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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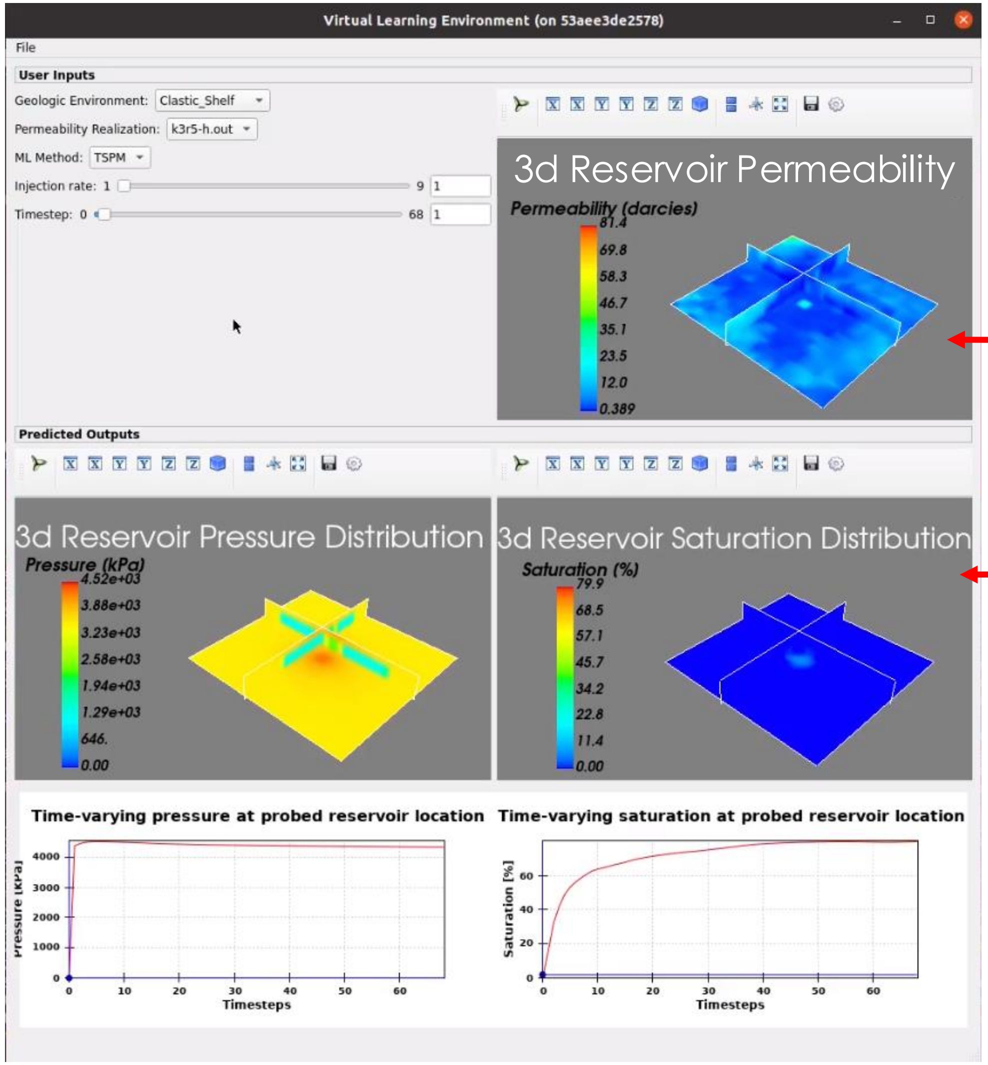
Task 5 Motivation

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

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

Phase 1 Goal: Demonstrate the proof-of-concept with a prototype



Interactively gain intuitive understanding of CO_2 storage site behavior by:

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Manipulating inputs &
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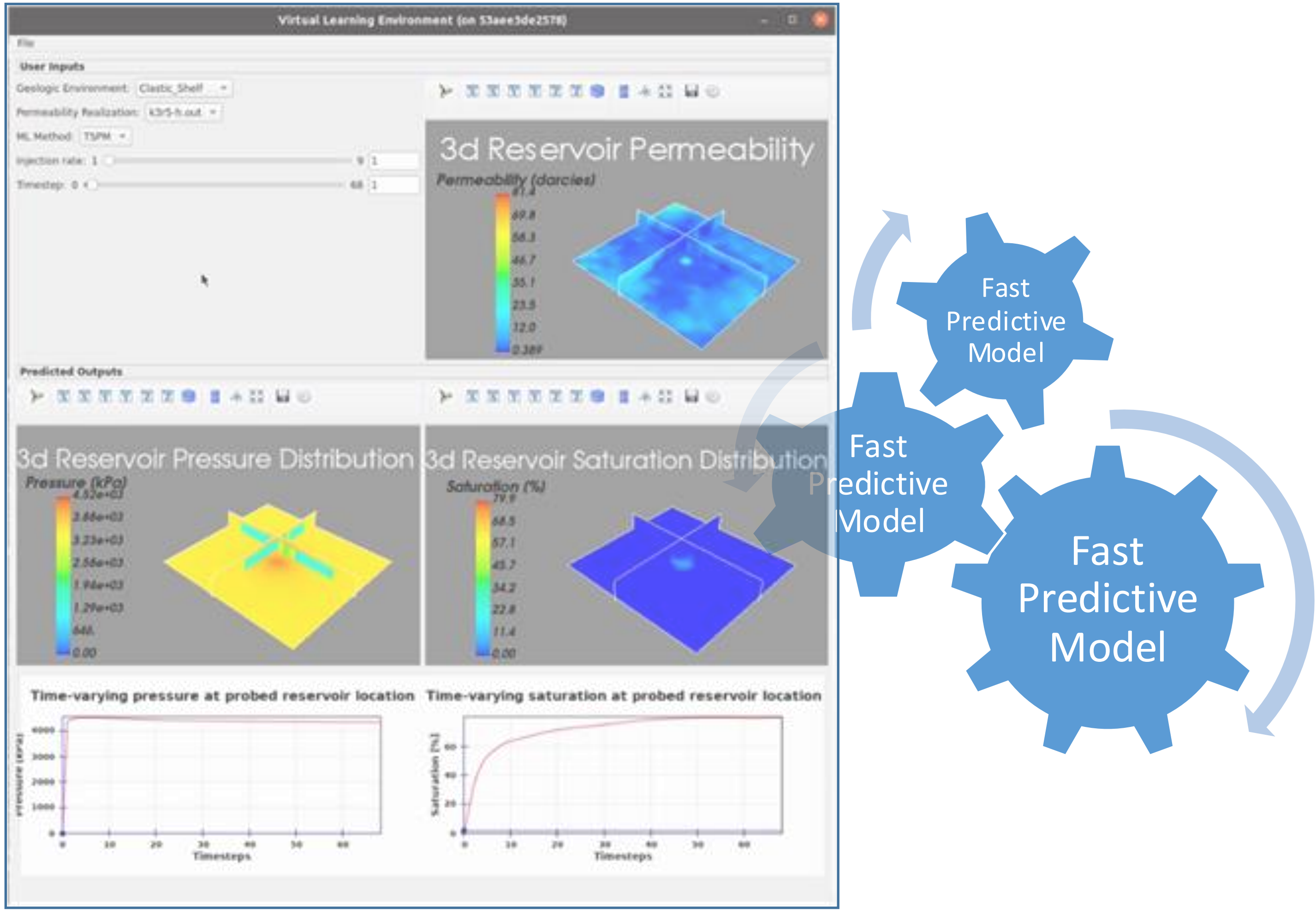
.
.
Exploring Outputs

