

Assessing the Community Fault Model Using Improved Earthquake Catalogs

Recent advances in the development of high-resolution earthquake catalogs motivate new approaches to extracting information from them. Under this project we proposed to extend the ridge clustering approach to earthquake clustering that we have previously developed (*Park et al., 2022*) to 3D fault structures, and to apply it to existing earthquake catalogs in California as a proof-of-concept for eventual application to the development of the Community Fault Model. We were not satisfied with the results we obtained through this process, so we developed an alternative approach.

Rather than ridge regression, we instead considered earthquake catalogs as 3D point clouds that illuminate the geometry of active fault systems. We developed FaultNet, which is a deep learning workflow that formulates fault extraction from earthquake hypocenters as a semantic segmentation problem (*Guo et al., 2024*). It is inspired by PointNet++ (*Qi et al., 2017*), which was developed for object identification using point clouds in machine vision applications. In our preferred workflow, we develop two FaultNet models (Figure 1). The first model carries out denoising, which in this case is a binary classification between hypocenters that belong to fault structures and hypocenters that are isolated and do not. The second FaultNet model hierarchically processes point coordinates to learn feature embeddings. It is trained on synthetic seismicity catalogs that contain complex fault structures with realistic dispersion and noise.

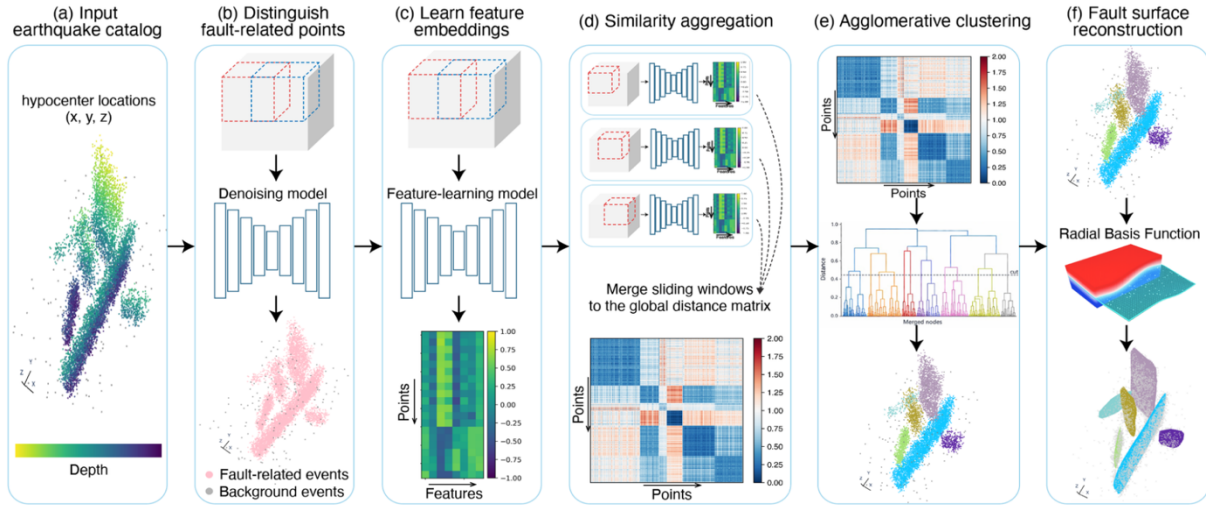


Figure 1. Schematic overview of the inference workflow in FaultNet. (a) Three-dimensional earthquake hypocenter catalog used as the input. (b) The denoising model distinguishes fault-related earthquakes from background seismicity. (c) The feature-learning model learns feature embeddings for the fault-related earthquakes. (d) Feature embeddings predicted from overlapping sliding windows are aggregated into a global distance matrix. (e) Agglomerative clustering groups earthquakes into individual fault clusters according to the aggregated distance matrix. (f) Clusters are reconstructed into continuous fault surfaces using radial basis function (RBF) interpolation (after Hu and Beroza, 2026).

