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Inventories of natural hazards in under-reported regions: a multi-method insight from a tropical mountainous landscape

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ABSTRACT

Impacts of natural hazards are on an increase globally. To mitigate these impacts, sound disaster risk reduction strategies must rely on comprehensive inventory of natural hazards. However, to date, many regions worldwide still suffer from a dearth of information. The goal of our research is to assess how, with limited means and several methods, environments that are typically under-researched can be covered with accurate information on which further research aiming at understanding and mitigating disaster risk could be set out. We focus on the Kigezi highlands, an under-reported and populated tropical region of Uganda (Africa) known to be impacted by natural hazards. We conducted a multi-method multi-temporal inventory over the entire region using satellite image analysis, exploration of literature and archives, and field surveys. We also set up a network of 15 geo-observers to collect accurate space-time data on seven natural hazards. Our multi-method inventory generated a database comprising over 4000 natural hazard occurrences with frequent natural and anthropogenic interactions. Our results indicate that Kigezi highlands is a hotspot for natural hazards associated with extensive risks, whose numbers are underestimated. We therefore highlight the importance of working with a multiple-method approach in characterizing natural hazards and their interactions.

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1. Introduction

Impacts associated with natural hazards are on an increase globally (IPCC, 2022). The large part of this rise is due to human population growth which pushes people to live in more hazardous terrain (Dille et al., 2022; Ozturk et al., 2022; Tellman et al., 2021). Furthermore, the human-induced transformation of the landscape alters the patterns of natural hazard risks in frequency and magnitude; conditions that are expected to be exacerbated by the changing climate (e.g., Depicker et al., 2021a; Ozturk et al., 2022). Moreover, multiple hazards can occur at the same location and at the same time, and interactions and compound effects between them are expected (Gill & Malamud, 2014; Tilloy et al., 2019). Cascading or compounding

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interactions commonly accelerate the impacts of the hazards to higher levels and exposes more population to disastrous risks (Zscheischler et al., 2018). For example, a heavy storm can trigger several landslides and debris flows which could block rivers and drainage ways, resulting into heavy flash floods (e.g., Jacobs et al., 2016).

The Sendai framework, which provides guidance for disaster risk reduction, emphasizes studying risk from natural hazards in a holistic manner for effective disaster risk reduction (UNISDR, 2015). This can be achieved through comprehensive inventories that coherently integrate transdisciplinary approaches (Gill et al., 2021). However, worldwide, many regions remain data scarce especially with respect to the information on the timing (recent and decadal-scale) of the processes (Dewitte et al., 2022; Merz et al., 2021). The reason for the data scarcity lies in the fact that most impact assessments are focussed on the disasters alone, and usually those with fatalities (Kirschbaum et al., 2010). Existing global databases are typical examples of biased information toward impactful hazards as they rely on reports from the (local) media and collections from country disaster portals (Osuteye et al., 2017).

Data collection on natural hazards used to be impeded by the high costs and time involved, limited imagery, scanty reporting, and remoteness of areas (Juang et al., 2019). Furthermore, mountainous regions in tropical climatic zones present environmental conditions such as pervasive cloud cover conditions and rapid natural vegetation regrowth that make data collection more challenging when it comes to, for example, collecting information on the timing of landslides and flash floods (Dewitte et al., 2022). Coupled with the hard-to-reach mountainous terrain generally more complex to access than in temperate areas, for example, limited resources dedicated to research on natural hazards as well as the absence of observation networks exacerbate the data collection challenges and hazard process understanding in these regions (Monsieurs et al., 2018). Recently, robust field data collection methods incorporating citizen science approaches have proven to offer a promising direction in improving data collection processes by providing detailed information on a variety of natural hazards, within a short response time (Hicks et al., 2019; Jacobs et al., 2019; Sekajugo et al., 2022).

Additionally, some researchers have established and recognized the importance of social media and other media as primary sources of information about hazards for the public but also a useful way of documenting impacts of events (Monsieurs et al., 2018; Taylor et al., 2015). Moreover, with the increasing availability of high and very high spatial resolution satellite imagery at low to no cost, it has now become possible to map natural hazards in remote hard-to-reach areas and therefore reduces the cost of fieldwork (Scheip & Wegmann, 2021). However, despite the several methods presented, many regions worldwide still suffer from a dearth of information. When it comes to building complete and reliable hazard inventories, it is advantageous to integrate the multi-inventory methods to constitute a comprehensive assessment of natural hazards for environments that are typically under-researched as each method complements another (Guzzetti et al., 2012; Sekajugo et al., 2022).

The objective of our research is to assess how, with limited means and several methods, environments that are typically under-researched, can be covered with accurate information on natural hazards on which further research aiming at understanding and mitigating disaster risk could be set out. The relevance of using multiple methods is a key research aspect we want to demonstrate. To address this objective, we target the Kigezi highlands, southwestern Uganda, where natural hazards are common. In this mountainous area, population growth and associated disturbances of the landscape are important (Section 2). At the core of our research is the building of a comprehensive multi-temporal inventory containing natural hazard information and the characterization of their natural and anthropogenic interactions. To achieve this, we applied a multi-method approach incorporating field survey, satellite image analysis, exploration of literature and archives, and the establishment of a citizen science network. The rest of the paper is organized as follows. In section 2, we provide a detailed description of the study area. In section 3, we elaborate on the methods employed in putting together the inventory and mapping the interactions between

