SMART-CS Initiative

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

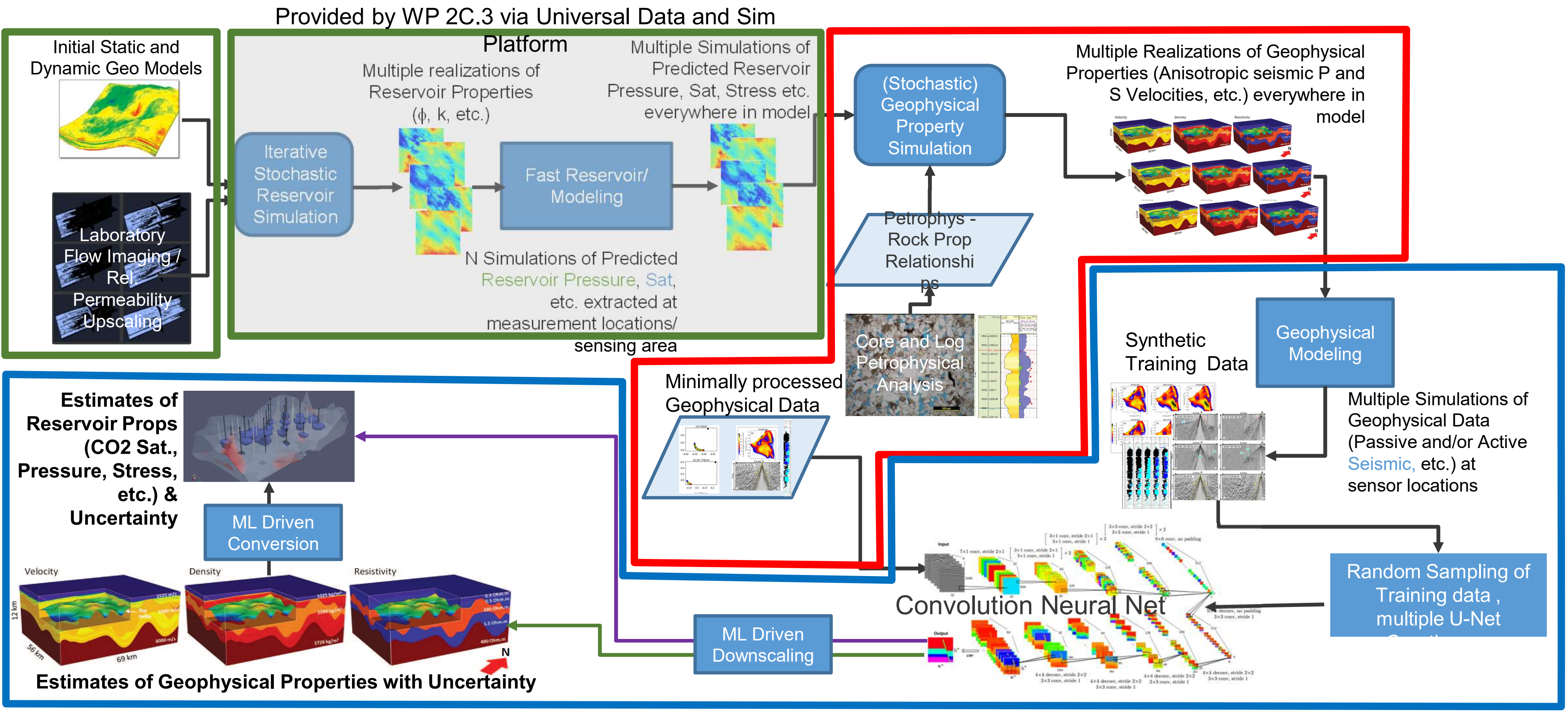
Work-Package 2C.2 : Field Deployment – Data Management and Imaging
Year 1 Update

***David Alumbaugh (LBNL) and Joe Morris (LLNL), WP 2C.2 Leads**
Youzuo Lin (LANL), Fault/Fracture Imaging Presentation

August 31, 2023

U.S. DEPARTMENT OF ENERGY

WP 2C.2 Reservoir Property Imaging Workflow



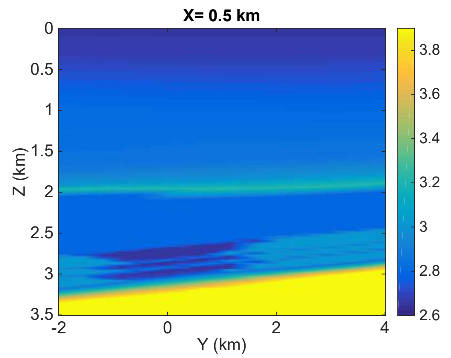
Work Package 2C.2 Activities and Structure

