

# Characterizing Mesozoic Strike-Slip Faults in China's Tahe Oilfield: A Multi-Method Comparison from Traditional Seismic Attributes to AI

Yanliang Jiang<sup>1,2</sup>, Changcheng Han<sup>2</sup>

1.Xinjiang University, Urumqi, China;

2.Sinopec Geophysical Research Institute Co., Ltd., Nanjing, China;

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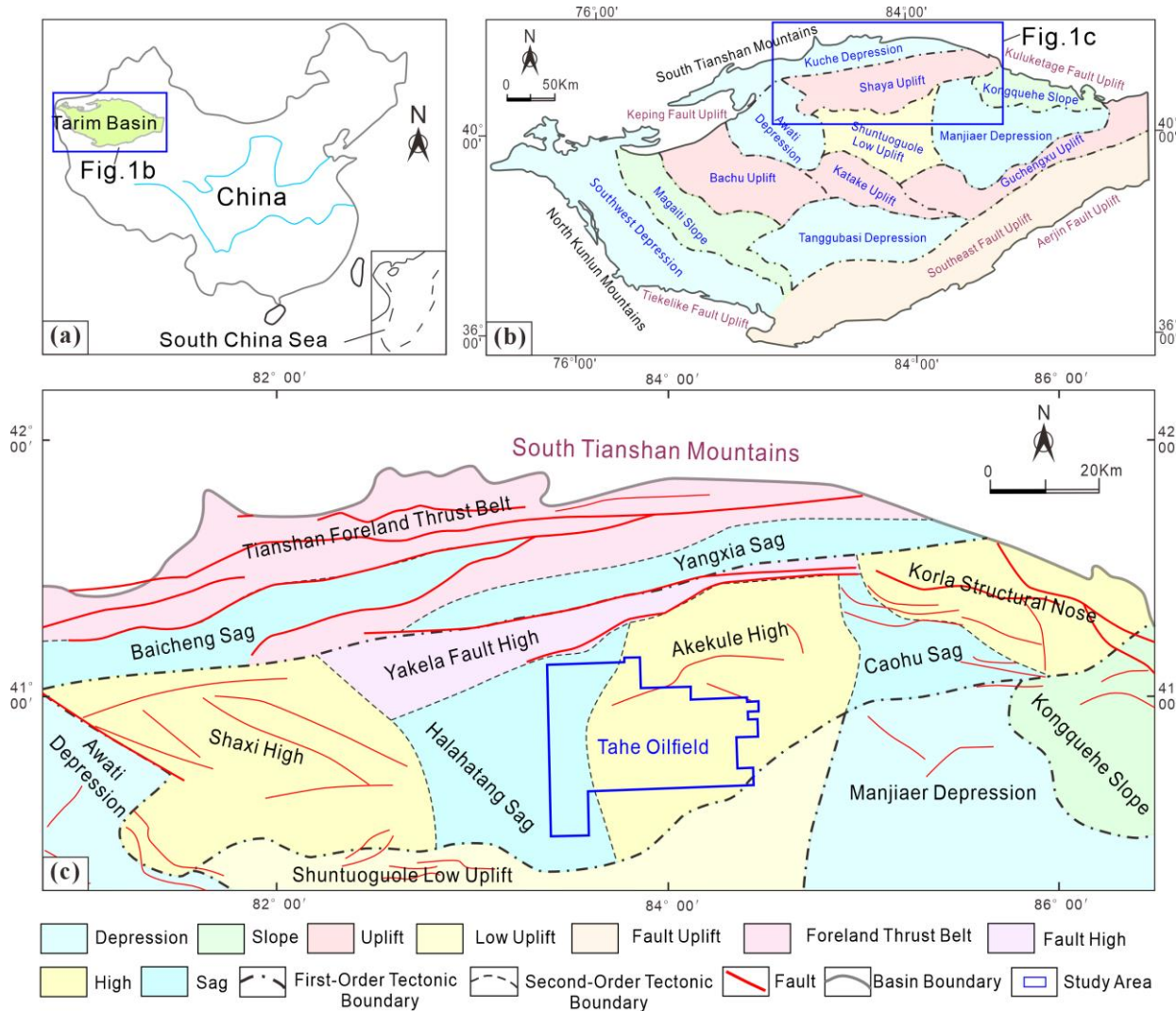
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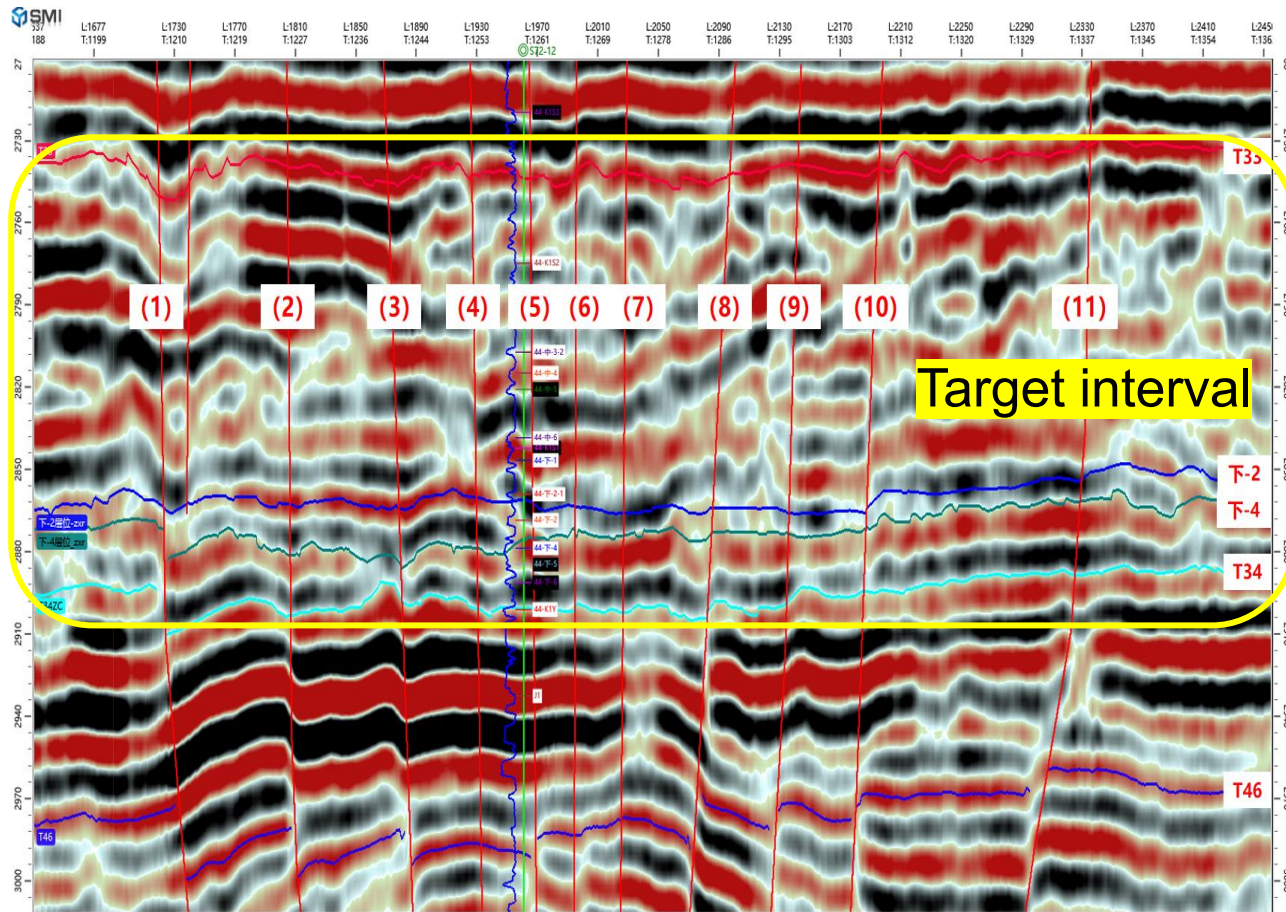


