Machine Learning for Geothermal Fault Detection and Flow Imaging

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Collaborators

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- **UT Dallas**: David Lumley
- **Industry**: Trenton Cladouhos (Quaise), Michael Swyer (Cyrq), Joel Edwards (Zanskar)

Outline

- Objectives
- Fault Detection Using Nested-Residual U-Net
- Image Denoising via Nested-Residual U-Net
- ConvNeXt-Based Fault Detection and Image Denoising
- Machine Learning for Flow Imaging
- Conclusions

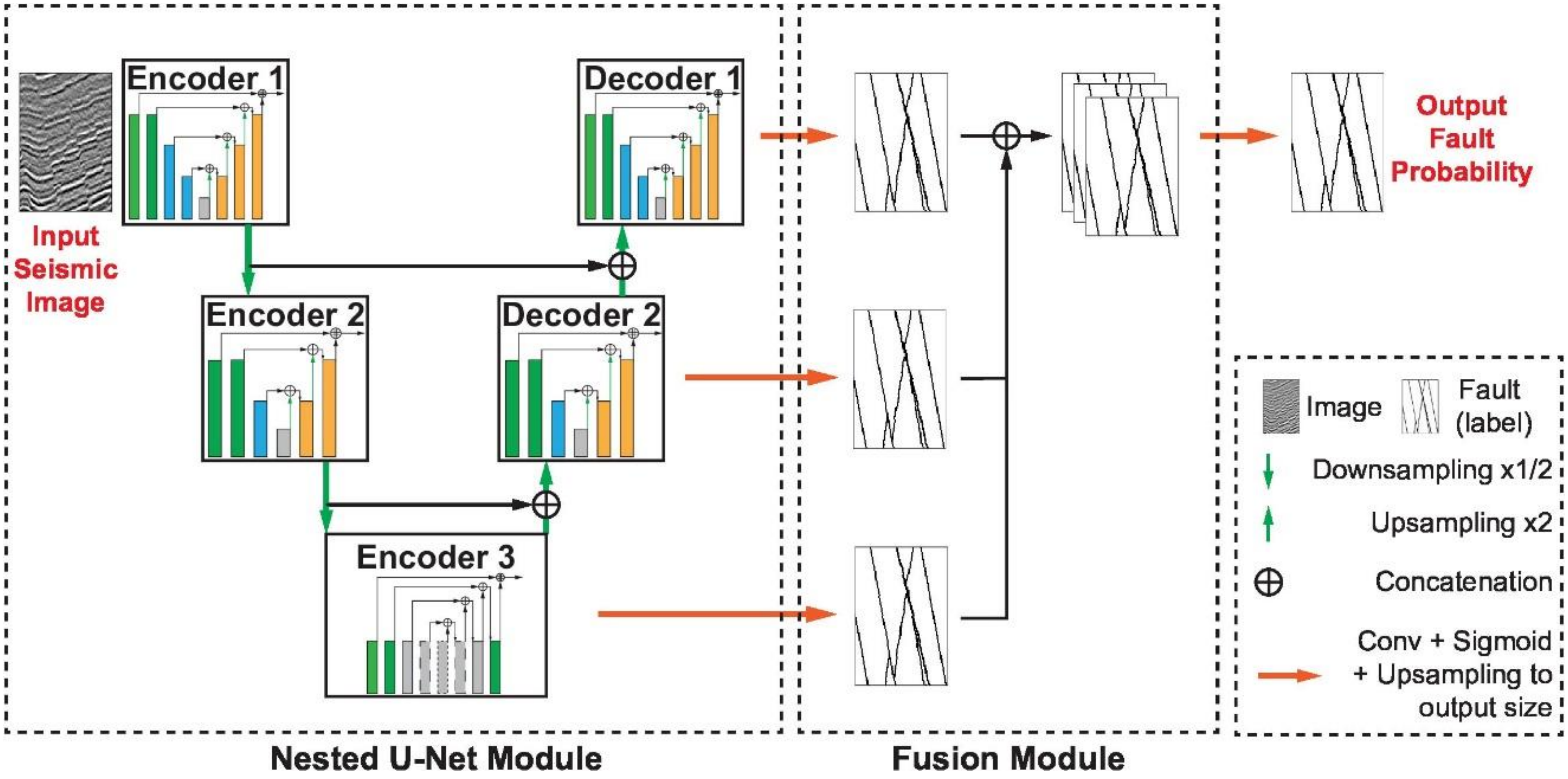
Objectives: Fault Detection

- **Purposes of Fault Detection**
  - Crucial for understanding subsurface fluid migration
  - Enables accurate well placement and reservoir modeling
  - Mitigates induced seismicity by identifying active vs. inactive faults
  - Boosts geothermal project cost-effectiveness and success rate
  - High-resolution fault maps improve exploration outcomes
- Use ML to enable efficient fault detection from complex 3D seismic migration images

Objectives: Flow Imaging

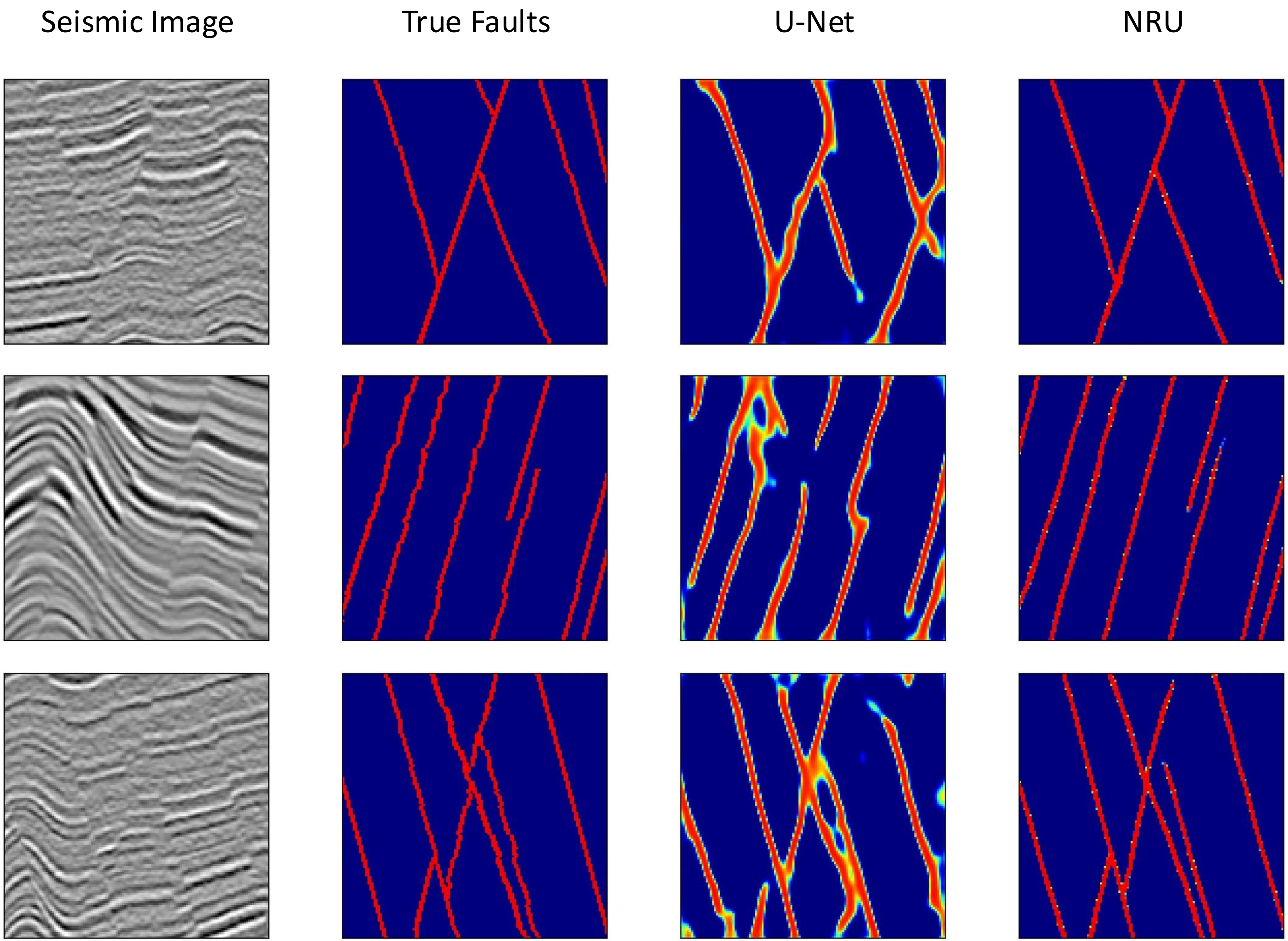
- **Purposes of Flow Imaging**
  - Identifies active fluid pathways
  - Maps permeability and fracture structures
  - Monitors injection/production dynamics
  - Detects thermal breakthroughs early
- Use continuous microseismic signals and unsupervised ML to extract fluid flow-induced signals for flow imaging

Fault Detection with Nested-Residual U-Net (NRU): Improved Fault Continuity

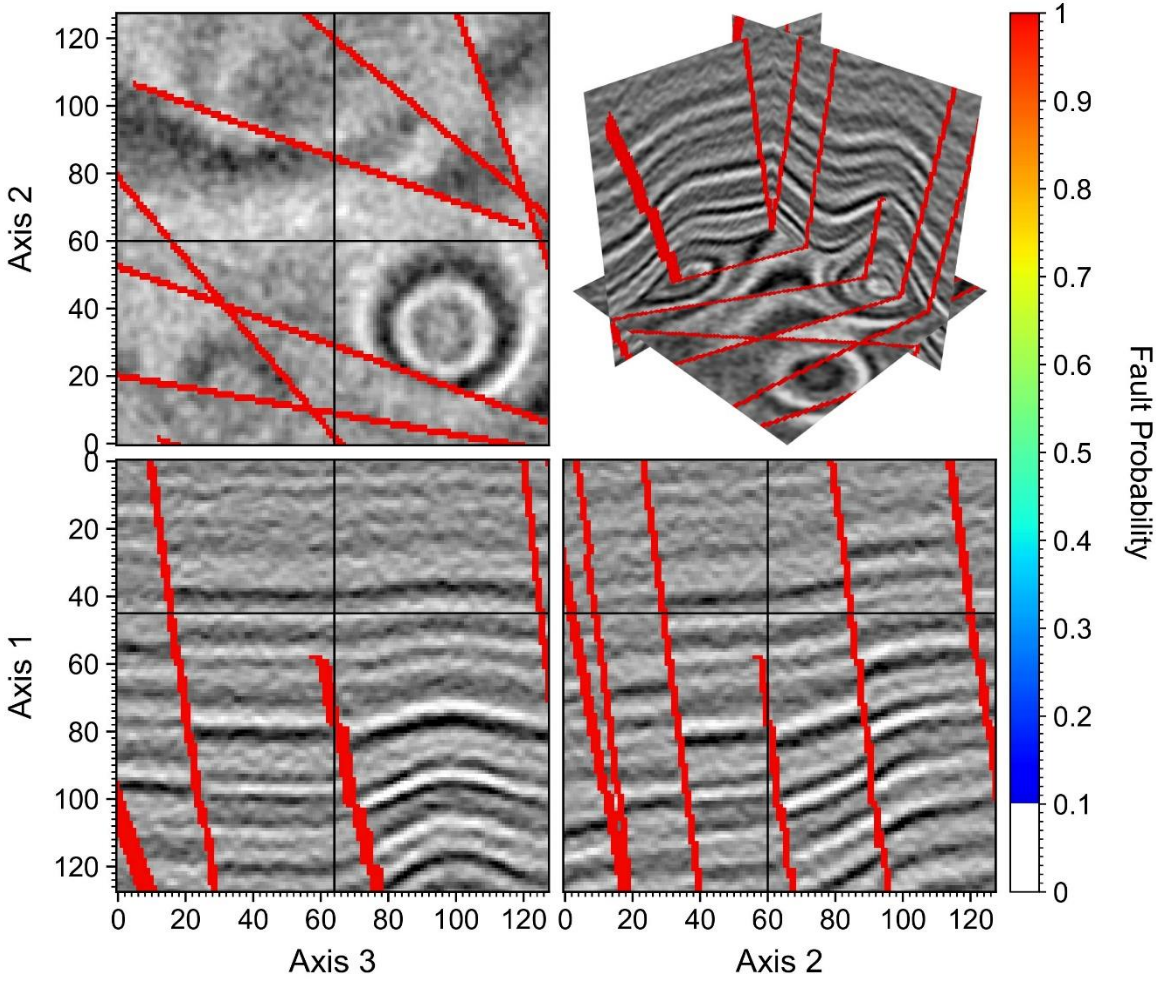


(Gao, Huang, Zheng, IEEE-TGRS, 2022)

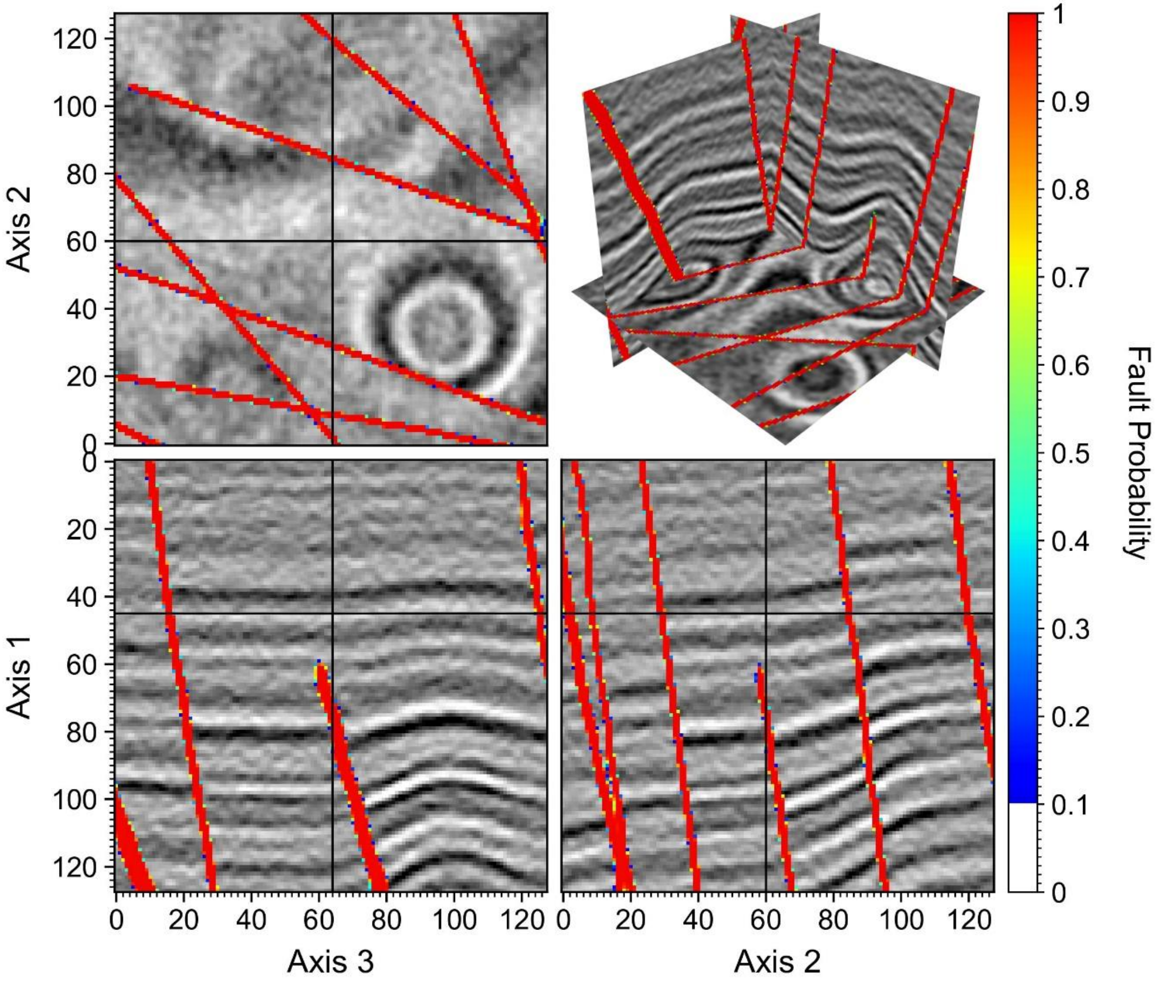
ML Fault Detection on Seismic Migration Images from Synthetic Data



