REPORT
doi:10.26443/seismica.v5i1.1478

SEISMICA

Seismic response of a slow-moving landslide: exploring data from two years of seismic monitoring at the Hollin Hill Landslide Observatory (UK)

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Abstract Early-warning of landslide failure relies on understanding subsurface processes that drive slope destabilisation, including changes in moisture content or mechanical behaviour. Material heterogeneity in landslide systems causes spatiotemporal variation in these dynamic processes. There is therefore a need to develop methods that can detect and measure changes in the subsurface to inform landslide stability. Seismic monitoring can record information on the elastic behaviour of the ground in response to immediate and long-term processes, such as slope displacement and moisture variation. Here, we report on data acquired by a seismic network deployed at a slow-moving clay-rich landslide in North Yorkshire UK, representative of many landslides in clay-rich lowland slopes. The temporary network was operational for two years with the aim of understanding how the seismic response of the landslide varies between sensors deployed on parts of the landslide with distinctly different hydrogeological properties. We present an overview of the rationale and deployment procedure, as well as a preliminary assessment of data quality, event analysis, tilt observations, horizontal-to-vertical spectral ratio (H/V) ratio calculations, and ambient noise cross-correlation. We conclude that the moisture dynamics of the slope have a significant influence on observed data, and make further recommendations for the analysis of the dataset. Our study demonstrates the feasibility of analytical techniques using these data, promotes the unique dataset to foster further in-depth analysis, and encourages similar seismological deployments on active landslides.

Production Editor:
Gareth Funning
Handling Editor:
György Hetényi
Copy & Layout Editor:
Théa Ragon

Received:
October 2, 2024
Accepted:
March 5, 2026
Published:
April 7, 2026

Résumé (French) La détection précoce des glissements de terrain repose sur la compréhension des processus souterrains qui conduisent au déclenchement des évènements, généralement liés à des variations de teneur en eau ou de comportement mécanique. L'hétérogénéité structurelle des glissement de terrain peut entraîner une variabilité spatio-temporelle de ces processus dynamiques. Il est donc important de développer des méthodes permettant une meilleure observation de ces changementa dans le sous-sol pour évaluer la stabilité des pentes. La surveillance sismique, par l'utilisation de capteurs déployés à la surface du glissement de terrain, peut permettre d'enregistrer des informations sur le comportement élastique du sol, en réponse à des phénomènes tels que les déplacements en surface et les variations d'humidité. Nous décrivons ici le jeu de données acquis par un réseau sismique déployé sur un glissement de terrain argileux à déplacement lent dans le North Yorkshire, au Royaume-Uni, représentatif d'un grand nombre de glissements de terrain argileux dans le monde. Le réseau temporaire, déployé sur une durée de 2 ans, avait pour but de comprendre comment la réponse sismique varie dans des zones du glissement de terrain aux propriétés hydrogéologiques différentes. Nous présentons un aperçu de la procédure de déploiement, ainsi qu'une évaluation de la qualité des données, de l'analyse des évènements, des observations de tilt, des calculs de rapport spectral horizontal/vertical (H/V), et de la corrélation croisée du bruit ambiant. Les premières conclusions indiquent que les données observées sont significativement influencées par la dynamique de l'humidité du sol de la pente, et nous permettent de formuler des recommandations pour l'analyse du jeu de données. Notre étude démontre la faisabilité des techniques d'analyse appliquées à ces données; promeut ce jeu de données unique pour encourager des analyses plus approfondies; et encourage la mise en place de déploiements sismologiques similaires sur des glissements de terrain actifs. évaluation de la qualité des données, des analyses d'événements, des observations de basculement, des calculs de rapport H/V et des corrélations de bruit ambiant.

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Non-technical summary Early warning of landslides is important for safety, and often relies on rainfall thresholds or on assessing visible signs of surface deformation. It is usually how wet the subsurface of the landslide is that drives slope failure and surface deformation generally occurs late in the process, with limited to no time for mitigation measures to be efficiently put in place. There is thus a need for innovative methods to observe and measure changes occurring underground. Seismic monitoring involves placing sensors measuring vibration on the landslide surface to track how the ground moves and responds over time, especially to changes in moisture. We set up a network of these sensors at a slow-moving landslide in North Yorkshire, UK. The goal was to see how the seismic readings differed in areas with different water content and ground properties. We explain why and how we set up the sensors, and present the data we collected. Our findings show that changes in moisture significantly affect how the ground responds, and how landslide activity can generate specific vibrations. Finally, we offer suggestions for further analyses.

1 Scientific background and motivation

1.1 Introduction

Landslide hazards impact population safety and infrastructure across the globe. The risk of landslides can be mitigated through engineering interventions or management, with the latter often favoured due to lower costs, particularly where slow-moving landslides are prevalent. One such method of landslide management is the implementation of an early-warning system that uses field observations to warn of impending slope failure events, thus allowing time for more efficient intervention planning or removal of the elements at risk (Intrieri et al., 2012). Slope-scale early warning systems typically tend to rely on observations of rainfall, ground moisture, or slope displacement to predict future failure events (Pecoraro et al., 2019).

Slow-moving landslides are characterised by slow ground motion, spanning from millimeters to meters per year, often seasonally influenced and persisting for long periods of time, from years to decades (Lacroix et al., 2020). Such landslides typically occur in geological contexts involving clay-rich or mechanically weak materials, and in areas with strong seasonal rainfall patterns. Despite slow-moving landslides being perceived as low risk to human life, they can lead to significant damages to critical infrastructure (such as road and railway network) and can be difficult to manage effectively (Gibson et al., 2013).

In recent years, geophysical techniques have been increasingly used for slope monitoring (Whiteley et al., 2019). Geophysical techniques offer unique advantages in that they can often obtain measurements from across large areas of the subsurface (unlike point sensors) and are able to infer processes occurring at depth within a landslide body (unlike surface observations). However, the sensitivity of geophysical methods to proxies, rather than direct measurements, of subsurface ground conditions means there can be ambiguity in interpreting the spatial and temporal variation in geophysical signals and related models (Le Breton et al., 2021). Identifying precursors to landslide events with sufficient lead time is particularly challenging.

The predominant ground-based geophysical monitoring approaches used on landslides are geoelectrical and seismic techniques (Le Breton et al., 2021; Whiteley et al., 2019). Geoelectrical monitoring has the advantage of providing detailed images of the subsurface at fixed time intervals, but its temporal resolution is limited due to the time required for data acquisition (typically >1 hour). Additionally, it is primarily sensitive to changes in the ground directly beneath the deployed sensor array; where electrodes are used outside of the zone of interest, changes in ground conditions are detectable but difficult to localise (Bièvre et al., 2021). In contrast, seismic monitoring using a network of seismometers provides time-continuous data and the ability to detect events both proximal and distal to the sensor array, offering insights into the mechanical properties of landslide materials, making the approach particularly valuable for detecting and monitoring dynamic slope processes (e.g., Feng et al., 2025).

In clay-rich slopes, deformation typically occurs under saturated or near-saturated conditions, exhibiting elastoplastic rather than brittle and inelastic behaviour. This likely affects the level of microseismic activity expected from slope movement (Walter et al., 2013). However, changes in shear strength due to elevated moisture and deformation likely impact seismic signals at the slope scale (Vouillamoz et al., 2018). Seismic monitoring could also shed new light on shallow processes affecting clay-rich slopes in drier conditions, such as the formation of desiccation cracks and fissures (Yfantis et al., 2021). The presence of fissures linking a permeable top layer and deeper slip surfaces are thought to play a role as a landslide triggering mechanism (Van Asch et al., 1999). Therefore, in addition to advancing our understanding of landslide processes during periods of increasing and full saturation, improving our ability to observe fissure generation in dry conditions might advance our understanding of landslide mechanisms.

Here, we present data and initial findings from a deployment of seismometers (the YJ 2020-2023 temporary network) at a slow-moving, clay-rich landslide in North Yorkshire, UK. The primary objective of this study is to encourage further, more advanced investigations on the acquired dataset, which has been made available for use by other researchers working in this field. Seismic monitoring is a complementary technique to the systems already deployed at the site, which have largely focused on understanding soil moisture dynamics through geoelectrical monitoring and soil sensor deployment (Uhlemann et al., 2016b).