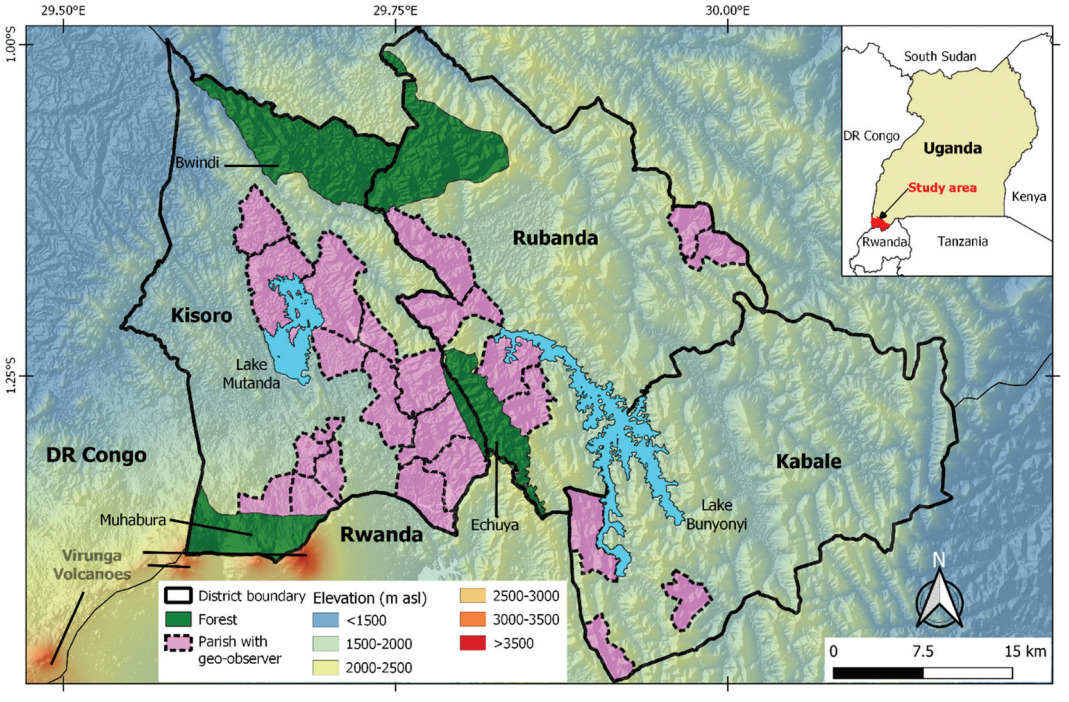


Figure 1. Location of the study area in the Kigezi highlands, Uganda. The 24 parishes locate the places where the citizen science network is implemented (Section 3.3). Forest cover data are from Google Earth imagery 2021.

natural hazards. We then present the results and a discussion of the findings in sections 4 and 5, respectively.

2. Study area

The Kigezi highlands are part of the southwestern highlands of Uganda bordering Rwanda and the Democratic Republic of Congo. More specifically, the study was conducted in a sub-region of ~2000 km^2 that comprises the districts of Kabale, Rubanda, and Kisoro (Figure 1). Part of the study area consists of Muhabura volcano, a dormant volcano in the Virunga Mountains. Kigezi highlands experiences high rainfall during the two wet seasons: March to May and September to November, averaging between 1000 and 1300 mm per annum. The region is densely populated with an average of 300 to 400 inhabitants per km^2 (UBOS, 2018), that are mainly smallholder farmers, dependent on subsistence agriculture and livestock production. The vegetation cover which largely comprised of montane forests a century ago (Bagoora, 1993) has been greatly changed due to human activities arising from increasing population (Carswell, 2002; Mwanjalolo et al., 2018). Whereas subsistence agricultural land has been increasing for more than five decades, forest and woodland that hold the soil have been declining and the trend is expected to continue by 2040 (Mwanjalolo et al., 2018).

Kigezi highlands are regularly affected by natural hazards such as (flash) floods, landslides, hailstorms, windstorms, lightning, and earthquakes (OPM, 2019). The recent national vulnerability and risk atlas of Uganda ranked the southwestern region comprising the Kigezi highlands as the most exposed region to natural hazards experienced in the country (OPM, 2019). Despite this, few studies have assessed the characteristics of the natural hazards and their spatial and temporal distributions (Nseka et al., 2019).

3. Materials and methods

3.1. Literature and archive sources

To have a first comprehensive overview of the state of knowledge on the natural hazards in the region, we looked at various secondary sources:

- Scientific literature explored for the period 1990–2022: Web of Science, Scopus, ScienceDirect, and Google Scholar.
- Reports and gray literature such as, NGO reports, government reports. Collaborating with the district stakeholders, we acquired local disaster assessment reports for additional information.
- Disaster databases/catalogs: the existing databases present a valuable and directly available source of information. We list global databases and catalogs that we explored in this study with respect to the seven natural hazards inventoried (Appendix I).
- Social media: Facebook and Twitter covering a period of 2005–2022.
- Print and online media 2005–2022: New Vision, The Informer, Daily Monitor, Ankole Times, Orumuri, Entatsi, etc.

For the media, we applied the methodological framework proposed by Monsieurs et al. (2018) which entails a systematic 'search', 'store', and 'validate' criteria. We used keywords combined with district/region names such as 'storm', 'heavy rain', 'floods', 'flash floods', 'landslides', 'mudslides' 'disasters', 'erosion', 'Kigezi', etc. Hazard types are listed here because we wanted to be as broad as possible by using common words that are normally used by the media. For the local media sources, Runyankore-Rukiga languages being the main dialects spoken in the region were used in the search.

3.2. Satellite data sources

To further sharpen the data collection, we visually analyzed Google Earth imagery and PlanetScope satellite images to identify landslides and flash floods. Google Earth imagery provides very high spatial resolution images at 0.3–0.6 m which are available at a frequency of 1–3 years for the study area since 2011. PlanetScope satellites provide images at a 3.7-m resolution. We used 128 images with a maximum of 10% cloud cover from December 2019 to December 2022, which allowed us to cover more than 90% of the study area.

3.3. Workshops

Stakeholder workshops were also a way to collect information. We conducted nine workshops as follows:

- The first three workshops, one in each district, were held in November 2019 and were aimed at identifying the main natural hazards in the region, as well as the places where the problems are most acute. Based on these, the workshops also allowed to identify the parishes that would be covered by the network of citizen-observers (Section 3.3). The workshops were attended by 40 participants in total comprising the District Disaster Management Committee (DDMC) members, district natural resource and environmental officers, planners, agricultural officers, and Red Cross officials.
- The other six workshops were conducted in a similar way targeting the same stakeholders to further enlist and validate natural hazards that are part of this inventory. The workshops were held in December 2020 and in January 2022. In addition to the same participants as in November 2019, these workshops were also attended by the geo-observers (Section 3.3).

3.4. The geo-observer network

A network of 15 geo-observers, i.e., citizens of local communities distributed across representative landscapes (parishes) of the study area, was established in December 2019. Tooled and trained at using smartphone technology, the geo-observers collected information (processes and impacts) on seven different natural hazards (droughts, earthquakes, floods, hailstorms, landslides, lightning, and windstorms) whenever they occurred. Data collection was done from December 2019 to December 2022 using KoBoToolbox, an open-source tool for mobile data collection. Structured questionnaires on the seven natural hazards were uploaded on the KoboToolbox. The data was submitted as reports using mobile internet. Data collected included the location of the event, extent/size of the event, likely causes and damages, and photos depicting the hazards and the damages caused as described in the protocol (Jacobs et al., 2019). Validation for quality checks was done at Mbarara University of Science and Technology using a checklist to verify the completeness of the questionnaire, validity of the photos taken, dates of reporting and location (Figure 2). Systematic field validation of the reports in a similar area proved high reliability of the data collected by the geo-observers but not the completeness (Sekajugo et al., 2022).

