Detection and forecasting of shallow landslides: lessons from a natural laboratory

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Key Points:

- Debris flow occurrence has been constrained by discernible thresholds in rainfall antecedence, intensity-duration and abrupt increases.
- Early detection and development of evolving slope hazards is achieved through novel time-lapse image vector tracking.
- Event occurrence and flow development can be automatically detected with low-cost seismic monitoring and hodogram analysis.

Abstract

Shallow landslides are a significant hillslope erosion mechanism and limited understanding of controls on initiation and development results in persistent risk on linear infrastructure. We present an inventory of 63 landslides (2007-2019) from the west of Scotland and show the patterns and development of debris flows, accounting for 58% of landslide source volume. Using rainfall data, we show that landslides are often triggered during abrupt changes in the rainfall trend. We derive empirical antecedent precipitation (>62mm) and intensity-duration (>10 hours) thresholds over which debris flows occur. Analysis shows the thresholds are more effective at raising landslide alert levels than the current management plan. We use novel time-lapse vector tracking to detect slope instabilities, quantify deformation rates and indicate imminent failure. Seismometers are used to detect a debris flow and locate the source area. The suite of sensors provides vital information to support operational decision-making for infrastructure with complex slope hazards.

Plain Language Summary

Landslide hazards present risks to road users and economic activity when associated with roads. Differences in the materials making up hillslopes determine landslide susceptibility and weather conditions can change the materials, altering the likelihood of landslide occurrence; these interrelated factors limit our understanding of what triggers landslides on a site-by-site basis. It is important to understand landslide triggers at high-risk sites so that they can be monitored or mitigated against. We present a new landslide record for a hillside above a strategic road in the west of Scotland. Using rainfall data, in combination with recorded landslides, we determine what rainfall conditions, both leading up to and at the point of triggering movement, generate debris flows at this site. A time-lapse camera allows landslide occurrence to be timed accurately and, using computer software, we calculate changes on the slope between camera images to detect and monitor the early stages of debris flows, providing vital early warning. Finally, we use a seismometer (usually used for earthquake monitoring) to detect when a debris flow has occurred and pinpoint its location on the slope. These tools can be used to monitor landslide hazards at this site and other at-risk sites on road networks.

1 Introduction

Debris flows are extremely rapid (>5 m/s), saturated debris-rich landslides from hillslopes (Hungr et al., 2014). Shallow landslides translate into debris flows given favorable material and fluidization conditions (e.g. Zimmerman et al., 2020). Debris flow runout potential and capacity to entrain water and sediment make them a significant global hazard, particularly where linear infrastructure traverses affected slopes (Geertsema et al., 2009; Meyer et al., 2015). They can be broadly grouped into channelized debris flows (CDFs) that are constrained for their flow path and hillslope debris flows (HDFs) that occur on non-incised slopes (Chen et al., 2009). CDFs and HDFs can transition into one another where HDFs meet gullies or CDFs breach channels and flow over slope; hillslope-gully coupling controls the hazard potential (Milne et al., 2009). CDFs often occur in torrent systems, such as the Illgraben, Switzerland (Badoux et al., 2009) where the repeated flow path removes some of the spatial risk uncertainty.

Where debris flows source across large areas with uncertain runout, a combination of active mitigation (physically controlling site aspects using engineering infrastructure) and passive mitigation (reducing impacts via land-use planning, closures and warning systems) methods can be used (Huebl and Fiebiger, 2005; Vagnon, 2020).

In Scotland, debris flows have repeatedly damaged linear infrastructure resulting in economic and social costs (Winter et al. 2019a). Here we demonstrate a novel combination of near-real-time, multi-disciplinary, monitoring techniques that allow remote detection and quantification of slope changes and supplement Landslide Management Plans (LMP). The objective of these techniques is to improve our understanding of shallow landslide trigger mechanisms and creeping deformation that threaten road users and infrastructure, and thus enhance alert capabilities for stakeholders at a debris flow prone site in the west of Scotland.

2 Study area

The A83 Rest and be Thankful (RabT), a key road into west Scotland, has the highest landslide frequency on the Scottish road network (McMillan and Holt, 2019). It bisects the south-western slope of Beinn Luibhean upslope from Glen Croe. The bedrock is Schist, with overlying till up to 3 m thick, interspersed with gullies, scars, levees and debris cones (Sparkes et al., 2017, Finlayson, 2020, BGS, 2020). Past debris flows have been linked to high-intensity rainfall (Winter et al., 2019b).