These feature embeddings are used to identify clusters of seismicity that belong to individual fault segments. The next stage in the workflow reconstructs continuous three-dimensional fault surfaces from these seismicity clusters by fitting planes modified by radial basis functions that can capture modest deviations from planarity. We apply FaultNet to three catalogs representing induced seismicity, mainshock-aftershock sequences, and volcanic seismicity (Figure 2). Across these diverse settings, the method successfully resolves coherent fault structures, including intersecting and segmented faults. We developed evaluation metrics to assess the quality of fault reconstructions and examined the degree to which they are consistent with independent geological mapping of surface traces and seismological fault plane solutions. Our results demonstrate that deep learning provides an effective and generalizable approach for reconstructing complex fault systems directly from earthquake hypocenter distributions. We have had several discussions with Scott Marshall about pathways for contributing to the SCEC CFM and have participated in planning for the fault geometries to be used in the ShakeOut 2.0 scenario earthquake preparedness exercise. Future work will account for location uncertainty and assimilate other sources of information including magnitudes, focal mechanisms, and time of occurrence.

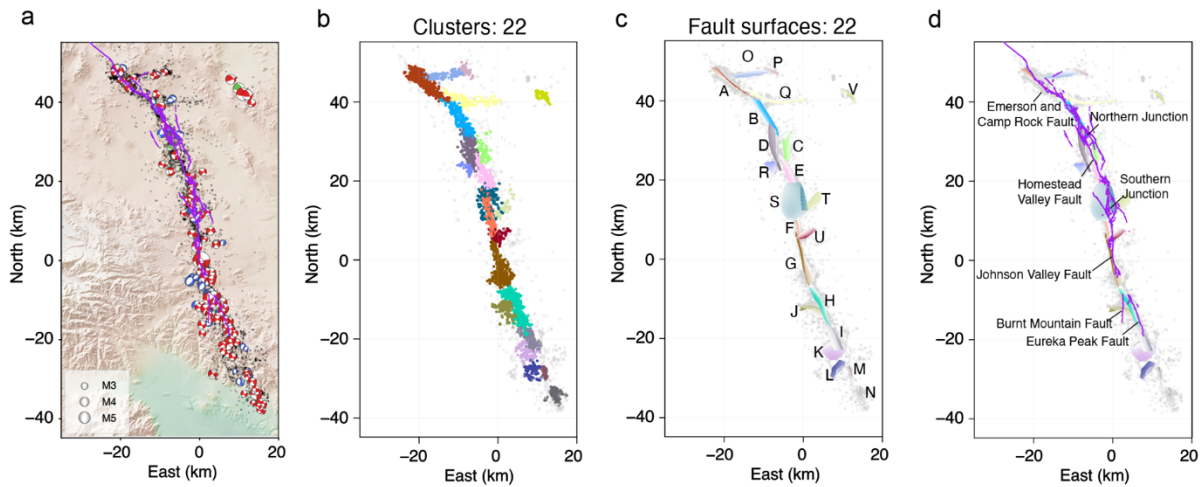


Figure 2. Earthquake clustering and fault-surface reconstruction of the 1992 M7.3 Landers earthquake sequence. (a) Earthquake catalog and focal mechanisms, with focal-mechanism sizes proportional to earthquake magnitude and colors indicating faulting style (reverse: green; strike-slip: red; normal: blue). Purple lines denote mapped surface rupture traces from the USGS. (b) FaultNet clustering results. A total of 22 clusters containing more than 50 events are shown in color, whereas smaller clusters and background earthquakes are shown in gray. (c) Reconstructed three-dimensional fault surfaces for the clusters identified in (b), labeled by fault code. Lighter colors within each fault surface indicate shallower depths. (d) Comparison between reconstructed fault surfaces and surface rupture traces, with major fault segments and junctions labeled. Coordinates are relative to the mainshock location (116.437°W , 34.200°N) (after Hu and Beroza, 2026).

References

Mo, Y., Wu, Y., Yang, X., Liu, F., & Liao, Y. (2022). Review the state-of-the-art technologies of semantic segmentation based on deep learning. *Neurocomputing*, **493**, 626–646.

<https://doi.org/10.1016/j.neucom.2022.01.005>

Hu, Y. and G. C. Beroza, (2026) FaultNet: Inferring Complex Fault Structures from Earthquake Hypocenter Distributions, *JGR: Machine Learning and Computation* (submitted).

Park, Y., Beroza, G. C., and Ellsworth, W. L. (2022). Basement fault activation before larger earthquakes in Oklahoma and Kansas. *The Seismic Record*, **2**(3), 197-206.

Qi, C. R., Yi, L., Su, H., and Guibas, L. (2017). Pointnet++: Deep hierarchical feature learning on point sets in a metric space. *Advances in neural information processing systems*, **30**.