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Review article: Rainfall-Induced Landslide Early Warning System: Advances, Gaps, and Perspectives

Roquia Salam [1], Bayes Ahmed [1], Peter Sammonds [1]

[1] Department of Risk and Disaster Reduction (RDR), University College London (UCL), Gower Street, London, WC1E 6BT, UK

Correspondence to: Roquia Salam (roquia.salam.22@ucl.ac.uk; roquiasalam@gmail.com)

Abstract

This review is necessary at this time to provide a comprehensive evaluation of the rainfall-induced landslide early warning system (LEWS) through the lens of the United Nations 'Early Warnings for All' (EW4All) framework. This study integrates EW4All pillars, incorporates overlooked literature, examines information sharing in academic publications, and evaluates the global feasibility of implementing EW4All for LEWS. Of 61 rainfall-induced LEWS identified in the literature covering 23 countries, 14 are considered operational, meaning they are currently implemented and actively used for warning purposes, across only 10 countries. Among local, regional, and national systems, local LEWS is often less scalable and more resource-intensive. Most operational systems target debris flows and shallow landslides and rely mainly on rainfall thresholds. While some include susceptibility maps, risk maps are largely absent. Real-time sensor data are used in some systems; however, high maintenance costs limit scalability. Reliability is further constrained by data scarcity, limited forecast verification, suboptimal use of AI, and the lack of standardised forecasting approaches. Community engagement and multi-hazard integration remain limited. Although EW4All is transformative, implementing effective LEWS in rainfall-induced landslide-prone areas worldwide by 2027 remains impractical without localised approaches, sufficient funds, and resources.

Keywords: Rainfall-induced landslides early warning system, early warning for all, rainfall threshold, risk map, community reflection

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1 Introduction

1.1 The early warning for all (EW4All) framework

Several initiatives have been undertaken since 1989 to develop an effective early warning system (EWS), aiming to minimise human suffering and disruption (Fig. 1). The global initial effort for disaster risk reduction (DRR) began in 1989, when the UN declared the 'International Decade for Natural Disaster Reduction' (IDNDR) (1989–1999) to enhance DRR activities.

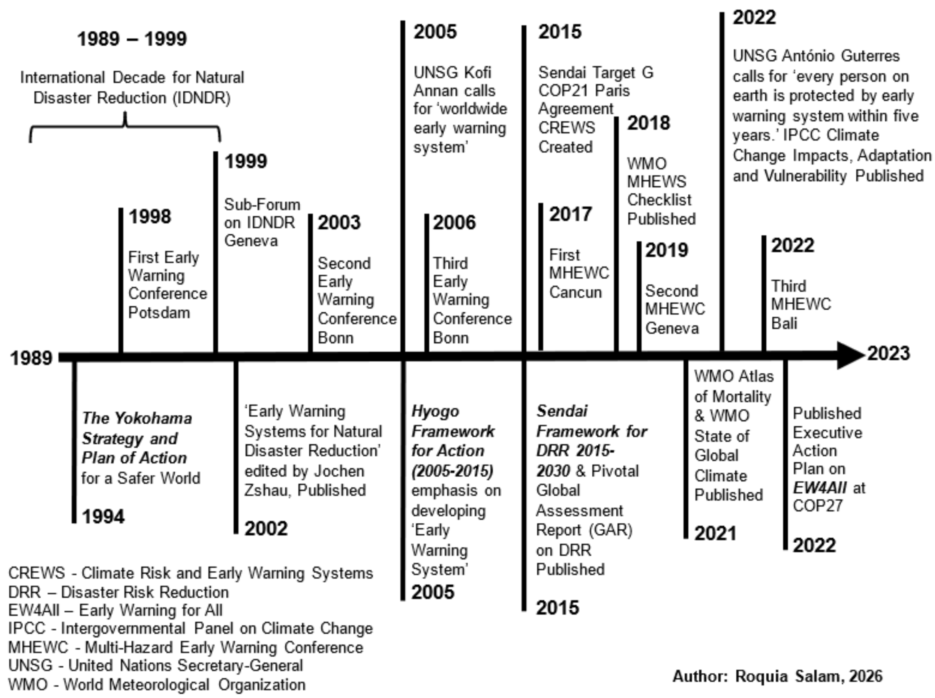

Figure 1: A brief history of event, publication, and announcement milestones in the development of early warning systems from 1989 to the present day [Figure modified after UN (2023)].

Within the IDNDR, the first landmark guidance and international framework for DRR, the 'Yokohama Strategy and Plan of Action for a Safer World' was launched in 1994. Under the principles of this framework, early warning (EW) was identified as a key factor in effective disaster prevention and preparedness activities (UNISDR, 1994). However, EW was a nascent concept in this framework that lacked a detailed and clear mechanism of EWS (UNISDR, 2005). The tragic catastrophe of the Indian Ocean Tsunami in December 2004, which killed more than 230,000 people around the Indian Ocean (Lay, 2012), made the international DRR community realise that an EWS could save thousands of lives (UNISDR, 2006). Therefore, soon after this tsunami, the first

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global blueprint for DRR, the ‘Hyogo Framework for Action (HFA) 2005–2015’, was adopted in January 2005 by the global DRR community.

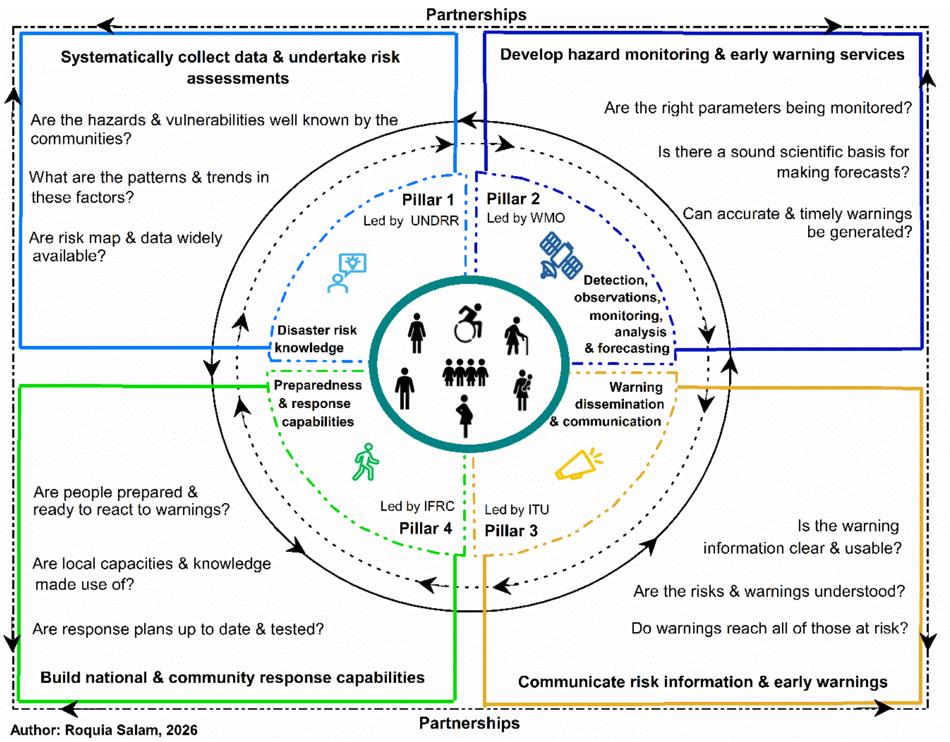

Figure 2: UN defined four pillars of the people-centred multi-hazards EW4All frameworks [Figure slightly modified after UN (2023)].

Among the 5 priorities for action, priority number 2 was ‘identify, assess and monitor disaster risks and enhance early warning’, where developing an EWS was emphasised (UNISDR, 2005). However, several limitations were identified (UNISDR, 2015), such as the HFA emphasising developing sector-specific (single-hazard) rather than integrated (multi-hazard) EWS. Besides, the engagement of all sectors (e.g., public, private, civil, academia, and scientific) was not ensured. Moreover, the HFA lacked a people-centred EWS. Furthermore, the HFA treated the EWS as a siloed system (not exclusively incorporated into disaster risk management plans and policy) that limits its effectiveness in tackling the causal (e.g., climate change, unplanned urbanisation) and compounding (e.g., demographic change, poor institutional capacity) factors of disaster risks. Additionally, the small island developing countries (SIDs), least developed countries (LDCs), and landlocked developing countries (LLDCs) were facing multifaceted issues in arranging financial, technical, and institutional resources. These limitations of HFA led to the adoption of a more comprehensive framework for DRR ‘Sendai Framework for Disaster Risk Reduction

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(2015–2030)', in 2015 (UNISDR, 2015). While people-centred multi-hazard EWS (MHEWS) is focused on the Sendai Framework under Target G, the implementation of MHEWS was slow and uneven under this policy framework. In 2022, it was reported that less than half of the countries in the world lacked proper EWS (UNDRR and WMO, 2022). Therefore, a more targeted initiative to accelerate the operationalisation of the MHEWS under the priorities of Target G has been launched in 2022, which is called early warning for all (EW4All) (UN, 2023).

EW4All is a groundbreaking initiative, and its main objective is to ensure that by the end of 2027, every human being on this planet is safeguarded from any form of hazardous weather, water, or climate events through timely alerts from EWS.

The EW4All initiative has three main targets, which are (UN, 2023):

i. global coverage,
ii. multi-hazard impact-based EWS, and
iii. people-centred EWS.

Although EWS exist in some parts of the world, global coverage of these systems is not yet ensured (UN, 2023). Some parts of the world are fully deprived of EWS, such as in LDCs and SIDs, and it is the worst in Africa (Guterres, 2022). Fig. 2 portrays the UN-defined framework of the people-centred multi-hazards early warning systems (MHEWS) for all (EW4All) with four pillars. Several organisations contributed to leading each pillar. EW4All has four pillars, which are as follows (UN, 2023):

Pillar 1: Disaster risk knowledge: Systematically collect data and undertake risk assessments.

Pillar 2: Detection, observation, monitoring, analysis, and forecasting: Develop hazard monitoring and early warning services.

Pillar 3: Warning dissemination and communication: Communicate risk information and early warnings.

Pillar 4: Preparedness and response capabilities: Build national and community response capabilities.

