

Earthquake magnitude with DAS: a transferable data-based scaling relation

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February 9, 2023

Abstract

Distributed Acoustic Sensing (DAS) is a promising technique to improve the rapid detection and characterization of earthquakes. Due to some instrumental limitations, current DAS studies primarily focus on the phase information but less on the amplitude information. In this study, we compile earthquake data from two DAS arrays in California, USA, and one submarine array in Sanriku, Japan. We develop a data-driven method to obtain the first scaling relation between DAS amplitude and earthquake magnitude. Our results reveal that the DAS amplitude in different regions follows a similar scaling relation. The scaling relation can provide a rapid magnitude estimation and effectively avoid uncertainties caused by the conversion to ground motions. We finally show that the scaling relation is transferable from one to another new region. The scaling relation highlights the great potential of DAS in earthquake source characterization and early warning.

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Key Points:

- We present the first data-based scaling relation for the DAS amplitude of earthquakes.
- Earthquake magnitude can be accurately estimated from DAS amplitude with the scaling relation.
- The DAS scaling relation is transferable and can be transferred from one area to another new area.

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Abstract

Distributed Acoustic Sensing (DAS) is a promising technique to improve the rapid detection and characterization of earthquakes. Due to some instrumental limitations, current DAS studies primarily focus on the phase information but less on the amplitude information. In this study, we compile earthquake data from two DAS arrays in California, USA, and one submarine array in Sanriku, Japan. We develop a data-driven method to obtain the first scaling relation between DAS amplitude and earthquake magnitude. Our results reveal that the DAS amplitude in different regions follows a similar scaling relation. The scaling relation can provide a rapid magnitude estimation and effectively avoid uncertainties caused by the conversion to ground motions. We finally show that the scaling relation is transferable from one to another new region. The scaling relation highlights the great potential of DAS in earthquake source characterization and early warning.

Plain Language Summary

Distributed Acoustic Sensing (DAS) is an emerging technique that can convert an optical fiber cable into a dense array to record clear earthquake signals. The recorded signals have essential information about earthquakes. For example, DAS can record higher amplitude signals from earthquakes with larger magnitude. However, conditions of the optical cables, such as how they are installed or how well they are attached to the surrounding medium, are often unknown, thus preventing quantitative measuring of earthquake magnitude from the DAS measurement. In this study, we investigate the earthquake data recorded by different DAS arrays and develop a data-driven method to get an empirical relation between the earthquake magnitude and the amplitude of DAS signals. We show that this empirical relation can accurately estimate the earthquake magnitude directly from the DAS data. Furthermore, the empirical relation we obtain from one area can also be applied to another new region with slight calibration. Our empirical relation can significantly expand the applications of the DAS technique in earthquake research, such as seismic hazard assessment and earthquake early warning.

1 Introduction

Rapid earthquake source characterization is critical for earthquake monitoring, Earthquake Early Warning (EEW), and prompt reactions to seismic hazards. However, this is still challenging for many remote areas with insufficient seismic station coverage. For example, subduction zones, which can hold the largest earthquakes, are generally poorly instrumented due to the large expenses involved in deploying and maintaining offshore seismic instruments. In this context, Distributed Acoustic Sensing (DAS), which can utilize pre-existing telecommunication fiber-optic cables in both onshore and offshore regions, appears to be a promising complementary sensing method to fill the geographical gaps of conventional seismic networks.

DAS is an emerging technique that has great potential in seismology. It converts every few meters of optical fiber into a single-component strainmeter (Benioff, 1935) to provide spatially coherent signals with high sensitivity. One single DAS array often consists of thousands of channels covering tens of kilometers, and can serve as a dense seismic array to achieve great spatial resolution. DAS has proved to be an effective tool to refine regional seismic structure (Ajo-Franklin et al., 2019; Trainor-Guitton et al., 2019; Yu et al., 2019; Spica, Nishida, et al., 2020; Yang et al., 2022; Spica, Perton, et al., 2020), detect local earthquakes (Ajo-Franklin et al., 2019; Li et al., 2021; Li & Zhan, 2018; Aterholt et al., 2022), and detect seismic signals from various sources (Williams et al., 2019; X. Wang et al., 2020; Zhan et al., 2021; Viens et al., 2022). The phase information of DAS has been well-validated to be accurate in the multiple aforementioned applications. However, DAS nano-strain amplitudes, which commonly represent the direct output from

70 an interrogator unit, are rarely considered for earthquake source characterization and
71 early-warning purposes.

72 The direct use of DAS amplitude information is mainly circumscribed by a few lim-
73 itations such as unknown cable coupling, single-component sensing, uncertain instrumen-
74 tal response, and uncommon amplitude saturation behaviors (Lindsey et al., 2020). DAS
75 instruments record phase shifts of light traveling in the optical fiber and the phase in-
76 formation is then converted into the strain along the cable direction (Lindsey et al., 2017;
77 Fernández-Ruiz et al., 2020; Lindsey & Martin, 2021). However, the instrumental strain
78 is not necessarily equal to the strain of the medium surrounding the cable due to differ-
79 ent installation methods of telecommunication cables (Ajo-Franklin et al., 2019). This
80 coupling issue commonly exists but varies with the unknown cable installation in differ-
81 ent regions (Ajo-Franklin et al., 2019; Lindsey et al., 2020; Trainor-Guitton et al., 2019;
82 Paitz et al., 2020). Moreover, the instrumental response of DAS is highly frequency-dependent
83 (Lindsey et al., 2020; Paitz et al., 2020) and often hard to quantify without co-located
84 seismometers. The frequency-dependent instrumental response can contaminate frequency
85 components of the DAS data, and may prevent robust spectral analysis. The DAS am-
86 plitude saturation is another issue and is sometimes observed for earthquakes close to
87 DAS instruments (Viens et al., 2022). The DAS amplitude saturation is often presented
88 by a flip from maximum to minimum due to the phase wrapping of the sensing laser pulse
89 in the cable (Ajo-Franklin et al., 2022), making this behavior hard to identify and re-
90 cover. All these instrumental limitations aggravate the accurate conversion of DAS am-
91 plitude to ground motions (e.g., velocity and acceleration), thus further challenging the
92 incorporation of DAS data into many seismology applications (Lindsey & Martin, 2021;
93 Farghal et al., 2022). There have been many attempts to convert DAS-recorded strain
94 to ground motions (Daley et al., 2016; H. F. Wang et al., 2018; Yu et al., 2019; Lindsey
95 et al., 2020; Lior et al., 2021). For example, H. F. Wang et al. (2018) showed a good match
96 between DAS amplitude and strain derived from individual co-located nodal sensors. How-
97 ever, Muir and Zhan (2022) systematically reconstructed the strain-rate wavefield with
98 the entire nodal array in the same experiment, and found that the DAS-recorded am-
99 plitudes are on average twice that of conventional sensors. In general, accurate conver-
100 sion requires good knowledge of the local geology, seismic velocity structure, and instru-
101 mental information; and is still an active research direction in the DAS community.

102 Instead of converting DAS-strain data to ground motion measurements (i.e., ve-
103 locity and acceleration), we propose a data-driven way to explore the relationship be-
104 tween the peak amplitude of DAS data and earthquake magnitude. In this study, we present
105 the first DAS amplitude scaling relation for a rapid magnitude estimation of DAS-recorded
106 earthquakes. Previous studies using conventional strainmeters show that the peak strain
107 amplitude follows an empirical relation that can be used to estimate the earthquake mag-
108 nitude (Barbour & Crowell, 2017; Barbour et al., 2021). Unlike conventional strainmeters,
109 one DAS array can easily provide thousands of peak amplitude measurements from a sin-
110 gle earthquake, allowing the development of robust scaling relation with fewer earthquakes.

111 We analyze earthquakes recorded by DAS arrays in California, USA, and Sanriku,
112 Japan (Figure 1). Both regions are seismically active and provide us with an unprece-
113 dented opportunity to develop and validate the DAS scaling relation. We measure peak
114 DAS amplitudes of earthquakes based on earthquake catalogs. We apply an iterative re-
115 gression analysis to these datasets to obtain a robust scaling relation between the peak
116 DAS strain rate, earthquake magnitude, and hypocentral distance, calibrated by channel-
117 specific site terms. The obtained scaling relation can then give a rapid but accurate earth-
118 quake magnitude estimation from the DAS amplitude measurements. Furthermore, we
119 show that the DAS amplitudes in different regions follow the same scaling relation. The
120 scaling relation built on terrestrial DAS arrays in California can be transferred to the
121 submarine DAS data in Japan. We conclude that our DAS scaling relation is transfer-

122 able for earthquakes within similar distance range, and have great potential in earthquake
 123 source study and EEW.

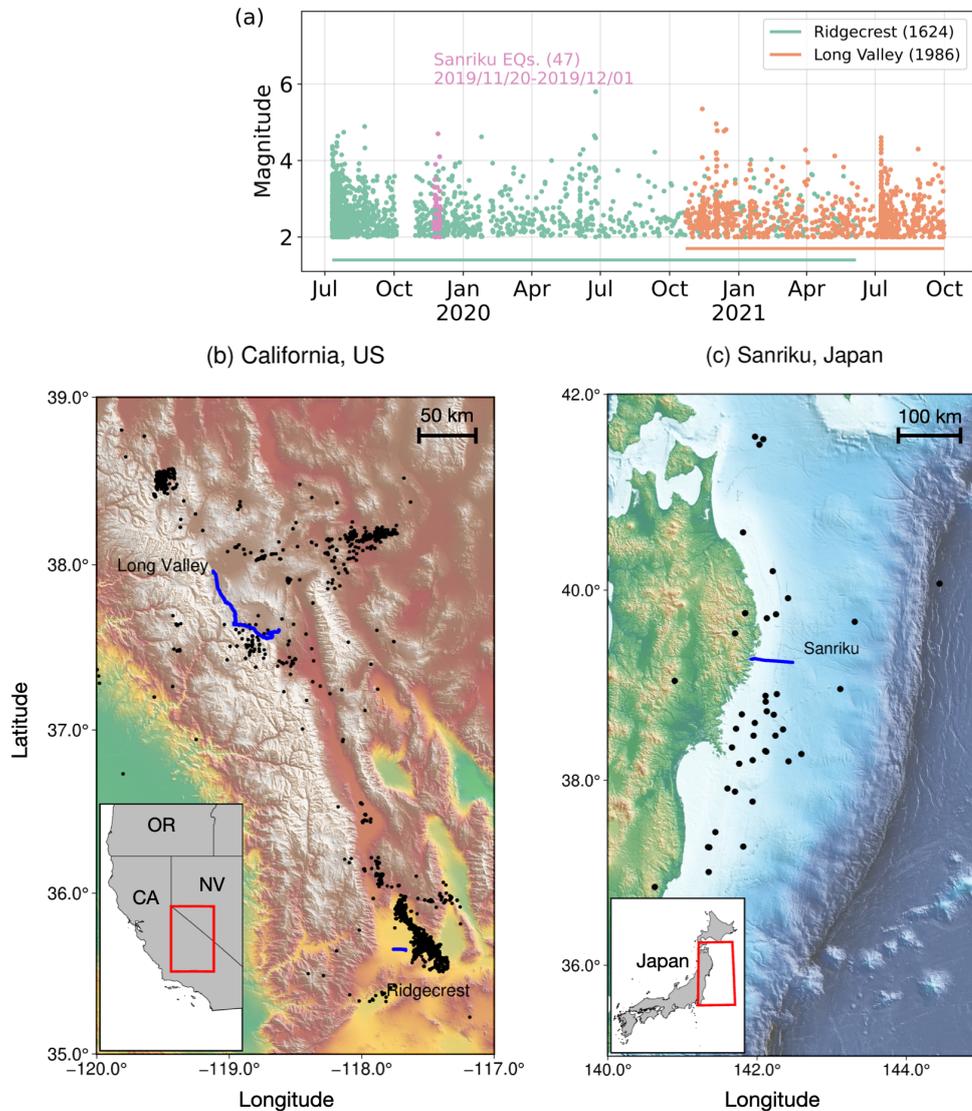


Figure 1. Earthquakes in the study areas. (a) Time variation of earthquakes used in the analysis. Colors indicate earthquakes recorded by different DAS arrays. (b) Topographic map including earthquake locations and the two California DAS arrays: Ridgecrest array and Long Valley. (c) Map showing the locations of earthquakes and the Sanriku DAS array. Earthquakes are indicated by the black dots and the DAS arrays are shown by blue lines.

2 Results

2.1 Data

We analyze strain-rate DAS data, which is shown to have a frequency-independent instrumental noise (Lior et al., 2022), recorded in both terrestrial and submarine environments (Figure 1 (a)). We start with the two terrestrial DAS arrays in the Ridgecrest (RC) and Long-Valley (LV) regions (Figure 1 (b)) in California. The two arrays recorded over two years of continuous data from July 10, 2019 to October 31, 2021. We first convert the DAS raw data, which is the phase shift of Rayleigh back-scattered laser signals in the optical fiber, to strain rate using Eq. S1 (Text S1 in the Supporting Information). We then apply PhaseNet-DAS (Zhu et al., 2022), which is a deep learning phase picker tailored for DAS data, to accurately pick P-wave and S-wave arrivals from earthquakes (Text S2 of the Supporting Information). We associate the picked earthquakes with the regional earthquake catalogs to determine their locations and magnitudes. We also investigate two weeks of submarine data (November 11, 2019 to December 1, 2019) from a DAS array in Sanriku, Japan (Shinohara et al., 2022). The submarine DAS data suffers from various types of ocean noise and earthquake P-wave arrivals are rarely observed. Due to these limitations, PhaseNet-DAS is not as effective on submarine data as on terrestrial DAS arrays. Instead, we apply a template matching method to detect S-waves from earthquakes, and associate them with the local Japanese Meteorological Agency (JMA) catalog for their location and magnitude (Text S3 of the Supporting Information). In this study, we assume that the difference in catalog magnitude of the two regions, California (local magnitude M_L for most earthquakes or moment magnitude M_w if available) and Sanriku M_{JMA} (velocity magnitude according to JMA (Katsumata, 1996; Funasaki, 2004)), is negligible to simplify the analysis.

