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REVIEW ARTICLE

Review of landslide inventories for Nepal between 2010 and 2021 reveals data gaps in global landslide hotspot

Erin L. Harvey[1,2] · Mark E. Kincey[3] · Nick J. Rosser[1,2] · Arishma Gadtaula[4] · Ethan Collins[1] · Alexander L. Densmore[1,2] · Alexandre Dunant[1,2] · Katie J. Oven[5] · Katherine Arrell[5] · Gopi K. Basyal[4] · Megh Raj Dhital[6] · Tom R. Robinson[7] · Maximillian Van Wyk de Vries[8,9] · Sarmila Paudyal[4] · Dammar S. Pujara[4] · Ram Shrestha[4]

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Abstract

A review of landslide inventories provides an essential assessment of the state of knowledge around landslide hazard and can guide the focus of future studies. This is especially true in Nepal, which is highly prone to landslides, but lacks a comprehensive overview of landslide occurrence nationally. Here, we compile a database of 117 landslide inventories for Nepal released between 2010 and 2021. We review how these existing inventories shape our understanding of landsliding in Nepal and discuss how future research efforts could mitigate current challenges. We find that 40% of the country was only manually mapped once across the study period, and, crucially, these areas did not always correspond with areas of low landslide susceptibility. Instead, existing landslide inventories typically focus on specific areas, such as the region affected by the 2015 Gorkha Earthquake and major highway corridors. We also extrapolated the individual inventory characteristics from within this unique database to infer a national-scale areal density of 0.05 landslides per km^2, equating to 6000 landslides across the country. This extrapolated value provides a baseline for future national-scale studies, especially for inventories created through automated mapping approaches. Our review highlights the importance of expanding the footprint of landslide inventories in Nepal to include regions with low mapping coverage and the need for inventories to be openly available, with clear protocols to enable inter-comparison. Whilst our review has focused on Nepal, these findings are likely to be relevant in other landslide-prone countries and our recommendations are intended to be applicable elsewhere.

Keywords Landslide inventories · Landslide hazard · Nepal

Arishma Gadtaula: Now at National Electricity Board, Kathmandu, Nepal.

Ethan Collins: Now at new employer.

Alexandre Dunant: Now at Center for Climate Change and Transformation, EURAC, Bolzano, Italy.

Extended author information available on the last page of the article

1 Introduction

The systematic collation of data on previous landslides, such as their location, spatial distribution, and cumulative impacts, can be used to guide our understanding of landslide risk as well as to help anticipate and mitigate future events (Guzzetti 2000). Whilst it is recognised that there is often a mismatch between the study areas for landslides and the places where their impacts, particularly in terms of loss of life, are most acutely felt (Petley 2012), advances in freely-available satellite imagery and open-source cloud-based computing have broken down some of the traditional resource and capacity barriers to landslide mapping (Guzzetti et al. 2012). As a result, it might be reasonable to expect that areas that experience the highest losses from landslides also have a good degree of mapping coverage, but this remains to be tested. 'Good' in this sense ultimately depends on the mapping purpose, but broadly encompasses considerations of resolution, precision, timeliness, and spatial extent. Although the number of landslide mapping campaigns is increasing on a global scale, the proportion of landmass mapped for landslides remains low (estimated as c. 1% by Guzzetti et al. 2012), and so landslide maps remain rare (Brabb and Harrod 1989; Nadim et al. 2006; Novellino et al. 2024). This data gap is particularly stark in mountainous lower- and middle-income countries exposed to high levels of landslide hazard and risk (Kirschbaum et al. 2015).

Landslide inventories are collated to document the location, character, and timing of landslides (Keefer 2002; Kargel et al. 2016; Fan et al. 2018). Inventory creation typically involves mapping landslides from aerial or satellite imagery, as well as ground surveys, to obtain the location, extent and classification or type (Malamud et al. 2004; Galli et al. 2008; Guzzetti et al. 2012). Depending on the method chosen, landslide inventories can be developed for a variety of different scales, with some, albeit few, also including a temporal dimension. The spatial scale and temporal resolution of an inventory predominantly reflects its purpose. For example, catchment-scale landslide inventories have been used to produce models of landslide susceptibility based on local geomorphic and geological characteristics (e.g., Carrara 1983; Reichenbach et al. 2018) Landslide susceptibility models can be considered alongside exposure metrics, such as population density and building maps, to infer landslide risk to people or property (Rusk et al. 2022; Kincey et al. 2024). However, the inventory data used to train landslide susceptibility models are often static, and the resulting model is thus not necessarily applicable to future patterns of landsliding (Fleuchaus et al. 2021). Any limitations with respect to inventory data quality and coverage will also propagate when upscaled into susceptibility maps (Reichenbach et al. 2018; Fleuchaus et al. 2021; Kincey et al. 2024). Subsequently, clear descriptions of the underpinning landslide inventories and their accuracy is crucial when applying susceptibility models.

Landslide inventories repeatedly collated over years to decades to form multi-temporal inventories can provide a longer-term assessment of landslide hazard and risk (Fan et al. 2018; Jones et al. 2021; Kincey et al. 2021). These inventories are crucial for assessing changing susceptibility in populated, mountainous locations, for comparison with changes in population density and road building (Rosser et al. 2021), as well as to document landscape evolution (Jones et al. 2021; Francis et al. 2022). These inventories are also used increasingly as both training and test datasets for more automated mapping approaches (Kirschbaum and Stanley 2018). The recent uptake in data-driven machine learning approaches to automatically map landslides and landslide susceptibility (e.g., Tehrani et al. 2022), further highlights the need for accessible and accurate existing datasets for validation.

Landslide inventories can also be produced to assess immediate impacts and guide humanitarian response to a specific event, such as an earthquake or intense rainstorm (e.g., Li et al. 2014; Roback et al. 2018). The purpose of an event inventory can shape its characteristics and completeness; for example, a rapidly-generated post-earthquake inventory following the 2015 M_w 7.8 Gorkha earthquake in Nepal underestimated the landslide number in later inventories by a factor of c. 1.8 (Williams et al. 2018). However, even incomplete inventories can be used to provide an initial assessment of landslide hazard, which could guide an immediate emergency response (Robinson et al. 2017). Recent developments in our ability to handle satellite imagery are likely to improve our response to specific landslide-triggering events by providing the opportunity to survey larger areas through (semi-) automated approaches to mapping (e.g., Fayne et al. 2019; Kirschbaum et al. 2010; Milledge et al. 2022; Scheip and Wegmann 2021). However, several limitations associated with the use of satellite imagery to produce landslide inventories are likely to remain in the near future, such as the dependency on image availability in mountain regions, especially those where cloud cover during the monsoon limits visibility (Williams et al. 2018; Robinson et al. 2019; Milledge et al. 2022). It is therefore important to conduct a review of current knowledge to date.

Thus, landslide inventories are an invaluable tool that can develop our understanding of landslide risk on a range of temporal and spatial scales. However, inconsistencies between landslide inventories, based on their purpose and the methods by which they were derived, can lead to large variation in terms of their precision, completeness, and scope. These inconsistences can limit the application of these inventories in the future, for example to build susceptibility models or to validate automated mapping approaches, and may bias our overall understanding of landslide hazard. In this study, we conduct a systematic, bibliometric review on landslide inventories collected for Nepal between 2010 and 2021. We consider how the number of landslide inventories and the properties of these inventories (such as their spatial and temporal coverage) have changed through time, and postulate how existing inventories both benefit and limit our understanding of landslide hazard (e.g., where, when, and why do landslides occur in Nepal?) and risk (e.g., how many people are at risk, and where?) across the country. Finally, we use this review to map out future priorities for landslide inventory collation in Nepal and similar landslide-prone settings.

1.1 Study site

Nepal sits at one extreme of global landslide risk, combining high landslide hazard, physical exposure, and population vulnerability (e.g., Nadim et al. 2006). Nepal is highly susceptible to landslides due to the combination of steep topography, monsoonal climate, and active tectonics, resulting in at least 590 fatal landslides and 1 300 fatalities between 2011 and 2021 (National Disaster Risk Reduction and Management Authority (NDRRMA) 2022). The hazard posed by landsliding in Nepal has been exacerbated in the last few decades in response to greater population exposure, urbanisation and road building, land use change, and a changing climate (Petley et al. 2007; Petley 2010). The complex relationship between these socio-economic factors and landslide susceptibility was explored in a review of landslide occurrence by Petley et al. (2007). They analysed landslide occurrence spatially and temporally between 1978 and 2005, noting that road building could in part explain the increase in fatal landslides.