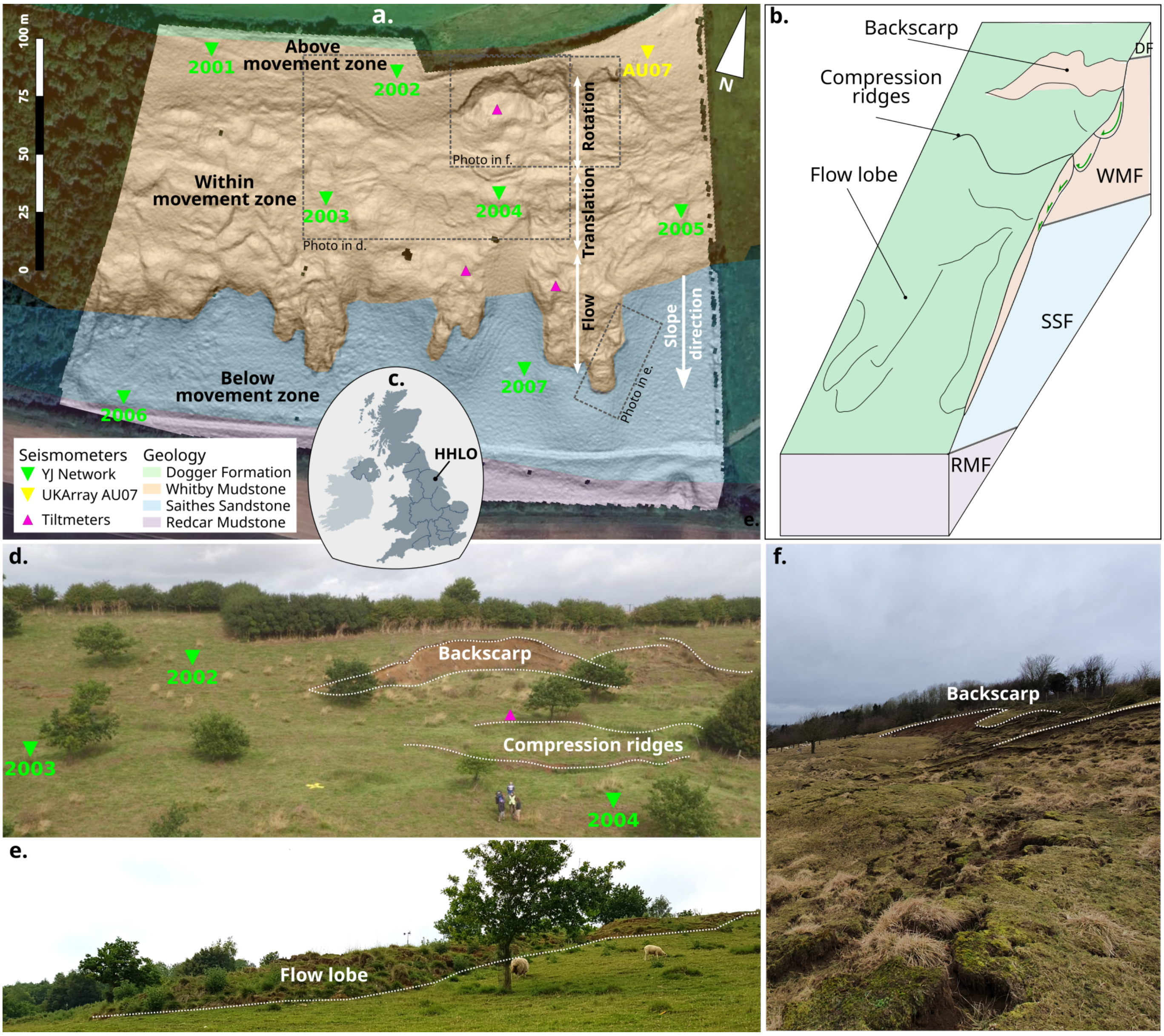

Figure 1 a) Map of the HHLO with major geomorphological features, underlying geology and seismometer locations. The extent of the Digital Terrain Model shown on the map covers the main area of reported active movement. b) Schematic model of the geological layers and main landslide features. c) Location of the HHLO in the UK. d) Photo of the central part of the landslide, looking north. e) Photo of a flow lobe, looking west. f) Photo of surface deformation near the backscarp, looking west.

1.2 Site description

The Hollin Hill Landslide Observatory (HHLO) is a field observatory and laboratory that has been operated by the British Geological Survey (BGS) since 2008. The site has been important in the research and development of novel geophysical, geotechnical and remote sensing technologies for the observation and monitoring of natural landslide processes. The Hollin Hill landslide is a slow-moving, clay-rich landslide, which is seasonally reactivated when soil moisture increases in winter (Uhlemann et al., 2017). In summer it experiences high shrinkage and surface fissuring, which may consequently impact the hydrological regime of the landslide in following years. The HHLO is representative of many landslide hazards in clay-rich lowland slopes worldwide, with the underlying Lias Group rocks accounting for 15% of all landslides in the UK (Hobbs et al., 2012).

The HHLO is located on a south facing slope made of a series of interbedded, north-dipping, shallow marine mudstones and sandstone, comprising (in descending order) the Dogger Formation (DF), which is a limestone and sandstone unit acting as a minor aquifer, the Whitby Mudstone Formation (WMF), the Staithes Sandstone Formation (SSF), and the Redcar Mudstone Formation (RMF) (Chambers et al., 2011). The WMF is the main unit prone to failure. Most of the reported movement occurs on a grass field covering 5 ha of land. The top of the slope exhibits rotational failures in the WMF leading to the formation of prominent backscarps, the most recent of which has been developing since 2016 (Boyd et al., 2021). The landslide failure mode becomes

ID	Latitude	Longitude	Elevation (m)	Location	Geological formation	Landslide domain
2001	54.11137	-0.961835	100.9	Crest	WMF	Undisturbed (above movement zone)
2002	54.111449	-0.96061	98.7	Crest	WMF	Undisturbed (above movement zone)
2003	54.110912	-0.960868	85.9	Mid-slope	WMF	Dormant (no active movement at time of monitoring)
2004	54.111074	-0.959778	86.7	Mid-slope	WMF	Highly active (located beneath active rotational failure)
2005	54.111179	-0.958567	86.7	Mid-slope	WMF	Partially active (located beneath recent rotational failures)
2006	54.109978	-0.96187	82.1	Toe	SSF	Undisturbed (below movement zone)
2007	54.110371	-0.959336	59.6	Toe	SSF	Undisturbed (between active flow lobes of landslide)

Table 1 Properties of the station locations in terms of geology and landslide domain at the HHLO.

translational mid-slope, with some large flow lobes of mudstone materials creeping on top of the SSF toward the base of the slope (Fig. 1). The cycle of slope movement initiates with the WMF reaching its liquid limit in the mid-slope, which then starts to move translationally. This removes support for the upslope, which initiates the formation of backscarps. Translationally failed WMF from the mid-slope progresses down slope until it is emplaced above the SSF, into which it drains and movement is arrested, leaving slowly progressing flow lobes toward the base of the hill.

Research at the HHLO over the past two decades has primarily focused on the development of geophysical systems for monitoring slope processes to enhance early-warning capability (Whiteley et al., 2019, 2021), with a particular focus on understanding spatiotemporal variations in moisture dynamics driving slope destabilisation (Chambers et al., 2022). Key findings from geoelectrical monitoring at the HHLO include: i) estimating spatiotemporal variation in key material properties such as moisture content (Merritt et al., 2013) and matric potential (Boyd et al., 2024) can be achieved using geophysical-geotechnical petrophysical relationships, ii) slope displacements typically occur once a threshold of 48% gravimetric moisture content (GMC) is reached, which is at a similar value to reported liquid limits for the WMF (Uhlemann et al., 2016a), and iii) changes in electrode positions can be used to recover slope movements from geoelectrical monitoring datasets (Wilkinson et al., 2016). Geoelectrical monitoring of subsurface moisture has been supported by studies also looking at corresponding slope displacements from point sensors (Uhlemann et al., 2016b), UAV surveys (Peppa et al., 2019), GPS time-series (Boyd et al., 2021), and InSAR measurements (Kelevitz et al., 2022).

More recently, seismic methods have been used at the HHLO to better understand how moisture dynamics influence the mechanical behaviour of saturated soils preceding failure. Whiteley et al. (2020) compared changes in seismic velocity from time-lapse active seismic refraction surveys with ground moisture and local rainfall data. They found that variations in the elastic properties of the sliding layer are linked to saturation levels (Whiteley et al., 2020). A conclusion of this study was that while repeated active surveys can provide insight into the saturation-driven mechanical variations at the HHLO, their implementation is impractical for long-term use. Hence, passive seismological monitoring was identified as a potentially viable option for long-term monitoring of slope processes, as previously demonstrated on other slow-moving landslides (Fiolleau et al., 2020; Mainsant et al., 2012; Tonnellier et al., 2013; Walter et al., 2012).

The HHLO has also been equipped with a permanent Güralp CMG-3ESP seismometer since 2015 (station AU07 of the UK Array, BGS seismic network). This dataset was used by Murray et al. (2025) to focus on detecting and characterising microseismic activity as precursors to landslide events using machine learning. Their study is particularly encouraging as it observes an increase in microseismicity prior to slope deformation. It also demonstrates that seismometers can record seismic signals originating from crack formation, propagation, or shear within the soil mass.

