Improving Subsurface Stress Characterization for Carbon Dioxide Storage Projects by Incorporating Machine Learning Techniques

(DE-FE0031684)

Dr. William Ampomah – New Mexico Tech – PRRC

Dr. Lianjie Huang – Los Alamos National Laboratory

U.S. Department of Energy

National Energy Technology Laboratory

2021 Carbon Management and Oil and Gas Research Project Review Meeting

August 2021

Acknowledgments

We thank DOE/NETL for the award opportunity through DE-FE0031684 and our partners.

Outline

- Project overview
- Project objectives
- Technical Approach
- Accomplishments
- Summary

Project Overview

– Funding Profile

– Project Performance Dates:

10/01/2018 – 09/30/2021*

	Budget		Budget		Budget	
	Project Year 1		Project Year 2		Project Year 3	
	DOE	Cost share	DOE	Cost share	DOE	Cost share
New Mexico Tech (Recipient) - Cash	$ 308,034.80	$ 64,856.06	$ 340,729.27	$ 64,639.40	$ 303,499.19	$ 63,595.20
Schlumberger Technology - InKind	$ -	$ 66,666.67	$ -	$ 66,666.67	$ -	$ 66,666.67
Non-FFRDC Subtotal:	$ 308,034.80	$ 131,522.73	$ 340,729.27	$ 131,306.07	$ 303,499.19	$ 130,261.87
Sandia National Lab	$ 50,000.00	$ -	$ 50,000.00	$ -	$ 50,000.00	$ -
Los Alamos National Lab	$ 150,000.00	$ -	$ 150,000.00	$ -	$ 100,000.00	$ -
FFRDC Subtotal:	$ 200,000.00	$ -	$ 200,000.00	$ -	$ 150,000.00	$ -

We have requested a no-cost extension for a year

NEW MEXICO TECH
SCIENCE • ENGINEERING • RESEARCH UNIVERSITY

Los Alamos NATIONAL LABORATORY EST. 1943 · SWP Southwest Regional Partnership on Carbon Sequestration · Sandia National Laboratories · Schlumberger · NETL NATIONAL ENERGY TECHNOLOGY LABORATORY · U.S. DEPARTMENT OF ENERGY · Perdure Petroleum

Project Team

New Mexico Tech

Dr. William Ampomah (PI)
Dr. Robert Balch
Mr. George El-Kasseh
Ms. Martha Cather

LANL

Dr. Lianjie Huang (Co-PI)
Dr. Xuejian Liu (postdoc)
Dr. Yan Qin (postdoc)
Dr. Jiaxuan Li (GRA)
Dr. Kai Gao

Consultants

Dr. Tom Bratton
Mr. Donald Lee

Students

Ms. Marcia McMillan

Program Overview

Goals and Objectives

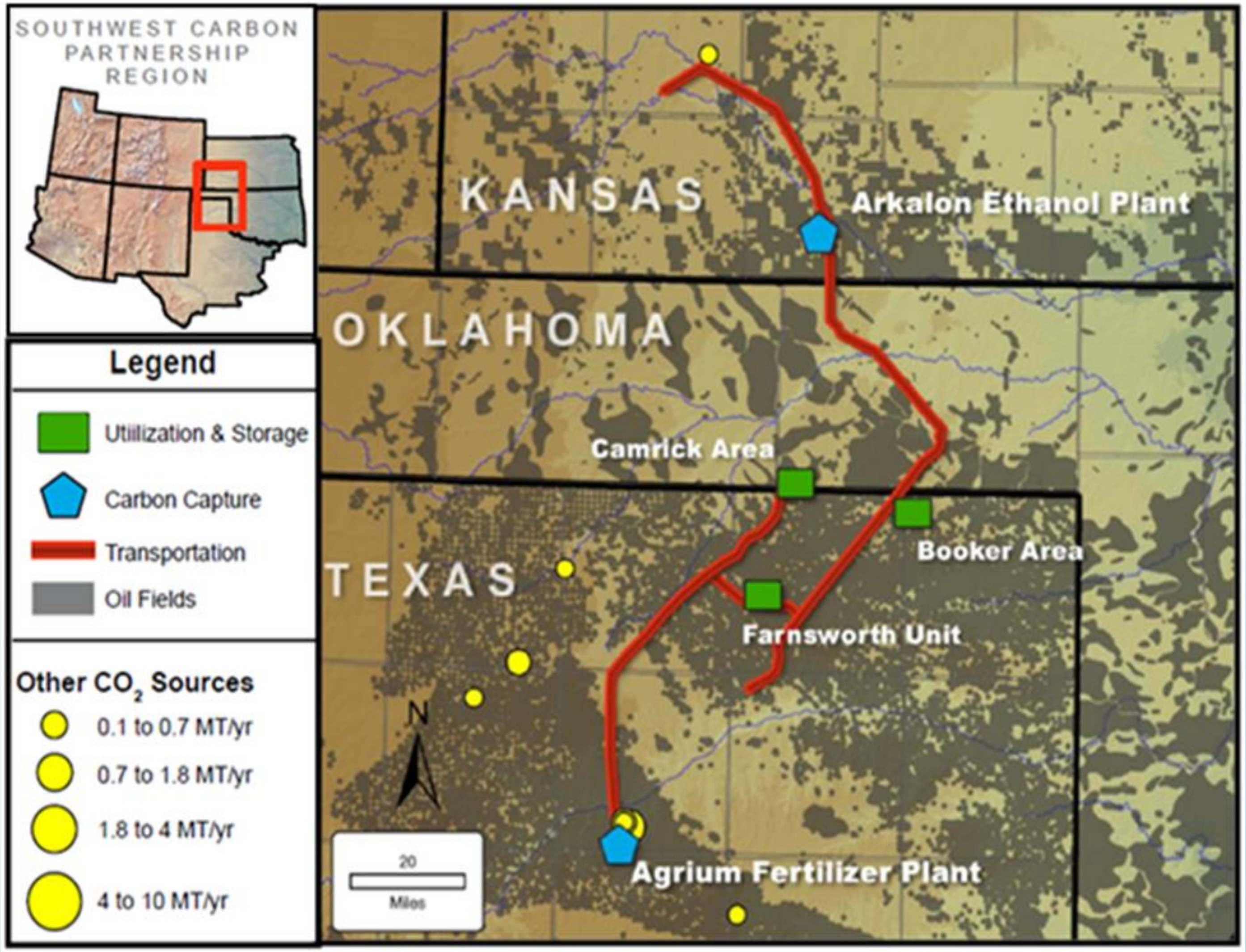
- The primary objective is to develop a framework to boost the reliability of characterization and prediction of the state of stress in the overburden and underburden (including the basement) in CO_2 storage reservoirs using novel machine learning and integrated geomechanics and geophysical methods.

- We use field data and models developed by the Southwest Regional Partnership on Carbon Sequestration (SWP) for the Farnsworth Unit (FWU), a CO_2 enhanced oil recovery (EOR) project being conducted by Perdure in Ochiltree County, Texas, to verify the improved capabilities of our methods.

- The integration methodology is an adaptation of industry accepted practices for calibration of flow simulation models to coupled geomechanical models for improved stress prediction. Computational challenges will be overcome through application of Machine Learning.

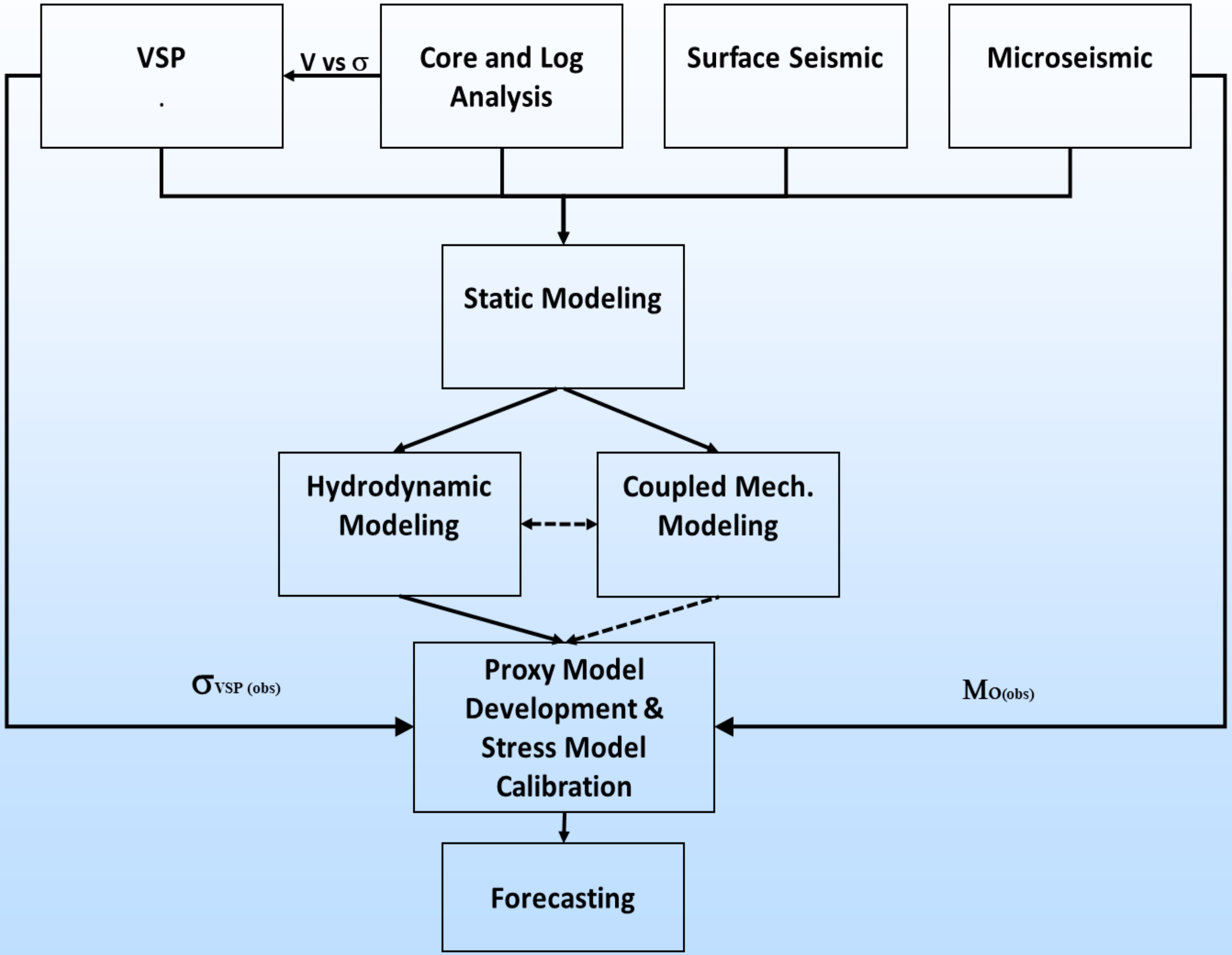
Technology/Site Selection

- Demonstrated at the Farnsworth Unit ongoing CO_2 EOR development:
  - Discovered 1956
  - Primary depletion until~ 1965
  - Waterflood until ~2010
  - CO2 WAG EOR Started 2010
- 2 anthropogenic CO_2 sources
- Extensive characterization dataset previously was acquired, and modeling performed by the SWP partnership



Technical Approach/Project Scope

- The final outcome of this work will be a methodology for integration of multi-disciplinary data to reduce uncertainty in estimation of stress changes in the storage complex and underburden.
- Significant project risks include stress-sensitivity of rock behavior under anticipated effective stress changes, and microseismic data characteristics.
- The robust characterization dataset which includes extensive geological, geophysical, and geomechanical, and seismological data provide opportunities for technical risk mitigation through alternative integration strategies.



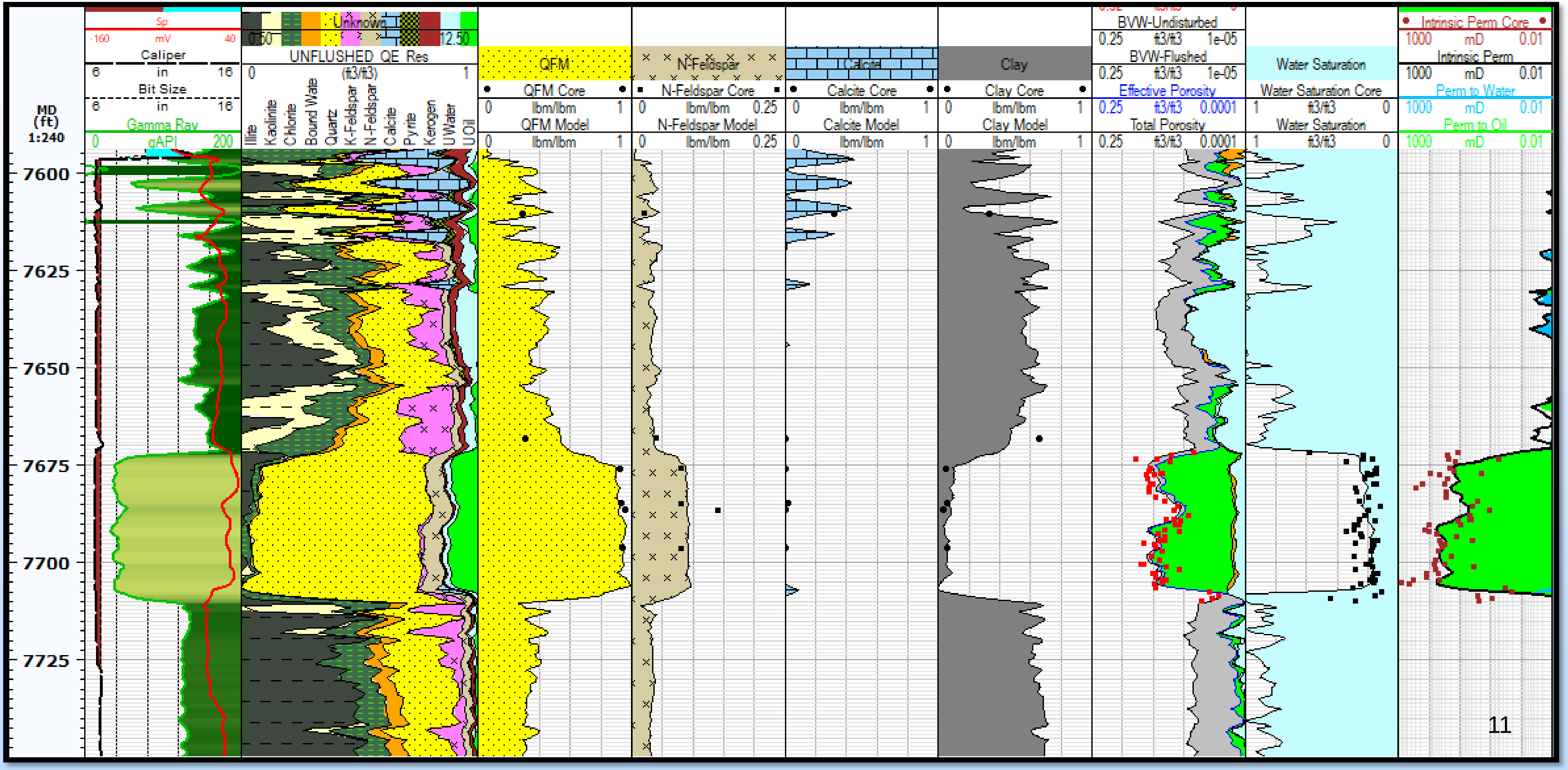
Technical Approach/Project Scope

Task/ Subtask	Milestone Title	Planned Completion	Status
1	Project Management Plan	1/31/2018	PMP file
1	Kickoff Meeting	11/31/18	Completed
2.2	1D MEM Model	2/28/2019	Completed
2.4	VSP Elastic Inversion	10/31/2019	Completed
2.6	VSP Stress Estimation	2/28/2019	Completed
3	Microseismic Analysis	11/31/2020	Ongoing
4	3D MEM Model	9/30/2019	Completed
5	Hydrodynamic History Matching	3/31/2020	Completed
6	Evaluation of one-way and two-way coupling process	8/30/2020	Completed
7.1	Stress Objective function formulation	7/30/2020	Completed
7.4/7.5	Completion of VSP - history matching	5/31/2021	Completed
7.4/7.5	Microseismic- Geomechanics history match	9/30/2022	Ongoing
8	Forecasting pressure and stress	8/30/2021	Ongoing