No Photos



## Research Background

- 📍 Tahe Oilfield, NW China
- 🏗️ Mesozoic clastic reservoirs
- 🔗 Strike-slip faults control hydrocarbon migration

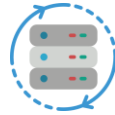


## Key Challenges

- ≡ Low impedance contrasts → weak reflections
- 📶 Steep dips & small throws → ambiguous signals
- 🗨️ Manual interpretation: inefficient & non-unique

Seismic Responses of Mesozoic Strike-Slip Faults in the Tahe Oilfield

# Objective



Systematically compare conventional seismic attributes vs. AI-based fault probability volume for strike-slip fault detection in the Tahe Oilfield.

## Evaluation Criteria



Fault boundary clarity



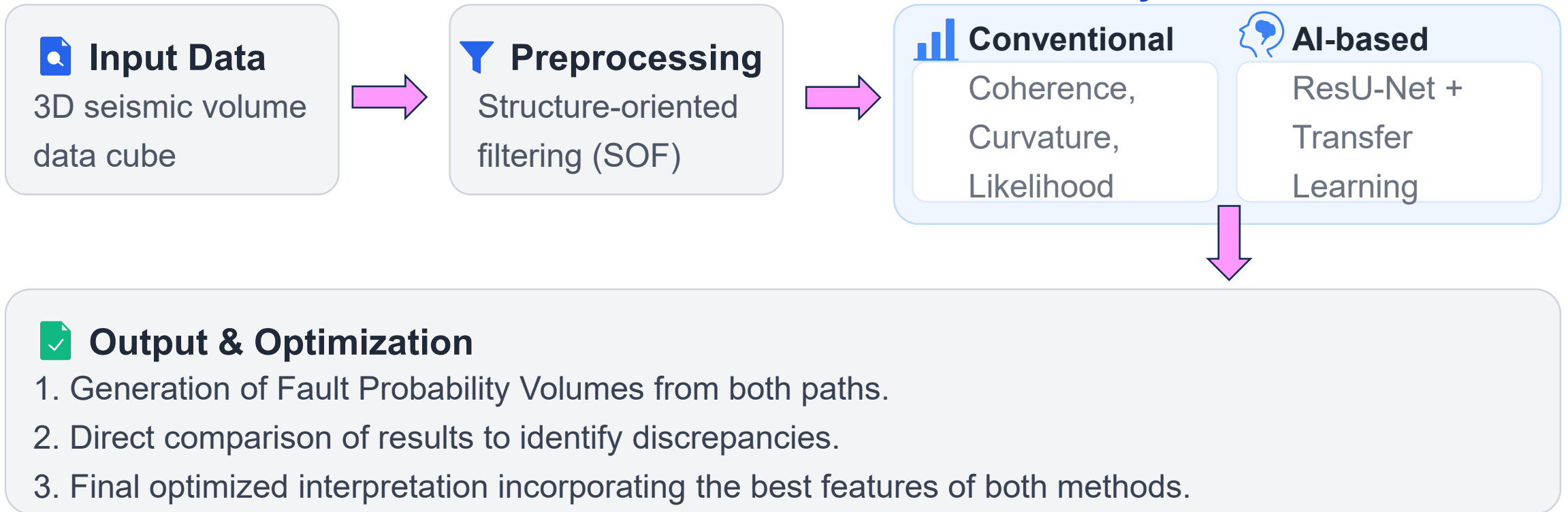
Detection of secondary faults



Geological plausibility

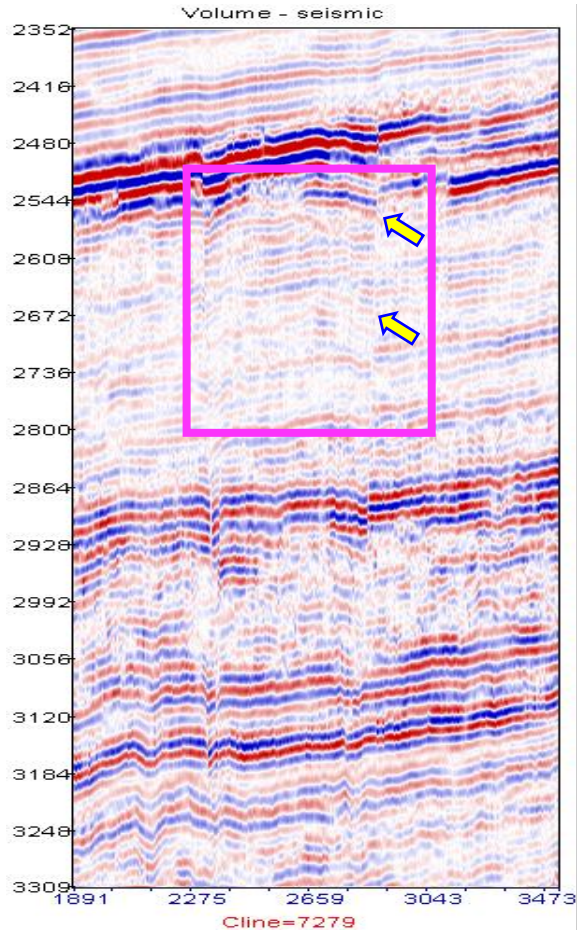


Noise resistance & continuity

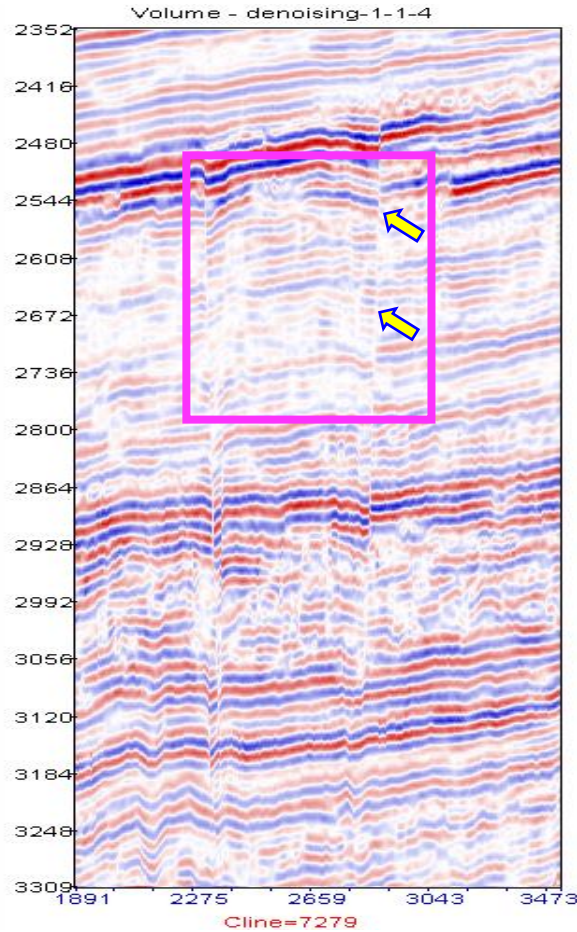


*This integrated workflow leverages the speed of AI with the interpretability of conventional attributes for robust subsurface fault detection.*

