Identification of Faults Susceptible to Induced Seismicity

Project Number DE-FE0031685

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U.S. Department of Energy

National Energy Technology Laboratory

Carbon Management and Oil and Gas Research Project Review Meeting – Carbon Storage

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Project Participants

- Geologic and geocellular modeling
  - Mansour Khosravi, James Damico (ISGS)
- Fault identification
  - Hongkyu Yoon (Sandia) machine learning
  - Michael Fehler (MIT) inversion modeling
- Pressure and stress perturbation modeling
  - Ruben Juanes (MIT)
  - Ola Babarinde, Scott Frailey (ISGS)
- Stress field modeling
  - Ahmed Elbanna (UIUC)

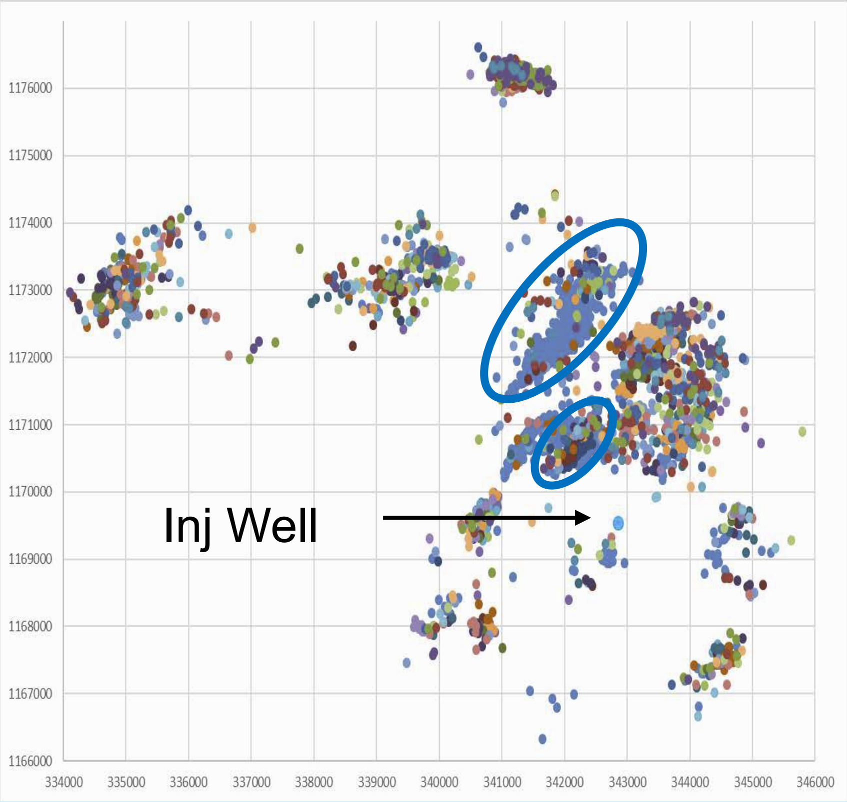
Presentation Outline

- Motivation, Objective, and Approach
- Technical Status
  - Expected Outcomes
  - Workflow
  - By Task
- Accomplishments to Date
- Lessons Learned
- Project Summary

Motivation

- At a "quiet" seismic area, microseismic events recorded and attributed to CO_2 injection at relatively low injection pressure
  - <10 events in 1.5 yrs pre-injection monitoring
  - Pressure
    - Injection 15% above Pi;
    - @1000 ft 5% above Pi
  - 4700+ located events
  - Located primarily in the crystalline basement rock

IBDP Site after 3 yrs injection



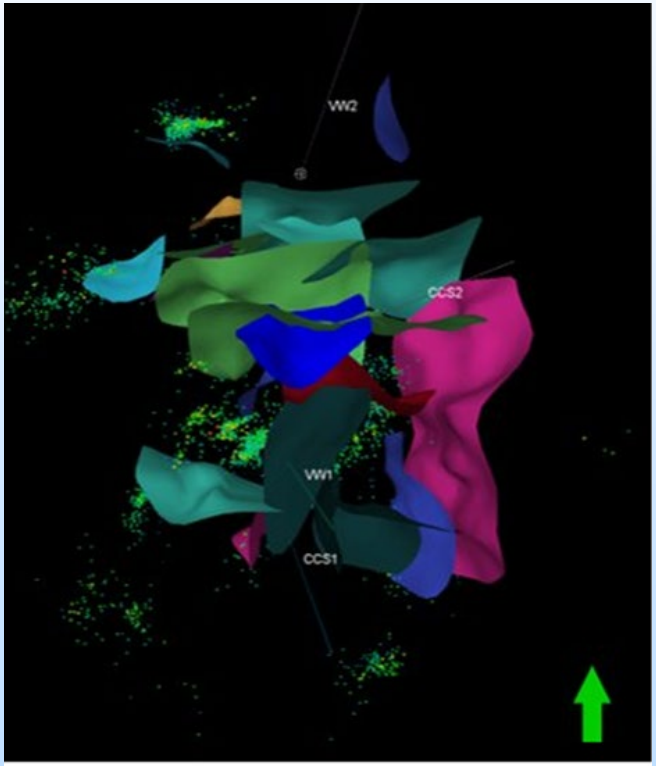
After R. Bauer, ISGS

1000 x 1000 ft squares

Objective

- Predict presence of faults susceptible to movement from fluid injection
  - identify characteristics of these faults
  - estimate in-situ stress field changes before and after fault slippage
  - explain pressure and stress perturbations between the storage unit and crystalline basement (vertical migration)

Fault Locations from Traditional Methods (Surface Seismic)



S. Williams-Stroud, H. Leetaru, 2020

Approach

- Test a series of geologically based, integrated forward and physics-constrained, data-driven (inverse) models that includes the following:
  - geocellular models of a well-characterized field site with microseismicity located within basement rock,
  - machine learning to better resolve basement faults unidentifiable via traditional surface seismic methods
  - poroelastic modeling to understand pressure and stress fields in the presence of characterized faults,
  - seismic modeling to determine geologic/petrophysical properties of crystalline basement rock, faults, and overlying storage units that control seismicity

Technical Status: Expected Outcomes

- Advance knowledge of the transmission of pressure and stress between the storage unit and underlying crystalline basements
- Establish workflow that can identify the presence of faults that are susceptible to induced seismicity in the presence of CO_2 injection
- Compare results with traditional means of identifying faults (e.g. surface seismic)
- Reduce the geomechanical risk component of storage

