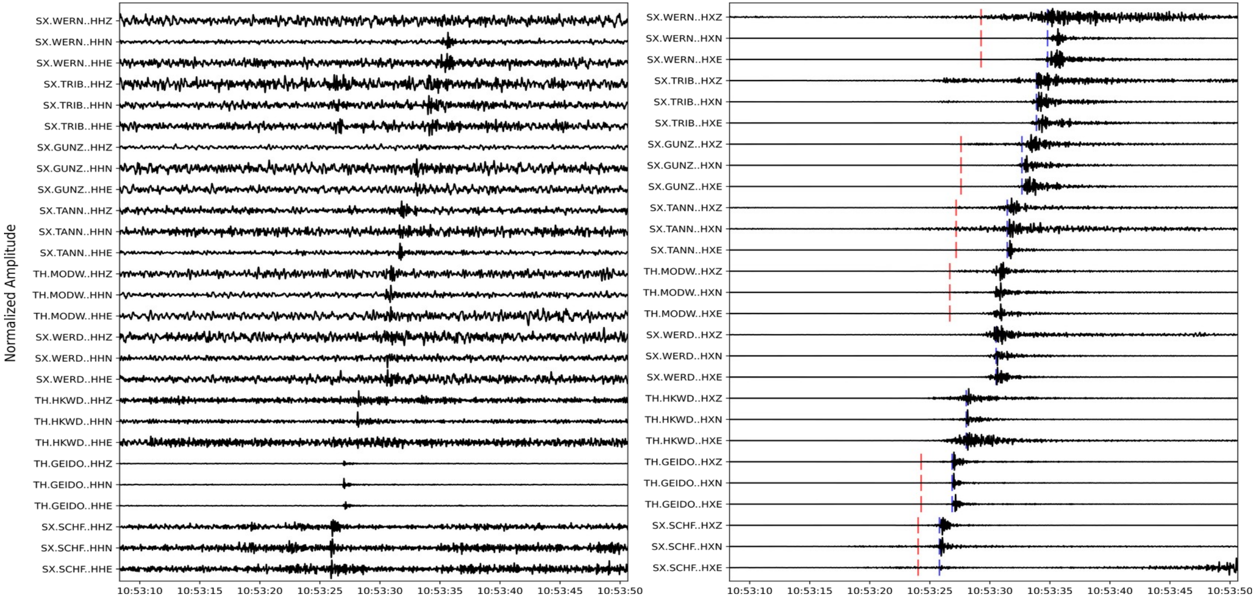


RUB

RUHR-UNIVERSITÄT BOCHUM

APPLICATION OF A DENOISING AUTOENCODER TO THREE MONTHS OF CONTINUOUS DATA FROM NETWORKS TH AND SX

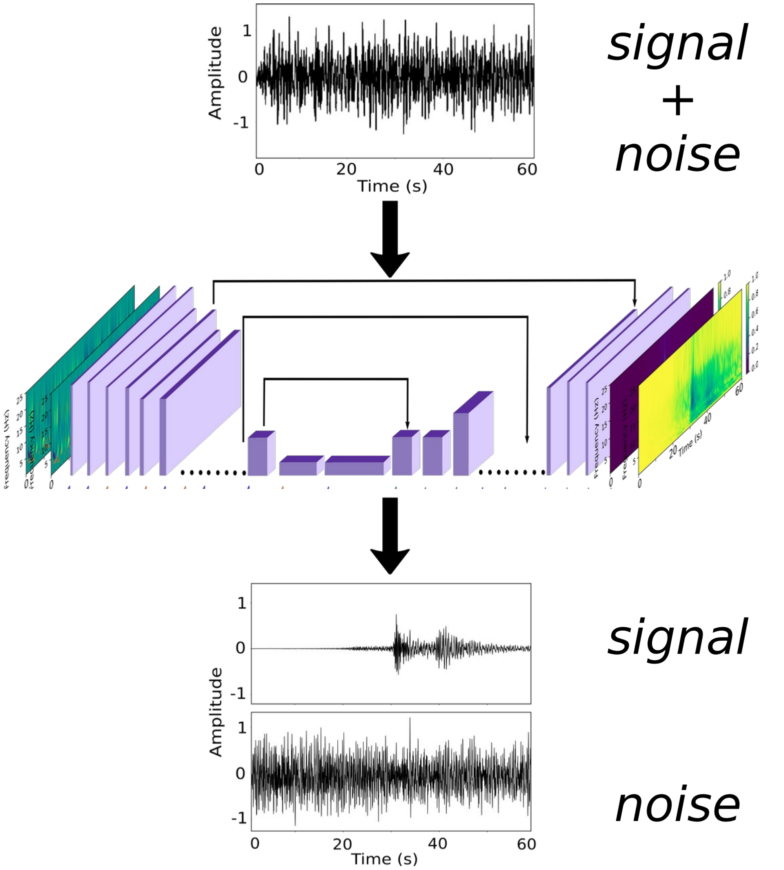
Janis Heuel, Martina Rische, Wolfgang Friederich | AG Seismologie | Freiburg im Brsg. | Sept. 27th, 2023

Motivation

- Denoising Autoencoders (DAE) are able to suppress seismic noise even when signal and noise share a common frequency band
- New seismic events can be detected in denoised data sets

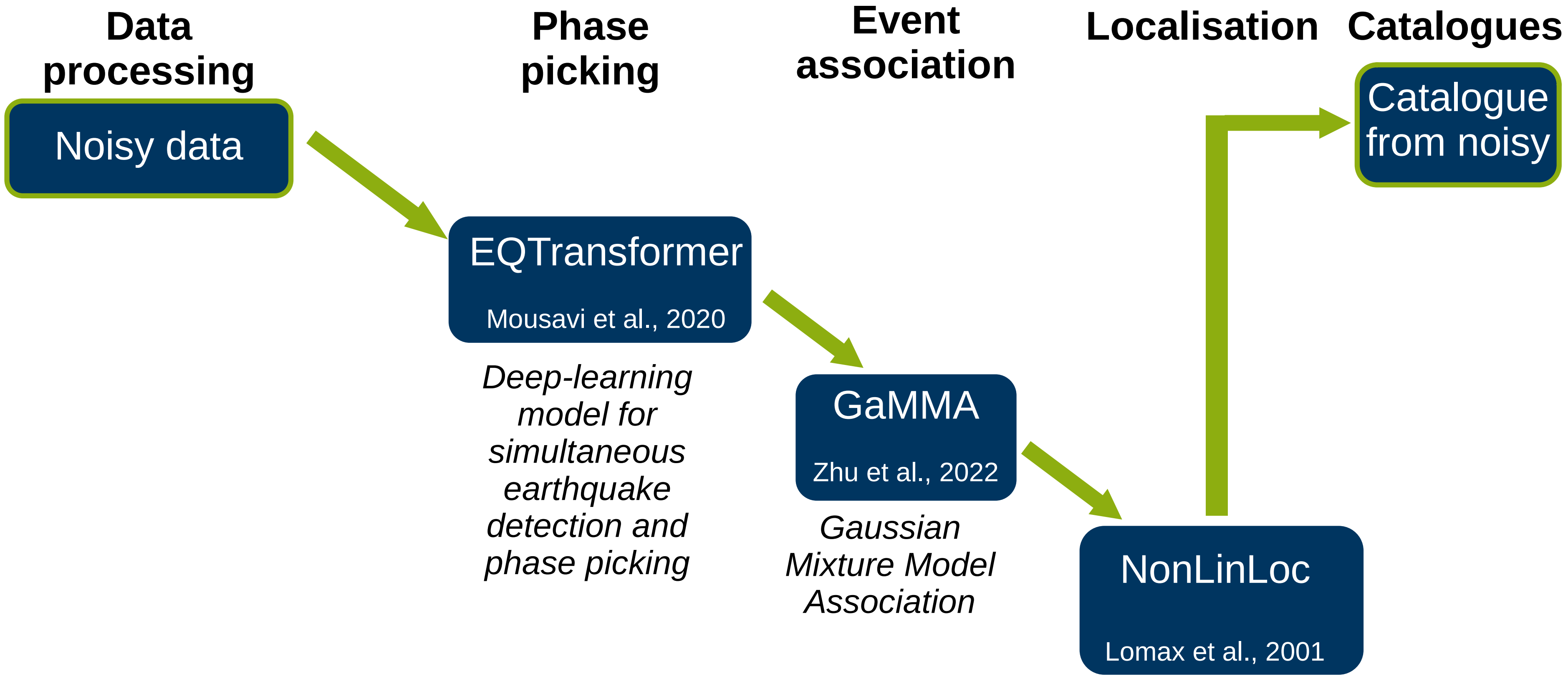
→ How many new events can be detected in “small” seismic networks? Automatic routine vs. manual picking

