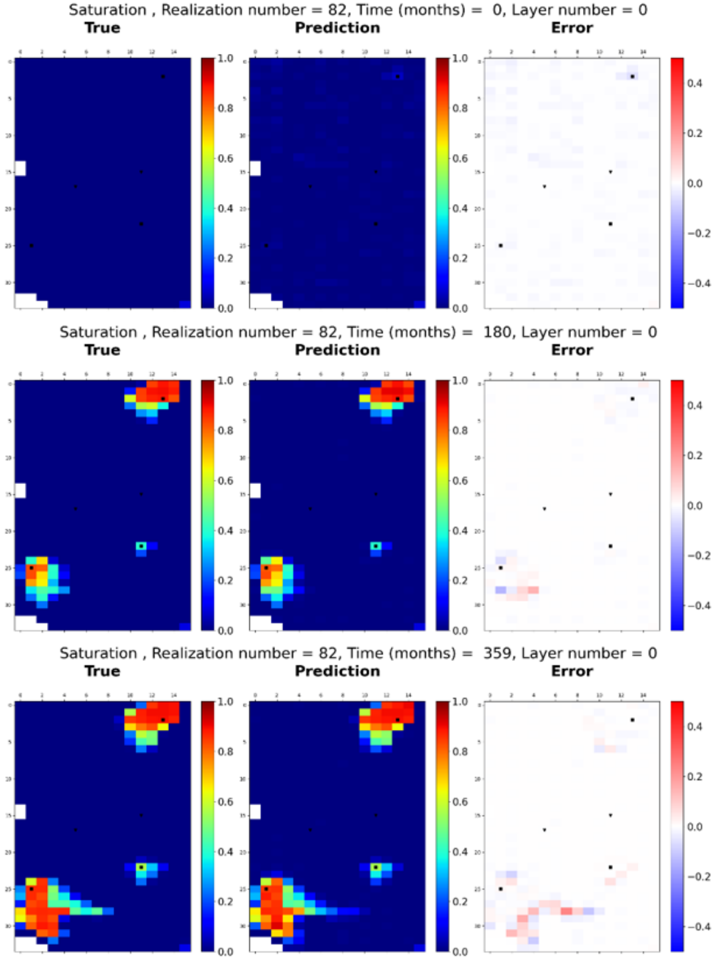
Pressure RMSE Across Layers, by Test Case



Production RMSE for Well P3 Over Time, by Test Case



Saturation Truth, Prediction, and Error at Start of Injection, Middle Injection, and End of Injection

