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Invited Talk for Alberta Energy Regulator

Machine Learning Application for Fracture Analysis: Use Case

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U.S. DEPARTMENT OF ENERGY
NATIONAL ENERGY TECHNOLOGY LABORATORY
SMART

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Content

- Background and Introduction

- Machine Learning Use Cases:
  - 1. Fracture mapping for CO_2 storage
  - 2. Multiple-level of fracture network study: HFTS1
  - 3. Frac-hit identification: Midland Basin

- Discussions and Remarks

- Future Work

Science-informed Machine Learning for Accelerating Real-Time Decisions in Subsurface Applications (SMART) Initiative

Phase 2

SMART - Visualization and Decision Support Platform

SMART Functionalities

Real-Time Visualization
"CT" for the Subsurface

ML-based Rapid Prediction
Virtual Learning

ML-based Real-Time Forecasting
"Advanced Control Room"

SMART Decision Support Platform

SMART Applications

Virtual Learning to Support Permitting
Injection Operational Control

PHASE 1
"Proof of Concept"

PHASE 2
"Development and Validation"

Background (cont.)

Making Better Decisions

Phase 2

Transforming decisions through clear vision of the present and future subsurface.

Decision-makers	Phases	Questions
Project Engineers	Site/Field Selection	❶ Where is the CO_2 now?
Regulators	Permitting	❷ How do I move the CO_2 where I want it to be?
High-level Executives	Development	❸ Is the project safe? • Will it leak, and if so, where? • Will it cause induced seismicity?
Landowners/Public	Operations	
	Closure	

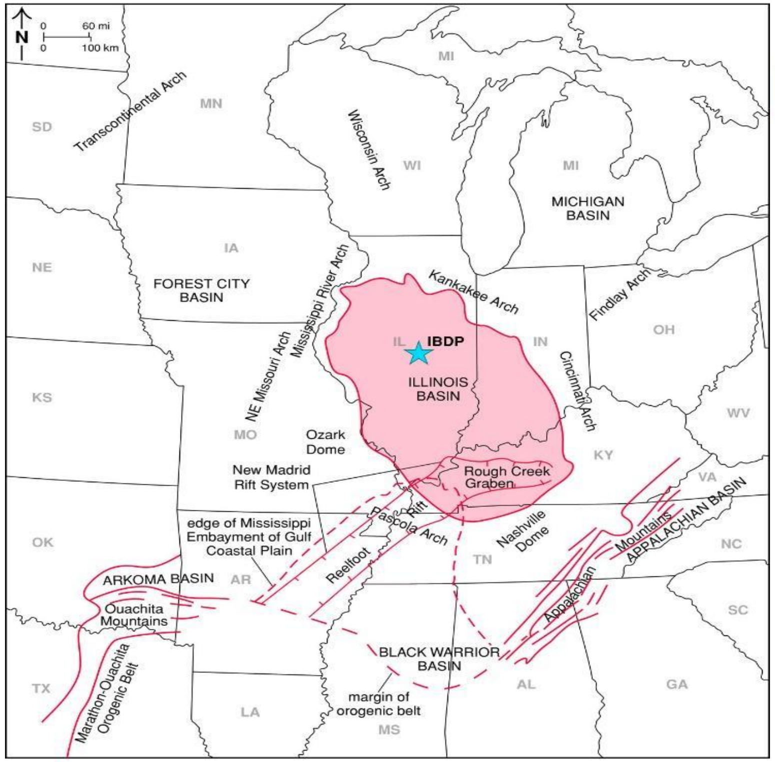
Introduction

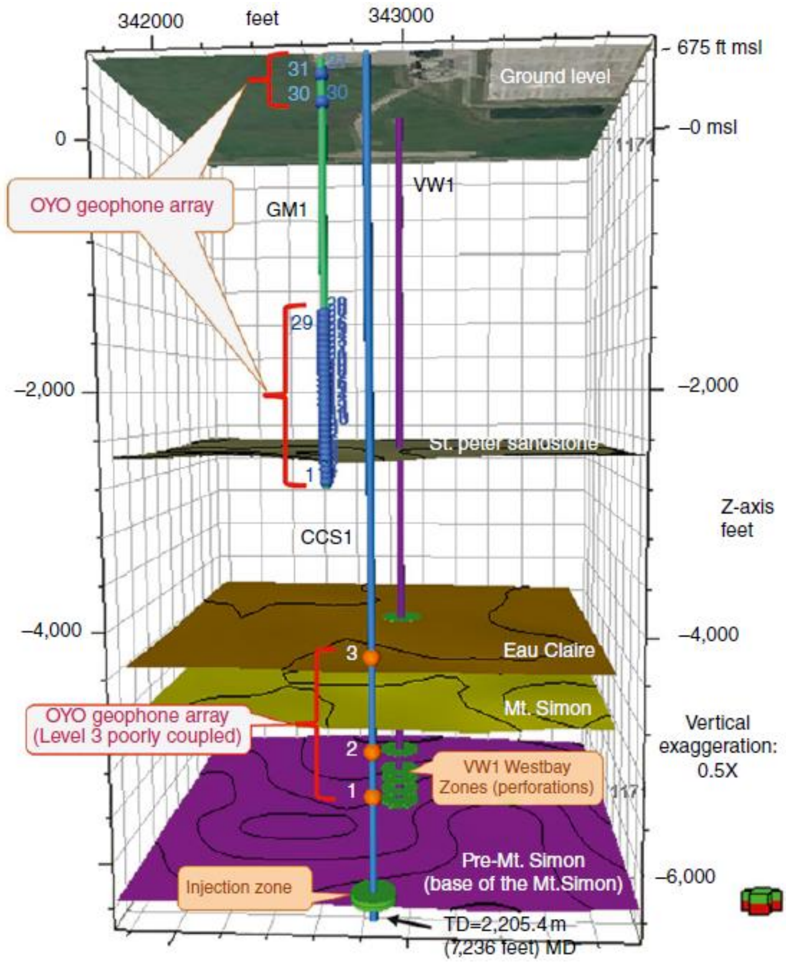
- Why does fracture/fault matter for CO_2 storage/sequestration?

- What are the impacts of fracture/fault for CO_2 storage in the reservoir?

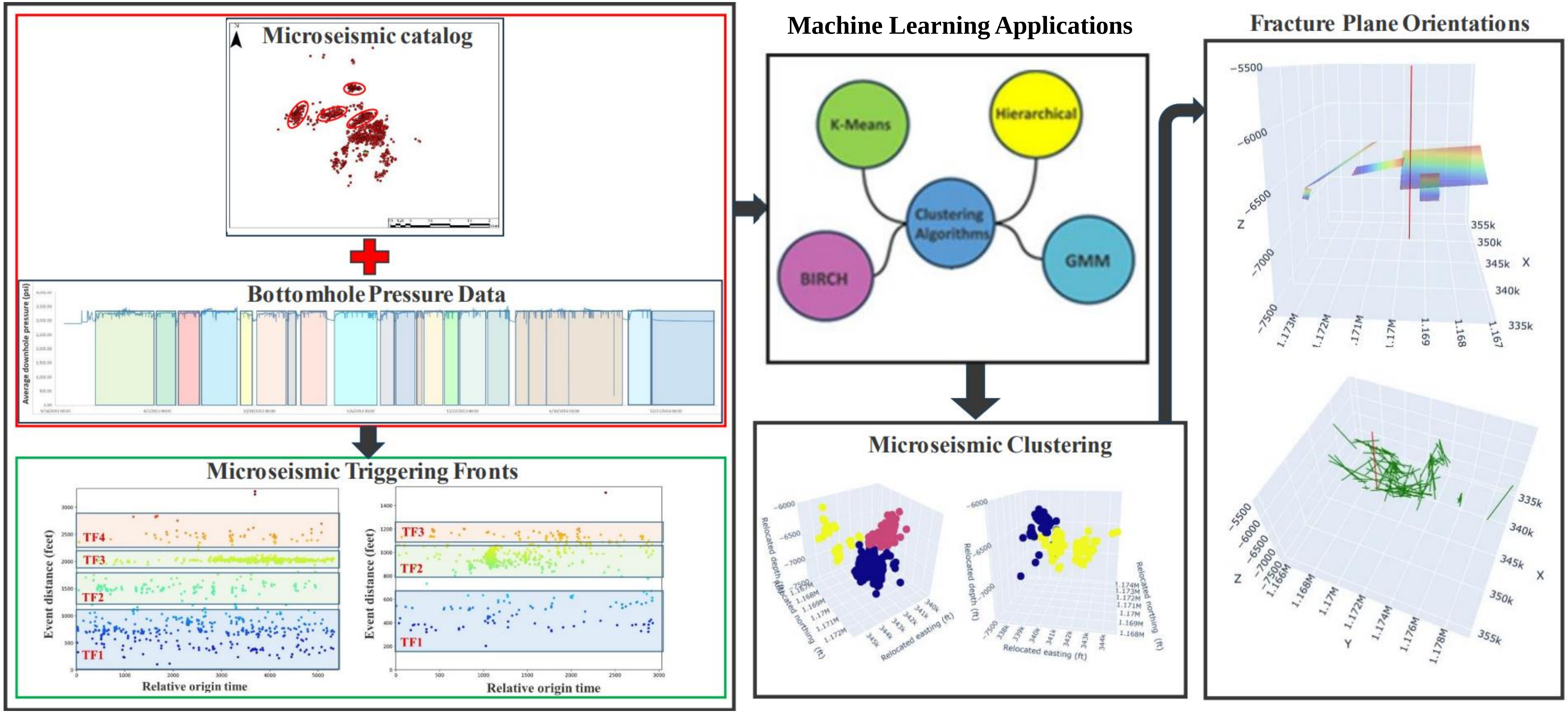
- How can machine learning help in the process and overall carbon storage decision making?

