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A review of statistically-based landslide susceptibility models

Paola Reichenbach[a,*], Mauro Rossi[a], Bruce D. Malamud[b], Monika Mihir[b,c], Fausto Guzzetti[a]

[a] CNR IRPI, via Madonna Alta 126, I-06128 Perugia, Italy
[b] Department of Geography, King's College London, Strand, London, UK
[c] CACI, Canal Court, 155 High Street, Brentford, UK

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ABSTRACT

In this paper, we do a critical review of statistical methods for landslide susceptibility modelling and associated terrain zonations. Landslide susceptibility is the likelihood of a landslide occurring in an area depending on local terrain conditions, estimating "where" landslides are likely to occur. Since the first attempts to assess landslide susceptibility in the mid-1970s, hundreds of papers have been published using a variety of approaches and methods in different geological and climatic settings. Here, we critically review the statistically-based landslide susceptibility assessment literature by systematically searching for and then compiling an extensive database of 565 peer-review articles from 1983 to 2016. For each article in the literature database, we noted 31 categories/sub-categories of information including study region/extent, landslide type/number, inventory type and period covered, statistical model used, including variable types, model fit/prediction performance evaluation method, and strategy used to assess the model uncertainty. We present graphical visualisations and discussions of commonalities and differences found as a function of region and time, revealing a significant heterogeneity of thematic data types and scales, modelling approaches, and model evaluation criteria. We found that the range of thematic data types used for susceptibility assessment has not changed significantly with time, and that for a number of studies the geomorphological significance of the thematic data used is poorly justified. We also found that the most common statistical methods for landslide susceptibility modelling include logistic regression, neural network analysis, data-overlay, index-based and weight of evidence analyses, with an increasing preference towards machine learning methods in the recent years. Although an increasing number of studies in recent years have assessed the model performance, in terms of model fit and prediction performance, only a handful of studies have evaluated the model uncertainty. Adopting a Susceptibility Quality Level index, we found that the quality of published models has improved over the years, but top-quality assessments remain rare. We identified a clear geographical bias in susceptibility study locations, with many studies in China, India, Italy and Turkey, and only a few in Africa, South America and Oceania. Based on previous literature reviews, the analysis of the information collected in the literature database, and our own experience on the subject, we provide recommendations for the preparation, evaluation, and use of landslide susceptibility models and associated terrain zonations.

1. Introduction

Landslide susceptibility is the likelihood of a landslide occurring in an area on the basis of local terrain conditions (Brabb, 1984). It predicts "where" landslides are likely to occur (Guzzetti et al., 2005). Several methods and approaches have been proposed and tested to ascertain landslide susceptibility, including (among others) geomorphological mapping, the analysis of landslide inventories, heuristic terrain and susceptibility zoning, physically-based numerical modelling, and statistically-based classification methods (Aleotti and Chowdhury, 1999; Guzzetti et al., 1999). In this paper, we focus on a critical review of statistically-based approaches for landslide susceptibility modelling and associated terrain zonations. We recognize that our experience in constructing and verifying landslide susceptibility models and maps in different physiographical and climatic settings has influenced our review discussion. However, we maintain that the approach we adopted is general, considering all the main aspects of susceptibility modelling and associated terrain zonation, and that the discussion is relevant to a wide audience. For our critical review, we use as evidence a database of 565 articles published in peer reviewed international journals from January 1983 to June 2016 and identified by a systematic search of Web of Science™ using a set of keywords and criteria.

* Corresponding author.
E-mail address: paola.reichenbach@irpi.cnr.it (P. Reichenbach).

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The review builds upon previous work published by some of us on various aspects of landslide susceptibility modelling and terrain zonation, including the work of: (i) Guzzetti et al. (1999), on the principles of landslide susceptibility assessments and modelling methods, (ii) Guzzetti et al. (2006b), Rossi et al. (2010) and Rossi and Reichenbach (2016), on the quality of landslide susceptibility models and the production of optimal zonations, (iii) Carrara et al. (1991, 1995), on the use of Geographic Information System (GIS) technology for susceptibility modelling and terrain zonation, and of (iv) Carrara et al. (1999) and Alvioli et al. (2016), on the production and use of slope units for the production of landslide susceptibility models and zonations.

The manuscript is organized as follows. In Section 2 we present background information on landslide susceptibility modelling and terrain zonation. This is followed, in Section 3, by a description of the construction and the analysis of the literature database. Next, in Section 4, we discuss critically all the components related to statistically-based landslide susceptibility modelling and zonation and, based on our experience, we provide specific and general recommendations on how to perform susceptibility modelling to obtain reliable terrain zonations. In Section 5, we outline what we consider the main remaining challenges for landslide susceptibility modelling and zonations. Finally, in Section 6, we conclude, summarising the lessons learnt and providing general recommendations for landslide susceptibility modelling and zonations.

2. Background

2.1. Definitions and general concepts

In geomorphology, a "landslide" is the movement of a mass of rock, debris or earth down a slope, under the influence of gravity (Cruden and Varnes, 1996). Unless otherwise specified, in this article we use the terms "landslide", "slope movement", "mass movement" and "slope failure" as synonyms.

In the literature, confusion exists between landslide "susceptibility" and landslide "hazard" (Chacón et al., 2006; Guzzetti, 2006). The terms are often used as synonyms despite the two words expressing different concepts (Fell et al., 2008a). Here, we consider landslide susceptibility as the likelihood of a landslide occurring in an area on the basis of the local terrain and environmental conditions (Brabb, 1984). Susceptibility measures the degree to which a terrain can be affected by future slope movements. In other words, it is an estimate of "where" landslides are likely to occur (Guzzetti, 2006). In mathematical language, susceptibility can be defined as the probability of spatial occurrence of slope failures, given a set of geo-environmental conditions (Guzzetti et al., 2005). This was called "landslide analysis" by Vandine et al. (2004). Susceptibility does not consider the size e.g., the length, width, depth, area or volume of the landslides, but susceptibility assessments can be prepared for different-sized landslides (Carrara et al., 1995). We note that the definition of landslide susceptibility adopted in this work differs from the definition given by Fell et al. (2008a).

We consider landslide "hazard" the probability that a landslide of a given magnitude will occur in a given period and in a given area. In addition to predicting "where" a slope failure will occur, landslide hazard predicts "when" or "how frequently" it will occur, and "how large" it will be (Guzzetti et al., 2005). Landslide hazard is more difficult to ascertain than landslide susceptibility, as susceptibility is a component (the spatial component) of the hazard (Guzzetti, 2006). When discussing previous works, in the paper we use the term "susceptibility" even when the original author(s) used the term "hazard", but the meaning was that of "susceptibility" as presented above.

Many different approaches and methods have been proposed to ascertain landslide susceptibility. Despite the differences, all the approaches and methods are based upon a few assumptions (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara et al., 1991; Hutchinson and Chandler, 1991; Hutchinson, 1995; Turner and Schuster, 1996; Guzzetti et al., 1999). First, landslides leave discernible signs that can be recognized, classified and mapped in the field or through the analysis of remote sensing imagery (Rib and Liang, 1978; Varnes, 1978; Hansen, 1984; Hutchinson, 1988; Cruden and Varnes, 1996; Dikau et al., 1996; Griffiths, 1999; Mondini et al., 2011; Guzzetti et al., 2012). Second, landslides and their occurrence are controlled by physical laws that can be analysed empirically, statistically, or deterministically. Conditions that cause landslides (i.e., the instability factors), or directly or indirectly linked to slope failures, can be collected and used to build predictive models of landslide spatial occurrence (Crozier, 1986; Hutchinson, 1988; Dietrich et al., 1995). Third, for landslides the past and present are considered keys to the future (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara et al., 1991; Hutchinson, 1995). This assumption implies that future slope failures will be more likely to occur under the conditions, which led to past and present instability (Furlani and Ninfo, 2015). Lastly, spatial landslide occurrence can be inferred from heuristic investigations, computed through the analysis of environmental information, or inferred from physical models. Thus, a territory can be zoned into susceptibility classes ranked according to different probabilities (Carrara et al., 1995; Soeters and van Westen, 1996; Aleotti and Chowdhury, 1999; Guzzetti et al., 1999).

Approaches and methods for assigning landslide susceptibility can be qualitative or quantitative, and direct or indirect. Qualitative approaches are subjective, ascertain susceptibility heuristically, and portray susceptibility levels using descriptive (qualitative) terms. Quantitative methods produce numerical estimates; in other words, probabilities of occurrence of landslide phenomena in any susceptibility zone (Guzzetti et al., 1999). All the approaches and methods proposed in the literature can be grouped into five broad categories, namely: (i) geomorphological mapping, (ii) analysis of landslide inventories, (iii) heuristic or index-based approaches, (iv) process based methods, and (v) statistically-based modelling methods.

Geomorphological mapping relies on the ability of an expert investigator to evaluate and map the actual and potential slope instability conditions. The quality of the geomorphological maps depends on the ability and experience of the investigator, and on the complexity of the study area (Humbert, 1977; Hansen et al., 1995; Reichenbach et al., 2005). Analysis of landslide inventories attempts to predict the future landslide spatial occurrence from the known distribution of past and present landslides. Typically, this is obtained preparing landslide density maps, and the quality of the assessment depends on the quality and the completeness of the inventories (Campbell, 1973; DeGraff, 1985; Galli et al., 2008). In the heuristic approach, investigators rank and weight the known instability factors based on their assumed or expected importance in causing landslides (Hansen, 1984; Hansen et al., 1995). The quality of a heuristic assessment depends largely on the ability of the investigators to understand the real causes and the instability factors causing landslides in an area (Nilsen and Brabb, 1977; Abella and van Westen, 2008; Ruff and Czurda, 2008). Physically-based methods rely upon simplified, physically-based landslide modelling schemes to analyse the stability/instability conditions using simple limit equilibrium models, such as the "infinite slope stability" model, or more complex approaches (Montgomery and Dietrich, 1994; Rigon et al., 2006; Simoni et al., 2008; van Asch et al., 2007; Baum et al., 2008; Anagnostopoulos and Burlando, 2012; Anagnostopoulos et al., 2015; Alvioli and Baum, 2016). Lastly, statistical approaches are based on the analysis of the functional relationships between known or inferred instability factors and the past and present distribution of landslides (Carrara, 1983; Guzzetti et al., 1999; Huabin et al., 2005; Chacón et al., 2006; van Westen et al., 2008).

Analysis of the literature database reveals that physically-based and statistically-based methods are preferred to ascertain landslide susceptibility in quantitative terms. In this article, we focus on the analysis of the statistically-based modelling methods, and the associated terrain zonations. In the following, unless otherwise specified, when presenting or discussing landslide susceptibility modelling we consider quantitative, statistically-based methods, and we use the words "susceptibility modelling" and "modelling" to refer to landslide susceptibility modelling.

Landslide susceptibility modelling requires the preliminary selection of an appropriate terrain unit. A terrain unit (or "mapping unit") is a portion of the land surface characterized by a set of ground conditions that differ from the adjacent units across distinct boundaries (Hansen, 1984; Meijerink, 1988; Carrara et al., 1995; Soeters and van Westen, 1996; van Westen et al., 1997; Guzzetti et al., 1999; Luckman et al., 1999; Guzzetti, 2006). At the scale of the analysis, a mapping unit is a geographical domain that maximizes the unit internal homogeneity and the between-unit heterogeneity. All the mapping units proposed in the literature for landslide susceptibility assessment fall into one of the following seven groups: (i) grid cells ("pixels"), (ii) terrain units, (iii) unique condition units, (iv) slope units, (v) geo-hydrological units, (vi) topographic units, and (vii) political or administrative units.

2.2. Early works on landslide susceptibility

Since the mid-1970s, a significant amount of literature has been published on landslide susceptibility (often referred as landslide "hazard" in the early literature, e.g., Carrara, 1983). These studies investigate the functional relations between the geographical distribution of landslides and of geo-environmental landslide predisposing factors, using different statistical approaches, operating at different geographical scales, and adopting a variety of mapping units (Guzzetti, 2006). Here we mention two key early studies, from the 1970s and 1980s.

Neuland (1976) was probably the first to exploit a statistical approach to explain the relations between morphometric, geo-mechanical, lithological and structural characteristics, and the stability or instability conditions of 250 stable and unstable slopes in south-west Germany, and to use bivariate discriminant analysis to construct a specific stability/instability landslide prediction model.