Technical Status: Workflow Diagram

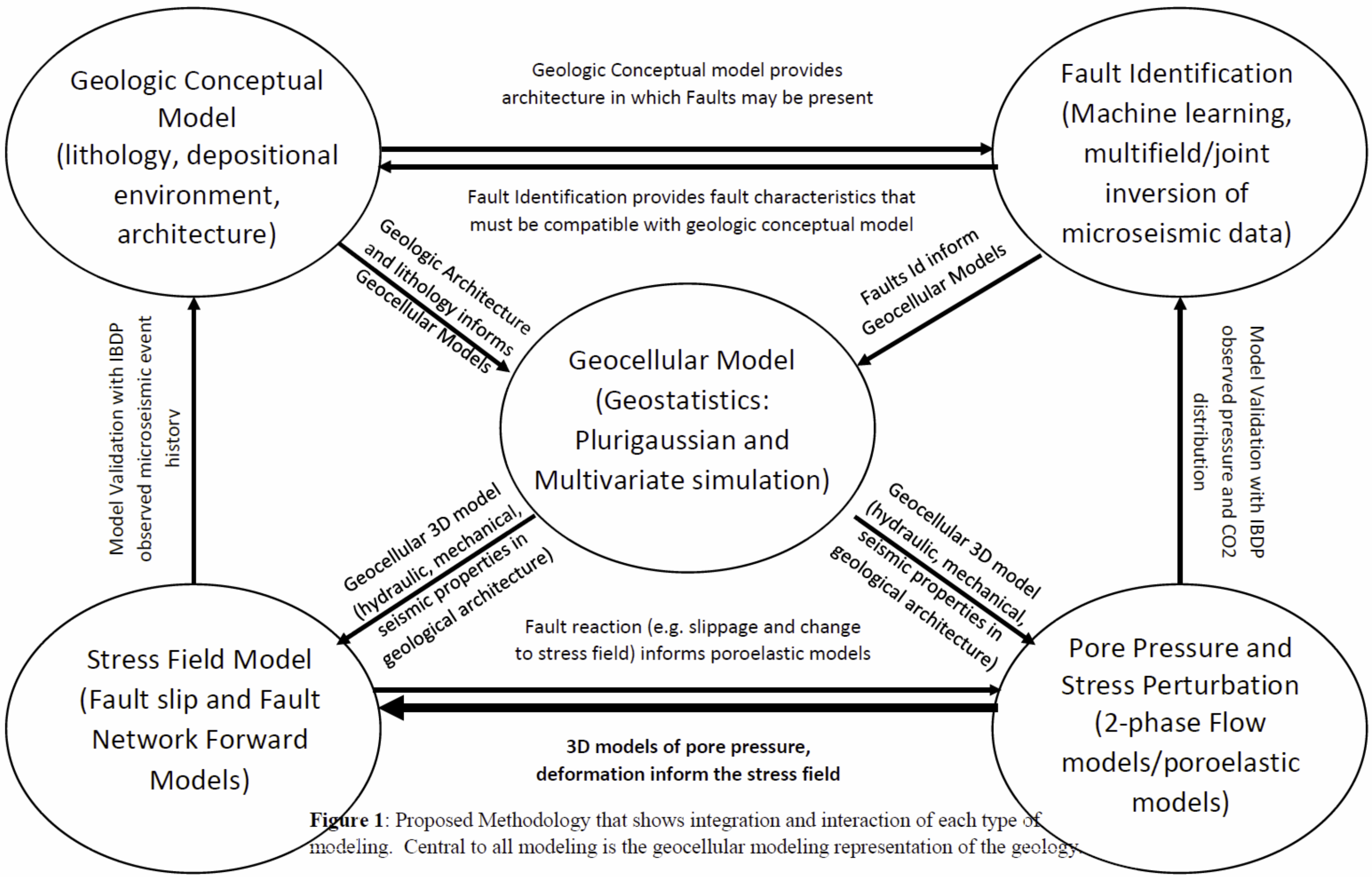
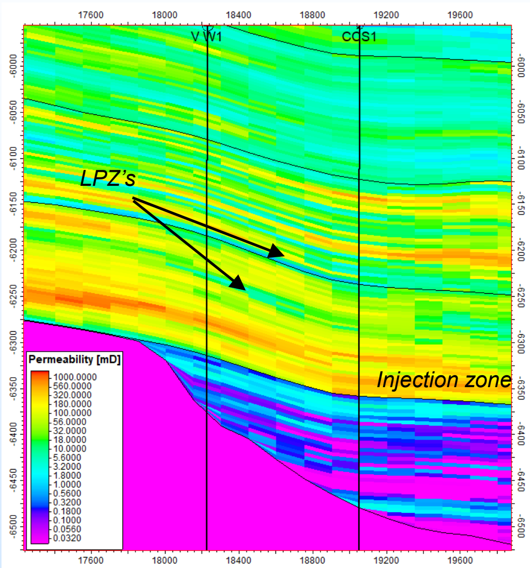


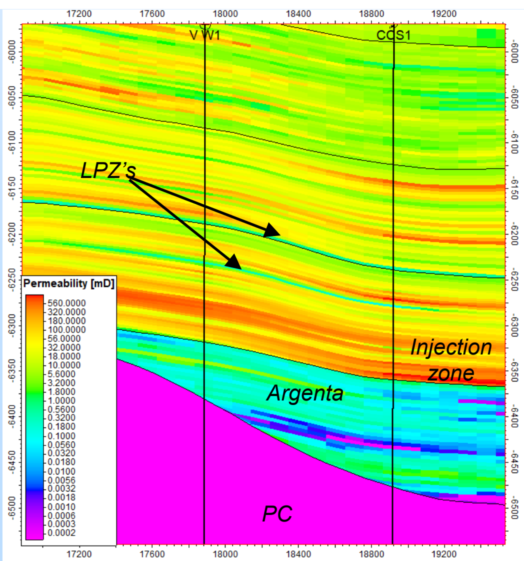
Figure 1: Proposed Methodology that shows integration and interaction of each type of modeling. Central to all modeling is the geocellular modeling representation of the geology.