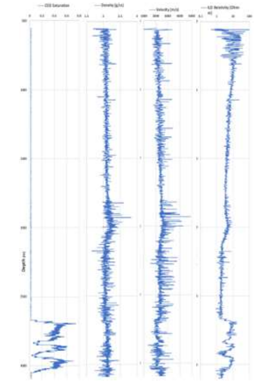
Activities

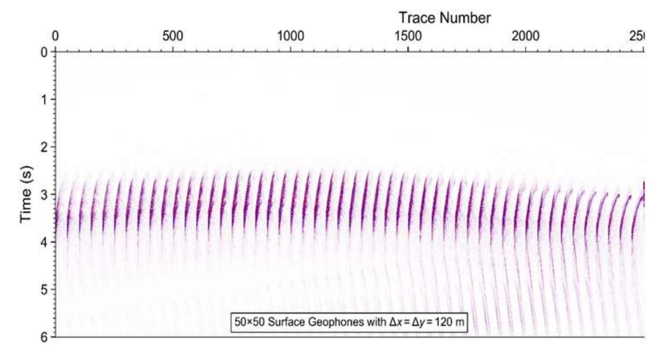
- **Activity 1: Initial Background Data Collection and Data Platform**
  - Cross-Cutting ‘Unified Platform Leadership Committee’ established (Task 5 presentation to address)
  - ISGS (Sherilyn Williams-Stroud) point contact for data not already on EDX
- **Activity 2: Advanced Data Processing and Data Preparation**
  - Seismic Event Detection and Source Mechanisms Team
  - Active Seismic Data Processing Team
  - Ensemble Generation Team
- **Activity 3: Data Inversion for Reservoir Images**
  - Fault/Fracture Imaging Team
  - Petrophysical Data Analysis Team
  - Reservoir Property Imaging Team
  - 3D Seismic Volume Enhancement Team

Data Curation: Publication and EDX Release of Kimberlina Data

- **Data and models released on public EDX site for public use**
- **Publication in Geosciences Data Journal***
- 100 Kimberlina reservoir simulations of CO_2 saturation
  - 35 time steps from 0 to 200 years
  - Injection stops after 50 years
- Corresponding 3D geophysical property models
  - Density
  - Vp and Vs
  - Resistivity
- 2D acoustic and pseudo 2D EM for SIM001 for all times and 2D slices
- 3D EM and gravity for and 'limited domain acoustic' for Sim001 years 0 and 20
- **NEW! - 3D MEQ data for SIM001**
- Synthetic well logs (sonic, density resistivity, CO_2 saturation)
- Images of Vedder Sandstone core







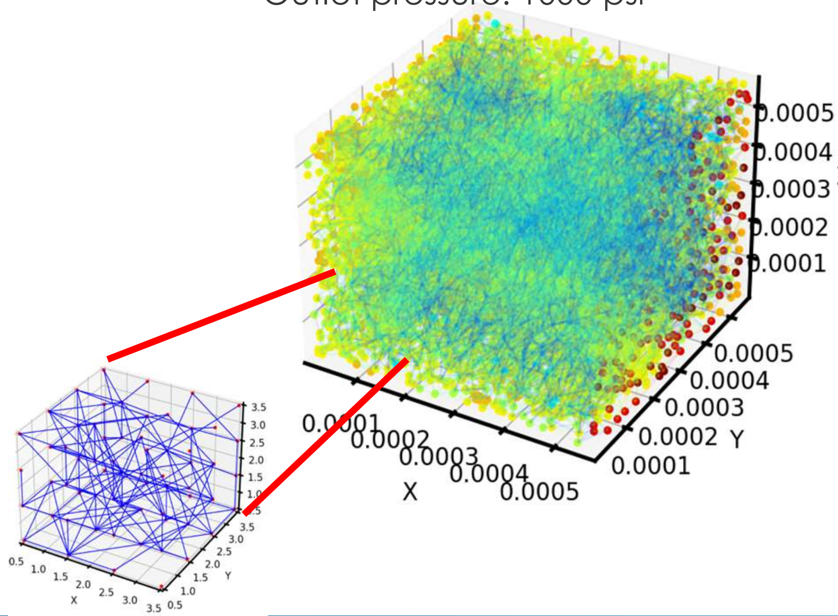
*Alumbaugh, D., Gasperikova, E., Crandall, D., Commer, M., Feng, S., Harbert, W., Li, Y., Lin, Y., and Samarasinghe, S., 2023, The Kimberlina synthetic multiphysics data set for CO2 monitoring investigations; Geosciences Data Journal, doi.org/10.1002/gdj3.191.

Data Curation: Informative / WP 2C.2 Useful IBDP Petrophysical and Geophysical Data

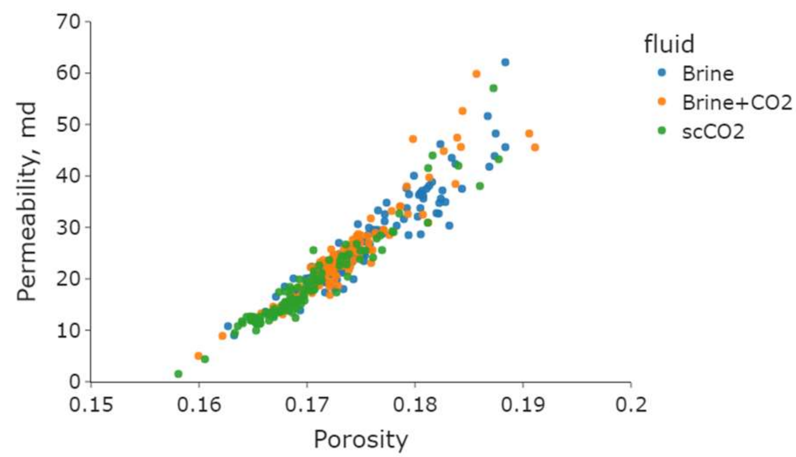
- Core
- Pre-injection well logs in 3 (CCS1,MV1, GM1) wells (sonic, resistivity, porosity, FMI, …)
- CO_2 Saturation (PNX) logs in 2 wells well (CCS1 and MV1)
- Passive seismic monitoring data
  - Full Time Series (72 TB – requires hard drive to be mailed)
  - 2 seconds of 'picked' events
  - Location and travel time catalogue
- 3D Surface Seismic - pre and post injection
  - EDX processed images – cant use for algorithms/workflows developed in Phase 1 except the 3D velocity model
  - Raw seismic data found by ISGS – delivered to EERC and LBNL in April/June 2023
- 3D VSP – One pre injection and four post injection
  - Processed images on EDX
  - All raw data needed for analysis received at LBNL in June of 2023
  - **Currently evaluating to determine if there is a seismic velocity anomaly due to CO_2 injection**
- 3D Geologic Models

