ML-Based Rock Physics Modeling and Reservoir Imaging

David Alumbaugh – LBNL, SMART Task 4 Co-Lead with Chris Sherman, LLNL

Stanislav Glubokovskikh and Evan UM, LBNL

Hanchen Wang and Youzuo Lin, Formerly LANL

Zihan Ren and Sanjay Srinivasan, Penn State University

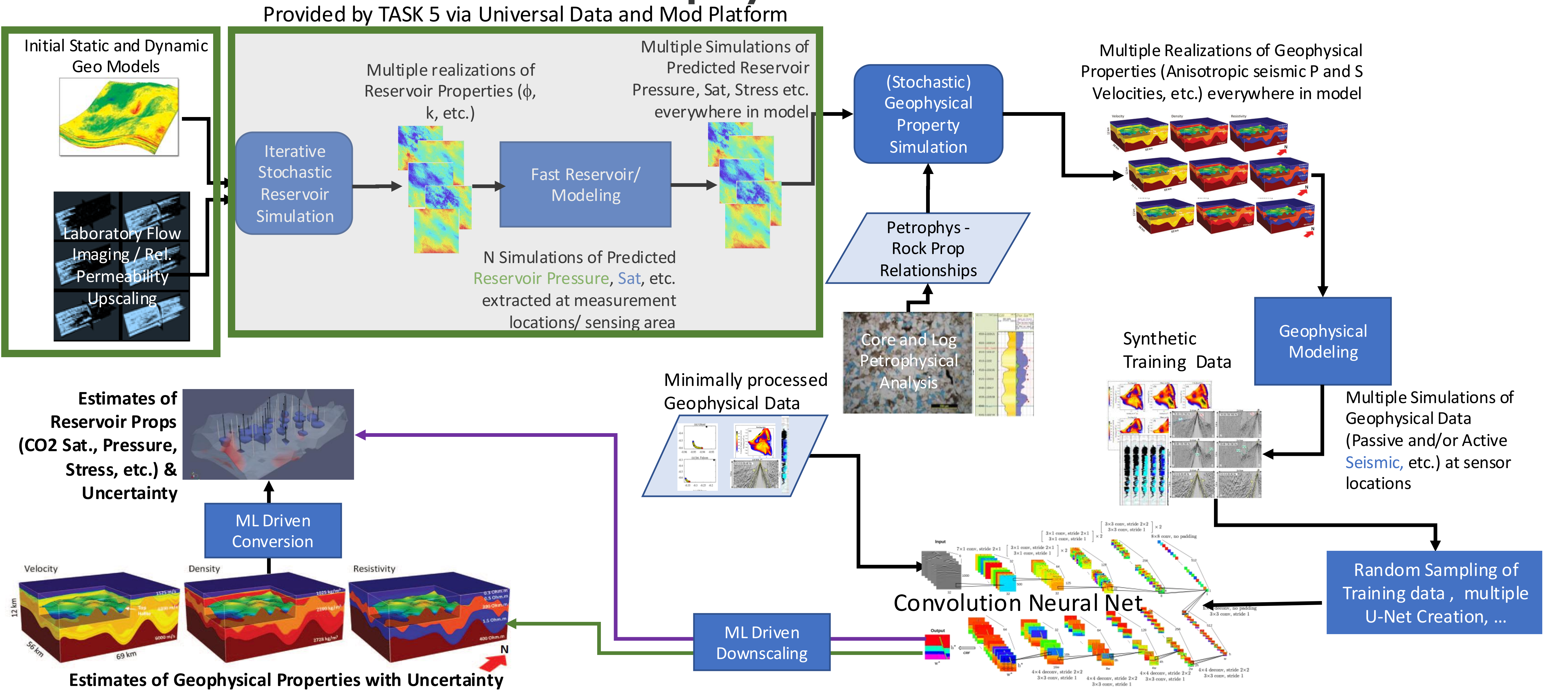
Hongkyu Yoon, SNL

Chengping Chai, ORNL

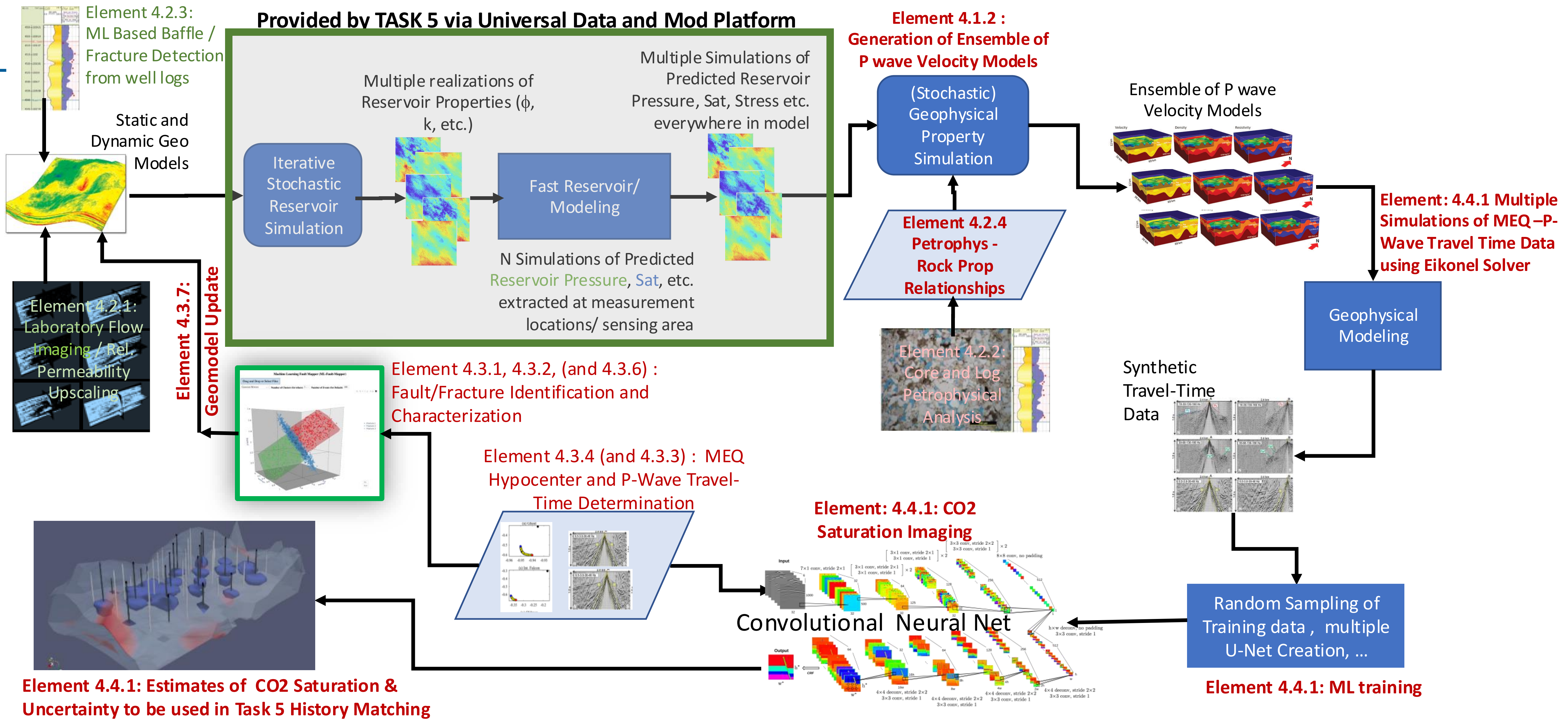
NATIONAL ENERGY TECHNOLOGY LABORATORY

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



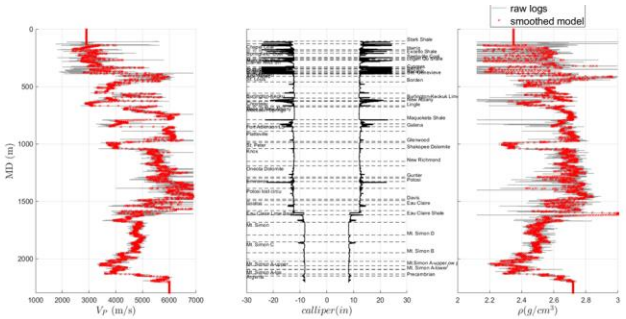
See notes for definitions of Green vs Red vs Blue shapes, and definitions of AS and PS

Rock Physics Modeling and Seismic Property Estimation

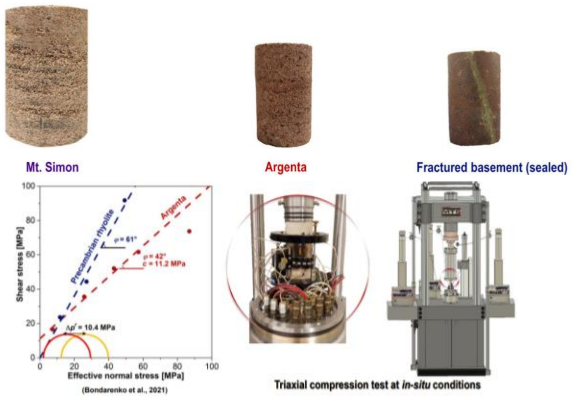
- Element 4.2.2 – Athos Nathanail and Manika Prasad, Colorado School of Mines
- Element 4.2.4 – Stas Glubokovskikh and David Alumbaugh, Lawrence Berkeley National Lab