On average 4,000 vehicles cross the RabT per day (Winter et al. 2019a). Closures divert traffic ~88 km, if the Old Military Road (OMR), a one-way convoy diversion downslope of the A83 is closed, casting a vulnerability shadow over 4,300 km2 (Fig 1a). A full road closure costs ~£90k per day (2012 prices; Winter et al. 2019a) and £13.3 M has been spent on protecting the A83 and improving the OMR (Scottish Parliament, 2020). Some debris flows still exceed mitigation measures and impact the A83 and OMR. Both semi-quantitative and quantitative risk assessments (QRA) at the RabT justified measures for the LMP (Winter at al., 2009; Winter and Wong, 2020) which sends out daylight patrols and activates warning lights on the RabT approach if forecast rainfall is >=25 mm in a 24-hour period or >=4 mm in a 3-hour period (Winter et al. 2020).

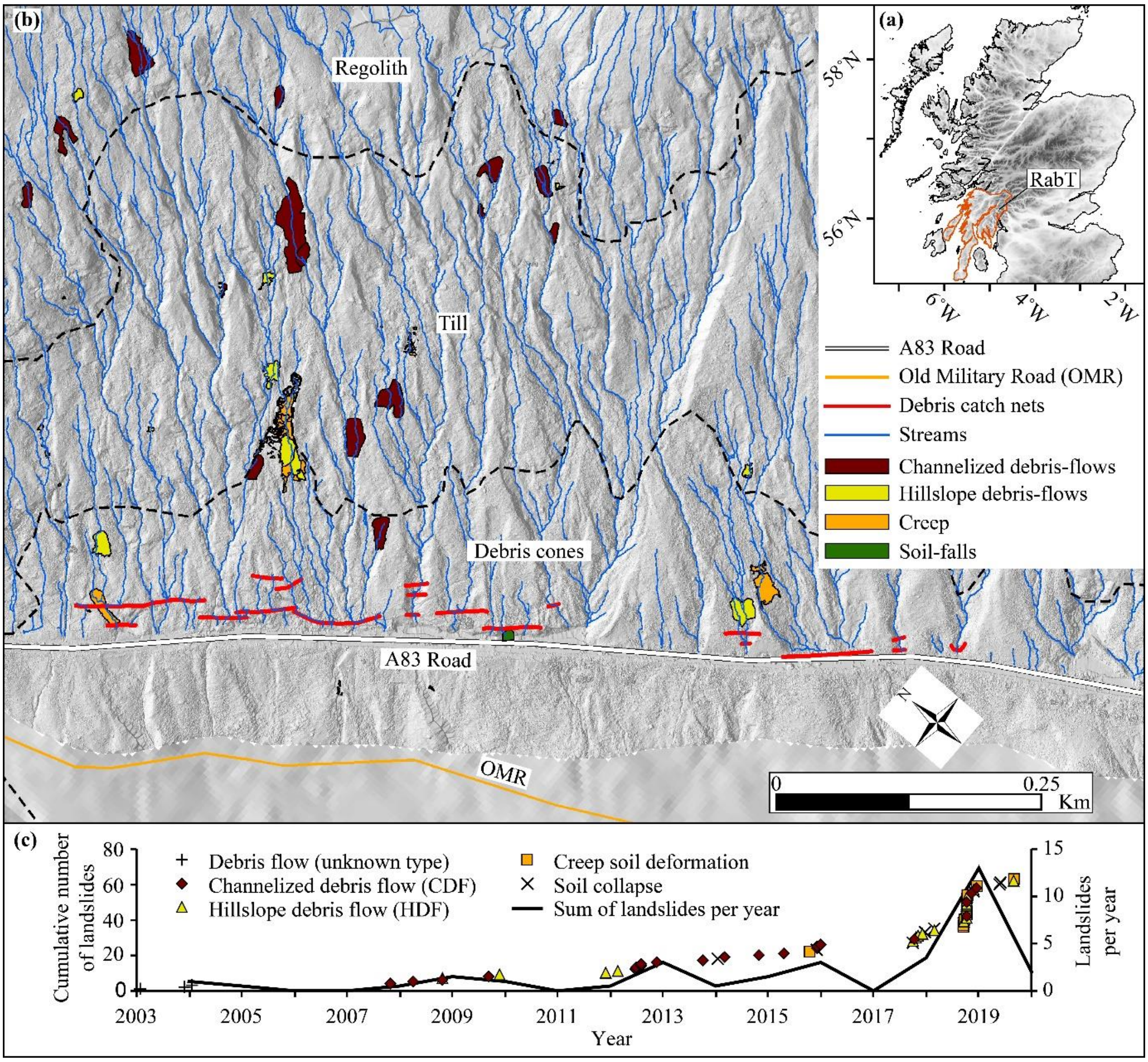

Figure 1. RabT landslide inventory. (a) Scotland digital terrain model showing the RabT site and area affected by an A83 road closure outlined in orange (vulnerability shadow, modified from Winter et al. 2019a). (b) TLS derived hillshade and 2007 to 2019 landslide source areas, colored by autumn-winter season (Sept-Feb), Spring (Spr) or Summer (Sum). Surface material delineation (dashed lines) modified from Finlayson, 2020. Landslide numbers refer to Fig 3. (c) 2003 to 2019 cumulative landslide timeseries and yearly totals.

3 Landslide activity

We have collated a new RabT landslide inventory from road reports (2003-2015), quarterly and event responsive terrestrial laser scans (TLS; 2015-2019) and time-lapse imagery (2017-2020). Post-2015 it is unlikely events are missing as TLS (0.1 m resolution) and time-lapse imagery was used (Sparkes et al., 2017 and this study). Pre-2015, debris flows