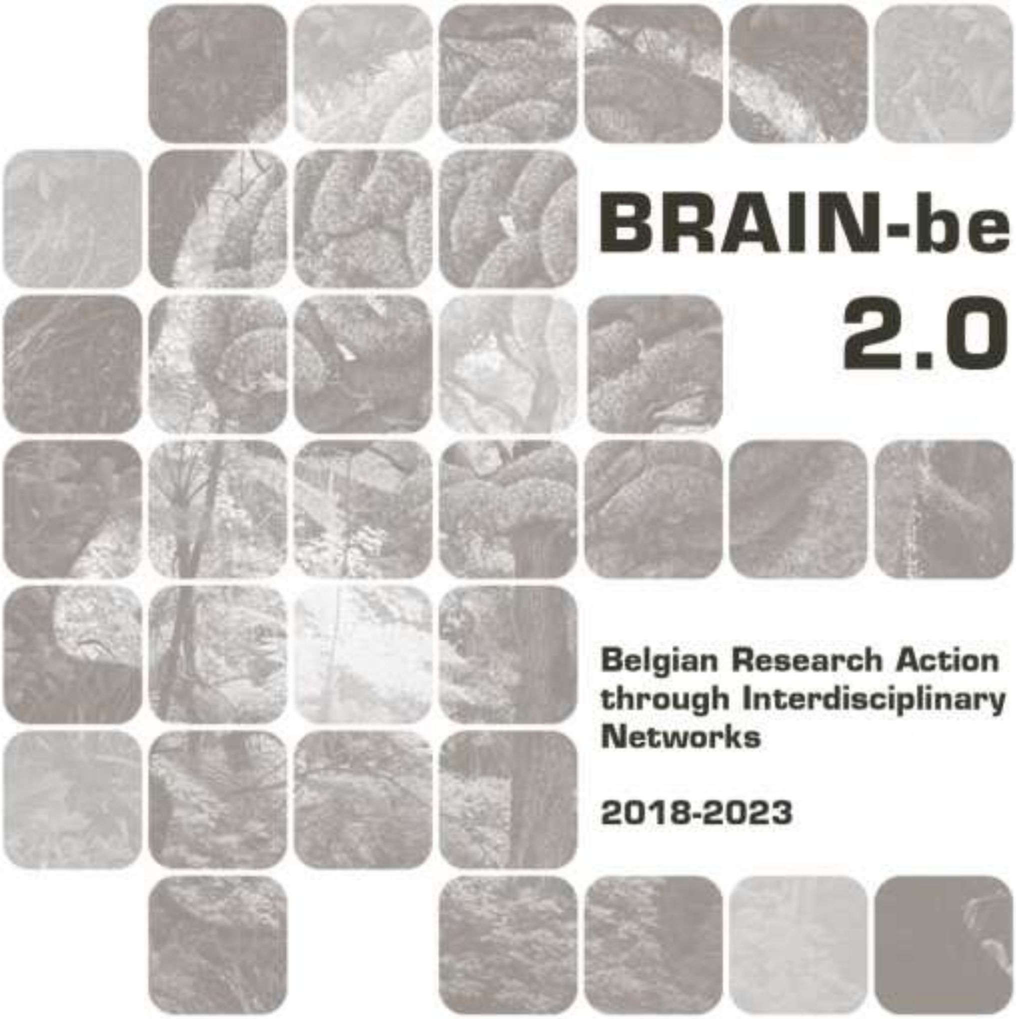

GEOTROP

GEOmorphic hazards and compound events in a changing TROPical East Africa

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Pillar 1: Challenges and knowledge of the living and non-living world

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Belgian Research Action through Interdisciplinary Networks

2018-2023

NETWORK PROJECT

GEOTROP

GEOmorphic hazards and compound events in a changing TROPical East Africa

Contract - B2/223/P1/GEOTROP

FINAL REPORT

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Published in 2026 by the Belgian Science Policy Office
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Deijns A. A.J., Dewitte O., Thiery W. ***GEOmorphic hazards and compound events in a changing TROPical East Africa***. Final Report. Brussels: Belgian Science Policy Office 2026 – 46 p. (BRAIN-be 2.0 - (Belgian Research Action through Interdisciplinary Networks))

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ABSTRACT

Flash floods occur worldwide. Triggered by intense rainfall spanning only a few hours, they frequently occur together with landslides. These landslides can deliver hillslope material to the river system, leading to amplified and devastating impacts. Landslides and flash floods are influenced by the daily to monthly variations in rainfall that precondition the landscape and change their likelihood of occurrence. The co-occurrence, interaction, and the preconditioning effect of rainfall reflects the compounding nature of these hazards. The tropics provide favourable conditions for their occurrence, with inequalities and challenging socioeconomic conditions often increasing their impact. Understanding their occurrence is therefore essential but require long-term datasets that are usually unavailable in these regions. In this project, we aim to better understand current and future spatial and temporal patterns of co-occurring landslide and flash flood events in the tropics and the effect of preconditioning rainfall in this process. To do this, we focus on the western branch of the East African Rift (WEAR). We developed two complementary remote sensing methodologies that allow for the spatio-temporal detection of landslide and flash flood events in the challenging data-scarce conditions of the tropics. Through these methodologies we have identified more than a hundred new co-occurring landslide and landslide and flash flood events in the WEAR. Our results suggest that preconditioning rainfall plays a central role in understanding their occurrence, along with land use and land cover and landscape geological history. We discuss that pessimistic future rainfall, population and land use scenarios could increase these co-occurring events and have a larger impact due to increase demographic pressures. This research offers new information and tools relevant to a region that is commonly underrepresented in global studies, and that can serve as a foundation for further landslide and flash flood research.

Keywords: Compound events, Landslide, Flash floods, Preconditioning rainfall, Remote sensing.

1. INTRODUCTION

The GEOTROP project (2022-2026) aims to assess the compounding nature of landslides and flash floods by untangling the geoenvironmental and preconditioning rainfall controls on their co-occurrence in tropical East Africa. GEOTROP has resulted in novel remote sensing-based detection techniques specifically tailored towards data-scarce tropical environments and has provided novel insights in the co-occurrence of landslides and flash floods within the western branch of the East African Rift. GEOTROP has additionally made a first preliminary insight into future trends of these events.

2. STATE OF THE ART AND OBJECTIVES

Below you can find an overview of the state-of-the-art that defines the basis of GEOTROP. For a complete version of the state of the art, we refer to the PhD thesis of A.A.J. Deijns (2024). The thesis that is attached in the Annex.

2.1 State of the art

Landslide and flash flood processes

Landslides and flash floods are worldwide phenomena that frequently make headlines due to their disastrous impacts on the landscape and the people in those landscapes. They can cause many casualties and inflict substantial damage to infrastructure and property (Ferro, 2005; Jonkman, 2005; Špitalar et al., 2014; Froude and Petley, 2018). Landslides can effectively shape the environment by transportation of hillslope material (Burbank et al., 1996; Gregory, 2010; Korup, 2012), and flash floods can transport large amounts of debris – from gravel to boulders – downstream (Hungr et al., 2014; Church and Jakob, 2020). Rainfall-induced landslides are by far the most common type of landslides (Sidle and Bogaard, 2016; Greco et al., 2023). They often occur in large clusters (e.g., Crozier, 2005) and frequently co-occur and interact with flash floods (Hapuarachchi et al., 2011; Catane et al., 2012; Jacobs et al., 2016; Alcantara et al., 2023; Marengo et al., 2023). These interactions result in landslide or landslide and flash flood events that are typically linked to a single, well-defined rainfall event. Landslides often act as sediment agents that feed large amounts of debris to the flash floods. Combinations of these hazard processes can as such exacerbate their impact and render those events especially damaging (Borga et al., 2014; Jacobs et al., 2016). This becomes particularly important when they occur in populated regions and impose substantial damage as a consequence (Jonkman, 2005; Froude and Petley, 2018). The increased population pressure in recent history and the rapid pace of urbanization is exposing more people to these types of events (McDermott, 2022; Ozturk et al., 2022), and understanding their occurrence is therefore highly relevant and needed.

Geoenvironmental and hydrological controls on landslide and flash flood occurrence

Rainfall-induced landslide and flash flood events are typically triggered by torrential rains when water infiltration exceeds the drainage capacity. Flash floods are usually characterized by their rapid onset (within six hours of rainfall)(NWS, 2024). Antecedent or preconditioning water content/ soil moisture is important in landslide and flash flood occurrence. Higher soil moisture content increases the potential for runoff generation (Noguchi et al., 1997; Grillakis et al., 2016). Prolonged wetting of a hillslope will mobilize larger landslides (Iverson, 2000; Zêzere et al., 2005; Bevacqua et al., 2021) and increase runout distance (Take et al., 2015; Könz et al., 2024). On the contrary, very low soil moisture content might favor the occurrence of shrinking or tension cracks that increase infiltration and can facilitate strong sudden pore water pressure changes and thus influence slope stability (Uchida et al., 2001; Krzeminska et al., 2013; Handwerger et al., 2019). Vegetation and land cover influence soil moisture content and runoff generation. They stabilize the soils and improve hillslope drainage (Uchida et al., 2001; Tarboton, 2003; Ghestem et al., 2011; Balzano et al., 2019). These roots may on the contrary also concentrate flow that might pool and decrease slope stability (Uchida et al., 2001;

Ghestem et al., 2011; Sidle and Bogaard, 2016). Forest cover does not necessarily decrease flash flood occurrence (Andréassian, 2004).

Better understanding landslide and flash flood events through a compound event framework

When multiple climatic drivers and/or hazards combine, their impacts are often amplified (Zscheischler et al., 2018). The spatial and temporal interdependencies of multiple interacting drivers can enhance their impact. Extreme events that involve these interdependencies are framed as 'compound events' (Zscheischler et al., 2018). Traditional analysis often does not consider these interdependencies leading to only a partial view of the story and an underestimation of the risks involved (Zscheischler et al., 2018, 2020). In this study we follow the proposed typology by Zscheischler et al. (2020) in analyzing the occurrence of landslides and flash flood events. Specifically, we investigate the co-occurrence of landslides and landslides and flash floods (defined as either multivariate or spatially compounding) and the influence of preconditioning rainfall (defines as preconditioning compounding) in this process. Literature highlights that the co-occurrence of landslides and flash floods exacerbates their impact (Jacobs et al., 2016) and the effect of preconditioning rainfall is important in understanding the characteristics and dynamics of landslide events (Bevacqua et al., 2021; Banfi and De Michele, 2024). While the analysis of compounding landslide and flash floods has received more attention recently (Jacobs et al., 2016; Alcantara et al., 2023; Maki Mateso et al., 2023; Marengo et al., 2023; Sharma et al., 2023), such analyses remain uncommon.

Landslide and flash flood events in the tropics

The tropics are areas where landslide and flash flood events frequently occur largely as a result of high rainfall totals and the high availability of mobilizable sediments. At the same time, people living in tropical landscapes are often at elevated risks to landslide and flash flood event impacts (Depicker et al., 2021a; Ozturk et al., 2022). These regions, particularly the low- and lower-middle income nations, are characterized by high and rising population densities that cause rapid deforestation (Hansen et al., 2013; Depicker et al., 2021a) and often show uncontrolled urbanization without considering proper land-use planning (Ozturk et al., 2022). This ultimately leads to people settling in hazard prone regions (Seto et al., 2012; Dille et al., 2022; McDermott, 2022; Ozturk et al., 2022). While understanding of landslide and flash flood event occurrence is therefor particularly important in these regions. The analysis of such events however, is hampered by the fact that data scarcity, driven by the remoteness, large human footprint, cloud cover and rapid vegetation growth, is often commonplace (Gariano and Guzzetti, 2016; Maes et al., 2017; Reichenbach et al., 2018; Ozturk et al., 2022) and exacerbated by low-data collection policy (Maes et al., 2017; Dewitte et al., 2021) and a lack of historical records.

Western branch of the East African Rift

The western branch of the East African Rift (WEAR) is representative of such a tropical region. It is a mountainous region that extend over terrains in Democratic Republic of the Congo (DRC), Uganda, Rwanda, Burundi, Tanzania and Zambia. This region is characterized by high population densities and landscapes ranging from highly forested to highly human-dominated landscapes. The region is shaped by active continental rifting (Chorowicz, 2005) that leads to seismic activity, active volcanism (Smets et al., 2016; Delvaux et al., 2017), and uplift-driven landscape rejuvenation through knickpoint retreat (Dewitte et al., 2021; Depicker et al., 2021b). The combination of intense rainfall, deep weathering, seismicity and steep landscapes makes this region highly susceptible not only to landsliding (Broeckx et al., 2018), but also to flash flooding. Evidently, landslides and flash floods highly impact this region (Monsieurs et al., 2018; Dewitte et al., 2021; Depicker et al., 2021b, 2024; Kubwimana et al., 2021; Maki Mateso et al., 2021, 2023; Nsabimana et al., 2023). Current landslide and flash flood related research in the WEAR has primarily focused on the densely populated North Tanganyika-Kivu (NTK) rift region (Dewitte et al., 2021), and the Rwenzori Mountains . These studies have put effort in mapping landslides (e.g., Jacobs et al., 2017; Monsieurs et al., 2018b; Dewitte et al., 2021; Depicker et al., 2021b; Kanyiginya et al., 2023; Maki Mateso et al., 2023) and flash floods (e.g., Jacobs et al., 2016a; Kanyiginya et al., 2023; Nsabimana et al., 2023). However, these inventories tend to be more localized and typically focus on isolated landslides or flash floods, rarely considering their co-occurrence in events. As a result, comprehensive multi-temporal datasets do not exist and understanding of landslide and flash flood event occurrence remains an open challenge.

The need for larger-scale multi-temporal event inventories

To untangle the role of preconditioning rainfall and landscape on landslide and flash flood event occurrence multi-decade inventories are ideally required (Schlögel et al., 2020a; Schlögl et al., 2021; Muñoz-Torrero Manchado et al., 2021). Despite recent advances in citizen-science based collection (Jacobs et al., 2019; Sekajugo et al., 2022) and web-scrapping tools (Li et al., 2024; Valkenborg et al., 2024), such suitable inventories do not yet exists in the WEAR. Multi-temporal inventories should ideally cover a large region and span a variety of diverse landscape and rainfall conditions (Tarolli et al., 2012; Guzzetti et al., 2012). This will capture the regional landslide and flash flood event trends and would allow to make the inventory less biased to the local stochastic nature of landslide and flash flood event occurrence, especially important for shorter-term multi-temporal inventories. Given the vast size and inaccessibility of many areas within the WEAR, a satellite-based remote sensing approach is the most viable option for creating regionally consistent, multi-temporal event inventories.

Satellite remote sensing for landslide and flash flood event detection

Satellite remote sensing provides the most suitable tool for a more unbiased and consistent regional detection of landslide and flash flood events. This is enabled by the availability of freely available satellite products that offer global coverage, high revisit times and reasonably high resolutions. Landslide and flash flood detection in space and in time is commonly done using two types of satellites. The optical satellites (e.g., Behling et al., 2014, 2016; Caballero et al., 2019; Shahabi et al., 2021; Notti et al., 2023; Bhuyan et al., 2023) and the radar satellites (e.g., Mondini et al., 2017, 2019; Burrows et al., 2019, 2020a, 2021; Esposito et al., 2020; DeVries et al., 2020; Jung and Yun, 2020). Most notable examples of such satellite constellations are the Copernicus Sentinel-1 (radar) and Sentinel-2 (optical) constellations (5-12 day revisit time with 10-20m spatial resolution) that have acquired imagery from 2015 onwards, and the Landsat constellation (optical; 8 day revisit time with 30m spatial resolution) that has acquired imagery from 1985 onwards. These satellite data products provide a consistent and continuous view of the Earth's surface and can as such be used to detect landslide and flash flood events. Optical satellite remote sensing are usually preferred for accurate spatial mapping of landslides and flash floods. However, they are unable to visualize the Earth's surface during cloudy conditions. This is particularly problematic in the tropics, where the year-round presence of clouds prohibits from accurate detection (Robinson et al., 2019). Radar-based satellite imagery, in particular Synthetic Aperature Radar (SAR) can provide a solution to this as they can penetrate through cloud cover and visualize the Earth's surface during these cloudy conditions. For this reason SAR-based methodologies demonstrate promising results than optical approaches in determining landslide and flash flood timing. The Copernicus Sentinel-1 and Sentinel-2 are complementary and clearly facilitate their use in a combined methodology.

Global and regional datasets for landslide and flash flood event analysis

The analysis of landslide and flash flood events in regional multi-temporal inventories requires consistently acquired datasets that provide full coverage at the location of the event inventories. Global and regionally acquired/modeled datasets are therefore required for a regional analysis. Products such as the Copernicus GLO-30 (global; 30m resolution) digital elevation model (DEM), the ESA CCI Land use and land cover product (Africa; 20m resolution; ESA, 2017), the Global forest loss change dataset (global; 30m resolution; Hansen et al., 2013), the iSDAsoil soil dataset (Africa; 30m resolution; 0.5m depth; Miller et al., 2021) are frequently used geoenvironmental datasets to analyze the occurrence of landslides and flash floods (e.g., Khosravi et al., 2016, 2018; Broeckx et al., 2018; Lombardo and Mai, 2018; Merghadi et al., 2020; Depicker et al., 2020; Smith et al., 2023; Dille et al., in preparation). Although serving as a proxy of the hydrology at the hillslope level, remotely sensed rainfall products provide traditionally useful tool for hydrological analysis of landslide and flash flood events(Terlien, 1998; Martelloni et al., 2012; Segoni et al., 2018; Zhai et al., 2018; Glade et al., 2000; Monsieurs et al., 2019; Bevacqua et al., 2021). Generally used global rainfall products are the GPM IMERG (10km resolution; Huffman et al., 2023), CHIRPS (5km resolution; Funk et al., 2015) and MSWEP (10km resolution; Beck et al., 2019), of which IMERG has been used and validated within East Africa (Ageet et al., 2022) and the WEAR (Monsieurs et al., 2019; Nakulopa et al., 2022; Uwihirwe et al., 2022) and is thus expected to accurately reflect rainfall conditions in the study area.

Understanding the effect of future climate on landslide and flash flood event occurrence

Future projections over the WEAR indicate an increase in rainfall intensities(Seneviratne et al., 2021), potential increases in drought length (Trisos et al., 2022), and shifts in timing, duration and magnitude of rain seasonality (Trisos et al., 2022; Palmer et al., 2023). Such changes in rainfall patterns may increase the incidence of compounding geo-hydrological hazard events. The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) provides a framework for consistent climate impact modelling across various sectors. This framework provides consistent climate and socioeconomic forcing data at ~50km resolution. While coarse, they provide an ideal continuous integrated datasets to allow for the better understand of future climate and socioeconomic conditions.