A few years later, Carrara (1983), in a landmark article, summarized the results of a long-term effort aimed at understanding the geological and geo-morphological factors controlling landslides in Calabria, southern Italy. For two catchments, Ferro in northern Calabria and Buonamico in southern Calabria, he used discriminant analysis and multiple regression analysis to predict landslide susceptibility (which he called "hazard") based on a large set of landslide, geological and geomorphological information. To handle the spatially distributed landslide and geo-environmental information, Carrara and his co-workers developed specifically designed software for automated thematic cartography (Carrara et al., 1977, 1978). These were early versions of original, grid-based Geographical Information Systems (GIS); an emerging technology at the time of their works (Goodchild, 2010).

2.3. Previous reviews of statistical approaches for landslide susceptibility

Following these pioneering attempts in the mid-1970s to mid-1980s, the next three decades saw a large number of papers presenting an increasing diversity of approaches and methods for statistically-based landslide susceptibility modelling and zonation, and their application to different landslide types and in different geographical regions. In this vast literature, only a few authors have reviewed critically the different landslide susceptibility approaches, discussing the data and methods used, their intrinsic or specific advantages and disadvantages, and problems related to the practical use of the resulting terrain zonations (Aleotti and Chowdhury, 1999; Guzzetti et al., 1999; Guzzetti et al., 2000; Huabin et al., 2005; Chacón et al., 2006; Fell et al., 2008a, 2008b; Galli et al., 2008; van Westen et al., 2008; Kanungo et al., 2009; Pardeshi et al., 2013). We discuss below a number of these key reviews, and then in subsequent sections we build on and expand the discussions presented in these articles.

A key report by Varnes and IAEG Commission on Landslides and other Mass-Movements (1984) identified and investigated conditions and processes that cause landslides, and on techniques for the identification of unstable and potentially unstable areas. Although other examples of landslide terrain zonations were available in the literature (Hansen, 1984), the Varnes and IAEG Commission on Landslides and other Mass-Movements (1984) report was the first to systematize the concept of landslide terrain zonation, and to propose a ranking scheme to evaluate the significance of the landslide triggering/predisposing factors in a qualitative, or semi-quantitative way.

In the late 1990s, Aleotti and Chowdhury (1999) and Guzzetti et al. (1999) examined critically the existing literature on landslide susceptibility assessment. In two separate articles, they considered qualitative and quantitative approaches, and discussed different aspects of susceptibility modelling and terrain zonation. Aleotti and Chowdhury (1999) focused on the applicability of various approaches at different geographical scales, from site-specific engineering methods applicable to single slopes or landslides, to geomorphological approaches best suited for regional analyses, highlighting their advantages and limitations. They also stressed the importance of susceptibility/hazard assessments for landslide risk analyses, and specifically for the assessment of acceptable landslide risk levels. Guzzetti et al. (1999), building on earlier works on landslide susceptibility modelling in southern (Carrara et al., 1982; Carrara, 1983) and central (Carrara et al., 1991, 1995) Italy, identified and discussed the general, conceptual assumptions underlying landslide susceptibility assessment. They stressed the need for good quality landslide and geo-environmental information, the selection of appropriate terrain subdivisions, and discussed and classified the different modelling approaches adopted for landslide susceptibility zonation, focusing on statistically-based modelling approaches.

More recently, a few authors have attempted more or less systematic reviews of landslide susceptibility assessment approaches, or have analysed specific aspects of statistically-based modelling methods for susceptibility evaluation (Huabin et al., 2005; Chacón et al., 2006; Fell et al., 2008a, 2008b; Galli et al., 2008; van Westen et al., 2008; Kanungo et al., 2009). We discuss each of these now.

Huabin et al., (2005) reviewed landslide susceptibility approaches, their application at different scales using various mapping units, and outlined advantages and drawbacks of heuristic, statistical, and deterministic (process based) methods. They further stressed the importance of GIS technology for landslide susceptibility assessment, a consolidated technology at the time of their review (Carrara and Guzzetti, 1995; Goodchild, 2010). Interestingly, in their review they highlighted what they considered drawbacks of statistically-based modelling methods, including the facts that (i) the models require large efforts to collect and validate the necessary input data, which are often not readily available, and for this reason the models are difficult to prepare, (ii) for better results, interaction is required between geomorphologists and statisticians to process the landslide and geo-environmental data, and to avoid statistically sound but geomorphologically unrealistic (or erroneous) results, (iii) statistical models are influenced (negatively) by the extent of the study area, making it difficult to compare susceptibility classes from different locations, and (iv) susceptibility maps are difficult to understand by non-specialists, including planners and policymakers.

Chacón et al. (2006) published a comprehensive review of GIS-based engineering geology mapping techniques, and discussed the general concepts of landslide mapping, including the production of inventory, susceptibility, hazard, and risk maps. They proposed a classification of landslide maps into three types, namely (i) maps portraying the spatial incidence of landslides (i.e., maps showing zones of similar relative amounts of landsliding, or of similar conditions for landslide processes, including landslide susceptibility maps), without any temporal or predicting implication, (ii) maps showing the spatial-temporal incidence and the prediction of landslides, mostly obtained exploiting physical-based modelling approaches, and (iii) maps representing expected landslide consequences, including landslide risk assessments. They recommended that efforts should be made to define and use a simple, clear, direct, and easy to understand language to present the maps, and to use standard colours to show different classes (of susceptibility, hazard, or risk), using red to show the most susceptible areas, green the least susceptible, and yellow for intermediate susceptibility levels. Noting that landslide maps (including susceptibility maps) were rarely exploited for practical applications, they further recommended involving stakeholders in the preparation of the landslide maps, making them aware of their advantages and limitations. Fell et al. (2008a, 2008b) recognized that landslide susceptibility zoning had experienced extensive development during the last few decades, and argued in favour of a more uniform use of the terminology for the description of the results of landslide susceptibility (but also hazard and risk) zoning. They provided general guidelines and recommendations for landslide susceptibility, hazard and risk zoning for land use planning, considering natural and engineered slopes.

Guzzetti et al. (2000) and Galli et al. (2008) analysed landslide and geo-environmental information at different scales for a number of study areas in Umbria, Central Italy, and compared the information content of various types of landslide maps, including reconnaissance, geomorphological, and multi-temporal inventory maps, landslide density maps, and landslide susceptibility maps obtained through statistically-based classification models. They concluded that the information content of landslide susceptibility maps was superior, because the maps encompassed information on factors such as lithology and morphology that were used to build the model, and that were not included in the inventory or density maps. They also indicated that the quality of different landslide inventory maps could be ascertained by comparing susceptibility models prepared using the same set of geo-environmental data and different landslide information.

van Westen et al. (2008) discussed the use of geo-environmental information for landslide susceptibility, hazard, and vulnerability assessments, focusing on the type and relevance of the thematic and environmental information needed for each assessment, and the methods used to obtain the information. A significant conclusion of the work was that the availability of geo-environmental information conditions the scale and the approach best suited for susceptibility, hazard and vulnerability analyses. Kanungo et al. (2009) proposed a scheme and an associated "taxonomy" for the classification of different susceptibility zonation approaches.

Although a specific statistical classification method may perform better than other methods in specific conditions, critical reviews of statistical methods and tools for landslide susceptibility modelling are lacking, surprisingly. Brenning (2005) reviewed the literature, and concluded that logistic regression and discriminant analysis were the most frequently adopted classification modelling tools, followed by likelihood ratio methods (Chung and Fabbri, 1999; Chung, 2003). Recently, Budimir et al. (2015) attempted a systematic review of landslide susceptibility experiments that have used logistic regression analysis, and observed that guidelines for the selection of the geo-environmental variables for susceptibility modelling are not available. They compiled a list of the variables used in the literature to model rainfall-induced and earthquake-induced landslides and, not surprisingly (Fabbri et al., 2003) they found that the most significant variables were terrain slope and aspect, and geology/lithology. A first conclusion of the work was that the most significant variables changed depending on the landslide type, and the type of the trigger. A second conclusion was that when selecting explanatory variables for logistic regression analysis, investigators should use their knowledge and understanding of the landslide processes.

Only a few authors have discussed methods for landslide susceptibility model fit, and for the evaluation of the model prediction performances (Huabin et al., 2005; Chacón et al., 2006). Brenning (2005) examined the evaluation approaches used by 12 authors who prepared landslide susceptibility models from 1998 to 2005. Beguería (2006) analysed the validation and evaluation of mathematical models for landslide susceptibility modelling, with a special focus on establishing their predictive power. He considered different standard evaluation tools, including the confusion matrix (Jollifee and Stephenson, 2003), and related indices and Receiver Operating Characteristic (ROC, Green and Swets, 1966; Mason and Graham, 2002; Fawcett, 2006) plots. Beguería (2006) also stressed the difference between model validation and model evaluation. A significant conclusion of Beguería (2006) was that the use of standard statistical metrics for the analysis of the performances of a classification model could be problematic when applied to landslide susceptibility assessments. Similarly, Guzzetti et al. (2006a,b) emphasized the importance of estimating the quality of landslide susceptibility models, and proposed a scheme to rank their quality considering model evaluation skills, model performance, and the uncertainty associated to the model prediction. In this work (Section 4.8), we exploit this scheme to rank the quality of the susceptibility models considered in our review analysis, for the 520 articles (92.0%) for which sufficient information is available.

3. Construction and analysis of the literature database

To construct the literature database, we searched peer-reviewed articles in the "Web of Science™" online platform (formerly a Thomson Reuters™ product (Reuters, 2014), now part of Clarivate™ Analytics) using key words and Boolean search criteria applied to the "title", "abstract", and "keywords" of the publications. Conference proceedings, "grey literature" (e.g., government, technical, and project reports), and dissertations were not considered to compile the database. Keywords we used included "Landslide", "Rockfall", "Debris Flow", "Hazard", "Susceptibility", "Slope", "Instability", "Statistic".

As we were interested in "popular" (and recent) statistical methods used in landslide susceptibility mapping, a subgroup of the literature was considered based on the following citation number criteria: (i) for articles published before 2007, we considered articles with ten or more citations, (ii) for articles published between 2007 and 2008, we considered articles with five or more citations, and (iii) for articles published between 2009 and June 2016, we considered all the articles, including those without any citation. We acknowledge that this has introduced a bias in the database. However, assuming that citations are a relevant measure of the impact of an article, the adopted strategy has not left out from the database any "relevant" old article.

After both search terms and citation number criteria were applied, each of the resultant articles were examined to see whether or not their content was including landslide susceptibility modelling using statistical modelling methods, and thus was relevant for our literature database. The relevance search was the most time-consuming part of the process. By relevance, we mean those articles to do with landslide susceptibility statistical modelling. In many cases, an examination of the title (about 60% of all articles found) and abstract (a further subset of 25% of all articles found) could clearly indicate whether an article was relevant. In the remaining articles (about 15% of all articles found), an examination of the entire document was needed. We double-checked the final version of the database to evaluate possible incompleteness, misinterpretations, and biases. We assume that the final version of the database contains only minor inconsistencies that will not affect the review analysis presented in the paper.

The selection and type of information extracted from the collected articles was based preliminary on our experience, and further refined after the reading of about 10% of the 565 articles. Five major categories of information (each with multiple sub-categories) were extracted and listed in the database, including article information (B), study area characteristics (C), landslide inventory characteristics (D), susceptibility model production (E), and susceptibility model evaluation (F). In addition, the database lists the Susceptibility Quality Level (SQL) index (G) calculated following the ranking schema proposed by Guzzetti et al. (2006a,b). The six major categories and 31 sub-categories for the database are given in Table 1.

Table 1
Summary statistics for categories and sub-categories used in our literature review database on statistical methods to do with landslide susceptibility models and terrain zonations. Based on 565 articles from 1983 to 2016 with articles identified from a systematic search of Web of Science™. In the Table, Counts is the number of occurrences as given by the authors. Classes and clusters refer to different levels of grouping performed in the analysis, with clusters being groups of classes. Counts, Classes and Clusters values are specified only where applicable.