that reached the A83 are recorded, but smaller landslides may not be. From 2003 to 2019 there were 63 landslides; 43 were debris flows (19 HDFs, 21 CDFs, three of unknown type), 11 slope creeps (slow gravitational deformation of material), and nine soil collapses (small ~1m^3 failures of surficial material, often from the top of bedrock outcrops, which do not propagate downslope). Fifteen debris flows closed the A83, on average nearly once a year since 2003; six reached the OMR.

60 landslides have known source areas (Fig. 1b), 45% (n=27) are in till, 35% (n=21) in debris cones and 20% (n=12) in regolith. 50 of these have source volumes derived from TLS (2015-2019) or estimates from reports (2007-2015). Debris cones cover 22% of the slope and account for 27% of the landslide volume; regolith (18% of the slope) and till (61% of the slope) account for 10% and 62% of the landslide volume respectively. Volumetric contributions from different materials reflect failure processes and depth to bedrock. Debris cone sources are generally long (15-30 m) and deep (average depth of 1.6m) and the slope of the failure plane is relatively shallow (average 31.5°; Fig. 2). Till and regolith failure planes are steeper (average 37° and 35° respectively) but generally short (5-15 m) with a shallower depth profile (average 0.79 m and 0.77 m respectively; Fig. 2). Extrapolation of gully pathways in GIS, from a TLS derived DEM, shows a strong coupling of source areas and stream flow (streams in Fig. 1b).

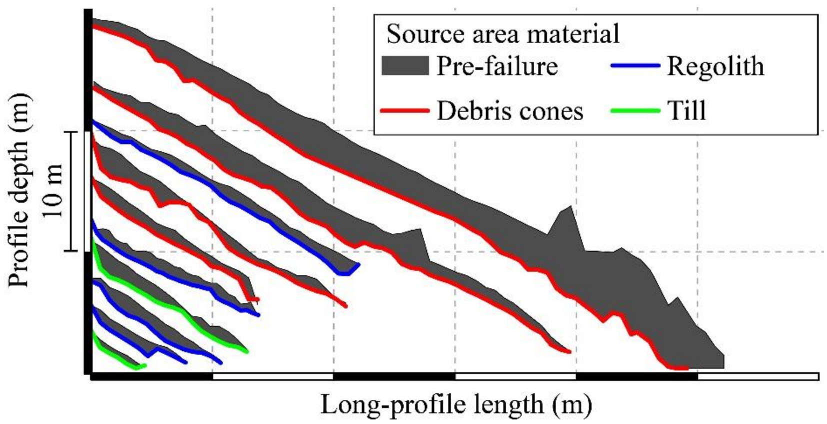

Figure 2. Landslide source area long profiles (2018-2019), derived from TLS point clouds, showing pre- and post-failure surface elevations. Profiles are colored by source material type. Axes are scaled together, one increment is 10m.

