# ML-Based Rock Physics Modeling and Reservoir Imaging


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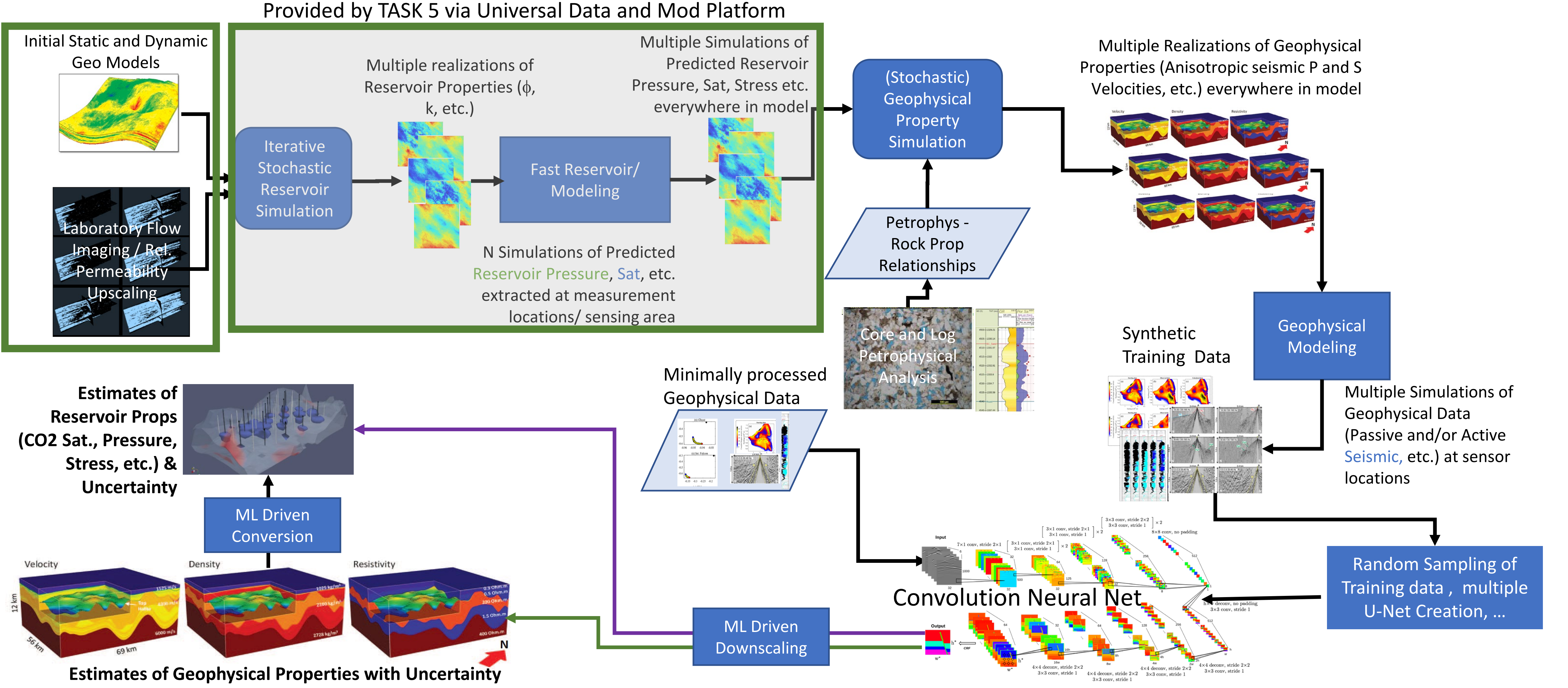
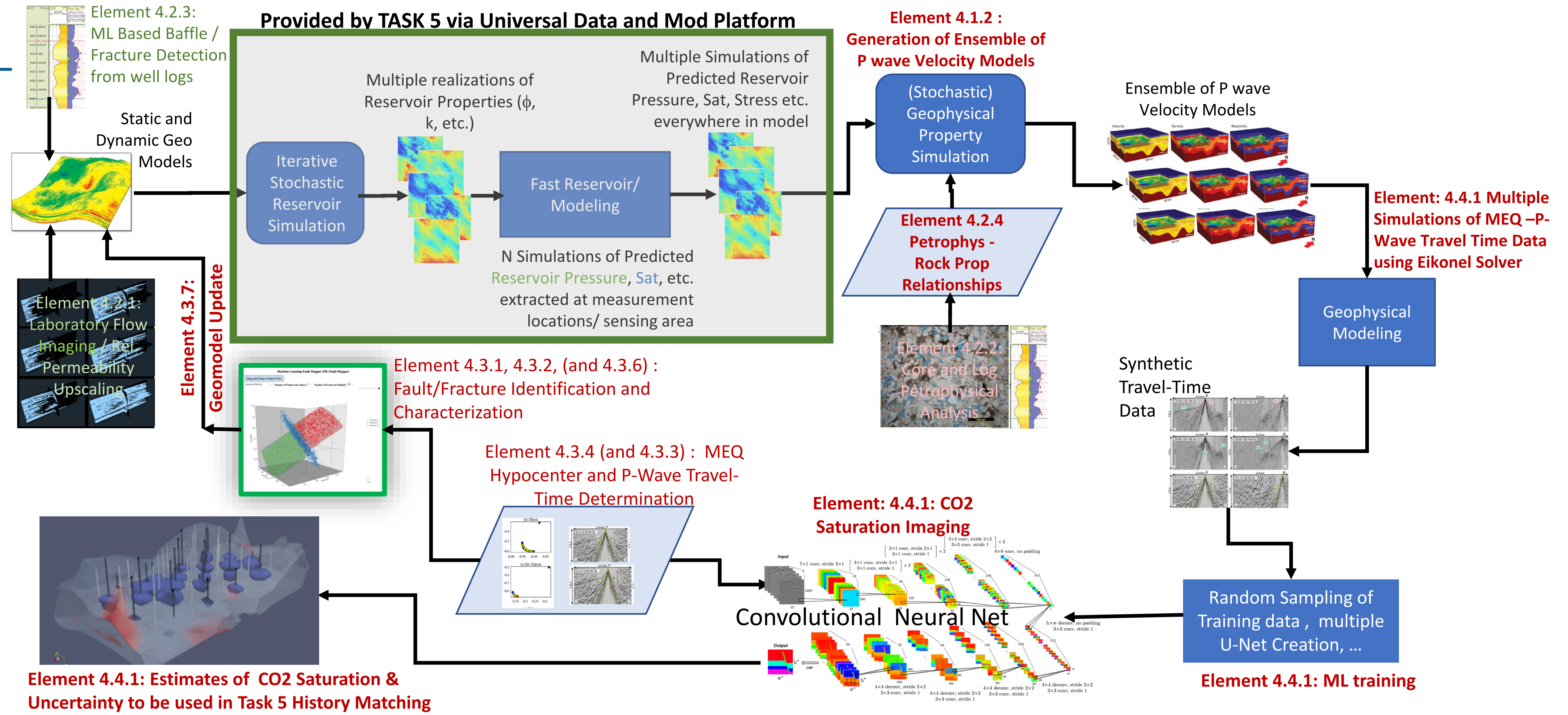
NATIONAL ENERGY TECHNOLOGY LABORATORY

U.S. DEPARTMENT OF ENERGY

# Task 4 - Reservoir Property Imaging Workflow for Any Type of Geophysical Data



# EY 23 Reservoir Property Imaging Workflow using Hypocenter Locations

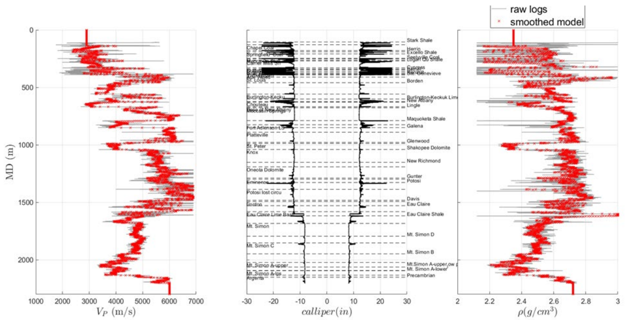


# Rock Physics Modeling and Seismic Property Estimation

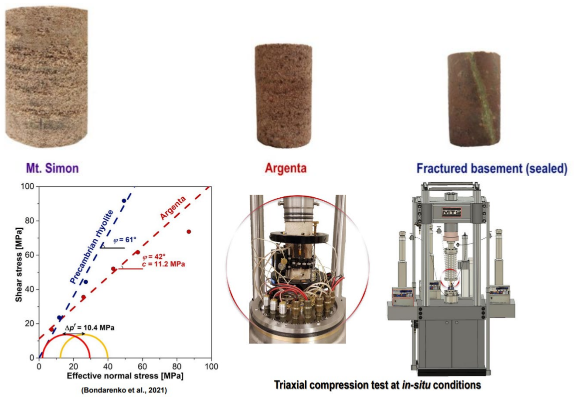
- Element 4.2.2 – Athos Nathanail and Manika Prasad, Colorado School of Mines
- Element 4.2.4 – Stas Glubokovskikh and David Alumbaugh, Lawrence Berkeley National Lab