1.2 The necessity of the early warning system

Since the United Nations (UN) initiated systematic efforts for DRR activities in 1989, significant progress has been made (UN, 2023). People are now more aware of when and how to deal with harsh environments than they were before. However, there is barely a single week when no devastating hazards or disasters responsible for catastrophic impacts are broadcast or reported. Due to the increase of human-induced greenhouse gases in the atmosphere that imbalances the meteorological cycle, the intensity and frequency of extreme climatic events (e.g., floods, landslides, droughts, cyclones, heatwaves, and so on) have increased over the period, and are expected to grow further (Lee et al., 2023). As the frequency of climatic extremes increases over time (Fig. 3), so does the number of affected people. Countless impacts, including

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death, injury, property damage, and loss of livelihood, are recorded every day. Besides, the environment is severely impacted, which makes the situation favourable for escalating the risks arising from further hazards. These extreme events are correlated with one or multiple hazards, giving them a multi-hazard risk status. It means that two or more hazardous events occur in an area simultaneously (e.g., flash floods and landslides), or cumulatively (e.g., recurrent flash floodings), or sequentially (e.g., tropical storms and landslides), responsible for a higher degree of disproportionate disastrous impacts on people and their property on the earth (Lee et al., 2024).

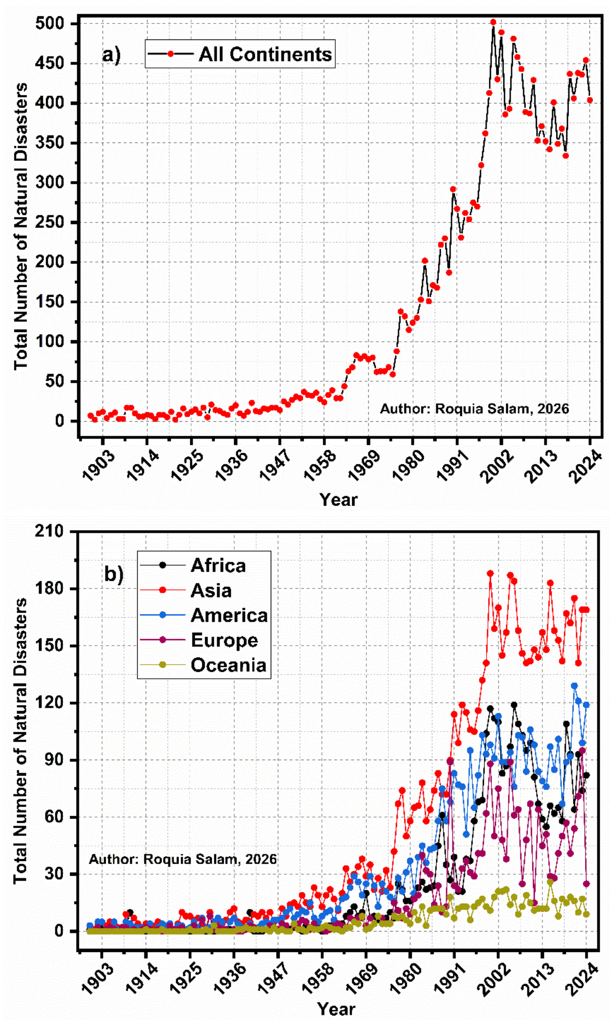

Figure 3: Temporal trend of the total number of natural disasters between 1900 and 2024, a) cumulative trend including all continents, and b) continent-specific trend (Data source: EM-DAT).

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It is very challenging to reduce or avoid hazards completely; however, a recognised way to reduce potential impacts is to ensure people have access to EWS and therefore have the opportunity to take some beneficial anticipatory action ahead of the hazards' occurrence. More specifically, an EWS is “an integrated system of hazard monitoring, forecasting, and prediction, disaster risk assessment, communication, and preparedness activities systems and processes that enables individuals, communities, governments, businesses, and others to take timely action to reduce disaster risks in advance of hazardous events” (UNDRR, 2017). Some affected people have access to timely EWS, allowing them to prepare for upcoming events.

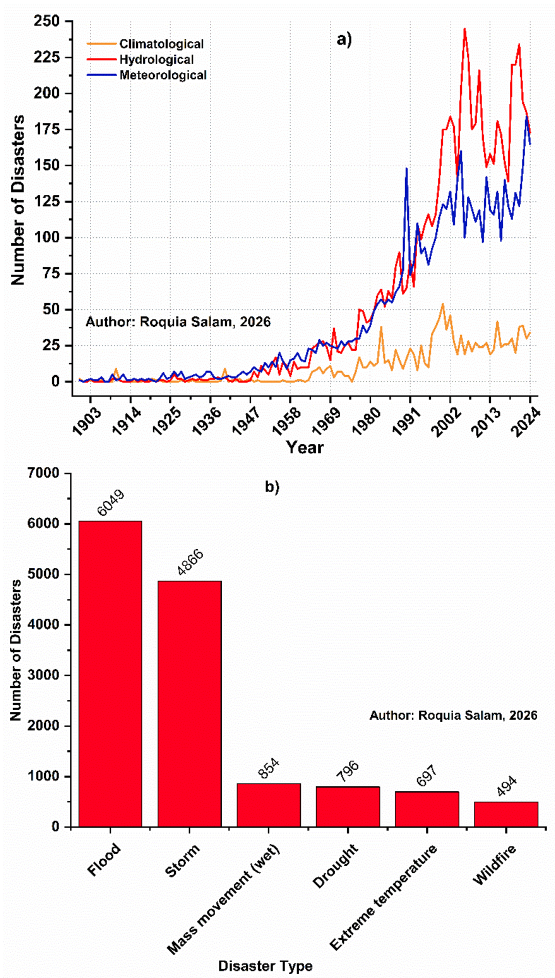

Figure 4: a) Temporal trend of the total number of climatological, hydrological, and meteorological disasters and b) specific disasters by type between 1900 and 2024 (Data source: EM-DAT).

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Besides, rapid urbanisation has forced people in low- and middle-income nations to reside in vulnerable and hazardous land areas, like industrial areas, unstable slopes, and floodplains (Ozturk et al., 2022). These people are often economically marginalised, struggling to afford homes in stable areas due to higher land prices. As displacement is increasing, more and more people are migrating to urban areas, ending up in these vulnerable and hazardous land areas. These lead to a rapid increase in informal settlements with low-quality housing materials, unstable political governance (Werthmann et al., 2024), and inadequate numbers of roads, drainage facilities, and other essential infrastructure. Therefore, in times of an emergency, people who are living in such areas are often unable to evacuate safely, leading to a disaster. EWS is badly needed for these people to minimise their overall loss and damage.

However, one-third of the world's population, especially from the LDCs as well as SIDS, do not have access to timely or proper EWS to enable themselves to prepare for the upcoming hazardous events leading to an accelerated loss, which is unacceptable (UN, 2023). Hence, there is a need to have an EWS that must be disseminated to alert all local people on time, enabling them to act properly to reduce the impacts.

1.3 Why are rainfall-induced landslides a concern?

A significant upward trend is observed in the occurrence of hydrological disasters (Fig. 4a), and hydrological disasters account for about 90% globally (Perera et al., 2019). Among these, rainfall-induced landslides (mass movement - wet) are identified as the third most common hydrological disaster globally (Fig. 4b). Recent studies showed that human activities like construction, illegal hill cutting, and mining activities mainly for urbanisation are increasingly driving fatal landslides nowadays (Alcántara-Ayala, 2025; Ozturk et al., 2022; Froude and Petley, 2018; Petley, 2009). Between 1998 and 2017, an estimated 4.8 million people were affected by landslides, resulting in more than 18,000 human deaths (WHO, 2025). Therefore, the combined effects of the greenhouse effect and rapid urban sprawl are expected to increase landslide risks globally, leaving a huge number of people residing in informal settlements at higher risk (Werthmann et al., 2024; Ozturk et al., 2022). Despite their prevalence and significant social, economic, and environmental impacts, rainfall-induced landslides frequently receive less attention than more visibly catastrophic events such as floods, tsunamis, volcanoes, and earthquakes (Guzzetti, 2021).

According to Varnes (1978), 'landslide is the downslope movement of soil, rock, and organic materials under the effects of gravity, which occurs when the gravitational driving forces exceed the frictional resistance of the material resisting on the slope'. Depending on the type of materials involved in the movement, landslides are classified into six major categories as follows: flow, fall, topple, spread, slide, and complex (Varnes, 1978). Among them, most of the landslides (88%) are rainfall-triggered (Haque et al., 2019; Froude and Petley, 2018). The Intergovernmental Panel on Climate Change (IPCC) has reported that increased greenhouse gases in the atmosphere are disturbing the global water cycle and, subsequently, intensifying the

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unevenly distributed extreme rainfall events (Seneviratne et al., 2021). Extreme rainfall events cause slopes to become oversaturated. Therefore, pore water pressure increases, leading to slope instability, and finally, slope failure occurs. Landslides usually occur close to the weak points, such as joints, cracks, drainage channels, and fault lines, of the slopes. First failures usually occur at these weak points, often triggered by factors such as rainfall, unplanned urbanisation, and others, which are responsible for slope destabilisation. Thus, the occurrence of the second failure accelerates and renders the area more susceptible to further landslides. Therefore, a feedback loop is created that triggers additional and larger landslides in that area.

Landslide risk is associated with the interaction between exposure, hazard, and vulnerability. When an external hazard factor, like rainfall, is coupled with high exposure in vulnerable areas, it results in varying degrees of landslides. Therefore, the current growing urban sprawl in vulnerable areas amplifies the risks of landslides in the absence of an adequate EWS. Landslides are often a compound hazard to floods and storms; they have specific challenges, particularly around uncertainties, forecasting, communication, and governance, which are made additionally challenging given that 'landslides' is an umbrella term encompassing multiple landslide types, each posing its own challenges in the EW4All context. Although EWS is proven effective in mitigating disasters, the application of the rainfall-induced landslide early warning system (LEWS) remains geographically limited and fragmented (Guzzetti et al, 2020). Besides, rainfall-induced LEWS are not always successful due to several reasons, like the absence of risk-based mapping and community reflection, lack of impact-based forecasting, and absence of anticipatory action plans. Only an effective LWES can mitigate the overall potential loss and damage arising from rainfall-induced landslides.

1.4 Novelty and originality

This study advances research on rainfall-induced LEWS by explicitly reframing the field through the United Nations EW4All framework. Although previous reviews have compared LEWS across local, regional, and national scales, they have generally focused on specific technical dimensions, such as thresholds, scale, or modelling approaches (Piciullo et al., 2018; Guzzetti et al., 2020). The distinct contribution of this review lies in its integrative and evaluative perspective, which considers LEWS through EW4All pillars and assesses their implications for implementation. In addition, this review incorporates relevant literature not considered in earlier syntheses, broadening the evidence base used to evaluate current practice. It also examines the extent to which LEWS-related information is shared in academic publications. Finally, it evaluates the feasibility of applying the EW4All framework, in its current form, to LEWS development worldwide.

Accordingly, the core objectives of this study are two-fold: first, to identify the main challenges and areas requiring improvement for rainfall-induced LEWS development through the EW4All lens; and second, to assess the feasibility of applying the EW4All framework to rainfall-induced LEWS development globally.