A collaborative transdisciplinary working process was employed to set up the geo-observer network. The selection of the parishes and recruitment of the geo-observers were done jointly with the relevant district stakeholders in form of workshops. Uganda is stratified into administrative units, namely, districts, counties, constituencies, sub-counties, parishes, and villages (UBOS, 2018). A consensus was reached to consider 24 parishes which are the most and frequently affected by natural hazards (Figure 1). The next step was the selection of potential geo-observers by the district stakeholders using a selection criteria that included spirit of volunteerism, native of the parish, etc. Preference was given to those with experience of working with community structures like village health teams, para-social workers, red cross, community based facilitators, lead farmer, change agent, and so on and ability to operate a smartphone. Upon successful recruitment, the geo-observers were equipped with smartphones for data collection and trained for two days on

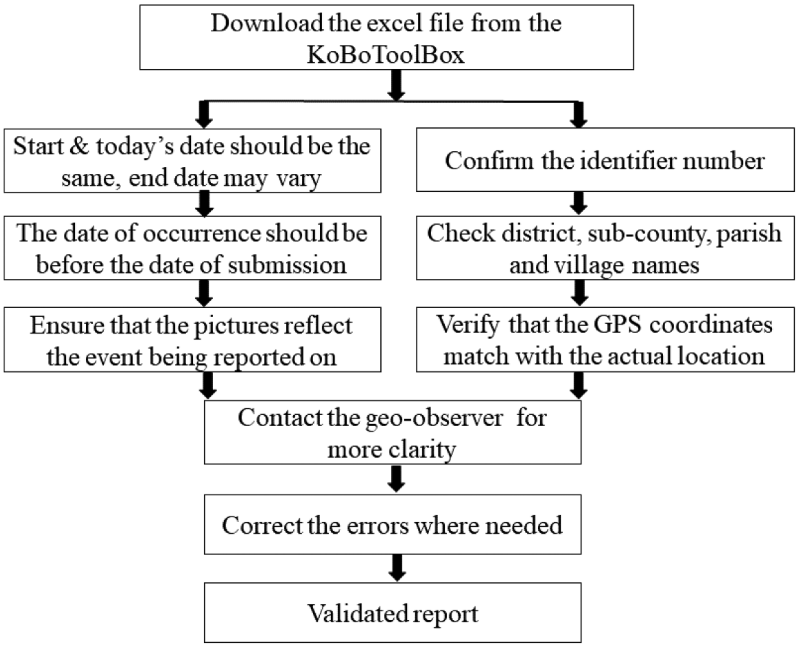


Figure 2. Validation chart for inventoried data from the geo-observer network.

identification and characterization of hazard events, the use of a smartphone and the KoBoToolbox reporting tool. In 2020, 2021, and 2022, yearly refresher trainings were organized.

3.5. Field surveys

In addition, we conducted nine field surveys in the period August 2019–October 2022 in targeted locations according to the occurrence of recent events mapped on satellite images and/or reported in the news, reports from the network and indications from local residents and stakeholders. Note that we also targeted regions in the western part of the study area where no hazards seemed to have happened in the last years to have a better idea of the completeness and bias of our analysis. The field survey focused on landslides and flood hazards, which are the topmost frequent and problematic hazards in the region (see Section 4). Each field observation was geo-located and recorded using KoboToolBox. The attributes recorded include location, timing and possible factors likely to have caused the event and prior land uses. Interacting with the local communities provided more information on the processes and interactions of natural hazards.

3.6. Hazard interactions

We used the qualitative visualization approach developed by Gill and Malamud (2014) and Gill and Malamud (2017) that considers interaction relationships for both natural and anthropogenic processes. The interactions we considered in this study include cascading and compound hazards. The latter impacts several locations during the same time, whereas the former denotes interactions where a hazard (primary) triggers another hazard (secondary) (Gill & Malamud, 2014; Tilloy et al., 2019). We also characterized the anthropogenic processes that are assumed and/or reported to have played a role on the hazard occurrences. We characterized the hazard interactions through field surveys/geo-observers, satellite image analysis, and a review of the literature as explained in Sections 3.1-3.5. Moreover, close interactions with local stakeholders and workshops facilitated further understanding of the hazard interactions. For instance, stakeholders described scenarios of known hazard occurrences with compounding or cascading hazard characteristics, as well as highlighting primary and secondary hazards, triggering mechanisms, and the associated impacts.

3.7. Impact assessment – a source of information as an extra

Although assessment of hazard impacts was not necessary for the compilation of the natural hazard database nor for further understanding of the processes, we collected information on the impacts. Specifically, this information was extracted from the secondary sources as well as from field observations and interactions with the residents and stakeholders. The questionnaire used by the geo-observers also includes queries related to impact assessments. Overall, this information on the impacts was conducted in a less rigorous and systematic way than that for the hazards.

4. Results

We inventoried a total of 4058 natural hazard occurrences and events based on the multi-method approach applied in the study (Table 1). Here, we define occurrences as an individual hazard impacted area. For example, let us assume a rainfall that triggers 50 landslides at once. This landslide event (all the processes associated with one well timely constrained triggering factor – here the rainfall) is composed of 50 occurrences. Inventories collected from the literature, reports, archives, global datasets, and geo-observes are events. Inventories from satellite images and field observation are occurrences. However, in some cases, when a cluster of landslide or flash flood occurrences is observed, we are able to classify it as an event. The geo-observer inventory is the dataset that contains by far the largest number of events (Table 1). The inventory based on field

Table 1. Number of natural hazard occurrences and events identified for each method-specific inventories. For the inventories from satellite images and field observation, the number in brackets corresponds to the number of events (see text for explanation) that could be derived from the occurrence pattern. N/A— not applicable.

Inventory source	Area surveyed (km^2)	Period surveyed	Drought	Earthquake	Floods/flash floods	Hailstorm	Landslide	Lightning	Windstorm	Total
Literature, reports & archives	N/A	1960–2022	0	4	18	4	30	1	3	56
Global databases	N/A	1989–2022	0	0	162	22	92	4	4	284
Geo-observers	391	December 2019-January 2022	3	0	93	24	213	4	33	370
Satellite images	1797	2005–2022	N/A	N/A	89 (11 events)	N/A	235 (13 events)	N/A	N/A	324
Field observation	1738	2019–2022	N/A	N/A	52 (21- events)	N/A	3001 (99- events)	N/A	N/A	3053

