

Internal Processes Driving the Slow-to-Fast Transition of a Rockslide

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Abstract

Landslides may creep slowly for centuries under external influences but can suddenly accelerate to catastrophic failure. Understanding when and how this transition occurs remains a major challenge because the internal processes driving failure are largely hidden from surface observations and difficult to monitor continuously. Here, we combine local seismic and geodetic measurements to investigate the internal processes during the 55 days preceding the 2023 collapse of the ~ 1.2 -million-m³ Brienz/Brinzauls rockslide (Switzerland). Using supervised machine learning applied to continuous seismic data, we detect and classify subsurface micro-earthquakes and rockfalls originating from the accelerating slope and track their temporal evolution. Initially, both subsurface micro-earthquakes and rockfall activity were primarily rainfall driven. However, around 37 days before collapse, we identified the onset of runaway acceleration as the system transitioned to an internally controlled regime, marked by accelerating subsurface seismicity despite the absence of rainfall. Seismic observations further indicated progressively more efficient basal sliding, suggesting declining frictional resistance. Surface rockfall activity surged about nine days later, indicating declining mechanical integrity of the moving mass and culminating in a sharp increase in the surface-to-subsurface event ratio during the final three days before collapse. We resolve the coupled evolution of the basal shear zone and the deforming mobile mass leading to catastrophic failure. We demonstrate that internal damage processes alone can sustain runaway acceleration for more than a month without significant rainfall. These observations provide field evidence for slow-to-fast transition dynamics previously inferred primarily from laboratory experiments and physical models, with important implications for landslide early-warning.

Key Points:

- Seismic monitoring captured the slow-to-fast transition of the Brienz/Brinzauls rockslide.
- A transition from rainfall-controlled to internally sustained seismicity marked the onset of runaway acceleration.

- Runaway acceleration coincided with increasingly efficient basal sliding relative to seismic activity.

Plain Language Summary

In summer 2023, the Swiss village of Brienz/Brinzauls narrowly escaped a disaster when a massive rockslide stopped just short of the village. The behavior of the rockslide became highly difficult to anticipate in the weeks preceding failure. Using seismic sensors, we tracked fractures deep within the mountain and surface rockfalls tumbling down the slope. Early on, rainfall controlled the slope's movement, but about 37 days before collapse, seismic activity revealed growing internal instability and a progressive loss of resistance to sliding, allowing the slope to accelerate even without rainfall. Surface rockfalls surged a few days later, and the slope eventually fragmented into an intense cascade of debris, marking the culmination of the event. The slow-to-fast transition observed in Brienz/Brinzauls is a key process governing the onset of runaway acceleration and is therefore critical for the development of reliable early-warning systems.

1 Introduction

Slope failures often occur abruptly and with little warning, causing loss of life (Froude & Petley, 2018; Petley, 2012) and extensive material damage (Dilley et al., 2012; Kjekstad & Highland, 2009). They can trigger cascading hazards that propagate far beyond the initial source, transport, and deposition zones (Cook et al., 2021; Sattar et al., 2025). Increasing population pressure (Ehrlich et al., 2021), together with changes in hydrosphere (Kirschbaum et al., 2020) and cryosphere (Patton et al., 2019), are further amplifying these risks. Despite decades of methodological advances in forecasting and risk mitigation, the anticipation of catastrophic slope failure remains a major scientific challenge (Intrieri et al., 2019), fundamentally limited by our ability to resolve and quantify the complex deformation processes occurring at depth.

At depth, rock-slope failure initiates through the nucleation, propagation, and coalescence of cracks under critical to subcritical stress conditions (Brantut et al., 2013; Voigtländer et al., 2018). Progressive damage localization eventually forms a rupture surface that detaches a rock volume from the surrounding rock. Once detached, the unstable mass may enter a phase of slow mobilization expressed as creeping, sliding, or toppling along the rupture plane (Hungr et al., 2014). This mobilization arises under grav-

ity, through the interplay between external forcing mechanisms—such as seismic shaking, thermal stressing, and hydraulic pore-pressure variations (Bontemps et al., 2020; Carey et al., 2019; Finnegan et al., 2021; Gischig et al., 2011; Loche et al., 2022; Lombardo et al., 2019; H. F. Wang et al., 1989; Zhang et al., 2024)—and the evolving internal state of the slope, including progressive fragmentation of the rock mass and changes in basal frictional properties (Agliardi et al., 2020; Noël et al., 2023; Paul et al., 2024). Despite being three-dimensional bodies, most numerical modeling and laboratory studies interpret slow-to-fast landslide transitions in terms of either the nucleation of a basal shear plane or frictional processes operating along it. (e.g., Agliardi et al., 2020; Chang et al., 2024; Ferri et al., 2011; Handwerger et al., 2016; Helmstetter et al., 2004; Kilburn & Petley, 2003; Paul et al., 2024; Sornette et al., 2004). Lithological variation within the mass, spatially heterogeneous deformation, and evolving rupture geometries challenge idealized models and limit the transferability of mechanistic insights, underscoring the need to resolve the coupled evolution of basal slip, and bulk fragmentation (Faillettaz et al., 2010).

Under sustained load, pre-failure deformation is commonly divided into primary, secondary, and tertiary creep stages, which exhibit decelerating, steady-state, and accelerating strain rates, respectively (Intrieri et al., 2019). Prior to tertiary failure, creep remains externally driven and self-stabilizing, whereas tertiary creep is governed by positive deformation–damage feedbacks that promote self-accelerating failure (Amitrano & Helmstetter, 2006; Corcoran & Davies, 2018; Kemeny, 2003; Main, 2000). This eventual transition to runaway acceleration, commonly termed a slow-to-fast transition, may coincide with peaks in external forcing, but can also occur weeks to months after forcing has subsided (Handwerger et al., 2019), or even in the absence of an identifiable external trigger (Lagarde et al., 2023; Schöpa et al., 2018). Effective landslide early warning therefore depends on detecting the earliest onset of tertiary creep and distinguishing reversible transient accelerations, which may produce false alarms, from irreversible accelerations that progressively evolve toward catastrophic failure; failure to identify the latter in time can result in missed warnings (Intrieri et al., 2019). Two fundamental limitations complicate this problem. First, the temporal expression of pre-failure deformation spans a wide range of timescales, making it difficult to reliably distinguish the onset of tertiary creep within limited monitoring windows. External forcings can mask or modulate the system response, complicating the identification of signatures associated

with internally driven destabilization. Second, internal damage evolution is not necessarily expressed at the surface, limiting the ability of surface-based observations to capture the underlying failure processes. Although geodetic and remote sensing techniques are effective for monitoring slow, progressive deformation, they may fail to resolve the terminal acceleration phase because of sparse temporal sampling and loss of signal coherence during rapid motion (Moretto et al., 2021; Manconi, 2021). In contrast, in situ instruments are often destroyed or rendered inoperable as deformation accelerates toward failure.

With high temporal resolution and the ability to monitor entire slopes using sparse distributed sensor networks, seismic monitoring provides a non-invasive means to track evolving instability. (Amitrano & Helmstetter, 2006; Dietze et al., 2021; Poli, 2017; Provost et al., 2018; Schöpa et al., 2018; Yamada et al., 2016). When combined with machine-learning approaches, even weak and intermittent precursory signals embedded in noise can be systematically detected and tracked, extending observational access to the internal evolution of landslides across both quiescent and rapidly accelerating phases (e.g., Provost et al., 2017; Seydoux et al., 2020). Here, we analyze continuous seismic data from a local sensor network to investigate the slow-to-fast transition of the 2023 Brienz/Brinzauls rockslide in the eastern Swiss Alps ($1.2 \times 10^6 \text{ m}^3$). This event provides a rare opportunity to examine the internal processes that drive large slope failures, as both the runaway acceleration and the final collapse occurred under dry conditions and above-freezing temperatures, allowing these processes to be investigated in the absence of significant meteorological influences. Using a supervised machine-learning model, we track the spatiotemporal evolution of subsurface cracks and surface rockfalls originating from the moving mass throughout the transition. By integrating seismic observations with surface kinematic measurements, we address three guiding questions: (1) how did the relative influence of external forcing and internal processes evolve over time? (2) how did the basal slip interface and the mobilized mass co-evolve? and (3) which observable markers signaled the onset of runaway acceleration? We find that the rockslide progressively transitioned from externally forced, rainfall-driven deformation to internally driven instability approximately 37 days before collapse, marking the onset of runaway acceleration that ultimately culminated in catastrophic failure.

2 Study site and the June 15, 2023 rock-slope failure at Brienz/Brinzauls

The 15 June 2023 rockslide that threatened the village of Brienz/Brinzauls (hereafter Brienz) occurred within a large Holocene deep-seated gravitational slope deformation (DSGSD) in eastern Switzerland. Extending from Piz Linard (2,767 m a.s.l.) to the Albula River (~ 900 m a.s.l.), this instability poses a substantial risk to critical infrastructure—including cantonal roads, a railway corridor with UNESCO World Heritage status, and transnational energy and communication lines—and has therefore been the focus of intensive long-term monitoring and mitigation efforts, accompanied by elevated public and scientific attention.

The most dynamic part of the complex comprises two mechanically coupled domains (Fig. 1A). The lower domain ($\sim 1\text{--}2 \times 10^8 \text{ m}^3$) hosting the village of Brienz is largely cultivated and forms a slowly creeping, undulating mass composed of Flysch ($\sim 1.5 \times 1.3$ km in extent, ~ 250 m of relief) bounded by a well-defined basal sliding surface (Fig. 1A, et al., 2022) between the Albula River to the south and sharp lateral boundaries to the east and west. The upper domain ($\sim 1\text{--}2.5 \times 10^7 \text{ m}^3$), located directly upslope of the village, consists of dolomites, rauhwackes, and marly schists (Krähenbühl & Nänni, 2017). In the two years preceding the collapse, a discrete kinematic unit, later termed the Insel section (Island), developed within the upper domain as a mechanically independent block (Fig. 1B), bounded by a fully formed basal rupture surface and well-defined lateral margins (Loew et al., 2025). During our analysis period, total-station measurements showed little variation in reflector plunge, indicating that deformation was primarily accommodated by sliding along a well-developed rupture surface rather than by progressive toppling. The same study further showed that the basal failure plane was steep beneath the upper Insel ($\sim 45^\circ$) but progressively flattened to $\sim 20^\circ$ beneath the lower Insel, where fractured Vallatscha dolomite transitioned downslope into weaker schistose units (Fig. 1B). By February 2023, the Insel compartment had become kinematically independent of the surrounding slope and subsequently underwent accelerating deformation until its collapse during the night of 15 June 2023 (Loew et al., 2025). The main failure registered on regional seismic stations at 21:38 UTC. The runout stopped just short of the village (Fig. 1C). Debris slides and secondary rockfalls continued for several hours afterwards. Because the failure occurred at night, optical and daylight-dependent monitoring systems did not capture the full sequence, and the exact timing and volumes of the sub-events remained only partially constrained.

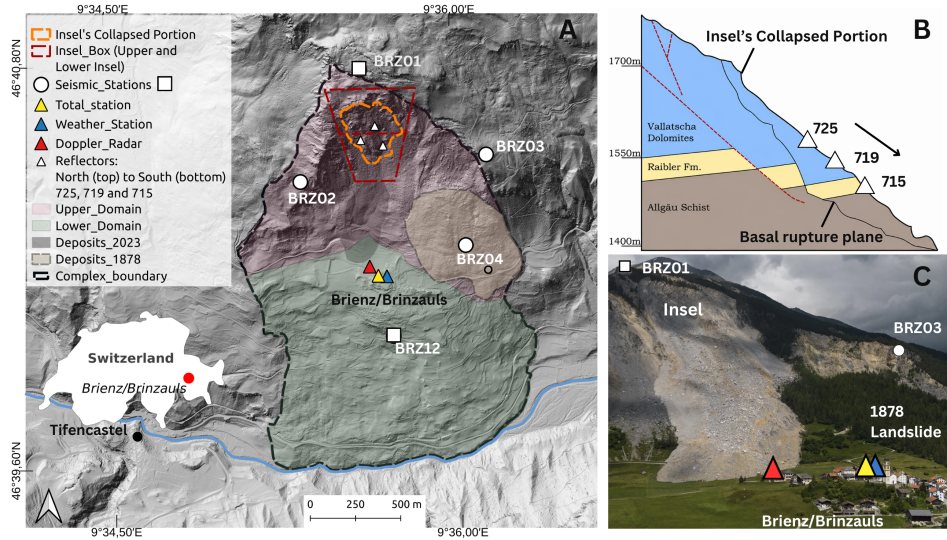


Figure 1: Overview of the Brienz/Brinzauls deep-seated gravitational slope deformation (DSGSD) and the 2023 rockslide source area. (a) Map showing the interconnected domains of the DSGSD complex and the source area of the June 2023 rockslide within the *Insel* sub-volume, together with surrounding seismic stations (TC120s shown as squares and PE6Bs as circles), a weather station, and Doppler radar directed toward the *Insel*. (b) Schematic cross-section of the failed *Insel* compartment illustrating the compound nature of the slide, with an active, brittle domain in Vallatscha dolomites overlying a passive wedge in weak Allgäu schists. Bedding in the Vallatscha Formation dips steeply out of the slope, while that in the Raibler and Allgäu Formations dips gently into the slope. The schematic cross-section is adapted from Loew et al. (2025). (c) Landslide above Brienz/Brinzauls, Switzerland, viewed north–northeast, showing recent debris runout that nearly reached the village. Image credit: Michael Buholzer/Keystone

For early warning, the Voight–Fukuzono approach (Voight, 1988; Fukuzono, 1985) was applied by the authorities (Loew et al., 2025), with alert thresholds based on expected velocities at predefined lead times (Crosta & Agliardi, 2003). However, deviations from classical creep behavior undermined the reliability of the forecasts. As deformation accelerated, authorities issued an evacuation instruction on 5 May 2023. The final abrupt acceleration on 15 June 2023 was not anticipated by any predictive model. The collapse has since been examined from multiple perspectives (Borgeat et al., 2025; Kang et al., 2024; Kenner et al., 2025; Loew et al., 2025; Manconi et al., 2024).

3 Materials and Methods

To monitor vibrations generated by internal deformation of the Insel compartment and mass movements at its surface, we deployed a small network of seismic stations consisting of three three-component geophones (PE-6/B) and two broadband seismometers (Trillium Compact 120 s) (Fig. 1A), all recording at 100 Hz using DIGOS DataCube3ext loggers. The seismic stations had operated intermittently since October 2020; our analysis focuses on a 57-day interval between 21 April and 17 June 2023. Within this interval, we analyze data from three stations (BRZ02, BRZ03, and BRZ04) situated in the upper domain, surrounding the deforming Insel rock mass. To complement the seismic observations, we use previously published surface kinematic and meteorological data presented by Loew (2024), including total-station reflector measurements from the Insel (Fig. 1B) and observations from the Brienz weather station.

We approach the analysis of internal slope processes as a seismic event detection and classification problem. Because no predefined event catalog exists, we first construct an initial event pool by scanning the continuous seismic record for discrete amplitude transients using a short-term average–long-term average (STA–LTA) detector (Allen, 1978) and clustering the resulting waveforms by similarity (Hotovec-Ellis, 2025) to identify families of repeating sources (Supplementary Text S1). These events are subsequently located (Supplementary Text S2) and compared with detections from a Doppler radar catalog (Geopraevent, 2022), which records only surface mass movements, allowing subsurface seismicity to be distinguished from processes at surface. We define and curate labels for four seismic classes—surface events, sub-surface events, tectonic earthquakes, and background/anthropogenic noise. Building on this initial classification, we perform a second analysis using a supervised machine-learning detector trained on manually curated examples to identify and classify seismic signatures, thereby enabling the construction of a more complete event catalog from the same time series. Details of the approach are provided below.

3.1 Construction of Training Labels for Supervised Learning

Surface Events: These correspond to surficial mass movements such as rockfalls, involving the detachment and downslope movement of rock fragments through sliding, rolling, or free fall. Rockfalls (Fig. 2B) generate long-duration (more than 5 sec), emer-

gent seismic signals composed of multiple short, high-frequency transients (1–45 Hz) due to successive impacts and inter-particle collisions (Burtin et al., 2016; Helmstetter & Garambois, 2010; Lacroix & Helmstetter, 2011). Doppler radar observations provide an independent record of downslope debris movement and were used to identify candidate surface events. The corresponding seismic spectrograms were then visually inspected to confirm characteristic surface-event signatures before assigning labels. This procedure yielded 287 labeled surface events for training (16 May–14 June 2023) and 72 labeled surface events for independent testing (15–16 June 2023).