1.3 The YJ temporary network

The YJ (2020-2023) network, subsequently referred to as YJ, consists of seven Güralp 6TD sensors deployed at the HHLO between March 2020 and March 2022 on a loan from the UK's Natural Environment Council (NERC) Geophysical Equipment Facility (GEF) (Brisbourne, 2012). The Güralp 6TD is a three component broadband seismometer with a standard frequency response of 0.033 - 100 Hz. The YJ network was designed so that seismometers were installed on different landslide domains, comprising areas with different failure mechanisms (i.e., translational/creep) and underlying geology (i.e., WMF/SSF) (Tab. 1). These domains have been identified by previous studies considering varying displacement rates across the slope (Boyd et al., 2021) and areas of different hydrogeological conditions (Uhlemann et al., 2016a, 2017) which allows us to test the hypothesis that seismometer setting will have an influence on the single-station analysis of seismological data. Additionally, the YJ network was designed to test the hypothesis that changes in relative surface-wave velocity, derived through cross-correlation of ambient noise, can be used to detect variations in shear strength of landslide materials, which is critical for early-warning of slope failures.

2 Instrument deployment

The seven Güralp 6TD seismometers were deployed between 9 and 11 March 2020 following the SEIS-UK deployment procedure (Lane et al., 2020). The seismometers were buried 40 cm below ground level in a pit filled with sand. Each station was powered by a 12V battery installed in a metal box recharged by two 20W solar pan-

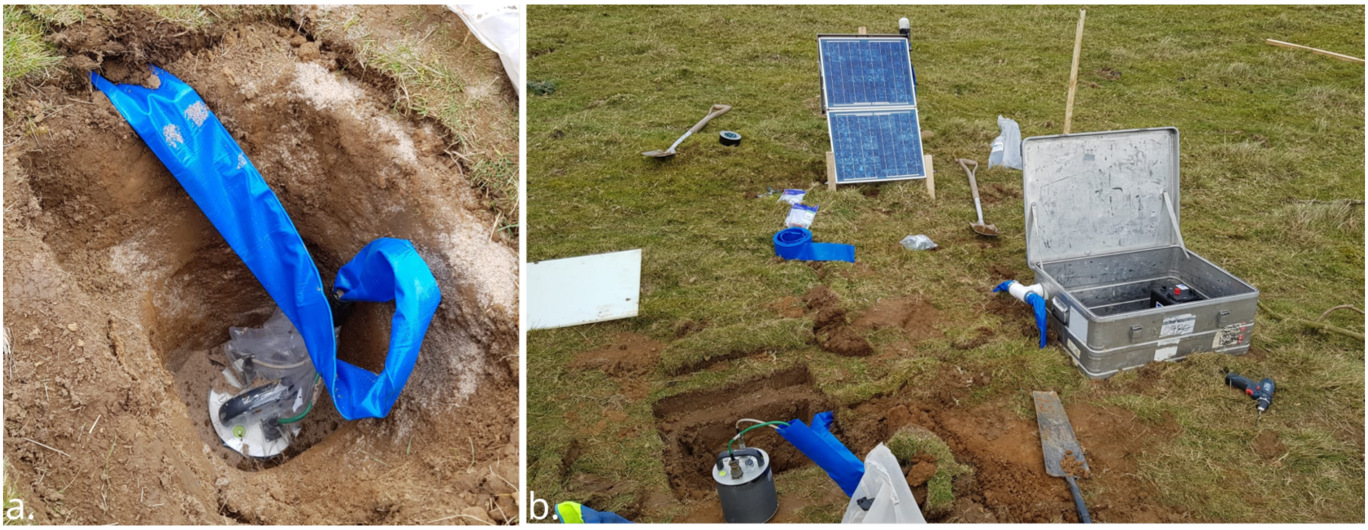

Figure 2 a) Typical Güralp 6TD seismometer installation at the HHLO site. b) Wider station setup showing solar panels and customised housing for battery, data storage and cable connection box.

els mounted on a wooden frame. The metal box was customised by BGS to allow the connection of two lengths of hose via plastic push-fit connectors into the storage box. This provided extra protection for the cabling from livestock and moisture ingress (Fig. 2).

The Güralp 6TDs were configured to record at 200 Hz. With this configuration, the instruments could store up to four months of data. Eight service runs were completed on schedule, with the exception of one run in Spring 2021 which was delayed due to the impact of Covid-19 on staff availability (Fig. 3). This service run was conducted a few days after the data storage disks reached capacity. Details of activities during deployment, on each service run and during decommission were recorded on service sheets, which were scanned and archived.

One seismometer (YJ.2004) failed during the monitoring period (in January 2021), likely due to extensive subsurface flooding of the installation housing, and a replacement sensor was deployed in February 2021. Two stations (YJ.2001 and YJ.2003) had persistently failed shortly after service runs, with issues commencing in winter and spring 2021, respectively. These issues were associated with blown fuses, although no exact cause was determined, but moisture reaching the electronic boards was suspected. Despite remediation attempts, including fuse replacement, neither station was able to record data for significant lengths of time after these dates. Five of the seven 6TDs had >95% data coverage, with network-wide data coverage being 85% for the two-year monitoring period (Fig. 3). The reduced data coverage in the second year (with only >70% data coverage)

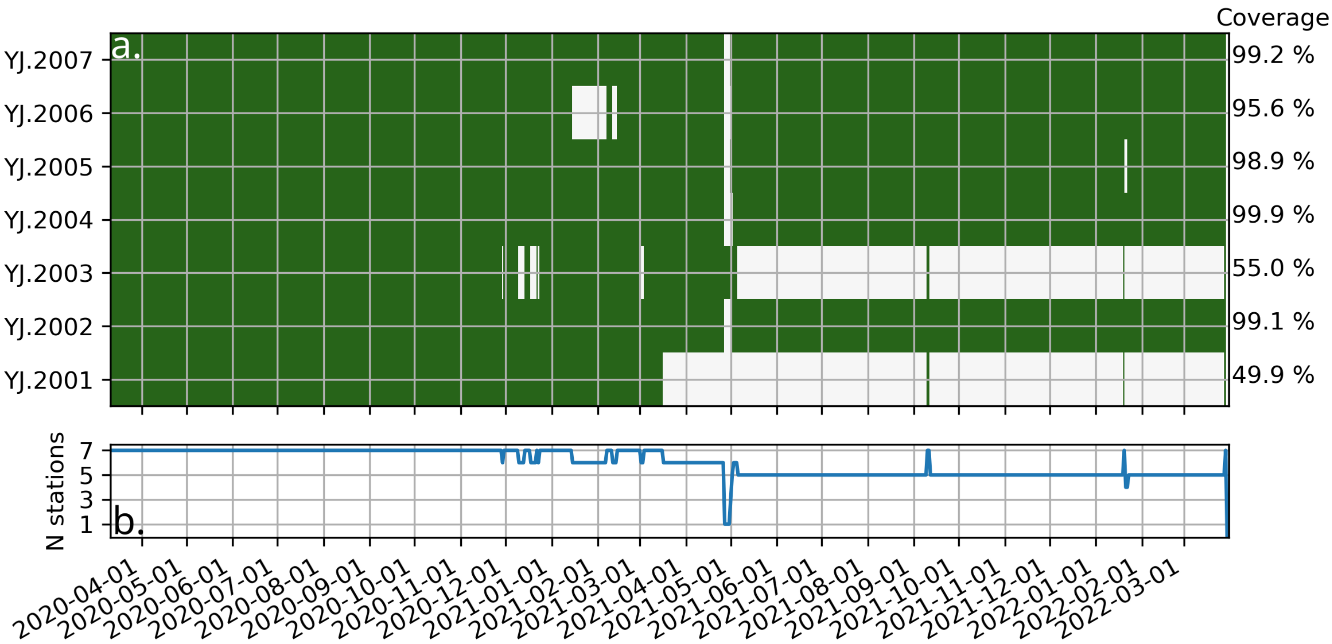

Figure 3 a) Data availability per station. b) Number of stations available per day.

