Advances in Techniques for Monitoring Induced Seismicity

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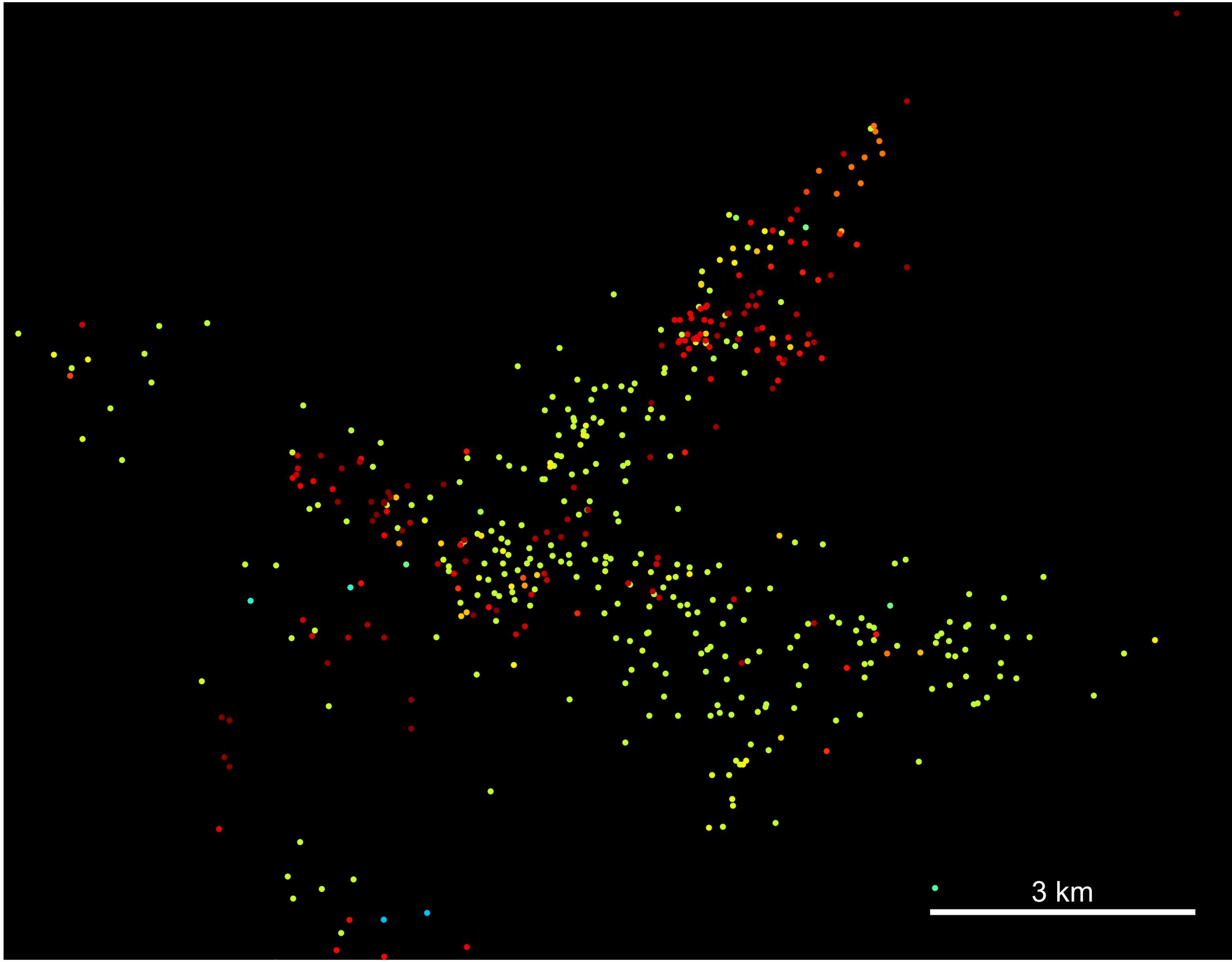
2016, M 5.8
Pawnee, OK

Standard
(*ComCat*)



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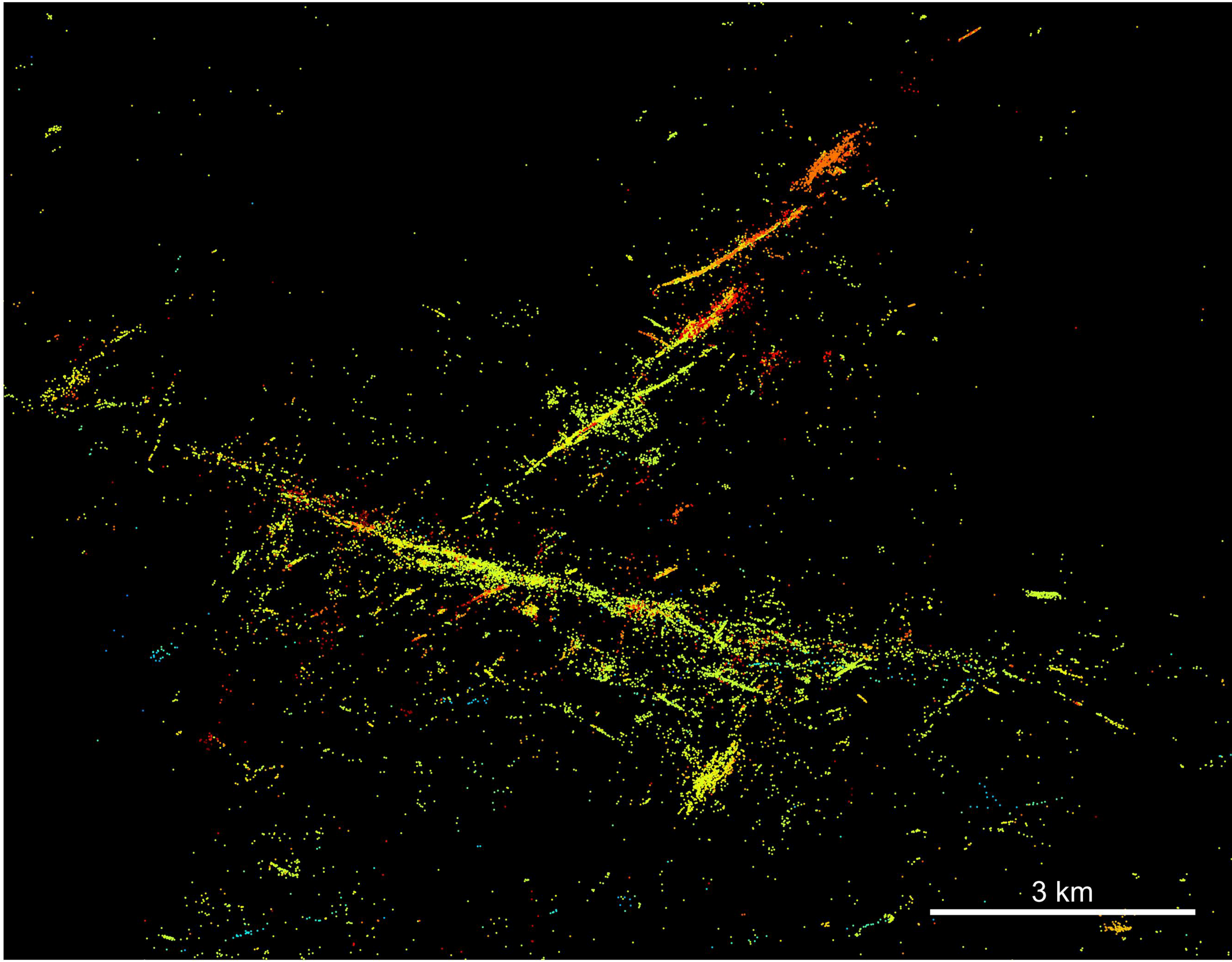
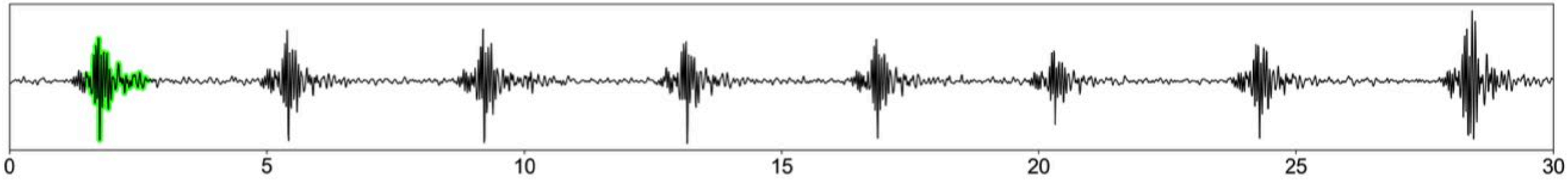
Deep-Learning