2.2 Objectives

Landslide and flash flood events can have severe impacts on the landscape and the people in those landscapes and understanding their compounding nature, defined through their co-occurrence and the influence of rainfall preconditioning in this process – remains poorly understood, particularly in the tropics. The lack of long-term impact data in tropical regions has so far prohibited such an analysis and establishing a multi-temporal inventory that covers a large region and that spans a variety of diverse landscape and rainfall conditions is therefore required. In this project we aimed to answer the following two main questions:

What are the spatio-temporal patterns of rainfall-triggered landslide and flash flood events in the tropics?

What are their main geoenvironmental and preconditioning rainfall controls in determining their behavior and how do these change in the future?

We aim to answer this question through the analysis of landslide and flash flood events in the western branch of the East African Rift (WEAR). Our main objectives during this project were:

1. Develop a SAR satellite-based methodology to determine timing of landslide and flash flood events, with the WEAR as a case study (WP1)
2. Develop an optical satellite-based methodology to detect spatial and temporal occurrence of landslide and flash flood events in large data-scarce regions, with the WEAR as a case study (WP1)
3. Analyze the occurrence of landslide and flash flood events through geoenvironmental and preconditioning rainfall controls in the WEAR. (WP2/3)
4. Analyze how land use, population and rainfall of the WEAR will change in the future and discuss the implications on the occurrence of landslide and flash flood events (WP4)

3. METHODOLOGY

Below you can find a methodological overview of the work carried out within GEOTROP. We provide a short version of the methodology presented in the papers Deijns et al., (2022), Deijns et al., (2024) and Deijns et al., (in review). For a full discussion we refer to those papers.

3.1 SAR-based detection methodology (WP1) (Deijns et al., 2022)

For this WP we aim to develop a methodology that automatically estimates GH event timing using Sentinel-1 (S1) SAR imagery on landslide and flash flood events spatially located, but with unspecified timing. We analyze landslides and flash floods together as co-occurring and interacting events. We create a methodology that can be applied in complex and various topographic and land use/land cover environments. The methodology is developed using four events either containing landslides, or a combination of landslides and flash floods located in contrasting landscape types observed within tropical Africa. We analyze various S1 SAR products, namely: amplitude, spatial amplitude correlation (a metric based on the common amplitude correlation) and coherence. Specifically, we: (1) create S1 SAR time series and analyze their patterns and behavior at the location of several GH events, (2) demonstrate and assess the ability to detect the timing of GH events using changes within the S1 SAR time series and, (3) investigate the influences of the landscape characteristics on the ability to derive the timing from S1 SAR timeseries through a sensitivity analysis. A short outline of the methodology can be found in following subsections.

GH events, SAR data and controlling factors

We investigate four GH events with known days of occurrence, and located in contrasting landscapes (from highly forested to a large human footprint) in Uganda, Rwanda, DRC and Burundi. SAR time series at the GH location are constructed using the Copernicus S1 Level-1 Single Look Complex (SLC) imagery acquired in Interferometric Wideswath (IW) using the C-band frequency. To study the four GH events we use all available high resolution S1 imagery (~15x15 meter resolution) from January 2016 to January 2021. We use both amplitude and coherence information. S1 images over the study area are provided in vertical-vertical (VV) and vertical-horizontal (VH) polarizations. Different polarizations result in different backscattering values (Shibayama et al., 2015; Psomiadis, 2016; Park and Lee, 2019; Burrows et al., 2022), but due to the overall better results show in literature (Burrows et al. 2022, Psomiadis 2016) and the more consistent acquisition at the locations of our GH events, decided to use VV polarization for our analysis.

SAR amplitude and coherence are influenced by local slope angle (Hanssen, 2001), soil moisture (Ulaby et al., 1996; Scott et al., 2017), vegetation (Balzter, 2001; Barrett et al., 2012), and terrain roughness (Dzurisin, 2007). Coherence is additionally influenced by atmospheric changes (Rocca et al., 2000) and due to the use of image pairs, also by the temporal baseline (time between acquisition of two images), the perpendicular baseline (distance between the location of acquisition of two images) and the difference in incident angle of the paired images (Hanssen, 2001). While landslides and flash floods theoretically lead to an increase in coherence, the amplitude reaction on their occurrence is often more complex reaction. Due to the influence of soil moisture and roughness change on the amplitude values, the occurrence of a GH event could both increase and decrease the amplitude values at the location of the GH event (Mondini et al., 2021; Burrows et al., 2022). To better assess the ability to detect GH timing, it is essential to understand the dynamic factors controlling the behavior of the signal. To this end we investigated the SAR timeseries dynamics using rainfall (GPM Level 3 IMERG Final Daily (10km spatial resolution) dataset), monthly vegetation patterns (Landsat-8 based normalized difference vegetation index (NDVI; Tucker, 1979)) and land cover (ESA Climate Change Initiative Land Cover product (ESA, 2017)).

Preprocessing, timing estimation and sensitivity analysis

The S1 images are pre-processed using the "InSAR automated Mass processing Toolbox for Multidimensional time series" (AmsTer) (Derauw et al., 2020; D'Oreye et al., 2021) processing chain. This toolbox allowed the creation of geocoded amplitude and coherence maps. We adapted the amplitude correlation approach, initially used for GH spatial detection (Mondini et al., 2017; Konishi and Suga, 2018; Jung and Yun, 2020), to allow for GH timing detection at the location of the GH. Spatial correlation is generally lost when the inter-pixel relationships between two images change at the location of a GH event. Therefore, a significant change within the landscape such as a landslide or a flash flood will cause a clear detectible signal in the timeseries. Since spatial correlation is only changing when the inter-pixel relationships change, general trends that affect the entire area do not influence the inter-pixel relationships. The spatial amplitude correlation (SAC) can therefore theoretically highlight the GH event occurrence within the time series, while reducing any seasonal dynamics

GH event timing is determined on two scales within separate workflows (1) deriving one timeseries per GH event using all pixels within that GH event, and (2) deriving a timeseries for each segment separately for each GH feature which results in multiple time series, equal to the amount of GH features, for amplitude, SAC, and coherence. Amplitude and coherence time series are generated by averaging the values within the identified impacted area per image and the SAC time series are generated by applying the SAC method within both workflows. The resulting time series are normalized using the time series average to improve comparability. We make an effort to remove the seasonal influence and atmospheric effect on the amplitude and coherence time series by subtracting the regional amplitude and coherence trend (i.e. time series) from the GH event scale amplitude and coherence time series in workflow 1. Timing is defined on every time series (for amplitude, SAC and coherence) using a binary segmentation change detection approach (Bai, 1997; Fryzlewicz, 2014) within both workflows. Workflow 1 resulting in one pre- and post event date and workflow 2 resulting in many event dates on which we derived the date that was in majority as event date.

We further analyse the influence of any controlling factors on the detectability of the event timing. We carry out a sensitivity analysis on GH feature area (effect of a changing number of pixels/pixel mixing, Deijns et al., 2020), slope angle (change in image acquisition geometry, Zebker and Villasenor, 1992; Hanssen, 2001), land cover (changing vegetation and soil moisture patterns, Giertz et al., 2005), and slope aspect (different effect of layover, shadowing within ascending and descending track, Hanssen, 2001; Dzurisin, 2007).

3.2 Optical-based detection methodology (WP1) (Deijns et al., 2024)

For this WP, we propose a new semi-supervised multi-temporal methodology for GH event detection in unexplored regions. It allows for the identification of both location and timing of GH events through satellite optical image time series. We aims to reduce manual user interventions. Our methodology does not require pre-existing knowledge on GH event location and timing and allows for GH event detection through the combined use of several spectral indices. We implement the use of an OBIA-ML based detection tool that acts to generalize the methodological workflow and allows to increase spatial detection accuracy while limiting false detections once general location and timing have been derived. We use Sentinel-2 optical image time series from 2016 to 2021 and we showcase our methodology on six Sentinel-2 tiles located in various natural and human-influenced mountainous landscapes across tropical east Africa, i.e., in environments where landslide and flash flood processes are under-researched, and their impact is disproportionally high. The methodology is implemented on a High-Performance Computing (HPC) infrastructure. The methodology consists of three main steps (1) Spectral index calculation (2) GH event detection using a pixel-based methodology (3) The OBIA-ML-based implementation using the results acquired in step 2. A short outline of the methodology can be found in following subsections.

Spectral index calculation and geomorphic hazard detection

Step 1: we use Sentinel-2 level-2A data for which each image we calculate we calculate six spectral indices sensitive to changes in vegetation, surface brightness and soil moisture and that are indicative of the drastic changes of surface properties induced by the occurrence of both landslides and flash floods (NDVI, SAVI, TSAVI, BI, Brgb, NBR; Bevington et al., 2018; Deijns et al., 2020; Scheip and Wegmann, 2021; Atefi and Miura, 2022).

Step 2: To create multi-temporal GH event inventories from satellite time series while reducing the user inputs, the methodology adhered to three main points (1) its independence of any knowledge on GH event location and timing, making it applicable to allow for the actual detection of new previously unknown events; (2) the possibility to apply it within a wide variety of landscapes, both spatially and temporally; (3) the possibility to apply it in highly cloud-covered areas. To separate impacted from non-impacted pixels we use the cumulative difference to the mean (CD) for each spectral index timeseries, a methodology adapted and upscaled from Deijns et al. (2020). Impacted pixels will display a prominent peak indicated by a clear triangle shaped time series in contrast to non-impacted pixels. We discriminate the impacted pixel time series from the non-impacted pixel time series by its prominence. We use the 'find_peaks' tool from the 'SciPy' python package (Virtanen et al., 2020) to identify peaks in the timeseries. If a pixel has an identified peak from low to high prominence over multiple indices, it is likely impacted throughout the time series. We apply this tool on six indices and we vary the prominence value 10 times from low to high. This results in 60 maps indicating 0 if there is zero or multiple peaks found and 1 if there is one peak found. We cumulate this into one IPMCUMUL map, where high values indicate high likelihood of impact and low values indicate a low likelihood. We use the location of the identified peak within the time series to date the GH-induced change within the impacted pixels. This therefore results in 60 timing maps which we culminated into one image by taking the median of all maps per pixel (IPMTIMING). The complexity of the study area, resulting from a variety of land covers and the influence of humans on the landscape, has significant impact on the noise levels within the time series. We therefore delineated the GH event impacted zone manually from the IPMCUMUL maps produced from the 2016-2019 time frame and the 2016-2021 time frame. We outlined their main impacted zone and for each high value IPMCUMUL pixel (>40) within outline, we assign the median timing of all these pixels as the date of the GH event.

Step 3: We use the resulting GH event impacted zones, the GH event timings and the IPMCUMUL maps as input to an OBIA-ML algorithm to allow for an improved detection accuracy of individual landslide and flash flood features within the GH event impacted zone. We use the ML-based landslide change detection service ALADIM (Automatic LAndslide Detection and Inventory Mapping; Stumpf et al., 2014a; Deprez et al., 2022). ALADIM is a supervised change detection method that can detect both landslides and flow-like (including flash flood) features (Schlögel et al., 2020b; Deprez et al., 2022) and has been seen to outperform other ML-based GH change detection techniques (Amatya et al., 2023). ALADIM requires the input of a pre- and a post- GH event image, a set of training samples (e.g., impacted training samples) and of training areas (e.g., non-impacted training samples). The output consists of an inventory map with a class membership likelihood (‘prob_true’) of that segment belonging to the GH class (Schlögel et al., 2020b; Deprez et al., 2022). Based on the identified GH event timing, we manually identify suitable pre- and post-event Sentinel-2 imagery. We use the IPMCUMUL and IPMTIMING outputs to create the impacted and non-impacted training samples. The variability in landscapes and cloud cover patterns will lead to varying amounts of noise within the IPMCUMUL maps so we set up a workflow with standard variable values that makes use of the impacted zone, the IPMCUMUL map, the IPMTIMING map, the vegetation change in the pre- and post-event imagery and the amount of cloud cover in the timeseries to allow for the automatic creation of the impacted and non-impacted training samples in contrasting landscapes. We apply ALADIM in two scenarios. For the first scenario, we use a buffer of 600m around the GH event zone for the non-impacted training sample and for the second scenario, we use no buffer around the GH event zone for the non-impacted training sample. This buffer potentially allows for better training over non-impacted terrain.

Validation strategy

To validate the IPMCUMUL and ALADIM products at the location of the GH events, we use several of the identified GH events and manually map their GH features. We evaluate the detection results through the common metrics F1-score, Matthew’s correlation coefficient and the Kappa coefficient. Detection accuracy from the IPMCUMUL was tested by iterating from 0 to 60 with steps of 1; for each iteration, we use this value as threshold to identify between impacted and non-impacted pixels for which we then calculate the confusion matrix. For ALADIM, we iterate over the ‘prob_true’ parameter from 0 to 1 with steps of 0.01. Timing accuracy is validated by manually browsing the Sentinel-2 imagery. We additionally analyze our results with respect to slope gradients and land cover classes.

3.3 Landslide and flash flood event analysis (WP2/3) [Deijns et al., *in review*]

In these WPs we aim to better understand the compounding nature of landslides and flash floods by quantifying their co-occurrence and by analysing how preconditioning rainfall shapes their dynamics in this tropical environment. A short outline of the methodology can be found in following subsections.

Detection, classification and clustering of landslide and flash flood events

In this work, pixels with abrupt changes in landscape vegetation cover signatures were detected without a priori information on location or timing of occurrence using the methodology described in Deijns et al. (2024). We applied it on 66 Sentinel-2 tiles covering approximately 640,000 km^2 between 2016 and 2021. We then applied ALADIM to improve detection accuracy. To improve the timing information associated with the detection of the sediment impacted pixels, we manually reviewed optical satellite data from the Sentinel-2 and PlanetScope constellations. Then, we applied the SAR-based method from Deijns et al. (2022) to improve the accuracy.

To better analyse the underlying processes, we differentiated the detected pixels into three components: landslide source areas, landslide runout areas and flash flood areas. For this, we employed a transfer learning adaptation of the methodology described in Dille et al., (2025). We combined a logistic regression and a random forest approach. We fed the models on common topographic and hydrological predictors. The models were run on the ALADIM outputs. The training of the models were done using pixels of eight representative events within different landscapes that were manually classified into one of the three classes. The output was a map per class consisting of the probability of each impacted pixel belonging to that specific class. These maps were used to create a composite image assigning the highest probability class to each pixel.

Four distinct types of landslide and flash flood events were distinguished within the regional inventory that we quantitatively clustered through a decision tree. First, we identified [i] events that contained landslides and a substantial proportion of flash flooding. The main discriminator for these events were the flash flood fraction. Second, we identified two overarching types of landslide-only events. [ii] Events that contained a large amount of landslides within the zone of initiation, i.e., high-density landslides (HD-LS). [iii] Events that contained sparsely positioned landslides with little to no interconnectivity i.e., low-density landslides (LD-LS). The main variables to discriminate between these events were the density of the landslide source and runout. Lastly we identified [iv] small-sized events discriminated by their size. These events had a limited area of impact. The decision-tree based clustering result proved to be valid after visual interpretation.

Extracting population, geoenvironmental and preconditioning rainfall metrics

To assess societal impacts of each event, we estimated the affected population and buildings within and close to the impacted areas. To provide a full overview of impacts, we manually mapped all flash flood areas outside this zone using cloud-free pre- and post-event Sentinel-2 imagery. The number of people affected by each event was estimated through the UN-adjusted WorldPop unconstrained 100 m dataset. WorldPop shows quite reliable results in the study area (Ilombe Mawe et al., 2025). The number of buildings affected was estimated through the global Open Buildings dataset (Sirko et al., 2021). This dataset was able to accurately estimate the impacts of cyclone Idai in Zimbabwe for example(Dille et al., 2025), and seemed robust for the area after visual interpretation. Both population and building data were estimated within the impacted areas and including a 100 m buffer distance from these impacted areas. Highlighting the impacts in the landslide and flash flood area and putting this in perspective with the 100m buffer area gives an indication on the scale of the societal impacts that these events cause.

Geoenvironmental properties were explored to better understand spatio-temporal trends within the landslide and flash flood event inventory. Geoenvironmental and rainfall variables were calculated for each individual segment. A mean value for all Copernicus GLO30-DEM (ESA, 2024) derived products created during the classification stage was extracted. Forest fraction is derived from the ESA Climate Change Initiative Land Cover product (ESA, 2017). Forest loss is derived from the Global Forest Change 2000-2022 dataset (Hansen et al., 2013). Top soil sand, silt and clay content were derived from the iSDAsoil dataset (Miller et al., 2021). We estimated the difference between the geoenvironmental distributions through the Kolmogorov-Smirnov (KS) test. Rainfall variables were derived from the 10km resolution Global Precipitation Measurement (GPM) Level 3 Integrated Multi-satellite Retrievals for GPM (IMERG) final daily V07 dataset spanning from 2001 to 2023 (Huffman et al., 2023). IMERG has been validated over the region (Ageet et al., 2022; Nakulopa et al., 2022; Tan et al., 2019). Similar to other products, IMERG shows high agreement with the rain gauge records for annual and monthly rainfall trends, medium agreement for dekadal, pentadal and daily rainfall and low agreement for rainfall extremes.

Counterfactual dataset and statistical analysis

To understand the rainfall patterns leading up to landslide and flash flood event occurrence, it is essential to understand the ‘normal’ climate conditions. Common multi-variate models are often unable to capture how local-scale rainfall variability drives event occurrence due to a coarse spatial resolution and a limited possibility to compare between multiple events. To allow for our preconditioning rainfall analysis, we established a counterfactual dataset to serve as non-impacted samples (Lesk et al., 2016). Each identified landslide source, landslide runout and flash flood segment was duplicated 10-fold. For each of these duplicated segments the timing of occurrence was changed to a new timing representing the same period but within a year between 2005 and 2016 (Lesk et al., 2016) and rainfall indicators were recalculated.

To statistically assess which climate variables explain the occurrence of different types of landslide and flash flood events, we conducted a multivariate analysis taking the factual-based values as occurrence (1), and the counterfactual-based values as non-occurrence (0). For the statistical analysis we used a LASSO (Least Absolute Shrinkage and Selection Operation) (Tibshirani, 1996) logistic regression, a commonly used method to reduce the large number of highly correlated features without losing variable interpretability (Vogel et al., 2021; Smith et al., 2023; Emberson et al., 2022). In short, to provide a more robust representation of the variability inherent in the model outputs, we created a synthesis of multiple LASSO logistic regression models varying the randomness, multicollinearity threshold and the input variables to provide a comprehensive view that allows to robustly relate the rainfall metrics to the occurrence of each even type. For each event type we counted the number of times a certain variable is considered in the synthesis of models within the LASSO logistic regression models and we visualized the distribution of the odds ratio associated with that variable.

3.4 Landslide and flash flood event future analysis (WP4)

In this WP we made a start to better understand future climate and socioeconomic conditions and the role of compounding landslide and flash flood events within those future conditions. A short outline of the methodology can be found in following subsection.