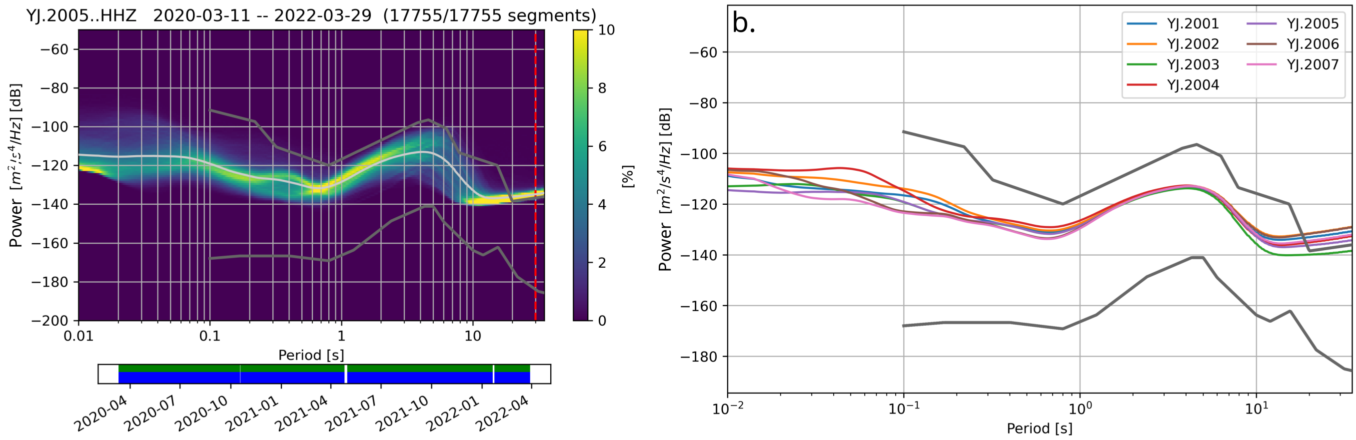

Figure 4 a) Vertical component probabilistic power spectral densities (PPSD) plot for the monitoring period for station YJ.2005. Grey lines indicate the low and high noise models of Peterson (1993), the red line marks the upper period bound of the 6TD response (30s). b) Average PPSD for each station.

is expected to have a relatively minimal impact on the data investigation since at least one seasonal cycle was captured at >95% data coverage, and at least one sensor in each landslide domain remained active throughout the monitoring period.

3 Description of obtained data

3.1 Repository details

Seismic data are archived on the SEIS-UK Octomore data management system and IRIS data management centre with network code YJ 2020 - 2023 (Watlet et al., 2020), under the name of Yorkshire Landslide Observatory (YoLO).

3.2 Data quality and noise level

The noise levels for all stations falls between the low- and high-noise model curves of Peterson (1993). All stations show relatively high noise levels at low frequencies, corresponding to the secondary microseism (periods of 1 to 3 s). The secondary microseism is generated by ocean wave interactions, and so stronger intensity can be expected in Great Britain (Fig. 4) due to the close proximity to the ocean. Seasonality in secondary microseisms is also evident, with periods of elevated low-frequency noise levels (0.1 to 0.5 Hz) reflecting the increased frequency of winter storms, typically occurring from October to March in the UK.

The HHLO site is relatively remote, located in a rural area approximately 20 km away from the closest city, York. Higher frequency noise is mainly influenced by farming activity, and especially the intermittent presence of sheep in the field, and to a smaller extent to a highway passing 7 km south-east. The site is also frequently exposed to wind which can contribute to increased noise levels at higher frequencies. The farming source of the high-frequency noise is evidenced by increases in noise intensity during periods of sheep breeding (Fig. 5), which presents an interesting but challenging noise source to consider in the processing steps. A seasonal effect in the high-frequency noise is also clearly visible in Figure 5b, with increased noise levels corresponding to daylight hours, which is attributed to reduced sheep activity at night.

High-frequency noise slightly varies in intensity across the network (Fig. 4), with station YJ.2004 being noisier in periods below 0.1 - 0.05 s (10 - 20 Hz) than other stations. This elevated noise level could be linked to YJ.2004 location being in an active zone of the landslide.

4 Preliminary interpretations

4.1 Seismic event analysis

We applied a series of STA/LTA (Short-Term Average/Long-Term Average) filters on the YJ network inventory and detected a range of seismic events, of which some have a local source. Amongst events attributed to local environmental noise sources (farming activities, livestock on site, etc.), one signal is thought to be more clearly related to the landslide activity (Fig. 6). This event type, usually recorded on several of the stations, was observed on various occasions (> 100 occurrences), mainly in dry conditions. It has a short duration (<2 s) and shows harmonic-like frequency components (in the 7-25 Hz band). We formulate the hypothesis that this type of events is linked to the opening of fractures during periods of clay-shrinkage. Many deep cracks (>0.5 m deep) can indeed be observed on the clay-rich slope in dry conditions, often extending over several meters laterally (see Figure S1 of the Supplementary Material for an example).

The harmonic frequencies generated by these events remain difficult to explain without more detailed source analyses, which lie beyond the scope of this data-based report, but can be supported by analogues in the literature. Similar short-duration, narrow-band signals have been reported during brittle failure and crack opening in landslide contexts, as well as in analogous environments. Vouillamoz et al. (2018) reported short-duration (< 2 s) quake-like signals associated with landslide activity (termed slidequakes). While they only observed harmonic components in longer events at the Super-

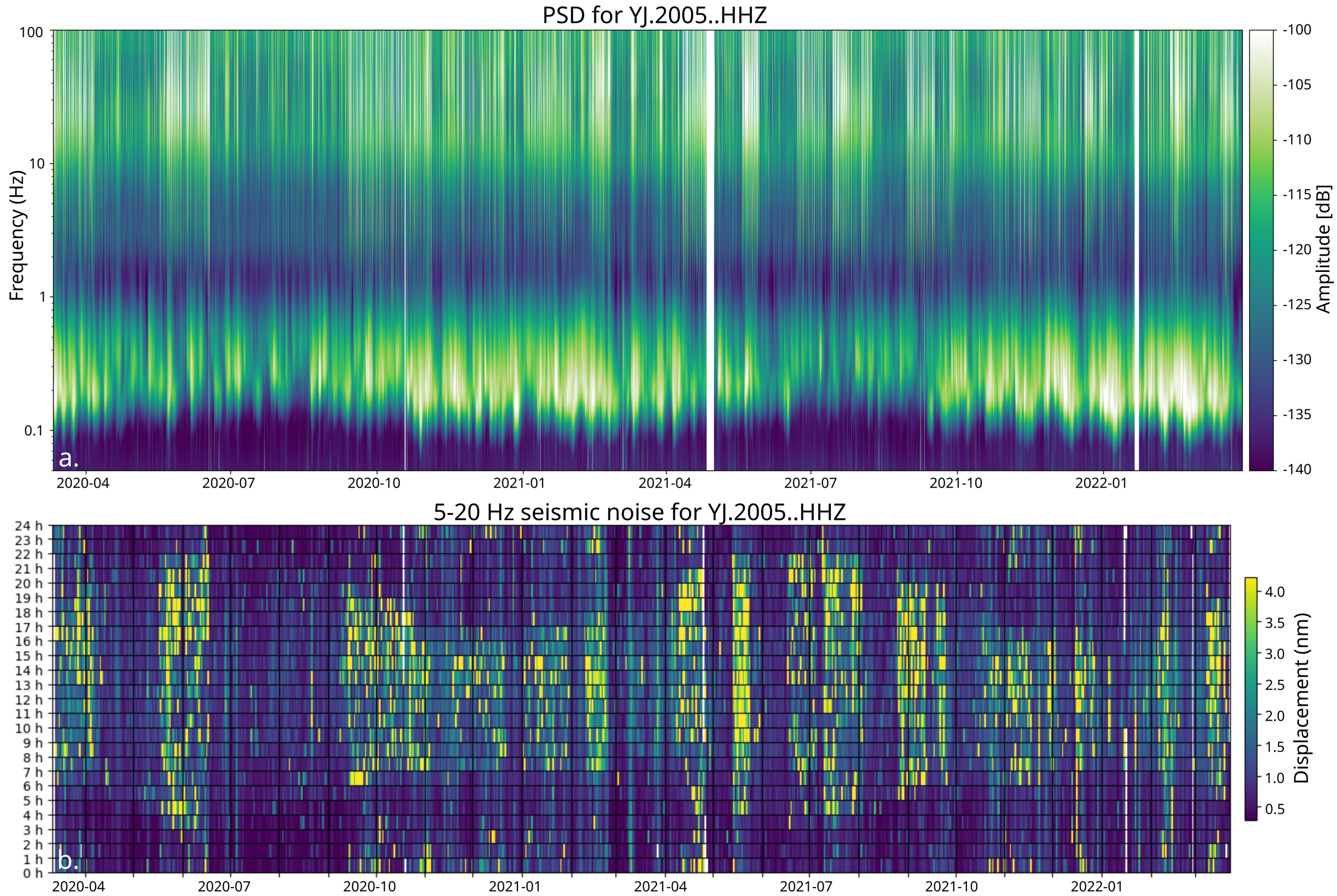

Figure 5 a) Spectrogram of ambient noise over time compiled from hourly averaged PSD for YJ.2005. b) Temporal evolution of high-frequency (5 to 25 Hz) ambient noise displayed as a matrix plot. Each row corresponds to an hour of data (produced using SeismoRMS by Lecocq et al., 2020). Higher frequency noise is most often linked with sheep presence in the field.

