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Abstract Landslide hazard remains poorly characterized on regional and global scales. In the tropics in particular, the lack of knowledge on landslide hazard is in sharp contrast with the high landslide susceptibility of the region. Moreover, landslide hazard in the tropics is expected to increase in the future in response to growing demographic pressure and climate and land use changes. With precipitation as the primary trigger for landslides in the tropics, there is a need for an accurate determination of rainfall thresholds for landslide triggering based on regional rainfall information as well as reliable data on landslide occurrences. Here, we present the landslide inventory for the central section of the western branch of the East African Rift (LIWEAR). Specific attention is given to the spatial and temporal accuracy, reliability, and geomorphological meaning of the data. The LIWEAR comprises 143 landslide events with known location and date over a span of 48 years from 1968 to 2016. Reported landslides are found to be dominantly related to the annual precipitation patterns and increasing demographic pressure. Field observations in combination with local collaborations revealed substantial biases in the LIWEAR related to landslide processes, landslide impact, and the remote context of the study area. In order to optimize data collection and minimize biases and uncertainties, we propose a three-phase, Search-Store-Validate, workflow as a framework for data collection in a data-poor context. The validated results indicate that the proposed methodology can lead to a reliable landslide inventory in a data-poor context, valuable for regional landslide hazard assessment at the considered temporal and spatial resolutions.

Keywords Landslide processes · Inventory framework · Field observations · Central Africa · Tropics

Introduction

Landslides present one of the most pervasive hazards in dissected and tropical landscapes (Sidle et al. 2006). Landslide hazard describes the likelihood of landslide occurrence in time and space along with the landslide's magnitude (Guzzetti et al. 1999). Despite its prominence, landslide hazard remains poorly characterized on regional and global scales (Kirschbaum et al. 2012). In the tropics in particular, the lack of knowledge on landslide hazard is in sharp contrast with the high landslide susceptibility of the region due to high precipitation and weathering rates, specifically in zones with steep topography and tectonic activity (Sidle et al. 2006). Moreover, landslide hazard in the tropics is expected to increase in the future in response to increasing demographic pressure, climate change, deforestation, and other forms of land use changes (DeFries et al. 2010; Gariano and Guzzetti 2016; Lorentz et al. 2016). In addition to this, climate change in tropical regions is reported to be very likely associated with an increasing trend in extreme rainfall intensity (IPCC 2013; Sillmann et al. 2013), which is the primary trigger for landslides here (Sidle et al. 2006). Consequently, increasing intensity and frequency of landslides is expected (Gariano and Guzzetti 2016). In this perspective, there is a need for an accurate determination of rainfall thresholds for landslide triggering, dependent on the involved landslide processes and their environmental conditions (Guzzetti et al. 2008). To achieve this, regional rainfall information as well as reliable data on landslide occurrence are needed.

With regard to regional rainfall data, the lack of adequate rainfall records from ground monitoring networks in the tropics can partly explain the scarcity of such threshold estimates in tropical areas (Guzzetti et al. 2008; Kirschbaum et al. 2015a). In recent decades however, climate models and satellite precipitation products have been developed and exhibit great potential to fill the void on precipitation data (Kirschbaum et al. 2009; Thiery et al. 2015). Currently, NASA's Tropical Rainfall Measuring Mission (TRMM: 1998–2015; ~ 25 km × ~ 25 km grid cell, 3-hourly temporal resolution) and its successor, Global Precipitation Measurement (GPM: 2014–present, ~ 10 km × ~ 10 km grid cell, half-hourly) provide the longest temporal record of freely available, highly homogeneous precipitation products over the tropics. The short latency of the near real-time satellite rainfall estimates, i.e., 8 and 6 h for TRMM and GPM respectively, is highly desirable for hazard assessment and disaster response.

With the emergence of satellite rainfall products, the main bottleneck in the establishment of rainfall thresholds for landslide triggering in the tropics is the availability of detailed data on landslide occurrences in time and space. The dearth of spatiotemporal information on landslide occurrence has indeed been repeatedly highlighted as one of the main factors limiting landslide hazard assessment (e.g., van Westen et al. 2008; Kirschbaum et al. 2010; Van Den Eeckhaut and Hervás 2012; Taylor et al. 2015). Especially in the developing world, spatiotemporal information on landslides is sparse even though most casualties from landslide disasters are estimated to occur in these areas (Petley 2012). An overview of the prevailing global landslide inventories that are publicly available (even if partially) and contain information on the timing of landslide occurrences is presented in Table 1. Floodlist, PreventionWeb, and Reliefweb are not strictly inventories but collections of reports which proved to be useful for data collection on landslide occurrences (Kirschbaum et al. 2015b). All of these inventories

Table 1 Overview of the current publicly available global inventories containing data on landslide occurrence, divided into "Global Landslide Inventories" comprising exclusively data on landslides, and "Global Disaster Inventories" comprising data on landslides and other disasters. Terminology used in "Included processes" comes from the original sources. [N. LS] is the total number of landslides (on June 2017) including those with unknown date of occurrence. [% from total] is the percentage of landslide events. [% LS Africa] is the percentage of landslide events in Africa. [A.] are approximations based on landslide reports or when the portion for disasters in Africa was not specified for each disaster separately. [N. study] is the number of landslides in the study area. [NA] when no information is available. Online accessible platforms are given in blue

Name	Institution (Country/Union)	Included processes	Start (AD)	End (AD)	N. LS	% LS Africa	N. Study
Global Landslide Inventories							
DFLD – Durham Fatal Landslide Database http://blogs.agu.org/landslideblog/	University of Durham (UK)	Fatal non-seismic triggered soil/rock failures, including slides, flows and fails. Debris flows are included when the movement can be clearly differentiated from a flood.	2004	2010	2620	NA	3
GLC – Global Landslide Catalog https://data.nasa.gov/Earth-Science/Global-Landslide-Catalog/h9d8-neg4/data	NASA – National Aeronautics and Space Administration (USA)	All types of mass movements triggered by rainfall.	1968	Present	6790	2	15
Global Disaster Inventories							
CatNat – Cattastrophes Naturelles http://www.catnat.net/	Ubyrisk Consultants (France)	Avalanches, Cyclones, Cold, Droughts, Earthquakes, Eruptions, Extraterrestrial Events, Fires, Floods, Hail, Heat Wave, Landslides, Lightning and Thunderstorms, Snow, Storms, Tornadoes, Tsunami	2001	Present	868 (6)	8	3
EM-DAT – Emergency Disaster Data Base http://www.emdat.be/	CRED – Centre for research on the Epidemiology of Disaster, at the Catholic University of Louvain (Belgium)	Biological, climatological, geophysical, hydrological, meteorological, and technical disaster which have killed 10 or more people, affected 100 or more people, or resulted in a declaration of a state of emergency or call for international assistance	1900	Present	725 (3)	6	13
Flood List http://floodlist.com/	Copernicus, the European Union (EU)	Flood-related issues (warning system, mitigation and control, flood recovery, flood damage repair and restoration, flood insurance)	1995	Present	A. 480 (24)	A. 6	3
GLIDE – The Global Disaster Indentifier Number http://www.glidenumber.net	ADRC – Asian Disaster Reduction Center (Japan)	Cold Wave, Complex emergency, Drought, Earthquake, Epidemic, Extratropical Cyclone, Extreme Temperature, Famine, Fire, Flashflood, Flood, Heat Wave, Insect Infestation, Land Slide, Mud Slide, Other, Severe Local Storm, Slide, Snow avalanche, Storm Surge, Technological Disaster, Tornadoes, Tropical Cyclone, Tsunami, Violent Wind, Volcano, Wave/Surge, Wild fire	A. 1900	Present	158 (3)	7	2
NatCatSERVICE – Natural catastrophe loss database https://www.munichre.com/en/reinsurance/business/non-life/natcatservice/index.html	Münich Reinsurance Company (Germany)	Natural disaster (excluding technological disasters): Avalanche, Drought, Earthquake, Eruption, Flooding, Landslide, Rock Fall, Storms, Subsidence, Volcanic Extreme temperatures, Wildfire	79	Present	A. 6149 (43)	A. 5	0

(continued)