→ Comparison of noisy and denoised earthquake catalogue

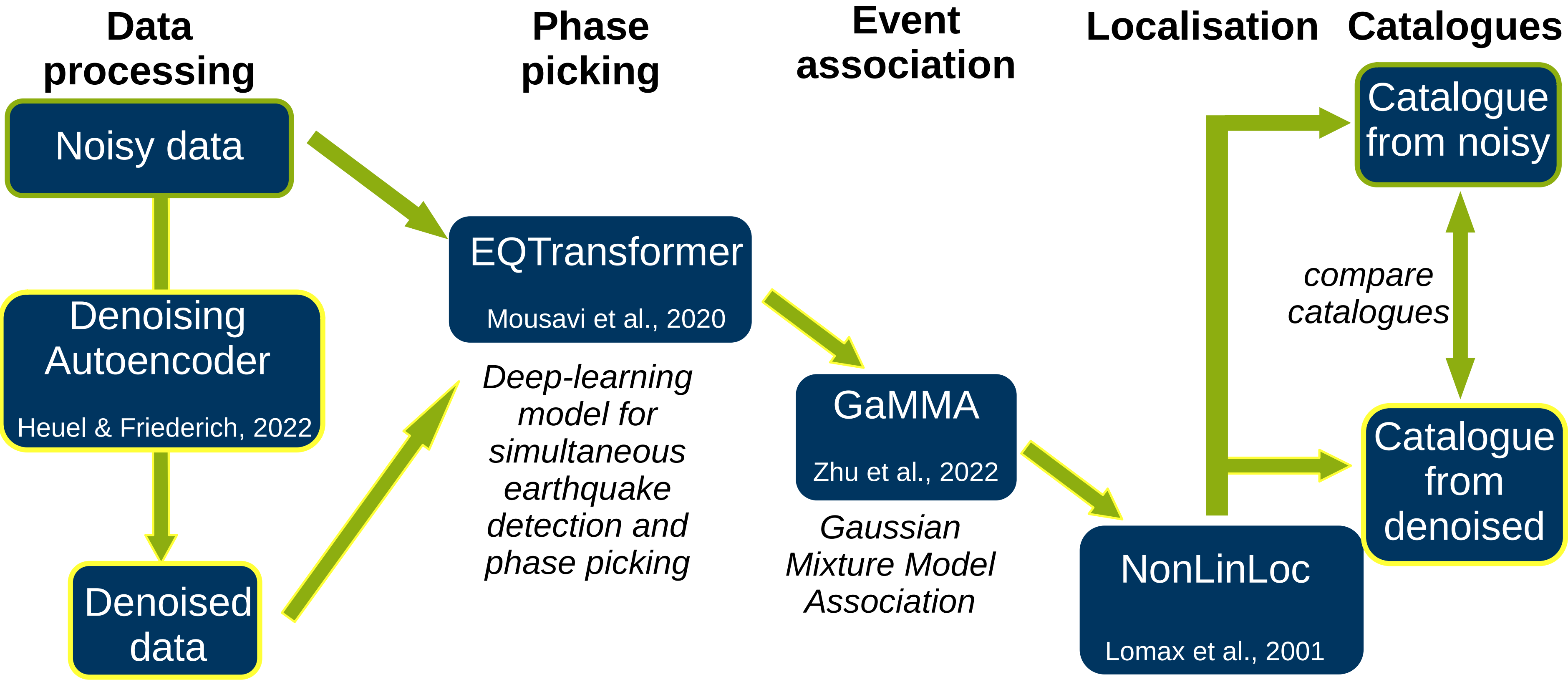


https://github.com/JanisHe/seisDAE

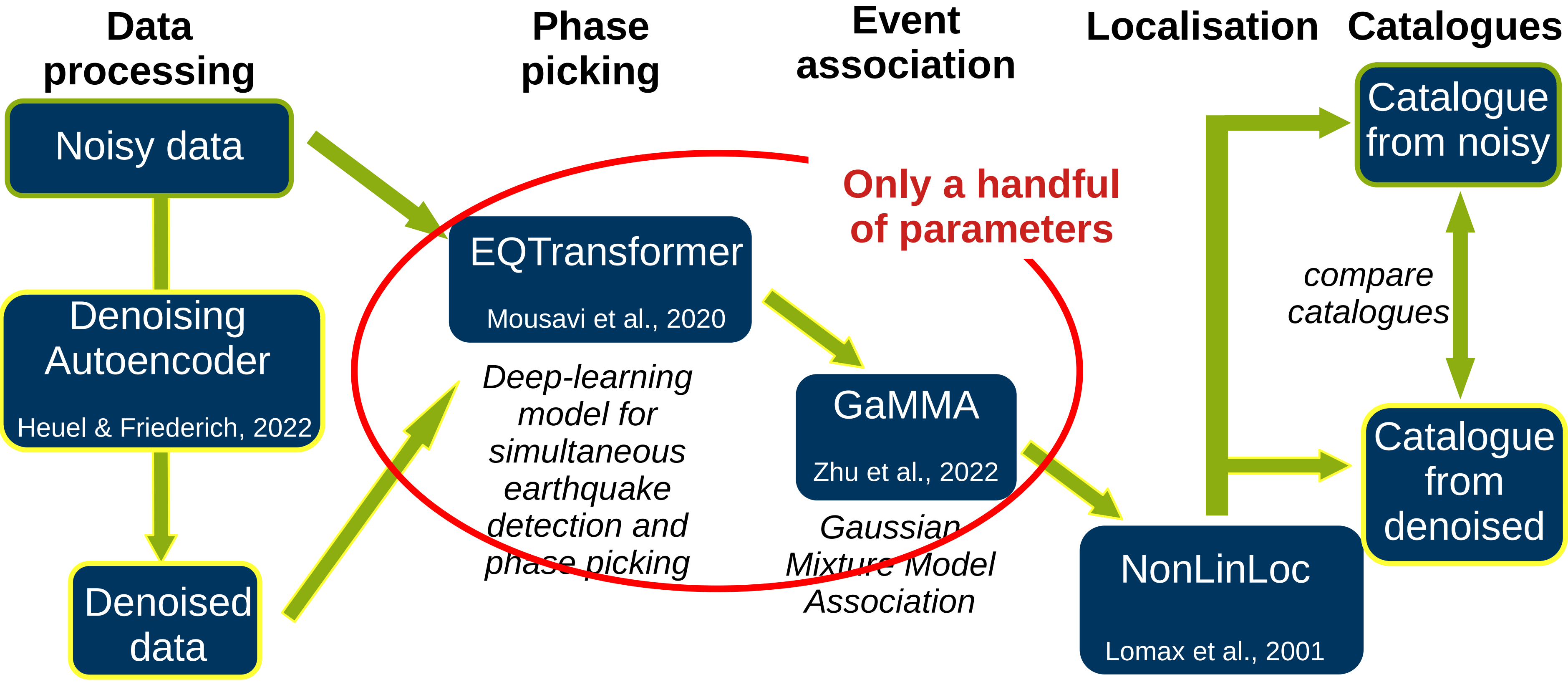
Catalogue building



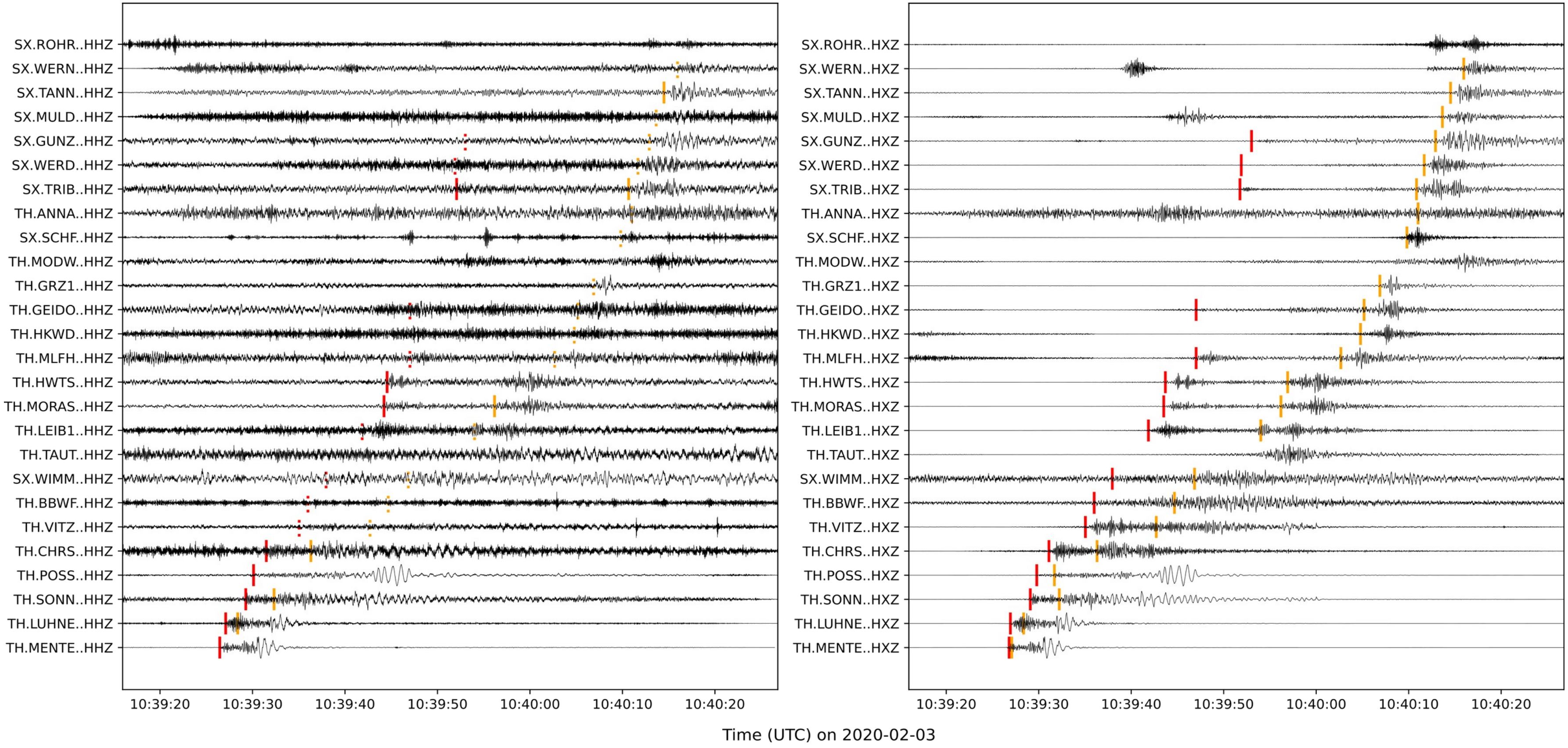
Catalogue building



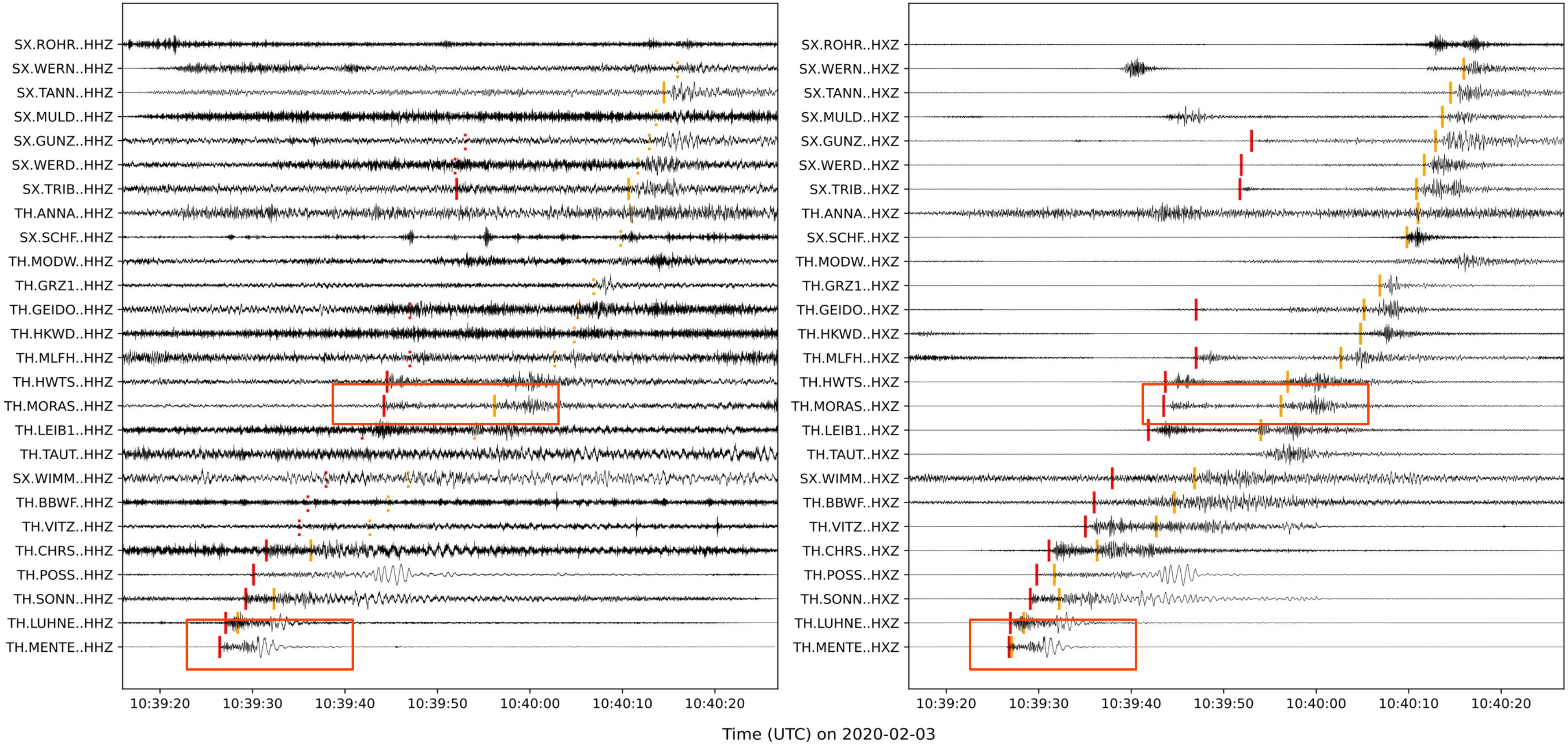
Catalogue building



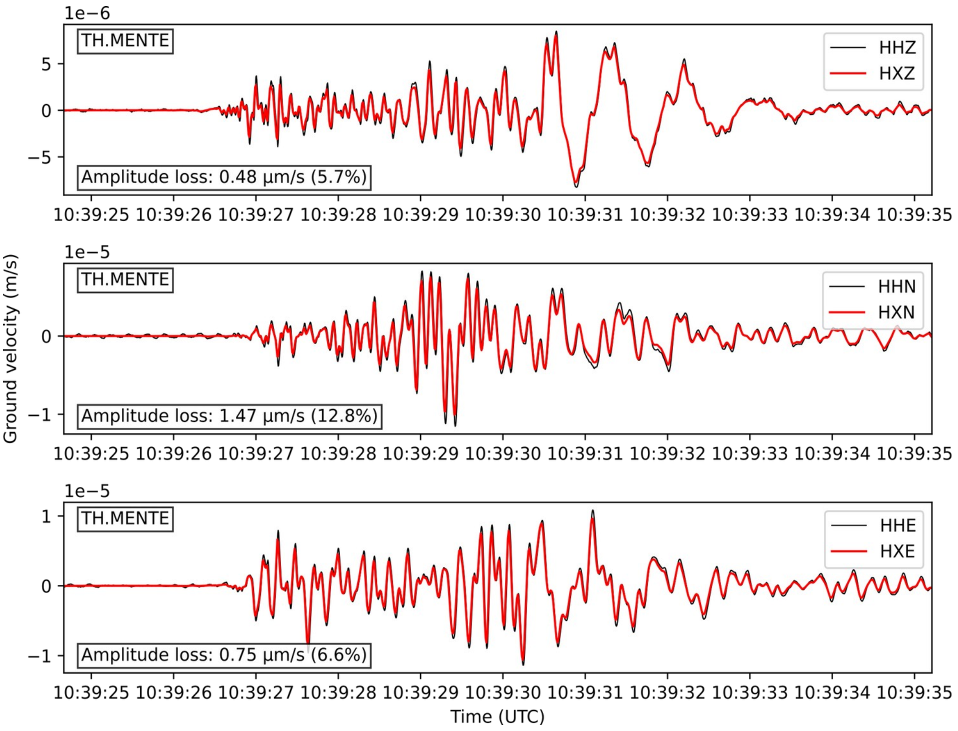
Examples

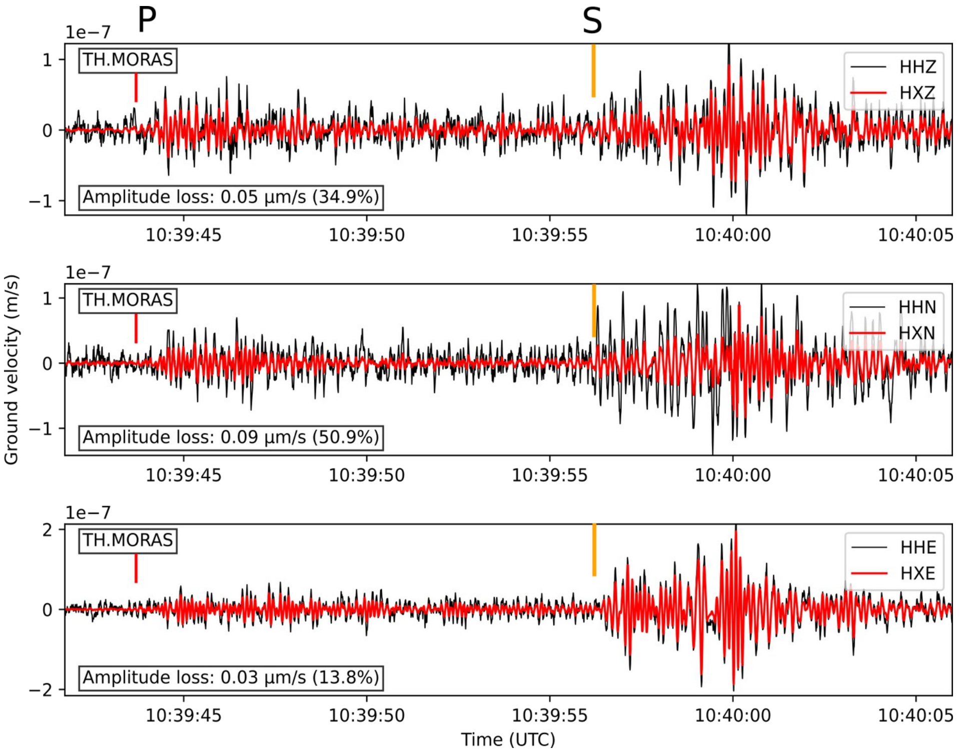

SX.ROHR..HHZ
SX.WERN..HHZ
SX.TANN..HHZ
SX.MULD..HHZ
SX.GUNZ..HHZ
SX.WERD..HHZ
SX.TRIB..HHZ
TH.ANNA..HHZ
SX.SCHF..HHZ
TH.MODW..HHZ
TH.GRZ1..HHZ
TH.GEIDO..HHZ
TH.HKWD..HHZ
TH.MLFH..HHZ
TH.HWTS..HHZ
TH.MORAS..HHZ
TH.LEIB1..HHZ
TH.TAUT..HHZ
SX.WIMM..HHZ
TH.BBWF..HHZ
TH.VITZ..HHZ
TH.CHRS..HHZ
TH.POSS..HHZ
TH.SONN..HHZ
TH.LUHNE..HHZ
TH.MENTE..HHZ
10:39:20
10:39:30
10:39:40
10:39:50
10:40:00
10:40:10