How can Task 5 help CCS decision-makers

	Decision Maker	Decision to Be Made	Current Approach to Decision	How might SMART change this decision? And, how would this new approach improve the decision?
Permitting	Regulator—State, Federal in Charge of Permitting	Will the proposed AOR and monitoring plan be sufficient?	Assess AOR and monitoring requirements based on information provided in permit application	Regulators can use VLE to gain and improve understanding of AOR and effective monitoring through exploring multiple, relevant scenarios in significantly shorter time
Site Development	Engineer—Storage Operation	How should the field be developed relative to injection wells?	Numerical reservoir simulations coupled with field injection tests	Engineers can use VLE to rapidly test different strategies for optimal reservoir management by exploring multiple, relevant scenarios
Site Development	Engineer—Storage Operation	How should the field and infrastructure be developed relative to brine extraction?	Numerical reservoir simulations coupled with field production tests	
Post Closure	Engineer—Storage Operation	When/where/how should I monitor to ensure there is no leak?	Monitoring observations during site-operations coupled with predictions of post-injection site behavior with reservoir models (validated)	Engineers can use VLE to efficiently test effectiveness of different post-injection monitoring strategies (when, where, what) prior to site operations in significantly shorter time

Interactive virtual learning platforms need fast, predictive models



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

Our Approach

Our approach uses synthetic training data to develop machine learning based models

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

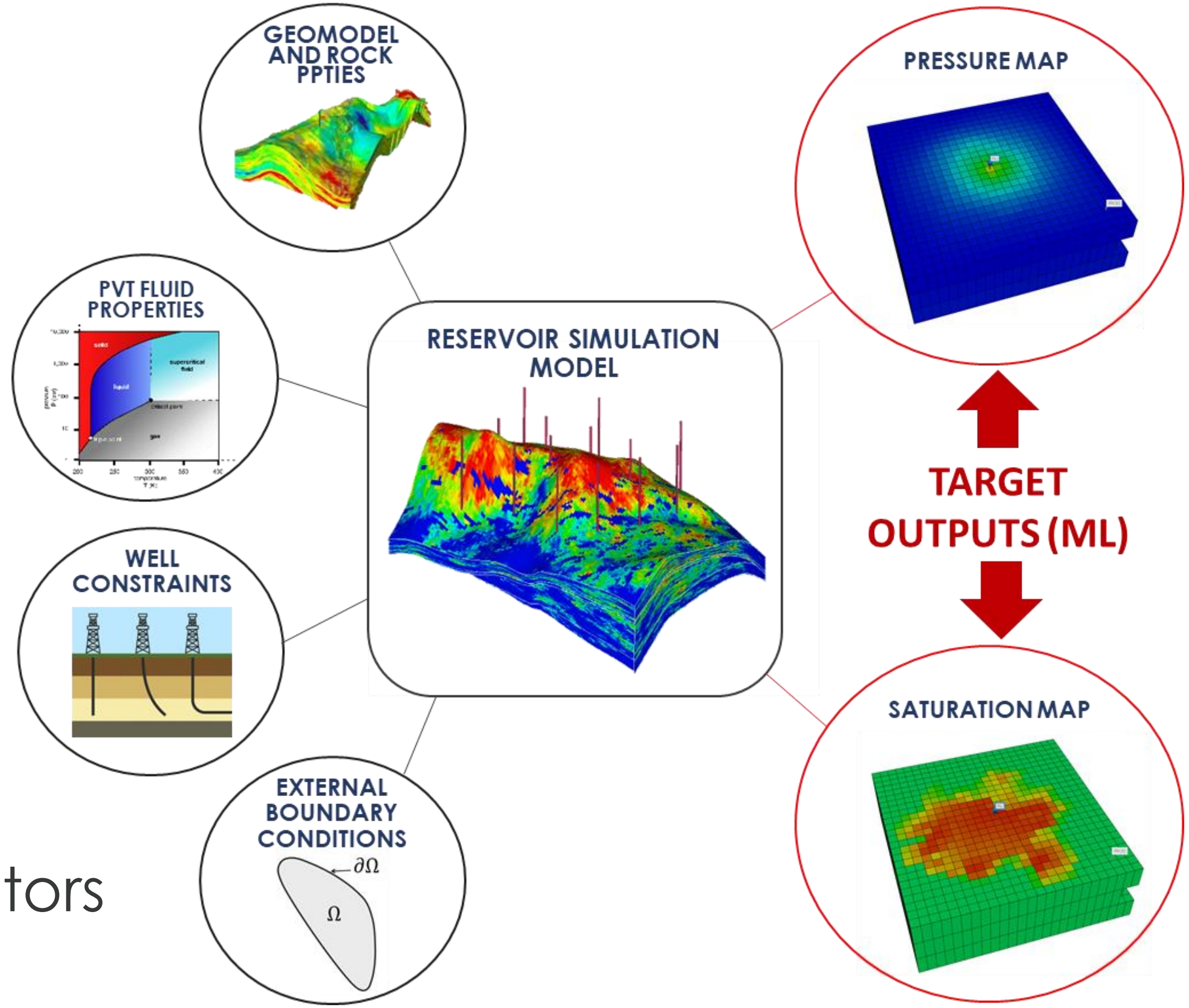
Geological uncertainty

- *Multiple depositional environments / res. Sites*
- *Heterogeneous porosity/permeability*

Operational uncertainty

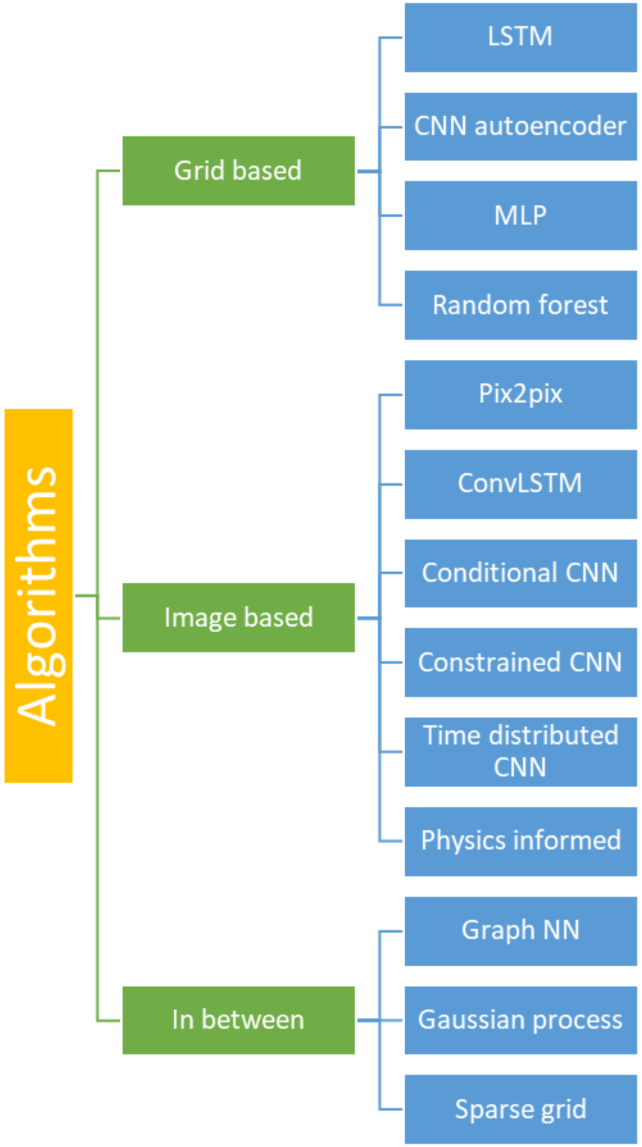
- *Variable cumulative CO_2 injection (up to 50 million tons)*
- *Variable injection allocation among injectors*

