

Impact of nested moisture cycles on cliff coast failure revealed by multi-seasonal seismic and topographic surveys

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Abstract

Cliff failure is a fundamental process shaping many coast lines worldwide. Improved insight into direct links between cliff failure and forcing mechanisms requires precise information on the timing of individual failures, which is hard to obtain with conventional observation methods for longer stretches of coastline. Here we use seismic records and auxiliary data spanning 25 months to precisely identify and locate 81 failures at the Jasmund chalk cliff coast, on Germany's largest island, Rügen. The sub-minute precision of event timing allows linking of individual failures to triggers over a wide range of relevant time scales. We show that during the monitoring interval, marine processes were negligible as triggers of cliff failure, although they are important for the removal of resulting deposits. Instead, cliff failure was associated with terrestrial controls on moisture. Most failures occurred when water caused a state transition of the cliff forming chalk, from solid to liquid. Water content was modulated by i) subsurface flow towards the cliff, ii) rain onto the cliff and iii) condensation of air moisture, leading to clustered failures during night. Seasonal water availability, controlled by plant activity, imposed an annual cycle of cliff failure, and wetter and drier than average years imposed a month-long legacy effect on cliff dynamics.

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1 **Impact of nested moisture cycles on cliff coast failure**
2 **revealed by multi-seasonal seismic and topographic**
3 **surveys**

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9 **Key Points:**

- 10 • Multi-year UAV and seismic monitoring yielded a catalogue comprising timing,
11 evolution, and location of 81 cliff coast failures
- 12 • Failures are controlled by water availability through subsurface flow, rain, and air
13 moisture condensation
- 14 • Failures are forced on diurnal, lunar, seasonal and multi-year scale

Abstract

Cliff failure is a fundamental process shaping many coast lines worldwide. Improved insight into direct links between cliff failure and forcing mechanisms requires precise information on the timing of individual failures, which is hard to obtain with conventional observation methods for longer stretches of coastline. Here we use seismic records and auxiliary data spanning 25 months to precisely identify and locate 81 failures at the Jasmund chalk cliff coast, on Germany's largest island, Rügen. The sub-minute precision of event timing allows linking of individual failures to triggers over a wide range of relevant time scales. We show that during the monitoring interval, marine processes were negligible as triggers of cliff failure, although they are important for the removal of resulting deposits. Instead, cliff failure was associated with terrestrial controls on moisture. Most failures occurred when water caused a state transition of the cliff forming chalk, from solid to liquid. Water content was modulated by i) subsurface flow towards the cliff, ii) rain onto the cliff and iii) condensation of air moisture, leading to clustered failures during night. Seasonal water availability, controlled by plant activity, imposed an annual cycle of cliff failure, and wetter and drier than average years imposed a month-long legacy effect on cliff dynamics.

Plain Language Summary

Cliffs line many coastlines world-wide. They are eroded by cliff falls, with consequences for human safety, land loss ecosystem dynamics and availability of sediment along the coast. The discrepancy between rapid, short-lived failure processes and episodic observation techniques does not allow a full analysis of the causes and drivers of cliff erosion. Combining measurements from a seismometer network on Germany's largest island, Rügen, with 3D models from drone surveys and weather station data, we detected, located and timed 81 cliff failures in two years, and analysed the circumstances that gave rise to their occurrence. These events were predominantly associated with the presence of water, which turns the solid, cliff-building chalk into a failure-prone slurry. Water availability is modulated at different scales by rain on the cliff and moisture condensation, soil water flow, vegetation water uptake, and possibly the lunar cycle. Our findings sharpen the picture of when and why cliffs fail, and allow a better understanding of global change impact on cliff coasts.

1 Introduction

Coast lines host about 40 % of the world's global population along with key infrastructure, cultural heritage and unique ecosystems (Menatschi et al., 2018). Coastal change can have a profound impact on these assets. Around half of the world's coasts consist of eroding cliffs (Young & Carilli, 2019). On these coasts, cliff failure occurs across a range of scales and by a multitude of processes acting on the different materials that are able to form cliffs (e.g. Duperret et al., 2005; Kogure et al., 2006; Collins & Sitar, 2008; Stephensen, 2014; Rosser et al., 2013). A fundamental mechanism of coastal retreat worldwide, cliff failure is driven by cyclic loading and activation due to climate-driven processes. After a preparation phase, during which a cliff section is driven to instability, for example by weathering, propagation of discontinuities or undermining at the cliff base (Duperret et al., 2005; Kogure et al., 2006), failures can be initiated by a variety of trigger mechanisms. These include impact of tide- and storm-driven waves that exert forces on the cliff and entrain abrasive sediment (Stephensen, 2014), wind-induced stress (Vann Jones et al., 2015) amplified when interacting with trees (Dietze, Turowski, et al., 2017), frost shattering or ice segregation and freeze thaw cycles (Letortu et al., 2015), and rainfall and groundwater recharge causing gravitational loading and reduced shear strength due to increased pore water pressure (Stephensen, 2014). In addition, failures can cause further failures, leading to upward propagation of cliff erosion with time (Rosser et al., 2013).

65 Robust attribution of cliff failure to a particular trigger depends on precise knowl-
 66 edge of the timing and location of the event, and of the preceding and concurrent con-
 67 ditions. Cliff failure is generally a rapid process once initiated, and relevant conditions
 68 can change on short time scales (minutes to days). Therefore, especially for large fail-
 69 ures, triggers can remain difficult to identify or to link with the actual process (Collins
 70 & Sitar, 2008; Rosser et al., 2013). Many past studies have used records of cliff failure
 71 with monthly or coarser time resolution (e.g. Lim et al., 2010; Vann Jones et al., 2015).
 72 While these studies have yielded useful insights, data with hourly or better resolution
 73 may help to robustly constrain causal links. In this context, environmental seismology
 74 offers a useful approach, because of its ability to deliver both high time resolution (at
 75 least sub-minute) and scalable location precision (usually 5–10 % of the inter station dis-
 76 tance) for individual cliff failures.

77 Networks of seismic sensors can be used to detect, locate, and estimate the volume
 78 and anatomy of mass movements at the landscape scale (e.g. Helmstetter & Garambois,
 79 2010; Hibert et al., 2011). The size limit of detection with a network with a given sta-
 80 tion spacing and instrument configuration is set by the ambient noise level, and depends
 81 on the transfer of energy from a mass movement into the substrate, as well as on ground
 82 properties that determine the propagation and attenuation of the resulting seismic waves.
 83 Dietze, Mohadjer, et al. (2017) were able to seismically detect rockfall volumes as small
 84 as 0.05 m^3 with a fall height of less than 50 m, and to locate them with deviations from
 85 independently constrained positions of about 80 m on average (7 % of the mean station
 86 spacing). This means that while discrete, failure-based erosional fluxes can be tackled
 87 by the seismic approach, the diffuse part of an erosional budget remains elusive. The main
 88 strength of this approach, however, is the continuous temporal coverage of a larger area
 89 and precise time information for the onset and duration of discrete events. The high tem-
 90 poral resolution of seismic data is a key to identifying triggers of failures by systemat-
 91 ically measuring time lags between potential triggers and recorded geomorphic processes
 92 (e.g. Dietze, Turowski, et al., 2017).

93 In this study we explore the drivers and triggers of coastal cliff failures on the Jas-
 94 mund peninsula, part of Germany’s largest island, Rügen. We use seismic and UAV mon-
 95 itoring to detect, date, locate, verify and quantify cliff failures over a period of two years.
 96 We analyse the spatial and temporal patterns of cliff failure in the context of marine,
 97 meteorological, biological and hydrological boundary conditions across scales from min-
 98 utes to years. This yields quantitative constraints on the relevance of triggers and drivers
 99 at distinct time scales.

100 2 Materials and methods

101 2.1 Study site and instrumentation

102 The study area on the Jasmund peninsula of Rügen comprises an iconic cliff coast
 103 section with a length of 8.6 km. The cliffs are steep ($57_{-4}^{+8} \text{ }^\circ$, median and quartiles – used
 104 here throughout to account for non-normally distributed data) to partly overhanging and
 105 up to 118 m high (48_{-13}^{+13} m). They are facing the Baltic Sea to the northeast, a semi-
 106 enclosed basin with a minimal tidal range (about 15 cm, IZW, 2003). Located in a Na-
 107 tional Park the area has been covered by a beech forest for more than 1000 years. The
 108 local weather is dominated by an oceanic regime (DWD, 2019), with less than $5 \text{ }^\circ\text{C}$ di-
 109 urnal temperature range, positive mean monthly temperatures throughout the year (7.9
 110 $^\circ\text{C}$ annual average, ranging between 0.2 and $16.5 \text{ }^\circ\text{C}$) and 286 mm precipitation during
 111 summer versus 236 mm during winter (522 mm annual average, ranging between 27 and
 112 60 mm/month). Access to this area is limited and restricted to the existing trails, and
 113 a human role in triggering cliff failure in the area can mostly be excluded.

