Earth-Science Reviews 200 (2020) 102973

Contents lists available at ScienceDirect

Earth-Science Reviews

journal homepage: www.elsevier.com/locate/earscirev

Geographical landslide early warning systems

Fausto Guzzetti*, Stefano Luigi Gariano, Silvia Peruccacci, Maria Teresa Brunetti, Ivan Marchesini, Mauro Rossi, Massimo Melillo

CNR IRPI, via della Madonna Alta 126, I 06128 Perugia, Italy

ARTICLE INFO

Keywords:
Landslide
Landslide early warning system
Forecast
Threshold
Model
Advisory

ABSTRACT

The design, implementation, management, and verification of landslide early warning systems (LEWSs) are gaining increasing attention in the literature and among government officials, decision makers, and the public. Based on a critical analysis of nine main assumptions that form the rationale for landslide forecasting and early warning, we examine 26 regional, national, and global LEWSs worldwide from 1977 to August 2019. We find that currently only five nations, 13 regions, and four metropolitan areas benefit from LEWSs, while many areas with numerous fatal landslides, where landslide risk to the population is high, lack LEWSs. Operational LEWSs use information from rain gauge networks, meteorological models, weather radars, and satellite estimates; and most systems use two sources of rainfall information. LEWSs use one or more types of landslide forecast models, including rainfall thresholds, distributed slope stability models, and soil water balance models; and most systems use landslide susceptibility zonations. Most LEWSs have undergone some form of verification, but there is no accepted standard to check the performance and forecasting skills of a LEWS. Based on our review, and our experience in the design, implementation, management, and verification of geographical LEWSs in Italy, we conclude that operational forecast of weather-induced landslides is feasible, and it can help reduce landslide risk. We propose 30 recommendations to further develop and improve geographical LEWSs, and to increase their reliability and credibility. We encourage landslide forecasters and LEWSs managers to propose open standards for geographical LEWSs, and we expect our work to contribute to this endeavour.

1. Introduction

The design, implementation, management, and verification of "landslide early warning systems" (LEWSs) are subjects that are gaining interest in the scientific and technical literature, and among decision makers. Analyses of the general and specific features of LEWSs exist, including the works of e.g., Aleotti (2004); Yin et al. (2007); Wieczorek and Glade (2005); Medina-Cetina and Nadim (2008); Huggel et al. (2010); Alfieri et al. (2012); Stahl et al. (2012); Thiebes (2012); Wilson (2012); Intrieri et al. (2012, 2013), Calvello (2017); Chae et al. (2017); Fathani et al. (2016); Park et al. (2019), and Pecoraro et al. (2019). Examination of these works reveals a clear emphasis on "local" systems designed to predict the short-term behavior of single landslides, individual slopes or small catchments. A recent exception is the work of Piciullo et al. (2018) who have examined geographical LEWSs, which they called "territorial" systems. Building on these works, and on our experience in the design, implementation, management, and verification of LEWSs in Italy, we review regional, national, and global LEWSs covering areas from a few hundreds of square kilometres to the major part of the globe. In the review, we do not consider local systems.

The paper is organized as follows. After the introduction of the terminology used in the work (Section 2), we present the rationale for landslide forecasting and early warning (Section 3). Next, we examine the characteristics of 26 past and existing LEWSs (Section 4). This is followed by a geographical and temporal analysis of the LEWSs, of the data and models used for landslide forecasting, and of the advisory schemes adopted by the LEWSs (Section 5). Next, we discuss open issues and perspectives in operational landslide forecasting, and in the design, management, and verification of LEWSs (Section 6). We conclude by outlining the lessons learned (Section 7), and summarizing 30 recommendations for the further improvement of existing and the development of future geographical LEWSs.

2. Terminology

There is no standard language in the literature for describing early warning systems for natural hazards. To avoid confusion, here we clarify the meaning of some key terms used in the work. We

* Corresponding author.
E-mail address: Fausto.Guzzetti@irpi.cnr.it (F. Guzzetti).

https://doi.org/10.1016/j.earscirev.2019.102973
Received 18 July 2019; Received in revised form 21 September 2019; Accepted 2 October 2019
Available online 28 October 2019

acknowledge that our use of some terms is different from what can be found in the literature.

The Oxford Learner's English Dictionary defines an "early-warning" as "*a thing that tells you in advance that something serious or dangerous is going to happen*". First used in the military, the term "early warning system" is "*a condition, system, or series of procedures indicating a potential development or impending problem*" (Oxford English Dictionary), or "*any series of steps established to spot potential problems*" (Dictionary.com). In this work, an "early warning system" (EWS) is a device, system or set of capacities that generates and disseminates timely and meaningful information to enable individuals, communities, and organizations threatened by a hazard to act timely and appropriately to avoid or to reduce the impact of the threat (Seibold, 2003; Zschau and Küppers, 2003; UNISDR, 2006; Di Biagio and Kjekstad, 2007; Huggel et al., 2010; Medina-Cetina and Nadim, 2008; Alfieri et al., 2012; United Nations, 2016). The meaning of "early" depends on the type of the hazard, and the perspective and responsibilities of who issues, and who receives and uses the warning message (Hamilton et al., 1997; Capparelli and Versace, 2011). A "warning" is an advice, a recommendation or an order to take an action e.g., to abandon an area, to remain inside a building or structure, to move to an upper floor (Hamilton et al., 1997). A "landslide early warning system", or LEWS, is an EWS devoted to landslides (Di Biagio and Kjekstad, 2007; Medina-Cetina and Nadim, 2008; Huggel et al., 2010; Stähli et al., 2015; Calvello, 2017; Greco and Pagano 2017; Piciullo et al., 2018; Segoni et al., 2018a).

We use the term "landslide" to encompass all types of mass movements (Hungr et al., 2014). Unless otherwise specified, in the work landslides are weather-induced, including rainfall and snowmelt induced landslides. Most LEWSs exploit thresholds, and a "threshold" is the minimum or maximum level of a quantity needed for a process to take place, or a state to change (White et al., 1996). A "rainfall threshold" is the minimum amount of rainfall for possible landslide occurrence in a period (Reichenbach et al., 1998; Guzzetti et al., 2007; Segoni et al., 2018b). Thresholds can be defined empirically, statistically, or using physically-based approaches. We use the terms "empirical" for thresholds defined heuristically (e.g., visually) and "statistical" for thresholds determined through statistical approaches including e.g., frequentist (Brunetti et al., 2010; Peruccacci et al., 2012, 2017), Bayesian (Guzzetti et al., 2007) and conditional probability (Berti et al., 2012) approaches.

We use the term "geographical" for LEWSs covering a geographical area (as opposed to site specific, "local" LEWS – not considered in this work), and we distinguish between regional, national, and global LEWSs. Our "geographical" systems were called "territorial" systems by Piciullo et al. (2018). A "regional" LEWS covers a large municipality, a metropolitan area, an administrative district, province or region, whereas a "national" LEWS covers an entire nation or a large part of a nation or state. We reserve the term "global" for LEWSs covering the larger portion of the globe.

In the literature, confusion exists between "prediction" and "forecast". Unless otherwise specified, we use the term "prediction" to refer to an estimate of an event happening in the future, the present or the past, and "forecast" for an estimate of the future state of a natural system obtained with a numerical model (Ramage, 1993). A "nowcast" is a short-term forecast, typically up to six hours (WMO, 2017), and a "hindcast" a forecast in the past, often used for testing a model using past data and information. We use the term "advisory" to encompass all stages or levels considered by the LEWSs, and the related messages.

To rank the development stage of the LEWSs, we use the terms "designed" for a system that is planned and designed, but for which a prototype does not exist; "experimental", when a working prototype exists and is undergoing testing and preliminary evaluation; "pre-operational" for a system that is working according to specifications but not necessarily regularly, that is undergoing testing, and it is not yet endorsed or certified by any organization; and "operational" when a system is working regularly according to specifications, and it is endorsed or certified by an organization. Finally, we use the term "dismissed" for a system that was abandoned or dismantled, irrespective of the reasons for abandoning or dismantling the system.

Albeit not clearly, the literature separates landslide models, warning models, and warning systems (Calvello, 2017). Here, we use the terms "landslide model", "forecast model", "process model", and "landslide forecast model" as synonyms, to describe a functional, empirical or physical relation linking measurements (e.g., rainfall) or variables (e.g., the water table depth in the slope) to the (possible) occurrence or lack of occurrence of landslides. Thus, a rainfall threshold is a type of landslide model. Further, a "warning model" is a framework for issuing landslide advisories. It can include one or more landslide models and advisory criteria i.e., rules, procedures, and protocols used to decide and issue advisories. Lastly, a "warning system" is the physical implementation of a warning model, which may contain one or more landslide forecast models.

3. Rationale for landslide forecasting and early warning

Systematic efforts to investigate concepts and frameworks for the early warning of natural hazards as cost-effective tools for disaster prevention and risk reduction begun in the 1990s, in the framework of the United Nations International Decade for Natural Disaster Reduction Early Warning Programme, and continued under its successor, the United Nations secretariat for Disaster Risk Reduction, first in the Hyogo Framework for Action 2005–2015 (UNISDR, 2005) and next in the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR, 2015). Descriptions of the concepts and frameworks of EWSs for different natural hazards are given e.g., by O'Neill et al. (1997); Hamilton et al. (1997); Zschau and Küppers (2003); Aleotti (2004); Basher (2006); UNISDR (2006); Calvello (2017); European Commission (2008); Huggel et al. (2010); Alfieri et al. (2012), and the United Nation (2016).

Focusing on landslides, Endo (1970) and Onodera et al. (1974) in Japan, Campbell (1975) in the USA, Lumb (1975) in Hong Kong, and Eyles (1979) in New Zealand, were first to identify empirical dependencies between rainfall and landslide occurrence, a key finding at the base of any modern, scientific attempt at operational landslide forecasting and landslide early warning. Campbell (1975) was probably the first to envision the possibility to forecast rainfall-induced landslides and to propose a framework for a LEWS – in his case for shallow landslides and debris flows in southern California. Recognizing that "The many variables that influence the origin of each individual debris flow make the prediction of small soil slips in specific places extremely difficult", he suggested that:

> *"A warning system […] could be constructed [using] three major elements, each of which is partly or wholly operative at the present time: (1) a system of rain gauges, recording the rainfall on an hourly basis; (2) a weather-mapping system capable of recognizing centers of high-intensity rainfall in the storm area and, at frequent intervals, plotting the location of these centers with respect to location of gauges with adequate registry for accurate transfer to slope maps or topographic maps; and (3) an administrative and communications network to collate the data, recognize when critical factors have been exceeded in a particular area, and inform the residents there. Such a system is probably well within the capability of existing technology".*

Campbell (1975) clear description of an operational LEWS and his lucid foresight were extraordinary; even more so considering that it took three decades to implement the vision in just a few regions of the world, as it will become apparent in the next section.

Forecasting landslides is a difficult and uncertain task that lays at the fuzzy boundary between science, technology, and decision making. The task is complex, and all the attempts towards operational landslide forecasting have adopted, implicitly or explicitly, a number of

Table 1
Rationale for landslide forecasting and landslide early warning. References: 1, Lyell (1830); 2, Furlani and Ninfo (2015); 3, Campbell (1975); 4, Keefer et al. (1987); 5, Wilson (2012); 6, Baum and Godt (2010); 7, Calvello and Piciullo (2016); 8, Versace et al (2018); 9, this work.

	Assumption	References
1	Landslides can be predicted, in space and time.	8, 9
2	The past is the key to the future.	1, 2
3	Rainfall is the primary trigger of landslides, and promotes the initiation of landslides through infiltration into the slope.	3, 4, 5
4	Rainfall is a good proxy for the groundwater conditions that lead to slope instability.	3, 4, 5
5	A threshold is a reliable descriptor of the behaviour of a slope forced by rainfall.	4, 5, 9
6	Rainfall can be measured and forecasted with the spatial and temporal accuracy necessary to predict landslides.	9
7	There is sufficient time to warn people leaving in potentially dangerous areas.	8, 9
8	Landslide forecasts can be used to issue useful landslide advisories.	5, 6, 7
9	Based on landslide advisory one can take actions to minimize landslide risk.	5

simplifying assumptions to reduce to a manageable extent the complex, and not yet fully understood, challenge of forecasting the possible occurrence of landslides, and the technological issues and operational problems related to the timely dissemination of meaningful information to administrations, organizations, communities, and individuals (Keefer et al., 1987; Wilson, 2012; United Nations, 2016). Below we discuss nine assumptions (Table 1).

The first assumption is that rainfall induced landslides can be predicted. The assumption is difficult to prove theoretically, but there is accumulating evidence that landsliding can be predicted, and that landslide forecasts can contribute to reduce landslide risk, particularly the risk to the population, at different temporal and geographical scales, and in different climatic and physiographical settings (Keefer et al., 1987; Wilson, 2012; Fathani et al., 2018; Rossi et al., 2019).

The second assumption descends from "uniformitarism" (Lyell, 1830; Hooykaas, 1963; Gould, 1965; Haff, 1996; Furlani and Ninfo, 2015), and it prescribes that "the past is a key to the future". Rainfall thresholds are defined studying past rainfall and landslide information, and spatially distributed slope stability models are calibrated using rainfall measurements and landslide information obtained from past events. Thresholds and slope stability models are then used to predict future landslides based on the assumption that future landslides will occur under the same conditions that caused landslides in the past. The assumption implies the stationarity of the rainfall and the landslide records, which are not guaranteed over long periods and where climate and environmental changes are large (Furlani and Ninfo, 2015; Gariano and Guzzetti, 2016).

The third assumption is that precipitation (chiefly rainfall) is the primary or the only trigger of (shallow) landslides. The simplification assumes that, infiltrating into the slope, rainfall accumulates in a saturated or partially saturated zone above a low permeability layer, often at or near the base of the colluvium, increasing pore-water pressure at shallow depth. This leads to a force imbalance that initiates the landslide. Debate exists on the role of the antecedent rainfall and soil-moisture conditions that can promote landslide initiation (Campbell, 1975; Brand et al., 1984; Keefer et al., 1987; Wilson, 2012). The relevance of the antecedent conditions depends on the local and regional settings, including e.g., the intensity and duration of the precipitation, the lithological characteristics of the rocks and soils, and the climate. Highly permeable soils and rocks are less sensitive to antecedent conditions, because water can drain easily; and where climate has distinct seasonal variations – such as in a Mediterranean climatic regime – the role of the antecedent rainfall is more relevant than where climate is stable throughout the year (Wilson, 2012).

The fourth assumption is that rainfall is a good proxy for the groundwater conditions that lead to shallow landslides. The simplification assumes that all (or most) of the rainfall that falls on a slope infiltrates (at least initially), reaches the saturated or partially saturated zone above the potential sliding surface, and contributes to slope instability at shallow depth (Campbell, 1975; Keefer et al., 1987; Wilson, 2012). The simplification is severe, as it implies that the surface and sub-surface morphological, lithological, and hydrological conditions are second order elements for landslide initiation. However, the simplification may prove reasonable over large areas (Alvioli et al., 2014).

The fifth assumption is that a threshold is an adequate descriptor of the stability/instability behaviour of a slope forced by rainfall. The simplification implies that over centuries or millennia, slopes equilibrate to the long-term precipitation regime conditioned by climate, and that for each slope a critical pore-water pressure – the result of a critical rainfall amount – exists and, when reached or exceeded, it triggers shallow landslides (Keefer et al., 1987; Wilson, 2012). Under low rainfall conditions a hillslope balances infiltration with evapotranspiration and surface and deep runoff, maintaining stability. When rainfall is intense the infiltration rate exceeds the deep drainage rate, a zone of partial or complete saturation forms, instability conditions occur and the slope fails. The assumption implies a "stable/unstable" behaviour of the slope, which is simplistic to describe the behaviour of single slopes, but may prove reasonably adequate for large areas or entire catchments (Reichenbach et al., 1998; Guzzetti et al., 2007).

The sixth assumption prescribes that rainfall can be measured and forecasted with sufficient spatial and temporal accuracy to predict landslide occurrence. The simplification assumes that the rainfall field obtained by rain gauges, weather radars or satellite estimates, is representative of the rainfall conditions and history at the location of the landslides, before and when landslides initiate. This may not be the case everywhere, given the low density of rain gauges (Michaelides, 2008; Kidd et al., 2017), particularly in mountain terrain (Nikolopoulos et al., 2015; Marra et al., 2017) where the radar signal is blocked or affected by other complications, in mountainous or complex terrain (Germann et al. 2006; Wilson 2012). Problems exists also with rainfall forecasts that are assumed to be accurate in space and time, and of adequate spatial and temporal resolution to predict landslides. Again, this may not be the case where the weather patterns are complex and were weather evolves rapidly.

The seventh assumption is that landslides can be forecasted with sufficient lead time to allow organizations, communities, and individuals to take mitigation actions (Wilson, 2012; Calvello and Piciullo, 2016). The lead time depends on the type and velocity of the landslides (Hungr et al., 2014), the extent of the area covered by the forecast, the scopes of the LEWS and of its users and beneficiaries. The assumption implies that LEWSs use different tools, data and information depending on the extent of the geographical and temporal coverages of the forecasts, and the type of landslides. As an example, to be effective, a LEWS designed to forecast soil slips and debris flows may use rainfall forecasts to extend the lead time, giving more time to react to the expected landslide events. However, since rainfall forecasts are affected by uncertainty, they reduce the temporal and spatial accuracy of the landslide predictions (Keefer et al., 1987; Wilson, 2012).

The eighth assumption is that landslide forecasts can be used to issue useful landslide advisories (Wilson, 2012; Calvello and Piciullo, 2016). The assumption implies that landslide forecasts are reasonably accurate and contain valuable information to help mitigating landslide risk, and that the inherent probabilistic content of the forecasts, and their uncertainties, are mapped into meaningful advisory levels (Calvello and Piciullo, 2016). In most cases, the mapping is not trivial and conditions the success (or failure) of a LEWS, and the usefulness of an advisory system. This is because the number and significance of the advisory levels control the performance of a LEWS (Piciullo et al., 2017a, 2017b). The assumption further implies that the same landslide forecast may be mapped differently (e.g., using different advisories schemes) depending on the beneficiaries and on the user needs.

The ninth assumption is that if (or when) organisations are informed that landslides are expected that could pose a threat to their assets or interests, or if (or when) communities or individuals are told that their safety or property is threatened by landslides, they would take appropriate measures to avoid or to minimize the threat (Wilson, 2012). The assumption implies that the information on the expected landslides is conveyed from the LEWS to the interested organisations, communities or persons in sufficient time, and in a way and format known to, and understood by the beneficiaries. Further, the users should have valid and effective actions to take, should be aware of them, and should be willing and prepared to take the actions. As such, the assumption implies preparative information campaigns before landslide advisories are issued regularly. It also implies that the advisories are issued by a trusted source (UNISDR, 2015).

4. Past and present landslide early warning systems

We now describe the main characteristics of 26 past and existing LEWSs. We present the systems based on their regional, national, or global coverage, loosely ordering the systems from the oldest to the newest in each geographical category. We consider only systems for which sufficient information was available to us to attempt a description and a critical analysis. We are aware that a few other LEWSs have existed or exist today (e.g., in Nicaragua, Indonesia, Sri Lanka, in Tennessee, North Carolina, Georgia, Virginia in the USA), but for these other systems we did not find sufficient (or any) information to allow a description and a thorough analysis. We further acknowledge that we may ignore the existence of a few other past and present LEWSs. However, we maintain that collectively the 26 LEWSs presented here, and analysed in the next section, are representative of the main characteristics, capabilities, and current problems of geographical LEWSs.

4.1. Regional systems

4.1.1. Hong Kong

The first regional geographical LEWS was set up in Hong Kong in 1977 by the Geotechnical Control Office (now Geotechnical Engineering Office, GEO) in response to catastrophic landslide events in 1972 and 1976 that caused many fatalities (Brand et al., 1984; Malone, 1988). Jointly operated by the GEO and the Hong Kong Observatory (HKO), the "Landslip Warning System" is the longest-lived and arguably the most successful LEWS in the world. Today, the LEWS issues landslide advisories for Hong Kong island, Kowloon and the New Territories (HGK, #1 in Figs. 1,2,3) (Chan et al., 2003; Choi and Cheung, 2013; Wong et al., 2014).

Through its more than 40 years of operation, the LEWS has undergone several changes. From 1977 to 1983, the system was in a pre-operational phase and used rainfall measurements collected by 20 rain gauges and two empirical rainfall thresholds defined by studying landslide and rainfall records from 1950 to 1973 (Lumb, 1975). The thresholds considered daily rainfall (from 1983, 24 h "rolling" rainfall, R_{24}) and cumulated (antecedent) rainfall in the previous 15 days. In this first phase, two landslide advisory levels were used internally. This was changed in the second phase (1984–1998), when the LEWS became operational and the advisories were announced publicly. In the second phase, the LEWS used empirical rainfall thresholds determined by analysing landslide and rainfall data from 1963 to 1982 (Brand et al., 1984) and considering R_{24} and 1 h rainfall intensity. Of the two advisory levels, the lowest was issued internally when R_{24} exceeded 100 mm at a single representative rain gauge, and the highest was released publicly when one or more of the following criteria were met: (i) R_{24} exceeded 175 mm; (ii) the cumulated rainfall in the previous 20 h and the rainfall forecasted for the next four hours exceeded 175 mm in at least ten rain gauges; and (iii) an intensity of 70 mm h^{-1} was exceeded at any rain gauge. In the third phase (1999–2003), the LEWS began considering landslide density i.e., the number of expected landslides per km^2, in vulnerable areas. This was done using an empirical relationship linking R_{24} to known (observed) landslide density (Pun et al., 1999). The advisory levels were increased to three, including, a "consultation" level, when R_{24} exceeded 100 mm in at least ten rain gauges, prompting dialogue between the GEO and HKO; an "alert" level, still internal, when the rainfall required to reach the next level was less than 100 mm; and a public "warning" level when the system forecasted at least ten (15 from 2001) landslides in the Hong Kong territory. The figure was obtained from an empirical relationship linking R_{24} (rainfall cumulated in the previous 21 h and forecasted for the next three hours) to landslide density, multiplying the density by the size of each vulnerable area, and summing the values for all the vulnerable areas.

The current phase of the LEWS is operational since 2004, and uses (i) improved rainfall measurements taken by a dense network of 122 automatic, high rate (5-min interval) rain gauges; (ii) rainfall estimates from SWIRLS radar nowcasts (Yeung, 2012); (iii) better weather forecasts; and (iv) a set of four empirical relationships linking R_{24} to landslide density for the four most common types of engineered slopes in Hong Kong i.e., soil cuts, rock cuts, fill slopes, and retaining walls (Yu, 2004; Chan et al., 2012). Using this complex information, for 1600 1.2 km × 1.5 km grid cells covering the Hong Kong territory, the LEWS forecasts the expected number of landslides for each of the four slope types. The system uses the same three advisory levels as in the previous phase, with three main differences. First, R_{24} is calculated cumulating the past 24 h rainfall. Second, during the "consultation" phase, HKO provides 1 to 3-h rainfall nowcasts based on radar data (Yeung, 2012). Third, the public "warning" level is reached when 15 or more slope failures are forecasted. Landslide advisories are disseminated to the public using various media including an official website, TV and radio channels, mobile phone apps, and social networks.

The LEWS predictive skills were evaluated quantitatively using 15 landslide events between 2001 and 2005 (Cheung et al., 2006). For each advisory in this period, the forecasted number of landslides in each level was compared to the number of reported landslides, and the obtained figure was used to determine the number of correct / incorrect forecasts. In the 5-year evaluation period, the LEWS proved successful in forecasting the failure of engineered slopes, with very few false alarms (Piciullo et al., 2018).

4.1.2. San Francisco Bay area, California, USA

From 1985 to 1995, the U.S. Geological Survey (USGS) and the U.S. National Weather Service (NWS) operated jointly a LEWS for the San Francisco Bay area (SFBA) (SFB, #2 in Figs. 1,2,3). Following a short experimental period, system operation began in February 1986 when the first public debris-flow hazard advisory in the United States was issued successfully. The system was terminated ten years later, in 1995, due to lack of human and economic resources (Wilson, 2012). This revolutionary LEWS used 24-h Quantitative Precipitation Forecasts (QPF) issued twice daily by the NWS with estimates of the total expected rainfall in four consecutive 6-h periods, and hourly rainfall measurements taken by 45 tipping-bucket rain gauges (in 1985, one rain gauge every ~400 km^2, increased to 60 in 1995, one gauge every ~300 km^2) operated by the NWS. The forecasted and the measured rainfall were compared against empirical rainfall thresholds for possible landslide occurrence in the SFBA (Keefer et al., 1987; Wilson, 2012).

In 1986, the first warnings were issued based on two empirical rainfall intensity–duration (ID) thresholds; a higher threshold was

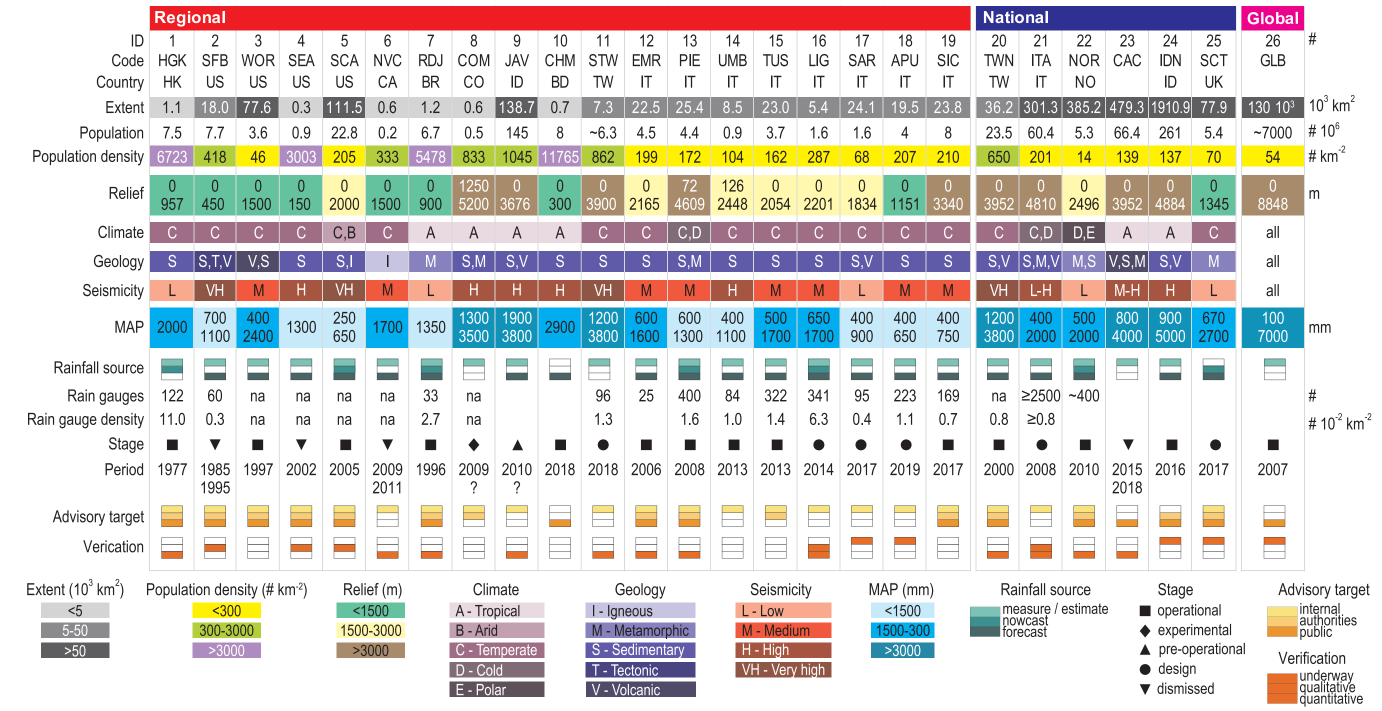

Fig. 1. Characteristics of 26 landslide early warning systems (LEWSs) considered in the work. Red, regional LEWS. Blue, national LEWS. Purple, global LEWS. ID, number of LEWS used in the text, figures, and tables. See Fig. 2 for LEWSs location. Code: HGK, Hong Kong; SFB, San Francisco Bay area; WOR, Western Oregon; SEA, Seattle; SCA, Southern California; NVC, North Vancouver; RDJ, Rio de Janeiro; COM, Combeima valley; JAV, Java; CHM, Chittagong metropolitan area; STW, Southern Taiwan, EMR, Emilia-Romagna; PIE, Piedmont; UMB, Umbria; TUS, Tuscany; LIG, Liguria; SAR, Sardinia; APU, Apulia; SIC, Sicily; TWN, Taiwan; ITA, Italy; NOR, Norway; CAC, Central America and Caribbean; IDN, Indonesia; SCT, Scotland; GLB, Global system. MAP, mean annual precipitation in the period 1970–2000 from Fick and Hijmans (2017). Köppen-Geiger climate types from Peel et al. (2007). Geological types from Chorlton (2007). Seismicity level from Giardini et al. (2003). References: (1) Brand et al. (1984); Malone (1988); Chan et al. (2003); Choi and Ceung (2013); Wong et al. (2014). (2) Keefer et al. (1987); Wilson (2012). (3) Mirus, pers. comm. (2019). (4) Chleborad (2003); Godt et al. (2006, 2009); Mirus, pers. comm. (2019). (5) NOAA-USGS Debris-Flow Task Force (2005); Mirus, pers. comm. (2019). (6) Jakob et al. (2012). (7) Ortigao et al. (2001); Ortigao and Justi (2004). (8) Cepeda and Murcia (1988); Godoy et al. (1997); Huggel et al. (2007). (9) Liao et al. (2010). (10) Ahmed et al. (2018). (11) Wei et al. (2018). (12) Martelloni et al. (2012); Lagomarsino et al. (2013); Segoni et al. (2015a, 2015b, 2018b). (13) Tiranti and Rabuffetti (2010); Tiranti et al. (2013, 2014). (14) Ponziani et al. (2013). (15) Segoni et al. (2014, 2015a); Rosi et al. (2015). (19) Brigandì et al. (2017). (20) Yin et al. (2015, 2016); Lin and Yin, pers. comm. (2019). (21) Rossi et al. (2012a, 2012b, 2018). (22) Boje et al. (2014); Devoli et al. (2015, 2018); Krøgli et al. (2018). (23) Kirschbaum et al. (2015). (24) Hidayat et al. (2019); Mulyana et al. (2019). (25) Reeves and Freeborough, pers. comm. (2019). (26) Kirschbaum and Stanley (2018); Mirus et al. (2019); Kirschbaum, pers. comm. (2019).

determined by examining shallow landslides and debris flows occurrence during six storms between 1955 and 1983 in the SFBA (Cannon and Ellen, 1985); and a lower threshold proposed for the La Honda study site in the Santa Cruz Mountains (Wieczorek, 1987). The second threshold was used in areas deemed particularly susceptible to rainfall-induced shallow landslides and debris flows (Wilson, 2012). By 1989, recognizing that antecedent seasonal rainfall was important for the initiation of debris flows in the SFBA, a threshold for the accumulated antecedent seasonal rainfall was added to the LEWS. This third seasonal antecedent threshold was calibrated using soil moisture measurements taken at the La Honda study site, which served as a benchmark for the entire San Francisco Bay region (Wilson, 2012).