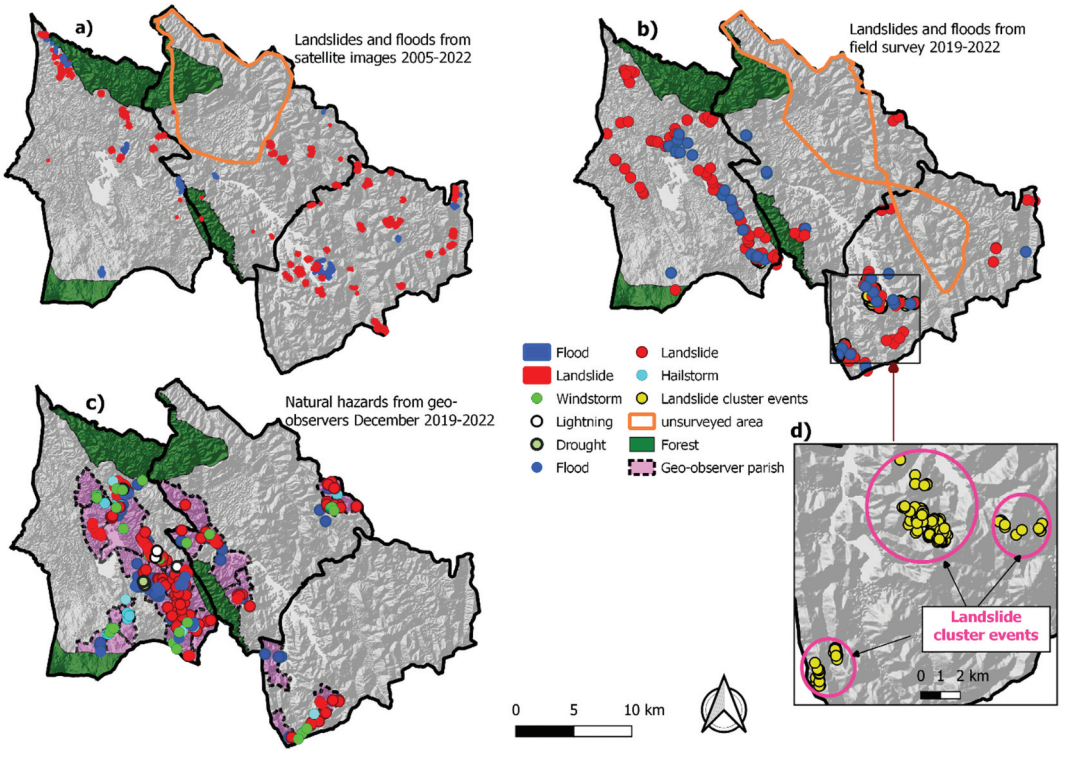


Figure 3. Spatial distribution of natural hazard occurrences and events documented based on a) satellite image; b) field survey and c) geo-observers. d) landslide cluster events observed in the field.

observations contains the highest number of occurrences. Note that 2902 occurrences of this field inventory corresponds to relatively small landslides that are associated with the same rainfall-triggered event. Those occurrences clearly observed in the field (Figures 3(d) and 4(a,b)) could not be correctly identified in the PlanetScope images due to the too low resolution of the product. Apart from the global databases with the highest number of flood reports, the other inventories highlight landslides as the most frequent hazard occurrence.

4.1. Inventory and spatio-temporal distribution of natural hazards

Inventory from reports, literature, archives, and global databases, hereinafter called 'reported inventory,' generated 340 natural hazard events over the last 62 years (Table 1 and Table 2), with the DesInventar database being the main source of information (Table 2). Social media, Twitter and Facebook, contributed to the identification of hazard events and offered timely reporting. Some occurrences reported in the Floodlist database, for example, were pre-reported by Twitter and were thus recorded under Twitter database. The events were allocated to a database that reported the event first, which in most cases was indicated as a reference by the reporting database. In addition, the district stakeholders and residents offered vital information in identifying natural hazards. Although the information on timing was not very accurate, the stakeholders provided accurate location information, which helped in the mapping of the spatial distribution of natural hazards. The frequency of occurrence was high for the months of March, April, and May (Figure 5(a)) and the highest number of events, especially landslides, were reported in 2010 (Figure 6). 2010 corresponds to the highest annual rainfall transition from low in 2009 to high in 2010. However, with similar high rainfall totals in 2011

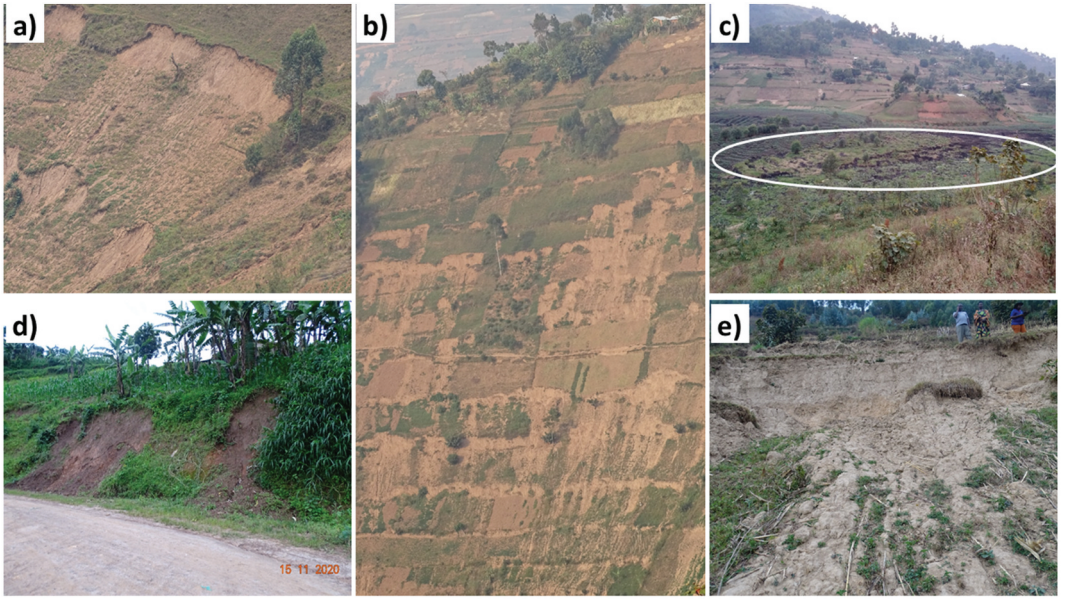


Figure 4. a) and b) shallow landslide clusters in Kabale. Photos taken in August 2020 (−1.383761°, 29.952607° and −1.434450°, 29.906351° respectively). c) foot area of a slow moving landslide in Kabale Butanda sub-county. Photo taken in August 2020. d) road-related landslides in Kisoro, Nyundo sub-county. Photo taken in November 2020 (−1.167316°, 29.665389°). e) deep-seated landslide in Kabale, Butanda sub-county. Photo taken in August 2020 (−1.449889°, 29. 897132°).

Table 2. Natural hazard events recorded from reported inventory.

Category	Source	Number of events
Government reports	District disaster relief reports	6
NGO reports	Red cross post disaster assessment reports	2
Social media	Facebook	12
	Twitter	18
Online and print media	The informer	4
	Daily monitor	4
	New vision	5
Disaster databases	Floodlist	4
	DesInventar	244
	National disaster portal	8
	EM-DAT – Emergency Disaster Data Base	7
	GLIDE – The Global Disaster Identifier Number	1
	Global Fatal Landslide Catalogue	2
	Global Landslide Catalogue	5
Scientific journals	Science direct journals (Web of Science, Google Scholar)	4

and 2018, less events were reported in 2010. We also see that in 2017 and 2018 no landslides are reported, but only flash floods (Figure 6).

