



Three decades of permafrost seismic velocity variations from ambient noise at the SPITS array, Svalbard

Konstantinos Kalaitzis¹, Andreas Köhler^{1,2}, Charlotte Bruland², and Alfred Hanssen¹

¹UiT The Arctic University of Norway, Tromsø, Norway

²NORSAR, Gunnar Randers Vei 15, Kjeller, Norway

Correspondence: Konstantinos Kalaitzis (konstantinos.kalaitzis@uit.no)

Abstract. Permafrost degradation in the High Arctic significantly impacts slope stability, infrastructure, and climate-related processes. However, long-term geophysical observations of subsurface mechanical changes remain scarce. We analyse more than three decades (1992–2025) of continuous recordings from the Spitsbergen Seismic Array (SPITS) near Longyearbyen, Svalbard, and interpret relative seismic velocity variations (dv/v) from ambient-noise interferometry as a path-averaged tracker of seasonal thermo-hydrological change in the active layer and uppermost permafrost. We begin by evaluating the quality and continuity of the SPITS data, accounting for changes in instrumentation and data availability across the array. The ambient noise field is characterized through probabilistic power spectral density analysis and frequency–wavenumber beamforming, which reveal seasonal variability and dominant directions of noise sources. Daily noise correlation functions are estimated between inter-station and single-station component pairs and stacked using several robust estimators to enhance signal stability under the variable noise conditions of the Arctic environment. Relative seismic velocity variations (dv/v) are then estimated from the coda of stacked correlations using the stretching method. Our analysis yields two key observations: (i) while the directional noise field varies seasonally, compatible with a mixture of far-field ocean-generated noise and regional environmental sources, it is more stable for the surface wave contribution used for dv/v , and (ii) seasonal dv/v fluctuations and long-term trends correspond closely with soil temperature and ground thermal conditions in the 2 m to 4 m range, particularly during freeze–thaw transitions. Long-term dv/v suggests a velocity decrease of $0.033\% \text{ decade}^{-1}$ since 1992, which is consistent with the recent Arctic warming. These results underscore the sensitivity of ambient noise interferometry for capturing long-term permafrost dynamics. Our study extends previous noise analyses of the SPITS array to its full operational period and to all available sensor components, and highlights the potential of seismic arrays for long-term monitoring of Arctic cryospheric processes in a changing climate.

1 Introduction

Permafrost, defined as ground that remains at or below 0°C for at least two consecutive years, underlies approximately 15% of the Northern Hemisphere land surface and is a critical component of the Arctic cryosphere (Obu et al., 2019). In the context of accelerating climate change, permafrost degradation has emerged as a major concern, with implications for slope and infrastructure stability, carbon cycle feedbacks, and ecosystem dynamics (Schuur et al., 2015; Biskaborn et al., 2019).



25 The high-Arctic Svalbard archipelago, where mean annual air temperatures at Svalbard Airport have increased at a rate of approximately 0.32°C per decade since 1898 (Nordli et al., 2020), provides an ideal natural laboratory for studying permafrost dynamics and their geophysical signatures. Traditional monitoring approaches, such as borehole temperature measurements, provide point-scale observations but are spatially limited and may not capture the full extent of subsurface thermal changes or mechanical responses.

30 Ambient seismic noise interferometry has revolutionized the field of passive seismology by enabling the extraction of empirical Green's functions from the cross-correlation of ambient noise recordings between pairs of seismic stations (Campillo and Paul, 2003; Shapiro and Campillo, 2004; Shapiro et al., 2005; Campillo, 2006; Bensen et al., 2007). This technique exploits the statistical properties of ambient seismic noise to retrieve information about wave propagation between seismic stations. By cross-correlating continuous noise recordings and stacking the correlations over time, coherent wave arrivals emerge that,
35 under suitable conditions, approximate the inter-station Green's function. The resulting correlation functions contain information about the subsurface structure and can be used to monitor temporal changes in seismic velocity ($\delta v/v$, commonly written dv/v), which are sensitive to a wide range of environmental processes including temperature variations, fluid content changes, stress perturbations, and mechanical deformation (Snieder et al., 2002; Sens-Schönfelder and Wegler, 2006; Wegler and Sens-Schönfelder, 2007; Brenguier et al., 2008; Hadziioannou et al., 2011; Obermann et al., 2013; Larose et al., 2015; Bruland et al., 2025). In permafrost environments, seismic velocity variations are particularly sensitive to freeze–thaw cycles, ice content changes, and thermal expansion–contraction of the subsurface, making ambient noise interferometry a powerful tool for continuous, non-invasive monitoring of permafrost dynamics (Overduin et al., 2015; Abbott et al., 2016; James et al., 2019; Albaric et al., 2021; Liu et al., 2024; Gajek et al., 2026; Zhao et al., 2026). Complementary evidence comes from controlled heating experiments, in which distributed acoustic sensing resolved active permafrost thaw and degradation in real time
45 (Cheng et al., 2022).

The Spitsbergen Seismic Array (SPITS), located on Janssonhaugen in central Spitsbergen, has been continuously operational since 1992 and represents one of the longest-running seismic arrays in the Arctic. The array's unique combination of long-term operation, high-quality broadband instrumentation, and location within a well-characterized permafrost environment has enabled several studies of Arctic and cryospheric seismicity and environmental processes. Early work at SPITS focused
50 on regional seismic monitoring (Bowers et al., 2001; Gibbons et al., 2011) and array processing techniques, including cross-correlation and three-component beamforming (Ruigrok et al., 2017), but more recent studies have exploited the array's capabilities for environmental monitoring. Previous studies have explored glacier-related seismicity in the Svalbard region using SPITS data, revealing processes such as glacier calving and surging (Köhler et al., 2015; Nuth et al., 2019; Köhler et al., 2022). Furthermore, Albaric et al. (2021) applied ambient noise interferometry to SPITS data to monitor seismic velocity variations
55 and demonstrated correlations between velocity changes and subsurface temperature fluctuations, providing the first direct evidence of permafrost thermal dynamics recorded seismically at this site. Most recently, Romeyn et al. (2022) documented the occurrence of frost quakes (cryoseisms) at SPITS associated with rapid cooling events, demonstrating the sensitivity of seismic monitoring to thermal stress in permafrost.



Building on Albaric et al. (2021), this study extends ambient-noise interferometry at SPITS with a clear interpretive focus: dv/v is used to track seasonal thermo-hydrological change—ground cooling and freezing versus warming and thawing—and the longer-term mechanical imprint of shallow permafrost warming. First, we expand the temporal coverage to include the full operational period of the array (1992–2025), enabling investigation of long-term and interannual variability in seismic velocity potentially related to permafrost thermal evolution and climate forcing (Liu et al., 2024; Steinmann et al., 2021). Second, we implement and evaluate a comprehensive suite of stacking methods to optimize the signal-to-noise ratio of correlation functions and assess the robustness of velocity monitoring estimates (Yang et al., 2023). Third, we conduct more detailed characterization of the ambient noise wavefield using multitaper spectral estimation (Thomson, 1982; Percival and Walden, 1993), probabilistic power spectral density analysis (McNamara and Buland, 2004), and frequency–wavenumber (F–K) beamforming (Rost and Thomas, 2002) to better understand noise source distributions, propagation characteristics, and their temporal variability across seasonal to interannual timescales (Stehly et al., 2006). Finally, we systematically evaluate processing parameters and quality control criteria (Bensen et al., 2007) to ensure reliable velocity monitoring, with particular attention to the challenges posed by the array’s instrumentation evolution and the Arctic noise environment. In addition, unlike Albaric et al. (2021), who relied mainly on vertical-component cross-correlations, we additionally analyse single-station cross-component and multi-component inter-station cross-correlations as complementary diagnostics within the same processing framework.

Relative to prior permafrost interferometry studies in Alaska (James et al., 2017, 2019), alpine sites (Lindner et al., 2021), and the first SPITS demonstration (Albaric et al., 2021)—which recovered dv/v over only a few years—the present work is distinguished by its full operational archive (1992–2025). Outside cryospheric settings, ambient-noise dv/v series of comparable length remain rare: multi-decadal examples include roughly 30 years at the Gräfenberg array (Lecocq et al., 2017), about two decades in Taiwan (Feng et al., 2021), and about 20 years across California (Clements and Denolle, 2023). At more than three decades, the SPITS record is therefore among the longest continuous ambient-noise dv/v time series reported to date and, to our knowledge, the longest yet obtained for permafrost. Combined with systematic multi-component evaluation, archive-aware quality control, and a time-domain stretching estimator in place of the frequency-domain method used at SPITS by Albaric et al. (2021), this baseline allows seasonal and decadal subsurface changes at Janssonhaugen to be assessed with far greater temporal weight than earlier short-window analyses.

This paper is organized as follows. Sect. 2 describes the study area, including the geological and environmental context of Janssonhaugen, the SPITS array configuration, and the available temperature and meteorological data. Sect. 3 characterizes the ambient noise wavefield. The spectrograms are shown in that section and the PPSD histograms in the Supplement materials. The frequency–wavenumber results that inform the selection of the analysis frequency band are presented in the same section. Sect. 4 details the preprocessing workflow, correlation estimation, waveform-coherence evaluation, and stacking of daily correlation functions (Sect. 4.4). Sect. 5 presents the estimation of relative seismic velocity variations. Sect. 6 reports the dv/v results; Sect. 7 interprets them in the context of permafrost monitoring and prior work; and Sect. 8 summarizes the main findings.



2 Study area and data

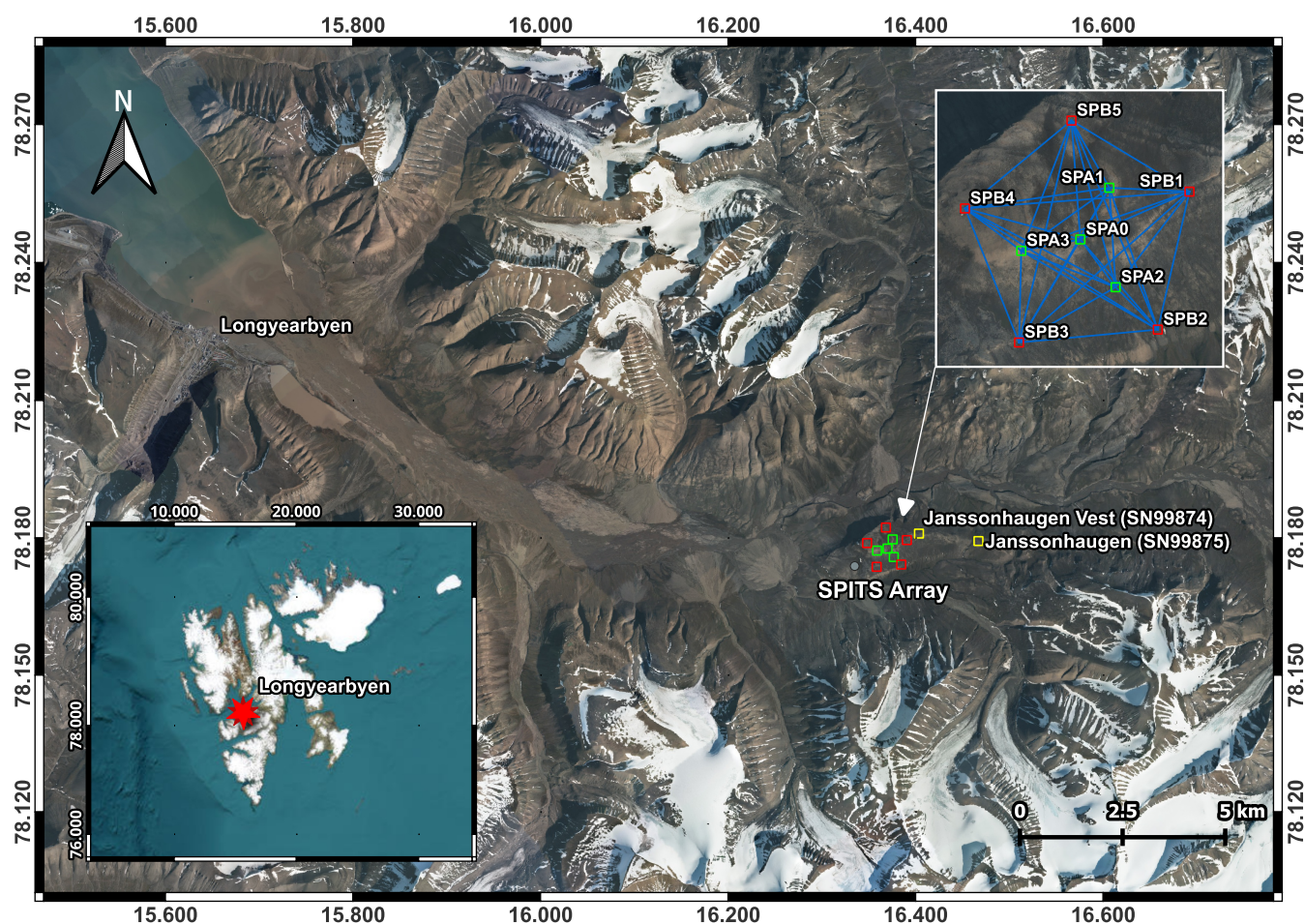


Figure 1. Satellite orthophoto overview of the SPITS seismic array near Longyearbyen, Svalbard. The main panel shows topography and array location; a regional inset places the study area on the Svalbard archipelago (star at Longyearbyen). A zoom inset shows the station geometry and all unique inter-station baselines used in cross-correlation. Longyearbyen is labelled on the main map. The Met Norway weather station Janssonhaugen Vest is marked by its station number SN99874; Janssonhaugen appears as SN99875. Graticule, north arrow, and scale bar indicate orientation and distance. Orthophoto © Norwegian Polar Institute (<https://npolar.no>). Map created using the Free and Open Source QGIS (QGIS Development Team, 2026).

2.1 Geological and environmental context

Janssonhaugen is a gently sloping bedrock ridge in the central part of Adventdalen, a valley in central Spitsbergen, part of the high-Arctic Svalbard archipelago (Fig. 1). The site exhibits a thin weathered sedimentary cover (0.2 m to 0.3 m) overlying bedrock of the Ullaberget Member of the Lower Cretaceous Rurikfjellet Formation, composed mainly of homogeneous sand-



stone and siltstone (Dypvik et al., 1991; Isaksen et al., 2001). The bedrock displays a density of approximately 2280 kg m^{-3} and a porosity of 20–25%, with a composition that is predominantly ($> 96\%$) SiO_2 . Temperature profiles obtained from borehole measurements indicate the presence of continuous permafrost to depths of approximately 220 m, based on thermal gradients measured to 102 m (Isaksen et al., 2001).

The annual precipitation range is between 300 mm to 500 mm yr^{-1} ; however, minimal snow accumulation is observed because strong prevailing winds frequently remove the snow cover (Isaksen et al., 2001). The landscape is largely flat to gently sloping and is characterized by polygonal surface structures indicative of cryoturbation and ice-wedge formation. These geomorphic and climatic conditions favour relatively stable ambient seismic noise, with homogeneous bedrock and seasonal snow cover modulating the contribution of wind and coastal processes to the recorded wavefield.

The region experiences a polar night from early October to late February, during which the sun remains below the horizon. Despite the absence of solar radiation, there are considerable fluctuations in daily temperatures, driven by synoptic-scale cyclones and advection of warm air masses from lower latitudes onto Spitsbergen (Łupikasza and Niedźwiedź, 2019). These meteorological processes, in conjunction with variations in snow cover and latent heat flux, generate considerable spatial and temporal variability in near-surface thermal conditions (Westermann et al., 2009). At Janssonhaugen, observations from the P11 temperature-monitoring borehole (GTN-P) and the Janssonhaugen Vest weather station show near-surface temperatures typically ranging from summer maxima of approximately 10°C to 15°C to winter minima of -20°C to -25°C , with seasonal amplitudes decreasing with depth and an active-layer thickness of about 2 m (Isaksen et al., 2001; Christiansen et al., 2010; Norwegian Centre for Climate Services, 2025).

2.2 Seismic stations

The Spitsbergen Seismic Array (SPITS) is a small-aperture permanent broadband array and auxiliary station of the International Monitoring System of the CTBTO situated on Janssonhaugen (Fig. 1). The array is located approximately 10 km southeast of Longyearbyen, the main settlement on Svalbard. SPITS has been continuously operational since 1992 and is operated by NORSAR (Schweitzer et al., 2021). The array consists of nine broadband seismometers (SPA0–SPA3 and SPB1–SPB5) arranged on two concentric rings with diameters of approximately 500 m and 1 km, resulting in inter-station distances greater than 250 m (Schweitzer et al., 2021). Each sensor is installed within a shallow borehole at a depth of approximately 6 m below the active layer of the permafrost with the aim of mitigating the effects of ground thawing, wind, temperature variations, and anthropogenic noise. Six stations are equipped with three orthogonal components (vertical, north–south, and east–west), and three stations (SPA1–SPA3) only record the vertical component. Since its installation, the SPITS network has undergone a series of instrumentation upgrades summarized in Table 1 (Schweitzer et al., 2021). Some SPITS stations experienced data-quality issues during specific time periods, including clock drift and polarity reversals of the horizontal components (Appendix, Table A1).



