Sensing optical fibers for earthquake source characterization using raw DAS records

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1	SENSING OPTICAL FIBERS FOR EARTHQUAKE SOURCE
2	CHARACTERIZATION USING RAW DAS RECORDS
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12	Key Points:
13	• A theoretical description of strain far field radiation from a seismic rupture is introduced
14	• Source parameters were evaluated from strain data for earthquakes in magnitude range
15	0.3 - 4.3
16	• DAS allows for investigation of source parameters and site effects with fine spatial
17	resolution.
18	
19	Abstract
20	Distributed Acoustic Sensing (DAS) is becoming a powerful tool for earthquake monitoring,
21	providing continuous strain-rate records of seismic events along the fiber. However, the use of
22	standard seismological techniques for earthquake source characterization requires the conversion
23	of data in ground motion quantities. In this study we provide a new formulation for far-field

24 strain radiation emitted by a seismic rupture, which allows to directly analyze DAS data in their

25 native physical quantity. This formulation naturally accounts for the complex directional

sensitivity of the fiber to body waves and to the shallow layering beneath the cable. In this

27 domain, we show that the spectral amplitude of the strain integral is related to the Fourier

transform of the source time function, and its modelling allows to determine the source

29 parameters.

We demonstrate the validity of the technique on two case-studies, where source parameters are consistent with estimates from standard seismic instruments. When analyzing events from a 1month DAS survey in Chile, moment - corner frequency distribution clearly shows a self-similar behavior with average stress drop of $\Delta \sigma = (0.7 \pm 0.4)$ MPa. The analysis of DAS data acquired in the Southern Apennines shows a dominance of the local attenuation that masks the effective corner frequency of the events. After estimating the local attenuation coefficient, we were able to retrieve the corner frequencies for the largest magnitude events in the catalog.

Overall, this approach shows the capability of DAS technology to depict the characteristic scales
of seismic sources and the released moment.

39 Plain Language Summary

A new formulation for far-field strain radiation from seismic ruptures is derived, leading to a 40 direct interpretation of DAS (Distributed Acoustic Sensing) data to retrieve source properties 41 42 (seismic moment and source size), via a spectral modelling. This approach is validated on real 43 data recorded in two different tectonic environments, the Chilean margin and the southern Apennines, in Italy. Despite the unique directional sensitivity and peculiar signal characteristics, 44 45 we demonstrated the high potential of DAS systems in characterizing the seismic ruptures over different space scales with accuracy increased by redundancy of information from the very-high 46 spatial resolution in the recording of seismic waves. 47

48 **1 Introduction**

49 Distributed Acoustic Sensing (DAS) is an emerging technology in seismology that allows 50 to get continuous recordings of seismic waves along an optical fiber. DAS systems exploit phase 51 variations in the backscattered light to record the axial strain along the fiber (Hartog, 2017). 52 Thus, a DAS system appears as a single-component seismic array, with main advantage to have a 53 very dense spatial coverage of sensors and a single endpoint for the collection of data, the 54 interrogator, which sends and receives the laser pulses to measure the strain rate. Also, the

so availability of existing telecom dark fibers allows to investigate environments usually difficult to

56 monitor, such as oceanic seafloors, volcanic flanks, and geothermal areas, over distances

between a few and hundreds of kilometers (e.g., Sladen et al., 2019; Currenti et al., 2021; Tsuji et

al., 2021). In the recent years, DAS technology has been successfully applied to seismology for

⁵⁹ earthquake location (Nishimura et al., 2021; Piana Agostinetti et al., 2022; Sladen et al., 2019),

60 focal mechanism determination (Li et al., 2023), seismic velocity estimation (Lellouch et al.,

61 2019) and site effect characterization (Ajo-Franklin et al., 2019; Spica et al., 2020).

While techniques based on time picking and polarity recognition can be directly applied to strain-rate data, determination of source parameters from DAS measurements requires further development, either processing data directly in the strain-rate domain or converting them into more classical kinematic quantities.

To provide a macroscopic characterization of the source of a seismic event, one needs to 66 determine the seismic moment, the radiated energy, the event size and the released stress drop, 67 referred to as source parameters. Classical techniques for determination of source parameters are 68 69 based on the modelling of body waves amplitude displacement spectra, that exhibit a flat level 70 followed by a power-law fall-off (Brune, 1970; Madariaga, 1976; Kaneko & Shearer, 2014). Uncertainty in source parameters depends on the knowledge of the Green's function, with a 71 strong correlation between the anelastic attenuation and the source spectral fall-off 72 (Abercrombie, 1995). This correlation can be correctly handled in the computation of 73 74 uncertainties, using Bayesian approaches (e.g., Supino et al., 2019) or reduced, using small earthquakes as Empirical Green's functions (EGF) (Prieto et al., 2004; Abercrombie & Rice, 75 2005) or data driven attenuation functions (Oth et al., 2007). 76

Different approaches have been proposed to apply classical strategies for source parameter estimation to DAS data, converting strain-rate data in ground motion quantities (acceleration, velocity, or displacement). When specific seismic phases dominate the DAS section, acceleration can be directly obtained from strain rate correcting for the apparent phase speed (Daley et al., 2016). The conversion to acceleration of dominant phases can be done using a slant-stack transform, that enables source parameter estimation, even in near real-time for early warning applications (Lior et al., 2021; 2023a). However, only locally dominant phases can be

correctly converted with this technique, while energy of smaller amplitude phases is smeared 84 along the seismogram. This issue may become critical for some applications, since DAS data are 85 more sensitive to slow, scattered waves (Trabattoni et al., 2022) and show reduced amplitude for 86 phases travelling at high apparent speeds (Van Den Ende & Ampuero, 2021). Phase independent 87 techniques were also developed for converting strain into ground motion quantities based on F-K 88 rescaling (Wang et al., 2018) and space integration using deformation (Trabattoni et al., 2023). 89 These techniques are sensitive to the rectilinearity of the cable and introduce low-frequency 90 artifacts that must be filtered out. This may affect the low frequency content of the seismic 91 spectra and bias the moment magnitude estimation. Nevertheless, they have been shown to 92 provide reliable estimations of Wood-Anderson local magnitude, which requires an accurate 93 displacement measurement above 1 Hz (Trabattoni et al., 2023). 94

Relative measurements of source parameters can be performed directly in the strain 95 domain using the EGF approach, when the seismic moment of a reference event is available 96 (Chen, 2023; Lior, 2023b). However, this technique is limited to co-located events that differ in 97 98 magnitude of at least one point (Abercrombie et al., 2017). Alternative approaches exploit correlations between measurements in the strain domain and source parameters. For instance, 99 elastodynamic energy rate from strain was shown to scale with the kinetic energy rate from 100 seismic sensors enabling for magnitude estimation from energy (Trabattoni et al., 2022), while 101 102 peak strain-rate was demonstrated to correlate with local magnitude (Yin et al., 2023).