# Element 4.2.4 Seismic detectability of the $CO_2$ plume at IBDP

## Data analysis workflow

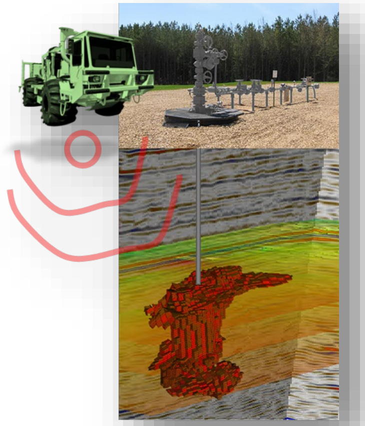


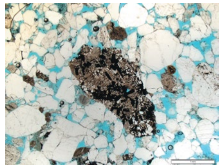

Well logs



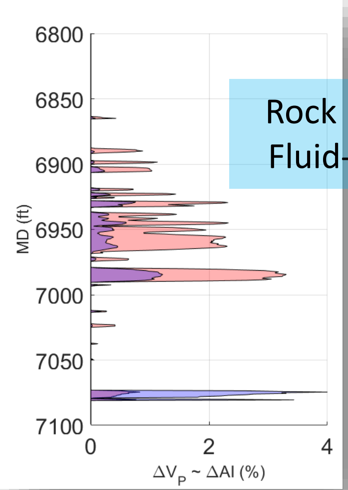

Core analysis

Rock imaging



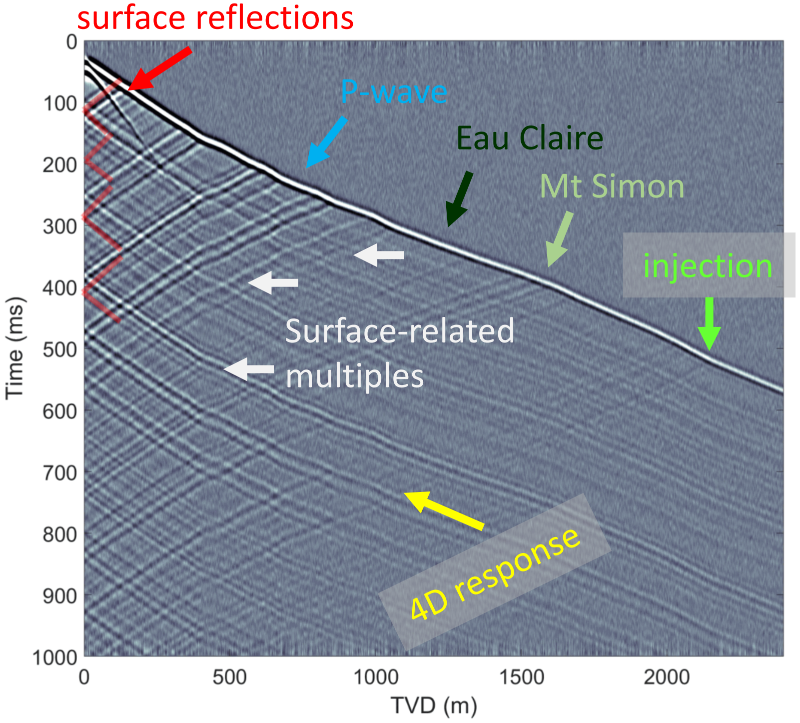


Field Borehole Seismic




Rock Physics of Fluid-response

Computer Seismic Simulations + Noise



# Seismic detectability of the $CO_2$ plume at Various Sites

## Comparison of the IBDP response to other CCS projects globally

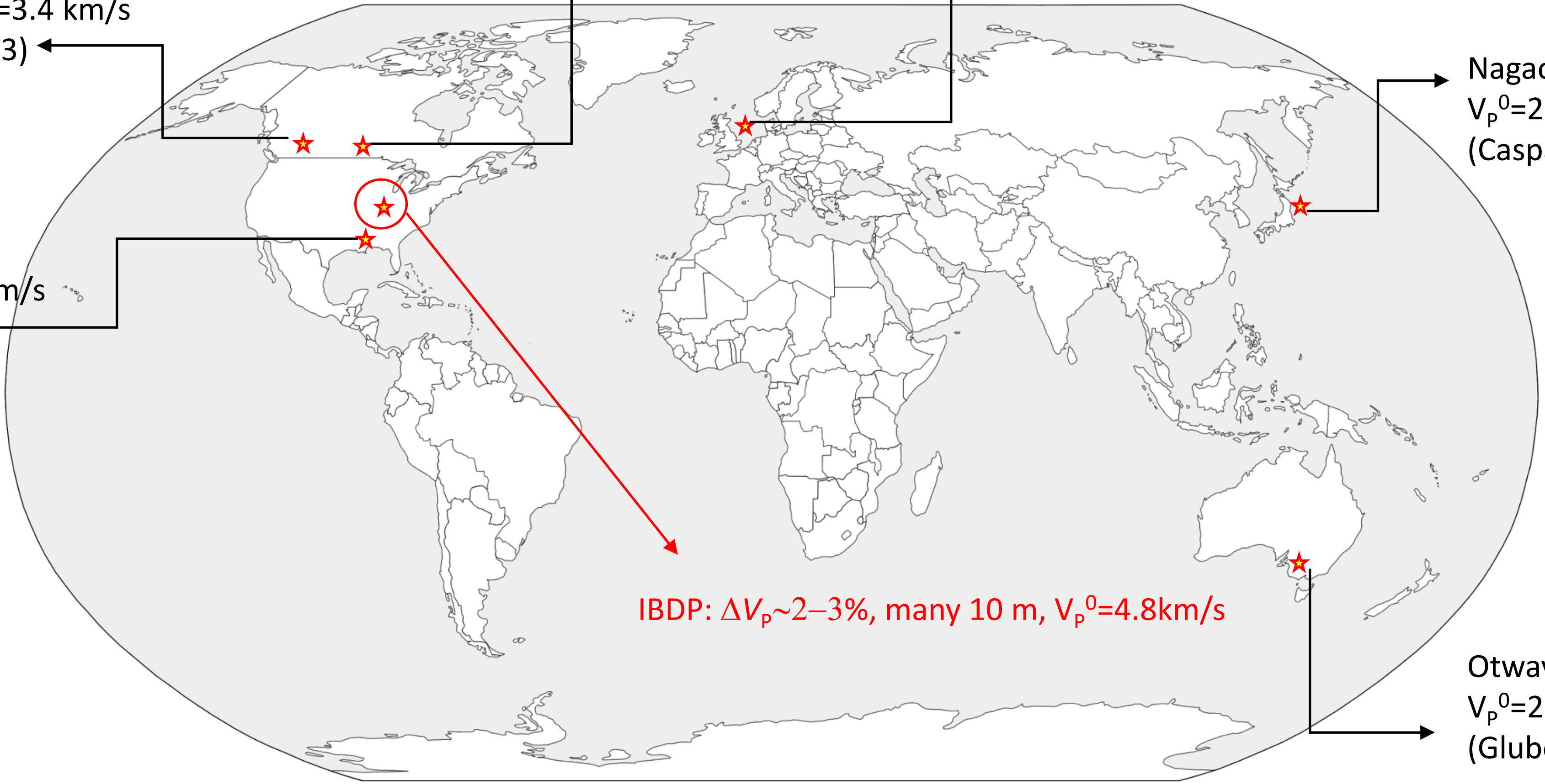
Aquistore: $\Delta V_P$~20%, 20 m, $V_P^0$=3.1 km/s
(Roach et al., 2015)

Sleipner: $\Delta V_P$~30%, many 20 m +, $V_P^0$=2.1 km/s
(Falcon-Suarez et al., 2015)

CaMI: $\Delta V_P$~15%, 12 m, $V_P^0$=3.4 km/s
(Kolkman-Quinn et al., 2023)

Nagaoka: $\Delta V_P$~25%, 8 m,
$V_P^0$=2.5 km/s
(Caspari et al., 2011)

Frio-II: $\Delta V_P$~5%, 12 m, $V_P^0$=3.0 km/s
(Daley et al., 2007)



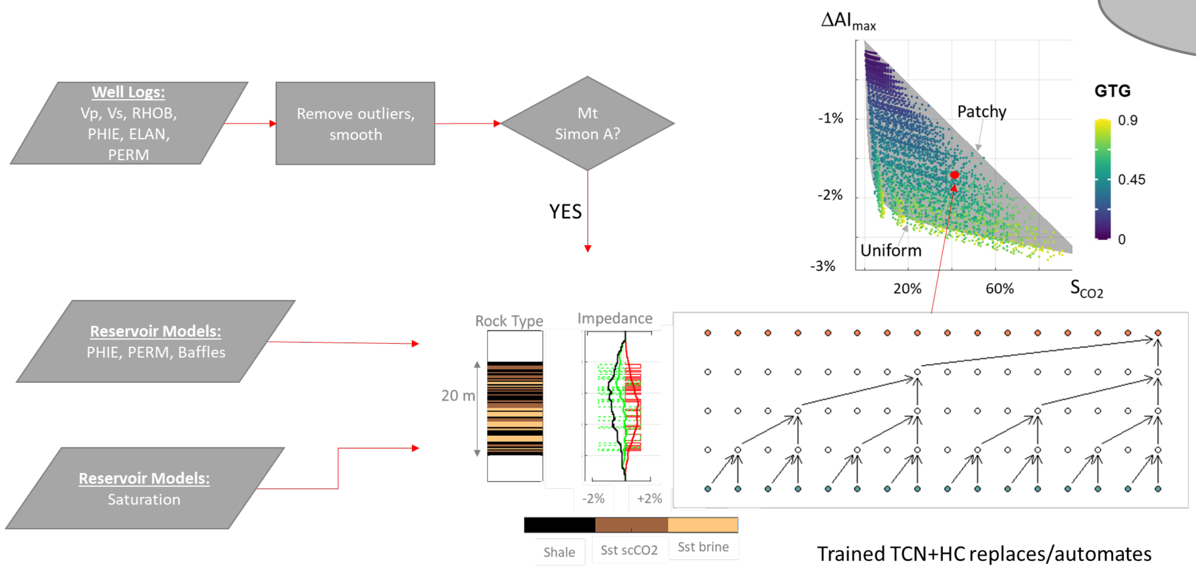
IBDP: $\Delta V_P$~2–3%, many 10 m, $V_P^0$=4.8km/s

Otway: $\Delta V_P$~10%, 12 m,
$V_P^0$=2.9 km/s
(Glubokovskikh et al., 2017)