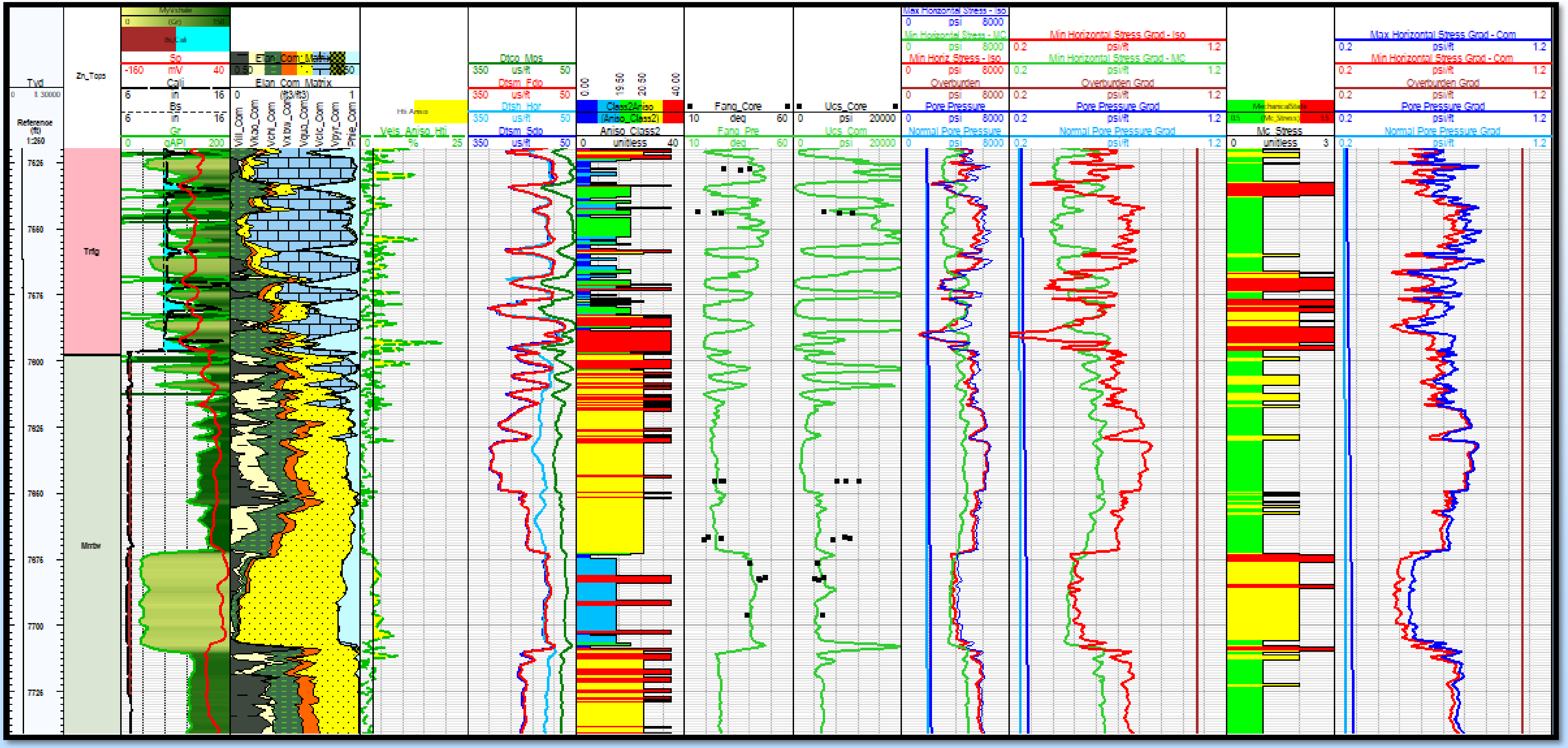
What is an Earth model? It can be 1D, 2D, 3D, and 4D

	Seismic, Wellbore images	Triple-combo, Sonic, Core	Wellbore images, Sonic, Core	Petrophysics, Sonic, Core
Intrinsic properties	**Framework** Structure Faults Horizons	**Petrophysics** Lithology, Vcl Porosity, Sw Matrix Perm Elastic Moduli	**Mechanical** Strat Column Facies Support Fracture Attributes	**Rock Strength** Compressive & Tensile Strength Friction Angle
Extrinsic properties	**Vertical Stress** Overburden	**Pore Pressure** Pore Pressure	**Stress Direction** Maximum Horizontal Stress Direction	**Stress Magnitude** Minimum & Maximum Horizontal Stress
	Density log, Petrophysics	Formation testing, Petrophysics, Mud logs	Wellbore images, Sonic, 4-Arm calipers	In-situ stress tests, Sonic

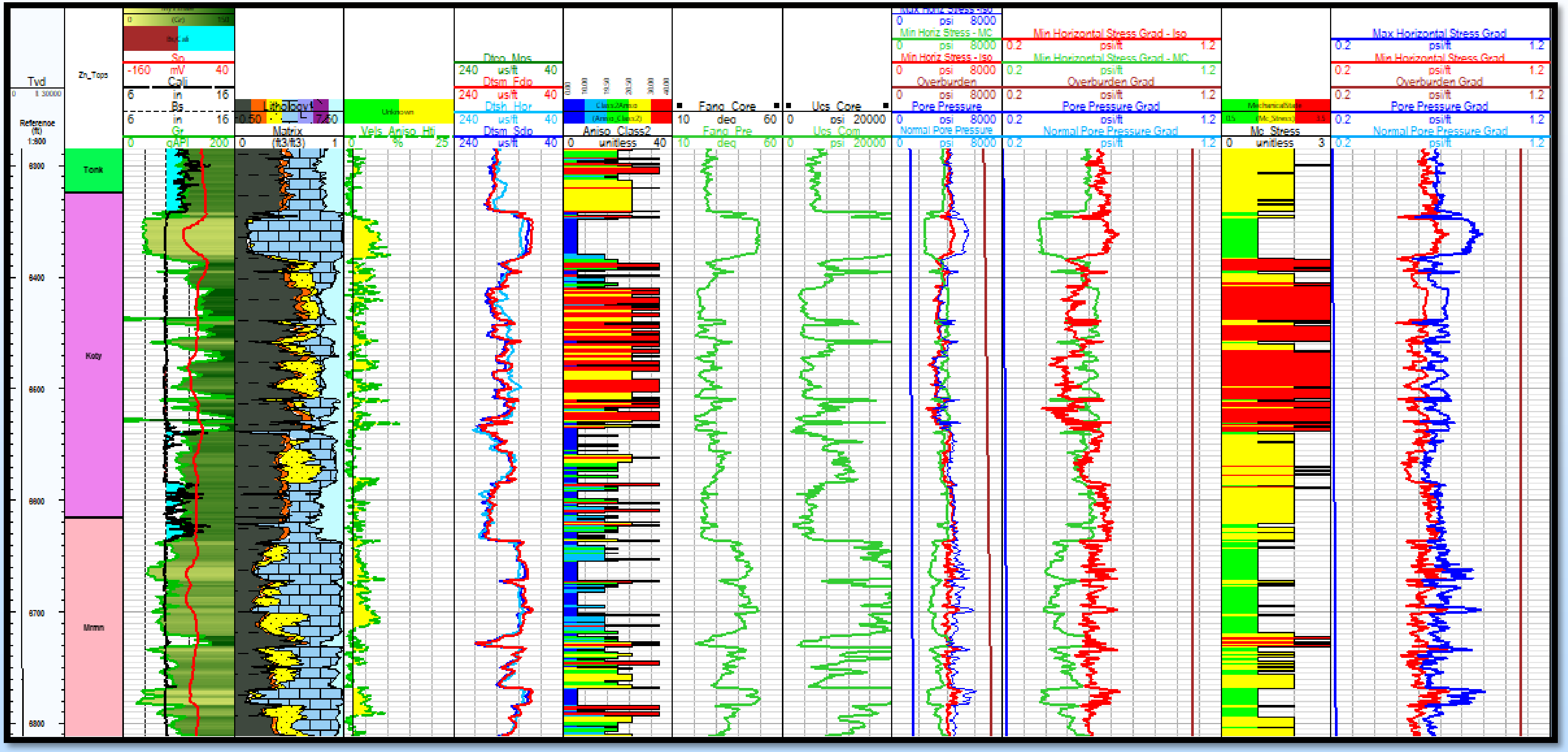
Morrow B petrophysics



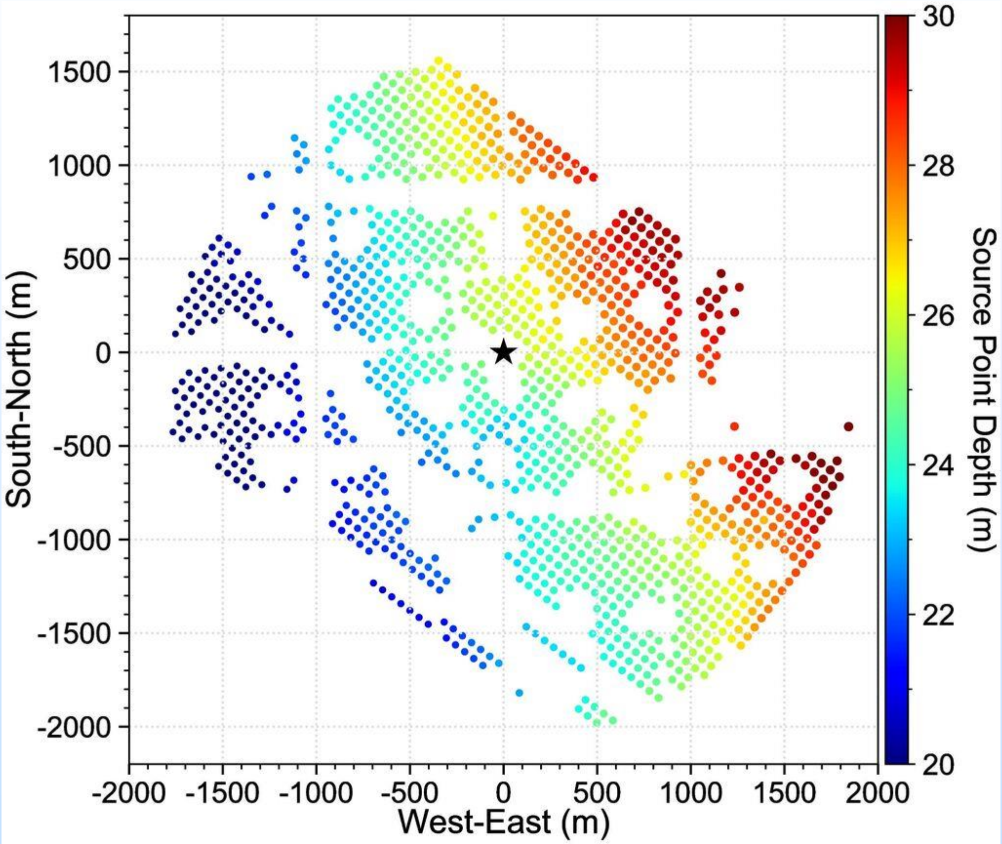
Horizontal stress model

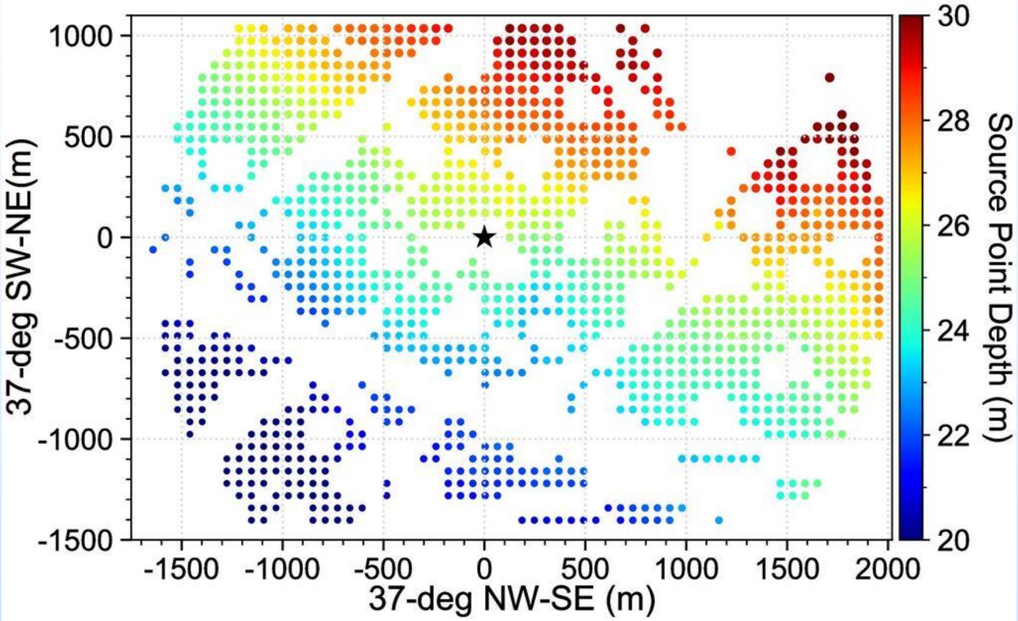


Horizontal stress model –Kansas City Formation



Time-lapse 3D (4D) VSP Monitoring





3D VSP Data Acquisition Geometry

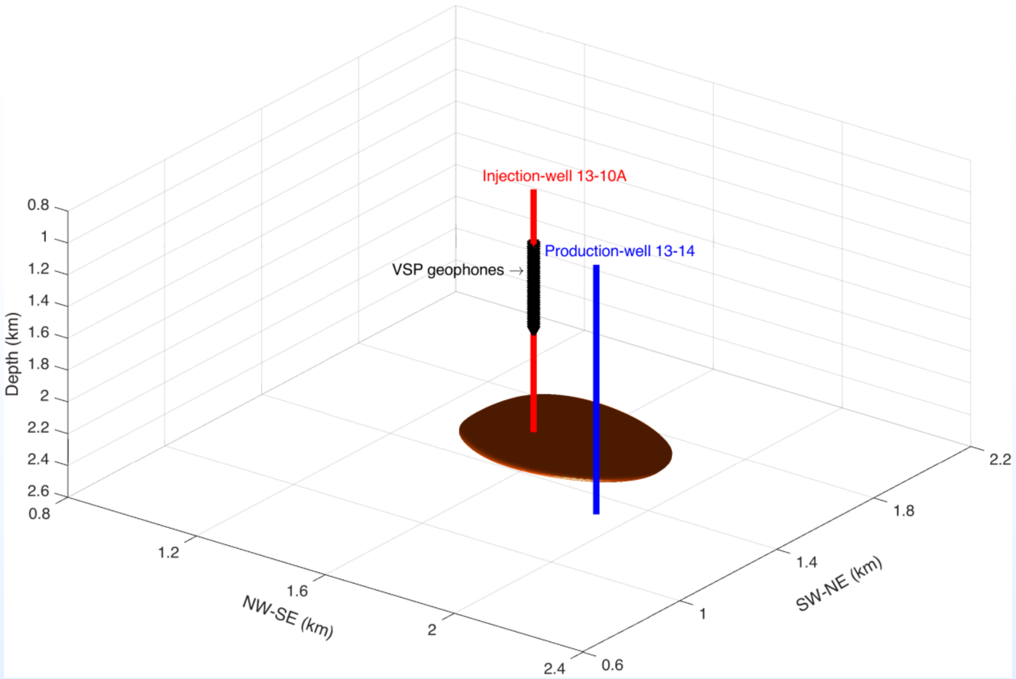
Time-Lapse Seismic Data and CO_2 Injection

