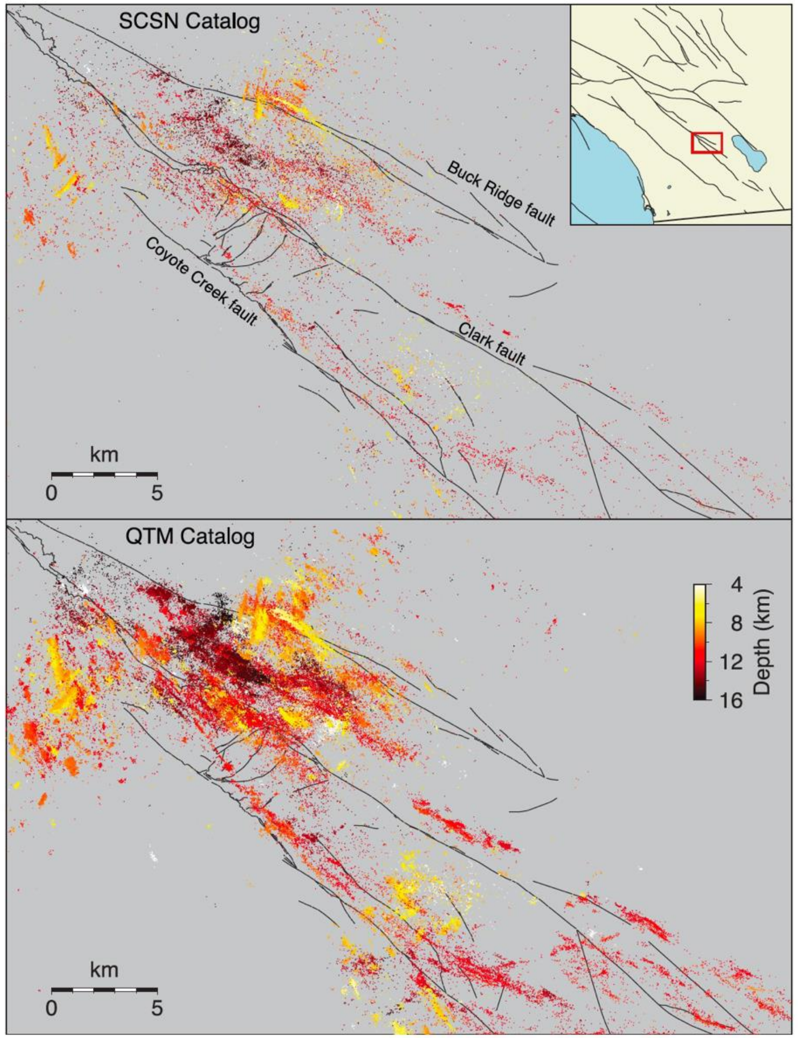
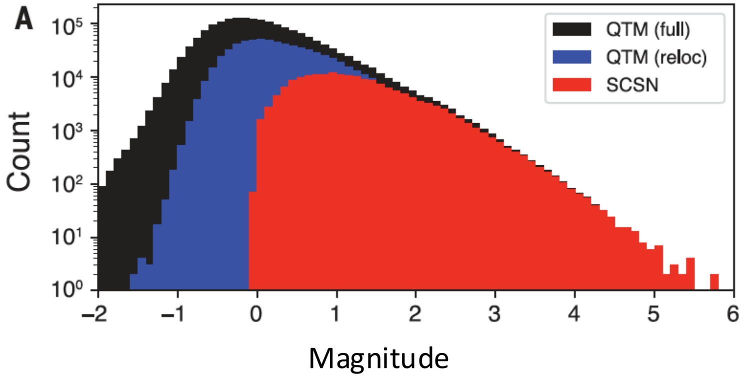
Lecture 4:
Introduction to earthquake detection and location

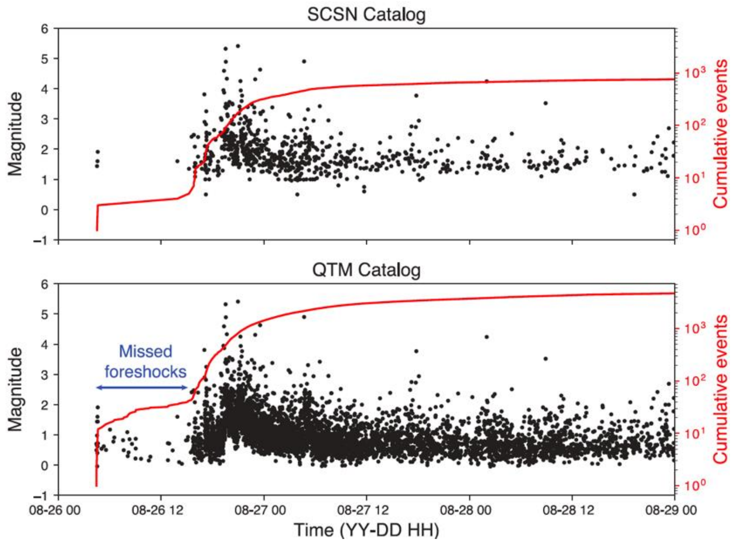
OBS training workshop, VUW, April 14-16, 2025

Earthquake detection and location

- Goals:
  - Determine when an earthquake happened (origin time)
  - Determine where it happened (latitude, longitude, depth)
  - How big the earthquake was (magnitude)
  - Detect and locate earthquakes:
    1. with magnitudes as small as possible (completeness)
    2. with locations as accurate as possible







Ross et al. (2019)

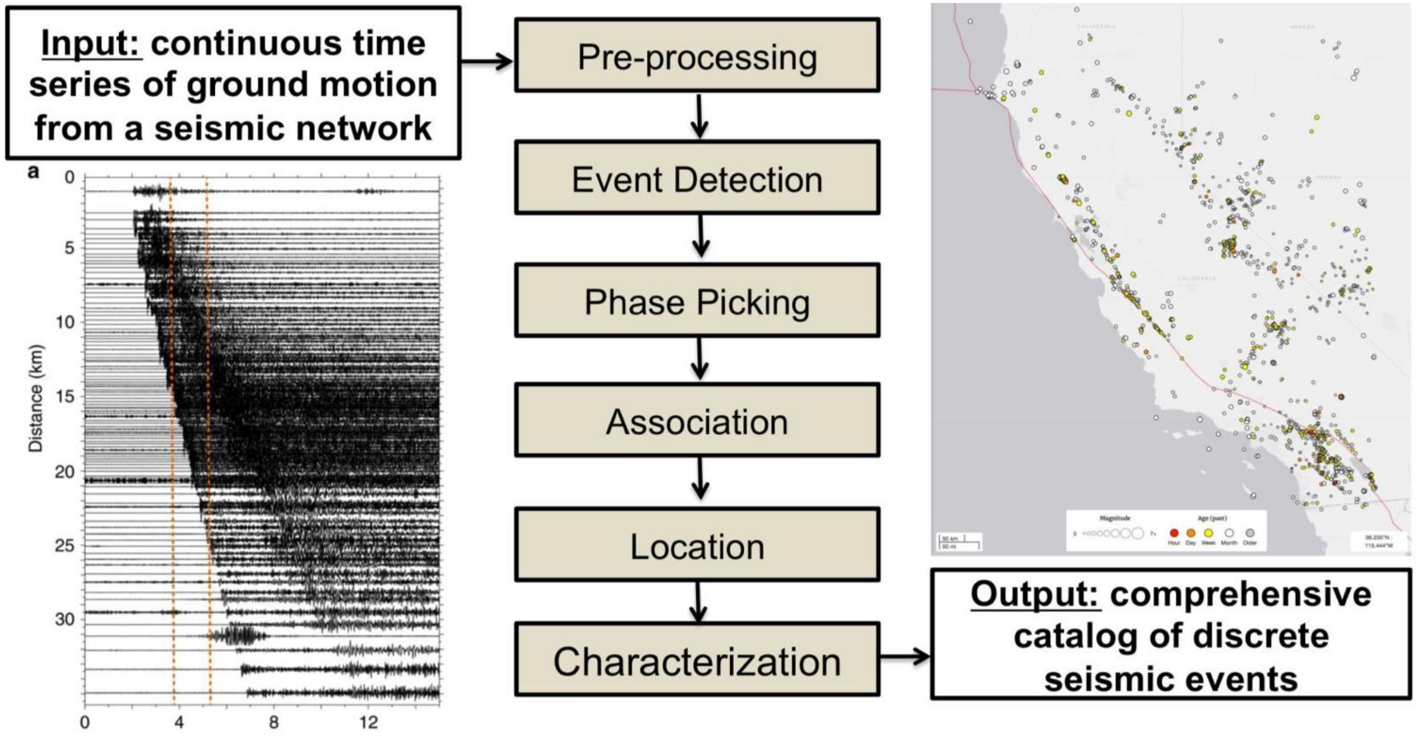
Content

- Traditional earthquake detection and location workflow
    - Traditional workflow: detection → picking → association → (Re)location → magnitude → catalogue
    - Waveform-based techniques

- AI approaches
    - Deep learning detection and picking
    - Phase association and location
    - Modern workflows

Traditional workflow

1. Detect earthquake signals from seismograms using characteristic functions
2. Pick body-wave arrival times
3. Associate picks with individual earthquakes
4. Invert arrival times to estimate location and origin time (& relocate)
5. Estimate magnitude
6. Determine focal mechanism/moment tensor solution
7. Estimate stress drop, energy, slip, etc.



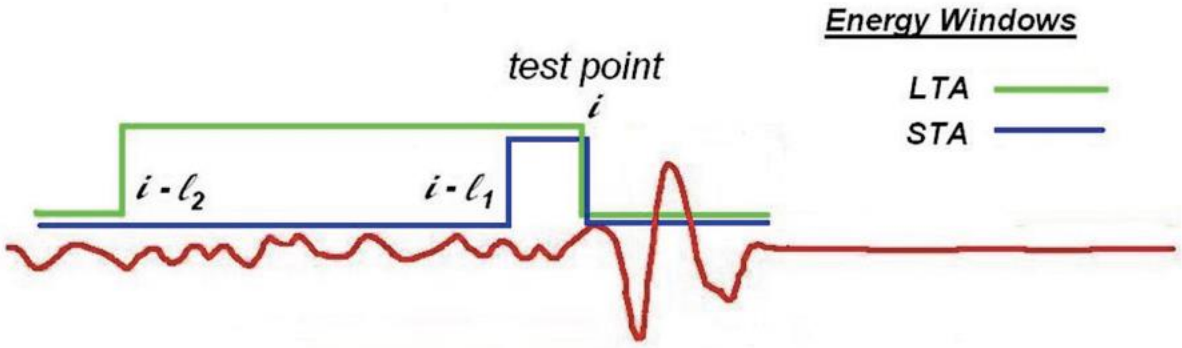
Characteristic functions

STA/LTA

$$STA = \sum_{j=i}^{i-l_1} grm(i)^2 / l_1$$ *Short-term average*

$$l_2 = 10 * l_1$$

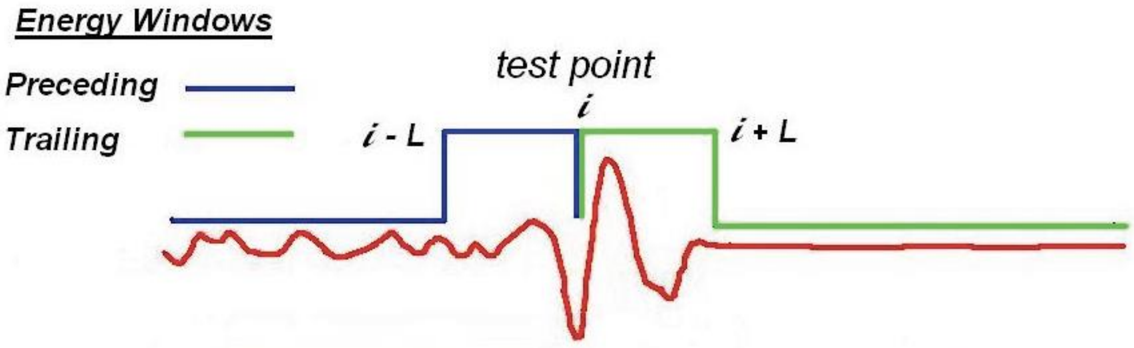
$$LTA = \sum_{j=i}^{i-l_2} grm(i)^2 / l_2$$ *Long-term average*



Modified energy ratio (MER)

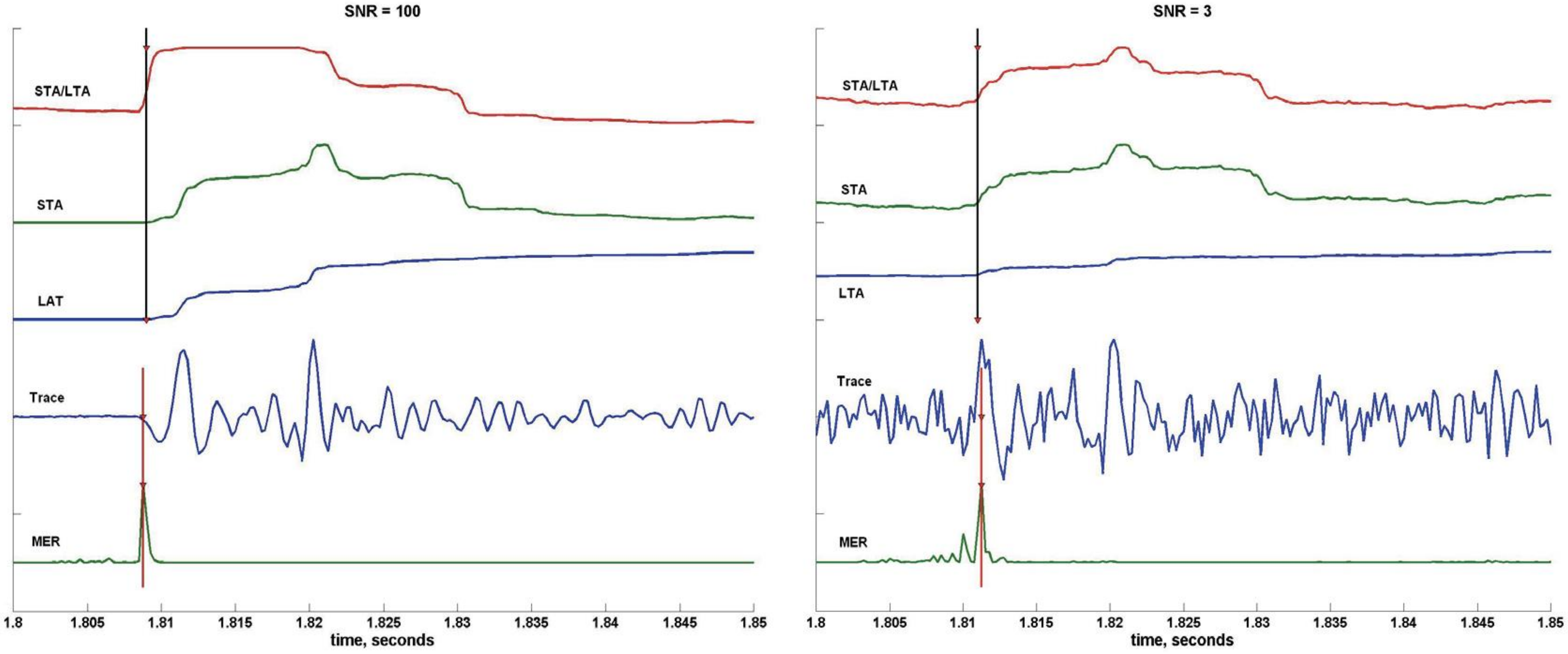
$$er(i) = \sum_{j=i}^{i+L} grm(j)^2 / \sum_{j=i-L}^{i} grm(j)^2$$

$$mer(i) = [er(i) * abs(grm(i)]^3$$



Han et al. (2009)

