SMART-CS Initiative

Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

Task 2 : Real Time Visualization of Rock and Fluid Properties

David Alumbaugh (LBL) and Dustin Crandall (NETL)

August 18, 2022

U.S. DEPARTMENT OF ENERGY

Task 2 : Rock Property Visualization

Task 2 Mission: Evaluate existing and state of the art technologies for incorporating multiple types of disparate scale data to assess rock properties (CO_2 saturation for Phase 1) in a ‘real time‘ sense and identify/apply/test machine learning strategies that can aid in this endeavor.

Task 2: Rock Property Visualization Project Leadership
David Alumbaugh (LBNL, Lead)
Dustin Crandall (NETL, Co-Lead)

Sub-Target Resolution Scale Team

Dustin Crandall, Paul Holcomb, Foad Haeri, Tom Paronish (**NETL**)

Zuleima Karpyn, Russ Johns, Sanjay Srinivasan, Zihan Ren, Prakash Purswani, Fangya Niu, Parisa Shokouhi (**PSU**)

Shane Butler, Beth Kurz, César Barajas-Olalde, Lingyun Kong, Xue Yu, Matt Burton-Kelly, (**EERC**)

Manika Prasad, Mathias Pohl, Savini Samarasinghe, Similoluwa Oduwole (**CSM**)

Tim Kneafsey (**LBNL**)

Supra-Target Resolution Scale Team

David Alumbaugh, Michael Commer, Erika Gasperikova, Evan Um (**LBNL**)

Jyoti Behura, Yaoguo Li, Andy McAliley, Savini Samarasinghe, Hua Wang (**CSM**)

Cesar Barajas-Olalde (**EERC**)

Youzuo Lin (**LANL**)

Xianjin Yang (**LLNL**)

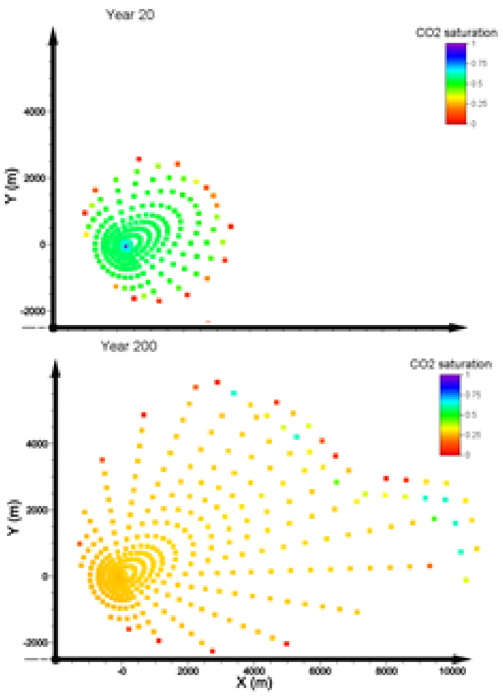
William Harbert (**NETL**)

Task 2 : Rock Property Visualization

- **Task 2 Goal For Phase 1 : Proof of concept for applying Physics-Based Machine Learning for providing estimates of CO_2 saturation at depth, along with uncertainties in those estimates, at 1 to 10m resolution.**
- **Specific Sub-Tasks**
    1. Determine data that we will be using for testing, and how that data will be used for estimating CO_2 saturation
        a. Core-to-Well scale: What data measured in lab provides value to estimating CO_2 saturation at target resolution?
        b. Well-to-field scale: What multi-physics data should we use, and how to use it to estimate CO_2 saturation?
    2. Implement and test physics-based approaches for estimating CO_2 saturation from various data types
    3. Implement and test ML approaches for
        1. Estimating CO_2 saturation from the various scales and types of data
            a. Upscaling from the Core-to-Well scale to the target resolution
            b. Downscaling from the Well-to-Field scale to target resolution, and provide images of CO_2 saturation rather than geophysical properties
        2. Provide estimates of uncertainty of CO_2 saturation at different scales

Task 2 Data : Kimberlina 1.2 Model/Data Creation

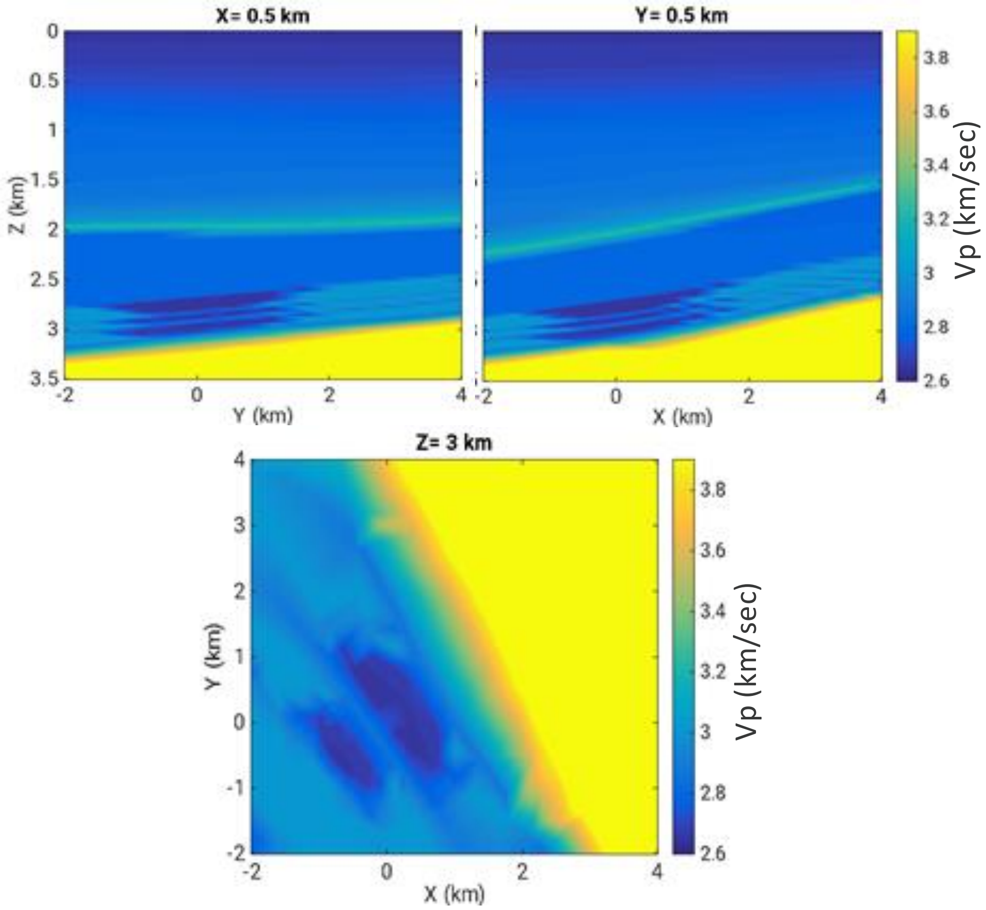
Unstructured TOUGH2 Mesh



Interpolation/Extrapolation

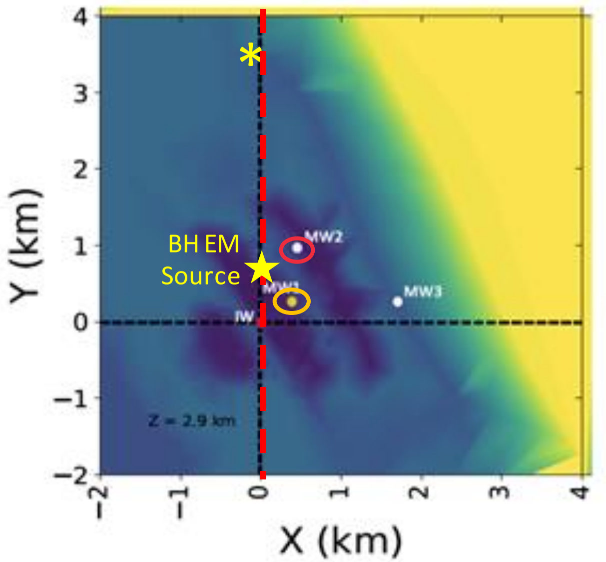
Regular fine mesh
CO_2 Saturation
Vp and Vs
Density
Resistivity

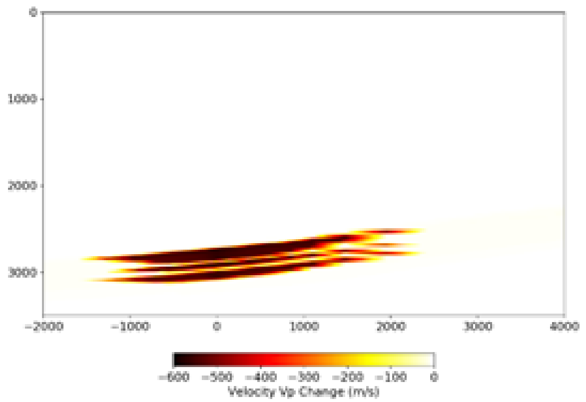
Vp at 20 Years on Regular (10m x 10m x 10m) grid



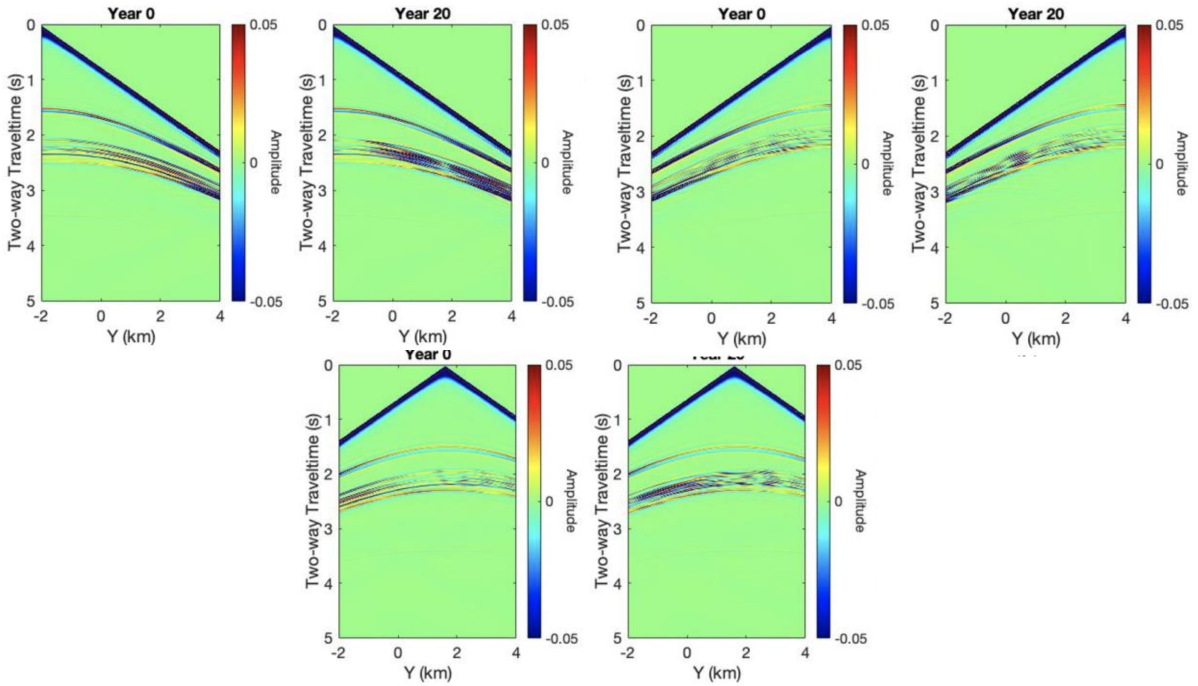
- **Using 100 different realizations / TOUGH2 runs of the Kimberlina 1.2 Model**
  - Each realization has 35 different time steps
  - Interpolation/extrapolation to regular grid more difficult than expected
- **Test Data sets computed for Year 0 and Year 20 from Sim001**
- **2D Testing**
  - Test data computed along Y direction at X=0 in Year 0 and Year 20
  - Training data computed along Y-Lines from X=-2 to X=3km for all 35 time steps in Sim001
    - 2D surface seismic at X=100m intervals
    - Borehole-to-surface EM with 2 sources at X=200m
    - Gravity in 2 boreholes per line and surf at X=200m
- **3D Testing**
  - Use all 100 Sims and 35 Time steps
  - For EM and Gravity use 3 monitoring wells shown to left for borehole sources/data
- **All models/data to be uploaded to EDX**

Task 2 Data : Kimberlina 1.2 Model/Data Creation
Time Lapse Calc. Geophysical Data (Year 20- Year 0)

