Landslides
DOI 10.1007/s10346-024-02215-x
Received: 6 April 2023
Accepted: 11 January 2024Crown 2024

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Mapping landslides from space: A review

Abstract Landslide hazards have significant social, economic, and environmental impact. This work provides a critical review of the main existing literature using satellite data for mapping landslides. We created and examined an extensive bibliographic database from Web of Science (WoS) consisting in 291 outputs from > 1,000 authors who studied almost 700,000 landslides across all continents, for a total of 52 countries represented with China and Italy on top of the list with more authors. The outputs are equivalent to ~ 5% of the whole landslide-related production for the period 1996–2022, with a 600% increase in the number of papers after 2014 driven by the availability of Sentinel-1 and Sentinel-2 data. Analysis of the geographical location across the 66 different countries analysed shows that, within the total number of contributions, the satellite imagery was used to detect and map two main types of landslides: flows and slides. When specified in the manuscripts, the events have been triggered by rainfall (104 cases), earthquakes (32 cases), or both (17 cases). Slope instabilities in these areas were predominantly identified through manual detection (40%); but since 2020, the advent of artificial intelligence is suppressing all other techniques. Despite the undisputed progress of EO-based landslide mapping over the last 26 years, which makes it a consolidated tool for many landslide-related applications, challenges still remain for an effective and operational use of EO images for landslide detection and mapping, and we provide a perspective for future applications considering the existing and the planned SAR satellite missions.

Keywords Earth Observation · Landslide · Landslide mapping · Web of Science

Introduction

Landslides represent a global hazard accounting for ~ 72,000 deaths and > $11.5B of damage worldwide between 1900 and 2022 according to the Emergency Events Database (EM-DAT 2023; Supplementary Material – S1), and these numbers are expected to increase as a result of anthropogenic climate change (Gariano and Guzzetti 2016). Our ability to mitigate and forecast landslides hazard is strongly limited by the lack of complete and accurate information on their temporal and spatial occurrence that, in turn, represent a key factor for geoscientists to understand their evolution and relationships with triggering factors (Wieczorek 1996). Despite their relevance for landslide hazard and risk assessment, landslide maps are unexpectedly rare with estimates that landslide maps cover less than 1% of slopes globally (Guzzetti et al. 2012). We argue that the situation has not improved significantly in the last 10 years, despite global community efforts to consistently use Earth Observation (EO) datasets to compile and organise geographical landslide information. Since the launch of the first EO satellite in 1975, Landsat-1, spaceborne techniques have become widely used and broadly recognised tools for landslide mapping and monitoring (Casagli et al. 2016).

In this article, we attempt a systematic, critical review of available literature on the use of (optical and radar) spaceborne imagery to detect and map landslide failures. Failures are defined by Hungr et al. (2014) as 'the single most significant movement episode in the [...] history of a landslide', and landslide failure events are one or many landslides in an area caused by a single trigger (Guzzetti et al. 2012). Systematic reviews of the literature on landslide detection and mapping techniques have been published over the last 20 years considering several input materials:

– Geomorphological mapping, topographic maps, and aerial photography (Parise 2001)
– Spaceborne, airborne, and terrestrial remote sensing technologies (Guzzetti et al. 2012)
– Synthetic Aperture Radar (SAR; Modini et al. 2021) and multi-temporal interferometric SAR (Schlögl et al. 2022)

Our work complements and updates these reviews with a unique focus on satellite data and how better observing methodologies and additional EO systems have improved our capabilities in landslide mapping. Compared to such recent reviews, our work provides the additional focus on how recent technologies are drastically changing the way EO is deployed in landslide mapping and based on the evolution of such discipline, the manuscript provides areas where future research can focus to tackle existing challenges. The article is organised as follows: a brief explanation of the terminology and traditional landslide mapping techniques (the 'Landslide mapping' section) followed by the main EO satellite missions that contributed to landslide mapping (the 'Earth observation datasets' section). Next, we give a description on the approach we used to scope the literature datasets (the 'Methodology for the data collection' section) and how we critically analysed the results (the 'Results' section). Ultimately, we discuss the theoretical, research, and operational frameworks for the future exploitation of satellite imagery for detecting and mapping landslides (the 'Discussions' section) and summarise the lessons learnt (the 'Conclusions' section) and what improvements are still needed for a better use of EO datasets according to end user and non-specialist needs.

Landslide mapping

A "landslide" is the movement of a mass of rock, debris, or Earth down a slope, under the influence of gravity (Cruden and Varnes 1996). Landslides can be sub-aerial and subaqueous, and different phenomena cause landslides, including intense or prolonged rainfall, earthquakes, rapid snow melting, volcanic activity, and multiple human actions. Landslides can involve flowing, sliding, toppling, or falling, and many landslides exhibit a combination of two or more types of movements, at the same time or during the lifetime of a landslide (Hungr 2014). In this work, the words 'landslide', 'mass movement', and 'slope failure' are used as synonyms. There are two main characteristics used to classify landslides (Fig. 1): type of movement according to Hungr et al. (2014) and velocity according to Cruden and Varnes (1996).

A landslide inventory map records the location of mass movements that have left discernible traces in an area along with, where known, the date of occurrence, the type of motion and velocity (Guzzetti et al. 2000), and, if complete, also the extent and volume. In this work, the words 'inventory', 'landslide map', 'landslide inventory', and 'landslide inventory map' are used as synonyms. There are different ways to compile a landslide inventory: collecting landslide distributions for a single triggering event; mapping landslides identified from satellite imagery or aerial photos, in situ mapping coupled or not with remote sensing observations; or cataloging reports from news media (Juang et al. 2019). Satellite imagery now represents a unique opportunity to regularly add and support landslide inventories at both local and large scales.

Conventionally, landslides have been mapped using geomorphological field mapping (Cardinali et al. 2002) and visual interpretation of stereoscopic aerial photographs (Turner and Schuster 1996). The need for rapid mapping of landslide events over large areas along with the regular availability of EO imagery has driven, over the last decade, the development of new methods specifically tailored for processing and interpreting satellite data.

