Probabilistic Plume Migration Prediction using ML at the GFV Site

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Motivation

The GFV site is characterized by small-scale heterogeneity, which requires **high-resolution** numerical simulation with **fine temporal resolution**

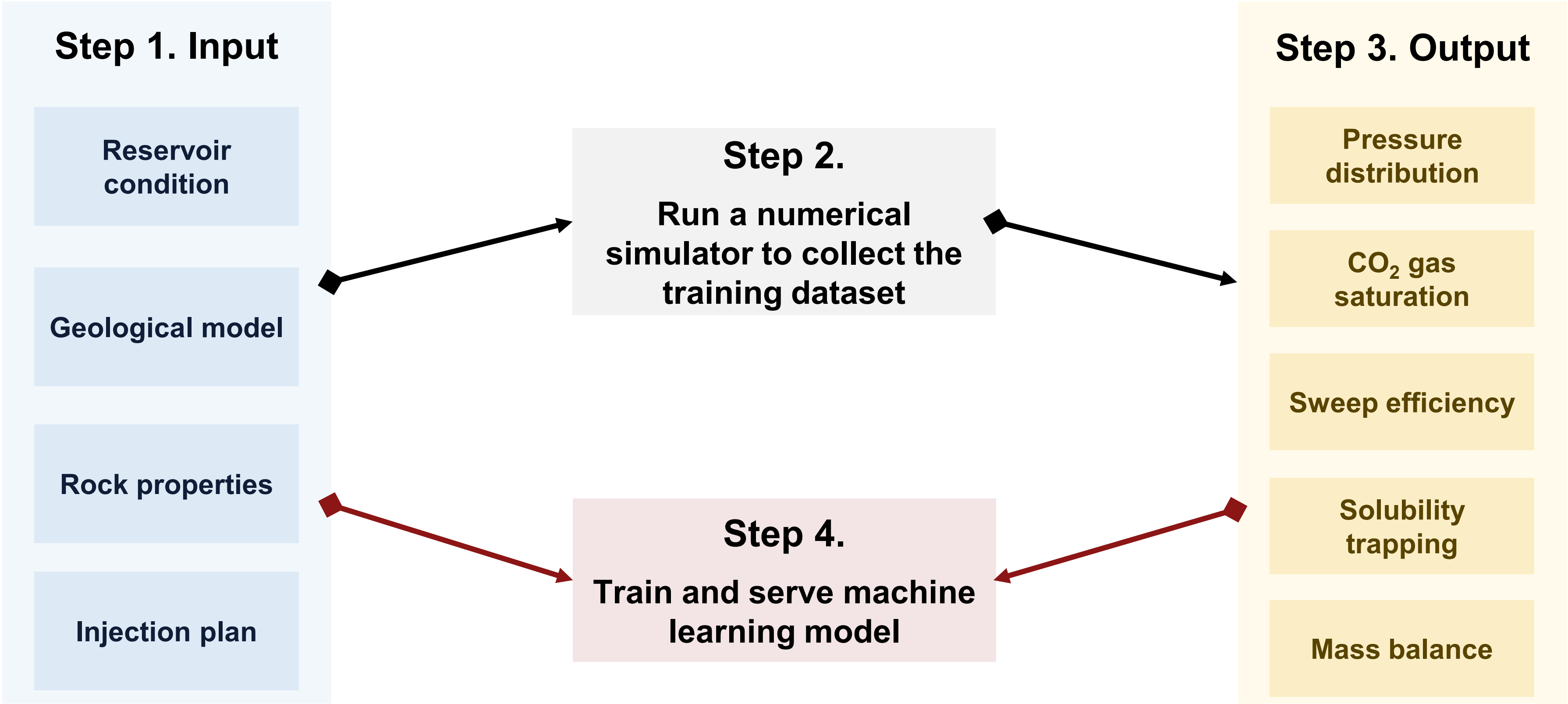
Combined with the highly nonlinear governing PDEs, multi-physics problems, multiscale heterogeneity and inherent uncertainty in the subsurface leads to **computationally expensive numerical simulations**

We want an option that allows to maintain the high temporal and spatial resolution and complexity of the simulations and accuracy, but is a **faster alternative**

CCSNet.ai, a general-purpose AI-based reservoir simulator, can be used to capture uncertainty space

CCSNet.ai provides **instant, full-physics** multiphase flow simulation predictions with high resolution and comparable accuracy to numerical simulation.