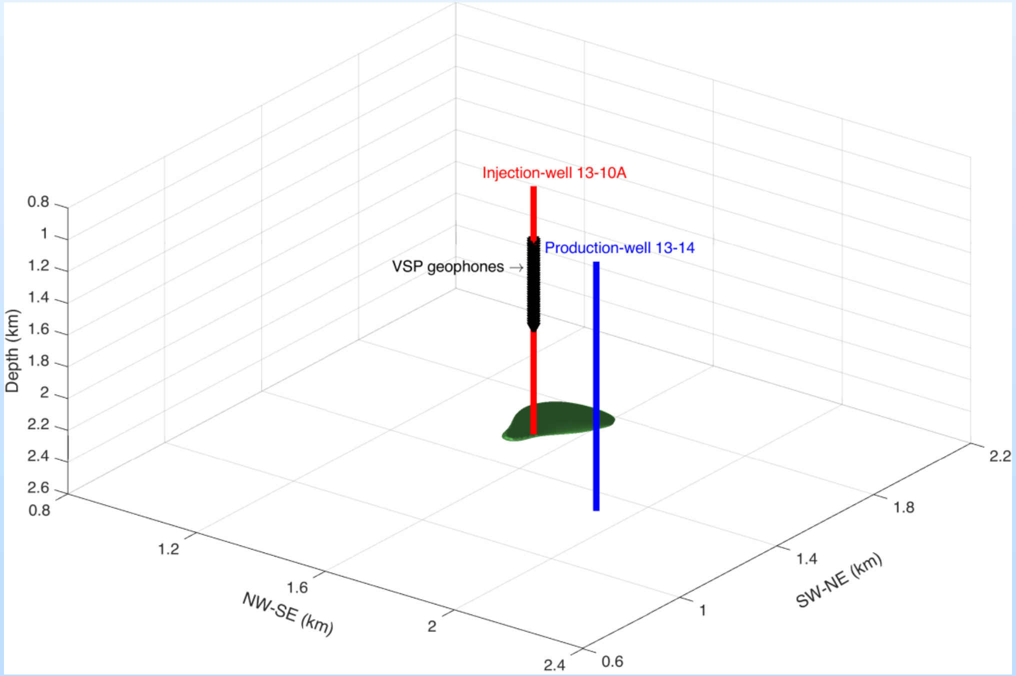
- 3D-1C surface seismic data: Nov 2013
- 3D-3C baseline VSP data : February 2014
- 3D-3C monitor1 VSP data : January 2015
- 3D-3C monitor2 VSP data : November 2016
- 3D-3C monitor3 VSP data : December 2017

- Base Line --> Monitor 1: Injected CO2= 33,070.25 tons
- Base Line --> Monitor 2: Injected CO2= 76,597.14 tons
- Base Line --> Monitor 3: Injected CO2= 94,286.38 tons

- Monitor 1 --> Monitor 2: Injected CO2 = 43,526.89 tons
- Monitor 2-->Monitor 3: Injected CO2 = 17,689.24 tons

