

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

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13 **Key Points:**

- 14 • We present the first data-based scaling relation between DAS amplitude and earth-
15 quake magnitude.
- 16 • Earthquake magnitude can be reliably estimated from DAS amplitude with the
17 scaling relation.
- 18 • The DAS scaling relation can be transferred from one region to another with mi-
19 nor calibrations.

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Abstract

Distributed Acoustic Sensing (DAS) is a promising technique to improve the rapid detection and characterization of earthquakes. Previous DAS studies mainly 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 earthquake amplitudes recorded by DAS in different regions follow a similar scaling relation. The scaling relation can provide a rapid earthquake magnitude estimation and effectively avoid uncertainties caused by the conversion to ground motions. Our results show that the scaling relation appears transferable to new regions with calibrations. 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 seismic waves from earthquakes. The recorded seismic signals contain essential information about earthquakes. For example, DAS can record high-amplitude signals from earthquakes with large magnitudes. However, the exact setting of the optical cables (i.e., installation conditions and coupling with the surrounding medium) is often unknown, thus preventing quantitative estimations of earthquake magnitudes with DAS. In this study, we analyze earthquake data recorded by different DAS arrays and develop a data-driven method to obtain 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 new regions with slight calibrations. Our empirical relation can significantly expand the applications of DAS in earthquake research, such as seismic hazard assessment and earthquake early warning.

1 Introduction

Rapid earthquake source characterization is critical to monitor earthquakes, provide Earthquake Early Warning (EEW) alerts 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 an 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; Viens, Perton, et al., 2022) and to detect local earthquakes (Ajo-Franklin et al., 2019; Li et al., 2021; Li & Zhan, 2018; Atterholt et al., 2022), and seismic signals from various sources (Williams et al., 2019; X. Wang et al., 2020; Zhan et al., 2021; Viens, Bonilla, et al., 2022). The phase information of DAS has been well-validated to be accurate in the multiple aforementioned applications. However, DAS amplitudes, which commonly

70 represent the direct strain/strain-rate output from an interrogator unit, are rarely con-
71 sidered for earthquake source characterization and 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 instru-
74 mental response, and uncommon amplitude saturation behaviors (Lindsey et al., 2020).
75 DAS instruments record phase shifts of light traveling in the optical fiber, and the phase
76 information is then converted into the strain along the cable direction (Lindsey et al.,
77 2017; Fernández-Ruiz et al., 2020; Lindsey & Martin, 2021). However, the instru-
78 mental strain is not necessarily equal to the strain of the medium surrounding the cable due
79 to different installation methods of telecommunication cables (Ajo-Franklin et al., 2019).
80 This coupling issue commonly exists but varies with the unknown cable installation in
81 different regions (Ajo-Franklin et al., 2019; Lindsey et al., 2020; Trainor-Guitton et al.,
82 2019; Paitz et al., 2020). Moreover, the instrumental response of DAS is highly frequency-
83 dependent (Lindsey et al., 2020; Paitz et al., 2020) and often hard to quantify without
84 co-located seismometers. The frequency-dependent instrumental response can contam-
85 inate frequency components of the DAS data and may prevent robust spectral analysis.
86 The DAS amplitude saturation is another issue and is sometimes observed for earthquakes
87 close to DAS instruments (Viens, Bonilla, et al., 2022). DAS amplitude saturation is of-
88 ten presented by a flip from maximum to minimum due to the phase wrapping of the
89 sensing laser pulse in the cable (Ajo-Franklin et al., 2022), making this behavior hard
90 to identify and recover. All these instrumental limitations aggravate the accurate con-
91 version of DAS amplitude to ground motions (e.g., velocity and acceleration), thus fur-
92 ther challenging the incorporation of DAS data into many seismology applications (Lindsey
93 & Martin, 2021; Farghal et al., 2022). There have been many attempts to convert DAS-
94 recorded strain to ground motions (Daley et al., 2016; H. F. Wang et al., 2018; Yu et al.,
95 2019; Lindsey et al., 2020; Lior et al., 2021). For example, H. F. Wang et al. (2018) showed
96 a good match between DAS amplitude and strain derived from individual co-located nodal
97 sensors. However, in the same experiment, Muir and Zhan (2022) systematically recon-
98 structed the strain-rate wavefield with the entire nodal array and found that the DAS-
99 recorded amplitudes are, on average, twice that of conventional sensors. In general, ac-
100 curate conversion requires good knowledge of the local geology, seismic velocity struc-
101 ture, and instrumental information; and is still an active research direction in the DAS
102 community.