Sub-surface Events: Prior field studies associate short-duration (< 5 s), high-frequency (~ 1 –20 Hz), impulsive microseismicity with crack growth and shear failure within a deforming mass (e.g., Dietze et al., 2021; Helmstetter & Garambois, 2010; Lacroix & Helmstetter, 2011; Provost et al., 2017). These signals (Fig 2A) show sharp onsets, rapid amplitude decay, and often appear on only a subset of stations due to attenuation (Lagarde et al., 2023). We manually reviewed STA–LTA triggers and retained 577 events originating from the Insel, together with 163 manually identified sub-surface events from the surrounding areas, yielding a total of 740 labelled sub-surface events for BRZ02. Of these, only seven unique sub-surface events occurred within ± 10 s of a Doppler-radar detection, whereas the remaining 733 events had no Doppler detection within this time window. Although the temporal proximity of these seven events introduces some uncertainty in their classification, they comprise less than 1% of the identified sub-surface catalogue. Because BRZ03 is installed under comparable site conditions, the same event catalogue was transferred. In contrast, BRZ04 is located on the deposits of the 1878 Igl Rutsch landslide, where strong attenuation and scattering substantially degrade waveform quality. Consequently, the BRZ02 catalog could not be directly transferred, and all candidate events were inspected individually, with only 82 events retained as clear sub-surface signals for training.

Tectonic Earthquakes: The Alps are seismically active. Therefore, we define a separate class for local and regional earthquakes. These events exhibit impulsive onsets with identifiable P- and S-phases and triangular spectrograms with high-frequency onset tapering to lower frequencies due to dispersion and scattering (Fig. 2C). We first use regional earthquake detections from the Swiss Seismological Service (Graubünden region), and additionally query the IRIS FDSN service (Incorporated Research Institutions for Seismology (IRIS), 2023) for cataloged events within 10° of the LIENZ station (400 km

away). By inspecting both catalogs and corresponding spectrograms, we match origin times to observations in the local Brienz network. This yields 75 labeled earthquakes at BRZ02, 16 of which are recorded across all three field stations during the core observation window (21 April–30 June 2023).

Noise: Noise includes both quiescent periods (Fig. 2D) and transient non-slope signals such as rainfall-induced broadband bursts and narrow band tonal energy linked to air and ground traffic and other anthropogenic sources. The final noise catalog consists of 113 manually selected windows (10–600 s) from 21 April–30 June 2023, supplemented by 146 additional windows from January 2023 (only BRZ02 was operational), ensuring representation of low-activity periods.

3.2 Supervised Classifier Training and Deployment on Continuous Seismic Data

3.2.1 Model Training and Testing

To classify seismic signals in continuous recordings, we train separate supervised multi-class XGBoost models (v2.1.4) for each station (BRZ02, BRZ03, and BRZ04) using manually labeled data. The objective is to learn discriminative mappings from a set of statistical features to the previously defined four seismic source classes. XGBoost, an ensemble tree-based method, enables effective class separation while limiting overfitting (Chen & Guestrin, 2016) and shows robust performance and generalization across sites and seismic event types in recent monitoring studies (T. Wang et al., 2023; Zhou et al., 2025). We extracted 92 statistical features from the labelled events using a 2 s sliding window applied between the manually defined start and end times of each event. A 50% window overlap was adopted as the standard sampling strategy for all event classes. An exception was made for sub-surface events, for which a higher 90% overlap was used to augment the comparatively limited training data, albeit at the cost of increased sample redundancy. Similarly, 37 of the 75 BRZ02 earthquake records were extracted using an effective window overlap of 75%, while the remaining earthquake records retained the standard 50% overlap.

Manual labeling indicates that sub-surface events typically last ~ 0.5 –7 s, whereas regional/teleseismic earthquakes and surface mass-movement signals (e.g., rockfalls and debris mobilizations) generally exceed 5 s. The 2 s analysis window therefore provides

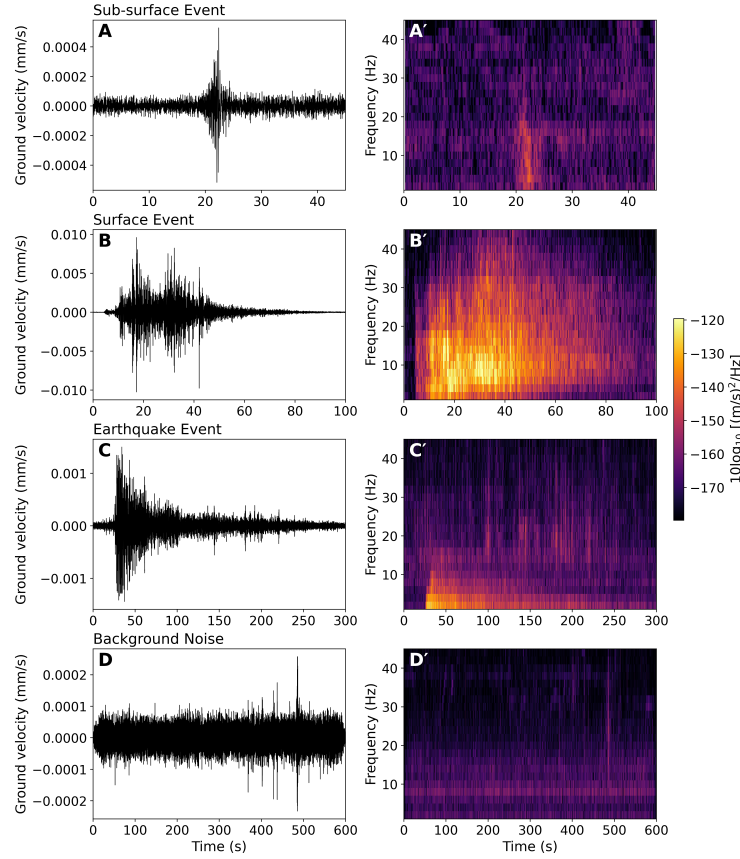


Figure 2: **Representative examples of seismic event classes.** Panels (a–d) show characteristic waveform and spectrogram signatures for the four categories used in this study: (a) surface events associated with rockfalls and mass movements, (b) subsurface (crack-like) events originating within the rockslide source area, (c) tectonic earthquakes displaying impulsive body-wave phases, and (d) background noise encompassing environmental and anthropogenic signals. These examples illustrate the features used to construct the labeled catalog for machine-learning analysis.

a practical, though not universally optimal, compromise: it is short enough to capture transient sub-surface signals while remaining sufficiently long to preserve the characteristic waveform structure of longer-duration sources. We compute features from the 1–49 Hz band, spanning time- and frequency-domain descriptors, including waveform-shape metrics (e.g., rise/fall time, skewness, peak-to-mean ratios) and frequency-domain properties (e.g., number of peaks in the power spectrum and mean and variance of spectral power). The seismic features were extracted using the `eseis` package (Dietze, 2018), with

the feature set supplemented by the fractal dimension proposed by Jaffar et al. (2024) (Supplementary Table S2). The labeled 2 s windows with features, is randomly split into 80% training and 20% testing subsets while preserving class proportions. Before training, all features were standardized using a StandardScaler fitted exclusively to the training data. The resulting scaling parameters were then applied unchanged to the test data and saved for use during future inference on newly detected events. Owing to inherent class imbalance, the number of samples per class varies between stations (see Supplementary Table S1 for details on training and testing set sizes). To evaluate model performance and generalization capability, we apply 5-fold cross-validation (Supplementary Figure S3) independently at each station. This approach tests the model’s sensitivity to any single train–test split, helps ensure that it learns general patterns and provides more reliable performance estimates across varying data subsets. We quantify model accuracy using standard classification metrics, with particular emphasis on the F_1 score, which balances precision (the fraction of predicted events that are correct) and recall (the fraction of true events that are correctly identified) (Supplementary Text S6). To further increase confidence, we combine predictions from the three station-specific models in an ensemble framework and evaluate performance at network level. Ensemble voting requires a minimum classification confidence of 0.7 and agreement from at least two models across all classes. For earthquake detections, however, we give precedence to classifications from BRZ02 over the ensemble outcome due to its consistently higher performance and larger earthquake training set. Details of the ensemble voting evaluation, including the construction of the shared test dataset and the station-specific and ensemble confusion matrices, are provided in Supplementary Text S6.

3.2.2 *Machine Learning Classification of Events in Continuous Seismic Data*

We applied the trained models to continuous seismic data from 21 April to 17 June 2023 across all three stations. For each station, the same set of features was extracted using a 2-second sliding window with 50% overlap. Prior to inference, features were standardized using the StandardScaler fitted during model training, ensuring identical preprocessing to that used during training. Each time step of the continuous data stream was then assigned to an event class together with its associated class probabilities. Classifications of surface and subsurface events were retained only when the predicted class

probability exceeded 0.7 at at least two stations. Since rockfalls (Surface events) typically span durations longer than the 2-second sliding window, consecutive windows with identical classifications are aggregated to form single continuous events. To minimize double counting during downslope propagation, detections occurring within 15 s of a preceding rockfall/avalanche signal were merged and treated as a single event. This approach reduces the likelihood of repeatedly counting the same mobilized rockfall or avalanche mass as it propagates downslope and generates multiple seismic detections. The selected 15 s merging window represents a conservative first-order transport timescale, justified by the site geometry, including an average slope inclination of 28° , a vertical relief of 538 m, and an estimated along-slope travel distance of 850–1000 m. Importantly, the adopted 15 s threshold remains substantially shorter than the minimum inter-event separation of 58 s observed in the Doppler-radar rockfall catalog. Each subsurface event is short-lived and may be represented by only one or two windows. As a result, their detection is more susceptible to undercounting when small travel-time differences occur between stations. Given the maximum inter-station spacing of approximately 1000 m and an assumed seismic velocity of 500 m s^{-1} , detections occurring within a 2 s time window across the array were grouped as originating from the same event. The rationale for the adopted velocity and a sensitivity analysis are provided in Supplementary Text S2, which also describes the event-location methodology. Surface events with durations shorter than 5 s were excluded from the final catalog. For longer-duration surface events, only the first 15 s of each signal were used for event location to capture the initiation of rockfall activity rather than subsequent downslope transport.

3.3 Analyzing the Machine Learning Derived Event Catalog

To separately analyze subsurface and surface seismicity, we first impose physically meaningful spatial constraints. We define a polygon outlining the rockslide source region (the Insel) and subdivide it into upper and lower sectors (Fig. 1A). This partition reflects the lithological zonation within the Insel, separating the schistose lower Insel from the dolomitic upper Insel (Loew et al., 2025).

3.3.1 Time-Resolved Growth Exponent

To quantify temporal changes in seismic sources, we computed the cumulative number of detected events, $\Omega(t)$, from the machine-learning event catalog and estimated a

local growth exponent, $\alpha(t)$, using overlapping windows of 100 consecutive events advanced in steps of 10 events (see Supplementary Text S4) enabling high resolution and continuous tracking of evolving growth behaviour. This procedure was applied independently to the surface and subsurface event catalogs, yielding $\alpha_{\text{surf}}(t)$ and $\alpha_{\text{sub}}(t)$, respectively. After smoothing, the relative growth of the two source populations was quantified as

$$R_{\text{surf-sub}}(t) = \frac{\alpha_{\text{surf}}(t)}{\alpha_{\text{sub}}(t)},$$

where values greater than unity indicate more rapid growth of surface seismicity relative to subsurface seismicity, and values below unity indicate the converse.

3.3.2 *Change Point Detection*

To identify statistically significant transitions in growth behavior, we apply a Bayesian Information Criterion (BIC)-optimized binary segmentation independently to the $\alpha_{\text{surf}}(t)$, $\alpha_{\text{sub}}(t)$, and $R_{\text{surf-sub}}(t)$ time series. This approach identifies change points while penalizing over-segmentation and reducing sensitivity to noise-driven fluctuations. Further methodological details are provided in the Supplementary Text S5. Gaussian BIC was evaluated independently for the $\alpha_{\text{surf}}(t)$, $\alpha_{\text{sub}}(t)$, and $R_{\text{surf-sub}}(t)$ time series. To facilitate direct comparison among the three time series, the four-changepoint solution was adopted consistently to represent the dominant temporal changes in growth behaviour. Additional changepoints can be resolved by fitting more highly segmented models, but these capture progressively finer-scale fluctuations and are not considered here.

3.3.3 *Correlation with meteorological drivers*

Rainfall episodes (P1–P5; Fig. 4B) were defined from manually selected time windows encompassing distinct precipitation events. Within each window, hours with measurable precipitation ($> 0 \text{ mm h}^{-1}$) were identified, and rainfall intervals separated by gaps of $\leq 12 \text{ h}$ were merged into a single rainfall episode. For each episode, total precipitation, active rainfall duration, elapsed time between the onset of the first and cessation of the last rainfall pulse, mean rainfall intensity during active rainfall hours, and maximum hourly intensity were calculated. To examine event-scale forcing and response, cumulative precipitation, daily surface reflector acceleration, and cumulative surface and

sub-surface seismic event counts were analysed jointly for each rainfall episode. To quantify the strength of rainfall-induced seismic amplification, daily event counts were compared with locally fitted 7-day trends. Prominence was defined as the maximum positive deviation from the local trend within each rainfall episode relative to the mean deviation outside the episode, thereby providing a measure of the transient enhancement of seismic activity above the evolving background (Supplementary Text S3). Potential thermal influences were evaluated independently using both 2-hourly and 6-hourly air temperature and seismicity. Air temperature was averaged within consecutive 2-hour and 6-hour intervals, and the corresponding temperature changes (ΔT_{2h} and ΔT_{6h}) were computed as the differences between successive interval means. Surface and sub-surface seismic events within the Insel were counted over the same intervals, and Spearman rank correlation coefficients were used to assess their relationships with the corresponding temperature changes.

3.3.4 Correlation with bulk kinetics

To investigate the relationship between seismic activity and surface kinematics, we analyze surface velocity measurements derived from three total-station reflectors (IDs 715, 719, and 725) that remained continuously operational throughout the study period. Two-hourly displacement measurements are first averaged to daily mean velocities for each reflector. These daily velocities are then averaged across the three reflectors to obtain a single Insel-wide daily surface velocity time series, $v(t)$. In parallel, seismic detections are aggregated into daily-binned event counts. Temporal co-variation between daily surface velocity and seismicity is first assessed using the Spearman rank correlation coefficient (ρ), computed in logarithmic space. While Spearman correlation captures monotonic relationships, it does not quantify proportional scaling between deformation and seismic release. To address this, we further examine the evolving relationship between seismic activity and Insel slip by evaluating the cumulative event–cumulative velocity ratio,

$$R_{\text{event-slip}}(t) = \frac{N(t)}{\Omega(t)}, \quad (1)$$

where $N(t)$ denotes the cumulative number of detected seismic events and $\Omega(t)$ is the cumulative surface slip obtained by integrating the daily velocity time series $v(t)$, with $v(t) = \frac{d\Omega}{dt}$. The ratio $R_{\text{event-slip}}(t)$ thus quantifies the number of microseismic events produced per unit of slip and provides a proxy for the evolving seismic efficiency of de-

formation. The corresponding event rate is given by $\frac{dN}{dt}$. The same analysis is repeated considering only surface seismic events.

4 Results

4.1 Spatial Distribution of Seismic Sources

During the 57-day study period, we detected 3,549 surface events and 3,107 subsurface events originating within the rockslide source area (the Insel polygon). Seismic activity exhibited a pronounced spatial asymmetry across the Insel. Surface seismicity was preferentially localized in the lower Insel, where 70.48% of events occurred, compared to 29.52% in the upper sector (Fig. 3A). Accounting for the difference in areal extent—the upper sector being 1.57 times larger—the lower Insel exhibited a ~ 3.75 -fold higher surface-event density (events per unit area). This spatial contrast was even more pronounced for subsurface seismicity. A total of 86.74% of subsurface events originated in the lower sector, with only 13.26% occurring in the upper Insel (Fig. 3B), corresponding to a ~ 10.27 -fold higher subsurface-event density in the lower sector after area normalization.

4.2 Temporal evolution of seismic sources

The system transitioned from quasi-linear, rainfall-modulated seismic growth to strongly non-linear acceleration preceding collapse. To resolve this progression, we subdivided the run-up phase into three successive intervals, labeled 1, 2, and 3 (Fig. 4). Interval 1 (21 April–12 May 2023) corresponded to a wet phase comprising four distinct rainfall episodes: P1 (23–24 April), P2 (30 April–2 May), P3 (5–9 May), and P4 (10–12 May). Interval 2 (13 May–26 May 2023) represented a comparatively dry phase containing a single rainfall episode, P5 (24–25 May). Interval 3 (27 May–15 June 2023) was entirely dry and contained no rainfall events.