Sauze landslide, other studies have highlighted the potential for finite fractures to resonate or oscillate during rapid opening. Sicking and Malin (2019) showed that fracture openings can generate short-duration energy pulses and harmonic resonances of the entire fracture, and Chouet (1986) discussed the resonant modes of cracks, demonstrating that modeled cracks produce multiple discrete frequency peaks whose frequencies depend on crack length and boundary stiffness. Such modeling experiments seem transferable to our landslide context and could explain the harmonic frequencies of this particular event. A more detailed spectral and source-mechanism analysis would be required to confirm this interpretation.

Furthermore, the fact that mainly brittle deformation generates energy high enough to be detectable with conventional STA/LTA approaches seems plausible. More ductile movements in highly saturated clay materials are likely to be less efficient at radiating seismic energy. More advanced, machine-learning algorithms are also likely to help detect smaller local events potentially associated with landslide activity. Recently, a machine-learning event-detection approach was successfully trialled at the HHLO site by Murray et al. (2025), based on the single-station AU07 broadband sensor from the UKArray network installed at the site. In this study, Murray et al. (2025) detected a significant number of events preceding landslide movement, promoting promising expectations for a similar approach to be applied in the future to the YJ network, thereby providing improved spatial information on landslide-related seismic activity.

Nonetheless, there has been discussion regarding the potential for clay shrinkage to act as a conditioning factor for landslide movement, particularly in clay-rich slopes (Krzeminska et al., 2013; Meisina, 2004). Increased opening of cracks under dry conditions may promote water infiltration rather than run-off during subsequent re-wetting periods, potentially explaining localised zones of elevated moisture that could drive slope failure. Techniques capable of detecting crack openings during the drying process could therefore help identify areas of interest where slope movement is more likely during later wet periods. We therefore consider the event type presented in Figure 6 to be relevant for landslide monitoring and that future studies could build up on these findings to investigate slope-scale clay shrinkage in more detail, potentially linked with larger scale information on slope deformation.

4.2 Tilt

In the landslide context, analysis of tilt from the internal masses of seismometers may provide insight into ongoing slope deformation. Conventional tiltmeters typically capture near-surface rotational movement,

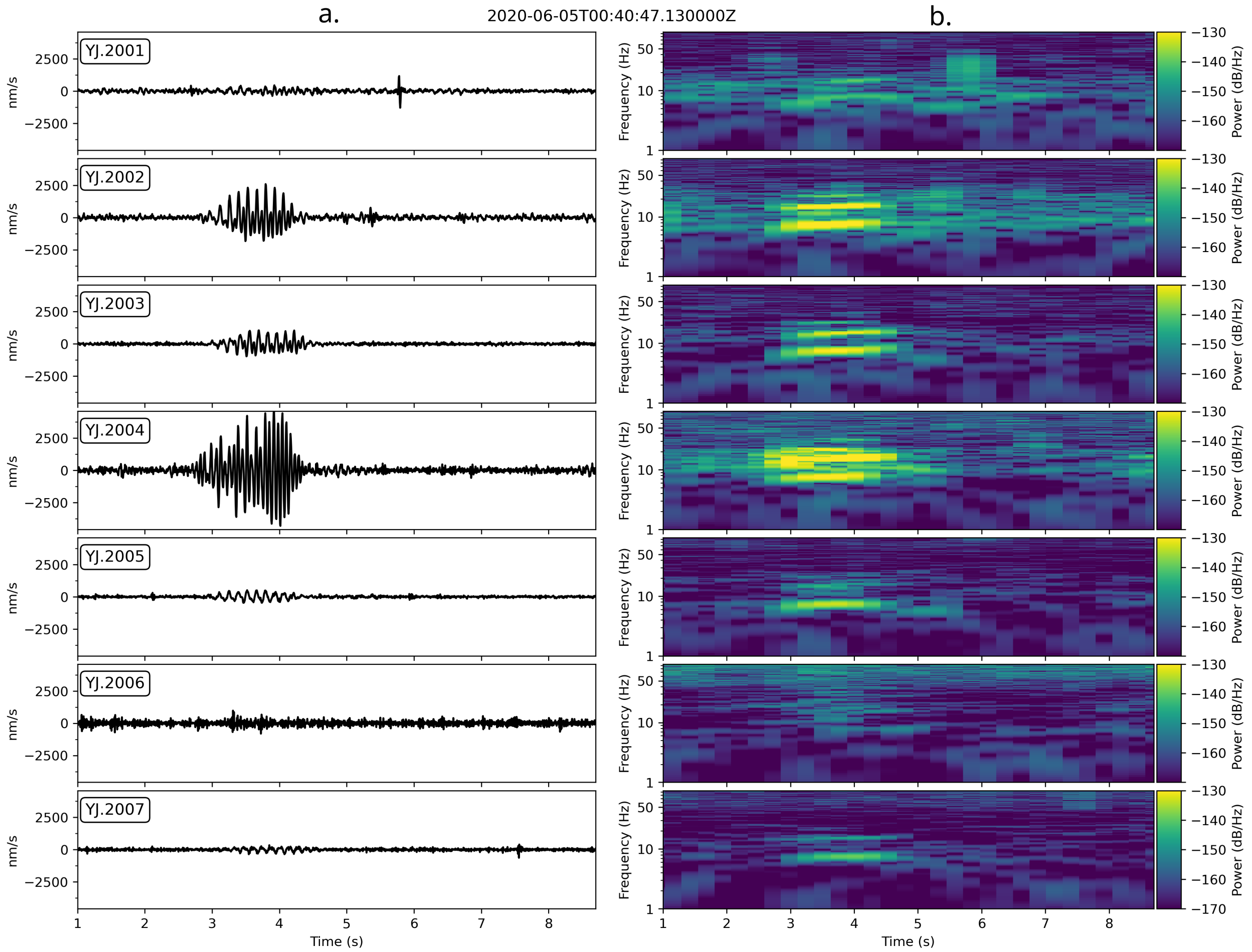

Figure 6 a) Example seismic events attributed to crack generation with vertical component traces. b) Accompanying spectrograms.

whereas our goal is to assess whether seismic traces can also be used to infer subsurface tilt generated by slope deformation processes.

The sensor mass position outputs recorded by the datalogger showed interesting variability across the monitoring period. However, these data are difficult to interpret in raw counts and are not publicly available on the EarthScope repository. We therefore focused on extracting tilt information directly from the seismic traces, following the approach developed in Wenner et al. (2022). In their study, tilt is retrieved signal by applying a very low-frequency filter to the seismic trace, followed by a conversion from counts to tilt angles using the instrument response. For the very low-frequency data (periods below the instrument's lower corner frequency), this conversion requires integrating the digitizer output signal and subsequently scaling the resulting time series by a factor that includes the instrument's corner frequency, sensitivity, and the negative gravitational acceleration. While Wenner et al. (2022) focused on short-duration tilt episodes, our analysis extends this approach to both shorter-term tilt variations (e.g., during an attested slope movement event) and longer-term, seasonal tilt.

Therefore, we adapted the approach of Wenner et al. (2022) by applying first a low-pass filter below 30 s (i.e., corner frequency of the Guralp 6TDs) instead of a band pass filter between the corner frequency and 2 hrs, to retain the lowest period tilt. Then we apply conversion before detrending and correcting for steps across data gaps. This approach assumes continuous, linear instrumental drift. A comparison between the retrieved tilt data and the internal mass position time series (Figure S2 of the Supplementary Material) highlights correlated signatures, with amplitude differences likely related to the conversion from counts to degrees and imperfect detrending. Our approach assumes no net tilt change between the start and end of the trace, meaning that any long-term trend is suppressed, which is a limitation when investigating seasonal-scale tilt.

Instrumental performance also affected tilt recovery for some stations. For instance, at YJ.2004, a datalogger failure in February 2021 led to replacement of the seismometer, and the low-frequency response before that period seems to have been limited by a digitiser issue. For YJ.2001, a levelling problem likely caused rapid out-of-range mass positions, preventing reliable tilt retrieval.

