ICML 2021 Workshop
Tackling Climate Change with Machine Learning

Enhancing Laboratory-scale Flow Imaging of Fractured Geological Media with Deep Learning Super Resolution

Manju Pharkavi Murugesu[1], Timothy I Anderson[2], Niccolò Dal Santo[3], Vignesh Krishnan[4], Anthony R Kovscek[1]

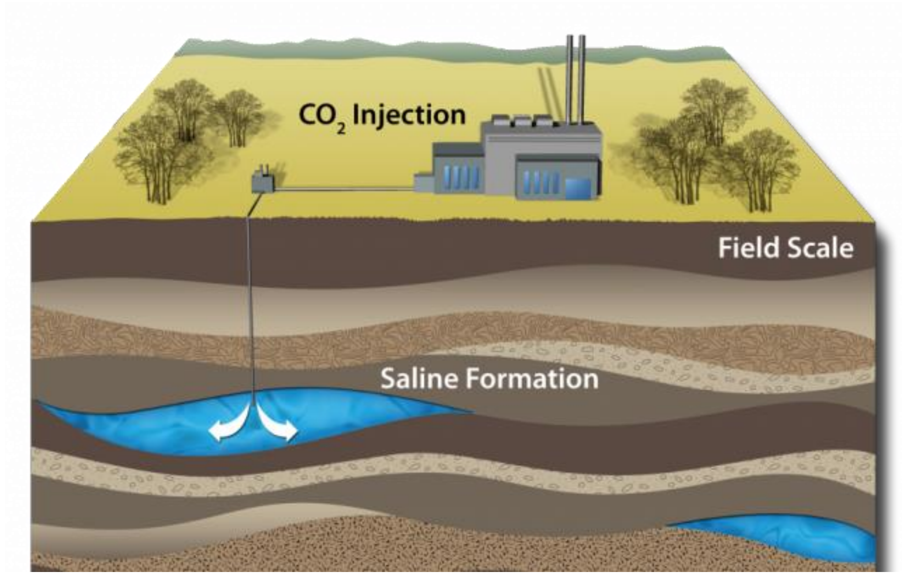
Department of Energy Resources Engineering, Stanford University, California, USA[1]
Department of Electrical Engineering, Stanford University, California, USA[2]
The MathWorks Ltd, Cambridge, UK[3]
The MathWorks Ltd, Natick, Massachusetts, USA[4]

MathWorks

Stanford University

Subsurface storage and utilization helps combat climate change

1. CO_2 Storage



Retrieved from Center for Climate and Energy Solutions

2. H_2 Storage

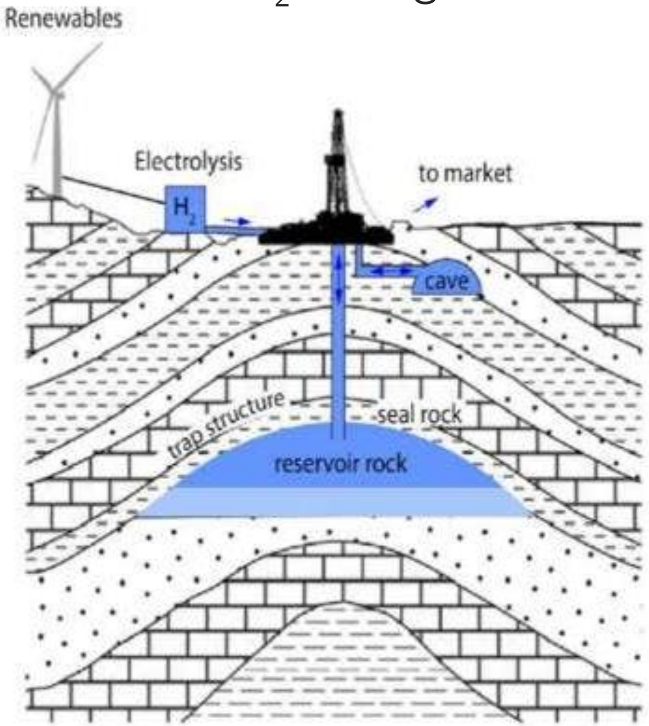
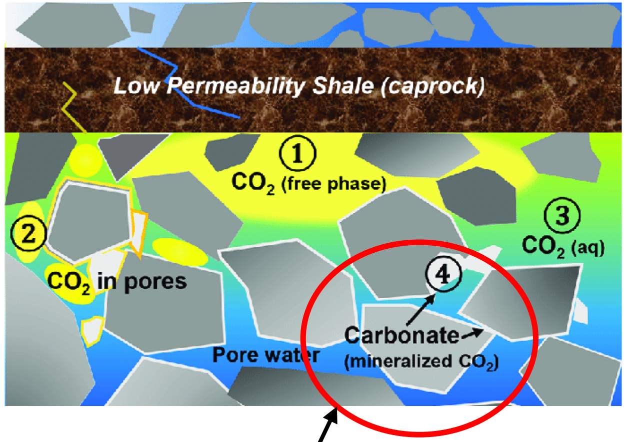


