Abstract The region of Tajikistan where the Rogun Hydropower Project is currently under construction has experienced large and catastrophic slope failures in the past, often triggered by earthquakes. Co-seismic slope failures are thus common and pose a high hazard potential; however, to date, no specific analysis of slope activity in this area has been presented in international journals. Here, we present an inventory of active landslides identified through satellite imagery analysis and in particular by exploiting space-borne differential radar interferometry. Surface displacements provide the basis for the detection of active slope instabilities, which are then further classified by using geomorphological indicators visible in optical satellite imagery. Additionally, the proximity of active landslides to tectonic lineaments, as well as regional seismicity, is analysed to investigate potential relationships and to provide an integrated river damming hazard potential. The results show that approximately 31% of all detected landslides would have a high damming hazard potential upon catastrophic failure, highlighting the importance of such phenomena for efficient long-term land use planning and management of hydropower plants.

Keywords Landslides · River damming · Hazard potential · Satellite radar interferometry · Tajikistan

Introduction

The stability and lifetime of hydropower construction projects in mountain areas are strongly dependent on local slope activity (Nadim et al. 2006; Strom and Abdrakhmatov 2018; Valagussa et al. 2019; Dini et al. 2020). In particular, landslide failure events leading to river damming can largely alter the local hydrological conditions and end in dam failure and/or breach with subsequent flood wave generation (Korup 2005; Strom 2010; Strom and Zhirkевич 2013; Fan et al. 2019; Dini et al. 2020). One of the most disastrous examples in history is the 1963 Vajont rockslide, an underestimated slope instability that involved approximately 250 Mm$^3$ and created a 140-m-high flood wave, claiming up to 2000 lives (Barla and Paronuzzi 2013; Wolter et al. 2014). Such catastrophic impacts highlight the need for extensive studies of ground surface instabilities in mountainous regions in the context of dam construction to assess potential hazards (Strom 2010; Harp et al. 2011; Strom and Zhirkевич 2013; Fan et al. 2019; Dini et al. 2019). Slope instabilities can be initially detected based on field evidence and in situ monitoring data. These methods include significant limitations in mountainous regions, however, which are often remotely located and entirely inaccessible. New emerging technologies involving satellite synthetic aperture radar (SAR) remote sensing therefore strongly complement existing in situ methods and enable a more systematic and regional analysis of surface activity (Colesanti and Wasowski 2006; Rosi et al. 2018; Bordoni et al. 2018; Solari et al. 2019). Among these, a prominent technique is standard synthetic aperture radar differential interferometry (DInSAR) that allows detection of surface motion at subcentimetric accuracies and has been widely applied to map and analyse slope instabilities at regional to local scales in a number of contexts (Strozzi et al. 2010; Barboux et al. 2014; Barra et al. 2017; Manconi et al. 2018; Dini et al. 2019; Crosetto et al. 2020). The generated surface velocity maps can subsequently act as the foundation for further analyses, including the assessment of potential hazards to local construction projects upon landslide acceleration or failure. This study explores the use of standard DInSAR to map slope instabilities and evaluate their damming hazard potential in a region in Tajikistan, Central Asia.

Study area

In Tajikistan, the Rogun Hydropower Project (HPP) is currently under construction on the tectonic border between the Tien Shan and Pamir mountain ranges, Central Asia, roughly between 38° 30′ N and 39° 30′ N and 69° 30′ E and 71° 30′ E (Fig. 1). The catchment covers a total area of 9.7 × 10$^3$ km$^2$ and is marked by mountainous topography with reliefs exceeding 5000 m a.s.l. The resulting high hydraulic potential is defined by two large river networks, the Vakhsh and Surkhob Rivers running roughly NE-SW along the north of the study area and Obikhingou River joining from the south. The Rogun HPP is under construction and plans to hold a water reservoir covering an area of approximately 161 km$^2$ (blue area indicated in Fig. 1), doubling the country’s energy production. The region comprising the Rogun catchment lies within continental to semi-arid climate zones, which are largely defined through local elevation and lead to vegetated valleys and snow-covered mountains with a snow line of roughly 5000 m a.s.l. in summer (Strom and Abdrakhmatov 2018). Glaciers are observed in the high-altitude eastern part of the study area. Mean annual precipitation is approximately 500 mm. Geologically, the study area consists of Proterozoic to Palaeozoic crystalline gneiss and granite bedrock, overlain by Cretaceous to Palaeogene shallow marine and non-marine sediments, including sand- and gypsiferous limestones and clay and marl layers, where intense fracturing and foliation structurally define most units (Molnar et al. 1973; Hamburger et al. 1992). Extensive loess covers with a plasticity index of 10 can additionally be observed along valleys and mountain flanks (Evans et al. 2009). Tectonically, the region is marked by the ongoing intracontinental collision driven by the Himalayan orogeny, where regional convergence results in high seismic activity along a series of ENE-WSW-striking and 25–40° S-dipping thrust faults (Hamburger et al. 1992; Streeker et al. 2003). Here, the main seismically active faults are the Darvaz-Karakul (D-K) strike-slip fault, running approximately along the Obikhingou River valley, and the low-angle Vakhsh and Petrovsky Thrusts defining the Vakhsh-Surkhob River valley and linking to the Main
Pamir Thrust (MPT) further east (Hamburger et al. 1992; Strecker et al. 2003; Lukk et al. 2008; Evans et al. 2009; Lou et al. 2009; Yuan et al. 2013). The region is thus marked by several shallow to intermediate zones of high seismic activity along these fault systems, which are reflected by a high peak ground acceleration (PGA) of > 3.2 to > 4.8 m/s² for a return period of 475 years, where 0.8 m/s² suffices to trigger landslides (Hamburger et al. 1992; Lukk et al. 1995; Lou et al. 2009; Fan et al. 2019) (Earthquake Model Central Asia (http://www.emca-gem.org/), accessed 25 November 2020). Recurrence times, despite their difficult estimation, may be as short as 10–20 years for earthquakes M>6 in the entire Tien Shan and northern Pamir region (Havenith and Bourdeau 2010).