Procedure to develop ML models for predicting CO2 storage



Modified from Wen et al. (2021)

Training Dataset Generation

- **500+** numerical simulations were run in E300
- Using uniform cartesian grid with dimensions 3.3m x3.3m x0.3m
- Uses 90+ different rocktype geomodels with additional realizations were generated by sampling k_h, k_v, and Φ
- Composite rock directional relative permeability and composite rock Pc curves were used
- Imbibition rel perm curves used Land Trapping model
- 67 days of injection of 150 tons/day and 60 days post-injection

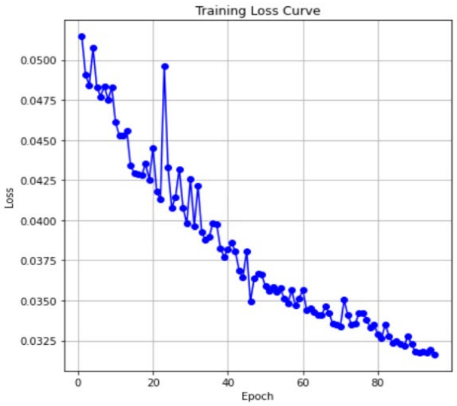
GFV U-FNO Model

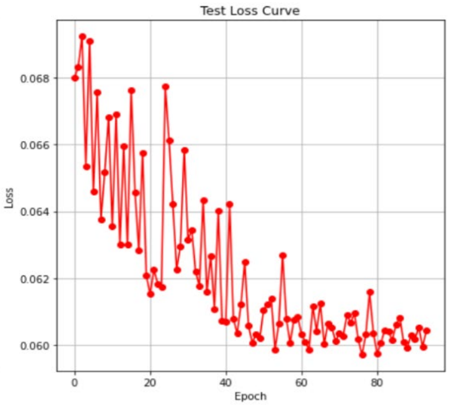
Architecture

- 3D U-FNO
- Single step time
- Inputs: kx, kz, porosity, rocktype cell ID
- Includes: hysteresis, directional relative permeability curves, composite rock modeling
- Output: Gas saturation

