Landslides (2023) 20:967–982
DOI 10.1007/s10346-022-02020-4
Received: 26 July 2022
Accepted: 30 December 2022
Published online: 13 February 2023
© The Author(s) 2023

Renata Pacheco Quevedo · Andrés Velastegui-Montoya · Néstor Montalván-Burbano · Fernando Morante-Carballo · Oliver Korup · Camilo Daleles Rennó

Land use and land cover as a conditioning factor in landslide susceptibility: a literature review

Abstract Landslide occurrence has become increasingly influenced by human activities. Accordingly, changing land use and land cover (LULC) is an important conditioning factor in landslide susceptibility models. We present a bibliometric analysis and review of how LULC was explored in the context of landslide susceptibility in 536 scientific articles from 2001 to 2020. The pattern of publications and citations reveals that most articles hardly focus on the relationship between LULC and landslides despite a growing interest in this topic. Most research outputs came from Asian countries (some of which are frequently affected by landslides), and mostly with prominent international collaboration. We recognised three major research themes regarding the characteristics of LULC data, different simulated scenarios of LULC changes, and the role of future scenarios for both LULC and landslide susceptibility. The most frequently studied LULC classes included roads, soils (in the broadest sense), and forests, often to approximate the negative impacts of expanding infrastructure, deforestation, or major land use changes involving agricultural practice. We highlight several articles concerned primarily with current practice and future scenarios of changing land use in the context of landslides. The relevance of LULC in landslide susceptibility analysis is growing slowly, though with much potential to be explored for future LULC scenario analysis and to close gaps in many study areas.

Keywords Slope stability · Mass movement · Land cover changes · Bibliometric analysis · Literature review

Introduction

Landslides are natural and potentially hazardous phenomena that move rock, debris, or earth downslope under the influence of gravity (Cruden and Varnes 1996). Landslides arise from interactions between slope geometry, soil and rock properties, as well as surface and groundwater dynamics (Bogaard and Greco 2016). These preconditioning characteristics influence weathering processes and may contribute to a decrease in shear strength (Skilodimou et al. 2018). This decrease, combined with triggering factors such as precipitation, earthquakes, snow melt, or human activities, can lead to potentially destructive landslides (Petley 2012; Haque et al. 2019). For example, Froude and Petley (2018) reported that 4862 landslides caused 55,997 fatalities between 2004 and 2016. Nevertheless, the impact of landslides on society remains underestimated because much of the damage attributed to earthquakes and storms is tied instead to resulting landslides (Varnes 1984; Aleotti and Chowdhury 1999). In this context, landslide susceptibility analysis has become essential for disaster risk reduction, aiming to prevent damages and casualties (Bragagnolo et al. 2020).

Landslide susceptibility maps identify terrain locations likely to be most prone to slope failure by analysing the characteristics of reported landslides (Guzzetti et al. 2005). For this purpose, it is necessary to identify the factors influencing landslide occurrence. Numerous studies have explored the influence of geology (Henriques et al. 2015; Kim and Song 2015), rainfall (Guzzetti et al. 2007; Zêzere et al. 2015), and geomorphometric characteristics (Vorpahl et al. 2012; Nugraha et al. 2015) in this respect. For example, Reichenbach et al. (2018) identified as many as 596 different conditioning factors used in 565 articles published between 1983 and 2016; geomorphometric variables made up 37% of all these conditioning factors, followed by those linked to land cover (18%).

Land cover refers to the biological and physical materials on the Earth's surface (Herold et al. 2006). It comprises natural elements, such as water bodies, forests, exposed rock or soil, and surfaces modified by humans, such as roads, buildings, and agriculture. In contrast, land use alludes to the socio-economic appropriation of the land (Herold et al. 2006), i.e., the purpose humans give to the terrain, to safeguard occupation or production. Land cover impacts soil mechanical behaviour and moisture in many ways. For example, vegetation may protect soil from erosion and improve slope stability through mechanical anchoring and soil suction by roots (Löbmann et al. 2020; Parra et al. 2021; Masi et al. 2021). On the contrary, deforestation, road construction, slope cutting, or building construction on hillslopes often reduce slope stability (Chen et al. 2019).

Therefore, land use and land cover (LULC) are important conditioning factors that influence rainfall-triggered landslides (Glade 2003), and many studies have argued that land use/cover changes (LUCC) might increase landslide susceptibility (Chen and Huang 2013). For example, Lehmann et al. (2019) explored the relationship between deforestation and landslide occurrence by looking at root reinforcement in four distinct climatic environments with different forest management practices. Since deforested lands had negligible root strength, the authors simulated forest alteration scenarios in which areas without forest regrowth showed higher landslide occurrence and impacts. Similarly, Mugagga et al. (2012) reported a spatial relationship between landslide occurrence and slopes deforested for cultivation. Apart from areas where crops have replaced forests, abandoned cultivated lands may also be highly susceptible to landslides (Galve et al. 2015; Persichillo et al. 2017). Like deforestation, most construction works compromise slope stability (Karsli et al. 2009; Meneses et al. 2019) by altering infiltration, surface runoff, and groundwater flows (Vuillez et al. 2018). Furthermore, excavation and blasting commonly used for construction may change the natural stress state and force equilibrium in a given hillslope (Liu et al. 2021).

Many studies argued that LUCC might alter landslide susceptibility (Chen and Huang 2013; Liu et al. 2021). In this sense, Pisano et al. (2017) analysed the influence of LUCC on landslide susceptibility through future scenarios. One of the future scenarios considered past trends, with increases in forest and cultivated areas, and another presented a decrease in forest area and agricultural activity. The authors concluded that reducing forest areas and abandoning farming lands might increase the erosional processes. Promper et al. (2014) analysed LUCC over 138 years in Austria to simulate the evolution of landslide risk. The authors considered two main future trends; the first adopted the LULC trends previously verified in the region, and the second took into account no newly built areas. The result was that the expansion of housing construction was predicted in landslide susceptibility areas. Both studies showed that LULC scenarios might aid landslide susceptibility studies for reducing disaster risk.

While an increasing number of studies have been considering LULC in landslide susceptibility (Quevedo et al. 2021) or inventory analysis (Uehara et al. 2022), most review articles separately focus on LULC (Montalván-Burbano et al. 2021), landslide susceptibility modelling (Budimir et al. 2015; Huang and Zhao 2018; Pourghasemi et al. 2018; Reichenbach et al. 2018; Merghadi et al. 2020; König et al. 2022; Lima et al. 2022), landslide classification system (Hungr et al. 2014; Li and Mo 2019), and landslide study area (Dikshit et al. 2020; Dias et al. 2021; Valdés Carrera et al. 2021). Here, we offer a systematic review of how landslide susceptibility studies include the multi-faceted aspects of LULC and bibliometric analysis of the use of LULC data in landslide susceptibility. Finally, we discuss major research themes, focusing on which and how LULC types were parameterised to arrive at a possible ranking.

Materials and methods

Research on natural hazards has seen an increasing number of bibliometric studies analysing the scientific output on landslides (Wu et al. 2015; Briones-Bitar et al. 2020; Carrión-Mero et al. 2021). However, none of the studies explored the use of LULC in susceptibility analyses. Below, we outline our database search criteria; filtering criteria; data pre-processing; bibliometric analysis; and strategies for reviewing (Fig. 1).

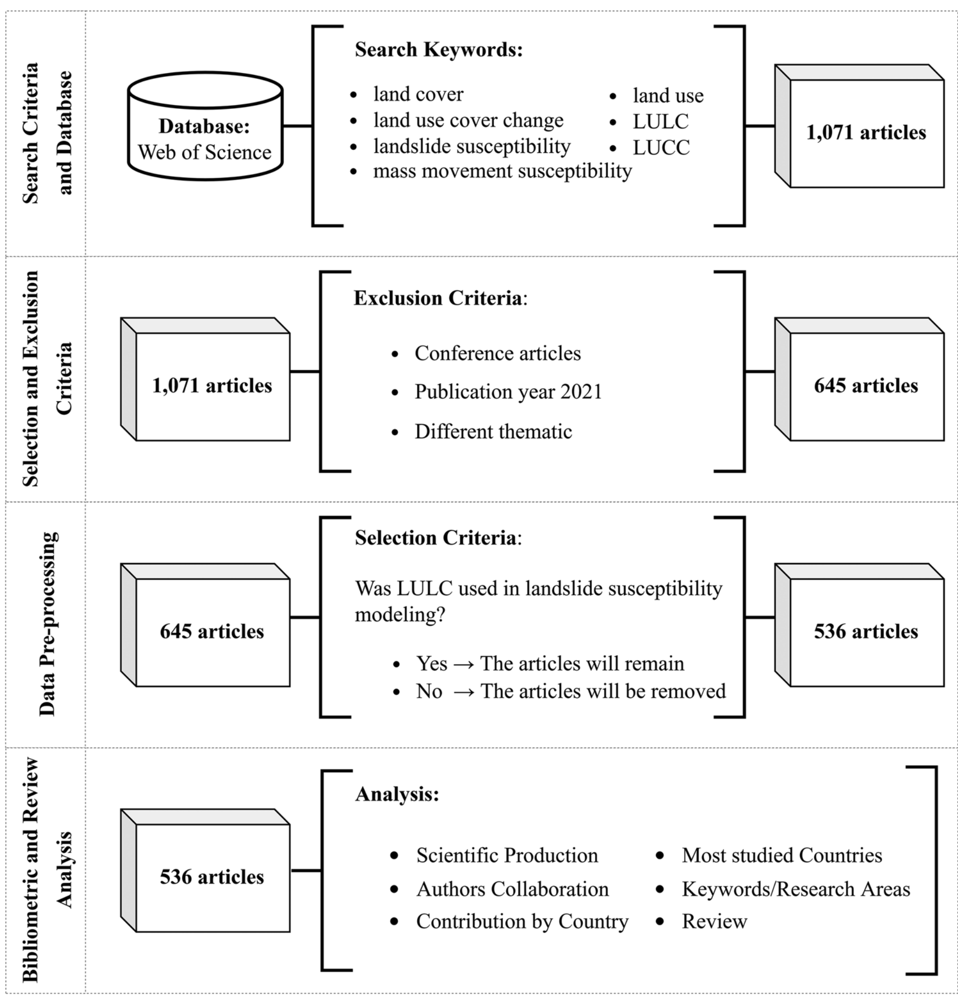


Fig. 1 Methodological flowchart

Search criteria, filters, and database

This study considered the Web of Science™ (WoS), since it is the oldest scholarly database (Birkle et al. 2020), maintained by Clarivate Analytics™, with more than 74.8 million records and 1.5 billion references in 254 subject disciplines (Singh et al. 2021). Furthermore, we follow the choice of many previous bibliometric studies of landslides (Gokceoglu and Sezer 2009; Reichenbach et al. 2018; Merghadi et al. 2020; Dias et al. 2021). We focused on search terms that express LULC to capture the effect of human activities on landslide susceptibility (Meneses et al. 2019; Knevels et al. 2020) and LUCC. We considered all fields (*topic* option) and applied the search argument: ((“landslide susceptibility” OR “mass movement susceptibility”) AND (“land cover” OR “land use” OR “land use cover change” OR “LULC” OR “LUCC”)). This first selection, carried out in July 2021, resulted in 1071 articles.