3D Seismic Image with True Faults



NRU-Detected Faults



Fault Detection with NRU

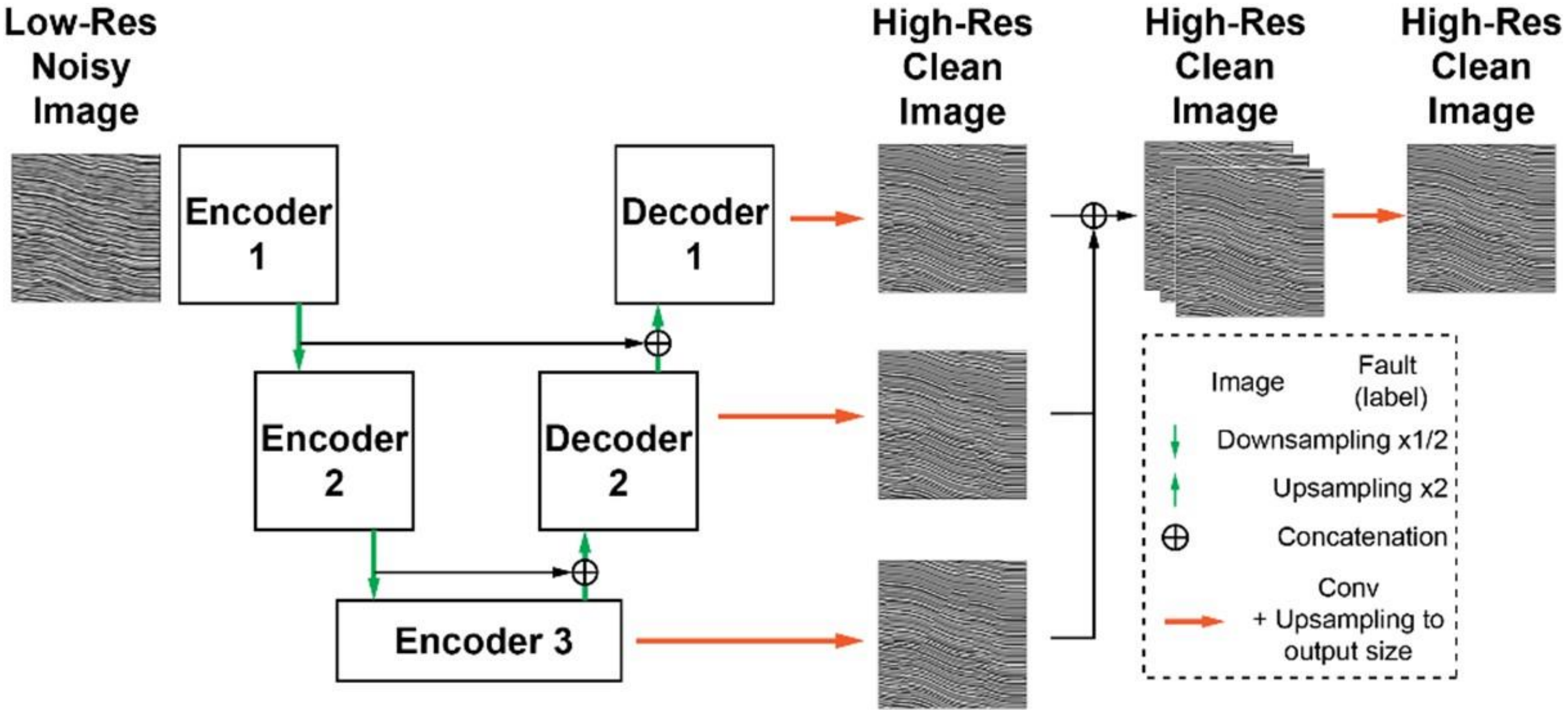
- **Nested-Residual U-Net (NRU)**
  - Trained on synthetic seismic data
  - Outperforms conventional U-Net in fault detection and clarity
  - Effectively detects true fault geometries in 3D migration images
- **Comparison**
  - Visual results show superior delineation with NRU
  - Demonstrates fault continuity in complex geological settings

Image Noise and the Need for Denoising

Impact of Seismic Image Noise:

- Noise in seismic images → Misinterpreted faults → Poor well placement
- Denoising boosts precision and model robustness

Nested-Residual U-Net (NRU) Image Denoising

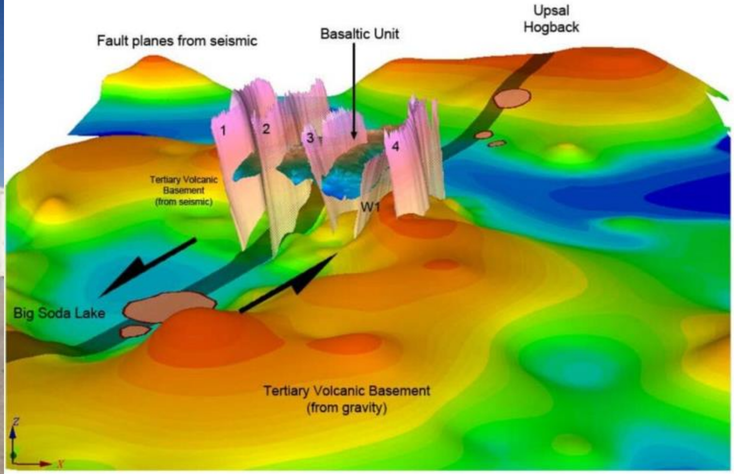


Case Study:
Soda Lake Geothermal Field

- 26.5 MW binary plant, Nevada
- Complex geology with basalt and fault systems
- Seismic image degraded by acquisition gaps and low SNR

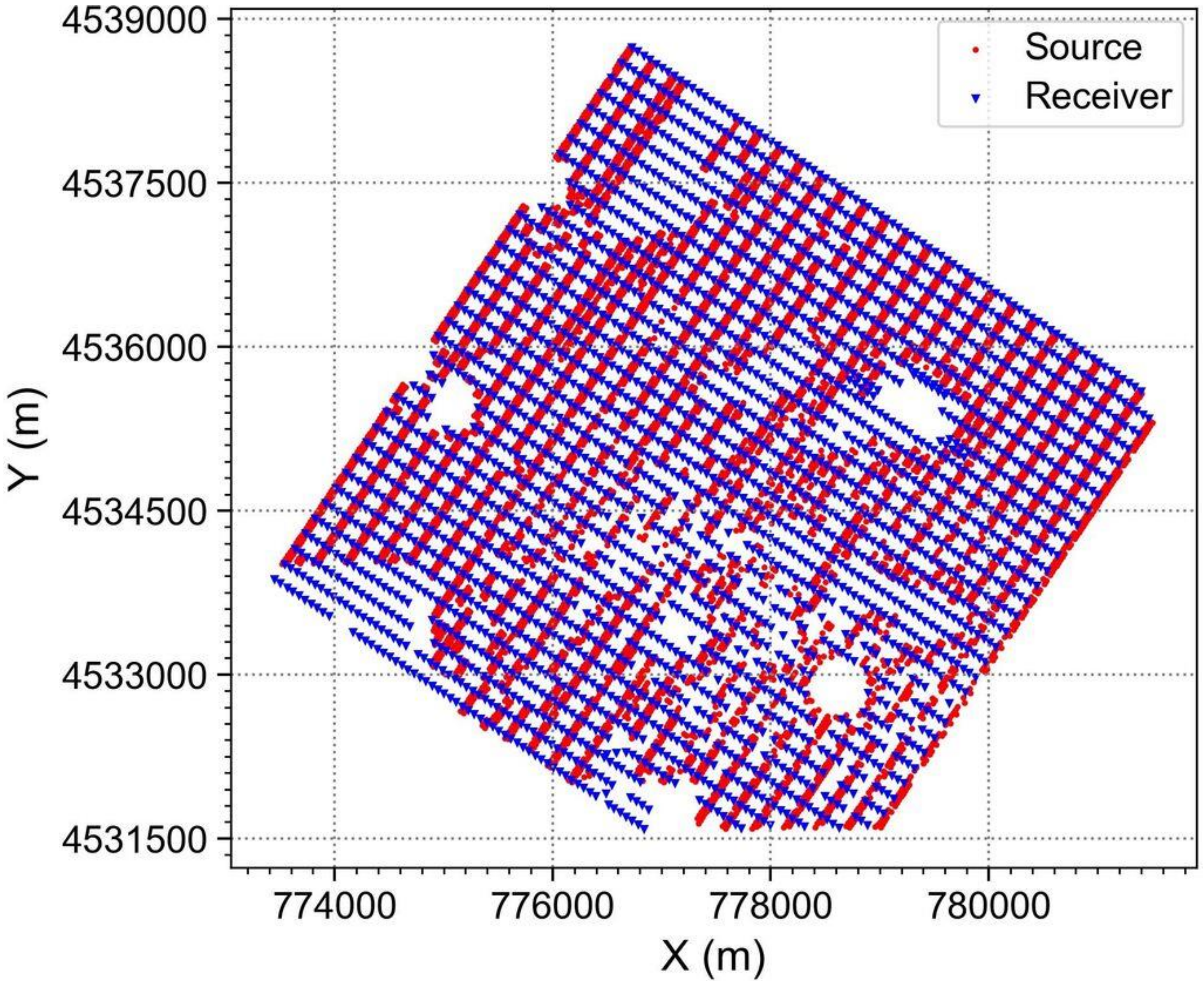
ML Processing

- NRU applied to 3D reverse-time migration (RTM) slices
- RMS balancing improves depth consistency
- Result: Enhanced fault visibility and clearer interpretation

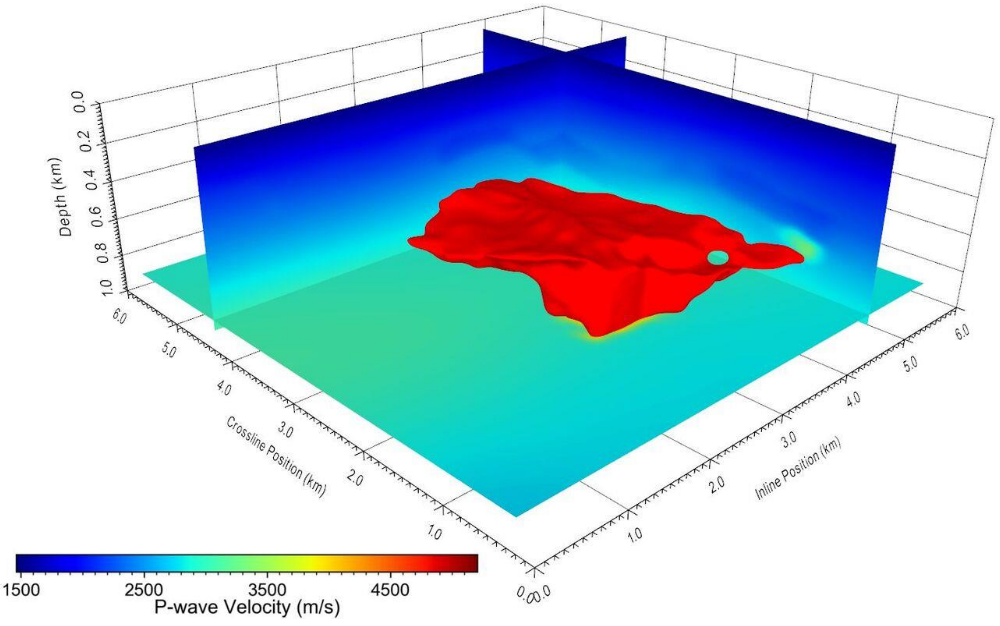


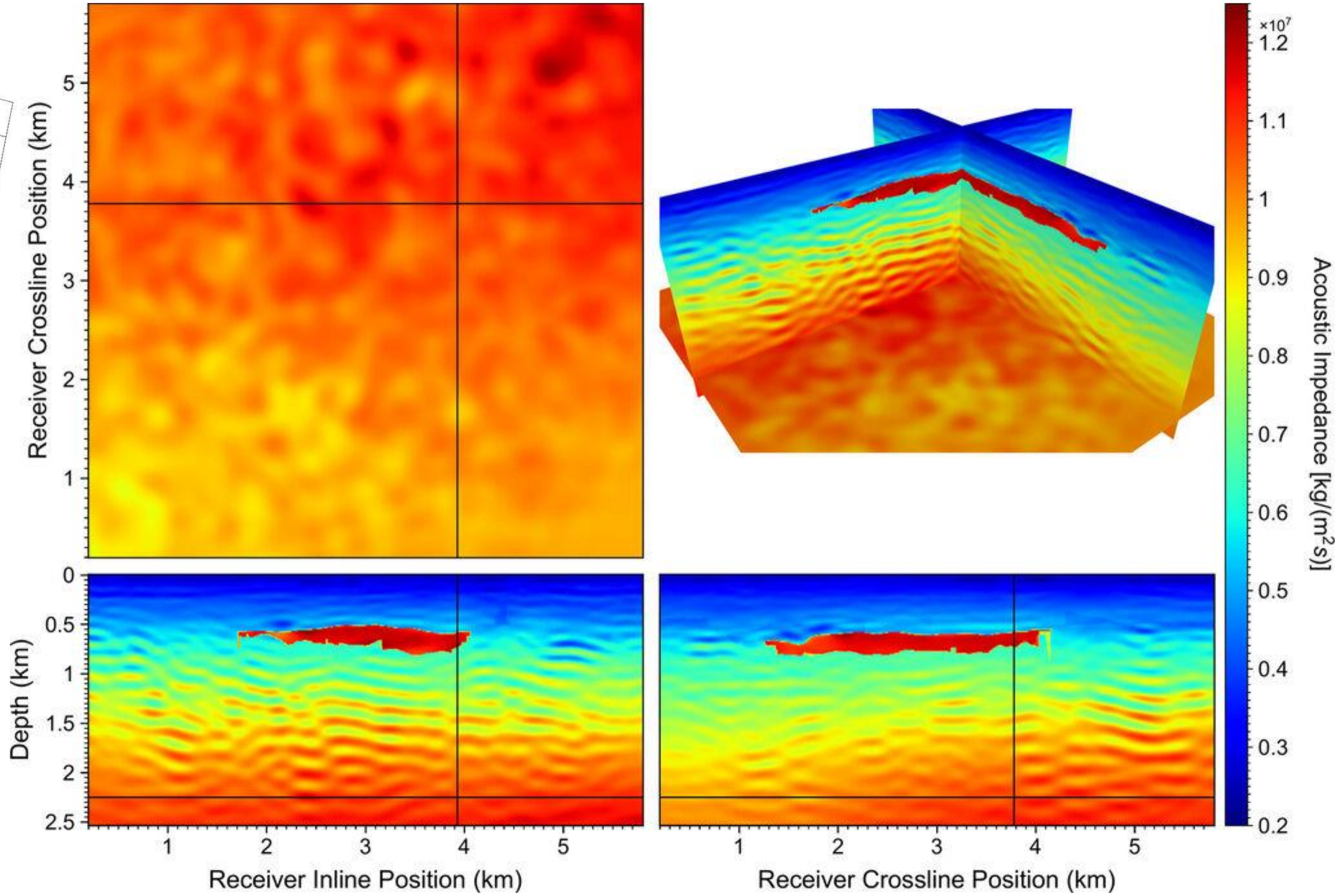
3D Seismic Survey

- Gaps in source and receiver coverage introduce migration artifacts
- Weak reflections beneath basalt and complex geology lead to low signal-to-noise ratios
- Seismic image resolution deteriorates with increasing depth
- High-quality, high-resolution migration is essential for accurate fault detection



