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# A machine learning method to automatically segment solid and multiple fluid phases in time-dependent 3D (4D) images

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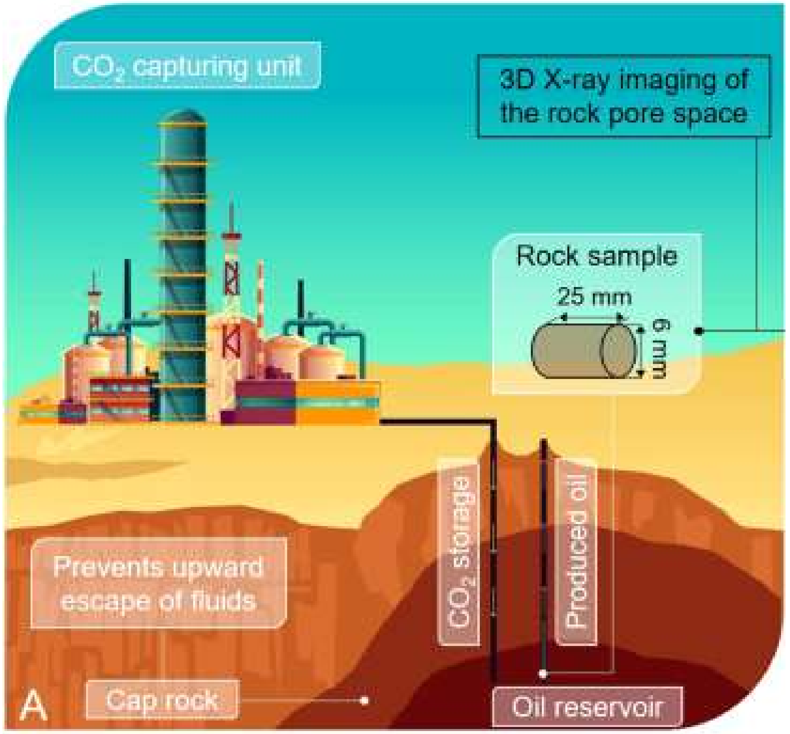
# Outline

1. Background and Motivation
2. Methodology
3. Current Results

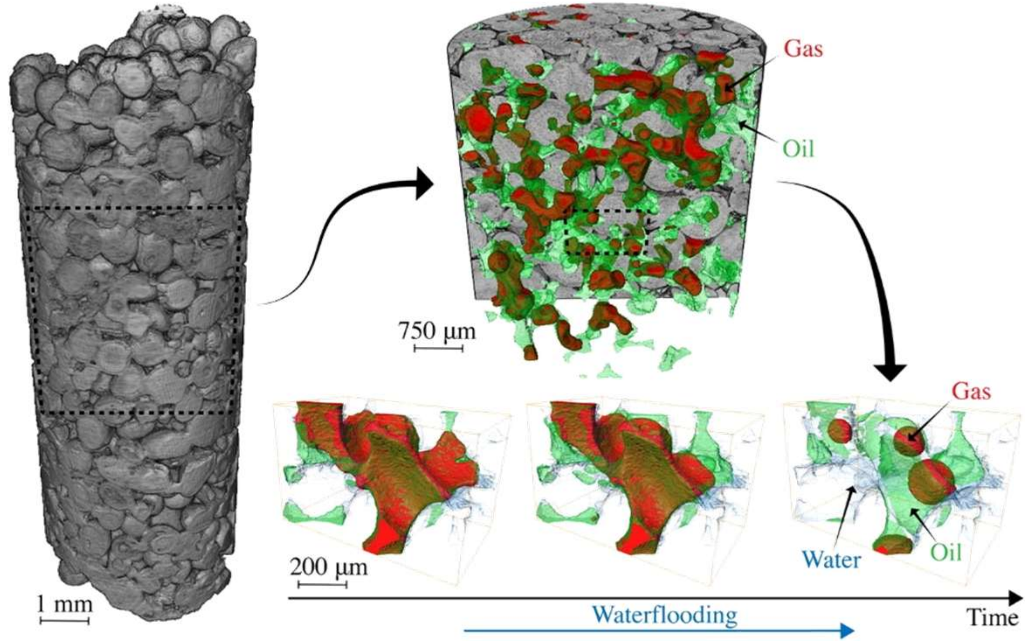
# 1. Background and Motivation

# Flow in porous media

- Fluid flow and mass transport in geological porous media play a key role in a number of significant geological applications.




