



Detecting and discriminating rockfall signals from anthropogenic noise using Distributed Acoustic Sensing along a Norwegian railway

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Abstract. In mountainous regions, railway lines frequently traverse terrain with elevated rockfall and avalanche risk. In recent years, several such events have struck railways, resulting in casualties and significant infrastructure damage. Continuous monitoring along railway corridors is therefore essential for early warning and preventive measures. Given that fibre-optic telecommunications cables are already installed along many railways, Distributed Acoustic Sensing (DAS) represents an operationally attractive solution for continuous, large-scale rockfall monitoring. Avalanches and rockfalls release seismic energy as they propagate, which can be recorded by seismic sensors installed along the railway. Here, we use a fibre-optic cable running parallel to a railway in Norway to acquire DAS data and characterise the seismic signatures of rockfall events. The DAS system also recorded a range of anthropogenic signals, including those from road vehicles and trains, and the frequency distribution are found to be distinctly different from rockfalls. Rockfall signals are characterised by higher dominant frequencies and apparent propagation velocities than anthropogenic noise sources. Furthermore, moving vehicles generate persistent low-frequency energy that is absent in rockfall signals, providing an additional basis for discrimination. In addition to natural rockfall events, we carried out controlled rockfall experiments in which rocks of various sizes were dropped along the railway. The smallest rockfall detected had a mass of approximately 50 kg and was observable over approximately 400 m of fibre, whereas the largest boulder could be observed over several kilometres. Combined, these characteristics indicate that rockfalls can be effectively discriminated from anthropogenic signals, forming a promising foundation for the development of automated detection algorithms using cost-efficient DAS system.

1 Introduction

Railway lines in mountainous regions frequently traverse areas with high avalanche risk, posing significant operational and safety challenges. In Norway, for example, hazards range from quick-clay avalanches in low-lying terrain to snow and rock avalanches in steep-sided valleys. Detecting and characterising mass movements, including rockfalls, landslides, debris flows, and snow avalanches, is therefore essential for protecting infrastructure and passenger safety.



Recent events illustrate the severity of this threat. In 2024 in Bjerka, Norway (nrk.no, 2024), a rock avalanche struck the railway, derailing a train, while the following year, a quick-clay avalanche by Nesvatnet, Levanger, triggered by nearby construction destroyed both the railway and an adjacent road (banenor.no, 2026). Near Gelida, Spain, in 2026 (bbc.no, 2026),
 25 a rock avalanche destabilised a retaining wall, which then collapsed onto the track, derailing a local train. These incidents underscore the need for continuous, real-time monitoring along railways.

Seismic monitoring has emerged as a key tool for monitoring, enabling both the detection and characterisation of mass-movement events (Allstadt et al., 2018). Seismic monitoring of mass movements has traditionally relied on sensor networks, and several studies using geophones have detailed the characteristics of rockfall and rockslide signals. Langet and Silverberg
 30 (2023) used the eight-geophone network on the Åknes rock slope in Norway and trained a convolutional neural network to classify continuous recordings spanning 15 years automatically. Of the eight classes identified, five were attributed to active movements on the slope. Helmstetter and Garambois (2010) monitored the Séchilienne rockslide in the French Alps using a geophone network, analysing several thousand seismic events. The authors found that rockfall occurrence increased linearly with precipitation and that rainfall induced a strong acceleration of rockslide movement. Spillmann et al. (2007) deployed a
 35 network of 12 three-component geophones on the Randa rockslide in the Swiss Alps to characterise the microseismicity of an active rock slope.

An emerging method with substantial potential for mass-movement monitoring is distributed acoustic sensing (DAS), which has received growing attention due to its dense spatial coverage and high temporal sampling. Most modern railways have fibre-optic telecommunications cables running parallel to the track, and DAS repurposes such cables as strain-rate sensors by
 40 transmitting laser pulses, or sweeps, and recording the Rayleigh backscattering that returns from refractive index fluctuations distributed along the fibre (Zhan et al., 2021; Waagaard et al., 2021; Taweesintananon et al., 2021). Phase shifts between subsequent backscattered signals are then used to infer external noise sources along the fibre cable, effectively turning the cable into thousands of seismic sensor points. Several studies have used DAS to study signals along railways (Wiesmeyr et al., 2020; Muñoz et al., 2023). Other studies have also investigated how to detect or characterise avalanche signals along railway
 45 and road corridors (Turquet et al., 2024; Kleine et al., 2025). Kang et al. (2024) applied a semi-supervised neural network to DAS data from Brienz, Switzerland, to screen and detect a series of rock collapses leading to a major failure of approximately 1.2 million m³ of rock. Ouellet et al. (2024) used DAS to reveal the kinematics of a slow-moving landslide at Hollin Hill, England, considering low-frequency signals (<1 Hz) recorded over three days. The authors demonstrated that rainfall-driven landslide motion could be resolved at timescales of minutes and spatial scales of metres, providing detailed insight into near-
 50 surface deformation processes and illustrating the potential of DAS for high-resolution monitoring of slow landslide dynamics. Xie et al. (2026) investigated the various factors influencing the signal responses captured by DAS for rockfall monitoring. They examined the effects of gauge length, installation method, and fibre coupling on the recorded signatures. Kleine et al. (2025) recorded and characterised both explosively induced and natural snow avalanches in Grasdalen, Norway, across three winter seasons, and additionally examined traffic-related signals to assess DAS as a monitoring tool for mountain road networks.

55 These studies demonstrate that seismic methods, whether traditional geophone networks or emerging fibre-optic sensing systems, can capture the characteristic signals of rockfalls, avalanches, and other mass-movement events. DAS offers partic-



ular promise for continuous, large-scale monitoring along infrastructure such as railways, where dense spatial coverage and the reuse of existing fibre-optic cables are clear operational advantages. However, few DAS studies have systematically compared rock fall and avalanche signals with the other signals encountered in railway monitoring settings, including those from trains, road traffic, and ambient environmental noise. In this study, we present seismic recordings of both controlled rockfall experiments and natural avalanche events captured by a DAS system installed parallel to a Norwegian railway, and compare these against anthropogenic noise sources including vehicle traffic and trains. We demonstrate that rockfall signals contain characteristics in both the t - x and f - k domains that allow them to be reliably distinguished from anthropogenic noise sources, creating a promising basis for future automated detection systems. The paper is organised as follows: Section 2 presents the data acquisition and tap-test used to correlate DAS channels to geographical coordinates; Section 3 describes the signal processing, hyperbolic fitting, and classification criteria; Section 4 presents and discusses the results; and Section 5 summarises the main conclusions.

2 Data

2.1 DAS data acquisition

In December 2024, an OptoDAS interrogator unit (IU) was deployed in Fauske, Norway, and has been recording until 22 July 2026. Only a subset of the data were used in this work, focusing on time periods where the various signals of interest were present in the data. Figure 1 shows a map depicting the interrogator unit position and the fibre position, which runs parallel to a railway. The interrogator collects DAS data over 98 km using either a gauge length of 8 or 16 m and a temporal sampling of 400 Hz. The periods of controlled rock drops were recorded at higher temporal sampling rates (800 Hz and 1000 Hz) to assess and quantify the frequency bandwidths of the various signals being studied.

The fibre traverses a varied landscape in terms of both geology and topography. Along the first 30 km and beyond 50 km, the railway runs through steep-sided valleys with several stretches of high avalanche danger. Between 30 km and 50 km, the terrain flattens considerably, reducing the avalanche risk but introducing other signal sources, as this section runs parallel to the European road E6 with car and truck traffic. The fibre also passes through a number of tunnels.

