Machine Learning Based Fracture Network Quantification at the IBDP CO_2 Sequestration Site

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Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

Introduction

- Fracture and fault network mapping plays a crucial role in ensuring the safety, security, and environmental sustainability of CO_2 sequestration projects.
- Accurate fracture network mapping enables the identification of preferential flow paths for CO_2 migration, understanding, which is essential in optimizing injection strategies and predicting CO_2 evolution in a target reservoir.
- As part of currently ongoing efforts for the SMART Phase II, suite of machine learning algorithms have been utilized to quantify the temporal and spatial distributions of fracture networks at the CO_2 injection site for the Illinois Basin – Decatur Project (IBDP).

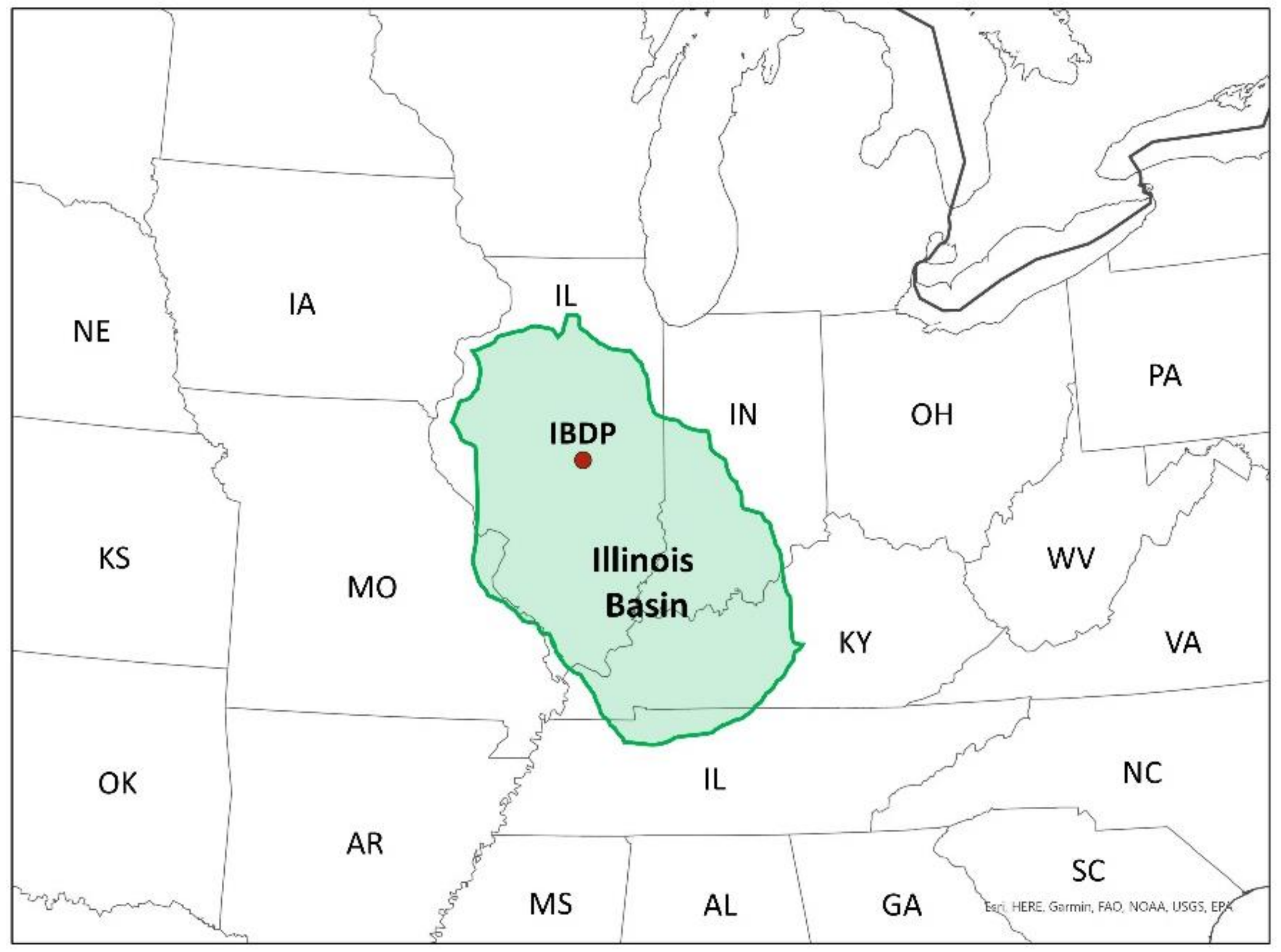

Figure 1. Map showing the location of IBDP site (red dot) within the Illinois Basin (green shaded region).