The LEWS adopted a protocol in four steps of increasing severity to analyse the storms and decide on the proper advisory level. Before the rainfall totals reached the seasonal antecedent threshold, debris flow occurrence was considered improbable, and no advisory was issued. When the seasonal threshold was exceeded, the individual storms were evaluated individually to see if the expected intensity and duration of the rainfall was sufficient to trigger debris flows. Storms with peak rainfall periods below the lower threshold of Wieczorek (1987) were considered unlikely to initiate dangerous debris flows, and in general were not considered for an advisory. Brief and general (unspecific) advisories were issued for storms with accumulated rainfall just above the lower threshold of Wieczorek (1987). When the accumulated rainfall was approaching the upper threshold of Cannon and Ellen (1985), a "flash-flood/debris-flow watch" was issued "advising people living on or below steep hillsides, or near creeks, to stay alert and be prepared to evacuate, as debris flows were a strong possibility during the watch period" (Wilson, 2012). Lastly, when the accumulated rainfall exceeded the upper threshold (Cannon and Ellen, 1985), or when information on significant debris flow activity was available (e.g., from the media), a "flash-flood/debris-flow warning" was issued. For seven storms between 1986 and 1995 one or more debris-flow advisories were issued by the NWS, and communicated to the public through local radio and televisions (Wilson, 2012). The advisories predicted accurately the time of major landslide events, but were less accurate about the areas where the landslides occurred (Keefer et al., 1987). Local government agencies used the advisories for planning emergency response and to suggest evacuations.

While the original LEWS described by Keefer et al. (1987) and Wilson (2012) was dismissed, at the time of writing there is an operational landslide monitoring system across the SFBA that informs NWS alerts to reduce landslide risk. The details of the thresholds and alert levels have not been published (Collins et al., 2012; Mirus et al., 2019).

4.1.3. Western Oregon, USA

From 1997 to 2007, the Oregon Department of Forestry (ODF) operated a LEWS to forecast the possible occurrence of debris flows in selected areas of Western Oregon (WOR, #3 in Figs. 1,2,3) (Wilson, 2012). In 2007, the NWS took over the operation and management of the LEWS (Baum and Godt, 2010). A result of the synergic effort by four Oregon state government departments and offices (ODF, DOGAMI,

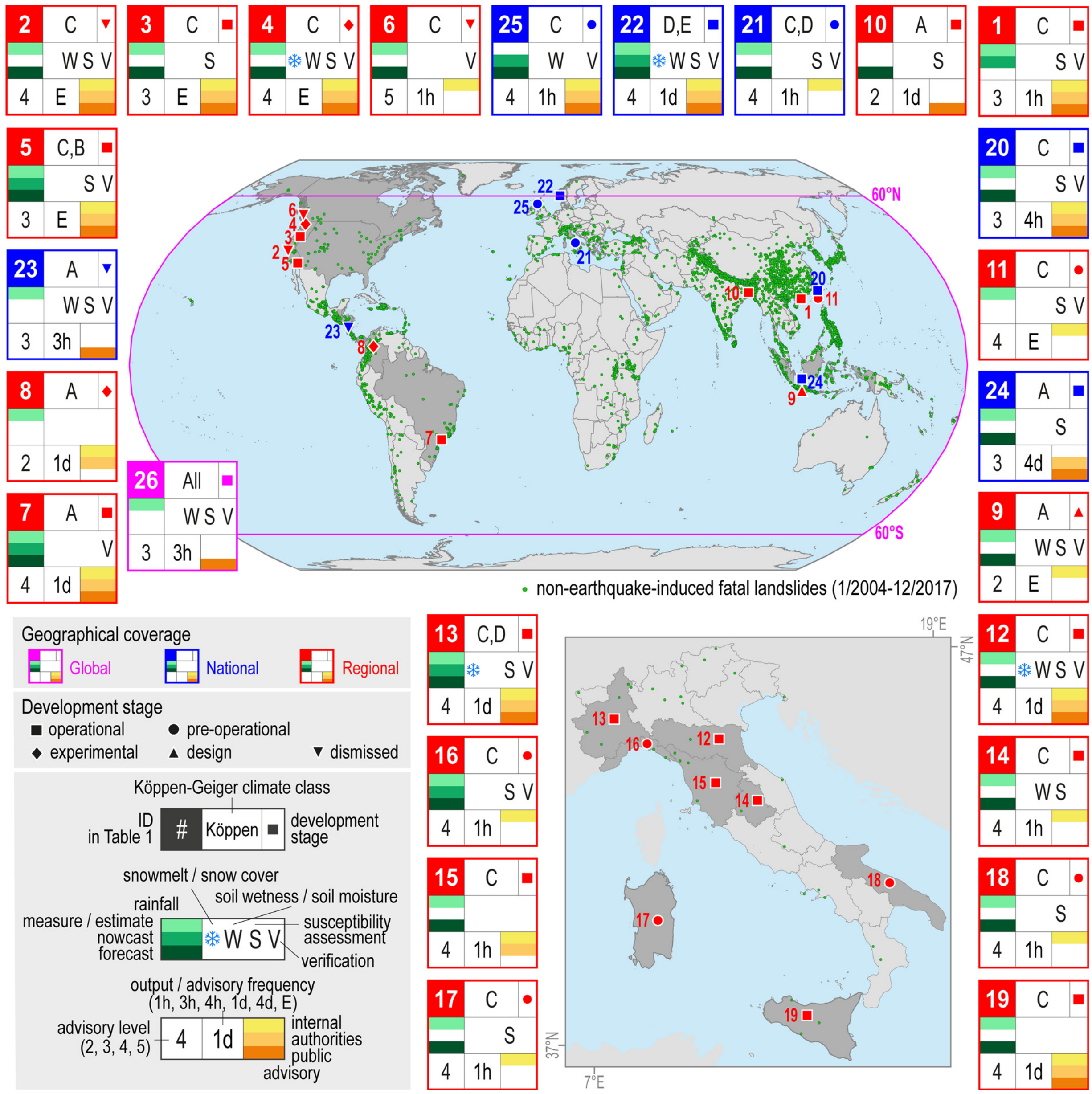

Fig. 2. Location of 26 past and present landslide early warning systems (LEWSs) considered in the work. See Fig. 1 for LEWSs numbering. Global map shows locations of eleven regional (red) and seven national (blue) LEWSs, and coverage of the global LEWS (violet). Green dots show non-earthquake-induced fatal landslides between 2004 and 2016 inventoried by Froude and Petley (2018) and updated recently to cover the period from January 2004 to December 2017 (Froude and Petley, personal comm. 2019). Map for Italy shows eight regional LEWSs (red). Both maps use the Equal Earth map projection (EPSG:2018.048) (Šavrič et al., 2019). For each LEWS, the coloured boxes show the geographical coverage (red, regional; blue, national, purple, global). Upper row of the box shows: LEWS ID (Fig. 1); Köppen-Geiger climate types of Peel et al. (2007); system development stage (in 5 classes). Middle row shows: sources of rainfall information (in 3 classes); if the system uses snowmelt / snow cover (snowflake), soil wetness / soil moisture (W) or susceptibility (S) information, and if the system was evaluated (V). Lower raw shows: number of alert levels (from 2 to 5), the advisory frequency and the advisory dissemination level (internal, authorities, public). See text for explanation.

ODOT, OEM) and the US National Weather Service, the LEWS uses rainfall measurements and forecasts that are compared to empirical ED rainfall thresholds established for debris flow prone areas based on the analysis of past rainfall events that caused a significant number of debris flows. ODF geotechnical specialists, on alert during critical conditions, may lower the thresholds heuristically considering specific weather conditions (e.g., snow at low elevation with warm rain expected, heavy rain after a hard freeze, storms moving from the south or over the Pacific Ocean), the geographical location of the debris flow prone areas, and the susceptibility to rapidly moving landslides. Between 1997 and 2006, the LEWS issued eight landslide "advisories" and four "warnings" (http://www.oregongeology.org/Landslide/ODFDebrisFlowWarningTechOverview.pdf, accessed 14 September 2019). The "advisories" were issued when the forecasts indicated that the threshold precipitation was reasonably possible, and "warnings" when the threshold was reached in coastal or inland debris flow prone areas, or was deemed likely to be exceeded during periods of darkness at critical locations (e.g., in populated areas). During "warning" periods, an ODF geotechnical expert was on alert.

4.1.4. Seattle, Washington, USA

Since 2002, the USGS, the NWS, and the City of Seattle operate a prototype LEWS for Seattle and the Puget Sound, along the NW coast of the US state of Washington (SEA, #4 in Figs. 1,2,3). The LEWS exploited complex information, including (i) near real time precipitation measurements taken by rain gauges in the City of Seattle and daily

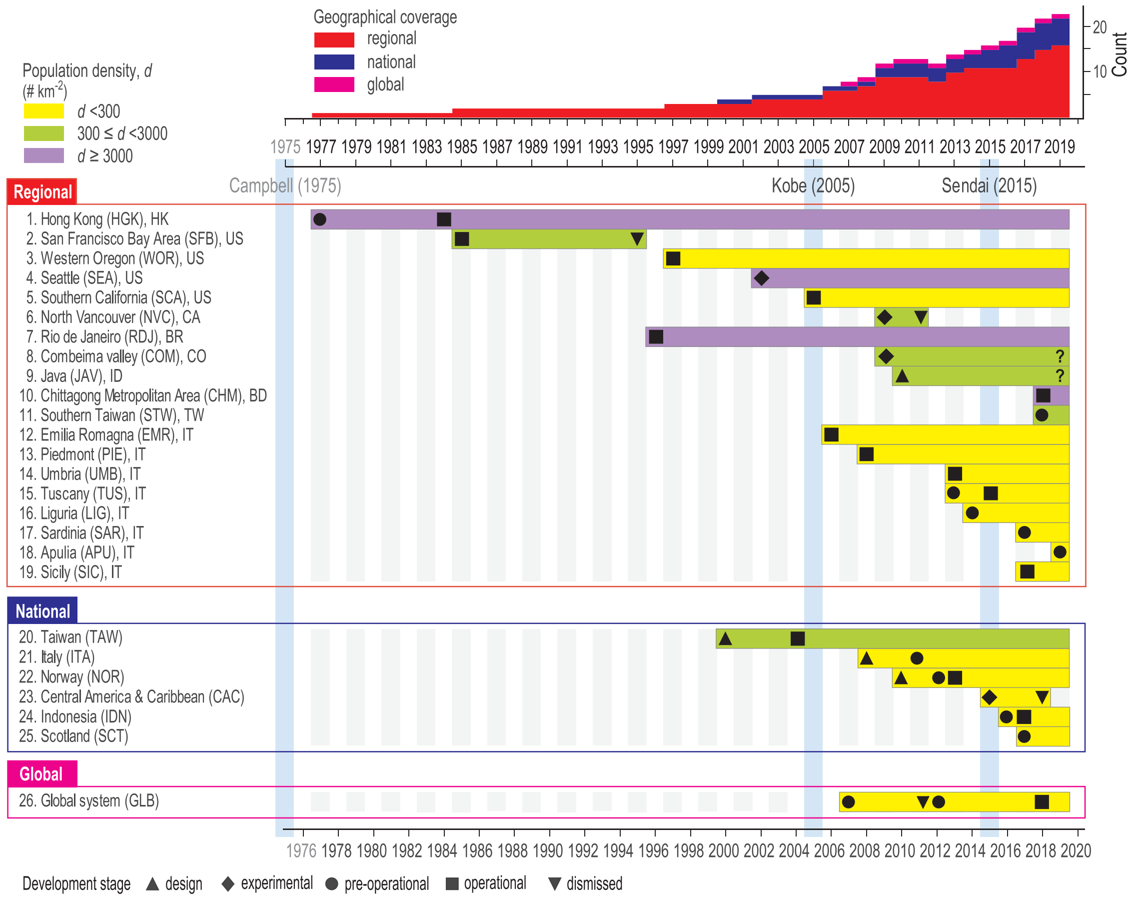

Fig. 3. Temporal coverage of 26 past and present landslide early warning systems (LEWSs) considered in this work. See Fig. 1 for the LEWSs characteristics, and Fig. 2 for the LEWSs numbering. Horizontal bar chart shows temporal coverage of the single LEWSs in the 44.5-year period from January 1977 to June 2019. Bars show temporal range of the LEWSs. Bar colours show population density (d, people per km^2) in the LEWSs areas, in three classes. Black symbols show LEWSs development stage, in five classes. Upper vertical bar chart shows count of LEWSs per year. Vertical light blue bars show years of the Kobe (UNISDR, 2005) and Sendai (UNISDR, 2015) UN global conferences and related frameworks.

climate measurements taken by twelve stations in the Seattle area; (ii) soil moisture and pore pressure measurements; (iii) QPFs provided by the NWS; (iv) snowmelt estimates; (v) empirical rainfall thresholds for possible landslide occurrence, including an antecedent threshold linking precipitation cumulated in the 72 h (3 days, P_3) before landslide activity to the precipitation in the 15 days (P_{15}) before P_3 (Chleborad, 2003) and an empirical ID threshold (Godt et al., 2006); and (vi) estimates for the Antecedent Water Index (AWI), a proxy for soil wetness and a substitute for soil moisture and pore pressure monitoring, which accounts for rainfall and evapotranspiration and uses an exponential decay to model soil drainage (Godt et al., 2006, 2009). The antecedent threshold was determined studying rainfall events that caused 199 "wet-season" (November to April) landslides from 1933 to 1997 (Chleborad, 2003), and the ID threshold examining six rainfall events with landslides between 1978 and 1997, validated using rainfall and landslide data from 1997 to 2003. To combine this complex information, the LEWS used a decision tree (Godt et al., 2006; Chleborad et al., 2008). The antecedent threshold was used in routine operations as an indicator of conditions favourable to landslide occurrence, and the ID threshold (40 or 55 mm day^{-1}, depending on wetness conditions, Baum and Godt, 2010), together with the AWI came into play during heavy rainfall periods (> 25 mm in 24 h) expected to last for at least one or two days, to indicate when large numbers of landslides were likely. In an attempt to improve the landslide prediction rate, a prototype hydrological threshold informed by soil moisture and pore-water pressure conditions was proposed recently by Smith et al. (2017) and Scheevel et al. (2017), but is not yet implemented operationally (Mirus et al., 2019).

To issue informal landslide advisories to government officials and the public, this LEWS used a 4-level advisory scheme (Chleborad et al., 2008; Baum and Godt, 2010). Rainfall conditions below the thresholds represented the "null" level, when landslides were not expected. Exceedance of the antecedent threshold by measured and forecasted rainfall, or exceedance of the ID threshold by forecasted rainfall (40 or 55 mm day^{-1}, depending on wetness conditions), represented an "outlook" and activated more intense monitoring of weather conditions, soil moisture and pore pressure, and tracking of the AWI. During an "outlook", measured or forecasted heavy rainfall or AWI > −0.1 raised the advisory level to a "watch", and the NWS informed government officials and the public of possible landslide occurrence. When the AWI exceeded 0.02 or soil saturation exceeded 60%, and the measured and forecasted rainfall exceeded the ID threshold, the advisory level was raised to a "warning", and the NWS alerted government officials and the public.

4.1.5. Southern California, USA

In 2005, NOAA and the USGS launched an innovative prototype LEWS for flash floods and debris flows in recently burnt areas in eight counties of Southern California (SCA, #5 in Figs. 1,2,3). The LEWS operates on a 24 -h, 7-day-a-week basis, and combines the NWS Flash Flood Monitoring and Prediction system with rainfall thresholds for debris flow and flash flood occurrence in burnt areas (NOAA-USGS Debris-Flow Task Force 2005). The LEWS monitors precipitation in near real time using rain gauge networks, C-band Doppler radars and satellite estimates. QPF are obtained from a suite of numerical and statistical weather models mediated by forecasters' expertise. Studying storms that did and did not produce debris flows in recently burnt areas, empirical ID thresholds were determined for the first winter after a fire, and following a year of vegetative recovery, for three different physiographic and weather settings in Southern California (Cannon et al., 2009; NOAA-USGS Debris-Flow Task Force 2005). The ID thresholds were updated repeatedly to improve predictions of post-fire debris-flow likelihood (Staley et al., 2013, 2016, 2017). The LEWS uses web-based technology to provide information about each fire, and to show hazard maps for catchments deemed likely to produce large debris flows in burnt areas. When measured and forecasted precipitation exceeds pre-defined thresholds, flash flood and debris flow advisories are delivered to emergency personnel and the public through the NOAA's Advanced Weather Information Processing System (AWIPS) using a 3-level advisory system, including "outlook", "watch", and "warning". Between 2005 and 2008, the LEWS issued 104 "warnings", 45% of which are known to have produced debris flows. Local communities and emergency response personnel successfully used the advisories for evacuations and to deploy equipment (Restrepo et al., 2009).

4.1.6. Vancouver, British Columbia, Canada

From October 2009 to April 2010, and from October 2010 to April 2011, Jakob et al. (2012) operated an experimental, near real-time debris-flow warning system for the District of North Vancouver, in British Columbia (NVC, #6 in Figs. 1,2,3). For four catchments covering $\sim 600\ km^2$, empirical ID thresholds had failed to forecast known debris-flows and were considered unsuited for operational debris-flow forecasting. Discriminant analysis of 25 rainfall variables, including cumulated storm rainfall, rainfall duration, and mean rainfall intensity for different periods, for 63 storms, of which 27 that caused and 36 that did not cause debris flows, allowed the identification of the 4-week antecedent rainfall, the 2-day antecedent rainfall, and the 48-h event rainfall intensity during the landslide-triggering storm as the three best variables to discriminate between storms that had, and had not resulted in debris flows. Based on these rainfall variables, two classification functions were defined for storms that did and did not cause debris flows. For each storm, subtraction of the classification scores obtained for the two functions gave the index ΔCS, a proxy for the likelihood of debris flow occurrence. Depending on ΔCS, the LEWS considered five advisory levels i.e., "no watch", "watch I", "watch II", "warning", and "severe warning". In the operational periods, nine debris flows were documented during four storms when the "warning" level was reached, and in one storm when the "watch II" level was exceeded for 26 consecutive hours. No debris flows were observed for the "watch I" and "no watch" levels. The "severe warning" level was never reached in the operational periods. In nine cases, the "warning" level was reached and debris flows were not observed, resulting in false alarms (false positives).

4.1.7. Rio de Janeiro, Brazil

Following multiple debris-flow disasters, in 1996 the city of Rio de Janeiro established an operational LEWS. Managed by the Fundacão Instituto de Geotechnica do Municìpio do Rio de Janeiro (GEO-Rio foundation), the Alerta-Rio (Rio Watch) system (RDJ, #7 in Figs. 1,2,3) uses (i) rainfall and meteorological data collected every 15 min by a network of 33 automated meteorological stations, corresponding to an average density of one station every $\sim 37\ km^2$; (ii) rainfall estimates obtained by two meteorological Doppler radars installed in 1999 and 2010; and (iii) short-term numerical weather forecasts issued twice daily by the Brazilian Centre for Weather Forecasting and Climate Studies (Ortigao et al., 2001; Ortigao and Justi, 2004). To issue the advisories, Rio Watch compares rainfall measured by the meteorological stations with empirical rainfall thresholds originally defined by D'Orsi et al. (1997) analysing 65 rainfall-induced landslides, and modified subsequently. Three thresholds that consider cumulated rainfall in 1, 24, and 96-h periods separate four landslide severity levels, characterized by an increasing expected landslide abundance, including (i) a low level for landslides not directly triggered by rainfall; (ii) a medium level for the occurrence of sporadic rainfall-induced landslides, mostly on artificial slopes; (iii) a high level for abundant landslides triggered by heavy rainfall on natural and artificial slopes; and (iv) a very high level, for abundant and widespread landslides on natural and artificial slopes. Landslide advisories are issued in Portuguese, once daily for four areas of the Rio de Janeiro municipality. To distribute the advisories to the authorities, emergency response agencies and the public, Rio Watch exploits multiple communication means, depending on the severity of the advisory. During normal operation, the system issues one advisory per day. Medium level warnings are updated every six hours and disseminated using a dedicated website and sent to identified municipality departments. In addition to this, high and very high warning levels are communicated to the public through television and radio stations. To evaluate the forecasting performances of the Rio Watch LEWS, Calvello et al. (2015a, 2015b) applied the "event, duration matrix performance" (EDuMaP) method of Calvello and Piciullo (2016) to known rainfall and landslide events in the 3-year evaluation period 2010–2012. Results revealed the overall good performance of the system, albeit with a significant number of false alarms in the SE zone, probably due to a low rainfall threshold.

4.1.8. Combeima valley, Colombia

In 2009, the Swiss Development and Cooperation Agency launched a project to develop a LEWS for the Combeima valley, a hilly and mountainous area in Colombia where rainfall induced landslides are frequent (COM, #8 in Figs. 1,2,3) (Cepeda and Murcia, 1988; Godoy et al., 1997; Huggel et al., 2007). Operative in 2011 (Thiebes, 2012), no further information on the functionality of the system was available to us at the time of writing. The LEWS used daily rainfall measurements taken by twelve rain gauges, and ECMWF ERA-40 6 h rainfall reanalyses from 1957 to 2002 at the centre of a $2.5^\circ \times 2.5^\circ$ grid cell located ~ 60 km NE of the valley. A stochastic approach was used to estimate the error associated to the ERA-40 rainfall reanalyses. Since a threshold for possible landslide occurrence was not available for the Combeima valley, and landslide and rainfall information to construct a threshold was not available, the LEWS adopted the minimum global ID threshold for shallow landslides and debris flows proposed by Caine (1980). The system further used an optimized cost function considering (i) the occurrence (or the lack of occurrence) of debris flows; (ii) the costs associated to human losses in case of a debris flow event without evacuation ("false negative"); and (iii) the costs of evacuation when debris flows do not occur ("false positive"). In addition, the LEWS used local geophones to detect debris flow activity in drainage channels of the Combeima valley. This geophysical information was transmitted in real time to the Regional Emergency Committee of Tolima, in Ibagué.

4.1.9. Java, Indonesia

Liao et al. (2010) described the design of a LEWS for Java, a 128,297 km^2 island of Indonesia where rainfall induced landslides are frequent (JAV, #9 in Figs. 1,2,3). The LEWS exploited satellite-based precipitation estimates provided by the NASA Tropical Rainfall Measuring Mission (TRMM), QPFs provided by a weather model, a statistically-based landslide susceptibility assessment, and a modified version of the physically-based SLIDE model for spatially-distributed slope stability evaluation (Montrasio and Valentino, 2008). Where susceptibility was deemed high or very high, the SLIDE model was run at $30\ m \times 30\ m$ resolution using pre-defined values for the necessary geometrical and mechanical properties of the slope terrains, forced by measured and forecasted rainfall. At the time of writing, no information is available on the status of this proposed LEWS.

4.1.10. Chittagong Metropolitan Area, Bangladesh

For the densely populated Chittagong Metropolitan Area (CHM,

#10 in Figs. 1,2,3) of Bangladesh, where rainfall-induced landslides are frequent and have repeatedly caused loss of lives and property, a team of scientists from five countries operates a LEWS on a voluntary basis (Ahmed et al., 2018). To prepare landslide forecasts, the LEWS exposits three empirical rainfall thresholds, daily quantitative rainfall forecasts, and a statistically-based landslide susceptibility zonation. Three ED rainfall thresholds, for 24, 48, and 72-h accumulation periods, were obtained from daily rainfall measurements in the 58-year period 1960–2017, and a record of 50 landslides in the same period, 14 of which were used to definite the thresholds and 36 for their validation. The daily rainfall forecasts are obtained from World Weather Online, a global weather forecast provider. The landslide susceptibility zonation was obtained from the same 50 landslides used to construct the thresholds, and a set of eleven thematic maps showing morphology, drainage, geology, soil and other environmental information, modelled using an artificial neural network classification approach. The LEWS produces landslide advisories heuristically, combining the rainfall forecasts, in three classes, and the susceptibility zonation, also in three classes. The worst scenario is when high cumulated rainfall is forecasted in a highly susceptible area. Less severe scenarios occur when high cumulated rainfall is forecasted in medium or low susceptibility areas, or when low or medium cumulated rainfall is forecasted in medium or low susceptibility areas. Landslide advisories are made available publicly on the web, and concerned citizens can also register to receive 3-day landslide scenarios via e-mail. At the time of writing, the LEWS was not adopted or endorsed by any public organization in Bangladesh.