Technical Status: Task 2
Conceptual Geologic Modeling

GCM:	Iteration 1	Iteration 2
LPZ	Subtle vert perm contrast; laterally discontinuous	Stark vert perm contrast; laterally continuous
Faults	Small, high perm	Small, low/no perm
Argenta	PC high Onlap	No PC high onlap
PC	Constant perm	



Initial model: SGS algorithm



Updated model: Kriging algorithm

<u>Geocellular Model</u>:

- Represent larger area statistical w/ four wells in area: Sequential Gaussian Simulation (SGS)
- Represent immediate area near two wells: Kriging

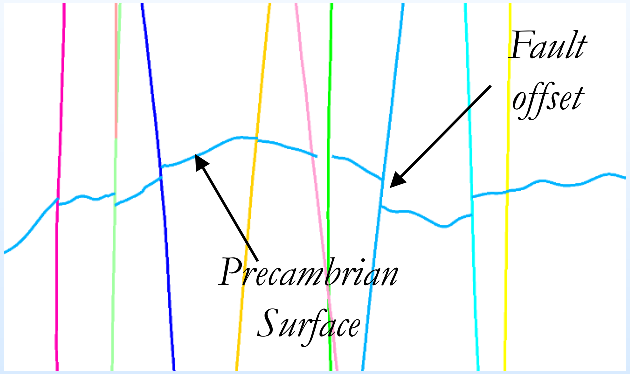
GCM: Geologic Conceptual Model; LPZ: Low Permeability Zone; PC: Precambrian basement

Technical Status: Task 2
Conceptual Geologic Modeling

<u>Precambrian (PC) Basement</u>

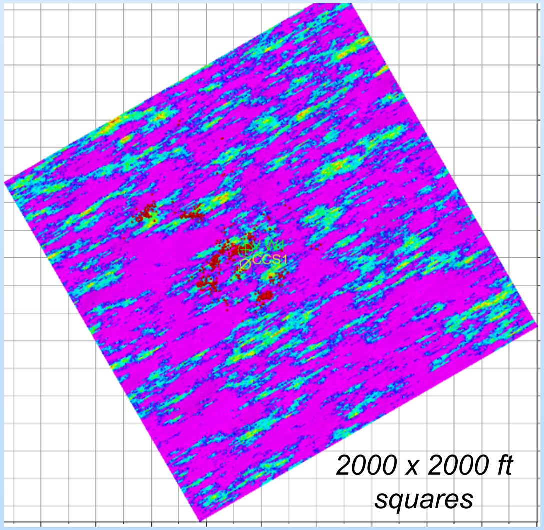
- <u>Faults</u>
  - Iteration 1: incorporate major faults from surface seismic interpretation (traditional)
  - Iteration 2: addition of faults and displacement identified through machine learning
- <u>Fractures</u>
  - Based on
    - image log (dip and orientation)
    - regional stresses
    - microseismic clusters
  - Permeability and porosity
    - upscaled from fracture network (Oda, 1985)

PC surface updated w/ fault displacement (from surface seismic)



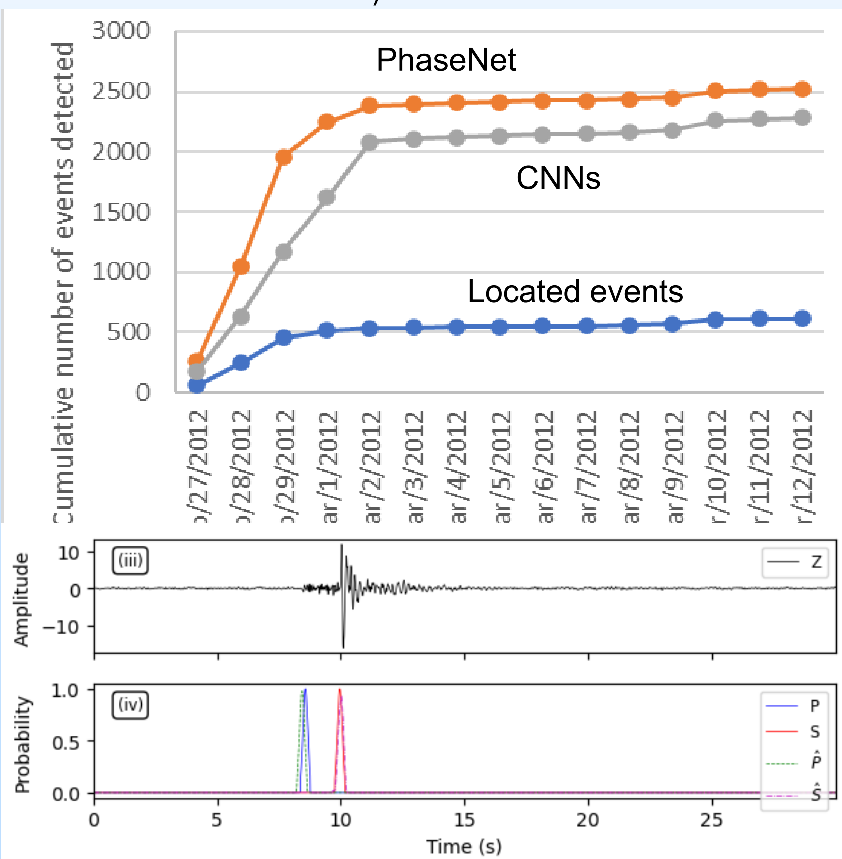
Fault surfaces- colored vertical lines

PC Fracture model: fracture intensity and micro-seismic locations



Technical Status: Task 3
Machine Learning

- Develop ML models to improve detection of low-magnitude events and p- and s-wave arrival times from cont. raw waveform data to discover undetected fault/fracture



Unsupervised: Fingerprint clustering

- Group: acoustic state -> failure mechanisms
- Waveform to spectrogram (short time Fourier transform)
- Non-negative matrix factorization (dimension reduction)
- Hidden Markov model (states)
- State change for clustering using K-means cluster