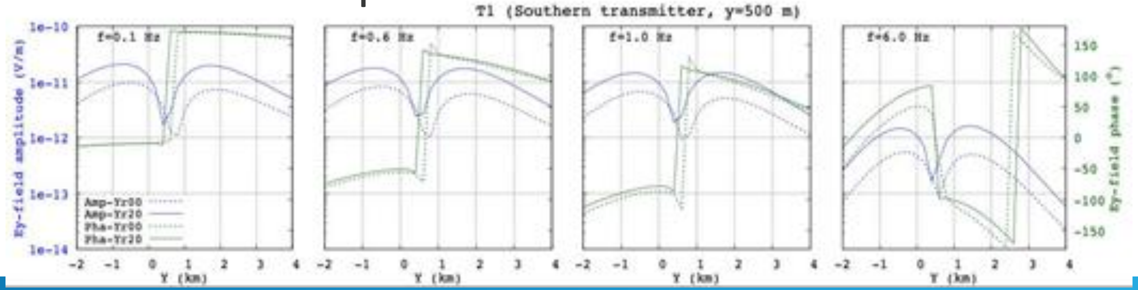




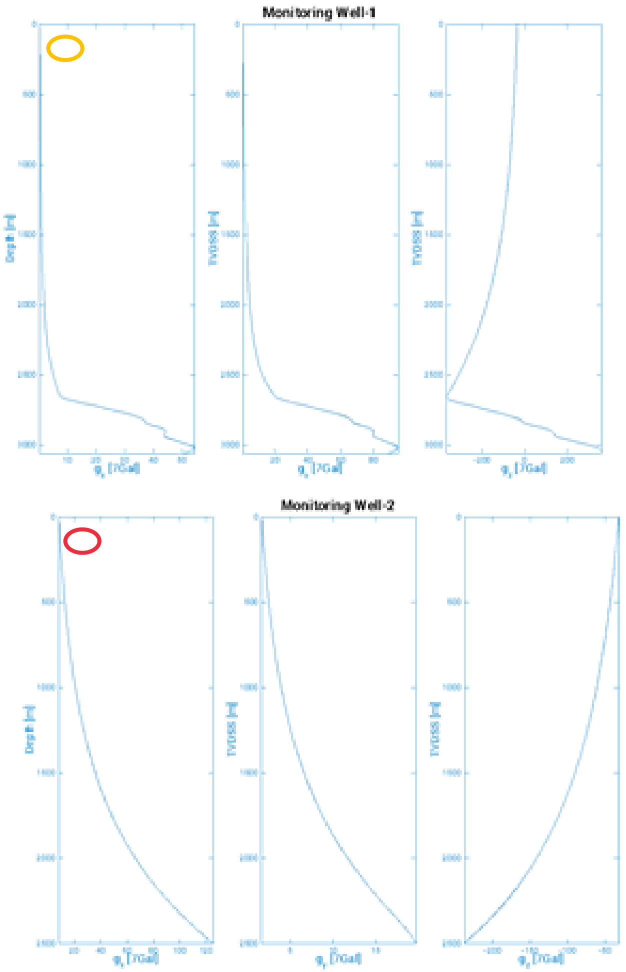
Time Lapse Surface Seismic



Time Lapse Borehole-to-Surface EM



Time Lapse Borehole Gravity

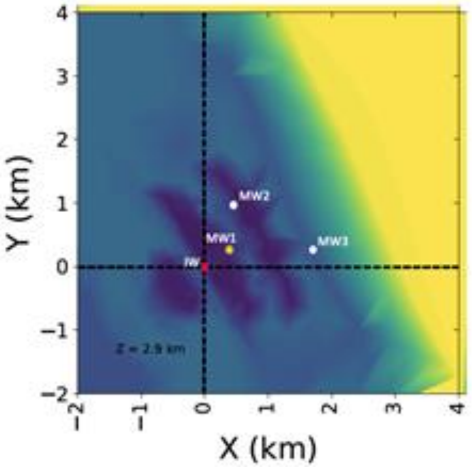


Task 2 Data : Kimberlina 1.2 Model/Data Creation

Creation of Kimberlina 1.2 Synthetic Well logs

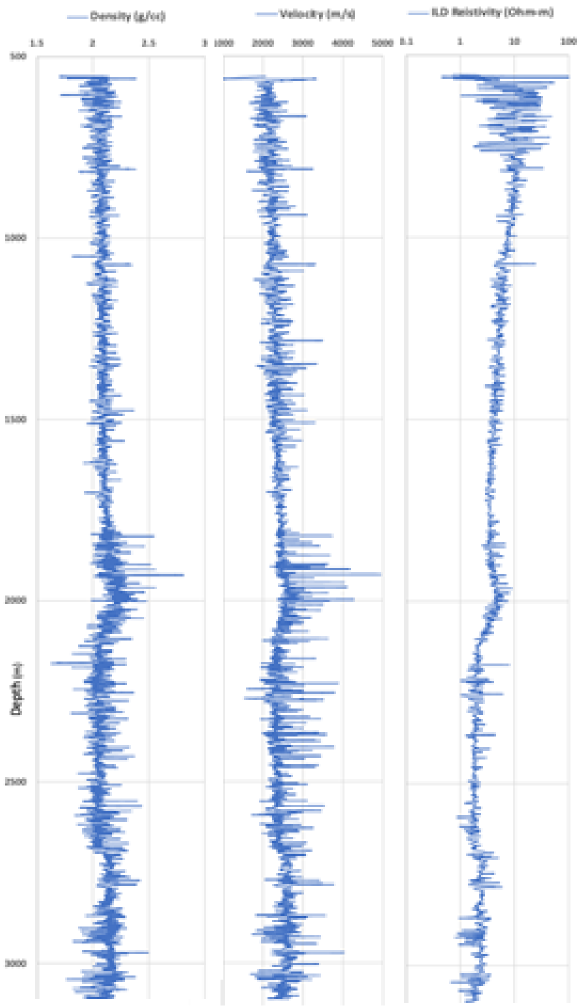
- Synthetic logs created in 4 hypothetical well locations
- Density, velocity and resistivity logs created in 3 monitoring wells at 0, 1,2, 5, 10, 15 and 20 years after injection start

Map view with well locations

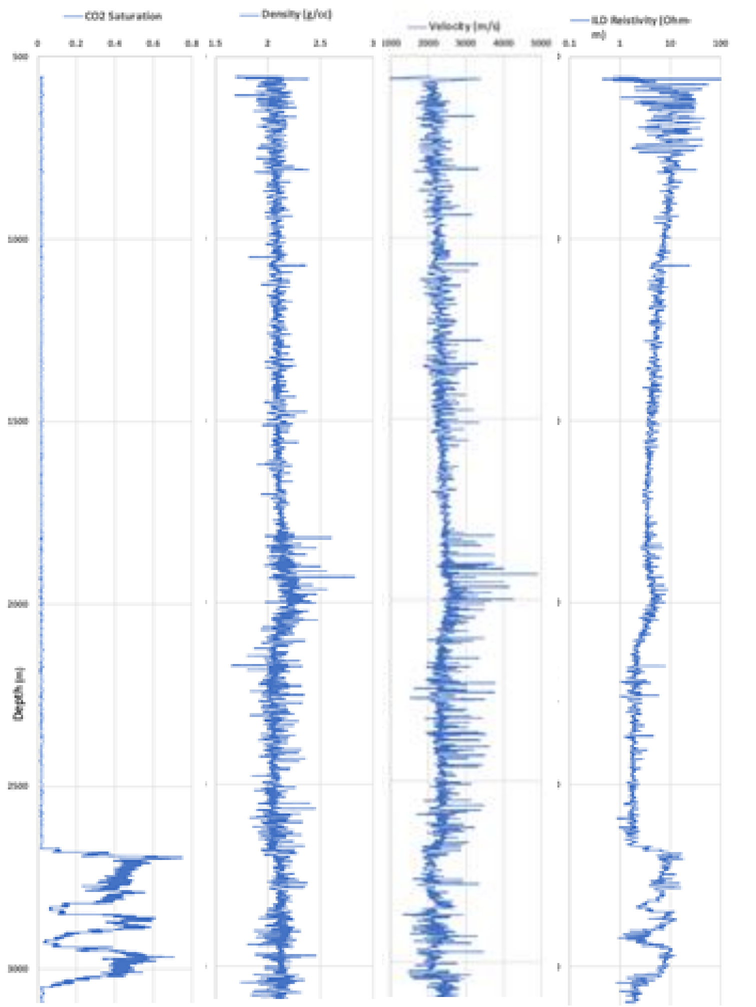


- Time lapse CO_2 saturation logs created in all wells at times after injection
- Geophysical logs created by taking high frequency content present in real Kimberlina 1 well log and adding to model property values at well locations. CO_2 saturation created by multiplying model CO_2 values by scaled porosity logs

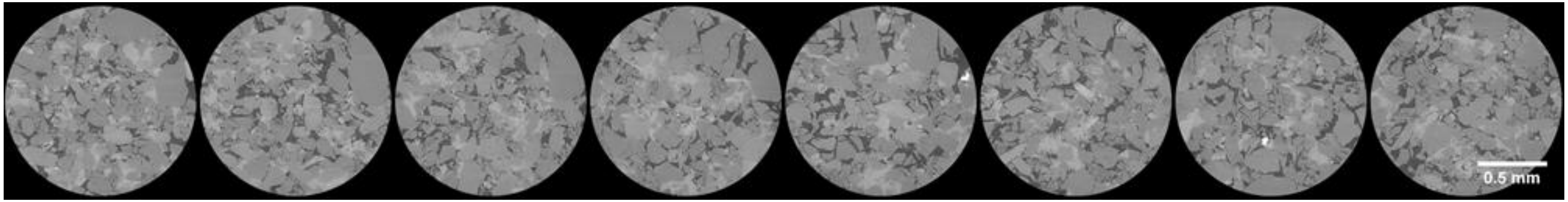
MW1 Pre-Injection Logs



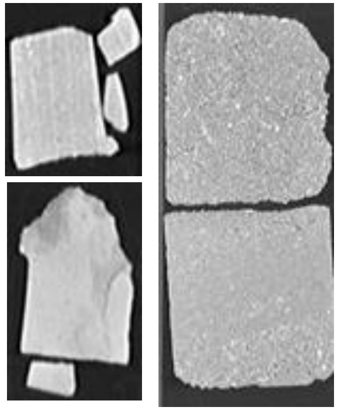
MW1 Logs after 20 Years of Injection



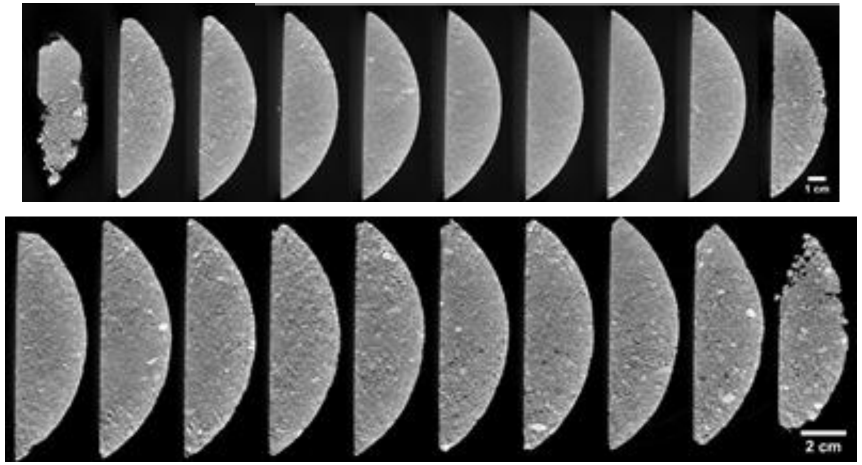
Task 2 Data : Kimberlina 1.2 Model/Data Creation



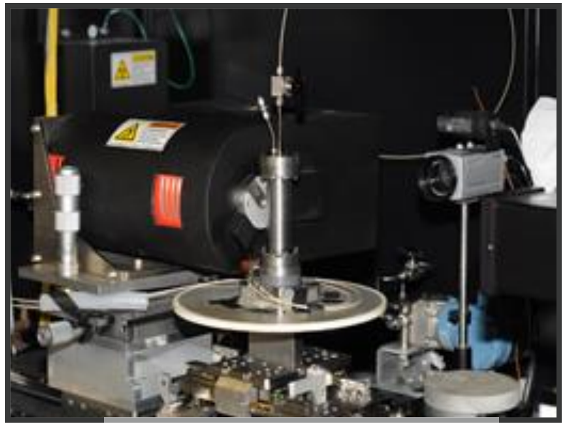
High-resolution micro-CT images (1 voxel = 1.4 microns)



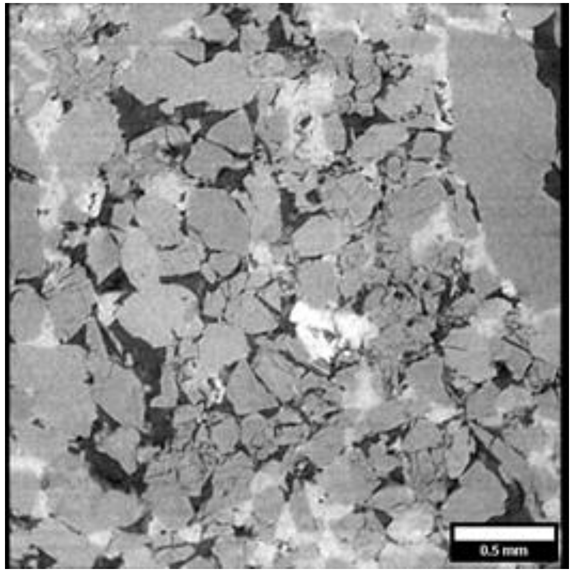
Low resolution medical CT images



High resolution industrial CT images



Micro-CT scanner with core holder



- Core to pore scale characterization underway of Round Mountain Well #1 (3500-3900’)
  - scCO_2 saturation tests in micro-CT scanner completed
  - Two zones initially tested too low permeability to perform scCO_2 injection

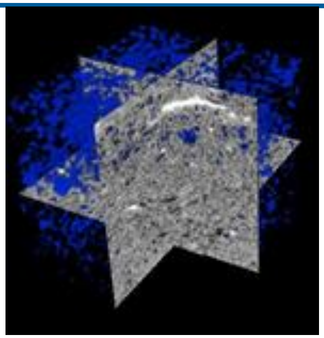
Pore-to-Well Scale Efforts

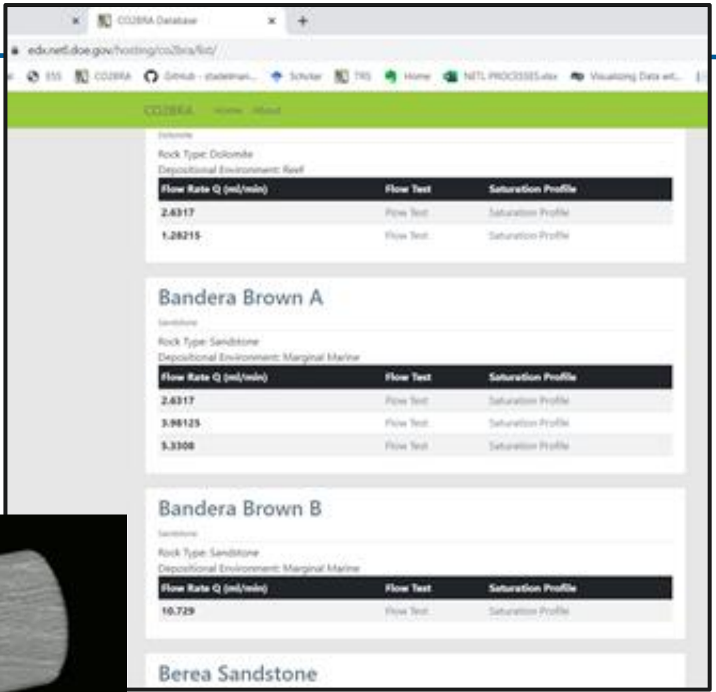
- **Four pore to core scale experimental data sets (CT to k_r, CT plus acoustic, NMR measurements of saturation, and thin section/2D image analyses) to create a robust set of data to upscale to well-scale properties.**
- **Two methods being evaluated to go from centimeters to meters**
- **Leveraging unique laboratory facilities to capture data that would not typically be available. ML to understand what features of pore to core scale properties could be further utilized to constrain and improve models of saturation evolution in injection reservoirs**
  - Efforts for site core characterization distilled down to a porosity, permeability, and maybe some heterogeneity.