The extreme topography and high seismic activity in the study area result in a high landslide susceptibility and multitude of recorded and studied slope failures that may often be directly related to earthquakes (Havenith and Bourdeau 2010; Strom 2010; Strom and Abdakhmatov 2018). Massive rockslides and rock avalanches, occurring in fractured bedrock and sediments, as well as loess earthflows, appear to be the predominant failure types in the Tien Shan and Pamir Mountains (Keef er 1984; Havenith and Bourdeau 2010), where several regional studies have shown that landslide activity is often triggered by a complex interplay of the observed regional seismicity with other geological, structural, anthropogenic and meteorological predisposing factors (Fan et al. 2019; Havenith and Bourdeau 2010; Strom and Abdakhmatov 2018). The distribution and size of co-seismic landslides are therefore likely controlled by a number of factors, including ground motion frequency and duration, distance to seismically active faults, relative location to the general topography and lithological controls that may favour slope failure in particular conditions (Meunier et al. 2008; Havenith and Bourdeau 2010; Yuan et al. 2013; Saponaro et al. 2015; Strom and Abdakhmatov 2018; Valagussa et al. 2019; Fan et al. 2019). Due to the region’s extensive river network, slope failures may often result in landslide river damming, where the stability of landslide dams is often labile and can lead to critical geotechnical hazards (Korup 2005; Korup et al. 2006; Strom 2010; Strom and Abdakhmatov 2018; Fan et al. 2019; Dini et al. 2020): for example, the famous Usoi rockslide dam in southern Tajikistan formed in 1911 due to an approximately M7.7 earthquake (Ambraseys and Bilham 2012).

The following study analyses the distribution of unstable slopes in the Rogun HPP catchment area and investigates the influence of seismic events on active slope movements. Based on the obtained results, the main goal is to estimate the river damming hazard potential of detected slope instabilities in the region and to discuss its potential impact on the Rogun HPP.

Methods and results—analysis of landslides and seismic activity

In order to understand the relationship between landslide occurrence and regional seismicity, we compiled inventories of known earthquake events and landslides and analysed the proximity of landslides to tectonic/structural features. In addition, a landslide displacement analysis based on space-borne DInSAR was developed to detect and quantify the slope activity in the study area, as
well as to derive spatial and temporal characteristics. Finally, we integrated all results to establish the landslide river damming hazard potential. To ensure optimum understanding of all steps of our workflow, each of the following sections includes both the methodology and obtained results immediately thereafter.

Landslide and earthquake inventories

The landslide inventory is based on existing literature (Strom and Abdrakhmatov 2018) and databases such as NASA’s Landslide Viewer (https://maps.nccs.nasa.gov/arcgis/apps/webappviewer/, accessed 16 July 2019). From these data, we include information on failure type and volume, involved rock types and impacts on humans and the surrounding environment.

The earthquake inventory is mainly based on available databases (USGS, https://earthquake.usgs.gov/earthquakes/map/, accessed 16 July 2019; and Annual issues of the Earthquakes of Northern Eurasia, http://www.gsras.ru/zse/, accessed 15 December 2020), largely covering the twenty-first century, and is supplemented by few historical events of $M \geq 6$ found in the existing literature (Evans et al. 2009; Havenith and Bourdeau 2010; Kondorskaya and Shebalin 1982). The location, depth and magnitude of earthquakes are considered to indicate their spatial distribution relative to tectonic features as well as their impact on the local geology and slope stability. Havenith and Bourdeau (2010) and Keefer (1984) define an earthquake magnitude threshold of $M \geq 4$ that may trigger slope failures; however, in order to also consider instabilities potentially induced by lower magnitude earthquakes, we include earthquake events with a threshold of $M \geq 3.5$ to ensure a generalised error margin.

A total of 30 landslides were reported during the last century and are distributed throughout the entire study area, including 24 rockslides, 3 mudslides, 1 earthflow and 2 additional landslides of unknown type (Fig. 2). We note that our inventory is only an excerpt of all occurred events, as many of them have likely remained unreported in such a large and remote region. The predominant occurrence appears to be along the Vakhsh-Surkhob and Obikhingou River valleys (Fig. 3). This is probably only because of easier access to these areas. Volumes are only known for four of the rockslide events and range from 0.006 to 0.3 km$^3$, including the catastrophic 1949 Khait failure (Evans et al. 2009; Strom and Abdrakhmatov 2018). Three (10%) of the identified events have formed natural dams of unknown stability in contiguous river valleys.

The earthquake inventory highlights >270 earthquakes of $M \geq 3.5$ that occurred in the region mainly during 2000 to 2019. A predominant distribution south of the Vakhsh-Surkhob River valley is noted due to the S-dipping Vakhsh and Petrovsky Thrusts and MPT, as well as along the Obikhingou River valley due to the D-K strike slip fault (Fig. 2). A magnitude-frequency analysis indicates that a majority of recorded earthquakes occur with magnitudes of $M_4$ to $M_5$, while approximately 11% exceed $M_5$, matching observations in Havenith and Bourdeau (2010). Recurrence times can be

![Fig. 2 Locations of known landslide events as well as earthquakes of $M \geq 3.5$ that occurred from 2000 to 2019 as recorded by USGS are mapped relative to the major fault lineaments. The $M \geq 7$ earthquake occurred in 1949.](image-url)
loosely estimated based on the time frame of the inventory, where M≥5 events occur approximately every 8 months and M≥4 events within 1 month. Earthquakes of M≥6 are only noted during the twentieth century with a minimum recurrence time of 30 years, while only a single event of M≥7 is noted in 1949.

**Structural and tectonic features**

We mapped linear structural and tectonic ground features detected on ESRI World Imagery optical base maps and NASA’s SRTM 1 arc second DEM. The DEM’s relatively low resolution of 30 m, however, limits the scale of feature detection and potential spatial analyses (http://srtm.csi.cgiar.org/srtmdata/, accessed 14 January 2019). Both large-scale structural features, such as main faults and folds defining the observed mountainous topography, and smaller extensive scars and failure planes occurring at the scale of rock faces and valley flanks are of importance here. Their distribution relative to slope instabilities can give an indication of the dominant predisposing factors influencing slope activity in the study area. The detection of active faults in particular may show a link to seismic activity, while understanding the relative location of slope movement to the main rivers is important to evaluate a potential river damming hazard.