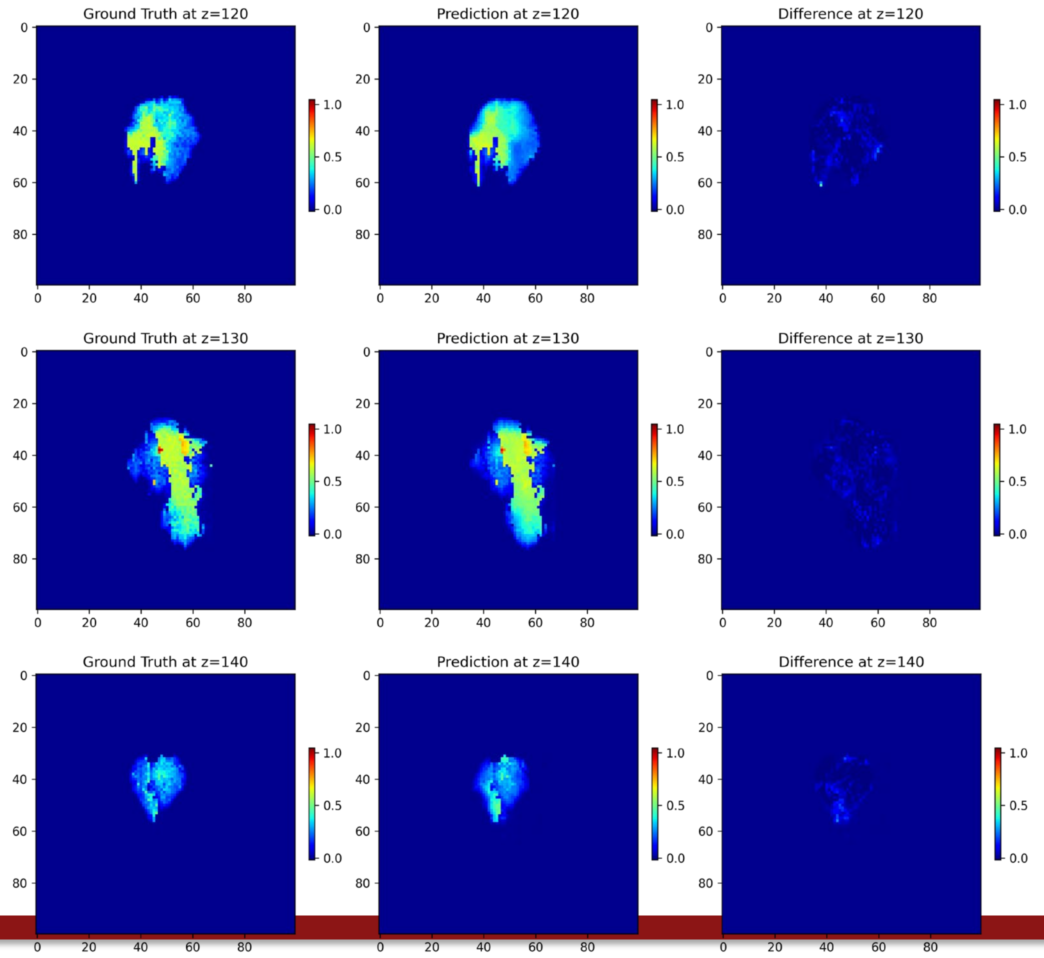
Accuracy

- Training Relative Loss= 3.2%
- Test Relative Loss = 6%





Gas saturation prediction at different z layers

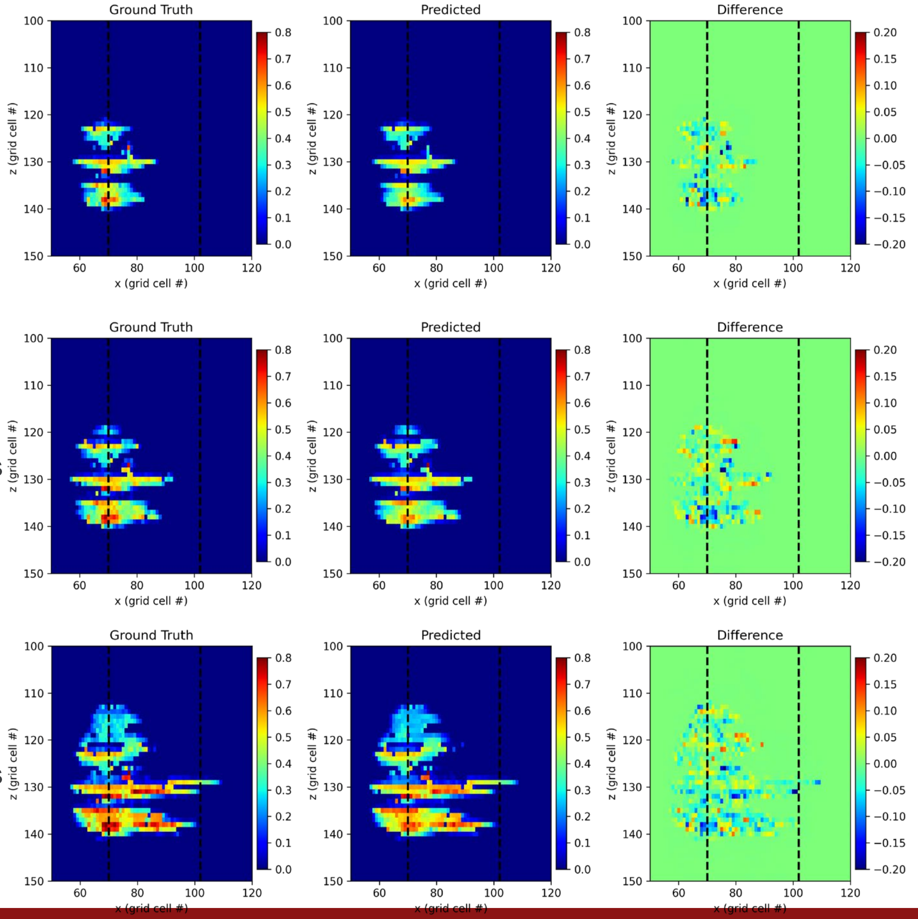


Gas saturation prediction at cross-section over time

t=8 days

t=12 days

t=15 days



Model results in **80,707x** average speed up in runtime

E300 runs are parallelized on 30 CPU on one machine

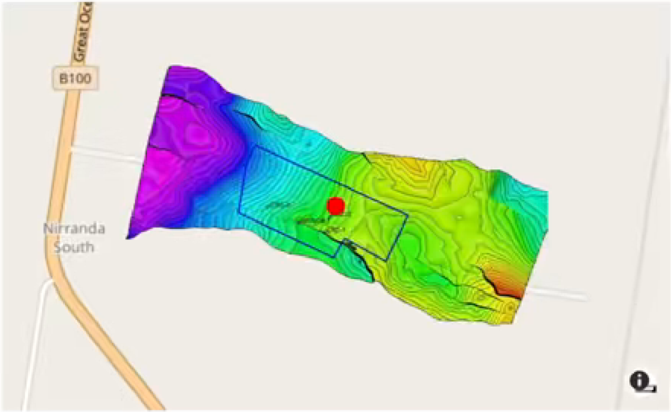
Average E300 run time (s)[a]	**UFNO Inference Time (s)[b]**
208,224	0.06 (1 timestep) 2.58 (43 timesteps)

[a] AMD EPYC 7543, 30-core parallel run
[b] On an NVIDIA A100 GPU

Home Realization 1 Realization 2 Realization 3 Realization 4

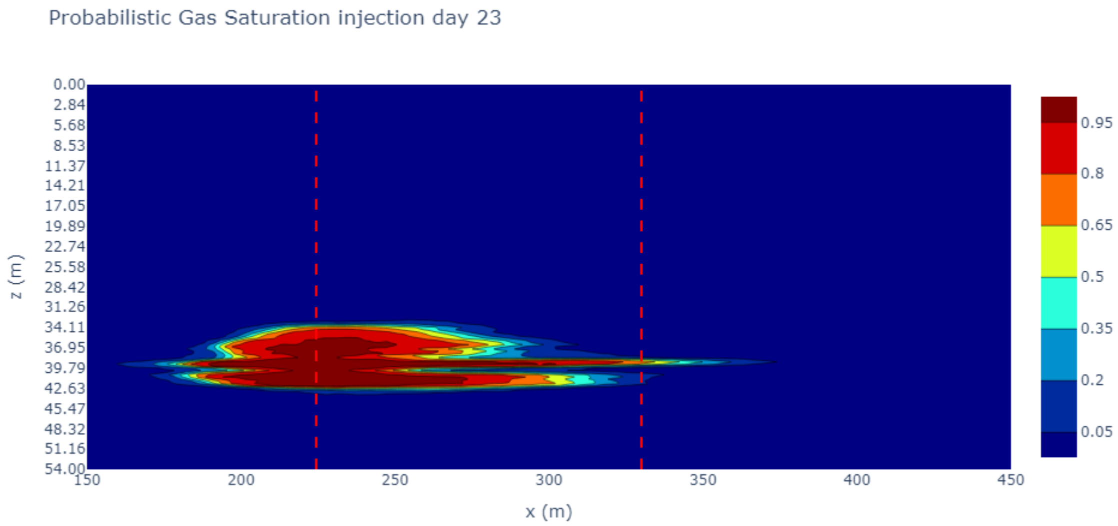
Otway Stage 4 GeoCquest Field Verification

This project demonstrates the power of machine learning models for probabilistic plume migration predictions and inverse modeling. The Stanford-developed machine learning model, CCSNet.ai, provides accurate flow simulation outputs 105 times faster than traditional numerical simulations (Wen et al., 2022, 2023). The significant improvement in computational efficiency can facilitate a probabilistic assessment of plume arrival times, shapes, and exhaustive exploration of the impact of geology heterogeneity at the GFV. As an example, we found that for a conditioned permeability map with the same well log, lateral and vertical correlation, and different random seeds, the plume radius can vary 60%. By running simulations for 500 different realizations of the same permeability field, we can calculate the probability that the plume will migrate different distances in the reservoir (bottom of Figure 102). As shown, for this example, there is 95% probability the plume will migrate 1000 m from the injection well, but only about 5% probability that it will migrate up to 2500 m. Performing these 500 simulations took less than 2.5 seconds. We have run over 400 simulations to train a high-resolution version of CCSNet.ai to support probabilistic assessment of plume migration for the GFV experiment as well as, supporting inverse modelling after the data is collected.



