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Earthquake-induced landslides susceptibility assessment: A review of the state-of-the-art

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ABSTRACT

Earthquake-induced landslides (EQL) can take a heavy toll on people's life and properties, thus attracting extensive attention of the geosciences community. Carrying out earthquake-induced landslide susceptibility assessment (EQLSA) is of great significance to the prevention and reduction of such disasters as well as recovery and reconstruction in affected areas. This study examined the research status of earthquake-induced landslide susceptibility using data aspects, variable model types, and evaluation scales. To begin, we will discuss the current state and shortcomings of the earthquake landslide inventory, as well as the common landslide influencing factors that serve as the foundation for EQLSA. Then we presented the most common EQLSA methods and discussed their advantages and disadvantages. Meanwhile, we used CiteSpace to visually analyze papers in the Web of Science database with the theme word "landslide susceptibility" from 2008 to 2020. Each paper is summarized in terms of the evaluation scale. Finally, the research difficulties of landslide susceptibility in spatial scale, qualitative and quantitative problems, and spatial representation of landslide information are discussed, and future research directions are suggested.

1. Introduction

The research shows that the critical magnitude of geological disasters triggered by earthquakes is M_L4.0 (Keefer 1984). There are many types of such geological effects, including landslides, debris flow, collapse, and ground fissures. They generally occur during the earthquake or in a short time after the event, and have various triggers and wide distribution ranges. Due to the duration of post-earthquake effects, the losses by such geological effects sometimes exceed that directly caused by the quake itself. For example, the September 5, 2018 (UTC Time) Mw6.6 earthquake of the 2018 Hokkaido Eastern Earthquake has triggered at least 9295 landslides, occupying an area of about 9.38 km^2, killing 36 people, damaging many roads and burying farmland and villages (Fig. 1). The total loss caused by this geological hazard was as high as 153.1 billion yen (Shao et al., 2019). On May 12, 2008, the Wenchuan Mw8.0 earthquake of China, with a horizontal acceleration of 0.4–1.0 g in the extreme seismic area, triggered nearly 200,000 landslides (Huang et al., 2009; Xu et al., 2014c), which swept about 20,000 people to their death, resulting in more than 10000 potential geological hazard sites (Yin et al., 2009).

We should also note that the triggering mechanism of coseismic landslides is complex, covering terrain, geology, seismology and other factors. For example, the 2018 Palu Mw7.5 earthquake triggered a tsunami and liquefaction as well as landslides, causing some areas to slip for 1 km. In this hazard, the death toll caused by the landslides reached thousand meters, more than that by the tsunami (Bradley et al., 2019).

The occurrence of coseismic landslides is also closely related to the level of human economic development and the capability of disaster prevention and reduction. In recent years, the expansion of the global economy, unplanned human activities, exploration and utilization of resources, the abuse of chemicals, and the improper treatment of wastes have exacerbated climate change, which has enhanced the destructive power of earthquake landslides (Guzzetti et al., 1999b).

Earthquake-induced landslide susceptibility assessment (EQLSA) has become a research direction closely concerned by scientific and technological personnel of relevant disciplines, an urgent task with great scientific research significance and practical value. The core idea of earthquake-landslide susceptibility assessment is to study the past and present slope failures to predict the possibility of landslide occurrence in the study area (Brabb 1985). This study analyzed the scientific research literature data in the Web of Science database by using CiteSpace (Version 5.1), and summarizes the current landslide susceptibility research from 4 aspects, including data source, evaluation method,

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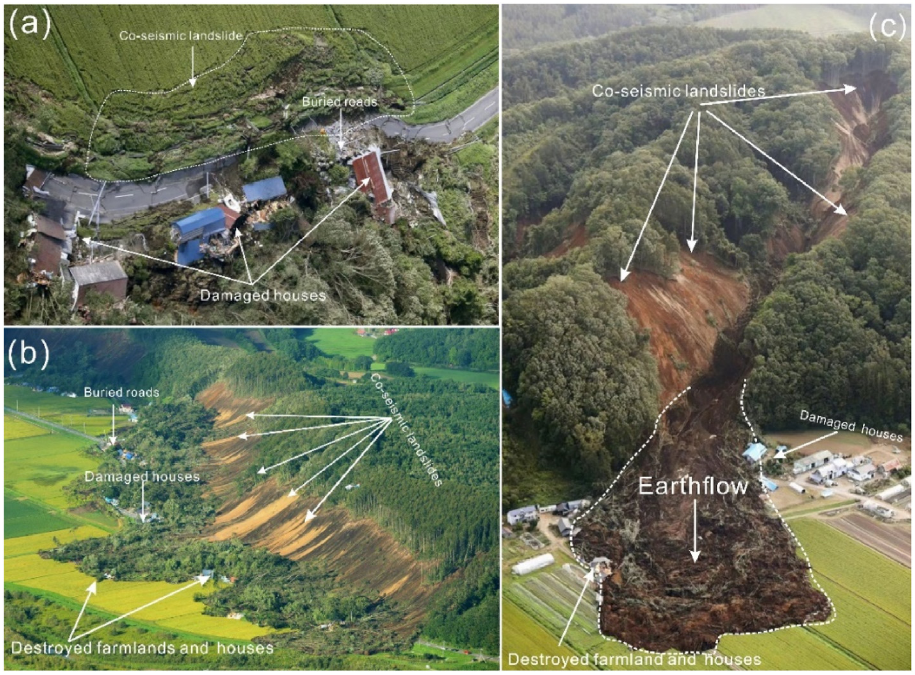

Fig. 1. Aerial photos of co-seismic landslides (taken by Asia Air Survey and Aera Asahi Corporation (Yamagishi and Yamazaki 2018)); (a) landslides blocked the roads and buried houses; (b) landslides are shallow, several meters deep-seated; and (c) landslides destroyed farmland and buried houses (photos from Kiyota Laboratory in the University of Tokyo).

model validation methods and evaluation scale, then we discuss the limitations of existing research, and provide suggestions for future research.

