

MACHINE LEARNING APPLIED TO PARAMETRIC ANALYSIS OF CO₂ MIGRATION DURING GEOLOGIC CARBON SEQUESTRATION IN A SANDSTONE RESERVOIR

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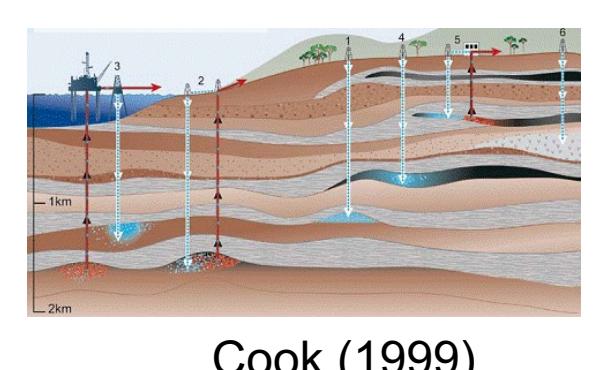


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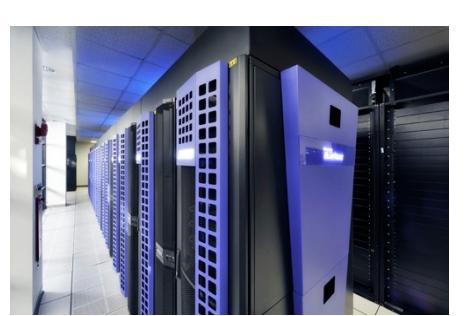
Fluid Flow Dynamics Uncertainties

Carbon Capture and Storage (CCS)

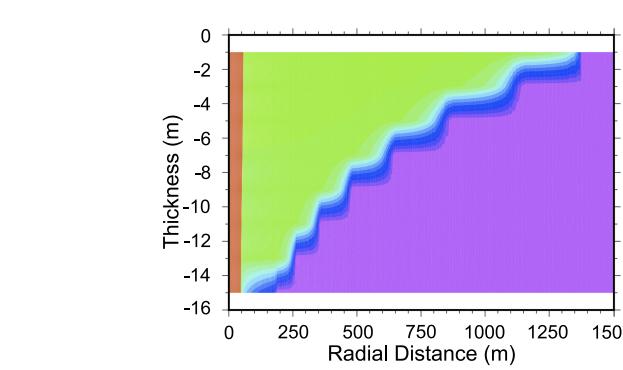
- Capillary pressure
- Buoyancy
- Relative permeability
- Thermal
-



Computational simulations



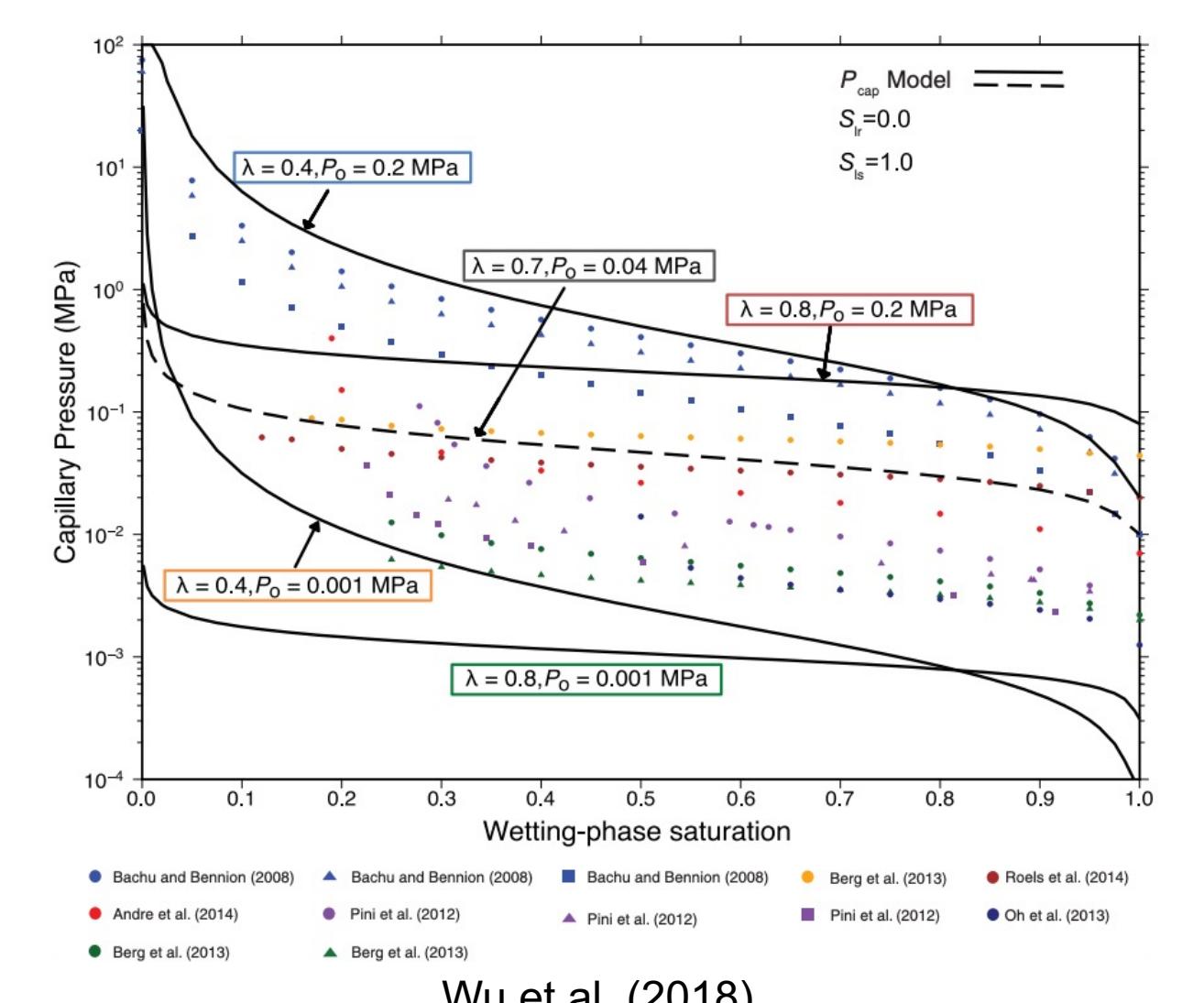
Multi-component
Multi-phase
Fluid flow dynamics
at reservoir scale



