Forecasting Multiphase Flow Through Fractures with Convolutional Neural Networks

Allen Ting[1,2], Eric J. Guiltinan[2], Javier E. Santos[3]

[1]The University of Texas at Austin
[2]Los Alamos National Laboratory, Earth System Observations (EES-14)
[3]Los Alamos National Laboratory, Center for Nonlinear Studies (CNLS)

MICKEY LELAND ENERGY FELLOWSHIP PROGRAM
U.S. DEPARTMENT OF ENERGY • OFFICE OF FOSSIL ENERGY & CARBON MANAGEMENT

TEXAS
The University of Texas at Austin

Problem & Motivation

THE CHALLENGE OF MULTIPHASE FLOW

Fractures are ubiquitous in the subsurface and serve as preferential channels for flow and transport. Investigating the multiphase flow properties of fractures is important for many engineering applications. These properties can be studied through lattice Boltzmann method (LBM) simulations, but they require high performance computing resources and have limited domain sizes.

We present a physics-constrained machine learning model that accurately predicts the displacement of water by supercritical CO_2, but only requires a few LBM simulations for training. By generating efficient simulations of micro-scale multiphase flow in fractures, we hope to investigate a wide range of fracture types and generalize our method to larger discrete fracture network simulations.

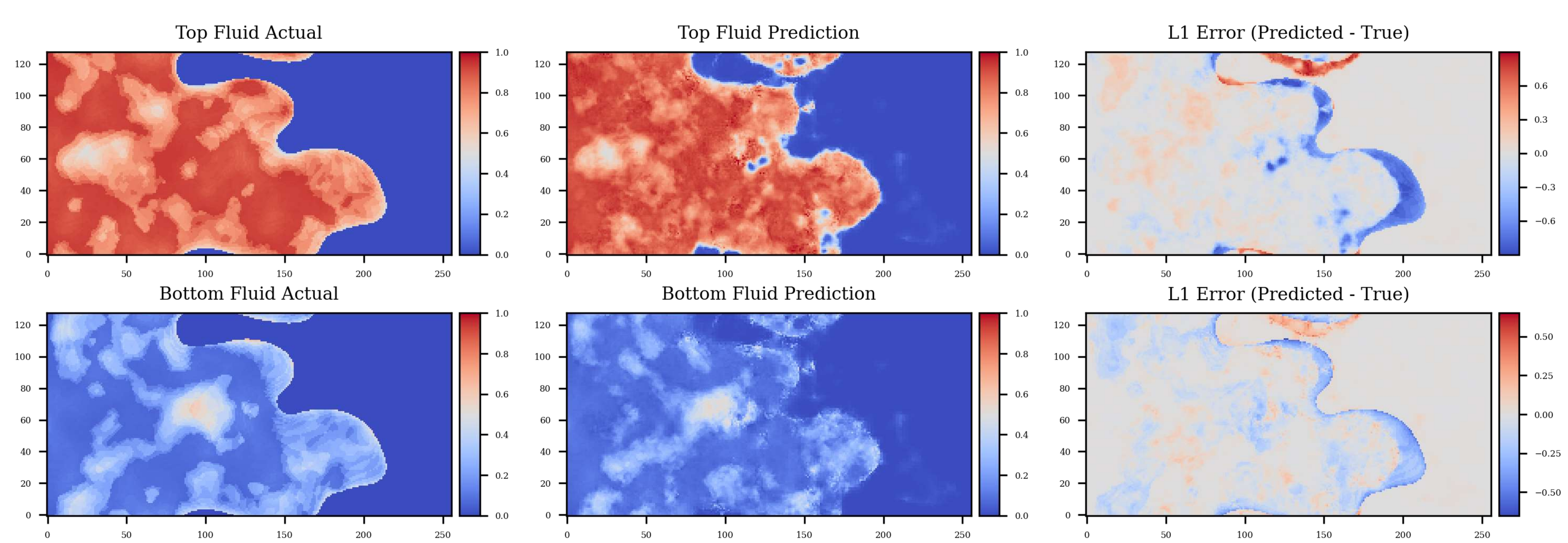
EXPERIMENTAL DATASET

Our dataset consists of twelve unique simulations of CO_2 drainage in shale fractures generated using the Taxila LBM simulator, an open-source code developed at LANL. Each simulation has about one hundred timesteps.