Data & Site Details

- IBDP is a carbon capture and storage (CCS) project of the Midwest geological sequestration consortium located in east-central Illinois in the north-central area of the Illinois Basin.
- Nearly 1 million tonnes of super critical CO_2 were injected into the lower Mt. Simon Sandstone over a 3-year period from November 2011 until November 2014 at the IBDP site.
- For the current study, microseismic catalog recorded by the subsurface arrays from three separate wells at the IBDP site is utilized.
- Apart from microseismic, injection data, such as bottomhole pressure and CO_2 flow rate is also incorporated in the current study.

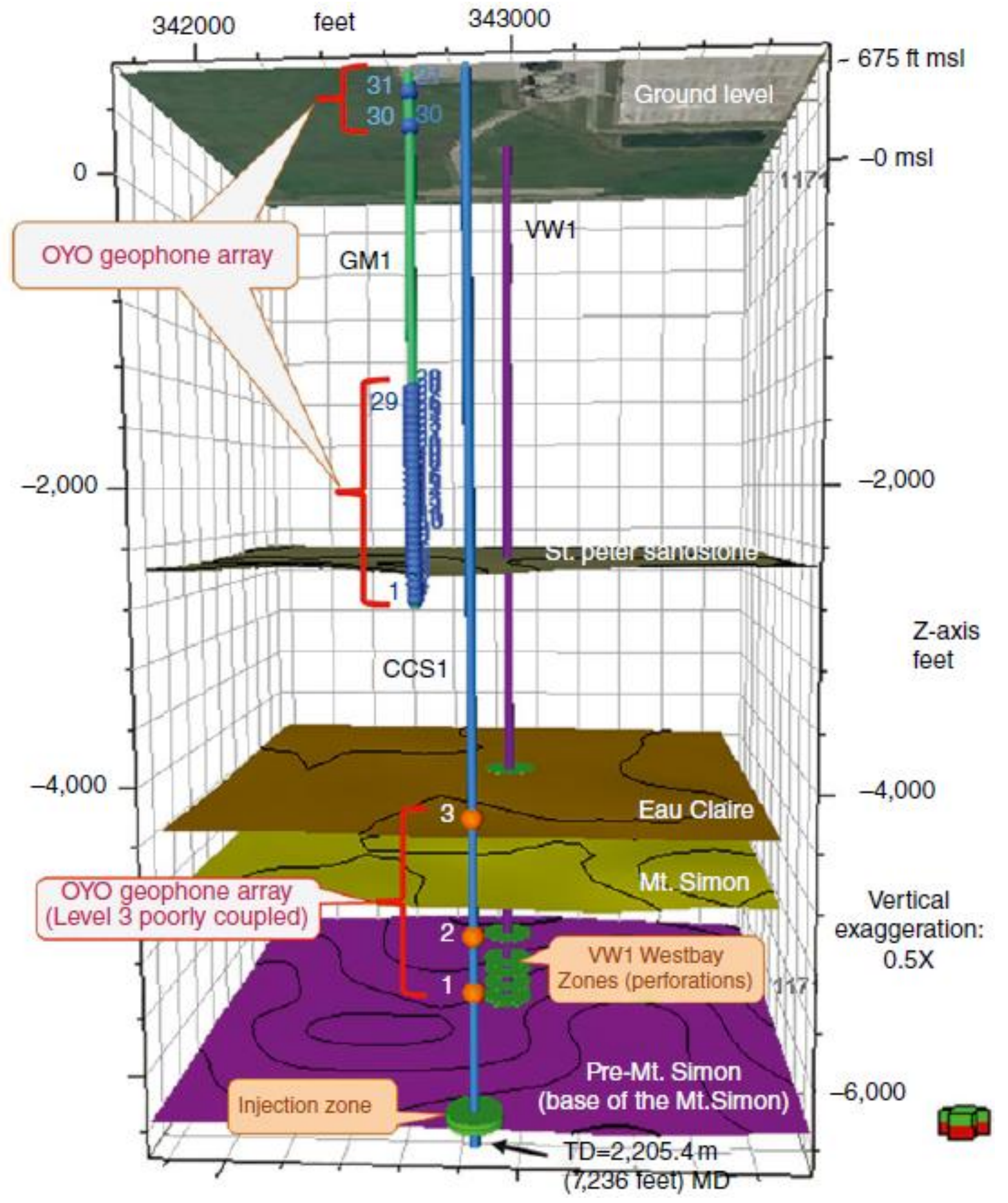

Figure 2. Configuration of borehole and seismic monitoring network at the IBDP site.