Element 4.2.4 Seismic detectability of the CO_2 plume at IBDP

Data analysis workflow

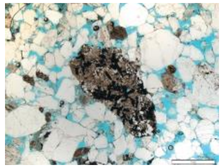


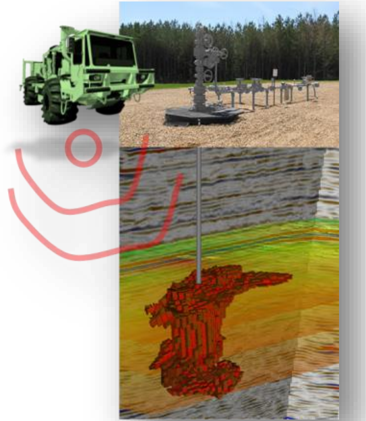
Well logs



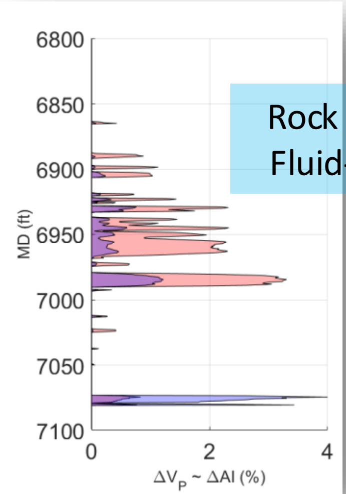
Core analysis

Rock imaging



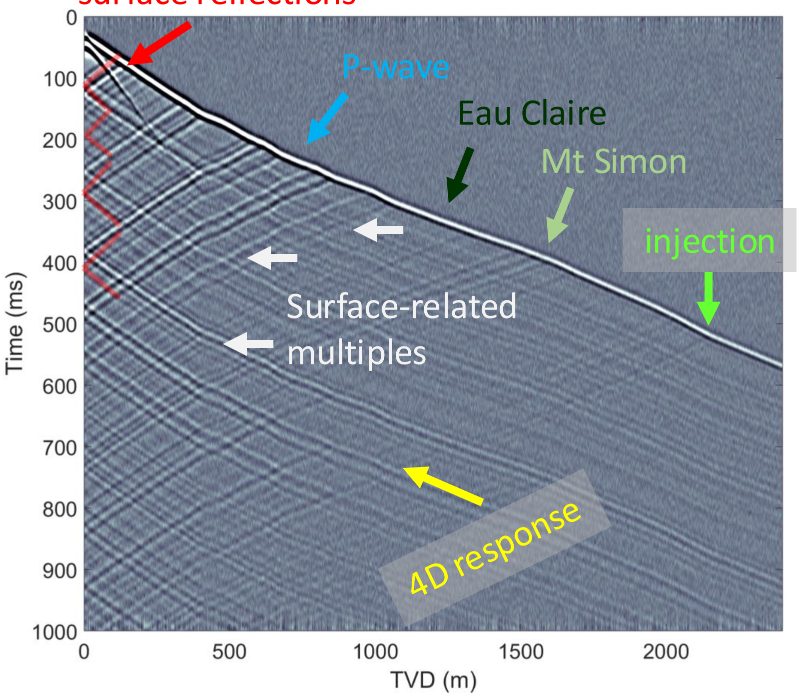


Field Borehole Seismic



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

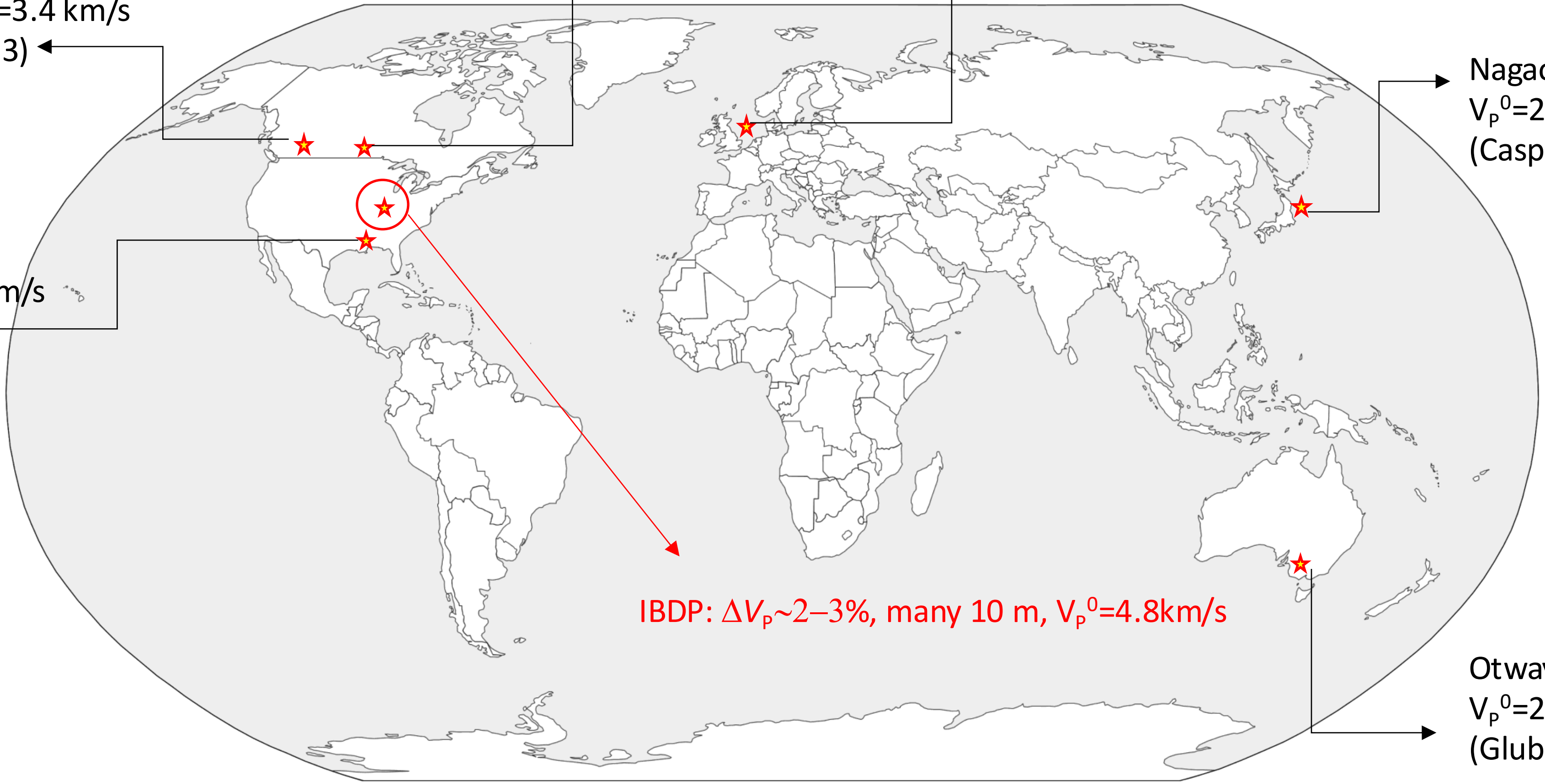
Aquistore: ΔV_P~20%, 20 m, V_P^0=3.1 km/s
(Roach et al., 2015)

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

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

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

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



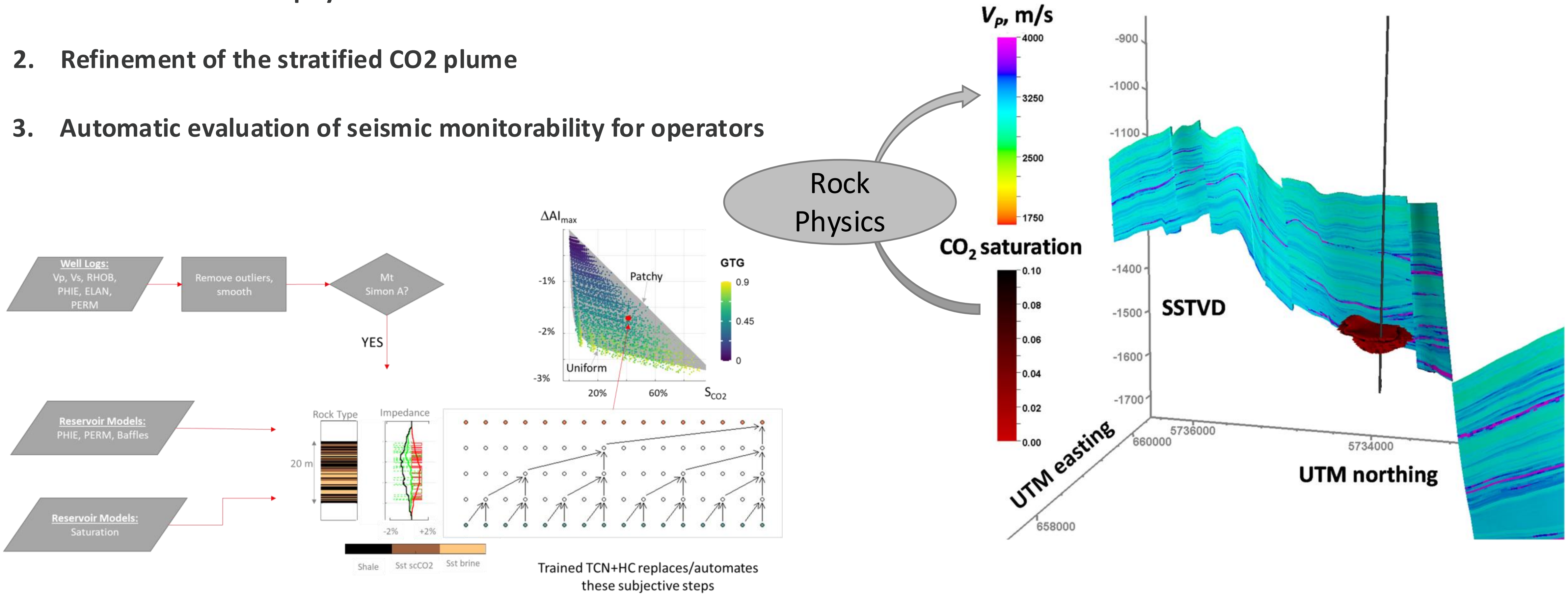
IBDP: ΔV_P~2–3%, many 10 m, V_P^0=4.8km/s