Significant tilt changes are observed only for sensors above and within the movement zone, while stable-

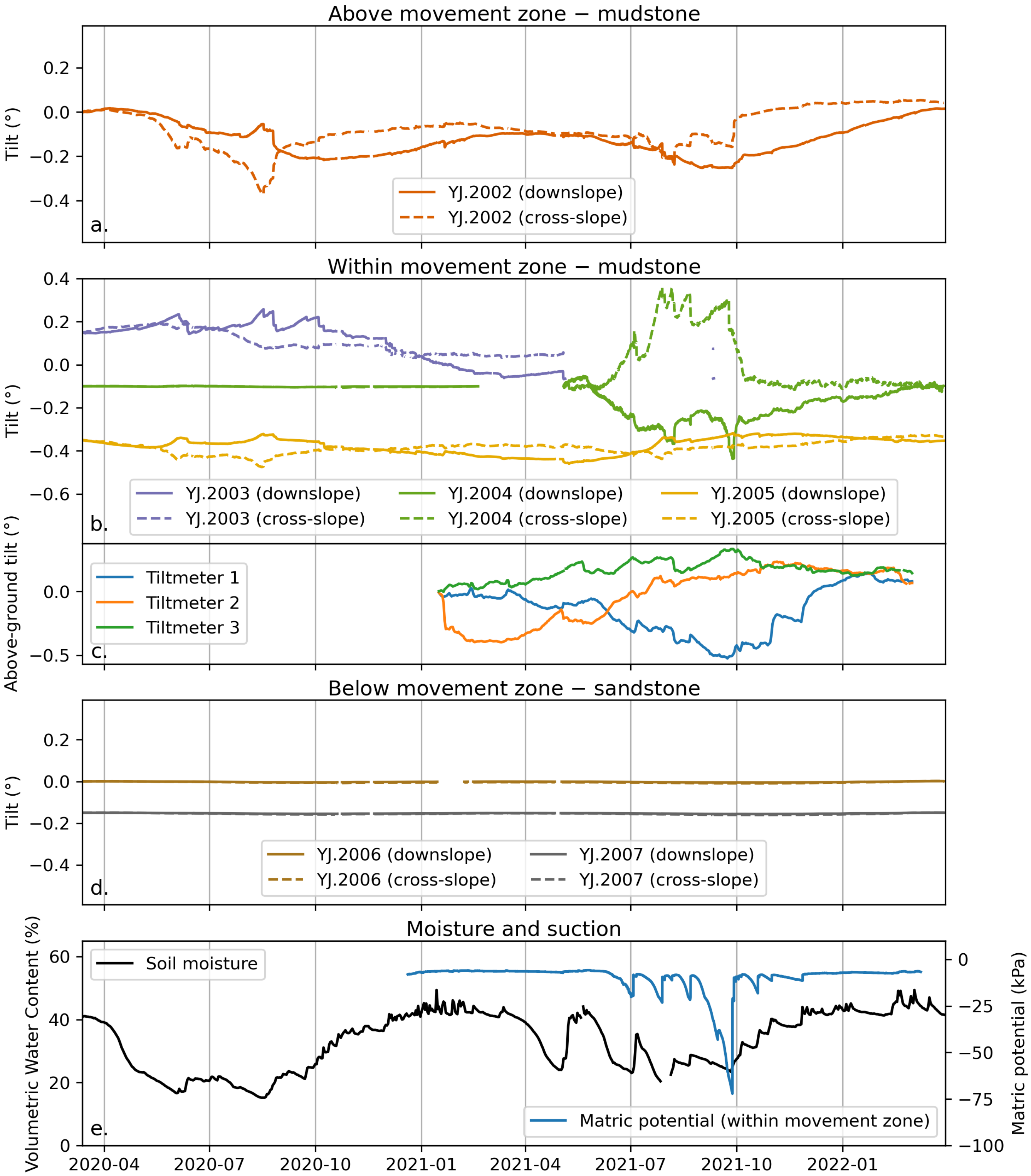

Figure 7 Seismically-derived tilt data for above movement zone (a), within movement zone (b) and below movement zone (c), both for the downslope and cross-slope components. These are compared with above-ground tilt data recorded by tiltmeters mounted on masts in the active zone (50 cm above ground) from January 2021 (d), and soil moisture and matric potential data (e).

ground stations (YJ.2006, YJ.2007) show only minor seasonal tilt, which we attribute to thermoelastic processes. For the other stations, individual sensor tilts, whose components were rotated in downslope and cross-slope directions, show both a seasonal signal (mainly visible for YJ.2002 and YJ.2004) and increased short-term variability between May and October 2020, typically the drier months at the HHLO (Fig. 7).

By early 2021, three mast-mounted tiltmeters were installed in the active movement zone (Fig. 7d). The tiltmeter data show no consistent general trend at the seasonal scale, but indicate that local morphological features of the slope, such as nearby compression ridges, or position on the slope, strongly influences tilt direc-

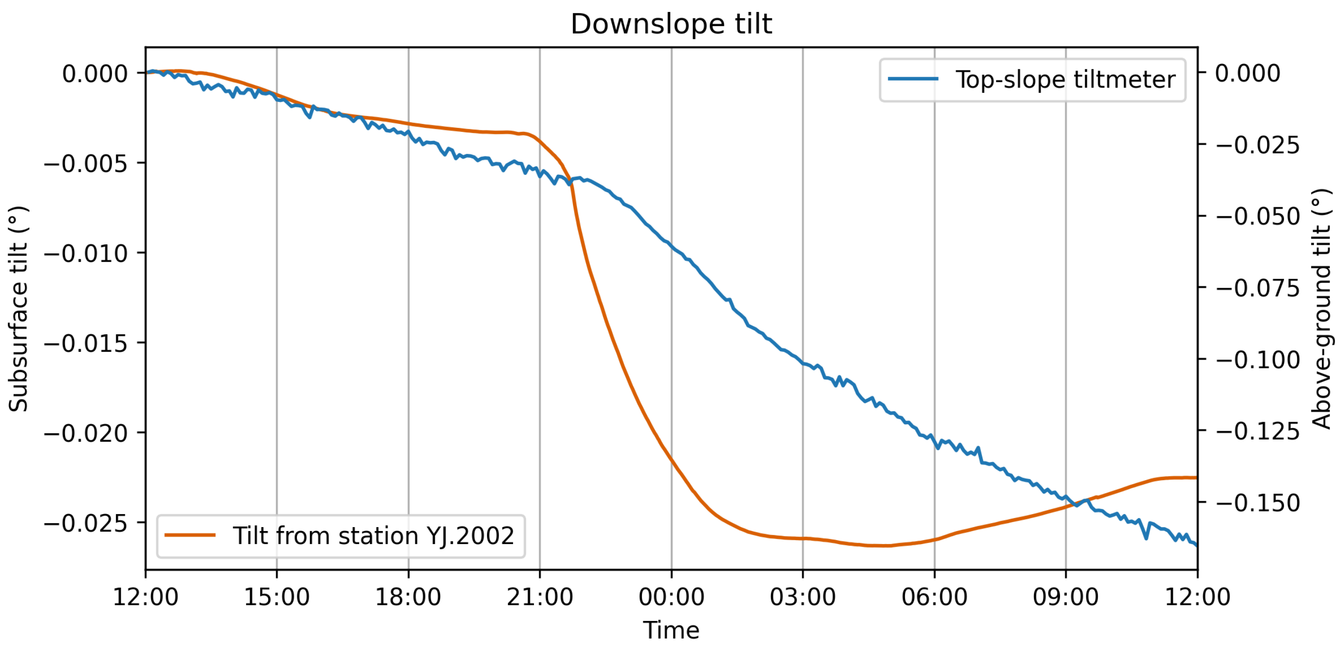

Figure 8 Tilt signals observed during a 24-hour window (20-21 January 2021) attested slope movement for seismically-derived tilt at station YJ.2002 and top-slope tiltmeter.

tion and magnitude. The seismically derived tilt data agree well with these above-ground tilt measurements. Both datasets confirm that tilt is not only recorded during active movement but may also be influenced by shrink–swell processes. Comparison of tilt variations with soil moisture and matric potential data shows a transition from slow, continuous drift to more rapid, pronounced tilt fluctuations during periods of depleted matric potential. This suggests a possible link between desiccation cracking and sensor stability at the HHLO.

Tilt induced by clay shrink–swell is likely linked to volume changes in the disturbed upper clay layer (2 m), where desiccation cracking may generate local rotational deformation depending on the morphology of the upper layer most affected by volume change. For instance, zones close to compression ridges are expected to accommodate volume change differently than the flow lobes areas. Repeated LiDAR scans of the slope previously highlighted seasonal uplift of several tens of centimetres during the wet months (Watlet et al., 2024) at the HHLO. Kelevitz et al. (2022) investigated slope deformation at the HHLO via long-term InSAR analyses and found that seasonal displacement was strongly correlated with volumetric water content. They suggest that these vertical changes are driven by volumetric deformation linked to the wetting and drying of the mudstone. Using repeated Seismic Refraction Tomography surveys, Whiteley et al. (2020) observed significant temporal variations in Poisson's ratio within the surface sliding layer, indicating bulk volumetric change. Observations in these studies tend to confirm slope-scale shrink-swell processes, and support the seasonality observed in our seismically-derived tilt timeseries.

We also examined whether the seismically derived tilt data captured deformation during the main slope movement event that occurred during the YJ network monitoring period (20-21 January 2021) (Watlet et al., 2024) (Fig. 8). This relatively minor event, as compared to the documented history of landslide activity, resulted in slope displacement of up to 0.5 m mainly concentrated in the backscarp region. In the absence of meaningful tilt data from YJ.2004 at that time, only YJ.2002 recorded significant tilt variation, indicating that the event induced tilt signals above the zones where slope displacement occurred, and also confirms that the retrieved tilt data from the seismic trace is effective at tracking slope movement.