Earth observation datasets

Since the US Landsat programme began in 1972, many nations have embarked on EO programmes and today, hundreds of operational satellites are available to geoscientists for mapping, measuring, and monitoring resources, land cover changes, and geohazards (Belward and Skoien 2015).

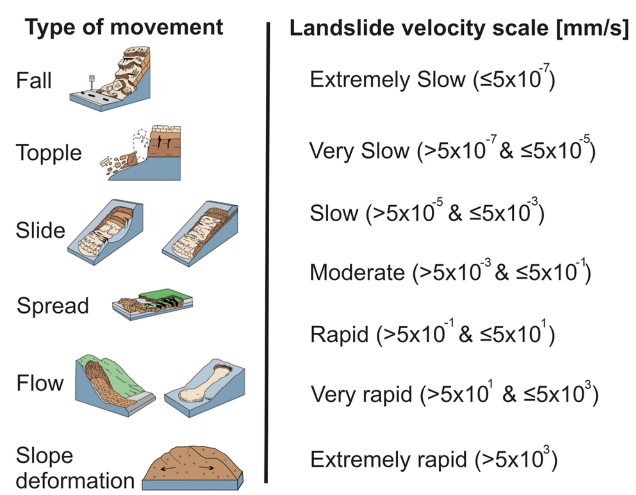

Fig. 1 Types of movement of a landslide regardless of the material involved (left) and landslide velocity scale (right). Complex landslides are movements that feature components of two or more of the basic types of landslides and can occur either simultaneously or at different times during the onset of slope failure. Modified from United States Geological Survey (USGS 2004) and Cruden and Varnes (1996)

According to the Observing System Capability Analysis and Review Tool (OSCAR, https://space.oscar.wmo.int/ accessed on 20/3/2023) of the World Meteorological Organization, 713 satellite launches of sun-synchronous orbiting satellites in low Earth orbit have occurred between 1972 and October 2022, from civilian and commercial providers (Supplementary Material – S2). Most of these belong to communication (like GNSS) or meteorological missions and only 337 EO missions (Fig. 2).

The increasing number of EO systems has allowed the monitoring of continental surfaces at local (from metric to decametric resolution sensors) to global (from decametric to kilometric resolution sensors) scales, with daily to multi-year observation frequency, and in different wavelengths (e.g. near-infrared and visible to microwave spectral domains). The improved availability and accessibility to satellite imagery have been driven by two major events: data from the NASA Landsat mission becoming available from 2008 through the United States Geological Survey (USGS) and the start of the Copernicus mission with the launch of the first Sentinel satellite in 2014 from the European Space Agency (ESA). These events have underpinned an exponential increase in geoscience research productivity (Tomás and Li 2017) and a growth in users downloading EO data (ESA 2021). The science, and market opportunity, around remote sensing is still rapidly growing given the innovations brought by the enhanced computing capabilities of cloud computing, more efficient processing techniques such as artificial intelligence (AI), and the improved affordability of satellites for the reduction in manufacturing costs, the possibility to build longer-lived payloads that are smaller in size and weight (also known as CubeSats), making it possible to ship multiple and independent payloads into orbit with the same spacecraft.

Methodology for the data collection

In this review work, we exploited the freely accessible search engine Web of Science (WoS) database (https://www.webofscience.com/, accessed on 4/4/2023) which provided access to multiple databases giving reference and citation data from academic journals, conference proceedings, and other documents from various academic disciplines (Clarivate 2019). This online tool has also been used recently for scientific reviews in Earth Sciences (Raspini et al. 2022) and is a database accepted as one of the most comprehensive bibliographic data sources (Zhu and Liu 2020). WoS was selected because it provides a simple but comprehensive picture of scholarly impact as it indexes only traditional peer-reviewed sources and discards sources such as theses or presentations (Martín-Martín et al. 2018). We collected original and peer-reviewed articles, book chapters, conference proceedings, and extended abstracts. The data collection is based on the following eight criteria as part of the advanced search:

1. Time interval: limited from July 1972, the launch of Landsat-1 which we considered as the start of the spaceborne EO era, until October 2022, the time of writing.
2. Title words (TI): this condition allowed us to select contributions from words included in the title. In this field, the following words were used: 'landslide mapping', 'satellite', 'Earth Observation', or 'Remote Sensing'. All these words could be inserted in the same string of conditions separated by 'OR'.

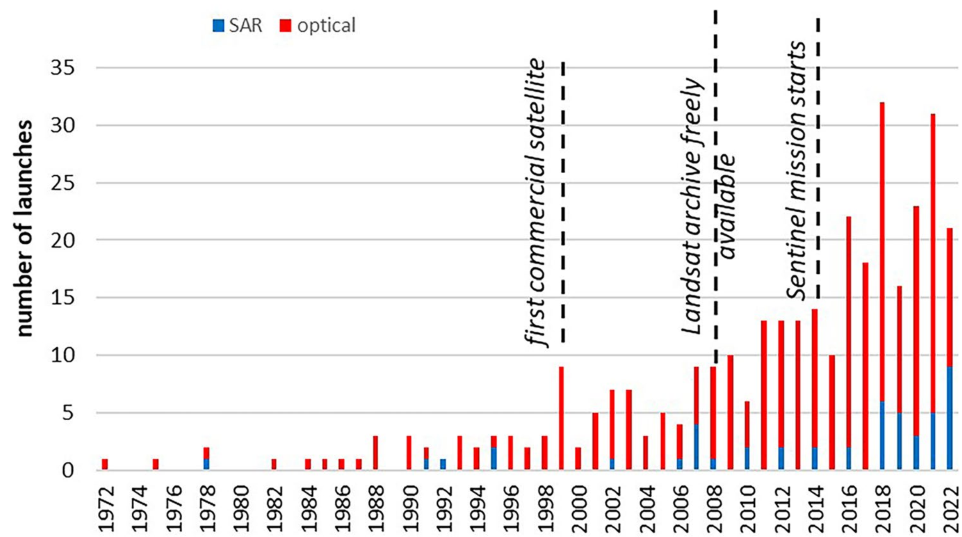

Fig. 2 The cumulative number of near-polar orbiting EO civilian and commercial satellite in low Earth orbit with the most important milestones in the EO space history

3. TI: we excluded submarine landslides, so we excluded the terms 'submarine' and 'subaqueous' from #2.
4. Author Keywords (AK): this condition allowed for selecting contributions from words included as keywords. In this field, we used the same terms adopted in #2.
5. AK: we excluded submarine landslides, so we excluded the terms 'submarine' and 'subaqueous' from #4.
6. Presence in the abstract of any of the following four combinations: 'landslide mapping' and 'satellite', 'landslide detection' and 'satellite', 'landslide mapping' and 'space', and 'landslide detection' and 'space'.
7. The language of the main text (not just the abstract or the title) must be in English.
8. We constrained the topic and science categories to the 'Remote Sensing' and 'Environmental Science' areas.