(*Park et al.* 2022)

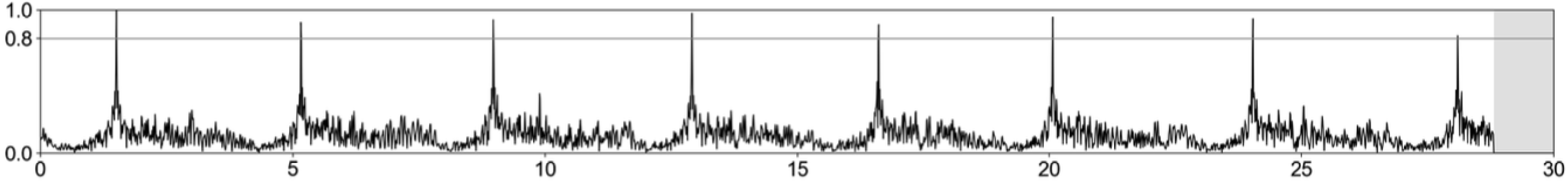


Prediction Inconsistency

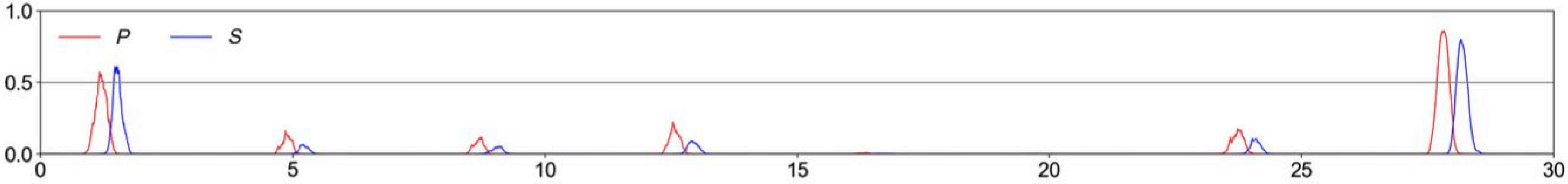
Repeating source in Oklahoma



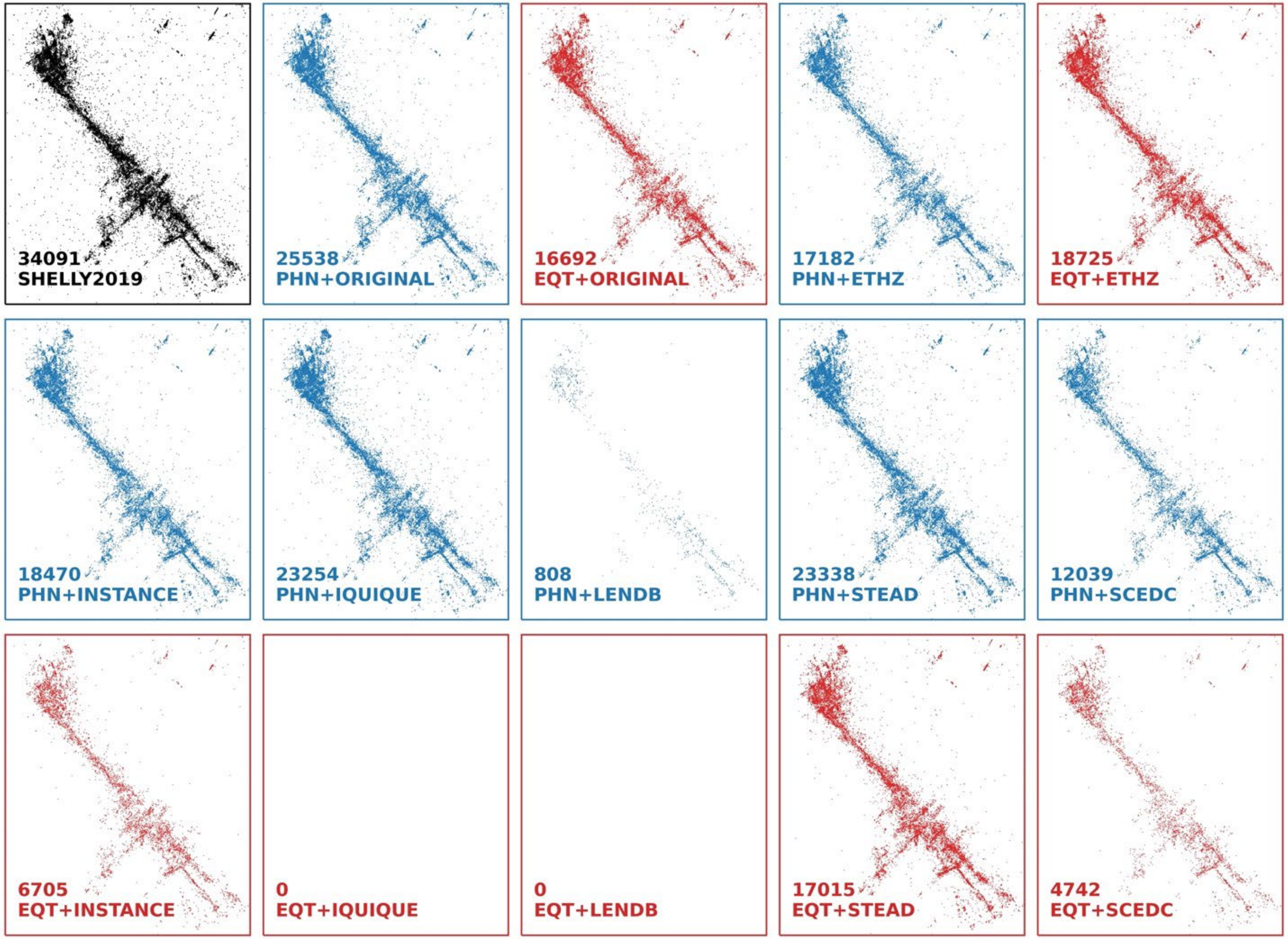
Template Matching



Machine Learning Output



Reproducibility depends strongly on model and data



False negatives are an issue.