Major and minor faults, fractures, bedding, fold axes, scars and lineaments of unknown type are identified in the study area. Foliation could not be detected at the mapped scale. Major faults are shown in Fig. 2, representing the Vakhsh-Petrovsky-Main Pamir Thrust system and D-K strike slip fault and associated fault splays, which highlight the seismic activity in the study area and show a clear link to the distribution of observed earthquake events. They follow a NE-SW arcuate trend that reflects the predominant regional N-S oriented compression (Hamburger et al. 1992; Lukk et al. 1995). Fractures are noted both parallel to the main regime and oblique in a number of orientations, likely reflecting subsequent deformational phases. Scars are identified on mountain ridges and parallel to slope flanks and typically coincide spatially with identified active slopes, thus retaining a potential predisposing influence.

**Space-borne DInSAR**

The technique applied in this study to measure surface displacements is differential radar interferometry (DInSAR). DInSAR measures changes in distance between the satellite and imaged ground in the line of sight (LOS) direction by exploiting the phase signal of two SAR acquisitions acquired at different times (temporal baseline) and covering largely the same area on Earth (spatial baseline), thus allowing the detection of surface movement at varying timescales of centimetres per day to centimetres per year (Bürgmann et al. 2000; Wasowski and Bovenga 2014).

This study explores data acquired by two space-borne sensors from 2016 to 2018, considering images from the snow-free season from April to November to ensure high phase coherence. The primary satellite used is the European Space Agency’s (ESA) Sentinel-1, which acquires images at C-band (wavelength \( \lambda = 5.6 \, \text{cm} \)) in repeat track TOPS Interferometric Wide Swath (IW) mode every 12 days in ascending (track 173) and descending (track 78) orbits over the entire study area, allowing systematic and continuous analysis of surface motion. Sentinel-1 data is processed to generate differential interferograms using the software developed by the company Gamma Remote Sensing AG (Switzerland). Processing steps include the initial co-registration of single-look complex images, subsequent generation of differential interferograms according to specified temporal baselines with multi-looking factors of 5 pixels in range and 1 pixel in azimuth, adaptive phase filtering to reduce phase noise (Goldstein and Werner 1998), exclusion of layover and shadowing effects through masking and finally geocoding using the SRTM 1 arc second DEM as reference. Temporal baselines range from short periods of 12 to 48 days to show faster, often smaller and possibly seasonally affected slope movement of centimetres per month to centimetres per day, to longer baselines of 2 to 6 months and 1 year, which are typically expected to highlight slower long-term activity of few millimetres per year to centimetres per year and involving larger areas (Valagussa et al. 2019). The use of ascending and descending data additionally minimises layover and shadowing effects (Wasowski and Bovenga 2014). The secondary satellite used is the Japan Aerospace Exploration Agency’s (JAXA) ALOS PALSAR-2, which acquires images in Stripmap mode at L-band (\( \lambda = 23.6 \, \text{cm} \)) with a potential revisit time of 14 days, allowing detection of more rapid surface displacements over longer temporal baselines and in areas of dense vegetation (Strozzi et al. 2005). The same processing chain and software are used to generate differential interferograms from descending orbit and frame 59/2830 and ascending orbit and frame 164/770, split up into NE and SW, for temporal baselines of 56 days to 2 years; shorter temporal baselines are not possible due to lacking data. Few images from June 2019 were additionally analysed here.
Initial recognition of surface displacements is done based on the visual detection of fringe patterns in the computed interferograms (Fig. 4 and Fig. 5). A total of 222 active surface features are identified in the study area (Fig. 6) based on 52 differential interferograms (see Online Resources 1 and 2). Eighty-five per cent of all features are detected in 38 Sentinel-1 differential interferograms.
and form the bulk of the developed database. This is supplemented with 33 features detected in 14 ALOS PALSAR-2 differential interferograms. Fifteen per cent of all features are clearly visible in both satellites. Sentinel-1 differential interferograms covering July, August and September with temporal baselines of 12 to 24 days most effectively show slope movement due to reduced snow cover and resulting high phase coherence. Sixty-nine per cent of all moving features are best detected at temporal baselines of 12 days. ALOS PALSAR-2 differential interferograms show less systematic coverage over the study area for summer periods during 2016–2019, with very few images of 56–84 days (2–3 months). Here, temporal baselines of 1 to 2 years with low decorrelation show best results.

Landslide classification

Following the results of the DInSAR analysis, we classified the detected active slope features according to their movement type based on geomorphological criteria. Additionally, we performed an analysis of their relative likelihood of true activity to assign a level of confidence to each movement (Dini et al. 2019), as well as spatial analyses to estimate average velocities and sizes.

Forty per cent of the slope movements identified in the DInSAR analysis are rock slope deformations and rockslides, 41% are soil creep and slides, 1% are debris flows, 12% are rock glaciers and ice debris and 6% are features of unknown type (e.g. unidentifiable due to cloud/snow coverage) (Fig. 7). The classification into movement type is based on optical images, such as those provided by Google Earth Pro and ESRI World Imagery, and the SRTM 1 arc second DEM. The classification parameters include the detection of vegetation patterns, exposed rock or soil, distinct scree cover, talus cones and debris fans, slope colour, angle and curvature and the presence of fractures and scarps (Humlum 1982; Hungr et al. 2014; Dini et al. 2019). A number of features do not allow a clear distinction between processes or show a possible combination and are thus identified as such, e.g. rockslides occurring within a larger rock slope deformation or soil creeping and sliding features.

The likelihood of true slope activity for the 189 active slope features detected solely in Sentinel-1 data is derived in a likelihood analysis (Fig. 8) (Dini et al. 2019). This is performed in two steps, following a classification of 1 (low) to 6 (high likelihood). First, the total number of Sentinel-1 differential interferograms that a feature is detected in is determined, where a higher count renders a higher level of confidence of true slope movement, applying thresholds of 25% and 50%. Second, the confidence increases if a feature is detected in both ascending and descending orbits (classes 2, 4 and 6) and decreases if only detected in one orbit (classes 1, 3 and 5). The results show that 4% of all analysed features are detected in > 50% of the used differential interferograms and have a very high activity likelihood of 5 and 6, 54% of all features are observed in 25 to 50% and have a moderate to high activity likelihood of 3 and 4 and 42% occur in > 25% and thus have a low activity likelihood of 1 and 2.