- Use case: Illinois Basin – Decatur Project (IBDP)



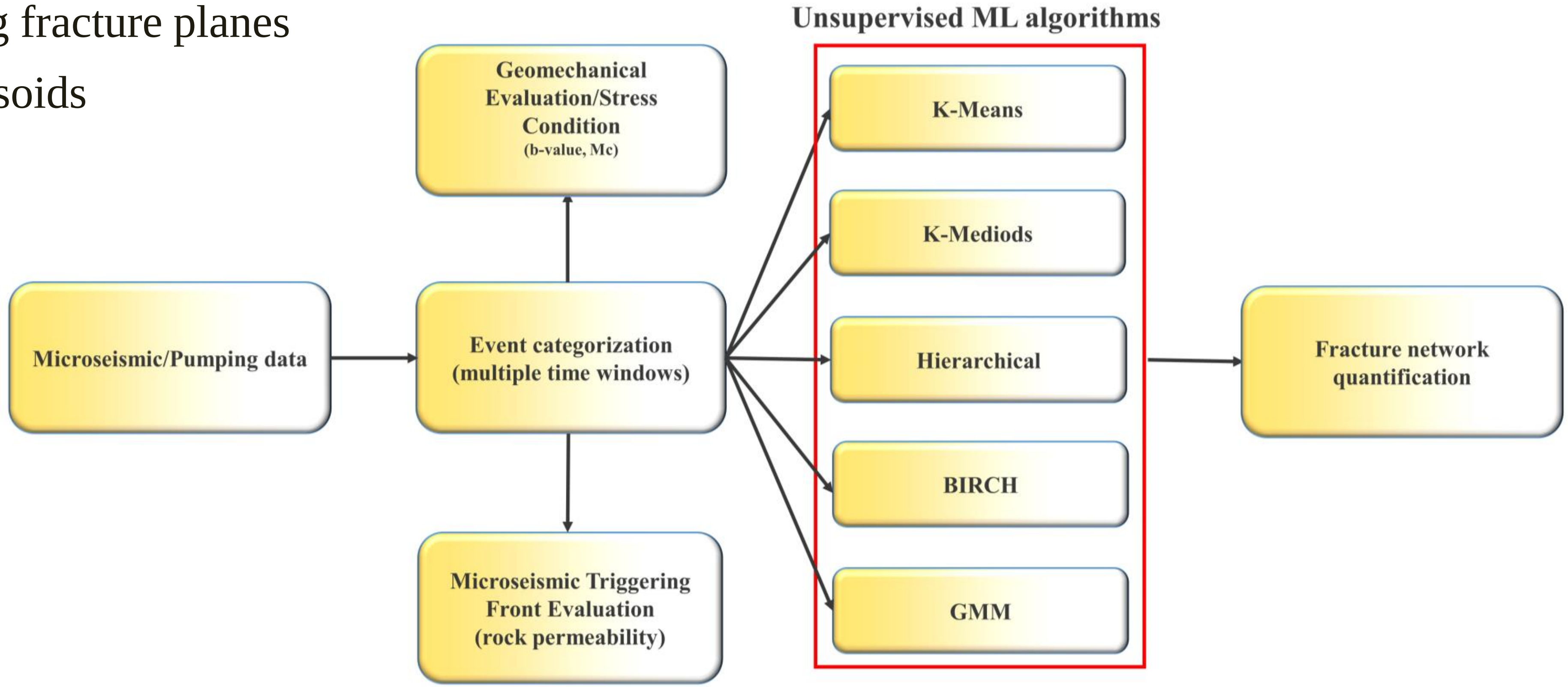


IBDP (Illinois Basin – Decatur Project) Use Case 1



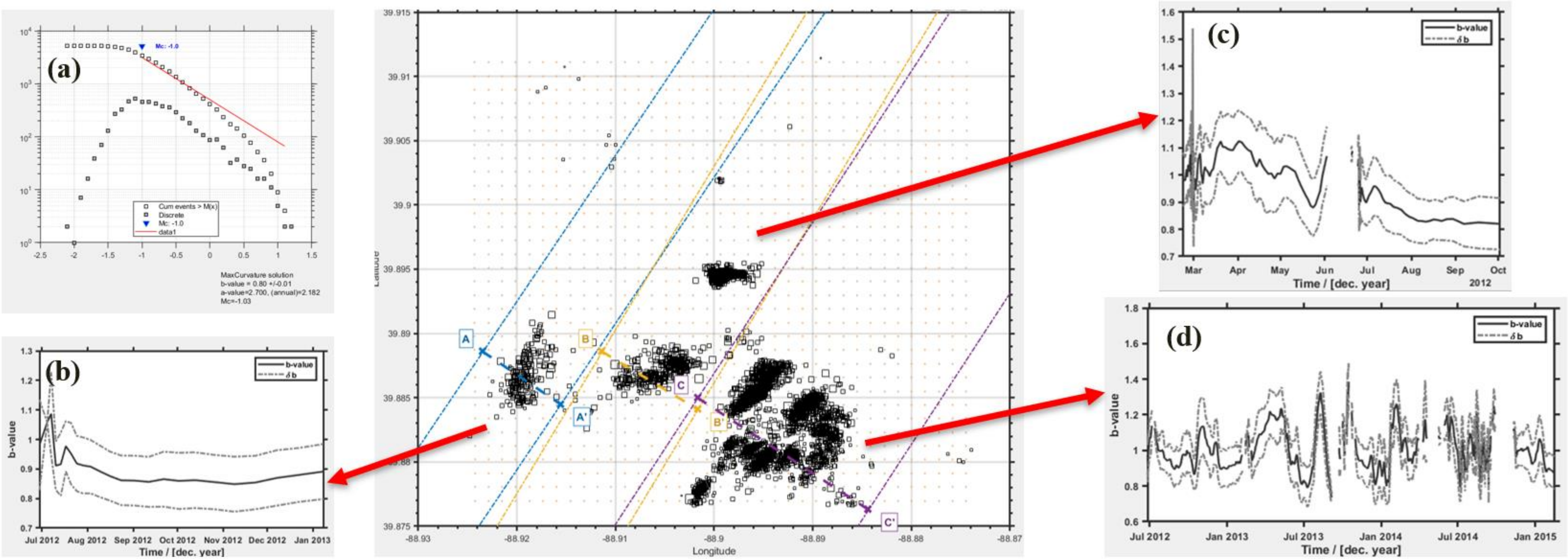
Methods

- Quantifying discrete microseismic time windows
- Microseismic triggering fronts identification
- ML-based microseismic cluster identification
- Quantification of best fitting fracture planes
  - ➢Standard deviational ellipsoids
  - ➢Eigen vector extraction



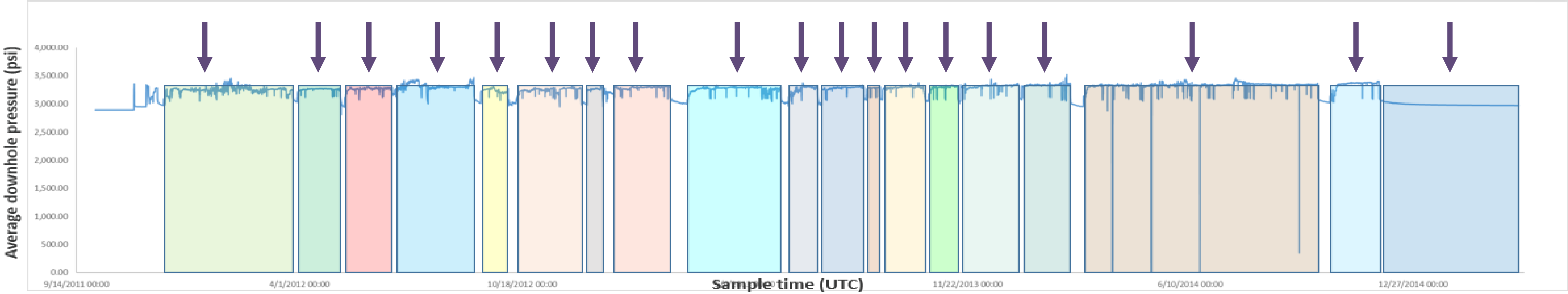
Microseismic Analysis

Spatial distribution of microseismic events at the IBDP site (center). (a) Magnitude of completeness, and (b-d) b-value variations for three separate regions.



Time Windows

Variations in average downhole pressure. Nineteen microseismic time windows (shaded boxes) marked by extended period of bottomhole pressure changes.



Name	Start Date/Time			Stop Date/Time			Number of Events
1	2011	12	15	2012	3	30	724
2	2012	4	1	2012	5	10	80
3	2012	5	12	2012	9	11	823
4	2012	9	11	2012	10	12	140
5	2012	10	13	2012	11	20	93
6	2012	11	20	2012	12	15	70
7	2012	12	15	2013	1	3	29
8	2013	1	9	2013	3	15	240
9	2013	3	16	2013	6	14	183
10	2013	6	14	2013	7	13	45
11	2013	7	14	2013	8	23	134
12	2013	8	24	2013	9	6	13
13	2013	9	7	2013	10	17	191
14	2013	10	18	2013	11	15	88
15	2013	11	16	2014	1	10	201
16	2014	1	11	2014	3	6	293
17	2014	3	6	2014	10	14	1357
18	2014	10	14	2014	12	2	152
19	2014	12	3	2015	3	30	210