Table 1. Instrumentation evolution of the SPITS array

Period	Instrumentation
1992–1994	Initial deployment with S-500 short-period sensors, recording only the vertical component (SHZ) at 40 Hz.
1994–2004	Replacement with Güralp CMG-3E broadband seismometers (100 s period to 50 Hz frequency response). Sampling rate: 40 Hz. One station (SPB4) was upgraded to three-component recording during this period.
2004–2015	Upgrade to Güralp CMG-3T/3TB sensors paired with DM24 digitizers. Only SPA0 and SPB1–SPB5 record three components (BHE, BHN, BHZ); SPA1–SPA3 remained vertical-only. Sampling rate: 80 Hz.
2015–present	Channel codes changed from “BH*” to “HH*” to reflect higher dynamic-range digitizers. Sampling rate: 80 Hz. All subsequent hardware replacements and calibrations are documented in the metadata.

For this study, we retrieved continuous seismic waveform data spanning January 1992 to December 2025 through FDSN from the Norwegian node of the European Integrated Data Archive (EIDA), jointly operated by the University of Bergen and
130 NORSAR (Ottemöller et al., 2021). The underlying SPITS recordings form part of the NORSAR station network (NORSAR, 1971). Waveforms were acquired as daily segments organized by station, year, and Julian day. We reviewed StationXML metadata and local archives to document step changes in instrumentation, sampling rate, and channel nomenclature (Table 1), and we reconciled the data collection with NORSAR’s internal storage by removing duplicates and completing incomplete epochs so that the final data set is internally consistent.

135 **2.3 Permafrost and temperature monitoring**

Long-term permafrost monitoring at Janssonhaugen is conducted within the framework of the Global Terrestrial Network for Permafrost (GTN-P). Two boreholes, designated P10 (102 m depth) and P11 (15 m depth), have been utilized for the continuous recording of subsurface temperature since April 1999 at 6-hour intervals (Isaksen et al., 2001). The P11 borehole, situated at a depth of approximately 13 m from P10, facilitates comprehensive observations of the shallow thermal regime (see Fig. 1).
140 Thermistors have been installed at depths ranging from 0.2 m to 15 m to ensure precise measurement of temperature variations. These sensors have been shown to capture both the ~2 m-thick active layer (Christiansen et al., 2010) and the upper permafrost, thereby documenting significant interannual variability in summer thawing, winter cooling, and a persistent long-term warming trend.

The Janssonhaugen Vest weather station (Fig. 1), which was installed in September 2019, provides additional meteorological
145 data by recording hourly air temperature and shallow ground temperature (0.1 m depth). When combined with borehole data, these records permit detailed comparisons of surface and subsurface thermal dynamics, thereby providing valuable environmental context for interpreting temporal changes in seismic velocities and ambient noise levels.



3 Characterization of the ambient noise wavefield

Before estimating ambient-noise correlation functions, we first examine the statistical and spectral behavior of the seismic wavefield. This step constrains frequency content, temporal variability, and directionality of the noise sources, which are all needed to choose robust processing parameters and frequency bands for cross-correlation, and to guide interpretation of the estimated velocity variations. To capture variability across time scales, we estimate yearly spectrograms to track seasonal and meteorological effects. In this section, wavefield characterization is based on multitaper spectral estimation for probabilistic power spectral density analysis and F–K analysis.

3.1 Probabilistic power spectral density analysis

To quantify how ambient-noise power spectra varies through time, we apply probabilistic power spectral density (PPSD) analysis (McNamara and Buland, 2004). We have chosen to obtain our PSD estimates by means of Thomson’s multitaper (MT) spectral estimation method (Thomson, 1982). The multitaper estimator has been shown to optimally reduce spectral leakage and variance simultaneously compared with conventional single-taper and segment averaging methods (Bronez, 1992). This is particularly important for ambient seismic noise where coloured spectra are common and stable estimates are required from finite records. The MT spectral estimation method relies on the use of a set of optimal orthogonal data tapers known as Discrete Prolate Spheroidal Sequences (DPSS) (Slepian, 1978). Useful multidimensional extensions are discussed by Hanssen (1997).

For SPITS data analysis, we apply multitaper spectral estimation to 60 s windows of continuous recordings from all nine stations, with a 30 s step size (50% overlap) to ensure adequate temporal sampling for the spectrograms. With a sampling rate of $f_s = 80$ Hz, each window contains $N = 4800$ samples. We choose a time–bandwidth product $NW = 3.5$, so the design half-bandwidth is $W = (NW)/N$ in normalized frequency. The associated Shannon number $2NW$ is the approximate dimension of the space of sequences that are essentially time-limited to N samples and band-limited to $[-W, W]$ (Slepian, 1978; Thomson, 1982). Correspondingly, only the first $\approx 2NW$ DPSS have concentration eigenvalues λ_k close to unity and therefore provide leakage resistance; eigenvalues then drop rapidly, and higher-order tapers concentrate poorly within the design band and therefore contribute excessive out-of-band leakage. To retain well-concentrated tapers while excluding leaky ones, we use

$$K = \lfloor 2NW - 1 \rfloor = 6, \quad (1)$$

where $\lfloor \cdot \rfloor$ denotes the floor operator (Percival and Walden, 1993). Averaging K approximately independent eigenspectra yields an approximate variance reduction of order $1/K \approx 1/6 \approx 0.16$ relative to a single taper, without paying for that reduction with uncontrolled leakage.

By default, the McNamara-style ObsPy (Beyreuther et al., 2010) PPSD uses 3600 s segments with a 1800 s step (50% overlap), yielding a coarser temporal cadence but improved low-frequency stability/resolution for yearly histogram statistics. At $f_s = 80$ Hz, this corresponds to $N_{\text{pps}} = f_s \cdot 3600 = 288,000$ samples per PPSD segment. Histogram accumulation uses 0.5 dB power bins, providing a statistical description of ambient-noise levels over long time spans (typically one year). In our implementation, we modified the ObsPy PPSD source path so that the per-segment Welch-type periodogram estimator



180 (Welch, 1967) is replaced by a Thomson multitaper estimator (DPSS), while preserving the original McNamara-style histogram aggregation workflow. The resulting variance reduction and robust aggregation stabilize the PPSD and improve interpretability of temporal noise variability within the target frequency bands. For PPSD analysis, instrument response was removed using the corresponding StationXML metadata and spectra were expressed as ground-acceleration power for comparison with the Peterson noise models (Peterson, 1993; McNamara and Buland, 2004). Days or segments with missing or inconsistent response
 185 metadata were skipped. For visualization and interpretation, we generate two types of figures: (1) multitaper spectrograms showing the time–frequency evolution of power spectral density for each component, and (2) PPSD histograms displaying the probability distribution of power levels as a function of frequency, with mean PSD curves overlaid for reference.

The PPSD results (Supplement, Fig. S1) indicate that across most periods, the modal and mean PSDs at SPITS lie between NLNM and New High Noise Model (NHNM). The long-period band exhibits generally moderate-to-low ambient noise, with
 190 the highest-probability PSD levels still close to the Peterson New Low Noise Model (NLNM) at around 10 s period (Peterson, 1993). The highest noise levels are observed as expected in the microseismic band (approximately 0.05 Hz to 0.3 Hz; 3 s to 20 s period). Persistent high-probability energy is observed, with PSD values on the order of -160 to -110 dB, consistent with sustained primary and secondary microseism forcing. At shorter periods down to about 0.5 s, still elevated levels are observed, consistent with stronger local environmental contributions, e.g., wind noise, coastal swell and cryospheric sources.
 195 Higher frequencies (>2 Hz) show systematically low noise levels, consistent with limited anthropogenic noise sources in the area. Although small inter-component differences remain, the three components display broadly similar power distributions. This indicates that no single component consistently dominates the recorded noise power, but it does not establish isotropy of the wavefield. Directionality is assessed independently using the F–K analysis described below.

The multitaper spectrograms (Fig. 2) resolve persistent and seasonally modulated structure in the SPITS ambient-noise field
 200 over the full calendar year at frequencies up to 40 Hz. Below roughly 3 Hz, power forms a persistent low-frequency floor, likely influenced by installation and site response, onto which seasonally and synoptically varying environmental energy is superimposed, including contributions from wind, near-surface thermal processes, and longer-period ambient forcing. From late June or July through September, power in the 2 Hz to 10 Hz band increases broadly and persistently. This melt-season enhancement is consistent with contributions from surface runoff and flowing water, active-layer thaw, and cryoseismic and
 205 ice-related activity—including glacier calving—in Adventdalen and neighboring valleys and fjords. The microseism band (approximately 0.05 Hz to 0.3 Hz) is examined in greater detail in the probabilistic power spectral density (PPSD) analysis (Supplement, Fig. S1). At 20 Hz to 35 Hz, short-lived vertical streaks, typically lasting from minutes to a few hours, and isolated broadband bursts indicate transient local or regional sources. These features are consistent with anthropogenic or cryoseismic activity, while some of the brief broadband signals may also represent regional seismic events; however, the spectrograms
 210 alone do not permit unambiguous source attribution. Some records (e.g. SPA0 in 2016 and SPB2 in recent years) exhibit slowly drifting ridges at approximately 15 Hz to 38 Hz over weeks to months. Changing subsurface resonances, such as those reported by Köhler and Weidle (2019), appear unlikely to provide the primary explanation for this frequency drift because the observed features show no clear relationship with active-layer thawing and freezing. We therefore interpret the gliding features as more consistent with near-site anthropogenic or installation-related sources, potentially including activity at the nearby



215 Grube 7 coal mine, where production ceased on 30 June 2025. Band-power tests in the 15 Hz to 38 Hz range (Supplement,
 Fig. S2) support an anthropogenic contribution: at SPB2, median power is approximately 1 dB higher during 08:00–20:00 UTC
 than during the night, consistent with the daily timing of work-related activity. The day–night contrast is strongest in July 2018
 and remains positive during July–December 2018, coinciding with peak production at Grube 7, whereas overall power is lower
 during July–December 2025 following mine closure. Although these temporal relationships are consistent with a contribution
 220 from Grube 7, they do not uniquely identify the mine as the source. Note however that the observed drifting ridges are outside
 the frequency band we use for dv/v and are therefore not crucial to uniquely identify.

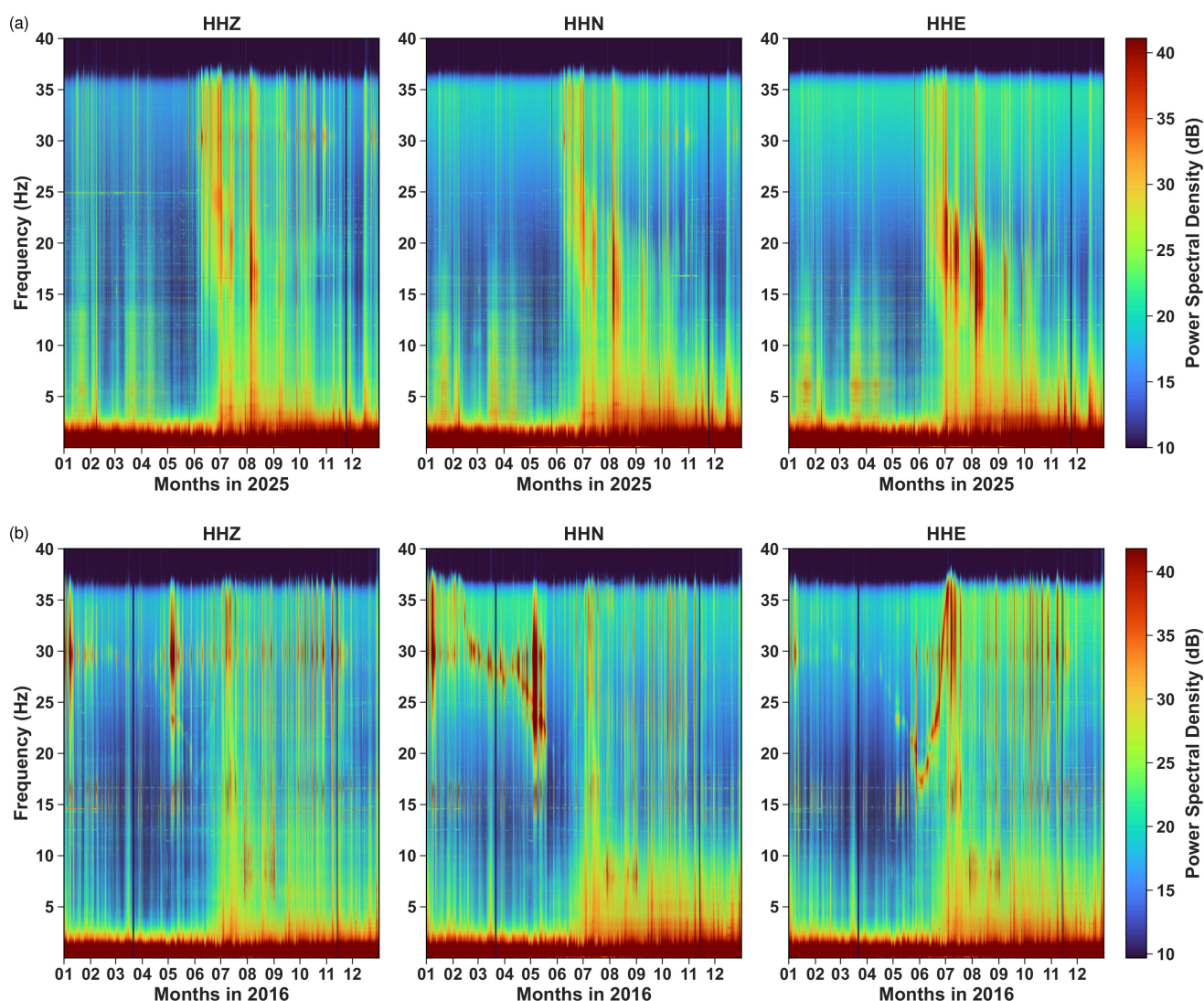


Figure 2. Multitaper spectrograms showing power spectral density (dB) as a function of time and frequency for the vertical (HHZ) and horizontal (HHN, HHE) components. (a) 2025. (b) 2016.



3.2 Frequency–wavenumber analysis

The benefit of a small-aperture seismic array such as SPITS is that beamforming techniques can be applied to investigate the propagation properties of the seismic wavefield. To examine directional wavefield properties and propagation behaviour, we
 225 apply frequency–wavenumber (F–K) analysis. The outputs are the dominant arrival direction, expressed as back-azimuth, the apparent horizontal slowness, and the beam power of the coherent ambient-noise energy. We use Bartlett (delay-and-sum) beamforming, in which traces are time-shifted according to a candidate propagation direction and coherently summed to form the beam. Bartlett beamforming was selected for its stability and interpretability for the SPITS array (Rost and Thomas, 2002).

We apply F–K analysis to the vertical components of all nine stations for representative years of continuous recordings. To
 230 resolve synoptic-to-seasonal variability, the continuous records are split into non-overlapping 3 h windows. Within each 3 h window, F–K analysis is performed on shorter, overlapping time segments. The segment length is chosen according to the frequency band to balance temporal resolution and spectral stability: 30 s segments for the 0.5–2.0 Hz band and 20 s segments for 1.5–4.5 Hz. Shorter segments are used at higher frequencies to maintain adequate frequency resolution while capturing rapid temporal variations. For each segment, we compute beam power on a 2D slowness grid and estimate the apparent horizontal
 235 slowness, back-azimuth, and semblance (a coherence metric quantifying the quality of the beamforming result) at maximum beampower. We use a maximum slowness of 1.2 s km^{-1} and a step of 0.2 s km^{-1} for the grid search. The results from all segments within each 3 h window are aggregated. Slowness–time histograms are built with 0.02 s km^{-1} bins from all retrieved segments, without a slowness cut-off, so that the full beamformed slowness distribution is displayed (Fig. 3b,c). Note that in the figures, each 3 hour segment count histogram is normalized with the maximum number of counts in that window. Back-
 240 azimuth–time histograms (Fig. 4) are shown both restricted to $s \in [0.33, 1.0] \text{ s km}^{-1}$ (a, b), following Albaric et al. (2021), and over the full scanned slowness range (c, d). Hourly wind speed and direction at Janssonhaugen Vest are shown in Supplement, Fig. S4.

To relate directional and slowness variability to meteorological forcing, we overlay hourly air temperature and surface air pressure on the F–K time series (Figs. 3 and 4), following the approach of Albaric et al. (2021), who compared slowness
 245 and back-azimuth with concurrent environmental series but did not identify the meteorological station. Because no co-located surface-pressure record was available near SPITS during their 2009–2013 study period, those series were most likely taken from Svalbard Airport (SN99840), approximately 22 km from the array in Adventdalen. We instead use Janssonhaugen Vest (SN99874), within about 1 km of the array, with air temperature from 2020 and surface pressure from 2022 onward (Sect. 2), which we consider more representative of the meteorological conditions governing near-surface wave propagation and cryo-
 250 seismic activity in the immediate study area. Hourly wind speed and direction at the same site provide additional context for near-field noise forcing (Supplement, Fig. S4).