	Category		Sub-category	Counts	Classes	Clusters
A	ID #	A1	Article identification number	565		
B	Article	B1	Journal	105		
		B2	Title			
		B3	Author(s)	1 to 6 per article		
		B4	Publication year	35		
		B5	Number of citations (June 2016)	0 to > 700		
C	Study area	C1	(C1a) Continent | (C1b) Country	7 | 65		
		C2	Location(s)	621 (including duplicates)		
		C3	Number of study areas	1 to 3 per article		
		C4	Spatial extent (km^2)			
		C5	Latitude and longitude of approximate centre			
D	Landslide inventory	D1	Single | Multiple | No inventory	458 | 92 | 6	3	
		D2	Inventory type(s)		4	
		D3	Inventory year(s)			
		D4	Mapping technique(s)		6	
		D5	Landslide types	99		3
		D6	Number of landslides in the inventory			
		D7	Total landslide area (m^2) in the inventory			
E	Susceptibility model production	E1	List of input thematic variable(s)	596	23	5
		E2	DEM pixel size (m)	1 to 1000		
		E3	Scale of thematic data			
		E4	Type of mapping unit(s)	3		
		E5	Pixel size (m), where different from DEM pixel size			
		E6	Model type(s)	163	19	6
F	Susceptibility model evaluation	F1	Model fit performance measure(s)	92	9	
		F2	Model fit description and results			
		F3	Model validation criteria		3	
		F4	Model prediction performance measure(s)	60	9	
		F5	Model prediction description and results			
		F6	Estimated model uncertainty			
G	Susceptibility quality	G1	Susceptibility Quality Level (SQL)		7	

For each of the 565 articles in the literature database, we read through and identified information to populate the six categories and 31 sub-categories of information listed in Table 1. For some categories, we took the original information (e.g., input thematic variable as given by the authors) and grouped it into classes. Below, we describe the information collected in the literature database. For each category and sub-category, we illustrate the procedure and the grouping criteria we have used to analyse the information.

3.1. Article

In the literature database, the article information consisted of the journal name (B1), the article title (B2), the author(s) (B3), the publication year (B4), and the number of citations (B5 as of June 2016) (Table 1). Analysis of the database revealed that the 565 articles were published in 105 different peer-review journals. Fig. 1 shows the number of articles, the total number of citations to those articles listed in the "Web of Science™" online platform, and the average number of citations per article for the period from January 1983 to June 2016. In this period, noting the bias of citation counts in our selection criteria (see introduction to Section 3) the average [median] citation rate (considering the articles selected in the database) was around 40 [20] citations per article, with a maximum of > 700 citations (Guzzetti et al., 1999).

In the past four decades, landslide susceptibility has been evaluated by many authors in different parts of the world. For the initial 12-year period, from 1983 to 1994, only six articles (0.5 articles $year^{-1}$) (Carrara, 1983; Aniya, 1985; Carrara et al., 1991; Anbalagan 1992; Jade and Sarkar, 1993; Maharaj, 1993) are listed in our literature database, three of which (Carrara, 1983; Carrara et al., 1991; Anbalagan, 1992) have a large number of citations (> 140 citations). In the next period, between 1995 and 1999 (5 years), there are 12 articles (2.4 articles $year^{-1}$) in the database, indicating an important increase in the number of published articles. Then, beginning in the year 2000, the number of articles per year has increased significantly, and in 2015 the database lists 64 articles (64 articles $year^{-1}$) published in 30 different journals.

Fig. 2 shows the top 18 journals (out of 105 in the database) in terms of the number of articles identified in the analysis, with the corresponding average citation information. The top three journals (Geomorphology, Natural Hazards, Environmental Earth Sciences) and the next set of four journals (Engineering Geology, Landslides, Arabian Journal of Geosciences, Natural Hazards and Earth System Sciences) account for 32% (top three journals) and 23% (next four journals) of the 565 articles in the database. Overall, 55% of the articles in the database were published in these seven journals, which are prominent in the geomorphology, engineering geology, and natural hazards communities. Geomorphology, Natural Hazards and Engineering Geology, are also according to other analyses of the international literature, the journals more frequently used by the landslide research community (Gökceoglu and Sezer, 2009). Of interest is the large number of articles published in the Arabian Journal of Geosciences, which has a regional significance in the Middle East and the Mediterranean areas. Further down the list of journals, a significant number of articles were published in remote sensing journals (e.g., International Journal of Remote Sensing, Journal of Applied Remote Sensing, Photogrammetric Engineering and Remote Sensing), and in journals dealing with computer applications in the geosciences (e.g., Computers & Geosciences, Environment and Urban Systems, Computers and Geotechnics).

Analysis of the database revealed that articles on landslide susceptibility statistical modelling were published, on average, by three authors. We consider this an indication of the need for different expertise to collect and analyse the landslide and the thematic information, and to construct and validate the landslide susceptibility models and the associated terrain zonations. Following a common trend in the literature on the geo-sciences, the number of authors per paper has

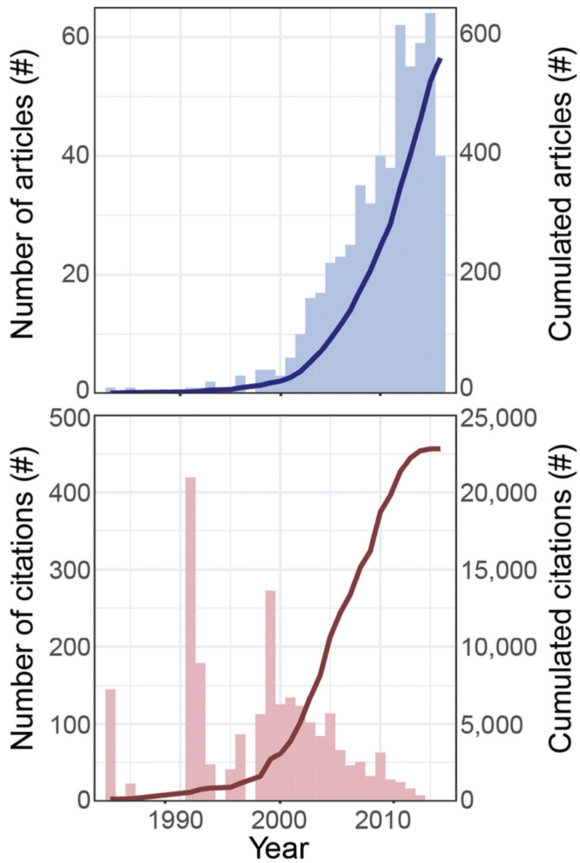

Fig. 1. Literature database. Analysis of the literature database listing 565 articles in the 35.5-year period from January 1983 to June 2016. Source of the articles was the "Web of Science™" (formerly a Thomson Reuters™ product, now part of Clarivate™ Analytics). Upper graph shows number of articles per year (vertical blue bars, left y-axis) and cumulated number of articles (solid blue line, right y-axis). Lower graph shows number of citations per year (vertical red bars, left y-axis) and cumulated number of citations (solid red line, right y-axis). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increased from 1980 to 2000, then reaching a stable average of three-four authors per article.

3.2. Study area

We grouped the information on the study areas into the following sub-categories: continent (C1a), country (C1b), geographical location (C2), number of study areas (C3), spatial extent (C4), and geographical coordinates (latitude, longitude) of the centroids of the study areas (C5) (Table 1). Of the 565 articles in the database, 524 articles (92.7%) had one study area, and the remaining (7.3%) two or three study areas, for a total of 621 study areas, but not all unique (a given study area might be studied in whole or in part by multiple papers). Excluding 81 study areas for which the extent was not known, and the European (continental) and global assessments, the remaining 534 areas collectively cover 4.6 million km^2, about half of the size of China or the U.S.A. A total of 65 countries in seven continents were identified, of which the most represented are China, Italy, India, and Turkey, with > 50 study areas each country (Fig. 3).

3.3. Landslide information

For each article in the database we analysed the characteristics of the landslide information, including the number of inventories produced or used (single or multiple) (D1), the type(s) of landslide map(s) (D2), the year(s) of the map(s) (D3), the mapping technique(s) (D4), the landslides types (D5), the number of landslides (D6), and the total landslide area (D7) (Table 1).

A given study area might have one or more inventories (D1). The majority of the articles (81%, 458 out of 565) described or used a single inventory, and only a small number (16%, 92) used two or more inventories. In a few articles, this information is unknown (1%, 6), and nine articles (2%) did not use any landslide inventory for their susceptibility assessments (Anbalagan, 1992; Anbalagan and Singh, 1996; Hong et al., 2007; Pandey et al., 2008; Zolfaghari and Heath, 2008; Haneberg et al., 2009; Avtar et al., 2011; Jia et al., 2012; Montoya-Montes et al., 2012). In 92 articles, out of 565 (16.3%), authors have described and used multi-temporal maps (e.g., covering the same area with landslides from different time periods), or inventories prepared using different techniques. However, in a number of cases the "same", or a very similar inventory (with identical period(s) and spatial extents) was used and described in different articles.

We classified the type of landslide inventory (D2) using the four classes given by Guzzetti et al. (2012), modifying slightly the definitions as follows:

- Geomorphological inventories (392, 65.1% of 602 inventories); the authors used the physical features of the landscape to identify the landslides.
- Event inventories (142, 23.6%); inventories of landslides associated with a given rainfall event, earthquake, or snowmelt triggering event. They may include seasonal inventories.
- Multi-temporal inventories (26, 4.3%); inventories prepared for the same area but for different time periods.
- Historical inventories (42, 7.0%); where authors called the inventory "historical", then we used this term in the classification. We note that in some cases, what authors called historical might be considered geomorphological.

During the searching, we collected and analysed information on the year(s) of the aerial photographs or satellite imagery used to prepare the inventory map(s). The information is highly heterogeneous, and in many cases unknown (268 out of 565, 47.4%). The oldest aerial photographs date back 1941 and were used in Italy and in Venezuela. Further, the information reveals that multi-temporal inventory maps consider up to seven different sources of information, including field mapping and aerial photographs (Remondo et al., 2003; Zêzere et al., 2008). We identified the landslide mapping techniques (D4), as described by the authors, considering traditional (consolidated) techniques and recent approaches (Guzzetti et al., 2012), and we recognized the following six mapping techniques, including: (i) visual interpretation of aerial photographs, (ii) interpretation of optical satellite imagery, (iii) field mapping, (iv) interpretation of high resolution DEM, (v) automatic or semi-automatic mapping using remote sensing imagery, and (vi) archive search (Fig. 4).

A given inventory might be prepared using multiple mapping techniques. As an example, the production of inventory maps through the visual interpretation of aerial photography is most commonly aided by more or less extensive field checks. For 93 articles, the landslide mapping technique was not described, and was classified as "unknown" in the database.

We analysed the landslide types (D5), and we identified 99 unique landslide type names as described by the authors in 383 articles. In 173 articles, the authors did not describe the landslide types, and nine articles were not relevant as they had no inventories. We attempted a classification of the large number of landslide types using the landslide classification proposed by Cruden and Varnes (1996), but we found that a more general classification was necessary due to missing or incomplete information, changes of meanings over the period considered, and regional variations. We therefore attributed to the landslide type names given by the authors the following three classes (Fig. 5):