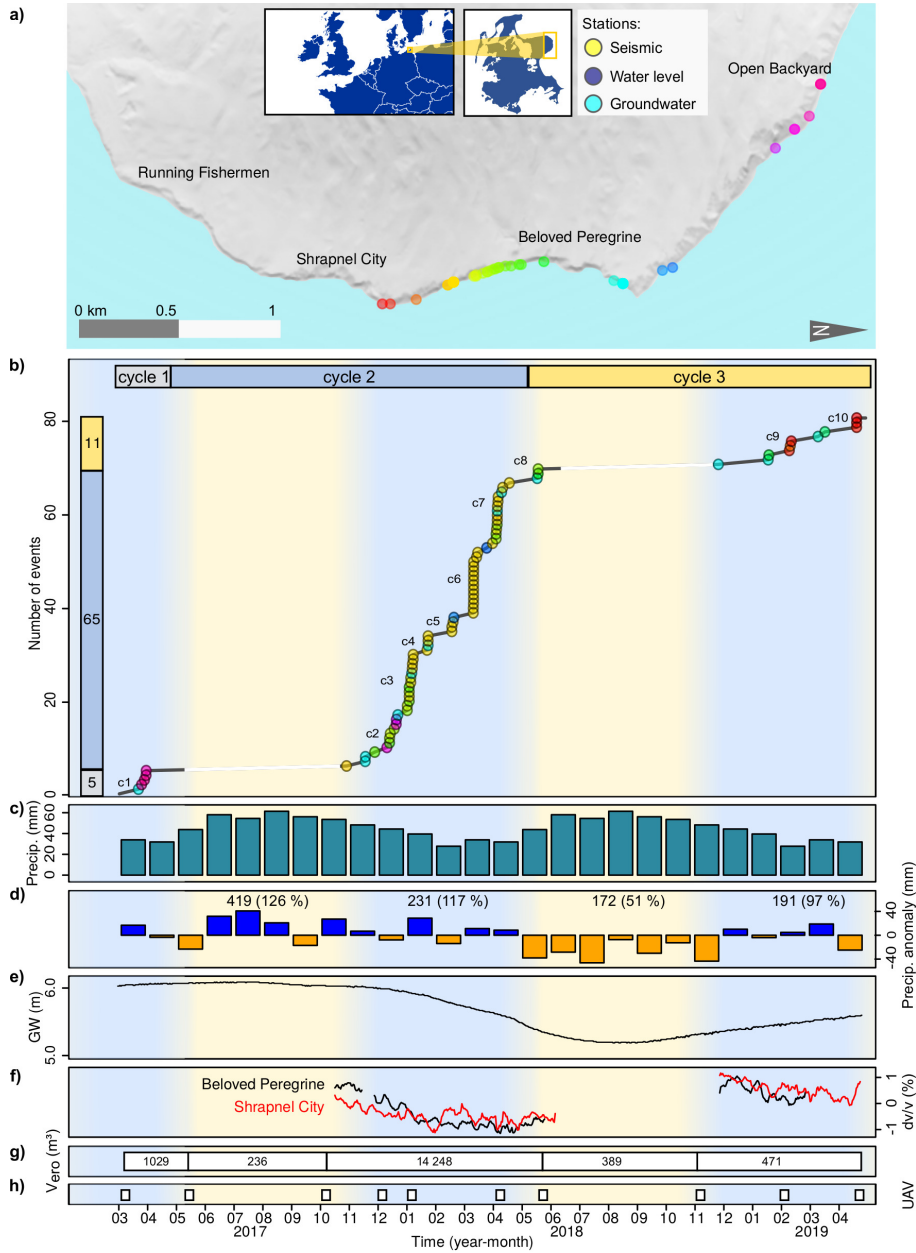


Figure 1. Study area and data sets. a) Hillshade map of study area with seismically detected failures (coloured by location). b) Failures with numbered event clusters. Vertical and horizontal bars denote seasonal cycles with cumulative number of failures per cycle. Circle colour corresponds to locations in a). White line sections depict periods without seismic data coverage. c) Monthly 30 year average precipitation sums (DWD, 2019). d) Precipitation deviations from monthly averages. Numbers denote precipitation sums per season, indicated by yellow and blue background colours. Values in parentheses denote relative deviations from 30 year averages. e) Groundwater level (STALUVP, 2019) above 108 m asl. f) Seismic wave velocity changes (dv/v). g) UAV based failure volume sums per season. h) UAV flight dates.

114 The Jasmund cliffs have formed in weakly cemented Maastrichtian chalk, which has
 115 been folded and thrust by the Scandinavian ice sheet into a sequence of stacked blocks
 116 and covered by till. Water content has an important effect on the stability of chalk in
 117 general and chalk cliffs in particular (Duperret et al., 2005; Obst & Schütze, 2005; Voake
 118 et al., 2019). A classic measure of rigidity in engineering geology, the plasticity index (I_p)
 119 (Williams, 2016) of the chalk bedrock of our study area is 7.8 ± 1.2 (pers. comm. Chris-
 120 tian Koepke, BAUGRUND Stralsund engineering office, 2019). This suggests that wa-
 121 ter content changes of less than 10 % can have fundamental effects on the state of the
 122 rock mass. In Rügen chalk, the transition from rigid to semi-rigid occurs at 22.0 ± 2.0 %
 123 and the transition to liquid at 29.8 ± 2.5 % water content. The average water content of
 124 Rügen chalk is around 23 % (LUNG, 2019). Hence, the cliff material is likely mostly in
 125 a meta stable state, and wetting and drying cycles may cause frequent transitions be-
 126 tween rigid, semi-rigid and liquid states. These material properties are consistent with
 127 more detailed studies from northwest France, where chalk also forms sea facing cliffs. Duperret
 128 et al. (2005) found minimum natural water contents between 9.6 and 27 % (19 % on av-
 129 erage) and measured strength reductions of 40–50 % when fresh water was added to the
 130 chalk, and 52–73 % strength reductions for sea water uptake.

131 The Jasmund cliffs have retreated by erosion at about 25 cm/yr on average, gener-
 132 ating a cumulative annual total of 103,000 m³ of debris along the coast section (Obst
 133 & Schütze, 2005). This erosion estimate is based on Holocene time scale evidence and
 134 allows for significant short-term variability. We note a similarity with rates of 25 cm/yr
 135 for other regions with comparable cliff forming rocks, such as in northwest France (Duperret
 136 et al., 2005), despite important differences in the wave and tidal energy of these coasts.

137 Between March 2017 and April 2019, we operated four seismic stations (Nanomet-
 138 rics TC 120s seismometers and PE6/B 4.5 Hz geophones, logged at 200 Hz by Digos Dat-
 139 aCubes) at intervals of about 1.2 km along 7 km of the Jasmund cliff coast. Instrumen-
 140 tation was active during the autumn to late spring season, and the sensors were disman-
 141 tled during the summer period and could not be used for cliff failure detection. Repeat
 142 UAV surveys were used to generate high resolution 3D point clouds to quantify topo-
 143 graphic changes. In addition, we used weather data at hourly resolution from the Arkona
 144 station of the Deutscher Wetterdienst, 20 km to the northwest (DWD, 2019), sea level
 145 data with minute resolution from a gauge at the southeast limit of the study area (WSV,
 146 2019), and daily groundwater data (STALUVP, 2019) from a well in chalk material 1.5
 147 km west of the cliff coast (Fig. 1 a). For subsequent analyses (see section 4.3) we also
 148 used the HORIZONS web interface (JPL, 2019) to retrieve hourly lunar Ephemerides
 149 (data of the distance between the study area and the Moon’s centre of gravity).