4.1.11. Southern Taiwan

In southern Taiwan, Wei et al. (2018) designed and tested a pre-operational LEWS (STW, #11 in Figs. 1,2,3) that uses rainfall measurements, a landslide susceptibility zonation, and empirical rainfall thresholds. The rainfall measurements are obtained by a network of 96 rain gauges managed by the Taiwan Central Weather Bureau (CWB), corresponding to an average density of one gauge every ~77 km^2. The susceptibility zonation, in three classes of low, moderate, and high susceptibility, was prepared through logistic regression modelling of landslide and thematic information, adopting a slope unit terrain subdivision. Rainfall thresholds were determined for each susceptibility level through an historical analysis of past rainfall events with landslides, based on 3 h mean rainfall intensity (I_3) and 24 h cumulated rainfall (R_{24}). The LEWS prepares landslide forecasts for each slope unit based on an empirical matrix that combines rainfall intensity, I_3 and cumulated rainfall, R_{24}. When the thresholds are reached or exceeded, the system issues advisories adopting a 4-level scheme of increasing severity. For the same severity level, the threshold values increase as susceptibility decreases, and a larger (smaller) rainfall amount is necessary to issue an advisory in less (more) susceptible slope units. The four advisory levels are linked to actions of increasing severity, namely, no action for the “low” level, advisory messages sent to authorities and the public for the “medium” level, recommended evacuation for the “high” level, and mandatory evacuation for the “extreme” danger level. The LEWS was validated quantitatively using three catastrophic shallow landslide events occurred in 2016, and two past event inventories. Results revealed the good forecasting performances of the LEWS.

4.1.12. Emilia-Romagna, northern Italy

In 2006, the regional government of Emilia-Romagna was the first in Italy to operate a regional LEWS to forecast landslides in their territory (EMR, #12 in Figs. 1,2,3). SIGMA, jointly developed by the University of Florence, the Geological Survey and the Civil Protection Agency of the Emilia-Romagna Region (Martelloni et al., 2012; Lagomarsino et al., 2013; Segoni et al., 2015a, 2018c), forecasts shallow and deep-seated landslides using quantitative, 72 h rainfall forecasts obtained from the COSMO-I7 numerical weather model, and hourly rainfall measurements taken by originally 19 (Martelloni et al., 2012) now 25 (Lagomarsino et al., 2013) automated rain gauges, each representative of the rainfall conditions in the originally 19, now 25 geo-hydrological alert zones covering the region. Every day, and for each alert zone, the LEWS compares against pre-defined, statistical rainfall thresholds the amount of rainfall cumulated in 1 to 3-day periods for shallow landslides, and in 4 to 245-day periods (eight months) for deep-seated landslides (Martelloni et al., 2012). SIGMA considers the effect of snow accumulation in the rain gauges, and of snowmelt on the ground that can generate landslides in the Emilia-Romagna region (Martelloni et al., 2013). The system adopts a 4-level scheme of landslide “criticality” based on the expected number of landslides in each alert zone, including “no landslides” (0 to 1 landslides), “low” (2–19 landslides), “moderate” (20–59), and “high” (≥ 60). To enhance the forecast spatial resolution, the system uses a 100 m × 100 m grid-based landslide susceptibility map, in four classes, obtained using a Bayesian, random forest approach used to model a set of 25 morphometric and thematic variables (Segoni et al., 2015b). A heuristic matrix is then used to modulate the landslide criticality levels with landslide susceptibility, and a nested, 4-tier system is adopted to prepare landslide forecasts at increasing spatial resolutions, from the large geo-hydrological alert zones (tier 1), through mid (tier 2, hundreds of km^2) and high (tier 3, tens of km^2) resolution for municipalities, to a very-high resolution (tier 4, 100 m × 100 m) used to highlight where landslides are more likely during a storm (Segoni et al., 2015b). The performance of SIGMA was evaluated for the 3-year period 2008–2010. Results showed that all the missed alarms and the majority of the false alarms (84%) occurred in the lowest critical level (Lagomarsino et al., 2013), and that the percentage of missed and correctly forecasted landslides for each critical level was independent of the local morphological and environmental settings (Martelloni et al., 2012).

4.1.13. Piedmont, northern Italy

Since 2008, the regional government of Piedmont operates a regional LEWS to forecast landslides in the mountains and the hills of their territory (PIE, #13 in Figs. 1,2,3). Building on early work by Aleotti (2004), the Piedmont Regional Environmental Protection Agency developed and operates a suite of three complementary landslide forecasting systems, namely, the DEFENSE (Tiranti et al., 2014), SMART (Tiranti and Rabuffetti, 2010) and TRAPS (Tiranti et al., 2013) systems. DEFENSE (Tiranti et al., 2014) compares hourly, empirical ID thresholds against rainfall intensity estimates obtained by a weather radar, using a storm-tracking algorithm (Cremonini and Bechini, 2010; Cremonini and Tiranti, 2018) and QPFs in good visibility areas, to forecast the occurrence of channelized debris flows in small mountain catchments. SMART (Tiranti and Rabuffetti, 2010) uses empirical ID thresholds to forecast shallow landslides in the mountains and the hills based on rainfall measured by a network of ~ 400 rain gauges, corresponding to an average density of one gauge every ~ 63 km^2, and precipitation forecasted by the COSMO-I7 numerical weather model. The spatial-temporal landslide forecasts are modulated locally using a 1:100,000 scale landslide susceptibility map. Lastly, TRAPS (Tiranti et al., 2013) compares cumulated rainfall thresholds against 60-day antecedent cumulated precipitation and snowmelt to forecast the (re-)activation of deep-seated translational and rotational slides common in the hills of southern Piedmont. The three nowcasting and forecasting systems are updated hourly, and the outcomes monitored through a dedicated web-based interface. Automatic landslide advisories, in the form of bulletins, are prepared at 13:00 daily for each of the eleven geo-hydrological alert zones covering the region, adopting a 4-level advisory scheme (“no significant phenomena”, “localized phenomena”, “widespread phenomena”, and “abundant and widespread phenomena”), and are delivered via email to civil protection and local authorities, and via SMS messages to forecasters on duty. The predictive performance of this complex LEWS was evaluated through a hindcast of two past events in 2013 (Devoli et al., 2018) and 2016 (Cremonini and Tiranti, 2018). Results revealed that both events were forecasted successfully, and that the forecasts proved valuable to decide appropriate civil protection actions.

4.1.14. Umbria, central Italy

Since 2013, the regional government of Umbria operates a LEWS in their territory (UMB, 14 in Figs. 1,2,3). The LANDWARN system (Ponziani et al., 2013) operates at two geographical scales i.e., on 111 known and instrumented landslides, mostly in urban and sub-urban areas; and on the entire regional territory. At the regional scale, every hour LANDWARN analyses rainfall and temperature measurements taken by a network of meteorological stations (i.e., an average density of one station every ~100 km^2) in the previous 20 days, and quantitative, 72 -h rainfall forecasts provided by COSMO-ME at 5 km × 5 km resolution. The LEWS compares measured and forecasted rainfall with pre-defined empirical ED thresholds, corrected considering soil moisture conditions estimated by a soil water balance model, based on the Green and Ampt (1911) infiltration model, using rainfall and temperature information for the preceding 20 days. The LEWS prepares near-real time, dynamic landslide risk scenarios combining measured and forecasted rainfall data with a susceptibility zonation of Umbria, at 100 m × 100 m resolution, and with vulnerability information for different types of elements at risk, including roads, infrastructures, and normal and strategic buildings. Using a 4-level advisory scheme of increasing risk, the system publishes maps showing the estimated risk levels in each grid cell. To our knowledge, no validation of the risk scenarios or evaluation of the system performance was performed.

4.1.15. Tuscany, central Italy

In 2015, after two years of testing, the regional government of Tuscany began operating a LEWS in their territory (TUS, #15 in Figs. 1,2,3). Designed by the University of Florence to support decisions of the regional civil protection authorities (Segoni et al., 2015a), the LEWS uses near real-time rainfall measurements taken by 322 automated rain gauges, corresponding to an average density of one gauge every ~ 71 km^2, quantitative rainfall forecasts provided by the COSMO I5/I7 weather model at 7 km × 7 km resolution for 6, 12, 24, and 48-h periods (Cacciamani et al., 2002), and 25 statistical ID thresholds, one for each geo-hydrological alert zone in the Region, determined studying rainfall records and information on more than 3000 landslides in Tuscany between 2000 and 2013 by Segoni et al. (2014) and Rosi et al. (2015). Every hour and for each rain gauge, the LEWS cumulates the measured and the forecasted rainfall for 6, 12, 24, and 48-h periods to define four landslide scenarios. For each alert zone, a landslide advisory is issued when the measured and the forecasted rainfall in at least one rain gauge exceeds the corresponding threshold, for any of the four scenarios. Civil protection personnel consult the forecasts through a proprietary web-based interface, and use them to prepare and publish daily bulletins showing landslide critical levels in each alert zone, adopting a 4-level advisory scheme. To our knowledge, no validation of the landslide risk scenarios or evaluation of the performance of the system was performed.

4.1.16. Liguria, northern Italy, Apulia and Sardinia, southern Italy

The regional governments of Liguria, Apulia and Sardinia are testing the pre-operational use of the SARF LEWS (LIG, SAR, APU; #16, 17, and 18 in Figs. 1,2,3). These are regional versions of the national SANF LEWS (ITA, #21) presented in section 4.2.2. Testing of the systems began in 2014 in Liguria, in 2017 in Sardinia, and in 2019 in Apulia. The three LEWSs exploit rainfall measurements taken by regional rain gauge networks, quantitative rainfall forecasts, ED rainfall thresholds, and a common landslide susceptibility assessment. The three regional LEWSs currently use hourly rainfall measurements taken by 341 rain gauges in Liguria and in the surroundings alert zones (an average density of one gauge every ~ 16 km^2), 95 in Sardinia (one gauge every ~ 250 km^2), and 223 in Apulia and in the surrounding regions (one gauge every ~ 91 km^2), and quantitative rainfall forecasts for 3, 6, 12, 24, and 48-h periods provided by the Italian COSMO-I7 numerical weather model at 7 km × 7 km resolution (shortly to become COSMO-I5 at 5 km × 5 km resolution), updated twice daily. The system for the Liguria region (#16) also exploits an ensemble of regional rainfall forecasts (Corazza et al., 2018), and an improved rainfall field obtained merging point rainfall measurements at the gauge locations and spatially distributed rainfall estimates obtained by a weather radar (Silvestro et al., 2009; Sinclair and Pegram, 2005; Pignone et al., 2013). In Liguria, the LEWS uses a regional, statistical ED threshold obtained studying 316 rainfall events triggering 381 landslides in the period between October 2004 and August 2014. Pending the definition of reliable regional thresholds, in Apulia and Sardinia the LEWSs use a national threshold defined for Italy by Peruccacci et al. (2017). Finally, due to the lack of specific regional susceptibility assessments, the three LEWSs use the same grid-based, statistical landslide susceptibility model used by the SANF national LEWS (#21).

Every hour, for their territory, the three LEWSs compute a “nowcast”, through a weighted sum of the probabilities of landslide occurrence for 24, 48, 72, and 96-h antecedent rainfall periods; a “forecast”, from the probabilities associated to rainfall forecasts for the next 3, 6, 12, 24, and 48 h; and a second “forecast”, combining the probabilities associated with the antecedent rainfall and the rainfall forecasts, modulated by landslide susceptibility. The “nowcasts” and the “forecasts” are prepared for each rain gauge, aggregated within each geo-hydrological alert zone in the regions, and interpolated at 1 km × 1 km resolution. The “nowcasts” and “forecasts” are made available to regional civil protection forecasters using a dedicated web-based platform. Evaluation of the LEWS prediction skills has started in Liguria by comparing the system “nowcasts” and “forecasts” against the time and location of 414 known landslides triggered by 230 rainfall events between April 2012 and September 2015. In Apulia and Sardinia, collection of information on the past landslides is underway, and will be used to evaluate the LEWSs performance adopting an hindcast approach.

4.1.17. Sicily, southern Italy

Since September 2017, the Civil Protection Department of the regional government of Sicily operates HEWS (Brigandì et al., 2017), a LEWS used to forecast rainfall-induced landslides in the island (SIC, #19 in Figs. 1,2,3). Designed by the University of Messina (Brigandì et al., 2017), HEWS uses two sets of empirical ED thresholds proposed by Gariano et al. (2015) for Eastern and Western Sicily studying a record of 265 shallow landslides in Sicily in the 12-year period 2002–2012, and hourly rainfall measurements taken by a network of 169 rain gauges in the same period. To issue landslide advisories, HEWS compares 48 -h QPFs for Sicily against the two sets of rainfall thresholds for Eastern and Western Sicily, for three non-exceedance probability levels (0.07, 0.20, 0.50, Gariano et al., 2015). The three thresholds, corresponding to “ordinary”, “moderate”, and “high hazard” conditions, are used to separate four levels of increasing severity, with each level associated to a risk condition, and to specific civil protection phases and actions. Once daily, based on the HEWS forecasts, the regional civil protection office prepares a bulletin with landslide advisory levels for the nine geo-hydrological alert zones in Sicily. The bulletins, valid from 16:00 on the issuing day to 23:59 on the following day, are made available to the public on a website. To our knowledge, no validation of the landslide advisories or evaluation of the LEWS performance was executed.

4.2. National systems

4.2.1. Taiwan

Due to its geographical location and the geological and climatic settings, Taiwan is highly prone to rainfall-induced landslides. It is therefore not surprising that the Taiwanese government has long been interested in operational landslide forecasting and related early warning. According to Wilson (2012), early attempts to establish an EWS for debris flow warning in the island's mountain areas began in the early 1990s, but proved "disappointing". The system often produced false and missed alarms, and people living in debris flow prone areas lost confidence in the system; which was terminated in 1998 (Wilson, 2012). Efforts resumed in 2000 when the Soil and Water Conservation Bureau (SWCB) pooled with the National Cheng-Kung University and the National Taiwan University to design and implement an operational system to forecast the possible occurrence of rainfall-induced debris flows in the island (TWN, #20 in Figs. 1,2,3). First, the potential of all mountain catchments to generate debris flows in response to high intensity rainfall was assessed, the torrents ranked, and the areas potentially affected by debris flows delineated. Next, nine threshold values for debris flow occurrence based on the "effective cumulated rainfall", a weighted sum of the event rainfall and the corresponding 7-day antecedent rainfall, were established heuristically based on the analysis of past events in catchments with different geomorphologic characteristics and debris flow potential. The higher the threshold, the less debris flow potential for the catchment.

Managed by the SWCB, the system was first used for evacuation purposes in 2004, and at the time of writing is operational (Yin et al., 2015, 2016; Lin and Yin, pers. comm. 2019). The system uses 10-min accumulated rainfall taken by a network of > 300 rain gauges (two rain gauges in each potential debris flow catchment), and quantitative rainfall forecasts provided by the Ensemble Typhoon Quantitative Precipitation Forecasts weather model (Hong et al., 2015), at a maximum 5 km × 5 km resolution, run by. Every hour, the system calculates the "effective cumulated rainfall" and compares the values against the established thresholds. Every four hours, regular debris flow advisories are issued for each village (0.05 ∼ 15 km^2) in pre-defined debris flow risk catchments. Additional advisories are issued during typhoons or severe storms, depending on rainfall conditions. The advisories are made available to central and local authorities, and to the public using a 3-level scheme. Above a lower "no-warning" level, the first advisory level ("yellow") uses rainfall forecasts, and is issued to invite people to leave the debris flow risk areas. The second advisory level ("red") uses rainfall measurements taken from rain gauges, and is issued to force evacuation from debris flow prone areas. To maximize the dissemination of the debris flow advisories, the SWCB uses multiple media, including TV, radio, website, telephone, e-mails, fax, voice broadcast, and SMS. The predictive performances of the system are evaluated annually, using information on new debris flow events, and reliability and accuracy indexes for the warning criteria (i.e., the thresholds) and the advisories.

4.2.2. Italy

For the Italian National Civil Protection Department, CNR IRPI has designed and manages SANF, a pre-operational LEWS for Italy (ITA, #21 in Figs. 1,2,3) (Rossi et al., 2012a, 2018). Design of the Italian LEWS began in 2008, and during ten years of testing and development the system has undergone multiple changes. In the current version, the LEWS uses hourly rainfall measurements, quantitative rainfall forecasts, an ED rainfall threshold, and a grid-based, synoptic-scale landslide susceptibility assessment to produce landslide "nowcasts" and "forecasts" for the whole of Italy. Hourly rainfall measurements are provided by more than 2500 rain gauges available from various regional networks in Italy, corresponding to an average density of one gauge every ∼ 120 km^2. Rainfall forecasts are provided by the COSMO-I7 numerical weather model at 7 km × 7 km resolution (shortly to become COSMO-I5 at 5 km × 5 km resolution), updated twice daily at 00-00 UTC and 12:00 UTC. Work is in progress to use rainfall estimates provided by a national mosaic of 24 C-band and X-band meteorological radars, which provide rainfall estimates updated every 15 min.

Designed to operate with multiple thresholds, the system currently uses a single statistical ED rainfall threshold obtained studying rainfall records and the location and time of occurrence of 2819 landslides in Italy between 1996 and 2014 (Peruccacci et al., 2017). The threshold is used to determine the probability of landslide occurrence for any given set of cumulated rainfall and rainfall duration value, from 1 to 1212 h. Finally, the LEWS uses a grid-based, 25 m × 25 m resolution statistical landslide susceptibility assessment obtained modelling a set of geomorphological, event, and multitemporal landslide inventory maps prepared by CNR IRPI, and small-scale morphometric, geo-lithological, and land use / coverage terrain information. In the model, susceptibility is given in probabilistic terms, and quantitative estimates of the model skill and prediction performance, and of the model errors and uncertainty were ascertained.

A team of 16 landslide forecasters with different backgrounds manages SANF. Every hour, and for the entire Italian territory, the LEWS computes one "nowcast" and two "forecasts". The landslide "nowcast" uses rainfall measurements obtained by rain gauges, and is calculated as the weighted sum of the probabilities for 24, 48, 72, and 96-h antecedent rainfall periods, given the ED threshold. The first "forecast" uses rainfall forecasts, and is calculated from the probabilities associated to the rainfall expected in the next 3, 6, 12, 24, and 48 h. The second "forecast" combines the "nowcast" and the first "forecast", and modulates the result with landslide susceptibility. The three probabilities of landslide occurrence – based on the measured and the forecasted rainfall, and of landslide susceptibility – are multiplied, assuming their statistical independence. The LEWS computes the landslide "nowcasts" and "forecasts" for each single rain gauge. Next, the probabilities at the point location of the rain gauges are aggregated for each of the 134 geo-hydrological alert zones in Italy, and are interpolated on a 5 km × 5 km national grid. Results are made available to national civil protection forecasters using a dedicated web-based platform, and are available as OGC services. SANF also provides ancillary information that can help landslide forecasters decide on the severity and expected impact of a rainfall-induced landslide event. The information includes e.g., the non-exceedance probability and the return period of measured cumulated rainfall for different periods, from 1 to 672 h (28 days), the location and magnitude of harmful landslide events in Italy (Salvati et al., 2010, 2018).

The predictive performance of the LEWS was estimated in an exercise that hindcasted 412 landslides between March 2014 and February 2017 for which accurate information on the time and place of occurrence was known. Results revealed that the landslide "nowcasts" were successful in predicting the time and location of the landslides, whereas the 24-h "forecasts" suffered from the uncertainty inherent in the forecasted rainfall.

A specialized version of the LEWS for the National Italian railway company is being tested. Centered around the 17,727 km railway infrastructure, SANF RFI produces "nowcasts" and "forecasts" used by the National railway company to help decide if and where trains should reduce velocity, traffic should be stopped pending inspections, or to plan for maintenance.

4.2.3. Norway

The Norwegian Water Resources and Energy Directorate (NVE) operates a LEWS for Norway (NOR, #22 in Figs. 1,2,3) (Boje et al., 2014; Devoli et al., 2015, 2018; Krøgli et al., 2018). The "Jordskredvarslingen" system is part of a larger EWS that covers floods and snow avalanches, in addition to landslides. Development of the LEWS began in February 2010, and following an experimental phase began in January 2012, the system went operational in October 2013. The LEWS uses (i) a complex set of measurements obtained by a national network of monitoring stations; (ii) a suite of numerical forecast models; (iii) a set of heuristic thresholds; and (iv) information on landslide susceptibility. The monitoring network consists of ∼ 400 meteorological stations that measure hourly and daily precipitation, temperature, wind speed and direction, and snow coverage and depth, ∼ 400 hydrological stations that measure river discharge, and snow depth and coverage, and ~ 80 hydrogeological stations to obtain point groundwater measurements. The forecast suite consists of two meteorological models, AROME MetCoOp (Müller et al., 2017) and an ECMWF model, the HBV hydrological model (Bergström, 1995; Beldring et al., 2003), and the S-Flow groundwater simulation model. The short-term AROME MetCoOp forecast model, at 2.5 km × 2.5 km resolution, produces 3 and 24-h weather forecasts and is used for the first three days of the landslide forecast. The long-term ECMWF forecast model, at 9.0 km × 9.0 km resolution, produces 24-h forecasts and is used for the longer period forecasts, up to nine days. The HBV is a distributed hydrological model that exploits observed and forecasted precipitation, and temperature data used in Scandinavia to forecast river runoff, snowmelt, groundwater, soil saturation, and soil frost. S-Flow is a one-dimensional soil water and heat flow model developed by NVE to simulate water and heat dynamics in a column of layered soil covered by vegetation. The thresholds are geo-hydrological, and consider the relative (percentage of annual mean) water supply vs. the relative soil saturation degree, eventually modulated by landslide susceptibility. Minimum, average and maximum thresholds were defined through expert judgment, analysing information on 206 historical landslides in Norway. As such, they may not be easy to reproduce objectively (Krøgli et al., 2018). The LEWS began operations using national thresholds for the whole of Norway. Later, recognizing that soil saturation and soil moisture conditions leading to landslides may differ geographically, regional thresholds were added for Southern and Eastern Norway (Boje, 2017). Information on landslide susceptibility includes a catchment scale susceptibility assessment for landslides in soils (Bell et al., 2014), and a 1:50,000 scale susceptibility assessment for debris avalanches and small debris flows (Fischer et al., 2012, 2014).

The LEWS updates daily a national assessment of landslide hazard at the regional scale (i.e., for each county and/or group of municipalities in Norway) for rainfall and snowmelt induced landslides, including shallow translational slides, channelized debris flows, debris avalanches and slush flows. The heuristic assessment is given in four levels of increasing dangerousness, represented by ramping colours nicely illustrated by a footwear of increasing height and protection against water and mud (fig. 7 in Krøgli et al., 2018), and is communicated to the public through a bulletin, in Norwegian, and since January 2018 also in English. The assessments and updates are published on a dedicated website at least twice daily, before 11:00 and before 15:00, depending on weather conditions. Each landslide forecast and advisory covers three days and is valid 24 h, from 07:00 on the day of issue to 06:59 on the following day (08:00 to 07:59 during daylight saving time). The LEWS delivers updates to national and regional stakeholders. Since early 2017, concerned citizens can subscribe to obtain advisories for specific natural hazards, including landslides, notified via text messages or e-mails.

A team of 14 experienced forecasters with different backgrounds operates the LEWS, five of whom are also flood forecasters and two are also snow avalanche forecasters. This favours a cross-hazard consistency of the forecasts issued by NVE. The system operated on a 24-h, 7-day-a-week basis, with one forecaster on duty every day. Outside the working hours, forecasters are "on call" from 08:00 to 21:00, and 24/7 during severe conditions. For their daily evaluations the landslide forecasters use a single tool to visualize observations and forecasts as thematic maps and time-series. The same information is available to the public (http://www.xgeo.no/, in Norwegian). This fosters transparency.

A quantitative evaluation of the performance of the Norwegian LEWS was conducted for the 4-year period 2013–2017, and revealed an overall rate of correct daily assessments of over 95%, including days when the weather was good and no landslide was expected (Krøgli et al., 2018). A survey among users of the forecasts in the same period yield positive feedbacks (Krøgli et al., 2018).

4.2.4. Central America and the Caribbean

Kirschbaum et al. (2015) described a prototype LEWS for Central America and the Caribbean, an area of ~480,000 km^2 encompassing nine countries (CAC, #23 in Figs. 1,2,3). This multi-national LEWS used a small-scale landslide susceptibility zonation, in five classes, obtained through a fuzzy logic approach applied to a set of coarse-scale (30 arcsec ×30 arcsec) thematic variables (Kirschbaum et al., 2016), and satellite-based rainfall estimates, at 0.25° × 0.25° spatial, and 3 h temporal resolutions provided by the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis Real Time version (TMPA-RT) (Huffman et al., 2007, 2010). Landslide "nowcasts" were considered only where susceptibility was moderate to very high. For these areas, the LEWS first computed the Antecedent Rainfall Index (ARI) as a time-weighted average of the rainfall in the previous 60 days, with the weights adjusted considering landslide reports. Next, it checked whether the ARI was equal or greater than the 50th percentile of the ARI calculated from daily TMPA estimates between 2000 and 2014. When the ARI was below the 50th percentile, landslides were not expected, and "nowcasts" were not issued. When the ARI was equal to or larger than the 50th percentile, the daily rainfall was considered. Where daily rainfall was below the 50th percentile of the daily rainfall in the period 2000-2014, landslides were not expected and "nowcasts" were not issued. Where daily rainfall was in the range of percentiles [50th–95th), the area was attributed a "moderate landslide hazard", and where daily rainfall was equal or larger than the 95th percentile, the area was given a "high landslide hazard". The "nowcasts" of the expected landslide "hazard" were issued publicly via a dedicated website, which has since been taken down (Kirschbaum pers. comm. 2019).

4.2.5. Indonesia

Working with Deltares and the Muhamadiyah University Yogyakarta, Balai Litbang Sabo (BLS), the Indonesian Sabo Research and Development Center, has designed and operates a LEWS for Indonesia, a country with more than 1.9 × 10^6 km^2 of land area (IDN, #24 in Figs. 1,2,3). System implementation began in 2016, and from 2017 the LEWS is operational, managed by BLS (Hidayat et al., 2019; Mulyana et al., 2019). Using Delft-FEWS (Werner et al., 2013) as a platform, the LEWS uses satellite rainfall estimates, quantitative rainfall forecasts, and two empirical rainfall thresholds to prepare national landslide forecasts at 0.25° × 0.25° latitude/longitude resolution. The satellite-based rainfall estimates are taken from TRMM. Quantitative rainfall forecasts are provided jointly by the Indonesia Research Centre for Water Resources and the Indonesia Meteorological, Climatological and Geophysical Agency. The two empirical rainfall thresholds were determined by studying 83 past rainfall events with landslides, considering the cumulated rainfall in the day of the landslide, and in the three days preceding the day of the landslide. Landslide advisories are prepared only for areas considered landslide prone by the Badan Geologi, the Geological Agency of Indonesia.

Twice weekly, on Tuesday and Friday, the LEWS issues new advisories for the next four days. When none of the two thresholds is exceeded, no advisory is issued. When one or the other of the two thresholds is exceeded, a "yellow warning" is given; and when both thresholds are exceeded, a "red warning" is issued. To support the decision to issue a "red warning", the USGS TRIGRS regional slope stability model (Baum et al., 2008, 2010), forced by 6-day TRMM cumulated rainfall estimates, is run at nine locations in Java and Sumatra for which soil data are available. If the computed factor of safety in the model areas falls below 1.2, a "red warning" is issued. The landslide advisories are disseminated publicly on a dedicated web site (http://202.173.16.248/status_longsor.html). In addition, BLS manages a WhatsApp group for national and local authorities. At the time of writing, the LEWS is not validated, but efforts are underway to collect systematic information on landslide occurrence, which will be used for validation and performance evaluation (Sutanto 2019, pers. comm.).

4.2.6. Scotland

The British Geological Survey (BGS) has designed and manages a LEWS for Scotland (SCT, #25 in Figs. 1,2,3) (Reeves and Freeborough, pers. comm. 2019). Established in 2017, the LEWS relies on a conceptual, spatially distributed Water Balance Model (WBM) with calibrated parameters that assesses the temporal and spatial variations of the soil moisture conditions in the near-surface. The assumption is that the likelihood of rainfall-induced shallow landslides depends upon the moisture conditions in the soil mantling the landscape, and on how much rain is expected for the following day. The BGS soil Parent Material Model (Lawley and Smith, 2008) is used to decide the dominant soil types at the near-surface, and their physical, mechanical and hydrological characteristics.