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2 Selection process of the articles for the systematic literature review

This literature review is mainly systematically conducted, as some criteria must be maintained. As the PRISMA 2020 methodology provides a standardised framework for identifying, screening, and selecting relevant studies, it has been adopted in this study for selecting the relevant articles (Fig. 5). Articles have been collected from six databases: SCOPUS, Web of Science (WoS), ScienceDirect, PubMed, the Institute of Electrical and Electronics Engineers (IEEE), and grey literature sources (e.g., ResearchGate, national websites).

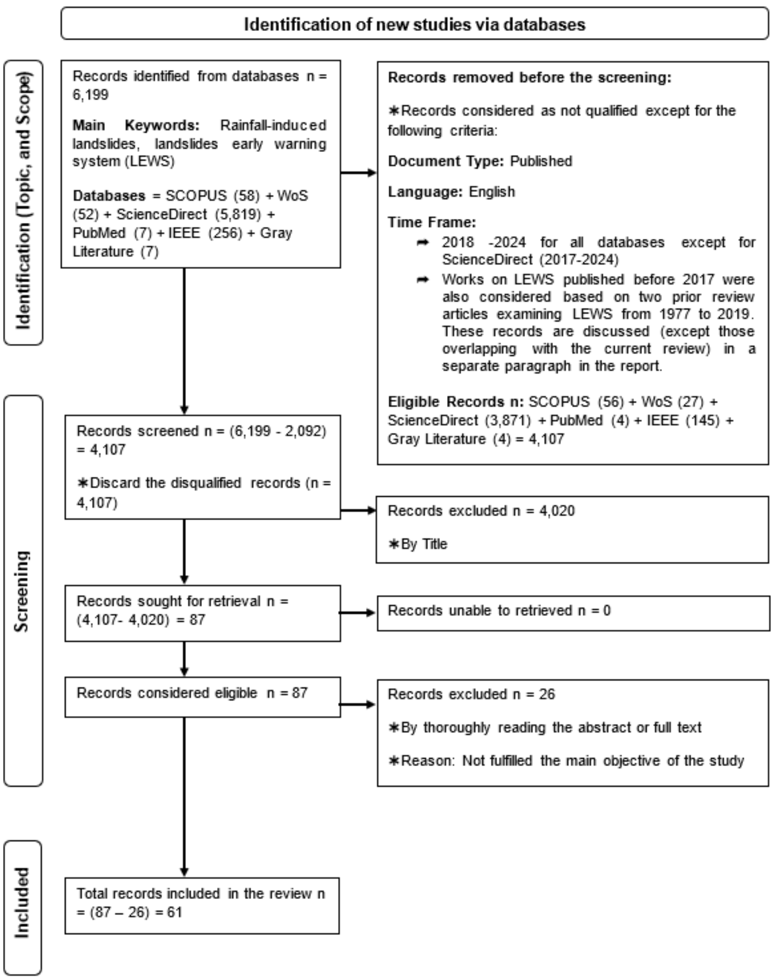

Figure 5: In alignment with the methodology of PRISMA 2020, the selection process was used to select the articles for the literature review on LEWS.

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There is a difference between 'forecasting' and 'early warning system'. Forecasting is an integral part of EWS. Forecasting is the prediction (e.g., upcoming hazards) of the near future (up to a few days). However, EWS is the dissemination of this forecast information to the right people at the right time with an understandable message so that the people can take appropriate actions to avoid unwanted impacts. In the journal articles, many authors frequently use the term 'EWS' to explain their work, although they only discuss up to the forecasting part. This review paper considers both articles where EWS and the forecasting of landslides are discussed.

The keywords used to search for the potential articles are 'Rainfall-induced landslides', and 'landslides early warning systems.' Where needed, the Boolean search query is used with the following query: '(landslide* AND (early warning OR forecasting) AND (real-time OR "real time") AND "rainfall-induced")'. Landslides can occur from earthquakes as well. However, there is no widely agreed-upon, reliable, and near-accurate system for forecasting earthquakes so far (Jarah et al., 2023). So, LEWS for earthquake-induced landslides is not that reliable. Therefore, in this article selection process, earthquake-induced LEWS is excluded.

After searching for potential articles using the mentioned keywords and query, a number of articles were found (a total of 6,199) in each database, such as 58 in SCOPUS, 52 in WoS, 5,819 in ScienceDirect, seven in PubMed, 256 in IEEE, and seven in grey literature. At this stage, several criteria were followed to select the articles, which are the documents that should be published, be written in English, and the time of publication between 2018 and 2024 (except for ScienceDirect, where the time frame applied between 2017 and 2024). This is because some articles related to LEWS found in ScienceDirect and published in 2017 are not featured in the existing review papers.

There are two review articles where LEWS that cover the time between 1977 and 2019, are discussed (Piciullo et al., 2018; Guzzetti et al., 2020). These articles are not completely excluded from discussion in this study. However, these are not included in this article selection process and are discussed in a separate section after getting the overall idea from the published review articles.

Next, the article screening process was initiated. After applying all the above-mentioned criteria, the total number of articles from all databases was 4,107. Then, after scrutinising the titles of the articles, 4,020 articles were eliminated from the list. Next, out of 87 articles, 26 were excluded as they did not meet the main objective of this study. The final inclusion and exclusion were conducted by reading the abstracts of the 87 articles, and if the main objectives were unclear from the abstract, the full texts were read. Finally, 61 articles have been selected for the literature review on LEWS. Among these 61 articles, there are some LEWS developed for the same area. However, the authors have used different methods and techniques to develop the LEWS. So, all of them are considered for this review.

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In addition to technical and methodological considerations, LEWS development is strongly influenced by institutional ownership and operational responsibility. In many contexts, geological surveys or comparable technical agencies may lack either the continuous operational capacity required for warning services or the formal mandate to issue warnings. Consequently, LEWS may emerge through community-led initiatives or be developed by sector-specific actors, such as transport agencies, that face recurrent landslide disruption. These forms of locally embedded practice are often insufficiently captured in academic publications, yet they are directly relevant to EW4All, whose implementation framework emphasizes social inclusion, local engagement, and people-centred warning systems.

3 Geographical distribution and the type of the selected LEWS

The selected articles discussed LEWS covering 23 countries worldwide (Table 1 and Fig. 6). Among 61 publications, the majority (42) discuss LEWS of Asia. Fig. 6 depicts the geographical distribution and the type of LEWS. There are three types of LEWS: national, regional, and local. More than one type of LEWS is found in six countries (China, Colombia, India, Italy, Norway, and Spain). All types of LEWS, national, regional, and local found in two countries, Italy and Norway. Regional and local LEWS are found in four countries: China, Colombia, India, and Spain. In Indonesia, national and local LEWS were found. The rest of the countries have a single type of LEWS.

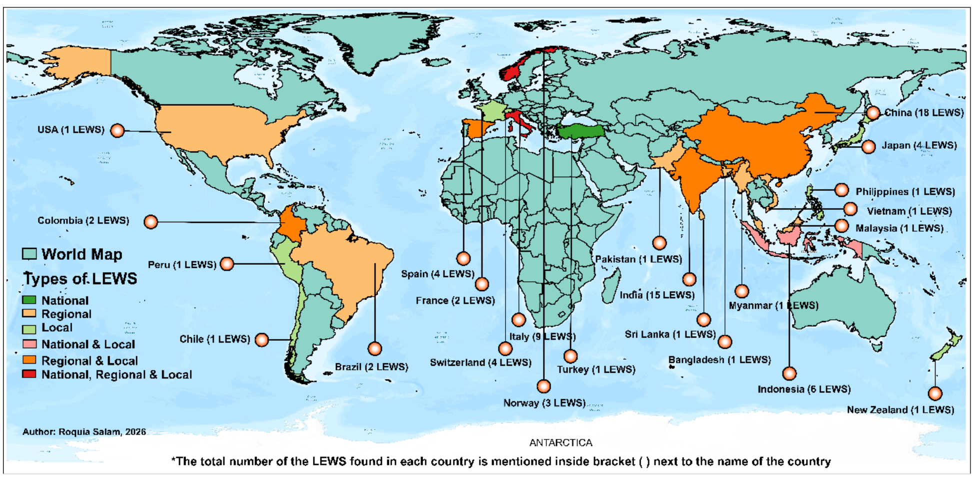

Figure 6: Geographical distribution and the type of LEWS found in the referenced publications.

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Table 1: Published studies reviewed for rainfall-induced LEWS, with study location, assigned code (not mentioned in the publication), and EW4All pillars addressed in each publication

ID	Location/Region	Country	Code	EW4All Pillars	Reference
1	Cox's Bazar	Bangladesh	BD	1, 2, 3, 4	Ahmed et al., (2020)
2	Blumenau, Petrópolis, and Nova Friburgo	Brazil	BR1	1, 2, 3	Andrade et al., (2023)
3	Guaruja and Recife cities	Brazil	BR2	1, 2	Sousa et al., (2023)
4	Wangmiao	China	CN1	1, 2	Li et al., (2017)
5	Yunyang County	China	CN2	1, 2	Guo et al., (2019)
6	Sichuan and Heifangtai area of Gansu Provinces	China	CN3	1, 2	Dai et al., (2020)
7	No info	China	CN4	1, 2	Wang. (2020)
8	Bazhou district	China	CN5	1, 2	Li et al., (2020)
9	Tibetan Bank of the Jinsha River at the junction of Baige Village, Boro Township, Jiangda County, Tibet Autonomous Region, and Zeba Village, Ronggai Township, Baiyu County, Sichuan Province	China	CN6	1, 2	Wu et al., (2020)
10	Southwest China	China	CN7	1, 2	Ju et al., (2020)
11	Loess Plateau	China	CN8	1, 2, 3, 4	Xu et al., (2020)
12	Quanzhou city, Fujian Province	China	CN9	1, 2	Liu et al., (2021)
13	Zizhou County, Yulin City, Shaanxi Province	China	CN10	1, 2	Yang et al., (2021)
14	Nanping city, Fujian Province	China	CN11	1, 2	Cao et al., (2022)
15	Huaihua City, Hunan Province	China	CN12	1, 2	Liu et al., (2023)
16	Chongqing	China	CN13	1, 2	Liu et al., (2024)
17	No info	China, Chile, Japan	ML1	1, 2	Du et al., (2023)
18	Puigcercós, Nevis Bluff, Bomba site, Otomura, Ca' Lita, Kunimi, Xintan, Masseria Marino, Preonzo, Roesgrenda, Baishuihe, Kagemori landslides	China, Italy, Japan, Spain, Switzerland, Norway, New Zealand	ML2	1, 2	Zhang et al., (2022)
19	Saleshan, Maoxian, Xintan, Vajont, Baishuihe, Muyubao, Shiliushubao, La Frasse, La Saxe, Shuping	China, Italy, Switzerland	ML3	1, 2	Zhang et al., (2024)
20	Muping, La Clapie`re, New Wolongsi, Huangci, Saleshan, Puigcerco`s, Ohto, Mt Beni, Maoxian, Xintan, Vajont, Baishuihe, Muyubao, Shiliushubao, La Frasse, La Saxe	China, Japan, France, Spain, Italy, Switzerland	ML4	1, 2	Zhang et al., (2024a)
21	Muping, La Clapie`re, New Wolongsi, Huangci, Saleshan, Puigcerco`s, Ohto, Mt Beni, Maoxian, Xintan, Vajont, Baishuihe, Muyubao, Shiliushubao, La Frasse, La Saxe	China, Japan, France, Spain, Italy, Switzerland	ML5	1, 2	Zhang et al., (2024b)
22	Bello Oriente neighborhood in Medellín	Colombia	CO1	1, 2	Gamperl et al., (2021)
23	Bello Oriente neighborhood, located on the urban–rural border of Medellín	Colombia	CO2	1, 2, 3, 4	Werthmann et al., (2024)
24	Nilgiri district	India	IN1	1, 2	Renuga et al., (2017)
25	Amboori, Kerala	India	IN2	1, 2	Naidu et al., (2018)
26	Chamoli-Joshimath Corridor on the Rishikesh-Badrinath Highway, Garhwal, Himalaya, Uttarakhand	India	IN3	1, 2	Joshi et al., (2019)
27	Himachal Pradesh	India	IN4	1, 2	Prakasam et al., (2021)
28	Chamoli-Joshimath Corridor on the Rishikesh-Badrinath Highway, Garhwal, Himalaya, Uttarakhand	India	IN5	1, 2	Joshi et al., (2022)
29	Nilgiris District	India	IN6	1, 2	Chinamuttevi et al., (2022)
30	Chandmari, Sikkim	India	IN7	1, 2, 3	Kumar and Ramesh (2022)
31	Uttarakhand state	India	IN8	1, 2	Thomas et al., (2023)
32	Narender Nagar, Uttarakhand	India	IN9	1, 2	Kumar et al., (2023)