Basaltic Unit in Red

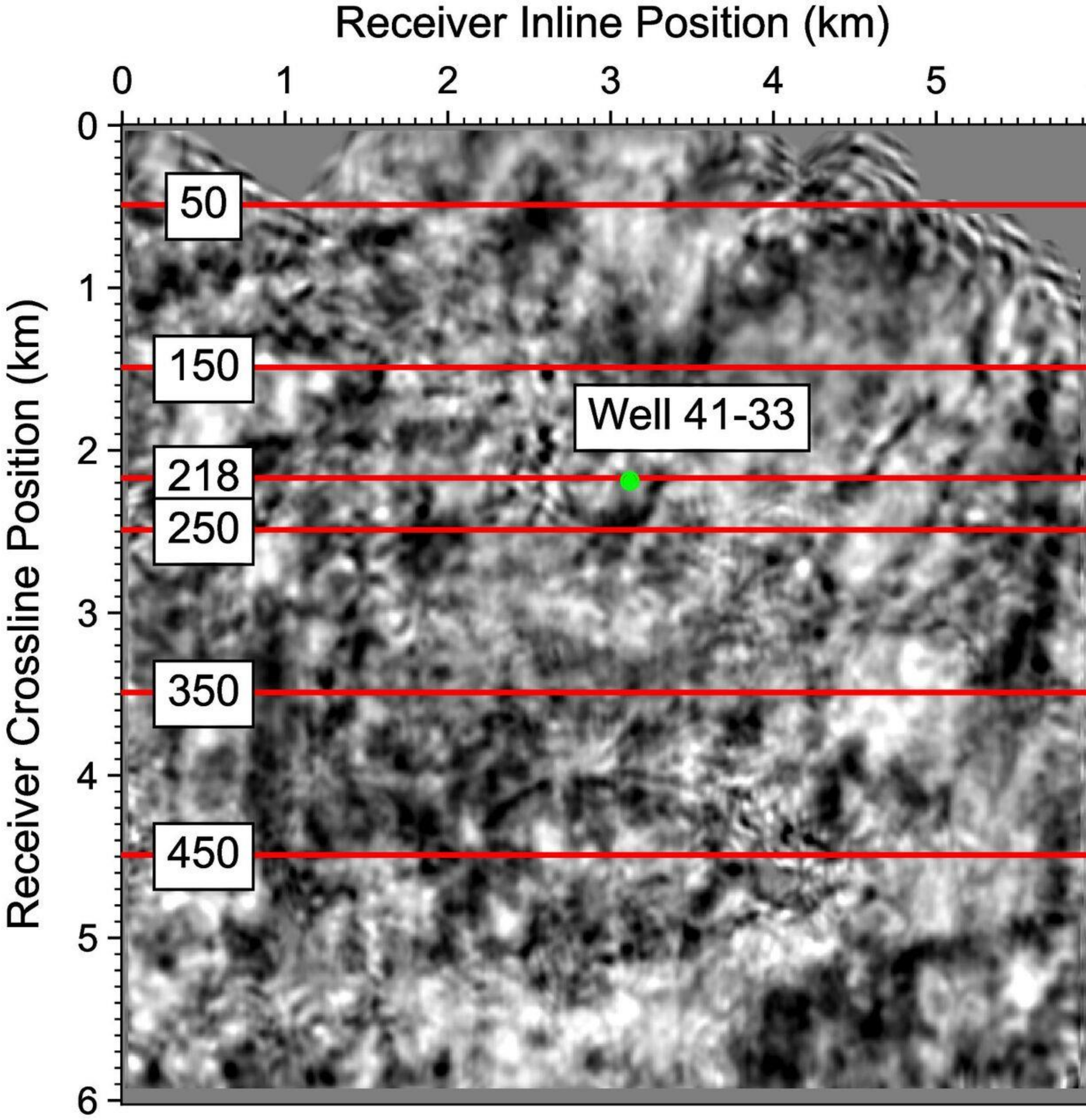




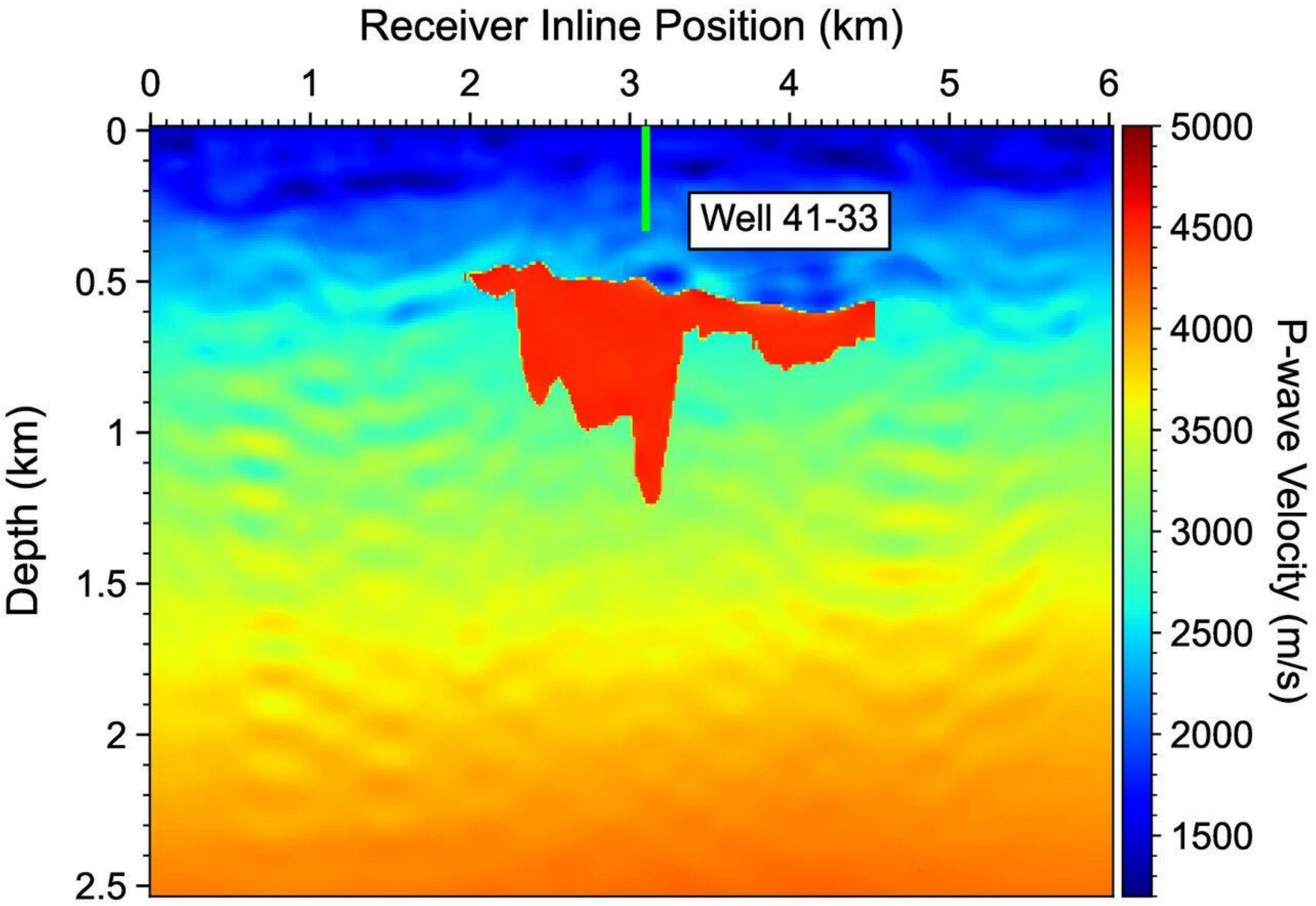
Acoustic impedance from FWI of 3D surface seismic data at Soda Lake geothermal field (Gao et al., 2021)

2D Slice of 3D RTM Image: Line 218 along Well 41-33

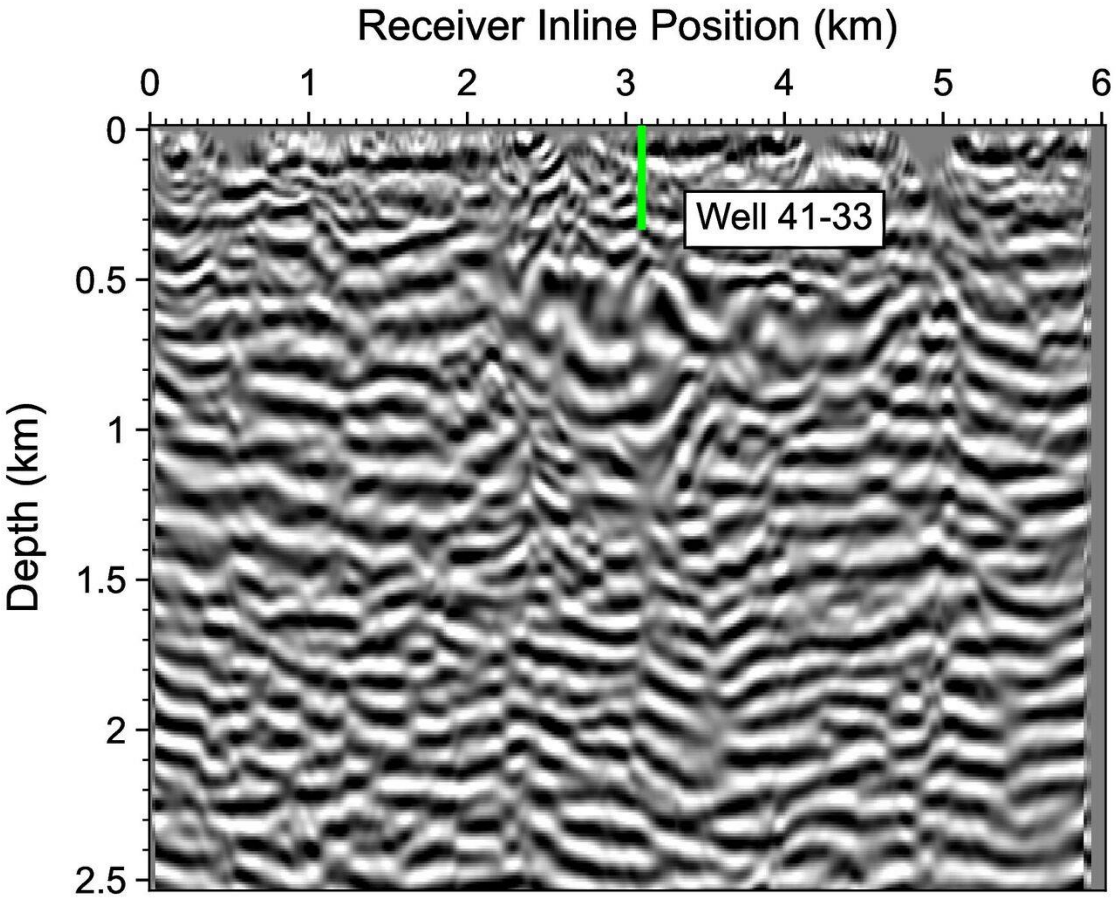
- Extract a 2D depth slice along Well 41-33 from the 3D RTM image of the Soda Lake geothermal field
- Well 41-33 is a geothermal production well producing energy from a steam zone.
- Apply windowed 2D RMS balancing to equalize image amplitudes from shallow to deep regions



