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Original Article

Special Issue on *Disaster Risk Reduction in Mountain Areas*

Literature review and bibliometric analysis on data-driven assessment of landslide susceptibility

Pedro LIMA[1*] https://orcid.org/0000-0003-2429-3752; e-mail: pedro.lima@univie.ac.at

Stefan STEGER[2] https://orcid.org/0000-0003-0886-5191; e-mail: stefan.steger@eurac.edu

Thomas GLADE[1] https://orcid.org/0000-0001-9676-4416; e-mail: thomas.glade@univie.ac.at

Franny G. MURILLO-GARCÍA[3] https://orcid.org/0000-0003-2064-4877; e-mail: fran.79v@gmail.com

**Corresponding author*

1 University of Vienna, Institute of Geography and Regional Research, Universitätsstraße 7, 1010, Vienna, Austria

2 Eurac Research, Institute for Earth Observation, Drususallee 1/Viale Druso 1, 39100, Bozen-Bolzano, Italy

3 Institute of Geography, National Autonomous University of Mexico (UNAM), Circuito Exterior, Ciudad Universitaria, 04510, Coyoacán, Mexico City, Mexico

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Abstract: In recent decades, data-driven landslide susceptibility models (DdLSM), which are based on statistical or machine learning approaches, have become popular to estimate the relative spatial probability of landslide occurrence. The available literature is composed of a wealth of published studies and that has identified a large variety of challenges and innovations in this field. This review presents a comprehensive up-to-date overview focusing on the topic of DdLSM. This research begins with an introduction of the theoretical aspects of DdLSM research and is followed by an in-depth bibliometric analysis of 2585 publications. This analysis is based on the Web of Science, Clarivate Analytics database and provides insights into the transient characteristics and research trends within published spatial landslide assessments. Following the bibliometric analysis, a more detailed review of the most recent publications from 1985 to 2020 is given. A variety of different criteria are explored in detail, including research design, study area extent, inventory characteristics, classification algorithms, predictors utilized, and validation technique performed. This section, dealing with a quantitative-oriented review expands the time-frame of the review publication done by Reichenbach et al. in 2018 by also accounting for the four years, 2017-2020. The originality of this research is acknowledged by combining together: (a) a recap of important theoretical aspects of DdLSM; (b) a bibliometric analysis on the topic; (c) a quantitative-oriented review of relevant publications; and (d) a systematic summary of the findings, indicating important aspects and potential developments related to the DdLSM research topic. The results show that DdLSM are used within a wide range of applications with study area extents ranging from a few kilometers to national and even continental scales. In more than 70% of publications, a combination of the predictors, slope angle, aspect and geology are used. Simple classifiers, such as, logistic regression or approaches based on frequency ratio are still popular, despite the upcoming trend of applying machine learning algorithms. When analyzing validation techniques, 38% of the publications were not clear about the validation method used. Within the studies that

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included validation techniques, the AUROC was the most popular validation metric, being used accounting for 44% of the studies. Finally, it can be concluded that the application of new classification techniques is often cited as a main research scope, even though the most relevant innovation could also lie in tackling data-quality issues and research designs adaptations to fit the input data particularities in order to improve prediction quality.

Keywords: Review; Landslide susceptibility; Statistical models; Machine learning; Bibliometrics

1 Introduction

Defined as the downslope movement of soil, rock, and/or debris (Cruden and Varnes 1996), landslides are an important part of the landscape evolution, occurring in hilly landscapes all over the globe. This makes landslides one of the most threatening natural hazards, causing multiple deaths, damage to infrastructure, and substantial economic losses (Petley 2012). Therefore, spatially predicting landslides is crucial to reduce undesired consequences. For this purpose, creating models able to estimate where landslides might occur is important for spatial planning and directly influences policies, especially in mountainous terrain. Predicting where (areas or zones) landslides (or a particular landslide type) might occur, given local terrain features, is the main objective of landslide susceptibility models (Brabb 1984; Crozier and Glade 2005; Fell et al. 2008; Guzzetti 2005; Guzzetti et al. 1999).

Different methodologies have been applied to spatially assess landslide susceptibility. The main methods can be divided into qualitative (known as knowledge-driven or heuristic) or quantitative (data-driven and physically-based) methods (Corominas et al. 2014, Shano et al. 2020). Qualitative methods are produced based on expert judgment, where values or weights are given to predisposing factors according to the expert's understanding of the underlying geomorphological processes. Heuristic methods are considered subjective since they are based on expert opinion about terrain properties able to create (or not) instability (Shano et al. 2020). Within the quantitative methods, physically-based models often refer to spatial infinite slope models that are often coupled with geo-hydrological modules, described commonly by complex algorithms. These kinds of models are able to estimate slope stability as a function of soil mechanical and hydrological measurements (Soeters and van Westen 1996). Physically-based models, therefore, are highly dependent on a large amount and detailed input data (e.g. geotechnical parameters), often restricting the application of these methods to site-specific surveys (Cascini 2008; Corominas et al. 2014; Soeters and van Westen 1996). Statistically-based and machine learning predictive models (here after, referred to as Data-driven Landslide Susceptibility Models (DdLSM)) use the empirical relationships between the observations and its underlying ground features (e.g., lithological or land cover layers) (Brenning 2005), instead of the complex physical relationships required in the physical-based models.

The selection of the modelling method relies on the size of the study area, data availability and quality required to perform the investigation (Corominas et al. 2014), giving clear inter-dependency between the size of the study area and data availability (in most cases). While site-specific analysis would require more locally detailed assessments; analysis covering large areas may require the application of data-driven or heuristic approaches (Cascini 2008; Cascini et al. 2005; Corominas et al. 2014; Fell et al. 2008; Soeters and van Westen 1996). Although some recent studies have aimed to apply physically based models for larger areas (e.g. Rossi et al. (2013); Salciarini et al. (2017); Salvatici et al. (2018)), the spatial heterogeneity and variability of the required parameters still restrict its application to overly large areas (de Lima Neves Seefelder et al. 2017). The modeling of extensive regions usually is conducted using models with less restrictive data requirements. Nowadays, due mostly to the relative ease of input data requirements, Cascini (2008); Kanungo et al. (2009); Van Westen et al. (2008) and Corominas et al. (2014) have all noted that, data-driven approaches are the most commonly applied techniques at a regional scale.

Past review publications related to DdLSM, provide varied overviews and a variety of insights (Budimir et al. 2015; Malamud et al. 2014; Reichenbach et al. 2018; Steger and Kofler 2019). However, due to the recent technological developments and changes in the research methodology it is worth to regularly review the area of research to keep good track of the recent developments. In this publication, we start by reviewing important theoretical aspects of DdLSM, then presenting a bibliometric analysis of 2585 research items. After, a quantitative-oriented and extensive review of a data-base containing 311 relevant publications (from 1985 to 2020) is given. The final chapter critically summarizes the findings and identifies important aspects related to the topic.

2 Main Aspects of DdLSM

Based on the uniformitarianism concept (Slaymaker 2004) that past knowledge is a key element to predict the future, DdLSM are built upon the assumption that landslide might happen under similar terrain conditions as they have occurred in the past. This implies the assumption that physical laws are constant over space and time. The environmental conditions are also assumed to be steady-state, especially when dealing with multi-temporal landslides observations. Consequently, the knowledge gained from past events and its empirical relations with the terrain conditions are used to predict the future occurrence of similar events (Brenning 2005).

The standard process of DdLSM assessments, can be usually represented by the following steps: (i) acquisition of the landslide inventory, including the determination of non-landslide sampling points and posterior splitting in test and training samples; (ii) identification and acquisition of relevant geo-environmental ground features (i.e., predictors) responsible for interfering on slope stability and definition of a modelling unit (i.e., pixels, slope units, among others); (iii) selection and application of the appropriate classification technique; (iv) quality estimation of the modeling performance, and (v) the generation of the landslide susceptibility map (Fig. 1).

2.1 Study site extent and landslide inventory

Usually, one of the first considerations for a DdLSM modeler is the balance between the size of the study area and the availability of input data (Corominas et al. 2014). As mentioned in many studies (e.g. Cascini (2008); Corominas et al. (2014); Crozier and Glade (2005); Fell et al. (2008); Soeters and van Westen (1996)), every landslide susceptibility map should ideally be created considering the potential and limitations of the available datasets.

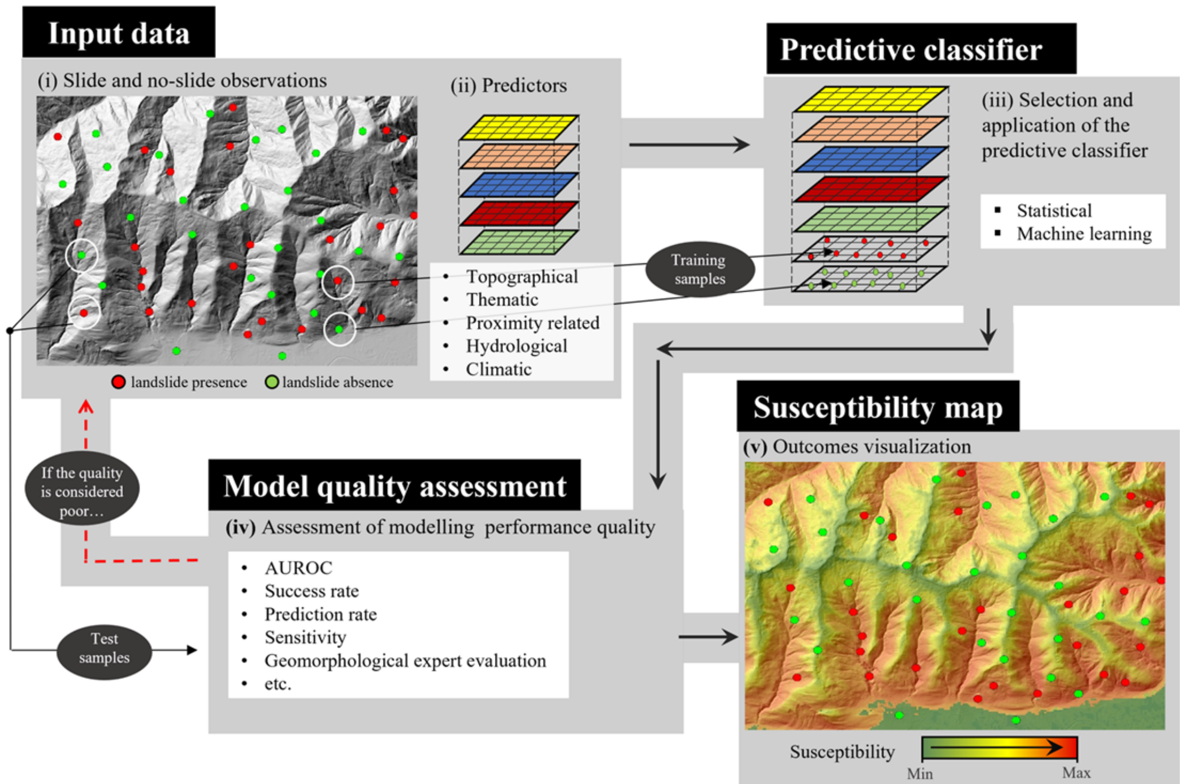

Fig. 1 Standard data-driven (statistical and machine learning) landslide susceptibility modeling process chain.

A landslide inventory is the spatial distribution of mapped landslides and is often one of the main input parameters for DdLSM (Glade 2001; Guzzetti et al. 2012; Van Westen et al. 2008). A "landslide inventory" could also include information such as location, type of movement and possibly also the date of occurrence (Fell et al. 2008; Guzzetti et al. 2012; Hervás 2013). The inventory can be derived from multiple or single triggering events and can be multi-temporal (historic) or event-based (Galli et al. 2008; Guzzetti 2005; Guzzetti et al. 2012; Malamud et al. 2014). Ideally, a complete, accurate and unbiased inventory is essential to build a robust relationship between the landslides and the geo-environmental predictors (Steger et al. 2017). Malamud et al. (2014) found that event-based inventories are more often used than multi-temporal inventories. The spatial DdLSM prediction is built under the empirical relationship between the response variable (here, the landslides observations) and the landslide predictors (cf. section 2.3 and section 2.4, respectively).

