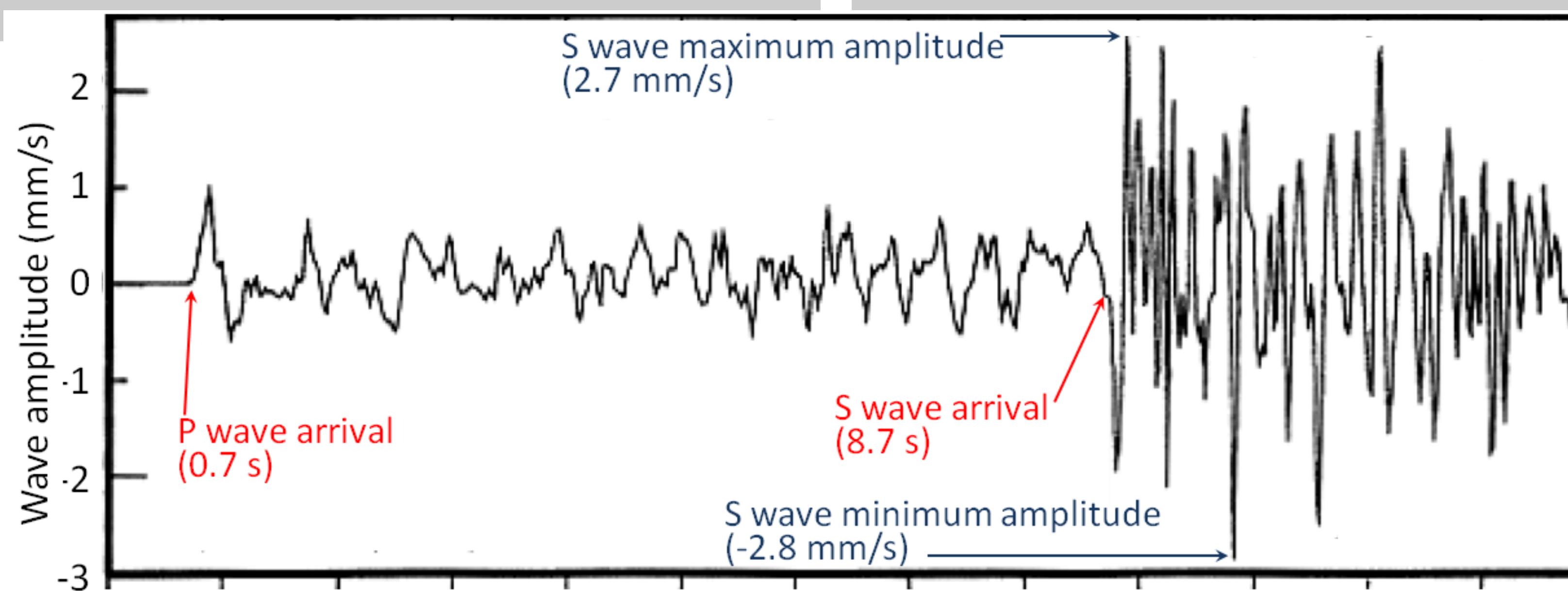
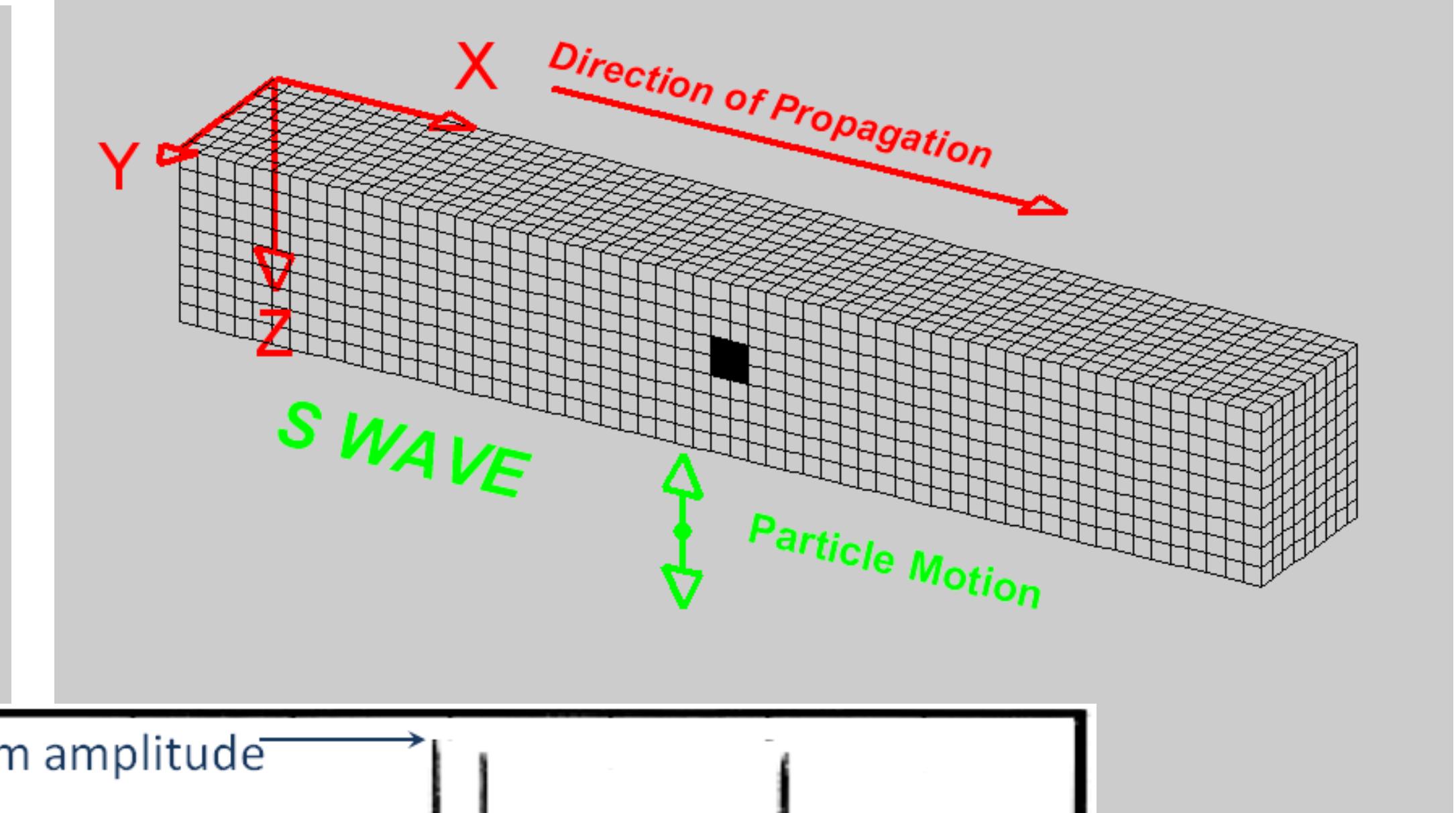
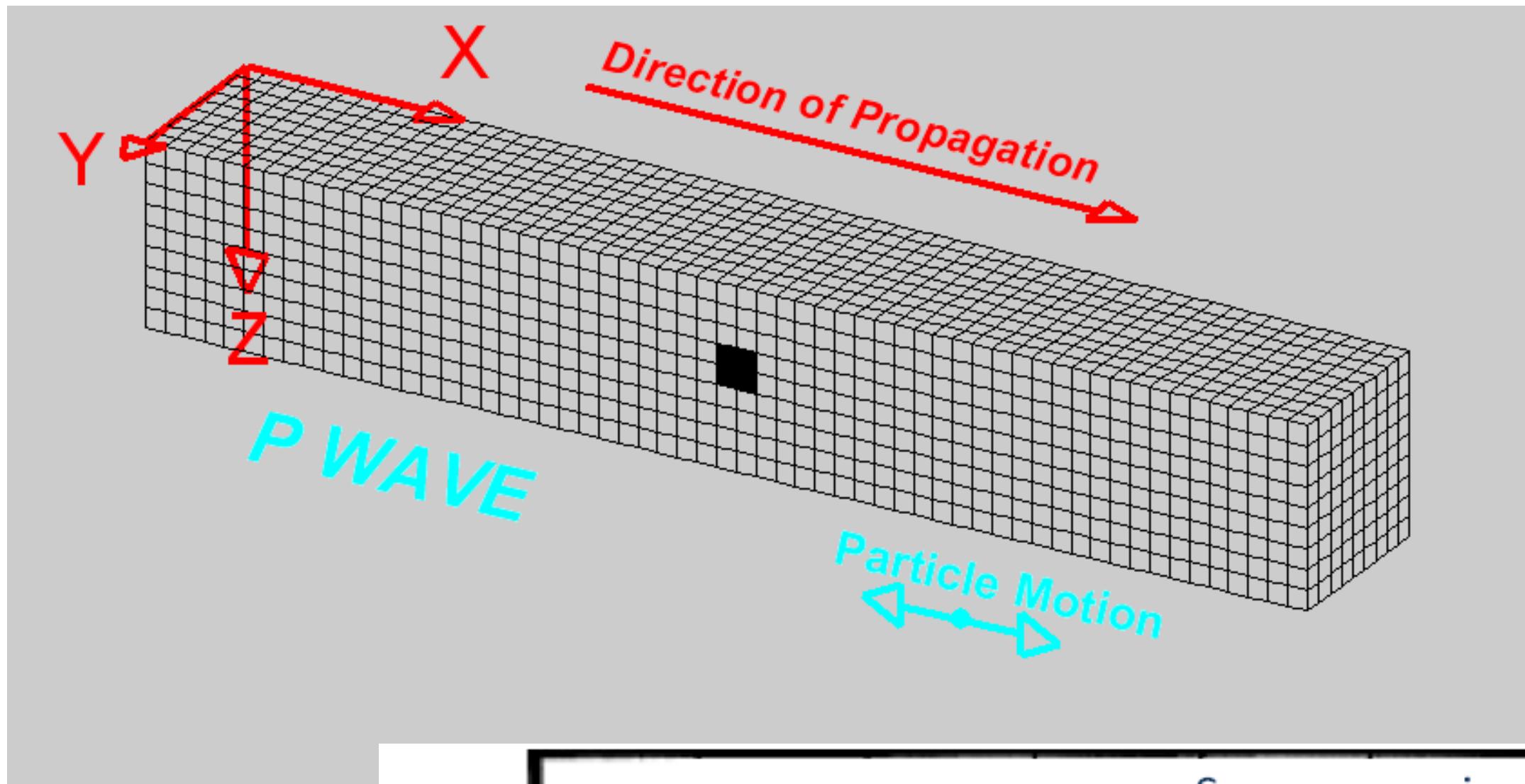