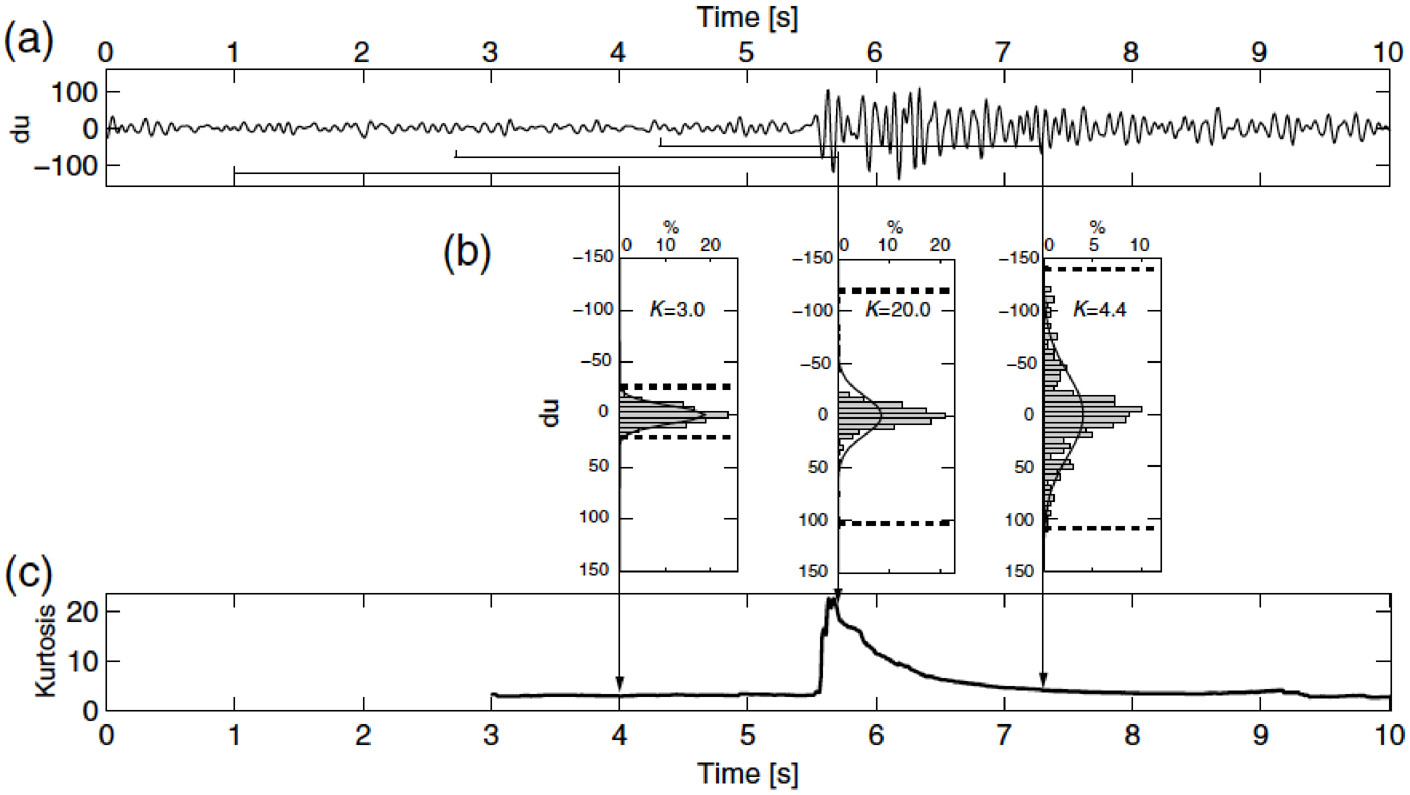
Detection and picking

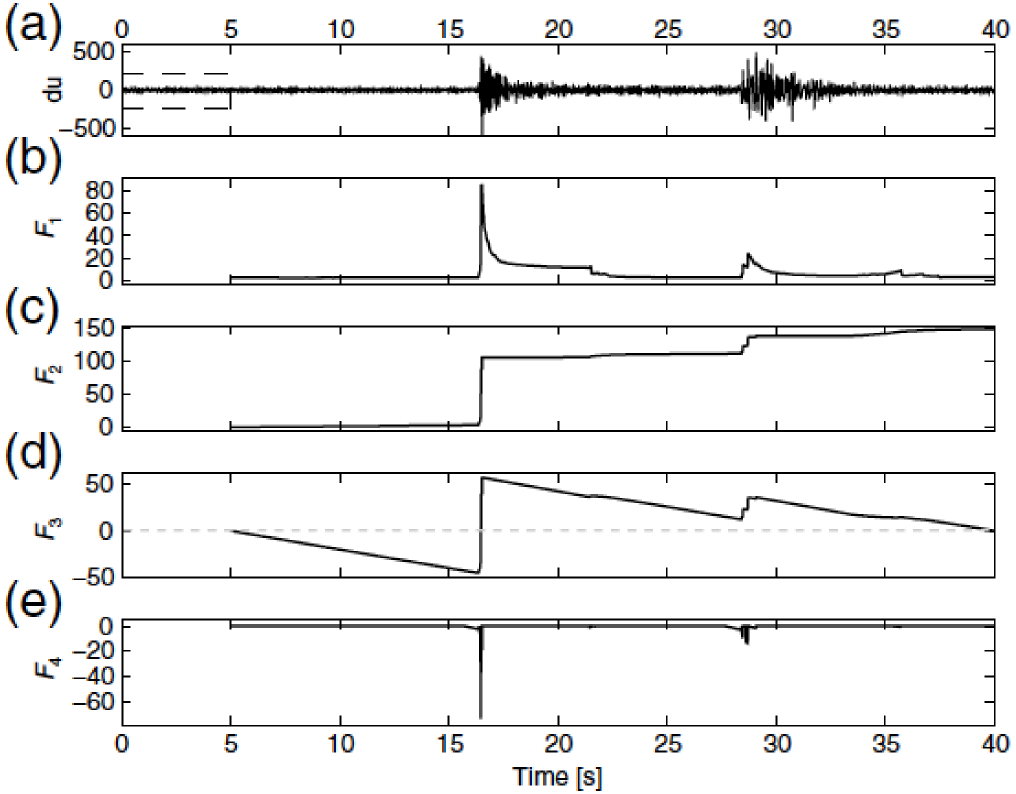


Han et al. (2009)

Detection and picking

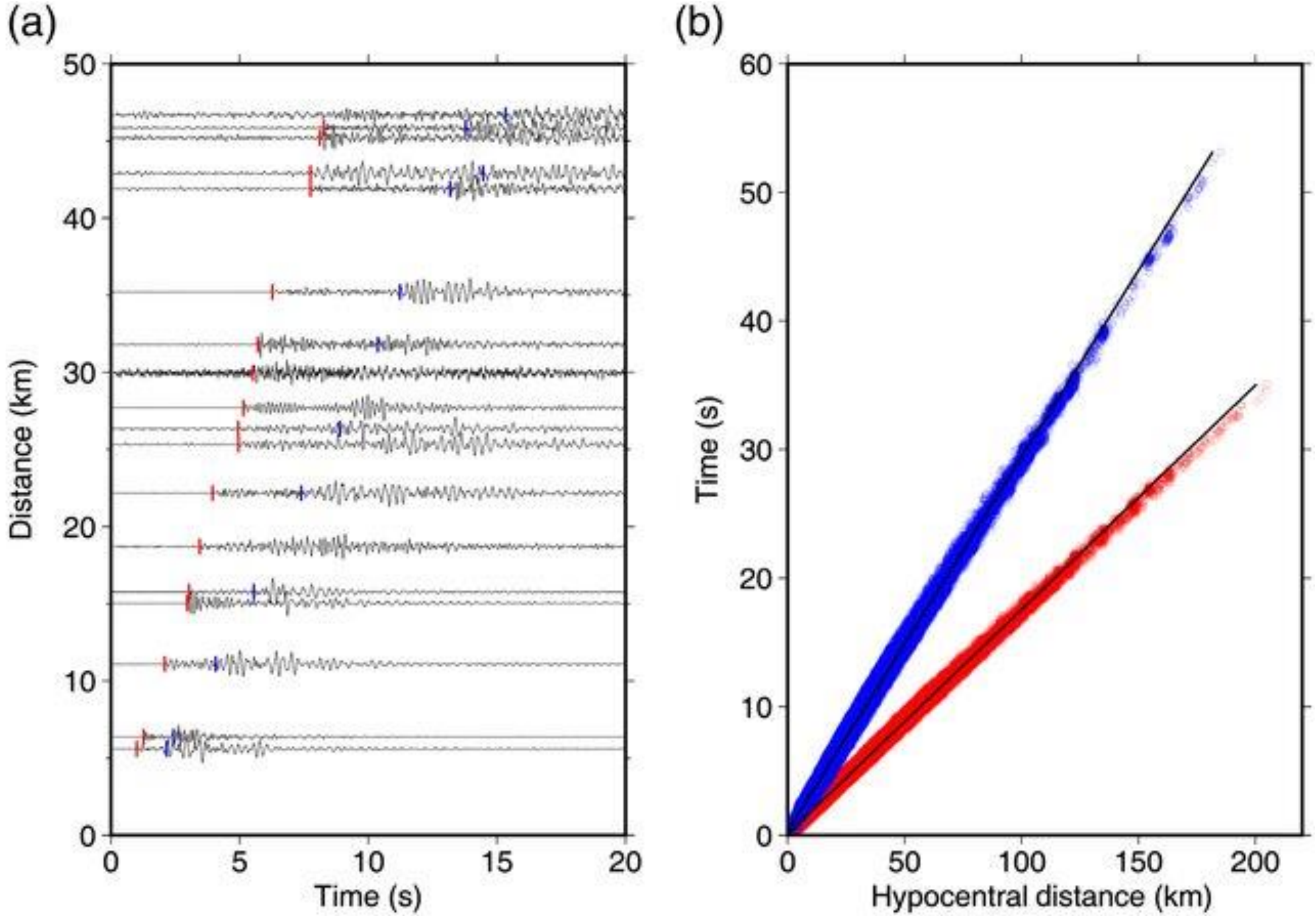
Kurtosis-based function





Baillard et al. (2014)

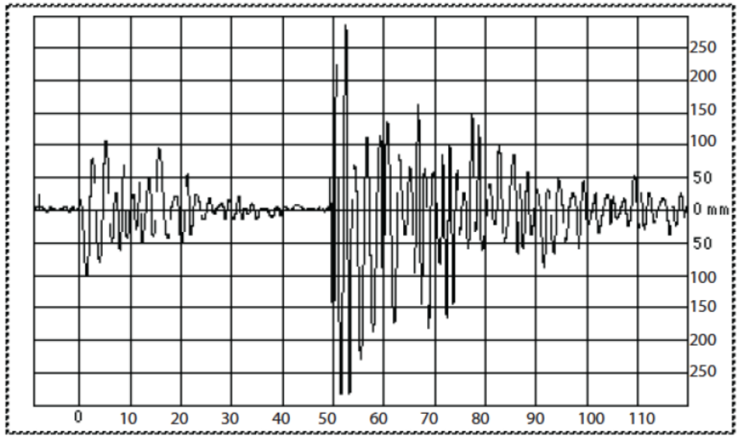
Phase association



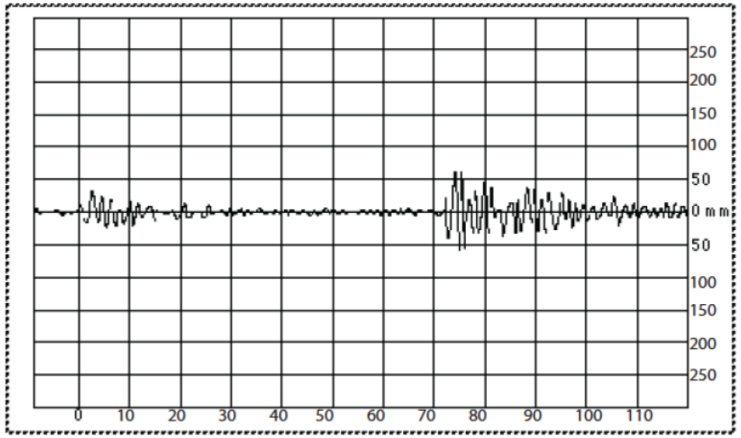
Feng et al. (2022)

Location

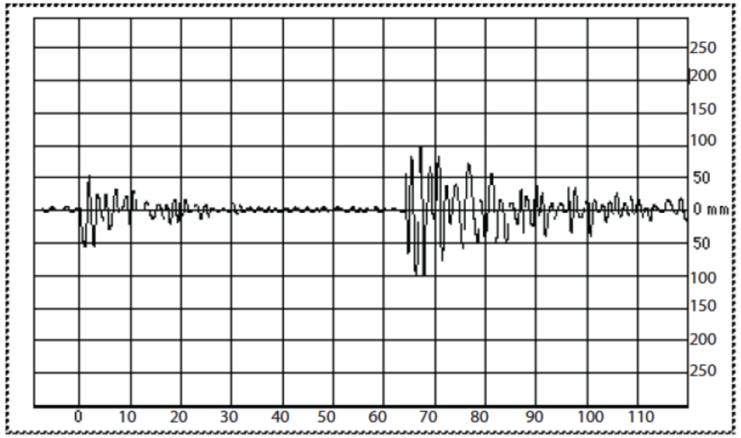
Seismogram from Eureka, CA

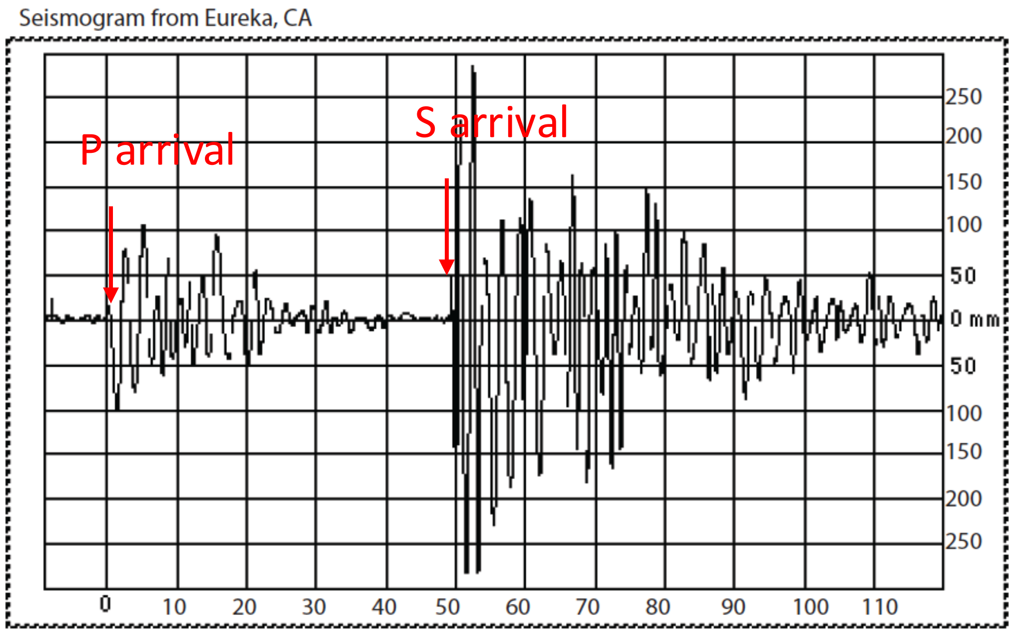


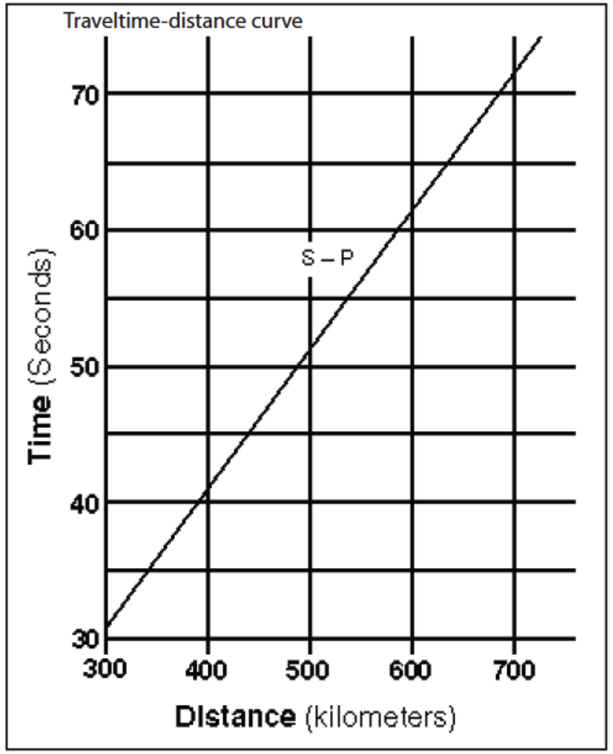
Seismogram from Elko, NV



Seismogram from Las Vegas, NV

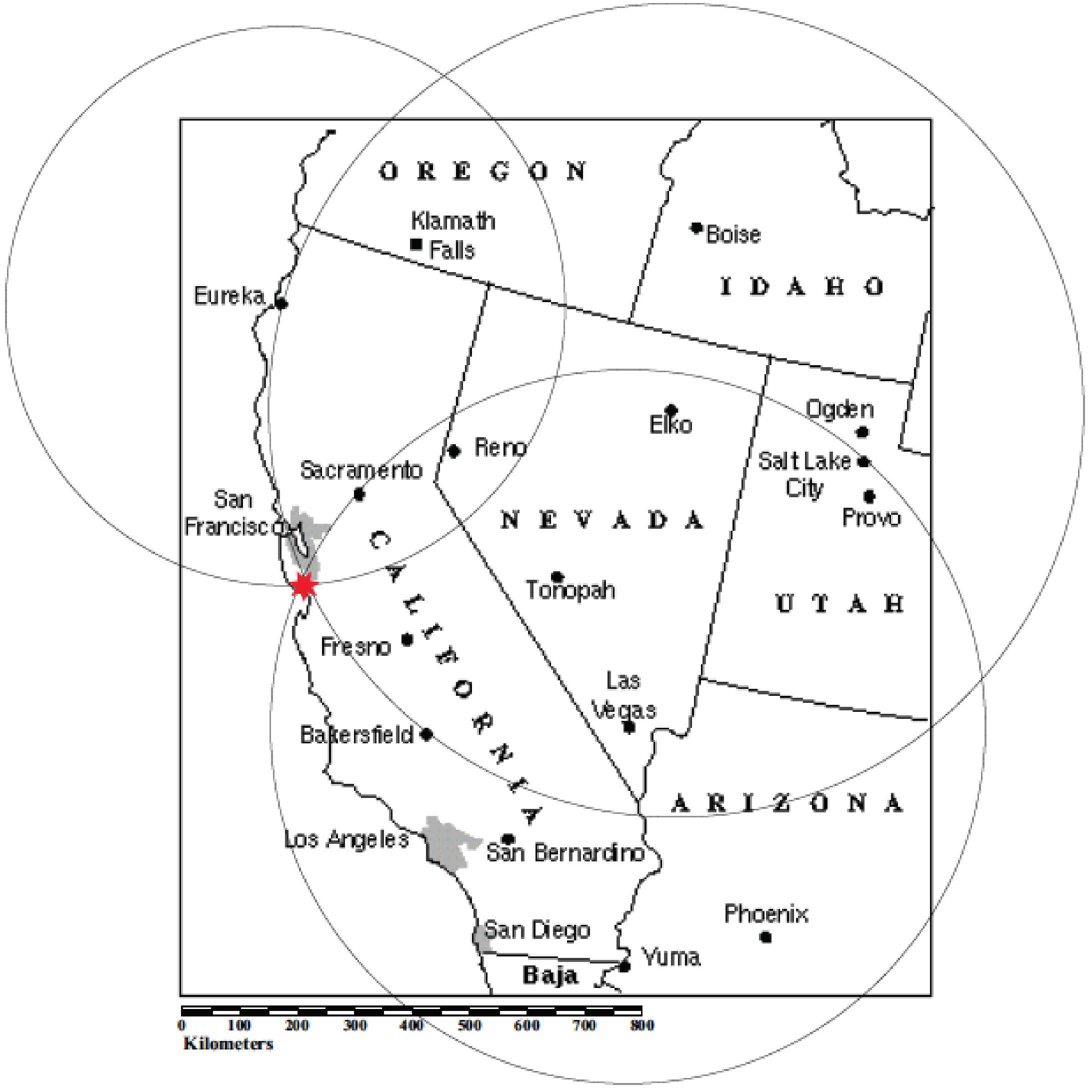






$$t_s - t_p = \frac{r}{v_s} - \frac{r}{v_p} = \left(\frac{1}{v_s} - \frac{1}{v_p} \right) r$$

	S-wave arrival time	P-wave arrival time	S−P (s)	Distance from epicenter (km)
Eureka, CA	50	0	50	487
Elko, NV	72	0	72	709
Las Vegas, NV	64	0	64	622