The search was limited to peer-reviewed articles and excluded books, book chapters, conference proceedings, and reports, as well as “grey literature”, theses, and dissertations (Reichenbach et al. 2018). All articles post-dating 2020 were also excluded from this collection, resulting in 814 articles. Next, we checked whether the remaining papers included mention of landslide susceptibility, as many articles focused on other natural hazards, such as soil erosion, gully occurrence, and soil subsidence, though with cursory reference to landslides. Nearly a fifth of the papers was irrelevant to the analysis, leaving us with 645 articles.

All abstracts were screened to ensure that the analysis considered only articles that used LULC as a conditioning factor in the susceptibility analysis. Where abstracts did not clearly indicate whether the article was suitable, the entire publication was screened. For example, some papers mentioned that landslide susceptibility might support land use planning but disclosed little about how LULC may affect landslide susceptibility instead. Hence, we manually removed articles focused on landslide inventory or susceptibility modelling without LULC as a conditioning factor, resulting in 536 articles in our final database.

Bibliometric analysis and review

The bibliometric analysis was conducted in three stages: (i) assessment of productivity and impact, based on publication and citation counts; (ii) network mapping to visualise collaborations among authors and countries; and (iii) most frequent keywords and research areas to portray major research themes.

The first stage explored trends in scientific output, considering publications, citations, cited references in each article, and the focus of the most cited papers. Next, we analysed co-authorship using bibliometric maps of collaboration networks generated through VOSviewer software (van Eck and Waltman 2010). Subsequently, the publication counts were mapped according to countries and study areas to depict the geographical focus of the studies, to explore which countries have been most studied at which scale, and to check whether the most studied countries also suffered major landslide disasters in the past.

The most frequent keywords approximate the personal and collective choice of technical jargon, the structure consistency (Herrera-Franco et al. 2021), and trends in the subject areas (Leung et al. 2017). The most frequent keywords in the abstracts and the most common authors’ keywords were computed using the **R** programming language and VOSviewer software, respectively. For the abstract analysis, a cleaning step was performed to remove stop words and the terms used to select the articles (i.e., landslide, landslide susceptibility, mass movement susceptibility, land cover, land use, land use cover change, LULC, LUCC). Then, only stem words were considered to avoid over-presenting slight variations of the same term in the word cloud, e.g., map, maps, or mapping. Finally, we analysed the authors’ keywords with a co-occurrence network map (van Eck and Waltman 2010) to identify prominent groupings.

Lastly, we highlighted articles that specifically explored the relationship between LULC and landslide susceptibility, following the more traditional line of literature review. While the massively rising publication numbers in the general field of landslide research may encourage, if not even partly justify, the use of bibliometric exploration, we see this as an addition to, rather than a replacement of, conventional literature reviews. Therefore, we selected articles that contained terms related to LULC in their titles, such as land use and land cover. This selection allowed us to thoroughly explore the contribution of these specific articles and highlight trends in the use of LULC in landslide studies.

Results

Publication trends

Among all the 536 articles, 533 were written in English, and the other three were in Korean, Malay, and Portuguese. The database comprises articles published between 2001 and 2020, divided into four equal intervals: (i) 2001 – 2005; (ii) 2006 – 2010; (iii) 2011 – 2015; and (iv) 2016 – 2020. In these phases, the annual average number of publications grew nearly 15-fold between the first and the last phase (Fig. 2).

Phase I had the highest proportion of individual publications (19%) and the least international collaboration (24%), with most articles addressing landslide susceptibility with statistical models, such as discriminant function (Dai and Lee 2001) and logistic regression (Lee and Min 2001; Baeza and Corominas 2001). These papers analysed LULC according to landslide occurrence (Baeza and Corominas 2001). In phase II, articles began to focus on model comparison, with increasing use of artificial neural networks for susceptibility modelling (Merghadi et al. 2020) and some studies about the influence of LULC characteristics on landslide susceptibility (Yesilnacar and Süzen 2006). In phase III, models such as logistic regression and frequency ratio remained popular, with several studies recognising the effects of LULC on landslide susceptibility (Reichenbach et al. 2014). Finally, phase IV amassed the highest fraction of publications concerned with the relationship between LULC and landslide susceptibility.

The rapid increase in publication numbers since 2012 reached a peak in 2019 when 80 articles were published. This peak may be partly related to the International Consortium on Landslides (ICL) strategies to understand and reduce landslide disaster risk (Sassa 2015). In 2012, for example, the 10th Anniversary Conference of ICL created a strategic plan for the period between 2012 and 2022 (Sassa 2012). Additional boosts for this rapid rise in

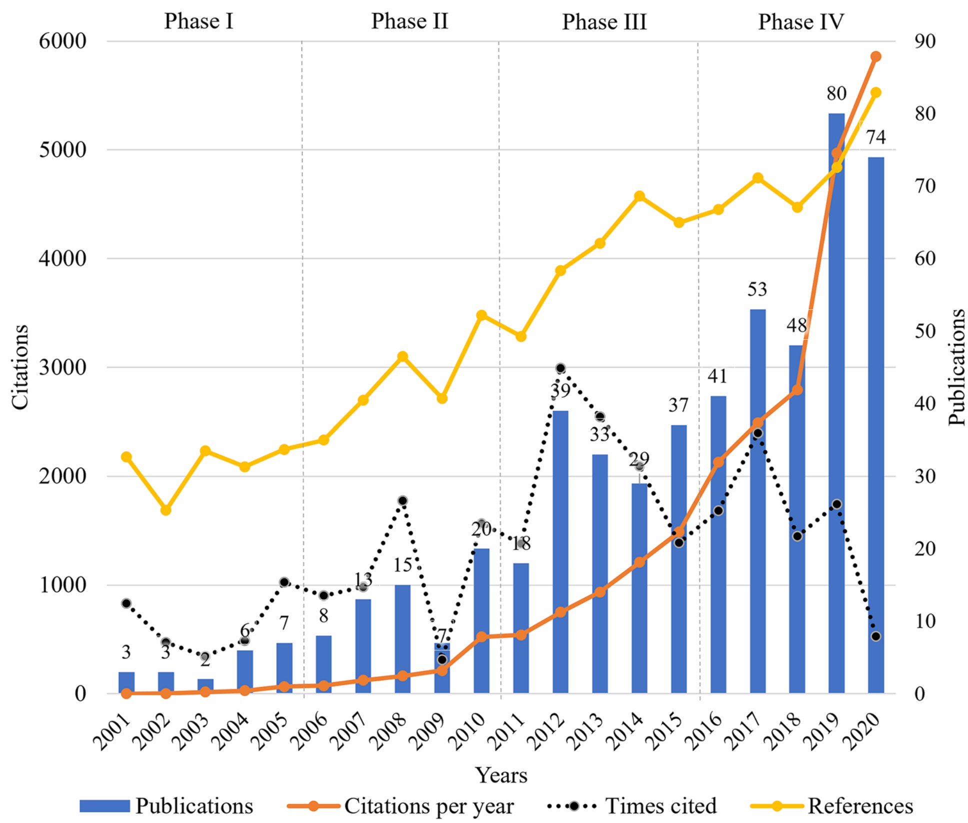


Fig. 2 Trends in publication numbers on LULC and landslide susceptibility, considering (i) publications: the number of **publications** per year; (ii) citations per year (left *y*-axis): **citations** registered in each year; (iii) times cited: how many **times** articles published in each year were **cited**; (iv) references (right *y*-axis): the average number of **references** cited in each article per year

research output are the substantial increase in freely available satellite imagery and topographic and LULC data (Wulder and Coops 2014; Jun et al. 2014; Gómez et al. 2016).

The number of references per article has also increased. The average reference list has roughly tripled in length over the past two decades, being the shortest in 2002, with 25 references per article, and surpassing 80 references per article in 2020. This increase in the number of current publications and references per article improves the probability of a published article being cited at least once. For example, the total number of citations per year increased considerably in 2016, reaching a maximum of 5860 citations in 2020 (Fig. 2). This increase in citations may be related to the "Sendai Partnerships 2015–2025 for global promotion of understanding and reducing landslide disaster risk", which was adopted for 33 countries aiming to improve landslide research (Sassa 2015).

Articles published in 2012 were the most cited: eight of the 39 papers received more than 150 citations each. The main contributions of these eight articles concerned the comparison of model performance, using an average of ten conditioning factors, focusing on study areas in Iran, Vietnam, Malaysia, and South Korea. In some of these studies, LULC was the second (Pourghasemi et al. 2012a, b) or the third (Tien Bui et al. 2012; Mohammady et al. 2012) most important landslide conditioning factor. Some authors found that settlements or residential land were mainly located in susceptible areas (Pourghasemi et al. 2012b; Althuwaynee et al. 2012), while many authors pointed out the higher susceptibility close to roads (Tien Bui et al. 2012; Althuwaynee et al. 2012; Mohammady et al. 2012).

The 15 most-cited articles represented 3% of all analysed papers and concentrated 18% of all citations between 2001 and 2017, most of them published during phases I (33%) and III (33%). These papers featured landslide susceptibility models based on two to four different algorithms. For example, the most cited article (Lee and Min 2001) exemplified how to model susceptibility with logistic regression and analysed the relationship between conditioning factors and landslide occurrence. In addition, the Annual Citation Index (ACI) represents the average citation according to the article publication year. Most articles (79%) received between one and 20 citations per year, while only 1% received more than 60 citations per year on average (Fig. 3). Among the 15 most cited articles, the paper with the highest ACI (Chen et al. 2017) pioneered the use of the logistic model tree for landslide susceptibility, showing that the normalised difference vegetation index (NDVI) was among the most relevant proxies of land cover in the study area.

Co-authorship and geographic spread

The 536 articles comprised 1305 authors; out of these, 1008 contributed only to a single paper. The articles had between one (3%) and 15 (1%) authors; most contributions had reached three to four authors. In depicting collaborations between co-authors, we considered a minimum publication threshold of five joint papers with the largest set of connected items. The resulting map of 34 authors shows that 12% collaborated with ten or more authors; 27 articles were single-authored (Fig. 4).