We successfully obtain 3,610 earthquakes with 2,363,585 P-wave and 2,411,592 S-wave peak measurements from the two California DAS arrays, and 47 earthquakes with 34,803 S-wave peak measurements from the Sanriku DAS array. The measured peak DAS strain rates present strong correlations with the event magnitude (Figures 2 (c) and (f)) and hypocentral distance (Figures 2 (d) and (g)), respectively. Furthermore, all arrays in different environments follow similar trends and imply the existence of a scaling relation (see Text S4 of the Supporting Information for details of data processing and quality control).

2.2 Scaling relation

Based on the statistical correlations of data (Figure 2), we fit the data with a general form of scaling relation similar to Barbour and Crowell (2017); Barbour et al. (2021):

$$\log_{10} E_i = aM + b\log_{10} D_i + K_i, \quad (1)$$

where E is the observed peak amplitude of DAS strain rate in microstrain/s ($10^{-6}/s$), D is the hypocentral distance in kilometers to each DAS channel and M is the earthquake magnitude. The subscript i corresponds to each DAS channel. We apply a channel-specific factor K_i to account for integrated local effects such as the cable construction, installation, instrumental coupling, and variety of regional geology.

We use an iterative regression method to fit for the magnitude coefficient a , distance coefficient b , and corresponding site terms K_i separately for P and S wave. We first apply it to individual DAS arrays and find that the values are almost the same among various arrays (Figure S1). Therefore, we further combine different data sets for an integrated regression. Because of the unbalanced amount of measurements and different processing steps of terrestrial and submarine DAS data, we separate the two data sets for different purposes. We use the California DAS dataset with both P- and S-wave mea-

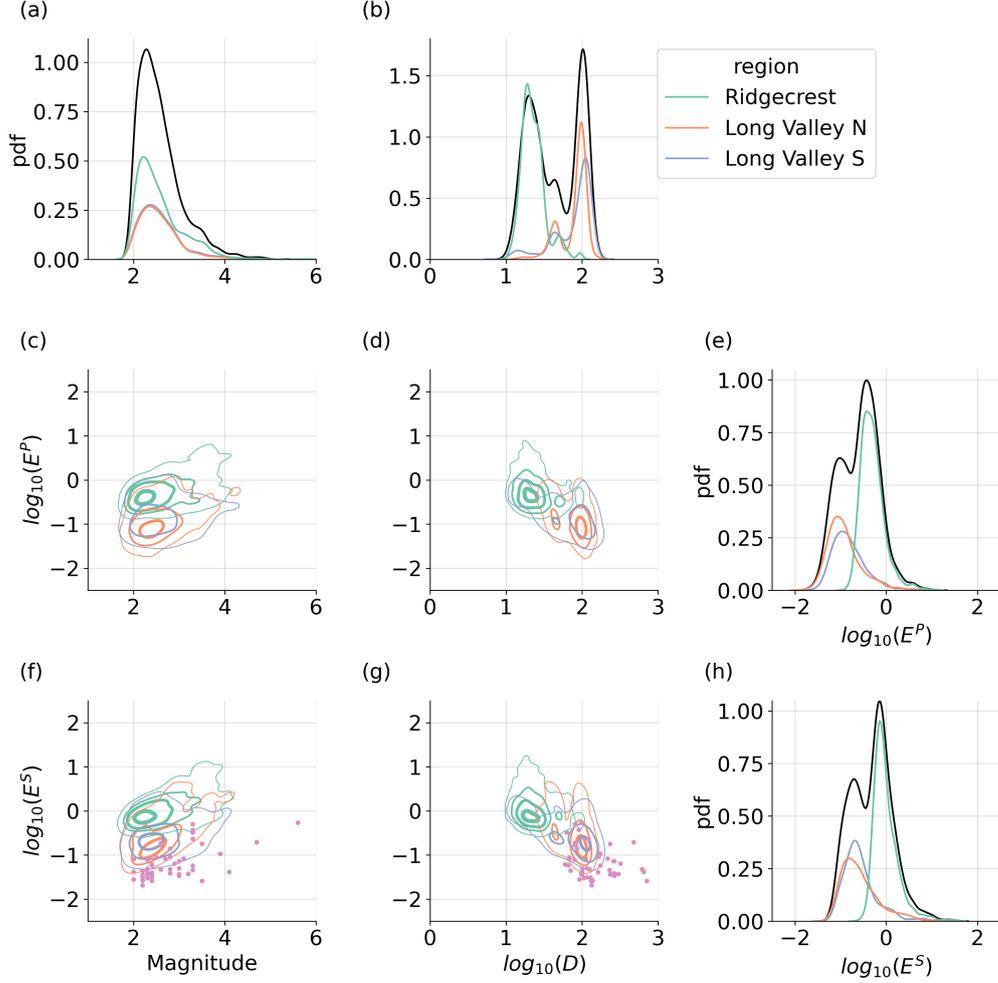


Figure 2. Distributions and correlations of DAS data. (a) Histograms of earthquake magnitude. (b) Histograms of hypocentral distance. (c) Correlation between magnitude and peak P-wave DAS strain rate E^P . (d) Correlation between hypocentral distance and peak P-wave DAS strain rate E^P . (e) Histograms of peak P-wave DAS strain rate E^P . (f) Correlation between magnitude and peak S-wave DAS strain rate E^S . (g) Correlation between hypocentral distance and peak S-wave DAS strain rate E^S . (h) Histograms of peak S-wave DAS strain rate E^S . For histograms, black lines indicate the entire data set of all DAS arrays. Colored lines are for individual arrays. For the 2-D correlation figures, peak DAS strain rate measurements have been averaged by events. Different California arrays are shown by the colored contours, whose levels correspond to 5%, 30%, 60% and 90% of the probability density from thin to thick lines. The Sanriku data points are shown by pink dots on (f) and (g).

171 surements to fit for the coefficients of Eq.(1), and the Sanriku submarine DAS data as
 172 a validation set. This splitting scheme aims at testing the generality of the scaling re-
 173 lation. The best-fit scaling relation we obtain for P waves is:

$$\log_{10} E_i^P = 0.437M - 1.269 \log_{10} D_i + K_i^P, \quad (2)$$

174 and for S waves is:

$$\log_{10} E_i^S = 0.690M - 1.588 \log_{10} D_i + K_i^S. \quad (3)$$

175 We refer the reader to Text S5 and Text S6 of the Supporting Information for further
 176 details about the iterative regressions and site calibration terms, respectively.

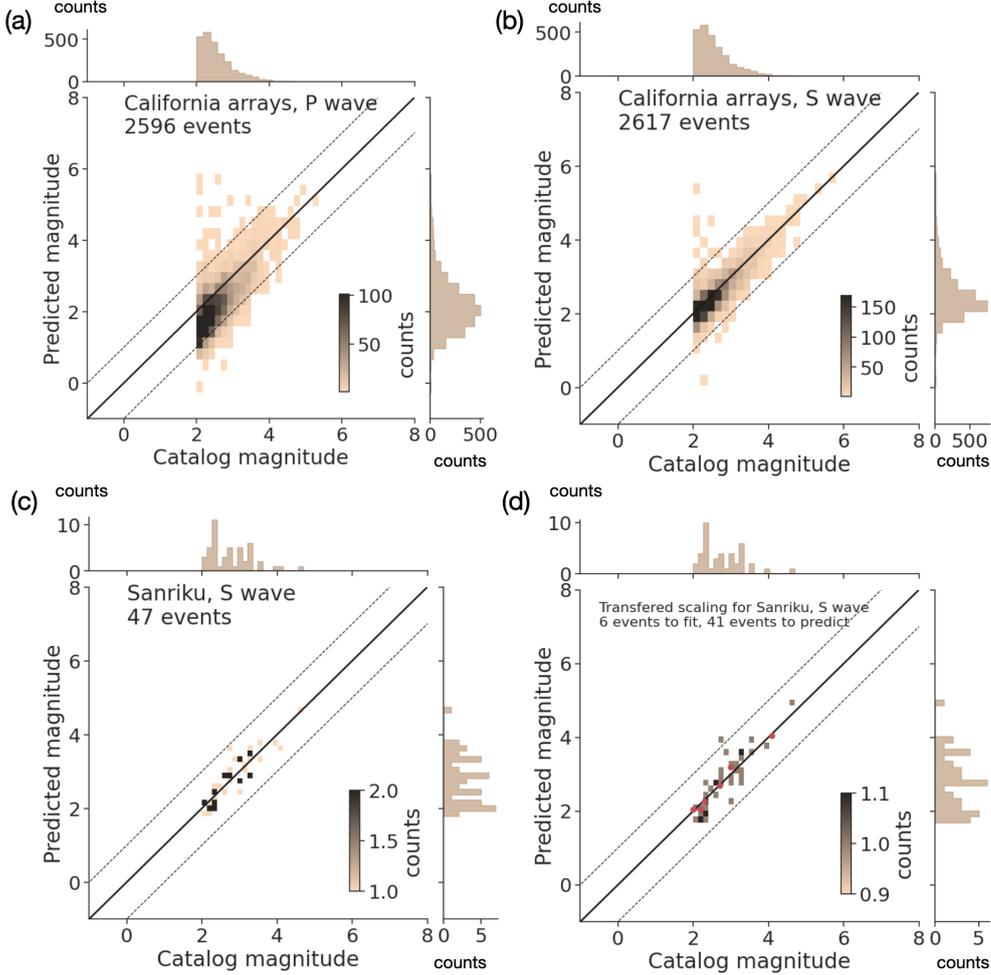


Figure 3. Comparison between earthquake catalog magnitude and magnitude estimated from the scaling relation. (a) Magnitude from the P-wave scaling relation applied to the California data. The scaling relation is from all three California DAS arrays. (b) Magnitude from the S-wave scaling relation applied to the California data. The scaling relation is from all three California DAS arrays. (c) Magnitude from the S-wave scaling relation applied to the Sanriku data. The scaling relation is from the Sanriku DAS array. (d) Magnitude from the S-wave scaling relation applied to the Sanriku data. The scaling relation is transferred from California DAS arrays. Red dots highlight the events used to calibrate the local site terms. Black solid lines indicate the accurate estimation that catalog magnitude is equal to the predicted magnitude. Dashed lines indicate the plus/minus 1 unit of magnitude errors.

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2.3 Magnitude estimation from DAS

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We validate the scaling relation by comparing the measured peak strain rate with those calculated by the scaling relation Eq.(1) to guarantee that the regression can robustly explain the features in the data (Text S7 and Figure S3 of the Supporting Information). Then, we reorganize the scaling relation Eq.(1) to estimate earthquake magnitudes from the DAS peak strain rate:

$$M_i = (\log_{10} E_i - b \log_{10} D_i - K_i)/a. \quad (4)$$

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Given the peak amplitude E_i and hypocentral distance D_i , we calculate the magnitude M_i for each DAS channel and then use the median magnitude of all channels as the final magnitude estimation M . Our results show that the magnitude can be accurately estimated with an error of less than 1 unit of magnitude by using only 2 seconds of either P or S waves (Figure 3 (a)-(c)) for most earthquakes in both the California and Sanriku regions, especially for the larger earthquakes. Moreover, we show that the scaling relation can be transferred from California to Sanriku, and work equally well as that obtained from the Sanriku-only measurements (Figure 3 (d)). The transferred scaling relation inherits the same magnitude a and hypocentral distance b coefficients from the California dataset. They only require a small number of local earthquakes to recalculate the site calibration terms K_i . We apply a systematic random test to show that for the Sanriku case, 6 events are sufficient to get robust values of the site calibration terms (Text S8 of the Supporting Information). The transferred scaling relation can provide an excellent estimation of the magnitude of earthquakes beyond the fitting dataset (Figure 3(d)).

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3 Discussion

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3.1 Transferable scaling relation of DAS amplitude

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Unlike conventional seismic sensors, DAS instruments are commonly deployed on preexisting telecommunication optical fibers with various properties and construction designs (Ajo-Franklin et al., 2019). These differences lead to difficulties in determining the instrument responses of DAS arrays. Some previous studies have shown that DAS instrument responses can be quantitatively determined by comparing DAS measurements with a co-located seismometer (Lindsey et al., 2020; Paitz et al., 2020), which is not always available, especially in marine environments. There are multiple ways to convert DAS measurements to ground motions: for instance, direct calibration with co-located seismometers (Lindsey et al., 2017); correction based on apparent local phase velocity (Daley et al., 2016; H. F. Wang et al., 2018; Yu et al., 2019; Shinohara et al., 2022); spatial integration from one co-located seismometer (H. F. Wang et al., 2018); rescaling in the $f-k$ or curvelet domains (Lindsey et al., 2020; Yang et al., 2022). Although shown to be effective, most of these methods require elaborate data preprocessing and analyst-intensive quality control, making them cable-dependent and thus limiting the applications of DAS in different regions and for real-time operations.

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In this study, we evaluate how DAS amplitude is related to earthquake magnitude in a data-driven methodology. With the abundant peak amplitude measurements of earthquakes in the Ridgecrest and Long-Valley regions, we apply the regression analysis to obtain a robust scaling relation for both P- and S-waves recorded by DAS instruments. Most importantly, we find that different regions have almost the same values of the scaling coefficients a and b (Figure S1) with regional site calibration terms K_i (Figures S2 and S4 in the Supporting Information). Our results show that the scaling relation can be transferred/extrapolated from one well-studied area to other DAS arrays for earthquakes within a similar distance range. The DAS peak amplitude scaling relation can be applied to earthquake source studies in different areas.