150 2.2 Data processing

151 Seismic data were processed with the R package ‘eseis’ v. 0.5.0 (Dietze, 2018a, 2018b).
 152 Typical seismic waveforms of gravitational mass wasting events are spindle shaped (Hibert
 153 et al., 2011), and registered at seismic stations with a few seconds offset across the lo-
 154 cal network due to the finite velocity with which the seismic waves travel through the
 155 ground (Fig. 2 f). To identify these discrete events in the continuous stream of seismic
 156 data, we used a STA-LTA picker (Allen, 1982). For details on the settings and param-
 157 eter constraints see SI. We screened these events with a series of automatic rejection cri-
 158 teria, admitting only those that lasted between 1 and 180 s (assuming that shorter cases
 159 are random signal coincidences and longer signals are caused by earthquakes or anthro-
 160 pogenic activity). We considered only events detected by at least three seismic stations
 161 (minimum required to locate an event), within 11 s (maximum time required for a seis-
 162 mic signal to travel through the network). All admitted events were manually checked
 163 for plausibility based on i) consistent amplitude decrease of the signals across the net-
 164 work as expected for a local seismic source, ii) consistent signal arrival time delay across
 165 the network, indicative of a local source predominantly emitting surface waves, iii) an

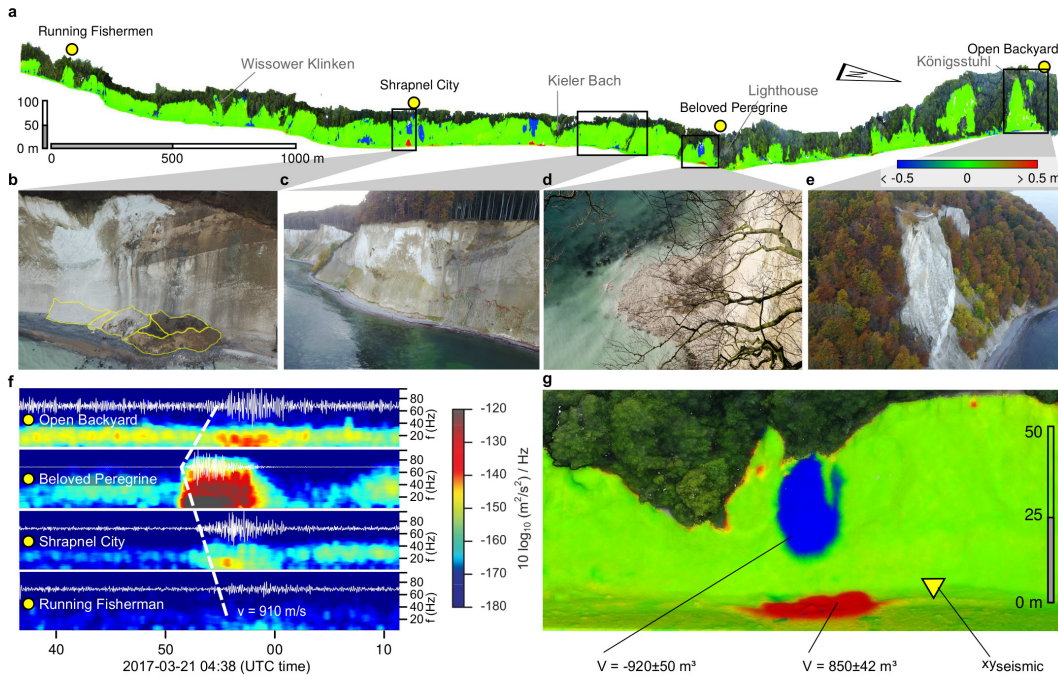


Figure 2. Cliff failure locations, anatomy and deposits. a) UAV-based cliff activity for the entire study period, shown as perspective oblique view from the sea. Tree carapace is shown in natural dark green colour. Colour bar indicates surface change in m. b) Site that exhibited repeated failure activity with discrete sub-deposits (yellow polygons), below station "Shrapnel City". c) Perspective view along cliff towards the South with sequence of stacked chalk units. d) Terrestrial picture of recently failed site. Note the suspension plume originating from failure deposit as direct consequence of waves affecting the material reaching beyond the beach zone. e) The Königsstuhl, highest part of the cliff section under survey. f) Failure from d) as recorded by the seismic stations with an apparent wave velocity of 910 m/s. The 5–10 Hz filtered signals with their spindle shaped evolution in time are plotted on top of spectrograms. g) UAV-based volume changes for the failure in d), based on UAV data from March and May 2017. Perspective from the sea. Yellow triangle depicts best match seismic location, about 37 m north of the UAV based location. For enlarged versions of photos in b)–e) see SI.

166 emergent onset and slow decay of the signal, as reported for many hillslope mass wast-
 167 ing processes (Helmstetter & Garambois, 2010; Hibert et al., 2011; Dietze, Mohadjer,
 168 et al., 2017), iv) absence of earthquake-like distinct arrivals of different wave types, and
 169 v) absence of tremor-like frequency patterns, often associated with overhead passage of
 170 aircraft.

171 Detected events that passed manual screening were located by the migration of the
 172 deconvolved, filtered vertical component signal envelopes (Burtin et al., 2013; Dietze, Mo-
 173 hadjer, et al., 2017). The final location estimates are reported as projections along the
 174 coast. This is done only for failures whose 90% confidence interval overlapped with the
 175 coast, which is the only likely area of active mass wasting in the otherwise gently undu-
 176 lating landscape. The migration approach requires an assumed seismic wave velocity. Here,
 177 we used an example failure (Fig. 2 f) for which we know the location independently and
 178 minimized the deviation of the seismic location estimate from the known location. Mi-
 179 gration results also depend on the window with which the seismic data are filtered. There-
 180 fore, we have also tested the location deviation as a function of filter width. For this, we

181 ran the optimization routine for different filter windows, keeping the lower corner fre-
182 quency constant at 5 Hz and gradually increasing the higher corner frequency from 6 to
183 20 Hz. All detailed processing steps are described in the Supporting Information (SI),
184 including annotated R scripts.

185 Seismic wave velocities vary in time, as the mechanical properties and water con-
186 tent of their medium change (Larose et al., 2015). Seismic noise cross correlation anal-
187 ysis can be used to infer changes in the relative seismic wave velocity (dv/v), and thereby
188 to monitor the properties of the local substrate (Snieder, 2004). We determined dv/v
189 for the two central stations ("Beloved Peregrine" and "Shrapnel City") with the MIIC
190 package (Sens-Schönfelder, 2014). Hourly signals were processed by filtering (4–8 Hz),
191 spectral whitening, clipping at two standard deviations and sign-normalization, and the
192 cross correlation functions were stacked to daily data. These results were converted to
193 dv/v values using the stretching technique of Sens-Schönfelder and Wegler (2006). For
194 details see SI.

195 UAV surveys were used to verify seismic failure detections and locations, to pro-
196 vide precise locations along the cliff, detachment heights above the shore line and be-
197 low the cliff top, and to estimate the volumes of failed material. In addition, we used the
198 UAV data to quantify failure volumes during the summer periods, for which no seismic
199 data were available. Surveys (Fig. 1 h) were performed using consumer-grade DJI UAVs,
200 including a Phantom 3 Advanced (March 2017, May 2017, December 2017), a Mavic Pro
201 (October 2017, January 2018, April 2018, May 2018), and a Mavic 2 Pro (November 2018,
202 February 2019, April 2019). Each survey consisted of multiple flights from up to seven
203 locations along the cliff, yielding 1000–2000 photos for a full survey. The December 2017,
204 Januar 2018 and April 2018 surveys were partial surveys, covering the most active cliff
205 sections between and about 500 m beyond the two central seismic stations. The UAVs
206 were flown manually and set to take photographs every three seconds. For a given sur-
207 vey, each section of the cliff was covered by at least two passes of the UAV with differ-
208 ent flight elevation and camera obliquity. Camera angles typically ranged from 40–80 de-
209 grees from nadir, and elevations from 30–150 m above sea level. The distance between
210 the camera and cliff varied depending on cliff height and weather conditions.

211 UAV data processing was done using Agisoft Photoscan (v. 1.4.2) structure from
212 motion (SfM) software. The cliff was split into five overlapping segments in order to re-
213 duce processing time. We were unable to deploy or measure ground control points for
214 the cliff surveys because of the National Park status of the study area, the inherent dan-
215 ger of failures preventing us from accessing the beach, and dense vegetation cover and
216 danger of failure of the overhanging top parts of the cliff. Thus, the surveys were geo-
217 referenced using only the GPS data recorded by the UAVs. In order to obtain reliable
218 change detection results, we followed the co-alignment workflow introduced in Cook and
219 Dietze (2019). For each pair of surveys that were compared, we combined photos from
220 both surveys for point matching, initial bundle adjustment, and optimization (follow-
221 ing removal of tie points with reconstruction uncertainty > 50). The two sets of photos
222 were then separated for the dense cloud construction. Parameters for alignment were:
223 high quality, key point limit of 40000, tie point limit of 4000, and adaptive camera model
224 fitting. Parameters for dense cloud construction were: medium quality and aggressive
225 depth filtering. The dense point clouds were compared using the M3C2 algorithm (Lague
226 & Leroux, 2013) in CloudCompare (GPL, 2019) using the parameters: core point spac-
227 ing 0.25 m, projection diameter 0.5 m, and normal scales 0.5 m to 4.5 m in 1 m steps.
228 The accuracy of the resulting change cloud was assessed using the calculated changes
229 in the stable areas of the cliff (typically the majority of the cliff face). We estimate a level
230 of detection of 10–15 cm or better for our change maps.