Otway: ΔV_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**

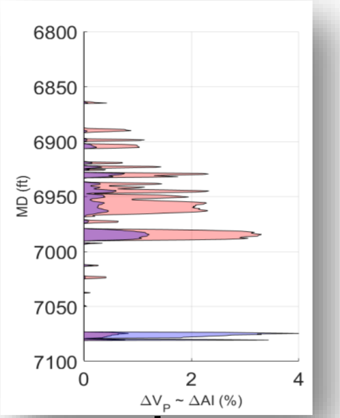


Element 4.1.2 Geophysical Property Ensemble Generation

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

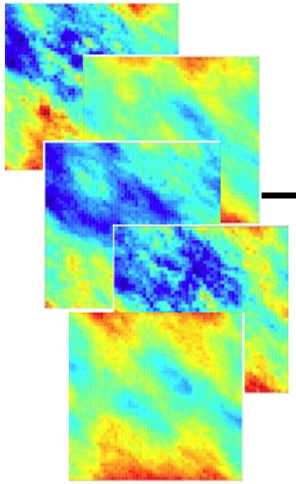
Element 4.2.4

Rock-Properties Relationship



Task 5

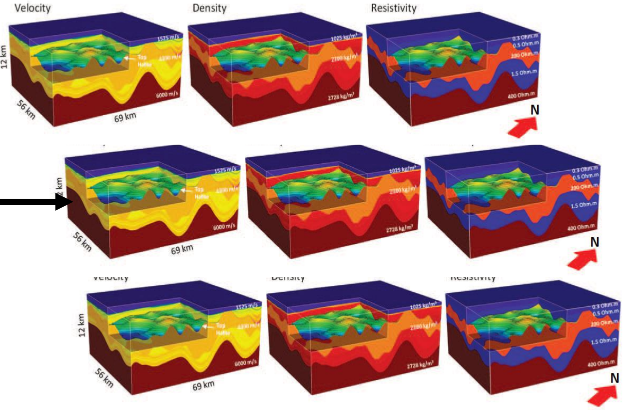
Ensemble (50*100 realizations) of reservoir CO2 Saturation