2. Earthquake-induced landslide inventory

A high-quality earthquake landslide inventory is an important basis for ELSA, and its completeness determines the accuracy of assessment results. The construction of landslide data mainly includes three methods: 1) Field Survey, 2) Hand-sketched inventory, 3) Paper inventory digitalization, 4) Computer-based visual mapping, 5) Automatic extraction (Harp et al., 2011a; Keefer 2002; Peng et al., 2020; Plafker et al., 1971).

With the development of computer, GIS, remote sensing and other technologies, more and more earthquake landslide inventories have been prepared and modified (Rodriguez et al., 1999; Schmitt et al., 2017; Tanyaş et al., 2017). And the criteria for establishing an earthquake landslide inventory have been gradually supplemented and improved (Guzzetti et al., 2012; Harp et al., 2011b; Xu, 2015a). It comprises the following provisions and instructions: 1) Requirements for image selection in the study area, 2) Mapping principles of ETLs. How to establish interpretation marks for seismic landslide identification to avoid subjective missing judgment and wrong judgment, and 3) How to distinguish the interpretation methods of large-scale landslide and continuous landslide.

However, limited by the above guidelines, there are very limited earthquake-landslide inventories with detailed, complete and surface elements to identify landslides. According to statistics, there are about 130 coseismic landslide inventories available worldwide. Fig. 2 shows the count of landslide inventories in each continent, and only 25% of them meet the requirements of the current landslide database. For the major earthquake of China in recent years, the coseismic landslide databases meeting the above requirements have been gradually improved. Fig. 3 shows the spatial distribution of these landslide inventories in China and neighboring countries. Publicly available include the Tongwei M7.5 earthquake in 1718 (Xu et al., 2020), Haiyuan M8.5 earthquake in 1920 (Xu et al., 2018), Taiwan Jiji earthquake in 1999 (Liao and Lee 2000), Wenchuan earthquake in 2008 (Xu et al., 2014c), Yushu earthquake in 2010 (Xu et al., 2013b) Lushan earthquake in 2013(Xu et al., 2015), Minxian earthquake in 2013 (Xu et al., 2014a), Ludian earthquake in 2014 (Xu et al., 2014b), Jiuzhaigou earthquake in 2017 (Fan et al., 2018), 2017 M_S 6.9 Nyingchi earthquake and so forth.

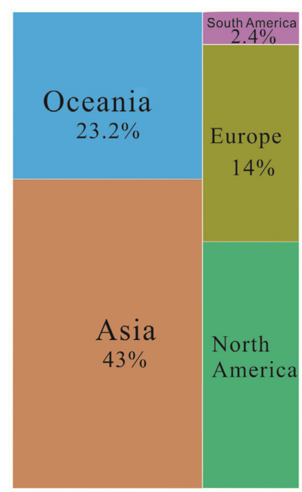

Fig. 2. Proportions of landslide inventories of each continent in the globe.

3. Earthquake-induced landslide influencing factor

Identifying and understanding the connections between Earthquake-induced landslide and influencing factors is critical for susceptibility mapping studies. Regarding the selection of the influencing factors data utilized in ELSA, there is no systematic procedure or general agreement. According to the principle proposed by Ayalew and Yamagishi (2005b) and several factors that have previously been used in the literature were

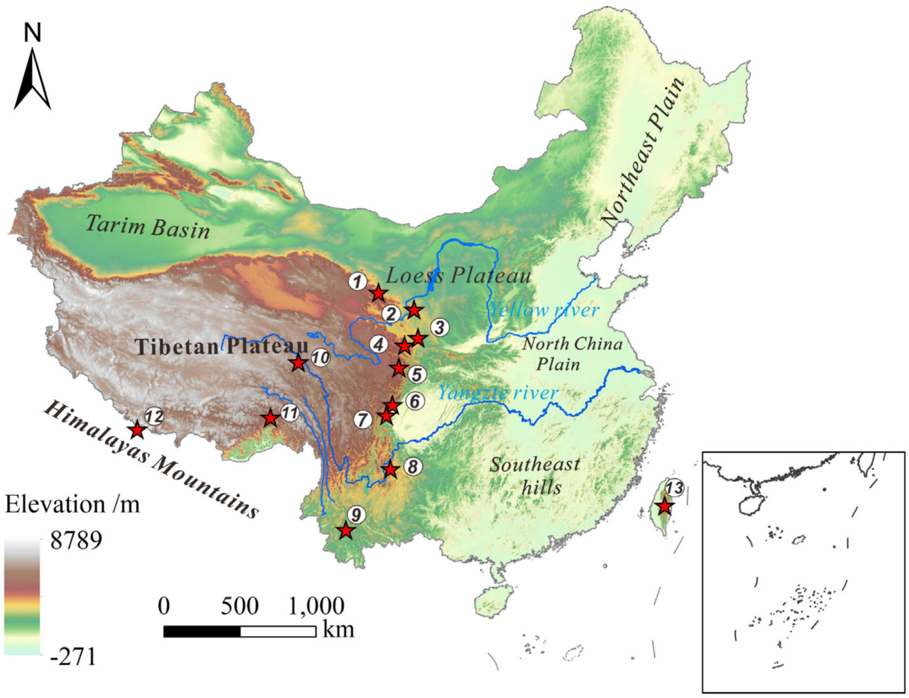

Fig. 3. Shaded terrain map showing earthquake-landslide inventories in China and neighboring countries. (1). 1927 Ms 8.0 Gulang earthquake, (2). 1920 Ms 8.5 Haiyuan earthquake, (3). 1718 Ms 7.5 Tongwei earthquake, (4). 2013 Ms 6.7 Minxian earthquake, (5). 2017 Ms 7.0 Jiuzhaigou earthquake, (6). 2008 Ms 8.0 Wenchuan earthquake, (7). 2013 Ms 7.0 Lushan earthquake, (8). 2014 Ms 6.6 Ludian earthquake, (9). 2014 Ms 6.9 Jinggu earthquake, (10). 2010 Ms 7.3 Yushu earthquake, (11). 2017 Ms 6.9 Milin earthquake, (12). 2015 Ms 8.0 Gorkha earthquake, (13). 1999 Ms 7.6 Chichi.

investigated (Paola et al., 2018). We summarize some commonly used influencing factors.