225 We further compare the DAS measurements with results from previous studies using
226 conventional strainmeters (Barbour et al., 2021). The distance coefficients of both
227 conventional strainmeters and DAS are close, meaning that the dynamic strain follows
228 the same geometrical spreading of wave propagation for both conventional strainmeters
229 and DAS instruments. However, the magnitude coefficients are different mainly because
230 the DAS scaling relation is built based on strain rate, while the scaling relation of con-
231 ventional strainmeters are built based on strain. The different physical quantities scale
232 differently with earthquake magnitude. Strain rate is theoretically proportional to ac-
233 celeration (Benioff, 1935). Therefore, we analyze the peak ground acceleration (PGA)
234 of the Next Generation Attenuation model (NGA-West2) project (Bozorgnia et al., 2014).
235 For consistent comparisons, we fit the PGA dataset with the same model as Eq.1, as-
236 signing the site calibration term to each station. We find that the distance coefficients
237 from DAS are close to those from PGA (Figure S1). Differences in the magnitude co-
238 efficients are probably due to the different frequency bands of DAS and conventional ac-
239 celerometers. Nowadays, Ground Motion Prediction Equations (GMPEs) with many pa-
240 rameters have been developed from various datasets to predict earthquake ground mo-
241 tions for engineering and seismological applications (Zhao et al., 2006; Kanno et al., 2006;
242 Boore & Atkinson, 2008; Bozorgnia et al., 2014; Boore et al., 2014; Campbell & Bozorg-
243 nia, 2014). Modern GMPEs have detailed definitions of the distance dependence (geo-
244 metrical and inelastic attenuation) and local site responses (local geology, seismic struc-
245 ture, instrument deployment, etc.) to explain the ground motion data in different regions.
246 Because of the relatively early stages of the DAS technique and limited data from dif-
247 ferent locations, we decide to start with the simplest form of scaling relation as Eq.1 in
248 this study for a first-order validation of the DAS scaling relation. We leave more com-
249 plex DAS strain prediction equations for future studies.

250 3.2 Potential applications of the DAS scaling relation

251 Our peak DAS amplitude scaling relation is fundamental and significant for var-
252 ious seismological studies such as earthquake seismology and EEW. Regarding earthquake
253 source analyses using DAS, the current studies only focus on earthquake detection and
254 location using the time information (Lindsey et al., 2017; Lellouch et al., 2020; Li et al.,
255 2021; Yang et al., 2022; Atterholt et al., 2022; Viens et al., 2022). Adding the amplitude
256 information and constraints on the earthquake magnitude can significantly help us to
257 resolve more source parameters and physical details about the earthquake rupture.

258 Another substantial application is for EEW, which has shown to be an effective method
259 to mitigate seismic risk. EEW aims to rapidly estimate the ground motion from real-
260 time data after an earthquake occurs and sends out alerts to specific users and the pub-
261 lic (Allen & Melgar, 2019). Current EEW algorithms use conventional seismic data for
262 ground motion predictions. As DAS leverages pre-existing telecommunication fiber-optic
263 cables, it can complement the current EEW systems. Converting most telecommunica-
264 tion cables located in highly seismic active regions into dense arrays of sensors could pro-
265 vide an economical approach to extend and improve the current EEW system, especially
266 in offshore seismogenic zones.

267 A recent study has attempted to apply DAS in EEW (Lior et al., 2022). Their ap-
268 plication relies on accurate conversion from DAS strain rate to ground acceleration, which
269 is used for earthquake magnitude estimation and ground motion prediction (Lior et al.,
270 2021). Our scaling relation provide an alternative and new approach to obtain earthquake
271 magnitude from DAS measurements. Compared with conversion-based methods, there
272 are a few advantages in using data-driven scaling relation of DAS measurements. Firstly,
273 the scaling relation is built upon abundant direct DAS measurements, and they do not
274 require an intensive manual pre-processing or parameter tuning, simplifying the deploy-
275 ment on edge-computing (Shi et al., 2016). Secondly, the scaling relation accounts for
276 the different coupling and regional effects among DAS channels with the site calibration

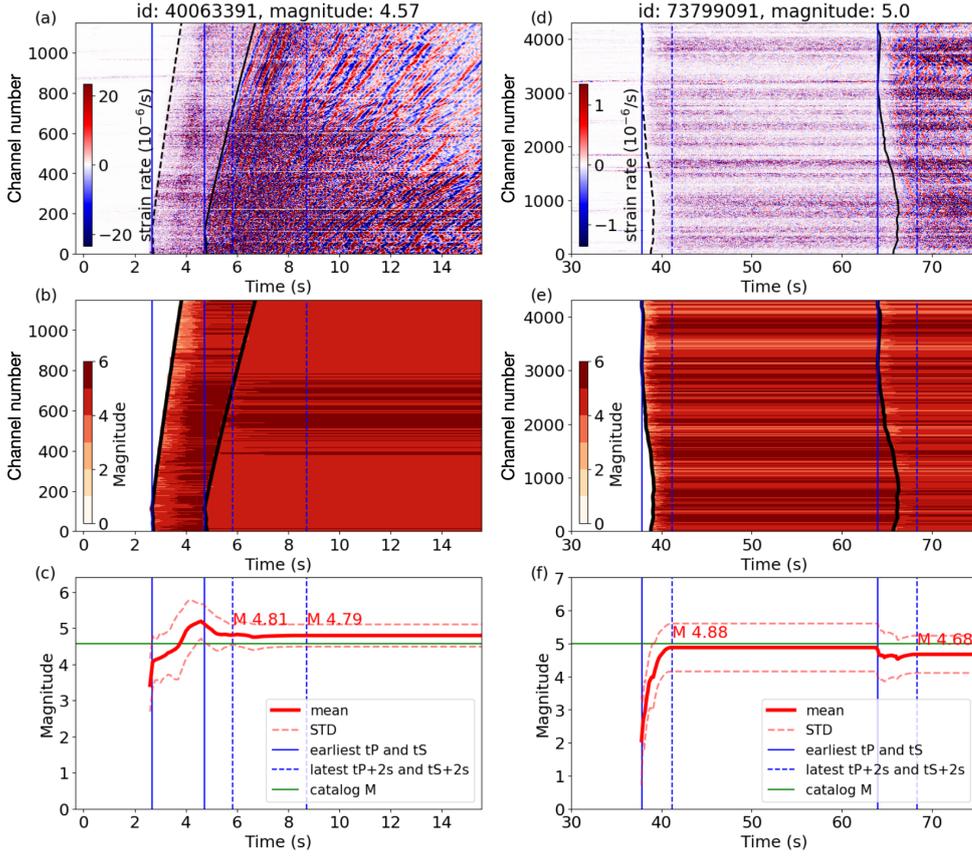


Figure 4. Idealized real-time earthquake magnitude estimation with the scaling relation. (a) Streaming DAS data from an M4.57 earthquake that occurred in Ridgecrest region. The initial time of earthquake is set as 0 second. (b) The corresponding magnitude estimation based on the peak DAS amplitude for each channel. The black lines indicate the arrival of the P-wave and the S-wave. (c) The final magnitude estimation from averaging magnitude estimation at all available channels, shown by the red line. The red dashed lines indicate the standard deviation of magnitude estimation from channels. The green horizontal lines indicate the catalog magnitude. The blue vertical lines show the earliest P- and S- arrivals, respectively. The blue vertical dashed lines show 2 seconds after the latest P- and S- arrivals, respectively. (d)-(f) show results of another M5.0 earthquake recorded by Long Valley north array.

277 terms, and no manual identification of well-coupled fiber is required. Last but not least,
 278 as demonstrated in the example of Sanriku results, the scaling relation is transferable.
 279 We can easily transfer the scaling relation from one well-studied region to other regions
 280 for deployment of new systems. Only a small number of earthquakes are required to cal-
 281 ibrate the site terms. Then, the scaling relation can be promptly employed for rapid earth-
 282 quake magnitude estimation in a new region. Technically, the regional scaling relation
 283 can also be consistently updated with more regional measurements of earthquakes.

284 Finally, we conduct an idealized experiment to illustrate the potential application
 285 of the DAS scaling relation for rapid magnitude estimation. We assume that the earth-
 286 quake can be immediately detected and located. Therefore, we can apply the scaling re-
 287 lation to convert the streaming DAS signals (Figure 4 (a) and (d)) to real-time estima-

288 tion of earthquake magnitude (Figure 4 (b) and (e)) at available DAS channels. We keep
 289 the median value of magnitude estimated at each channel as the final estimation and keep
 290 updating it with time (Figure 4 (c) and (f)). We experiment with the recent M4.57 and
 291 M5.0 earthquakes recorded by the Ridgecrest and Long-Valley north arrays, respectively.
 292 The M4.57 earthquake occurred on July 15, 2022 in the Ridgecrest region and is about
 293 15 km from the Ridgecrest array. The M5.0 earthquake occurred on October 25, 2022,
 294 near Alum Rock and San Jose, California and is about 244 km from the Long Valley ar-
 295 ray. Both events are not included in the data sets that are used for the regression, and
 296 therefore are good candidates to test our scaling relation on earthquakes from different
 297 distance. We can accurately estimate the event magnitude with its uncertainty less than
 298 0.5 only 2 seconds after the earliest P-wave arrival. When some channels begin to de-
 299 tect the S wave, we also include the S wave information by averaging the magnitude from
 300 both P-wave and S-wave amplitudes to further update the magnitude estimation. It is
 301 also possible to combine rapid estimation of earthquake magnitude with the GMPEs (Atkinson
 302 & Boore, 2006; Boore & Atkinson, 2008; Bozorgnia et al., 2014; Douglas & Edwards, 2016)
 303 to predict the ground shaking and seismic intensity, similar to the conventional EEW
 304 systems based on earthquake point source modeling (Allen & Melgar, 2019). More de-
 305 tails about the method are provided in Section 9.

306 However, this data-driven scaling analysis method also has some limitations that
 307 require further studies. The scaling relation of peak DAS amplitude relies on correct event
 308 association and peak amplitude measurement. Measurement of peak amplitude in the
 309 improper waveform window can lead to errors in the magnitude estimation. For instance,
 310 there are a few small events with largely overestimated magnitudes in our results (Fig-
 311 ures 3(a)-(b)). We investigate the waveforms of those events and find that the overes-
 312 timation is due to an incorrect event association. For instance, an M2 event in the Long-
 313 Valley region is estimated as an M6 earthquake, because this event is a foreshock occur-
 314 ring only 8 seconds before the M6.0 earthquake. We also find a few instances where mul-
 315 tiple events occur in different places but are recorded at the same time, leading to over-
 316 lapped arrivals in the same time window. In such cases, the peak amplitudes of weaker
 317 arrivals will be overestimated. Combining DAS with other independent seismic sensors
 318 can help to exclude the incorrectly associated event, thus improving the magnitude es-
 319 timation. Finally, our current datasets only contain moderate magnitude earthquakes
 320 ($M < 6$) due to the short period of DAS deployment. Future DAS campaigns focus-
 321 ing on EEW and recording large earthquakes should explore if the scaling relation still
 322 holds or behaves differently due to potential complex non-linear site response (Bonilla
 323 et al., 2011; Astorga et al., 2018; Viens et al., 2022).

324 4 Conclusion

325 This work presents the first scaling relation between DAS peak amplitude, earth-
 326 quake magnitude, and hypocentral distance from terrestrial and submarine DAS arrays.
 327 We show that we could use the scaling relation to rapidly estimate the magnitude of earth-
 328 quakes in near real time. Furthermore, we find that the scaling relation is transferable
 329 from terrestrial DAS arrays in California to a submarine DAS array in Sanriku, Japan.
 330 Our results indicate a possibly universal scaling relation for DAS recorded peak ampli-
 331 tudes. The DAS amplitude scaling relation has great potential in different seismologi-
 332 cal studies such as EEW and earthquake source characterization.

333 Acknowledgments

334 The authors would like to thank Jessie Saunders at California Institute of Technology
 335 and Richard Allen at University of California, Berkeley for their constructive suggestions.
 336 This work was supported by Office of Emergency Services, State of California, under MCG.CEEWS3-
 337 1-CALIFOES.NEWS, funding source award number 6113-2019. YM and LV were sup-

ported by NSF award EAR2022716. This article has a Los Alamos National Laboratory (LANL) Unlimited Release Number (LA-UR-23-20408).

Data Availability Statement

The measured peak strain rate amplitude from multiple DAS arrays is available from the Caltech DATA repository with the link in a separate supplement document. This is temporarily used for the reviewers and will become publicly available upon publication. The Python scripts to process the data and reproduce results are available at https://github.com/yinjiuxun/das_strain_scaling.

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Earthquake magnitude with DAS: a transferable data-based scaling relation

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Key Points:

- We present the first data-based scaling relation for the DAS amplitude of earthquakes.
- Earthquake magnitude can be accurately estimated from DAS amplitude with the scaling relation.
- The DAS scaling relation is transferable and can be transferred from one area to another new area.

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Abstract

Distributed Acoustic Sensing (DAS) is a promising technique to improve the rapid detection and characterization of earthquakes. Due to some instrumental limitations, current DAS studies primarily focus on the phase information but less on the amplitude information. In this study, we compile earthquake data from two DAS arrays in California, USA, and one submarine array in Sanriku, Japan. We develop a data-driven method to obtain the first scaling relation between DAS amplitude and earthquake magnitude. Our results reveal that the DAS amplitude in different regions follows a similar scaling relation. The scaling relation can provide a rapid magnitude estimation and effectively avoid uncertainties caused by the conversion to ground motions. We finally show that the scaling relation is transferable from one to another new region. The scaling relation highlights the great potential of DAS in earthquake source characterization and early warning.

Plain Language Summary

Distributed Acoustic Sensing (DAS) is an emerging technique that can convert an optical fiber cable into a dense array to record clear earthquake signals. The recorded signals have essential information about earthquakes. For example, DAS can record higher amplitude signals from earthquakes with larger magnitude. However, conditions of the optical cables, such as how they are installed or how well they are attached to the surrounding medium, are often unknown, thus preventing quantitative measuring of earthquake magnitude from the DAS measurement. In this study, we investigate the earthquake data recorded by different DAS arrays and develop a data-driven method to get an empirical relation between the earthquake magnitude and the amplitude of DAS signals. We show that this empirical relation can accurately estimate the earthquake magnitude directly from the DAS data. Furthermore, the empirical relation we obtain from one area can also be applied to another new region with slight calibration. Our empirical relation can significantly expand the applications of the DAS technique in earthquake research, such as seismic hazard assessment and earthquake early warning.