10:40:20
SX.ROHR..HXZ
SX.WERN..HXZ
SX.TANN..HXZ
SX.MULD..HXZ
SX.GUNZ..HXZ
SX.WERD..HXZ
SX.TRIB..HXZ
TH.ANNA..HXZ
SX.SCHF..HXZ
TH.MODW..HXZ
TH.GRZ1..HXZ
TH.GEIDO..HXZ
TH.HKWD..HXZ
TH.MLFH..HXZ
TH.HWTS..HXZ
TH.MORAS..HXZ
TH.LEIB1..HXZ
TH.TAUT..HXZ
SX.WIMM..HXZ
TH.BBWF..HXZ
TH.VITZ..HXZ
TH.CHRS..HXZ
TH.POSS..HXZ
TH.SONN..HXZ
TH.LUHNE..HXZ
TH.MENTE..HXZ
10:39:20
10:39:30
10:39:40
10:39:50
10:40:00
10:40:10
10:40:20
Time (UTC) on 2020-02-03

Examples

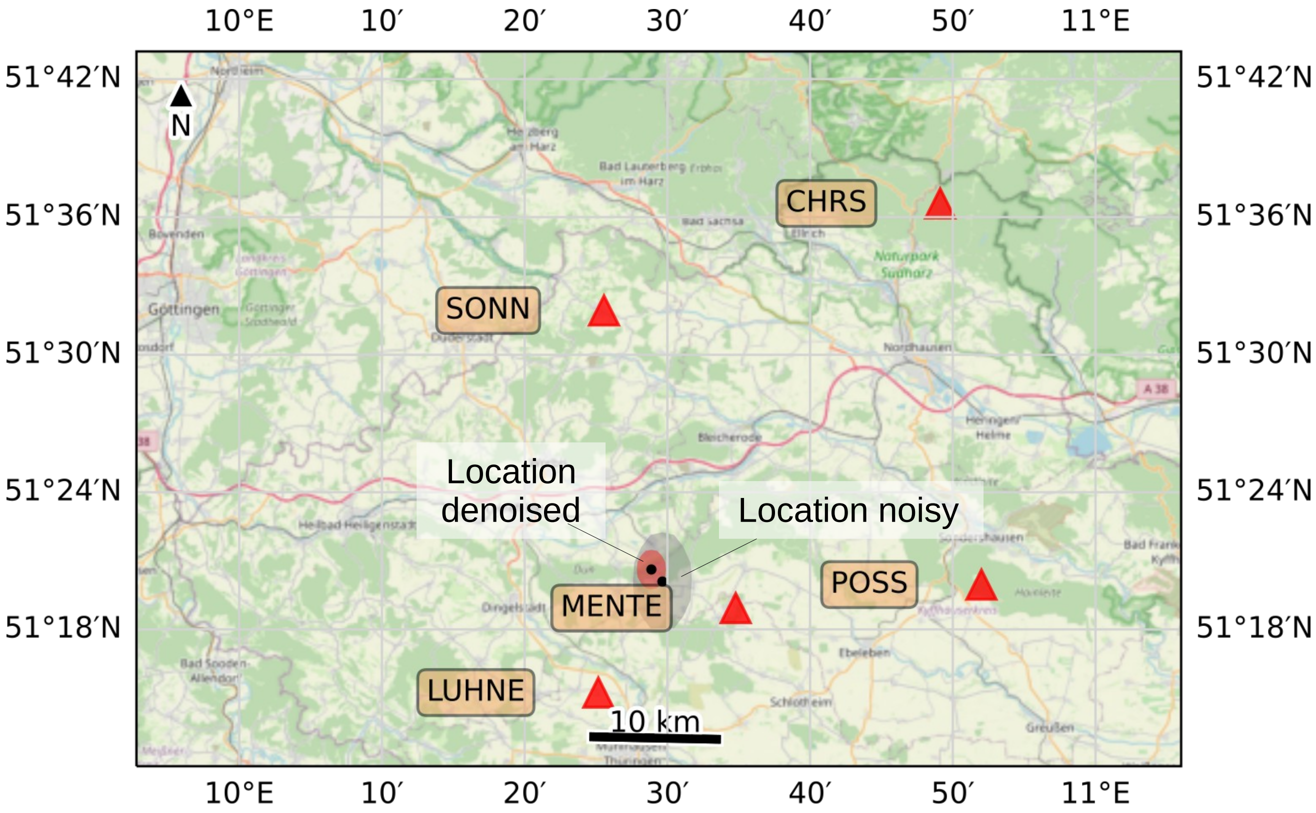

SX.ROHR..HHZ
SX.WERN..HHZ
SX.TANN..HHZ
SX.MULD..HHZ
SX.GUNZ..HHZ
SX.WERD..HHZ
SX.TRIB..HHZ
TH.ANNA..HHZ
SX.SCHF..HHZ
TH.MODW..HHZ
TH.GRZ1..HHZ
TH.GEIDO..HHZ
TH.HKWD..HHZ
TH.MLFH..HHZ
TH.HWTS..HHZ
TH.MORAS..HHZ
TH.LEIB1..HHZ
TH.TAUT..HHZ
SX.WIMM..HHZ
TH.BBWF..HHZ
TH.VITZ..HHZ
TH.CHRS..HHZ
TH.POSS..HHZ
TH.SONN..HHZ
TH.LUHNE..HHZ
