

Source parameter estimation of acoustic emissions induced by hydraulic fracturing in the laboratory

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SUMMARY

The hydraulic fracturing technique is used for resource production, such as in shale gas/oil extraction and enhanced geothermal systems. The effects of fracturing are often monitored via induced earthquakes, and obtaining as much information as possible from those earthquakes is desirable. The stress drop—calculated from the seismic moment M_0 and corner frequency f_c —is an earthquake-related parameter that can help identify additional characteristics of the seismicity. To investigate the relationship between stress drops and hydraulically induced seismic events, we estimated the M_0 and f_c of acoustic emission (AE) events during hydraulic fracturing experiments performed in the laboratory in previous studies using 2 Eagle Ford shale and 10 Kurokami-jima granite samples. We estimated M_0 by fitting the theoretical spectra to the observed spectra after correcting for the following effects: (1) frequency response of AE transducers under the installation method used in the fracturing experiment, including differences in sensitivity across every transducer used in each experiment; and (2) the difference in radiation pattern coefficients, which depends on the focal mechanisms of each AE event. This analysis used 46 857 focal mechanisms obtained from moment tensor solutions estimated using a deep learning technique. The range of the resultant M_0 was found to be $2.8 \times 10^{-5} \leq M_0 \leq 4.5 \times 10^{-1}$ [N·m], corresponding to $-9.1 \leq M_w \leq -6.3$, where M_w is the moment magnitude. We also estimated f_c using the multiple-empirical Green's function method, reducing the influence of modelling errors in the AE sensor response and transfer function of the medium. Out of the 1053 events whose M_0 and f_c were estimated, 465 events (44.2 per cent)—regardless of their focal mechanisms—were found to have M_0 and f_c values consistent with the constant stress drop scaling of shear failure (i.e. shear failures have 0.1–100 MPa stress drops independent of their magnitude) that has been repeatedly confirmed in many previous studies. The remaining events showed lower f_c values than those expected from the scaling law. This indicates that high pore pressure in a source region induced by fluid stimulation contributes to the occurrence of low-frequency earthquakes. Overall, we demonstrated that source parameter estimation was possible for laboratory AEs induced by hydraulic fracturing, which can improve our understanding of the characteristics of fluid-induced earthquakes.

Key words: Fracture and flow; Earthquake source observations; Induced seismicity; Fractures, faults, and high strain deformation zones.

1 INTRODUCTION

Hydraulic fracturing is used to increase the permeability of rocks during resource production, such as in shale gas/oil extraction (Soeder 2018) and enhanced geothermal systems (Li *et al.* 2016). This process induces many seismic events, and their activity is often monitored to investigate the influence of fracturing (Maxwell 2014). It is essential to obtain as much information as possible from the seismic data to understand the fracturing process and improve resource extraction efficiency.

Stress drop ($\Delta\sigma$) is a fundamental parameter representing the source characteristics of seismic events (e.g. Kanamori & Anderson 1975). It is potentially helpful for obtaining additional information from seismic observation data. This parameter is estimated from the seismic moment (M_0) and corner frequency (f_c), determined from seismic wave data. Previous studies have suggested that stress drops can help distinguish induced earthquakes from natural (tectonic) earthquakes (Abercrombie & Leary 1993; Hough 2014) and that these are essential for predicting strong ground motion due to induced earthquakes (Atkinson 2015).

The source parameters of shear failures, such as tectonic earthquakes, have been reported to exhibit the relationship $M_0 \propto f_c^{-3}$, resulting in a constant stress drop of 0.1–100 MPa, independent of magnitude (e.g. Abercrombie 1995; Kwiatak *et al.* 2011; Yoshimitsu *et al.* 2014). For earthquakes induced by hydraulic fracturing and fluid injection, lower stress drops than for tectonic earthquakes have been observed (Abercrombie & Leary 1993; Hough 2014), likely resulting from the high pore pressure in the source region. Goertz-Allmann *et al.* (2011) and Kwiatak *et al.* (2014a) reported that earthquake stress drops induced by hydraulic stimulation in geothermal fields increase with increasing distance from the injection wells. The authors interpreted this as resulting from high pore pressure around the well, decreasing effective normal stress and stress drops. Significant temporal changes in stress drops have also been reported for swarms and were likely influenced by temporal changes in the fluid pressure of the source regions (Yoshida *et al.* 2017; Yoshida 2020). Stress drops are potentially helpful in monitoring the spatiotemporal distribution of pore pressure (Goertz-Allmann *et al.* 2011). In contrast, other studies have concluded that fluid-induced earthquakes and tectonic earthquakes in the same region do not significantly differ in stress drops (Clerc *et al.* 2016; Huang *et al.* 2016; Wang *et al.* 2020). Stress drops of fluid-induced earthquakes remain a controversial issue. Therefore, a more profound understanding is necessary to utilize the stress drop parameter in actual resource production.

Laboratory experiments involving acoustic emission (AE) measurement are one approach to investigate the characteristics of fluid-induced earthquakes and their relation to the fracture generation process. Previous studies have successfully monitored the preparation process of hydraulic fracture, which strongly depended on the rock types and viscosities of the fracturing fluid, through the spatiotemporal distribution of AE events (e.g. Stanchits *et al.* 2014; 2015). Polarity analysis of *P*-wave first motions (Bennour *et al.* 2015; Stoeckert *et al.* 2015) and moment tensor (MT) analysis (Rodriguez *et al.* 2017; Yamamoto *et al.* 2019; Naoi *et al.* 2020) of such AE events have provided information on the fracture modes of individual AEs, which have been helpful to understand the progression of macroscopic fractures. Tanaka *et al.* (2021) have revealed a detailed preparation process of hydraulic fracturing from many MT solutions (54 727 for 10 experiments) that were obtained by introducing a deep learning technique.

As described above, the generation of hydraulically induced fractures can be monitored by AE activities in laboratory experiments. Estimating source parameters such as M_0 , f_c and $\Delta\sigma$ of the laboratory-induced AEs helps understand the relationship between the fracturing process and the induced seismic events. For instance, Goodfellow *et al.* (2015) have estimated the M_0 of AEs induced by hydraulic fracturing in a laboratory to investigate the contribution of aseismic deformation in the fracture generation process. However, analyses estimating such parameters using AE records are rare owing to the difficulty in overcoming the following challenges.

(1) Calibration of AE transducer response: an AE transducer has a complex frequency response, which must be estimated to use its spectrum. Goodfellow *et al.* (2015) have achieved this using the calibration sources of ball impact and glass capillary fracture (McLaskey & Glaser 2012). However, the frequency response depends on its coupling condition. Thus, the response under the installation method used in the actual experiments should be evaluated. Even when AE transducers are attached to a specimen using the same installation method, a difference in coupling conditions influences their sensitivity (Kwiatak *et al.* 2014b). Hence, the sensitivity should be estimated for each transducer after its installation. Some studies (Yamamoto *et al.* 2019; Naoi *et al.* 2020; Tanaka *et al.* 2021) have overcome this problem by estimating the relative sensitivity of each transducer using data from pulse radiation tests that were conducted immediately before each experiment.

(2) Measurable frequency band of AE transducer: if the frequency response of an AE transducer is obtained, the f_c can be evaluated by estimating the amplitude spectrum of the ground motion (Yoshimitsu *et al.* 2014). Even if an accurate estimation of frequency response is difficult, the empirical Green's function (eGF) method (e.g. Hough *et al.* 1999; Ide *et al.* 2003), which minimizes the influence of unmodelled errors in the frequency response, is a potentially effective approach for f_c estimation. However, these methods necessitate evaluating the bending points in a spectrum, and the use of traditional narrow-band AE transducers with a strong resonance makes accurate estimation unachievable. A broad-band AE transducer, such as the one used by Naoi *et al.* (2020) and Tanaka *et al.* (2021), is preferable.

(3) Radiation pattern correction: when focal mechanisms are unknown, many studies (e.g. Edwards *et al.* 2010; Naoi *et al.* 2014; Goodfellow *et al.* 2015; Ross *et al.* 2016) assumed events to be shear failures and used the root mean square (RMS) values of the radiation pattern coefficients (Boore & Boatwright 1984) to estimate their M_0 . However, this assumption is possibly inappropriate for hydraulic fracturing experiments because of the occurrence of many AEs having various types of focal mechanisms (Yamamoto *et al.* 2019; Naoi *et al.* 2020; Tanaka *et al.* 2021). Appropriate corrections to reflect the actual focal mechanisms of AEs are necessary.

In the present study, we estimated the M_0 and f_c using the AE records obtained by Naoi *et al.* (2020) and Tanaka *et al.* (2021) by carefully considering the above challenges (1)–(3) and investigated the relation between these parameters to assess the stress drops of hydraulically induced seismic events. We selected the data from these studies because the data were obtained using rare laboratory experiments of hydraulic fracturing, in which broad-band AE transducers were used for the measurement and MT solutions were obtained.

In Section 2, the experimental method and the analyses of the AE data, including those sourced from Naoi *et al.* (2020) and Tanaka *et al.* (2021), are briefly summarized. Section 3 explains the estimation method of the frequency response of AE transducers, and Section 4 explains the estimation method of M_0 after overcoming

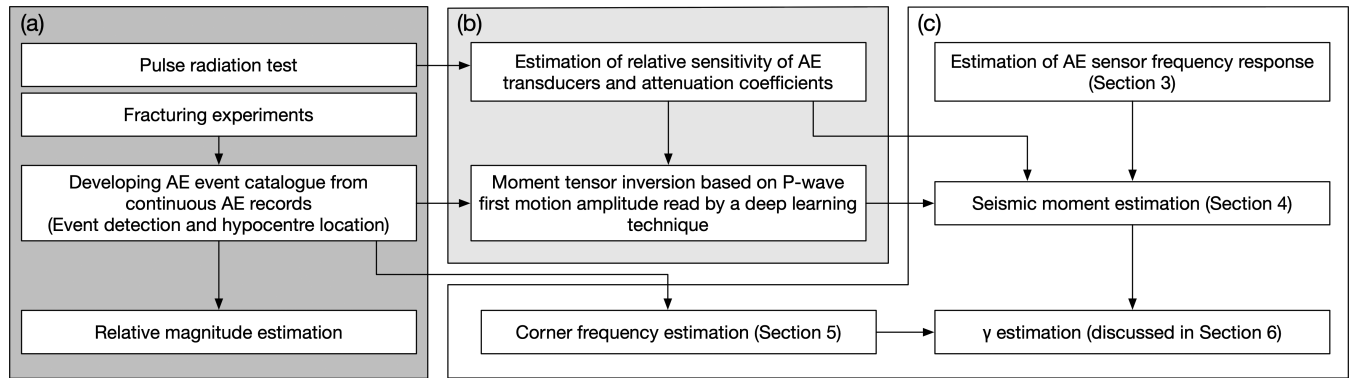


Figure 1. Analyses flowchart of AE data, including that in studies by Naoi *et al.* (2020) and Tanaka *et al.* (2021), to achieve source parameter estimations. The experiments and the analyses in the dark grey box (a) were conducted in the previous studies, and the present study used these results. The analyses in the light grey box (b) were re-conducted using updated, consistent methodologies (Appendices A–C). The white box (c) represents the novel analyses in the present study.

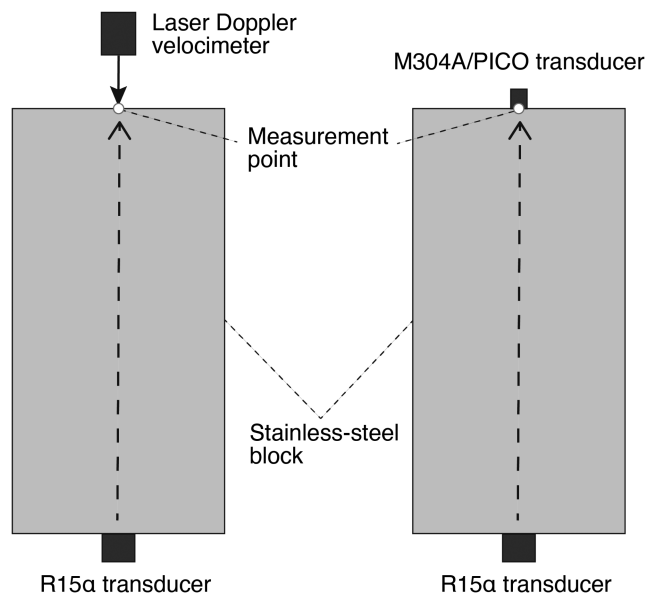


Figure 2 Diagram illustrating the measurement of AE sensor frequency response. The measurement point corresponds to the irradiated point of LDV or the contact between an AE transducer and the specimen.

problems (1) and (3) above. In Section 5, we describe the estimation of f_c using the multiple-empirical Green's function (MEGF) method (Hough *et al.* 1999; Ide *et al.* 2003). Finally, we discuss the biases that appeared in the M_0 and f_c estimations and discuss the implications for fluid-induced earthquakes (Section 6). This study involves updating the analyses previously reported by Naoi *et al.* (2020) and Tanaka *et al.* (2021). A description of these analyses is summarized in Appendices A–C, including an update on the application of a deep learning technique to MT analysis, which is necessary to remove a bias that tensile-type solutions were preferably obtained in the MT estimates of Tanaka *et al.* (2021) (Appendix C).