(1) Seismic factor

PGA or intensity is frequently utilized in the assessment of seismic landslide risk since it is one of the most critical ground motion factors for triggering earthquake landslides. The available global earthquake landslide inventories and other coseismic landslide statistical findings reveal that landslides are centered in the intensity 6 or PGA less than 0.2 range, and the landslide density gradually reduces as the intensity or PGA lowers (Chen et al., 2020; Meunier et al., 2007).

(2) Geological features

Because the study area suffered strong tectonic structures in different ages, the geotechnical characteristics of the same lithology or stratigraphy of the different ages have a huge difference; in contrast, the lithological properties (like cohesion and internal friction angle) of the same ages have few differences. Therefore, referring to previous studies (Gallen et al., 2015), they classify the lithology based on Stratigraphic age.

Seismogenic faults regulate the spread of coseismic landslides in numerous seismic events (Tatard and Grasso 2013). Seismic landslides are frequently densely distributed along the coseismic surface fracture zone, and the distribution of landslides in each segment of the surface fracture zone is plainly varied due to the geometric properties and movement habits of faults in different sections Xu et al. (2015). Earthquake landslides have distinct distribution patterns around faults with different movement behaviors. Landslides generated by a thrust earthquake are primarily found on the fault's hanging wall. The attenuation rate of the landslide in the hanging wall is much lower than that in the footwall as the distance from the seismogenic fault increases, and the hanging wall effect is quite visible. The Wenchuan earthquake is the most prominent example. According to statistical study, the richness index of the hanging wall (landslide area %, landslide center point density, and source area point density) is higher than that of the footwall in all aspects for the landslides caused by the Wenchuan earthquake. The attenuation speed of the footwall increases as the distance from the fault increases (Qing et al. 2008, 2011; Xu 2015). Many other earthquake cases also show that the distribution of landslides is closely related to faults, such as the 1994 Northridge, in which most landslides occur at a distance of 20 km from the seismogenic fault (Harp and Jibson 1996). The majority of landslides in the 1999 Chichi event are not found near the fault (0–5 km), but rather 5–10 km and 10–15 km from the fault (Lin and Tung 2004). For the 2005 Kashmir quake, more than one-third of the landslides were distributed within 1 km from the active fault and concentrated on the hanging-wall side of the seismogenic fault (Owen et al., 2008).

(3) Geomorphometric features

The control factors of earthquake-triggered landslides are elevation, slope, aspect and Landforms. Earthquake-caused landslides typically occur in areas of similar altitudes. Chang et al. (2007) found that earthquake-induced landslides often occur in ridge areas. What's more, the occurrence of landslides may be affected by the directionality of earthquake-related fault sliding and the propagation of seismic waves (Chen et al., 2020; Tanyas et al., 2017).

(4) Hydrological features

River erosion is one of the major factors influencing landslides, and it is primarily manifested in the weakening of the resistance to the slope's front edge and the increase of free surface during erosion, both of which affect the slope's stability.

The effect of rainfall and terrain humidity on landslides is primarily reflected in the massive infiltration of rainwater on the slope, and even ponding on the impermeable layer at the lower part of the slope, which increases the weight of the landslide and reduces the shear strength of the earth rock layer, resulting in landslide (Aditian et al., 2018). Twi can quantify the influence of terrain on the spatial distribution of soil moisture.

(5) Environmental features

The commonly used environmental features include Land use, Distance to Roads Networks, and Soil type (Nowicki Jessee et al., 2018b). Zhao et al. (2021) analyzed the 2017 Ms 6.9 Nyingchi earthquake landslides and pointed out that Rock avalanches are the most common failure pattern in the landslide-affected area. Mountain road construction has a significant impact on the local natural and geographical environment. Slope instability may be exacerbated by road construction. Landslides on both sides of the road are especially vulnerable to seismic forces. This phenomenon is well illustrated by many earthquakes, such as the 2018 Jiuzhaigou (Fan et al., 2018).

4. Earthquake-landslide susceptibility method

Broadly, there are four main types of ELSA approaches: Mechanical models (physics-based models), heuristic or index-based approaches, statistical analysis models, machine learning and deep learning models (Fig. 5).

4.1. Mechanical models

Mechanical models combine with the classic seismic landslide stability analysis method and the pseudo-static method. By subtracting the ground motion acceleration value from the critical acceleration of the slope body (determined by the quasi-static method), the difference is quadratic integrated with the time, then the permanent displacement is obtained. This idea fully considers the mechanism of earthquake-landslides, and uses the analysis results of the slope instability mechanism and sliding process to quantitatively classify the risk of landslides. The physics-based model provides the highest prediction accuracy for landslide prediction involving detailed site characteristics, which are suited for sub-catchment scale mapping and analysis (Hovland 1976; Huang et al., 2017; Hungr et al., 1989).

Newmark (1965) gave more stringent assumptions to ensure the accuracy of the assessment results, mainly including (1) the slope sliding body is an ideal rigid body without any mechanical deformation; (2) when the block slides, its rock and soil strength will not decrease; (3) any component of ground motion in the vertical direction is ignored; (4) the critical acceleration of the sliding body is a fixed value, and the displacement of the sliding body occurs when only external force is applied; (5) the failure surface will occur when the slope slides; (6) the sliding direction of landslide mass is fixed; and (7) ignore the pore pressure.