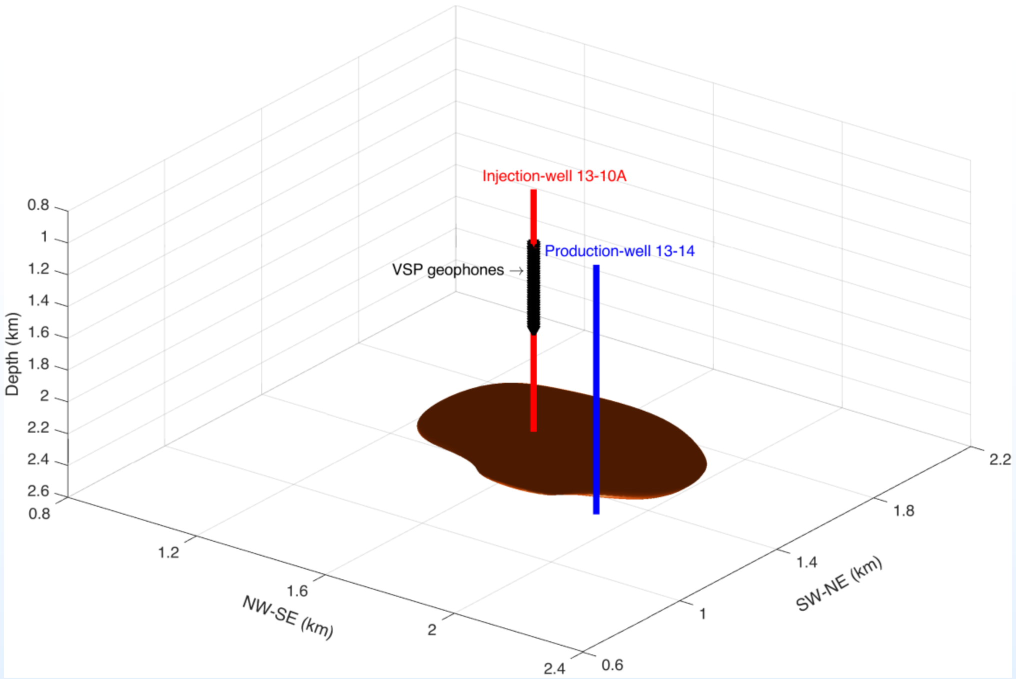
ΔVp = -10 m/s
ΔVs = -10 m/s

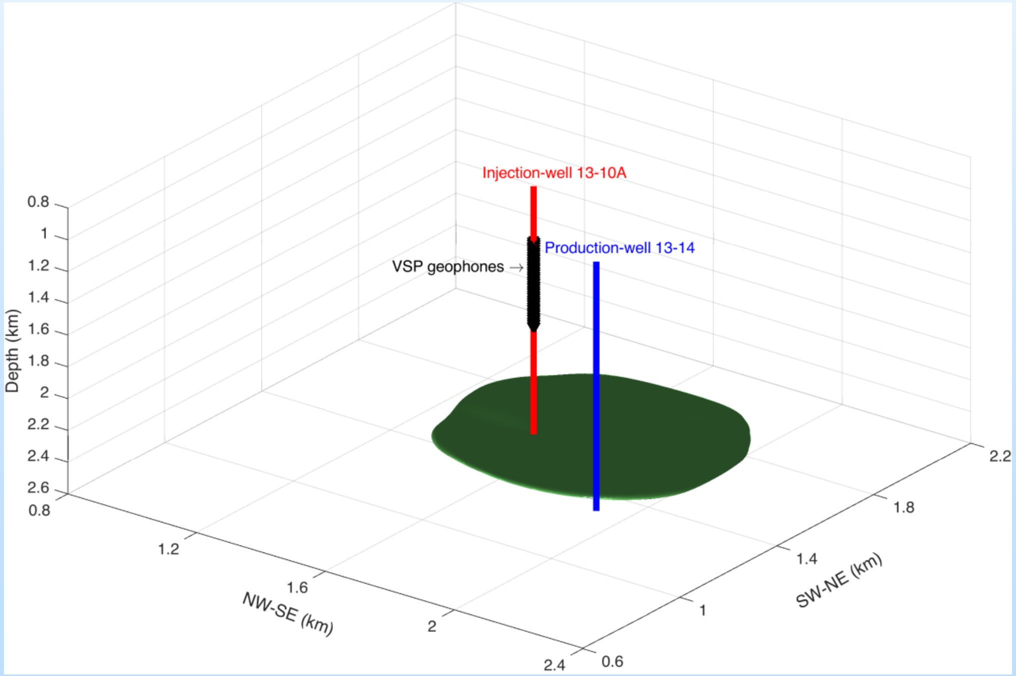




Time-lapse Vp & Vs between Monitor 1 and Baseline

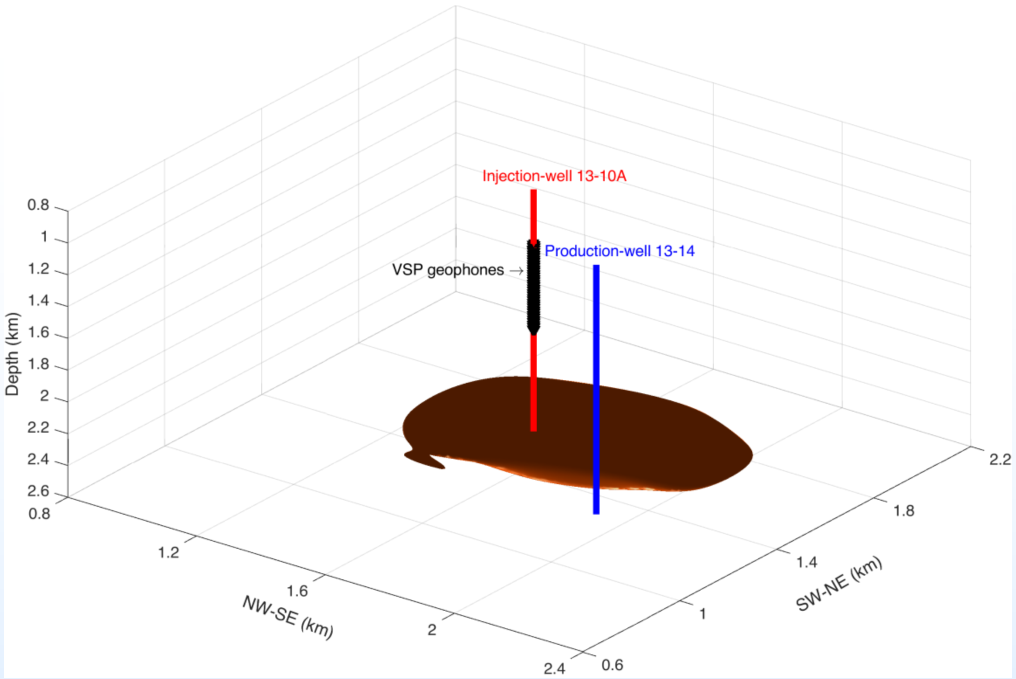
ΔVp = -10 m/s
ΔVs = -10 m/s

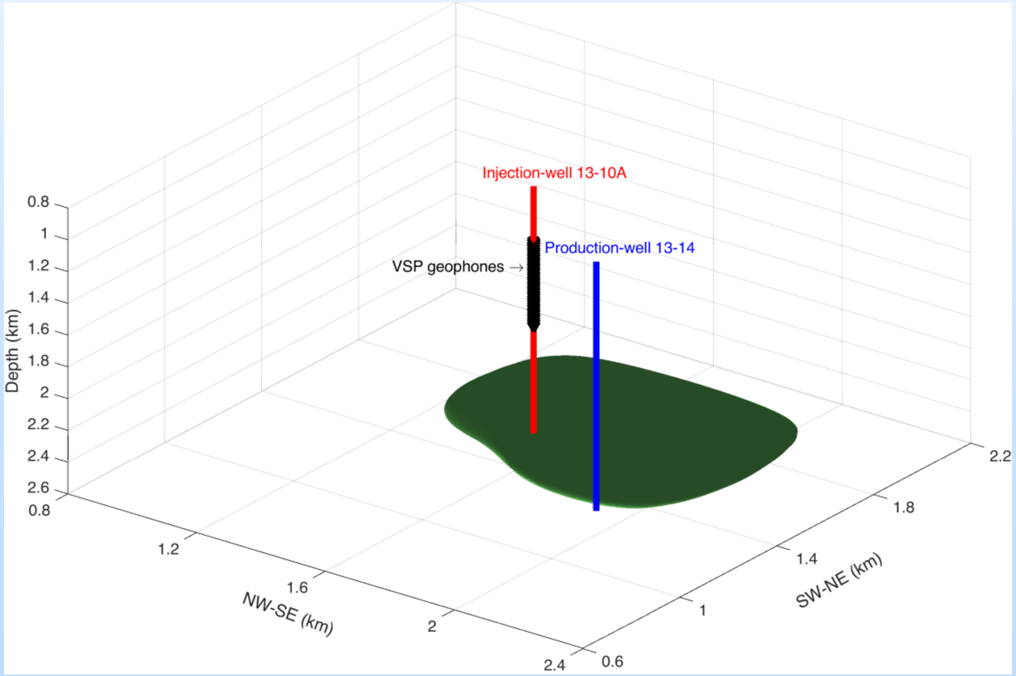




Time-lapse Vp & Vs between Monitor 2 and Baseline

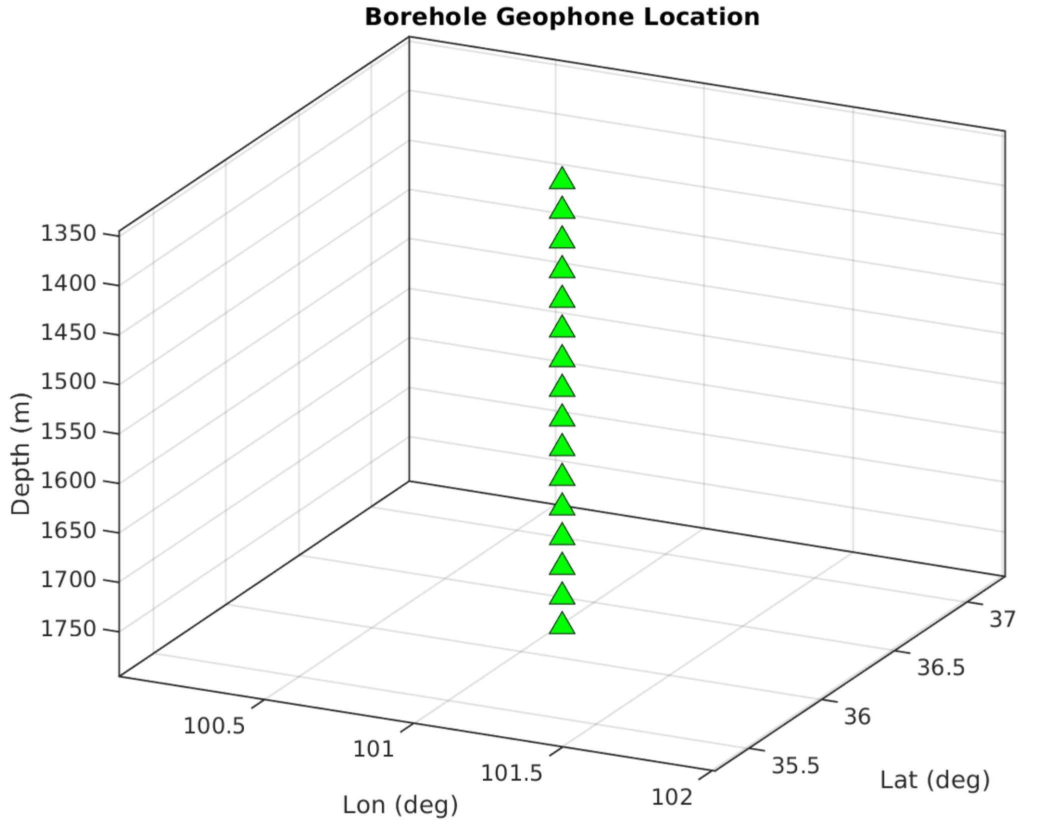
ΔVp = -10 m/s
ΔVs = -10 m/s

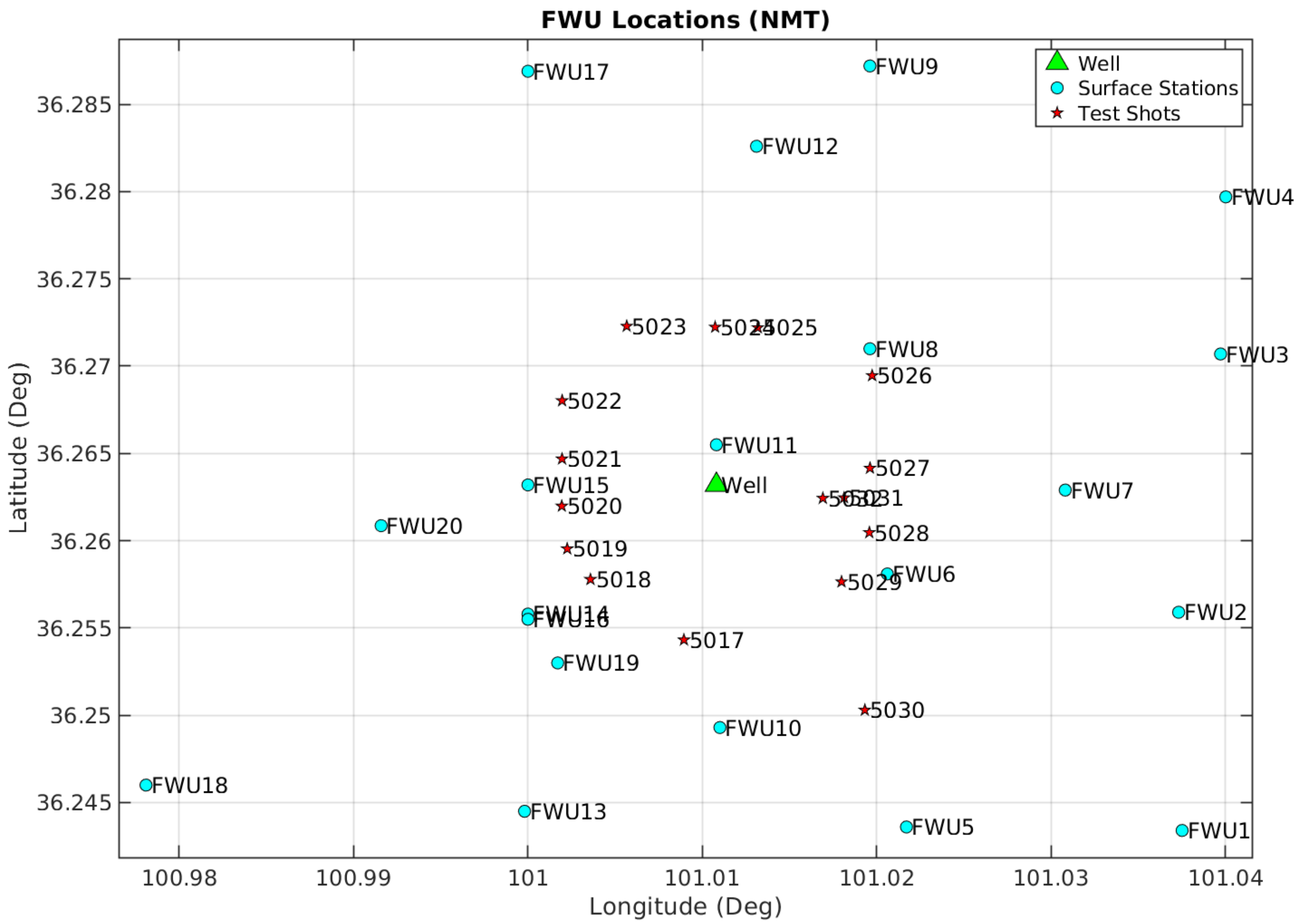




Time-lapse Vp & Vs between Monitor 3 and Baseline

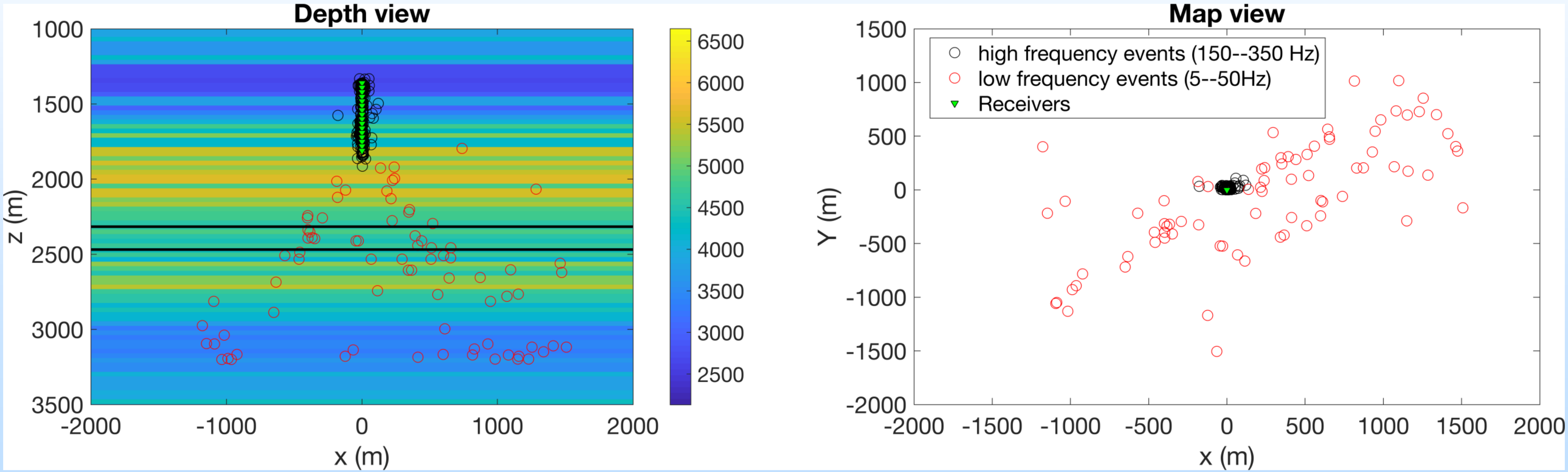
Microseismic Monitoring

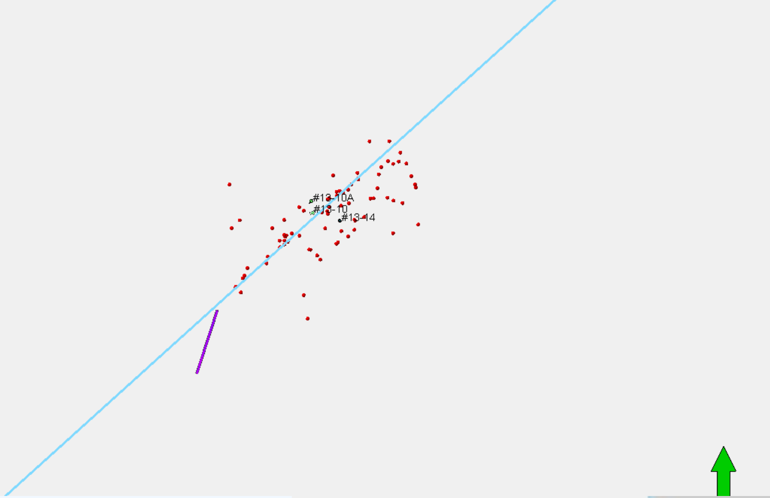


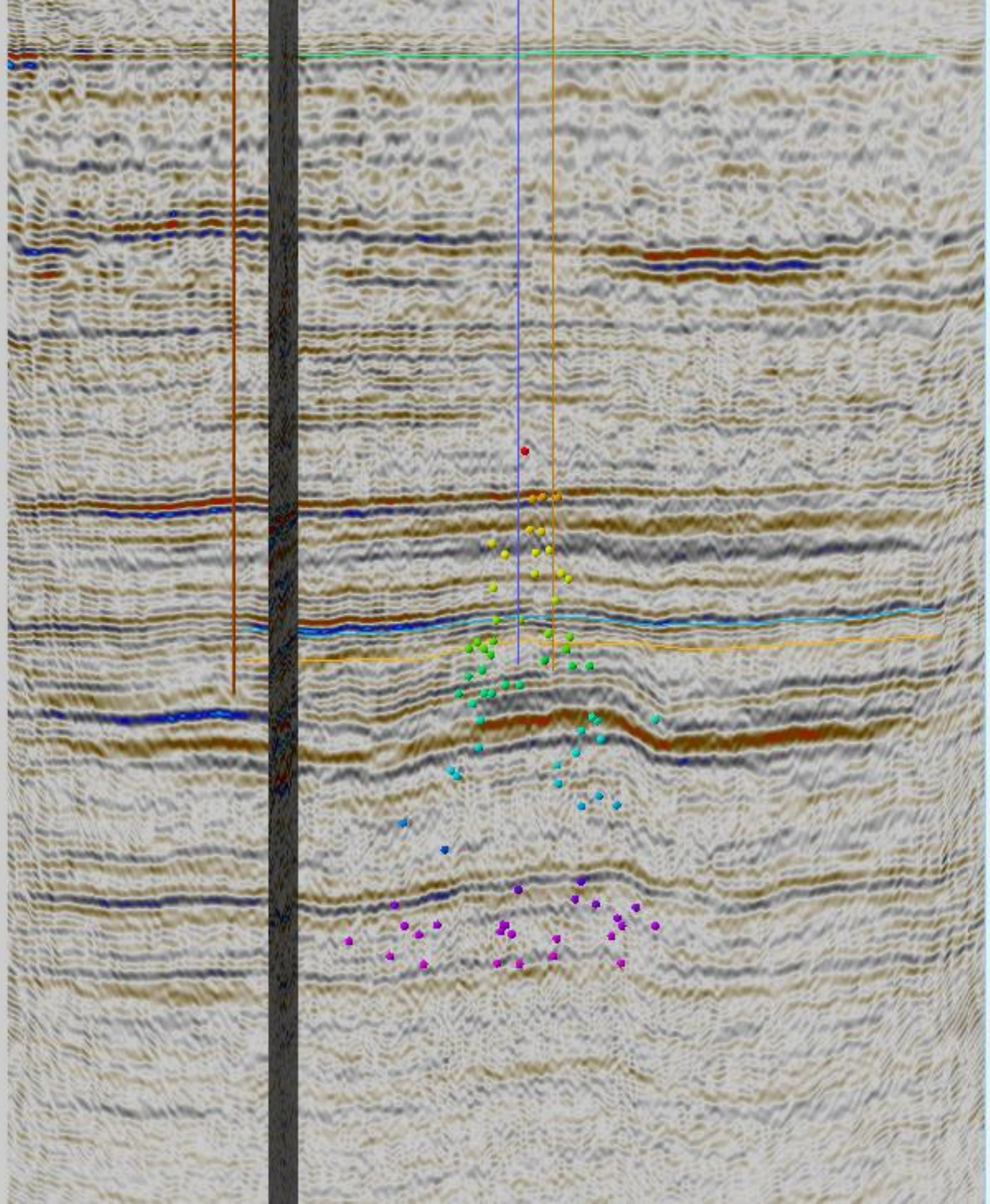


3D Location results

- high-frequency microseismic events (150--350 Hz), close to the borehole
- low-frequency microseismic events (10—50 Hz), distributed above, within, and below the reservoir. They also form a SW-NE distribution.