2 HYDRAULIC FRACTURING EXPERIMENTS AND AE DATA TREATMENT

This study estimated the M_0 and f_c of the AEs observed during 12 laboratory hydraulic fracturing experiments conducted by Naoi

et al. (2020) and Tanaka *et al.* (2021). The data from two experiments with Eagle Ford shale (hereinafter referred to as EFS samples) by Naoi *et al.* (2020) and 10 experiments with Kurokami-jima granite (hereinafter referred to as KJG samples) by Tanaka *et al.* (2021) were employed. Fracturing was induced via the injection of a thermosetting acrylic resin (viscosity, ~ 0.8 mPa·s) into a packer set in blocks with 65 mm $\times$ 65 mm $\times$ 130 mm dimensions under 5 MPa uniaxial loading (Fig. S1, Supporting Information). Tanaka *et al.* (2021) have also performed fracturing experiments using resins whose viscosity was adjusted to ~ 10 , 50, 300 and 1000 mPa·s. All experimental results are summarized in Table S1 (Supporting Information).

Naoi *et al.* (2020) and Tanaka *et al.* (2021) measured the AE signals using 16 high-sensitivity broad-band transducers (M304A; Fuji Ceramics Corp.) and 8 transducers with a resonance frequency of ~ 550 kHz (PICO; Physical Acoustics) attached to a specimen (Fig. S1, Supporting Information). Based on the AE waveforms that were continuously recorded at a 10 MHz sampling rate, Naoi *et al.* (2020) and Tanaka *et al.* (2021) have developed AE event catalogues. We used these catalogues in the present study to estimate the M_0 and f_c of AE events.

Naoi *et al.* (2020) and Tanaka *et al.* (2021) also estimated the MT solutions of the AE events using slightly different methodologies in the estimation of the coupling coefficients of each transducer and the inelastic attenuation coefficients of the samples. In the present study, we re-estimated these coefficients (Appendix A) and MTs (Appendix B) with updated parameters using a consistent methodology, which includes the modification of a deep learning technique to remove the possible bias in the MT solutions of Tanaka *et al.* (2021) (Appendix C). The resultant coupling coefficients and re-estimated 46 857 MT solutions (Appendix B) were used for the M_0 estimation (Section 4). Fig. 1 shows the flowchart of AE data analyses to achieve M_0 and f_c estimations.

3 CHARACTERISTICS OF AE TRANSDUCERS

As described in Introduction, the complicated frequency response of AE transducers under the installation method used in the actual experiments needs to be evaluated to estimate the M_0 of the AEs. Yoshimitsu *et al.* (2014) have suggested a calibration method of the frequency response using a laser Doppler velocimeter (LDV), which

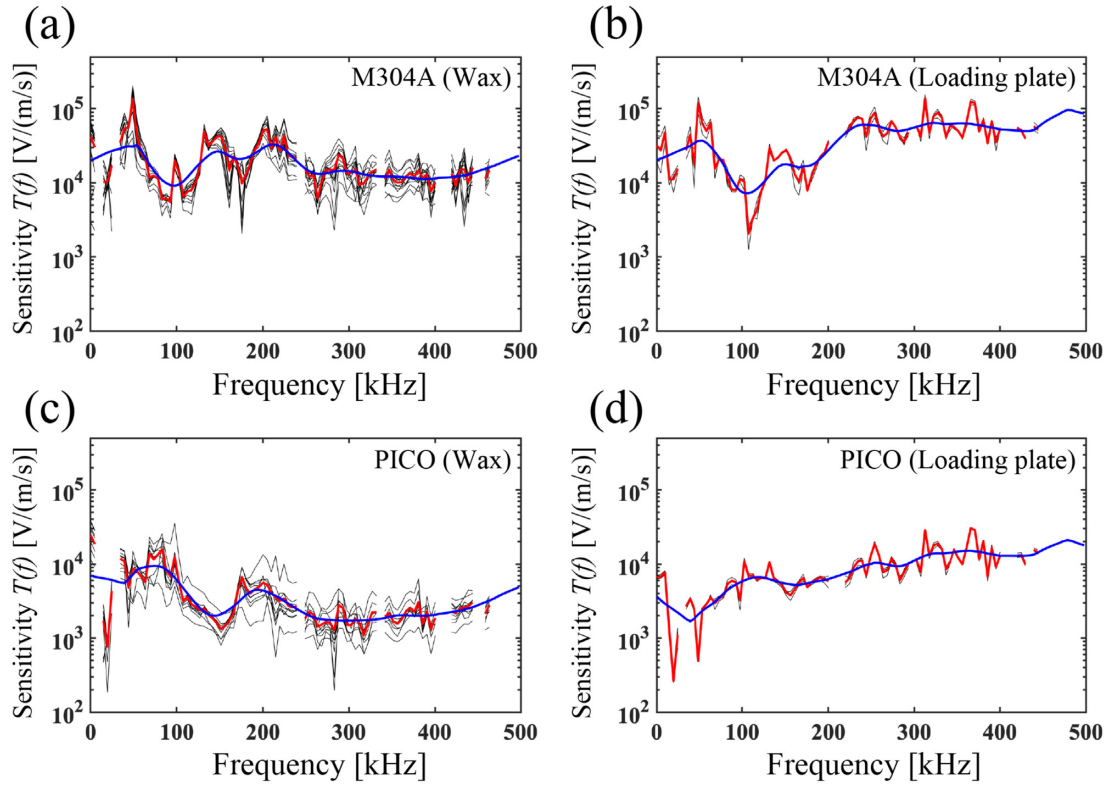


Figure 3. Frequency response of AE transducers. Black lines represent the deconvolution of AE transducer records by LDV records for each transmission test (the sensitivity of LDV was corrected). Red lines represent the stacking results of the black lines. Blue represents the moving average of red lines with a bandwidth of 78.125 kHz, which corresponds to the fast Fourier transform frequency resolution for a 128-sample record used in the M_0 analysis (Section 4). (a) Results for M304A attached using thermofusible wax, (b) M304A attached using a spring in a loading plate, (c) PICO attached using thermofusible wax and (d) PICO attached using a spring in a loading plate. The results correspond to the case where the amplification of 45 and 46 dB for M304A and PICO (the same gains as those used in the fracturing experiments; Naoi *et al.* 2020; Tanaka *et al.* 2021), respectively, were applied for the AE transducer records.

has a flat frequency response to ground motions and can measure vibrations without contact. Therefore, the data obtained are free of influence from the coupling conditions between the measurement device and the specimen, and they can be used as the reference for the ground motion in the estimation of the frequency response of AE transducers. The present study adopted an approach similar to that of Yoshimitsu *et al.* (2014) with a modification to reveal the difference in sensitivities arising from the different installation methods.

We evaluated the frequency responses of the M304A and PICO transducers under the installation methods used in the experiments of Naoi *et al.* (2020) and Tanaka *et al.* (2021). Fig. 2 shows the schematic diagram of this measurement. We used a stainless-steel block (65 mm × 65 mm × 130 mm) and attached a pulser (R15α transducer, resonance frequency 75–150 kHz; Physical Acoustics) to a face of the block using thermofusible wax. We applied a step voltage change to the pulser to radiate the acoustic pulse. An LDV (Melectro Laser Vibrometer V100; DENSHIGIKEN Corporation) was used to measure the vibration at the opposite side (measurement point in Fig. 2) of the block without contact, with a flat frequency response of < 1 MHz. We then placed an AE transducer (M304A or PICO) at the measurement point and recorded the same vibrations. We estimated the $T(f)$ of the AE transducer, that is, the transfer function in frequency domain that converts from the recorded voltage to the vibration velocity in the direction perpendicular to the sensor surface, by deconvolving the AE transducer records using LDV records.

In the fracturing experiments performed by Naoi *et al.* (2020) and Tanaka *et al.* (2021), the AE transducers were attached to the specimens using two different methods: transducers on the side faces were fixed with thermofusible wax and transducers on the upper and lower surfaces were attached using a spring in a small hole drilled into a loading plate. The frequency response was measured for the two transducer-installation methods. With the wax, transducer sensitivity significantly changed each time the sensor was reattached. Thus, we averaged the results of 16 tests for M304A and 12 tests for PICO to estimate the frequency responses. Since the spring installation method showed better reproducibility, the results of only three tests were averaged. The acoustic wave amplitude radiating from the pulser (R15α) is also affected by the coupling condition, as is the receiver. We, therefore, did not reattach it during any of the tests, which allowed us to assume a constant amplitude of the wave radiating from the pulser for all data. Waveforms were recorded at 12-bit ADC and 20 MHz sampling rate using the PXI-5122 Module (National Instruments Co.) after amplification and stacking (10 000 times for LDV records and 100 times for M304A and PICO).

From the recorded waveforms, we extracted 4096 samples (204.8 μs) around P -wave arrivals for spectral analysis. The estimated frequency responses from the extracted waveforms can be regarded as P -wave responses because the sensitivity of AE transducers and the LDV is in the vertical direction relative to the top face of the block, despite the waveforms including S and later phases. We confirmed that similar results—except for the frequency resolution—were obtained when using shorter windows that did not include S waves and

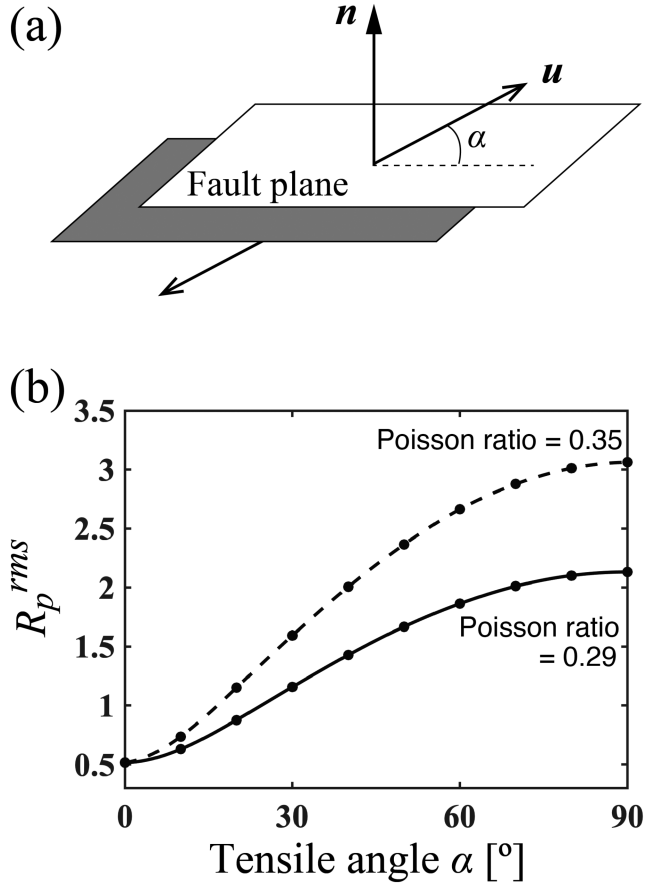


Figure 4. (a) Schematic illustration of the shear-tensile model (Vavryčuk 2001; 2011). n indicates the normal vector of the fault plane, u indicates the dislocation vector and α indicates the tensile angle of the dislocation vector that was defined as the angle from the fault plane. (b) Relationship between α and R_p^{rms} (RMS values of the P -wave radiation pattern coefficients). Results for a Poisson ratio of 0.29 (Kurokami-jima granite) and 0.35 (Eagle Ford shale). R_p^{rms} of every 10 degrees was estimated from 100 000 Monte Carlo sampling, and curves shown as solid and dashed black lines represent the results of spline interpolation.

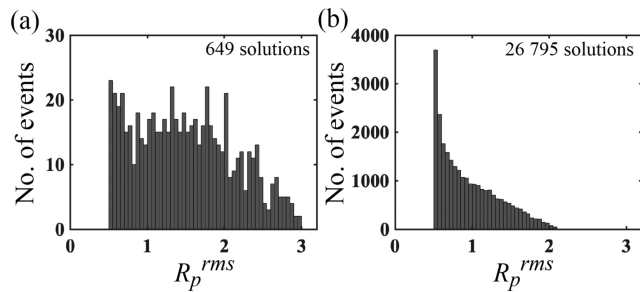


Figure 5. Histograms of R_p^{rms} estimated from the MT solutions for each event. (a) and (b) correspond to the EFS and the KJG samples, respectively.

used a relatively long window of the 4096 samples to improve the frequency resolution and the reliability of frequency characteristics at low frequencies. In the analysis, we used signals with a frequency band with SNR (signal-to-noise ratio) ≥ 5 against the noise amplitude spectrum calculated for the pre-signal part. Fig. 3 shows the obtained $T(f)$ for M304A and PICO; the unanalysed frequency bands resulted from a lack of SNR mainly in the LDV records.