Illustration by Alan Bischoff

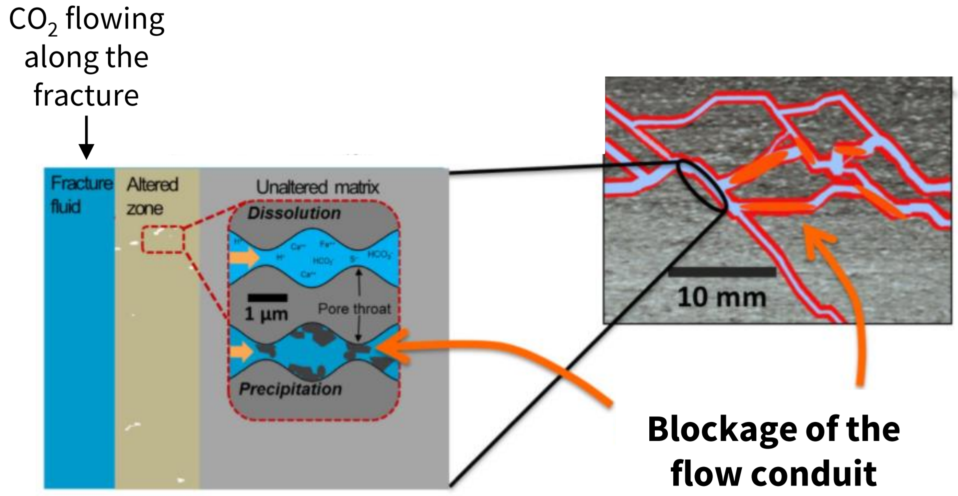
We need to understand the reactions and alterations that occur at the subsurface during CO_2 or H_2 injection

Example: CO_2 Storage



CO_2 reacts with rock minerals to cause dissolution or precipitation

Retrieved from Jun et al. (2017)

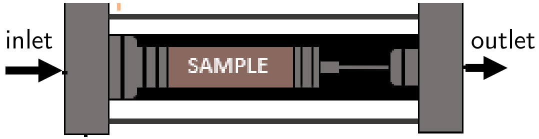


Precipitation or dissolution of rock minerals in fractured geological media alters fracture properties and affects how well CO_2/H_2 flows and gets stored.

Illustration by SLAC National Accelerator Laboratory

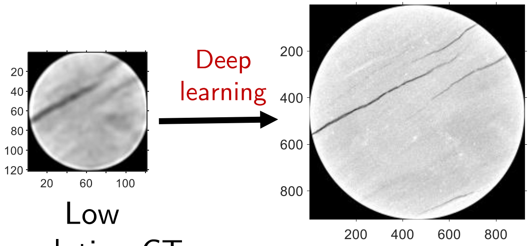
Laboratory experiments help visualize the fluid transport and reaction processes

Simulate reactive fluid injection into fractured shale → **Simultaneously image using computed tomography** → **Enhance resolution of acquired images**



- Set up to **inject fluid into the fractured geological media** from inlet to outlet

- The fluid flow and reactions at the fracture interface of the geological media are **imaged by computed tomography at various time intervals**



Low resolution CT

High resolution

- We use **deep learning to enhance the resolution** of computed tomography images

