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Analyzing low-magnitude induced seismicity using deep learning phase picking: a case study from Preston New Road, UK

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Introduction

- Deep learning (DL) phase pickers have emerged as efficient and valuable tools for automated seismic phase picking.
- The impacts of DL enhanced phase detection on induced microseismicity ($M_W < 2$) is unexplored.
- We investigate the magnitude range of the new event detections of a DL phase picker, PhaseNet (Zhu and Beroza, 2019), on a borehole seismic dataset.
- We apply PhaseNet to a subset of the PNR-1z dataset, a high frequency (2000 Hz) borehole seismic dataset from an unconventional shale gas exploration site in Preston New Road, UK.

Challenges in magnitude estimation

- **Waveform clipping:** Visual checks of the PNR-1z waveforms indicate that events with M_W > -0.2 are affected by waveform clipping at around ± 39 V (Fig. 1).

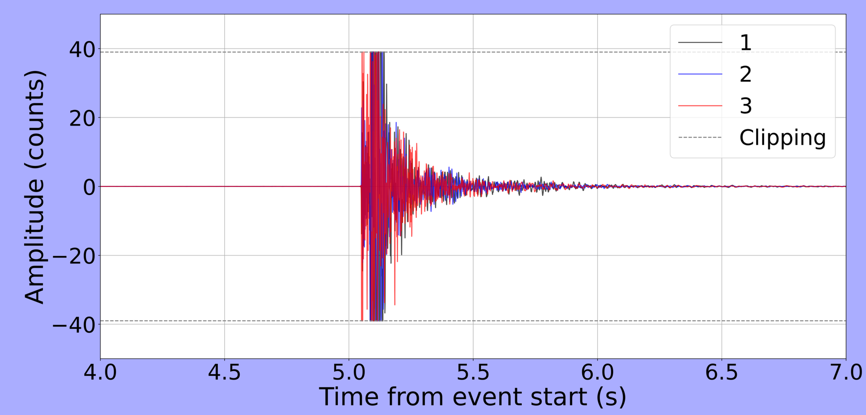
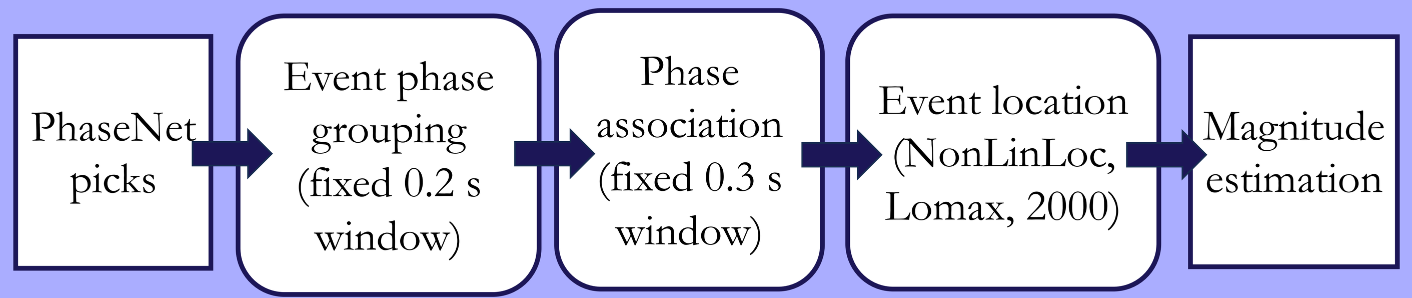


Figure 1: A clipped event waveform from PNR-1z (M_W 1.1). All three components are clipped at ± 39 V.

- **Borehole resonance frequencies:** Holmgren et al. (2021) showed that borehole geophones are also susceptible to high-frequency resonance issues, which can affect the estimation of source parameters (corner frequency, f_c and the low-frequency plateau, Ω_0).
- To overcome these challenges in estimating surface moment magnitudes for the new events, we estimate coda duration magnitudes, M_d as a proxy for surface moment magnitudes, M_W for the new events (Rodriguez-Pradilla and Eaton, 2019).

Preston New Road (PNR-1z) data

- PhaseNet detected over 52,000 events in the PNR-1z dataset, surpassing the 38,452 events (Clarke et al., 2018) detected by the Coalescence Microseismic Mapping (CMM) method (Drew et al., 2013).
- The workflow to produce our event catalog from DL phase picks is:



- We select a subset of the PNR-1z dataset (11 December 2018, 9am-10am), with 986 surface moment magnitudes, M_W ranging from -1.5 to 1.1 (Baptie et al., 2020; Kettlety et al., 2021).
- Here, PhaseNet detected 364 additional events (+39%) and recalled 92% of the PNR-1z events (1,265 events total). We also detected 20 (1.5%) clipped events.