A scheme of $CO_2$ storage in depleted oil reservoirs (Alhosani et al., 2020)




Scanziani *et al.*, *Applied Energy* (2020)

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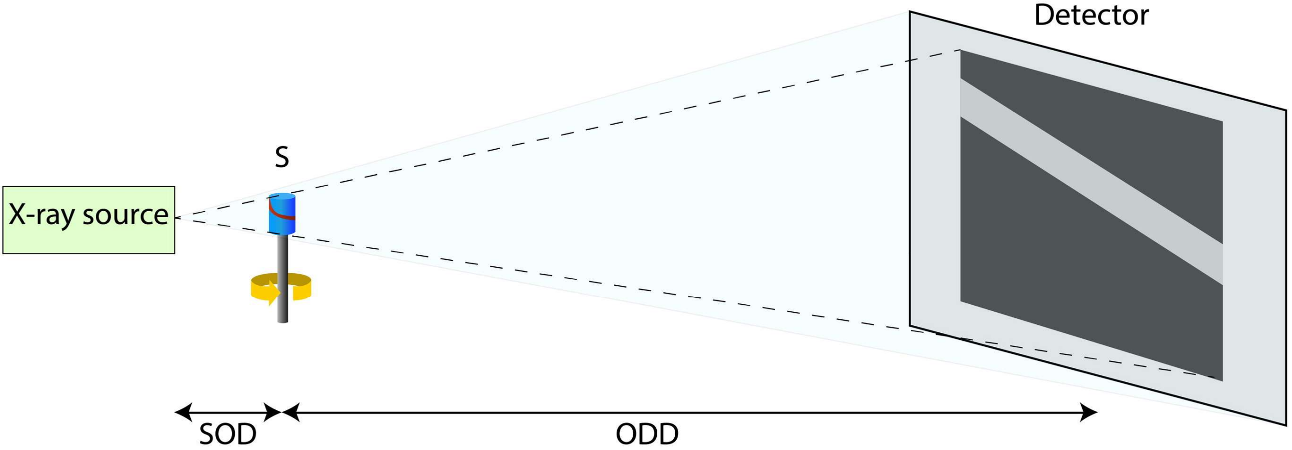
# Micro-CT imaging

- The structure of rocks, and the fluids distribution are important for fluid flow and mass transport in porous media.

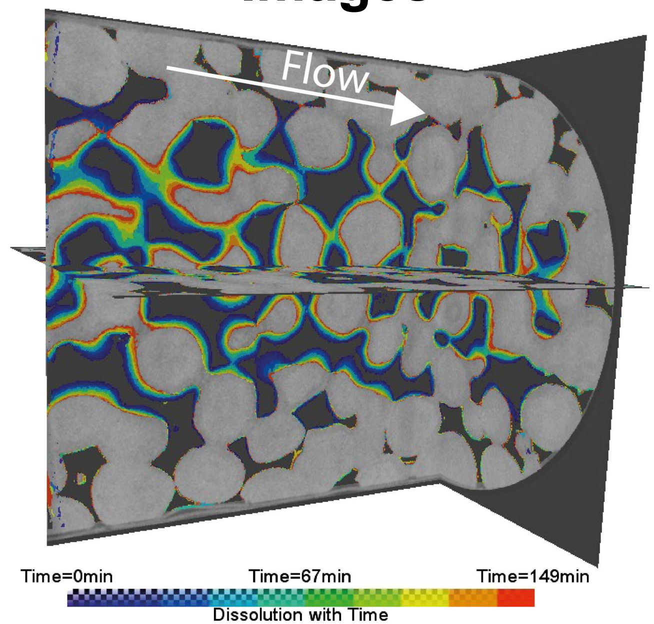
**Measurement techniques**

**Images**




A typical laboratory micro-CT setup (Bultreys et al., 2015)

Obtain




A visualized Ketton carbonate rock core (Menke et al., 2015)

# Synchrotron-CT imaging


The Diamond Manchester Imaging Branchline (I13-2)