4 Managing debris flow risk - Monitoring strategies for alert, tracking and detection

Here we use 2018, an active year with 19 of the 63 landslides (Fig 1c), as a case study for pro-active, near-real-time monitoring to alert stakeholders to increased landslide risk based on rainfall thresholds, tracking slope creep, and detecting debris flow occurrence.

Rainfall on seasonal, daily, and 15-minute timescales has been used to indicate raised landslide risk. The 2013-2019 seasonal rainfall trend was examined for Scottish Environment Protection Agency (SEPA) RabT rain gauge data (SEPA, 2020) using the Bayesian Estimator of Abrupt change, Seasonality and Trend (BEAST) analysis package (Zhao et al., 2019). BEAST uses ensemble modelling, where multiple competing models analyze data, and Bayesian statistics derive a model average with associated probabilities that detect if seasonal and trend changes are 'true'. BEAST identifies seasonal change points (SCPs) when rainfall has large inter-annual variations, i.e. the seasonal component of the rainfall time-series changes between the same time in different years. Trend change points (TCPs) are identified when the rainfall time-series trend changes abruptly. For seasonal and trend components, not all variations will lead to SCPs and TCPs being assigned, only those that have a high probability of being a genuine and significant difference, based on the agreement between competing models.

We calculated the Antecedent Precipitation Index (API; Fedora and Beschta, 1989), a proxy for ground saturation (Segoni et al., 2018), for daily rainfall totals using Equation 1, as an indicator of raised debris flow risk.

$$API_i = k(API_{i-1}) + P_i \qquad \textbf{(1)}$$

Where API_i is the API at time *i*, P_i is the daily rainfall total at *i* and *k* is a constant decay function defined by the user (*k*=0.8). Rainfall was measured with an on-slope Davis Vantage Pro 2 gauge, better reflecting on-slope conditions than the off-slope SEPA gauge.

Using 15-minute rainfall intensity data, we developed an intensity-duration (I-D) threshold. Duration and mean rain intensity for all storms in the study period were plotted (Brunetti et al., 2010; Guzzetti et al., 2008), with a six-hour inter-event period. An I-D threshold above which landslides occur was visually derived from the results. Mean rain intensity over an entire storm was used as not all landslide timings were known.

Alerts of slope changes allow stakeholders to be on stand-by, pre-position resources, or proactively manage risk. Here, we process time-lapse imagery in a particle image velocimetry tool (PIVLab; Thielicke and Stamhuis, 2014; Thielicke, 2020) to detect creep on the 19 September 2018. Displacement vectors and velocity were established between consecutive slope-wide images at 16x16 pixel resolution (~2.7 m^2). Cumulative deformation was derived for a point tracked through the photo sequence and inverse velocity (I-V), a tool used to predict failure in brittle materials (Carlà et al., 2017), was used as a tentative metric for till failure prediction despite the non-brittle materials involved. Imminent failure is predicted when I-V values reach zero (infinite velocity). Intervals between images was not uniform due to poor visibility, so velocity data from PIVLab were interpolated to 12h intervals, with a moving average smoothing of 24h. I-V was calculated for smoothed data using $1/(Vw)$ (e.g. Manconi and Giordan, 2016), where V is velocity over the defined time window (w).

We used seismic monitoring to detect debris flow onset. Seismometers are widely used in torrent debris flows systems (Walter et al., 2017), but here a Raspberry Shake 3D seismometer (Raspberry Shake, 2020; Manconi et al., 2018) was deployed for detection on a hillslope with uncertain flow routing. The seismogram trace shows characteristic debris flow signals, generated through clast-clast and flow-substrate interactions, above the long-term average. Hodograms (plotting signal direction through time) were used to confirm the direction of debris flow signals to the seismometer. Hodograms are seldom used in geosciences but have been used in rockfall monitoring (Borella et al., 2019).