Velocities for detected ground surface movements are determined based on a comparison of multi-temporal baseline differential interferograms. The velocity is estimated from representative differential interferograms that show distinct and coherent fringe cycles for the identified slope instability. For 69% of the detected slope features, this occurs at temporal baselines of...
12 days, and for 85% of all features within temporal baselines of 48 days. For only 12% of all detected instabilities are the velocities best calculated at temporal baselines of > 1 year, representing those features detected in ALOS PALSAR-2 data. Each velocity is extrapolated for a period of 12 days to compare velocity statistics, as well as 4 months to represent summer velocities, e.g. June–September, and 1 year to indicate long-term displacements. As slope displacement is not expected to occur linearly but is likely affected by seasonal and seismic influences, the velocity values must be treated with uncertainty. The results are listed in Table 1 and the Online Resource 2. In terms of maximum recorded velocities in centimetres per 12 days, rock slope deformations and rockslides generally form the fastest slope instabilities, while the slowest minimum velocities are noted for soil creep and few rock glaciers. Mean velocities reflect a slightly different distribution, where rock glaciers and debris flows show fastest movement, while rock slope deformations generally move more moderately. This discrepancy is reflected in the relatively high standard deviation of rock slope deformations and rockslides compared to other features and is likely due to the higher number of detected features of this type. In general, mean velocities are high enough to lead to temporal phase aliasing in the majority of detected features in both satellites, highlighting the dependence on the satellite radar wavelength and thus a major limiting factor when using DInSAR (cf. section 2.5) (Wasowski and Bovenga 2014; Manconi 2021). For both satellites, the observed displacement falls within the slow (1.6 m/year) to very slow (16 mm/year) velocity classes defined by Hungr et al. (2014), where features detected only in ALOS PALSAR-2 differential interferograms typically show lower velocities compared to Sentinel-1 data, thus not enabling the expected enhanced detection of fast slope movements. Note that the developed database is not exhaustive and is limited by both temporal aliasing and the low ALOS PALSAR-2 image availability.

The area of each detected slope movement is calculated in ESRI ArcGIS based on the developed map of active ground surface features and ranges from minimum 0.0047 to maximum 2.49 km², covering only 0.78% of the entire study area (Table 2). Rock slope deformations and rockslides clearly form the largest slope instabilities in terms of mean area (0.39 to 0.54 km²), followed by soil creep (0.27 km²), debris flows (0.15 km²), ice debris (0.14 km²), rock glaciers (0.12 km²) and soil slides (0.1 km²). Unknown type movements cover a wide range of area sizes with a mean of 0.31

Fig. 7 Distribution of detected active slope features according to movement type based on a geomorphological classification.
km² and thus likely include a number of different movement types. Volumes of detected slope instabilities cannot be determined from the DInSAR analysis directly due to lacking knowledge of the depth and location of failure planes and are therefore approximated using the empirical relation derived by Strom and Abdurakhmatov (2018) for mapped rockslides and rock avalanches in the Tien Shan and Pamir regions:

\[ V = 26.875A^{1.419} \]  

where \( V \) is the volume (Mm³) and \( A \) the area (km²). This equation considers the deposit area of failed landslides, i.e. the moving mass, to derive the landslide volume, which here is related to the area of detected slope movements. This

---

**Table 1** Velocity statistics in cm/12 days for each movement type

| Movement type (# of features) | Minimum velocity (cm/12 days) | Maximum velocity (cm/12 days) | Mean velocity (cm/12 days) | Standard deviation (cm/12 days) |
|-----------------------------|-------------------------------|-------------------------------|-----------------------------|-------------------------------|
| Rock slope deformation (58) | 0.158                         | 5.6                           | 1.288                       | 1.121                         |
| Rockslide (31)              | 0.438                         | 5.6                           | 1.519                       | 1.011                         |
| Soil slide (4)              | 0.306                         | 1.05                          | 0.722                       | 0.278                         |
| Soil creep (88)             | 0.119                         | 4.2                           | 1.217                       | 0.712                         |
| Debris flow (2)             | 0.963                         | 2.8                           | 1.881                       | 0.919                         |
| Rock glacier (22)           | 0.007                         | 2.8                           | 1.738                       | 0.729                         |
| Ice debris (5)              | 0.394                         | 2.625                         | 1.129                       | 0.794                         |
| Unknown (12)                | 0.175                         | 2.625                         | 1.295                       | 0.729                         |
provides a first-order indication of the volumes’ order of magnitude but can be affected by significant scatter. Less conservative estimations include those derived by Guzzetti et al. (2008).

**Limitations**

Despite its valuable use in systematically detecting and mapping surface motion at local to regional scales, DInSAR carries certain inherent limitations, particularly when applied in mountainous regions (Wasowski and Bovenga 2014; Barboux et al. 2014; Manconi 2021). Data coverage is limited by layover and shadowing effects, as well as coherence loss in summer due to vegetated areas and in winter due to frequent extensive snow cover (Wasowski and Bovenga 2014; Barboux et al. 2014). The deliberate exclusion of images acquired during the winter season is therefore necessary to generate coherent differential interferograms, but reduces the amount of data during the affected seasons. This affects the number of detectable features during surface activity mapping. Additionally, the maximum detectable surface velocities are limited depending on the used satellite SAR sensor and wavelength due to temporal phase aliasing (Wasowski and Bovenga 2014; Manconi 2021). Thus, maximum detectable velocities in this study are limited to 1.4 cm/temporal baseline, relating to 85 cm/year, due to the use of Sentinel-1. The inclusion of longer wavelength L-band ALOS PALSAR-2 satellite data ideally overcomes this limitation and allows detection of faster slope movement also in vegetated areas; due to lacking data over the study area, however, no considerable additional information was obtained (Barboux et al. 2014).

Results in the landslide classification analysis are subsequently limited by the use of DInSAR, as well as the relatively low DEM resolution and a lack of field data. Mapped landslide velocities are largely calculated from 12 to 24 days differential interferograms with good phase coherence and thus retain a high level of confidence, despite lacking field data which could validate the results. Few velocities are determined from longer temporal baselines with stronger decorrelation effects, however, and must therefore be treated with uncertainty. Additionally, the extrapolation across seasonal and annual time frames assumes linear surface motion, which is unlikely due to seasonal effects. The classification into movement types and activity likelihood, as well as the detection of structural and tectonic surface features, are limited by the relatively low DEM resolution of 30 m, where a higher resolution DEM may enable better recognition of surface features and classification based on these. Furthermore, lacking field data prevents more detailed studies of particular surface structures and landslides and thus a thorough cross-validation of the obtained results. As remote sensing methods are frequently applied in remote areas explicitly due to the lack of ground truthing data, however, this limitation is expected.