Three Boolean operators were used for combining these criteria, for extracting all the contributions respecting these requirements: AND (both), OR (at least one), and NOT (eliminates items that contain the specified term).

WoS initial results were exported as a.csv file (Supplementary Material – S3) where we:

- kept contributions even when the landslide inventory map was not the core of the work (e.g. inventory used to produce susceptibility or risk maps).
- removed contributions outside the topics of Earth Sciences, retracted or pre-print articles, papers where the full text was not available in English, and finally works that mapped landslides on other planets such as Mars (Crosta et al. 2018) and the Moon (Scaioni et al. 2018).
- labelled the contributions in different categories: articles including technical notes and early access (i); books, chapters, and proceedings (ii); reviews (iii); and letter and editorial material (iv). Some proceedings in (ii) were later collected as chapters of a book, this is why we group them together.
- in order to fully characterise the studies in our collection, each article was read and critically analysed, and the following information was extracted, when available: continent and country hosting the institute of the corresponding author and where the study area was located, satellite(s) used to perform the work, triggering factor and type of motion, validation through field surveys, or ground truthing. We could not always consider the individual country since works sometimes cross administrative borders and authors might have double affiliations.

Results

Following the filtering and criteria described in the 'Methodology for the data collection' section, we narrowed down a total of > 76 M scientific contributions available on WoS to just 518 works (Fig. 3) to which we added 40 contributions not intercepted by WoS, but still relevant to our literature review, for a total of 558 works analysed. The authors have also tried synonyms and other similar keywords for the WoS search (e.g. map instead of mapping), with the corresponding results not generating significant changes to the final number of outputs.

To assess the performance of our WoS search for relevant works, a confusion matrix has been calculated. The check of the collection returned an accuracy close to 1, sensitivity of 0.48, and specificity of 0.99. Indeed, upon expert reading, the total number of papers relevant for this work is down to 291, which is the number we have based any calculations on for the results. Essentially, WoS search is particularly effective in removing outputs not relevant to this work, although the number of false positives (papers not related to the scope of this analysis) is still high compared to true positives, namely, the number of outputs correctly identified as pertinent for this work. The database comprises a range of publication types including articles (~ 82%), followed by books, chapters, editorial material and proceedings (~ 13%), and reviews (~ 5%).

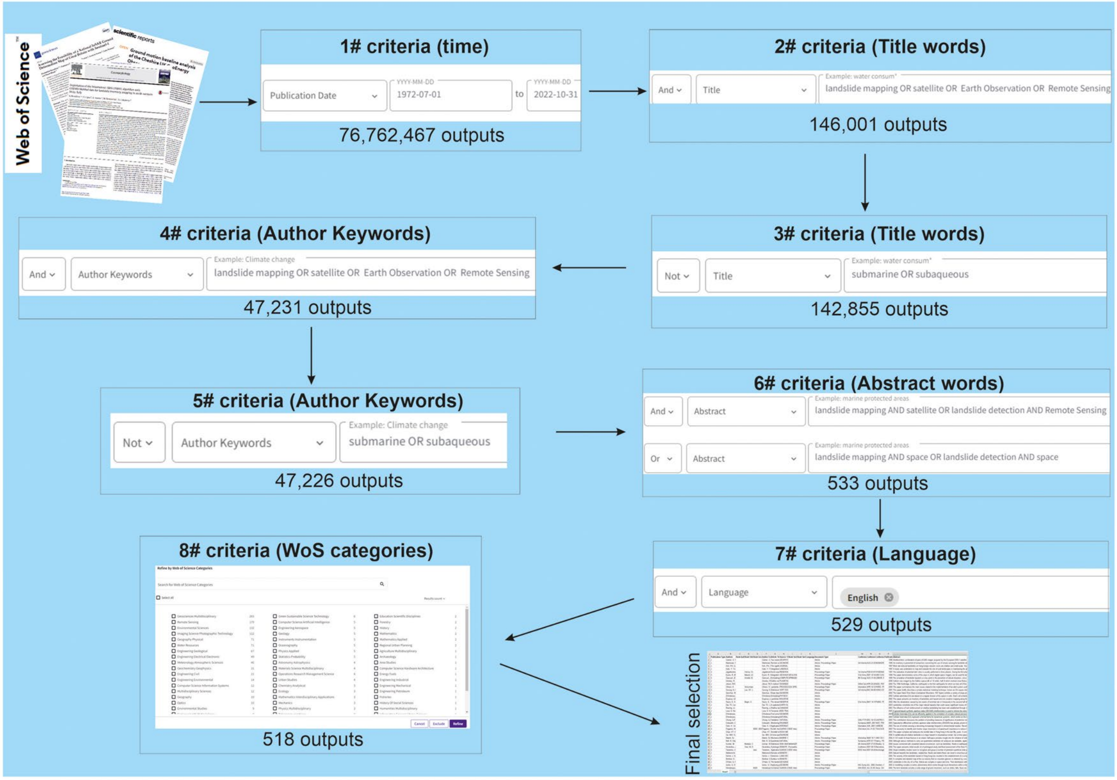

Fig. 3 Steps used to refine the bibliographic research through Web of Science with the relative number of outputs generated every time

In order to fully characterise the studies in our collection, we read and critically analysed each article, extracting the following information, when available: country hosting the institute of the corresponding author and country(ies) where the study area is located (the 'Temporal and spatial analysis' section), satellite(s) used to perform the work (the 'Satellite data' section), triggering factor and type of motion (the 'Landslides analysed' section), and technique(s) used (the 'Techniques used' section).