Probabilistic Gas Saturation over Time

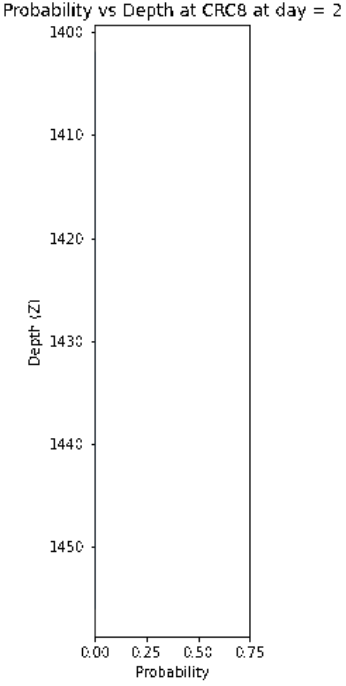
Probability of Breakthrough at CRC8	5%	50%	>80%
Top Layer	33 days	51 days	65 days
Middle Layer (fastest)	13 days	19 days	23 days
Bottom Layer	19 days	33 days	45 days



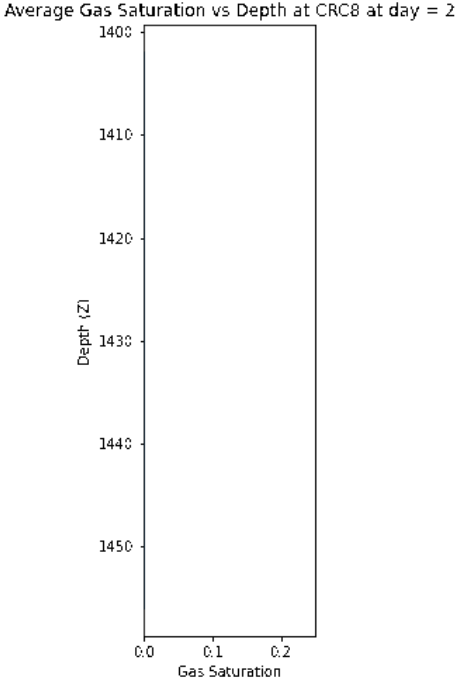
3D Video of probabilistic gas saturation

Gas saturation profile at CRC8:

<u>Probabilistic Gas Saturation</u>



<u>Average Predicted Gas Saturation</u>

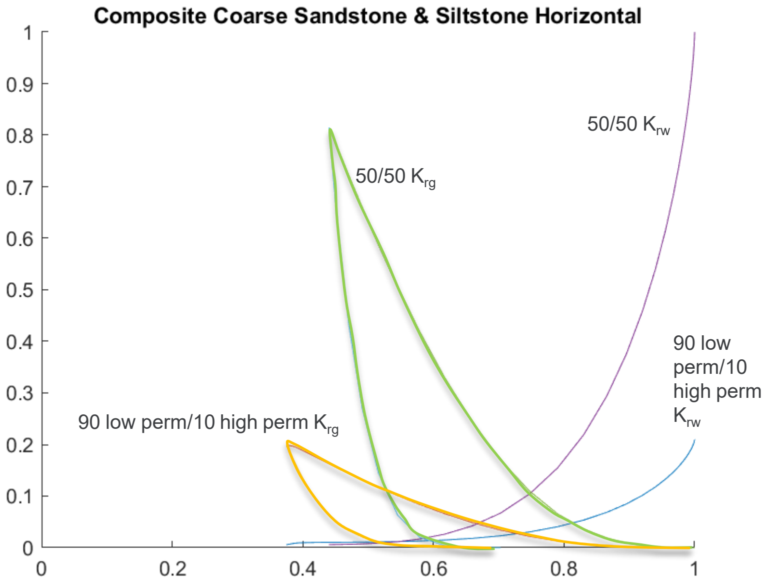


Sensitivity Study: Impact of Composite Rock Rel Perms

Changing composite rock rel perms from 50/50 to 90% low perm/ 10% high perm **decreases the breakthrough time by 3-7 days**

	Breakthrough Time 50/50 Composite Rel Perms	Breakthrough Time 90low/10 high Composite Rel Perms
Withoutseismic_12	19 days	12 days
Withoutseismic_12_case_1	19 days	12 days
Withseismic_8_case10	13 days	10 days

	50/50 Rel Perm		90/10 Rel Perm
Fastest Run	13 days	→	6 – 10 days



Future Work

Adding additional parameters to vary such as:

- Composite rock make up in directional rel perms
- Directional Pc curves
- Permeability ranges
- Horizontal correlation length of rocktype cell id

Extend model for full injection time and investigate changes in model architecture