Line 218: Original Image

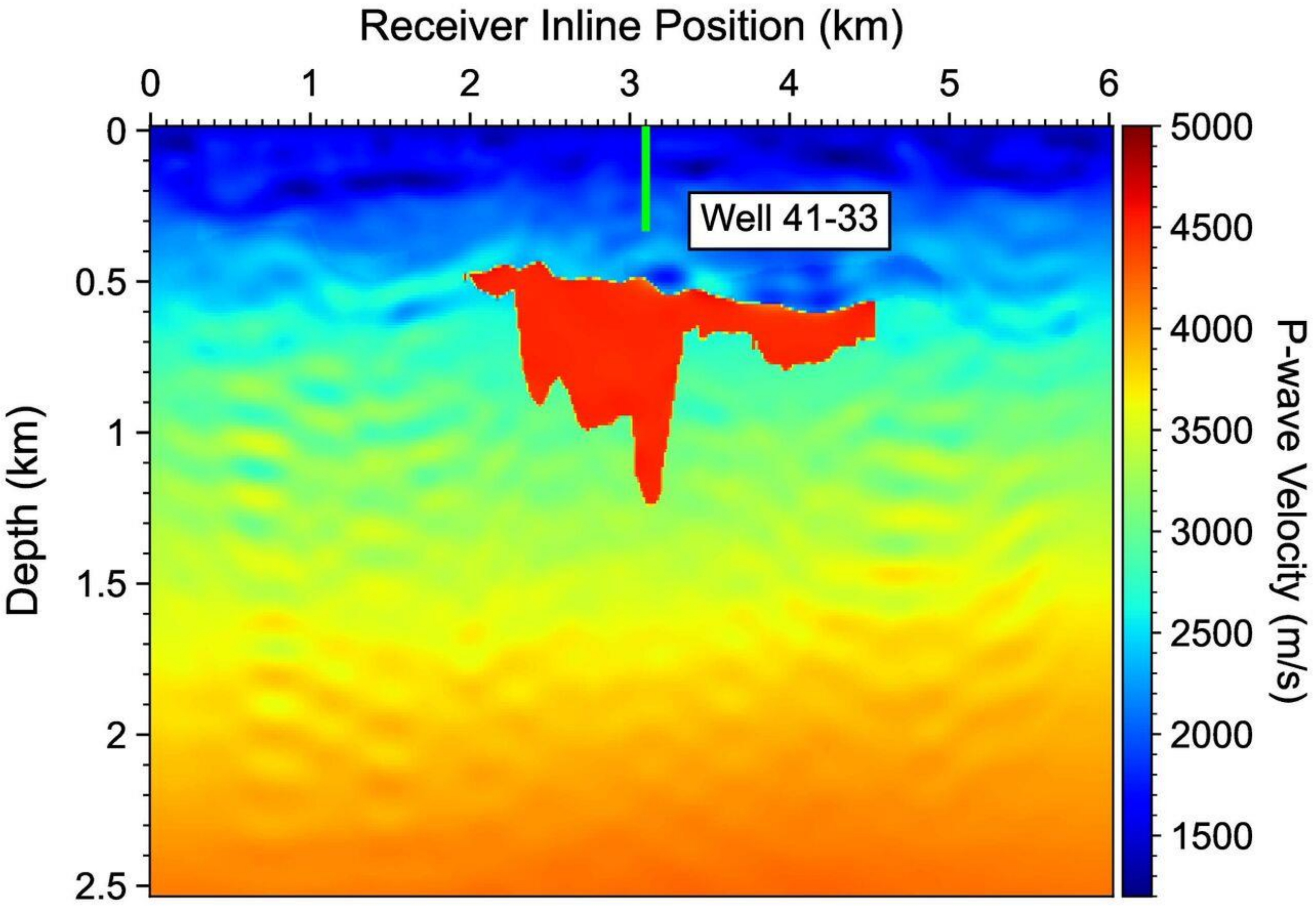


FWI Velocity Model

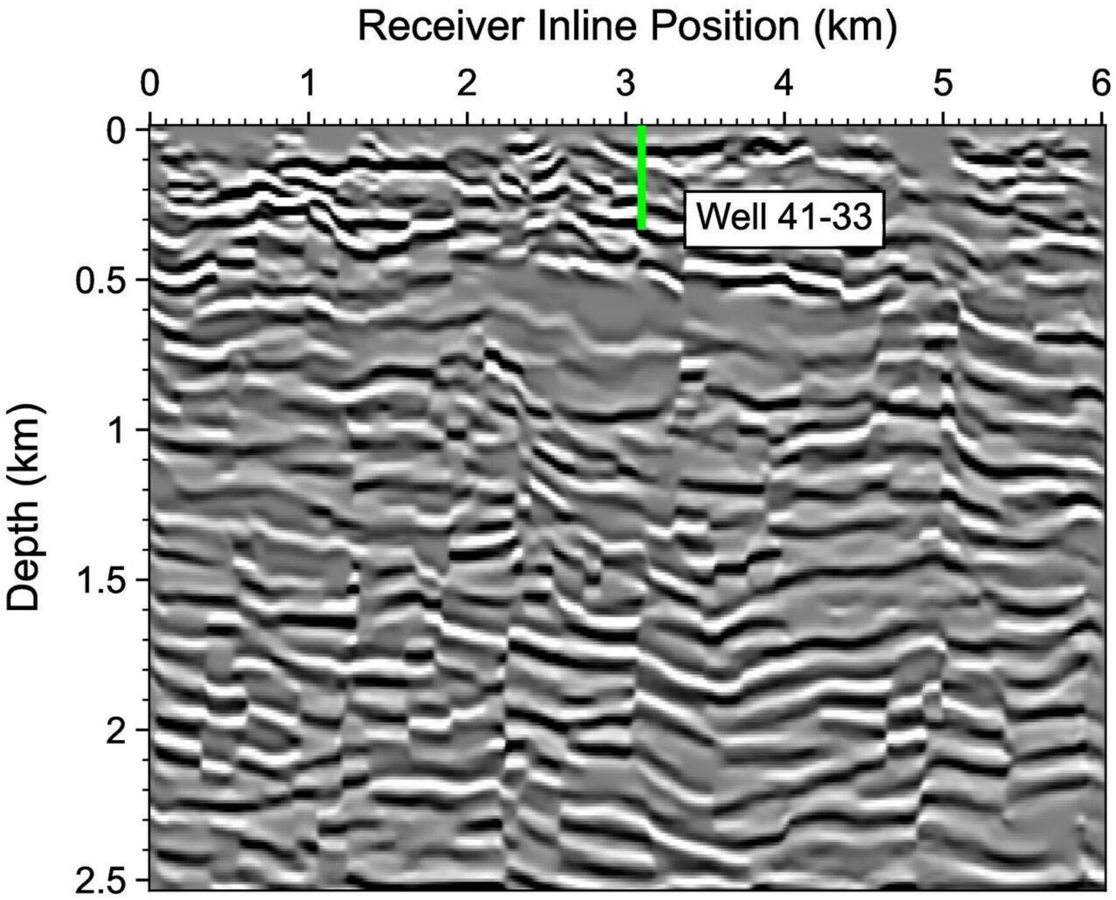


Original RTM Image

Line 218: NRU-Denoised Image with Enhanced Resolution



FWI Velocity Model



NRU-Denoised RTM Image

Line 218: NRU Fault Detection on Original Image

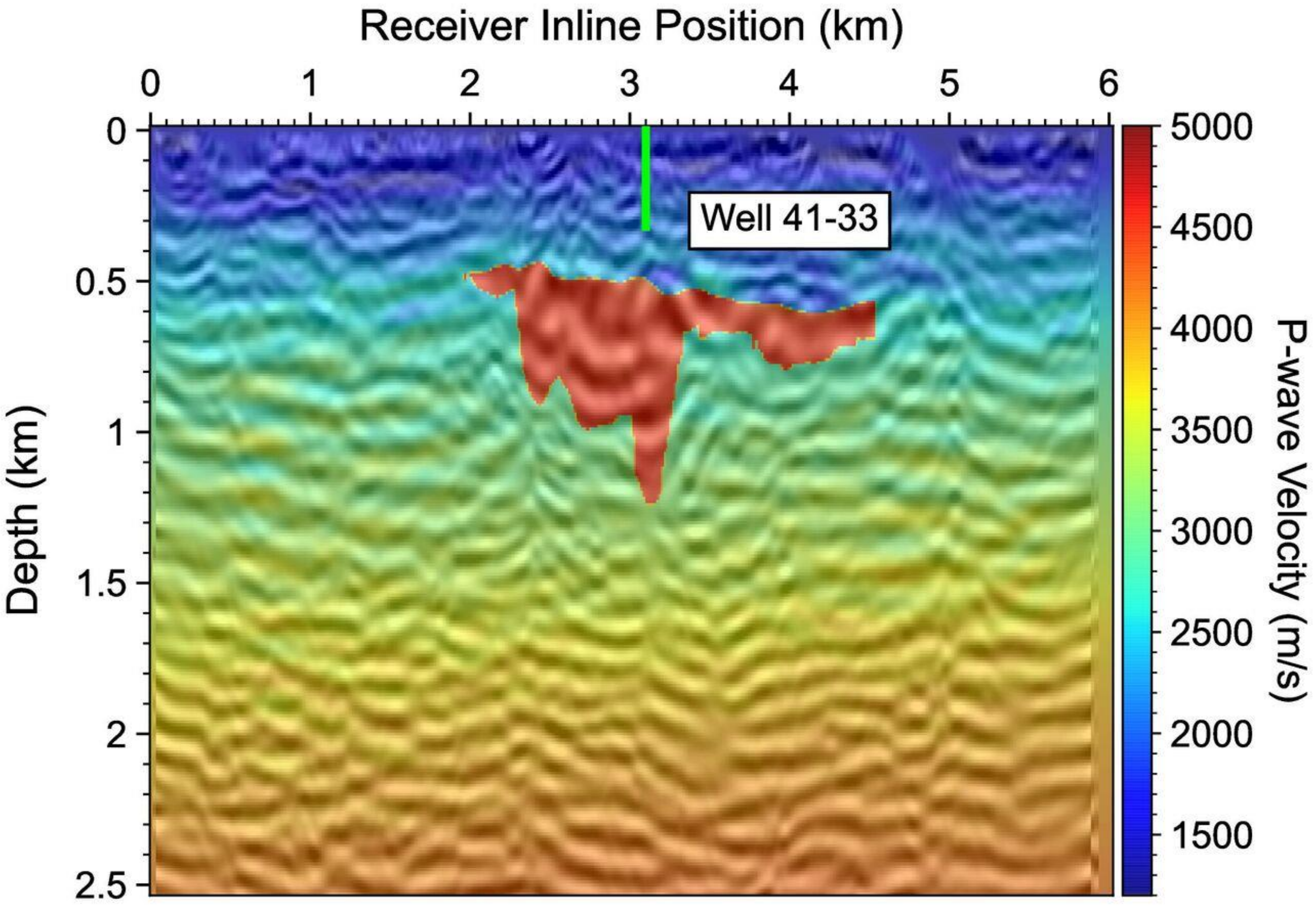
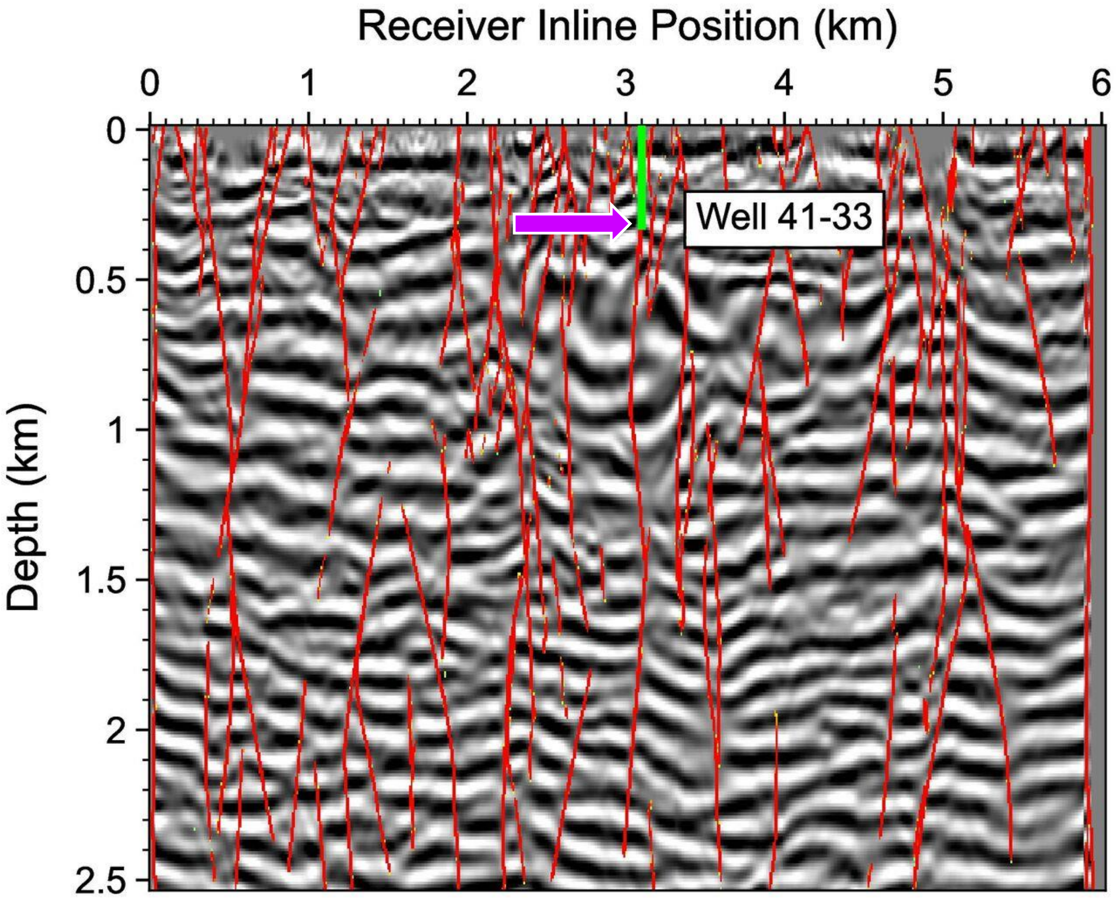
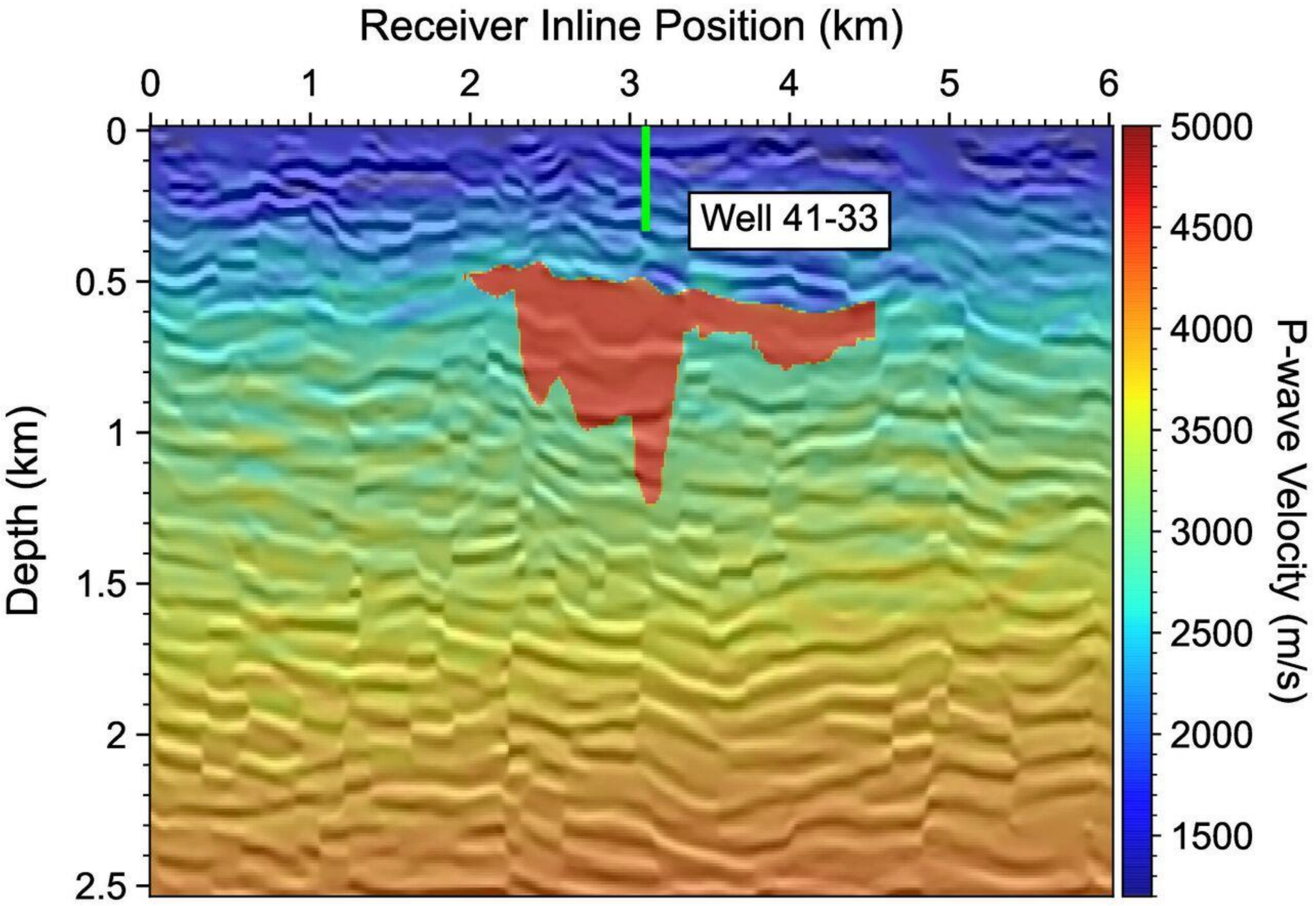