TH.MENTE..HHZ
10:39:20
10:39:30
10:39:40
10:39:50
10:40:00
10:40:10
10:40:20
SX.ROHR..HXZ
SX.WERN..HXZ
SX.TANN..HXZ
SX.MULD..HXZ
SX.GUNZ..HXZ
SX.WERD..HXZ
SX.TRIB..HXZ
TH.ANNA..HXZ
SX.SCHF..HXZ
TH.MODW..HXZ
TH.GRZ1..HXZ
TH.GEIDO..HXZ
TH.HKWD..HXZ
TH.MLFH..HXZ
TH.HWTS..HXZ
TH.MORAS..HXZ
TH.LEIB1..HXZ
TH.TAUT..HXZ
SX.WIMM..HXZ
TH.BBWF..HXZ
TH.VITZ..HXZ
TH.CHRS..HXZ
TH.POSS..HXZ
TH.SONN..HXZ
TH.LUHNE..HXZ
TH.MENTE..HXZ
10:39:20
10:39:30
10:39:40
10:39:50
10:40:00
10:40:10
10:40:20
Time (UTC) on 2020-02-03

Examples


1e−6
TH.MENTE
HHZ
HXZ
Amplitude loss: 0.48 µm/s (5.7%)
1e−5
TH.MENTE
HHN
HXN
Amplitude loss: 1.47 µm/s (12.8%)
1e−5
TH.MENTE
HHE
HXE
Amplitude loss: 0.75 µm/s (6.6%)
Ground velocity (m/s)
10:39:25 10:39:26 10:39:27 10:39:28 10:39:29 10:39:30 10:39:31 10:39:32 10:39:33 10:39:34 10:39:35
Time (UTC)