Main Results

Linear coda-magnitude scales to estimate M_W for new events

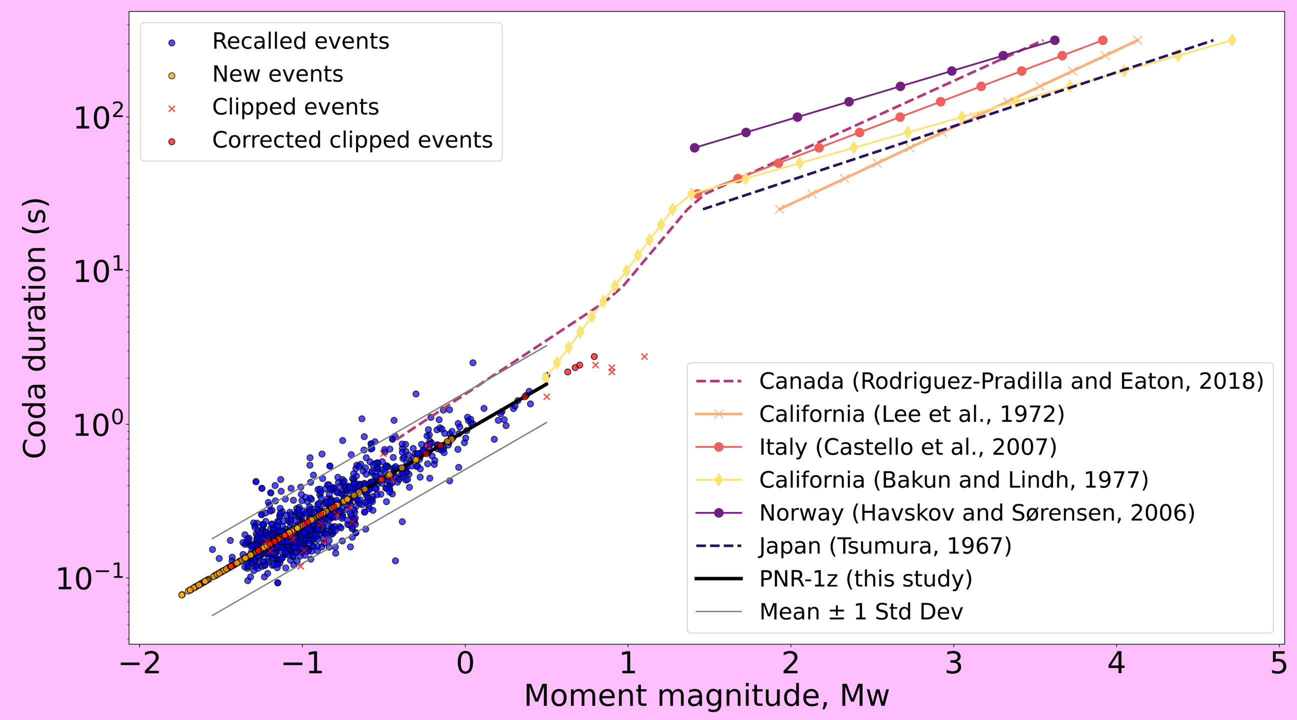


Figure 3: Linear regression of the measured coda duration and M_W of the recalled events (blue circles) and the other coda-magnitude scales from Havskov and Ottenmöller (2010) and Rodriguez-Pradilla and Eaton (2019). Clipped events (red crosses) are in their original M_W units while new (yellow circles) and corrected clipped events (red circles) are in M_d.