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

112 We analyze earthquakes recorded by DAS arrays in California, USA, and Sanriku,
113 Japan (Figure 1). Both regions are seismically active and provide us with an unprece-
114 dented opportunity to develop and validate a DAS scaling relation. We measure peak
115 DAS amplitudes of earthquakes based on earthquake catalogs. We apply iterative regres-
116 sion analysis to these datasets to obtain a robust scaling relation between the peak DAS
117 strain rate, earthquake magnitude, and hypocentral distance, calibrated by channel-specific
118 site terms. The obtained scaling relation can be used for rapid and reliable earthquake
119 magnitude estimation from the DAS amplitude measurements. Furthermore, we show
120 that the DAS amplitudes in different onshore regions follow the scaling relation with sim-
121 ilar coefficients. The scaling relation built on terrestrial DAS arrays in California can be
122 transferred to the submarine DAS data in Japan with calibration on the site terms.

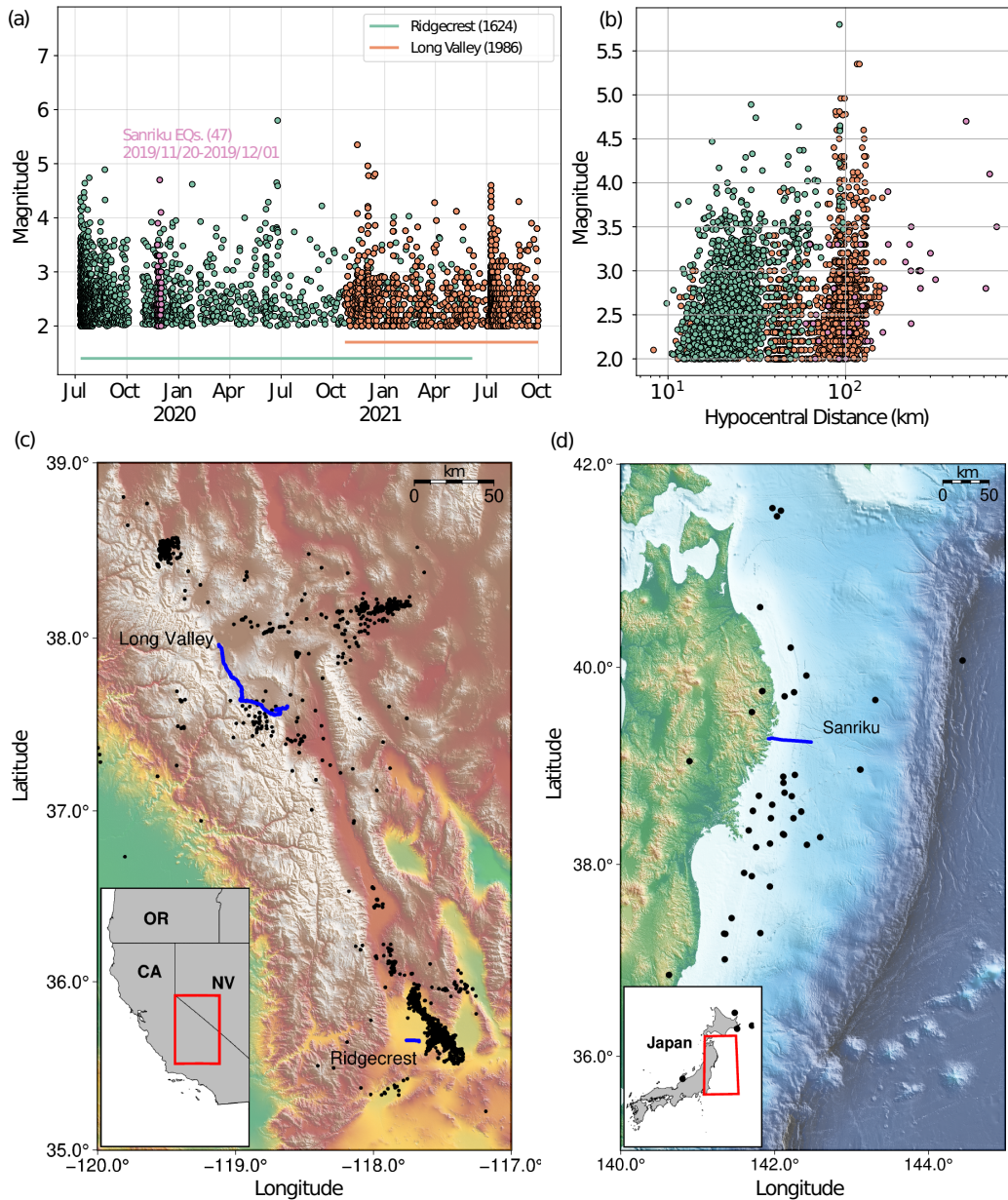


Figure 1. (a) Temporal distribution of earthquake magnitude from the three DAS arrays (colored circles) used in the analysis. (b) Hypocentral distance and magnitude range of earthquakes used in the analysis. The distance is the median over the array for each earthquake for better visualization. (c) Topographic map including the earthquake locations (black dots) and the Ridgecrest and Long-Valley DAS arrays (blue lines) in California, USA. (d) Map showing the locations of earthquakes (black dots) and the Sanriku DAS array (blue line) in Japan. Four earthquakes outside the main panel in (d) are shown in the inset map.