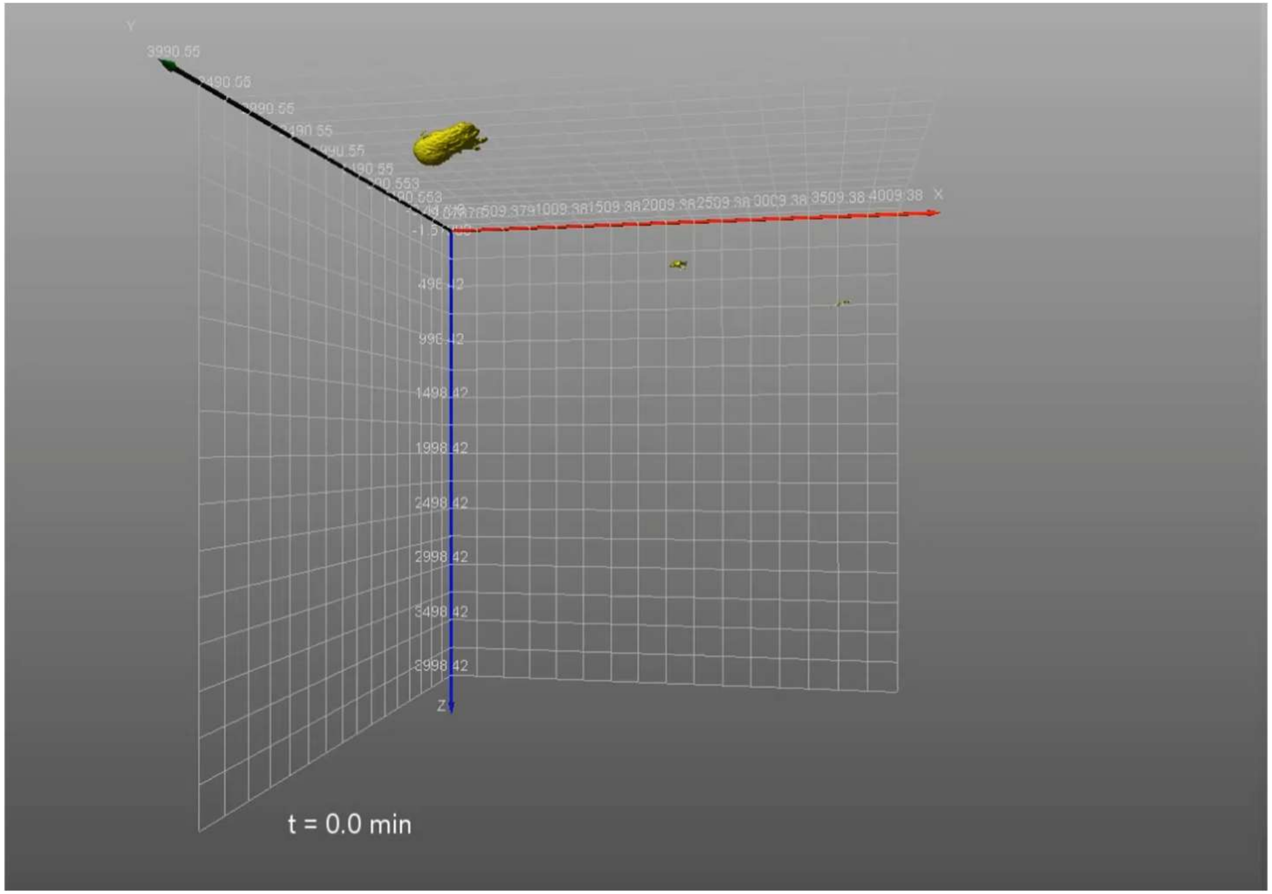
# Synchrotron-CT imaging

## Exceptional Speed

- Enables **4D imaging (3D + time)**, allowing us to capture dynamic processes in real-time.

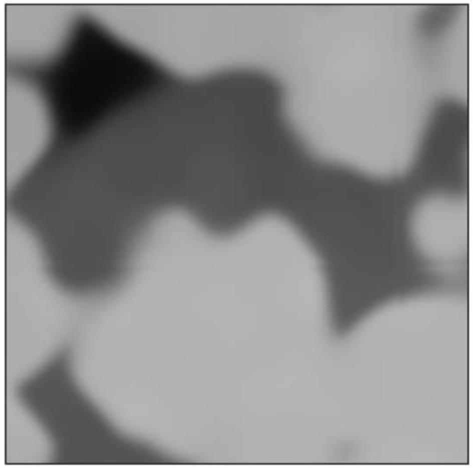
## High Resolution

- Resolves microscopic features **down to the sub-micron scale**, making it possible to visualize fine details of the pore and fluids.




4D Visualization of Drainage in the Rock Sample(Singh et al., 2017)

# The Challenge:
# multiphase flow image segmentation



Greyscale image


Segmented image

## Semantic Segmentation

- The goal of segmentation is to assign a physical label to every single voxel in the 3D image, classifying it as one of the distinct phases.

## Why is it so Difficult?

- A time-series (4D) experiment consists of **hundreds or thousands of 3D volumes**, creating datasets that are **terabytes (TB)** in size. Manually processing this amount of data is impossible.

# The 4D segmentation dilemma

## Option 1: A Full 4D Model-Prohibitive Memory Cost

- Training a full 4D U-Net on a representative data patch requires an estimated **40-70GB of GPU memory (VRAM)**.
- Extremely high computational overheads and unacceptable training time.
- Impossible to prepare sufficient labelled data.

## Option 2: Independent 3D Models-Temporal Inconsistency

- We lost the precious temporal information, which may likely cause inconsistent fluid distributions along time dimension.

## Key challenge

- How can we create a model that is **computationally feasible** like the 3D approach, but also **temporally consistent** like a 4D approach?