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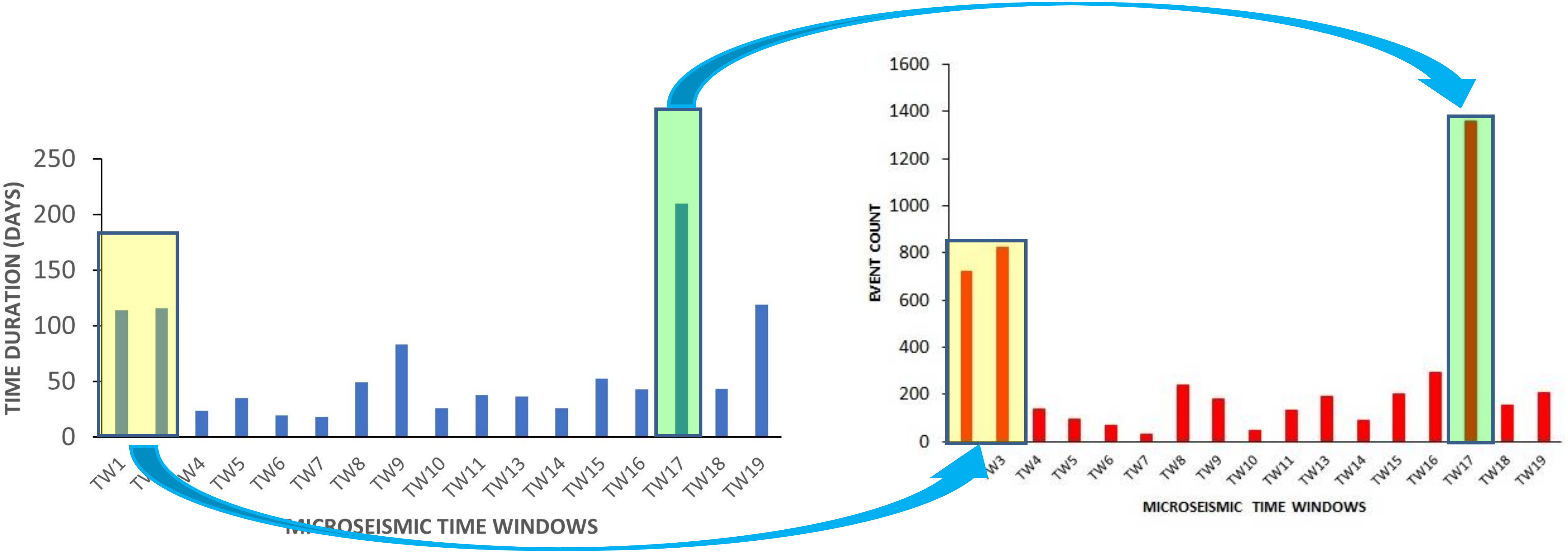
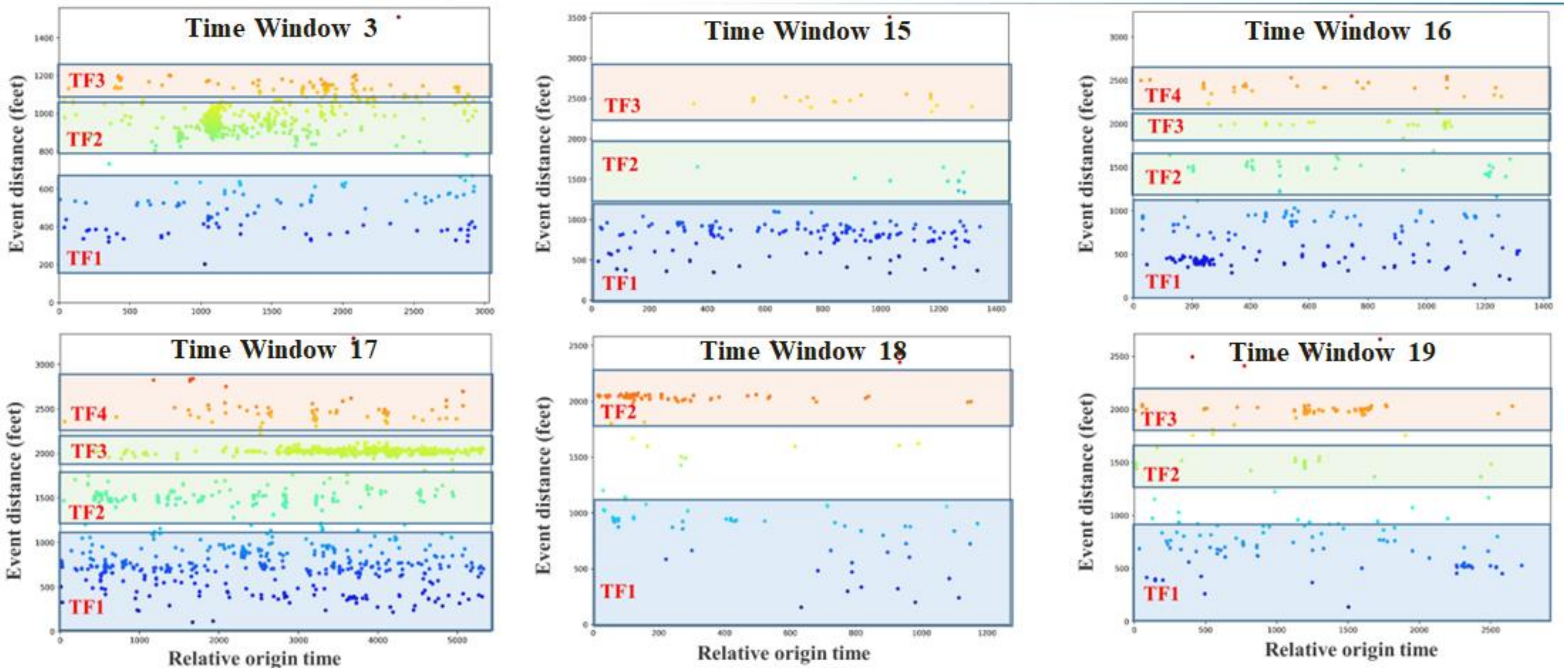
Microseismic time windows statistics (Duration-Event Counts)



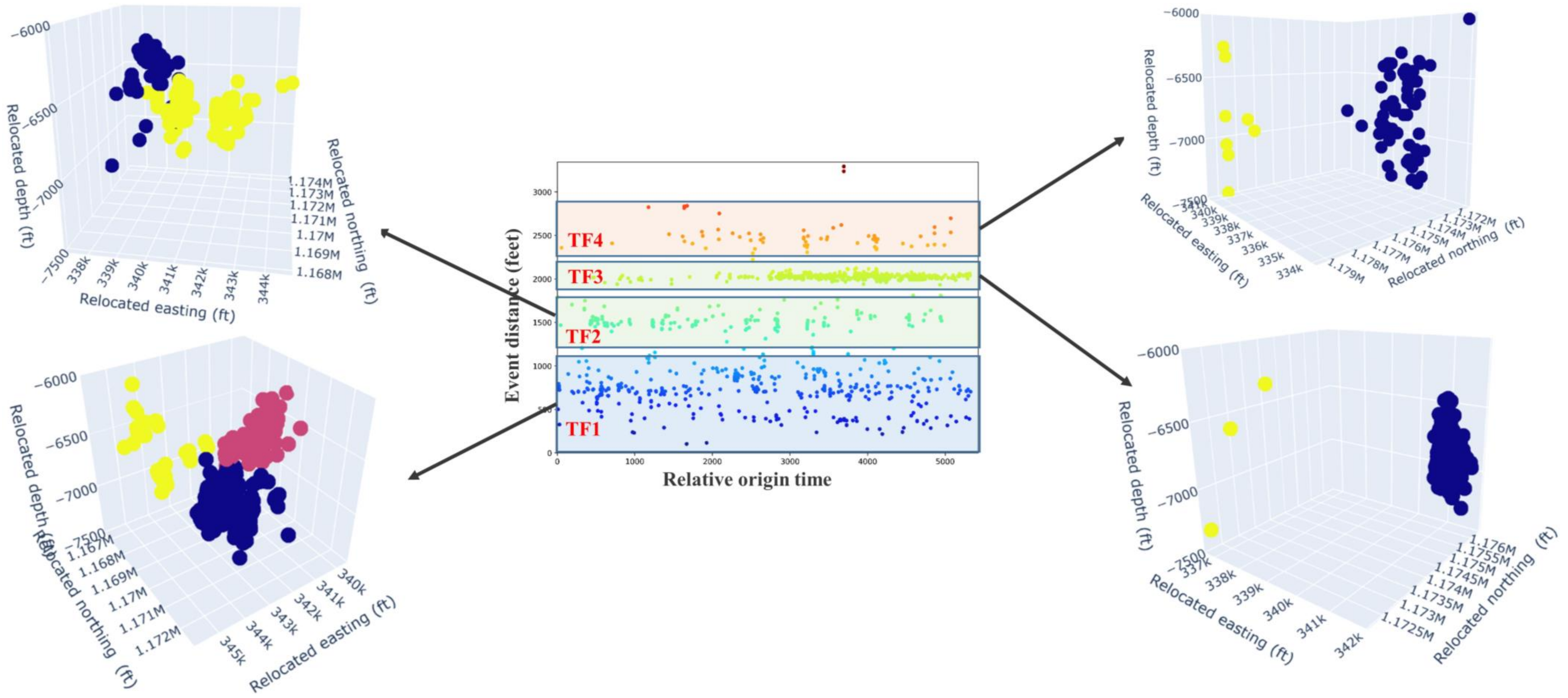
Triggering Fronts

Discrete triggering fronts (shaded rectangles) identified within each microseismic time window by hydraulic diffusivity analysis.