Temporal and spatial analysis

All the outputs combined account for almost 12,000 citations (up to October 2022) with the first relevant output from 1996 (Mantovani et al. 1996), although opportunities to map landslides with satellite were mentioned almost 20 years before this baseline date (Sauchyn and Trench 1978) (Fig. 4). The total number of outputs retrieved accounts for just ~ 3% of the landslide-related scientific production for the period 1996–2022 according to a conservative WoS search, with a share growing with time. Indeed, the increase in the satellite data discussed in the 'Earth observation datasets' section, is the main reason driving a growing trend in scientific productivity with an average of 4 papers (and ~ 370 citations) per year between 1996 and 2014 followed by a 700% increase in publication rates (and ~ 170% in citation rates) between 2014 and 2022 with 2014 being the year of launch of Sentinel-1, a milestone in the EO science (see the 'Earth observation datasets' section). Following the same policies of space agencies, in recent years, it has been more common to publish with open-access (via gold, bronze, or green routes) with 126 out of 138 freely available works published from 2014 onwards.

A comprehensive review on the full potential of EO for landslide mapping was missing until the start of the twenty-first century due to the poor spatial and temporal resolution of the data available before that time (Mantovani et al. 1996), and by that time, most of the inventories were still produced by interpretation of topographic maps and aerial photos (Parise 2001).

The geographical distribution of the corresponding author's institution considers cross-national institutions (e.g. ESA or the Central Asian Institute of Applied Geosciences) and any double affiliations (Fig. 5a). The analysis shows that, although all continents are represented, works are concentrated in few countries with Italy and China alone accounting for ~ 35% of the contributions.

Out of the 291 works, only 9 did not provide a specific area of interest, either because they were reviews or focussed on the technical aspect of the mapping. Similarly with the location of authors, the studied areas are inevitably affected by the location of the corresponding authors (Fig. 5b). However, along with Italy (52) and China (51), also small countries emerge: Taiwan (21) and Nepal (20). In both countries, frequent typhoons (e.g. Mondini et al. 2017) or large earthquakes like Gorkha 2015 (Kincey et al. 2021) with at least 23 dedicated works have provided opportunities to develop new techniques for landslide mapping given the high spatial density of slope failures occurred in a short time

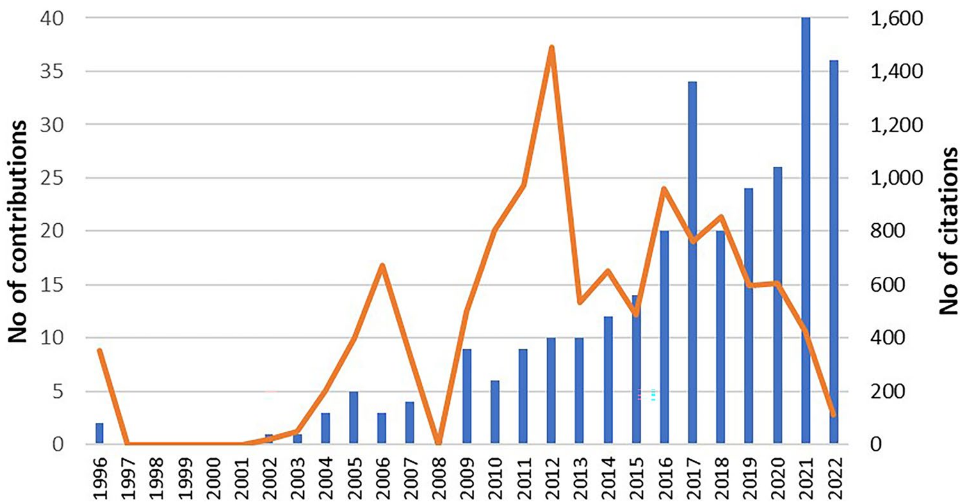

Fig. 4 Temporal distribution of the 291 contributions published from 1996 to October 2022

span. On the other hand, large countries such as Canada (5 works, e.g. Deijns et al. 2020) and Russia (3 works, e.g. Verdonen et al. 2020) have a limited number of contributions despite their large geographical scale. This might reflect the main language used for the outputs, as we only included works in English.

We performed a cross-country analysis, in order to understand the trends in both the outcoming and incoming influx of the contributions by country and continent (Fig. 6). In 98 cases, the corresponding author has worked in a country different from her/his own institution with authors from China and Italy working most of the time in their own country (> 74% of the cases); for India, the percentage is up to 100%. In 28 cases, the work involved the analysis of landslides over multiple countries, up to a maximum of 7 different nations (Meena et al. 2022).