Several factors combine to make Nepal a global hotspot of landslide occurrence. The annual southwest Asian monsoon runs from approximately May to September each year and covers much of Nepal. The monsoon is characterised by high humidity and high precipitation, with 80% of the average total annual precipitation occurring during this season (Babel et al. 2014). Over 90% of rainfall-triggered landslides recorded in Nepal occur during the monsoon period (Rajan et al. 2024). Nepal is also characterised by high rates of rock uplift and tectonic activity on numerous active faults across the country (Lavé and Avouac 2001). This rapid rock uplift produces steep, rugged topography that is highly susceptible to landsliding. In April and May 2015, two ruptures along the Main Himalayan Thrust (MHT) resulted in the M_w 7.8 and 7.2 Gorkha earthquakes (Avouac et al. 2015) that are estimated to have triggered 25 000 coseismic landslides (Roback et al. 2018). After the earthquakes, the 2015 monsoon triggered an elevated number of additional landslides and led to the runout of many coseismic failures (Dahlquist and West 2019; Kincey et al. 2021), increasing the spatial extent of earthquake-related landslide impacts (Rosser et al. 2021; Arrell et al. 2024).

In more recent years, there has been significant in-country and overseas research interest in landsliding in Nepal. Extensive donor agency investment has often focused on infrastructure such as roads and hydropower schemes, which can have landslide-related consequences. Following the 2015 Gorkha earthquakes, the number of landslide inventories increased (e.g., Bhandari and Dhakal 2019; Kincey et al. 2021; Roback et al. 2018; Yagi et al. 2018) and others have been developed in the aftermath of intense storms (e.g., Dhital 2000; Muñoz-Torrero Manchado et al. 2021). Some of these inventories aimed to address specific governance needs (e.g., Pradhan et al. 2022; Rosser et al. 2021) and others were more focussed around scientific enquiry on landscape change (e.g., Jones et al. 2021) or methodological development (e.g., Burrows et al. 2019, 2023). These inventories typically have a relatively small spatial footprint involving one or a few catchments, and are often used to develop localised susceptibility maps (e.g., Budha et al. 2016; Kayastha et al. 2013; Pokharel and Thapa 2019; Yang et al. 2016), better understanding of the effects of rural road construction on landslides (e.g., McAdoo et al. 2018; Poudel and Regmi 2016; Vuillez et al. 2018), or evaluation of landsliding through time and the effect of cascading hazards (e.g. Dahlquist and West 2019; Kincey et al. 2023). As a result, there is a diverse range of landslide maps and inventories across Nepal.

2 Methods

2.1 Bibliometric analysis

We identified existing landslide inventories for Nepal through a bibliometric analysis of articles published between 2010 and 2021. Online searches were conducted through Google Scholar and Web of Science (WoS) using the following series of predetermined keyword terms: “Landslide inventories in Nepal”, “Landslides in Nepal”, “Landslide distribution in Nepal”, “Landslide inventory Nepal”, and “Landslide map Nepal”. Every item returned in the first 30 pages of the Google Scholar search results was considered (300 entries per search term, sorted by relevance), as well as every entry returned within the WoS Core Collection between 2010 and 2021. This date range was selected to capture both the time period covered by landslide incidents recorded in the Building Information Platform Against Disaster (BIPAD) Portal, which is the online disaster information system operated by the Government of Nepal (National Disaster Risk Reduction and Management Authority (NDRRMA) 2022), and the effect of the 2015 Gorkha earthquakes on the collation of landslide inventories across the country. Our database includes published inventories from 2010 to 2021 to capture the more recent increase in both in-country and international interest on landsliding and to describe the diverse range of landslide maps that have been published in recent years (Petley et al. 2007). While the inventories reported within this database have all been published since 2010, some inventories were mapped using imagery from as early as 1960 and therefore our database does contain information on landslides triggered prior to 2010. We made the decision not to include any global (i.e., larger than national scale) landslide inventories within our analyses, given (1) their typical focus on impactful events only, and (2) their limited accuracy and completeness at a national or sub-national level.

To capture unpublished landslide inventories, we also distributed an online questionnaire that was designed to collate data held by in-country organisations which play a role in landslide hazard and risk research or management in Nepal. The questionnaire was sent to representatives from 18 different Nepali institutions, including governmental bodies, professional societies (e.g., Nepal Geotechnical Society), universities, NGOs, and INGOs (see Supplementary Information, S1).

Information on each landslide inventory returned through both the online literature searches and the questionnaire was recorded using a set of structured database fields. These fields captured the source of the record (publication date, authors, journal name), as well as the properties of the landslide inventory (e.g., mapping date range, mapping methodology, landslide geometry type, study area extent, number of landslides mapped and, when stated, landslide type). We used three categories to define the landslide trigger for the mapped inventories: rainfall-triggered landslides, earthquake-triggered landslides, and both rainfall- and earthquake-triggered landslides. The latter category includes inventories where both rainfall and earthquake-landslides have been mapped, for example in a multi-temporal inventory that spans the 2015 Gorkha earthquakes or compares the earthquake inventory to a pre-earthquake inventory (e.g., Kincey et al. 2021; Regmi et al. 2016; Tanoli et al. 2017). The full database is available to download from Zenodo (Harvey et al. 2023).

2.2 Spatial analysis

The spatial extent of the landslide inventory for each database entry was digitised as a polygon using either bounding coordinates provided within each record, or by georeferencing relevant location maps from within each source document. Spatial analysis of the landslide inventories and accompanying datasets was based on a consistent grid of 10 km^2 hexagons distributed across Nepal (n = 1 641), with such hexagonal grids having distinct advantages over standard square (fishnet) grids, especially when working over large spatial extents (Birch et al. 2007). Each hexagonal grid cell was populated with attributes derived from all the landslide inventories that intersected that cell, as well as information from a range of other published datasets of relevance to landslide hazard and risk to enable exploration of patterns in their distribution. These included topographic derivatives from a 30 m resolution Advanced Land Observing Satellite World 3D—30 m (AW3D30) DEM, mean annual rainfall totals for 2001 to 2020 from NASA's Global Precipitation Measurement (GPM) Integrated MultisatellitE Retrievals for GPM (IMERG) (Huffman et al. 2014), total population from WorldPop (2020), total road length (OpenStreetMap Foundation contributors 2022), minimum, mean and maximum landslide susceptibility and exposure (Kincey et al. 2024), and a record of landslide incidents obtained from the Government of Nepal's BIPAD Portal (National Disaster Risk Reduction and Management Authority (NDRRMA)

2022). Here, we define cell-wise landslide exposure as population multiplied by susceptibility (Kincey et al. 2024). All of the datasets are freely available, cover comparable time scales, and can be upscaled to 10 km^2, excluding the landslide impacts and fatalities in the BIPAD Portal which are recorded at a ward scale (National Disaster Risk Reduction and Management Authority (NDRRMA) 2022) (Table S2). Click or tap here to enter text.The specific metrics were selected since they relate to existing understanding of landslide triggers (e.g., rainfall), susceptibility (e.g., slope, elevation, and road locations) and impacts (e.g., landslide fatalities and exposure) and therefore provide a simplified guide to areas most at risk from landsliding in Nepal. By comparing these metrics to the number of landslide inventories within 10 km^2 cells, we can assess whether areas considered most at risk are mapped more frequently. A full description of the published datasets used for comparison is provided in Supplementary Information, Table S2.

3 Results

3.1 General observations

In total, we recorded 117 landslide inventories between 2010 and 2021 covering part or all of Nepal, of which 110 were published. Of the 117 landslide inventories within our database, only 15 inventories were available via unrestricted download without contacting the authors of the publications. The inventories spanned four orders of magnitude in their spatial extent, with some including tens to hundreds of landslides within small catchments (e.g., 152 landslides over 20 km^2; Gyawali and Tamrakar 2018) and others including several administrative districts, covering an area of > 30 000 km^2 and including > 10 000 landslides (e.g., Jones et al. 2021; Kincey et al. 2021) (Fig. 1). Most studies were conducted on local scales (catchment, ward, or municipality) or regional scales (district), with 78 inventories (67%) covering an area that was smaller than the average district area for Nepal (1 922 km^2). Smaller-scale studies of rainfall-triggered landslides were often found to track road corridors, administrative unit extents, or watersheds (e.g., Basnet et al. 2013; Devkota et al. 2013) (Fig. 1a). In contrast, larger-scale studies typically focused on using a new technique (e.g., automated landslide mapping from satellite images, Marc et al. 2019; Milledge et al. 2022) or on the impact footprint of a specific large event, such as the 2015 Gorkha earthquakes (Xu 2018; Kincey et al. 2021). Our database also included five national-scale inventories, one of which was derived manually (Bhuju and Pokharel 2016) and four that were collated using automated techniques. Four of these national scale inventories have been published (Bhuju and Pokharel 2016; Chen et al. 2018; Fayne et al. 2019; Bragagnolo et al. 2021) and the fifth is held within the Water Resources Research and Development Centre (WRRDC) (pers. comm. 2021).