Advances: Permeability calculation using Pore Network Modeling (PNM) (EERC and NETL)

- **Test model 256 × 256 × 256**
- **Total number of pore: 17,252**
- **Total number of throat: 107,214**
- **Calculate hydraulic conductance**
  - Inlet pressure: 2000 psi
  - Outlet pressure: 1000 psi



- Utilized PNM simulations to estimate perm-porosity correlation and its evolution after injecting multi-phase fluid
- Developing 3D-CNN predictive model is in progress.

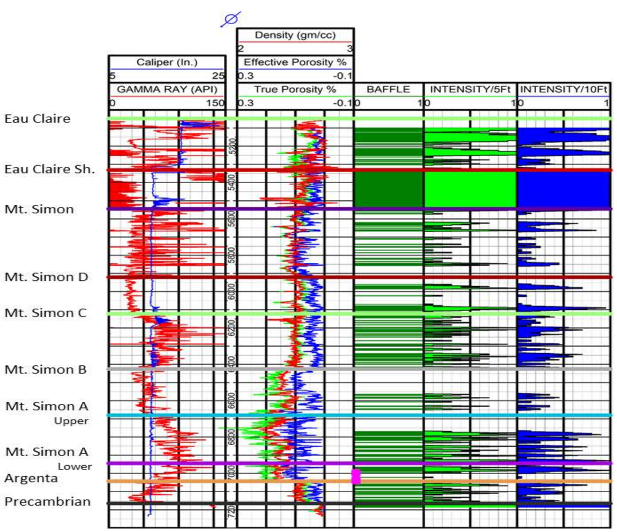


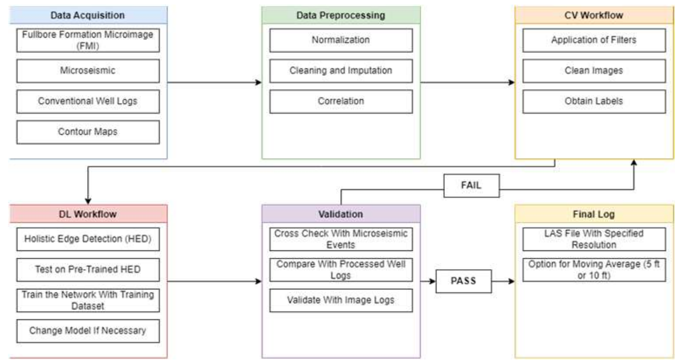
Fluid	Perm, md	k_final / k_ini	Porosity
Brine	28.4		0.176
Brine+CO2	25.5	0.89	0.174
scCO2	18.6	0.67	0.170

Also Can Be integrated into Task2 (WP 2A)

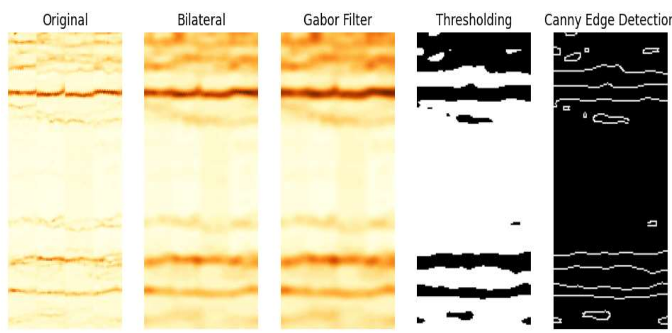
Advances: ML Guided Baffle and Fracture Detection (WVU)

- The Mount Simon formation has low permeability baffles that inhibit upward flow and produce an anisotropic permeability
- Baffles were identified/interpreted in the IBDP gamma and porosity logs using a very expensive/time consuming process that is subject to interpreter bias

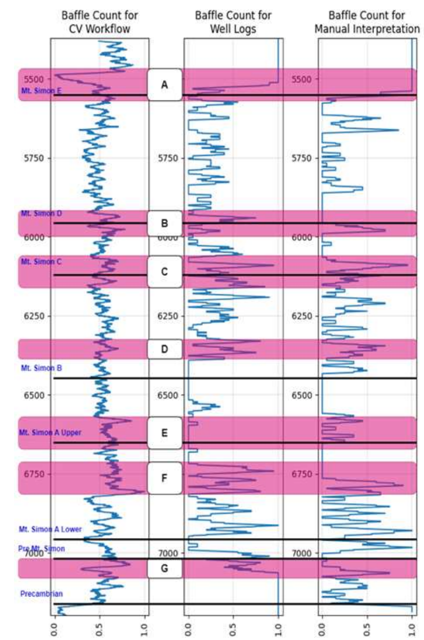




- WVU researchers modified a ML Computer Vision workflow/algorithm (above) originally developed for fracture identification in FMI logs for baffle identification that employs five main steps (below)



- The workflow was applied to FMI logs in CCS1 (below left) and nearly instantaneously produced much more uniform results compared with manual interpretation of well logs (below center) and FMI logs (below right) at 2ft resolution



Advances: PA/ML Velocity and Density Estimation (CSM)