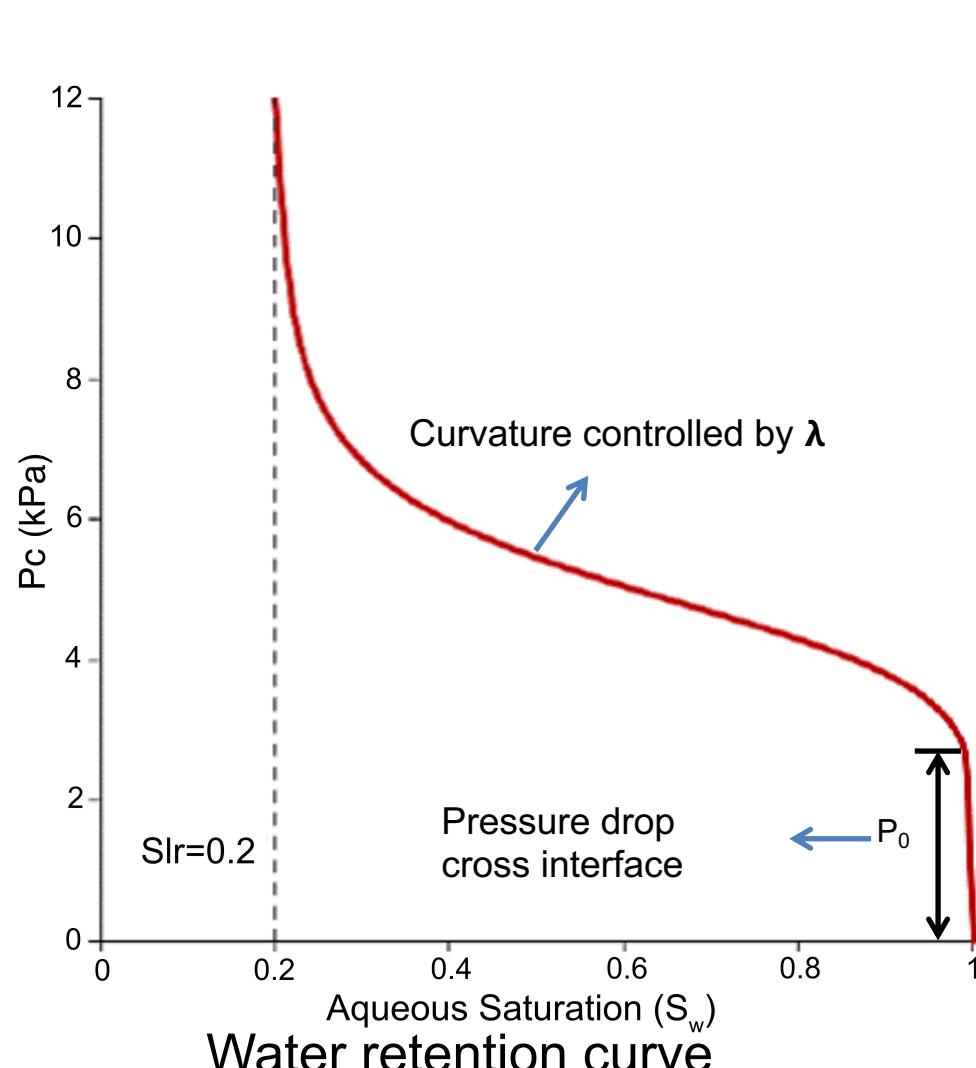
To study the fluid flow dynamics, there are feedbacks between reservoir properties should be considered, and computational methods provide benefits to learn how the reservoir system will behave at a large scale.