Figure 4B shows the temporal evolution of the growth exponents for surface mass-movement events (α_{surf}) and subsurface micro-quakes (α_{sub}) across the three intervals. During Interval 1, both growth exponents remained predominantly in a sub-linear to near-linear regime, with rainfall episodes producing short-lived perturbations superimposed on this baseline behaviour. During P1, α_{surf} increased from approximately 0.51 to 1.31, while α_{sub} rose from approximately 0.43 to 0.93, before both exponents relaxed toward the levels observed before the onset of rainfall. The response became stronger during P2,

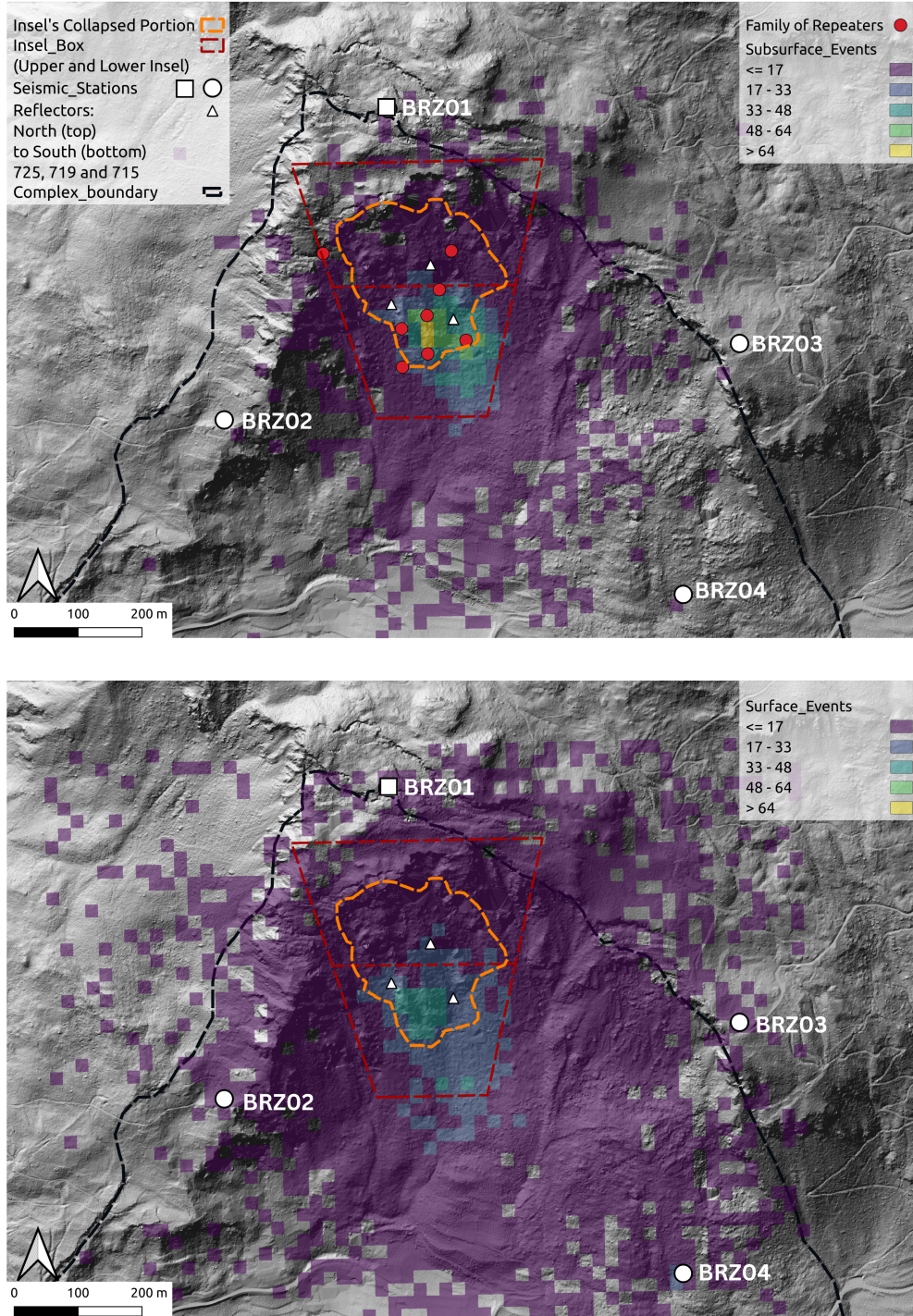


Figure 3: **Spatial distribution of seismic sources.** (a) Corresponding sub-surface detections, including families of repeating events. (b) Locations of all detected surface events. White triangles mark total-station reflectors; from north (top) to south (bottom) these are 725, 719, and 715. Only events within the Insel polygon are retained for subsequent analyses. The orange boundary delineates the mapped source area of the rockslide, adopted from Loew et al. (2025).

when α_{surf} reached approximately 3.02 and α_{sub} approximately 2.71, representing the largest rainfall-induced excursion observed during Interval 1. Following this event, both exponents declined again. The subsequent rainfall episode, P3, produced little response, with both exponents remaining within the sub-linear regime. P4 marked a clear departure from this behavior. Although α_{surf} briefly increased from approximately 1.04 to 2.36 and α_{sub} from approximately 1.03 to 1.47, α_{sub} did not relax back to the lower levels characteristic of the earlier rainfall episodes, marking the onset of divergent trajectories. During Interval 2, α_{sub} increased rapidly from approximately 1.17 at the beginning of the interval and remained persistently super-linear, fluctuating between approximately 1.28 and 1.50 before ending the interval at approximately 1.31. In contrast, α_{surf} initially decreased from approximately 1.15 to a minimum of approximately 0.71 on 17 May before gradually recovering during the second half of the interval, reaching approximately 1.22 by 26 May. Continuing into Interval 3, both growth exponents remained super-linear and strengthened progressively toward collapse. Over this interval, α_{sub} increased from approximately 1.31 at the beginning of the interval to 2.76 by 12 June, while α_{surf} increased from approximately 1.22 to 1.72 over the same period. Within this overall increase, around 30 May–1 June both series exhibited a transient synchronous excursion above their underlying super-linear trends, with α_{sub} reaching approximately 3.9 and α_{surf} approximately 2.9, before returning to their underlying trends. During the following two weeks, both exponents continued to strengthen through a sequence of increasingly frequent transient acceleration bursts superimposed on the long-term upward trend, with the recurrence interval between successive bursts progressively shortening toward collapse. Immediately prior to collapse, both exponents attained their highest values, with α_{surf} peaking at approximately 14.3 and α_{sub} at approximately 9.9. The exponent ratio ($\alpha_{\text{surf}}/\alpha_{\text{sub}}$) was initially greater than unity, remained consistently below 1 from 12 May until 30-May–1 June, after which it recovered above unity and continued to increase, indicating progressively stronger surface-dominated super-linear growth toward collapse.

Filled circles denoted Gaussian–BIC changepoints (Fig. 4B), marking statistically significant shifts in the evolution of the corresponding growth exponent. The first changepoint occurred exclusively in α_{surf} , coinciding with the transient synchronous excursion of surface and subsurface seismicity around 30 May–1 June. Approximately 3 days before collapse, α_{surf} and α_{sub} underwent a simultaneous changepoint, followed by additional individual changepoints in both exponents over the subsequent day. The expo-

461 nent ratio ($\alpha_{\text{surf}}/\alpha_{\text{sub}}$) exhibited its first changepoint approximately 4 days before col-
 462 lapse, followed by a second changepoint nearly coincident with the final α_{sub} changepoint
 463 approximately 42 hours before collapse, and two further ratio-only changepoints approx-
 464 imately 16 and 7 hours before collapse.

465 A total of 432 surface events were detected on 15 June, with a large cluster that
 466 started at 21:14 UTC, marking the onset of final collapse as rockfall activity became so
 467 intense that individual events could no longer be distinguished in the seismic record, which
 468 instead became dominated by high-amplitude signals characteristic of dry granular flow
 469 (Fig. 5). Rather than a single rupture, mass mobilization progressed over approximately
 470 24 minutes as a sequence of overlapping debris pulses, leading to near-field signal sat-
 471 uration. This late-stage dominance of rockfall and debris mobilization is consistent with
 472 observations reported by Kang et al. (2024), obtained farther downslope. The terminal
 473 pulse (21:38–21:39 UTC) was resolved using low-frequency (0.02–0.08 Hz) seismic waves
 474 recorded at station BRZ12 (Fig. 5A), which captured both the acceleration and subse-
 475 quent deceleration of the descending mass. Rockfall activity remained elevated imme-
 476 diately after the main collapse, with a post-collapse cluster of 48 events occurring be-
 477 tween 22:01 and 23:37 UTC. Thereafter, rockfall activity declined rapidly, with daily event
 478 counts falling to 71 on 16 June and 17 on 17 June, indicating that much of the unsta-
 479 ble material had already been evacuated from the source area.

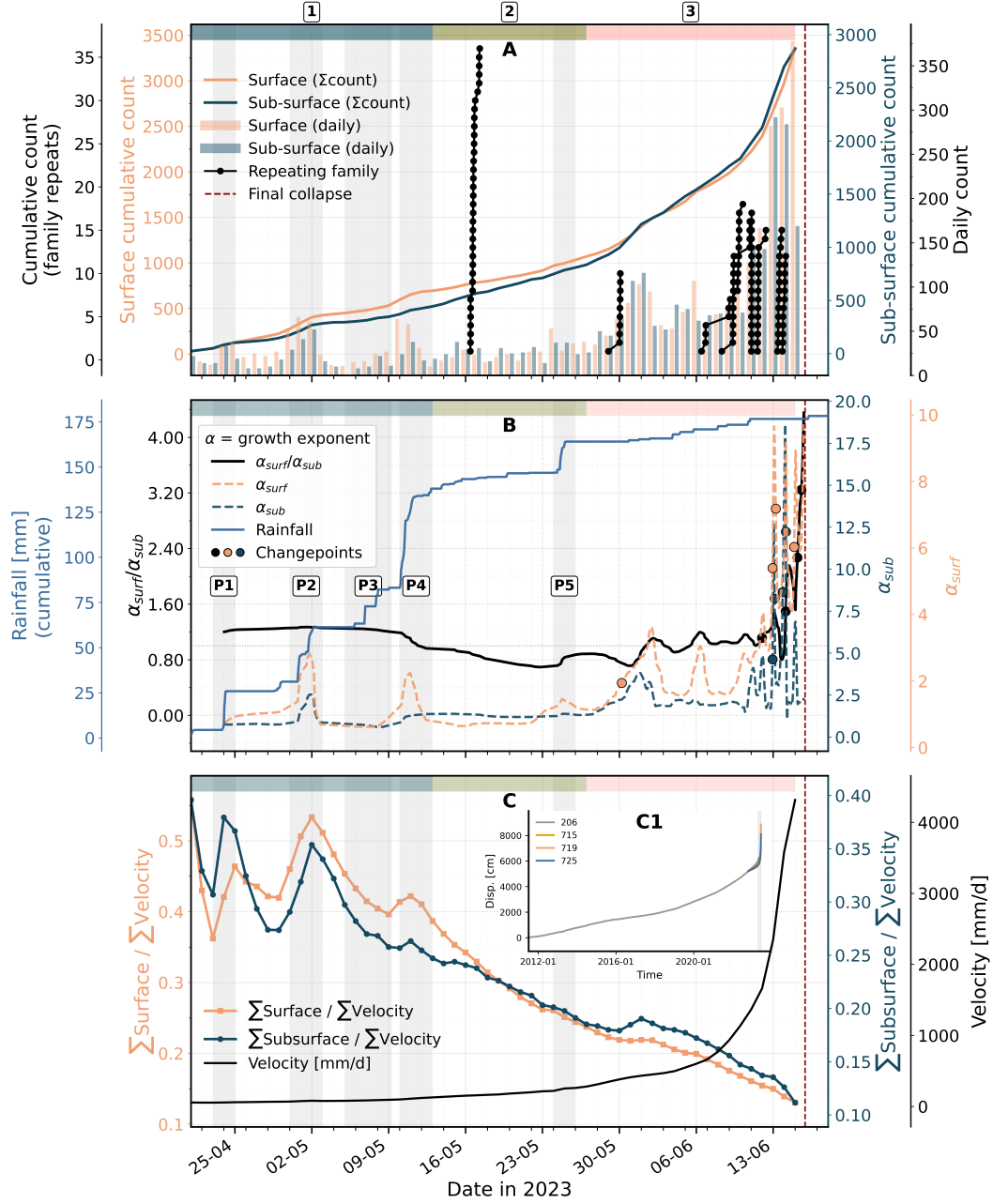


Figure 4: **Temporal evolution of seismicity, slope kinematics, and rainfall during the tertiary creep phase.** (a) Cumulative counts of surface and subsurface seismic detections, together with repeating sub-surface families and daily detection rates. Colored header bands define Intervals 1–3, highlighting successive phases of activity evolution. (b) Time-dependent local growth exponents $\alpha_{\text{surf}}(t)$ and $\alpha_{\text{sub}}(t)$, their smoothed ratio $\alpha_{\text{surf}}/\alpha_{\text{sub}}$, and BIC-selected changepoints identifying statistically distinct scaling regimes. P1 - P5 mark the main rainfall episodes. (c) Evolution of seismic productivity relative to displacement, expressed as $\Sigma \text{Events} / \Sigma \text{Velocity}$ ratios, together with the combined surface velocity. The inset shows the long-term displacement evolution of key reflectors. The red dashed line marks the 15 June 2023 collapse.

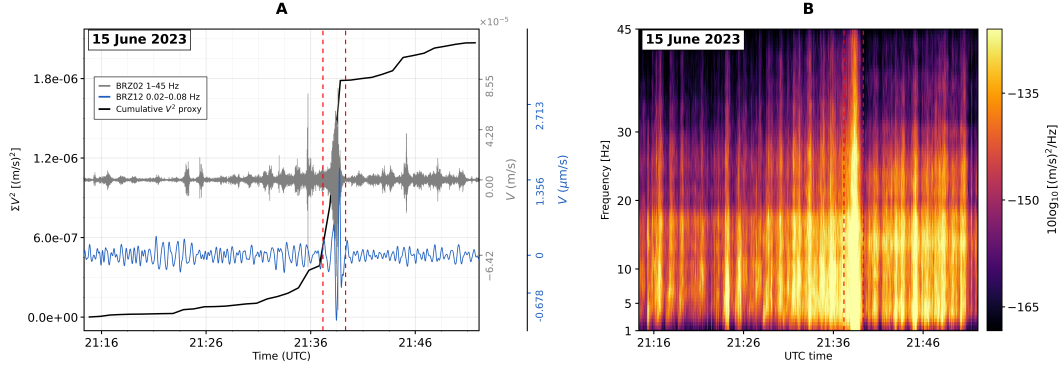


Figure 5: **Final collapse sequence.** (a) Waveform recorded at station BRZ02 (band-pass 1–45 Hz) overlaid with 60 s sliding-window cumulative seismic energy. The low-frequency vertical component (0.02–0.08 Hz) from the broadband station BRZ12 is superimposed for comparison. (b) Unfiltered spectrogram for the same time interval, illustrating the broadband energy release accompanying the terminal collapse.

4.3 Families of Repeating events

Within the pool of STA/LTA-detected transients, we identified eight repeater families using a waveform cross-correlation threshold of $CC \geq 0.8$ (Fig. 4A). These eight families comprised 142 subsurface events, representing 4.57% of the 3,107 machine-learning-detected subsurface events, indicating that repeating sources constituted only a small fraction of the overall subsurface seismicity. Spatially, repeater families mirrored the broader distribution of subsurface seismicity, with six of the eight families concentrated within the seismically dense lower Insel and the remaining two located in the upper Insel (Fig. 3A).

Repeater activity was episodic and transient, with families emerging and disappearing prior to collapse rather than persisting throughout the deformation history. No repeater families were detected during Interval 1. The first family (Family 1) appeared on 16 May in interval 2 (Fig. 6A), shortly after a 4-fold jump in acceleration of reflector 715 on the Insel surface comprising 37 events over approximately 20.5 h during a period when the subsurface growth exponent had reached sustained super-linear regime ($\alpha_{\text{sub}} \approx 1.6$), after which repeater activity became concentrated within Interval 3. The second family followed on 29–30 May (Fig. 4A), immediately preceding the a major transient acceleration of both α_{sub} on 30 May–1 June, during which α_{sub} and α_{surf} (Fig. 4B). Between 7 and 12 June, slope velocity increased from approximately 20 to more than 220 mm day⁻¹,

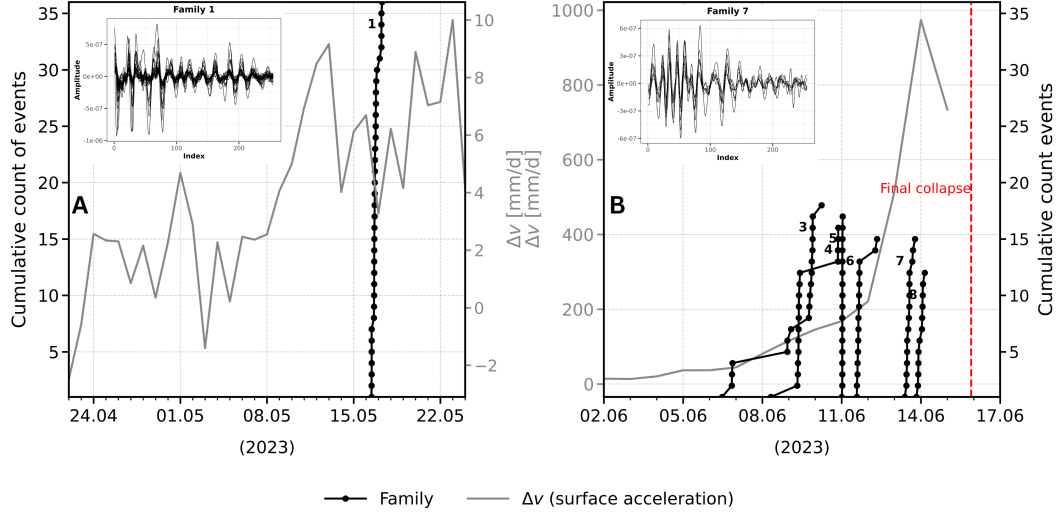


Figure 6: **Activity of Family of Repeaters compared with surface acceleration.**

Black curves show the cumulative number of detections within two representative repeating families (Family 1 and Family 7) as a function of time. The grey curve shows the contemporaneous surface acceleration Δv (first temporal derivative of surface velocity), computed from the displacement time series of reflector 715. The red dashed line marks the final collapse. Insets show representative aligned waveforms from each family, illustrating their high waveform similarity. Waveforms from all identified repeating families are provided in Supplementary Figure S4.

coinciding with the emergence of repeater Families 3–6, which evolved from multi-day sequences (Families 3–4) to progressively shorter-lived transient swarms (Families 5–6). Between 12 and 14 June (Fig. 6B), as velocity increased by a further ~ 4 -fold to approximately 950 mm day^{-1} , Families 7 and 8 emerged sequentially during the final phase of peak acceleration preceding collapse.