In this study we develop a new strategy for computing source parameters in the strain-103 104 domain, deriving an analytical formulation that links the source time function with the strain. This formulation allows to evaluate the source parameters inverting strain integral amplitude 105 spectra. The manuscript is organized as follows. In Section 2 we present the new formulation, 106 together with the inversion strategy and the estimation of the average radiation pattern 107 coefficients, that account for the different sensitivity of the along-fiber strain with respect to the 108 displacement. In Section 3, the new technique is validated through an application to real data for 109 two case studies: a 150 km-long fiber offshore Chile and a 1.1 km-long fiber buried in a dry lake 110 inside the Irpinia Near Fault Observatory. 111

112 **2 Source modelling in strain domain**

113 **2.1 Far Field source radiation**

Evaluating source parameters from native DAS recordings requires a new formulation that can directly digest dynamic quantities (i.e., strain or strain rate). This formulation can be derived from the far-field radiation emitted by a seismic source and recorded at a receiver at a hypocentral distance r on the Earth's surface.

In a homogeneous medium, the far-field displacement associated with a seismic event and characterized by a source time function I(t) (hereinafter referred to as STF) can be described in spherical coordinates, separating P and S contributions (Haskell, 1964):

$$u_{r} = \frac{\beta^{2}}{4\pi\alpha^{3}r} \sin 2\theta \cos\phi I\left(t - \frac{r}{\alpha}\right)$$

$$u_{\theta} = \frac{1}{4\pi\beta r} \cos 2\theta \cos\phi I\left(t - \frac{r}{\beta}\right)$$

$$u_{\phi} = \frac{1}{4\pi\beta r} \cos\theta \sin\phi I\left(t - \frac{r}{\beta}\right)$$
(1)

121 Here α and β are the P- and S-wave velocities respectively, while the STF depends on the retarded time due to wave propagation from the source to the receiver. We assumed a circular 122 crack with fixed slip direction as source model (Madariaga, 1976). The spherical coordinates 123 (θ the colatitude; ϕ the longitude) are defined on a Cartesian reference frame W centered on the 124 fault, where x and z are the along-slip and fault-normal directions, respectively. Here, x and z 125 also represent the directions of the two couples of forces responsible for the earthquake rupture. 126 The three angular functions in equation (1) are indicated respectively as $P(\theta, \phi)_P$, $P(\theta, \phi)_{SV}$, 127 $P(\theta, \phi)_{SH}$, and correspond to the far-field components of the displacement radiation patterns. 128

We derived equation (1) to evaluate the strain at the receiver (see Supplementary Text S1). Ruling out the contributions that decay faster than 1/r (far-field approximation), we obtain: manuscript submitted to Journal of Geophysical Research

$$\varepsilon_{rr}^{FF} = \frac{\beta^2}{4\pi\alpha^3 r} P(\theta, \phi)_P \frac{\partial I\left(t - \frac{r}{\alpha}\right)}{\partial r}$$

$$\varepsilon_{r\theta}^{FF} = \frac{1}{8\pi\beta r} P(\theta, \phi)_{SV} \frac{\partial I\left(t - \frac{r}{\beta}\right)}{\partial r}$$

$$\varepsilon_{r\phi}^{FF} = -\frac{1}{8\pi\beta r} P(\theta, \phi)_{SH} \frac{\partial I\left(t - \frac{r}{\beta}\right)}{\partial r}$$
(2)

131 where ε is the far-field strain tensor in spherical coordinates. This representation 132 preserves the separation between P and S contributions.

133 Radial derivatives of the STF can be written as a function of their time derivatives:

$$\frac{\partial I\left(t-\frac{r}{c}\right)}{\partial r} = -\frac{1}{c} \frac{\partial I\left(t-\frac{r}{c}\right)}{\partial t}$$
(3)

134 where *c* is the wave velocity at the receiver. Replacing (3) in (2) and computing the time 135 integral of the strain $\xi = \int \varepsilon dt$, we get

$$\xi_{rr}^{FF} = -\frac{\beta^2}{4\pi\alpha^4 r} P(\theta, \phi)_P I$$

$$\xi_{r\theta}^{FF} = -\frac{1}{8\pi\beta^2 r} P(\theta, \phi)_{SV} I$$

$$\xi_{r\phi}^{FF} = \frac{1}{8\pi\beta^2 r} P(\theta, \phi)_{SH} I$$
(4)

In the equation above we omitted the dependence of the STF on the retarded time. For a
1D layered model equation (4) becomes (Aki & Richards, 2002):

$$\xi_{rr}^{FF} = -\frac{\beta_{S}^{2}}{4\pi\alpha_{S}^{3}\alpha_{R}r} P(\theta,\phi)_{P} I$$

$$\xi_{r\theta}^{FF} = -\frac{1}{8\pi\beta_{S}\beta_{R}r} P(\theta,\phi)_{SV} I$$

$$\xi_{r\phi}^{FF} = \frac{1}{8\pi\beta_{S}\beta_{R}r} P(\theta,\phi)_{SH} I$$
(5)

138 with subscripts S and R indicating that the value is computed at the source and receiver 139 locations. The strain integral is proportional to the STF as for the far-field displacement, enabling 140 for the inversion of ξ amplitude spectra to estimate the source parameters. It is worth to note that equation (4) shows a larger sensitivity of DAS to the shallow velocity structure beneath thecable, as compared to the displacement.

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144 **2.2 Spectral modelling**

To estimate the source parameters, we transformed eq. (5) in the frequency domain, to get the spectral amplitude $\tilde{X}(\omega) = |FFT(\xi(t))|$. Separating the source term $\tilde{S}(\omega)$ from the propagation and site effect terms, respectively $\tilde{G}(\omega)$ and $\tilde{Z}(\omega)$, leads to:

$$\tilde{X}(\omega) = \tilde{G}(\omega) \cdot \tilde{S}(\omega) \cdot \tilde{Z}(\omega)$$
(6)

148 The Green's function $\tilde{G}(\omega)$ for a layered medium and a frequency independent quality 149 factor Q^c can be written as

$$\tilde{G}(\omega) = \tilde{K}^c A^c e^{-\left(\frac{\omega T^c(r)}{2Q^c}\right)}$$
(7)

150 $A^{c}(r) = 1/r$ is the geometrical spreading contribution and $T^{c}(r)$ is the source-receiver 151 travel time for the selected phase *c*. The factor \tilde{K}^{c} writes:

$$\widetilde{K}^{c} = \frac{\overline{B}_{c}^{FF}F}{8\pi\rho_{S}^{1/2}\rho_{R}^{1/2}c_{S}^{5/2}c_{R}^{3/2}}$$
(8)

In the above formula, *F* is the free surface contribution, ρ the density, also evaluated at the source and receiver locations, and \overline{B}_{c}^{FF} the mean radiation pattern that averages the directivity effects of the different cable segments along all possible fault orientations. We assume *F* = 2. The radiation pattern is discussed in detail in the next section.