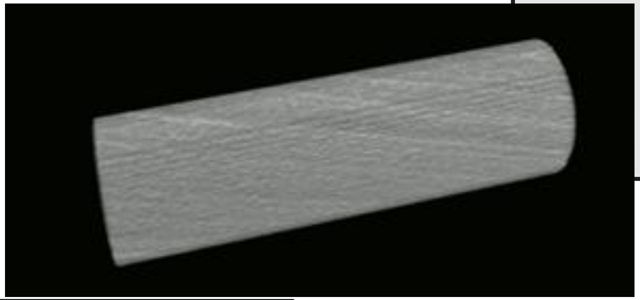
Pore Scale Isolation & Core Flow

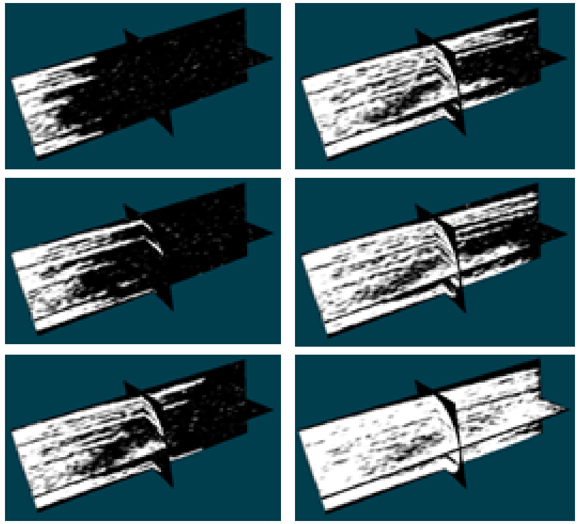
With Medical CT scanner

- $scCO_2$/brine relative permeability measurements through the samples that have had pore scale imaging performed on sub-cores.
- And porting to core scale simulations









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Advances in Water Resources

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Rapid determination of supercritical CO_2 and brine relative permeability using an unsteady-state flow method

Johnathan Moore[a,b,*], Paul Holcomb[a,b], Dustin Crandall[a], Seth King[a,b,1], Jeong-Hoon Choi[a,b], Sarah Brown[a,b,2], Scott Workman[a,c]

[a] U.S. Department of Energy, National Energy Technology Laboratory, 3610 Collins Ferry Road, Morgantown, WV 26507 United States
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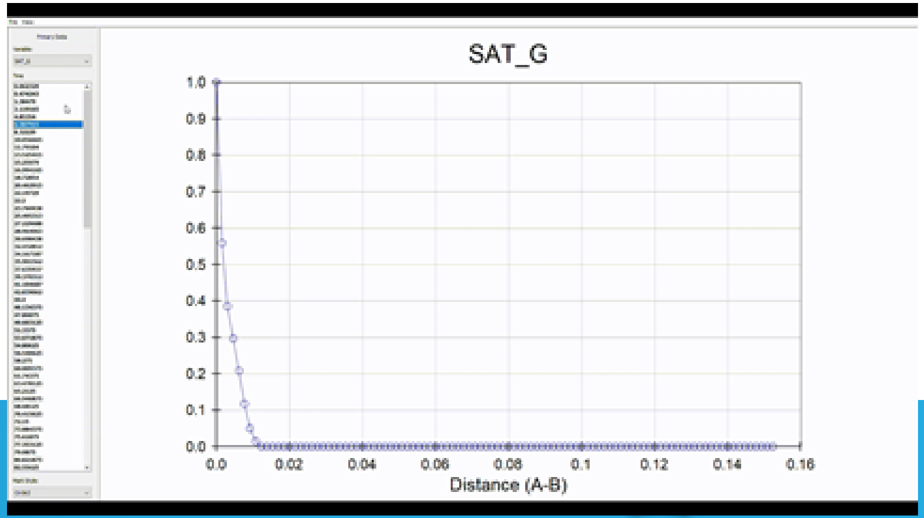

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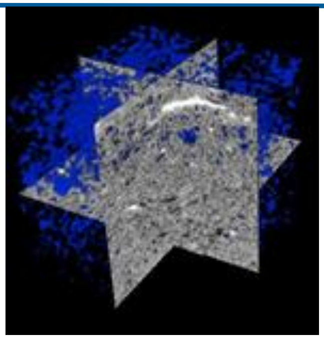

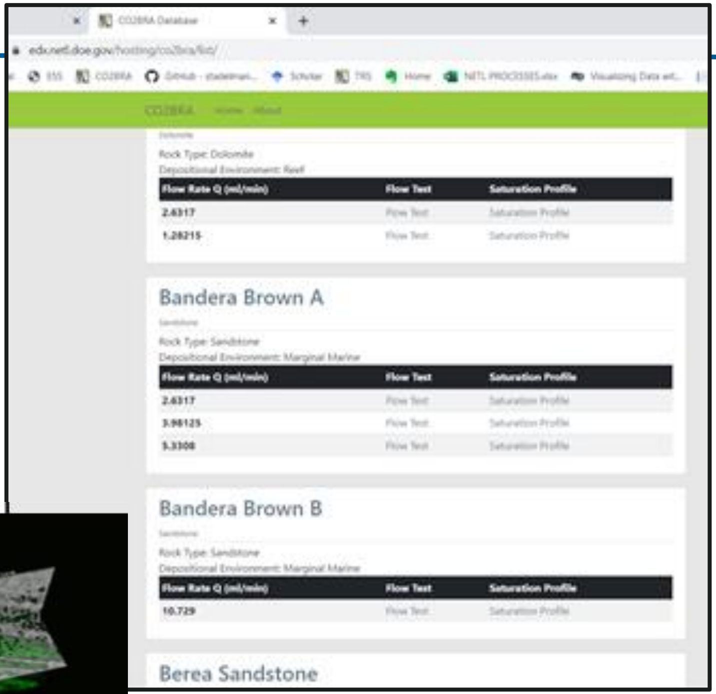

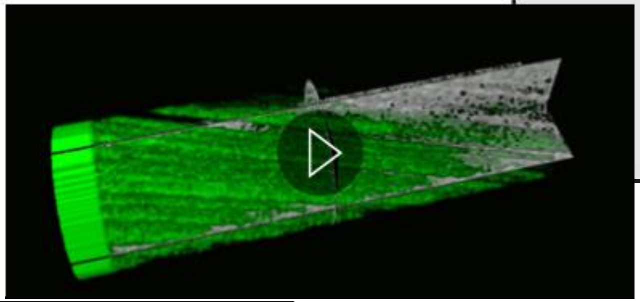

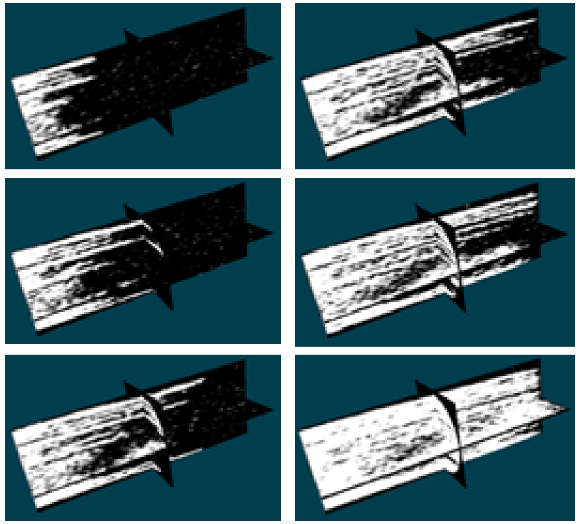

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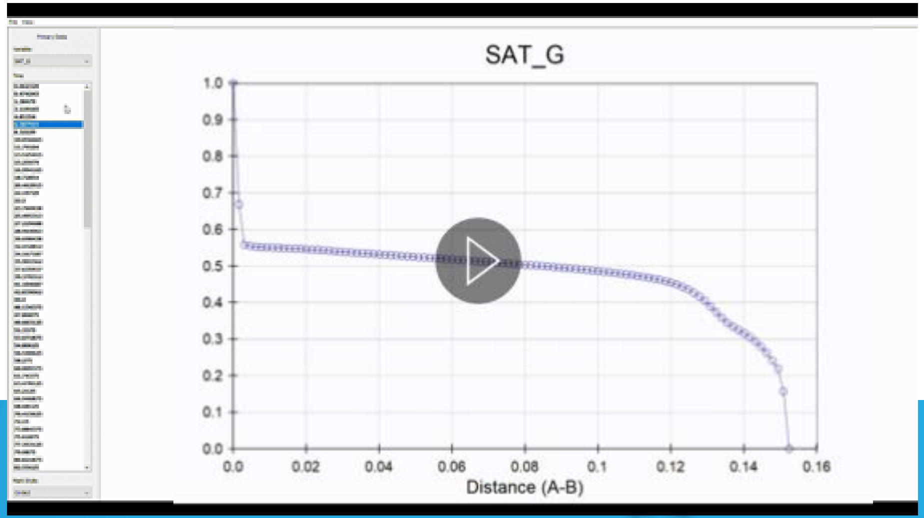
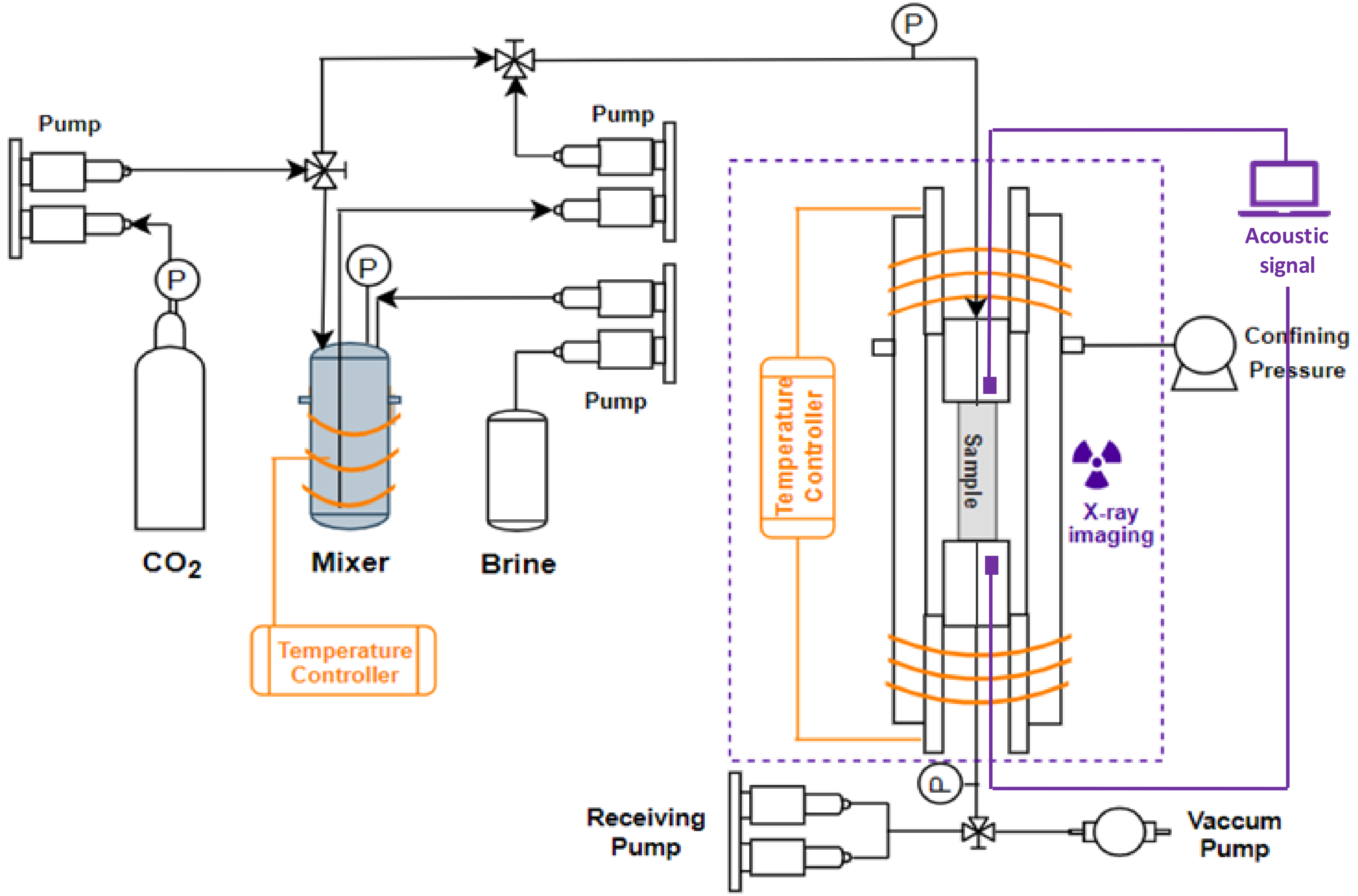