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



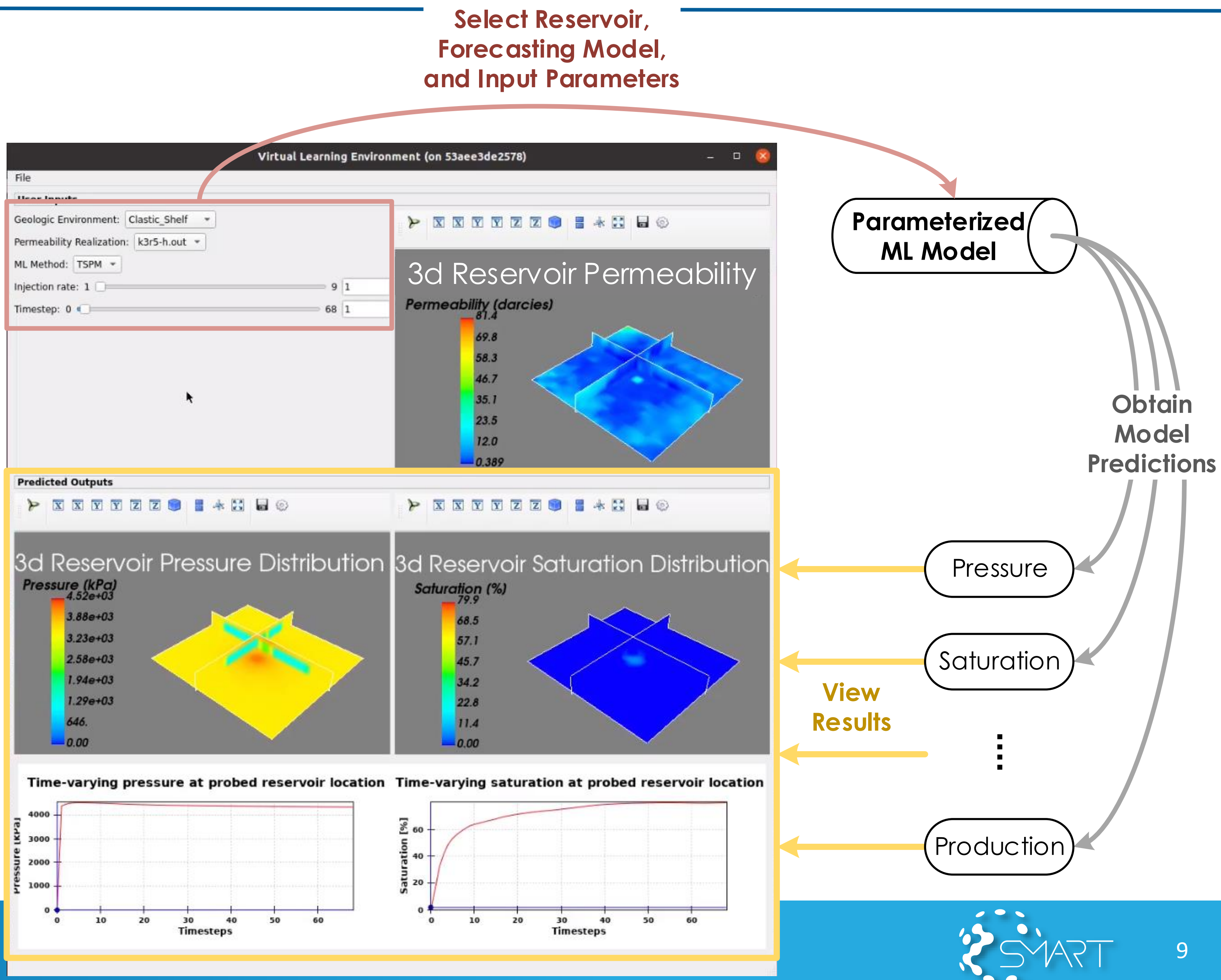
We have explored multiple machine learning approaches

- Approaches that can effectively capture time & space-dependent evolution of reservoir response:
  - Extensive literature search to identify appropriate approaches
- Applicability of approaches tested using 2D and 3D small-scale test problems of varying complexities:
  - Over 16 different models developed by team members
- Workflow for field-scale ML model dev was defined
  - A Browser-based test suite to facilitate ML model inter-comparison

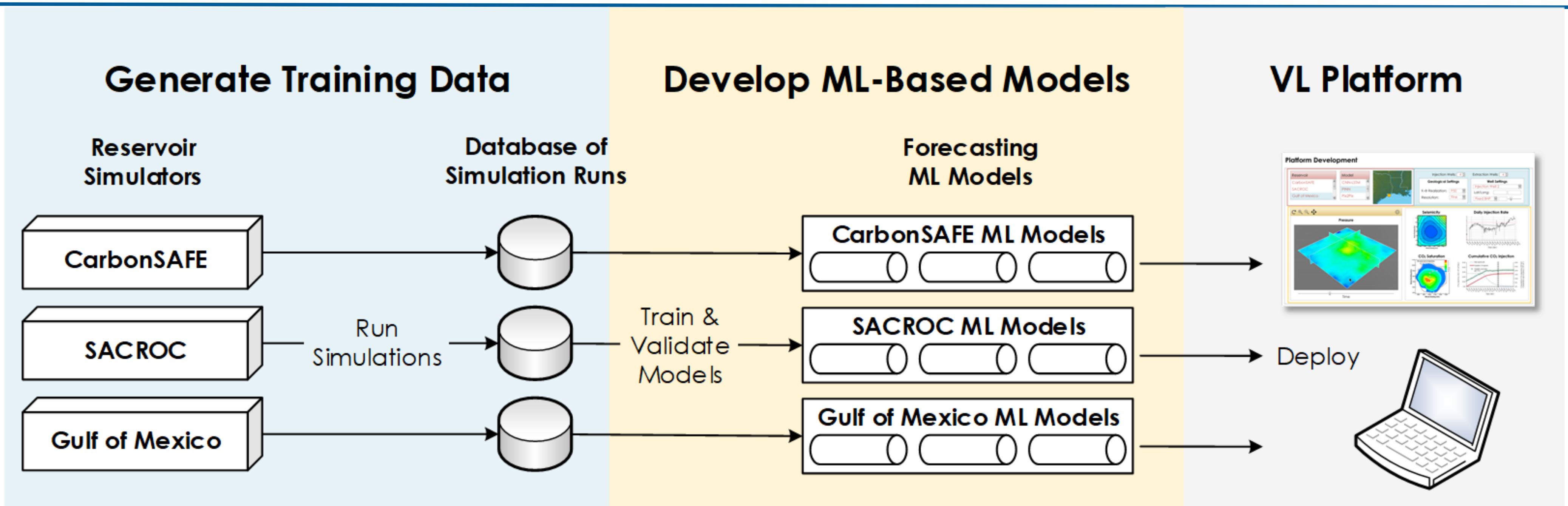


A prototype interactive platform has been developed with ML-based fast, predictive models