The WBM is run twice daily, approximately every 12 h, depending on the transfer times of the near-real time data, at 1 km × 1 km grid resolution, using 24 h cumulated rainfall obtained by meteorological radars, and temperature and relative humidity measurements provided by the UK Met Office. The model estimates the effective rainfall and the potential soil moisture antecedent conditions in the upper one meter of the landscape's soil profile. The modelled soil moisture is then evaluated against 24-h ensemble rainfall forecasts, also provided by the UK Met Office, to produce forecasts of the potential water stress in the landscape. Three threshold curves are used to represent transitions between four zones of stressed landscape potential, considered a proxy for the likelihood of shallow landslide occurrence. The threshold levels, which indicate indicative levels of soil saturation, were generated from dated landslide events in Scotland available from the Great Britain's National Landslide Database (Foster et al., 2011; Pennington et al., 2015).

The LEWS does not issue automatic advisories. Instead, BGS landslide forecasters compare the WBM probability forecasts to susceptibility and vulnerability maps, and prepare heuristic daily landslide advisories, valid for next 24 h, using a scheme of increasing landslide hazard impact consistent with the 4-level scheme adopted by the UK Natural Hazard Partnership to issue their Daily Hazard Assessment (DHA) for Great Britain, for twelve hazards, including landslides. The landslide assessments are sent to the UK Met Office team that prepares the DHA. When the assessment is "green", the evaluation is not included in the DHA; when instead the assessment is "yellow" or above, details on the expected landslide hazard impact are included in the DHA. The LEWS is under validation, and the threshold curves for the zones of the stressed landscape potential are being tested (Reeves and Freeborough, pers. comm. 2019).

4.3. Global systems

Hong and Adler (2007) were the first to propose a global LEWS for rainfall and earthquake triggered landslides (GLB, #26 in Figs. 1,2,3). The prototype LEWS worked at 0.25° × 0.25° grid resolution from 50 °N to 50 °S. For rainfall-induced landslides, it produced a dynamic assessment of possible landslide occurrence using rainfall information provided by TMPA-RT, which was evaluated every three hours against a single, global ID rainfall threshold established using TRMM estimates between 1999 and 2006 and ~ 70 landslides globally in the same period (Hong et al., 2006). When the ID threshold was exceeded in a grid-cell, the LEWS used a synoptic-scale landslide susceptibility zonation obtained through a heuristic, weighted linear combination of elevation, slope, soil properties, and land cover landslide predisposing factors (Hong and Adler, 2007) to predict landslide occurrence in the two highest susceptibility classes.

Using information on 205 landslides in 2003, and 350 landslides in 2007, Kirschbaum et al. (2009, 2012) tested the predictive performance of the global LEWS, which they found poor and which they attributed to (i) the unreliability of the susceptibility zonation; (ii) the inability of the satellite rainfall estimates to capture high intensity precipitation events; (iii) the inadequacy of a single global threshold to predict landslide occurrence in multiple geomorphological and climatological settings; and to (iv) the incompleteness of the landslide catalogue used to define the threshold. In an attempt to address these issues, Kirschbaum et al. (2012) tested a modified version of the LEWS in four countries of Central America. The modified system used a more accurate, statistically-based landslide susceptibility map and the empirical ID threshold proposed by Guzzetti et al. (2008) for humid subtropical regions, to produce landslide forecasts at the original (0.25° × 0.25°) and at a finer (0.1° × 0.1°) geographical resolution that performed better than the original global model of Hong and Adler (2007).

Building on this experience, Kirschbaum and Stanley (2018) introduced the global Landslide Hazard Assessment model for Situational Awareness (LHASA). The new global LEWS operates at 0.01° × 0.01° grid resolution from 60 °N to 60 °S, and produces global landslide "nowcasts" showing where and when rainfall-induced landslides are likely. The LEWS uses 7-day daily rainfall estimates provided by the Integrated MultisatellitE Retrievals for GPM (IMERG) and calculates the ARI for the past 7 days using a weighted accumulation, a proxy for the antecedent rainfall conditions (Crozier, 1999; Glade et al., 2000). The model then considers a global landslide susceptibility map at 1 km × 1 km resolution prepared through heuristic fuzzy modelling of landslide, slope, geology, distance to fault zones, presence of roads, and forest loss geographical data (Stanley and Kirschbaum, 2017).

To combine the rainfall and susceptibility information, the system uses a decision tree approach (Kirschbaum and Stanley, 2018). Every three hours, LHASA updates the ARI at each pixel and compares it against a rainfall threshold, defined as the 95th percentile of the ARI calculated from daily TMPA rainfall estimates in the 15-year period 2000–2014 and subsequently transformed to use the IMERG estimates based on GPM data (Stanley et al., 2017). When the ARI is below the 95th threshold, landslides are not expected and "nowcasts" are not issued. When instead the ARI is above the threshold, susceptibility is considered. Where susceptibility in a grid cell is "very low" or "low", landslides are not expected and "nowcasts" are not issued. Where susceptibility is "moderate-high" or "very high", then the grid cells are assigned a "moderate-high" or "high" hazard level, respectively (Kirschbaum and Stanley, 2018). In a hindcast exercise, LHASA was validated using TMPA estimates from 1 January 2007 to 31 December 2016 (3652 days), and IMERG estimates from 25 March 2014 to 2 October 2017 (1287 days), against 4930 landslides globally, and against 384 fatal landslides in Nepal from 2007 to 2016. Results revealed the acceptable performance of the new global LEWS. A current limitation of LHASA lays in the inability to consider rainfall forecasts, but efforts are underway to bridge this gap (Kirschbaum, pers. comm. 2019; Mirus et al., 2019).

5. Analysis

5.1. Geographical analysis

At the time of writing, only five nations, 13 regions and the metropolitan areas of Chittagong, Hong Kong, Rio de Janeiro, and Seattle benefit from LEWSs (Figs. 1,2). Collectively, these LEWSs cover a minute percentage of the terrain potentially affected by landslides globally (Nadim et al., 2006). Visual analysis of the global distribution of fatal, non-seismically-induced landslides from 2004 to 2016 compiled by Froude and Petley (2018), and updated recently to cover the period January 2004 – December 2017 (green dots in Fig. 2), reveals that many regional and national LEWSs do not operate where fatal landslides are numerous i.e., where landslide risk to the population is high. The global system of Kirschbaum and Stanley (2018) fills in where no alternative exists, but it cannot substitute for regional or national LEWSs, chiefly because of inherent limitations in the considered variables, the inability of a simple model to describe the wide variety of hillslope processes, and the difficulty of the IMERG rainfall estimates to capture local intense rainfall events that generate landslides. We

Table 2
Recommendations for the further development and improvement of geographical LEWSs, and to increase their reliability and credibility.

	We recommend to:	Section
Establishment and operation of LEWSs		
1	Deploy and manage regional and national LEWSs covering large parts of the continents.	5.1
2	Increase rate of LEWS deployment. Cover large areas rapidly with national LEWSs.	5.2
3	Maintain existing LEWSs. Extend their operational life.	5.2
4	Implement new LEWSs where landslide risk to the population is high.	5.2
Landslide and rainfall data		
5	Collect accurate information on the time of occurrence of landslides.	6.1
6	Establish strategies for landslide and rainfall data collection.	6.1
7	Improve quantification and comparison of landslide triggering rainfall fields.	6.1
8	Address incompleteness and non-stationarity of landslide and rainfall records.	6.1
9	Use multiple sources of rainfall information. Consider source type and uncertainty.	5.3
Landslide models and advisories		
10	Define and use standard methods to define landslide threshold models.	6.1
11	Define and use open criteria to decide the number of the threshold models.	6.1
12	Define and use open criteria to evaluate landslide forecast models.	6.1
13	Explain how susceptibility is used in operational LEWSs.	5.3, 6.2
14	Use sound probabilistic approaches for landslide models, forecasts and advisories.	6.2
15	Address the role of climate and environmental changes on landslide forecast models.	6.1
LEWS evaluation		
16	Consider uncertainties in landslide models, forecasts and advisories.	5.3
17	Consider lack of landslide information when evaluating forecasts and advisories.	5.3
18	Use optimization procedures to decide and revise advisory levels.	5.3, 5.5
19	Advance and use clear and open criteria to evaluate the LEWS skills and performance.	5.3, 6.4
20	Assess consequences of using external or general advisory schemes.	5.4, 6.3
21	Evaluate all parts of a LEWS using appropriate tools and criteria.	6.4
LEWS management		
22	Log LEWS system activity and events systematically.	5.3
23	Integrate site specific monitoring and physically-based models in LEWS.	6.2
24	Improve all aspects and components of existing landslide forecast models and LEWS.	6.5
25	Share openly landslide models, advisory systems and LEWSs frameworks.	6.5
26	Use of long-range weather forecasts for seasonal landslide forecasting.	6.5
27	Use multiple models for landslide forecasts and advisories.	6.5
Communication and dissemination		
28	Use simple, common, standard vocabulary for advisory and messages.	5.5, 6.3
29	Define open standards for LEWSs design, implementation, maintenance, evaluation.	6.5, 7
30	Landslide community to decide on and disseminate open standards for LEWSs.	7

recommend that more national and regional LEWSs are implemented, covering a larger proportion of the landmasses (Table 2).

Fig. 1 lists information on terrain elevation and relief where LEWSs operate (or operated), which we jointly take as a loose proxy for the variability and complexity of the topographic and morphological settings in the LEWSs areas. We note that LEWSs were implemented in a broad range of terrain elevations and relief, and we conclude that topography and terrain morphology do not limit the implementation, operation, and management of LEWSs. This is a positive conclusion for operational landslide forecasting and early warning. However, terrain morphology, mainly elevation, may affect the triggering factors and local conditions of meteorologically-induced landslides. At high elevation and where climate is cold, snow and ice may condition the initiation of landslides (Hungr et al., 2014). Only three regional LEWS (#4, 12, 13) and the national system for Norway (#22) use information on snowmelt and/or snow cover (Fig. 2). These are areas where snowmelt induced landslides are known to occur. However, other LEWSs in areas where snowfall is common and snowmelt induced landslides occur do not use information on snow cover or snowmelt (#3, 6, 14, 15, 16, 21, 25); and this is a problem that may degrade the performance of the LEWSs.

Fig. 1 and the 26 boxes in Fig. 2 show the predominant climate type in the areas covered by the LEWSs. To assign a climate to each LEWS, we used the world climate map compiled by Peel et al. (2007) who considered five Köppen-Geiger climate types i.e., tropical, arid, temperate, cold, and polar. Of the 26 LEWSs, 21 were assigned a predominant climate type, four (#5, 13, 21, 22) a predominant and a secondary climate type, and the global LEWS all climate types. Regional and national LEWSs cover all the Köppen-Geiger climates, with the majority of the systems (18) in the temperate climate, followed by the tropical (6) and cold (3) climates (Fig. 4). One LEWS operates in the arid climate of Southern California (#5), and the system for Norway (#22) partly in a polar climate. Considering the areal extent covered by the LEWSs, the majority of the area covered by the systems is in temperate (72.0%) and tropical (24.0%) climates. Although the arid (30.2%) and polar (12.8%) climates cover 43.0% of the landmasses, landslides are more frequent and abundant in tropical (19.0%), temperate (13.4%), and subordinately in cold (24.6%) areas (Nadim et al., 2006). This is matched by the proportion of the area of the LEWSs in the main climate types.

Geology and seismicity are known to condition the distribution and abundance of non-seismically-induced landslides (Vanmaercke et al., 2014, 2017). To assign a prevalent geological domain to each LEWS, we used the generalized global geological map compiled by Chorlton (2007), who considered five main rock type domains i.e., igneous, metamorphic, sedimentary, tectonic, and volcanic rocks; and to attribute to the LEWSs a seismicity level, we used the Global Seismic Hazard Map of Giardini et al. (2003), in four classes (Fig. 4). We found, that the regional and the national LEWSs were implemented in all the geological domains, and primarily in sedimentary (55.0%) rocks and subordinately in volcanic (20.0%) and metamorphic (17.5%) rocks. Similarly, we found that LEWSs were implemented in all seismic classes, and are more numerous in the medium (36.0%) and the high (28.0%) classes, followed by the low (20.0%) and the very high (16.0%) seismicity classes. Considering the areal extent covered by the LEWSs, the majority of the systems were implemented in sedimentary (46.8%) and

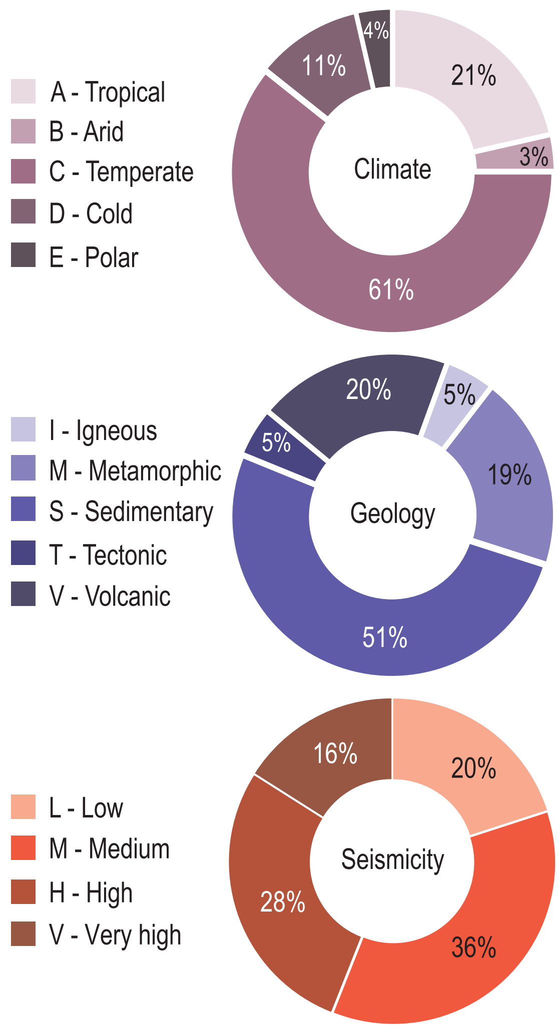

Fig. 4. Donuts show percentage of count of LEWSs in (upper) the Köppen-Geiger climate types of Peel et al. (2007), in five classes; (centre) the main geological types of Chorlton (2007), in five classes; and (lower) the seismicity levels of Giardini et al. (2003), in four classes.

volcanic (46.7%) rocks, followed by metamorphic rocks (14.7%); and in the medium (68.6%) seismicity class, followed by the very high (16.7%), high (12.8%), and low (1.9%) seismicity classes.

From this geographical analysis, we conclude that LEWSs can be deployed and operated virtually everywhere in the world, without any morphological, climate, geological, seismic, or tectonic constraint (Fig. 4).

5.2. Temporal analysis

Only two years after the visionary description of an operational LEWS proposed by Campbell (1975), the first prototype system was established in Hong Kong (Chan et al., 2003; Choi and Cheung, 2013; Wong et al., 2014), followed seven years later by the system in the San Francisco Bay area (Keefer et al., 1987) (Fig. 3). The year after the system in the SFBA was terminated (1995, Wilson, 2012), a new system was launched in Rio de Janeiro (1996), followed a year later by the LEWS for Western Oregon (1997). At the turn of the millennium, the systems in Hong Kong (#1), Western Oregon (#3), and Rio de Janeiro (#7) were the only three operational LEWSs, globally (Fig. 3). Only in the mid of the first decade of the new century new LEWSs became operational in Taiwan (#20), Seattle (#4), and Southern California (#5). At about the same time, Hong and Adler (2007) experimented with the first global LEWS. In 2015, the year of the Sendai conference that called for a renewed effort to use EWSs as cost-effective tools to mitigate the consequences of natural hazards (UNISDR, 2015; Teisberg and Weiher, 2009; Rogers and Tsirkunov, 2010; Alfieri et al., 2012), 17 LEWSs were operational, pre-operational or in their design phase, globally (Fig. 3); in the Hong Kong and the Rio de Janeiro metropolitan areas, and in six nations (Colombia, Indonesia, Italy, Norway, Taiwan, USA).

Since 2005, due to increased data availability and technological readiness, and an augmented interest amongst landslide scientists and with decision makers, the number of LEWSs has increased at a rate of about one new system every year, further increased to 1.5 new systems per year in the last five years (Fig. 3). This is positive; but we note that at the present rate it will take several decades before a significant portion of the landmasses potentially affected by landslides will be covered by regional or national systems. We recommend the pace of LEWS deployment be increased, focusing on national LEWSs – which allow coverage of large areas more rapidly – and where landslides risk to the population is high or very high (Nadim et al., 2006; Froude and Petley, 2018; Haque et al., 2019; Rossi et al., 2019) (Fig. 2, Table 2).

Campbell (1975); Wieczorek et al. (1983); Brand et al (1984); Malone (1988); Wiley (2000); Einstein and Sousa (2006), and Piciullo et al. (2018) have noted that in many areas LEWSs were established after major landslide disasters. If this was acceptable in the early years of LEWSs design, the harmfulness of landslides and the global relevance of the landslide problem are now clear (Nadim et al., 2006; Petley, 2012; Froude and Petley, 2018; Haque et al., 2019), as is the potential effectiveness of LEWSs (Baum and Godt, 2010; Wilson, 2012; Krøgli et al., 2018). We argue that there is no reason for waiting further disruption and, in line with the Sendai Framework for Disaster Risk Reduction (UNISDR, 2015) and European recommendations (Alfieri et al., 2012), we advocate that new LEWSs are established wherever possible (Table 2).

Hong Kong has the longest-lived LEWS that has been operational for more than 40 years, followed by the system in Rio de Janeiro that has been running for more than 20 years (Figs. 1,3). Of the other LEWSs, six have been operational or pre-operational for ten or more years, six for five to ten years, and six for less than five years. The limited number of LEWSs active for long periods (two or more decades) limits the possibility to evaluate and compare the performances of the systems, and to execute reliable cost-benefit analyses. It also limits the assessment of the effects of climate and environmental changes on the systems and their performances (Wilson, 2012; Gariano and Guzzetti, 2016). We therefore recommend that existing LEWSs are maintained to extend their operational period (Table 2).

We further note that three LEWSs ceased in the 42.5-year examined period (Fig. 3); of which the USGS–NWS LEWS for the SFBA (#2) was the only one that was dismissed due to lack of human and economic resources, and motivation (Wilson, 2012). Other dismissed LEWSs (#6, 23) were design, proof of concept or prototype systems, or were managed by university or research groups that lacked a mandate and the motivation for the long-term management of the LEWSs. The first global system by Hong and Adler (2007) was discontinued, but replaced by the new LHASA global system of Kirschbaum and Stanley (2018). We note that, with the exception of the initial attempt in the early 1990s in Taiwan (Wilson, 2012), none of the pre-operational or operational systems managed by government organizations was terminated. We conclude that once a LEWS is established and is properly managed in a region or nation, the system proves useful and it is maintained.

5.3. Data and forecast models

All the examined LEWSs use rainfall information, including measurements from rain gauge networks (20, 76.9%), forecasts obtained from numerical weather models (21, 80.8%), nowcasts obtained from weather radars (7, 26.9%), and satellite-based rainfall estimates (4,

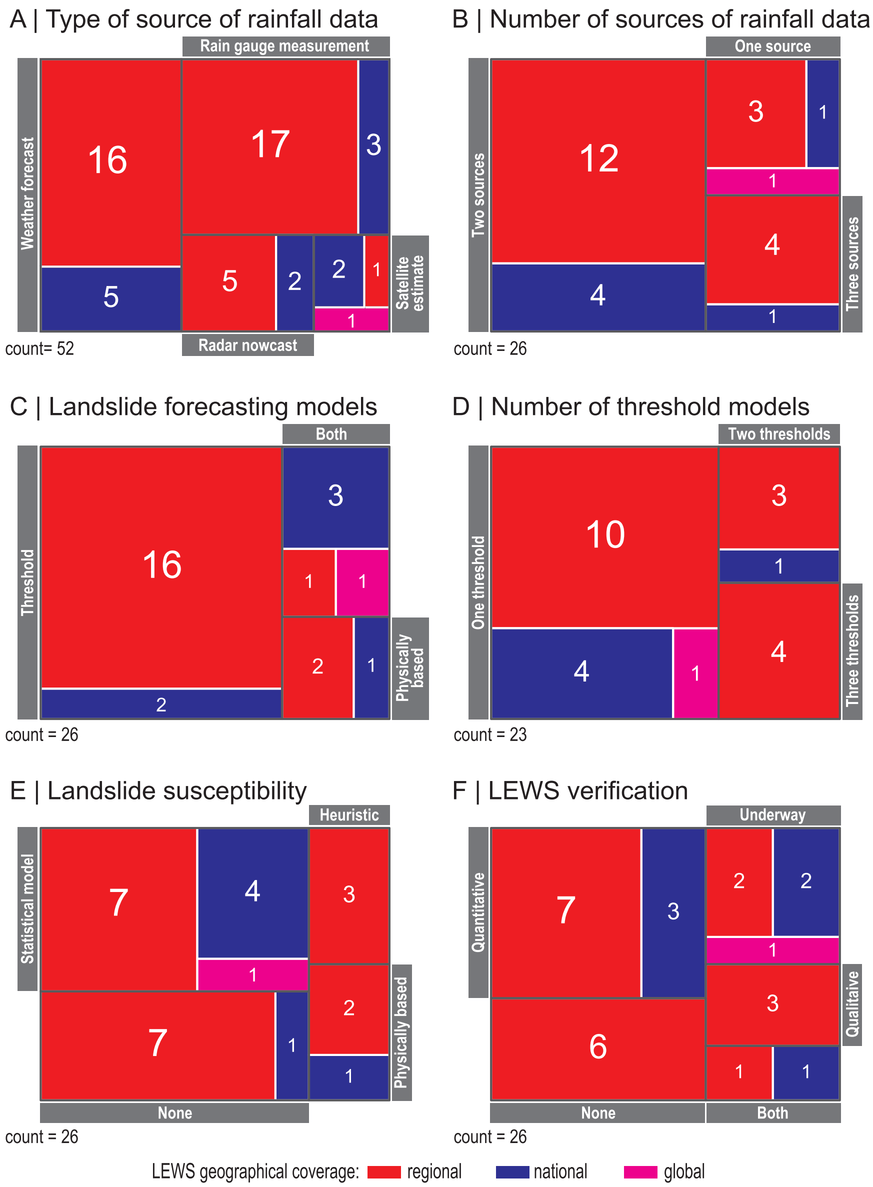

Fig. 5. Threemap charts show proportions of LEWSs for: (A) the type of source of the rainfall data, in four classes (rain gauge measurement, weather forecast, radar nowcast, satellite estimate); (B) the number of sources of rainfall data, in three classes (one, two, three sources); (C) the type of landslide forecasting models, in three classes (threshold model, physically-based model, both model types); (D) number of thresholds used, in three classes (one, two, three thresholds); (E) landslide susceptibility model types, in three classes (statistical classification model, physically-based model, both model types, no model used); and (F) the verification procedures used, in four classes (qualitative, quantitative, both, underway at the time of writing). Boxes are colored based on the LEWS geographical coverage: red, regional; blue, national; purple, global.

15.4%) (Fig. 5A). The majority of the LEWSs (16, 61.5%) rely on two sources of rainfall information, five (19.3%) on three, and five (19.3%) on a single source (Fig. 5B). The most common combinations are rainfall measurements and forecasts (12, 46.2%), and rainfall measurements, forecasts, and nowcasts (5, 19.3%), but examples exist of LEWSs that use nowcasts and forecasts (#25), or rainfall measurements and radar nowcasts (#1). We conclude that LEWSs can operate with different sources of rainfall information and with combinations of rainfall measurements, estimates, and forecasts. We further note that most LEWSs do not consider the inherent uncertainty associated with rainfall measurements, forecasts, nowcasts or satellite estimates. An exception is the regional system for Liguria (#16) that uses an ensemble of rainfall forecasts and produces ensembles of landslide forecasts, whose spread measures the uncertainty in the forecasts. We recommend that the LEWSs exploit multiple sources of rainfall information, considering the characteristics and uncertainties typical of the sources (Table 2).

A few LEWSs use information on soil moisture and soil wetness (#2, 4, 22), snow cover or snow depth (#4, 22), surface air temperature (#14, 22), and burnt areas (#5). In Seattle (#4), recent studies using soil moisture and pore-water pressure conditions lead to the definition of hydrological thresholds that proved more accurate than the old thresholds (Mirus et al., 2018a, 2018b). The new hydrological thresholds are not used operationally in the LEWS yet. We encourage landslide forecasters to use information on transient events or processes that can change the propensity ("susceptibility") or the frequency of landslide occurrence, including e.g., snow coverage, temperature (for evapotranspiration and rapid snowmelt), recently burnt areas, forest clear-cutting, and other land use/cover changes.

All the examined LEWSs adopt models for their landslide forecastsLEWSs (76.9%) use rainfall threshold models, and seven (26.9%) physically-based models (Fig. 5C), including distributed slope stability models (#9, 24), soil water balance models (#14, 22, 23, 26); one system (#25) uses both distributed slope stability and soil water balance models. Of the 20 systems that use rainfall threshold models, the majority (12, 60%) use one empirical threshold type, five two threshold types (25%), and three systems three threshold types (15%) (Fig. 5D). The most common threshold type is the mean rainfall intensity–rainfall duration (ID), followed by the cumulated event rainfall–event rainfall duration (ED) (Guzzetti et al., 2007). The SANF and SARF LEWSs in Italy adopt a probabilistic approach based on a 50% ED non-exceedance probability threshold (Rossi et al., 2018), and the LEWS for North Vancouver (#6) uses a regression model built from 25 rainfall variables to discriminate rainfall conditions that cause and do not cause debris flows (Jakob et al., 2012). Although it is known that statistical and physically-based models have (often large) uncertainties (Peruccacci et al., 2012), none of the examined LEWSs incorporate uncertainty in their landslide forecasts. We recognize that this is not easy to do, but we encourage landslide forecasters to incorporate and propagate model uncertainties in their forecasts (Table 2).

When a landscape is forced by rainfall, one expects landslides to occur with less or more probability depending on susceptibility (Brabb, 1984; Guzzetti, 2006; Reichenbach et al., 2018). This is true assuming the rainfall trigger is homogeneous; a condition that seldom occurs. In fact, the likelihood of rainfall-triggered spatial landslide occurrence (i.e., susceptibility) depends on the transient rainfall forcing and the terrain conditions (Lombardo et al., 2018). Thus, susceptibility is important for landslide forecasting. Of the 26 examined LEWSs, 18 (69.2%) used and eight (30.8%) did not use information on landslide susceptibility. Of the LEWSs that used susceptibility, twelve (46.2%) obtained the information from statistically-based models, three (17.6%) used expert-based evaluations, three (17.6%) a physically-based approach (Fig. 5E). The LEWS for Scotland (#25) uses spatially distributed soil moisture / water content estimates, which are dynamic proxies for susceptibility.

The examined systems exploit information on landslide susceptibility in different ways, depending e.g., on the extent of the area covered by the LEWS, and the type and scale of the susceptibility information. In the SFBA, the LEWS used expert opinion to help select the appropriate threshold (Wilson, 2012). In Taiwan, for the national LEWS (#20) mountain catchments were ranked based on their propensity to generate debris flows (Yin et al., 2015, 2016), whereas the regional system uses susceptibility to group slopes in three classes for which separate thresholds are used (Wei et al., 2018). The LEWS for Chittagong (#10) uses susceptibility with forecasted rainfall in an expert-based matrix to select from different landslide scenarios. In Umbria (#14), the LEWS uses susceptibility together with rainfall and vulnerability information to prepare dynamic landslide risk scenarios (Ponziani et al., 2013). In Italy, the national LEWS (#21) and the regional systems for Liguria, Sardinia, and Apulia (#16, 17, 18), use a probabilistic susceptibility assessment to modulate the landslide forecasts based on measured and forecasted rainfall. They can also show "non-susceptible" landslide areas (Marchesini et al., 2014) to help inform landslide forecasters. The LHASA global LEWS (#26) uses a predefined decision tree to combine a 1 km × 1 km resolution susceptibility assessment to the TMPA rainfall estimates (Kirschbaum and Stanley, 2018). Overall, use of susceptibility information in the examined LEWSs is not always clear. For this reason, we reiterate the recommendation of Reichenbach et al. (2018) who encouraged investigators to be explicit when describing how susceptibility is combined with rainfall measurements, estimates, and forecasts in operational LEWSs (Table 2).