Based on the above assumptions, mechanical models are divided into three types: (1) rigid slider analysis method; (2) decoupling analysis method (Bray and Rathje 1998); and (3) coupling analysis method (Bray and Travasarou 2007). Since its complex assumptions cannot meet the actual situation, a simplified Newmark method was proposed, which uses parameters such as the safety factor (Fs), critical acceleration (ac) and the cumulative displacement (Dn), and employees empirical formula to determine the cumulative displacement of the block, which is more advantageous than other mechanical evaluation models (Jibson 2011; Jibson et al., 2000; Jibson and Jibson 2007). After the improvement by many scholars, the classical mechanical analysis method has realized an important leap from monolithic landslides to regional hazard assessment, and has been applied in the quantitative hazard assessment of earthquake landslides in the different regions (Daniel et al., 2013; Gallen et al., 2017; Miles and Keefer 2000; Peng et al., 2009; Wang et al. 2013a, 2013b).

4.2. Heuristic or index-based approaches

The heuristic approach is to build a model based on limited information, in which the expert opinion is very important for estimating landslide potential from intrinsic variables like the geological environment. Assigning weights of variables and rating hazard assessment are very subjective and the results are usually not replicable (Anbalagan 1992; Fall et al., 1996; Guzzetti et al., 1999b; Kouli et al., 2010; Msilimba and Holmes 2005; Pandey et al., 2008; Saha et al., 2002; Wachal and Hudak 2000; Westen et al., 1999). Therefore, the application of this method is less in the evaluation of regional large scale landslide susceptibility.

4.3. The statistical analysis model

The statistical analysis method was first introduced into the ELSA by Carrara et al. (1995). This method assumes that the geological conditions will not change with the occurrence of geological disasters and future events may occur under the same conditions It uses a coseismic landslide inventory to establish the relationship between the landslides and their controlling factors, which is then extended to the entire research area to realize susceptibility analysis (Guzzetti et al., 1999a). The landslide-related controlling factors usually involve three major aspects: seismology, topography and geology. In the past decade, the statistical model has benefited the most from the progress of GIS (Geographic Information System). Many scholars combined the above controlling factors with the information method, weight of evidence(Agterberg et al., 1993), discriminant analysis (He et al., 2012), binary statistical analysis (Singh et al., 2005; Xu et al., 2013a; Zhou et al., 2015), and multivariate statistical model (Kavzoglu et al., 2015) to carry out landslide susceptibility assessment for different earthquake events. It has been proved to be more applicable in multiple earthquakes (Ayalew and Yamagishi 2005a; Nowicki Jessee et al., 2018a; Nowicki et al., 2014b; Parker et al., 2017).

4.4. Machine learning and deep learning model

The machine learning technology is increasingly used in LSM mainly for the following reasons: 1) This method can solve two main problems in big-data spatial analysis, one is the theoretical knowledge range of big data which is incomplete (Lary et al., 2016), the other is the statistical presupposition is unreliable in big-data spatial analysis (Dou et al., 2019a). 2) This method can better solve the non-linear geo--environmental problems. The relationship between the probability of landslide occurrence and the independent variables can be expressed through regression without assuming a data structural model. 3) There is no need to train accurately for a specific variable. The machine learning model "learns" and develops the model from the data by simulating the relationship between a set of input samples and output variables. This process does not need complex and rigorous physical processes. 4) For regional scale prediction, the boosting algorithms and Gradient Boosting improve the accuracies of ML models (Luo et al., 2019).

The main difference between the machine learning and statistical methods is that the former learns from data without relying on rule-based functions, emphasizing optimization and performance, while the latter simplifies the relationship between variables in the data through mathematical equations. Formula reasoning is the main concern of statistical models (Merghadi et al., 2020). In recent years, the more popular machine learning algorithms also learn from statistical methods, which develop and establish a series of new machine learning methods based on statistical learning theory. Logistic regression (LR) is an example, in which the algorithm is a statistical model for solving binary classification problems. LR is borrowed from the field of the statistical model in machine learning, which contains more variable information and is more suitable for landslide evaluation in complex geological environments. Furthermore, the combination of the two ideas also solves the high-dimensional and nonlinear problems (Ayalew and Yamagishi 2005a).

At present, the popular machine learning algorithms include: (1) logistic regression (LR); (2) artificial neural network (ANNET); (3) support vector machine (SVM); (4) decision tree (DT) and extreme random tree (EXT); (5) random forest (RF); (6) Naive Bayes (NB); (7) quadratic discriminant analysis (QDA); (8) K nearest neighbor (KNN); (9) gradient lifting (GB); and (10) neuro fuzzy (NF). According to the web of sciences, the number of articles on four machine learning methods from 2008 to 2021 is counted here (Fig. 4). The results show that the LR method is the

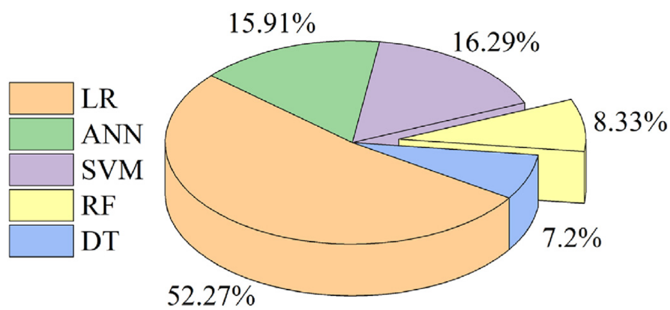

Fig. 4. Proportions from published literature on the most popular methods of machine learning in landslide sensitivity models.

most widely used, up to 51%.

With the combined development of big data and deep learning concepts, the ELSA method based on data mining is gradually favored by people (Aditian et al., 2018). For example, complex neural networks (Ayalew and Yamagishi 2005a; Pradhan and SaRo 2010), genetic algorithms (Chen et al., 2012), etc.

However, this kind of methods needs to design complex network structure in advance, and its regionality is obvious. At present, it is not widely used in earthquake-landslide susceptibility assessment.

5. Model validation method

Validation typically entails comparing the model prediction to the actual data to assess the model's accuracy or prediction ability (Guzzetti et al., 2006). To quantify the prediction accuracy of the models, The statistical indexes like the ACC (the overall accuracy) and AIC information criterion (Akaike information criterion) were used (Abedini et al., 2017; Paola et al., 2018). Furthermore, in order to quantify the overall performance results, the area under the ROC curves (AUC) and the Cohen's kappa Index (kappa) are employed. Table 1 summarizes the commonly used model validation indexes and Criterion.