PhaseNet detects new small events

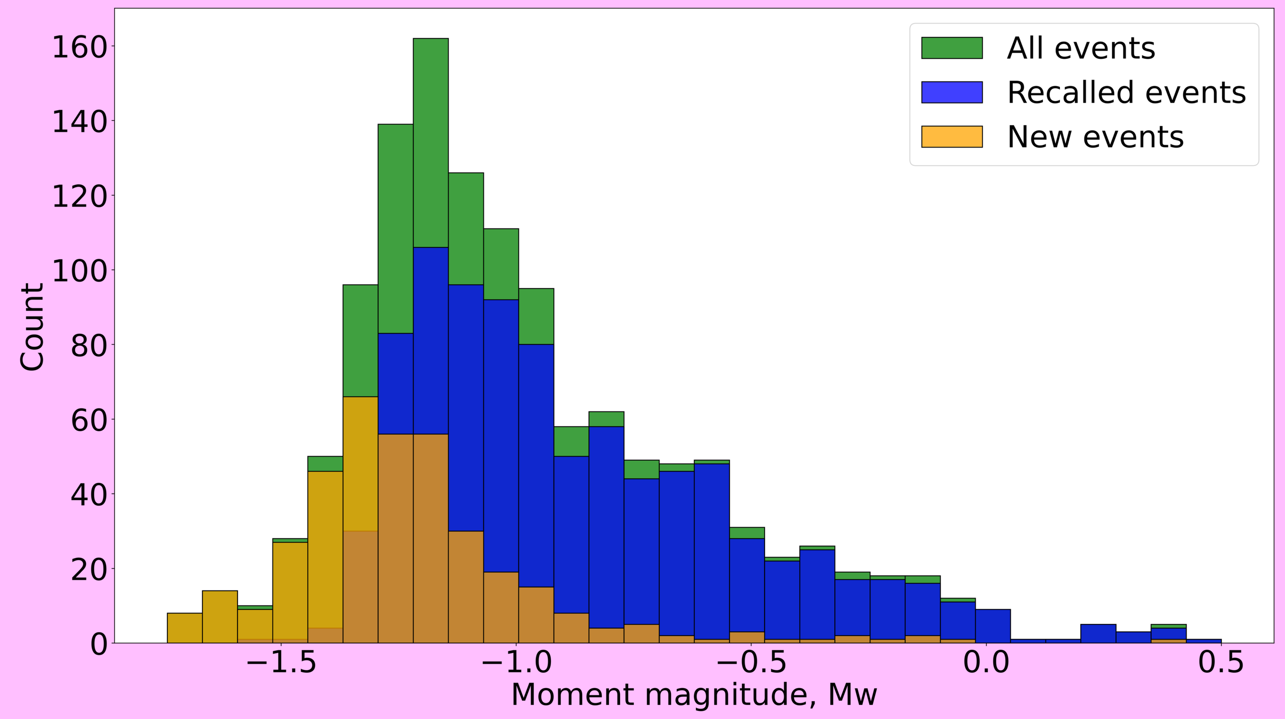


Figure 4: The magnitude distribution of the recalled events (blue), new events (yellow) and all events detected by PhaseNet (green).

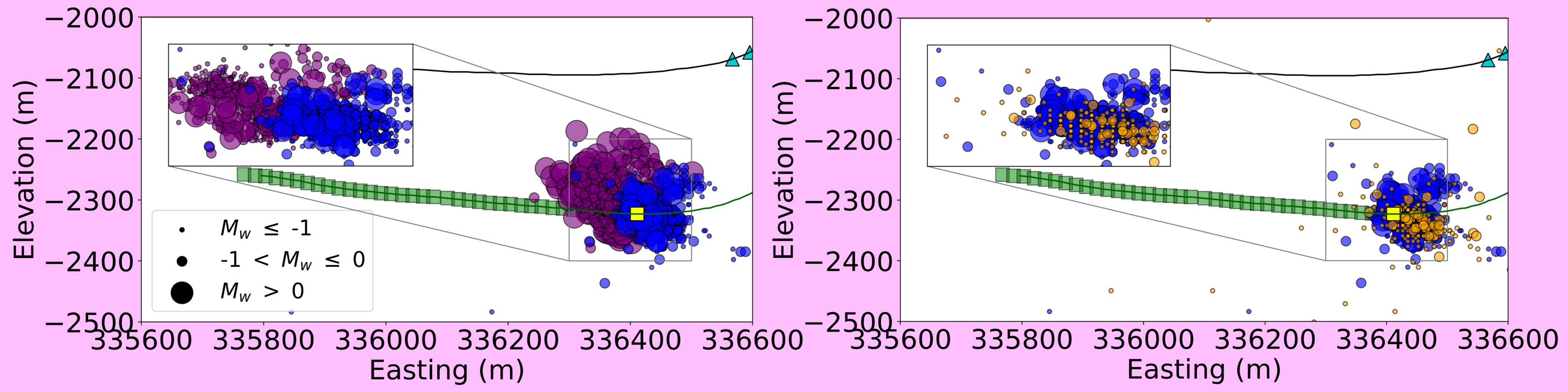


Figure 5: (Left) Locations of the events from the initial CMM catalog (purple circles), and NonLinLoc locations of recalled (blue) and (Right) new (yellow) events scaled by M_W . The PNR-1z well (dark green line), observation well (black line), well stages (green squares) and borehole geophones (teal triangles). The active stage (Stage 38) is plotted as a yellow square.