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ID	Location/Region	Country	Code	EW4All Pillars	Reference
33	Pakhi landslide site in Garhwal, Himalayas, Uttarakhand	India	IN10	1, 2	Joshi et al., (2023)
34	Uttarakhand, Himachal Pradesh, and Jammu and Kashmir	India	IN11	1, 2	Amune et al., (2023)
35	Uttarakhand, Himachal Pradesh, and Jammu and Kashmir	India	IN12	1, 2	Kumar et al., (2024)
36	South-eastern region	India	IN13	1, 2	Singha et al., (2024)
37	Lambagad Landslide Zone near the Joshimath Badrinath Highway in Uttarakhand	India	IN14	1, 2	Gupta and Satyam (2024)
38	Kalimpong, Darjeeling, West Bengal, Tamil Nadu, Himachal Pradesh, Karnataka, Assam, Meghalaya, Mizoram, Uttarakhand, Kerala, Sikkim, Kolkata, and Nilgiri	India	IN15	1, 2, 3, 4	GSI (2024)
39	Indonesia	Indonesia	ID1	1, 2	Amelia et al., (2018)
40	Tulungrejo Village, Batu City	Indonesia	ID2	1, 2	Wardana et al., (2018)
41	Indonesia	Indonesia	ID3	1, 2, 3	Hidayat et al., (2019)
42	Indonesia	Indonesia	ID4	1, 2	Sofwan and Azka (2019)
43	Indonesia	Indonesia	ID5	1, 2	Fatimah et al., (2020)
44	Siantar-Parapat highway	Indonesia	ID6	1, 2	Sigiro et al., (2023)
45	Italy	Italy	IT1	1, 2, 3, 4	Rossi et al., (2018)
46	Aosta Valley	Italy	IT2	1, 2	Ponziani et al., (2020)
47	Metropolitan City of Florence, Tuscany	Italy	IT3	1, 2	Collini et al., (2022)
48	Umbria Region	Italy	IT4	1, 2	Ponziani et al., (2023)
49	Italy	Italy	IT5	1, 2	Guzzetti et al., (2024)
50	Pulau Pinang, Genting Highlands, and Tanjung Bungah, Penang Island	Malaysia	MY	1, 2	Nong et al., (2023)
51	Mon State	Myanmar	MM	1, 2	Thein et al., (2020)
52	Vestlandet, Western Norway	Norway	NO1	1, 2, 3	Piciullo et al., (2017)
53	Norway	Norway	NO2	1, 2,3, 4	Krøgli et al., (2018)
54	Muzaffarabad	Pakistan	PK	1, 2	Binu et al., (2024)
55	Chanchamayo district	Peru	PE	1, 2	Curipaco et al., (2023)
56	Subic Bay Freeport Zone	Philippines	PH	1, 2	Sejera et al., (2020)
57	Catalonia	Spain	ES	1, 2	Palao et al., (2023)
58	No info	Sri Lanka	LK	1, 2, 3, 4	Konagai et al., (2023)
59	Turkey	Turkey	TR	1, 2	Fang et al., (2023)
60	Sitka, southeast Alaska	USA	US	1, 2, 3, 4	Patton et al., (2023)
61	Quang Ninh	Vietnam	VN	1, 2	Nguyen et al., (2024)

Table 1 exhibits the country codes of the countries for easy identification in the graphs. Here, internationally accepted codes (ISO codes) are used (ISO, n.d.). However, as there is more than one work covering the same country in multiple studies, a number is added to the ISO code to differentiate them. For instance, the country code of Italy is IT, and there are five different studies discussing LEWS of Italy; so, the country code for these studies is assigned as IT1, IT2, IT3, IT4, and IT5. In 5 studies, multiple (ML) countries' LEWS were discussed. In such cases, ML is assigned as the base code, and the numeric number is added to the base code (e.g., ML1, ML2, ML3, ML4, and ML5) to differentiate each study. These country codes are used subsequently in this study to reference specific studies.

Table 1 also illustrates the EW4All pillars addressed by each study. Mostly, this information has been extracted from the referenced articles. In some cases, additional documents or national websites were analysed to better understand and obtain this

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information. It is explored that eight countries have addressed four pillars of the EW4All framework: Bangladesh, China, Colombia, India, Italy, Norway, Sri Lanka, and the USA. Out of 23 countries, four addressed the first three pillars: Brazil (Blumenau, Petrópolis, and Nova Friburgo), India (Chandmari, Sikkim), Indonesia, and Norway (Vestlandet, Western Norway). The rest of the countries, Brazil, Chile, France, Japan, Malaysia, Myanmar, New Zealand, Pakistan, Peru, Philippines, Spain, Switzerland, Turkey, and Vietnam, addressed the first two pillars. All the elements under each pillar are not addressed by a single country, indicating the requirement for improvement of the existing systems and implementing them in a way that would be actionable.

4 Results and Discussion

The information on LEWS presented in the plots in this section is derived exclusively from the referenced publications. Only details explicitly reported by the authors are included. No supplementary sources are used to recover unreported information; thus, where relevant information is omitted in an article, it is treated as not included for that LEWS in this analysis. Furthermore, because the study selection process involved several filtering stages, some potentially relevant publications were excluded. As a result, the plots and associated discussion may reflect some degree of missing or incomplete information.

4.1 Pillar 1: Landslide risk knowledge

Within the EW4All framework, Pillar 1 emphasises disaster risk knowledge as the foundation of effective EW. When people take the initiative to assess the type of landslides, their susceptibility, or seek to develop an LEWS, it indicates an awareness of existing hazards and their potential consequences. Such actions demonstrate that communities possess, or are beginning to acquire, the knowledge required to recognise landslide risk and to support informed preparedness and risk reduction measures.

Fig. 7 shows the status, stages, types of landslides, and the integration of the susceptibility map for the selected countries' LEWS. It is found from the reviewed articles that out of 61 LEWS, only 14 are operational, benefiting 10 countries in Bangladesh, Brazil, China, Colombia, India, Indonesia, Italy, Norway, Sri Lanka, and the USA. All these operational LEWS do not cover the whole landslide-affected areas of the respective nations, rather most of them cover a part of the landslide-affected zones. Together, they are disseminating EW in a tiny fraction of the total landslide-affected area worldwide.

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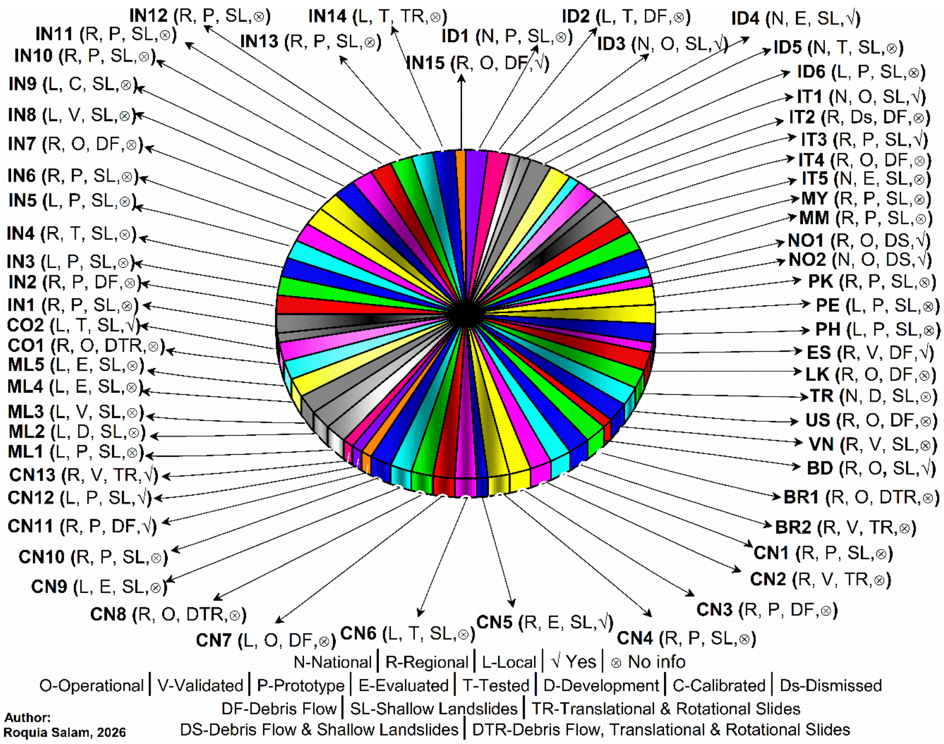

Figure 7: Respectively (in brackets from left to right), the status, stages, types of landslides, and integration of the susceptibility map for the selected countries' LEWS.