# **Microearthquakes detection, phase picking, and location**

**Basic theory, applications, and challenges**

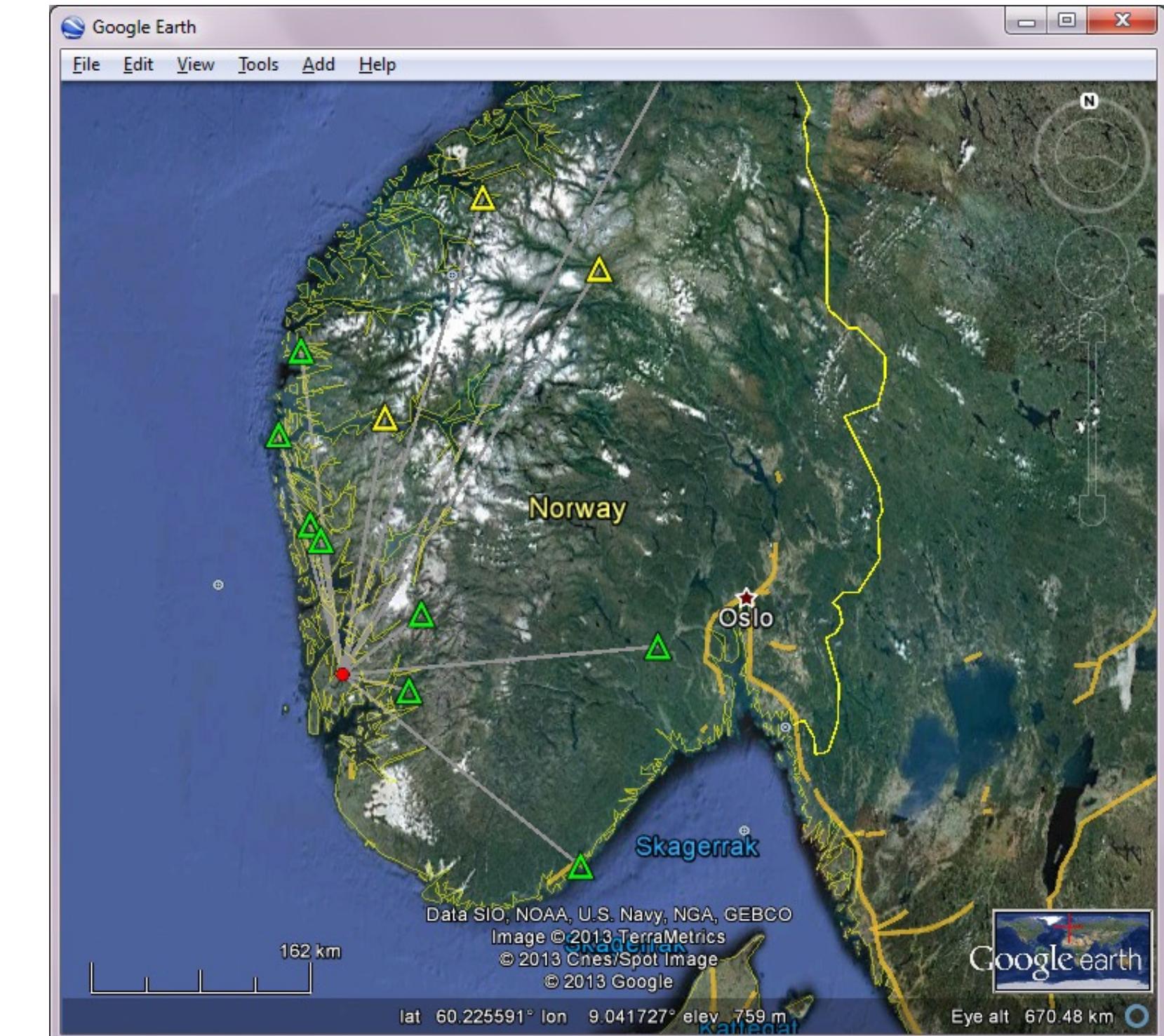
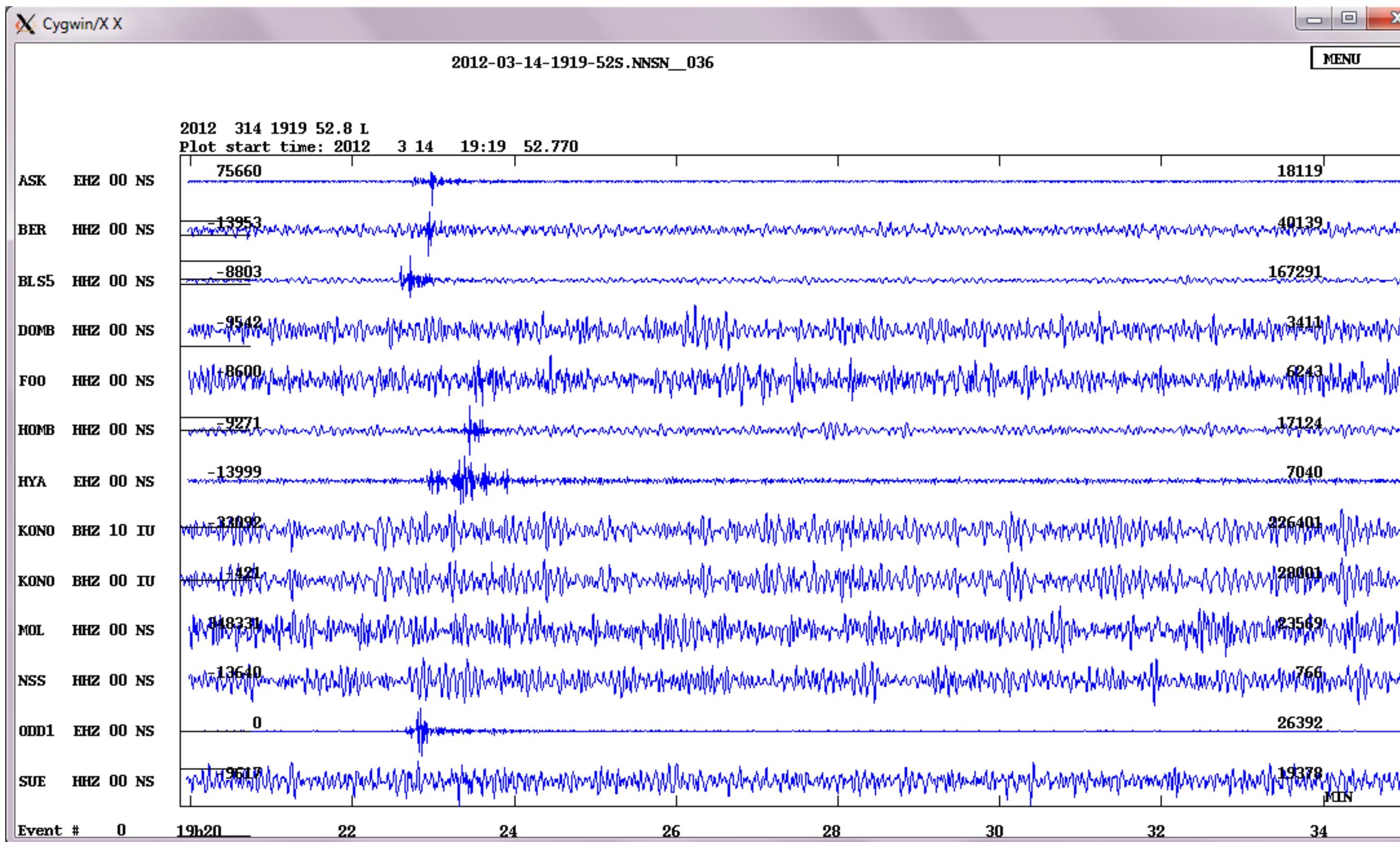
**S.M. Momeni, 16 November, 2020**