156 For $\tilde{S}(\omega)$ we adopted a generalized Brune model:

$$\tilde{S}(\omega) = \frac{M_0}{1 + \left(\frac{\omega}{\omega_c}\right)^{\gamma}}$$
(9)

This function depends on the seismic moment M_0 , proportional to the plateau level of the spectrum at low frequency, the corner angular frequency ω_c that separates the long wavelengths coherently propagating away from the crack from the interfering small wavelengths, and the decay spectral fall-off γ . 161 Finally, the site term $\tilde{Z}(\omega)$ was assumed to follow and exponential decay (Anderson & 162 Hough, 1984):

$$\tilde{Z}(\omega) = e^{-\frac{\omega k^c}{2}} \tag{10}$$

163 where k^c is local attenuation coefficient.

Following Supino et al. (2019), we inverted the amplitude spectra with a probabilistic Bayesian approach (Tarantola, 2004) where the best parameter evaluation and uncertainties come from the integration of the a-posteriori joint Probability Density Function (PDF) in the parameter space. In the general formulation of the inverse problem, we can retrieve up to 5 parameters: the source parameters M_0 , $f_c = \omega_c/2\pi$ and γ (f_c is the corner frequency); the regional attenuation factor Q^c and the local attenuation coefficient k^c . The search for maximum of the PDF is performed using a basin-hopping technique on Markov chain paths (Supino et al., 2019).

172 **2.3 Radiation pattern**

The average description of the radiation pattern for the displacement (Boore & Boatwright, 1984) cannot be simply extended to fiber recorded strain, due to limited azimuthal sensitivity of the DAS. The cable allows to recover only one out of the six components of the symmetric tensor ξ , while a three-component instrument provides a complete description of the displacement. In the case of DAS, we averaged the radiation pattern over all the possible fault orientations, and also over all the possible directions of the fiber cable on Earth's surface.

A generic direction of a ray emitted from the source can be described by the take-off and azimuth angles (θ, ϕ) , in the reference *W* centered at the hypocenter. This ray intercepts a portion of the fiber at the Earth surface, whose local orientation can be described by a different couple of angles (θ', ϕ') in the same reference frame *W*. To account for these new additional degrees of freedom, the average is performed over the focal sphere and all the possible directions of the fiber relatively to the source. This yields:

$$\bar{B}_c^{FF} = \frac{1}{16\pi^2} \int_0^{2\pi} \int_0^{\pi} \int_0^{2\pi} \int_0^{\pi} |A_{1i}P(\theta,\phi)_c A_{j1}^T| \sin\theta \sin\theta' d\theta' d\phi' d\theta d\phi$$
(11)

Here the matrix *A* accounts for the rotation of the spherical frame from (θ, ϕ) to (θ', ϕ') (see Supplementary Text S2). The terms $P_{ij,c}$ are the angular functions defined in eq. (2). The contributions associated with *P* and *S* = (*SV* + *SH*) waves can be separated. The integral (11) can be evaluated numerically, leading to:

$$\bar{B}_{P}^{FF} = 0.2586 \bar{B}_{S}^{FF} = 0.2518$$
 (12)

As an example, we show in Figure S1 (Supplementary material) wave contributions recorded by fibers oriented along the three-coordinate axes of the reference frame *W*, as a function of the take-off and azimuth.

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193 **3 Data and Results**

The proposed technique was applied to evaluate the source parameters on two different datasets. First, we considered DAS data recorded by a 150-km long marine telecommunication cable, located offshore the Chilean margin; then we applied the same technique to earthquakes recorded by a 1.1 km-long cable deployed in the Southern Apennines (Italy).

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3.1 Submarine DAS data offshore Chile

DAS data in Chile were recorded during the month of November 2021, when an 199 interrogator unit (OptoDAS – Alcatel Submarine Networks) was connected to a submarine fiber 200 optic telecom cable, operated by the GTD group and linking Concón to La Serena. The DAS was 201 able to sense 150km-long portion of the cable. A map of the cable is represented in Figure 1b. 202 Data were processed using a gauge length of 8.16 m with a repetition rate of 625 Hz and a spatial 203 sampling of 1.02m averaged over 4.08m. They were further decimated to a sampling rate of 125 204 Hz and a spatial sampling of 65.28m. In Figure 1a an example of DAS recording along the cable 205 is shown for a $2.9M_L$ event, along with a zoom on a record from a single channel. 206

For the analysis, we focused on a subset of 55 events, whose local magnitude M_L ranges between 2.5 and 4.3, also recorded by the seismic network from the Centro Sismologico National (CSN). These events are representative of the magnitude and distance ranges of earthquakes occurred during the period of the experiment. Origin times from CSN catalog were used as reference times to create three-minute-long DAS records. We individuated the S-wave

- arrival time on single traces using the machine learning algorithm Earthquake Transformer (EqT)
- 213 (Mousavi et al., 2020).





Figure 1: (a) Space-time representation of the strain rate wavefield recorded at the fiber for a $2.9M_L$ event occurred on the 2021/11/19. The black line marks the channel, whose time signal is shown on the left side. (b) Event location

- 217 (yellow star) with respect to the fiber section used in the analysis (filled red curve). (c) S-wave spectrum of the
- 218 selected channel (blue points, gray open circles) and of the noise (gray points) are represented. The vertical lines
- 219 individuate the frequency domain where the SNR is larger than the selected threshold and the inversion was
- 220 performed. The red curve is the best-fit spectrum obtained from the inversion.

The associator GaMMA (Zhu et al., 2022) was then applied to evaluate the consistency of the S-picks along the fiber, based on the apparent wave velocity. Accuracy on the picks has been shown to be sufficient for extraction of the S window for spectral analysis (Scotto di Uccio et al., 2023). The analysis focused on the inversion of S phase, which represents the dominant contribution since horizontally deployed fibers are poorly sensitive to P wave motion (Papp et al., 2017; Trabattoni et al., 2022).

Before inversion, the highest quality channels along the cable were selected based on their Signal to Noise Ratio (SNR). This latter quantity was evaluated by computing the ratio between the 90th percentile of the amplitude in a 6s window after the S arrival time, and the 90th percentile of the amplitude in a noise window of 20s before the origin time of the event. We selected channels with SNR>4, and we processed events only if the number of available channels was larger than 200, that represents almost 1/10 of the total number of channels. Following this approach, we were able to estimate the source parameters for 37 events.

To model the spectral amplitude expressed in eq. (8) we used $c_s = 4500$ m/s and Q =800 as provided by the tomographic model of Marot et al., (2014). Also, we set $\rho_s = \rho_R =$ 2700 kg/m³ and the S-velocity at the receiver $c_R = 400$ m/s, according to the analysis of f-k diagrams. The length of the signal used to evaluate the spectra depends on the event magnitude, to account for the size dependence of the source duration (Trifunac & Brady, 1975; Supplementary TextS3). This window also contains a small portion (10%) of signal before the Spick to account for uncertainties in the arrival times.

In Figure 1c we represent the amplitude spectrum of a channel from the DAS records. The signal exhibits a clear plateau level at low frequencies and a decay in the high frequency band. For each channel the inversion is performed in a specific frequency band (delimited in the figure by the vertical black lines), where the spectral amplitude of the signal overcomes the noise of a factor larger than 3.5. Low SNR typical of DAS recordings (Lellouch et al., 2020) results in narrower frequency band to be used for the inversion, as compared to standard seismic instruments.