5 Rainfall thresholds

BEAST identified three rainfall seasonal change points (SCP) in winter periods from 2013 to 2016 (Fig. 3a). SCP3 coincides with Storms Desmond and Frank which caused debris flows at the RabT. No SCPs are seen from 2016-2019. However, debris flows are coincident with abrupt rainfall trend change points (TCPs) 2, 6 and 7, their subsequent falling trends and in long period high trends (TCP1; Fig. 3b). TCP7 starts the 2018 landslide period. For this period Fig. 3c shows when LMP forecast rainfall thresholds were exceeded and warning lights were operating, along with the same thresholds plotted using on-slope, live rain data. These data are summarized in confusion matrices (Fig. 3d and f) which describe the performance of the rainfall thresholds in detecting conditions that triggered landslides; data are described as times where thresholds predict landslides will or will not happen against times where landslides did occur or not. False alarms and missed landslides account for 6.9% of the study period for warning lights and 12.2% for on-slope data (Fig. 3d). Warning lights are human operated, reducing false alarms through expert judgement. However, on-slope data would raise alert levels two times where landslides occurred, that are not fully covered by the warning lights (Fig. 3c i and ii). Landslide producing storms were medium (>10h) to long duration (max. 72h; Fig. 3e); for two storms it is not known in which the landslide happened. Mean rain intensity for landslide initiation ranges from 2.95 mm/hr to 8.15 mm/hr. Landslides occur above the threshold described by Equation 2.