# Seismic waves

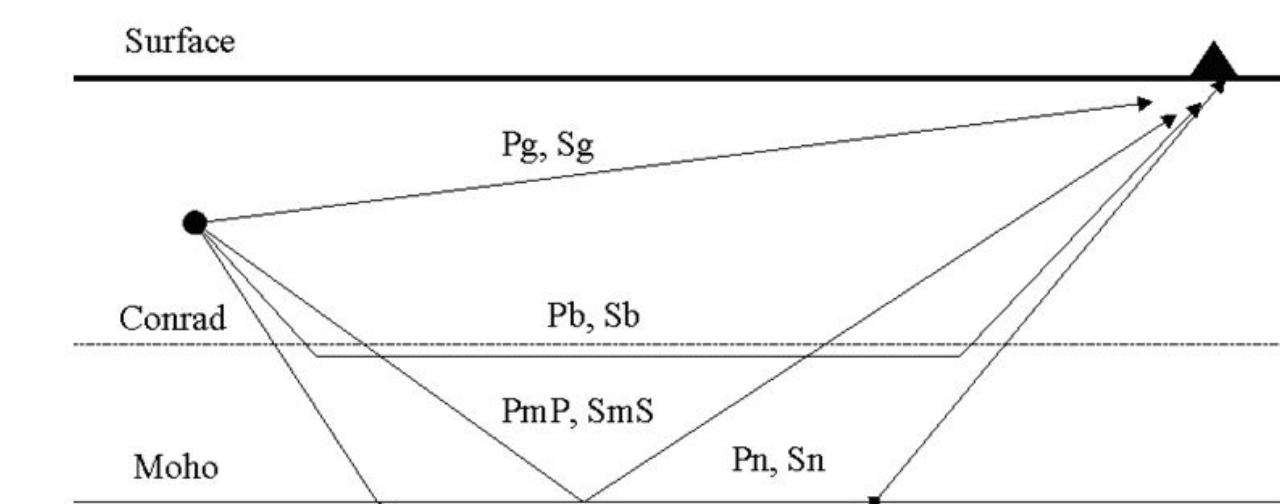


# What continuous Seismic waves look like?

## Local seismic data



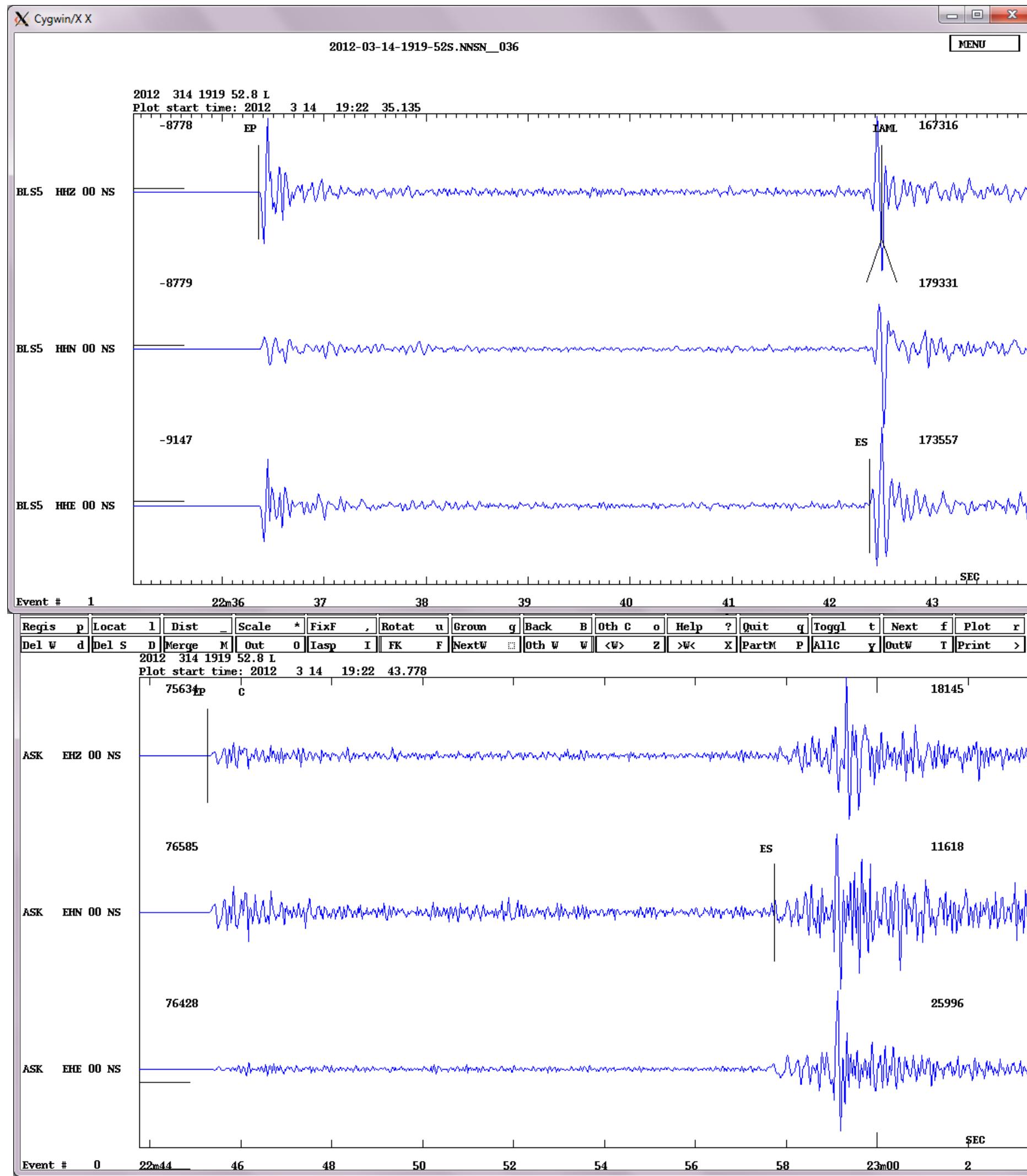
Local layered model



A simplified model of the crust showing the most important crustal phases observed at local and regional distances