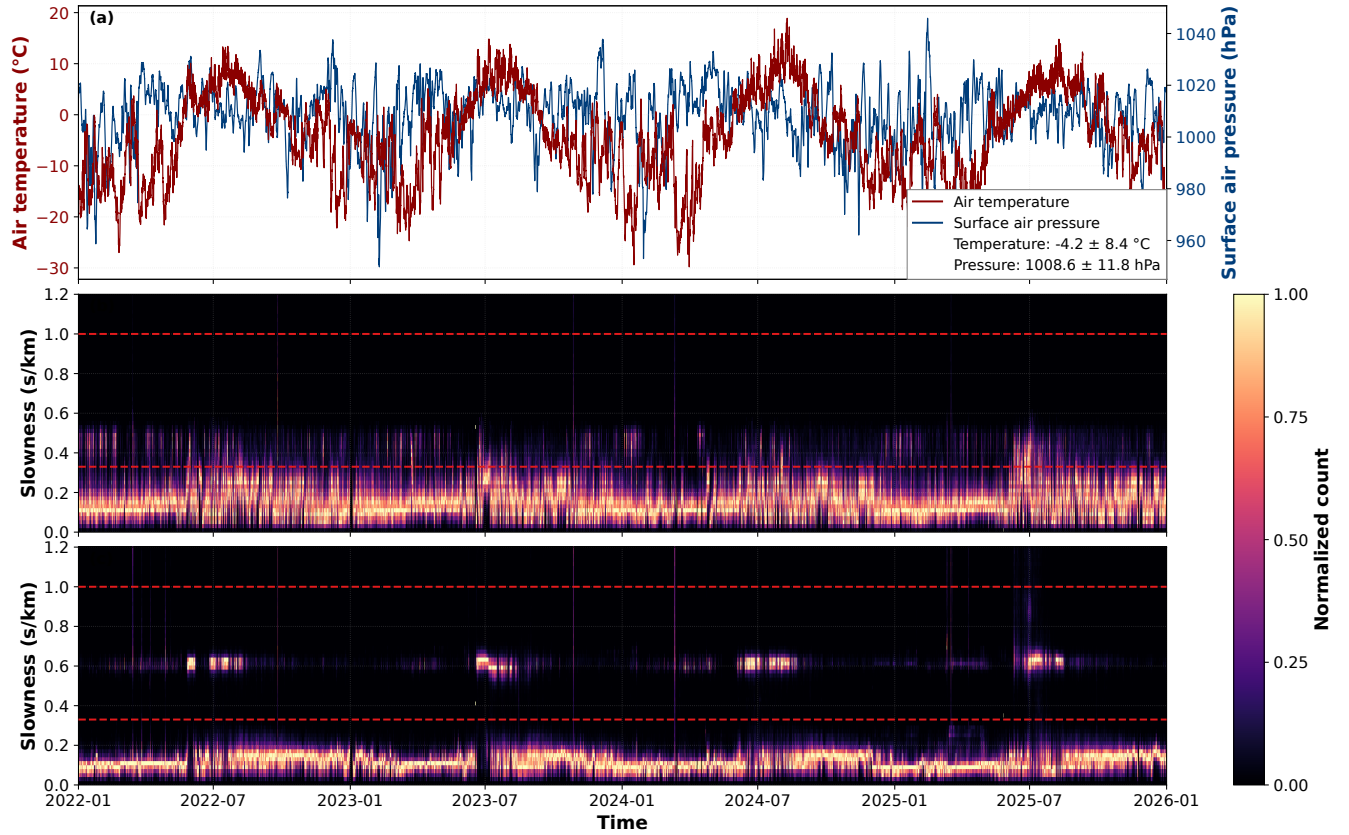


Figure 3. Janssonhaugen Vest (SN99874) meteorology and 3 h F–K slowness histograms (2022–2025). (a) Hourly air temperature and surface air pressure. (b) Normalized slowness distribution versus time in the 0.5 Hz to 2.0 Hz band (all retrieved slownesses). (c) Same as (b) for 1.5 Hz to 4.5 Hz. Red dashed lines mark $s \in [0.33, 1.0]$ s km⁻¹, the slowness gate used for the restricted back-azimuth histograms. Colour scale: normalized count within each 3 h bin (0–1). Month on the time axis; vertical gaps indicate periods without usable array data.

In addition, we generate daily polar F–K power maps (slowness–back-azimuth distributions; full slowness range) for each year (Supplement, Fig. S3). For visualization of seasonal transitions, we select, for each month, the daily map with the largest band-averaged beam power among available records, which highlights intervals when coherent array energy is strongest and therefore most informative of month-to-month changes in the illuminating field.

The F–K summaries for 2022–2025 (Figs. 3 and 4) reveal directionally selective propagation regimes that vary with time. In the slowness–time histograms (Fig. 3b,c), most of the energy is concentrated at apparent horizontal slownesses of approximately 0.1 s km⁻¹ to 0.4 s km⁻¹, with intermittent contributions at higher slownesses. These values correspond to apparent horizontal velocities, $V_{\text{app}} = 1/s$, of approximately 2.5 km/s to 10 km/s. The upper part of this velocity range is too high for typical surface waves. Although steeply incident body waves would generally map to low horizontal slowness on the F–K grid, the wave type cannot be determined uniquely from apparent horizontal slowness alone. Therefore, body-wave contributions



to the ambient-noise field, particularly along the low-slowness branch, are likely. The limited SPITS aperture (~ 1 km) also reduces the resolution of the lowest-slowness estimates.

The two frequency bands exhibit different slowness distributions. In the 0.5 Hz to 2.0 Hz band (Fig. 3b), the principal lobe is relatively broad, whereas in the 1.5 Hz to 4.5 Hz band (Fig. 3c), the dominant energy is concentrated near $\sim 0.1 \text{ s km}^{-1}$ ($V_{\text{app}} \sim 10 \text{ km/s}$). This shift toward lower slowness at higher frequency is opposite to the trend commonly expected for fundamental-mode Rayleigh-wave dispersion. However, a quantitative interpretation would require a subsurface velocity model, predicted dispersion curves, and an assessment of the array response. The high-frequency, low-slowness branch may therefore be dominated partly by body-wave energy. By contrast, the intermittent summer streaks near $\sim 0.6 \text{ s km}^{-1}$ ($V_{\text{app}} \sim 1.7 \text{ km/s}$) are more compatible with surface-wave propagation, although a definitive phase identification is not possible from the present F–K analysis alone.

F–K therefore describes the azimuthal-dominant incident array wavefield, whose low-slowness branch is compatible with body-wave or steeply incident energy. However, relative velocity variations in Sect. 5 are not necessarily measured on the dominant wave field contribution: dv/v is measured on the reconstructed correlation coda after the ballistic (first) arrival. Hence, F–K dominance of low slowness does not imply a body-wave dv/v product. The back-azimuth–time histograms in Fig. 4c,d use the full slowness range of the F–K analysis, so that changes in the illuminating noise field, including the dominant low-slowness branch, are not excluded from the wavefield description. The slowness-gated panels (Fig. 4a,b) restrict the same histograms to $s \in [0.33, 1.0] \text{ s km}^{-1}$. This restricted range corresponds to apparent horizontal velocities of 1 km/s to 3 km/s and is used to emphasize the presence of slower arrivals that are more compatible with surface-wave propagation. Following the same reasoning as Albaric et al. (2021), these waves are more likely to contribute dominantly in the correlation coda window used for dv/v .

The full back-azimuth distributions are non-uniform and vary seasonally. Prominent energy occurs between approximately 100° and 170° , corresponding broadly to the east to south-southeast sector, while another persistent contribution occurs between approximately 300° and 360° , corresponding to the northwest through north sector. In the higher-frequency band, the seasonal enhancement near 150° occurs at approximately the same times as the higher-slowness arrivals in Fig. 3c. This temporal correspondence suggests that the slower summer arrivals originate predominantly from this direction.

The lower-frequency band appears directionally more stable throughout the year when restricting the interpretation to the surface wave slowness range $s \in [0.33, 1.0] \text{ s km}^{-1}$, despite some seasonal changes in beam power, whereas the higher-frequency band shows stronger seasonal reorganization. Such changes in the directional and wave-type composition of the noise field may alter the reconstructed correlations and could therefore bias coda-based dv/v estimates. This potential effect is expected to be less pronounced in the primary 0.5 Hz to 2.0 Hz analysis band than at higher frequencies, but it should nevertheless be considered when interpreting seasonal dv/v variations. The monthly polar maps for 2011 (Supplement, Fig. S3) similarly show pronounced month-to-month changes, with the dominant noise sectors shifting between the eastern and northwestern quadrants.

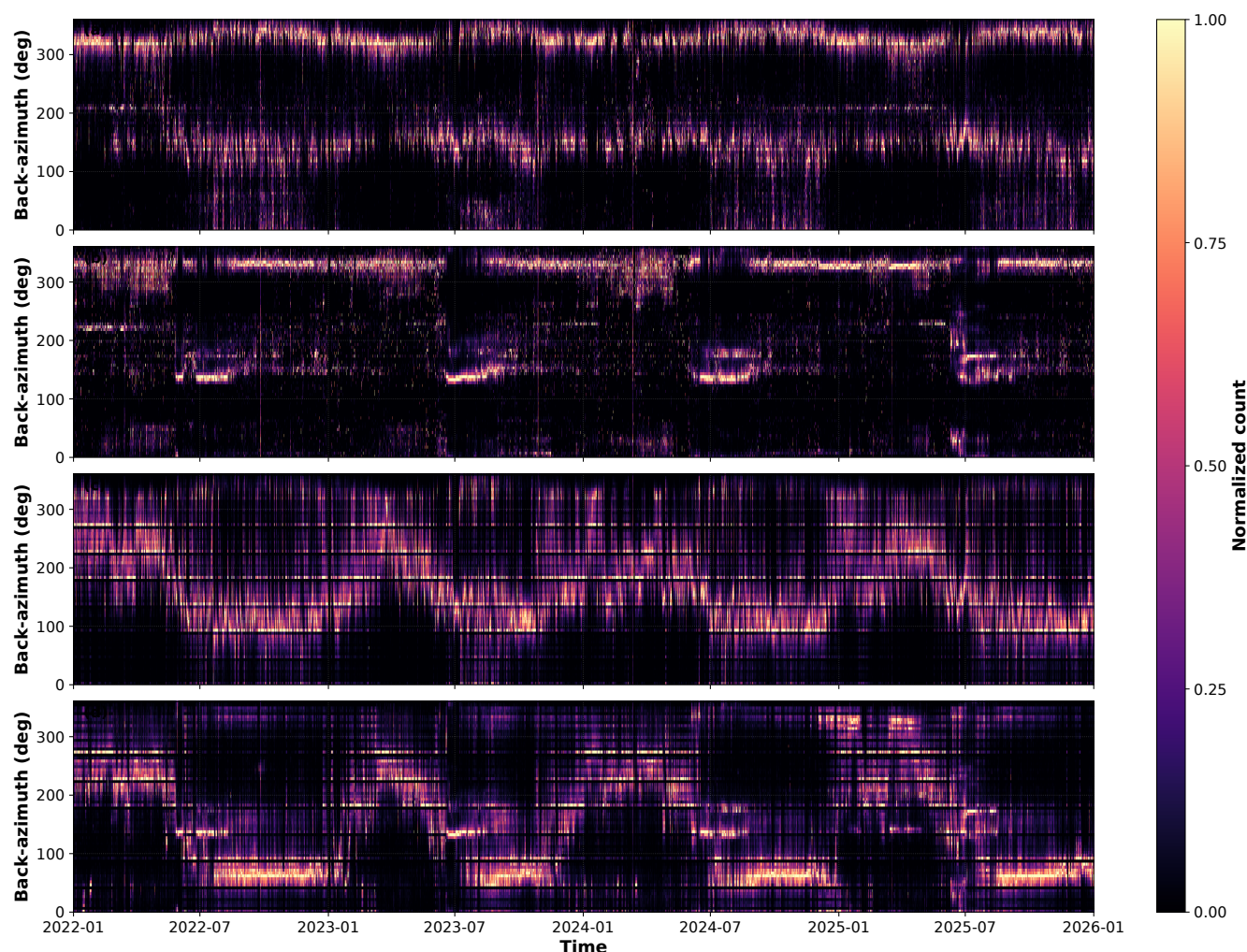


Figure 4. Three-hour F–K back-azimuth histograms at SPITS (2022–2025). **(a)** Normalized back-azimuth in the 0.5 Hz to 2.0 Hz band for $s \in [0.33, 1.0] \text{ s km}^{-1}$; **(b)** same as (a) for 1.5 Hz to 4.5 Hz; **(c)** same as (a) without a slowness threshold (all retrieved slownesses); **(d)** same as (b) without a slowness threshold. Colour scale: normalized count within each 3 h bin (0–1). Month on the time axis; vertical gaps indicate periods without usable array data.

295 Attribution of specific back-azimuth sectors to particular noise source regions would require assessing if great-circles are
 consistent with storm tracks, which is beyond the scope of this study. Nonetheless, the persistence of low-slowness, horizontally
 organized F–K energy in this band is broadly compatible with the distributed, far-field character of secondary microseism noise
 fields and with long-range propagation from active North Atlantic source regions at high northern latitudes (Stehly et al., 2006),
 while the seasonally varying eastern-sector weight may additionally reflect changes in local/regional noise sources related to
 300 cryospheric processes during the melt seasons or other competing source distributions.



4 Estimation of ambient seismic noise correlation

Notation and discretization. We formulate signals, correlation functions, and estimators in continuous time and distinguish among three levels. First, the continuous ground-motion signal at channel i is represented by a real-valued random process $x_i(t)$. The quantity $s_{i,d,k}(t)$ denotes the preprocessed finite segment recorded at channel i on day d , with segment index k , and is treated as a realization of an underlying wide-sense stationary and ergodic process $s_i(t)$. Second, ensemble (true) quantities are statistical properties of the underlying processes. For example, the interchannel cross-correlation is defined as

$$C_{ij}(\tau) = \mathbb{E}[s_i(t) s_j(t + \tau)], \quad (2)$$

where $\mathbb{E}[\cdot]$ denotes the ensemble expectation. These ensemble quantities are the quantities we ultimately seek. Note that two channels to be correlated can be from the same or different stations, and vertical or horizontal components.

Third, because only finite records are available, ensemble quantities are approximated by sample estimators computed from the observations. Estimators are denoted by a hat, as in $\hat{C}_{ij}$, $\hat{\rho}$, $\hat{W}$, $\hat{\varepsilon}^*$, $\hat{r}$, and $\hat{R}^2$. Under the relevant stationarity, ergodicity, and regularity assumptions, time-averaged estimators converge to their corresponding ensemble quantities as the amount of available data increases (Peebles, 1993). Daily averages of segment-level estimators are denoted by an overline, for example, $\overline{C}_{ij,d}$. Derived working traces—including the daily cross-correlation function c_d , the Selective-stack reference r (or b at intermediate iterations), and the resulting stacked correlation functions—are also sample-derived quantities. For readability, hats are omitted from these working traces in subsequent equations.

For the correlation and dv/v workflow, all records are resampled to

$$f_s = 40 \text{ Hz}, \quad \Delta t = f_s^{-1} = 0.025 \text{ s}. \quad (3)$$

The PPSD and spectrogram analyses described in Sect. 3 are instead performed at the native sampling rate of the corresponding data epoch, which is 80 Hz for the examples presented in the section and in Supplement, Fig. S1. Accordingly, each continuous-time integral is evaluated numerically on the sampling grid

$$t_m = m\Delta t. \quad (4)$$

For example, an integral over a window of duration T , containing $N = T/\Delta t$ samples, is approximated by

$$\int_0^T g(t) dt \approx \Delta t \sum_{m=0}^{N-1} g(m\Delta t). \quad (5)$$

Similarly, the continuous lag τ is evaluated on the discrete grid

$$\tau_n = n\Delta t. \quad (6)$$

We retain continuous-time notation for clarity and report the corresponding sample counts when they are relevant to the implementation. Frequency bins in the discretized spectral calculations are indexed by ℓ .



4.1 Data pre-processing

Before ambient noise correlations are estimated, all continuous waveforms of all stations pass through the same preprocessing chain to remove instrumental artifacts (e.g., spikes, DC offset, long-period drift), suppress transient seismic events (e.g., earthquakes, explosions) that would otherwise dominate the correlation, and ensure stable inter-station comparison. The preprocessing strategy follows the framework of Bensen et al. (2007), with adaptations for SPITS data and the objectives of this study.

Supplement, Fig. S5 summarizes the spatial and temporal heterogeneity of the SPITS dataset and delineates the periods used in the ambient-noise and monitoring analyses discussed in this study. To reduce computational cost and to harmonize the database, traces are downsampled from 80 Hz to 40 Hz. Before decimation, each trace $x(t)$ is filtered in the frequency domain with a cosine-ramp low-pass mask centred at $f_c = 18$ Hz. The filtered signal is transformed back to the time domain and decimated by a factor of 2. We apply this low-pass in the frequency domain rather than with a causal time-domain filter so that decimation and correlation are not affected by frequency-dependent phase delays; the symmetric mask yields an approximately zero-phase response while suppressing energy above the new Nyquist frequency. All subsequent correlation and dv/v processing therefore uses a uniform sampling rate $f_s = 40$ Hz.