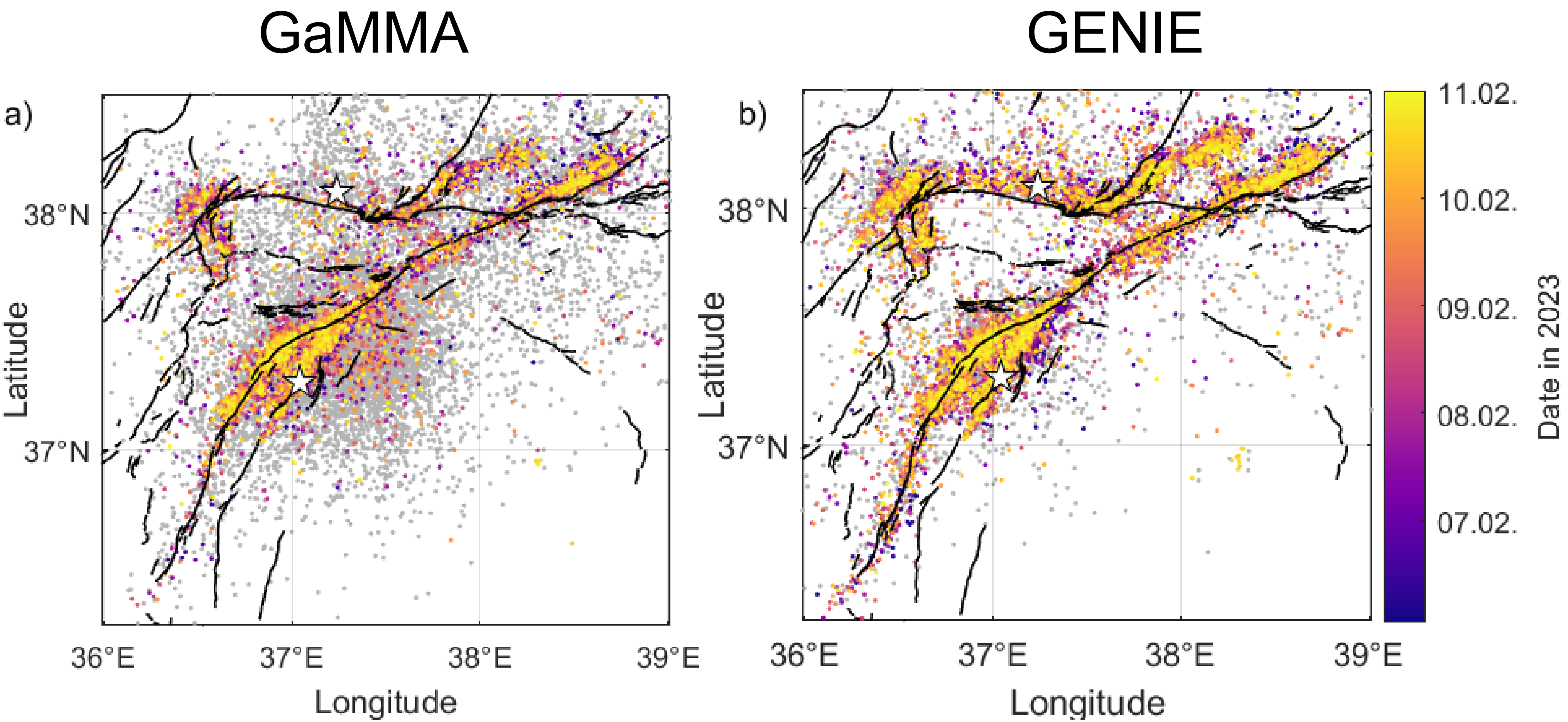
ML models have variable performance that is not fully understood.

Data quality is critical to good model performance.

Incomplete picking can be somewhat mitigated by oversampling and a voting-based threshold