4 SEISMIC MOMENT ESTIMATION

Using spectral fitting, we estimated the M_0 of AE events. In this analysis, we assumed an ω -square model as a source spectrum. That is, the Fourier spectrum of seismic waveform radiated from a source is flat in $f < f_c$ and falls off at a rate of $\omega^{-2} = (2\pi f)^{-2}$ in $f > f_c$, where f_c is the corner frequency. The adequacy of this assumption has been repeatedly confirmed for shear events in many previous studies (e.g. Aki 1967; Imanishi & Ellsworth 2006). For the other types of focal mechanisms, especially for the mixed-mode type, observational evidence of specific fall-off rates were limited, although some kinematic models expect the ω^{-2} fall-off rate for tensile-type sources (Walter & Brune 1993). Therefore, we applied an ω -square model, which is typically used in spectral analyses of shear events, for all AEs regardless of their focal mechanisms.

The displacement spectrum $D(f, r)$ of the P -wave ground motion observed at a station can be expressed as follows:

$$D(f, r) = \frac{R_c}{4\pi\rho V_P^3 r} \frac{M_0}{\sqrt{1 + (f/f_c)^4}} \exp\left(-\frac{\pi r f}{Q V_P}\right), \quad (1)$$

where r is the distance between the source and receiver, R_c is the radiation pattern coefficient, ρ is the density of the specimen (Ide *et al.* 2003), V_P is the P -wave velocity and Q is the inelastic attenuation parameter (quality factor). We assumed V_P as

$$V_P = \sqrt{V_P^2 l_x^2 + V_P^2 l_y^2 + V_P^2 l_z^2}, \quad (2)$$

under the assumption of an orthorhombic anisotropy, l_x , l_y and l_z are the direction cosines of a vector from the transmitter to the receiver. This equation corresponds to a 3-D elliptical approximation (Petrušálek *et al.* 2013), which has symmetric axes along the x -, y - and z -directions and was also previously used in hypocentre location analysis of these AE events (Naoi *et al.* 2020; Tanaka *et al.* 2021). We also assumed Q as the same function (eq. A1), which was estimated simultaneously with sensor coupling coefficients based on pulse radiation tests (Appendix A). From eq. (1), the amplitude spectrum of the ground motion, $D_c(f)$, obtained after correcting for geometrical spreading and inelastic attenuation, can be written as:

$$D_c(f) = r \exp\left(\frac{\pi r f}{Q V_P}\right) D(f, r) = \frac{R_c}{4\pi\rho V_P^3} \frac{M_0}{\sqrt{1 + (f/f_c)^4}}. \quad (3)$$

The logarithm of eq. (3) gives:

$$\log_{10} D_c(f) = \log_{10} M_0 + \log_{10} \frac{R_c}{4\pi\rho V_P^3} - \frac{1}{2} \log_{10} \left[1 + \left(\frac{f}{f_c} \right)^4 \right], \quad (4)$$

where $D_c(f)$ is estimated from the observed AE spectra by correcting for the frequency response of the AE transducer, geometrical spreading, inelastic attenuation, directivity and coupling coefficients, as described in the next paragraph. Then, M_0 and f_c were estimated by fitting eq. (4) to $D_c(f)$ using the Levenberg–Marquardt method of least squares (Moré 1978). From the obtained M_0 , we estimated the moment magnitude M_w using the following equation (Hanks & Kanamori 1979):

$$M_w = \frac{2}{3} (\log_{10} M_0 - 9.1), \quad (5)$$

rounding off the result to 0.1 intervals. For ρ in eq. (4), we used a value of 2600 kg m⁻³ for both EFS and KJG samples based on the measurement results for plug cores of 1' (25.4 mm) in diameter and

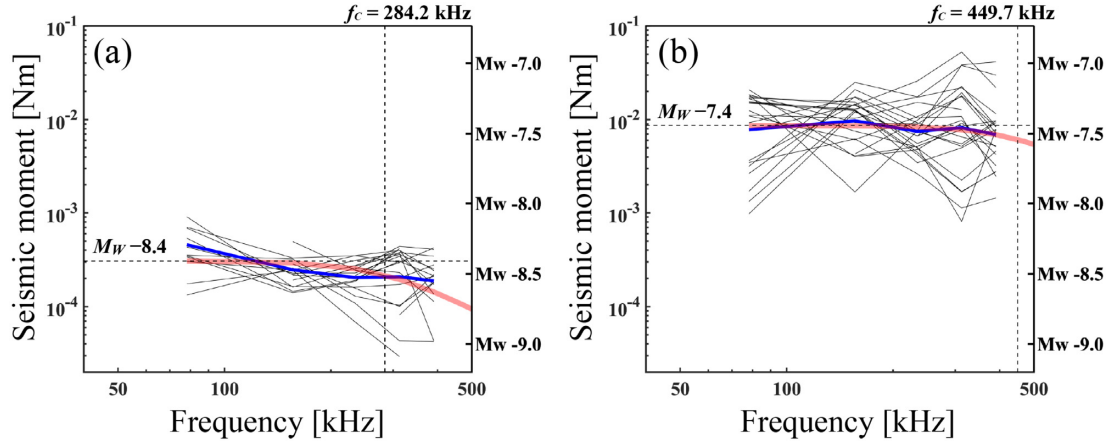


Figure 6. Examples of M_0 and M_w estimation results by spectral fitting. (a) Examples of an AE event occurring at $t = -4.3$ s [hypocentre coordinates $(x, y, z) = (1.67 \text{ mm}, 1.01 \text{ mm}, -4.90 \text{ mm})$] in the experiment of sample EFS1704. (b) Examples of an AE event occurring at $t = 3.3$ s [$(x, y, z) = (-28.89 \text{ mm}, -1.60 \text{ mm}, -5.51 \text{ mm})$] in the experiment of sample KJG1811. Black lines represent corrected spectra for each transducer record, while the blue line represents the stacking results. Red lines represent the theoretical spectra obtained by fitting the blue lines using the Levenberg–Marquardt least-squares algorithm (Moré 1978).

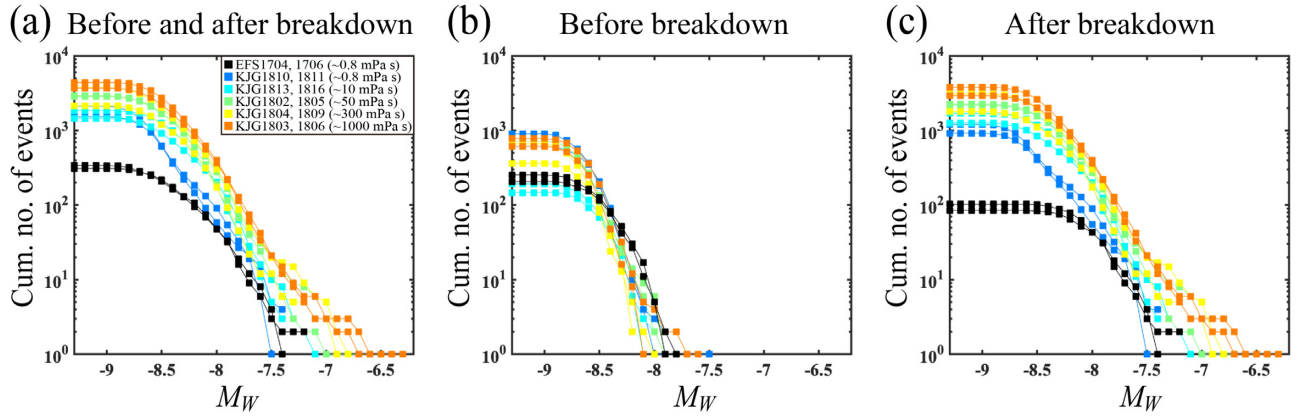


Figure 7. Frequency–magnitude distribution of the M_w -determined events (only solutions with $c \geq 0$). (a) For all M_w -determined AEs in each experiment. (b) For AEs before breakdown. (c) For AEs after the breakdown. Lines with different colours indicate different rock types and different viscosities of fracturing fluid used in the experiment.

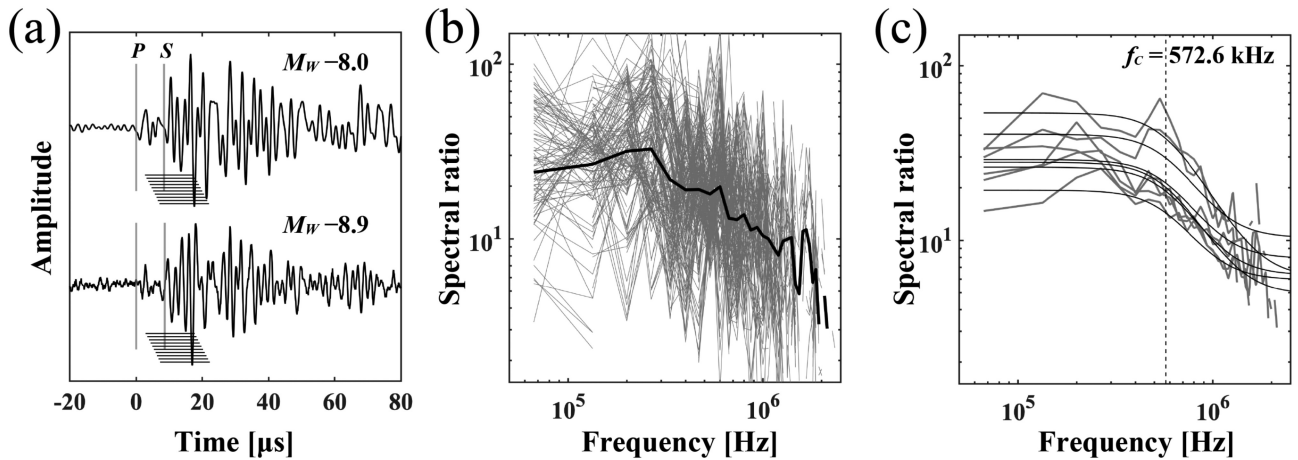


Figure 8. Examples of f_c estimation for AE events occurring with the sample KJG1804. (a) Waveforms recorded by M304A for an $M_w = -8.0$ event (target event of this f_c estimation) and an $M_w = -8.9$ event used as an eGf. Black horizontal lines plotted below each waveform show the time windows for spectrum calculation. (b) Spectral ratios for the two events. Thin grey lines show the results for each sensor and window. Results for bands with $\text{SNR} \geq 3$ are shown. The thick black line represents the stacking result. (c) Stacked spectral ratios between the target event and six eGfs (grey lines). One of the grey lines corresponds to the black line in (b). The black lines in (c) represent the fitting results by a nonlinear least-squares method for all grey lines.

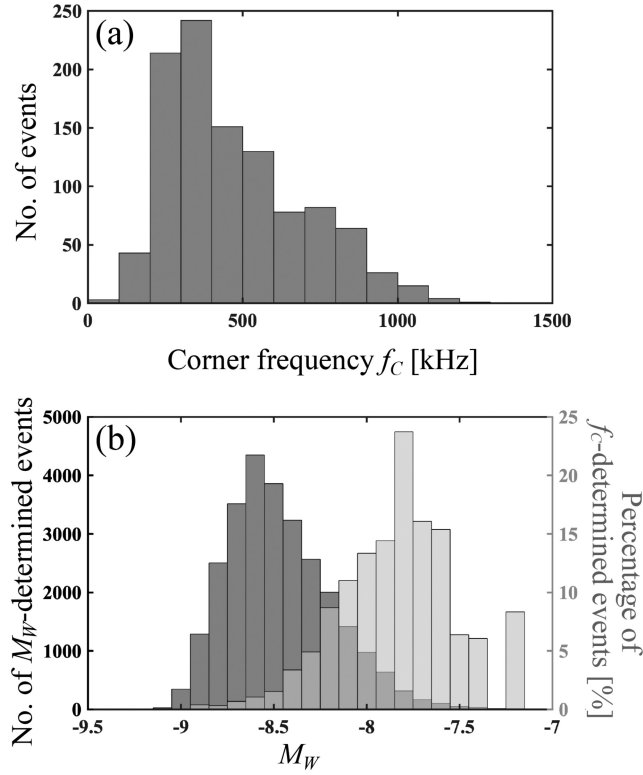


Figure 9. (a) Histograms of the evaluated f_c using the MEGF method. (b) Frequency–magnitude distribution of the percentage of events whose f_c was successfully estimated (light grey) and the number of all M_w -determined events (dark grey).

2" (50.8 mm) in length. For EFS samples, 10 cores were prepared from the neighbouring parts of the blocks used in fracturing experiments, and the average density was 2600 kg m^{-3} (Naoi *et al.* 2020) with a standard deviation of 20 kg m^{-3} . For KJG samples, six cores were prepared based on the block from the same quarry, and the average density was 2622 kg m^{-3} with a standard deviation of 2 kg m^{-3} .