248 Seismic moments and corner frequencies evaluated from the selected dataset exhibit self-249 similar behavior at almost constant stress drop (Figure 2 a). Using the relationship from Keylis-250 Borok, (1959):

$$\Delta \sigma = \frac{7}{16} \left(\frac{f_c}{C_k \beta} \right)^3 M_0 \tag{13}$$

and the geometrical factor of $C_k = 0.26$ from Kaneko & Shearer (2014), the averaged 251 stress drop could be estimated to $\Delta \sigma = (0.7 \pm 0.4)$ MPa. We also compared moment magnitude 252 estimations with moment magnitude obtained from the inversion of seismic records from on land 253 CSN stations. We found great coherency between estimates (Figure 2b). This indicates that the 254 observed plateau level at low frequencies is representative of the event moment release and is not 255 significantly affected by instrumental effects. Furthermore, we also compared moment 256 magnitude obtained from DAS data with local magnitudes from CSN catalog (Supplementary 257 TextS4) showing that our estimations are consistent with M_L and that for this range of 258 magnitudes the low frequency plateau is coherent with the energy content of the signal. 259



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Figure 2: (a) Corner frequency as a function of the seismic moment for the Chilean dataset, exhibiting a constant stress drop scaling, with average value of (0.7 ± 0.4) MPa and values ranging between 0.1 MPa and 10 MPa. (b) Comparison between DAS and CSN moment magnitudes; CSN *Mw* are obtained from inversion of seismic from in land stations for the same dataset. Estimations exhibit a scaling consistent with a 1:1 relationship.

The consistency of the modeling of the amplitude decay with the event distance could be asserted by taking advantage of the dense spatial sampling provided by the DAS technology. For each event, we computed the residual for both M_w and f_c at each channel, by removing the average value estimated for the whole cable from the single channel estimate. We grouped residuals by hypocentral distances in bins of 1 km (from 20 to 150 km) regardless of their event or channel origin. The median and standard median absolute deviations for residuals were computed for each bin as a function of the hypocentral distance (Fig. 3). The estimations are

- unbiased in the whole distance range. Only for distances below 40km the moment magnitude
- exhibits residuals slightly larger than zero; this overestimation of the geometrical spreading
- correction could be ascribed to possible uncertainty in event location.



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Figure 3: Analysis of the source parameters residuals as a function of the hypocentral distance. Bold lines represent the median of the residuals for each distance bin, while the error is represented as the Standard Median Absolute Deviation (SMAD). (a) M_w residuals exhibit a slight bias at short distances (<40 km), while no other trend is evident at other distances. (b) f_c residuals are unbiased, showing that the exponential decay as a model for regional attenuation well describes the spectral decay for a wide range of hypocentral distances.

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3.2 Southern Apennines DAS measurements

In contrast to Chilean events, the Southern Italy DAS survey focused on smaller microseismic events ($M_L \le 2.5$), that represent a challenging test for the resolution of source parameters. The data were acquired during a 5-month experiment, involving a DAS interrogator (Febus A1-r) connected to a 1.1km-long L-shaped fiber optic cable, buried into a shallow trench (0.3m - 1.0m) in a dry lake near the town of Colliano (Fig. 4b). The instrument was set to work with a sampling rate of 200Hz, further downsampled to 100Hz, and a spatial sampling of 2.4m, with a gauge length of 4.8m (see more details in Trabattoni et al. (2022)).

The site of the installation was near the emergence of the main segment of the normal fault system that generated the devastating 1980 *M* 6.9 Irpinia earthquake in the Southern Apennines. The area is nowadays monitored by the Irpinia Near Fault Observatory (INFO), (Chiaraluce et al., 2022) that detected several dozens of events during the deployment period

- (Fig. 4a). Figure 5 shows the recordings of a $M_L 2.3$ event occurred on 2021/09/20 at 13:07:55
- and reveals the specific propagation pattern due to the shallow sedimentary layering, as
- described in Trabattoni et al. (2022).



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Figure 4: (a) Map showing the location of the fiber (white square) and the events recorded during the survey (red circles). The green point marks the event represented in Figure 5 (almost 20km away from the installation site).
Panel (b) depicts the area contained in the white square, showing the L-shaped fiber (magenta line), with a kink in B, and the nearest INFO station COL3 (yellow triangle), located at less than 2km from the interrogator. The white-pattern area represents the dry lake where the cable was buried for the experiment.

As for the Chilean dataset, we considered events in the local bulletin (M_L from 0.3 to 2.3 and epicentral distances up to ~60km from the interrogator unit) and extracted related DAS waveforms from the continuous data-stream. We selected the highest quality channels in the AC section of the cable following a procedure similar to what was described for the previous dataset.





Figure 5: The space-time representation of the strain rate wavefield recorded by the DAS system for a $M_L 2.3$ event occurred on 2021/09/20. The black filled line marks the channel, whose time signal is shown on the left side, while the dashed black lines individuate specific points along the cable, shown in Figure 4b.

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For this dataset, we evaluated the source parameters for channels satisfying SNR>8 for 26 events that meet that criterion for at least at 40 channels. We selected 5s time windows around the S-pick (from 0.5s before to 4.5s after the S-pick) of a nearby station (COL3, distance from the fiber < 2km, see Figure 4b) to compute the amplitude spectra.

By analyzing the spectra of the events along the fiber, we observed that the spectral decay 316 following the plateau level starts around an apparent corner frequency of 5.5Hz (Figure 7b), 317 irrespective of the event magnitude and location and of the channel along the fiber (Fig. 6a and 318 7a). This decay can be ascribed to local site effects that are dominant in the spectral behavior 319 because spectral decays due to the source and to the anelastic attenuation are both expected to 320 show a cut-off frequency dependent on magnitude (source contribution) and distance (regional 321 anelastic attenuation). Moreover, assuming an average values of the quality factor Q for the area 322 (Q = 230; Zollo et al., 2014; Amoroso et al., 2017) the spectral decay due to the anelastic 323 attenuation is generally expected to start at frequencies higher than 5.5Hz for the range of 324 hypocentral distances associated with events recorded at the fiber. 325

We modelled the local site effects using the local attenuation coefficient k^c , as described 326 in eq. (10) (Anderson & Hough, 1984; Butcher et al., 2020; Ktenidou et al., 2014, 2015). To 327 infer an average value for k^c , we selected small magnitude events in the dataset ($M_w < 1.8$) for 328 which the source corner frequency is expected to be much larger than the observed cut-off 329 frequency (Zollo et al., 2014). For these events, after removal of regional anelastic attenuation 330 assuming Q = 230, we fit the logarithm of the amplitude spectra as a function of the frequency 331 to evaluate k^{c} for each channel and each event (Figure 6a). In Figure 6b, we represent the spatial 332 variability of k^c along the fiber. The local attenuation coefficient has its maximum in the central 333 section of the cable, decreasing almost linearly toward the ends of the cable, and possibly 334 mimicking the shape of the lake basement. We computed the median and the SMAD values from 335 k^c single-channel averages, leading to $\bar{k}^c = (0.08 \pm 0.02)$ s. 336



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Figure 6: (a) Example of the linear fit (red curve) estimated on the log-linear spectrum (blue circles) at a specific channel of the fiber to obtain a single-channel estimate of k^c . The spectrum is fitted in the frequency band where the SNR exceeds the imposed threshold of 3.5 (black vertical bars). (b) k^c variability along the cable by the mean of average (blue bold curve) and standard deviation (shaded area). The dashed black line individuates the position where the cable kinks (Figure 4b). (c) Log-log spectrum at a fixed channel for a $M_L 2.2$ event recorded on the fiber on the 2023/11/04 with the same color code described in Figure 1. The f_c estimation is marked by a vertical green line.