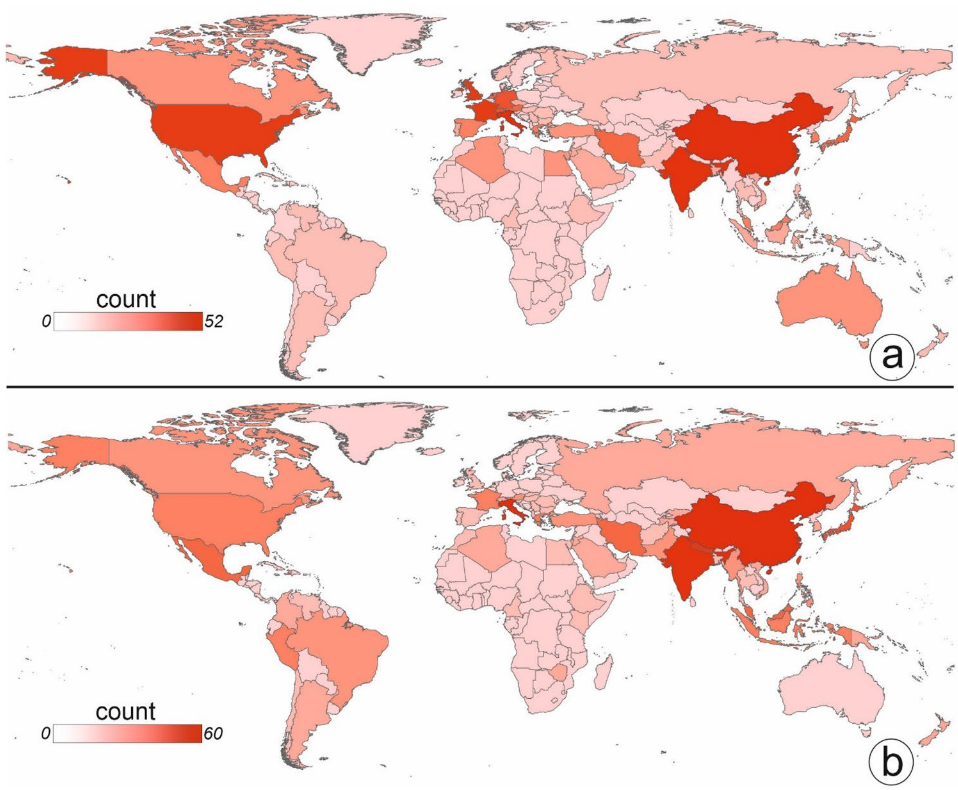

Fig. 5 Global map showing the geographical distribution of the corresponding author of EO studies for landslide mapping (**a**) and of the country where the study has been conducted (**b**)

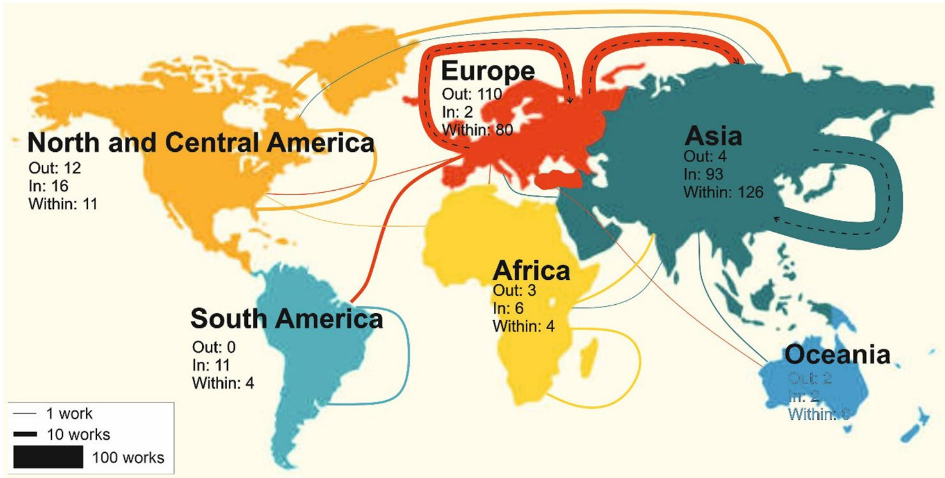

Fig. 6 Sankey map showing the volumes of works on mapping landslides with EO across the globe in terms of numbers of contributions on incoming, outcoming, and within the continent

Around 86% of the works involve at least a country between Europe and Asia, in terms of corresponding author or study area. Specifically, there is a large outflow of papers (110) from Europe across the whole world, with Asia being the primary study area. On the other side, most of the works (126) produced in Asia are focussed in the continent (Fig. 6).

Satellite data

In total, 40 different satellites have been used 484 times across the 291 works (Supplementary Material – S3). We could not retrieve information on the satellites used for ~ 4% of the works, mainly because they were reviews or not focussed on the landslide mapping itself (see criteria of the search in the 'Methodology for the data collection' section), so this information was deemed not necessary by the authors. In 53% of the cases, the satellite data are freely and publicly available, while in the other cases, data is commercial or, even if free, comes with restricted access. We have single satellites used in half of the contributions (53%) and ~ 43% of contributions deploying multiple satellite platforms, up to 6 different sources. In terms of wavelengths, the sensors most used are multispectrals (346 times, as some papers use more than 1 satellite) compared to radar (138 times). In terms of satellite platforms, the Sentinel and Landsat constellations prevail (67 and 48 times, respectively), followed by the group of satellites whose imagery is collectively displayed through Google Earth (40 times). Among the commercial datasets, SPOT is by far the most popular platform (39 times). Given the different range of satellite platforms used across the different years, we have summarised the results considering a binary classification for the satellite imagery (multispectral vs. radar) and the minimum and maximum resolution available for these two categories used in each given year (Fig. 7).

Our analysis reveals that the increase in the use of satellite data happened together with the increased availability of data in terms of both sensors and pixel resolution, especially starting from the 2010s (Fig. 6).

Landslide mapping is also facilitated by the increased frequency of revisiting time of the latest satellite missions. This factor is more influential than improved spatial resolution, which has remained almost unchanged since 2014. The increased frequency translates into a greater number of repeated images and therefore a higher probability of being able to detect changes to the Earth surface and the identification of landslides soon after their occurence.

Such a wealth of data, more easily available if not free, has inevitably made it easier for scholars to work and extend their analysis to remote or difficult to access locations. Indeed, before 2014, only 18 countries were represented among the corresponding authors; at the end of 2022, the number of countries was up to 52. Likewise, the number of countries where EO studies focussed on landslides was 20 until 2014, with the number rising up to 66 by the end of 2022.

In terms of agency, provider, or operator, the landscape is heterogeneous with 21 different organisations involved. Over the last 15 years, additional, and mainly private, organisations have been providing data in addition to the main national and international public institutions. Examples include the Disaster Monitoring Constellation (5 different missions), the European Space Agency, the Indian Space Research Organisation, and the National Aeronautics and Space Administration, each with 4 different constellations.