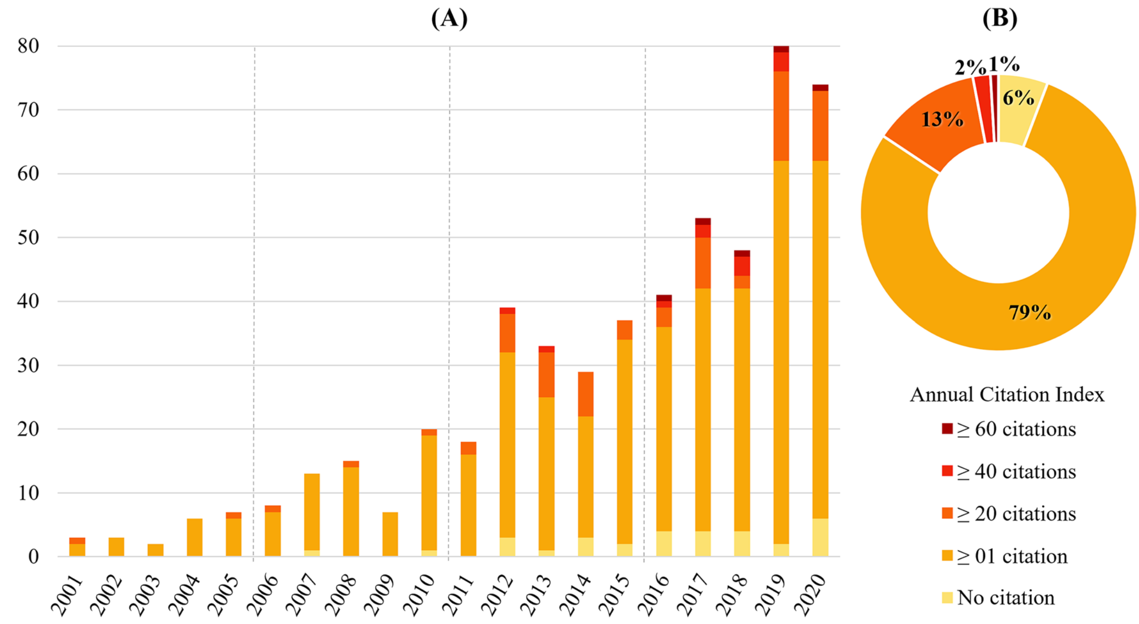


Fig. 3 The distribution of articles over time according to ACI (**A**) and their total percentage (**B**)

The most collaborative authors work from Asia. For example, cluster 1 (red) has nine authors from six institutions in China, Iran, and Malaysia; cluster 2 (green) binds eight researchers from institutions in Australia, Belgium, Iran, Nepal, and Turkey; cluster 3 (blue) includes five authors associated with three institutions from Austria, India, and Iran (Fig. 4). The remaining clusters have three authors, each with fewer variations in institutions: all researchers in clusters 4 (olive-yellow) and 5 (purple) are from South Korea and China, respectively; clusters 6 (light blue) and 7 (orange) include authors from Norway and India, respectively, with one collaborator from Vietnam.

Regarding the top contributing countries (Table 1), 53% are in Asia, 33% in Europe, and 13% in America and Oceania. Authors from the People's Republic of China were the most numerous, being involved in 102 publications in collaboration with 28 countries, mainly Iran and Malaysia. These articles focused on landslide susceptibility modelling performance, drawing on various machine learning algorithms. Based on the performance of each country, the average citation (AC) values exceeded 100 for Malaysia, Turkey, Norway, and South Korea.

The data on landslide disasters was compiled to check if these most-contributing countries were also among the most impacted by landslides. We used the Emergency Events Database (EM-DAT) (Guha-Sapir et al. 2009) (Fig. 5), which has been recording disasters since 1903, for selecting the 20 most-affected countries by landslide disasters. These 20 countries had 66% of all recorded landslide disasters and 64% of all fatalities. Only five of the most affected countries between 2001 and 2020 had commensurately high numbers of publications: China, India, Japan, Turkey, and Italy (Table 1). However, we stress that this representation is only a rough indication and may hardly capture the international mobility of landslide researchers working abroad or targeted international research programmes.

The study areas of each analysed article and the national research output support the observation that almost all the most affected countries featured as study areas (Fig. 6). Also, the most studied and productive countries, such as China, India, Iran, and Italy, have LULC mapping initiatives at the national scale (Congedo et al. 2016; Moulds et al. 2018; Zhang et al. 2019; Ghorbanian et al. 2020). However, not all studied regions were represented by authors in these countries, which means that not necessarily the most studied and affected areas are the most contributing. For example, there are studies about Afghanistan, Colombia, Costa Rica, Ecuador, and El Salvador, carried out by researchers whose affiliation is associated with countries such as China and Nepal, the Czech Republic, USA, Germany and Canada, and Spain, respectively.

Keywords and research areas

The most common term in the abstracts of all 536 articles was "map" (Fig. 7), which appeared more than 1700 times, describing the characteristic research product of landslide susceptibility studies. Other common words were "factor", "slope", and the stem form of distance ("distanc"). About two dozen terms were related to landslide conditioning factors and eight to LULC. Among the 15 most used LULC keywords, "road" was the top ranking, followed by "soil" and "forest" (Fig. 8). References to the proximity of roads appeared mainly as a landslide conditioning factor, while only two abstracts informed about the presence of roads in unstable areas. Rawat and Joshi (2012) and Sujatha et al. (2012), for example, highlighted, respectively, that up to 9% of the roads in the Igo river basin, and intense anthropogenic activities, such as busy roads, in Tevankarai Ar sub-watershed, both in India, were located in high landslide susceptible areas. Other common, though similarly generic, LULC terms such as "settlement" or "agriculture" remain comparably scarce in the publication record.

Table 1 Top 15 most-contributing countries to research on landslide susceptibility and LULC

Rank	Country	Region	TP	TP (%)	TC	TC (%)	AC	TR	R/MI
1	People's Republic of China	Asia	102	19%	4382	15%	42.96	1,536,502	1089
2	Iran	Asia	91	17%	7218	25%	79.32	57,031	0679
3	India	Asia	83	15%	2227	8%	26.83	215,281	0156
4	South Korea	Asia	64	12%	6415	22%	100.23	353,454	6826
5	Malaysia	Asia	59	11%	6668	23%	113.02	66,480	2054
6	Italy	Europe	48	9%	2295	8%	47.81	116,488	1956
7	Vietnam	Asia	46	9%	2811	10%	61.11	66,093	0679
8	Turkey	Asia	41	8%	4551	16%	111.00	97,833	1160
9	USA	America	35	7%	1368	5%	39.09	1,385,481	4205
10	Norway	Europe	27	5%	2801	10%	103.74	30,582	5685
11	Germany	Europe	21	4%	1452	5%	69.14	359,599	4320
12	Japan	Asia	21	4%	1261	4%	60.05	670,454	5328
13	Australia	Oceania	20	4%	1160	4%	58.00	116,414	4532
14	Greece	Europe	18	3%	640	2%	35.56	29,907	2791
15	Austria	Europe	16	3%	420	1%	26.25	44,113	4947

TP total number of publications, *TC* total number of citations, *AC* average citations, *TR* total number of researchers, *R/MI* researchers per million inhabitants (UNESCO Institute for Statistics 2021)

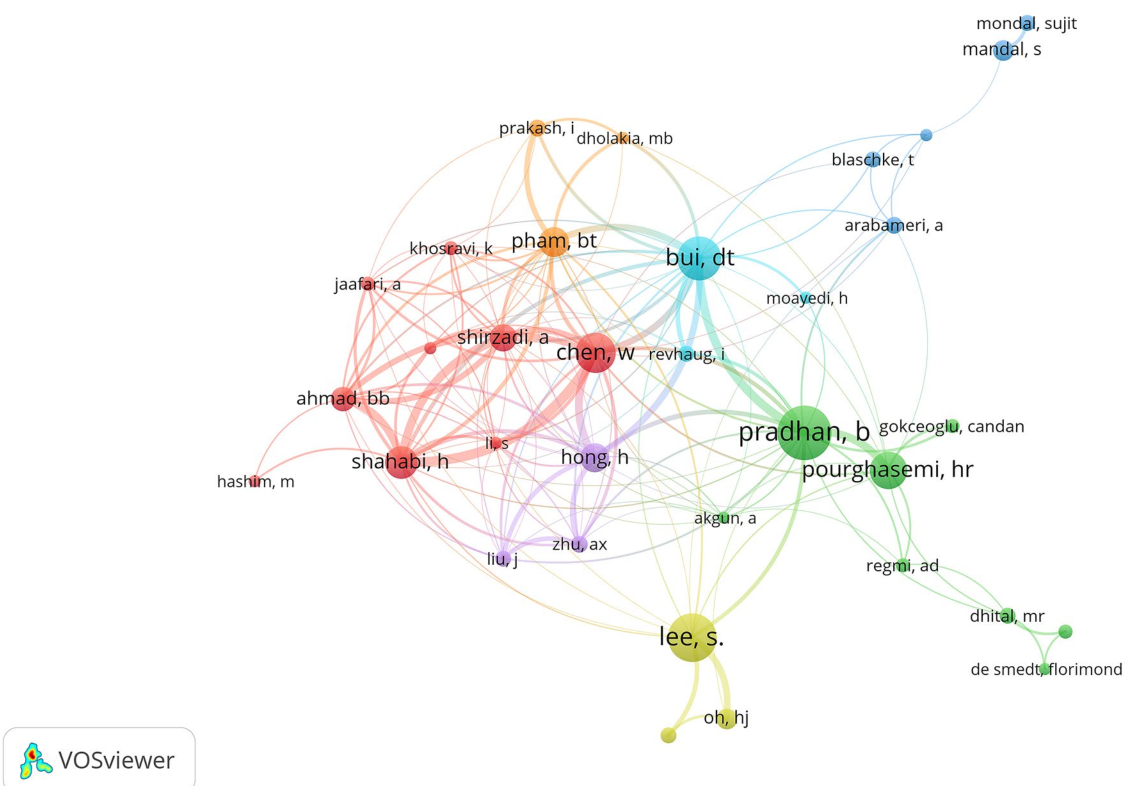


Fig. 4 Co-authorship network map showing seven main collaboration clusters in studies on landslide susceptibility and LULC. Circle sizes represent the publication counts of each author, i.e., the higher the dot size, the higher the publication count. The line thickness shows the collaboration among the authors, in which thicker connecting lines represent more articles jointly co-authored

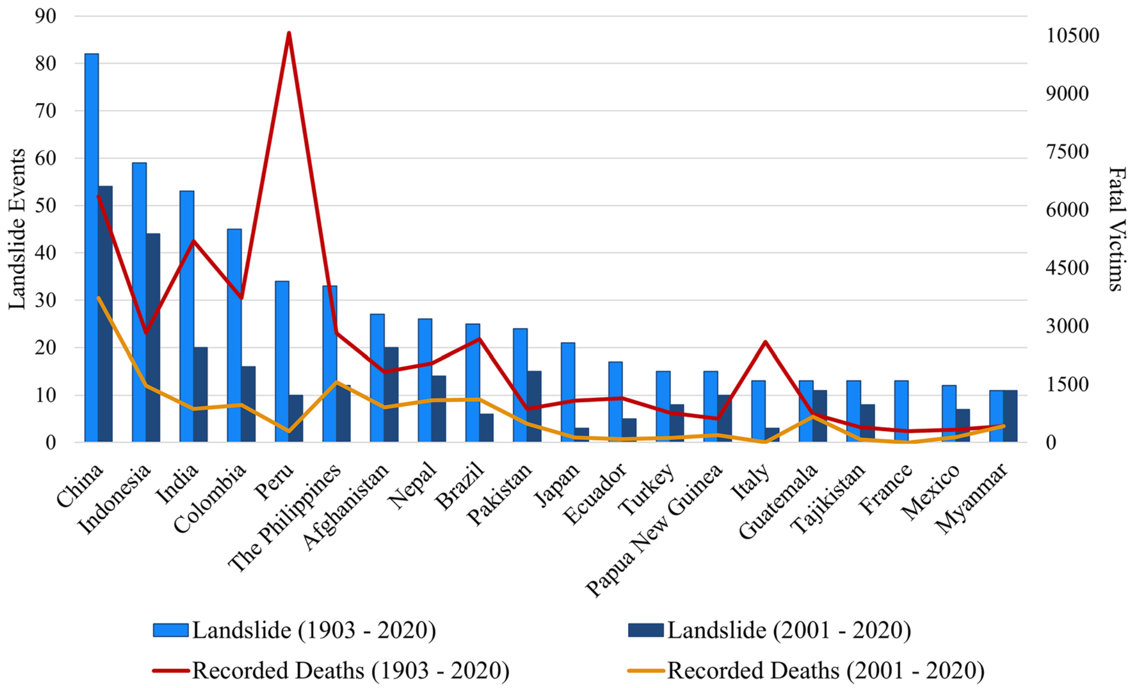


Fig. 5 Countries most affected by landslide disasters, according to EM-DAT (www.emdat.be) records from 1903 to 2020 (blue) and the deaths caused by these events (red); and the records of landslide disaster events (dark blue) and the number of fatal victims (orange) in the timespan covered by this literature review (2001–2020)