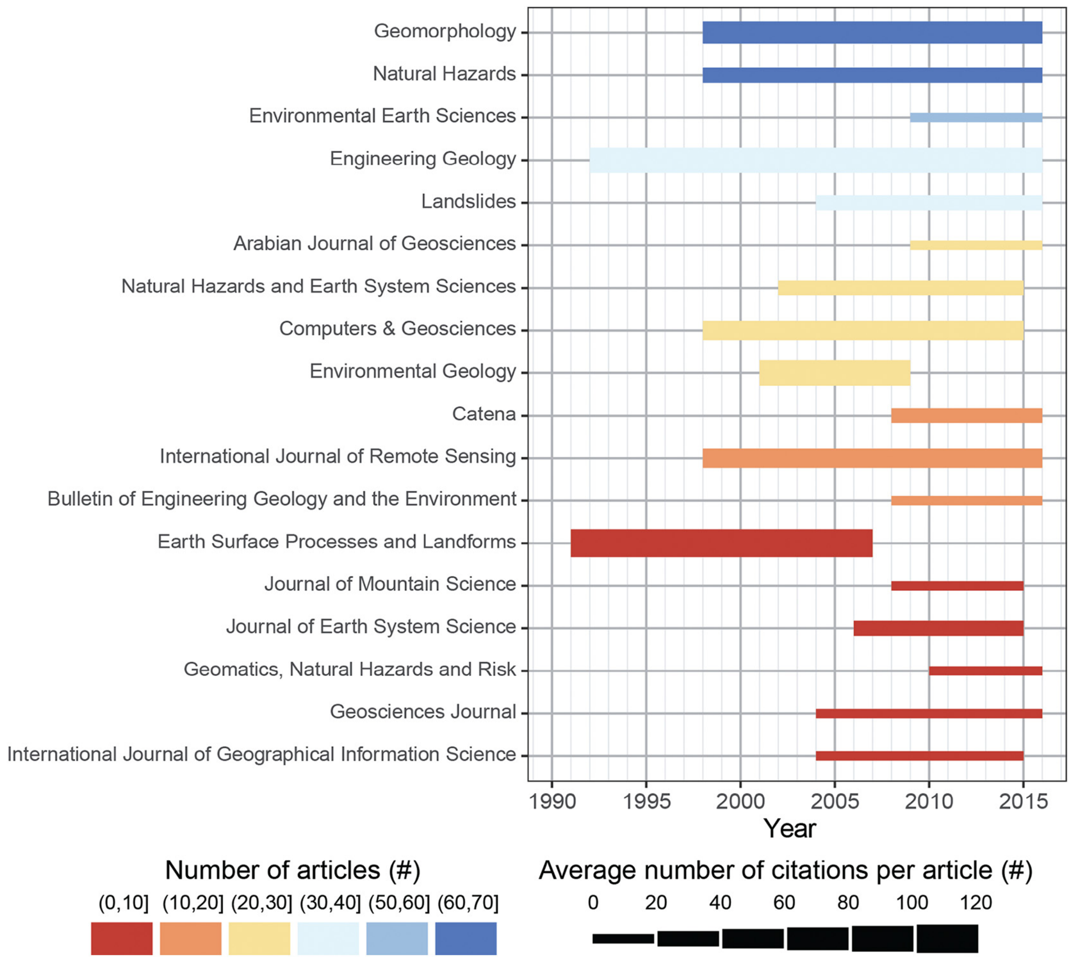

Fig. 2. Eighteen top journals (out of 105) in terms of number of articles listed in the literature database. Colour of horizontal bars shows number of articles, in six classes. Height of horizontal bars shows average number of citations, in six classes. Square brackets indicate class limit is included, and round brackets that class limit is not included. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(i) the types of landslide movement, in eight classes,
(ii) the landslide material, in three classes (earth, debris, rock), and
(iii) the estimated depth of the landslide, in two classes (shallow, deep seated).

We were able to associate a "movement" type to 94 of the 99 landslide type names. The majority of the movement types (55.2%) were rotational or translational slides. Flows were reported in 19.3% of the articles, falls in 9.4%, and topples and lateral spreads collectively

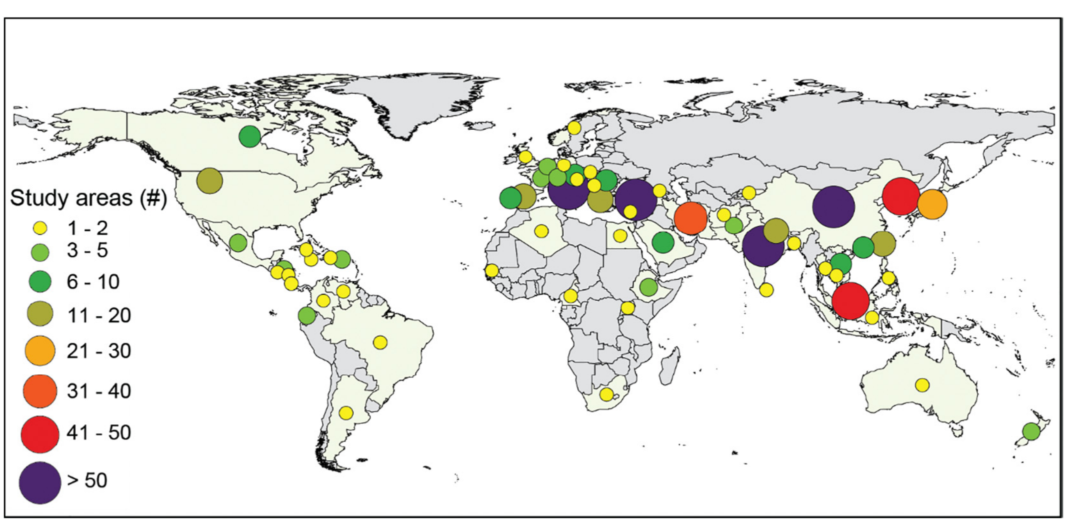

Fig. 3. Map showing the geographical distribution of the 621 study areas, including duplicates, listed in the literature database. Light green shading indicates those 63 countries with study areas in the literature database. Coloured circles show the number of study areas in each country, in eight classes. The size of the circle is proportional to the number of articles in each country. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

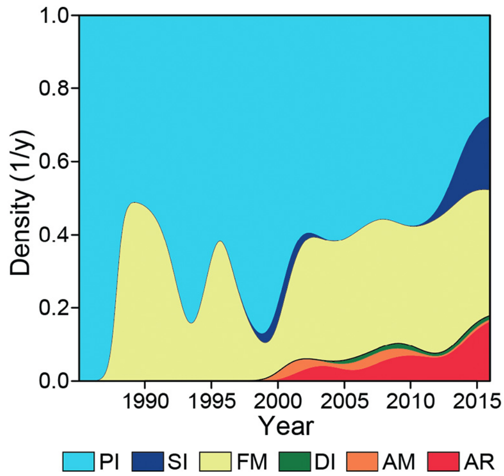

Fig. 4. Landslide mapping techniques. The conditional density plot shows the distribution of the mapping techniques usage for each year, as described in the articles listed in the literature database. Legend: PI, visual interpretation of aerial photographs; SI, visual interpretation of satellite images; FM, field mapping; DI, visual interpretation of DEM derivatives; AM, automatic or semi-automatic mapping using remote sensing imagery; AR, analysis of archive and historical sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

accounted for 2.2% of the studies. The "material" type was determined for 42% of the articles, with "debris" – associated chiefly to debris flows – the most common (17.6%), followed by "earth" (13.2%) – encompassing "mud", "soil" and "earth" that in many articles were used to describe similar materials, and by "rock" (11.2%). The landslide "depth" was established for only 25.8% of the cases in the database, with the majority of the landslides classified as "shallow" (21.1%) and only 4.7% as "deep seated".

In the database, we have also tabulated the number of landslides listed in each inventory (D6), and the total landslide area (D7). We obtained this information from 467 (83%) and 141 (25%) of the articles, respectively.

3.4. Susceptibility model production

Searching the literature database, we extracted information on the production of the susceptibility models, including the input thematic variables (E1), the ground resolution (pixel size) of the DEM (E2), the scale of the thematic data (E3), the mapping units (E4), the pixel size, if different from the DEM pixel size (E5), and the model type (E6) (Table 1).

3.4.1. Thematic variables

Overall, the authors have used a total of 596 different input thematic variables. For each single susceptibility model, from two to 22 thematic variables were used, with an average of nine variables. Of the 596 original variable names, 445 (74.6%) occurred only once or twice in the database. We re-classified this very large number of input thematic variable names into 23 classes. Each variable name was grouped according to the following two main criteria. First, thematic variable names that were synonyms were grouped together, for example, "gradient" and "slope" were grouped into the class "slope". Second, thematic variables related to similar descriptors (but not necessarily with the same meaning) were grouped together, for example, "geological age" and "geological formation" were grouped into the class "geo-lithology". The reclassified thematic variable groups encompassed from one to 105 original input variable names, with seven groups accounting for 57% of all occurrences, including slope, geo-lithology, aspect, hydrology, landslide, river/catchment and curvature. The 23 identified classes were further grouped into five thematic clusters i.e., geological, hydrological, land cover, morphological, and other variables (Fig. 6).

3.4.2. Mapping unit

Regardless of the adopted modelling approach, selection of the mapping unit is an important pre-requisite for landslide susceptibility modelling (Guzzetti et al., 1999; Guzzetti, 2006). Searching the database, we identified three common mapping units (E4), namely, pixels (grid cells), slope units, and unique condition units. Pixels, used in 86.4% of the articles, were by far the most common mapping unit. The other mapping units were less frequent, with slope units used in 5.1% of the articles, and unique condition units used in 4.6% of articles. In 3.9% of the articles, authors used other types or combinations of the different mapping units (i.e., pixels, slope units, and unique condition units) (e.g., Carrara et al., 2008; Van Den Eeckhaut et al., 2009; Erener and Düzgün, 2012).

We further examined the resolution of the DEM(s) used in the analysis (E2), and found resolutions (and corresponding mapping units) in the range from < 1 m × 1 m (Petschko et al., 2014; Yusof et al., 2015) to > 1 km × 1 km (He et al., 2003; Günther et al., 2013). In 79.5% of the pixel-based assessments, the pixel size of the DEM controlled the resolution of the susceptibility zonation.

3.4.3. Model type

About 60% of the articles used only one type of landslide susceptibility model. The remaining used two (23.7%) or more model types, and up to eight different model types (Vorpahl et al., 2012). We re-classified the 163 model type names as given by the authors into 19 classes. The reclassification was not straightforward, and required multiple iterations, with the final proposed grouping subjective and based on our expert opinion. Identifying the model types also resulted in bias, as different authors used different names for the "same" model type, or the same name for a model might be used with different meanings. The results of the re-classification are given in Fig. 7, with four model types accounting for 46% of all the occurrences, and specifically logistic regression analysis (18.5%), data overlay (10.7%), neural network (8.3%), and index-based models (8.2%).

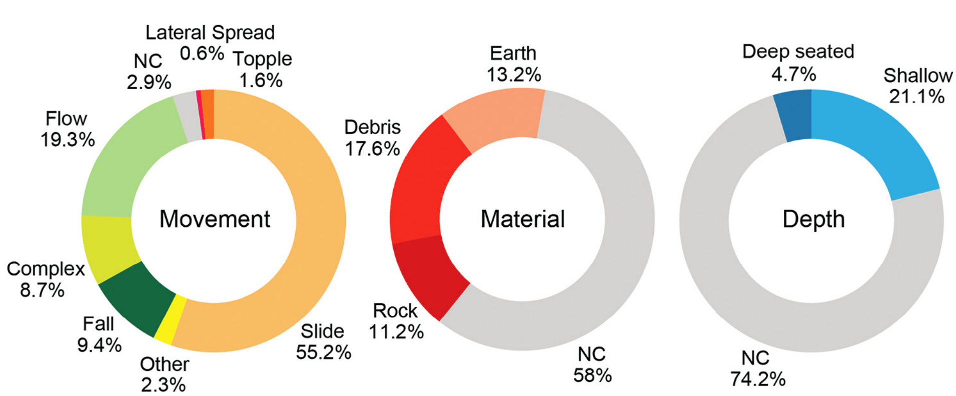

Fig. 5. Landslide types. The three donuts illustrate (left) the type of landslide movement, in eight classes; (centre) the type of landslide material, in four classes; and (right) the estimated landslide depth, in two classes, as given in the articles listed in the literature database. For all three donuts, NC indicates non-classified. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