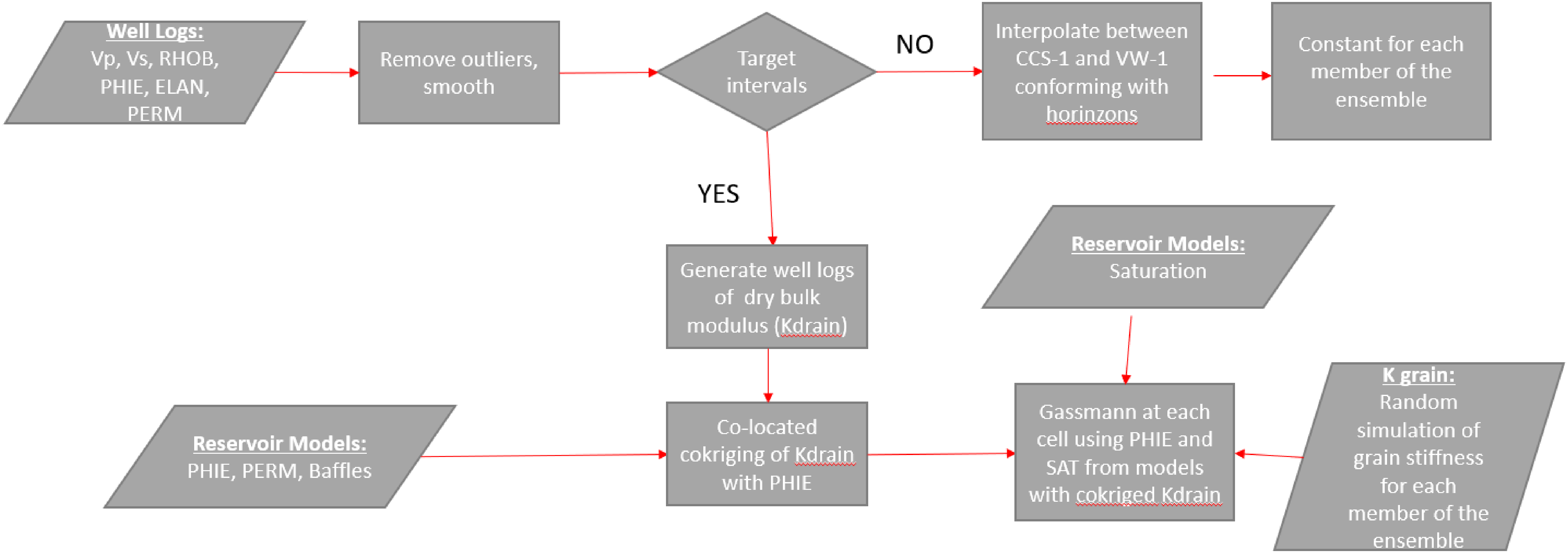
Element 4.1.2

Geostatistical Property (Seismic Velocity) Conversion

Ensemble (50*100 realizations) of seismic velocity



Element 4.1.2 Geophysical Property Ensemble Generation



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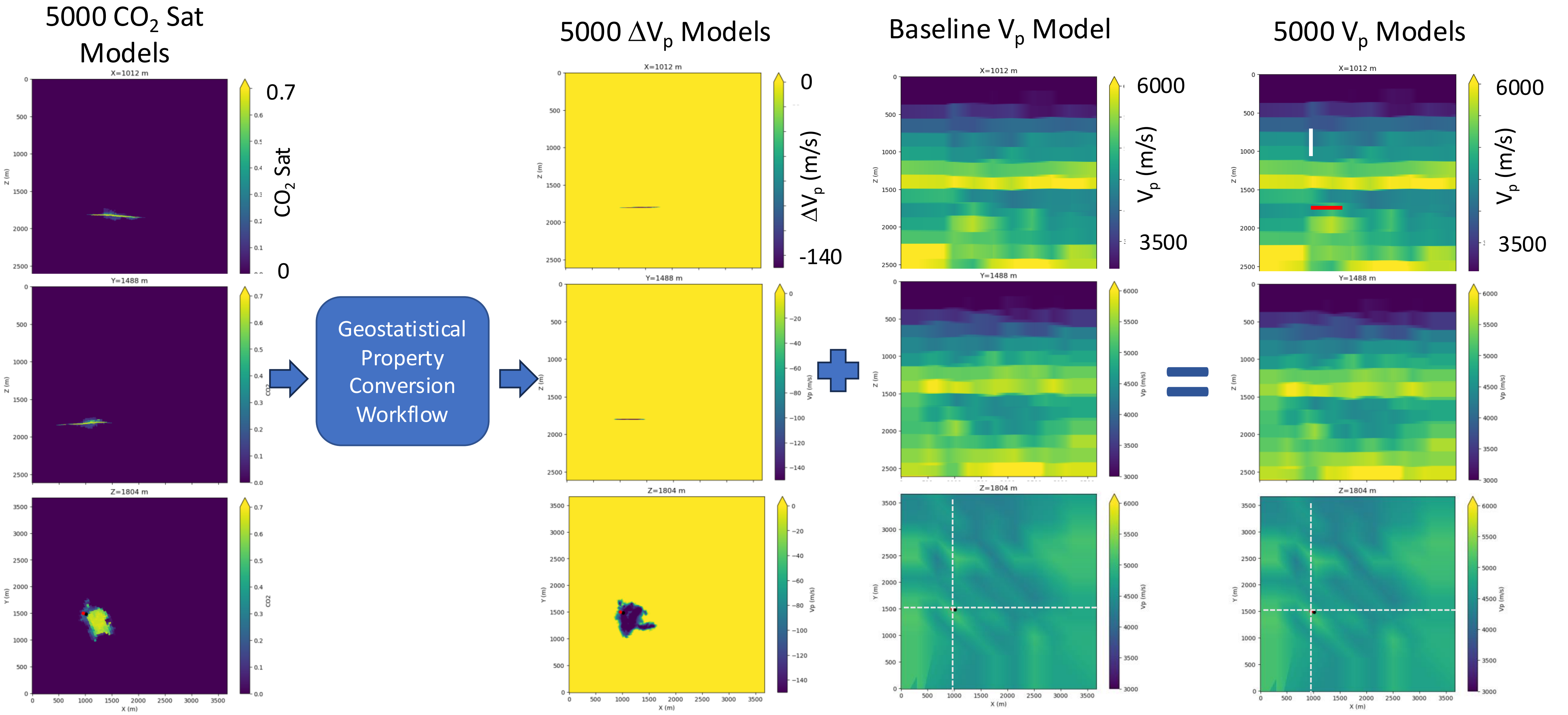
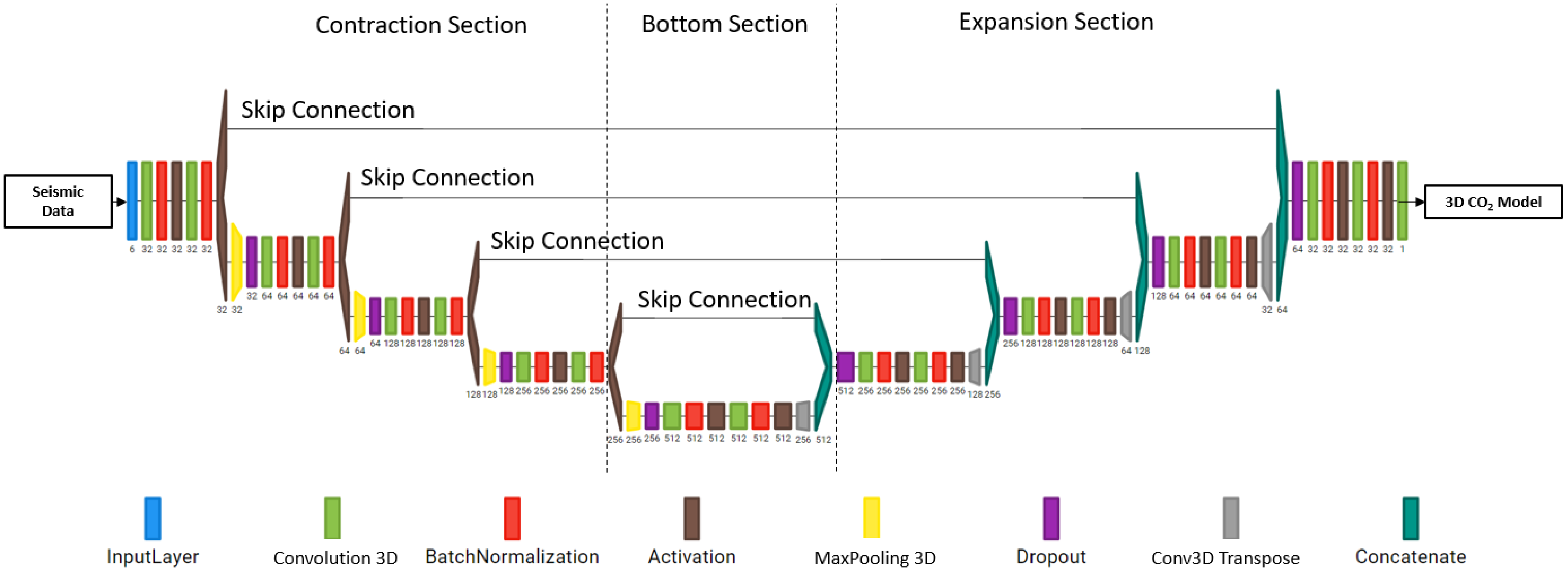


Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data

3D ML Inversion Network for MEQ Data



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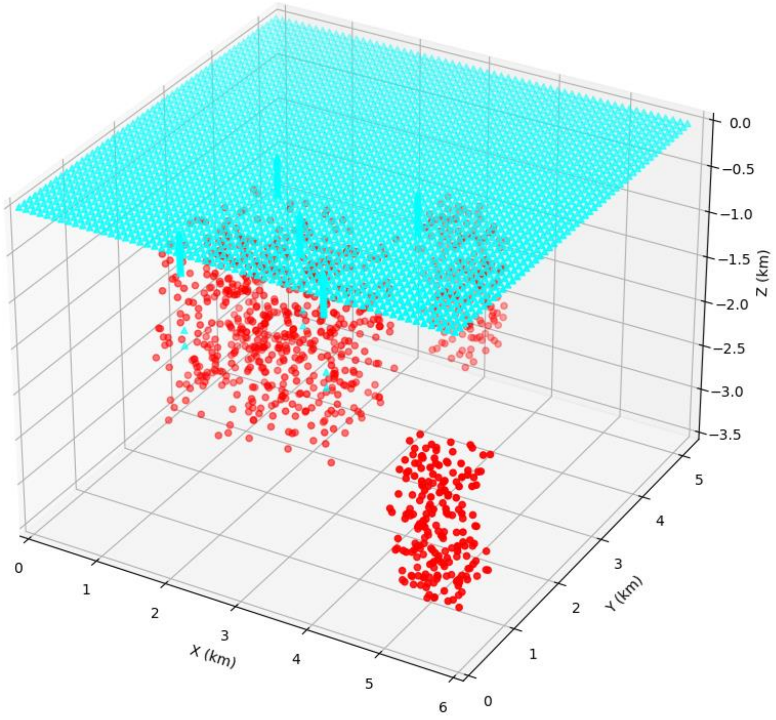
- Hanchen Wang and Youzuo Lin, Formerly Los Alamos National Lab

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.

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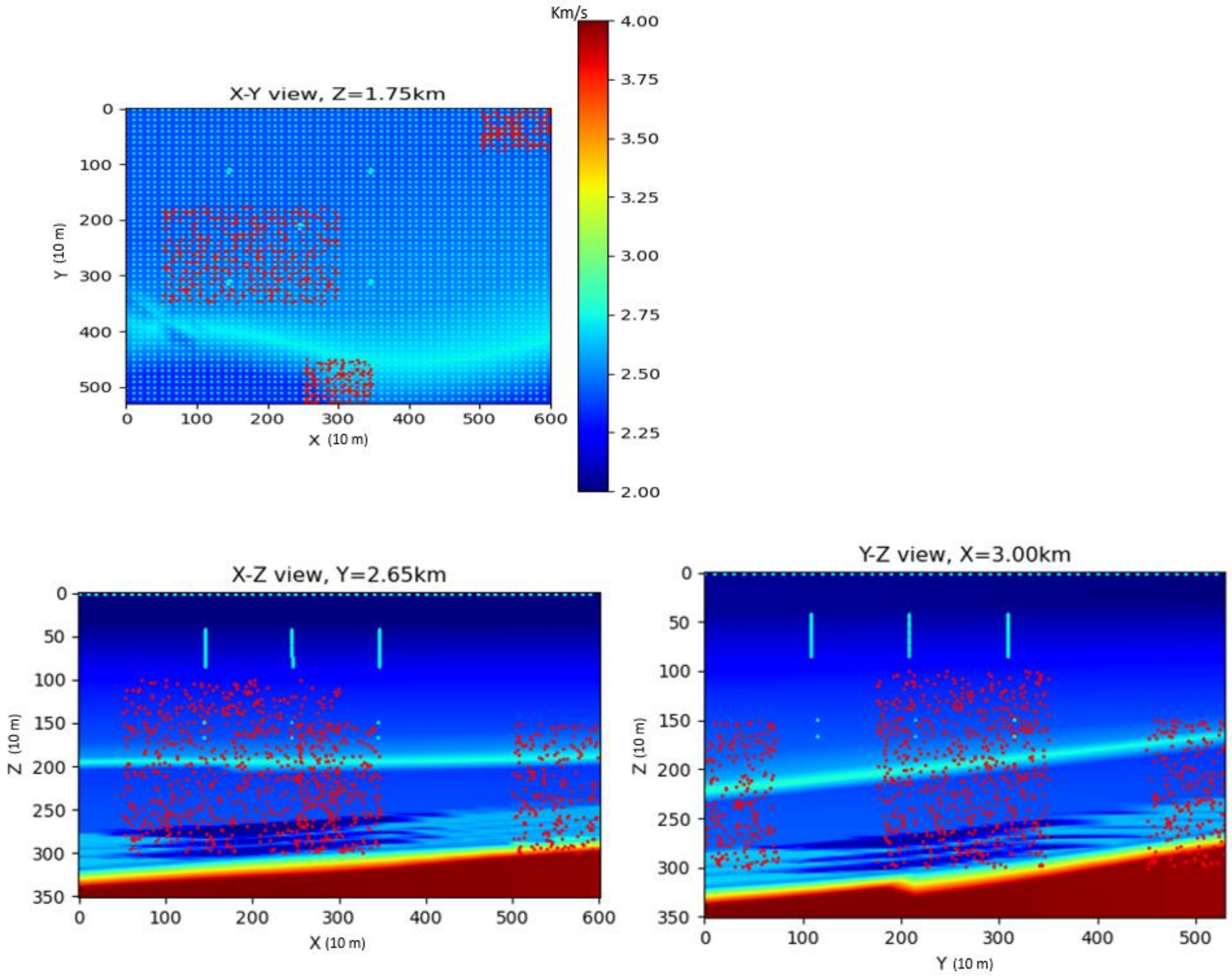
Microseismic Event Locations and Surface Geophone Grids