Regarding keywords provided by the authors, a total of 542 different entries were identified and corrected for minor inconsistencies. We focused on those 50 keywords that appeared at least five times: "landslide susceptibility" occurred in 45% of all articles, followed by "GIS" (Geographic Information System) (43%), "landslide" (35%), and "frequency ratio" (15%). The keywords "land use" and "land cover" appeared only in seven and five articles, respectively. The authors' keywords were analysed with a co-occurrence network map, considering seven words as the minimum cluster size (Fig. 9). All four clusters have keywords related mainly to algorithms used for landslide susceptibility modelling, underscoring the strong methodological focus in this field, and many less

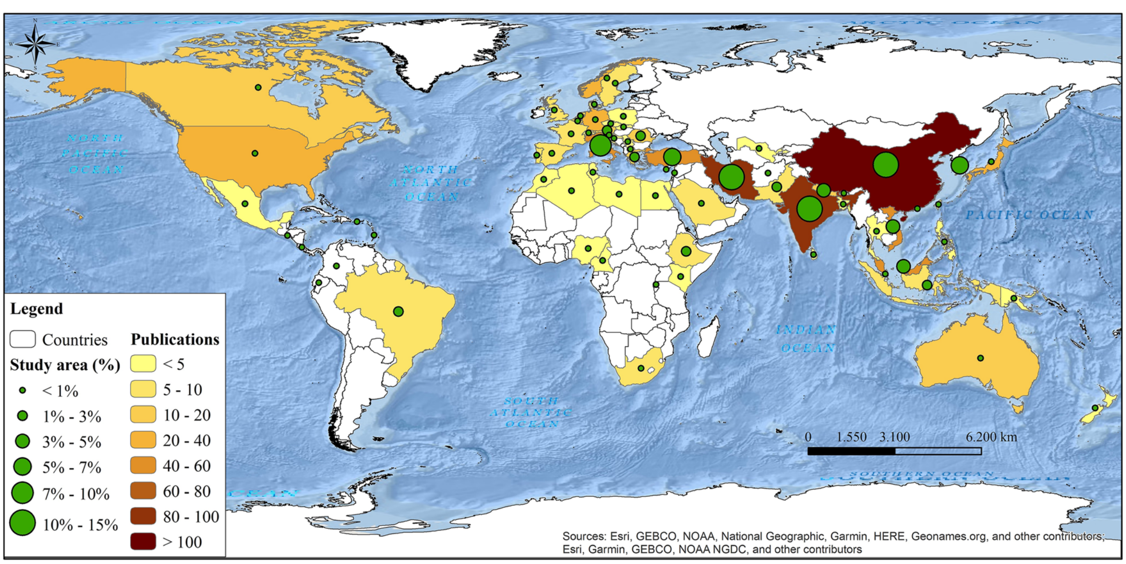


Fig. 6 Comparison of most studied countries and national research output on landslide susceptibility and LULC: (i) the study area (green dots) shows the percentage of articles that studied a given country; (ii) the publications (gradient colour) are the number of articles published by each country, according to the authors' affiliation

Fig. 7 Word cloud of the most frequent terms in the 536 abstracts of studies on landslide susceptibility and LULC

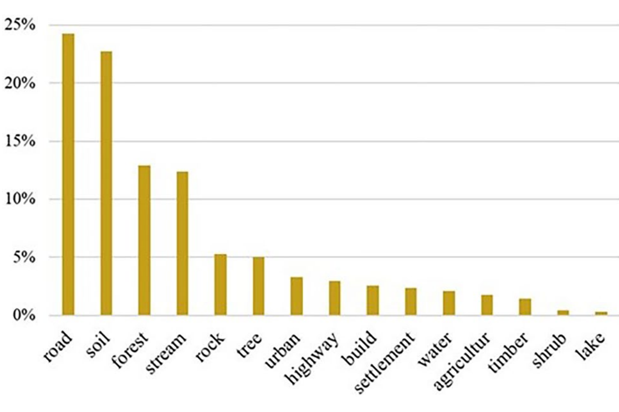


Fig. 8 The 15 most frequently mentioned LULC keywords in the abstracts. The percentage refers to the number of abstracts in which each keyword was mentioned

frequently mentioned keywords refer to specific statistical methods. The central core of the network has three nodes (relevant topics) with similar importance and many connections among the clusters.

The research covered 27 subject areas, reflecting the interdisciplinary nature of landslide and LULC studies. The most frequent research areas (Fig. 10) were Geology (30%), followed by Water Resources (15%), and Environmental Sciences and Ecology (14%). Despite the predominance of areas focused on science, technology, engineering, and mathematics (STEM), few of them are also related to social analysis and public management, i.e., fields closely studying LULC from various perspectives. Furthermore, the analysed articles were published in 128 different journals, of which the top 15 most frequent journals covered 57% of all publications and 74% of all citations. The greatest number of articles was published in the "Environmental Earth Sciences" journal. On

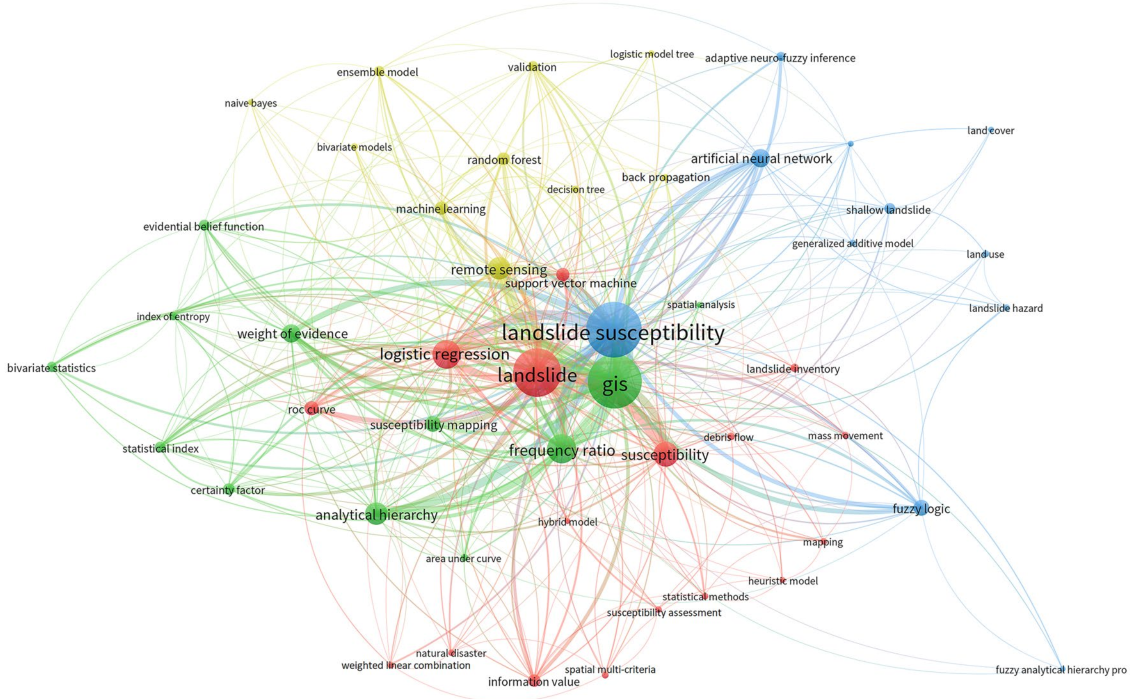
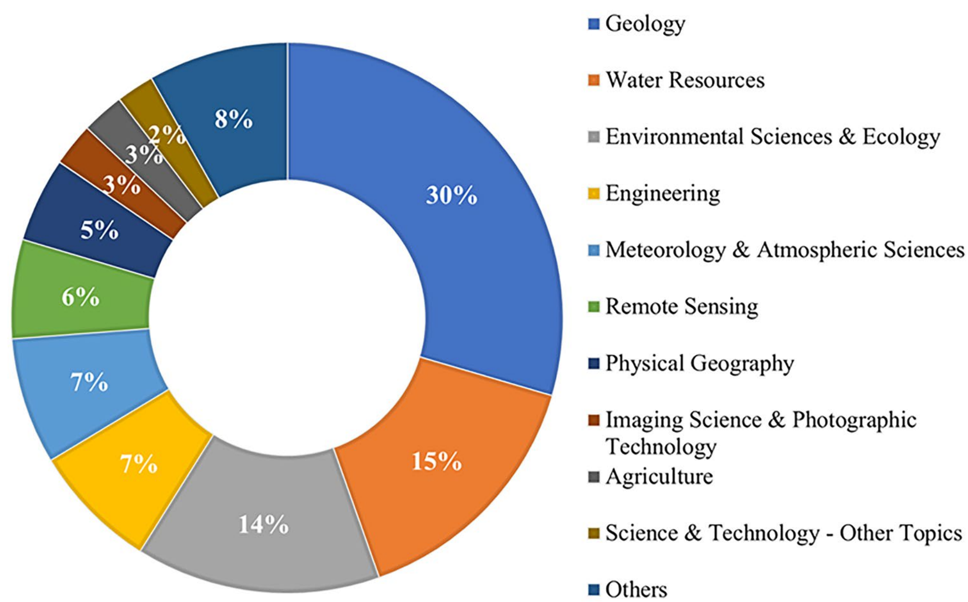


Fig. 9 Co-occurrence network map of keywords provided by authors in publications on landslide susceptibility and LULC. The circles are the keywords, while lines connect the words supplied together. Circle sizes are scaled to word frequencies; the thicker the connecting lines, the more related the terms

the other hand, considering the citations, the highlighted journal was "Environmental Geology", which presented the highest average citation by article. According to the database, the journal that showed the longest activity was "Natural Hazards", with publications between 2004 and 2020, followed by "Landslides" and the "International Journal of Remote Sensing", both since 2005. Both research areas and journals may confirm the pattern of interdisciplinarity shown by the keyword analysis.