1 Introduction

Rapid earthquake source characterization is critical for earthquake monitoring, Earthquake Early Warning (EEW), and prompt reactions to seismic hazards. However, this is still challenging for many remote areas with insufficient seismic station coverage. For example, subduction zones, which can hold the largest earthquakes, are generally poorly instrumented due to the large expenses involved in deploying and maintaining offshore seismic instruments. In this context, Distributed Acoustic Sensing (DAS), which can utilize pre-existing telecommunication fiber-optic cables in both onshore and offshore regions, appears to be a promising complementary sensing method to fill the geographical gaps of conventional seismic networks.

DAS is an emerging technique that has great potential in seismology. It converts every few meters of optical fiber into a single-component strainmeter (Benioff, 1935) to provide spatially coherent signals with high sensitivity. One single DAS array often consists of thousands of channels covering tens of kilometers, and can serve as a dense seismic array to achieve great spatial resolution. DAS has proved to be an effective tool to refine regional seismic structure (Ajo-Franklin et al., 2019; Trainor-Guitton et al., 2019; Yu et al., 2019; Spica, Nishida, et al., 2020; Yang et al., 2022; Spica, Perton, et al., 2020), detect local earthquakes (Ajo-Franklin et al., 2019; Li et al., 2021; Li & Zhan, 2018; Aterholt et al., 2022), and detect seismic signals from various sources (Williams et al., 2019; X. Wang et al., 2020; Zhan et al., 2021; Viens et al., 2022). The phase information of DAS has been well-validated to be accurate in the multiple aforementioned applications. However, DAS nano-strain amplitudes, which commonly represent the direct output from

70 an interrogator unit, are rarely considered for earthquake source characterization and
71 early-warning purposes.

72 The direct use of DAS amplitude information is mainly circumscribed by a few lim-
73 itations such as unknown cable coupling, single-component sensing, uncertain instrumen-
74 tal response, and uncommon amplitude saturation behaviors (Lindsey et al., 2020). DAS
75 instruments record phase shifts of light traveling in the optical fiber and the phase in-
76 formation is then converted into the strain along the cable direction (Lindsey et al., 2017;
77 Fernández-Ruiz et al., 2020; Lindsey & Martin, 2021). However, the instrumental strain
78 is not necessarily equal to the strain of the medium surrounding the cable due to differ-
79 ent installation methods of telecommunication cables (Ajo-Franklin et al., 2019). This
80 coupling issue commonly exists but varies with the unknown cable installation in differ-
81 ent regions (Ajo-Franklin et al., 2019; Lindsey et al., 2020; Trainor-Guitton et al., 2019;
82 Paitz et al., 2020). Moreover, the instrumental response of DAS is highly frequency-dependent
83 (Lindsey et al., 2020; Paitz et al., 2020) and often hard to quantify without co-located
84 seismometers. The frequency-dependent instrumental response can contaminate frequency
85 components of the DAS data, and may prevent robust spectral analysis. The DAS am-
86 plitude saturation is another issue and is sometimes observed for earthquakes close to
87 DAS instruments (Viens et al., 2022). The DAS amplitude saturation is often presented
88 by a flip from maximum to minimum due to the phase wrapping of the sensing laser pulse
89 in the cable (Ajo-Franklin et al., 2022), making this behavior hard to identify and re-
90 cover. All these instrumental limitations aggravate the accurate conversion of DAS am-
91 plitude to ground motions (e.g., velocity and acceleration), thus further challenging the
92 incorporation of DAS data into many seismology applications (Lindsey & Martin, 2021;
93 Farghal et al., 2022). There have been many attempts to convert DAS-recorded strain
94 to ground motions (Daley et al., 2016; H. F. Wang et al., 2018; Yu et al., 2019; Lindsey
95 et al., 2020; Lior et al., 2021). For example, H. F. Wang et al. (2018) showed a good match
96 between DAS amplitude and strain derived from individual co-located nodal sensors. How-
97 ever, Muir and Zhan (2022) systematically reconstructed the strain-rate wavefield with
98 the entire nodal array in the same experiment, and found that the DAS-recorded am-
99 plitudes are on average twice that of conventional sensors. In general, accurate conver-
100 sion requires good knowledge of the local geology, seismic velocity structure, and instru-
101 mental information; and is still an active research direction in the DAS community.

102 Instead of converting DAS-strain data to ground motion measurements (i.e., ve-
103 locity and acceleration), we propose a data-driven way to explore the relationship be-
104 tween the peak amplitude of DAS data and earthquake magnitude. In this study, we present
105 the first DAS amplitude scaling relation for a rapid magnitude estimation of DAS-recorded
106 earthquakes. Previous studies using conventional strainmeters show that the peak strain
107 amplitude follows an empirical relation that can be used to estimate the earthquake mag-
108 nitude (Barbour & Crowell, 2017; Barbour et al., 2021). Unlike conventional strainmeters,
109 one DAS array can easily provide thousands of peak amplitude measurements from a sin-
110 gle earthquake, allowing the development of robust scaling relation with fewer earthquakes.

111 We analyze earthquakes recorded by DAS arrays in California, USA, and Sanriku,
112 Japan (Figure 1). Both regions are seismically active and provide us with an unprece-
113 dented opportunity to develop and validate the DAS scaling relation. We measure peak
114 DAS amplitudes of earthquakes based on earthquake catalogs. We apply an iterative re-
115 gression analysis to these datasets to obtain a robust scaling relation between the peak
116 DAS strain rate, earthquake magnitude, and hypocentral distance, calibrated by channel-
117 specific site terms. The obtained scaling relation can then give a rapid but accurate earth-
118 quake magnitude estimation from the DAS amplitude measurements. Furthermore, we
119 show that the DAS amplitudes in different regions follow the same scaling relation. The
120 scaling relation built on terrestrial DAS arrays in California can be transferred to the
121 submarine DAS data in Japan. We conclude that our DAS scaling relation is transfer-

122 able for earthquakes within similar distance range, and have great potential in earthquake
 123 source study and EEW.

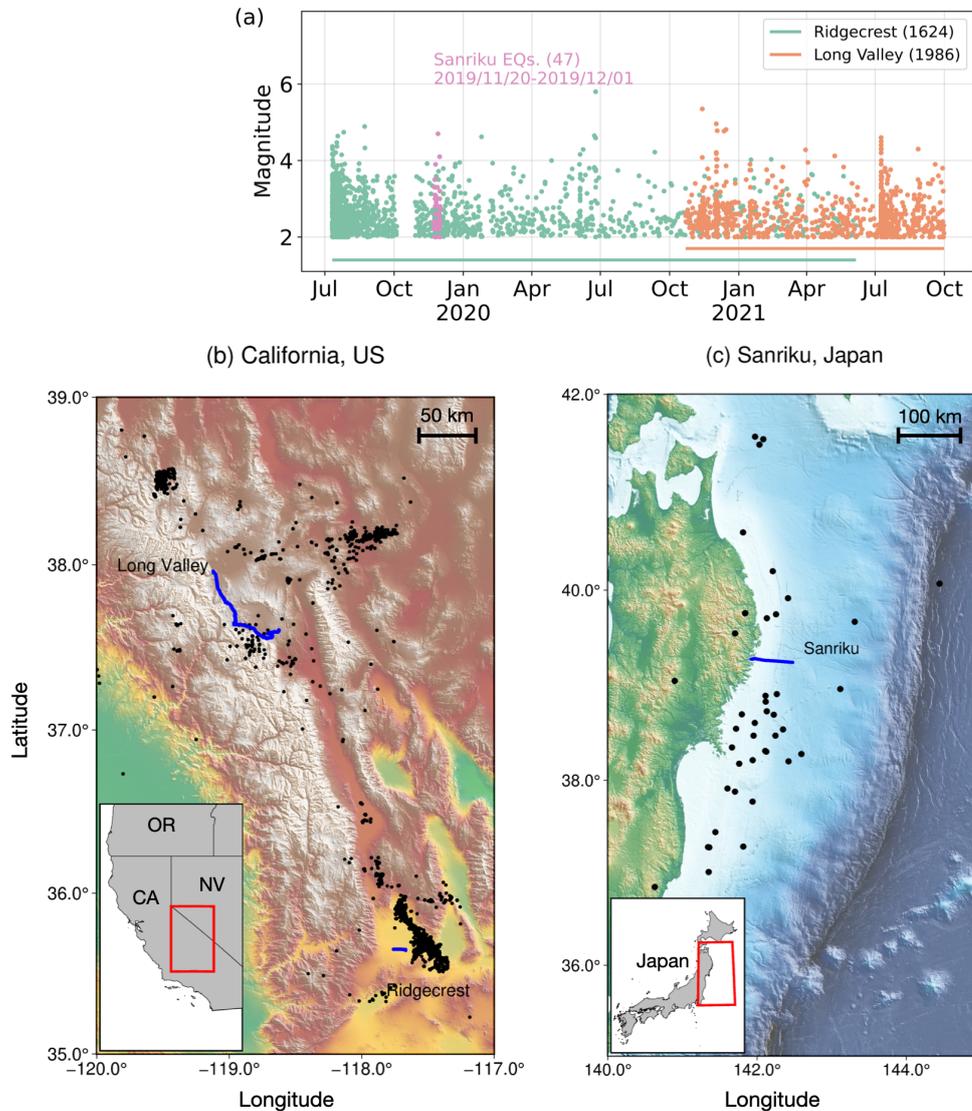


Figure 1. Earthquakes in the study areas. (a) Time variation of earthquakes used in the analysis. Colors indicate earthquakes recorded by different DAS arrays. (b) Topographic map including earthquake locations and the two California DAS arrays: Ridgecrest array and Long Valley. (c) Map showing the locations of earthquakes and the Sanriku DAS array. Earthquakes are indicated by the black dots and the DAS arrays are shown by blue lines.

2 Results

2.1 Data

We analyze strain-rate DAS data, which is shown to have a frequency-independent instrumental noise (Lior et al., 2022), recorded in both terrestrial and submarine environments (Figure 1 (a)). We start with the two terrestrial DAS arrays in the Ridgecrest (RC) and Long-Valley (LV) regions (Figure 1 (b)) in California. The two arrays recorded over two years of continuous data from July 10, 2019 to October 31, 2021. We first convert the DAS raw data, which is the phase shift of Rayleigh back-scattered laser signals in the optical fiber, to strain rate using Eq. S1 (Text S1 in the Supporting Information). We then apply PhaseNet-DAS (Zhu et al., 2022), which is a deep learning phase picker tailored for DAS data, to accurately pick P-wave and S-wave arrivals from earthquakes (Text S2 of the Supporting Information). We associate the picked earthquakes with the regional earthquake catalogs to determine their locations and magnitudes. We also investigate two weeks of submarine data (November 11, 2019 to December 1, 2019) from a DAS array in Sanriku, Japan (Shinohara et al., 2022). The submarine DAS data suffers from various types of ocean noise and earthquake P-wave arrivals are rarely observed. Due to these limitations, PhaseNet-DAS is not as effective on submarine data as on terrestrial DAS arrays. Instead, we apply a template matching method to detect S-waves from earthquakes, and associate them with the local Japanese Meteorological Agency (JMA) catalog for their location and magnitude (Text S3 of the Supporting Information). In this study, we assume that the difference in catalog magnitude of the two regions, California (local magnitude M_L for most earthquakes or moment magnitude M_w if available) and Sanriku M_{JMA} (velocity magnitude according to JMA (Katsumata, 1996; Funasaki, 2004)), is negligible to simplify the analysis.

We successfully obtain 3,610 earthquakes with 2,363,585 P-wave and 2,411,592 S-wave peak measurements from the two California DAS arrays, and 47 earthquakes with 34,803 S-wave peak measurements from the Sanriku DAS array. The measured peak DAS strain rates present strong correlations with the event magnitude (Figures 2 (c) and (f)) and hypocentral distance (Figures 2 (d) and (g)), respectively. Furthermore, all arrays in different environments follow similar trends and imply the existence of a scaling relation (see Text S4 of the Supporting Information for details of data processing and quality control).

2.2 Scaling relation

Based on the statistical correlations of data (Figure 2), we fit the data with a general form of scaling relation similar to Barbour and Crowell (2017); Barbour et al. (2021):

$$\log_{10} E_i = aM + b\log_{10} D_i + K_i, \quad (1)$$

where E is the observed peak amplitude of DAS strain rate in microstrain/s ($10^{-6}/s$), D is the hypocentral distance in kilometers to each DAS channel and M is the earthquake magnitude. The subscript i corresponds to each DAS channel. We apply a channel-specific factor K_i to account for integrated local effects such as the cable construction, installation, instrumental coupling, and variety of regional geology.