2.2 Tap-test

A tap-test was carried out in collaboration with BaneNOR, the railway and fibre-optic cable owner, using a Robel maintenance vehicle and sledgehammer shots. The test served three purposes: to map individual DAS channels to geographical coordinates, hence establishing the fibre locations shown in Fig. 1; to identify sections of the route with elevated avalanche risk; and to characterise the fibre's sensitivity as a function of the underlying near-surface geology. The vehicle stopped at regular intervals, where several taps, i.e., sledgehammer shots, were carried out. The signal from the vehicle stop also served as a tap, as it almost completely disappears when it stops. Figure 2 shows the two signals. First, the Robel can be observed to stop at 53.55 km for ~ 60 s. By collecting the geographic coordinates at the stop position, we can correlate them with the distance at which the

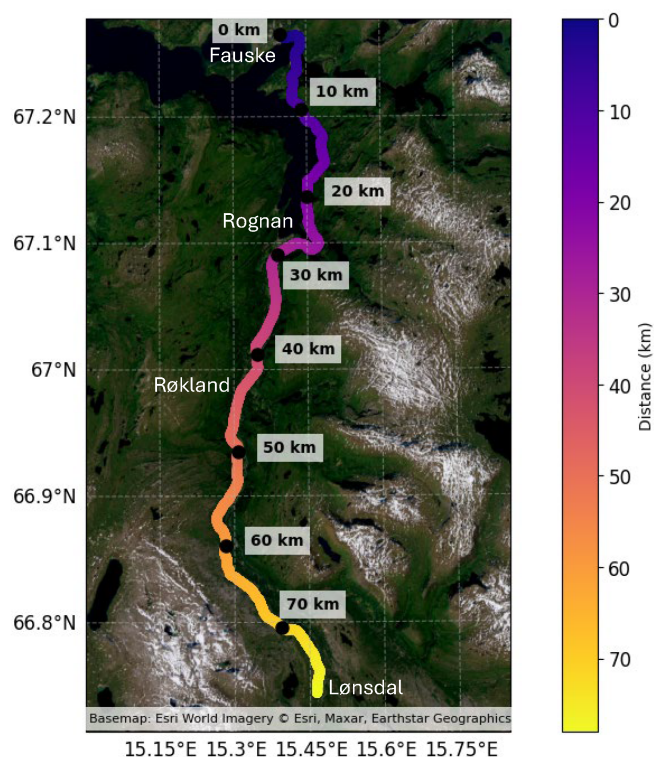


Figure 1. Overview map of the survey area. The interrogator unit was placed in Fauske at the 0 km mark.

Robel stopped. However, the Robel is 10–20 m long and generates interface waves as it drives along the fibre. This creates a large uncertainty in the stop position and consequently also in the assigned fibre channel. From the extent of the Robel signal in Fig. 2, we quantify this uncertainty to be ± 50 m. To reduce uncertainty, we use the sledgehammer shots. The middle section of Fig. 2 (dashed rectangle) shows an example of three sledgehammer taps where the channel in the apex is related to the recorded geographical coordinates. These taps reduce the uncertainty to ± 25 m. During the drive along the track, different segments running parallel to steep mountain sides were noted and later checked against topographic maps of the area (ngu.no, 2026) to map and mark avalanche-prone areas. In addition, all tunnels were registered. These are not avalanche-prone, but single rocks can fall from either the roof or the walls and cause damage to passing trains.

3 Methods and signal classification

3.1 Data processing

The data processing ahead of the main data analysis is done using the following steps. First, the data are converted from raw time-differentiated phase-change data to strain (Taweessintananon et al., 2021). Second, the data are resampled to 200 Hz from

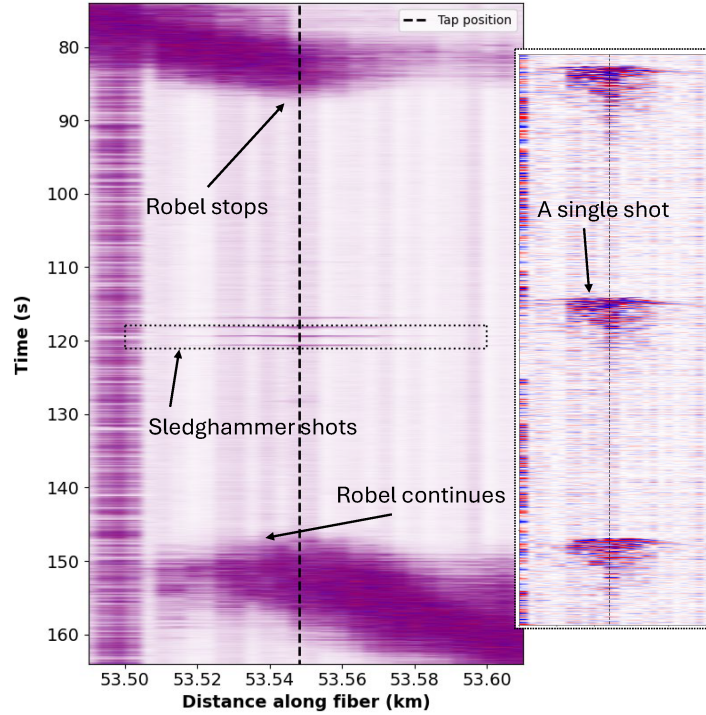


Figure 2. Different tap examples. When the Robel maintenance vehicle stops, the resulting DAS signature can be used as part of a tap-test. However, the Robel is long and it is hard to pick an accurate channel related to the stop position. Sledgehammer shots can be carried out during the Robel stop, providing a more accurate channel location. The inset (data in dashed rectangle) shows three sledgehammer shots with the picked apex channels indicated.

100 800 Hz. Third, a Butterworth band-pass filter is applied to focus on the various signal bandwidths in the data. For avalanches and traffic, cut-off frequencies of 5 and 70 Hz are used, while 0.15 Hz and 2 Hz are used to investigate their low frequency content. Tukey tapering is used before the filtering. Finally, the interrogator's common-mode noise is reduced by computing a model for all time samples using the median value along the channel axis. This model is then subtracted from the DAS data.

3.2 Hyperbolic fitting

105 We estimate the propagation velocity of the different signals by fitting a hyperbola to their move-out in the t - x domain. An impulsive source close to the fibre, such as a rock impacting the ground, generates seismic waves that arrive later at channels further from the source. For a source at position x_0 along the fibre, at a perpendicular distance d , releasing energy at time t_0 , the arrival time at a channel at position x is

$$t(x) = t_0 + \frac{1}{c} \sqrt{d^2 + (x - x_0)^2}, \quad (1)$$



110 where c is the propagation velocity. Equation (1) describes the upper branch of a hyperbola in the t - x domain, with its apex at the channel closest to the source and asymptotes of slope $\pm 1/c$. By estimating the four parameters (t_0, x_0, d, c) , we obtain both the source position and the propagation velocity. The hyperbola is fitted not to the wavefield directly, but to a single arrival pick automatically extracted per channel. The picks are obtained as follows. First, the data in a window around the event are band-pass filtered between 5 and 50 Hz, and the absolute amplitude is computed. Second, for the rockfall events, the
115 fractional change in absolute amplitude over a 0.2 s lag is computed to enhance sharp energy onsets and suppress the slowly varying background. Third, a moving-median filter (0.1 s in time, 20 channels in space) is applied to remove isolated spikes. Finally, the time sample with the maximum value on each channel is retained as the arrival pick. Because picking is performed independently per channel, it is insensitive to amplitude variations along the fibre caused by changes in coupling and near-surface geology. Note that channels located on excess fibre coils are removed prior to picking, and the remaining channels are
120 mapped back onto a uniform spacing.

Some of the picks fall on background noise, particularly on channels where the event signal is weak or absent. The fitting is therefore made robust in two ways. First, the misfit between the picked and modelled arrival times is measured using the Huber loss (Huber, 1964), which is quadratic for small residuals and linear for large ones, limiting the influence of outliers. Second, the minimisation is carried out directly on the physical parameters (t_0, x_0, d, c) using the derivative-free Powell method
125 (Powell, 1964) as implemented in SciPy (Virtanen et al., 2020), which allows bounds to be placed on each parameter. For the rockfall events, the origin time is constrained to a 1 s window around the onset visible in the data, the velocity to 0.1–3 km/s, and the source offset to 1–17 m, consistent with the landing distances observed during the controlled experiments. The vehicle signals are fitted without constraints, as their offset and velocity vary too widely to justify fixed bounds. The goodness of fit is quantified using the mean absolute error (MAE) of the arrival-time residuals, normalised by the duration of the analysis
130 window, which yields a dimensionless measure where smaller values indicate a closer fit.

3.3 Signal classification

3.3.1 Tunnels

The fibre segment within tunnels is coupled to bedrock and produces different signatures in the DAS data compared to the outside segments, where the fibre rests on superficial deposits of varying thickness and composition (ngu.no, 2026). During the
135 tap-test, all tunnel sections were recorded in a database together with their associated DAS channels. We further used signals from passing trains and a local earthquake to quality-control the tap-test results, as the response from these varies along the fibre depending on local geology.