4.4 Seismic Response to external forcing

Figure 7 illustrates the evolving relationship between rainfall and seismic activity during rainfall episodes P1–P5. Rainfall-driven amplification is quantified using a prominence analysis of daily event-rate deviations, which measures how strongly the maximum departure from a locally fitted background trend within each rainfall episode exceeds the mean deviation outside that episode (Supplementary Text S3). Higher prominence there-

fore indicates a stronger transient rainfall-induced increase in seismic activity, whereas values approaching zero indicate little distinction from the evolving background behaviour. Episodes P1 and P2 produced delayed seismic responses following rainfall onset. P1 (Fig. 8A; mean rainfall intensity $\sim 2.38 \text{ mm, h}^{-1}$, peak intensity $\sim 8.86 \text{ mm, h}^{-1}$) produced a response in both subsurface and surface seismic events approximately 6 h after rainfall onset, with event rates requiring nearly 48 h to return to background levels (prominence: surface = 10.04; subsurface = 13.34). P2 (Fig. 8B; mean rainfall intensity $\sim 1.16 \text{ mm, h}^{-1}$, peak intensity $\sim 3.89 \text{ mm, h}^{-1}$), consisting of two rainfall pulses separated by a $\sim 10 \text{ h}$ dry interval, generated an even stronger response. Surface and subsurface seismicity increased within approximately 1–2 h of rainfall onset and decayed within $\sim 30 \text{ h}$ after the second rainfall pulse (prominence: surface = 25.47; subsurface = 25.56). As seismicity relaxed following P2, the subsurface growth exponent reached a local minimum ($\alpha_{\text{sub}} \approx 0.54$) on 5 May. Despite the subsequent rainfall episode P3 (Fig. 7C; 5–7 May; mean rainfall intensity $\sim 1.98 \text{ mm, h}^{-1}$, peak intensity $\sim 4.84 \text{ mm, h}^{-1}$), neither surface nor subsurface seismicity exhibited a discernible rainfall-induced increase (prominence: surface = -7.02 ; sub-surface = 2.65). Instead, while α_{sub} remained subdued ($\sim 0.55\text{--}0.70$) until 7 May, it began increasing on 8 May and entered a sustained super-linear regime ($\alpha_{\text{sub}} \sim 1.03\text{--}1.18$) during 8–9 May (*transition*; Fig. 7C). Coincident with this transition, reflector 715 in the southeastern Lower Insel exhibited an abrupt four-fold increase in surface acceleration, approximately 48 h before the onset of the next rainfall episode. P4 (mean rainfall intensity $\sim 1.45 \text{ mm, h}^{-1}$, peak intensity $\sim 7.50 \text{ mm, h}^{-1}$) triggered an immediate increase in surface rockfall seismicity, whereas the subsurface event trajectory, already undergoing acceleration, exhibited a more subdued inflection (prominence: surface = 28.57; subsurface = 12.81). The isolated rainfall episode P5 (Fig. 7D; 24–25 May; mean rainfall intensity $\sim 1.02 \text{ mm, h}^{-1}$, peak intensity $\sim 4.97 \text{ mm, h}^{-1}$) produced a measurable inflection in surface seismicity, whereas the sub-surface response remained weak (prominence: surface = 17.62; sub-surface = 6.24).

Two-hour temperature changes exhibited negligible associations with seismic event rates, with Spearman correlation coefficients of $\rho = -0.08$ ($p = 4.46 \times 10^{-2}$) for subsurface events and $\rho = -0.01$ ($p = 7.27 \times 10^{-1}$) for surface events. For six-hour bins, subsurface events showed a negative association ($\rho = -0.34$, $p = 2.65 \times 10^{-7}$), whereas surface events showed little association ($\rho = 0.05$, $p = 4.69 \times 10^{-1}$). The corresponding correlation plots are shown in Supplementary Figure S5.

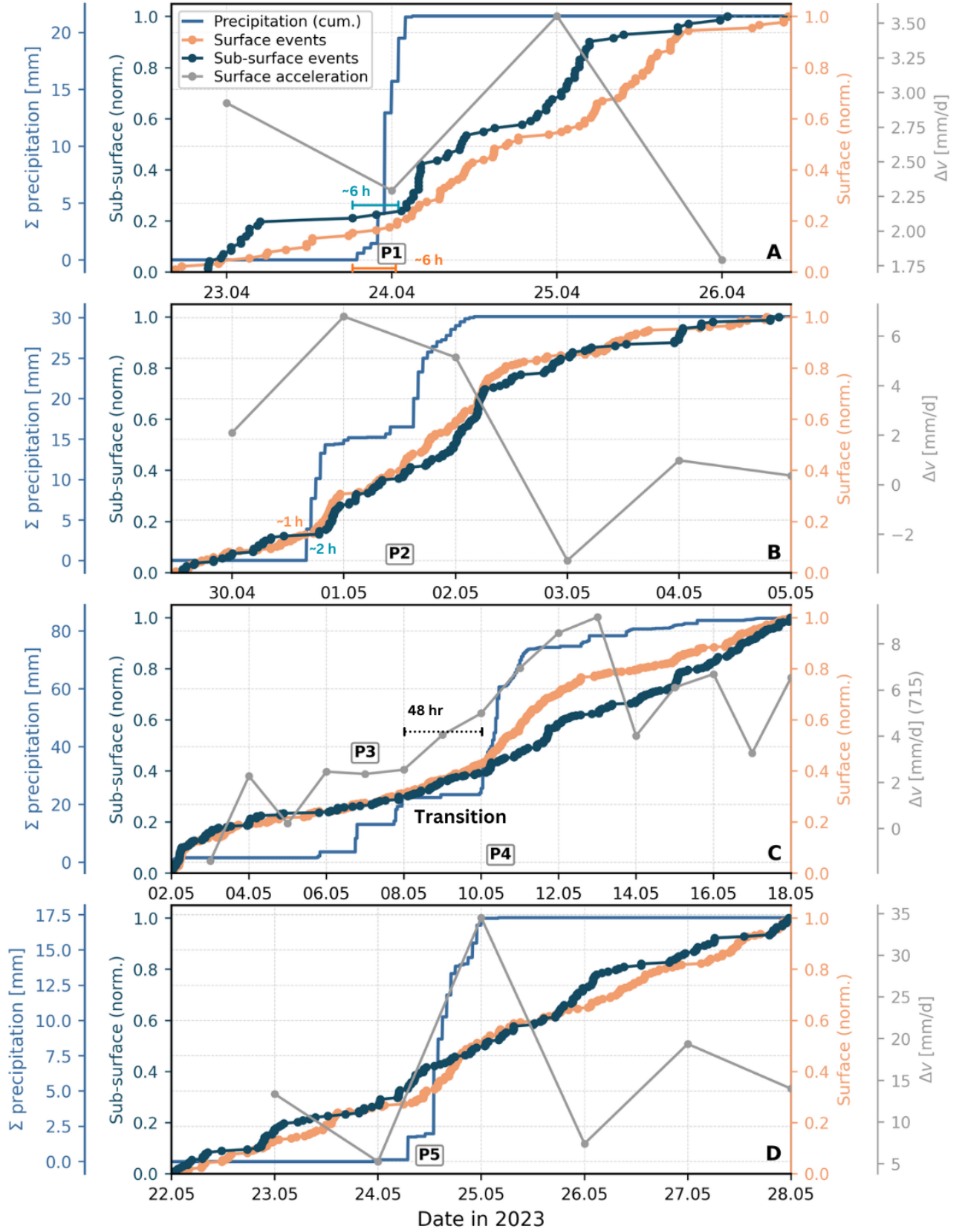


Figure 7: **Rainfall episodes and seismic response.** Each panel compares cumulative precipitation, cumulative surface and sub-surface event counts, and daily surface acceleration (Δv) during (a) P1, (b) P2, (c) P3–P4, and (d) P5. Axes are scaled independently.

4.5 Relationship Between Surface Motion and Seismic Sources

Over the observation period, surface reflector velocities ranged from approximately 4 to more than 500 cm day⁻¹ prior to collapse. Surface velocity and subsurface seismicity exhibited a strong monotonic relationship in double-logarithmic space (Spearman $\rho = 0.81$, $p < 0.001$; Fig. 8), indicating systematic co-evolution over the duration of observation. Initially, subsurface event counts displayed substantial scatter for a given surface velocity, reflecting the influence of rainfall episodes P1–P4. As conditions transitioned from wet to dry toward the end of Interval 1, this scatter progressively diminished. Individually, Intervals 1 ($r = 0.15$, $p = 0.51$) and 2 ($r = 0.12$, $p = 0.68$) showed no significant linear correlation, although interpretation was limited by the relatively small number of observations (21 and 14 days, respectively). In contrast, Interval 3 was characterized by a tightly coupled regime with markedly reduced scatter and a strong correlation ($r = 0.86$, $p < 0.001$).

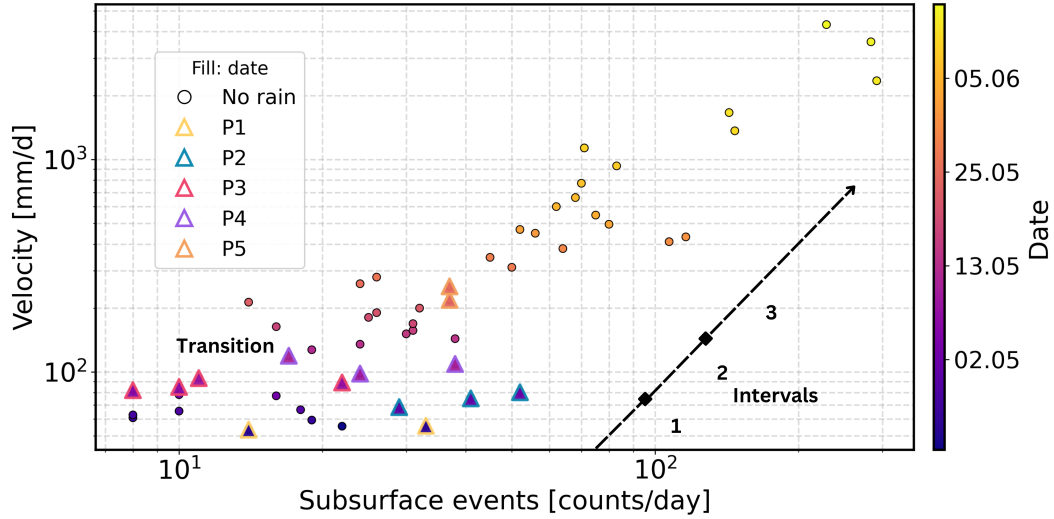


Figure 8: **Log–log relationship between daily sub-surface event counts and daily mean velocity.** Each point represents one day; circular markers correspond to days without significant rainfall, while colored triangular outlines highlight rainfall episodes P1–P5. The filled color denotes temporal progression from 21 April to 15 June 2023. A strong positive monotonic correlation is observed (Spearman $\rho \simeq 0.81$). Dashed arrows with interval labels (1–3) indicate the temporal subdivisions used for comparison with the seismic event and velocity time series in Fig. 4. The observation for 5 May 2023 is omitted because it comprises only a single detected seismic event.

Resolving the relative scaling between seismicity and slip, we found that during Interval 1 (Fig. 4C), both surface and subsurface event-to-velocity ratios ($\Sigma_{\text{surf}}/\Sigma_v$ and $\Sigma_{\text{sub}}/\Sigma_v$) exhibited pronounced, near-synchronous oscillations associated with rainfall episodes. Local maxima occurred during P1 and P2, followed by progressively weaker responses during P3–P4. These fluctuations indicated transient, externally forced increases in seismic productivity that rapidly relaxed once rainfall subsided, without leaving a sustained imprint on the longer-term slip–seismicity relationship. Interval 2 marked a clear change that continued through Interval 3 until final collapse. Across Intervals 2–3, both ratios declined steadily as surface velocity (from reflectors) accelerated more rapidly than seismic event production. The $\Sigma_{\text{sub}}/\Sigma_v$ ratio decreased from ~ 0.25 to ~ 0.11 (a $\sim 56\%$ reduction), while the $\Sigma_{\text{surf}}/\Sigma_v$ ratio dropped from ~ 0.42 to ~ 0.12 (a $\sim 71\%$ reduction), reaching their minimum values on 14–15 June, immediately prior to collapse. This broader decline was interrupted only briefly by a subtle transient around 30 May–1 June, after which the long-term downward trend resumed. This decline in the seismic event-rate-to-slip-rate ratio was unlikely to result from reduced detection capability caused by increasing background noise. Although the cumulative daily mean RMS amplitude (used as a proxy for background noise) increased throughout the observation period, cumulative surface and subsurface seismic detections increased at an even faster rate (Supplementary Figure S6).

5 Discussions

The commonly invoked “slow-to-fast” transition observed in laboratory experiments and physical models (Agliardi et al., 2020; Chang et al., 2024; Handwerger et al., 2016; Paul et al., 2024) has rarely been resolved during the tertiary creep evolution of natural slopes. While seismic monitoring has revealed internal deformation preceding catastrophic failure, most observations derive from sparse regional networks that capture only the high-energy terminal stages of runaway acceleration. As a result, reported seismic precursors have generally appeared only minutes to, at most, less than a day before collapse (Poli, 2017; Schöpa et al., 2018; Shugar et al., 2026; Tiwari et al., 2022), leaving the preceding weeks to months of progressive internal evolution effectively unobserved. To address this observational gap, we focus on the transition identified on 8 May, 37 days before failure. We first examine how the evolving rate and state of internal deformation are encoded within the seismic catalogue. We then use these observations to investigate

changes along the basal sliding surface and within the moving rock mass before, during, and after the transition, place them within the broader evolution of tertiary creep, and assess their implications for both early-warning forecasting and rockslide mechanics.

5.1 Linking Subsurface Seismicity to Internal Processes

The strong monotonic relationship between surface velocity and sub-surface seismicity (Spearman $\rho = 0.81$; Fig. 8) indicates that internal damage systematically intensified with increasing sliding rates. Faster downslope motion promotes progressive crack growth within the unstable mass, increasing the rate of transient seismic emissions (Branat et al., 2013; Dietze et al., 2021; Kilburn & Petley, 2003; Weber et al., 2018). The abrupt cessation of sub-surface seismicity immediately after collapse argues against significant contributions from deeper, persistent sources and instead suggests that these signals were generated within the moving Insel mass and/or along its basal rupture interface, although their precise source depths remain unconstrained. Two end-member processes likely contributed to the observed seismicity: (1) stick-slip failure of interlocking asperities along the basal rupture surface during sliding (Aspaas et al., 2024; Brace & Byerlee, 1966; Finnegan et al., 2022; Poli, 2017; Schöpa et al., 2018; Yamada et al., 2016), and (2) distributed internal damage within the deforming rock mass driven by stress concentrations and fracture growth away from the basal shear zone (Faillettaz et al., 2010; Meng et al., 2024; Renard et al., 2020). As these processes cannot be uniquely distinguished, we interpret the sub-surface seismic catalogue as representing their combined expression. This interpretation is supported by the nearly 10-fold increase in sub-surface seismicity and the clustering of repeating waveform families within the lower Insel (Fig. 3A). The underlying weak schist likely sustains increased loading as it buttresses the overlying competent dolomite, while the shallowly dipping rupture surface underneath provides relatively high resistance to sliding. Together, these conditions promote stress accumulation, enhanced basal shearing, stick-slip failure, crack growth, and progressive internal fragmentation.