3.2 Landslide counts and areal densities

Overall, 103 studies stated a total landslide count in their inventory, with the number of landslides mapped by inventories ranging from 12 (Ray et al. 2018) to 47 200 (Xu 2018) over a single time period. We observed a weak positive relationship ($r^2 = 0.46$, $p < 0.001$) between total study area and landslide count for all inventories where both variables were provided (57% of inventories) (Fig. 2). The correlation improved ($r^2 = 0.61$, $p < 0.001$) when excluding the three studies that focused on a single landslide type, such as debris

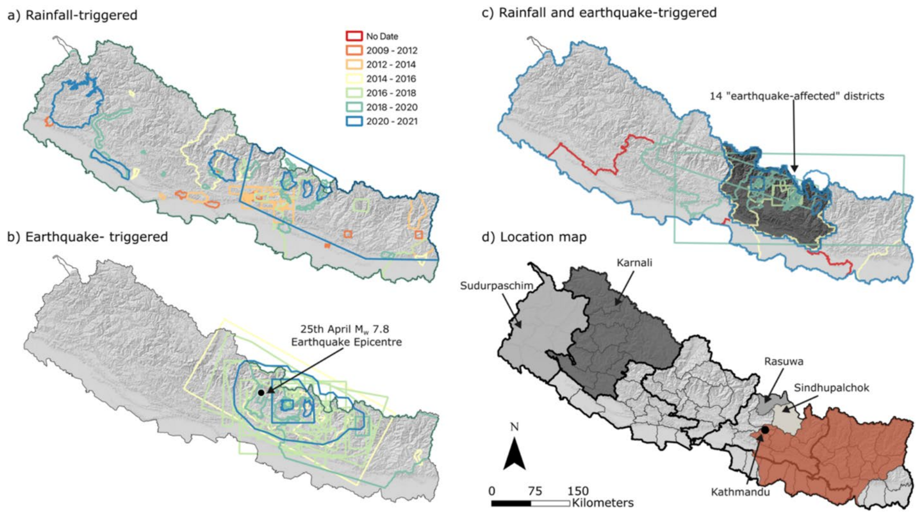

Fig. 1 Maps showing the spatial extents of landslide inventories published between 2010 and 2021 for Nepal. (**a**) Extents of rainfall-triggered landslide inventories. (**b**) Extents of earthquake-triggered landslide inventories, with clustering around the epicentre of the 2015 Gorkha earthquake (black circle) and a single inventory for the 2011 Sikkim earthquake in the east. (**c**) Extents of inventories which included both earthquake- and rainfall-triggered landslides. (**d**) Major administrative divisions of Nepal. Provinces are denoted by thick lines and districts by thinner lines. Locations referred to in the paper are shown in Fig. 1d and the Koshi Basin area mapped frequently by ICIMOD is shaded in red

flows, as these either had a lower landslide count because they only included a subset of all landslides (e.g., Dahlquist and West 2019) or were conducted over a relatively small study area within which there were dense concentrations of landslides (Regmi et al. 2014, 2016). The gradient of the relationship between study area and landslide count varied depending on the triggering mechanism recorded within the inventory. For example, the areal density (landslide count per unit area mapped) in earthquake-triggered landslide inventories was higher, indicative of high landslide densities following an earthquake as well as the paucity of localised, catchment-scale studies focused on the earthquake. In contrast, a simple least-squares regression of the rainfall-triggered landslide data in Fig. 2 suggests a mean national-scale areal density of 0.05 landslides per km^2 and from that, a total number of c. 6 000 landslides across the area of Nepal with slopes > 10^o (77% of the total area). This national-scale areal density estimate is much lower than the mean (1.4 landslides per km^2) and median (0.6 landslides per km^2) values obtained across all rainfall-triggered inventories, which is reasonable considering that most studies focus exclusively on catchments renowned for landsliding (e.g., Dahal et al. 2012) or on landsliding over long periods of time (Jones et al. 2021; Muñoz-Torrero Manchado et al. 2021). The national-scale areal density estimate fits within the range of landslide densities derived from the four national inventories, which have areal densities ranging from 0.001 landslides per km^2 (275 landslides in total; Bragagnolo et al. 2021) to 0.4 landslides per km^2 (57 000 landslides in total; Water Resources Research and Development Center pers. comm. 2021) (Fig. 2). The large variability in landslide areal density between inventories is likely to be an artefact of both the mapping approach (e.g., spatial and temporal resolution of the imagery or fieldwork) and the location (e.g., in localised areas susceptible to landslides). However, the weak correlation between landslide count and study area presented here can still provide an

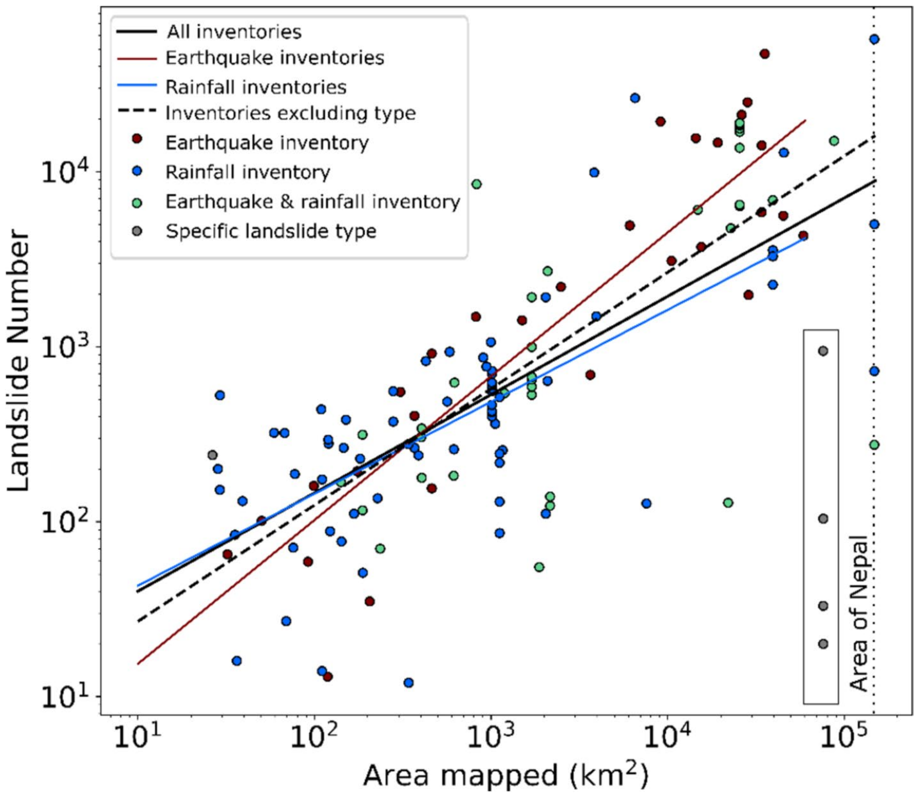

Fig. 2 Mapped landslide number against study area, with earthquake-triggered landslide inventories in red, rainfall-triggered landslide inventories in blue, and inventories containing both earthquake- and rainfall-triggered landslides in green. Grey symbols represent inventories aimed at sampling a single landslide type which were excluded when calculating the black dashed regression line ($r^2=0.61$). The r^2 values for the full dataset, rainfall-triggered inventories and earthquake-triggered inventories were 0.46, 0.50 and 0.80, respectively. The rectangle highlights the debris flow inventory published by Dahlquist and West (2019), which consists of multiple points that represent different periods of the multi-temporal inventory. The total extent of Nepal is depicted by the vertical black dotted line. The four, out of a total of five, national-scale inventories where inventory count was available are plotted along this line

approximation for future mapping efforts, even if this is an overestimate based on areas more susceptible to landslides.

3.3 Methods of mapping

Seventeen out of the 117 inventories were generated using semi-automated or entirely automated approaches, including four of the five national inventories (Fig. 3a). Automated landslide inventories in this instance typically recorded pixel- or polygon-based footprints of landslides (Fig. 3a). Both pixel and cell can be used interchangeably, here we use cell to refer to individual 10 km^2 hexagons within our grid and therefore opt for pixel here. The remaining inventories (100 out of 117, 85%) were collated entirely using manual mapping, often combining two or three methods to identify and delineate landslides (Fig. 3b).