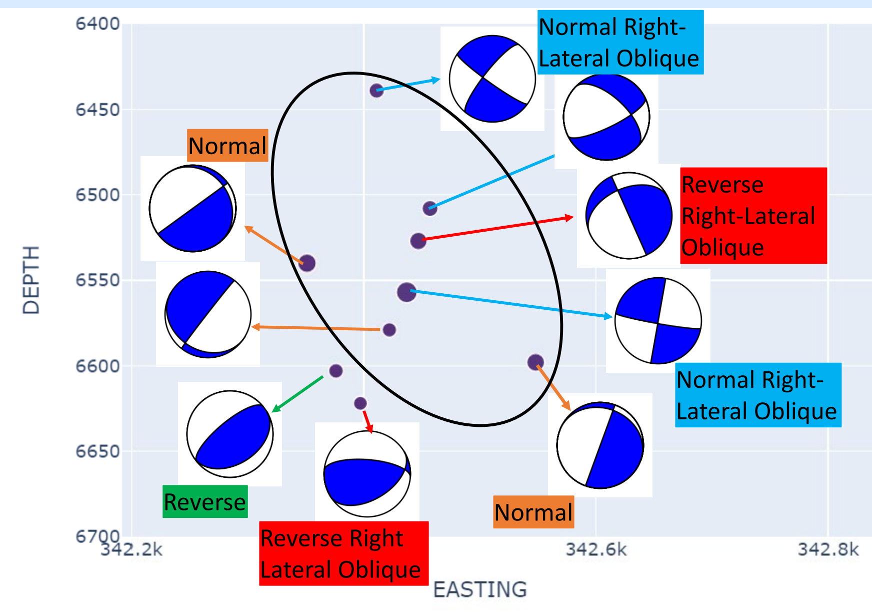
(top) Comparison of two event detection ML models for raw continuous waveform data with located events in the catalog over Feb 27 to Mar 12, 2012.

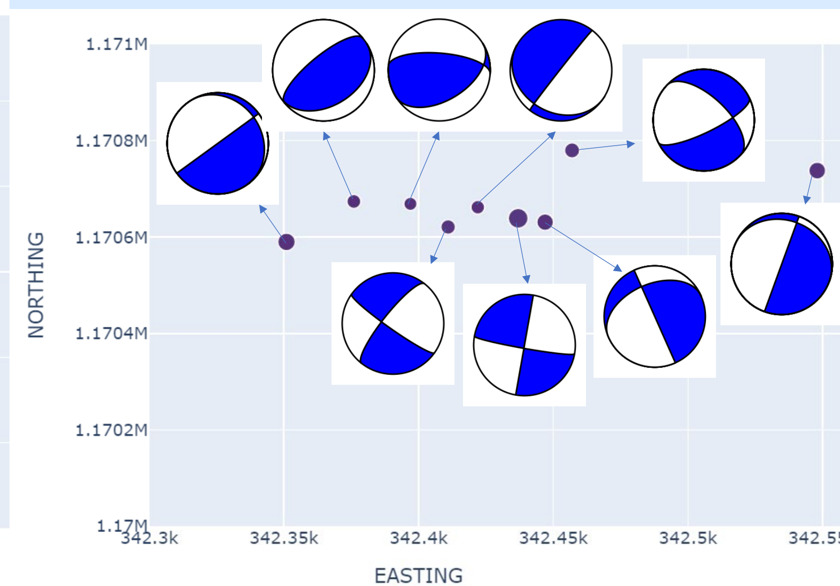
(bottom) p- and s-wave arrival time estimates of newly detected waveform data using PhaseNet.

Technical Status: Task 3
Microseismic Mechanisms

- Constructed fault planes from microseismic events using the spatio-temporal analysis of seismic events, statistical three-point method, and machine learning methods.
- Applied focal mechanism analysis tool (e.g., USGS HASH) based on the first motion and p- and s-wave magnitude ratio for selected events from unsupervised machine learning clustering.

One example fault plane identified from a cluster of microseismic events from cluster #2 (Feb. 27-29, 2012) region. Focal mechanisms from USGS HASH software are also shown. All events in the black circle (left) have the steepest dip angles with possibly normal slips. Right figure shows the same data.

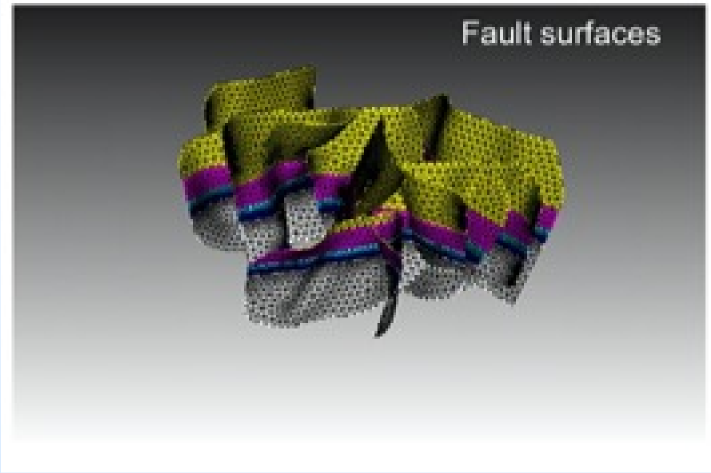


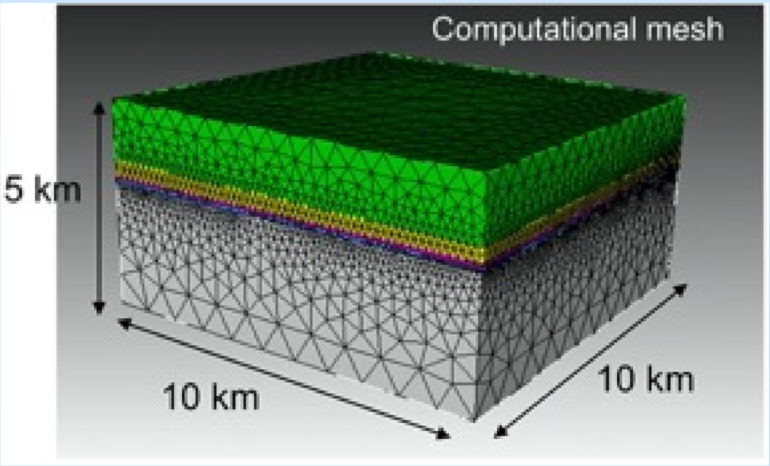


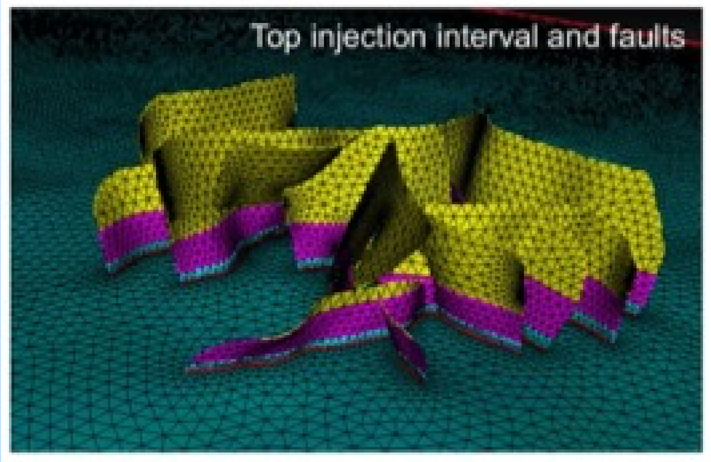
Technical Status: Task 4
Flow-Geomechanics Model Mesh