Fig. 10 The ten most-frequent WoS research areas



Landslide susceptibility focused on LULC

Most of the studied papers sought better models for landslide susceptibility analysis. Some identified LULC as one of the most influential landslide conditioning factors for susceptibility modelling. For example, Arabameri and Rezaei (2019) found that LULC, NDVI, and distance to road were the most important landslide conditioning factors in the Sangtarashan watershed, Iran. All these factors are related to LULC. Similarly, LULC was the most important factor in the susceptibility modelling in the Sarkhoun catchment, Iran (Shirani et al. 2018), and in Mezam Division, Cameroon (Afungang et al. 2017). The former study highlighted that poor rangeland, agriculture, and rock outcrops were the most related to landslide susceptibility; the latter pointed out that predicted landslides are concentrated in a hilly area with an expanding urban population. Austin et al. (2013) analysed the effects of the Three Gorges Dam on local urban areas and landslide susceptibility in Yichang City, China. With the flooding of the reservoir area, numerous settlements were moved to higher-elevation areas. In this sense, the authors assessed the landslide occurrence likelihood in these new urban areas, concluding that the new constructions are below steep slopes, which could lead to high susceptibility. The influence of LULC on landslide susceptibility was also explored by Galve et al. (2015) in Cinque Terre, Italy. The authors generated scenarios by changing LULC classes, i.e., they used maps with abandoned lands and simulated scenarios in which vineyards, forests, or structural measurements replaced the abandonment. They found that vineyards may slightly reduce landslide susceptibility; on the other hand, forests might be more effective in reducing susceptibility. With a focus on vegetation class, Miller (2013) proposed to use the Surface Cover Index in landslide susceptibility analysis in Dominical, Costa Rica. This index represents vegetation vigour and degradation and improved the model performance when incorporated into the landslide susceptibility analysis. While these studies focused on model performance improvement or urban land cover changes and landslide susceptibility, they hardly explored why LULC was the most important factor for a given study area or how it could alter susceptibility.

Indeed, few publications explored the influences of LULC in detail. Yesilnacar and Süzen (2006) pioneered LULC mapping, considering multispectral satellite images, vegetation indices, topographic indices, and transformation components (principal component analysis). In studying the Asarsuyu basin, Turkey, the authors showed that including multiple indices and principal component analysis improved the overall classification accuracy while estimating the influence of LULC classes using the logistic regression algorithm. Although the logistic regression overall accuracy rose by only 2%, the landslide locations estimation improved by up to 20%. Moreover, young forests (forests removed by fires or deforestation and regrown after the 1980s) and a moist mixed group (rocks, grassland, and agriculture) were the most frequent LULC classes in landslide bodies and high susceptibility areas. Meneses et al. (2019) evaluated the influence of different LULC datasets on landslide susceptibility in the Zêzere watershed, Portugal, to identify road networks that could be more predisposed to future blockages caused by landslides. For that, the authors included the same predisposing factors in all models; the only change in modelling processes corresponded to variation in LULC spatial resolution. The study results demonstrated that more detailed LULC data improved the landslide susceptibility mapping, though not necessarily their transferability to similar catchments elsewhere. The authors emphasised the lack of studies that compare LULC maps with different properties (scale and spatial resolution) since LULC is usually taken from pre-existing cadastres or mapped from satellite imagery. Both studies exemplify that including LULC data in landslide susceptibility analysis may provide more insights about LULC and landslides; however, the approaches remained static since they considered a single slice.

Given that human activities can modify vast areas quickly (Glade 2003), LULC may need more dynamic scenarios. For example, Chen et al. (2019) tracked LULC over 21 years (1992, 2002, and 2013) to quantify their relevance for landslides in Xuan'en County, China, an area marked by a substantial increase in anthropic activities such as clearing forests for grass and arable lands. The authors reported that these conversions compromised slope stability, though less so in recent years, commensurate with lower deforestation rates. The study suggested that including LUCC in landslide assessment and proper land use planning in urbanisation may decrease landslide susceptibility. A similar temporal analysis was also done by Persichillo et al. (2017), who studied landslide-prone terrain in rural areas, mainly agriculture fields and vineyards, in three different catchments in Altrepò Pavese, Italy. The study built on 58 years of data with five pre-existing LULC maps and found that LULC was one of the most important conditioning factors on slope stability, especially in abandoned lands. Maintaining cultivated areas seemed crucial to support land conservation and reduce shallow landslide activity. Similarly, Reichenbach et al. (2014) classified the LULC for 2 years (1954 and 2009) before and after reported landslides in the Briga catchment, Italy. The study contemplated various scenarios to explore the relationship between forest and landslide susceptibility and pointed to more stable slopes in 1954, likely because of the increase in forested areas. Comparing 1954 and 2009 through different land use scenarios, the authors demonstrated an increase in landslide susceptibility with decreasing forest areas and expanding patches of bare soil. The scenarios of reforestation resulted in more stable slopes in the model. This study used only DEM-derived variables and LULC classification, offering high reproducibility.

The relationship between forest and landslide susceptibility was also explored by Malek et al. (2015) for Buzau County, Romania. The authors studied past (1989, 2000, and 2010) and future scenarios (2040) for three LUCC classes: persistent forest, forest expansion, and deforestation. The study points out forest cover changes in different landslide susceptibility classes and how these modifications can be considered for risk management. For example, areas with higher susceptibility had more non-forest but were also more likely to expand forests in the future; hence, landslide susceptibility is prone to change accordingly. Shu et al. (2019) explored how LULC changed along with landslide susceptibility over 150 years (1946 – 2097) in the Val d'Aran region, Spain. Again, outcomes showed an increase in areas with low susceptibility and a decrease in high susceptibility zones, possibly related to the 163% increase in forest cover areas from 1946 to 2097 in one of the scenarios. The authors excluded other future impacts, such as climate changes or rainfall regimes. Finally, Pisano et al. (2017) considered past land cover (1954, 1981, and 2007) trends for simulating LULC scenarios for the Rivo basin, Italy, for 2030 and 2050. Then, more cultivated areas decreased landslide susceptibility, likely because cultivation replaced areas without prior maintenance, resulting in better land and water management practices. The authors argued that good management practices would lower landslide susceptibility in the future. Hence, simulating different LULC scenarios allows to identify how LUCC may alter landslide susceptibility, thus aiding decision makers in territorial planning for disaster risk reduction.

Discussion

Landslides are a widespread phenomenon that causes disasters around the world. In this sense, many researchers have been seeking the most influential landslide conditioning factors to improve landslide susceptibility mapping. Some of these factors are physical, such as geology and geomorphometry; others are related to human activity (Skilodimou et al. 2018) that rapidly transforms the landscape (Guzzetti et al. 2005). In this sense, considering the impact of anthropic activities on slopes, researchers have increasingly been trying to relate LULC changes and slope instability (Karsli et al. 2009; Mugagga et al. 2012; Chen and Huang 2013; Austin et al. 2013). In the following, we discuss how the influence of LULC on landslide susceptibility modelling has been assessed.

Landslides and LULC studies

Landslides have been studied for a long time (Radbruch-Hall and Varnes 1976) due to their impacts on society (Haque et al. 2019). However, much landslide research became more structured as an independent discipline during and following the International Decade for Risk Reduction of the United Nations in 2000. In this process, the core study was defined, aiming to standardise and review terminologies (Sassa 2007) and further quantitative susceptibility assessment studies (Cruden 1997). This mission may partly explain the focus on model performance that most reviewed articles focused on. We recognise a trend from landslide susceptibility studies to a stronger focus on statistical (Dai and Lee 2001), deep learning (Pradhan and Lee 2010), machine learning (Tien Bui et al. 2012), and hybrid models (Shirzadi et al. 2017; Roy et al. 2019) in the past two decades.

Furthermore, LULC classifications have been done since the 1970s (Phiri and Morgenroth 2017) but have rapidly improved in coverage and resolution thanks to the increase in available satellite imagery (Wulder and Coops 2014; Gómez et al. 2016). He et al. (2022) highlighted that the LUCC research focused on modelling until 2004; between 2005 and 2013, eco-environmental impacts were emphasised, while the current phase focused on improving global sustainability. These different focuses on LULC and LUCC research are reflected broadly in our literature database. For example, there was an increasing trend in the number of publications on landslide susceptibility that used LULC data as a conditioning factor since about 2004, and more studies that explored LULC and LUCC impacts on hillslopes to assess landslide susceptibility (Persichillo et al. 2017).

The importance of considering LULC or LUCC on landslide assessment relies on the impacts of human activities on slopes, mainly agricultural and forestry activities, which are also affected by global warming and call for efficient management strategies to reduce landslide susceptibility (Gariano and Guzzetti 2016). However, considering that landslides will occur under the same conditions as past landslides might represent a limited vision, as hillslope conditions change drastically in response to human activities (Guzzetti et al. 2005). Hence, considering LULC's future scenarios in landslide susceptibility analysis would provide more practical results to aid public administrators in long-term land use management and landslide disaster risk reduction.

LULC as a landslide conditioning factor

One confounding issue is that LULC encompasses various impacts on soil structure according to each cover class (Chen et al. 2019; Löbmann et al. 2020; Masi et al. 2021). For example, a developed forest presents more significant root reinforcement than undergrowth or cultivation areas (Lehmann et al. 2019). Also, changes in LULC likely modify soil shear strength, causing slope instability, and in some cases, rapid changes can become a landslide trigger (Davies 2015).

Our analysis found that the most common LULC classes were road, soil, and forest (Fig. 8), most likely because the relevant data are easy to obtain most objectively. Generally, roads enter susceptibility models regarding the distance from mapped landslides (Yan et al. 2019). Road construction and maintenance directly or indirectly impact the slope through slope cuts or changes in surface water runoff (Vuillez et al. 2018). Other road impacts include the construction of paths for forestry logging (Jaafari et al. 2015), which generally follow different regulations than those for official roads. "Soil" is also frequently reduced to patches of bare land or poorly vegetated ground instead of distinct soil types. Many studies reported that deforestation or logging exposes soil to erosion processes and slope instability (Reichenbach et al. 2014; Cohen and Schwarz 2017; Persichillo et al. 2017). Again, forests are commonly associated with an increase in slope stability (Cohen and Schwarz 2017). While many studies concur that deforestation raises landslide susceptibility (Dai et al. 2002), few mention the roles of forest type, structure, health, or natural disturbances (Parra et al. 2021).

Hence, while the different classes of LULC can be analysed separately, they are also often interconnected, which may compromise some statistical models in terms of collinearity. Furthermore, when analysing LUCC, not only will the change be a determining factor of landslide occurrences, but also the relative gains and losses for a given LULC class (Liu et al. 2021). For example, replacing forests for agriculture may promote more slope instability (Lehmann et al. 2019), whereas cultivating previously abandoned areas may decrease landslide susceptibility (Pisano et al. 2017). Scenario-based approaches to LUCC (Promper et al. 2014; Malek et al. 2015; Pisano et al. 2017; Shu et al. 2019) can guide future actions for reducing landslide disaster risk.

Countries' contribution and landslide disasters

The pattern of countries with more publications in landslide research differs from other reviews (Carrión-Mero et al. 2021; Huang et al. 2022) because only articles that included LULC data in landslide susceptibility analysis were considered. Nonetheless, many studies agree that the countries with the most publications about landslides tend to be from Asia (Pourghasemi et al. 2018; Reichenbach et al. 2018). For example, South Korea has the highest number of researchers per million inhabitants (R/MI), whereas China and the USA have the highest total number of researchers (TR) (Table 1). On the other hand, Greece, Norway, and Austria had the lowest TR, probably because of their small populations.