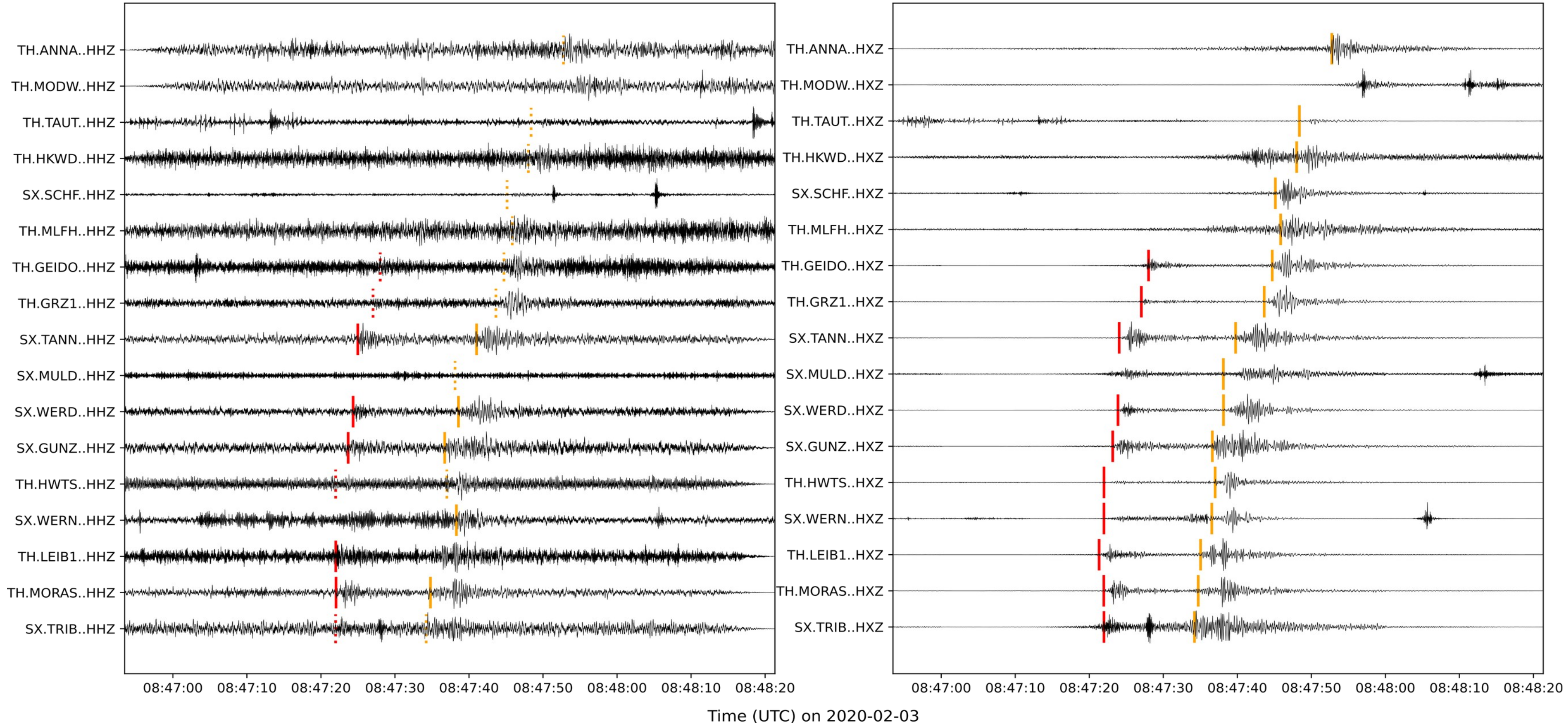

P
S
1e−7
TH.MORAS
HHZ
HXZ
Amplitude loss: 0.05 µm/s (34.9%)
1e−7
TH.MORAS
HHN
HXN
Amplitude loss: 0.09 µm/s (50.9%)
1e−7
TH.MORAS
HHE
HXE
Amplitude loss: 0.03 µm/s (13.8%)
Ground velocity (m/s)
10:39:45 10:39:50 10:39:55 10:40:00 10:40:05
Time (UTC)

Examples

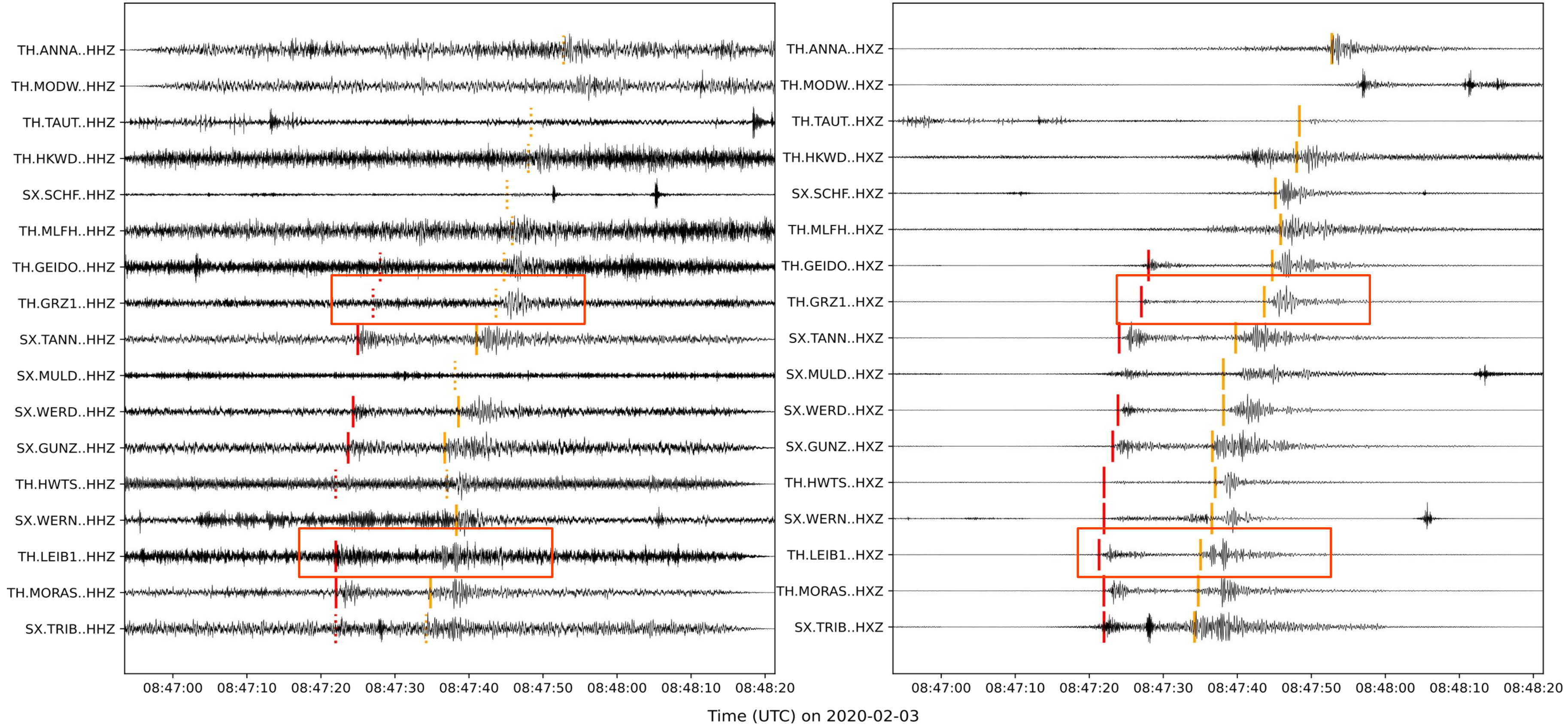


10°E
10′
20′
30′
40′
50′
11°E
51°42′N
51°36′N
51°30′N
51°24′N
51°18′N
N
CHRS
SONN
Location denoised
Location noisy
POSS
MENTE
LUHNE
10 km
Göttingen
Nordhausen
Bleicherode