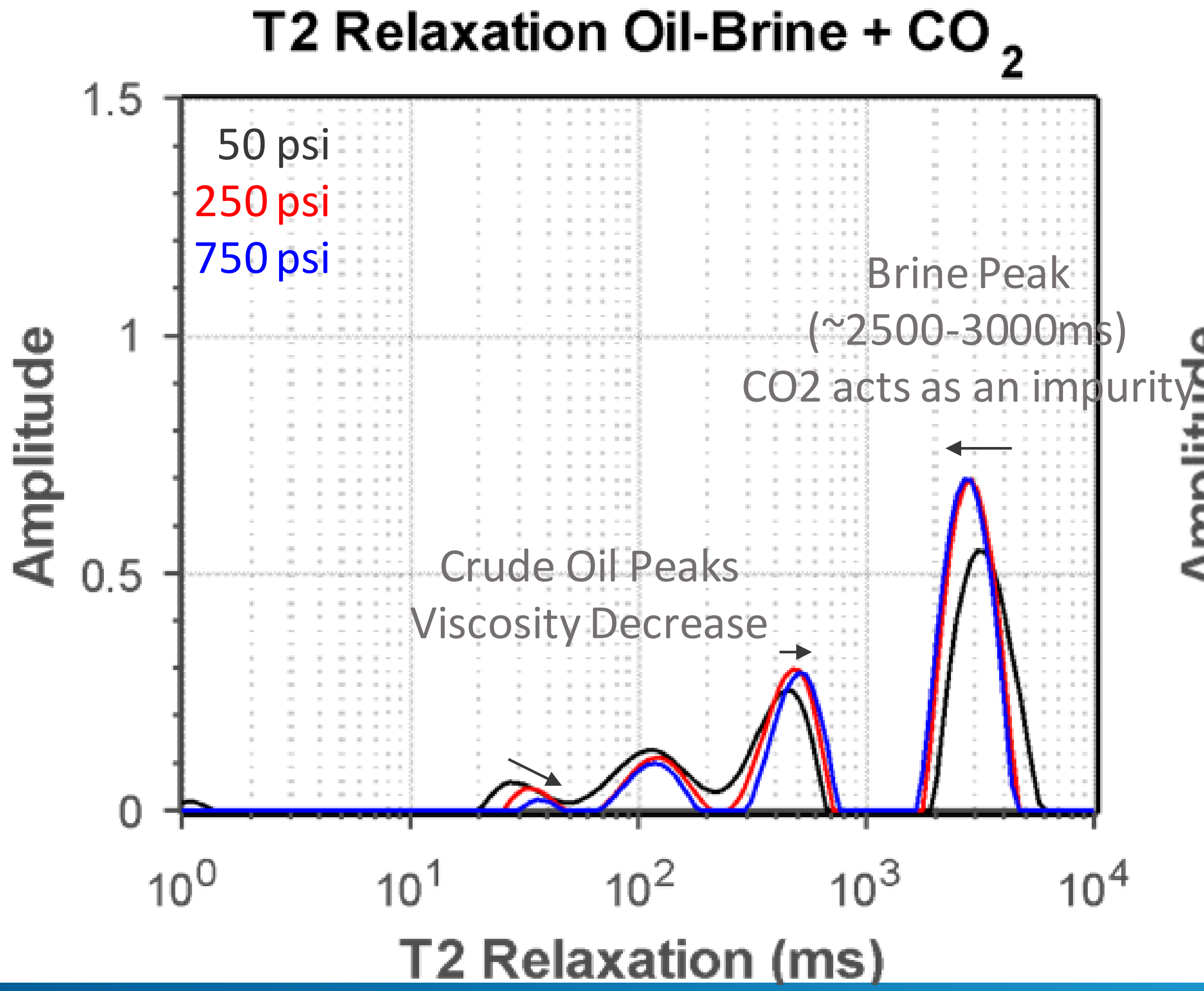
Pore-scale Imaging Experimental Setup

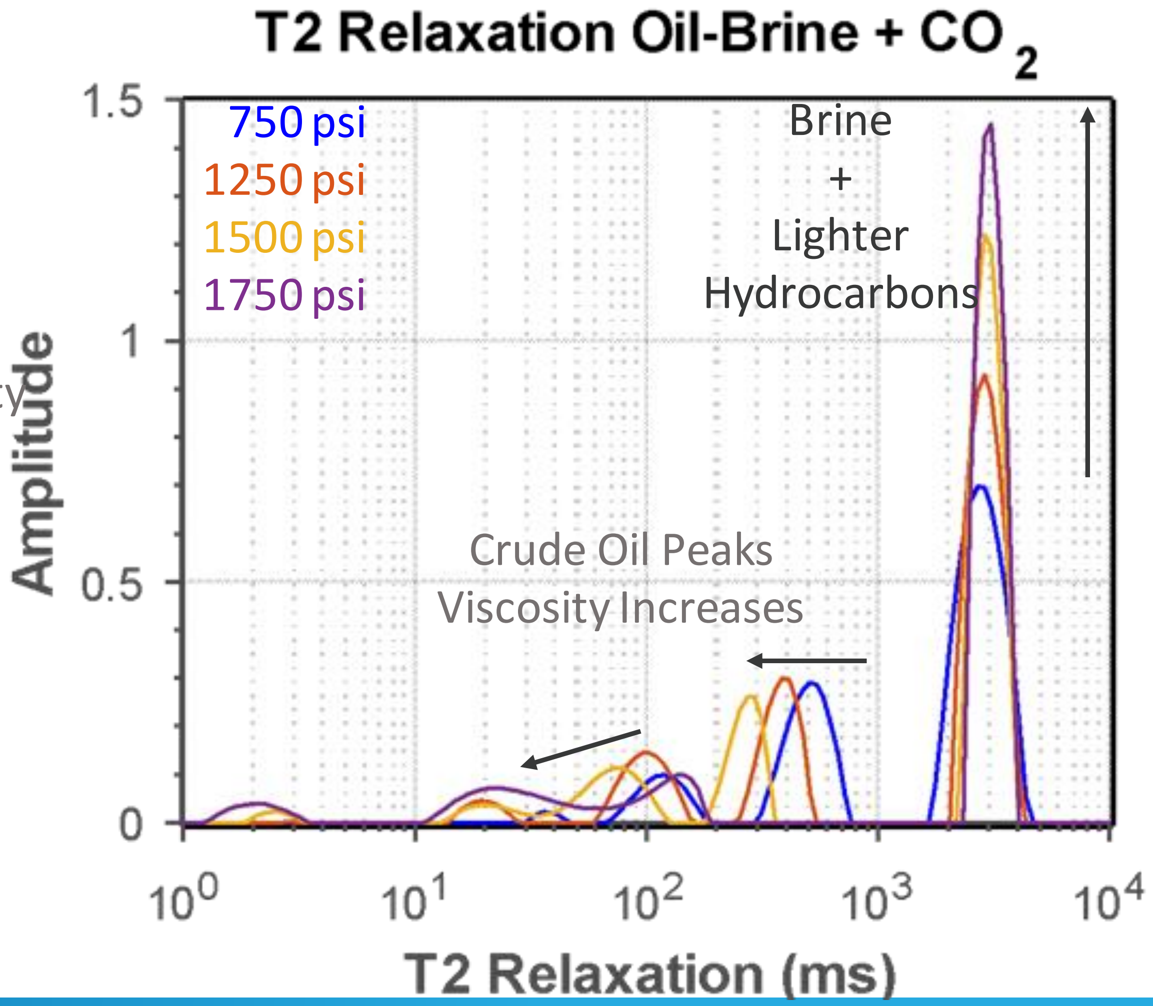
PSU Core Imaging Scale

Schematic and photograph of the CT + ultrasonic measurement setup at PSU



Nuclear Magnetic Resonance Results: Oil-Brine + CO2

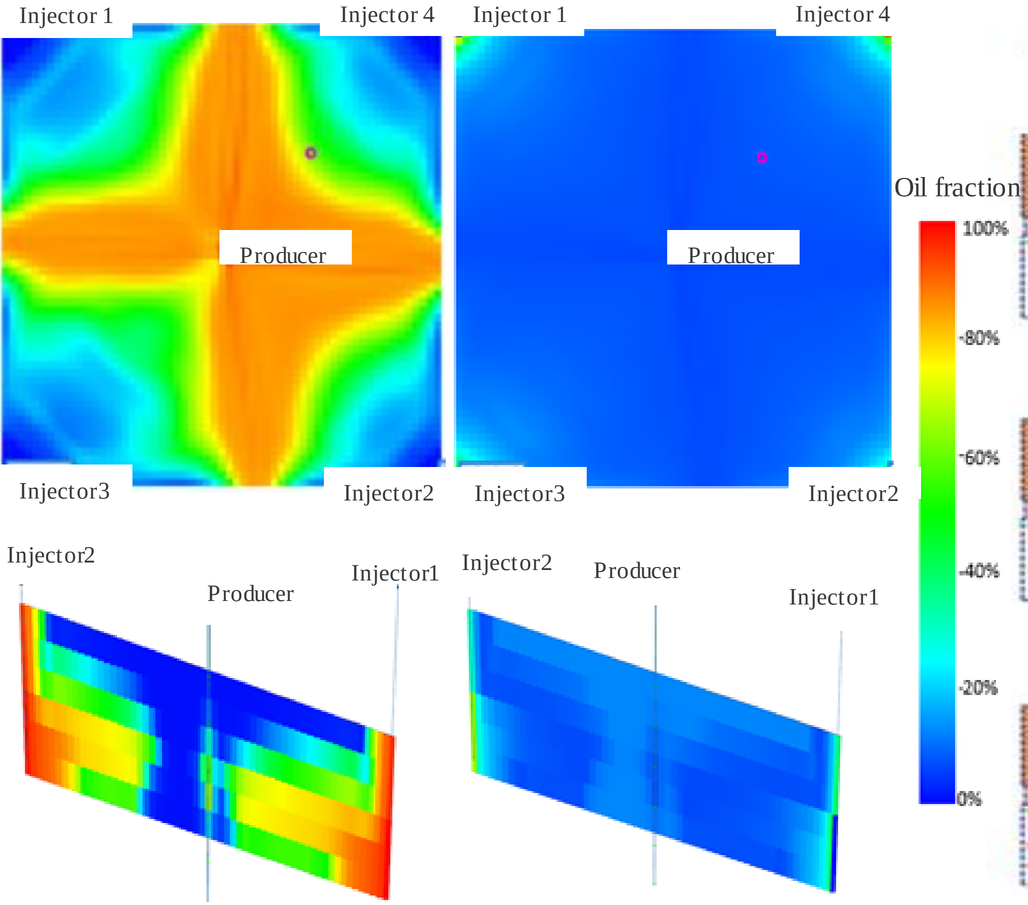




Reservoir Simulation

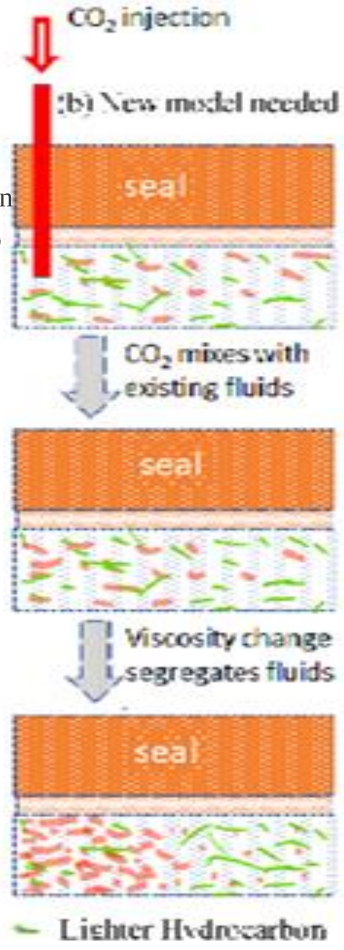
Reservoir Fluid Analysis

Light fraction | Heavy fraction

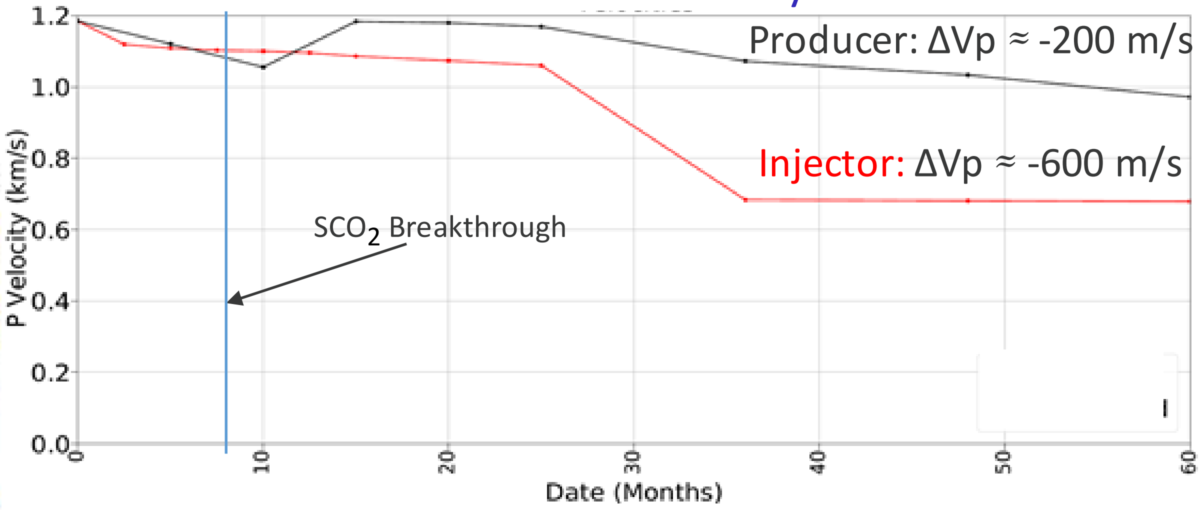


Fluid segregation (1 year)