We use an iterative regression method to fit for the magnitude coefficient a , distance coefficient b , and corresponding site terms K_i separately for P and S wave. We first apply it to individual DAS arrays and find that the values are almost the same among various arrays (Figure S1). Therefore, we further combine different data sets for an integrated regression. Because of the unbalanced amount of measurements and different processing steps of terrestrial and submarine DAS data, we separate the two data sets for different purposes. We use the California DAS dataset with both P- and S-wave mea-

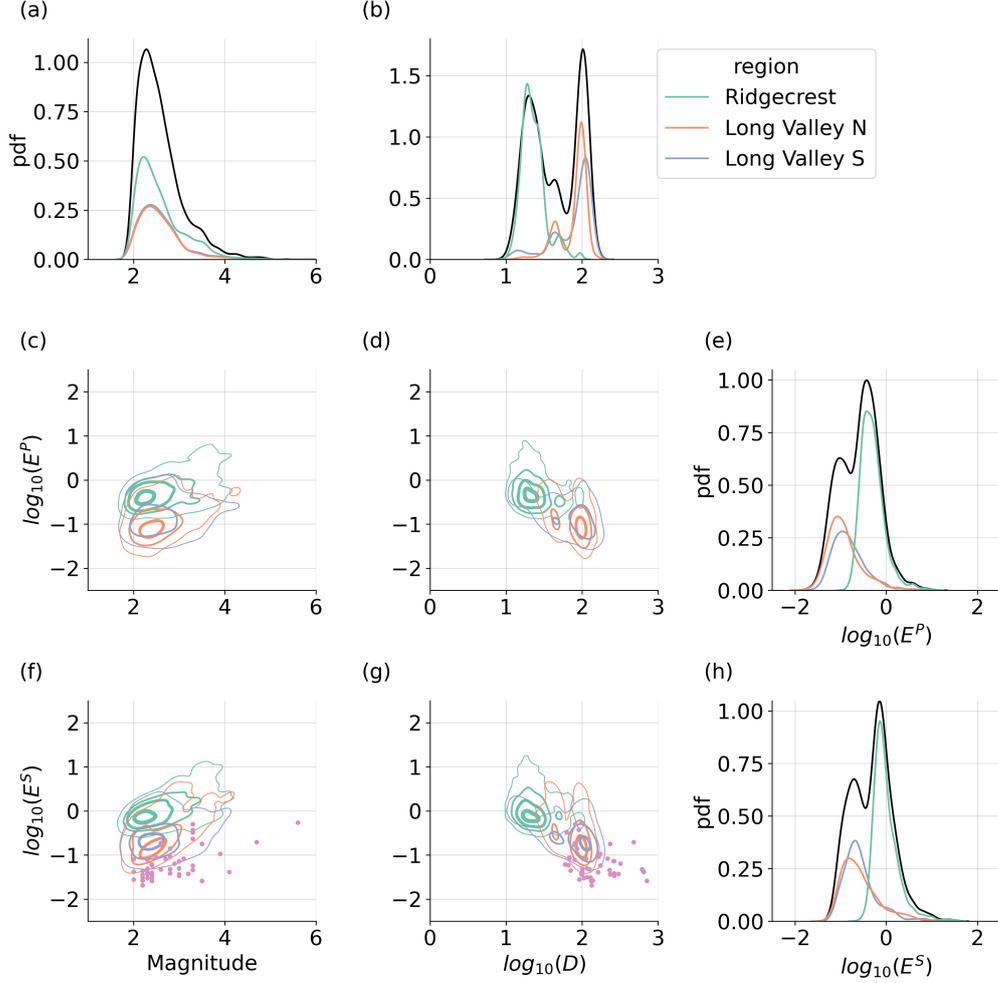


Figure 2. Distributions and correlations of DAS data. (a) Histograms of earthquake magnitude. (b) Histograms of hypocentral distance. (c) Correlation between magnitude and peak P-wave DAS strain rate E^P . (d) Correlation between hypocentral distance and peak P-wave DAS strain rate E^P . (e) Histograms of peak P-wave DAS strain rate E^P . (f) Correlation between magnitude and peak S-wave DAS strain rate E^S . (g) Correlation between hypocentral distance and peak S-wave DAS strain rate E^S . (h) Histograms of peak S-wave DAS strain rate E^S . For histograms, black lines indicate the entire data set of all DAS arrays. Colored lines are for individual arrays. For the 2-D correlation figures, peak DAS strain rate measurements have been averaged by events. Different California arrays are shown by the colored contours, whose levels correspond to 5%, 30%, 60% and 90% of the probability density from thin to thick lines. The Sanriku data points are shown by pink dots on (f) and (g).

171 measurements to fit for the coefficients of Eq.(1), and the Sanriku submarine DAS data as
 172 a validation set. This splitting scheme aims at testing the generality of the scaling re-
 173 lation. The best-fit scaling relation we obtain for P waves is:

$$\log_{10} E_i^P = 0.437M - 1.269 \log_{10} D_i + K_i^P, \quad (2)$$

174 and for S waves is:

$$\log_{10} E_i^S = 0.690M - 1.588 \log_{10} D_i + K_i^S. \quad (3)$$

175 We refer the reader to Text S5 and Text S6 of the Supporting Information for further
 176 details about the iterative regressions and site calibration terms, respectively.

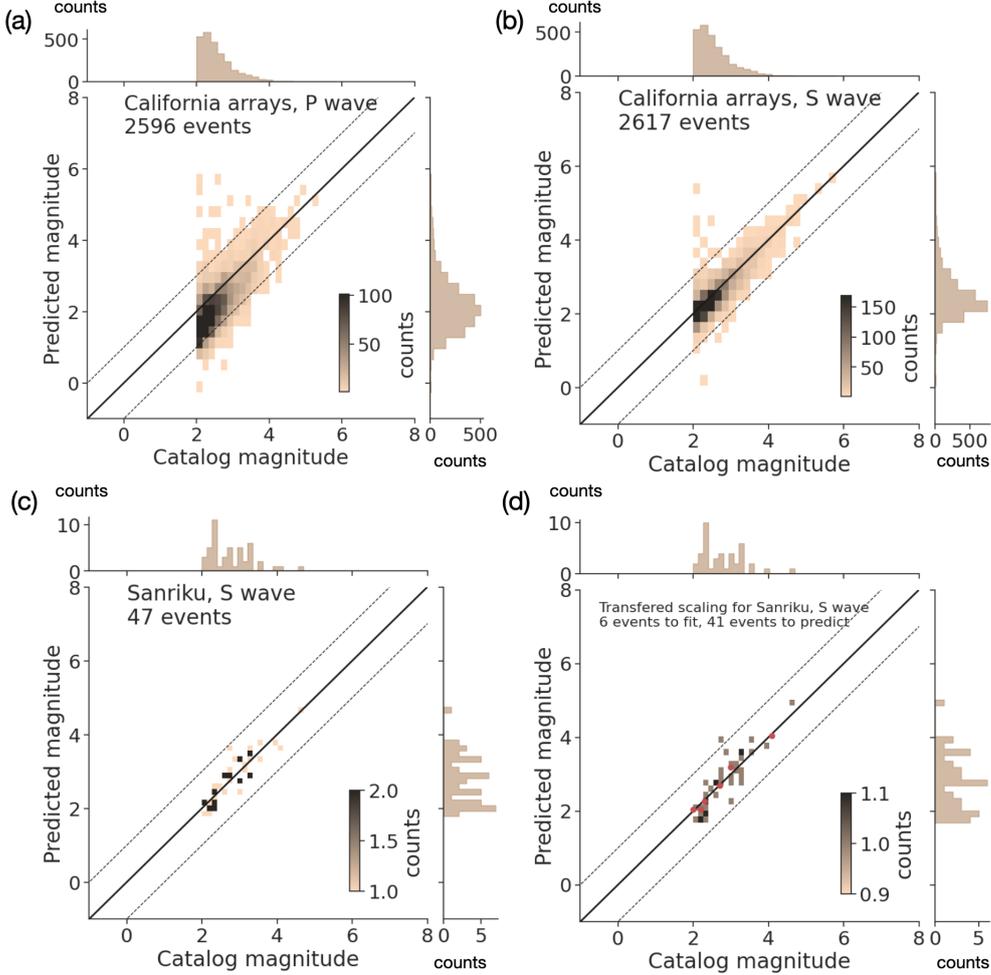


Figure 3. Comparison between earthquake catalog magnitude and magnitude estimated from the scaling relation. (a) Magnitude from the P-wave scaling relation applied to the California data. The scaling relation is from all three California DAS arrays. (b) Magnitude from the S-wave scaling relation applied to the California data. The scaling relation is from all three California DAS arrays. (c) Magnitude from the S-wave scaling relation applied to the Sanriku data. The scaling relation is from the Sanriku DAS array. (d) Magnitude from the S-wave scaling relation applied to the Sanriku data. The scaling relation is transferred from California DAS arrays. Red dots highlight the events used to calibrate the local site terms. Black solid lines indicate the accurate estimation that catalog magnitude is equal to the predicted magnitude. Dashed lines indicate the plus/minus 1 unit of magnitude errors.

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2.3 Magnitude estimation from DAS

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We validate the scaling relation by comparing the measured peak strain rate with those calculated by the scaling relation Eq.(1) to guarantee that the regression can robustly explain the features in the data (Text S7 and Figure S3 of the Supporting Information). Then, we reorganize the scaling relation Eq.(1) to estimate earthquake magnitudes from the DAS peak strain rate:

$$M_i = (\log_{10} E_i - b \log_{10} D_i - K_i)/a. \quad (4)$$

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Given the peak amplitude E_i and hypocentral distance D_i , we calculate the magnitude M_i for each DAS channel and then use the median magnitude of all channels as the final magnitude estimation M . Our results show that the magnitude can be accurately estimated with an error of less than 1 unit of magnitude by using only 2 seconds of either P or S waves (Figure 3 (a)-(c)) for most earthquakes in both the California and Sanriku regions, especially for the larger earthquakes. Moreover, we show that the scaling relation can be transferred from California to Sanriku, and work equally well as that obtained from the Sanriku-only measurements (Figure 3 (d)). The transferred scaling relation inherits the same magnitude a and hypocentral distance b coefficients from the California dataset. They only require a small number of local earthquakes to recalculate the site calibration terms K_i . We apply a systematic random test to show that for the Sanriku case, 6 events are sufficient to get robust values of the site calibration terms (Text S8 of the Supporting Information). The transferred scaling relation can provide an excellent estimation of the magnitude of earthquakes beyond the fitting dataset (Figure 3(d)).

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3 Discussion

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3.1 Transferable scaling relation of DAS amplitude

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Unlike conventional seismic sensors, DAS instruments are commonly deployed on preexisting telecommunication optical fibers with various properties and construction designs (Ajo-Franklin et al., 2019). These differences lead to difficulties in determining the instrument responses of DAS arrays. Some previous studies have shown that DAS instrument responses can be quantitatively determined by comparing DAS measurements with a co-located seismometer (Lindsey et al., 2020; Paitz et al., 2020), which is not always available, especially in marine environments. There are multiple ways to convert DAS measurements to ground motions: for instance, direct calibration with co-located seismometers (Lindsey et al., 2017); correction based on apparent local phase velocity (Daley et al., 2016; H. F. Wang et al., 2018; Yu et al., 2019; Shinohara et al., 2022); spatial integration from one co-located seismometer (H. F. Wang et al., 2018); rescaling in the $f-k$ or curvelet domains (Lindsey et al., 2020; Yang et al., 2022). Although shown to be effective, most of these methods require elaborate data preprocessing and analyst-intensive quality control, making them cable-dependent and thus limiting the applications of DAS in different regions and for real-time operations.

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In this study, we evaluate how DAS amplitude is related to earthquake magnitude in a data-driven methodology. With the abundant peak amplitude measurements of earthquakes in the Ridgecrest and Long-Valley regions, we apply the regression analysis to obtain a robust scaling relation for both P- and S-waves recorded by DAS instruments. Most importantly, we find that different regions have almost the same values of the scaling coefficients a and b (Figure S1) with regional site calibration terms K_i (Figures S2 and S4 in the Supporting Information). Our results show that the scaling relation can be transferred/extrapolated from one well-studied area to other DAS arrays for earthquakes within a similar distance range. The DAS peak amplitude scaling relation can be applied to earthquake source studies in different areas.

225 We further compare the DAS measurements with results from previous studies using
226 conventional strainmeters (Barbour et al., 2021). The distance coefficients of both
227 conventional strainmeters and DAS are close, meaning that the dynamic strain follows
228 the same geometrical spreading of wave propagation for both conventional strainmeters
229 and DAS instruments. However, the magnitude coefficients are different mainly because
230 the DAS scaling relation is built based on strain rate, while the scaling relation of con-
231 ventional strainmeters are built based on strain. The different physical quantities scale
232 differently with earthquake magnitude. Strain rate is theoretically proportional to ac-
233 celeration (Benioff, 1935). Therefore, we analyze the peak ground acceleration (PGA)
234 of the Next Generation Attenuation model (NGA-West2) project (Bozorgnia et al., 2014).
235 For consistent comparisons, we fit the PGA dataset with the same model as Eq.1, as-
236 signing the site calibration term to each station. We find that the distance coefficients
237 from DAS are close to those from PGA (Figure S1). Differences in the magnitude co-
238 efficients are probably due to the different frequency bands of DAS and conventional ac-
239 celerometers. Nowadays, Ground Motion Prediction Equations (GMPEs) with many pa-
240 rameters have been developed from various datasets to predict earthquake ground mo-
241 tions for engineering and seismological applications (Zhao et al., 2006; Kanno et al., 2006;
242 Boore & Atkinson, 2008; Bozorgnia et al., 2014; Boore et al., 2014; Campbell & Bozorg-
243 nia, 2014). Modern GMPEs have detailed definitions of the distance dependence (geo-
244 metrical and inelastic attenuation) and local site responses (local geology, seismic struc-
245 ture, instrument deployment, etc.) to explain the ground motion data in different regions.
246 Because of the relatively early stages of the DAS technique and limited data from dif-
247 ferent locations, we decide to start with the simplest form of scaling relation as Eq.1 in
248 this study for a first-order validation of the DAS scaling relation. We leave more com-
249 plex DAS strain prediction equations for future studies.

250 3.2 Potential applications of the DAS scaling relation

251 Our peak DAS amplitude scaling relation is fundamental and significant for var-
252 ious seismological studies such as earthquake seismology and EEW. Regarding earthquake
253 source analyses using DAS, the current studies only focus on earthquake detection and
254 location using the time information (Lindsey et al., 2017; Lellouch et al., 2020; Li et al.,
255 2021; Yang et al., 2022; Atterholt et al., 2022; Viens et al., 2022). Adding the amplitude
256 information and constraints on the earthquake magnitude can significantly help us to
257 resolve more source parameters and physical details about the earthquake rupture.

258 Another substantial application is for EEW, which has shown to be an effective method
259 to mitigate seismic risk. EEW aims to rapidly estimate the ground motion from real-
260 time data after an earthquake occurs and sends out alerts to specific users and the pub-
261 lic (Allen & Melgar, 2019). Current EEW algorithms use conventional seismic data for
262 ground motion predictions. As DAS leverages pre-existing telecommunication fiber-optic
263 cables, it can complement the current EEW systems. Converting most telecommunica-
264 tion cables located in highly seismic active regions into dense arrays of sensors could pro-
265 vide an economical approach to extend and improve the current EEW system, especially
266 in offshore seismogenic zones.