Workflow from image acquisition to real-time application

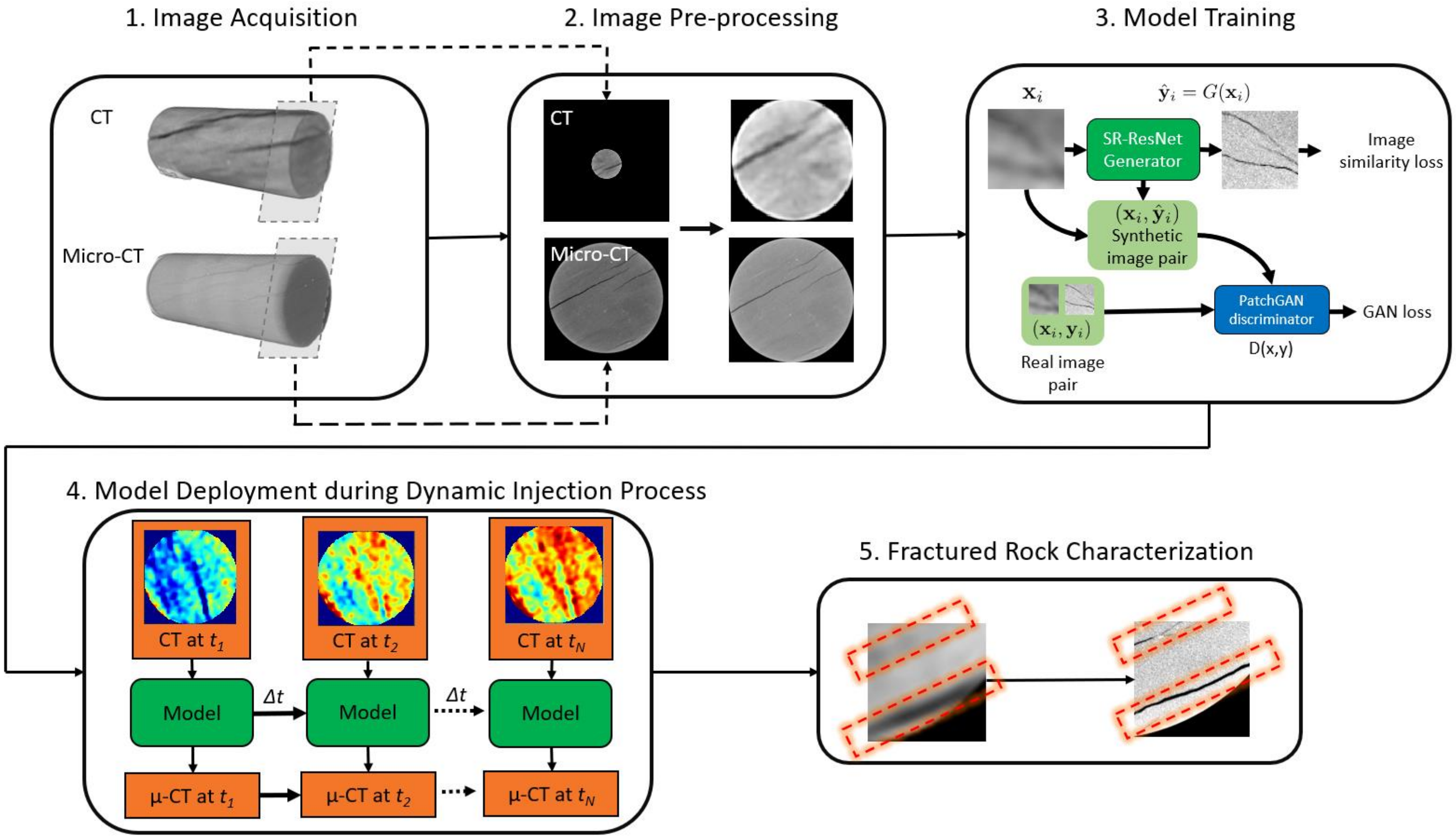
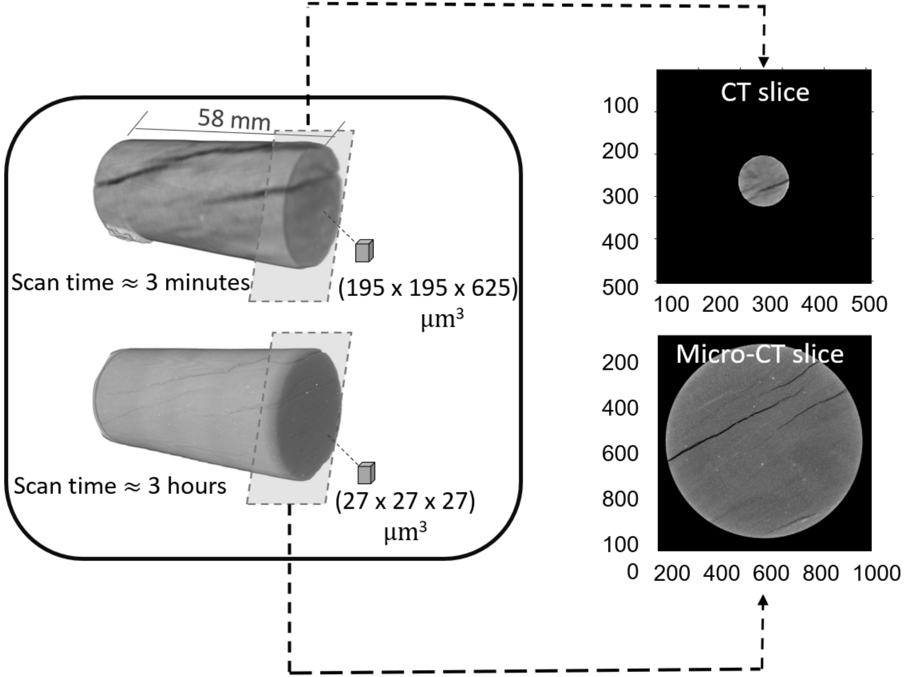