Name	Institution (Country/Union)	Included processes	Start (AD)	End (AD)	N. LS	% LS Africa	N. Study
Prevention Web Hazard database	United Nations International Strategy for Disaster Reduction (UNISDR)	Avalanche, Biological, Chemical, Cold Wave, Cyclone, Drought, Earthquake, Epidemic & Pandemic, Flood, Heat Wave, Insect infestation, Nuclear, Storm Surge, Technical Disaster, Tornado, Tsunami, Volcano, Wild Fire	A. 1970	Present	A. 1993 (6)	A. 10	1
http://www.preventionweb.net/english/hazards/							
Relief Web	UN Office for the Coordination of Humanitarian Affairs (OCHA)	Cold Wave, Drought, Earthquake, Epidemic, Extratropical Cyclone, Fire, Flashflood, Flood, Heat Wave, Insect Infestation, Land Slide, Mud Slide, Other, Severe Local Storm, Snow Avalanche, Storm Surge, Technological Disaster, Tropical Cyclone, Tsunami, Volcano, Wild Fire	1980	Present	A. 222 (7)	A. 10	15
http://reliefweb.int/							

have their specific constraints and limitations, to which incompleteness in number and timing of the events can be attributed (see "Included processes" in Table 1). Africa has been estimated to be underrepresented in all the inventories in Table 1, due to the proportion of remote areas in this continent (Kirschbaum et al. 2009). The fraction of landslides in Africa ranges between 2 and 10% (Table 1). None of these inventories has been validated nor provides any level of reliability for data entries.

The main objective of this paper is to collect spatiotemporal information on landsliding in a remote and underrepresented region to move towards regional hazard assessment. The latter, however, is not within the scope of this paper. As region of interest, we select the central section of the western branch of the East African Rift (Fig. 1; hereafter referred to as WEAR). It is a landslide-prone area representative of many other mountainous regions in the tropics (Maki Mateso and Dewitte 2014; Jacobs et al. 2016a; Nobile et al. 2018). Moreover, it is a prime example of a tropical region where landslides cause loss of life and livelihood and damage to infrastructure on a yearly basis but where landslide hazard remains poorly understood. Data collected at the global level are not sufficient to perform hazard analysis in the study area, with only 15 events reported by the Global Landslide Catalog (Kirschbaum et al. 2015b) (Table 1). Therefore, within this work, a methodological framework is presented to construct a landslide inventory (referred to as LIWEAR) with specific attention for spatial and temporal accuracy, reliability, and geomorphological meaning of the data.

Study area

The study area covers about 200,000 km^2 along the western branch of the East African Rift (Fig. 1). Little attention has so far been given to this area as a hazardous region for landslides (Maes et al. 2017), although important predisposing factors are being observed (Maki Mateso and Dewitte 2014; Jacobs et al. 2016a). Both earthquakes and rain have been reported to trigger landslides, although the former only marginally (Maki Mateso and Dewitte 2014; Jacobs et al. 2016a, 2017b; Nsengiyumva et al. 2018). Experiences during fieldwork in the study area between 2014 and 2016 confirm these findings indicating that rainfall manifests as the dominant trigger for recent landsliding. Additionally, human-related parameters are found to be major drivers of increased vulnerability to, and risk of, geo-hazards in the WEAR, namely high population densities, land use changes, deforestation, high poverty levels, and poor political stability (Karamage et al. 2016; Michellier et al. 2016; Trefon 2016).

Currently, two regional spatiotemporal inventories cover all or part of the study area: an inventory of 48 landslides in the Rwenzori Mountains (Jacobs et al. 2016a) and a natural hazard database for Central Africa (Vandecasteele et al. 2010) with 107 landslides located in the WEAR. Both lack consistent information on the timing of landslide events and acknowledge the likelihood of underestimated numbers of events due to limited communication opportunities (Internet, roads, etc.) in the region. Maki Mateso and Dewitte (2014) mapped more than 600 landslides in the study area, yet the lack of temporal information prevents exploitation of this data set for hazard analyses. Still other studies refer to landslide occurrence in the WEAR, without addressing their temporal aspect (Munyololo et al. 1999; Moeyersons et al. 2004; Mavonga 2007; Wafula et al. 2007).

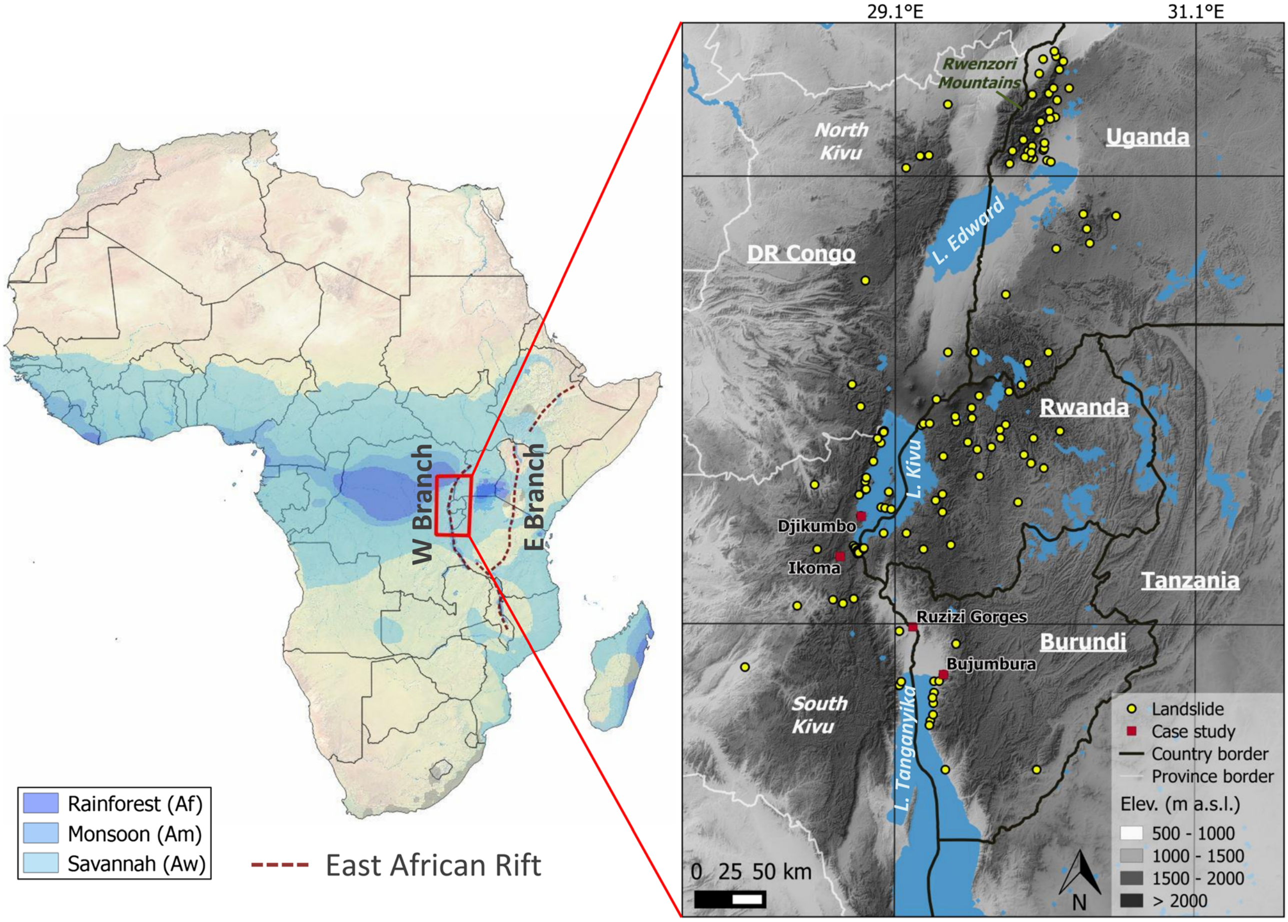

Fig. 1 Location of the study area in the western branch of the East African Rift. Left: tropical Köppen-Geiger climate types (Peel et al. 2007); source map for Africa from NaturalEarth (2016). Right: spatial distribution of 156 landslides with known date and localization from 1968 to 2016 (yellow dots); topography from 90-m resolution SRTM DEM

Methodology

We propose a framework adapted from Taylor et al. (2015) to optimize the collection of spatiotemporal landslide information on a regional scale. The methodological workflow goes through three successive phases: Search-Store-Validate (Fig. 2).