267 A recent study has attempted to apply DAS in EEW (Lior et al., 2022). Their ap-
268 plication relies on accurate conversion from DAS strain rate to ground acceleration, which
269 is used for earthquake magnitude estimation and ground motion prediction (Lior et al.,
270 2021). Our scaling relation provide an alternative and new approach to obtain earthquake
271 magnitude from DAS measurements. Compared with conversion-based methods, there
272 are a few advantages in using data-driven scaling relation of DAS measurements. Firstly,
273 the scaling relation is built upon abundant direct DAS measurements, and they do not
274 require an intensive manual pre-processing or parameter tuning, simplifying the deploy-
275 ment on edge-computing (Shi et al., 2016). Secondly, the scaling relation accounts for
276 the different coupling and regional effects among DAS channels with the site calibration

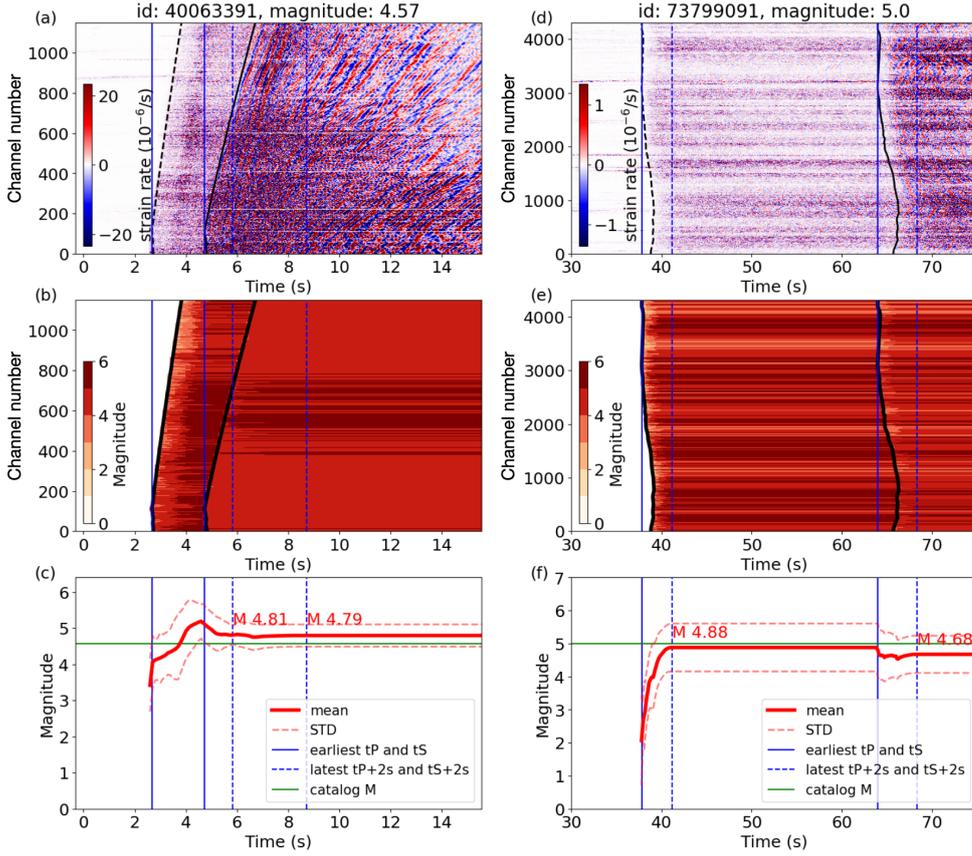


Figure 4. Idealized real-time earthquake magnitude estimation with the scaling relation. (a) Streaming DAS data from an M4.57 earthquake that occurred in Ridgecrest region. The initial time of earthquake is set as 0 second. (b) The corresponding magnitude estimation based on the peak DAS amplitude for each channel. The black lines indicate the arrival of the P-wave and the S-wave. (c) The final magnitude estimation from averaging magnitude estimation at all available channels, shown by the red line. The red dashed lines indicate the standard deviation of magnitude estimation from channels. The green horizontal lines indicate the catalog magnitude. The blue vertical lines show the earliest P- and S- arrivals, respectively. The blue vertical dashed lines show 2 seconds after the latest P- and S- arrivals, respectively. (d)-(f) show results of another M5.0 earthquake recorded by Long Valley north array.

277 terms, and no manual identification of well-coupled fiber is required. Last but not least,
 278 as demonstrated in the example of Sanriku results, the scaling relation is transferable.
 279 We can easily transfer the scaling relation from one well-studied region to other regions
 280 for deployment of new systems. Only a small number of earthquakes are required to cal-
 281 ibrate the site terms. Then, the scaling relation can be promptly employed for rapid earth-
 282 quake magnitude estimation in a new region. Technically, the regional scaling relation
 283 can also be consistently updated with more regional measurements of earthquakes.

284 Finally, we conduct an idealized experiment to illustrate the potential application
 285 of the DAS scaling relation for rapid magnitude estimation. We assume that the earth-
 286 quake can be immediately detected and located. Therefore, we can apply the scaling re-
 287 lation to convert the streaming DAS signals (Figure 4 (a) and (d)) to real-time estima-

288 tion of earthquake magnitude (Figure 4 (b) and (e)) at available DAS channels. We keep
 289 the median value of magnitude estimated at each channel as the final estimation and keep
 290 updating it with time (Figure 4 (c) and (f)). We experiment with the recent M4.57 and
 291 M5.0 earthquakes recorded by the Ridgecrest and Long-Valley north arrays, respectively.
 292 The M4.57 earthquake occurred on July 15, 2022 in the Ridgecrest region and is about
 293 15 km from the Ridgecrest array. The M5.0 earthquake occurred on October 25, 2022,
 294 near Alum Rock and San Jose, California and is about 244 km from the Long Valley ar-
 295 ray. Both events are not included in the data sets that are used for the regression, and
 296 therefore are good candidates to test our scaling relation on earthquakes from different
 297 distance. We can accurately estimate the event magnitude with its uncertainty less than
 298 0.5 only 2 seconds after the earliest P-wave arrival. When some channels begin to de-
 299 tect the S wave, we also include the S wave information by averaging the magnitude from
 300 both P-wave and S-wave amplitudes to further update the magnitude estimation. It is
 301 also possible to combine rapid estimation of earthquake magnitude with the GMPEs (Atkinson
 302 & Boore, 2006; Boore & Atkinson, 2008; Bozorgnia et al., 2014; Douglas & Edwards, 2016)
 303 to predict the ground shaking and seismic intensity, similar to the conventional EEW
 304 systems based on earthquake point source modeling (Allen & Melgar, 2019). More de-
 305 tails about the method are provided in Section 9.

306 However, this data-driven scaling analysis method also has some limitations that
 307 require further studies. The scaling relation of peak DAS amplitude relies on correct event
 308 association and peak amplitude measurement. Measurement of peak amplitude in the
 309 improper waveform window can lead to errors in the magnitude estimation. For instance,
 310 there are a few small events with largely overestimated magnitudes in our results (Fig-
 311 ures 3(a)-(b)). We investigate the waveforms of those events and find that the overes-
 312 timation is due to an incorrect event association. For instance, an M2 event in the Long-
 313 Valley region is estimated as an M6 earthquake, because this event is a foreshock occur-
 314 ring only 8 seconds before the M6.0 earthquake. We also find a few instances where mul-
 315 tiple events occur in different places but are recorded at the same time, leading to over-
 316 lapped arrivals in the same time window. In such cases, the peak amplitudes of weaker
 317 arrivals will be overestimated. Combining DAS with other independent seismic sensors
 318 can help to exclude the incorrectly associated event, thus improving the magnitude es-
 319 timation. Finally, our current datasets only contain moderate magnitude earthquakes
 320 ($M < 6$) due to the short period of DAS deployment. Future DAS campaigns focus-
 321 ing on EEW and recording large earthquakes should explore if the scaling relation still
 322 holds or behaves differently due to potential complex non-linear site response (Bonilla
 323 et al., 2011; Astorga et al., 2018; Viens et al., 2022).

324 4 Conclusion

325 This work presents the first scaling relation between DAS peak amplitude, earth-
 326 quake magnitude, and hypocentral distance from terrestrial and submarine DAS arrays.
 327 We show that we could use the scaling relation to rapidly estimate the magnitude of earth-
 328 quakes in near real time. Furthermore, we find that the scaling relation is transferable
 329 from terrestrial DAS arrays in California to a submarine DAS array in Sanriku, Japan.
 330 Our results indicate a possibly universal scaling relation for DAS recorded peak ampli-
 331 tudes. The DAS amplitude scaling relation has great potential in different seismologi-
 332 cal studies such as EEW and earthquake source characterization.

333 Acknowledgments

334 The authors would like to thank Jessie Saunders at California Institute of Technology
 335 and Richard Allen at University of California, Berkeley for their constructive suggestions.
 336 This work was supported by Office of Emergency Services, State of California, under MCG.CEEWS3-
 337 1-CALIFOES.NEWS, funding source award number 6113-2019. YM and LV were sup-

ported by NSF award EAR2022716. This article has a Los Alamos National Laboratory (LANL) Unlimited Release Number (LA-UR-23-20408).

Data Availability Statement

The measured peak strain rate amplitude from multiple DAS arrays is available from the Caltech DATA repository with the link in a separate supplement document. This is temporarily used for the reviewers and will become publicly available upon publication. The Python scripts to process the data and reproduce results are available at https://github.com/yinjiuxun/das_strain_scaling.

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Supporting Information for “Earthquake magnitude with DAS: a transferable data-based scaling relation”

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Contents of this file

1. Text S1 to S9
2. Figures S1 to S5

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Text S1. Conversion of raw DAS phase shift data to strain

A DAS system measures the phase/phase shift of Rayleigh back-scattered laser signal. When the DAS amplitude information is the focus, conversion from phase to strain is required:

$$d\phi = \frac{4\pi n G \xi}{\lambda} \epsilon, \quad (1)$$

where $d\phi$ and ϵ are the phase and strain, respectively. $n \approx 1.468$ and $\lambda = 1550$ nm are the refractive index of sensing fiber and optical wavelength, respectively. $\xi = 0.78$ is the photo-elastic scaling factor and G is the gauge length. Among all the parameters, only the gauge length G can be configured. All other parameters are related to cable properties and regarded as constants.

Text S2. Event detection and phase arrival-time picking using PhaseNet-DAS on the California arrays

Fast and accurate detection and picking of seismic phase arrivals are critical to an effective earthquake early warning (EEW) system. We used a deep learning model, PhaseNet-DAS (Zhu et al., 2022), to detect and pick the arrival times of both P and S phases from earthquakes. Deep-learning-based phase-picking models, such as PhaseNet (Zhu & Beroza, 2019), have dramatically improved earthquake detection and phase picking on conventional seismic stations. The DAS-tailored PhaseNet-DAS (Zhu et al., 2022) model is based on semi-supervised learning to transfer deep learning models trained on large seismic datasets to DAS data (Zhu & Beroza, 2019). We use the two California DAS arrays (i.e., the Ridgecrest and Long-Valley arrays) to train PhaseNet-DAS so it can di-

rectly process 2-D spatio-temporal DAS data. The trained model achieves a high-picking accuracy and good earthquake detection performances on DAS data.

Text S3. Waveform Similarity Search on the Sanriku array

PhaseNet-DAS cannot be directly applied to the submarine Sanriku DAS array because it is trained based on terrestrial data. Therefore, we apply a Waveform Similarity Search (WSS), which utilizes the spatial coherency of earthquake waveforms across DAS channels for detection from the Sanriku dataset. We collect 10,379 high-SNR S-wave waveforms from 34 nearby Hi-net seismometers (Aoi et al., 2020), and cross-correlate them with continuous DAS data to find similar events. Before cross-correlating waveforms, the entire dataset is downsampled from 500 to 25 Hz and bandpass filtered between 1-8 Hz, which is the average dominant frequency band of earthquakes recorded along the array. Cross-correlations are finally computed independently for each individual DAS channel. A detection is triggered when the cross-correlation value exceeds nine times the median absolute deviation of the cross-correlation function at a single channel (Shelly et al., 2007). Then, a new event is kept if it matches at more than 40 channels. This relatively high threshold guarantees a large spatial consistency (i.e., an earthquake is detected over at least a 208-m section of the cable) and excludes non-coherent detections. In total, we detect 10,321 events over the 12-day period.

We then associate these events with the Japan Meteorological Agency (JMA) catalog to find their epicenter locations and magnitude information. We first compute the theoretical arrival time based on the 1-D preliminary reference Earth model (Dziewonski et al., 1981). We also apply an amplitude attenuation threshold to filter out cataloged earthquakes that

are likely too weak to be recorded. A body wave geometrical spreading model is applied: $A(r) = A_0 e^{-Br}/r$, where r is the hypocentral distance, A_0 is the amplitude at the source and B is a constant when assuming all earthquakes coming from different azimuth with a constant frequency (i.e., 2 Hz) as well as a homogeneous medium. This allows us to constrain further and refine the association process and only keep high-probability events in our analysis. Finally, a total of 464 earthquakes were selected as detected earthquakes for further analysis.

Text S4. Peak strain rate from DAS

With the event picking, we further extract the peak amplitude. We apply a series of quality control steps to ensure reliable peak amplitude extraction. Because of the different picking methods on the land (California) and submarine (Sanriku) DAS data, their processings are slightly different.

The California DAS arrays use the OptaSense ODH Plexus interrogator unit (IU), which gives the phase-converted raw measurement of strain. We down-sample the data to 100 Hz and convert strain data to strain rate to remove the low-frequency noise and instrumental drifts. No further filtering is applied to the land DAS data. The Sanriku DAS array is probed with an AP Sensing N5200A IU, which is different from that used in California. The submarine DAS data are contaminated by oceanic noise at low frequencies (<0.5 Hz), especially for the channels near the coast (Spica et al., 2020). Therefore, we apply a 0.5 Hz high-pass filter to remove most of the ocean noise.