Future climate and socioeconomic trends, local and regional

To asses general future trends over the region, we analyse timeseries of rainfall, population and land use of ISIMIP3a for the historical record and ISIMIP3b for the future projections. ISIMIP3b future projects consists of three Shared Socioeconomic Pathways (SSPs): SSP1 (Sustainability), SSP3 (Regional Rivalry) and SSP5 (Fossil-fuelled Development). Based on the results acquired in WP3 we investigate yearly rainfall sums, Rx5day and SPI12 for their temporal trends. We separately analyse the trends for each country within the region. Finally, we investigate the spatio-temporal through a linear regression analysis. Additionally we made an effort to more closely investigate rainfall, land use and population patterns for one of the most mpactful landslide and flash flood event recorded in the study area over the past years, the event that struck the city of Uvira, DRC, on 16-17 April 2020. We georeferenced historical aerial photographs from 1959 conserved at the RMCA and make preliminary local assessment on the occurrence of landslide and flash flood events and any prospects for the future.

4. SCIENTIFIC RESULTS AND RECOMMENDATIONS

The main scientific results can be found in the peer-reviewed papers Deijns et al., (2022), Deijns et al., (2024) and Deijns et al. (*in review)*. We provide a short overview of the main results WP's in the subsections below. WP2 and 3 are both addressed in Deijns et al., (*in review*) and are therefore discussed in one section. WP4 has remained a preliminary analysis and is presented as such.

4.1 Landslide and flash flood event inventory (WP1)

Timing detection (Deijns et al., 2022)

In this study we present a methodology to automatically determine GH event timing using S1 SAR data within contrasting landscapes. Our study improves on the recent advances in GH event timing estimation research as: (1) we analyze the use of amplitude, SAC and coherence time series in a systematic manner to detect the timing of GH events (2) we defined a methodology where no prior knowledge of the GH event timing is required, (3) we applied our methodology on contrasting landscapes and (4) we combined landslides and flash floods in a single detection approach. Here we discuss our insights, and the potential improvements and future perspectives of our methodology.

Through the SAR timeseries (Fig. 4.1), we show that the distinctiveness of the GH event occurrence within the time series varies significantly per data product. SAC (Fig. 4.1i-l) and coherence (Fig. 4.1m-t) time series showcase the timing of the event with a significant change of value at the time of the event occurrence. Amplitude does not prove to be an effective approach to accurately determine the timing of GH events since it gives an estimation accuracy of 13 to 1000 days with the actual time occurrence of the events. A clear increase in accuracy is obtained from SAC with an accuracy of 1 to 85 days. However, the most accurate results are achieved with coherence and detrended coherence with a 1 to a 47 day accuracy. GH event timing accuracies are higher for GH events that occurred in remote areas with low amounts of cultivation and human influence. The magnitude of the seasonal vegetation oscillations, which shows connectivity with the precipitation patterns varies significantly with changing landscapes and results in profound seasonal cyclicity in both the amplitude and coherence timeseries. Denser and taller vegetation, result in lower seasonal cyclicity within the amplitude and coherence time series. An increase in GH feature area improves the accuracy of timing detection. Accuracy is not correlated with slope angle. Although a clear difference can be observed in time series response to GH events located in different landscapes, the comparison with the land cover does not allow to find a clear relationship with the type of vegetation. We see that, generally, the GH features on the west-facing slopes have higher timing estimation accuracies using the descending track imagery and the GH features on the east-facing slopes have higher timing estimation accuracies using the ascending track imagery.

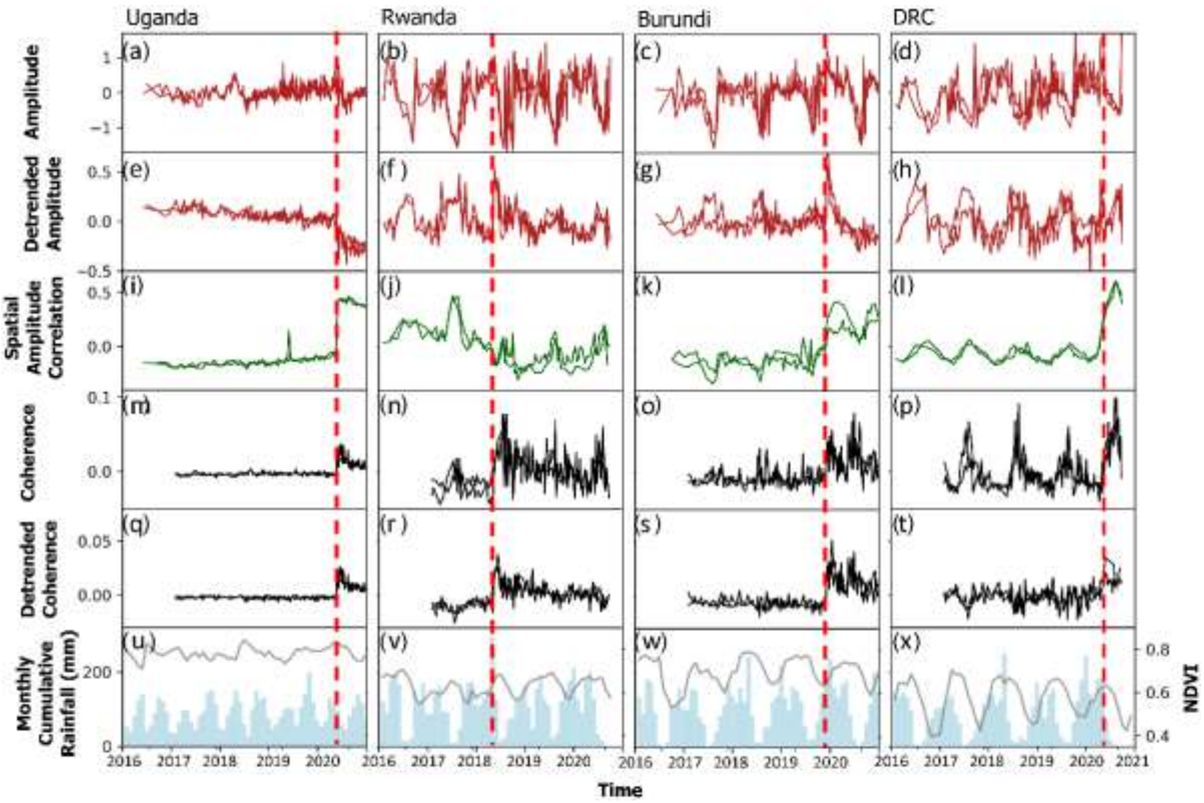

Fig. 4.1 | GH event (detrended) amplitude (red), spatial amplitude correlation (SAC, green) and (detrended) coherence (black) time series. *The dashed red line represents the timing of the GH event occurrence within the time series. All coherence, amplitude and SAC time series show two lines of a similar color representing the ascending and descending track time series. The time series are created according to the complete GH event scale workflow. The bottom row shows the monthly cumulative precipitation (light blue bars) from IMERG satellite data and the monthly averaged NDVI values (grey line) from Landsat-8.*

The current methodology allows to determine GH event timing from SAR, but several improvements can be considered in future research. Improvements can focus on a more in-depth detrending, a different change detection algorithm, further fine-tuning of the preprocessing workflow and further development of the SAC methodology. In terms of perspectives (1) our methodology could be used in further multi-hazard based approaches. (2) We show that both amplitude and coherence should be included to accurately estimate timing (3). Our methodology should be transferability to similar regions, but different rainfall regimes should be taken into account. (4) Our methodology could be fed with other SAR satellite products, but different bands will likely have an impact on the accuracy (5) The methodology could benefit from implementation on a cloud computing service. However, to our knowledge, so far, no cloud computing platform offers the possibility for processing and using coherence data. (6) The methodology can potentially be combined with optical data (e.g., Deijns et al., 2020) that could serve as additional data to help narrow down the time window and filter out any non-sense timing estimations.

Spatio-temporal detection (Deijns et al., 2024)

Our semi-supervised methodology successfully allows for the identification of GH events on a tile-by-tile basis without the need for prior knowledge on either location or timing. We detected 29 GH events out of which 25 were initially unknown (Fig. 4.2). The methodology shows skills in a variety of landscapes and allows the detection of both landslides and flash floods with relatively accurate timing. We highlight 4 identified events that occurred in contrasting landscapes (from forested to human dominated) and their IPMCUMUL and ALADIM output. We choose 12 of these GH events and manually mapped their landslide and flash flood outlines to validate the IPMCUMUL and ALADIM products (Fig. 4.2). GH events occurring in highly forested areas show a distribution skewed towards smaller sized GH features, whereas GH events occurring in human-dominated landscapes (grassland, cropland, urban) generally contain larger features. There we observe landslides with larger runout and a higher amount of flash floods. Together with more amalgamation and interconnectivity, this has led to larger GH features. An example of the results of four events including IPMCUMUL and ALADIM based refinement can be found at Fig. 4.3.

A clear influence of landscape is observed within the IPMCUMUL maps with an increase in noise towards more human dominated landscapes. The amount of human influence on the landscape increases the difficulty in multi-temporal GH event detection, mainly due to the constant changing landscape throughout the time series. Nonetheless, we have been able to identify GH events in all the different landscapes within our study area, due to their distinct impact on the landscape. Slope gradient additionally influences the detection accuracy with a low general IPMCUMUL detection accuracy for pixels with low slope gradients. In addition, the time of GH event occurrence plays an role in GH event detectability. Shortening the overall timeframe allows to better identify GH events that occurred earlier in the time series from the IPMCUMUL maps at the expense of a higher amount of noise**.** GH events occurring late in the time series show good detectability. The methodology shows relatively high timing accuracies, despite the high cloud cover within the study area, in comparison to previous research using optical imagery (Deijns et al., 2020; Fu et al., 2023). Satellite SAR-based approaches such as presented by Burrows et al. (2022) and Deijns et al. (2022) may as support to further reduce timing accuracy.

Application of ALADIM with the training samples created from the IPMCUMUL maps improves the accuracy of the results, and the flattening of the accuracy curves. Additionally, ALADIM is less dependent on land cover and slope gradient classes than IPMCUMUL and allows for an improved detection of the GH events. We show that although the detection accuracy from IPMCUMUL is low, the training samples created within this GH event zone are useful to provide much improved results after ALADIM application. The fact that we do not need a priori timing or location to identify GH event zones allows for the use of our methodology before applying a more data-intensive ML tool. We show that our pixel-based methodology allows us to create training samples, through a semi-supervised approach, to input into a ML change detection algorithm. This combination shows a high potential in areas such as the western branch of the East African Rift, where limited a priori information is available. The quality of the IPMCUMUL maps propagates into the training samples and therefore influences the results of the ML detection tool, we therefore expect the quality of the training samples to generally be lower in human-influenced landscapes.

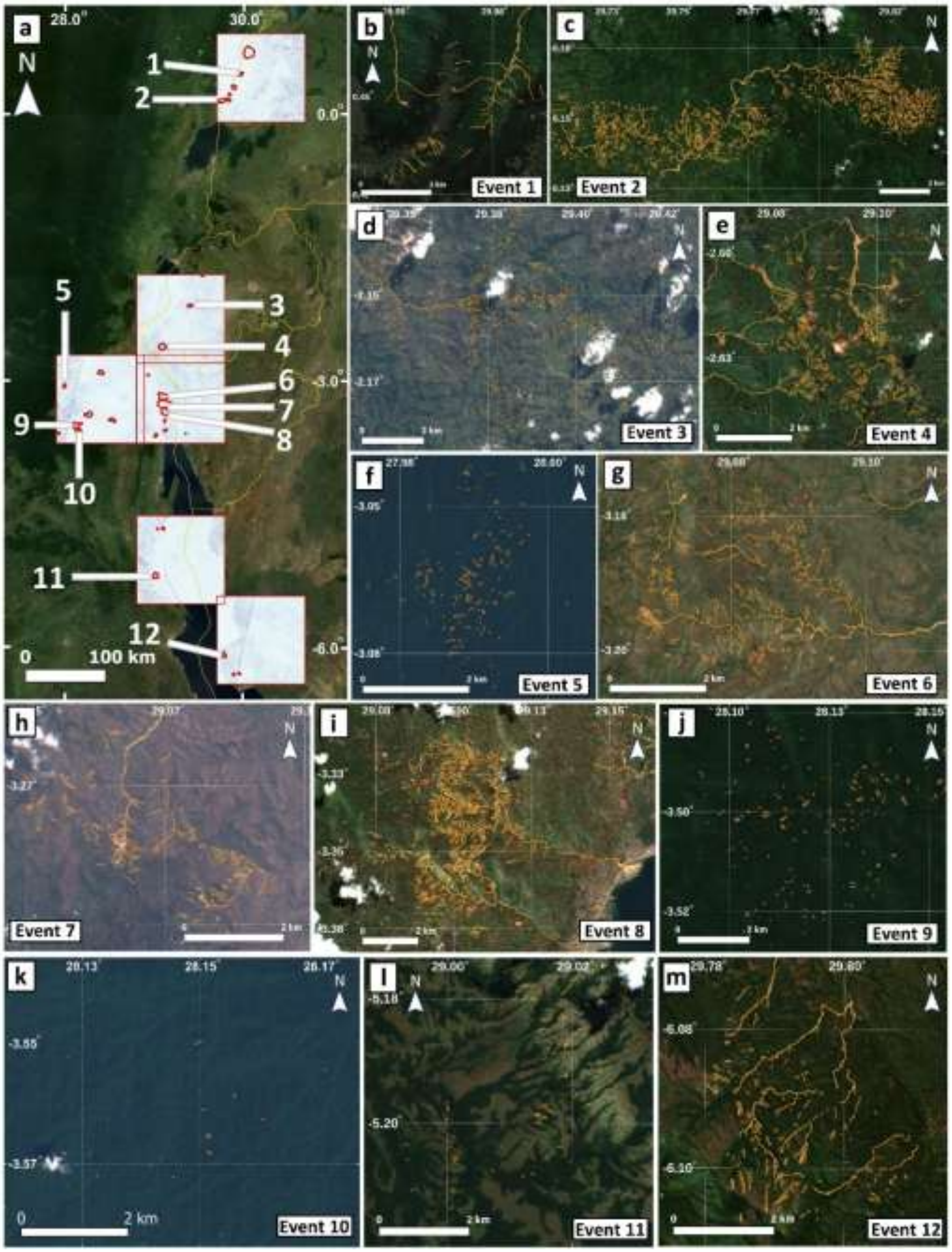

Fig. 4.2 | Overview of GH events detected with IPMCUMUL methodology. *(a) The 29 GH events detected with IPMCUMUL for the Sentinel-2 tiles: 35NRA, 35MQT, 35MPS, 35MQS, 35MQQ, 35MRP. Background: 25th percentile composite of cloud masked Sentinel-2 imagery from 2016-2020 created in Google Earth Engine (Gorelick et al., 2017). (b-m) 12 GH events with the manually mapped GH features in yellow used for validation. Events located in: (1-2) Uganda, Rwenzori Mountains, (3) Rwanda, Karongi, (4) Burundi, Cibitoke, (5-11) DRC, South-Kivu, (12) Tanzania, Mahale Mountains. The background for each event consists of a post-event Sentinel-2 image. Image credit: Contains modified Copernicus Sentinel data (2024).*

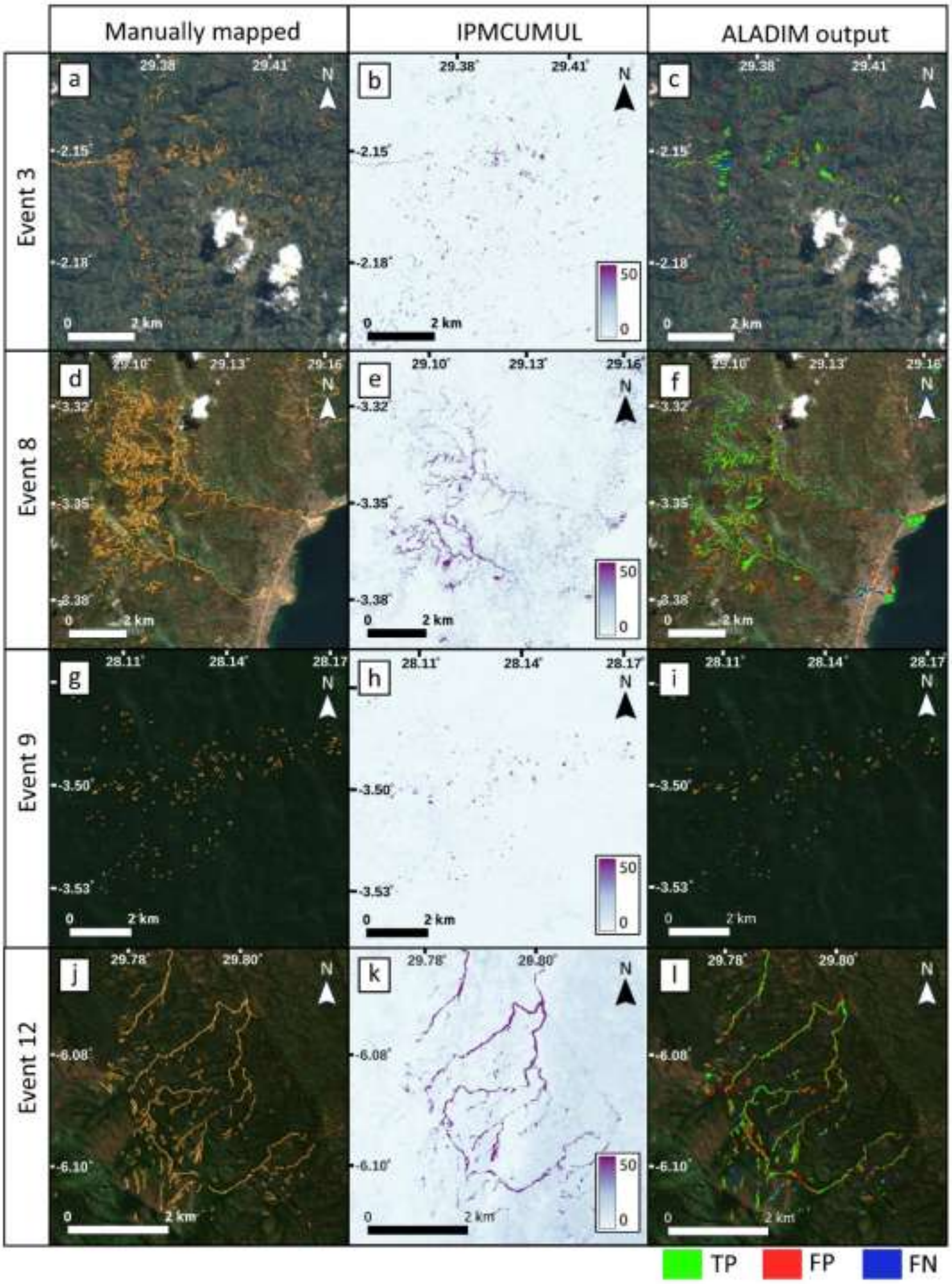

Fig. 4.3 | IPMCUMUL and ALADIM results in relation to manually delineated events for contrasting landscapes. *Left column: manually delineated GH events 3, 8, 9 and 12 in yellow with Sentinel-2 post-event imagery in the background (a, d, g, j). Middle column: IPMCUMUL maps per GH event (b, e, h, k). The darker the color, the higher the likelihood of a significant change within the pixel. Right column: ALADIM output per GH event (c, f, i, l). TP is true positive, FP is false positive and FN is false negative. The background consists of post-event Sentinel-2 images. Image credit: Contains modified Copernicus Sentinel data (2024).*

In terms of perspective (1) the automatization of the methodology for a systematic processing has to be investigated with a focus on reducing any manual step. For example, the outlining of the GH events and the manual identification of pre- and post event imagery before ALADIM application. Also it should aim to reduce or deal with noise sources and should focus on the clustering of pixels that are affected by the same change. (2) Optimization of the ALADIM application could be envisaged focusing on adapting input parameters to each event specifically. (3) Transferability of the methodology should yield positive results within other tropical regions as the methodology is based on the use of spectral indices that behave similarly in other regions when conditions are the same The use of our methodology in other areas, for example, arid areas or areas affected by seasonal snow cover remains to be investigated. (4)The addition of other optical satellite image time series to the workflow could be beneficial. For example, although lower in spatial resolution (30 m), the use of Landsat optical satellite time series could lengthen the timespan of the multi-temporal GH event inventory (~1985 to present). Increasing the time series length within our methodology will have implications on the usability of the methodology and remains to be investigated. (5) Currently, the methodology has no co-registration implemented. While we expect additional co-registration to have a limited effect on their detectability implementing a co-registration method such as Co-REGIS (Stumpf et al., 2018) however, could improve detection accuracy, especially when targeting smaller features. (6) The methodology has been optimized for large computation on High-Performance Computing clusters therefore it could be ported to cloud-computing facilities or other web-services that would allow for dissemination of the product to the public (Foumelis et al., 2019). (7) Another possible application lies in the detection of forest change patterns. The methodology shows potential to be adapted to detect forest cover change dynamics.