- Identified requirements for interactive platform:
  - Inputs
  - Predictions
  - Performance
  - Analysis capabilities
- Proof-of-concept of the platform was successfully tested with ML-based model for 3D small-scale test problem



Task Management



Sub-task	Description	Sub-task Lead
5.2.1	Develop Specifications for Platform	Hongkyu Yoon (SNL)
5.2.2	Identify Candidate Phase 2 Reservoirs	Tom McGuire (EERC)
5.2.3	Define ML Model Training Workflows	Alex Sun (UT-BEG)
5.2.4	Synthetic Data Generation	Luis Ayala (PSU)
5.2.5	ML Forecasting Model Development	Seyyed Hosseini (UT-BEG)
5.2.6	Develop Alpha Version of Platform	Alex Hanna (PNNL)

Field Sites

Criteria for reservoir models selection

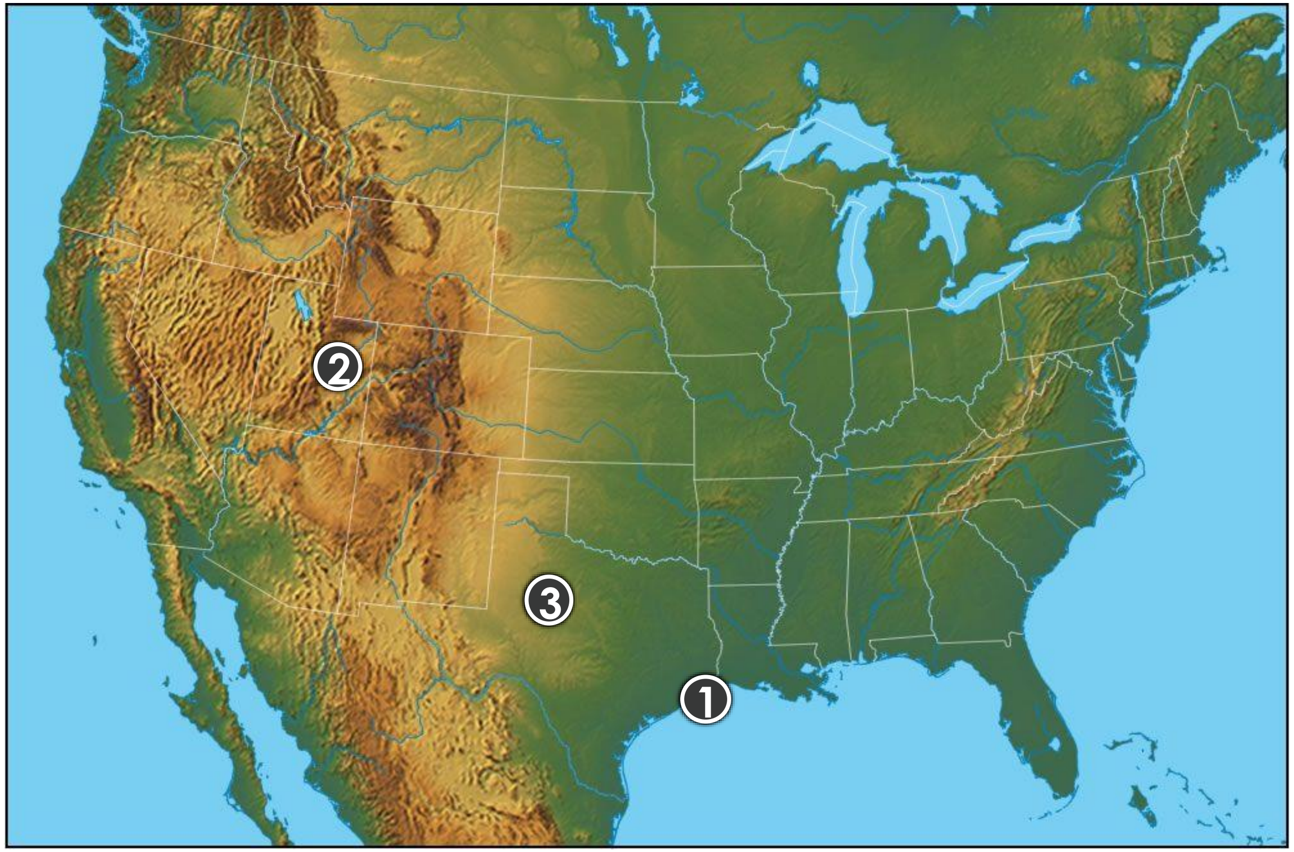
1. Capability to store up to 50 million tons of CO_2 over 50 years (injection + post injection periods)
2. Variety of geological depositional settings
3. Public availability and accessibility of multiple geological realizations to capture uncertainty
4. Preference to models created in previous DOE funded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