# Our goal

## earthquake detection, phase picking, and location



$$d_1 = V_p^* T_{p1}$$

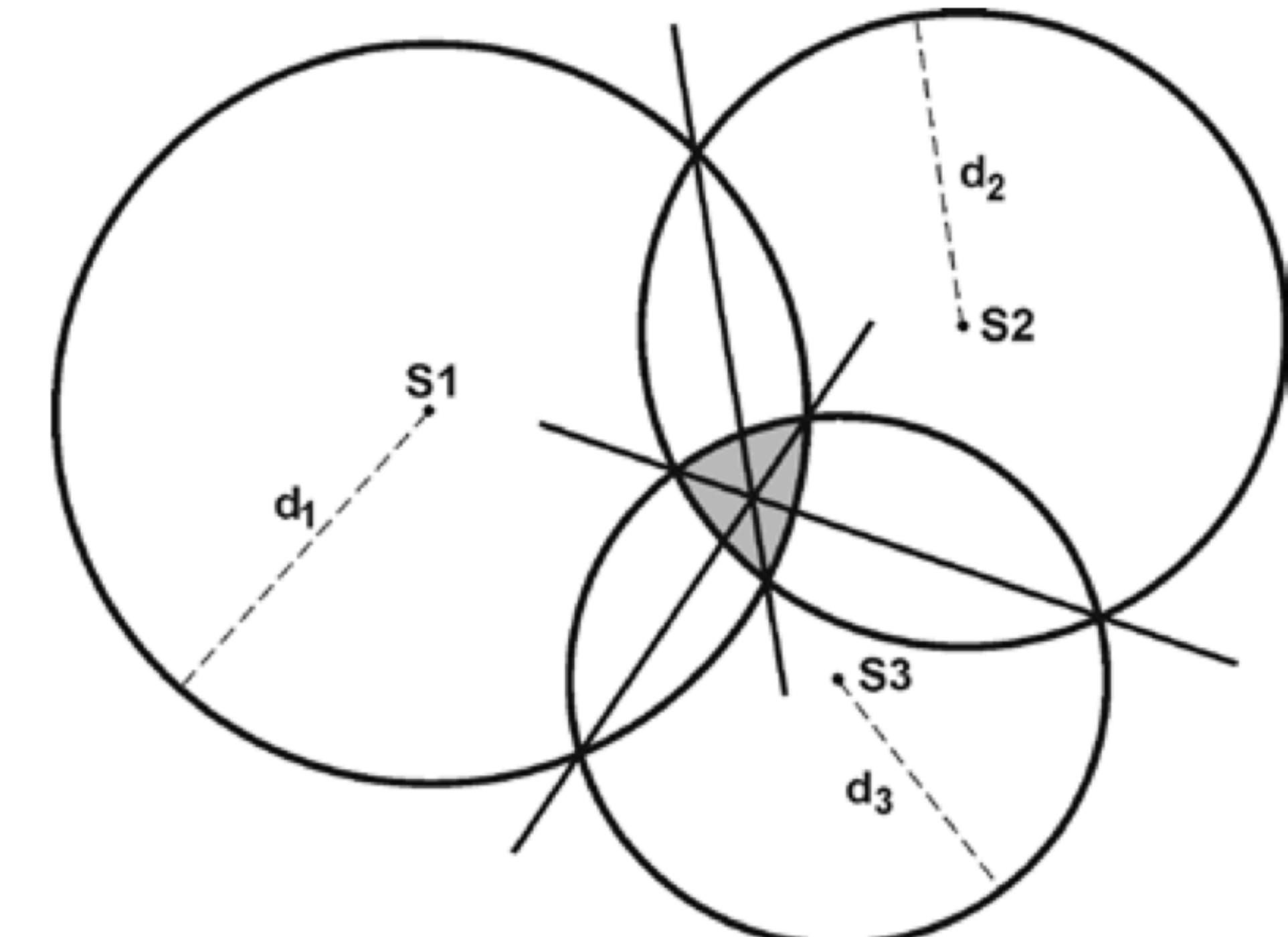
$$d_2 = V_p^* T_{p2}$$

$$d_3 = V_p^* T_{p3}$$

$$d_1 = V_s^* T_{s1}$$

$$d_2 = V_s^* T_{s2}$$

$$d_3 = V_s^* T_{s3}$$



ARTICLE



<https://doi.org/10.1038/s41467-020-17591-w> OPEN

# Earthquake transformer—an attentive deep-learning model for simultaneous earthquake detection and phase picking

S. Mostafa Mousavi<sup>1</sup>✉, William L. Ellsworth<sup>1</sup>, Weiqiang Zhu<sup>1</sup>, Lindsay Y. Chuang<sup>2</sup> & Gregory C. Beroza<sup>1</sup>

Earthquake signal detection and seismic phase picking are challenging tasks in the processing of noisy data and the monitoring of microearthquakes. Here we present a global deep-learning model for simultaneous earthquake detection and phase picking. Performing these two related tasks in tandem improves model performance in each individual task by combining information in phases and in the full waveform of earthquake signals by using a hierarchical attention mechanism. We show that our model outperforms previous deep-learning and traditional phase-picking and detection algorithms. Applying our model to 5 weeks of continuous data recorded during 2000 Tottori earthquakes in Japan, we were able to detect and locate two times more earthquakes using only a portion (less than 1/3) of seismic stations. Our model picks P and S phases with precision close to manual picks by human analysts; however, its high efficiency and higher sensitivity can result in detecting and characterizing more and smaller events.

# EQtransformer

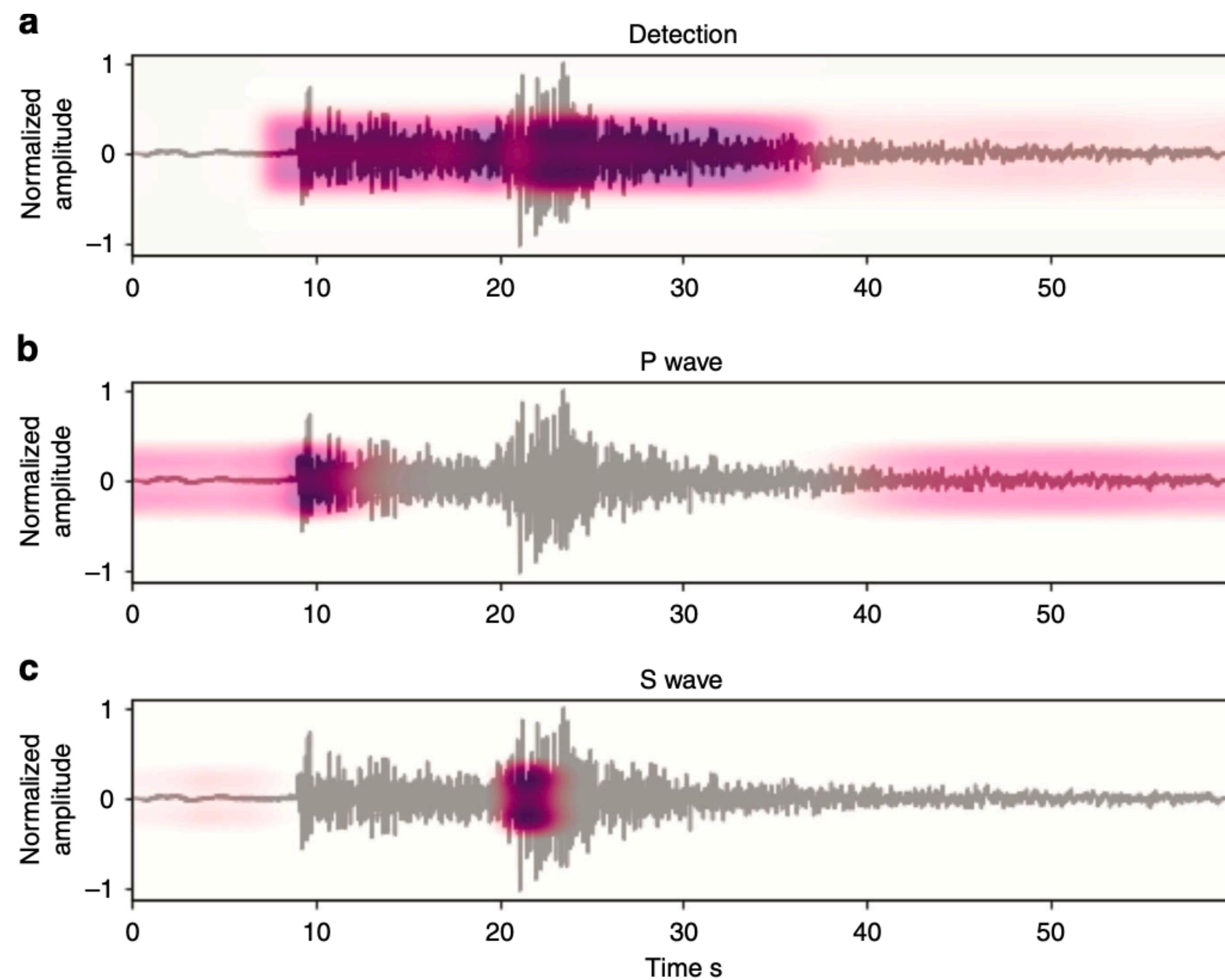
## Algorithm

The Network is trained by the Stanford earthquake dataset (>1 million earthquake waves)

The global attention algorithm detects the earthquake

The local attention algorithm reads the P and S wave arrival times.