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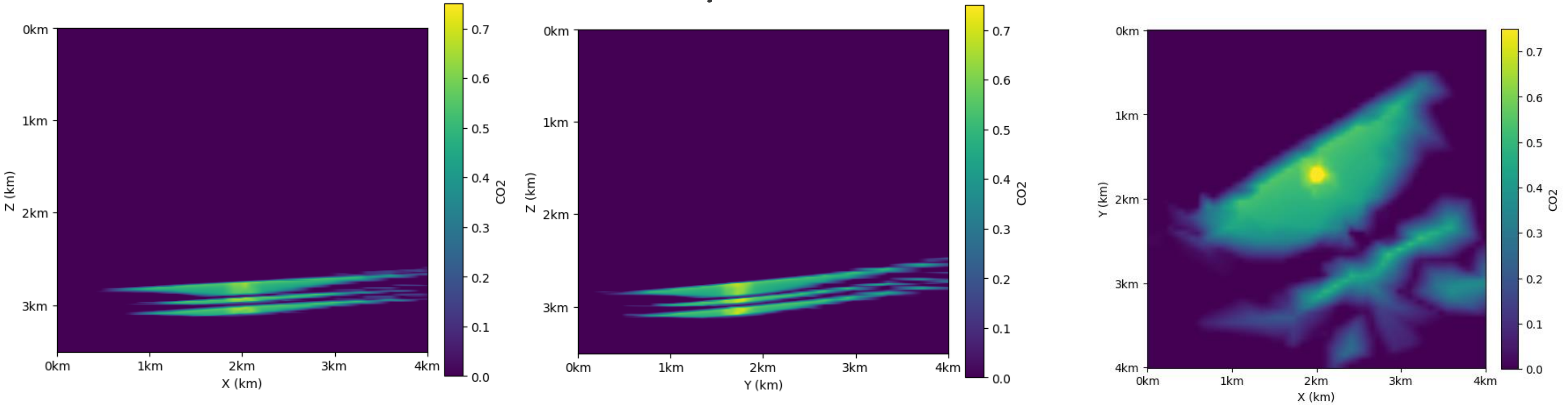
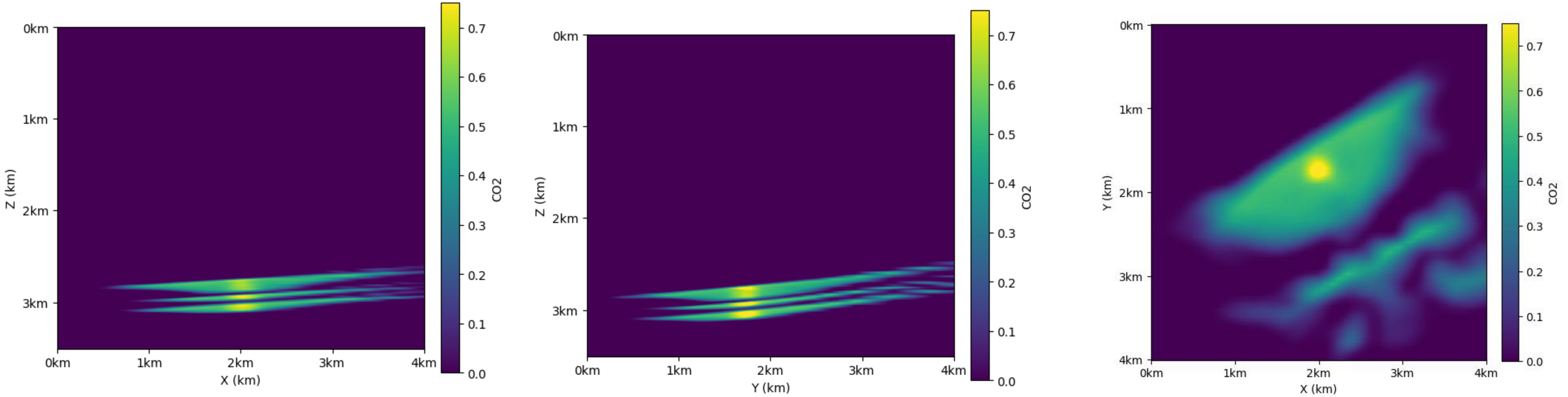
3D ML Inversion with Synthetic Kimberlina Test Data

Ground Truth:

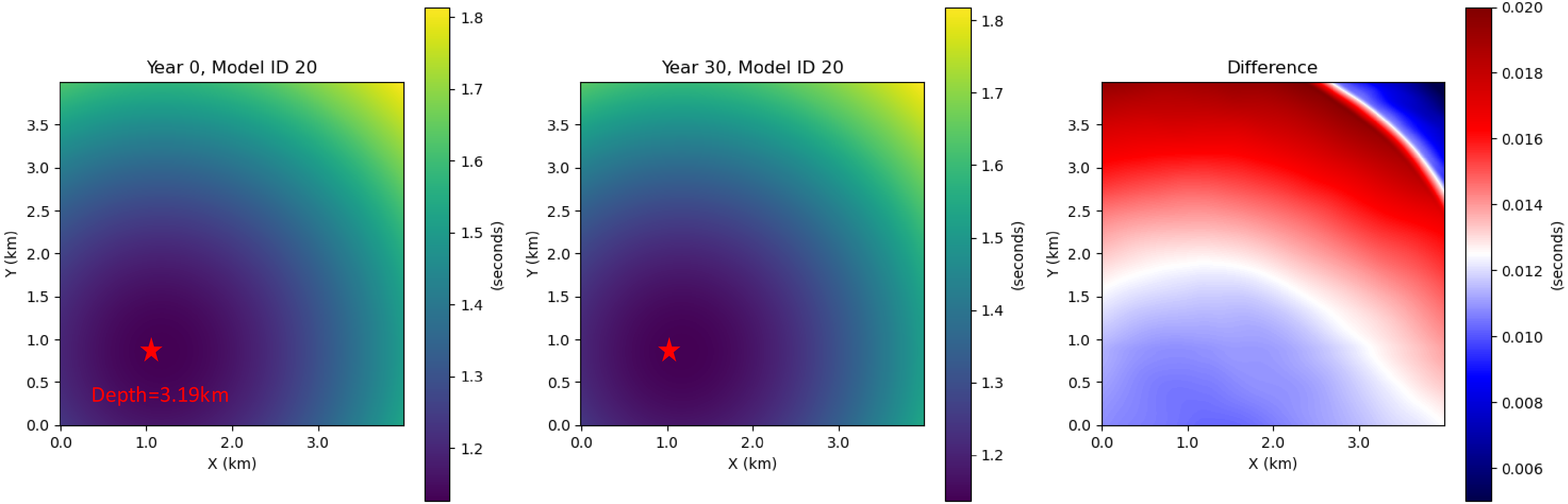


Prediction:



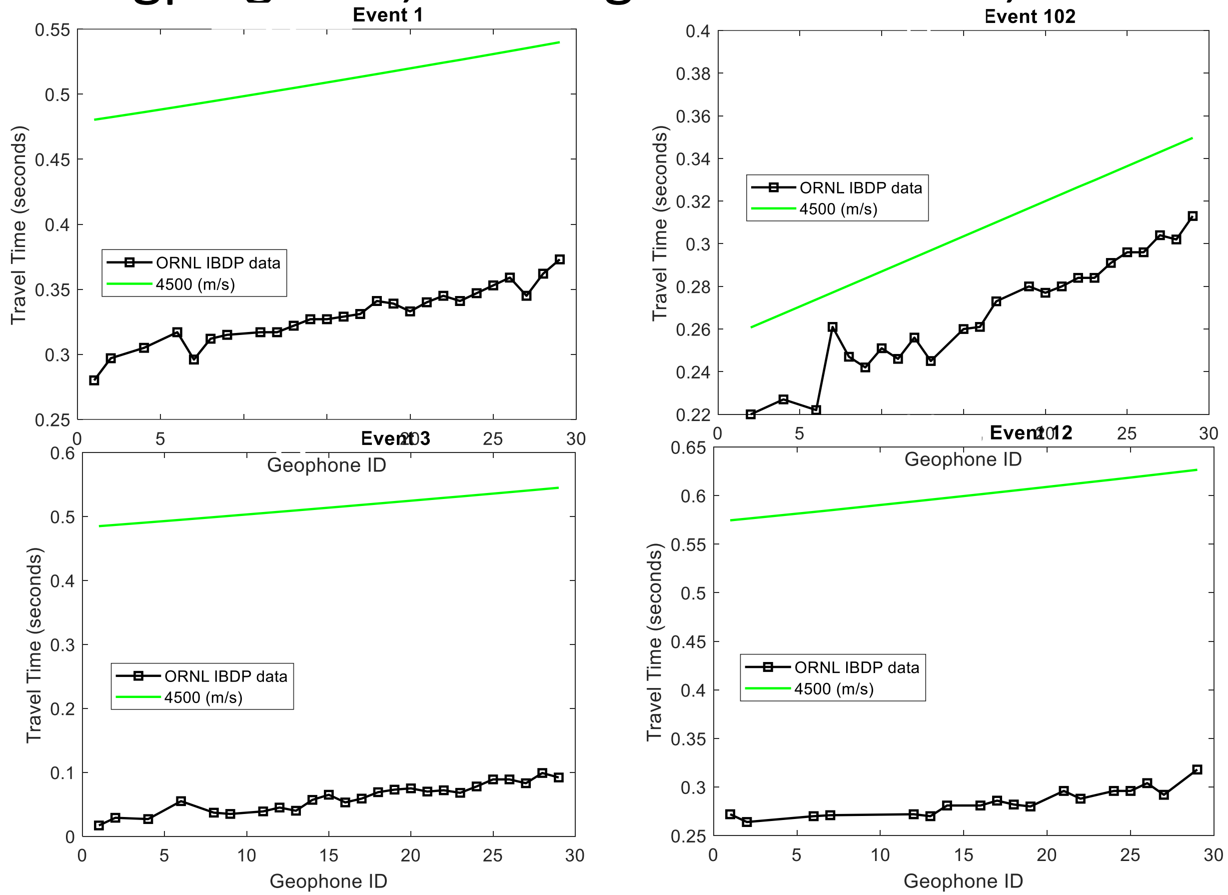
Element 4.4.1 – Modification of Active Source Seismic ML Imaging to use Microseismic locations as sources, and testing with Kimberlina Synthetic Data