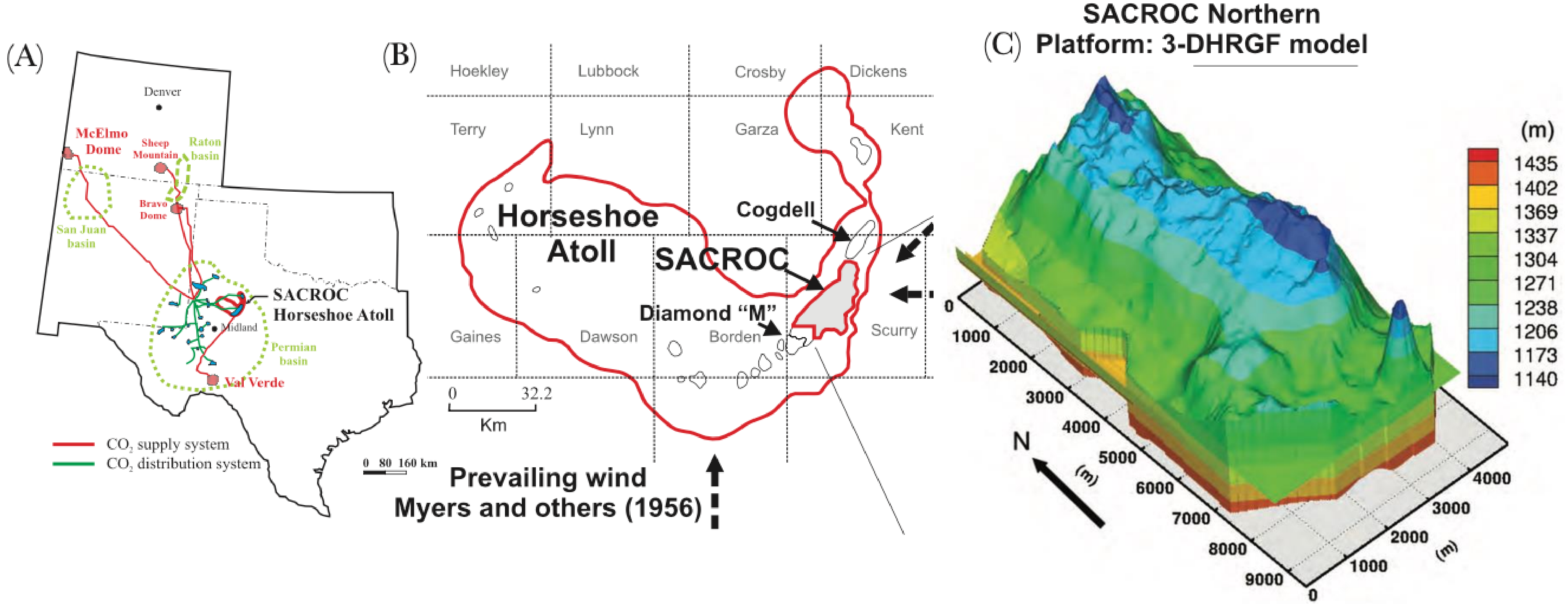


SACROC Example

SACROC Northern Platform

The Scurry Area Canyon Reef Operators Committee Unit

- CO_2-EOR since 1972
- For Task 5 purpose target reservoir approximated as a saline aquifer



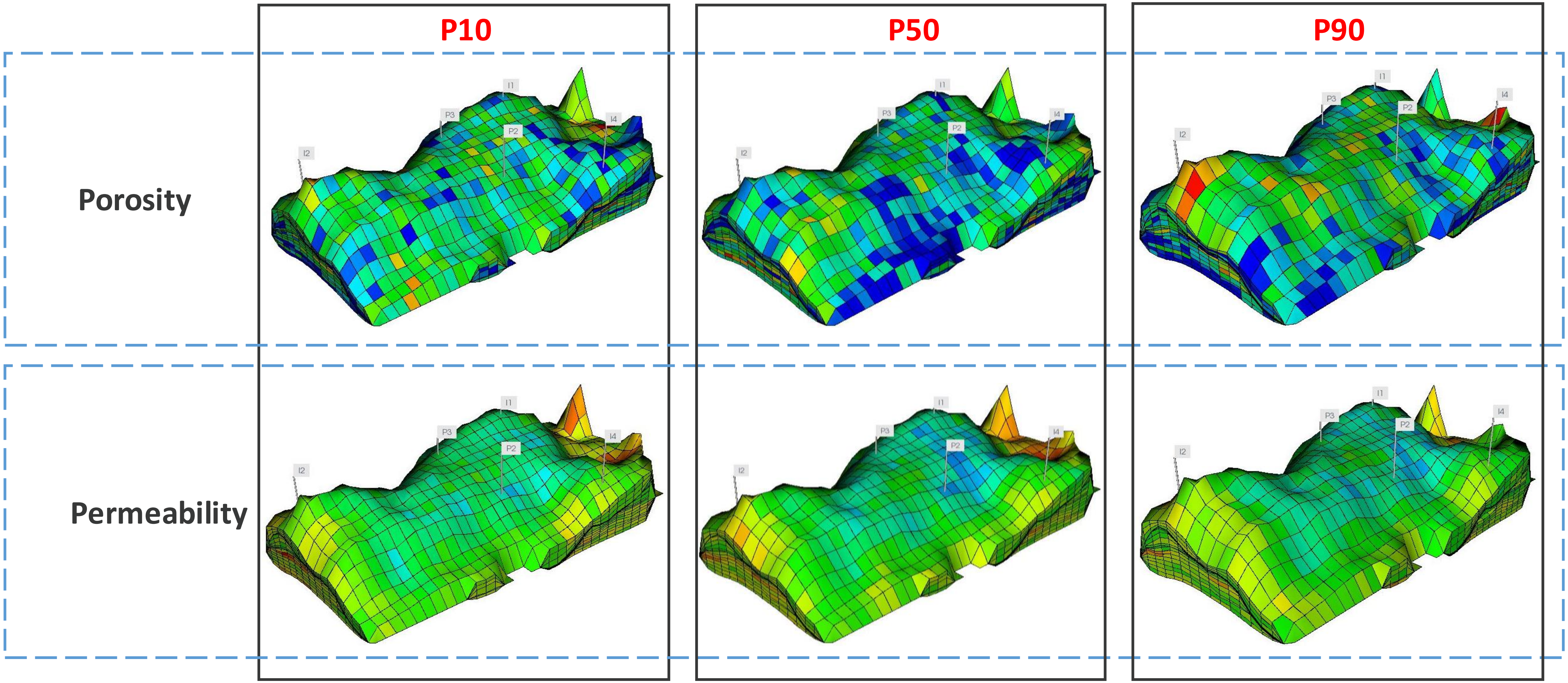
Reservoir simulations

- Reservoir model originally developed by Southwest Regional Partnership
  - CMG-GEM
  - 13600 cells (34 × 16 × 25)
- Scoping simulations performed to determine optimal net CO_2 storage
  - Ensure industrial scale storage
  - Optimal net capacity achieved with 3 injectors and 2 producers
- Iterative approach used to ensure that the underlying physics was honored
  - Bottom-hole-pressure response at the injectors
  - Iterated with boundary conditions and local-grid-refinement
- Average simulation run time: ~ 4 hours/run

Net CO2 Storage in Coarse SACROC Model (MMT)					
Producers					
4				22.7	
3			22.5	22.9	
2		15.6	22.5	22.7	
1	12.4	13.2	15.8	16.0	
0	6.1	6.1	6.1	6.1	
	1	2	3	4	Injectors

Multiple property realizations to account for geological uncertainties

3 porosity-permeability realizations: P10, P50, P90



Simulation case matrix

Variables:

- Injection amount
- Injection allocation among wells
- k and phi values

81 training cases

9 testing cases

I1 & I2 & I3

Injection Allocation	Total CO2 Injection (MMT)	k-phi p10	k-phi p50	k-phi p90
33/33/33	22.4	-	-	-
	11.2	1	2	3
	5.6	4	5	(1) 6
60/20/20	22.4	7	8	9
	11.2	13	14	15
	5.6	22	23	24
20/60/20	22.4	(2) 10	11	12
	11.2	16	17	18
	5.6	25	26	27
20/20/60	22.4	-	-	-
	11.2	19	(3) 20	21
	5.6	28	29	30

I1 & I2

Injection Allocation	Total CO2 Injection (MMT)	k-phi p10	k-phi p50	k-phi p90
50/50	22.4	31	32	(4) 33
	11.2	34	35	36
	5.6	43	44	45
90/10	22.4	-	-	-
	11.2	52	53	54
	5.6	64	65	66
10/90	22.4	-	-	-
	11.2	(5) 55	56	57
	5.6	67	68	69