For each station-day, available waveform segments are merged into a continuous daily time series at $f_s = 40$ Hz. Where segments overlap in time (e.g., at file boundaries from the data archive), the overlapping samples are averaged. Short gaps of up to 2 s are filled by linear interpolation. The merged daily trace is then detrended and demeaned to remove long-period drift and DC offset.

Each daily trace is divided into consecutive, non-overlapping segments of length $T_{\text{seg}} = 600$ s. Each segment thus contains $T_{\text{seg}}f_s = 24,000$ samples, and the segments are processed independently in the subsequent steps. A cosine Tukey taper (Tukey, 1967) with fractional length $\gamma = 0.05$ is applied at the edges of each segment to limit spectral leakage.

Bensen et al. (2007) recommend time-domain normalization (e.g., one-bit or running absolute mean) to suppress the influence of transient high-amplitude events on the correlation. We do not apply one-bit normalization, which maps every sample to ± 1 and distorts the coda waveforms used for dv/v monitoring; instead, Median Absolute Deviation MAD-based segment rejection provides a more selective alternative. To reject transient-contaminated windows, segment energy is computed as

$$\hat{E}_{i,d,k} = \frac{1}{T_{\text{seg}}} \int_0^{T_{\text{seg}}} x_{i,d,k}^2(t) dt, \quad (7)$$

where, in the discrete implementation, the integral is evaluated as the sample mean square over $M = T_{\text{seg}}f_s = 24,000$ samples per segment. Let $\text{med}_{i,d}$ be the median of $\{\hat{E}_{i,d,k}\}_k$ and $\text{MAD}_{i,d}$ its median absolute deviation; the robust scale is (Huber, 1981)

$$\sigma_{\text{rob},i,d} = 1.4826 \text{MAD}_{i,d}. \quad (8)$$

The factor 1.4826 is the Gaussian consistency constant for MAD, i.e., $1/\Phi^{-1}(0.75) \approx 1.4826$, where Φ^{-1} is the inverse standard normal cumulative distribution function; this rescales MAD so that σ_{rob} is a consistent estimator of the standard deviation



under normally distributed residuals (Rousseeuw and Croux, 1993). Segments are rejected when

$$\hat{E}_{i,d,k} > \text{med}_{i,d} + k_{\text{MAD}} \sigma_{\text{rob},i,d}, \quad (9)$$

with $k_{\text{MAD}} = 8.0$, a threshold that is not unique but was chosen empirically at SPITS after testing stricter and looser values; in practice it removes the small fraction of segments whose energy is far above the station-day background, as expected for
 365 short-lived earthquake or icequake contamination, while retaining enough segments for stable daily correlations.

For each retained segment used in interchannel cross-correlations, we apply full-band spectral whitening over the resolvable segment band at $f_s = 40$ Hz (Nyquist 20 Hz), with practical usable content constrained by the preprocessing low-pass at 18 Hz; this step suppresses strong spectral peaks (Bensen et al., 2007). As a second time-domain normalization step, residual amplitude outliers are controlled by clipping each whitened segment to $\mu_{i,d,k} \pm 4\sigma_{i,d,k}$, where $\mu_{i,d,k}$ and $\sigma_{i,d,k}$ are the segment mean and
 370 standard deviation. Full definitions are given in Appendix B.

4.2 Cross-correlation estimation

Under the assumptions of wide-sense stationarity and ergodicity of the ambient noise field (Peebles, 1993), time averages over sufficiently long records converge to the ensemble correlation and can be used to estimate the interstation Green's function. Let $s_{i,d,k}(t)$ denote the preprocessed segment at channel i , day d , and segment index k . The segment cross-correlation estimators
 375 between channels i and j are obtained by lagged time integration,

$$\hat{C}_{ij,d,k}(\tau) = \frac{1}{T_{\text{seg}}} \int_0^{T_{\text{seg}} - |\tau|} s_{i,d,k}(t) s_{j,d,k}(t + \tau) dt, \quad (10)$$

which in the discrete implementation reduce to lagged sums over the $M = T_{\text{seg}} f_s$ segment samples. These integrals are the conventional biased sample estimators of the ensemble cross-correlations (Peebles, 1993; Percival and Walden, 1993).

Following Steinmann et al. (2021), we compare 1-day and 10-day segment stacks of ZZ cross-correlations through 2011
 380 using waveform coherence (WFC) and signal-to-noise ratio (SNR) (Supplement, Fig. S6).

The cross-correlations are evaluated for lags $\tau \in [-\tau_{\text{max}}, \tau_{\text{max}}]$ with $\tau_{\text{max}} = 50$ s (numerically on the uniform grid $\tau = n\Delta t$). Daily correlation functions are obtained by averaging the segment correlations using linear stacking; long-term stacking is described in Sect. 4.4.

Beyond the standard preprocessing above, changes in archive metadata and additional data-quality problems, including
 385 distorted waveform intervals, UTC and sampling-rate inconsistencies, seismometer clock offsets, coexistence of SH*, BH* and HH* recordings, and horizontal polarity or component misconfigurations, became apparent only after initial correlations were estimated. This required epoch-specific daily quality control before computing the final correlation archive. Failing days were excluded throughout, i.e., daily CCFs were not lag-shifted or clock-realigned. Mis-timed or low-coherence days are further rejected when building long-term references and dv/v series through Selective stacking (Sect. 4.4). Appendix, Table A1
 390 summarizes each identified issue, affected period, and mitigation; affected cross-correlation products are listed in Table 2.



4.3 Frequency band selection

To choose the final analysis band for dv/v , waveform coherence is evaluated over a broad range using these daily CCFs following the method proposed by Steinmann et al. (2021). The coherence map is computed at sampling rate $f_s = 40$ Hz, with centre frequencies from 0.01 Hz to 18 Hz discretized at 24 bands per octave (bpo) and lag τ evaluated numerically on
 395 the uniform grid $\tau = n\Delta t$ ($\Delta t = 1/f_s$). For each centre frequency f_c , each daily CCF is band-limited and compared with a reference stack (see next section) in moving lag windows. The underlying waveform coherence $\rho_d(f_c, \tau_0)$ between the band-limited daily CCF and the reference is not known a priori; we estimate it by the sample correlation coefficient

$$\hat{\rho}_d(f_c, \tau_0) = \frac{\int_{\mathcal{L}_{\tau_0}} (c_d^{(f_c)}(\tau) - \bar{c}_d^{(f_c)}) (r^{(f_c)}(\tau) - \bar{r}^{(f_c)}) d\tau}{\sqrt{\int_{\mathcal{L}_{\tau_0}} (c_d^{(f_c)}(\tau) - \bar{c}_d^{(f_c)})^2 d\tau} \sqrt{\int_{\mathcal{L}_{\tau_0}} (r^{(f_c)}(\tau) - \bar{r}^{(f_c)})^2 d\tau}}, \quad (11)$$

where $\mathcal{L}_{\tau_0}$ is the lag window centred at lag τ_0 , and $\bar{c}_d^{(f_c)}$ and $\bar{r}^{(f_c)}$ are the corresponding window means. Equation (11) is
 400 therefore a sample estimator of ρ_d rather than a definition of the coherence itself, evaluated in practice as a sum over the lag samples in $\mathcal{L}_{\tau_0}$. The estimated coherence field is the sample mean over the N_d days,

$$\widehat{W}(f_c, \tau_0) = \frac{1}{N_d} \sum_{d=1}^{N_d} \hat{\rho}_d(f_c, \tau_0). \quad (12)$$

Supplement, Figs. S7 and S8 show the estimated waveform-coherence metric $\widehat{W}(f_c, \tau)$ as a function of centre frequency f_c and time lag τ for representative vertical (ZZ) and horizontal (NN) inter-station pairs, each computed from one year of daily
 405 correlation functions. Coherence is strongest below ~ 2.5 Hz and centred near $\tau = 0$; with increasing f_c the high-coherence region narrows in lag, indicating a shorter day-to-day stable coda at higher frequencies. Following Steinmann et al. (2021), $\widehat{W}(f_c, \tau)$ is used to select frequency bands and lag intervals with repeatable correlation waveforms for dv/v monitoring. In the 2.5–4.5 Hz range, coherence remains high to lags of several seconds, showing that early–middle coda segments in that band may be sufficiently stable for velocity monitoring, although the causal and anti-causal sides are not equally coherent within the
 410 coda window chosen for the dv/v estimation. The primary analysis band 0.5 Hz to 2.0 Hz was chosen in this study because it shows the broadest and most stable coherence of up to about 20 s lag time. Note that causal and anti-causal sides are not always identical when noise sources are unevenly distributed around the array. Above ~ 12 Hz, $\widehat{W}$ is low and that band is not used.

Based on these results (coda coherency) and the results of the F–K analysis (stable noise source distribution for surface waves), we can define the most suitable band for dv/v , and consequently bandpass-filter records in 0.5 Hz to 2.0 Hz before
 415 correlation (Eq. (10)).

4.4 Stacking and quality control

Stacking is a fundamental operation in ambient-noise analysis and is used to enhance the signal-to-noise ratio (SNR) of empirical Green's functions estimated from daily correlation functions. By combining many daily auto or cross correlation functions, coherent wavefield contributions associated with stable propagation paths interfere constructively, while incoherent fluctua-



tions are suppressed by averaging (Bensen et al., 2007). The stacking of daily correlation functions is mainly required to obtain a suitable reference for measuring dv/v and was also already used for frequency bands selection above.

In this study, the selection of the preferred stacking estimator is guided by two strict criteria. First, stable phases should be visible in the late coda on both the causal and anti-causal sides. Furthermore, the stacking method should be able to effectively handle data issues. Clock drifts and other data-quality problems at SPITS affect some stations and intervals (Appendix, Table A1). The stacking method should therefore be able to remove such time windows, following the principle that timing errors in noise correlations must be distinguished from physical velocity changes (Stehly et al., 2007). The candidate stacking method is selected that most consistently yields stable, time-aligned (clock-error-free) correlation waveforms for subsequent monitoring analyses.

Following the framework and comparative analysis of Yang et al. (2023), we evaluated Linear, Robust (Pavlis and Vernon, 2010), Selective (Olivier et al., 2015; Yang et al., 2023), Phase-Weighted Stacking (PWS; Schimmel and Paulssen 1997), and time-frequency Phase-Weighted Stacking (tf-PWS; Schimmel and Gallart 2007; Schimmel et al. 2011) estimators.

Long-term correlation functions are built in two steps. For each day, segment-level correlations are linearly averaged to obtain one daily CCF. These daily traces are then stacked over D days using one of the estimators listed above; definitions of Linear, Robust, PWS, and tf-PWS are given in Appendix C. We adopt Selective stacking for all reference CCFs (Sect. 5); its estimator is defined below.

Selective stacking (Olivier et al., 2015; Yang et al., 2023) builds the long-term reference iteratively by retaining only daily cross-correlation functions (CCFs) that are sufficiently coherent with an evolving reference stack. We follow the correlation-based formulation of Yang et al. (2023), but set the selection threshold adaptively at each iteration rather than to a fixed value. For each station pair, let N denote the number of days with a daily CCF, $c_i(\tau)$ the daily CCF for day i ($i = 1, \dots, N$), and $b(\tau)$ the reference stack at the current iteration (initialised as the linear mean of all c_i). At each iteration, the coherence of day i with the current reference is estimated by the sample correlation coefficient

$$\hat{\rho}_i = \frac{\int c_i(\tau) b(\tau) d\tau}{\sqrt{\int c_i^2(\tau) d\tau} \sqrt{\int b^2(\tau) d\tau}}, \quad \hat{\rho}_t = \frac{1}{N_{\text{valid}}} \sum_{i \in \text{valid}} \hat{\rho}_i, \quad (13)$$

which measures how well day i matches the current estimated reference (N_{valid} is the number of days with non-zero variance); Eq. (13) is thus a sample estimator rather than a definition of the coherence. Days with below-average coherence are excluded using the adaptive threshold ρ_t , taken as the mean of all valid $\hat{\rho}_i$. The reference is then updated from the retained days only:

$$w_i = \begin{cases} 1/n_{\text{sel}} & \text{if } \hat{\rho}_i \geq \hat{\rho}_t \\ 0 & \text{otherwise} \end{cases}, \quad b(\tau) = \sum_{i=1}^N w_i c_i(\tau), \quad (14)$$

where w_i is the stacking weight for day i ($w_i = 0$ rejects that day), $n_{\text{sel}} = \sum_i \mathbb{1}(\hat{\rho}_i \geq \hat{\rho}_t)$ is the number of retained days, and $\mathbb{1}(\cdot)$ is the indicator function. The factor $1/n_{\text{sel}}$ assigns equal weight to each retained day, so the estimated stack $b(\tau)$ is the arithmetic mean of the accepted daily CCFs rather than their sum. Iteration repeats until $b(\tau)$ stabilizes or after 50 passes. The final converged stack $b(\tau)$ is saved as the long-term reference $r(\tau)$ used for dv/v estimation in Sect. 5. Note that for dv/v ,



all days are initially included; days with a correlation coefficient below ($\rho = 0.5$) are subsequently rejected by the stretching method.

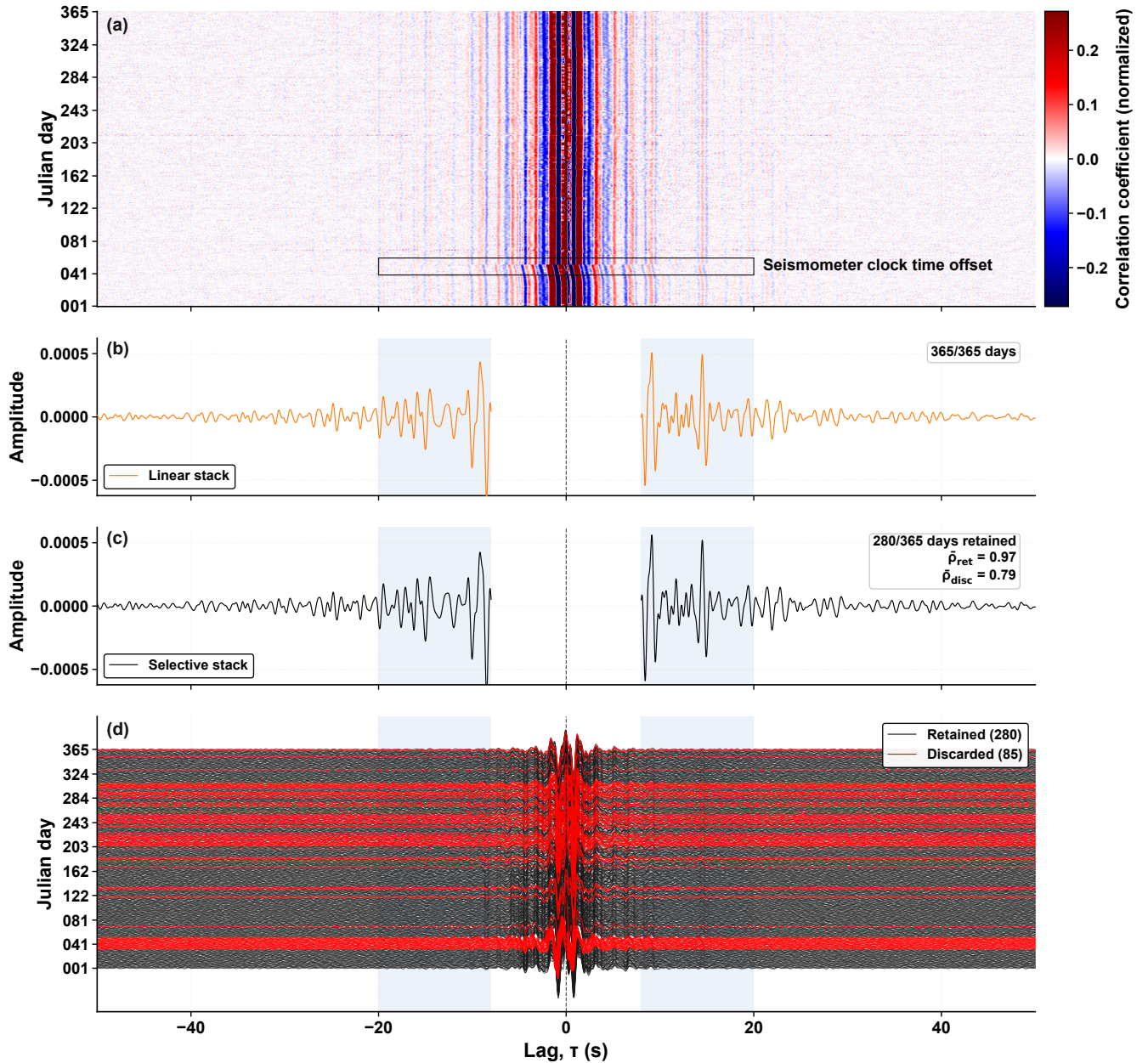


Figure 5. Daily cross-correlations, linear and selective stacking for station pair SPB3–SPB5, 2011 (0.5 Hz to 2.0 Hz). (a) Heatmap of daily normalized CCFs; the boxed interval (Julian days 40–60) marks a seismometer clock-time offset. (b) Linear stack (all days included). (c) Selective stack after day-wise rejection (retained days shown with mean correlation $\bar{\rho}_{\text{ret}}$; discarded days with $\bar{\rho}_{\text{disc}}$). (d) Daily CCF wiggle overlay; discarded days are shown in red. Shaded bands in (b)–(d) mark the 8 s to 20 s coda window used for dv/v monitoring. In (b) and (c) the direct arrival ($|\tau| < 8$ s) is muted and the traces are scaled to the coda so that coda amplitudes are shown at larger scale.