5.2 Transition: External control to Internal control

Rainfall can transiently enhance slope deformation by increasing pore pressure along the basal shear zone and by pressurizing pre-existing fractures, thereby promoting sliding and crack growth within the rock mass (Dutler et al., 2020; Guglielmi et al., 2021;

Handwerger et al., 2013). Rainfall episodes P1 and P2 preceding the transition produced short-lived accelerations in both seismicity and bulk motion that rapidly decayed following rainfall cessation, indicating deformation sustained primarily by external hydrological forcing. Once the hydrological forcing was removed, both seismic activity and surface acceleration decreased, consistent with pore-pressure dissipation, recovery of effective normal stress, and a corresponding regain in basal frictional resistance, suggesting a largely reversible deformation response during this stage. The available observations do not constrain the hydrological conditions within the shear zone, including potential water accumulation along the basal interface or whether the shear zone remained efficiently drained. This pattern changed across the 8 May transition. Sub-surface seismicity began accelerating nearly 48 h before rainfall episode P4 (Fig. 7C) and remained persistently elevated after rainfall ceased. In the absence of further rainfall, subsurface seismicity entered a sustained super-linear acceleration, with its growth rate increasingly outpacing that of surface rockfall activity, resulting in a sustained decline in the surface-to-subsurface seismicity ratio (Fig. 4B). This decoupling from external hydrological forcing marks a change from a rainfall-modulated regime characterized by cyclic acceleration–deceleration behaviour to an internally controlled regime dominated by progressive, seismically registered damage accumulation under gravitational loading. Further evidence for the growing dominance of internal processes is provided by the negligible sub-surface response during the subsequent rainfall episode P5. Despite exhibiting a mean rainfall intensity comparable to P2 (P5: 1.02 versus P2: 1.16 mm h⁻¹) and a higher peak intensity (P5: 4.97 versus P2: 3.89 mm h⁻¹), P5 produced no discernible rainfall-induced increase in subsurface seismicity, indicating that rainfall no longer exerted a measurable control on the already accelerating subsurface seismicity.

Surface kinematics exhibited the same regime transition. Mean reflector acceleration increased only modestly from 1.57 mm d⁻² before P1 to 1.79 mm d⁻² between P1 and P2, before declining to 0.97 mm d⁻² between P2 and P4, indicating a largely reversible kinematic response to rainfall forcing. Following the transition, however, acceleration no longer relaxed after rainfall. Instead, mean reflector acceleration remained persistently elevated at 7.23–8.79 mm d⁻² over the subsequent ~10 days, approximately 7–9 times greater than during the P2–P4 interval, before intensifying further toward collapse. Similar transitions have been documented in laboratory experiments and theoretical models, although attributed to diverse mechanisms, including progressive frictional weaken-

ing, strain localization, accumulating water within the shear zone, and other time-dependent damage processes that ultimately overcome stabilizing feedbacks and trigger runaway acceleration (Agliardi et al., 2020; Handwerger et al., 2016; Paul et al., 2024).

5.2.1 *Evolving condition of the Basal Surface as an Internal Driver*

To identify a plausible mechanism governing the shift from externally forced deformation to internally driven acceleration, we synthesize the key concurrent observations following the transition: (1) a steady decrease in the ratio of sub-surface seismicity to slip, suggesting progressively more efficient sliding, whereby slip accumulated faster than sub-surface seismicity. (Fig. 4C); (2) a similar decline in the ratio of cumulative surface events to slip (Fig. 4C); and (3) a divergence between surface and sub-surface seismicity, with surface activity progressively lagging behind the accelerating sub-surface trend (Fig. 4B). At this stage, the landslide volume is expected to comprise a continuum of material ranging from coherent rock blocks to highly fragmented rock debris. The decline in rockfall activity relative to both sliding rates and sub-surface seismicity despite progressively accelerating motion therefore suggests that deformation became increasingly concentrated at depth, as a surge in activity throughout the moving volume is expected to sustain or increase rates of surface detachment. Taken together, the simultaneous increase in sliding rate and sub-surface seismicity, coupled with declining surface rockfall activity, suggests that deformation became progressively localized at depth, most likely along the basal shear zone, rather than becoming more widely distributed throughout the moving rock mass. Such localization would promote the maturation of the basal slip surface through asperity wear, gouge production, and frictional weakening, allowing increasingly efficient slip accumulation prior to collapse (Guérin-Marthe et al., 2023; Goebel et al., 2024; Noël et al., 2023). Sliding efficiency appears to have continued increasing toward collapse as sliding rates accelerated despite the absence of significant rainfall forcing, suggesting that progressive reduction of basal resistance had become a self-sustaining driver of instability.

5.2.2 *Origin of Repeaters*

The small subset of subsurface events forming repeating families of nearly identical waveforms indicates stable source and propagation conditions (e.g., Nadeau & McEvilly, 1999), suggesting mechanically persistent asperities or localized stick-slip patches along

the basal slip surface. Across all families, inter-event intervals do not systematically shorten toward failure but instead display pronounced irregularity and over-dispersion, with variances comparable to or exceeding the mean recurrence interval, while peak amplitudes within each family remain temporally erratic and show no monotonic trend. The transient nature of these repeating families, their irregular recurrence, and their preferential emergence during periods of rapid acceleration—including the appearance of the first repeater family following the ~ 4 -fold increase in surface acceleration (transition) and the subsequent occurrence of families 3–8 during the final runaway phase (Fig. 6 A,B)—point to evolving asperity-scale mechanics. These may reflect intermittent engagement of freshly detached fragments with the shear layer or episodic reactivation of pre-existing sticky patches under variable stress conditions. However, their overall contribution remains limited, comprising only $\sim 4.57\%$ of all sub-surface events, and they are therefore not examined further.

5.2.3 *Response from the Sliding Mass*

Surface seismic events reflect material detachment and downslope mobilization at the slope surface (e.g., Dietze et al., 2017; Schneider et al., 2023) and are independently corroborated by Doppler radar observations (Supplementary Text S7). A random (homogeneous Poisson) process is expected to produce exponentially distributed inter-event times. During 12–23 May, rockfall occurrence already departed from this expectation, indicating temporal clustering. Extending the catalogue until collapse (Supplementary Figure S7) revealed an even stronger departure from Poisson behaviour: the coefficient of variation increased from 1.31 to 2.13, where values greater than 1 indicate increasingly variable and bursty inter-event times, demonstrating that rockfall activity became progressively more clustered as collapse approached. Following the 8 May transition and the temporally overlapping P4 rainfall event, the surface-to-sub-surface seismicity growth ratio declined by $\sim 50\%$, from ~ 1.13 near the transition to a minimum of ~ 0.56 on 17 May, approximately nine days later. This decline reflects a period during which sub-surface deformation accelerated more rapidly than rockfall activity. Thereafter, the ratio increased by $\sim 67\%$ to ~ 0.94 by the end of Interval 2 (26 May), indicating a gradual increase in rockfall activity relative to sustained crack-related seismicity. Because this rebound occurred in the absence of rainfall or temperature forcing, it likely reflects internal mechanical evolution of the landslide volume. This may involve progressive stiffness degrada-

tion driven by continued fracture growth and coalescence within intact rock, unjamming and mobilization of fragmented material, or both, ultimately increasing the susceptibility of material to detach and generate rockfalls. Such progressive fragmentation and disaggregation may also influence the evolution of internal hydrological pathways within the moving rock mass, consistent with the reduction in seismic response lag from ~ 6 h during P1 to ~ 2 h during P2, despite P2 having only about half the mean rainfall intensity of P1 (1.16 versus 2.38 mm h $^{-1}$). Furthermore, no detectable seismic response occurred during P5, even though its mean rainfall intensity (1.02 mm h $^{-1}$) was broadly comparable to that of P2.

Progressive degradation of the mechanical stiffness of the landslide volume became most evident immediately prior to failure. A BIC-derived breakpoint on 12 June marked the onset of a new acceleration phase, during which α_{surf} rapidly increased to a transient peak exceeding ~ 9 on 13 June, approximately two days before collapse. This transition was followed by a rapid increase in the surface-to-sub-surface seismicity ratio, which rose by a factor of ~ 3 over the final two days before failure, indicating strongly enhanced near-surface fragmentation and rockfall activity. Cumulative seismic energy—used as a proxy for transported volume (e.g., Hibert et al., 2014)—shows that the largest terminal pulse between 21:38 and 21:39 UTC accounted for only $\sim 78\%$ of the total seismic energy released during the final collapse sequence (Fig. 5A). Thus, a substantial fraction of the mass was released progressively throughout the collapse sequence rather than during a single instantaneous failure.

5.3 Internal Processes as Markers of Runaway Acceleration Onset

Operational early-warning systems critically depend on distinguishing the onset of sustained tertiary creep from transient accelerations occurring during secondary creep. However, transient accelerations during secondary creep, often driven by external forcings such as rainfall, can be misinterpreted as the onset of tertiary failure in empirical failure-time forecasting models (Fukuzono, 1985; Voight, 1988). Such misclassification can bias forecasts, leading to underestimated critical velocity thresholds and premature failure-time predictions that are not sustained once deformation subsequently decelerates or stabilizes (Crosta & Agliardi, 2003; Leinauer et al., 2023). Recent approaches attempt to identify tertiary acceleration as a statistical anomaly within long-term velocity records of secondary creep (Lei et al., 2023). In practice, however, such extended high-

quality datasets are rarely available prior to failure. Moreover, the identification of regime transitions is inherently scale-dependent, as the apparent curvature of displacement and velocity time series varies with the observation window, complicating a robust distinction between secondary and tertiary behaviour. These limitations highlight a fundamental challenge: detecting the onset of internally driven runaway deformation from short, evolving time series without prior knowledge of the system’s long-term evolution. In this study, we identify two diagnostic markers of this transition from joint seismic and kinematic observations: (1) a driver–response decoupling, marked by accelerated sub-surface seismicity independent of external forcing, indicating the emergence of self-sustained feedbacks; and (2) a relative increase in growth sliding rates compared to growth of seismicity, reflecting declining frictional resistance and progressively more efficient sliding. Together, these markers may contribute to the early identification of impending slope failure. Several observations warrant further evaluation as potential early-warning indicators, beginning with the anomalous transient surge in seismic activity approximately 15 days before collapse, when both surface and subsurface events accelerated disproportionately relative to slope velocity, followed during the final 10 days by the emergence of multiple transient repeating-event families, successive changepoints in the surface-to-subsurface seismicity ratio, and increasing rockfall burstiness.

Geodetic observations at Insel (Fig. 4C1) indicate that irreversible acceleration associated with tertiary creep had already emerged before 2023 (Loew et al., 2025). The seismically identified transition therefore may not mark the onset of tertiary creep itself, but rather a transition within the broader tertiary regime from an externally controlled to an internally controlled regime. This transition occurred approximately 37 days before collapse and coincided with the point at which operational monitoring based on Voight’s law first indicated a remaining time to failure of approximately 15 days, prompting evacuation recommendations for the village of Brienz (Loew et al., 2025).

6 Conclusions

Identifying when slow-moving landslides transition to catastrophic acceleration remains a fundamental challenge because the controlling processes largely occur at depth. At the Brienz/Brinzauls rockslide (Switzerland), we deployed seismic sensors in close proximity to the unstable slope and combined continuous seismic monitoring with supervised machine-learning based event detection to track the evolution of internal microseismic-

ity and surface rockfalls during the final 55 days preceding the June 2023 catastrophic collapse. We identify a clear transition from an externally controlled to an internally driven regime approximately 37 days before collapse. During the externally controlled phase, rainfall was required to trigger bursts of seismicity and enhanced deformation, both of which decayed once rainfall ceased. Following the transition, seismicity and sliding rates accelerated progressively under predominantly dry conditions. A key characteristic of this phase was increasingly efficient sliding, whereby displacement accumulated faster than seismic cracking, suggesting declining resistance along the failure surface. Following the transition, the rockfall-to-subsurface micro-quakes ratio first decreased as internal damage accumulated, then reversed and rose rapidly during the final days before collapse, marking the progressive disaggregation of the moving rock mass. Our findings establish seismic monitoring as a means of identifying the onset of runaway acceleration, enabling earlier recognition of impending catastrophic failure.

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8 Conflict of Interest

The authors declare that they have no conflicts of interest.

9 Software and Data Availability

The seismic data used in this study have been archived in GFZ Data Services (DOI: <https://doi.org/10.14470/81964787>) and will be made publicly available upon publication of the manuscript. This study also uses the open-access Brienzen/Brinzauls Insel

Compartiment dataset published by ETH Zurich, specifically the terrestrial positioning system (TPS) displacement measurements and local meteorological observations (DOI: <https://doi.org/10.3929/ethz-b-000670494>). Clustering of repeating seismic events was performed using REDPy (Version 1.1.3; Hotovec-Ellis, 2025; <https://doi.org/10.5066/P13SRZTC>). Data processing and visualization were carried out using Spyder, Jupyter Notebook, and RStudio. The code and workflows required to reproduce the analyses presented in this study are archived on Zenodo (<https://doi.org/10.5281/zenodo.21510347>).

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Supporting Information for Internal Processes Driving the Slow-to-Fast Transition of a Rockslide

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Text S1. Preliminary Event Picking and Waveform clustering

We apply a classical Short-Term Average to Long-Term Average (STA–LTA) detector (Allen, 1978) to the continuous seismic record at station BRZ02—the sensor closest to the active deformation zone—to construct an initial pool of potential slope-related and other transient events. At this exploratory stage, completeness is not a priority; the aim is to capture a broad diversity of signal types for subsequent analysis. Prior to detection, we remove the instrument response, de-trend the signal, and apply a 5–15 Hz band-pass filter to the vertical component to suppress background and anthropogenic noise while preserving the frequency range most sensitive to slope seismicity (typically 1–45 Hz; (Provost et al., 2018)). Each waveform reflects both the source mechanism and the effects of wave propagation, so STA–LTA detections are grouped by waveform similarity using REDPy (Repeating Earthquake Detector in Python; (Hotovec-Ellis, 2025), Version 1.1.3). REDPy extracts representative templates from the triggered detections and clusters similar signals into families of repeating sources based on waveform cross-correlation. We process all nine channels from BRZ02, BRZ03, and BRZ04 using identical STA–LTA settings in REDPy. The trigger window is designed to capture short, impulsive sources: a 0.5 s STA, a 180 s LTA, and a trigger ratio of 5 with a de-trigger ratio of 2. Based on our observations that crack events typically last 2–5 s, we use a 256-sample waveform window and apply a 1–10 Hz band-pass filter. We retain detections that trigger on at least five of the nine channels. For event association into repeating families, we require a minimum inter-event correlation of 0.8 on at least four channels. Given the short source–receiver distances (500–800 m), these conservative criteria minimize the risk of grouping distinct sources together. We then focus exclusively on repeating families that (i) have their final

occurrence before 16 May, thereby excluding late-initiating clusters that are unlikely to be related to the progressive acceleration leading to the Insel collapse, and (ii) contain at least seven members, ensuring that only persistent repeating sources are retained while excluding short-lived or poorly developed clusters.

Text S2. Source Location

Event locations were estimated using a signal-migration approach originally developed for the localization of seismic signals generated by geomorphic processes (Burtin et al., 2016) and is implemented in the R package `eseis` (Dietze, 2018). The approach relies on aligning waveform envelopes across the sensor network and is particularly effective for locating emergent sources. For each station pair, empirical envelope time delays were obtained via cross-correlation. To account for geometric spreading and topography, we generated distance maps on a regular grid surrounding the network using a 30 m resolution DEM, and converted these distance fields into theoretical travel-time grids assuming an apparent seismic velocity. The observed inter-station time delays were then compared with the synthetic time delays predicted at every grid node. This yields a spatial probability distribution of source locations, ranging from 0 to 1, where high values indicate a stronger match between empirical and modeled travel times. Apart from the minimum three stations required for triangulation (BRZ02–BRZ04), we also use BRZ01 to provide additional spatial constraints, but exclude the more distant BRZ12 (1 km south) because it rarely records the small-amplitude signals originating within the *Insel*.

To assess how the assumed apparent seismic velocity affects source localization, we perform a sensitivity analysis on a reported failure at 15:37 local time on 15 June, when a substantial portion of the Insel toe collapses (Loew et al., 2025). We manually pick

the event onset from spectrogram and define an area of interest (AOI) around the lower Insel. We then repeat the signal-migration procedure for apparent velocities between 100 and 1000 m s⁻¹ in 50 m s⁻¹ increments, allowing us to evaluate how the choice of velocity influences the estimated source position (Fig S1). The corresponding source coordinates were compared to the predefined AOI to determine whether the estimated location fell inside or outside the collapse zone. For each tested velocity, the location corresponding to the maximum of the spatial probability distribution was identified. The distance between this location and the center of the AOI was then calculated.