Landslide inventories can be obtained using a wide range of techniques, depending on the purpose, the extent of the study site, and the available resources (Guzzetti et al. 2012). The most common techniques used are, field mapping, remote sensing techniques, aerial photos interpretation, incidents reports, bibliographic analysis, and semi-automatic extraction from high-resolution DTM's (Guzzetti et al. 2012, 2006; Harp et al. 2011; Hervás 2013; Malamud et al. 2014). However, photo interpretation and field mapping are currently the main technique used for inventory creation (Malamud et al. 2014).

For DdLSM purposes, landslides are usually represented as points or polygons. The following landslide sampling strategies are highlighted in the DdLSM literature: (a) multiple points sampled throughout the whole landslide body, (b) multiple points within the landslide scarp, (c) single-point at the scarp centroid, (d) single-point at the landslide centroid, and (e) multiple points at the landslide vicinity, resembling the original landslide conditions, also named seed cells (Fig. 2). Publications dealing with the effects of landslide sampling strategies are numerous (e.g. Alvioli et al. (2016); Bordoni et al. (2020); Conoscenti et al. (2016); Dou et al. (2020); Erener and Düzgün (2012); Heckmann et al. (2014); Hong et al. (2019); Nefeslioglu et al. (2008a); Poli and Sterlacchini (2007); Regmi et al. (2014); Shirzadi et al. (2019)).

When applying DdLSM's, it is essential to focus on one movement type, most commonly classified by the Cruden and Varnes (1996); Dikau (1996) or Hungr et al. (2013) schemes. Every model should be applied separately for each particular landslide type (Corominas et al. 2014; Regmi et al. 2014; Zêzere 2002; Zêzere et al. 2017). Distinct failures typologies can be conditioned by distinct terrain conditions. It is the responsibility of the modeler to associate the specific landslide type to its respective related influencing factors.

2.2 Modelling unit and spatial resolution

By definition, a modelling unit is a portion of the territory with a defined boundary, where the

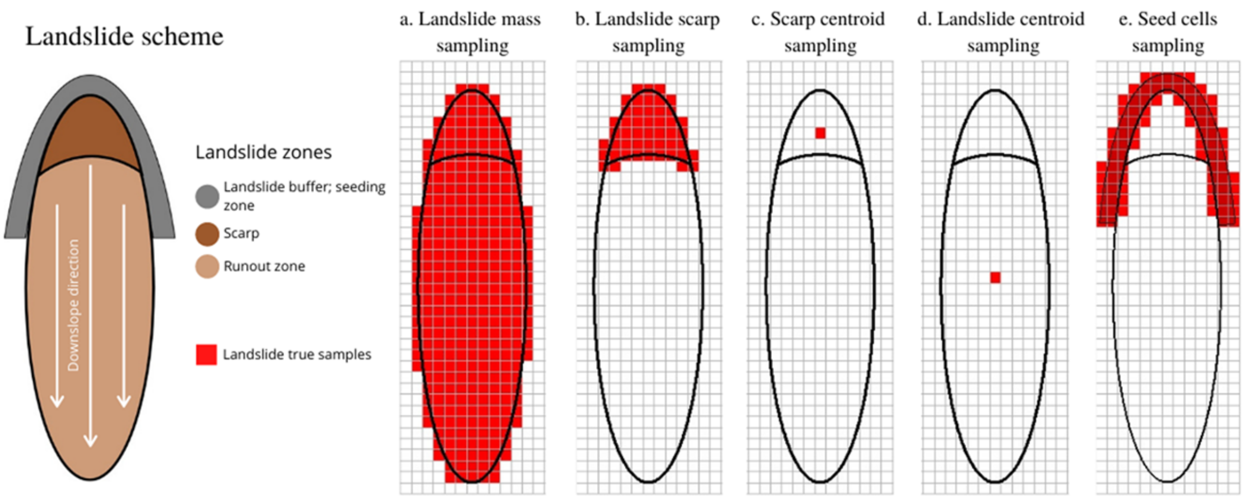

Fig. 2 Schematic plot of landslide sampling strategies (figure based on Regmi et al. (2014); Steger (2017).

underlying terrain conditions are summarized (Carrara et al. 1999), either by a categorical, binary, or a continuous variable. The modelling unit should represent parts of the terrain with internal homogeneity and external (between units) heterogeneity (Alvioli et al. 2016). Modelling units for DdLSM are usually: (i) pixel; grid cells based or (ii) polygon based, like slope units, unique condition units and terrain units (Guzzetti 2005; Zêzere et al. 2017).

Environmental and geomorphological conditions related to landslide occurrence are often represented by raster maps, which are defined by a set of georeferenced quadrangular grid of pixels. Such information can be, for instance, numerical values representing slope inclination; categorical values, representing a certain land cover type; or binary information, representing presence or absence of certain features (Guzzetti 2005). Recent advances in computer hardware and storage have made it possible to run DdLSM using very detailed raster resolutions, even for very large areas. The interplay between inventory positional accuracy and resolution of the input data should be one of the initial concerns (Lima et al. 2021). The role of predictors resolution and its effects on DdLSM, were assessed in publications like Arnone et al. (2016); Claessens (2005); Durić et al. (2019); Lee et al. (2004); Palamakumbure et al. (2015); Shirzadi et al. (2019). However, defining the best resolution is still an ongoing debate (Murillo-García et al. 2019; Trigila et al. 2015).

2.3 Landslide susceptibility predictors

Also frequently called "conditioning", "environmental", or "predisposing" factors, landslide predictors are used to describe typical terrain conditions for landslide occurrence. They are the terrain geo-environmental features that influence the instability of the slope within a study site (Corominas et al. 2014; Crozier and Glade 2005; Van Westen et al. 2008). The selection of a predictor, besides being related to data availability at the appropriate scale, should also adequately describe the landslide occurrence (Crozier and Glade 2005; Salciarini et al. 2017; Van Westen et al. 2008; Zêzere et al. 2017). The inclusion of biased predictors; irrelevant ones; as well as the omission of appropriate ones, may significantly interfere in the prediction competence of the assessment (Steger et al. 2016b).

Landslide predictors can be subdivided into (i) thematic variables (e.g., lithology, and soil type), (ii) topographical (e.g., slope angle, curvature, aspect), (iii) climatic (e.g., rainfall total, intensity, or duration), (iv) hydrological (e.g., topographic wetness index), or (v) proximity variables (e.g., distance to rivers or road). An extensive overview of these parameters is provided by Budimir et al. (2015); Corominas et al. (2014); Kanungo et al. (2009); Süzen and Kaya (2012), and Pourghasemi and Rossi (2016). Between different landslide predictors, topographic parameters (e.g., elevation, slope angle) were recognized as the most relevant (Coe et al. 2004; Fabbri et al. 2003) and therefore also the most adopted in DdLSM (Budimir et al. 2015; Malamud et al. 2004; Pourghasemi and Rossi 2016; Süzen and Kaya 2012).

2.4 Classification techniques

Many statistical, and also machine learning classification techniques have been used for landslide prediction Malamud et al. (2014); Reichenbach et al. (2018). Pioneer studies such as, Bernknopf et al. (1988); Carrara (1983); Carrara et al. (1990, 1991); Chung and Fabbri (1999); Guzzetti et al. (1999); Rice et al. (1985), and Van Westen et al. (1997) can be regarded as the starting point for the adoption of DdLSM. DdLSM techniques assign to an object, in this case a modelling unit, relative values, or classes reflecting the likelihood of phenomena occurrence (Brenning 2005). The classifiers themselves, considering the relationships between the observations and the predictors, estimate relative probabilities related to occurrence probabilities, usually ranging from 0 (zero) to 1 (one). A very low score (near zero) represents very similar terrain conditions where no or very few landslides occurred in the past. While a higher score (near one), would represent very similar terrain conditions where landslides have happened in the past (Brabb 1984; Guzzetti et al. 2006).

DdLSM methods are numerous, and although similar in theory, adopt their own classification algorithms. Some are more mathematically based (e.g. statistical methods), and others are more flexible (e.g. machine learning methods), based on skilled patterns recognition (Ayalew and Yamagishi 2005; Brenning 2005; Dai and Lee 2002; Micheletti et al. 2014). Which often give these models reduced transparency, suggesting a 'black-box' behavior (Goetz et al. 2015).

Machine learning approaches, differently to statistical approaches are less based on statistical premises, but rather in a very flexible patterns recognition algorithms, usually aiming a maximized predictive performance (Schratz et al. 2019; Steger and Kofler 2019). However, literature, suggests that there are probably more similarities than differences between statistical and machine learning algorithms (Hastie et al. 2011). When it comes to the topic of landslide prediction using machine learning algorithms, it is important to acknowledge the high adaptation power of the method to the training samples (Hastie et al. 2011; James et al. 2013). Which may be of concern to landslide predictive studies, especially when dealing with imperfect (e.g., biased) input data, which can lead to overfitting, possibly overestimated predictive performances and harder to interpret predictive maps (Brenning 2012; Goetz et al. 2015; Schratz et al. 2019; Steger and Kofler 2019). Differences aside, statistical and machine learning predictive methods for landslide prediction will be, in the context of this publication referred to as "data-driven" and analyzed together, since both derive generalized modelled relationships from data on empirical observations. Although there are numerous options of proposed for selection of classifiers used to delineate landslide susceptibility in literature, there is still no consensus on standardized criteria. Some simpler, but still efficient classifiers like weight of evidence were extensively used in the past decades (Malamud et al. 2014). Typical machine learning algorithms, such as neural networks or decision trees, have gained popularity in the recent years (Goetz et al. 2015).

2.5 Model quality. Sampling partitioning strategies and performance evaluation

Assessing how good a predictive model fits using similar landslide observations, indicates how reliable this same model is to foresee future events. Also named as "measure of significance", "degree of success" or "significance of predictions" (Chung and Fabbri 2003), validation methods are normally performed through estimation of error measures. A validation procedure is essential to supply the study with scientific rigor and reliability. Nevertheless, Malamud et al. (2014) have shown that 37% of the publications did not apply any validation technique or measure to the models. Addressed under qualitative (e.g., field surveys and geomorphic plausibility of the outcomes) or quantitative basis, the options to assess the model quality are many. The most frequent validation techniques applied to DdLSM are Receiver operating characteristic (ROC) curve, success, and prediction rate(s) (Chung and Fabbri 2003; Frattini et al. 2010). Extensive overviews on validation of landslide susceptibility models can be found in Beguería (2006); Brenning (2005); Chung and Fabbri (2003); Erener et al. (2017); Frattini et al. (2010); Guzzetti et al. (2006); Remondo et al. (2003); Zêzere et al. (2017).

Crucial in order to get an impartial estimate of how the model can predict future landslides, the models need to be tested against an unused set of observations (test sample), different from the samples used to train the model (training sample) (Brenning 2005; Chung and Fabbri 2003). Correctly predicting unknown landslide locations as unstable zones and landslide absence as stable zones are what most of the validation metrics are based on (Frattini et al. 2010). The Receiver Operating Characteristic (ROC) curve is mostly used as performance evaluator for most DdLSM. It is built by analyzing a series of multiple confusion matrices, which correlates wrong (false positives and false negatives) and correctly (true positives and true negatives) classified samples (Beguería 2006). A ratio of true positives to false negatives provides a measure of sensitivity, while the ratio of true negatives to false positives a measure of specificity. This gives a range of 0-1 values that are the basis for the ROC curve. The 0-1 range typically informs how good the model was able to predict landslide occurrence.