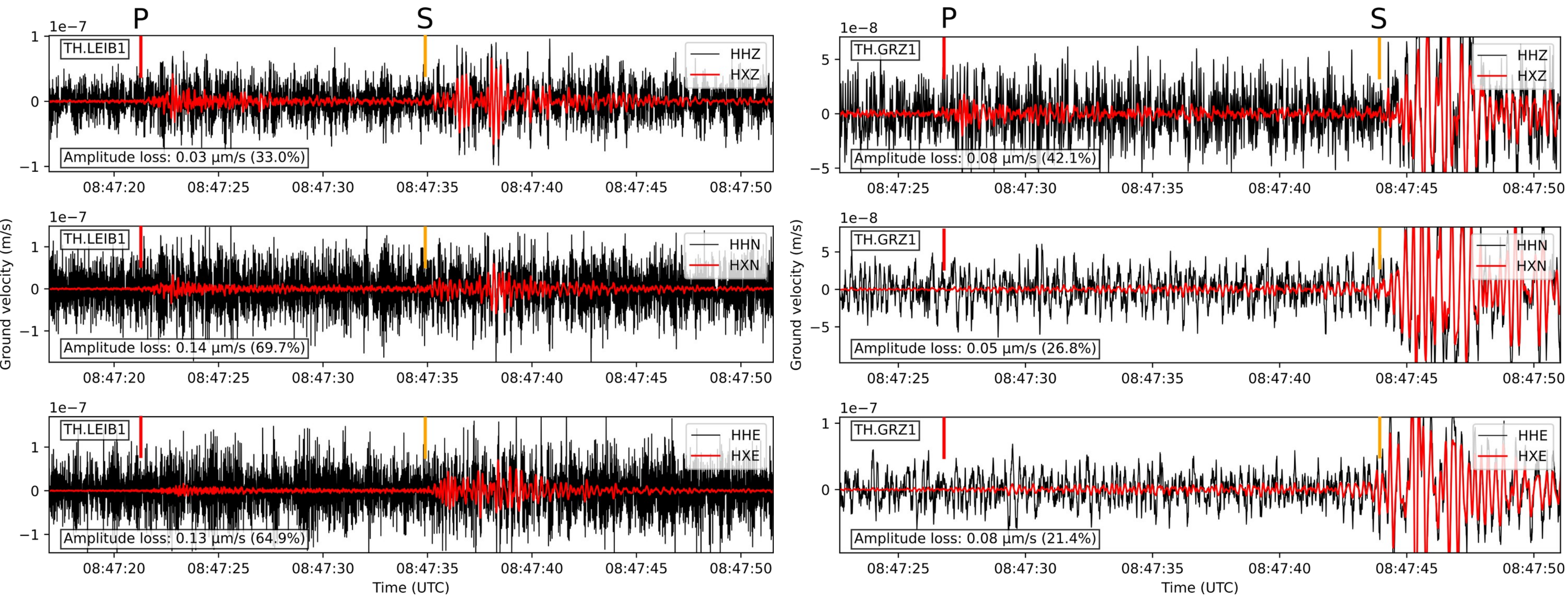
Examples


TH.ANNA..HHZ
TH.MODW..HHZ
TH.TAUT..HHZ
TH.HKWD..HHZ
SX.SCHF..HHZ
TH.MLFH..HHZ
TH.GEIDO..HHZ
TH.GRZ1..HHZ
SX.TANN..HHZ
SX.MULD..HHZ
SX.WERD..HHZ
SX.GUNZ..HHZ
TH.HWTS..HHZ
SX.WERN..HHZ
TH.LEIB1..HHZ
TH.MORAS..HHZ
SX.TRIB..HHZ
TH.ANNA..HXZ
TH.MODW..HXZ
TH.TAUT..HXZ
TH.HKWD..HXZ
SX.SCHF..HXZ
TH.MLFH..HXZ
TH.GEIDO..HXZ
TH.GRZ1..HXZ
SX.TANN..HXZ
SX.MULD..HXZ
SX.WERD..HXZ
SX.GUNZ..HXZ
TH.HWTS..HXZ
SX.WERN..HXZ
TH.LEIB1..HXZ
TH.MORAS..HXZ
SX.TRIB..HXZ
08:47:00 08:47:10 08:47:20 08:47:30 08:47:40 08:47:50 08:48:00 08:48:10 08:48:20
Time (UTC) on 2020-02-03

Examples


TH.ANNA..HHZ
TH.MODW..HHZ
TH.TAUT..HHZ
TH.HKWD..HHZ
SX.SCHF..HHZ
TH.MLFH..HHZ
TH.GEIDO..HHZ
TH.GRZ1..HHZ
SX.TANN..HHZ
SX.MULD..HHZ
SX.WERD..HHZ
SX.GUNZ..HHZ
TH.HWTS..HHZ
SX.WERN..HHZ
TH.LEIB1..HHZ
TH.MORAS..HHZ
SX.TRIB..HHZ
TH.ANNA..HXZ
TH.MODW..HXZ
TH.TAUT..HXZ
TH.HKWD..HXZ
SX.SCHF..HXZ
TH.MLFH..HXZ
TH.GEIDO..HXZ
TH.GRZ1..HXZ
SX.TANN..HXZ
SX.MULD..HXZ
SX.WERD..HXZ
SX.GUNZ..HXZ
TH.HWTS..HXZ
SX.WERN..HXZ
TH.LEIB1..HXZ
TH.MORAS..HXZ
SX.TRIB..HXZ
08:47:00
08:47:10
08:47:20
08:47:30
08:47:40
08:47:50
08:48:00
08:48:10
08:48:20
Time (UTC) on 2020-02-03

Examples

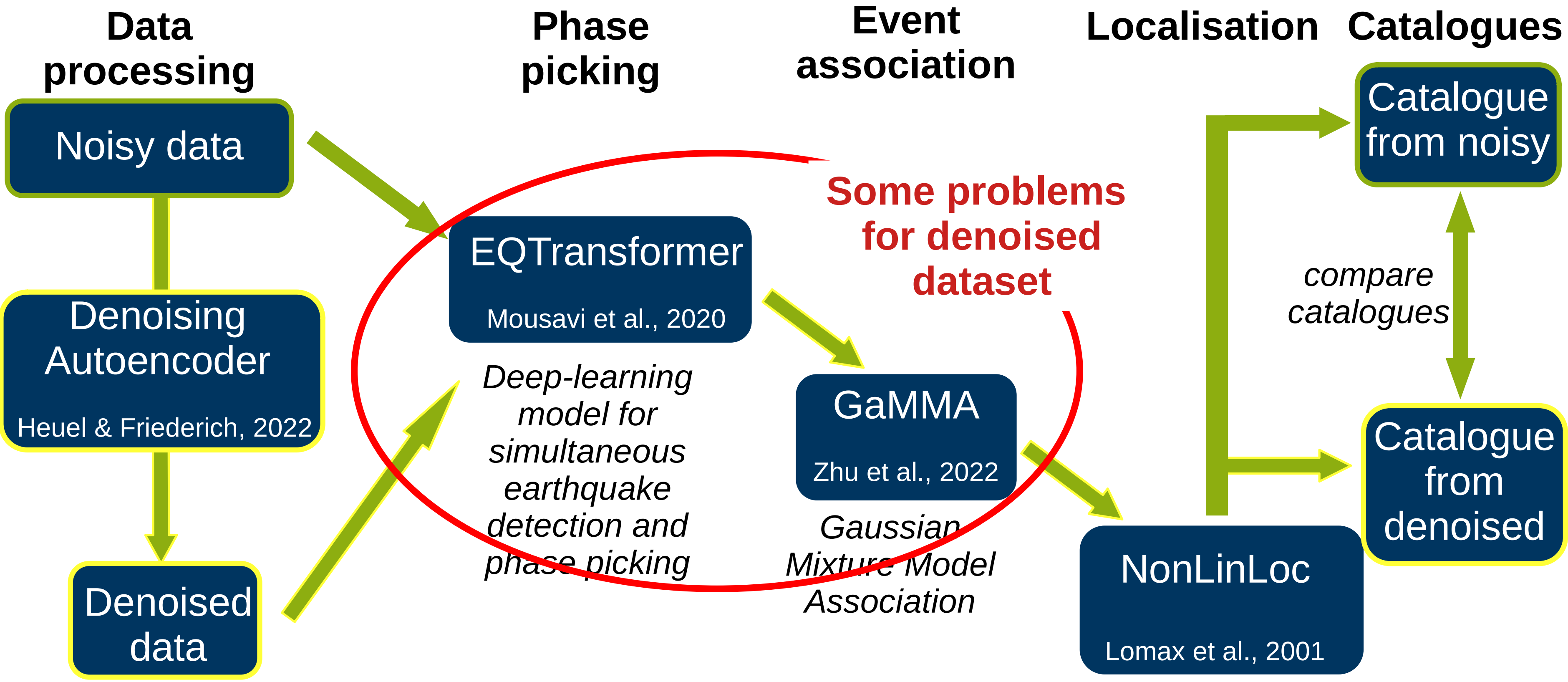


P
S
TH.LEIB1
HHZ
HXZ
Amplitude loss: 0.03 µm/s (33.0%)
HHN
HXN
Amplitude loss: 0.14 µm/s (69.7%)
HHE
HXE
Amplitude loss: 0.13 µm/s (64.9%)
TH.GRZ1
Amplitude loss: 0.08 µm/s (42.1%)
Amplitude loss: 0.05 µm/s (26.8%)
Amplitude loss: 0.08 µm/s (21.4%)
Ground velocity (m/s)
Time (UTC)