For the estimation of $D_c(f)$, we used the amplitude spectra of 128-sample waveforms around P arrivals of M304A records. Based on the results obtained by the procedure explained in Appendix A, we first converted the spectrum of AE waveform $A(f)$ recorded by an AE transducer to the corrected spectrum $A_{AE}(f)$ using the following equation:

$$A_{AE}(f) = CSI(f, \theta) A(f), \quad (6)$$

where $I(f, \theta)$ is the directivity of the AE transducer for a wave with an incident angle θ , which is assumed by a bell-shaped curve (Naoi *et al.* 2020; Appendix A), and S is the sensitivity coefficient of the transducer estimated by the procedure presented in Appendix A. C is a constant determined such that an average coefficient $\Sigma S_i/N$ equals to one among the same type of transducers attached to the block using the same installation method, where S_i is the sensitivity of transducer i and N is the number of such transducers attached to a specimen. From the spectrum $A_{AE}(f)$ obtained by the above correction, we estimated $D(f)$ using the following equation:

$$D(f) = \frac{1}{2\pi f} \frac{A_{AE}(f)}{T(f)}, \quad (7)$$

and then estimated $D_c(f)$ using eq. (3) by correcting attenuation effects. The frequency response $T(f)$ was the one estimated in Section

3. We used $T(f)$ after applying a moving average with a bandwidth of 78.125 kHz (blue lines in Fig. 3), corresponding to the fast Fourier transform frequency resolution for a 128-sample record at a 10 MHz sampling rate. For this analysis, we used the frequency bands of signals that had $\text{SNR} \geq 2$. To avoid extracted waveforms with S -waves, we terminated the data window up to 5 samples before the theoretical arrival time of the S wave and padded zeros to adjust the signal length to 128 samples in case necessary. We fitted eq. (4) to the stacked spectrum for all stations after re-sampling to obtain constant intervals for the logarithm of the frequency.

The radiation pattern coefficient R_c in eq. (4) depends on the MT solutions and the relative positions between the source and station. For seismic events whose MT solution was not determined, previous studies often used the RMS value of the radiation pattern coefficients of the shear source ($2/\sqrt{15}$ for P wave; Aki & Richards 2002) for M_0 estimation (e.g. Edwards *et al.* 2010; Naoi *et al.* 2014; Goodfellow *et al.* 2015; Ross *et al.* 2016). However, for the AE events analysed in the present study, almost all AEs occurring in EFS experiments were of the tensile type (Naoi *et al.* 2020), whereas various AE events, including shear, tensile and compressive events, were observed in KJG experiments (Tanaka *et al.* 2021). These tendencies were also confirmed in the source-type plots (Figs S2 and S3, Supporting Information) of the MT solutions re-estimated in the present study (Appendix B). Therefore, we cannot assume $2/\sqrt{15}$ and must use appropriate values depending on the MT solutions.

To account for the influence of R_c , we assumed the shear-tensile model (Fig. 4a, Vavryčuk 2001; 2011), where shear and tensile deformation occur on a fault plane. To check whether each MT solution corresponds to the shear-tensile model or not, we used the c -value (Vavryčuk 2011), which was also used in Naoi *et al.* (2020) and Tanaka *et al.* (2021) studies to classify their MT solutions. It is defined as follows:

$$c = \text{sign} \left(\frac{M_{\text{ISO}}}{M_{\text{CLVD}}} \right) \left| 1 - \frac{M_{\text{DC}}}{100} \right|, \quad (8)$$

where M_{ISO} , M_{DC} and M_{CLVD} are the percentages of isotropic (ISO), shear (double couple; DC) and compensated linear vector dipole (CLVD) components, respectively. These components are obtained by decomposing MT solutions using a simplified decomposition method (Vavryčuk 2015). The c -values are between -1 and 1 , where $c \geq 0$ corresponds to the shear-tensile model (Vavryčuk 2011), $c \approx 1$ corresponds to a large tensile/compressive component, and $c \approx 0$ corresponds to a shear-dominant solution. $c < 0$ indicates significant deviation from the shear-tensile model or large errors in the MT estimations. In the following analysis, we focused on the 27 444 solutions with $c \geq 0$, out of the re-estimated 46 857 MT solutions (Section 2 and Appendix B).

Kwiatek & Ben-Zion (2013) evaluated the RMS average of the radiation pattern coefficients of the P and S waves for a shear-tensile source using the Monte Carlo method suggested by Boore & Boatwright (1984). For shear-tensile sources, the RMS value for the P wave (R_p^{rms}) depends on the Poisson ratio. It can be represented as a function of the tensile angle α (Fig. 4a), defined as the angle between the crack plane and displacement vector. Fig. 4(b) shows the resultant R_p^{rms} for cases with a Poisson ratio of 0.35 (measured value for Eagle Ford shale) and 0.29 (for Kurokami-jima granite). In this study, we estimated α for individual MTs using the equation (Vavryčuk 2011):

$$\sin \alpha = \frac{M_1 + M_3 - 2M_2}{M_1 - M_3}, \quad (9)$$

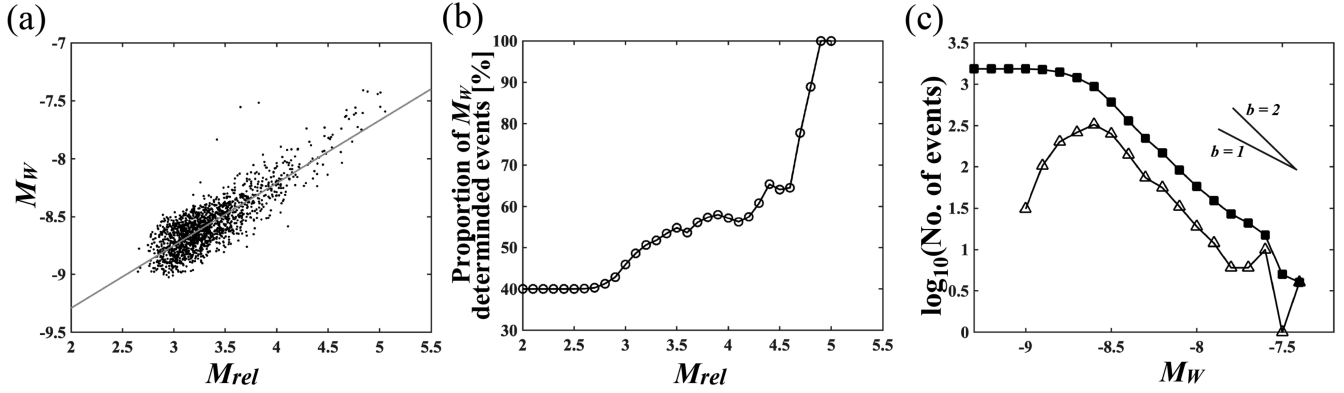


Figure 10. Estimation result of M_w for sample KJG1811. (a) Relationship between relative magnitudes M_{rel} and M_w . Results before 0.1-interval rounding were plotted to see the density of the dots. The grey line represents the regression line of $M_w = 0.54M_{rel} - 10.4$. (b) The ratio between the number of M_w - and M_{rel} -determined events. The proportion of the M_w -determined events among all events having M_{rel} exceeding a specific value is plotted. (c) Frequency–magnitude distribution of the M_w estimates. Square indicates the diagram based on cumulative counts, while the triangle is based on non-cumulative counts.

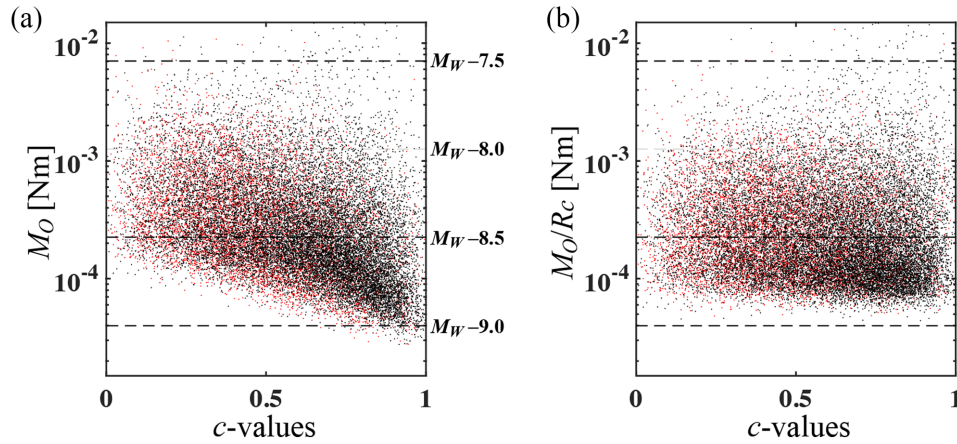


Figure 11. (a) Relationship between c -values and seismic moment M_0 . (b) The same plot but after removing the influence of R_c . Black and red dots represent events with tensile (i.e. with positive M_{ISO} after decomposition) and compressive (negative M_{ISO}) components, respectively.

where M_1 , M_2 and M_3 are the maximum, intermediate and minimum eigenvalues of MTs, respectively. We used the corresponding R_p^{rms} as R_c in the M_0 estimation.

The MT solutions estimated in this study did not include the seismic moment because the sensor coupling coefficient reflected was only relative (Appendix A). By accounting for the sensitivity using $T(f)$, it becomes possible to estimate MT with the seismic moment information. However, in the present MT analysis, the amplitude of the P -wave first motions was measured in the time domain (Appendix C), which makes it challenging to combine the frequency response analysis (Section 3) and MT inversion. In addition, the present approach can obtain a rough estimation of M_0 by assuming a certain R_c , even if its MT was not well determined. Although this is an advantage of the present method, we did not discuss M_0 for events whose MTs were not determined.

Fig. 5 shows the distributions of R_p^{rms} obtained for each MT solution of the EFS and the KJG samples. Reflecting the dominance of the tensile events in the EFS experiments (Fig. S2, Supporting Information; Naoi *et al.* 2020), larger R_p^{rms} tended to be obtained in the EFS experiments than in the KJG experiments. It is to be noted that low R_p^{rms} (i.e. ~ 0.5) values can be associated with relatively large c -values (e.g. $c \sim 0.7$) because of the nonlinearity of the relation between c (eq. 8) and α (eq. 9).

Using the above procedures, we estimated M_0 and M_w for 27 444 events that had MT solutions with $c \geq 0$. We obtained M_0 values corresponding to $-9.1 \leq M_w \leq -7.2$ ($2.8 \times 10^{-5} \leq M_0 \leq 2.0 \times 10^{-2}$ N·m) for the EFS samples and $-9.1 \leq M_w \leq -6.3$ ($2.8 \times 10^{-5} \leq M_0 \leq 4.5 \times 10^{-1}$ N·m) for the KJG samples. Fig. 6 shows examples of the spectral fitting results, where f_c did not appear to be accurately estimated due to the ambiguous fall-off corner frequency of the spectrum. We thus did not adopt f_c obtained using the procedure explained in this section and re-estimated f_c more accurately using the eGF method in Section 5.

Fig. 7(a) shows the frequency–magnitude distributions of the M_w -determined AEs with $c \geq 0$ in each experiment. In these experiments, a rapid drop in borehole pressure, which can be interpreted as the result of macroscopic fracture propagation, was observed after the peak pressure (Naoi *et al.* 2020; Tanaka *et al.* 2021). Figs 7(b) and (c) show the results of AEs before and after the pressure drop (hereinafter referred to as breakdown), respectively. When fracturing fluids with higher viscosities were injected, a larger M_w was obtained for the KJG samples (Fig. 7a). As shown in Figs 7(b) and (c), the difference in magnitude was observed only after the breakdown. This tendency may have resulted from the higher breakdown pressure obtained with higher viscosity fluids (Tanaka *et al.* 2021). Unfortunately, more detailed discussions based on the frequency–magnitude distribution were difficult, as discussed in Section 6.1.

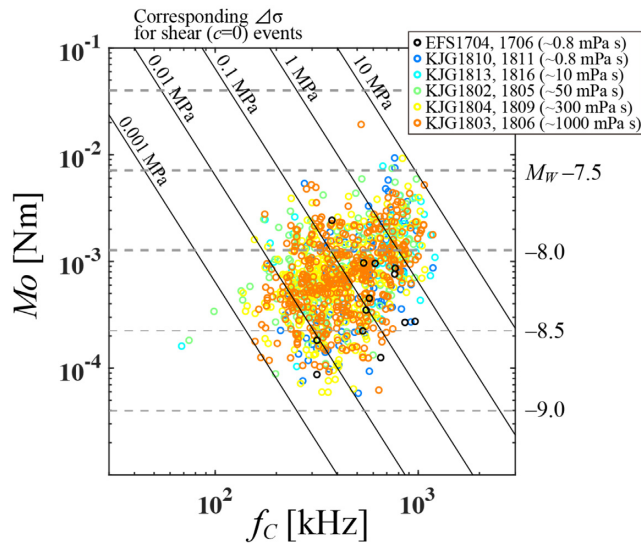


Figure 12. Relationship between f_c and M_0 estimates. The results are colour-coded by the specimen. Diagonal lines represent f_c – M_0 relationships when the stress drop is constant under the assumption of $k = 0.21$ (corresponding to rupture $V_r = 0.9V_S$) and $V_S = 3113 \text{ m s}^{-1}$ (average V_S among all specimens) for eq. (11). Although these relationships do not apply to non-shear AEs, these can be used as a rough indication of the magnitude of f_c compared to M_0 .