The sampling partitioning strategy is also an important element in the validation. The testing and training samples are mostly selected using three main strategies: (i) random, (ii) temporal, and (iii) spatial partitioning (Chung and Fabbri 2003). Random sampling, also named single holdout, is recognized as the most widely used method, which consists of an exclusive split of the inventory between training and test samples (e.g., 70% as training and 30% as test samples) (Chung and Fabbri 2003; Juliev et al. 2019; Kohavi 1995; Panahi et al. 2020; Wang et al. 2020). Temporal partitioning, consists of testing a model with a set of observations that occurred in different circumstances than the observations used to train the model (usually a different triggering event) (Brenning 2005; Chung and Fabbri 2003; Ciurleo et al. 2016; Poonam et al. 2017). Spatial partitioning uses the landslides with in a specific area(s) as a the training samples and subsequently the remaining landslides as a test sample (Chung and Fabbri 2003; Depicker et al. 2020; Gorsevski et al. 2016; Lombardo et al. 2014). The partitioning process can also be repeated multiple times, randomly or spatially. When using multiple repeated partitioning techniques (Fig. 3C and 3D), the training and testing samples are randomly selected multiple times, with or without a spatial component. The n-fold and n-repetition will define how many times the model will be re-sampled and validated. The random non-spatial component for separating test and training samples is named "Non-spatial cross-validation", while when the spatial location of the samples is considered, the term "Spatial cross-validation" is used. These main partitioning methods are illustrated in Fig. 3.

3 Bibliometric Analysis

Bibliometric analysis is a tool to analyze publications databases in order to identify trends, patterns, and important information related to specific research fields (Glänzel 2012). This technique has been broadly used in many research fields. Within geomorphology, Gokceoglu and Sezer (2009); Piégay et al. (2015); Sassa et al. (2015); Stott (2010, 2011, 2013); Wu et al. (2015) have used bibliometric analyzes to evaluate patterns related to fluvial geomorphology and also landslides. Wu et al. (2015) pointed out some research trends related to the term "landslide", highlighting a growing usage in recent decades. They demonstrate a dynamic behavior of different related key-terms, often describing methodologies or internal aspects. Using bibliographic analysis, Wu et al. (2015) presented the 30 top key-terms related to "landslide", including "logistic regression," which has risen from a non-ranked position in the period between 1991 - 1999 to the 13th place between 2010 and 2014. Based on a bibliometric analysis of 1136 publications available in Scopus, Steger and Kofler (2019) demonstrated the exponential growth over the last years of publications with "statistical landslide susceptibility" as terms in the title.

3.1 Bibliographic database acquisition and processing

Assuming that meaningful methodological aspects and features are present on the publication titles, abstract and keywords, bibliographic analysis can be used to get an overview of specific research patterns of a certain topic. In order to access the research productivity and trend patterns related to DdLSM publications, a query was performed in May 2020 through the Web of Science, Clarivate Analytics database. The query was realized by gathering query terms like "landslide susceptibility" and/or "landslide

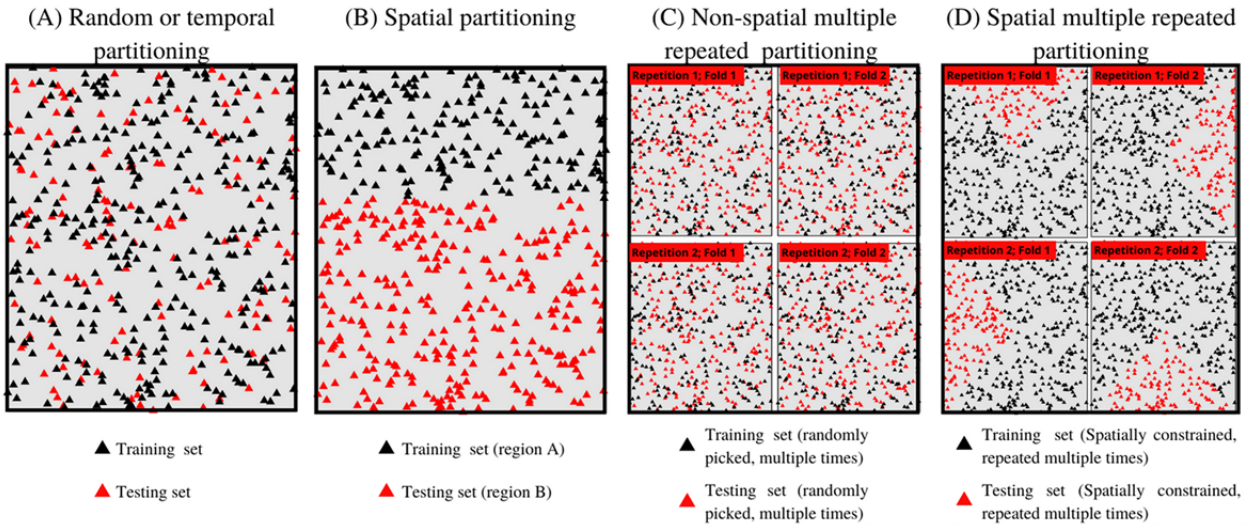

Fig. 3 Schematic visualization of varied partitioning strategies based on artificial data. (A) Random or temporal partitioning; can be usually split using varied proportions (%) for training and testing sets. The visual representation of the temporal partitioning is the same as the random. (B) Spatial partitioning: model is usually trained with samples from a well-documented area and tested over larger areas. (C) Non-spatial multiple repeated partitioning: also called as non-spatial cross-validation. (D) Spatial multiple repeated partitioning: also called spatial cross-validation.

hazard" and "statistic*" or "machine learning" when contained on the titles, abstract, or keywords of publications. Although landslide hazard and susceptibility have a different meaning, the inclusion of both expressions as query terms is justified by evidence provided by the literature that clear distinctions of both terminologies were not always adopted in some publications. The misconception of many authors between both terms is especially found in publications dating prior to the 2000's. For this reason, the authors have decided to use both terms in order to cover all the relevant literature on the topic. Only articles, reviews, conference papers, and book chapters written in English were considered. The key terms cited above were manually removed from the following bibliometric analysis.

The complete data set was processed by the bibliometric software, 'VOSviewer', version 1.6.5 (Eck and Waltman 2010). To filter the results, corresponding terms like "geographic information system" and "GIS"; or "maps" and "map" were manually merged using the "thesaurus" tool. This last process can avoid double counting of similar terms and provides a correct count of the key terms. Since only the most repeatedly cited terms are the main interest of the bibliometric analysis, only the items with an occurrence greater than ten times were further processed. To collate just relevant key terms, an additional step removed terms defining locations (e.g., Iran, China, Southern Italy).

Based on this inquiry, 2585 research items were identified, while 2083 were classified as research articles, 429 proceedings papers, 39 general reviews, and 34 book chapters. The query revealed research items produced between 1985 and 2020.

3.2 Temporal research development

The temporal investigation of publications dealing with the topic demonstrates an increasing number of publications, especially after the 2000's, reaching the maximum value of 380 items in 2019 (Fig. 4F). This constantly growing number of publications dealing with landslide susceptibility mapping can be attributed to the increasing number of landslide reports, causalities, people and infrastructure affected by landslides in the last decades (Kirschbaum et al. 2015; Nadim et al. 2013, 2006; Petley 2012).

The journals with the greatest number of related publications were Geomorphology and Natural Hazards (both with 153 publications), followed by Environmental Earth Sciences (141), Landslides (137) and Engineering Geology (93). The top-5 (Fig. 4) most productive journals contributed to 26% of the total research items, and 32% of the research articles. All the 2083 research articles were divided between 327 sources. Journals like Natural Hazards and Earth

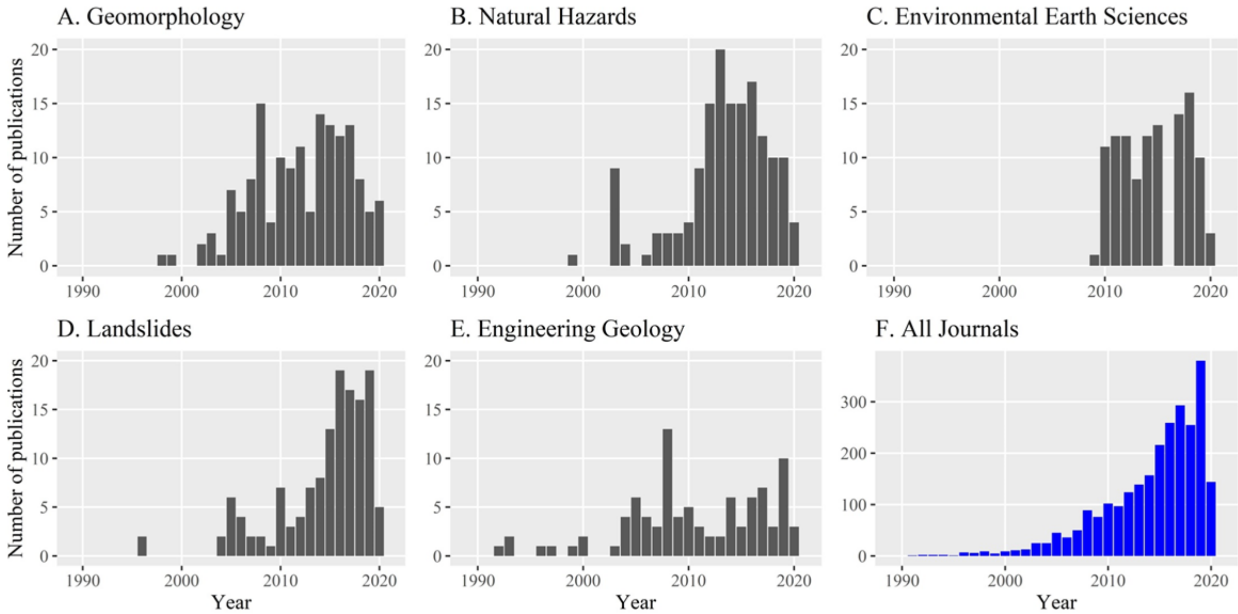

Fig. 4 Temporal productivity of the top 5 most active journals find in the database. Source: Database gathered from Web of Science, Clarivate Analytics in May 2020.

Table 1 Top five scientific journals on the topic of statistical landslide susceptibility models, from Web of Science, Clarivate Analytics (Thomson Reuters 2014).

Journals	Total number of publications	Cumulative citations	Average citations per publication
Geomorphology	153	11252	73.5
Natural Hazards	153	5762	37.6
Environmental Earth Sciences	141	3996	28.3
Landslides	137	4963	36.2
Engineering Geology	93	7707	82.8

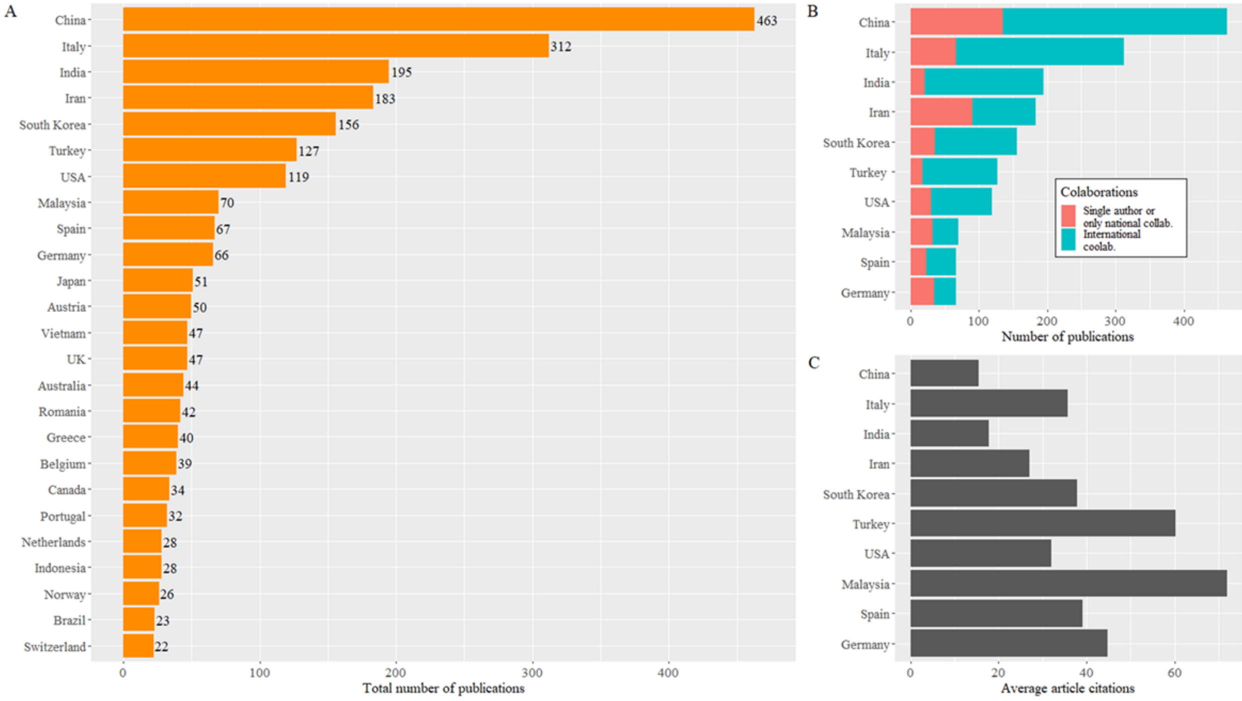

Fig. 5 Histogram representing the 25 top-most productive countries (Source: Web of Science; Clarivate Analytics; May 2020) (A). Observed number of publications of the top 10 countries, divided by the type of collaboration (single or only national collaboration, versus multiple authorship, with international collaboration) (B); Average number of citations per publication per country of the top 10 most productive countries (C). The countries correspond to the declared nationality of the 1st author institution.