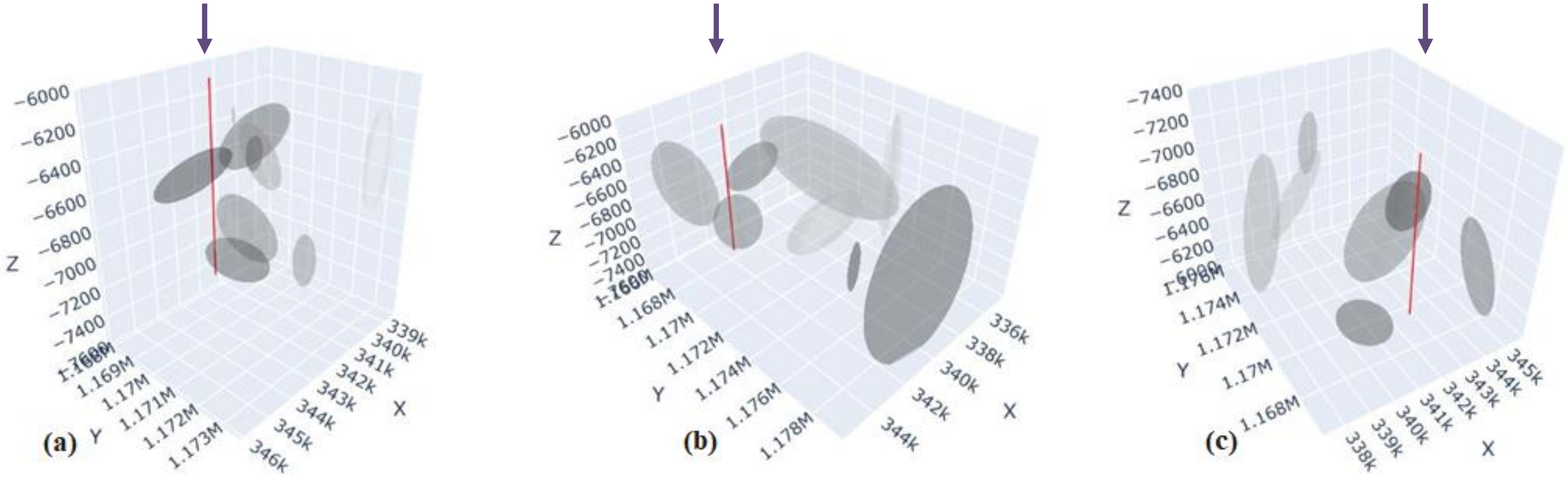
Microseismic Analysis (cont.)

Identified clusters of microseismic events within each triggering front of time window 17 (center plot).



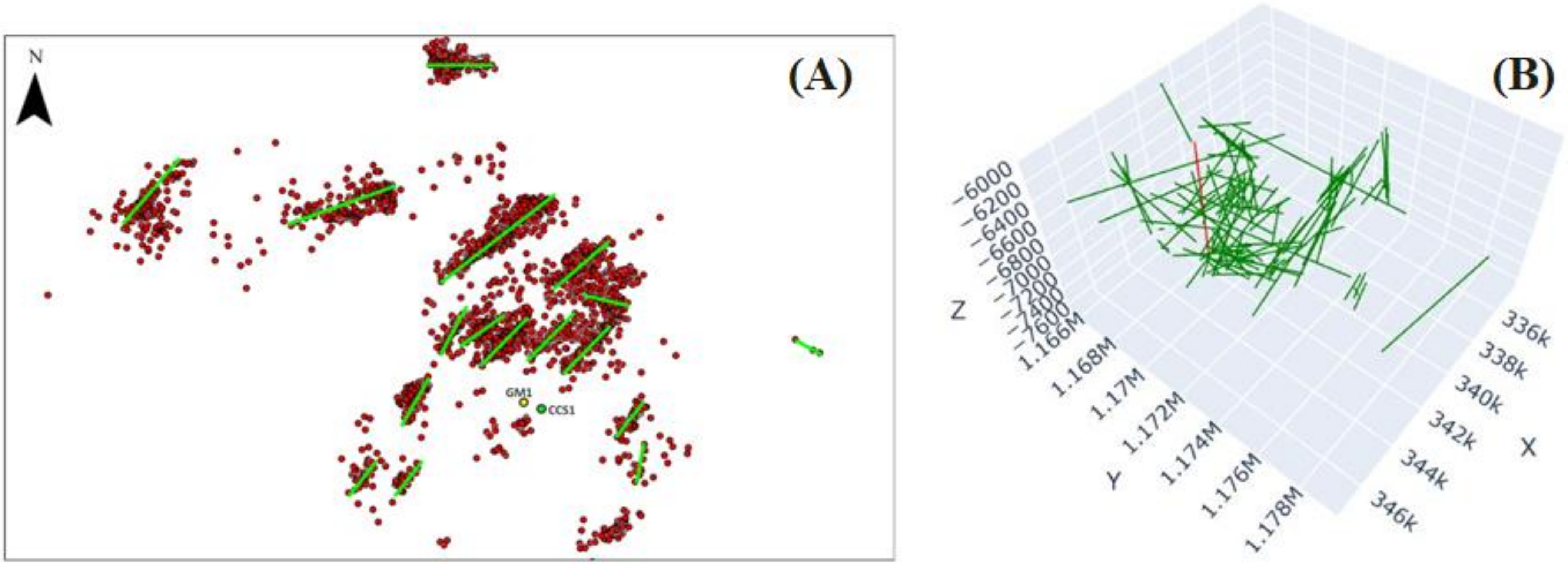
Fracture Mapping

3D distribution of fracture planes (shaded 2-sigma ellipsoids) around the injection well (red line) for time windows: (a) time window 9, (b) time window 17, and (c) time window 19.



Fracture Mapping (cont.)

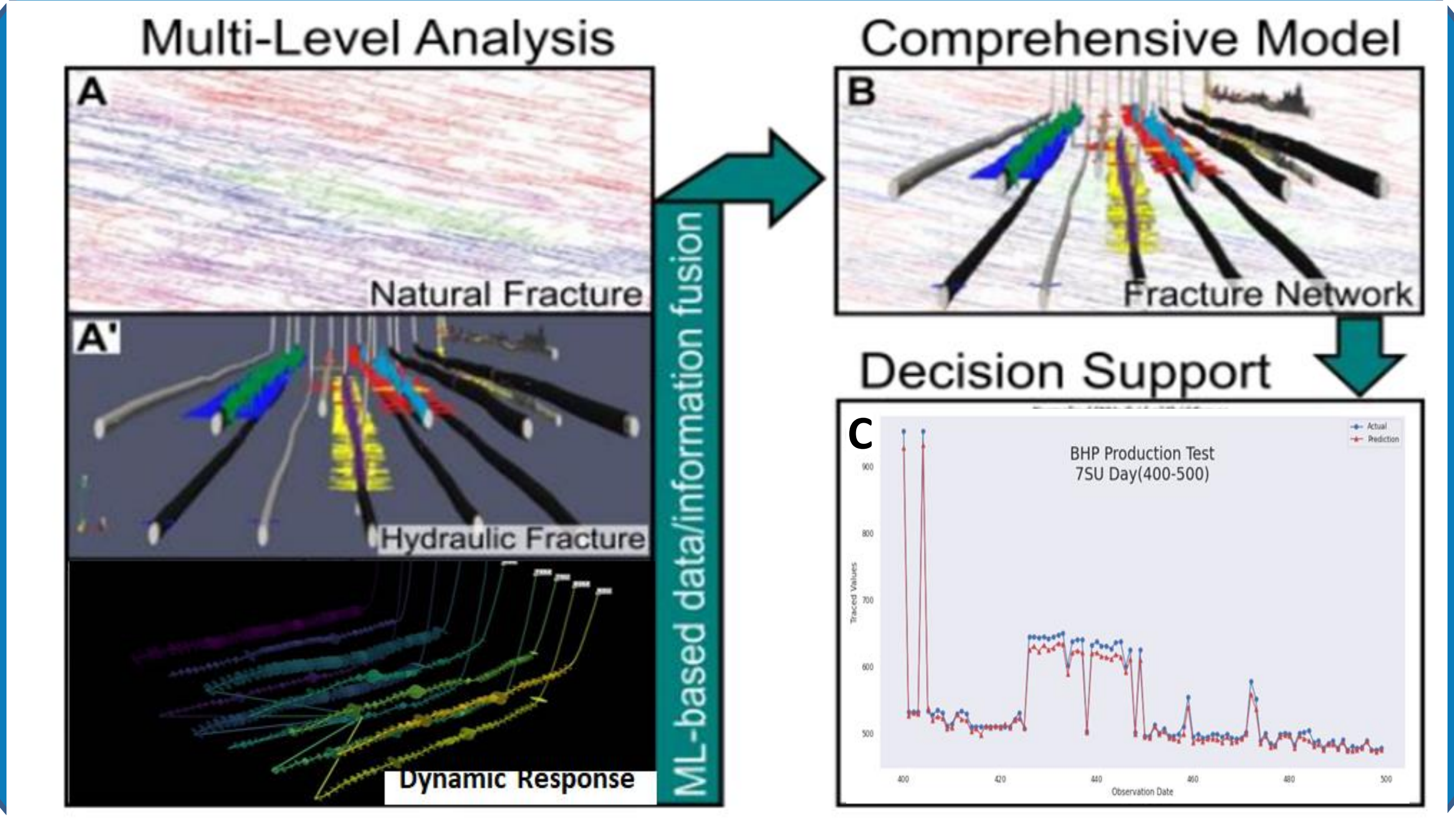
(A) Previously identified fault plane solutions (green lines) for the microseismic clusters. (B) 3D distribution of fracture network (green lines) around the injection well as determined using machine learning techniques in the current study.