5 ESTIMATION OF CORNER FREQUENCY

In the previous section, M_0 and f_c were estimated by fitting the theoretical spectra to the observed ones. Through this approach, f_c can be estimated only for the frequency range in which the absolute frequency response is evaluated. In addition, this method is strongly affected by the modelling error of Green's function (i.e. transfer function in the medium and AE transducer response including its directivity), resulting in an inaccurate estimation of f_c values. To overcome these problems, we re-estimated the f_c of AEs using the MEGF method (Hough *et al.* 1999; Ide *et al.* 2003).

We considered two AE events whose hypocentres are close to each other. The two corresponding Green's functions between each hypocentre and the transducer, as well as the transducer responses, are nearly identical. The influence from the Green's functions can be cancelled by spectral division in frequency domain. The spectral ratio of the observed AE waveforms at a station can be expressed as follows:

$$F(f) = \frac{D_1(f, r)}{D_2(f, r)} = \frac{M_{01}}{M_{02}} \left(\frac{1 + (f/f_{c2})^4}{1 + (f/f_{c1})^4} \right)^{\frac{1}{2}}, \quad (10)$$

where $D_1(f, r)$ and $D_2(f, r)$ are the displacement spectra observed at the same station, and f_{c1} and f_{c2} are the corner frequencies of the two AEs constituting the event pair. These corner frequencies can be estimated by fitting the theoretical spectral ratio to the observed ratio. In the MEGF method, eq. (10) is formulated simultaneously for multiple event pairs to robustly estimate the f_c of all events constituting the pairs and their relative moments. The detailed analysis procedure is described in the following paragraphs.

For an AE event whose f_c is to be estimated (referred to as 'target event'), we selected a maximum of 20 events that were located the closest to the target event (within 2 mm) as eGf. For these selected events, we calculated the S-wave spectra using the time windows

of 150 sample lengths. To increase the robustness in the spectral ratio estimation, we adopted the multi-window spectral ratio method (Imanishi & Ellsworth 2006), where the spectra are calculated for 10 windows with an interval of five samples for each waveform. The spectral ratios between the target event and eGfs were evaluated using eq. (10) for each window, where the spectrum of the target event was used as the numerator (i.e. D_1 , M_{01} and f_{c1} are the values for the target event, whereas D_2 , M_{02} and f_{c2} are those for the eGf). A maximum of 240 spectral ratios (24 stations $\times$ 10 windows) were obtained for an event pair. Then, we stacked the spectral ratios among all stations and obtained one spectral ratio for an event pair (the 'stacked spectral ratio'). For one target event, a maximum of 20 stacked spectral ratios was obtained for 20 eGfs. We estimated f_{c1} , f_{c2} , M_{01} and M_{02} using the Levenberg–Marquardt method of least squares.

Although the influence of Green's function should be eliminated in the above approach, a relatively large misfit and scattering among the different sensors (stations) were often observed in the fitting (Yoshimitsu *et al.* 2019). This can be caused by the differences in Green's function between an event pair, for example, due to large errors in hypocentre location or due to temporal changes in Green's functions. Another problem arises when the difference between f_{c1} and f_{c2} is small. In this case, their spectral ratio becomes flat and significant bending cannot be identified, causing inaccurate estimation of f_c . To select stacked spectral ratios well described by the assumed model (i.e. eq. 10) and contributable to f_c constraint, we first fitted $F(f)$ in eq. (10) to each ratio and used the ones in the MEGF method when these satisfied all of the following criteria: (1) $d\Omega = \log_{10}(F(f_0)) - \log_{10}(F(f_1)) > 0.4$, where $[f_0, f_1]$ represents the frequency range used in the analysis; (2) $\log_{10}(f_1) - \log_{10}(f_0) > 1$; (3) the proportion of a frequency band that could not be used in the inversion (after re-sampling at a constant interval for the logarithm of the frequency) is less than 10 per cent; (4) $\log_{10}(r_e) < d\Omega/8$, where r_e is the RMS residual of the spectral fitting and (5) the obtained f_{c1} falls in $[f_0, f_1]$. From criterion (1), only spectral ratios satisfying $f_{c1} < f_{c2}$ are used in this inversion. Although f_{c2} is obtained through this inversion, the values are often close to the edge or out of the analysis band, resulting in unreliable estimates. Therefore, we employed only f_{c1} as a resultant f_c in the subsequent analysis (i.e. we ignored all estimation results of f_{c2} , which is the f_c of the eGfs).

In the above analysis, we used the spectrum in the frequency bands with an SNR ≥ 3 with respect to the pre-signal amplitude spectrum. We excluded frequency bands from each stacked spectral ratio where the number of analysed ratios were less than 20 (240 being the maximum). We evaluated f_c only for target events with two or more eGfs. We used the results in the following analysis when the logarithm of the final RMS residuals in the spectral fitting were less than 0.08. Fig. 8(a) shows an example of the waveforms recorded for an M_w –8.0 event and one of its eGfs (M_w –8.9) in the KJG1804 experiment. The spectral ratio between the events is shown in Fig. 8(b), and the stacked spectral ratios between the target event and six eGfs are shown in Fig. 8(c). Although a large scattering was observed for the spectral ratios shown in Fig. 8(b), similar corner frequencies of the target events were identified in the stacked spectral ratios for different eGfs (Fig. 8c), indicating that the stacking process significantly reduced the error in the estimation of the spectra and enabled an accurate estimation of f_c . The f_c was estimated to be 572.6 kHz for the M_w –8.0 target event.

Fig. 9(a) shows the histogram of all f_c values (i.e. the results for all specimens in Table S1, Supporting Information) obtained by the

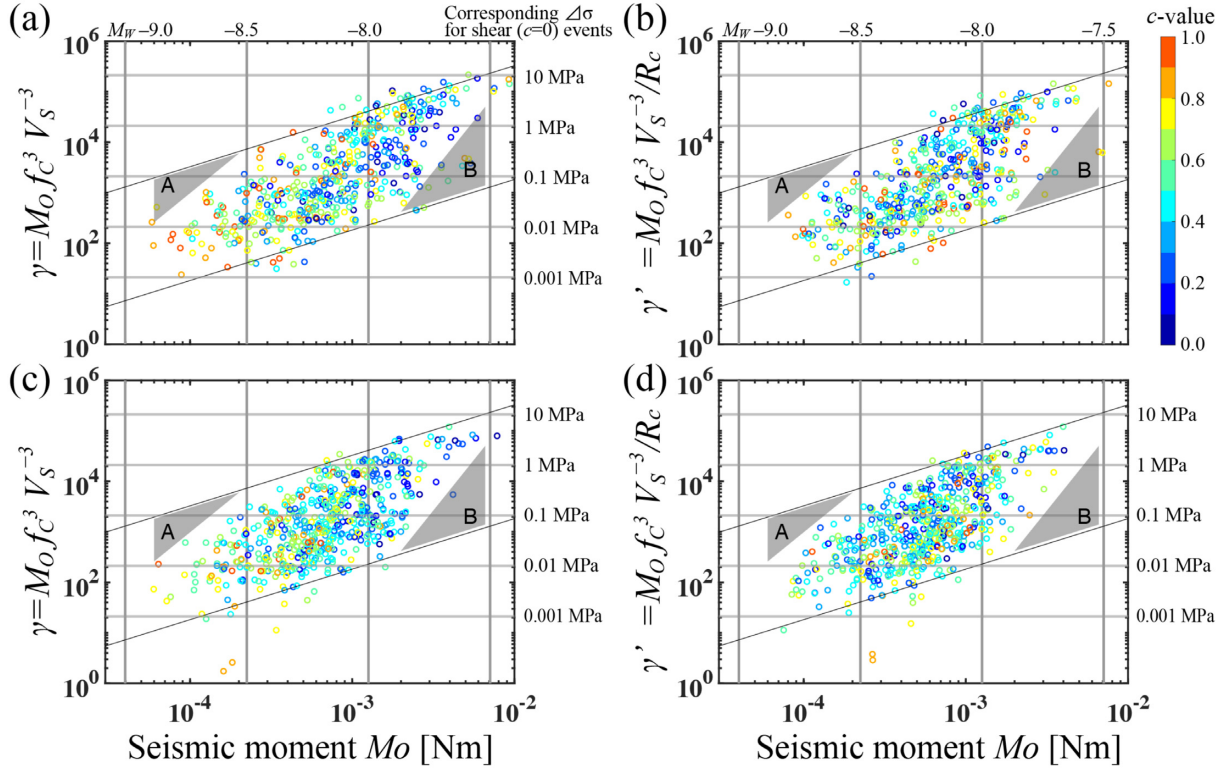


Figure 13. (a) and (c) Relationship between M_o and $\gamma = M_o f_c^3 V_s^{-3}$. (b) and (d) The same plot but after removing the R_c correction effect. The result for events with tensile components is shown in (a) and (b) and with a compressive component in (c) and (d). The grey horizontal lines represent γ -values corresponding to $\Delta\sigma = 0.001, 0.01, 0.1, 1$ and 10 MPa using the same parameter as Fig. 12. In each figure, two grey diagonal lines represent γ -values when $f_c = 176.6$ and 995.6 kHz (2nd and 98th percentile of the f_c estimates, respectively) were assumed. Grey triangles A and B highlight the regions lacking data (Section 6.2).

procedure described above. We obtained 1053 f_c values of 68.4–1208.0 kHz, which is roughly consistent with the frequency band of M304A with a good SNR. As described in the next section, this narrow measurable band caused biases in the resultant distribution of f_c and its related parameters. As shown in Fig. 9(b), the f_c was determined mainly for $M_w \geq -8.5$ (f_c of 6.29 per cent of $M_w \geq -8.5$ events were determined) and was rarely determined for $M_w < -8.5$ events (0.69 per cent of $M_w < -8.5$).

6 DISCUSSION

6.1 Estimation biases of the seismic moment

Fig. 10(a) shows the comparison between the moment magnitude (M_w) estimated in Section 4 and the relative magnitude (M_{rel}), which was estimated by Tanaka *et al.* (2021) from the logarithm of the peak-to-peak amplitude of the recorded AE waveforms (Naoi *et al.* 2018), for the case of the KJG1811 experiment. M_w correlated with M_{rel} very well (Fig. 10a; the correlation coefficient is 0.84 with a 95 per cent confidence interval of [0.82, 0.85]), indicating that M_{rel} is an appropriate indicator of the magnitude of AE events, even though sensor coupling and inelastic attenuation effects were not corrected.

For the AE catalogue used in this study, M_{rel} was determined for almost all (99.01 per cent) of the events, and hence, the ratio of the number of M_w - and M_{rel} -determined events represents the dependency of success rate of the M_w determination on their size. Fig. 10(b) shows the proportion of M_w -determined events. The proportion against the cut-off M_{rel} exhibited a complicated curve that

roughly increased alongside M_{rel} ; the complexity of this curve may have resulted, in part, from the correction of R_c , depending on focal mechanisms. When a spectrum with the same low-frequency flat level is obtained, a small M_w is determined for events with large tensile/compressive components owing to a large R_c , resulting in a low detection limit for M_w estimation. The curve in Fig. 10(b) depends on the frequency–magnitude distributions and proportion of MT-determined events, which also depend on the focal mechanisms.

Fig. 11 shows the relationship between c -values and M_o . As shown in Fig. 11(a), a smaller M_o was obtained for larger c -values; this strong trend disappeared when we removed the effect of R_c correction (Fig. 11b), which became larger for large tensile/compressive components (Fig. 4b). This strong artificial trend resulted from the use of only P waves in the M_o estimation. The use of S waves likely mitigates the trend; however, for such an analysis, the absolute sensitivity and directivity of AE transducers for S waves need to be estimated, and this issue will be addressed in future studies.