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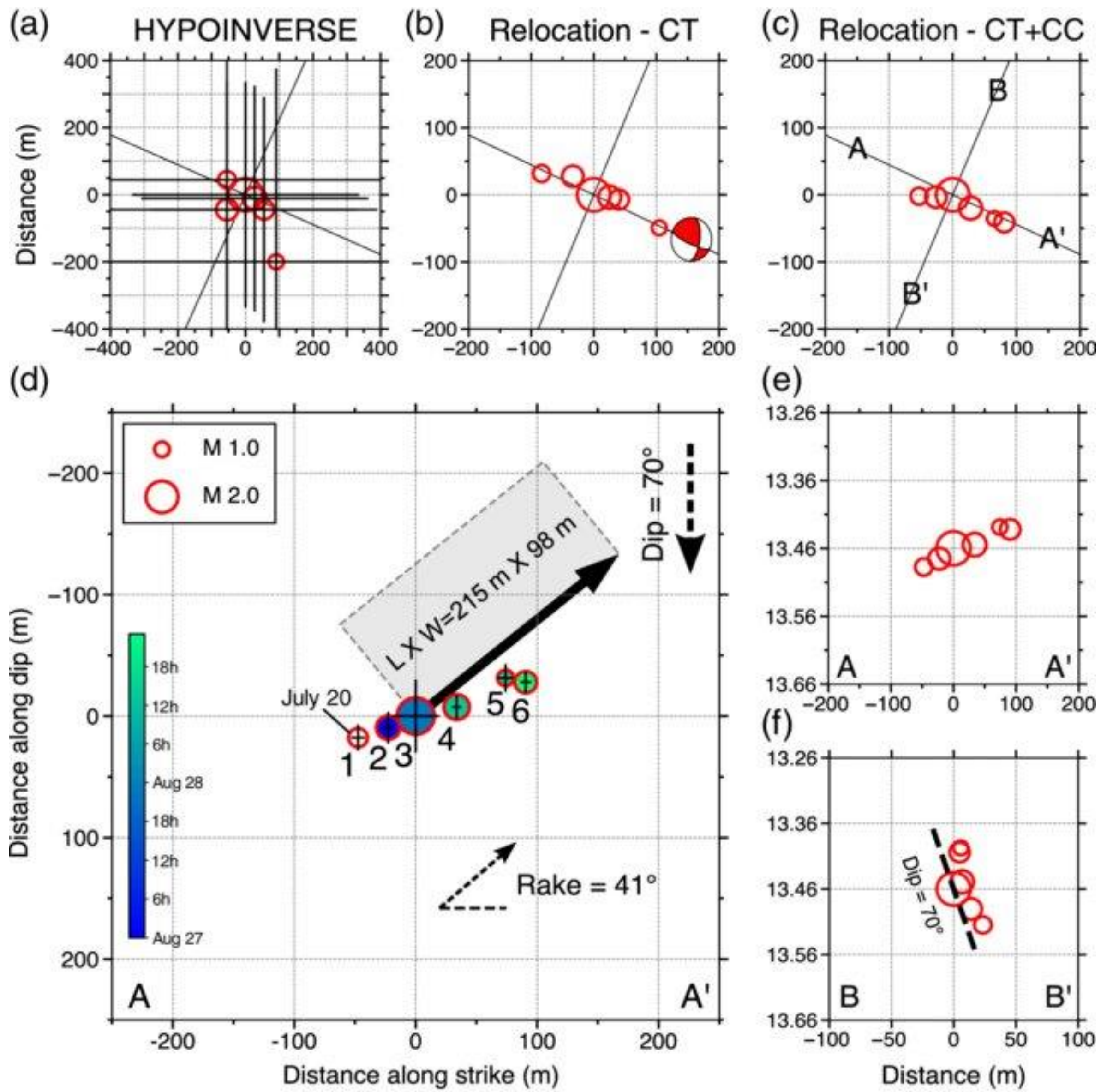
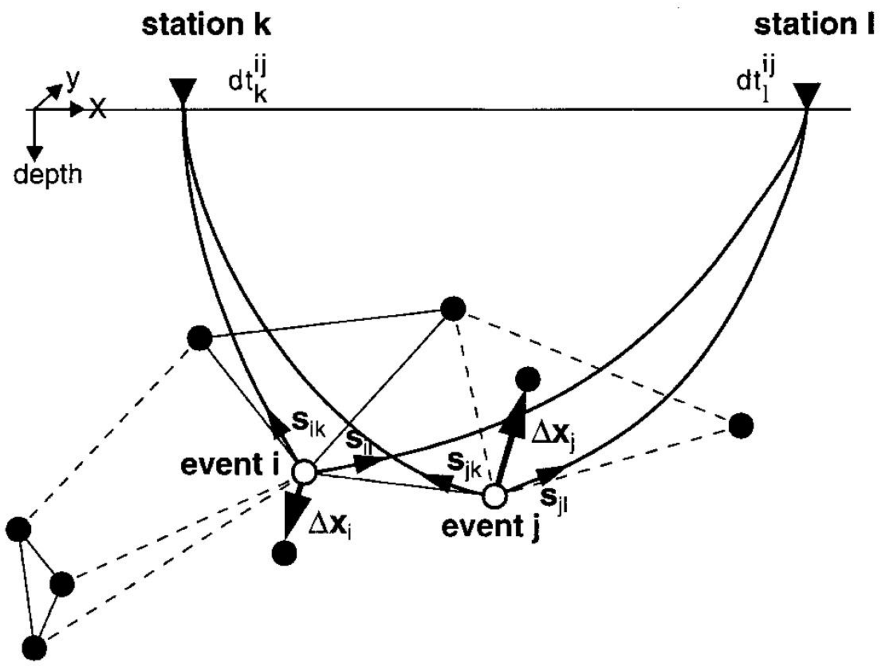
(Re)Location methods

- Hypoinverse
  - Linearized, least-squares method that minimizes pick time residuals
- NonLinLoc
  - Probabilistic non-linear method also minimizes pick time residuals
- HypoDD
  - Relative relocation from travel-time double-differences
- GrowClust
  - Relative relocation using hierarchical clustering

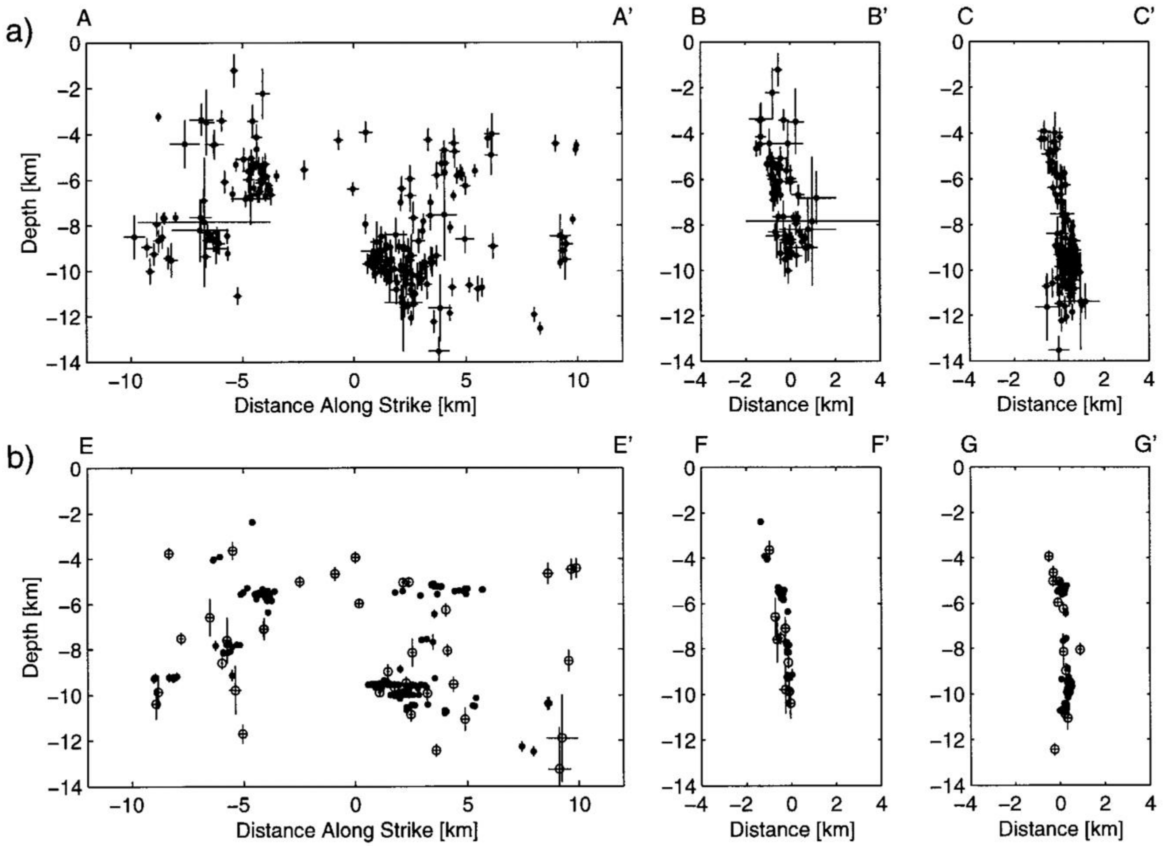


Seo et al. (2022)

HypoDD: Relative Relocation from Double-Difference



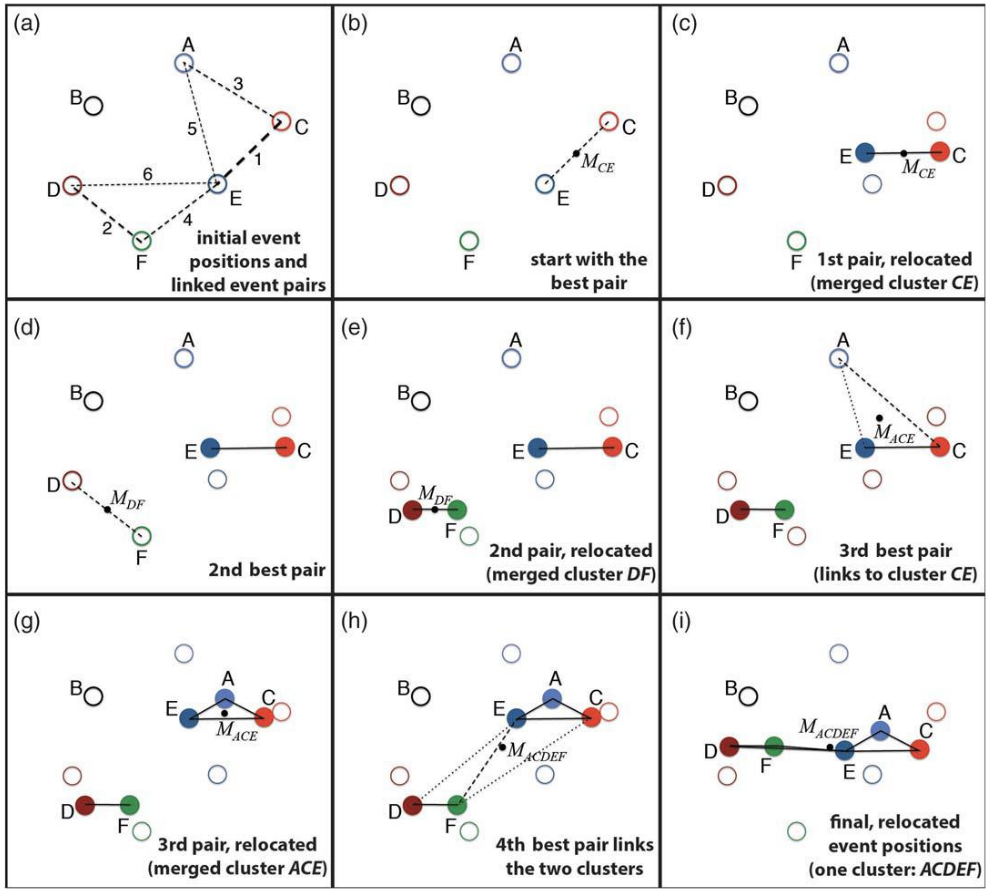
$$dr_k^{ij} = (t_k^i - t_k^j)^{obs} - (t_k^i - t_k^j)^{cal}.$$

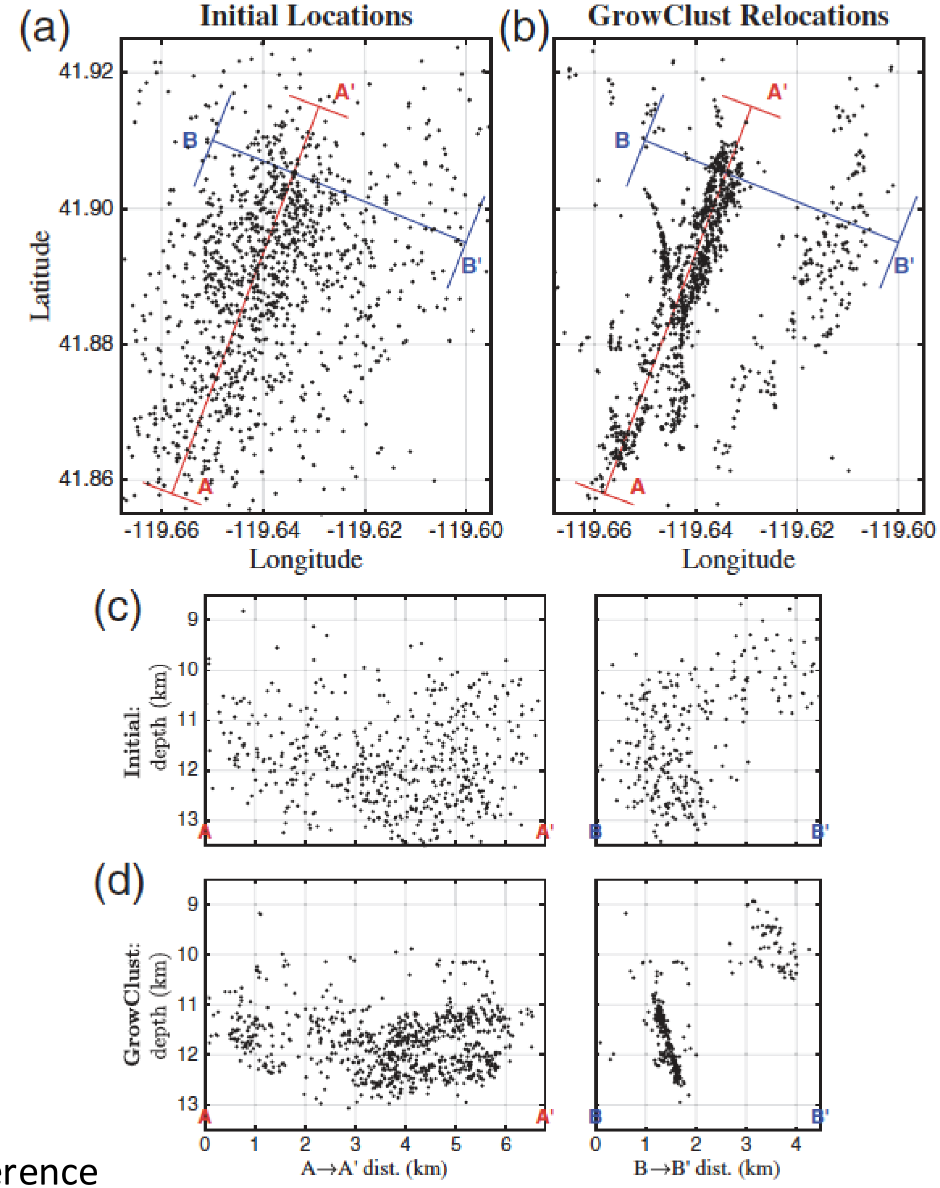


- Precisely relocates earthquakes by calculating and minimizing the **difference in arrival time differences** between pairs of earthquakes recorded at the same seismic station.
- Cancels out common errors related to the path between the source and the station.

Waldhauser and Ellsworth (2000)

GrowClust: Cluster relocation

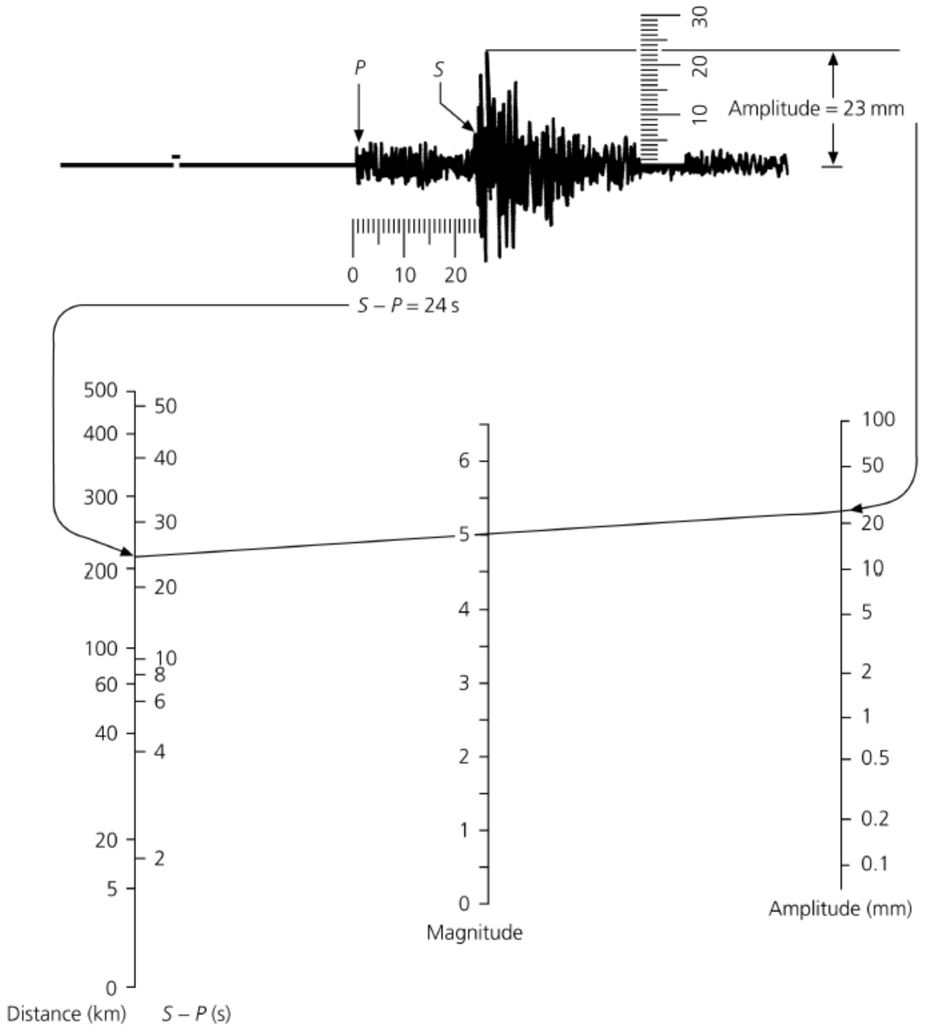




- Relative relocation: uses differential travel times, cross-correlation values, and reference starting positions
- Applies a hybrid, hierarchical clustering algorithm to simultaneously group and relocate events within similar event clusters.