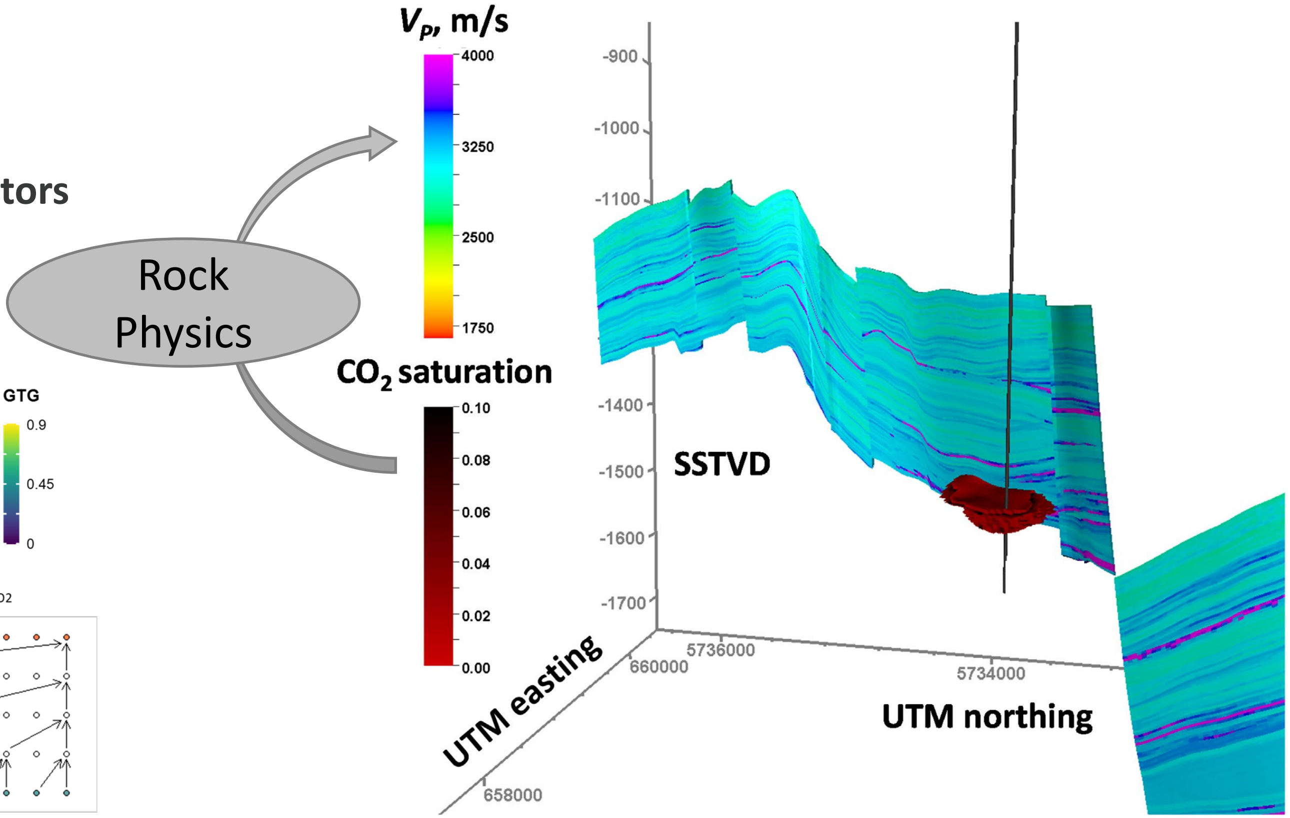
# New Element ML for automated seismic monitorability evaluation

Rock physics modeling requires expertise and involves subjective judgement. We aim to alleviate that.

1. **Automation of rock physics simulations**
2. **Refinement of the stratified CO2 plume**
3. **Automatic evaluation of seismic monitorability for operators**




Trained TCN+HC replaces/automates these subjective steps

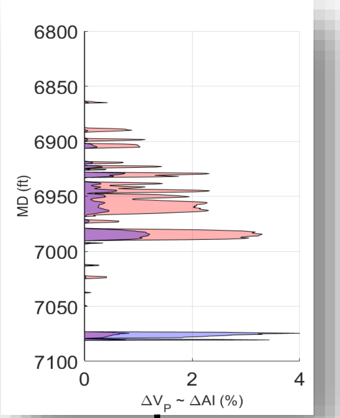


# Element 4.1.2 Geophysical Property Ensemble Generation


- Zihan Ren and Sanjay Srinivasan, Penn Stat University
- Stas Glubokovskikh, Lawrence Berkeley National Lab
- Hongkyu Yoon, Sandia National Lab

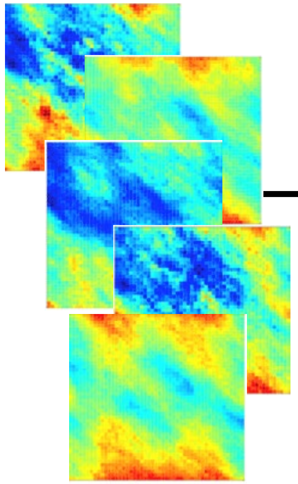

**Element 4.2.4**

Rock-Properties Relationship




**Task 5**

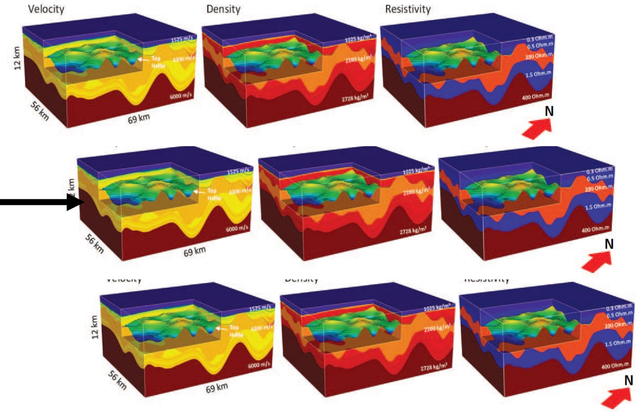
Ensemble (50*100 realizations) of reservoir CO2 Saturation



**Element 4.1.2**

Geostatistical Property (Seismic Velocity) Conversion

Ensemble (50*100 realizations) of seismic velocity



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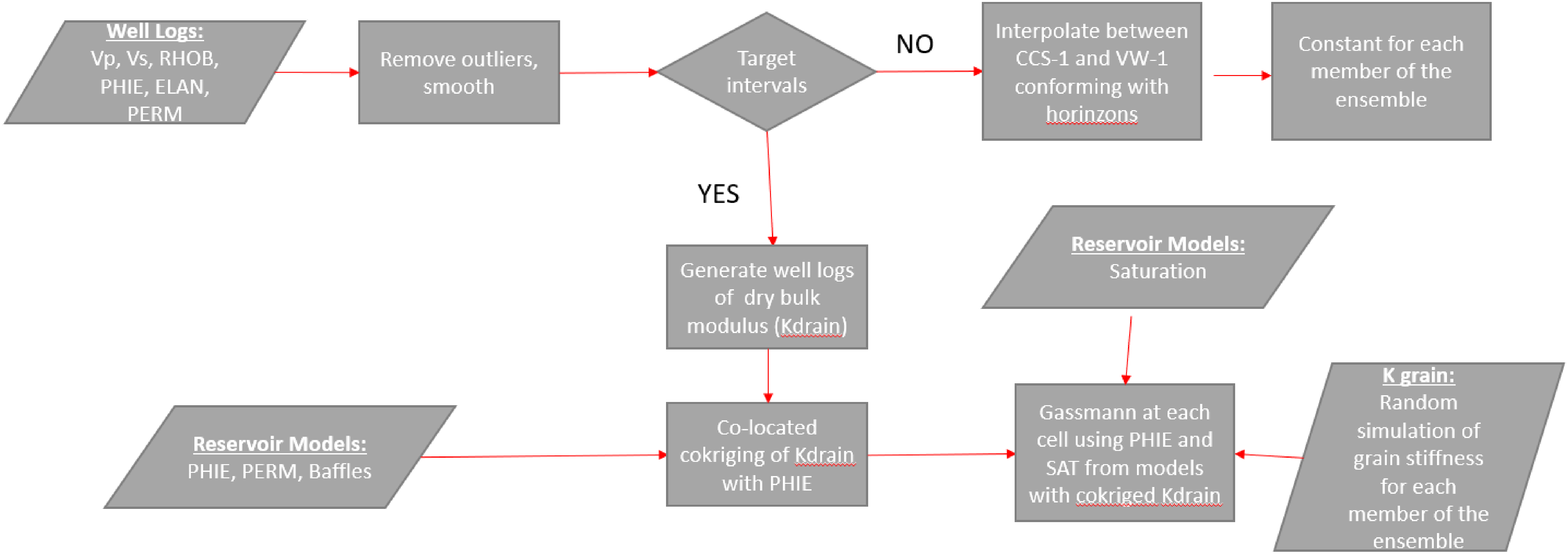