I1 & I3

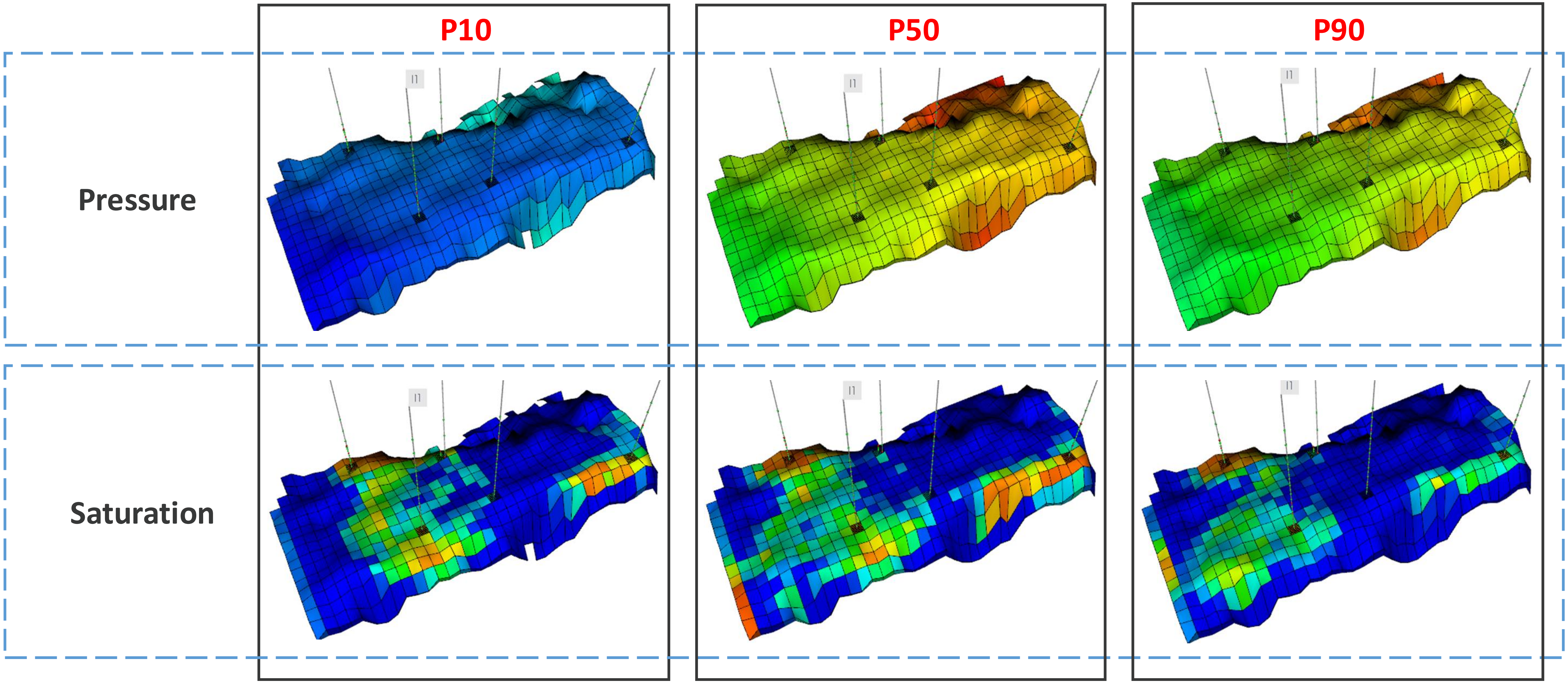
Injection Allocation	Total CO2 Injection (MMT)	k-phi p10	k-phi p50	k-phi p90
50/50	22.4	-	-	-
	11.2	(6) 37	38	(7) 39
	5.6	46	47	48
90/10	22.4	-	-	-
	11.2	58	59	(8) 60
	5.6	70	71	72
10/90	22.4	-	-	-
	11.2	-	-	-
	5.6	76	77	78

I2 & I3

Injection Allocation	Total CO2 Injection (MMT)	k-phi p10	k-phi p50	k-phi p90
50/50	22.4	-	-	-
	11.2	40	41	42
	5.6	49	50	51
90/10	22.4	-	-	-
	11.2	61	(9) 62	63
	5.6	73	74	75
10/90	22.4	-	-	-
	11.2	-	-	-
	5.6	79	80	81

Example results – Pressure and saturation distributions at the end of injection in one of the model layers for one simulation run

3 porosity-permeability realizations: P10, P50, P90



Machine learning based model development

- Results of reservoir simulations converted in formats appropriate for ML
  - Numpy format
  - New conversion script developed
  - Converted output size - ~ 0.4 GB/run
- Input data for ML-models included
  - Space-dependent permeability, porosity
  - Locations & time-dependent injection rates for 3 injectors
  - Time & space dependent pressure & saturation
  - Locations & time-dependent production rates for 2 producers

Six different ML approaches were applied

ML-Approach	Team
Fourier Neural Operator (FNO)	LANL
Autoencoder + Multilayer Perceptron (Pressure & Saturation)	NETL-SSAE
Autoencoder + Long Short Term Memory (Water Production)	NETL-SSAE
Long Short Term Memory	NETL-GES
Pix2Pix	PNNL
CNN-LSTM-DNN (Pressure & Saturation)	SNL
CNN-LSTM (Water Production)	SNL
AU-Net	UT-BEG