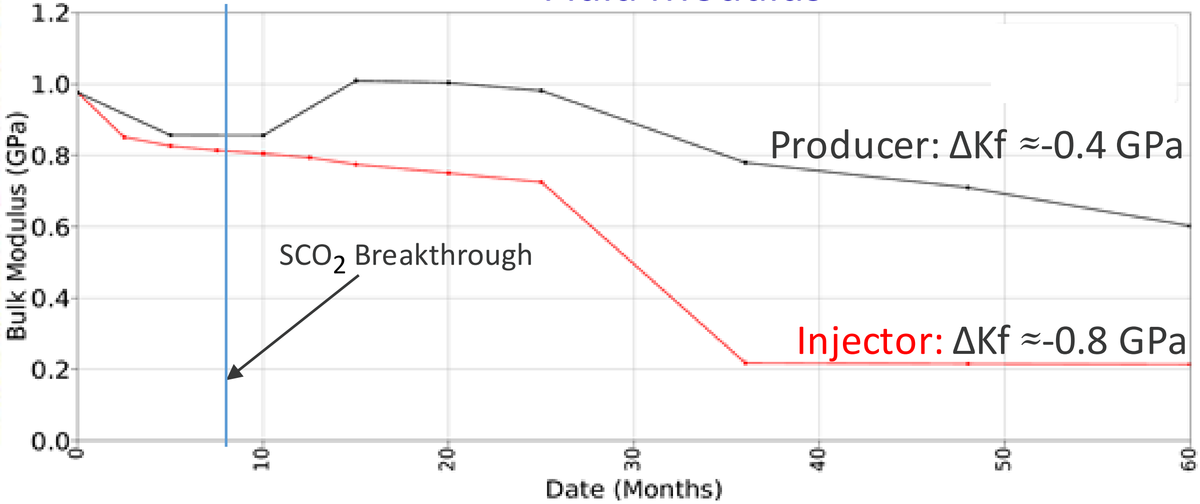
Flow Concept



Fluid Velocity

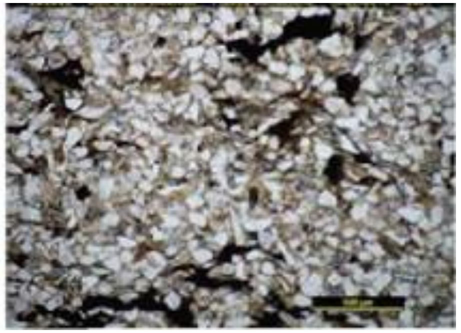


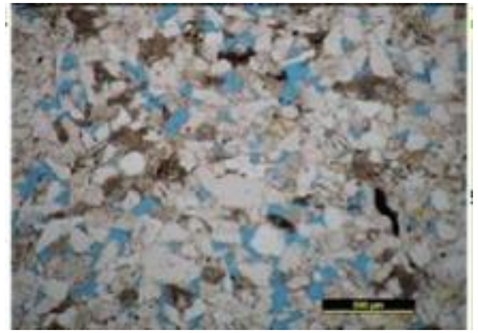
Fluid Modulus



Upscaling Pore Features to Well Scale

CORES

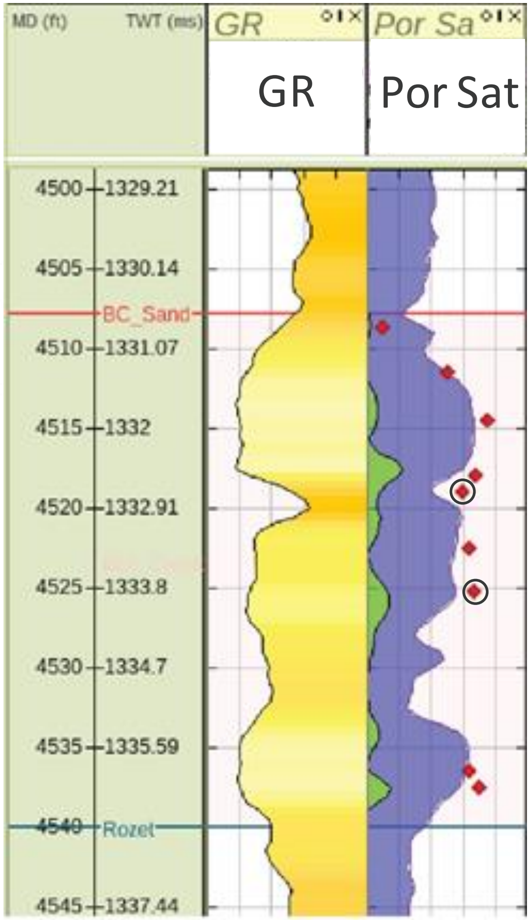




2D and 3D machine learning-driven image analysis coupled with fractal theory to estimate rock properties

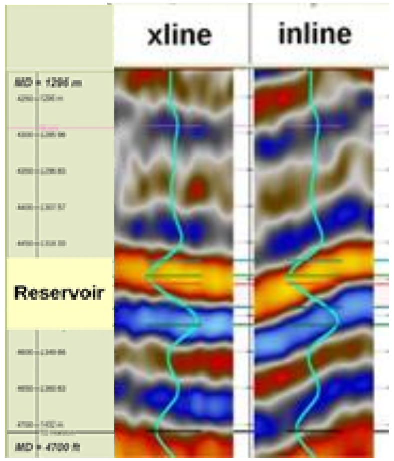
UPSCALE

WELL LOGS



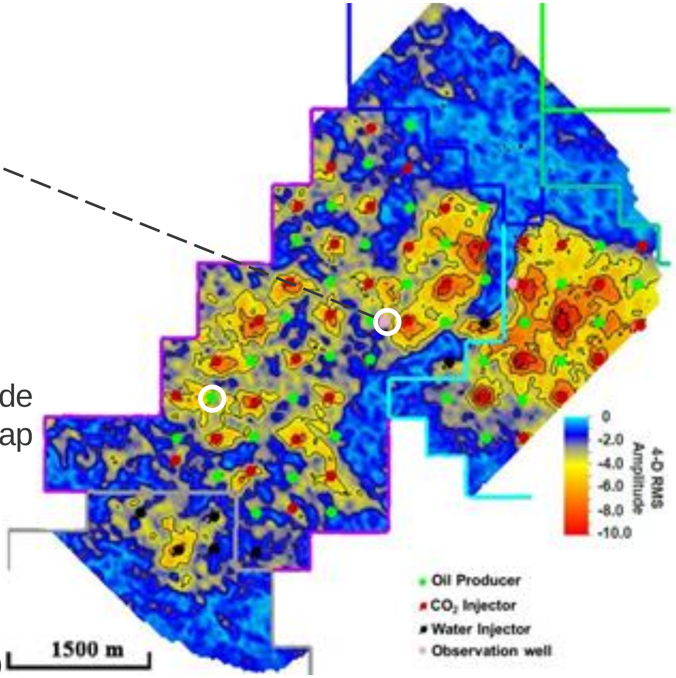
BELL CREEK DATA

SEISMIC DATA



DOWNSCALE

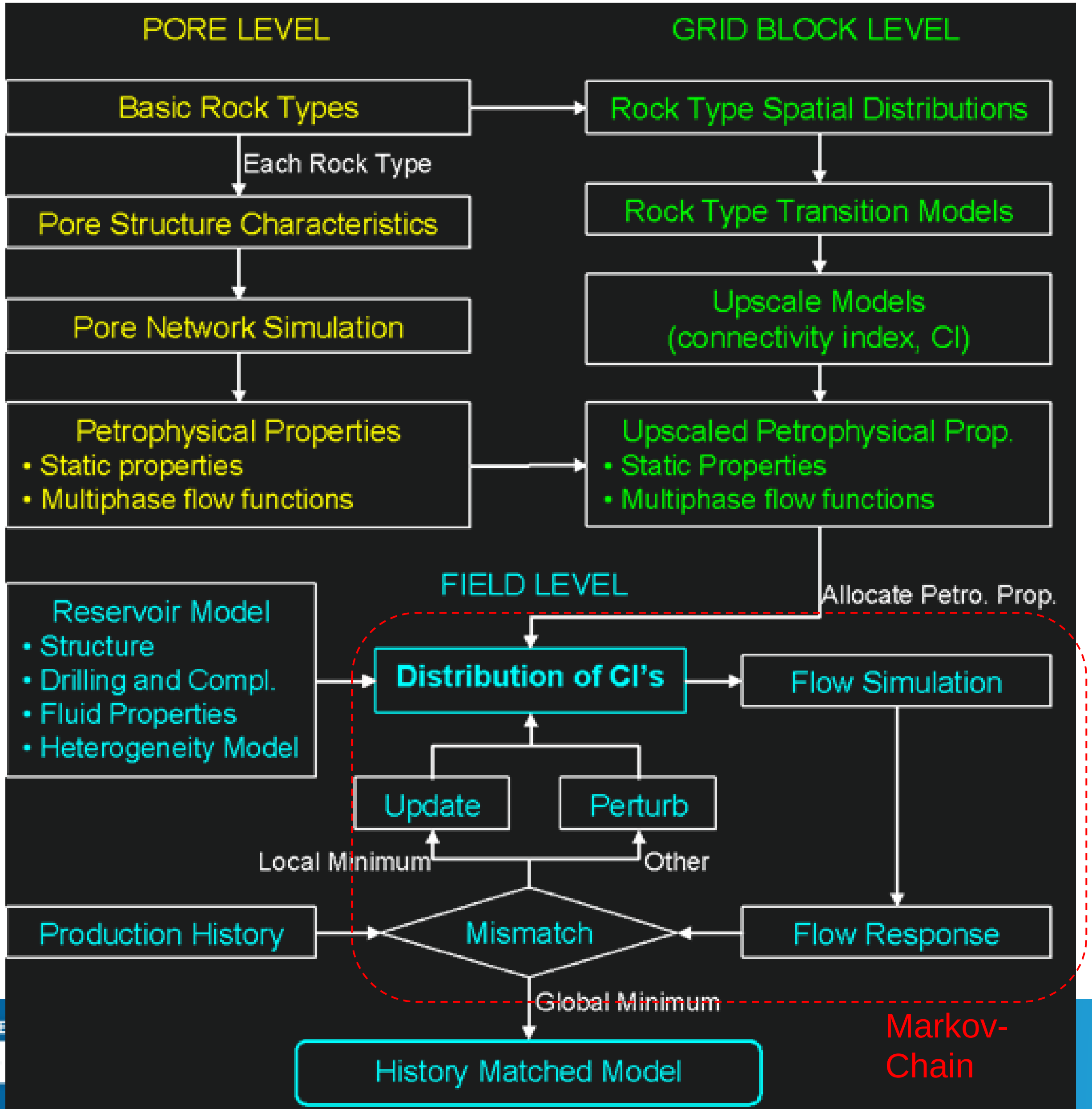
RMS Amplitude Difference map (2014-2012)



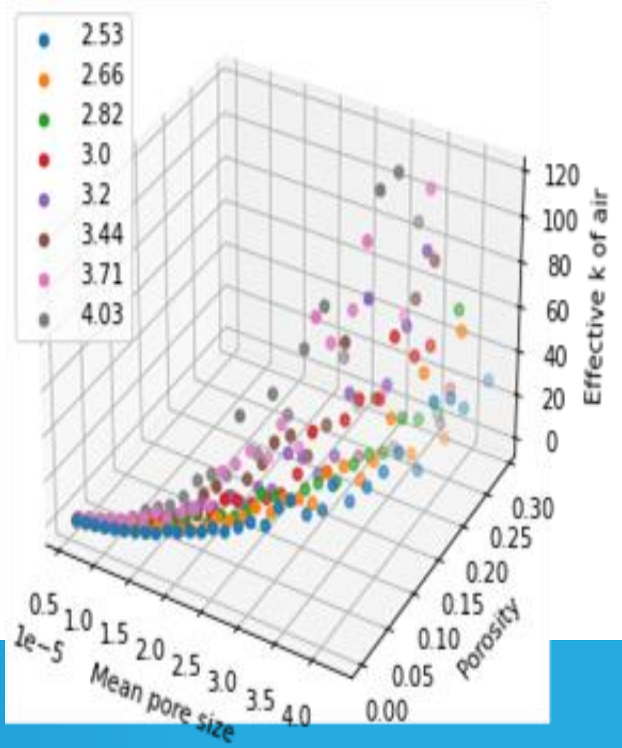
(Salako et al., 2017)