System Sciences, Catena, Bulletin of Engineering Geology and the Environment, Arabian Journal of Geosciences; and Geomatics Natural Hazards & Risk were also within the topmost productive journals. A further comparison between the previously cited journals (Table 1), illustrates that the number of publications is not necessarily related to the number of cumulative or average citations.

3.3 Spatial distribution of author affiliations

The countries of affiliations of the first authorship of the 2585 publications are distributed over 76 countries. The global distribution of the first author's affiliations is predominantly from the countries, China, Italy, India, Iran, South Korea, Turkey, United States, Malaysia, Spain, and Germany (Fig. 5A). The top 10 countries represent 68% of the total number of publications. It was also observed in that same analysis that 67% of all publications were international collaborations. This reveals a strong international network of collaboration between researchers within this research topic. The identified country of affiliation of the first author can be used as a measure of hot-spots within this research field (Fig. 5B). However, it is noted that the quantity of research items does not necessarily reflect the overall quality of the publications. An approximated assessment of the general research impact within the field was calculated by analyzing the mean number of citations for the top 10 most productive countries of each publication. However, it should be kept in mind that

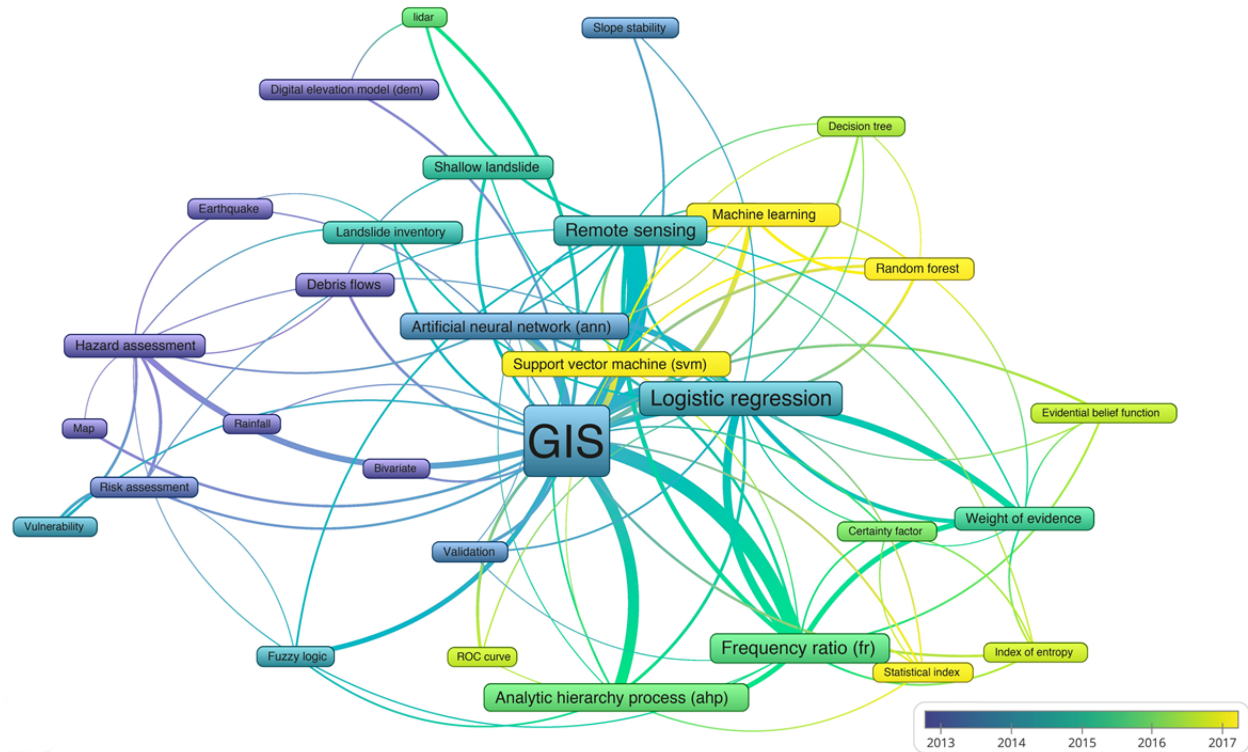

Fig. 6 Temporal co-occurrence network of the most used keywords. (Data source: Web of Science, Clarivate Analytics; April 2020). The line thickness represents the connection strength between the key terms on the publications. Following the legend, the color of the boxes and lines represents the chronological usage density of each term. The frame size represents the relative usage of the term as key term.

self-citation could contribute to a significant bias towards an increased citation rate of a publication or a researcher. It is important to stress that the implications of self-citations were not explored in this research and the productivity scenario might be biased towards self-citation.

3.4 Key terms analysis as a potential research trend indicator

A total of 4299 different key terms were used by the authors in the respective publications. The most frequently used key terms are illustrated in Fig. 6 and the detailed described in Table 2. Fig. 6 shows a large variation of terms mainly related to important DdLSM classification techniques, methodological aspects, input parameters, landslide predictors and landslide typologies. Table 2 addresses more in detail the temporal quantified usage development of the 30 topmost used terms. The 30 most mentioned terms were analyzed in terms of chronological ranking as key terms (Table 2). Within the top terms, techniques such as “Logistic Regression”, “Frequency Ratio (FR)”, “Analytic Hierarchy Process (AHP)”, “Artificial Neural Networks (ANN)”, “Support Vector Machine (SVM)”, “Weight of Evidence”, “Machine Learning”, “Random Forest”, “Fuzzy Logic”, “Certainty Factor”, “Bivariate”, “Decision Tree” and “Evidential Belief Function” appear to provide an overview of the most applied classifications techniques on DdLSM. Important geospatial tools and techniques like “GIS” and “Remote Sensing” were also often mentioned. The occurrence of terms describing landslide typologies such as “Debris Flows” and “Shallow Landslide” indicates a great usage of DdLSM related to these landslide types. It is also important to highlight the usage of terms such as “Validation”, “Roc Curve” and “Landslide Inventory”, possibly representing importance that many researchers place on the quality and reliability of the outcomes. Additionally, terms such as “Digital Elevation Model (DEM)” and “LIDAR” are one of the most cited terms since the topographical factors related to landslide occurrence mostly used as landslide predictors within the frame of DdLSM (e.g., slope, aspect, elevation, curvature, etc.) are derivatives of these data. Landslide triggering factors such as “Earthquake” and “Rainfall” are also mentioned often within this topic of research.

Table 2 Predominant keywords find on the 2585 publications through the bibliometric software. The signals after the terms correspond to the invariable (=); ascending (↑); descendant (↓); or oscillating (↑ ↓) comportment along the chronological sequence. (Source: Web of Science; May 2020).

Keywords	Total occurrence 1985 – 2020		Occurrences 1985 – 2004		Occurrences 2005 – 2008		Occurrences 2009 – 2012		Occurrences 2013 – 2016		Occurrences 2017 – 2020	
	Count	Rank	Count	Rank	Count	Rank	Count	Rank	Count	Rank	Count	Rank
Gis =	687	1st	27	1st	70	1st	158	1st	162	1st	270	1st
Logistic regression =	214	2nd	6	2nd	17	2nd	48	2nd	54	2nd	89	2nd
Frequency ratio (FR) ↑ ↓	154	3rd	1	29th	7	8th	26	5th	39	3rd	81	3rd
Remote sensing ↑ ↓	145	4th	-	-	9	6th	38	3rd	38	4th	60	7th
Analytic hierarchy process (AHP) ↑	116	5th	-	-	5	10th	20	6th	28	5th	63	5th
Artificial neural network (ANN) ↑ ↓	102	6th	2	11th	11	3rd	27	4th	23	6th	39	9th
Support vector machine (SVM) ↑	91	7th	-	-	1	69th	9	12th	18	9th	63	6th
Weight of evidence ↑ ↓	73	8th	1	30th	2	33rd	16	7th	19	8th	35	10th
Machine learning ↑	67	9th	-	-	-	-	-	-	3	72nd	64	4th
Shallow landslide ↑ ↓	67	10th	3	5th	4	13th	7	16th	20	7th	33	11th
Debris flows ↑ ↓	63	11th	6	3rd	10	4th	11	8th	15	10th	21	13th
Random forest ↑	57	12th	-	-	-	-	1	-	5	37th	51	8th
Landslide inventory ↑ ↓	55	13th	3	6th	4	14th	8	14th	9	14th	31	12th
Fuzzy logic ↑ ↓	42	14th	2	12th	3	19th	9	11th	11	11th	17	15th
Risk assessment ↑ ↓	40	15th	1	13th	10	11th	6	9th	6	22nd	17	14th
Validation ↑ ↓	40	16th	2	31st	5	5th	9	19th	6	23rd	18	17th
Digital elevation model (DEM) ↑ ↓	39	17th	2	15th	9	15th	7	10th	9	17th	12	19th
Slope stability ↑ ↓	39	18th	2	14th	4	7th	9	15th	8	15th	16	25th
Earthquake ↑ ↓	32	19th	3	7th	3	20th	6	20th	10	13th	10	31st
Lidar ↑ ↓	30	20th	-	-	2	34th	3	75th	9	12th	16	16th
Roc curve ↑ ↓	30	21st	-	-	-	-	2	35th	11	16th	17	18th
Vulnerability ↑ ↓	28	22nd	-	-	3	21st	7	18th	8	18th	10	32nd
Rainfall ↑ ↓	26	23rd	2	16th	5	12th	2	62nd	6	24th	11	28th
Certainty factor ↑ ↓	23	24th	-	-	-	-	5	24th	5	32nd	13	23rd
Natural hazard ↑ ↓	22	25th	1	32nd	3	22nd	3	34th	1	34th	14	21st
Geomorphology ↑ ↓	21	26th	2	17th	4	16th	7	17th	3	54th	5	77th
Map ↑ ↓	20	27th	3	8th	7	9th	1	-	2	94th	7	54th
Bivariate ↑ ↓	19	28th	1	33rd	3	23rd	4	26th	7	20th	4	96th
Decision tree ↑	19	29th	-	-	-	-	3	43rd	5	34th	11	30th
Evidential belief function ↑ ↓	19	30th	-	-	-	-	2	76th	6	25th	11	29th

Table 2 displays the chronological relative position (ascendant or descendent) of each term. Novel techniques like "Support Vector Machine (SVM)", "Machine learning", "Random Forest", and "Decision Tree" exhibit a constant increased usage throughout the whole period. This trend is likely related to the recent increased popularity and usage of modern programming software and tools (Goodchild 2010; Reichenbach et al. 2018; Steger and Kofler 2019). Increases in online code availability and usability of open-source software have also improved the uptake of these modern techniques. Noteworthy recent efforts in this direction are Brenning et al. (2018); Muenchow et al. (2017); Rossi and Reichenbach (2016) and Bivand et al. (2019). A good example of increased usage of modern classifiers predictors can be revealed by analysing the usage of the term "Machine Learning". From no citations prior to 2013, the term became the fourth most cited between 2017 and 2020. Innovative statistical classification techniques such as "Artificial Neural Network" and "Frequency Ratio" were also frequently used during this period. However, these terms have oscillated within the top 30 through time. Non

DdLSM methods like "Analytic Hierarchy Process", "Weight of Evidence" and "Fuzzy logic" were also mentioned very often.