**Discussion—link between seismicity and slope instabilities?**

A potential link between the observed slope instabilities and seismic activity in the study area can be evaluated by understanding the occurrence of slope activity relative to the location of seismic fault systems, as well as considering velocity changes observed in the DInSAR analysis relative to specific known earthquake events.

Detected active slopes are distributed throughout the entire study area, showing distinct trends parallel to the seismogenic MPT and D-K fault traces and thus clearly indicating that tectonic features play a role in influencing landslide occurrence (Meunier et al. 2008; Valagussa et al. 2019; Fan et al. 2019). This is supported by the observed density distribution of active slopes, as all detected slope instabilities are located within 24 km of seismic faults and thus strongly indicate a potential seismic triggering (Keefer 1984; Valagussa et al. 2019). Of these, 88% occur within 10 km and 21% within 1 km of seismic faults.

Additionally, changes in velocity of particular slope instabilities are observed in the DInSAR analysis, which are likely induced by a number of possible triggering factors. Whether these potentially include seismic influences can be evaluated by analysing the relationship between an acceleration in slope movement relative to known earthquake events. This is done for two different slope instabilities: a rockslide/rock slope deformation and soil sliding/creeping complex. The general rock mass heterogeneity of these movement types, including expected fractures, joints and scarpers, provides the necessary predisposition to allow strong motion amplification that may result in seismically induced movement even at earthquakes with magnitudes as low as M4 (Fan et al. 2019; Keefer 1984).

A detected rockslide along the Obikhingou River clearly shows two distinct areas of different displacement rates in both Sentinel-1 and ALOS PALSAR-2 differential interferograms, indicating a faster moving part within the slower main rockslide body (Fig. 9). Slope-parallel scarpers identified in orthophotos hint at a currently stable and motionless larger rock slope deformation. Estimated velocities in 2016 and 2017 decrease from approximately

| Movement type (# of features) | Minimum area (km²) | Maximum area (km²) | Minimum volume (Mm³) | Maximum volume (Mm³) |
|------------------------------|--------------------|--------------------|----------------------|----------------------|
| Rock slope deformation (58)  | 0.05               | 2.49               | 0.44                 | 98.02                |
| Rockslide (31)               | 0.04               | 1.56               | 0.25                 | 50.33                |
| Soil slide (4)               | 0.08               | 0.13               | 0.76                 | 1.56                 |
| Soil creep (88)              | 0.04               | 1.39               | 0.26                 | 42.87                |
| Debris flow (2)              | 0.01               | 0.69               | 0.01                 | 15.85                |
| Rock glacier (22)            | 0.03               | 0.32               | 0.16                 | 5.28                 |
| Ice debris (5)               | 0.09               | 0.25               | 0.88                 | 3.82                 |
| Unknown (12)                 | 0.05               | 1.28               | 0.37                 | 37.93                |
1.925 cm/12 days in August to 1.75 cm/12 days in September, e.g. due to seasonal influences including reduced pore pressure and the onset of snow fall, and accelerate to 2.8–3.8 cm/12 days by June–July 2018. An additional potential source of this observed increase in velocity are earthquakes on the D-K fault. Possible events include the M4.3 earthquake that occurred on June 04, 2018, 70 km to the SW; for the given magnitude, however, it falls outside the distance range estimated by Keefer (1984). Another earthquake of M4.3 occurred only 11 km to the SW but 6 months prior to the noted acceleration, on December 15, 2017, and thus may have induced post-seismic movement within this particular rockslide. As the entire feature decelerates in late August–September 2018, any seismically induced velocity increase must have occurred temporarily and does not appear to have affected the overall stability of the slope movement. Additional predisposing factors on increased movement are likely.

The second example of potentially seismically induced increased slope velocity is observed in two active soil slides along the Surkhob River in the east of the study area (Fig. 10). They occur within a larger soil creeping complex, indicated by roughly slope parallel scarps identified in the orthophoto but showing no motion in the differential interferograms. The larger active soil slide to the west shows an estimated minimum summer velocity increase from 2.1 to 3.325 cm/24 days between 2016 and 2017 and subsequent decrease to 1.75 cm/24 days in 2018. The slower, smaller feature is only detectable in ALOS PALSAR-2, for which velocity data is too scarce to show a similar trend. Due to the complex’s location in the Surkhob River valley, the observed acceleration may possibly be triggered at least partly by seismic activity on the MPT. One potential trigger is the M4.2 earthquake that occurred 67 km to the WSW of the soil slide on August 05, 2017; however, it lies outside the distance range for M4–5 earthquakes as found by Keefer (1984). Another earthquake of M4.3 on December 02, 2017, occurred only 8.7 km SE but 8 months prior to the observed velocity acceleration and thus may have induced a post-seismic increase in movement.

Other trigger mechanisms

While the discussed results clearly highlight a possible seismic link to the observed slope activity in the study area and in particular the acceleration of specific landslide features through earthquake events, additional trigger mechanisms must be considered. A very relevant influence in triggering landslides is rainfall (Crosta and Frattini 2008). With an annual mean precipitation of approximately 500 mm (Strom and Abdrakhmatov 2018), rainfall certainly represents a likely factor in the acceleration of slope motion in the study area. This is confirmed by those landslides collected in the inventory that are based on the NASA Landslide Viewer database, for which rainfall has been noted as a probable trigger. The role of precipitation in specific detected slope instabilities, however, cannot be assessed due to lacking data on single rainfall events.

In the context of global climate warming, permafrost degradation in high-altitude regions such as the eastern part of the study area may also trigger moving slope instabilities, where sporadic to discontinuous permafrost is observed (Kääb et al. 2005; Zhao et al. 2010; Strom and Abdrakhmatov 2018). This is likely the case for detected rock glaciers and moving ice debris, which
occur above 3000 m a.s.l. and thus may be located within zones of permafrost (Zhao et al. 2010).