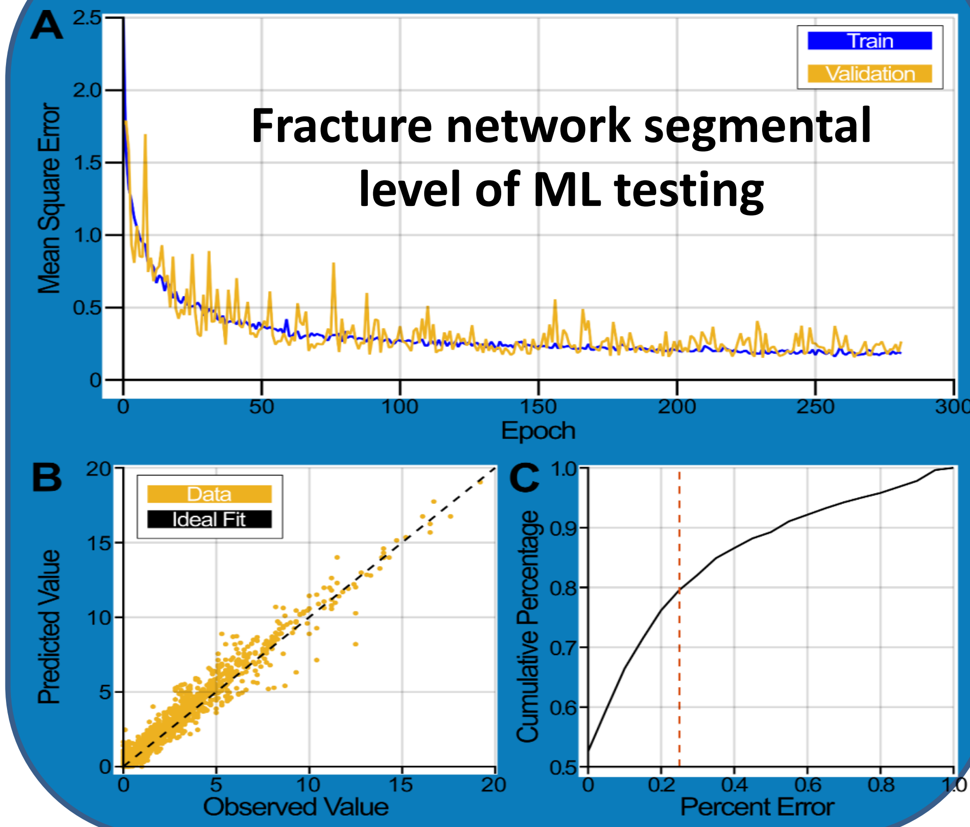


Multi-Level Fracture Network Analysis and Visualization

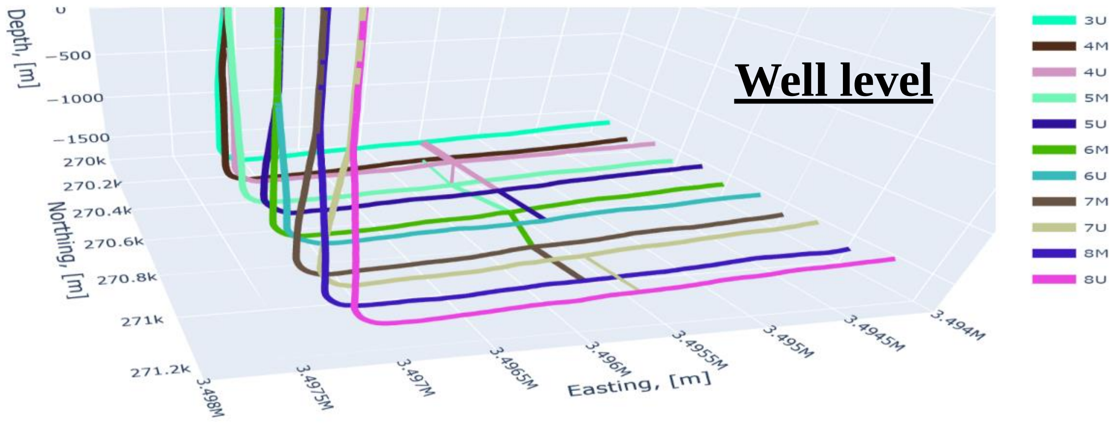
HFTS-1 Dataset

- **Microseismic Data** **Well Layout/Distance** **Log/Core Data** **Fracking/Pumping Data**
- **Tracer Data** **Production Data** **Pressure Interference Testing** **Flowback/DFI Data**

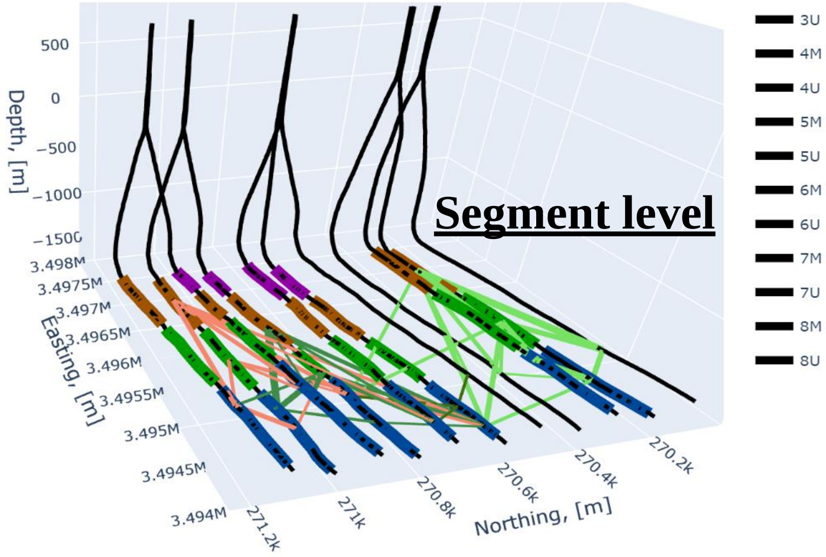




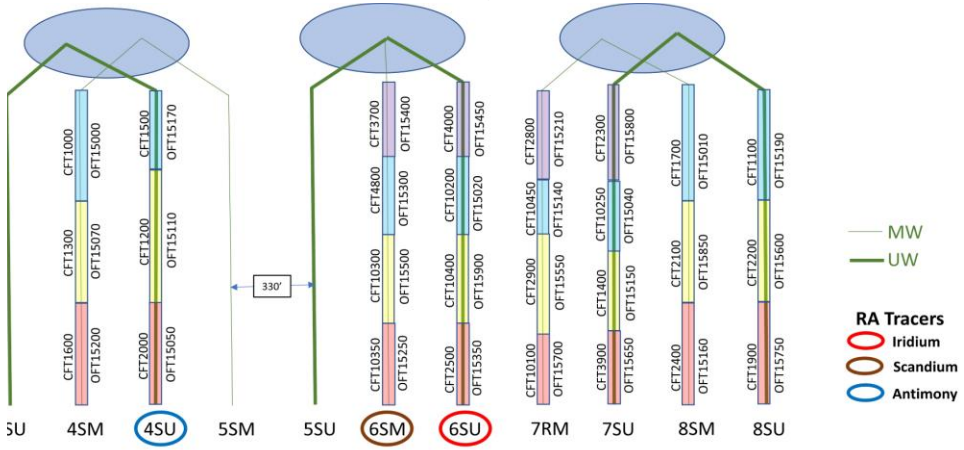
Use Case 2: HFTS-1 (Hydraulic Fracturing Test Site)



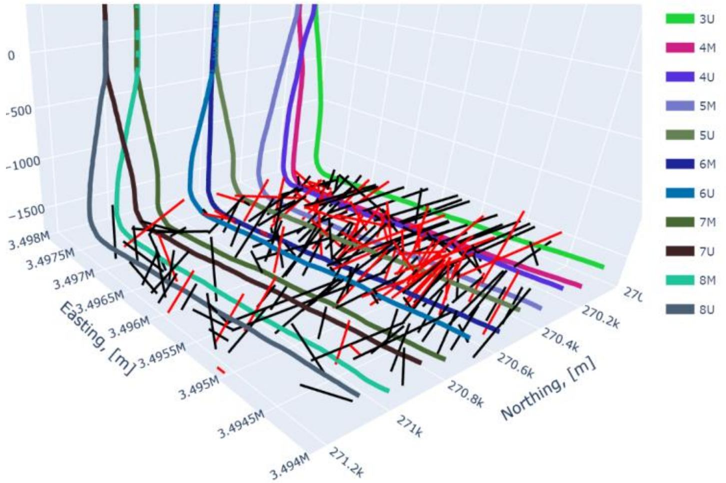
- **Well level:** pressure interference test, DFIT/Flowback
- **Segment level:** Tracer data, pumping data, well trajectory/distance
- **Stage level:** Pumping data, microseimic data, log/core data