231 We manually inspected each of the change maps in concert with the available be-
232 fore and after photographs to identify cliff failures. For each identified failure, we clipped
233 the before and after point clouds to the area of measured change and calculated the vol-

234 ume using the 2.5D volume tool in CloudCompare. We calculated each volume three times
 235 using the X, Y, and Z reference planes to determine the most appropriate reference plane
 236 for a given failure and estimate a relative volume uncertainty (9.7 % on average). In ad-
 237 dition, we measured the elevation of the centre of each failure to give the height above
 238 the shoreline and the vertical distance from the cliff top.

239 **2.3 Estimation of seismic detection limit**

240 A cliff failure will only be detected when it emits sufficient kinetic energy to the
 241 ground. Since we need such a signal to be recorded by at least three seismic stations to
 242 locate the seismic source, the energy must be high enough to allow signal propagation
 243 over at least twice the average seismic station distance. On 26 January 2019 National
 244 Park staff cut trees along the main road crossing the forest. The felling sites were be-
 245 tween 2.0 and 2.5 km away from the closest three seismic stations of our coastal array.
 246 Forest staff confirmed that the largest trees had weights of up to 10 t and heights of up
 247 to 30 m. During this felling period, we had a further seismic station running in the study
 248 area, located 1.7 km northwest of the station "Shrapnel City", recording with the same
 249 instruments and parameters as the other stations (4). We screened the seismic records
 250 of all stations during the tree felling to obtain conservative estimates of the minimum
 251 detectable volume of chalk material failing along the cliff. Therefore, we assume that max-
 252 imum energy can be delivered to the ground if a tree would fall without any internal ab-
 253 sorption of energy by swaying and bending branches, and treat a tree fall as free fall pro-
 254 cess of the entire tree mass from the mean tree height.

255 **2.4 Trigger analysis**

256 A wide range of triggers may cause rock slope failure. From this range we can ex-
 257 clude geophysical (earthquake, volcanic eruption; Hibert et al., 2014) and mass wast-
 258 ing (snow/rock avalanches, ice falls, debris flows; Stock et al., 2013) triggers due to the
 259 location of the study site. Biological/anthropogenic triggers (animal traffic, human ac-
 260 tivities; Wiczorek, 1996) are unlikely in a protected area with virtually no access to the
 261 cliff face. Thermal dilation and contraction (Stock et al., 2013) are assumed to play a
 262 subordinate role in generating major stress cycles within the rock mass, given that the
 263 northeast-facing aspect of the cliff prevents intense and prolonged exposure to direct sun-
 264 light, especially during winter time. The daily amplitude of air temperature was $3.7^{+1.3}_{-1.1}$
 265 °C for the entire study period, with even lower amplitudes during the November–May
 266 period ($3.1^{+1.3}_{-0.9}$ °C). Since the propagation of temperature changes into the ground is as-
 267 sociated with significant attenuation of the amplitude within a few cm (e.g. Holmes et
 268 al., 2008) and mechanical tests of the temperature effect on tensile strength of chalk (e.g.
 269 Voake et al., 2019) showed only minimal effects compared to the impact of wetting, it
 270 appears unlikely that such small air temperature amplitudes play a primary role in af-
 271 fecting the chalk material properties. The tidal range of the Baltic Sea is about 15 cm,
 272 equivalent to the diameter of larger sediment clasts on the beach at the foot of the cliff.
 273 Moreover, in many places the beach forms a ramp of 2 m height from the water line to
 274 the cliff base. Thus, we consider tidal effects irrelevant for processes affecting the cliff.

275 Geotechnical measurements suggest that, under normal conditions, the chalk rock
 276 mass of the Jasmund peninsula may be close to or beyond a critical state, and addition
 277 of comparatively small amounts of water may have significant effects on the stability of
 278 landforms built by this material. With the concept of a system sensitive to water con-
 279 tent in mind, we focused our exploration for likely triggers of cliff failure on precipita-
 280 tion, wind, freeze-thaw transitions, sea level and wave action (Kennedy et al., 2017; Di-
 281 etze, Turowski, et al., 2017).

282 We assessed the relevance of these trigger types by analysis of the time difference
 283 between a failure and the preceding trigger occurrence (Dietze, Turowski, et al., 2017).

284 This assumes that a geomorphic response occurs while a trigger is active or after it has
 285 been active, either without delay or with a trigger-specific time lag (cf. Dietze, Mohad-
 286 jer, et al. (2017) for detailed discussion of expected time lags). The resolution of any trig-
 287 ger analysis is limited by the resolution of both event timing and trigger proxy data. We
 288 were able to achieve at least sub-minute resolution of event timing, rendering trigger proxy
 289 timing (< 1 h) the limiting factor.

290 To evaluate the role of precipitation in triggering of cliff failures, we calculated time
 291 lags with rain fall of 0.1 mm/h (smallest measurement increment), 0.2 mm/h (quantile_{0.05}
 292 of the range of recorded rain intensities) and 0.5 mm/h (quantile_{0.10}). Further thresh-
 293 olds could be included but would most likely result in systematically changing time lags
 294 as during rain storms the rain intensity is temporally autocorrelated. For wind as a trig-
 295 ger we defined wind events as episodes with one-hour average wind speeds at Beaufort
 296 scale 6, labelled "strong wind", or higher. Freeze-thaw episodes were defined as transi-
 297 tions from negative to positive Celsius near-ground air temperatures, acknowledging that
 298 heat dissipation into the ground can take several hours (Dietze, Turowski, et al., 2017)
 299 and that there may be differences in air temperature between the study site and the me-
 300 teorological station. The role of sea level as direct trigger of cliff failures (i.e., minimal
 301 time lags) was assessed by calculating time lags for levels corresponding to the quantiles_{0.75,0.90,0.95}
 302 of the full distribution of sea level data (i.e., 16, 26 and 33 cm above average sea level,
 303 respectively). In the absence of wave buoy data, we cannot directly constrain wave height.
 304 Thus, we calculated the standard deviation of sea level in a moving window of 20 min,
 305 assuming that during storms higher wave amplitudes will result in greater standard de-
 306 viation values (i.e. increased variability of sea level around the mean).

307 The time lags for all triggers are visualized as kernel density plots, which provide
 308 a continuous representation of the empirical density distribution of the data, and are sim-
 309 ilar to histograms but without the bias created by definitions of bin sizes and class bound-
 310 aries (Dietze et al., 2016). We restricted the analysis to a maximum time lag of 72 h,
 311 assuming that all triggers operate at time scales shorter than three days. To estimate
 312 the significance of our analyses we tested the time lag distributions resulting from the
 313 empirical failure catalogue for statistical difference from 1001 synthetic event data sets
 314 of the same size as the empirical catalogue. Each synthetic data set was generated by
 315 randomly assigning start times for the entire study period. We used the two-sample Kolmogorov-
 316 Smirnov (KS) test to evaluate whether the distributions are significantly different.

317 The length of the monitoring period (25 months) allows us not only to investigate
 318 time lags to triggers, but also to identify activity variations across time scales from di-
 319 urnal to lunar orbital and annual. For these cycles we calculated spectra of the contin-
 320 uous time series of potential triggers and drivers. The discrete distribution of cliff fail-
 321 ures was converted to a continuous distribution by calculating a kernel density estimate
 322 with hourly resolution and a window size of two days, and normalizing the resulting den-
 323 sity values.