River damming hazard analysis
Integration of the results of the landslide classification and evaluation of a potential seismic trigger in the detected slope movements allow development of a damming hazard analysis. A slope instability’s potential to form a landslide dam and the resulting impact on construction projects such as the Rogun HPP are subject to a number of factors, including landslide, geomorphological and seismic properties (Strom 2010; Fan et al. 2019). If and when such a landslide dam may form cannot be predicted for the study area, however, a hazard map based on an integrated damming hazard analysis is developed for detected slope instabilities of ongoing slope deformation that may result in river damming upon catastrophic failure.

According to the Swiss guidelines for Protection against Mass Movement Hazards (Swiss Federal Office for the Environment, 2016), we calculate the river damming potential in an intensity-probability approach for landslides that are defined as permanent, i.e. show continuous although possibly accelerating and/or decelerating motion and have a probability of occurrence of 100% (thus setting the probability as 1). The intensity is derived by integrating relevant data from all previous results and analyses for a total of 161 features. This excludes rock glaciers and ice debris as well as all features detected solely in ALOS PALSAR-2 differential interferograms. The final hazard per detected slope instability is calculated by adding the weighted intensity inputs according to Yang et al. (2013):

\[
x_i = w_1\sigma_1 + w_2\sigma_2 + w_3\sigma_3 + w_4\sigma_4 + w_5\sigma_5
\]

where \(x_i\) is the hazard value, \(\sigma_i\) the input intensity data and \(w_i\) an associated relative weighting factor reflecting the input’s expected influence, per analysed landslide. Prior to calculating \(x_i\), each intensity input \(\sigma_i\) is normalised to a scale of 0 to 1 based on the highest relative value according to:

\[
\sigma_{ni} = \frac{\sigma_i - \sigma_{min}}{\sigma_{max} - \sigma_{min}}
\]

where \(\sigma_{ni}\) is the normalised intensity input and \(\sigma_i\) the original intensity input per analysed landslide, and \(\sigma_{min}\) and \(\sigma_{max}\) are the respective minimum and maximum intensity input values of all analysed landslides. The intensity inputs used in this analysis are defined as follows:

1. The primary intensity input \(\sigma_1\), with a weighting of \(w_1 = 3\) is given by a landslide’s distance to rivers contributing to the Rogun Dam catchment area, where short distances constitute a higher damming hazard upon failure.
2. The secondary intensity input \(\sigma_2\), with a weighting of \(w_2 = 2\) is defined by the activity likelihood of detected slope movements, where a higher likelihood class, and thus confidence of true movement, marks a higher damming hazard potential.
3. Three equally weighted third-order intensity inputs are assigned. The first is given by the estimated volume of a detected slope instability, \(\sigma_3\), with a weighting of \(w_3 = 1\), where higher volumes increase the hazard due to larger failure energies (Strom and Abdrakhmatov 2018). Note that the volume in this study is estimated based on an empirical relationship as indicated in Eq. 1 and thus cannot be considered as truly representative.
4. The second third-order input \(\sigma_4\), with a weighting of \(w_4 = 1\) is defined by the velocity per year of a detected landslide, where high velocities reflect a high hazard due to potentially high failure energies. Note that velocities per year are extrapolated linearly in a worst-case scenario and are likely not representative of true surface displacement rates.
5. The final intensity input \(\sigma_5\), with a weighting of \(w_5 = 1\) is given by the distance of landslides to seismogenic faults, where a

Fig. 10 Velocity changes within soil creeping and sliding on a N-facing slope in the Surkhob River valley are observed in 24 days descending (78) Sentinel-1 orbit and 672 days ascending (164) ALOS PALSAR-2 orbit. Scars are indicated in white in the orthophoto.
Fig. 11 Histogram of normalised integrated hazard according to a 30%-30%-40% distribution. A low damming hazard potential is marked as yellow, a medium hazard as blue and a high hazard as red.

Fig. 12 Integrated river damming hazard analysis considering multiple weighted intensity inputs.
shorter distance constitutes a higher damming hazard. Note that this is associated with uncertainty as PGA values, which would allow for a more precise estimation of potential seismic triggers, remain unknown.

Intensity inputs $\sigma_i$ and $\sigma_s$ are normalised using the invert of Eq. 3. The calculated hazard $x_i$ per analysed landslide is also normalised to its highest value to give a range of 0 to 1 according to:

$$x_{ni} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

(4)

where $x_{ni}$ is the normalised final hazard per analysed landslide and $x_{min}$ and $x_{max}$ are the respective minimum and maximum hazard values of all analysed landslides.

The results are shown in Fig. 11 and Fig. 12 and are provided in Online Resource 3. Based on the histogram range in Fig. 11, hazard classes are defined according to a simplified 30%-30%-40% distribution. Thirty-one per cent of the analysed features have a high damming hazard upon failure, 53% a medium hazard and 16% a low hazard (Fig. 12). Only 4% of the analysed features lie within 1 km of the planned Rogun HPP reservoir and 19% within 1-10 km. Based on these results, rough damming hazard scenarios affecting the Rogun HPP construction and lifetime can be specified considering the distance to seismic faults and assumed recurrence time of earthquakes along these faults. As all detected slope instabilities lie within the distance threshold to be triggered by M4 earthquakes (Keefer 1984; Havenith and Bourdeau 2010), a worst-case scenario of frequent slope failures is given by earthquakes of M4 to M4.9 with a recurrence time of 1 month. M5 to M5.9 earthquakes have an estimated recurrence time of 8 months and may thus trigger slope failures on an annual timescale. Both scenarios can cause failures during dam development that may directly affect and damage the ongoing construction works. In particular, features classified with a high damming hazard should therefore be studied in more detail, including analyses of volume, possible failure plane locations, rock mass characteristics and potential specific seismic influences such as local PGA, to enable a more precise and reliable hazard analysis. As only three earthquakes of $M \geq 6$ with an estimated recurrence time of minimum 30 years and a single event of $M \geq 7$ are noted in the earthquake inventory in the twentieth century, slope failures following such events are not expected to impact the dam construction itself but may potentially affect the area and lifetime of the Rogun reservoir and dam after its completion.