Reservoir Properties and Parameter Variabilities

Capillary pressure

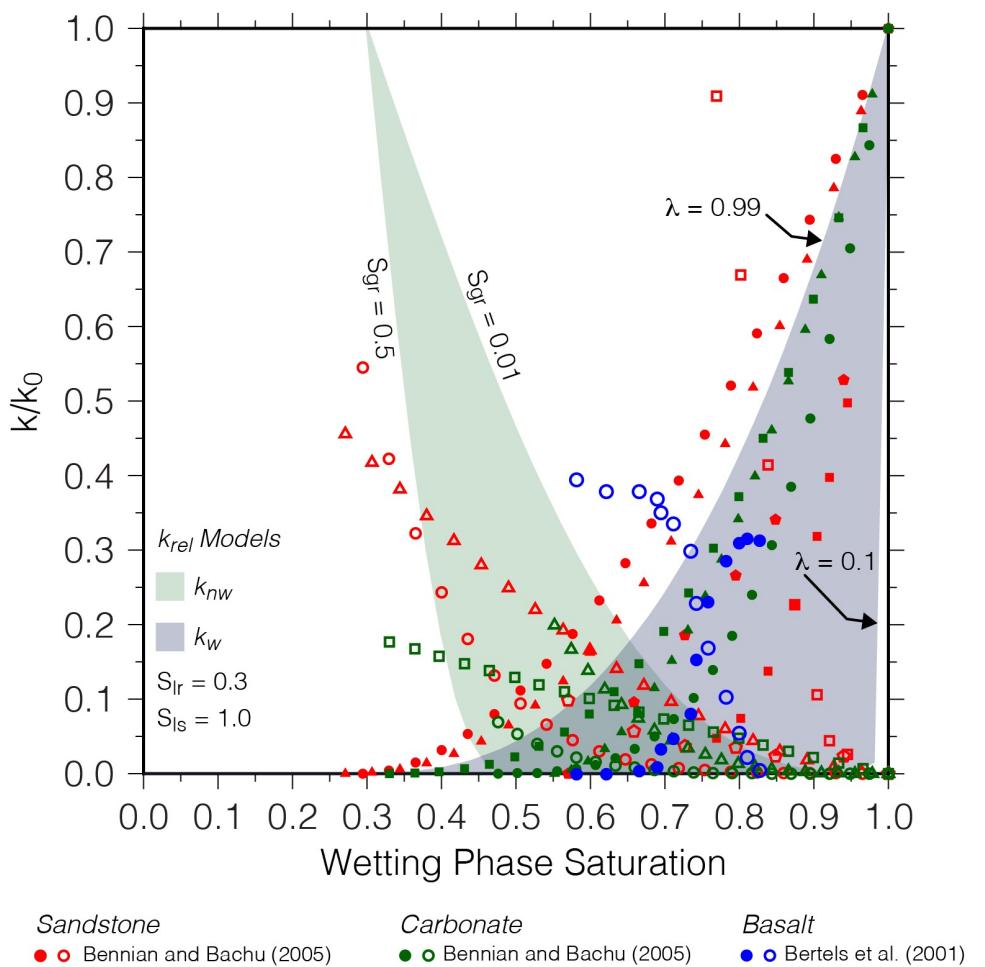


$$P_{cap} = -P_0([S^*]^{\frac{1}{\lambda}} - 1)^{1-\lambda}, \quad S^* = \frac{S_l - S_{lr}}{S_{ls} - S_{lr}}$$