Trugman and Shearer (2017)

Earthquake magnitude - Local magnitude

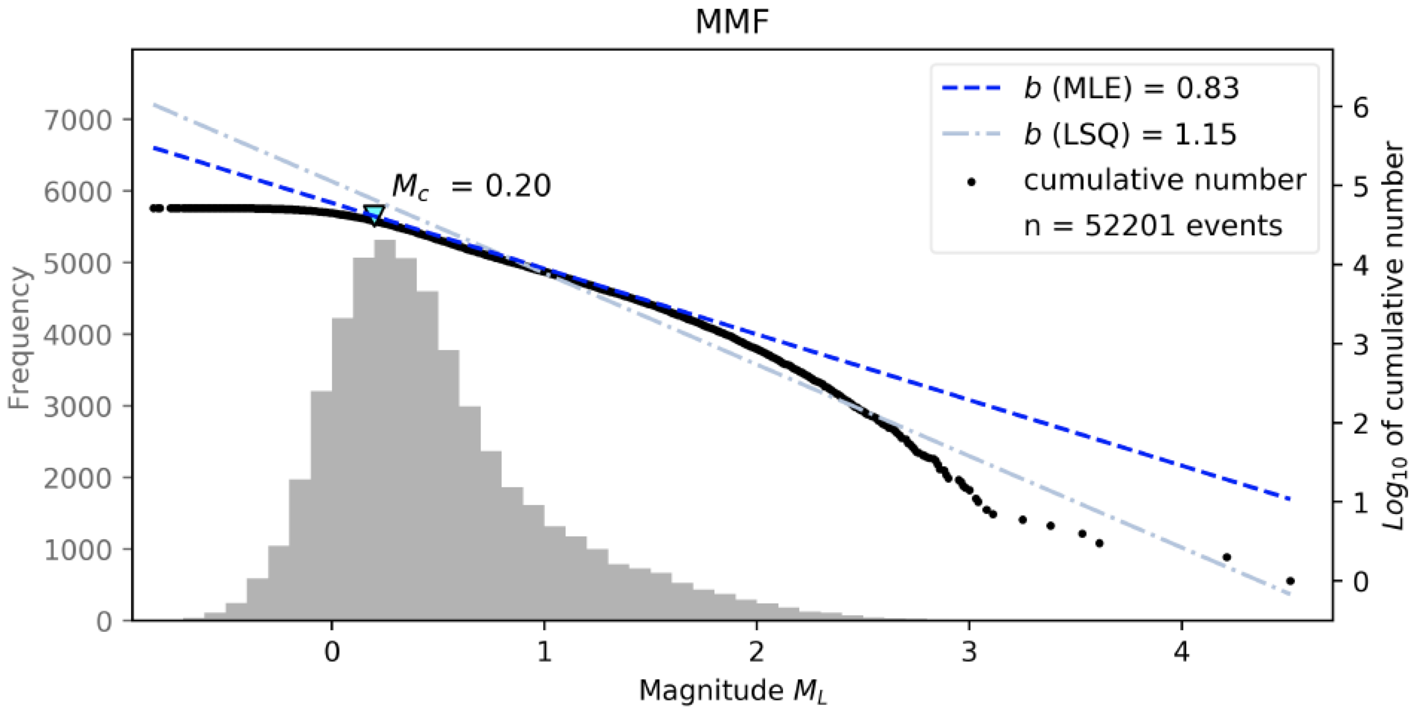


$$M = \log_{10}(A) + 2.76\log(D) - 2.48$$

- Originally a specific local scale for southern California earthquakes, designed for shallow-depth events recorded at the Wood-Anderson seismometer, with an instrument period 0.8 s.

- Now, a local magnitude, still reported because many buildings have resonant frequencies near 1 Hz. Thus, $\mathbf{M_L}$ is a good indicator of structural damage an earthquake can cause.

Frequency-magnitude (Gutenberg-Richter) scaling



Hydraulic fracturing-induced seismicity in Montney Formation, BC, 2017/07-2020/12, ~52,000 events [Ricarda Wache, MSc thesis, 2022]

$\log_{10}(N) = a - bM$

M earthquake magnitude,

N number of events $\geq M$.

a, b are constants. Global average $b = 1$.

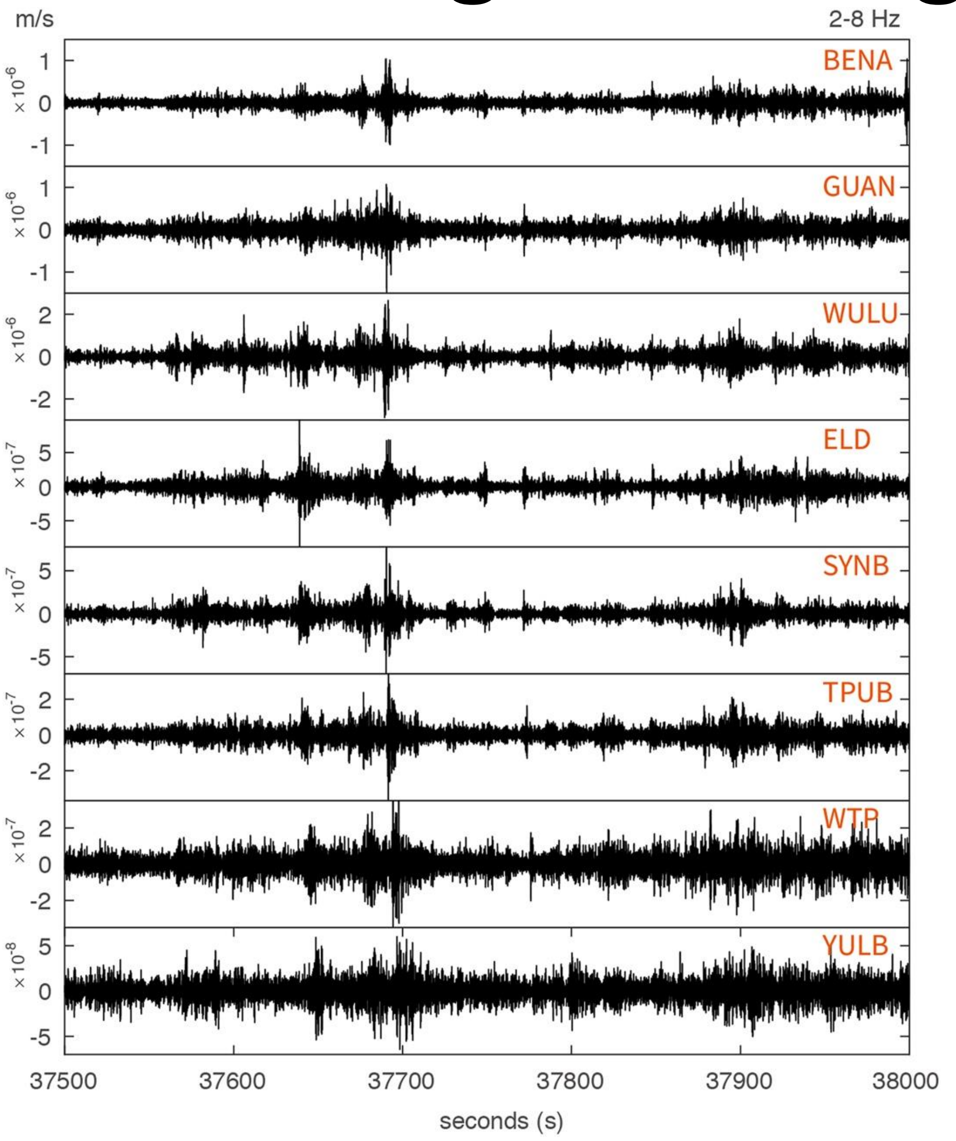
Mc: completeness magnitude

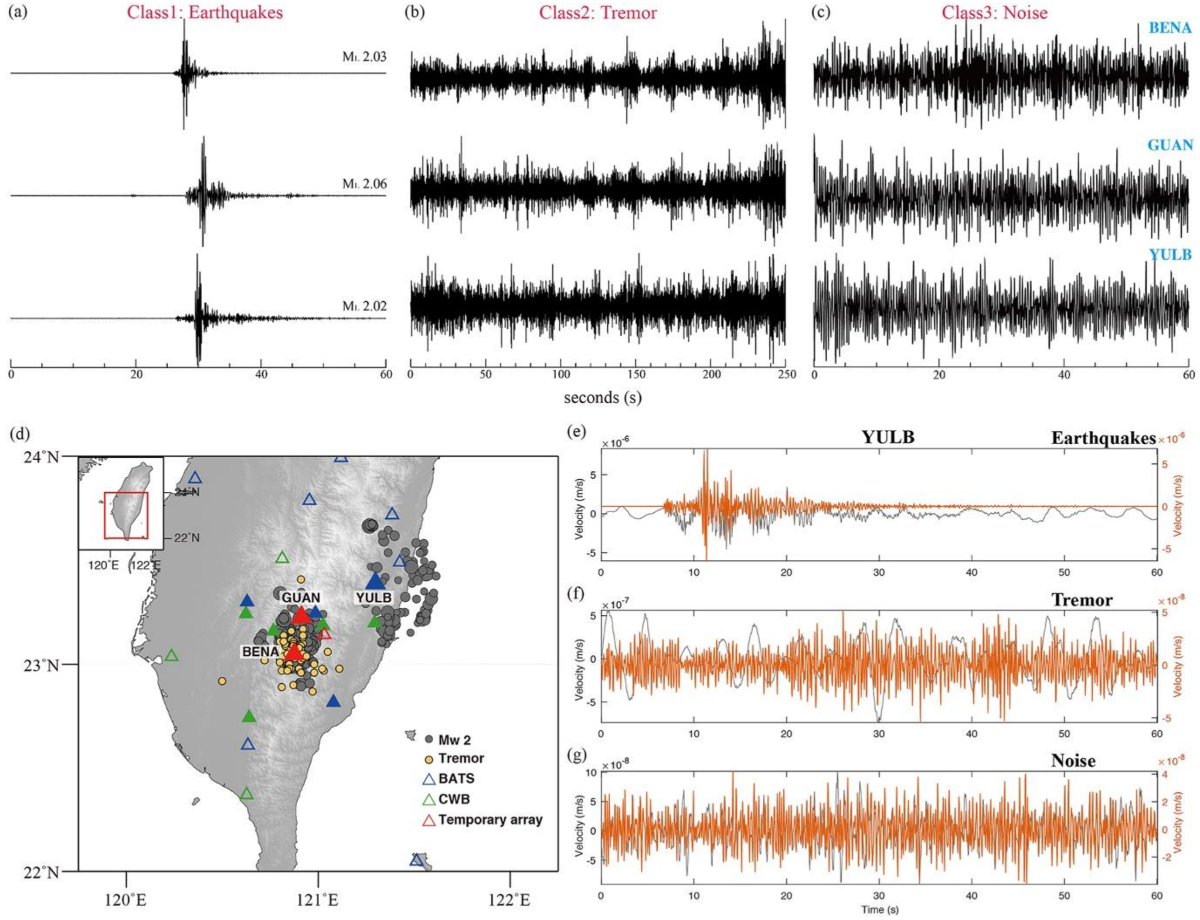
b-value: relative occurrence frequencies of small vs. large events

b>1: "earthquake swarm", volcanic regions, magmatic fluid migration or caldera development;

b<1: shorter recurrence time, possible asperities or stress concentrations, frictional property variations

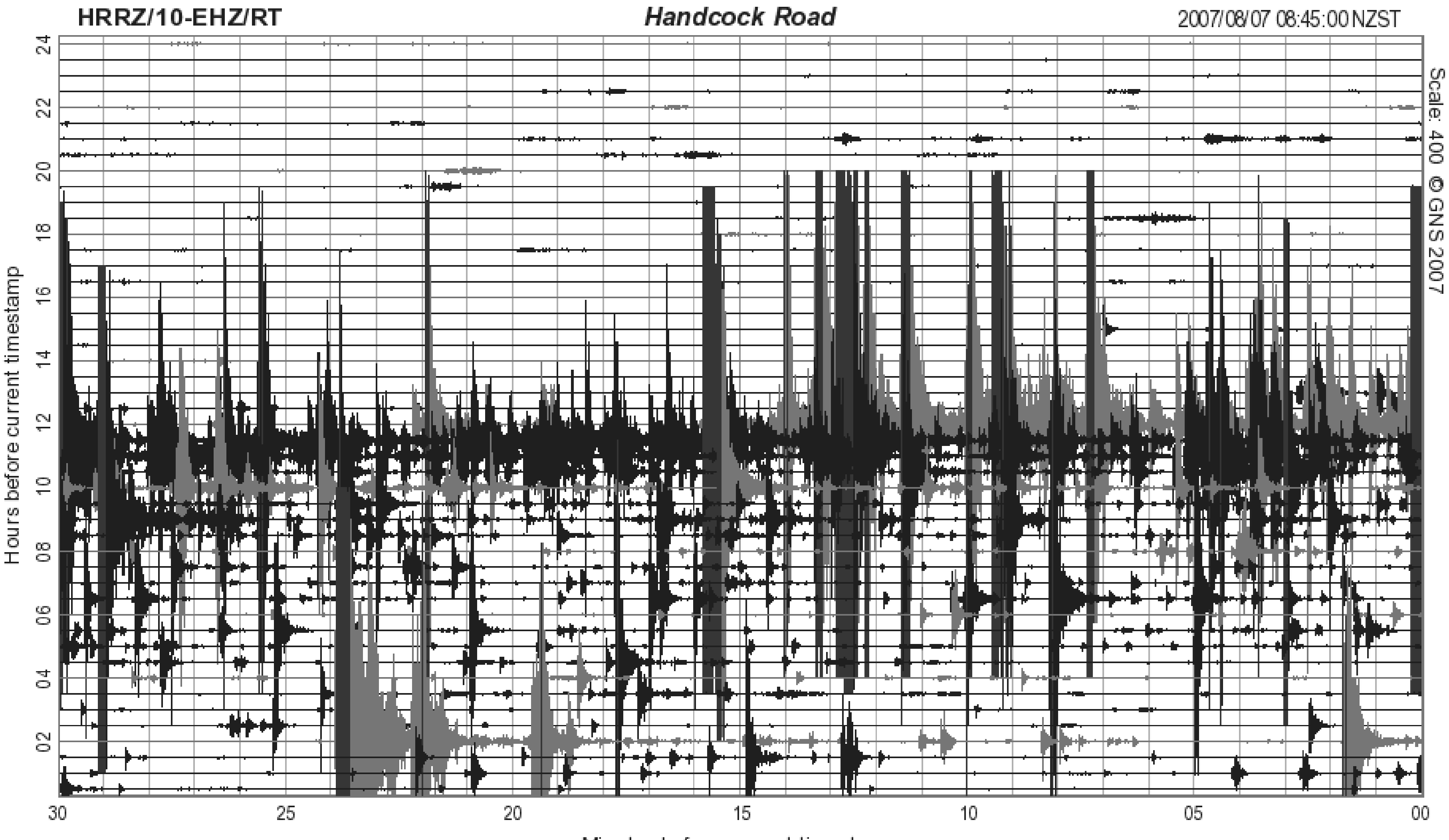
Challenges: Emergent signals



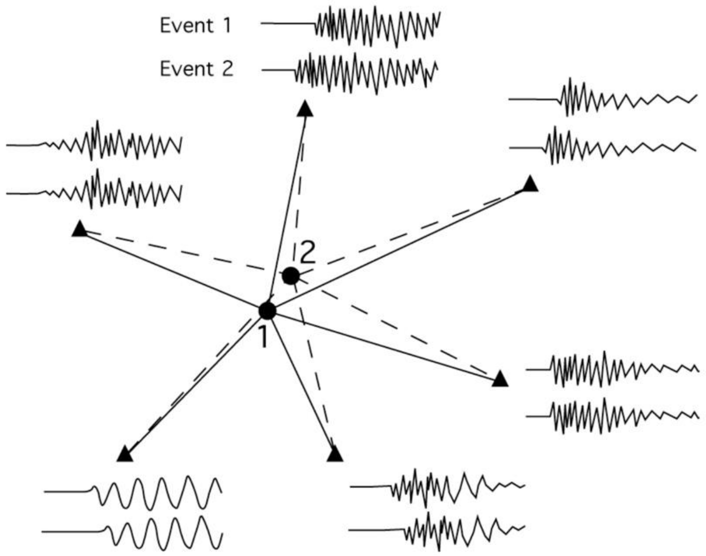


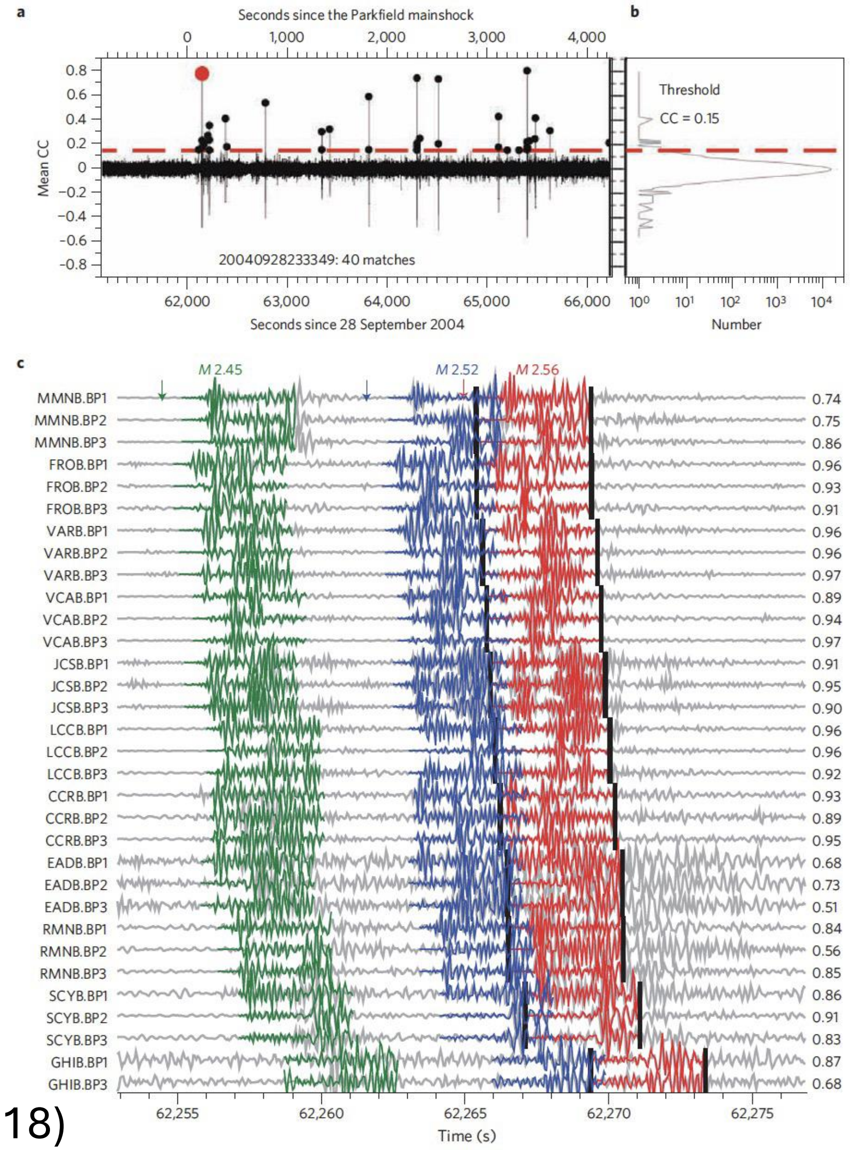
Liu et al. (2019)