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Methods

- We measure coda-duration t_{coda} of each event by estimating the time between the P-wave arrival and the return of average logarithmic amplitude level to pre-event noise levels defined as the root mean square trace of a 150-sample window before the P-wave (Fig. 2).

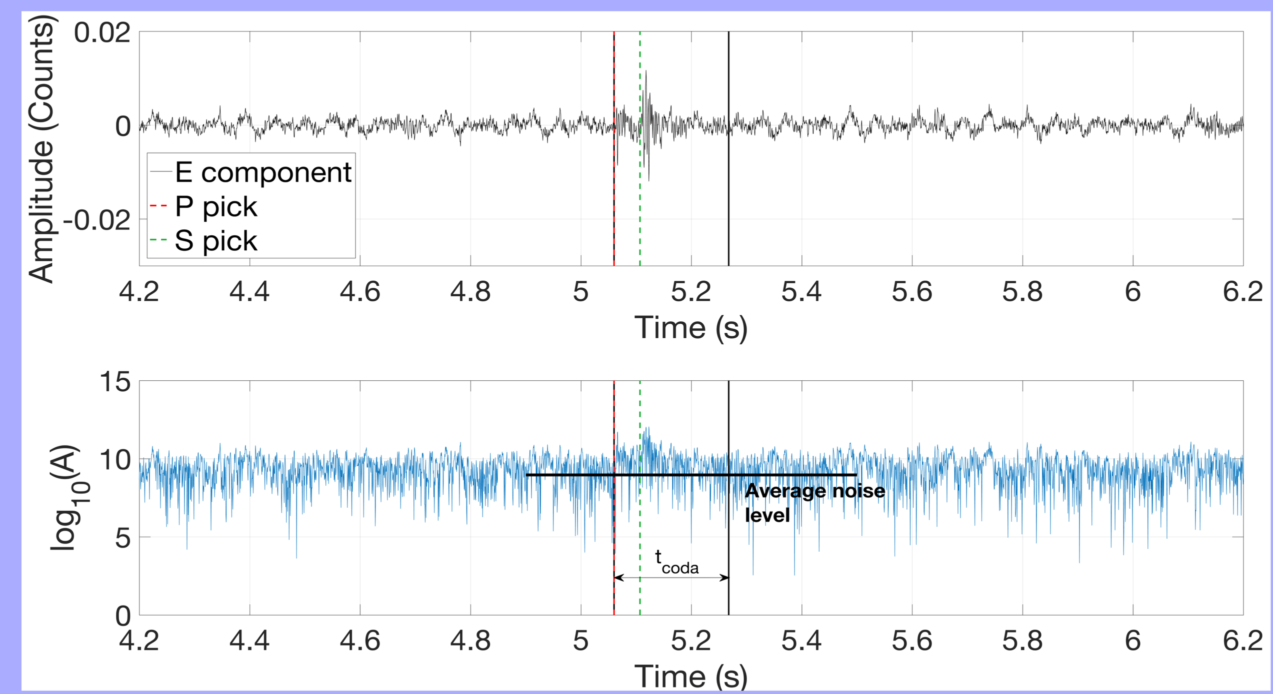

Figure 2: (Top panel) An event on the E-component with the P (red) and S (green) arrival picks from PhaseNet. (Bottom panel) The log of the trace through time.

- We fit a linear relationship $\log_{10}(t_{coda}) = 0.611\ M_W - 0.0437$ with a standard deviation (± 0.36 M_w) between the measured t_{coda} and the moment magnitudes of the recalled events (Fig. 3). Based on our fit, we then estimate the coda-duration magnitudes M_d using (Havskov and Ottemöller, 2010):

$$M_d = a \log_{10}(t_{coda}) + \mathrm{br} + c$$

where t_{coda} is the measured coda duration in seconds, r is the hypocentral distance in kilometres (for this initial pass, we set b = 0 since coda durations are almost unaffected by epicentral distance for distances < 100 km, Aki and Chouet, 1975) and a, b and c are constants from our fitted coda-magnitude scale.

Conclusions and future research

- Here, we use coda-duration magnitudes as proxy for M_W when waveforms are affected by amplitude clipping and borehole resonance frequencies.
- We find that PhaseNet detects more lower magnitude events, leading to more densely sampled magnitude distributions and a lower magnitude of completeness, which could affect the estimation of the Gutenberg-Richter b-value.
- More events allow us to estimate b-value more accurately and improve identification of event clusters.
- Future research: upscale estimation of M_d and evaluate b-values across the complete PNR-1z downhole catalog.
- This could enhance seismic hazard assessments and offer opportunities to investigate the spatio-temporal evolution of induced seismicity in higher resolution.

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