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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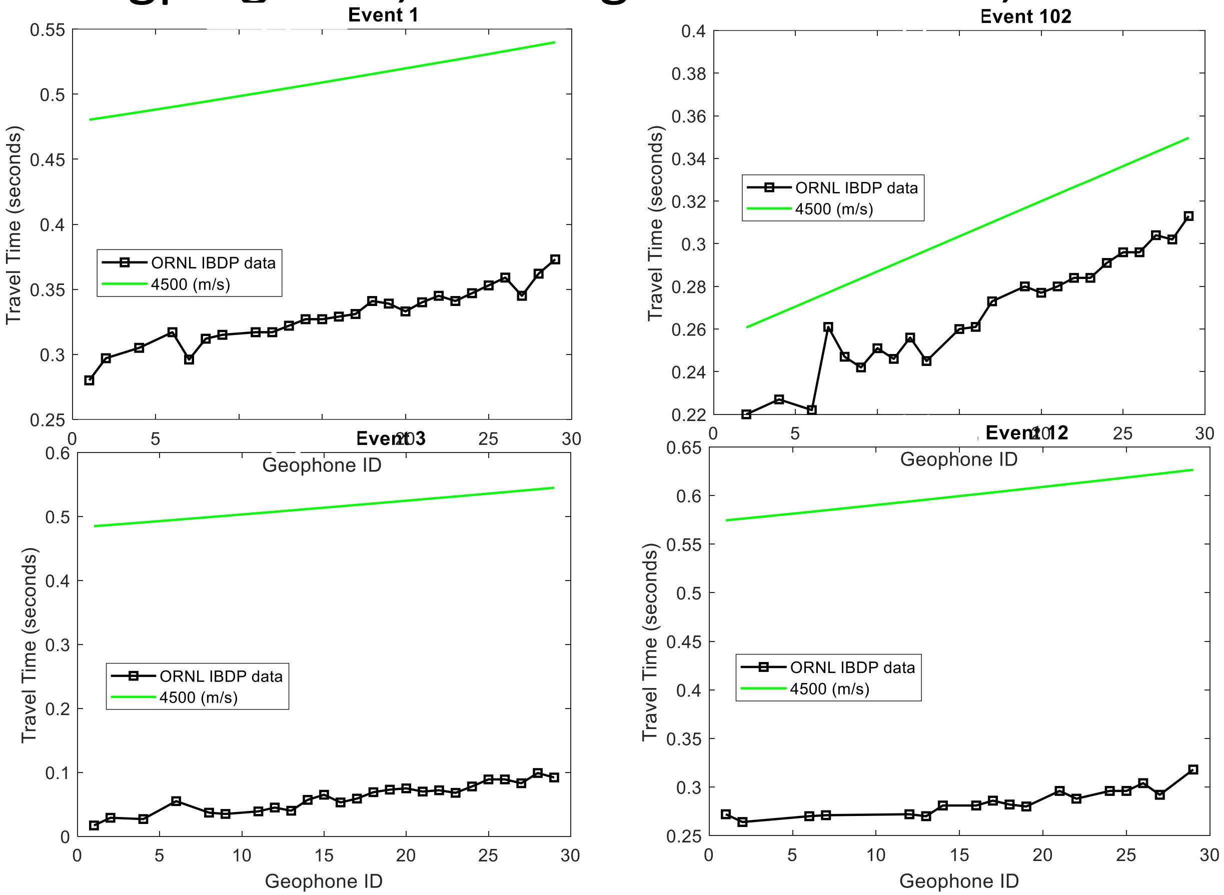