Methods

- Magnitude of completeness and seismogenic b-value are estimated for the microseismic catalog to infer the dominant stress regime and failure mode of the recorded seismic events.
- Discrete microseismic time windows are identified from the variations in bottomhole pressure recording.
- Concept of hydraulic diffusivity is utilized to identify discrete microseismic triggering fronts within each time window.
- A suite of unsupervised machine learning algorithms are tested to identify spatial clusters of microseismic events within each triggering front of individual time windows.
- 2-sigma standard deviational ellipsoids are fit to individual microseismic clusters that capture the spatial variation of event distribution in the respective cluster.
- Eigen vectors of the largest eigen value of each standard deviational ellipsoid is extracted to represent the trace of 3D distribution of fracture plane around the injection well.

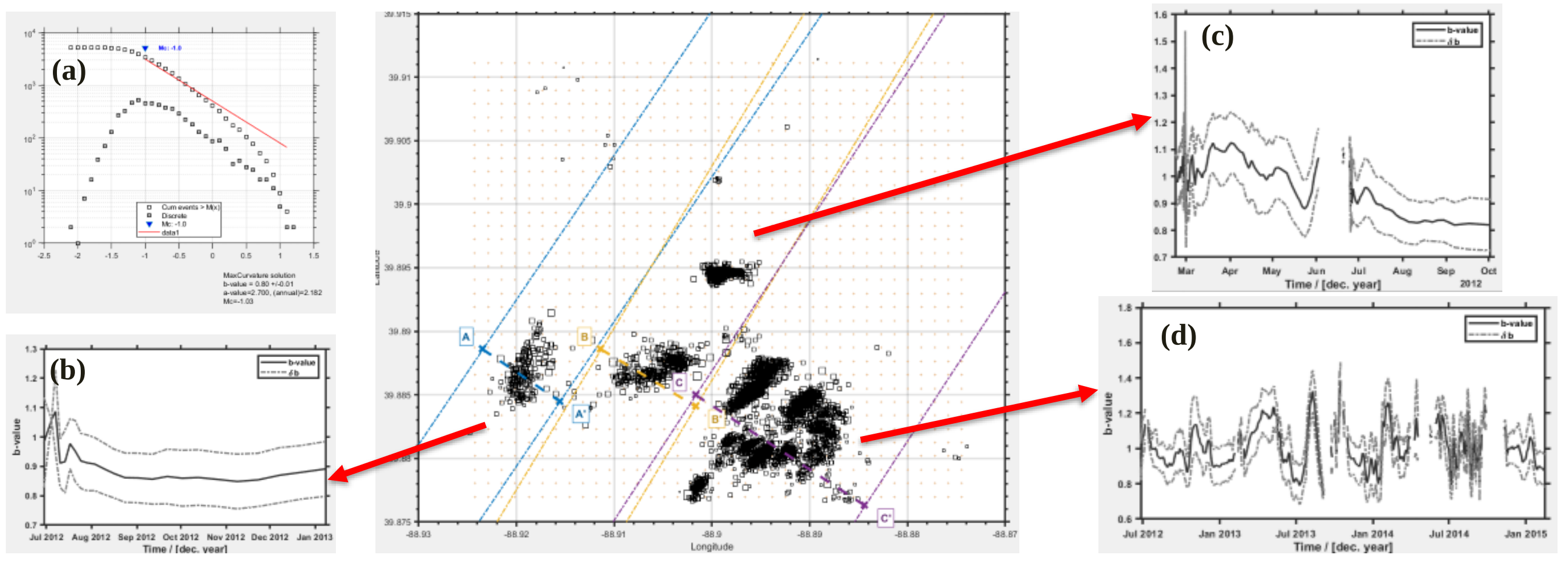

Figure 3. Map showing the spatial distribution of microseismic events at the IBDP site (center). Subplots showing (a) Magnitude of completeness, and (b-d) b-value variations for three separate regions.