Image on FWI Velocity Model

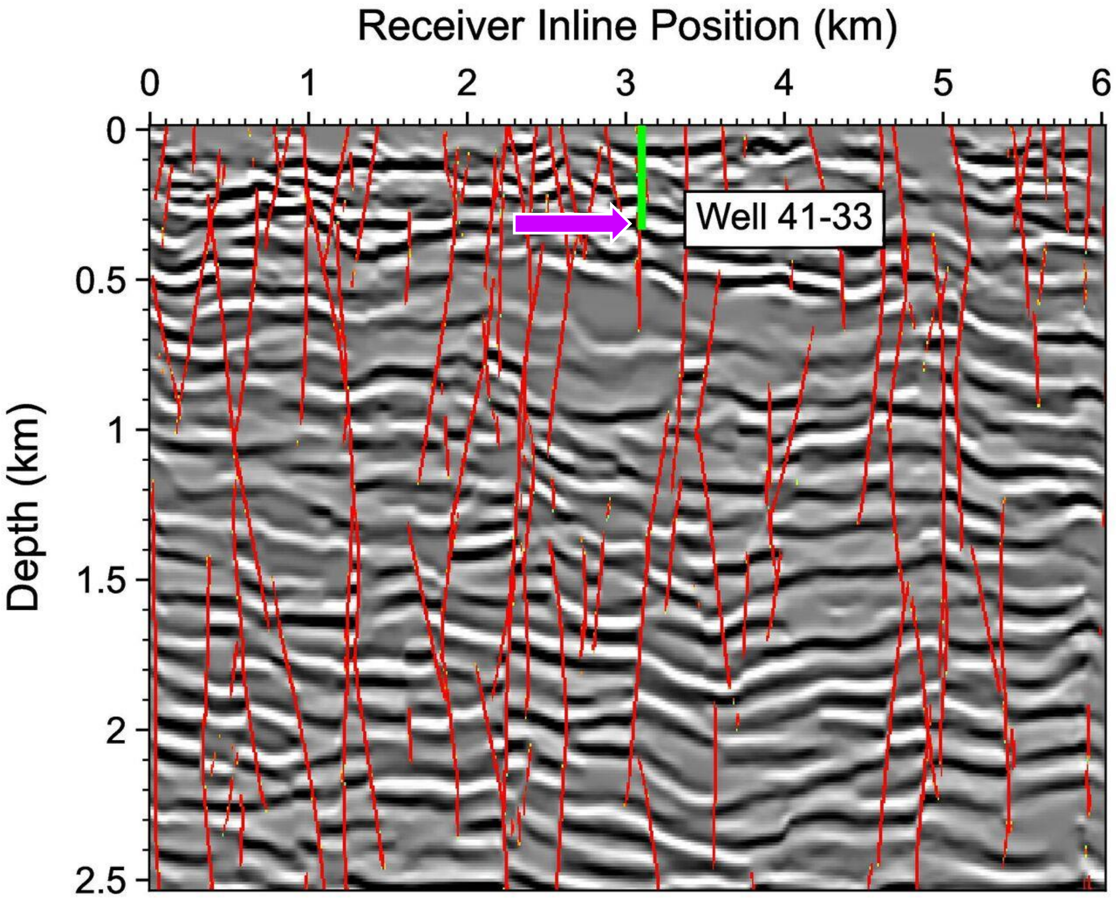


NRU Fault Detection on Original Image

Line 218: NRU Fault Detection on Denoised Image

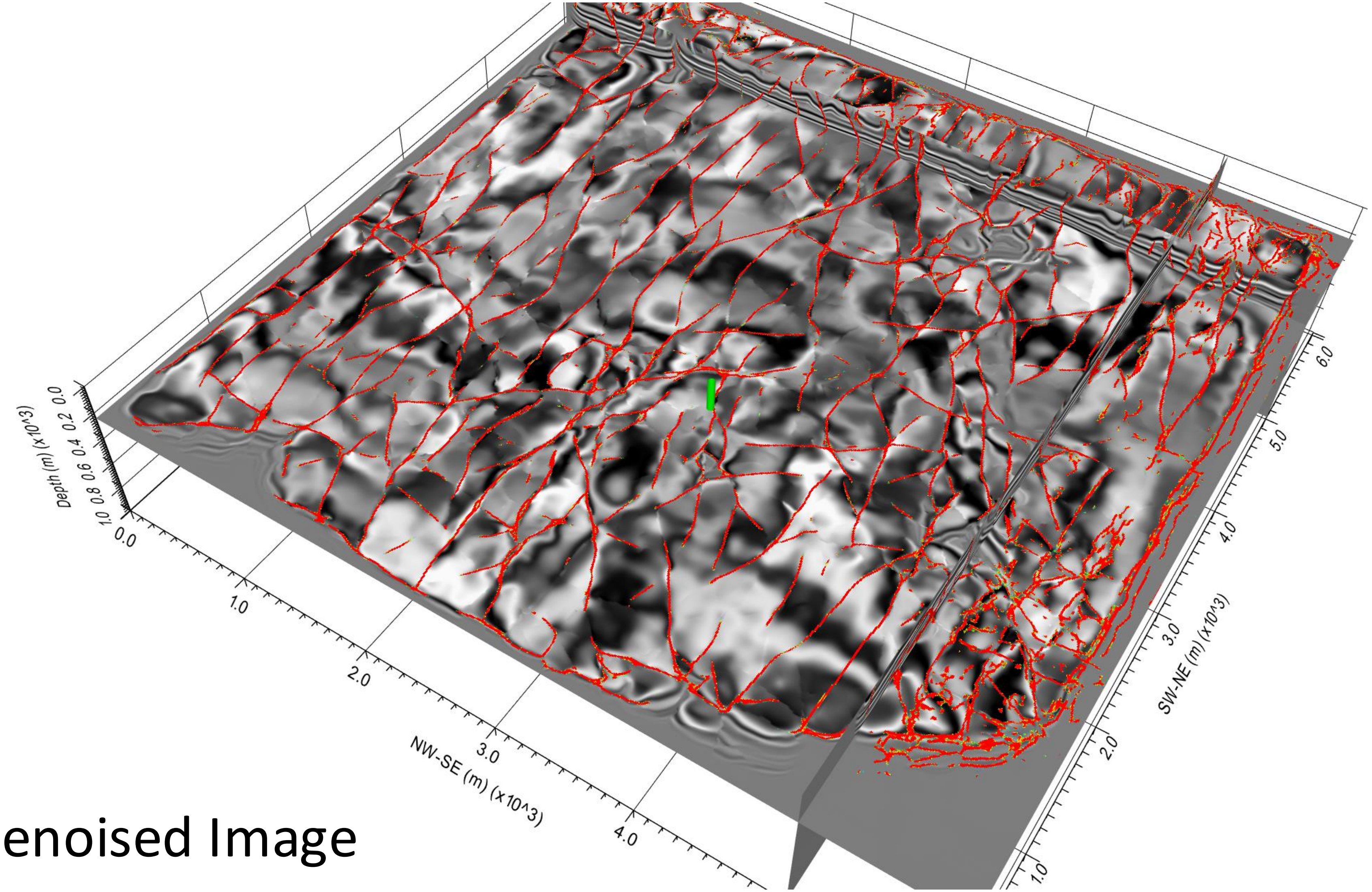


Denoised Image on FWI Velocity Model



NRU Fault Detection on Denoised Image

Steam Zones at Depth of 800 ft:
NRU faults align with Well 41-33 steam zone → Validated model



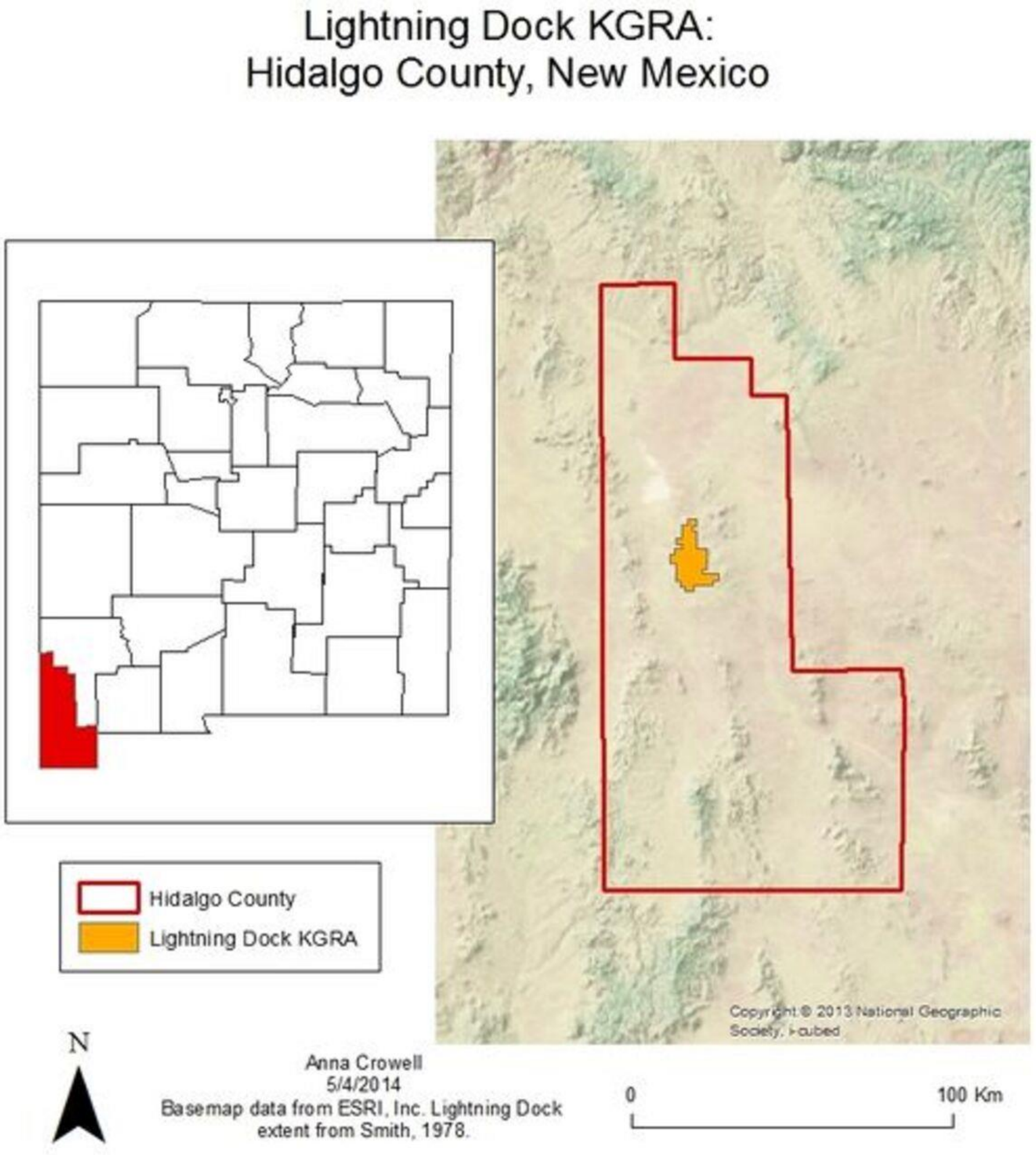
Faults on Denoised Image

Lessons Learned

- **Verification**: Well 41-33, a geothermal production well extracting energy from a steam zone, intersects a detected fault, confirming the model's accuracy.
- **Image Denoising**: Essential for improving the accuracy of ML-based fault detection.
- **Practical Value**: Detected faults offer critical guidance for siting new injection and production wells.

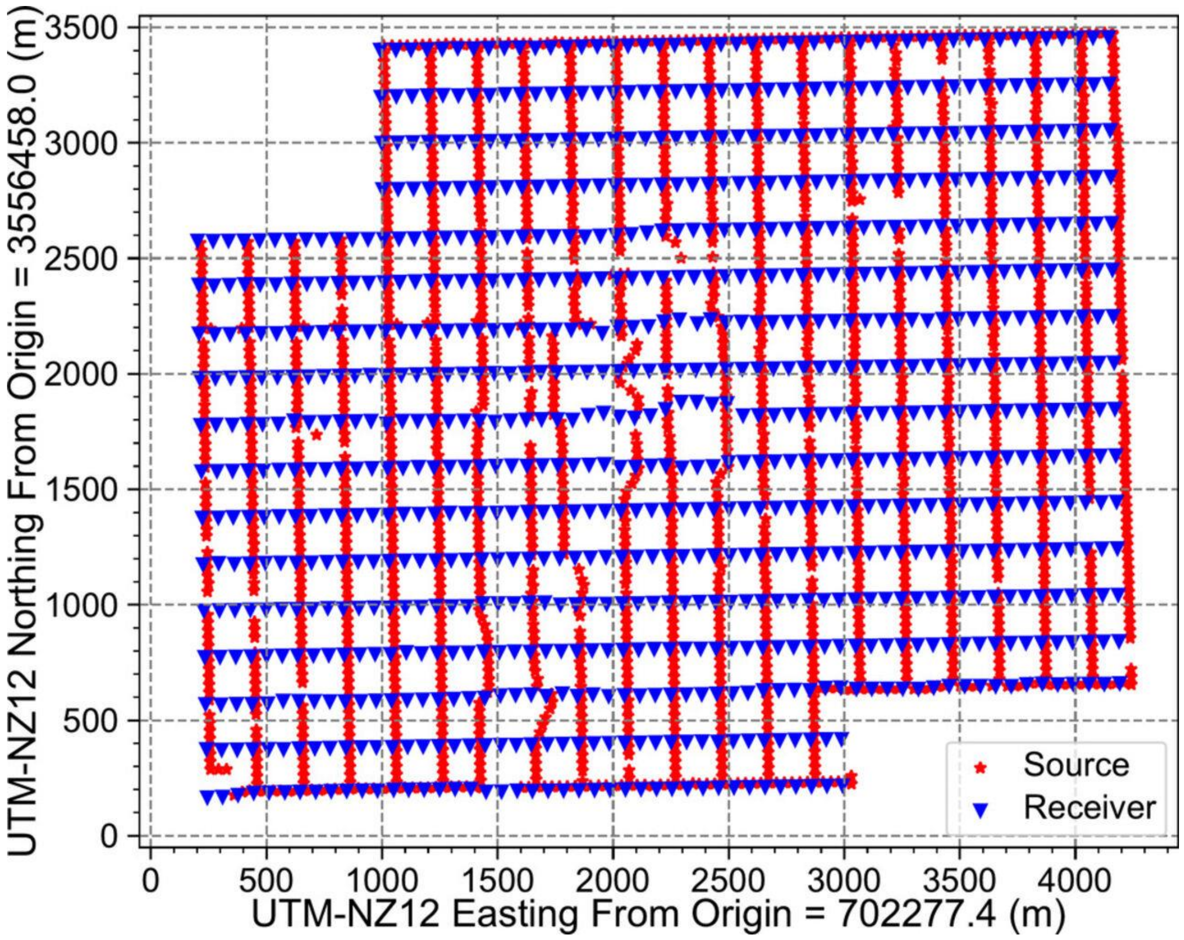
Case Study:
Lightning Dock Geothermal Field

- Located in New Mexico, USA.
- Increased from 4 MW to 12 MW (2013–2018).
- 3D seismic data with RTM and FWI processing
- NRU used to detect faults post-denoising
- Output: High-fidelity structural imaging