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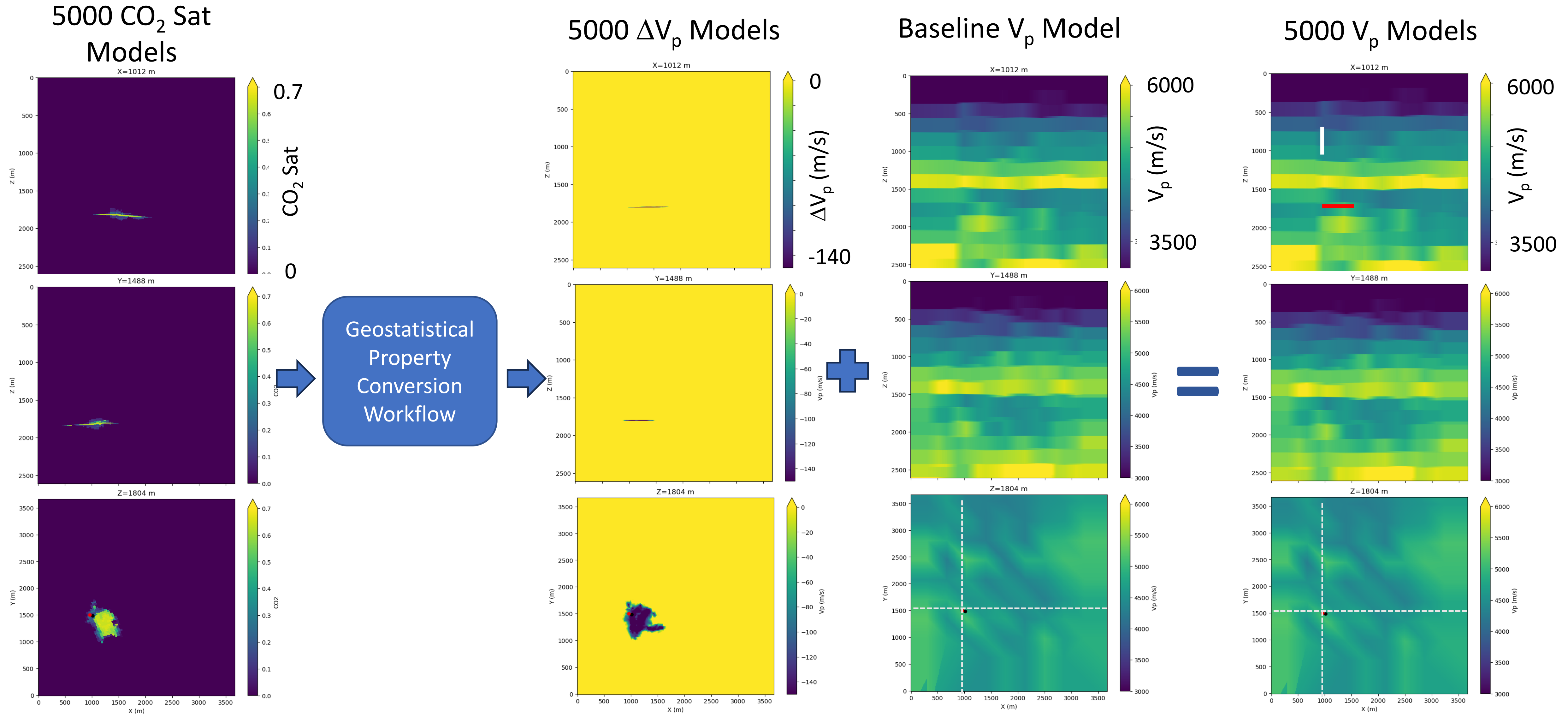
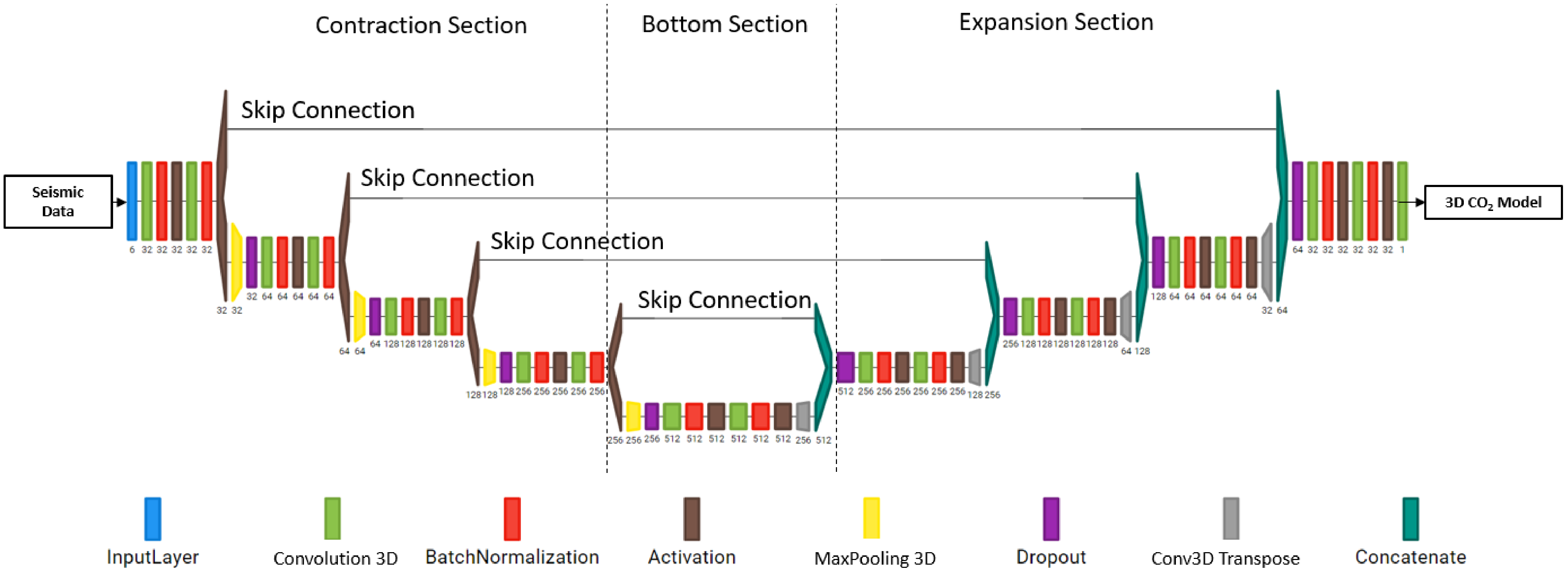


# Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data

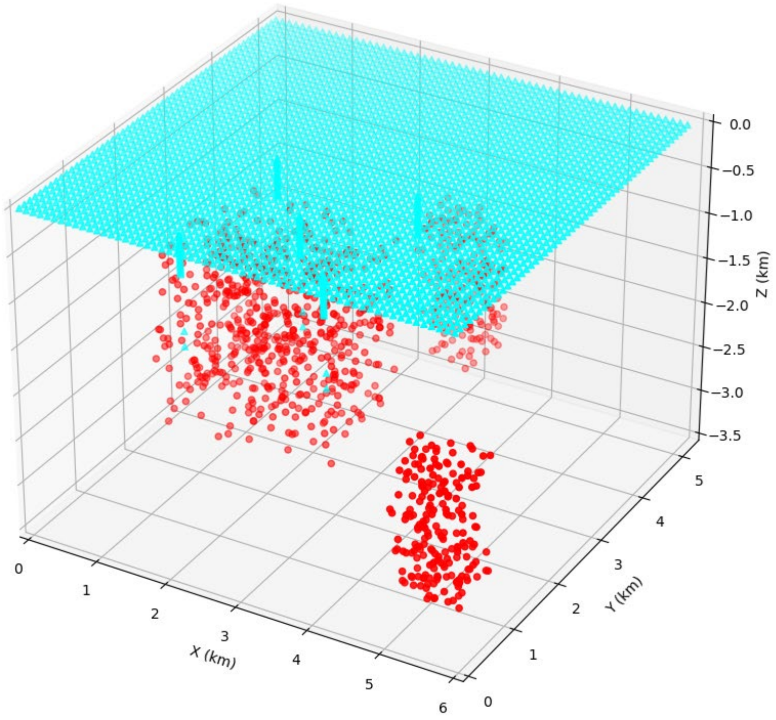
## 3D ML Inversion Network for MEQ Data



# Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data


- Evan Um and David Alumbaugh, Lawrence Berkeley National Lab
- Hanchen Wang and Youzuo Lin, Formerly Los Alamos National Lab