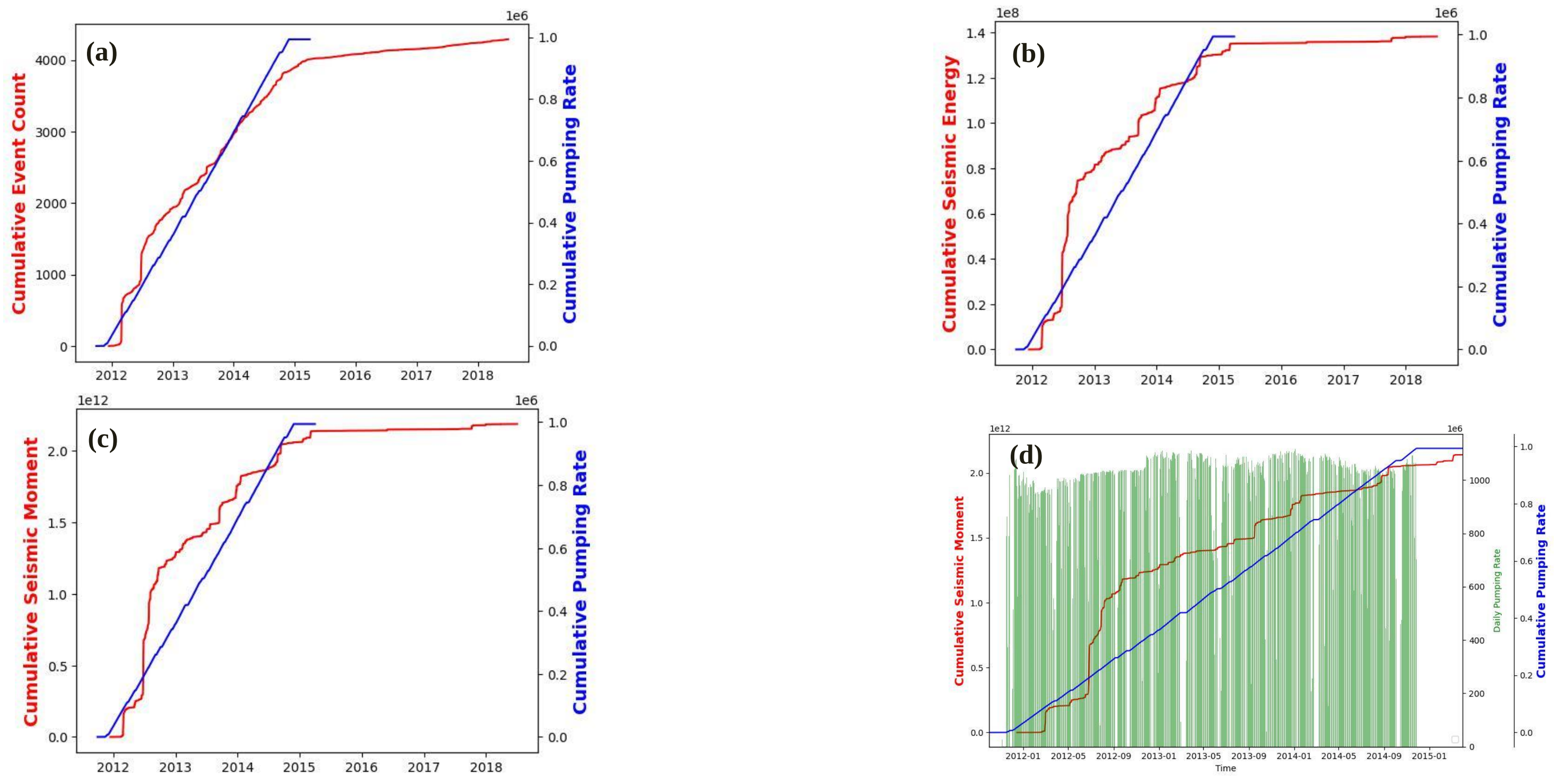

Figure 4. Plots showing the comparison of cumulative pumping rate with (a) event count, (b) seismic energy, (c) seismic moment, and (d) joint variation of seismic moment and daily pumping rate (green bars).