- Built unstructured mesh that adapts to all fault planes interpreted using 3D seismic data

- Included additional fault planes interpret based on microseismicity locations



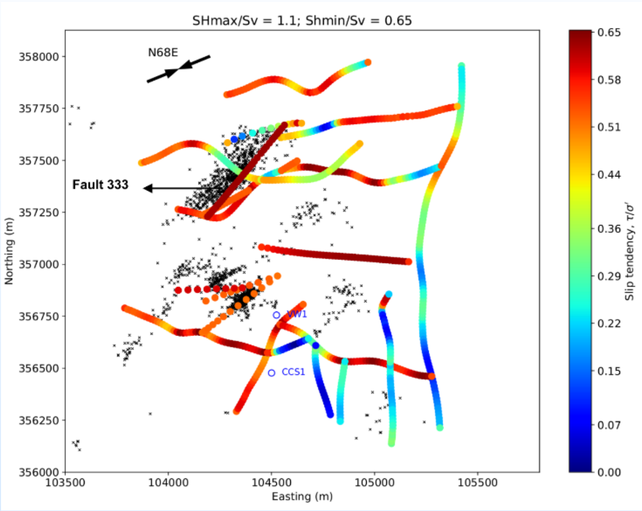




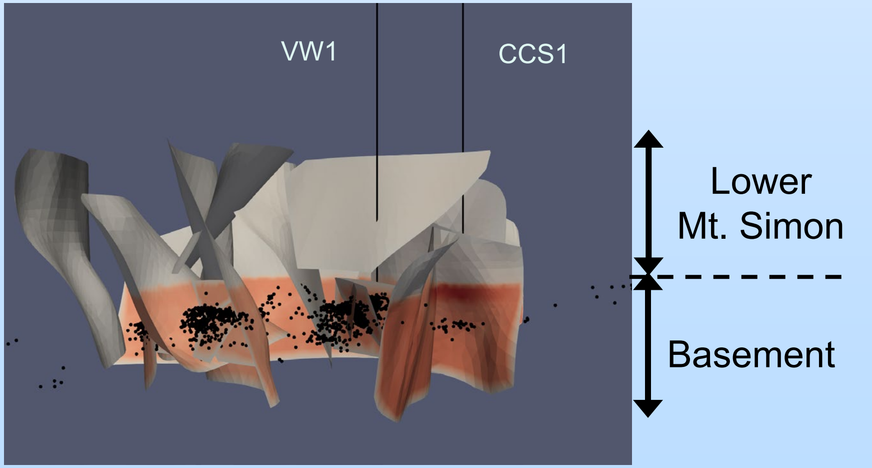
Technical Status: Task 4
Flow-Geomechanics Model Results

- Fault proximity to failure (slip tendency) and changes in Coulomb Failure Function (DCFF) over time
- Faults near the main clusters of seismicity are very close to failure, with slip tendency ~0.65
- Pore pressure increase due to CO2 injection process destabilizes the basement faults
- Stress changes from poroelastic effects are small and tend to stabilize the faults