Sources for landslide data collection (Search)

As highlighted by Taylor et al. (2015), it is important to define what is considered as a landslide event prior to landslide data collection. Following Kirschbaum et al. (2010), a single "landslide event" entry in the LIWEAR is defined as either a single landslide or a group of landslides with a common trigger over the same area. To separate local convective rainstorms (Jackson et al. 2009; Thiery et al. 2015), we defined the "event area" by calculating the spatial representativeness for daily precipitation anomalies as proposed by Orlowsky and Seneviratne (2014). Precipitation anomalies are calculated by subtracting the wet day (≥1 mm) seasonal cycle from the wet day precipitation amounts. Constants for the Pearson correlation threshold and ratio of similar points in the convex hull were set at 0.6 and 90%, respectively. Hence, the spatial representativeness of a pixel gives the area where minimum 90% of the comprising pixels have a correlation coefficient of at least 0.6 with this pixel. This correlation is based on precipitation anomalies during concurrent wet days. COSMO-CLM^2-modeled rainfall (1999–2008) was used for this analysis. It is currently the best available model regarding performance and spatial resolution (~7 km) over the study area (Thiery et al. 2015, 2016; Docquier et al. 2016), whereas TRMM and GPM data are not yet validated over the WEAR. We found that most pixels have a minimum spatial representativeness of 500 km^2, i.e., a circle area (approximation of the convex hull) with a radius of ~12 km (Fig. 3). Therefore, landslides are grouped in one event if they occur at the same time at less than 12 km from each other. The distance is calculated for each of the landslides separately to the nearest landslide. Throughout the paper, "landslide event" is used for a group of landslides, and "landslide" systematically refers to a single landslide.

The Search phase is dedicated to an as exhaustive as possible search through a broad variety of sources. Key websites and terminology are determined for a systematical scanning of the identified websites and the Internet, in both English and French, the latter being the main language in this region of Central Africa. This extensive search includes a wide spectrum of sources ranging from gray literature such as eyewitnesses and blogs to scientific papers. A search string using Boolean operators and wildcards (! = wildcard of one or more characters) is created in Google Alerts

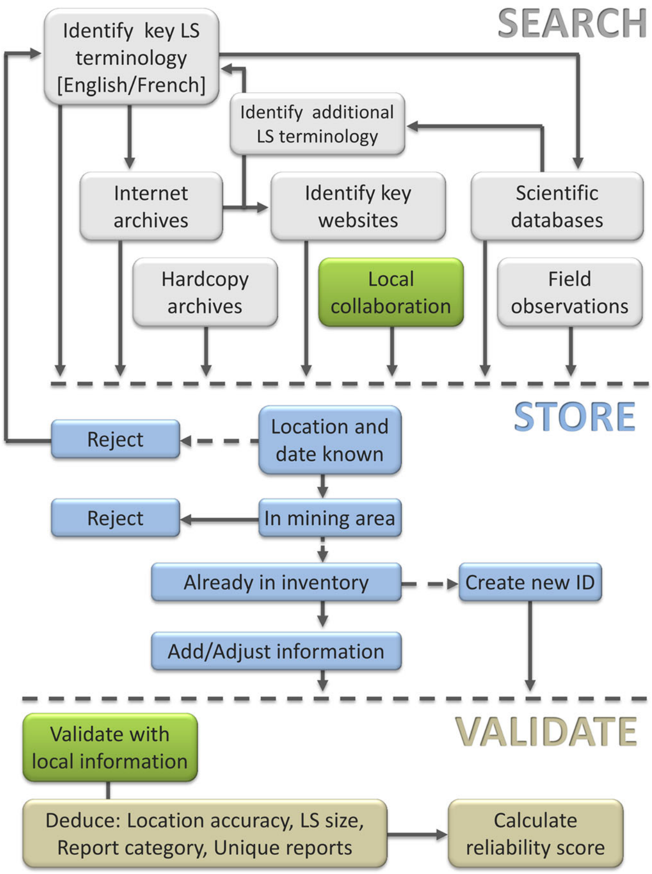

Fig. 2 Flow chart of the three-phase methodological framework to create a landslide (LS) inventory, adapted from (Taylor et al. 2015) for a data-poor context. Dashed arrows are used for "No," and full arrows for "Yes." Green fields are optional steps when collaborations with local partners are established

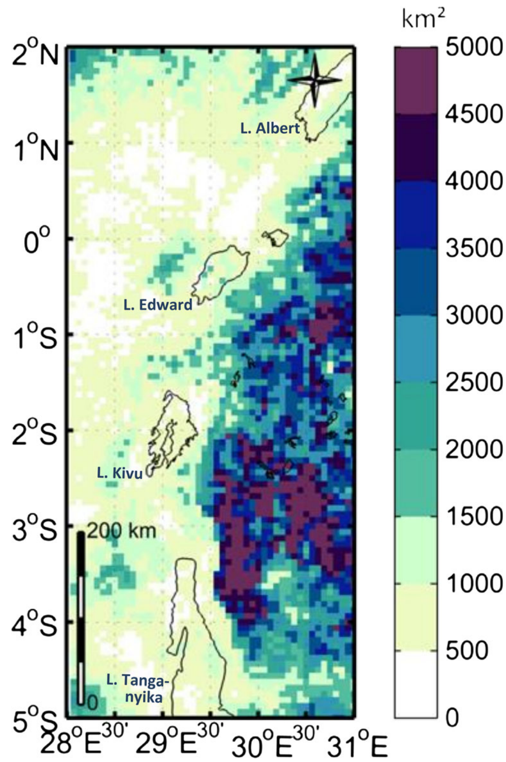

Fig. 3 Area of spatial representativeness for daily precipitation anomalies calculated with COSMO-CLM^2-modeled rainfall at a horizontal resolution of 0.0625° (~ 7 km) (Thiery et al. 2015) for 1999–2008 with 0.60 rank correlation threshold and 90% similar points (Orlowsky and Seneviratne 2014)

(Google Alerts 2016): *[Terminology! AND (StudyArea! OR MajorCities!) AND NOT (Constraints)]*, with

- *Terminology* = keywords for landslides;
- *StudyArea* and *MajorCities* = country and big city names in the study area;
- *Constraints* = inventory's restraints and context to be avoided (e.g., electoral victory).

Search criteria are less strict than the criteria applied for the inventories in Table 1. All landslides are included, regardless of size, impact, date of occurrence, or trigger, except those in mining and quarrying areas (see Store phase under "Data tailoring for inclusion in the inventory (Store)" section). Even though flash floods and landslides are different processes, we know from field experience that confusion can ensue when defining "flash flood," "landslide," or "debris flow" and that they often interact, such as the supply of material or dam formation by landslides (Gill and Malamud 2014; Jacobs et al. 2016a,b). Therefore, flash flood events are included when linked to a depletion area on the hillslope. Additional information is gathered through field observations, local collaborations, and targeted hardcopy archive search. Though the latter is a time-consuming resource with a low return rate, it is indispensable in data-poor contexts. For this research, we have been closely collaborating with the Université du Burundi (Burundi), Université Polytechnique de Gitega (Burundi), Centre de Recherche en Sciences Naturelles de Lwiro (DR Congo), Civil Protection of South Kivu (DR Congo), Université Officielle de Bukavu (DR Congo), and Meteo Rwanda (Rwanda).

Data tailoring for inclusion in the inventory (Store)

In the second phase, landslide information found in the Search phase is evaluated for two constraints before inclusion. The first constraint is the availability of information on the primary attributes including Location and Date of Occurrence (Table 2). Both are fundamental when anticipating the LIWEAR's use for hazard assessment. Landslide events lacking these attributes are excluded. Given the limited data availability in the study area, landslide size is not considered as a primary attribute, as we noticed that this information is often lacking. Second, landslides in mining and quarrying areas are excluded from the inventory. The reason for exclusion is to be able to use this inventory in future research for calibrating rainfall thresholds for a regional landslide hazard model, and therefore, input data is needed that is representative for the overall characteristics of the region (i.e., no mining area). Thresholds that include landslides in mining areas will be much lower and not representative for the natural conditions (Gill and Malamud 2017). We anticipate other human-induced biases such as road networks (Kirschbaum et al. 2016; Tsangaratos and Ilia 2016) and deforested areas (Holcombe et al. 2016), which resulting landslides are however not withheld from the inventory.