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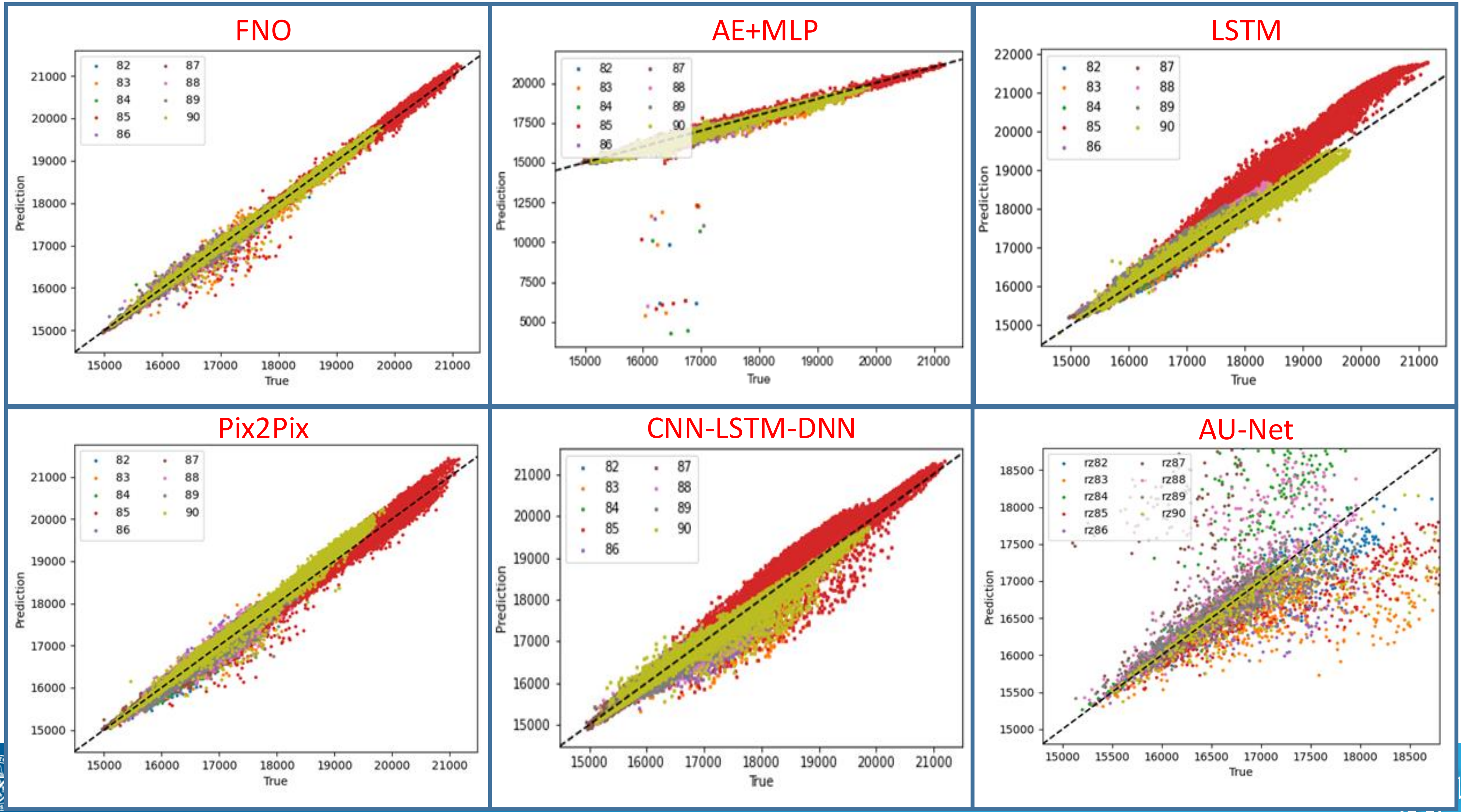
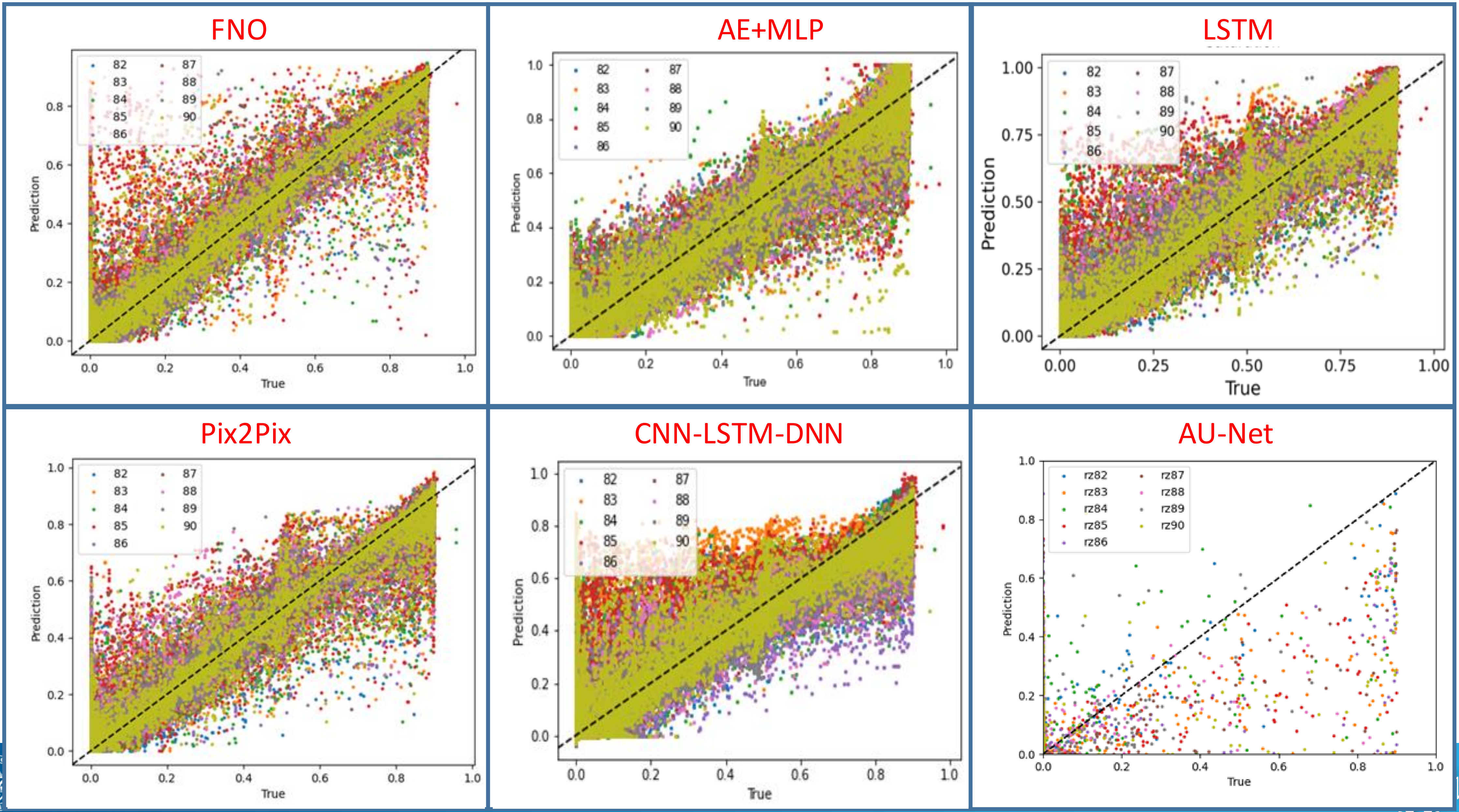
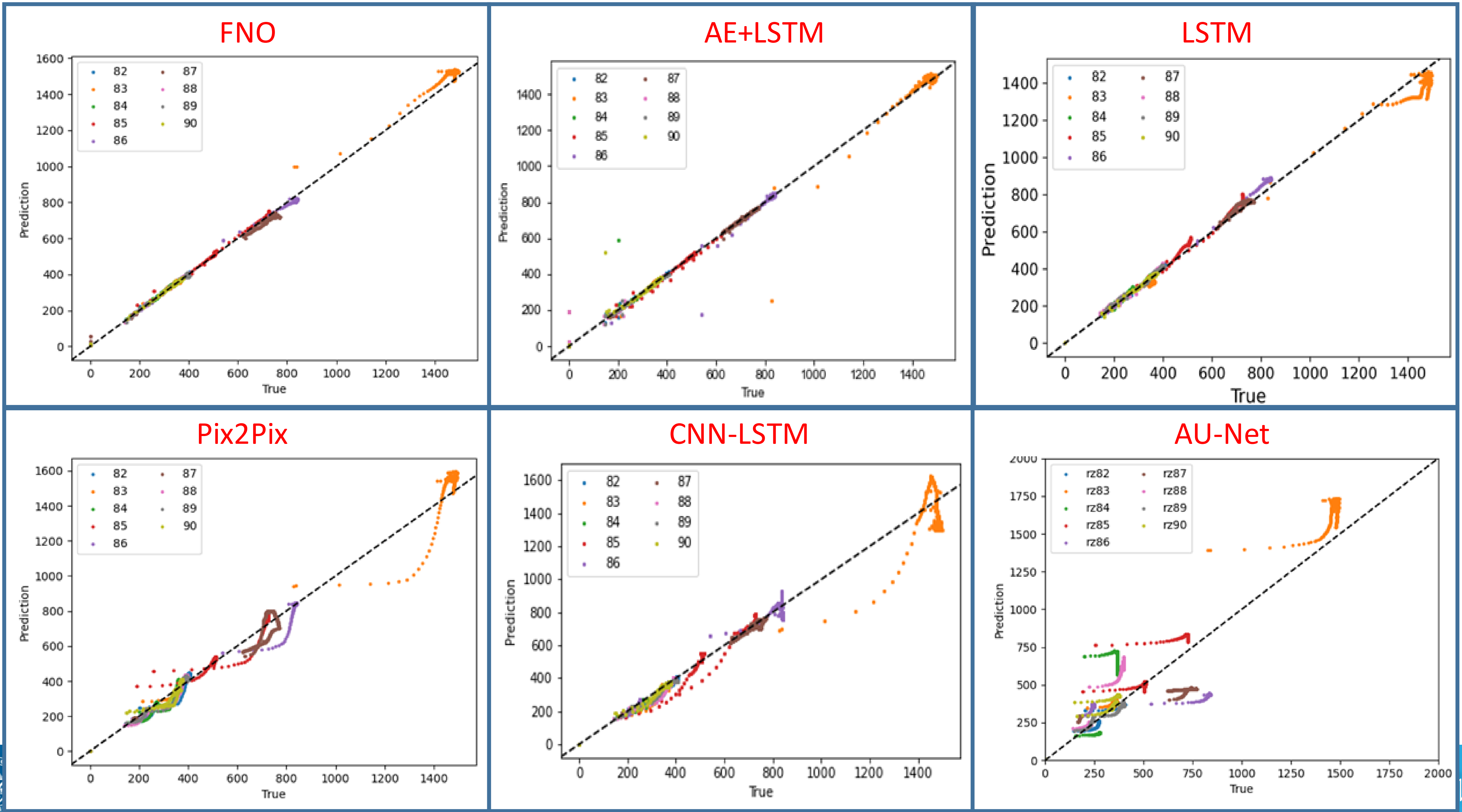
ML-based models – pressure predictions for test cases