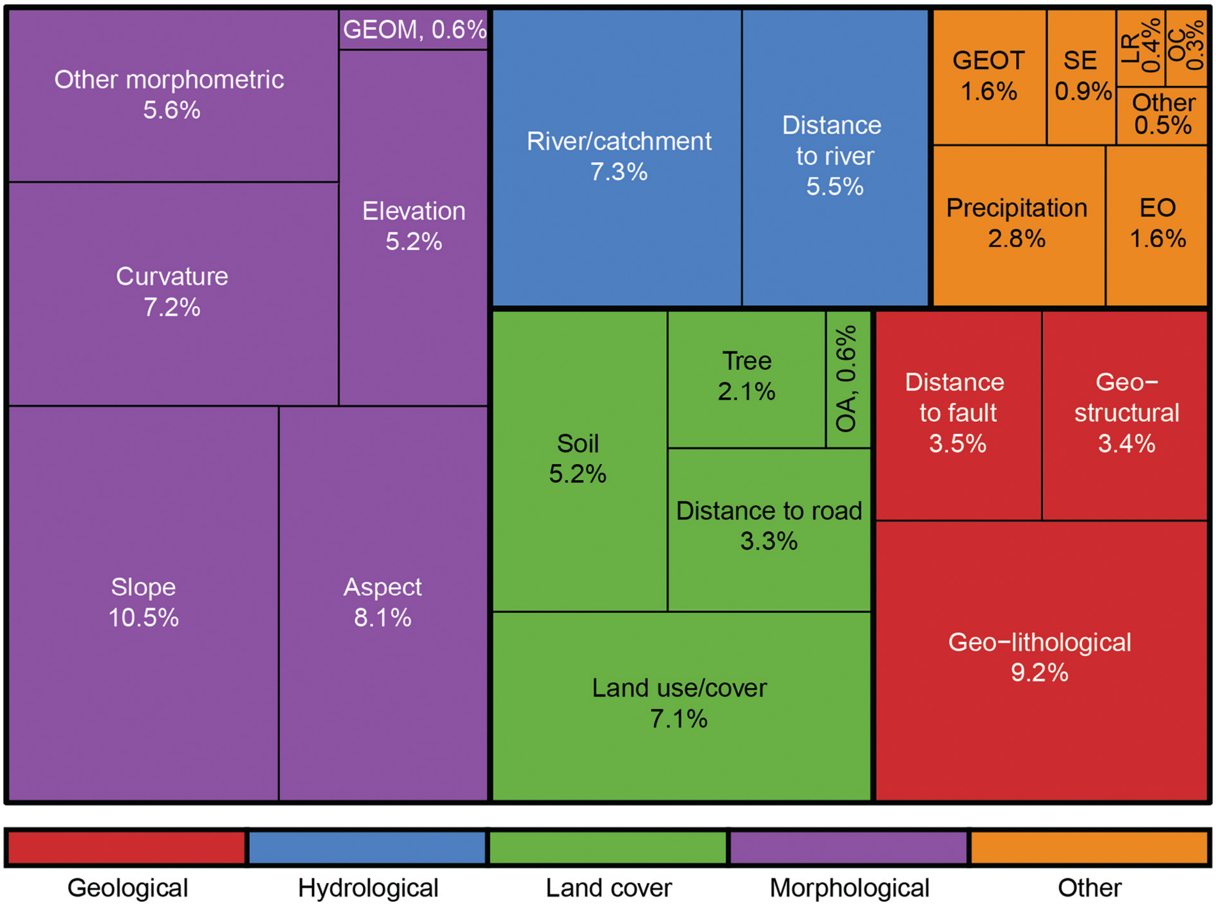

Fig. 6. Thematic variables. The treemap chart shows the proportion of the original thematic variables as listed in the articles in literature database. Variables are grouped in 23 classes pertaining to five thematic clusters, shown with different colours. Legend: EO, Earth observation; GEOM, geomorphological; GEOT, geotechnical; LR, landslide related; OA, other anthropic; OC, other climatic; SE, seismic. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.5. *Susceptibility model evaluation*

We examined the criteria proposed and used for the evaluation of the susceptibility models, including: measures of model fit performance (F1), model fit description and results (F2), model validation criteria (F3), measures of the model prediction performance (F4), model prediction description and results (F5), and estimated model uncertainty (F6) (Table 1).

3.5.1. *Model validation*

Statistical models for landslide susceptibility zonation reconstruct the relationships between dependent and independent variables using training sets, and verify these relationships using validation sets (Guzzetti et al., 2006a,b). To identify and separate the training and the validation sets, different criteria can be adopted, guiding the type of the validation analysis. In the literature, temporal, spatial and random selection strategies have been used. When adopting a temporal validation, the landslide information is segmented into two groups based on temporal information (e.g., landslides known to have occurred before and after a given date). In the database, the validation set is typically more recent than the training set. When adopting a spatial or a random validation, the landslide information is segmented using spatial (geographical) criteria. In the spatial case, the validation set typically represents a different (contiguous or not contiguous) portion of the territory, whereas in the second case the validation set is obtained through a random geographical selection. Analysis of the literature database revealed that 60% of the 335 articles that described the model performance validation adopted a random selection, 20% a temporal selection, 15% a geographical selection, and 5% a combination of the three basic selection strategies.

3.5.2. *Model fitting performance*

Analysis of the different metrics used in the literature to evaluate the model fitting performance of a susceptibility model revealed that in 38.2% of the 565 articles authors used only one metric, in 14.5% two metrics, and in the remaining 15.2% more than two metrics, up to 14 (Guzzetti et al., 2006a,b). Significantly, for 181 articles (32.0%) no evaluation of the model fitting performance was executed. In the remaining 384 articles (68.0%), we identified 92 unique metrics (as described by the authors) to evaluate the model fit. We re-classified this very large number into nine classes (F1 in Table 1), and found that the most common were success rate curve (22.5%), landslide density or frequency (19.0%), Receiver Operating Characteristic (ROC) curve (16.0%), and other indices obtained combining the four main elements of a typical two-entry confusion matrix (13.2%), including true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) (Fig. 8).

3.5.3. *Model prediction performance*

We obtained very similar results to the model fitting performance when analysing the metrics adopted to evaluate the model prediction performance. Of the 565 articles in the literature database, 220 articles (38.9%) did not perform any model evaluation assessment. In the remaining 345 articles (61.1%), we identified 60 unique metrics used by the authors. We re-classified the metrics/indices into nine classes (F4 in Table 1), and found that the most common were prediction rate curve (27.2%), landslide density or frequency (22.9%), ROC curve (22.7%), and other indices obtained from a standard confusion matrix (18.8%)

Fig. 7. Susceptibility model types. Horizontal bar chart shows the count of 19 model type classes used to group the 163 model names given by the authors in the articles in the literature database. Darker (lighter) colours indicate a larger (smaller) number of single models in the group. Square brackets indicate class limit is included, and round brackets that class limit is not included. Grey histograms show yearly number of articles, per model type. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

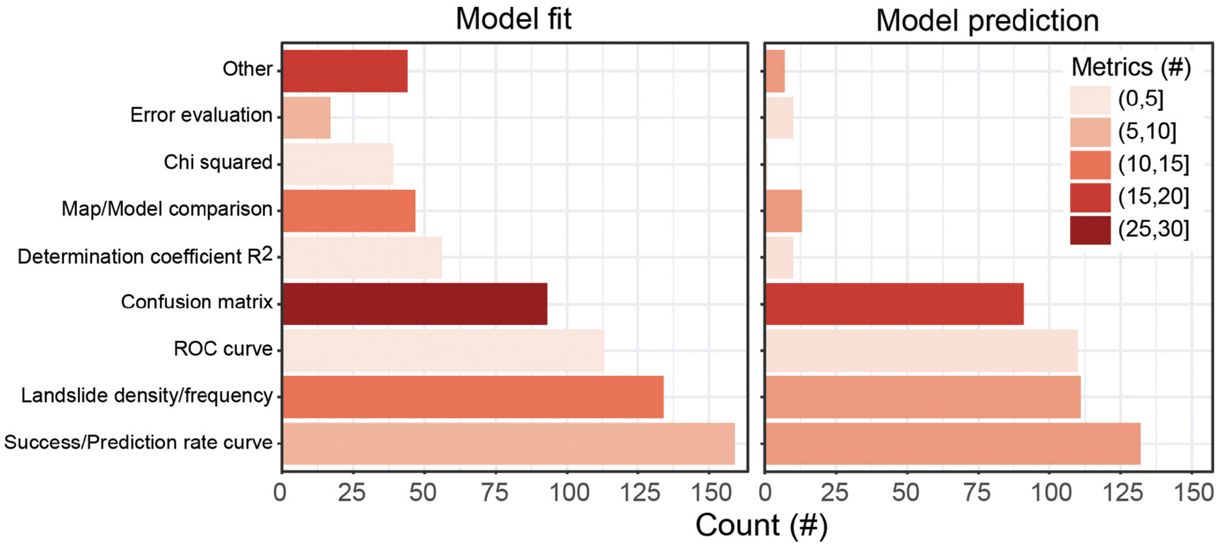

Fig. 8. Model fit and model prediction. Count of 92 metrics used for model fit (left) and 60 metrics used for model prediction (right), arranged in nine groups, listed in the articles in the literature database. Darker (lighter) colours indicate a larger (smaller) number of single metrics included in a group. Square brackets indicate class limit is included, and round brackets that class limit is not included. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

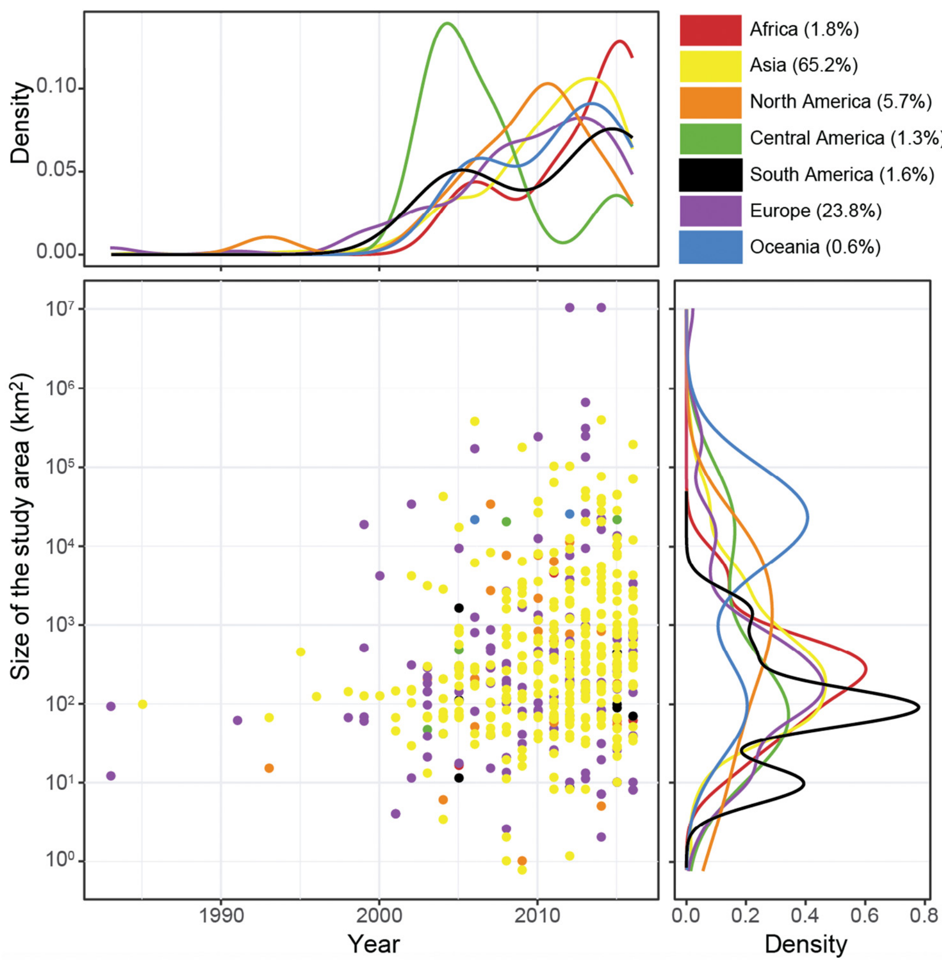

Fig. 9. Size of the study areas. Scatter plot shows the distribution of the size (extent) of the study areas, per year. Top plot shows the kernel density estimate of the study areas, per year. Right plot shows kernel density estimate of study area, per size (extent). Colours show cases in seven different continents. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Fig. 8).

3.5.4. Model uncertainty

Lastly, we evaluated the number of articles that attempted an estimate of the model uncertainty (F6 in Table 1), and we noted that only fairly recently (i.e., after the year 2000) this type of analysis was performed by a few authors in a limited number of articles (17, 3.0%) (Capolongo et al., 2002; Guzzetti et al., 2006b; Gorsevski and Jankowski, 2010; Petschko et al., 2014).

4. Discussion

Here, we analyse and discuss critically all the categories and the information collected in the literature database on statistically-based landslide susceptibility modelling, and associated zonations. Based on previous review articles (Aleotti and Chowdhury, 1999; Guzzetti et al., 1999; Guzzetti et al., 2000; Huabin et al., 2005; Chacón et al., 2006; Galli et al. 2008; Fell et al., 2008a, 2008b; van Westen et al., 2008; Kanungo et al., 2009) and on our experience, we provide specific and general recommendations on how to perform susceptibility modelling for reliable terrain zonations. We divide this section into ten major subsections, discussing the following themes: extent and location of the study areas (Section 4.1); landslide types (Section 4.2); source of landslide information (Section 4.3); geo-environmental information (Section 4.4); mapping units (Section 4.5); model types (Section 4.6); model performance evaluation (Section 4.7); susceptibility Quality Level (Section 4.8); non-susceptibility modelling (Section 4.9); and use of landslide susceptibility and non-susceptibility assessments (Section 4.10). Throughout these sections, we attempt to identify recommendations, based on the analysis of the literature review and our own expertise, recognizing there are biases in both sources of evidence.