Table 2 Description of the attributes in the landslide inventory (Appendix). Primary and deduced attributes are underlined and italicized, respectively; the remaining are secondary attributes

Attribute	Description
ID	Unique identification number composed of land code + number. Land code: Burundi (BU); DR Congo (DC); Rwanda (RW); Uganda (UG); Tanzania (TA)
Date	Date of the landslide event (MM/DD/YYYY), not when it was reported
Time	Time of the landslide event, approximative (morning, afternoon, daytime, evening, night) or HH:MM (24 clock, local time). "Night" refers to the night from the date shown to the date shown + 1
Lat	Latitude landslide event (WGS 84, decimal)
Lon	Longitude landslide event (WGS 84, decimal)
Loc. acc.	Radius from the event coordinates (Lat; Lon) describing the area of uncertainty (in kilometers). This number is taken directly from the original source or calculated as the longest distance of uncertainty (e.g., distance to administrative border when an administrative zone was indicated)
Fat.	Number of reported fatalities
Inj.	Number of reported injured people
Cause	All factors reported to have caused the event (more than one where applicable)
Type (orig.)	Most specific (e.g., "mudslide" instead of "mass wasting")/frequently reported name of the event (shown in original language of report)
Type (E)	Type (orig.), translated in English
Size	Identification of the relative size of the landslide based on Kirschbaum et al. (2010, 2015b): *Small*: small landslide affecting one hillslope or small area. Minimal impact to infrastructure. No fatalities. *Medium*: moderately sized landslide that could be either a single event or multiple landslides within an area and involves a large volume of material. Moderate impact to infrastructure. May result in fatalities. *Large*: large landslide or series of landslides that occur in one general area but cover a wide area. Substantial impacts to infrastructure. Likely moderate to high number of fatalities. *Very large*: very large landslide or multiple events that affect an entire region (entire village or large area). Catastrophic impact to infrastructure. High number of fatalities.
Rep. cat.	All different categories of reports that have described the event are listed here as numbers. Reports have been categorized under the following terms (with their specific number): (1) (inter)governmental reports; (2) NGO reports; (3) (inter)national news sites; (4) international disaster relief websites; (5) scientific literature; (6) eyewitness description, blogs, and local collaboration
Un. rep.	Number of unique reports found for the same landslide event, where the content is not just a copy from another source
R	Expert-based scoring for the reliability of the entry for hazard assessment purpose: (1) very reliable; (2) reliable; (3) little reliable; (4) not reliable

Secondary attributes provide additional information when available, including Time, Number of Fatalities, Number of Injuries, Cause, and Type. Note that Time is a precision to the primary attribute Date (Table 2). Under "Cause" are recorded all factors that are mentioned as having contributed to generate the landslide, integrating what is considered as predisposing and triggering factors in the scientific literature. In-depth hazard analyses are required to identify the triggering and predisposing conditions that resulted in the reported landslide, which is out of scope of this paper. General terms are attributed to the sometimes subjective reported factors related to the landslide event (e.g., "heavy rain" is recorded as "Rain"). Landslide Type is reported as terms copied from the sources using both the original language and its translation to English when applicable, to allow for deeper metadata analysis. We use the terminology defined by Hungr et al. (2014) to discuss landslide processes when background information is available.

A third category of attributes includes deduced variables: Location Accuracy, Size, Report Category, Number of Unique Reports, and Reliability Scoring. When no accuracy for the landslide location was reported, we estimated Location Accuracy as the longest distance from Location to the border of the smallest administrative entity that was given. Owing to the uncertainties in fatalities and injured people records (Petley 2012), we use the sum as a more reliable measure in further analyses and assume zero when not reported. Number of Fatalities and Injuries do not include people reported missing. The qualitative landslide size categories are described in Table 2, based on Kirschbaum et al. (2010, 2015b).

When no geographical coordinates are reported for the landslide event, we use the following alternative sources of information (in order of priority): GPS points that we collected in the field; published maps (GeoNetwork 2015); data on administrative boundaries provided by the government; Référentiel Géographique Commun (DR Congo) (CartONG 2016); Global Administrative Areas (2012); GeoNames (2016); and Google Earth Pro (2016). All the mentioned sources except for the first are freely available.

Evaluation of the reliability (Validate)

Data stored in the inventory are validated in the last phase of the methodological workflow (Fig. 2) using local information when available from own fieldwork or collaboration with local partners. Systematic validation of the LIWEAR is however challenging for a number of reasons. Current security levels in most parts of the WEAR preclude validation through systematic field observations on a regional scale (Monsieurs et al. 2017). Moreover, analyses of multi-temporal satellite images is limited because evidence of small landslides quickly vanishes due to modifications by subsequent erosional processes, reclamation for agriculture and other anthropic influences, and high rates of vegetation regrowth in the tropics (Malamud et al. 2004; Gourlet-Fleury et al. 2013). Furthermore, frequent cloud coverage over the tropics is a common problem in the use of optical satellite imagery.

Therefore, a decision tree is developed using the attributes Location Accuracy, Number of Unique Reports, and Report Category to derive an expert-based reliability scoring to evaluate the entry's solidity (Fig. 4). We assume that an entry is more reliable when multiple sources that are not exact copies from one another confirm the same information. An entry is considered as most reliable when published in a scientific paper. For example, an entry with a location accuracy of 2 km, with three reports describing the event (where the content is not a copy from one another), from which one falls in the category of "scientific literature," gets the highest reliability score of 1 (Fig. 4).

Earlier studies found human presence to introduce the main bias in landslide inventories (Guzzetti 2000; Kirschbaum et al. 2010; Jacobs et al. 2016a). Therefore, an explanatory factor analysis is performed using CIESIN (2016) open-source population density data. In addition, we use the 1-km resolution global landslide susceptibility model developed by Stanley and Kirschbaum (2017) to check how this factor affects landslide reporting. We also present field observations for selected landslides in order to gain complementary insights into the geomorphological processes at work.

Results

Landslide event reporting

The LIWEAR includes 143 landslide events comprising 156 dated and localized landslides over a span of 48 years between 1968 and 2016 (Fig. 1, Appendix). Landslide events have been reported mainly in DR Congo, which covers about 50% of the study area, followed by Uganda, Rwanda, and Burundi (Fig. 5(a)). No reports were located in Tanzania within the limits of the study area (Fig. 1). The relative number of landslide events per month has been plotted in Fig. 6 against the average monthly rainfall, starting from September. The latter was chosen to present the effect of the accumulated rainfall throughout the two rainy seasons with respect to the amount of landslide events. The highest number of events was reported in May, during which relative low average monthly rainfall occurs, but when the soils have become heavier due to the higher water content. Fewer landslides are reported during the driest season (June–August). Most recorded events occurred after 2000, with only seven events prior to that year (Fig. 7). The cumulative number of fatalities and injuries is mostly attributed to two high-impact landslide events in 2006 in Rwanda and 2010 in DR Congo (Fig. 7).