Conclusions
A total of 222 rock slope deformations, rockslides, soil creep and slides, debris flows, rock glaciers and ice debris with a largely moderate to high likelihood of activity are detected in the Rogun Dam catchment area using the DInSAR technique, indicating considerable surface slope activity of various movement types. These findings highlight the suitability of DInSAR to successfully map slope instabilities in large and remotely located mountainous areas despite inherent limitations. Subsequent velocity extraction of the collected database shows that while mean summer velocities greatly vary between < 5 and > 90 cm/120 days, all movements fall within the slow to very slow velocity categories defined by Hung et al. (2014) and thus initially do not appear imminently prone to failure. Velocity extraction is limited by temporal phase aliasing effects, where in 85% of all features the velocities are best calculated based on 12 to 48 days Sentinel-1 differential interferograms of good coherence. Velocities extracted from larger temporal baselines and based on ALOS PALSAR-2 differential interferograms must be treated with uncertainty due to stronger decorrelation. Despite these limitations, spatial and statistical analyses on mapped surface instabilities indicate a clear link between slope movement and seismic activity along the MPT and D-K faults, with 88% of all detected features located within 10 km of these. A potential direct correlation between specific earthquake events and post- or co-seismic triggering is observed for selected rock slope deformation/rockslide and soil slide/creep complexes when comparing their relative displacement rates in the processed differential interferograms. To determine such a direct link more accurately, an inventory of co-seismic landslides triggered by a particular earthquake should be developed and their morphology and displacement discussed.

An integration of the obtained data allows development of a probability-intensity river damming hazard analysis to evaluate the hazard potential of each detected slope instability considering a seismic influence. The results indicate that 31% of the analysed detected slope instabilities present a high damming hazard to the Rogun HPP, 53% a medium hazard and 16% a low hazard. Note that the developed analysis represents an approximation of the hazard distribution in the study area and is strongly dependent on the available data quality. Four per cent of all features excluding rock glaciers and ice debris have a high and 19% a medium secondary hazard of flood wave generation in the Rogun Dam reservoir.

Author contribution Research and methods: N.J., A.M. and A.S. Writing of original draft: N.J. Supervision: A.M. and A.S. Review of manuscript: N.J., A.M. and A.S.

Funding
Open Access funding provided by ETH Zurich.

Data availability Additional data is provided in the Supplementary Information (SI).

Code availability Not applicable.

Declarations
Conflict of interest The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.
References