Because of the nature of the earthquake signals recorded by a DAS array, coherent signals should appear on most DAS channels as seismic waves propagate through the

cable within a short period (less than the cable length divided by the apparent wave speed). We inspect the event picking and exclude events that are only detected by a few channels (≤ 100) in the DAS array. If the waveforms of an earthquake are only detected by a few channels, the detection is likely a false detection, and the recorded waveforms are mostly from local noise signals. Including those false-detected waveforms can lead to a magnitude overestimation of many small earthquakes ($M2 - 3$). We also tune this threshold of detection channel number to make sure the channel number we use can give the optimal results, regarding the qualified event number and final results of magnitude estimation.

We further calculate the signal-to-noise ratio (SNR) for P and/or S waves of each channel with the detected events. In this study, SNR is defined as $10 \log_{10}(\|S\|^2/\|N\|^2)$, which is the average power ratio of the signal window (S) to the noise window (N) in decibel (dB). For the California data with clear P and/or S arrivals, the noise window is chosen as a 2-second time window ending 1 second before the detected P-wave arrival. The signal windows are the 2-second time window after the P and/or S direct arrivals, respectively. For the Sanriku DAS array, the situation is different. The Sanriku events are mainly detected by template-matching of S-waves, and it is difficult to get clear P phase arrivals. Therefore, we approximate the noise window as a 10-second-long window ending 10 seconds before the detected event time. The signal window is chosen as 10-second long centered around the detected event time after we carefully check the event waveforms to ensure the SNR is robustly estimated. For the California data, we only keep the channels from $M2+$ earthquakes with $\text{SNR} > 10\text{dB}$ to ensure a good signal quality.

For the Sanriku data, which is mainly used for validation, we only keep M2+ events with SNR values higher than 5dB.

After quality control, we measure the peak DAS strain rate for all available channels of the qualifying events. For the California DAS arrays with clear P and/or S pickings, we measure the peak amplitude of strain rate 2 seconds after the corresponding phase arrivals. We also test other window lengths up to 10 seconds. We find that the final regression results do not vary much with window lengths, but shorter time windows significantly help to suppress incorrect measurements due to noise from vehicle traffic. We show the results from the California DAS arrays using a 2-second window length in the main manuscript. For the Sanriku DAS array, we directly measure the peak S-wave amplitude from the 20-s long signal window centered at the event detection time.

Text S5. Iterative regression analysis

Based on the strong correlations between the peak amplitude and earthquake catalog magnitude and hypocentral distance (Figure 2), we fit for the empirical relations between earthquake magnitude, hypocentral distance, and peak amplitude (strain rate) for both P and S waves. Previous results on strainmeters (Barbour & Crowell, 2017; Barbour et al., 2021) have validated the use of a generalized functional model to describe the observed peak values of dynamic strain:

$$\log_{10} E_i = aM + b \log_{10} D_i + K_i, \quad (2)$$

where E is the observed peak amplitude of dynamic strain/strain rate, D is the hypocentral distance in kilometers to each station/channel and M is the earthquake magnitude.

The subscript i corresponds to each channel, and K_i is the corresponding site calibration term that compensates for the combined local effects such as instrumental coupling, fiber material properties, geological features, and noise. The goal is to fit the corresponding magnitude coefficient a , distance coefficient b , and K_i . We apply an iterative regression method to obtain the coefficients. Firstly, we assume that all channels in a DAS array share a constant site calibration term K_0 . With the peak amplitude measurements and the targeting scaling relation, we apply regression to the data to fit for the coefficients a , b and the constant site calibration term K_0 . Secondly, we fix the coefficients a and b , and fit for the specific site calibration term K_i for each channel to minimize the data misfit. Thirdly, we fix the site calibration terms K_i and further update the coefficients a and b . The second and third steps are repeated until the data misfit does not improved. We found that our dataset only need 3-5 iterations for the misfit values to converge within 1%. The regression can be done flexibly for either individual DAS arrays or multiple arrays at the same time. We test all cases and show our final coefficients a , b , and site calibration terms in Figure S1 and Figure S2, respectively.

The dynamic strain signal may also include earthquake-specific source terms (Barbour & Crowell, 2017; Barbour et al., 2021). For real time EEW applications, however, such prior information on the source process is difficult to obtain. Therefore, we do not explicitly fit for the source terms.

Text S6. Site calibration terms

Through our regression, we can also obtain the site calibration terms. Unlike conventional seismic sensors, which have standardized sensor designs and well-quantified instru-

mental responses, DAS instrument response is not as well constrained. The DAS cables used in this study are all dark fibers of the telecommunication optical fibers, and the cable constructions and installations vary significantly with regions. Both local conditions and cable installation properties greatly affect the recorded DAS data. Potential coupling issues are commonly noticed in the data (Ajo-Franklin et al., 2019; Lindsey et al., 2020; Trainor-Guitton et al., 2019; Paitz et al., 2020), but challenging to characterize from the instruments.

Our fully data-driven methodology, however, can directly quantify the local differences of DAS channels by introducing the site calibration terms K_i measured from earthquakes. The site-calibration terms K_i aim at quantifying all local effects that can change the measured amplitude, and are functions of channel locations. The obtained K_i are shown in Figure S2. We find that the values of K_i vary significantly along the cables in different regions. There are a few spikes of K_i values along the cables, which are caused by poorer data quality at local channel, likely due to fiber loops or the fiber not being coupled to the ground. Moreover, we find that the patterns of site calibration terms from P- and S-waves are similar. Understanding the local variations of K_i is essential to characterize the local cable properties. Nevertheless, we emphasize that the site calibration terms are just calibration terms that integrate many different local factors, such as the cable properties, instrumental coupling, and local geology. It is non-trivial to interpret K_i as a proxy of some specific factor, although we do see strong correlations between K_i and local shallow velocity structure (Spica et al., 2020; Viens, Bonilla, et al., 2022; Viens, Pertou, et al., 2022) or wave amplification (Yang et al., 2022).

We also notice that the land (Figure S1) and submarine DAS arrays (Figure S4) are quite different in terms of the local site effects. The site calibration term values from the California arrays are all above 1 except for a few channels located at fiber loops. However, site calibration terms of the Sanriku array present larger variations. The site calibration terms in Sanriku are mostly less than 1 and indicate a local attenuation in the DAS-recorded amplitude. Further investigations of the differences between the land and submarine DAS and the transition from amplification to attenuation along DAS arrays would be an important future direction to explore.

Text S7. Validation of strain rate measurements and magnitude estimation

We first validate the scaling relation by comparing the measured peak strain rate with that calculated by the scaling relation Eq. (2) with the catalog magnitude M and hypocentral distance D (Figure S3). Most of the calculated values of peak strain rate are consistent with the measured values. The difference between predicted and measured values is less than one in logarithmic scale for all arrays. This validation guarantees that the regression is done properly, and the fitted scaling relation can robustly explain features in the data.

We can then use the determined scaling relation to estimate earthquake magnitude by reorganizing the scaling relation:

$$M_i = (\log_{10} E_i - b \log_{10} D_i - K_i)/a. \quad (3)$$

Given the distance D_i and measured peak amplitude E_i , the magnitude can be calculated at each individual DAS channel to get an estimation M_i , and the final magnitude M can be obtained by calculating the mean and median values of all M_i .

Text S8. Transferring scaling relation from California to Sanriku

We find that different regions have similar values of the scaling coefficients a and b (Figure S1). The regional differences mainly lie in the regional site calibration terms K_i (Figure S2). This implies that the DAS-recorded strain rate data follow the same magnitude scaling relation that can be transferred/extrapolated to other DAS arrays in different regions.

To test this hypothesis, we transfer the scaling relation obtained solely from California data to the Sanriku region, where the tectonic setting is different. We fix the magnitude and distance coefficients to the same as the values from California. Then, we randomly choose n events from the 47 qualified earthquakes in the Sanriku dataset as the fitting Set 1. Peak measurements of events in Set 1 are used to constrain the local site calibration term $K_{i(Sanriku)}^S$. The remaining events are used as validation Set 2 for magnitude estimation. This allocation of data sets allows us to test both the validity and transferability of the obtained scaling relation Eqs.(1)-(3) at the same time. Finally, we measure the percentage of good estimation for Set 2 events, which is defined as the percentage of events whose magnitude is estimated within 0.5 unit of its catalog magnitude, as the metric to quantify how well the transferred scaling relation performs.

We systematically explore the event allocation: we increase the number of events n in Set 1 from 2, 3, ... to 30. For each n , we repeat the test for 50 times to measure the average percentage of good estimation. The variation of percentage is shown in Figure S5.

Our results show that only a few events are needed to calibrate the regional site terms (Figure S5), then the updated scaling relation can be used to estimate the earthquake magnitude (Figure 3). On average, two events give about 80% of good estimation percentage; and 5 events give relatively stable percentage from most random tests. Theoretically, we only need one well-cataloged earthquake measurement for each channel to measure the corresponding site calibration. Considering the uncertain data quality in a real situation, a few events with clear waveforms are sufficient to robustly constrain the site terms.

Text S9. Real-time magnitude estimation

We provide an idealized experiment to illustrate the application of our scaling relation for EEW. We assume that we can immediately detect and locate earthquakes. When the P wave arrives and the earthquake is detected, the system begins to measure the peak P-wave amplitude from the incoming DAS waveforms, and calculates the corresponding magnitude with the P-wave scaling relation Eq.(4) for the available channels. If the S-wave is also detected, the system also measures the peak S-wave amplitude and uses the S-wave scaling relation to estimate the magnitude. If one channel happens to have both P-wave and S-wave estimated magnitude, the mean value is taken. Our scaling relations are obtained with the peak amplitude in the 2-second window after P- or S-arrivals. Therefore, for each channel the peak amplitude is measured and updated to estimate magnitude until 2 seconds after the corresponding P-arrival or S-arrival. This time window can be easily adjusted based on how the scaling relations are built.

In this way, the incoming DAS data at each channel can be efficiently converted to real-time magnitude estimation. Finally, the magnitude estimations at all available channels

are averaged to give the final magnitude estimation for the earthquake, and the standard deviation of magnitude estimation is taken as the uncertainty estimation. We tested on many events, including one event outside of our regression data sets, and find that all of them can give an accurate estimation of the magnitude.

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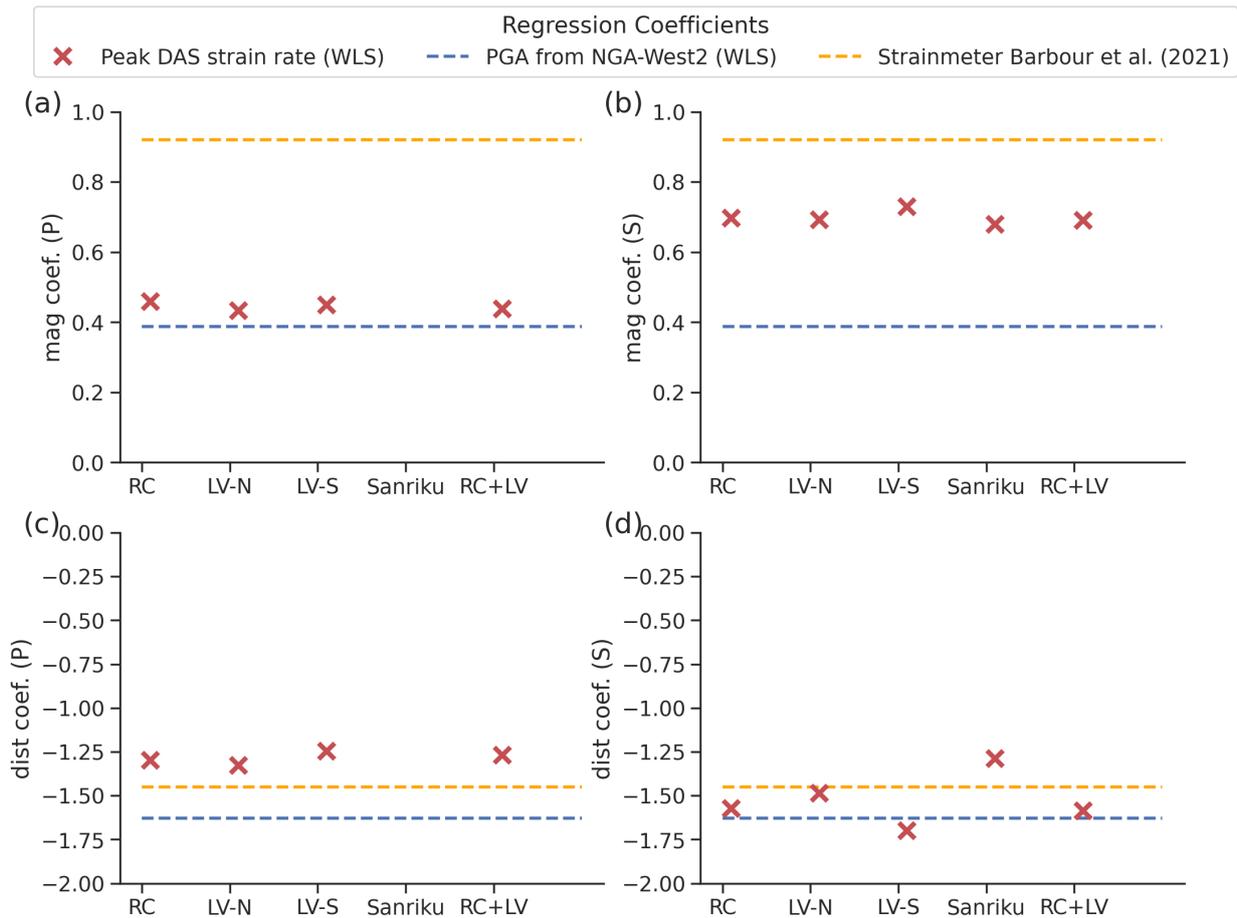


Figure S1. Regression coefficients from different data sets: (a) the P wave magnitude coefficients; (b) the S wave magnitude coefficients; (c) the P wave hypocentral distance coefficients; (d) the S wave hypocentral distance coefficients. RC is for Ridgecrest data only; LV-N is for Long-Valley northern array data only; LV-S is for Long-Valley southern array data only; Sanriku is for Sanriku data only; RC+LV are the results from combining RC, LV-N and LV-S arrays' data. The dashed lines also indicate the coefficients from strainmeter data (Barbour et al., 2021) and fit the same model Eq.(1) with the NGA-West 2 PGA dataset, respectively.