To further constrain the migration velocity, we used eight rockfall events identified in the Doppler-derived rockfall catalogue, for which the occurrence time was known but the source location was not. For each event, only the first 15 s of the seismic signal were migrated to focus on the initial high-energy phase and to ensure a consistent comparison among events irrespective of their total duration. The migration was repeated over the same range of assumed propagation velocities used in the previous analysis. For each velocity, the coordinates corresponding to the maximum of the spatial probability distribution were identified. Rockfalls released from the Insel are expected to originate from a relatively narrow source corridor aligned with the downslope direction. Consequently, an appropriate migration velocity should minimize the lateral (cross-slope) dispersion of the migrated source locations. Assuming that the X coordinate approximates the cross-slope direction, we quantified the absolute deviation of each migrated location from the Insel centerline together with the inter-event spread of the recovered X coordinates. For each tested velocity, we calculated the mean, median, maximum, and standard deviation of the X-coordinate deviations, together with the median absolute deviation (MAD) and

interquartile range (IQR) as robust measures of lateral scatter. All measures consistently exhibited a pronounced minimum for propagation velocities between 400 and 500 m,s⁻¹. The smallest mean distance from the Insel centerline was obtained at 500 m,s⁻¹ (124.5 m), closely followed by 400 m,s⁻¹ (131.2 m). Similarly, the inter-event standard deviation of the migrated X coordinates reached its minimum at 500 m,s⁻¹ (155.6 m), compared with 338.0 m at 200 m,s⁻¹ and 472.6 m at 700 m,s⁻¹. Thus, adopting a migration velocity of 500 m,s⁻¹ reduced the lateral dispersion of independently located rockfalls by approximately 54% relative to 200 m,s⁻¹ and by approximately 67% relative to 700 m,s⁻¹. The convergence of independently migrated rockfalls onto a common source corridor indicates that apparent propagation velocities of 400–500 m,s⁻¹ best represent wave propagation within the unstable slope. Because 500 m,s⁻¹ consistently minimized both the distance to the Insel centerline and the inter-event lateral scatter across multiple independent metrics, this velocity was adopted for the migration and location of all seismic events analysed in this study. This value is also consistent with propagation velocities previously employed for seismic migration of rockfall sources in Alpine environments (Lagarde et al., 2023).

Text S3 Prominence Analysis

Prominence analysis identifies short-lived amplifications in a time-varying signal by quantifying how strongly local peaks rise above the surrounding background. Here, we apply this approach to the event–slip ratio.

The ratio is defined as

$$R_{\text{event-slip}}(t) = \frac{N(t)}{\Omega(t)}, \quad (1)$$

where $N(t)$ is the cumulative number of detected seismic events and $\Omega(t)$ is the cumulative surface slip obtained by integrating the daily velocity time series $v(t)$, with $v(t) = \frac{d\Omega}{dt}$.

We estimate a slowly varying background of $R_{\text{event-slip}}(t)$ using a rolling linear regression over 7-day windows,

$$\hat{R}_{\text{event-slip}}(t_i) = \beta_0 + \beta_1 t_i, \quad (2)$$

where $\hat{R}_{\text{event-slip}}(t_i)$ is the local background estimate at time t_i , and β_0 and β_1 are window-specific coefficients. Deviations from this background are defined as

$$\Delta(t) = R_{\text{event-slip}}(t) - \hat{R}_{\text{event-slip}}(t), \quad (3)$$

which isolates short-term changes in seismic productivity relative to the local trend.

We quantify the strength of rainfall-related peaks in $\Delta(t)$ over predefined rainfall intervals. For each interval, the prominence metric is defined as

$$\text{Prominence} = \max[\Delta(t)]_{\text{rain}} - \mu_{\text{outside}}, \quad (4)$$

where $\max[\Delta(t)]_{\text{rain}}$ is the maximum deviation during the rainfall interval and μ_{outside} is the mean deviation computed from all observations outside that rainfall interval.

Text S4. Quantification of Seismic Source Growth Rates

Let t denote continuous time and $\{t_i\}$ the occurrence times of detected seismic events. Cumulative seismicity is defined as

$$N(t) = \sum_{t_i \leq t} 1, \quad (5)$$

where $N(t)$ is the cumulative number of detected events up to time t . The known failure time, t_f , is used only as a temporal reference for visualization and does not enter the fitting procedure.

Temporal variations in seismic growth behaviour were quantified using moving windows of 100 consecutive events advanced in steps of 10 events. Within each window, cumulative event counts were related to elapsed time since the first event in the catalogue by fitting

$$\log N(t) = \alpha \log(t - t_0 + \varepsilon) + \beta, \quad (6)$$

where α is the local growth exponent, β is the regression intercept, t_0 denotes the occurrence time of the first event in the analysed catalogue, and ε is a small positive constant introduced to avoid the logarithmic singularity at $t = t_0$. Linear least-squares regression was performed in logarithmic space, and each exponent estimate was assigned to the midpoint time of its corresponding event window.

Local growth exponents were computed independently for the surface and subsurface seismic catalogues, yielding $\alpha_{\text{surf}}(t)$ and $\alpha_{\text{sub}}(t)$. Both time series were smoothed using a Savitzky–Golay filter to suppress short-term fluctuations. Surface and subsurface exponent estimates were then aligned by nearest timestamp before computing the relative growth ratio,

$$R_{\text{surf-sub}}(t) = \frac{\alpha_{\text{surf}}(t)}{\alpha_{\text{sub}}(t)}, \quad (7)$$

where the ratio was calculated from the smoothed exponent series and subsequently smoothed using a second, longer Savitzky–Golay filter to emphasize dominant temporal regimes. Values of $R_{\text{surf-sub}}(t) > 1$ indicate that surface seismicity is increasing more rapidly than subsurface seismicity, whereas values below unity indicate relatively faster growth of the subsurface source population.

Text S5. Gaussian BIC Changepoint Analysis

Temporal changes in seismic growth behaviour were identified using exact dynamic programming implemented in the **ruptures** Python package (Dynp) with an L2 cost function. For each time series, models containing between zero and four changepoints were evaluated. For each candidate segmentation, the residual sum of squares (RSS) was used to compute the Gaussian Bayesian Information Criterion (BIC),

$$\text{BIC} = n \log \left(\frac{\text{RSS}}{n} \right) + p \log(n), \quad (8)$$

where n is the number of observations, RSS is the residual sum of squares obtained by fitting a constant mean to each segment, and $p = n_{\text{seg}} + 1$ is the number of fitted parameters, comprising one mean parameter for each segment together with a single residual-variance parameter shared across all segments.

The Gaussian BIC was evaluated independently for the $\alpha_{\text{surf}}(t)$, $\alpha_{\text{sub}}(t)$, and $R_{\text{surf-sub}}(t)$ time series. BIC values for models containing 0–4 changepoints are reported. To facilitate direct comparison among the three time series, the four-changepoint solution was adopted consistently to represent the dominant temporal changes in growth behaviour. Additional changepoints can be resolved by fitting more highly segmented models, but these capture progressively finer-scale fluctuations and are not considered here.

Text S6. Model Evaluation

Model performance was evaluated independently for each station using stratified five-fold cross-validation (Fig S2), in which the labelled dataset was partitioned into five folds while preserving class proportions, with each fold used once for testing and the remaining four folds for training. BRZ02 achieved the highest performance, with recall (precision) of 97.6% (99.3%), 99.4% (97.4%), 92.5% (96.1%), and 94.3% (97.8%) for earthquake, noise,

sub-surface, and surface events, respectively. Performance decreased at BRZ03, with recall (precision) of 74.5% (95.1%), 98.0% (94.5%), 78.7% (92.1%), and 89.9% (93.8%). BRZ04 showed the lowest overall performance, with recall (precision) of 58.3% (95.0%), 96.7% (89.7%), 82.5% (93.7%), and 80.4% (91.6%) for the respective classes. BRZ02 is located closest to the toe of the active rockslide, where seismic signals exhibit the highest signal-to-noise ratios. BRZ03 is located farther away, while BRZ04 is installed on older landslide deposits, where increased attenuation and scattering are expected to reduce waveform fidelity. To assess whether spectral power differed systematically between stations, the distributions of s_{mean} were compared using two-sided Mann–Whitney rank-sum tests across the pooled five-fold cross-validation partitions. The median s_{mean} decreased systematically with increasing distance from the active rockslide, from -155.1 dB at BRZ02 to -157.4 dB at BRZ03 and -162.3 dB at BRZ04. Relative to BRZ02, median spectral power was reduced by 2.3 dB at BRZ03 and 7.2 dB at BRZ04, with all pairwise differences highly significant ($p < 0.001$). These results indicate progressively weaker seismic amplitudes at the more distant stations, consistent with increased attenuation and scattering. Across all three station-specific classifiers, feature importance (Fig S3) was distributed across a broad range of spectral, polarization, and statistical descriptors rather than being dominated by a single predictor.

To evaluate ensemble-voting performance (Figure S2-d), we repeated the analysis across five stratified random 80/20 train–test splits. For each split, 20% of the BRZ04 dataset was reserved as a reference test set while preserving the representation of all event classes. Windows with matching timestamps were then identified at BRZ02 and BRZ03 and excluded from their respective training datasets, ensuring that the common test windows

were not used to train any of the three station-specific models. Each model was trained independently using the remaining station-specific data. Predictor variables were standardized using the mean and standard deviation of the corresponding training dataset, and the trained models were subsequently applied to the common test windows. Predictions with confidence values of at least 0.70 were combined using majority voting, requiring agreement between at least two stations. An exception was made for earthquakes: when BRZ02 classified a window as an earthquake, this decision bypassed the majority-voting procedure irrespective of its confidence value. Across the five repeated splits, the common test dataset contained an average of 15,513 windows, of which 96.28% received an ensemble consensus. The remaining 3.72% were left unclassified because the station models did not reach the required agreement. Among windows for which a consensus was obtained, the ensemble achieved an overall accuracy of $97.50\% \pm 0.09\%$. Noise events were classified with the highest recall, reaching 99.83%, indicating strong separability from the signal-based event classes. Surface events achieved a recall of 93.42% and a precision of 99.23%. Most surface-event errors involved classification as noise, accounting for 6.48% of true surface events, whereas misclassification as either earthquakes or sub-surface events accounted for only 0.05% each. Furthermore, 79.68% of the surface events classified as noise exhibited very low spectral power ($s_{\text{mean}} < -160.10$ dB), with a median and mean s_{mean} of -164.48 and -163.76 dB, respectively, and values ranging from -172.09 to -143.36 dB. These results indicate that weak or degraded signals challenged the classifier's ability to distinguish surface activity from ambient noise. Sub-surface events achieved a recall of 95.55% and a precision of 97.55%. The remaining sub-surface events were primarily classified as surface events (2.91%) or earthquakes (1.54%), while none were classified

as noise. Earthquakes achieved a recall of 89.70% and a precision of 95.59%. Of the earthquake events, 9.21% were misclassified as surface events and 1.10% as noise, whereas none were assigned to the sub-surface class. Overall, ensemble voting suppressed many station-specific errors and provided robust network-level classifications, while the rejected non-consensus windows explicitly retained uncertainty rather than forcing low-confidence classifications.

Text S7. Comparison with Doppler Radar

The Doppler-radar catalog (16 May–27 June 2023), originally acquired as part of the operational early-warning system for road closure and previously utilized in (Kang et al., 2024; Schneider et al., 2023), was used here to evaluate the machine-learning-based seismic surface-event detections during the 15–17 June 2023 failure period, which was excluded from model training and validation. Because the seismic classifier operates using 50% overlapping sliding windows, a single radar-detected rockfall can produce multiple consecutive seismic detections. To account for this, consecutive seismic surface-event predictions (class = 3) were first collapsed into individual events using the 2 s sliding-window duration and subsequently merged when separated by gaps of ≤ 10 s, yielding a catalogue of unique seismic surface events. We then performed an event-level comparison by testing whether each of the 72 Doppler-radar events was associated with at least one seismic surface-event prediction within ± 1 s of the radar onset time. The seismic models recovered nearly all Doppler events, with recall values of 98.6% for BRZ02, 98.6% for BRZ03, and 94.4% for BRZ04, demonstrating highly consistent detection performance across stations.

Outside the Doppler-radar event windows, the models identified additional unique seismic surface events, ranging from 1149 at BRZ02 to 2118 at BRZ04 after temporal merging. These unmatched detections represent small, short-duration rockfalls or localized surficial instabilities that remained below the effective detection or spatial-resolution threshold of the radar system. In addition, radar performance may have been reduced during the highly active pre-collapse phase because of overlapping motion, dust generation, and partial line-of-sight occlusion.

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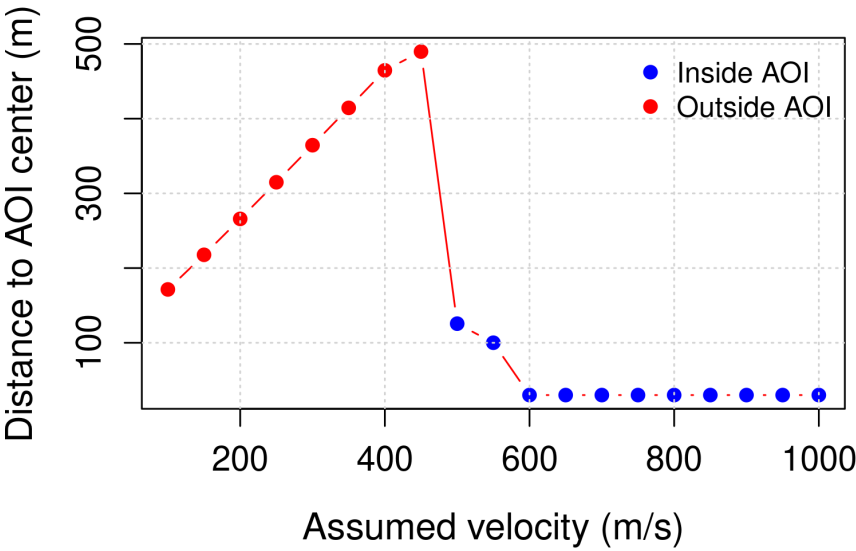


Figure S1: Sensitivity of the migration-derived source position to the assumed seismic wave velocity. Each point represents the distance between the maximum migration energy and the center of the area of interest (AOI) for a given trial velocity. Blue symbols indicate that the maximum-energy location lies within the AOI, while red symbols denote locations outside it. The distance decreases sharply above $\sim 500\text{ m s}^{-1}$, beyond which all solutions remain spatially stable within the AOI. This relationship provides a quantitative constraint on the effective propagation velocity that best focuses the migration energy in the observed collapse region.