In addition to the perspectives associated with the methodological aspects, the results can potentially be used in light of GH event process understanding at a regional scale. We are able to identify impacted areas, give an estimate on the number of features within a GH event, and, for example, by using a DEM there is a potential to differentiate landslides from flash floods by means of their river network (Barták, 2010) allowing for analysis of connectivity and landslide/flash flood ratios. In addition, our results could be helpful in GH event process understanding at the regional scale. Source area and deposition area are both detected and could potentially allow for additional calculation of sediment budgets.

4.2 Landslide and flash flood event spatio-temporal analysis (WP2/3)

We develop a landslide and flash flood event inventory across a region of 640,000 km^2 covering a four-year period from mid 2017 to mid 2021 (Fig. 4.4a, b). We locate and date 101 events containing landslides or a combination of landslides and flash floods. Although all events occur within areas previously identified as highly susceptible to landslides each type shows a distinct spatial pattern (Fig. 4.4a). LD-LS and LM-LS events exhibit a scattered distribution across the study area. In contrast, FF-LS and HD-LS events are more spatially concentrated. FF-LS events mainly occur in the rejuvenated landscape between the two rift shoulders, where hillslopes are generally steeper due to erosion from migrating knickpoints associated with rifting activity (Depicker et al., 2021b). This rejuvenated landscape also features higher population densities and a larger proportion of cultivated land. HD-LS events predominantly occur in the forested regions of DR Congo; i.e., within the relict landscape of the rift (Depicker et al., 2021b), characterized by gentler slopes and a smaller human footprint.

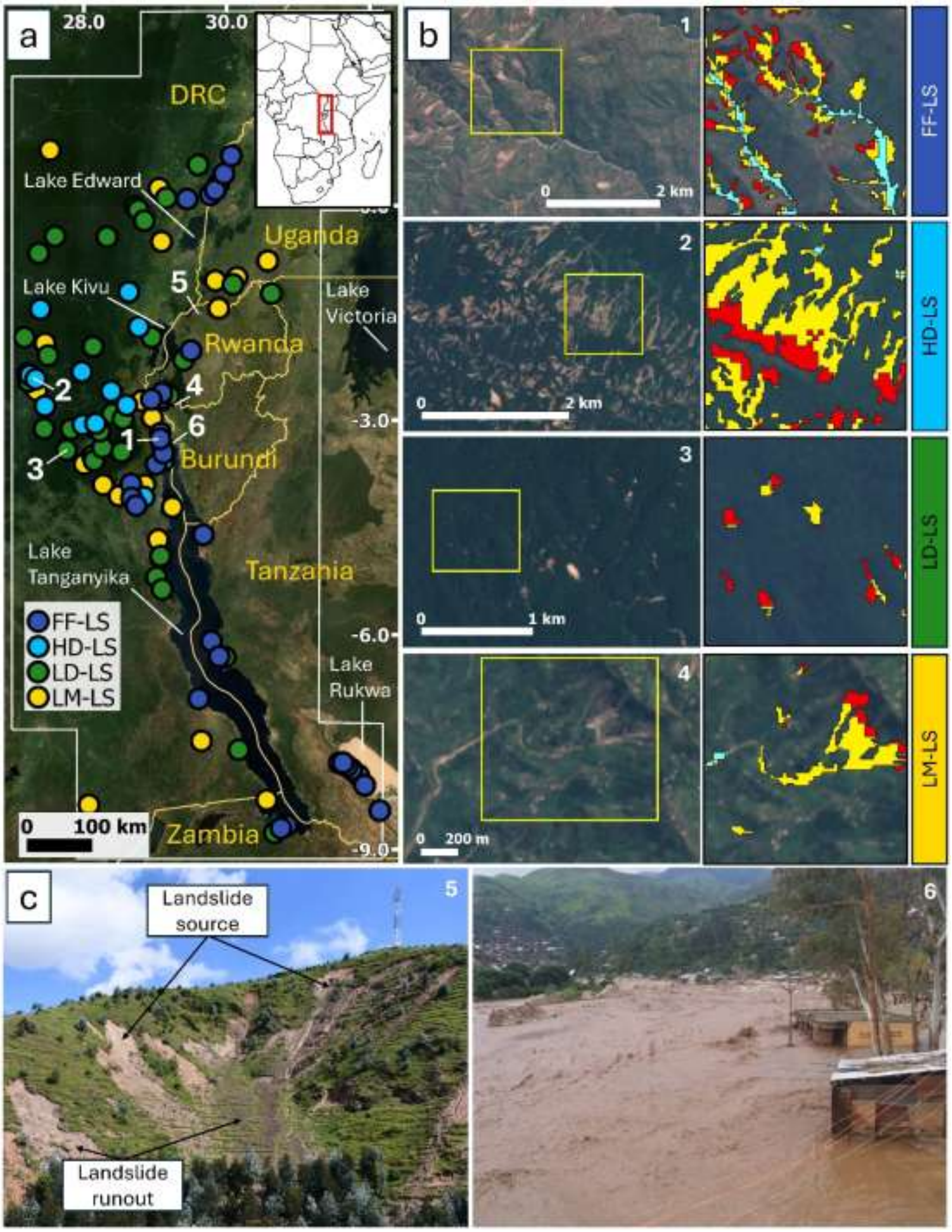

Fig. 4.4| Overview of landslide and flash flood events in the western branch of the East African Rift. ***(a)*** *The landslide and flash flood event inventory over the 2017-2021 period. The color of each dot indicates the event type. The white line delimits the investigated region where satellite images were processed. The white numbers indicate the location of the photographs or satellite images presented in panels b and c.* ***(b)*** *Close-up of each event type. Yellow squares highlight the location of the image on the right that shows the results of the automatic classification of landslide source (red), landslide runout (yellow) and flash flood (blue) used for identification and clustering of the events (Methods). Backgrounds are post-event Copernicus sentinel-2 imagery. The white numbers are associated with their location in panel a* ***(c)*** *Photographs showing co-occurring landslides that were part of a 2023*

event in northern Rwanda indicating landslide source and landslide runout locations (event [5]; Photograph by O. Dewitte; coordinates: 1.5223°S; 29.5793°E) and a devastating flash flood in the city of Uvira, Democratic Republic of the Congo (DRC), in 2020 (event [6]; Photograph by Kivu citizen-observer network; coordinates: 3.376664°S; 29.144055°E). The white numbers are associated with their location in panel a. FF-LS: flash flood and landslide event, HD-LS: high-density landslide event, LD-LS: low-density landslide events. LM-LS: low-magnitude landslide events. Image credit: Contains modified Copernicus Sentinel data (2025).

Landslides affected up to ~33.6 km^2 of terrain, while flash floods inundated at least 41.1 km^2 during the 2017-2021 period. We estimate that over this time, these compound events directly impacted a total of ~17,100 people and over 2,500 buildings. Including a 100 m buffer, the total affected population increases to ~84,600 people and over 19,000 buildings were impacted. FF-LS events stand out as those impacting the largest overall terrain area. There is variability in event occurrence between years that can partly be explained by the used methodology and rainfall patterns. Events typically occur during or shortly after the month of the seasonal rainfall peak, consistent with previous regional findings (Monsieurs et al., 2018). Regression models confirm rainfall preconditioning observed trends with high accuracies. FF-LS short- (up to 1 month), mid-(up to 6 months) and long-term (up to 1 year) rainfall metrics consistently indicate wetter-than-average conditions. For HD-LS, we find that short-term (up to 1 month) rainfall metrics indicate wetter-than-average conditions, and transistion to long-term drier-than-average conditions with a strong emphasize on the climatological metrics (up to 1 year). The LD-LS and LM-LS event models show short-term wetter-than-average conditions (up to 1 month). LD-LS event models do not show a clear consistent trend for the mid- to long-term.

FF-LS events occur in topographic settings shaped by long-term rejuvenation of the landscape, that is, areas with steeper slopes and higher flow convergence that promote runoff concentration and flash flood occurrence (O'Connor and Costa, 2004; Merz and Blöschl, 2009). In addition, cultivated and deforested lands dominate in the rejuvenated landscapes, leading to higher soil erosion rates and reduced regolith depth (Depicker et al., 2021b). We discuss that long-term wetter-than-average rainfall preconditioning in these regions increases the likelihood of co-occurring landslides and flash floods (Fig. 4.5a). HD-LS mainly occur in relict – often forested – landscapes (Fig.4b). These landscapes are less steep, geomorphologically older, and less impacted by human-induced soil erosion. We discuss that drier-than-average conditions in these forested landscapes can trigger failure at greater depths, causing a uniform decrease in slope stability and, therefore, landslides that tend to affect larger areas with limited flash flooding. LD-LS events are the most frequent type in the region, preliminary driven by short-term rainfall. Their wide spatial distribution suggests they represent the background event type (Fig. 4.5c). LM-LS events also highlight the importance of short-term rainfall but indicate additional long-term preconditioning effects. However, since LM-LS is a mixed category that includes both flash flood and non-flash flood events, interpretations should be made with caution.

Ultimately, we demonstrate that the combination of preconditioning rainfall, geological history and human activities modulate geo-hydrological hazard events within this tropical region of East Africa. In particular, it can promote the co-occurrence of landslide and flash flood events in more densely populated areas. We also show that these compounding hazards occur frequently and consistently; emphasizing that such everyday processes lead to cumulative impacts that should not be overlooked. Landslides and flash floods often make the highlight only after causing substantial human and infrastructure losses, leaving many events largely under-reported in remote regions, especially in the Global South (Stein et al., 2024). Our study highlights the compounding nature of landslides and flash floods and emphasizes the complexities underlying their occurrence. The compounding of landslides and flash floods is not unique as evidenced by cases in diverse environments and climates (Ozturk et al., 2018; Aristizábal et al., 2020; Alcantara et al., 2023). However, we find that preconditioning periods longer-than-usually investigated (up to a year) are important for explaining the dynamics in co-occurrence of landslides and flash floods, at least in the African tropics.

These findings offer valuable insights for disaster risk management. Integrating knowledge of rainfall over longer periods than is typically considered in hazard and risk prediction, early-warning systems, and disaster risk reduction strategies could boost their effectiveness (van Westen et al., 2008; Guzzetti et al., 2020; Corral et al., 2019). For example, preconditioning rainfall over our specified time periods could be analyzed in combination with weather forecasts to highlight the potential increased susceptibility to certain event types, especially when combining this information with land use/land cover data. The need to incorporate the concept of compounding within disaster risk reduction strategies and multi-hazard early-warning systems has been highlighted recently in Rwanda due to the devasting co-occurrence of both landslides and flash floods (Idukunda et al., 2025). Further research should aim to link the compounding hazard dynamics with their associated impacts to further aid disaster risk reduction strategies.

Beyond the role of climate, we demonstrate the key importance of interacting natural and human-influenced geoenvironmental drivers in shaping hazards. The legacy of the role of human activities on hazard occurrence, and consequently risk, remains underexplored in the literature (Depicker et al., 2021a; Aristizábal et al., 2025). Although focused on a geodynamically specific region, our study evidences the role of geological history on hazard patterns, here via the landscape rejuvenation associated with rift formation. These findings highlight that a fundamental understanding of geomorphology, in combination with land use and climate science, is essential to grasp the complexities of geo-hydrological hazard co-occurrence (Arango-carmona et al., 2025; Yanites et al., 2025).

Future projections over the region indicate an increase in rainfall intensities (Seneviratne et al., 2021), potential increases in drought length (Trisos et al., 2022), and shifts in timing, duration and magnitude of rain seasonality (Trisos et al., 2022; Palmer et al., 2023). Climate whiplash occurrence is also expected to increase in this part of Africa (Chen et al., 2022). While an increase in rainfall intensity does not necessarily lead to more landsliding over the long term (Saito et al., 2014), such changes in rainfall patterns may increase the incidence of more impactful compounding geo-hydrological hazard events. Continuous data acquisition and further analysis are therefore essential to better understand and anticipate the impacts of these climate change trajectories.

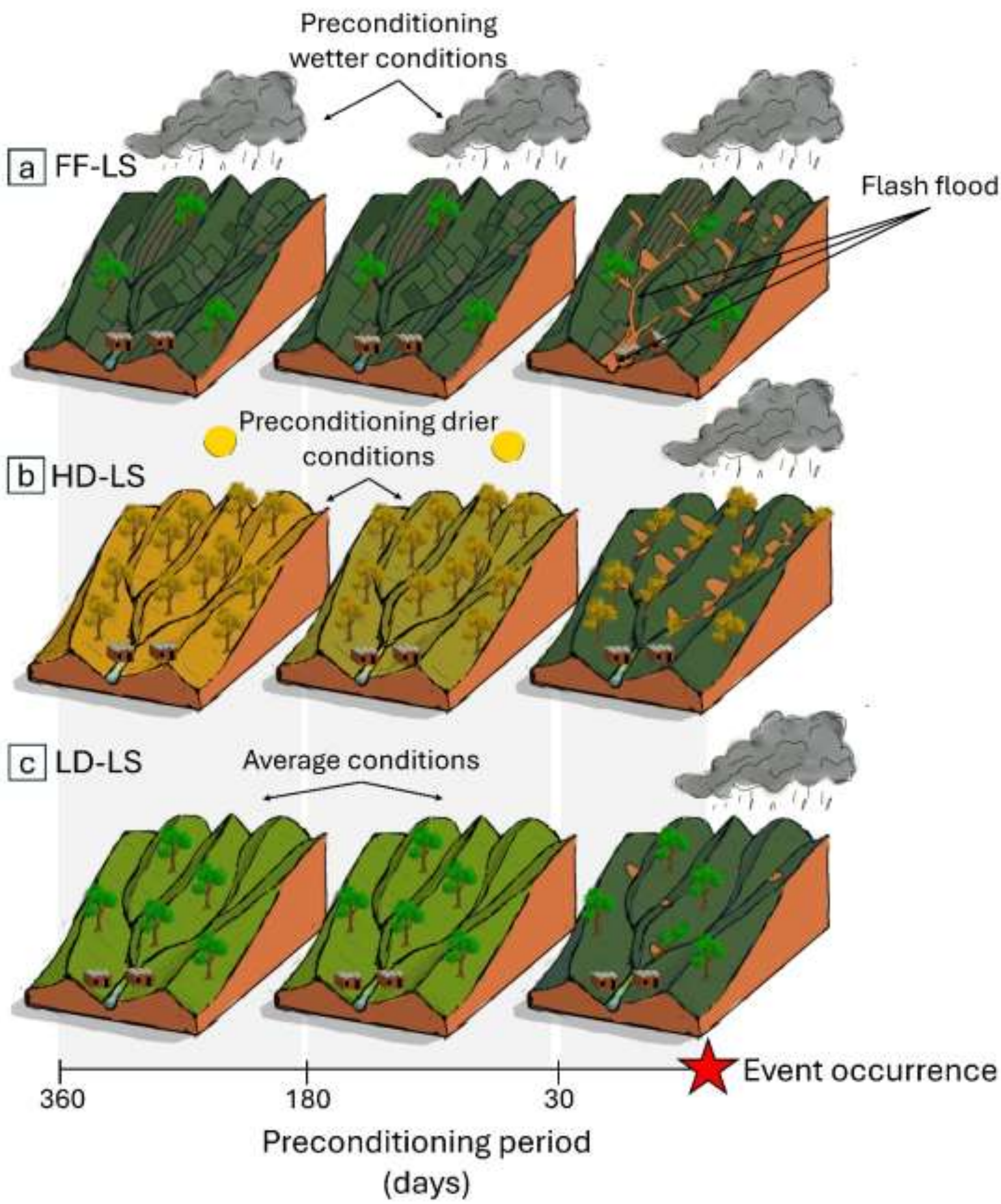

Fig. 4.5 | Conceptual model of the compounding nature of landslide and flash flood event occurrence in the western branch of the East African Rift. *The models highlight the influence of preconditioning rainfall conditions on different event types. Light green represents normal conditions, dark green represents wetter-than-average conditions, and yellow represents drier-than-average conditions (with darker yellow shades showing more intense dryness).* ***(a)*** *Landslide and flash flood events (FF-LS) are commonly occurring in steeper landscapes that are also more cultivated. The events show wetter-than-average preconditioning over the full timeseries* ***(b)*** *High-density landslide events (HD-LS) occur predominantly in forested regions and show drier-than-average preconditioning over periods up to a year. The long term trends are more pronounced than the trends up to six months* ***(c)*** *Low-density landslide events (LD-LS) are the more common event type, mainly associated with short-*

term wetter-than-average preconditioning (up to one month). FF-LS: landslide and flash flood event, HD-LS: high-density landslide events, LD-LS: low-density landslide events.