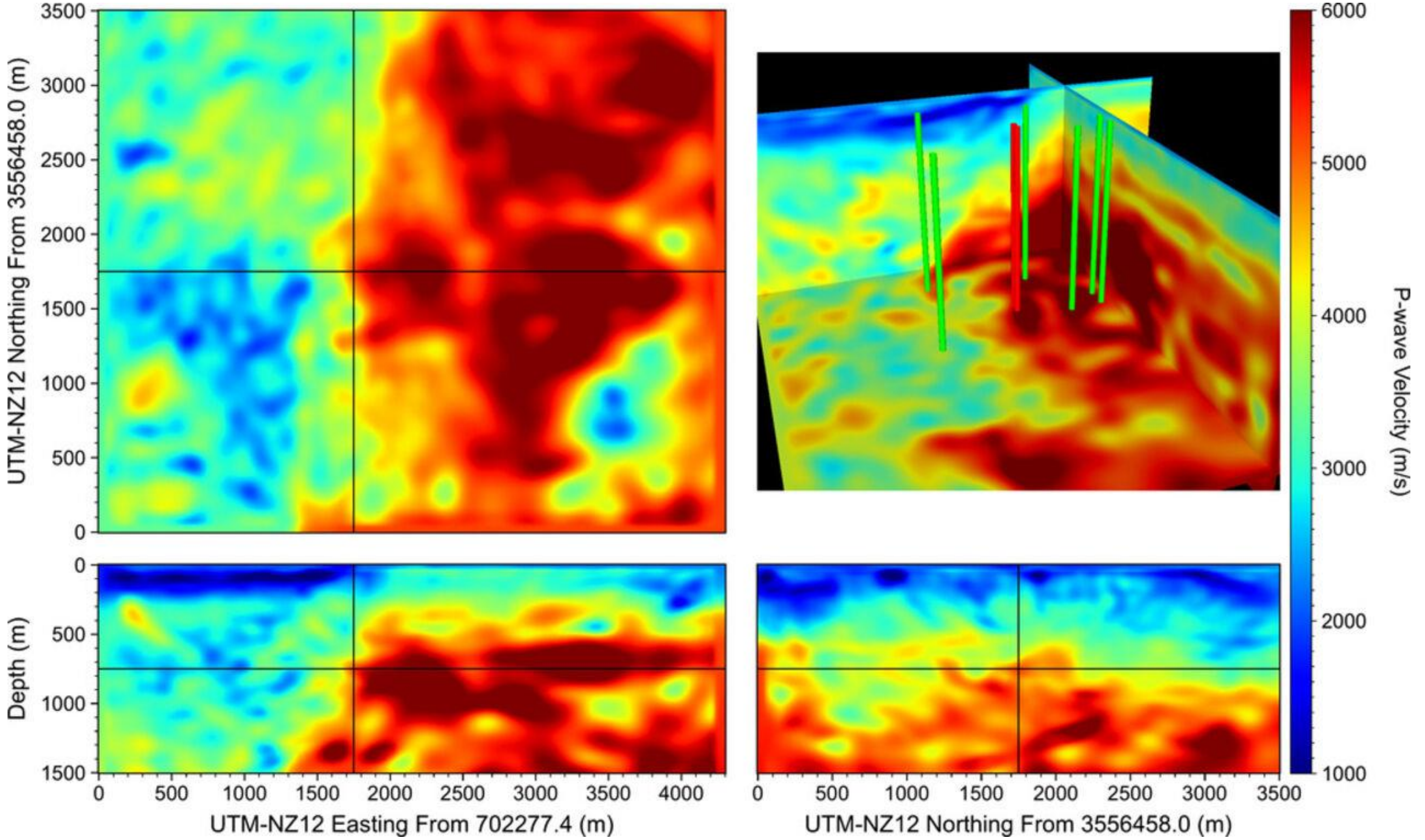


3D Seismic Survey

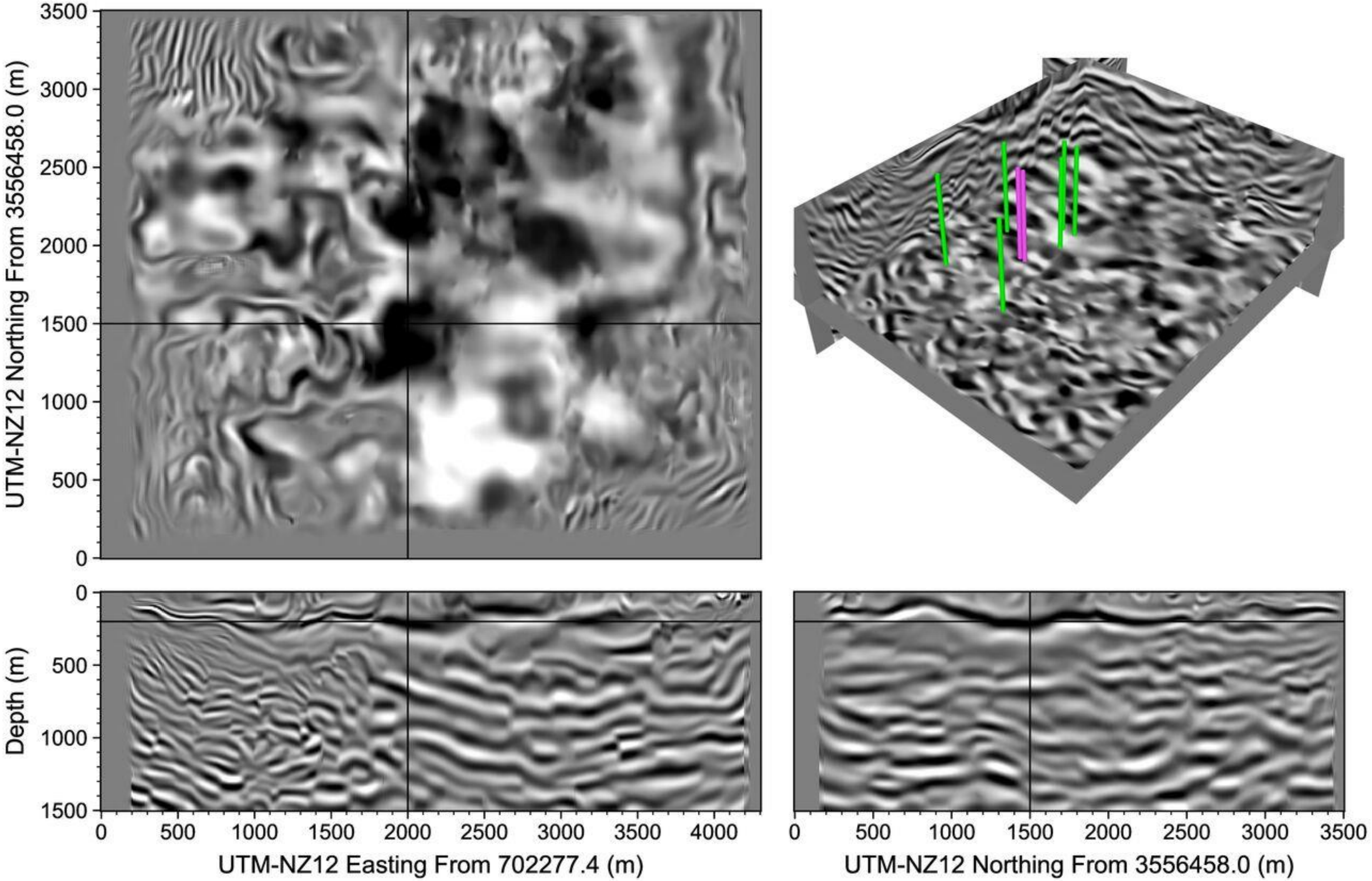
- A 3D active seismic dataset was acquired in 2011 using accelerated weight drop sources.
- Process the 3D seismic data, build a 3D velocity model, and perform reverse time migration.
- Detect faults in the 3D image using machine learning.



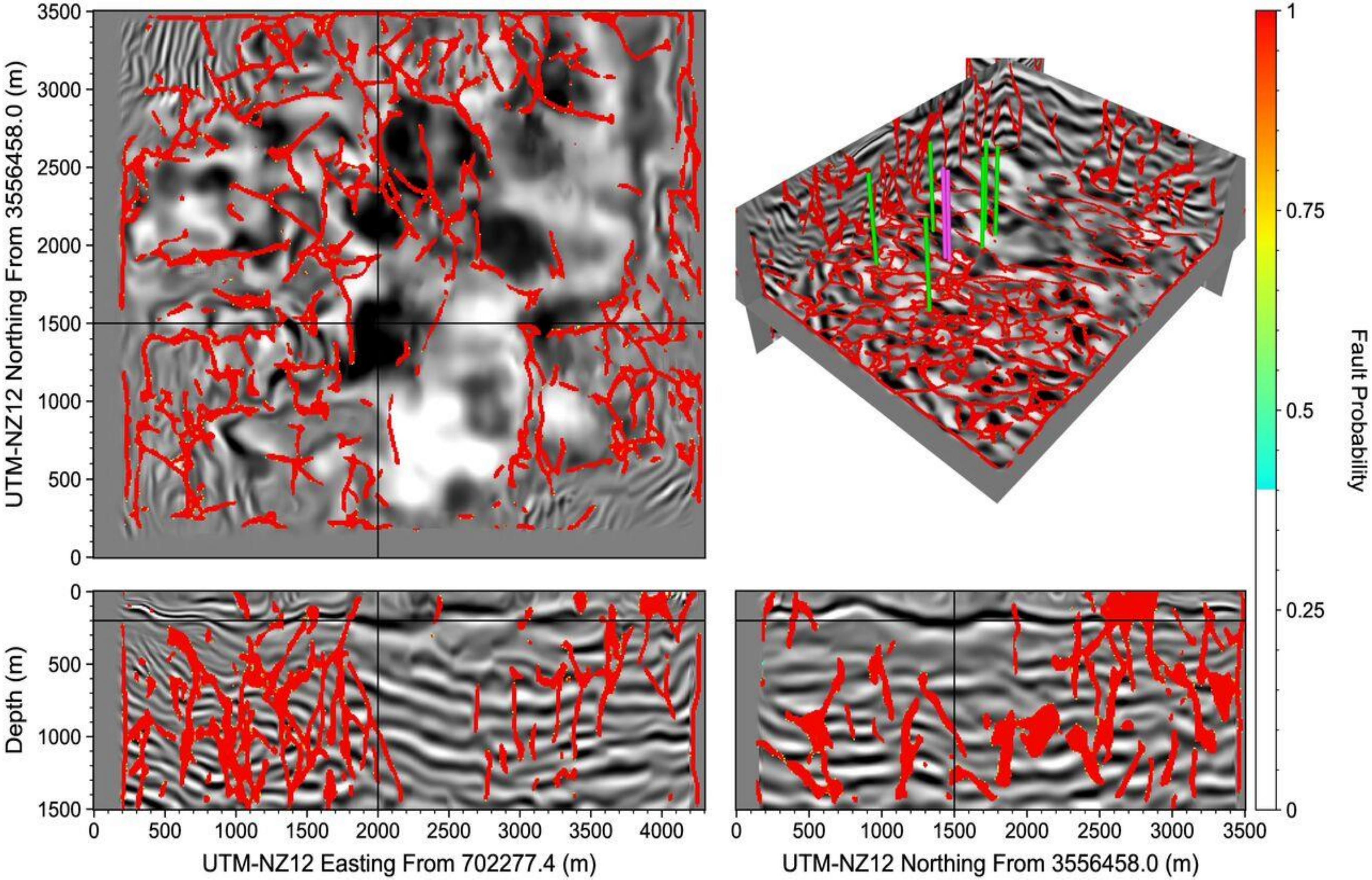
3D FWI Velocity Model from 3D Active Seismic Data



Denoised 3D RTM Image



Faults Detected on the Denoised 3D RTM Image



Lessons Learned:
Noisy weight-drop source data → NRU denoising → Improved fault detection

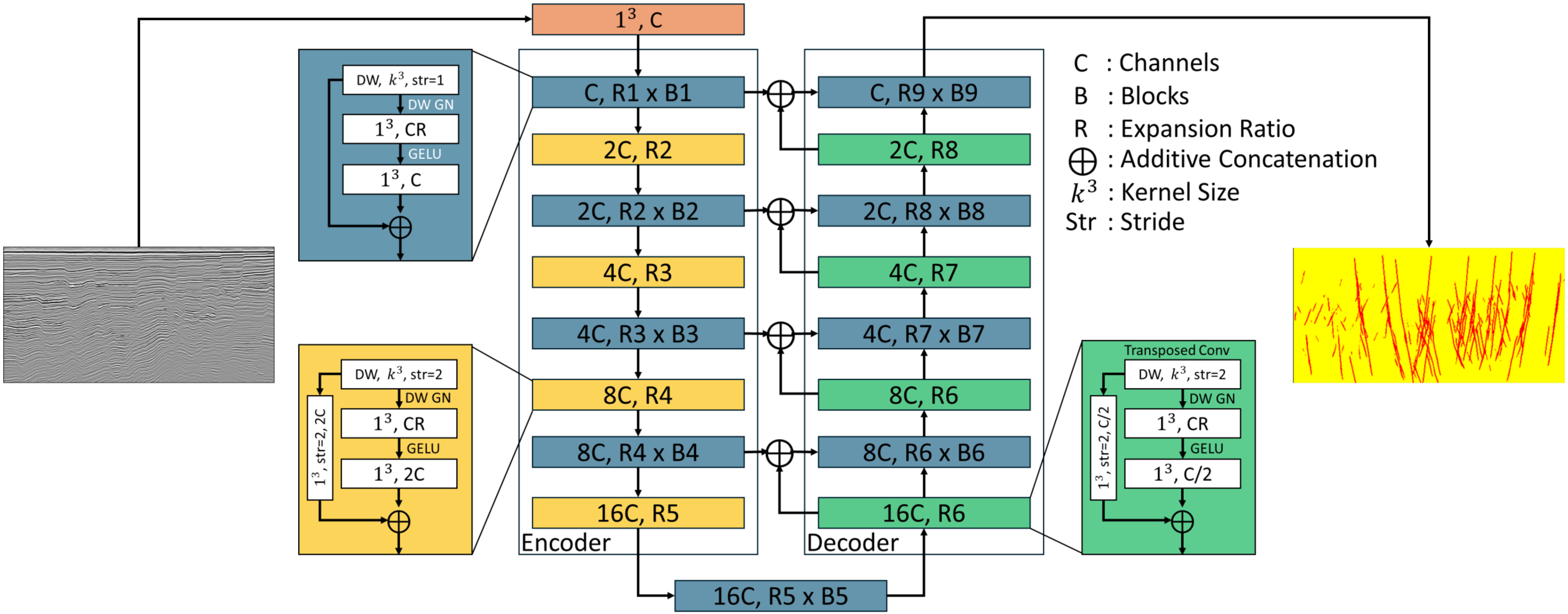
- **Data Quality**: Seismic data acquired using accelerated weight drop sources are highly noisy. Vibroseis sources are recommended to enhance data quality.
- **Geological Structures**: Structural features differ significantly between the east and west sides of the geothermal field, indicating varying subsurface conditions.
- **Practical Value**: Faults detected on denoised seismic migration images can provide crucial guidance for optimal siting of new injection and production wells.