Challenges: Data overload



Waveform-based: Templates



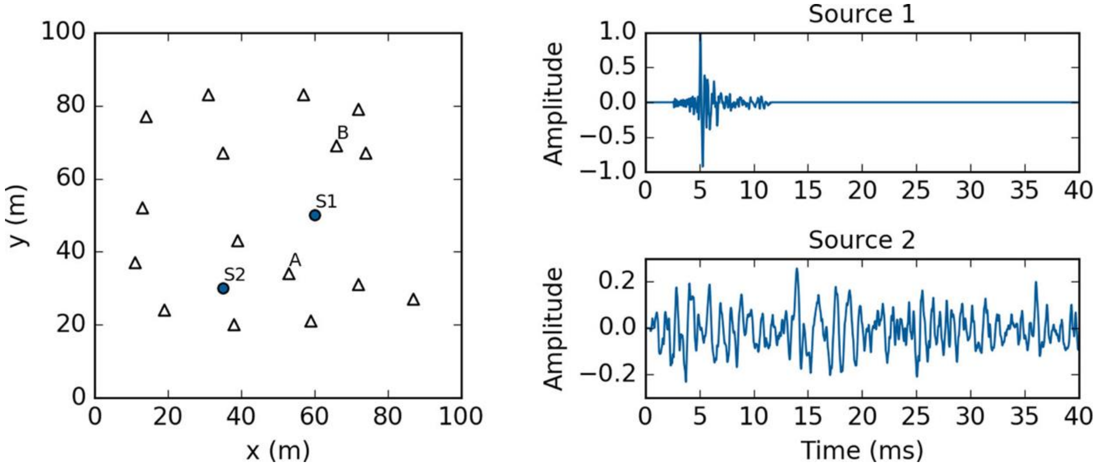


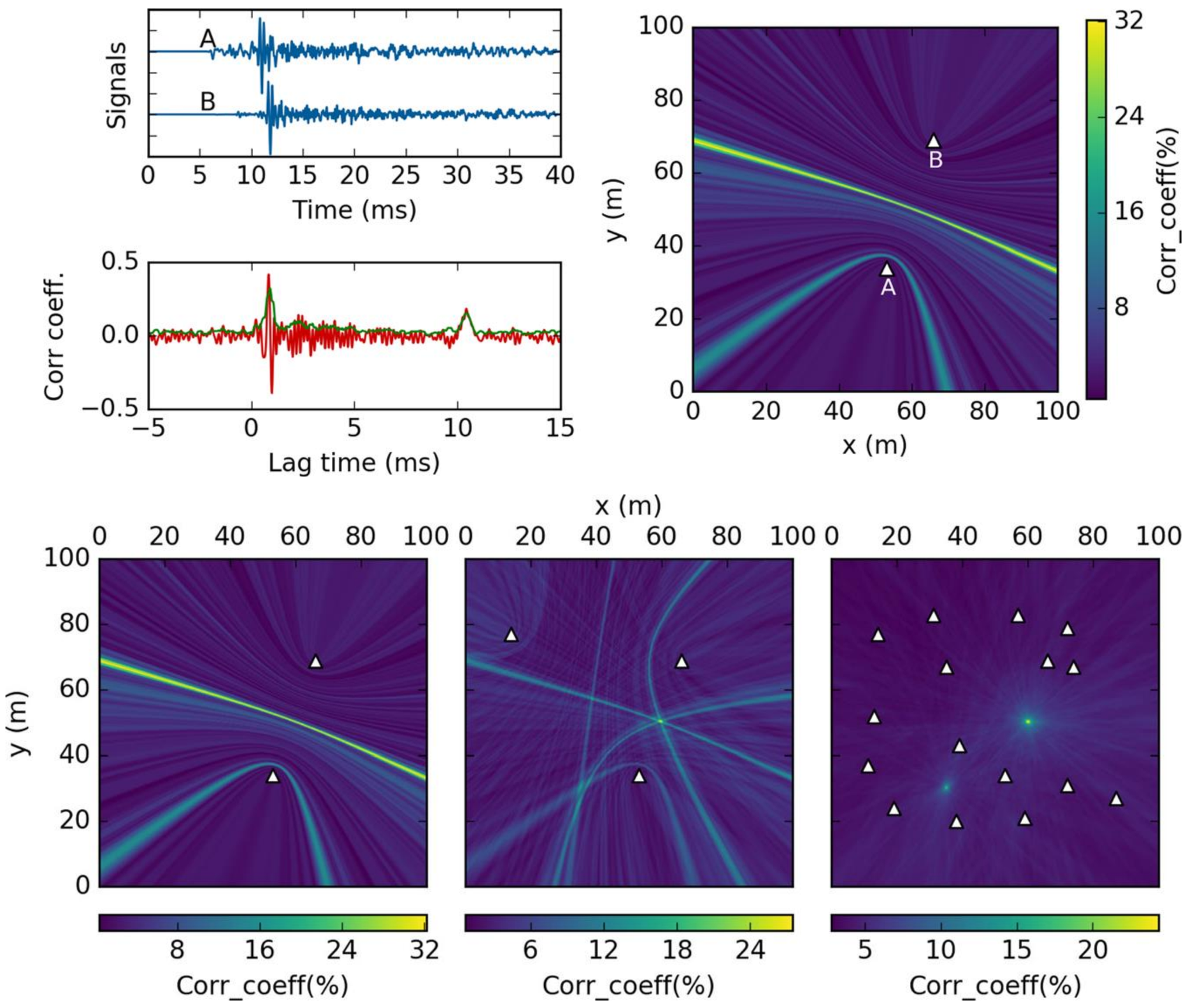
- Use a « template » from a catalogue and scan the seismograms for similar shapes using cross-correlation.
- Small waveform delays determine new locations of repeaters.
- Cannot detect new events with different shape

EQcorrscan
Correlation for earthquake detection in Python

Gibbons and Ringdal (2006); Shelly et al. (2007); Chamberlain et al. (2018)

Waveform-based: Delay and sum



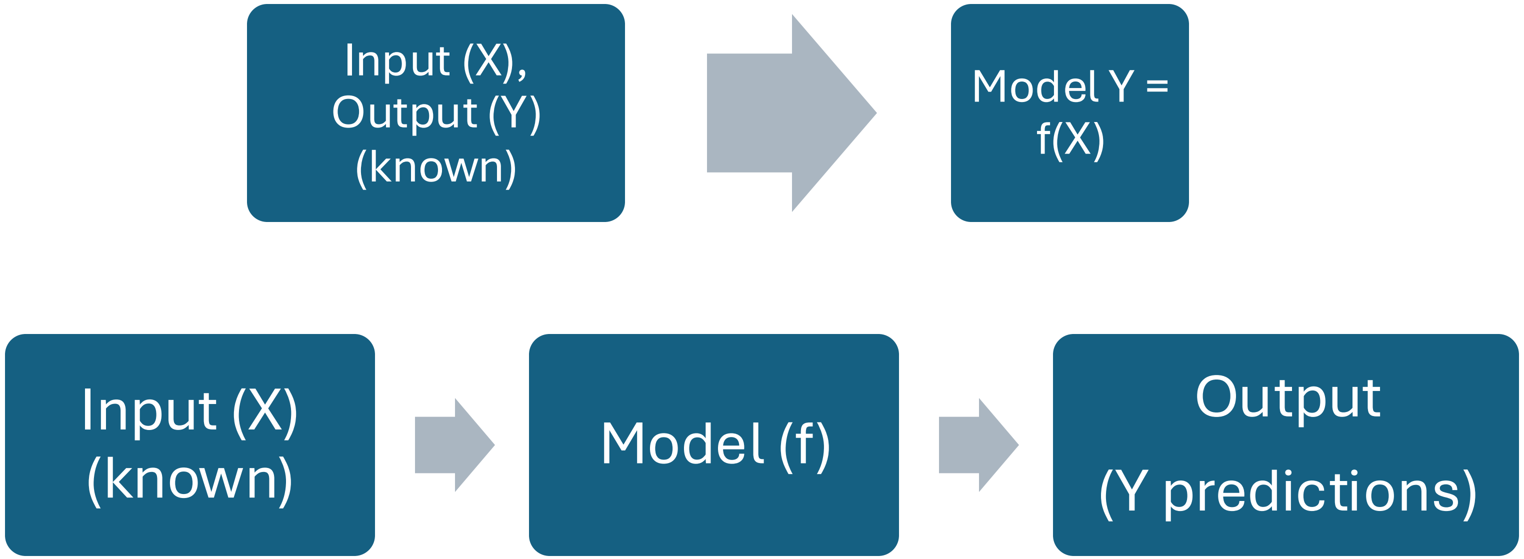


- Instead of relying on a derived piece of information (i.e., picks, template), cross-correlate the wavefield continuously for all station pairs.
- For a single station pair, map the cross-correlation into space.
- Average all maps; coherent energy arises and noise cancels at source locations.
- Computationally very expensive.

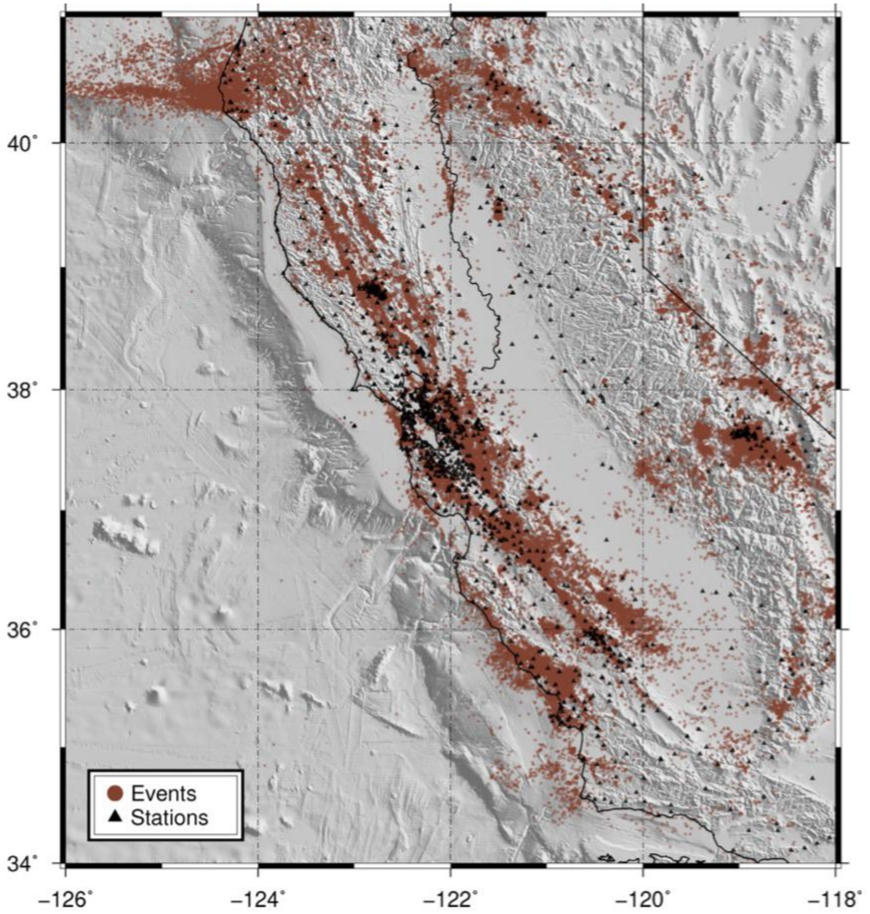
Dales et al. (2017)

Machine learning methods

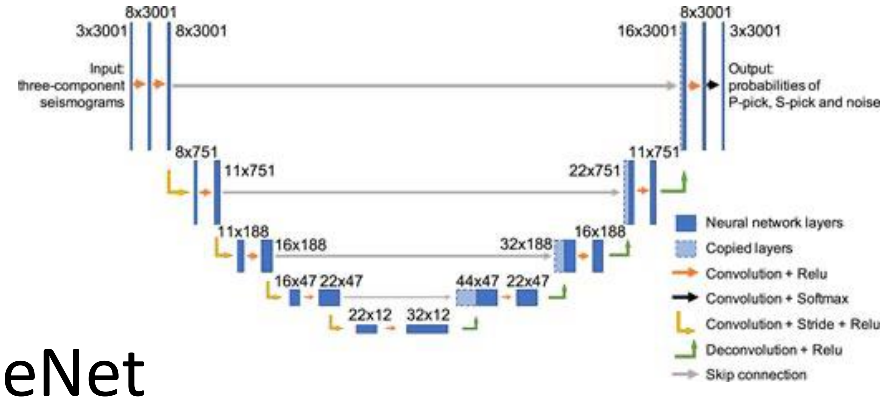
- In machine (deep) learning, a « model » is a function that maps inputs to predictions (outputs).
- For phase-picking tasks, inputs (X) are seismic waveforms, and output/predictions(Y) are seismic phase picks (and/or detections).
- The process of « learning » how the outputs are related to inputs is called « training ».



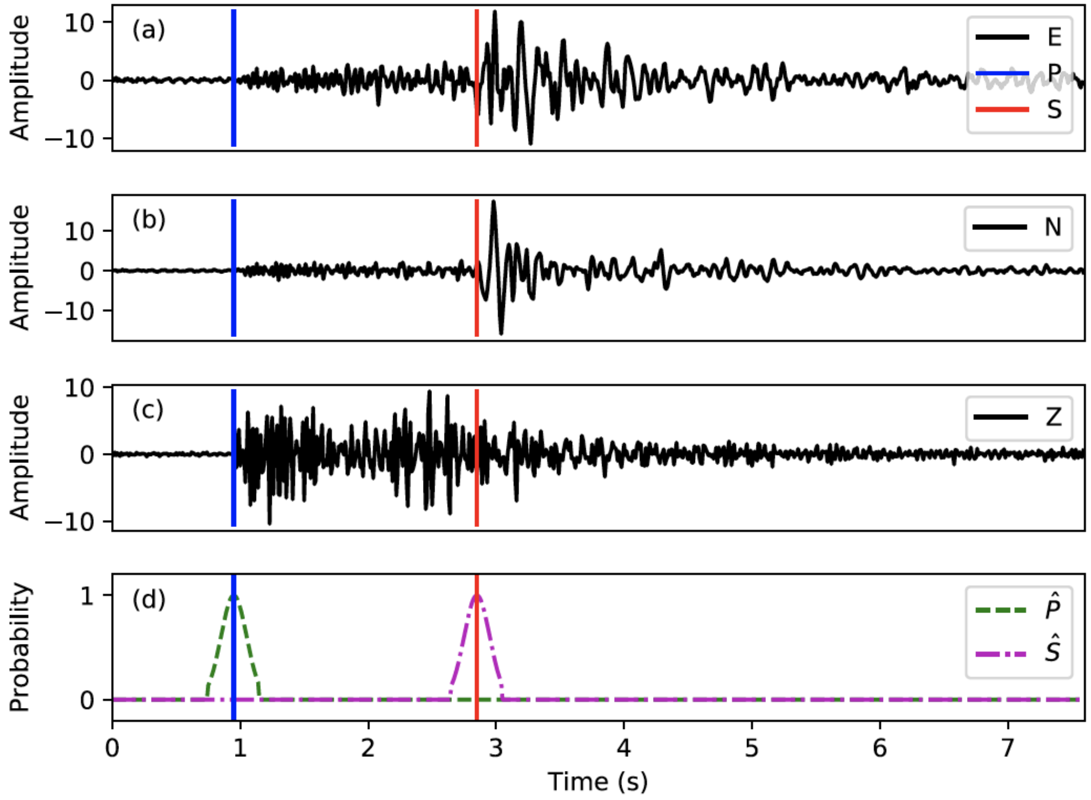
Machine learning detection and picking



Training dataset (CA)
30-year earthquakes
0.7 M samples

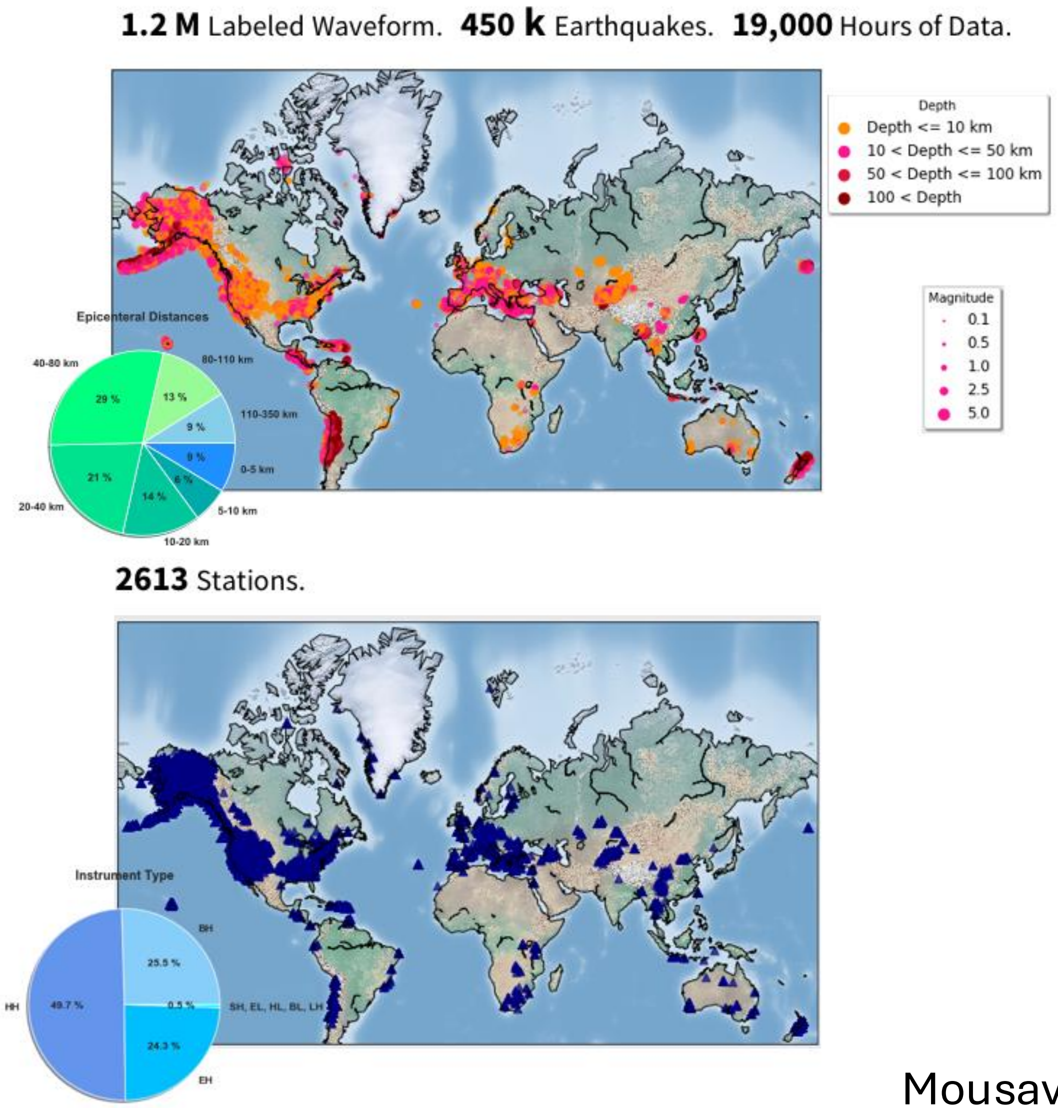


PhaseNet

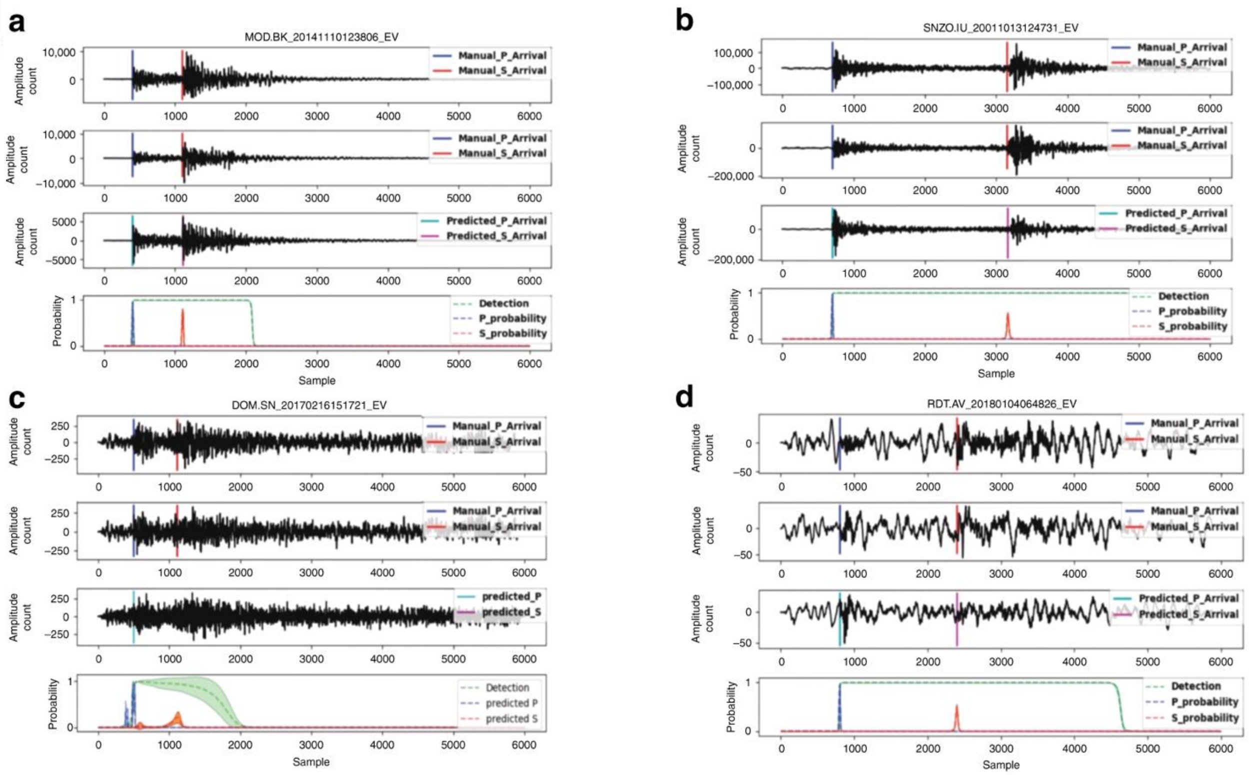


Zhu and Beroza (2019)