Landslides analysed

From the analysed contributions, a total of 693,319 landslides were mapped, redrawn, and validated or updated in terms of their state of activity. EO is used for mapping single landslides 17 times, but in 205 cases, multiple landslides have been analysed: most of the contributions work on tens to hundreds of slope instabilities. Milledge et al. (2022) alone use a database of > 237,000 landslides from EO for the validation of landslide locations extracted from their newly proposed approach. This highlights how impactful the use of satellite data for large scale and rapid mapping can be.

The number of landslides analysed inevitably does not facilitate the reporting of additional information such as type of movement and velocity. In 24 cases where velocity information

Fig. 7 Time series showing the different amount of satellite data available with the relative resolutions. For detailed information on the list of satellites classified as multispectral and radar, see Supplementary Material – S4

was clearly available, displacement rates fall within the extremely slow (< 16 mm/year) and the moderate velocity (< 13 mm/year) of the Cruden and Varnes (1996) classification.

In terms of type of motion (Fig. 8), most of the cases (182 times), the works deal with landslides with different types of motion that are not specified. Slides and flows are analysed in 30 times each, fall landslides 6 times, complex landslides 3 times, and deep-seated gravitational slope deformation (DSGSD) once (Manconi 2021).

In terms of landslide triggering factors, 104 cases analyse rainfall-induced (storms) landslides, 32 studies include earthquake-driven landslides, and 17 works include a combination of both, as the works analyse different events. In two cases, snow melting (Kyriou and Nikolakopoulos 2018) and volcanic activity (Di Traglia et al. 2018) are mentioned as triggering factors.

Some large earthquakes such as the Sichuan in 2008 and Gorkha in 2015 disasters have provided EO scientists with an opportunity to study thousands of landslides occurred at the same time and

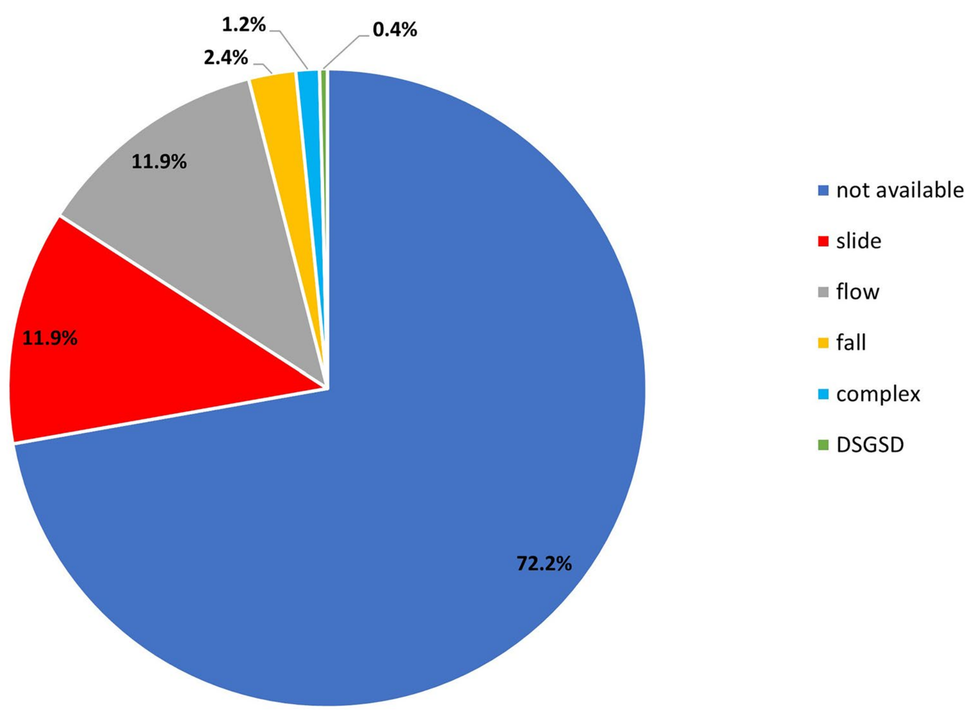

Fig. 8 Extraction methods. For more details, see S3

distributed over regional- to country-scale. These events have represented the chance to deploy and test innovative solutions for mapping multiple events at large scale (Burrows et al. 2019).

Techniques used

For most of the works (85%), we could clearly identify one (216 cases) or multiple (32 cases) satellite data analysis techniques used. We grouped the techniques in the following categories: change detection (i), indexing (ii), segmentation (iii), displacements-measurement (iv), and AI (v) (Fig. 9). A similar distinction has been recently applied for EO-based classifications for waterline mapping in McAllister et al. (2022).

In 40% of the cases, a change detection approach has been used, namely, basic principles of image interpretation where events are manually mapped based on the discretionary presence of landslide features resulting from a slope failure and reflected in the geomorphology: scarps, trenches, bulging toes, and double ridges. Usually a pre- and a post-event image is used (Psomiadis et al. 2020). These methods were dominant during the 2000s and 2010s but are time-consuming for landslide mapping over large spatial extents and require high-resolution imagery.

The indexing (or pixel-based) group of techniques, representing ~ 9% of the database, includes thresholding methods, manually or automatically selected (supervised or unsupervised, respectively) thresholding methods. Such thresholds are used for identifying pixels belonging to landslides and refer to the assumption that landslides are more likely to occur under conditions similar to those that have caused them in the past. Usually, the parameters used are well-known indices such as the Normalised Difference Vegetation Index (NDVI, Fiorucci et al. 2019), topographic parameters (Scheip and Wegmann 2021), or SAR back-scatter values (Burrows et al. 2020). These methods still require extensive human involvement with a large degree of subjectivity in order to decide the parameters and the relative thresholds; despite the application of filters, they still produce the salt-and-pepper effect due to single pixels being demarcated as landslides (Hölbling et al. 2017).

Segmentation is an alternative to pixel-based methods with basic analysis units used as image objects instead of individual pixels. This method, representing ~ 6% of the database, intends to bypass the problem of artificial square cells as used in per-pixel indexing methods by grouping a number of pixels into shapes with a meaningful representation of the objects based on homogeneous spectral, textural, morphological, and topographical characteristics (Amatya et al. 2021). The segmentation ruleset is created based on site-specific characteristics and manual thresholding of landslide diagnostic features (e.g. slope and relief), so the selected features might not work well beyond the study area.