Rock Typing to Upscale Flow Properties

Work Flow

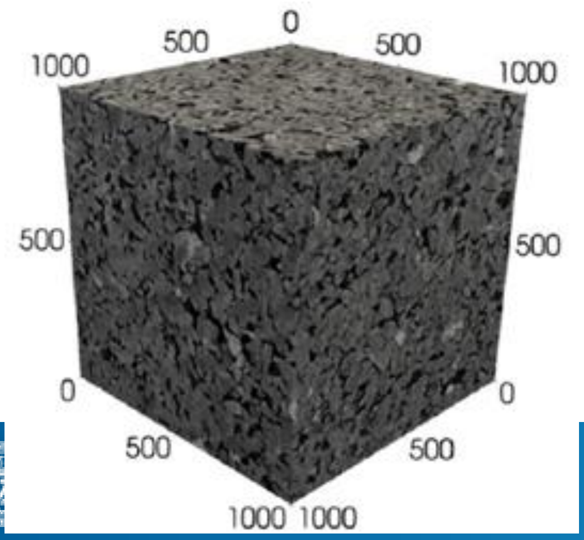


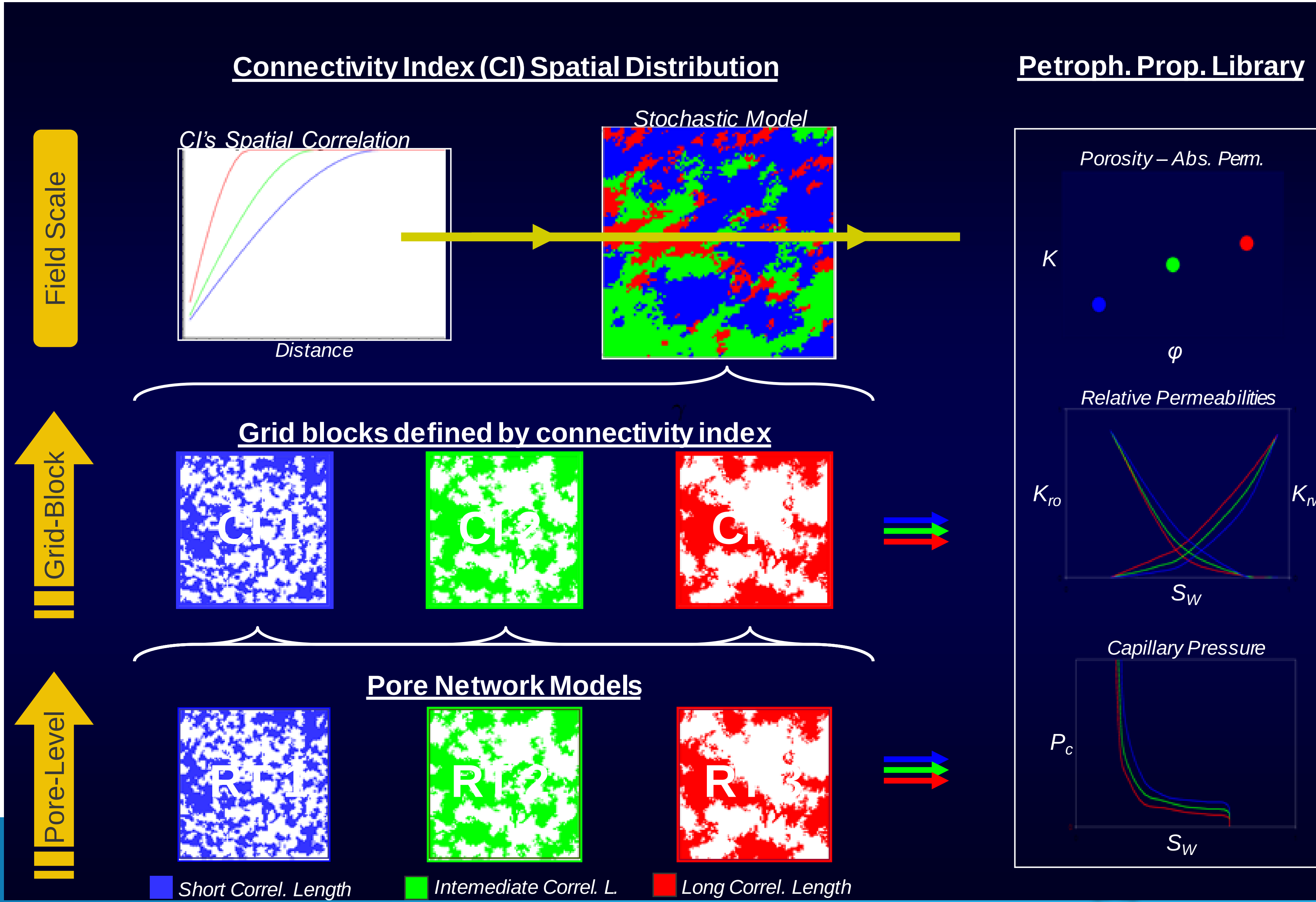
- Upscaling saturation functions via multiscale geologic models
- Random forest to train data set. Feature space: saturation, mean pore size, mean throat size, porosity, permeability and coordination number. Target: permeability.



Upscaling Saturation Functions from to Meter Scale

- Connectivity index, pore/throat features, and bulk properties being used to create near-well models of representative flow

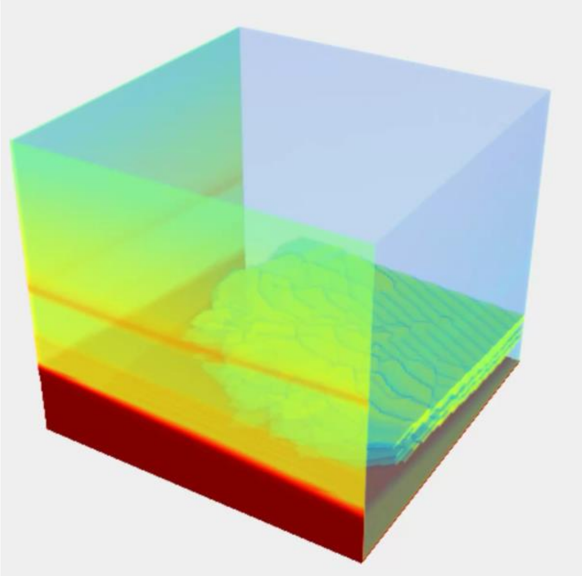




Well - to - Field Scale Efforts

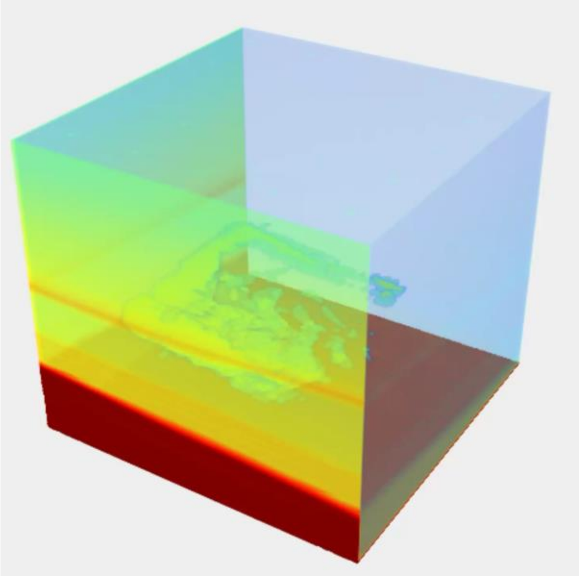
- **Developed different ML algorithms that used reservoir-simulation-converted geophysical models to generate the ML training data. After training, the ML algorithms then employ the seismic and/or multiphysics data to generate**
  - Estimates of geophysical properties
  - Estimates of CO_2 saturation
  - Uncertainty analysis
- **ML based downscaling methodologies that use well log data were also investigated to produce higher resolution images than the geophysical imaging provides**

Real-Time 3D Seismic Imaging



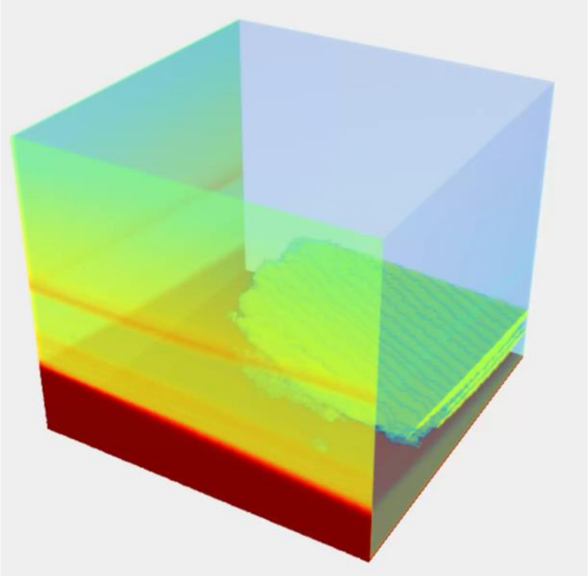
GT

a



Conventional FWI

b



ML Velocity Imaging

c

InversionNet takes 1/10 of sensors, but yields much better 3D imaging.

- Conventional 3D Imaging takes 1 day (on 25 CPUs) to invert.
- Ours takes 5 hours (on 32 GPUs) to train and a few seconds to invert.

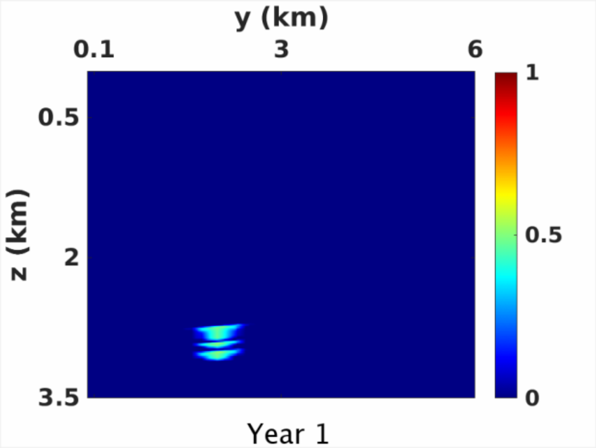
Qili Zeng, Shihang Feng, Brendt Wohlberg, and Youzuo Lin, "InversionNet3D: Efficient and Scalable Learning for 3D Full Waveform Inversion", Under Review in IEEE Transactions on Geoscience and Remote Sensing , 2021 (arXiv available).

Physics-Guided Time-lapse CO_2 Imaging

Spatio-Temporal Dynamics of Saturation Imaging

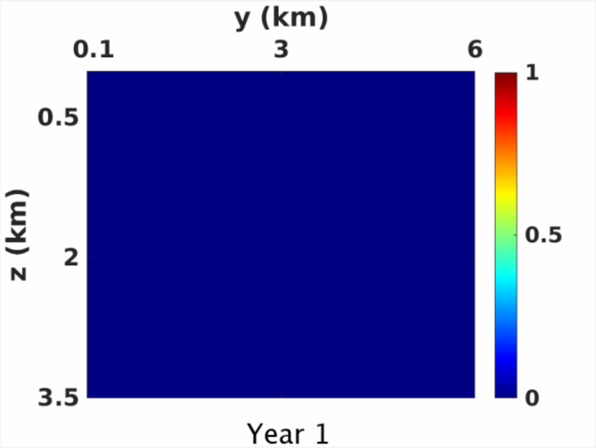
- Physics-driven and deep neural networks are incorporated
- 10,000 velocity models are generated based on baseline Vp model and log data statistics.
- **Temporal saturation dynamics is estimated via InversionNet.**

InversionNet trained with synthesized training set produces accurate estimation of saturation and spatio-temporal dynamics.



Saturation (Ground Truth)

1



Saturation Estimation

2

Yanhua Liu, Shihang Feng, Ilya Tsvankin, David Alumbaugh, and Youzuo Lin, "Mitigating Data Scarcity for Joint Physics-Based and Data-Driven Time-Lapse Seismic Inversion" (Under Review)

Physics-Guided Time-lapse CO_2 Imaging

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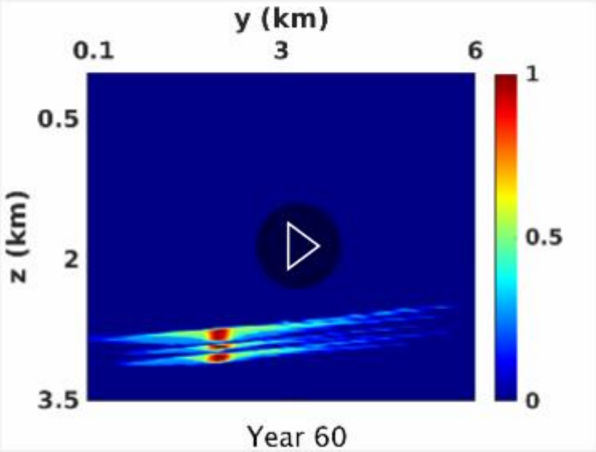

Saturation (Ground Truth)

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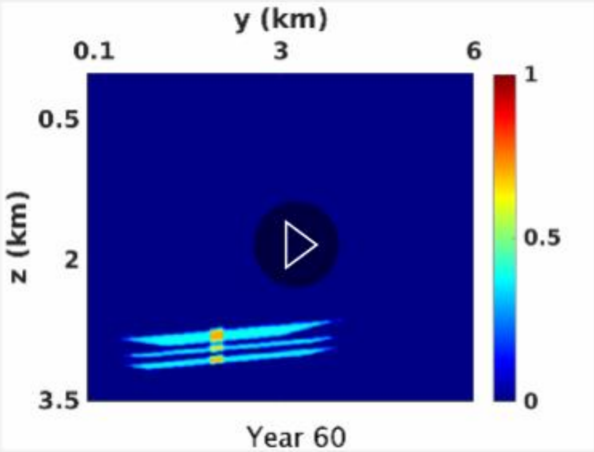