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The latter value was used in the source inversion of the largest magnitude events ($M_w >$ 1.8) to remove local site effects from their observed spectra, thereby evaluating their seismic moment and source corner frequency.

We compared source parameters estimation from DAS and INFO network seismic 349 records (Figure 7). M_w estimations from DAS are found to be consistent with the ones retrieved 350 from the INFO network, obtained inverting local seismic records (Fig. 7a). The correlation 351 between both estimates is lower than in the Chilean case. For Southern Apennines, this can be 352 attributed to the short length of the cable that does not capture the variability of the M_w estimates 353 due the distance and azimuth. Corner frequencies recovered from DAS saturate at 5.5 Hz 354 without the site correction (gray dots) but are compatible with the ones obtained from INFO 355 seismic stations when modelling the site attenuation (green dots, Fig. 7b). 356 357



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Figure7: (a) Moment magnitude comparison between estimates from DAS and from INFO network. Moment magnitude estimated from DAS data follows a 1:1 scaling (red line) with standard seismic station results. (b) Corner frequency comparison between DAS and local network. Without correction for local site effects (gray dots) DAS estimates saturate resulting in an apparent f_c around 5.5*Hz*. After the correction for local site effects (green dots), the two estimates become comparable.

364

365 4 Discussions

The new formulation of the far field strain spectra developed in this work does not require to convert waveforms from strain to velocity (e.g., Wang et al., 2018; Lior et al., 2021;

Trabattoni et al., 2023) and can be directly applied to raw DAS data. Signal manipulation during 368 the conversion to kinematic quantities could modify the seismic spectra. For example, the low-369 wavenumber accuracy of the conversion of the strain rate to displacement by direct integration is 370 limited by the rectilinearity of the fiber (Trabattoni et al., 2023). Also, the use of the slant-stack 371 transform for the evaluation of the dominant apparent velocity (Lior et al., 2021, 2023a), only 372 allows to correctly convert the most energetic phase, and the spurious contribution of other not 373 well-integrated, superimposing phases cannot be easily evaluated. The proposed strategy also 374 disengages from the colocation hypothesis and the knowledge of parameters for a reference 375 event, as required for EGF based approaches (Chen, 2023; Lior, 2023b) that also rely on raw 376 DAS data. 377

From the theoretical formulation, we retrieve an enhanced sensitivity of strain measurements to the shallow structure beneath the cable, with a dependence on the wave velocity at three-halves power instead of one-half, as compared to the displacement formulation. Knowledge of a-priori shallow S (and P) wave velocities is thus relevant to avoid biases in the estimation of the seismic moment. It is worth to note that this velocity also enters (as apparent velocity) in the conversion from strain-rate to acceleration (Daley et al., 2016).

We also report average radiation pattern contributions which are more than twice smaller than the ones retrieved for seismometer records, in agreement to the lower and complex directional sensitivity of DAS to body waves (Martin et al., 2021). Moreover, the presence of additional nodes in the radiation pattern diagrams suggests cable deployments with changes in the fiber orientation, to improve the resolution in the source parameters.

Finally, the proposed approach, when integrated in a probabilistic formulation, can be fully automated, with the quality of the solutions based on the shape of the a-posteriori probability density functions (Supino et al., 2019). Also, when extending this approach to the Pwaves, this strategy could be applied in real-time, when few seconds of early P wave signal are available (e.g., Caprio et al., 2011).

Validation of this approach on Chilean dataset ($M_L = 2.6 - 4.3$) shows a reliable estimation of source parameters, comparable with results from standard seismometers. We do not observe any dependence of parameters on the hypocentral distance, showing that attenuation correction is consistent throughout the whole cable, enabling DAS to characterize the source of events in wide range of hypocentral distances. Moreover, source parameters exhibit self-similar behavior with a mean stress drop of $0.7 \pm 0.4MPa$, consistent with the values retrieved for events in Central Chile (Sen et al., 2015).

In the second application we estimated source parameters for smaller size events (M_L = 401 0.3 - 2.3), using DAS data recorded on a much shorter (1.1km) cable installed in the active 402 tectonic environment of Southern Apennines (Italy). We found good agreement for moment 403 magnitude estimates from DAS as compared to the ones from standard seismic stations. Because 404 of the specific installation site (a dry lake), local attenuation plays a crucial role, masking the 405 effect of the source size in the spectrum. Using a parametric EGF-based approach, we estimated 406 an average local attenuation coefficient $\bar{k}^c = (0.08 \pm 0.02)$ s that is comparable with the values 407 estimated in very soft soils (Ktenidou et al., 2015). Also, the analysis of the variability of k^{c} 408 shows linear trends with distance along the cable, coherent with the increase in attenuation with 409 the distances from the tips of the basin (Trabattoni et al., 2022), and that can be correlated with 410 the depth of the basin (Campbell, 2009). This indicates the possibility to use DAS to infer 411 mechanical properties of the shallow layering, beyond the source parameters. When removing 412 this attenuation from the spectra of the largest magnitude events in the catalog, we were able to 413 resolve the corner frequencies, that now result to be coherent with the estimates from velocity 414 seismograms. 415

Working with DAS spectral amplitudes, especially for time integrated strain data, 416 displays unique instrumental noise, with coherent low frequency contribution that tightens the 417 bandwidth where the signal can be inverted (Lior et al., 2023a). This issue is related to 418 instrumental properties rather than seismic information in the signal, and could be mitigated with 419 420 the evolution and increasing demand of distributed sensing sensors. However, for events for which we estimated both seismic moment and event size (M_w between 2.0 and 4.3) we report 421 that the corner frequency lies in the middle of the frequency band available for the inversion, 422 allowing for an accurate estimation of source parameters. This is demonstrated by the 423 comparison with results from standard seismic instruments. For smaller magnitude events, we 424 were able to capture only the flat level of the spectrum, preventing from the estimate of 425 earthquake size. We might also expect a limitation in the use of DAS data for source parameter 426 estimation for events with magnitude larger than 4.5 - 5.0 (not included in the analyzed 427

428 catalogs), where the expected corner frequency approaches the lower limit of the informative

frequency bandwidth. In this case, the inversion could provide biased estimates for the momentmagnitude, as compared to standard instruments.

Consistency of estimates between DAS and seismic data guarantees that the contribution
 of secondary phases in the selected S-wave window, to which the DAS could be more sensitive,
 does not introduce significant biases in the retrieved source parameters.