Previous studies found that although there are operational national, regional, or local LEWS in some countries, many very high-risk landslide-affected areas, where losses and damages are very high, are not covered by any of these LEWS (Guzzetti et al., 2020; Froude et al., 2018). The LEWS that are in the validated stage are recommended by the authors to be practically implemented (Liu et al., 2024; Guo et al., 2019). In this case, these LEWS might not be practically implemented due to the limitation of successful coordination and collaboration with the relevant departments, agencies, or authorities.

Each slope is distinct from others due to its unique geological and geomorphological characteristics that require a tailored monitoring approach (Khan et al., 2021; Wieczorek and Snyder, 2009). Considering this, some LEWS were developed focusing on individual slopes; however, most of them are prototypes or are in the development stage. Out of 19 local LEWS, only one is operational for providing EW to a community residing on a slope in Southwest China (Ju et al., 2020). This occurs because implementing local LEWS for a single community on a specific slope may not be feasible, as the cost-benefit analysis indicates the associated cost outweighs the potential benefits (Sapena et al., 2023).

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The selected LEWS were developed to provide EW for four types of landslides: debris flow, translational slides, rotational slides, and shallow landslides (Fig. 7). Approximately 66.66% of LEWS were developed only for shallow landslides. However, out of 14 operational LEWS, only three were developed for shallow landslides; six for debris flow; three for both debris flow, translational slides, and rotational slides; and two for debris flow and shallow landslides. Debris flow is one of the most destructive rainfall-induced landslides. It is comparatively easier to monitor the factors of debris flow, and the early sign of the event occurrence can be detected by utilising the rainfall threshold techniques that help to develop more effective LEWS (Segoni et al., 2018; USGS, 2018).

It is explored from the selected literature that so far, no LEWS has incorporated a landslide risk map; therefore, lacking impact-based modelling. However, some LEWS (14) used a static susceptibility map. Out of these 14 LEWS, six are operational. Except for an individual point, incorporating the susceptibility map into LEWS enhances forecasting capability (Singh et al., 2024). Landslide susceptibility levels are not equal everywhere in a landslide-affected locality, area, or region. These vary from slope to slope and catchment to catchment based on land use patterns, soil composition, geology, human intervention, hydrology, slope, amount of rainfall received, presence of any weak point (e.g., fault, joint, cracks, drainage channels), and so on. A susceptibility map can integrate all these conditions and provide the spatial information of the respective area through susceptibility levels (e.g., very low, low, medium, high, very high) to the occurrence of landslides in different parts of the study area (Azarafza et al., 2021). Therefore, incorporating a susceptibility map into the LEWS enhances the forecasting capabilities of the LEWS as it can prioritise specific zones (high risks) in providing targeted EW rather than a generalised EW for the whole affected area. This helps to reduce the number of false alarms. Moreover, having an accessible susceptibility map can enable the community to take proactive measures. However, human modifications on hills like unplanned urbanisation and deforestation are ongoing issues (Hidayat et al., 2019) that change the susceptibility levels of an area dynamically. In most areas, the authority has no control over these human modifications. Therefore, a static susceptibility map cannot precisely represent the actual ground scenarios.

From the above analysis, it can be stated that there is a data gap in many countries that hinders them from incorporating the risk map or even the susceptibility map into the LEWS. Even the basic data is unavailable in the data-sparse regions. For instance, in the case of landslides, sometimes it is not possible to record the event areas immediately after the event due to the extreme weather, inadequate and unavailability of communication networks, and so on (Salam et al., 2024). Nowadays, artificial intelligence (AI) is used extensively to fill this data gap in several ways (Pfeiffer et al., 2024). For example, AI can support identifying landslide locations in remote areas by using Earth Observation (EO) data. Besides, a large amount of data for better achieving landslide risk knowledge can be processed swiftly with the help of AI, which is otherwise very difficult to implement. Although AI is a very powerful tool for

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performing tasks, it is necessary to provide the correct commands to the AI by obtaining reliable information from the local community. Moreover, AI cannot be useful in detecting landslides in areas of high cloud coverage, especially during the monsoon. Lastly, a risk map is important to have in hand so that the community can understand the potential and specific impact of landslides on their livelihoods and resources and be prepared for them.

4.2 Pillar 2: Landslide detection, observation, monitoring, analysis, and forecasting

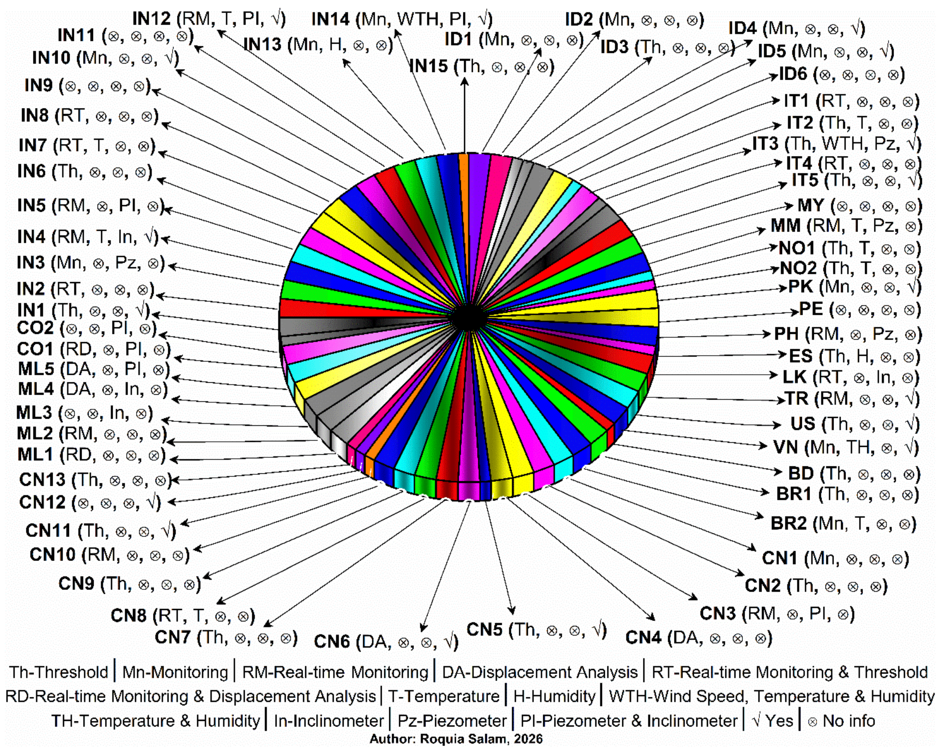

Figure 8: Countries used, respectively (in brackets from left to right), types of rainfall monitoring and analysis, other meteorological parameters, use of the Inclinometer and Piezometer, and utilising AI for creating LEWS.

After developing the proper knowledge of landslide risks, it is time for detection, observation, monitoring, analysis, and forecasting, the second pillar of the EW4All framework, led by the World Meteorological Organization (WMO). The elements used for developing the LEWS are important to study because integrating the right elements into the system can provide more efficient warnings (Calvello, 2017). Fig. 8 demonstrates, respectively (in brackets from left to right), the types of rainfall

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monitoring and analysis, other meteorological parameters, use of equipment such as the Inclinometer and Piezometer, and utilising AI for developing LEWS.

A precise observation is the foundation of accurate monitoring and analysis of landslides. Many countries in the world still have serious challenges in observing landslides due to data shortages in surface and space, such as countries in the global south, Africa, western Latin America, and the Pacific (UN, 2023). This data scarcity is a major hindrance to developing LEWS in these countries. Even forecast verification is not possible due to the lack of adequate data. Moreover, the right parameters for landslides are not always available to monitor, affecting the development of a reliable forecasting system.

Monitoring and analysing rainfall is very important as it is one of the most significant triggering factors of rainfall-induced landslides. There are four types of rainfall monitoring and analysis methods found in existing LEWS: monitoring (no information found on what type of monitoring), real-time monitoring, threshold, and displacement analysis. Some LEWS are developed by utilising a single rainfall monitoring method, and some are based on multiple rainfall monitoring methods. The most popular threshold is intensity–duration (I-D), and another method is the antecedent rainfall threshold (Naidu et al., 2018; Ahmed et al., 2020; Liu et al., 2021; Cao et al., 2022; Andrade et al., 2023).

Among the 61 selected LEWS, rainfall is not included in eight LEWS as an element; perhaps, due to data limitations. However, none of these eight LEWS is operational. About 21 LEWS utilised threshold, 12 monitoring, four displacement analysis, nine real-time monitoring, five both real-time monitoring and threshold, and two real-time monitoring and displacement analysis.

Interestingly, out of 14 operational LEWS, except one (which used real-time monitoring and displacement analysis), in 13 LEWS, thresholds were used to analyse rainfall. In this thresholding approach, both historical rainfall and past landslide data are used to find a critical rainfall level that has previously triggered the occurrence of landslides (Satyaningsih et al., 2023). This critical rainfall level is called the threshold, and it is then used as the benchmark in LEWS. Therefore, when rainfall is about to reach or cross this threshold level, the system issues a warning for the probable occurrence of landslides. This threshold level is not the same everywhere in the world. It varies from country to country, region to region, place to place, and even slope to slope (Barthélemy et al., 2024). So, identifying the correct threshold level for the specific place or region is the most crucial aspect of developing effective and reliable LEWS for that respective place or region (Harilal et al., 2019). Apart from rainfall, in some LEWS (14 out of 61, and among these 14, four are operational), other meteorological parameters like temperature, humidity, and wind speed were also analysed. However, these parameters are not the primary factor of rainfall-induced landslides and are less crucial to consider when developing LEWS (Werthmann et al., 2024; Abbate et al., 2021).

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Out of 61 selected LEWS, only four used piezometers[1], four used inclinometers[2], and seven used both piezometers and inclinometers (Fig. 8). However, only two LEWS are operational among these 15 LEWS. Monitoring pore water pressure[3] is important as it can decrease the soil's shear strength and slope stability. Pore water pressure can increase due to external factors like rainfall, drainage pattern change, groundwater infiltration, and so on. If any slope has more than one groundwater table at multiple depths, it makes the slope more critical in terms of slope instability, and this is not very unusual (Tang et al., 2020). If the soil becomes saturated, it increases pore water pressure and the overall weight of the soil, and further decreases the shear strength, making a favourable condition for ground movement leading to slope failure (Wu et al., 2021). In this case, a piezometer is a powerful tool to measure the pore water pressure, and an inclinometer is used for detecting ground movement. Therefore, integrating the piezometer and inclinometer into the LEWS makes the system more reliable. However, the maintenance cost of these sensors is so high as well, and they can only provide data about a specific point. So, if any LEWS is operational for even a small place, it requires a number of these sensors to get data on pore water pressure and ground movement from different points of the slopes covering the whole area. Thus, integrating the piezometer and inclinometer into the LEWS is not cost-effective for proving EW to a region, but rather effective for a specific point (Sapena et al., 2023). Again, developing a costly LEWS for a specific point is not feasible for a landslide-affected community, as the whole community cannot benefit from the system (Sapena et al., 2023).