Image Acquisition to Processing Pipeline

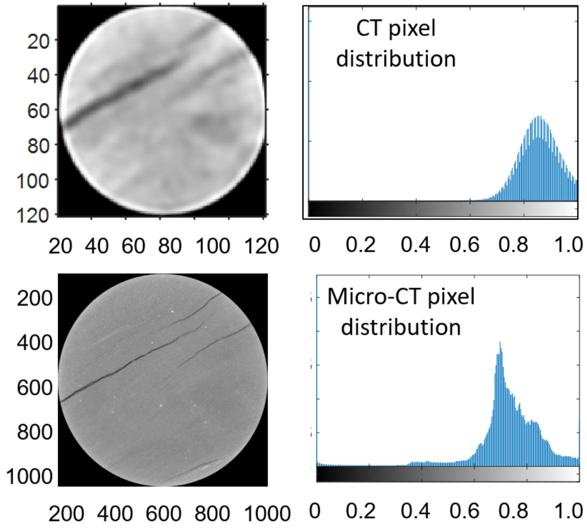
Raw Images



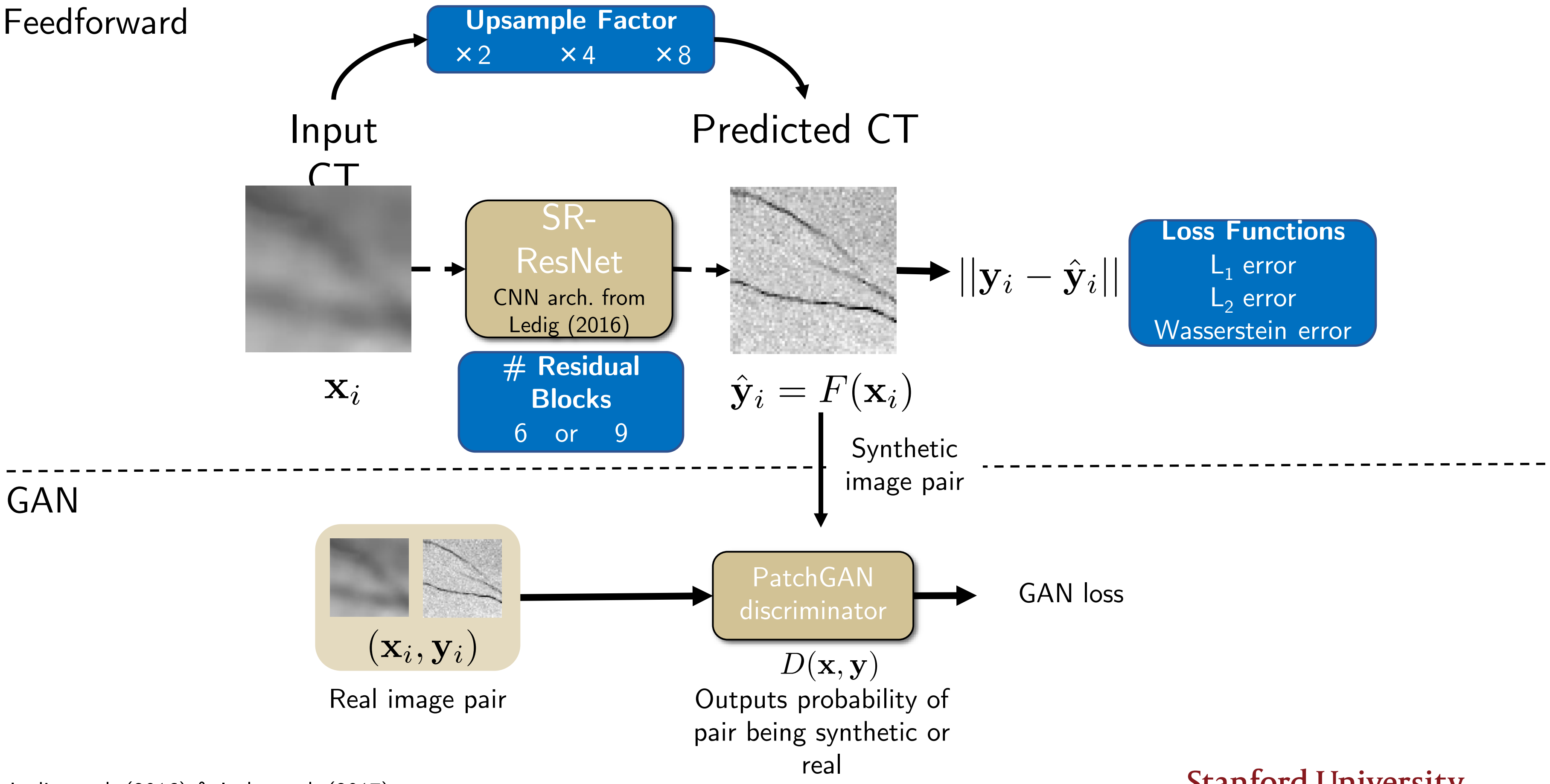
Processing steps

- **Crop background** using circle detector
- **Normalize** pixels from [0,1]
- **Align Images** using particle swarm optimization

Processed Images

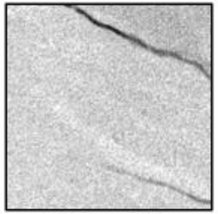