4.4.1 Comparison of stacking methods

Figure 5 and Supplement, Figs. S9–S11 compare the five stacking methods that perform reliably at SPITS (Linear, Robust, Selective, PWS, and tf-PWS) for the station pair SPB3–SPB5 over 2011. Each figure shows the daily cross-correlations as a heatmap (top), the stacked normalized cross-correlation function (CCF) in the middle panel, and an overlay of individual daily CCFs (bottom). All methods retrieve a strong, coherent signal centred near zero lag, with alternating positive and negative lobes characteristic of empirical Green’s function retrieval in ambient-noise interferometry (Shapiro et al., 2005; Campillo, 2006; Bensen et al., 2007). The coherent signal persists across most Julian days, indicating stable noise sources and propagation paths for this pair and year.

On short Julian-day intervals, the vertical coherent bands in the heatmaps and wiggle overlays shift horizontally by a few seconds (e.g. around days 40–50 in Figure 5), consistent with seismometer clock or timing offsets on some days at SPITS (Stehly et al., 2007). Those mis-timed daily traces remain in the Linear, Robust, PWS, and tf-PWS stacks: Robust stacking iteratively down-weights traces that deviate strongly from a reference but does not apply a hard day-wise rejection rule, and PWS and tf-PWS emphasize phase-coherent energy rather than enforcing temporal alignment. A bulk clock error is therefore not equivalent to random incoherence, and phase-weighted stacks can still retain a residual imprint of mis-timed days when those traces remain partially coherent after stacking. Selective stacking is the only method among these five that excludes entire daily CCFs when their correlation to the iterative reference falls below a threshold; excluded days appear in red in the bottom panels (Figure 5) and correspond to the intervals where the coherent bands are visibly shifted in the heatmaps.

When the stacked CCFs are compared in the middle panels, the differences are often subtle by eye. For this example, the Linear and Robust stacks are nearly identical, and the Selective stack differs only modestly from them despite removing the clock-offset days, which indicates that a limited number of mis-timed days do not dominate the year-long average waveform shape. PWS yields slightly higher peak amplitudes and somewhat sharper waveform definition than the linear stack, whereas tf-PWS produces the clearest coherent waveform in our comparison.

For relative-velocity monitoring (Sect. 5), each daily CCF is compared with a long-term reference $r(\tau)$ built by stacking many daily traces. Our comparison shows that the shape of the long-term stack is insensitive to the stacking method for representative pairs: Linear, Robust, and Selective references are almost identical once only a few outlier days are involved (Figure 5). We therefore adopt Selective stacking not primarily to obtain a sharper reference waveform—PWS and tf-PWS can improve signal visibility (Yang et al., 2023)—but because it provides an explicit, correlation-based rule for identifying and excluding mis-timed or low-coherence daily CCFs before they enter dv/v estimation (Stehly et al., 2007). Unbiased dv/v requires that bad days be removed rather than down-weighted or left in the stack. Selective stacking is the only method among these five that enforces hard day-wise rejection. The same global Selective stack still defines $r(\tau)$, while the rejection map identifies which daily traces are trustworthy on each day. A further benefit appears in the stretching quality metric itself. When $r(\tau)$ is built with Selective rather than Linear stacking, the peak coda correlation ρ^* between retained daily CCFs and the reference is systematically higher ($\bar{\rho}_{\text{ret}} > \bar{\rho}_{\text{disc}}$ in Figure 5), because mis-timed and low-coherence days are excluded from the



reference and from the retained ensemble. Selective stacking is therefore adopted both for archive-aware quality control and because it yields more stable, higher-correlation dv/v estimates against the long-term reference.

5 Estimation of relative seismic velocity variations

Temporal variations in seismic velocity carry information about subsurface changes in temperature, stress, fluid content, and mechanical properties. In ambient-noise and coda-wave monitoring, relative velocity change (dv/v) is estimated by comparing a seismic response representing the current medium with a reference response representing a baseline state. The comparison is commonly performed in the coda, either earthquake coda or noise CCF coda, where multiply scattered waves provide sensitivity to spatially distributed changes in the medium (Snieder et al., 2002; Sens-Schönfelder and Wegler, 2006; Wegler and Sens-Schönfelder, 2007; Brenguier et al., 2008; Hadziioannou et al., 2011). The sensitivity to velocity changes becomes larger due to longer travel path, and the effect of dominant noise source direction is mitigated.

5.1 Stretching method

Each daily CCF $c_d(\tau)$ is compared with a long-term reference $r(\tau)$, constructed here as a global all-years Selective stack (Table 2; e.g. 1992–2025 for ZZ). The all-years reference expresses the estimated velocity variations relative to a long-term average state. Because each daily CCF contributes to the reference, the estimates may be subject to mild reference self-inclusion. As a sensitivity test, we also recompute array-median ZZ dv/v with a Selective-stack reference restricted to 2015–2025 (Supplement Fig. S19): the seasonal cycle and the sign of the long-term trend are unchanged, while absolute dv/v levels shift because the reference defines the zero of the relative-velocity scale.

In the stretching technique, the daily CCF is interpolated at times $\tau(1+\epsilon)$ for a range of trial stretch parameters ϵ in the coda window $\mathcal{W}$. The similarity to the reference is quantified by the sample normalized correlation coefficient estimator

$$\hat{\rho}_d(\epsilon) = \frac{\int_{\mathcal{W}} c_d[\tau(1+\epsilon)] r(\tau) d\tau}{\sqrt{\int_{\mathcal{W}} c_d^2[\tau(1+\epsilon)] d\tau \cdot \int_{\mathcal{W}} r^2(\tau) d\tau}}, \quad (15)$$

where $\mathcal{W}$ is the coda lag set defined below. The optimal stretch $\hat{\epsilon}_d^* = \arg \max_{\epsilon} \hat{\rho}_d(\epsilon)$ is itself a sample estimator, found on a uniform grid $\epsilon \in [-0.01, 0.01]$ with 201 trial values ($\pm 1\%$ relative lag scaling), followed by a denser local refinement around the best coarse-grid point. With this sign convention, the estimated relative velocity variation is

$$\frac{dv}{v}(d) \approx -\hat{\epsilon}_d^*. \quad (16)$$

In practice, $\hat{\rho}_d(\epsilon)$ is maximized only within selected coda windows to reduce sensitivity to source-side and near-zero-lag effects. We fix coda lapse times at $t_{\min} = 8\text{ s}$ and $t_{\max} = 20\text{ s}$ on both causal and anti-causal branches, guided by the waveform-coherence results in Supplement, Figs. S7 and S8 and the rationale that multiply scattered energy in the late correlation coda



is more repeatable than direct arrivals for daily resolution (Hadziioannou et al., 2011). Only lags with $|\tau| \in [t_{\min}, t_{\max}]$ define $\mathcal{W}$ in Eq. (15). Inter-station distances at SPITS span approximately 0.25 km to 1 km, so ballistic travel times are $\lesssim 1$ s even for
515 slow surface waves (~ 1 km/s to 3 km/s) and much shorter for body waves. Thus $t_{\min} = 8$ s lies well after the direct arrival: $\mathcal{W}$ samples the late correlation coda—multiply scattered energy whose environmental dv/v sensitivity is volumetric and shallow. Waveform coherence confirms that the (0.5 Hz to 2.0 Hz) frequency band remains coherent in both the causal and acausal parts of the waveform for lag times of up to approximately (20 s). Note that the apparent-slowness dominance of body-wave-compatible energy in the propagation field (see F–K slowness analysis in Sect. 3) does not determine the dominant wave type
520 in the selected coda window. We treat the measurement as a mixed scattered-coda observable and do not assign it to a unique body- or surface-wave mode.

Among n_{st} stations that contribute usable inter-station CCFs on day d , at most $N_{\text{pairs}} = n_{\text{st}}(n_{\text{st}} - 1)/2$ unordered pairs are available; on any given day, fewer pairs may contribute when daily traces are missing. Let $(dv/v)_p(d)$ denote the pair-wise estimate from Eq. (16) for pair p , with peak stretch correlation $\hat{\rho}_p^* = \hat{\rho}_p(\hat{\varepsilon}_p^*)$. Array-median dv/v is the daily median over
525 pair-days with sufficiently high $\hat{\rho}_p^*$:

$$\left(\frac{dv}{v}\right)_{\text{arr}}(d) = \text{median} \left\{ \left(\frac{dv}{v}\right)_p(d) : p \in \mathcal{P}_d \right\}, \quad (17)$$

where $\mathcal{P}_d = \{p : \hat{\rho}_p^* \geq 0.5\}$ is the set of pairs retained on day d . Residual pair-to-pair scatter remains in the unsmoothed daily estimates; formal uncertainty on the smoothed array-median curve is quantified by bootstrap resampling (Eqs. (18)–(19)).

For the full nine-station SPITS array when all pair paths are available, $n_{\text{st}} = 9$ and $N_{\text{pairs}} = 36$. After the array aggregation
530 in Eq. (17), $(dv/v)_{\text{arr}}(d)$ is temporally smoothed (post-estimation regularization): the day-by-day series is convolved with a Gaussian kernel of $\sigma = 20$ day to suppress short-period scatter from varying noise sources and data gaps while retaining slower seasonal trends. This convolution does not change the per-day stretch solution; it only stabilizes the series used for interpretation and comparison with borehole temperature records. The channel/year combinations used for estimation are listed in Table 2. Compared with the spectral doublet method, also known as the moving-window cross-spectral (MWCS) method (Poupinet
535 et al., 1984; Ratdomopurbo and Poupinet, 1995; Clarke et al., 2011), used by Albaric et al. (2021), we prefer stretching because it operates directly in the time domain on coda waveforms and is less sensitive to frequency-domain disturbances (e.g., narrow-band contamination and transient spectral anomalies).

5.2 Uncertainty estimation

Analytical single-pair stretching error models, such as the apparent-dilation theory of Weaver et al. (2011), assume stationary
540 Gaussian coda with comparable spectra and are not applicable to the SPITS coda (Appendix D). Uncertainty on $(dv/v)_{\text{arr}}(d)$ is obtained by bootstrap resampling (Efron, 1982; Zoubir and Iskander, 2004), following the philosophy of Lecocq et al. (2017) for long noise (dv/v) series when Gaussian error models are inappropriate. For each station pair p with D_p daily correlation functions, bootstrap replicate $b \in \{1, \dots, B\}$ draws D_p indices uniformly with replacement, rebuilds a Selective-stack reference $r_p^{(b)}(\tau)$, and re-estimates $(dv/v)_p^{(b)}(d)$ by maximizing Eq. (15) with the same quality-control thresholds as in Eq. (17). The
545 bootstrap array aggregate is



$$\left(\frac{dv}{v}\right)_{\text{arr}}^{(b)}(d) = \text{median} \left\{ \left(\frac{dv}{v}\right)_p^{(b)}(d) : p \in \mathcal{P}_d \right\} \quad (18)$$

With $B = 200$ replicates, the daily bootstrap standard error is

$$\sigma_{\text{arr}}(d) = \sqrt{\frac{1}{B-1} \sum_{b=1}^B \left(\left(\frac{dv}{v}\right)_{\text{arr}}^{(b)}(d) - \overline{\left(\frac{dv}{v}\right)}_{\text{arr}}(d) \right)^2} \quad (19)$$

where $\overline{(dv/v)}_{\text{arr}}(d)$ is the mean over bootstrap replicates at day d . The envelope shown in Fig. 6b is $\pm\sigma_{\text{arr}}(d)$ about the Gaussian-smoothed array-median curve, with σ_{arr} convolved by the same $\sigma = 20$ day kernel used for $(dv/v)_{\text{arr}}$, so that the plotted band reflects uncertainty on the smoothed series used for interpretation.

Table 2. Recommended channel pairs, year windows, and frequency bands for noise correlation functions and dv/v estimation at the SPITS array.

Category	Pairs and recommended years	Frequency band
<i>Cross-correlation (inter-station, $A-B$, $A \neq B$)</i>		
Same-component	ZZ (primary): 1992–2025	0.5–2.0 Hz
	NN, EE (primary): 2005–2025	0.5–2.0 Hz
Radial–transverse (R/T)	RR, TT (primary): 2005–2025	0.5–2.0 Hz
Vertical–radial/transverse	ZR, ZT (supporting): 2005–2025	0.5–2.0 Hz
Cross-component	ZN, ZE, NE (supporting): 2005–2025	0.5–2.0 Hz
<i>Cross-correlation (single station, $A-A$)</i>		
Cross-component	ZN, ZE, NE (supporting): 2005–2025	0.5–2.0 Hz

5.3 Correlation with borehole temperatures

To correlate dv/v with borehole temperatures at different depths, to summarize long-term trends, and to estimate lag times of seasonal variations, we use two standard sample estimators. Let $T(d)$ denote the daily GTN-P soil temperature and let $(dv/v)(d)$ denote the Gaussian-smoothed array-median relative velocity variation on day d . The sample correlation estimator between the two series at lag τ (in days) is

$$\hat{r}\left(T, \frac{dv}{v}; \tau\right) = \frac{\sum_d (T(d) - \bar{T}) ((dv/v)(d - \tau) - \overline{dv/v})}{\sqrt{\sum_d (T(d) - \bar{T})^2} \sqrt{\sum_d ((dv/v)(d - \tau) - \overline{dv/v})^2}}, \quad (20)$$



where the sums run over days with both series available and overbars denote the corresponding sample means. We write $\hat{r}(T, dv/v)$ for the zero-lag value $\tau = 0$, and report lagged correlations when scanning τ to assess seasonal lead-lag. For
560 a daily time series $y(d)$ fitted by ordinary least squares to a linear model $\hat{y}(d) = \hat{a} + \hat{b}t(d)$ in calendar time t , the sample coefficient of determination is

$$\hat{R}^2 = 1 - \frac{\sum_d (y(d) - \hat{y}(d))^2}{\sum_d (y(d) - \bar{y})^2}, \quad (21)$$

i.e. the fraction of sample variance explained by the linear trend. Reported numerical values of r and R^2 below are these estimators.

565 The reported trend rates are the ordinary-least-squares slope $\hat{b}$. Time t is counted in days, and $\hat{b}$ is multiplied by 365.25 so that the rate is per year. The fit uses only days on which y is finite. For dv/v , and for the mean soil temperature at 2 m to 4 m, y is the daily series after the same Gaussian smoothing ($\sigma = 20$ d). $\hat{R}^2$ in Eq. (21) is evaluated on that fit.

6 Results

6.1 Vertical component cross-correlation

570 We interpret the array-averaged dv/v primarily as a continuous tracker of seasonal thermo-hydrological conditions in the shallow ground: freezing and winter cooling stiffen the active layer and uppermost permafrost (higher dv/v), whereas thawing and summer warming reduce ice-bonded stiffness (lower dv/v). Fig. 6 shows this behaviour for 1992–2025. The general observation is that the array-averaged ZZ dv/v is anti-correlated with GTN-P soil temperature at Janssonhaugen ($r = -0.43$ on Gaussian-smoothed daily series), with the expected physical phasing—velocity maxima during cold seasons and minima
575 during warm seasons.

These results use the full data archive, a per-pair Selective-stack reference (Yang et al., 2023), and median aggregation over 36 inter-station ZZ pairs in the 0.5 Hz to 2.0 Hz band. However, dv/v may differ among individual station pairs due to possible noise-wavefield directionality and/or small-scale variations in the subsurface thermo-hydrological conditions beneath the SPITS array. We therefore inspect the 36 Gaussian-smoothed pair series that enter that median for 2015–2025 (Supplement
580 Fig. S14a; one panel per pair in Fig. S18), coloured by path orientation in Fig. S14a (0° N–S, 90° E–W). On each day the red band is the interquartile range of those 36 estimates: (25th to 75th percentiles), so half of the pairs lie inside the shaded interval around the pair median (black). That daily spread remains small relative to the shared seasonal cycle, which is in antiphase with GTN-P soil temperature at 2 m to 4 m (Fig. S14b,c). Hence, no station pair shows a persistent high or low bias relative to the array median, with one clear exception in 2016: all eight ZZ paths that include SPB5 lie well above the other pairs through
585 winter and spring (smoothed peaks of about 0.8% in early April on SPA2–SPB5 and SPA1–SPB5) and then rejoin the common envelope after the thaw season (Fig. S18). That offset is unique to 2016 in the 2015–2025 window, so we interpret it as a local and temporary SPB5-related effect rather than a stable path or station pair orientation bias. It is likely an instrument issue not



caught by the automatic quality control using correlation thresholds. Maintenance and instrument upgrades at the SPITS array between 2015 and 2016 could be the cause for this. However, because the array dv/v estimate is a median, those eight SPB5
590 paths do not control the reported dv/v in 2016.