Ambroseys N, Billham R (2012) The Sarez-Pamir earthquake and landslide of 18 February 1911. Seismol Res Lett 83:294–314. https://doi.org/10.1785/021112031
Barboux C, Delaloye R, Lambiel C (2014) Inventorying slope movements in an Alpine environment using DInSAR. Earth Surf Process Landf 39:2087–2099. https://doi.org/10.1002/esp.3603
Barla G, Paronuzzi P (2013) The 1963 Vajont landslide: 50th anniversary. Rock Mech Rock Eng 46:1267–1270. https://doi.org/10.1007/s00603-013-0483-7
Barra A, Solari L, Béjar-Pizarro M, Monserrat O, Bianchini S, Herrera G, Crespo M, Sarro R, González-Alonso E, Mateos R, Liguierzana S, López C, Moretti S (2017) A methodology to detect and update active deformation areas based on Sentinel-1 SAR images. Remote Sens 9:1002. https://doi.org/10.3390/rs9101002
Bordoni M, Boni R, Colombo A, Lanteri L, Meisina C (2018) A methodology for ground motion area detection (GMA-D) using A-DInSAR time series in landslide investigations. CATENA 163:89–110. https://doi.org/10.1016/j.catena.2017.12.013
Bürgmann R, Rosen PA, Fielding EJ (2000) Synthetic aperture radar interferometry to measure Earth’s surface topography and its deformation. Annu Rev Earth Planet Sci 28:169–209. https://doi.org/10.1146/annurev.earth.28.1.169
Colesanti C, Wasonovsk J (2006) Investigating landslides with space-borne Synthetic Aperture Radar (SAR) interferometry. Eng Geol 88:173–199. https://doi.org/10.1016/j.jenggeo.2006.09.013
Crespo M, Solari L, Moréz M, Barba A, Solari L, Béjar-Pizarro M, Mateos R, Liguierzana S, López C, Moretti S (2019) Investigation of slope instabilities in NW Bhatan as derived from systematic DInSAR analyses. Eng Geol 259:105111. https://doi.org/10.1016/j.jenggeo.2019.04.008
Dini B, Manconi A, Loew S (2014) Landslide inventories: the essential part of seismic earthquake hazard and landslide hazard analyses. Eng Geol 122:9–16. https://doi.org/10.1016/j.enggeo.2013.06.013
Evans SG, Roberts NJ, Ischuk A, Delaney KB, Morozova GS, Tutubalina O (2009) Landslides illuminated by InSAR multitemporal analyses. Sci Rep 10:8304. https://doi.org/10.1038/s41598-020-6519-w
Goldstein RM, Werner CL (1998) Radar interferogram filtering for geophysical applications. Geophys Res Lett 25:4035–4038. https://doi.org/10.1029/98GL000033
Harp EL, Keefer DK, Sato HP, Yagi H (2011) Landslide inventories: the essential part of seismic earthquake hazard and landslide hazard analyses. Eng Geol 122:9–16. https://doi.org/10.1016/j.enggeo.2013.06.013
Kääb A, Huggel C, Fischer L, Guex S, Paul F, Roer I, Salzmann N, Schlaffer S, Schmutz K, Schneidier D, Strozzi T, Weidmann Y (2005) Remote sensing of glacier and permafrost-related hazards in high mountains: an overview. Nat Hazards Earth Syst Sci 5:527–554. https://doi.org/10.5194/nhess-5-527-2005
Keefer DK (1984) Landslides caused by earthquakes. Geol Soc Am Bull 95:406–421
Korup O (2005) Geomorphic hazard assessment of landslide dams in South Westland, New Zealand: fundamental problems and approaches. Geomorphology 66:167–188. https://doi.org/10.1016/j.geomorph.2004.09.013
Korup O, Strom AL, Weidinger JT (2006) Fluvial response to large rock-slope failures: examples from the Himalayas, the Tian Shan, and the Southern Alps in New Zealand. Geomorphology 78:3–21. https://doi.org/10.1016/j.geomorph.2006.01.020
Lou X, Cai C, Yu C, Ning J (2009) Intermediate-depth earthquakes beneath the Pamir-Hindu Kush region: evidence for collision between two opposite subduction zones. Earthq Sci 22:659–665. https://doi.org/10.1007/s11559-009-0659-9
Lukk AA, Leonova VG, Shevchenko VI (2008) Seismotectonic characteristics of the northern flank and axial part of the Tajik Depression (the Garn Geodynamic Research Area). Izv Phys Solid Earth 44:965–1001. https://doi.org/10.1134/S1069351308120201
Lukk AA, Yunga SL, Shevchenko VI, Hamburger MW (1995) Earthquake focal mechanism, deformation state, and seismotectonics of the Pamir-Tien Shan region, Central Asia. J Geophys Res Solid Earth 100:20321–20343. https://doi.org/10.1029/95JB01258
Manconi A (2021) How phase aliasing limits systematic space-borne DInSAR monitoring and failure forecast of alpine landslides. Eng Geol 287:106094. https://doi.org/10.1016/j.jenggeo.2021.106094
Manconi A, Kourkoulis P, Caduff R, Strozzi T, Loew S (2018) Monitoring surface deformation over a failing rock slope with the ESA Sentinel-1: insights from Moosfluh Instability, Swiss Alps. Remote Sens 10:672. https://doi.org/10.3390/rs10050672
Meunier P, Hovius N, Haines JA (2008) Topographic site effects and the location of earthquake-induced landslides. Earth Planet Sci Lett 275:221–232. https://doi.org/10.1016/j.epsl.2008.07.020
Mohran FA, Fitch TJ, Wu FT (1973) Fault plane solutions of shallow earthquakes and contemporary tectonics in Asia. Earth Planet Sci Lett 19:101–112. https://doi.org/10.1016/0012-821X(73)90194-0
Nadim F, Kjekstad O, Peduzzi P, Herold C, Jaedicke C (2006) Global landslide and avalanche hotspots. Landslides 3:159–173. https://doi.org/10.1007/s10346-006-0036-1
Nesi A, Tofani V, Tanteri L, Taccioni Stefanelle C, Agostini A, Catanzi F, Casagli N (2018) The new landslide inventory of Tuscany (Italy) updated with PS-InSAR: geomorphological features and landslide distribution. Landslides 15:5–19. https://doi.org/10.1007/s10346-017-0127-0
Saponaro A, Pilz M, Bindi D, Parolai S (2015) The contribution of EMCA to landslide susceptibility mapping in Central Asia. Annals of Geophysics 58
Sunari L, Del Soldato M, Montalti R et al (2019) A Sentinel-1 based hot-spot analysis: landslide mapping in north-western Italy. Int J Remote Sens 40:7898–7921. https://doi.org/10.1080/01431161.2019.1607612
Strecker MR, Hillege AR, Arrowsmith JR, Coutard I (2003) Differential structural and geomorphic mountain-front evolution in an active continental collision zone: the northwest Pamir, southern Kyrgyzstan. Geol Soc Am Bull 116
Strom A (2010) Landslide dams in Central Asia region. Jpn J Landslide Sci 47:309–324. https://doi.org/10.1007/s10346-010-0036-y
Strom A, Abradakhmatov K (2018) Rockslides and rock avalanches of Central Asia: distribution, morphology, and internal structure. Elsevier, Amsterdam, Netherlands; Cambridge, MA, United States
Strom A, Zhirkich A (2013) “Remote” landslide-related hazards and their consideration for dams design. Ital J Eng Geol Environ 295–303. https://doi.org/10.4408/ijeg.2013.06-B-27
Strozzi T, Delaloye R, Kääb A, Ambrosi C, Perruchoud E, Wegmüller U (2010) Combined observations of rock mass movements using satellite SAR interferometry, differential GPS, airborne digital photogrammetry, and airborne photography interpretation. J Geophys Res 115:F00104. https://doi.org/10.1029/2009jF001311
Strozzi T, Farina P, Corsini A, Ambrosi C, Thüring M, Zilger J, Wiesmann A, Wegmüller U, Werner C (2005) Survey and monitoring of landslide displacements by means of L-band satellite SAR interferometry. Landslides 2:193–201. https://doi.org/10.1007/s10346-005-0003-2
Valargassa A, Marc O, Frattini P, Crosta GB (2019) Seismic and geological controls on earthquake-induced landslide size. Earth Planet Sci Lett 506:268–281. https://doi.org/10.1016/j.epsl.2018.11.005
Wasowski J, Bovenga F (2014) Investigating landslides and unstable slopes with satellite multi temporal interferometry: current issues and future perspectives. Eng Geol 174:103–138. https://doi.org/10.1016/j.jenggeo.2014.03.003
Wolter A, Stead D, Clague JJ (2014) A morphologic characterisation of the 1963 Vajont Slide, Italy, using long-range terrestrial photogrammetry. Geomorphology 206:147–164. https://doi.org/10.1016/j.geomorph.2013.10.006

Yang S-H, Pan Y-W, Dong J-J, Yeh KC, Liao JJ (2013) A systematic approach for the assessment of flooding hazard and risk associated with a landslide dam. Nat Hazards 65:41–62. https://doi.org/10.1007/s11069-012-0344-9

Yuan Z, Chen J, Owen LA, Hedrick KA, Caffee MW, Li W, Schoenbohm LM, Robinson AC (2013) Nature and timing of large landslides within an active orogen, eastern Pamir, China. Geomorphology 182:49–65. https://doi.org/10.1016/j.geomorph.2012.10.028

Zhao L, Wu Q, Marchenko SS, Sharkhuu N (2010) Thermal state of permafrost and active layer in Central Asia during the international polar year. Permaf Periglac Process 21:198–207. https://doi.org/10.1002/ppp.688

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10346-021-01706-5.

N. Jones (✉) · A. Manconi
Engineering Geology, Geological Institute ETH Zurich, Zurich, Switzerland
Email: jones@gamma-rs.ch

N. Jones
Gamma Remote Sensing AG, Bern, Switzerland

A. Strom
Geodynamics Research Centre LLC, Moscow, Russia