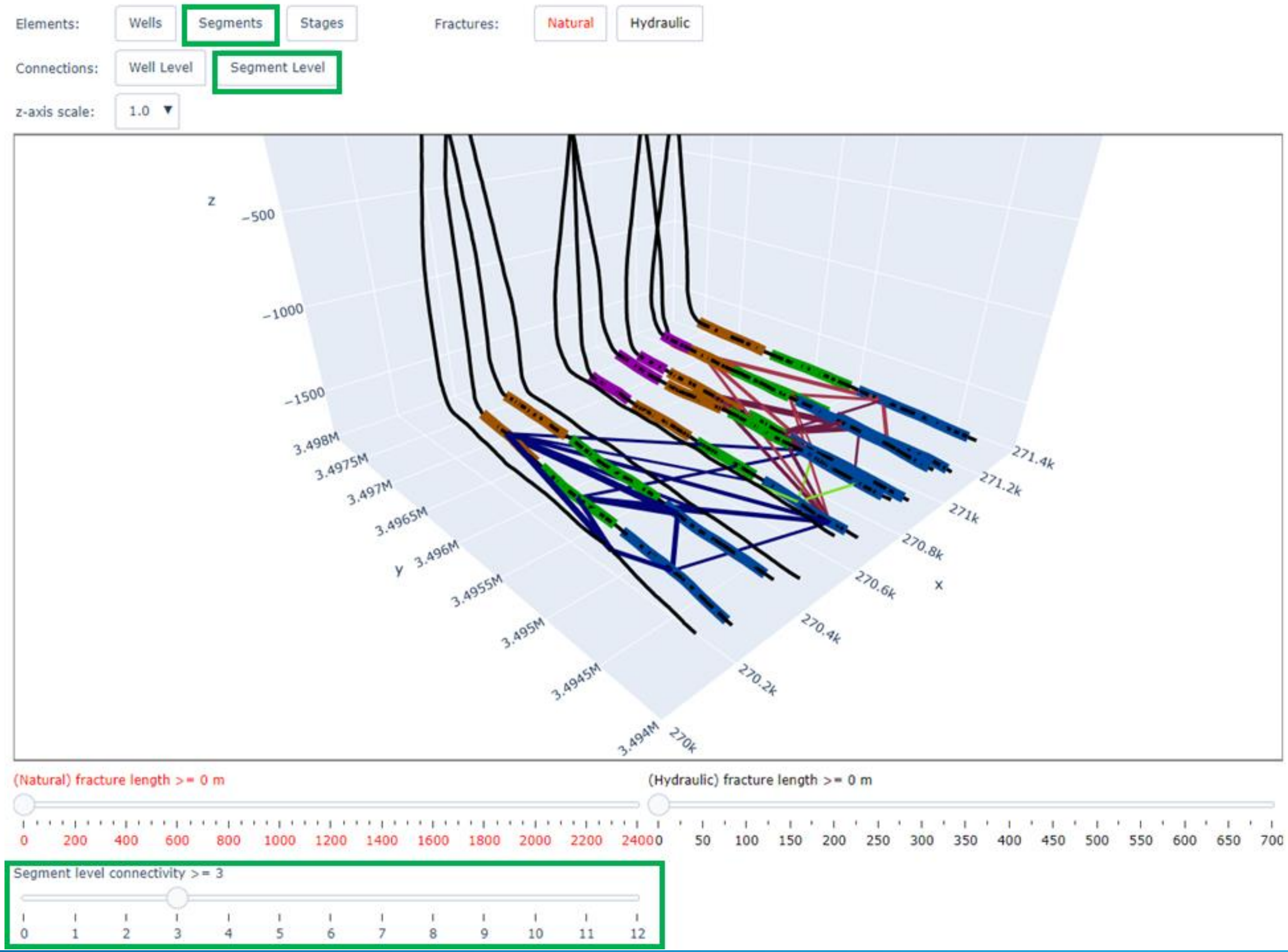
Tracer Testing Layout



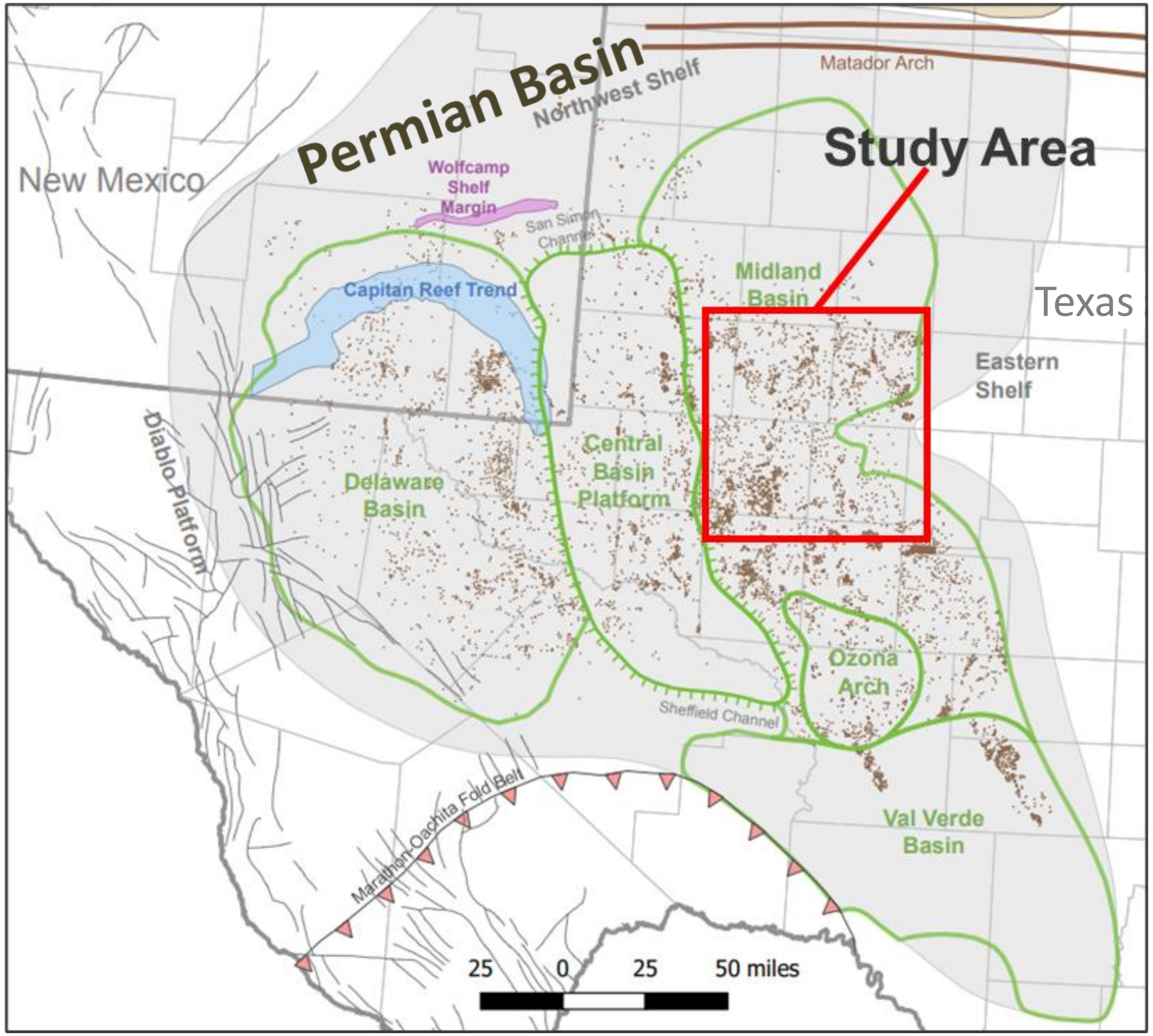
Stage level



HFTS-1 (Hydraulic Fracturing Test Site) Use Case (Cont.)



Use Case 3: Fracture Interference



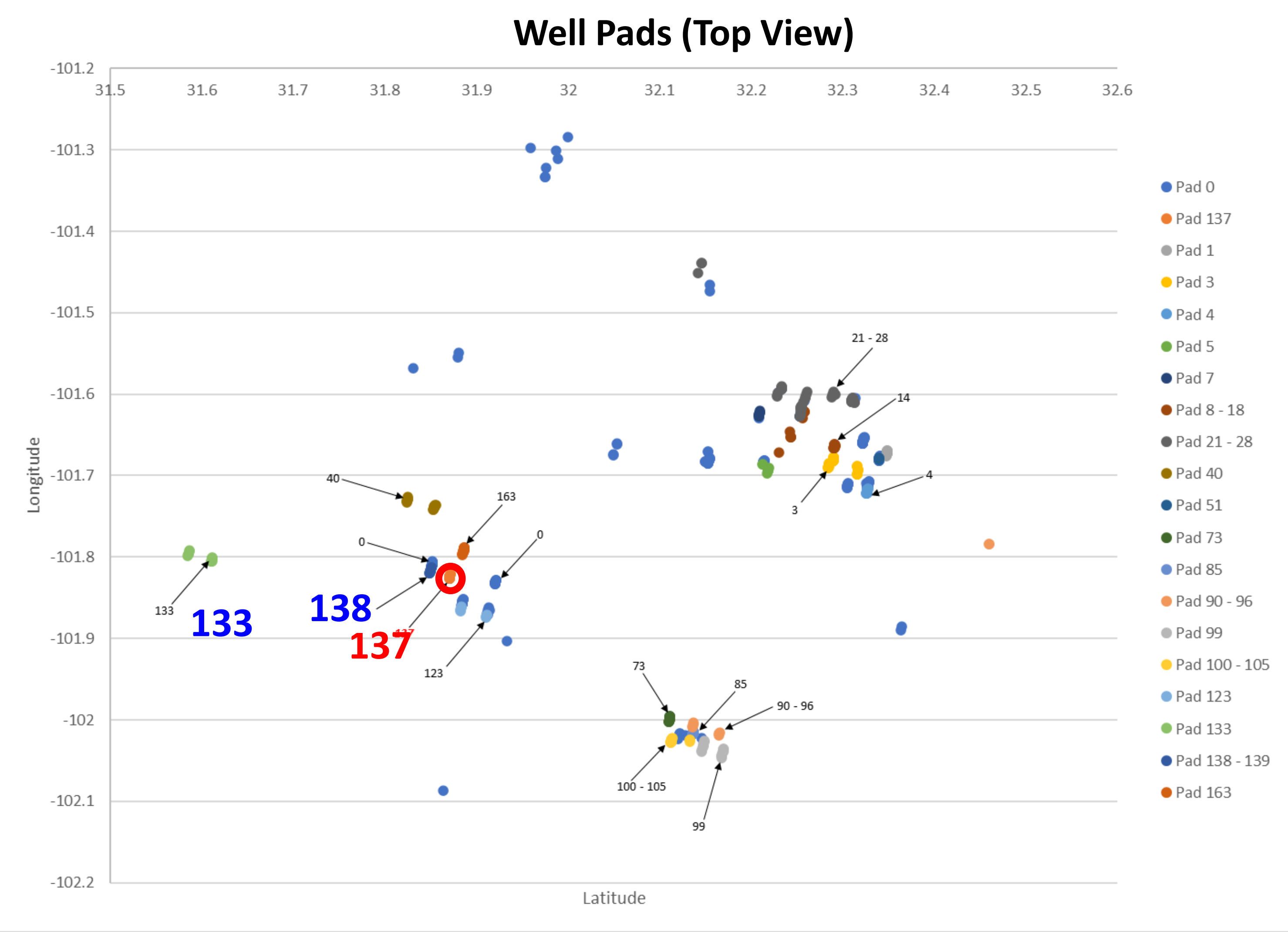
- Midland basin (local field with many active pads and a total of several hundred wells)
- Proprietary oil and gas field operations data:
  - Incomplete and partially accessed production details
  - Well distance
  - Pressure

Well Pads Selection

- Pad 137 was the point of interest in the **<u>within-pad frac-hits</u>** study
  - ➢ 12 interacting wells identified
  - ➢ Fracking was primarily done in two batches