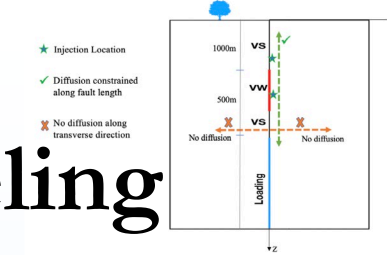
Slip tendency: top of basement



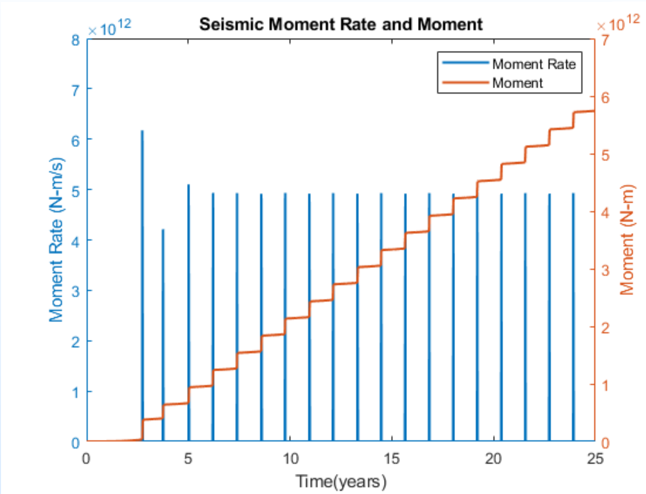
Slip tendency: 3D view

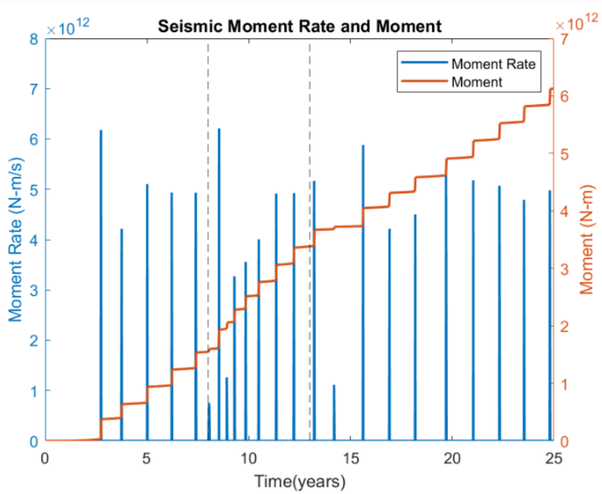


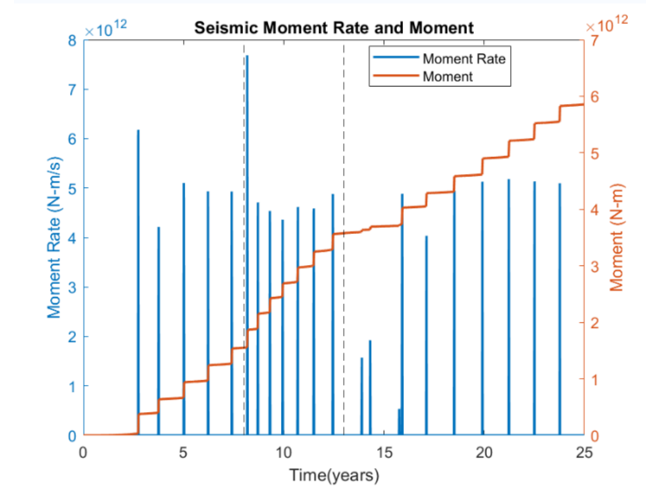
Technical Status – Task 5: Stress Field (Mechanical) Modeling

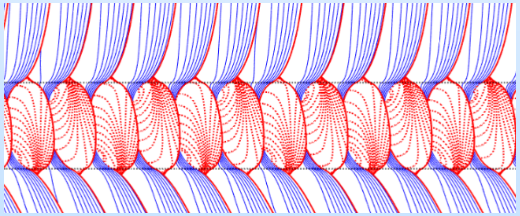


Without Injection	Injection within Creeping Region (VS)	Injection within Locked Region (VW)

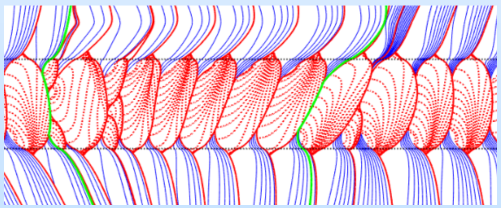




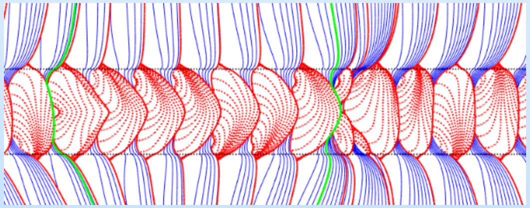




Increasing slip



Increasing slip



Increasing slip

Without Injection

- Events are periodic and regular

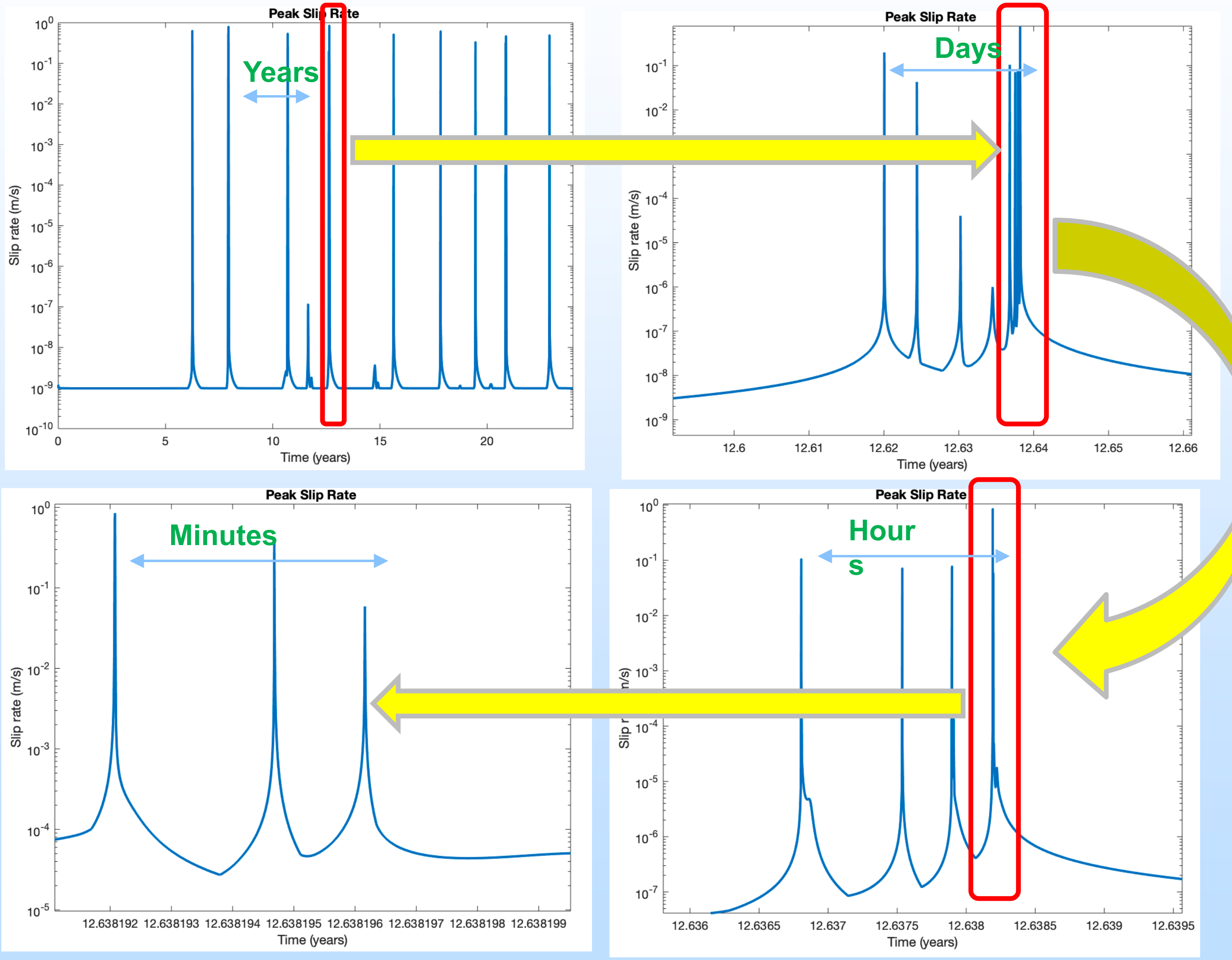
Injection within Creeping Region (VS)

- Periodic pattern of events is broken. (time clustering)
- Partial ruptures occur during injection. (spatial clustering)
- Risk of a large event after shut off.