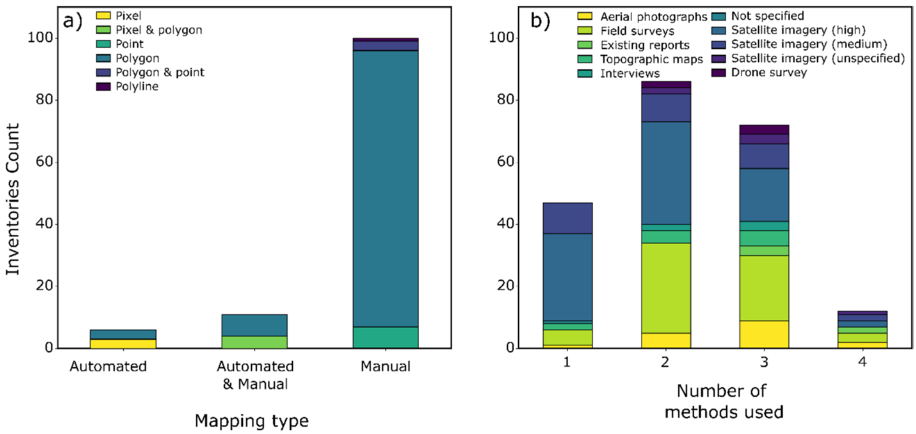

Fig. 3 (**a**) The number of inventories produced using automated versus manual mapping techniques; and b) the methods used to produce the landslide inventories. High-resolution satellite imagery refers to images with a ground sampling distance of < 10 m, such as imagery available in Google Earth and PlanetScope, and medium-resolution satellite imagery refers to images with a sampling distance of between 10 and 30 m, which includes both Sentinel-2 and Landsat. Note that the count in panel (**b**) refers to the number of times each method has been used and therefore the total of the count equals 217 and not the total number of inventories analysed

Satellite images were used in just over 50% of all cases (Fig. 3b). Where studies only relied upon one method, 38 used satellite imagery, five used field surveys, one used aerial images, and two used interviews. The use of satellite images to generate landslide inventories for Nepal is increasing over time. For example, high-resolution satellite images (ground sampling distance < 10 m) were used in at least 40% of studies between 2016 and 2021 compared to less than 20% between 2010 and 2015. For six inventories the resolution of the satellite imagery used was unspecified. In contrast, 43% of inventories mapped between 2010 and 2011 used aerial imagery, dropping to only 4% in 2018–2019 and 0% in 2020–2021. The proportion of inventories using field surveys was consistently around 25–30% each year. A summary of the approaches used to generate the landslide inventories reported in this database can be found in Table S3 in the Supplementary Information.

3.4 Spatial distribution of landslide inventories across Nepal

An overlay of mapped inventories shows that most inventories prior to 2015 were collated in areas in close proximity (< 50 km) to Nepal's capital, Kathmandu, reaching a maximum of nine inventories recorded in four of the 10 km^2 hexagons (Fig. 4a). There were also multiple landslide inventories collected within the Koshi Basin in eastern Nepal by ICIMOD within this time period (Fig. 1d). A single manually-mapped, national-scale inventory was created prior to the 2015 earthquakes and provided a record of all landslides > 1 km^2 (Bhuju and Pokharel 2016). Following the Gorkha earthquakes in April 2015, the spatial distribution of landslide inventories broadened considerably to include the areas thought to be most affected by the earthquake, such as the districts surrounding and north of Kathmandu (Fig. 4b). The increased number of inventories in this region was reflected in both earthquake- and rainfall-triggered landslide inventories (Figs. 1 and 4). Sections of the Pasang Lhamu and Araniko Highways were covered by the highest number of landslide

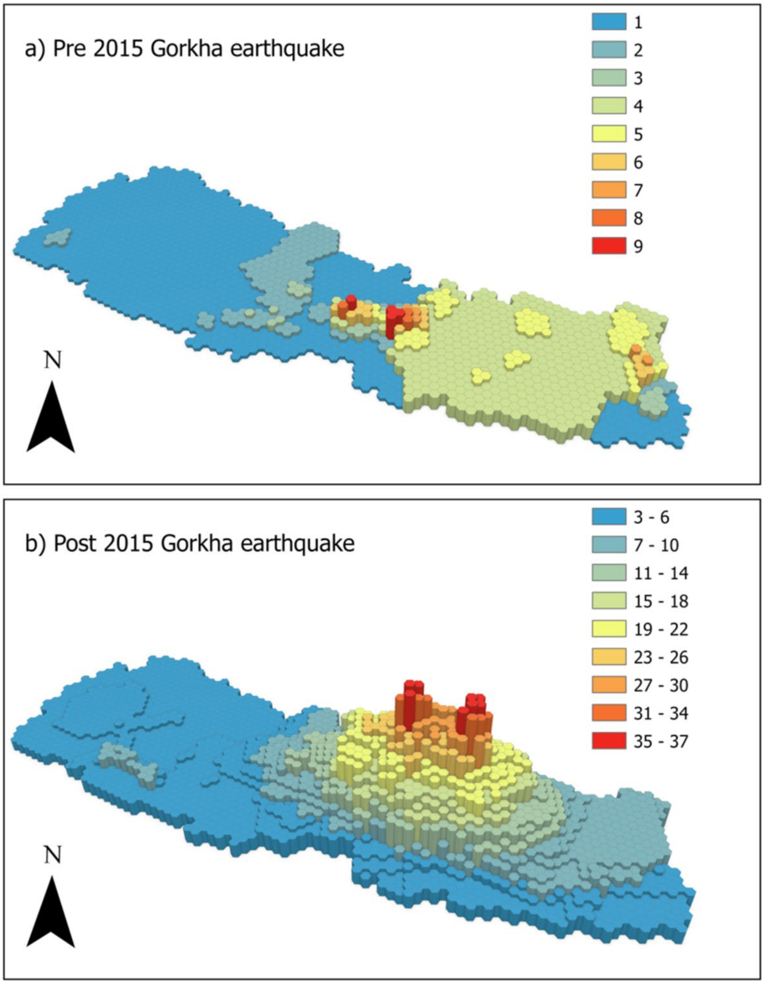

Fig. 4 Number of landslide inventories per 10 km^2 hexagonal tile. (**a**) The spatial pattern and numbers of landslide inventories produced using data collected prior to the 2015 Gorkha earthquakes. Note concentrations near Kathmandu in central Nepal and the Koshi Basin in eastern Nepal. (**b**) As panel a, but using data collected following the Gorkha earthquakes. Thirteen studies did not provide an indication of when the landslide inventory was created and therefore have been excluded from the count. If a landslide inventory was published before 2015 but did not give a date range, we included the inventory in panel (**a**). Where landslide inventories were multi-temporal, we considered the date of the final inventory and therefore most multi-temporal inventories are included in panel (**b**), as they tended to focus on the change in landsliding before and after the 2015 earthquakes. North is toward the top of both panels

inventories between 2015 and 2021, with the count along sections of the Pasang Lhamu Highway in Rasuwa district increasing from 1 (2010–2014) to 37 (2015–2021) (see Fig. 1d for location). The two most well-mapped districts, Rasuwa (with between 20 and 37 inventories per 10 km^2 hexagon) and Sindhupalchok (with 24–36 inventories per 10 km^2 hexagon), were also some of the most heavily affected by landslides triggered by the 2015 earthquakes (Roback et al. 2018; Kincey et al. 2021). The wide variation in the number of inventories across the more well-mapped districts represents the relatively high number of small-scale studies (typically covering up to a few 10 s of km^2) along highways and within single catchments. Conversely, significant parts of the country outside of this core area have only been mapped a small number of times over the same period. For example, regions in Karnali and Sudurpashchim provinces (see Fig. 1d for locations) have only been covered by a patchwork of localised manually-mapped inventories and automatically-generated national-scale landslide inventories, with many areas only being mapped manually once at most.