Create model for the post-injection period

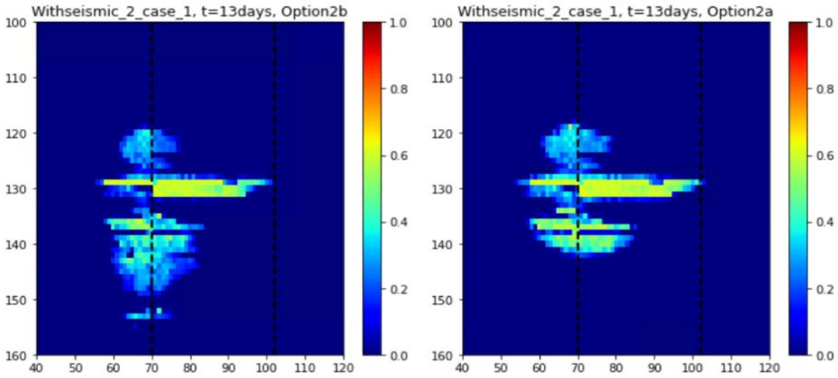
History matching

Thank You for listening

Appendix

Sensitivity Study: Perforation Interval

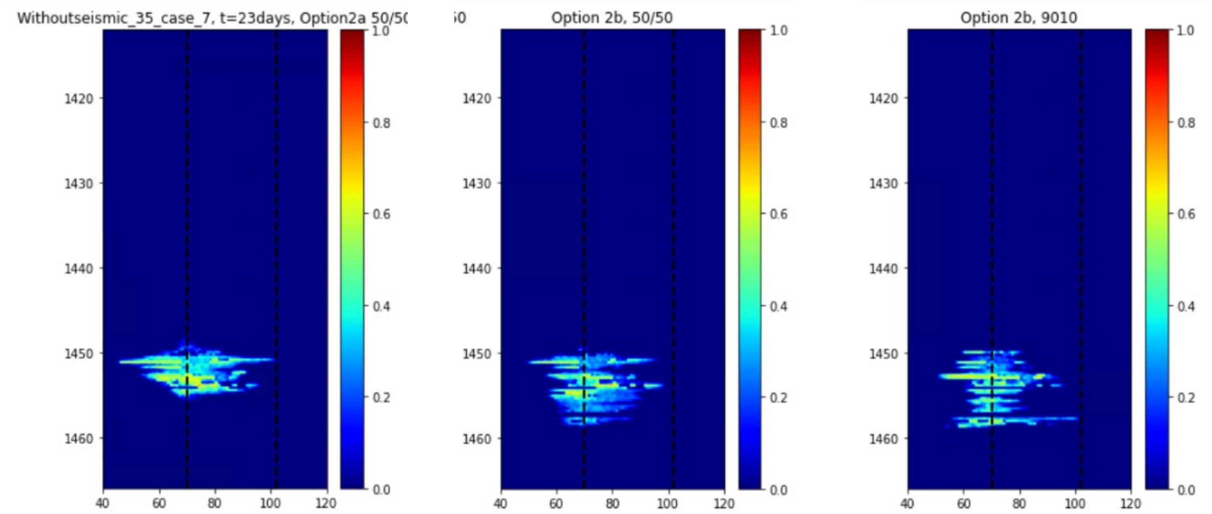
Adds on average **~4 days** to breakthrough time (range: 0 to 5 days)



	Breakthrough Time 2a (1450-1455m) Option	Breakthrough Time 2b (1450-1460m) Option
Withoutseismic_14_case_1	13 days	17 days
Withoutseismic_14_case_5	13 days	17 days
Withoutseismic_14_case_7	13 days	15 days
Withoutseismic_35_case_7	23 days	27 days
Withseismic_2_case_1	13 days	13 days
Withseismic_8_case_10	13 days	17 days

Impact of perforation interval & composite rock rel perms on one realization

		Extending perforation interval	+ 90/10 Composite Rel Perms
Breakthrough Time:	23 days	27 days	25 days