While novel techniques applied to the field of DdLSM predictions appear to be increasingly used, the term "Bivariate" demonstrates an opposite tendency. Bivariate methods have been gradually substituted by more modern methods (e.g., "Generalized Additive Models", "Random Forest", "Support Vector Machines"). This pattern might be connected to the availability of modern statistical software and or related programming languages (especially the open-source like R and Python), which offer multiple online tools, packages, and scripts for landslide susceptibility modelling.

A vital component of the DdLSM predictions is the classification technique applied. Fig. 7, shows a relative temporal importance rank between classifiers based on the chronological bibliometric data. This was calculated by selecting only the DdLSM classification method in the top 30 most cited terms. The most cited classifier "Logistic Regression" (Lr) appears to reduce over time. With a prevalence of 54% in the first time-period (1985-2004), the occurrence of the term Logistic regression between the key terms dropped to 19% in the last analyzed period (between 2017 and 2020, in Fig. 7). Oppositely, "Support Vector Machine" gained a substantial presence within the key citations, from 0% between 1985 and 2004 to 14% between 2017 and 2020. A similar pattern is associated with "Machine Learning", which was not a top term during the period between 2009 and 2012 and reached 14% in the period between 2017 and 2020. The term "Bivariate" shows a similar trend to "Logistic Regression" reducing its presence as top-cited terms within the frame of DdLSM publications, ranging from 9% predominance in the first period, 1985 to 2004, to circa 1% (only four research items) between 2017 and 2020. This trend, increasing prevalence of modern high-flexible classifiers, and decreasing prevalence of "Logistic Regression" and "Bivariate", might foresee a future trend in the topic of DdLSM. It is also observed a trend towards the application of modern, computer expensive and complexes machine learning algorithm-methods. This could be a signal of a trend shift from geomorphological research towards GIS and programming experts, possibly less concerned with the process understanding, and more focused on performance, applying more modern, however less

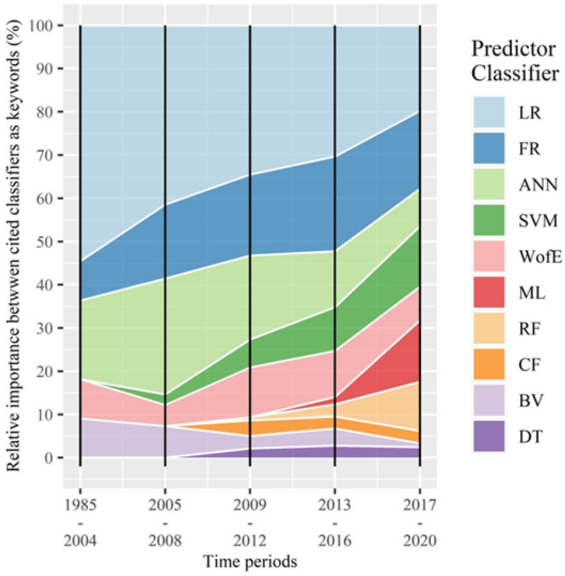

Fig. 7 Relative usage rank between data-driven classifiers found within the top 30 key terms. In the legend, "LR" stands for Logistic regression;" FR" for Frequency ratio; "ANN" for Artificial neural network; "SVM" for Support vector machine; "WofE" for Weight of evidence; "ML" for Machine learning; "RF" for Random forest; "CF" for Certainty factor; "BV" for Bivariate; and "DT" for Decision tree.

transparent methods (Goetz et al. 2015).

The interpretation of bibliometric results should be performed carefully. This is related to the observation that the many publications, despite having the query items in the titles, keywords, or abstract, are not necessarily using the cited terms. Therefore, bibliometric analysis should only be used as a preliminary tool to investigate a research field. To have a complete overview of the topic and trends within DdLSM, a quantitative oriented literature evaluation is presented in the following section.

4 Quantitative-Oriented Analysis of Relevant Publications

4.1 Baseline approach

A database containing over than 400 topic related publications was created using the following criteria: (i) main source: Science Direct website and the proceedings from the World Landslide Forums II and III, (ii) query terms: "landslide susceptibility", and "landslide hazard", (iii) time frame: 1985 to 2020 (last query on June 12th, 2020) and (iv) document type: journal papers; book chapters and conference proceedings exclusively written using English as the official language. Additionally, publications using the term "hazard" have been carefully investigated for how the authors defines hazard. If a hazard is correctly defined by the frequency and magnitude of a given landslide in a specific place and time, then this paper has been excluded from further analysis. However, if the authors use hazard in a similar meaning as "susceptibility", this paper has been included in this analysis. Finally, a subset of 313 research items was selected. These research items were distributed over 40 varied sources (book chapters, proceedings, and scientific journals).

4.2 Findings

From the 313, 65% (206 research items) were found within the following journals: Geomorphology, Natural Hazards, Landslides, Engineering Geology, and Catena. After, factors such as: study site features (extent and location) and landslide inventory features; modelling unit and spatial resolution (when applicable); landslide predictors; classification technique used; and the applied performance evaluation technique were further quantitatively investigated. A deeper focus on those elements will be given in the following sections. The results presented here will be based on over a clear summarizing percentage indicator from the totality of 313 publications (100%).

4.2.1 Study site extent and landslide inventory

Globally, the total sum coverage of the studies is 17.7 million km², representing approximately 11% of the total land surface plan area (Blakemore 2018). However, a very large portion of these studies could contain overlapping extents. Following the categorical scales set by Cascini (2008), analysis from the selected publications (Fig. 8), shows the application of DdLSM over varied territories sizes. Although some studies assessed multiple areas with differing sizes, the major adoption of DdLSM techniques was found for assessments comprising areas between 10 and 100 km², and in territories between 100 to 500 km². A small number of studies have applied DdLSM techniques for specific site locations (Costanzo et al. 2012; Das et al. 2012; Nefeslioglu et al. 2008a; Santacana et al. 2003; Singh et al. 2005; Vorpahl et al. 2012). It was also observed, polygons are the most commonly used unit to represent a landslide inventory (55%), followed by points (39%). For the remaining publications, either this information was missing or unclear.

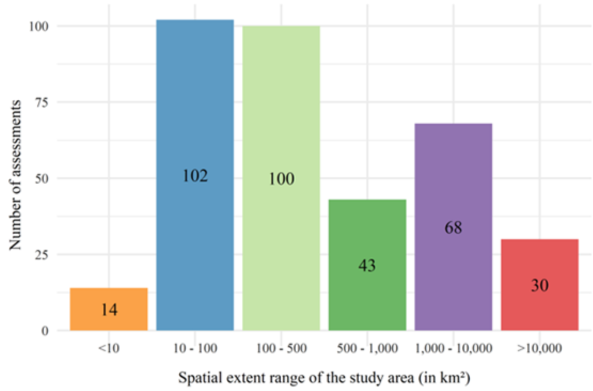

Fig. 8 Distribution of the spatial extent range of the study areas found in selected publications.

4.2.2 Modelling unit and spatial resolution

The results show 88% of the studies use pixel-based as the standard modelling unit for DdLSM. Although polygon-based units have been increasingly gained attention in landslide susceptibility modeling, the percentage of studies using polygon-based units is 10%. For a few studies, the modelling unit used was not clear. Within the polygon-based units, slope units and unique condition units were the most used modelling units. Within the pixels-based studies, a varied range of pixel resolution was found (Fig. 9). It is possible to observe a clear relationship between the spatial extent of the assessments and the adopted pixel size (Fig. 9). Assessments over large areas, using pixels as mapping units tends to adopt larger pixels sizes. Varying from very small pixel sizes, usually applied to small areas assessments (Lombardo et al. 2018; Oztekin and Topal 2005; Steger and Kofler 2019) to relatively large pixel sizes, commonly the case of large areas assessments (Catani et al. 2013; Depicker et al. 2020; Sabatakakis et al. 2013).

4.2.3 Landslide predictors

A total of 116 different landslide predictors were found in use within the predictive models. On average, each research item used seven variables as predictors. Only a small number of research items used one or two predictors (e.g. Chang et al. (2014); Reichenbach et al. (2018)), and some had a maximum of twenty (Durić et al. 2019). Predictors like slope angle (present on 88% of the studies), slope aspect, and rock type (both with 72%), land cover (63%), and curvature (61%) were the five most frequently used

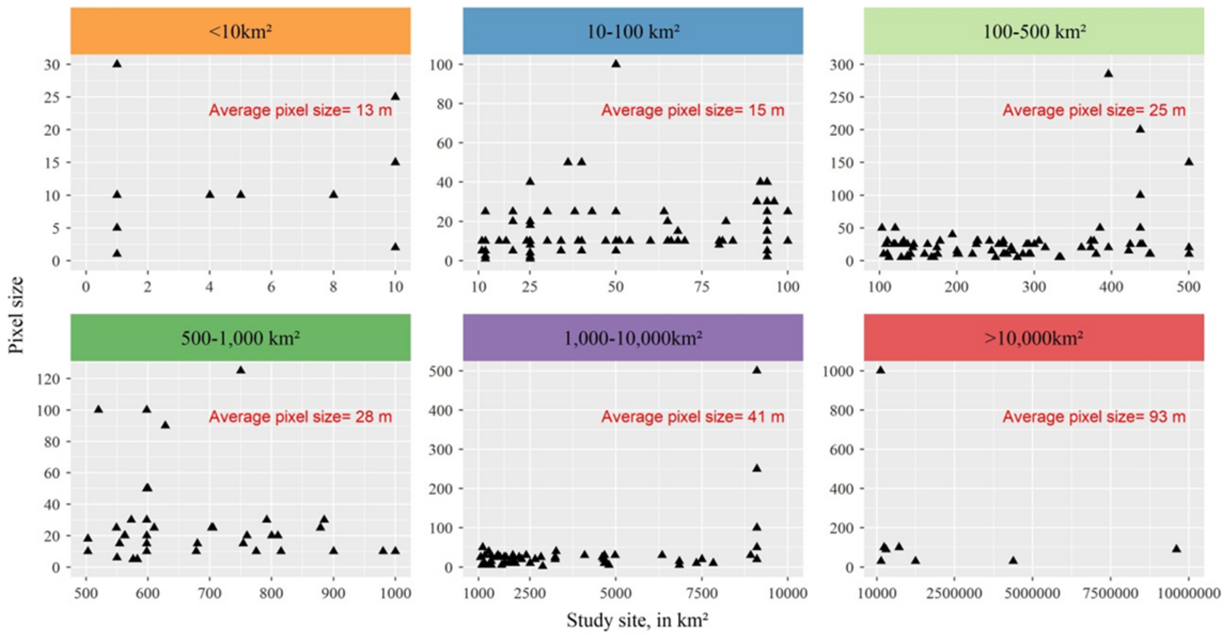

Fig. 9 Relationship between the spatial extent of the study area and the pixel sizes for the assessments contained in the selected publications.