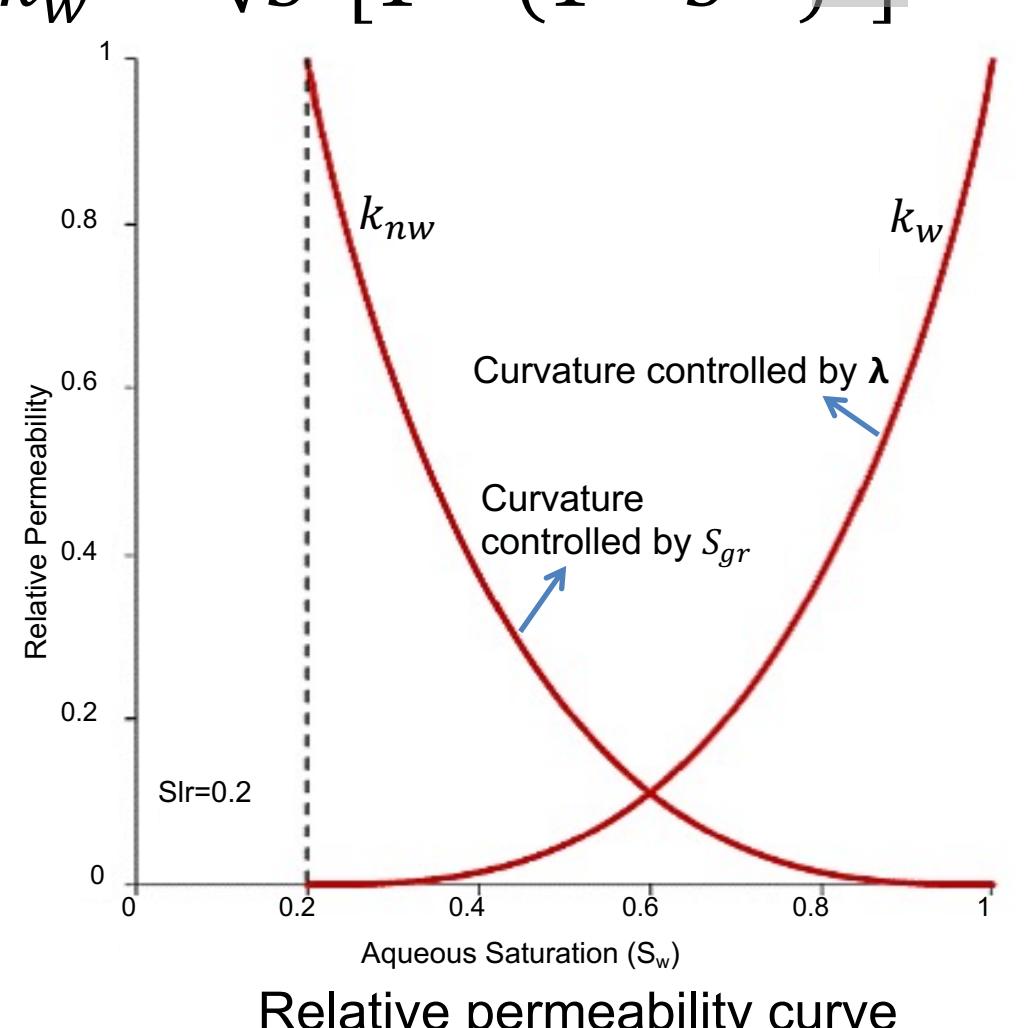


For different types of sandstone, capillary pressure and relative permeability measurements both show a large variability at a laboratory scale. To test the effect of these variabilities on fluid flow dynamics at reservoir scale, three parameters (grey) are picked to quantify the variabilities (same λ).

Relative permeability



$$k_{nw} = (1 - \hat{S})^2 (1 - \hat{S}^2), \quad \hat{S} = \frac{S_l - S_{lr}}{1 - S_{lr} - S_{gr}}, \quad k_w = \sqrt{S^*} [1 - (1 - S^* \lambda)^{\frac{1}{\lambda}}]^2$$



Model Setup

Objective

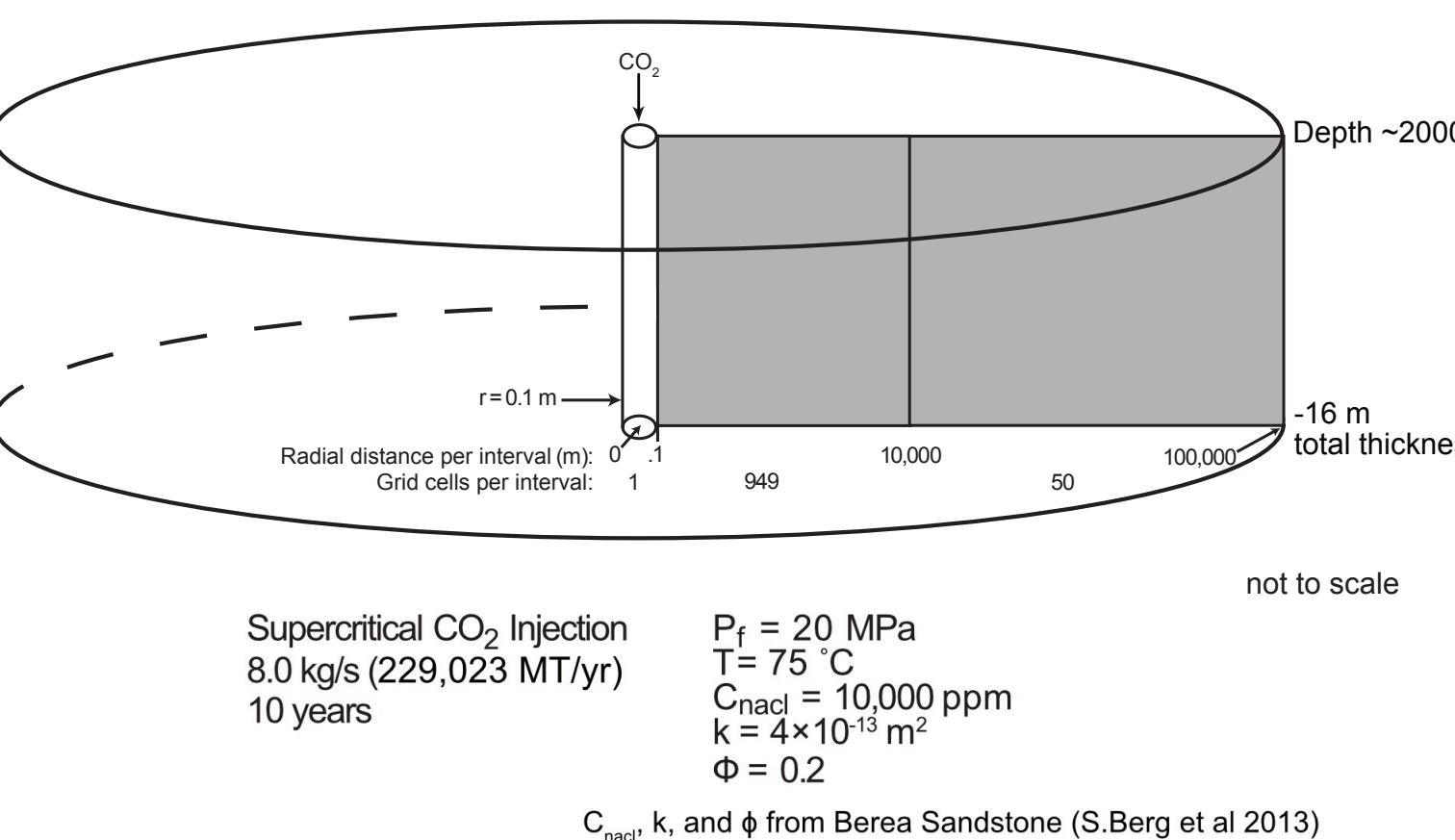
Understanding the effects of the capillary pressure and relative permeability variabilities:

- CO₂ plume geometry
- Fluid pressure perturbation

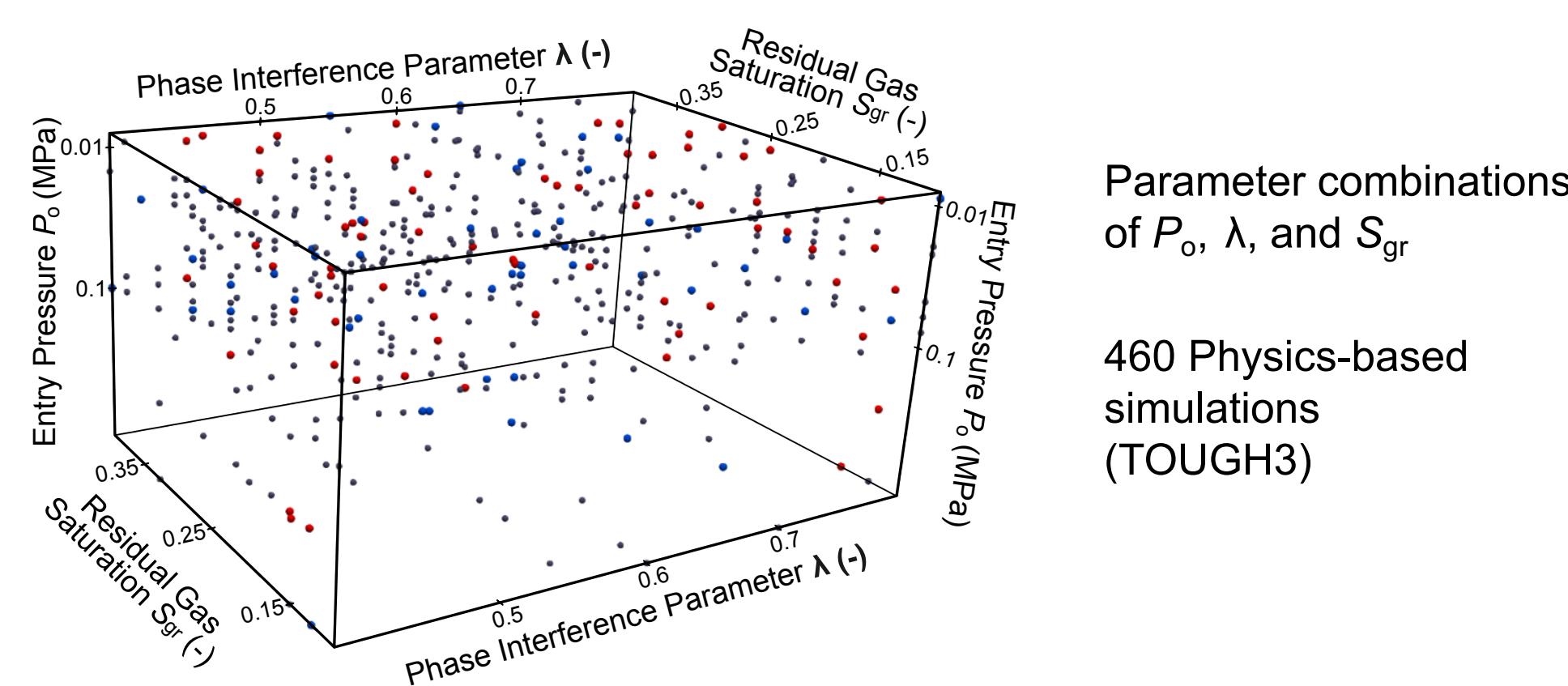
Method: Physics-based numerical simulation
Machine Learning method

- Machine learning increases the computation efficiency of computational simulations of CO₂ sequestration
- Predictions over large parameter space provide a more comprehensive understanding of parametric variability