Machine learning detection and picking

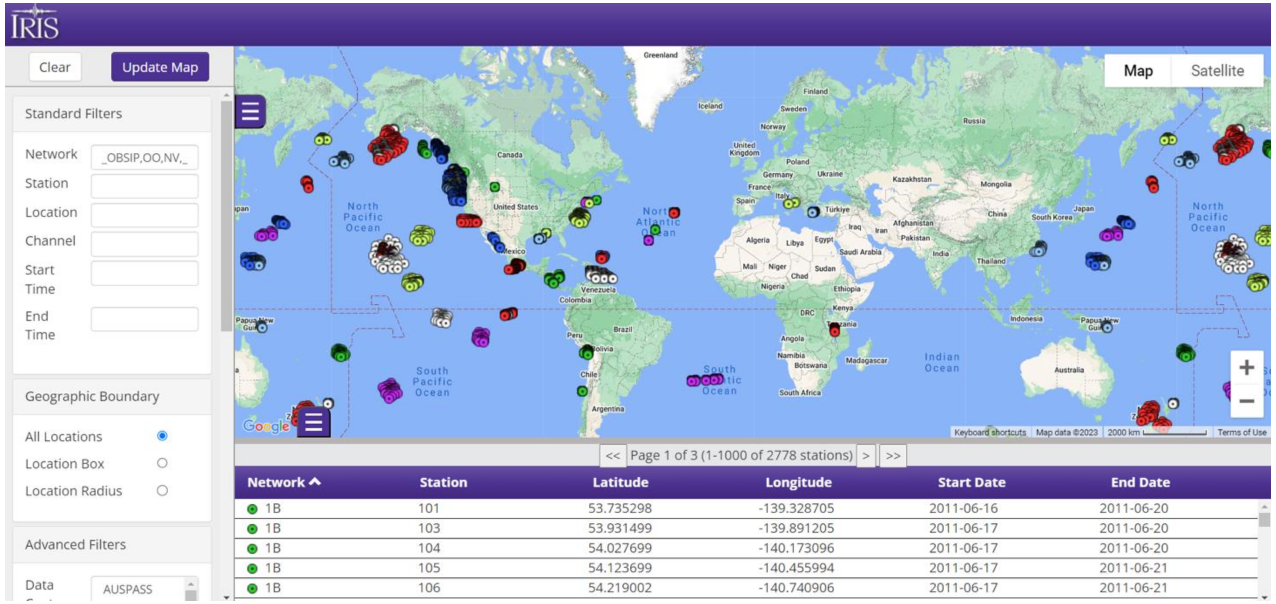


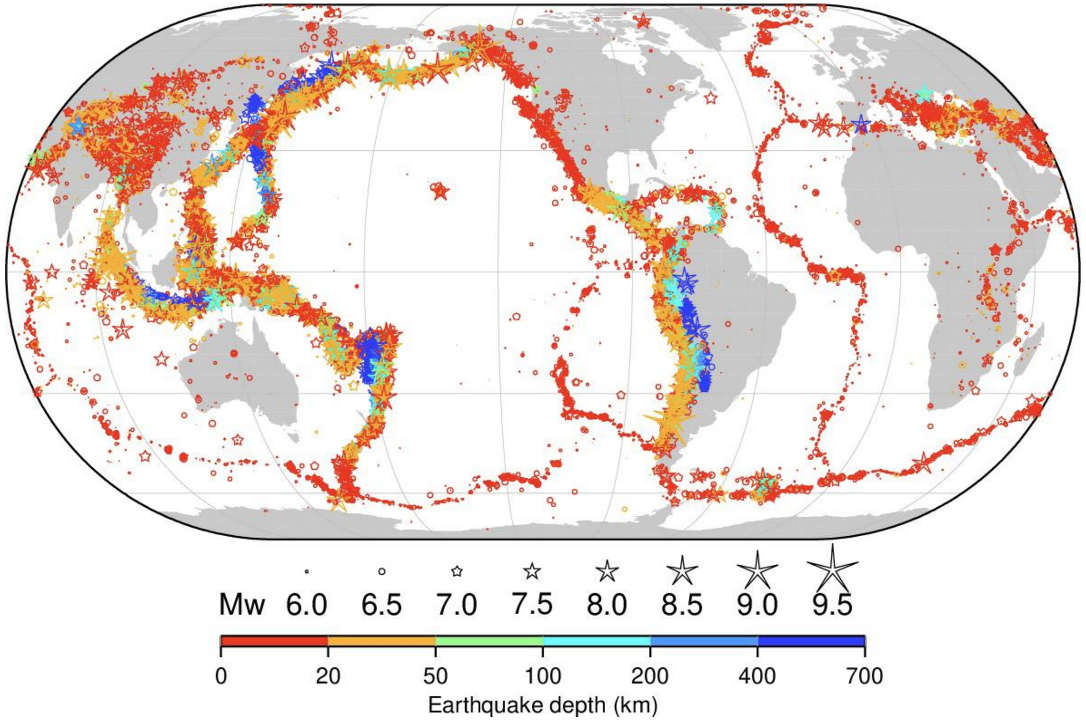
EQTransformer



Mousavi et al. (2022)

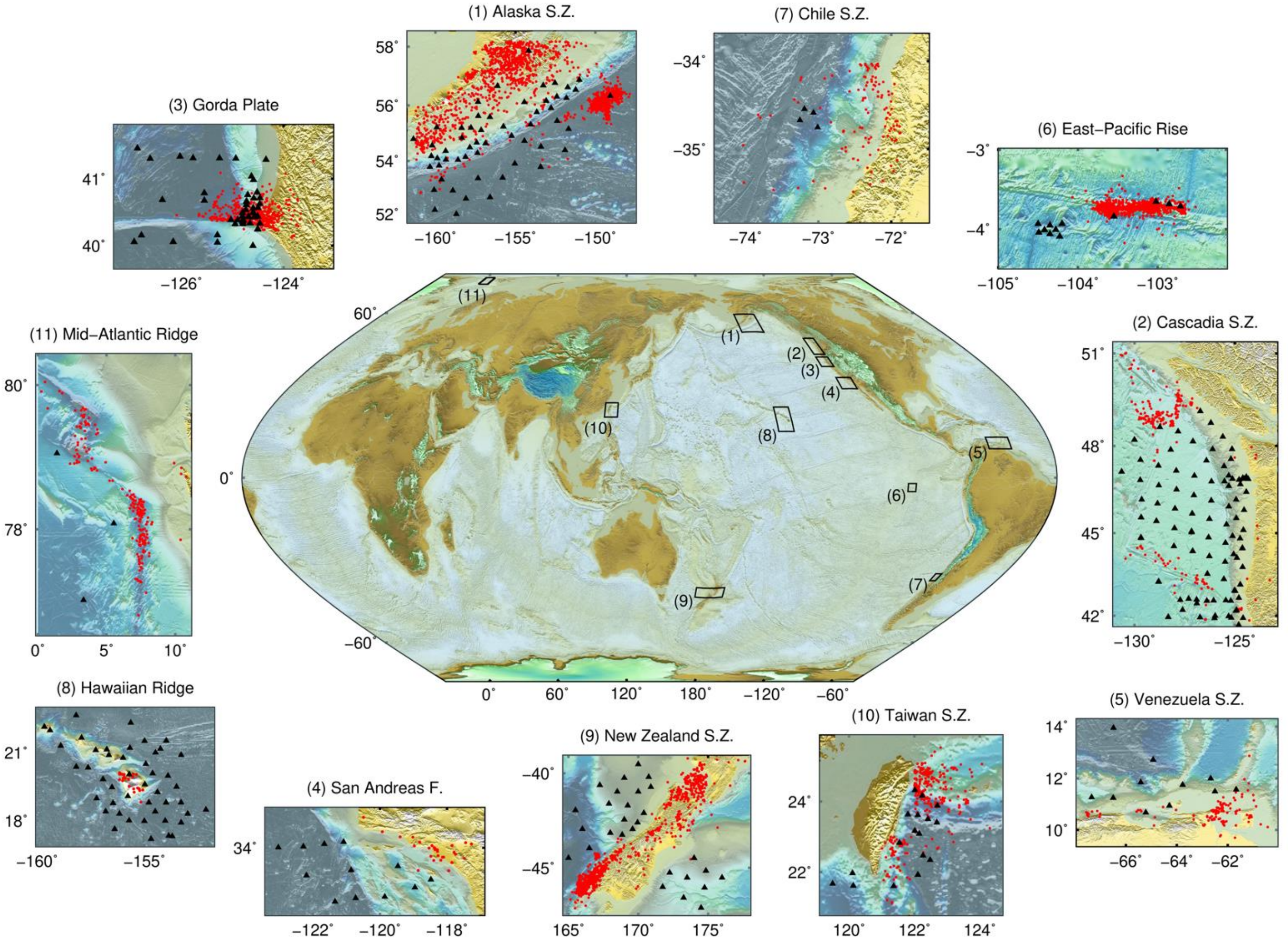
ML models for offshore data





- Noise and waveform complexity on OBS data are different than land-based seismic data.
- **None of the ML pickers use OBS data or offshore earthquakes for training**, which reduces their ability to pick those data accurately.

OBSTransformer

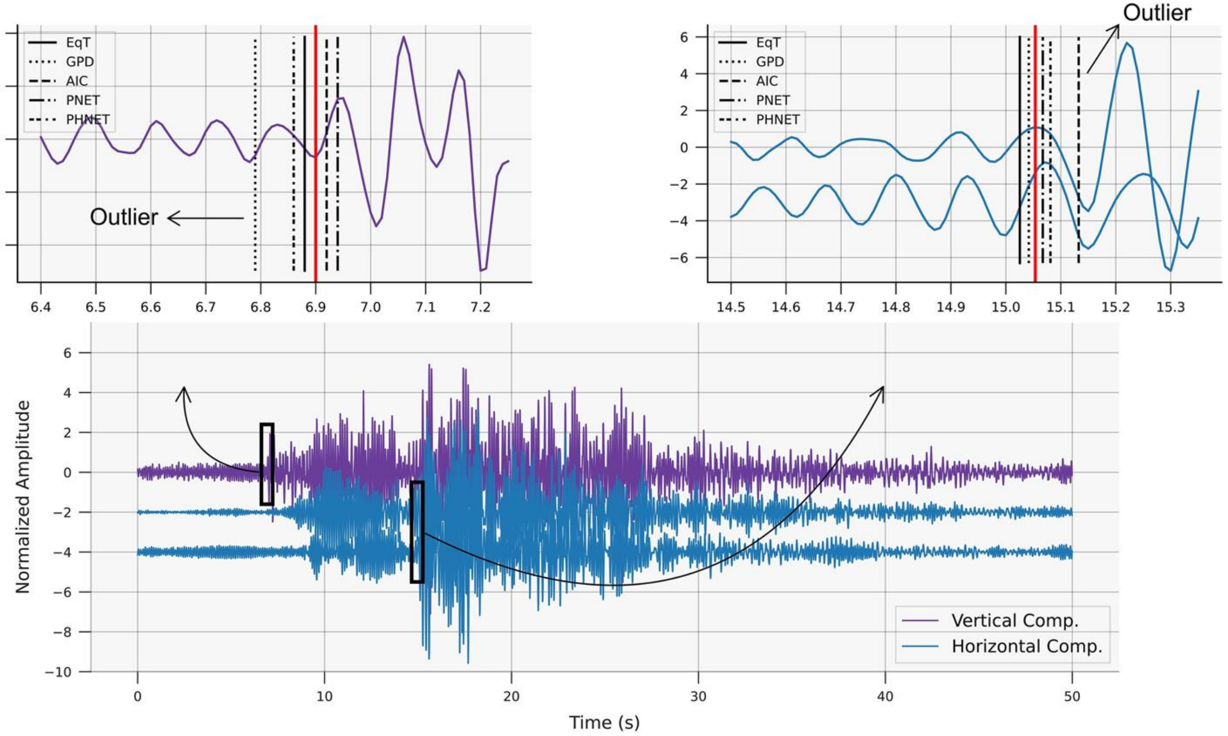


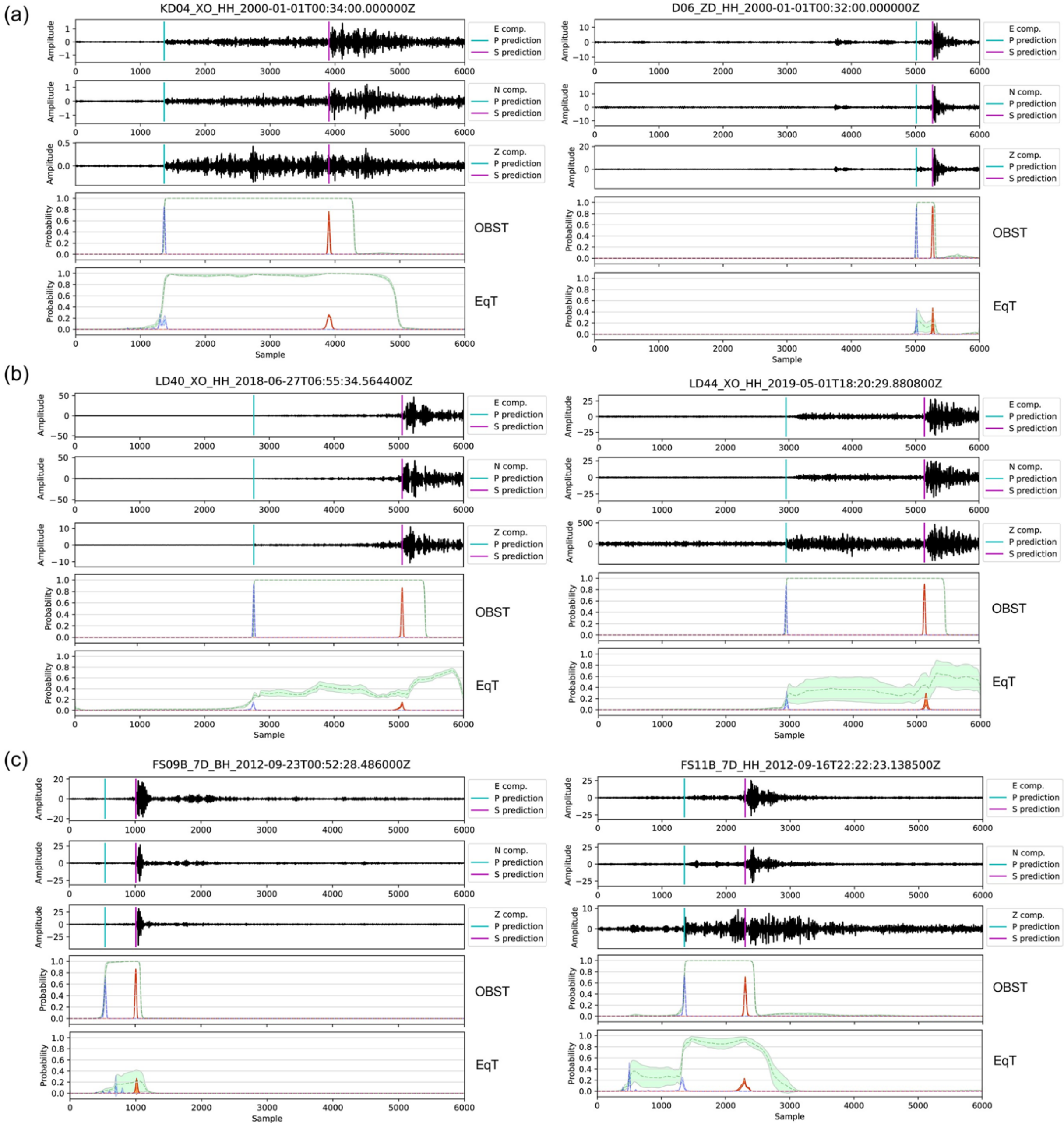
Niksejel and Zhang (2024)

- Compile a comprehensive data set of catalogued earthquakes recorded by 423 OBSs from 11 temporary deployments worldwide.
- Label the P and S phases of these earthquakes by analysing the consistency of at least three arrivals from widely used machine learning pickers (e.g., EQTransformer, PhaseNet).
- Use this data set for transfer learning and utilize EQTransformer as the base model.
- Add 25,000 OBS noise samples from the same OBS networks, which are then used for model training alongside the labelled earthquake samples.