We identified 235 landslides and 89 flash flood occurrences from Google Earth and PlanetScope images which were mapped from images of 2011, 2014, 2018, 2019, 2020, and 2022. Large flash floods occurred in 2018 in catchments around Lake Bunyonyi, caused by a single rainstorm event (Figure 3(a)). Landslide clusters and flash floods were mapped around Bwindi impenetrable forest in the north-western part of the study area in 2014 and in the eastern region of the study area in 2011 (Figure 3(a)). The geo-observers reported 370 natural hazard events within the first 37 months of data collection, i.e., over the period December 2019 – December 2022. Most occurrences were reported during the months of

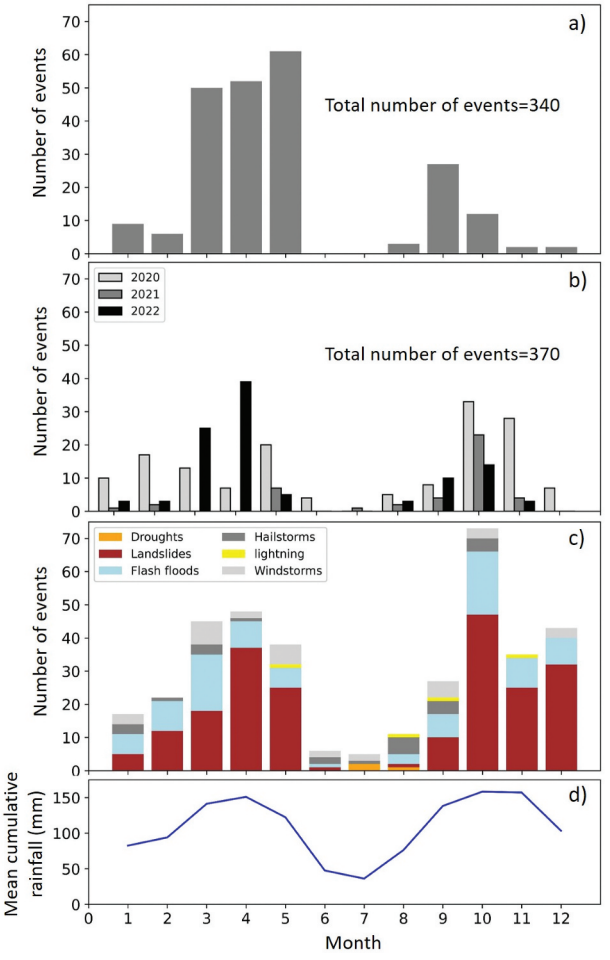


Figure 5. Monthly distribution of natural hazard events. a) reported inventory (1960–2022) b) geo-observer inventory (2020–2022). c) type of natural hazard events in the geo-observer inventory. d) average rainfall pattern for the region over the period 2000–2020. Rainfall data are from IMERG (integrated multi- satellite retrievals for GPM) final run data.

October, followed by April, November, and March (Figure 5(b)), which corresponds to months of the wet season in this part of Uganda. The year 2020 experienced the highest number of natural hazards (161) compared to 2021 (53) and 2022 (121). Note that December 2019 shows a high number of records (35), but we do not use this information here. This is indeed when the geo-observer network started reporting, and we cannot exclude a bias at that moment since some events were probably from the preceding months. Overall, landslides are the most reported hazards (213; 58%) followed by floods (93; 25%) including flash floods, windstorms were 33 (9%); hailstorm 24 at 6%; lightning (4; 1%) and drought being the least reported (3; 1%) (Figure 5(c)). The geo-observer inventory shows that, contrary to the reported inventory, landslides occur during every wet season. While the association between landslide and flash flood is clear at the seasonal level, the monthly distribution of the occurrences with respect to the difference of rainfall is not always straightforward (Figure 7). To be noted also is the outbreak of COVID-19 that hindered the data collection process by the geo-observers, especially between the months of March–July 2020 and 2021 when public transport was restricted (Figure 7). The corresponding number of reported hazard occurrences for these months represent those reported around the homes of geo-observers.

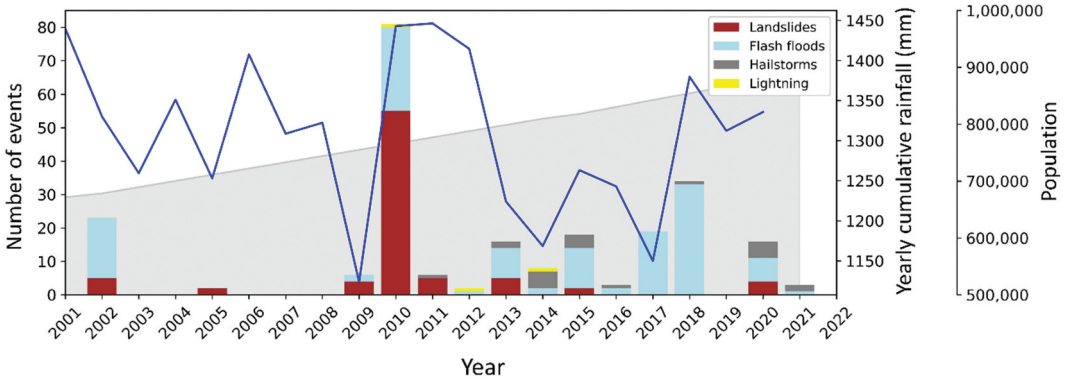


Figure 6. Yearly distribution of natural hazard events based on reported inventory, as compared with rainfall and population (the grey trend) in the same period. Rainfall data are from IMERG (integrated multi- satellite retrievals for GPM) final run data. Population data are from UBOS (Uganda Bureau of Statistics).

Inventory from the field surveys revealed 52 flash flood occurrences and over 3000 easily identifiable shallow landslides that often occurred in spatial clusters (Figure 4(a,b)). This is an indication that most of the landslides observed are triggered by rainfall. All the reported landslide events as well as the very large majority of the landslide occurrences mapped from satellite images and/or observed in the field are slide and debris avalanche processes that occur suddenly and are moving fast. Added to these, a few slow-moving landslides were observed. For some of them, local residents report pervasive movements with deformation patterns associated with the rainfall seasonality (Figure 4(c)).

4.2. The interaction relationships of natural hazards

We identified 40 hazard events with interactions. Out of this, we selected 24 hazard events for detailed characterization and visualization in a hazard matrix. The selected events are those which had sufficient information for analyzing hazard interactions. The types of hazards highlighted with interactions were mainly storm, hailstorms, (flash) floods, and fast- and slow-moving landslides. The associated anthropogenic processes considered include road cuts, deforestation, brick laying, mining and quarrying, bush burning, overgrazing, wetland reclamation, over cultivation on slope, and boundary disputes (Table 3). In the latter scenario, a natural drainage channel was blocked by the residents of one upstream parish to prevent water from flowing over to the neighboring downstream parish, resulting in heavy floods at the upstream one.