434 **5** Conclusions

In this work we estimated source parameters from a spectral inversion of DAS data in their native representation, based on a novel formulation describing the far-field radiation in the strain domain. The theoretical modeling displays an enhanced sensitivity to the velocity structure beneath the cable and the radiation pattern.

Including this model in a probabilistic framework for the inversion (Supino et al., 2019)
 allowed us to estimate the moment magnitude and the corner frequency from two different
 datasets, showing consistent values when compared to authoritative catalogs.

When analyzing data acquired from a 150km ocean-bottom dark fiber cable near the Chilean trench ($M_L = 2.6 - 4.3$), we found a self-similar behavior of the seismicity with an mean stress drop of $0.7 \pm 0.4MPa$. Despite their natural variability, we report no biases of average estimations of source parameters with hypocentral distance along the cable.

446 Application of the technique to microseismic data ($M_L = 0.3 - 2.3$) acquired in the 447 Southern Apennines (Italy) represent a challenging test for the achievable resolution in the 448 characterization of small earthquakes using DAS. We coherently estimated the seismic moment 449 in the whole magnitude interval. Site effects were shown to dominate the high frequency part of 450 the spectrum and need to be modelled and corrected for to retrieve the source extension.

The two case studies presented in this work reveal the high potential of DAS for source characterization, while the dense spatial sampling could be a key ingredient for understanding source parameters variability and their relationship with the rupture behavior and the local structure. Nonetheless, fiber optic data require careful processing both for the peculiar signal properties, and for the large amount of data that requires efficient storage and processing.

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- 461

Data Availability Statement 462

- The strain rates of the Chilean earthquakes and seismic traces from CSN used in this article are 463
- available at the link: https://doi.org/10.5281/zenodo.8340063 (Rivet et al., 2023). DAS 464
- waveforms from the Southern Apennines dataset are available at: 465
- https://doi.org/10.5281/zenodo.8337580 (Strumia et al., 2023). Seismic data from Chilean 466
- seismic station can be accessed through the from IRISDMC (http://ds.iris.edu/mda/), network 467
- code C1. Products from INFO network can be accessed through the Irpinia Seismic Network 468
- infrastructure (ISNet: https://isnet.unina.it). Seismic data can be accessed through EIDA portal 469
- (https://eida.ingv.it/it/, network code IX). 470
- Catalog of the analyzed events and codes used to produce the Figures in the paper are available 471
- 472 on GitHub (https://github.com/ClaudioStrumia). Figures were made using matplotlib version
- 3.6.3. Map in Figure 4 was made using PyGMT (Uieda et al., 2021) using Generic Mapping 473
- 474 Tools (GMT) version 6 (Wessel et al., 2019).
- 475
- 476 **Supporting Information summary**
- 477 Text S1 to S4
- Figures S1 to S2 478
- 479
- References 480
- Abercrombie, R. E. (1995). Earthquake source scaling relationships from -1 to 5 ML using 481 seismograms recorded at 2.5-km depth. Journal of Geophysical Research: Solid Earth, 482 100(B12), 24015–24036. https://doi.org/10.1029/95JB02397 483

484	Abercrombie, R. E., Bannister, S., Ristau, J., & Doser, D. (2017). Variability of earthquake
485	stress drop in a subduction setting, the Hikurangi Margin, New Zealand. Geophysical
486	Journal International, 208(1), 306-320. https://doi.org/10.1093/gji/ggw393
487	Abercrombie, R. E., & Rice, J. R. (2005). Can observations of earthquake scaling constrain
488	slip weakening? In Geophysical Journal International (Vol. 162, Issue 2, pp. 406-
489	424). https://doi.org/10.1111/j.1365-246X.2005.02579.x
490	Ajo-Franklin, J. B., Dou, S., Lindsey, N. J., Monga, I., Tracy, C., Robertson, M., Rodriguez
491	Tribaldos, V., Ulrich, C., Freifeld, B., Daley, T., & Li, X. (2019). Distributed Acoustic
492	Sensing Using Dark Fiber for Near-Surface Characterization and Broadband Seismic
493	Event Detection. Scientific Reports, 9(1). https://doi.org/10.1038/s41598-018-36675-8
494	Aki, K., & Richards, P. G. (2002). Quantitative seismology.
495	Amoroso, O., Russo, G., De Landro, G., Zollo, A., Garambois, S., Mazzoli, S., Parente, M.,
496	& Virieux, J. (2017). From velocity and attenuation tomography to rock physical
497	modeling: Inferences on fluid-driven earthquake processes at the Irpinia fault system in
498	southern Italy. Geophysical Research Letters, 44(13), 6752-6760.
499	https://doi.org/10.1002/2016GL072346
500	Anderson, J. G., & Hough, S. E. (1984). A model for the shape of the Fourier amplitude
501	spectrum of acceleration at high frequencies. In Bulletin of the Seismological Society of
502	America (Vol. 74, Issue 5).
503	Arthur H. Hartog. (2017). An introduction to distributed optical fibre sensors (A. H. Hartog,
504	Ed.). CRC Press.
505	Boore, D. M., & Boatwright, J. (1984). Average body-wave radiation coefficcients. In
506	Bulletin of the Seismological Society of America (Vol. 74, Issue 5).
507	Brune, J. N. (1970). Tectonic stress and the spectra of seismic shear waves from
508	earthquakes. Journal of Geophysical Research, 75(26), 4997–5009.
509	https://doi.org/10.1029/JB075i026p04997
510	Butcher, A., Luckett, R., Kendall, J. M., & Baptie, B. (2020). Seismic magnitudes, corner
511	frequencies, and microseismicity: Using ambient noise to correct for high-frequency
512	attenuation. Bulletin of the Seismological Society of America, 110(3), 1260–1275.
513	https://doi.org/10.1785/0120190032