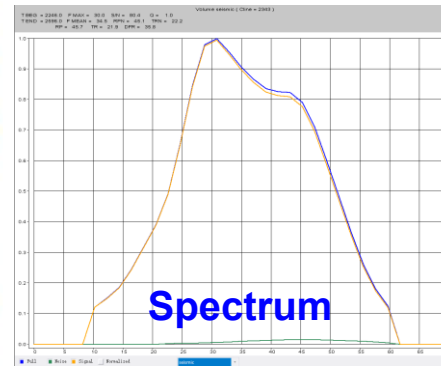
# ➤ Structure-Oriented Filtering



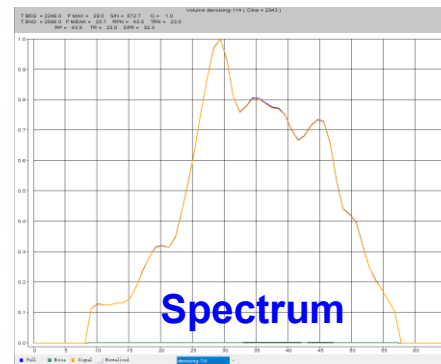
**Before Filtering**  
Low S/N, Disrupted Continuity.



**After Filtering**  
High S/N, Continuous Events.



**Before Filtering**



**After Filtering**

## Key Functions of Filtering




**Continuity Enhancement**  
Improves lateral continuity of seismic events



**Discontinuity Preservation**  
Retains fault-related geological features




**Noise Suppression**  
Eliminates random background noise

 *"Improved S/N ratio and event continuity for subsequent analysis, ensuring reliable attribute calculation and AI model training."*


# ➤ Conventional Seismic Attributes

Attribute	Principle	Limitation
Coherence	Measures waveform similarity across traces	Highly sensitive to random and coherent noise
Curvature	Quantifies strata bending and flexure	Primarily captures large-scale folds, limited resolution
Ant Tracking	Agent-based foraging algorithm for line detection	Prone to redundant artifacts and poor lateral continuity
Likelihood	Measures deviation from a seismic reflection trend	Difficult to distinguish main faults from secondary fractures


## Typical Output Characteristics (Schematic)




**Coherence**  
Sharp discontinuities



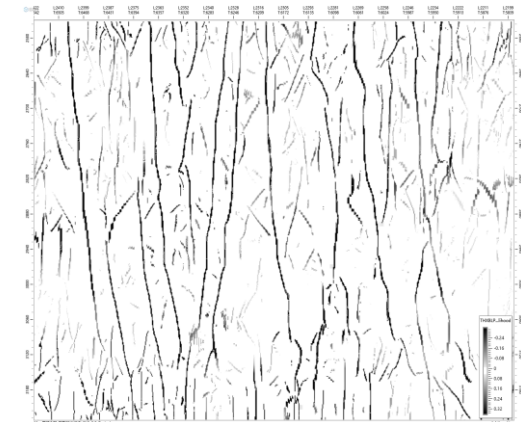
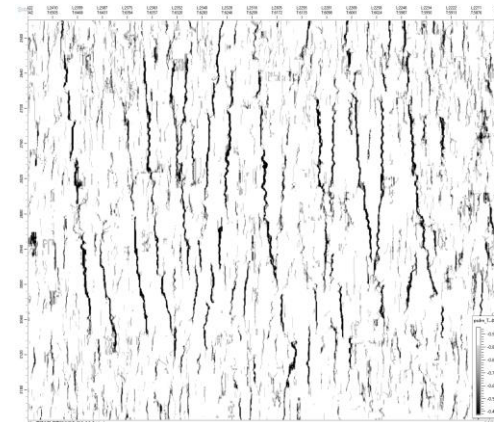
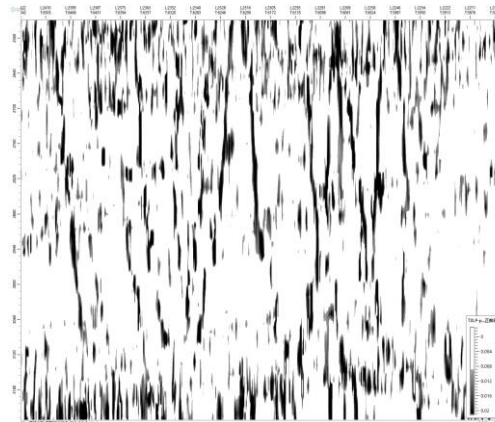
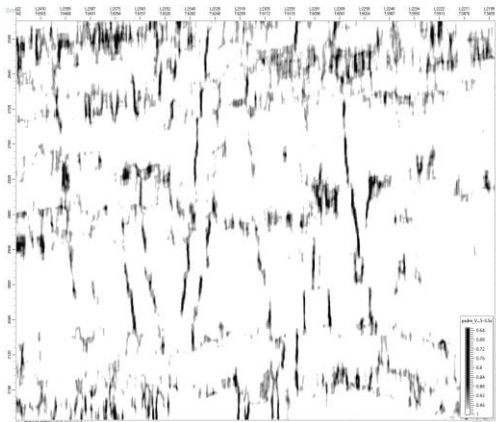
**Curvature**  
Curved structural features