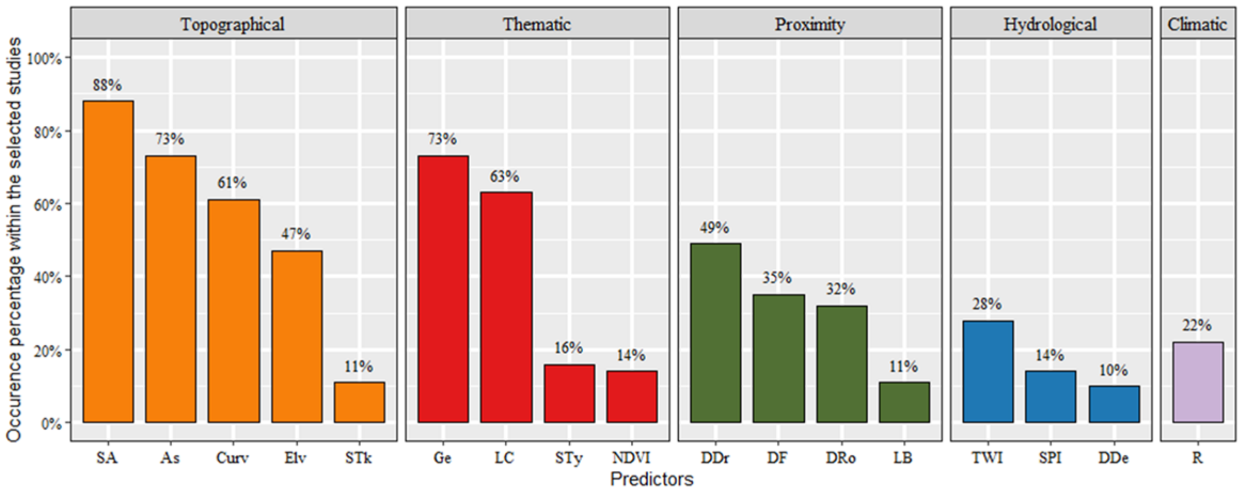

Fig. 10 Most used geo-environmental predictors variables within the assessments contained in the selected publications. Legend: “SA”, slope angle; “As”, aspect; “Curv”, Curvature (including possible multiple variations like planar and profile curvatures);“Elv”, elevation; “STk”, Soil thickness; “Ge”, Geology (rock type); “LC”, land cover; “STy”, Soil type; “NDVI”, Normalized difference vegetation index; “DDr”, distance to drainage; “DF”, distance to faults; “DRo”, distance to roads; “LB”, Distance to lineaments; “TWI”, Topographic wetness index; “SPI”, Stream power index; “DDe”, Drainage density and “R”, rainfall.

predictors (Fig. 10 and Table 3). Although multiple curvature variations were used in literature (e.g., profile, plan, and total curvatures), they were treated in this analysis as synonyms. These topmost used predictors were then followed by distance to drainage network (49%); elevation (47%); distance to faults (35%); distance to roads (32%); and topographic-wetness index (28%), completing the top ten.

Fig. 10 illustrates the most used predictors classified into categories. Topographical and thematic variables are the most used within the analyzed set of publications. However, proximity, hydrological and climatic describing variables are also often used. The most used topographical variables were slope angle (SA, 88%), Aspect (As, 73%), Curvature (Curv, 61%), Elevation (Elv, 47%) and Soil thickness (STk, 11%)

(Fig. 10). Within the thematic variables, lithological describing layers (Ge, 73%), and Land Cover (Lc, 63%), Soil Type (STy, 16%) and the Normalized Difference Vegetation Index (NDVI, 14%) had the highest usage rates. For proximity related variables, Distance to Drainage (DDr), Distance to Faults (DF), Distance to Roads (DRo) and Distance to Lineaments (LB) had the greatest usage rates with 49%, 35%, 32% and 11% respectively. Topographic Wetness Index (TWI, 28%) was the most used hydrological related factor, followed by Stream Power Index (SPI, 14%) and Drainage Density (DDe, 10%). Some studies (22%)

Table 3 Top 15 landslide predictors identified within the selected publications. The table describes landslide predictors, quantification of the usage on the publications, the description, and their respective sources.

Landslide predictors	Total usage	Percentage (%)	Definition and importance on landslide susceptibility according to the literature	Sources
Slope angle or gradient	276	88	Slope inclination. Usually expressed in degrees (°), but can also be represented by percentage, radians or classes. Aims to inform gravitational related downslope forces.	Digital elevation models or topographic maps.
Aspect	228	73	Define the orientation of the slope. It can be input express as a continuous or categorical variable.	Digital elevation models.
Geology (rock type)	227	73	Lithology units or class. Customarily used as a categorical variable.	Geological maps and/or field surveys.
Land cover	197	63	It describes the superficial coverage of the terrain. Customarily used as a categorical variable, act as a hydrological and mechanical condition indicator.	Satellite and aerial imagery interpretation; landcover maps and/or field surveys.
Curvature	192	61	Generally used as a continuous variable, this predictor describes the morphological structure of the terrain, like erosional and runoff processes. Include all types of curvatures (e.g., plain, total, profile, tangential).	Digital elevation models.
Distance to drainage network	153	49	Describes distancing of a determined point to the drainage network system. Generally used as a continuous variable, this predictor illustrates the hydrological and saturation characteristic of the terrain.	Digital Elevation models or topographic maps.
Elevation	148	47	This layer portrays the altimetric variation of the terrain. Normally used as a continuous variable, this predictor is also used to indirectly indicate unmeasured processes related to altimetric variations.	Topographic map or digital elevation models.
Distance to faults	108	35	Continuous variable (normally) describing the distance from a determined point to geological discontinuities.	Stereo imagery interpretation; geological maps and/or field surveys.
Distance to roads	100	32	Continuous variable (normally) describing the distance from a determined point to roads, railroads, or tracks. This predictor is usually considered when on the study site is observed some failures caused by defective geotechnical considerations on the pathways.	Topographic and infrastructure maps.
Topographic wetness Index	89	28	Describes the spatial extend of saturated zones for runoff generation. This continuous variable is a function of the upslope contributing area and slope gradient. High values indicate areas with a high probability of being drained by the saturated flow.	Digital Elevation models.
Rainfall	70	22	One of the most important landslides triggering elements, this continuous or categorical predictor, is used to indicate the water input on the terrain. It is also used as a weathering proxy to describe terrain stability. It can be represented in many different magnitudes, and the adoption on landslide susceptibility assessments is questionable.	Meteorological records.
Soil type	51	16	Categorical variable describing the soil type coverage of the terrain. Represent geotechnical variations and discontinuities between the soils.	Pedological maps and/or field surveys.

(-To be continued-)

used some variation of rainfall measurement (R) to relate to landslide occurrences. Table 3 contains the 15 most used predictors within the analyzed research items, together with a brief description and its main sources. A minimum adoption threshold of 10% was used to establish these top 15 predictors.

4.2.4 Classification techniques

Within the database of publications, a total of 518 classifiers were used, suggesting that multiple studies have applied, more than one classifier per study. The majority, 198 (64%) used only a single predictor, while 36% used more than one. Two and three classifiers appear in 20% and 12% of the research items, respectively. Some publications have applied a very larger number of classifiers, such as, Vorpahl et al. (2012) and Pourghasemi and Rahmati (2018), using seven and ten different classifiers respectively. The use of multiple classifiers was usually adopted in the publications aiming to compare the outcome patterns from different techniques. From an average of 1.3 classifiers per publication between 1985 and 2004, this average number was found to have increase to two different classifiers per publication in the period between 2017 and 2020. Studies comparing statistical classification techniques with physically-based approaches (Carrara et al. 2008; Cervi et al. 2010; Goetz et al. 2011; Weidner et al. 2019) or heuristic models (Akgün and Bulut 2007; Du et al. 2020; Van Westen et al. 1997; Zhu et al. 2018) were also identified.

Logistic regression was present in 127 (41%) of the studies (Fig. 11). Artificial neural networks were applied within 45 (14%) of the research items and was the second most used technique. With 41 occurrences (13%), Likelihood frequency ratio, a bivariate classifier, is the third most used technique. Completing the top 10 most used techniques the analysis shows respectively: Weight of evidence with 33 occurrences (11%), Information value with 25 occurrences (8%), Support Vector Machine, with 23 occurrences (7%), Linear discriminant analysis occurring 22 times (7%), Decision tree, with 21 occurrences (7%), Conditional probability model occurring 18 times (6%) and finally Random Forest occurred in 15 research items (5%). Although this overall picture of the total classifier's usage may inform important trends within the topic of DdLSM, it is necessary to understand how the classifiers' adoption evolves over time.

To focus on the most recent trends, we examined a subset of the whole collection for the period between 2017 and 2020. Within these selected publications, Logistic regression was used 19 times and is still the most used classifier to predict landslides. The others five most used terms in this subset were machine

(-Continued-)

Table 3 Top 15 landslide predictors identified within the selected publications. The table describes landslide predictors, quantification of the usage on the publications, the description, and their respective sources.

Landslide predictors	Total usage	Percentage (%)	Definition and importance on landslide susceptibility according to the literature	Sources
Stream power index	45	14	Continuous variable indicating the potential erosion flow at the given point of the topographic surface. It is an indicator of erosional power, considering the slope geometry and contributing area.	Digital elevation models.
Normalized difference vegetation index (NDVI)	43	14	The index is used to estimate the quality, quantity, and development of the vegetation in a given region.	Analyzing of multi-band imagery.
Distance to lineaments	35	11	Used similarly to the distance to faults, this normally continuous variable represents the distance from a determined point to a topographic feature of regional extent representing a crustal structure.	Imagery interpretation; geological map and/or field surveys.
Soil thickness	33	11	This predictor might be used to describe differing weathering, geotechnical and hydrological patterns. Also determines the potential slide volume.	Literature and field measurements.
Drainage density	30	10	Rate between upslope contributing size and length of the channels. It informs how efficient the water is conducted along the slopes. It relates closely with hydrological and geotechnical parameters.	Topographic maps; field surveys or extracted from digital elevation models.

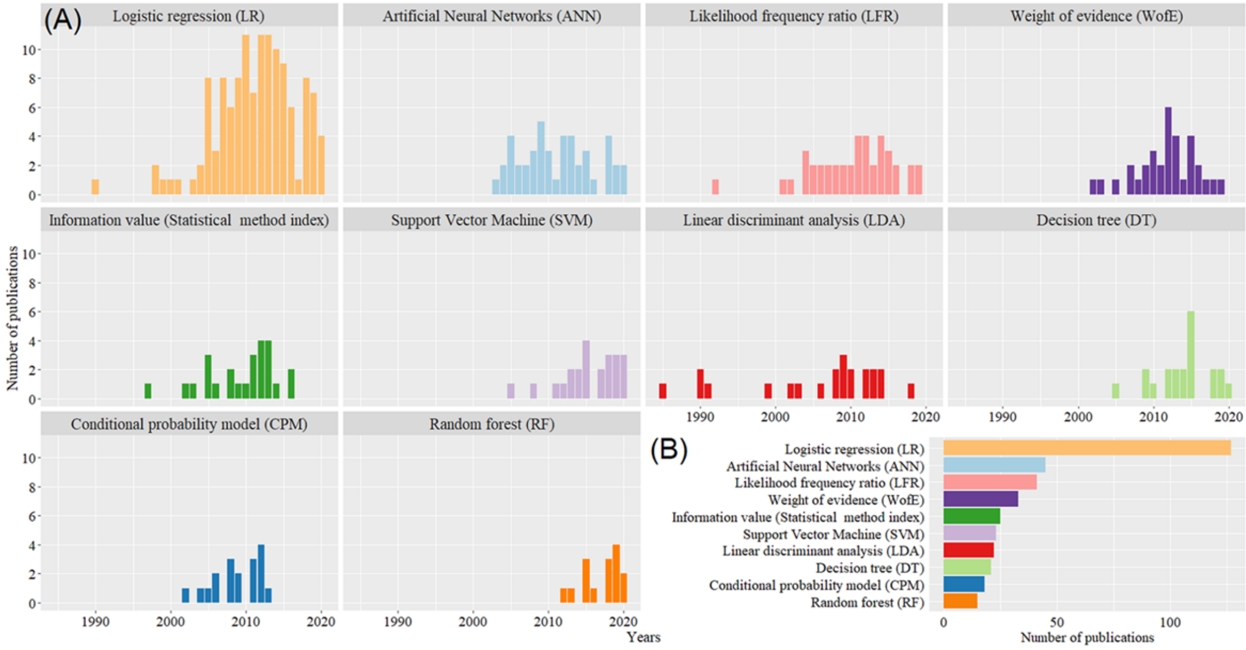

Fig. 11 Overview of the classification techniques used over the selected publications database. Histograms (A): Chronological usage of the top 10 most used classifiers. Bar graph (B): Cumulative sum of the respective classifier usage.

learning related. While Random Forest is in the 10th place overall, it was ranked second for the period 2017 and 2020 and accounts for nine of the 42 publications. In addition, support vector machine was mentioned in nine publications. Artificial neural networks and decision tree (with respectively eight and five appearances) completed the top used classifiers within the period 2017-2020. The analysis of these last years of publications indicates the usage decay of simpler (e.g., bivariate classifiers), while the usage of sophisticated machine learning algorithms is clearly increasing.