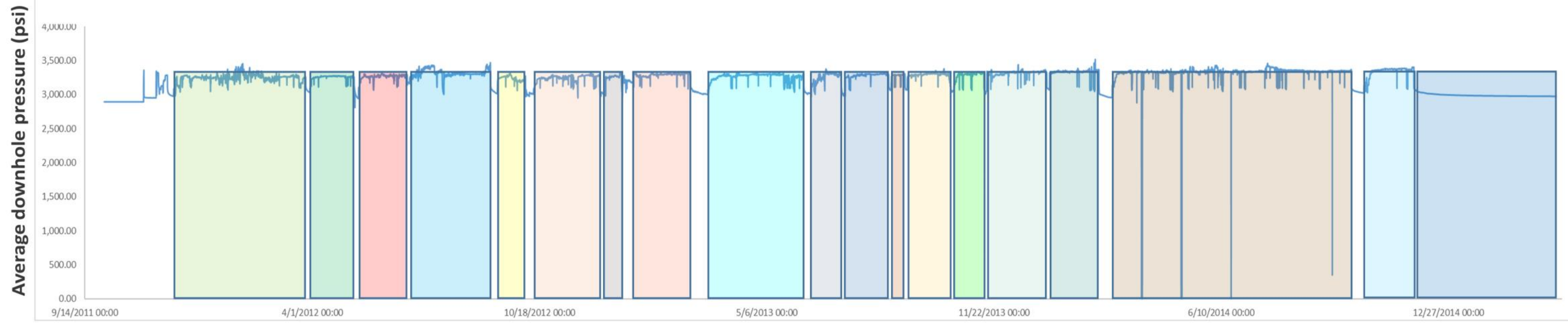

Figure 5. Plots showing the variation in average downhole pressure. Nineteen microseismic time windows (shaded boxes) marked by extended period of bottomhole pressure changes.