324 **3 Results**

325 **3.1 Event detection, location and anatomy**

326 Automatic picking yielded a total of 2818 potential cliff failures. After manual screen-
 327 ing and validating that seismic locations were along the coast, we confirmed 81 as likely
 328 actual cliff failures (Fig. 1). We use an event on 21 March 2017 at 4:38 am UTC time
 329 to illustrate the insights from combining the seismic monitoring and UAV surveying (Fig. 2 f-
 330 g). This failure, located about 200 m south of station "Beloved Peregrine", generated
 331 a seismic signal with an emergent onset, a rise time (time from signal onset to maximum
 332 amplitude) of 1.5 s, and a fall time (time from maximum amplitude to event end) of 7.3
 333 s (see white signal time series on top of spectrograms in Fig. 2 f). Photographs taken

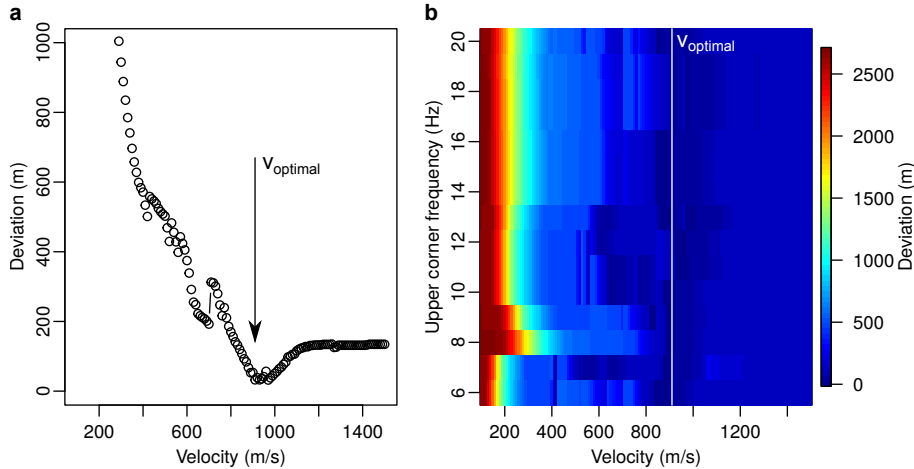


Figure 3. Estimate of apparent seismic wave velocity by minimization of model location deviations from empirically known location. a) Deviation as function of wave velocity for 5–10 Hz filtered signals. b) Deviation map resolving deviation as function of wave velocity and filter frequency width (5 Hz as fixed lower corner frequency).

334 by park authorities 3 days after the event confirmed it as a cliff failure involving around
 335 800 m^3 of material that fragmented during transport and covered the beach as a flow-
 336 like deposit, extending into the sea (Fig. 2 d). Our UAV-based change model, based on
 337 a survey in May 2017, shows a cliff failure with a volume of $920 \pm 50 \text{ m}^3$, located at 32
 338 m above sea level, and a corresponding deposit of $850 \pm 42 \text{ m}^3$ (Fig. 2 g). The 81 seis-
 339 mically detected failures (figures in SI A5) lasted in general $9.0^{+2.9}_{-2.0}$ s, almost exclusively
 340 with an emergent onset, signal rise times of $2.8^{+1.5}_{-0.8}$ s and fall times of $6.7^{+2.0}_{-2.0}$ s. The sig-
 341 nals had central frequencies of $15.9^{+6.6}_{-4.2}$ Hz. In 26 % of all cases, a failure was followed
 342 by at least one other event less than 200 m away within 24 hours. We recorded one event
 343 cluster composed of 11 discrete failures during 10.5 hours, starting on 2018-03-09 16:17:15
 344 UTC (see Tab. SI 3).

345 The optimal apparent seismic wave velocity for event location (Fig. 3) yielded a
 346 constant value of 910 m/s regardless of the width of the filter window applied to the seis-
 347 mic data. For this seismic velocity, the location error was minimized at 37 m. Assum-
 348 ing constant conditions, we used this velocity value for location of all other detected fail-
 349 ures.

350 Based on UAV-derived 3D models, we measured compound failure volumes between
 351 1.10 and 4985 m^3 ($20.0^{+35.8}_{-13.6} \text{ m}^3$). The cumulative detected failure volumes were 236 and
 352 389 m^3 for the seasons with vegetation activity (May–November) of 2017 and 2018, re-
 353 spectively. For the non-vegetative seasons 2017, 2018 and 2019, the cumulative volumes
 354 were 1029 (March to May only), 14248 and 471 m^3 (Fig. 1 g). In many cases the UAV
 355 imagery showed that new cliff base deposits are amalgams of multiple failures (Fig. 2 b).
 356 Failures initiated at heights of $29.0^{+10.5}_{-16.0}$ m a.s.l. and $24.0^{+3.7}_{-9.0}$ m below the cliff top. Many
 357 failure scars and deposits are the result of multiple events. This prevents us from con-
 358 straining the relationship between individual event seismic amplitudes and volumes, and
 359 precludes a robust volume-frequency analysis.

360 Screening for precursor activity during 60 minutes before the failures revealed ran-
 361 dom brief pulses of seismic activity at the closest station in a few instances (e.g., 18-04-
 362 09 19:04, 18-03-10 02:50, 18-03-09 23:34, 18-02-15 02:15, 18-01-01 02:17). We did not find

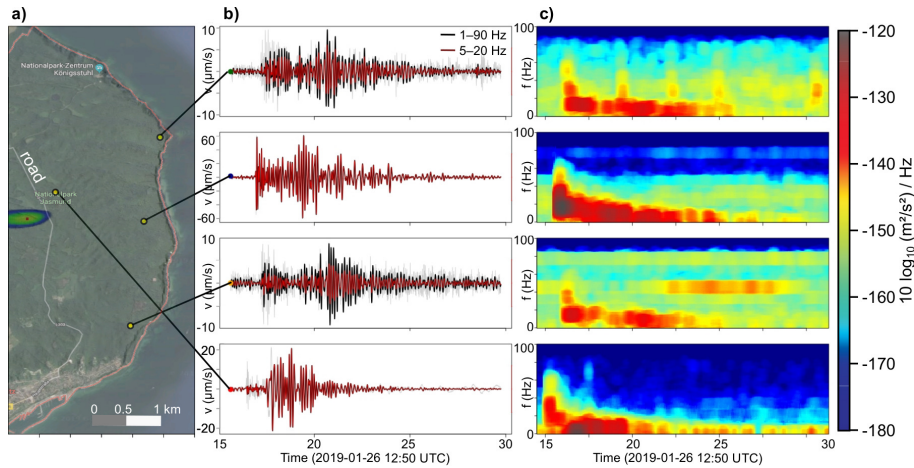


Figure 4. Seismic characteristics of a tree cutting process. a) Map showing the location of the seismic stations used to analyse the event. Note additional station close to main road only used in this experiment. Seismically determined location of tree cutting event is shown as coloured polygon with centre 100 west of the road, where the tree was actually cut. b) Seismic signals of the event at two different filter windows (black and red lines). c) Seismic spectrograms of the signals.

363 a systematic increase in amplitude or decrease in recurrence time of these pulses towards
 364 the cliff failure.

365 During the period of tree felling by National Park staff we were able to detect a
 366 series of at least 15 seismic signals (see Fig 4 for an example). The signals were always
 367 recorded well above background noise levels at all operating stations, by a factor of 5 to
 368 30, and the sources were, in many cases, located along the road where the trees were be-
 369 ing cut. This allowed us to determine a conservative limit of seismic detection. In the
 370 extreme case, a 10 t tree (based on the estimates of National Park staff and a specific
 371 density of the wood of about 1000 kg/m^3), falling freely from an altitude of 15 m (half
 372 the stem height), and without impact damping by branches, litter or loose soil, gener-
 373 ated a seismic signal that can be detected by stations of our seismic array at a distance
 374 of at least 2.5 km. Such a mass would correspond to a chalk volume of 4 m^3 falling from
 375 a height of 15 m, given a specific density of the chalk of 2500 kg/m^3 . The distance be-
 376 tween our stations and the monitored cliff section is considerably smaller, and the true
 377 limit of systematic detection is thus likely lower.