While the susceptibility to landslides may be a strong incentive for landslide research, it is also the government investment in research and science (Habib et al. 2019). For example, India has the second-highest population in the world and presents low TR, possibly related to the low investment in research and development (R&D) (UNESCO Institute for Statistics 2021). Furthermore, some countries that suffered disasters, such as Afghanistan, Colombia, and Ecuador, hardly published, at least internationally (Fig. 6). For example, Colombia and Ecuador presented low investments in R&D (UNESCO Institute for Statistics 2021) and few researchers (there is no available data for Afghanistan). On the other hand, the authors' affiliations that studied the aforementioned countries are related to China, the Czech Republic, Germany, and Canada, which corroborate the importance of investment in R&D to encourage more studies on the landslide topic.

Some of the most productive countries, in terms of publication numbers (Table 1), suffered from recent landslide disasters (Fig. 5). The landslide disaster occurrence may be related to the difficulty of establishing official regulations and strategies for landslide risk reduction due to budgetary constraints or cultural factors, among other causes (Winter and Bromhead 2012). For example, Mateos et al. (2020) indicated that even in Europe, there are no general regulations for landslide risk reduction, and not all European countries have official landslide guidelines for territorial planning or methodological guides.

Limitations and future trends

The selection of the scholarly database and the search keywords might add some limitations to this study. The focus on WoS may render a one-sided perspective. For example, Valdés Carrera et al. (2021) used multiple database platforms (WoS, Scopus, SciELO, REDIB, and Redalyc) of Latindex to analyse landslide studies in Latin America. Hence, the low number of studies from South America, Central America, and the Caribbean might be an artefact of the database choice.

Moreover, our analysis focused on articles that considered LULC as a conditioning factor in landslide susceptibility assessment; yet, LULC classes are diverse and multiple and sometimes non-exclusive. Then, limitations on the keywords used in the first search criteria might result in a limited articles database. As we considered only words directly related to LULC (land cover, land use, land use cover change, LULC, and LUCC) on the first search, it may result in not including relevant articles in our database (Guns and Vanacker 2013). For example, the road was not taken into account as a keyword in the first search, which generally appears as a specific conditioning factor (Jaafari et al. 2015), such as distance or proximity to roads (Brenning et al. 2015).

Some publications were excluded from the database because of keyword choices (e.g., landslide susceptibility vs. mass movement susceptibility). Preliminary searches did not include studies with terms such as "landslide occurrence" (Van Beek and Van Asch 2004; Wasowski et al. 2010; Promper et al. 2014; Cohen and Schwarz 2017; Gariano et al. 2018; Vuillez et al. 2018; Knevels et al. 2021), "debris flow" (Rogelis and Werner 2014; He et al. 2018), or "rockfall" (Lopez-Saez et al. 2016; Farvacque et al. 2019) or articles published after 2020 (Knevels et al. 2021; Rabby et al. 2022).

Furthermore, it is worth mentioning that the analysis of the influence of LULC on landslide susceptibility is a theme of expanding interest and interdisciplinary relevance and is still in need of studies. We identify several challenges for the future:

(i) Bibliometric studies: executing a comprehensive search, including specific LULC classes and landslide occurrence, may provide a complete database. For example, including the LULC keywords "roads" and "forest" may provide specific articles which analyse the relationship between landslides and these land cover classes;
(ii) Review articles: since reviews tend to be applied to a small number of papers, the limitation of the preliminary search to the article title may generate a more restricted database focused on LULC in landslide analysis;
(iii) Research articles—modelling performance: there is an increasing interest in studies that apply hybrid models in landslide susceptibility analysis, which may focus more on LULC effects on landslide occurrence;
(iv) Research articles—LULC influence: simulating LULC future scenarios and evaluating how it modifies the landslide susceptibility seems to be a potential hotspot in landslide topics. This mapping is interesting to show for public managers which changes in LULC increase and which of them decrease the landslide susceptibility;
(v) Research articles—other topics: the inclusion of possible climate change impacts; the consideration of variations in rainfall conditions; the root reinforcement according to different plant species and LULC classes.

Conclusions

This study explored the use of LULC data on landslide susceptibility assessment through bibliometric and review approaches. The literature database was composed of 536 articles, which revealed that most publications focused on landslide susceptibility modelling using LULC data as a conditioning factor. The lion's share of scientific research was on model performance, varying from statistical and index-based models to deep learning and machine learning algorithms. In addition, we found that countries most affected by landslides were not necessarily the most productive in terms of international authorship quantities, likely reflecting national imparity in investment in research and development. Notably, South American and African nations seem strikingly absent from the international community of authors. Our analysis emphasises how LULC and LUCC influence on landslide susceptibility has become more common only gradually since 2016 onwards. The first approach focused on how LULC mapping influences landslide susceptibility, especially classification method, scale, and spatial resolution. More recent works consider the simulation of future LULC scenarios and how this changed landslide susceptibility. The future landslide susceptibility scenarios may provide helpful information for landslide risk management and land use planning. In conclusion, the analysis of LULC influence on landslide susceptibility is an expanding theme, which has the potential to be explored for future scenario analysis and to close gaps in study areas.

Acknowledgements

The authors are thankful to Dr. Evlyn Marcia Leão de Moraes Novo for the insights and motivation to carry out a review study.

Author contribution

Conceptualisation, R.P.Q., A.V.M., and N.M.B.; methodology, N.M.B., F.M.C.; software, N.M.B., O.K.; validation, R.P.Q., A.V.M., N.M.B., and F.M.C.; formal analysis, A.V.M., N.M.B., and F.M.C.; investigation, R.P.Q.; resources, R.P.Q., A.V.M., N.M.B., and F.M.C.; data curation, R.P.Q., A.V.M., and N.M.B.; writing—original draft preparation, R.P.Q.; writing—review and editing, A.V.M., N.M.B., F.M.C., O.K., and C.D.R.; visualisation, R.P.Q. and A.V.M.; supervision, C.D.R.; project administration, R.P.Q.; funding acquisition, A.V.M. All authors have read and agreed to the published version of the manuscript.

Funding

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior-Brazil (CAPES)-Finance Code 001. The APC was funded by ESPOL Polytechnic University.

Declarations

Conflict of interest The authors declare no competing interests.

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

References

Afungang RN, de Meneses Bateira CV, Nkwemoh CA (2017) Assessing the spatial probability of landslides using GIS and informative value model in the Bamenda highlands. Arab J Geosci 10:384. https://doi.org/10.1007/s12517-017-3155-1

Aleotti P, Chowdhury R (1999) Landslide hazard assessment: summary review and new perspectives. Bull Eng Geol Environ 58:21–44. https://doi.org/10.1007/s100640050066

Althuwaynee OF, Pradhan B, Lee S (2012) Application of an evidential belief function model in landslide susceptibility mapping. Comput Geosci 44:120–135. https://doi.org/10.1016/j.cageo.2012.03.003

Arabameri P, Rezaei L (2019) Assessment of landslide susceptibility using statistical- and artificial intelligence-based FR–RF integrated model and multiresolution DEMs. Remote Sens 11:999. https://doi.org/10.3390/rs11090999

Austin NJ, Muller JP, Gong L, Zhang J (2013) A regional investigation of urban land-use change for potential landslide hazard assessment in the Three Gorges Reservoir Area, People's Republic of China: Zigui to Wanzhou. Int J Remote Sens 34:2983–3011. https://doi.org/10.1080/01431161.2012.744528

Baeza C, Corominas J (2001) Assessment of shallow landslide susceptibility by means of multivariate statistical techniques. Earth Surf Process Landforms 26:1251–1263. https://doi.org/10.1002/esp.263

Birkle C, Pendlebury DA, Schnell J, Adams J (2020) Web of Science as a data source for research on scientific and scholarly activity. Quant Sci Stud 1:363–376. https://doi.org/10.1162/qss_a_00018

Bogaard TA, Greco R (2016) Landslide hydrology: from hydrology to pore pressure. Wires Water 3:439–459. https://doi.org/10.1002/wat2.1126

Bragagnolo L, Silva RV d, Grzybowski JMV (2020) Artificial neural network ensembles applied to the mapping of landslide susceptibility. Catena 184:104240. https://doi.org/10.1016/j.catena.2019.104240

Brenning A, Schwinn M, Ruiz-Páez AP, Muenchow J (2015) Landslide susceptibility near highways is increased by 1 order of magnitude in the Andes of southern Ecuador, Loja province. Nat Hazards Earth Syst Sci 15:45–57. https://doi.org/10.5194/nhess-15-45-2015

Briones-Bitar J, Carrión-Mero P, Montalván-Burbano N, Morante-Carballo F (2020) Rockfall research: a bibliometric analysis and future trends. Geosci 10:1–25. https://doi.org/10.3390/geosciences10100403

Budimir MEA, Atkinson PM, Lewis HG (2015) A systematic review of landslide probability mapping using logistic regression. Landslides 12:419–436. https://doi.org/10.1007/s10346-014-0550-5

Carrión-Mero P, Montalván-Burbano N, Morante-Carballo F et al (2021) Worldwide research trends in landslide science. Int J Environ Res Public Health 18:9445. https://doi.org/10.3390/ijerph18189445

Chen CY, Huang WL (2013) Land use change and landslide characteristics analysis for community-based disaster mitigation. Environ Monit Assess 185:4125–4139. https://doi.org/10.1007/s10661-012-2855-y

Chen L, Guo Z, Yin K et al (2019) The influence of land use and land cover change on landslide susceptibility: a case study in Zhushan Town, Xuan'en County (Hubei, China). Nat Hazards Earth Syst Sci 19:2207–2228. https://doi.org/10.5194/nhess-19-2207-2019

Chen W, Xie X, Wang J et al (2017) A comparative study of logistic model tree, random forest, and classification and regression tree models for spatial prediction of landslide susceptibility. CATENA 151:147–160. https://doi.org/10.1016/j.catena.2016.11.032

Cohen D, Schwarz M (2017) Tree-root control of shallow landslides. Earth Surf Dyn 5:451–477. https://doi.org/10.5194/esurf-5-451-2017

Congedo L, Sallustio L, Munafò M et al (2016) Copernicus high-resolution layers for land cover classification in Italy. J Maps 12:1195–1205. https://doi.org/10.1080/17445647.2016.1145151

Cruden DM (1997) Panel discussion: landslides and the international decade for natural disaster reduction. In: 14th Int Conf Soil Mech Found Engng Balkema Rotterdam 2301–2304.

Cruden DM, Varnes DJ (1996) Landslide types and processes. In: Turner AK, Shuster RL (eds) Landslides: investigation and mitigation. Transp Res Board, Washington, D.C 36–75.