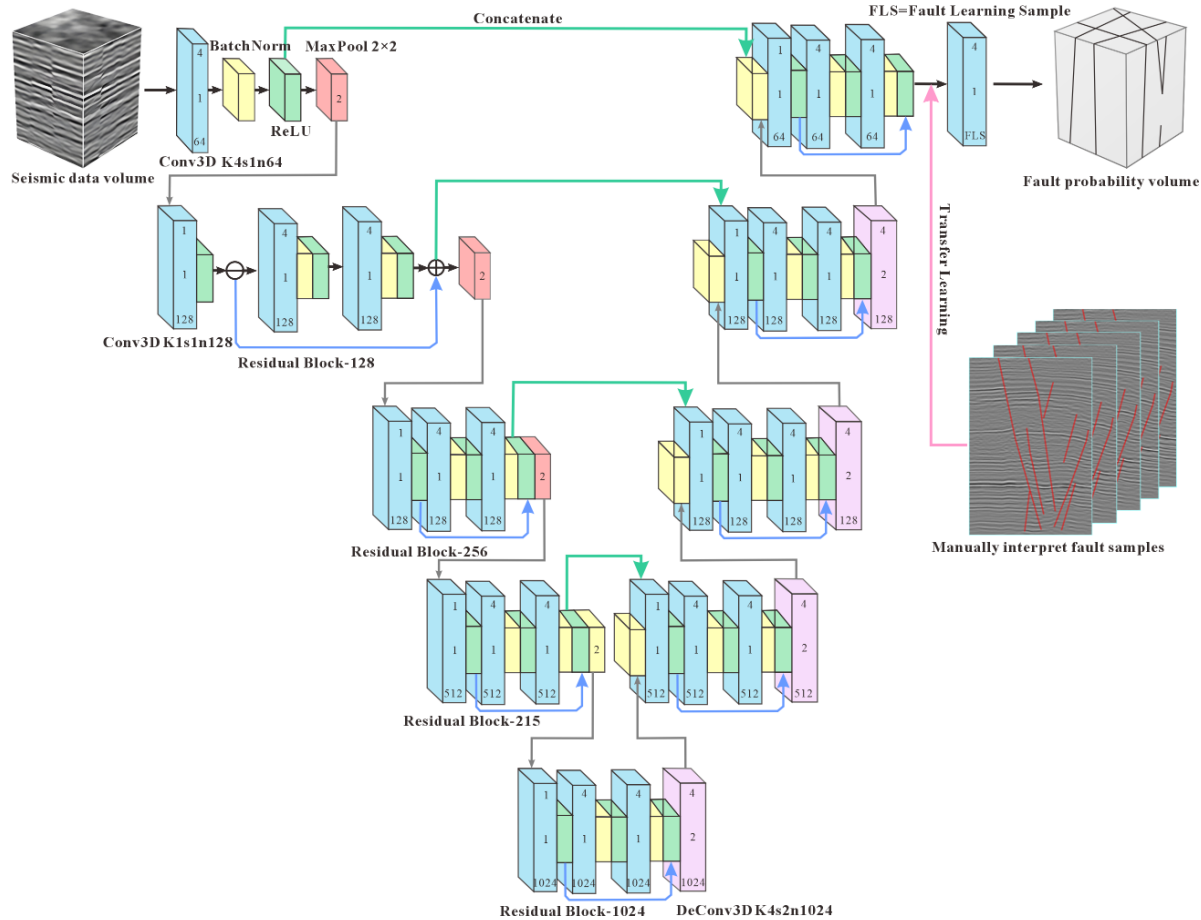
**Ant Tracking**  
Linear fault traces



**Likelihood**  
Trend deviation map



# AI Model: ResU-Net Architecture



ResU-Net Network Structure

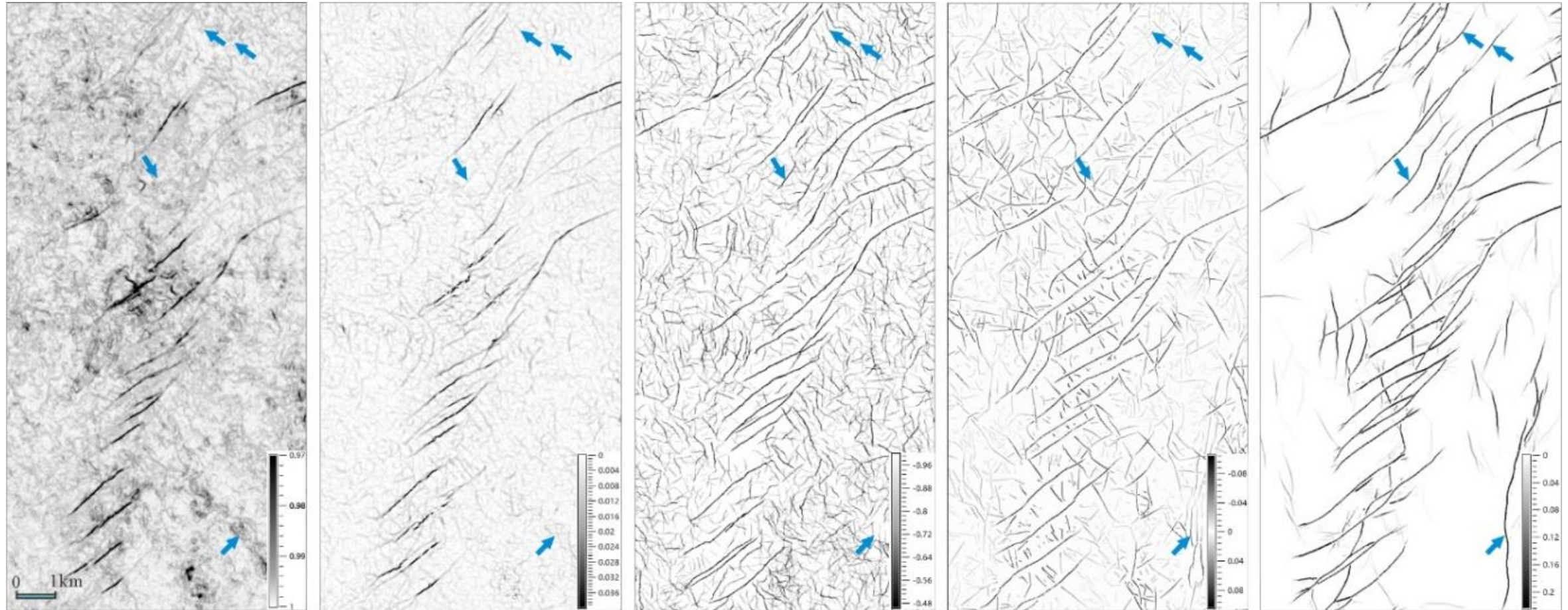
**Architecture**  
U-Net encoder-decoder + ResNet residual connections (>100 layers)

**Pre-training Data**  
>1×10<sup>5</sup> synthetic & real seismic samples from diverse geological settings

**Transfer Learning**  
Fine-tuned with 65 manual fault traces (Tahe Oilfield, 20% validation)