Evaluation (or verification) is an important, often overlooked task of any system that attempts to forecast natural events, including landslides (NOAA-USGS Debris Flow Task Force, 2005; Baum and Godt, 2010; Piciullo et al., 2018). Our analysis revealed that the majority of the LEWSs (20, 76.9%) have undergone (or are under) some form of evaluation, including ten (38.5%) with a quantitative evaluation, three (11.5%) with a qualitative verification, two (7.7%, #16, 21) with both quantitative and qualitative evaluations of the forecasting skills, and five (19.2) for which the verification has started or is in progress (Fig. 5F). Albeit this is a positive result, it reveals that one national and seven regional systems are operated with no evaluation of their forecasting skills. We note that no standard method exists to perform the quantitative or qualitative evaluations. Gariano et al. (2015) and papers in Segoni et al. (2018a, 2018b) discussed the inherent difficulty in evaluating the performances of rainfall thresholds, due primarily to the lack of accurate and complete information on landslide occurrence, and Calvello and Piciullo (2016) proposed a standard procedure for the assessment of the performances of a LEWS. We recommend that landslide forecasters consider the possible (or probable) lack of accurate landslide information when evaluating their forecasts. Event landslide inventory are often incomplete, or are affected by systematic biases e.g., along roads or in populated areas (Van Den Eeckhaut and Hervás, 2012). New advances in detecting event-triggered landslides (Mondini et al., 2019) may improve our ability to validate LEWSs, and to quantify their performances. Exploitation of social media, through various ways of manual or automatic harvesting of information, may prove a valuable alternative (Kirschbaum et al., 2010, 2015; Baum et al., 2014; Calvello and Pecoraro, 2018; Froude and Petley, 2018; Juang et al., 2019). We further recommend that landslide managers evaluate the systems using the approach proposed by Calvello and Piciullo (2016), or a similar one (Park et al., 2019). Lastly, we encourage LEWS managers to perform, preferably quantitative, systematic logging and evaluations of the LEWS adopting a common set of evaluation criteria (Table 2).

5.4. Operational framework

To analyze the LEWSs operational framework, two issues are important. First, whether the LEWS operates continuously, like a weather forecast system, or "on demand", when the need arises. Second, whether the LEWS runs automatically, or it requires expert intervention. Intermediate conditions exist, and we use the four cases identified above for descriptive purposes.

Most of the examined LEWSs operate continuously, and provide model outputs and advisory information at predefined time intervals (mostly daily) and fixed times, determined based on organizational constraints (e.g., the need to issue a bulletin at a given hour). During storms or severe weather conditions, or when landslides are expected, some of the LEWSs can run additional or specific forecast models (#1, 20, 24), and extra personnel are informed or called on duty (#13, 22). Most of the LEWSs increase the frequency of their advisories or issue a new advisory when a higher level is reached or exceeded, or they give updates; but exceptions exist. The LEWS for the SFBA (#2) was operated only when the seasonal conditions and the weather forecasts were deemed favourable to the initiation of shallow landslides and debris flows (Keefer et al 2010; Wilson, 2012). The national LEWS for Italy (#21) and the regional systems for Liguria, Sardinia, and Apulia (#16, 17, 18), adopt an intermediate approach, and operates in two modes: a standard mode that automatically provides a new landslide forecast every hour, valid for the next 24 h; and a monitoring mode, that allows forecasters to examine the evolution of the landslide forecasts during a storm. The difference between "on demand" and continuously operating systems is reflected in the operational costs and in the performances of the systems.

Selection between "automatic" and "manual" systems depends on multiple issues, including e.g., landslide location, abundance, and types, location, type, number, and value of the elements at risk, response capacity, and on the LEWS characteristic time (Baum and Godt, 2010; Chae et al., 2017; Capparelli and Versace, 2011; Versace et al., 2018) i.e., the time required for possible effective responses to an advisory. Since the latter is a particularly relevant information, we searched for it in the examined LEWS. However, we did not find quantitative, or even qualitative or anecdotal information on how long the systems can provide advance warning i.e., the lead-time between an advisory and the landslide occurrence. For geographical LEWSs, forecasters and managers assume that the time between the landslide forecast and the landslide onset or impact is sufficient to take appropriate risk mitigation actions (Baum et al., 2005; Chleborad et al., 2008; Baum and Godt, 2010; Huggel et al., 2010; Jakob et al., 2012; Chae et al., 2017; Versace et al., 2018).

The scientists who designed and managed the LEWS for the SFBA (#2) recognized that their system could not operate automatically, and that expert judgement was required to assimilate the complex and changing rainfall, and landslide information to make an informed decision about the potential hazard, and choose the appropriate advisory (Wilson, 2012). This is the choice of most regional and national LEWSs, for which a landslide advisory is the result of a supervised process involving consultation and expert judgement. An exception is the global system of Kirschbaum and Stanley (2018) (#26) – and previously the global system of Hong and Adler (2007), and the LEWS for Central America and Caribbean (Kirschbaum et al., 2015) (#23) – that provide automatic forecasts and related advisories. This is justified by the extent of the geographical area covered by the global LEWS that does not allow for supervised forecasts. Another exception is the LEWS for Chittagong (#10) that adopts an automatic, unsupervised procedure to prepare the forecasts and issue the advisories. The LEWS for Piedmont (#13) distributes automatic advisories to civil protection personnel, local authorities, and forecasters on duty.

5.5. Advisory systems

Preparation and dissemination of timely and meaningful information is a crucial task for any LEWS (Sorensen, 2000; Baum and Godt, 2010; Huggel et al., 2010; Wilson, 2012; Chae et al., 2017); an exercise of decision making under uncertainty (Polasky et al., 2011; Dimitrakakis and Ortner, 2019). The task poses a threefold problem. First, one has to select to whom to address the advisory (the "audience"). Second, one has to select the number of advisory levels, which depend on the audience, the uncertainty associated to the forecast, and the capability to make decisions based on inherently uncertain forecasts. Third, one has to decide the content and scope of the messages for each advisory level, which also depend on the audience, the confidence on the forecasts, and the ability to make decisions under uncertainty.

The 26 LEWSs use from two to five advisory levels to address three main "audiences", namely (Fig. 6): (i) an internal audience, when the forecast information is used only by those who manage the LEWS and is not distributed outside of the forecasting team; (ii) the authorities, when the forecast information is given to the authorities mandated to decide and take actions (e.g., civil protection personnel, elected or nominated authorities, infrastructure or asset managers); and (iii) the public, when the information is open to the public. Most regional and national LEWSs adopt an escalating approach. The information is first used internally to analyse the situation and make decisions (e.g., perform other analyses, change the monitoring frequency, consult with experts, call additional personnel). When pre-defined thresholds are reached or exceeded, or based on consultation, the information is then passed to the authorities, who may take actions, including the dissemination of the forecast information to the public.

Fig. 6 shows that two systems (#8, 9) use a two-level advisory scheme for internal use (#8 also to advice authorities), and only one system (#10) uses a two-level scheme for issuing public messages. Similarly, only one LEWS (#6) adopted a five-level scheme to address the general public. Most LEWSs use four or three advisory levels, with more levels used for public advisories than for internal use. We maintain that the use of three to four advisory levels is a reasonable compromise between the complexity and uncertainty of operational landslide forecasting, and the need to provide effective information to authorities and the public, who typically are not landslide experts (Wilson, 2012). Use of a small number of advisory levels helps the evaluation of and can increases the forecasting skills of a LEWS, and Piciullo et al. (2017a, 2017b) have proposed an optimized selection of the levels based on the EDuMaP method (Calvello and Piciullo, 2016). We note that none of the examined LEWSs has determined their advisory levels through an optimization procedure. This may be because the advisory levels are dictated by organizational or legal constraints, or by the need to combine the landslide advisories with those for other hazards in multi-risk frameworks (Gunawan et al., 2017). We encourage landslide forecasters and LEWS managers to decide or revise the number and characteristics of the landslide advisory levels based on optimization procedures (Table 3).

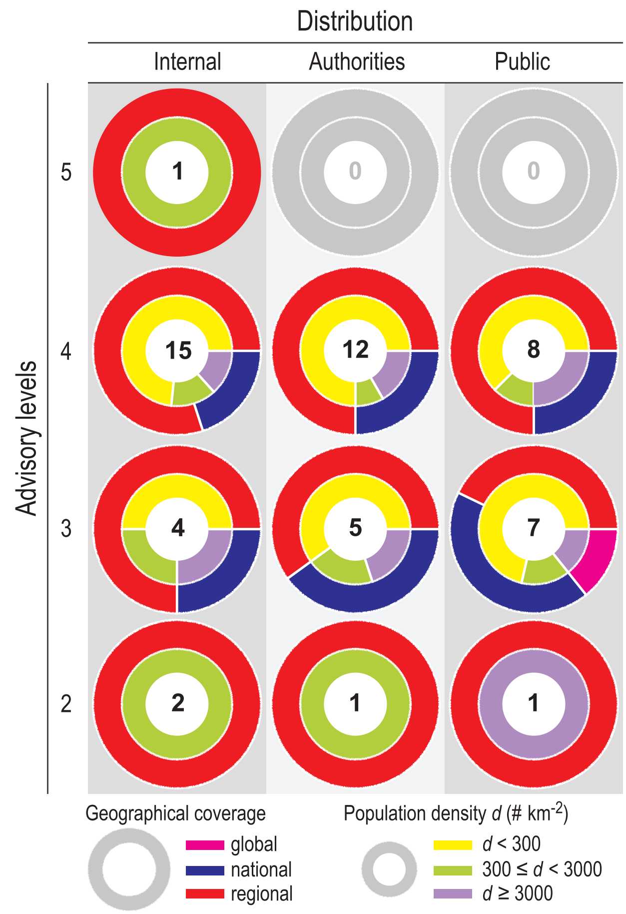

Fig. 6. Relationships between the number of advisory levels (from 2 to 5), in four classes, y-axis, and the distribution level of the landslide advisories, in three classes (internal distribution, distributed to the authorities, distributed to the public), x-axis. Large external donuts show LEWSs geographical coverage, in three classes: red, regional; blue, national; purple, global. Small internal donuts show population density d, people per km^2, in three classes: yellow, $d < 300$; green, $d \leq 300 < 3000$; purple, $d \geq 3000$. Bold numbers in the centre of each donut show LEWSs count.

Usually, LEWSs adopt the international traffic light colour scheme (green, amber, red), with the number of colours varying depending on the number of the advisory levels. There are clear advantages in using this scheme, and chiefly the fact that it is recognized and understood worldwide. However, there are possible problems when the scheme is used for landslide (or other hazards) advisories. First, colour blind people (> 330 million, globally) may not see red and green colours, or they may mix colours with red or green components. Second, "green" is intuitively associated to "safe", which is not what is meant by most landslide advisory schemes (Table 3). In the UK, "green" means that "landslides are not likely and there are no reports of landslides"; in Norway it indicates "generally safe conditions"; and in Italy the "absence of significant predictable phenomena, although small landslides and rockfalls cannot be excluded locally." In all these cases, landslides can occur even in the "green" level condition. Given the landslide variability (Guzzetti et al., 2012; Hungr et al., 2014) and the uncertainty in landslide forecasting, this is reasonable for landslide experts, but it may not be easy for citizens or non-experts to understand.

Analysis of the content and efficacy of the messages issued by the LEWSs is outside the scope of this work. However, we note that the content and type of messages vary substantially (Keefer et al., 1987; Wilson et al., 1993; Wiley, 2000; Wieczorek and Glade, 2005; NOAA-USGS Debris-Flow Task Force 2005; Baum and Godt, 2010; Wilson, 2012). With a few exceptions (e.g., Norway, Taiwan), the information is

Table 3
Examples of language used in 4-level advisory schemes. For ID and name of LEWSs see Fig. 1. For LEWSs location see Fig. 2. (*) Source: Dipartimento della Protezione Civile (2016).

ID	Advisory level	1	2	3	4
4	Seattle	Landslides very unlikely, isolated slides may occur even during dry weather.	Cumulative rainfall threshold (CT) exceeded or forecast amounts of rainfall and estimated snowmelt expected to exceed thresholds. Landslides might occur.	Probability of landslides increased significantly … the ground is wet enough to produce landslides with additional heavy rainfall. Isolated landslides may occur even without additional rainfall.	Widespread, shallow landslides are occurring or have a very high probability of occurring.
7	Rio de Janeiro	Landslides not directly triggered by rainfall.	Sporadic rainfall-induced landslides, mostly on artificial slopes	Abundant landslides triggered by heavy rainfall on natural and artificial slopes	Abundant and widespread landslides on natural and artificial slopes.
12	Emilia Romagna	0–1 landslide	2–19 landslides	20–59 landslides	≥ 60 landslides
13	Piedmont	No significant phenomena.	Localized phenomena.	Widespread phenomena.	Abundant and widespread phenomena.
22	Norway	Generally safe conditions.	Situation requires vigilance and may cause local damages. Expected some landslide events, certain large events may occur.	Severe situation that occurs rarely, requires contingency preparedness and may cause severe damages. Expected many landslides, some with considerable consequences.	Extreme situation that occurs very rarely, requires immediate attention and may cause severe damages. Expected many landslide events, several with considerable consequences.
25	Scotland	Landslides are unlikely, but isolated landslides can occur.	Likelihood or reports of isolated landslides.	Increased likelihood or reports of multiple landslides.	High likelihood or reports of major landslide events.
	Italy (*)	No or local phenomena expected. Local rock falls possible.	Local, intense phenomena expected. Shallow slides, debris and mud flows in small catchments, rock falls. Local danger to people. Possible fatalities.	Widespread, intense, persistent phenomena likely. Deep slides in critical settings, shallow landslides, debris and mud flows, rock falls. Danger to people. Possible fatalities.	Widespread, very intense, persistent phenomena likely. Activation, reactivation, acceleration of large deep slides, numerous shallow slides, debris and mud flows; rock falls. Serious danger to people. Possible fatalities.

given only in the local language, and this may limit the comprehension of the messages by tourists or foreigners.

The text of the first landslide warning issued by the USGS and the NWS on 14 February 1986 for the SFBA was as follows (Keefer et al., 1987):

"Due to continued very heavy precipitation in the Lexington Burn area of the Santa Cruz Mountains, the USGS and NWS advise of an increased hazard of mudslides and debris flows. This is based upon earth measurements taken in the burn area by the USGS and estimated rainfall from the Weather Service continuing at approximately 2 inches per 6 hours*. If the precipitation rate increases to 3* inches per 6 hours *or more, the USGS advises that mudslides are possible throughout much of the San Francisco Bay area. Persons living in the mountainous areas of the Bay area should watch for earth slippage and be prepared to move to safe ground."*

With 110 words, the message was very carefully written, and it included all the important elements of an advisory (Baum and Godt, 2010). In the first sentence, it gave the trusted sources ("USGS and NWS") (UNISDR, 2015), and the type ("mudslides and debris flows") and reason ("continued very heavy precipitation") for the threat. The next two sentences provided the scientific evidence, and quantitative measures to use the advisory in the next hours. The last sentence offered advice ("watch for earth slippage and be prepared to move"). A similar message is probably too long for modern media (635 characters, more than twice the maximum length of a "tweet"); and today LEWSs prefer short, concise, pre-coded messages, or they issue messages with different information levels.

We note that confusion exists on the language of the advisory levels. As an example, for four-level schemes, the words "null", "no landslides", "no significant", "low", "no watch", "normal", "normal vigilance" are used to describe the lowest level; "outlook", "attention", "low", "localized", "medium", "watch I", "watch II", "quiet", for the second level; "moderate", "watch", "high", "warning", "pre-alarm", "widespread" for the third level; and "warning", "alarm", "high", "very high", "extreme", "severe warning", "abundant and widespread" for the highest level. Some LEWSs link the advisory levels to the number of the expected landslides; with the number and limits of the classes also not common (Table 3). We recognize that adopting a common, standard language for the levels and the messages may be difficult, as they may depend on country or region specific organizational, liability, and legal constraints. Nonetheless, we encourage LEWS managers to adopt a standard vocabulary to define the advisory levels and the messages associated to each level.

Lastly, we note that the LEWSs use a variety of media and strategies to disseminate their advisories. In the 1980′s, the systems in Hong Kong (#1) and the SFBA (#2) used messages broadcasted by TV stations. Today, LEWSs exploit a wide range of media, including dedicated web sites, text messages, emails, fax, instant text, image, audio and video services, audio and video news for radio and TV stations, apps for smartphone and tablets, and changing road signs.

6. Discussion and perspectives

Geographical LEWSs have proven valuable tools to forecast landslides operationally, and by means of their advisories they can contribute to saving lives and reducing damage. But, LEWSs are complex systems, and several issues with their design, implementation, management, and verification remain open. Here, we discuss what we consider the most relevant open issues with LEWSs' design, implementation and management.

6.1. Landslide and rainfall data, and threshold models

LEWSs use different forms and combinations of rainfall data and forecast models (Figs. 1,5), the latter determined based on the analysis of landslide and rainfall data. This is not surprising, as rainfall is the main trigger of landslides. Surprising is the fact that little attention is given to the quality of the landslide and the rainfall data used to determine and use the landslide forecast models.

Knowing the time of occurrence of landslides is of paramount importance to determine a rainfall threshold; but it is often difficult due to the lack of accurate information on the time or period of occurrence of the landslides (Brunetti et al., 2010; Gariano et al., 2015; Peruccacci et al., 2017; Peres et al., 2018). Use of uncertain or wrong temporal landslide information may result in erroneous thresholds, in wrong forecasts, and in flawed verifications. For thresholds determined heuristically (i.e., visually) or statistically, the number of observations is important. Some of the thresholds are (or were) based on a very small number of landslides. The threshold used for the Chittagong metropolis was decided using 14 landslides (Ahmed et al., 2018), the threshold for Rio de Janeiro using 65 landslides (D'Orsi et al., 1997), the threshold for Indonesia with 83 landslides (Mulyana et al., 2019), and the threshold used by Hong and Adler (2007) for their global LEWS using ~ 70 landslides globally. A small landslide catalogue results in large uncertainties and in potentially inaccurate, or wrong thresholds (Kirschbaum et al., 2009, 2012). Efforts are needed to collect more accurate information on the time of occurrence of the landslides, as this will improve the prediction performance of the forecast models (Table 2).

Essential to the definition of accurate rainfall thresholds is the quality (i.e., abundance, distribution, accuracy) of the rainfall data. With a few exceptions (Wilson, 2012), little is known about the quality of the rainfall data used to define the thresholds, and for operational landslide forecasting. This is puzzling, because it is known that rainfall data can have significant spatial, temporal and quantitative uncertainties (Nikolopoulos et al., 2014, 2015; Kidd et al., 2017). The density and frequency of the rainfall data also have consequences on the thresholds, and the forecast skills (Marra et al., 2015, 2017; Sungmin and Foelsche, 2019). The rain gauge density used by the LEWSs varies from one gauge every ~ 10 (#1) to ~ 800 (#22) km^2, and the temporal sampling from 5-min (#1) to daily measurements (#8, 10) (Fig. 1). The rain gauge density influences the performance of the LEWSs, and the large observed differences limits the significance of the possible comparisons. The source of the rainfall data also conditions the thresholds and their use. Rossi et al. (2012b, 2017) and Brunetti et al. (2018) showed that rainfall thresholds can be determined using satellite-based rainfall estimates, but the satellite-based thresholds are different from similar thresholds prepared using rain gauge data in the same areas. We argue that thresholds can only be used with the same type of rainfall data used to prepare them (Rossi et al., 2017). This has consequences for operational landslide forecasting, and for the evaluation of the LEWS performances. Efforts are required to improve the quantification of landslide triggering rainfall fields, and to compare and combine rainfall fields obtained from different sources e.g., rain gauge measurements and radar estimates (Sinclair and Pegram, 2005; Pignone et al., 2013), or satellite-based products (Huffman et al., 2010, 2015) (Table 2).

A long-lived issue is the exportability of rainfall thresholds, which proves difficult, forcing investigators to compile records of historical landslides and spatially and temporally coincident rainfall data in each new area (Govi and Sorzana, 1980; Wilson, 1997; Crosta, 1998; Guzzetti et al., 2007, 2008; Baum and Godt, 2010). The difficulty is now mitigated by tools that facilitate and accelerate the collection (Calvello and Pecoraro, 2018) and the organization and management (Napolitano et al., 2018) of landslide information, and of algorithms and software to reconstruct rainfall events and to calculate rainfall thresholds (Melillo et al., 2015, 2018; Baum et al., 2018). However, even large datasets may not be sufficient to obtain reliable thresholds. Peruccacci et al. (2017) segmented a catalogue of > 2200 rainfall events with landslides in Italy and obtained 26 topographic, lithological, land-use/cover, climatic, and meteorological thresholds.

Considering the uncertainties, the thematic thresholds overlapped in the range of durations from one to 48 h of interest for operational landslide forecasting, making it difficult to select and use the thresholds operationally.

Little or no information is available on the methods and techniques used to determine the thresholds used in the LEWSs. With a few exemptions (#4, 16–18, 21), rainfall threshold models were defined heuristically or using elementary statistics, and the uncertainties associated to the models are rarely defined (Brunetti et al., 2010) and used. This is surprising, as a forecast without uncertainty is of little use. Model uncertainty has multiple sources, including the number, distribution, and accuracy of the empirical data points, the definition of the rainfall conditions that initiate the landslides, and the methods used to decide the thresholds. To address the issue, Rossi et al. (2012a); Vessia et al. (2014) and Melillo et al. (2015) proposed methods, procedures, and algorithms for the objective reconstruction of rainfall events responsible for landslides. Melillo et al. (2018) released software for the automatic definition of rainfall thresholds and their uncertainties, and Rossi et al. (2017) proposed methods and procedures to propagate the rainfall measurement uncertainty to determine rainfall thresholds and the associated uncertainties. Additional efforts are needed to standardize the methods used to define the threshold models (Table 2). Use of standard methods will allow for better and more meaningful comparisons of the models, and of the LEWSs performances. It may also help exporting threshold models to neighbouring or distant areas (Guzzetti et al., 2007).

Although examples exist of areas where simple threshold models proved ineffective for landslide forecasting (Jakob et al., 2012), rainfall thresholds are generally reliable and an effective tool for operational landslide forecasting (Fig. 1). A threshold assumes a dichotomic behaviour, with landslides either expected or not expected given a certain amount of rainfall in a period (Reichenbach et al., 1998; Guzzetti et al., 2007). However, this is a simplification. Reality is different, and poses multiple questions. Here, we address questions related to the threshold models. Below (Section 6.3), we discuss issues with the conversion of landslide forecasts into advisories.

First, how many thresholds are needed for operational landslide forecasting? Piciullo et al. (2017a, 2017b) proposed to select the number and level of the thresholds based on an optimization procedure that minimizes the false alarm rate (Calvello and Piciullo, 2016). Rossi et al. (2018) defined a probabilistic ED rainfall space that allows forecasters and LEWSs managers to decide multiple non-exceedance probability thresholds depending on their needs and expectations, and Martinotti et al. (2017) proposed an ensemble-non-exceedance probability algorithm for the prediction of rainfall-induced landslides. Despite these promising results, further experimentation is needed to decide on the number of thresholds needed for operational landslide forecasting, how to verify the threshold models, and even if – or to what extent – a threshold model is adequate for operational landslide forecasting and early warning (Table 2).

Second, how often should the threshold models be updated? One could argue that the thresholds should be revised and updated whenever new landslide and rainfall data becomes available. Scheevel et al. (2017) used new data for the Seattle area and obtained slightly different thresholds from Godt et al. (2006) and Chleborad et al. (2008) for the same area. We added 335 data (14.5% increase) collected in the same period with the same methodology to the dataset used by Peruccacci et al. (2017) to define the national threshold for Italy, and the threshold remained unchanged. The different results may depend on the size, the quality, and the period covered by the datasets, and by the local meteorological, physiographic and environmental conditions. New information should be considered with care, as it may introduce biases in the data and the thresholds, particularly if the dataset used to decide the original thresholds is small, and if the new information derives from a single, large or extreme event. We stress that, to a large extent, consistency and representativeness of the data samples is more important than the number of the empirical data points used to decide reliable thresholds. Research is needed to establish reliable and effective strategies for landslide and rainfall data collection, and threshold definition (Guzzetti et al., 2007, 2008) (Table 2). Further, changing thresholds frequently complicates the validation of the threshold models.

Third, to what extent can we use past rainfall and landslide data to predict current and future landslides? The question is difficult to answer (Furlani and Ninfo, 2015). Past landslide and rainfall data may not have the same accuracy and resolution of present and future data, conditioning the reliability of the threshold models and forecasts. Global and regional climate and environmental changes may affect the number, abundance, distribution, type, frequency, and activity of landslides in ways and at rates that we are only beginning to understand and measure (Gariano and Guzzetti, 2016; Haque et al., 2019), limiting the applicability of threshold models prepared with historical data. To address the problem, for their national and regional LEWSs in Italy, Rossi et al. (2012a, 2017) have narrowed the time span of the landslide and rainfall data used to decide the thresholds, trading length of the record for accuracy and completeness of the data. The choice limited the number of the empirical data used to constrain the thresholds (Peruccacci et al., 2017). Efforts are needed to study the role of climate and environmental changes on rainfall thresholds and their operational use, and to address the inherent incompleteness and non-stationarity of historical landslide and rainfall records (Table 2).

6.2. Landslide susceptibility

In their landmark paper, Baum and Godt (2010) clarify that "precipitation thresholds for landslide occurrence are useful in constraining when landslides are likely to occur; however, they are not spatially explicit", and do not provide information on where landslides are expected, given threshold-exceeding rainfall. This is information potentially available from landslide susceptibility maps (Reichenbach et al., 2018). LEWSs require an understanding of the areas potentially affected by landslides (Baum et al., 2005; Stähli et al., 2015), as one expects landslides to be more frequent and abundant where susceptibility is high; and many LEWSs use information on landslide susceptibility (Brabb, 1984; Guzzetti, 2006). Godt et al. (2012) and Marchesini et al. (2014) have explored the concept of "non-susceptibility" i.e., the definition of areas where landslide susceptibility is null or negligible, and where landslides are not expected. This geographical information can also be used in LEWSs. However, multiple issues remain open with the integration of susceptibility information in LEWSs for operational landslide forecasting. Firstly, the scale, resolution, and spatial domains of landslide susceptibility assessments and of rainfall data and thresholds are typically very different. How to combine susceptibility and threshold models prepared at very different scales remains an open problem. An option is to prepare susceptibility assessments specifically designed for operational landslide forecasting, at scales and with spatial resolutions compatible with those required or expected by landslide forecasts. Secondly, susceptibility is by definition time invariant (Guzzetti, 2006) i.e., it should not change when a landscape is forced by a specific trigger. How to use long term (decades to millennia) susceptibility assessments for short term (hours to days) landslide forecasts remains a conceptual and operational problem. Thirdly, combination of probabilistic susceptibility and threshold models should follow the laws of probability e.g., the probabilities should be conditionally independent or the marginal probabilities should be known and treated appropriately. In the literature, it is not always clear if the LEWSs adopt sound probabilistic approaches. Further research is needed to address these issues.