# 2. Methodology

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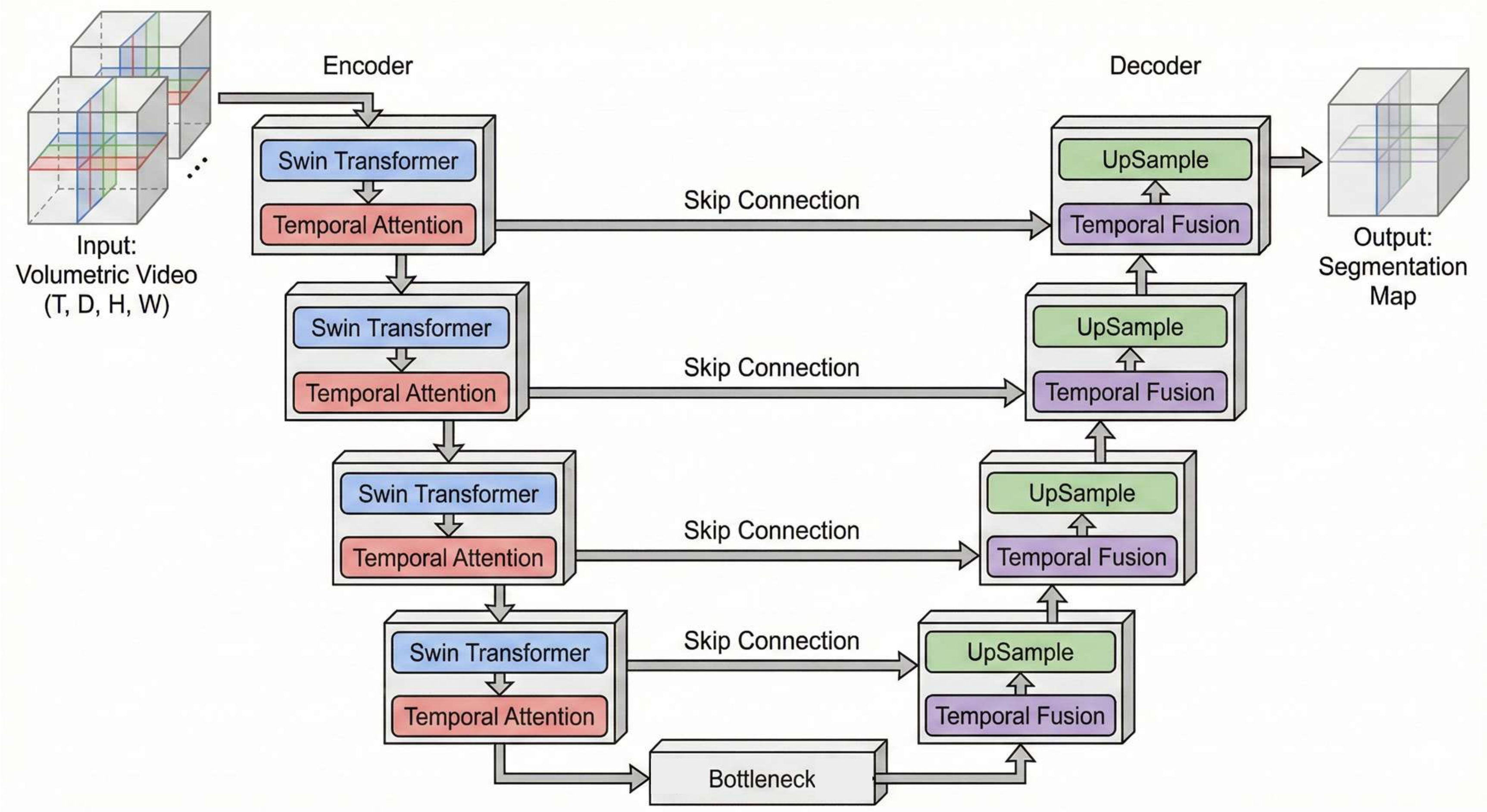
# Temporal-Spatial SwinUNet