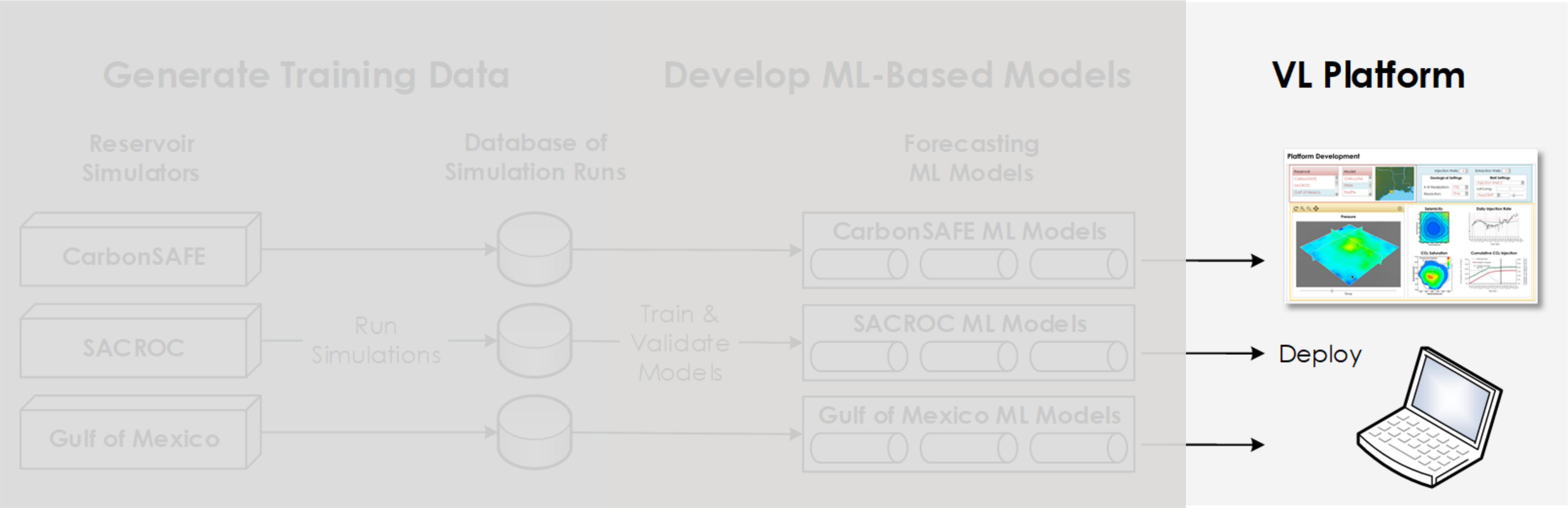


Development on Field Scale Reservoirs

- Most models are accurate and show good visual agreement with simulation runs
- Each reservoir had at least one model with low forecast times (time to generate all time steps for a single run configuration)
- Predictions can be made up to 5000x faster than simulations can be run

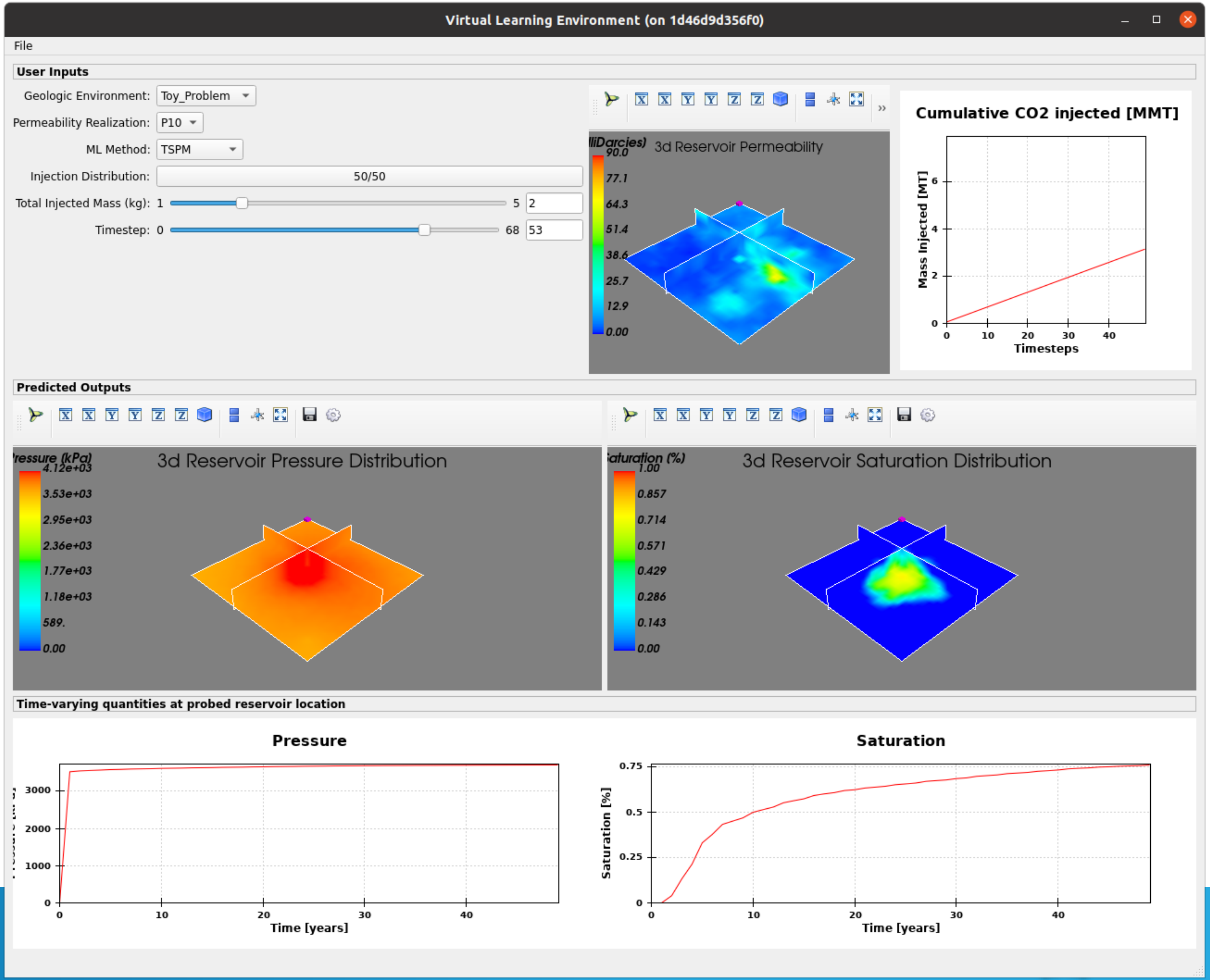
Reservoir Model	Institution	Model Reported	Best RMSE Achieved: Pressure (psi)	Best RMSE Achieved: Saturation	Best RMSE Achieved: Water Production Rate (bbl/day)	Forecast Time (secs)	~Speed-up relative to physics-based simulator
CARBON SAFE	NETL	LSTM	26.70	0.0064	36.86	1.15	5000X
	UU	MLP	20.50	0.0350	20.8	800	10X
	LBNL	CNN AENC	36.17	0.0105	N/A	131	50X
	SNL	CNN/LSTM	2.655	0.0006	3.59	93	60X
SACROC	LANL	FNO	4.94	0.0296	99.5	9.54	250X
	NETL-SSAE	MLP	22.77	0.0350	90	1.59	1500X
		LSTM	34.50	0.0390	52.39	1.24	2000X
	NETL-GES	LSTM	22.4	0.0280	121.83	0.48	5000X
	PNNL	GAN	12.14	0.0295	221.59	0.98	2500X
	SNL	CNN/LSTM	11.17	0.0358	245.24	2.17	400X
	UTBEG	U-NET	16.30	0.0029	45	6.9	400X
Gulf of Mexico	UTBEG	CNN/MLP	2.06	0.0053	13.86	5	2000X
	Battelle	GNN (multi)	296.62	0.0444	N/A	204	50X
	PSU	MLP	0.16	0.0068	6.5	165	60X
		LSTM	0.12	0.0429	9.09	190	50X