Figure 3 shows a freight train and a local earthquake recorded across a section where the fibre transitions between tunnel and open sections. In Fig. 3(a), the freight train generates seismic surface waves outside the tunnel that propagate along the
140 fibre. Inside the tunnel no such wave energy is observed. We attribute this to the bedrock coupling seismic energy directly into the subsurface, where the absence of near-surface layers prevents wave trapping and amplification. For the earthquake in Fig. 3(b), signal amplitudes within tunnels are systematically lower than those outside. We interpret this as reflecting the

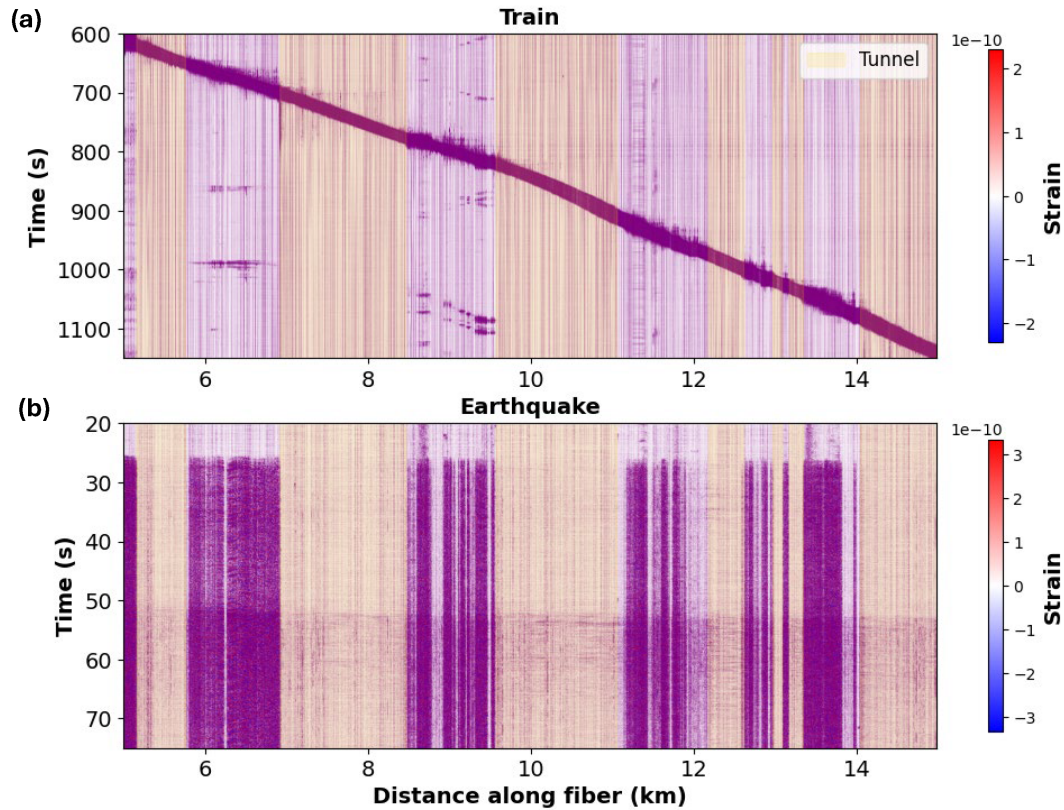


Figure 3. Identification of tunnels using trains and earthquakes. (a) Train over a subsection of the fibre containing seven tunnels (transparent gold region). (b) Earthquake over the same subsection of the fibre. For trains the DAS recordings contain less surface wave energy in tunnels, whereas for the earthquake no energy is trapped in the near-surface layers inside the tunnel.

absence of surficial deposits beneath the fibre in tunnel sections, consistent with freight train observations. This is similar to results from Taweesintananon et al. (2024) where they observed seismic waves resonating within near-surface deposits on the sea floor, amplifying both ambient noise and earthquake arrivals for specific fibre segments.

Combined, train and earthquake signals can be used to map variations in near-surface geology along the railway. While the variation in surficial deposits clearly influences the DAS response, a detailed characterisation of these deposits along the fibre is beyond the scope of this study and remains a topic for future work. It should be noted that tunnels cannot be readily distinguished from sections where the fibre lies directly on bedrock outside the tunnels (see, e.g., response at 12 km in Fig. 3(b)), and tap-tests are still necessary to precisely delineate tunnel extents.

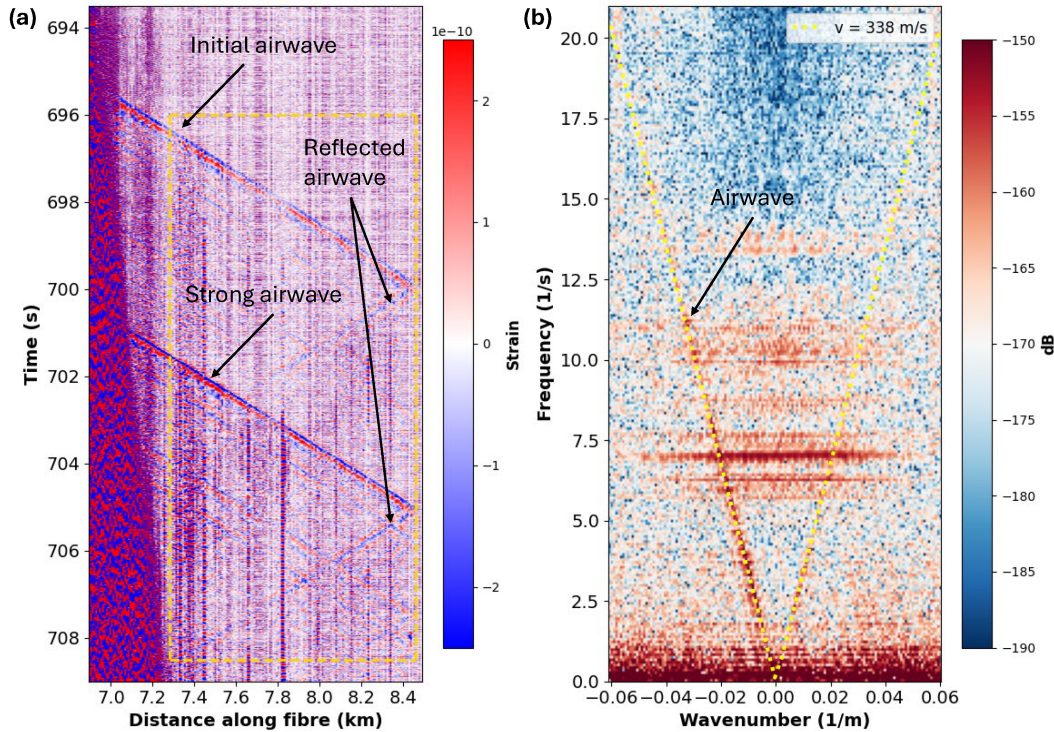


Figure 4. Typical signatures that occur when a train enters a tunnel. (a) The t - x domain of the train (high amplitude region to the left in the panel) with generated airwaves propagating with a speed of 338 m/s and reflected from the other side of the tunnel. (b) The associated f - k domain representation showing the airwave and single frequency noise sources related to individual noisy channels.

3.3.2 Trains with associated acoustic and seismic signatures

Trains have been successfully captured and tracked across different DAS systems due to the strong seismic energy they generate (He et al., 2019; Milne et al., 2020; Wiesmeyr et al., 2020). A moving train produces a range of different seismic signatures as it drives along the railway. As discussed in Section 3.3.1, there are distinct differences between a train moving on surficial sediments and on bedrock, like in tunnels. Trains also generate impulsive events that translate into different wave types. For example, when a train passes over a level crossing, it generates strong seismic waves, consisting primarily of surface waves. Moreover, when the train enters a tunnel, it generates airwaves that propagate inside the tunnel and are reflected from the opening at the other end. Such airwaves are shown in Fig. 4(a). The first wave is generated as the freight train enters the tunnel at 695.5 s, followed by several weaker airwave signatures. At 700.5 s, another stronger airwave is observed, which we interpret as originating from one or several carriages without containers. At the end of the tunnel, the airwave is reflected back with a clear polarity reversal. The reflection is due to the opening at the far end of the tunnel acting as a pressure-release boundary, which reflects the energy back with an opposite polarisation (in principle the same as in a Kundt's tube).



To better understand the generated airwaves, we investigate the same train in several subsequent tunnels and another train in the same tunnels. One freight train example recorded in different tunnels shows the same airwave pattern. For a second freight train in the same tunnels, we observe the same initial airwave but no strong airwaves among the weaker, later-arriving airwaves. This indicates that each train generates unique airwave patterns as it moves through the tunnel, most likely governed by the cargo it carries.