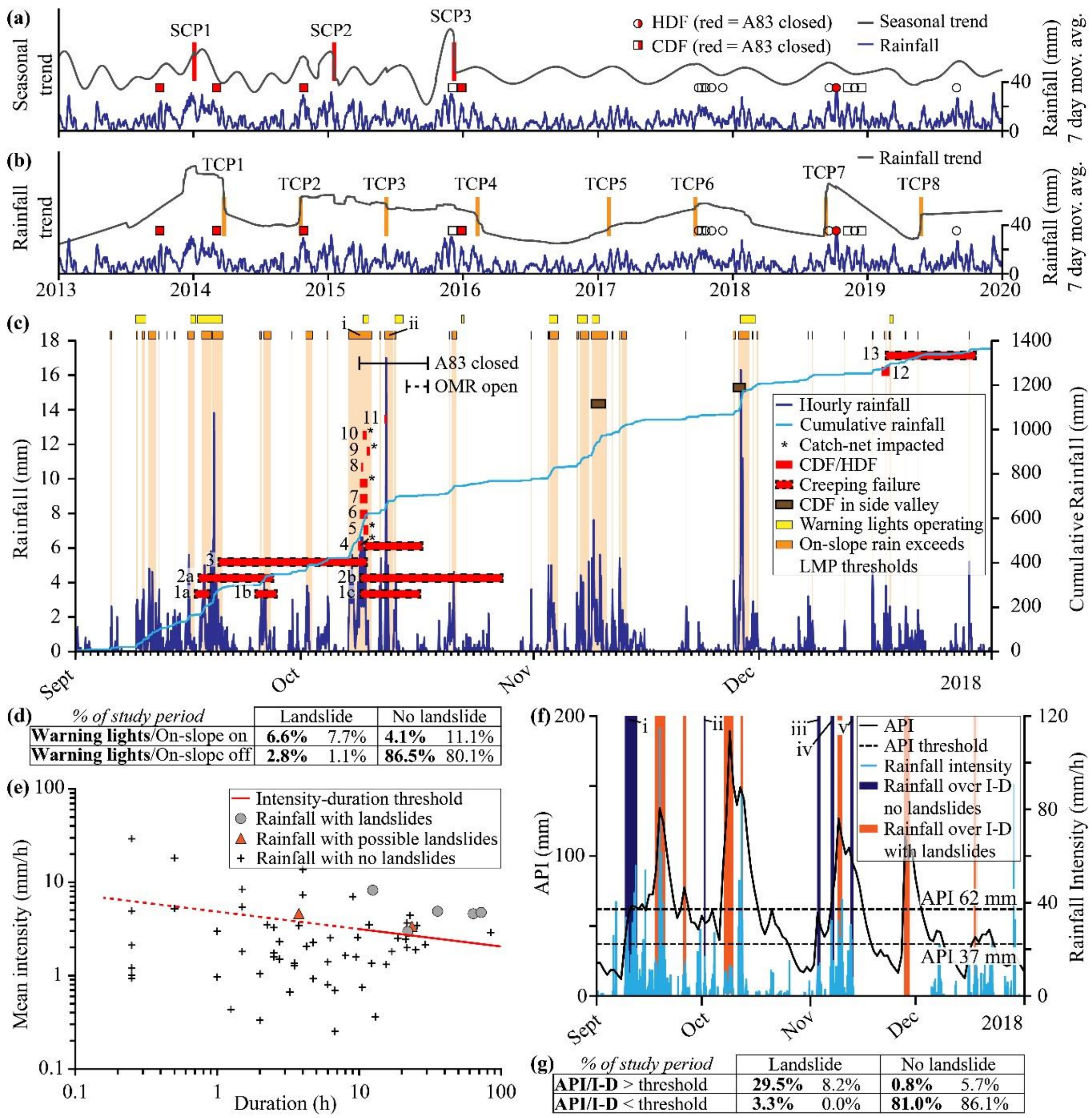

Figure 3. (a) BEAST seasonal rainfall component. (b) BEAST rainfall trend. (c) 01 September 2018 to 31 December 2018 landslide timeline. (d) Warning light and on-slope alert operation confusion matrix. (e) September to December rainstorm intensity-duration (I-D) plot. (f) Antecedent Precipitation Index (API) with 37 mm and 62 mm thresholds. Rainfall intensity (data loss 13 November to 05 December) with storms >10h duration exceeding the I-D threshold. (g) API and I-D threshold confusion matrix.

$$I = 4.75D^{-0.18} \qquad \textbf{(2)}$$

Where I is mean rain intensity and D is duration. As all confirmed landslide storms were >10h duration, the threshold may not apply to <10h storms. The I-D threshold gives a false alarm for 5.7% of the study period (Fig. 3g).

All landslides (n=18) occur over an API threshold of 37 mm, with three false alarms and long periods of alert with no landslides (Fig. 3f). A 62 mm API threshold covers 90% of landslides (n=16), reduces false alarms to 0.8% of the study period (Fig. 3g), but misses two mid-December events. A combination of I-D and API thresholds maximizes landslide detection and minimizes false alarms (Fig. 3g). All landslide inducing storms exceed the I-D threshold with five false alarms (Fig. 3f i to v) which API thresholds reduce to two (Fig. 3f iv, v).

6 Time-lapse vector tracking

We monitored the creep of Failure 2 (Fig. 3b) via time-lapse image vector tracking from initiation (19 September 2018) to arrest (27 September 2018) using PIVLab (Thielicke and Stamhuis, 2014; Thielicke, 2020; Khan et al., 2021). Vectors of change and a velocity heat map between consecutive images are shown in Figures 4a and 4b.