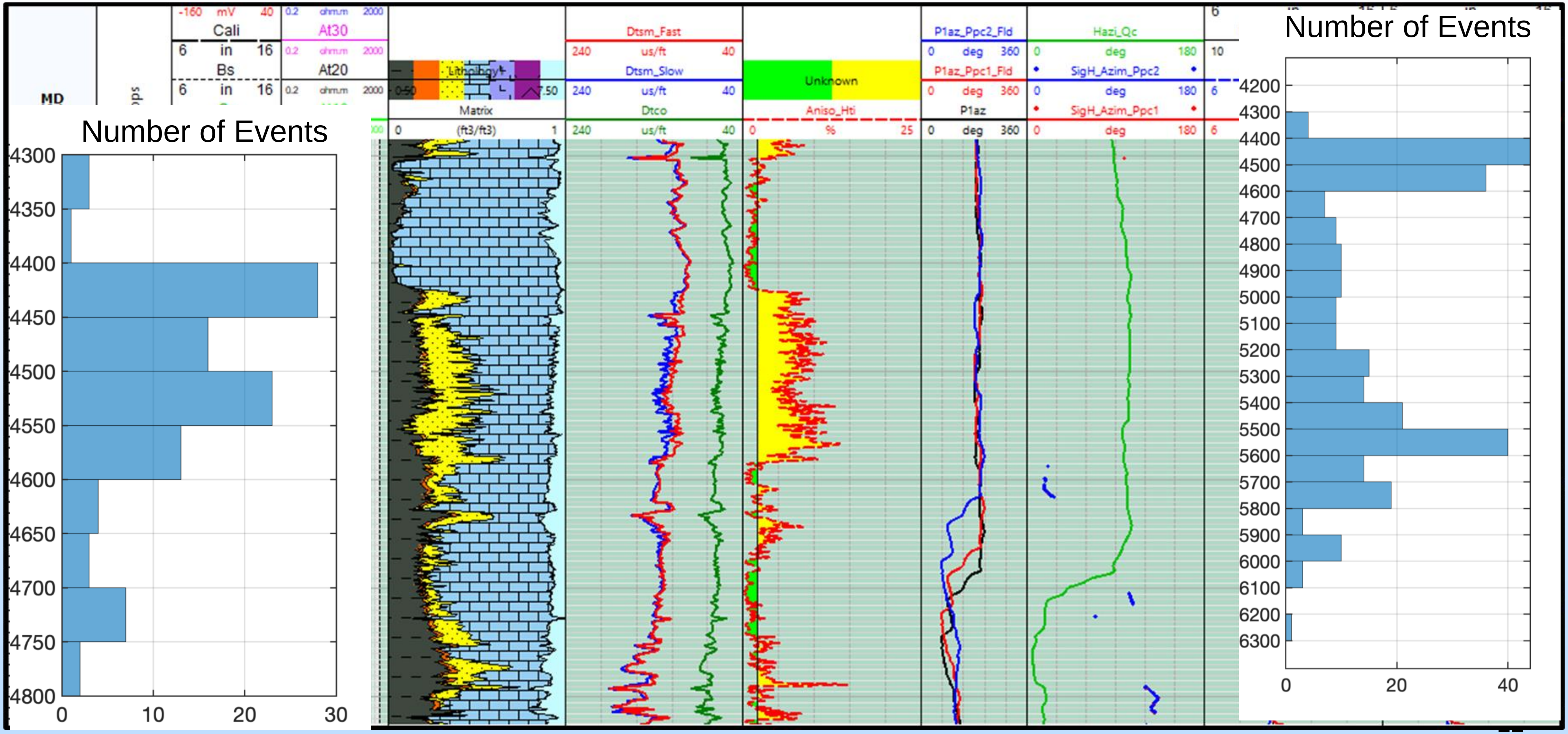




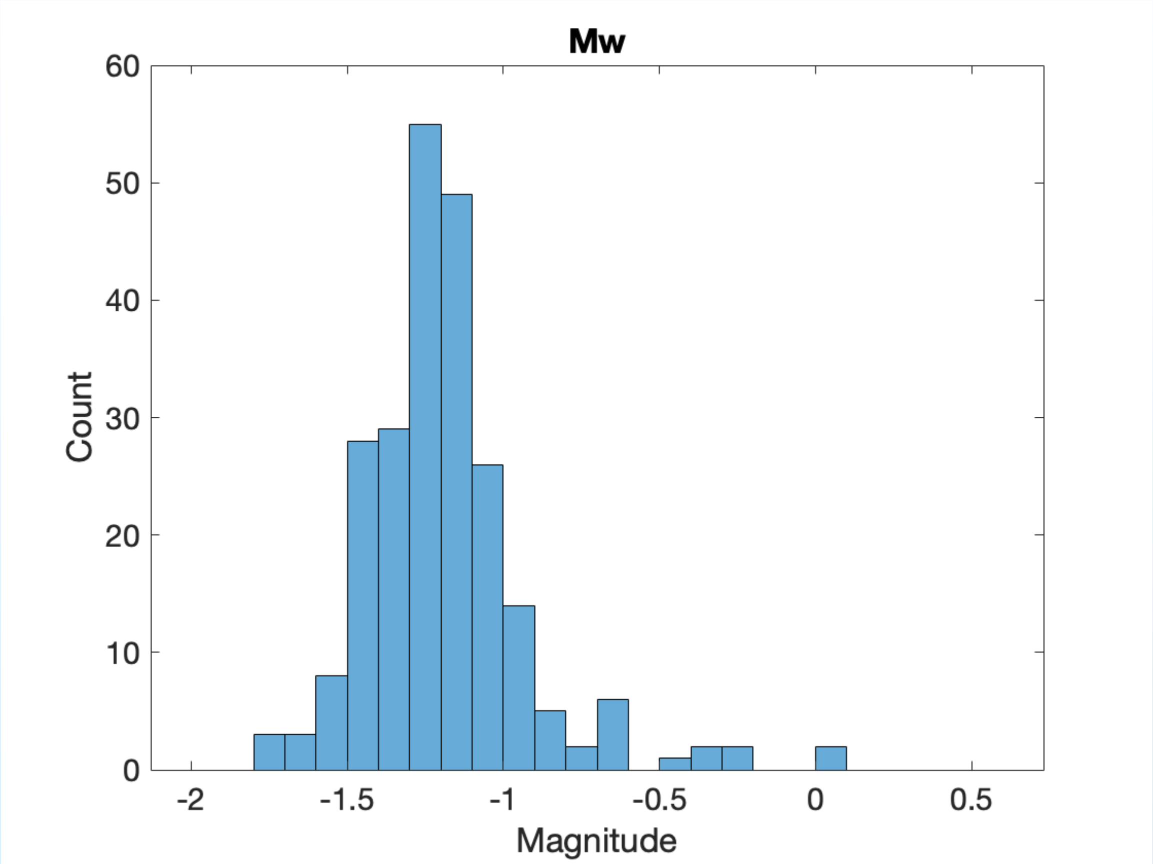
Seismic lines perpendicular to axis of microseismic event azimuth (NE-SW)

Location Results for High-frequency Signals (150-350 Hz)

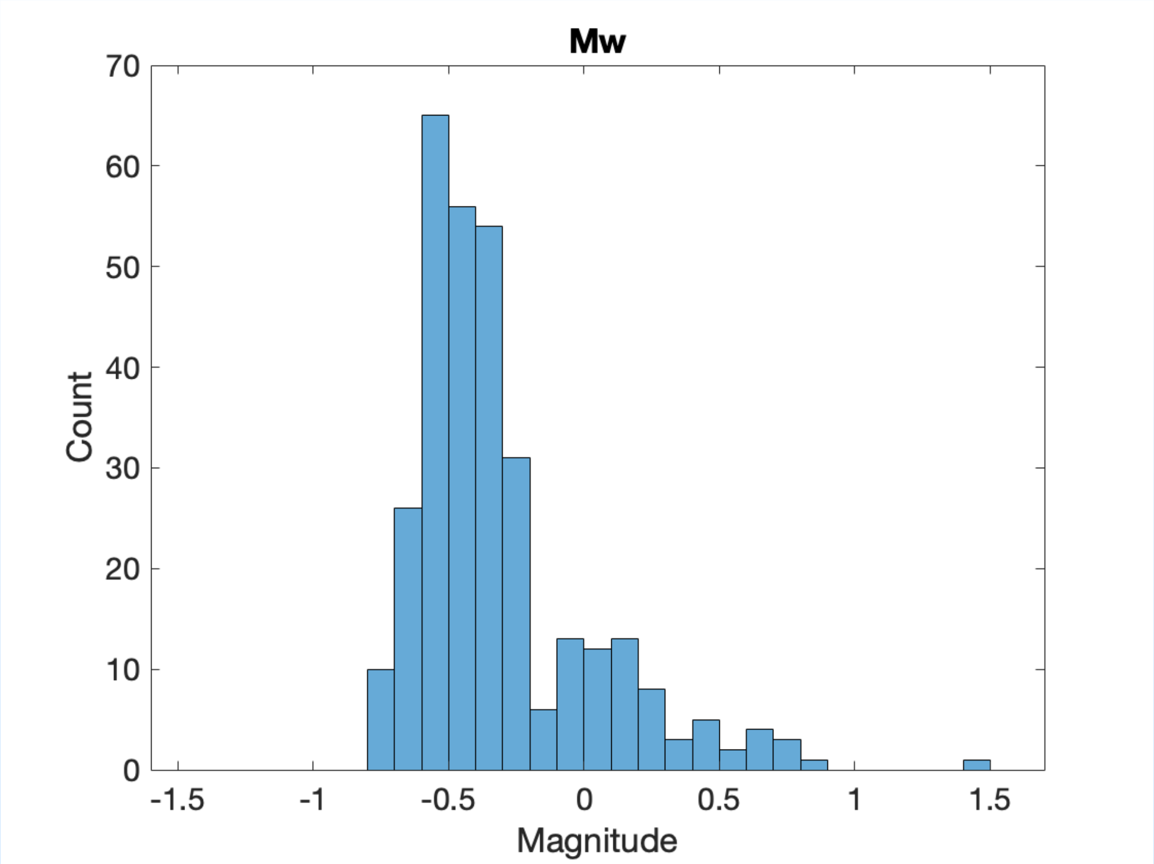
clustered in two layers: the upper layer corresponds to a highly-anisotropic layer from well logging measurements.



Magnitudes of Microseismic Events

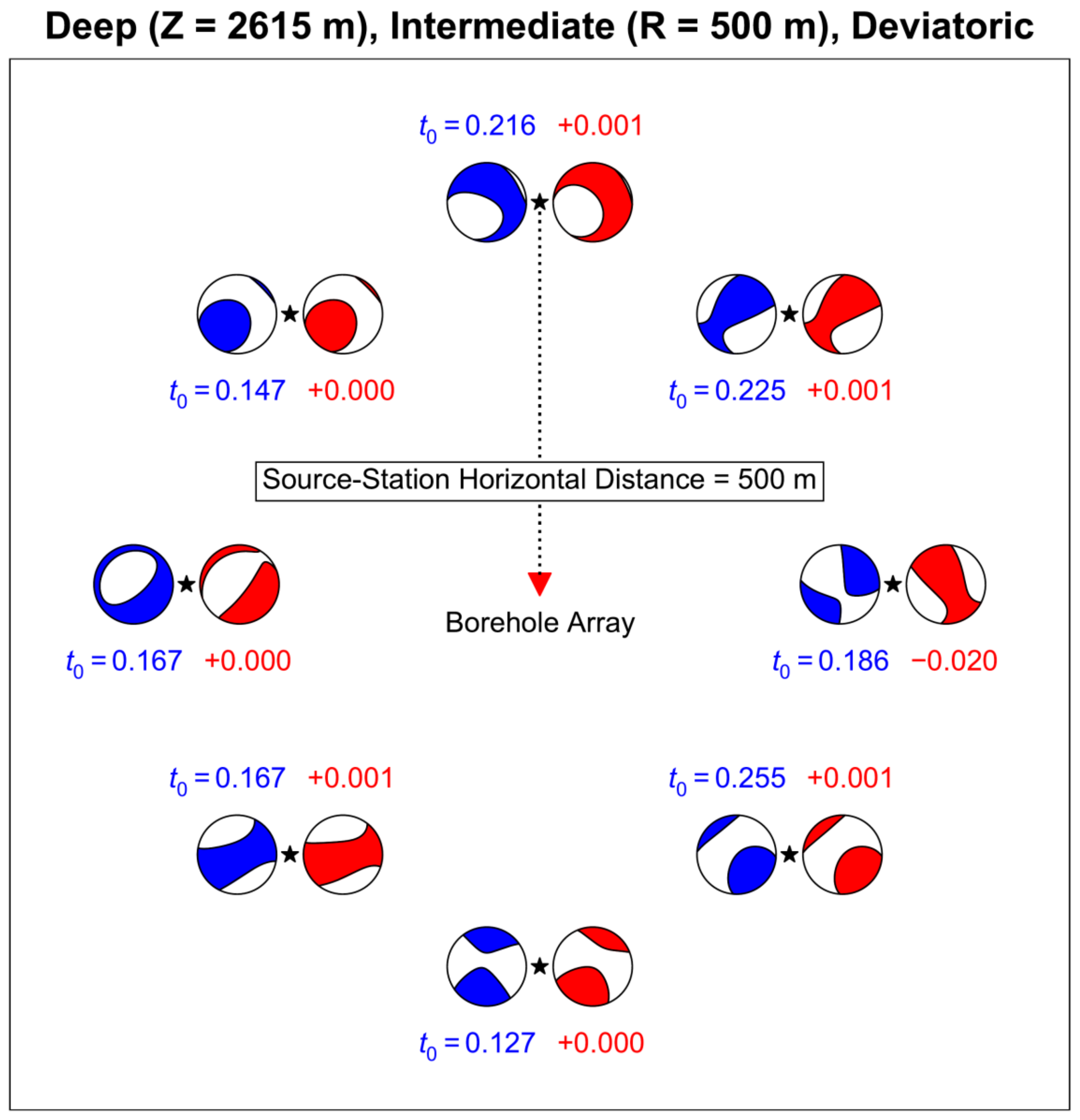


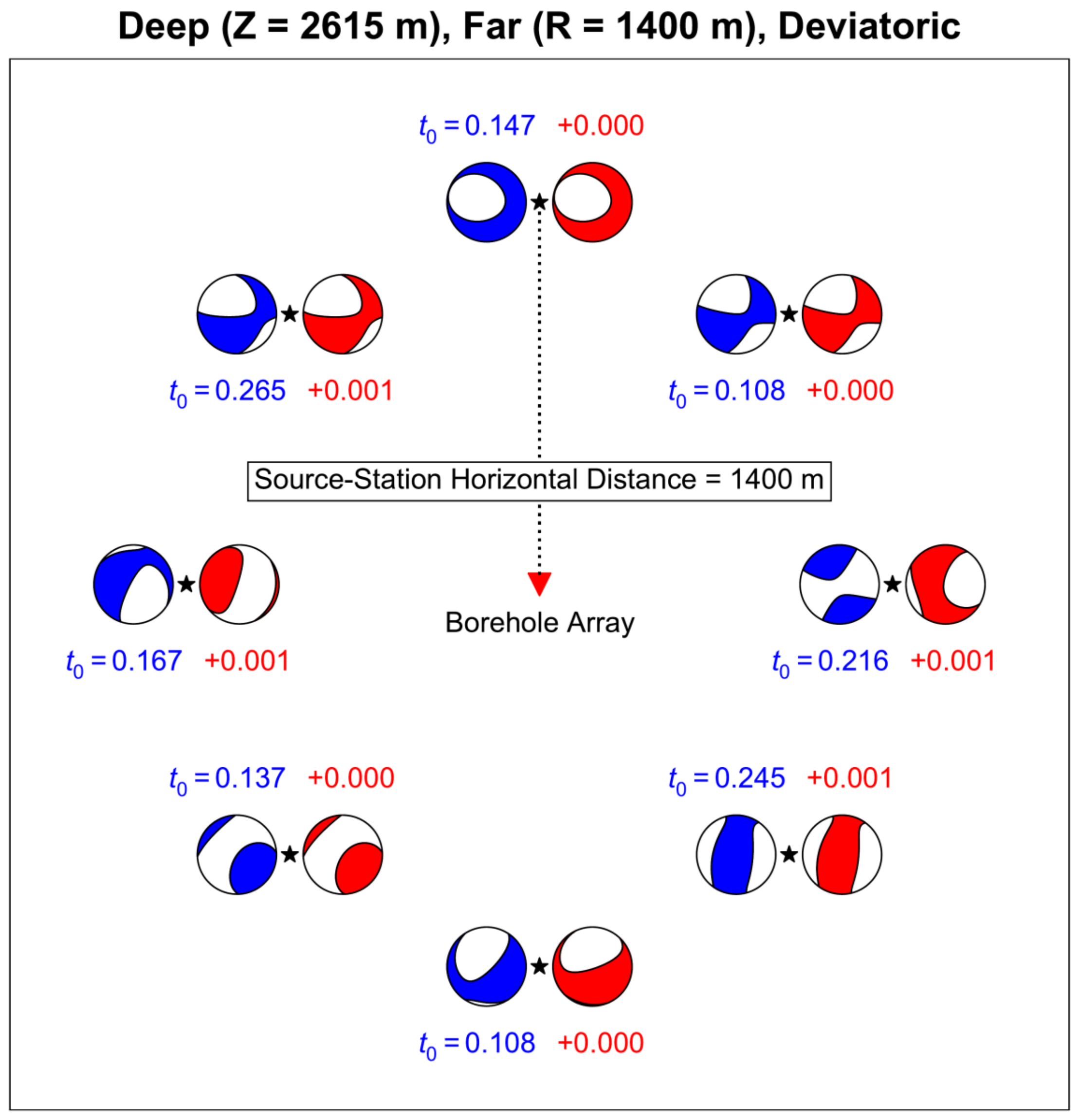
High-frequency events (July, 2019-Feb. 2020)



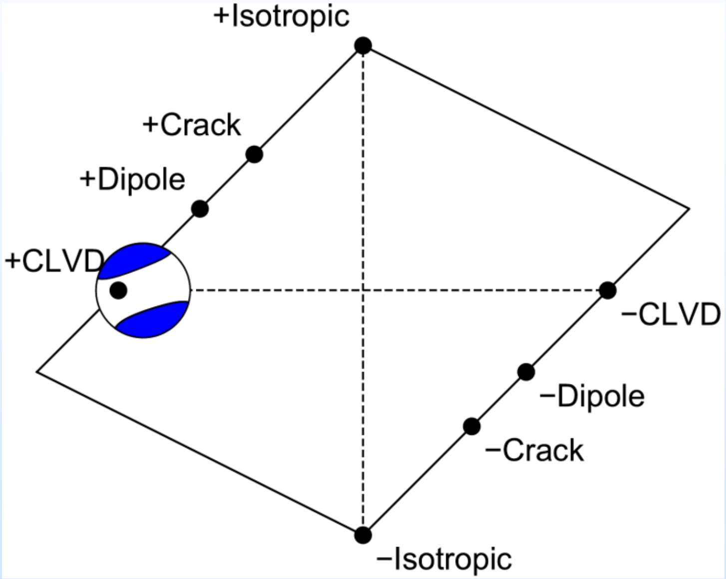
Low-frequency events (Feb.-July, 2020)