514	Campbell, K. W. (2009). Estimates of Shear-Wave Q and K0 for unconsolidated and
515	semiconsolidated sediments in Eastern North America. Bulletin of the Seismological
516	Society of America, 99(4), 2365-2392. https://doi.org/10.1785/0120080116
517	Caprio, M., Lancieri, M., Cua, G. B., Zollo, A., & Wiemer, S. (2011). An evolutionary
518	approach to real-time moment magnitude estimation via inversion of displacement
519	spectra. Geophysical Research Letters, 38(2). https://doi.org/10.1029/2010GL045403
520	Chen, X. (2023). Source parameter analysis using distributed acoustic sensing - an example
521	with the PoroTomo array. Geophysical Journal International, 233(3), 2207-2213.
522	https://doi.org/10.1093/gji/ggad061
523	Chiaraluce, L., Festa, G., Bernard, P., Caracausi, A., Carluccio, I., Clinton, J. F., Di Stefano,
524	R., Elia, L., Evangelidis, C. P., Ergintav, S., Jianu, O., Kaviris, G., Marmureanu, A.,
525	Šebela, S., & Sokos, E. (2022). The Near Fault Observatory community in Europe: a
526	new resource for faulting and hazard studies. Annals of Geophysics, 65(3), 1-17.
527	https://doi.org/10.4401/ag-8778
528	Currenti, G., Jousset, P., Napoli, R., Krawczyk, C., & Weber, M. (2021). On the
529	comparison of strain measurements from fibre optics with a dense seismometer array at
530	Etna volcano (Italy). Solid Earth, 12(4), 993-1003. https://doi.org/10.5194/se-12-993-
531	2021
532	Daley, T. M., Miller, D. E., Dodds, K., Cook, P., & Freifeld, B. M. (2016). Field testing of
533	modular borehole monitoring with simultaneous distributed acoustic sensing and
534	geophone vertical seismic profiles at Citronelle, Alabama. Geophysical Prospecting,
535	64(5), 1318–1334. https://doi.org/10.1111/1365-2478.12324
536	Haskell, N. A. (1964). Total energy and energy spectral density of elastic wave radiation
537	from propagating faults. Bulletin of the Seismological Society of America, 54(6A),
538	1811–1841. https://doi.org/10.1785/BSSA05406A1811
539	Kaneko, Y., & Shearer, P. M. (2014). Seismic source spectra and estimated stress drop
540	derived from cohesive-zone models of circular subshear rupture. Geophysical Journal
541	International, 197(2), 1002-1015. https://doi.org/10.1093/gji/ggu030
542	Keylis-Borok, V. (1959). On estimation of the displacement in an earthquake source and of
543	source dimensions. Annals of Geophysics, 12(2).

544	Ktenidou, O. J., Abrahamson, N. A., Drouet, S., & Cotton, F. (2015). Understanding the
545	physics of kappa (κ): Insights from a downhole array. <i>Geophysical Journal</i>
546	International, 203(1), 678-691. https://doi.org/10.1093/gji/ggv315
547	Ktenidou, O. J., Cotton, F., Abrahamson, N. A., & Anderson, J. G. (2014). Taxonomy of κ :
548	A review of definitions and estimation approaches targeted to applications.
549	Seismological Research Letters, 85(1), 135–146. https://doi.org/10.1785/0220130027
550	Lellouch, A., Lindsey, N. J., Ellsworth, W. L., & Biondi, B. L. (2020). Comparison between
551	distributed acoustic sensing and geophones: Downhole microseismic monitoring of the
552	FORGE geothermal experiment. Seismological Research Letters, 91(6), 3256-3268.
553	https://doi.org/10.1785/0220200149
554	Lellouch, A., Yuan, S., Spica, Z., Biondi, B., & Ellsworth, W. L. (2019). Seismic Velocity
555	Estimation Using Passive Downhole Distributed Acoustic Sensing Records: Examples
556	From the San Andreas Fault Observatory at Depth. Journal of Geophysical Research:
557	Solid Earth, 124(7), 6931-6948. https://doi.org/10.1029/2019JB017533
558	Li, J., Zhu, W., Biondi, E., & Zhan, Z. (2023). Earthquake focal mechanisms with
559	distributed acoustic sensing. Nature Communications, 14(1), 4181.
560	https://doi.org/10.1038/s41467-023-39639-3
561	Lior, I. (2023). Accurate Magnitude and Stress Drop using the Empirical Green's Function
562	Method Applied to Distributed Acoustic Sensing.
563	https://doi.org/https://doi.org/10.22541/essoar.169008302.27323942/v1
564	Lior, I., Rivet, D., Ampuero, J. P., Sladen, A., Barrientos, S., Sánchez-Olavarría, R.,
565	Villarroel Opazo, G. A., & Bustamante Prado, J. A. (2023). Magnitude estimation and
566	ground motion prediction to harness fiber optic distributed acoustic sensing for
567	earthquake early warning. Scientific Reports, 13(1). https://doi.org/10.1038/s41598-
568	023-27444-3
569	Lior, I., Sladen, A., Mercerat, D., Ampuero, J. P., Rivet, D., & Sambolian, S. (2021). Strain
570	to ground motion conversion of distributed acoustic sensing data for earthquake
571	magnitude and stress drop determination. Solid Earth, 12(6), 1421-1442.
572	https://doi.org/10.5194/se-12-1421-2021

573	Madariaga, R. (1976). Dynamics of an expanding circular fault. Bulletin of the
574	Seismological Society of America, 66(3), 639–666.
575	https://doi.org/10.1785/bssa0660030639
576	Marot, M., Monfret, T., Gerbault, M., Nolet, G., Ranalli, G., & Pardo, M. (2014). Flat
577	versus normal subduction zones: A comparison based on 3-D regional traveltime
578	tomography and petrological modelling of central Chile and western Argentina (29°-
579	35°S). Geophysical Journal International, 199(3), 1633–1654.
580	https://doi.org/10.1093/gji/ggu355
581	Martin, E. R., Lindsey, N. J., Ajo-Franklin, J. B., & Biondi, B. L. (2021). Introduction to
582	Interferometry of Fiber-Optic Strain Measurements. In Distributed Acoustic Sensing in
583	Geophysics: Methods and Applications (pp. 113–129). wiley.
584	https://doi.org/10.1002/9781119521808.ch09
585	Mousavi, S. M., Ellsworth, W. L., Zhu, W., Chuang, L. Y., & Beroza, G. C. (2020).
586	Earthquake transformer—an attentive deep-learning model for simultaneous
587	earthquake detection and phase picking. Nature Communications, 11(1).
588	https://doi.org/10.1038/s41467-020-17591-w
589	Nishimura, T., Emoto, K., Nakahara, H., Miura, S., Yamamoto, M., Sugimura, S., Ishikawa,
590	A., & Kimura, T. (2021). Source location of volcanic earthquakes and subsurface
591	characterization using fiber-optic cable and distributed acoustic sensing system.
592	Scientific Reports, 11(1). https://doi.org/10.1038/s41598-021-85621-8
593	Oth, A., Bindi, D., Parolai, S., & Wenzel, F. (2007). S-Wave Attenuation Characteristics
594	Beneath the Vrancea Region (Romania)-New Insights from the Inversion of Ground
595	Motion Spectra.
596	Papp P. Donno D. Martin J. E. & Hartog A. H. (2017) A study of the goophysical
	rapp, B., Donno, D., Martin, J. E., & Hartog, A. H. (2017). A study of the geophysical
597	response of distributed fibre optic acoustic sensors through laboratory-scale
597 598	response of distributed fibre optic acoustic sensors through laboratory-scale experiments. <i>Geophysical Prospecting</i> , 65(5), 1186–1204.
597 598 599	 rapp, B., Donno, D., Martin, J. E., & Hartog, A. H. (2017). A study of the geophysical response of distributed fibre optic acoustic sensors through laboratory-scale experiments. <i>Geophysical Prospecting</i>, 65(5), 1186–1204. https://doi.org/10.1111/1365-2478.12471
597 598 599 600	 rapp, B., Dohno, D., Martin, J. E., & Hartog, A. H. (2017). A study of the geophysical response of distributed fibre optic acoustic sensors through laboratory-scale experiments. <i>Geophysical Prospecting</i>, 65(5), 1186–1204. https://doi.org/10.1111/1365-2478.12471 Piana Agostinetti, N., Villa, A., & Saccorotti, G. (2022). Distributed acoustic sensing as a
597 598 599 600 601	 rapp, B., Dohno, D., Martin, J. E., & Hartog, A. H. (2017). A study of the geophysical response of distributed fibre optic acoustic sensors through laboratory-scale experiments. <i>Geophysical Prospecting</i>, 65(5), 1186–1204. https://doi.org/10.1111/1365-2478.12471 Piana Agostinetti, N., Villa, A., & Saccorotti, G. (2022). Distributed acoustic sensing as a tool for subsurface mapping and seismic event monitoring: A proof of concept. <i>Solid</i>