Displacement-measurements include Interferometric Synthetic Aperture Radar (InSAR) and pixel offset and represent ~ 17% of the database. Collectively, these techniques are capable of providing wide-area coverage (thousands of square kilometre) and precise (millimetre–centimetre resolution), spatially dense information (from hundreds to thousands of measurement points/square kilometre) of ground surface deformations (Wasowski and Bovenga 2014). Such information is particularly useful because tiny displacements (in the order of millimetre or centimetre) are not detectable even with high-resolution imagery. However, InSAR processing can be time-consuming and is not always applicable due to the maximum detectable displacements and topographic constraints (van Natijne et al. 2022).

AI (~ 16% of the database) is mainly driven by the quantity of satellite data available over recent years; AI methods map landslides by training data-driven models on a variety of parameters that are combined to form an input or training dataset. These parameters can include both the effect and the cause of a landslide: scarps,

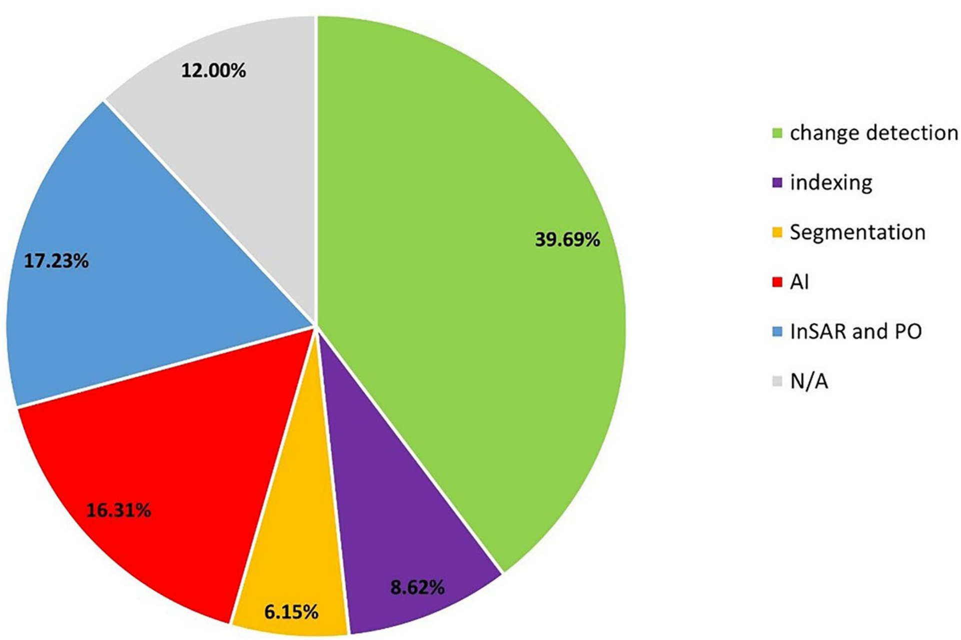

Fig. 9 Extraction methods. For more details, see S3

lack of vegetation, geology, slope, and weather conditions, as well as satellite imagery. The training process eliminates the requirement for a well-defined physical or numerical model and relies on ad hoc learning of the relationships between the existing landslide inventory and the derived features. This is the most promising approach, with better accuracy compared to other approaches (Prakash et al. 2020), and the predominant technique used for landslide mapping since 2020. Although data-driven algorithms such as principal component analysis (Đurić et al. 2017) and maximum likelihood (Modini et al. 2017) have been recently used to map landslides, in recent years, there is a growing consensus towards the use of U-Net Convolutional Neural Networks (CNN) (e.g. Amankwah et al. 2022). Compared with other AI methods, like neural networks, U-Net is a deep learning model that can exploit small (on the order of hundreds of individual events) or large datasets and extract the most effective features for mapping landslides automatically by segmenting the image and then assigning each individual pixel to a class (i.e., landslide/no landslide). However, a large training dataset and computational power are required for most of the AI methods.

Apart from the change detection approaches, all the other methods do not require pre- and post-event imagery but can work only with the post-event data.

Discussions

Over the last three decades, EO has proven to be a highly valuable, if not the only tool available (e.g. in remote areas) for landslide identification and mapping under different scenarios, scales, and in different geological settings, being deployable across all stages of the disaster management cycle.

The discussion will cover both the literature search we performed and the successive analysis. Our analysis shows that the WoS is a good starting point for refining the initial online research of relevant works but cannot be considered sufficient for a full and complete literature analysis, mainly because of the number of false positives and the number of outputs deemed not relevant for this work. At the same time, we are aware that an extensive manual search and quality check would still be needed with other search engines. Despite this, we are confident that we reported the main works, based on the citations rates, in the field of EO for landslide mapping. In the future, complementary engines might be used to extend the analysis to other digital library database such as Google, Constellate (https://constellate.org/), or Google Ngram Viewer (https://books.google.com/ngrams/) or beyond the scientific community with Google Trends (https://trends.google.com/trends/). This will allow us to have a complete database that automatically intercepts other outputs, equally valuable in such a rapidly evolving environment, such as presentations, promotional pages, table of contents, and course readings. In that case, the main concern is avoiding duplication of reporting (papers occurring both on a journal and ResearchGate, for example) and multiple citations. Regardless of the tool used for the search, older and hardcopy papers might be still completely missing since they have never been uploaded on any digital archive or repositories online. Finally, some of these works might not be focussed on the EO mapping of landslides, so their inclusion/exclusion remains discretionary.

Spatial distribution of the works and study areas (the 'Temporal and spatial analysis' section) reflects countries (e.g. China, India, and Italy) where landslides represent a major natural hazard (Herrera et al. 2018) resulting from earthquakes or severe weather events, so the attention of the academic and research community is greater. Other factors to be considered, even if they are out of the scope of this work, are socio-economic and political drivers. Examples might be that we have less focus on areas where there is less impetus in terms of people making insurance claims that research is funded or more fundable in some countries compared to others or that (internet) accessibility to the data is simply poor. While satellite data are not directly influenced by this, what is reported on the Internet also depends on and controls general levels of education. There is definitely a future opportunity to increase the number of landslide mapping works in large countries such as Brazil, Canada, and Russia where, even if slope movements might not represent the major geohazards, available techniques give the opportunity to quickly analyse large regions at a limited cost.