6. Assessment scales of earthquake landslide susceptibility

ELSA mainly focuses on three scales: small regions, national scale and global scale. According to the web of sciences, we have counted the SCI papers on landslide susceptibility mapping from 2008 to 2021 (Fig. 6). The results show that a total of 816 papers were published and cited, with an upward trend year by year.

6.1. Single-site scale

For single-site earthquake-induced landslides, the landslide risk assessment focuses on the landslide mechanism, stability, motion

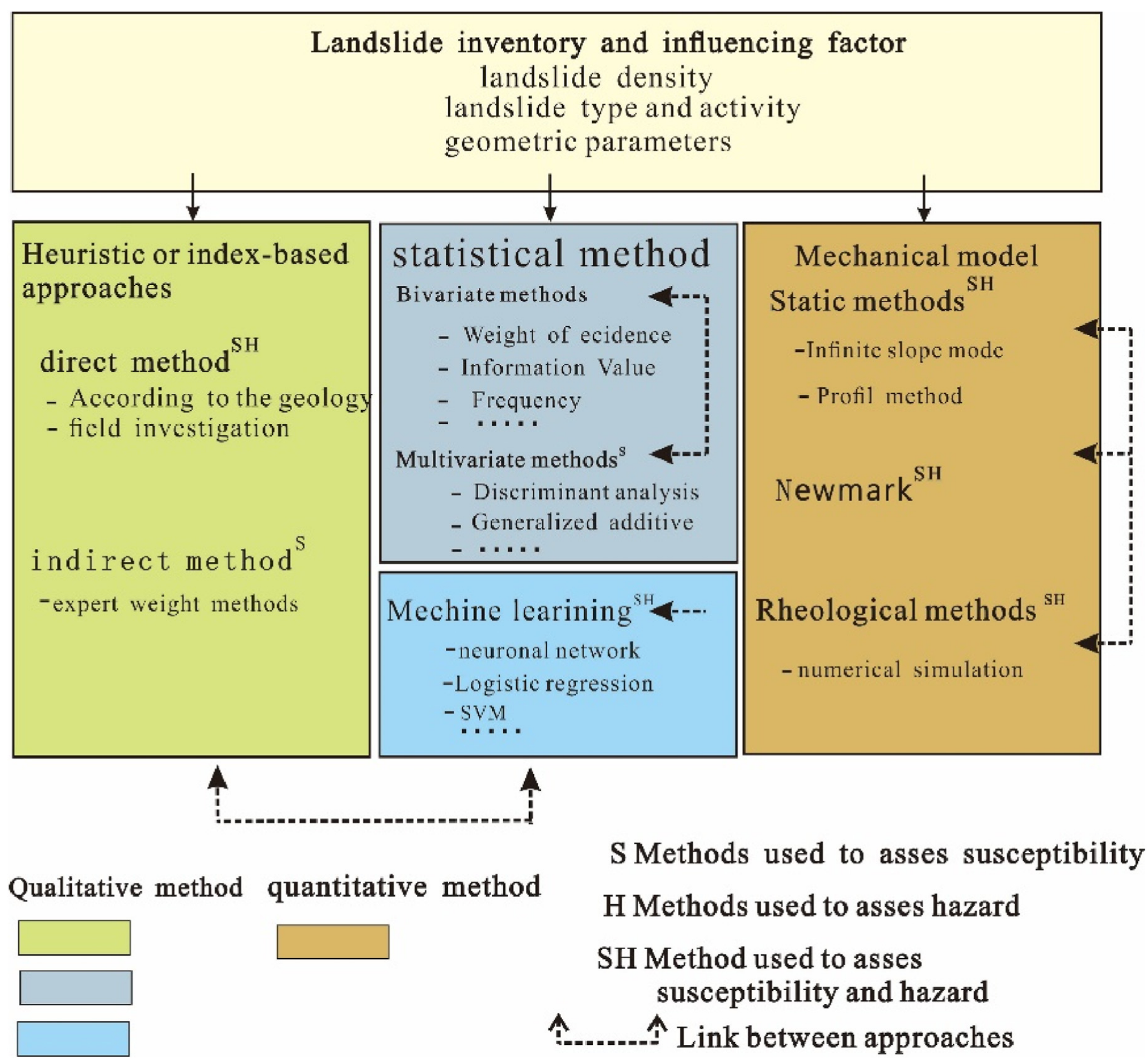

Fig. 5. Methods for landslide susceptibility assessment (Corominas et al., 2014; Fell et al., 2008; Thiery et al., 2020; van Westen et al., 2006).

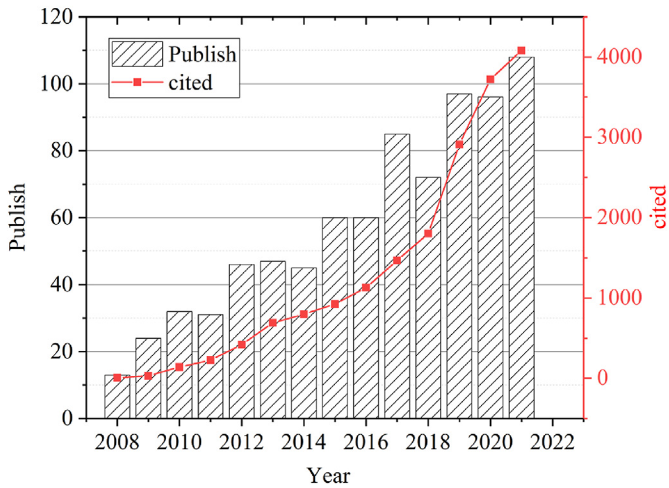

Fig. 6. Literature database. From January 2008 to June 2021.

Table 1
Model validation method.