***Park et al.* (2023)**

Example for Phase Association



Kahramanmaraş Aftershock Sequence

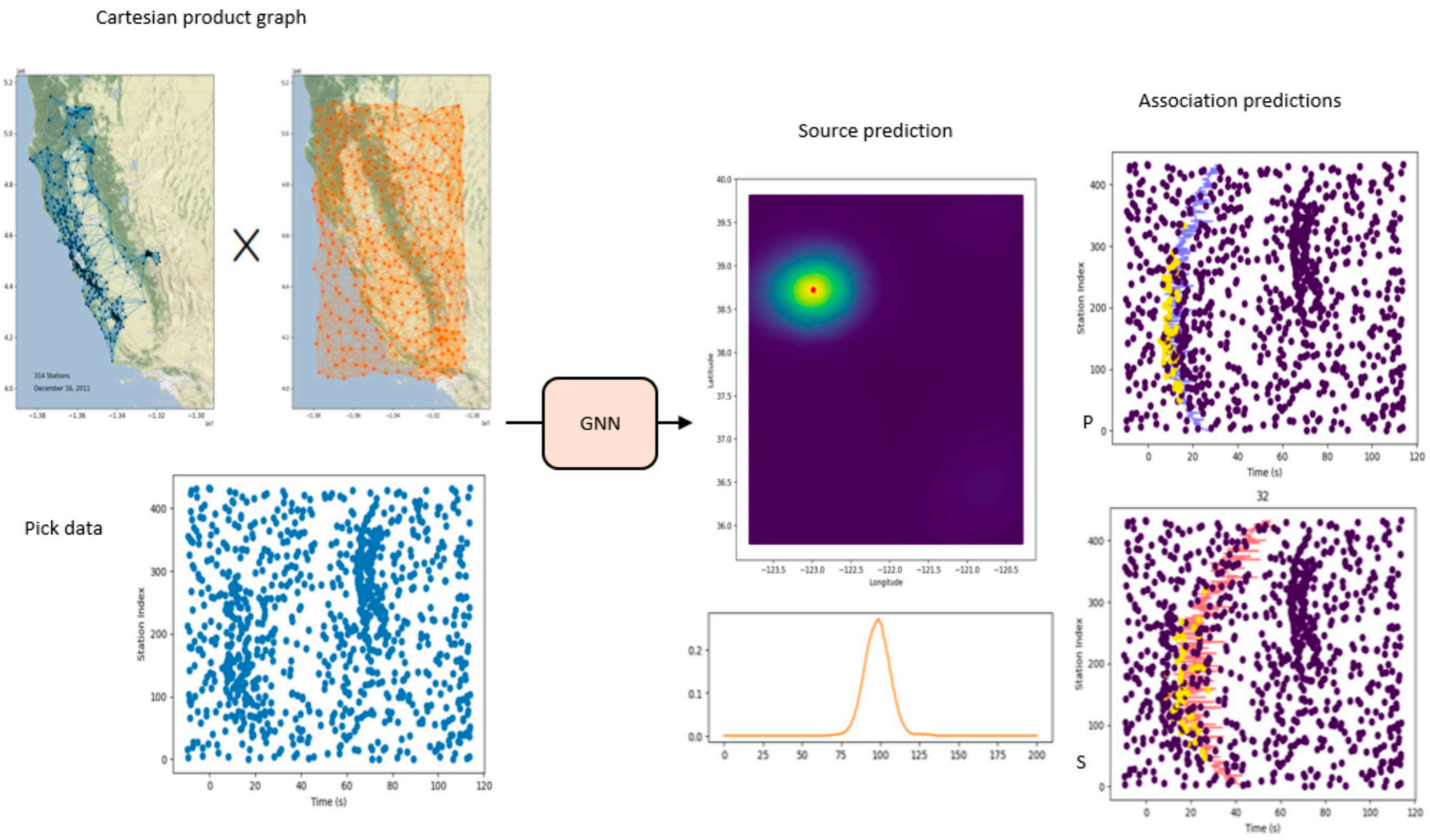
***Becker et al.* (2024)**

Graph Neural Networks

GNNs for heterogeneous, non-Euclidean problems.

Combines deep learning and graphs.

Accommodates variable network with many picks.

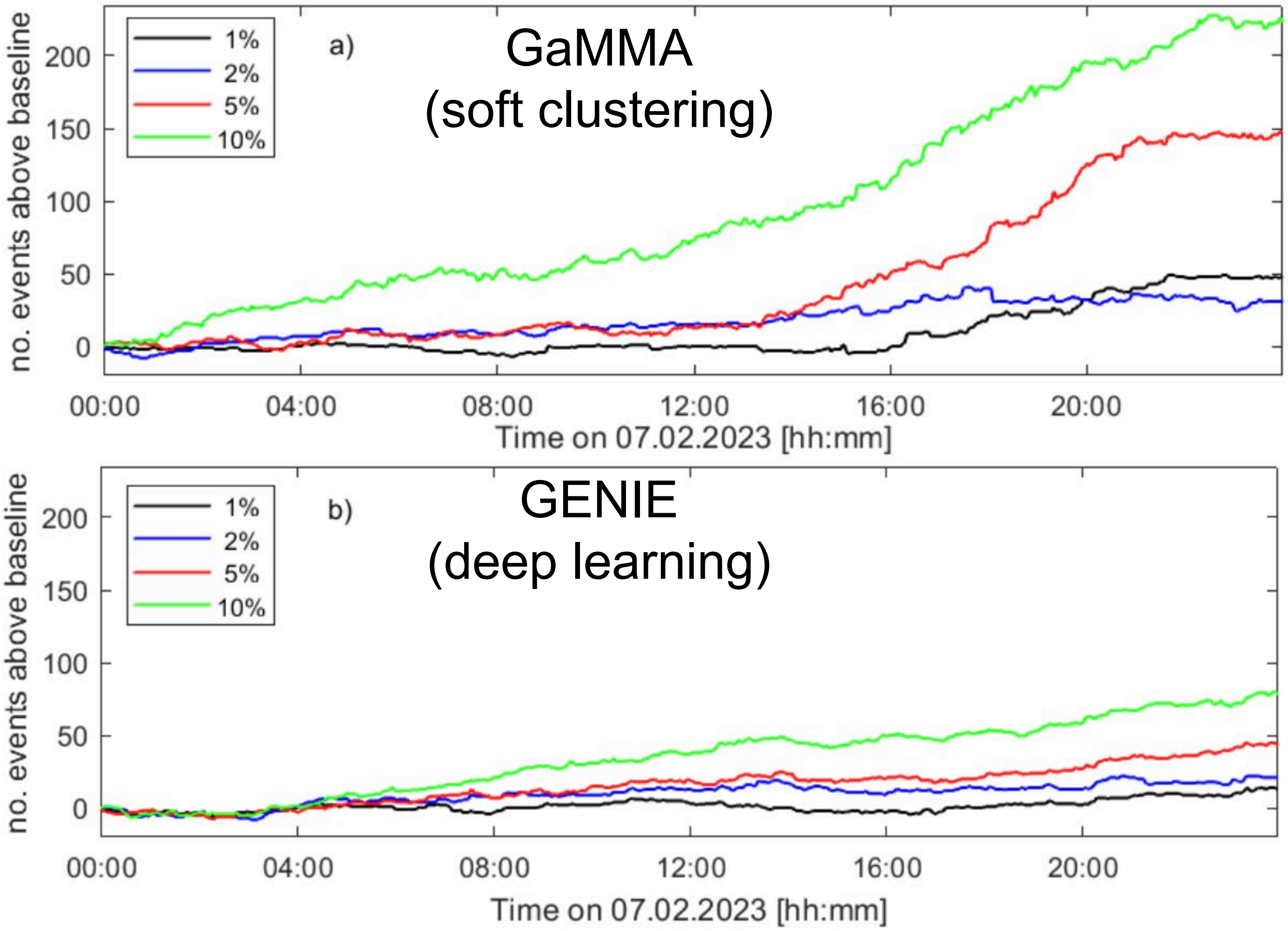


Notice that we train with bad picks, so it learns to ignore them.

***McBrearty and Beroza* (2023)**

Effect of Bad Data on Two Phase Association Algorithms

GENIE is more robust with respect to bad data (doesn't create phantom events)