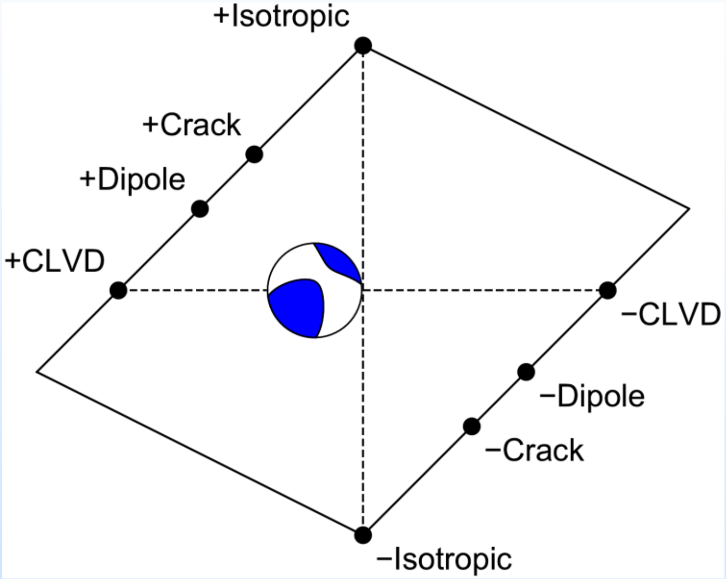
Novel adaptive moment-tensor inversion using single borehole data: Synthetic data results





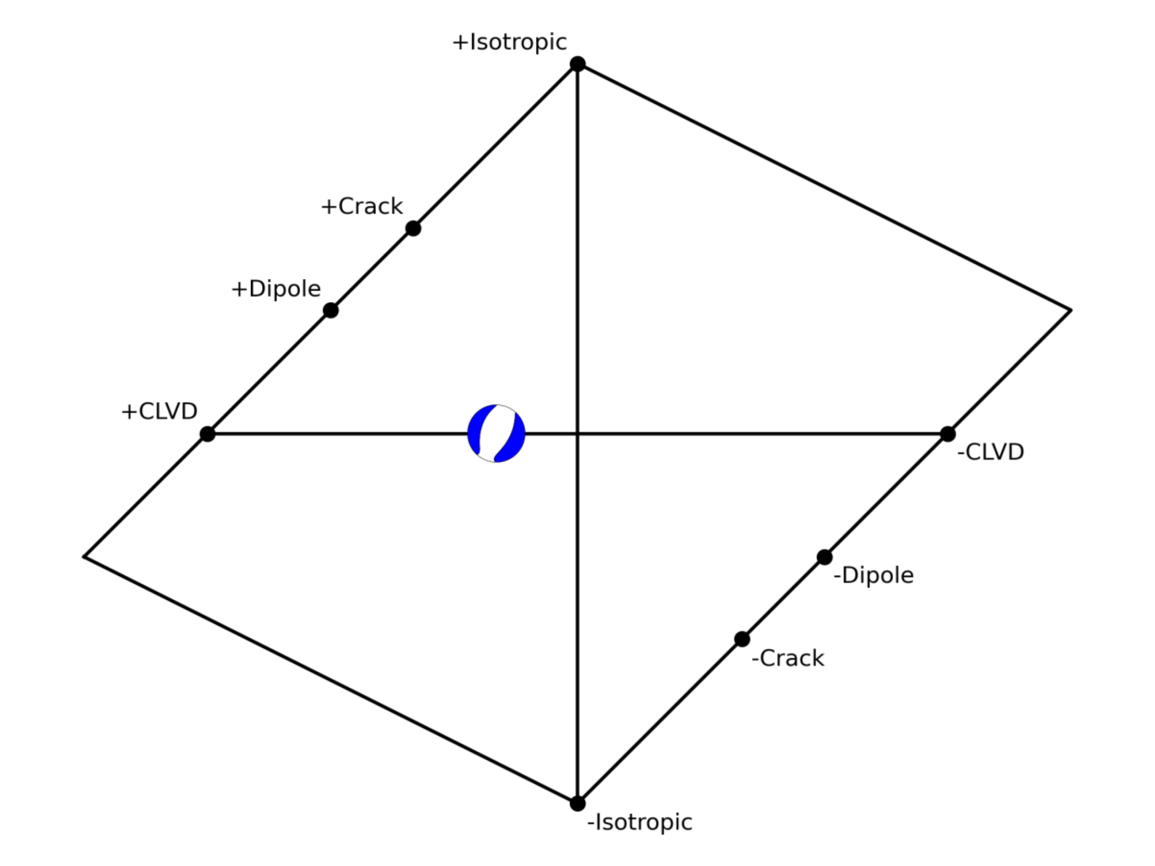
Adaptive moment-tensor inversion: Preliminary results of borehole microseismic data





Diamond CLVD-ISO plots (Hudson diagrams)
show positive CLVD: Fracture opening

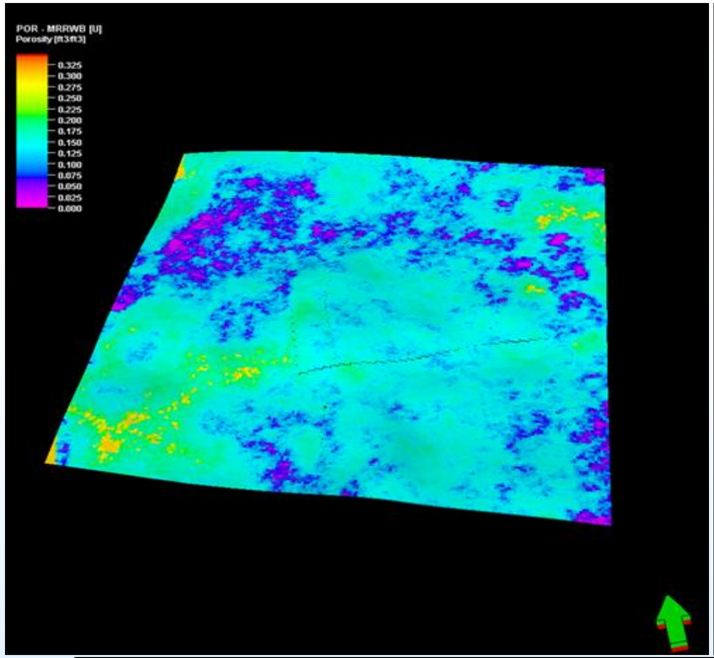
Adaptive moment-tensor inversion: Preliminary result of surface microseismic data

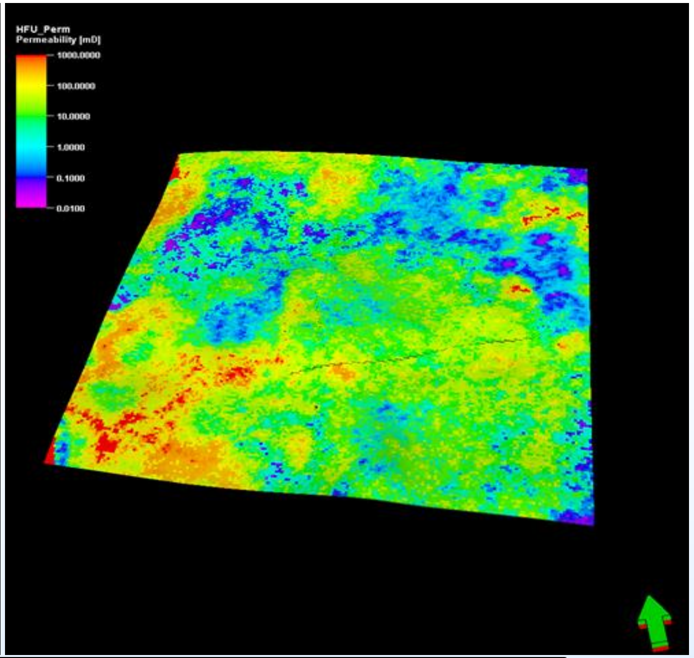


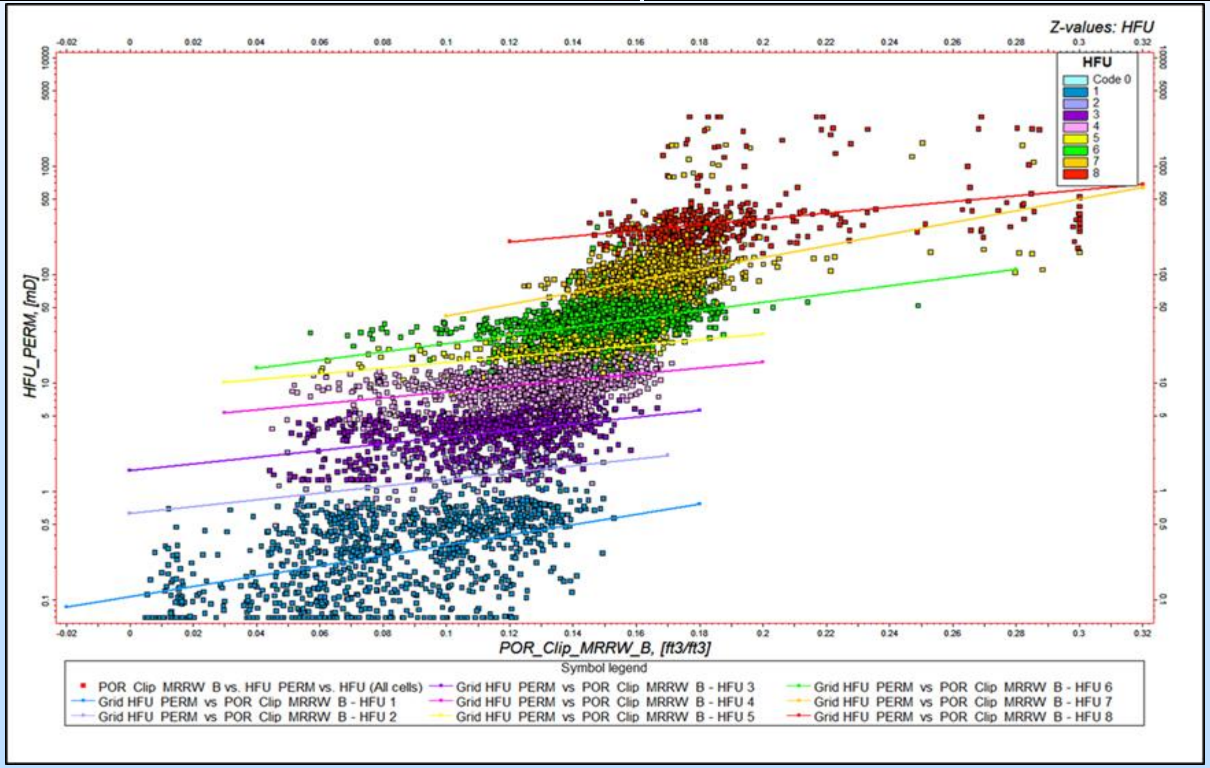
Diamond CLVD-ISO plot (Hudson diagram) shows positive CLVD: Fracture opening

Geological and Geomechanical Static Modeling

- The geological model developed by SWP has been updated with structural and stratigraphic reinterpretation of newly depth imaged seismic data.
- The updated model extends from ground surface to below the injection zone (Morrow B reservoir).
- Petrophysical properties of the reservoir and caprock have been updated through integration of geophysical logs, core, and seismic elastic inversion products.
- Elastic properties of the reservoir, underburden, and overburden have been updated through integration of well data based 1-D Mechanical Earth Models (MEM) derived from geophysical logs and core analysis.