378 3.2 Trigger time lags and activity cycles

379 We measured the time difference between the 81 recorded cliff failures and the pre-
 380 ceding manifestation of a potential trigger, and call this the trigger time lag (Fig. 6 a).
 381 Freeze-thaw time lags were considered within a 72-hour window. The time lags of the
 382 20 failures that fall within this window peaked around 48 h. Time lags for precipitation
 383 showed bimodal distributions for all three threshold values (0.1, 0.2, 0.5 mm/h) at 0–
 384 3 and 16–20 h, for between 62 and 67 out of the 81 failures depending on the rainfall rate.
 385 Time lags for wind showed a plateau between 1 and 10 h and secondary modes at 35–
 386 55 h for a total of 71 failures. Sea level time lags were 0–2 h for all three thresholds, ap-
 387 plying to 17–30 failures. Sea level standard deviation within the 20 min moving window
 388 was $4.18^{+3.01}_{-1.54}$ cm (maximum 30.2 cm). Time lag analysis showed that only 7 (q_{75}) to 15
 389 (q_{95}) failures had sea level-related time lags within 0–2 h during the three day period

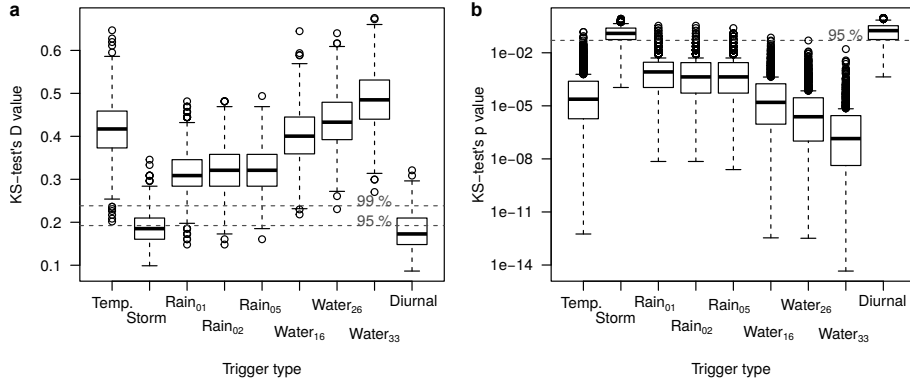


Figure 5. Statistical (Kolmogorov-Smirnov) significance tests for the triggers of cliff failures. a) D-values and b) p values with 95 and 99 % thresholds indicated by horizontal dashed lines. Triggers are listed along the x axis, including freeze thaw transitions (temperature), high wind speeds (storm), precipitation at three intensities (rain₀₁, 02 and 05 mm/h), sea levels (water₁₆, 26, 33 cm above average), and preference of failures at night versus day time (diurnal).

of interest. Except for wind, all time lag distributions were significantly different from random (i.e., Kolmogorov-Smirnov (KS) test D values > 0.24 and p values < 0.01, see Fig. 5).

Failures showed a tendency to happen during night time hours. 50 failures occurred between 8 pm and 8 am, and 31 between 8 am and 8 pm (Fig. 6 b), but this variability is not significantly different from random ($D = 0.17_{-0.02}^{+0.04}$, $p = 0.18_{-0.12}^{+0.16}$). A diurnal pattern was also observed in air humidity, ranging on average between 75 % and 87 % over a day-night cycle in summer ($D = 0.38_{-0.04}^{+0.08}$, $p < 0.07$) and between 82 % and 90 % in winter ($D = 0.46_{-0.04}^{+0.04}$, $p < 0.002$). During days with failures, air humidity was especially high, between 85 % and 94 % ($D = 0.38_{-0.04}^{+0.08}$, $p < 0.07$), with peak values preceding cliff failure by 1–2 hours.

At the monthly scale, failures occurred more frequently when the moon was farther away from the cliff (Fig. 6 c). The lunar distance ranges from 350,000 to 410,000 km, a 14.4 % difference. Spectral analysis revealed statistically significant periodicity modes between 25 and 29 days for lunar distance, precipitation and cliff failures (Fig. 6 d). The systematic relationship with cliff failure was only violated during the days around the year end 2017/18 (Fig. 6 c, cluster c3 in Fig. 1). That episode, with a total of 12 subsequent failures, seven of them at nearly the same location, was associated with persistent precipitation (31 mm in 7 days, compared to a 30-year monthly average of 46 mm).

Detected failure occurrence as inferred from seismic and UAV data was highly seasonal (Fig. 1 b and g) with most of the volume mobilized between November and May. In contrast, precipitation was stronger between May and November (331 mm versus 250 mm). A cyclic trend was also observed in the seismic velocity data (Fig. 1 f) with high dv/v values during May–November, decreasing with the onset of late autumn. However, this pattern was decoupled from the evolution of the groundwater level (Fig. 1 e).

Finally, over the instrumented period we have recorded the imprint of a comparatively wet year with 121 % of the 30-year average precipitation, including 124 % for May to November 2017, followed by a drier-than-average year with precipitation totalling 74 % of the 30-year average, including a summer season with only 51 % of the average seasonal rainfall (Fig. 1 d). We have seismically detected 65 cliff failures during the wet year, and only 11 failures in the dry year.

4 Discussion

4.1 Spatial patterns of cliff failures

Our estimate of the limit of seismic detection, about 4 m^3 over a distance of 2.5 km, is consistent with previous seismic rockfall detection work (Dietze, Mohadjer, et al., 2017), which found even lower limits. The UAV-based failures were in general well above this threshold ($20.0^{+35.8}_{-13.6} \text{ m}^3$, following a log-normal distribution), with six volumes between 1.0 and 3.7 m^3 . Any geometric bias in failure detection due to the seismic network layout was minimal for the central part of the cliff section, where the distance to a set of three stations is less than two km throughout. Note, however, that this bias only potentially affects the event location, not the detection limit. The size of our catalogue was small compared to catalogues from other approaches (e.g. Lim et al., 2010; Vann Jones et al., 2015). Thus, our data did not allow for a meaningful evaluation of magnitude-frequency relationships and the role of small failures ($<4 \text{ m}^3$) in long-term cliff erosion, and we did not attempt a full erosional budget. However, the catalogue does permit the analysis of activity patterns along the entire cliff coast and an investigation of the kinetics of single failures, temporal clustering of cliff failures and the links between failures and trigger mechanisms.

Recorded events had similar rise and fall times, durations and frequency contents of seismic signals. Combined with the UAV based locations at $29.0^{+10.5}_{-16.0} \text{ m}$ above the cliff base and $24.0^{+3.7}_{-9.0} \text{ m}$ below the cliff top, this suggests that the failures had comparable detachment and displacement processes. We observed predominantly spindle shaped seismograms, which reflect the avalanching movement of fragmented chalk volumes that spread out at the cliff base. Many of the detected events were not intact block falls, which would produce single seismic pulses (Hibert et al., 2011; Dietze, Turowski, et al., 2017). These results are in agreement with observations of the example failure (Fig. 2). This event generated a deposit with a volume of about 800 m^3 estimated shortly after the failure happened, forming a radial sediment body that could be eroded and modified by waves immediately. The UAV based volumes, resulting from a survey about two months after the failure, suggest a 7.6 % reduction of the sediment volume compared to the socket volume in the cliff. The erosive action of the Baltic Sea is visible in Fig. 2 d, where the deposit feeds a plume of bright chalk material into suspension.

During the entire survey period, recorded activity was focused predominantly in the central cliff section, between stations "Beloved Peregrine" and "Shrapnel City", with only 7 failures outside this area (Fig. 1 a). This activity pattern is also expressed in the shape of the different cliff sections. Between the two central stations, the cliff is steepest ($46 \pm 16^\circ$ average slope), and has the most overhanging facets. It is mostly devoid of vegetation, and has waterfalls at the outlets of creeks. North and south of the two central stations, slopes are gentler, $38 \pm 13^\circ$ and $41 \pm 16^\circ$, respectively, and several channels have incised to sea level. This contrast suggests that segmentation of activity has been persistent on geomorphologically significant time scales, with failure-driven cliff retreat in the centre of the Jasmund coast and diffusive or catchment-confined hillslope sediment transport to the north and south.

4.2 Triggers of cliff failures

The seismic record is incomplete during the summer periods. However, according to the UAV results the volumes of failures during summer were always lower than during winter periods, especially when considering that the first winter season only contains data from March to May. Without seismic information we cannot include the summer periods into our subsequent trigger, introducing a possible seasonal bias. However, the UAV based information showed similar detachment elevations and deposit shapes. Thus, we infer that unrecorded summer failures should be comparable to those for which we have seismic data.

472 Cliff failures were significantly linked with precipitation in about half of the cases.
 473 Time lags show two clusters, at 0–3 ($n = 19$) and 16–20 ($n = 20$) hours (Fig. 6 a).
 474 This suggests that rain may impact the cliff through two different mechanisms. We in-
 475 terpret the rapid response as the effect of rain directly onto the cliff face, and the delayed
 476 response as the consequence of water flow towards the cliff face within the soil covering
 477 the chalk landscape at the cliff top. Typical hydraulic conductivity values for unfractured
 478 Rügen chalk, $k_f \sim 10^{-10}$ m/s (Krienke & Koepke, 2006), allow flow rates of only a few
 479 micrometers per day, whereas the higher conductivity of the cover material, $k_f \sim 10^{-4}$
 480 m/s, permits water from up to 8.6 m hinterland to seep into the cliff face within a day.
 481 Note that seepage can have a longer range where preferential, lateral flow paths are present,
 482 for example along fractures and discontinuities, or in sediment-filled hollows.