# 3. Current Results

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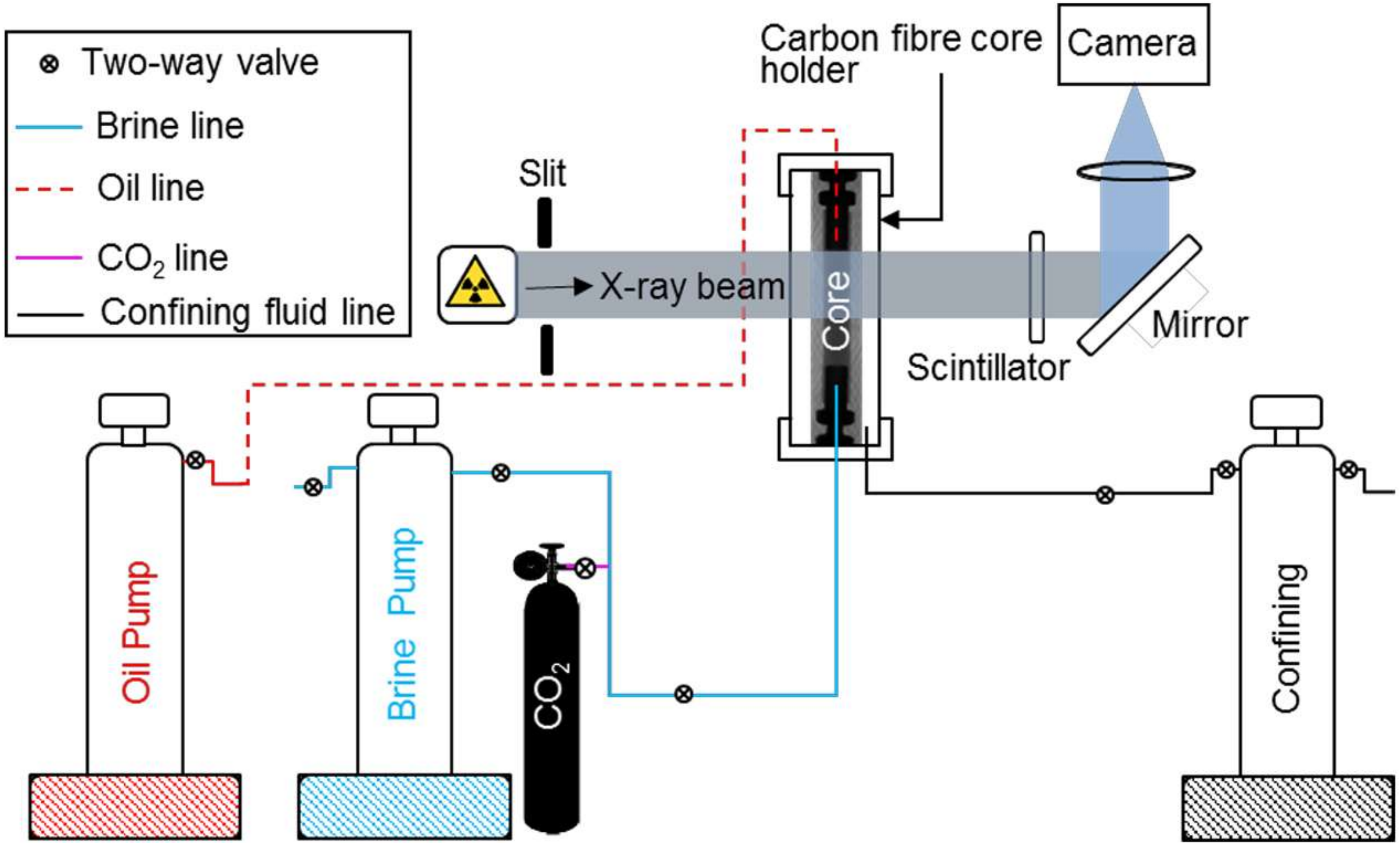
## Dataset




Experimental apparatus (Singh et al., 2017)

# Dataset

- Ketton limestone was used to implement training and test.
- Training dataset:
  - Input size: 400 x 1000 x 1000 x 1000
  - voxel size: 3.58 microns
  - time scale: 38s
- Test dataset:
  - Input size: 400 x 1000 x 1000
  - voxel size: 3.58 microns
  - time scale: 38s
- All training and inference tasks were performed on a server with 4 x NVIDIA A100 GPUs.
- It took around 72 hours to train, and 24 hours to inference.