Our results from the visualization matrix generated 36 hazard interactions relevant for the study region. Out of these interactions, 16 hazards directly triggered and increased the probability of occurrences of the secondary hazards (Figure 8). The cascading hazards occurred mostly in the months of May, April, and September, associated with the wet season. Similarly, 20 interaction types were recorded from the anthropogenic processes that catalyzed or increased the probability of secondary hazards occurring (Figure 8). For example, according to the residents, many compound events comprising flash floods and landslides that occurred in the eastern part of the study area were due to the vegetation removal by overgrazing, animal trampling, and fires that happened in the past in from 1970 to 80 (Figure 9(b-d)).

4.3. Impacts

We have recorded 97 fatalities in all the multi-inventories conducted and a lot of property (houses, crops, livestock, public institutions, etc.) destroyed. These impacts are associated with frequent and

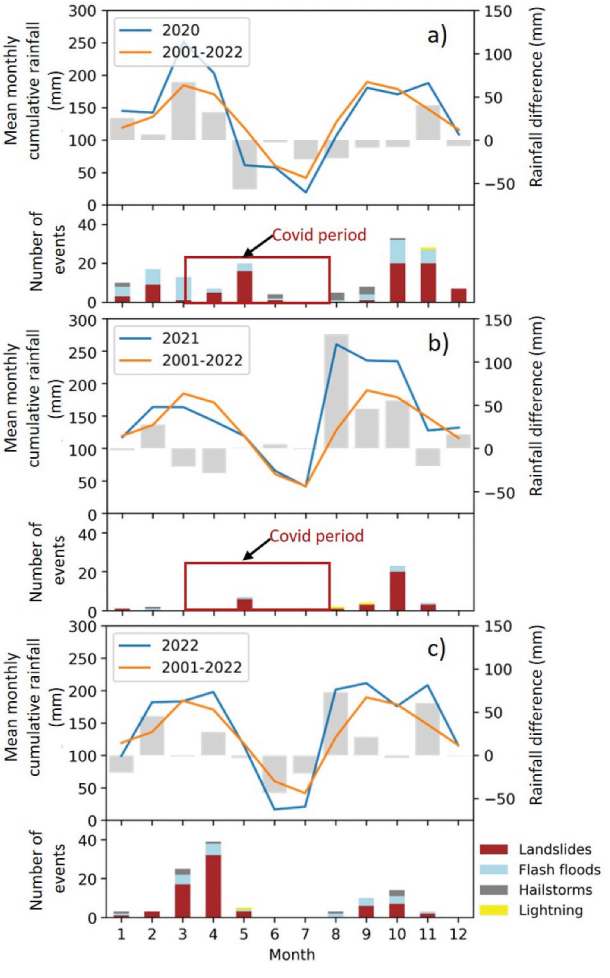


Figure 7. Distribution of hazard events based on the geo-observer network in a) 2020, b) 2021, and c) 2022. The events are represented together with the rainfall distribution of the respective year versus the average rainfall distribution for the 2001–2022 period. The gray bars represent the difference between the annual rainfall and the average rainfall. Rainfall data are from IMERG (integrated multi-satellite retrievals for GPM) late run data.

small (and not that impactful) events but whose cumulative impact is grave. Needless to mention, the severity of small frequent events is exacerbated by the increased exposure of the population and the extensive risk context of the region. Interactions with local communities expressed a lot of the indirect impacts especially those associated with degradation of the soil as a result of landslides and flash floods.

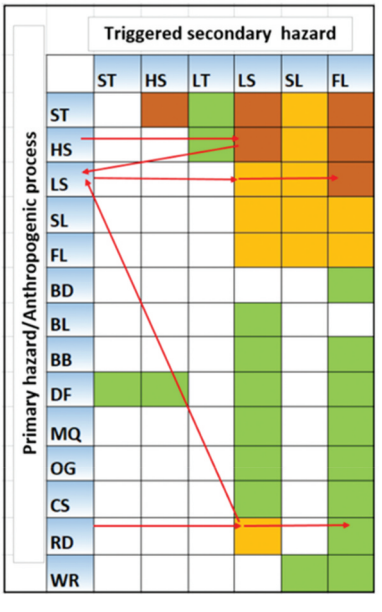
5. Discussion

With a database of over 4000 natural hazard occurrences, our results clearly confirm in a more comprehensive and reliable way that Kigezi highlands are highly exposed to natural hazards. It also reveals that the natural hazards were clearly underreported and their associated problems were underestimated. We show that many of the occurrences are associated with events that are of relatively small magnitude. Although not necessarily associated with strong direct impacts such as fatalities, these frequent and widely spread events are clearly pointed out by the population as having a high cumulative impact on

Table 3. Hazard inventory methods and their information and potential applications in a disaster risk reduction (DRR) perspective in the context of this study.

		Inventory method				
Potential for DRR		Literature, archives, reports, and global databases	Workshops	Geo-observers	Satellite images	Field observations
Process characterization	Detailed physical process characterization	♣	♣	♣♣	♣♣	♣♣♣
	Accurate temporal information	♣♣	♣♣	♣♣♣	♣	♣
	Causes & triggers	♣♣	♣♣	♣♣♣	♣♣	♣♣
	Hazard interactions	♣♣	♣♣♣	♣♣	♣♣♣	♣♣
	Past hazards	♣♣♣	♣♣♣	x	♣♣♣	♣♣
Quantitative applications	Susceptibility assessment (spatial prediction)	♣	♣	♣	♣♣♣	♣♣
Awareness	Temporal prediction of hazards	♣	♣	♣♣	♣♣	♣
	Early warning systems	x	x	♣♣♣	x	x
	Impacts caused	♣♣	♣♣♣	♣♣♣	♣♣	♣♣
	Interactions with local communities	x	♣	♣♣♣	x	♣

Key: ♣♣♣ high suitability; ♣♣ moderate suitability; ♣ low suitability; x not suitable.



Group	Hazard	Code
Atmospheric	Storm	ST
	Hailstorm	HS
	Lightning	LT
Geophysical	Landslide	LS
	Slow-moving landslide	SL
Hydrological	Flood	FL
Anthropogenic process	Boundary disputes	BD
	Brick laying	BL
	Bush burning	BB
	Deforestation	DF
	Mining & quarrying	MQ
	Overgrazing	OG
	Over cultivation on slope	CS
	Road construction	RD
	Wetland reclamation	WR

	Natural hazard/anthropogenic process triggers and increases probability of secondary hazard occurrence - potential for many/multiple hazard occurrences
	Natural hazard/anthropogenic process triggers and increases probability of secondary hazard occurrence - potential for individual/a few occurrences
	Natural hazard/anthropogenic process increases probability of secondary hazard occurrence

Figure 8. Hazard matrix showing interactions between natural hazards and anthropogenic processes. The illustration with arrows shows how a hailstorm triggered landslides which triggered more landslides and floods. The road construction triggered landslides which further led to an increased probability of floods. Road construction also created more impervious surfaces which increased the probability of floods. The figure layout is adapted from Gill and Malamud (2014, 2017).

agricultural activities. For instance, a study by (Mertens et al., 2016) in a similar region in Uganda also revealed the significant impacts of landslides on agriculture, which was further translated into losses of total household incomes. As stressed, for example, by UNISDR