The speed of the airwave can be computed both in the $t-x$ (Fig. 4(a)) and $f-k$ (Fig. 4(b)) domains. For the train example in Fig. 4 we find the speed to be 338 m/s, which agrees with the expected airwave speeds.

3.3.3 Road traffic

The European road E6 runs parallel to the railway along a substantial portion of the 100 km fibre, and between 23 and 46 km the two routes are in proximity for almost the entire stretch. We use this geometry to characterise the seismic signatures of different vehicle types as they pass along the road. Figure 5 shows typical traffic signatures in both the time-distance ($t-x$) and frequency-wavenumber ($f-k$) domains. Panel (a) shows a single truck with a car briefly present between 2040 and 2060 s, panel (c) shows three cars recorded simultaneously, and panel (e) shows several vehicles travelling in opposite directions. At 1360 s and 35.8 km in panel (e), one truck overtakes another, producing clearly distinguishable differences in apparent velocity. The corresponding $f-k$ representations are shown in panels (b), (d), and (f). These panels show that all vehicles generate seismic waves with apparent velocities between 200 and 2200 m/s, with the majority of the energy concentrated from 200 to 500 m/s. While all vehicle types produce similar apparent velocity ranges, a single truck generates notably higher signal amplitudes than cars, even when three cars are recorded simultaneously.

The $f-k$ spectra in Fig. 6 focus on the low-frequency content of the three traffic examples. Clear linear ridges are visible at apparent velocities consistent with the road speed limit of 22.2 m/s. The sign of the wavenumber indicates the direction of travel, energy at positive wavenumbers corresponds to vehicles moving away from the interrogator unit, and vice versa. Panel (c) is particularly informative, containing multiple ridges corresponding to vehicles travelling at different speeds and in opposite directions. The fastest vehicle travels well above the speed limit at 27–28 m/s, while the slowest travels at approximately half that speed. The majority of vehicles travel close to the speed limit. We interpret these low frequency signals to be generated by the vehicle's weight pushing on the pavement. At each time instance the vehicle pushes on the subsurface, it produces a velocity field of an expanding half sphere (a full sphere if the source were inside the subsurface). This is translated along the vehicle's trajectory, creating the signatures in the $t-x$ and $f-k$ domains.

To further investigate how source-receiver distance affects the recorded amplitude, we analyse a single truck driving northward along E6. During the analysed time window, the source-receiver distance varies from ~ 15 m to a few hundred metres. This variation in distance provides valuable information that can be used to characterise the low-frequency signal and how it can be used to distinguish vehicles from avalanche signatures. Figure 7 illustrates how the varying distance affects the recorded signal amplitude. Panels (a) and (c) show traces corrected using the apparent speed of the vehicle (to align the traces) and colour-coded by extraction time (the same vehicle as shown in Fig. 5). Panel (a) shows the higher-frequency content, dominated by surface waves, while panel (c) shows the lower-frequency content. By extracting the maximum strain amplitude and

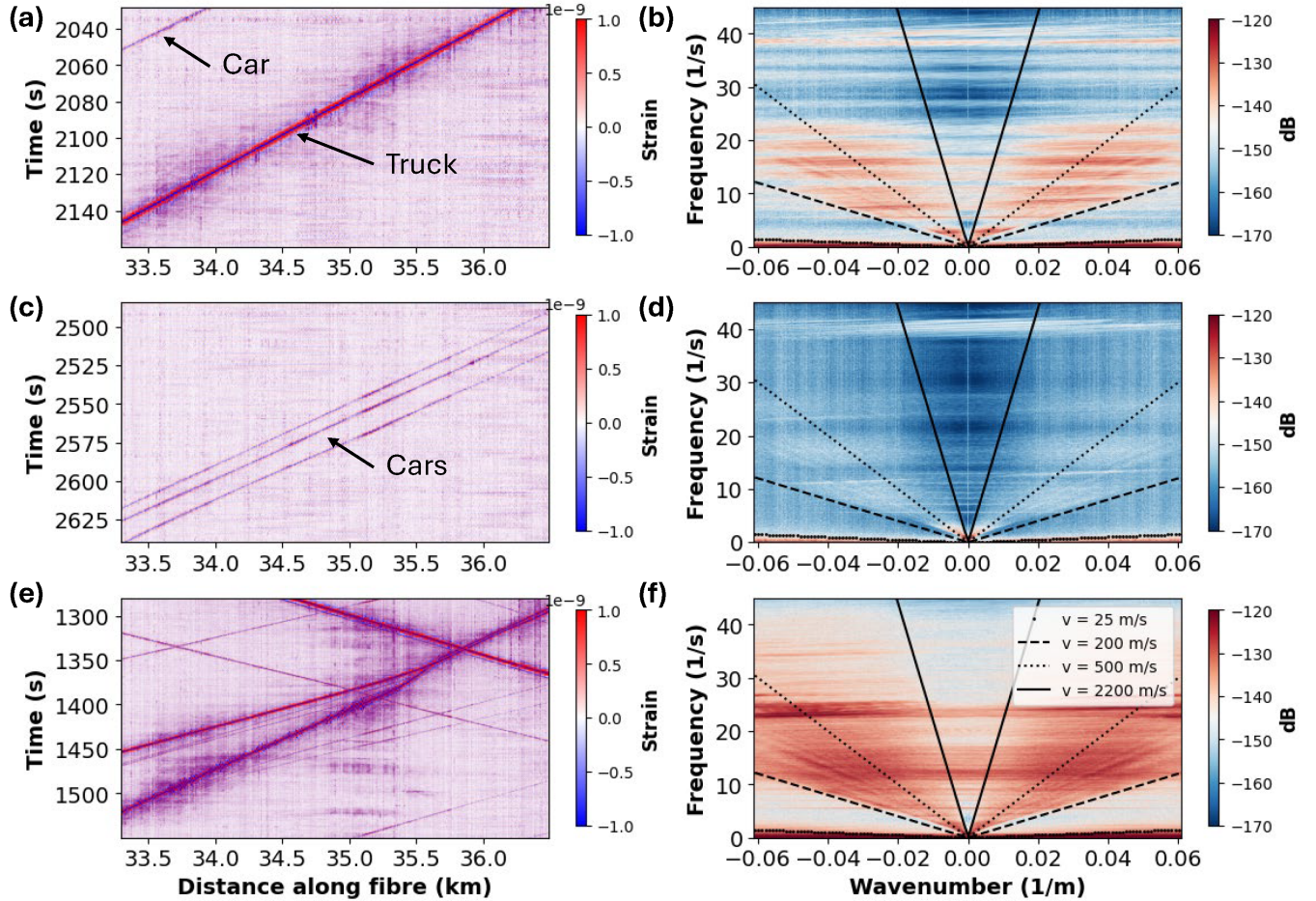


Figure 5. Typical t - x and f - k signatures for road vehicles observed in the DAS data. (a) The t - x domain of a truck and (b) the corresponding f - k domain of a truck. (c) and (d) the same for three cars driving in the same direction parallel to the fibre. (e) and (f) many vehicles driving in both directions along the fibre.

its corresponding channel at each time step, we examined how seismic energy decays with increasing distance from the fibre. The higher-frequency surface wave amplitude in panel (b) decays as $r^{-1/2}$, consistent with the expected geometrical spreading of Rayleigh waves (Stein and Wysession, 2003). In contrast, the low-frequency energy in panel (d) decays faster, following an r^{-3} relationship. Interestingly, this decay agrees with that of signatures (translating hydrodynamic pressure fields) generated by ships sailing at the sea surface (Rørstadbotnen and Landrø, 2025).