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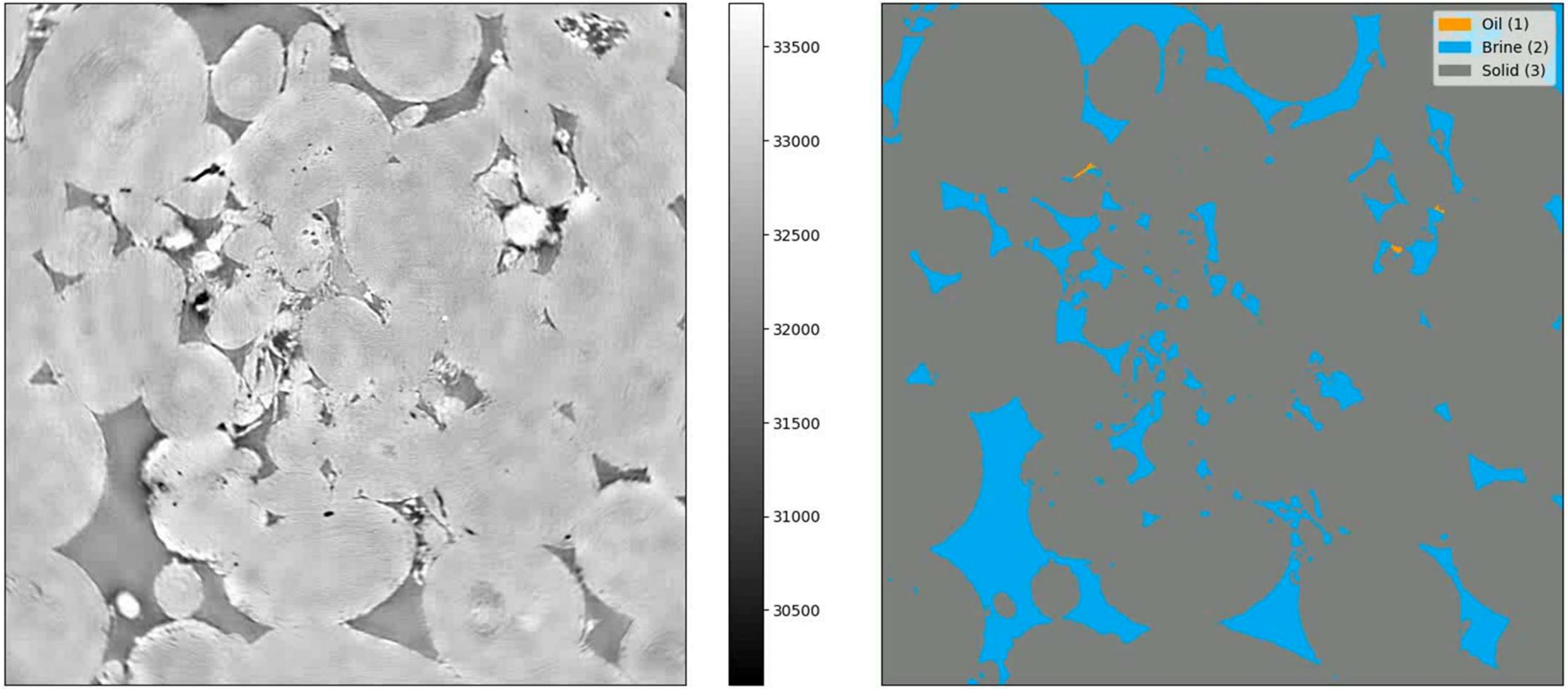
# Visualisation



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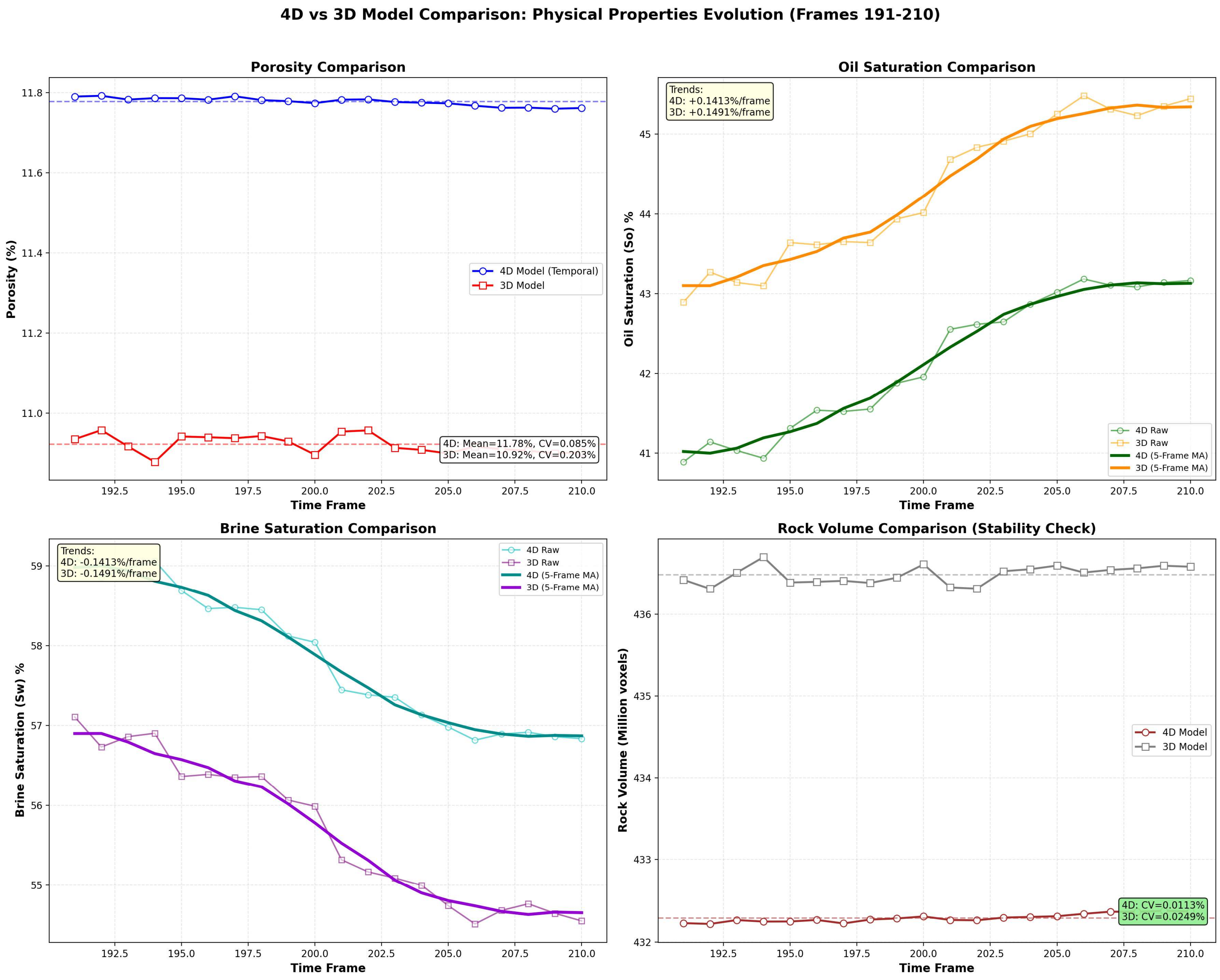