Domain: a synthetic sandstone reservoir



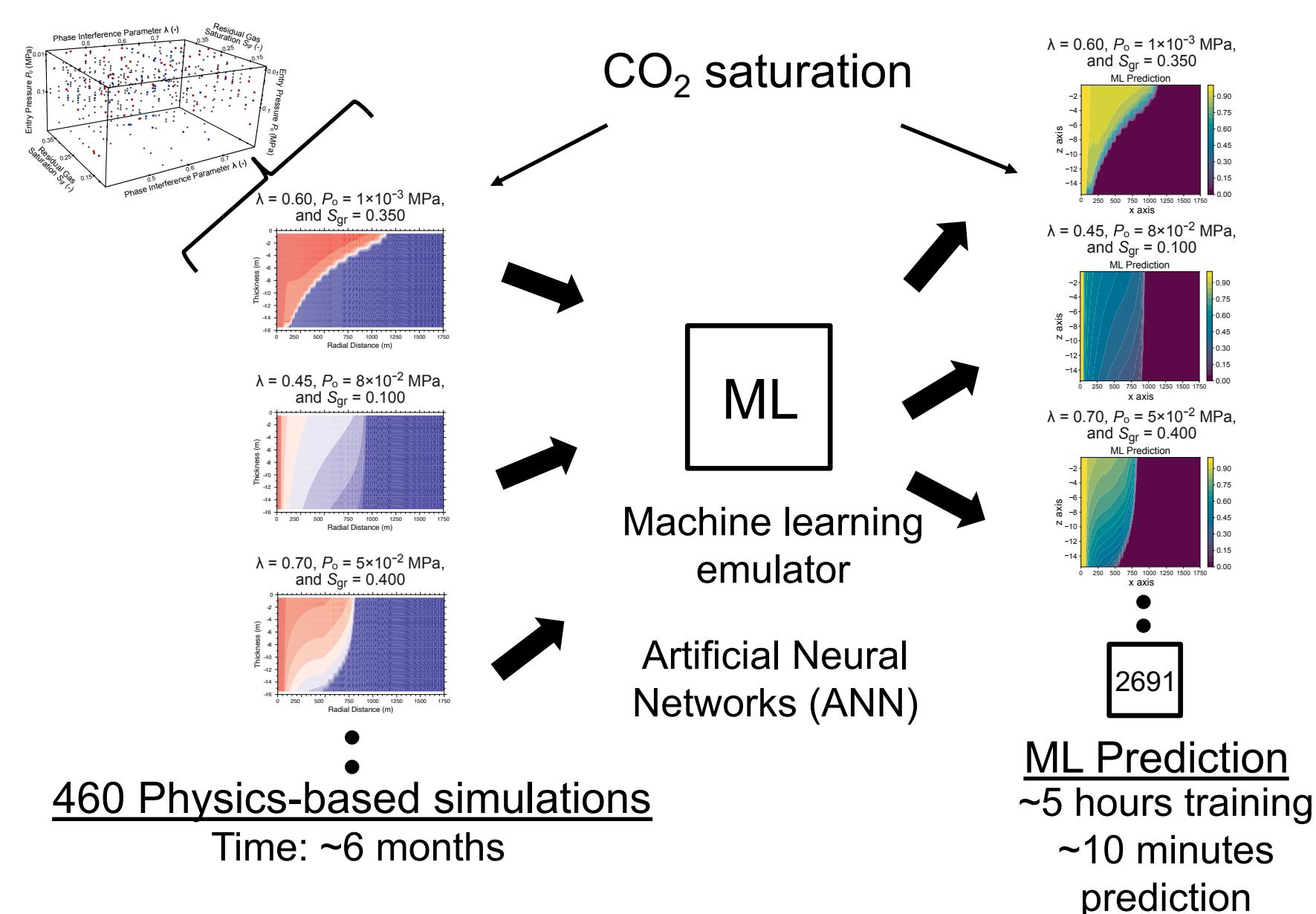
3-D Parameter Table



Parameter combinations of P_o , λ , and S_{gr}
460 Physics-based simulations (TOUGH3)

To explain the effects of capillary pressure and relative permeability, a simulation ensemble is produced for unique combinations of P_o , λ , and S_{gr} . The results are then analyzed to quantify the variability in both CO₂ migration and fluid pressure perturbation. A total of 460 different parameter combinations are randomly selected from the 3-D parameter space.