Reported Category, Number of Unique Reports, and the Reliability Score are deduced attributes for all entries. The following secondary and deduced attributes are only available for a portion of the entire LIWEAR (in decreasing order): Location Accuracy, Size, Fatalities, Cause, Time, and Injuries (Fig. 5(i)). For 126 out of 143 events, landslide Size could be estimated, with 74% categorized as Medium or Large. Small and Very Large events are rather exceptional (Fig. 5(b)). Landslides have been reported in very general terms, grouped as (in decreasing order) Landslide, Mudslide, Debris flow, Rockslide, and Complex (Fig. 5(c)). The latter refers to the interaction of different processes, including flash floods. Rain is the most frequently reported causal factor for landslides, followed by Demographic Pressure which includes derived impacts such as manipulation of natural drainage systems and anarchic housing; only Deforestation and Water Canalization are reported separately (Fig. 5(d)). Time is reported for ~ 50% of all events, equally distributed over night- (25%) and daytime (24%) hours (Fig. 5(e)). The fact that nocturnal landslides seem

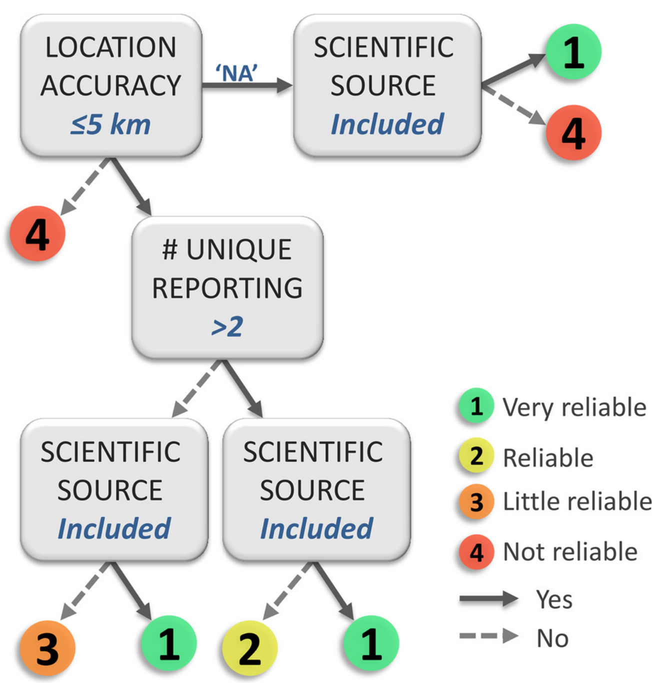

Fig. 4 Decision tree for reliability scoring of the LIWEAR, i.e., evaluating an entry's solidity for further use in landslide hazard assessment. Attributes in the decision tree are specified in Table 2. *NA* = not available

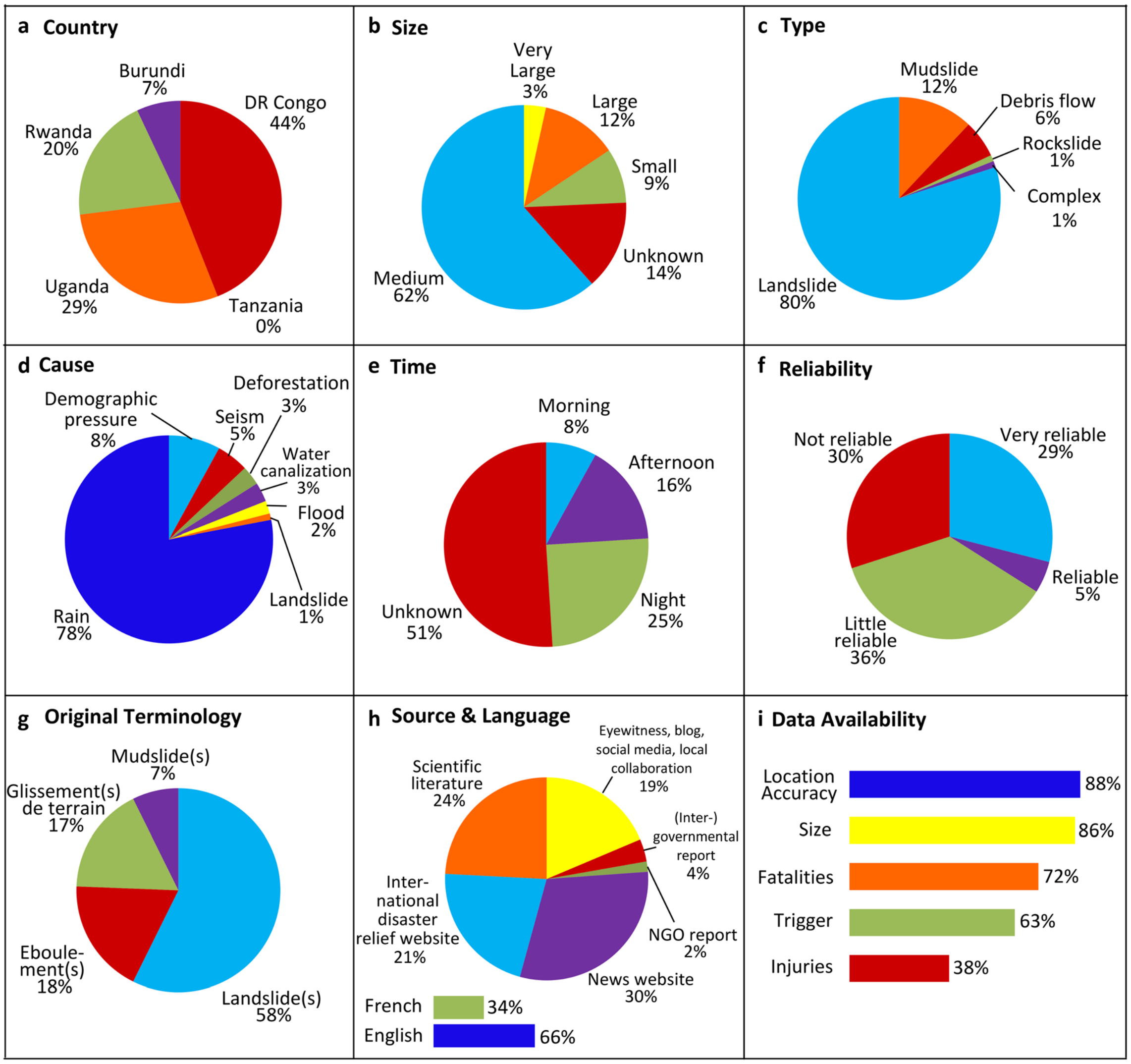

Fig. 5 Statistics of landslide event reporting in the LIWEAR (attribute description in Table 2). a Distribution of events per country; b Proportion of event Size, based on Kirschbaum et al. (2010, 2015b); c Proportion of reported Type; d Reported Cause; e Portion of reported Time of event occurrence; f Reliability scoring; g Used terminology in reporting; h Source partitioning and language for data collection, with *NGO* as non-governmental organization; i Obtained portion for secondary attributes and deduced variables

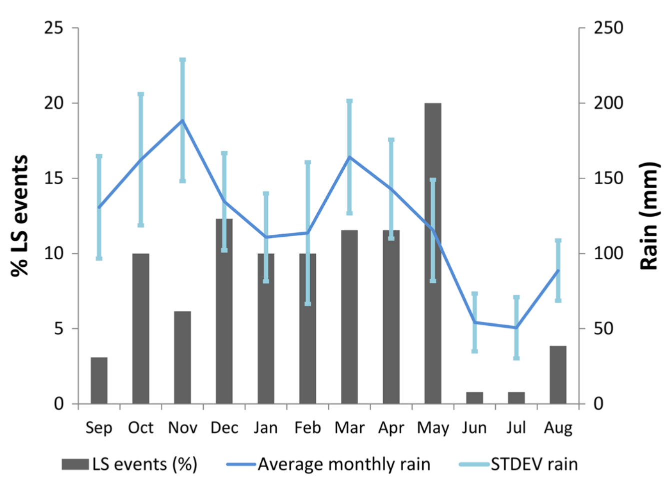

Fig. 6 Monthly distribution of landslide events in the LIWEAR as a percentage of total reported landslide events. The presented mean monthly rainfall is based on 17 years (1999–2015) of TRMM (3B42) daily data, downloaded from http://giovanni.sci.gsfc.nasa.gov