LEWSs can run physically-based susceptibility models, singularly (#9) or in combination with threshold models (#24). The approach is promising, but has limitations. Firstly, the area where the physically-based model is run is typically smaller (or much smaller) than the area for which the forecast is prepared. Secondly, physically-based modelling requires site specific geotechnical and hydrological information which is usually available only for small areas. Thirdly, the test area should be forced by the same rainfall field as the larger forecast area. The issues are closely related, and question the representativeness of the model outputs (and forecasts) obtained in small test areas for the large forecast areas. Experiments are underway to test spatially distributed, physically-based models over large areas (Bellugi et al., 2011; Raia et al., 2014). Modern computers can handle the computational load needed by physically-based models over large areas (Alvioli et al., 2014; Alvioli and Baum, 2016; Raia et al., 2014), producing results at spatial resolutions and time intervals adequate for operational landslide forecasting. However, the approach has conceptual and practical drawbacks, the most relevant of which is the difficulty to collect the static and dynamic geotechnical and hydrological information required to run the models, capturing the natural variability of the properties at the right scales. Further, existing models consider small shallow landslides (Montgomery and Dietrich, 1994; Baum et al., 2008; Brien and Reid, 2007, 2008; Alvioli and Baum, 2016). Spatially-distributed models that consider large deep-seated landslides exist (Brien and Reid, 2007, 2008; Mergili et al., 2014a,b) but, at the time of writing, they do not consider the dynamic meteorological forcing needed for operational landslide forecasting. Large, complex, deep-seated landslides driven by rainfall or snowmelt, may be difficult to predict even by dynamic models. Accurate mapping of existing landslides (Guzzetti et al., 2012) coupled with satellite DInSAR monitoring (Del Ventisette et al., 2013; Handwerger et al., 2019; Raspini et al., 2018) are needed to inform the prediction of the activity of deep-seated landslides over large areas.

An additional, potentially synergic approach consists in the integration in regional LEWSs of monitoring and modelling information obtained for single catchments (Fathani et al., 2016, 2018) or deep-seated landslides (#14) (Martelloni et al., 2012; Ponziani et al., 2013; Tiranti et al., 2013). Here the challenge is in the technological and operational difficulty in extrapolating the monitoring and modelling information regionally, or nationally. Albeit, modern monitoring and communication technologies do not limit the number of landslides that can be monitored and modelled (Stähli et al., 2015), the approach is limited to areas where monitoring networks are already installed or where the value and relevance of the elements at risk justify the effort (Baum and Godt, 2010). Further, the approach does not consider first time landslides that may occur with lower forcing than reactivated landslides. Experimentation is needed to exploit and integrate site specific monitoring and physically-based models for improved operational landslide forecasting, at different geographical scales (Stähli et al., 2015; Mirus et al., 2018a, 2018b) (Table 2).

6.3. From landslide forecasts to advisories

Landslide forecast models, including rainfall thresholds or more complex statistical or physically-based models and their combinations, make process-based predictions that anticipate where and when landslides are expected to occur. This is important, but it is not sufficient to authorities, emergency managers, stakeholders or the public (Chleborad et al., 2008; Baum and Godt, 2010). For them, landslide advisories providing information on the consequences of the expected landslides and giving recommendations or orders on what to do (or not do) when a warning is in effect, are necessary. Converting landslide forecasts into proper advisories requires a change in perspective, from process-based to impact-based predictions (WMO, 2015; Potter et al., 2018). The step is not straightforward, and its complexity and relevance are often underestimated (Calvello and Piciullo, 2016; Piciullo et al., 2017a, 2017b). The difficulty of making the conversion is compounded by the fact that some storms might cause tens of thousands of landslides but few or no fatalities, whereas a small storm might produce a single landslide with numerous casualties. Also, large storms may produce fatal landslides distant from the storm centre where landslides are most numerous. In November 1994, a large storm in northern Italy caused several thousand landslides in the southern part of Piedmont region, and only a few soil slips in the northern part of the region. At Varallo Sesia, in the north of the region, one of these soil slips killed 14 people (Crosta, 1998).

Albeit very little information is available in the literature on how process forecasts are used to issue advisories, the conversion is typically expert-driven (Chleborad et al., 2008; Baum and Godt, 2010) and performed following more or less strictly or explicitly sets of pre-defined rules (a “landslide protocol” Guzzetti et al., 2000) linking the outcomes of one or more landslide forecast models to pre-defined advisory levels for which specific or general recommendations (#1, 2, 22) or orders (#20) are given. The protocol should consider the uncertainties inherent in the landslide forecast models, and how the uncertainties are expressed in the advisories. It should also reflect the number and levels of the advisories, which conditions the performance of a LEWS (Piciullo et al., 2017b). As discussed before, the number of the advisory levels may depend on organizational, societal, and legal constraints external to the LEWS. We recommend that where this is the case, an honest assessment of the consequences of adopting an external, general advisory scheme is executed (Table 2). In particular, the extent to which the information and insight given by the process models is adequate for the predefined advisory schemes, considering the inherent uncertainties, should be clear.

The awareness of the people exposed to landslide hazard is important for their response to a warning (Huggel et al., 2010), and communication and sociological problems must be considered and addressed when designing an effective landslide advisory scheme. Cannon et al. (2009) argued that a lead time of hours to days is more useful for emergency response than shorter lead times of minutes to hours typical of emergency advisories. In this complex process, a crucial step is the selection of the language and content of the advisory messages. The language should be clear and unambiguous. However, our analysis of the literature revealed that the language used for landslide advisories and messages is often confusing, misleading, and far from standard. We encourage LEWSs managers to establish a common language for their advisories (Stähli et al., 2015) (Table 3) as this will facilitate dissemination (Sorensen, 2000), will contribute to improving the LEWS performance, and will increase the credibility of the system. The instructions given in a landslide advisory should be easy to understand by the public, who are generally uninformed about landslides and their risk (Baum and Godt, 2010; Wilson, 2012). The actions to take when an advisory is given should be reasonable and practicable. Further, any landslide protocol should consider that frequent wrong advisories – warnings not followed by landslides, or landslides that occur without warning – can destroy trust in a LEWS (Wilson, 2012). It should also be clear that perceived false/true alarms may be as important as real false/true alarms in building or undermining trust in a LEWS. This should be considered when preparing and issuing a landslide advisory.

6.4. Performance evaluation

A vital part of a LEWS is the evaluation of its performance i.e., how successfully the system does against expectations and user requirements. The operation is complex, and it includes an evaluation of the model forecasts, of the advisories, and of the system technological implementation and functioning. All parts of a LEWS should be evaluated using appropriate metrics and criteria (Table 3). However, no standard exists to evaluate the performance of a LEWS (Baum and Godt, 2010; Fathani et al., 2016; Chae et al., 2017; Piciullo et al., 2018; Segoni et al., 2018a). This limits the comparability and credibility of the LEWSs.

Evaluation should start with a verification of the performances of the process forecast models. This is difficult and poses serious limitations, because the lack of systematic (instrumental) information on landslide occurrence (or the lack of occurrence) does not allow to exploit fully typical contingency tables (Staley et al., 2013; Gariano et al., 2015), and the many related forecast verification indexes (Jollifee and Stephenson, 2003). Instrumental monitoring can help, but it is typically limited to a small number of sites, and it does not consider first-time failures. Analysis of remote sensing images can help detect new landslides (Mondini et al., 2019), and prepare landslide event inventory maps (Mondini et al., 2011, 2019; Mondini, 2017), but it is not systematic. Further, it allows to verify a forecast in space, but with poor time information. Detection of non-earthquake-induced landslides using local to global seismic networks is promising, but it works only for failures that produce a detectable seismic signal (Ekström and Stark, 2013; Hibert et al. 2014; Fuchs et al., 2018; Schimmel et al., 2018). When it works, the technique gives very accurate information on the time of occurrence of the landslide. Combination of remote sensing and seismic signal processing techniques may be part of the solution of the problem. Automatic, semi-automatic or manual collection of information on landslide occurrence from media sources provides valuable information, but is limited to landslides that cause damage or that occur in built-up areas or along infrastructures (Chleborad et al., 2008; Van Den Eeckhaut and Hervás, 2012; Calvello and Pecoraro, 2018; Pecoraro et al., 2019). Manual collection is labour intensive, and the automatic and semi-automatic methods require independent checking. As an alternative, Peruccacci et al. (2017) measured the long-term performance of a rainfall threshold model showing that all 52 rainfall-induced fatal landslides in Italy between 2002 and 2012 were hindcasted correctly by the model. The result was good, but failed to quantify false alarms, and measured the model predictive skills only with respect to fatal landslides.

LEWS evaluation should continue with the assessment of the advisory part. One has to assess if, or to what extent, a LEWS was able to give the proper messages to different, prescribed audiences in terms of the predicted consequences, as well as the response of the audiences in terms of their understanding of the messages and of the actions taken (or not taken), and the extent to which landslide risk was reduced. The evaluation should consider the timing (Cannon et al., 2009; Jakob et al., 2012; Wilson, 2012) and efficacy of the communication strategy (e.g., media and language used) (Baum and Godt, 2010; Stähli et al., 2015), risk perception, awareness and preparedness (Huggel et al., 2010; Scolobig et al., 2012; Wilson, 2012; Salvati et al., 2014; Chae et al., 2017; Potter et al., 2018), and gender and age disparities in landslide risk exposure, awareness and averseness (Badoux et al., 2016; Salvati et al., 2018).

The last step should evaluate the technological performance of the LEWS, including e.g., mean time between failures, total up/down time, mean down time, time to recovery. These metrics are simple to calculate and compare against benchmarks or minimum and optimal user requirements once the system events are logged. However, we note that in the literature no information is given on the LEWSs technological performances, on the minimum and optimal user requirements, and even on the fact that the main system events are logged.

Urgent, multi-disciplinary efforts are needed to advance the limited capacity to evaluate the performances of the LEWSs (Table 2). We stress that standard and shared performance evaluations approaches will allow the discovery of problems in existing LEWSs and possible fixes, and will increase the credibility and authority of the LEWSs; a key aspect for landslide risk reduction.

6.5. Perspectives

Despite the efforts and the definite progress, current models for operational landslide forecasting remain limited in their ability to predict landslides. Many LEWSs use forecast models that consider only rainfall, and ignore other triggers e.g., rapid snowmelt, irrigation, permafrost melting. Only a few models consider the soil moisture and groundwater conditions that control landslide initiation (Fig. 1). With a few exceptions (Tiranti et al., 2013; Segoni et al., 2015a, 2018c), LEWSs consider only shallow landslides and associated flows, but ignore deep-seated landslides that can occur hours or days after the end of a storm. Most of the forecast models do not consider transient events that alter the amount of rainfall that can initiate landslides and local susceptibility to meteorologically-driven landslides, including e.g., forest and wild fires (NOAA-USGS Debris-Flow Task Force 2005; Cannon et al., 2009), forest cutting, seasonal or long-term agricultural changes. Most models predict the location of the landslide initiation points or areas but do not consider the landslide runout, which is crucial for rapidly moving failures that may travel long distances in a short time, and can affect areas distant from the initiation points (NOAA-USGS Debris Flow Task Force, 2005; Baum and Godt, 2010; Hungr et al., 2014). Most LEWSs do not consider the direct or indirect consequences of the landslides (Ponziani et al., 2013), and those based on rainfall thresholds may provide only approximate landslide risk conditions (Cannon et al., 2009). Further, due to the limited ability to detect, locate, and report new or re-activated landslides over wide areas (Chleborad et al., 2008), verification of forecast models and landslide advisories remains uncertain and LEWSs skills questionable. We maintain that there is scope for new research aimed at improving all these aspects of current operational landslide forecasting models and LEWSs (Table 2). Lastly, and with only few exceptions (#13, 22), LEWSs typically operate single (or a few) landslide models. We expect operational landslide forecasting and LEWSs to improve significantly when landslide forecasters and LEWS managers will share openly their landslide models and advisory protocols, and will use multiple models for their landslide forecasts and associated advisories (Table 2).

In meteorology, efforts are made towards long-range (seasonal) weather forecasts. Albeit the predictive skills of long-range forecasts are debated (Weisheimer and Palmer, 2014; Yang et al., 2018), seasonal weather forecasts are being used increasingly for multiple applications, and we see scope for long-range (seasonal) landslide forecasts. In line with weather forecasts, long-range landslide forecasts should be attempted using potential weather landslide precursors – such as monthly to seasonal rainfall and temperature – obtained from model ensembles, producing ensembles of landslide forecasts. Seasonal landslide forecasts are not expected to predict the exact or even approximate location or number of landslides at any given site or area; but instead to provide insight on the expected trends in landslide activity. This may help preparedness and guide maintenance activities, contributing to reduce damages and costs, and the design and implementation of effective mitigation strategies. Research is needed to understand how to use long-range weather forecasts for seasonal landslide modelling, and how to cope with uncertainties and their percolation through the weather-landslide modelling chain. There is scope for new research aimed at better understanding the impact of the current and projected climate and environmental changes on landslides and their consequences (Gariano and Guzzetti, 2016).

Lastly, we note that a few authors have argued in favour of standards or shared frameworks for the design, implementation, management, and verification of LEWSs (UN-ISRD 2006; Chleborad et al., 2008; Stähli et al., 2015; Fathani et al., 2016; Chae et al., 2017; Piciullo et al., 2018; Segoni et al., 2018a). Such standards are currently lacking, and this limits the credibility and usefulness of LEWS (Guzzetti et al., 2012; Reichenbach et al., 2018). Recently, the international standard ISO 22327:2018(E) was issued with “Guidelines for implementation of a community-based landslide early warning system” (ISO, 2018). It is not clear if this standard was discussed openly, and if it is accepted broadly by the international landslide community. We recommend that the landslide community become involved openly in the definition of standards for LEWSs and operational landslide forecasting at all geographical and temporal scales (Table 2).

7. Conclusions

Based on our review of 26 past and existing landslide early warning systems (LEWSs) in a period of 42.5 years (Figs. 1,2,3), and on our experience in the design, implementation, management and verification of national and regional LEWSs in Italy, we conclude that operational forecasting of weather-induced landslides is possible and feasible today, and it can contribute to mitigate landslide risk, reducing fatalities and economic loses. However, LEWSs remain complex, and operational landslide forecasting a difficult and uncertain task. Both require conceptual developments and technological improvements. Critical examination of the 26 LEWSs considered in this work allowed us to identify a list of recommendations for the further development and improvement of geographical LEWSs (Table 2). We conclude by adding a last recommendation. We encourage the community of landslide forecasters and LEWS managers to pull together and propose shared, open standards for the design, the implementation, the management, and the verification of geographical ("territorial" Piciullo et al., 2018) LEWSs. We foresee that such standards will contribute to save lives and to mitigate landslide risk, and we expect our work to contribute to this endeavour.

Lastly, we acknowledge that the expansion of LEWSs will require resources, which most probably will have to be taken from other, competing safety strategies and risk reduction programs and measures. We expect that in many areas, local, regional, and national priorities, the availability of resources, the relative frequency of landslide casualties, and the extent and amount of landslide damage, will control the development and expansion of new landslide early warning systems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Research partially supported by grants from the Italian National Civil Protection Department, and from the UK NERC SHEAR funded project (grant number NERC/DFIDNE/P000649/1) LANDSLIP (http://www.landslip.org/). We are grateful to Massimo Arattano (CNR IRPI, Italy), Shiho Asano (Forestry & Forest Production Research Institute, Japan), Cinzia Bianchi (CNR IRPI, Italy), Michael Crozier (Victoria University of Wellington, New Zealand), Graziella Devoli (NVE, Norway), Katy Freeborough (BGS, UK), Melanie Froude (University of Sheffield, UK), Johnathan Godt (USGS, USA), Sara Pignone (Emilia-Romagna Region, Italy), Dalia Kirschbaum (NASA, USA), Meei-Ling Lin (National Taiwan University, Taiwan), Andrew Malone (Hong Kong University, Hong Kong), Lorenzo Marchi (CNR IRPI, Italy), David Petley (University of Sheffield, UK), Luca Piciullo (NGI, Norway), Helen J. Reeves (BGS, UK), Samuele Segoni (University of Florence, Italy), Samuel Jonson Sutanto (BLS, Indonesia), Hsiao-Yean Yin (SWCB, Taiwan), Lun-Wei Wei (Sinotech, Taiwan), and Robert Ziemer (Humboldt State University, USA) for sharing papers, reports, and information. We thank the journal editor, Robert Jacobson, Benjamin B. Mirus, and a second anonymous referee for their constructive comments that helped us to improve the content, quality, and readability of the work.

References

Ahmed, B., Rahman, M., Islam, R., Sammonds, P., Zhou, C., Uddin, K., Al-Hussaini, T., 2018. Developing a dynamic Web-GIS based landslide early warning system for the Chittagong Metropolitan Area. Bangladesh. ISPRS Int. J. Geo-Inf. 7 (12), 485. https://doi.org/10.3390/ijgi7120485.

Aleotti, P., 2004. A warning system for rainfall-induced shallow failures. Eng. Geol. 73, 247–265. https://doi.org/10.1016/j.enggeo.2004.01.007.

Alfieri, L., Salamon, P., Pappenberger, F., Wetterhall, F., Thielen, J., 2012. Operational early warning systems for water-related hazards in Europe. Environ. Sci. Pol. 21, 35–49. https://doi.org/10.1016/j.envsci.2012.01.008.

Alvioli, M., Baum, R.L., 2016. Parallelization of the TRIGRS model for rainfall-induced landslides using the message passing interface. Environ. Model. Softw. 81, 122–135. https://doi.org/10.1016/j.envsoft.2016.04.002.

Alvioli, M., Guzzetti, F., Rossi, M., 2014. Scaling properties of rainfall induced landslides predicted by a physically-based model. Geomorphology 213, 38–47. https://doi.org/10.1016/j.geomorph.2013.12.039.

Badoux, A., Andres, N., Techel, F., Hegg, C., 2016. Natural hazard fatalities in Switzerland from 1946 to 2015. Nat. Hazards Earth Syst. Sci. 16, 2747–2768. https://doi.org/10.5194/nhess-16-2747-2016.

Basher, R., 2006. Global early warning systems for natural hazards: systematic and people-centred. Phil. Trans. R. Soc. A 364, 2167–2182. https://doi.org/10.1098/rsta.2006.1819.

Baum, R.L., Godt, J.W., 2010. Early warning of rainfall-induced shallow landslides and debris flows in the USA. Landslides 7, 259–272. https://doi.org/10.1007/s10346-009-0177-0.

Baum, R.L., Coe, J.A., Godt, J.W., Harp, E.L., Reid, M.E., Savage, W.Z., Schulz, W.H., Brien, D.L., Chleborad, A.F., McKenna, J.P., Winchell, M., 2005. Regional landslide-hazard assessment for Seattle, Washington. USA. Landslides 2, 266–279. https://doi.org/10.1007/s10346-005-0023-y.

Baum, R.L., Highland, L.M., Lyttle, P.T., Fee, J.M., Martinez, E.M., Wald, L.A., 2014. "Report a Landslide" A Website to Engage the Public in Identifying Geologic Hazards. In: Sassa, K., Canuti, P., Yin, Y. (Eds.), Landslide Science for a Safer Geoenvironment. Springer, Cham.

Baum, R.L., Fischer, S.J., Vigil, J.C., 2018. THRESH—Software for tracking rainfall thresholds for landslide and debris-flow occurrence, user manual. U.S. Geological Survey Techniques and Methods n. 14-A2. Reston, Virginia.

Baum, R.L., Godt, J., Savage, W., 2010. Estimating the timing and location of shallow rainfall-induced landslides using a model for transient, unsaturated infiltration. J. Geophys. Res. 115, F03013. https://doi.org/10.1029/2009JF001321.

Baum, R.L., Savage, W., Godt, J.W., 2008. TRIGRS — a FORTRAN program for transient rainfall infiltration and grid-based regional slope-stability analysis, version 2.0. U.S. Geological Survey Open-file Report 2008-1159. 75 pp, Washington DC. https://pubs.usgs.gov/of/2008/1159.

Beldring, S., Engeland, K., Roald, L.A., Sælthun, N.R., Voksø, A., 2003. Estimation of parameters in a distributed precipitationrunoff model for Norway. Hydrol. Earth Syst. Sci. 7, 304–316. https://doi.org/10.5194/hess-7-304-2003.

Bell, R., Cepeda, J., Devoli, G., 2014. Landslide susceptibility modelling at catchment level for improvement of the landslide early warning system in Norway. In: Proc. 3rd World Landslide Forum. 2–6 June 2014, Beijing.

Bellugi, D., Dietrich, W.E., Stock, J.D., McKean, J.A., Kazian, B., Hargrove, P., 2011. Spatially explicit shallow landslide susceptibility mapping over large areas. Ital. J. Eng. Geol. Environ. https://doi.org/10.4408/IJEGE.2011-03.B-045.

Bergström, S., 1995. The HBV model. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Res. Publ., Highlands Ranch, CO, pp. 443–476.

Berti, M., Martina, M.L.V., Franceschini, S., Pignone, S., Simoni, A., Pizziolo, M., 2012. Probabilistic rainfall thresholds for landslide occurrence using a Bayesian approach. J. Geophys. Res. 117, F04006. https://doi.org/10.1029/2012JF002367.

Boje, S., 2017. Hydrometeorologiske terskel for Jordskredfare på Sørlandet og Østlandet. NVE Report 64. Accessed 17 June 2019 (in Norwegian). http://publikasjoner.nve.no/rapport/2017/rapport2017_64.pdf.

Boje, S., Devoli, G., Cepeda, J., Hervé, C., 2014. Landslide thresholds at regional scale for an early warning system in Norway. In: Proc. of the 3rd World Landslide Forum, 2014. Beijing. pp. 1–7.

Brabb, E.E., 1984. Innovative approaches to landslide hazard mapping. In: Proc. of the 4th International Symposium on Landslides, 1. Toronto, Canada, 16-21 September 1984. pp. 307–324.

Brand, E.W., Premchitt, J., Phillipson, H.B., 1984. Relationship between rainfall and landslides in Hong Kong. In: Proc. of the 4th International Symposium on Landslides, 1. Toronto, Canada, 16–21 September 1984. pp. 276–284.

Brien, D.L., Reid, M.E., 2007. Modeling 3-D slope stability of coastal Bluffs using 3-D Ground-Water flow. Scientific Investigations Report No. 2007–509. U.S. Geological Survey, Southwestern Seattle, Washington.

Brien, D.L., Reid, M.E., 2008. Assessing deep-seated landslide susceptibility using 3-D groundwater and slope-stability analyses, southwestern Seattle, Washington. Landslides and Engineering Geology of the Seattle. Area. Geol. Soc. Am., Washington. https://doi.org/10.1130/2008.4020(05).

Brigandì, G., Aronica, G.T., Bonaccorso, B., Gueli, R., Basile, G., 2017. Flood and landslide warning based on rainfall thresholds and soil moisture indexes: the HEWS (Hydrohazards EarlyWarning System) for Sicily. Adv. Geosci. 44, 79–88. https://doi.org/10.5194/adgeo-44-79-2017.

Brunetti, M.T., Melillo, M., Peruccacci, S., Ciabatta, L., Brocca, L., 2018. How far are we from the use of satellite rainfall products in landslide forecasting? Remote Sens. Environ. 210, 65–75. https://doi.org/10.1016/j.rse.2018.03.016.

Brunetti, M.T., Peruccacci, S., Rossi, M., Luciani, S., Valigi, D., Guzzetti, F., 2010. Rainfall thresholds for the possible occurrence of landslides in Italy. Nat. Hazards Earth Syst. Sci. 10, 447–458. https://doi.org/10.5194/nhess-10-447-2010.

Cacciamani, E.P., Ferri, M., Minguzzi, E., 2002. High resolution verification of hydrostatic and non-hydorstatic LAM precipitation forecasts in Italy. In: Doms, G., Shatter, U. (Eds.), COSMO Newsletter, II. Offenbach, Germany, pp. 176–186.

Caine, N., 1980. The rainfall intensity - duration control of shallow landslides and debris flows. Geografiska Annaler 62 (1-2), 23–27. https://doi.org/10.1080/04353676.1980.11879996.

Calvello, M., 2017. Early warning strategies to cope with landslide risk. Riv. Ital. Geotec. 2, 63–69. https://doi.org/10.19199/2017.2.0557-1405.063.

Calvello, M., Pecoraro, G., 2018. FraneItalia: a catalog of recent Italian landslides.

Geoenviron. Disast. 5, 13. https://doi.org/10.1186/s40677-018-0105-5.

Calvello, M., Piciullo, L., 2016. Assessing the performance of regional landslide early warning models: the EDuMaP method. Nat. Hazards Earth Syst. Sci. 16, 103122. https://doi.org/10.5194/nhess-16-103-2016.

Calvello, M., d'Orsi, R.N., Piciullo, L., Paes, N., Magalhaes, M., Lacerda, W.A., 2015a. The Rio de Janeiro early warning system for rainfall-induced landslides: Analysis of performance for the years 2010–2013. Int. J. Disast. Risk Reduc. 12, 3–15. https://doi.org/10.1016/j.ijdrr.2014.10.005.

Calvello, M., d'Orsi, R.N., Piciullo, L., Paes, N.M., Magalhaes, M.A., Coelho, R., Lacerda, W.A., 2015b. The Community-based alert and alarm system for rainfall induced landslides in Rio de Janeiro, Brazil. In: In: Lollino, G., Giordan, D., Crosta, G.B., Corominas, J., Azzam, R., Wasowski, J., Sciarra, N. (Eds.), Engineering Geology for Society and Territory Vol. 2. Springer International Publishing, Cham, pp. 653–657. https://doi.org/10.1007/978-3-319-09057-3_109.

Campbell, R.H., 1975. Soil slips, debris flows, and rainstorms in the Santa monica mountains and vicinity, Southern California. U.S.G.S. Professional Paper 851. pp. 51.

Cannon, S.H., Ellen, S., 1985. Rainfall conditions for abundant debris avalanches, San Francisco Bay region. California. California Geology 38 (12), 267–272.

Cannon, S.H., Laber, J., Jackson, M., Werner, K., Restrepo, P., 2009. NOAA/USGS demonstration flash-flood and debris-flow early-warning system for recently burned areas in southern California, and lessons learned from four years of operation. In: 2009 GSA Annual Meeting. 18–21 October 2009, Portland.

Capparelli, G., Versace, P., 2011. FLaIR and SUSHI: two mathematical models for early warning of landslides induced by rainfall. Landslides 8, 67–79. https://doi.org/10.1007/s10346-010-0228-6.

Cepeda, H., Murcia, L.A., 1988. Mapa preliminar de amenaza volcánica volcán Nevado del Tolima, Colombia, S.A., Ministerio de Minas y Energía. Informe 2070 50pp. (in Spanish).

Chae, B.-G., Park, H.-J., Catani, F., Simoni, A., Berti, M., 2017. Landslide prediction, monitoring and early warning: a concise review of state-of-the-art. Geosci. J. 21, 1033–1070. https://doi.org/10.1007/s12303-017-0034-4.

Chan, R.K.S., Pang, P.L.R., Pun, W.K., 2003. Recent developments in the landslip warning system in Hong Kong. In: . Proc. of the 14th Southeast Asian Geotechnical Conference. Balkema, Lisse, The Netherlands. pp. 137–151.

Chan, C.H.W., Ting, S.M., Wong, A.C.W., 2012. Development of Natural Terrain Landslip Alert Criteria. Geotechnical Engineering Office, Hong Kong.

Cheung, P.Y., Wong, M.C., Yeung, H.Y., 2006. Application of rainstorm nowcast to realtime warning of landslide hazards in Hong Kong. In: Proc. of WMO PWS Workshop on Warnings of Real-Time Hazards by Using Nowcasting Technology. Sydney, Australia, 9–13 October 2006.

Chleborad, A.F., 2003. Preliminary evaluation of a precipitation threshold for anticipating the occurrence of landslides in the Seattle, Washington, Area. U.S.G.S. Open-File Report 03-463. 39pp.

Chleborad, A.F., Baum, R.L., Godt, J.W., Powers, P.S., 2008. A prototype system for forecasting landslides in the Seattle, Washington, area. In: Baum, R.L., Godt, J.W., Highland, L.M. (Eds.), Landslides and Engineering Geology of the Seattle, Washington, Area. Geological Society of America. https://doi.org/10.1130/2008.4020(06).

Choi, K.Y., Cheung, R.W., 2013. Landslide disaster prevention and mitigation through works in Hong Kong. J. Rock Mech. Geotech. Eng. 5 (5), 354–365. https://doi.org/10.1016/j.jrmge.2013.07.007.

Chorlton, L.B., 2007. Generalized geology of the world: bedrock domains and major faults in GIS format: a small-scale world geology map with an extended geological attribute database. Geological Survey of Canada. https://doi.org/10.4095/223767. Open File 5529.