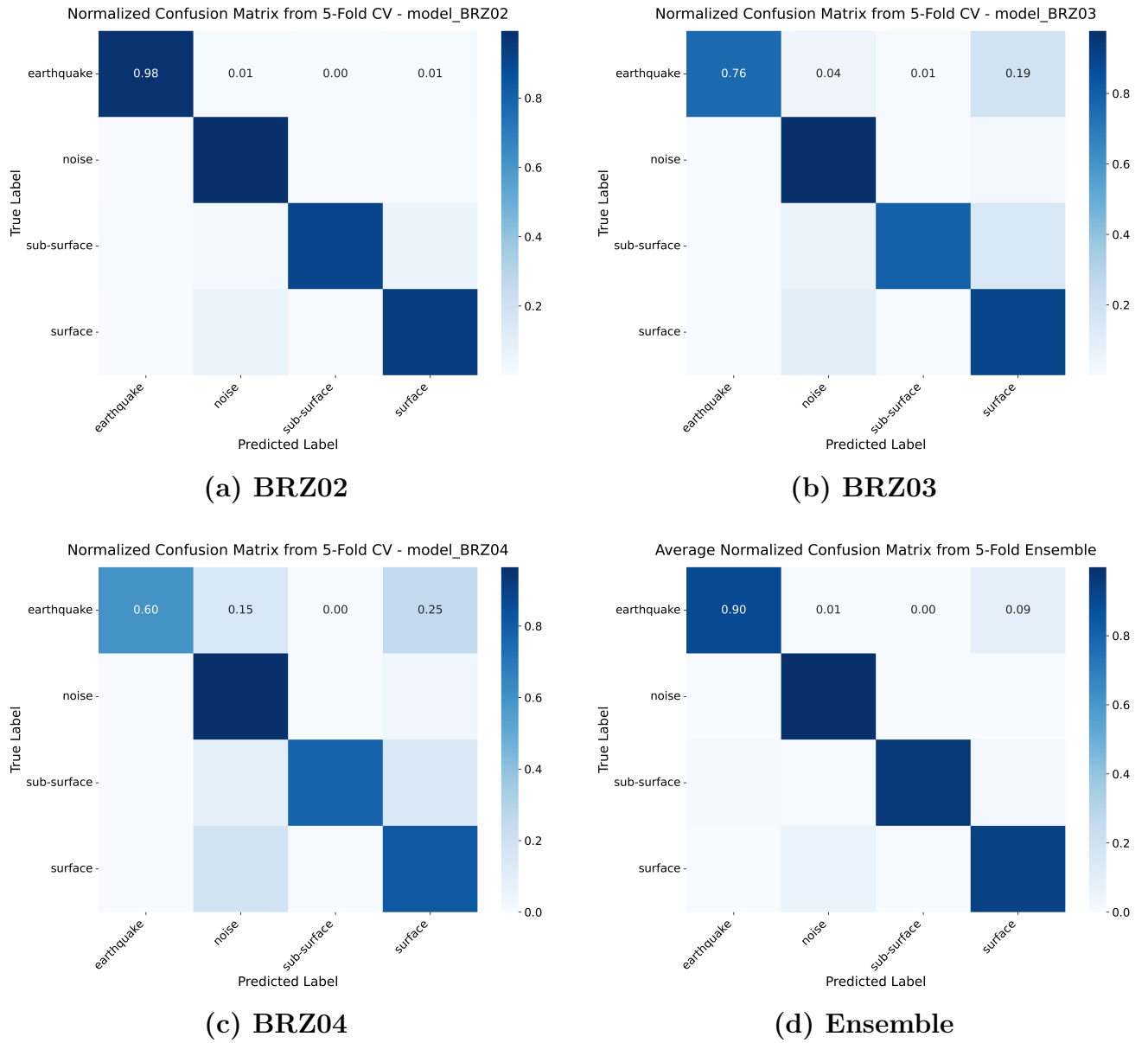
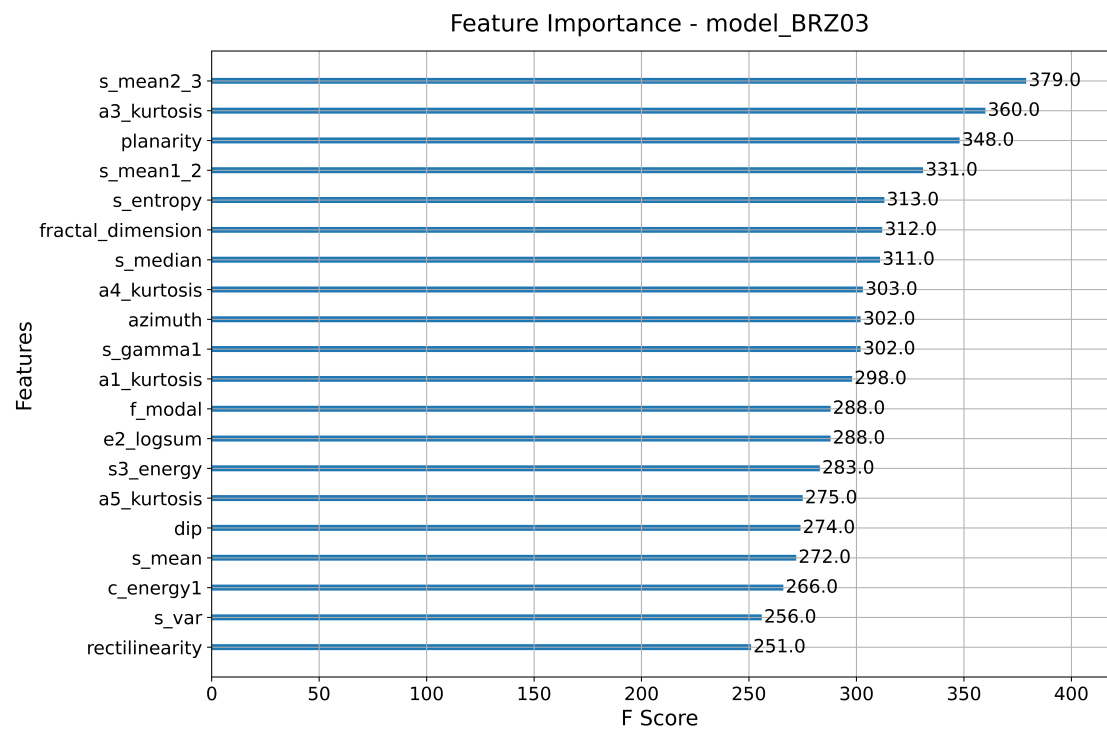
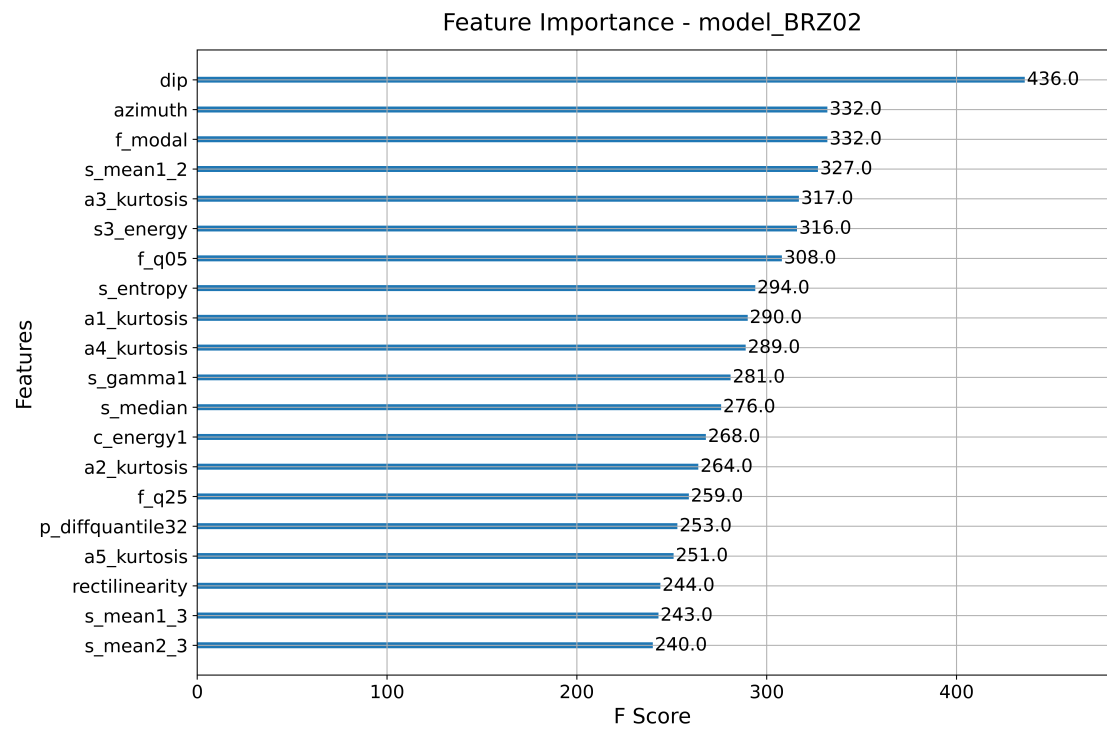


Figure S2: Five-fold cross-validated, row-normalized confusion matrices for the station-specific classifiers at (a) BRZ02, (b) BRZ03, and (c) BRZ04, and for (d) the ensemble classifier.



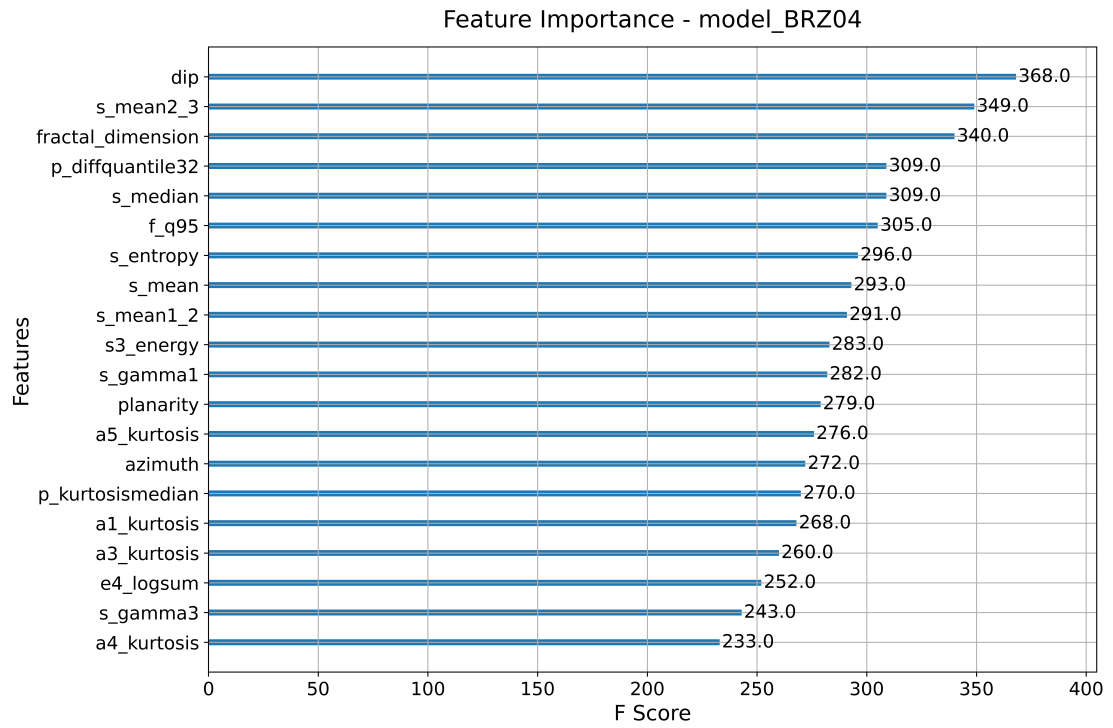


Figure S3: Feature importance rankings derived from the station-specific XGBoost classifiers for BRZ02, BRZ03, and BRZ04.

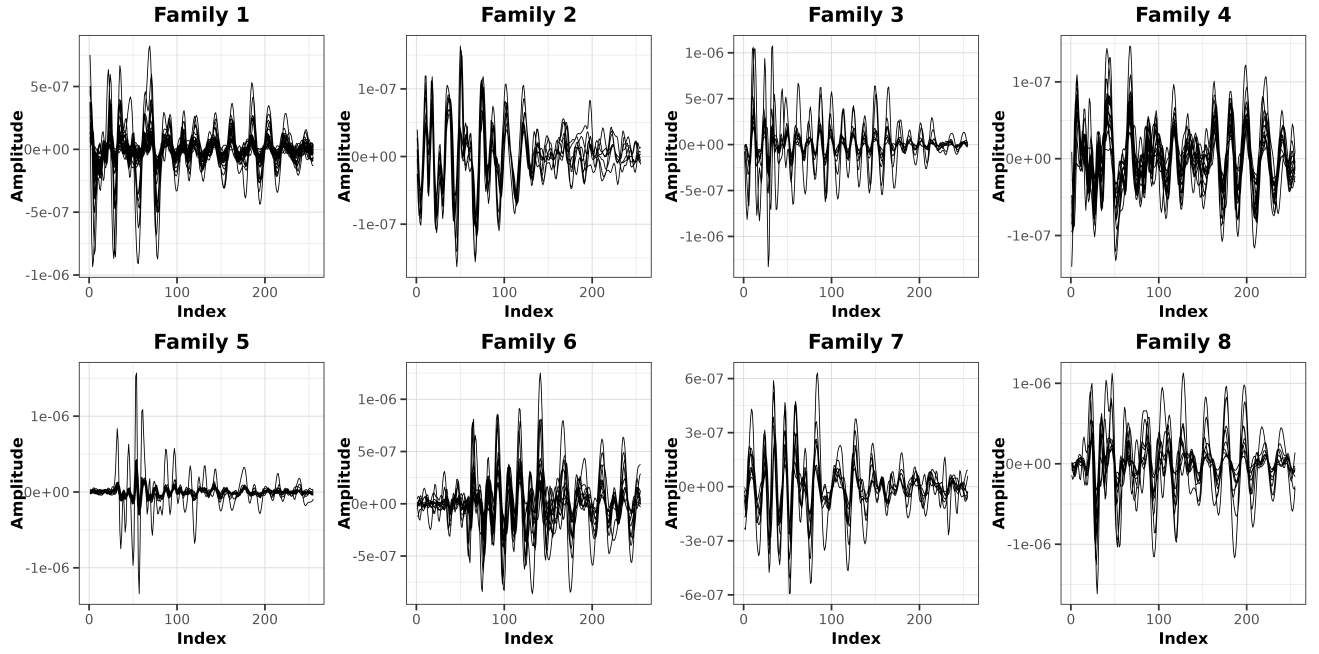


Figure S4: Spaghetti plots of the eight repeating event families identified in the STA–LTA event catalog using REDPy. A cross-correlation threshold of 0.8 was applied to group events into families. Each subplot corresponds to one family, showing the aligned member waveforms (component BHN, station BRZ02), highlighting the high waveform repeatability within each family.

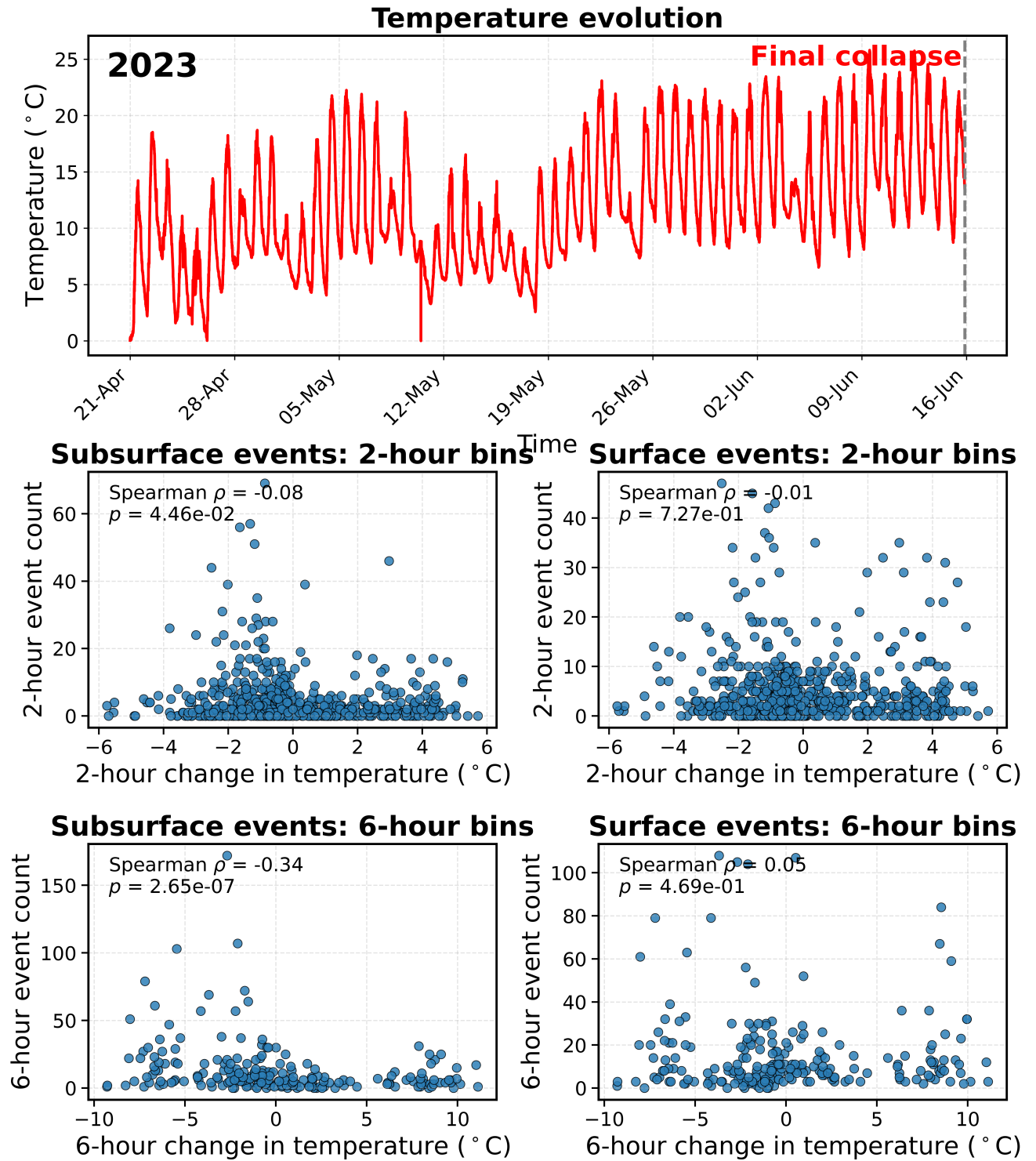


Figure S5: Relationship between short-term air-temperature changes and seismic activity at the Brienz/Brinzauls rockslide from 21 April to 15 June 2023. The top panel shows the hourly air-temperature record. The middle and bottom rows compare 2-hour (ΔT_{2h}) and 6-hour (ΔT_{6h}) temperature changes, respectively, with corresponding subsurface and surface seismic event counts. Spearman correlation coefficients (ρ) and associated p -values are reported in each panel.