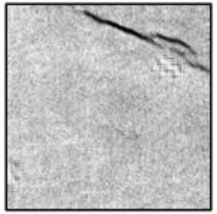
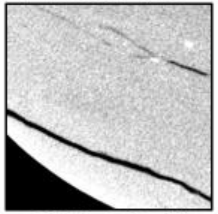
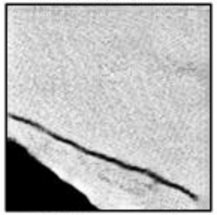
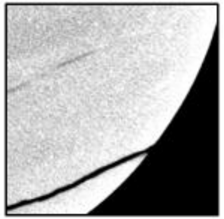
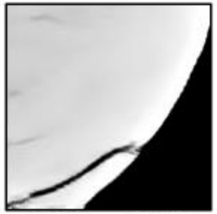


Deep Learning Model Architectures



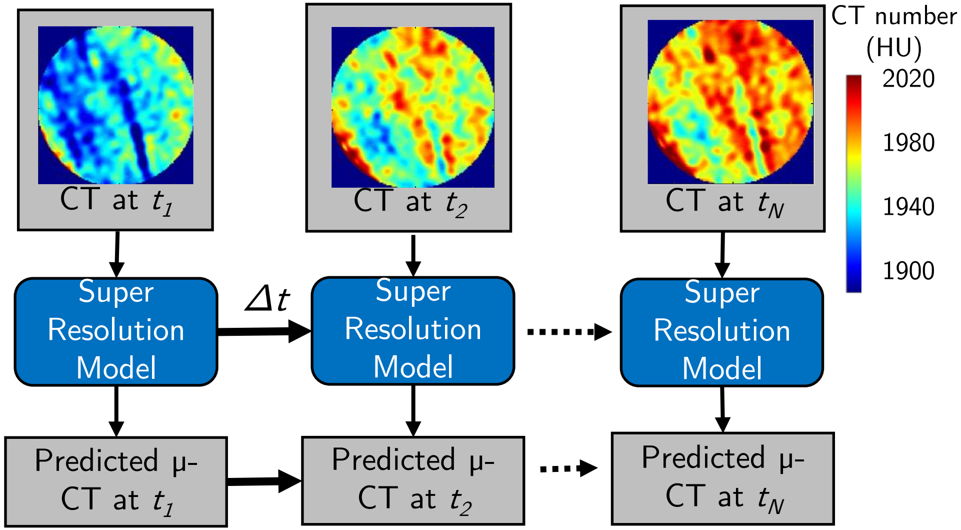
Ledig et al. (2016) & Isola et al. (2017)