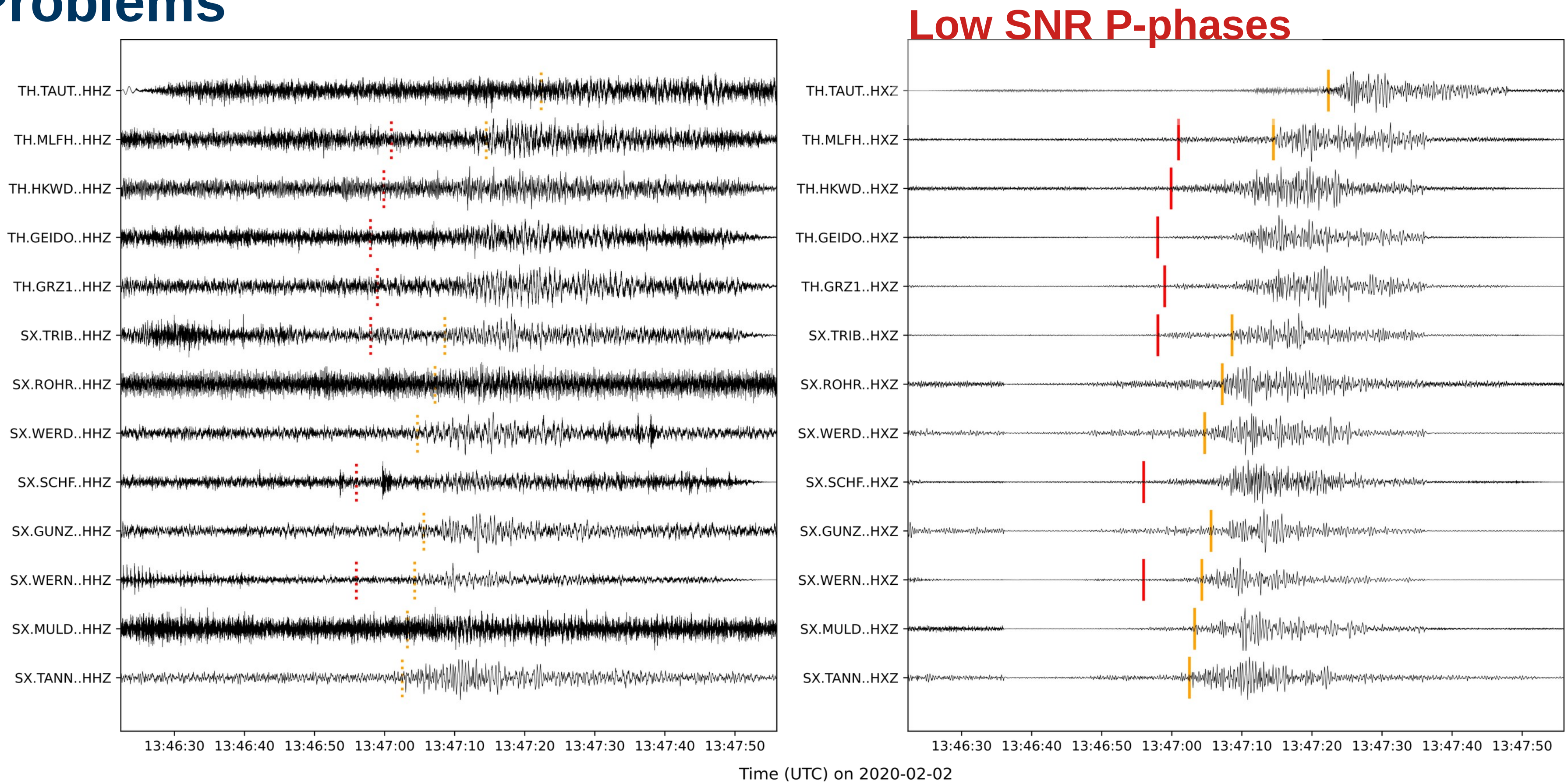
Intermediate Results

- Analysed continuous data of **three months** (2020) from **41 stations** with automatic routine (EqT and GaMMA) and **manually picked seismic phases of six days** for verification
  - Automatic (three months):
    402 (noisy) and 2110 (denoised) events
  - Automatic (six days):
    28 (noisy) and 127 (denoised) events
  - Manual:
    24 (noisy) and 65 (denoised) events (24 noisy events are also in denoised)
    BUT 23 denoised events are hard to localise and many events were detected several times because of settings for phase association (GaMMA)
- **Too many false picks by Earthquake Transformer and thus false detections for denoised data**