If a directional incident field biased dv/v , N–S and E–W paths would diverge. Fig. S14b therefore compares sector medians for pairs within $\pm 30^\circ$ of N–S and of E–W with the 36-pair median. Both sectors follow the array median through most of 2015–2025 (Pearson $r = 0.68$ for N–S and $r = 0.54$ for E–W), with larger departures in 2016 and 2023. The 2016 N–S excursion is consistent with several of the SPB5 paths lying closer to N–S than to E–W. Those years do not overturn the seasonal pattern,
595 so the array median remains a usable proxy for the mean velocity change at SPITS. Finally, we also compute medians on only pairs showing anti-correlation with temperatures, i.e., $\hat{r}(T, dv/v) < 0$ (Fig. S14c). However, the resulting dv/v time series is very similar to the full-path median. We therefore retain all 36 pairs rather than recomputing dv/v from an orientation-selected subset, or from only those pairs that individually anticorrelate with temperature.

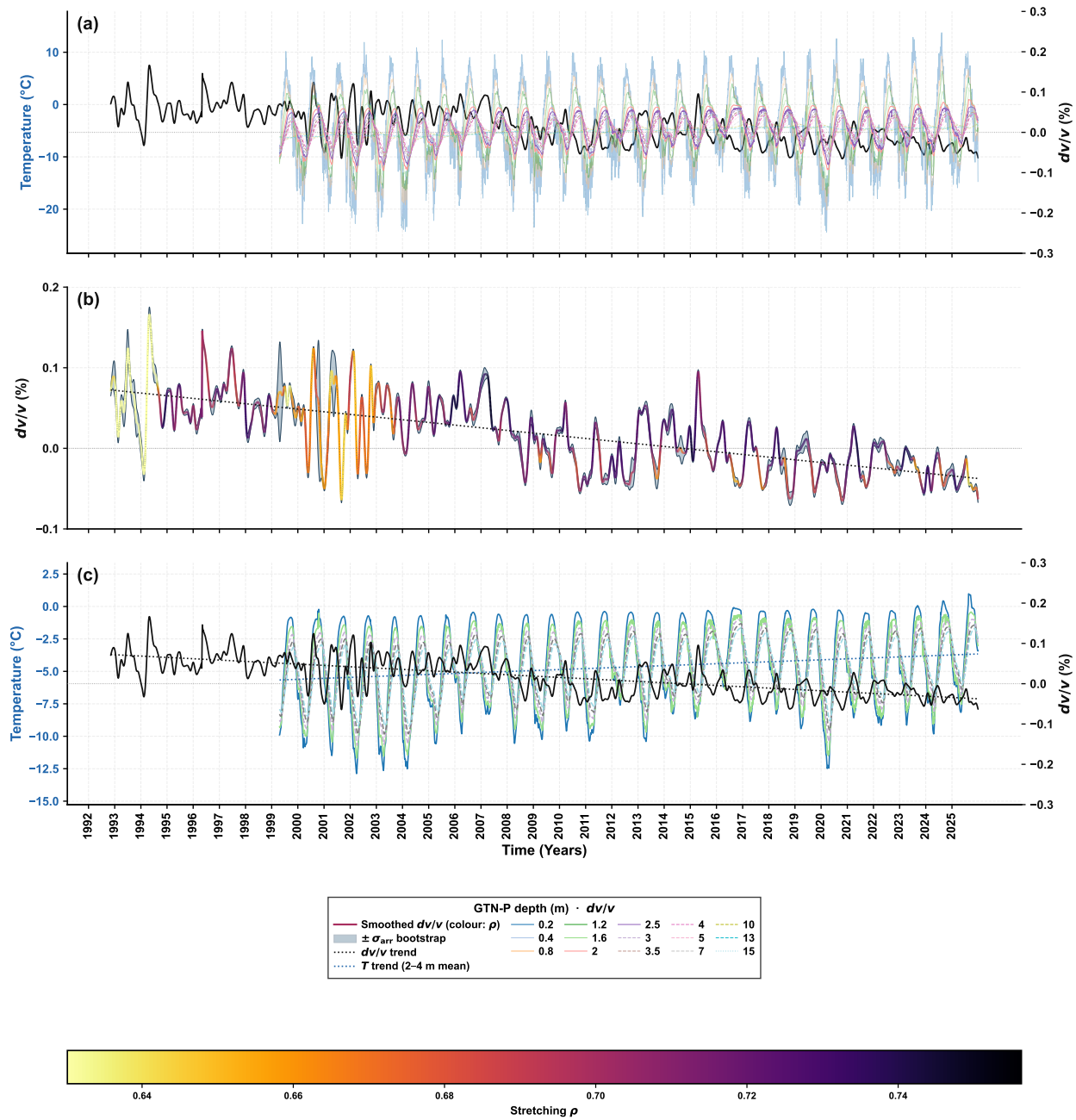


Figure 6. Array-averaged inter-station ZZ dv/v and GTN-P soil temperatures at Janssonhaugen (1992–2025). (a) Smoothed dv/v against soil temperature at all GTN-P depths (dual axis). (b) Smoothed dv/v coloured by stretching correlation coefficient ρ , with bootstrap uncertainty and linear trend. (c) Soil temperature at 2 m to 4 m coloured by depth with smoothed dv/v (dual axis) and trends; seasonal anti-correlation $r = -0.43$.

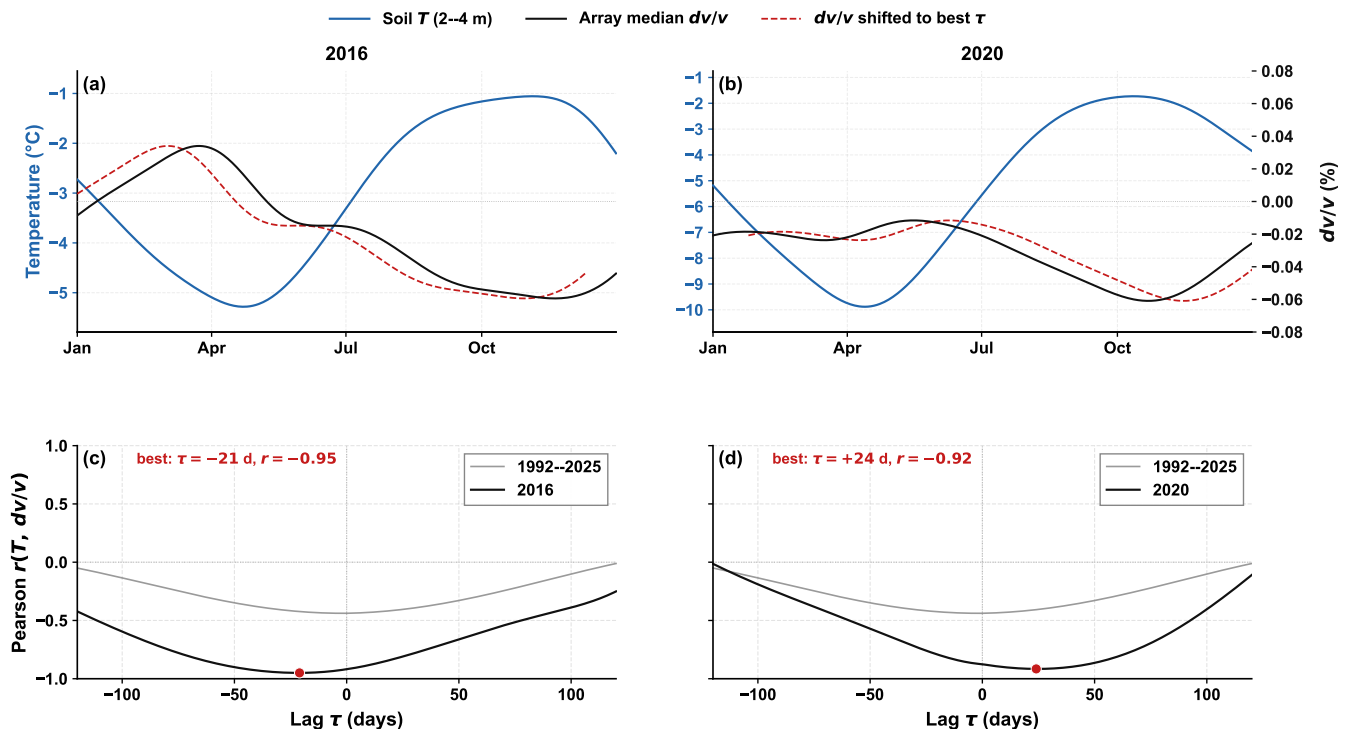


Figure 7. One-year seasonal T - dv/v coupling for 2016 and 2020 (array-median ZZ; GTN-P 2 m to 4 m). 2016 is the pair-level anomaly in Supplement Figs. S14 and S18; 2020 is a representative later year without that outlier. **(a, b)** Smoothed soil temperature and dv/v on magnified per-year axes (month ticks); dashed red curves use the best lag τ from (c, d). **(c, d)** Pearson $\hat{r}(T, dv/v)$ versus lag τ (grey: 1999–2025 overlap; black: zoom year).

Figure 7 shows the year-by-year lag between dv/v and soil temperature at 2 m to 4 m for two contrasting calendar years. We use 2016 because it shows higher winter temperatures than average and 2020 because of anomalously low winter temperatures. Note that 2016 also shows the above-mentioned anomaly for SPB5 paths (see Supplement Fig. S14 and S18: SPB5 paths above the array median through winter and spring), which however had no effect on the array median dv/v amplitude. However, we need to keep this in mind since the SPB5-issue can have an effect on the seasonal T - dv/v phasing of the array median. While the median remains strongly anti-correlated with borehole temperature, the strongest anti-correlation for 2016 is at $\tau = -21$ d ($r = -0.95$). In contrast, the 1992–2025 average shows a lag close to zero ($\tau = -2$ d, $r = -0.44$), that is, the depth sensitivity of dv/v is on average in the range 2 m to 4 m. For 2020 the same scan gives $\tau = +24$ d ($r = -0.92$), a bit later than the average. Both year-specific correlations are much stronger than the 1999–2025 average at the same depths, because one annual cycle lines up more tightly than the multi-year record. Positive τ (2020) means that dv/v lags temperature, and a negative lag means that dv/v precedes temperature (2016). Hence, deviations from the average for 2016 and 2020 could indicate changing depth sensitivity of dv/v , possibly caused by temperature anomalies.



To investigate these anomalies further, Figure 8 extends the same $(\tau_{\min}, r_{\min})$ search to every calendar year and to each of the 15 GTN-P thermistors (0.2 m to 15 m). The aim is to identify the depth range to which our dv/v results are most sensitive, i.e. where the absolute time lag is smallest. For array-median ZZ (1999–2025; Fig. 8a,c), $|\tau_{\min}|$ over the full overlapping archive is smallest in the 2 m to 4 m band, with a minimum of +2 d at 2.5 m. Shallower temperature sensors (0.2 m to 1.6 m) give systematically larger positive lags (surface temperature leads the coda). Below about 5 m, lags become increasingly negative toward the ± 120 d search-window edges because conduction delays the annual temperature cycle. Full-archive $|\tau_{\min}|$ (Fig. 8c) therefore has its minimum in the same 2 m to 4 m band. While the depth of smallest lag remains in that interval for most years, several anomalous years are observed, so the 2016 lag anomaly is not unique (e.g. 2003–2005, 2011, 2015). In 2021–2025 the ZZ depth of smallest lag deepens relative to earlier years, coincident with warmer summers at Janssonhaugen. The corresponding TT scan is described with the horizontal-component results, and we return to these anomalies in the Discussion.

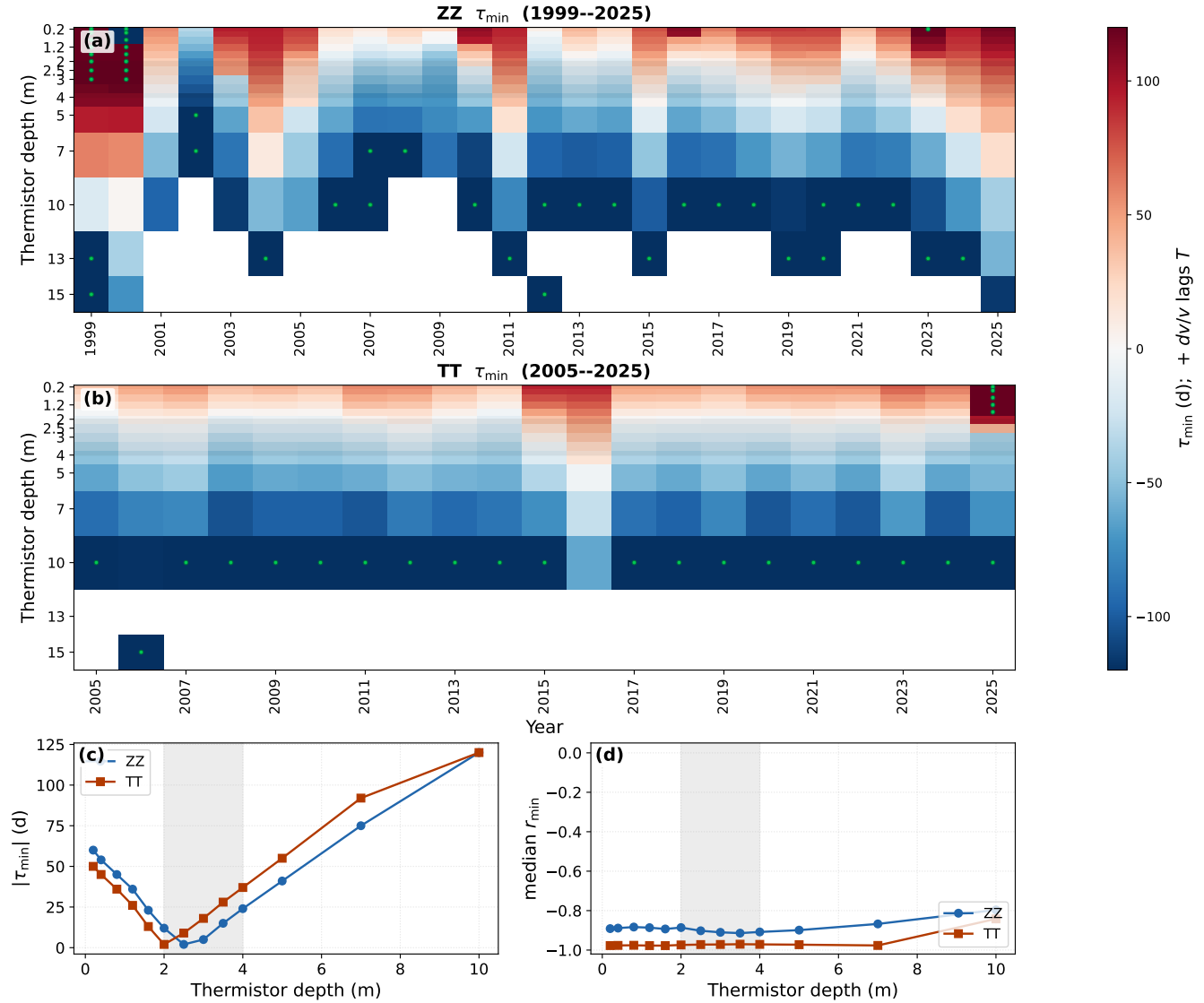


Figure 8. Lag of strongest T - dv/v anti-correlation versus GTN-P thermistor depth (0.2 m to 15 m). **(a, b)** Yearly $\tau_{\min}$ for array-median ZZ (1999–2025) and TT (2005–2025). Positive τ : dv/v lags temperature. Grey band: 2 m to 4 m. Green dots: $|\tau_{\min}|$ saturates at the ± 120 d search-window edge. Blank cells below 10 m, and the $+120$ d cells at 10 m, are the same annual match seen from the positive side of the window and are not interpreted. **(c)** Full-archive $|\tau_{\min}|$ versus depth. Temperature is the daily mean, smoothed with a Gaussian kernel of $\sigma = 20$ d. **(d)** Year-median $r_{\min}$.

The negative linear trend in smoothed array-median dv/v (Fig. 6b; $-0.0033\% \text{ yr}^{-1}$, or $-0.033\% \text{ decade}^{-1}$, $R^2 = 0.51$) is superimposed on the seasonal cycle. Mean soil temperature at 2 m to 4 m warmed at $+0.0751^\circ\text{C yr}^{-1}$ ($+0.751^\circ\text{C decade}^{-1}$, $R^2 = 0.06$). Coda dv/v averages paths across the ~ 1 km array, whereas GTN-P samples one borehole. If P11 happens to be



located where warming is weaker than the array average, the point record will understate the array-scale change. Temperature
625 at 2 m to 4 m is also buffered by latent heat (Westermann et al., 2009), while dv/v responds to ice-bonded stiffness along the
coda paths. We cannot separate those two effects here.