Measure	Method/Definition	Criterion
AIC	AIC = 2k + nln*(sum square of residue/n)	The Akaike Information Criterion (AIC) is a statistical measure used to represent the goodness of fit of a model to the data with which it was trained, the AIC value decreases with better model fit
ACC	$\frac{Numberofcorrectpredictions}{Totalnumberofpredictions}$	the ACC value decreases with better model fit
The area under the ROC curve	which range from 0.5 to 1.0.	The higher AUC value means the higher prediction accuracy of the model (Kandrika 2005).
Cohen's kappa	$\frac{p_o - p_e}{1 - p_o}$ p_o : Overall classification accuracy	

dynamics and accumulation simulation (Fig. 7) (Dang et al., 2016; Havenith et al., 2003) Traditional methods include five categories, i.e. geological analysis, mechanical analysis, discrete element numerical simulation, and physical model experiment (Xu 2015). The geological analysis gives the understanding on genesis of large-scale landslides mainly according to different geological, ground motion, geomorphic evolution, deformation parameters and other conditions(Dai et al., 2011; Deng et al., 2019). The experimental approach refers to testing the geotechnical parameters using laboratory apparatuses, including cyclic ring shear, triaxial compression tests, and shaking tables. The numerical simulation is mainly used for large deformation and failure, and the discrete element numerical calculation can simulate the dynamic process of slope failure (Liu et al. 2013, 2015, 2017a; Pham et al., 2018; Scaringi et al., 2018).

The development of remote sensing technology promotes the monitoring of single-site landslides, which is characterized by strong macro, good timeliness, multi-level satellite remote sensing platform, rich and diverse data processing technology and data sources. Microwave remote sensing technology represented by Insar/SAR technology has great advantages in landslide surface deformation monitoring and early warning research because of its higher resolution, shorter return periods and accurate acquisition of micro and typical landslide deformation information. Goldstein et al. (1988) first proved that synthetic aperture radar differential interferometry (DInSAR) technology can be used for surface deformation monitoring at a centimeter level. Subsequently, D-InSAR, MT-InSAR, DS-InSAR, SBAS- InSAR and other technologies have been widely used in earthquake- or rainfall-induced landslides, land subsidence, glacier movement, landslide monitoring and early warning (Baer et al., 2002; Carla et al., 2019; Casu et al., 2006; Hyde et al., 2006; Intrieri et al., 2018; Kim et al., 2009; Ouyang et al., 2019). In recent years, with the development of Beidou/GNSS monitoring network in China, combined with multi temporal or UAV data, many research institutions have successfully predicted some major landslides through long-term dynamic monitoring, such as loess landslides along Jinsha River and in Gansu Province (Fan et al., 2019).

6.2. Small region scale

On a small region scale, evaluation based on physical model and statistical model is involved. A series of simplified Newmark displacement analysis methods based on mechanical model have been applied to the quantitative susceptibility assessment of seismic landslides in many regions. Like 1979 Coyote Lake earthquake (Wilson and Keefer 1983)、1994 North Mw6.7 earthquake (Jibson et al., 2000), 1989 Loma Prieta Mw6.9 earthquake (McCrink 2001), 2013 Lushan Mw6.6 earthquake (Chen et al., 2013)、2015 Nepal Mw7.8 earthquake (Gallen et al., 2016), 2017 Jiuzhaigou Mw7.0 eathquake (Liu et al., 2017b). Most previous studies are based on single and incomplete earthquake landslides or historical landslides and landslide influencing factors, and the assessment results are given by using the machine learning method. For instance, Kamp et al. (2008), based on Aster satellite images and GIS technology, constructed a landslide database of the Mw7.6 Kashmir earthquake on October 8, 2005 (2252 landslides). Combined with landslide multivariate evaluation criteria, they selected 8 landslide factors to predict 4 types of landslide prone areas. Lee and Evangelista (2006) used seven influence factors, combined with artificial neural network, to prepare a distribution map of landslide susceptibility in Baguio City, Philippines based on the landslides induced by the earthquake on July 16, 1990. Their result was compared with known landslide locations and prediction accuracy reached 93.20%. Xu et al. (2012), relying on 1m resolution color aerial photos, visual interpretation and extensive field investigation, using SVM, produced a detailed landslide map of the Jianjiang River watershed (with an area of about 411 square kilometers), including 3147 landslides related to the 2008 Wenchuan earthquake. Using the SVM model, the distribution map of earthquake triggered landslides in this area was prepared. Umar et al. (2014) adopted the integrated ensemble frequency ratio and logistic regression models, based on 89 landslides triggered by the 2004 Sumatra earthquake, combined with 14 trigger factors, and established a multi factor impact model of the seismic landslides in the Padang Pariaman area. Then the model was applied to West Sumatra Province to produce a comprehensive landslide sensitivity map (LSM) under the experienced seismic intensities of 7.5, 8, 8.6 and 9. Shrestha and Kang (2017) used the maximum entropy model to evaluate the landslide sensitivity in the middle of the Gorkha district, Nepal based on 690 landslides and related landslide impact factors.

These studies mostly rely on incomplete landslide databases to conduct the landslides susceptibility assessment in local quake-affected areas, which cannot fully reflect the overall distribution of landslides triggered by a single earthquake. In recent years, with the development and improvement of earthquake coseismic landslide databases, more and more researchers combined with a single complete landslide database in the earthquake affected area, based on machine learning methods, obtained the seismic landslide susceptibility distribution in the whole affected area (Fan et al., 2018; García-Rodríguez and Malpica 2010; Kamp et al., 2008; Shao et al., 2019).