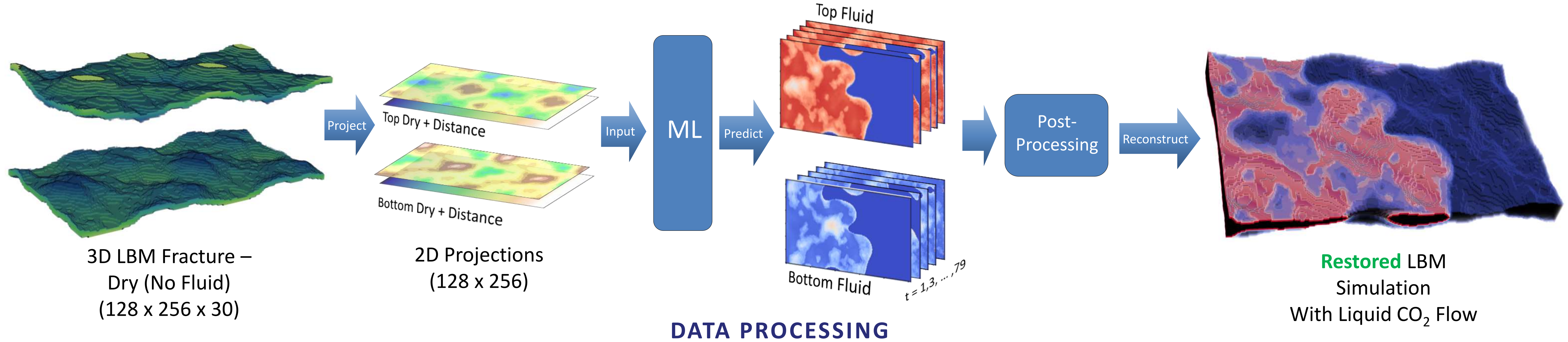
Results

PREDICTIONS AND ACCURACY

When tested on eight unseen LBM simulations, our results show that the model makes accurate predictions. In terms of CO_2 saturation, predictions are approximately 95% accurate across all timesteps. When projected back to 3D, the accuracy is about 98%. While physics-based simulations require runtimes in the order of days, our model trains in just a few hours and can predict on various fracture geometries in a fraction of a second.



Methods



DATA PROCESSING

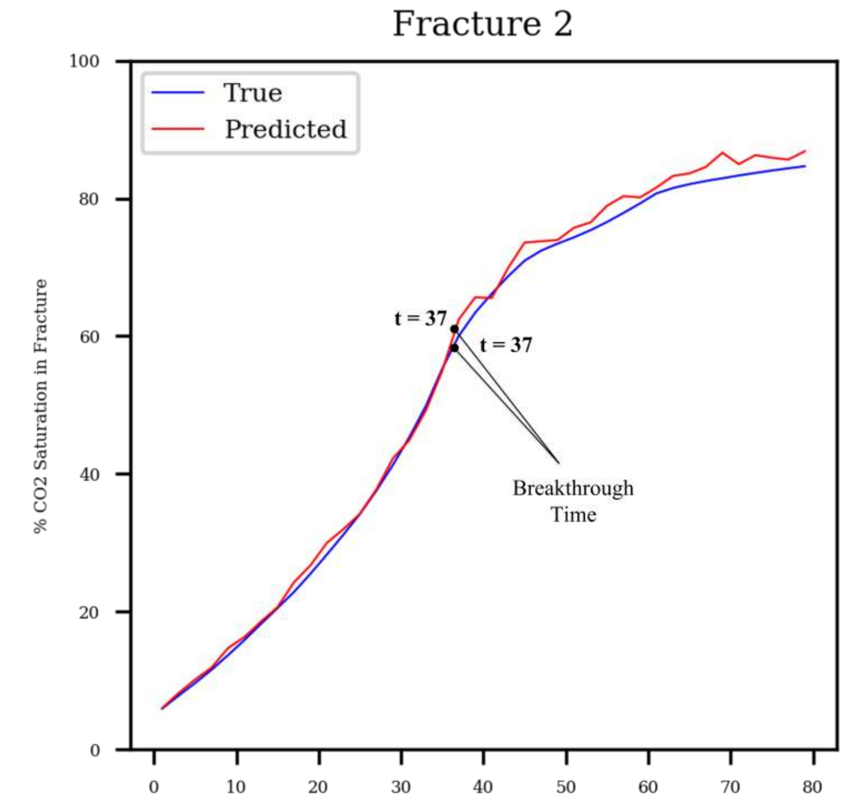
To make computations lightweight, and fracture size and aperture agnostic, we propose a workflow to project the 3D time-dependent data into 2 dimensions. The 3D fracture is projected into two 2D arrays that represent the position of the top and bottom surfaces of the fracture with respect to the simulation's domain, which serve as inputs to our model. Subsequently, each timestep of the simulations is projected into two 2D arrays where the positions of the top and bottom of the menisci of the CO_2 are recorded with respect to the fracture's aperture size, serving as our prediction targets.