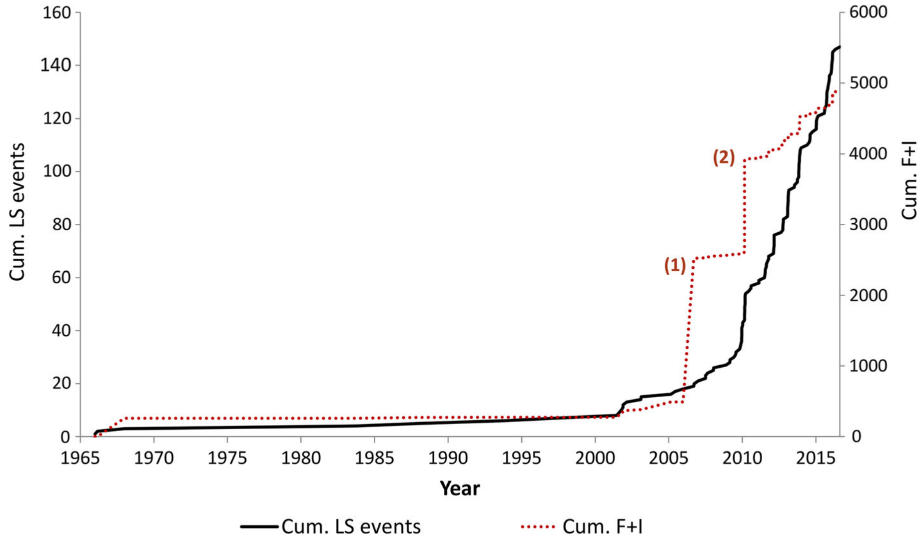

Fig. 7 Cumulative amount of reported landslide events (Cum. LS events) and their respective cumulative sum of fatalities and injured people (Cum. F+I) in the LIWEAR. Two high-impact landslide events are highlighted: (1) 28 November 2006: 2024 casualties in Kigali, Rwanda; (2) 15 May 2010: 1297 casualties in North Kivu, DR Congo

to cause on average larger number of fatalities and injuries than diurnal ones, with mean fatalities and injuries of 43 and 18 respectively, obviously results from the nocturnal occurrence of the 15 May 2010 event ((2) in Fig. 7). No Time estimate is available for the 28 November 2006 event ((1) in Fig. 7). Also, the "surprise effect" of landslides happening during the night might play a role, similar to that of night-time earthquakes which are generally considered to be the most deadly (Allen et al. 2009). For each report, the different names used to describe the landslide have been listed. Based on this list, we found that the following terminology is mostly used: Landslide(s), Eboulement(s), Glissement(s) de terrain, and Mudslide(s) (Fig. 5(g)). While the French term "Glissement de terrain" literally means "Landslide," and "Eboulement" is a vaguer term that can equally mean rockfall or landslide. This list enhances targeted scanning of the Internet.

Thirty-four percent of all landslide reports were in French and 66% in English. (Inter)governmental and non-governmental organization reports have only marginally contributed to the inventory, whereas the contribution of scientific literature, international disaster relief websites, news websites, and eyewitness descriptions, blogs, social media, and local collaboration are fairly equally distributed (Fig. 5(h)). An important source of information, comprising 9% of all used sources and in many cases of otherwise unmentioned landslides, comes from collaboration with local partners in the study area.

Uncertainties and reliability of the inventory

Uncertainty in Time and Date arose when the indication for morning/afternoon was missing or when the sequence of dates was not mentioned for landslides that happened during the night. Localization ambiguities are related to untraceable village names, wrongly spelled locations, and vague reporting of the landslide location. Reported Fatalities and Injuries are ambiguous due to the assumption of zero fatalities or injuries when it was not reported. For Cause and Type, terms are copied from reports knowing that the scientific research required for ascertaining these terms was most generally not conducted. Size estimation is constrained by the uncertainties inherent to variables constituting this attribute (Table 2). The Number of Unique Reports is also not an exact figure since an exhaustive search for reports on landslide events is impossible (Malamud et al. 2004) but the extensive search we conducted allows us to assume that it is a good approximation.

Two thirds of the landslide reports show some degree of reliability (Fig. 5(f)). Location Accuracy is ≤ 25 km (~TRMM grid size) for most of the reported landslides (84%), ≤ 10 km (~GPM grid size) for 72% of them, and the same proportion (72%) is found for landslides with Location Accuracy ≤ 12 km (~COSMO-CLM^2-based spatial representativeness, Fig. 3). In some cases (8%), additional information could be retrieved from a local partner living close to the event, resulting in an average increase of 67% in the Location Accuracy of these events. To test if Location Accuracy was affected by other attributes, correlation coefficients were calculated with Number of Fatalities and Injuries, Number of Unique Reports, and the inclusion of a scientific report, but no significant correlation was found.

The LIWEAR is found to be biased towards densely populated areas, with 59% of landslide events falling in areas with more than 350 inhabitants per km^2, which constitutes only 18% of the study area (Fig. 8). According to the global landslide susceptibility model of Stanley and Kirschbaum (2017), the study area is for 41% very lowly to lowly, 35% moderately, and 24% highly to very highly susceptible to landslides. Only few landslide events have been reported in low-susceptibility classes (Fig. 8). In other words, 52% of landslide events occurred in the most landslide-prone 24% of the area.

We highlight four types of landslide events from field observations between 2014 and 2016 to illustrate the geomorphological processes in the study area and how these events are reported (Figs. 1 and 9):

- The 9 February 2014 event in Bujumbura, Burundi, has extensively been reported in the media as a large "landslide" or "mudslide" triggered by heavy rainfall that affected the northern communities. Field investigation, however, showed that this was a debris-rich flash flood that resulted from the meeting of several flooded rivers sourcing from watersheds 5 km

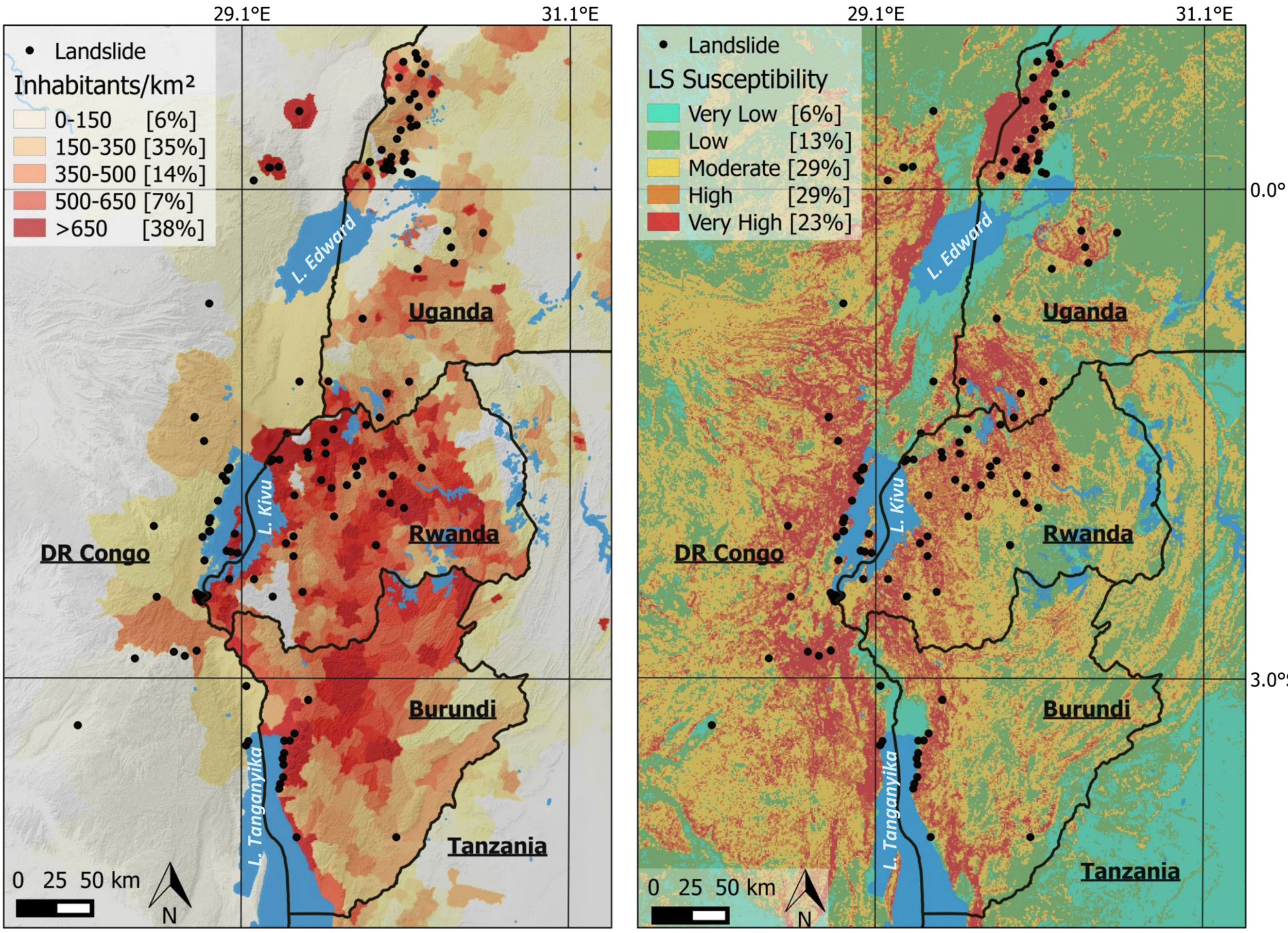

Fig. 8 Left: LIWEAR with population density (CIESIN 2016). Right: LIWEAR with landslide susceptibility (Stanley and Kirschbaum 2017). Values in brackets are the portion of landslide events for each category