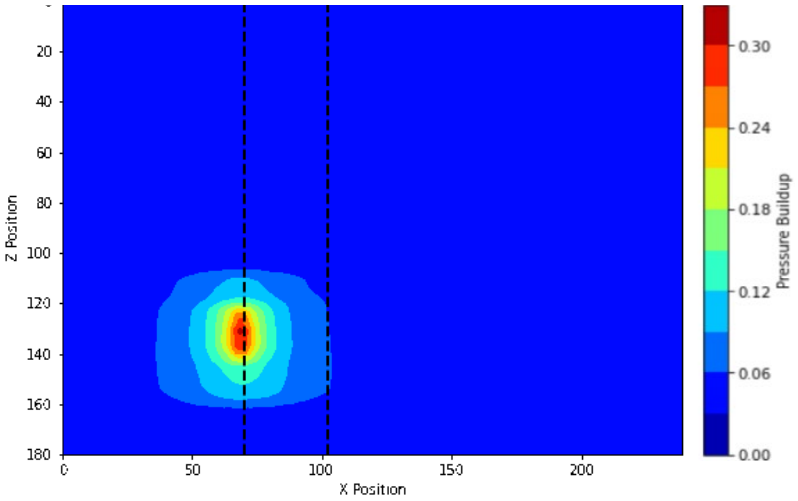
Impact of perforation interval & composite rock rel perms on one realization

Withoutseismic_35 _option 2a

Withoutseismic_35 9010_option 2b

Average pressure buildup

Cross Section of Average Pressure Buildup at Injection Well over time

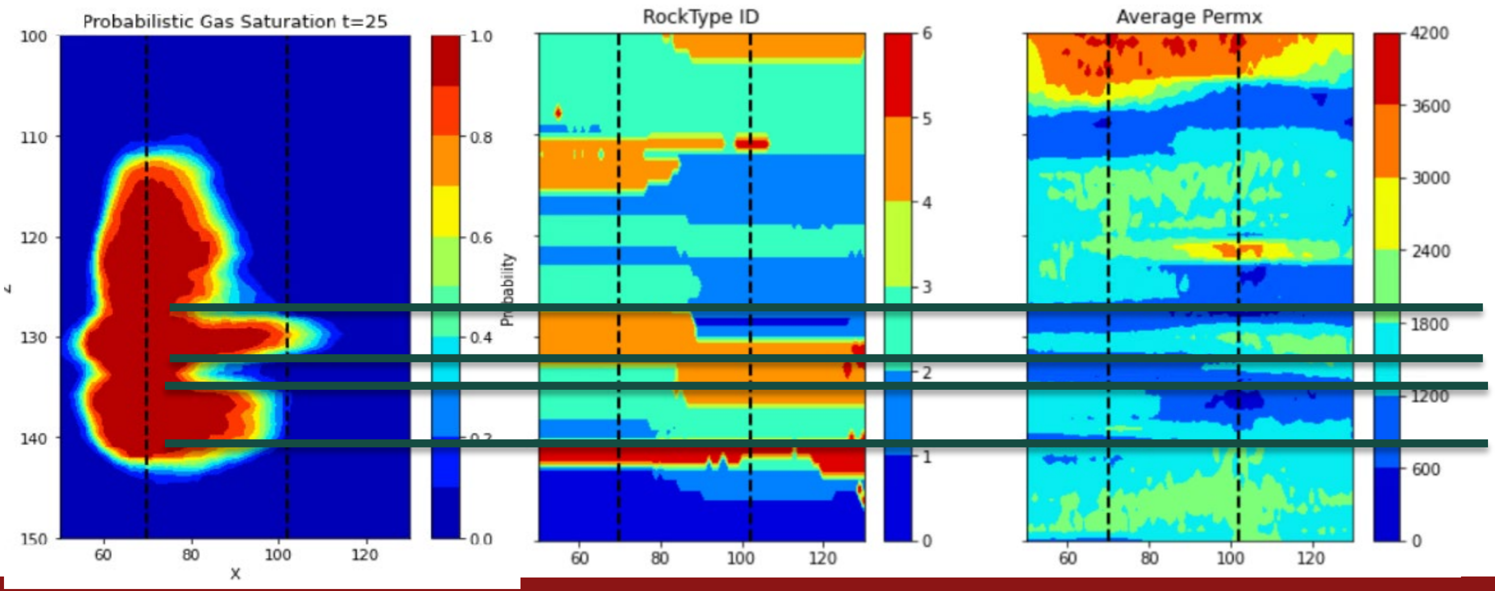


Composite Siltstone and Coarse Sandstone is the primary rock type in the fastest layers