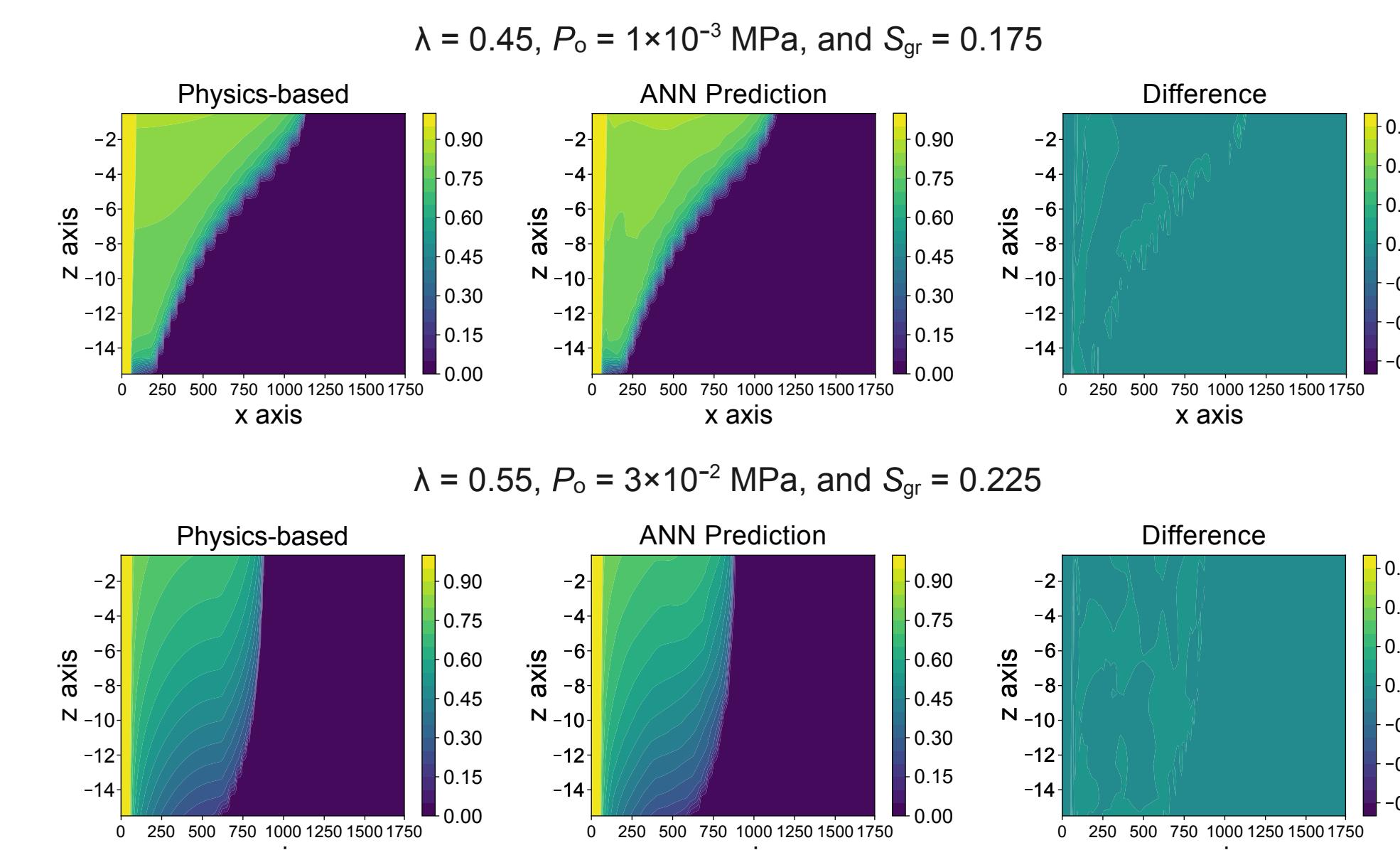
Machine Learning Application



Results Analysis

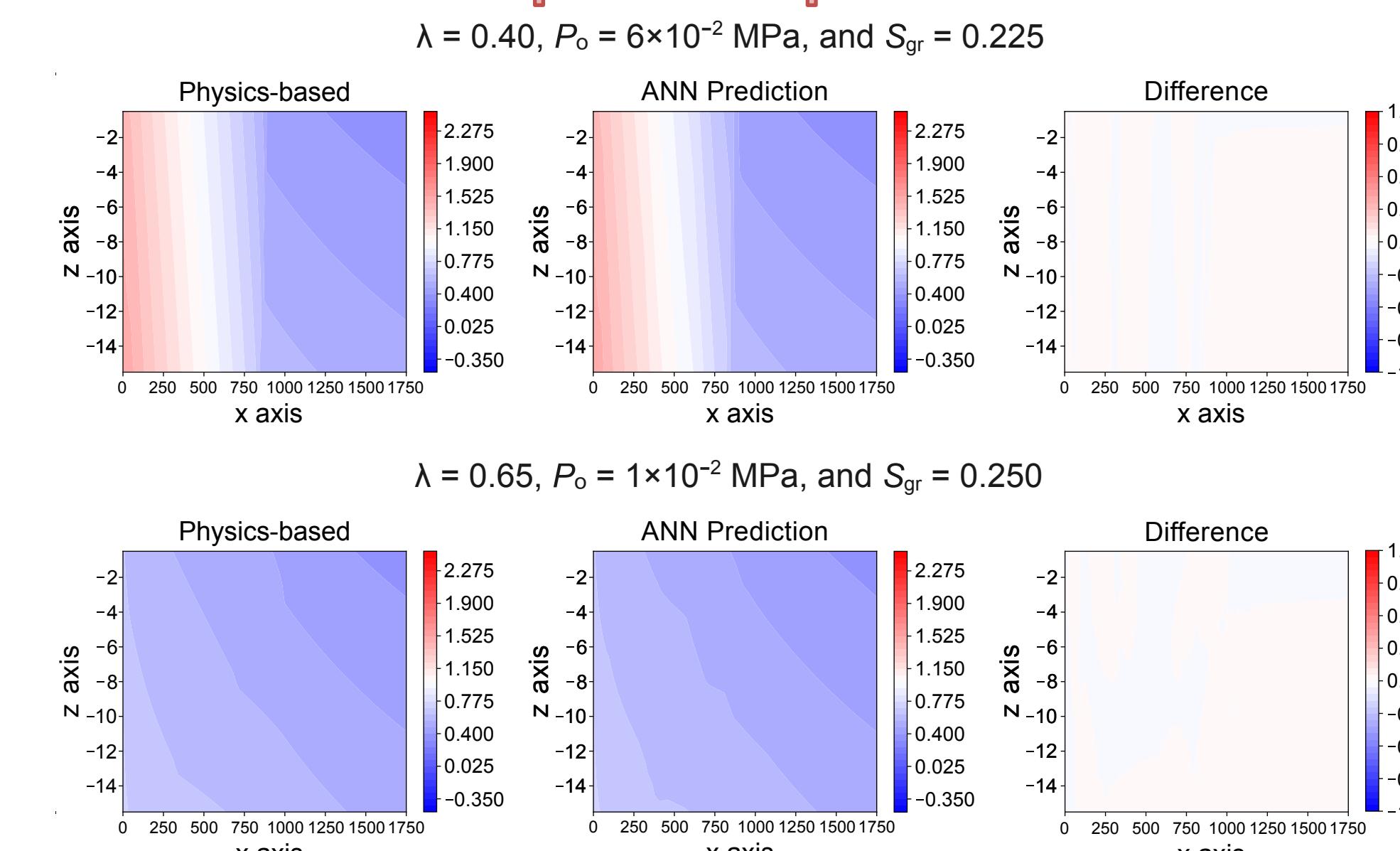
Testing Results Analysis

CO₂ saturation



Four different parameters combinations of capillary pressure and relative permeability models (P_o , λ , and S_{gr}) are represented to analyze accuracy of ANN model prediction for CO₂ saturation and pressure perturbation.