Fig. 6b shows two time periods with larger seasonal dv/v variability: 1993–1998 and 2001–2003. Those periods are also
characterized by low stretching correlation ρ , suggesting that those measurements are not well constrained. We therefore do not
interpret these as anomalous years with increase soil freezing and thawing, since temperatures for 2001–2003 do not suggest
630 such effects, and attribute them instead to station-quality issues.

6.2 Horizontal component cross-correlation

The horizontal-component dv/v results are in general similar to the vertical component results and provide additional insights
(Fig. 9). Array-averaged dv/v from inter-station NN and EE pairs (2005–2025) reproduces the seasonal anticorrelation with
soil temperature observed in the ZZ series, with the same phasing: velocity maxima during winter cooling and minima fol-
635 lowing summer thaw. The long-term trends are again negative— $-0.0059\% \text{ yr}^{-1}$ ($R^2 = 0.45$) for NN and $-0.0057\% \text{ yr}^{-1}$
($R^2 = 0.35$) for EE—and somewhat steeper than the ZZ trend of $-0.0033\% \text{ yr}^{-1}$. NN and EE results are mutually similar in
both seasonal phasing and decadal trend, as expected when both components sample a comparable mix of P–SV and SH energy
on inter-station paths. Rotating the horizontal components into pair-specific radial–radial (RR) and transverse–transverse (TT)
coordinates provides a cleaner separation between Rayleigh-type (radial) and Love-type (transverse) surface-wave energy in
640 the inter-station great-circle frame. The decadal trend magnitudes remain comparable across all five same-component products
(RR: $-0.005\% \text{ yr}^{-1}$, $R^2 = 0.52$; TT: $-0.0058\% \text{ yr}^{-1}$, $R^2 = 0.33$), but the seasonal amplitudes are not identical. The dv/v
variations from TT have significantly larger seasonal amplitudes than those from RR. This observation is consistent with the
different depth sensitivities of Love and Rayleigh waves; Love waves are more sensitive to shallower S-wave structure, which
may respond more strongly to freeze–thaw processes in the active layer. The lower explained variance of the EE and TT series
645 ($R^2 = 0.35$ and 0.33 , versus 0.45 for NN and 0.52 for RR) indicates larger interannual scatter in those combinations, but the
sign and approximate magnitude of the decadal trend are shared by all five products. Over the same 2005–2025 window, mean
soil temperature at 2 m to 4 m warmed at $+0.058^\circ\text{C yr}^{-1}$ ($R^2 = 0.03$), the low explained variance reflecting the dominance of
the seasonal cycle over the secular trend.

The same lag-versus-depth search for array-median TT (2005–2025; Fig. 8b–d) likewise has its smallest $|\tau_{\min}|$ in the 2 m
650 to 4 m band, but the minimum is slightly shallower than for ZZ: $+2 \text{ d}$ at 2.0 m over the full archive, and a year-median $|\tau_{\min}|$
of 8 d at 2 m (Fig. 8c). As for ZZ, shallower temperature sensors yield larger positive lags and depths below about 5 m trend
toward the $\pm 120 \text{ d}$ window edges (green dots in Fig. 8b). TT phasing is more stable from year to year than ZZ. Together
with the larger seasonal TT amplitude relative to RR, that slightly shallower minimum is consistent with greater Love-wave
sensitivity in the active layer. We therefore assume the same 2 m to 4 m as the sensitive range for the featured TT (and RR)
655 time series. Note that similar to ZZ, the years 2015, 2016 and 2025 also stands out as anomalies with respect to temperature
time lags.

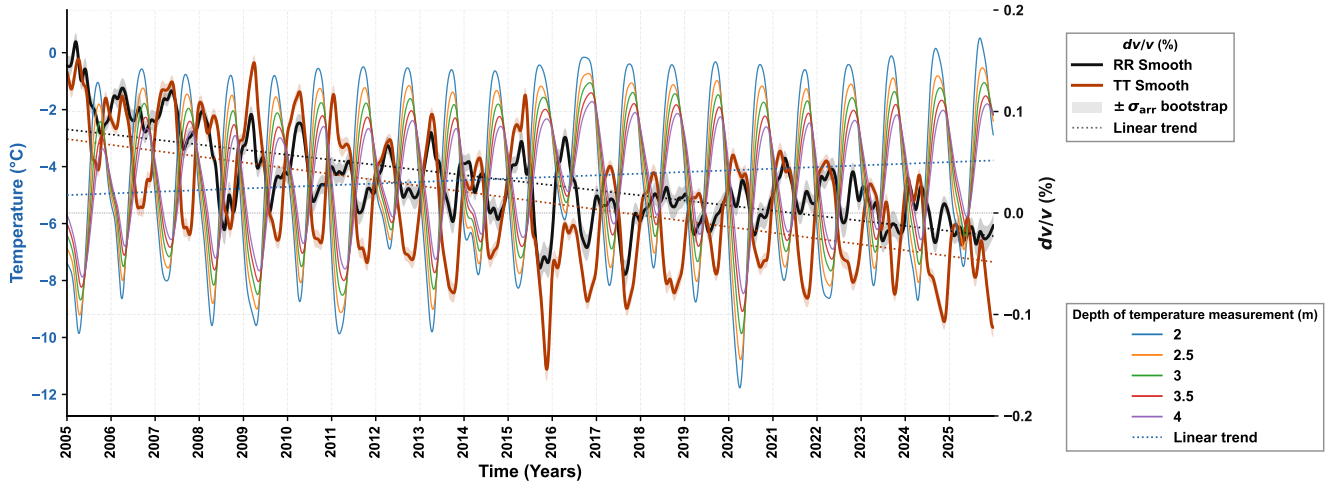


Figure 9. Array-averaged inter-station radial–radial (RR) and transverse–transverse (TT) dv/v compared with GTN-P soil temperature at Janssonhaugen (2005–2025). Smoothed daily soil temperature (selected depths between 2 and 4 m), linear trends, and $\pm\sigma_{arr}$ bootstrap uncertainty are shown (see in-figure legend).

6.3 Supporting cross-component correlation

Single-station correlations have previously been shown to be sensitive to dv/v and are especially suitable for sparse seismic networks where inter-station correlation is not feasible (Bruland et al., 2025; Zhao et al., 2026). Here, we use cross-component correlations of single stations as well as between station pairs as supporting constraints for the dv/v results (Table 2. The inter-station ZZ, NN, and EE products (Fig. 6 and Fig. 9) remain our main interpretive series. Single-station cross-component correlations and inter-station correlations could have a different spatial footprint. Hence, comparing the results allows assessing potential spatial inhomogeneities below the SPITS array.

Cross-component dv/v from single-station and inter-station correlations (Supplement, Fig. S14 and Fig. S15) reproduce, in broad terms, the seasonal anti-correlation with soil temperature seen in the primary results: dv/v tends to increase during winter cooling and decrease during summer thaw. Among the single-station products (Fig. S13a), the NE combination is markedly more variable than ZN and ZE, with larger peak-to-trough amplitudes, stronger short-period scatter, and the steepest negative linear trend ($-0.0061\% \text{ yr}^{-1}$, $R^2 = 0.40$) over 2005–2025. This is consistent with our primary TT results: ZN and ZE primarily recover Rayleigh-wave energy through vertical–horizontal coupling, whereas NE emphasizes Love-wave energy through correlation of the two horizontal components on the same station. As mentioned above, Love-wave correlations are expected to be more sensitive to shallow subsurface shear-velocity changes in the active layer and upper permafrost. The ZN and ZE single-station series show the same seasonal phasing but with smaller long-term trends (-0.0021% and $-0.0028\% \text{ yr}^{-1}$, respectively) and lower explained variance. For inter-station cross-component pairs (Fig. S13b), all three products are more mutually consistent: trends remain negative (ZN: $-0.0046\% \text{ yr}^{-1}$, $R^2 = 0.50$; ZE: $-0.0052\% \text{ yr}^{-1}$, $R^2 = 0.73$; NE: $-0.0045\% \text{ yr}^{-1}$, $R^2 = 0.51$), and ZE exhibits the most stable long-term behaviour.



Vertical–radial (ZR) and vertical–transverse (ZT) inter-station products (Supplement, Fig. S17) provide additional constraints. For an ideal source distribution, ZR should recover the same Rayleigh-wave sensitivity as ZZ. ZT measures coupling between vertical (Rayleigh-type) and transverse (Love-type) motion and would be weak if these wavefields were uncorrelated and noise sources would be distributed uniformly. Both series nevertheless show the seasonal anti-correlation with soil temperature and negative long-term trends of comparable magnitude to RR (ZR: $-0.0051\% \text{ yr}^{-1}$, $R^2 = 0.63$; ZT: $-0.0049\% \text{ yr}^{-1}$, $R^2 = 0.66$), but are in general more noisy.

7 Discussion

7.1 Insights into permafrost degradation at SPITS

The seasonal behaviour of array-averaged ZZ dv/v is consistent with the environmental dv/v behaviour first resolved at SPITS by Albaric et al. (2021). Using moving-window cross-spectral analysis (MWCS) on vertical-component cross-correlation functions in the 0.5 Hz to 2.0 Hz band, they showed that relative velocity variations are anticorrelated with temperature at 2 m to 4 m depth, which they linked to seasonal freeze–thaw and ice-content changes in the shallow active layer and upper permafrost.

In that sense, the present results do not define a new mechanism but confirm and extend the permafrost–seismology link established at Janssonhaugen under an independent dv/v estimator and a substantially longer observational baseline. Relative to the wider environmental-seismology literature (Wegler and Sens-Schönfelder, 2007; Brenguier et al., 2008; Larose et al., 2015), SPITS remains unique in combining small-aperture array geometry, borehole installations below the active layer, GTN-P thermometry, and multi-decadal continuity (Isaksen et al., 2001; Christiansen et al., 2010; Liu et al., 2024), which together allow seasonal thermal modulation of coda velocities to be tested with far greater statistical weight than in the three-year window of Albaric et al. (2021).

More importantly for long-term permafrost monitoring, the negative linear trend in smoothed array-median dv/v (Fig. 6; $-0.0033\% \text{ yr}^{-1}$, or $-0.033\% \text{ decade}^{-1}$, $R^2 = 0.51$) indicates that the continued decrease in seismic velocity inferred by Albaric et al. (2021) for 2009–2012—interpreted as progressive shallow permafrost warming and reduced ice-bonded stiffness in the 2 m to 4 m layer—is not confined to their analysis period. Albaric et al. (2021) reported a linear decline in velocity over years when coincident borehole temperatures at Janssonhaugen were rising, establishing the first seismic evidence of a warming-related mechanical trend at SPITS. When the same site is revisited with 1992–2025 inter-station ZZ correlations and the workflow described in Sect. 5, that decreasing dv/v tendency persists on decadal scales, superimposed on the dominant seasonal cycle. In terms of utilizing the most up-to-date data, these findings reinforce the argument that passive monitoring at fixed Arctic arrays can track not only freeze-thaw cycles (James et al., 2019; Albaric et al., 2021; Cheng et al., 2022) but also longer-term drift of the shallow mechanical regime related to climate change, provided that reference stacks, frequency bands, and quality control are stable enough to separate environmental signals from noise-source variability (Steinmann et al., 2021; Bruland et al., 2025). The SPITS record therefore suggests an ongoing velocity decrease at Janssonhaugen rather than a transient 2009–2012 anomaly, and highlights the value of extending campaign-style permafrost seismology to full operational existing array (Schweitzer et al., 2021).



Seasonal dv/v peak-to-trough amplitudes are of order tenths of a percent, much larger than the multi-decadal trend of
 710 $-0.033\% \text{ decade}^{-1}$, consistent with reversible freeze–thaw modulation superimposed on slower mechanical drift. Investigation
 of time lags between soil temperatures at different depths and velocity changes (Fig. 8) supports the previously found sensitive
 depth range by Albaric et al. (2021): for both ZZ and TT, $|\tau_{\min}|$ is smallest in the 2 m to 4 m band (full-archive minima of
 +2 d at 2.5 m for ZZ and at 2.0 m for TT), whereas shallower and deeper temperatures show as expected systematically larger
 absolute lag times. The slightly shallower TT minimum is consistent with stronger Love-wave sensitivity near the base of the
 715 active layer; however, this needs to be confirmed by forward modeling sensitivity kernels. Nevertheless, our results demonstrate
 that using three-component data allows resolving a broader depth range than from vertical noise correlations alone.

While most years exhibit similar seasonal seismic velocity variations, several years stand out with unusually large positive
 time lags relative to soil temperature variations at the temperature-inferred average sensitivity depth of 2 m to 4 m. These larger
 lags could suggest an increase in the effective depth sensitivity. However, given the relatively stable frequency content and
 720 wave-type composition of the ambient noise wavefield, such changes are difficult to explain without substantial modifications
 to the subsurface structure. An alternative explanation is that additional processes affecting permafrost properties, beyond
 temperature variations alone, influence the seasonal seismic velocity response. Interestingly, the recent trend toward larger
 positive time lags during 2021–2025 coincides with soil temperatures exceeding 0°C for the first time within the 2 m to
 4 m depth interval (Fig. 6). Seasonal thawing of previously frozen ground at these depths could potentially delay the dv/v
 725 response. In this scenario, seismic velocities would not only decrease as temperatures rise but could continue to decrease
 during the thawing process, even as soil temperatures remain close to 0°C . This could produce the larger time lags observed
 in recent years. However, this mechanism alone cannot explain the anomalous behavior observed in other years. Additional
 factors, such as winter temperature anomalies, variations in snow cover, or changes in subsurface moisture and ice content,
 may also influence the seasonal response. A more comprehensive understanding of the interannual variability would require
 730 coupled thermal–hydrological–mechanical modelling of the subsurface, which is beyond the scope of the present study. This
 would also allow for a more quantitative climatic attribution of the long-term tendency and is left to a future study.

Permanent small-aperture arrays such as SPITS offer several advantages for permafrost dv/v monitoring that are difficult
 to reproduce with campaign deployments. Station geometry, instrument type, and processing parameters remain stable over
 decades, so that daily correlation functions can be stacked against long-term Selective-stack references and compared with
 735 co-located GTN-P thermometry. Sensors installed below the active layer reduce near-surface thaw and wind contamination
 relative to surface geophones. Campaign arrays can target a thaw season at high spatial density, but they lack the multi-decadal
 baseline needed to separate the seasonal freeze–thaw cycle from slow mechanical drift.

7.2 Limitations and challenges

Permanent seismic-array deployments in the Arctic, such as SPITS, or in mountain permafrost areas are rare, wider applica-
 740 bility is limited. However, IMS broadband arrays in northern America (YKA, ILAR) and northern Norway (ARCES) could be
 candidates for similar studies. On the other hand, we showed that cross-component single-station correlation results in similar



dv/v . Hence, every permanent single station in target regions can potentially be used for permafrost monitoring and historic analysis of past changes (Zhao et al., 2026), provided that the noise wave field permits it.

The frequency range at SPITS is limited by ambient noise wavefield characteristics. Better resolving changes in shallower
 745 depth (e.g. active layer) would benefit from measurements of dv/v at higher frequencies. Removing seasonal noise source variability from dv/v could potentially allow estimation of long-term trends in future studies.

Assessing Variations of noise sources is crucial for interpreting the dv/v results. F–K analysis at SPITS describes the incident wavefield, but it does not uniquely identify the coda used for stretching. We assume in our analysis that the late coda is dominated by surface waves. The presence of surface waves at SPITS is supported by the F–K results once the body-
 750 wave slowness range is excluded. Importantly, the surface waves show a rather stable seasonal back-azimuth distribution. The dominant incident field at SPITS, however, has low slowness and is compatible with body waves. Those arrivals correspond to the ballistic part of the correlation functions and are excluded from the dv/v window. Resolving the seasonal cycle and the long-term trend in dv/v do not require a unique wave type, provided the illuminating field remains stable, but a potential mixture of body and surface waves limits how tightly the depth sensitivity of dv/v can be interpreted.

Temporal resolution is a further limitation. Daily estimates are smoothed with a Gaussian kernel of $\sigma = 20$ day, which suppresses short-period scatter and is suited to seasonal and decadal signals. The aim of this study is to resolve that seasonality and the long-term trend. For applications requiring higher temporal resolution, such as early-warning systems for permafrost-related slope instability and active-layer detachment slides, the dv/v estimation approach would need further refinement. For example, season-specific stacks, yearly reference stacks, or a moving reference could be explored to better account for long-
 760 term changes and strong seasonal variations associated with freezing and thawing. Furthermore, longer, overlapping correlation stacks or alternative stacking methods could improve the stability of the cross-correlations, potentially reducing the need for strong temporal smoothing that might otherwise suppress sharp velocity changes. A first check with a recent-years (2015–2025) Selective-stack reference leaves the seasonal cycle and the sign of the long-term trend unchanged (Supplement Fig. S19).

The uncertainty analysis is also limited. The bootstrap uncertainty treats the station pairs as the resampled units. It does
 765 not account for correlation from one day to the next after smoothing, and it does not fold in the instrument changes listed in Table 1. The shaded band in Fig. 6b is therefore a measure of station-pair-to-pair spread, not a formal confidence interval on the trend.