Collins, B.D., Stock, J.D., Foster, K.A., Whitman, M.P.W., Knepprath, N.E., 2012. Monitoring the subsurface hydrologic response for precipitation induced shallow landsliding in the San Francisco Bay area, California, U.S.A. In: Eberhardt, E., Froese, C., Turner, K., Leroueil, S. (Eds.), Landslides and Engineered Slopes: Protecting Society Through Improved Understanding. Taylor and Francis Group, London, UK, 978-0-415-62123-6, pp. 1249–1255.

Corazza, M., Sacchetti, D., Antonelli, M., Drofa, O., 2018. The ARPAL operational high resolution Poor Man's Ensemble, description and validation. Atmos. Res. 203, 1–15. https://doi.org/10.1016/j.atmosres.2017.11.031.

Cremonini, R., Bechini, R., 2010. Heavy rainfall monitoring by polarimetric C-band weather radars. Water 2, 838–848. https://doi.org/10.3390/w2040838.

Cremonini, R., Tiranti, D., 2018. The weather radar observations applied to shallow landslides prediction: a case study from north-western Italy. Front. Earth Sci. 6, 134. https://doi.org/10.3389/feart.2018.00134.

Crosta, G.B., 1998. Regionalization of rainfall thresholds: an aid to landslide hazard evaluation. Environ. Geol. 35, 131–145. https://doi.org/10.1007/s002540050300.

Crozier, M.J., 1999. Prediction of rainfall-triggered landslides: a test of the antecedent water status model. Earth Surf. Processes 24, 825–833. https://doi.org/10.1002/(SICI)1096-9837(199908)24:9<825::AID-ESP14>3.0.CO;2-M.

D'Orsi, R.N., D'Avila, C., Ortigao, J.A.R., Moraes, L., Santos, M.D., 1997. Rio-watch: the Rio de Janeiro landslide watch. In: Proc. of the 2nd PSL, Pan-Am Symposium on Landslides, 1. Rio de Janeiro, Brazil. pp. 21–30.

Del Ventisette, C., Ciampalini, A., Manunta, M., Calò, F., Paglia, L., Ardizzone, F., Mondini, A.C., Reichenbach, P., Mateos, R.M., Bianchini, S., García-Moreno, I., Füsi, B., Deák, Z., Rádi, K., Graniczny, M., Kowalski, Z., Piatkowska, A., Przylucka, M., Retzo, H., Strozzi, T., Colombo, D., Mora, O., Sánchez, F., Herrera Garcia, G., Moretti, S., Casagli, N., Guzzetti, F., 2013. Exploitation of large archives of ERS and ENVISAT C-Band SAR data to characterize ground deformations. Remote Sensing 5, 3896–3917. https://doi.org/10.3390/rs5083896.

Devoli, G., Kleivane, I., Sund, M., Orthe, N.-K., Ekker, R., Johnsen, E., Colleuille, H., 2015. Landslide early warning system and web tools for Real-time scenarios and for distribution of warning messages in Norway. In: Lollino, G., Giordan, D., Crosta, G.B., Corominas, J., Azzam, R., Wasowski, J., Sciarra, N. (Eds.), Engineering Geology for Society and Territory, 2. Springer International Publishing, Cham, pp. 625–629. https://doi.org/10.1007/978-3-319-09057-3_104.

Devoli, G., Tiranti, D., Cremonini, R., Sund, M., Boje, S., 2018. Comparison of landslide forecasting services in Piedmont (Italy) and Norway, illustrated by events in late spring 2013. Nat. Hazards Earth Syst. Sci. 18, 1351–1372. https://doi.org/10.5194/nhess-18-1351-2018.

Di Biagio, E., Kjekstad, O., 2007. In: Early Warning, Instrumentation and Monitoring Landslides.2nd Regional Training Course, RECLAIM II. Phuket, Thailand, 29th January–3rd February 2007.

Dimitrakakis, C., Ortner, R., 2019. Decision Making Under Uncertainty Reinforcement Learning. http://www.cse.chalmers.se/-chrdimi/downloads/book.pdf.

Dipartimento della Protezione Civile, 2016. Indicazioni per l'omogeneizzazione dei messaggi del Sistema di allertamento nazionale: livelli di criticità e di allerta e relativi scenari d'evento. Accessed 20 June 2019 (in Italian). http://www.protezionecivile.gov.it/documents/20182/823803/Allegato + 1 + livelli + di + criticit%C3%A0 + e + di + allerta + e + relativi + scenari + d%27evento/108c1f84-c130-4fc1-bac9-d16596e83046.

Einstein, H.H., Sousa, R., 2006. Warning systems for natural threats. Georisk Assess. Manag. Risk Eng. Syst. Geohazards 1, 3–20. https://doi.org/10.1080/17499510601127087.

Ekström, G., Stark, C.P., 2013. Simple scaling of catastrophic landslide dynamics. Science 339, 1416–1419. https://doi.org/10.1126/science.1232887.

Endo, T., 1970. Probable distribution of the amount of rainfall causing landslides (annual report). Annual Report of the Hokkaido Branch, Government Forest Experiment Station, Sapporo. Government Forest Experiment Station, Hokkaido, Japan.

European Commission, 2008. European Commission DG Environment. Member States' Approaches Towards Prevention Policy - a Critical Analysis (Final Report).

Eyles, R.J., 1979. Slip-triggering rainfalls in Wellington City, New Zealand. New Zeal. J. Sci. 22, 117–121.

Fathani, T.F., Karnawati, D., Arbanas, Ž., Casagli, N., McSaveney, M., Dang, K., 2018. TXT-tool 2.062-1.1: a landslide monitoring and early warning system. In: Sassa, K., Guzzetti, F., Yamagishi, H. (Eds.), Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer International Publishing, Cham, pp. 297–308. https://doi.org/10.1007/978-3-319-57774-6_21.

Fathani, T.F., Karnawati, D., Wilopo, W., 2016. An integrated methodology to develop a standard for landslide early warning systems. Nat. Hazards Earth Syst. Sci. 16, 2123–2135. https://doi.org/10.5194/nhess-16-2123-2016.

Fick, S.E., Hijmans, R.J., 2017. Worldclim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37, 4302–4315. https://doi.org/10.1002/joc.5086.

Fischer, L., Rubensdotter, L., Sletten, K., Stalsberg, K., Melchiorre, C., Horton, P., Jaboyedoff, M., 2012. Debris flow modelling for susceptibility mapping at regional to national scale. In: Eberhardt, E., Froese, C., Turner, K., Leroueil, S. (Eds.), Landslides and Engineered Slopes, Protecting Society through Improved Understanding. CRC Press, pp. 723–729.

Fischer, L., Rubensdotter, L., Stalsberg, K., 2014. Aktsomhetskart jordog flomskred: Metodeutvikling og landsdekkende modellering, NGU report 2014.019. Accessed 17 June 2019 (in Norwegian). http://www.ngu.no/upload/Publikasjoner/Rapporter/2014/2014_019.pdf.

Foster, C., Pennington, C.V.L., Culshaw, M.G., Lawrie, K., 2011. The national landslide database of Great Britain: development, evolution and applications. Env. Earth Sci. 66, 941–953. https://doi.org/10.1007/s12665-011-1304-5.

Froude, M.J., Petley, D.N., 2018. Global fatal landslide occurrence from 2004 to 2016. Nat. Hazards Earth Syst. Sci. 18https://doi.org/10.5194/nhess-18-2161-2018. 21612181.

Fuchs, F., Lenhardt, W., Bokelmann, G., the AlpArray Working Group, 2018. Seismic detection of rockslides at regional scale: examples from the Eastern Alps and feasibility of kurtosis-based event location. Earth Surf. Dynam 6, 955–970. https://doi.org/10.5194/esurf-6-955-2018.

Furlani, S., Ninfo, A., 2015. Is the present the key to the future? Earth-Sci. Rev. 142, 38–46. https://doi.org/10.1016/j.earscirev.2014.12.005.

Gariano, S.L., Guzzetti, F., 2016. Landslides in a changing climate. Earth-Sci. Rev. 162, 227–252. https://doi.org/10.1016/j.earscirev.2016.08.011.

Gariano, S.L., Brunetti, M.T., Iovine, G., Melillo, M., Peruccacci, S., Terranova, O.G., Vennari, C., Guzzetti, F., 2015. Calibration and validation of rainfall thresholds for shallow landslide forecasting in Sicily, southern Italy. Geomorphology 228, 653–665. https://doi.org/10.1016/j.geomorph.2014.10.019.

Germann, U., Galli, G., Boscacci, M., Bolliger, M., 2006. Radar precipitation measurement in a mountainous region. Q. J. R. Meteorolog. Soc. 132, 1669–1692. https://doi.org/10.1256/qj.05.190.

Giardini, D., Grünthal, G., Shedlock, K.M., Zhang, P., 2003. The GSHAP global seismic hazard map. In: Lee, W., Kanamori, H., Jennings, P., Kisslinger, C. (Eds.), Eds.), Int Handbook Earthquake & Eng Seism, International Geophysics Series 81 B. Academic Press, Amsterdam, pp. 1233–1239.

Glade, T., Crozier, M., Smith, P., 2000. Applying probability determination to refine landslide-triggering rainfall thresholds using an empirical "antecedent daily rainfall model. Pure Appl. Geophys. 157, 1059–1079. https://doi.org/10.1007/s000240050017.

Godoy, B.F., Guerrero, M.V., Hoyos, C., Núñez, T.A., 1997. Análisis de la vulnerabilidad de líneas vitales y edificaciones estratégicas en la zona rural de la cuenca del Río Combeima Municipio de Ibagué, Tolima Evento avalancha, detonante lluvia. Universidad del Tolima, Facultad de Ingeniería Forestal, in Spanish), pp. 139.

Godt, J.W., Baum, R.L., Chleborad, A.F., 2006. Rainfall characteristics for shallow landsliding in Seattle, Washington, USA. Earth Surf. Processes 31, 97–110. https://doi.

org/10.1002/esp.1237.
Godt, J.W., Baum, R.L., Lu, N., 2009. Landsliding in partially saturated materials. Geophys. Res. Lett. 36 (2), L02403. https://doi.org/10.1029/2008GL035996.
Godt, J.W., Coe, J.A., Baum, R.L., Highland, L.M., Keaton, J.R., Roth, R.J., 2012. Prototype landslide hazard map of the conterminous United states. In: Eberhardt, E., Froese, C., Turner, K., Leroueil, S. (Eds.), Landslides and Engineered Slopes: Protecting Society through Improved Understanding. Taylor & Francis Group, London.
Govi, M., Sorzana, P.F., 1980. Landslide susceptibility as a function of critical rainfall amount in Piedmont Basin (North-Western Italy). Studia Geomorphologica Carpatho-Balcanica 14, 43–60.
Gould, S.J., 1965. Is uniformitarism necessary? Am. J. Sci. 263, 223–228.
Green, H.W., Ampt, G., 1911. Studies on soil physics. J. Agric. Sci. 4 (1), 1–24. https://doi.org/10.1017/S0021859600001441.
Greco, R., Pagano, L., 2017. Basic features of the predictive tools of early warning systems for water-related natural hazards: examples for shallow landslides. Nat. Hazards Earth Syst. Sci. 17, 2213–2227. https://doi.org/10.5194/nhess-17-2213-2017.
Gunawan, O., Mooney, J., Aldridge, T., 2017. Natural Hazards Partnership Hazard Impact Framework, first edition. Natural Hazards Partnership, Buxton, Derbyshire, SK17 9JN.
Guzzetti, F., 2006. Landslide Hazard and Risk Assessment. Mathematisch-Naturwissenschaftlichen Fakultät der Rheinischen Friedrich-Wilhelms-Universität. Ph.D. Thesis, 389pp.. University of Bonn, Bonn, Germany. https://geomorphology.irpi.cnr.it/Members/fausto/PhD-dissertation.
Guzzetti, F., Cardinali, M., Reichenbach, P., Carrara, A., 2000. Comparing landslide maps: a case study in the upper Tiber River Basin, central Italy. Environ. Manage. 25, 247–263. https://doi.org/10.1007/s002679910020.
Guzzetti, F., Mondini, A.C., Cardinali, M., Fiorucci, F., Santangelo, M., Chang, K.-T., 2012. Landslide inventory maps: new tools for an old problem. Earth-Sci. Rev. 112, 42–66. https://doi.org/10.1016/j.earscirev.2012.02.001.
Guzzetti, F., Peruccacci, S., Rossi, M., Stark, C.P., 2007. Rainfall thresholds for the initiation of landslides in central and southern Europe. Meteorol. Atmos. Phys. 98, 239–267. https://doi.org/10.1007/s00703-007-0262-7.
Guzzetti, F., Peruccacci, S., Rossi, M., Stark, C.P., 2008. The rainfall intensity-duration control of shallow landslides and debris flows: an update. Landslides 5, 3–17. https://doi.org/10.1007/s10346-007-0112-1.
Haff, P.K., 1996. Limitations on predictive modeling in geomorphology. In: Rhoads, B.L., Thorn, C.E. (Eds.), The Scientific Nature of Geomorphology, Proc. of the 27th Binghamton Symposium in Geomorphology. 27-29 September 1996. pp. 337–358 John Wiley & Sons Ltd.
Hamilton, R.M., Wieczorek, G.F., Evans, S.G., Kato, T., Sobolev, G., Wyss, M., Newhall, C.G., Blong, R., Wagner, J.-J., Munoz-Carmona, F., Tilling, R.I., Highland, L.M., Guzzetti, F., Sassa, K., 1997. Early warning capabilities for geological hazards. Intern Decade Nat Disast Reduc, Geneva.
Handwerger, A.L., Fielding, E.J., Huang, M., Bennett, G.L., Liang, C., Schulz, W.H., 2019. Widespread initiation, reactivation, and acceleration of landslides in the Northern California coast ranges due to extreme rainfall. J. Geophy. Res.: Earth Surf. 124, 1782–1797. https://doi.org/10.1029/2019JF005035.
Haque, U., da Silva, P.F., Devoli, G., Pilz, J., Zhao, B., Khaloua, A., Wilopo, W., Andersen, P., Lu, P., Lee, J., Yamamoto, T., Keellings, D., Wu, J.-H., Glass, G.E., 2019. The human cost of global warming: deadly landslides and their triggers (1995–2014). Sci. Tot. Environ 682, 673–684. https://doi.org/10.1016/j.scitotenv.2019.03.415.
Hidayat, R., Sutanto, S.J., Hidayah, A., Ridwan, B., Mulyana, A., 2019. Development of a landslide early warning system in Indonesia. Geosciences 9 (10), 451. https://doi.org/10.3390/geosciences9100451.
Hibert, C., Ekström, G., Stark, C.P., 2014. Dynamics of the Bingham Canyon Mine landslides from seismic signal analysis. Geophys. Res. Lett. 41, 4535–4541. https://doi.org/10.1002/2014GL060592.
Hong, J.-S., Fong, C.-T., Hsiao, L.-F., Yu, Y.-C., Tzeng, C.-Y., 2015. Ensemble typhoon quantitative precipitation forecasts model in Taiwan. Weather Forecast. 30, 217–237. https://doi.org/10.1175/WAF-D-14-00037.1.
Hong, Y., Adler, R.F., 2007. Towards an early-warning system for global landslides triggered by rainfall and earthquake. Int. J. Remote Sens. 28, 3713–3719. https://doi.org/10.1080/01431160701311242.
Hong, Y., Adler, R.F., Huffman, G.J., 2006. Evaluation of the potential of NASA multi-satellite precipitation analysis in global landslide hazard assessment. Geophys. Res. Lett. 33, L22402. https://doi.org/10.1029/2006GL028010.
Hooykaas, R., 1963. In: Brill, E.J. (Ed.), Natural Law and Divine Miracle: The Principle of Uniformity in Geology, Biology, and Theology, Leiden, 241pp.
Huffman, G.J., Adler, R.F., Bolvin, D.T., Nelkin, E.J., 2010. The TRMM multi-satellite precipitation analysis (TMPA). In: Gebremichael, M., Hossain, F. (Eds.), Satellite Rainfall Applications for Surface Hydrology. Springer, Dordrecht. https://doi.org/10.1007/978-90-481-2915-7_1.
Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman, K.P., Stocker, E.F., 2007. The TRMM multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. J. Hydrometeorol. 8, 38–55. https://doi.org/10.1175/JHM560.1.
Huggel, C., Ceballos, J.L., Ramírez, J., Pulgarín, B., Thouret, J.C., 2007. Review and reassessment of hazards owing to volcano-ice interactions in Colombia. Ann. Glaciol. 45, 128–136. https://doi.org/10.3189/172756407782282408.
Huggel, C., Khabarov, N., Obersteiner, M., Ramírez, J.M., 2010. Implementation and integrated numerical modeling of a landslide early warning system: a pilot study in Colombia. Nat. Hazards 52, 501–518. https://doi.org/10.1007/s11069-009-9393-0.
Hungr, O., Leroueil, S., Picarelli, L., 2014. The Varnes classification of landslide types, an update. Landslides 11, 167–194. https://doi.org/10.1007/s10346-013-0436-y.
Intrieri, E., Gigli, G., Casagli, N., Nadim, F., 2013. Brief communication "Landslide Early Warning System: toolbox and general concepts. Nat. Hazards Earth Syst. Sci. 13, 85–90. https://doi.org/10.5194/nhess-13-85-2013.
Intrieri, E., Gigli, G., Mugnai, F., Fanti, R., Casagli, N., 2012. Design and implementation of a landslide early warning system. Eng. Geol. 147–148, 124–136. https://doi.org/10.1016/j.enggeo.2012.07.017.
ISO, 2018. ISO 22327, Security and resilience — Emergency management — Guidelines for implementation of a community- based landslide early warning system, first edition. 2018-10.
Jollifee, I.T., Stephenson, D.B., 2003. Forecast verification. A Practitioner's Guide in Atmospheric Science. John Wiley, Chichester 240pp.
Jakob, M., Owen, T., Simpson, T., 2012. A regional real-time debris-flow warning system for the District of North Vancouver, Canada. Landslides 9, 165–178. https://doi.org/10.1007/s10346-011-0282-8.
Juang, C.S., Stanley, T.A., Kirschbaum, D.B., 2019. Using citizen science to expand the global map of landslides: introducing the Cooperative Open Online Landslide Repository (COOLR). PLoS One 14, e0218657. https://doi.org/10.1371/journal.pone.0218657.
Keefer, D.K., Wilson, R.C., Mark, R.K., Brabb, E.E., Brown, W.M., Ellen, S.D., Harp, E.L., Wieczorek, G.F., Alger, C.S., Zatkin, R.S., 1987. Real-time landslide warning during heavy rainfall. Science 238, 921–925.
Kidd, C., Becker, A., Huffman, G.J., Muller, C.L., Joe, P., Skofronick-Jackson, G., Kirschbaum, D., 2017. So, how much of the Earth's surface is covered by rain gauges? Bull. Am. Meteorol. Soc. 98, 69–78. https://doi.org/10.1175/BAMS-D-14-00283.1.
Kirschbaum, D., Stanley, T., 2018. Satellite-based assessment of rainfall-triggered landslide hazard for situational awareness. Earths Future 6, 505–523. https://doi.org/10.1002/2017EF000715.
Kirschbaum, D.B., Adler, R., Hong, Y., Hill, S., Lerner-Lam, A., 2010. A global landslide catalog for hazard applications: method, results, and limitations. Nat. Haz. 52, 561–575. https://doi.org/10.1007/s11069-009-9401-4.
Kirschbaum, D., Adler, R.F., Hong, Y., Kumar, S., Peters-Lidard, C., Lerner-Lam, A., 2012. Advances in landslide nowcasting: evaluation of a global and regional modeling approach. Environ. Earth Sci. 66, 1683–1696. https://doi.org/10.1007/s12665-011-0990-3.
Kirschbaum, D., Adler, R., Hong, Y., Lerner-Lam, A., 2009. Evaluation of a preliminary satellite-based landslide hazard algorithm using global landslide inventories. Nat. Hazards Earth Syst. Sci. 9, 673–686. https://doi.org/10.5194/nhess-9-673-2009.
Kirschbaum, D., Stanley, T., Simmons, J., 2015. A dynamic landslide hazard assessment system for Central America and Hispaniola. Nat. Hazards Earth Syst. Sci. 15, 2257–2272. https://doi.org/10.5194/nhess-15-2257-2015.
Kirschbaum, D., Stanley, T., Yatheendradas, S., 2016. Modeling landslide susceptibility over large regions with fuzzy overlay. Landslides 13, 485–496. https://doi.org/10.1007/s10346-015-0577-2.
Krøgli, I.K., Devoli, G., Colleuille, H., Sund, M., Boje, S., Engen, I.K., 2018. The Norwegian forecasting and warning service for rainfall- and snowmelt-induced landslides. Nat. Hazards Earth Syst. Sci. 18, 1427–1450. https://doi.org/10.5194/nhess-2017-426.
Lagomarsino, D., Segoni, S., Fanti, R., Catani, F., 2013. Updating and tuning a regional scale landslide early warning system. Landslides 10, 91–97. https://doi.org/10.1007/s10346-012-0376-y.
Lawley, R., Smith, B., 2008. Digital soil mapping at a national scale: a knowledge and GIS based approach to improving parent material and property information. In: Hartemink, A.E., McBratney, A., Mendonça-Santos, M. (Eds.), Digital Soil Mapping with Limited Data, Springer. Dordrecht, Netherlands, pp. 173–182. https://doi.org/10.1007/978-1-4020-8592-5_14.
Liao, Z., Hong, Y., Wang, J., Fukuoka, H., Sassa, K., Karnawati, D., Fathani, F., 2010. Prototyping an experimental early warning system for rainfall-induced landslides in Indonesia using satellite remote sensing and geospatial datasets. Landslides 7, 317–324. https://doi.org/10.1007/s10346-010-0219-7.
Lombardo, L., Opitz, T., Huser, R., 2018. Point process-based modeling of multiple debris flow landslides using INLA: an application to the 2009 Messina disaster. Stoch. Environ. Res. Risk Assess. 32 (7), 2179–2198. https://doi.org/10.1007/s00477-018-1518-0.
Lumb, P., 1975. Slope failures in Hong Kong. Q. J. Eng. Geol. Hydrogeol. 8, 31–65. https://doi.org/10.1144/GSL.QJEG.1975.008.01.02.
Lyell, C., 1830. The principles of geology. Being an Attempt to Explain the Former Changes of the Earth's Surface, by Reference to Causes Now in Operation. John Murray, London.
Malone, A.W., 1988. The role of government in landslide disaster prevention in Hong Kong and Indonesia. Geotech. Eng. 19, 227–252.
Marchesini, I., Ardizzone, F., Alvioli, M., Rossi, M., Guzzetti, F., 2014. Non-susceptible landslide areas in Italy and in the Mediterranean region. Nat. Hazards Earth Syst. Sci. 14, 2215–2231. https://doi.org/10.5194/nhess-14-2215-2014.
Marra, F., Destro, E., Nikolopoulos, E.I., Zoccatelli, D., Creutin, J.D., Guzzetti, F., Borga, M., 2017. Impact of rainfall spatial aggregation on the identification of debris flow occurrence thresholds. Hydrol. Earth Syst. Sci. 21, 4525–4532. https://doi.org/10.5194/hess-21-4525-2017.
Marra, F., Nikolopoulos, E.I., Creutin, J.D., Borga, M., 2015. Space-time organization of debris flows-triggering rainfall and its effect on the identification of the rainfall threshold relationship. J. Hydrol. 541, 246–255. https://doi.org/10.1016/j.jhydrol.2015.10.010.
Martelloni, G., Segoni, S., Fanti, R., Catani, F., 2012. Rainfall thresholds for the forecasting of landslide occurrence at regional scale. Landslides 9 (4), 485–495. https://doi.org/10.1007/s10346-011-0308-2.
Martelloni, G., Segoni, S., Lagomarsino, D., Fanti, R., Catani, F., 2013. Snow accumulation/melting model (SAMM) for integrated use in regional scale landslide early warning systems. Hydrol. Earth Syst. Sci. 17, 1229–1240. https://doi.org/10.5194/hess-17-1229-2013.

Martinotti, M.E., Pisano, L., Marchesini, I., Rossi, M., Peruccacci, S., Brunetti, M.T., Melillo, M., Amoruso, G., Loiacono, P., Vessia, G., Trabace, M., Parise, M., Guzzetti, F., 2017. Landslides, floods and sinkholes in a karst environment: the 1-6 September 2014 Gargano event, southern Italy. Nat. Hazards Earth Syst. Sci. 17, 467–480. https://doi.org/10.5194/nhess-17-467-2017.

Medina-Cetina, Z., Nadim, F., 2008. Stochastic design of an early warning system. Georisk. 2, 223–236. https://doi.org/10.1080/17499510802086777.

Melillo, M., Brunetti, M.T., Peruccacci, S., Gariano, S.L., Guzzetti, F., 2015. An algorithm for the objective reconstruction of rainfall events responsible for landslides. Landslides 12, 311–320. https://doi.org/10.1007/s10346-014-0471-3.

Melillo, M., Brunetti, M.T., Peruccacci, S., Gariano, S.L., Roccati, A., Guzzetti, F., 2018. A tool for the automatic calculation of rainfall thresholds for landslide occurrence. Environ. Model. Softw. 105, 230–243. https://doi.org/10.1016/j.envsoft.2018.03.024.

Mergili, M., Marchesini, I., Alvioli, M., Metz, M., Schneider-Muntau, B., Rossi, M., Guzzetti, F., 2014a. A strategy for GIS-based 3-D slope stability modelling over large areas. Geosci. Model Develop. 7, 2969–2982. https://doi.org/10.5194/gmd-7-2969-2014.

Mergili, M., Marchesini, I., Rossi, M., Guzzetti, F., Fellin, W., 2014b. Spatially distributed three-dimensional slope stability modelling in a raster GIS. Geomorphology 206, 178–195. https://doi.org/10.1016/j.geomorph.2013.10.008.

Michaelides, S., 2008. Precipitation: Advances in Measurement, Estimation and Prediction. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-77655-0.

Mirus, B.B., Becker, R.E., Baum, R.L., Smith, J.B., 2018a. Integrating real-time subsurface hydrologic monitoring with empirical rainfall thresholds to improve landslide early warning. Landslides 15, 1909–1919. https://doi.org/10.1007/s10346-018-0995-z.

Mirus, B.B., Morphew, M.D., Smith, J.B., 2018b. Developing hydro-meteorological thresholds for shallow landslide initiation and early warning. Water 10, 1274. https://doi.org/10.3390/w10091274.

Mirus, B.B., Staley, D.M., Kean, J.W., Smith, J.B., Wooten, R., McGuire, L.A., Ebel, B.A., 2019. Conceptual framework for assessing disturbance impacts on debris-flow initiation thresholds across hydroclimatic settings. In: In: Kean, J.W., Coe, J.A., Santi, O.M., Guillen, B.K. (Eds.), Proceedings 7th International Conference on Debris-Flow Hazards Mitigation, Association of Environmental & Engineering Geologists, Special Publication 28. pp. 524–531 ISBN: 978-0-578-51082-8.

Mondini, A.C., 2017. Measures of spatial autocorrelation changes in Multitemporal SAR images for event landslides detection. Remote Sens. 9, 554. https://doi.org/10.3390/rs9060554.

Mondini, A.C., Guzzetti, F., Reichenbach, P., Rossi, M., Cardinali, M., Ardizzone, F., 2011. Semi-automatic recognition and mapping of rainfall induced shallow landslides using optical satellite images. Remote Sens. Environ. 115, 1743–1757. https://doi.org/10.1016/j.rse.2011.03.006.

Mondini, A.C., Santangelo, M., Rocchetti, M., Rossetto, E., Manconi, A., Monserrat, O., 2019. Sentinel-1 SAR amplitude imagery for rapid landslide detection. Remote Sens. 11, 760. https://doi.org/10.3390/rs11070760.

Montrasio, L., Valentino, R., 2008. A model for triggering mechanisms of shallow landslides. Nat. Hazards Earth Syst. Sci. 8 (5), 1149–1159. https://doi.org/10.5194/nhess-8-1149-2008.

Montgomery, D.R., Dietrich, W.E., 1994. A physically based model for the topographic control on shallow landsliding. Water Resour. Res. 30, 1153–1171.