MACHINE LEARNING MODEL

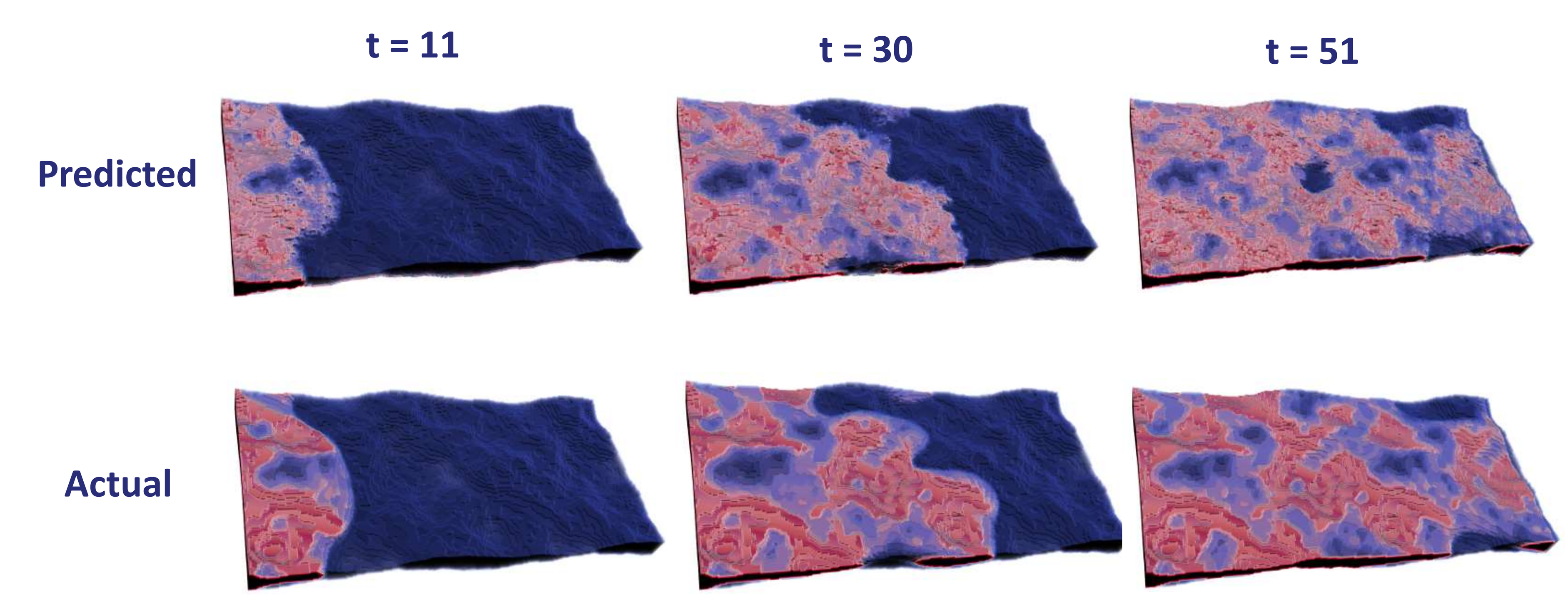
Our machine learning model consists of a convolutional neural network based on the Residual U-Net [1] and ConvNeXt [2] architectures. It learns a mapping between the shape of the dry fracture and the position of the injected supercritical CO_2 at 40 different timesteps throughout the simulation. We also supplement the base architecture with a series of constraints and auxiliary inputs. Our loss function is shown below.

$$\mathcal{L}_{\underbrace{k=\{t,b\}}_{\text{Top + Bottom Predictions}}} = \underbrace{\frac{1}{N_{pix}}\sum_{i=1}^{N_{pix}}}_{\text{Average Error Over All Pixels}}\left(\underbrace{\frac{(y_{i,k}-\hat{y}_{i,k})^2}{\bar{y}_{train,k}}}_{\text{Pixel-wise Mean Squared Error}}\underbrace{(1+\lambda M_i)}_{\text{Weighted Border Pixel Mask}} - \underbrace{(y_{i,k} > \epsilon_k)\log(\hat{y}_{i,k} > \epsilon_k)}_{\text{Binary Cross-Entropy Loss}}\right)$$

We additionally augment our dataset during training by reflecting the 2D arrays across the x and y-axes, quadrupling the size of the data. Our model is trained for 20,000 epochs per timestep, taking up 4 GB of GPU memory for about 4 hours.



3D Prediction vs. Real Simulation



Los Alamos NATIONAL LABORATORY

NNSA National Nuclear Security Administration

Managed by Triad National Security, LLC, for the U.S. Department of Energy's NNSA.

LA-UR-22-27829

References:
[1] Liu, Z., Mao, H., Wu, C.-Y., Feichtenhofer, C., Darrell, T., & Xie, S. (2022). A ConvNet for the 2020s. arXiv. https://doi.org/10.48550/ARXIV.2201.03545

[2] Zhang, Z., & Liu, Q. (2017). Road Extraction by Deep Residual U-Net. IEEE Geoscience and Remote Sensing Letters, PP. https://doi.org/10.1109/LGRS.2018.2802944