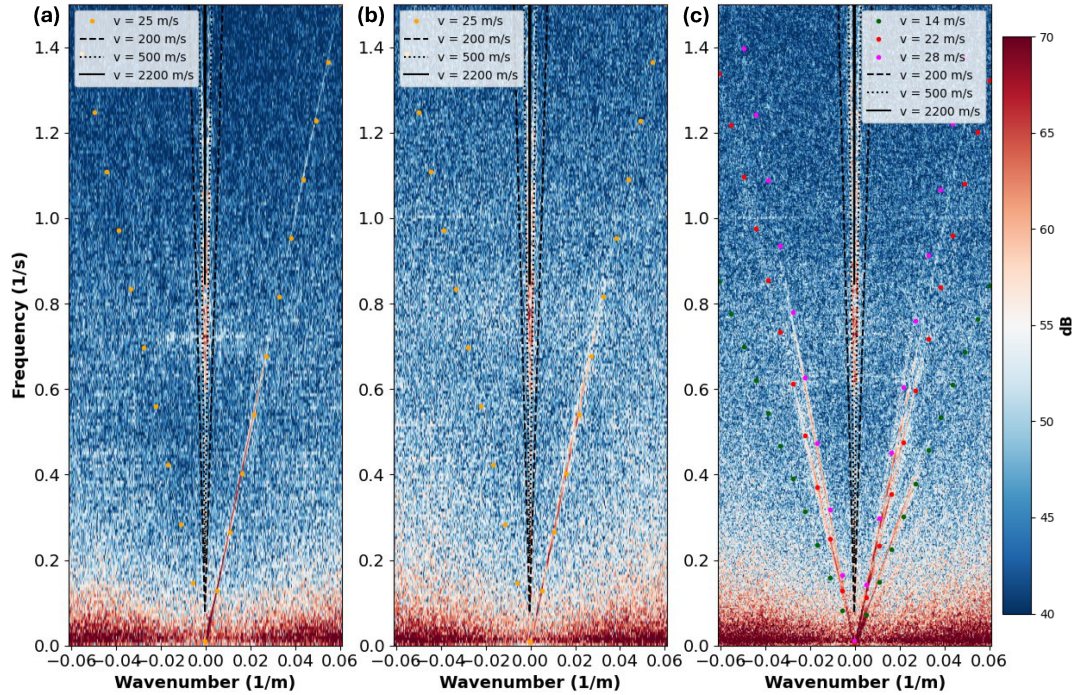


Figure 6. The low frequency content of the example in Fig. 5. Clear linear ridges can be observed, which originate from a moving source. (a) Single truck. (b) Three cars. (c) Many vehicles.

3.3.4 Controlled rockfall experiments

During the acquisition period, two controlled rockfall experiments were carried out. The first took place on 27 March 2025, during which rocks of various sizes were released from a point ~ 16 m above the landing zone, falling ~ 13 m vertically over a horizontal distance of ~ 14 m, and landing primarily on snow at distances of 0–3 m from the rail. Figure 8 shows the results: panel (a) presents the experiment in the t – x domain, panel (b) the corresponding f – k representation, and panel (c) a photograph taken after the experiment. Over ten rocks were dropped in total, producing a signal lasting 7–8 s with high amplitudes concentrated near the drop zone. Coherent seismic waves propagated approximately 300 m along the fibre (17.48–17.88 km from IU) at a velocity of around 2.0 km/s. A clear asymmetry in the wavefield is observed due to the proximity of a tunnel on one side of the drop zone (17.33–17.48 km from IU); upon entering the tunnel, the waves were strongly attenuated and propagated no more than 150 m in that direction, consistent with the strong attenuation observed in Section 3.3.1. The f – k representation reveals two distinct waves propagating at approximately 2.2 km/s and 0.9 km/s respectively, suggesting the presence of multiple seismic phases.

The second experiment took place on 8 January 2026, during which a single rock was dropped by an excavator from approximately 3 m above the ground, coming to rest roughly 6 m from the nearest point on the fibre. Figure 8 shows the

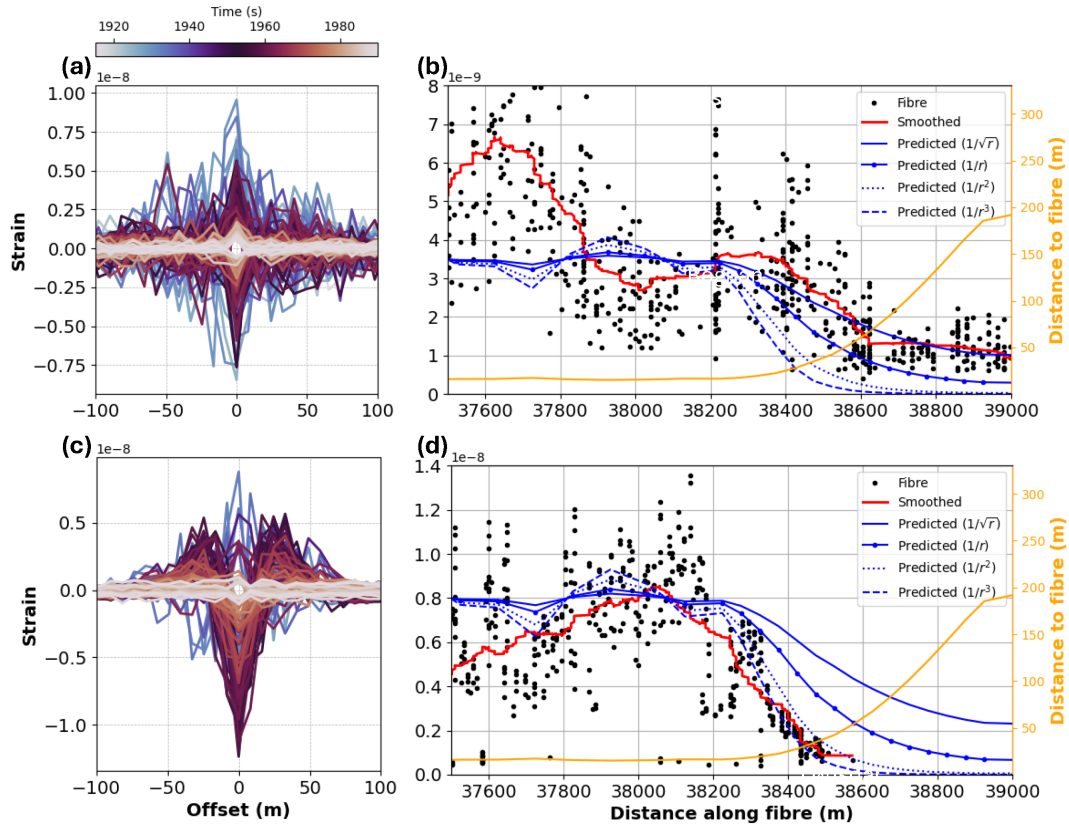


Figure 7. Decay of surface waves and the velocity field of an expanding sphere as created by a truck. (a) Amplitude along fibre from individual channels over a time period where the source-receiver distance decreases. (b) Strain amplitudes (black dots) extracted for each time sample where the truck is observable overlaid by distance from the truck to the fibre and various decay functions. (c) and (d) the same for the low frequency velocity field signal.

results: panel (d) presents the $t-x$ domain signal, panel (e) the corresponding $f-k$ representation, and panel (f) a photograph taken just before the rock hit the ground. Similar trends to the first experiment are observed in both domains: coherent seismic waves propagated at approximately 2.2 km/s in both directions along the fibre, with signal amplitudes strongest at the fibre channel closest to where the rock impacts the ground. The $f-k$ representation shows a similar response to that in panel (e), but with lower resolution due to the shorter signal duration. Apparent velocities of around 2.2 km/s are similarly observed in this panel.