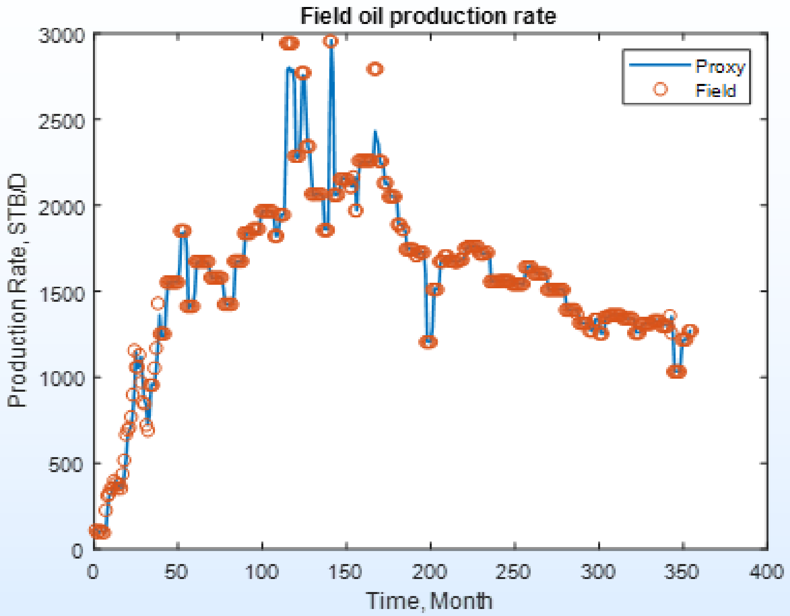


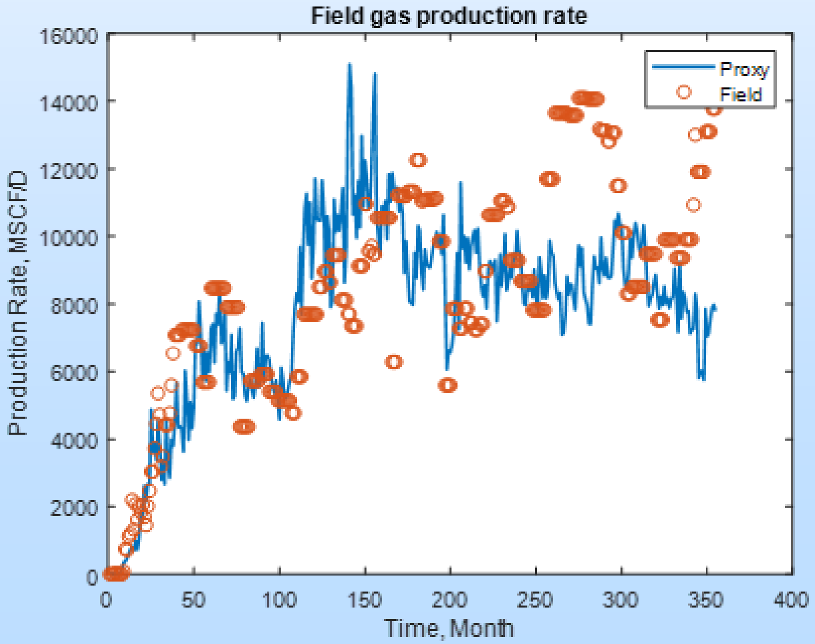




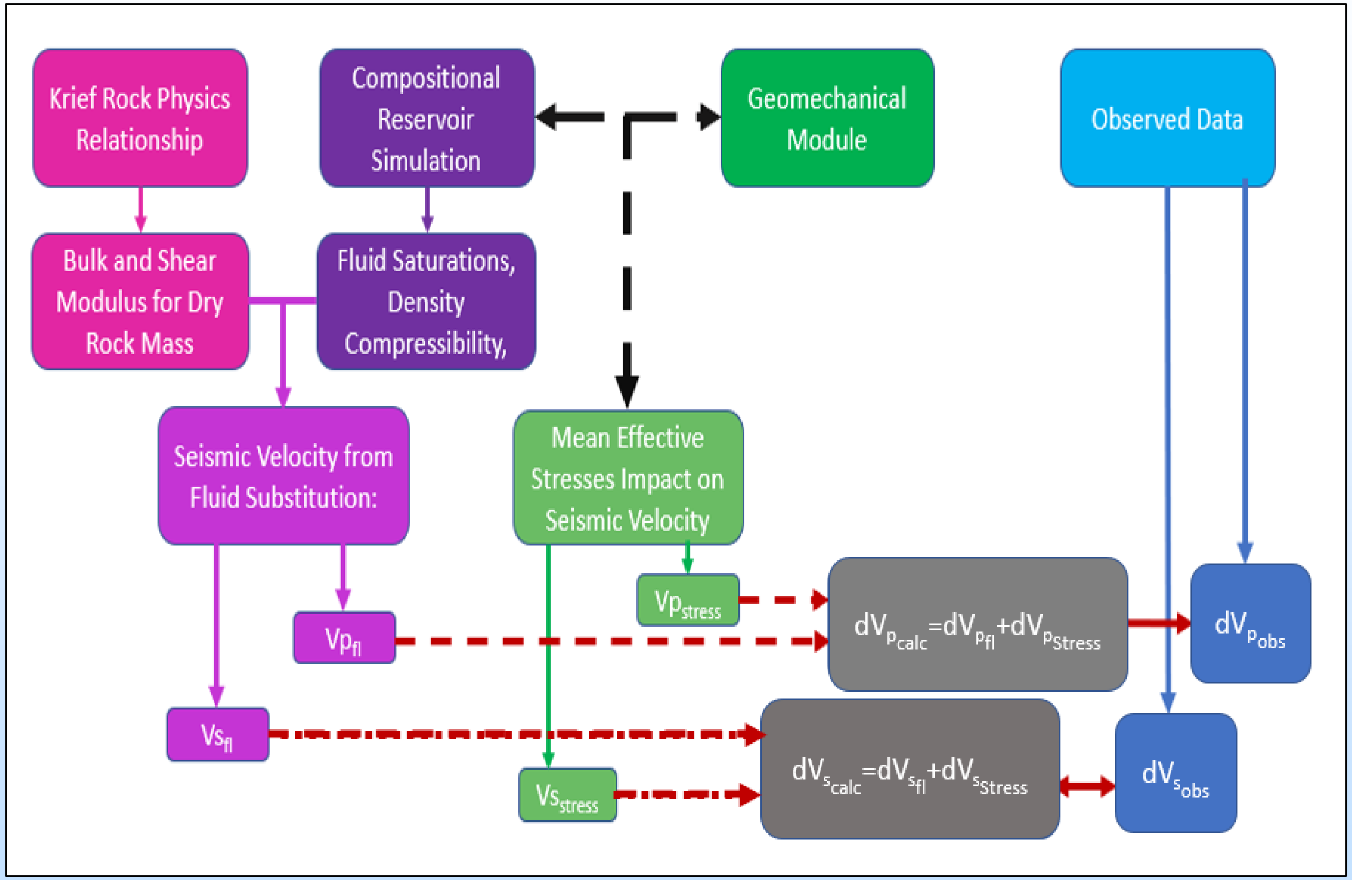
Hydrodynamic Flow Calibration

- Primary/Secondary (pressure depletion/waterflood) and tertiary (CO_2 WAG) periods were history matched using proxy modeling and machine learning optimization.
- Separate proxy models were developed for primary/secondary and CO_2 WAG development periods each using 100 full physics runs to train and verify proxy models.
- Particle swarm optimization was employed and coupled with the proxy models to minimize the history matching error
- Optimized reservoir parameters were verified in full physics simulations.





VSP Integration Workflow



Goal: *Minimization of the VSP Objective Function*

Modelled Seismic Velocity:

Based on the Principle of Superposition

$$dV^{mon}{}_{modeled} = dV^{mon}{}_{fluid} + dV^{mon}{}_{stress} \ ,$$

dV= dVp , dVs

Seismic Velocity Mismatch:

$$dV^{mon}{}_{mismatch} = dV^{mon}{}_{modelled} - dV^{mon}{}_{obs} \ ,$$

dV= dVp , dVs

VSP Objective Function Formulation: *Task 7.3*

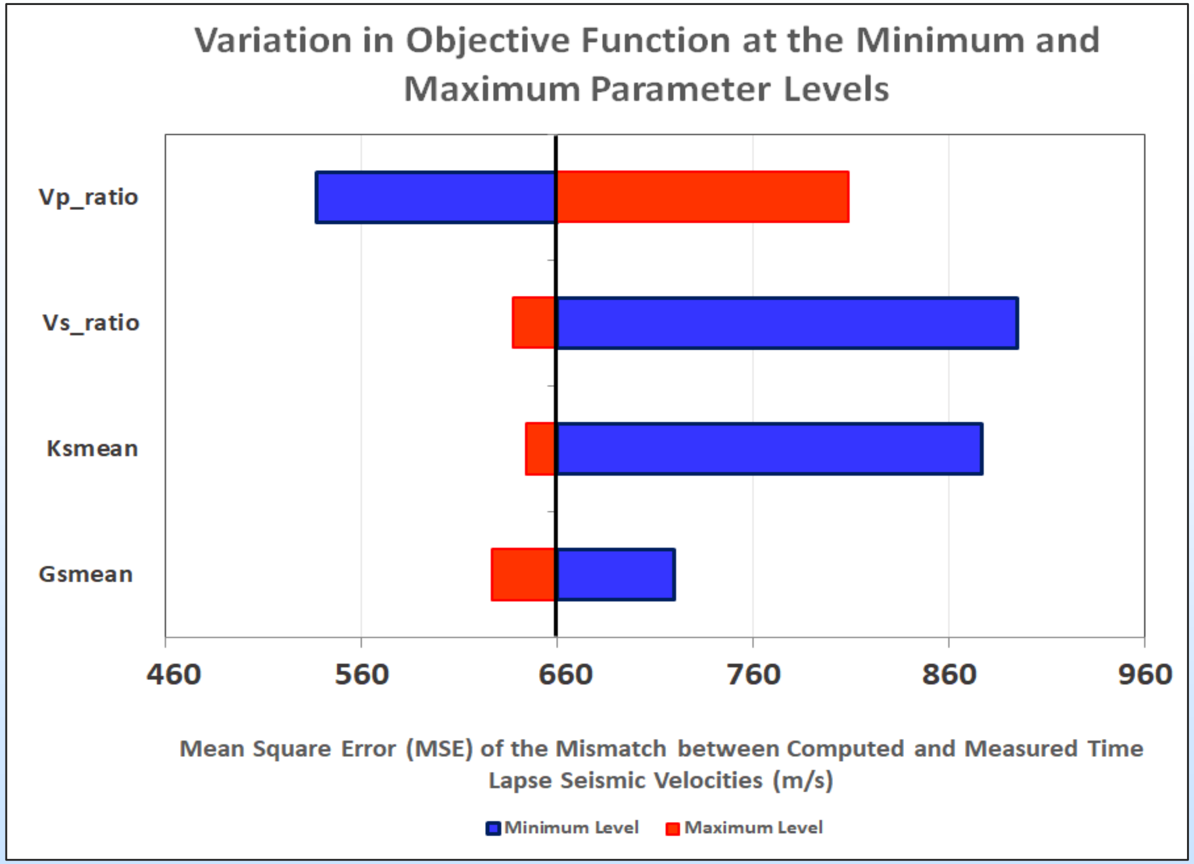
Summation of all six(6) seismic velocity mismatches

$$VSP\ Objective = \sum dV^{mon}$$

dV= dVp , dVs ***mon= 1,2,3***

Geomechanical Calibration: Parameter Sensitivities

Task 7.2 and 7.3



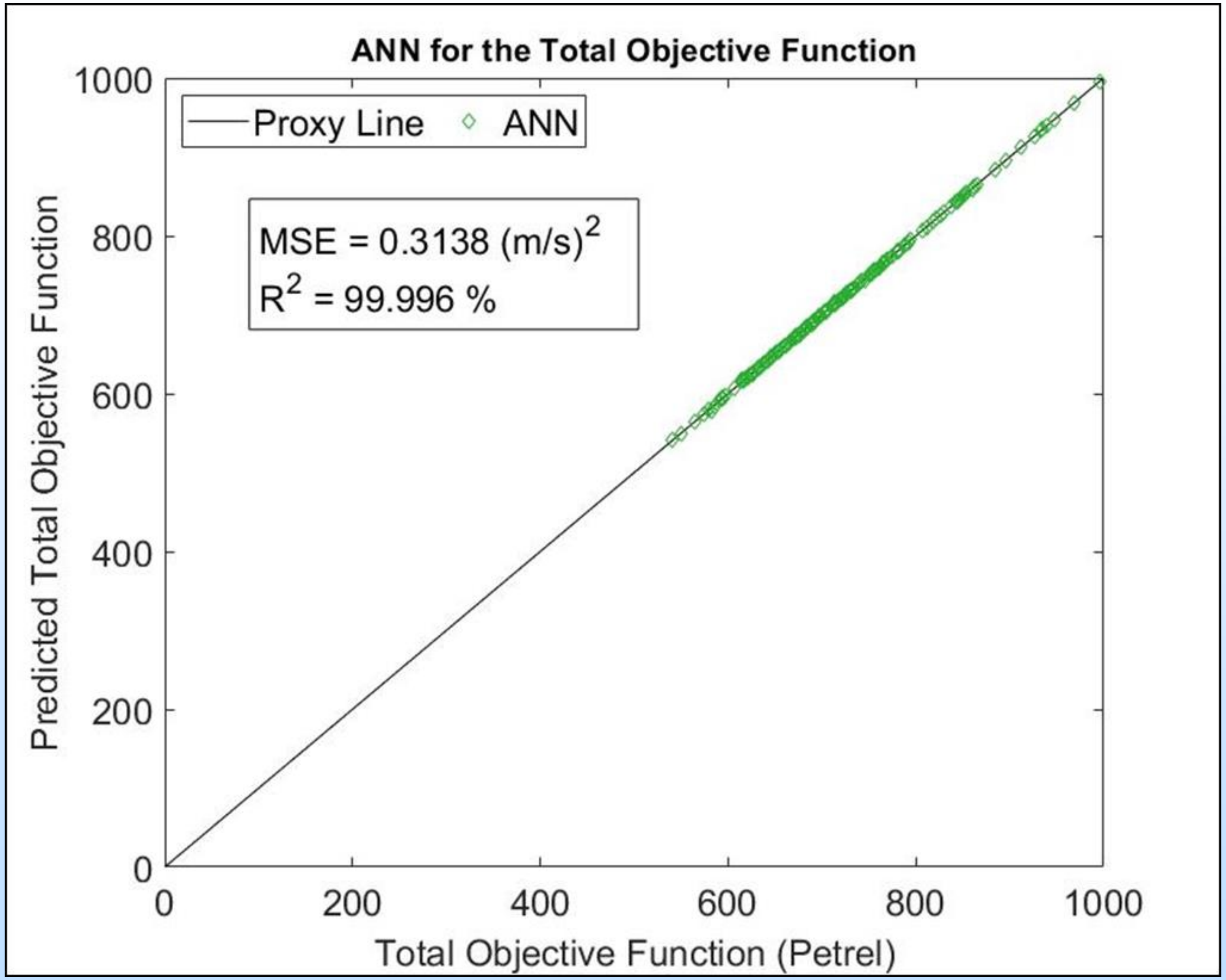
Variable	Objective Function for Minimum Variable Value	Objective Function for Maximum Variable Value	Variable Minimum	Variables for Intermediate Case	Variable Maximum
Gsmean	722.9	630.0	2.40	2.70	3.00
Ksmean	879.7	647.1	3.00	3.45	3.90
Vs_ratio	897.7	640.7	7.0	70.0	115.0
Vp_ratio	540.4	811.7	15.0	152.0	175.0

- Four Independent variables control both the fluid substitution and mean effective stress impacts on shear and compressional seismic velocity changes
  - P-velocity – Mean Effective Stress Ratio
  - S-velocity – Mean Effective Stress Ratio
- Reflects the larger influence of mean effective stress changes on the Total Objective Function.
- Gs_{mean} and Ks_{mean} impacts
  - Fluid substitution: Saturated Bulk modulus and Shear Modulus
  - Mean effective stress through the linear elastic assumption.
  - Bulk Modulus incorporates the effect of fluid compressibility and saturation distribution. Shear modulus is unchanged.

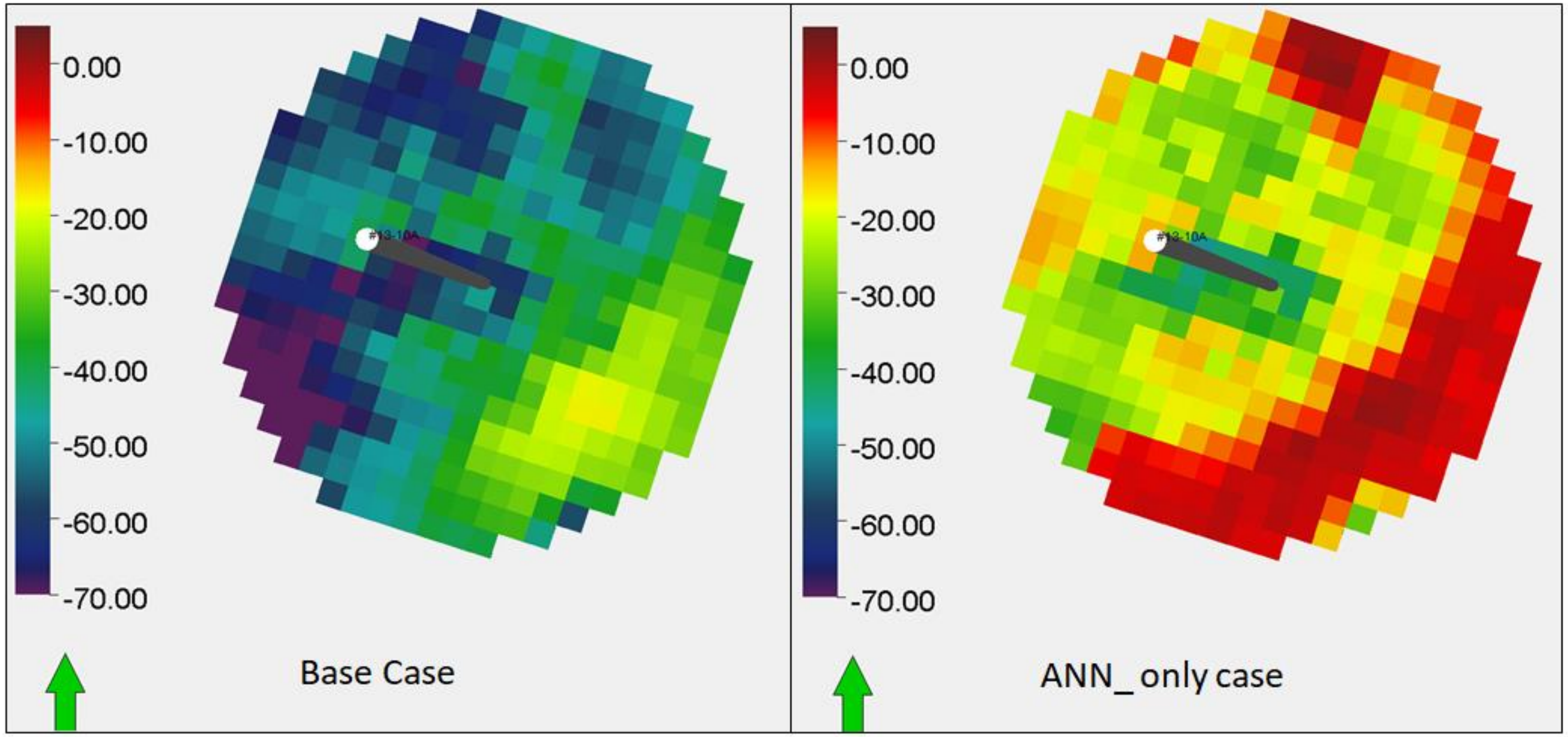
Regression Analysis: Artificial Neural Network

- Artificial Neural Networks (ANN) are inspired by the structure of the Human Brain.
  - Comprised of layers of neurons that form the core processing units of the ANN
  - Weights are assigned at each layer prior to neuron activation throughout the network to generate the output(s)
  - Utilize the Backpropagation algorithm (supervised algorithm) to train ANN and update the weights until the error between the computed and simulated outputs are minimized.