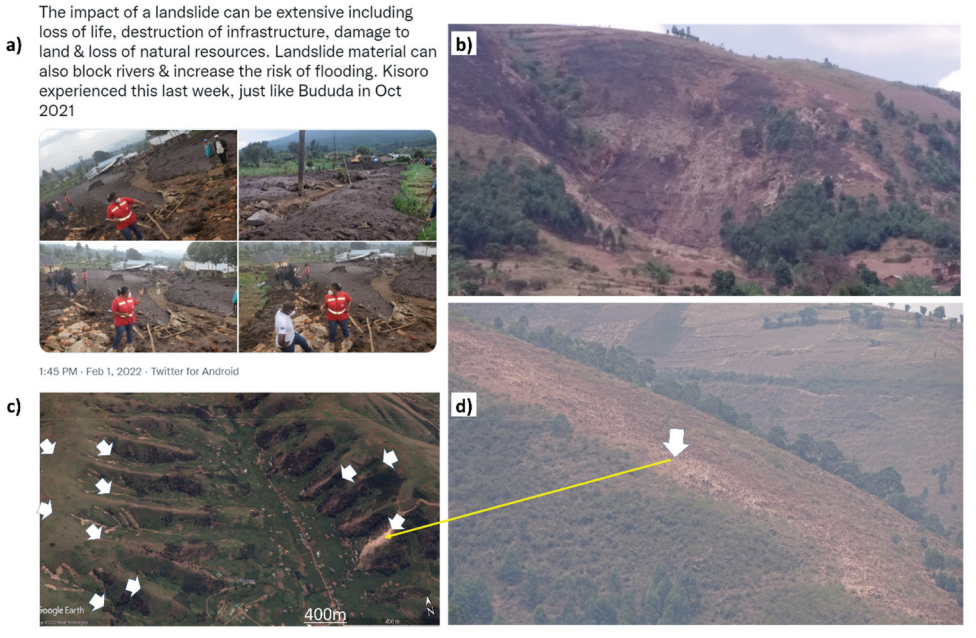


Figure 9. Examples of natural and human-induced hazard interactions. a) tweet from the Uganda Red Cross spokesperson confirming cascading hazards in Kisoro. b) vegetation removal by bush burning (photo taken on 19th August 2021). c) and d) vegetation removal likely to have played a role on the occurrence of floods and landslides in the eastern part of the study area by overgrazing and trampling of livestock (cattle trails shown by white arrows) mapped on Google Earth imagery of June 2011 and confirmed in the field.

(2015), the everyday small hazards, also referred to extensive risks in the literature, have the potential of being much more problematic in the long term than rare major catastrophic events.

5.1. Value added by the multi-method inventory

The database established in the study highlights the advantages as well as limitations of each individual method in terms of building an accurate and reliable inventory. This is summarized in Table 3 with respect to information and potential applications for understanding and mitigating disaster risk.

We have collected much more information than the 340 events available for our study area in the reported inventory, although we targeted a shorter period of investigation. This shows that these inventories which focus on the most impactful events clearly miss the largest majority of the problems in space and time. Such dataset is therefore irrelevant for susceptibility, hazard and early warning. Nevertheless, it provides insight on hazard interactions and it is definitely a key for the knowledge of the past. This biased reporting is also reflected in 2010 when the highest number of events was reported (Figure 6). Despite being a wet year as shown in the rainfall time series (Figure 6), which could explain the high number of natural hazard experienced, similar rainfall values were experienced in 2018 and 2011 but did not have such striking events reported. Evidence from the geo-observer network inventory shows that landslides occur every year and are the most frequent events (Figure 5c); however, there are no landslides reported in 2017 and 2018 from the reported inventory (Figure 6), which further confirms the reporting biases. The overall slow rising trend in the number of hazard events is therefore certainly due, at least partly, to a combined effect of improved reporting mechanisms and

technology (Monsieurs et al., 2018) and increased exposure associated with population growth (UBOS, 2018) as shown in Figure 6.

Mapping hazard occurrences and events on satellite images presents a rather unbiased inventory in terms of location of landslides and flash floods, which facilitates understanding of spatial distribution of events and the implementation of subsequent susceptibility analysis, for example. With the availability of images of suitable quality and resolution, satellite images offer an advantage of capturing landslides and flash floods in inaccessible areas, where the geo-observers and field survey cannot reach. However, satellite images were not suitable for identifying small landslides, which misses major analyses of low magnitude, frequent events that remain problematic in the region. In a landscape like Kigezi highlands which is highly fragmented and cultivated, it can be difficult to distinguish between the small landslides from the cultivated fields on a satellite image. This was especially encountered with PlanetScope images whose resolution is lower than Google Earth imagery.

Although targeting a smaller region within a rather short-time period of observation, the number of reports produced by the geo-observers is 12 times more numerous than the archives, reports, and literature over the whole study area for the same time period, demonstrating the value added by the citizen science network in data collection. Other researchers, not only in the region (Jacobs et al., 2019; Sekajugo et al., 2022), but also elsewhere (Hicks et al., 2019; Juang et al., 2019) have recently established this positive role of citizen scientists in data collection. The fact that the geo-observers are close to the affected areas is advantageous in quickly recording every event that occurs. While other sources of inventory such as the media reports and global databases will concentrate on large events that have caused huge losses and fatalities, the geo-observers record both the small and large events and the associated impacts. The geo-observer's close to real-time reporting offers accurate timing and georeferenced data, which attributes make the data reliable for analyzing hazard interaction relationships as well as the characterization of the triggering mechanism of the hazard. Due to timely and accurate data qualities, the geo-observer inventory so far offers the most reliable dataset for developing early warning systems, a major element of disaster risk reduction. Indeed, in regions like our study area where dense rain gauge networks are absent, early warning systems commonly rely on precipitation data from satellites, i.e., on km-scale resolution products that tolerate spatial biases (Guzzetti et al., 2020). Inevitably, the geo-observers' inventory process offers citizens' empowerment and awareness about natural hazards and their impacts.

Despite the positive attributes of the database, the spatial biases existing in the geo-observer inventory cannot be ignored. For instance, the reporting of geo-observers is highly clustered to the administrative boundaries of the geo-observers' home area as well as in accessible locations, such as close to road networks. As revealed by Arazy and Malkinson (2021) and Sekajugo et al. (2022), proximity to the citizen observers' residence is a key factor in determining where data collection is done by the geo-observer. As such, events that occur, for example, in hilly terrain, deep valleys, and forested areas, are missed by the geo-observers. Secondly, how the geo-observer gets information about an event depends on their social network and how well known they are in the community. We observed that geo-observers that have an additional leadership role or those that are involved in community work like red cross, often reported more hazard occurrences than other geo-observers because they are more informed about the events. Since the data collection covers a period of three years, it is not possible to use the geo-observers' data for seasonality analysis, such as rainfall understanding, which requires long-term data. With the data gaps in space and time, it implies that the geo-observers' information cannot be used for susceptibility assessment, for example. Another potential limitation of the inventory is the relatively high costs involved in establishing and maintaining the network of geo-observers and relatively great amount of time consumed in data collection, which is much more than mapping features from satellite images. The costs are related to the recruitment process, acquisition of equipment, facilitation/enumeration, and maintenance of the network (e.g.,

refresher trainings, monitoring visits, etc). It should be noted that much as the citizen science concept is based on the spirit of volunteerism, there are different factors that motivate citizen scientists to effectively collect data, which require additional costs to maintain the network (Mintz et al., 2022; Weeser et al., 2021). Therefore, one should take into account all the possible costs that might be involved before setting up the geo-observer network for successful data collection.