GENIE is more robust to false picks

***Becker et al.* (2024)**

Earthquake Monitoring

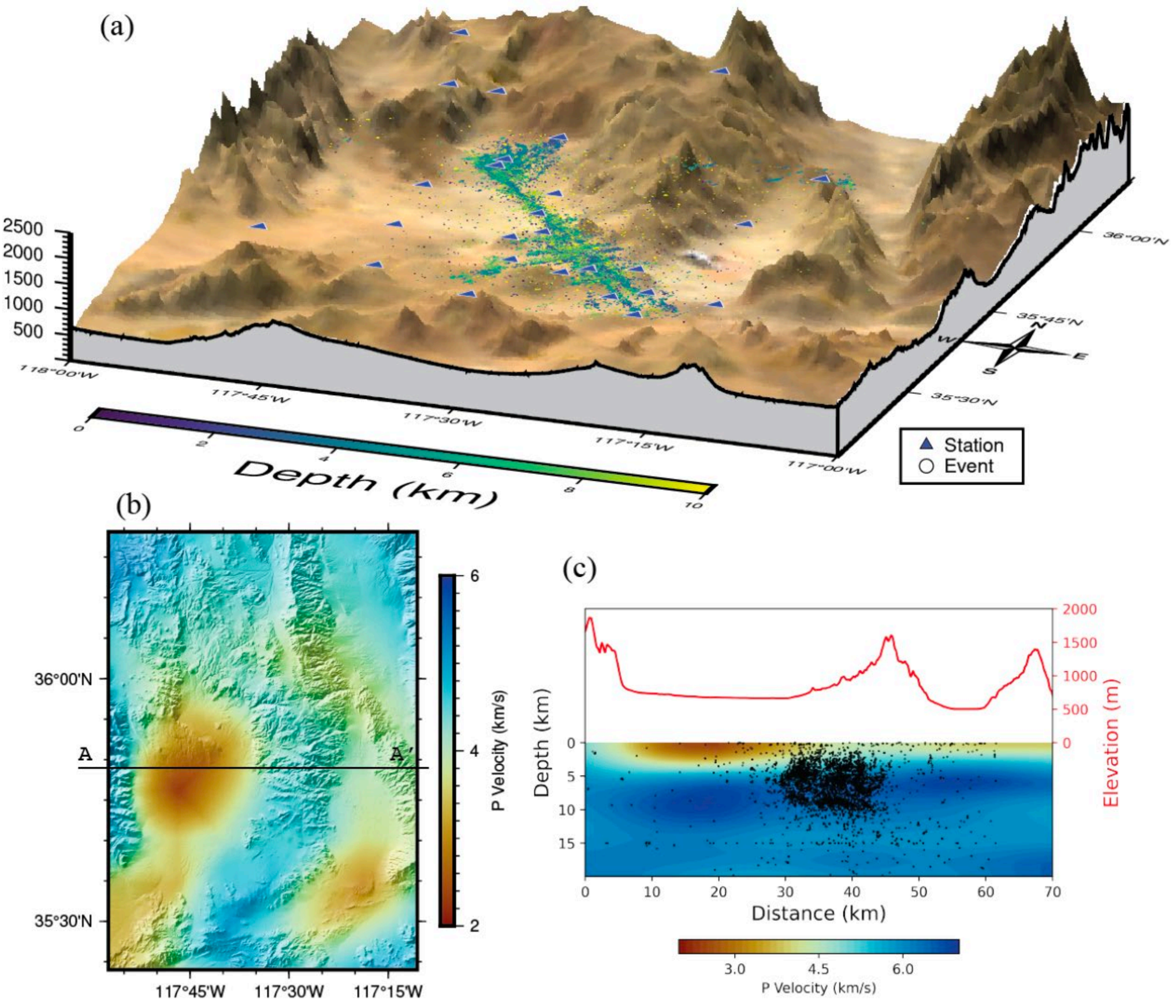
Mechanisms

- Pore-fluid Pressurization
- Poroelastic Stressing
- Aseismic Slip
- Thermal Stressing
- Chemical Effects

Requirements of observed seismicity

- Consistent and Complete Catalogs
- Accurate Locations
- Accurate Magnitudes
- Focal Mechanisms/Moment Tensors

Precision, Accuracy, and UQ of Different Earthquake Location Methods



Solve realistically complex forward problem such that ground truth is known.

How well do different location methods recover ground truth locations given their usual assumptions?

How good is UQ?

***Yu et al.* (2025)**

Comparison with Ground Truth

Method	Mean Accuracy Error (km)		Chamfer	Mean Precision Error (km)	
	Horizontal	Depth	Distance	Horizontal	Depth
Hypoinverse	0.824	1.118	1.617	0.571	0.684
Velest	0.696	0.559	1.170	0.380	0.656
NonLinLoc	0.953	0.969	1.626	0.580	0.694
NonLinLoc_SSST	0.440	0.538	1.071	0.158	0.307
HypoSVI	0.429	$\boxed{0.338}$	$\boxed{0.828}$	0.317	0.383
HypoDD	$\boxed{0.315}$	0.571	0.974	$\boxed{0.080}$	$\boxed{0.141}$
XCORLOC	0.746	0.818	1.507	0.101	0.256
GrowClust	0.846	1.066	1.701	0.148	0.304

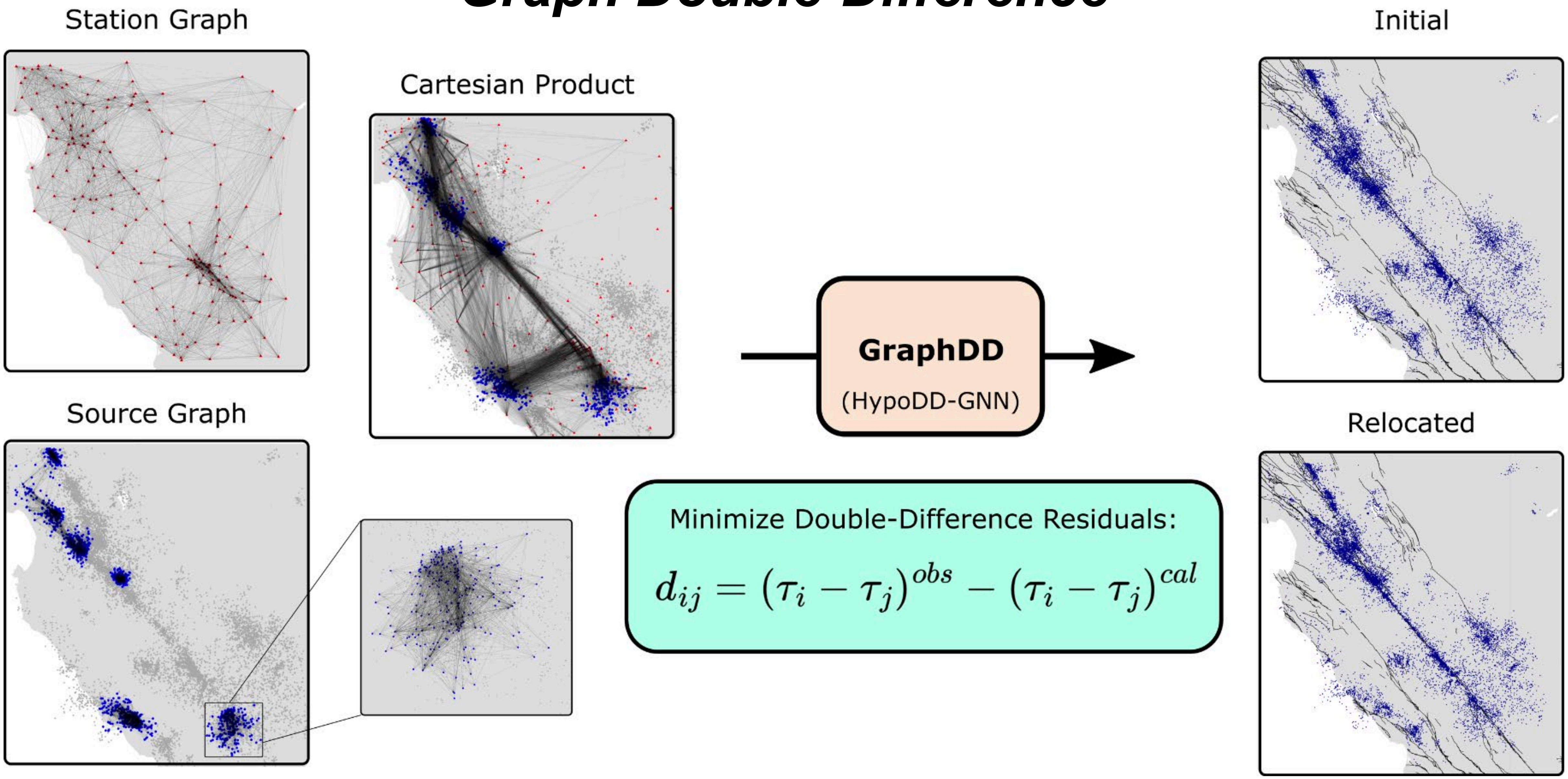
All methods underestimate uncertainty (some by a lot).