**Model Output**  
Fault probability volume (0–1) indicating the likelihood of fault presence

# ➤ Results: Fault Detection Along T34 Horizon



(a) Intrinsic Coherence

Major faults only,  
noisy

(b) Maximum Curvature

Large-scale  
features, misses  
secondary faults

(c) Ant Body

Fragmented, high  
redundancy

(d) Likelihood

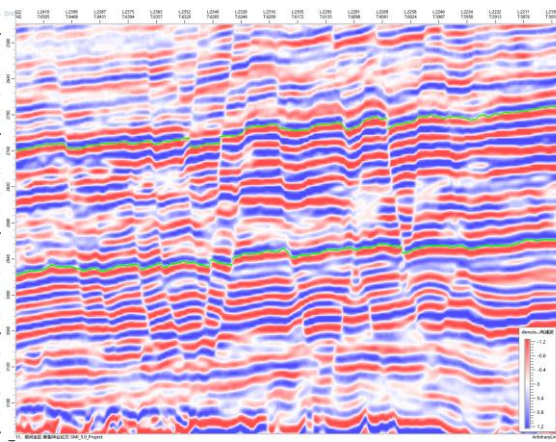
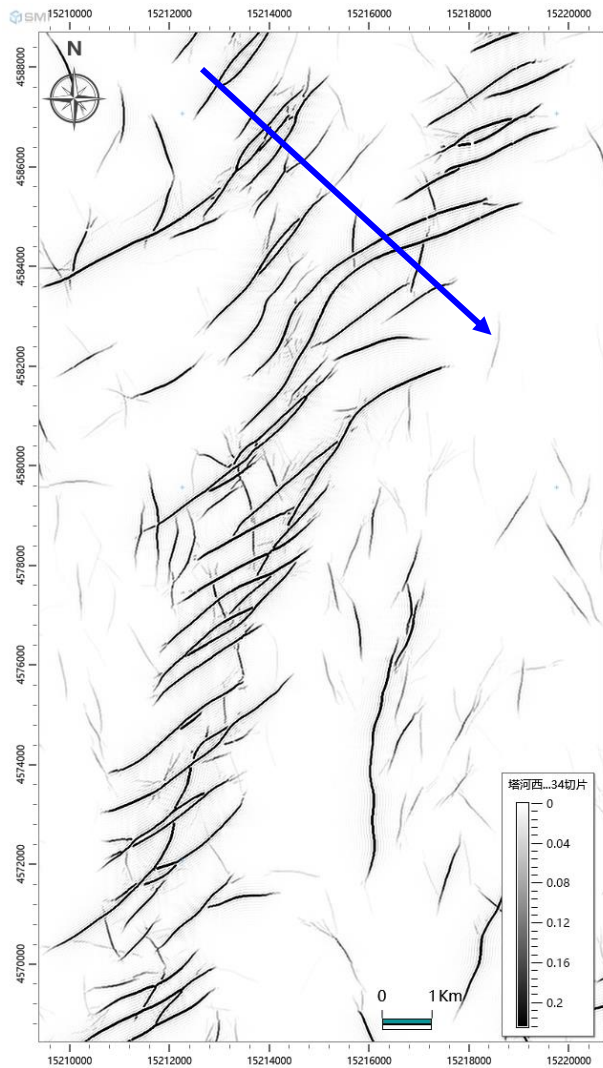
Linear but with false  
positives