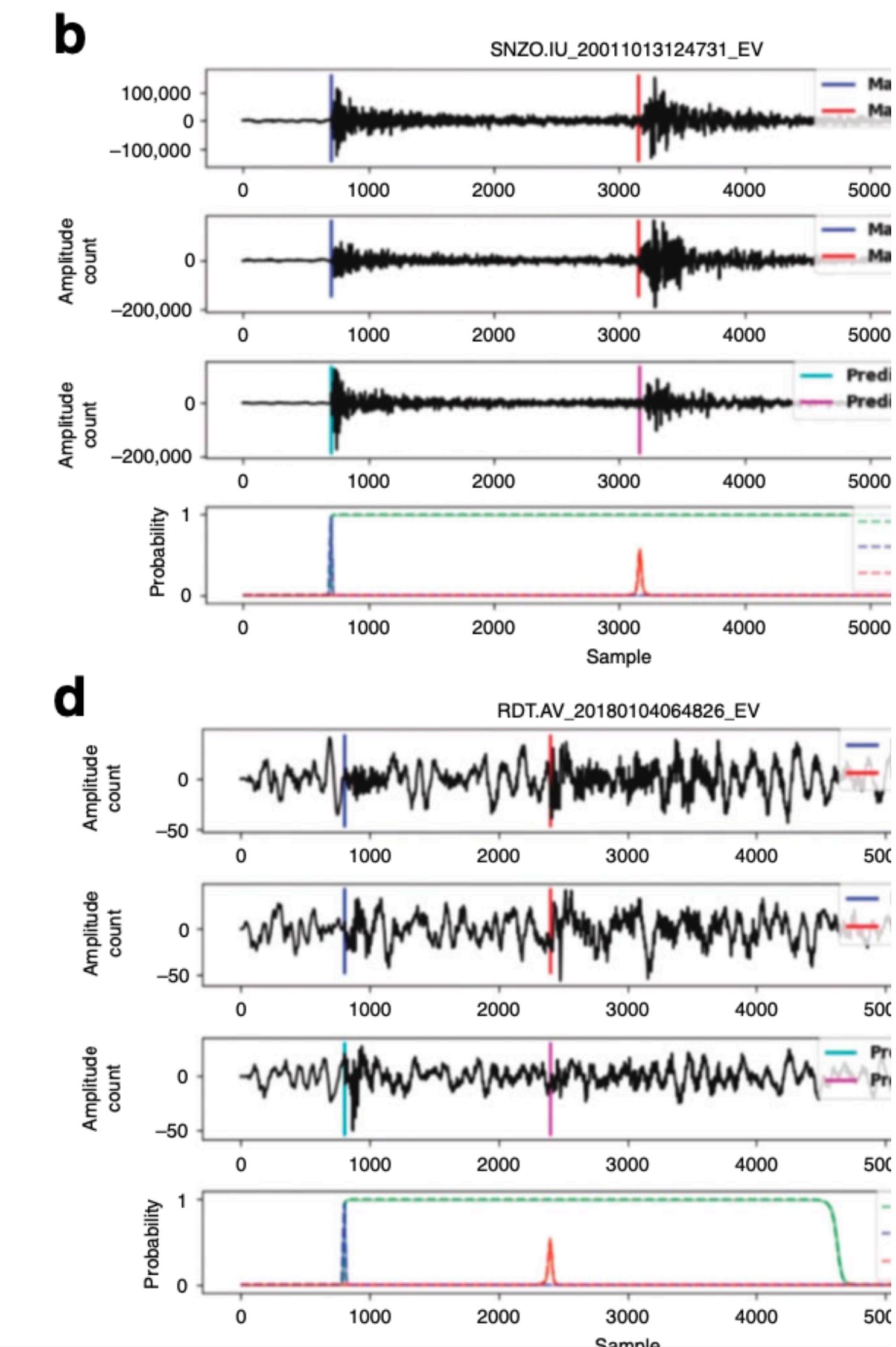
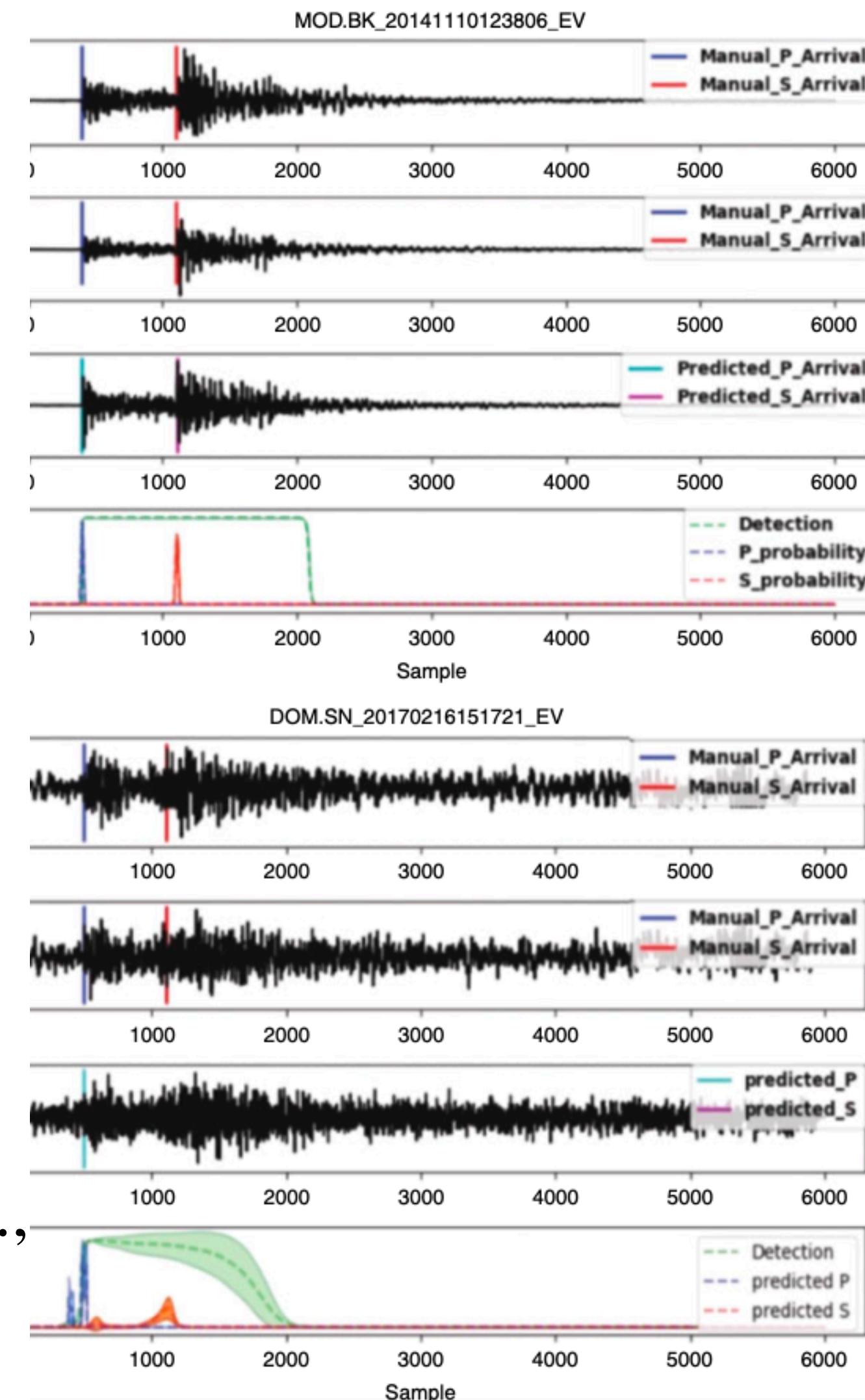
S. Mostafa Mousavi et al., (2020)



**Fig. 3 Attention weights.** Input waveform overlain by contextual information - output of the attention layers for **a** transformer (I in Fig 1), **b** local attention for P-phase (II in Fig 1), and **c** the local attention for S-phase (III in Fig 1).