upslope of the reported landslide location. We identified about a hundred, sometimes very small, landslides in these watersheds that provided debris to the rivers (Fig. 9(a)). One landslide was big enough to create a temporary dam of which its breaching contributed to the sudden component of the event. The flash flood event had thus wrongly been reported as a "landslide" or "mudslide," and the upslope trigger area had not even been noticed. The event has been categorized as "Complex" for landslide Type and the location of the upslope trigger area is given for Location in the LIWEAR. Similar cases have been reported at various moments in time for a debris flow in DR Congo (Maki Mateso and Dewitte 2014) and a flash flood in Uganda (Jacobs et al. 2016b).

- In Djikumbo, DR Congo, local inhabitants informed us (translated from Swahili) that heavy rain on 20 February 2016 had caused large parts of their agricultural fields to be destroyed, but without fatalities or injuries. The event had been reported neither by the local media nor by the civil protection. We observed big boulders up to ~ 2 m^3 in size that had been transported by a debris flow (Fig. 9(b)) and shallow planar slides connected to the channel in the trigger area, 1 km upslope the affected area. While shallow slides and debris flows are generally immediately triggered by high rainfall intensities under the saturated conditions of the rainy season (Sidle and Bogaard 2016), the closest (10 km apart) rainfall gauge showed that the temporally closest intense rainfall event had occurred 1 week before the landslide date (Monsieurs et al. 2017). It might be that the gauge site did not record a locally intense rainfall event at the debris flow site on 20 February. We hypothesize however that most probably the upslope planar slides got unnoticed by inhabitants the previous week because damming limited downstream mass transport until it was breached by a smaller rainfall-triggered debris flow on 20 February. Similar to the case study in Bujumbura, the landslide type is "Complex" and the location of the upslope trigger area is recorded in the LIWEAR. This is the only event in the LIWEAR where information was derived from a language other than English or French.
- In June 2016, a deep-seated rotational slide was observed in Ikoma, DR Congo (Fig. 9(c)). Based on field observations and interviews, we found that this slope progressively failed based on traces of cracks and tilted trees observed in previous years before the main failure in 2015. This made the identification of a triggering event more difficult. Despite its large size, impact on several households, and proximity of ~ 10 km to Bukavu, a major city of 800,000 inhabitants

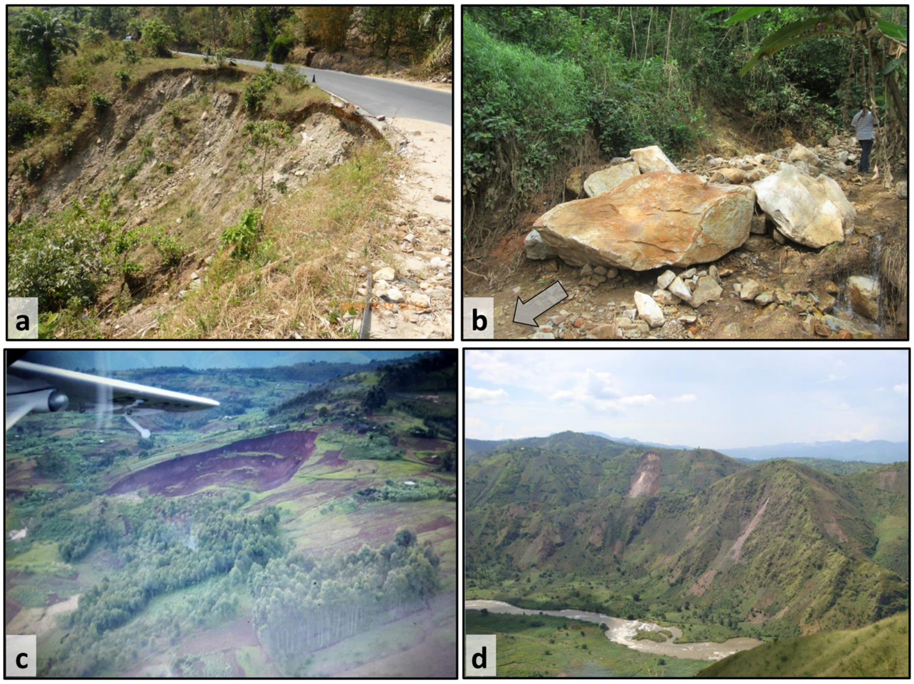

Fig. 9 Landslide case studies. **a** Planar debris slide in Bujumbura, Burundi. Photo taken in July 2014. **b** Transported debris during debris flow in Djikumbo, DR Congo. The flow direction is indicated with an arrow. Photo taken in February 2016. **c** Deep-seated rotational slide in Ikoma, DR Congo. Photo taken by Thierry Bollen in June 2016. **d** Debris slides along the Ruzizi gorges, Rwanda. Photo taken in May 2013

(Michellier et al. 2016), this event has not been reported so far. We have no information on the date of this event and it is therefore not included in the LIWEAR.

- Along the Ruzizi river in Rwanda, we observed debris slides that occurred during the 2012–2013 wet season (Fig. 9(d)). The Ruzizi gorge is frequently affected by landslides because of deforestation on steep slopes related to the exponential population growth in the area. However, no specific dates could be linked to these events precluding their inclusion in the LIWEAR.

In addition to our own field observations, data collection by local partners has proven to be useful. Yet, we found that the full potential of this information source cannot be reached due to security issues (Monsieurs et al. 2017). The region further west from Lake Kivu (Fig. 1), for example, is known to be regularly affected by landslides, but event dates could not be investigated because of continuous tension, road blockage, and armed groups present in the area. Access to the Internet is very limited, whereas the use of mobile phones significantly increased in the late 1990s in the WEAR (Trefon 2016). First attempts for data collection through crowdsourcing in the study area are promising (Jacobs et al. 2017a) and we continue to explore the potential use of mobile phones.

Discussion

Relevance of the three-phase inventory framework

The Search-Store-Validate approach (Fig. 2) is found to be effective for landslide spatiotemporal data collection in remote areas, with 143 identified landslide events in the LIWEAR, compared to 15 in the Global Landslide Catalog for the same area (Table 1). The focus in this framework is on online sources, while following the general trend that increasingly shapes academic research in Africa which favors remote methodologies (Trefon and Cogels 2006). The approach differs from previous inventory research in the following combination of methodological features:

1. applying a regional-scale approach in a data-poor context with limited field access;
2. imposing fewer constraints for entry in the inventory, compared to previous landslide inventory compilations (Table 1);
3. using a broad variety of sources (Fig. 5(h)), as earlier applied by, e.g., Jacobs et al. (2016a);
4. including the local language more than marginally (Fig. 5(h));
5. focusing on open-source information throughout the compilation and analysis procedure;
6. calculating a reliability score for inventory entries (Fig. 4).>

A possible future improvement in the Search phase of the current framework would include the use of Big Data technology that goes beyond the capacities of Google Alerts for screening the Internet (Chen et al. 2014; Li et al. 2015).