- Pads 133 and 138 were selected to study **<u>inter-pad interactions</u>**

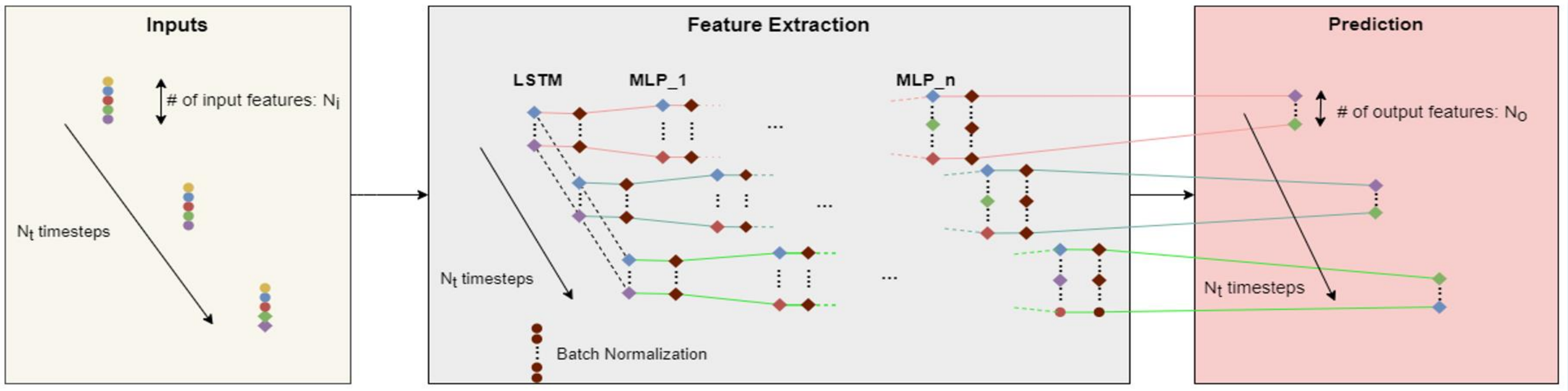
- Emphasis was made on the pressure and production anomalies and fracking time



Methodology

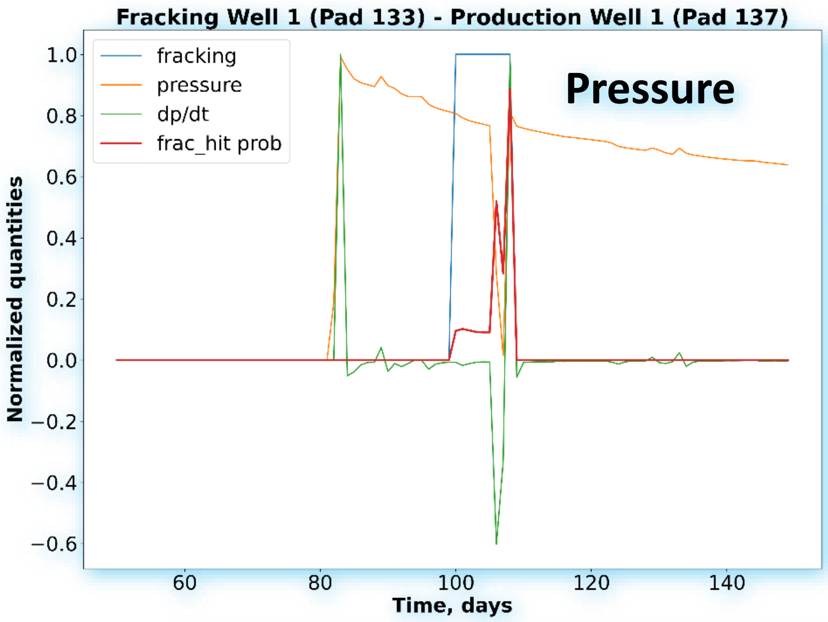
- **Frac-hit probability:** Feature-weighted estimation,

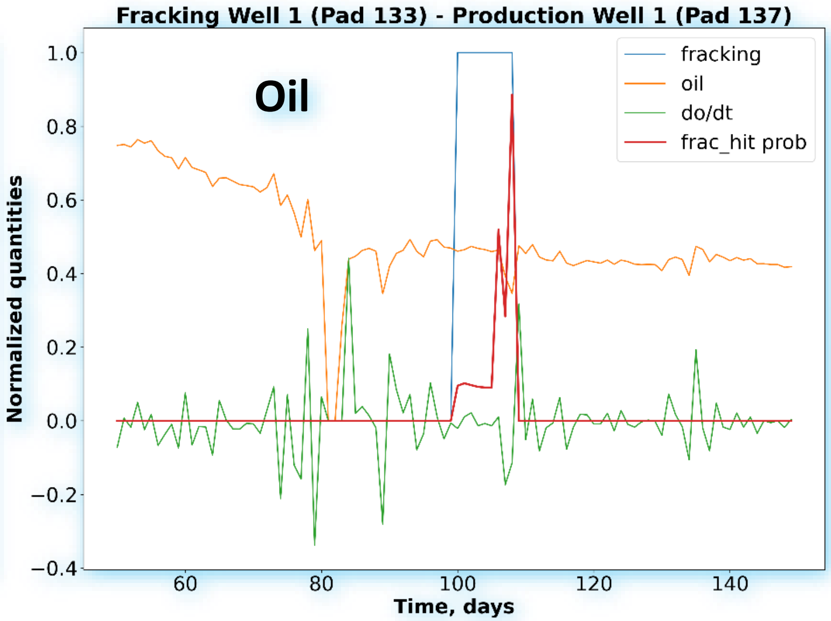
  such as: $p = 0.1 * P + 0.8 * \left|\frac{dP}{dt}\right| + 0.01 * O + 0.04 * \left|\frac{dO}{dt}\right| + 0.01 * W + 0.04 * \left|\frac{dW}{dt}\right|$
- **Machine learning models:** LSTM + multilayer perceptron (MLP) structure
- **Frac-hit identification:** Pairs interaction (one-to-one); pad interaction (multiple-to-one)

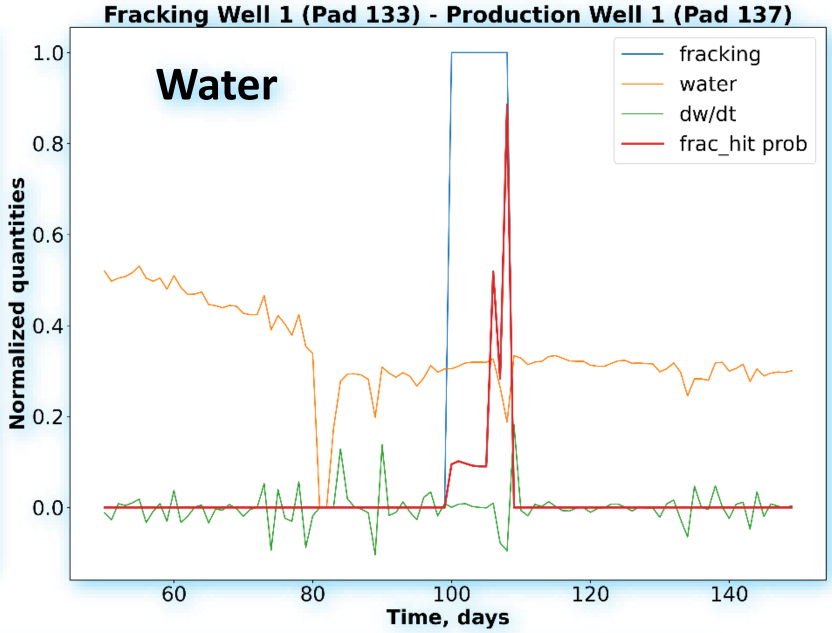


Frac-Hit Instance Examples

$$p = 0.1 * P + 0.8 * \left|\frac{dP}{dt}\right| + 0.01 * O + 0.04 * \left|\frac{dO}{dt}\right| + 0.01 * W + 0.04 * \left|\frac{dW}{dt}\right|$$







- Effects of fracking well in pad 133 on production well in pad 137
- High probability of a frac-hit due to large pressure and production-rate swings
- Extra potential frac-hits outside of the selected fracking window
- Flexible probability definition based on the data features and operating conditions