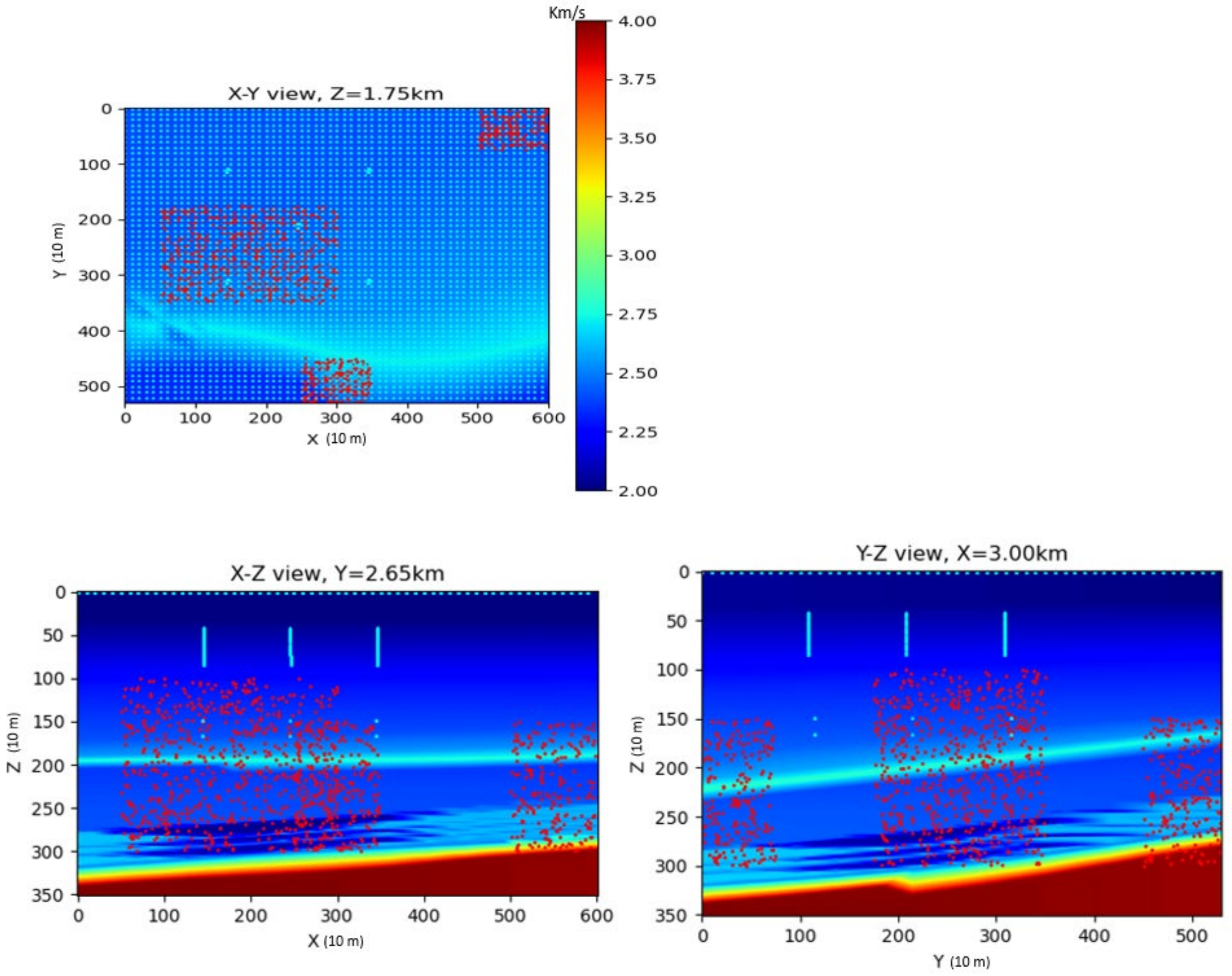

Micro-seismic Event Locations and Surface Geophone Grids




- Data type: travel time data (first arrival picks)
- Groups of event locations:
  - Cluster 1: X=[5,5.99], Y=[0,0.75], Z=[1.5,3] km
  - Cluster 2: X=[2.5,3.5], Y=[4.5,5.29], Z=[1.5,3] km
  - Cluster 3: X=[0.5,3], Y=[1.75,3.5], Z=[1,3] km
- # of Kimberlina $CO_2$ models: 2079 (=33*63)
- # of events per model: 1000
- For training, a 64x64 geophone grid is used.

# Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data

## Microseismic Event Locations and Surface Geophone Grids

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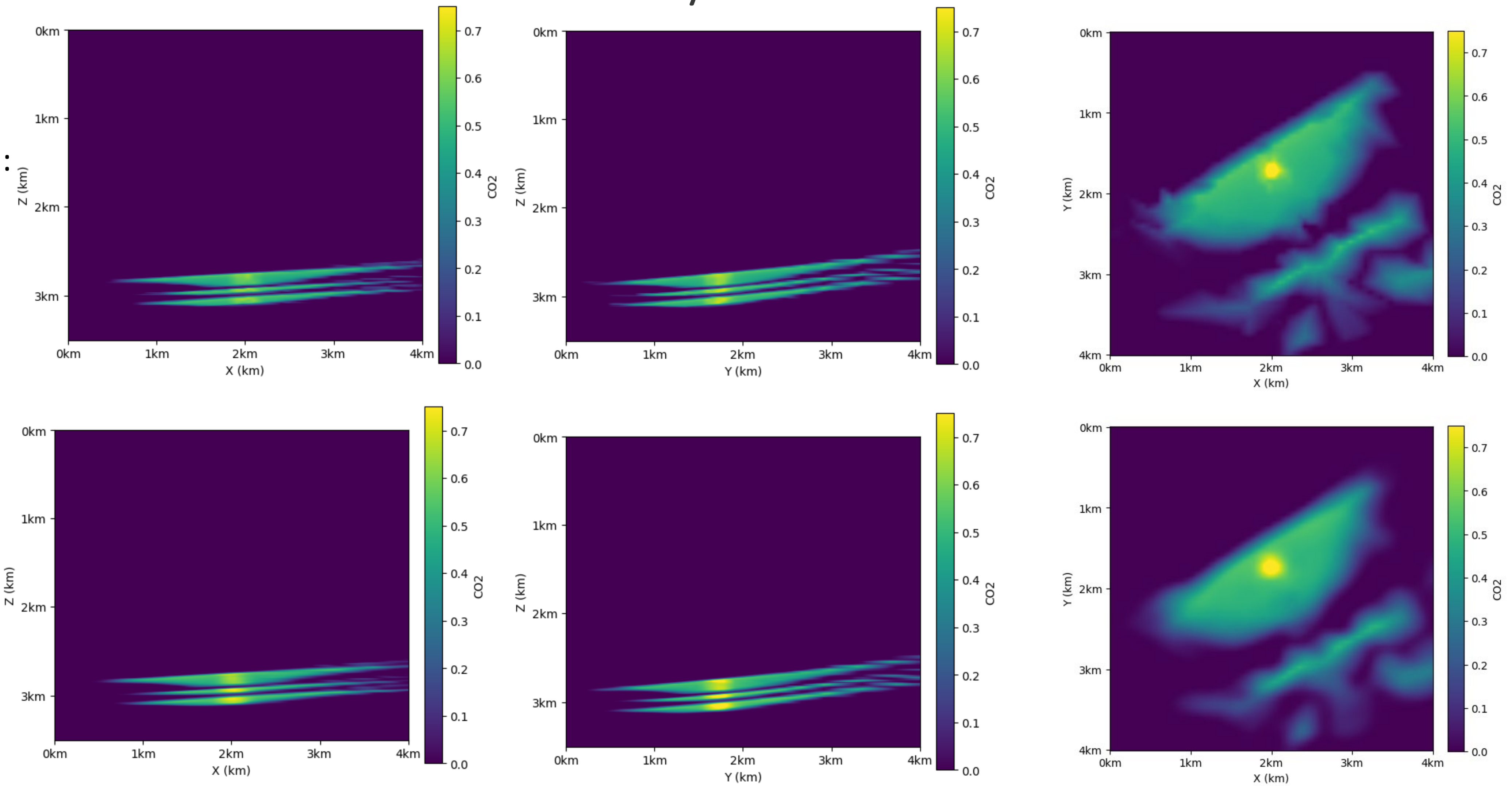
# Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data

## 3D ML Inversion with Synthetic Kimberlina Test Data

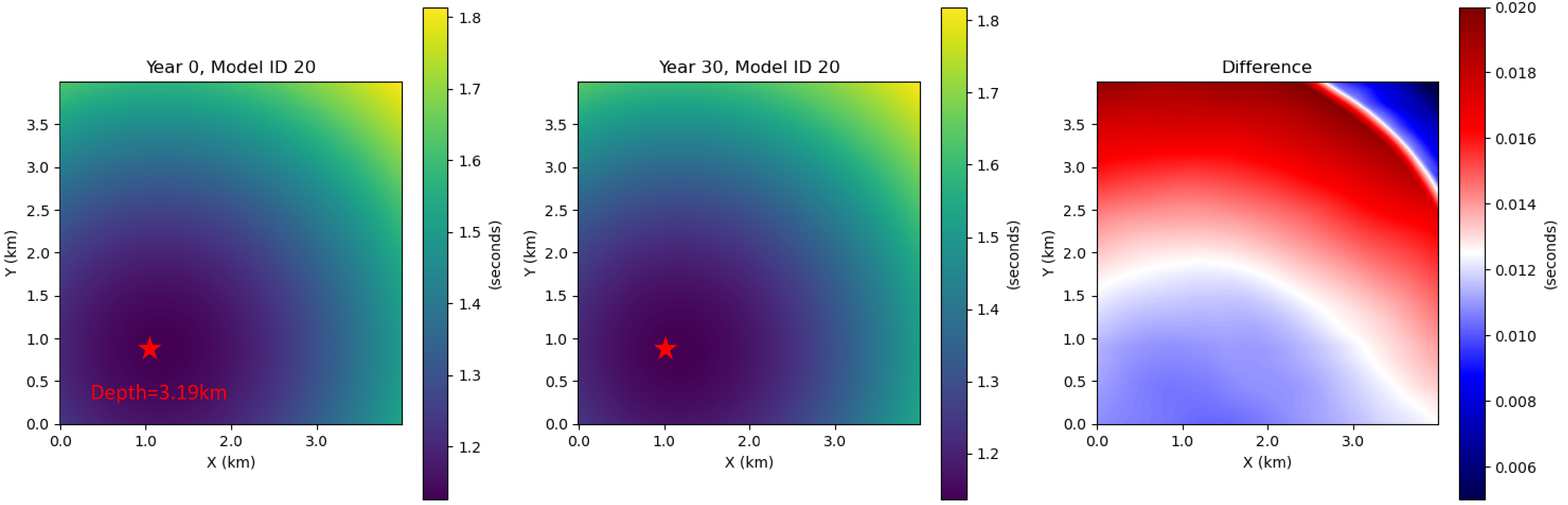
Ground Truth:

Prediction:



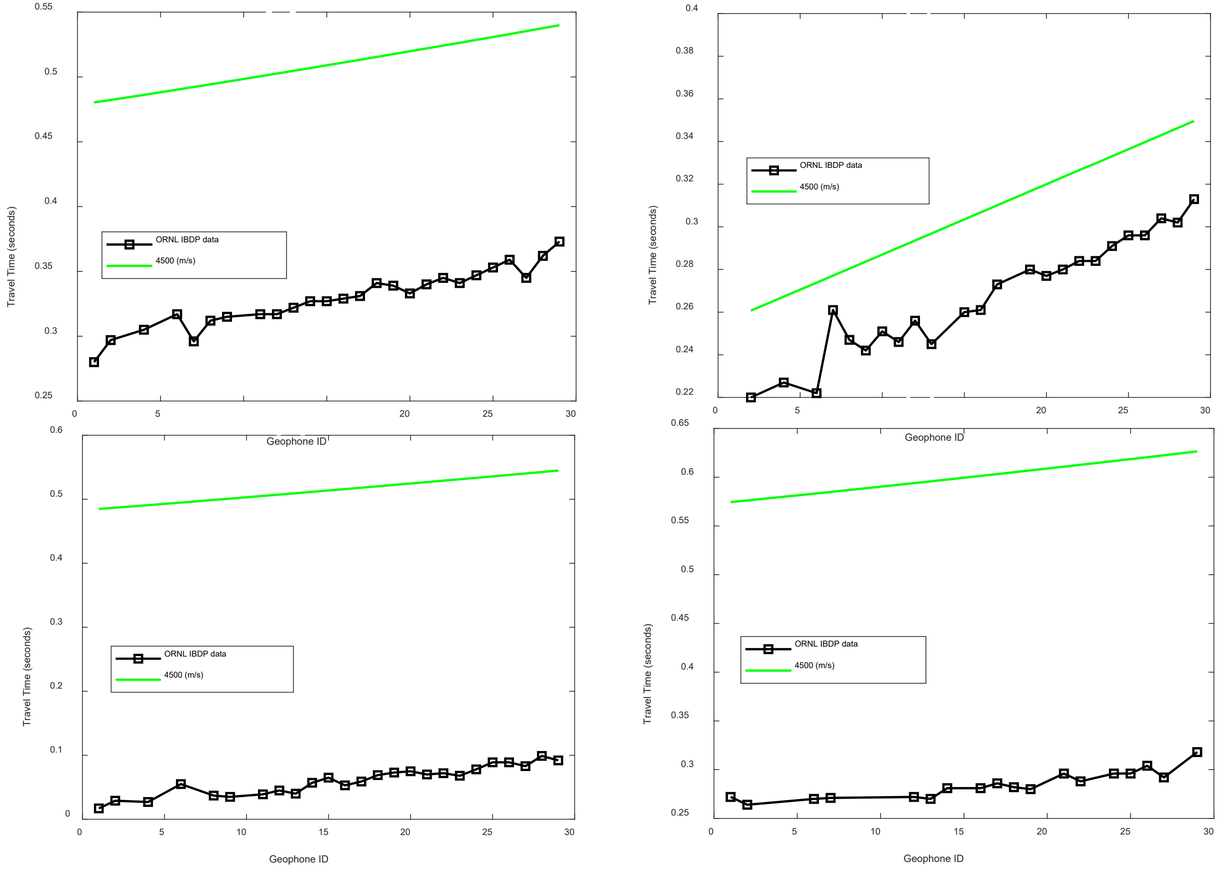
# Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data

## Training Data Example and Sensitivity to $CO_2$ plume



# Element 4.4.1 – Application to IPDP Microseismic Data Set

- Evan Um and David Alumbaugh, Lawrence Berkeley National Lab, ML Imaging
- Hanchen Wang and Youzuo Lin, Formerly Los Alamos National Lab, Training Data Generation
- Chengping Chai, Oakridge National Lab, Microseismic Data Curation




Training Data Generation Issues

- The number of training model: 5,000 (100*50)
- The number of geophones: 31 (GM1 borehole geophone array)
- The number of MEQ events: 194 (from May 2014 to Nov 2014)

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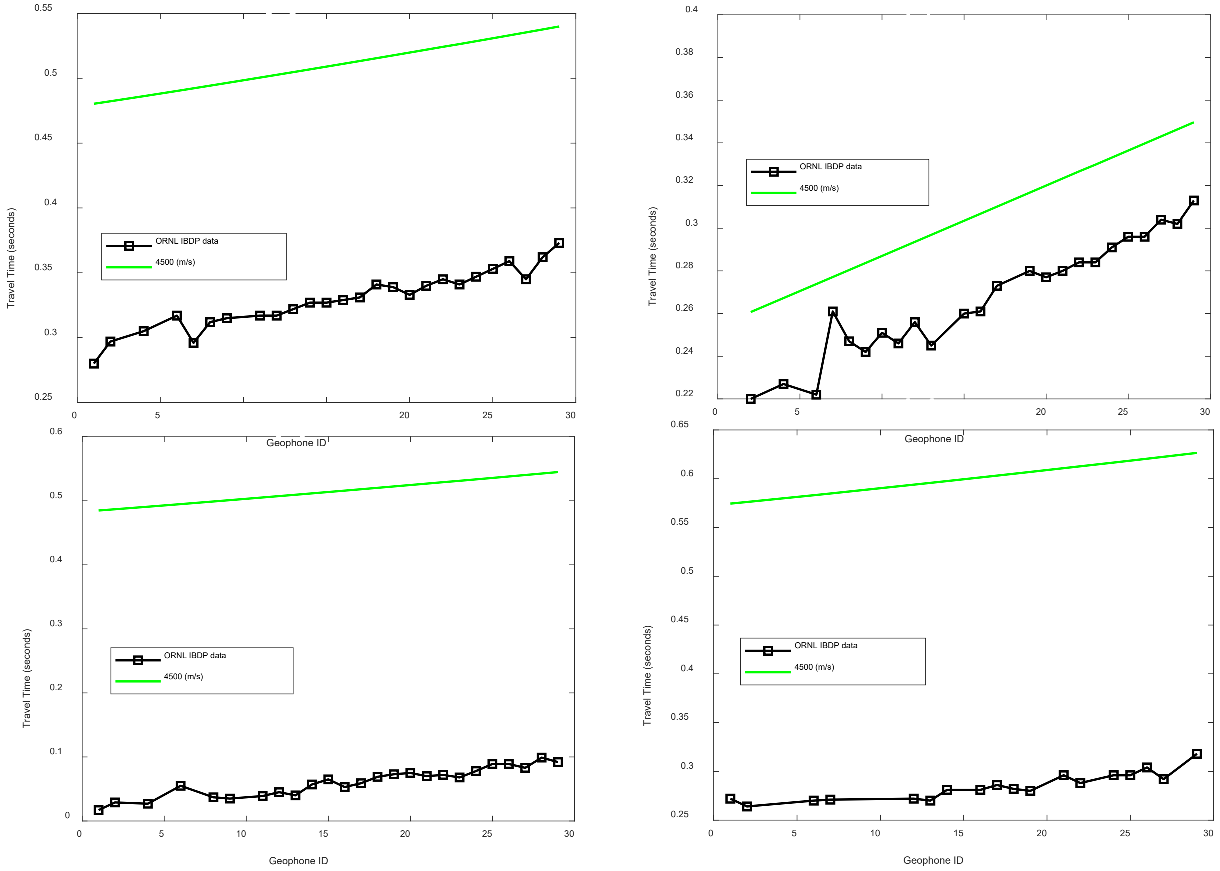