The framework (Fig. 2) comprises building blocks that can be easily applied in, or adapted for, other parts of the world. To optimize its transferability to other contexts, attention should be paid to the environmental and socioeconomic characteristics of the study area. More specifically, knowledge on the geographical background is essential to define the initial search key terminology and to understand the types of landslide events that are described in the media. The principal languages used should be defined and applied throughout the three-phase workflow, as well as the use of different scales, i.e., local, regional, national, and international. Also, identifying potential spatiotemporal biases specific to the study area will elevate an effective adoption of the inventory approach, e.g., spatial distribution of the population and access to Internet and other digital media. Finally, the inclusion of multiple collaborations with local institutions was found in this study to be a great asset for gathering data in remote areas and improving the location accuracy. These recommendations also apply when adopting the proposed inventory framework in data collection research related to other hazards such as earthquakes or floods.

Even though the LIWEAR comprises more landslide events identified in space and time than ever recorded before in the WEAR, we are aware that 143 landslide events over a span of 48 years largely underestimates the actual number of landslides. No completeness estimate based on frequency-area distribution (Malamud et al. 2004) could be calculated, because the size of most landslides is only qualitatively estimated. The difficulty related to landslide size determination in a regional catalog has been acknowledged in previous research (Kirschbaum et al. 2015a). Yet overall, we found a satisfying degree of reporting for the given attributes (Fig. 5(i)).

We propose in this study, a decision tree methodology to estimate the reliability of the collected data (Fig. 4). Based on this approach, documented landslide entries do not score very well, with only 34% having a Reliable or Very Reliable score. Reporting these uncertainties is important for the inventory's further implication in hazard assessment, whereas previous studies rarely report on the reliability of their landslide inventory (Guzzetti et al. 1999; Kirschbaum et al. 2010). We also emphasize the constraints imposed by the particular conditions of the region (Monsieurs et al. 2017), especially regarding communication and security (Trefon 2016), which affect the reliability of the sources.

Biases and uncertainties specific to data-poor contexts were identified, in addition to previously documented uncertainties inherent to spatiotemporal landslide inventories (Guzzetti 2000; Tschoegl et al. 2006; Kirschbaum et al. 2010; Van Den Eeckhaut and Hervás 2012; Jacobs et al. 2016a). The most prominent bias is related to the lack of a long-standing tradition of systematic data recording in the study area (Michellier et al. 2016). The reported location is biased towards the zone of impact, whereas somewhat remote landslide trigger locations are mostly omitted. Also, small landslides without fatalities or injuries are underrepresented. Information collected with the help of local collaborators is spatially biased towards these people's living places and security constraints. Landslides tend to be relatively more reported in densely populated areas. We assume this is not only related to the increased number of people present to observe landslides, but also because of human interferences with the environment which makes those areas more prone to landslides (Gill and Malamud 2017). Reported landslides are also more frequent in areas which have been estimated as moderately to highly susceptible to landslides (Fig. 8). In passing, we note that the latter result brings some support to the susceptibility model of Stanley and Kirschbaum (2017). One frequently highlighted bias towards English-language media (Kirschbaum et al. 2010; Kirschbaum et al. 2015b) is largely overcome by the LIWEAR, which used both English and French sources (Fig. 5(h)). We acknowledge that the systematic inclusion of vernacular languages (e.g., Swahili, Lingala) would make the search still more comprehensive but we assume that the added value would be marginal as even civil protection is writing their reports in English or French.

Relevance of the LIWEAR for regional landslide hazard assessment

The main reason for establishing the LIWEAR collection was to prepare a meaningful data set to anticipate its future use in combination with the currently most accurate and freely available rainfall satellite products over the tropics in a regional-scale landslide hazard assessment. Both earthquake- and rainfall-triggered landslides have been reported in the WEAR, although the latter dominate (Fig. 5(d)). This is confirmed in Fig. 6 where reporting and rainfall patterns seem to be related. The convective nature of rainfall in the study area causes storms to be localized (Jackson et al. 2009; Fig. 3), which is echoed by the resulting localized occurrence of slope destabilization. Hazard analyses have now to be performed to clarify the impact of rain on landsliding.

Seven events predate the TRMM data availability window (Fig. 7) and five others are reported to be related to seismic activity. In principle, these 12 events should be discarded from the rainfall threshold analyses (Guzzetti et al. 2008). However, we cannot rule out a possible role of (antecedent) rainfall for seismic related events, given that these events were reported through non-scientific sources. Information from the seismic network that was installed by the RESIST project (http://resist.africamuseum.be/) comprising 15 operational stations since 2015 in the WEAR will improve the identification of recent landslides related to seismicity (Oth et al. 2016).

Although Time could be deduced for only 49% of the events (Fig. 5(e)), information on the date of landslide occurrence has proven to be sufficient for regional landslide hazard assessment (Kirschbaum et al. 2015a). The Location Accuracy of 127 landslides is sufficient (i.e., ≤ 25 km) for regional-scale hazard analyses using TRMM precipitation estimates, to be compared with 56 out of 79 landslides with the same location accuracy used for the landslide hazard modeling in the study by Kirschbaum et al. (2015a). The LIWEAR would still retain 108 landslides complying with the stronger accuracy constraint when modeling landslide hazard using GPM (i.e., ≤ 10 km). The Reliability Score could be used either to weight the dependent variable in hazard analyses or to spot events we should pay attention to when interpreting results from hazard analyses.

Based on field observations (Fig. 9), we state that the actual separation between landslide types is not represented in the LIWEAR, with 79% of the occurrences being simply reported as "landslide." Reactivated landslides are difficult to distinguish from new slope failures because of the lack of recorded landslide histories. We ascribe this bias to the limited geomorphological expertise of people reporting the event. We also found that landslides in the study area may involve complex interactions of different processes, whereas detailed information on processes at play is rarely available. We suggest that most reliable regional-scale hazard analyses will be obtained if no discretization for landslide size or type is applied. Such a general analysis is valuable, although we acknowledge that different rain patterns may determine different hillslope processes (Sidle and Bogaard 2016; Gariano and Guzzetti 2016). Moreover, explorative research is of utmost relevance in data-poor settings.

From Fig. 5(d), we mainly deduce trends people are aware of in the region, stressing in particular that human-induced pressure on slopes does not go unnoticed. This confirms studies by Michellier et al. (2016) and Gariano and Guzzetti (2016), who found natural hazards to be related with increasing demographic pressure. This is an important factor to highlight in the African context where population projections indicate a rapid growth in the next decades, especially in urban areas (Cohen 2006; Seto et al. 2012). Using the LIWEAR, landslide hazard analyses and susceptibility maps can be produced to identify suitable disaster risk reduction measures to be implemented by local decision makers, with whom interactions already exist from the start of this inventory research (Maes et al. 2017).

Conclusion

The landslide inventory for the central section of the western branch of the East African Rift (LIWEAR) presents the first regional landslide inventory in a tropical African environment that includes spatiotemporal landslide information. It comprises 143 dated and localized landslide events over a span of 48 years from 1968 to 2016. Reported landslides are found to be distributed over the year in accordance with the rainfall pattern, more in densely populated areas, and in areas that have been estimated moderately to highly susceptible to landslides. Demographic pressure is second most reported after rain, as causal factor for landslides, which is important to highlight in the context of the African population growth projections. Based on limited field observations, we found the actual number of landslides and the identification of specific processes only partly recognized in the LIWEAR (type, reactivation, interactions with other hazards) and the landslide location can be biased towards the impact zone at the expense of the actual trigger areas. In order to optimize data collection and minimize biases and uncertainties, a three-phase Search-Store-Validate methodological workflow is proposed. This methodology differs from previous inventory studies in (1) applying a regional-scale approach to a data-poor context; (2) imposing no constraints on landslide size, impact, date of occurrence, or trigger for entry in the inventory; (3) using a broad variety of sources; (4) including local languages, and here especially French, more than marginally; (5) focusing on open-source information; and (6) calculating a reliability score for the inventory entries. Reliability is scored on the basis of a decision tree in order to improve the interpretation of hazard analyses. Location accuracy and numbers of events in the LIWEAR were substantially enhanced due to input from local partners, proving the added value of such collaborations in data-poor settings. We conclude that the LIWEAR is a valuable data set for future application in regional landslide hazard modeling in the East African Rift and that the proposed inventory approach clearly improves data collection for spatiotemporal information on landsliding.

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