2 Results

2.1 Data

We analyze strain-rate DAS data, which removes the instrumental drifts in our strain data and is also shown to have a frequency-independent instrumental noise at low fre-

127 quency < 0.1 Hz (Lior et al., 2023), recorded in both terrestrial and submarine envi-
 128 ronments (Figure 1 (a)). The DAS recording parameters and configurations are shown
 129 in Table S1. We start with analyzing the two terrestrial DAS arrays in the Ridgecrest
 130 (RC) and Long-Valley (LV) regions (Figure 1 (b)) in California. The two arrays have
 131 recorded over two years of continuous data from July 10, 2019, to October 31, 2021. We
 132 first convert the DAS raw data, which is the phase shift of Rayleigh back-scattered laser
 133 signals in the optical fiber, to strain rate using Eq. S1 (Text S1 in the Supporting In-
 134 formation). We then apply PhaseNet-DAS (Zhu et al., 2023), which is a deep learning
 135 phase picker tailored for DAS data, to accurately pick P-wave and S-wave arrivals from
 136 earthquakes (Text S2 of the Supporting Information). We associate the picked earthquakes
 137 with the regional earthquake catalogs to determine their locations and magnitudes. We
 138 also investigate two weeks of submarine data (from November 11 to December 1, 2019)
 139 from a DAS array in Sanriku, Japan (Shinohara et al., 2022). The submarine DAS data
 140 suffer from various types of oceanic noise, and earthquake P-wave arrivals are rarely ob-
 141 served. Due to these limitations, PhaseNet-DAS is not as effective on submarine data
 142 as on terrestrial DAS arrays. Instead, we apply a template matching method to detect
 143 S-waves from earthquakes and associate them with the local Japanese Meteorological Agency
 144 (JMA) catalog for their location and magnitude (Text S3 of the Supporting Information).
 145 In this study, we assume that the difference in catalog magnitude between the two re-
 146 gions, California (local magnitude M_L for most small $M < 3$ earthquakes or moment
 147 magnitude M_w for larger $M > 3.3$ earthquakes if available) and Sanriku M_{JMA} (veloc-
 148 ity magnitude according to JMA (Katsumata, 1996; Funasaki, 2004)), is negligible and
 149 can be approximated as the moment magnitude to simplify the analysis (Katsumata, 2004;
 150 Clinton et al., 2006; Uhrhammer et al., 2011). This is a reasonable assumption for the
 151 earthquake magnitude range $2 \leq M \leq 6$ analyzed in the current study, but careful
 152 analysis on different local magnitude scales is required for large $M > 7$ earthquakes.

153 We successfully obtain 3,610 earthquakes with 2,363,585 P-wave and 2,411,592 S-
 154 wave peak measurements from the two California DAS arrays and 47 earthquakes with
 155 34,803 S-wave peak measurements from the Sanriku DAS array. The California earth-
 156 quakes have magnitudes ranging between M2.0 and M5.8 within hypocentral distances
 157 ranging between 5.2 and 182.6 km. The Sanriku earthquakes have magnitudes between
 158 M2.0 and M4.7 and hypocentral distances from 59.7 to 709.5 km. The measured peak
 159 DAS strain rates present strong correlations with the event magnitude (Figures 2 (c) and
 160 (f)) and hypocentral distance (Figures 2 (d) and (g)). Furthermore, all arrays follow sim-
 161 ilar trends, which imply the existence of a scaling relation (see Text S4 of the Support-
 162 ing Information for details of data processing and quality control).

163 2.2 Scaling relation

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

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

166 where E is the observed peak amplitude of DAS strain rate in microstrain/s ($10^{-6}/s$),
 167 D is the hypocentral distance in kilometers to each DAS channel, and M is the earth-
 168 quake magnitude. The subscript i corresponds to each DAS channel. We apply an in-
 169 tegrated channel-specific factor K_i to account for all local effects such as cable construc-
 170 tion, installation, instrumental coupling, and the variety of regional geology.

171 We use an iterative regression method to fit for the magnitude coefficient a , dis-
 172 tance coefficient b , and corresponding site terms K_i separately for P and S waves. We
 173 first apply the regression method to each individual DAS array and find that the val-
 174 ues are almost the same among the arrays (Figure S1). Therefore, we combine the three