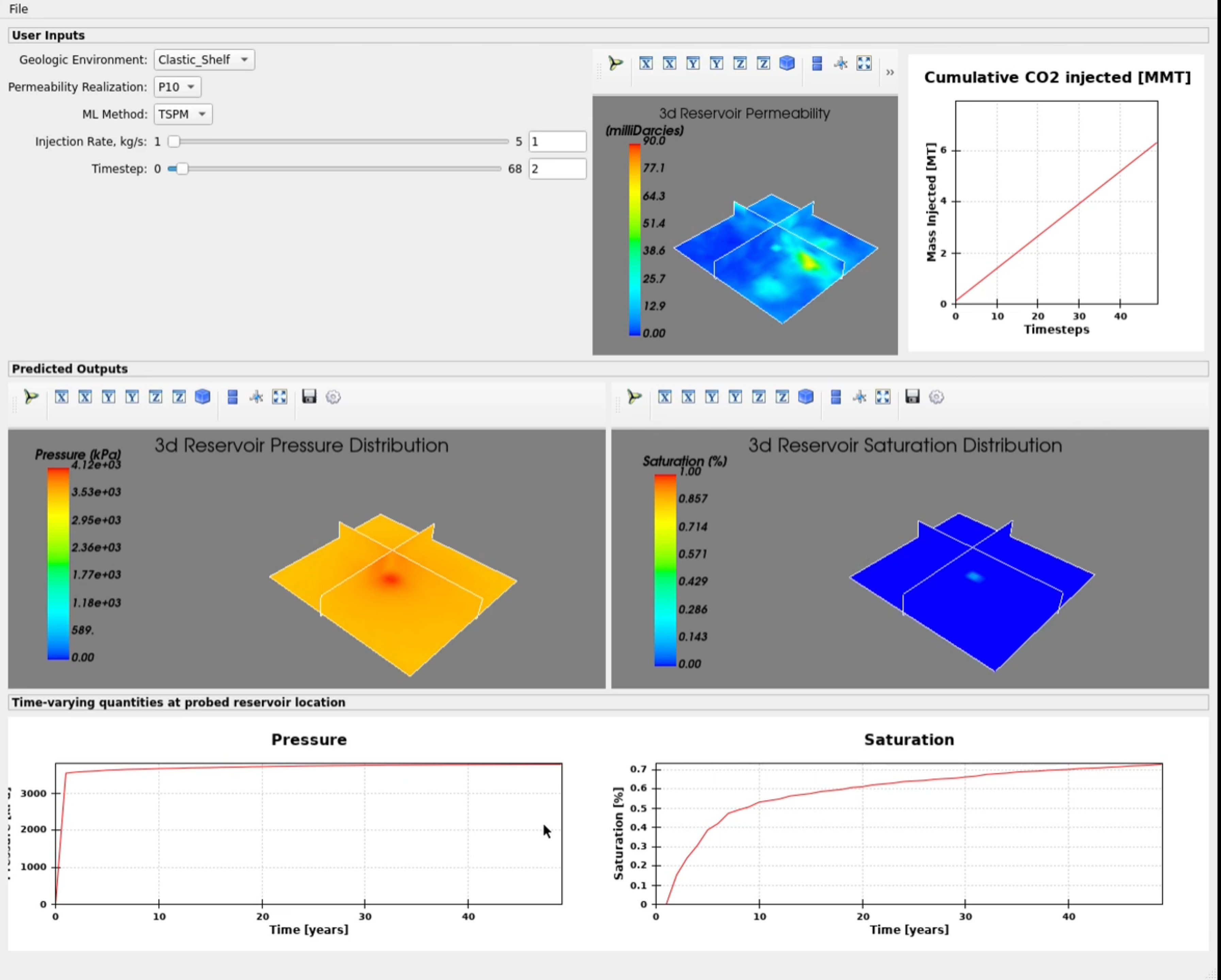
Part 3 – VL Platform Prototype



Development of VLE Prototype

- Bundles disparate ML models into a single, deployable package
- Interactive with ability to vary different inputs and explore outputs in different formats
- Windowed GUI system as well as web-browser based




File
User Inputs
Geologic Environment: Clastic_Shelf
Permeability Realization: P10
ML Method: TSPM
Injection Rate, kg/s: 1 5 1
Timestep: 0 68 2
3d Reservoir Permeability
(milliDarcies)
90.0
77.1
64.3
51.4
38.6
25.7
12.9
0.00
Cumulative CO2 injected [MMT]
Mass Injected [MT]
0
2
4
6
0 10 20 30 40
Timesteps
Predicted Outputs
3d Reservoir Pressure Distribution
Pressure (kPa)
4.12e+03
3.53e+03
2.95e+03
2.36e+03
1.77e+03
1.18e+03
589.
0.00
3d Reservoir Saturation Distribution
Saturation (%)
1.00
0.857
0.714
0.571
0.429
0.286
0.143
0.00
Time-varying quantities at probed reservoir location
Pressure
0
1000
2000
3000
0 10 20 30 40
Time [years]
Saturation
Saturation [%]
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0 10 20 30 40
Time [years]

Phase I: Summary

- We have generated a large volume of synthetic data for CO_2 injection scenarios from three representative reservoirs, and have used them to build 15 machine learning-based forecasting models

  - The ML-based models captured the physics of fluid flow during CO_2 storage operations while approximating simulation outputs at 50 to 5000 times faster than the original runs

- We have built a prototype virtual learning environment with the ML-based models to demonstrate how a stakeholder can develop an intuitive understanding of CO_2 storage site behavior by interacting with them

- **All results are publicly available, contact SMARTFE@netl.doe.gov**

Phase I: Lessons Learned

- **Reservoir Modeling and Simulation**
  - It is important to ensure that the reservoir models (and synthetic training data) accurately capture the underlying physics – engagement of SMEs is vital

- **Machine Learning Model Development**
  - Simpler and established models (e.g., CNN, MLP, LSTM) appear to balance speed and accuracy well, while complex methods are more accurate but significantly slower
  - Data reduction/dimensionality reduction methods are promising, but have the overhead to transform data back to original scale which may affect the gains in prediction time from a smaller data size
  - Results show that a relatively small number of simulation runs (dozens) may be sufficient to develop accurate ML-based forecasting models
  - Inclusion of physics-based constraints improves ML prediction accuracy and training time. But, simultaneous training of pressure and saturation can be challenging due to unbalanced data structure and different underlying spatio-temporal features. More complex (or hierarchical) spatio-temporal ML models need to be explored to evaluate applicability of these models
  - Models trained separately for pressure and saturation can be more accurate compared to those trained simultaneously

Thanks from the Team

Los Alamos National Laboratory EST. 1943
- Bicheng Yan
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Questions?