Fluid pressure perturbation



The broad similarity between the physical and predicted images implies that the ANN model captures the salient aspects of the physics-based model.

Overall Accuracy

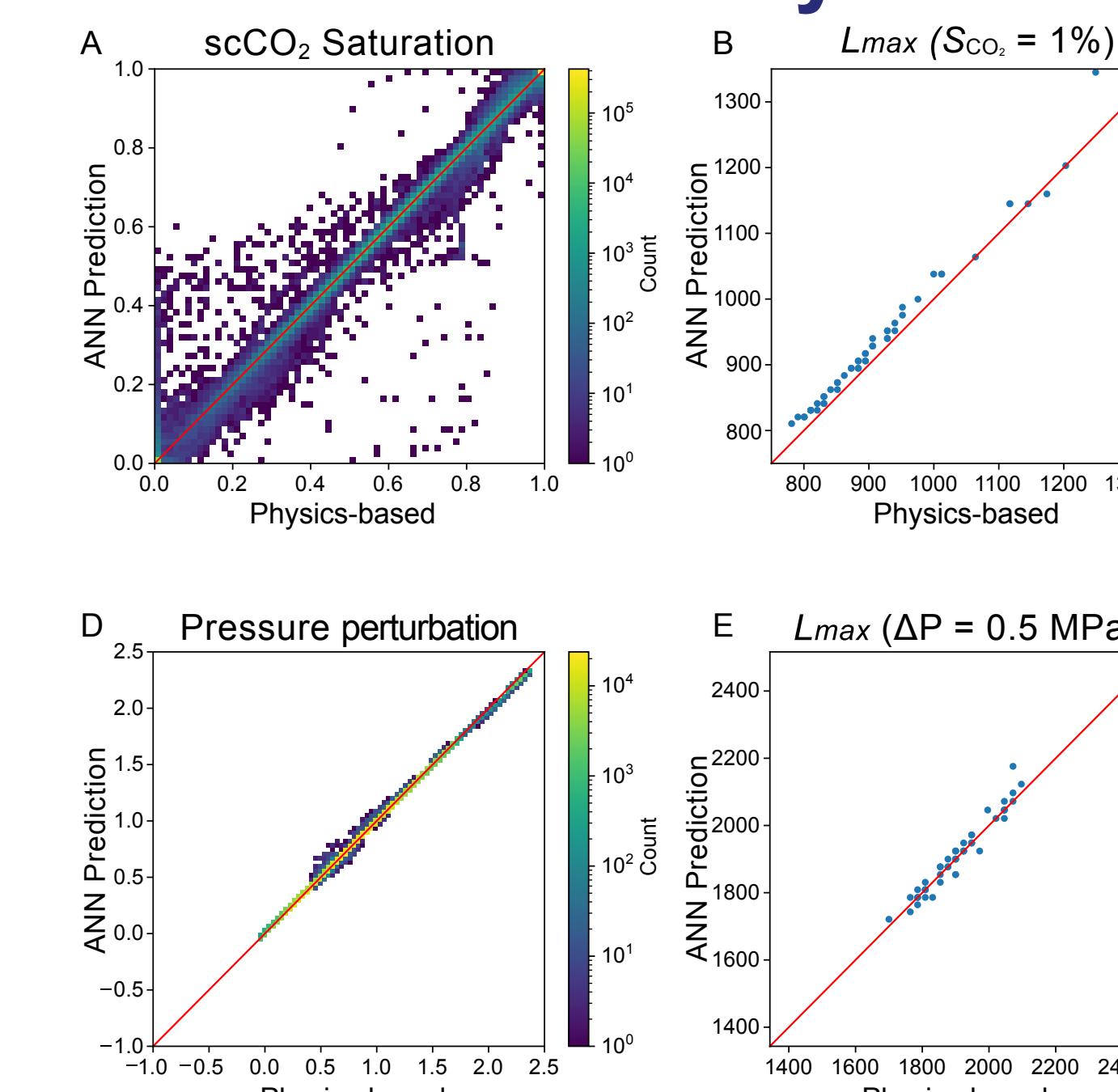


Fig A, D illustrate the comparison for each grid cell of the reservoir domain for 50 testing data. B presents the comparison on the maximum length of the plume when CO₂ saturation is 0.01 (boundary of the plume). E demonstrates the maximum length of pressure perturbation distribution when ΔP is 0.5 MPa.

ANN emulation methods provide excellent results for capturing the major distribution of both CO₂ saturation and fluid pressure change when trained on physics-based numerical simulations.

Conclusion

ML model offers an alternative method for simulating CO₂ sequestration across a high-dimensional parameter space
computational efficiency (460 vs. 2691)
run-time acceleration (6 months vs. 10 minutes)
ML model provides an immense potential for predicting fluid flow dynamics over an extended parameter range