4.3 Continuous H/V observations

We computed temporal horizontal-to-vertical spectral ratios (H/V ratios) (Nakamura, 1989) based on the ratios between hourly power spectral density (PSD) spectrograms of the horizontal and vertical components, in a similar way as van Ginkel et al. (2024). The H/V ratios a are determined as follows:

$$a = \frac{\frac{\sqrt{10^{E/10}} + \sqrt{10^{N/10}}}{2}}{\sqrt{10^{Z/10}}} \quad (1)$$

Where E, N and Z are the hourly PSD expressed in dB for the east, north and vertical components respectively. Figure 9a, b and c shows that our approach delivers similar H/V plots as those computed with the Geopsy software (Wathelet et al., 2020) for a 1-hour time window. Temporal H/V spectrograms display the evolution of hourly H/V plots, providing information on the temporal stability and shifts of major and minor frequency peaks. Temporal H/V spectrograms are useful to study the subsurface changes at each station. On the YJ network dataset, the primary peak at 1.2 Hz is relatively stable across the network and corresponds to a regional

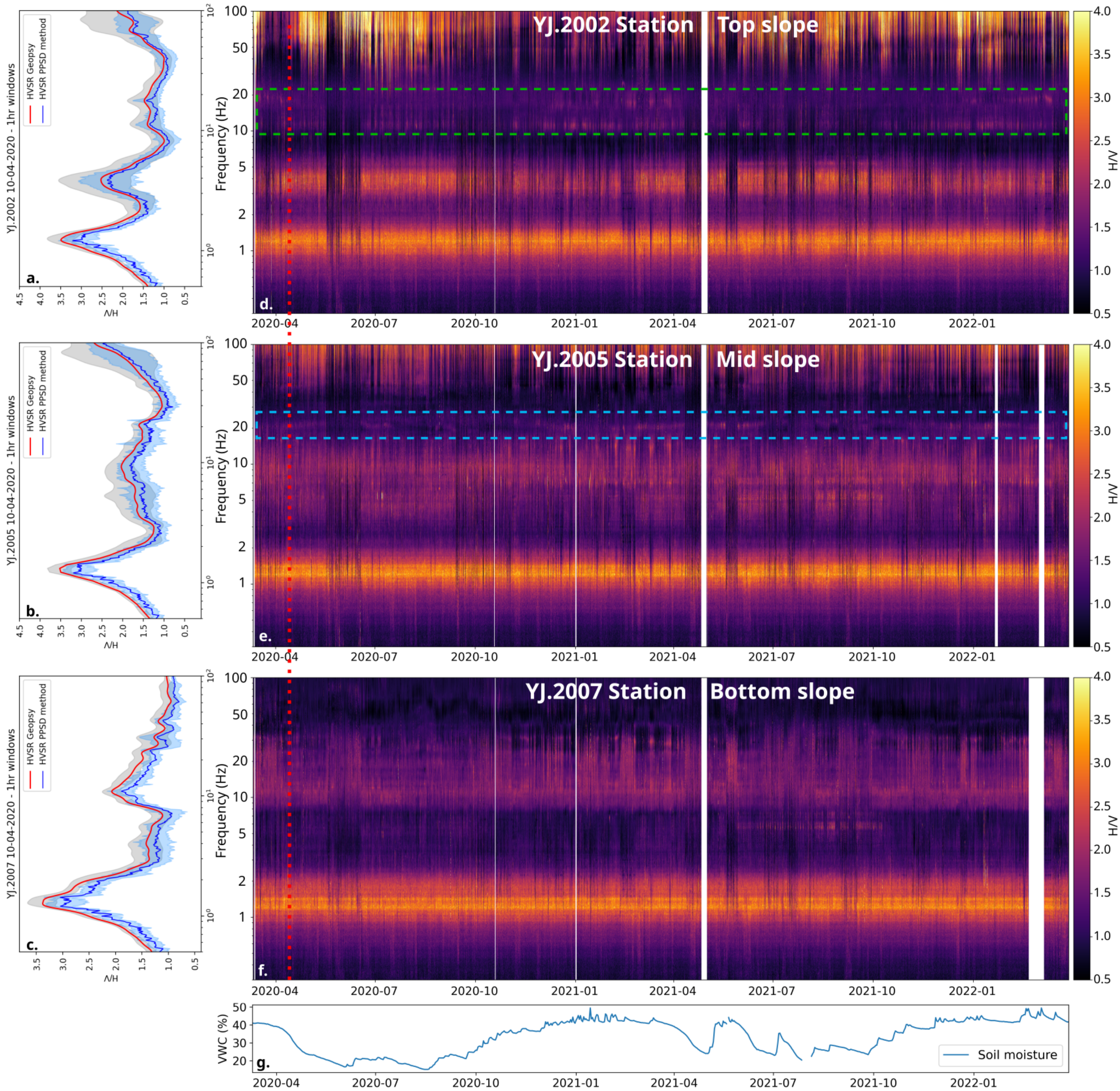

Figure 9 Comparison between H/V ratios computed using Geopsy software (Wathelet et al., 2020) and the probabilistic power spectral densities PPSD ratio method for station YJ.2002 (a), YJ.2005 (b), and YJ.2007 (c) respectively, as calculated on a 1 hour period on the 10-04-2020. d, e, f: Spectrograms of H/V ratios over time for station YJ.2002 (d), YJ.2005 (e) and YJ.2007 (f), as well as soil moisture recorded at 10 cm by the COSMOS-UK station at Hollin Hill (g). Green and blue dashed boxes highlight frequency bands 10-20 Hz and 18-22 Hz respectively. Red dashed line indicates day sampled in a, b and c subplots.

impedance boundary at depth (>150 m deep). A secondary peak at 4.5 Hz for YJ.2002 (top slope) and 10Hz for YJ.2005 (mid slope) is thought to reflect the WMF-SSF interface boundary. Other secondary peaks at higher frequencies are also visible and appear seasonally (e.g. in the 10-25 Hz frequency band for YJ.2002), which can be related to the occurrence of temporary perched water tables in winter, as suggested by Uhlemann et al. (2016b). Using seismic refraction tomography (SRT), Uhlemann et al. (2016a) imaged clear contrasts in the P- and S-wave distributions at the interface between undisturbed and disturbed materials in the active part of the landslide, as well as between mudstone and sandstone layers. More pronounced impedance contrasts could occur in summer between relatively drier mudstone and wetter underlying sandstone, contributing to explain the occurrence of seasonal H/V peaks.

Data for some of the stations also experience shifts in the secondary peak frequency (e.g. in the 18-22 Hz frequency band for YJ.2005), which may be linked to shear wave velocity variations in the upper layers due to changes in moisture content. Whiteley et al. (2020) investigated the temporal variations in P- and S- wave velocity inferred from repeated SRT surveys at the HHLO

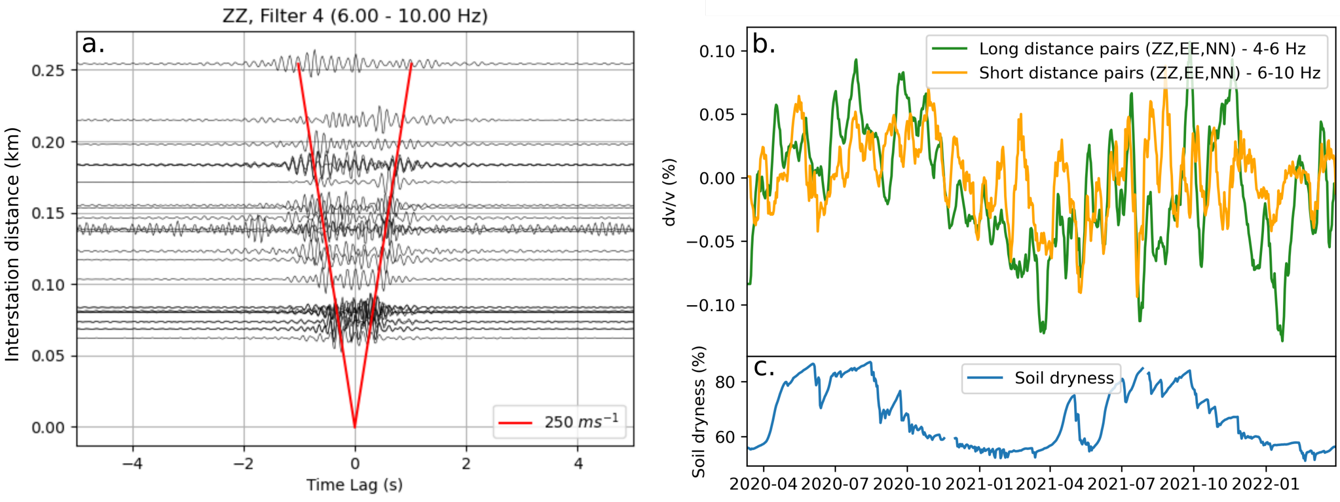

Figure 10 a) Average cross correlation functions for each pair displayed as a function of the interstation distance (for the 6-10 Hz band). b) Example dv/v plot for long distance (> 150 m) and short distance (< 150 m) pairs at two selected frequency bands. c) Soil dryness (inverse of soil moisture).

and highlighted a seasonal shift in Vs comprised between 100 and 150 m/s in the disturbed material of the sliding layer. Similar observations were identified in a different slope context by Guo et al. (2023). The fact that such shifts are present on data from YJ.2005 and not as clearly on YJ.2002 could be linked to their respective locations on the landslide. YJ.2005 is sited on the reworked WMF mudstone materials, which experience larger seasonal amplitudes in wetting and drying processes than for the above movement zone of the WMF mudstone where YJ.2002 sits.