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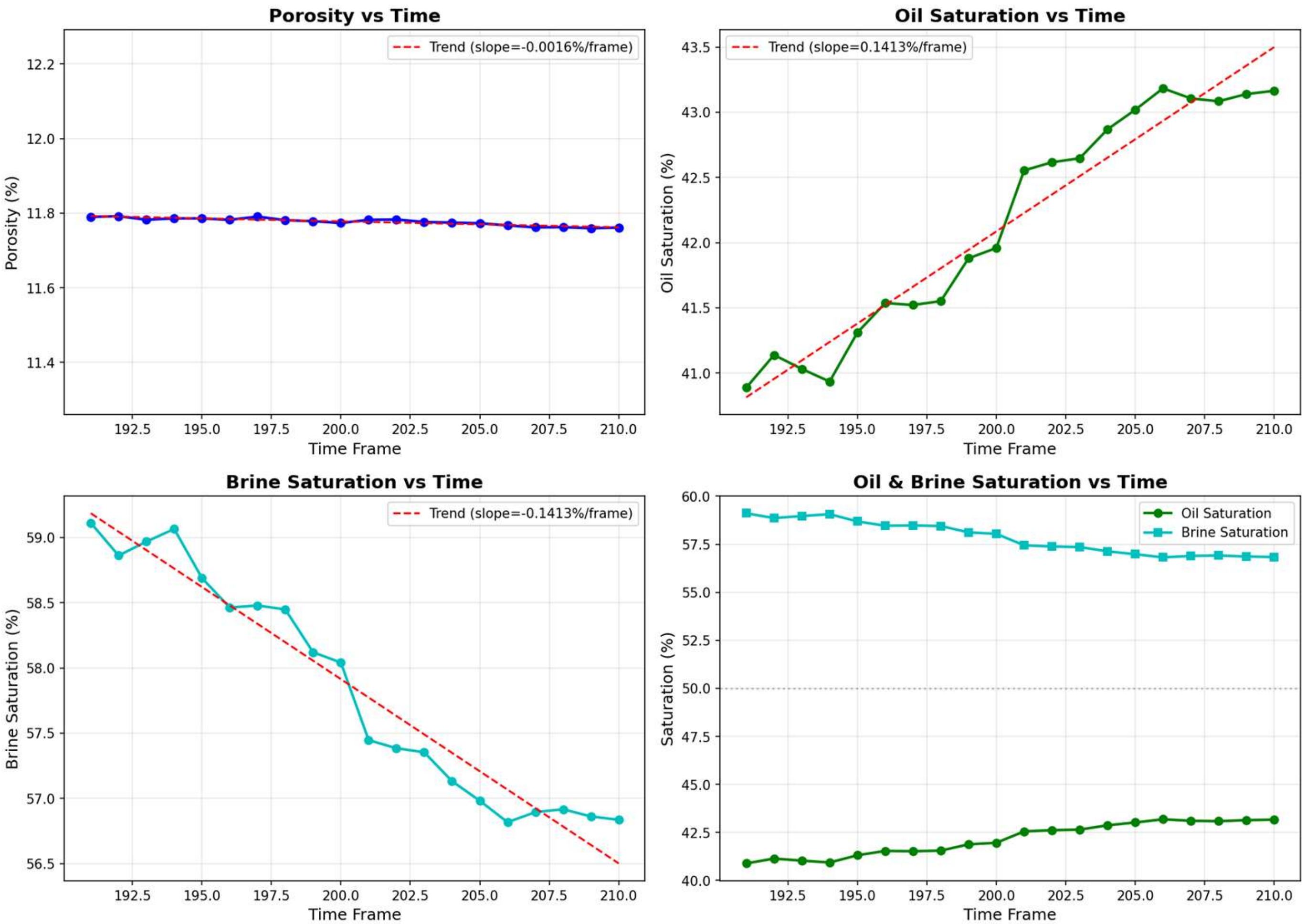
# Evaluation