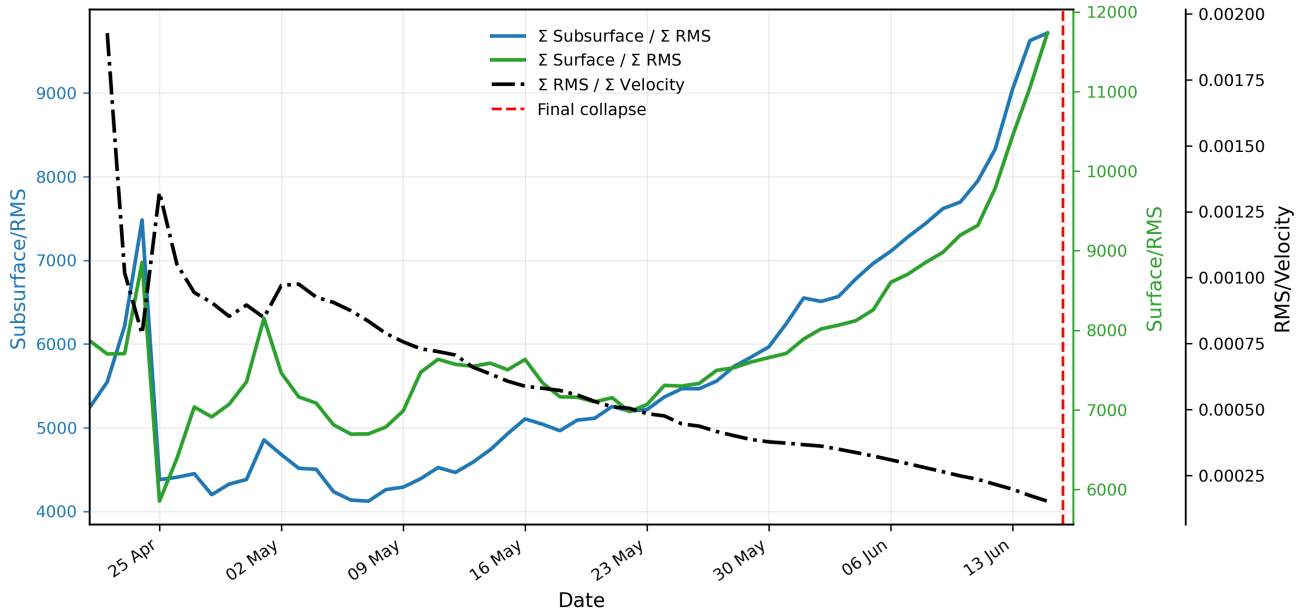


Figure S6: Cumulative precursor ratios during the 21 April–15 June 2023 acceleration phase, illustrating how event detection rates evolved relative to increasing background noise, represented by the daily mean RMS amplitude. Shown are cumulative subsurface seismicity normalized by cumulative seismic RMS amplitude ($\Sigma \text{ Subsurface} / \Sigma \text{ RMS}$), cumulative surface seismicity normalized by cumulative RMS amplitude ($\Sigma \text{ Surface} / \Sigma \text{ RMS}$), and cumulative RMS amplitude normalized by cumulative surface velocity ($\Sigma \text{ RMS} / \Sigma \text{ Velocity}$). The steady increase in both seismicity-to-RMS ratios from mid-May onward indicates that seismic event rates increased faster than the background seismic noise. The dashed red line marks the collapse on 15 June 2023.

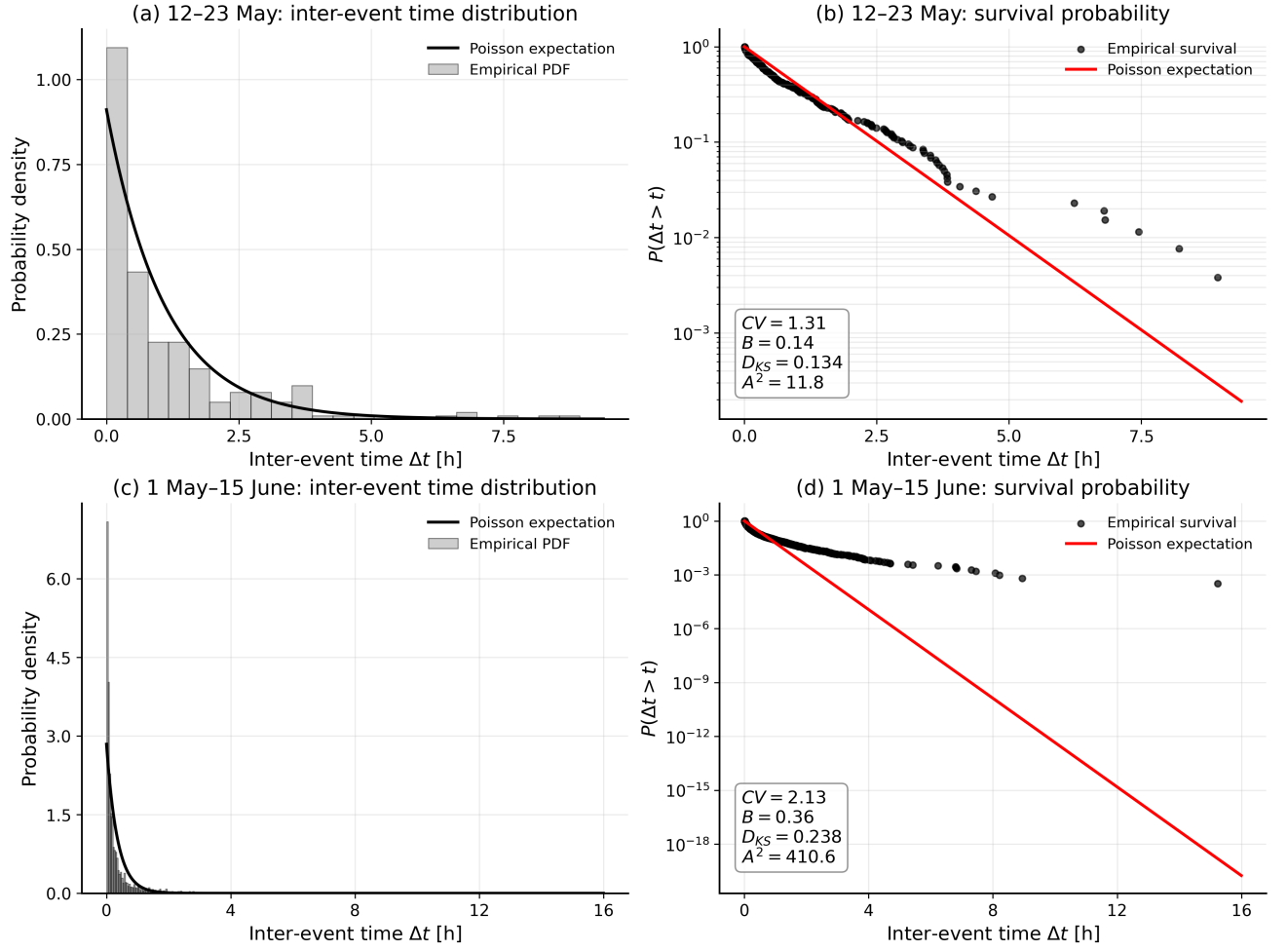


Figure S7: Comparison of surface-seismicity inter-event time statistics during 12-23 May 2023 (a,b) and over the extended catalogue from 1 May to 15 June 2023 (c,d). Panels (a,c) show the empirical inter-event time probability density functions together with the exponential distributions expected for homogeneous Poisson processes fitted using the observed mean inter-event time. Panels (b,d) compare the corresponding empirical survival probabilities, $P(\Delta t > t)$, with the Poisson expectations. The early interval already exhibits clustered event occurrence, whereas the extended catalogue shows substantially stronger departures from Poisson behaviour, characterized by an excess of short waiting times and a heavier survival tail.

Inter-event time metrics. Inter-event times (Δt) were calculated as the elapsed time between consecutive surface-seismic events after chronological sorting. The Poisson reference assumes an exponential waiting-time distribution with rate parameter $\lambda = 1/\overline{\Delta t}$, where $\overline{\Delta t}$ is the observed mean inter-event time.

Temporal clustering was quantified using the coefficient of variation,

$$CV = \frac{\sigma_{\Delta t}}{\overline{\Delta t}}, \quad (9)$$

for which $CV = 1$ corresponds to a homogeneous Poisson process, $CV > 1$ indicates clustered or bursty event occurrence, and $CV < 1$ indicates more regular spacing.

The burstiness index was calculated as

$$B = \frac{CV - 1}{CV + 1}, \quad (10)$$

with $B = 0$ corresponding to a Poisson process, $B > 0$ indicating increasing burstiness, and $B < 0$ indicating increasingly regular event occurrence.

The Kolmogorov–Smirnov distance (D_{KS}) measures the maximum difference between the empirical and fitted exponential cumulative distributions, whereas the Anderson–Darling statistic (A^2) places greater weight on discrepancies in the distribution tails and is therefore particularly sensitive to excesses of very short or very long waiting times. Larger values of CV , B , D_{KS} , and A^2 indicate progressively stronger departures from homogeneous Poisson behaviour.

Model Station	Noise	Surface	Earthquake	Sub-surface
Training Counts (80%)				
BRZ02	49633	21533	7525	2251
BRZ03	39022	21533	1036	2251
BRZ04	39022	21532	1036	506
Testing Counts (20%)				
BRZ02	12409	5383	1881	563
BRZ03	9756	5383	259	563
BRZ04	9756	5384	259	126
Total Samples				
BRZ02	62042	26916	9406	2814
BRZ03	48778	26916	1295	2814
BRZ04	48778	26916	1295	632

Table S1: Number of labeled samples in the training and testing datasets for the three single-station classifiers. Data were partitioned using a stratified 80%/20% train–test split to preserve class proportions across the earthquake, noise, surface, and sub-surface classes.

#	Feature Name	Definition
Time-Related Features		
1	t_duration	Duration of the signal.
2	t_rise	Signal rise time: time from start to maximum amplitude.
3	t_fall	Signal fall time: time from maximum amplitude to end.
4	t_risefall	Ratio of rise to fall time (t_{rise}/t_{fall}).
Amplitude and Raw-Signal Statistics		
5	a_skewness	Skewness of the signal amplitude distribution.
6	a_kurtosis	Kurtosis of the signal amplitude distribution.
7	raw_skewness	Skewness of the raw (unprocessed) signal.
8	raw_kurtosis	Kurtosis of the raw (unprocessed) signal.
9	a1_kurtosis	Kurtosis of band-limited amplitude in 0.1–1 Hz.
10	a2_kurtosis	Kurtosis of band-limited amplitude in 1–3 Hz.
11	a3_kurtosis	Kurtosis of band-limited amplitude in 3–10 Hz.
12	a4_kurtosis	Kurtosis of band-limited amplitude in 10–20 Hz.
13	a5_kurtosis	Kurtosis of band-limited amplitude in 20–50 Hz.
Envelope Statistics		
14	e_maxmean	Ratio of maximum to mean envelope value.
15	e_maxmedian	Ratio of maximum to median envelope value.
16	e_skewness	Skewness of the signal envelope distribution.
17	e_kurtosis	Kurtosis of the signal envelope distribution.
18	e1_logsum	log of the summed envelope in 0.1–1 Hz band.
19	e2_logsum	log of the summed envelope in 1–3 Hz band.
20	e3_logsum	log of the summed envelope in 3–10 Hz band.
21	e4_logsum	log of the summed envelope in 10–20 Hz band.
22	e5_logsum	log of the summed envelope in 20–50 Hz band.
23	e_rmsdecphaseline	RMS of envelope residuals from a linear decrease model (departure from linear decay).
24	e_devlinearfall	Deviation of the envelope fall from an ideal linear decrease (envelope fall-shape irregularity).
Cross-Correlation Function Features		
25	c_peaks	Number of peaks in the signal cross-correlation function (excursions above 75% of the maximum).
26	c_energy1	Sum of the first third of the cross-correlation function.
27	c_energy2	Sum of the last two thirds of the cross-correlation function.
28	c_energy3	Ratio $c_energy1/c_energy2$.
Spectral Power Statistics		
<i>Continued on next page...</i>		

#	Feature Name	Definition
29	s_peaks	Number of peaks in spectral power (excursions above 75% of the maximum).
30	s_peakpower	Mean power of spectral peaks.
31	s_mean	Mean spectral power.
32	s_median	Median spectral power.
33	s_max	Maximum spectral power.
34	s_var	Variance of the spectral power.
35	s_flatness	Spectral flatness.
36	s_entropy	Spectral entropy.
37	s_precision	Spectral precision (as defined by the spectral-property routine).
38	s_sd	Standard deviation of spectral power.
39	s_sem	Standard error of the mean of spectral power.
Band-Limited Spectral Energy		
40	s1_energy	Spectral energy in 0.1–1 Hz band.
41	s2_energy	Spectral energy in 1–3 Hz band.
42	s3_energy	Spectral energy in 3–10 Hz band.
43	s4_energy	Spectral energy in 10–20 Hz band.
44	s5_energy	Spectral energy in 20–30 Hz band.
45	s_gamma1	Gamma 1: spectral centroid.
46	s_gamma2	Gamma 2: spectral gyration radius.
47	s_gamma3	Gamma 3: spectral centroid width.
Frequency-Domain Descriptors		
48	f_modal	Modal frequency.
49	f_mean	Mean (central) frequency.
50	f_median	Median frequency.
51	f_q05	0.05 quantile of the spectrum.
52	f_q25	0.25 quantile of the spectrum.
53	f_q75	0.75 quantile of the spectrum.
54	f_q95	0.95 quantile of the spectrum.
55	f_iqr	Interquartile range of the spectrum.
56	f_centroid	Spectral centroid.
Time-Frequency Peak-Shape Features		
57	p_kurtosismax	Kurtosis of the maximum spectral power over time.
58	p_kurtosismedian	Kurtosis of the median spectral power over time.
59	p_maxmean	Mean over time of the ratio (max / mean) spectral power.
60	p_maxmedian	Mean over time of the ratio (max / median) spectral power.
<i>Continued on next page...</i>		

#	Feature Name	Definition
61	p_peaksmean	Number of peaks in normalised mean spectral power over time.
62	p_peaksmedian	Number of peaks in normalised median spectral power over time.
63	p_peaksmax	Number of peaks in normalised max spectral power over time.
64	p_peaksmaxmean	Ratio of peaks in normalised max vs mean spectral power over time.
65	p_peaksmaxmedian	Ratio of peaks in normalised max vs median spectral power over time.
66	p_peaksfcentral	Number of peaks over time at the central frequency.
67	p_diffmaxmean	Mean difference between max and mean power over time.
68	p_diffmaxmedian	Mean difference between max and median power over time.
69	p_diffquantile21	Mean difference between power quantiles 2 and 1 over time.
70	p_diffquantile32	Mean difference between power quantiles 3 and 2 over time.
71	p_diffquantile31	Mean difference between power quantiles 3 and 1 over time.
Signal-to-Noise Ratio (SNR) Features		
74	snr_B1	Signal-to-noise ratio in the 1–10 Hz frequency band (B1).
75	snr_B2	Signal-to-noise ratio in the 10–20 Hz frequency band (B2).
76	snr_B3	Signal-to-noise ratio in the 20–30 Hz frequency band (B3).
77	snr_B4	Signal-to-noise ratio in the 30–40 Hz frequency band (B4).
78	snr_B5	Signal-to-noise ratio in the 40–49 Hz frequency band (B5).
79	snr_B1_B2	Ratio of signal-to-noise ratios between the 1–10 Hz and 10–20 Hz bands ($\text{SNR}_{B1}/\text{SNR}_{B2}$).
80	snr_B3_B4	Ratio of signal-to-noise ratios between the 20–30 Hz and 30–40 Hz bands ($\text{SNR}_{B3}/\text{SNR}_{B4}$).
81	snr_B4_B5	Ratio of signal-to-noise ratios between the 30–40 Hz and 40–49 Hz bands ($\text{SNR}_{B4}/\text{SNR}_{B5}$).
82	snr_B1_B5	Ratio of signal-to-noise ratios between the 1–10 Hz and 40–49 Hz bands ($\text{SNR}_{B1}/\text{SNR}_{B5}$).
Spectral Mean Ratios Across Frequency Subranges		
83	s_mean1_2	Ratio of band-limited spectral mean: $s_mean(1-15Hz)/s_mean(15-30Hz)$.
84	s_mean2_3	Ratio of band-limited spectral mean: $s_mean(15-30Hz)/s_mean(30-49Hz)$.
85	s_mean1_3	Ratio of band-limited spectral mean: $s_mean(1-15Hz)/s_mean(30-49Hz)$.
Station-Level Amplitude Feature		
86	rms_station	RMS amplitude of the (filtered) vertical component: $\sqrt{\text{mean}(BHZ^2)}$.
<i>Continued on next page...</i>		

#	Feature Name	Definition
Polarization and Particle-Motion Features		
87	rectilinearity	Rectilinearity from covariance eigenvalues ($\lambda_1 \leq \lambda_2 \leq \lambda_3$): $1 - \frac{\lambda_1 + \lambda_2}{2\lambda_3}$.
88	azimuth	Azimuth (degrees) of the principal polarization direction from the dominant eigenvector: $\arctan\left(\frac{p_{2,3}}{p_{1,3}}\right) \cdot \frac{180}{\pi}$.
89	dip	Dip (degrees) of the principal polarization direction: $\arctan\left(\frac{p_{3,3}}{\sqrt{p_{2,3}^2 + p_{1,3}^2}}\right) \cdot \frac{180}{\pi}$.
90	planarity	Planarity from eigenvalues: $1 - \frac{2\lambda_1}{\lambda_2 + \lambda_3}$.
Fractal / Roughness Feature		
91	fractal_dimension	Fractal dimension estimated from the variogram scaling (Jaffar et al., 2024): compute variogram vs lag τ , fit slope on the first 4 points in log-log space, then $D = 2 - \frac{\text{slope}}{2}$.

Table S2. Summary of the 91 features used for training the Random Forest classifier.