3.5 Temporal coverage

The time period covered by each inventory differs greatly between studies, from inventories triggered by single events (e.g., Dahal 2015; Shrestha et al. 2017; Tsuchida et al. 2015) to longer-term studies over years or decades (Ghimire 2011; Dhakal et al. 2020; Kincey et al. 2021) (Fig. 5a). Ninety-three inventories (79%) either covered a single event or were collected using data from over a long time period with no temporal discretisation, as reflected by some of the longer time windows in Fig. 5a. Seventeen inventories were multi-temporal with inventories collected over multiple discrete time intervals. Only 13 of the multi-temporal inventories extended beyond one year, though we note that some single event or static inventories were collected over longer time periods. For seven inventories it was unclear whether they were multi-temporal or not as no data was provided on whether multiple inventories were produced over the time period. The earliest inventory within our database was collated by ICIMOD (2017) to map landslides in the Koshi Basin in 1960 using topographic maps. Thirty inventories included a mapping window earlier than 2010, half of which included field surveys to map landslides and seven used topographic maps, often complemented with other approaches (Fig. 3b). Twenty-five inventories did not state the dates over which landslides

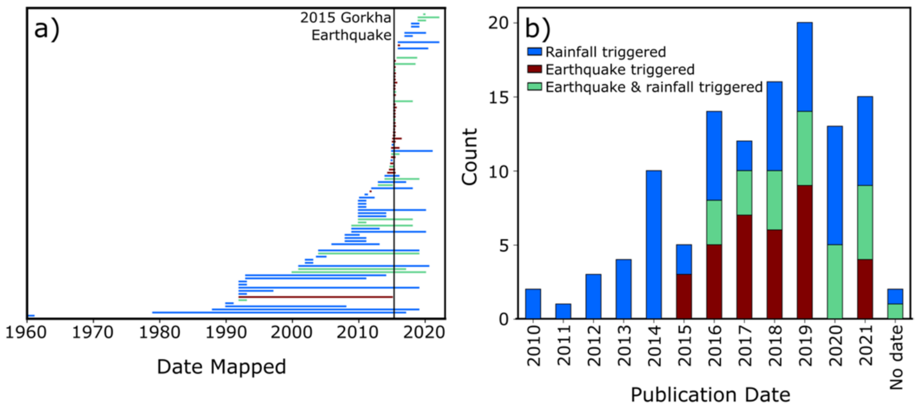

Fig. 5 The temporal pattern of inventory creation in terms of (**a**) the time period covered by the inventories published between 2010 and 2021 and (**b**) the publication date. Blue represents rainfall-triggered inventories, red represents earthquake-triggered inventories, and green represents earthquake and rainfall-triggered inventories. Whilst continuous lines have been used in panel (**a**) to represent the date range mapped for each inventory, some inventories only involve a small number of images within this time range and are not a continuous representation of landslide occurrence within the period. Inventories are stacked by start date on the vertical axis in ascending order

were mapped. All 25 were assumed to be static inventories based on our interpretation of the published articles; these inventories are not shown in Fig. 5a.

The 2015 Gorkha earthquakes had a large impact on the overall number of published landslide inventories for Nepal, with the total number doubling between 2014 and 2019 (Fig. 5b). In total, 33 inventories were exclusively related to co-seismic landslides triggered by the Gorkha earthquakes. Five multi-temporal inventories focused specifically on immediate pre- and post-event landslides following the Gorkha earthquakes.

3.6 Comparisons between mapping coverage, methods, susceptibility, and exposure

Since manually-mapped inventories are currently the primary verification tool for automated techniques and automatically-generated inventories (e.g. Milledge et al. 2022), it is also important to consider the spatial distribution of manually-mapped inventories across the country and how this coverage relates to susceptibility and impact (Fig. 6). Only 60% of the country (85 000 km^2), which is home to approximately two-thirds of the population (16 million), has been manually mapped more than once based on published inventories (Fig. 6d). We make the distinction between published and unpublished inventories since unpublished inventories remain difficult to access and therefore unlikely to be widely used, but we note that similar challenges can arise from published inventories with inaccessible datasets. Similarly, automatically mapped inventories ideally require some form of manually-mapped inventory for verification, and so for 40% of the country this verification is only possible using the national scale inventory of landslides > 1 km^2 created by Bhuju and Pokharel (2016). Therefore, our understanding of simple metrics for smaller landslides, such as area, count, or areal density, is largely unknown for 40% of Nepal's land area.

We assess how the area for which we have greater mapping coverage, defined as the 60% where manual mapping has been conducted more than once, compares with current understanding of landslide susceptibility and impacts (Fig. 6). We use mean susceptibility since this provides a measure of the overall susceptibility within each 10 km^2 cell, whereas maximum susceptibility may only represent a very small proportion of susceptibility values within a single cell. Only 58% of grid cells within the top quintile of tile-average susceptibility were covered by multiple manually-mapped, published landslide inventories. Many of these high-susceptibility, less frequently mapped areas lie in the High Himalayas in the north of Karnali Province (Figs. 1d and 6d). We also considered how exposure to landsliding was captured within the 60% of Nepal that had been repeatedly manually mapped in published landslide inventories. We found that for the top quintile of tiles calculated as most exposed to landsliding, 79% were within the area of Nepal covered by multiple manually-mapped published landslide inventories. There were no significant correlations between inventory count and other nationwide metrics potentially related to landslide susceptibility (e.g., slope, elevation, rainfall) and exposure (population, road length), although grid cells with the highest inventory count ($n > 40$) did correspond to high values of mean slope, elevation, and rainfall (Supplementary Information, S4). Regions with the highest inventory counts were also typically in areas with a higher total population.

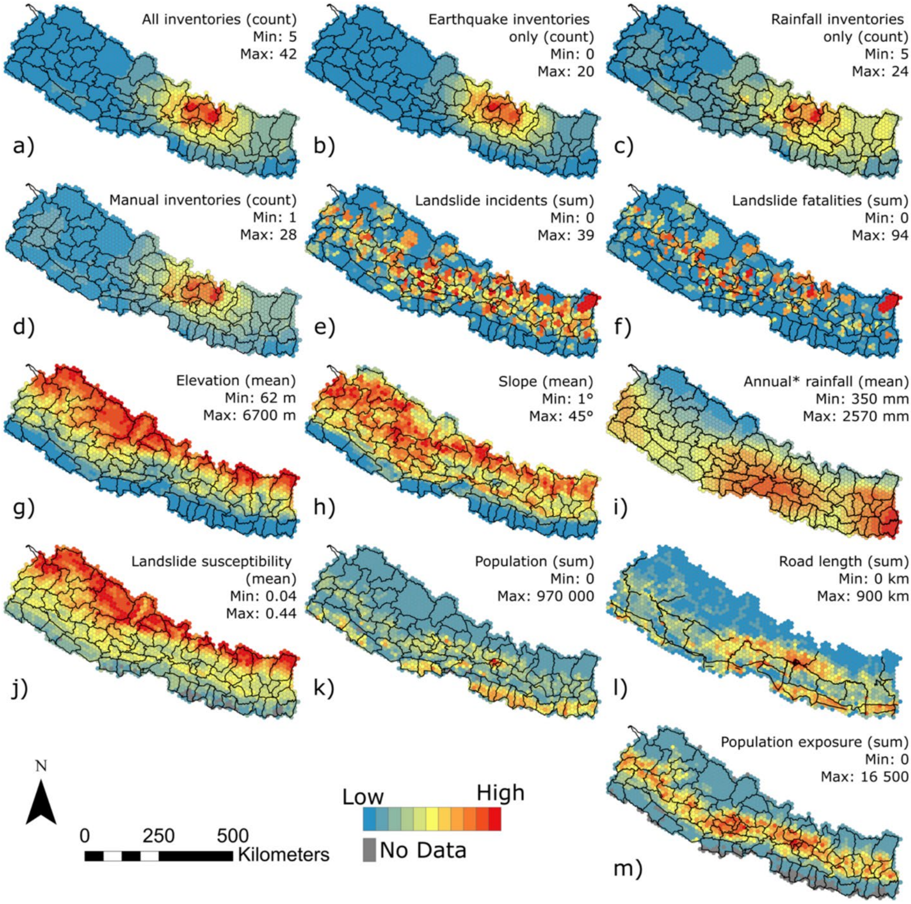

Fig. 6 The spatial patterns of (**a**) the count of all landslide inventories in our database, (**b**) the count of all earthquake-triggered landslide inventories, (**c**) the count of all rainfall-triggered landslide inventories, (**d**) the count of all published, manually-mapped landslide inventories (n = 94). Note that 40% of the country is only covered by one manually-mapped published landslide inventory, (**e**, **f**) total landslide incidents and total landslide fatalities during the period 2011–2021 downloaded from the BIPAD Portal (National Disaster Risk Reduction and Management Authority (NDRRMA) 2022). Incidents were downloaded with ward level locational precision which at times is larger than the 10 km^2 hexagons used to present the data, (**g**) mean elevation, (**h**) mean slope, (**i**) mean annual rainfall for the period 2001–2020, (**j**) mean landslide susceptibility (Kincey et al. 2024). The 30 m susceptibility raster has been averaged (mean) for each 10 km^2 hexagon, (k) total population (WorldPop 2020), (**l**) road length (OpenStreetMap Foundation contributors 2022), and (**m**) total population exposure, generated using the product of the landslide susceptibility and population datasets (Kincey et al. 2024). All datasets are gridded on the same hexagonal grid, with an individual cell area of 10 km^2. The source and description for each dataset can be found in Table S2