(e) ResU-Net

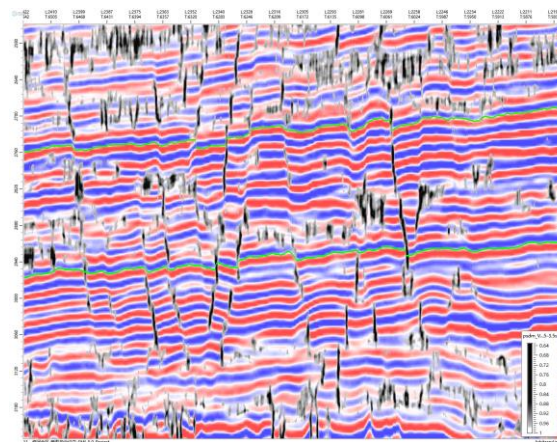
Continuous, clear  
boundaries, detects  
subtle faults



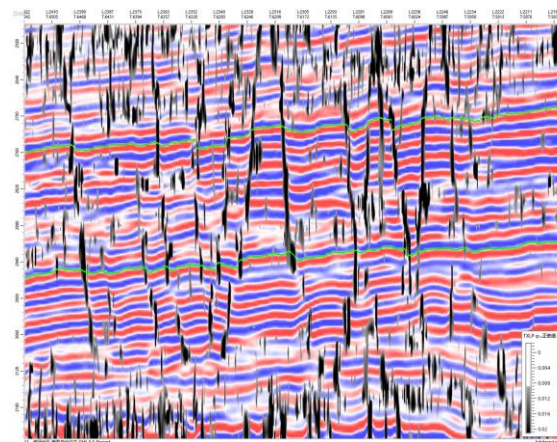
# Results: Fault Identification Profile Comparison