The success of M_w estimation using AE records may help accurately analyse the frequency–magnitude distributions of minimal seismic events observed in the laboratory. However, the complicated curve of the success rate of M_w determination (Fig. 10b) remains a problem; for example, the M_w distribution of the KJG1811 experiment appears to obey the Gutenberg–Richter relationship of $b > 2$ (Fig. 10c). b -values are usually estimated using the events with a magnitude greater than the completeness magnitude M_c , and M_c appears to be $M_w \approx -8.6$ from Fig. 10(c). This magnitude corresponds to $M_{rel} \approx 3.3$ based on the regression line in Fig. 10(a), and Fig. 10(b) shows that the M_o and M_w were not determined for many events with $M_{rel} > 3.3$. This indicates the presence of an

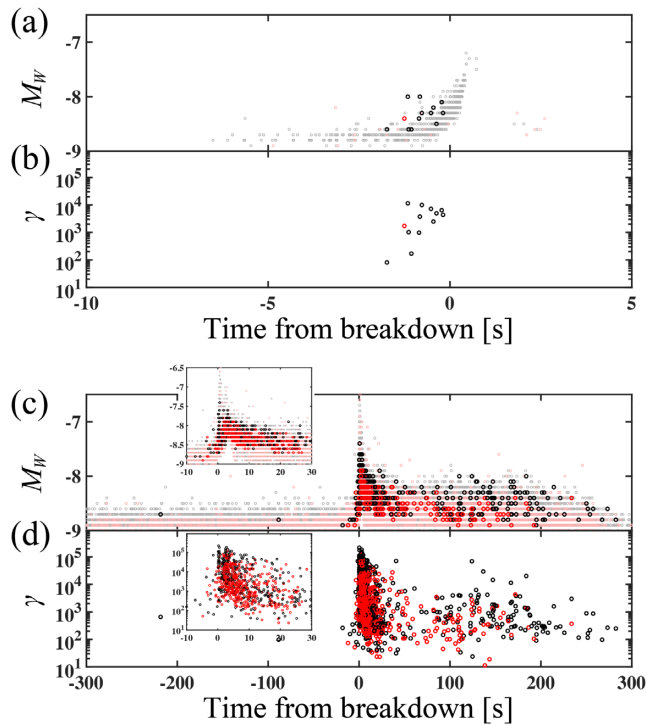


Figure 14. Magnitude–time and γ –time diagrams of the AE activities. All results of the related specimens were plotted against the event occurrence time measured from the breakdown. (a) and (b) Results for the two EFS samples. (c) and (d) Results for the 10 KJG samples. Enlarged view around the breakdown is shown in the insets. Large circles represent events whose f_c values were determined by the MEGF method. Large black and red circles indicate events with tensile and compressive components, respectively. Small circles in (a) and (c) represent events whose f_c values were not determined. Grey and light red circles indicate tensile and compressive events, respectively.

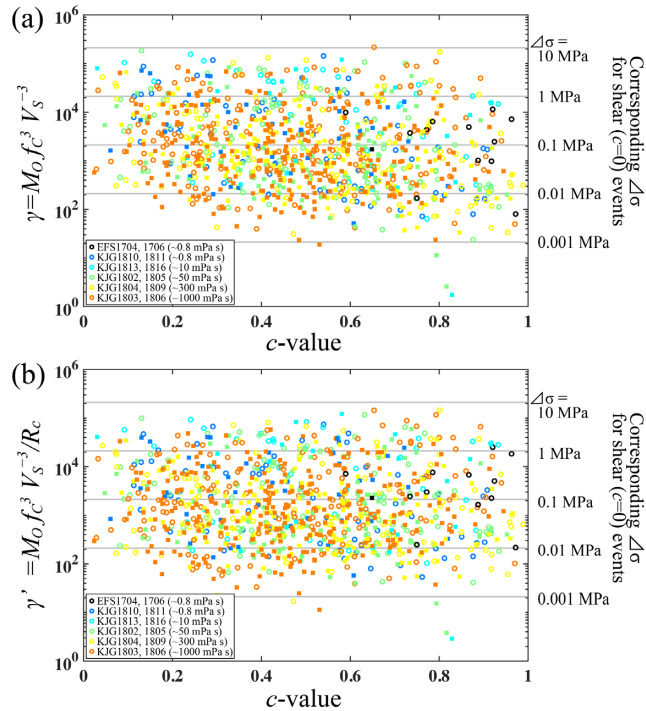


Figure 15. (a) Relationship between c -values and $\gamma = M_o f_c^3 V_s^{-3}$. (b) The same plot but after removing the R_c correction effect. Lines of constant stress drop were estimated using the parameters in Figs 12 and 13. Open circles indicate events with a tensile component, and filled squares indicate those with a compressive component.

incomplete frequency–magnitude distribution even for the M_w values greater than the apparent M_c , thereby rendering it difficult to accurately estimate b -values. In addition, in these experiments, the dominant type of MT solution (Tanaka *et al.* 2021; Appendix B) and noise levels (Naoi *et al.* 2020) changed over time, resulting in a complicated discussion of b -values. We, thus, do not go into a detailed discussion of the magnitude–frequency distributions obtained in this study.

6.2 Relationship between f_c and M_o

As described in Introduction, previous studies have reported that the relationship $M_o \propto f_c^{-3}$ is valid for shear failures independent of their magnitude (e.g. Abercrombie 1995; Kwiitek *et al.* 2011; Yoshimitsu *et al.* 2014). According to the circular crack models of Eshelby (1957) and Madariaga (1976), the relationships among $\Delta\sigma$, M_o and f_c can be expressed as follows:

$$\Delta\sigma = \frac{7}{16k^3} \gamma, \quad \left(\text{where } \gamma = \frac{M_o f_c^3}{V_s^3} \right) \quad (11)$$

where k is a constant that depends on the rupture velocity V_r . Since M_o is proportional to f_c^{-3} , the $\Delta\sigma$ of shear failures estimated from eq. (11) becomes constant, typically falling within 0.1–100 MPa, independent of their magnitude (constant stress drop scaling). In this study, we analysed AEs with various focal mechanisms, including a mixed-mode of shear and tensile components (Figs S2 and S3, Supporting Information), for which eq. (11) cannot be applied. For such non-shear events, there is no widely used source model, such as eq. (11), and therefore, we used γ in eq. (11) (i.e. the model-dependent constant was removed), instead of the stress drop, as an indicator to represent the relationship between f_c and M_o .

Fig. 12 shows the f_c – M_o relationship obtained herein. Diagonal lines were overlaid representing f_c – M_o relationships expected from eq. (11) with assumed stress drops of 0.001, 0.01, 0.1, 1 and 10 MPa. If the $M_o \propto f_c^{-3}$ relationship holds, the results should show a downward trend with increasing f_c along these lines; however, the weak opposite trend was observed. This is likely caused by the narrow frequency band of the f_c estimates and by the γ -values being in a broader range than expected from the constant stress drop scaling. In the present study, many events under the line of 0.1 MPa were found. A broader frequency band (e.g. an order of magnitude broader range) of f_c estimates is necessary for observing a downward trend even if the $M_o \propto f_c^{-3}$ relationship is valid.

As mentioned in Section 5, we obtained f_c values only in the range of 68.4–1208.0 kHz due to measurement limitations. f_c was determined only for 3.8 per cent of the AEs whose M_o and M_w were determined. This likely limited the distribution of the resultant γ -values. Fig. 13 shows the relationship between M_o and γ ; the two oblique grey lines indicating the 2nd and 98th percentiles of the f_c estimates (176.6 and 995.6 kHz) were overlaid to show the limits of the analysable γ -values in this study. Although γ -values do not depend on magnitudes if $M_o \propto f_c^{-3}$ holds, apparent dependency can appear with a narrow analysable band because we can obtain γ -values only in the area sandwiched by these lines. For example, in Fig. 13, the maximum values of γ corresponds to the $\Delta\sigma = 10$ MPa line, which may be reasonable under our experimental conditions where the loading stress is 5 MPa, resulting in tensile stress of 15 MPa, which is expected to be around the borehole. However, it should be noted that events with large γ -values cannot

be estimated due to the limitation in observable frequency bands if such events occur. The obtained γ -value distribution delineated the region sandwiched by the grey lines, indicating that the observed M_0 dependence of γ was an artefact due to the narrow measurement band.

The distribution of the obtained γ -values likely includes further bias. In Figs 13(a) and (c), a small number of events are plotted (or completely absent) in the grey triangles A and B, resulting in a trend with a slope larger than the expected, only due to the band limitation of AE measurement. These areas are also found after removing the influence of the correction of R_c (Figs 13b and d). f_c estimation is fundamentally difficult for events in region A because these radiate high-frequency dominant waves with small amplitudes, which are difficult to observe. This likely caused an artificial lack of events in this region. Events in region B radiate large-amplitude waves with lower f_c values, for which f_c estimation should be relatively easy, indicating that the lack of events in region B possibly represents an actual tendency.

For the discussion of the dependency of γ on M_0 , it is worth noting that the timing of the occurrence of γ -determined events was biased. Figs 14(a) and (b) show the temporal changes in M_w and γ , respectively, for the EFS samples. All results of EFS1704 and EFS1706 were plotted against the event occurrence time measured from the breakdown. In the EFS experiments, AEs occurred only in several seconds before the breakdown (Naoi *et al.* 2020), and the γ -values were evaluated for only 13 events occurring between 1.7 and 0.2 s before the breakdown, corresponding to the timing of their magnitude increase. In the case of the KJG experiments, as shown in Fig. 14(c), only small AEs (typically $M_w < -8.5$) occurred until ~ 5 s before the breakdown. Tanaka *et al.* (2021) have interpreted that the AEs in this period are induced by the fluid penetration from the borehole. As shown in Fig. 14(d), γ -values of these AEs were hardly determined (Fig. 14d), and $M_w \geq -8.5$ events for which γ -values could be evaluated started to occur around the breakdown. Comparatively larger events ($M_w \geq -8.0$) were concentrated around the breakdown and they were interpreted as events induced during the main fracture formation of hydraulic fracturing (Tanaka *et al.* 2021). The current re-estimated MT solutions also supported this interpretation as discussed in Appendix B. For example, the existence of region B in Fig. 13 might be explained by large stress drops of large AEs during the main fracture generation process. However, in any case, the magnitudes and corner frequencies of these events were close to the measurable limit, and it is desirable to discuss these based on data measured in a broader frequency range.

We observed many events with γ -values smaller than the expectation from the constant stress drop scaling. The relationship between c - and γ -values were plotted in Fig. 15. Out of the 1053 γ -estimated events, 44.2 per cent (465) were plotted in the 0.1–100 MPa area (only one event was plotted in the area of > 10 MPa), but 55.5 per cent (584) were in the 0.001–0.1 MPa area. Such small- γ events were observed regardless of their focal mechanisms, including shear-dominated events (i.e. events with small c -values), for which the appropriateness of the constant stress drop scaling has been repeatedly confirmed in many previous studies. Incidentally, a weak downward trend with increasing c -value can be recognized in Fig. 15(a) (correlation coefficient -0.11 with 95 per cent confidence interval of $[-0.17, -0.05]$), but this trend disappeared after removing the influence of the R_c correction (correlation coefficient 0.00 with 95 per cent confidence interval of $[-0.06, 0.06]$). This could be an artificial trend caused by the apparent correlation between the c -value and M_0 (Fig. 11a) and the correlation between M_0 and γ (Fig. 13).

6.3 Implication of stress drops for the events induced by hydraulic fracturing

As described in the previous sections, we identified the AE events with γ -values smaller by 1–2 orders of magnitudes than the expected constant stress drop scaling. Based on the definition of γ (eq. 11), a small γ corresponds to a small f_c when the M_0 is fixed. f_c can be assumed to be proportional to the rupture velocity V_r , and a small f_c value corresponds to a small V_r value. From the definition of M_0 ($M_0 = \mu d S$, where d is the average displacement and S is the area of the rupture), a small γ -value can also be explained by a small d when S is fixed, resulting in a small stress drop $\Delta\sigma$.

Seismic events with f_c values lower than what was expected from the constant stress drop scaling (i.e. low-frequency dominant events) were reported in broad-frequency bands at plate boundaries (Beroza & Ide 2011), in volcanic regions (Maeda *et al.* 2019), and during fluid stimulations (Das & Zoback 2013). Such events were considered to have low-stress drops (Supino *et al.* 2020), whose generation was suggested to involve fluid (Introduction). Urata *et al.* (2013) suggested that high pore pressure causes low-stress drops and low rupture velocities based on numerical simulations, indicating that events with small γ -values tend to occur under conditions of high pore pressure by fluid stimulation. Herein, the maximum loading was only 5 MPa, and the maximum fluid pressure reached 22 MPa. Under such stress conditions, it may be natural to generate seismic events with low-stress drops. Notably, we successfully confirmed that many low-frequency events occurred in the actual experiments.

Incidentally, we did not observe a significant dependency of γ -values on the distance from the injection well, as reported by Goertz-Allmann *et al.* (2011) and Kwiitek *et al.* (2014a). We do not consider this as surprising because we could not estimate f_c for the events that were likely induced by fluid penetration before the breakdown (Section 6.2; Tanaka *et al.* 2021), where there is likely a significant spatial heterogeneity of pore pressure. The lack of f_c -estimated events in this phase was possible because their magnitude was too small (typically $M_w < -8.5$; see Fig. 14c) and SNR at high-frequency components was not large enough to obtain high f_c values. Therefore, it is necessary to employ smaller specimens and AE transducers sensitive to higher frequencies in future studies.