We present a new inventory that offers valuable insights into the dynamics of co-occurring landslides and flash flood in a data-scarce region, that are potentially applicable in other tropical regions. By examining these hazards through the 'compound event' lens – a approach rarely applied in this context – we achieve a deeper understanding of their dynamics. Moreover, our study addresses a critical gap in global impact data, as spatially and temporally explicit geo-hydrological hazard data in the tropics is often lacking in compound event and multi-hazard research (Kreibich et al., 2022; Ward et al., 2020).

4.3 Landslide and flash flood event future analysis (WP4)

Our preliminary analysis using rainfall, land use and population models from ISIMIP3a (historical) and ISIMIP3b (future) highlights what we find in literature. Wetness in the region is increasing towards the future (Fig. 4.6) including higher intensities. This increase in wetness is higher under more pessimistic future scenarios. The ssp3.70 and ssp5.85 scenarios are associated with a reduction in forest cover and an increased population pressure (in particular for ssp3.70). Putting this increased wetness and reduced soil infiltration capacity through land use change in relation with the occurrence of flash flood vents, we can definitely expect an increase in their occurrence. As for the landslides, their occurrence depends on the availability of soil/regolith/sediment in the landscape. An increase of wetness will definitely favour their occurrence whenever hillslope material is available. However, such peak of landslide activity will not last indefinitely. Once the material is washed away, the incidence of landsliding will be reduced (Parker et al., 2016). Land use change, in association with deforestation and population pressure (road construction, mining activities, agricultural terracing and urbanisation) will increase the incidence of landsliding, also for a certain period of time constrained by the availability of hillslope material. These temporary changes in landslide occurrence have already been demonstrated for some parts of our study area (Depicker et al., 2021a, 2024, Maki Mateso et al., 2023; Sibomana et al., 2025. Therefore, given the overall increase in wetness and the increase in population pressure a shift towards the co-occurrence of landslides and flash floods could be expected in regions that face an increasing human footprint and a reduction of natural vegetation. In addition, the increased amount of population under pessimistic scenarios increases the change of exposure and hence higher impacts; as exemplified by examining the Uvira 2020 landslide and flash flood event.

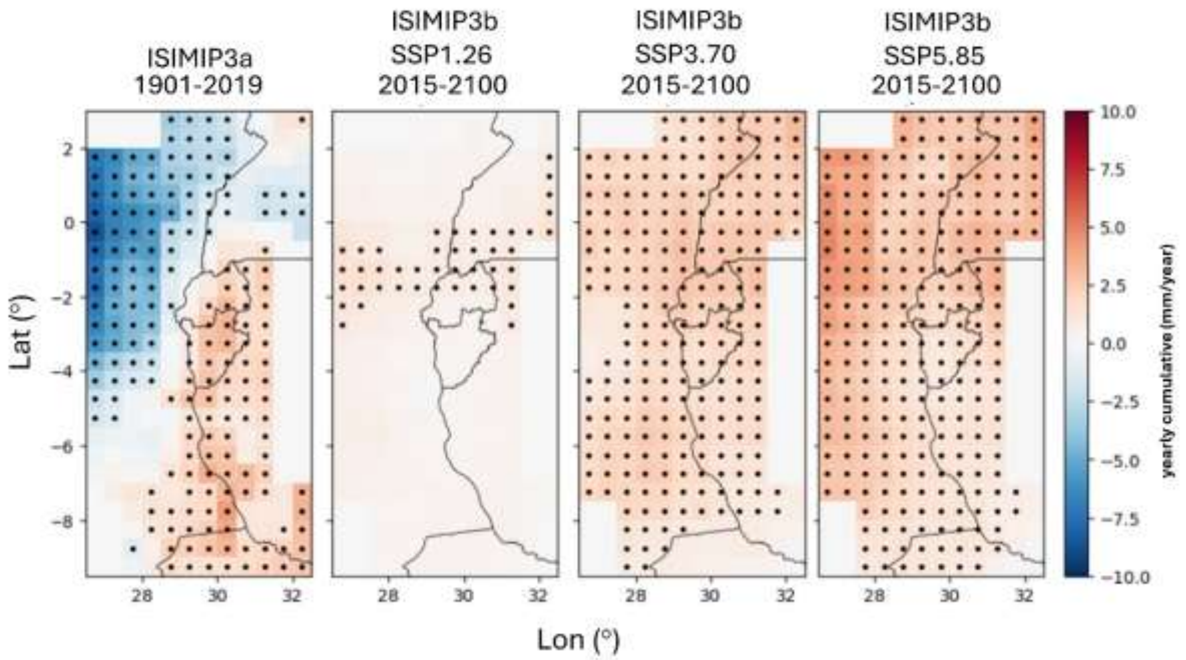

Fig. 4.6 | Spatio-temporal trends of yearly sums over historical and future ISIMIP models/projections. Each pixels shows the slope of the linear regression for that specific pixel. A black dot indicates if the linear fit is significant ($p < 0.05$). The stronger the trend, the darker the color. Blue indicates a negative trend, whereas red indicates a positive trend.

On a local level, our preliminary analysis shows that rainfall trends have not significantly changed over the historical period (also visible in 4.6a). However, we see that population has expanded rapidly, specifically on the alluvial plains; a patterns that is visible all throughout the city of Uvira (Fig. 4.7). This pattern of increased exposure is probably at the crossroad of a (partial) ignorance of the constrains of the environment and the weakness in implementing planning policies While rainfall and land transformation trends seem minimal, this shows that an increase in impact would mainly be a result of an increase in population.

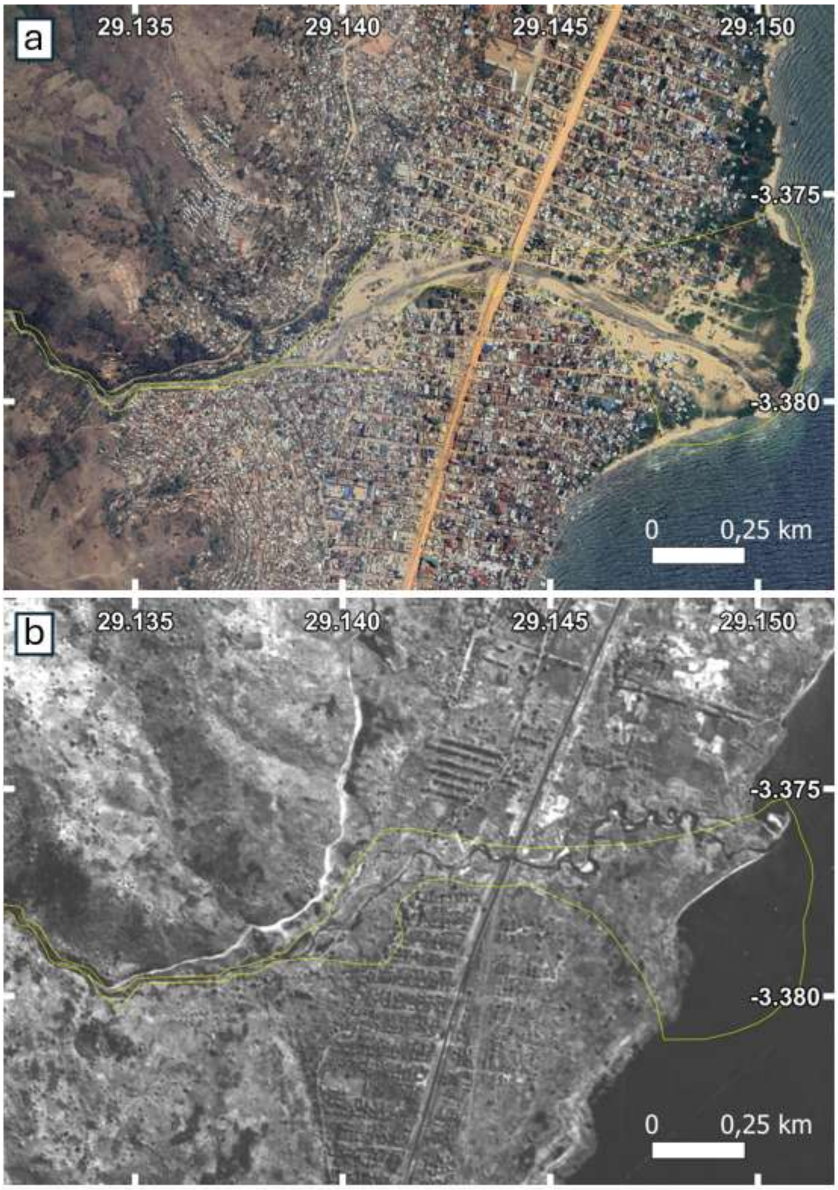

Fig. 4.7 | Comparison of Google Earth imagery with 1959 historical aerial photographs . (a) Google Earth imagery (30-08-2025) after the Uvira 2020 event **(b)** 1959 photograph .

5. DISSEMINATION AND VALORISATION

Dissemination and valorisation mainly consist of publication of papers, conference talks, and the presentation of posters. Teaching activities at the VUB were done and material was created with data and insight from GEOTROP. A PhD defence presentation was held. And the supervision of students and internships complete the direct outputs of the project. In addition, a Symposium entitled "Natural hazard and land degradation risks: towards operational land use management and disaster risk reduction" was planned to be set up son 20, 21, 22 and 23 May 2025 in Rwanda 2025. This Symposium would gather 100 participants (scientist and stakeholders – mostly from Rwanda, DRC, Burundi and Uganda). GEOTROP was strongly involved in the organization of this event and, in addition, several training sessions led by GEOTROP would be delivered. However, initially postponed, the event had to be cancelled due to the volatile geopolitical situation in the region. In addition to the direct input of GEOTROP, the research activities led within the project provided support to other research activities associated with other projects. These extras appear in the form of publications, conferences and student support. They are highlighted with a (*) hereunder.

5.1 Presentation at (inter)national conferences

- Dewitte, O., Deijns, A.A.J. Dille, A., Laghmouch, M., Michellier, C., Smets, B., Kervyn, F., 2025. Geo-hydrological hazard risks in changing tropical Africa: natural or human-induced processes? 103rd Journée Luxembourgeoises de Géodynamique, Luxembourg, Luxembourg, 19-21 November 2025 (Oral).
- Deijns, A.A.J., Thiery, W., Michéa, D., Dille, A., Maki Mateso, J.-C., Malet, J.-P., Mugisho Bachinyaga, J., Sekajugo, J., Sibomana; P., Zscheischler, J., Kervyn, F., Dewitte, O., 2025. Compounding landslides and flash floods in tropical East Africa. Journée Aléas Gravitaires. JAG 2025, Aosta, Italy, 23-25 September 2025 (Oral)
- *Sibomana, P., Dewitte, O., Van den Dries, P., Deijns, J.A., and Vanmaercke, M., 2025. Effect of land use on soil moisture in a landslide-prone tropical environment: field-based monitoring in Rwanda. SSB Day of the Young Soil Scientists 2025, Brussels, Belgium, https://www.soilbelgium.be/wpcontent/uploads/2025/03/DYSS2025_PosterProgram.pdf.Antoine IAG
- Deijns, A., Thiery, W., Déprez, A., Dille, A., Malet, J.-P., Maki Mateso, J.-C., Michéa, D., Mugisho Bachinyaga, J., Sekajugo, J., Sibomana, P., Zscheischler, J., Kervyn, F., Dewitte, O., 2025. How preconditioning rainfall controls landslide and flash flood events in tropical East Africa. In EGU General Assembly Conference – EGU25-10781, Vienna, Austria, 27-april – 2 may(Oral).
- Deijns, A.A.J., Dewitte, O. Thiery, W. Michéa, D. Depréz, A. d'Oreye, N. Malet, J.-P., Kervyn, F. 2024. A novel workflow to detect landslides and flash floods in large unexplored tropical regions. In Geologica Belgica Luxemburga, Liège, Belgium 13 September (Oral)
- Deijns, A.A.J., Thiery, W., Kervyn, F., Malet, J.-P., d'Oreye, N., Dille, A., Zscheischler, J., Dewitte, O., 2024. Regional landslide and flash flood compound event analysis in the African tropics. Natural Hazards and Risks in a Changing World, Amsterdam, The Netherlands, 12-13 June. (Oral)

- Dewitte, O., Deijns, A.A.J., Dille, A., Kervyn, F., Laghmouch, M., Michellier, C., Smets, B., 2024. Geo-hydrological hazard risks in changing tropical African environments: natural or unnatural processes? Belgian Science for Climate Action Conference, Brussels, Belgium, 19-20 February (Poster).
- Deijns, A.A.J., Thiery, W., Kervyn, F., Malet, J-.P., d'Oreye, N., Dille, A., Zscheischler, J., Dewitte, O., 2024. Landslide and flash flood event inventories to understand the impact of climatic extremes. In Belgian Science for Climate Action Conference. P19 Brussels, Belgium, 19 February (Poster)
- *Mugisho Bachinyaga, J., Deijns, A.A.J., Ilombe Mawe, G., Kervyn, F., Michellier, C., Mugaruka Bibentyo, T., Nkere Buliba, J., Nzolang, C., Smets, B., Dewitte, O., 2023. Les crues soudaines d'avril 2020 à Uvira, RD Congo : histoire d'un événement géo-hydrologique à l'impact extrême. Assemblée générale de l'AFGP 2024, Avignon, France, 25-27 January 2024 (Poster).
- *Kervyn, F., Dewitte, O., Michellier, C., Smets, B., Laghmouch, M., Ashepet, M., Deijns, A.A.J, Dille, A., Barrière, J., Ilombe Mawe, G., Kanyiginya, V., Katembo, H., Maki Mateso, J.-C., Mugaruka Bibentyo, T., Mafuko Nyandwi, B., Nsabimana, J., d'Oreye, N., Oth, A., Subira, J., Muhashi Habiyaremye, F., Ndayisenga, A., Nzolang C., Twongyirwe, R., 2023. The challenge of sustainable development facing natural hazard risks in an African mountainous region. Géologie et ressources naturelles en Afrique centrale, impact sociétal et développement durable – Conférence internationale, Brazaville, Republic of the Congo, 05–07 December 2023 (Oral).
- Deijns, A.A.J., Michéa, D., Deprez, A., Dewitte, O., Kervyn, F., Thiery, W., Malet J-.P., 2023. Detecting landslides and flash flood events in data-scarce regional contexts: a methodology developed over the East African tropics. In World Landslide Forum 6 – P4.8, Florence, Italy, 14-17 November (Poster)
- *Muheki, D., Deijns, A.A.J., Bevacqua, E., Messori, G., Zscheischler, J., Thiery, W., 2023. The perfect storm? Concurrent climate extremes in East Africa. In EGU General Assembly Conference - EGU23-3172, Vienna, Austria, 23-28 April (Poster)
- Deijns, A.A.J., Deprez, A., Michéa, D., Dewitte, O., Kervyn, F., Thiery, W., Malet J-.P., 2023. Regional Detection of Landslides and Flash Flood Events in the East African Rift. In EGU General Assembly Conference - EGU23-7832, Vienna, Austria, 23-28 April (Oral)
- Deijns, A.A.J., Dewitte, O., Thiery W., Malet J.P., d'Oreye N., Kervyn F, 2023. Using remote sensing to understand landslide and flash flood event occurrence in a changing tropical East Africa. In RMCA Geowebinar , Tervuren, Belgium, 31 March (online-presentation)
- Deijns, A.A.J., Michea D., Deprez A., Dewitte O., Kervyn F., Thiery W., Malet J.P., 2022. Regional landslide and flash flood event detection. In AGU fall meeting, NH23C-05, Chicago, USA, 12-16 December (online-presentation).

5.2 Teaching activities

- [2025] Natural Hazards | invited guest lecture | Utrecht University
- [2023-2024] Environmental programming in python | VUB
- [2023-2024] Land-Climate Dynamics remote sensing practical | VUB

5.3 Supervision, training and coaching

- *[2025-2026] Theo Naïm Vandamme from Belgium| MSC student in geography at VUB. Coaching MSc thesis
- *[2025] Anthony Bastier from France| MSc student at BBB ~5 month internship
- *[2025] Pascal Sibomana from Rwanda| PhD student at ULiège, KUL Leuven and RMCA. Collaboration and coaching
- *[2023-2025] Violet Kanyiginya from Uganda | PhD student at the RMCA and VUB - Collaboration and coaching
- [2020-2024] Axel Deijns (Full-time PhD student – GEOTROP project, Department of Earth Sciences, RMCA, and Department of Water and Climate, VUB, Belgium). "Compounding landslides and flash floods in tropical East Africa: a remote sensing perspective". Supervisors: Olivier Dewitte (RMCA), François Kervyn (RMCA) and Wim Thiery (VUB). Defended 03 December 2024.

5.4 Research stays and international collaborations

- [2024] Research stay at UFZ - Helmholtz-Centre for Environmental Research under Jakob Zscheischler, Germany, 3 Mar – 6 Apr 2024
- [2024] We have submitted two contributions (results from GEOTROP) to a multi-hazard community paper coordinated by IIASA and VU Amsterdam that will try to assess challenges for disaster risk management in the context of multi-hazard risk on a global scale. These contributions focus on case studies on DRC and Uganda. They have been done in partnership with the Université Officielle de Bukavu (DRC) and the Mountains of Moon University Uganda). These will lead to two community papers (foreseen in 2026). EGU presentation on their progress: https://doi.org/10.5194/egusphere-egu25-17791

6. PUBLICATIONS

6.1 Scientific papers

- Deijns, A. A. J., Malet, J.-P., Michéa, D., Déprez, A., Kervyn, F., Thiery, W., and Dewitte, O., 2024: A semi-supervised multi-temporal landslide and flash flood event detection methodology for unexplored regions using massive satellite image time series, ISPRS J. Photogramm. Remote Sens., 215, 400–418, https://doi.org/10.1016/j.isprsjprs.2024.07.010
- *Muheki, D., Deijns, A. A. J., Bevacqua, E., Messori, G., Zscheischler, J., and Thiery, W., 2024: The perfect storm? Co-occurring climate extremes in East Africa, Earth Syst. Dynam., 15, 429–466, https://doi.org/10.5194/esd-15-429-2024.
- *Niyokwiringirwa, P., Lombardo, L., Dewitte, O., Deijns, A.A.J., Wang, N., van Westen, C., Tanyas, H., 2024. Event-based rainfall-induced landslide inventories and rainfall thresholds for Malawi, Landslides. https://doi.org/10.1007/s10346-023-02203-7.
- *Kanyiginya, V., Twongyirwe, R., Kagoro-Rugunda, G., Mubiru, D., Sekajugo, J., Mutyebere, R., Deijns, A.A.J., Kervyn, M., Dewitte, O., 2023. Inventories of natural hazards in under-reported regions: a multi-approach insight from a tropical mountainous landscape. Afr. Geogr. Rev. https://doi.org/10.1080/19376812.2023.2280589
- Deijns, A.A.J., Dewitte, O., Thiery, W., d'Oreye, N., Malet, J.-P., and Kervyn, F., 2022. Timing landslide and flash flood events from SAR satellite: a regionally applicable methodology illustrated in African cloud-covered tropical environments, Nat. Hazards Earth Syst. Sci., 22, 3679–3700, https://doi.org/10.5194/nhess-22-3679-2022.