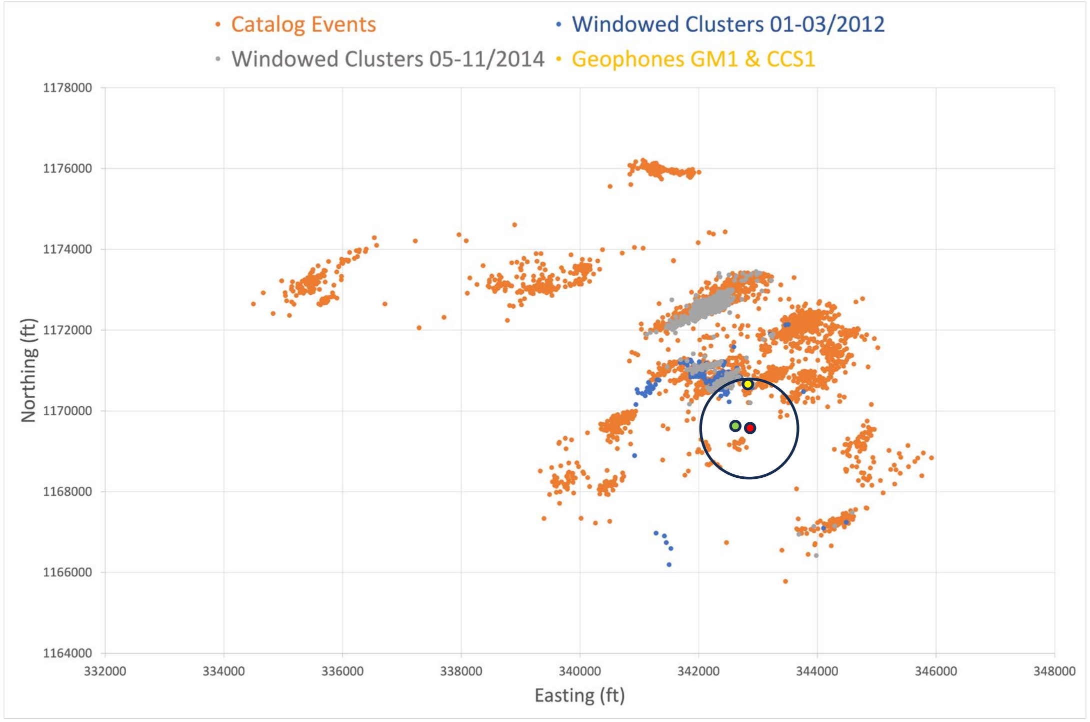

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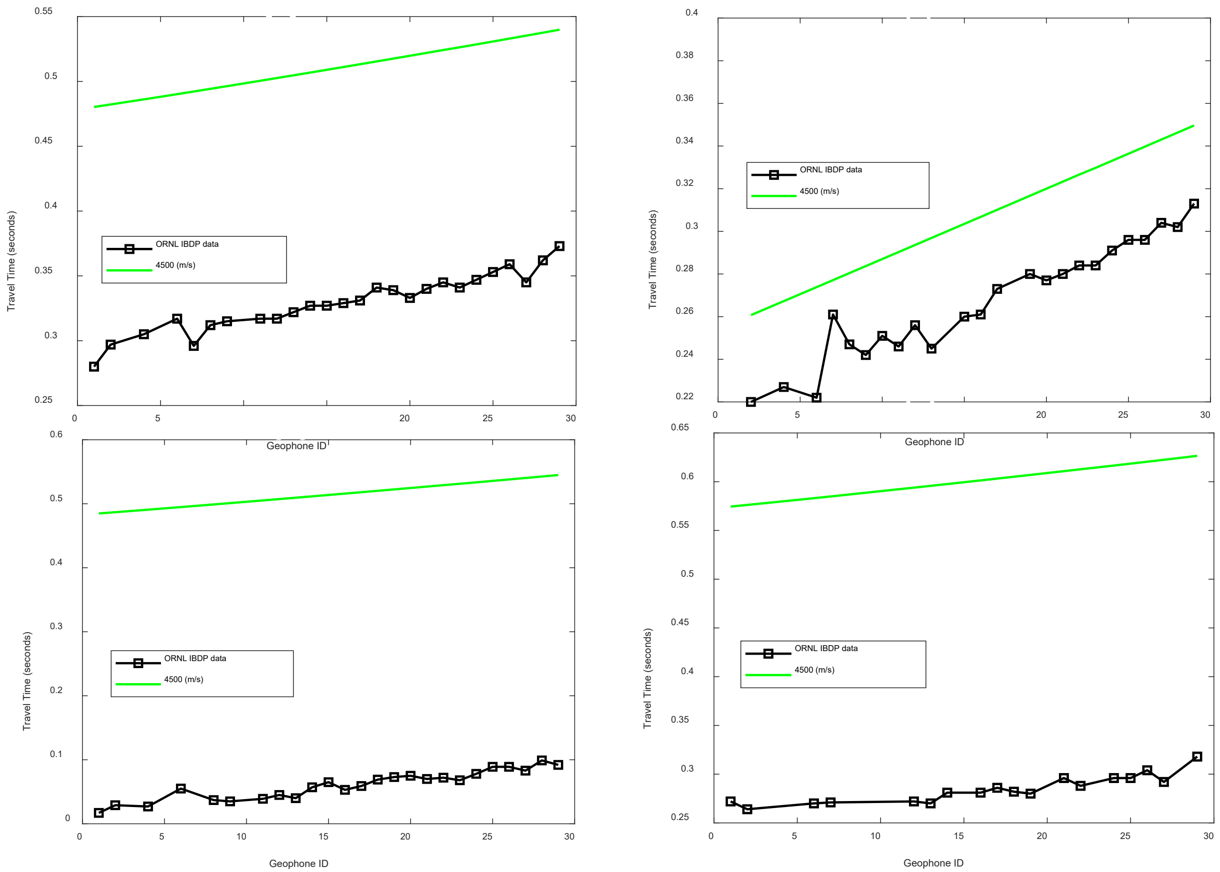