Model Performance: Frac-Hit Identification

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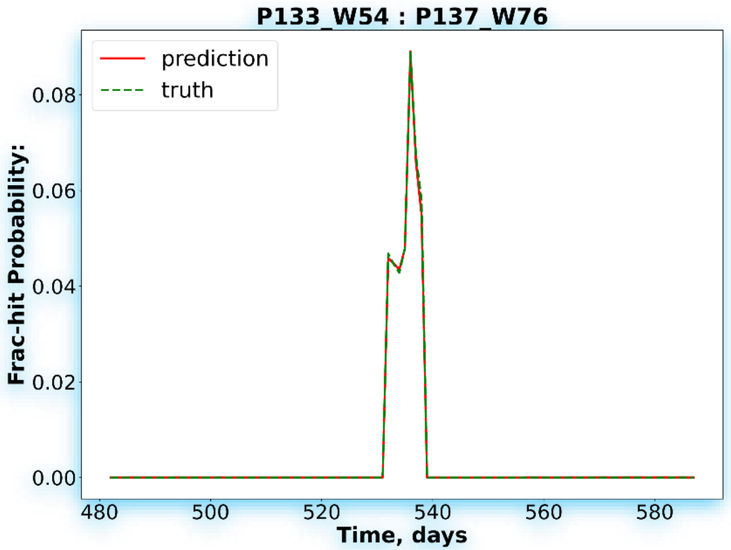
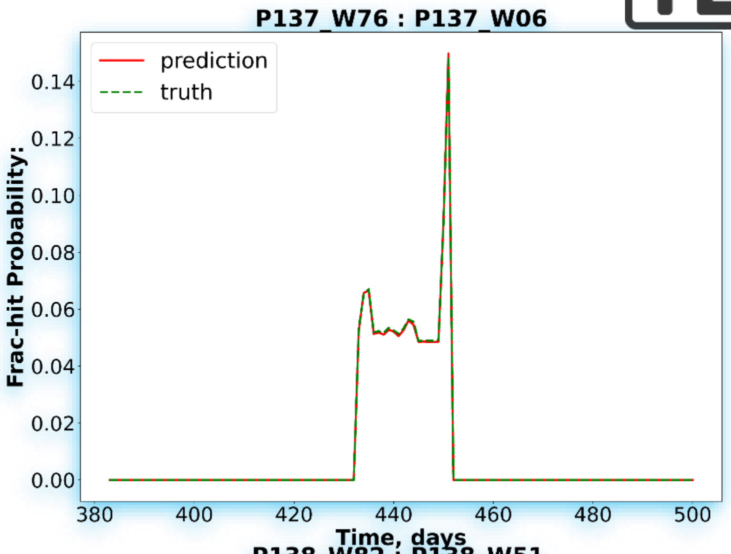
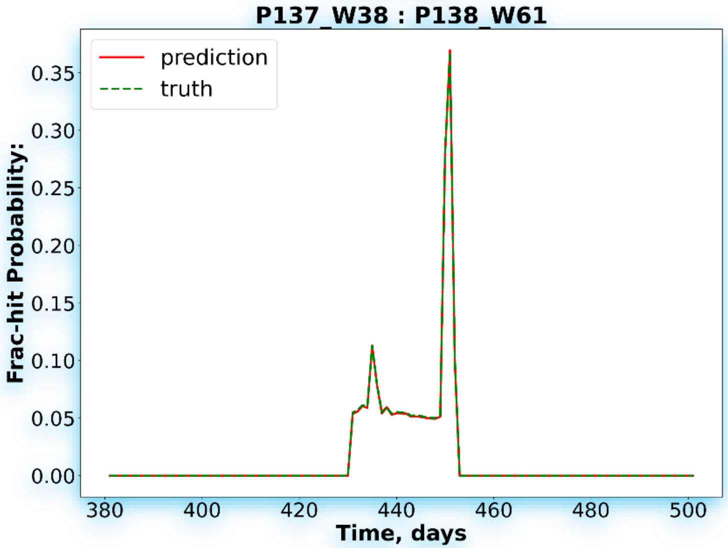
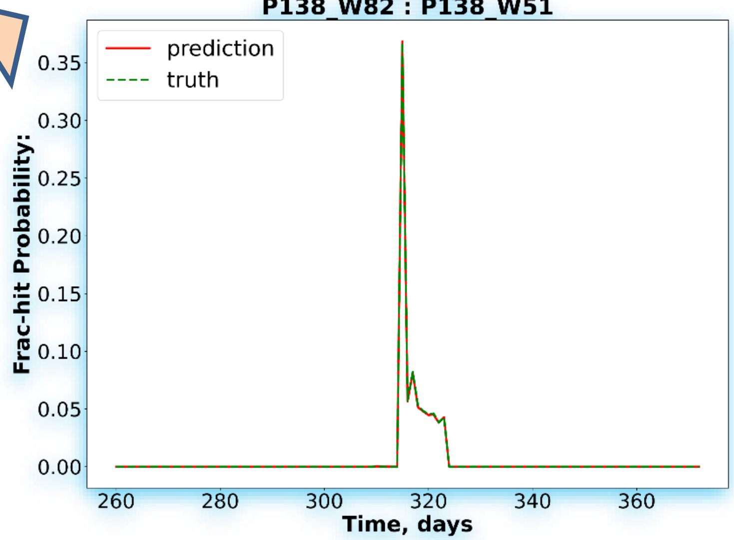


Frac-hit due to the inter-well interactions



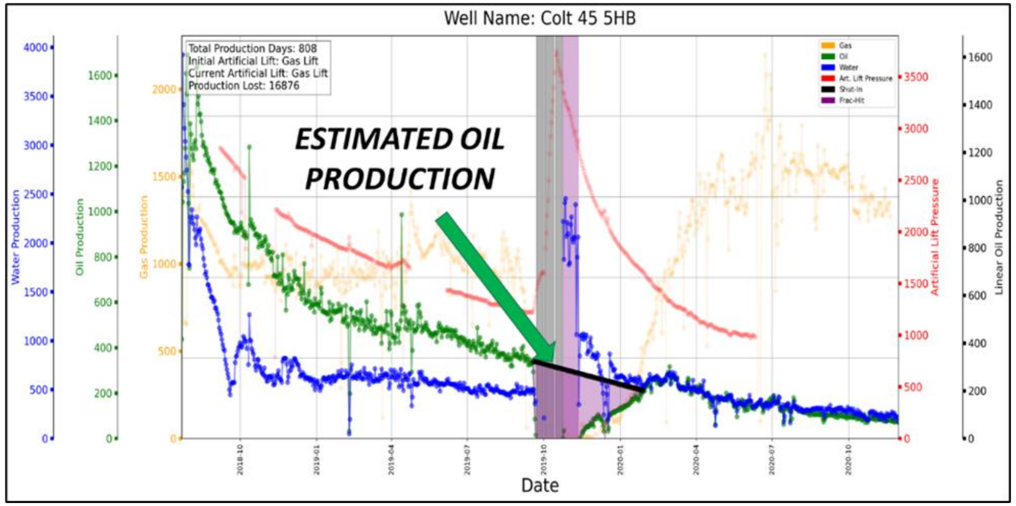


Frac-hit due to the intra-well interactions

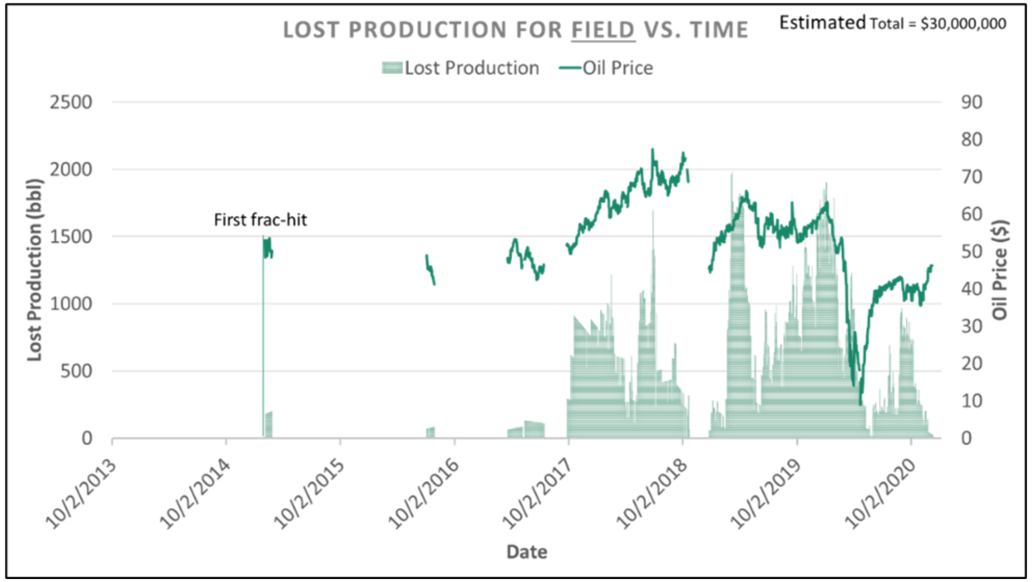


Frac-Hit Economic Impact

Well biography for the "Colt 45 5HB" well, indicating the range used to estimate lost oil production for the well.



With Lost Production calculated for complete dataset of 287 wells, historical oil price ($/bbl) was correlated with the collected dates of 'Shut-in' and 'Frac-hit' periods.



Estimated total loss: $30 million due to 'Shut-in' and 'Frac-hit' events

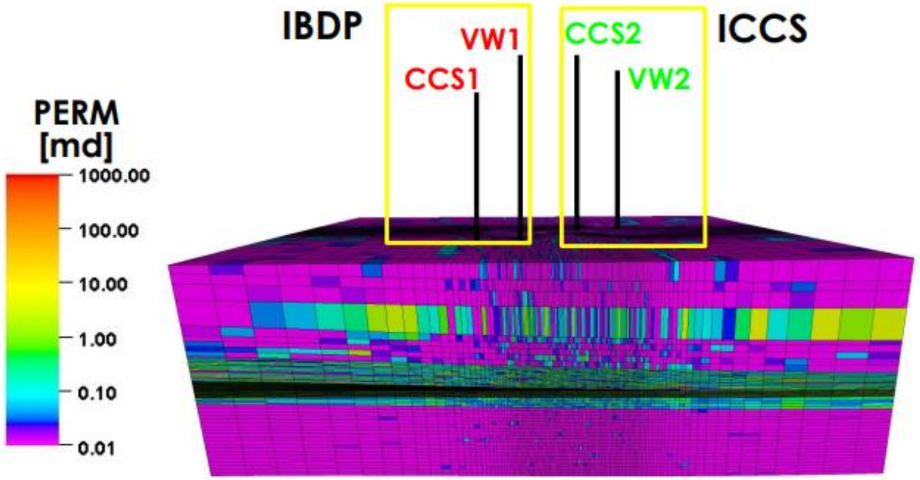
Details were reported in ML4SS FWP final report, 2022

Remarks

- Successful assimilation of data from multiple sources (microseismic, pumping, CO_2 flow rate, etc.)
- Implementation of physics-based machine learning algorithms to quantify the microseismic event clusters and time series production and pressure data are promising
- Spatial mapping of reservoir scale fracture network, enclosed volume measures, as well as frac-hit are benefitable from MLs
- Python based ML software tools for scalable deployment for field data processing and interpretation

Following Steps

- More features from other datasets well logs/core testing etc.
- Collaborate with other expertise from team/crossing-team
- Leverage fracture network results and outcomes to geological modeling, geomachenical & simulation studies



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Acknowledgements

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