Injection within Locked Region (VW)

- Periodic pattern of events is broken. (time clustering)
- Partial ruptures occur after shut off (spatial clustering)
- Largest event occur during injection

Technical Status – Task 5: Stress Field (Mechanical) Modeling



- Fault slip may generate damage in off-fault surrounding rocks.
- Aseismic and seismic off-fault damage regulate the stresses on the fault and enable generation of events with broad distribution of inter-event times.
- Similar hierarchical seismicity is observed in IBDP clusters

Accomplishments to Date

Through two iterations of the proposed workflow

Task 2:

- 28 faults added to the geologic model
- Fracture model was constructed for the Precambrian Crystalline basement
- Faults identified from machine learning processes were given geologic context and added to the model

Task 3:

- Workflow using cont. raw waveform data to detect new events and arrival times using supervised CNN
- Transformed raw four to three orthogonal channel data and estimated source locations using 1D velocity model
- Waveform groups characterized using unsupervised ML fingerprints to identify potential fault planes

Task 4:

- Finished 3D computational mesh including all Iteration 2 faults
- Main hydrological controls on pore pressure variation away from the injection well
- Impact of uncertainty in regional stresses on slip tendency and proximity to failure

Task 5:

- Constructing a seismicity conceptual model to explore the effect of injection location, injection pressure, and injection rate on seismicity pattern.
- Modeling sequence of earthquake and aseismic slip in complex fault zones, including non-planar faults and inelastic rheology (enables quantitative comparisons with observations)

Lessons Learned

Geologic Conceptual and Geocellular Models

- Thin (3-10 ft)horizontal LPZ acting as a vertical barriers to CO_2 movement required to *match CO_2 saturation*.
- Small (vertical-100s ft; horizontal-1000s ft) vertical no-flow barriers best *match to pressure*
- Fracture intensity and inter-fracture connectivity strongly influence upscaled perm

Flow geomechanics modeling:

- Stress changes from poroelastic effects are small and tend to *stabilize the faults*
- Pore pressure diffusion to basement faults is main mechanism to *destabilize faults*

Machine Learning

- Supervised and unsupervised MLs detected *more seismic events* per cluster than catalog
- *Rapid recognition* of fault slip/ fracture activations *achieved* using open-source data analytic framework

Forward seismic modeling

- Fluid injection leads to spatio-temporal clustering of events, reduces inter-event time and accelerates slip.
- Post-injection shut-in may have *larger events* if injection occurs in the creeping region of the fault.

LPZ-Low Permeability Zone

Project Summary

Key Findings

- Faults-identified with traditional interpretation of active (surface) seismic data, had *no to little* associated *induced seismicity*
- Faults, presumably the source of induced seismicity, were *not identifiable* from traditional interpretation of active (surface seismic data)
- Supervised ML model for waveform data transferable by retraining (from cluster 2 to 4)
- Poroelastic stress alone *cannot be responsible* for *seismicity*; it is more stabilizing because of fault properties and pore pressure
- Off-fault damage accumulates during seismic and aseismic slip and enables clustering of events over a hierarchy of time/space scales.

Next Steps

- Improve the accuracy of source location estimation using ML analytics and p- and s-arrival time estimation
- Construct rapid recognition of the presence of fault and fault/fracture response associated with microseismic events
- Perform additional flow-geomechanics simulations accounting for anisotropy in the matrix and fault permeability
- Model validation through integration of data from Task 3 and Task 4 regarding seismicity pattern and fluid pressure model.
- Continuing progress on the conceptual model for seismicity to inform geocellular model and validate workflow

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Appendix: Project Benefits Statement

- This project is supportive of AoI 2- Methods for Understanding Impact of Vertical Pressure Migration due to Injection on State of Subsurface Stress.
- Mechanisms of transmitting pressure and stress vertically from a storage unit to a fractured and faulted crystalline rock will be identified via a series of unique modeling efforts that are calibrated to injection results at a DOE sponsored demonstration project.
- Identification of characteristics of faults that are more likely to release seismic energy upon injection will lead to technology development that can identify these characteristics a priori to injection at specific sites.

Appendix: Project Overview

Goals and Objectives

- To predict the presence of faults that will be susceptible to movement in the presence of fluid injection as a consequence of vertical pressure migration from the storage unit to the crystalline basement (underburden).
  - *BP1 (Year 1):* Complete at least one initial geocellular model for each of the three forward modeling efforts and complete initial assessment of fault locations using machine learning and based on joint inversion modeling using Illinois Basin Decatur Project (IBDP) microseismic data.
  - *BP2 (Year 2):* Complete at least one static model (predicted) of pressure and stress in the storage unit, across the geologic interface between the storage unit and the faulted crystalline basement, and the faulted crystalline basement, and identify effective techniques to represent faults and fault zones in geocellular models based on conceptual geologic models.
  - *BP3 (Year 3):* Validate results of a single fault and network model with known and suspected IBDP faults from previous seismic interpretations and conceptual geologic models and document results and finalize conclusions in order to advance the methodology to Technology Readiness Level (TRL) 4.