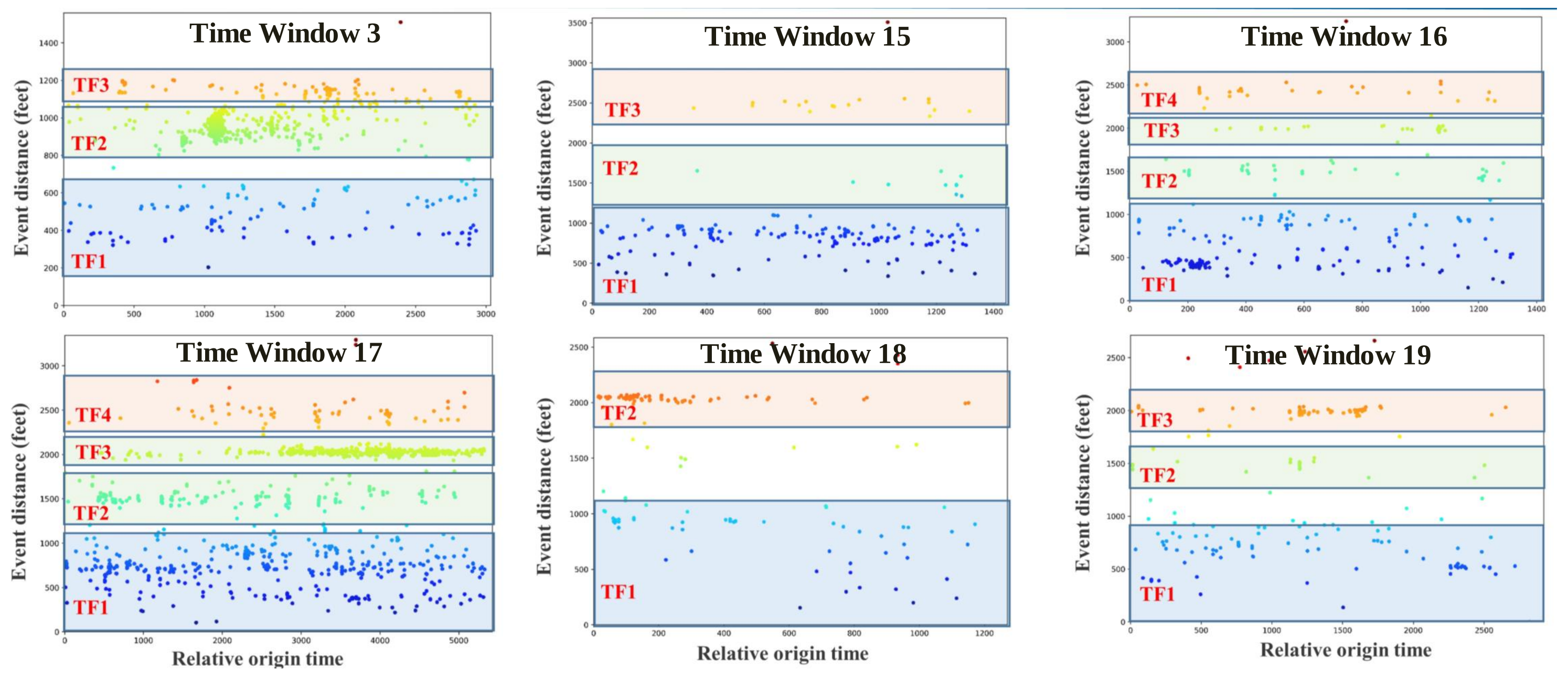

Figure 6. Discrete triggering fronts (shaded rectangles) identified within each microseismic time window.

Workflow

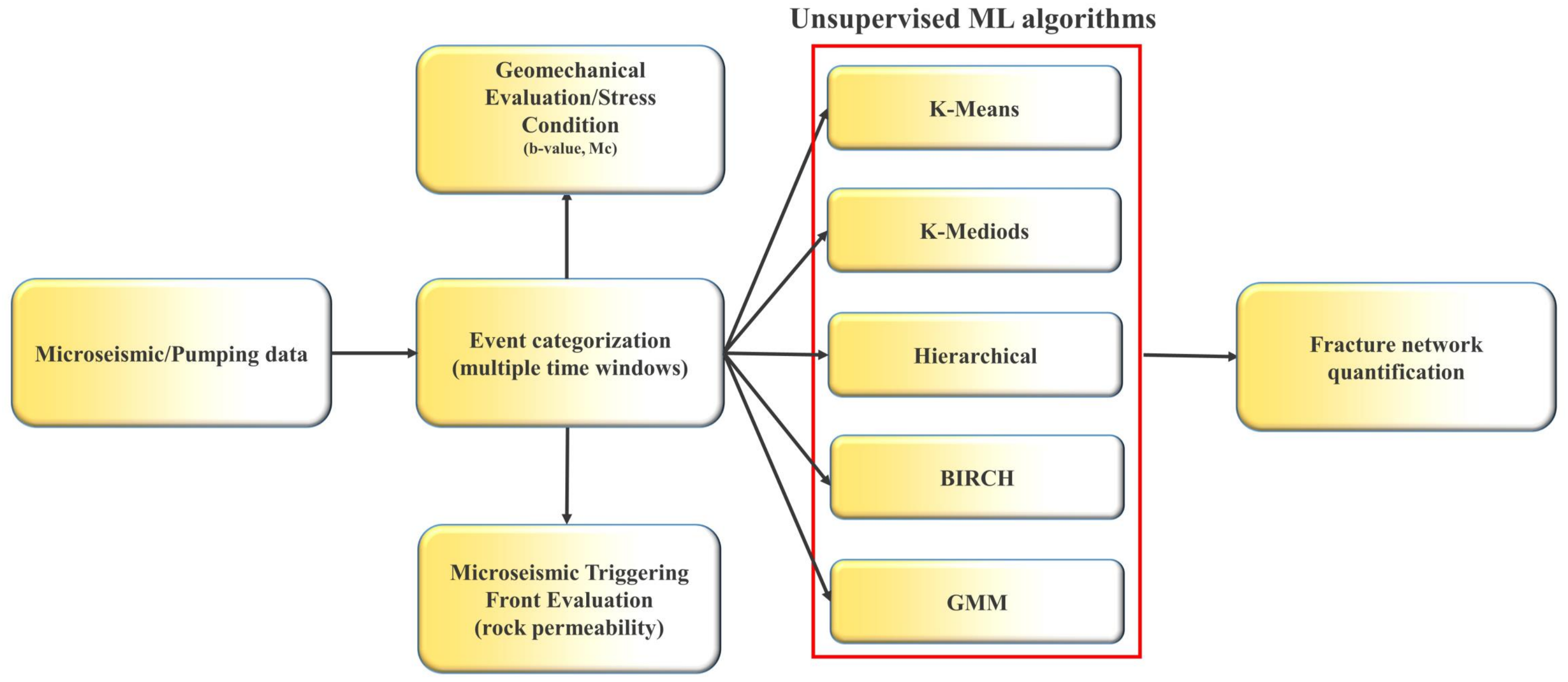

Figure 7. Diagram showing the workflow of the current study for fracture network mapping.