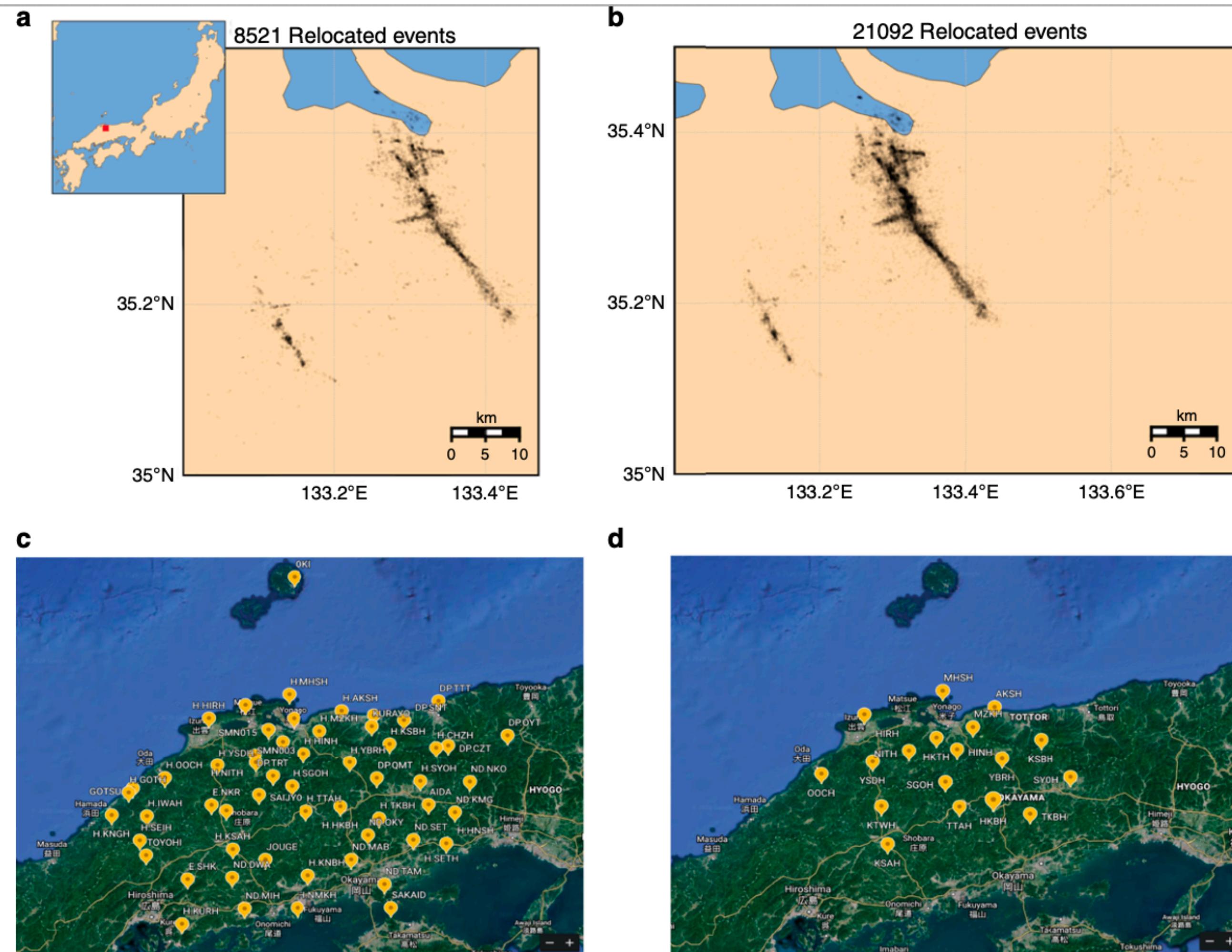
# EQtransformer

## Picking performance



# EQtransformer

## Test

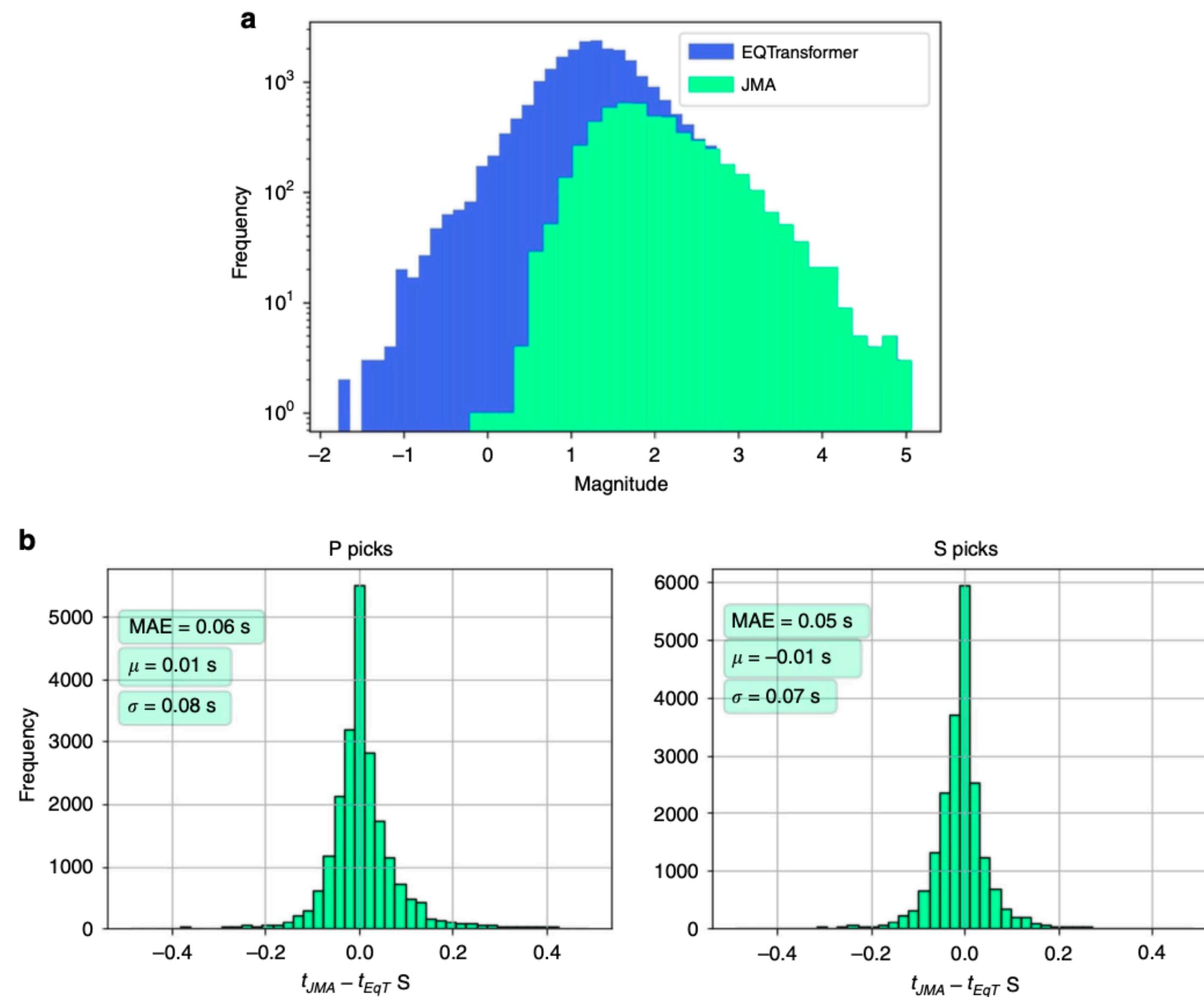


S. Mostafa Mousavi et al.,  
(2020)

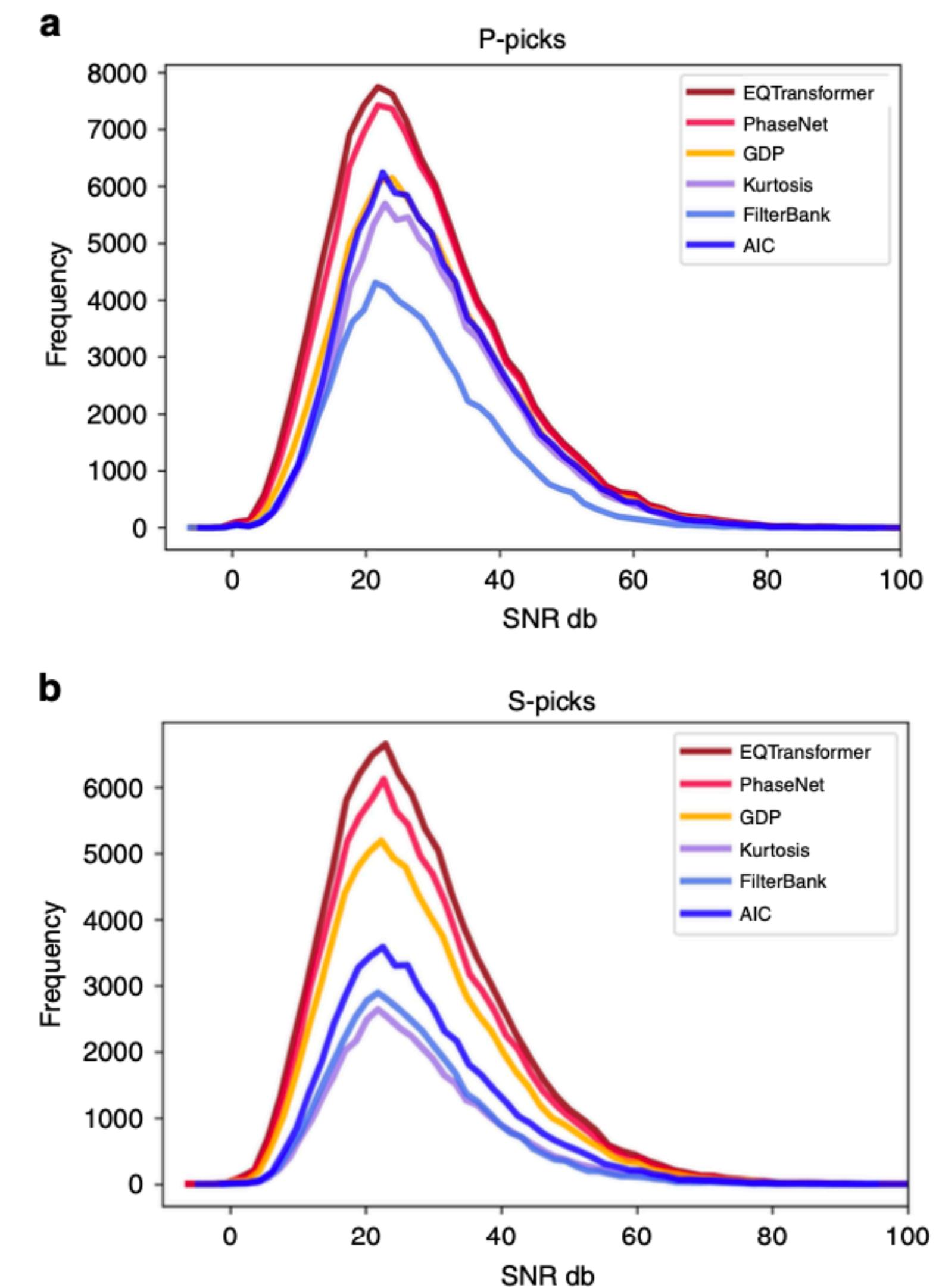
**Fig. 5 Tottori Earthquakes.** Seismicity of Tottori region between 6 October and 17 November 2000. **a** relocated events in Fukuyama et al.<sup>22</sup> using manual phase picks by JMA. **b** relocated events using the automatic phase picker (EQTransformer) of this study. **c** Distribution of 57 seismic stations used by JMA and Fukuyama et al.<sup>22</sup> **d** distribution of 18 stations used in our study to detect and locate earthquakes in Tottori region.

# EQtransformer

## Advantages

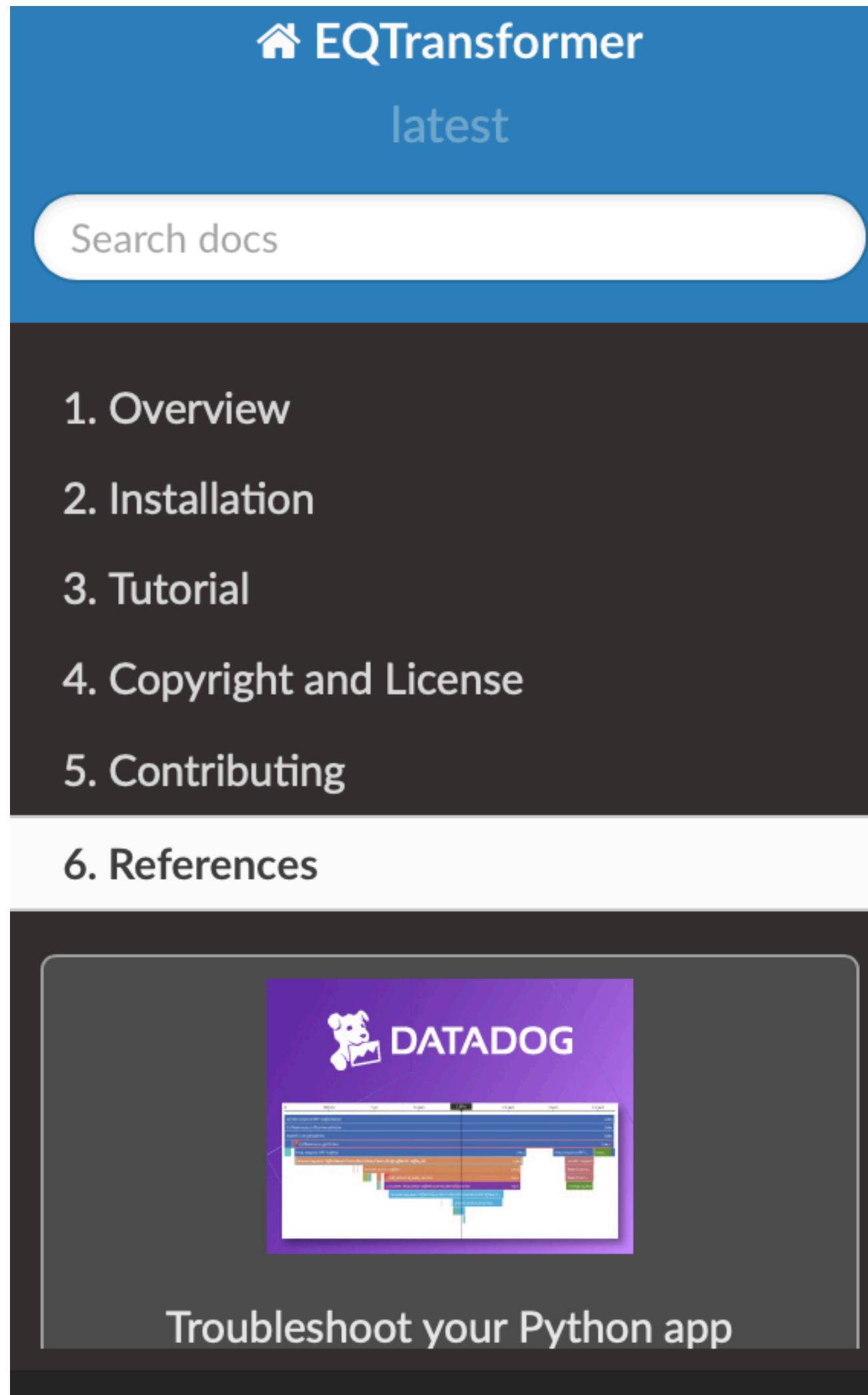


**Fig. 6 Distributions of frequency magnitude of earthquakes and picking errors.** **a** frequency-magnitude distributions of located events in JMA catalog and relocated events in our catalog (EQTransformer). Magnitudes for all events have been estimated using a local magnitude scale. **b** distributions of arrival-time differences (in second) between P (left) and S (right) picks by JMA's analysts and EQTransformer.



**Fig. 7 Phase picking performance as a function of noise level.** **P** (**a**) and **S** (**b**) phase picks as a function of signal-to-noise ratio (SNR) for three deep-learning and three traditional pickers.

# EQtransformer page <https://eqtransformer.readthedocs.io/en/latest/>



The screenshot shows the left sidebar of the EQTransformer documentation. At the top is a blue header bar with the 'EQTransformer' logo and the word 'latest'. Below it is a search bar labeled 'Search docs'. The sidebar contains a vertical list of navigation links: '1. Overview', '2. Installation', '3. Tutorial', '4. Copyright and License', '5. Contributing', and '6. References'. At the bottom of the sidebar is a purple rectangular box containing the Datadog logo and the text 'Troubleshoot your Python app'.