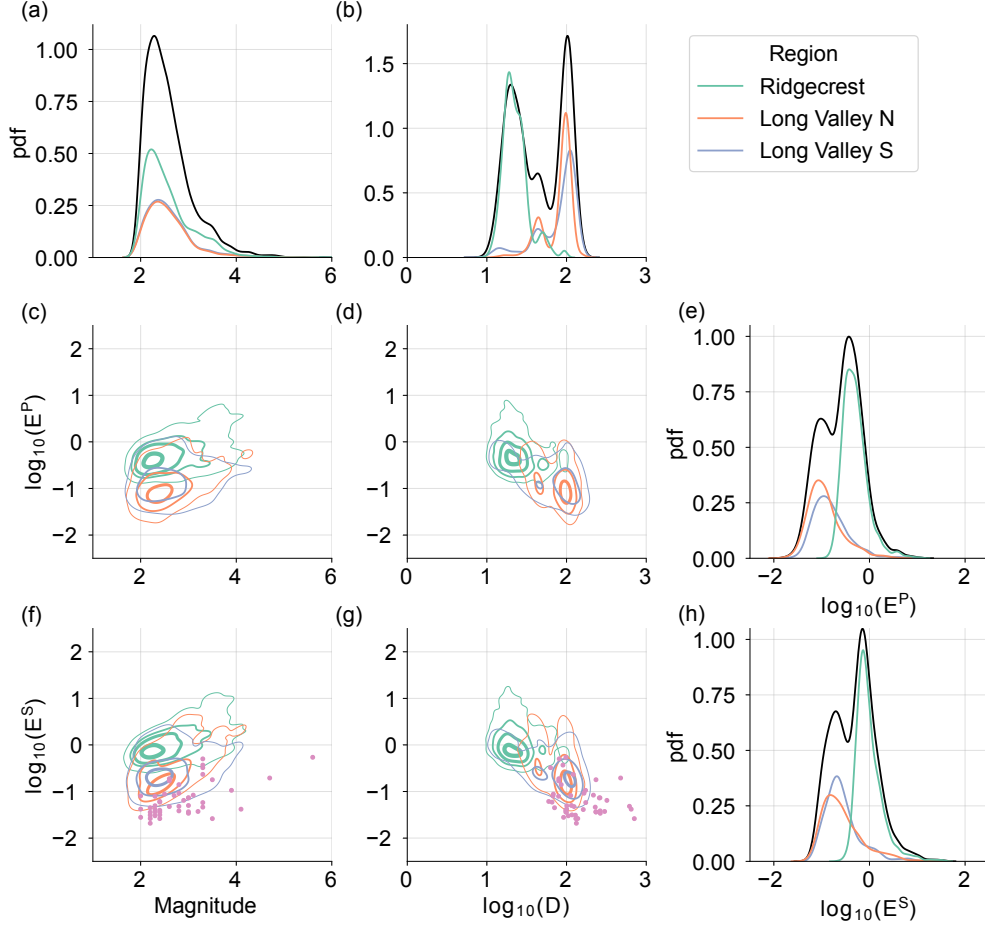


Figure 2. (a) Histograms in probability density function (pdf) of earthquake magnitude. (b) Histograms in pdf of hypocentral distance. (c) Magnitude versus peak P-wave DAS strain rate (E^P). (d) Hypocentral distance versus peak P-wave DAS strain rate. (e) Histograms in pdf of peak P-wave DAS strain rate. (f) Magnitude versus peak S-wave DAS strain rate (E^S). (g) Hypocentral distance versus peak S-wave DAS strain rate. (h) Histograms in pdf of peak S-wave DAS strain rate. For all the histograms, the black lines indicate the entire dataset from all DAS arrays. Colored lines are for the individual arrays. For the 2-D correlation figures, peak DAS strain rate measurements are 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 in (f) and (g).

175 California terrestrial data sets into one data set for an integrated regression. Because
 176 of the unbalanced amount of measurements and different processing steps of terrestrial
 177 and submarine DAS data, we use the California DAS dataset with both P- and S-wave
 178 measurements to fit for the coefficients of Eq.(1) and the Sanriku submarine DAS data
 179 as a validation set. This splitting scheme aims at testing the generality of the scaling re-
 180 lation. The best-fit scaling relation we obtain for P waves is:

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

181

and for S waves is:

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

182

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

183

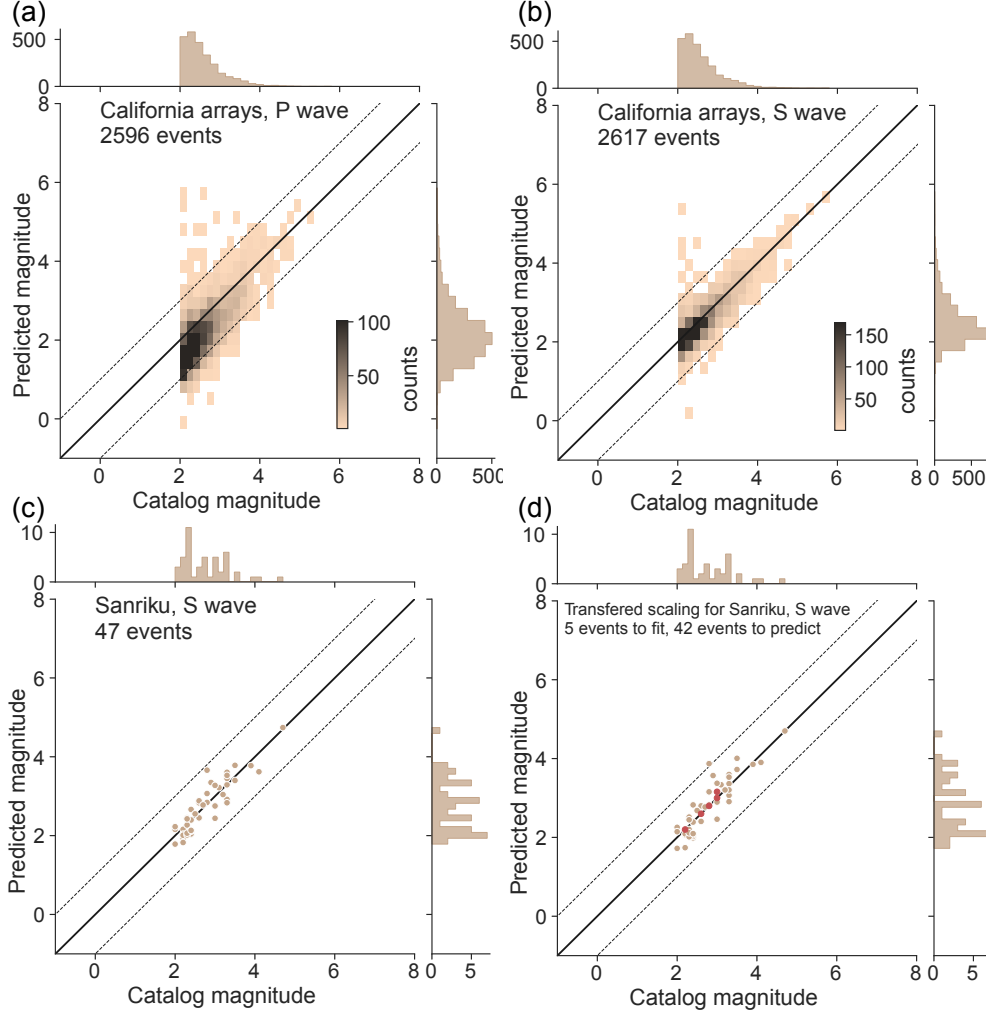


Figure 3. (a) P-wave scaling relation applied to the California data using all three DAS arrays. (b) S-wave scaling relation applied to California data using all three DAS arrays. (c) S-wave scaling relation applied to Sanriku data using only the Sanriku DAS array. (d) S-wave scaling relation applied to Sanriku data using scaling relation transferred from California DAS arrays. (a) and (b) show the 2D histograms, while (c) and (d) show the individual event. Red dots indicate events used for calibrating local site terms. Solid black lines show accurate estimation where catalog magnitude equals predicted magnitude, while dashed lines show plus/minus 1 unit of magnitude errors.

184

2.3 Magnitude estimation from DAS

185

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 ro-

186

187 bustly explain the features in the data (Text S7 and Figure S3 of the Supporting Infor-
 188 mation). Then, we reorganize the scaling relation Eq.(1) to estimate earthquake mag-
 189 nitudes from the DAS peak strain rate:

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

190 Given the peak amplitude E_i and hypocentral distance D_i , we calculate the mag-
 191 nitude M_i for each DAS channel and then use the median magnitude of all channels as
 192 the final magnitude estimation M . Our results show that the magnitude can be reliably
 193 estimated with an error of less than 1 unit of magnitude by using either P or S waves
 194 peak amplitude in a given time window (a 2-second time window is used here, but other
 195 time windows have also been tested, see Text S4 and Table S2 for details) for most earth-
 196 quakes in both the California and Sanriku regions, especially for the larger earthquakes
 197 (Figure 3 (a)-(c)). Moreover, we show that the scaling relation can be transferred from
 198 California to Sanriku and works equally well as that obtained from the Sanriku-only mea-
 199 surements (Figure 3 (c) and (d)). The transferred scaling relation inherits the same mag-
 200 nitude a and hypocentral distance b coefficients from the California dataset and only re-
 201 quires a small number of local earthquakes to recalculate the site calibration terms K_i .
 202 We apply a systematic random test to show that for the Sanriku case, only a limited num-
 203 ber of local events (i.e., 3-6 earthquakes) are sufficient to obtain robust values of the site
 204 calibration terms (Text S8 of the Supporting Information). The transferred scaling re-
 205 lation can provide a robust estimation of the magnitude of earthquakes (Figure 3(d)).