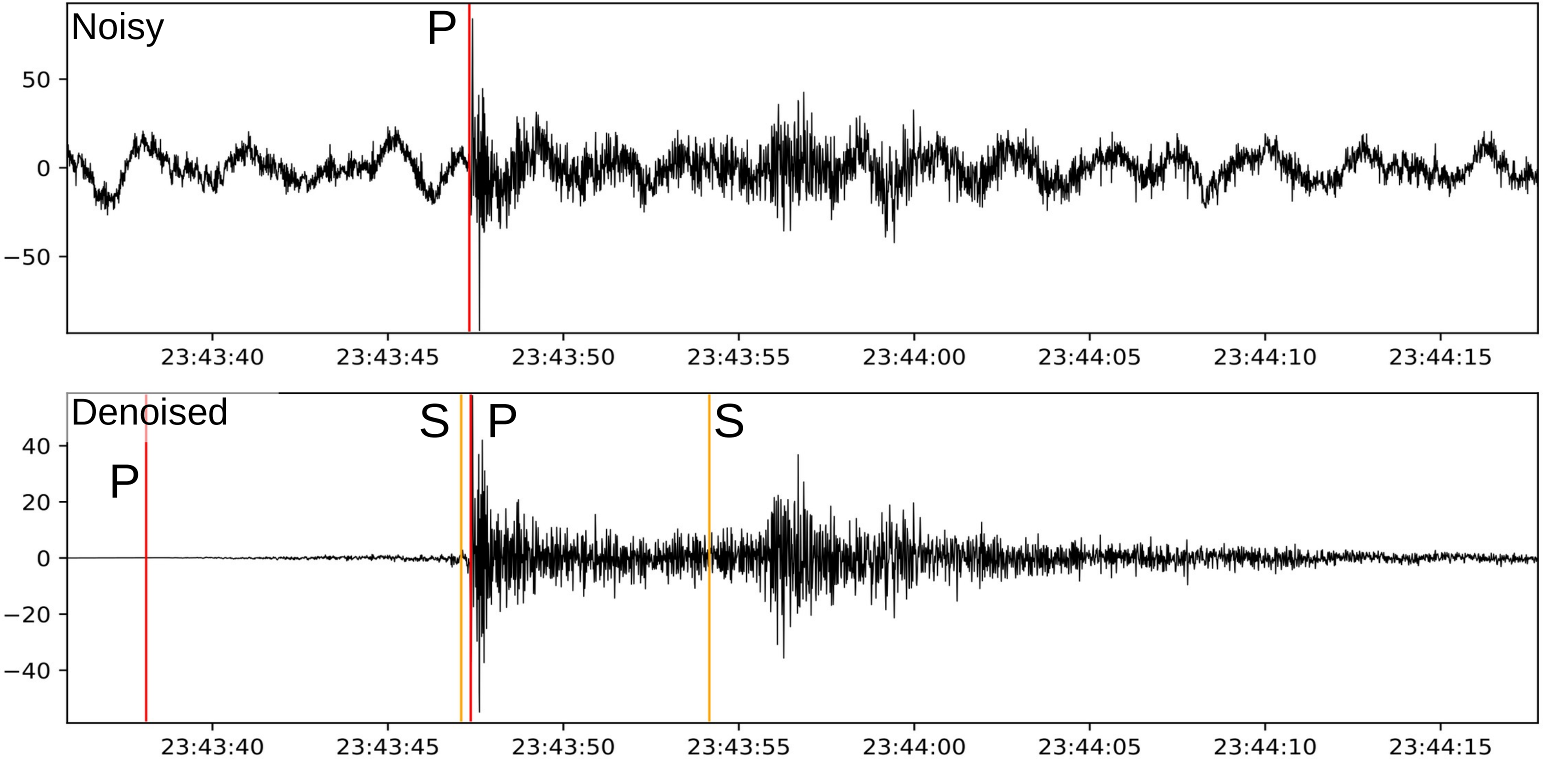
Problems | Catalogue building



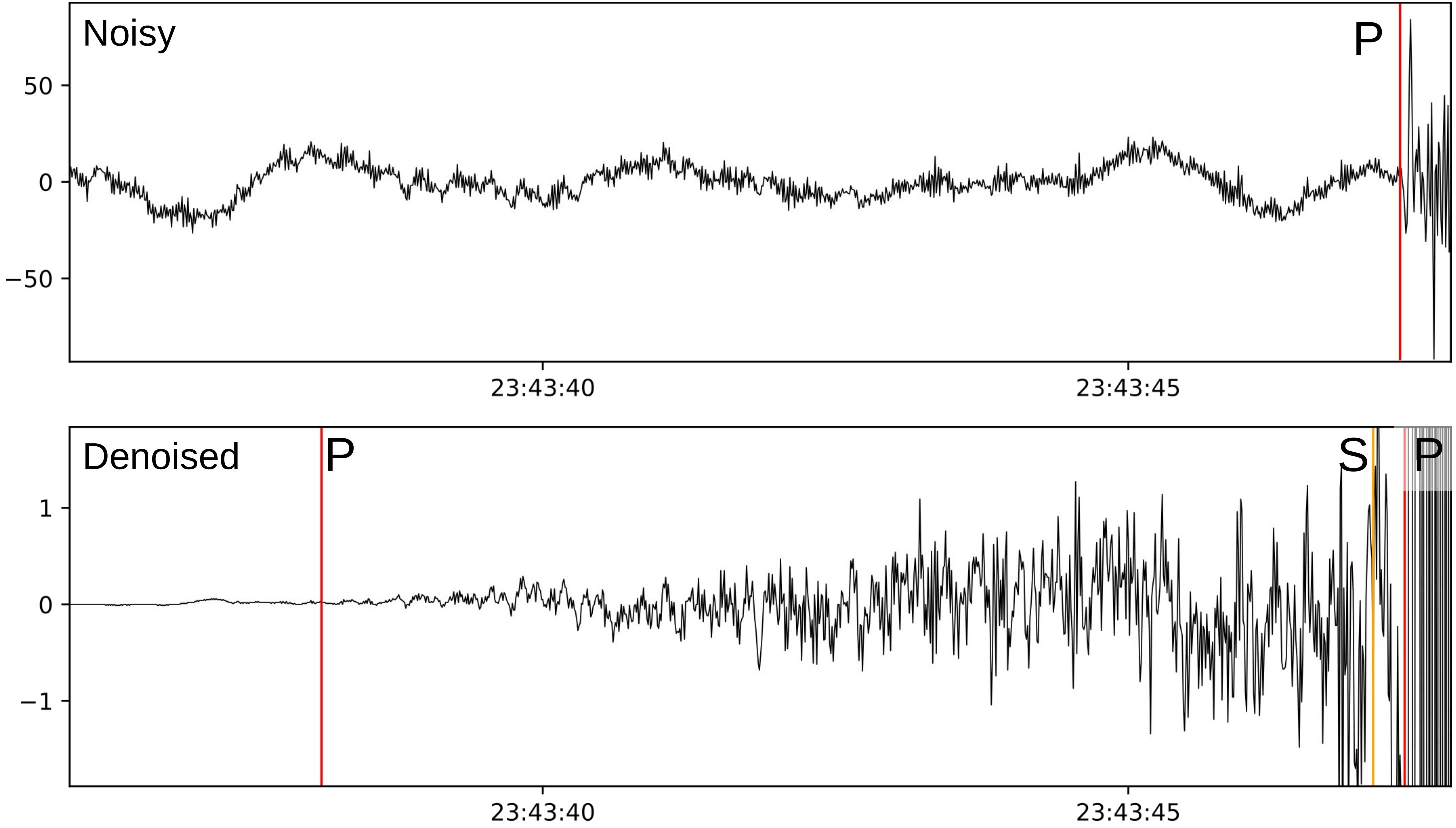
Problems


Low SNR P-phases
TH.TAUT..HHZ
TH.MLFH..HHZ
TH.HKWD..HHZ
TH.GEIDO..HHZ
TH.GRZ1..HHZ
SX.TRIB..HHZ
SX.ROHR..HHZ
SX.WERD..HHZ
SX.SCHF..HHZ
SX.GUNZ..HHZ
SX.WERN..HHZ
SX.MULD..HHZ
SX.TANN..HHZ
TH.TAUT..HXZ
TH.MLFH..HXZ
TH.HKWD..HXZ
TH.GEIDO..HXZ
TH.GRZ1..HXZ
SX.TRIB..HXZ
SX.ROHR..HXZ
SX.WERD..HXZ
SX.SCHF..HXZ
SX.GUNZ..HXZ
SX.WERN..HXZ
SX.MULD..HXZ
SX.TANN..HXZ
13:46:30 13:46:40 13:46:50 13:47:00 13:47:10 13:47:20 13:47:30 13:47:40 13:47:50
Time (UTC) on 2020-02-02

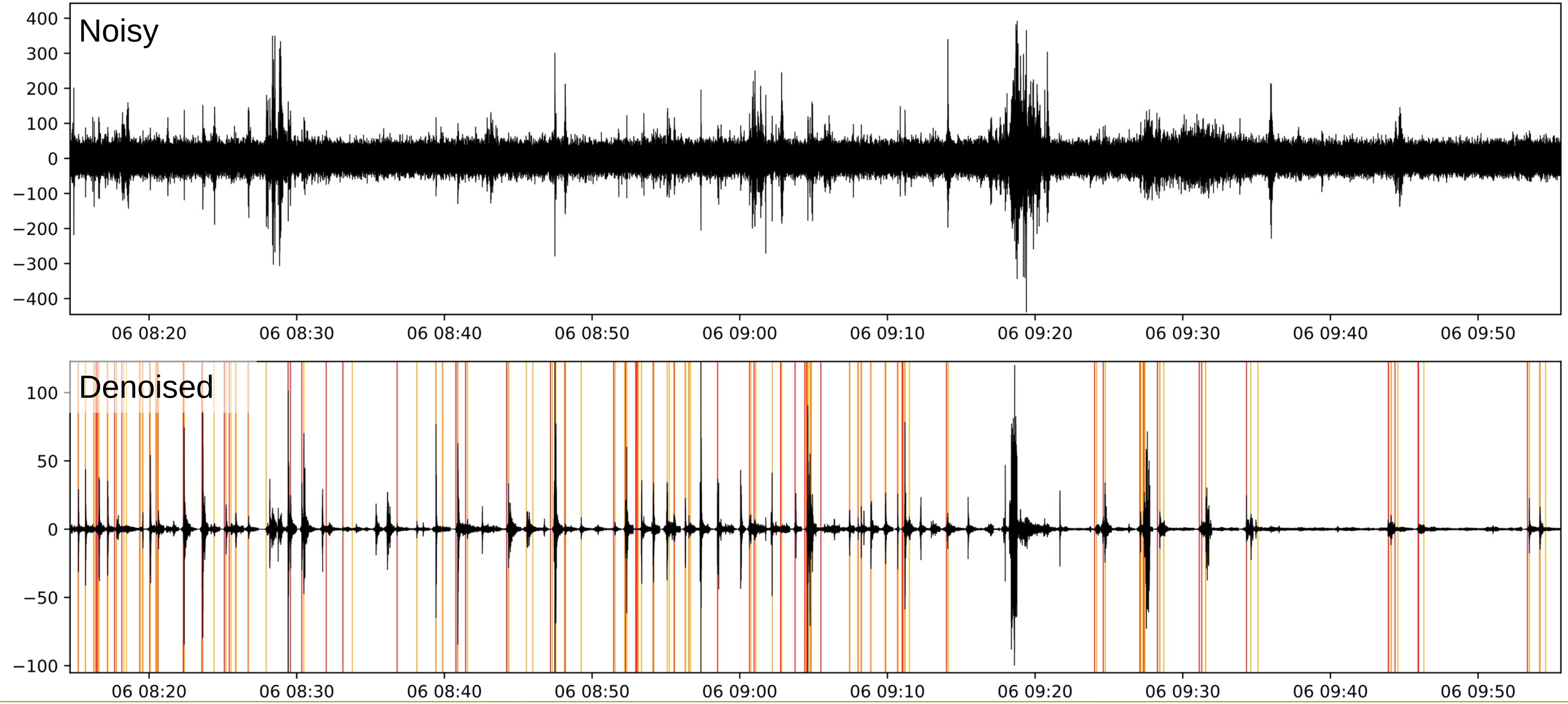
Problems | False P onset



Problems | False P onset



Problems | Too many picks



Problems | Too many picks

JGR Solid Earth

RESEARCH ARTICLE
10.1029/2021JB023249

Special Section:
Machine learning for Solid Earth observation, modeling and understanding

Earthquake Phase Association Using a Bayesian Gaussian Mixture Model

Weiqiang Zhu[1], Ian W. McBrearty[1], S. Mostafa Mousavi[1], William L. Ellsworth[1], and Gregory C. Beroza[1]

[1]Department of Geophysics, Stanford University, Stanford, CA, USA

Key Points:

- We proposed an new approach to solve phase association as an unsupervised clustering problem using the Bayesian Gaussian Mixture Model
- We used the multivariate Gaussian distribution to represent both phase arrival time and amplitude to improve association
- Our unsupervised method is fast without the need for conventional grid-search or supervised training

Supporting Information:
Supporting Information may be found in the online version of this article.

Correspondence to:
W. Zhu,
zhuwq@stanford.edu

Abstract Earthquake phase association algorithms aggregate picked seismic phases from a network of seismometers into individual sesimic events and play an important role in earthquake monitoring and research. Dense seismic networks and improved phase picking methods produce massive seismic phase datasets, particularly for earthquake swarms and aftershocks occurring closely in time and space, making phase association a challenging problem. We present a new association method, the Gaussian Mixture Model Association (GaMMA), that combines the Gaussian mixture model with earthquake location, origin time, and magnitude estimation. We treat earthquake phase association as an unsupervised clustering problem in a probabilistic framework, where each earthqual
moveout of arrival times and a decay of ampli
to model the collection of phase picks of an ev
given by the predicted arrival time and amplit
to each earthquake and determine earthquake
and magnitude) under the maximum likelihoo
The GaMMA method does not require typical
supervised training. The results for both synth
that GaMMA effectively associates phases fro
producing useful estimates of earthquake loca

Figure 5. An example of association results from a dense sequence of phase picks starting at time 2019-07-08T00:00:00 (UTC). GaMMA associates 24 events during this period, while there are only 2 events in the SCSN catalog and 20 events in Ross, Idini, et al. (2019)'s template matching catalog.

unknown ground truth and the trade-off between the number of predictions and the false positives, it is challenging to evaluate the false positive associations in these catalogs.

Summary

- Using a denoising autoencoder (DAE) can lead to an increase of earthquake detections **BUT**
  - We have **too many false detections**

    → Using a threshold for the SNR of the P-phase might reduce some false detections
  - Are there other algorithms that can **check whether it is an earthquake or not**?
  - Earthquake **magnitudes cannot be calculated** with the DAE

- At the moment, the DAE can only be used to find more picks

Further questions? Janis.Heuel@rub.de

Code available at https://github.com/JanisHe