4 Discussion

The number of landslide inventories across Nepal has increased considerably over the last decade, with more than twice as many new landslide inventories published following the 2015 Gorkha earthquakes when compared to before this event (Fig. 5). These landslide inventories provide the opportunity to better understand landslide hazard and have contributed to improved assessment of hazard via the creation of landslide susceptibility models (e.g., Ghimire 2011; Budha et al. 2016; Poudel and Regmi 2016; Kincey et al. 2024) and by informing risk reduction policy (Datta et al. 2018). However, the number of spatially continuous inventories remains limited, even across areas which experience perennial landslide impacts (Figs. 6e, l; Adhikari and Tian 2021). The absence of systematic and widely accessible landslide inventories across the full extent of Nepal, and in particular across those areas which have experienced recurrent impacts, severely limits understanding of the scale and nature of landsliding in Nepal (Dhakal 2014). Questions such as 'How many people are at risk of landslides in Nepal?', therefore, remain extremely difficult to answer and plan for. Here, we discuss the spatial coverage, resolution, precision, and timeliness of the landslide inventories published between 2010 and 2021 and provide suggestions for future priorities.

4.1 Limitations to existing inventories: spatial extent, resolution, precision and methodology

The spatial distribution of landslide inventories collated for Nepal between 2010 and 2021 is disproportionately focused on the '14 earthquake-affected districts' identified by the Government of Nepal after the 2015 Gorkha earthquakes (see: Rosser et al. 2021) and do not mirror the distribution of landslide impacts (Fig. 6e, f), susceptibility (Fig. 6j) or exposure (Fig. 6m) across the country. This reactive mapping response to the earthquake vastly improved understanding of landslide hazard in the earthquake-affected districts and stems largely from the anticipated increase in landslide risk immediately following the earthquakes (Gnyawali and Adhikari 2017; Martha et al. 2017; Roback et al. 2018; Xu 2018; Rosser et al. 2021) (Fig. 4). These inventories have also added valuable learning for other regions and the wider academic community, particularly when compared to recent earthquakes of a similar magnitude (Fan et al. 2019). In the years following the 2015 earthquakes, the focus of mapping has remained concentrated in the earthquake-affected areas (Figs. 5 and 6). Some of these inventories specifically aimed to understand the evolution of hazard following an earthquake (Dahlquist and West 2019; Marc et al. 2019; Dhakal et al. 2020; Kincey et al. 2021), and reflect perhaps a renewed interest in developing capacity in landslide hazard and risk assessment in Nepal. However, the high density of landslide inventories in the 14 earthquake-affected districts may distort our understanding of landslide susceptibility and risk in other parts of the country, which remain poorly mapped (Meena et al. 2021). Many of the inventories generated in response to the earthquake were conducted along highway corridors due to accessibility and the critical needs for roads to remain open (Fig. 4b and 6b). These post-earthquake surveys were not consolidated or extended to the national scale, leaving a fragmented patchwork of mapping (Datta et al. 2018). Prior to the earthquake, inventories were also clustered around central and eastern Nepal (Fig. 4a), demonstrating that the heterogenous mapping coverage was not solely as a result of the 2015 earthquakes. A consequence of this patchiness is that data to train susceptibility models may be biased by not covering the full range of controlling conditions, making wider application and upscaling challenging. Future studies which utilise a historic landslide inventory from Nepal must carefully consider the landslide triggering type in their application, for example when generating susceptibility models or using these inventories to train machine-learning based landslide detection algorithms, to ensure that their outputs can be widely applied. The increased availability of satellite imagery will hopefully reduce the limitations associated with inaccessible locations and allow for landslide inventories to be collated for more remote regions with high landslide susceptibility in the future (Fig. 3b).

Most (103) of the studies included in this database stated the number of landslides mapped in the inventory, with both the total number and areal density varying by several orders of magnitude. In addition to landslide triggering type as discussed earlier, much of the variation in landslide number and areal density relates to (i) the spatial resolution of the imagery that was used for the mapping, (ii) the methodology, (iii) the study area over which the inventories have been conducted, with inventory landslide count and study area positively correlated for different regions across the country (Fig. 2), and (iv) the reasons for generating the inventory. It is difficult to discern how much each of the above controls affect the precision and uncertainty of the inventories within this database because only 13% of the studies (n = 15) have inventories which can be publicly accessed, meaning that the polygon, point or raster landslide inventory could be freely downloaded. Given that these metrics are vital in any assessment of inventory quality, inventories without shared datasets (87%) and those conducted over unspecified time intervals (21%) cannot be validated independently or used to validate future inventories. Where landslide inventories can be compared, stark differences can arise, as was found following the 2008 Wenchuan and 2015 Gorkha earthquakes (Fan et al. 2019; Meena and Piralilou 2019) and through a comparison of manual versus automated mapping (Milledge et al. 2022). We demonstrate this within Nepal by comparing three publicly available co-seismic landslide inventories for the 2015 Gorkha earthquakes from within the Langtang Valley located in Rasuwa District (Figs. 1d and 7) (ICIMOD 2016; Roback et al. 2018; Jones et al. 2020). Visually, it is evident that the most landslides were mapped in the inventory by Roback et al., (2018). This inventory was collated using the highest resolution imagery (20–50 cm resolution) obtained rapidly after the earthquake, with most images were taken between 2nd May and 8th May 2015. In contrast, the inventory collated by Jones et al. (2020) used RapidEye imagery with a 5 m resolution in combination with field surveys conducted three years after the earthquake. There is generally good agreement between the Roback et al. (2018) and Jones et al. (2020) inventories, with narrower channelised failures less likely to be mapped in the latter inventory (Fig. 7). The third inventory is an unpublished but open-access inventory by ICIMOD (2016), which used freely available Google Earth Pro imagery. Despite the differences in the inventories, all three serve their specific primary objectives. The inventory produced by ICIMOD (2016) was the earliest inventory online following the earthquake and used openly-available resources to generate a rapid 'snapshot' of the coseismic landslide pattern. The thorough investigation by Roback et al. (2018) took several years but provided unique insight into the characteristics of landsliding triggered by the Gorkha earthquake over a large area. Finally, the more local-scale inventory produced by Jones et al. (2020) captured not only landslide location but also the type of failure based on geomorphological field assessments. The comparisons in Fig. 7 highlight the challenges associated with combining or comparing inventories which use different methods and image sources, even when imagery is of a similar resolution as shown by ICIMOD (2016) and Roback et al. (2018), and which have different primary objectives. To fully assess their relative strengths and weaknesses, it is therefore critical to ensure that inventories are made openly available.

The influence of image spatial resolution on the number of landslides mapped is unclear from our review, with inventories created using high-resolution satellite imagery (defined here as < 10 m) used to map both the most and fewest number of landslides reported. However, previous studies have explored this limitation, with Kincey et al. (2021) showing that landslide counts based on an image resolution of 15 to 30 m were 50% lower than landslide

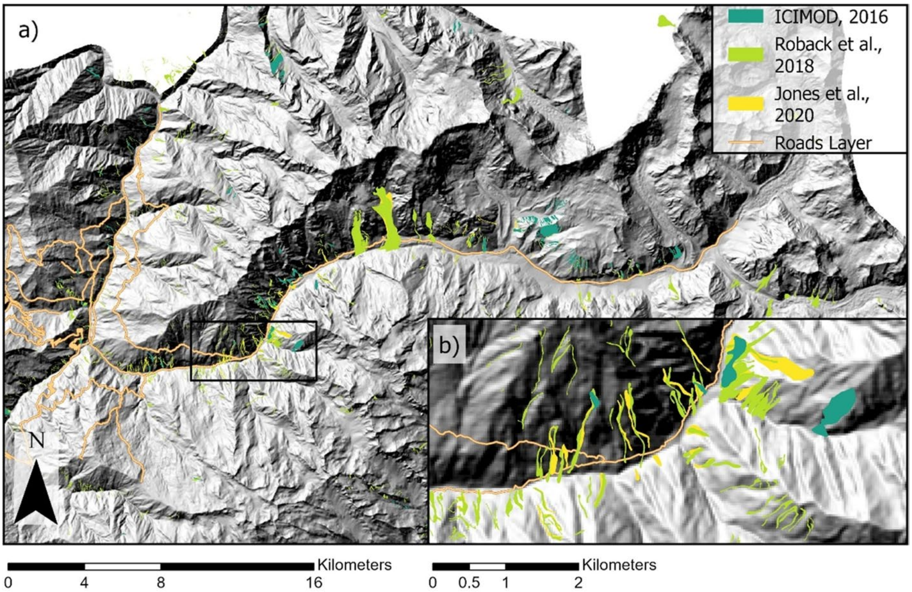

Fig. 7 Comparison between three open-access coseismic landslide inventories published by ICIMOD (2016) (dark green), Roback et al. (2018) (light green), and Jones et al. (2020) (yellow) within a portion of the area affected by the 2015 Gorkha earthquake. The inventories were generated using imagery with different resolutions and across different time periods, but all sought to map coseismic landslides from the 2015 Gorkha earthquake. The inventory by Jones et al. (2020) only extends along the main trekking routes within the valley. Panel (b) shows an example region covered by all three inventories. The basemap is a hillshade produced using the freely available ALOS (Advanced Land Observing Satellite) DEM