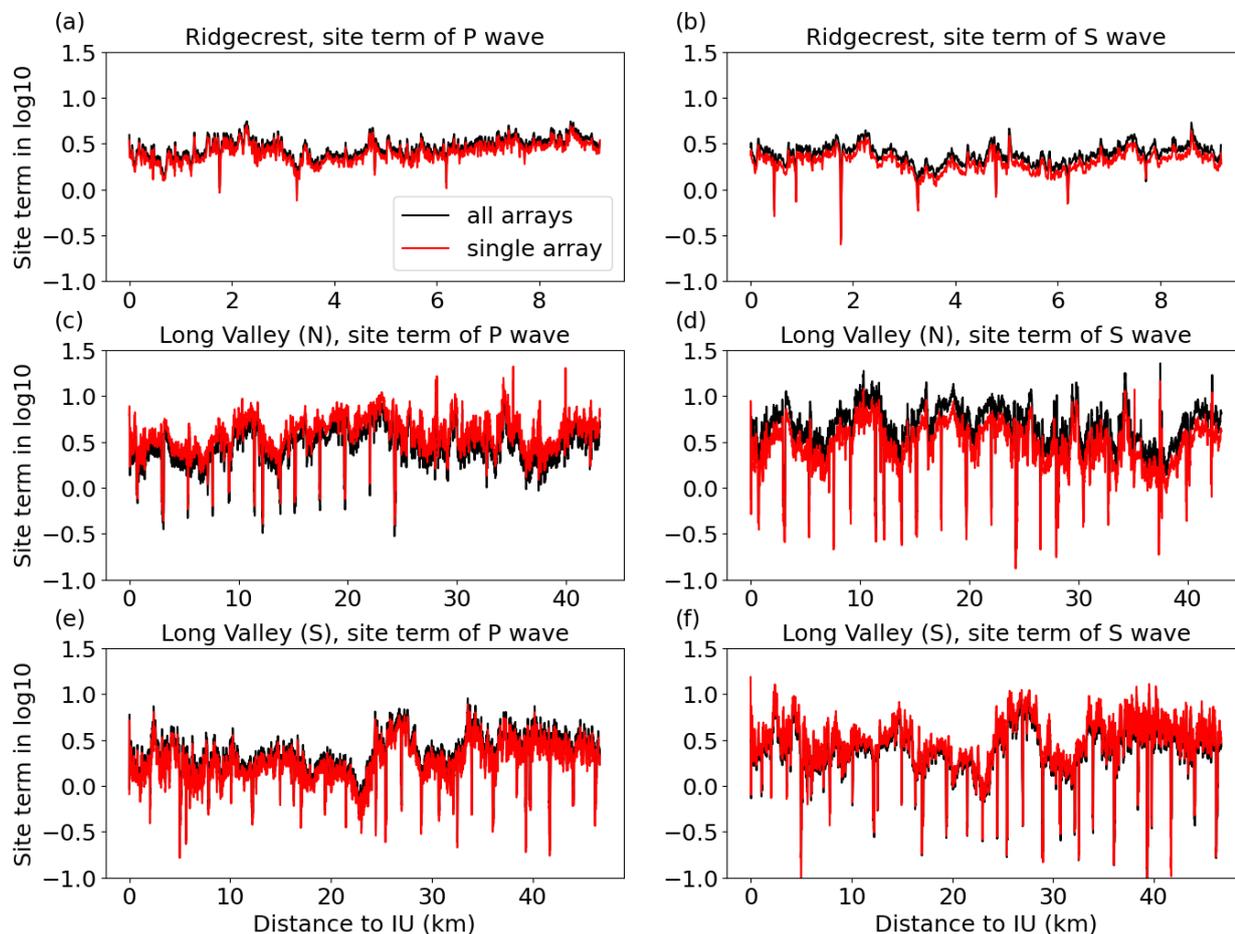


Figure S2. Site calibration terms of arrays: (a) Ridgecrest array, P wave; (b) Ridgecrest array, S wave; (c) Long-Valley Northern array, P wave; (d) Long-Valley Northern array, S wave; (e) Long-Valley Southern array, P wave; (f) Long-Valley Southern array, S wave. Black lines are results from fitting all arrays and red lines are results from fitting individual array data.

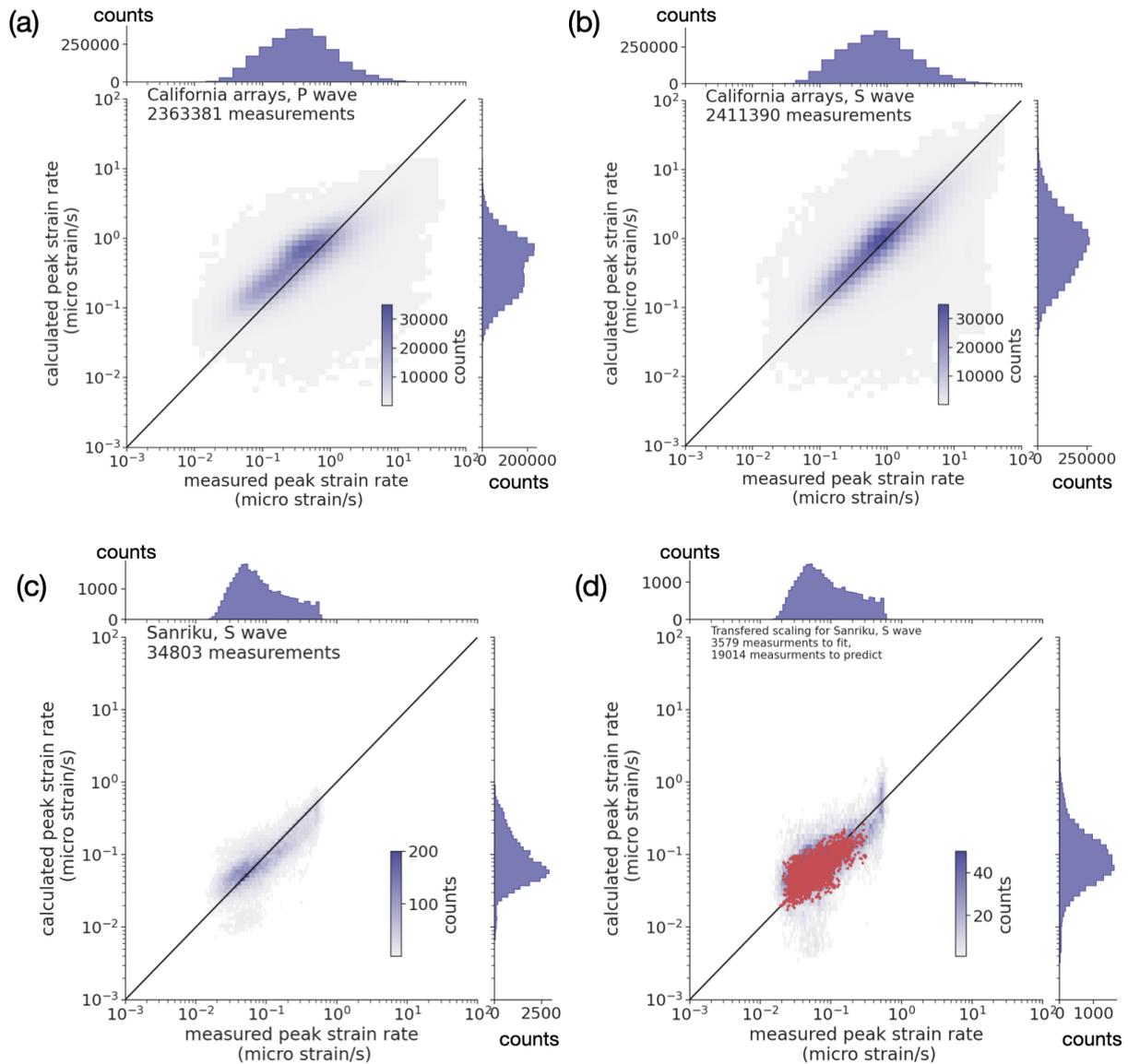


Figure S3. Validation on the peak DAS strain rate by comparing the measured strain rate and calculated peak strain rate based on the scaling relations. (a) Validation on the P-wave scaling relation applied to the California data. The scaling relation is from all three California DAS arrays. (b) Validation on the S-wave scaling relation applied to the California data. The scaling relation is from all three California DAS arrays. (c) Validation on the S-wave scaling relation applied to the Sanriku data. The scaling relation is from the Sanriku array. (d) Validation on the S-wave scaling relation applied to the Sanriku data. The scaling relation is transferred from California DAS arrays. Red dots highlight measurements that are used to calibrate the local site terms. Black solid lines indicate the accurate estimation.

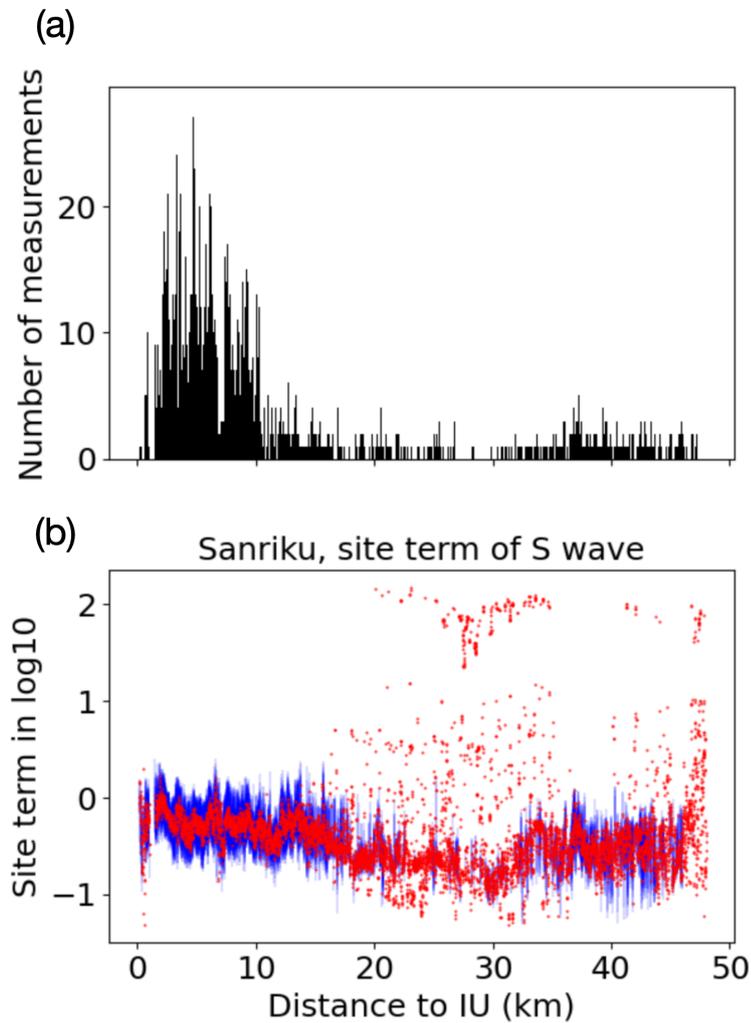


Figure S4. Site calibration terms of Sanriku array. (a) Number of peak DAS strain rate measurements at each channel. (b) Best fit site calibration term at each channel is shown by the red dots. The standard deviation is indicated by the blue error bars.

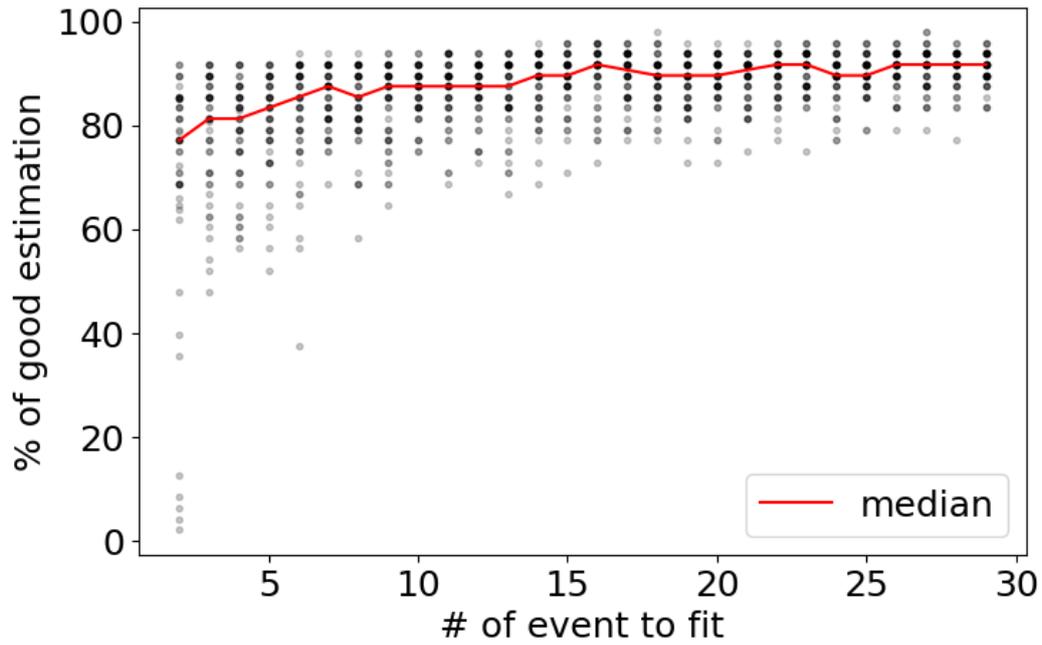


Figure S5. Number of events for transferring scaling relation. Each black dot corresponds to results of one random test. The red line is the average percentage of good magnitude estimation with uncertainty less than 0.5 units of magnitude.