~80 m

~140 m

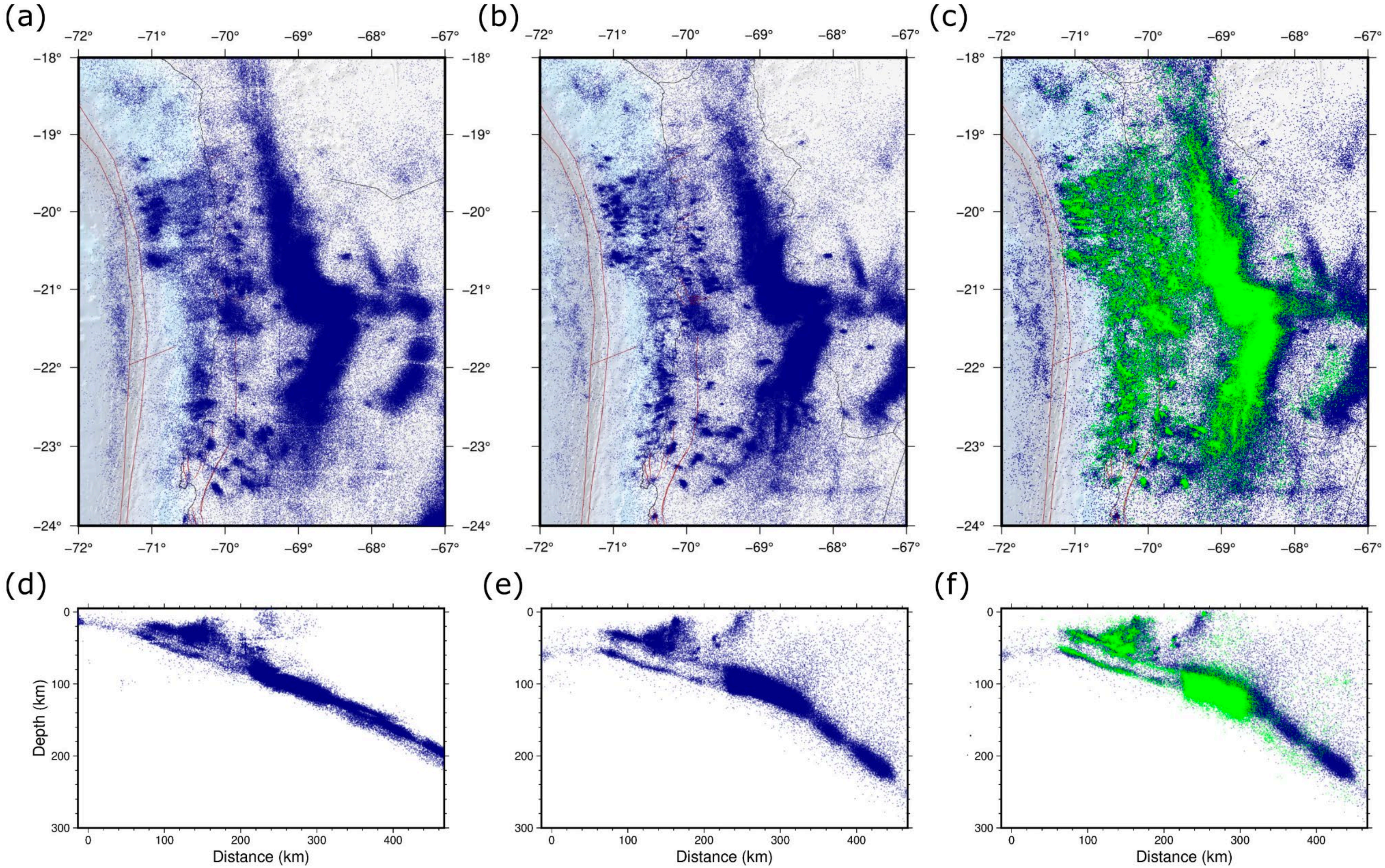
***Yu et al.* (2025)**

Graph Double-Difference



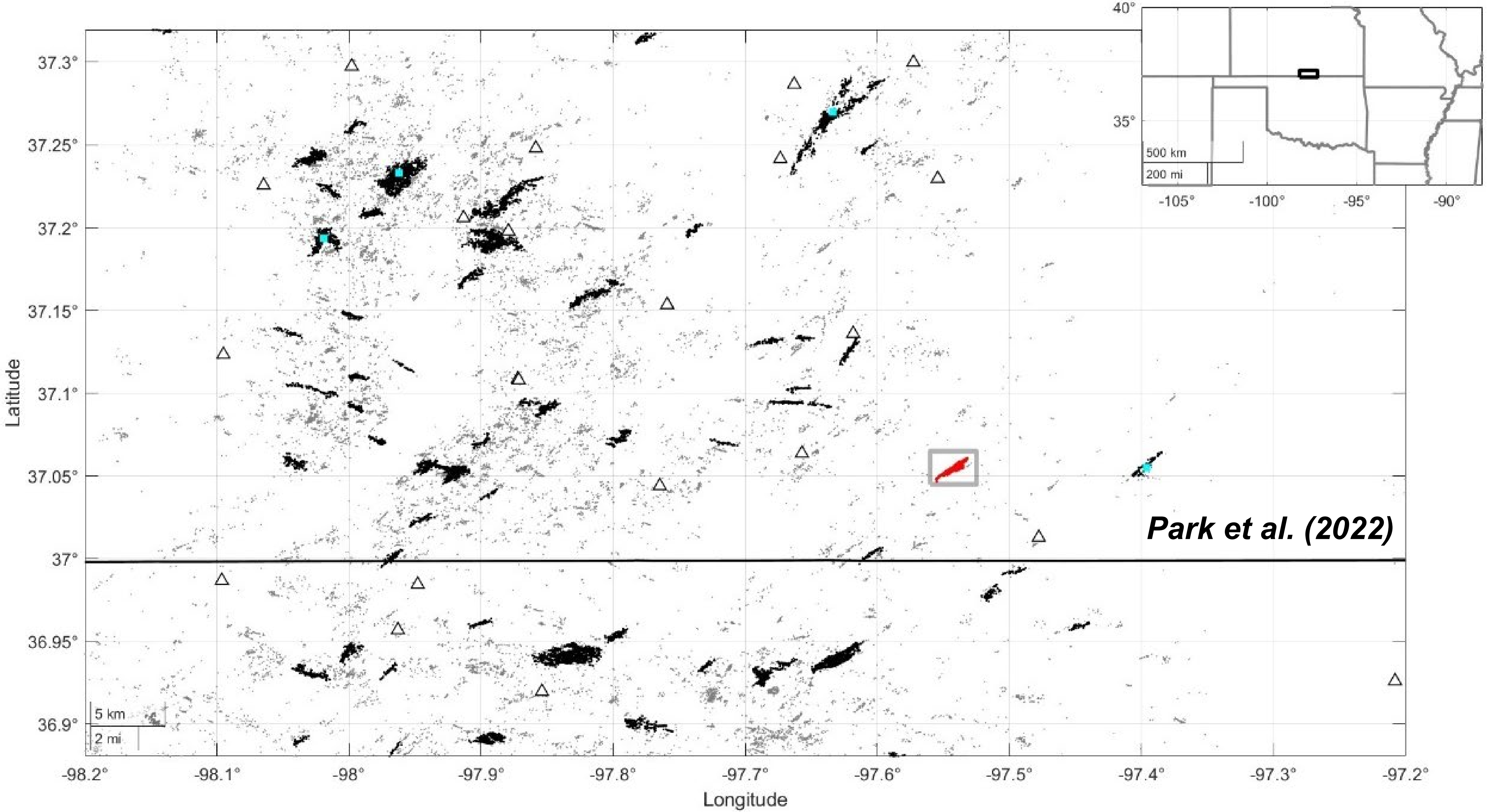
***McBrearty and Beroza* (2025)**

Graph-Double-Difference: No Limit on Size of Relocations