AI is used in one or more steps of developing 17 of 61 LEWS (Fig. 9). Among these 17 LEWS, only a single LEWS is operational (Patton et al., 2023). It is proven that AI is a fantastic tool to solve complex problems (Jarrahi, 2018). It is extensively used in filling data gaps, especially by integrating satellite remote sensing (Pfeiffer et al., 2024). However, there are some drawbacks to using AI. It requires a huge amount of high-quality data to train the model. In the case of a data-sparse region, fulfilling this requirement is a major challenge. For instance, satellite-based detection is often hindered during the monsoon season due to cloud cover (Salam et al., 2024). Moreover, many AI models tend to overlook social and community dimensions, such as local knowledge, cultural contexts, and communication preferences, which are critical for effective early warning and community response. There are open-access global-level different categories of datasets available that can be used for training. However, every landslide is unique, and the characteristics of the triggering factors (e.g., vegetation, land use pattern, soil composition, hydrology, slope, and so on) of each landslide-affected area are distinctive. Therefore, using these available datasets to train the AI model and extract data for another region can be oversimplified, leading

[1] Piezometer is a geotechnical instrument used for measuring pore water pressure or groundwater pressure in the surrounding soil and rock.
[2] Inclinometer is used to monitor and measure the displacement of the ground and deformation of the slope. It is usually used for detecting soil or rock movement.
[3] Pore water pressure is the pressure exerted by the water (groundwater) within the porous medium (pore) of soil and rock. Elevated pore water pressure increases the chance of landslides occurring.

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to inaccurate warnings. Second, apart from data generation, even using AI in further steps like landslide susceptibility mapping, generating an early prediction of slope failure, and so on, can produce a huge distrust. Because several AI (e.g., artificial neural networks – ANN), especially deep-learning (DL) techniques, run as a 'black box' as these techniques produce a quick result without providing any transparent and underlying logic in internal decision-making (Welchowski et al., 2022). In most cases, it is impossible to customise the contribution of the influencing factors of landslides by using AI to produce the results. Although these results can be statistically significant and excellent, they may not be reliable practically due to the complex nature of the landslide disasters, due to the dynamic human intervention, changes in weather patterns, and social vulnerability aspects. Because of these reasons, using AI directly in developing an effective and near-reliable LEWS is very challenging.

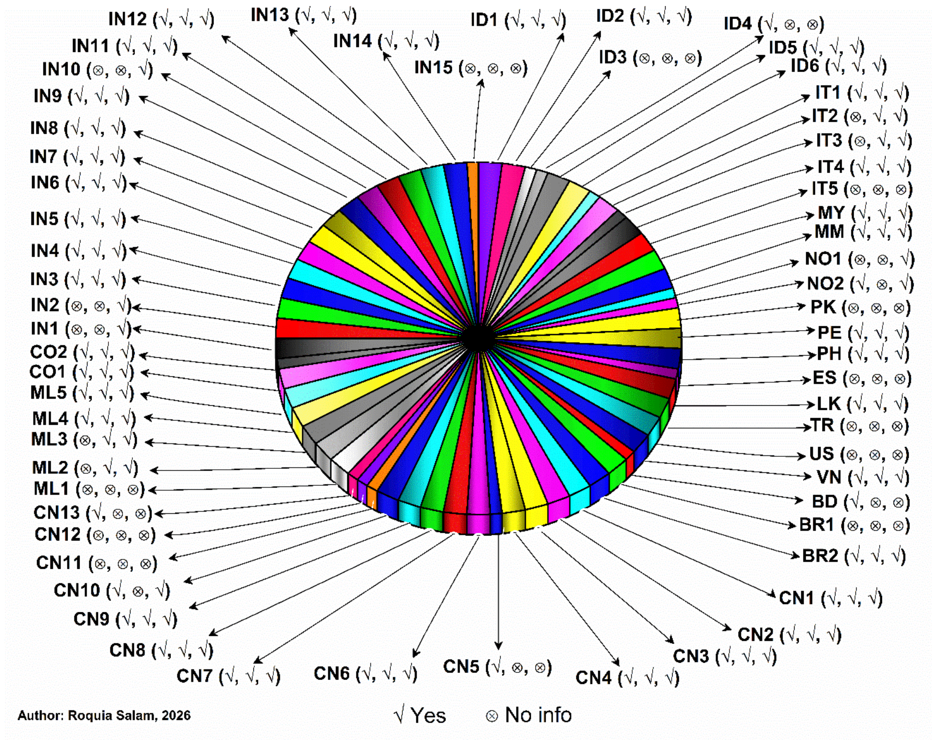

Figure 9: Countries used, respectively (in brackets from left to right), API, IoT, and other sensors for creating LEWS.

Fig. 9 depicts, respectively (in brackets from left to right), application programming interfaces (API), internet of things (IoT), and other sensors (apart from inclinometer and piezometer) for creating LEWS. Out of 61 LEWS, the API for integrating different categories of data is used in 42 LEWS. Among these 42 LEWS, nine are operational (Figs. 7 and 9). In some cases, API is used to merge data generated from other

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systems (Ofoeda et al., 2019). For instance, to develop a LEWS dedicated to rainfall-induced landslides, forecasted rainfall data is required to calculate the potential accumulated rainfall for the next day (s) (Ahmed et al., 2018). This helps to understand whether rainfall is crossing the threshold and issue an EW for potential upcoming events. Some dedicated institutions forecast rainfall (hourly, daily) using advanced statistical modelling. This forecasted rainfall is usually used through API into the LEWS, which significantly improves the warning (Krøgli et al., 2018).

IoT technology[4] is used in 42 LEWS, and seven of them are operational (Fig. 9). Similarly, apart from the piezometer and inclinometer, other sensors like the accelerometer, rain gauge, crack meter, tiltmeter, and so on are used in 47 LEWS, and nine of them are operational. Among these seven and nine operational LEWS that use, respectively, IoT and other sensors, seven are in common. There is a linear relationship between IoT and data transmission from these sensors. It is a very convenient way to immediately transfer the data measured by the sensors to the LEWS system using wireless communication like IoT, making this monitoring real-time (Liu et al., 2022).

From the above-mentioned analysis, it is clear that the precise landslides detection, observation, monitoring, analysis, and forecasting are compromised due to data scarcity. In this case, EO data and AI can mitigate this issue by filling the data gap using advanced statistical and hydrometeorological modelling to enhance observation, monitoring, and forecasting capabilities. However, these models should be scientifically sound and reliable, and to ensure this, capable human resources are needed. Besides, AI-generated data needs to be verified on the ground to ensure the quality of the data. The UN has initiated the Global Basic Observing System (GBON) to close this gap in LDCs and SIDs to support EW4All initiatives (UN, 2023). Another important aspect of pillar 2 is to facilitate data exchange among countries, increasing the scalability of the LEWS. An essential element of Pillar 2 is to reduce the compound effects of landslides, emphasising the need to collaborate with multiple disciplines. By incorporating these points, it will be easier to develop an actionable and targeted LEWS. However, above all, funding is the most critical factor in executing the aforementioned tasks, and securing it is a major challenge, especially for the least developed and developing countries. This challenge should be more prominently addressed, with a focus on promoting access to international climate finance. Mechanisms under the Paris Agreement, particularly the Loss and Damage fund, and other UN climate frameworks offer critical opportunities for vulnerable countries to secure the necessary resources to build and sustain effective EWS. Prioritising LEWS within these funding channels is essential to protect lives and livelihoods in high-risk areas.

[4] IoT technology in a LEWS refers to the network of interconnected sensors and devices (e.g., piezometer, inclinometer, rain gauge) that transmit real-time data through a wireless communication system over the internet to the cloud or central server. It enables algorithms on the server to analyse the real-time data and generate a timely alert.

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4.3 Pillar 3 and Pillar 4

The referenced publications lack sufficient details on how warnings are disseminated and communicated (Pillar 3) to the last mile[5]. In addition, discussions on preparedness and response capabilities (Pillar 4) are missing from most articles. Only a handful of papers (five in total) address one or more of the following steps: warning dissemination, communication, preparedness, and response planning (Krøgli et al., 2018; Ahmed et al., 2020; Kumar and Ramesh, 2022; Patton et al., 2023; Werthmann et al., 2024). However, even among these few, most focus primarily on the frameworks they propose. Perhaps, these information might avaiable in other sources which were not concisered for this study.

It has been observed from the referenced publications that LEWS are generally limited to issuing forecast alerts, which are typically made available on official websites. The decision on whether to disseminate these warnings to the last mile rests with the relevant authorities. More detailed discussions on warning dissemination and communication can be found in the reviews by Guzzetti et al. (2020) and Piciullo et al. (2018). In these studies, the authors draw not only on their academic research but also on their own field experience and information obtained through personal contacts with the relevant authorities.

Therefore, it remains difficult to gain a comprehensive understanding of any country's LEWS solely from selected academic publications. To capture the full picture, deeper engagement with national systems, through direct communication with stakeholders, field visits, or other means, is often necessary. This points to a significant gap in the literature and practice, as the available academic sources provide only partial insights into how LEWS actually operate on the ground.

4.4 Additional LEWS from the review papers

A few pieces of related information on the additional LEWS are mainly gathered from two peer-reviewed published articles by Guzzetti et al. (2020) and Piciullo et al. (2018). Available information on the characteristics of the LEWS discussed in the review papers includes their stages, status, the type of landslides they focused on, the use of rainfall thresholds, and sustainability mapping (Table 2). Information on all these LEWS is not available in the existing academic databases, according to the authors (Guzzetti et al., 2020, and Piciullo et al., 2018). The authors collected information about those LEWS from several sources, including academic databases, websites, and personal contacts. So, these are discussed separately from the previous sections because the information is directly gathered from the two above-mentioned publications. The information presented in this section is related to the previous

[5] The last mile refers to the final step of disseminating the alert directly to the people who are at risk. It ensures that understandable and actionable alert information reaches the right individuals.

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sections in the sense that similar information was extracted from the 61 referenced publications. This information is useful to understand the basic characteristics of rainfall-induced LEWS.

Table 2: Overview of the characteristics of the LEWS discussed in previous review articles.