Appendix: Project Overview

Success Criteria

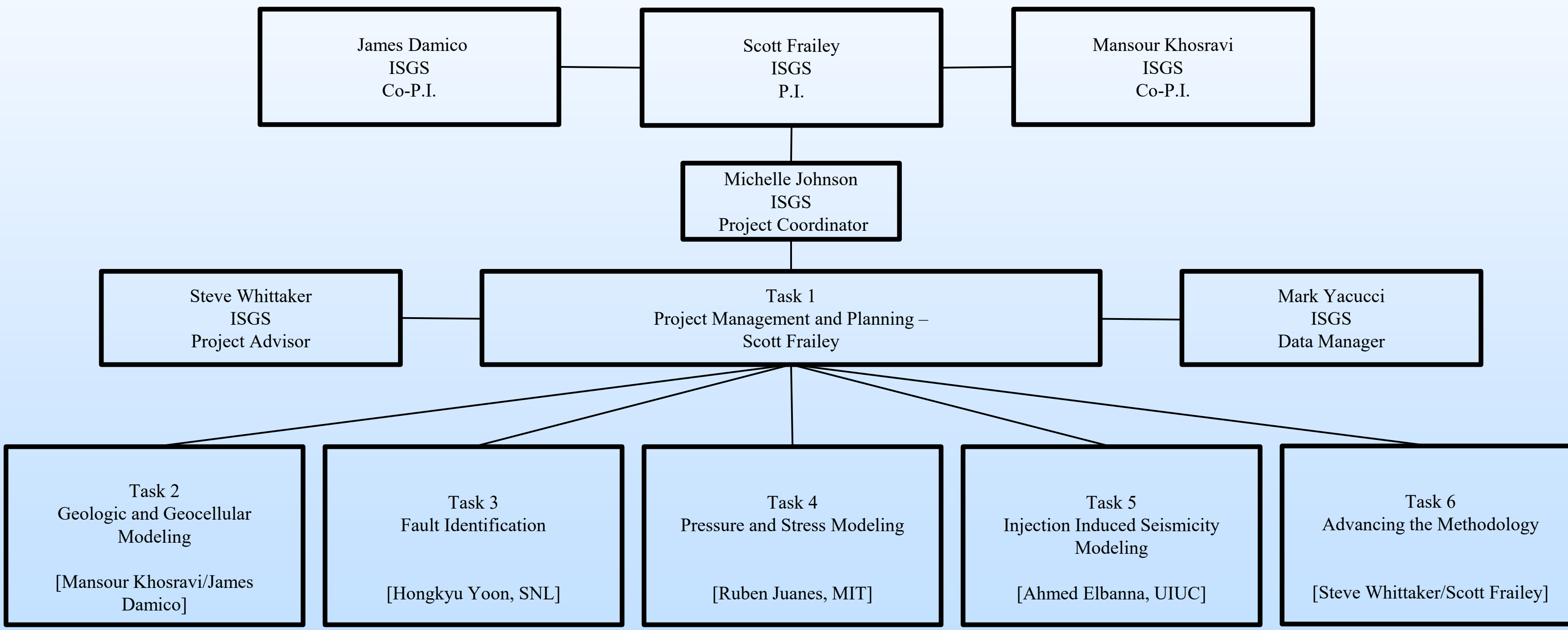
- *BP 1*: The initial geocellular models will be assessed as being successful upon completion and review by the project team. The initial fault model produced via inverse methods will be judged successful by the identification of any faults through inversion methods.
- *BP 2:* The initial model of pressure and stress will be assessed as being successful by completion and convergence with microseismic data. The updated geocellular model with faults will be assessed as being successful by completion of a new model that incorporates faults identified in the conceptual model and review by the project team.

Appendix: Project Overview, contd.

Success Criteria

- *BP 3:* Data-driven fault models produced by the machine learning process will be assessed as being successful by the presence of newly identified faults that agree with the seismic data characteristics and the forward and inverse modeling results. The summary of findings will be assessed as being successful by completion and acceptance by the funding administration of the final report and the submission of one paper on the major findings of the project to a peer-reviewed scientific journal.

Appendix: Organization Chart



Appendix: Gantt Chart

Task	Responsible Party	2018	2019				2020				2021		
Task	Responsible Party	4	1	2	3	4	1	2	3	4	1	2	3
Task 1.0 – Project Management and Planning													
1.1 Kickoff, monthly task leader, and monthly task meetings	Task Leaders, Johnson												
1.2 - Quarterly reports and project meetings	Task Leaders, Johnson, Prete												
1.3 – Annual DOE reports and meetings	Task Leaders, Johnson, Prete												
Milestone: Project Management Plan	Frailey & Johnson	100%											
Task 2.0 – Geologic and Geocellular Modeling													
2.1 – Comprehensive review of existing models	Kosravi, Damico	100%											
2.2 – Conceptual geologic models of storage unit and crystalline basement	Kosravi, Damico	100%											
2.3 –Geocellular modeling techniques for creating 3D models of hydraulic, mechanical, and seismic rock properties within the framework of the architecture of the geologic conceptual model	Kosravi, Damico	75%											
2.4 –Geocellular representation of the conceptual geologic model based on characterization data	Kosravi, Damico	15%											
Subtask 2.5 – Geologic and geocellular model realizations based on forward and inverse stress and pressure modeling	Kosravi, Damico	25%											
Milestone: Initial geocellular models	Kosravi, Damico	100%											
Milestone: Update of geocellular models with faults	Kosravi, Damico	0%											
Task 3.0 – Fault Identification	Yoon & MIT												
3.1 – Detection of microseismic events	Yoon & MIT	50%											
3.2 – Characteristics of microseismic events	Yoon & MIT	40%											
3.3–Bayesian inversion of time-lapse microseismicity data into coupled flow-geomechanics models	Yoon & MIT	10%											
3.4 - Rapid recognition of the presence of (undetected) faults and fault interactions using deep learning approach	Yoon & MIT	0%											
Milestone: Initial assessment of fault locations	Yoon & MIT	35%											
Go/No-Go Point 1 - Identification of Faults via multivariate inverse modeling	Yoon & MIT												
Milestone: Validate fault model with seismic data/conceptual model	Yoon & MIT	0%											
Go/No-Go Point 2 - Identification of Faults via machine learning	Yoon & MIT												
Task 4.0 – Pressure and Stress Modeling													
4.1 – Pressure perturbation	Juanes	40%											
4.2 – Fracture flow	Juanes	0%											
4.3 – Stress perturbation	Juanes & Frailey	0%											
Milestone: Initial model of pressure and stress	Juanes	10%											
Task 5.0 – Injection Induced Seismicity Modeling													
5.1 – Curation of input data and model output	Elbana & Juanes	15%											
5.2 – Fault slip modeling	Elbana & Juanes	45%											
Go/No-Go Point 3 - Fault slippage via seismicity modeling	Elbana & Juanes												
5.3 – System level seismicity modeling	Elbana & Juanes	50%											
5.4 – Development of conceptual model for induced seismicity	Elbana & Juanes	0%											
5.5 – Model Validation and updating	Elbana & Juanes	0%											
Task 6.0 – Advancing the Methodology													
6.1 – Field site calibration	Task Leaders	20%											
6.2 – Improvement over current state-of-the-art to identify	Task Leaders	0%											
Milestone: Summary of findings	Task Leaders, Johnson, Prete	0%											

Bibliography

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