- 1. Overview
- 2. Installation
- 3. Tutorial
- 4. Copyright and License
- 5. Contributing
- 6. References

Troubleshoot your Python app

Docs » 6. References

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## 6. References

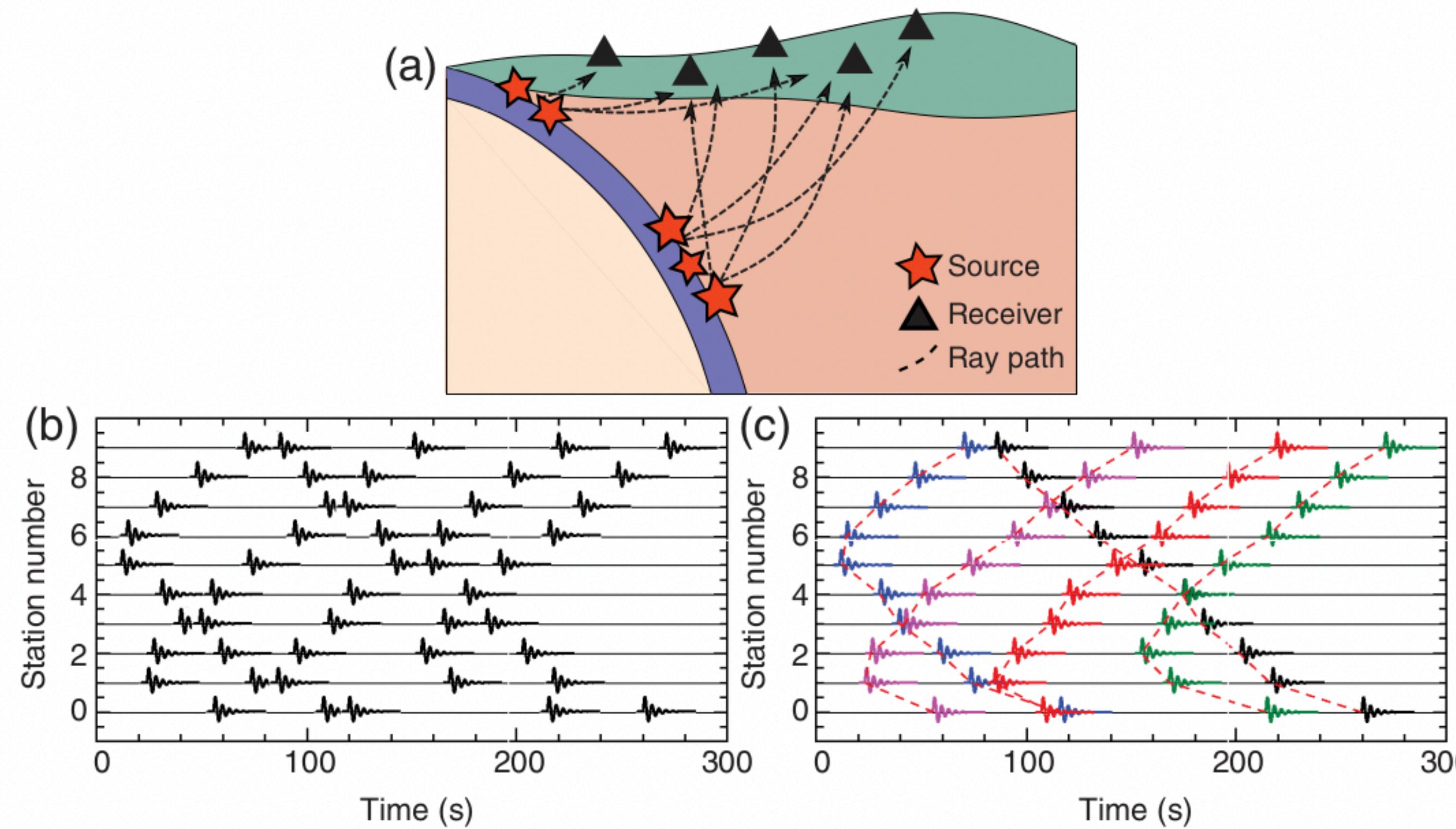
Wang, J., Xiao, Z., Liu, C., Zhao, D. & Yao, Z. Deep-Learning for Picking Seismic Arrival Times. *Journal of Geophysical Research: Solid Earth* (2019).

Zhu, L. et al. Deep learning for seismic phase detection and picking in the aftershock zone of 2008 Mw7.9 Wenchuan Earthquake. *Physics of the Earth and Planetary Interiors* (2019).

Zhou, Y., Yue, H., Kong, Q. & Zhou, S. Hybrid Event Detection and Phase-Picking Algorithm Using Convolutional and Recurrent Neural Networks. *Seismological Research Letters* 90, 1079–1087 (2019).

Mousavi, S. M., Zhu, W., Sheng, Y. & Beroza, G. C. CRED: A deep residual network of convolutional and recurrent units for earthquake signal detection. *Scientific reports* 9.

# Your contribution



# Applications

Earthquake hazard assessment for :  
Cities, power plants, dams, mines...

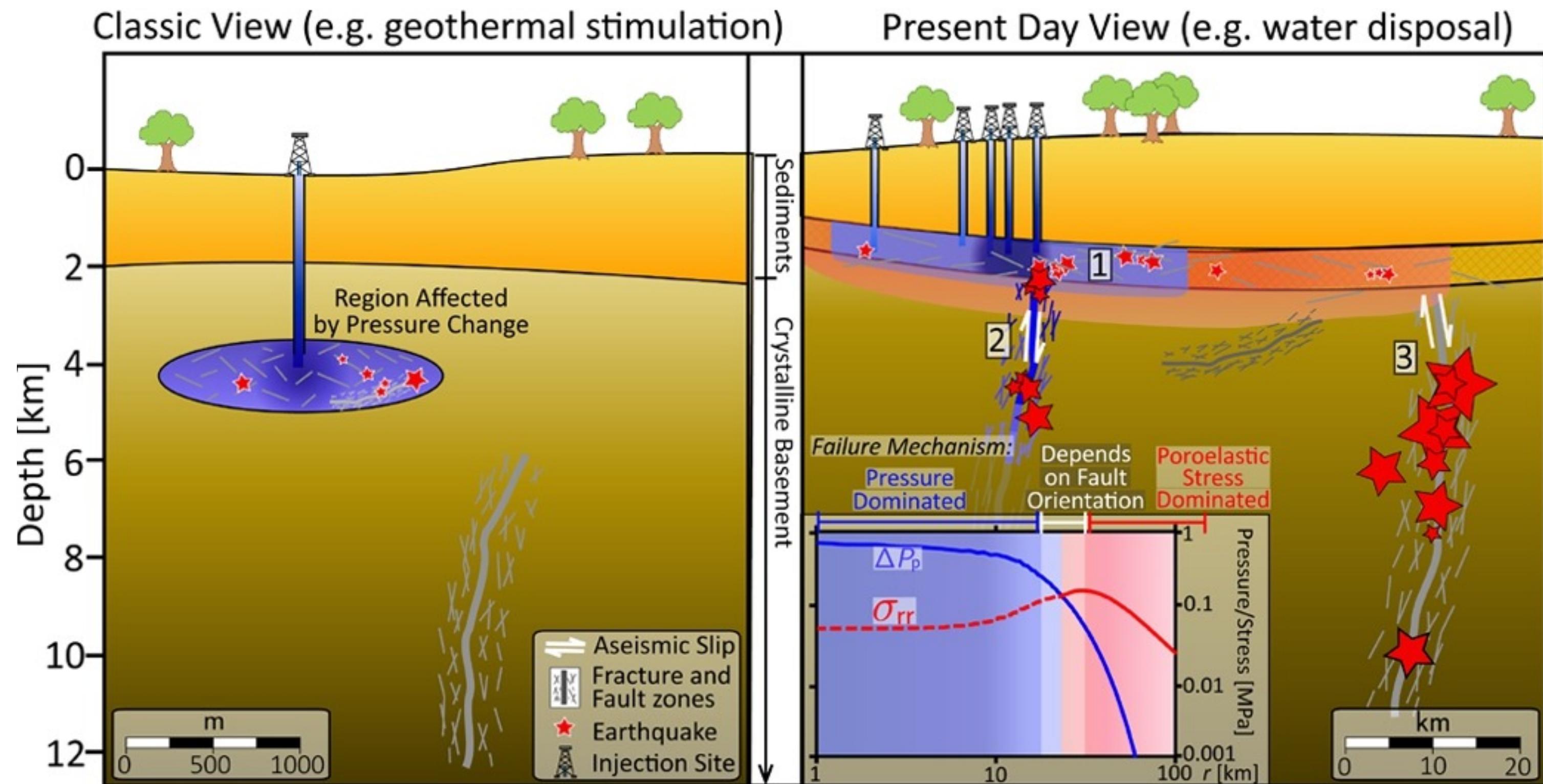
Monitoring Volcanoes activities

Hydraulic fracturing

Crack monitoring

Military purposes

...



Goebel et al., 2017. The 2016 Mw5.1 Fairview, Oklahoma earthquakes:  
Evidence for long-range poroelastic triggering at >40 km from fluid disposal wells