Müller, M., Homleid, M., Ivarsson, K.-I., Køltzow, M.A.Ø., Lindskog, M., Midtbø, K.H., Andrae, U., Aspelien, T., Berggren, L., Bjørge, D., Dahlgren, P., Kristiansen, J., Randriamampianina, R., Ridal, M., Vignes, O., 2017. AROME-MetCoOp: A Nordic Convective-Scale Operational Weather Prediction Model. Weather Forecast 32, 609–627. https://doi.org/10.1175/WAF-D-16-0099.1.

Mulyana, A.R., Sutanto, S.J., Hidayat, R., Ridwan, B.W., 2019. Capability of Indonesian Landslide Early Warning System to detect landslide occurrences few days in advance. Geophys. Res. Abs. 21 EGU2019-18102.

Nadim, F., Kjekstad, O., Peduzzi, P., Herold, C., Jaedicke, C., 2006. Global landslide and avalanche hotspots. Landslides 3 (2), 159–173. https://doi.org/10.1007/s10346-006-0036-1.

Napolitano, E., Marchesini, I., Salvati, P., Donnini, M., Bianchi, C., Guzzetti, F., 2018. LAND-deFeND – an innovative database structure for landslides and floods and their consequences. J. Environ. Manage. 207, 203–218. https://doi.org/10.1016/j.jenvman.2017.11.022.

Nikolopoulos, E.I., Borga, M., Creutin, J.D., Marra, F., 2015. Estimation of debris flow triggering rainfall: influence of rain gauge density and interpolation methods. Geomorphology 243, 40–50. https://doi.org/10.1016/j.geomorph.2015.04.028.

Nikolopoulos, E.I., Crema, S., Marchi, L., Marra, F., Guzzetti, F., Borga, M., 2014. Impact of uncertainty in rainfall estimation on the identification of rainfall thresholds for debris flow occurrence. Geomorphology 221, 286–297. https://doi.org/10.1016/j.geomorph.2014.06.015.

NOAA-USGS Debris Flow Task Force, 2005. NOAA-USGS Debris-Flow Warning System—Final Report (U.S.G.S. Circular No. 1283) U.S. Geological Survey Circular. U.S. Geological Survey, Washington, DC.

Sungmin, O., Foelsche, U., 2019. Assessment of spatial uncertainty of heavy rainfall at catchment scale using a dense gauge network. Hydrol. Earth Syst. Sci. 23, 2863–2875. https://doi.org/10.5194/hess-23-2863-2019.

O'Neill, D., Mukolwe, E., Hooke, W., Kootval, H., Fernandez, B., O'Loughlin, K., Wilhite, D., Stewart, B., Parker, D., Heng, L., Garanganga, B.J., Recalde, P., 1997. Report on Early Warning for Hydrometeorological Hazards Including Drought. IDNDR Secretariat, Geneva.

Onodera, T., Yoshinaka, R., Kazama, H., 1974. In: Proc. of the 2nd International Congress of the Int. Ass. Eng. Geol. San Paulo. Slope failures caused by heavy rainfall in Japan 11. pp. 1–10. https://doi.org/10.5110/jjseg.15.191.

Ortigao, B., Justi, M.G., 2004. Rio-watch: the Rio de Janeiro Landslide Alarm System. Geotechnical News 22, 28–31.

Ortigao, J.A.R., Justi, M.G., D'Orsi, R., Brito, H., 2001. Rio-watch 2001: the Rio de Janeiro landslide alarm system. In: Proceedings 14th Southeast Asian Geotechnical Conference. Hong Kong. Balkema. pp. 237–241.

Park, J.-Y., Lee, S.-R., Lee, D.-H., Kim, Y.-T., Lee, J.-S., 2019. A regional-scale landslide early warning methodology applying statistical and physically based approaches in sequence. Eng. Geol. 260, 105193. https://doi.org/10.1016/j.enggeo.2019.105193.

Pecoraro, G., Calvello, M., Piciullo, L., 2019. Monitoring strategies for local landslide early warning systems. Landslides 16 (2), 213–231. https://doi.org/10.1007/s10346-018-1068-z.

Peel, M.C., Finlayson, B.L., McMahon, T.A., 2007. Updated world map of the Köppen-Geiger climate classification. Hydrol. Earth Syst. Sci. 11, 1633–1644. https://doi.org/10.5194/hessd-4-439-2007.

Pennington, C.V.L., Freeborough, K., Dashwood, C., Dijkstra, T.A., Lawrie, K., 2015. The national landslide database of Great Britain: acquisition, communication and the role of social media. Geomorphology 249, 44–51. https://doi.org/10.1016/j.geomorph.2015.03.013.

Peres, D.J., Cancelliere, A., Greco, R., Bogaard, T.A., 2018. Influence of uncertain identification of triggering rainfall on the assessment of landslide early warning thresholds. Nat. Hazards Earth Syst. Sci. 18, 633–646. https://doi.org/10.5194/nhess-18-633-2018.

Peruccacci, S., Brunetti, M.T., Gariano, S.L., Melillo, M., Rossi, M., Guzzetti, F., 2017. Rainfall thresholds for possible landslide occurrence in Italy. Geomorphology 290, 39–57. https://doi.org/10.1016/j.geomorph.2017.03.031.

Peruccacci, S., Brunetti, M.T., Luciani, S., Vennari, C., Guzzetti, F., 2012. Lithological and seasonal control on rainfall thresholds for the possible initiation of landslides in central Italy. Geomorphology 139–140, 79–90. https://doi.org/10.1016/j.geomorph.2011.10.005.

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

Piciullo, L., Calvello, M., Cepeda, J.M., 2018. Territorial early warning systems for rainfall-induced landslides. Earth-Sci. Rev. 179, 228–247. https://doi.org/10.1016/j.earscirev.2018.02.013.

Piciullo, L., Dahl, M.-P., Devoli, G., Colleuille, H., Calvello, M., 2017a. Adaptation of the EDuMaP method for the performance evaluation of the alerts issued on variable warning zones. Nat. Hazards Earth Syst. Sci. 17 (6), 817–831. https://doi.org/10.5194/nhess-17-817-2017.

Piciullo, L., Gariano, S.L., Melillo, M., Brunetti, M.T., Peruccacci, S., Guzzetti, F., Calvello, M., 2017b. Definition and performance of a threshold-based regional early warning model for rainfall-induced landslides. Landslides 14 (3), 995–1008. https://doi.org/10.1007/s10346-016-0750-2.

Pignone, F., Rebora, N., Silvestro, F., 2013. A new method for combining radar and raingauge data: modified Conditional merging. Geophys. Res. Abs. 15 EGU2013-13669.

Polasky, S., Carpenter, S.R., Folke, C., Keeler, B., 2011. Decision-making under great uncertainty: environmental management in an era of global change. Trends Ecol. Evol. 26, 398–404. https://doi.org/10.1016/j.tree.2011.04.007.

Ponziani, F., Berni, N., Stelluti, M., Zauri, R., Pandolfo, C., Brocca, L., Moramarco, T., Salciarini, D., Tamagnini, C., 2013. LANDWARN: an operative early warning system for landslides forecasting based on rainfall thresholds and soil moisture. In: Margottini, C., Canuti, P., Sassa, K. (Eds.), Landslide Science and Practice. Springer, Berlin, Heidelberg, pp. 627–634. https://doi.org/10.1007/978-3-642-31445-2_82.

Potter, S.H., Kreft, P.V., Milojev, P., Noble, C., Montz, B., Dhellemmes, A., Woods, R.J., Gauden-Ing, S., 2018. The influence of impact-based severe weather warnings on risk perceptions and intended protective actions. Int. J. Disaster Risk Reduct. 30, 34–43. https://doi.org/10.1016/j.ijdrr.2018.03.031.

Pun, W.K., Wong, A.C.W., Pang, P.L.R., 1999. Review of Landslip Warning Criteria 1998/1999. Geotechnical Engineering Office, Hong Kong.

Raia, S., Alvioli, M., Rossi, M., Baum, R.L., Godt, J.W., Guzzetti, F., 2014. Improving predictive power of physically-based rainfall-induced shallow landslide models: a probabilistic approach. Geosci. Model Develop. 7, 495–514. https://doi.org/10.5194/gmd-7-495-2014.

Ramage, C.S., 1993. Forecasting in meteorology. Bulll. Am. Meteorol. Soc. 74, 1863–1871.

Raspini, F., Bianchini, S., Ciampalini, A., Del Soldato, M., Solari, L., Novali, F., Del Conte, S., Rucci, A., Ferretti, A., Casagli, N., 2018. Continuous, semi-automatic monitoring of ground deformation using Sentinel-1 satellites. Sci. Reports 8. https://doi.org/10.1038/s41598-018-25369-w.

Reichenbach, P., Cardinali, M., De Vita, P., Guzzetti, F., 1998. Regional hydrological thresholds for landslides and floods in the Tiber River Basin (Central Italy). Environ. Geol. 35 (2-3), 146–159. https://doi.org/10.1007/s002540050301.

Reichenbach, P., Rossi, M., Malamud, B.D., Mihir, M., Guzzetti, F., 2018. A review of statistically-based landslide susceptibility models. Earth-Sci. Rev. 180, 60–91. https://doi.org/10.1016/j.earscirev.2018.03.001.

Restrepo, P., Cannon, S.H., Laber, J., Jorgensen, D., Werner, K., 2009. NOAA/USGS demonstration flash-flood and debris-flow early-warning system. Geophys. Res. Abs. 11 EGU2009-4692.

Rogers, D., Tsirkunov, V., 2010. Costs and benefits of early warning systems. Global Assessment Report on Disaster Risk Reduction. The World Bank 17pp.

Rosi, A., Lagomarsino, D., Rossi, G., Segoni, S., Battistini, A., Casagli, N., 2015. Updating EWS rainfall thresholds for the triggering of landslides. Nat. Hazards 78, 297–308. https://doi.org/10.1007/s11069-015-1717-7.

Rossi, M., Guzzetti, F., Salvati, P., Donnini, M., Napolitano, E., Bianchi, C., 2019. A predictive model of societal landslide risk in Italy. Earth-Sci. Rev. 196, 102849,. https://doi.org/10.1016/j.earscirev.2019.04.021.

Rossi, M., Kirschbaum, D., Luciani, S., Mondini, A.C., Guzzetti, F., 2012b. TRMM satellite rainfall estimates for landslide early warning in Italy: preliminary results. SPIE Asia-Pacific Remote Sensing. https://doi.org/10.1117/12.979672. 85230D-85230D-7.
Rossi, M., Kirschbaum, D., Valigi, D., Mondini, A.C., Guzzetti, F., 2017. Comparison of satellite rainfall estimates and rain gauge measurements in Italy, and impact on landslide modeling. Climate 5, 90. https://doi.org/10.3390/cli5040090.
Rossi, M., Marchesini, I., Tonelli, G., Peruccacci, S., Brunetti, M.T., Luciani, S., Ardizzone, F., Balducci, V., Bianchi, C., Cardinali, M., Fiorucci, F., Mondini, A.C., Reichenbach, P., Salvati, P., Santangelo, M., Guzzetti, F., 2018. TXT-tool 2.039-1.1 Italian national early warning system. In: Sassa, K., Guzzetti, F., Yamagishi, H., Arbanas, Ž., Casagli, N., McSaveney, M., Dang, K. (Eds.), Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer International Publishing, Cham, pp. 341–349. https://doi.org/10.1007/978-3-319-57774-6_24.
Rossi, M., Peruccacci, S., Brunetti, M.T., Marchesini, I., Luciani, S., Ardizzone, F., Balducci, S.V., Bianchi, C., Cardinali, M., Fiorucci, F., Mondini, A.C., Reichenbach, P., Salvati, P., Santangelo, M., Bartolini, D., Gariano, S.L., Palladino, M., Vessia, G., Viero, A., Antronico, L., Borselli, L., Deganutti, A.M., Iovine, G., Luino, F., Parise, M., Polemio, M., Guzzetti, F., 2012a. SANF: national warning system for rainfall-induced landslides in Italy. In: Eberhardt, E., Leroueil, S., Turner, A.K., Froese, C.R. (Eds.), Landslides and Engineered Slopes: Protecting Society through Improved Understanding. Taylor & Francis Group, London, pp. 1895–1899 ISBN 978-0-415-62123-6.
Salvati, P., Bianchi, C., Rossi, M., Guzzetti, F., 2010. Societal landslide and flood risk in Italy. Nat. Hazards Earth Syst. Sci. 10, 465–483. https://doi.org/10.5194/nhess-10-465-2010.
Salvati, P., Bianchi, C., Fiorucci, F., Giostrella, P., Marchesini, I., Guzzetti, F., 2014. Perception of flood and landslide risk in Italy: a preliminary analysis. Nat. Hazards Earth Syst. Sci. 14, 2589–2603. https://doi.org/10.5194/nhess-14-2589-2014.
Salvati, P., Petrucci, O., Rossi, M., Bianchi, C., Pasqua, A.A., Guzzetti, F., 2018. Gender, age and circumstances analysis of flood and landslide fatalities in Italy. Sci. Total Environ 610-611, 867–879. https://doi.org/10.1016/j.scitotenv.2017.08.064.
Šavrič, B., Patterson, T., Jenny, B., 2019. The equal Earth map projection. Int. J. Geogr. Inf. Sci. 33, 454–465. https://doi.org/10.1080/13658816.2018.1504949.
Scheevel, C., Baum, R.L., Mirus, B.-B., Smith, J.B., 2017. Precipitation thresholds for landslide occurrence near Mukilteo and Everett, Washington. U.S. Geological Survey Open File Report 2017-1039. https://doi.org/10.3133/ofr20171039. 51pp.
Schimmel, A., Hübl, J., McArdell, B.W., Walter, F., 2018. Automatic identification of alpine mass movements by a combination of seismic and infrasound sensors. Sensors 18. https://doi.org/10.3390/s18051658.
Scolobig, A., De Marchi, B., Borga, M., 2012. The missing link between flood risk awareness and preparedness: findings from case studies in an Alpine Region. Nat. Hazards 63, 499–520. https://doi.org/10.1007/s11069-012-0161-1.
Segoni, S., Battistini, A., Rossi, G., Rosi, A., Lagomarsino, D., Catani, F., Moretti, S., Casagli, N., 2015a. Technical note: an operational landslide early warning system at regional scale based on space–time-variable rainfall thresholds. Nat. Hazards Earth Syst. Sci. 15, 853–861. https://doi.org/10.5194/nhess-15-853-2015.
Segoni, S., Lagomarsino, D., Fanti, R., Moretti, S., Casagli, N., 2015b. Integration of rainfall thresholds and susceptibility maps in the Emilia Romagna (Italy) regional-scale landslide warning system. Landslides 12, 773–785. https://doi.org/10.1007/s10346-014-0502-0.
Segoni, S., Piciullo, L., Gariano, S.L., 2018a. Preface: landslide early warning systems: monitoring systems, rainfall thresholds, warning models, performance evaluation and risk perception. Nat. Hazards Earth Syst. Sci. 18, 3179–3186. https://doi.org/10.5194/nhess-18-3179-2018.
Segoni, S., Piciullo, L., Gariano, S.L., 2018b. A review of the recent literature on rainfall thresholds for landslide occurrence. Landslides 15, 1483–1501. https://doi.org/10.1007/s10346-018-0966-4.
Segoni, S., Rosi, A., Fanti, R., Gallucci, A., Monni, A., Casagli, N., 2018c. A regional-scale landslide warning system based on 20 years of operational experience. Water 10 (10), 1297. https://doi.org/10.3390/w10101297.
Segoni, S., Rosi, A., Rossi, G., Catani, F., Casagli, N., 2014. Analysing the relationship between rainfalls and landslides to define a mosaic of triggering thresholds for regional-scale warning system. Nat. Hazards Earth Syst. Sci. 14, 2637–2648. https://doi.org/10.5194/nhess-14-2637-2014.
Seibold, E., 2003. Natural disasters and early warning. In: Zschau, J., Küppers, A. (Eds.), Early Warning Systems for Natural Disaster Reduction. Springer-Verlag, Berlin, Heidelberg, pp. 3–10.
Silvestro, F., Rebora, N., Ferraris, L., 2009. An algorithm for real-time rainfall rate estimation by using polarimetric radar: RIME. J. Hydrometeor. 10 (1), 227–240. https://doi.org/10.1175/2008JHM1015.1.
Sinclair, S., Pegram, G., 2005. Combining radar and rain gauge rainfall estimates using conditional merging. Atmos. Sci. Lett. 6 (1), 19–22. https://doi.org/10.1002/asl.85.
Smith, J.B., Baum, R.L., Mirus, B.B., Michel, A., Stark, B., 2017. Results of hydrologic monitoring on landslide prone coastal Bluffs near Mukilteo, Washington. U.S. Geological Survey Open-File Report 2017-1095. https://doi.org/10.3133/ofr20171095. 47pp.
Sorensen, J.H., 2000. Hazard warning systems: review of 20 years of progress. Nat. Hazards Rev. 1, 119–125. https://doi.org/10.1061/(ASCE)1527-69882000.1:2(119).
Stahl, K., Tallaksen, L.M., Hannaford, J., van Lanen, H.A.J., 2012. Filling the white space on maps of European runoff trends: estimates from a multi-model ensemble. Hydrol. Earth Syst. Sci. 16, 2035–2047. https://doi.org/10.5194/hess-16-2035-2012.
Stähli, M., Sättele, M., Huggel, C., McArdell, B.W., Lehmann, P., Van Herwijnen, A., Berne, A., Schleiss, M., Ferrari, A., Kos, A., Or, D., Springman, S.M., 2015. Monitoring and prediction in early warning systems for rapid mass movements. Nat. Hazards Earth Syst. Sci. 15, 905–917. https://doi.org/10.5194/nhess-15-905-2015.
Staley, D.M., Kean, J.W., Cannon, S.H., Schmidt, K.M., Laber, J.L., 2013. Objective definition of rainfall intensity–duration thresholds for the initiation of post-fire debris flows in southern California. Landslides 10 (5), 547–562. https://doi.org/10.1007/s10346-012-0341-9.
Staley, D.M., Negri, J.A., Kean, J.W., Laber, J.L., Tillery, A.C., Youberg, A.M., 2017. Prediction of spatially explicit rainfall intensity–duration thresholds for post-fire debris-flow generation in the western United States. Geomorphology 278, 149–162. https://doi.org/10.1016/j.geomorph.2016.10.019.
Staley, D.M., Negri, J.A., Kean, J.W., Laber, J.L., Tillery, A.C., Youberg, A.M., 2016. Updated logistic regression equations for the calculation of Post-fire debris-flow likelihood in the Western United States. U.S. Geological Survey Open-File Report 2016-1106. https://doi.org/10.3133/ofr20161106. 13pp.
Stanley, T., Kirschbaum, D., 2017. A heuristic approach to global landslide susceptibility mapping. Nat. Hazards 87, 145–164. https://doi.org/10.1007/s11069-017-2757-y.
Stanley, T., Kirschbaum, D., Huffman, G.J., Adler, R.F., 2017. Approximating long-term statistics early in the Global Precipitation Measurement era. Earth Interact. 21, 1–10. https://doi.org/10.1175/EI-D-16-0025.1.
Teisberg, T.J., Weiher, R.F., 2009. Global Facility for Disaster Reduction and Recovery. World Bank 68pp.
Thiebes, B., 2012. . Landslide analysis and early warning systems. Local and Regional Case Study in the Swabian Alb, Germany. Springerhttps://doi.org/10.1007/978-3-642-27526-5. 226pp.
Tiranti, D., Rabuffetti, D., 2010. Estimation of rainfall thresholds triggering shallow landslides for an operational warning system implementation. Landslides 7, 471–481. https://doi.org/10.1007/s10346-010-0198-8.
Tiranti, D., Cremonini, R., Marco, F., Gaeta, A.R., Barbero, S., 2014. The DEFENSE (debris Flows triggEred by storms nowcasting system): An early warning system for torrential processes by radar storm tracking using a Geographic Information System (GIS). Comput. Geosci. 70, 96–109. https://doi.org/10.1016/j.cageo.2014.05.004.
Tiranti, D., Rabuffetti, D., Salandin, A., Tararbra, M., 2013. Development of a new translational and rotational slides prediction model in Langhe hills (north-western Italy) and its application to the 2011 March landslide event. Landslides 10, 121–138. https://doi.org/10.1007/s10346-012-0319-7.
UNISDR, 2015. Sendai Framework for Disaster Risk Reduction 2015-2030. United Nations Office for Disaster Risk Reduction 37pp.
UNISDR, 2006. Platform for the promotion of early warning - developing early warning systems: a checklist. In: Proc. of EWC III, Third International Conference on Early Warning, From Concept to Action, UN Secretariat of the International Strategy for Disaster Reduction (UN/ISDR). Bonn. 13pp.
UNISDR, 2005. Hyogo framework for action 2005-2015. Building the resilience of nations and communities to disasters. In: World Conference on Disaster Reduction. 18-22 January 2005, Kobe, Hyogo, Japan. 55pp.
Nations, United, 2016. Report of the Open-ended Intergovernmental Expert Working Group on Indicators and Terminology Relating to Disaster Risk Reduction. 41pp.. .
Van Den Eeckhaut, M., Hervás, J., 2012. State of the art of national landslide databases in Europe and their potential for assessing landslide susceptibility, hazard and risk. Geomorphology 139–140, 545–558. https://doi.org/10.1016/j.geomorph.2011.12.006.
Vanmaercke, M., Ardizzone, F., Rossi, M., Guzzetti, F., 2017. Exploring the effects of seismicity on landslides and catchment sediment yield: an Italian case study. Geomorphology 278, 171–183. https://doi.org/10.1016/j.geomorph.2016.11.010.
Vanmaercke, M., Kettner, A.J., Eeckhaut, M.V.D., Poesen, J., Mamaliga, A., Verstraeten, G., Rădoane, M., Obreja, F., Upton, P., Syvitski, J.P.M., Govers, G., 2014. Moderate seismic activity affects contemporary sediment yields. Prog. Phys. Geog. 38, 145–172. https://doi.org/10.1177/0309133313516160.
Versace, P., Capparelli, G., De Luca, D.L., 2018. TXT-tool 2.039-4.2 LEWIS project: an integrated system for landslides early warning. In: Sassa, K., Guzzetti, F., Yamagishi, H., Arbanas, Ž., Casagli, N., McSaveney, M., Dang, K. (Eds.), Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer International Publishing, Cham, pp. 509–535. https://doi.org/10.1007/978-3-319-57774-6_38.
Vessia, G., Parise, M., Brunetti, M.T., Peruccacci, S., Rossi, M., Vennari, C., Guzzetti, F., 2014. Automated reconstruction of rainfall events responsible for shallow landslides. Nat. Hazards Earth Syst. Sci. 14 (9), 2399–2408. https://doi.org/10.5194/nhess-14-2399-2014.
Wei, L.-W., Huang, C.-M., Chen, H., Lee, C.-T., Chi, C.-C., Chiu, C.-L., 2018. Adopting the I3-R24 rainfall index and landslide susceptibility for the establishment of an early warning model for rainfall-induced shallow landslides. Nat. Hazards Earth Syst. Sci. 18, 1717–1733. https://doi.org/10.5194/nhess-18-1717-2018.
Weisheimer, A., Palmer, T.N., 2014. On the reliability of seasonal climate forecasts. J. R. Soc. Interface 11, 20131162. https://doi.org/10.1098/rsif.2013.1162.
Werner, M., Schellekens, J., Gijsbers, P., van Dijk, M., van den Akker, O., Heynert, K., 2013. The Delft-FEWS flow forecasting system. Environ. Modell. Softw. 40, 65–77. https://doi.org/10.1016/j.envsoft.2012.07.010.
White, I.D., Mottershead, D.N., Harrison, J.J., 1996. Environmental Systems, 2nd edition. Chapman & Hall, London 616pp.
Wieczorek, G.F., 1987. Effect of rainfall intensity and duration on debris flows in central Santa Cruz mountains, California. In: Costa, J.E., Wieczorek, G.F. (Eds.), Debris Flows/Avalanches: Process, Recognition, and Mitigation, Reviews in Engineering Geology. Geological Society of America, Boulder, pp. 93–104. https://doi.org/10.1130/REG7.
Wieczorek, G.F., Glade, T., 2005. Climatic factors influencing occurrence of debris flows. In: Jakob, M., Hungr, O. (Eds.), Debris-Flow Hazards and Related Phenomena. Spinger, pp. 325–362.
Wieczorek, G.F., Ellen, S., Lips, E.W., Cannon, S.H., 1983. Potential for Debris Flow and Debris Flood Along the Wasatch Front Between Salt Lake City and Willard, Utah, and Measures for Their Mitigation. Open File Report 83-635. U.S.G.S., Washington, DC.
Wiley, T.J., 2000. Relationship between rainfall and debris flows in western Oregon.

Oregon Geol 62, 27–34.

Wilson, R.C., 2012. The rise and fall of a debris-flow warning system for the San Francisco Bay region, California. In: Glade, T., Anderson, M., Crozier, M.J. (Eds.), Landslide Hazard and Risk. John Wiley & Sons, Ltd, Chichester, West Sussex, England, pp. 493–516. https://doi.org/10.1002/9780470012659.ch17.

Wilson, R.C., 1997. Normalizing rainfall/debris-flow thresholds along the U.S. Pacific coast for long-term variations in precipitation climate. In: Proceedings of the 1st International Conference on Debris-Flow Hazards Mitigation: Mechanics, Prediction, and Assessment. ASCE, New York, NY, United States. pp. 32–43.

Wilson, R.C., Mark, R.K., Barbato, G., 1993. Operation of a real-time warning system for debris flows in the San Francisco bay area, California. In: Proc. of National Conference on Hydraulic Engineering, San Francisco, CA, USA. 25-30 July 1993, ASCE, New York, NY. pp. 1908–1913.

Wong, A.C.W., Ting, S.M., Shiu, Y.K., Ho, K.K.S., 2014. Latest developments of Hong Kong's landslip warning system. In: Sassa, K., Canuti, P., Yin, Y. (Eds.), Landslide Science for a Safer Geoenvironment. Springer International Publishing, Cham, pp. 613–618. https://doi.org/10.1007/978-3-319-05050-8_95.

WMO, 2015. WMO Guidelines on Multi-hazard Impact-based Forecast and Warning Services. World Meteorological Organization, Geneva, pp. 34.

WMO, 2017. Guidelines for Nowcasting Techniques. World Meteorological Organization, pp. 68.

Yang, D., Yang, X.-Q., Ye, D., Sun, X., Fang, J., Chu, C., Feng, T., Jiang, Y., Liang, J., Ren, X., Zhang, Y., Tang, Y., 2018. On the relationship between probabilistic and deterministic skills in dynamical seasonal climate prediction. J. Geophys. Res. Atmos. 123, 5261–5283. https://doi.org/10.1029/2017JD028002.

Yeung, H.Y., 2012. Recent developments and applications of the SWIRLS nowcasting system in Hong Kong. In: Proc. of 3rd WMO International Symposium on Nowcasting and Very Short-Range Forecasting (WSN12). 6–10 August 2012, Rio De Janeiro. pp. 6–10.

Yin, H.-Y., Lee, C.-Y., Jan, C.-D., 2015. A web-based decision support system for debris flow disaster management in Taiwan. In: Lollino, G., Arattano, M., Rinaldi, M., Giustolisi, O., Marechal, J.-C., Grant, G.E. (Eds.), Engineering Geology for Society and Territory 3. Springer, Cham, pp. 109–113. https://doi.org/10.1007/978-3-319-09054-2_21.

Yin, H.-Y., Lee, C.-Y., Jan, C.-D., Lin, M.-L., 2016. Practical management of debris-flow-prone torrents in Taiwan. In: Proceedings Interpraevent 2016. Lucerne. pp. 178–185.

Yin, K., Chen, L., Zhang, G., 2007. Regional landslide hazard warning and risk assessment. Earth Sci. Front. 14 (6), 85–97. https://doi.org/10.1016/S1872-5791(08)60005-6.

Yu, Y.F., 2004. Correlations Between Rainfall, Landslide Frequency and Slope Information for Registered Man-made Slopes. Geotechnical Engineering Office, Hong Kong.

Zschau, J., Küppers, A., 2003. Early Warning Systems for Natural Disaster Reduction. Springer-Verlag, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-55903-7.