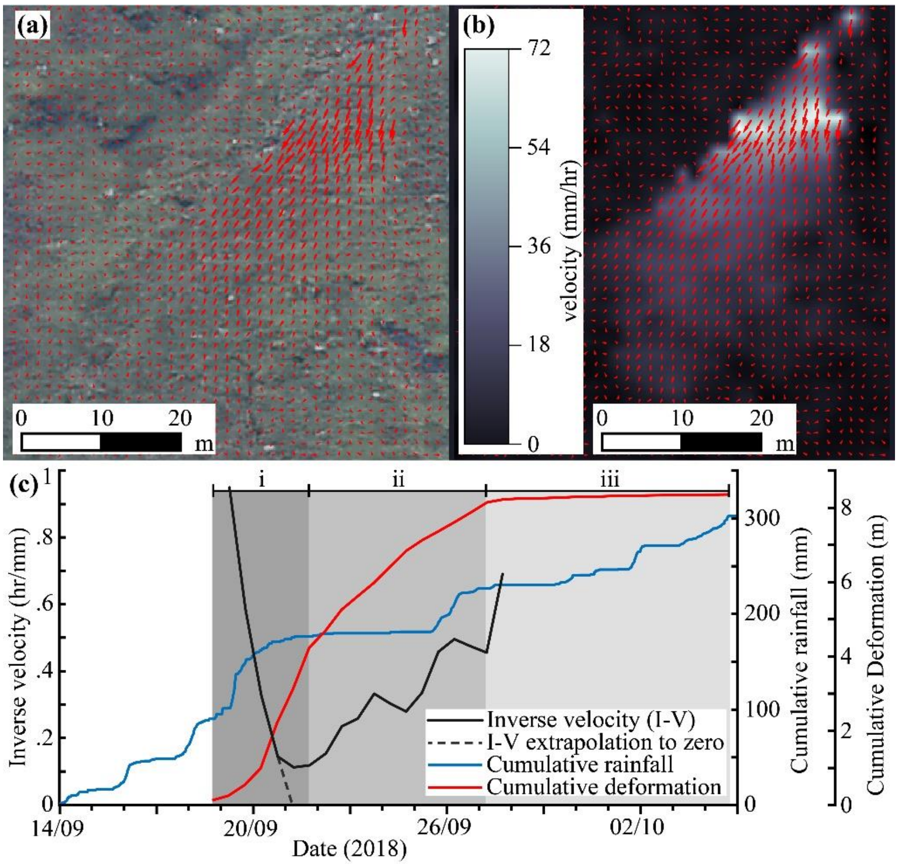

Figure 4. (a) PIVLab deformation vector plot (Thielicke and Stamhuis, 2014). (b) Velocity heat map. (c) Cumulative rainfall, cumulative deformation, and I-V.

Creep initiation coincides with a rainstorm on the 18 September 2018 (Fig. 4C i). Half of the total cumulative deformation occurs in the first 2.5 days. Inverse velocity (I-V) rapidly decreases towards zero on the 19-20 September 2018; extrapolation of the I-V trend predicts failure on the 21 September 2018. However, I-V values increase on the 21 September, indicating reduced velocity after rainfall ceases. The deformation rate slows until arrest and subsequent rainfall does not affect the deformation rate (Fig. 4c ii and iii). Operationally, alert levels would be raised in Phase i when imminent failure seemed likely but lowered in Phase ii.

7 Passive seismic debris flow detection

Seismic monitoring identified a HDF (Figs. 5a and 5b) on the 09 October 2018 and located the source area. The z-axis seismogram (Fig. 5c) shows a high-amplitude signal lasting ~15s, corresponding with the failure time derived from time-lapse imagery, which is likely the HDF in motion. Short duration, lower amplitude signals follow and are likely post-landslide sediment and boulder reworking. Hodograms show very little activity at first (Fig. 5c i), but signal strength increases as the HDF signal arrives (ii) before subsiding (iii). Stacked hodograms, overlain on a DEM, point to the HDF source area as the direction of the incoming signal (Fig. 5d).