6.3. The national or continental evaluation scale

On a national scale, the accuracy of large-scale prediction by physical model is coarse. Wang et al. (http://www.cgs.gov.cn/gzdt/zsdw

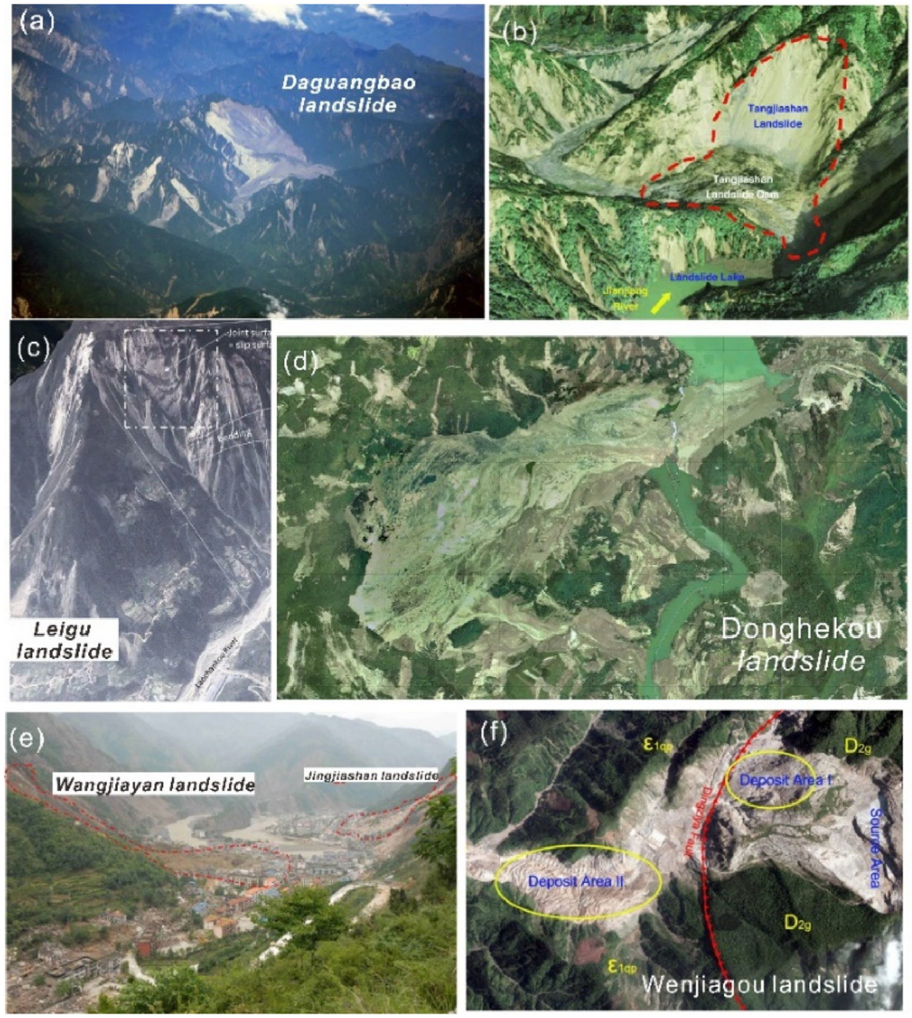

Fig. 7. Typical giant landslides induced by the 2008 Wenchuan earthquake. (a) Daguangbao landslide (Huang and Fan 2013); (b) Tangjiashan landslide (Peng and Zhang 2013); (c) Leigu landslide (Yuan et al., 2019); (d) Donghekou landslide (Zhou et al., 2013); (e) Wangjiayan landslide (Wang et al., 2009); (f) Wenjiagou landslide (Tang et al., 2018).

/201904/t20190412_479049.html) combined the information model with the Newmark model and considered the seismic risk assessment results, conducted assessment of seismic landslide hazard in Chinese mainland. With the development of GIS technology, based on a large number of landslide databases (triggered by multiple historical earthquakes) and landslide influencing factors, some researchers conducted assessment of landslide susceptibility assessment by using the machine learning method, which makes a better solution to this problem. Xu et al. (2019) based on the logistic regression method, combined with the landslide database of 9 earthquakes and the fifth generation seismic intensity distribution map of China, prepared a landslide probability distribution map of earthquake-landslides in China considering 13 trigger factors. The limited access to data also makes the national scale ELSA difficult to apply statistical methods.

The heuristic or index-based approaches are widely used in ELSA on a national scale. For instance, Gao (2011) adopted the "earthquake intensity index" and "earthquake disaster prediction index" as the judgment criteria to make a qualitative assessment of earthquake landslide susceptibility in China. Gaprindashvili and Van Westen (2016) compiled a national landslide database using the historical landslide records and field surveys in Georgia, generating a qualitative landslide susceptibility index using spatial multicriteria evaluation (SMCE). They also used the expert based smce of expert experience to generate a qualitative landslide risk index, and preliminarily predicted the landslide loss within 50 years.

With the improvement of landslide database, the results of this kind of methods are more reliable. In Europe, 22 of the 37 countries have national landslide databases available, and the other 6 countries have only regional landslide databases. These national databases contain a total of about 633,700 landslides, of which about 75% are in Italy and more than 10,000 landslides are in Austria, the Czech Republic, France, Norway, Poland, Slovakia and the United Kingdom. Among the 37 European countries, only 6 countries have enough information for risk analysis, and 14 countries can at least conduct sensitivity analysis (Fig. 8). Broeckx et al. (2018) compiled all available landslide inventories (ca. 10,800 landslides), supplemented by additional landslide mapping using Google Earth imagery in underrepresented regions (ca. 7250 landslides), which resulted in a dataset of approximately 18,050 landslides. And based on the above landslide inventory, two landslide susceptibility maps for Africa: one for all landslide types and one excluding the known rockfalls, were obtained.