ID	Country	Stages	Status	Focused landslide types	Used rainfall threshold	Integrated susceptibility map
1	Taiwan	Operational	National	Debris flow	Yes	No info
2	Italy	Design	National	No info	Yes	Yes
3	Norway	Operational	National	Debris flow, and shallow landslides	Yes	Yes
4	Central America and the Caribbean	Dismissed	National	No info	Yes	Yes
5	Indonesia	Operational	National	No info	Yes	No info
6	Scotland, UK	Design	National	Shallow landslides	Yes	No info
7	Malaysia	Operational	National	Debris flows, and shallow landslides	Yes	No info
8	Japan	Operational	National	No info	Yes	No info
9	Appalachians, USA	Operational	No info	Shallow landslides	Yes	No info
10	Hong Kong, China	Operational	Regional	Cut slopes, rock slopes, fill slopes, and retaining walls	Yes	No info
11	San Francisco Bay area, USA	Dismissed	Regional	Debris flow	Yes	No info
12	Western Oregon, USA	Operational	Regional	Debris flow	Yes	No info
13	Seattle, USA	Dismissed	Regional	Debris flow and shallow landslides	Yes	No info
14	Southern California, USA	Operational	Regional	Debris flow	Yes	No info
15	North Vancouver, Canada	Dismissed	Regional	Debris flow	Yes	No info
16	Rio de Janeiro, Brazil	Operational	Regional	Debris flow	Yes	No info
17	Combeima Valley, Colombia	Experimental	Regional	Debris flow	Yes	No info
18	Java, Indonesia	Pre-operational	Regional	No info	No info	Yes
19	Chittagong Metropolitan Area, Bangladesh	Operational	Regional	Shallow landslides	Yes	Yes
20	Southern Taiwan	Design	Regional	No info	Yes	Yes
21	Emilia-Romagna, Italy	Operational	Regional	Shallow landslides	Yes	Yes
22	Piedmont, Italy	Operational	Regional	Debris flow and shallow landslides	Yes	Yes
23	Umbria, Italy	Operational	Regional	No info	Yes	No info
24	Tuscany, Italy	Operational	Regional	No info	Yes	No info
25	Liguria, Italy	Design	Regional	No info	Yes	Yes
26	Sardinia, Italy	Design	Regional	No info	Yes	Yes
27	Apulia, Italy	Design	Regional	No info	Yes	Yes
28	Sicily, Italy	Operational	Regional	Shallow landslides	Yes	No info
29	Zhejiang Province, China	Operational	Regional	No info	Yes	Yes
30	Hubei Province, China	Operational	Regional	No info	Yes	No info

All the LEWS were developed to issue warnings for rainfall-induced landslides. In total, eight and 21 LEWS are national and regional categories, respectively. However, it is not clear what type (national, regional, or individual) of LEWS is operational in Appalachians, USA. Practically, four LEWS found in Central America and the Caribbean; North Vancouver, Canada; San Francisco Bay Area, USA; and Seattle, USA are already dismissed. Six LEWS were only designed (four from Italy, one from Scotland, and Taiwan). One LEWS was found in the experimental stage from Combeima Valley, Colombia, and one was found in the pre-operational stage from Java, Indonesia.

Among these 30 LEWS, the one still operational in Hong Kong, China, is the first known LEWS in the world and has been operational since 1977 (Guzzetti et al., 2020). It is the most successful LEWS in history. Since its initial operation, it has gone through several improvements. Unlike other areas, landslides in Hong Kong are not purely natural, as the slopes of this region are human-made, and due to rainfall, these human-made slopes often fail.

Out of these 30 LEWS, 18 (12 are regional, from five in Italy, two in the USA, three in China, one from Bangladesh, and one from Brazil; five are national from Japan, Taiwan, Malaysia, Indonesia, and Norway) are found as operational by Guzzetti et al. (2020) and Piciullo et al. (2018). Mostly, these operational LEWS (12 LEWS out of 18) focus on two types of landslides: debris flow and shallow landslides, which are analogous to the findings of the systematic review of this study. However, it is not clear what type of landslides are focused on by the six other operational LEWS. In all these 18 LEWS, one or more rainfall thresholds are integrated, indicating the significance of local thresholds in issuing an effective warning. The landslide susceptibility map is integrated into five LEWS out of 18. Among all these 30, no LEWS incorporated a risk map.

4.5. Gaps in the referenced 61 LEWS in the lens of the EW4All framework

While considerable contextual variation exists, the reviewed literature suggests that a typical LEWS warning value chain comprises four interrelated pillars: landslide risk knowledge; risk monitoring, detection, forecasting, evaluation, and warning formulation; warning dissemination through appropriate communication channels; and the uptake of warnings to support preparedness and early action. These pillars are functionally interconnected, as each stage provides the basis for the next. Weaknesses in one pillar can reduce the effectiveness of subsequent stages and ultimately compromise the performance of the system as a whole. Accordingly, a LEWS can be considered successful only when all four pillars operate in a coordinated manner, enabling warnings to be generated, communicated, understood, and translated into timely and appropriate action. Although the 61 reviewed publications do not provide comprehensive coverage of all four pillars of a LEWS, they do reveal important strengths and weaknesses in existing systems when considered against the EW4All framework. However, the analysis in this section is confined to Pillars 1 and 2, since these pillars were reported more consistently and in greater comparable detail

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across the reviewed cases. Accordingly, 11 priority areas for improvement were identified within these two pillars. Fig. 10 illustrates these key areas requiring further attention in relation to Pillars 1 and 2.

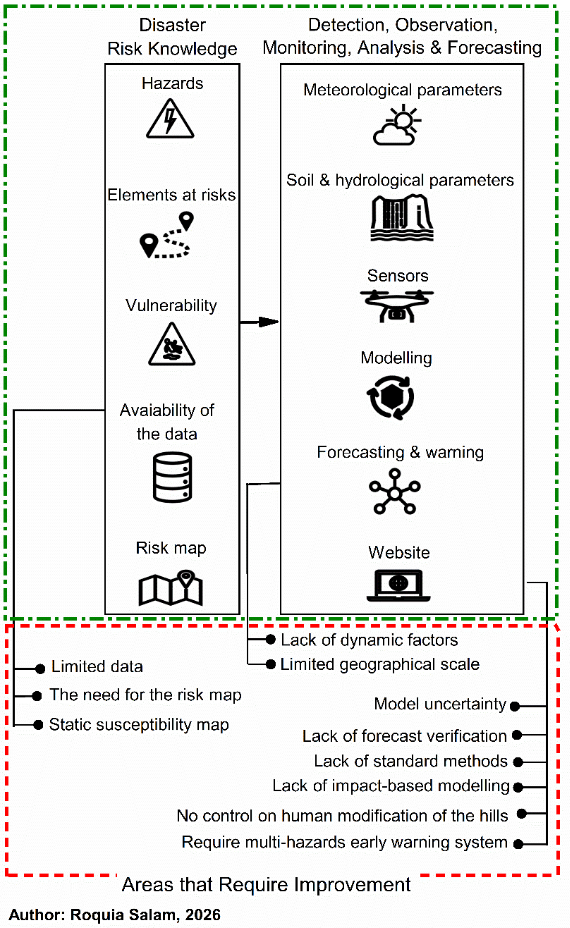

Figure 10: Elements of Pillars 1 and 2 for LEWS based on UN-defined EW4All, and areas that require improvement in each pillar identified from the referenced publications.

4.5.1 Gaps under Pillar 1

4.5.1.1 Limited data

Data scarcity is one of the most critical problems. It is quite difficult and sometimes impossible to collect basic data like landslide inventories from many landslide-prone areas (Patton et al., 2023; Liu et al., 2024). Based on the types of landslides, the categories of inventories are different. Therefore, it is important to prepare the database of the different categories of inventories separately and make sure inventories of one category are not mixed with another type. Because each category

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has varying types of risks. Consequently, mixing multiple categories of inventories for analysis does not properly represent the risk; rather, it simplifies the risk, which is a major issue still in many areas. Each landslide inventory category gives an idea of where landslides can happen and how they would impact an area. Therefore, having landslide inventories in hand indicates that the analyst knows which areas are more and less prone to landslides.

However, except for some developed countries like Italy, Hong Kong (in China), Norway, and so on, it is still a major limitation. Apart from the inventories, to better understand the pattern and risk of landslides in an area, several datasets (e.g., hydrological, meteorological, geological, lithological, and so on) are required to analyse. However, all these datasets are not available everywhere (because of several reasons like lack of adequate resources, funds, and others) (Ponziani et al., 2020; Ponziani et al., 2023; Palau et al., 2023). Although some dedicated institutions provide simulated data. However, these are not as accurate as the station data. The same happens to the gridded data. Therefore, without analysing the gridded or simulated data with station data to explore the most suitable one (among many simulated or gridded data), the perception of landslide risk for an area is not highly accurate. Low temporal and spatial resolution of the satellite data is further impacting the accuracy of the LEWS (Dai et al., 2020; Fang et al., 2023). Data limitation is a major concern because landslide forecasting and warning require the integration of information across a range of institutions and specialist disciplines, including meteorology, hydrology, geology, engineering, and communication. In this context, 'limited data' is not simply a matter of insufficient observations within a single domain; rather, it reflects a broader, cross-sectoral challenge concerning the routine collection, integration, and sharing of critical parameters relevant to LEWS. This issue is therefore closely connected to governance, especially with regard to institutional coordination, data-sharing agreements, and the mechanisms through which information is exchanged between relevant actors.

4.5.1.2 The need for the risk map

A risk map is a vital element of a LEWS. Because it usually integrates data on all the components of risk, like hazard, vulnerability, and exposure. Even, each component does not have the same impact on the risk level. Exposure is the most dominant component in the risk level. Therefore, it is essential to provide the right importance to the components in creating a risk map. From the existing literature review, it is explored that a risk map is missing in the referenced LEWS (Ahmed et al., 2020; Andrade et al., 2023; Konagai et al., 2023). However, a susceptibility map is used to categorise the risk zones. Most people confuse susceptibility with risk maps due to a lack of disciplinary background training. This is not an adequate method. Several factors of landslides are used here altogether to create a susceptibility map without providing relevant importance to each component. Even elements of all these components are not included. For instance, some elements of hazard and vulnerability components may be considered to create the susceptibility map, where any element of exposure is not included. In some cases, this map is created without any element

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of exposure and is used as a risk map, which is a very big misconception. A susceptibility map can never be a risk map.

4.5.1.3 Static susceptibility map

In some LEWS, a susceptibility map is integrated into the system. However, it is found that this susceptibility map is not dynamic (Rossi et al., 2018; Ahmed et al., 2020). However, most of the landslide-prone areas are continuously changing. It means that because of hill cutting, slope alteration, deforestation, urbanisation, demographic changes, and other factors, the at-risk areas are changing. Therefore, the risk levels of these areas are also changing, which requires an updated susceptibility map. This change can be done automatically or semi-automatically after a reasonable time gap. However, it is observed that the susceptibility map, which was used initially to develop the system, did not change later. This reflects that the warning generated from the old susceptibility map is not the same as they claim.