4.2.5 Model quality. Sampling partitioning strategies and performance evaluation

Within the selected research items, 38% of the publications have no or unclear information about the inventory partition procedure that was used. Random single holdout partitioning was the most applied method, used in 36% of the publications (Fig. 12). Temporal partitioning was the second most adopted, used in 9% of the publications. Repeated multiple partitioning, are used here as synonyms to all varieties of cross-validation techniques (spatial and non-spatial) and adopted in 8% of the publications. Analyzing a most recent subset of the publications set (2017-2020), repeated multiple partitioning (cross-validation) were applied in a quarter of the publications. The higher uptake of this method in the last few years, highlights the promising nature of this sampling strategy (Amato et al. 2019; Chen et al. 2018; Dou et al. 2019; Steger et al. 2020; Sun et al. 2020).

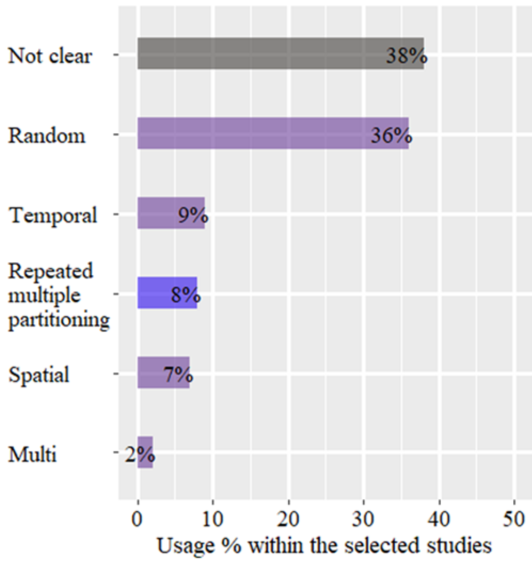

Fig. 12 Inventory test and training sampling partitioning technique. The numbers represent the usage percentage of each technique. Repeated multiple partitioning is represented in purple color since it can use a randomized either spatial, non-spatial and even temporal splitting component.

Within the selected research items, 43% reported to use a single performance evaluation measure, and 44% used multiple techniques. It was also observed in 13% of the publications there was no clear information about the technique used. Within the investigated literature, nearly half of the publications (44%) included the Area Under the Receiver Operating Characteristic Curve (AUROC), as one of the assessment quality evaluators (Fig. 13). Metrics based on success and predictive rates were present in 25% of the publications. Sensitivity, also called hit rate, which informs the rate of true positives (the rate of actual landslides correctly classified as unstable), was used in 12% of the publications. The next most used procedures were metrics based on the R^2 coefficient (10%), Confusion matrix interpretation (7%), and Cohen Kappa coefficient-based techniques, present in 7% of the publications (Fig. 13). Methods like Akaike Information criteria and expert evaluation of the prediction's map were also considerably adopted, but with a usage adoption lower than 5%.

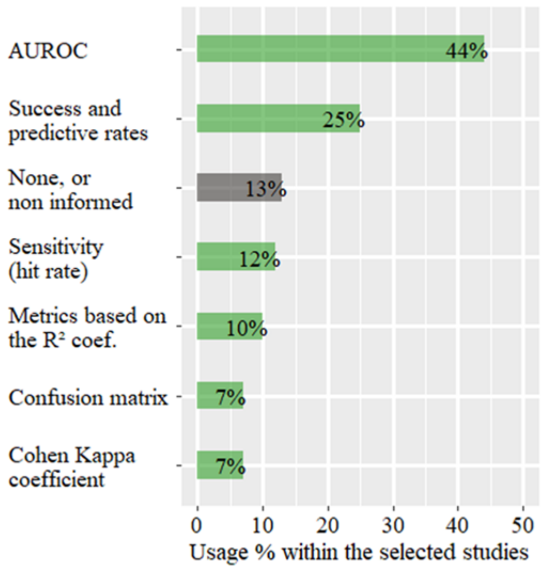

Fig. 13 Most used validation error measure techniques within the selected studies.

5 Scrutinizing the Quantitative Analysis

Creating reliable maps is the objective of all DdLSM's. However, literature suggests that researchers should adopt a wide range of research designs in order to reach this aim. There are numerous choices related to the DdLSM methodological design. Methodological combinations to produce landslide predictive maps using DdLSM seem to be endless. Examination of what has been applied in the published research might help to understand research trends.

5.1 Study site extent and landslide inventory

Earlier studies have tried to establish defined standards related to the scale and spatial extension of the study area (Cascini 2008; Corominas et al. 2014; Soeters and van Westen 1996). Based on the typical limitation of quality/availability, propositions were suggested. In the past, very large areas were mostly assessed through expert-based (heuristic) models due to the lack of computational resources to process large databases, and the lack of comprehensive data to cover large territories. National and even continental-scale studies made, especially recently, were assessed under DdLSM (e.g., Günther et al. (2013); Havenith et al. (2015); Hu et al. (2020); Lima et al. (2017); Nsengiyumva et al. (2019); Sabatakakis et al. (2013); Schicker and Moon (2012); Van Den Eeckhaut and Hervás (2012)). This research has shown that most of the publications were performed over large spatial extent assessments (areas from 10 to 1,000 km²). In the last decade a great number of assessments dealing with DdLSM and covering very large areas were published (e.g., Guo et al. (2015); Hu et al. (2020); Jiao et al. (2019); Liu et al. (2013); van Den Eeckhaut et al. (2012)). Nowadays, the definition of a suitable model is based on the data availability and quality, rather than on purely predefined guidelines using spatial study site extension.

Challenges related to landslide inventory quality and its effects on the predictive maps are numerous and include the positional (in)accuracy and its propagated effects (Ardizzone et al. 2002; Steger et al. 2016b); numerical (in)completeness (Du et al. 2020; Hussin et al. 2016; Steger et al. 2017); the adopted sampling strategy (Bordoni et al. 2020; Conoscenti et al. 2016; Erener and Düzgün 2012; Heckmann et al. 2014; Hong et al. 2019; Nefeslioglu et al. 2008b; Poli and Sterlacchini 2007; Regmi et al. 2014; Shirzadi et al. 2019); and the expert interpretation on inventory mapping (Galli et al. 2008; Guzzetti et al. 2000; Zêzere et al. 2009).

Positional inaccuracy has significant influences on the appearance and quality of the outcomes (Ardizzone et al. 2002; Fressard et al. 2014; Galli et al.

2008; Santangelo et al. 2015; Steger et al. 2017). Imprecise positioned inventories would still predict landslide susceptibility, but inaccurately. A positional mismatch of a few tens of meters might, for instance, systematically associate samples to inaccurate steepness or land-cover classification (Steger et al. 2016b). For this reason, assuring inventory's best positional accuracy is extremely important. It is known that historical and accurate landslide inventories are virtually never available, especially when dealing with very large areas (Herrera et al. 2018; Lima et al. 2021; Lin et al. 2021; van den Eeckhaut and Hervas 2014). However emerging landslide mapping techniques that enable, immediate and precise event-based cataloging or techniques allowing past landslide extraction from high-resolution digital terrain models can positively contribute (Guzzetti et al. 2012). Systematic errors and uncertainties related to each mapping procedure should be taken into consideration, since they can highly influence the outcomes (Ardizzone et al. 2002; Carrara 1993; Guzzetti et al. 2006; Hoffman and Hammonds 1994; Karam 2005; Malamud et al. 2004; Oberkampf et al. 2002, 2004; Petschko et al. 2014b). When dealing with inaccurate positional samples is the only possibility, the adoption of a larger mapping unit (e.g., slope units in Alvioli et al. (2016); Lima et al. (2021); Schlögel et al. (2018)) might reduce the effects caused by a positional inaccuracy.

The minimum number of landslide samples able to provide meaningful result from DdLSM is also often a major concern for researchers. Beyond the fundamental numerical representativeness of the samples, the (in)completeness might impact the results even more and when the (in)completeness is systematically associated with a predictor, cause biases. A low number of landslide samples might also reduce the confidence and reliability of the predictions. For example, Hussin et al. (2016) demonstrate that although the validation of a model is not substantially influenced by under-sampling (e.g., reducing the number of samples by half), the lower number of landslide samples influences the appearance of the map output, and consequently its interpretation (Petschko et al. 2014). Steger et al. (2017), by artificially simulating a systematical scarcity (under sampling bias) over a particular predictor, demonstrated the propagation of undesirable bias effects on predictive maps. They suggest the adoption of a mixed-effects model in situations where the bias is clear. Du et al. (2020) suggests for regions with incomplete and uncertain inventories, expert judgment capable of weighting the landslide samples, according to its (un)certainty. These weighted landslide samples are then used in multinomial, rather than a binomial predictive classification.

The sampling strategy is also an important DdLSM component. Poli and Sterlacchini (2007) suggest that a multiple point sampling method is more effective when compared to a single centroid sampling, due to the possible uncertain location of the landslide centroid. Regmi et al. (2014) have shown that similar models built using samples taken from landslide masses and scarps outperform models using singular samples from landslide centroids or scarps. Nefeslioglu et al. (2008b) supports the application of seed cells for landslide representation. Aiming for a more realistic representation of the pre-failure topographical conditions, some authors also choose to sample the landslide vicinity (seed-cells) (Che et al. 2012; Nefeslioglu et al. 2008b; Süzen and Doyuran 2004; Yesilnacar and Topal 2005; Yilmaz 2010). Similar findings were also presented by Hussin et al. (2016). However, even though many authors have proposed a multiple point's representation either the scarp or landslide body, Zêzere et al. (2017) showed that a single point per landslide can also generate accurate landslide susceptibility maps. Due to the limited number of publications trying to compare multiple strategies, the literature does not present a clear definitive agreement on the landslide representation strategy. Publications supporting a single point are normally based on the argument that mapping is more time effective, computational power needs are reduced, there are fewer uncertainties related to the delineation of landslide boundaries and prevent the size weighting effect. On the other hand, the publications that advocate for a multiple points per landslide feature, mentions the size weighting effect as positive. However, this could over-represent large landslides compared to small ones (Steger 2017). Besides the advantages and disadvantages of each strategy, the landslide representation should be performed considering: (i) the characteristics of the inventory available (e.g., point or polygon-based), and also (ii) the resolution (i.e., pixel size) of the landslide predictors; since high resolution predictors related to positional inaccurate inventories could lead to uncertain predictions.

Several studies have been focused on the advantages and disadvantages of landslide presence sampling strategies. In any landslide modelling design, landslide-free areas should also be adequately sampled (Steger and Glade 2017; Van Den Eeckhaut et al. 2012). However, the literature lacks publications focusing on the efforts to evaluate the importance of a landslide absence sampling design strategy. Only a few publications have attempted to uses strategies the incorporates non-landslide sampling (Conoscenti et al. 2016; Hervás 2013; Hong et al. 2019; Steger and Glade 2017; van Den Eeckhaut et al. 2012). The design of a non-landslide sampling strategy also acknowledges in some of the previously cited references to be able to possibly counterbalance outcome's effects imposed by biased inventories.

5.2 Modelling unit and spatial resolution

The results show that a large amount of the literature uses a grid cell approach within DdLSM. This is also in agreement with the findings of Malamud et al. (2014) and Reichenbach et al. (2018), who showed grid-based models are the majority of the modelling units used in DdLSM. These previous studies pointed respectively to 84% and 86%, while this study calculated 88% for grid-based approaches. Polygon-based units, slope units are a well-established modelling unit and are being increasingly used in DdLSM research. Automated algorithms and software for slope units delimitation (e.g., *r.slopeunits* in Alvioli et al. (2016)), and publications debating optimized slope units delimiting procedures depending on input DEM resolutions (Schlögel et al. 2018) strengthen the adoption of slope units as an alternative to pixels. Even though polygon-based modelling units, due to its general large size, might open the discussion about the heterogeneity of large internal features. Some contributors (e.g., Camilo et al. (2017); Jacobs et al. (2020)) have suggested the use of multiple summarizing values to represent predictors with the slope units (e.g., mean, median, standard deviation, between others). The best performing metrics would subsequently be selected based on their mathematical importance to describe the phenomena. Some other valuable contributions demonstrated the advantages of adopting polygon-based as terrain units (Camilo et al. 2017; Carrara et al. 1999; Galli et al. 2008; Guzzetti 2005; Guzzetti et al. 1999; Zêzere et al. 2017). Debates about the use of polygon-based units are usually around the subjective delineation of the respective units. However, there are nowadays automatic tools able to perform this delineation, guaranteeing its reproducibility (Alvioli et al. 2016). Although the modelling unit representation is a particular researcher's decision, this choice should take into account the landslide inventory, predictors' characteristics and the accuracy (Lima et al. 2021; Zêzere et al. 2017).