6.4. The global scale

In the past few years, many scholars have summarized and compiled the global landslide databases, which is an important basis for the global ELSA based on the machine learning method (Tanyas et al., 2019). Several well-known global landslide databases include CRED (2011) released by Catholic Leuven University in Brussels, Belgium, ICL (2011),

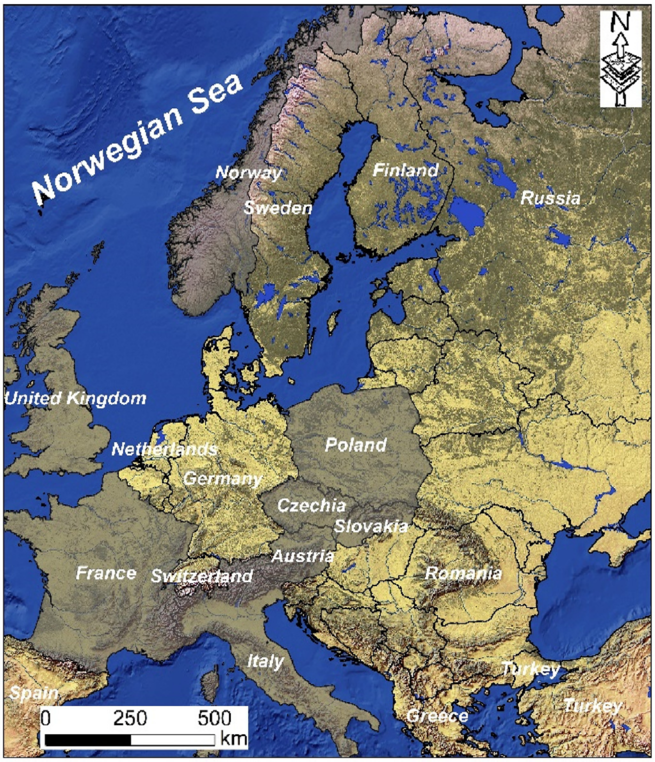

Fig. 8. European countries with landslide risk prediction ability (shadow).

Munich (2011) released by Munich reinsurance company, GSC released by Canadian geological survey and USGS (2011). Although they are, however, valuable to improve our understanding of the occurrence and impact of global landslides, these databases are incomplete, and the evaluation results are easy to be underestimated. So far there are few attempts to assess landslide susceptibility on a global scale.

Considering the limitations in data availability and details, it does not allow the use of physically based models. The combination of statistical methods and physical methods makes a better solution to this problem. Godt et al. (2008) developed a model with a spatial resolution of 1 km to test the possible spatial range of seismic landslides, which was based on the landslide data of two historic earthquakes in 1976 and Beiling earthquake in 1994, which combines the simplified Newmark method and heuristic model.

With the improvement of landslide data, statistical analysis methods are more and more popular on a global evaluation scale. Farahmand and Aghakouchak (2013) established a global landslide susceptibility model based on SVM using the global landslide database prepared by NASA. This model includes three variables, satellite remote sensing precipitation, DEM and land cover types. Compared with complex numerical methods such as SVM, the LR method provides a simple approach to generate global landslide susceptibility maps, which is helpful to popularize this research achievement, and contributes to the further development of the model. In addition, the results of logistic regression analysis can explain the relative importance of different factors in explaining landslides, which cannot be achieved by numerical methods such as the support vector machine. Nowicki et al. (2014a), relying on the ground motions given by USGS shakemapatlas 2.0, considering triggering factors such as topographic slope, surface geological and climatic parameters, and combined with statistical models, four earthquake coseismic landslide databases (Guatemala (1976), Northridge (1994), Chi, Wenchuan (2008)), produced a global landslide susceptibility assessment model with a spatial resolution of 1 km. Nowicki Jessee et al. later, using a 250m grid and 23 seismic landslide databases and the logistic regression method, constructed a new global model of landslide susceptibility. Tanyas et al. (2019), using grid units, the logistic regression model and 25 landslide databases, established a global model of landslide susceptibility assessment. He et al. (2021) developed a global model for rapidly assessing earthquake-induced landslide susceptibility based on the random forest (RF) algorithm using globally available data (288,114 landslides from 16 high-quality EQIL inventories), and the results match the actual landslide locations fairly well.

7. Research challenges

Each earthquake-landslide susceptibility has benefits and drawbacks. For example, although the mechanical model has a relatively clear physical meaning and a strict theoretical basis, it does not take into account the local differences and complexity of the regional geology, the landslide scale and other factors. In order to acquire accurate slope displacement, it is necessary to obtain clear geophysical and geotechnical properties and ground motion parameters. Secondly, there are many factors affecting the occurrence of earthquake landslides. The setting of model parameters is different from the actual fault structure, and the more complex the model, the more hypothetical conditions are, which leads to the uncertainty of the evaluation results. So the landslide susceptibility assessment based on the Newmark model remains not ideal (Wang et al., 2015; Wasowski et al., 2011). For statistical model or machine learning method, the results depend on the selection of evaluation factors. For deep learning methods need to design complex network structure in advance, and its regionality is obvious. So finding the most suitable model for any given general case study is a challenge (Paola et al., 2018).

Despite many achievements in the ELSA, it is almost entirely guided by the concept of probability from a small region to a global scale. It only takes into account the relative probability of landslides occurred and does not connect to the actual landslide, resulting in regional restrictions or different classification standards. Several studies on the probability distribution of real coseismic geological disasters have been conducted in recent years, one after the other. Nowicki Jessee et al. (2018b) attempted to establish the fitting curve of relative prediction probability and absolute probability by comparing the relative probability value with the real landslide data, which has achieved the purpose of correcting this deviation and giving the prediction results of landslide occurrence probability by calculating the percentage of real landslide occurrence within the width of 0.05. However, there are some errors and uncertainties in this approximate fitting, and the prediction results are still excellent (Allstadt et al., 2018). Xu (2020) applied this concept to earthquake landslide prediction and proposed a method for selecting sample points based on the area ratio of landslide and non-landslide, which achieved good prediction effect, but there is still prediction deviation in large-scale popularization.

8. Conclusions

In this paper, we summarize the mainstream assessment models for ELSA, including landslide data and their influencing factor, evaluation method, model validation methods and evaluation scale, then we discuss the limitations of existing research, and provide suggestions for future research. It is noted that when applied to practical case studies, there are significant differences in the performance of various machine learning models. Finding the most suitable ML model for any given general case study is a challenge, because the model performance depends not only on the performance results, but also on the integrity of the landslide database behind landslide modeling, the uncertainty of the influencing factors of the model and the limitations of each model.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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