Data Used: Publicly available datasets from WOGCC

Data Selection and Logs used: Depth, Vp, Vs, Density

Reviewed over 1000 well data from WOGCC → 46 wells selected with important log suites → 7 wells with applicable log data → 3 wells traverse through reservoir zones (4265 data points)

Procedure

- Geologic formation (Muddy, Lakota, Hullet and Minnelusa)
- Lithology

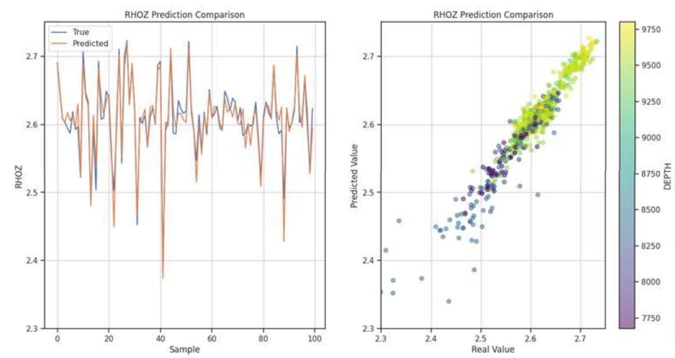
Model Development

- Random Forest Regression
- Multi-feed forward Neural Network
- Long Short Term Neural Network

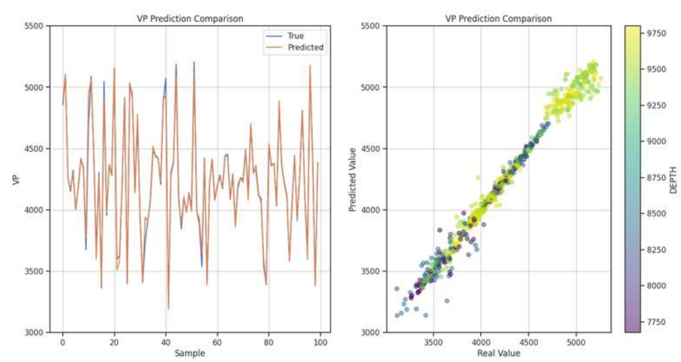
Future Work

- Vs prediction, Saturation Model
- Assess value of porosity prediction in error analysis

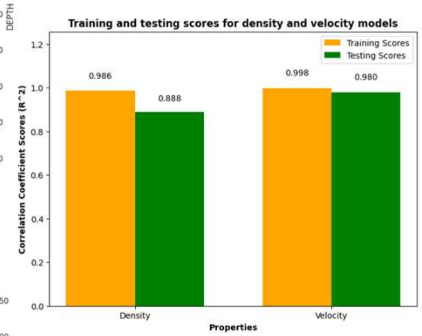
Combined Zone : Density Model Testing



Combined Zone : Vp Model Testing



Error Analysis



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Real **T**ime (SMART) Decisions in Subsurface Applications

Work-Package 2C.2 : Fracture and Fault Imaging Update

David Alumbaugh (LBNL) and Joe Morris (LLNL), WP 2C.2 Leads
***Youzuo Lin (LANL), Fault/Fracture Imaging Presentation**

August 31, 2023

U.S. DEPARTMENT OF ENERGY

Task Objectives, Significance, Preliminary Study, and Challenges

Objectives:

1. To improve the imaging description of fractures & faults at IBDP
2. To obtain a site-agnostic ML-assisted toolset and workflow
3. To demonstrate the benefits of using ML methods

Significance:

- Provide fast fluid pathway and flow barrier (input for update reservoir model in task 5)
- Indicate and monitor potential induced seismicity (input for ORION in task 6)

Preliminary Study:

- Dando et al., (2021) deployed a modified double-difference method to identify microseismicity, and further delineated linear clustering of events with uncertainty.

Challenges:

- Expensive computational cost
- Limited imaging resolution
- Lack of training dataset

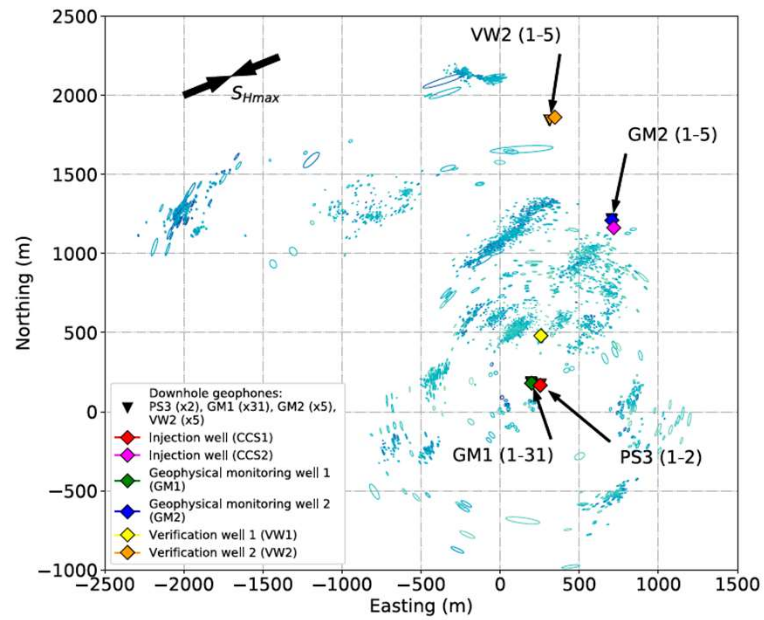
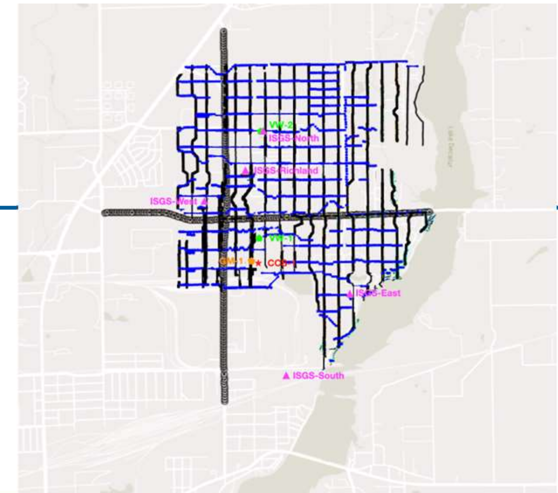