Results

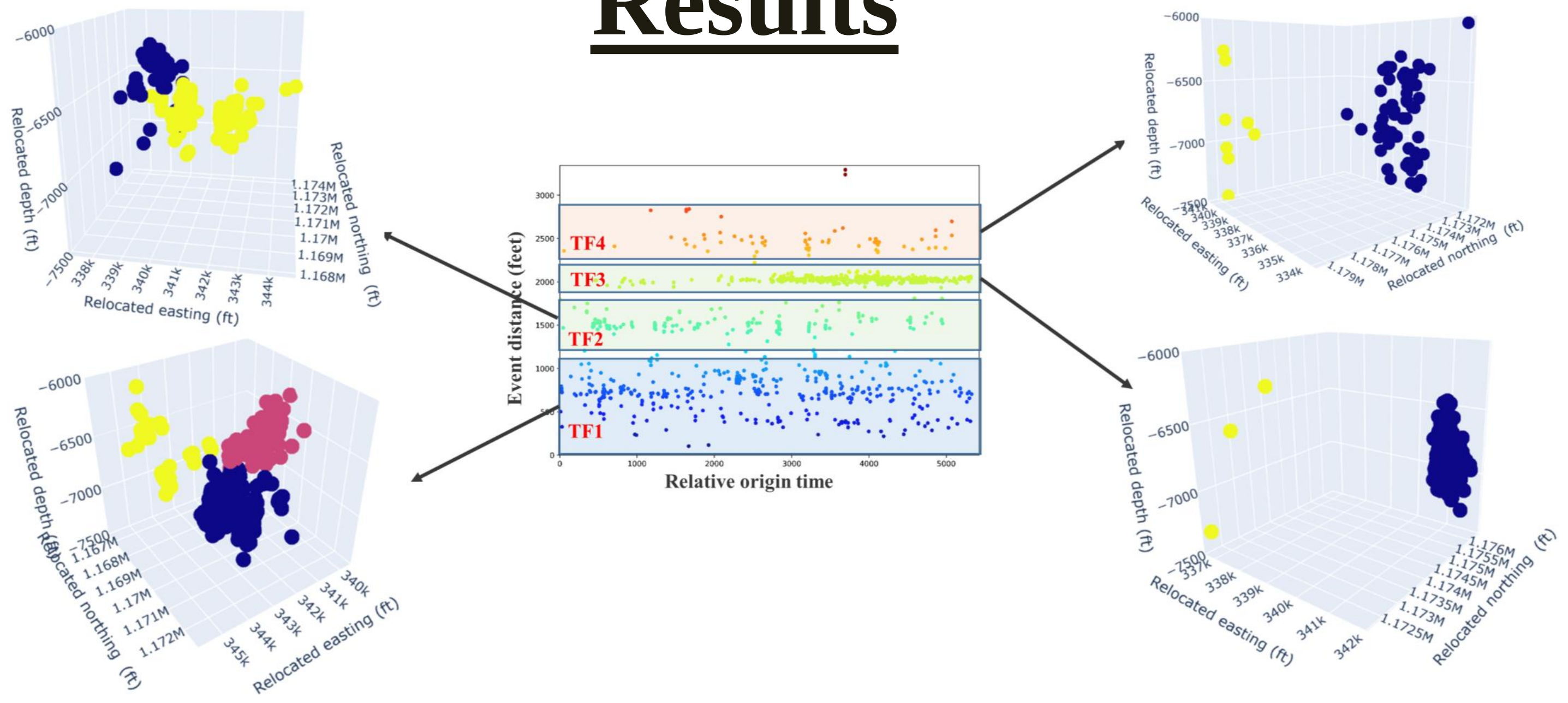

Figure 8. Identified clusters of microseismic events within each triggering front of time window 17 (center plot).