Dai FC, Lee CF (2001) Terrain-based mapping of landslide susceptibility using a geographical information system: a case study. Can Geotech J 38:911–923. https://doi.org/10.1139/cgj-38-5-911

Dai FC, Lee CF, Ngai YY (2002) Landslide risk assessment and management: an overview. Eng Geol 64:65–87. https://doi.org/10.1016/S0013-7952(01)00093-X

Davies T (2015) Landslide hazards, risks, and disasters: introduction. In: Landslide hazards, risks, and disasters. Elsevier Inc 1–16

Dias HC, Hölbling D, Grohmann CH (2021) Landslide susceptibility mapping in Brazil: a review. Geosciences 11:425. https://doi.org/10.3390/geosciences11100425

Dikshit A, Sarkar R, Pradhan B et al (2020) Rainfall induced landslide studies in indian himalayan region: a critical review. Appl Sci 10. https://doi.org/10.3390/app10072466

Farvacque M, Lopez-Saez J, Corona C et al (2019) How is rockfall risk impacted by land-use and land-cover changes? Insights from the French Alps. Glob Planet Change 174:138–152. https://doi.org/10.1016/j.gloplacha.2019.01.009

Froude MJ, Petley DN (2018) Global fatal landslide occurrence from 2004 to 2016. Nat Hazards Earth Syst Sci 18:2161–2181

Galve JP, Cevasco A, Brandolini P, Soldati M (2015) Assessment of shallow landslide risk mitigation measures based on land use planning through probabilistic modelling. Landslides 12:101–114. https://doi.org/10.1007/s10346-014-0478-9

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

Gariano SL, Petrucci O, Rianna G et al (2018) Impacts of past and future land changes on landslides in southern Italy. Reg Environ Chang 18:437–449. https://doi.org/10.1007/s10113-017-1210-9

Ghorbanian A, Kakooei M, Amani M et al (2020) Improved land cover map of Iran using Sentinel imagery within Google Earth Engine and a novel automatic workflow for land cover classification using migrated training samples. ISPRS J Photogramm Remote Sens 167:276–288. https://doi.org/10.1016/j.isprsjprs.2020.07.013

Glade T (2003) Landslide occurrence as a response to land use change: a review of evidence from New Zealand. CATENA 51:297–314. https://doi.org/10.1016/S0341-8162(02)00170-4

Gokceoglu C, Sezer E (2009) A statistical assessment on international landslide literature (1945–2008). Landslides 6:345–351. https://doi.org/10.1007/s10346-009-0166-3

Gómez C, White JC, Wulder MA (2016) Optical remotely sensed time series data for land cover classification: a review. ISPRS J Photogramm Remote Sens 116:55–72. https://doi.org/10.1016/j.isprsjprs.2016.03.008

Guha-Sapir D, Below R, Hoyois P (2009) EM-DAT: The CRED/OFDA International Disaster Database. Belgium, Brussels

Guns M, Vanacker V (2013) Forest cover change trajectories and their impact on landslide occurrence in the tropical Andes. Environ Earth Sci 70:2941–2952. https://doi.org/10.1007/s12665-013-2352-9

Guzzetti F, Peruccacci S, Rossi M, Stark CP (2007) Rainfall thresholds for the initiation of landslides in central and southern Europe. Meteorol Atmos Phys 98:239–267. https://doi.org/10.1007/s00703-007-0262-7

Guzzetti F, Reichenbach P, Cardinali M et al (2005) Probabilistic landslide hazard assessment at the basin scale. Geomorphology 72:272–299. https://doi.org/10.1016/j.geomorph.2005.06.002

Habib M, Abbas J, Noman R (2019) Are human capital, intellectual property rights, and research and development expenditures really important for total factor productivity? An empirical analysis. Int J Soc Econ 46:756–774. https://doi.org/10.1108/IJSE-09-2018-0472

Haque U, da Silva PF, Devoli G et al (2019) The human cost of global warming: deadly landslides and their triggers (1995–2014). Sci Total Environ 682:673–684. https://doi.org/10.1016/j.scitotenv.2019.03.415

He C, Zhang J, Liu Z, Huang Q (2022) Characteristics and progress of land use/cover change research during 1990–2018. J Geogr Sci 32:537–559. https://doi.org/10.1007/s11442-022-1960-2

He S, Wang D, Li Y, Zhao P (2018) Land use changes and their driving forces in a debris flow active area of Gansu Province. China Sustainability 10:2759. https://doi.org/10.3390/su10082759

Henriques C, Zêzere JL, Marques F (2015) The role of the lithological setting on the landslide pattern and distribution. Eng Geol 189:17–31. https://doi.org/10.1016/j.enggeo.2015.01.025

Herold M, Latham JS, Di Gregorio A, Schmullius CC (2006) Evolving standards in land cover characterization. J Land Use Sci 1:157–168. https://doi.org/10.1080/17474230601079316

Herrera-Franco G, Montalván-Burbano N, Carrión-Mero P et al (2021) Worldwide research on geoparks through bibliometric analysis. Sustainability 13:1175. https://doi.org/10.3390/su13031175

Huang Y, Xu C, Zhang X, Li L (2022) Bibliometric analysis of landslide research based on the WOS database. Nat Hazards Res 118159. https://doi.org/10.1016/j.nhres.2022.02.001

Huang Y, Zhao L (2018) Review on landslide susceptibility mapping using support vector machines. CATENA 165:520–529. https://doi.org/10.1016/j.catena.2018.03.003

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

Jaafari A, Najafi A, Rezaeian J et al (2015) Planning road networks in landslide-prone areas: a case study from the northern forests of Iran. Land Use Policy 47:198–208. https://doi.org/10.1016/j.landusepol.2015.04.010

Jun C, Ban Y, Li S (2014) Open access to Earth land-cover map. Nature 514:434–434. https://doi.org/10.1038/514434c

Karsli F, Atasoy M, Yalcin A et al (2009) Effects of land-use changes on landslides in a landslide-prone area (Ardesen, Rize, NE Turkey). Environ Monit Assess 156:241–255. https://doi.org/10.1007/s10661-008-0481-5

Kim K, Song Y (2015) Geometrical and geotechnical characteristics of landslides in Korea under various geological conditions. J Mt Sci 12:1267–1280. https://doi.org/10.1007/s11629-014-3108-z

Knevels R, Brenning A, Gingrich S et al (2021) Towards the use of land use legacies in landslide modeling: current challenges and future perspectives in an austrian case study. Land 10:1–28. https://doi.org/10.3390/land10090954

Knevels R, Petschko H, Proske H et al (2020) Event-based landslide modeling in the styrian basin, Austria: accounting for time-varying rainfall and land cover. Geosci 10:217. https://doi.org/10.3390/geosciences10060217

König T, Kux HJH, Corsi AC (2022) Advanced models applied for the elaboration of landslide-prone maps, a review. Int J Geosci 13:174–198. https://doi.org/10.4236/ijg.2022.133010

Lee S, Min K (2001) Statistical analysis of landslide susceptibility at Yongin, Korea. Environ Geol 40:1095–1113. https://doi.org/10.1007/s002540100310

Lehmann P, von Ruette J, Or D (2019) Deforestation effects on rainfall-induced shallow landslides: remote sensing and physically-based modelling. Water Resour Res 55:9962–9976. https://doi.org/10.1029/2019WR025233

Leung XY, Sun J, Bai B (2017) Bibliometrics of social media research: a co-citation and co-word analysis. Int J Hosp Manag 66:35–45. https://doi.org/10.1016/j.ijhm.2017.06.012

Li Y, Mo P (2019) A unified landslide classification system for loess slopes: a critical review. Geomorphology 340:67–83. https://doi.org/10.1016/j.geomorph.2019.04.020

Lima P, Steger S, Glade T, Murillo-García FG (2022) Literature review and bibliometric analysis on data-driven assessment of landslide susceptibility. J Mt Sci 19:1670–1698. https://doi.org/10.1007/s11629-021-7254-9

Liu J, Wu Z, Zhang H (2021) Analysis of changes in landslide susceptibility according to land use over 38 years in lixian county, China. Sustain 13:1–23. https://doi.org/10.3390/su131910858

Löbmann MT, Geitner C, Wellstein C, Zerbe S (2020) The influence of herbaceous vegetation on slope stability – a review. Earth-Science Rev 209:103328. https://doi.org/10.1016/j.earscirev.2020.103328

Lopez-Saez J, Corona C, Eckert N et al (2016) Impacts of land-use and land-cover changes on rockfall propagation: insights from the Grenoble conurbation. Sci Total Environ 547:345–355. https://doi.org/10.1016/j.scitotenv.2015.12.148

Malek Ž, Boerboom L, Glade T (2015) Future forest cover change scenarios with implications for landslide risk: an example from Buzau Subcarpathians, Romania. Environ Manage 56:1228–1243. https://doi.org/10.1007/s00267-015-0577-y

Masi EB, Segoni S, Tofani V (2021) Root reinforcement in slope stability models: a review. Geosciences 11:212. https://doi.org/10.3390/geosciences11050212

Mateos RM, López-Vinielles J, Poyiadji E et al (2020) Integration of landslide hazard into urban planning across Europe. Landsc Urban Plan 196:103740. https://doi.org/10.1016/j.landurbplan.2019.103740

Meneses BM, Pereira S, Reis E (2019) Effects of different land use and land cover data on the landslide susceptibility zonation of road networks. Nat Hazards Earth Syst Sci 19:471–487. https://doi.org/10.5194/nhess-19-471-2019

Merghadi A, Yunus AP, Dou J et al (2020) Machine learning methods for landslide susceptibility studies: a comparative overview of algorithm performance. Earth-Science Rev 207:103225. https://doi.org/10.1016/j.earscirev.2020.103225

Miller AJ (2013) Assessing landslide susceptibility by incorporating the surface cover index as a measurement of vegetative cover. L Degrad Dev 24:205–227. https://doi.org/10.1002/ldr.1115

Mohammady M, Pourghasemi HR, Pradhan B (2012) Landslide susceptibility mapping at Golestan Province, Iran: a comparison between frequency ratio, Dempster-Shafer, and weights-of-evidence models. J Asian Earth Sci 61:221–236. https://doi.org/10.1016/j.jseaes.2012.10.005

Montalván-Burbano N, Velastegui-Montoya A, Gurumendi-Noriega M et al (2021) Worldwide research on land use and land cover in the Amazon Region. Sustainability 13:6039. https://doi.org/10.3390/su13116039

Moulds S, Buytaert W, Mijic A (2018) A spatio-temporal land use and land cover reconstruction for India from 1960–2010. Sci Data 5:180159. https://doi.org/10.1038/sdata.2018.159

Mugagga F, Kakembo V, Buyinza M (2012) Land use changes on the slopes of Mount Elgon and the implications for the occurrence of landslides. CATENA 90:39–46. https://doi.org/10.1016/j.catena.2011.11.004

Nugraha H, Wacano D, Dipayana GA et al (2015) Geomorphometric characteristics of landslides in the Tinalah Watershed, Menoreh Mountains, Yogyakarta, Indonesia. Procedia Environ Sci 28:578–586. https://doi.org/10.1016/j.proenv.2015.07.068

Parra E, Mohr CH, Korup O (2021) Predicting Patagonian landslides: roles of forest cover and wind speed. Geophys Res Lett 48:1–10. https://doi.org/10.1029/2021GL095224

Persichillo MG, Bordoni M, Meisina C (2017) The role of land use changes in the distribution of shallow landslides. Sci Total Environ 574:924–937. https://doi.org/10.1016/j.scitotenv.2016.09.125

Petley D (2012) Global patterns of loss of life from landslides. Geology 40:927–930. https://doi.org/10.1130/G33217.1