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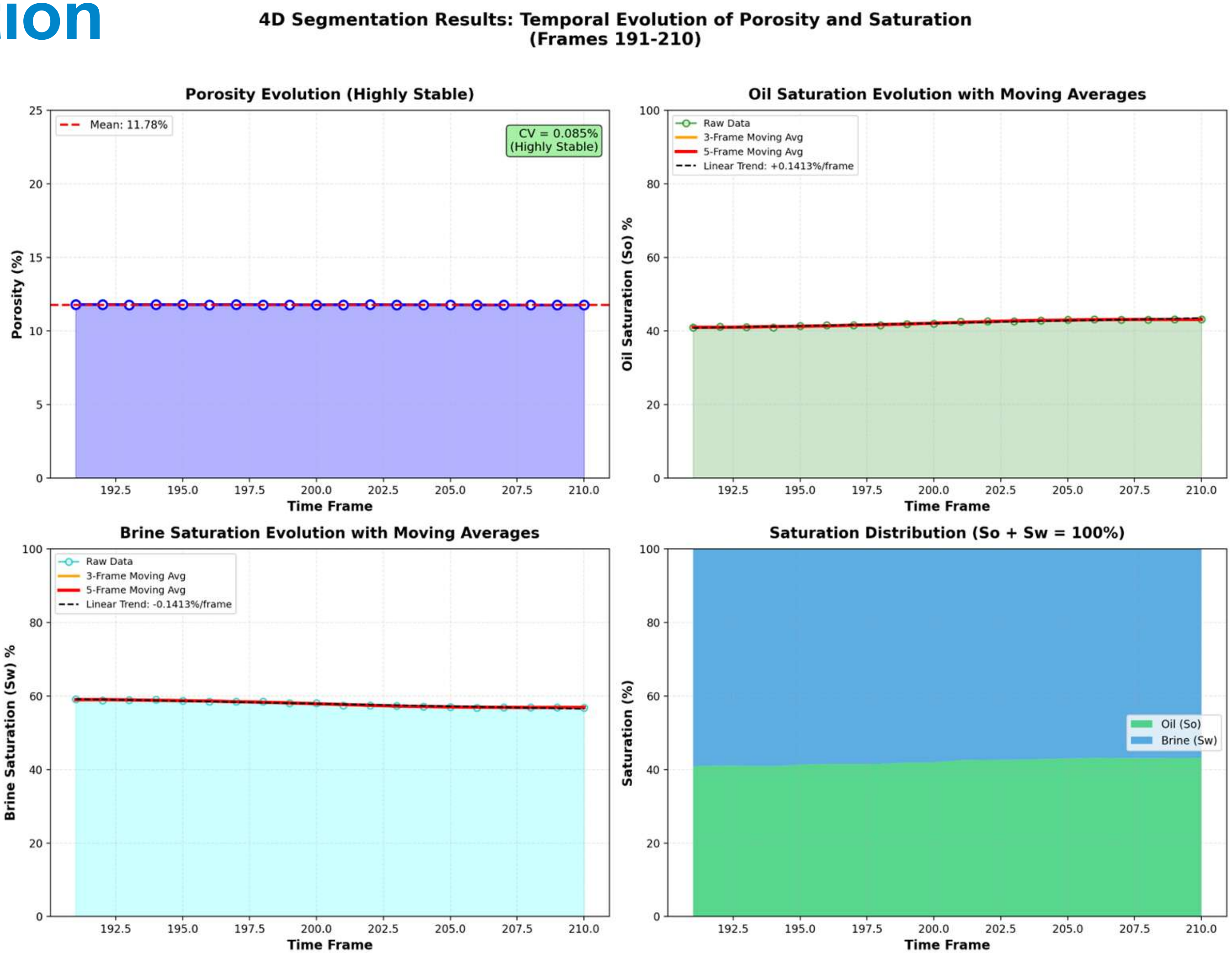
# Evaluation



# Next step

- **Methodology: Sampling Protocol**
  - Temporal Stride (T=10):
    - Ground truth labels are manually refined every 10-time steps. Total Samples: Approximate 80 high-quality labelled volumes (40 per process).
  - Workflow:
    - Utilises "Model-Assisted Annotation" to focus solely on correcting topological errors, significantly reducing workload. Spatial Selection (Active Core): Instead of random cropping, we extract a 192 x 192 x 192 Representative Elementary Volume (REV).
  - Criteria:
    - Selected based on Temporal Variance Maps to ensure the region contains the most active fluid displacement events.
- **Evaluation Objectives: Trend Analysis**
  - Micro-Level Accuracy:
    - Compute geometric metrics (Dice, IoU, HD95) on the 80 sampled keyframes.
  - Macro-Level Physical Consistency:
    - Saturation Profile (Sw): Plot and compare the water saturation curves of the Ground Truth vs. Prediction to verify mass conservation.
    - Topological Evolution: Compare the Euler Characteristic curves to validate that the model correctly captures pore connectivity changes (e.g., Snap-off events) over time.

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# Acknowledgments

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