Efficient Fault Detection Using ConvNeXt Architecture

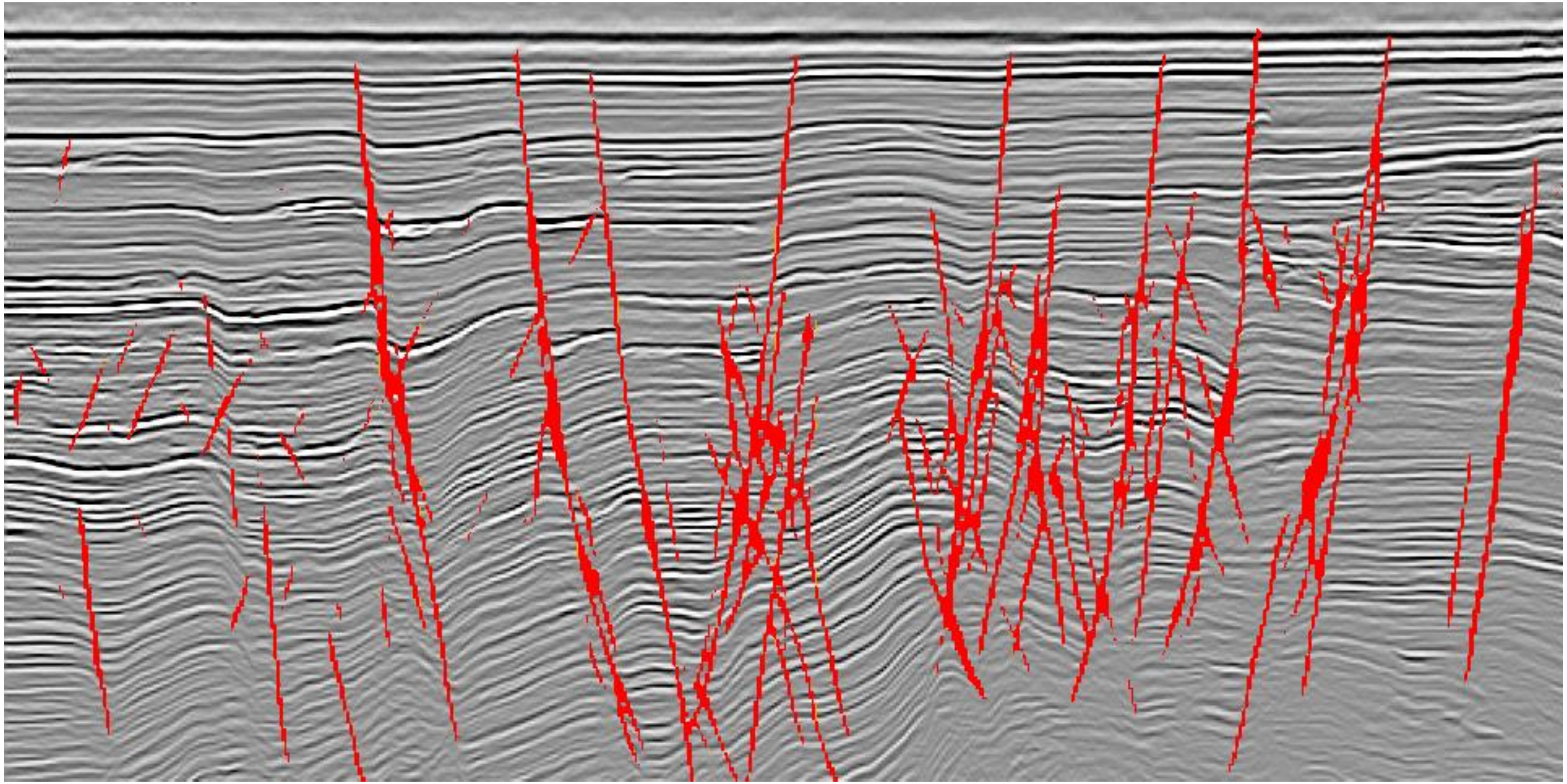
Hybrid CNN Architecture (McNease, Huang, et al., 2025):

- Combines CNN and Transformer efficiency
- ~40% faster inference than Res U-Net++
- Requires less training data, achieves high accuracy
- Applied to real seismic datasets (e.g., Opunake, F3)

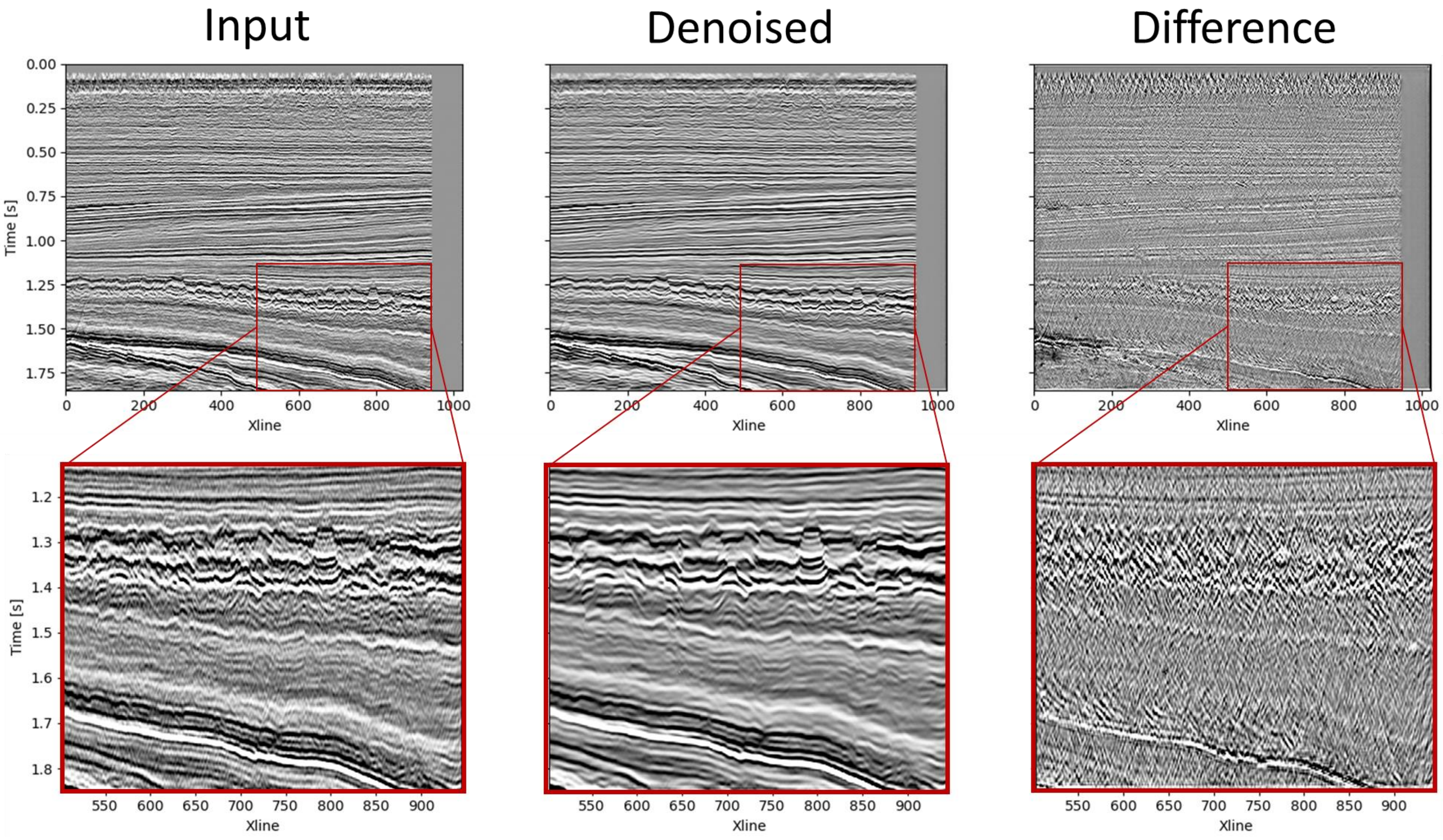
Efficient Fault Detection Using ConvNeXt Architecture



An Inline of the Opunake 3D Seismic Image (Real Data)



ConvNeXt for Efficient Image Denoising (Netherlands Offshore F3 Data)



ConvNeXt Fault Detection and Denoising

- ConvNeXt detects subtle faults in complex structures
- Efficient → Deployable on large real datasets

From static structures (faults) → to dynamic processes (flow)

- Machine Learning for Flow Imaging
- Continuous microseismic data → ML classification (LFLD, FDLD, HFSD, LFSD) → Flow pathways

Flow Imaging Using Continuous Microseismic Data and Unsupervised ML

Approach

- Unsupervised 7-layer U-Net on continuous microseismic data
- Classifies low-frequency, long-duration (LFLD) seismic events
- Links LFLD events to fracture flow during hydraulic fracturing

Data Source

- 18 3C geophones at 4 kHz
- HF-1 and HF-2 stages in Wolfcamp Shale, Permian Basin

(Duan, Huang, et al, IEEE-TGRS, 2024)

Flow Event Classification

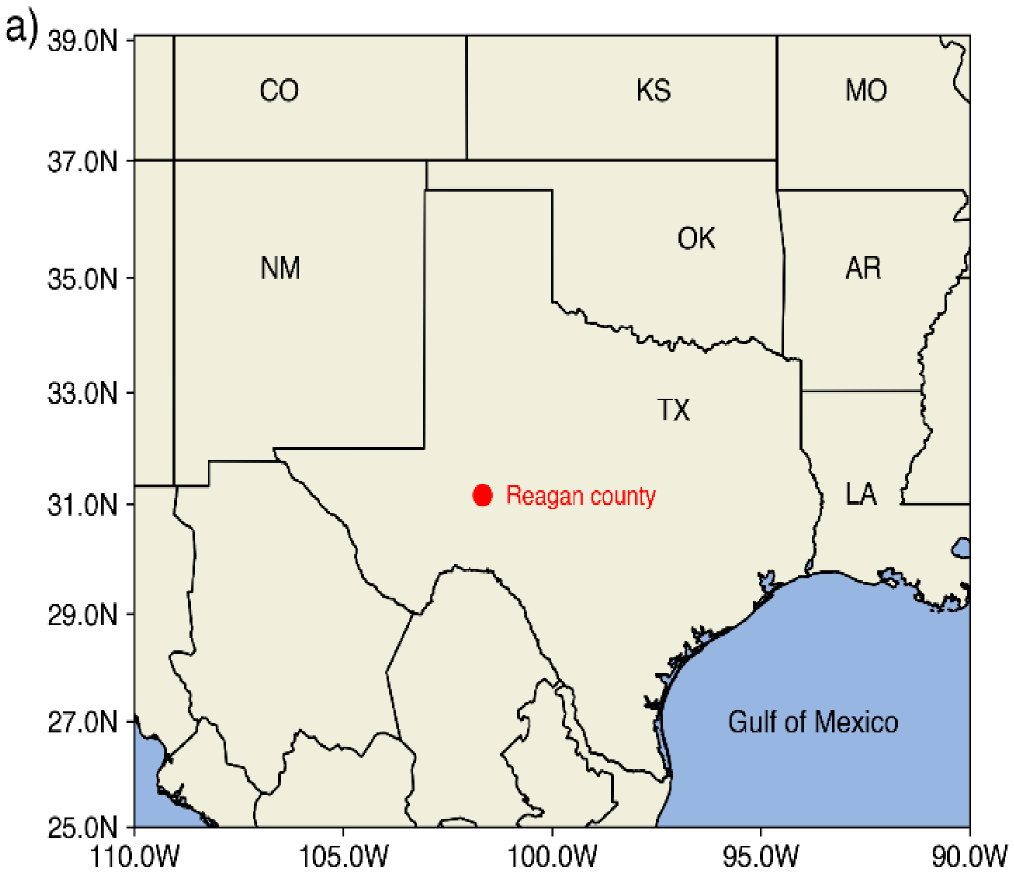
Detected Event Types

- LFLD: Low-frequency, long-duration
- FDLD: Frequency-drop, long-duration
- HFSD: High-frequency, short-duration
- LFSD: Low-frequency, short-duration

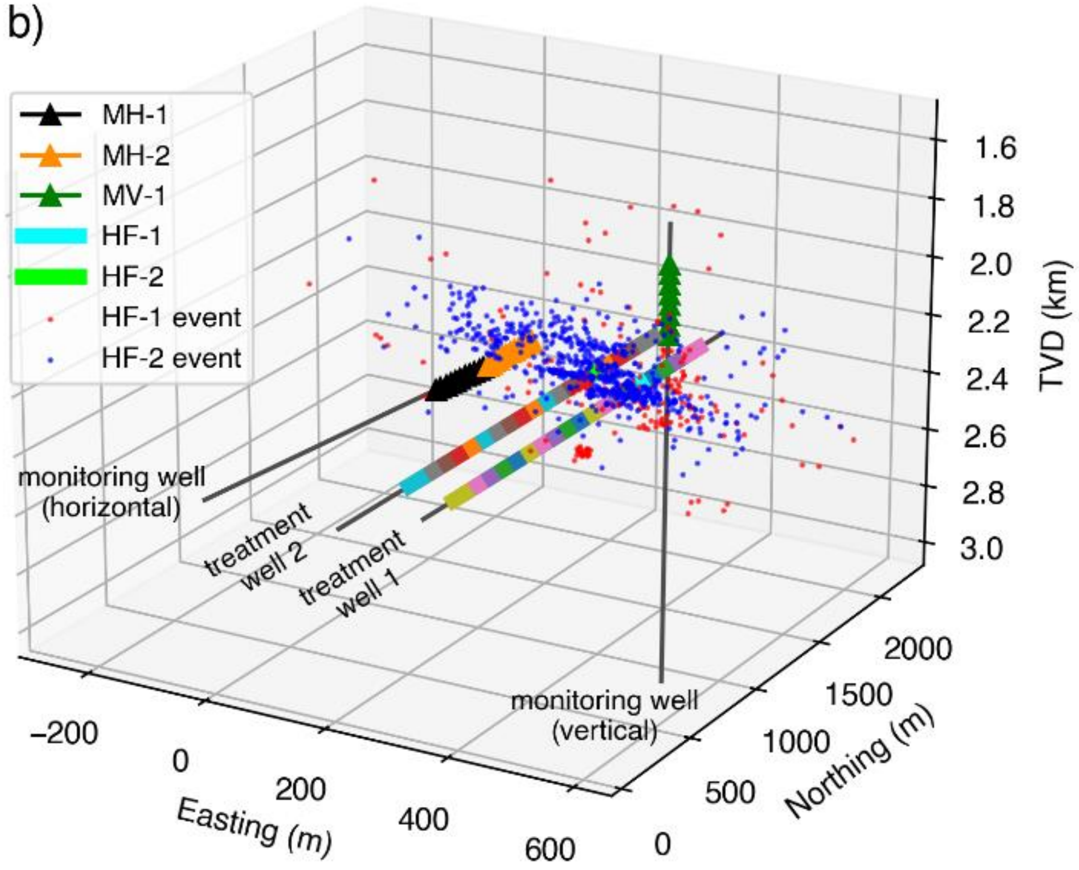
Visualization

- Correlation with injection data
- Spatiotemporal distributions of LFLD and the others