Inventory through field surveys generated a higher density of landslides and flash flood records as well as a detailed understanding of hazard interactions through direct observations and interactions with the residents. Field surveys enabled collecting more accurate spatial and temporal information than that collected from satellite images and archives. Moreover, it was an added advantage to collect accurate information related to the impacts caused as well as causes and triggers associated with the hazards, which is not possible to get from satellite images. Our field survey also covered an area larger than the geo-observer's area and thus enabled more observations to be made. Having conducted the fieldwork for three months just after the wet season allowed observation of fresh and rather small shallow landslides, too small to be clearly detected on satellite images as well as being reported in media reports. However, land reclamation was already well in place, leading to a quick disappearance of the scars. In addition to the fast natural growth of the vegetation of the region, land reclamation is clearly to be considered when compiling inventories in such a populated landscape (Van Eynde et al., 2017). In comparison to satellite images, field-based inventories are often inefficient in temporally constraining natural hazards and are costly when detailed surveys of spatially extensive events are to be investigated, as it requires a long period to complete (Scheip & Wegmann, 2021).

The compiled inventory in this study, which is very detailed for such a type of landscape, gives hope to improve the assessment of natural hazards and the associated risks in the region. Nevertheless, the discrepancies of density of information between the different sources of data (Table 2) show that care must be taken with these spatio-temporal biases (Table 3). Not to mention that field data collection was impeded by COVID-19 measures, especially between March and June in 2020 and 2021 when the country imposed travel restriction measures (Figure 7).

5.2. Natural hazard processes in a human-induced changing landscape

Despite the advantages and biases discussed about our multi-method inventory, the data we have collected here allow gaining insight on the understanding of the processes. The seasonality of the natural hazard patterns is well pronounced, most of the records being associated with rainfall conditions (Figures 5, 6 and 7). Similar temporal distribution trends have been reported by other work in the Rift region (Jacobs et al., 2016; Monsieurs et al., 2018). Our work is a good case for highlighting the importance of hazard interactions.

Human population increase in the region is reported to be associated with widespread land use and land cover changes. This is confirmed by Mwanjalolo et al. (2018) that show that major land conversions from forest/grassland to agriculture took place in Uganda and Kigezi in particular from 1995 to 2015, and were linked to the increasing population that demands more land for agriculture and settlement. Some researchers such as Kilama Luwa et al. (2021) have confirmed this trend. The information we gathered in this study highlights a possible link between changes in land use and hazard patterns. Such links have been demonstrated in a similar region located in the south of our study area with the occurrence of landslides and deforestation (Depicker et al., 2021b). However, the study by Depicker et al. (2021b) is built on thousands of landslide and forest cover change observations for which we know the year of occurrence; i.e., information that we do not have in our dataset. In our study, the role of land use on the occurrence of natural hazards is assumed/reported but not quantified. The quantification of land use change and natural hazard patterns is a research topic on its own that we do not aim to address here. This would need more investigation not only on the dynamics of the land use but also on the collection of hazard information.

5.3. Implication of the study results for under-reported regions

Here, we demonstrate that regions that are remote and impacted by extensive risks can be documented, which has implications for natural hazard studies in general and also for DRR strategies. We argue that despite difficult conditions in data collection, it is possible to develop suitable strategies to collect extensive inventories to represent the diversity of hazards over regions that are commonly labeled as 'data scarce.' Despite the amount of information that can be extracted from empirical analysis of satellite images, our study also demonstrates the need to collect field-based information when processes must be understood at the very high level of detail. In this respect, citizen science is of great added value relative to data collected directly by researchers in the field. Another important hinge exhibited in our study is the transdisciplinary component, which integrated iteratively stakeholders in elaborating and mapping of natural hazards and their interactions. Interacting with stakeholders offered an additional advantage of inventorying historical hazard occurrences, their triggering mechanisms and damages caused.

6. Conclusions

Although the Kigezi highlands were already highlighted as a natural hazard hotspot, not only in Uganda but also in regional-continental-scale assessments, our analysis demonstrates that the figures based on global databases were an underestimate. This underestimate is associated with the fact that most hazard events are associated with extensive risks. Undoubtedly, the study has generated new knowledge in understanding the spatio-temporal distribution of natural hazards in Kigezi highlands as well as complementing the existing natural hazard databases. Hazard interactions do occur in Kigezi highlands, mainly triggered by both natural and anthropogenic factors, especially rainfall and land use changes. With population increase and intensification of land use activities in the region, a linkage of anthropogenic activities and the magnitude and frequency of natural hazards can be expected.

We further highlight the applicability of the diverse methods in building hazard inventories. It is clear that each method applied generated data of different characteristics and qualities and can therefore be applied to different applications in DRR efforts. In the current era of improved access to information, we must question the relevance of many studies that still build their analysis with very limited datasets and insight on understanding of the processes that are being investigated.

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Disclosure statement

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Appendix

Appendix I: Global catalogues/databases on natural hazards used in this study

Catalogue/database	Institution	Period of data availability
DesInventar Disaster information system https://www.desinventar.net/	UNDRR DesInventar Sendai	1989-present
EM-DAT – Emergency Disaster Data Base https://www.emdat.be/emdat	CRED – Centre for research on the Epidemiology of Disasters, at the University of Louvain (Belgium)	2000 – present
Flood list http://floodlist.com/?s=uganda	Copernicus, the European Union (EU)	1995-present
GLIDE – The Global Disaster Identifier Number http://glidenumber.net/glide/public/search/search.jsp?	Asian Disaster Reduction Centre (ADRC)	2000-present
Global Fatal Landslide Catalogue https://www.un-spider.org/links-and-resources/data-sources/global-fatal-landslide-database-gfld-university-sheffield	University of Sheffield Froude and Petley	2004–2017
Dartmouth Flood Observatory. http://floodobservatory.colorado.edu	DFO	2020-present
Global Landslide Catalogue https://data.nasa.gov/Earth-Science/Global-Landslide-Catalog-Export/dd9e-wu2v/data	National Aeronautics and Space Administration (NASA)	2007 – 2017
National Emergency Coordination and Operations Centre (NECOC) https://www.necoc.opm.go.ug/index.html	Uganda Disaster Risk Information Centre Office of the Prime Minister	2014-present