counts based on images with a 2 m resolution in the area affected by the Gorkha earthquakes. The inevitable trade-off between mapping all landslides and using imagery which is widely available is reflected in the only national-scale manually-mapped landslide inventory between 2010 and 2021, where the total number of landslides mapped (Bhuju and Pokharel 2016; n = 5 000, 0.03 landslides per km^2) was less than the number of landslides mapped across much smaller study areas before the Gorkha earthquake (e.g., Kincey et al. 2021: 6 400 pre-2015 landslides, 0.25 landslides per km^2; Zhang et al. 2019: 5 800 pre-2015 landslides, 0.17 landslides per km^2). This difference can also in part be explained by the minimum landslide area of 1 km^2 used by Bhuju and Pokharel (2016). In terms of post-earthquake landslide hazard, a minimum landslide area of 1 km^2 would exclude 99% of the landslides mapped by Kincey et al. (2021) and would therefore be of limited value. For the three inventories shown in Fig. 7 the stated minimum landslide area was 9 m^2 (Roback et al. 2018), 70 m^2 (ICIMOD 2016) and 300 m^2 (Jones et al. 2020), which related to both the imagery used and the threshold determined by the mappers. In our full database, very few inventories explicitly stated either the minimum landslide area or the total area covered by landslides and so we could not explore the relationship between minimum area, study area, image source, and methodology further in this review. It is important to consider that the variability in landslide areal density values reported here may at least in part be an artefact of method and study area choice.

Methodological choices, such as the amalgamation of multiple landslides as a single mapped feature, can subsequently alter the simple metrics used to describe landslide inventories, with amalgamation leading to overestimation of landslide volumes by up to 200% (Marc and Hovius 2015). To avoid this, manual and automated checks are conducted in some inventories (e.g., Marc et al. 2019). It is crucial that these steps are well described to ensure the method is replicable and the inventory can be compared against future studies. Similarly, it is critical to provide detail on the satellite images used and the time period covered by the inventory. In a multi-temporal study over four years, Kincey et al. (2021) found that some landslides were not detected in specific epochs due to cloud cover, shadowing, or poor image contrast, although they were visible in earlier and sometimes in later epochs. To better understand this phenomenon, they used a series of structured spatial overlap queries to determine whether a landslide was persistent after the missing epoch, to avoid underestimating the potential hazard.

It is evident that many complexities can affect the precision of landslide inventories and ultimately under- or overestimate the potential landslide hazard within a landscape. To minimise these challenges, clear descriptions of the methods and data used are critical. By including information on the minimum landslide area or resolution of the imagery used when publishing landslide inventories, policy makers will have a greater awareness of the completeness of the dataset and can tailor their decisions accordingly. Efforts to establish a central repository for landslide inventories along with a template with required fields and metadata prompts, as done by Tanyaş et al. (2017) for earthquake-triggered landslides, would help to improve reproducibility and reuse of landslide inventories for Nepal. Alternatively, a platform similar to the Government of Nepal's BIPAD Portal could be used to host landslide inventories and provide updates on spatial coverage. Bottom-up approaches with standardised templates could also encourage the collection of additional landslide inventories in remote areas which can be combined. Meena et al. (2021) recommended compiling a web-based platform to share information about landsliding, which they termed the Nepalese Landslide Information System (NELIS) and which would allow communities to record landslide event information, including timing and specific location. Such a platform would provide information about landslide risk and hazard on a fine scale and could be extremely useful for those responsible for anticipating landslide impacts. However, this bottom-up approach would require a local government official to take on additional work and have sufficient technical understanding of landsliding. Focusing effort on collating, and providing access to, existing inventories with metadata clearly presented, such as minimum landslide size, landslide type(s) included and detailed accounts of the methods used, would be highly beneficial to provide greater insight into long-term patterns of landslide hazard across Nepal. Whilst further small-scale inventories in well-mapped areas can form an excellent additional snapshot in time, a focus should be on ensuring their comparability with other datasets from that same area (Fig. 6d).

4.2 Future implications and priorities

In our database, only 85 000 km^2 (c. 60%) of Nepal has been manually mapped by a published inventory more than once (Fig. 6d). Most areas of Karnali and Sudurpaschim provinces have only been manually mapped once, meaning that only a static understanding of large (> 1 km^2) landsliding is available. The lack of inventories that cover Karnali and Sudurpaschim likely relates to lower population densities, extremely steep topography and the remoteness from Kathmandu of this part of Nepal (Figs. 4d, 6h, 6k and 6l). There may also be linked issues around access to funding, national or local research priorities and capacity, in addition to wider development and political dimensions which may also act to perpetuate this discrepancy. Despite this, the numbers of landslides and landslide-related fatalities, as well as patterns of exposure, are comparable to the rest of the country (Fig. 6e, 6f and 6m). Both provinces were also outside of the area impacted by the Gorkha earthquakes, and so knowledge of landsliding in this regions has not benefitted from increased attention over the last decade. A validated national-scale inventory, or one that is at least nationally consistent in terms of methodology and imagery used, will enable us to decipher whether existing perceptions of landslide hazard and risk are applicable for the full country. Promisingly, attempts to develop national-scale inventories have been made, with a published manual inventory for pre-earthquake landslides with areas > 1 km^2 led by Bhuju and Pokharel (2016) and four automated inventories identified in our database. Since our database was collated, a new landslide inventory which maps 107,900 rainfall-triggered landslides on a national scale over five time periods has been published as a point dataset (Gnyawali et al. 2023). It is likely than any national-scale inventory able to capture landslides < 1 km^2 as a raster or polygon will be generated using a semi- or fully-automated approach, as seen with the four automated approaches considered in this review. We note that the four existing automated national inventories were variable in the number of landslides detected and the areal density. The lack of appropriate training datasets that cover the climatic and topographic gradients present in Nepal makes the development of accurate, widely applicable automated approaches challenging for in the near future. In addition, organisations in Nepal likely to maintain a national dataset have argued that they lack the capacity to undertake sustained, regularly-updated landslide mapping efforts (a point raised by seven out of eight respondents interviewed in Meena et al. 2021). Avenues which responsibly utilise the existing inventories in this database should therefore be considered.

Landslide early warning systems (EWS) are gaining traction in many areas heavily impacted by landsliding, but effective EWS require long-term records of landsliding on a local scale with high temporal precision (e.g., the date of event, for comparison to possible triggering conditions) (Baum and Godt 2010; Guzzetti et al. 2020). All the inventories considered in this review used raster cells, points, polygons, or polylines to represent an individual landslide event (Fig. 3a). Crucially, this provides specific location details which can be used to better understand both the geomorphic and long-term climatological controls for each event. However, in order to develop EWS, we first must link landslide occurrence to short-term weather controls, such as event rainfall totals or rainfall intensity. To build this link requires high temporal resolution information on landslide occurrence, which is lacking and can only be inferred from local observations primarily for impactful events (Thapa and Adhikari 2019). Just over 50% of the studies in this database used satellite imagery to identify landslides, which for the most commonly-used sensors has at best a temporal accuracy of ~ 5 days. Achieving this temporal resolution alone is very challenging with, for example, Burrows et al. (2022) only able to estimate the timing for on average 30% of landslides in existing inventories, with an 80% accuracy, using Synthetic Aperture Radar (SAR) satellite data. Dating landslide events is specifically challenging in countries with monsoonal climates, where cloud cover inhibits coverage for several months each year (Robinson et al. 2019). As a result, our ability to evaluate current landslide susceptibility models and rainfall intensity-duration curves across Nepal is hampered by the absence of a complete national-scale inventory as well as the lack of landslide inventories with a temporal resolution (daily, or even weekly) sufficient to link to triggering conditions.