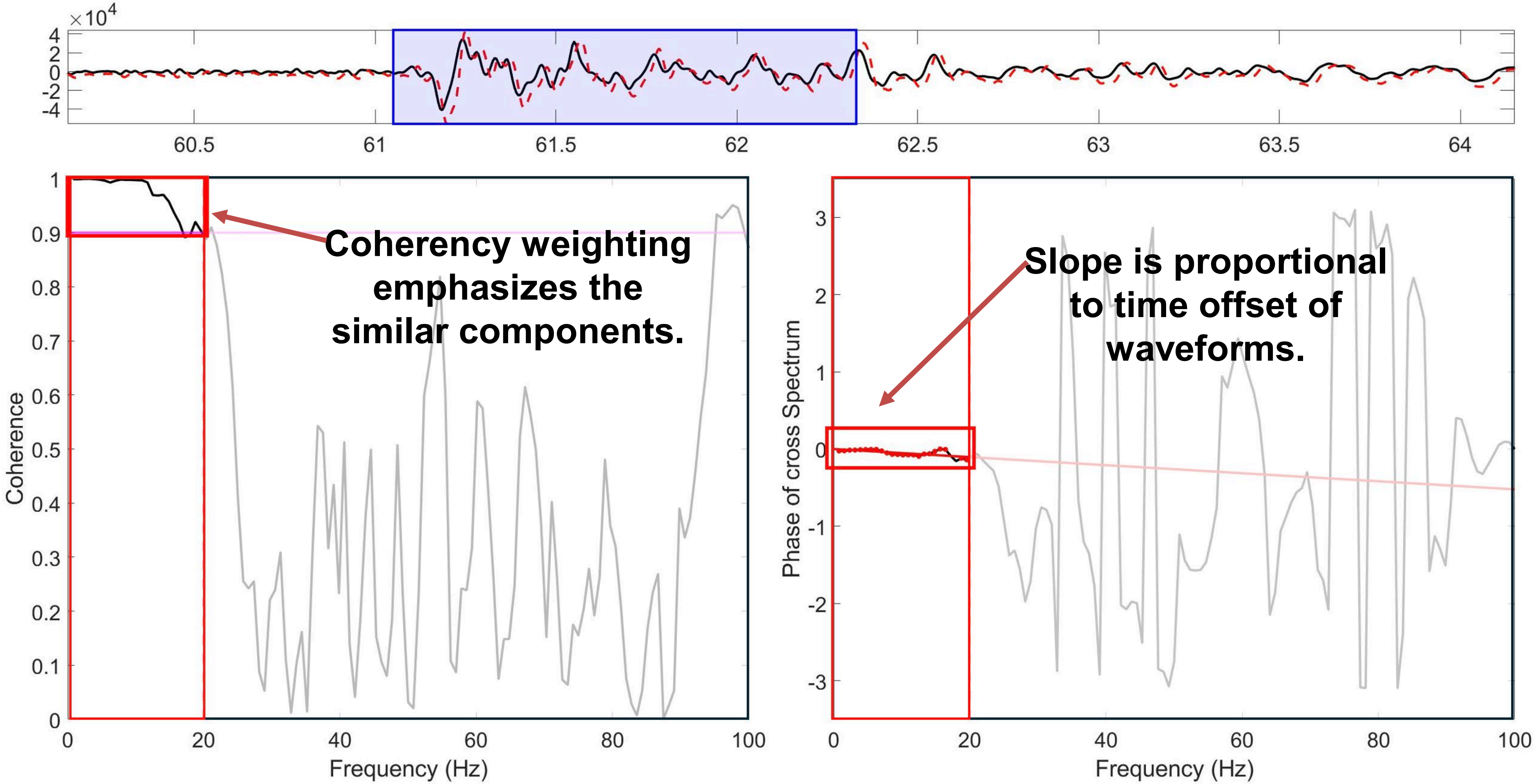


***McBrearty and Beroza* (2025)**

Induced Seismicity in Oklahoma-Kansas



High-Resolution Location



For similar events - sub-sample precision of a few milliseconds.
S-wave velocity of ~ 3.5 meters/millisecond.