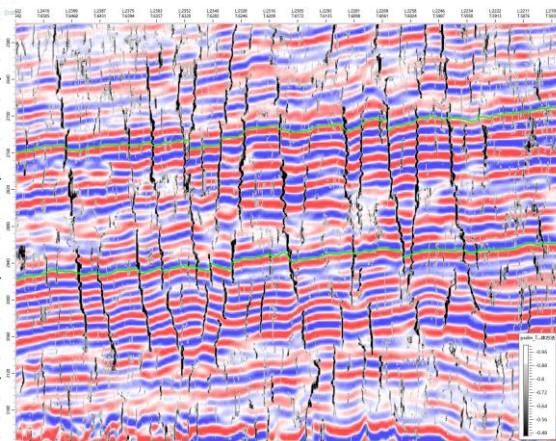
**Raw Seismic Profile**



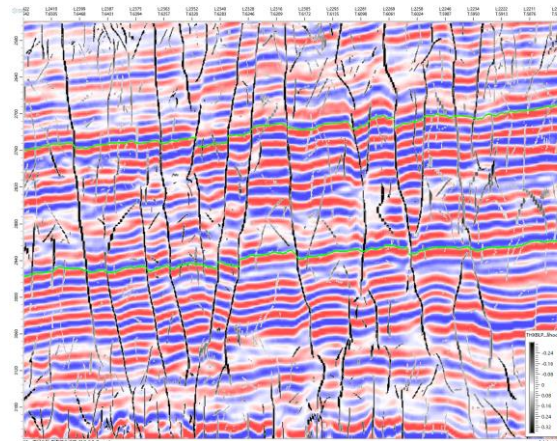
**Intrinsic Coherence**



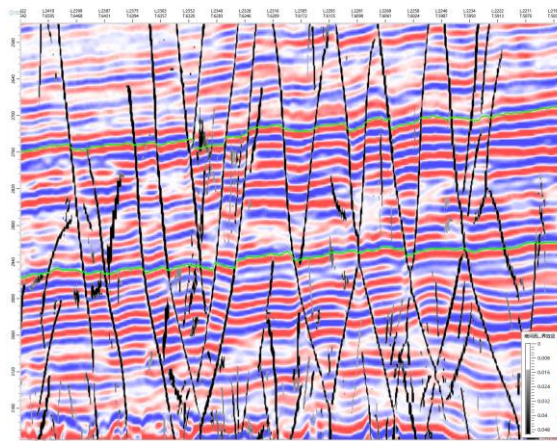
**Maximum Curvature**



**Ant Tracking**

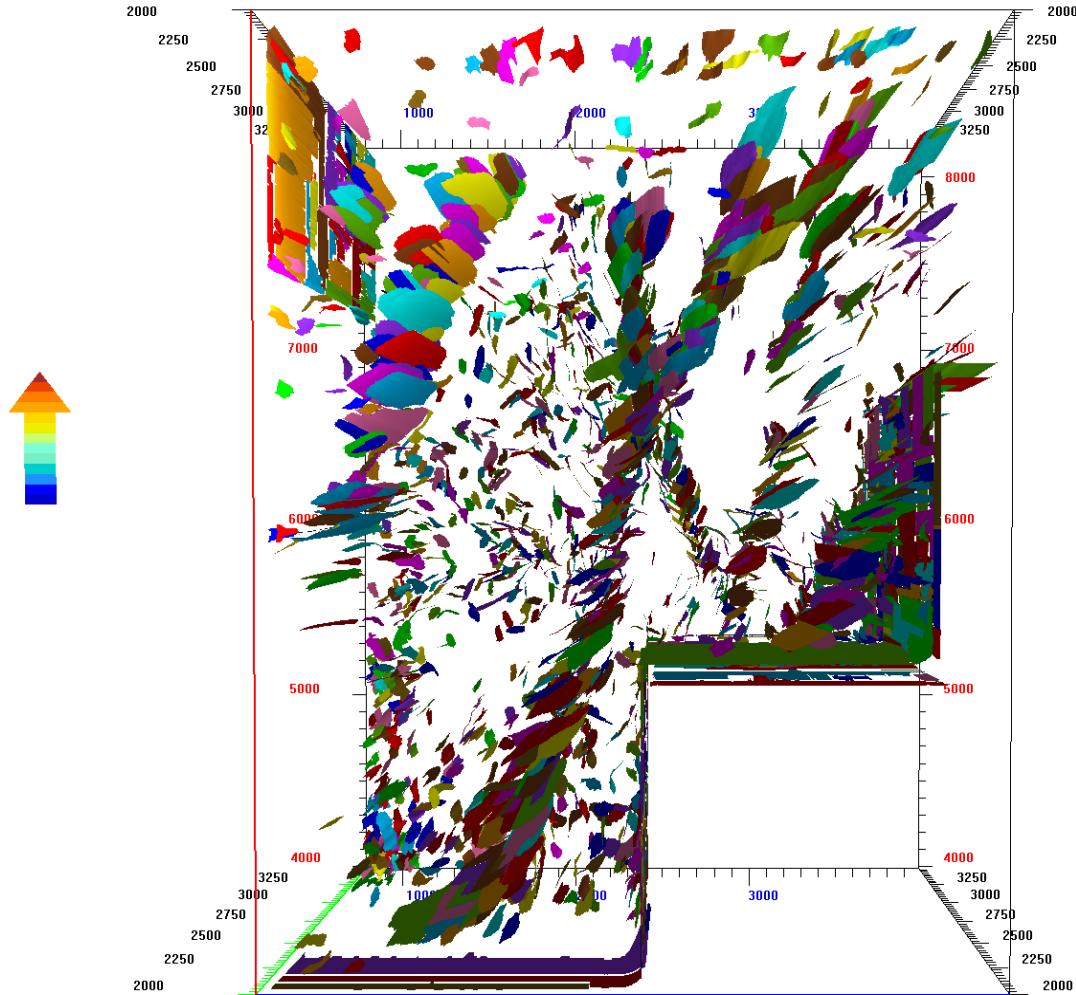


**Likelihood**



**ResU-Net**

# ➤ Results: 3D Fault Surface Extraction



3D Visualization of Extracted Surfaces

## 🔧 AI-Driven Automatic Extraction

Directly derived from AI probability volumes, eliminating manual interpretation bias and significantly reducing processing time.

## 🌐 Geologically Plausible Closed Models

Generates structurally consistent and closed fault surfaces that adhere to geological principles, avoiding non-physical artifacts.

## 🏗️ Foundation for Reservoir Modeling

High-quality fault models serve as critical input for accurate reservoir characterization and hydrocarbon prediction workflows.

# ➤ Performance Comparison

Method	Continuity	Noise Resistance	Small-Fault Detection	Geological Plausibility
Coherence	★★★★☆	★★★★☆	★★★★☆	★★★★☆
Curvature	★★★★☆	★★★★☆	★★★★☆	★★★★☆
Ant Tracking	★★★★☆	★★★★☆	★★★★☆	★★★★☆
Likelihood	★★★★☆	★★★★☆	★★★★☆	★★★★☆
<b>AI (Ours)</b>	★★★★★	★★★★★	★★★★★	★★★★★



**Conclusion:** AI probability volume integrates strengths of all conventional methods while suppressing their weaknesses, achieving superior performance across all metrics.

# ➤ Discussion: Why AI Outperforms



## Spatial Coherence

Learns 3D fault geometries, not just 2D slices, providing a complete spatial understanding.



## Context-Aware

Distinguishes reservoir-controlling faults from micro-fractures using contextual analysis.



## Transfer Learning

Adapts generic fault patterns to local geology with minimal manual labeling required.



## Efficiency

Once trained, can process large seismic volumes automatically and consistently.

## Key Takeaway

AI brings unprecedented spatial understanding and processing speed to geological fault interpretation, significantly reducing manual effort.

## **Limitations of Conventional Methods**



Conventional attributes (coherence, curvature) delineate major faults but lack resolution for secondary networks; ant tracking & likelihood suffer from redundancy and poor continuity.

## **Superiority of AI-Based Fault Detection**



AI-based fault probability volume delivers superior continuity, noise resistance, and detection of subtle strike-slip faults critical for hydrocarbon migration.

## **Robust Workflow for Complex Reservoirs**



The proposed ResU-Net + transfer learning workflow provides a robust, scalable template for multi-scale fracture characterization in complex reservoirs.

## 👍 Acknowledgements

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