4.1. Extent and location of the study areas

Analysis of the literature database of 565 articles revealed that investigators have prepared landslide susceptibility models and maps in 621 study areas (non-unique, and not considering continent/entire-world scale) located in 63 different countries and in seven continents. Only a few authors have conducted or discussed landslide susceptibility evaluation at continental scale in Europe (Van Den Eeckhaut et al., 2012a,b; Günther et al., 2013, 2014). Similarly, only a few articles have conducted or discussed attempts to global, synoptic scale assessments of landslide susceptibility (Nadim et al., 2006; Hong et al., 2007). Excluding the continental and the global studies, the study areas range in size from a few to hundreds of thousands of square kilometres, with most of the areas extending around 100 km^2 (Fig. 9), for a total of 4.6 million km^2 (with non-unique study areas being counted multiple times), or 0.03% of the Earth's land area. This value (even considering the issue of non-uniqueness of study areas) is significantly less than the area estimated to be covered by landslide inventory maps (Guzzetti et al., 2012).

In the early period covered by the literature database, from 1983 to 1994, landslide susceptibility assessments were completed for only a very limited number of test sites (7), in four countries (Italy (3), Japan (1), India (2), Jamaica (1)), with the test sites of limited extent ($<$ 100 km^2). The number of the test sites and their geographical coverage increased significantly after 2005, when the average size of the investigated areas also increased. Inspection of Fig. 9 reveals a significant geographical bias in the studied areas, with the majority of the susceptibility zonations in Asia (402; China (67), India (56), Turkey (54) South Korea (48)) and Europe (147; Italy (63), Spain (17), Greece (13)), followed by North America (35), Africa (11), South America (10), Central America (8), and Oceania (4).

Despite the fact that the geographical coverage of landslide susceptibility studies has increased in the recent periods, for large parts of the world (e.g., Africa, South America, Oceania) the number of landslide susceptibility assessments remains very limited (Fig. 9). Analysis of Fig. 10, which shows the density of the extent of the study areas in five continents, confirms that most of the studies were executed in Europe and Asia, and in areas with a similar average size. In Africa, South America and Central America, susceptibility assessments were less abundant, and limited to areas of a smaller average size. The study areas were most abundant in Europe, particularly in the period 2010–2015.

We recommend that investigators reduce the existing geographical bias in landslide susceptibility modelling, concentrating their efforts in areas that were not previously investigated. This will increase the number of sites and the extent of the areas covered by landslide susceptibility modelling and zonation, and it will augment the possibility to use landslide susceptibility maps for practical applications (e.g., improved urban and land planning, landslide early warning) at different geographical scales, and in different physiographical, climatic and social environments.

4.2. Landslide types

Despite the fact that an accepted landslide classification exists, and it was refined and integrated in the period covered by the literature database (Varnes, 1978; Cruden and Varnes, 1996; Hungr et al., 2013), inspection of database articles revealed inaccuracy and imprecision in the use of the common landslide taxonomy. Of the 565 database articles, 182 (32.2%) did not provide any information on the type (or types) of the investigated landslides. This limited the possibility to evaluate the relevance of the results obtained by these studies. In the remaining 383 (67.8%) articles, the authors collectively used a large number (99) of different landslide type names, with a number of inconsistencies. As an example, the terms “debris flow” and “mudflow” were occasionally used as synonyms, and in other cases, they described different types of very to extremely rapid landslides (Hungr et al., 2013). A similar confusion exists with the use of the terms “debris avalanche” and “debris flows”. Use of the landslide taxonomy reveals regional and local biases, complicating the analysis.

Overall, the main landslide types considered in susceptibility modelling (Fig. 5) were slide (55.2%), flow (19.3%), followed by fall (9.4%), complex/composite failure (8.7%) and by other landslide types (topple, avalanche, lateral spread, 4.5%). This was expected, because statistically-based landslide susceptibility assessments are best suited to consider landslides that (i) do not move much from their source area, and (ii) do not change significantly their size and geometry during the movement (e.g., rotational or translational slides). These assessments are less suited to predict landslides that (i) travel long distances (hundreds to thousands of meters), and that (ii) can change significantly their volume and geometry moving from the source to the depositional area (e.g., rock falls, debris flows). The susceptibility of the latter landslide types is best predicted using physically-based models (Guzzetti et al., 2002; Agliardi and Crosta, 2003; Dorren, 2003).

We note that lack of accurate information on the type of landslides predicted by susceptibility models has adverse consequences on the comparison of the results of the different models, and may limit the practical application of the models and the associated zonations.

We recommend that investigators use standard, accepted landslide taxonomy (Cruden and Varnes, 1996; Hungr et al., 2013) to define clearly and unambiguously the type (or types) of landslides considered in their predictive models. We expect this to contribute to reduce ambiguities, and to facilitate the comparison of susceptibility models and associated terrain zonations prepared in different areas, or using different modelling approaches.

4.3. Source of landslide information

Analysis of the literature database reveals that in the majority of the susceptibility assessments landslide information was obtained from

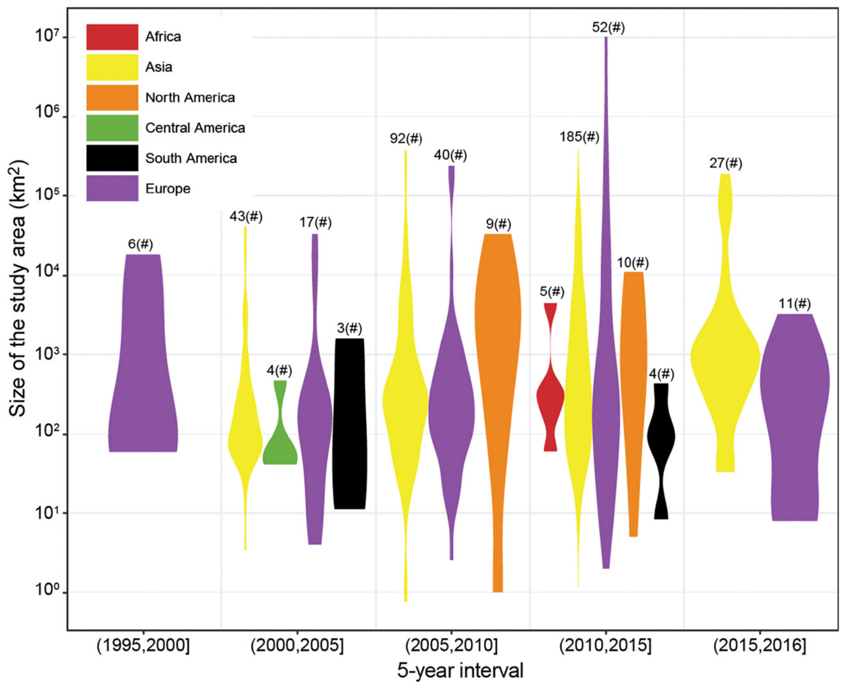

Fig. 10. Size of the study areas. Violin plot shows density of the size (extent) of the study areas, per 5-year intervals, and for six continents (colours). Violins trimmed to show the range of the size of the study areas in the given continent. Data shown from 1995 to 2016. For each continent/interval, the number of the study areas is shown above the violin plots. On x-axis, square brackets indicate class limit is included, and round brackets that class limit is not included. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

inventory maps prepared through the visual interpretation of stereoscopic aerial photographs (41.0%) or satellite images (6.4%) and dedicated field surveys (30.1%), followed by the inspection of archives, chronicles and journals, and of technical and scientific reports (7.6%), the automatic or semi-automatic recognition from remote sensing imagery (1.0%), and the interpretation of DEM derivatives (0.8%).

Compilation of landslide information through the interpretation of aerial photographs, field surveys, and historical or archive sources is time consuming and resource intensive (Guzzetti et al., 2012). For this reason, investigators have recently introduced the use of new and experimental methods to obtain the landslide information required to evaluate landslide susceptibility, including visual, semi-automatic, or automatic analysis of derivatives of high resolution (HR) and very high resolution (VHR) digital elevation models (DEM) (Ardizzone et al., 2007; Schulz, 2007; Haneberg et al., 2009; Jaboyedoff et al., 2012; Van Den Eeckhaut et al., 2012a,b), and of HR and VHR optical satellite imagery (Martha et al., 2010; Lu et al., 2011; Mondini et al., 2011; Stumpf and Kerle, 2011; Guzzetti et al., 2012; Mondini and Chang, 2014) (Fig. 4). Recently, Google Earth™ imagery has been used as a source of information for landslide distribution mapping (Posner and Georgakakos, 2015; Conoscenti et al., 2016; Broeckx et al., 2017). About 40% (225 out of 565) of the articles in the literature database used multiple sources of landslide information, and primarily the combined visual interpretation of aerial photographs and field mapping, with the later most commonly used to check the completeness and quality of the mapped landslide information. In some cases, the number of landslides used to prepare a model was too small for the extent of the study area to be geomorphologically relevant (Chen et al., 2016).

We recommend, where possible, using multiple and complementary landslide mapping techniques, as this contribute to increase the quality of the information and of the susceptibility assessment. The number, distribution, and type of landslides should be appropriate and significant to prepare susceptibility models and associated zonations.

The information content of a landslide map depends on the type of the inventory (Guzzetti et al., 2000, 2012). For susceptibility modelling, investigators have preferred geomorphological inventories (65.1%), which show the general distribution and abundance of landslides in an area. A common problem of geomorphological inventory maps is that they do not show all the landslides that have occurred in an area, because slope failures can be easily (and rapidly) obliterated by other mass movements, erosional processes, growth of vegetation, and human actions (e.g., ploughing, land levelling). This is particularly the case for small landslides, even if human actions can also obliterate medium-size failures. We note that lack of some landslides in a geomorphological inventory may not represent a problem for susceptibility modelling, as long as the inventory provides a reasonable representation of the abundance and distribution of the landslides in the area. In other words, if the inventory does not miss or underestimate specific landslide types, or it has no significant geographical biases with some area covered more accurately or completely than other areas. To some extent, consistency is more important than completeness for geomorphological inventories used for susceptibility modelling. We note that use of variables such as slope units as the mapping unit of reference contributes to limiting the bias introduced by the incompleteness of a landslide inventory map.

Event inventories show landslides caused by a single trigger (e.g., a rainfall event, rapid snowmelt event, earthquake), and are the second most used type of inventory for susceptibility modelling (23.6%). Single event inventories are less appropriate to construct new susceptibility models, as the distribution of the event landslides does not depend only on the local terrain conditions, but also on the location, extent and magnitude of the trigger. On the other hand, event inventories are suited to evaluate the predictive performance of a susceptibility model (Guzzetti et al., 2006a,b; Rossi et al., 2010).

Seasonal or multi-temporal inventories show landslides triggered by multiple events over periods ranging from a season to decades and represent the optimal ("best") source of landslide information for susceptibility modelling (Galli et al., 2008). Multi-temporal inventories allow for (i) constructing reliable susceptibility models, as they contain the same information shown in geomorphological inventories, (ii) testing the long-term performances of a susceptibility model (Guzzetti et al., 2004; Guzzetti et al., 2005), which is particularly important if the model has to be used for practical applications, and (iii) determining the "learning curve" for a susceptibility model i.e., finding the minimum number of landslides, or the minimum landslide period, necessary to obtain a reliable predictive model (Guzzetti et al., 2004).

Multi-temporal inventories can also be used to evaluate possible changes in the spatial distribution (and in the size distribution and the temporal frequency) of landslides in an area. This information can be used to falsify (or confirm) the general assumption that "future landslides will be more likely to occur under the conditions which led to past and present landslides" (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara et al., 1991; Hutchinson, 1995; Furlani and Ninfo, 2015), which is at the base of susceptibility modelling. Where susceptibility is found to be changing over time in an area, multi-temporal inventories provide valuable information to investigate the causes and the rates of the changes.

A drawback of multi-temporal inventories is that they are operationally difficult and time consuming to prepare, and they require substantial resources (Guzzetti et al., 2006a,b). However, the increasing availability of HR and VHR terrain elevation data and satellite imagery, together with new methods, techniques and tools for the semi-automatic or automatic detection of landslides from remote sensing imagery and VHR elevation data, may help reducing the costs and efforts, augmenting the possibility to prepare multi-temporal maps (Guzzetti et al., 2012). We expect that this will have positive consequences for landslide susceptibility modelling.

We recommend that geomorphological and multi-temporal inventories be used to calibrate and to test the predictive performance of landslide susceptibility models, and the associated terrain zonations. Event inventories are good to evaluate the predictive capability of the susceptibility models. However, they should be used with caution, as the geographical distribution and abundance of the event landslides depend on the pattern and extent of the trigger (e.g., the pattern and the extent of the rainfall, of the seismic intensity) in addition to the pattern of the geo-environmental variables that control landslide susceptibility. For large and very large areas, lack of event landslides in an event inventory does not mean that the susceptibility model is incorrect, necessarily.