603	Prieto, G. A., Shearer, P. M., Vernon, F. L., & Kilb, D. (2004). Earthquake source scaling
604	and self-similarity estimation from stacking P and S spectra. Journal of Geophysical
605	Research: Solid Earth, 109(8). https://doi.org/10.1029/2004JB003084
606	Rivet, D., Trabattoni, A., & Baillet, M. (2023). DAS Chile waveforms [Data set]. Zenodo.
607	https://doi.org/10.5281/zenodo.8340063
608	Scotto di Uccio, F., Scala, A., Festa, G., Picozzi, M., & Beroza, G. C. (2023). Comparing
609	and integrating artificial intelligence and similarity search detection techniques:
610	application to seismic sequences in Southern Italy. Geophysical Journal International,
611	233(2), 861-874. https://doi.org/10.1093/gji/ggac487
612	Şen, A. T., Cesca, S., Lange, D., Dahm, T., Tilmann, F., & Heimann, S. (2015). Systematic
613	Changes of Earthquake Rupture with Depth: A Case Study from the 2010 Mw8.8
614	Maule, Chile, Earthquake Aftershock Sequence. Bulletin of the Seismological Society
615	of America, 105(5), 2468-2479. https://doi.org/10.1785/0120140123
616	Sladen, A., Rivet, D., Ampuero, J. P., De Barros, L., Hello, Y., Calbris, G., & Lamare, P.
617	(2019). Distributed sensing of earthquakes and ocean-solid Earth interactions on
618	seafloor telecom cables. Nature Communications, 10(1).
619	https://doi.org/10.1038/s41467-019-13793-z
620	Spica, Z. J., Perton, M., Martin, E. R., Beroza, G. C., & Biondi, B. (2020). Urban Seismic
621	Site Characterization by Fiber-Optic Seismology. Journal of Geophysical Research:
622	Solid Earth, 125(3). https://doi.org/10.1029/2019JB018656
623	Strumia, C., Festa, G., & Trabattoni, A. (2023). DAS Irpinia waveforms [Data set]. Zenodo.
624	https://doi.org/10.5281/zenodo.8337580
625	Supino, M., Festa, G., & Zollo, A. (2019). A probabilistic method for the estimation of
626	earthquake source parameters from spectral inversion: Application to the 2016-2017
627	Central Italy seismic sequence. Geophysical Journal International, 218(2), 988-1007.
628	https://doi.org/10.1093/gji/ggz206
629	Tarantola, A. (2004). Inverse Problem Theory and Methods for Model Parameter
630	Estimation.
631	Trabattoni, A., Biagioli, F., Strumia, C., Van Den Ende, M., Scotto Di Uccio, F., Festa, G.,
632	Rivet, D., Sladen, A., Ampuero, J. P., Métaxian, JP., & Stutzmann, É. (2023). From

633	strain to displacement: using deformation to enhance distributed acoustic sensing
634	applications. https://doi.org/http://dx.doi.org/10.31223/X5ZD3C
635	Trabattoni, A., Festa, G., Longo, R., Bernard, P., Plantier, G., Zollo, A., & Strollo, A.
636	(2022). Microseismicity Monitoring and Site Characterization With Distributed
637	Acoustic Sensing (DAS): The Case of the Irpinia Fault System (Southern Italy).
638	Journal of Geophysical Research: Solid Earth, 127(9).
639	https://doi.org/10.1029/2022JB024529
640	Trifunac, M. D., & Brady, A. G. (1975). A study on the duration of strong earthquake
641	ground motion. In Bulletin of the Seismological Society of America (Vol. 65, Issue 3).
642	Tsuji, T., Ikeda, T., Matsuura, R., Mukumoto, K., Hutapea, F. L., Kimura, T., Yamaoka, K.,
643	& Shinohara, M. (2021). Continuous monitoring system for safe managements of CO2
644	storage and geothermal reservoirs. Scientific Reports, 11(1).
645	https://doi.org/10.1038/s41598-021-97881-5
646	Uieda, L., Tian, D., Leong, W. J., Toney, L., Schlitzer, W., Yao, J., Grund, M., Jones, M.,
647	Materna, K., Newton, T., Ziebarth, M., & Wessel, P. (2021). PyGMT: A Python
648	interface for the Generic Mapping Tools (v0.3.1) [Software]. Zenodo.
649	https://doi.org/10.5281/zenodo.4592991
650	Van Den Ende, M. P. A., & Ampuero, J. P. (2021). Evaluating seismic beamforming
651	capabilities of distributed acoustic sensing arrays. Solid Earth, 12(4), 915–934.
652	https://doi.org/10.5194/se-12-915-2021
653	Wang, H. F., Zeng, X., Miller, D. E., Fratta, D., Feigl, K. L., Thurber, C. H., & Mellors, R.
654	J. (2018). Ground motion response to an ML 4.3 earthquake using co-located
655	distributed acoustic sensing and seismometer arrays. Geophysical Journal
656	International, 213(3), 2020-2036. https://doi.org/10.1093/GJI/GGY102
657	Wessel, P., Luis, J. F., Uieda, L., Scharroo, R., Wobbe, F., Smith, W. H. F., & Tian, D.
658	(2019). The Generic Mapping Tools Version 6. Geochemistry, Geophysics,
659	Geosystems, 20(11), 5556-5564. https://doi.org/10.1029/2019GC008515
660	Yin, J., Zhu, W., Li, J., Biondi, E., Miao, Y., Spica, Z. J., Viens, L., Shinohara, M., Ide, S.,
661	Mochizuki, K., Husker, A. L., & Zhan, Z. (2023). Earthquake Magnitude With DAS:
662	A Transferable Data-Based Scaling Relation. Geophysical Research Letters, 50(10).
663	https://doi.org/10.1029/2023GL103045

664	Zhu, W., McBrearty, I. W., Mousavi, S. M., Ellsworth, W. L., & Beroza, G. C. (2022).
665	Earthquake Phase Association Using a Bayesian Gaussian Mixture Model. Journal of
666	Geophysical Research: Solid Earth, 127(5). https://doi.org/10.1029/2021JB023249
667	Zollo, A., Orefice, A., & Convertito, V. (2014). Source parameter scaling and radiation
668	efficiency of microearthquakes along the Irpinia fault zone in southern Apennines,
669	Italy. Journal of Geophysical Research: Solid Earth, 119(4), 3256–3275.
670	https://doi.org/10.1002/2013JB010116
671	