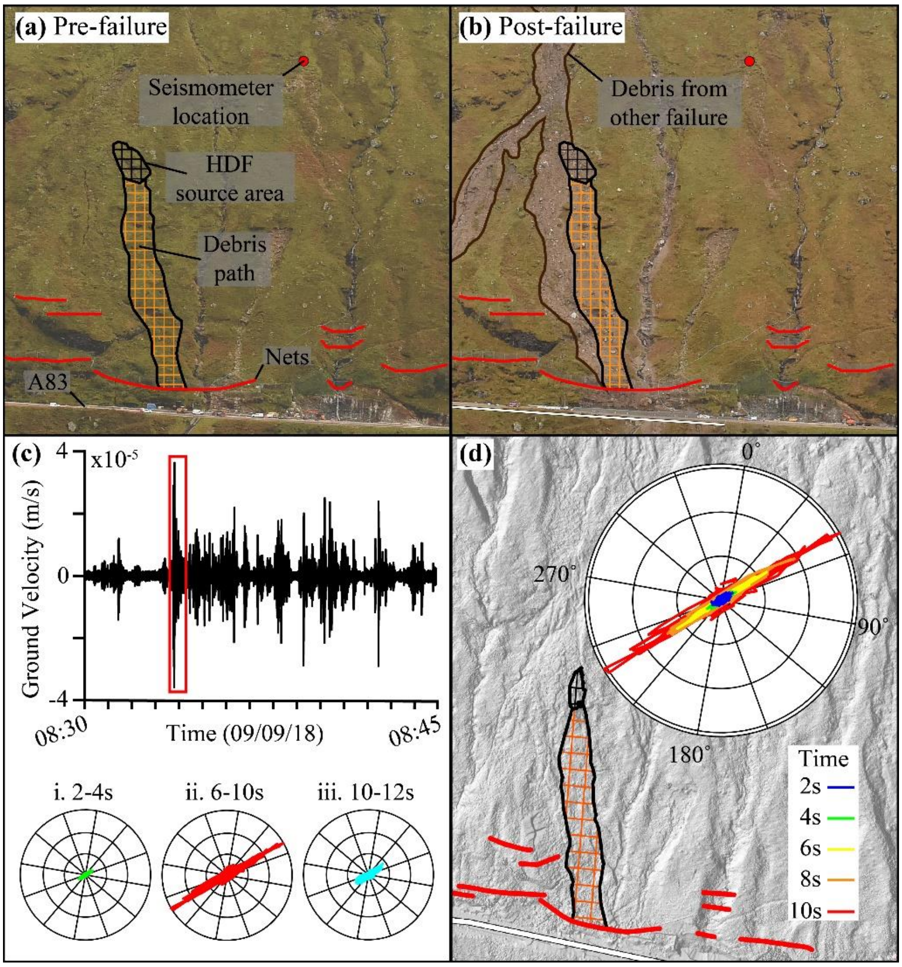

Figure 5. (a) Pre-failure HDF source and seismometer location. (b) Post-failure. (c) Fifteen-minute seismogram with HDF signal (red box) and three hodogram time-steps (i, ii, iii). (d) Hillshade with HDF location and ten second stacked hodogram.

RabT debris flow seismic signals are brief due to short, steep flow paths, with boulder and sediment reworking post-event. Another deposit on Fig. 5b, which is a thin, fine-grained drape but has a large deposit footprint, was not detected by seismic monitoring; indicating that whilst high debris content flows can be detected, hyper-concentrated flows may need larger station arrays for detection.

8 Discussion and conclusions

This paper presents on-site monitoring at the RabT, aimed at supplementing the existing LMP (Winter et al., 2009). Between 2003 and 2019 there are 63 landslides recorded, including 43 debris flows. Two landslide processes lead to debris flows, shallow translational slides (mean depth c.1 m), generally below hydrological convergence zones in regolith and till, and deep-seated (>2 m) rotational slides in debris cones. Material type exerts control on landslide volumes. Total material export from source areas on the slope are 6,829 m^3, with debris cones accounting for 27% (1,853 m^3), regolith 10% (697 m^3) and till the remaining 63% (4,278 m^3).

BEAST rainfall analysis shows that landslides are primarily associated with abrupt rainfall trend changes. In the 2018 study period, antecedent, and medium- to long-duration, high-intensity rainfall is shown to be an important factor in debris flows initiation. New local API and I-D rainfall thresholds, identify all landslide inducing storms and minimize false alarms, improve on the LMP and provide road authorities time to consider actions. 90% of RabT landslides occurred over a 62 mm API, indicating a critical antecedent rainfall threshold. Rainstorm I-D >10h is key for landslide initiation with largely higher mean rain intensity than non-landslide storms. Shadow trials with confusion matrices against LMP thresholds are needed before full deployment.

Time-lapse vector tracking located and quantified creeping deformation in response to rainfall drivers. I-V calculations forecast imminent failure in the initiation phase, however creep slowed when rainfall ceased and arrested despite further rainfall. This method can detect slope movement and indicate times of heightened risk of failure for management authorities.

24-7 passive seismic detection and hodograms were used to identify a HDF. In this instance, and likely others due to short RabT flow paths, the 15 second event duration is too brief for live warnings but allows for 24/7 event detection and rapid response, outside of time-lapse image capture. Additional seismometers (now deployed) extend the range of detection and allow more traditional geo-location.

Our novel combination of sensors and processing techniques allows near-real-time monitoring and quantification of shallow landslides as demonstrated at the RabT in the west of Scotland. Results show that local sensor systems improve our understanding of triggers by allowing landslides to be attributed to specific conditions due to better landslide timing capabilities. This allows the forecasting of conditions that can likely induce landslides at this site, however the techniques could be readily applied to other sites. Low-cost sensors can be replicated at high- and lower-risk sites where cost-benefit would normally prevent monitoring. Increased high-intensity rainfall due to climate warming is expected in Scotland (UKCP, 2018) and more sites will have increased debris flow risk; greater low-cost monitoring capacity is a necessary advancement.

Acknowledgements

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