4.4. Geo-environmental information

In addition to landslide data (the "dependent" variable), statistically-based landslide susceptibility models require information on geo-environmental predisposing factors, as the "independent" (or "explanatory") variables (Carrara 1983; Guzzetti et al., 1999; Guzzetti, 2006; Budimir et al., 2015). Analysis of the literature database reveals that investigators have used a broad range of geo-environmental variables. Despite uncertainty due to the lack of a common language and standard taxonomy to describe and classify the geo-environmental information (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984), we have classified the many input thematic variables (596 unique variables) used in the literature database into five clusters: (i) morphological (152 variables, 25.5% of 596), (ii) geological (114, 19.1%), (iii) land cover (105, 17.6%), (iv) hydrological (83, 13.9%) and (v) other variables (142, 23.9%) (Fig. 11). Inspection of Fig. 11 confirms that most of the articles used variables related mainly to terrain morphology.

Variables describing morphology are obtained by processing terrain elevation data, typically in the form of a DEM, and have proven particularly effective in predicting the spatial distribution of landslides (Fabbri et al., 2003), or the lack of landslides (Marchesini et al., 2014). Fabbri et al. (2003), working in Portugal, showed that the performance of a susceptibility model constructed using elevation, aspect, and slope was significantly better than a model that used bedrock geology, surficial deposits and land use, and slightly better than a model that used (together) the morphometric and the geo-environmental variables. Although their result may have been conditioned by the local setting and the quality of the DEM and the geo-environmental information, it outlines the relevance of terrain morphology in predicting landslide susceptibility. Similarly, Marchesini et al. (2014) identified non-susceptible landslide areas in Italy and in the landmasses surrounding the Mediterranean Sea using only two morphometric variables: terrain slope and relative relief computed in different-sized windows. The classification proved accurate even in areas and with landslides not used to calibrate the non-susceptibility model.

Analysis of the literature database revealed that investigators prefer "simple" (direct) measures of terrain morphology, including elevation, relief, slope, aspect, and curvature. This is because these variables are simple to calculate in a modern GIS where a DEM is available. For some of the "simple" morphologic measures theoretical reasons exist that justify their use for susceptibility modelling. Terrain slope controls the balance of the retaining and the destabilizing forces acting on a slope (Taylor, 1948; Wu and Sidle, 1995), and a larger resistance is mobilized to maintain stable a steep slope than a gentle slope. Similarly, a concave slope concentrates surface runoff and subsurface groundwater flow, increasing slope instability. We note that terrain slope has proved to be the single most-effective geo-environmental variable used for susceptibility modelling (Carrara et al., 1991, 1995; Fabbri et al., 2003; Budimir et al., 2015), and for the definition of non-susceptible landslide areas (Marchesini et al., 2014). For other "simple" morphometric variables (e.g., aspect, elevation, curvature), their use is less justified, theoretically and empirically, and may be controlled by local conditions.

"Simple" morphometric variables may not be the best ("optimal") variables to capture the morphometric signature of landslides, and particularly of large and very large failures. Other metrics may prove to be the most effective, for example, the standard deviation of elevation or slope measures terrain roughness, which is expected to be larger in landslide areas than in stable areas (Pike, 1988; Carrara et al., 1991; García-Rodríguez et al., 2008; Lee et al., 2008; Peng et al., 2014). Complex variables capturing the overall morphology of an entire slope (e.g., full profile geometry of a slope) or sub-catchment are also good descriptors of landslide terrain (Carrara et al., 1991, 1995; Rowbotham and Dudycha, 1998; Lee and Min, 2001). Use of these more complex variables is less common in the literature, primarily because of the lack of specialized software and of ready-to-use tools in GIS environments capable of calculating these variables (Alvioli et al., 2016) — although existing GIS toolkits (e.g., ESRI© ARC-GIS©, GRASS, SAGA) can be programmed to calculate complex morphological and hydrological variables for susceptibility modelling. In addition, the relevance of some of the complex variables for susceptibility modelling may prove site- or region-specific, making it difficult to compare results obtained in different and distant areas.

Investigators have used different types of geological data for landslide susceptibility modelling. The most common geological information consists in the type of rock as shown in standard geological maps. However, the rationale for the use of this information is often not clear, as geological maps typically show the bedrock, with chronostratigraphic units and formations that may not have a relationship with the mechanical properties of the materials involved by landsliding.

Investigators have also used information on bedding attitude (Clerici et al., 2002; Ruff and Czurda, 2008), the presence of faults (mainly in tectonically active areas) (Gökceoglu and Aksoy, 1996; Saha et al., 2005; He and Beighley, 2008), and the local hydrogeological settings (Carrara et al., 1991; Neuhäuser and Terhorst, 2007). As an example, through the visual interpretation of aerial photographs and field surveys, Carrara et al. (1991) determined that the hydrogeological and structural settings were responsible for the location of landslides in the Tescio catchment, Umbria, central Italy. Using this evidence, they determined a set of bedding attitude classes (e.g., bedding dipping into or out of the slope at different angles), and of lithological combinations in the slope (e.g., permeable rocks overlaying impermeable sediments, impermeable sediments throughout the slope) that proved good predictors of the distribution of landslides.

A problem with structural and bedding data is that they are time consuming to collect, and difficult to interpolate spatially over large areas. To simplify the process, Santangelo et al. (2015b) have developed a strategy and specific software that exploits a DEM and bedding traces obtained by interpreting stereoscopic aerial photographs to

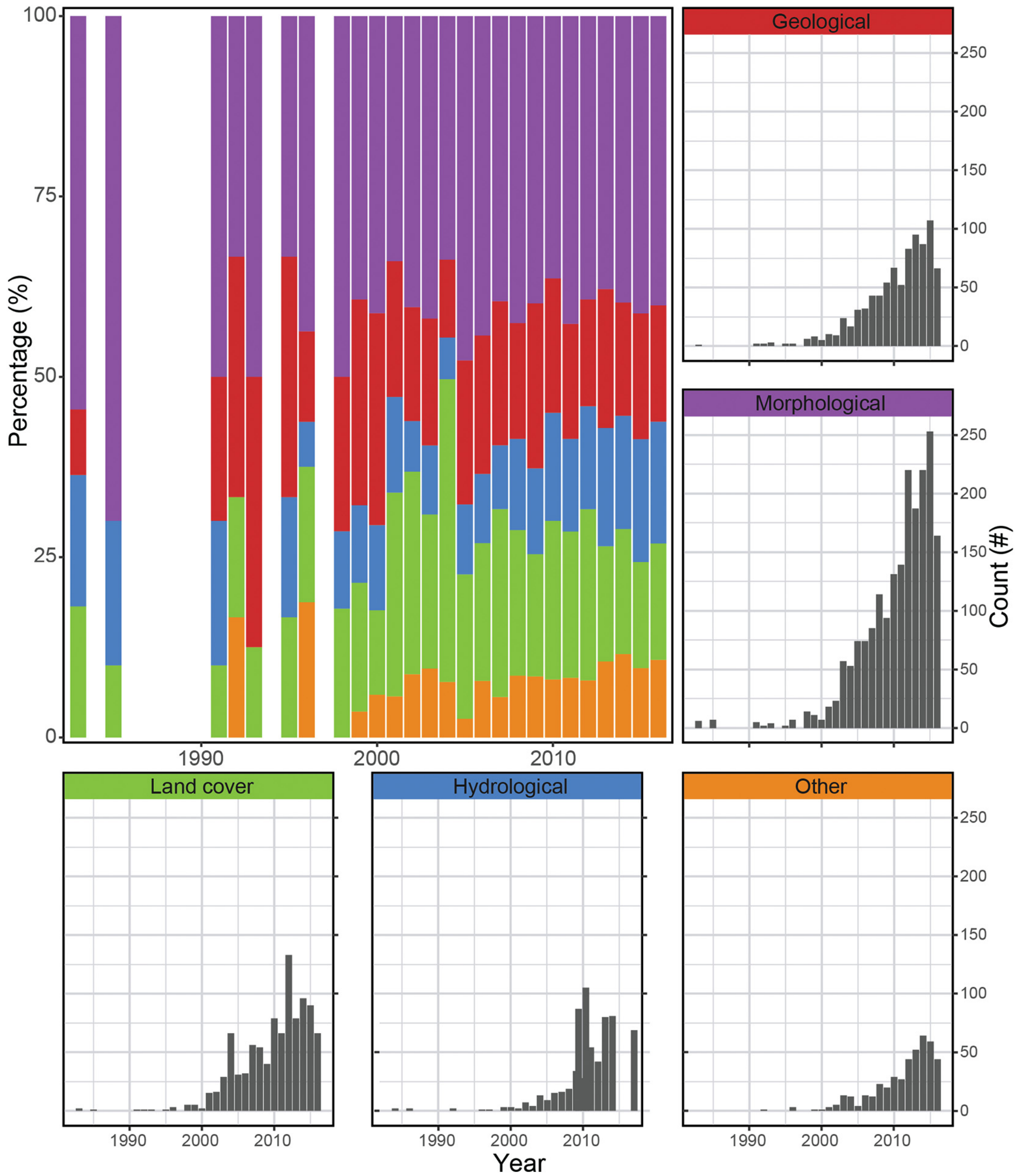

Fig. 11. Thematic variables. Stacked bar chart shows percentage of clusters of thematic variables used for susceptibility modelling, per year. Grey histograms show number of articles per year, per cluster of thematic variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

obtain spatially-distributed bedding attitude information, and morpho-structural terrain zonations that can be used for landslide investigations and for susceptibility modelling. The authors suggested that the strategy works well where layered rocks crop out with a simple structural setting, and was not tested in complex settings.

For land cover, the majority of the investigators have used combinations of vegetation, land cover, and land use data obtained from existing maps prepared through the visual interpretation of aerial photographs and, more recently, the automatic or semi-automatic processing of optical satellite imagery, at various scales (Lee et al., 2008; Mondini et al., 2011). In places, maps showing changes in the vegetation cover or land use were also used (Pontius Jr and Schneider, 2001; Glade, 2003; Pontius Jr and Hao, 2006; Reichenbach et al., 2014). The rationale behind the use of land cover information is that land cover conditions slope stability (e.g., through increased/decreased evapotranspiration and root strength). Specific land cover types are also indicative of the presence (or absence) of landslides, and of stable (or unstable) conditions. As an example, Carrara et al. (1991) showed that in the Tescio catchment (Umbria, central Italy), a land cover of "forest" was a good predictor of stable slopes and uncultivated areas of landslides. However, Carrara et al. (1995), who worked in the nearby Carpina catchment, also in Umbria, central Italy, found that forest was a good predictor of unstable slopes. This outlines the difficulty in understanding the functional links between landslides and land use or land cover types.

Investigators have also used variables measuring physical characteristics of the vegetation cover, including the Normalized Difference Vegetation Index (NDVI) or the Normalized Difference Moisture Index (NDMI). The main advantage of the NDVI, and of other similar indexes, is that they can be obtained rapidly and for very large areas processing optical satellite imagery. A problem is the lack of a clear (and unique) relationship linking the vegetation cover to slope stability/instability conditions, and their variations. Reichenbach et al. (2014), working in NE Sicily, showed that landslide susceptibility changed in their study area in the 56-year period 1954–2009 in response to land cover changes. Their analysis revealed a significant variation in the susceptibility zonation, with an overall reduced proportion of unstable terrain in 1954 than in 2009. This was justified by the smaller extent of bare soils, balanced by a larger extent of the forests in 1954, compared to 2009. The simulation of a larger extent of forests confirmed the association between forest and landslides in their study area.

Investigators have also used landslide information as an explanatory variable for susceptibility modelling. As an example, Carrara et al. (1995), working in the Carpina catchment (Umbria, central Italy) used the presence of large, very old deep-seated landslides as a predictor of more recent landslides. The rationale was that the very old landslides formed in a different climatic and seismic setting, and they altered the mechanical properties of the rocks where the more recent landslides occur. Samia et al. (2017a,b) described and quantified the effect of old landslides on more recent failures, introducing the concept of landslides path dependency and legacy. In their study area, this effect is relevant and significant over a timescale of about a decade.

A number of investigators have used explanatory variables obtained from simple cartographic operations on geo-environmental and other data. The most popular are distances to linear features such as faults, rivers, and roads, which are calculated using basic spatial operations in a GIS environment (e.g., buffer, proximity, density). A problem with the use of "distance" variables is that their geomorphological or geological significance and their relevance to explain the distribution of landslides in an area is often unclear, misleading, or missing entirely.