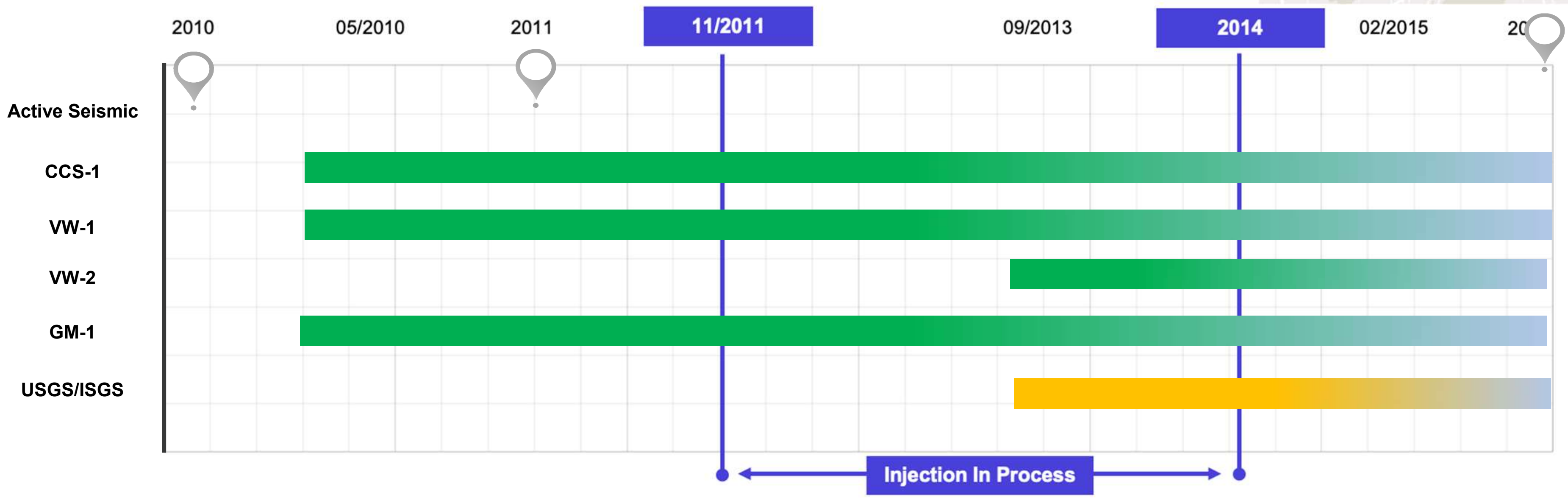
Figure Courtesy of Dando et al., 2021

Dando et al., “Relocating microseismicity from downhole monitoring of the Decatur CCS site using a modified double-difference algorithm” GJI , 2021.

Data Availability and Chronology



- **Passive Seismic Acquisition**
  - **IBDP Installation**
    - Borehole arrays located at **CCS-1**, **VW-1**, **VW-2**, **GM-1**
    - Total: 31 stations (z-component: 2/4 CCS-1 + 29/31 GM-1)
  - **USGS/ISGS Installation**
    - 20 surface seismometers (15 **USGS** + 5 **ISGS**)