483 We reject wind, sea level, waves, and freeze-thaw transitions as important triggers
 484 based on KS test results (Fig. SI 6) and a lack of plausible mechanisms for the measured
 485 time lags. Wind time lags plateau between 0–10 h (Fig. 6 a) and within this window they
 486 are not distinct from random. We have not found a plausible mechanistic interpretation
 487 of this distribution, especially with failures predominantly occurring at $29.0^{+10.5}_{-16.0}$ m above
 488 the beach and $24.0^{+3.7}_{-9.0}$ m below the cliff top, and thus outside the range of processes at
 489 the cliff toe or the tree covered cliff top. Sea level time lags of 0–3 hours (for 17–30 out
 490 of 81 failures) are an effect of the seasonally changing sea level (514 cm in winter ver-
 491 sus 502 cm in summer), which results in winter cliff failures mapping onto high sea lev-
 492 els. A wave amplitude variability (running window standard deviation of sea level) of
 493 a few cm, with a maximum of 30.2 cm, is one order of magnitude smaller than the height
 494 of the beach ramp. In this configuration, direct impact of waves on the base of the cliff
 495 is rare, and indirect impact will be damped by the coarse, unconsolidated beach sedi-
 496 ment. Moreover, the persistence of fine-grained deposits at the cliff base (Cook & Di-
 497 etze, 2019) throughout multiple UAV surveys (i.e. throughout several months) further
 498 indicates that waves rarely impact the base of the cliff. It is likely that waves have not
 499 acted as as triggers of cliff failure over the monitoring interval. However, waves may play
 500 an important role in episodically removing the loose failure material from the base of the
 501 cliff (e.g., Rosser et al., 2013). Tides of ~ 15 cm appear to be irrelevant given that the ramp
 502 of the shore platform has a height range of 1–2 m. In addition, most of the failures oc-
 503 cur at $29.0^{+10.5}_{-16.0}$ m height above the beach, without indications of undermining at the
 504 base. Thus, we reject high sea levels and tides as trigger mechanisms. Freeze-thaw time
 505 lags of about two days (Fig. 6 a) render this mechanism an unlikely trigger because heat
 506 dissipation probably happens within hours rather than days (Dietze, Mohadjer, et al.,
 507 2017). A further potential cause for failures could be the occurrence of a previous fail-
 508 ure, destabilizing the cliff’s stress field. Indeed, we find that in 26 % of cases, another
 509 failure happened within 24 hours after a preceding one at or near the same location. How-
 510 ever, the spatial confidence of the seismic location approach is too low to pursue this in
 511 the context of our network geometry and station spacing. Future studies engaging with
 512 this particular topic require denser instrument networks and higher sampling rates. Fi-
 513 nally, note that there may be failures without any detectable (or detected) trigger mech-
 514 anism (e.g. Stock et al., 2013), a phenomenon we also see in our trigger results, specifi-
 515 cally in the number of events within the trigger lag time analysis window (numbers in
 516 parentheses in fig. 6 a), which is always smaller than the size of the failure catalogue.

517 Precipitation is a typical cause of rock slope failure, but from our data we see a fur-
 518 ther aspect of water in the environment. Another (though not statistically significant)
 519 trend is that cliff failures occurred more frequently during the night (Fig. 6 b). Rain has
 520 a mostly uniform distribution throughout the day (Fig. 6 b), so cannot explain this di-
 521 urnal pattern of failures. During days with failures, the relative humidity values were
 522 systematically higher than during other days in the winter and especially summer sea-
 523 sons (Fig. 6 b). But most importantly, cliff activity followed the daily relative humid-
 524 ity cycle with a time lag of 1–2 hours. Therefore, we propose that relative humidity may
 525 contribute to cliff activity at this time scale, even in the absence of rain. During the cool-

ing hours at the end of the day, increased humidity and decreasing temperature can lead to crossing of the dew point. Rates of dew formation on various surfaces range between 10^{-2} and 10^{-1} mm/h (Garratt & Segal, 1988), with controls exerted by meteorological conditions and surface properties. These dew formation rates can cause cumulative overnight water deposition at the order of the precipitation thresholds (0.1, 0.2, 0.5 mm/h) used in the trigger analysis. This water can migrate quickly into the fractured chalk at the cliff face and increase the water content of the material, possibly causing rheological changes.

We propose that the observed cliff failures occur primarily due to wetting of the fractured chalk. This wetting can be due to rain directly onto the cliff face, subsurface flow towards the cliff, or condensation of atmospheric water vapour at the cliff face. Regardless of the pathway, increased water content can result in a sharp transition in rheological behaviour of the cliff-forming material, from rigid to liquid. Increased water content contributes to failures by loading and shear strength reduction, which adds to the instantaneous effect of the material state transition at the cliff face upon sufficient wetting.

4.3 Cliff activity at the lunar cycle

The overlapping spectral peaks of cliff activity and lunar distance are unexpected. At a first glance, one would expect lunar distance (JPL, 2019) to affect the net local gravitational force at the Earth surface, imposing dilation of bedrock, changes in pore space and decreasing groundwater potential via tidal stress (e.g. Inkenbrandt et al., 2005). However, effects on the net gravitational force are negligible: a 10^{-7} decrease of the Earth's gravitational pull when the moon is closest to the study area. Similarly, tides in the Baltic sea are small, and sea level does not appear to be a direct cause of detected cliff failures. An influence of the moon on groundwater has been reported, although predominantly on the diurnal and semi diurnal scale (Briciu, 2014). However, groundwater on Jasmund does not show any significant lunar periodicity (Fig. 6 d).

Perhaps more relevant, Cervený et al. (2010) found a robust lunar signal in river discharge across the United States, which they attributed to a precipitation cycle synchronized with the lunar month. Such synchronous effects were also identified in other settings around the globe (Bradley et al., 1962; Adderley & Brown, 1962; Roy, 2006; Lethbridge, 1990). Quoting Cervený et al. (2010) it emerges that "as a potential cause to these previous findings of tidal forcing's influence on precipitation and thunderstorms, past climatological and astronomical research has proposed that the lunar synodic cycle may be linked to (a) lunar distortion of the Earth's magnetic tail [Lethbridge, 1970, 1990], (b) the occurrence of cosmic rays [Markson, 1981], and (c) variations in meteoric dust [Adderley and Brown, 1962] acting as condensation nuclei, among other explanations". This relationship is in line with our data showing agreement of spectral peaks of precipitation, lunar distance, and cliff failures (Fig. 6 d). Thus, based on these long-standing, robust findings, we propose that lunar cyclicity affects cliff failures indirectly, through the mediating role of precipitation.

4.4 Biotic cliff preconditioning

There is an important seasonal effect that preconditions the Jasmund cliff system for failure on shorter, lunar (Fig. 6 c) and diurnal (Fig. 6 a-b) time scales. Although we missed seismic evidence of cliff failures during the summer period when no sensors were operational, we recorded only minor released volumes based on the UAV data (236 and 389 m³, respectively), indicating that the summer period is less active than the November–May window. We attribute this seasonal pattern to water uptake by the dense beech forest covering the cliff hinterland. On Jasmund, the vegetative season typically starts in early May and ends in October–November. In this season, water uptake by trees leads to progressive drying of the subsurface beyond the recharge capacity of summer rain. Beech