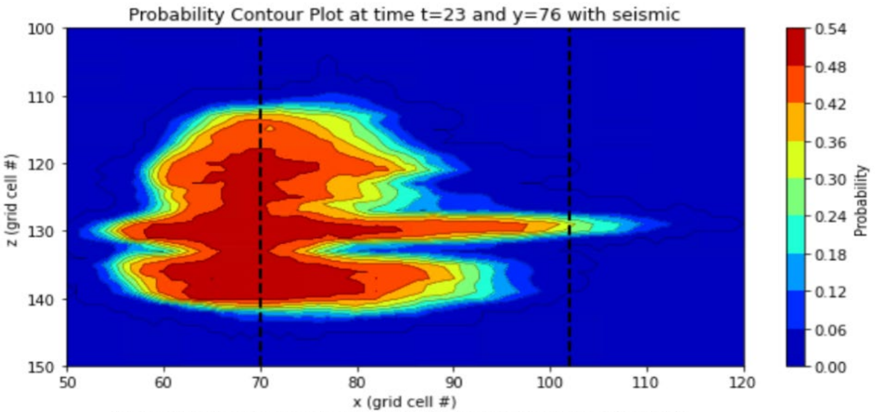
Fastest moving layer in the middle is on average rock type 3 & 5

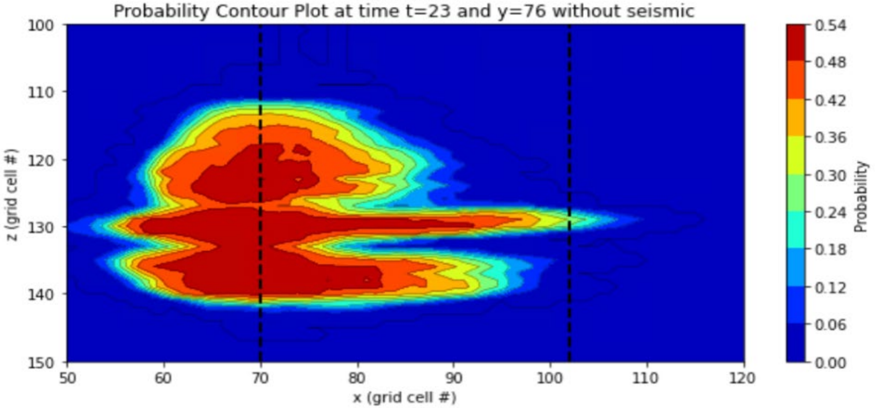
2nd fastest layer mostly rock type 3 and 5

KRNUMX	
1	Homogeneous coarse sandstone (Code: 0)
2	Composite of siltstone and fine sandstone (Code: 1 and 6)
3	Composite of siltstone and coarse sandstone (Code: 2 and 7)
4	Composite of mudstone and fine sandstone (Code: 3 and 8)
5	Composite of mudstone and coarse sandstone (Code: 4 and 9)
6	Homogeneous carbonate cement (Code:10)



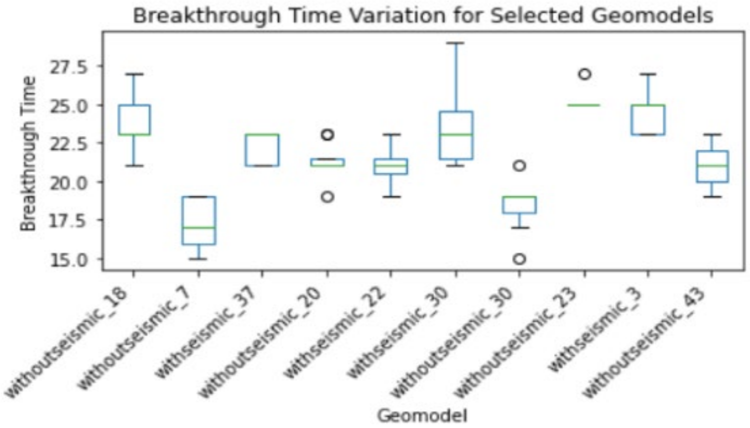
Probabilistic Plume: One w/ seismic, one w/o seismic





Inter-geomdel vs. Intra-geomodel (between geomodels vs. within geomodel)

	Inter-Geomodel	Intra-Geomodel
Average Breakthrough Time	21.5 days	21.4 days
Standard Deviation Breakthrough Time	4.3 days	1.7 days



Key Takeaways

Rock type is a driving factor plume differences

Directional relative permeabilities have strong influence on breakthrough time

FNO vs. UFNO (UFNO outperformed)