Phiri D, Morgenroth J (2017) Developments in landsat land cover classification methods: a review. Remote Sens 9:967. https://doi.org/10.3390/rs9090967

Pisano L, Zumpano V, Malek Ž et al (2017) Variations in the susceptibility to landslides, as a consequence of land cover changes: a look to the past, and another towards the future. Sci Total Environ 601–602:1147–1159. https://doi.org/10.1016/j.scitotenv.2017.05.231

Pourghasemi HR, Mohammady M, Pradhan B (2012a) Landslide susceptibility mapping using index of entropy and conditional probability models in GIS: Safarood Basin. Iran CATENA 97:71–84. https://doi.org/10.1016/j.catena.2012.05.005

Pourghasemi HR, Pradhan B, Gokceoglu C (2012b) Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed. Iran Nat Hazards 63:965–996. https://doi.org/10.1007/s11069-012-0217-2

Pourghasemi HR, Teimoori Yansari Z, Panagos P, Pradhan B (2018) Analysis and evaluation of landslide susceptibility: a review on articles published during 2005–2016 (periods of 2005–2012 and 2013–2016). Arab J Geosci 11. https://doi.org/10.1007/s12517-018-3531-5

Pradhan B, Lee S (2010) Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia. Landslides 7:13–30. https://doi.org/10.1007/s10346-009-0183-2

Promper C, Puissant A, Malet J-P, Glade T (2014) Analysis of land cover changes in the past and the future as contribution to landslide risk scenarios. Appl Geogr 53:11–19. https://doi.org/10.1016/j.apgeog.2014.05.020

Quevedo RP, Maciel DA, Uehara TDT et al (2021) Consideration of spatial heterogeneity in landslide susceptibility mapping using geographical random forest model. Geocarto Int 1–20. https://doi.org/10.1080/10106049.2021.1996637

Rabby YW, Li Y, Abedin J, Sabrina S (2022) Impact of land use/land cover change on landslide susceptibility in Rangamati Municipality of Rangamati District, Bangladesh. ISPRS Int J Geo-Information 11. https://doi.org/10.3390/ijgi11020089

Radbruch-Hall DH, Varnes DJ (1976) Landslides—cause and effect. Bull Int Assoc Eng Geol 13:205–216. https://doi.org/10.1007/BF02634797

Rawat JS, Joshi RC (2012) Remote-sensing and GIS-based landslide-susceptibility zonation using the landslide index method in Igo River Basin, Eastern Himalaya, India. Int J Remote Sens 33:3751–3767. https://doi.org/10.1080/01431161.2011.633121

Reichenbach P, Busca C, Mondini AC, Rossi M (2014) The influence of land use change on landslide susceptibility zonation: the Briga catchment test site (Messina, Italy). Environ Manage 54:1372–1384

Reichenbach P, Rossi M, Malamud BD et al (2018) A review of statistically-based landslide susceptibility models. Earth-Science Rev 180:60–91

Rogelis MC, Werner M (2014) Regional debris flow susceptibility analysis in mountainous peri-urban areas through morphometric and land cover indicators. Nat Hazards Earth Syst Sci 14:3043–3064. https://doi.org/10.5194/nhess-14-3043-2014

Roy J, Saha S, Arabameri A et al (2019) A novel ensemble approach for landslide susceptibility mapping (LSM) in Darjeeling and Kalimpong Districts, West Bengal. India Remote Sens 11:2866. https://doi.org/10.3390/rs11232866

Sassa K (2015) ISDR-ICL Sendai Partnerships 2015–2025 for global promotion of understanding and reducing landslide disaster risk. Landslides 12:631–640. https://doi.org/10.1007/s10346-015-0586-1

Sassa K (2012) ICL strategic plan 2012–2021—To create a safer geo-environment. Landslides 9:155–164. https://doi.org/10.1007/s10346-012-0334-8

Sassa K (2007) Landslide science as a new scientific discipline. Progress in landslide science. Springer, Berlin Heidelberg, Berlin, Heidelberg, pp 3–11

Shirani K, Pasandi M, Arabameri A (2018) Landslide susceptibility assessment by Dempster-Shafer and index of entropy models, Sarkhoun basin, Southwestern Iran. Nat Hazards 93:1379–1418. https://doi.org/10.1007/s11069-018-3356-2

Shirzadi A, Bui DT, Pham BT et al (2017) Shallow landslide susceptibility assessment using a novel hybrid intelligence approach. Environ Earth Sci 76:60. https://doi.org/10.1007/s12665-016-6374-y

Shu H, Hürlimann M, Molowny-Horas R et al (2019) Relation between land cover and landslide susceptibility in Val d'Aran, Pyrenees (Spain): historical aspects, present situation and forward prediction. Sci Total Environ 693:1–14. https://doi.org/10.1016/j.scitotenv.2019.07.363

Singh VK, Singh P, Karmakar M et al (2021) The journal coverage of Web of Science, Scopus and Dimensions: a comparative

analysis. Scientometrics 126:5113–5142. https://doi.org/10.1007/s11192-021-03948-5
Skilodimou HD, Bathrellos GD, Koskeridou E et al (2018) Physical and anthropogenic factors related to landslide activity in the northern Peloponnese, Greece. Land 7:1–18. https://doi.org/10.3390/land7030085
Sujatha ER, Rajamanickam GV, Kumaravel P (2012) Landslide susceptibility analysis using probabilistic certainty factor approach: a case study on Tevankarai stream watershed, India. J Earth Syst Sci 121:1337–1350. https://doi.org/10.1007/s12040-012-0230-6
Tien Bui D, Pradhan B, Lofman O, Revhaug I (2012) Landslide susceptibility assessment in Vietnam using support vector machines, decision tree, and Naïve Bayes models. Math Probl Eng 2012:1–26. https://doi.org/10.1155/2012/974638
Uehara TDT, Sehn Körting T, Soares A dos R, Quevedo RP (2022) Time-series metrics applied to land use and land cover mapping with focus on landslide detection. J Appl Remote Sens 16. https://doi.org/10.1117/1.JRS.16.034518
UNESCO Institute for Statistics (2021) How much does your country invest in R&D? In: Res. Exp. Dev. (full dataset). Accessed 20 Mar 2022. http://uis.unesco.org/apps/visualisations/research-and-development-spending/
Valdés Carrera AC, Mendoza ME, Allende TC, Macías JL (2021) A review of recent studies on landslide hazard in Latin America. Phys Geogr 00:1–44. https://doi.org/10.1080/02723646.2021.1978372
Van Beek LPH, Van Asch TW (2004) Regional assessment of the effects of land-use change on landslide hazard by means of physically based modelling. Nat Hazards 31:289–304. https://doi.org/10.1023/B:NHAZ.0000020267.39691.39
van Eck NJ, Waltman L (2010) Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics 84:523–538. https://doi.org/10.1007/s11192-009-0146-3
Varnes DJ (1984) Landslide hazard zonation: a review of principles and pratice
Vorpahl P, Elsenbeer H, Märker M, Schröder B (2012) How can statistical models help to determine driving factors of landslides? Ecol Modell 239:27–39. https://doi.org/10.1016/j.ecolmodel.2011.12.007
Vuillez C, Tonini M, Sudmeier-Rieux K et al (2018) Land use changes, landslides and roads in the Phewa Watershed, Western Nepal from 1979 to 2016. Appl Geogr 94:30–40. https://doi.org/10.1016/j.apgeog.2018.03.003
Wasowski J, Lamanna C, Casarano D (2010) Influence of land-use change and precipitation patterns on landslide activity in the Daunia Apennines, Italy. Q J Eng Geol Hydrogeol 43:387–401. https://doi.org/10.1144/1470-9236/08-101
Winter MG, Bromhead EN (2012) Landslide risk: some issues that determine societal acceptance. Nat Hazards 62:169–187. https://doi.org/10.1007/s11069-011-9987-1
Wu X, Chen X, Zhan FB, Hong S (2015) Global research trends in landslides during 1991–2014: a bibliometric analysis. Landslides 12:1215–1226. https://doi.org/10.1007/s10346-015-0624-z
Wulder MA, Coops NC (2014) Satellites: make Earth observations open access. Nature 513:30–31. https://doi.org/10.1038/513030a
Yan F, Zhang Q, Ye S, Ren B (2019) A novel hybrid approach for landslide susceptibility mapping integrating analytical hierarchy process and normalized frequency ratio methods with the cloud model. Geomorphology 327:170–187. https://doi.org/10.1016/j.geomorph.2018.10.024
Yesilnacar E, Süzen ML (2006) A land-cover classification for landslide susceptibility mapping by using feature components. Int J Remote Sens 27:253–275. https://doi.org/10.1080/01431160500300042
Zêzere JL, Vaz T, Pereira S et al (2015) Rainfall thresholds for landslide activity in Portugal: a state of the art. Environ Earth Sci 73:2917–2936. https://doi.org/10.1007/s12665-014-3672-0
Zhang X, Liu L, Chen X et al (2019) Fine land-cover mapping in China using Landsat Datacube and an operational SPECLib-based approach. Remote Sens 11:1056. https://doi.org/10.3390/rs11091056

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10346-022-02020-4.

Renata Pacheco Quevedo · Camilo Daleles Rennó
Earth Observation and Geoinformatics Division, National Institute for Space Research (INPE), São José Dos Campos 12227010, São Paulo, Brazil

Renata Pacheco Quevedo
Email: renata.quevedo@inpe.br

Camilo Daleles Rennó
Email: camilo.renno@inpe.br

Andrés Velastegui-Montoya (✉) · Néstor Montalván-Burbano · Fernando Morante-Carballo
Centro de Investigación y Proyectos Aplicados a las Ciencias de la Tierra (CIPAT), ESPOL Polytechnic University, P.O. Box 09-01-5863, Guayaquil, Ecuador
Email: dvelaste@espol.edu.ec

Andrés Velastegui-Montoya
Facultad de Ingeniería en Ciencias de la Tierra, ESPOL Polytechnic University, P.O. Box 09-01-5863, Guayaquil, Ecuador
Email: dvelaste@espol.edu.ec

Andrés Velastegui-Montoya
Geoscience Institute, Federal University of Pará, 66075-110 Belém, Brazil
Email: dvelaste@espol.edu.ec

Néstor Montalván-Burbano
Department of Business and Economics, University of Almería, 04120 Almería, Spain
Email: nmb218@inlumine.ual.es

Fernando Morante-Carballo
Facultad de Ciencias Naturales y Matemáticas (FCNM), ESPOL Polytechnic University, P.O. Box 09-01-5863, Guayaquil, Ecuador
Email: fmorante@espol.edu.ec

Fernando Morante-Carballo
Geo-Recursos y Aplicaciones GIGA, ESPOL Polytechnic University, P.O. Box 09-01-5863, Guayaquil, Ecuador
Email: fmorante@espol.edu.ec

Oliver Korup
Institute of Environmental Science and Geography, University of Potsdam, 14476 Potsdam, Germany
Email: oliver.korup@geo.uni-potsdam.de

Oliver Korup
Institute of Geosciences, University of Potsdam, 14476 Potsdam, Germany
Email: oliver.korup@geo.uni-potsdam.de