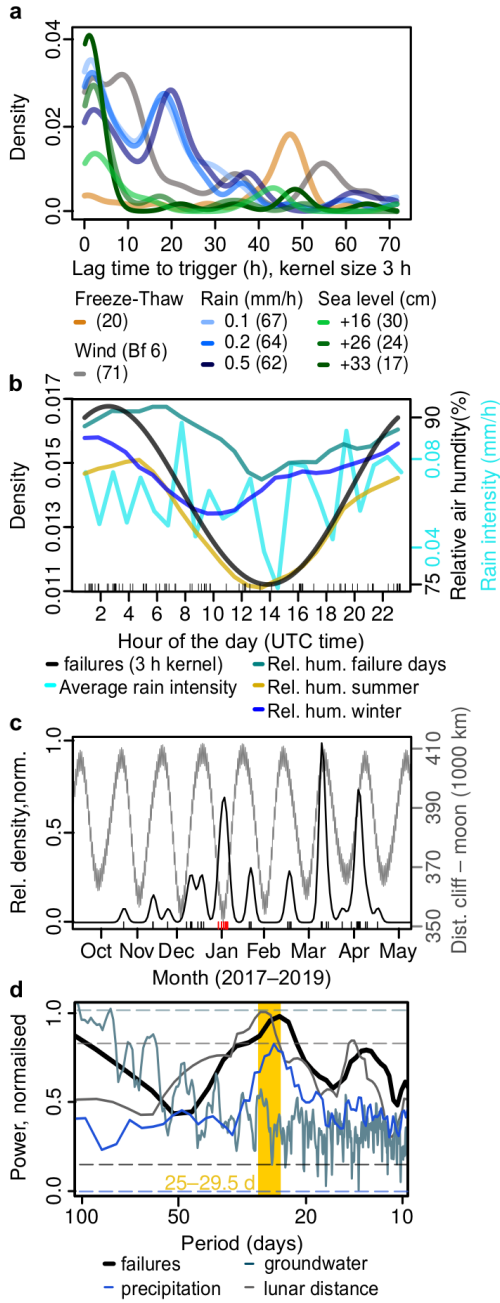


Figure 6. Drivers and triggers of cliff failures on Jasmund. a) Kernel density estimates (72 h duration) of time lags between triggers and failures. Values in parentheses denote number of failures within 72 h. b) Diurnal failure activity density estimate (black line), relative air humidity, and average diurnal precipitation intensity. c) Seasonal failure density estimates (period 2017–2019). Rugs along the x axis denote individual failures (red rugs indicate anomalous failure phase around the year end 2018). Grey curve shows lunar distance, i.e., distance between the gravity centre of the moon and the cliff area. d) Spectra of cliff failures and potential drivers. Lunar distance, precipitation and failures share a common periodicity window (orange polygon) at 25–29.5 days. Horizontal dashed lines depict significance thresholds for the spectra.

576 trees can transpire hundreds of litres of soil water per day (Střelcová et al., 2002), lead-
 577 ing to prolonged negative water potentials during the vegetative season. In the case of
 578 a beech dominated natural forest in central Europe (Střelcová et al., 2002), soil water
 579 potential throughout the first 70 cm graded from -80 to -700 hPa between late spring
 580 and autumn. This prevents major lateral soil water movements during the vegetative sea-
 581 son. Moreover, leaves contribute about 30 % to evaporation of rain water before it reaches
 582 the ground (interception loss), further contributing to systematically drier soil conditions
 583 between spring and autumn (Friesen & Van Stan II, 2019). During vegetation dormancy,
 584 from November to May, water uptake by roots and interception loss is limited, and rain
 585 storms can optimally recharge the water content of the ground (Fig. SI 2). Hence, we
 586 infer that there is a vegetation control on cliff stability on Jasmund, expressed on the
 587 seasonal scale, and implemented through the regulation of the water content within the
 588 soil.

589 The seasonal soil water content cycle is supported by our data on near surface seis-
 590 mic wave velocities (Fig. 1 f). Since the dv/v values result from an inversion process that
 591 finds those values within a sliding time window that can best explain the change in the
 592 seismic properties, there is no uncertainty estimate associated with the results. However,
 593 overall similar trends in the dv/v time series of two stations standing more than a km
 594 apart from each other indicates a coherent forcing mechanism. Estimated dv/v values
 595 of our two central seismic stations were high by the end of the vegetative season and started
 596 to decline around November, before rising again in late spring. We attribute this to dry-
 597 ing of the near-surface substrate in summer, and wetting in winter. Relative wave ve-
 598 locity increases as the ground material becomes more rigid (, or when its temperature
 599 increases; Clements & Denolle, 2018) and vice versa. In the case of the chalk from our
 600 study region, rigidity is strongly controlled by moisture content, and less so by temper-
 601 ature changes, especially at several decimetres depth and under a dense beech canopy.
 602 These dv/v trends were not consistent with the groundwater levels, which fluctuated by
 603 about one meter at a depth of about 15 m below the surface, suggesting that our wave
 604 velocity monitoring was mostly sensitive to near surface soil moisture content. Moreover,
 605 in the long term, groundwater levels (see SI for details) are forced not only at the an-
 606 nual scale (about 0.2–0.3 m amplitude of change) but more drastically at the multi-year
 607 scale (up to 1.5 m amplitude of change during the last decade), masking annual effects
 608 completely. Our instrumented period actually captures one such large scale effect: the
 609 above average wet year 2017 resulted in a groundwater high stand and the above aver-
 610 age dry year 2018 caused a local low stand of groundwater (Fig. 1 e) independent of smaller
 611 amplitude changes at the seasonal scale.

612 4.5 Multi-year scale of cliff activity

613 We identified a legacy of climatic boundary conditions, expressed in a large num-
 614 ber and volume of cliff failures in winter 2017/18 after a wet summer with 126 % of av-
 615 erage seasonal precipitation (117 % in the subsequent winter) and a smaller failure num-
 616 ber and volume in winter 2018/19, after a dry summer with only 51 % (97 % in the sub-
 617 sequent winter) of the average precipitation. Whether the effect is driven by the sum-
 618 mer period, with more intense deviations from the average patterns, or the winter pe-
 619 riod with less (2018) to negligible (2019) deviations, remains elusive from our data. How-
 620 ever, in the light of the above explained effect that vegetation causes overall dry soil con-
 621 ditions during summer and allows restoring sufficient moisture conditions predominantly
 622 upon dormancy, it appears more likely that it is the summer period that sets the bound-
 623 ary conditions for the subsequent winter period of cliff failure density.

624 Future climate projections for Jasmund include generally drier conditions and more
 625 variable precipitation events (Frei et al., 2006; Umweltbundesamt, 2015). With sustained
 626 moisture in the cliff and frequent precipitation being the dominant driver and trigger for
 627 failures identified in our study, the chalk cliffs may experience fewer failures as the de-

628 creasing lateral water input fails to precondition the system to a state where rain and
 629 relative air humidity can trigger failures in the volume range witnessed during our study
 630 period. On the multi-year turn, this may result in a decreasing sediment supply via fail-
 631 ures to the cliff base and beach environment for uptake by waves agitating those deposits
 632 (cf. fig. 2 b and d, Stephensen, 2014). As a consequence, the erosive action of waves will
 633 extract more and more fine material from the beach instead, until the currently 2 m high
 634 ramp has become sufficiently lower and waves will be able to affect the cliff base directly.
 635 Ultimately, the coast cliffs may become increasingly prone to undercutting, as the ab-
 636 sence of a sediment apron and the proximity to breaking waves makes them more prone
 637 to net basal erosion. This may eventually lead to less frequent but more catastrophic fail-
 638 ures with significantly larger volumes, as failures will not initiate at $29.0_{-16.0}^{+10.5}$ m height
 639 and due to local destabilisation caused by a moisture-driven chalk state transition, but
 640 at the cliff base and due to destabilising process that penetrates deeper into the chalk
 641 material. Thus, although under generally drier conditions the rigidity of the cliff would
 642 increase, the failure volumes will increase, as well (see for example discussion by Dus-
 643 sauge et al., 2003). Unlike sandy beaches, cliffs are not able to recover after erosive events
 644 by aggradation of new material from other than cliff derived sources (Stephensen, 2014).
 645 Thus, there is no adjusting response mechanism in such an erosive system, which makes
 646 estimating the consequences of climate change for cliff coasts even more important.

647 5 Conclusions

648 We have used a combined seismic and UAV approach to gain new insight to dy-
 649 namics and triggers of coastal cliff activity, allowing the exploration of geomorphic re-
 650 lationships across a larger spatial and temporal range than would be possible with other
 651 existing techniques. This has revealed that, in the absence of strong tidal and wave forc-
 652 ing as direct triggers of failures, patterns and frequencies of cliff failures along the chalk
 653 coast of Jasmund, Germany, are affected by the presence of water in the cliff on a range
 654 of time scales. Water controls the rigidity of the material and causes a state transition,
 655 from solid towards liquid. This gives rise to distinct cycles of cliff failure at annual, sea-
 656 sonal, lunar and diurnal time scales. Climatic dryness/wetness sets the baseline for fail-
 657 ure frequency, soil moisture uptake by trees suppresses failures in the vegetation period,
 658 precipitation causes failures by direct rain onto and groundwater flow towards the cliff
 659 surface, and higher atmospheric moisture levels may promote failures during the night.
 660 Failure deposits are typically amalgams and our seismic data reveals their formation from
 661 clusters of geomorphic activity rather than from single failures. Under increasingly drier
 662 climate conditions the cliff may grade into a transient, characterized by less frequent small
 663 failures due to insufficient moisture preconditions, which in turn may prepare the cliff
 664 for more large events driven by erosion processes at the cliff base.

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