OBSTransformer

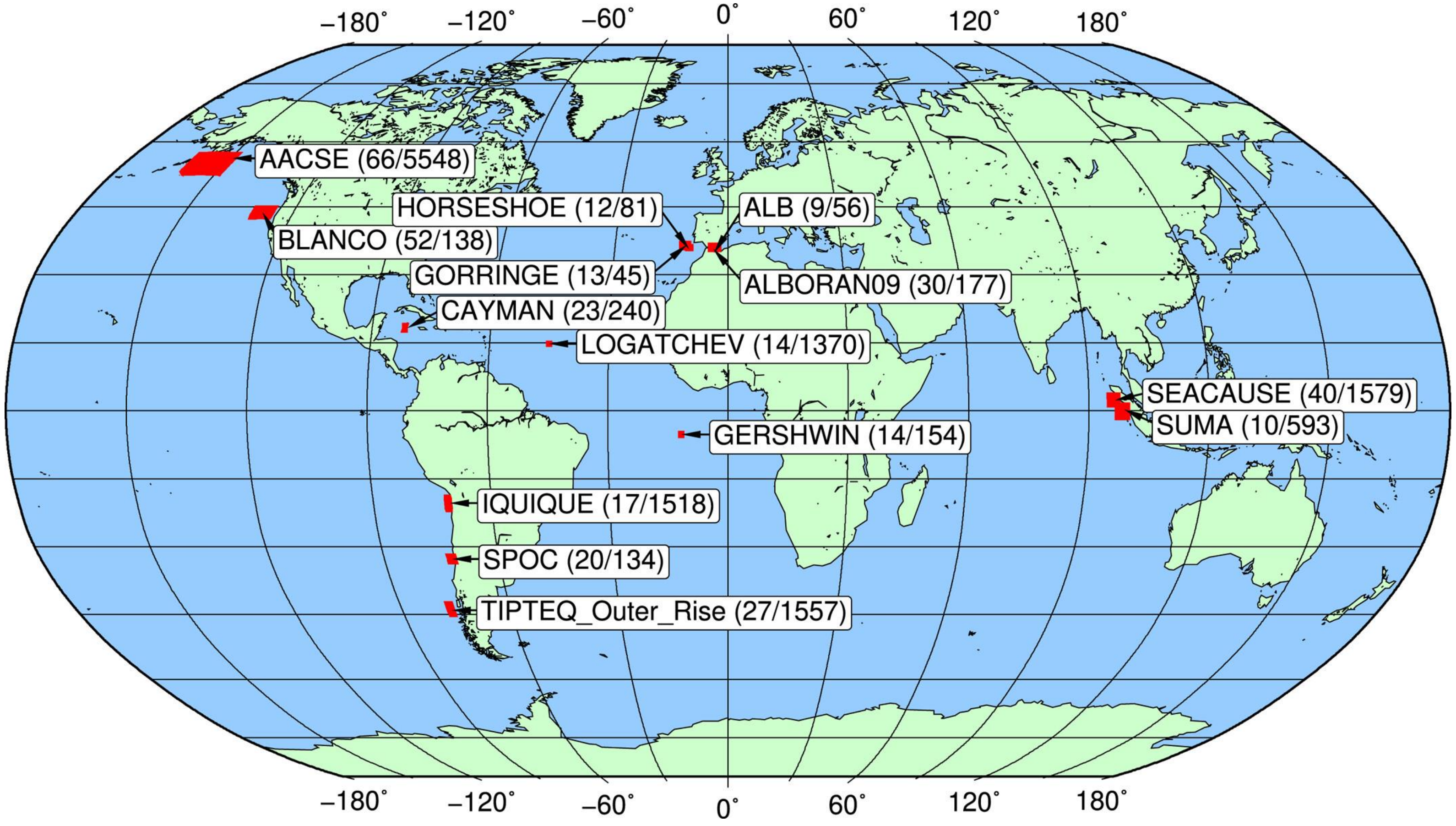
Auto-labeler





Niksejel and Zhang (2024)

PickBlue

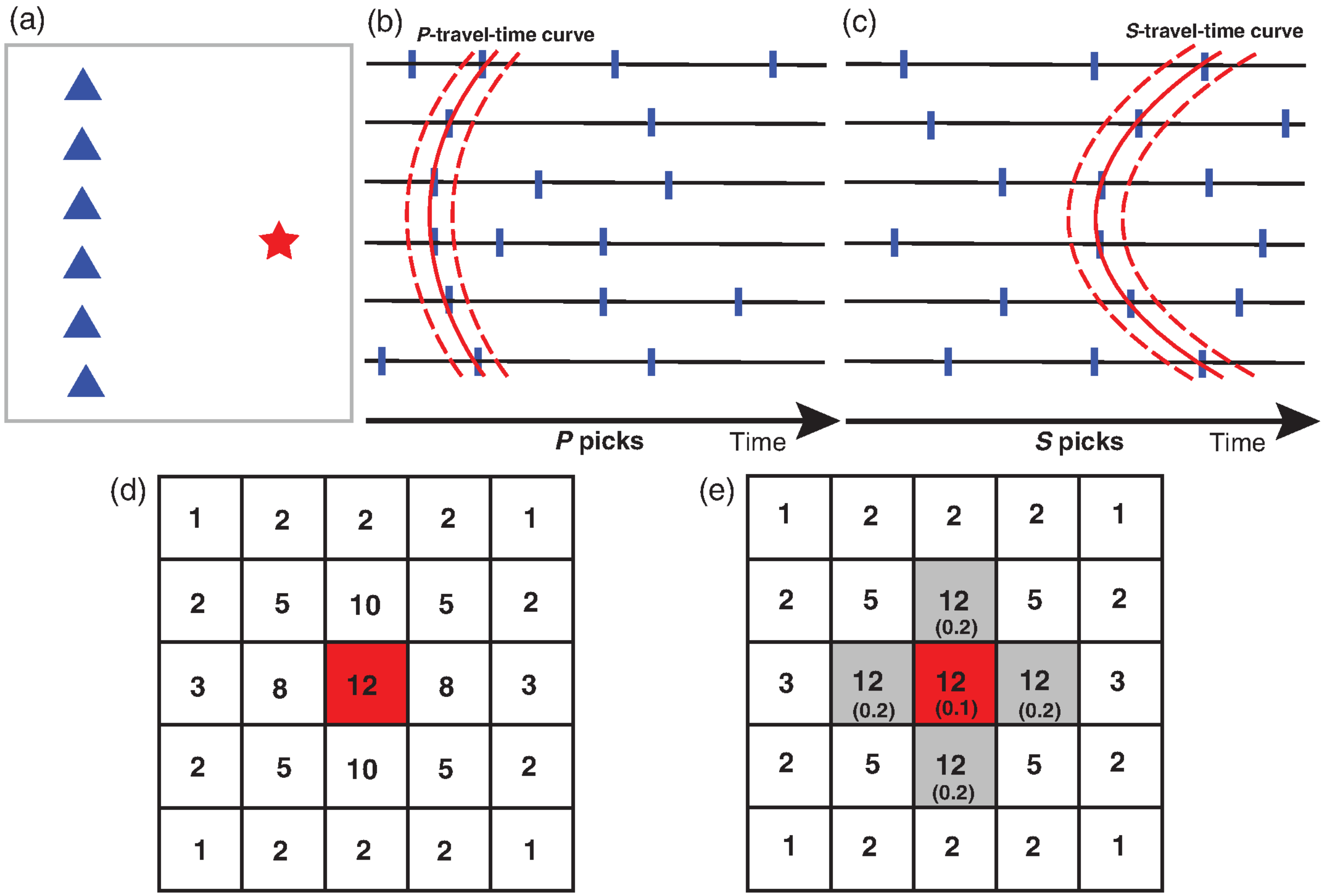


Bornstein et al. (2023)

- Compiled an extensive and labelled OBS data set from 15 deployments in different tectonic settings. C
- Data set comprises ~90,000 P and ~63,000 S manual picks from 13,190 events and 355 stations.
- Includes hydrophone component.
- Transfer learning of DL models based on the architecture of either PhaseNet and EQTransformer trained on land data.
- Applied to HOBITSS

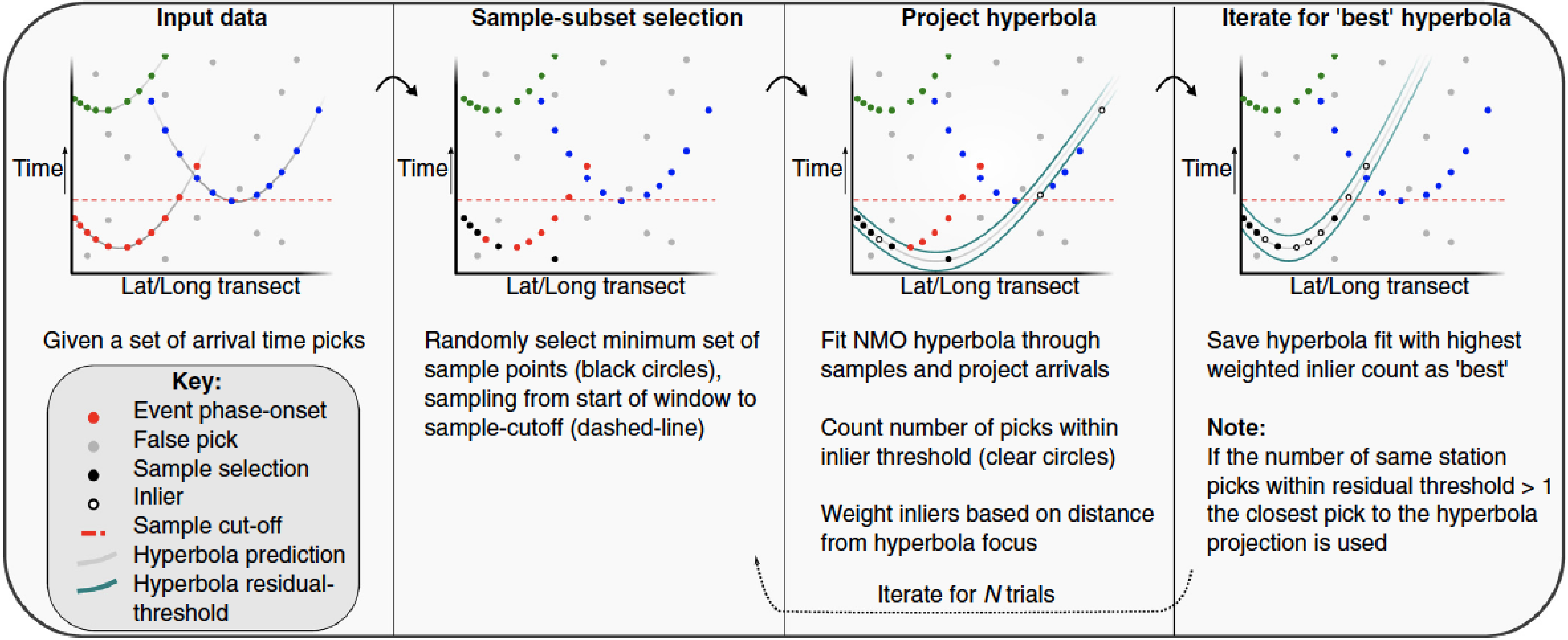
Rapid **E**arthquake **A**ssociation and **L**ocation (REAL)

- Optimized grid-search algorithm.
- Instead of searching a full space-time grid, REAL is based on the assumption that a station close to the event will record the first P pick.
- Starting with one P pick, a grid search is performed in a volume around the picking stations.
- This reduces the search space from the whole study area to a smaller volume.
- In addition, it removes the time dimension from the search, as the approximate origin time for each potential origin can be inferred from the starting pick.
- REAL can use homogeneous and 1D velocity models.



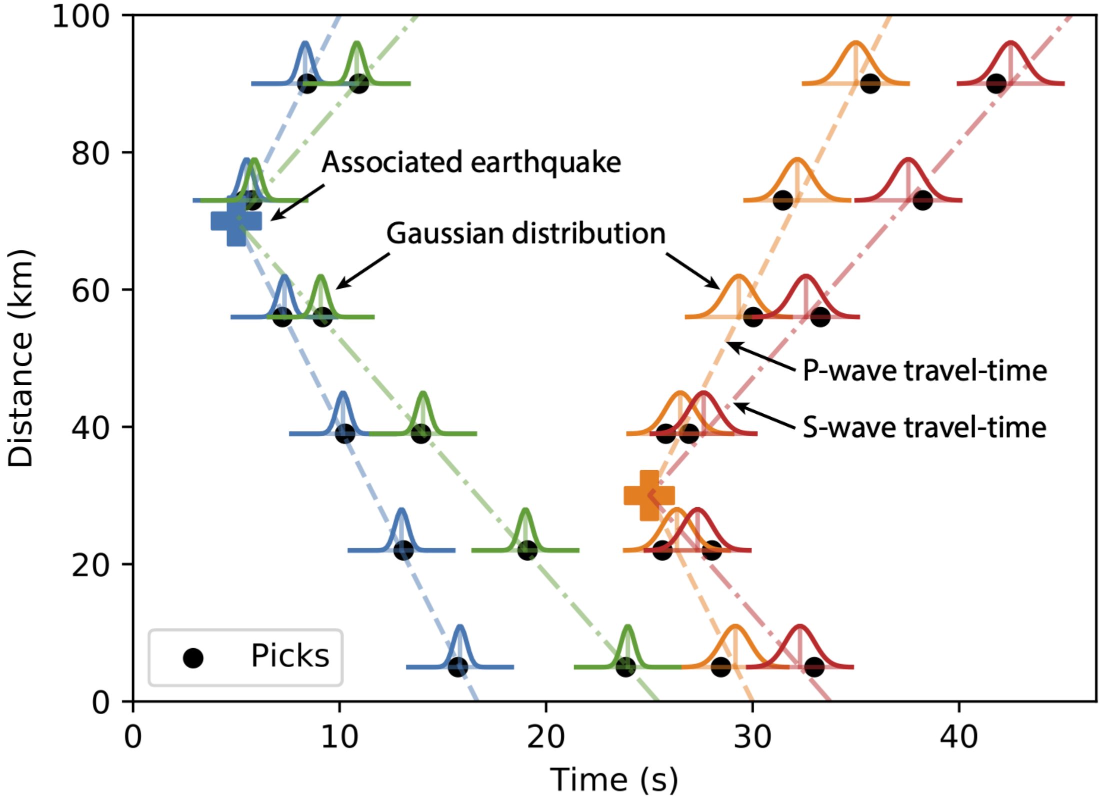
Zhang et al. (2019)

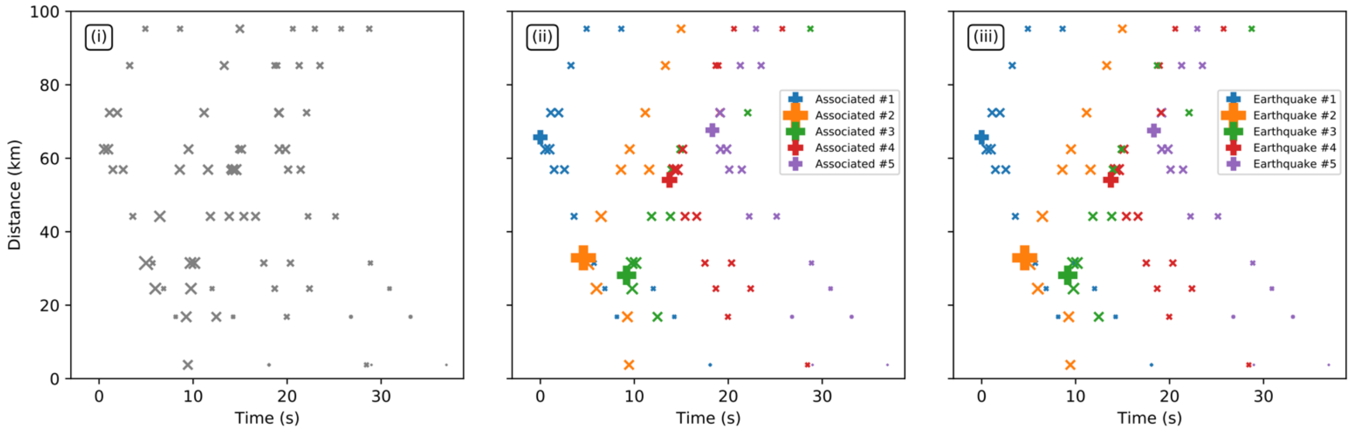
HEX: **H**yperbolic **E**vent e**X**tractor

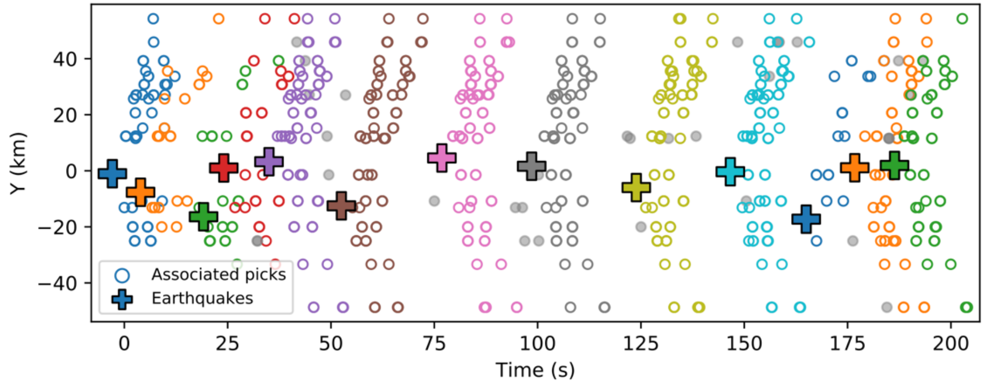


Woollam et al. (2021)