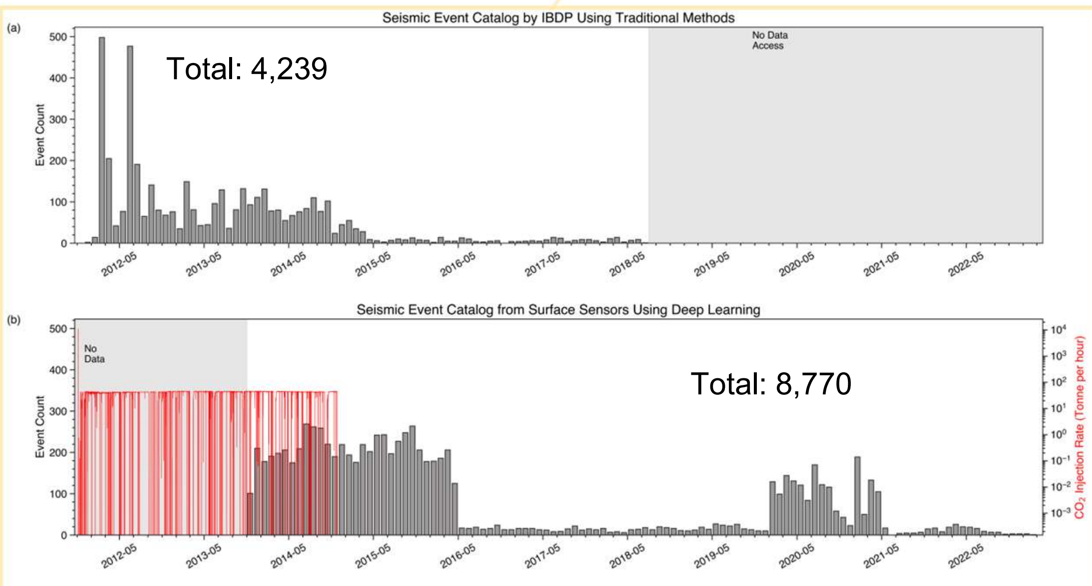


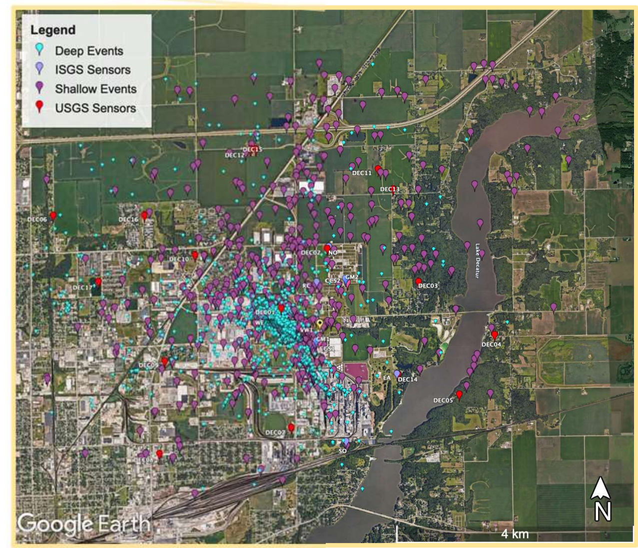
Fracture Imaging Workflow – An Overview

01	• **Event Detection**	Extract useful microseicmic events from continuous waveform measurements
02	• **Velocity Inversion**	Produce 3D velocity model from active/passive seismic data (SubTask 4.4.1)
03	• **Source Inversion**	Obtain microseismic source parameters (location, moment tensors, amplitude, etc)
04	• **Fracture Analysis**	Deploy spatio-temporal clustering analysis to obtain fracture lines
05	• **Uncertainty Quantification**	Analyze the uncertainty of the fracture and fault zones
06	• **Visualization**	Display final fault/fracture representation to field operators

ORNL – Fault & Fracture Identification

Continuous Seismic Data → (Deep Learning Models; Physics-based Algorithms) → Initial Seismic Event Catalog → (ML Model) → High-Precision Seismic Event Catalog → (ML Model) → Fault & Fractures





Shallow: depth < 5 km

We detected and located **8,770** seismic events using 10 years of continuous seismic data from 17 USGS stations.

We will collaborate with LANL and improve the seismic event catalog by using continuous seismic data from the IBDP project.

SNL – Fault Imaging via Event Detection & Source estimation

- Integrated ML approaches of event detection and source location estimation
- Data pre-processing of raw continuous microseismic data & event detection
- Data augmentation using WGAN (Wasserstein Generative Adversarial Network)

- PhaseNet used to downselect generated event data with high quality
- CNN model with multi-modal input for source location estimation of events

Data processing of raw waveform continuous data → **Event detection & arrival time: CNN & U-Net models** → **Synthetic data generation: SeismoML (WGAN)** → **Multi modal CNN for source locations of newly detected events** → **Event clustering & construct faults**

Data processing of raw waveform continuous data

- 10s raw continuous waveform data (e.g., 4 to 3 channels)

Event detection & arrival time: CNN & U-Net models

- Train a CNN model for event detection with 3 channel & energy feature as input and retrain PhaseNet for arrival time

Synthetic data generation: SeismoML (WGAN)

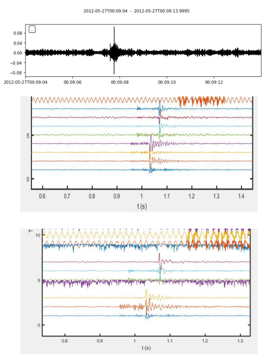
- WGAN model Input: source locations and distance of ~400 events from catalog and output of waveform
- Apply trained seismoML model to generate synthetic waveforms of each channel (H1,H2,V)
- Screen generated waveform data by phase arrival times (PhaseNet)

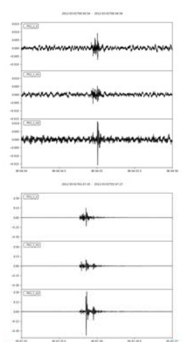
Multi modal CNN for source locations of newly detected events

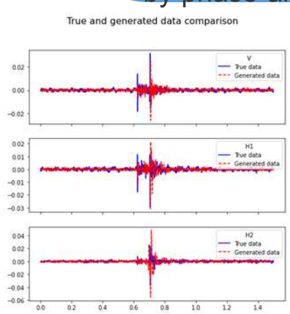
- Construct synthetic waveform data over a range of source locations & distance
- Train a multi modal CNN with spectrograms and P&S arrival (binary) of each channel data

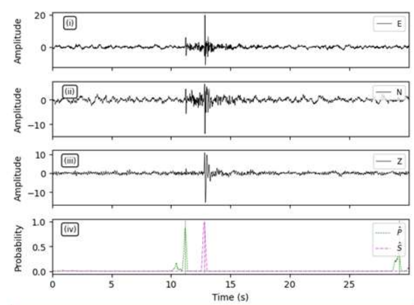
Event clustering & construct faults

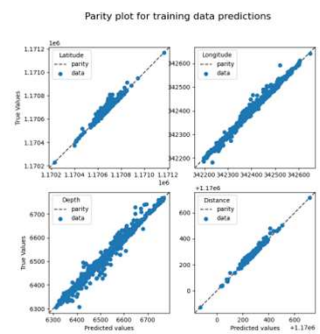
- Event clustering using NMF-HMM (Non-negative matrix factorization Hidden Markov Model) to construct planar faults