206 3 Discussion

207 3.1 Transferable scaling relation of DAS amplitude

208 Unlike conventional and well-calibrated seismic sensors, DAS instruments are com-
 209 monly deployed on preexisting telecommunication optical fibers with various properties
 210 and construction designs (Ajo-Franklin et al., 2019). This generally leads to difficulties
 211 in determining the instrument responses of DAS arrays. Some previous studies have shown
 212 that DAS instrument response can be quantitatively determined by comparing DAS mea-
 213 surements with a co-located seismometer (Lindsey et al., 2020; Paitz et al., 2020). How-
 214 ever, co-located sensors are not always available, especially in marine environments. There
 215 are multiple ways to convert DAS measurements to ground motions: for instance, direct
 216 calibration with co-located seismometers (Lindsey et al., 2017), correction based on ap-
 217 parent local phase velocity (Daley et al., 2016; H. F. Wang et al., 2018; Yu et al., 2019;
 218 Shinohara et al., 2022), spatial integration from a co-located seismometer (H. F. Wang
 219 et al., 2018), and rescaling in the $f-k$ or curvelet domains (Lindsey et al., 2020; Yang
 220 et al., 2022). Recently, a local slant-stack transform method was developed to convert
 221 strain to ground motion in real-time for EEW (Lior et al., 2021, 2023). Although shown
 222 to be effective, most of the conversion methods require elaborate data preprocessing and
 223 analyst-intense quality control. Improving those methods and developing new ones are
 224 still active directions of current DAS research in the community.

225 This study evaluates how DAS amplitude is related to earthquake magnitude in
 226 a data-driven methodology. With the abundant peak amplitude measurements of earth-
 227 quakes in the Ridgecrest and Long-Valley regions, we apply regression analysis to ob-
 228 tain a robust scaling relation for both P- and S-waves recorded by DAS instruments. Most
 229 importantly, we find that different regions have almost the same values of the scaling co-
 230 efficients a and b (Figure S1). With region-specific site calibration K_i (Figures S2 and
 231 S4 in the Supporting Information), we show that it is feasible to transfer/extrapolate the
 232 scaling relation from one well-studied area to DAS arrays in other regions for earthquakes
 233 within similar distance/magnitude ranges. The DAS peak amplitude scaling relation can
 234 be applied to earthquake source studies in different areas.

We further compare the DAS measurements with results from previous studies using conventional strainmeters (Barbour et al., 2021). The distance coefficients of both conventional strainmeters ($b = -1.45$) and DAS are close, meaning that the dynamic strain follows the same geometrical spreading of wave propagation for both conventional strainmeter and DAS instruments. However, the magnitude coefficients are different ($a = 0.92$ from strainmeters) mainly because the DAS scaling relation is obtained from strain-rate data, while the strainmeter scaling relation is based on strain data. The different physical quantities scale differently with earthquake magnitude. Strain rate is theoretically proportional to acceleration (Benioff, 1935). Therefore, we analyze the peak ground acceleration (PGA) of the Next Generation Attenuation model (NGA-West2) project (Bozorgnia et al., 2014). For consistent comparisons, we fit the PGA in the NGA-West2 dataset with the same model as Eq.1, assigning the site calibration term to each station. We find that the distance coefficients from DAS ($b = -1.27$ for the P wave and 1.59 for the S wave) are close to those from PGA ($b = -1.63$, Figure S1). The difference in the magnitude coefficients ($a = 0.44$ for the P wave and 0.69 for the S wave from DAS versus $a = 0.39$ from PGA) is probably due to the different frequency bands of DAS and conventional accelerometers. Nowadays, Ground Motion Prediction Equations (GMPEs) with many parameters have been developed from various datasets to predict earthquake ground motions for engineering, and seismological applications (Zhao et al., 2006; Kanno et al., 2006; Boore & Atkinson, 2008; Bozorgnia et al., 2014; Boore et al., 2014; Campbell & Bozorgnia, 2014). Modern GMPEs have detailed definitions of distance dependence (geometrical and inelastic attenuation) and local site responses (local geology, seismic structure, instrument deployment, etc.) to explain the ground motion data in different regions. Because of the relatively early stages of the DAS technique and limited earthquake data from different locations, we only implemented the simplest form of scaling relation (i.e., Eq.1) in this study for a first-order validation of the DAS scaling relation. We leave the development of more complex DAS strain-rate prediction equations, for example, with physically defined and/or frequency-dependent site calibration terms, to future studies.

3.2 Potential applications of the DAS scaling relation

Our peak DAS amplitude scaling relation is fundamental and significant for various seismological studies such as earthquake seismology and EEW. Regarding earthquake source analyses using DAS, the current studies mainly focus on earthquake detection and location using the time information (Lindsey et al., 2017; Lellouch et al., 2020; Li et al., 2021; Yang et al., 2022; Atterholt et al., 2022; Viens, Bonilla, et al., 2022). Adding the amplitude information and constraints on the earthquake magnitude can significantly help us resolve more source parameters and physical details about the earthquake rupture (Lior et al., 2023).