Recent remote technological advances enabling the generation of very high-resolution data have produced a more realistic representation of landscape characteristics through high-resolution grid cells. However, more pixels (relatively small pixel sizes) do not necessarily increase the quality and performance of the predictions (Brock et al. 2020; Shirzadi et al. 2019). Studies such as (Arnone et al. 2016; Catani et al. 2013; Palamakumbure et al. 2015; Paudel et al. 2016; Paulin et al. 2010), demonstrated that the aspect of the final maps and their validations highly vary depending on the spatial resolution of the input parameters.

The interplay between landslide size, inventory positional (in)accuracy, and the size/resolution of the modelling unit should always be kept in mind. This is vital for imprecise landslide inventories as the incorrectly mapped landslide location could lead to association with incorrect predictors. The landslide occurrence and propagation over multiple units (grids or polygon-based) should also be of concern. For instance, when using small slope-units or high-resolution grid pixels (i.e., relatively small pixel size), large landslides can impact more than a single modelling unit. When the usage of such imprecise inventories is inevitable, the adoption of a slightly larger modelling unit is recommended in order to limit the propagation of uncertainty (Lima et al. 2021). Therefore, the size or resolution of the modelling unit should consider the estimated mean positional inventory accuracy and landslide size.

5.3 Landslide susceptibility predictors

Out of all of the predictor's types, topographically related predictors (e.g., elevation, aspect, curvature, and slope angle) were the ones most adopted. Within these, the slope angle, followed by aspect were the most applied predictors. This is in clear agreement with what was already measured by Malamud et al. (2014); Pourghasemi and Rossi (2016); Van Westen et al. (2008) and Reichenbach et al. (2018). Previously, Budimir et al. (2015); Malamud et al. (2014); Süzen and Kaya (2012) and Pourghasemi and Rossi (2016) have found similar patterns in the application of landslide predictors within the field of DdLSM. Comparing the findings of this research with the publications cited above, predictors such as slope angle, lithology, aspect, land cover; curvature, elevation, distance to drainage and distance to geo-structural features (faults) were the most prevalent. However, these findings represent only the recurrently most used predictors, and not a suggestion of which ones to use. Although proximity related predictors are useful, they should be used with caution, together with a good understanding of possible limitations. For instance, establishing binomial (true/false) presence, based on a distance to a feature, can be questionable. For example, is the influence of the distance to a road equally relevant over the whole "true" (e.g., 0 - 100m) range buffer around the road?

Although some publications have included triggering factors, such as precipitation related to landslide predictors (e.g., accumulated rainfall in a given time interval, rainfall intensity, average annual precipitation), theoretically the inclusion of those triggering variables on landslide susceptibility models, should be avoided. Landslide triggering factors, normally describe temporal-magnitude relationships, scope-related to hazard assessments (Cascini et al. 2005; Fell et al. 2008; Guzzetti 2005; Guzzetti et al. 1999). However, it is important to highlight that the long term measured spatial rainfall patterns (e.g., maximum annual 24-hour rainfall) might also geographically describe areas where rainfall induced landslides are likely (or not) to occur.

The selection and representation of landslide predictors are an important step in DdLSM. Some authors have suggested the application of methods for automated predictor selection (Goetz et al. 2011; Steger et al. 2016a; Vorpahl et al. 2012). However, these methods should be implemented carefully since the automated selection of predictors is likely to introduce biased predictors into the model (Steger et al. 2016a), leading to propagation of bias throughout the model. It has been shown that many landslide inventories are strongly spatially associated with some predictors, which often causes biases (Carrara et al. 1995; Malamud et al. 2014; Petschko et al. 2014). Nearly all biases within DdLSM research arise from the landslide mapping procedure. Many of these biases are responsible for determining the appearance of the outcomes maps and for the results of the validations (Lima et al. 2017, 2021; Steger et al. 2016b). The adoption of biased predictors is not recommended and can lead to overestimated validation metrics and possibly non-reliable landslide susceptibility maps. Therefore, a careful interpretation of the maps is necessary. As an alternative, a specific classifiers able to deal with bias should be considered (Lima et al. 2021; Lin et al. 2021; Steger et al. 2017).

5.4 Classification techniques

The spatial prediction patterns and validation results are mainly dependent on the classifiers utilized (Goetz et al. 2015; Steger et al. 2017, 2016a). The examples of DdLSM techniques used to spatially predict landslides are many, but as identified previously (Budimir et al. 2015; Malamud et al. 2014; Reichenbach et al. 2018; Wu et al. 2015) and also according to this analysis, logistic regression is the most adopted technique. Linear models such as logistic regression, besides being considered simple, have proved to be a reliable landslide classification method (Brenning 2008). Nonlinear classifiers such as Generalized Additive Models (also named GAM's) were also noted in some publications as an exponential and trustworthy classifier in the field, due to their capability to reproduce nonlinear relations (Brenning 2005, 2012; Goetz et al. 2015, 2011; Lin et al. 2021). Within the collection of analyzed publications, some examples which have used non-linear classifiers are Brenning (2008); Chen et al. (2017); Goetz et al. (2015); Petschko et al. (2013); Pourghasemi and Rahmati (2018); Vorpahl et al. (2012). The validation of Machine Learning models can often return higher AUROC values when compared to other DdLSM (Goetz et al. 2015). This could partially explain the rising popularity of this type of model. The overestimated importance on higher predictive performance rather than a model understanding and transparency (Steger 2017), is not only observed within the topic of landslide predictions, but also, in other scientific fields.

An adequate landslide susceptibility map should not only provide satisfactory predictive performance, but also need to produce realistic and meaningful geomorphological outcome. Some DdLSM methods produce easier to interpret outputs, which in turn make the results easier to implement into planning decisions (Petschko et al. 2014). Machine learning algorithms due to a very high-flexibility and qualified pattern recognition character, are frequently pointed to be significantly prone to overfitting, sometimes at the cost of a noisy, pixelated and hard to interpret predictive maps (Brenning 2005, 2012; Goetz et al. 2015; Steger et al. 2016a). The selection of classifiers should consider the attributes of the input parameters (Lima et al. 2021). The interpretation of the results should be carefully considered, considering the models' particularities, scale, and input data quality.

5.5 Model quality. Sampling partitioning strategies and performance evaluation

Malamud et al. (2014) and Reichenbach et al. (2018) both found that nearly 40% of the publications did not mention or did not clearly describe what quality assessment were undertaken and it appears to be unfortunate ongoing conduct within the field of DdLSM. However, the percentage of publications not accessing or not clarifying a quality assessment methodology appears to be reducing. Within this research, 13% of the publications do not describe any model quality assessment or at least they are not clear about how this procedure was performed.

Common findings between the previously cited research, and this one is the prevalence of adoption of the AUROC and the success and predictive rates curves as the most used metrics to assess model quality. Although these metrics are constantly used to judge and prioritize a model or approach over others, recent literature shows the necessity of interpreting the validations' achievements carefully. As demonstrated by Steger et al. (2016a) and Zêzere et al. (2017), nearly equivalent validation metrics can be achieved by models using different quality of input datasets, questioning any possible interpretation or judgment merely based on validation metrics. Sterlacchini et al. (2011) also pointed out that the spatial appearance and reliability of the outcome maps are not necessarily connected to the calculated predictive performance, also suggesting that the inference of the best model is solely through quantitative validations metrics, may be mistaken. The selection of the most reliable map should bring together in conjunction with the quantitatively measured validation an extensive expert geomorphological plausibility evaluation of the maps (Demoulin and Chung 2007; Petschko et al. 2014b; Steger et al. 2016a).

Within the publications that communicated the validations clearly, random splitting was the most adopted partitioning strategy. It was also observed within this publication that the random threshold criteria-established to split between training and test samples (e.g., 60% — 40%; 70% — 30%) was not frequently communicated and therefore was not computed within this study. The influence of this sample splitting ratio was however, assessed by publications like Dou et al. (2020); Heckmann et al. (2014); Hussin et al. (2016); Shirzadi et al. (2019). A common finding between those is that the splitting ratio and sample size indeed affected the accuracy of the models; however, no clear split ratio guideline could be established. Even though only present in a low portion of the publications, repeated multiple partitioning strategies Brenning (2012) are gaining considerable space on the field of DdLSM (Brenning 2012; Depicker et al. 2020; Goetz et al. 2015; Hong et al. 2018; Palamakumbure et al. 2015; Steger et al. 2020; Sun et al. 2020; Tien Bui et al. 2012; Vargas-Cuervo et al. 2019). This technique, by repeatedly fragmenting the samples in different pools of training and test samples, might increase the reliability of the validation outcomes. Cross validations processes are also acknowledged to improve the robustness of the validation (Brenning 2012; Brenning et al. 2015; Goetz et al. 2015; Petschko et al. 2014b; Steger et al. 2017, 2016a) and to prevent overfitting (Tien Bui et al. 2012). As also suggested by Brenning (2012), the adoption of a repeated spatially-based partitioning might avoid training overfitting caused by spatial auto-correlation, especially when using highly flexible predictors (e.g., machine learning algorithms).

6 Conclusions

Over the past decades, considering the great number of assessments published on spatial landslide prediction, DdLSM have been proven useful to appropriately predict landslides. However, the literature analyses also highlight numerous current challenges and limitations to be overcome by these models. This publication has shown, the outcomes of landslide susceptibility maps generated through DdLSM are highly reliant on many factors. However, despite the challenges, recent trends show approaches expanding this frontier's research topic. For instance, the work of Lombardo et al. (2020), which reassess the classical spatial susceptibility score by introducing extra dimensions (e.g., landslide intensity) to the standard spatial prediction.

This review demonstrates that the publications released over the years 2017- 2020 were not sufficient to significantly change the overview observed by Reichenbach et al. (2018). It is also observed that there are still various unresolved challenges related within the topic of DdLSM. It is also important to stress that despite the identified trends, the topic is currently experiencing a rapid development. However, this study would like to highlight the following points related to DdLSM, which can affect the quality and reliability of the models.

Every study area and the available data are unique and might require individualized handling and possibly a custom research-design.

Quality should come over quantity. Increased sample sizes do not alter substantially the validations achievements; however, over-sampling can create bias; and underestimated inventories might also alter substantially predictions on quality and reliability.

Inventories are the most crucial input data. They are usually already available, and frequently full of imperfections. Remapping, depending on the area size and resources available, is nearly impossible. Therefore, it is the job of the researcher to invest time in a preliminary exploratory analysis to gain a detailed knowledge of potential weaknesses. The model design should be built around this knowledge, in a manner to avoid error and propagation of uncertainty. The weaknesses should also be properly recorded and communicated.

It is important to be aware of the positional uncertainty of the inventory samples. Associating uncertain positional samples with high-resolution predictors might create flawed predictions. It should be considered re-sampling the predictors to resolutions matching the accuracy of the inventory or the use of polygon-based landscape representations (e.g., slope units).

The classification techniques selection is important. Every classifier is basically unique. Therefore, a deep knowledge of the input data characteristics might help in selecting the most appropriate classifier. A reliable classifier must: (i) effectively represent future landslide locations and conform with the geomorphological process, (ii) avoid overfitting, (iii) create reliable and usable maps for the final users and decision-makers; and (iv) avoid data error's propagation.

Flexible machine learning algorithms should be selected and interpreted carefully; especially when dealing with imperfect input-datasets. The high adaptation power to the training samples makes these algorithms likely to reproduce errors within the training data.

The use of multiple partitioning algorithms (e.g., spatial, and non-spatial cross-validation) for training/test partitioning should be preferred method.

Model quality measures are crucial. However, its interpretation should be made with care. Input data and classifiers might influence (over or underestimate) predictive performances. Good validations results do not necessarily imply a meaningful geomorphological prediction. With regard to the technique choice, a geomorphological evaluation of the prediction maps should be conducted.

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