6.2 Scientific code and data

- SAR Timing –GH Event Inventories. Scripts. https://zenodo.org/records/7198322, https://doi.org/10.5281/zenodo.7198321. Authors: Deijns, A.A.J., Dewitte, O., Thiery, W., d'Oreye, N., Malet, J.-P., Kervyn, F., 2022
- SAR Timing -Scripts. https://zenodo.org/records/7198346, https://doi.org/10.5281/zenodo.7198346 Authors: Deijns, A.A.J., Dewitte, O., Thiery, W., d'Oreye, N., Malet, J.-P., Kervyn, F., 2022

6.3 Scientific papers in review

- Deijns, A.A.J, Thiery, W., Michéa, D., Dille, A., Maki Mateso J.-C., Malet J.-P., Mugisho Bachinyaga, J., Sekajugo, J., Sibomana, P., Zscheischler, J., Kervyn, F., Dewitte, O., *in review,* Nature Communications. The compounding nature of landslides and flash floods in tropical East Africa
- *Mugaruka Bibentyo, T., Dille, A., Deijns, A.A.J., Nzolang, C., Dewaele, S., Dewitte, O., *in review*. Geomorphological, lithological and age controls on the size and mobility of deep-seated landslides in the North Tanganyika - Kivu Rift region, Africa. Geomorphology
- *Kanyiginya, V., Deijns, A.A.J., Mubiru, D., Kagoro-Rugunda, G., Kervyn, M., Twongyirwe, R., Dewitte, O., *in review*. Spatio-temporal characterization of flash floods in small data-scarce watersheds of the tropical Kigezi highlands, southwestern Uganda. Natural Hazards.

6.4 Phd Thesis

- Deijns A.A.J., 2024. Compounding landslides and flash floods in tropical East Africa a remote sensing perspective, Vrije Universiteit Brussels and Royal Museum for Central Africa, Brussels.

REFERENCES

Ageet, S., Fink, A. H., Maranan, M., Diem, J. E., Hartter, J., Ssali, A. L., and Ayabagabo, P.: Validation of Satellite Rainfall Estimates over Equatorial East Africa, J. Hydrometeorol., 23, 129–151, https://doi.org/10.1175/JHM-D-21-0145.1, 2022.

Alcantara, E., Marengo, J. A., Mantovani, J., Londe, L. R., San, R. L. Y., Park, E., Lin, Y. N., Wang, J., Mendes, T., Cunha, A. P., Pampuch, L., Seluchi, M., Simões, S., Cuartas, L. A., Goncalves, D., Massi, K., Alvalá, R., Moraes, O., Filho, C. S., Mendes, R., and Nobre, C.: Deadly disasters in southeastern South America: flash floods and landslides of February 2022 in Petrópolis, Rio de Janeiro, Nat. Hazards Earth Syst. Sci., 23, 1157–1175, https://doi.org/10.5194/nhess-23-1157-2023, 2023.

Amatya, P., Scheip, C., Déprez, A., Malet, J. P., Slaughter, S. L., Handwerger, A. L., Emberson, R., Kirschbaum, D., Jean-Baptiste, J., Huang, M. H., Clark, M. K., Zekkos, D., Huang, J. R., Pacini, F., and Boissier, E.: Learnings from rapid response efforts to remotely detect landslides triggered by the August 2021 Nippes earthquake and Tropical Storm Grace in Haiti, Nat. Hazards, 118, 2337–2375, https://doi.org/10.1007/s11069-023-06096-6, 2023.

Andréassian, V.: Waters and forests: From historical controversy to scientific debate, J. Hydrol., 291, 1–27, https://doi.org/10.1016/j.jhydrol.2003.12.015, 2004.

Arango-carmona, M. I., Voit, P., Hürlimann, M., Aristizábal, E., and Korup, O.: Hillslope torrential hazard cascades in tropical mountains, Nat. Hazards Earth Syst. Sci., 25, 3641–3663, 2025.

Aristizábal, E., Arango Carmona, M. I., Gómez, F. J., López Castro, S. M., De Villeros Severiche, A., and Riaño Quintanilla, A. F.: Hazard Analysis of Hydrometeorological Concatenated Processes in the Colombian Andes, in: Advances in Natural Hazards and Hydrological Risks: Meeting the Challenge, 7–10, 2020.

Aristizábal, E., Sanchez Patiño, O., and Korup, O.: Landslide timing and rainfall regimes in a rapidly urbanizing tropical mountain valley in Colombia [preprint], 0–21, https://doi.org/https://doi.org/10.21203/rs.3.rs-7442810/v1, 2025.

Atefi, M. R. and Miura, H.: Detection of Flash Flood Inundated Areas Using Relative Difference in NDVI from Sentinel-2 Images: A Case Study of the August 2020 Event in Charikar, Afghanistan, Remote Sens., 14, https://doi.org/10.3390/rs14153647, 2022.

Bai, J.: Estimating multiple breaks one at a time, Econom. Theory, 13, 315–352, https://doi.org/10.1017/s0266466600005831, 1997.

Balzano, B., Tarantino, A., and Ridley, A.: Preliminary analysis on the impacts of the rhizosphere on occurrence of rainfall-induced shallow landslides, 16, 1885–1901, https://doi.org/10.1007/s10346-019-01197-5, 2019.

Balzter, H.: Forest mapping and monitoring with interferometric synthetic aperture radar (InSAR), Prog. Phys. Geogr., 25, 159–177, https://doi.org/10.1177/030913330102500202, 2001.

Banfi, F. and De Michele, C.: Temporal Clustering of Precipitation Driving Landslides Over the Italian Territory, Earth's Futur., 12, https://doi.org/10.1029/2023EF003885, 2024.

Barrett, B., Whelan, P., and Dwyer, N.: The Use of C- and L-Band Repeat-Pass Interferometric SAR Coherence for Soil Moisture Change Detection in Vegetated Areas, Open Remote Sens. J., 5, 37–53, https://doi.org/10.2174/1875413901205010037, 2012.

Barták, V.: How to extract river networks and catchment boundaries from DEM: a review of digital terrain analysis techniques, J. Landsc. Stud., 2, 57–68, 2010.

Beck, H. E., Wood, E. F., Pan, M., Fisher, C. K., Miralles, D. G., Van Dijk, A. I. J. M., McVicar, T. R., and Adler, R. F.: MSWep v2 Global 3-hourly 0.1° precipitation: Methodology and quantitative assessment, Bull. Am. Meteorol. Soc., 100, 473–500, https://doi.org/10.1175/BAMS-D-17-0138.1, 2019.

Behling, R., Roessner, S., Kaufmann, H., and Kleinschmit, B.: Automated spatiotemporal landslide mapping over large areas using rapideye time series data, Remote Sens., 6, 8026–8055, https://doi.org/10.3390/rs6098026, 2014.

Behling, R., Roessner, S., Golovko, D., and Kleinschmit, B.: Derivation of long-term spatiotemporal landslide activity—A multi-sensor time series approach, Remote Sens. Environ., 186, 88–104, https://doi.org/10.1016/j.rse.2016.07.017, 2016.

Bevacqua, E., De Michele, C., Manning, C., Couasnon, A., Ribeiro, A. F. S., Ramos, A. M., Vignotto, E., Bastos, A., Blesić, S., Durante, F., Hillier, J., Oliveira, S. C., Pinto, J. G., Ragno, E., Rivoire, P., Saunders, K., van der Wiel, K., Wu, W., Zhang, T., and Zscheischler, J.: Guidelines for Studying Diverse Types of Compound Weather and Climate Events, Earth's Futur., 9, 1–23, https://doi.org/10.1029/2021EF002340, 2021.

Bevington, A., Gleason, H., Giroux-Bougard, X., and De Jong, J. T.: A Review of Free Optical Satellite Imagery for Watershed-Scale Landscape Analysis, Conflu. J. Watershed Sci. Manag., 2, 1–22, https://doi.org/10.22230/jwsm.2018v2n2a18, 2018.

Bhuyan, K., Tanyaş, H., Nava, L., Puliero, S., Meena, S. R., Floris, M., van Westen, C., and Catani, F.: Generating multi-temporal landslide inventories through a general deep transfer learning strategy using HR EO data, Sci. Rep., 13, 162, https://doi.org/10.1038/s41598-022-27352-y, 2023.

Borga, M., Stoffel, M., Marchi, L., Marra, F., and Jakob, M.: Hydrogeomorphic response to extreme rainfall in headwater systems: Flash floods and debris flows, J. Hydrol., 518, 194–205, https://doi.org/10.1016/j.jhydrol.2014.05.022, 2014.

Broeckx, J., Vanmaercke, M., Duchateau, R., and Poesen, J.: A data-based landslide susceptibility map of Africa, Earth-Science Rev., 185, 102–121, https://doi.org/10.1016/j.earscirev.2018.05.002, 2018.

Burbank, D. W., Leland, J., Fielding, E., Anderson, R. S., Brozovic, N., Reid, M. R., and Duncan, C.: Bedrock incision, rock uplift and threshold hillslopes in the northwestern himalayas.pdf, Nature, 379, 505–510, https://doi.org/10.1038/379505a0, 1996.

Burrows, K., Walters, R. J., Milledge, D., Spaans, K., and Densmore, A. L.: A new method for large-scale landslide classification from satellite radar, Remote Sens., 11, https://doi.org/10.3390/rs11030237, 2019.

Burrows, K., Walters, R. J., Milledge, D., and Densmore, A. L.: A systematic exploration of satellite radar coherence methods for rapid landslide detection, Nat. Hazards Earth Syst. Sci., 20, 3197–3214, https://doi.org/10.5194/nhess-20-3197-2020, 2020.

Burrows, K., Milledge, D., Walters, R. J., and Bellugi, D.: Integrating empirical models and satellite radar can improve landslide detection for emergency response, Nat. Hazards Earth Syst. Sci., 21, 2993–3014, https://doi.org/10.5194/nhess-21-2993-2021, 2021.

Burrows, K., Marc, O., and Remy, D.: Using Sentinel-1 radar amplitude time series to constrain the timings of individual landslides: a step towards understanding the controls on monsoon-triggered landsliding, Nat. Hazards Earth Syst. Sci., 22, 2637–2653, https://doi.org/10.5194/nhess-22-2637-2022, 2022.

Caballero, I., Ruiz, J., and Navarro, G.: Sentinel-2 satellites provide near-real time evaluation of catastrophic floods in the West Mediterranean, Water, 11, https://doi.org/10.3390/w11122499, 2019.

Catane, S. G., Abon, C. C., Saturay Jr., R. M., Mendoza, E. P. P., and Futalan, K. M.: Landslide-amplified flash floods-The June 2008 Panay Island flooding, Philippines, 169–170, 55–63, https://doi.org/10.1016/j.geomorph.2012.04.008, 2012.

Chen, D., Norris, J., Thackeray, C., and Hall, A.: Increasing precipitation whiplash in climate change hotspots, Environ. Res. Lett., 17, https://doi.org/10.1088/1748-9326/aca3b9, 2022.

Chorowicz, J.: The East African rift system, J. African Earth Sci., 43, 379–410, https://doi.org/10.1016/j.jafrearsci.2005.07.019, 2005.

Church, M. and Jakob, M.: What Is a Debris Flood?, Water Resour. Res., 56, 1–17, https://doi.org/10.1029/2020WR027144, 2020.

Corral, C., Berenguer, M., Sempere-Torres, D., Poletti, L., Silvestro, F., and Rebora, N.: Comparison of two early warning systems for regional flash flood hazard forecasting, J. Hydrol., 572, 603–619, https://doi.org/10.1016/j.jhydrol.2019.03.026, 2019.

Crozier, M. J.: Multiple-occurrence regional landslide events in New Zealand: Hazard management issues, 2, 247–256, https://doi.org/10.1007/s10346-005-0019-7, 2005.

D'Oreye, N., Derauw, D., Samsonov, S., Jaspard, M., and Smittarello, D.: A Full Automatic Multi-Satellite InSAR Mass Processing Tool for Rapid Incremental 2D Ground Deformation Time Series., Proc. IEEE Int. Geosci. Remote Sens. Symp., https://doi.org/10.1109/IGARSS47720.2021.9553615, 2021.

Deijns, A. A. J., Bevington, A. R., van Zadelhoff, F., de Jong, S. M., Geertsema, M., and McDougall, S.: Semi-automated detection of landslide timing using harmonic modelling of satellite imagery, Buckinghorse River, Canada, Int. J. Appl. Earth Obs. Geoinf., 84, https://doi.org/10.1016/j.jag.2019.101943, 2020.

Deijns, A. A. J., Dewitte, O., Thiery, W., D'Oreye, N., Malet, J.-P., and Kervyn, F.: Timing landslide and flash flood events from SAR satellite: a regionally applicable methodology illustrated in African cloud-covered tropical environments, Nat. Hazards Earth Syst. Sci., 3679–3700, 2022.

Deijns, A. A. J., Malet, Jean-Philippe, Michéa, D., Déprez, A., Kervyn, François, Thiery, W., and Dewitte, O.: A semi-supervised multi-temporal landslide and flash flood event detection methodology for unexplored regions using massive satellite image time series, ISPRS J. Photogramm. Remote Sens., 215, 400–418, https://doi.org/10.1016/j.isprsjprs.2024.07.010, 2024.

Delvaux, D., Mulumba, J. L., Ntabwoba Stanislas Sebagenzi, M., Bondo, S. F., Kervyn, F., and Havenith, H.-B.: Seismic hazard assessment of the Kivu rift segment based on a new seismotectonic zonation model (western branch, East African Rift system), J. African Earth Sci., 134, 831–855, https://doi.org/10.1016/j.jafrearsci.2016.10.004, 2017.

Depicker, A., Jacobs, L., Delvaux, D., Havenith, H. B., Maki Mateso, J. C., Govers, G., and Dewitte, O.: The added value of a regional landslide susceptibility assessment: The western branch of the East African Rift, 353, https://doi.org/10.1016/j.geomorph.2019.106886, 2020.

Depicker, A., Jacobs, L., Mboga, N., Smets, B., Van Rompaey, A., Lennert, M., Wolff, E., Kervyn, F., Michellier, C., Dewitte, O., and Govers, G.: Historical dynamics of landslide risk from population and forest-cover changes in the Kivu Rift, Nat. Sustain., 4, 965–974, https://doi.org/10.1038/s41893-021-00757-9, 2021a.

Depicker, A., Govers, G., Jacobs, L., Campforts, B., Uwihirwe, J., and Dewitte, O.: Interactions between deforestation, landscape rejuvenation, and shallow landslides in the North Tanganyika-Kivu rift region, Africa, Earth Surf. Dyn., 9, 445–462, https://doi.org/10.5194/esurf-9-445-2021, 2021b.

Depicker, A., Govers, G., Jacobs, L., Vanmaercke, M., Uwihirwe, J., Campforts, B., Kubwimana, D., Mateso, J. C., Mugaruka Bibentyo, T., Nahimana, L., Smets, B., and Dewitte, O.: Mobilization rates of landslides in a changing tropical environment: 60-year record over a large region of the East African Rift, Geomorphology, 454, https://doi.org/10.1016/j.geomorph.2024.109156, 2024.

Deprez, A., Marc, O., Malet, J.-P., Stumpf, A., and Michéa, D.: ALADIM – A change detection on-line service for landslide detection from EO imagery., EGU General Assembly 2022, Vienna, Austria, 23-27 May 2022, EGU22-3536, https://doi.org/10.5194/egusphere-egu22-3536, 2022.

Derauw, D., Nicolas, d'Oreye, Jaspard, M., Caselli, A., and Samsonov, S.: Ongoing automated ground deformation monitoring of Domuyo - Laguna del Maule area (Argentina) using Sentinel-1 MSBAS time series: Methodology description and first observations for the period 2015–2020, J. South Am. Earth Sci., 104, 102850, https://doi.org/10.1016/j.jsames.2020.102850, 2020.

DeVries, B., Huang, C., Armston, J., Huang, W., Jones, J. W., and Lang, M. W.: Rapid and robust monitoring of flood events using Sentinel-1 and Landsat data on the Google Earth Engine, Remote Sens. Environ., 240, 111664, https://doi.org/10.1016/j.rse.2020.111664, 2020.

Dewitte, O., Dille, A., Depicker, A., Kubwimana, D., Maki Mateso, J.-C., Mugaruka Bibentyo, T., Uwihirwe, J., and Monsieurs, E.: Constraining landslide timing in a data-scarce context: from recent to very old processes in the tropical environment of the North Tanganyika-Kivu Rift region, 18, 161–177, https://doi.org/10.1007/s10346-020-01452-0, 2021.

Dille, A., Dewitte, O., Handwerger, A. L., d'Oreye, N., Derauw, D., Ganza Bamulezi, G., Ilombe Mawe, G., Michellier, C., Moeyersons, J., Monsieurs, E., Mugaruka Bibentyo, T., Samsonov, S., Smets, B., Kervyn, M., and Kervyn, F.: Acceleration of a large deep-seated tropical landslide due to urbanization feedbacks, Nat. Geosci., 15, https://doi.org/10.1038/s41561-022-01073-3, 2022.

Dille, A., Dewitte, O., Broeckx, J., Verbist, K., Dube, A. S., and Vanmaercke, M.: Capturing the complete landslide – debris-rich flood continuum for accurate inventory , susceptibility and exposure mapping – lessons from Cyclone Idai, 1–24, https://doi.org/https://doi.org/10.5194/egusphere-2025-5056, 2025.

Dille, A., Dewitte, O., Broeckx, J., Verbiest, K., Sindiso Dube, A., Poesen, J., and Vanmaercke, M.: Source, runout and debris-rich floods: capturing the complete landslide continuum for accurate inventory, susceptibility and exposure mapping following an extreme climate event [in preparation], n.d.

Dzurisin, D.: Volcano deformation: geodetic monitoring techniques, edited by: Blondel, P., Springer, Berlin, https://doi.org/10.5860/choice.44-6250, 2007.

Emberson, R., Kirschbaum, D. B., Amatya, P., Tanyas, H., and Marc, O.: Insights from the topographic characteristics of a large global catalog of rainfall-induced landslide event inventories, Nat. Hazards Earth Syst. Sci., 22, 1129–1149, https://doi.org/10.5194/nhess-22-1129-2022, 2022.