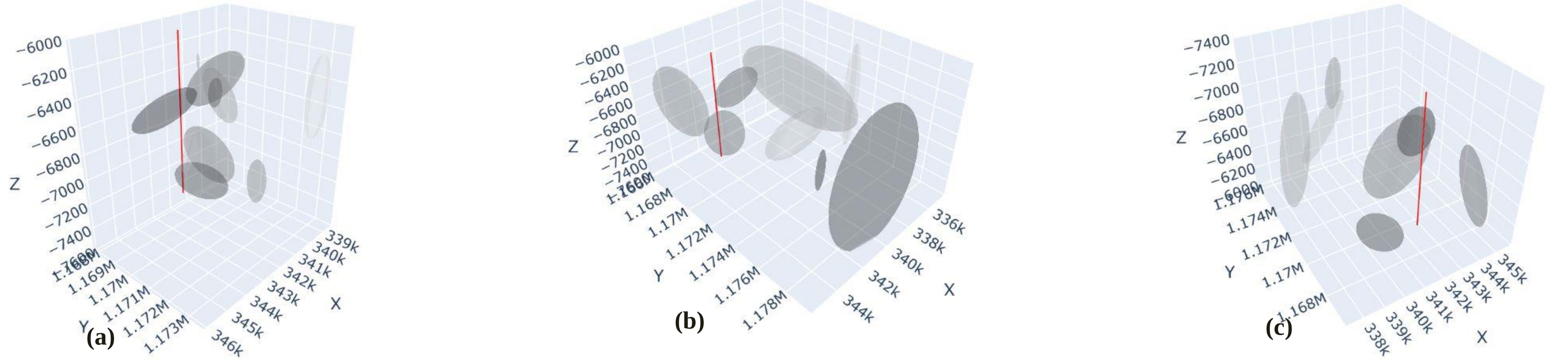

Figure 9. 3D distribution of fracture planes (shaded ellipsoids) around the injection well (red line) for time windows (a) 9, (b) 17, and (c) 19.

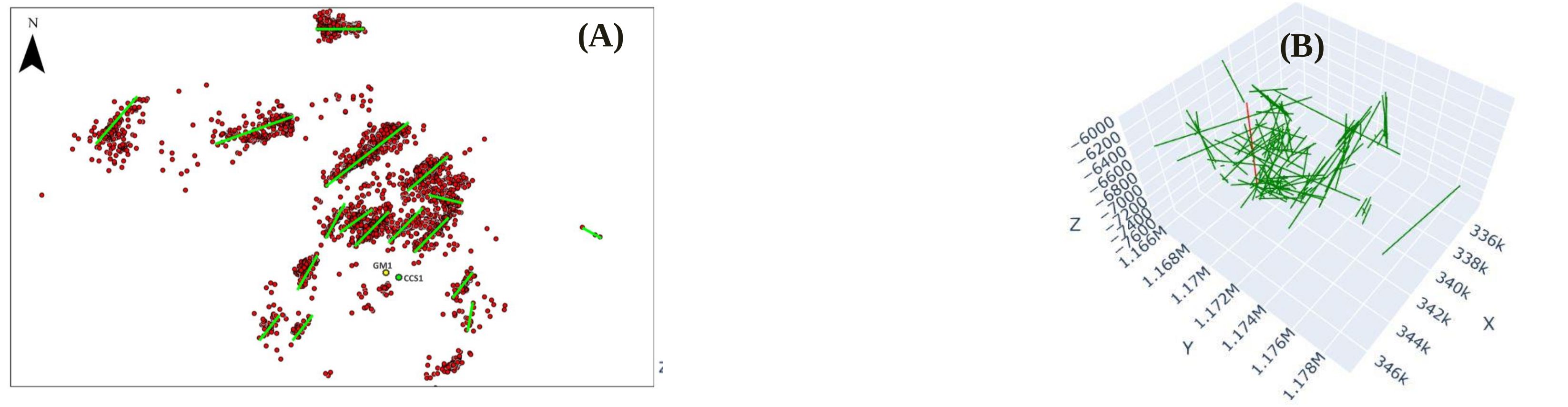

Figure 10. (A) Previously identified fault plane solutions (green lines) for the microseismic clusters. (B) 3D distribution of fracture network (green lines) around the injection well as determined using machine learning techniques in the current study.

Acknowledgements

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References

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