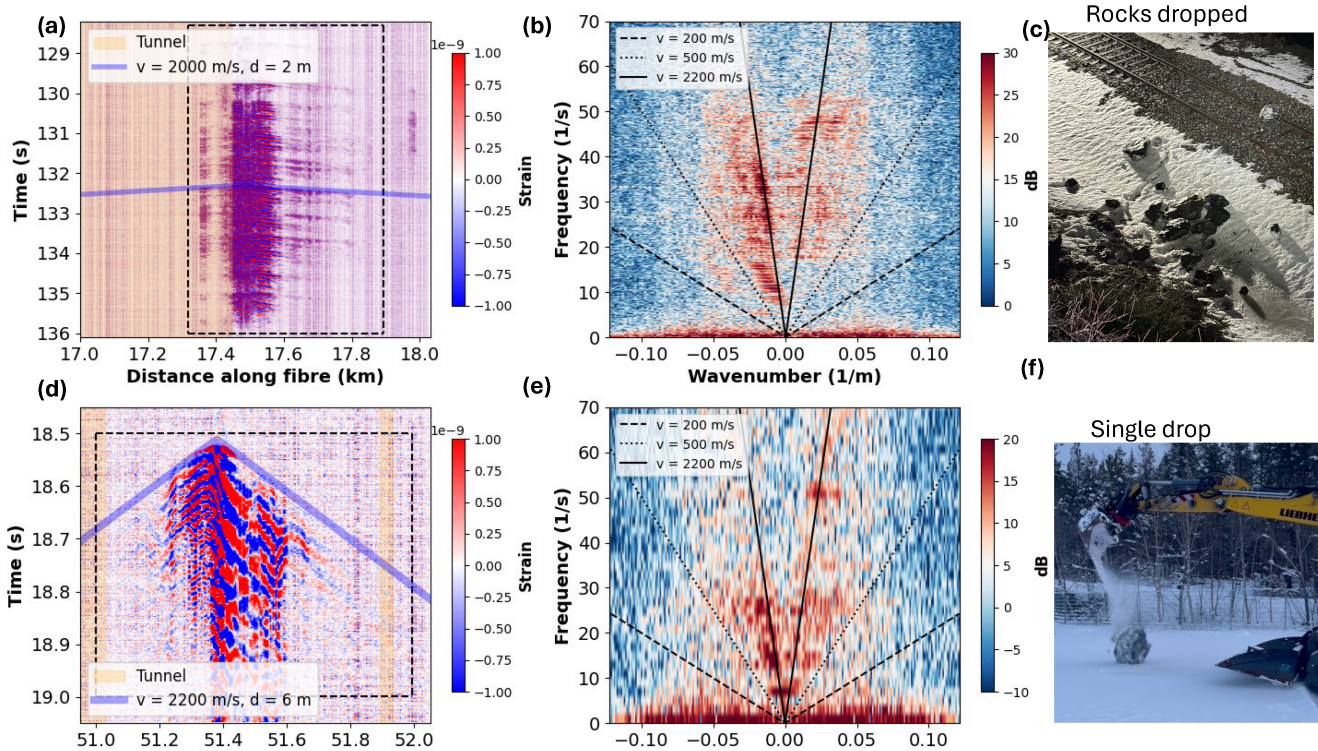


Figure 8. Different controlled rock avalanche signatures in the t - x and f - k domains. (a), (b) The controlled rock avalanche in t - x and f - k domains, respectively. (c) The drop zone after the experiment. (d), (e) An example of a single rock drop in t - x and f - k domains, respectively. (f) The rock before it hit the ground.

3.3.5 Real avalanches

During the acquisition period, two natural rockfall events of different sizes were recorded. The first occurred on 14 May 2025 and consisted of at least one large boulder together with a considerable amount of soil (Fig. 9(f)). The material travelled roughly 20–30 m before coming to rest approximately 15 m from the rail. The t - x plot in Figure 9(d) shows that the event lasted approximately 10 s and produced observable signals along 3 km of fibre. Compared to the controlled rockfall experiment, fewer individual impacts are apparent; only two clear hyperbolic arrivals were observed, with apices at 59 and 61 s. The seismic waves generated when the material hit the ground near the fibre propagated through sections where the fibre overlies surficial deposits (e.g., 49.3–49.8 km) as well as through tunnel sections (e.g., 49.0–49.3 km). Seismic energy appears to be trapped within the surficial deposits in the former sections. In contrast, waves travel directly through the tunnels with no residual trapped energy.

The corresponding f - k representation is shown in Fig. 9(e). In contrast to the controlled rockfall experiment, no clear seismic phases are visible, although energy is concentrated over the same apparent velocity range. We attribute this to the

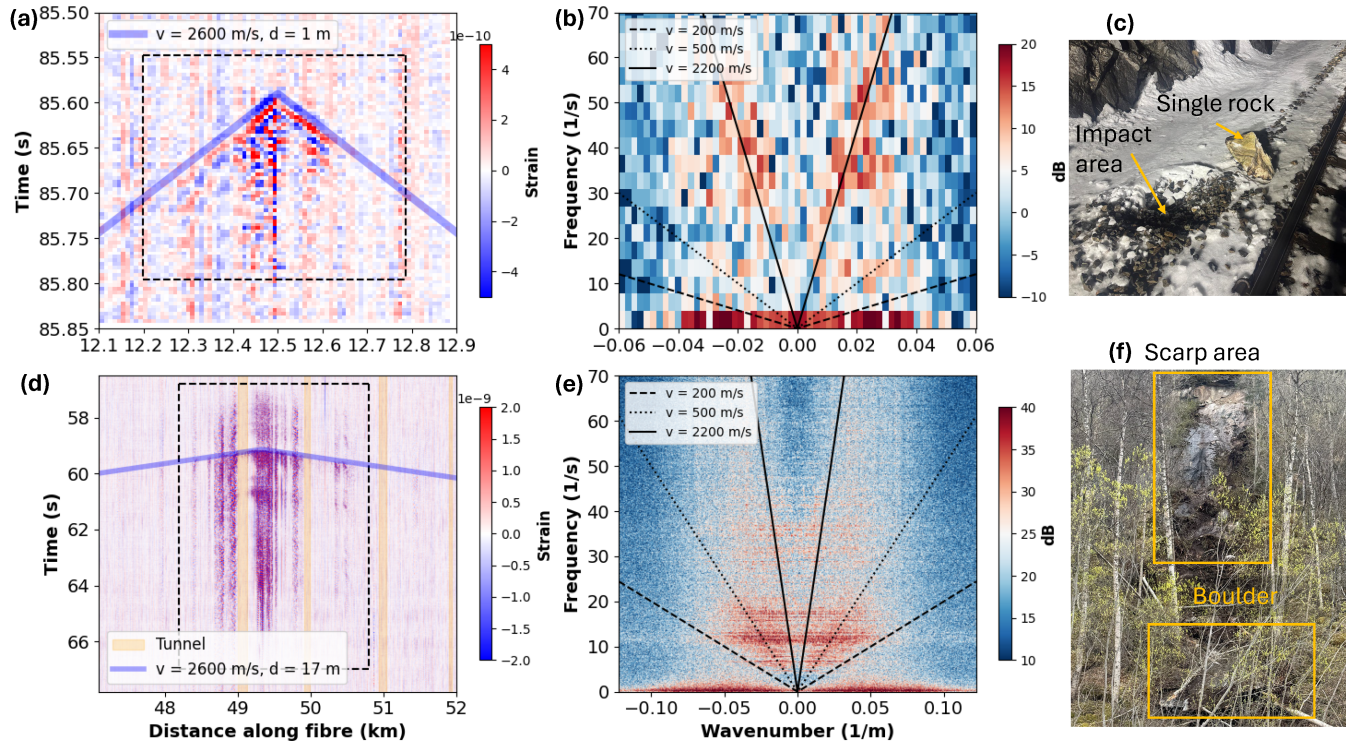


Figure 9. Different real rockfall signatures in the $t-x$ and $f-k$ domains. (a), (b) An example of a single rock that landed close to the fibre cable in $t-x$ and $f-k$ domains, respectively. (c) The rock that landed close to the fibre. (d), (e) The real rock avalanche in $t-x$ and $f-k$ domains, respectively. (f) The avalanche.

alternating near-surface geology along the recording section. This rapid lateral variation in amplitude along the fibre distorts the $f-k$ representation, resulting in the absence of coherent seismic phases.

The second natural rockfall occurred on 2 March 2026, during which a single rock came to rest 25–50 cm from the rail. Figure 9(a) shows the $t-x$ plot, in which a short-duration signal was observed with an apparent velocity of 2.2 km/s. The impacting rock was smaller than the one used in the second controlled rockfall experiment, and the signal was consequently recorded over a smaller fibre segment of approximately 400 m and for a shorter duration. Several weaker hyperbolic signatures were observed prior to the main impact signal (not shown), which we interpret as successive impacts of the rock as it descended the slope, as well as impacts from other rocks that came to rest on the slope before reaching the railway. Figure 9(b) shows the corresponding $f-k$ representation, in which the majority of the energy is concentrated at apparent velocities between 0.5 and 2.2 km/s.



4 Results and Discussion

245 Surface waves generated by trucks are strong and clearly visible at frequencies below 25 Hz, as seen in both the t - x plots in Fig. 5 and the f - k representations in Fig. 11. The apparent velocities of these signals range from 200 to 500 m/s, consistent with Rayleigh waves. Road traffic along E6 travels at a roughly constant lateral distance of 15–17 m from the fibre. At this offset, surface waves impinge on the fibre at an incidence angle close to 90° , at which the fibre is maximally sensitive to axial strain. As surface waves propagate away from the vehicle that generated the Rayleigh waves, the incidence angle decreases, and the recorded signal weakens accordingly due to the DAS's axial sensitivity. In contrast, seismic waves generated by a source located closer to the railway, such as a rock or avalanche impacting the ground at lateral offsets of 0–10 m, impinge on the fibre at a less favourable angle, resulting in weaker recorded signals. Moreover, the short duration and relatively small size of the rocks that fell during the avalanche result in limited generation of surface waves, with the majority of the captured seismic energy being compressional waves and shear waves. In addition, the vehicles act as moving sources, whereas rockfalls release their energy within a confined section of the fibre rather than translating along it. Because a rockfall source does not move along the fibre, it produces no moving-source signature, as confirmed by its absence in the 0.2 to 1.5 Hz band in Fig. 11. Both the fact that the rock avalanches do not generate any moving-source energy in the 0.2 to 1.5 Hz band and the limited amount of surface-wave energy in the 1.5 to 5 Hz band make them readily distinguishable from moving vehicles.