Landslide occurrence in Nepal is highly dynamic and cannot be simply related to rainfall patterns and geomorphic characteristics (Petley et al. 2007). The static view of landslide hazard and risk presented by most existing landslide inventories (that is, the single-event inventories or those without a specified time window, which make up at least 79% of our database) leads to difficulties for decision makers preparing for future triggering events outside of the Gorkha earthquake-affected region. It is critical to consider details, such as whether inventories analyse a specific triggering event or long-term changes, when considering future applications. In the future, the rapidly changing landscape in both urban and rural areas of Nepal (due, for example, to urbanisation, land use change, road building) will affect landslide risk, meaning that landslide hazard cannot be simply inferred from past processes as observed in more developed locations (Guzzetti et al. 2020) and that regular updates to landslide data are therefore critical. This issue becomes particularly pressing in the context of a changing climate, where multiple influences on landsliding overprint, hindering our ability to project future changes in hazard with confidence. For example, a widely cited driver of landsliding in mountain regions is rural road construction. This has been particularly prevalent in Nepal, with ~ 11 000 km of roads built between 2020 and 2021 alone, according to the Department of Roads (DoR 2021). Unplanned roads and limited adherence to guidelines have resulted in unstable, steep slopes which have a greater potential for contributing to landsliding (Pradhan et al. 2022). For example, McAdoo et al. (2018) found that rainfall-triggered landslides were twice as likely to be within 100 m of a road than earthquake-triggered landslides, attributing the increase to over-steepened slopes, poor drainage, and limited debris management. The risk posed by roadside slopes may also be overlooked by current approaches to collecting landslide inventories which may be unable to map these features from satellite imagery. Without an up-to-date map of both roads and landslides, it is difficult to fully explore the relationship between roads and landslide risk and how this is evolving through time. Collecting systematic, consistent data on road and landslide locations through time thus remains an outstanding research priority.

4.3 Wider application

We have presented a review of landslide inventories from Nepal over the last decade, highlighting the impact of the 2015 Gorkha earthquakes, as well as the initial pre-earthquake bias, on the spatial and temporal distribution of mapping (Figs. 4 and 6) from which we identify limitations of the current datasets available. Whilst we have focused on Nepal, many of the challenges identified are likely to be applicable for other countries prone to landsliding, particularly locations that are expected to be disproportionately affected by rapid road building, land use change, and urbanisation in the future (Petley 2010; Froude and Petley 2018; Kumar et al. 2023). We highlight the limitations of using static landslide inventories in these rapidly-evolving landscapes and reiterate the benefits of producing inventories with clear guidelines and methods that enable past inventories to be reused for future benefit to form multi-temporal assessments. Multi-temporal perspectives on a local scale are insightful in terms of relating landslides to land use and road building (McAdoo et al. 2018; Vuillez et al. 2018), yet the challenges outlined here limit the longer-term upscaling of these studies. Furthermore, many of the multi-temporal inventories in our database relate to the aftermath of the 2015 Gorkha earthquake (Meena and Piralilou 2019; Kincey et al. 2021). We observed a tendency to continue mapping these areas several years after the event, albeit over a variety of scales and temporal intervals (Figs. 1 and 4). This tendency may be because of the significant longer-term landslide footprint an earthquake can have on the landscape. However, this has led to a disproportionate distribution of our understanding of landsliding across the country, with much of what we know about landslide susceptibility inferred from landslides within 14 of the 77 districts in Nepal (Kincey et al. 2024). The record of impactful landslides in the BIPAD Portal also highlights the variable spatial distribution of landslides across Nepal, with landslide impacts not directly relating to existing static maps of susceptibility or exposure or the current density of inventories across the country (Fig. 6). Whilst approaches such as susceptibility and exposure maps help to narrow the focus to those at risk (Petley et al. 2007), identifying those who *will* be impacted by landslides from those who *could* be impacted remains immensely challenging, not just in Nepal (Petley 2010). A record of landslide occurrence across the different climatic, geomorphic and geological conditions is crucial to progress towards landslide EWS not just in Nepal but globally (Guzzetti et al. 2020) and to appreciate how climate change will affect landslide occurrence across the Himalayas (Petley 2010; Devkota et al. 2018).

Our discussion of landslide inventory quality and completeness is also timely given recent advances in the use of machine learning to identify landslides that are reliant on high-quality training and validation datasets. To keep pace with the need for accurate, rapidly-generated landslide inventories through time, it is likely we will need to maximise the use of machine learning to detect landslides (Prakash et al. 2020; Milledge et al. 2022; Novellino et al. 2024). The variability observed for automatically generated national inventories in this review emphasises the importance of viewing existing inventories with a critical perspective and with an understanding of their completeness, prior to using the inventories as test datasets. If not clearly acknowledged, these inaccuracies will be transferred when automated approaches based on specific datasets, such as those trained on fatal landslide inventories (Kirschbaum and Stanley 2018) or inventories from specific events like earthquakes (Milledge et al. 2022), are used beyond their initial purpose. Complete, well-documented manually-mapped inventories are therefore critical to provide better training datasets that can ultimately improve the performance of automated approaches in the future. In Nepal, these inventories could be collated using one of the well-established country-specific or more general guidelines for building landslide inventories (Guzzetti et al. 2012; Meena et al. 2021) and by enhancing the event recording in the BIPAD portal to include all landslide events with a locational precision greater than ward level (National Disaster Risk Reduction and Management Authority (NDRRMA) 2022).

5 Conclusions and future work

Our review revealed that 117 landslide inventories were created in Nepal between 2010 and 2021, suggesting great potential for our understanding of landslide hazard across the country. These inventories were clustered spatially and temporally both prior to the earthquakes in 2015 and then around the 2015 Gorkha earthquakes in the years that followed. Across the full study period, inventories were commonly obtained along roads and within close proximity to Kathmandu. The western part of the country, particularly Karnali and Sudurpashchim provinces, remains poorly mapped and in some areas has only been manually mapped once as part of a national inventory for large landslides (>1 km^2), despite similar landslide susceptibility and exposure scores to the better-mapped central part of the country.

The inventories within this database have been collated using a variety of different techniques, including field-based reports and larger-scale satellite-based approaches. The use of a range of methods is beneficial in terms of capturing landslide inventories on a variety of scales, for identifying different landslide types and creating local and regional susceptibility maps. Future efforts should prioritise the establishment of a set of protocols for the methods commonly used to create landslide inventories, especially satellite imagery and field surveys. By standardising these approaches, future landslide inventories will be consistent and comparable with other inventories produced using the same method. This will enable the development of multi-temporal landslide time-series, which can tackle timely concerns such as climate change and the pressures of road building, as well as provide data to validate future automated landslide mapping efforts. When designing the protocols, we must ensure that the inventories will be fit for purpose. The output must also be considered to ensure that the datasets produced are accessible and well-maintained. Whilst we focused on Nepal, the future priorities outlined here are likely to be relevant to many other landslide-prone countries. The landslide community should utilise the wealth of knowledge obtained from existing approaches to landslide mapping in Nepal to improve consistency and comparability when creating landslide inventories for parts of the world with minimal coverage.

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Data availability The database of landslide inventories and the hex plot shapefile presented in Fig. 6 can be accessed here: https://zenodo.org/records/10410752 (https://doi.org/10.5281/zenodo.10410751) (Harvey et al. 2023).

Declarations

Conflict of interest The authors declare no competing interests.

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Authors and Affiliations

Erin L. Harvey[1,2] · Mark E. Kincey[3] · Nick J. Rosser[1,2] · Arishma Gadtaula[4] · Ethan Collins[1] · Alexander L. Densmore[1,2] · Alexandre Dunant[1,2] · Katie J. Oven[5] · Katherine Arrell[5] · Gopi K. Basyal[4] · Megh Raj Dhital[6] · Tom R. Robinson[7] · Maximillian Van Wyk de Vries[8,9] · Sarmila Paudyal[4] · Dammar S. Pujara[4] · Ram Shrestha[4]

✉ Erin L. Harvey
erin.l.harvey@durham.ac.uk

1 Department of Geography, Durham University, Durham, UK

2 Institute of Hazard, Risk and Resilience, Durham University, Durham, UK

3 School of Geography, Politics and Sociology, Newcastle University, Newcastle, UK

[4] National Society for Earthquake Technology, Lalitpur, Nepal

[5] Department of Geography and Environmental Sciences, Northumbria University, Newcastle, UK

[6] Tri-Chandra Multiple Campus, Ghantaghar, Tribhuvan University, Kathmandu, Nepal

[7] School of Earth and Environment, University of Canterbury, Christchurch, New Zealand

[8] Department of Geography, University of Cambridge, Cambridge, UK

[9] Department of Earth Science, University of Cambridge, Cambridge, UK