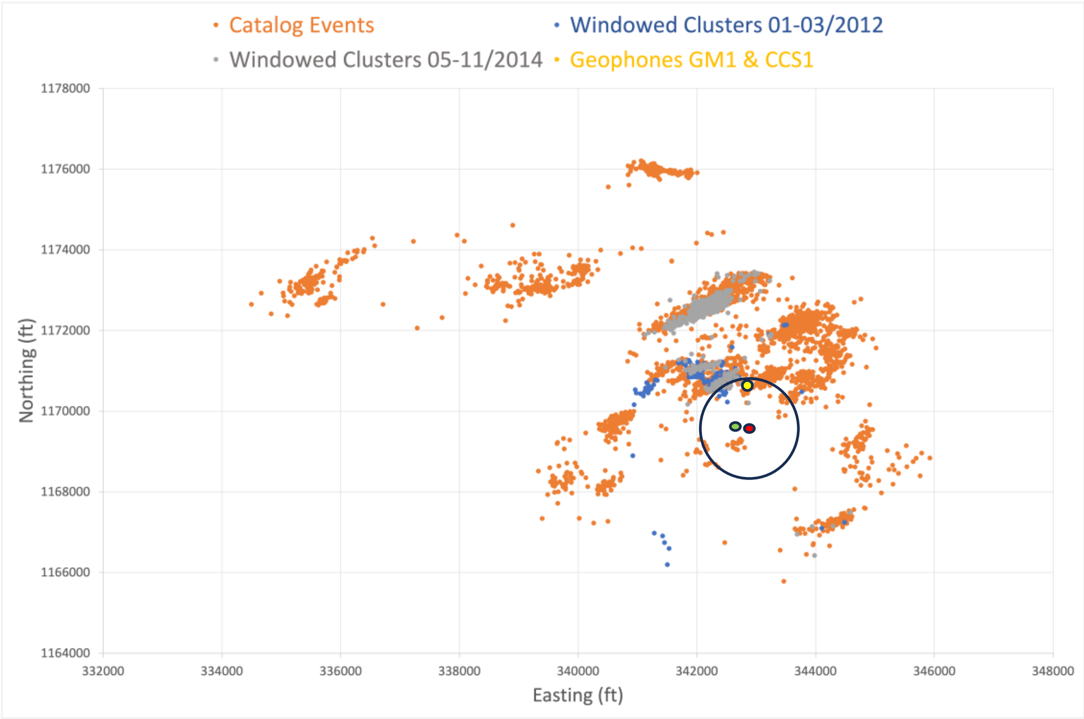

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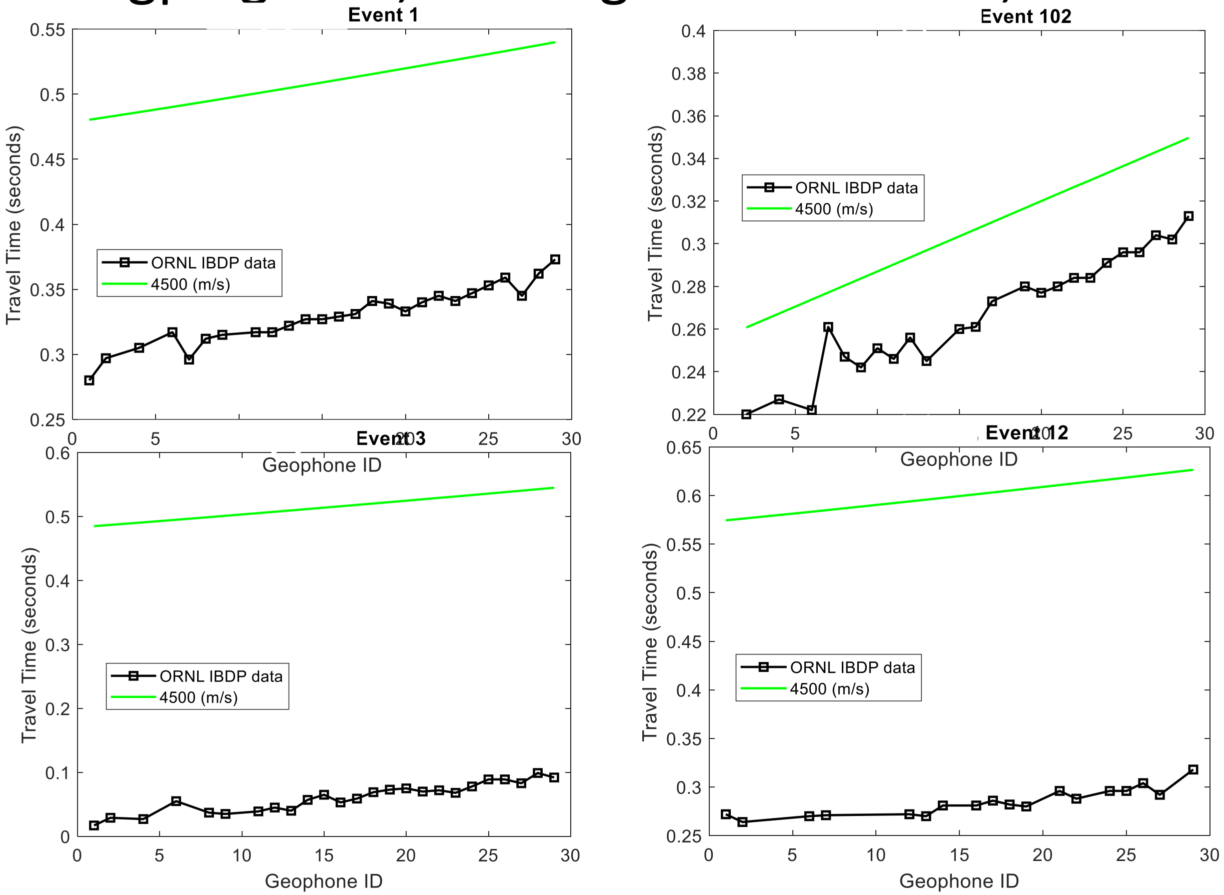