Hydraulic Stimulation and Microseismicity

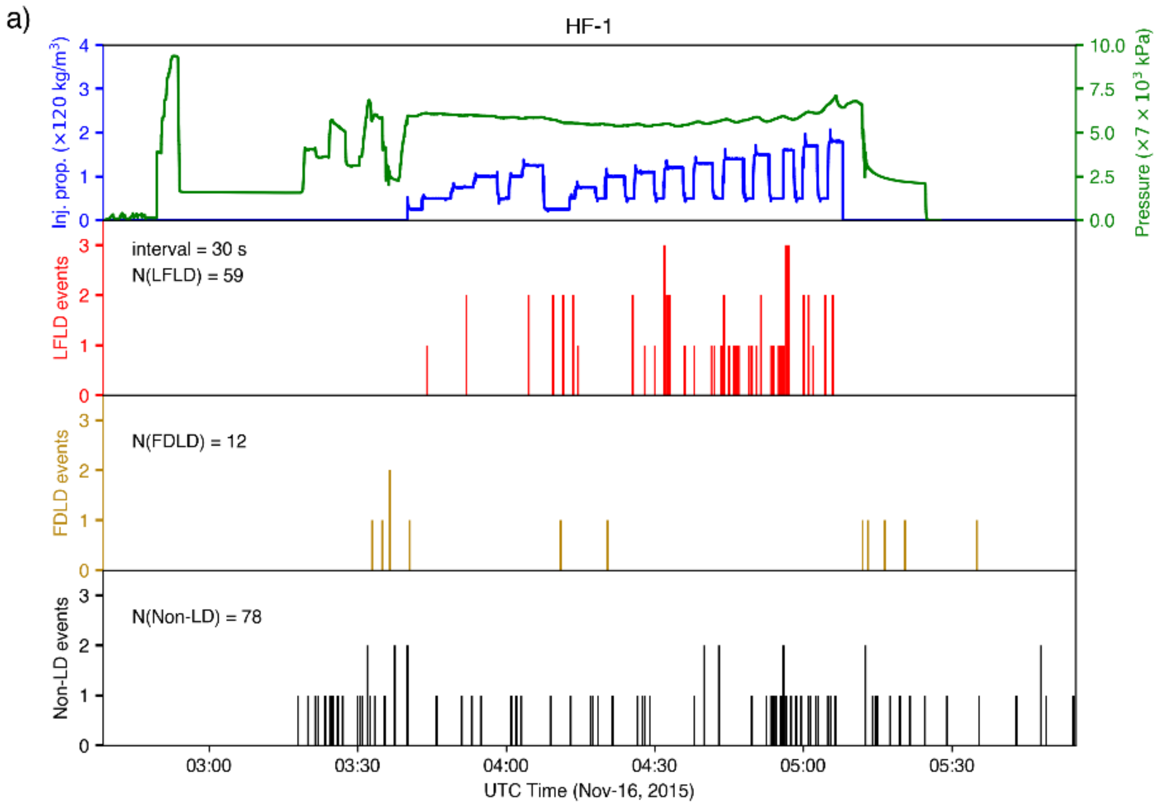


Midland basin, Reagan County, Texas

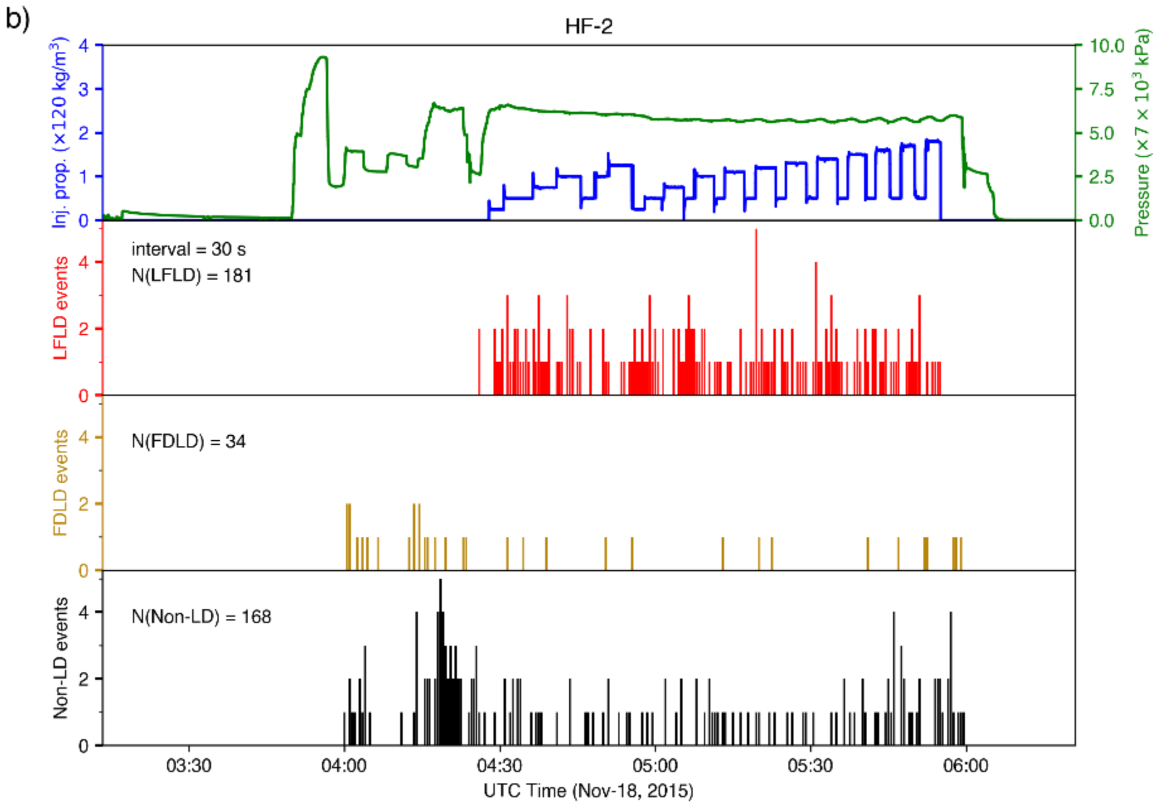


3D view of the fluid injection for hydraulic fracturing

Comparison of Injected Proppant Density and Pressure with LFLD, FDLD, and Non-LD Event Timings



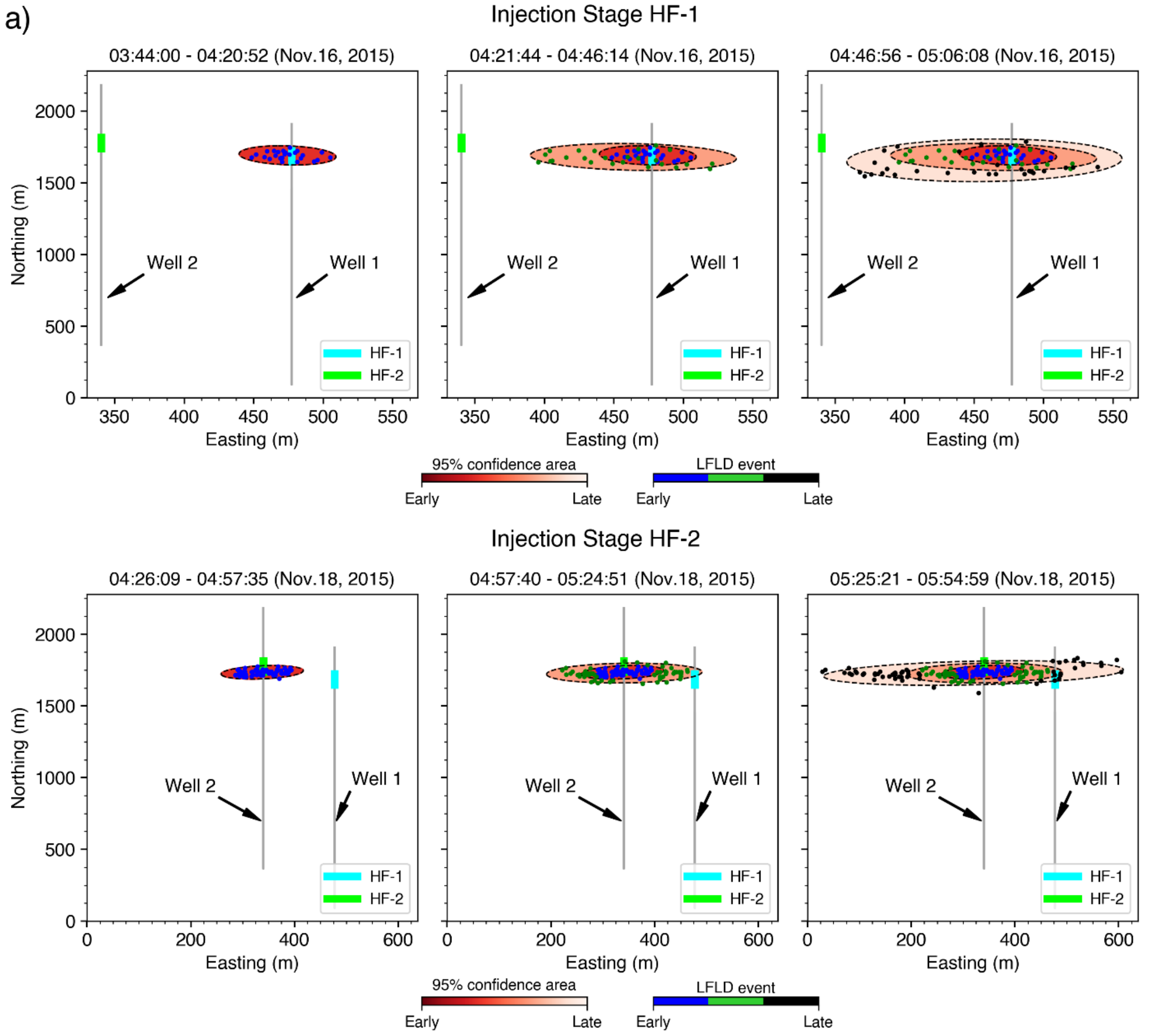
HF-1



HF-2

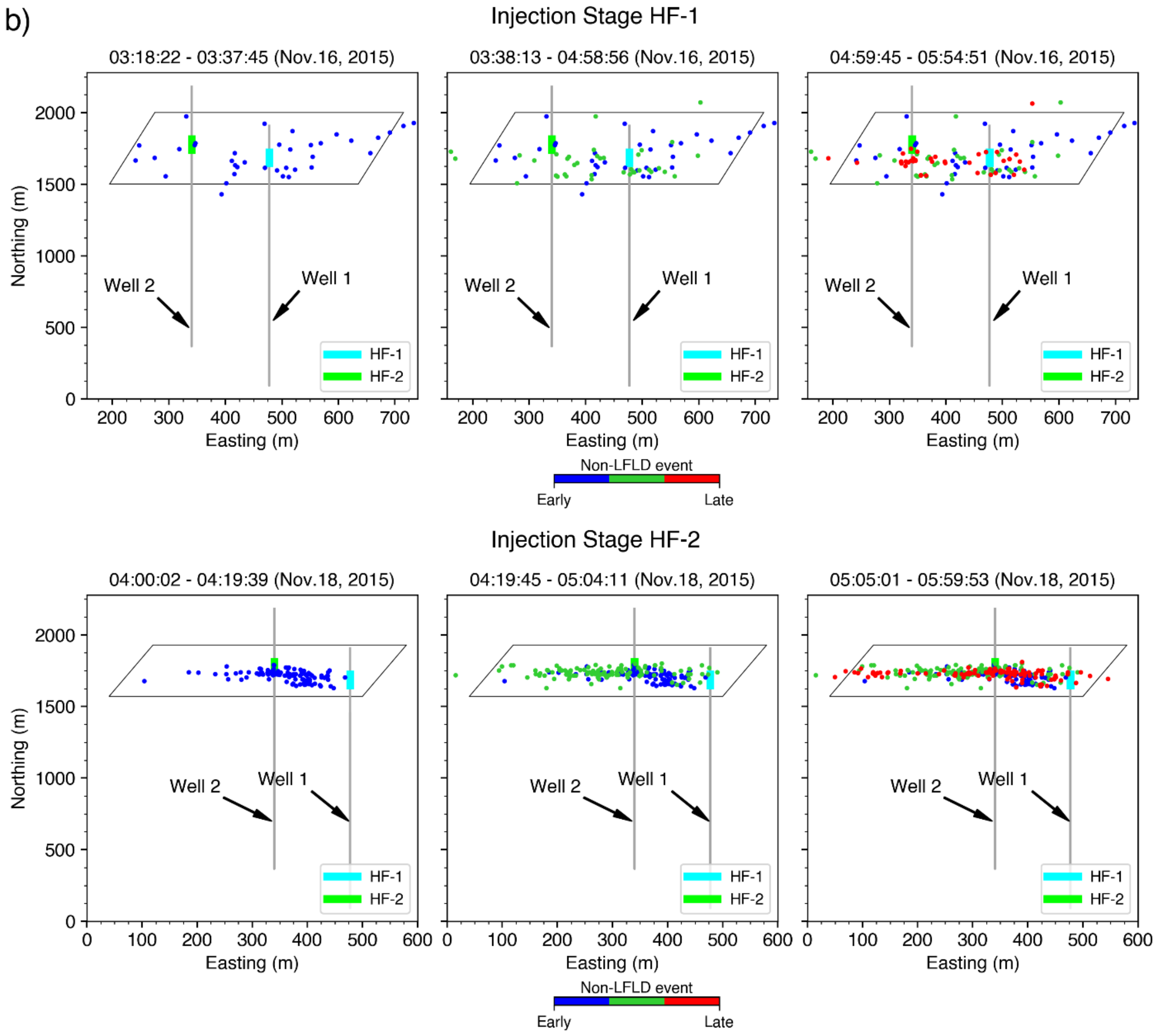
Spatiotemporal Distribution of LFLD

- Spatiotemporal distributions of LFLD events projected onto an East-North plane.
- Suggests correlation between flow paths and LFLD signals.
- Only LFLD events trace fluid flow

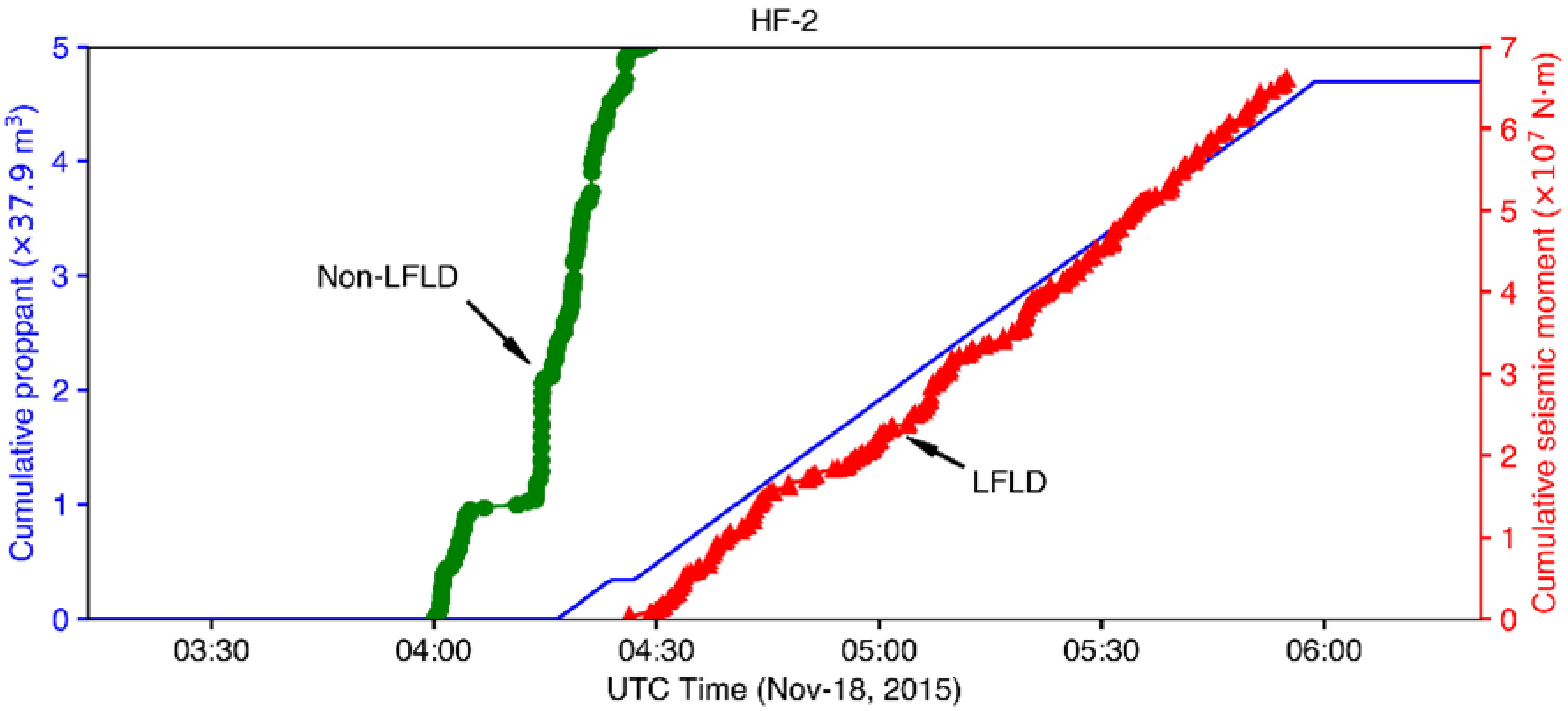


Spatiotemporal Distribution of non-LFLD

- Spatiotemporal distributions of non-LFLD events projected onto an East-North plane.
- Indicates a lack of correlation between flow paths and non-LFLD signals.



LFLD Seismic Moment Scales with Proppant Injection, Validating Its Role as a Real-Time Flow Proxy



Conclusions

- **Fault Detection & Denoising**: NRU/ConvNeXt improve accuracy, robustness, efficiency
- **Flow Imaging**: Microseismic ML reveals active flow paths, useful for monitoring
- **Faults + Flow**: Integrated geothermal reservoir characterization and monitoring

Conclusions

- **Impact of ML for Geothermal Exploration & Monitoring**:
  - 🎯 Accuracy ↑: Better fault maps
  - 💰 Cost ↓: Fewer dry wells
  - 🛡️ Risk ↓: Safer drilling
  - 🌱 Sustainability ↑: Optimize reservoir performance

Acknowledgments

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- Thanks to collaborators for data and insights.