GaMMA: **Ga**ussian **M**ixture **M**odel **A**ssociator



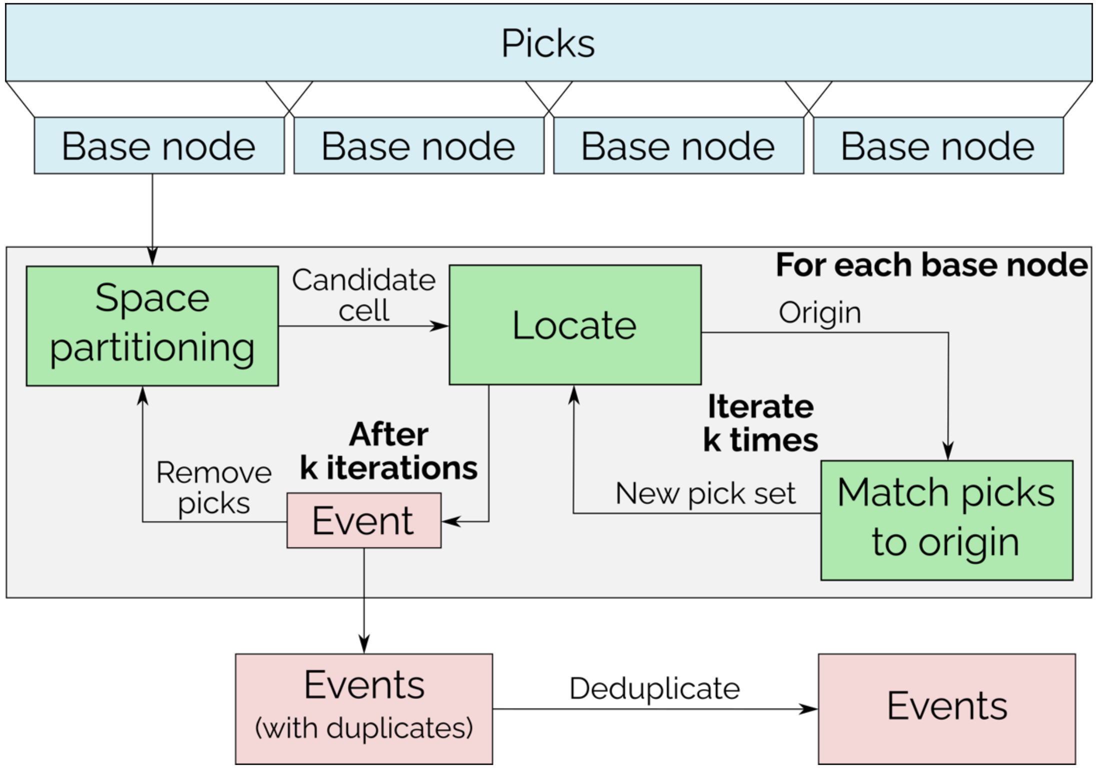




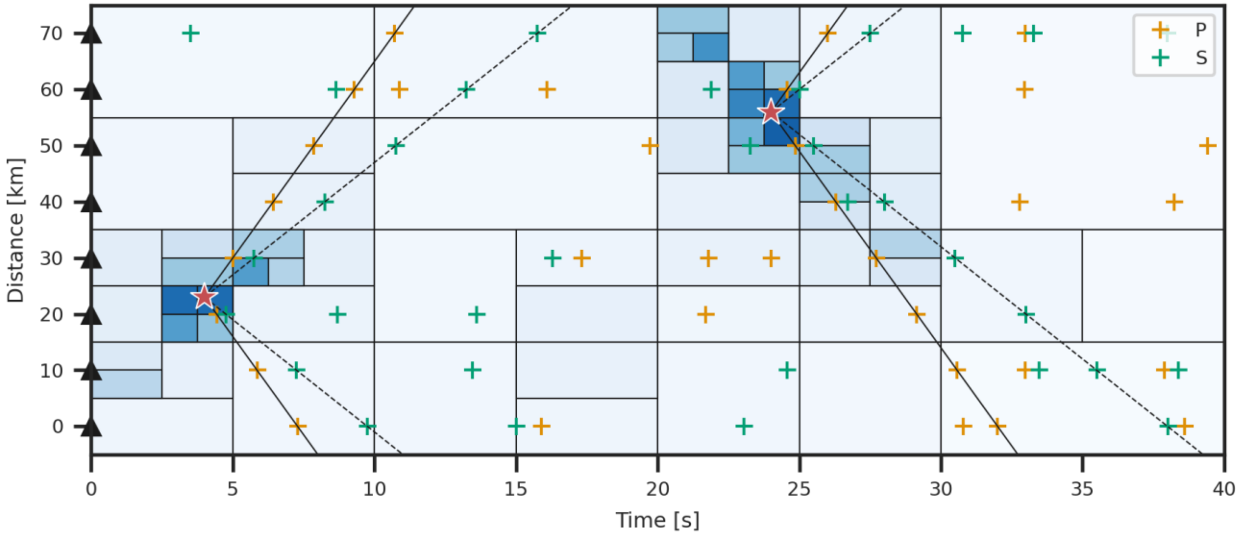
- Based on hyperbolic phase association that follows the physics of wave propagation in a homogeneous medium.
- The method interprets the picks as a Gaussian mixture, with each event being a different mixture component.
- GaMMA uses DBSCAN (Ester et al., 1996) to group picks before applying the EM algorithm to each cluster.
- Has been extended to 1D velocity and 3D velocity models (Ross et al., 2023)

Zhu et al. (2021)

PyOcto: **Py**thon associator using **Octo**tree data structure

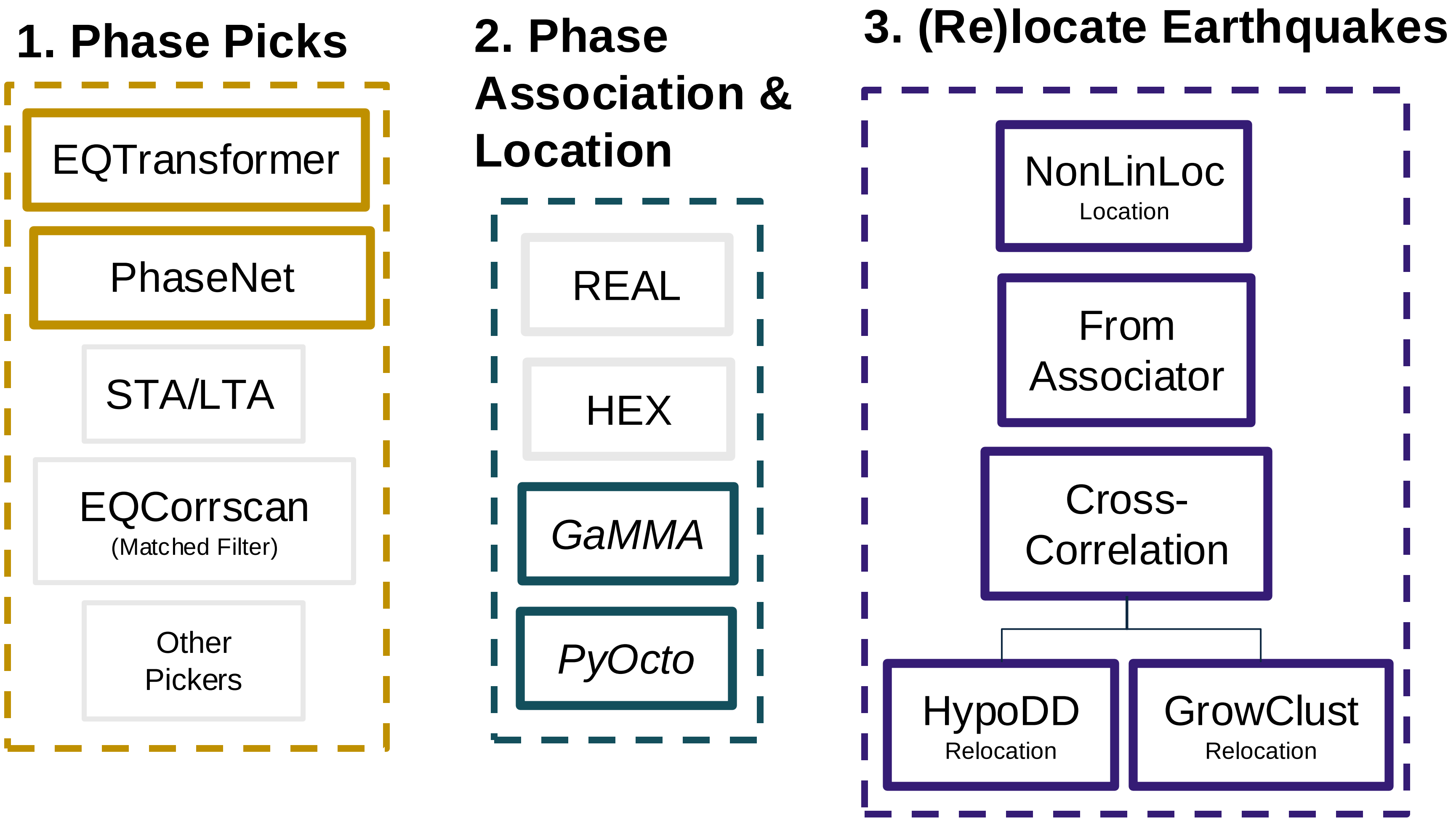


Münchmeyer (2024)



- Based on the idea of partitioning 4D space-time space into potential origins based on octotree structure.
- Mimics a grid-search associator while only looking at “useful” grid cells.
- Uses 1D velocity structure.
- Achieves fast run times by only exploring promising origin regions, making it a high-throughout phase associator.

Modern workflow



So many options!!

Modern workflow: labelling and (re)training

QuakeLabeler

Fast AI Seismic Annotation Tool

ML platform in seismology for:

- Retrieving raw waveforms from online data centers
- Customizing automation modules
- Processing and augmenting data
- Annotating by online reviewed catalog
- Visualizing data distribution

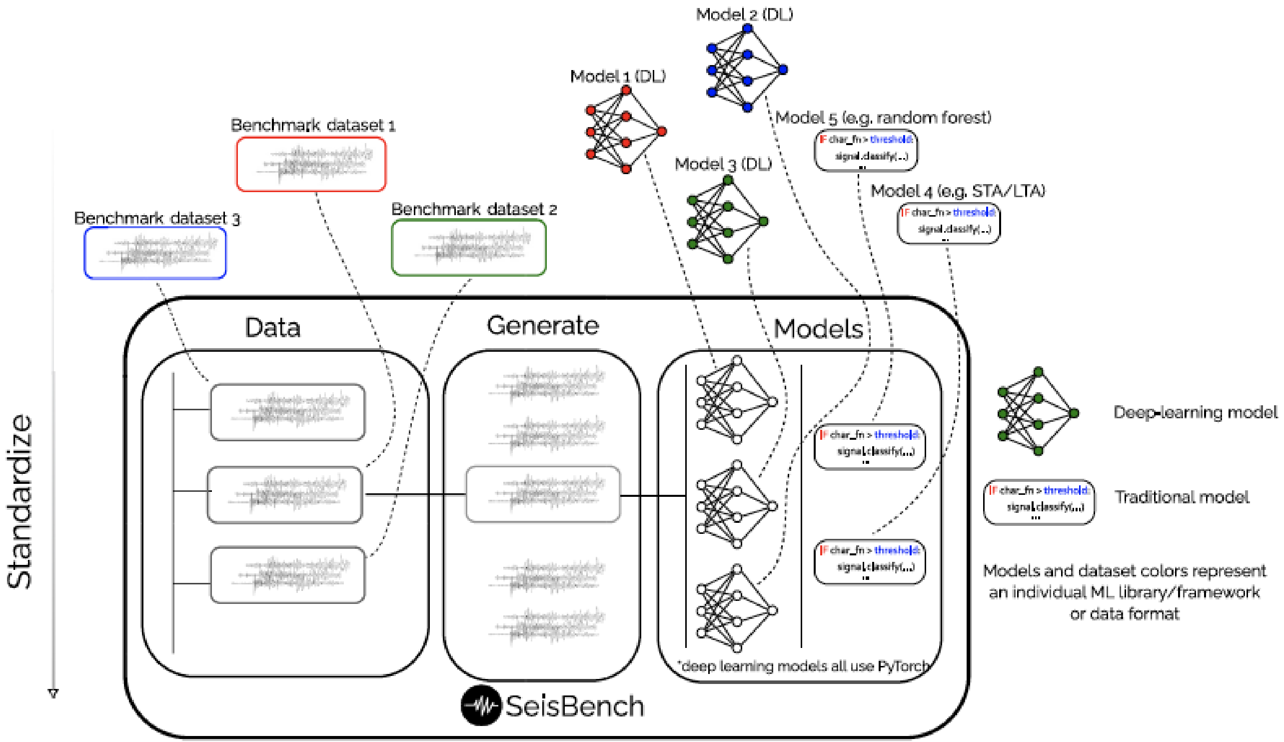
Mai and Audet (2022)

blockly eqtransformer

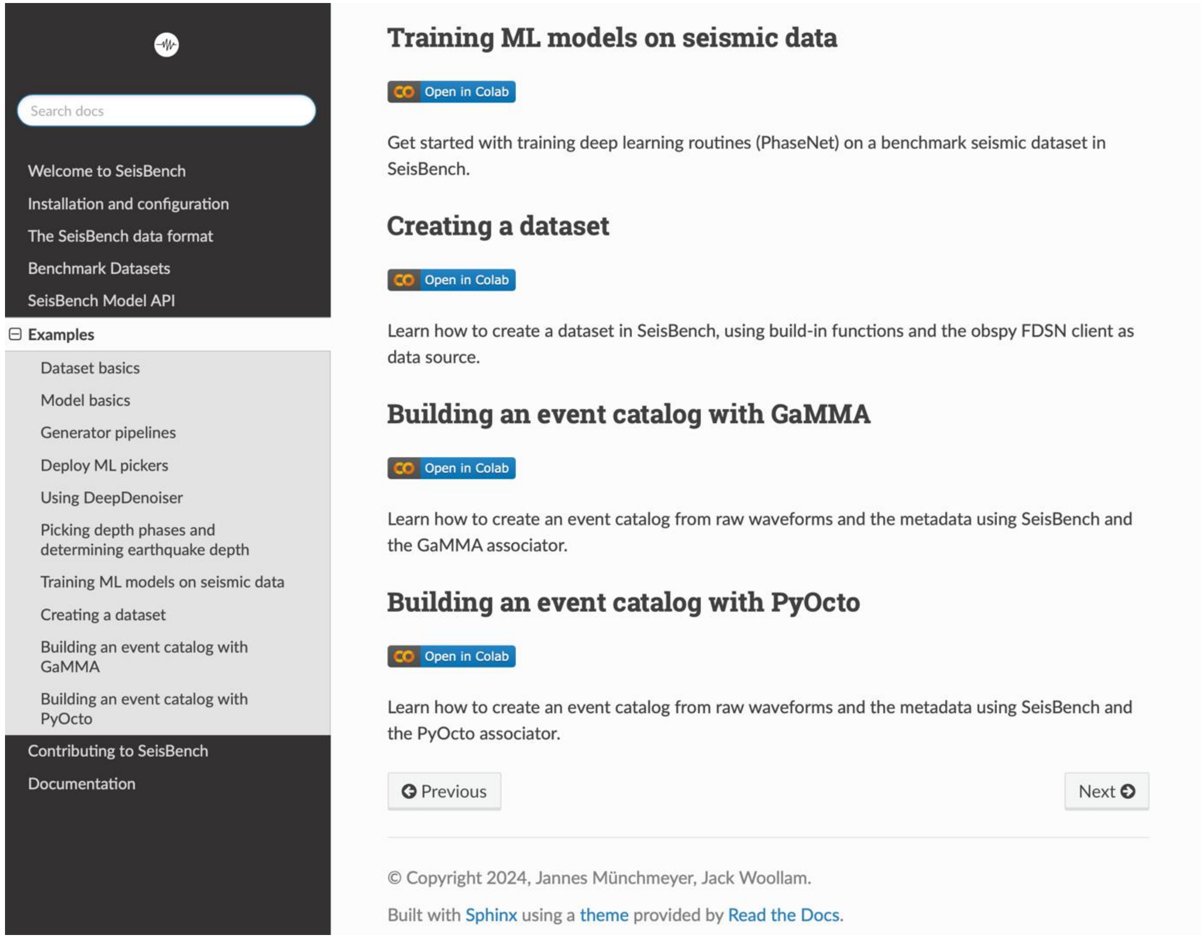
- No-code, deep learning approach using the EqT model
- Transfer learning is available to extend the phase picking range from P and S phase to additional phase types, e.g., Pn, Pg, Sn, Sg.
- The fine-tuning module customizes EqT model architecture to achieve better performance on specific datasets than currently published models.

Mai et al. (2023)

Modern workflow: SeisBench



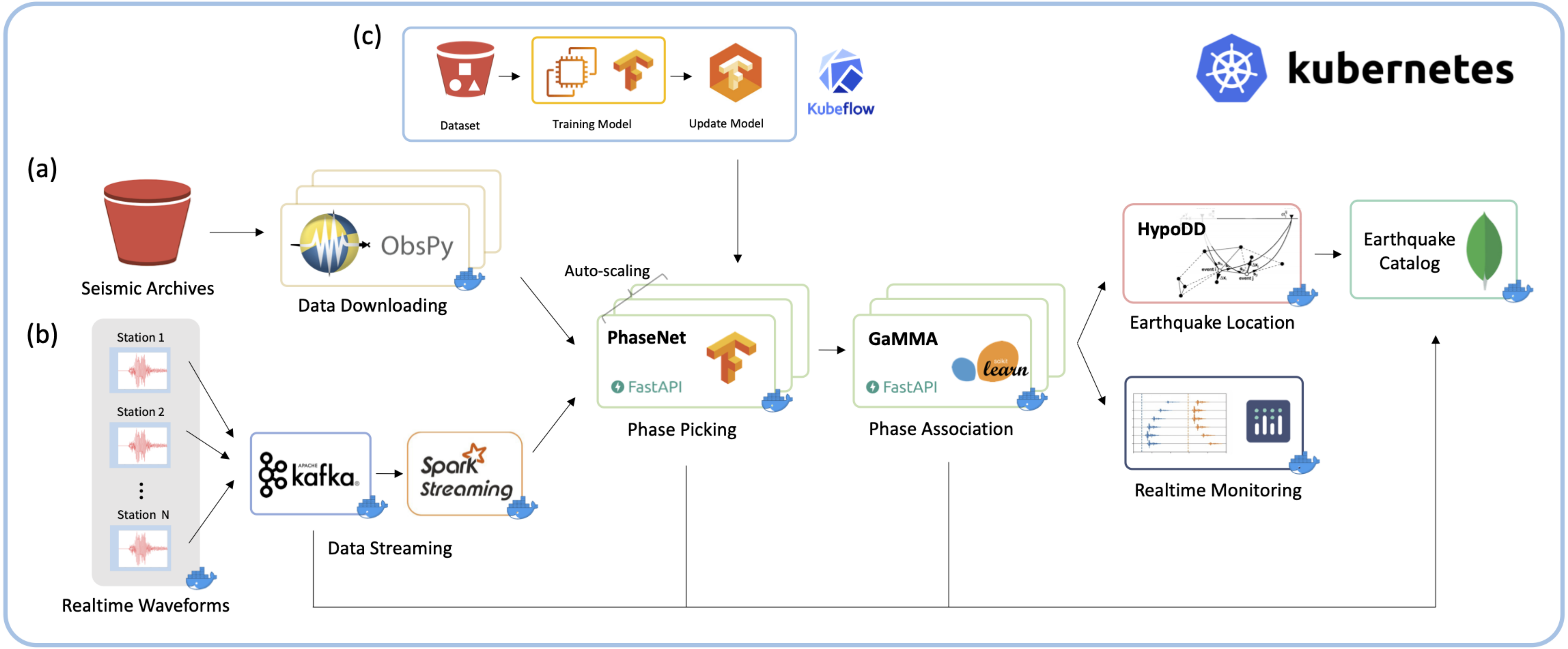
- Platform for ML in seismology
- All-in-one solution for ML picker deployment, (re)training, denoising, creating catalogue, etc.



Woollam et al. (2022)

Modern workflow: QuakeFlow

- All-in-one: from seismic data to (real-time) earthquake catalogues
- Cloud-based computing



Zhu et al. (2023)

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