ESA: CCI land cover - S2 prototype land cover 20m map of africa 2016, https: //2016africalandcover20m.esrin.esa.int/ [last acces: 18-09-2024], 2017.

ESA: Copernicus Global Digital Elevation Model. Distributed by OpenTopography. https://doi.org/10.5069/G9028PQB. Accessed: 2025-03-05, 2024.

Esposito, G., Marchesini, I., Cesare Mondini, A., Reichenbach, P., Rossi, M., and Sterlacchini, S.: A spaceborne SAR-based procedure to support the detection of landslides, Nat. Hazards Earth Syst. Sci., 20, 2379–2395, https://doi.org/10.5194/nhess-20-2379-2020, 2020.

Ferro, G.: Assessment of major and minor events that occurred in italy during the last century using a disaster severity scale score, Prehosp. Disaster Med., 20, 316–323, https://doi.org/10.1017/S1049023X00002776, 2005.

Foumelis, M., Papadopoulou, T., Bally, P., Pacini, F., Provost, F., and Patruno, J.: Monitoring Geohazards Using On-Demand And Systematic Services On ESA's Geohazards Exploitation Platform, IEEE Int. Geosci. Remote Sens. Symp., 5457–5460, https://doi.org/10.1109/IGARSS.2019.8898304, 2019.

Froude, M. J. and Petley, D. N.: Global fatal landslides occurrence from 2004 to 2016, Nat. Hazards Earth Syst. Sci., 18, 2161–2181, https://doi.org/10.5194/nhess-18-2161-2018, 2018.

Fryzlewicz, P.: Wild binary segmentation for multiple change-point detection, Ann. Stat., 42, 2243–2281, https://doi.org/10.1214/14-AOS1245, 2014.

Fu, S., de Jong, S. M., Deijns, A., Geertsema, M., and de Haas, T.: The SWADE model for landslide dating in time series of optical satellite imagery, 20, 913–932, https://doi.org/10.1007/s10346-022-02012-4, 2023.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J.: The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes, Sci. Data, 2, 1–21, https://doi.org/10.1038/sdata.2015.66, 2015.

Gariano, S. L. and Guzzetti, F.: Landslides in a changing climate, Earth-Science Rev., 162, 227–252, https://doi.org/10.1016/j.earscirev.2016.08.011, 2016.

Ghestem, M., Sidle, R. C., and Stokes, A.: The influence of plant root systems on subsurface flow: Implications for slope stability, Bioscience, 61, 869–879, https://doi.org/10.1525/bio.2011.61.11.6, 2011.

Giertz, S., Junge, B., and Diekkrüger, B.: Assessing the effects of land use change on soil physical properties and hydrological processes in the sub-humid tropical environment of West Africa, Phys. Chem. Earth, 30, 485–496, https://doi.org/10.1016/j.pce.2005.07.003, 2005.

Glade, T., Crozier, M., and Smith, P.: Applying probability determination to refine landslide-triggering rainfall thresholds using an empirical "Antecedent Daily Rainfall Model," Pure Appl. Geophys., 157, 1059–1079, https://doi.org/10.1007/s000240050017, 2000.

Greco, R., Marino, P., and Bogaard, T. A.: Recent advancements of landslide hydrology, Wiley Interdiscip. Rev. Water, 10, 1–23, https://doi.org/10.1002/wat2.1675, 2023.

Gregory, K. J.: The Earth's Land Surface, SAGE Publications Ltd, https://doi.org/10.4135/9781446251621, 2010.

Grillakis, M. G., Koutroulis, A. G., Komma, J., Tsanis, I. K., Wagner, W., and Blöschl, G.: Initial soil moisture effects on flash flood generation – A comparison between basins of contrasting hydro-climatic conditions, J. Hydrol., 541, 206–217, https://doi.org/10.1016/j.jhydrol.2016.03.007, 2016.

Guzzetti, F., Mondini, A. C., Cardinali, M., Fiorucci, F., Santangelo, M., and Chang, K. T.: Landslide inventory maps: New tools for an old problem, Earth-Science Rev., 112, 42–66, https://doi.org/10.1016/j.earscirev.2012.02.001, 2012.

Guzzetti, F., Gariano, S. L., Peruccacci, S., Brunetti, M. T., Marchesini, I., Rossi, M., and Melillo, M.: Geographical landslide early warning systems, Earth-Science Rev., 200, https://doi.org/10.1016/j.earscirev.2019.102973, 2020.

Handwerger, A. L., Huang, M. H., Fielding, E. J., Booth, A. M., and Bürgmann, R.: A shift from drought to extreme rainfall drives a stable landslide to catastrophic failure, Sci. Rep., 9, 1–12, https://doi.org/10.1038/s41598-018-38300-0, 2019.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., and Townshend, J. R. G.: High-Resolution Global Maps of 21st-Century Forest Cover Change, Science (80-.)., 342, 850–854, https://doi.org/10.1126/science.1244693, 2013.

Hanssen, R. F.: Radar interferometry: data interpretation and error analysis, edited by: van der Meer, F., Kluwer Academic Publishers, 2001.

Hapuarachchi, H. A. P., Wang, Q. J., and Pagano, T. C.: A review of advances in flash flood forecasting, Hydrol. Process., 25, 2771–2784, https://doi.org/10.1002/hyp.8040, 2011.

Huffman, G. J., Stocker, E. F., Bolvin, D. T., Nelkin, E. J., and Tan, J.: GPM IMERG Final Precipitation L3 1 day 0.1 degree x 0.1 degree V07, edited by: Andrey Savtchenko, Goddard Earth Sciences Data and Information Services Center (GES DISC) [accessed 29-09-2024], Greenbelt, MD, https://doi.org/10.5067/GPM/IMERGDF/DAY/07, 2023.

Hungr, O., Leroueil, S., and Picarelli, L.: The Varnes classification of landslide types, an update, Landslides, 11, 167–194, https://doi.org/10.1007/s10346-013-0436-y, 2014.

Idukunda, C., Henry, S., Twarabamenye, E., de Longuiville, F., and Michellier, C.: Evaluating Disaster Risk Management System: A Case Study of Rwanda’s Response to the 2nd-3rd May 2023 disaster event [preprint], 1–28, https://doi.org/10.5194/egusphere-2025-2112, 2025., 2025.

Ilombe Mawe, G., Lutete Landu, E., Dujardin, E., Makanzu Imwangana, F., Nzolang, C., Michellier, C., Poesen, J., Bielders, C., Hubert, A., Dewitte, O., and Vanmaercke, M.: Mapping urban gullies in the Democratic Republic of the Congo, Nature, 644, https://doi.org/10.1038/s41586-025-09371-7, 2025.

Iverson, R. M.: Landslide triggering by rain infiltration, Water Resour. Res., 36, 1897–1910, https://doi.org/10.1029/2000WR900090, 2000.

Jacobs, L., Maes, J., Mertens, K., Sekajugo, J., Thiery, W., van Lipzig, N., Poesen, J., Kervyn, M., and Dewitte, O.: Reconstruction of a flash flood event through a multi-hazard approach: focus on the Rwenzori Mountains, Uganda, Nat. Hazards, 84, 851–876, https://doi.org/10.1007/s11069-016-2458-y, 2016.

Jacobs, L., Dewitte, O., Poesen, J., Maes, J., Mertens, K., Sekajugo, J., and Kervyn, M.: Landslide characteristics and spatial distribution in the Rwenzori Mountains, Uganda, J. African Earth Sci., 134, 917–930, https://doi.org/10.1016/j.jafrearsci.2016.05.013, 2017.

Jacobs, L., Kabaseke, C., Bwambale, B., Katutu, R., Dewitte, O., Mertens, K., Maes, J., and Kervyn, M.: The geo-observer network: A proof of concept on participatory sensing of disasters in a remote setting, Sci. Total Environ., 670, 245–261, https://doi.org/10.1016/j.scitotenv.2019.03.177, 2019.

Jonkman, S. N.: Global perspectives on loss of human life caused by floods, Nat. Hazards, 34, 151–175, https://doi.org/10.1007/s11069-004-8891-3, 2005.

Jung, J. and Yun, S. H.: Evaluation of coherent and incoherent landslide detection methods based on synthetic aperture radar for rapid response: A case study for the 2018 Hokkaido landslides, Remote Sens., 12, 1–26, https://doi.org/10.3390/rs12020265, 2020.

Kanyiginya, V., Twongyirwe, R., Kagoro-Rugunda, G., Mubiru, D., Sekajugo, J., Mutyebere, R., Deijns, A. A. J., Kervyn, M., and Dewitte, O.: Inventories of natural hazards in under-reported regions: a multi-method insight from a tropical mountainous landscape, African Geogr. Rev., 00, 1–20, https://doi.org/10.1080/19376812.2023.2280589, 2023.

Khosravi, K., Pourghasemi, H. R., Chapi, K., and Bahri, M.: Flash flood susceptibility analysis and its mapping using different bivariate models in Iran: a comparison between Shannon’s entropy, statistical index, and weighting factor models, Environ. Monit. Assess., 188, https://doi.org/10.1007/s10661-016-5665-9, 2016.

Khosravi, K., Pham, B. T., Chapi, K., Shirzadi, A., Shahabi, H., Revhaug, I., Prakash, I., and Tien Bui, D.: A comparative assessment of decision trees algorithms for flash flood susceptibility modeling at Haraz watershed, northern Iran, Sci. Total Environ., 627, 744–755, https://doi.org/10.1016/j.scitotenv.2018.01.266, 2018.

Konishi, T. and Suga, Y.: Landslide detection using COSMO-SkyMed images: A case study of a landslide event on Kii Peninsula, Japan, Eur. J. Remote Sens., 51, 205–221, https://doi.org/10.1080/22797254.2017.1418185, 2018.

Könz, A. L., Hirschberg, J., McArdell, B. W., Mirus, B. B., de Haas, T., Bartelt, P., and Molnar, P.: Debris-flow entrainment modelling under climate change: Considering antecedent moisture conditions along the flow path, Earth Surf. Process. Landforms, 1–15, https://doi.org/10.1002/esp.5868, 2024.

Korup, O.: Landslides in the Earth system. In: Landslides: Types, Mechanisms and Modeling, edited by: Clague, J.J. Stead, D., Cambridge University Press, 10–23 pp., https://doi.org/10.1017/cbo9780511740367.003, 2012.

Kreibich, H., Van Loon, A. F., Schröter, K., Ward, P. J., Mazzoleni, M., Sairam, N., Abeshu, G. W., Agafonova, S., AghaKouchak, A., Aksoy, H., Alvarez-Garreton, C., Aznar, B., Balkhi, L., Barendrecht, M. H., Biancamaria, S., Bos-Burgering, L., Bradley, C., Budiyono, Y., Buytaert, W., Capewell, L., Carlson, H., Cavus, Y., Couasnon, A., Coxon, G., Daliakopoulos, I., de Ruiter, M. C., Delus, C., Erfurt, M., Esposito, G., François, D., Frappart, F., Freer, J., Frolova, N., Gain, A. K., Grillakis, M., Grima, J. O., Guzmán, D. A., Huning, L. S., Ionita, M., Kharlamov, M., Khoi, D. N., Kieboom, N., Kireeva, M., Koutroulis, A., Lavado-Casimiro, W., Li, H. Y., LLasat, M. C., Macdonald, D., Mård, J., Mathew-Richards, H., McKenzie, A., Mejia, A., Mendiondo, E. M., Mens, M., Mobini, S., Mohor, G. S., Nagavciuc, V., Ngo-Duc, T., Thao Nguyen Huynh, T., Nhi, P. T. T., Petrucci, O., Nguyen, H. Q., Quintana-Seguí, P., Razavi, S., Ridolfi, E., Riegel, J., Sadik, M. S., Savelli, E., Sazonov, A., Sharma, S., Sörensen, J., Arguello Souza, F. A., Stahl, K., Steinhausen, M., Stoelzle, M., Szalińska, W., Tang, Q., Tian, F., Tokarczyk, T., Tovar, C., Tran, T. V. T., Van Huijgevoort, M. H. J., van Vliet, M. T. H., Vorogushyn, S., Wagener, T., Wang, Y., Wendt, D. E., Wickham, E., Yang, L., Zambrano-Bigiarini, M., Blöschl, G., and Di Baldassarre, G.: The challenge of unprecedented floods and droughts in risk management, Nature, 608, 80–86, https://doi.org/10.1038/s41586-022-04917-5, 2022.

Krzeminska, D. M., Bogaard, T. A., Malet, J.-P., and Van Beek, L. P. H.: A model of hydrological and mechanical feedbacks of preferential fissure flow in a slow-moving landslide, Hydrol. Earth Syst. Sci., 17, 947–959, https://doi.org/10.5194/hess-17-947-2013, 2013.

Kubwimana, D., Brahim, L. A., Nkurunziza, P., Dille, A., Depicker, A., Nahimana, L., Abdelouafi, A., and Dewitte, O.: Characteristics and distribution of landslides in the populated Hillslopes of Bujumbura, Burundi, Geosci., 11, https://doi.org/10.3390/geosciences11060259, 2021.

Lesk, C., Rowhani, P., and Ramankutty, N.: Influence of extreme weather disasters on global crop production, Nature, 529, 84–87, https://doi.org/10.1038/nature16467, 2016.

Li, N., Thiery, W., Zscheischler, J., Messori, G., Guillou, L., Nivre, J., Görnerup, O., Lampe, S., Flynn, C., Madruga de Brito, M., and Jezequel, A.: A new climate impact database using generative AI, EGU General Assembly 2024, Vienna, Austria, 14–19 Apr 2024, EGU24-677, https://doi.org/10.5194/egusphere-egu24-677, 2024.

Lombardo, L. and Mai, P. M.: Presenting logistic regression-based landslide susceptibility results, Eng. Geol., 244, 14–24, https://doi.org/10.1016/j.enggeo.2018.07.019, 2018.

Maes, J., Kervyn, M., de Hontheim, A., Dewitte, O., Jacobs, L., Mertens, K., Vanmaercke, M., Vranken, L., and Poesen, J.: Landslide risk reduction measures: A review of practices and challenges for the tropics, Prog. Phys. Geogr., 41, 191–221, https://doi.org/10.1177/0309133316689344, 2017.

Maki Mateso, J., Bielders, C. L., Monsieurs, E., Depicker, A., Smets, B., Tambala, T., Bagalwa Mateso, L., and Dewitte, O.: Natural and human-induced landslides in a tropical mountainous region: the Rift flanks west of Lake Kivu (DR Congo), Nat. Hazards Earth Syst. Sci [preprint], 1–35, https://doi.org/10.5194/nhess-2021-336, 2021.

Maki Mateso, J. C., Bielders, C. L., Monsieurs, E., Depicker, A., Smets, B., Tambala, T., Bagalwa Mateso, L., and Dewitte, O.: Characteristics and causes of natural and human-induced landslides in a tropical mountainous region: the rift flank west of Lake Kivu (Democratic Republic of the Congo), Nat. Hazards Earth Syst. Sci., 23, 643–666, https://doi.org/10.5194/nhess-23-643-2023, 2023.

Marengo, J. A., Alcantara, E., Cunha, A. P., Seluchi, M., Nobre, C. A., Dolif, G., Goncalves, D., Assis Dias, M., Cuartas, L. A., Bender, F., Ramos, A. M., Mantovani, J. R., Alvalá, R. C., and Moraes, O. L.: Flash floods and landslides in the city of Recife, Northeast Brazil after heavy rain on May 25–28, 2022: Causes, impacts, and disaster preparedness, Weather Clim. Extrem., 39, https://doi.org/10.1016/j.wace.2022.100545, 2023.

Martelloni, G., Segoni, S., Fanti, R., and Catani, F.: Rainfall thresholds for the forecasting of landslide occurrence at regional scale, Landslides, 9, 485–495, https://doi.org/10.1007/s10346-011-0308-2, 2012.

McDermott, T. K. J.: Global exposure to flood risk and poverty, Nat. Commun., 13, 6–8, https://doi.org/10.1038/s41467-022-30725-6, 2022.

Merghadi, A., Yunus, A. P., Dou, J., Whiteley, J., ThaiPham, B., Bui, D. T., Avtar, R., and Abderrahmane, B.: Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance, Earth-Science Rev., 207, 103225, https://doi.org/10.1016/j.earscirev.2020.103225, 2020.

Merz, R. and Blöschl, G.: A regional analysis of event runoff coefficients with respect to climate and catchment characteristics in Austria, Water Resour. Res., 45, 1–19, https://doi.org/10.1029/2008WR007163, 2009.

Miller, M. A. E., Shepherd, K. D., Kisitu, B., and Collinson, J.: iSDAsoil: The first continent-scale soil property map at 30 m resolution provides a soil information revolution for Africa, PLoS Biol., 19, 2–5, https://doi.org/10.1371/journal.pbio.3001441, 2021.

Mondini, A. C., Chang, K. T., Chiang, S. H., Schlögel, R., Notarnicola, C., and Saito, H.: Automatic mapping of event landslides at basin scale in Taiwan using a Montecarlo approach and synthetic land cover fingerprints, Int. J. Appl. Earth Obs. Geoinf., 63, 112–121, https://doi.org/10.1016/j.jag.2017.07.016, 2017.

Mondini, A. C., Santangelo, M., Rocchetti, M., Rossetto, E., Manconi, A., and Monserrat, O.: Sentinel-1 SAR amplitude imagery for rapid landslide detection, Remote Sens., 11, 1–25, https://doi.org/10.3390/rs11070760, 2019.

Mondini, A. C., Guzzetti, F., Chang, K. T., Monserrat, O., Martha, T. R., and Manconi, A.: Landslide failures detection and mapping using Synthetic Aperture Radar: Past, present and future, Earth-Science Rev., 216, https://doi.org/10.1016/j.earscirev.2021.103574, 2021.

Monsieurs, E., Jacobs, L., Michellier, C., Basimike Tchangaboba, J., Ganza, G. B., Kervyn, F., Maki Mateso, J. C., Mugaruka Bibentyo, T., Kalikone Buzera, C., Nahimana, L., Ndayisenga, A., Nkurunziza, P., Thiery, W., Demoulin, A., Kervyn, M., and Dewitte, O.: Landslide inventory for hazard assessment in a data-poor context: a regional-scale approach in a tropical African environment, 15, 2195–2209, https://doi.org/10.1007/s10346-018-1008-y, 2018.

Monsieurs, E., Dewitte, O., and Demoulin, A.: A susceptibility-based rainfall threshold approach for landslide occurrence, Nat. Hazards Earth Syst. Sci., 19, 775–789, https://doi.org/10.5194/nhess-19-775-2019, 2019.

Muñoz-Torrero Manchado, A., Allen, S., Ballesteros-Cánovas, J. A., Dhakal, A., Dhital, M. R., and Stoffel, M.: Three decades of landslide activity in western Nepal: new insights into trends and climate drivers, Landslides, 18, 2001–2015, https://doi.org/10.1007/s10346-021-01632-6, 2021.