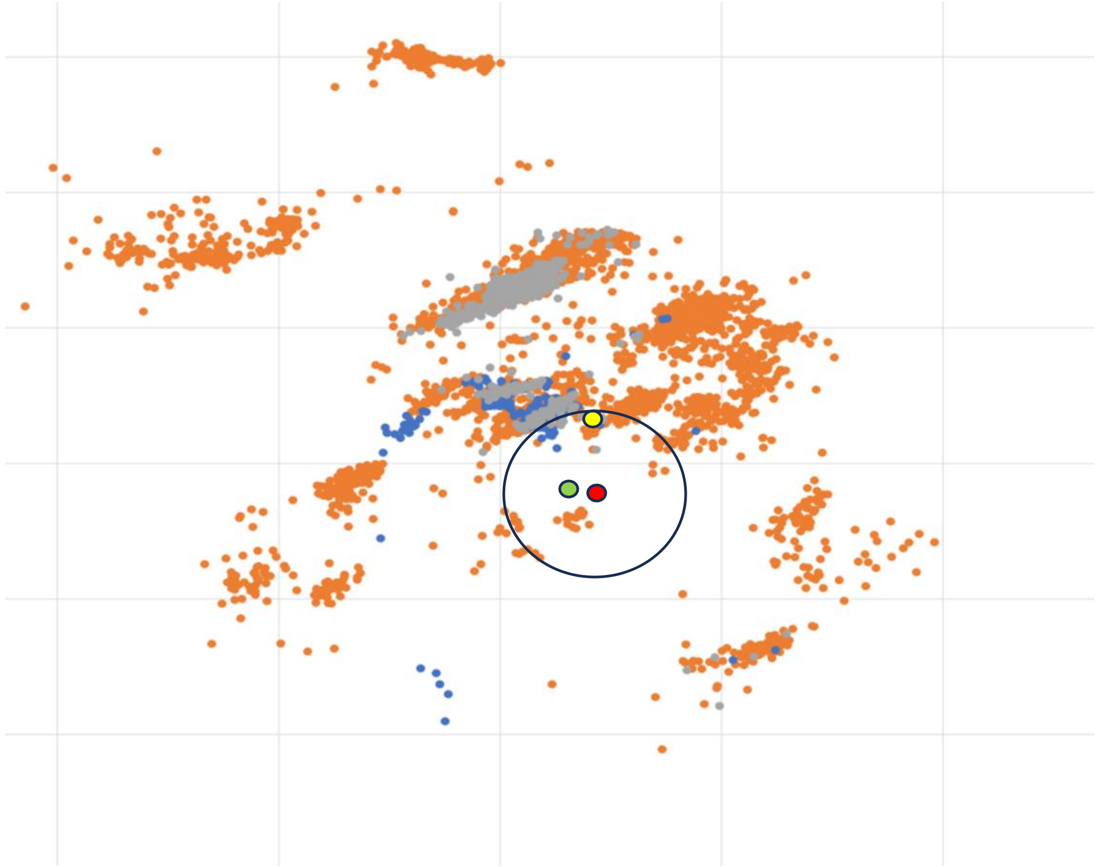

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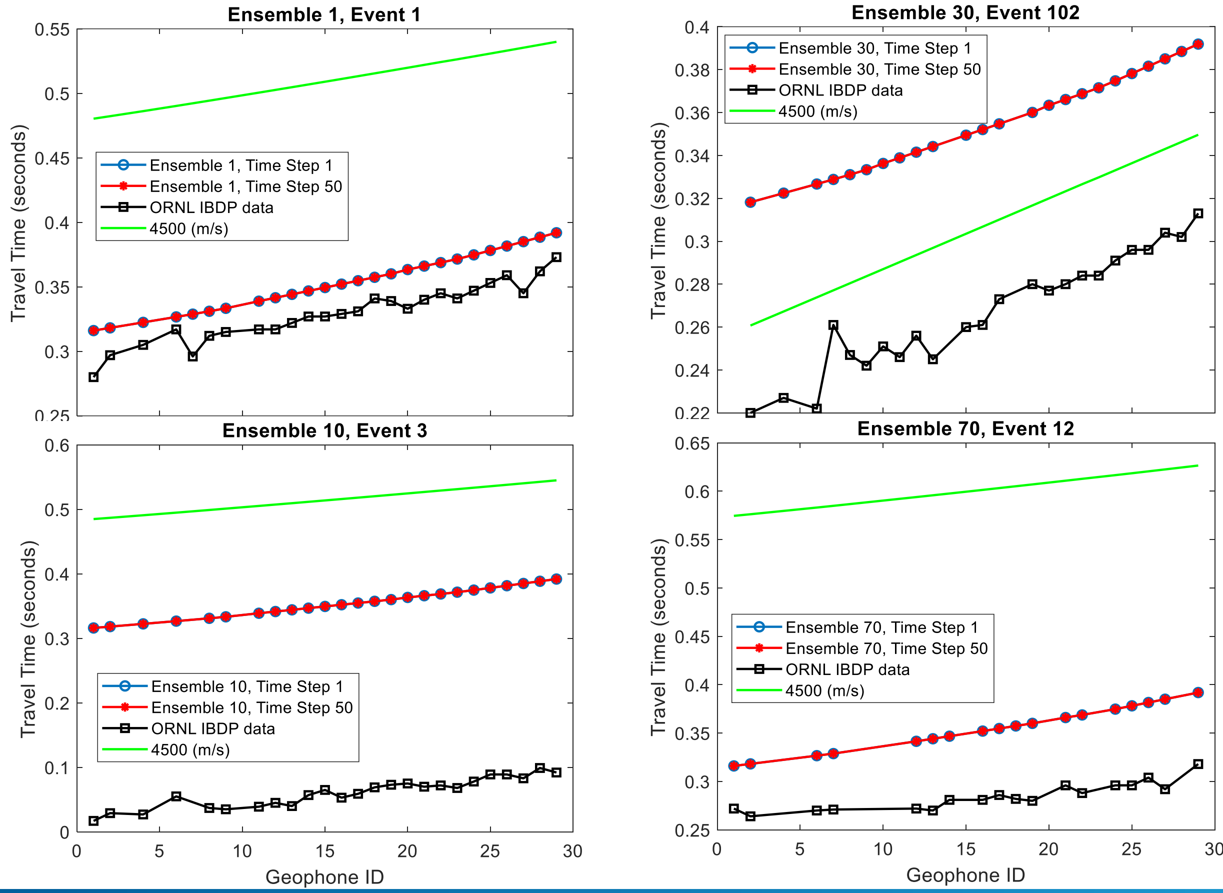
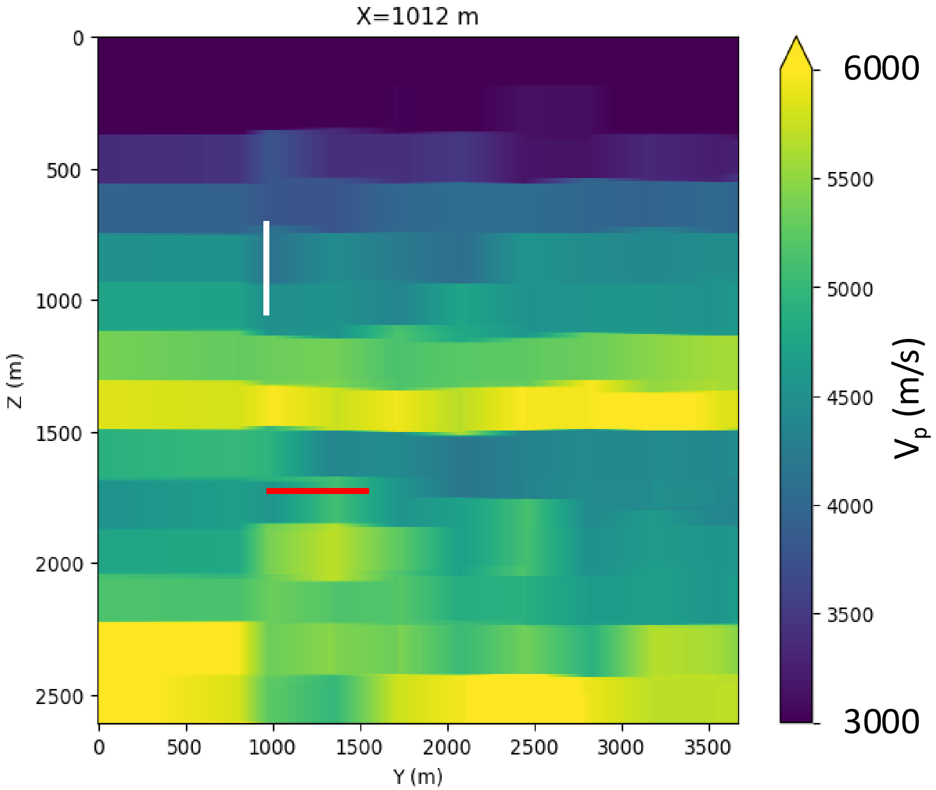
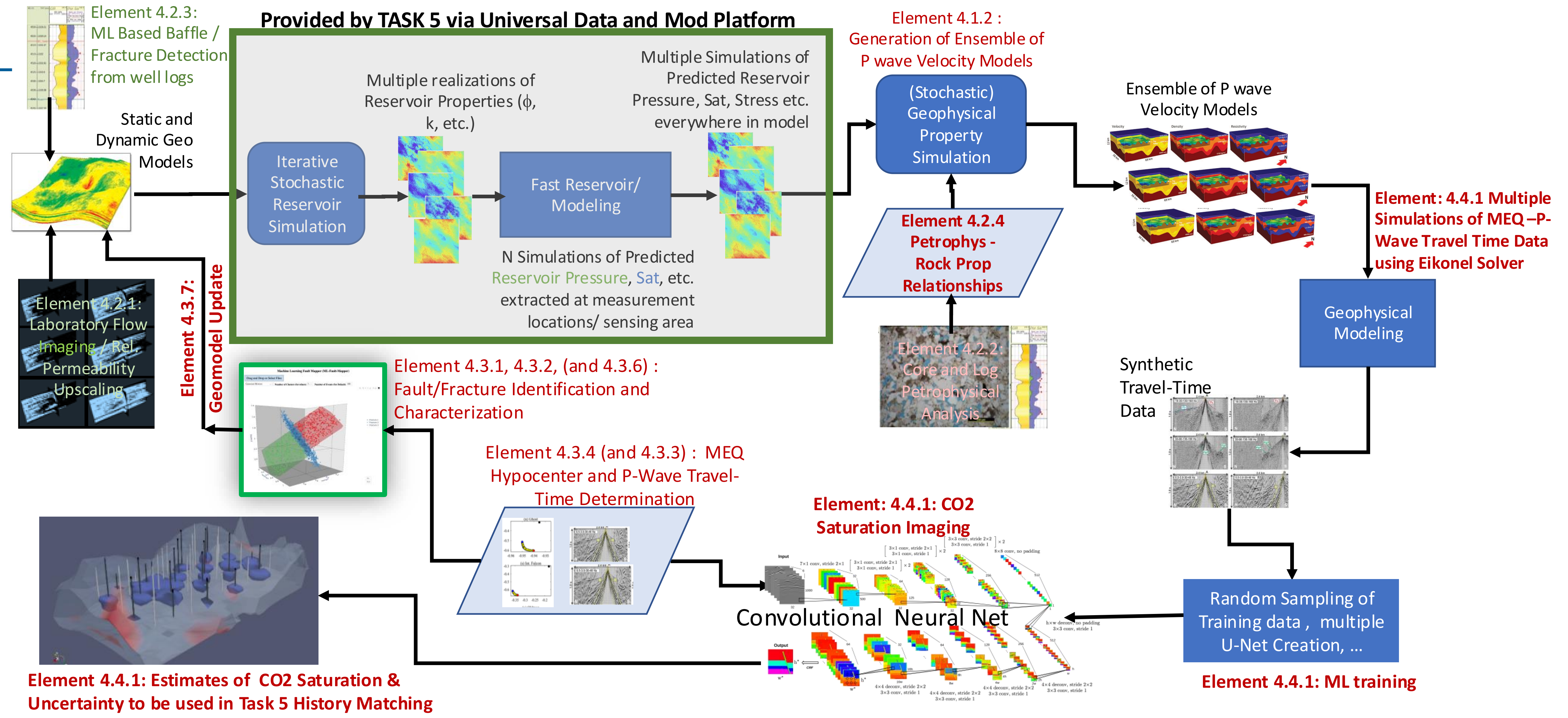
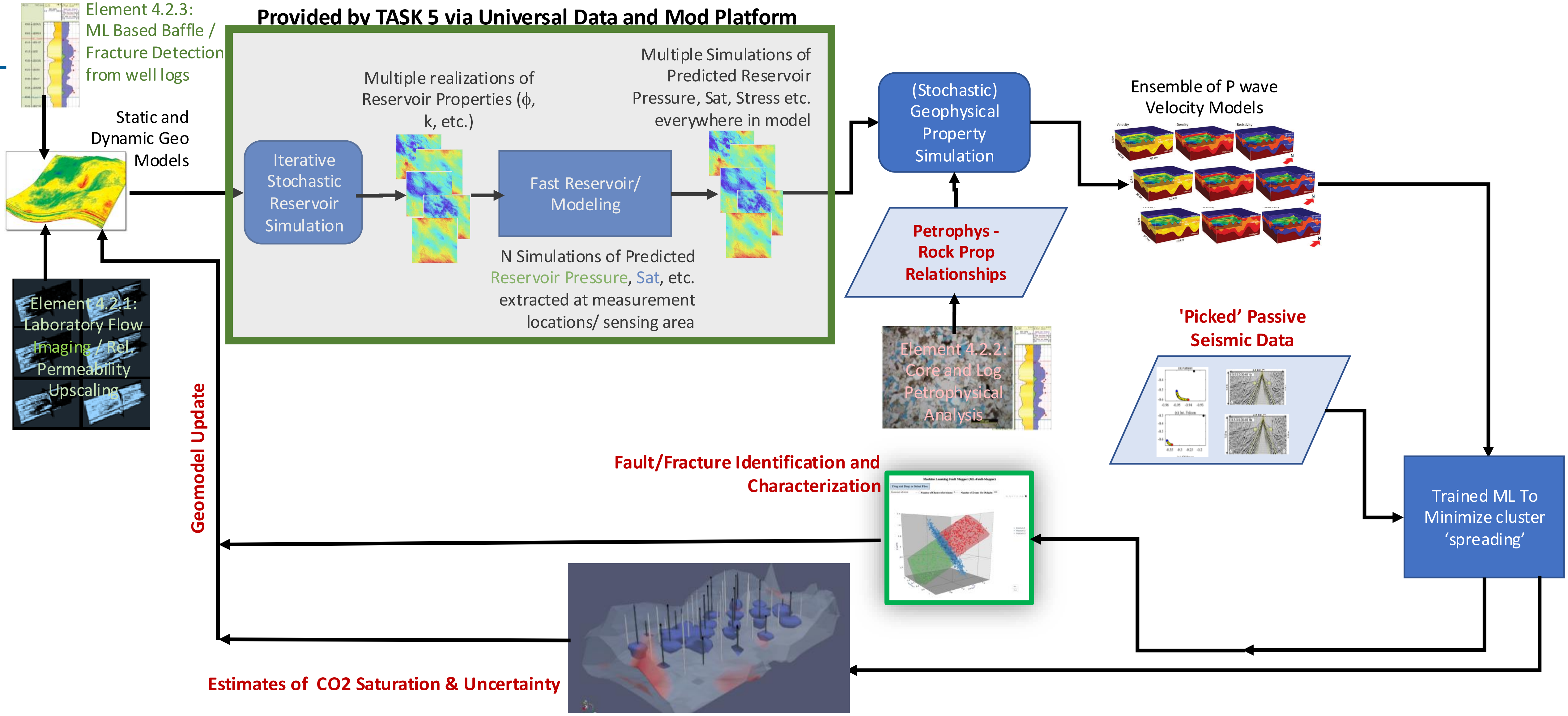




EY 23 Reservoir Property Imaging Workflow using Hypocenter Locations



Recommended Reservoir Imaging Workflow using Hypocenter Locations



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