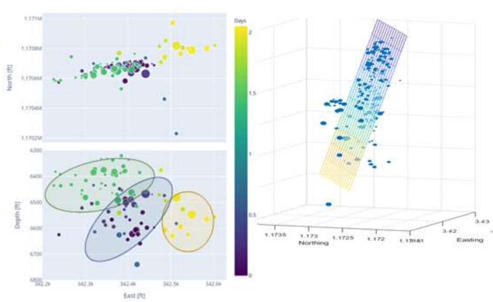




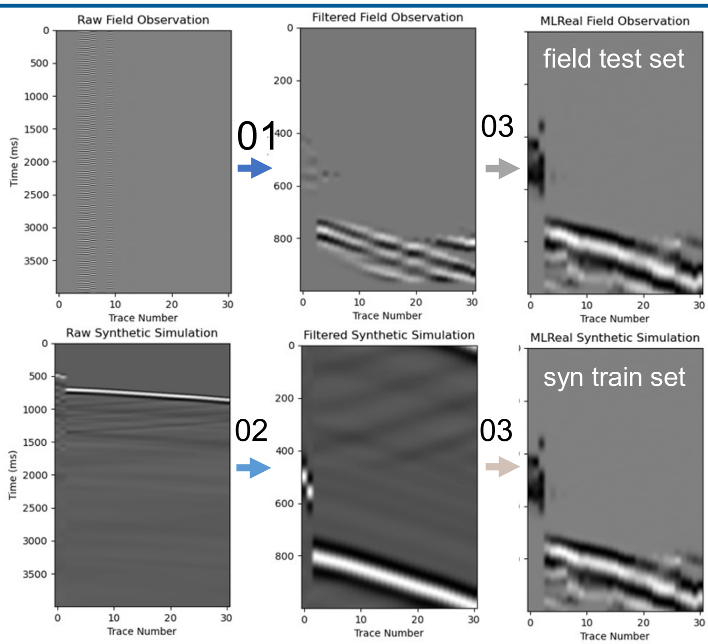


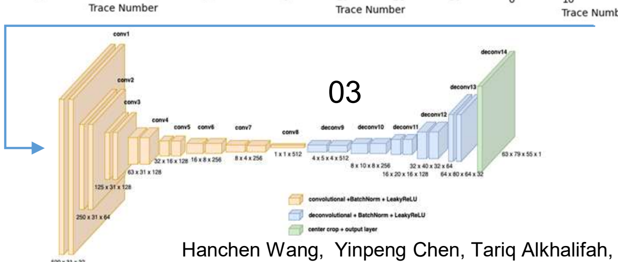






LANL – DeFault: Deep-learning-based Fault Delineation





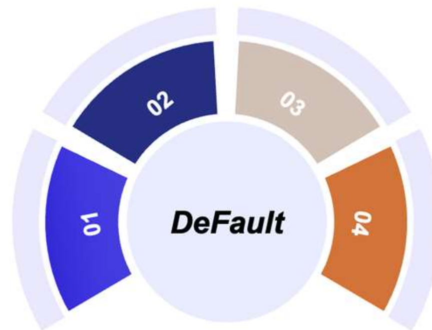
01 – Data Pre-Processing on Raw Seismic Waveform

Enhance waveform data by carrying out bandpass filters, amplitude normalization, F-k dipping filter, time-domain noise removal, averaged F-k envelop filter

02 – Full-waveform data synthesis to build high-fidelity traning set

Leverage 3D velocity model and acoustic wave equation to generate full-physics training data

Gaussian heatmaps centering at true source locations – spatial distribution



DeFault [Wang et al., 2023]

03 – ML-based Full-Waveform Inversion to Relocate Source Parameters

MLReal data domain adaptation, deploy encoder-decoder full-waveform inversion to obtain microseismic event location heatmaps

Heatmap upsampling to remove griding effect, interpolation of first and second maximum values to get coordinates predictions

04 – Employ Spatio-temporal clustering analysis to delinate Fracture imaging

Temporal period selection, K-means spatial clustering, outlier removal, least squared distance fault plane estimation

Hanchen Wang, Yinpeng Chen, Tariq Alkhalifah, Ting Chen, David Alumbaugh, and Youzuo Lin, “DeFault: Deep-learning-based Delineation Using Domain Adaptation Training and Automatic Clustering”, 2023.