260 The velocities estimated using the hyperbolic fitting in Section 3.2 provide an additional quantitative basis for this discrimination. Figure 10 shows the fitted hyperbolas on top of the t - x data for the six event classes analysed in this study, and Table 1 summarises the fitted velocities. For the car and the truck, we find velocities of 24–25 m/s. These do not correspond to a seismic wave but to the speed of the vehicles themselves. This occurs as the strongest signal on each channel is recorded as the vehicle passes it, the onset of this signal is therefore picked and we are tracing the vehicle trajectory. We manually overlay hyperbolas to find the apparent velocities of the surface wave generated by the vehicles. The result is shown in Fig. 10 (a) and (d) and we find that the apparent velocities correspond to 430 m/s. Another feature is that the trucks generate much more surface wave energy compared to regular passenger cars, likely due to the trucks extra weight. For the controlled and real rockfall events, the fitted velocities are 1.2–2.6 km/s, consistent with body waves propagating in the near surface. The estimates from road vehicles and rockfalls differ by two orders of magnitude, meaning the fitted velocity clearly separates them.

270 The accuracy of the fitted velocities depends on the quality of the automatic picks. Since each pick is taken at the strongest amplitude on its channel, the method implicitly assumes that the first arrival is the dominant signal on every channel. This assumption breaks down where the first arrival is weak. The clearest example is the controlled single drop, for which the fit gives 1240 m/s against a manual overlay of 2200 m/s. Here the first arrival is weaker than the later arrivals on several channels (Fig. 8(a)). The picks then trace a combination of several arrivals instead of a single wavefront, which biases the fitted velocity towards lower values.

275 Based on the signal characteristics shown in this study, rock avalanche signals recorded by DAS along the railway are distinguishable from other coherent noise sources, including those from road vehicles, earthquakes, and trains. For road vehicles, the dominant frequencies and apparent velocities differ from those of rockfalls; signals related to vehicle movement are

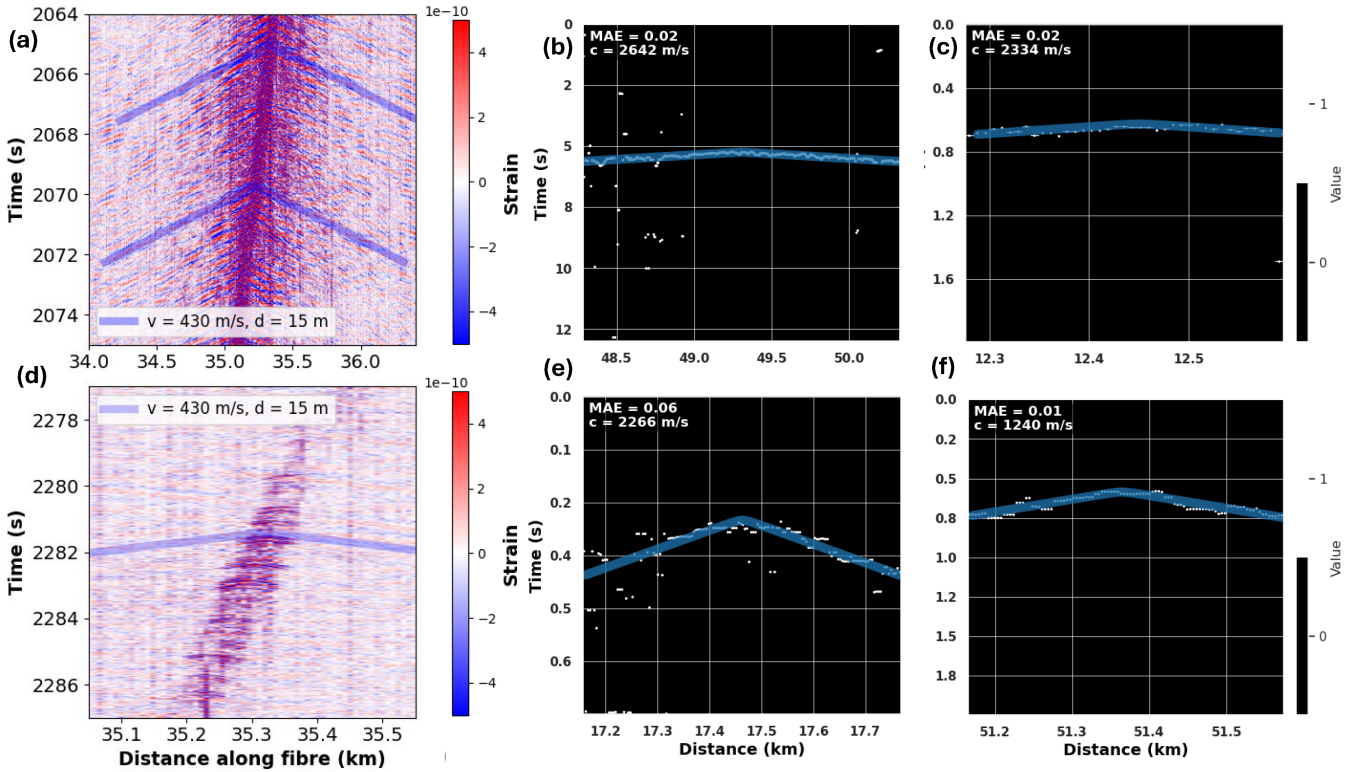


Figure 10. Hyperbolic fits to the t - x signatures of the six event classes analysed in this study. (a) Truck. (b) Real rock avalanche. (c) Real single rockfall. (d) Car. (e) Controlled rock avalanche. (f) Controlled single rock drop. (a), (d) the band-pass filtered DAS data of road vehicles with manual hyperbola overlaid. (b), (c), (e), (f) The fitted hyperbola and the datapoints used. The annotations give the estimated propagation velocity and the normalised mean absolute error (MAE) of the fit.

concentrated in the 0.2–1.5 Hz band and decrease rapidly in amplitude with increasing source-receiver distance. Moreover, the vehicles generate Rayleigh waves as they drive, which are observed at apparent velocities of 0.2–0.5 km/s. Rockfall signals span higher frequencies and apparent velocities compared to these. Figure 11 illustrates this contrast in the f - k domain for two vehicle examples alongside controlled and natural rockfall events. Earthquake signals exhibit apparent velocities of 0.5–2.2 km/s, intermediate between those of vehicles and rockfalls. They are characterised by lower dominant frequencies than rockfall signals. Taken together, these spectral and apparent velocity differences provide a basis for discriminating rock avalanche signals from both vehicle and earthquake noise. Trains present a more challenging case. They pass along the track several times per day and generate the highest signal amplitudes across the widest frequency band of any source recorded in this study. The amplitudes are sufficiently high that the nearest DAS channels saturate, rendering the data unusable. As a consequence, an avalanche occurring simultaneously with a passing train at the same location would not be distinguishable



Table 1. Velocities estimated from the hyperbolic fits for the six event classes shown in Figure 10. For the car and the truck, the fitted velocity corresponds to the speed of the vehicle, whereas the fitted values for the rockfall events corresponds to the propagation velocity of the seismic waves. Values in parentheses give the normalised MAE of the fit (dimensionless; see Section 3.2). The manual overlaid hyperbolas are shown with the associated velocities used.

Event	Fitted velocity - m/s (norm. MAE)	Manual overlay - m/s
Car	24 (0.01)	430
Truck	25 (0.01)	430
Controlled single drop	1240 (0.01)	2200
Controlled rock avalanche	2266 (0.06)	2000
Real single rockfall	2334 (0.02)	2600
Real rock avalanche	2642 (0.02)	2600

from the train signal. This represents a fundamental limitation of the current monitoring setup that needs to be studied in future work.