4.5.2 Gaps under Pillar 2

4.5.2.1 Lack of dynamic factors

Some factors of landslides are regularly changing, such as rainfall, pore water pressure, ground movement, land use, and others. Several barriers (e.g., lack of funds, maintenance issues) exist to getting data dynamically from the rain gauge station, piezometer, and inclinometer. Most of the LEWS lack most of these data (Rossi et al., 2018; Ahmed et al., 2020; Patton et al., 2023; Ponziani et al., 2023), and a few have one or more dynamic factors integrated into the system. Therefore, there is a limitation in the monitoring, observing, and analysing stage. Integrating these dynamic data into the system helps it issue an effective warning.

4.5.2.2 Limited geographical scale

There are very few developed countries where the entire landslide-prone area is covered under one or more LEWS. It is identified that, except for the area where there is a single landslide site and a local LEWS is present, most of the landslide-prone countries have the limitation of covering the whole landslide-prone area under LEWS (Ahmed et al., 2020; Ju et al., 2020; Andrade et al., 2023; Singha et al., 2024). For instance, the whole Chittagong Hill District (CHD) situated in the southeastern part of Bangladesh has five districts, and each district is affected by varying degrees of landslides. However, this area has an LEWS covering a small part of a single district, which is a small portion of the whole landslide-affected area. There might be a higher cost of operating several LEWS to cover the entire affected area. Then, a single LEWS can be operated to cover the entire affected area, which would be cost-effective and cover the whole area. Therefore, securing enough funding is another challenge (especially for LDCs and SIDS) to ensure LEWS in all areas affected by landslides. Beyond financial constraints, institutional barriers also hinder progress. For instance, limitations in capacity, expertise, or infrastructure within national agencies can significantly affect the development, operation, and sustainability of effective warning systems.

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4.5.2.3 Absence of the community reflection

The local community of the landslide-prone area is very important. They should have given the highest priority while developing a LEWS. LEWS are primarily dedicated to ensuring their safety and security. However, it is explored that community engagement is absent in most LEWS, which is one of the major reasons for the failure of the purpose of the system. It is essential to consult with them about what resources are present and absent in their area, which helps to customise the system accordingly. Besides, they are the only reliable source who can provide the information on how they need the warning, and which medium is suitable for them to receive the warning. It can be email, SMS, radio/TV announcements, megaphone miking, and others. A very good LEWS can fail if it cannot disseminate information to the locals effectively. Because the locals cannot respond to the warning if the warning is not disseminated to them via the correct medium.

4.5.2.4 Model uncertainty

Model uncertainty is a major gap in LEWS. It means that there are some internal limitations and possible inaccuracies within the modelling (Ponziani et al., 2020; Zhang et al., 2024a). For instance, to reduce the data gap, AI is extensively used. However, the product created by AI is not reliable in many cases (Li et al., 2024). There are always some errors. In many cases, the LEWS do not incorporate this uncertainty into the system, making it less reliable. Besides, if a model is customised for an area with specific characteristics, and then used for another area, that is completely different in temporal and spatial extent, leading to model uncertainty. Because of this model uncertainty, a LEWS can produce a very simplified warning that may not reflect the ground truth. To address these issues, generating multiple scenarios based on varying input conditions and conducting sensitivity analysis can help identify how changes in key parameters affect model outputs

4.5.2.5 Lack of standard methods

So far, there is no known standard methodology for developing LEWS. For instance, there are several monitoring methods, such as remote sensing, community-based, and ground-based. These data are collected using different methods by different users, reflecting inconsistency in the instrumentation and protocol of data collection (Piciullo et al., 2017; Liu et al., 2024). This leads to the degradation of the quality of the data and even makes it sometimes difficult to integrate into the system. Another example is the rainfall threshold, which is a very potent element of any rainfall-induced LEWS. However, in all LEWS, thresholds are not used. In some LEWS, dynamic rainfall data is used directly. All these can increase the false alarm rate. However, it is unclear from the EW4All framework how to ensure a standard method applicable to the whole world when the characteristics of each landslide are different.

4.5.2.6 Lack of impact-based modelling

A key gap in the existing LEWS is impact-based modelling (Guzzetti et al., 2020). Very few LEWS can be able to perform this task like the one in Hong Kong, China. Although the LEWS in Hong Kong is very impactful, in many areas in China, there is no

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operational LEWS where it is required. To date, most of the existing LEWS are just informing the community about upcoming hazards instead of informing them about the impact of the hazards. It means the LEWS should be developed to inform the local community about the impacts on the specific structures and livelihoods. If there is an impact-based warning, the local community can plan better to minimise their risks.

4.5.2.7 Lack of forecast verification

Forecast verification is an essential part of LEWS. Still, a lot of LEWS do not perform verification, which limits their applicability (Guzzetti et al., 2020; Gamperl et al., 2021). It can occur due to several factors. One of the main factors is the lack of historical data. If there is a lack of enough historical records, it is not possible to perform the verification. Data limitation is a big challenge in many areas. Second, it can happen if there are multiple significant underlying factors of past occurrences, like rainfall, earthquakes, human modification, and others. Third, the spatial and temporal information of past events can vary widely, and thus, make it difficult to perform forecast verification. The lack of forecast verification indicates that the system did not develop by following a precise way, decreasing reliability. Moreover, forecast verification demands substantial funding and human resources, which are often unavailable. The absence of these resources suggests gaps in the development process, ultimately undermining system reliability.

4.5.2.8 No control on the human modification of the hills

To date, there is no single landslide-prone area where human modification of the hills can be controlled, not even in Hong Kong and Italy. Every day, there are small or huge modifications (e.g., toe cutting, slope cutting, and so on) of hills happening. Even if there is a very advanced LEWS, it cannot perform 100% accurately, because of this human modification (Hidayat et al., 2019; Thomas et al., 2023). Because if there is any modification on any slope, the risk level of this slope is changed instantly. Therefore, to get an accurate warning, there is a need to integrate this new risk data (through susceptibility or risk map) into the system immediately, which is not yet possible. Because it is a huge task to update it daily. It is only possible if there is a dynamic susceptibility or risk map in the system.

4.5.2.9 Require a multi-hazard early warning system

Although it is complex to develop a multi-hazard EWS, it is very much required because of the cascading or simultaneous nature of the hazards. However, it is explored that only a few (2-3) LEWS are focusing on multi-hazards like landslides and floods (Krøgli et al., 2018; Guzzetti et al., 2020; Prakasam et al., 2021). However, the rest of the LEWS are not MHEWS. MHEWS is essential to reduce the overall risks and losses. For instance, before hitting a rainfall-induced landslide, there is a high probability of the occurrence of flash floods. A cyclone can result in landslides. Therefore, if a LEWS is only focusing on landslides but the area is affected by multiple hazards, the community may be impacted by the first hazard or another simultaneous hazard. This instantly reduces the capacity of the community to respond to the next hazard. Consequently, an MHEWS can solve this problem.

4.6 Feasibility of implementing EW4All for LEWS

The EW4All framework is very comprehensive. It clearly urges action on several fronts and, for the first time in history, focuses so strongly on the betterment of humans. However, it also has a number of issues beyond the general challenges and gaps that were discussed in the earlier section. Some of the feasibility concerns are outlined briefly here.

First, it calls for the implementation of MHEWS worldwide. Funding is a major challenge in this regard, especially for SIDS and LDCs. At present, the UN is providing direct financial support to only 30 selected countries under this framework, which is far from adequate. How the rest of the countries will secure the necessary resources to ensure EW4All is not clearly specified in the current mandate. This creates a significant feasibility concern, since securing funding is not an easy task, and is in fact the essential first step for initiating any such programme.

Second, the framework seems to emphasise the application of similar methods or models everywhere. This is problematic, as lithology, physiography, geology, climatology, and other characteristics differ considerably across the globe. Given these variations, it is not viable to apply a single approach to developing LEWS everywhere.

Third, while the framework highlights inclusivity, which is indeed vital, it does not provide clear guidelines on how to achieve it in practice. Experience shows that even in regions or countries with a relatively strong number of landslide forecasting systems, warning dissemination and response often fail due to extreme weather, difficult geography, or other barriers. Since "safety first" is a fundamental principle for all emergency workers, they cannot be expected to risk their lives in the immediate aftermath of a disaster. Responders often need to wait until conditions become less hostile before they can assist affected people. As these situations are largely shaped by nature, ensuring complete inclusivity is practically impossible.

Fourth, the framework calls for the use of a standard forecasting model. In reality, reliable landslide forecasting systems require the definition of local thresholds and proper calibration, which does not align with the idea of a uniform global model. Relying on a standard model risks producing overly general outputs that are less useful at the local level. Moreover, the framework does not explain how such a standard model implementation could actually be achieved.

Fifth, last-mile communication presents another challenge, particularly in areas with high linguistic diversity.

Sixth, the framework aims to achieve universal MHEWS coverage by the end of 2027. It is unclear how this target will be met, given that it is already midway through 2026 and many of the designated countries still face serious resource and capacity constraints. While the UN is providing some support, the countries outside the current

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support pool face even greater uncertainty. For them, implementing this framework within the stated timeframe seems unrealistic.

Other feasibility issues may hinder the success of EW4All. Therefore, a more detailed and region-specific framework is needed, one that accounts for contextual realities rather than relying solely on a broad global model.

5 Conclusion

By examining 61 LEWS, it is found that significant progress has been made to make the LEWS operational. Both advancements and gaps are identified through the lens of the EW4All framework. Some gaps can be improved with experts' collaborative efforts. Currently, more landslide-affected areas are covered under LEWS than before. This indicates that LEWS are no longer a dream for the affected people, which enhances people's preparedness, response, and mitigation capabilities, ultimately reducing the overall risks. Several activities have been undertaken for developing LEWS in different areas over the past few years; however, they lack proper coordination and collaboration. These activities are often fragmented into several places, making the development of LEWS quite difficult. Institutional barrier is another issue that hinders the successful implementation of a LEWS.

While EW4All provides an important global framework, its feasibility for LEWS is limited by insufficient funding, the push for standard models that neglect local thresholds, and persistent challenges in inclusivity and last-mile communication. Unless region-specific approaches are prioritised and enough resources secured, establishing effective LEWS everywhere by 2027 will remain unrealistic.

Declaration of generative AI and AI-assisted technologies in the writing process

The main text of this work was originally written by the authors. ChatGPT and Copilot were used selectively on a very few paragraphs to improve clarity and correct grammatical errors, while ensuring that the original ideas and meaning remained unchanged. After using these tools, the authors carefully reviewed and edited the content as needed.

Author contributions

RS, BA, and PS conceptualised the research. RS and BA designed the methodology. RS collected the resources, carried out the analysis, and wrote the associated interpretation. BA and PS supervised and reviewed the manuscript. RS prepared the manuscript with contributions from all co-authors.

Competing interests

One of the co-authors is a member of the editorial board of NHESS.

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