***Poupinet et al.* (1984)**

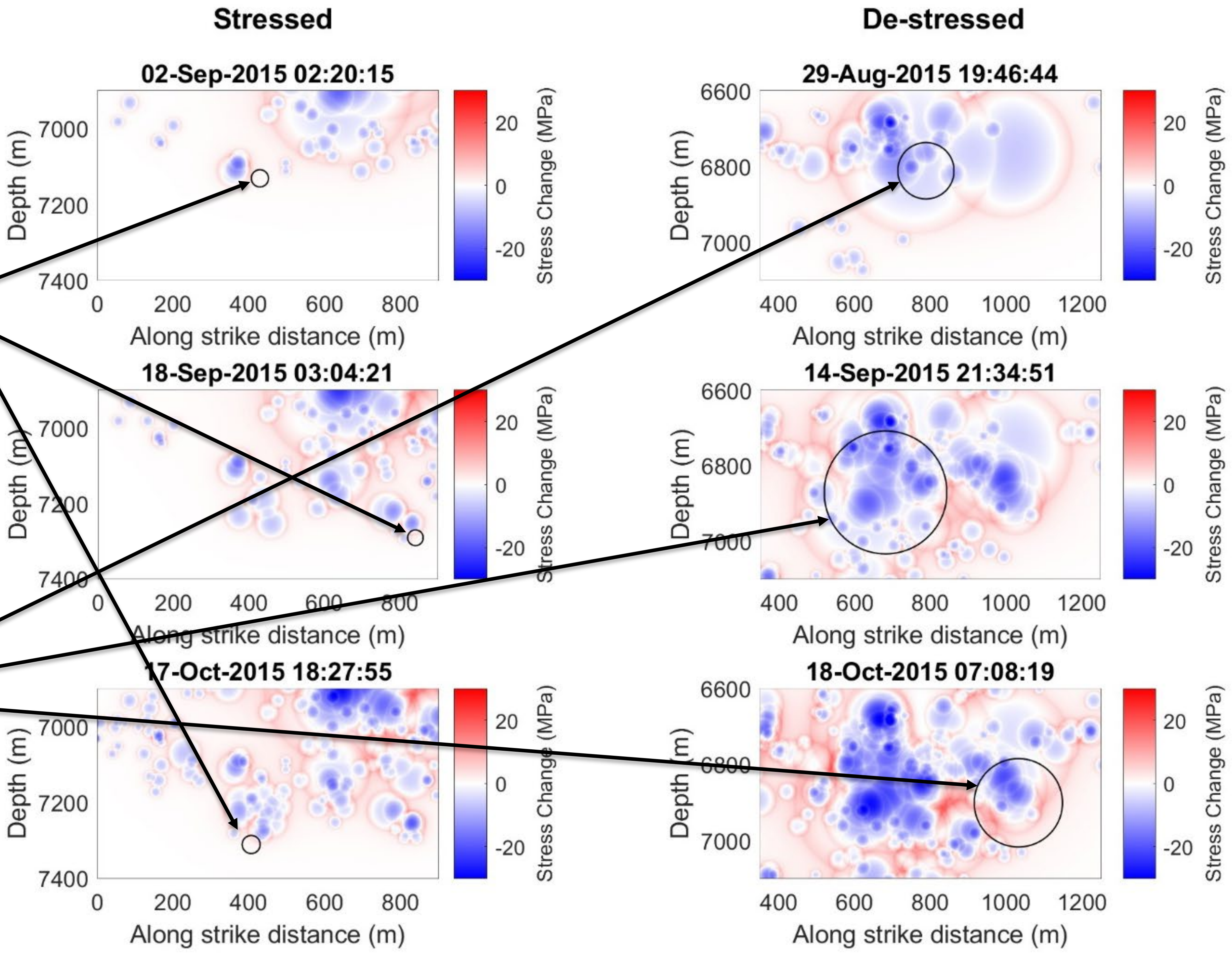
Stress-Change Modeling

Stressed

Previous earthquakes encourage rupture by static stress triggering

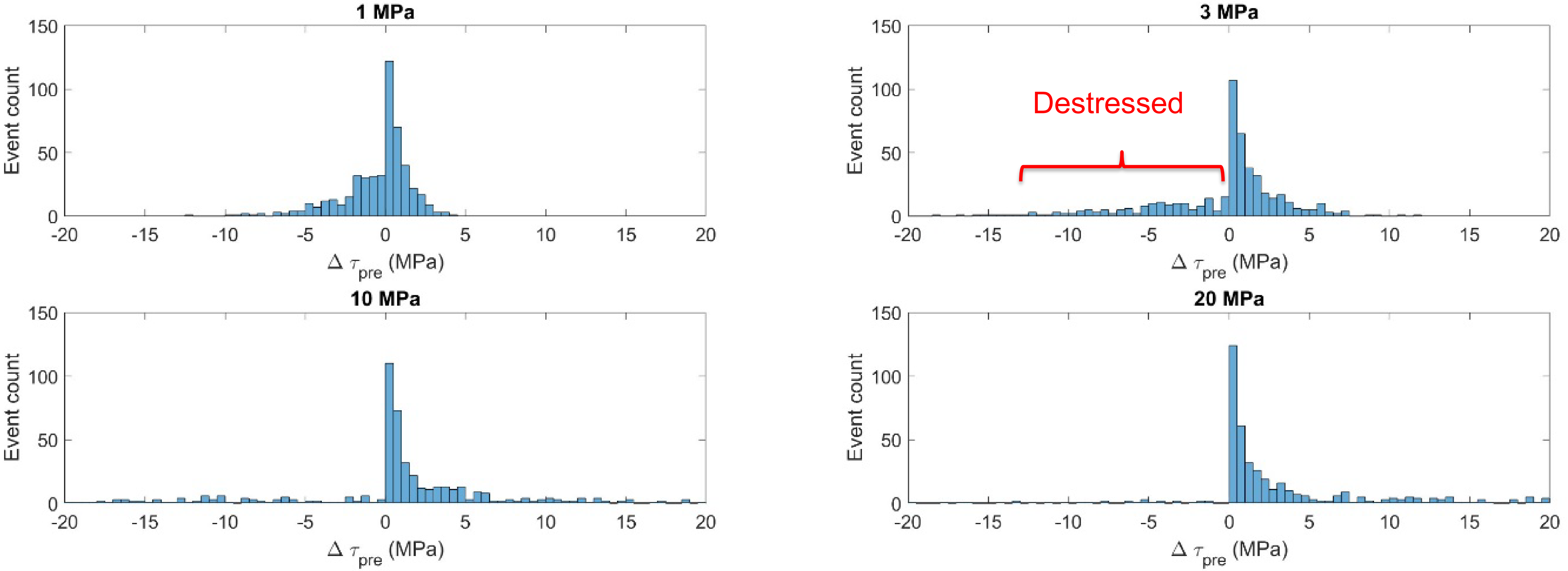
Destressed

Previous earthquakes discourage rupture, so something else at play – aseismic slip? gradual weakening?



Ries et al. (2025)

Stress vs. Destressed Populations



Results depend on assumed stress drop, but there appears to be a significant population of events do not to fail by stress triggering.

Monitoring Induced Seismicity

- The last 5 years have seen a tremendous increase in our ability to detect and characterize induced seismicity.
- Some issues remain, and we need to do some forensics on the new generation of earthquake catalogs to understand them better.
- There should be continuing progress in methods/models, and that will be amplified by new sensing technologies (e.g., DAS) as they become more widely deployed.
- A principal challenge is to take advantage of these improved catalogs tp reach a deeper, process-based, understanding of the factors that influence induced seismicity.