- Subdivide Inputs (randomly determined)
  - Training (70%), Validation (15%), Blind Testing (15%)
  - Single hidden layer comprised of 15 neurons



Preliminary Geomechanical Calibration Task 7.4



Gs=2.5 Mpsi , Ks=3.3Mpsi ,
Vp=152 m/s per 1000 Psi Eff Change
Vs = 70 m/s per 1000 psi Eff Change

Gs=2.4 Mpsi, Ks=3.45Mpsi ,
Vp= 175 m/s per 1000 psi Eff Change,
Vs= 80.5 m/s per 1000 psi Eff Change

- Shear and Compressional Seismic velocity Mismatches at Monitor 2
- The cooler colors on the “Base Case” parameters on the left show much higher mismatches than the optimized values on the right.

Accomplishments to Date

- We have rebuilt new initial anisotropic velocity models by upscaling well logs using the Schoenberg-Muir method.
- Have determined the HTI positions and parameters besides VTI parameters in most areas.
- The depth interval of observed high-frequency microseismicity corresponds with an interval of strong stress anisotropy in borehole geomechanical analysis.
- Continue to detect and locate hundreds of microseismic events from borehole geophone array and surface microseismic stations (seismometers).
- Estimated event magnitudes and started to perform moment tensor inversion.

Accomplishments to Date

- Completed final geological and geomechanical static models for hydrodynamic flow and coupled simulations
- Completed final production history matching modeling utilizing machine learning based workflow
- Completed evaluation of 1-way and 2-way coupling options for stress calibration process
- Completed machine learning based VSP-Stress calibration process
- Completed a forecast modeling post VSP-Stress History Match
- Developing a framework for Geomechanics- Microseismic Calibration process

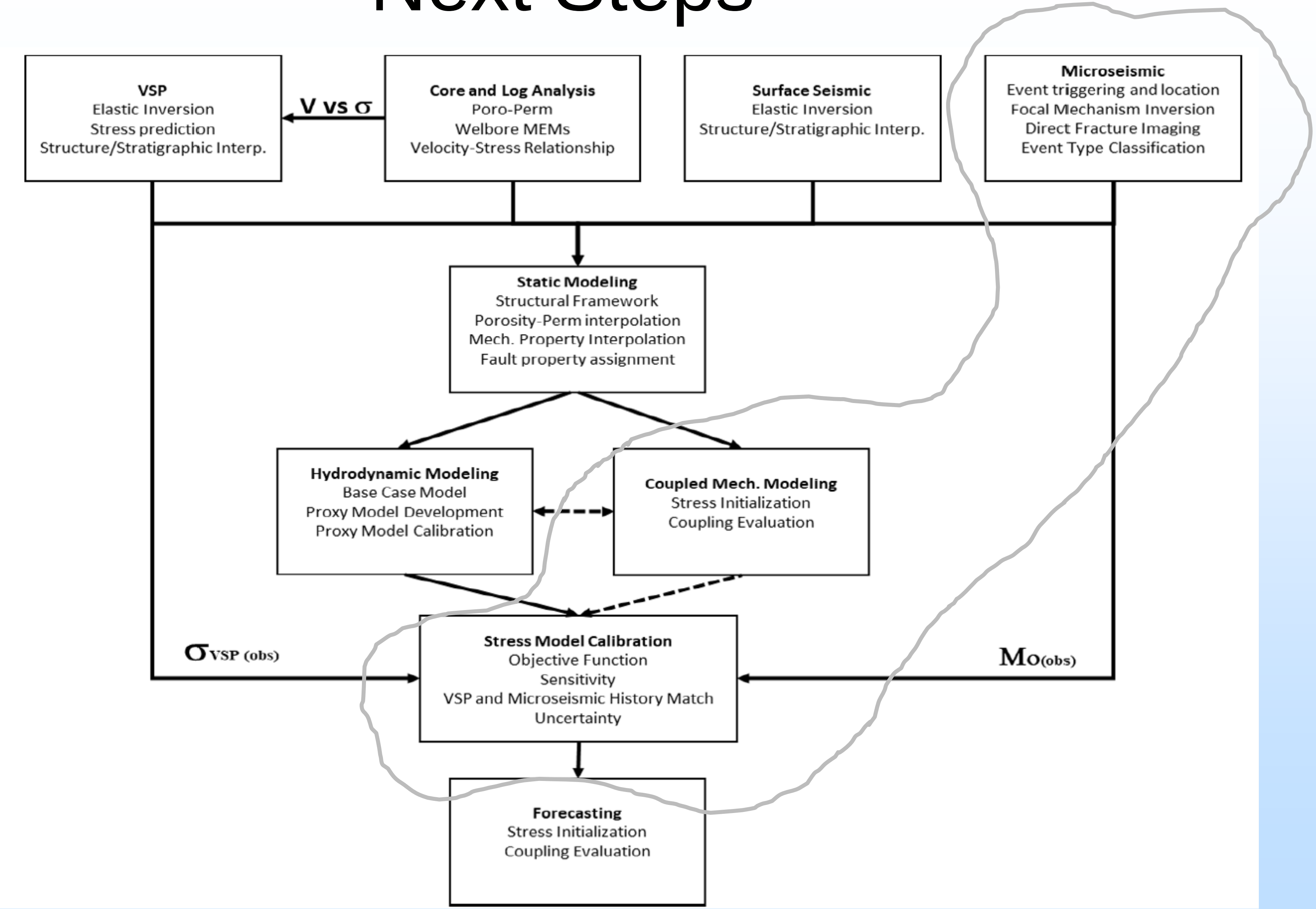
Summary: Key Findings/ Lessons Learned

- Detected both high- and low-frequency microseismic events distributed in different regions.
- Low-frequency microseismic events occurred above, within, and below Morrow B, the CO2 injection formation.
- Moment magnitudes of low-frequency microseismic events are mostly around -0.5.
- Analyzing borehole microseismic data is challenging because of strong borehole waves, noises, and a short borehole sensor array. Machine learning denoising is ongoing.
- Moment tensor inversion using single borehole array is challenging but feasible using our novel adaptive moment tensor inversion algorithm.
- Microseismic event location, moment magnitudes, and moment tensors will be used for geomechanical stress modeling and prediction.

Summary: Key Findings/ Lessons Learned

- The far-field stresses are aggressive enough to cause significant mechanical deformation and variations in velocities at three different scales (core – log – seismic).
- The differential horizontal stresses are large enough to cause mechanical breakouts and dipole velocity anisotropy.
- The stress changes due to fluid injection/removal and fluid properties can cause enough observable changes in timelapse seismic signature.
- The quality of initial anisotropic parameters plays an important role in convergence rates and reliability of anisotropic inversion.
- Machine learning based optimization workflow has been successfully developed and utilized to calibrate VSP-Stress mismatch.

Next Steps


VSP
Elastic Inversion
Stress prediction
Structure/Stratigraphic Interp.
V vs σ
Core and Log Analysis
Poro-Perm
Welbore MEMs
Velocity-Stress Relationship
Surface Seismic
Elastic Inversion
Structure/Stratigraphic Interp.
Microseismic
Event triggering and location
Focal Mechanism Inversion
Direct Fracture Imaging
Event Type Classification
Static Modeling
Structural Framework
Porosity-Perm interpolation
Mech. Property Interpolation
Fault property assignment
Hydrodynamic Modeling
Base Case Model
Proxy Model Development
Proxy Model Calibration
Coupled Mech. Modeling
Stress Initialization
Coupling Evaluation
σVSP (obs)
Mo(obs)
Stress Model Calibration
Objective Function
Sensitivity
VSP and Microseismic History Match
Uncertainty
Forecasting
Stress Initialization
Coupling Evaluation

Thank you for your attention!

Organization Chart

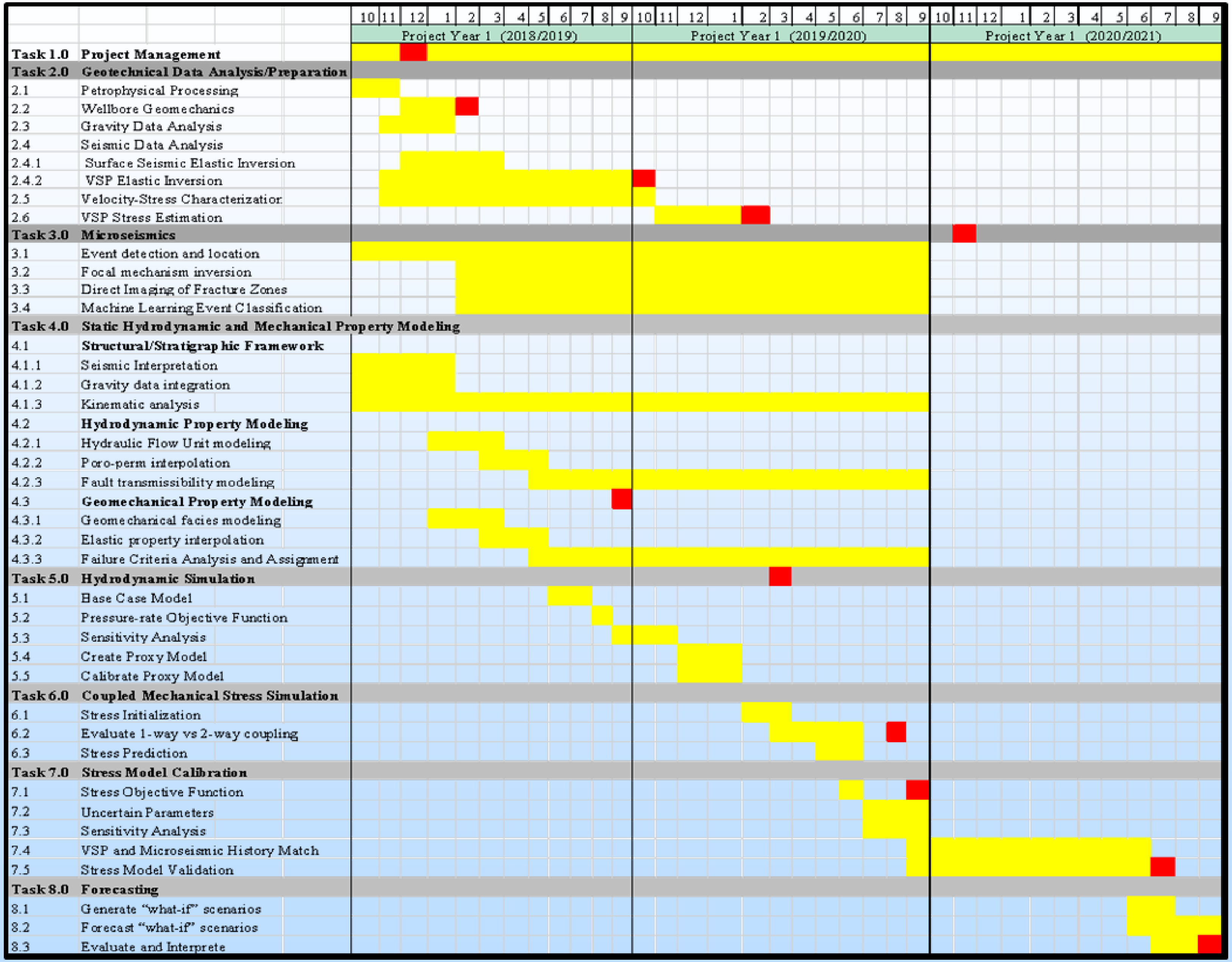
New Mexico Tech - Prime Contract
PRRC - Project Management, (Tasks 1-8)
Ampomah - PI
Balch - Project Manager, Co-PI
Czoski, Will, El-Kaseeh, RAs
EES - Axen - Fault kinematics (Tasks 4-8)

Los Alamos National Laboratory
Huang (Co-PI) - Seismic imaging, inversion (Tasks 1-3, 8)

Sandia National Laboratory
Draelos - Machine Learning (Tasks 3, 5, 8)

Consultants
Rutledge - Geophysical methods, passive seismic monitoring (Tasks 2, 8)
Lee - Development of models (Tasks 4, 6, 7, 8)
Bratton - Geophysical methods, passive seismic monitoring (Tasks 2, 4, 6,7)

Gantt Chart


10 11 12 1 2 3 4 5 6 7 8 9 10 11 12 1 2 3 4 5 6 7 8 9 10 11 12 1 2 3 4 5 6 7 8 9
Project Year 1 (2018/2019)
Project Year 1 (2019/2020)
Project Year 1 (2020/2021)
Task 1.0 Project Management
Task 2.0 Geotechnical Data Analysis/Preparation
2.1 Petrophysical Processing
2.2 Wellbore Geomechanics
2.3 Gravity Data Analysis
2.4 Seismic Data Analysis
2.4.1 Surface Seismic Elastic Inversion
2.4.2 VSP Elastic Inversion
2.5 Velocity-Stress Characterization
2.6 VSP Stress Estimation
Task 3.0 Microseismics
3.1 Event detection and location
3.2 Focal mechanism inversion
3.3 Direct Imaging of Fracture Zones
3.4 Machine Learning Event Classification
Task 4.0 Static Hydrodynamic and Mechanical Property Modeling
4.1 Structural/Stratigraphic Framework
4.1.1 Seismic Interpretation
4.1.2 Gravity data integration
4.1.3 Kinematic analysis
4.2 Hydrodynamic Property Modeling
4.2.1 Hydraulic Flow Unit modeling
4.2.2 Poro-perm interpolation
4.2.3 Fault transmissibility modeling
4.3 Geomechanical Property Modeling
4.3.1 Geomechanical facies modeling
4.3.2 Elastic property interpolation
4.3.3 Failure Criteria Analysis and Assignment
Task 5.0 Hydrodynamic Simulation
5.1 Base Case Model
5.2 Pressure-rate Objective Function
5.3 Sensitivity Analysis
5.4 Create Proxy Model
5.5 Calibrate Proxy Model
Task 6.0 Coupled Mechanical Stress Simulation
6.1 Stress Initialization
6.2 Evaluate 1-way vs 2-way coupling
6.3 Stress Prediction
Task 7.0 Stress Model Calibration
7.1 Stress Objective Function
7.2 Uncertain Parameters
7.3 Sensitivity Analysis
7.4 VSP and Microseismic History Match
7.5 Stress Model Validation
Task 8.0 Forecasting
8.1 Generate "what-if" scenarios
8.2 Forecast "what-if" scenarios
8.3 Evaluate and Interprete