Another substantial application is for EEW, which has shown to be an effective method to mitigate seismic risk (Allen & Melgar, 2019). EEW aims to rapidly estimate ground motion from real-time data after an earthquake occurs and sends out alerts to specific users and the public. Current EEW algorithms use conventional seismic data for ground motion predictions. DAS leverages pre-existing telecommunication fiber-optic cables and can complement the current EEW systems. Converting most telecommunication cables located in highly seismic active regions into dense arrays of sensors could provide an economical approach to extending and improving the current EEW system, especially in offshore seismogenic zones.

A recent study combined DAS and GMPEs for EEW purposes (Lior et al., 2023). Their method requires conversion from DAS strain rate to ground acceleration and estimation of earthquake stress drop for earthquake magnitude estimation. Our scaling relation provides an alternative and new approach to estimating earthquake magnitude from DAS measurements. Compared with conversion-based methods, there are advantages to using a scaling relation from direct DAS measurements. Firstly, the scaling re-

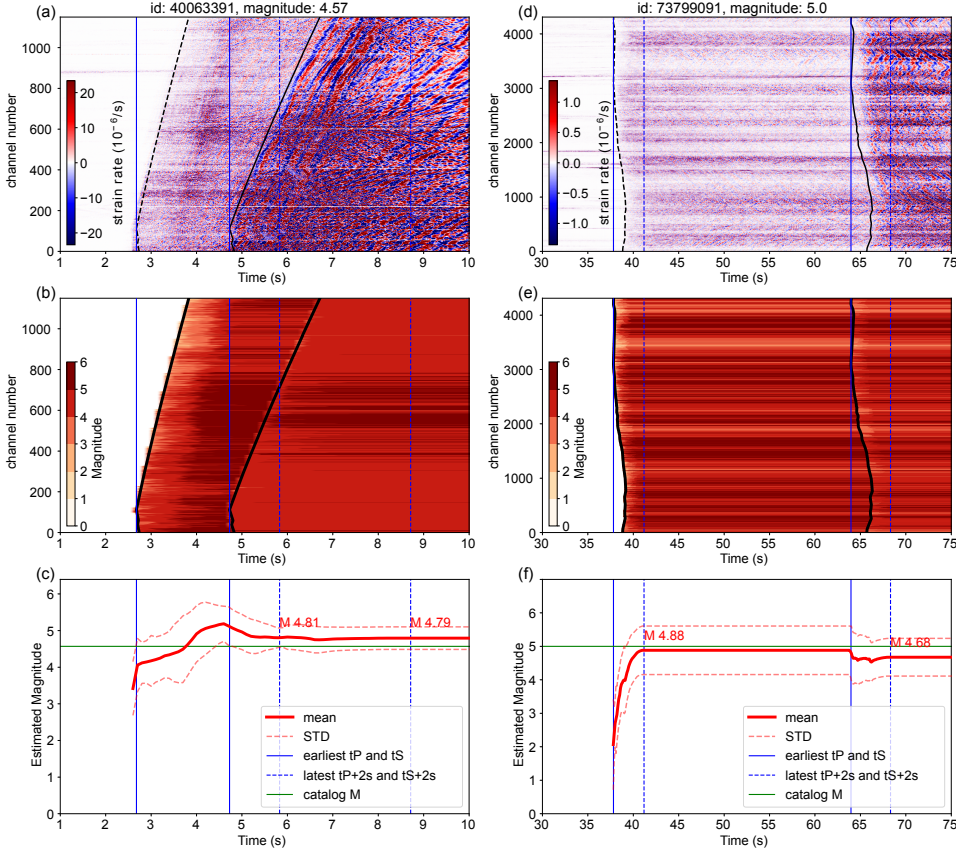


Figure 4. (a) Streaming DAS data from an M4.57 earthquake that occurred in the Ridgecrest region. The initial time of the earthquake is set as 0 seconds. (b) The corresponding magnitude estimation from the peak DAS amplitude at each channel. The black lines indicate the arrival of the P-wave and the 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.

287 lation accounts for the different coupling and regional effects among DAS channels with
 288 the site calibration terms, and no manual identification of well-coupled sections of the
 289 fiber is required. Secondly, the scaling relation can avoid a prior estimation of stress drop:
 290 although Lior et al. (2023) have shown that the stress drop does not significantly affect
 291 the final ground motion prediction for EEW purposes, the uncertainty in stress drop es-
 292 timation can bias magnitude estimation.

293 The scaling relation is built upon direct DAS measurements, and they do not re-
 294 quire much pre-processing or parameter tuning, simplifying the deployment on edge-computing
 295 (Shi et al., 2016) at the instrumental sites. Furthermore, the scaling relation appears trans-
 296 ferable to other regions, as demonstrated in the example of Sanriku data. Given a few
 297 earthquake measurements to calibrate the site terms, we can transfer the scaling relation
 298 from one well-studied region to another to apply rapid earthquake magnitude es-
 299 timation.