290 The smallest rockfall captured by the DAS system involved a rock measuring $0.4 \times 0.3 \times 0.2$ m (volume ≈ 0.024 m³), with an estimated mass of 40–50 kg assuming a granite lithology typical of the area. The signal generated by the rock's impact was clearly visible in the DAS data over approximately 400 m and with a duration of 0.2–0.3 s. By comparison, the larger rock dropped during the second controlled experiment (200–300 kg) generated seismic energy detectable over approximately 1 km and lasting 1.5–2.0 s. Sporadic impulsive events with hyperbolic moveouts were observed along the fibre that produced signals
 295 similar to those of single rockfall impacts. Note that these signals occurred in areas without steep slopes adjacent to the railway and cannot be attributed to rockfalls. Without knowing the avalanche risk of an area, such signals could easily be misinterpreted as single rockfall events. Characterising these signals in terms of their geophysical properties and spatial distribution along the fibre is left for future research. Nevertheless, events involving multiple rocks impacting the ground simultaneously or in rapid succession will produce combined signatures that are readily distinguishable from both single-rock impacts and impulsive
 300 noise sources.

An automatic, near-real-time rockfall detection and warning system represents a natural next step following this study. Building on the signal characteristics documented here, such a system would analyse the continuous DAS stream for impulsive events and classify each one as rockfall or non-rockfall. The classification would use the differences in dominant frequency, apparent velocity, and moving-source behaviour to distinguish rockfalls from anthropogenic noise. By operating continuously
 305 along the full length of the fibre, the system could locate each rockfall accurately enough to support early warning and, subsequently, help with traffic management. The rockfall signals characterised in this work, together with the traffic, train, and earthquake signals documented alongside them, would form the basis of a labelled training dataset, helping to minimise false-positive detections. Restricting detections to slopes mapped as avalanche-prone during the tap-test could further reduce false alarms by screening out sporadic impulsive events observed earlier along flat sections.

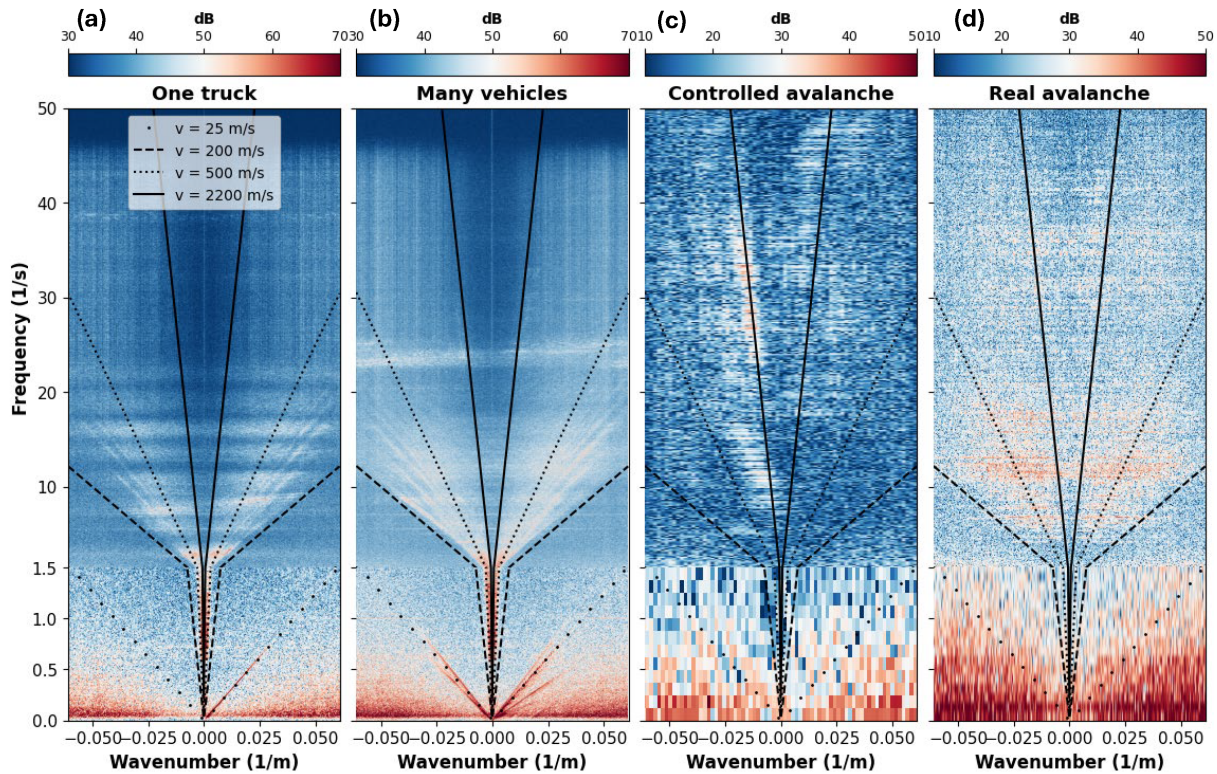


Figure 11. Frequency-wavenumber comparison between vehicle and avalanche signatures. The y -axes have been separated into two intervals to highlight the differences in signatures and frequency content. (a) One truck driving along the fibre. (b) Many vehicles driving along the fibre. (c) The controlled rock avalanche. (d) The real rock avalanche.

310 5 Conclusions

In this study, we investigated how rock avalanche signals recorded by a distributed acoustic sensing (DAS) system deployed along a fibre-optic cable running parallel to a Norwegian railway could be detected and distinguished from other coherent noise sources, including road vehicle traffic, trains, and earthquakes. Signal characterisation was performed in both the time-distance and frequency-wavenumber domains, complemented by hyperbolic moveout fitting to identify and characterise individual events that occurred along the fibre cable.

A tap-test, using signals generated by both a Robel maintenance train and sledgehammer shots, was conducted to correlate individual DAS channels with their geographical coordinates along the railway. This test revealed a clear correlation between the type of surficial deposits beneath the fibre and the strength of the recorded signal. To further investigate this relationship, we analysed signals generated by a freight train and an earthquake. In both cases, signals recorded in sections where the fibre overlies a thick layer of surficial deposits were more energetic and reverberated for longer than signals recorded in sections where the fibre is in direct contact with bedrock, such as within tunnels.



We recorded a range of rockfall events, from relatively small impacts of approximately 50 kg to larger multi-rock avalanches involving soil and boulders. To complement the natural observations, two controlled rockfall experiments were carried out in which rocks of various sizes were dropped along the railway. These rockfall events exhibited consistent signal characteristics, including similar frequency content and apparent propagation velocities.

Road vehicle traffic was recorded along a large proportion of the fibre. It was characterised by lower dominant frequencies and lower apparent propagation velocities than rockfall signals. By applying hyperbolic fitting to the seismic waves generated by vehicles and avalanches, we found that their apparent velocities along the fibre differed. The vehicles generated consistently lower velocities of 0.43 km/s compared to avalanches that generated velocities exceeding 2 km/s. Furthermore, vehicles are continuously moving sources and generate persistent low-frequency energy. This characteristic is absent in rockfall signals, which provides an additional basis for discrimination. Trains produced the highest signal amplitudes of any source recorded in this study, passing within a few metres of the fibre and saturating the nearest DAS channels. This saturation renders rockfall signals occurring in the immediate vicinity of a passing train effectively undetectable, representing a key limitation of the current system. Trains also generate airwaves upon entering tunnels, which propagate along the fibre like vehicle signals but at higher apparent velocities.

The results presented in this study demonstrate that DAS, using fibre-optic cables already installed along railway corridors, is a promising, operationally attractive approach to continuous rockfall monitoring in mountainous terrain. The ability to discriminate rockfall signals from the anthropogenic noise sources provides a basis for developing automated, near-real-time early-warning systems. Such systems have the potential to improve railway safety in areas with elevated rockfall and avalanche hazards, where the consequences of undetected events can be severe.

Code and data availability. The code and data used to generate the figures shown in this work will be made available on DataverseNO upon acceptance.

Author contributions. RAR (Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing—original draft), KH (Formal analysis, Investigation, Visualization, Writing, review & editing), KT (Methodology, Software, Visualization, Writing, review & editing), ML: (Methodology, Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing, review & editing), JE: (Methodology, Conceptualization, Supervision, Validation, Writing, review & editing), AIAP: (Conceptualization, Project administration, Writing, review & editing), RB: (Conceptualization, Project administration, Writing, review & editing)

Competing interests. The authors declare that there is no conflict of interest.



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