Results

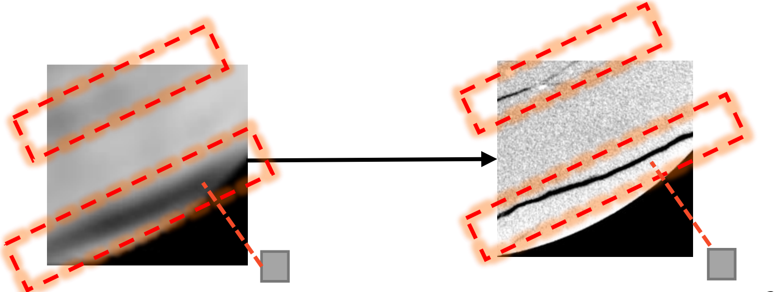
Model	Low resolution	Ground truth	Predicted image	Quantitative Metrics
Conditional GAN Wasserstein loss	 64 x 64	 256 x 256	 256 x 256	PSNR: 15.957 $\pm$ 0.190 SSIM: 0.148 $\pm$ 0.010
Conditional GAN vanilla loss	 64 x 64	 256 x 256	 256 x 256	PSNR: 18.657 $\pm$ 0.369 SSIM: 0.210 $\pm$ 0.007
Feedforward CNN L1 loss	 64 x 64	 256 x 256	 256 x 256	PSNR: 19.587 $\pm$ 0.266 SSIM: 0.228$\pm$ 0.009

Ongoing Work

Model Deployment during Dynamic Injection Process

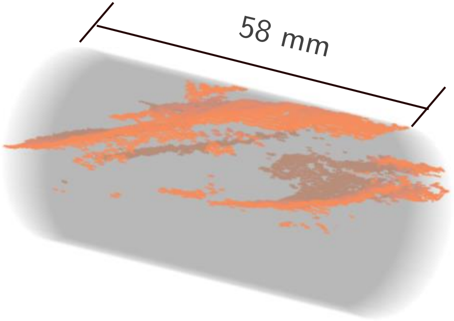


Fractured Rock Characterization



- Greater spatial and temporal resolution
- Greater Signal to Noise Ratio
- Accurate fracture characterization
- Accurate porosity inversion

Path to Climate Action



Objective: To use machine learning to enhance visualization of fractured rock during dynamic injection processes

- Accurate fracture segmentation
- 3D porosity characterization

Characterization and **monitoring** of underground injection and storage

H_2 storage

CO_2 utilization & sequestration

Enhanced geothermal system

Acknowledgement

- Dr. Anthony Kovscek
- Code is based on framework from Isola (2016), Zhu (2017)
- MathWorks
- SUPRI-A team and industrial affiliates
- Manju Pharkavi Murugesu is supported by Knight-Hennessy fellowship & Timothy I Anderson is supported by Siebel Scholars Foundation
- This work was supported as part of the Center for Mechanistic Control of Water-Hydrocarbon-Rock Interactions in Unconventional and Tight Oil Formations (CMC-UF), an Energy Frontier Research Center funded by the U.S. Department of Energy, Office of Science under DOE (BES) Award DE-SC0019165

References

Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, & Alexei A. Efros. (2016). Image-to-Image Translation with Conditional Adversarial Networks.

Justin Johnson, Alexandre Alahi, & Li Fei-Fei. (2016). Perceptual Losses for Real-Time Style Transfer and Super-Resolution.

Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, & Wenzhe Shi. (2016). Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network.

Jun-Yan Zhu, Taesung Park, Phillip Isola, & Alexei A. Efros. (2017). Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks.

Jun, Young-Shin, Lijie Zhang, Yujia Min, and Qingyun Li. (2017) Nanoscale chemical processes affecting storage capacities and seals during geologic CO2 sequestration.