300 However, this data-driven scaling analysis method also has some limitations that
301 require further studies. The scaling relation of peak DAS amplitude relies on correct event
302 association and peak amplitude measurement. Measurement of peak amplitude in the
303 improper waveform window can lead to errors in the magnitude estimation. For instance,
304 there are a few small events with largely overestimated magnitudes in our results (Fig-
305 ures 3(a)-(b)). We investigate the waveforms of those events and find that the overes-
306 timation is due to an incorrect event association. For instance, an M2 event in the Long-
307 Valley region is estimated as an M5.5 earthquake because waveforms of this small event
308 overlap with another large M5+ earthquake. We also find a few instances where mul-
309 tiple events occur in different places but are recorded at the same time, leading to over-
310 lapped arrivals in the same time window. In such cases, the peak amplitudes of weaker
311 arrivals will be overestimated. Combining DAS with other independent seismic sensors
312 can help to exclude the incorrectly associated event, thus improving the magnitude es-
313 timation. Amplitude saturation of DAS data (Ajo-Franklin et al., 2022; Viens, Bonilla,
314 et al., 2022) can also affect the results and lead to under-estimated magnitude. For ex-
315 ample, an M5.6 earthquake in the Sanriku data set has been found to be saturated (Viens,
316 Bonilla, et al., 2022), and we had to exclude it in this study. In fact, our DAS amplitude
317 scaling relation can help to identify whether the DAS waveform from an earthquake gets
318 saturated if its DAS-estimated magnitude is significantly smaller than the magnitude from
319 other methods. Finally, our current datasets only contain moderate magnitude earth-
320 quakes ($M < 6$) in a few regions due to the short period of DAS deployment. Extend-
321 ing the similar analysis to more areas can help to further verify and improve the scal-
322 ing relation. Future DAS campaigns focusing on EEW and recording large earthquakes
323 should explore if the scaling relation still holds or behaves differently due to potential
324 complex non-linear site response (Bonilla et al., 2011; Astorga et al., 2018; Viens, Bonilla,
325 et al., 2022).

326 Finally, we conduct an idealized experiment to illustrate the potential application
327 of the DAS scaling relation for rapid magnitude estimation. We assume that earthquakes
328 can be immediately detected and located. Therefore, we can apply the scaling relation
329 to the streaming earthquake signals at available DAS channels (Figure 4 (a) and (d)) for
330 real-time estimation of earthquake magnitude (Figure 4 (b) and (e)). We keep the me-
331 dian value of magnitude estimated at each channel as the final estimation and keep up-
332 dating it with time (Figure 4 (c) and (f)). We experiment with the recent M4.57 and
333 M5.0 earthquakes recorded by the Ridgecrest and Long-Valley north arrays. The M4.57
334 earthquake occurred on July 15, 2022, in the Ridgecrest region and is about 15 km from
335 the Ridgecrest array. The M5.0 earthquake occurred on October 25, 2022, near Alum
336 Rock and San Jose, California, and is about 244 km from the Long Valley array. Both
337 events are not included in the data sets that are used for the regression and, therefore,
338 are good candidates to test the scaling relation for generalization. We can reliably es-
339 timate the magnitude of both events with a magnitude uncertainty of less than 0.5 shortly
340 after the earliest P-wave arrival. When some channels begin to detect the S wave, we
341 also include the S wave information by averaging the magnitude from both P-wave and
342 S-wave amplitudes to further update the magnitude estimation. Text S9 in the Support-
343 ing Information provides more details about the method. We also apply the same pro-
344 cess to an M5.8 earthquake, which is the largest event in our data set recorded by the
345 Ridgecrest array (Figure S6). Since this event has been used for regression, the error of
346 magnitude estimation is less than 0.1. Lior et al. (2023) have also shown that the DAS-
347 estimated earthquake magnitude can be combined with GMPEs (Atkinson & Boore, 2006;
348 Boore & Atkinson, 2008; Bozorgnia et al., 2014; Douglas & Edwards, 2016) to further
349 predict the ground shaking and seismic intensity, similar to conventional EEW systems
350 based on earthquake point source modeling (Allen & Melgar, 2019). A similar workflow
351 also applies to the magnitude estimation from our scaling relation, and we leave that as
352 future work.

4 Conclusion

This work presents the first scaling relation between DAS peak amplitude, earthquake magnitude, and hypocentral distance from terrestrial and submarine DAS arrays. We show that the scaling relation can be used to rapidly estimate the magnitude of earthquakes. Furthermore, we find that the scaling relation appears transferable from terrestrial DAS arrays in California to a submarine DAS array in Sanriku, Japan, with minor calibrations. The DAS amplitude scaling relation has great potential in different seismological studies, such as EEW and earthquake source characterization.

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Data Availability Statement

The measured peak strain rate amplitude from multiple DAS arrays is available from the Caltech DATA repository <https://data.caltech.edu/records/sk6em-th949> with DOI:10.22002/sk6em-th949. The Python scripts to process the data and reproduce results are available at <https://github.com/yinjiuxun/das-strain-scaling>.

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