Observed temporal variations in H/V ratios have implications for slope stability assessment. H/V ratios are linked to shear wave velocity (Tsai, 1970), which is an important variable in the understanding of material behaviour via determination of elastic moduli, such as the shear modulus (e.g., Carrière et al., 2018). Slope stability is also strongly linked with the degree of saturation in the shallow subsurface (Huang et al., 2012), which explains the observed correlation between H/V ratio changes and soil moisture at the HHLO.

4.4 Ambient noise cross-correlation and velocity change

We investigated changes in seismic velocity using ambient noise cross-correlation. Ambient noise data were processed with MSNoise (Lecocq et al., 2014), broadly following the steps described by (Bensen et al., 2007). Hourly seismograms were split into 60s long segments which were cross correlated between each possible pair (21 pairs when all stations were recording) for the ZZ, EE and NN components. The cross-correlations were stacked for each day. The seismic velocity change was computed following the moving window cross-spectral (MWCS) technique (Clarke et al., 2011) on the coda of the cross-correlations. Seismic velocity changes (dv/v) are derived from relative travel-time variations (dt/t) detected in a sliding window of the coda wave.

Preliminary results on specific frequency bands suggest a link between soil moisture and velocity change (Fig. 10), with velocity decreasing as soil dryness decreases. Further analyses on a broader range of frequency bands should be considered following the approach presented by Oakley et al. (2021). These further analyses could include rotation into a coordinate system aligned with the local surface slope, because high-frequency surface waves are expected to follow the surface topography. Potential thermoelastic mechanisms linked with changes in soil temperature could also be further investigated.

4.5 Discussion of preliminary observations

Wetting and drying processes within clay materials are thought to drive landslide activity and slope displacement at Hollin Hill (Uhlemann et al., 2017). Our observations suggest that changes in soil moisture, and pore water pressure at shallow depth impact the seismic signals recorded by the YJ network. Clay shrinkage associated with decreasing water content generates tilt on the horizontal masses of the seismometers. Desiccation and large crack openings seem to generate specific seismic events, some of which are recorded throughout the network.

Conversely, temporal H/V ratios spectrograms indicate that secondary H/V peaks vary both in frequency and intensity and are thought to be linked to impedance contrasts and seismic velocities fluctuating in the shallow subsurface due to changes in soil moisture and the occurrence of seasonal perched water tables. Further investigating the links between H/V ratios and slope stability could be useful in a landslide monitoring context. For instance, shear-wave velocity profiles could be extracted from H/V ratios inversions, and used to derive temporal changes in Poisson's ratios. Seismic interferometry has also been trialled on data from the network and similarly highlights changes in seismic velocities in medium to high-frequency bands, likely linked to changes in soil moisture.

Topic	Perspective for future works
Slidequakes detection and analysis	• Perform detailed spectral analysis to characterize signal frequency content (as performed in Murray et al. (2025)). • Compare with known seismic signatures of landslides. • Investigate correlations between signal occurrence and other landslide-related changes (e.g., slope displacement, soil moisture).
Tilt data and relationships with soil moisture	• Expand research analysis on desiccation cracking influencing tilt signals, potentially including laboratory experiments. • Identify and account for other factors that may affect tilt measurements.
H/V ratio and seasonal variations	• Develop automated detection of temporal shifts in H/V peaks. • Extract V_s profiles via H/V ratio inversions and relate to Poisson's ratio estimations. • Investigate how H/V ratio variations relate to slope stability.
Ambient noise cross-correlation analysis	• Expand the analysis to incorporate wavelet-based dv/v estimation. • Conduct a more quantitative analysis of the relationship between soil moisture and velocity change.

Table 2 Perspectives for future work to be conducted on the YJ network dataset and their implications for landslide research.

The primary aim of this study is to introduce and promote the dataset from the YJ network, and the authors recognise that there are many limitations in the analysis of the data presented in this data-based report. Key limitations include: i) absence of in-depth noise analysis, ii) impact of failed sensors on network wide analyses, iii) further investigation into the drivers of sensor tilt at the site and an evaluation of the use of this data for monitoring landslide processes in and of itself. A notable limitation of the tilt analysis is the observation that rapid, out-of-range mass positions in the sensors can prevent reliable retrieval of the tilt angles, which is a likely scenario when deploying sensors to active slopes.

Overall, our preliminary observations suggest that, subject to further investigations, seismic records from the YJ network show a strong potential to shed new light on the link between landslide activity and seismic activity in clay-rich, slow-moving landslides. Challenges related to tilting sensors, anthropogenic (and sheep) noise variations, as well as source noise location analyses need to be addressed in order to further determine the reliability of the data throughout the monitoring period. However, some limitations could be overcome by deploying a greater number of seismic sensors, such as using seismic node arrays, or by using more robust instruments, such as a new generation of seismometers less sensitive to tilt (e.g., Reis et al., 2021). Table 2 summarises several avenues for future work based on the YJ network dataset, highlighting where further analysis could provide additional insight into slope-scale processes. These include improved characterisation of slidequake signals, a deeper investigation of tilt–moisture interactions, automated detection of temporal changes in H/V ratios, and more advanced ambient-noise cross-correlation approaches.

5 Conclusion

From March 2020 to March 2022, we operated the YJ network composed of seven Güralp 6TD seismometers, provided by SEIS-UK, at the HHLO to monitor subsurface processes. This dataset has demonstrated the potential for the application of approaches typically applied to monitoring large-scale geohazards (volcanoes, earthquakes, etc.) to investigate shallow, hydrologically controlled landslides. The investigation approaches include i) the use of seismic event detection (STA/LTA filters) to identify crack generation during dry summers, ii) seasonal tilt observations, iii) determination of continuous H/V profiles to monitor changes in resonance frequencies associated with hydrologically controlled impedance contrasts and velocity changes, and iv) ambient noise cross-correlation to obtain broad changes in near-surface velocity associated with soil wetting and drying. Although the analysis of data from this network is preliminary, we show that soil moisture dynamics influence the mechanical behaviour of landslide-prone materials at the site, an observation consistent with other recent studies (e.g., Watlet et al., 2024; Whiteley et al., 2020; Ouellet et al., 2024).

Acknowledgements

We would like to acknowledge the feedback of two anonymous reviewers whose comments greatly helped to shape the structure of this manuscript, and the handling editor György Hetényi, all of whom have been very patient while waiting for our revisions. The seismometers deployed in this report were provided via the NERC GEF (Loan 1127). We would like to thank all of the staff at SEIS-UK for their invaluable training and assistance with deployment issues and instrument repairs. Our thanks go to the staff in the BGS workshop who were able to help with the customisation of the deployment infrastructure. We would also like to thank Frances and James Standen for their continued support in permitting the HHLO to be operated on their land. Arnaud Watlet's work on writing this manuscript has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101034383 and from the Horizon Europe research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101211994. BGS authors publish with the permission of the Executive Director, British Geological Survey (UKRI-NERC).

Data and code availability

Data are archived on the SEIS-UK Octomore data management system and IRIS data management centre with network code YJ 2020 - 2023 (Watlet et al., 2020). We used Obspy (Krischer et al., 2015, obspy.org) for computing the STA/LTA filters and PPSDs, the procedure defined in Wenner et al. (2022) to extract tilt data from the seismic traces, MSNoise 2.0 (Lecocq et al., 2014, www.msnoise.org) for computing the temporal H/V ratios, as well as the dv/v analysis, and SeismoRMS (Lecocq et al., 2020) for computing the ambient noise matrix plot. Visualisations have been made using Matplotlib (Hunter, 2007). In addition to these references, a sample dataset of the seismic traces, data from relevant sensors, as well as python codes and Jupyter notebooks of custom analyses are available on Zenodo: https://doi.org/10.5281/zenodo.18788509.

Competing interests

No competing interests.

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