Saturation Estimation

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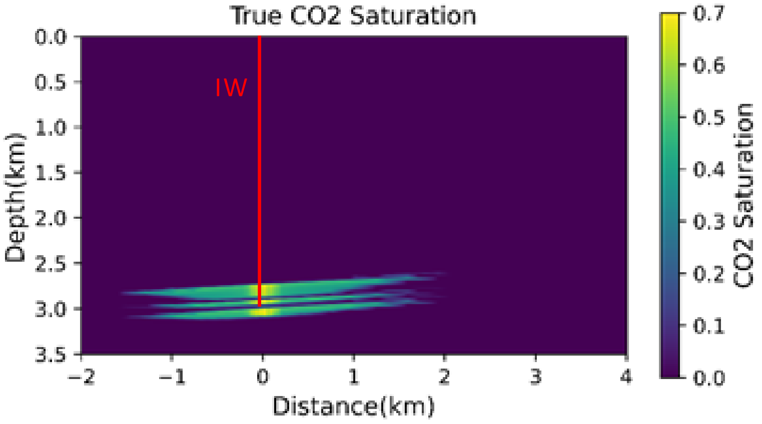
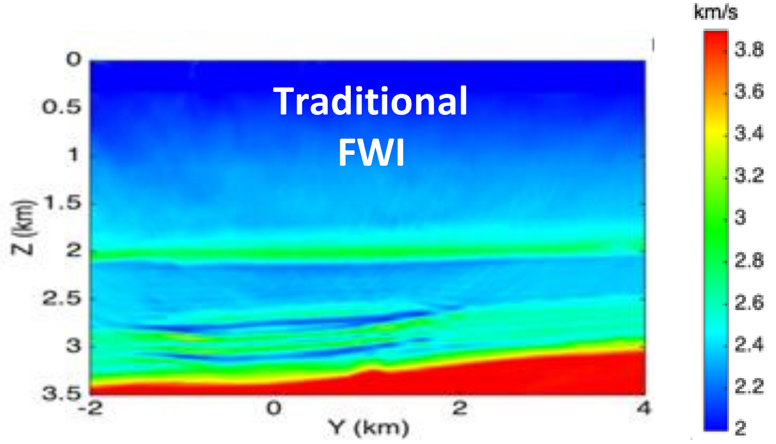
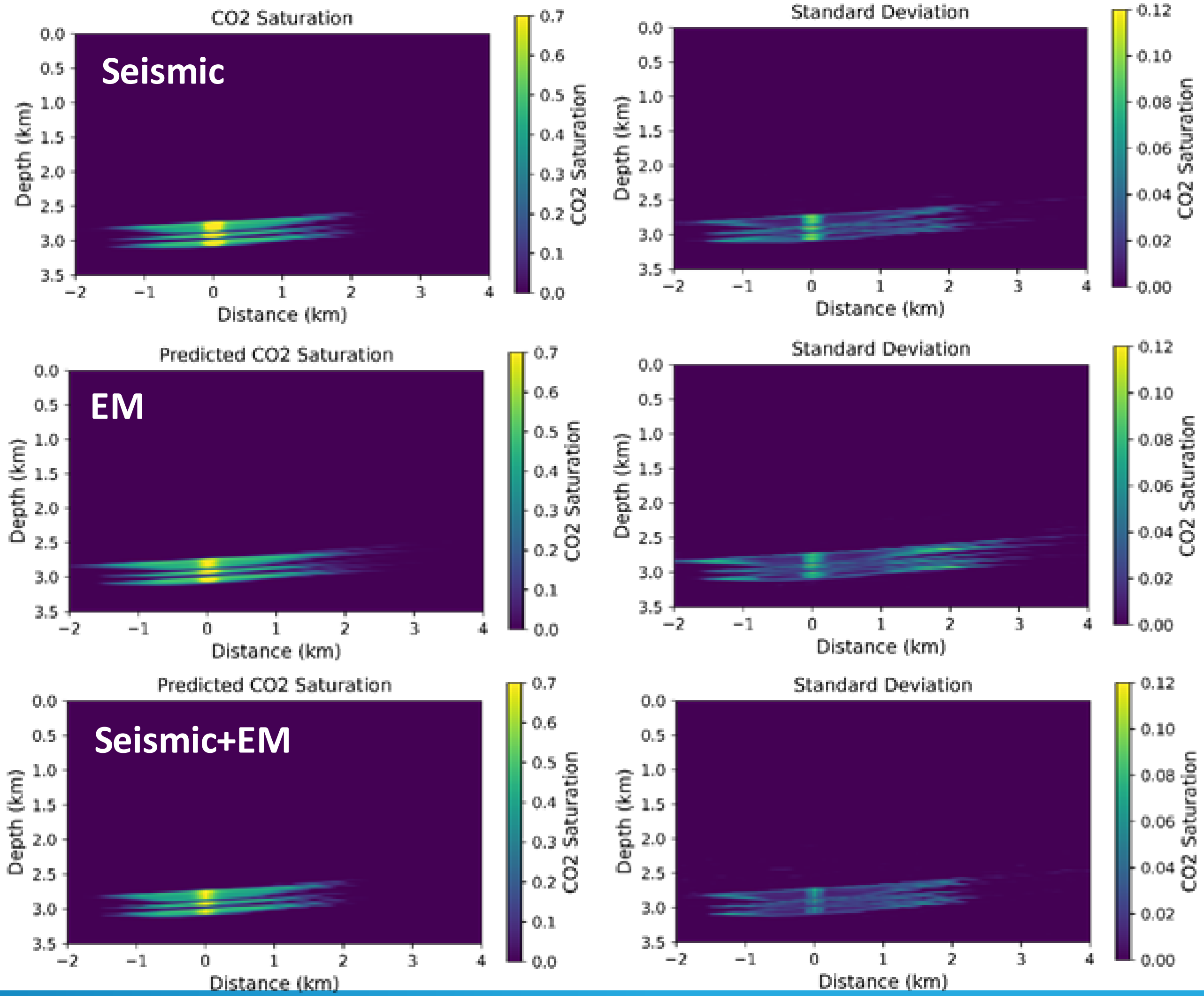
Task 2 Well–to–Field Scale Imaging / Visualization
2D Stochastic U-Net Example (LBL Approach)

Kimberlina GCS Model





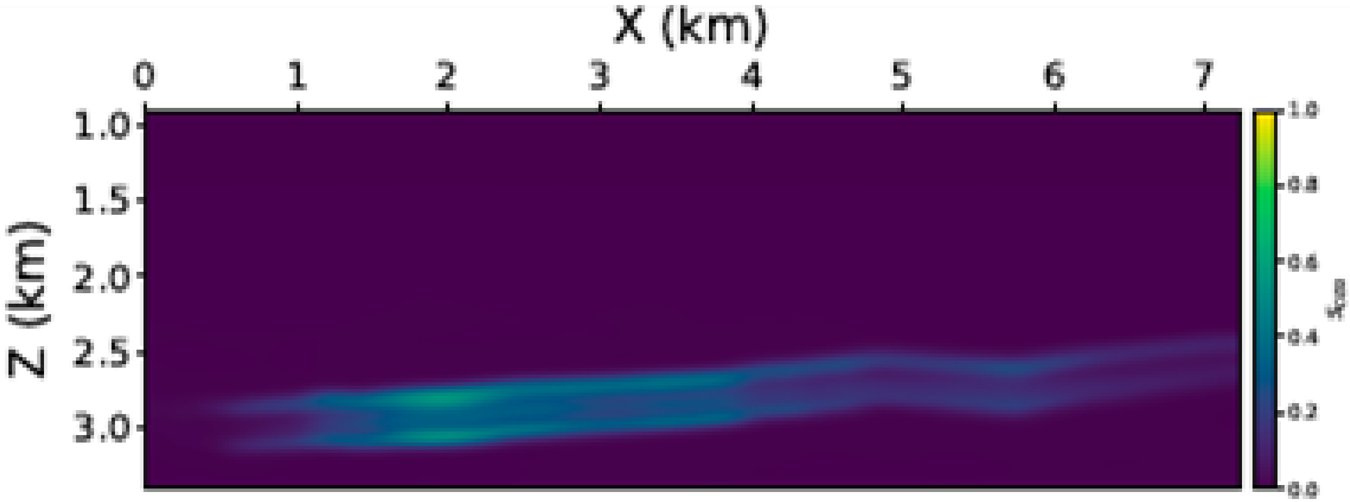


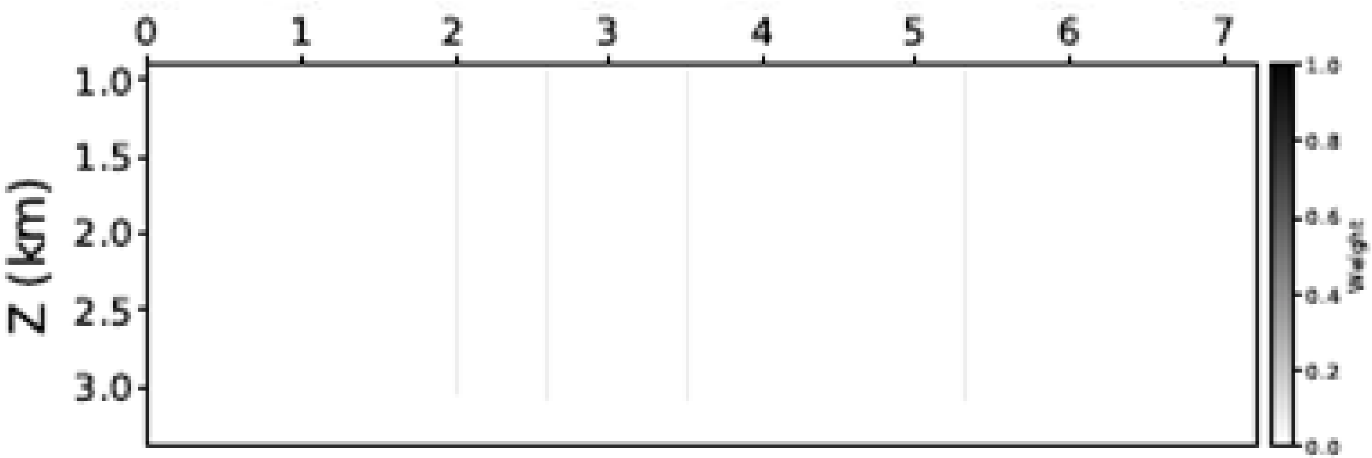
Task 2 Well–to–Field Scale Imaging / Visualization
Resolution Enhancement by Supervised Learning (CSM)

Behura & Prasad, CSM

Concept

- Well-log resolution result
- Applicable to other attributes
- Apply to any field with wells
- Works with wells of any geometry
- Hi-resolution poro-perm fields





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Note: Testing of a 'CGAINS' ML algorithm for downscaling was shown by CSM researchers not to perform.

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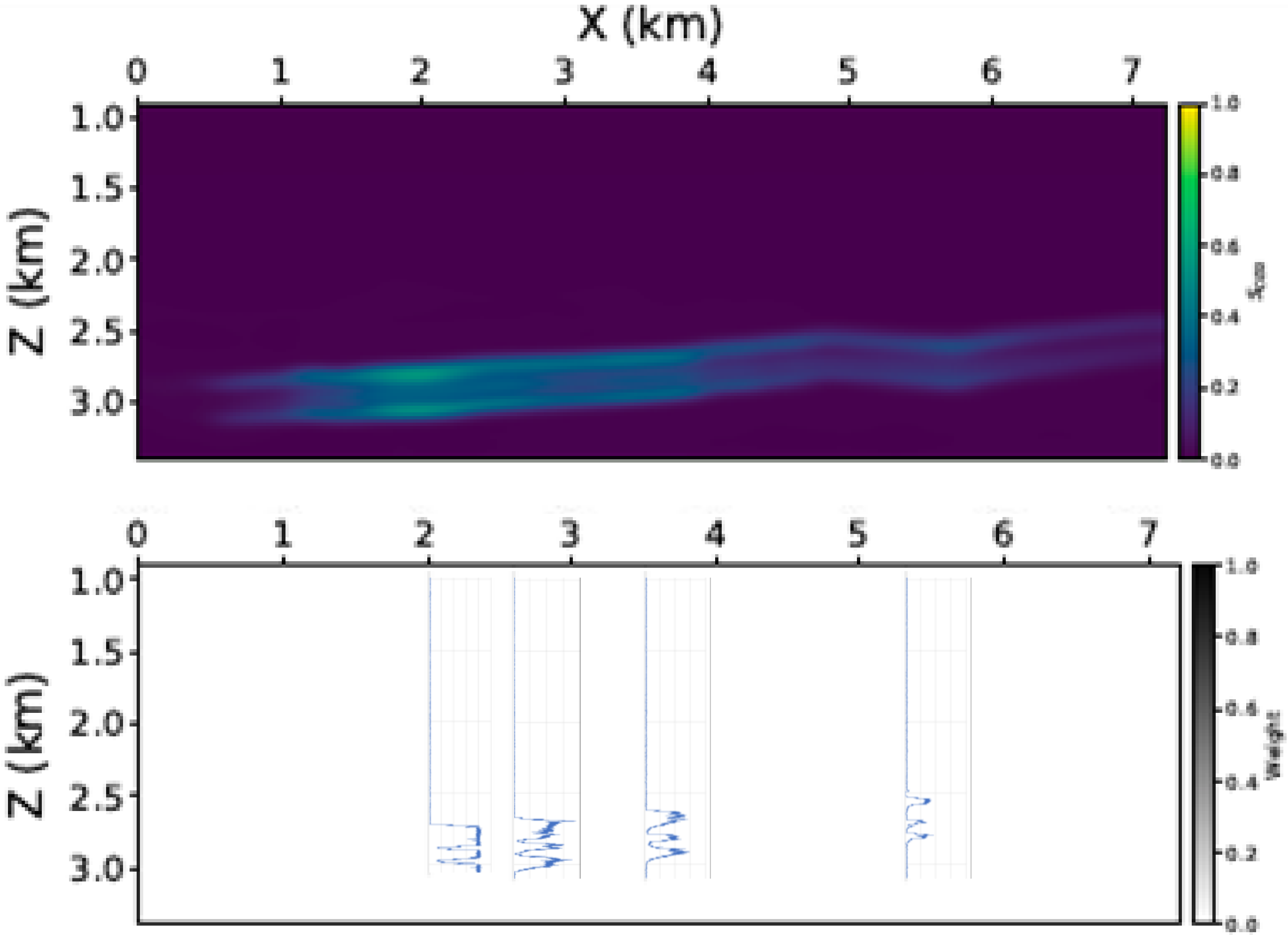