7 CONCLUSIONS

Herein, we aimed to estimate the source parameters of AE events induced by hydraulic fracturing in a laboratory setting to enhance our knowledge of stress drops in hydraulically induced earthquakes. The complicated frequency response and sensitivity depending on the coupling conditions should be corrected to estimate seismic moments from AE sensor records. To achieve this, we used an LDV and the data obtained via pulse radiation tests immediately before every experiment. We also carefully corrected the influence of radiation pattern coefficients of various focal mechanisms, including non-shear events, and successfully estimated the seismic moment and moment magnitude of the AEs. The corner frequencies of the AEs were estimated using the MEGF method, where the influence of the inaccurate Green's functions can be eliminated. Although 44.2 per cent of the obtained f_c values were consistent with the constant stress drop scaling, the remaining f_c values were lower than expected, regardless of their focal mechanisms. Our results indicate that high pore pressure in the source region induced by fluid stimulation contributes to the generation of low-frequency dominant events. Overall, our study demonstrated that source parameter

estimation is possible for hydraulically induced AEs in the laboratory, with certain difficulties resulting mainly from measurement limitations, providing insights into the characteristics of hydraulically induced earthquakes and the role of fluids in earthquake generation.

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SUPPORTING INFORMATION

Supplementary data are available at [GJI](https://doi.org/10.1002/gji.10000) online.

Figure S1. Sample size, AE sensor configuration and coordinate system used in the present study (fig. 2b in Naoi *et al.* 2020). A 6 mm-diameter borehole was made at the centre of the specimen to perform hydraulic fracturing.

Figure S2. Source-type plot of MT solutions for the two experiments with EFS samples. The colours indicate the number of events in each grid. Solutions in the yellow dashed lines correspond to events with DC components of ≥ 50 per cent (i.e. $|c| \leq 0.5$). The orange line, which is evaluated from the ratio of V_P to V_S , corresponds to the

ideal shear-tensile event (Vavryčuk 2011; 2015). The right- and left-hand edges of the line correspond to pure tensile and compressive events, respectively.

Figure S3. Source-type plot of MT solutions for the 10 experiments with the KJG samples. The colours indicate the number of events in each grid. Solutions in the yellow dashed lines correspond to events with DC components of ≥ 50 per cent (i.e. $|c| \leq 0.5$). The orange line, which is evaluated from the ratio of V_P to V_S , corresponds to the ideal shear-tensile event (Vavryčuk 2011; 2015). The right- and left-hand edges of the line correspond to pure tensile and compressive events, respectively.

Figure S4. Temporal changes in φ , which is the smaller angle between the y -axis and the two candidates for crack-opening axes of each MT solution for the EFS samples. The black dots indicate the angles for the solutions satisfying $c > 0.5$ and $M_{ISO} \geq 0$ (i.e. tensile-dominated events). The blue lines indicate the borehole pressure history.

Figure S5. Temporal changes in the c -values for the obtained MT solutions (only $c \geq 0$) for the KJG samples. The black and red dots indicate the solutions with $M_{ISO} \geq 0$ and $M_{ISO} < 0$, respectively. The blue lines indicate borehole pressure history.

Figure S6. Temporal changes in φ , which is the smaller angle between the y -axis and the two candidates for the crack-opening axes of each MT solution for the KJG samples. The black dots indicate the angles for the solutions satisfying $c > 0.5$ and $M_{ISO} \geq 0$ (i.e. tensile-dominated events). The blue lines indicate the borehole pressure history.

Figure S7. Changes in loss for training and validation data during the training of the network shown in Fig. C1(a).

Table S1. Experimental results for EFS and KJG samples, which were analysed by Naoi *et al.* (2020) and Tanaka *et al.* (2021), respectively.

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APPENDIX A: RE-ESTIMATION OF SENSOR COUPLING AND ATTENUATION COEFFICIENTS

For the two EFS samples and the 10 KJG samples (Table S1, Supporting Information), Naoi *et al.* (2020) and Tanaka *et al.* (2021), respectively, estimated MT solutions using slightly different procedures. In this study, we re-estimated MTs for the AEs observed in these experiments using a consistent procedure to use the results in the M_0 estimation (Section 4) and in subsequent discussions. In Appendices A–C, we describe the MT analysis performed in the present study with modifications from the previous studies.

As the AE transducer has directivity, this effect should be corrected to obtain the P -wave amplitude of the ground motion. Naoi *et al.* (2020) estimated the directivity ($I(f, \theta)$ in eq. 6) when M304A and PICO were used as receivers (receiver directivity) using a semi-circular aluminium block. They assumed that the receiver directivities follow bell-shaped curves, as suggested by Kwiatek *et al.* (2014b). In this study, we also evaluated the directivity when PICO was used as a transmitter (transmitter directivity) by a similar method, where the positions of receiver and transmitter were switched and the vibrations were measured by LDV. We concluded that the transmitter directivity of PICO is almost identical to its

receiver directivity. This measurement confirmed the appropriateness of the assumption used by Naoi *et al.* (2020) and Tanaka *et al.* (2021) that the receiver and transmitter directivities are the same.

As described in Introduction, the difference in coupling conditions among AE transducers influences their sensitivity; therefore, it should be estimated for every transducer in every experiment for MT analysis where amplitudes at each transducer are used. Naoi *et al.* (2020) and Tanaka *et al.* (2021) inversely estimated the coupling coefficients (S in eq. 6) for each experiment using the amplitudes of the P -wave first motions, which were measured for waveforms obtained by a pulse radiation test immediately before each fracturing experiment after applying a 5 MPa load. In this test, pulses were radiated from PICO by applying a step voltage change, and the signals were received by the other 23 transducers. Using this data set, Tanaka *et al.* (2021) also estimated the inelastic attenuation parameter (quality factor Q) simultaneously with the coupling coefficients under the following assumptions: Q does not depend on frequency; the measured amplitudes were regarded similar to those at the representative frequency, corresponding to the median pulse width of the observed P -wave first motion. Tanaka *et al.* (2021) assumed that the attenuation anisotropy was expressed by the same function as that of P -wave velocity (Stanchits *et al.* 2003) and applied an ellipsoid approximation as:

$$Q = \sqrt{Q_x^2 I_x^2 + Q_y^2 I_y^2 + Q_z^2 I_z^2}, \quad (\text{A1})$$

for inelastic parameter Q , where Q_x , Q_y and Q_z are the quality factors in each direction (unknown parameters in the inversion).

In this study, we re-estimated the coupling and the attenuation coefficients according to a method proposed by Tanaka *et al.* (2021) for all 12 experiments. As for the KJG samples, the representative frequency was updated. Tanaka *et al.* used the value of 265 kHz, which was obtained from the pulse widths of the P -wave first motion in the pulse radiation test. They measured the pulse width from zero-crossing timings of the P -wave first motions based on waveforms after removing their offset, which was evaluated by the median amplitude of each waveform. However, the slight difference between the evaluated offset and actual offset often causes the overestimation of the pulse width. To avoid this problem, in the present study, we re-estimated the zero-crossing point as the timing where the amplitudes reached 1 per cent of the absolute peak value of the P -wave first-motion amplitude from the evaluated offset, resulting in the 300 kHz of the representative frequency. For the EFS samples, we obtained the representative frequency of 400 kHz using this method. The Q -values obtained in the present study are listed in Table S1 (Supporting Information).

APPENDIX B: RE-ESTIMATION OF MOMENT TENSORS

Using the coupling coefficients and the Q -values obtained using the procedure presented in Appendix A, we re-estimated the six independent components for the MTs of AE events from the P -wave first motion polarities and their amplitudes after correcting for the influence of transducer directivities, coupling coefficients and attenuation. The analysis procedure basically follows that of Tanaka *et al.* (2021), although the automatic reading of the first motion amplitudes using a deep learning technique was updated (Appendix C). The effect of inelastic attenuation was corrected using a representative frequency for AE events in the fracturing experiments. This was estimated from the pulse width of the P -wave first motions automatically read by the deep learning technique

Table B1. The number of obtained MT solutions.

	Present study	Naoi <i>et al.</i> (2020)	Tanaka <i>et al.</i> (2021)
EFS1704	421	134	N/A
EFS1706	462	118	N/A
KJG1810	3560	N/A	3812
KJG1811	2557	N/A	2808
KJG1813	2453	N/A	2393
KJG1816	3011	N/A	2933
KJG1802	5120	N/A	6471
KJG1805	4846	N/A	6142
KJG1804	6348	N/A	7909
KJG1809	3753	N/A	4805
KJG1803	7981	N/A	9897
KJG1806	6345	N/A	7557

($f = 455$ kHz for the KJG samples and $f = 555$ kHz for the EFS samples).

From the obtained MT solutions, we selected the results satisfying the following criteria: (1) polarities and amplitudes at 10 or more stations were used in the inversion and (2) the variance reduction R -values were 50 per cent or more. Variance reduction was defined as:

$$R = \left(1 - \frac{\sum |A_e|^2}{\sum |A|^2}\right) \times 100, \quad (\text{B1})$$

where A indicates the observed amplitude of the P -wave first motions for individual sensors, and A_e indicates the residuals of the amplitudes for the inversion results. The number of solutions satisfying these criteria were 46 857 (883 for the 2 EFS samples and 45 974 for the 10 KJG samples). Table B1 shows the number of obtained solutions for each specimen with the results by Naoi *et al.* (2020) and Tanaka *et al.* (2021). Note that the selection criteria of the final MT solutions differ depending on the studies.

Tanaka *et al.* (2021) analysed events with the number of valid polarities were 10 or more for M304A transducers. Naoi *et al.* (2020) analysed events (1) with an SNR ≥ 8 for at least eight of the transducers and (2) where P -wave polarities can be read from 10 or more transducers. Both studies selected MT solutions whose R (variance reduction in amplitude; eq. B1) was 50 per cent or more.

For the EFS samples, we obtained MT solutions 3.5 times more than the manually processed results of Naoi *et al.* (2020). The resultant source-type plot (Fig. S2, Supporting Information) shows the extreme dominance of tensile-type AEs. These MTs showed small φ values (the smaller angle between the y -axis and the two candidates of the crack-opening axes of each MT solution; Fig. S4, Supporting Information), indicating crack openings subparallel to the y -axis. This is the crack-opening direction theoretically expected from the stress around the borehole (Hubbert & Wills 1957). Naoi *et al.* (2020) obtained the same conclusion based on their MT solutions. Figs B1(a) and (c) show the histograms of the corresponding c -values for the result of Naoi *et al.* (2020) and the present study, respectively. The nearly identical distributions, except for the number of solutions, were obtained for the EFS samples.

As for the KJG samples, the number of the obtained solutions was 84 per cent of that reported by Tanaka *et al.* (2021) (54 727 solutions) wherein a deep learning technique was also used. In the c -value distribution shown in Figs B1(b) and (d), the fraction of events with $c \leq 0.5$, corresponding to the shear-dominated events, was found to increase. This tendency could also be found in the source-type plot (Fig. S3, Supporting Information) especially for the experiments with high-viscosity fluid, when comparing to fig. 11 of Tanaka *et al.* (2021). This change likely resulted from the overcoming of biased

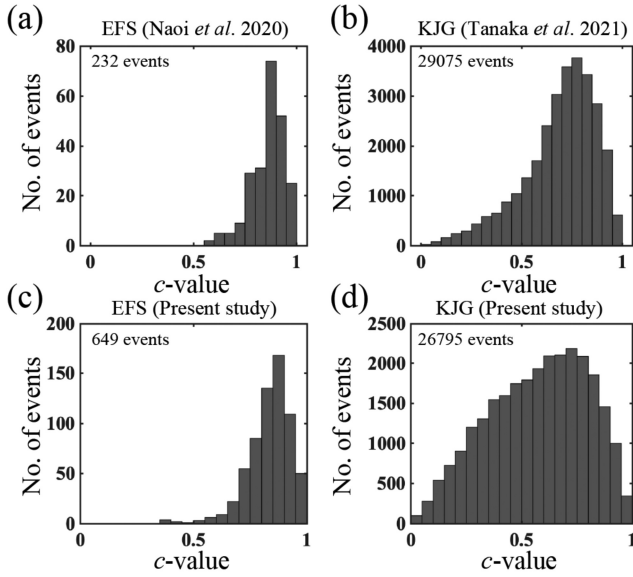


Figure B1. Histograms of c -values obtained in the present and the previous (Naoi *et al.* 2020 and Tanaka *et al.* 2021) studies. (a) For the MT solutions obtained by Naoi *et al.* (2020) for the EFS experiments. (b) For the MT solutions obtained by Tanaka *et al.* (2021) for the KJG experiments. (c) For the solutions obtained in the present study for the EFS experiments and (d) for the KJG experiments.

training data set and improvement of the treatment of low-SN data, as described in Appendix C.