Regarding the temporal analysis of the list of works extracted (the 'Satellite data' section), we can clearly see that there is an increase in the use of satellite data from 2010s due to more frequent acquisitions. This has driven a constant proliferation of novel methodologies for automatically processing and interpreting satellite data in the context of landslide mapping. A trend that it is now directed towards continental or global scales, fuelled by upcoming missions (NISAR and Sentinel-2c and -2d), will further increase the availability of data.

Flows and slides remain the easiest types of landslide to detect (the 'Landslides analysed' section). This is due mainly to the size and characteristic shape of the landscape area affected. Falls and topples are more challenging to identify unless high-resolution satellite data is available. This is due to their small footprint on the environment and tendency to occur on steep slopes which might be in the shadow of the satellite line of sight. Conversely, DSGSD despite being large events are usually very slow and do not leave visible markers in the environment as vegetation can quickly cover the unstable area.

With reference to techniques, our literature analysis (the 'Techniques used' section) reveals that until the 2020s, the combinations of satellite data and investigation methods used are of the same order of magnitude as published articles. This implies that there is no predominance of one specific mapping method, as already noted in Mondini et al. (2021). Such fragmentation of techniques, whose programming code is not usually available, indicates the narrow interest of scientists to experiment and test their own mapping techniques without any strategic interest or effort towards a common pathway for improving EO landslide mapping. However, the last few years have seen the extensive use of AI, specifically CNN, where code is publicly released in online repositories; recent initiatives such as Landslide4Sense (https://www.iarai.ac.at/landslide4sense/, accessed on 1/4/2023) signal a change in working practice towards common efforts in sharing best practices. In order to contribute to this, we recommend and encourage repeating detection and mapping experiments comparing different quantitative methods in different geomorphological settings.

AI has proven so far to provide the best results in terms of mapping accuracy (Prakash et al. 2020). A substantial number of limitations, not related to the technique itself, exist for AI models to be extended at a global scale with different geological, geomorphological, and climatic settings. These limitations include (i) availability of large freely available computing capabilities that support CNN architectures and (ii) data latency between an event and the first satellite image becoming available, limiting the usefulness of landslide maps during emergency responses. The timing of suitable datasets for an initial evaluation of landslide disaster impacts will depend on the timing of an event relative to acquisition schedules of the satellite platforms and their uploading time on the data hubs. The delay can be in the order of days or weeks in the worst-case scenario according to atmospheric conditions (e.g. cloud cover during or following a rainfall-triggered mass-wasting event or smoke from long-burning wildfires) and seasonal considerations. In this regard, integration of SAR imagery with, for example, optical data is a favourable approach. (iii) The absence of DTM data following a landslide is a limiting and almost inevitable factor at the moment. Most of the works that include geomorphometric parameters for mapping landslides are actually based on elevation models that precede the event, such as the SRTM produced in 2000 that are used for filtering out portions of a region like flat areas (Handwerger et al. 2022), or as training factors (Yang et al. 2022). The possibility of including DTMs at global scale, updated at regular intervals, and with resolutions able to capture small events (in the orders of thousands of square metre) would represent the breakthrough step for adding geomorphometric parameters to spectral information, but such type of data does not currently exist. This last step will in turn provide enough information to retrieve, not just the location, but also the (iv) size and speed of the landslide, difficult parameters to constrain, especially in the absence of geomorphometric information.

Conclusions

In this work, three decades of literature data on EO applied to landslide mapping has been analysed. The growing accessibility to satellite data along with processing software and platforms is driving a surge in new techniques with more accurate results. These results have allowed researchers to collect and compare data from different constellations and techniques on different landslide types and sizes and in various geomorphological settings, while supporting the use of open-available platforms such as the NASA Global Landslide Catalog (accessed on 1/4/2023). We envisage that additional improvements can be reached in the short term involving topics beyond the field of EO and landslide research, such as Citizen Science. Data mining from news and social media is indeed a promising support to constrain time and spatial location where satellite data can be analysed (Pennington et al. 2022). Having rapid information on landslide events is a key factor, especially during disaster response activities when emergency responders need information on safe/unsafe areas and where support needs to focus. This brings us to the second and final point. Research is still required if these tools are to be effective in an operational environment, for example, through the establishment of common guidelines on the mapping of landslides with satellite data (e.g. during the training of the AI models which are now becoming predominant). With this regard, one limiting factor is the lack of expertise needed by scientists to communicate the results to a wider and non-technical audience and the capability to meet end user requirements (e.g. for civil protection agencies, land managers, and emergency responders). However, the last few years of work provide promising trends towards the consistent use of AI, and we do believe that the next 5 to 10 years will see the development of more landslide inventories with CNN-based techniques. The development of more complete and regularly up-to-date inventories will (i) allow a deeper understanding of landslide location, type, volume, and run-out distances needed to advance our understanding of the physical process itself and (ii) improve our knowledge on the spatio-temporal relationships between landslides and other natural hazards (e.g. floods and earthquakes) and key information for establishing possible triggering and cascading effects during multi-hazard events. Finally, by integrating these multi-hazard outputs, (iii) policy makers and disaster risk reduction specialists will have more accurate and complete information during the decision-making process.

Acknowledgements

The authors would like to thank Dr. Ekbal Hussain from the British Geological Survey (UK), Dr. Pierluigi Confuorto from the University of Florence (Italy), and Dr. David Huntley of the Geological Survey of Canada who provided comments to improve the quality of this work.

Funding

Natural Environment Research Council, NE/X006255/1.

Data availability

The data that support the findings of this investigation are available as supplementary data.

Declarations

Consent for publication The paper is published by with the permission of the Director of the British Geological Survey.

Conflict of interest The authors declare no competing interests.

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Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10346-024-02215-x.

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