ML-based models – saturation predictions for test cases



ML-based models – production rate predictions for test cases



Combined Results

We have successfully developed fast, predictive models for three reservoirs

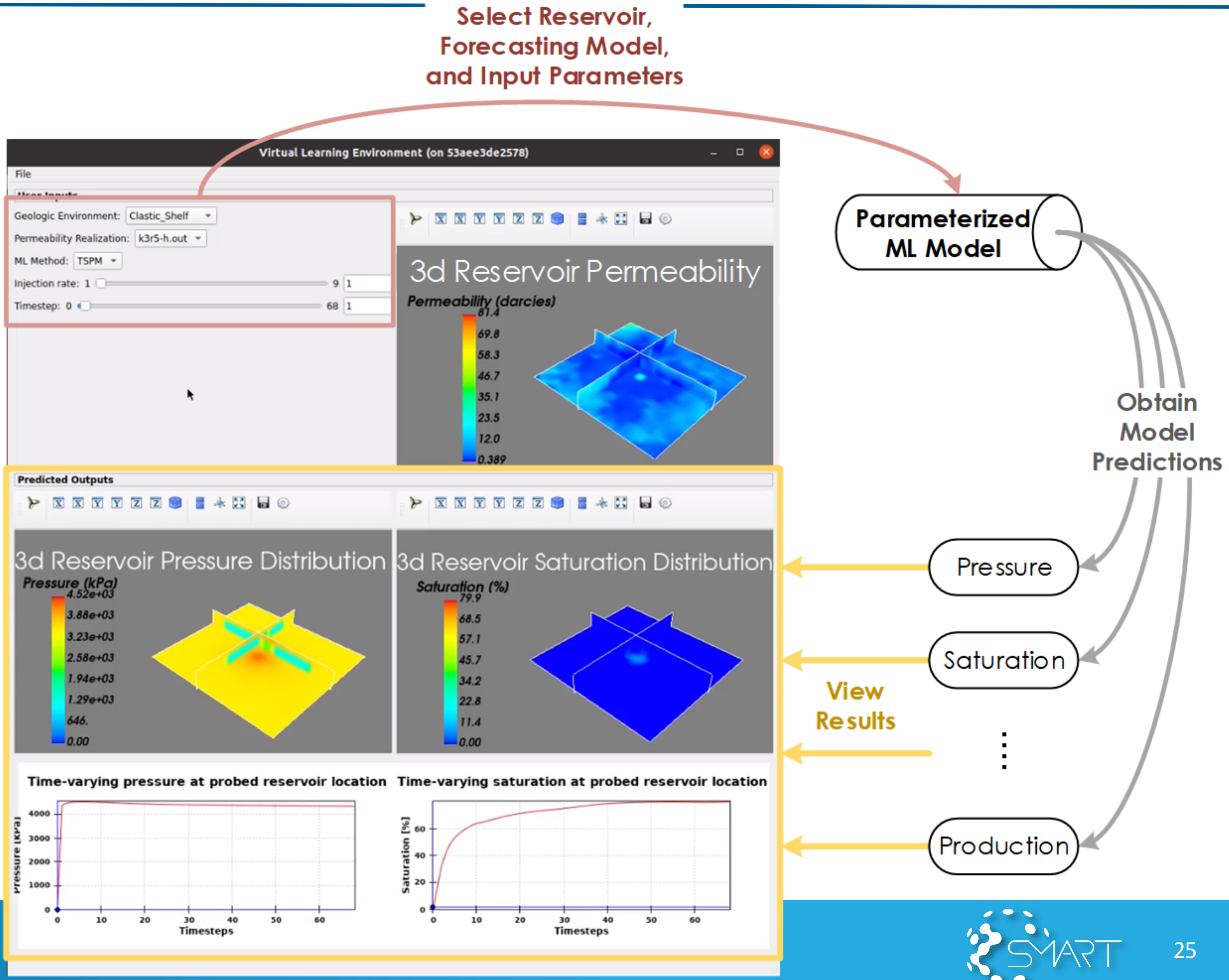
- 250 reservoir simulation runs for 3 reservoirs:
  - CarbonSAFE: 40 runs
  - SACROC: 90 runs
  - Gulf of Mexico: 120 runs
- Multiple teams applied different machine-learning approaches
  - CarbonSAFE – 4 models
  - SACROC – 7 models
  - Gulf of Mexico – 4 models
- ML-based models have high accuracy and good speed-up (10x – 5000x) compared to physics-based simulators

Reservoir Model	Institution	Model Reported	Best RMSE Achieved			Forecast Time (secs)	~Speed-up relative to physics-based simulator
			Pressure (psi)	Saturation	Water Production Rate (bbl/day)		
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
CARBONSAFE	NETL	LSTM	26.70	0.0064	36.86	1.15	5000X
	UU	MLP	20.50	0.0350	20.8	800	10X
	LBNL	Model1	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	78.76	0.1000	628.98	6.9	400X

Future Work

Future work in Phase I

- Perform detailed comparison of ML-based models
  - Test speed-ups using common computational platform
- Complete incorporation of ML-based models in the VLE and demonstrate its utility
- Assess applicability of ML approaches for Phase II



Questions?

Thank you!

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