Tanaka *et al.* (2021) have pointed out the existence of two preparation phases of the breakdown based on the AE activities and their MT solutions. Despite the revision in c -value distributions, the re-estimated MTs showed temporal evolutions similar to those reported by Tanaka *et al.* (2021), deriving the same conclusion. Figs S5 and S6 (Supporting Information) show the temporal changes in c - and ϕ -values, respectively, based on the re-estimated MTs using the same format as that of Figs 12 and 13 of Tanaka *et al.* (2021). AEs before the breakdown have tensile mechanisms (Fig. S5, Supporting Information) in various directions (Fig. S6, Supporting Information), similar to the results of Tanaka *et al.* (2021). They interpreted that this AE activity was induced by fluid penetration from the borehole. Immediately before the breakdown, the proportion of shear-dominated AEs increased (Fig. S5, Supporting Information), and many tensile events, likely corresponding to crack opening in the direction expected from the classical theory of hydraulic fracturing (Hubbert & Wills 1957), also occurred (i.e. events with small ϕ ; Fig. S6, Supporting Information). Tanaka *et al.* (2021) have interpreted that these AEs occurred during the main fracture formation. AEs with compressive-type focal mechanisms likely corresponding to crack closure were also found after the breakdown (Fig. S5, Supporting Information), as reported by Tanaka *et al.* (2021).

APPENDIX C: AUTOMATIC READING OF P -WAVE FIRST MOTION AMPLITUDE BY A DEEP LEARNING TECHNIQUE

For MT analysis, Tanaka *et al.* (2021) automatically read P -wave first motion amplitudes of more than 50 000 events that were observed in the 10 KJG experiments shown in Table S1 (Supporting

Information) using a deep learning technique. Their approach consisted of the following two steps: (1) reading P -wave first motion polarities using a deep learning technique as a binary classification problem, (2) reading maximum (minimum) amplitudes around the theoretical P -wave arrival times when the polarities were judged as ‘up’ (‘down’). However, this approach involved the following problems: (1) misreading of the amplitudes easily occurred for a station with large arrival time residuals; (2) it was difficult to check the adequateness of the reading results for low-SNR waveforms because the deep learning model did not provide information about the timing of the peak amplitude; (3) the training and validation were conducted using waveforms with high SNR, whereas the prediction (i.e. applying the trained model to new data) was conducted for low-SNR waveforms, and hence, the metrics (accuracy was used by Tanaka *et al.* 2021) obtained for the validation data did not represent the actual performance for the analysed data set at all and (4) amplitudes were read even for very low-SNR waveforms (e.g. SNR < 1), likely resulting in large estimation errors in the subsequent MT analysis for small events.

To overcome these problems, we developed another procedure using a deep learning network that reads the ‘timings’ of the peak amplitudes of P -wave first motions. In the training process, we used composite waveforms with various SNR, which were made by combining high-SNR waveforms and noise waveforms. Using the trained model, we re-estimated MT solutions of the AE events obtained by the 12 experiments shown in Table S1 (Supporting Information, Appendix B). We referred to the approach of Zhu & Beroza (2019) for the traveltime-reading problem. Similar to their study, we adopted a Unet type architecture (Fig. C1a; Ronneberger *et al.* 2015), where a waveform of 512 samples (Fig. C1b) was the input and a vector of 512 samples that represent scores between 0–1 corresponding to the probability of peak timing of P -wave first motions was the output. A triangle-shaped label with a base length of 1.0 μ s (10 samples), which takes one at the manually read peak timing, was used as ground truth for the reading results (Fig. C1c).

A training data set was prepared based on the manual reading results of P -wave first motions by Naoi *et al.* (2020) and Tanaka *et al.* (2021). For the EFS samples, Naoi *et al.* (2020) processed events for waveforms with SNR ≥ 8 that were recorded at 8 or more stations, for which SNR was measured using the ratio between the peak-to-peak amplitude of event waveforms and pre-signal noises. For the KJG samples, Tanaka *et al.* (2021) processed events for waveforms with SNR ≥ 15 that were recorded at 14 or more stations. From the manual reading results, we selected the results satisfying $P_{\text{SNR}} \geq 3$, where P_{SNR} was defined as the ratio between the obtained peak amplitude of P -wave first motions against the half of peak-to-peak amplitude of the pre-signal noise. The number of the remaining waveforms was 2630 for the EFS samples (2217 for M304A and 413 for PICO) and 35 951 for the KJG samples (31 249 for M304A, and 4702 for PICO).

From the selected waveforms, 70 per cent of them (27 013) were used to make a training data set, 20 per cent (7715) were used for a validation data set and 10 per cent (3853) were used for a test data set. These proportions were kept for each specimen and sensor type (i.e. M304A and PICO). In the peak amplitudes for the selected waveforms, positive values (i.e. corresponding to the ‘up’ polarity of the first motion) were 2.7 times that of the negative values (corresponding to ‘down’). To avoid this biased data set causing the preferred reading of ‘up’, we randomly inverted the polarity of waveforms to keep the numbers of ‘ups’ and ‘downs’ nearly identical.

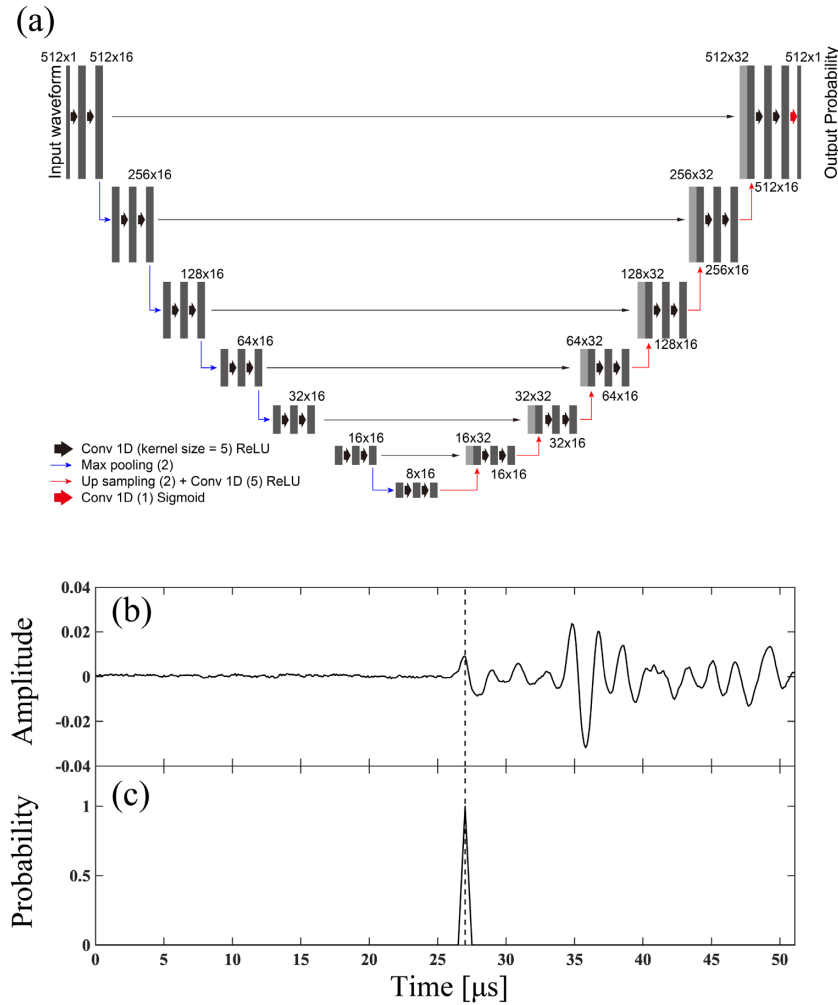


Figure C1. (a) Network architecture for automatic reading of peak timing of *P*-wave first motion, (b) input waveform and (c) output probability (ground truth of the training). The vertical dashed lines in (b) and (c) represent the manually read timing of peak amplitude of *P*-wave first motion.

Although the selected waveforms based on the manual picking results showed high SNR, it was necessary to process many waveforms with lower SNR in the MT inversions, and a training data set needed to involve such low-SNR records. To achieve this, we made composite waveforms by combining signal waveforms obtained by the above procedure with noise waveforms obtained from the AE records in the initial part of each experiment before starting AE activities. We used the signal waveforms after multiplying factors that were randomly determined so that P_{SNR} of the composite waveforms became 1/3–5. Signal waveforms were extracted using a window the centre of which corresponded to a *P*-wave theoretical arrival time with a perturbation within 3.0 μs (30 samples). This perturbation was added to avoid the possibility that the model might learn the timing of the peak amplitudes in the window.

We also applied data augmentation for the training data set by changing the factor used to control P_{SNR} , signal cut-out timing, and added noise waveforms. This augmentation was conducted ten times for a signal waveform, resulting in ten times greater availability of training data. The polarities of the signal waveforms were reversed for half of all augmentation processes for each signal. We obtained 234 189 and 35 812 training waveforms for M304A and PICO, respectively. This augmentation was not applied for the validation and test data. Using the obtained data set, we trained the network

shown in Fig. C1(a), where the binary cross-entropy was used as the loss function and Adam (Kingma & Ba 2014) as the optimizer. The losses for the training and validation data set are shown in Fig. S7 (Supporting Information). We used the model obtained in the final epoch (100) for subsequent analysis.

The performance of the trained model was measured based on the prediction results for the test data set. From the obtained probability vectors, we read the maximum probability (P_{net} ; the values between 0.19 and 0.99 were obtained for the test data set) and the corresponding timing (t_{net}). We read amplitude at t_{net} as the peak amplitudes of the *P*-wave first motion (A_{net}) based on waveforms after applying a 200–1000 kHz bidirectional bandpass filter to reduce the influence of low- and high-frequency noises. In the subsequent MT inversion (Appendix B), we used A_{net} for waveforms satisfying the criteria of $P_{\text{net}} \geq 0.7$ and $P_{\text{SNR}} \geq 1$ for the sake of quality control. Out of 3853 waveforms in the test data set, the prediction results of 2805 (72.8 per cent) satisfied this criterion. Figs C2(a) and (b) show the difference between the results by manual picking and automatic reading with the trained model for the selected results. Here, the peak amplitude by the manual picking (A_{org}) was re-estimated based on the filtered waveform and the corresponding peak timing (t_{org}). As shown in this figure, the difference in peak timing and amplitudes were typically smaller than ± 2 samples (0.2 μs) and 5 per cent, respectively. Fig. C2(c) shows relationship between P_{SNR} and

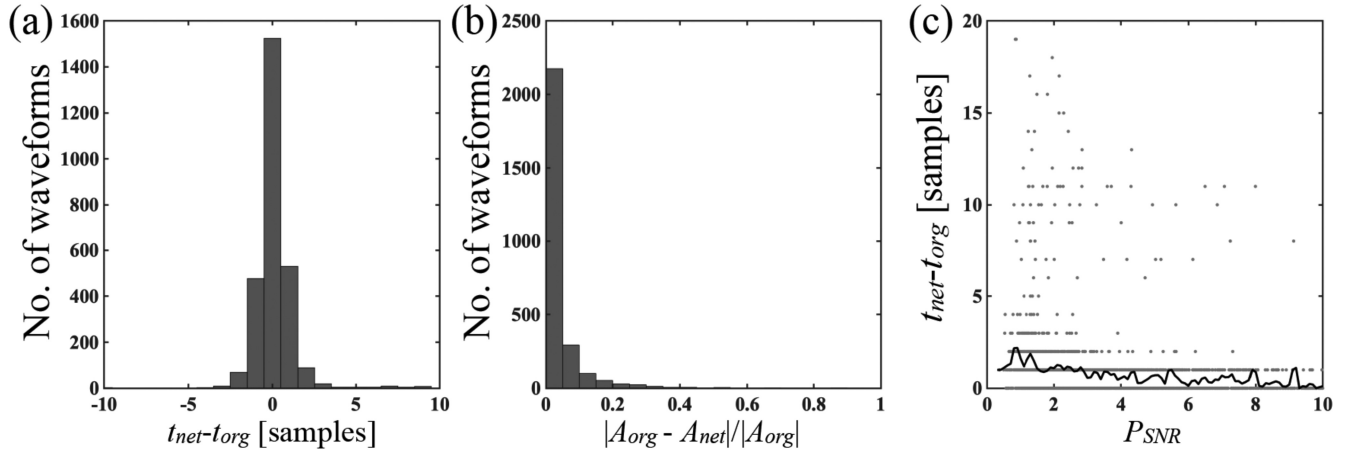


Figure C2. Difference in the peak timing and amplitude of P -wave first motions between the results by manual reading and by automatic reading with the deep learning technique. (a) Residuals of peak timings. (b) Difference in peak amplitudes. (c) Relationship between P_{SNR} and peak timing residuals. The thick black line represents the average for each 0.1 interval of P_{SNR} .

the peak timing residuals for all $P_{net} \geq 0.7$ results. We found that the trained model accurately read peak timings even for the waveforms with small P_{SNR} (e.g. < 1), keeping average residuals smaller than three samples, indicating that the model learns the characteristics of the noise. The criterion of $P_{SNR} \geq 1$ was introduced in the selection

of the prediction results to avoid large errors in amplitude estimation for noisy waveforms. We applied the trained model to all waveforms for the events listed in the catalogue built by Naoi *et al.* (2020) and Tanaka *et al.* (2021) and evaluated MT solutions as described in Appendix B.