Despite these limits, our results demonstrate that the SPITS archive is an unprecedented continuous seismic record of shallow Arctic permafrost mechanics through the recent High Arctic warming.

770 8 Conclusions

We used more than three decades (1992–2025) of ambient-noise recordings from the SPITS array on Janssonhaugen, Svalbard, to measure relative seismic velocity variations in shallow permafrost. The noise field at SPITS is suitable for interferometry. Power spectral densities lie mostly between the Peterson low- and high-noise models. Energy is strongest in the microseism band, and the 2 Hz to 10 Hz band is enhanced during the melt season. In the 0.5 Hz to 2.0 Hz band used here, F–K analysis



775 shows that the incident field has low apparent slowness and arrives mainly from the east and north-west. We do not measure dv/v on that body-wave dominated direct arrival. Instead we stretch the late coda ($|\tau| \in [8, 20]$ s), which is multiply scattered and repeats from day to day and we assume to be dominated by surface waves. Of the stacking methods we tested, Selective stacking was the most effective at rejecting clock-affected and low-coherence days while keeping the coda phases stable, so we used it to build the per-pair reference stacks. Array-averaged inter-station ZZ and TT dv/v follows the seasonal freeze–
780 thaw cycle. It is anti-correlated with GTN-P soil temperature at 2 m to 4 m ($r = -0.43$): velocity rises when the ground cools and falls after the summer thaw. This confirms the behaviour first reported at SPITS by Albaric et al. (2021), now with a different dv/v estimator, a much longer record, and including horizontal seismic component records. Scanning all 15 borehole thermistors shows that 2 m to 4 m is also the depth range where dv/v and temperature are closest in phase, for both ZZ and TT. The seismic signal therefore tracks the base of the active layer and the uppermost permafrost rather than the full ~ 220 m
785 frozen column. Superimposed on that seasonal cycle is a long-term velocity decrease of $0.033\% \text{ decade}^{-1}$ ($R^2 = 0.51$). The horizontal-component dv/v results all show a decrease of the same sign. We interpret this as a gradual loss of ice-bonded stiffness in the active layer and upper permafrost. The decline reported for 2009–2012 is thus not limited to that short window. Single-station cross-component products show the same seasonal anti-correlation and support this result. Overall, our results clearly demonstrate that a long-running small-aperture Arctic seismic array with a borehole at the same site can resolve both
790 the seasonal thermal cycle and a multi-decadal mechanical trend in shallow permafrost in unprecedented detail and duration.



Appendix A: Archive data-quality issues and mitigations

Table A1. Summary of known data-quality problems in the SPITS archive and the mitigations applied in this study (documentation for future work on the same dataset). SPA0 and SPB3 horizontal corrections follow NORSAR operations notes; rotations are relative to true north.

Period	Issue	Manifestation / detection	Mitigation
1993–1996, 1998	Archive glitches	Header errors, non-nominal day lengths, distorted waveforms; spurious vertical correlations	Matched SHZ–SHZ or BHZ–BHZ pairs; reject low coherence ($\gamma < 0.06$), unbalanced RMS, or weak correlation amplitude
1999–2004	Timing and metadata	Start times not at UTC midnight; day lengths not 86 400 s at 40 Hz; distorted intervals	Slice to UTC-day windows at 40 Hz; reject days failing $\gamma \geq 0.18$, amplitude, peak-lag (± 2 s), or yearly-stack similarity
1992–2025 (intermittent)	Clock / timing offsets	Horizontally shifted coherent bands in stacking heatmaps; typically 1 s to 3 s (up to ~ 5 s)	No CCF lag realignment; exclude mis-timed days by daily QC and Selective stacking
2015–present	BH*/HH* coexistence	Overlapping broadband and high-gain files; length or timing mismatch after decimation to 40 Hz	One coherent $Z/N/E$ set per day; correlate only the common UTC overlap
6 May 2015– 20 May 2016	HH* polarity reversals	Inverted ZE and NE CCFs vs. long-term references; strongly negative stretching ρ	Flip sign of affected daily CCFs if ρ vs. the 2017 reference is negative; ZZ, NN, EE unchanged
25 Mar 2023– 26 Aug 2026	SPB3 N/E interchange	$N-S \leftrightarrow E-W$ channel swap	Swap N and E before correlation
From 26 Aug 2026	SPB3 swap and polarity	$N-S \leftrightarrow E-W$ swap plus polarity reversal on both horizontals	Swap N/E and reverse both polarities before correlation
6 May 2015– 20 May 2016	SPA0 polarity and orientation	North polarity reversal and rotation -27.5°	Flip North and rotate -27.5° before correlation
20 May 2016– 6 Jul 2023	SPA0 swap, polarity, orientation	$N-S \leftrightarrow E-W$ swap; North and East polarity reversals; rotation $+27.5^\circ$	Apply swap, both polarity flips, and $+27.5^\circ$ rotation before correlation
6 Jul 2023– 16 Jan 2025	SPA0 polarity and orientation	East polarity reversal and rotation $+27.5^\circ$	Flip East and rotate $+27.5^\circ$ before correlation
16 Jan 2025– 26 Aug 2026	SPA0 interchange and orientation	$N-S \leftrightarrow E-W$ swap and rotation $+27.5^\circ$	Swap N/E and rotate $+27.5^\circ$ before correlation
From 26 Aug 2026	SPA0 polarity and orientation	East polarity reversal and rotation $+27.5^\circ$	Flip East and rotate $+27.5^\circ$ before correlation



Appendix B: Pre-processing definitions

Before decimation, each trace $x(t)$ is filtered in the frequency domain with a cosine-ramp low-pass mask. The transfer function is

$$H_{LP}(f) = \begin{cases} 1, & |f| \leq f_1, \\ \frac{1}{2} \left[1 + \cos \left(\pi \frac{|f| - f_1}{f_2 - f_1} \right) \right], & f_1 < |f| < f_2, \\ 0, & |f| \geq f_2, \end{cases} \quad (B1)$$

with $f_1 = f_c - \Delta f/2$, $f_2 = f_c + \Delta f/2$, and $\Delta f = \alpha f_c$ (typically $\alpha \approx 0.1$). For this study, the cutoff frequency is $f_c = 18$ Hz. The filtered signal is transformed back to the time domain and decimated by a factor of 2. Because the filter is applied symmetrically in the frequency domain, phase distortion is minimized.

For each preprocessed segment $x_{i,d,k}(t)$ at station i , day d , and segment index k , let $X_{i,d,k}(f)$ denote its Fourier transform, computed in practice as a discrete Fourier transform (DFT) evaluated at frequency bins indexed by ℓ . Stabilized spectral whitening (Bensen et al., 2007) is applied pointwise as

$$\tilde{X}_{i,d,k}(f_\ell) = \frac{X_{i,d,k}(f_\ell)}{\max(|X_{i,d,k}(f_\ell)|, \epsilon_{i,d,k})}, \quad (B2)$$

where $\tilde{X}_{i,d,k}$ is the whitened spectrum, $|X_{i,d,k}(f_\ell)|$ is the amplitude spectrum, and $\epsilon_{i,d,k} = \eta \text{median}_\ell\{|X_{i,d,k}(f_\ell)|\}$ is a segment-dependent stabilization floor with $\eta = 10^{-3}$. This relative floor prevents unstable amplification at spectral notches; when $|X_{i,d,k}(f_\ell)| \gg \epsilon_{i,d,k}$, Eq. (B2) approaches phase-only normalization. The whitened time-domain segment $\tilde{x}_{i,d,k}(t)$ is obtained by inverse DFT of $\tilde{X}_{i,d,k}$ over the resolvable band at $f_s = 40$ Hz (Nyquist 20 Hz), with usable content limited by the low-pass cutoff at 18 Hz.

As a final time-domain normalization step, residual amplitude outliers are controlled by clipping

$$\tilde{x}_{i,d,k}(t) \leftarrow \text{clip}(\tilde{x}_{i,d,k}(t), \mu_{i,d,k} - k_{\text{clip}}\sigma_{i,d,k}, \mu_{i,d,k} + k_{\text{clip}}\sigma_{i,d,k}), \quad (B3)$$

where $\mu_{i,d,k}$ and $\sigma_{i,d,k}$ are the segment mean and standard deviation, $k_{\text{clip}} = 4.0$, and $\text{clip}(y, a, b) = \min(\max(y, a), b)$. The clipped segment defines $s_{i,d,k}(t)$ used in Eq. (10) of the main text.

Appendix C: Stacking estimators

Long-term correlation functions are built in two steps: segment correlations are averaged within each day, and daily traces are then combined using one of the stacking estimators compared in Sect. 4.4. Supplement, Figs. S9–S11 show Robust, PWS, and tf-PWS results for comparison with Selective stacking (main text, Fig. 5).



C1 Daily segment averages

For each day d , the correlations of all retained segments are averaged to obtain daily autocorrelation and cross-correlation functions:

$$\bar{A}_{i,d}(\tau) = \frac{1}{K_{i,d}} \sum_{k=1}^{K_{i,d}} \hat{A}_{i,d,k}(\tau), \quad \bar{C}_{ij,d}(\tau) = \frac{1}{K_{ij,d}} \sum_{k=1}^{K_{ij,d}} \hat{C}_{ij,d,k}(\tau), \quad (\text{C1})$$

820 where $K_{i,d}$ and $K_{ij,d}$ are the numbers of retained segments on day d .

C2 Linear stacking

The linear stack is the arithmetic mean of all daily correlation functions over D days:

$$\hat{C}_{ij}^{\text{linear}}(\tau) = \frac{1}{D} \sum_{d=1}^D \bar{C}_{ij,d}(\tau). \quad (\text{C2})$$

C3 Robust stacking

825 Robust stacking (Pavlis and Vernon, 2010) iteratively reweights daily correlation functions $\mathbf{d}_i$ ($i = 1, \dots, N$) toward a stable reference, where $\mathbf{d}_i$ denotes the daily correlation function $\bar{C}_{ij,d}(\tau)$ for day i and the inner product $\cdot$ and norm $\|\cdot\|$ are taken over lag τ (i.e. $\mathbf{a} \cdot \mathbf{b} = \int a(\tau)b(\tau) d\tau$, discretized as a sum over lag samples). The initial stack $\mathbf{b}_1$ is the pointwise median over days of all daily traces, and at iteration j the weight of trace i is

$$w_i = \frac{|\mathbf{b}_j \cdot \mathbf{d}_i|}{\|\mathbf{d}_i\|} \cdot \frac{1}{\|\mathbf{r}_i\|}, \quad (\text{C3})$$

830 where the modified residual

$$\mathbf{r}_i = \mathbf{b}_j - \frac{(\mathbf{b}_j \cdot \mathbf{d}_i)}{\|\mathbf{d}_i\|^2} \mathbf{d}_i \quad (\text{C4})$$

measures the part of $\mathbf{b}_j$ not explained by $\mathbf{d}_i$. The updated stack is $\mathbf{b}_{j+1} = \sum_i w_i \mathbf{d}_i / \sum_i w_i$, and iteration stops when

$$\frac{\|\mathbf{b}_{j+1} - \mathbf{b}_j\|}{\|\mathbf{b}_j\|} < \varepsilon, \quad (\text{C5})$$

with $\varepsilon = 10^{-5}$ following the explanation in Pavlis and Vernon (2010), for which there is no single choice for this value.

835 C4 Phase-weighted stacking

Phase-weighted stacking (PWS) (Schimmel and Paulssen, 1997) uses instantaneous phase information to weight the stack. For each trace $d_i(\tau)$, the analytic signal is

$$\tilde{d}_i(\tau) = d_i(\tau) + i\mathcal{H}\{d_i\}(\tau), \quad (\text{C6})$$



where i is the imaginary unit and $\mathcal{H}\{\cdot\}$ is the Hilbert-transform operator (Oppenheim and Schaffer, 2009). With an instantaneous

840 phase $\phi_i(\tau) = \angle(\tilde{d}_i(\tau))$, the phase-coherence weight is

$$c(\tau) = \left| \frac{1}{N} \sum_{i=1}^N e^{i\phi_i(\tau)} \right|^2, \quad (C7)$$

the PWS stack is

$$b_{\text{PWS}}(\tau) = \bar{d}(\tau) c(\tau), \quad \bar{d}(\tau) = \frac{1}{N} \sum_{i=1}^N d_i(\tau). \quad (C8)$$

C5 Time-frequency phase-weighted stacking

845 Because PWS is nonlinear, the stacked waveform can change substantially relative to the linear stack. Schimmel et al. (2011) therefore extended PWS to the time–frequency domain (tf-PWS). Each daily correlation function $d_i(\tau)$ is transformed with the Stockwell (S) transform (Stockwell et al., 1996),

$$S_i(\tau, f) = \int_{-\infty}^{\infty} d_i(t) w(\tau - t, f) e^{-i2\pi ft} dt, \quad (C9)$$

where the frequency-dependent Gaussian window is

$$850 \quad w(\tau - t, f) = \frac{|f|}{k\sqrt{2\pi}} \exp\left(-\frac{f^2(\tau - t)^2}{2k^2}\right), \quad k > 0. \quad (C10)$$

The time–frequency phase-coherence weight is then

$$c(\tau, f) = \left| \frac{1}{N} \sum_{i=1}^N \frac{S_i(\tau, f)}{|S_i(\tau, f)|} \right|^2, \quad (C11)$$

the tf-PWS spectrum is the coherence-weighted linear stack in the time–frequency domain,

$$S_{\text{tf-PWS}}(\tau, f) = c(\tau, f) S^{\text{linear}}(\tau, f), \quad S^{\text{linear}}(\tau, f) = \frac{1}{N} \sum_{i=1}^N S_i(\tau, f). \quad (C12)$$

855 An inverse S transform of $S_{\text{tf-PWS}}(\tau, f)$ yields the time-domain stack $b_{\text{tf-PWS}}(\tau)$ (Schimmel and Gallart, 2007; Schimmel et al., 2011).

Appendix D: Why an analytical stretching error model is not used

Analytical single-pair error models for stretching, such as the apparent-dilation theory of Weaver et al. (2011), assume two stationary, Gaussian, noise-like coda signals with comparable spectra centred on ω_c , provided that the analysis window $\mathcal{W}$ is

860 long relative to $1/\omega_c$ and that both signals are normalized to unit variance. These assumptions do not hold for our data. Pooling the coda amplitudes of the array-mean Selective-stack reference (36 inter-station ZZ pairs, 2011) on the causal and anti-causal



branches within the analysis window gives $N_S = 962$ samples $\{x_j\}$, whose departure from Gaussianity we quantify with the excess kurtosis. For a random variable X with mean μ , the excess kurtosis is

$$\kappa = \frac{\mathbb{E}[(X - \mu)^4]}{(\mathbb{E}[(X - \mu)^2])^2} - 3, \quad (\text{D1})$$

865 which vanishes for a Gaussian and is positive for a leptokurtic distribution (heavier tails and a sharper peak). With sample mean $\bar{x} = N_S^{-1} \sum_{j=1}^{N_S} x_j$, the r th central sample moment is

$$m_r = \frac{1}{N_S} \sum_{j=1}^{N_S} (x_j - \bar{x})^r. \quad (\text{D2})$$

The biased excess kurtosis uses only the second and fourth central moments, $g_2 = m_4/m_2^2 - 3$. Because g_2 is biased for finite samples, we estimate κ with the bias-corrected estimator of Joanes and Gill (1998), which is unbiased under normality,

$$870 \quad \hat{\kappa} = \frac{N_S - 1}{(N_S - 2)(N_S - 3)} [(N_S + 1)g_2 + 6]. \quad (\text{D3})$$

The pooled coda amplitudes yield $\hat{\kappa} \approx 2.3$ (clearly leptokurtic and non-Gaussian; Supplement, Fig. S12b), and the amplitude envelope decays with lag (Supplement, Fig. S12a), so the coda is not amplitude-stationary. Because the Gaussianity and stationarity conditions of Weaver et al. (2011) are not met, we do not adopt an analytical error model. Uncertainty on the array-median dv/v series is instead quantified by bootstrap resampling as described in Sect. 5.2.

875 *Code and data availability.* Seismic waveform data from the NORSAR station network (network code NO) are publicly available via the Norwegian EIDA node at <https://eida.geo.uib.no> (University of Bergen 2026; NORSAR 1971). Meteorological observations from the Janssonhaugen Vest weather station are publicly available from the Norwegian Centre for Climate Services at <https://seklima.met.no/> (Norwegian Centre for Climate Services 2025). GTN-P borehole temperature records from Janssonhaugen (P11) are available from the Global Terrestrial Network for Permafrost upon request to the data custodian. Processing scripts used in this study are available from the
880 corresponding author upon reasonable request.

Author contributions. KK and AK conceptualised the study. KK and AH developed the methodology and theory. KK curated the data, performed the analyses, and prepared the figures. CB contributed expertise on ambient-noise and cultural-noise monitoring and critically revised the manuscript. KK drafted the manuscript with contributions from all co-authors; AH contributed substantially to the theoretical sections. AH and AK supervised the project.

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