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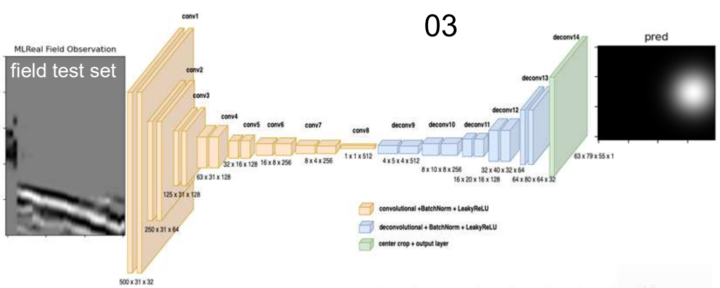

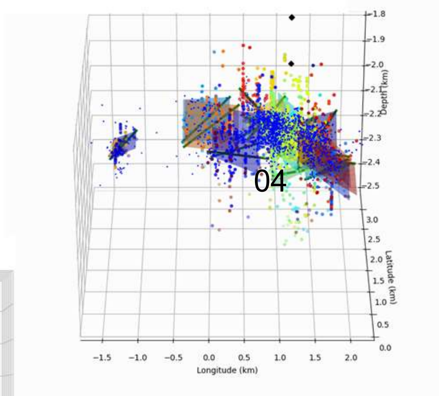

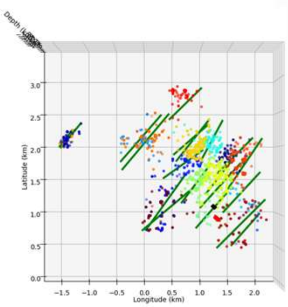

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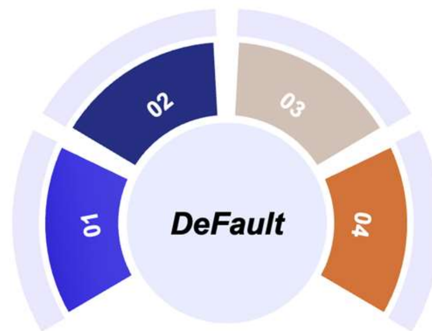

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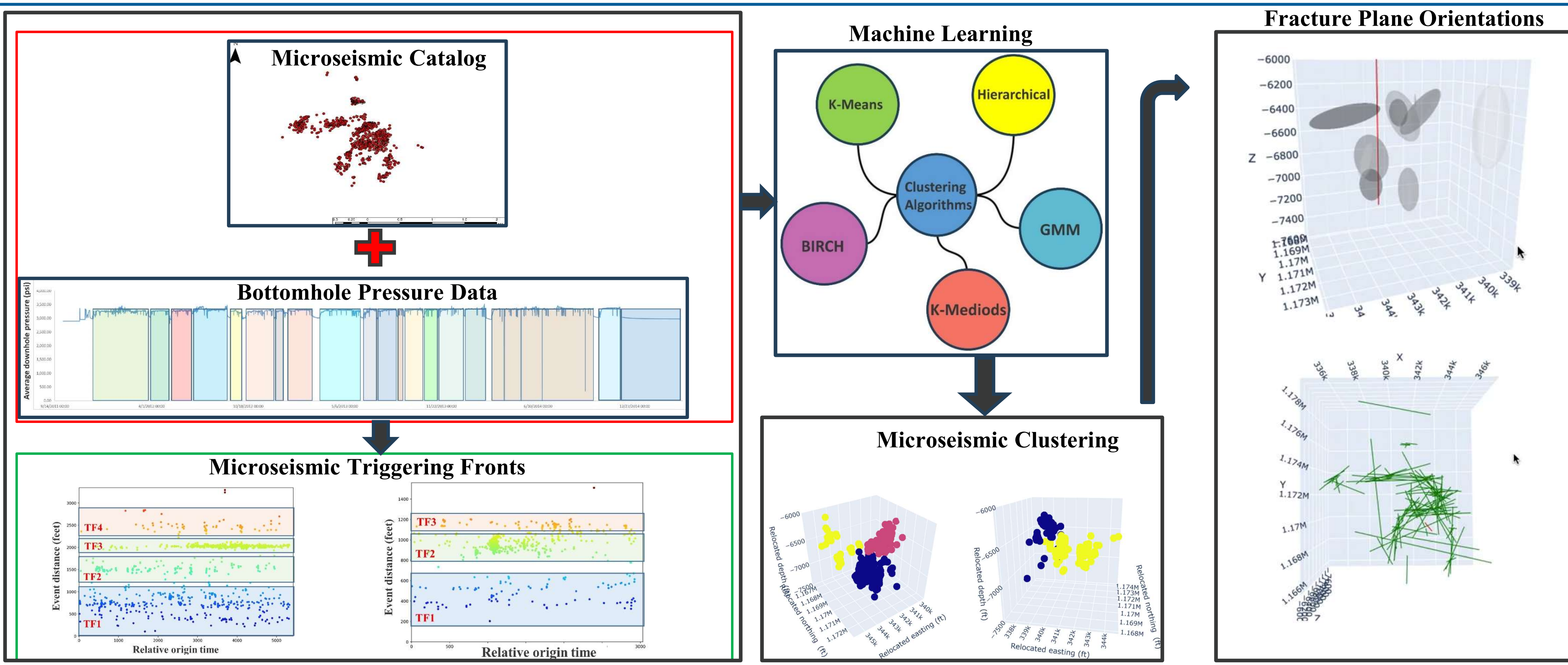
NETL – ML-Based Fracture Network Quantification



Collaborative Effort

		NETL	ORNL	SNL	LANL	SMART
	• Data Usage	Borehole Waveform	USGS Travel-time	Borehole Travel-time	Borehole Waveform	All Data
01	• Event Detection		●	●	●	◔
02	• Velocity Inversion		◍	Task 4.4.1	◍	
03	• Source Inversion		●	●	●	◔
04	• Fracture Analysis	●	◍	●	●	◔
05	• Uncertainty Quantification				●	◔
06	• Visualization			Task 6		

Fracture Imaging Workflow – Lessons Learned

- Pure ML methods suffers from **weak generalization ability**, **high training cost**, and **require a large volume of training data**
- One solution is to incorporate underlying physics, geology knowledge – **Physics-guided ML**

Questions?

Thank you!

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