Nakulopa, F., Vanderkelen, I., Van de Walle, J., Van Lipzig, N. P. M., Tabari, H., Jacobs, L., Tweheyo, C., Dewitte, O., and Thiery, W.: Evaluation of High-Resolution Precipitation Products over the Rwenzori Mountains (Uganda), J. Hydrometeorol., 23, 747–768, https://doi.org/10.1175/JHM-D-21-0106.1, 2022.

Noguchi, S., Nik, A. R., Yusop, Z., Tani, M., and Sammori, T.: Rainfall-runoff responses and roles of soil moisture variations to the response in tropical rain forest, Bukit Tarek, Peninsular Malaysia, J. For. Res., 2, 125–132, https://doi.org/10.1007/BF02348209, 1997.

Notti, D., Cignetti, M., Godone, D., and Giordan, D.: Semi-automatic mapping of shallow landslides using free Sentinel-2 images and Google Earth Engine, Nat. Hazards Earth Syst. Sci., 23, 2625–2648, https://doi.org/10.5194/nhess-23-2625-2023, 2023.

Nsabimana, J., Henry, S., Ndayisenga, A., Kubwimana, D., Dewitte, O., Kervyn, F., and Michellier, C.: Geo-Hydrological Hazard Impacts, Vulnerability and Perception in Bujumbura (Burundi): A High-Resolution Field-Based Assessment in a Sprawling City, Land, 12, https://doi.org/10.3390/land12101876, 2023.

NWS: Flash Flooding Definition, https://www.weather.gov/phi/FlashFloodingDefinition [last access: 25-11-2024], 2024.

O'Connor, J. E. and Costa, J. E.: Spatial distribution of the largest rainfall-runoff floods from basins between 2.6 and 26,000 km2 in the United States and Puerto Rico, Water Resour. Res., 40, 1–11, https://doi.org/10.1029/2003WR002247, 2004.

Ozturk, U., Wendi, D., Crisologo, I., Riemer, A., Agarwal, A., Vogel, K., López-tarazón, J. A., and Korup, O.: Rare flash floods and debris flows in southern Germany, Sci. Total Environ., 626, 941–952, https://doi.org/10.1016/j.scitotenv.2018.01.172, 2018.

Ozturk, U., Bozzolan, E., Holcombe, E. A., Shukla, R., Pianosi, F., and Wagener, T.: How climate change and unplanned urban sprawl bring more landslides, Nature, 608, 262–265, https://doi.org/10.1038/d41586-022-02141-9, 2022.

Palmer, P. I., Wainwright, C. M., Dong, B., Maidment, R. I., Wheeler, K. G., Gedney, N., Hickman, J. E., Madani, N., Folwell, S. S., Abdo, G., Allan, R. P., Black, E. C. L., Feng, L., Gudoshava, M., Haines, K., Huntingford, C., Kilavi, M., Lunt, M. F., Shaaban, A., and Turner, A. G.: Drivers and impacts of Eastern African rainfall variability, Nat. Rev. Earth Environ., 4, 254–270, https://doi.org/10.1038/s43017-023-00397-x, 2023.

Park, S. E. and Lee, S. G.: On the use of single-, dual-, and quad-polarimetric SAR observation for landslide detection, ISPRS Int. J. Geo-Information, 8, https://doi.org/10.3390/ijgi8090384, 2019.

Parker, R. N., Hales, T. C., Mudd, S. M., Grieve, S. W. D., and Constantine, J. A.: Colluvium supply in humid regions limits the frequency of storm-triggered landslides, Sci. Rep., 6, 1–7, https://doi.org/10.1038/srep34438, 2016.

Psomiadis, E.: Flash flood area mapping utilising Sentinel-1 radar data, Earth Resour. Environ. Remote Sensing/GIS Appl. VII, 10005, https://doi.org/10.1117/12.2241055, 2016.

Reichenbach, P., Rossi, M., Malamud, B. D., Mihir, M., and Guzzetti, F.: A review of statistically-based landslide susceptibility models, Earth-Science Rev., 180, 60–91, https://doi.org/10.1016/j.earscirev.2018.03.001, 2018.

Robinson, T. R., Rosser, N., and Walters, R. J.: The Spatial and Temporal Influence of Cloud Cover on Satellite-Based Emergency Mapping of Earthquake Disasters, Sci. Rep., 9, 1–9, https://doi.org/10.1038/s41598-019-49008-0, 2019.

Rocca, F., Prati, C., Guarnieri, A. M., and Ferretti, A.: SAR interferometry and its applications, Surv. Geophys., 21, 159–176, https://doi.org/10.1023/A:1006710731155, 2000.

Saito, H., Korup, O., Uchida, T., Hayashi, S., and Oguchi, T.: Rainfall conditions, typhoon frequency, and contemporary landslide erosion in Japan, Geology, 42, 999–1002, https://doi.org/10.1130/G35680.1, 2014.

Scheip, C. M. and Wegmann, K. W.: HazMapper: A global open-source natural hazard mapping application in Google Earth Engine, Nat. Hazards Earth Syst. Sci., 21, 1495–1511, https://doi.org/10.5194/nhess-21-1495-2021, 2021.

Schlögel, R., Kofler, C., Gariano, S. L., Van Campenhout, J., and Plummer, S.: Changes in climate patterns and their association to natural hazard distribution in South Tyrol (Eastern Italian Alps) (Scientific Reports, (2020), 10, 1, (5022), 10.1038/s41598-020-61615-w), Sci. Rep., 10, 1–14, https://doi.org/10.1038/s41598-020-61615-w, 2020a.

Schlögel, R., Déprez, A., Belabbes, S., Dell Oro, L., Malet, J.-P., Belabbes, S., and Boivin, C.: Disastrous landslides under changing forcing factors triggered end 2019 in West Kenya, EGU General Assembly 2020, Online, 4–8 May 2020, EGU2020-19153, https://doi.org/10.5194/egusphere-egu2020-19153, 2020b.

Schlögl, M., Fuchs, S., Scheidl, C., and Heiser, M.: Trends in torrential flooding in the Austrian Alps: A combination of climate change, exposure dynamics, and mitigation measures, Clim. Risk Manag., 32, https://doi.org/10.1016/j.crm.2021.100294, 2021.

Scott, C. P., Lohman, R. B., and Jordan, T. E.: InSAR constraints on soil moisture evolution after the March 2015 extreme precipitation event in Chile, Sci. Rep., 7, 1–9, https://doi.org/10.1038/s41598-017-05123-4, 2017.

Segoni, S., Piciullo, L., and Gariano, S. L.: A review of the recent literature on rainfall thresholds for landslide occurrence, Landslides, 15, 1483–1501, https://doi.org/10.1007/s10346-018-0966-4, 2018.

Sekajugo, J., Kagoro-Rugunda, G., Mutyebere, R., Kabaseke, C., Namara, E., Dewitte, O., Kervyn, M., and Jacobs, L.: Can citizen scientists provide a reliable geo-hydrological hazard inventory? An analysis of biases, sensitivity and precision for the Rwenzori Mountains, Uganda, Environ. Res. Lett., 17, https://doi.org/10.1088/1748-9326/ac5bb5, 2022.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S. M., Wehner, M., and Zhou, B.: Weather and Climate Extreme Events in a Changing Climate. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climage Change, edited by: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., and Zhou, B., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1513–1766 pp., https://doi.org/10.1017/9781009157896.013, 2021.

Seto, K. C., Güneralp, B., and Hutyra, L. R.: Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools, Proc. Natl. Acad. Sci. USA, 109, 16083–16088, https://doi.org/10.1073/pnas.1211658109, 2012.

Shahabi, H., Rahimzad, M., Piralilou, S. T., Ghorbanzadeh, O., Homayouni, S., Blaschke, T., Lim, S., and Ghamisi, P.: Unsupervised deep learning for landslide detection from multispectral sentinel-2 imagery, Remote Sens., 13, https://doi.org/10.3390/rs13224698, 2021.

Sharma, S., Talchabhadel, R., Nepal, S., Ghimire, G. R., Rakhal, B., Panthi, J., Adhikari, B. R., Pradhanang, S. M., Maskey, S., and Kumar, S.: Increasing risk of cascading hazards in the central Himalayas, Nat. Hazards, 119, 1117–1126, https://doi.org/10.1007/s11069-022-05462-0, 2023.

Shibayama, T., Yamaguchi, Y., and Yamada, H.: Polarimetric scattering properties of landslides in forested areas and the dependence on the local incidence angle, Remote Sens., 7, 15424–15442, https://doi.org/10.3390/rs71115424, 2015.

Sidle, R. C. and Bogaard, T. A.: Dynamic earth system and ecological controls of rainfall-initiated landslides, Earth-Science Rev., 159, 275–291, https://doi.org/10.1016/j.earscirev.2016.05.013, 2016.

Sirko, W., Kashubin, S., Ritter, M., Annkah, A., Bouchareb, Y. S. E., Dauphin, Y., Keysers, D., Neumann, M., Cisse, M., and

Quinn, J.: Continental-Scale Building Detection from High Resolution Satellite Imagery, 1–15, https://doi.org/10.48550/arXiv.2107.12283, 2021.

Smets, B., Delvaux, D., Ross, K. A., Poppe, S., Kervyn, M., D'Oreye, N., and Kervyn, F.: The role of inherited crustal structures and magmatism in the development of rift segments: Insights from the Kivu basin, western branch of the East African Rift, Tectonophysics, 683, 62–76, https://doi.org/10.1016/j.tecto.2016.06.022, 2016.

Smith, H. G., Neverman, A. J., Betts, H., and Spiekermann, R.: The influence of spatial patterns in rainfall on shallow landslides, 437, https://doi.org/10.1016/j.geomorph.2023.108795, 2023.

Špitalar, M., Gourley, J. J., Lutoff, C., Kirstetter, P. E., Brilly, M., and Carr, N.: Analysis of flash flood parameters and human impacts in the US from 2006 to 2012, J. Hydrol., 519, 863–870, https://doi.org/10.1016/j.jhydrol.2014.07.004, 2014.

Stein, L., Mukkavilli, S. K., Pfitzmann, B. M., Staar, P. W. J., Ozturk, U., Berrospi, C., Brunschwiler, T., and Wagener, T.: Wealth over Woe: global biases in hydro-hazard research, Earth's Futur., 12, https://doi.org/https://doi.org/10.1029/2024EF004590, 2024.

Stumpf, A., Lachiche, N., Malet, J.-P., Kerle, N., and Puissant, A.: Active learning in the spatial domain for remote sensing image classification, IEEE Trans. Geosci. Remote Sens., 52, 2492–2507, https://doi.org/10.1109/TGRS.2013.2262052, 2014.

Stumpf, A., Michéa, D., and Malet, J.-P.: Improved co-registration of Sentinel-2 and Landsat-8 imagery for Earth surface motion measurements, Remote Sens., 10, 1–20, https://doi.org/10.3390/rs10020160, 2018.

Take, W. A., Beddoe, R. A., Davoodi-Bilesavar, R., and Phillips, R.: Effect of antecedent groundwater conditions on the triggering of static liquefaction landslides, 12, 469–479, https://doi.org/10.1007/s10346-014-0496-7, 2015.

Tan, J., Huffman, G. J., Bolvin, D. T., and Nelkin, E. J.: Diurnal Cycle of IMERG V06 Precipitation, Geophys. Res. Lett., 46, 13584–13592, https://doi.org/10.1029/2019GL085395, 2019.

Tarboton, D. G.: Rainfall -Runoff Processes, https://hydrology.usu.edu/rrp/pdfs/RainfallRunoffProcesses.pdf [last access 30-06-2025], Utah State University, 1–159 pp., 2003.

Tarolli, P., Borga, M., Morin, E., and Delrieu, G.: Analysis of flash flood regimes in the North-Western and South-Eastern Mediterranean regions, Nat. Hazards Earth Syst. Sci., 12, 1255–1265, https://doi.org/10.5194/nhess-12-1255-2012, 2012.

Terlien, M. T. J.: The determination of statistical and deterministic hydrological landslide-triggering thresholds, Environ. Geol., 35, 124–130, https://doi.org/10.1007/s002540050299, 1998.

Tibshirani, R.: Regression Shrinkage and Selection via the Lasso, J. R. Stat. Soc. Ser. B, 58, 267–288, https://doi.org/https://doi.org/10.1111/j.2517-6161.1996.tb02080.x, 1996.

Trisos, C. H., Adelekan, I. O., Totin, E., Ayanlade, A., Efitre, J., Gemeda, A., Kalaba, K., Lennard, C., Masao, C., Mgaya, Y., Ngaruiya, G., Olago, D., Simpson, N. P., and Zakieldeen, S.: Africa. In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Climate Ch., edited by: Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegria, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., and Rama, B., Cambridge University Press, Cambridge, UK and New York, NY, USA, 1285–1455 pp., https://doi.org/10.1017/9781009325844.011., 2022.

Tucker, C.: Red and photographic infrared linear combinations for monitoring vegetation, Remote Sens. Environ., 8, 127–150, https://doi.org/https://doi.org/10.1016/0034- 4257(79)90013-0, 1979.

Uchida, T., Kosugi, K. N. I., and Mizuyama, T.: Effects of pipeflow on hydrological process and its relation to landslide: A review of pipeflow studies in forested headwater catchments, Hydrol. Process., 15, 2151–2174, https://doi.org/10.1002/hyp.281, 2001.

Ulaby, F. T., Dubois, P. C., and Van Zyl, J.: Radar mapping of surface soil moisture, J. Hydrol., 184, 57–84, https://doi.org/10.1016/0022-1694(95)02968-0, 1996.

Uwihirwe, J., Riveros, A., Wanjala, H., Schellekens, J., Sperna Weiland, F., Hrachowitz, M., and Bogaard, T. A.: Potential of satellite-derived hydro-meteorological information for landslide initiation thresholds in Rwanda, Nat. Hazards Earth Syst. Sci., 22, 3641–3661, https://doi.org/10.5194/nhess-22-3641-2022, 2022.

Valkenborg, B., Dewitte, O., and Smets, B.: A semi-automatic natural language tool to minimize systematic biases in geo-hydrological disaster datasets in tropical Africa. EGU General Assembly 2024, Vienna, Austria, 14–19 Apr 2024, EGU24-7652, https://doi.org/https://doi.org/10.5194/egusphere-egu24-7652, 2024.

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat, İ., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., Vijaykumar, A., Bardelli, A. Pietro, Rothberg, A., Hilboll, A., Kloeckner, A., Scopatz, A., Lee, A., Rokem, A., Woods, C. N., Fulton, C., Masson, C., Häggström, C., Fitzgerald, C., Nicholson, D. A., Hagen, D. R., Pasechnik, D. V., Olivetti, E., Martin, E., Wieser, E., Silva, F., Lenders, F., Wilhelm, F., Young, G., Price, G. A., Ingold, G. L., Allen, G. E., Lee, G. R., Audren, H., Probst, I., Dietrich, J. P., Silterra, J., Webber, J. T., Slavič, J., Nothman, J., Buchner, J., Kulick, J., Schönberger, J. L., de Miranda Cardoso, J. V., Reimer, J., Harrington, J., Rodríguez, J. L. C., Nunez-Iglesias, J., Kuczynski, J., Tritz, K., Thoma, M., Newville, M., Kümmerer, M., Bolingbroke, M., Tartre, M., Pak, M., Smith, N. J., Nowaczyk, N., Shebanov, N., Pavlyk, O., Brodtkorb, P. A., Lee, P., McGibbon, R. T., Feldbauer, R., Lewis, S., Tygier, S., Sievert, S., Vigna, S., Peterson, S., More, S., Pudlik, T., et al.: SciPy 1.0: fundamental algorithms for scientific computing in Python, Nat. Methods, 17, 261–272, https://doi.org/10.1038/s41592-019-0686-2, 2020.

Vogel, J., Rivoire, P., Deidda, C., Rahimi, L., Sauter, C. A., Tschumi, E., Van Der Wiel, K., Zhang, T., and Zscheischler, J.: Identifying meteorological drivers of extreme impacts: An application to simulated crop yields, Earth Syst. Dyn., 12, 151–172, https://doi.org/10.5194/esd-12-151-2021, 2021.

Ward, P. J., Blauhut, V., Bloemendaal, N., Daniell, E. J., De Ruiter, C. M., Duncan, J. M., Emberson, R., Jenkins, F. S., Kirschbaum, D., Kunz, M., Mohr, S., Muis, S., Riddell, A. G., Schäfer, A., Stanley, T., Veldkamp, I. E. T., and Hessel, W. C.: Review article: Natural hazard risk assessments at the global scale, Nat. Hazards Earth Syst. Sci., 20, 1069–1096, https://doi.org/10.5194/nhess-20-1069-2020, 2020.

van Westen, C. J., Castellanos, E., and Kuriakose, S. L.: Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview, Eng. Geol., 102, 112–131, https://doi.org/10.1016/j.enggeo.2008.03.010, 2008.

Yanites, B. J., Clark, M. K., Roering, J. J., West, A. J., Zekkos, D., Baldwin, J. W., Cerovski-Darriau, C., Gallen, S. F., Horton, D. E., Kirby, E., Leshchinsky, B. A., Mason, H. B., Moon, S., Barnhart, K. R., Booth, A., Czuba, J. A., McCoy, S., McGuire, L., Pfeiffer, A., and Pierce, J.: Cascading land surface hazards as a nexus in the Earth system, Science (80-.)., 388, https://doi.org/10.1126/science.adp9559, 2025.

Zebker, H. A. and Villasenor, J.: Decorrelation in interferometric radar echoes, IEEE Trans. Geosci. Remote Sens., 30, 950–959, https://doi.org/https://doi.org/10.1109/36.175330, 1992.

Zêzere, J. L., Trigo, R. M., and Trigo, I. F.: Shallow and deep landslides induced by rainfall in the Lisbon region (Portugal): Assessment of relationships with the North Atlantic Oscillation, Nat. Hazards Earth Syst. Sci., 5, 331–344, https://doi.org/10.5194/nhess-5-331-2005, 2005.

Zhai, X., Guo, L., Liu, R., and Zhang, Y.: Rainfall threshold determination for flash flood warning in mountainous catchments with consideration of antecedent soil moisture and rainfall pattern, Nat. Hazards, 94, 605–625, https://doi.org/10.1007/s11069-018-3404-y, 2018.

Zscheischler, J., Westra, S., Van Den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., Aghakouchak, A., Bresch, D. N., Leonard, M., Wahl, T., and Zhang, X.: Future climate risk from compound events, Nat. Clim. Chang., 8, 469–477, https://doi.org/10.1038/s41558-018-0156-3, 2018.

Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A., Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., and Vignotto, E.: A typology of compound weather and climate events, Nat. Rev. Earth Environ., 1, 333–347, https://doi.org/10.1038/s43017-020-0060-z, 2020.