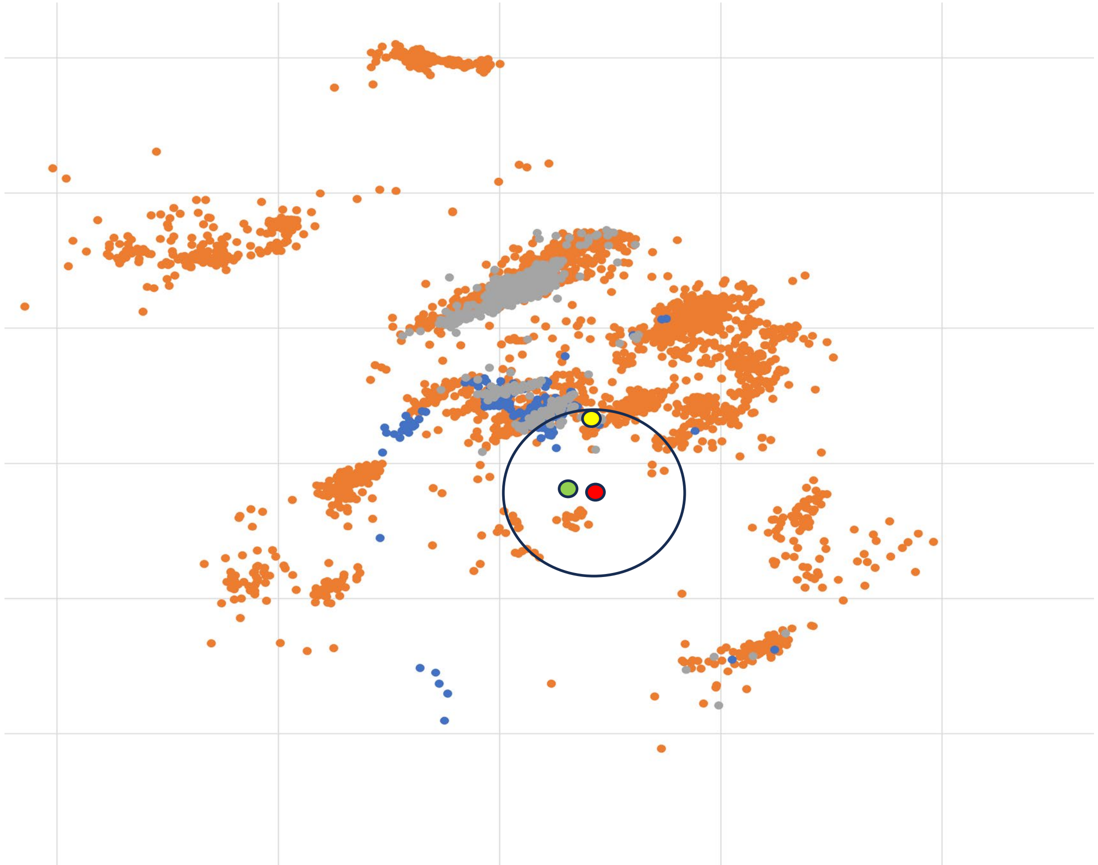

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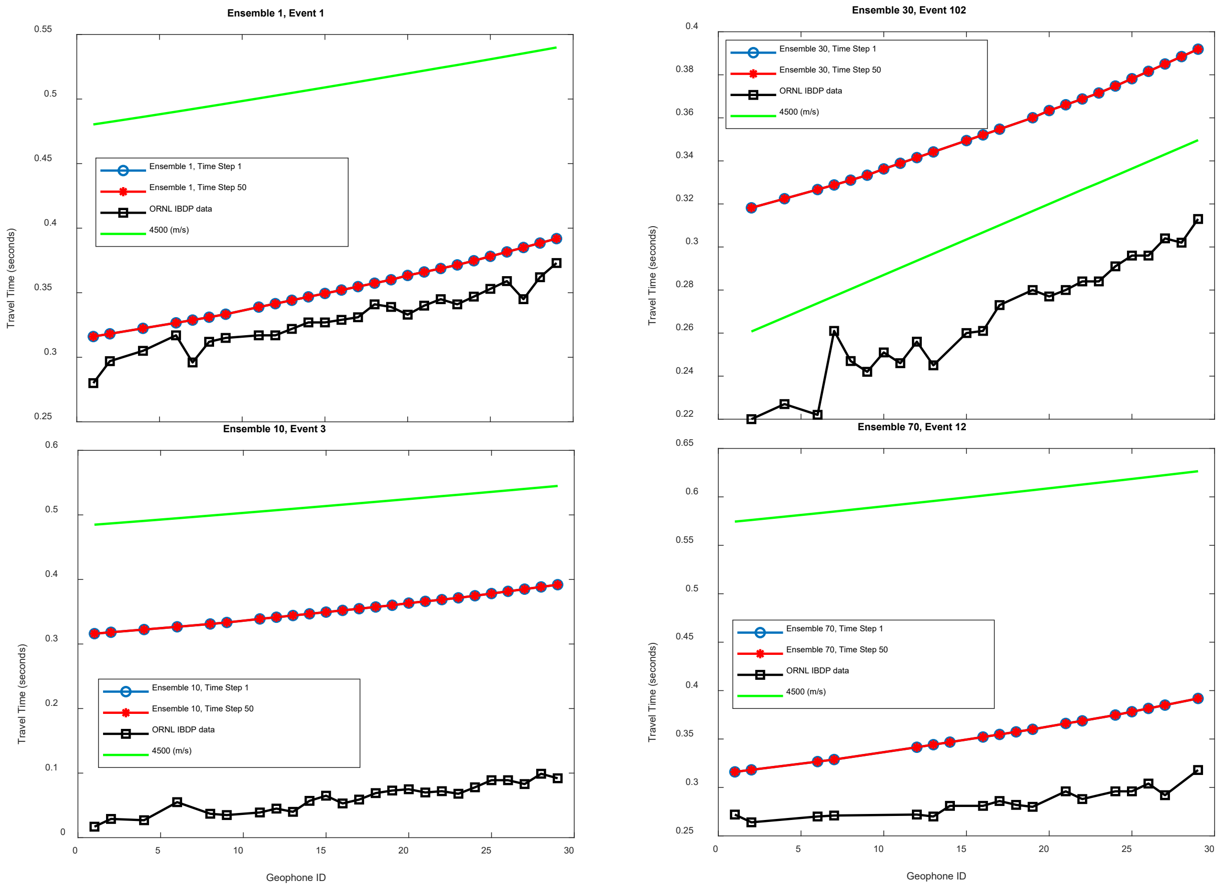
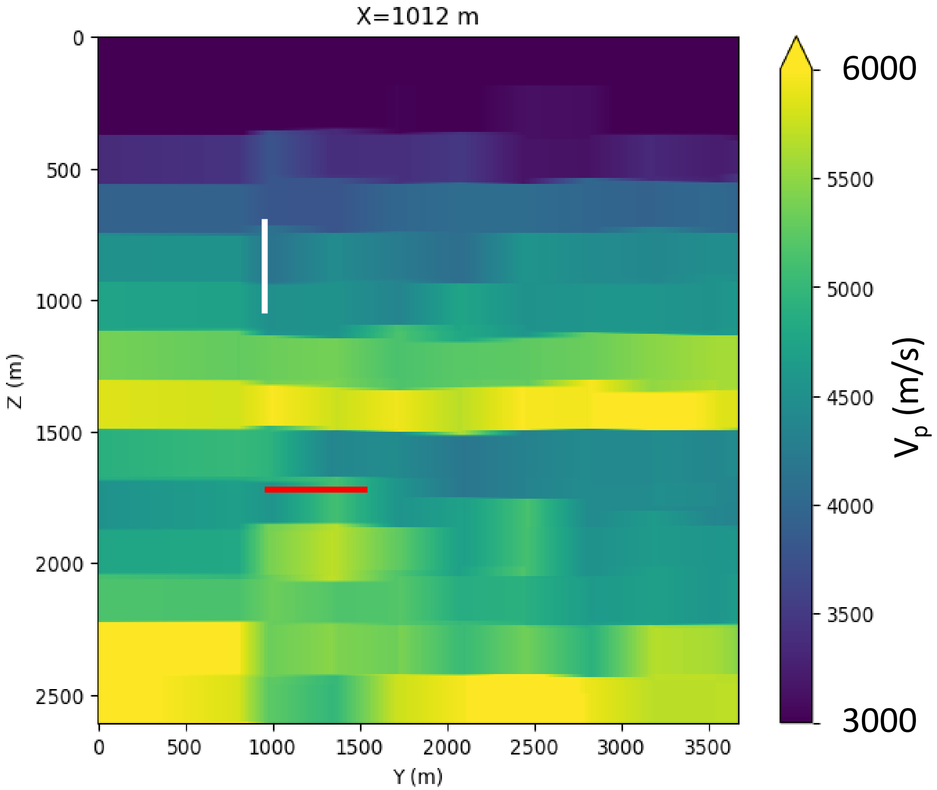
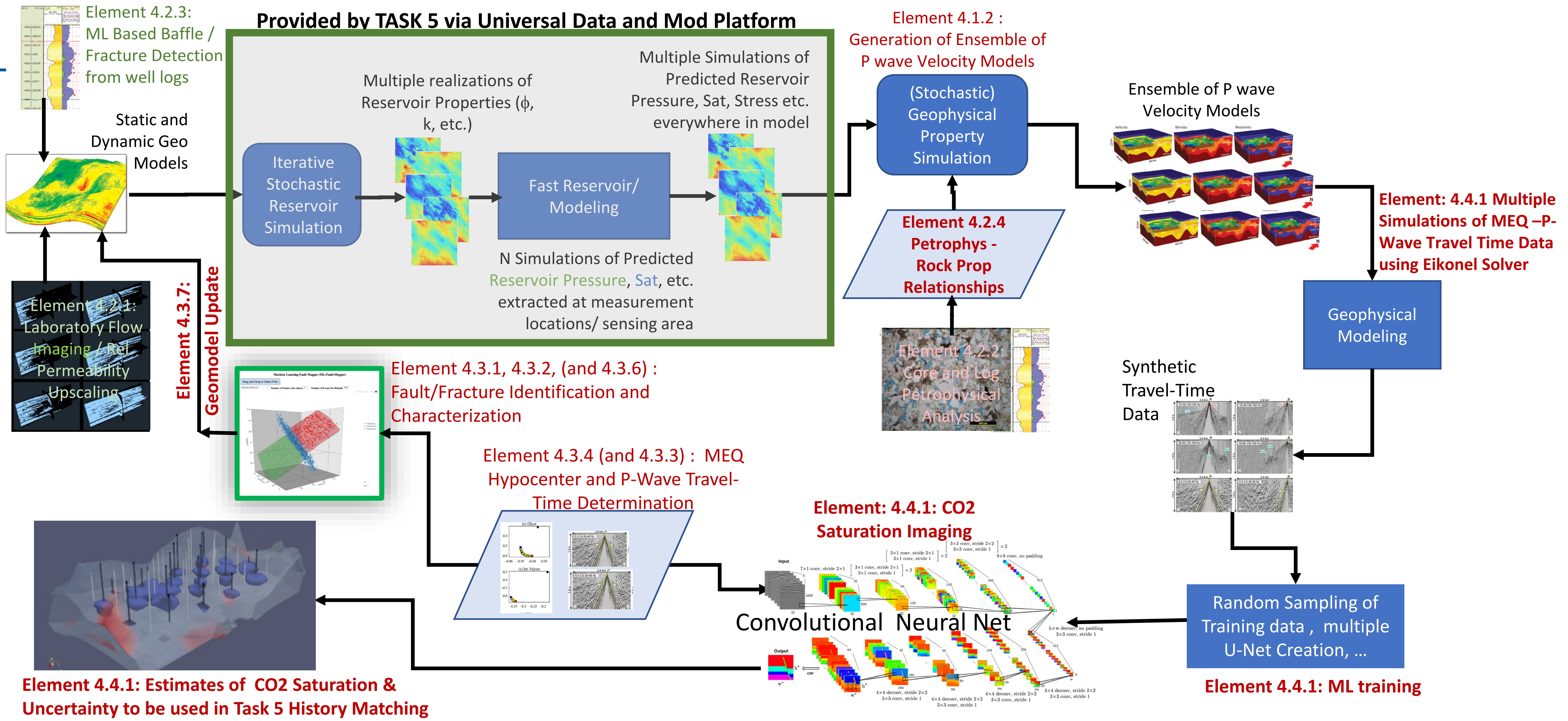


# EY 23 Reservoir Property Imaging Workflow using Hypocenter Locations

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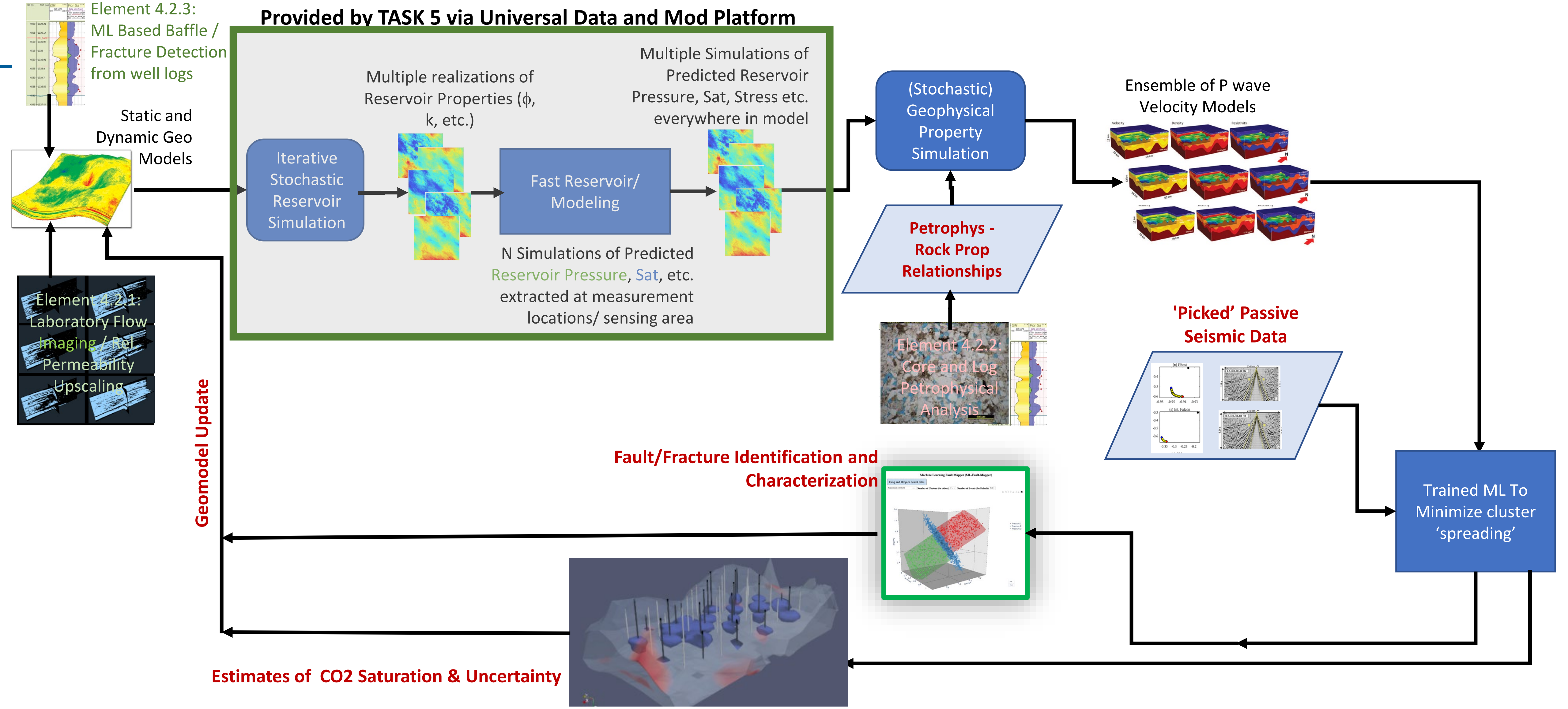
See notes for definitions of Green vs Red vs Blue shapes, and definitions of AS and PS

SMART

# Recommended Reservoir Imaging Workflow using Hypocenter Locations

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# Conclusions

- A workflow has been designed to image $CO_2$ saturations using micro-seismic hypocenter locations as known source points
- The 'stiff' reservoir rocks at the IBDP site limit the usefulness of the approach due to
  - Relatively small rock velocity perturbations due to the introduction of $CO_2$ into the reservoir plus
  - Relatively thin reservoir interval yielding
  - Very small to non-existent travel time changes
- The small (1% to 2%) changes in travel time data in synthetic Kimberlina results suggest that even when there is a 15% to 20% change in velocity due to $CO_2$ injection, the 'data' changes may still too small to provide good imaging.
- We will be working in the next few months to improve the rock physics modeling and other workflow elements to incorporate it into the RNG module
- It may be better in areas of large travel time changes due to $CO_2$ injection to develop a ML workflow that uses time lapse velocity changes to image both hypocenter locations and $CO_2$ saturation