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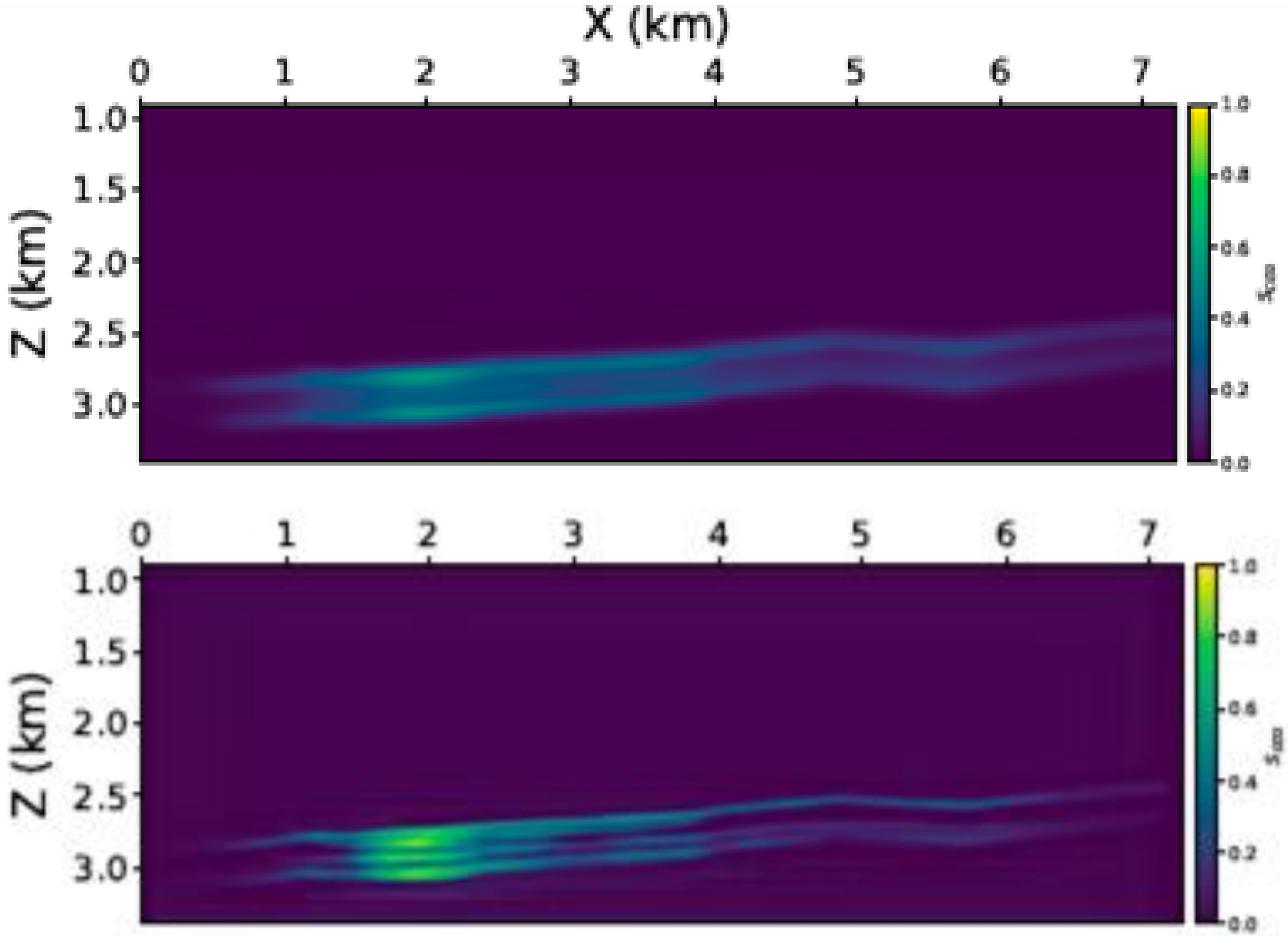

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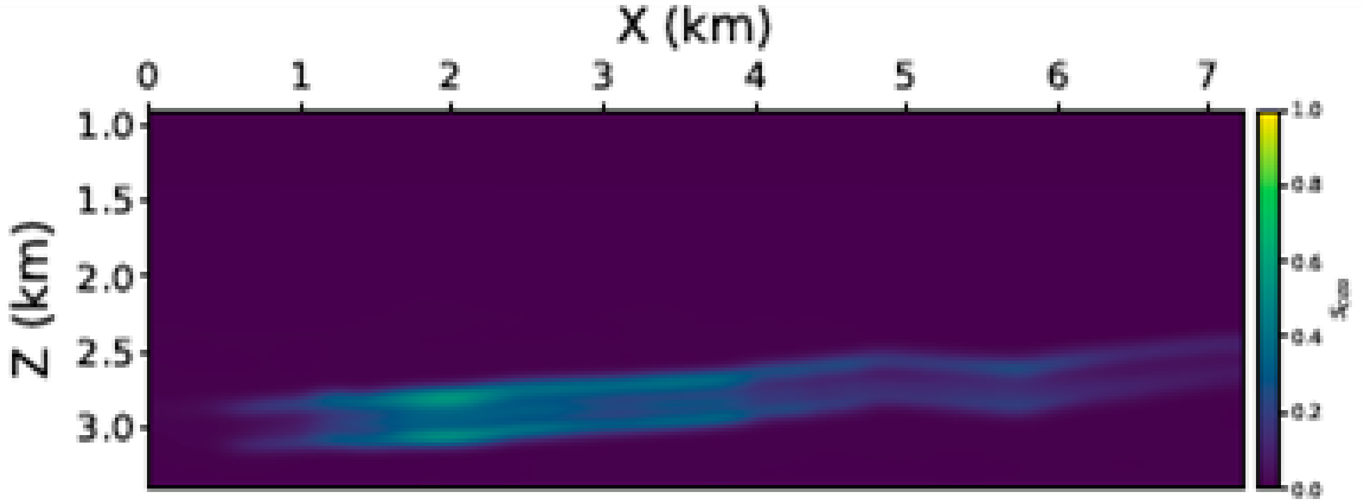

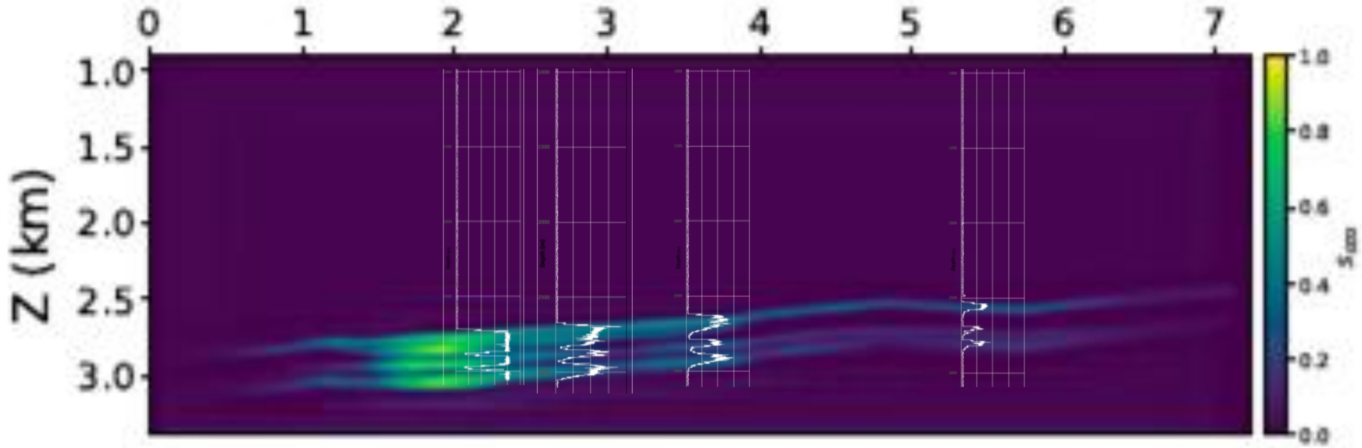

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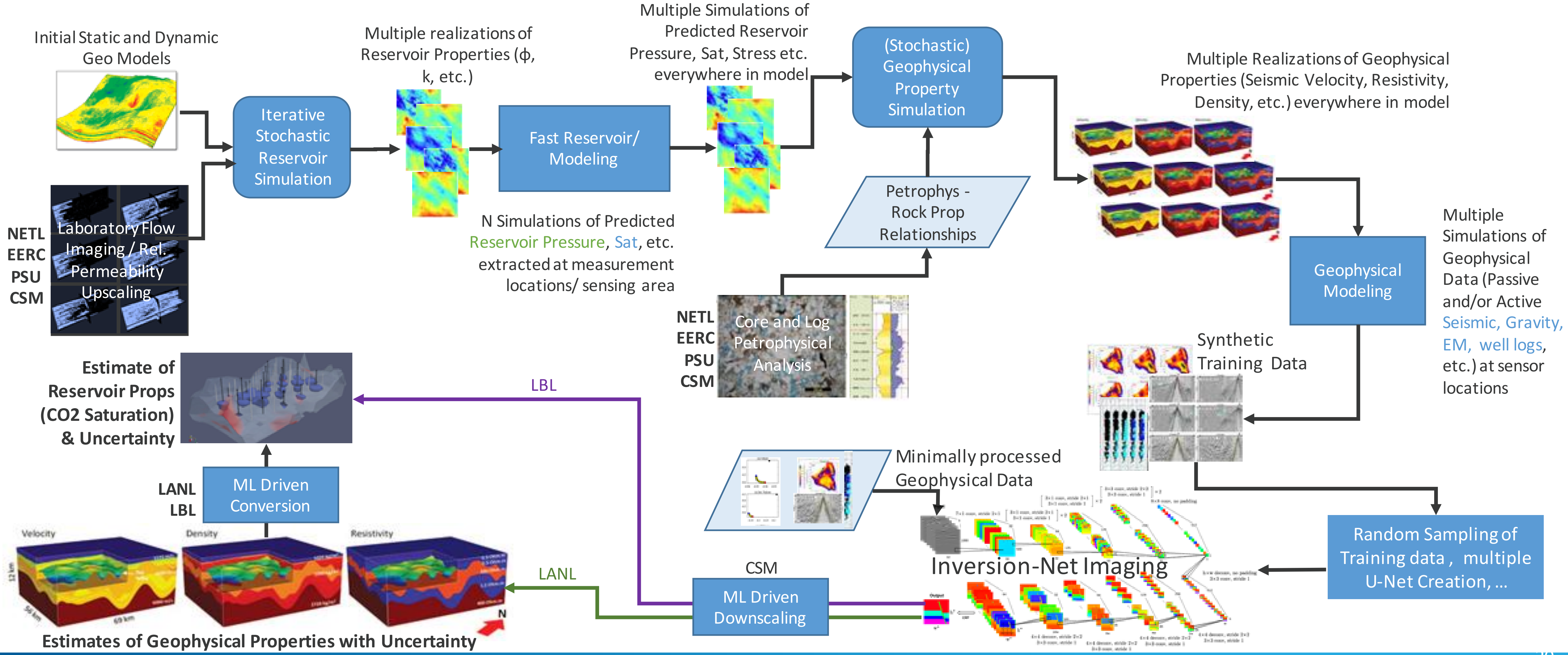
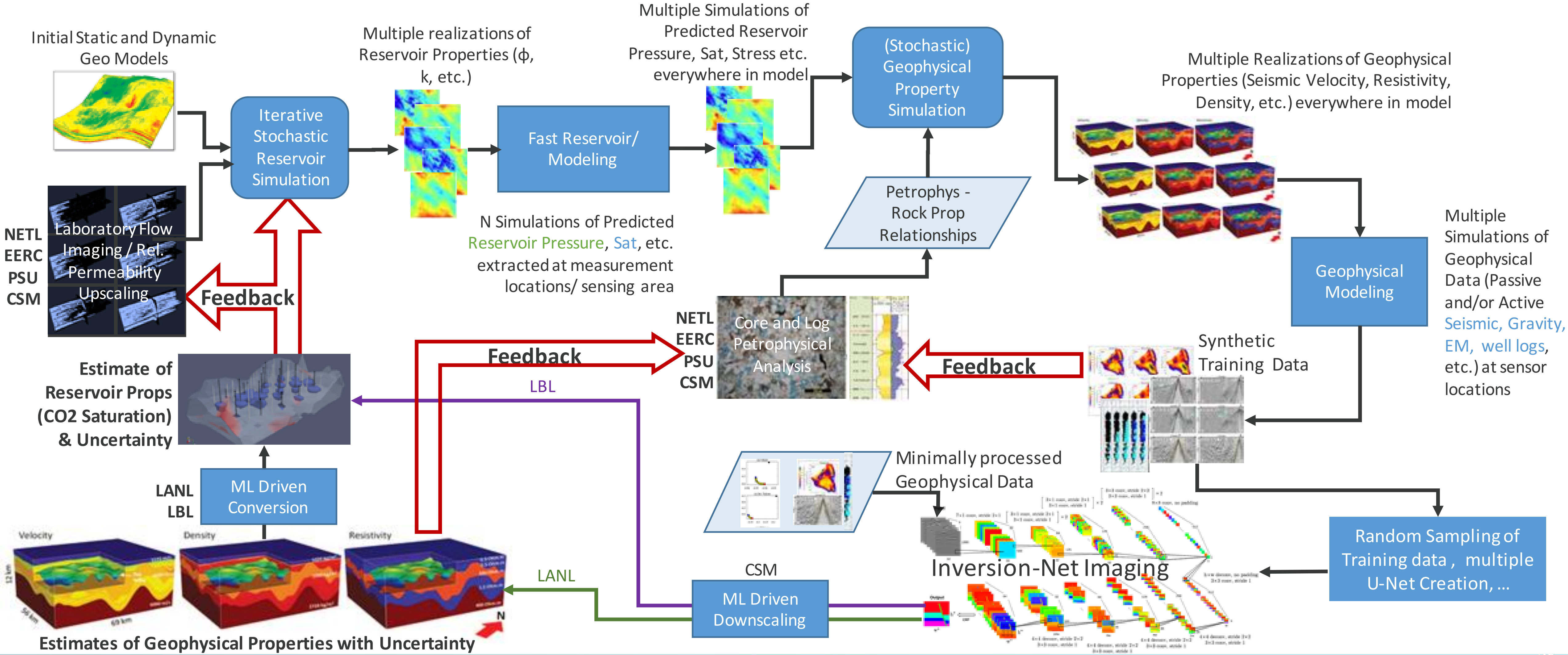
Task 2: Real-Time Rock Property Visualization Workflow
Stochastic Neural-Net Workflow



Task 2: Real-Time Rock Property Visualization Workflow

Example of Internal Feedback Loops



Questions?

Thank you!

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