Distance to faults is one of the common distance variable used in susceptibility modelling (Binaghi et al., 1998; Süzen and Doyuran, 2004). The measure is relevant for modelling if one knows the size (width) of the fault-zone, and that the rock mechanical and hydrological properties in the fault zone are different (poorer or better) than in the surrounding non-faulted rocks, and this has conditioned landslide susceptibility. However, this detailed information is seldom available. In addition, a fault zone and the terrain surrounding the fault are known to respond differently to an earthquake, and not all the faults respond equally to a seismic trigger, even in the same fault system. This challenges the motivation for using fault-related information for landslide susceptibility modelling.

Distance to rivers is another variable used for susceptibility modelling (Weirich and Blesius, 2007; Kıncal et al., 2009). The rationale is that this distance captures relevant hydrogeological conditions that are less favourable to slope stability towards the bottom of a slope due to the concentration of the groundwater flow, and the destabilizing effect of river incision that favours slope instability. We note that these effects are relevant mainly to hydrologically-controlled landslides, and not for seismically-triggered slope failures. When using distance to rivers, the distance should be limited within the slope where the instabilities can occur (there is no meaning in measuring the distance to a river across a divide), and the metric should be paired to the distance to the divide, an option seldom pursued in the literature.

The least justified distance often used for landslide susceptibility modelling is the distance to a road (Bai et al., 2010; Lepore et al., 2012). Unless one is interested in determining the effects of roads on the local or regional stability (Petley et al., 2005; Sidle et al., 2010) or ecological (Forman and Alexander, 1998) conditions, the rationale for considering the presence of a road is limited. We note that the presence of a road on a natural slope has different effects on the slope above and below the road. This difference is not captured by the distance metrics commonly used in susceptibility modelling.

For landslide susceptibility modelling, a key difference exists between the morphometric (e.g., terrain slope) and the other geo-environmental (e.g., geological, land cover) variables, and their derivatives. Morphometric variables are more "general", and simpler to compare than the geo-environmental variables. Despite differences in the way that even the simplest morphometric variables (i.e., slope) are calculated (Warren et al., 2004), and their dependence on the quality and resolution of the DEM (Tarolli, 2014), the morphometric metrics, and their role for susceptibility modelling, are straightforward to compare in different and distant regions. This is typically not the case for the geo-environmental variables. Wechsler (2007) and Wechsler and Kroll (2006) have recognized uncertainty and errors associated to DEMs and their propagation into derivative terrain variables, and have given recommendations to overcome the problem, which is particularly relevant where the morphometric variables are derived from a DEM acquired after the occurrence of the slope failures.

When using geological (lithological, structural, bedding attitude) data, investigators use the geological units/formations shown in lithological or geological maps. These are often identified using their regional or local names and characteristics, making it difficult (or impossible) to compare in different and distant areas. The problem can be addressed by reclassifying the rock classes using physical characteristics of the rocks (e.g., the mechanical properties), or a qualitative ranking describing, for example, the relative strength/weakness of a rock type compared to other rock types. This will facilitate the comparison of susceptibility models, and their application outside the area where they were constructed and calibrated. It will also contribute to understanding what are the relevant geological factors most important (i.e., "best suited") to explain the distribution of past and future landslides.

Analysis of the literature database revealed that investigators have used primarily the geo-environmental information that was available to them, and which was not necessarily the best (i.e., "optimal", "more relevant") information necessary for landslide susceptibility modelling in a specific area or region. This might be because information such as the scale, information content, or thematic accuracy were not adequate. Only a few authors have discussed convincingly the geomorphological significance, and the relevance of the single geo-environmental variables in explaining the stability/instability conditions of the slopes. This is a problem, as the quality of a statistically-based susceptibility model depends on the quality and relevance of the geo-environmental information used to construct it.

We recommend that investigators spend more time and resources to collect geo-environmental information relevant for landslide susceptibility modelling, and that they discuss the known or inferred role of the different geo-environmental variables in determining landslide susceptibility (Guzzetti et al., 1999). We further recommend that the environmental information is representative of the conditions existing before the landslide occurrence i.e., of the geo-environmental conditions that affected the local slope stability conditions that have resulted in the landslides. Changes in the values, classes, and distribution of the geo-environmental conditions (e.g., land use/land cover, surface morphology, hydrology) have consequences on landslide susceptibility zonation.

A related problem is that for their susceptibility assessments investigators have used geo-environmental information at a broad range of scales, from very large (1:5000) (Lee and Min, 2001; Pellicani et al., 2014) to synoptic (1:1,000,000) (Günther et al., 2013; Ahmed et al., 2014) scales. The problem is most severe in developing countries where geological information is available only at small scale (e.g., 1:100,000 to 1:250,000 scale, or smaller). We were expecting a dependency between the size of the investigated area and the scale of the landslide and the geo-environmental information used for the modelling. Such dependency did not emerge from our literature analysis. Instead, we found that investigators have used landslide and geo-environmental information captured at different (in cases very different) cartographic scales even for the same study area (Dhakal et al., 1999; Lee, 2007; Kavzoglu et al., 2015).

In general, little (or no) consideration is given to the geographic and thematic consistency of the different geo-environmental data. However, lack of geographic consistency may introduce serious biases (and errors) in the susceptibility models. In principle, the landslide and the geo-environmental information should be captured at the same (or similar) scale and using the same cartographic base maps (Santangelo et al., 2015a). Operationally, this is rarely possible, and landslide and the geo-environmental data are captured at different scales, using different base maps, and different mapping methods. This contributes to increasing the epistemic uncertainty of the susceptibility models.

Further, the geo-environmental information may not have been collected for the specific purpose of ascertaining landslide susceptibility. This is a problem, because the maps may show information, which is thematically correct, but not relevant for susceptibility modelling. This is the case of geological maps that show chronostratigraphic units and formations that may not have a direct relationship with the mechanical properties of the rocks that control the local stability/instability conditions. In this case, a lithological map may prove more effective than a more complex geological map in determining landslide susceptibility.

We recommend that a careful analysis of the available geo-environmental information is performed prior to its use for susceptibility modelling, considering the relevance (or lack of relevance) of the variables. In case the analysis reveals that the available geo-environmental information is partly, or not relevant, then the information should be discarded and investments made to collect new, relevant geo-environmental information. We expect that this will result in better and more reliable susceptibility models and zonations.

In 1999, Guzzetti et al. (1999) wrote: “Identification and mapping of a suitable set of instability factors (thematic mapping) bearing a relationship with slope failures – such as surface and bedrock lithology and structure, bedding attitude, seismicity, slope steepness and morphology, stream evolution, groundwater conditions, climate, vegetation cover, land-use and human activity (Carrara et al., 1995; Hutchinson, 1995) – require an a priori knowledge of the main causes of landsliding (Schuster and Krizek, 1978; Crozier, 1989)”. Almost 20 years later, and after hundreds of landslide susceptibility assessments, the situation has not changed, and investigators seem more interested in experimenting new modelling techniques – that may not be too different from existing techniques, and thus are not expected to produce different results – rather than concentrating on the acquisition of good quality landslide and geo-environmental data significant for landslide susceptibility modelling.

We expect that new and emerging mapping methods and techniques based on remotely sensed information captured by airborne and satellite sensors will contribute to solve the long-lasting problem of the availability of geo-environmental information relevant for landslide susceptibility modelling. The increasing availability of HR DEM (Tarolli, 2014), coupled with the known ability of DEM derivatives to contribute to detect and classify stable and unstable slopes (Pike, 1988; Carrara et al., 1991; Fabbri et al., 2003; Haneberg et al., 2009; Chen et al., 2013; Marchesini et al., 2014) will foster the production of susceptibility assessments at different scales. Analysis of the literature database revealed that the resolution of DEM used for susceptibility modelling has increased significantly since the turn of the century, with the majority of the articles using DEMs with ground resolution better than 25 m × 25 m. The increasing availability of repeated HR DEM can also prove relevant to describe and compare morphometric variables before and after landslide events. We expect this to improve landslide susceptibility modelling.

The increasing availability of VHR elevation data obtained by airborne LiDAR sensors, and by future satellite laser altimeters (e.g., NASA's ATLAS — Advanced Topographic Laser Altimeter System), will contribute significantly to the visual and the automatic or semi-automatic detection of landslides (Ardizzone et al., 2007; Guzzetti et al., 2012; Van Den Eeckhaut et al., 2012a,b), and to the production of improved elevation data useful for susceptibility assessments. The combined landslide and elevation information will foster the production of more reliable landslide susceptibility models. DEM with ground resolution better than 30 m × 30 m are already available for very large geographical areas (e.g., the U.S. Geological Survey 3D Elevation Program (3DEP) at 1/3-arc-second (10 m × 10 m) for the conterminous USA, and at 1/9-arc-second (3 m × 3 m) for parts of the USA; the European EU-DEM — digital elevation model over Europe, at 1-arc-second, 30 m × 30 m), and globally (e.g., the NASA's SRTM 1 arc-second global elevation data with an almost global coverage at approximately 30 m × 30 m resolution at the equator, and the most recent JAXA's ALOS Global Digital Surface Model, with a similar 30 m × 30 m nominal resolution). We expect that these continental to global elevation data sets will play a significant role in the production of small-scale landslide susceptibility assessments.

We further expect that multi-spectral satellite images captured by the medium-resolution sensors on board the NASA's Landsat satellites and the similar ESA's Sentinel-2 satellites will allow for the production of maps showing land coverage and land use, and their seasonal and long-term variations driven by global/regional climate, environmental and socio-economic changes. This thematic information will also prove useful for regional to global scale landslide susceptibility assessments, and for their temporal variations. We expect that the satellite imagery will be less useful to improve the existing geological (i.e., lithological, structural, bedding) information required for landslide susceptibility modelling and that obtaining geological (i.e., lithological, structural and bedding attitude) information relevant to landslide susceptibility modelling will remain a challenge.

4.5. Mapping units

Selection of a mapping unit is a fundamental step of any landslide susceptibility modelling that affects significantly the susceptibility terrain zonation (Guzzetti et al., 1999). A description of the advantages and the drawbacks of the different mapping units can be found in Guzzetti (2006). Here, we limit the discussion to the types of the mapping units most commonly found in the literature. Our review revealed that by far the most common type of mapping unit are grid-cells (i.e., “pixels”, 86.4%), with all other types being valuable alternatives to grid cells but occurring much less frequently, including slope units (5.1%), unique conditions units (4.6%), and other types or combinations of the above three types (3.9%) (Fig. 12).

Grid-cells are very popular among landslide susceptibility investigators, and their popularity is because they are simple to process, at all resolutions and geographical scales. Modern GIS can treat effectively grid-based data, can readily transform vector information shown as polygons, lines and points into a corresponding grid-based (raster) representation, and have many functions to handle raster data. Terrain

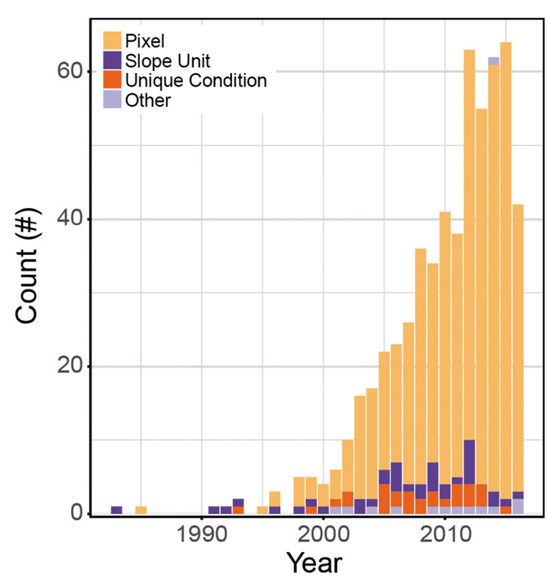

Fig. 12. Mapping unit types. Stacked chart shows the number of articles in the literature database per mapping unit type, in four classes, per year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

elevation data, a main source of information for susceptibility modelling, are commonly prepared and distributed in raster format, and GIS have specific functions to treat elevation data and to compute derivative maps useful for susceptibility modelling. Modern computers have overcome previous hardware (memory and storage) limitations that hampered the use of grid-cells over very large areas (Carrara et al., 1999). A few authors have investigated the effects of the pixel resolution on the accuracy of the susceptibility model outcomes (Claessens et al., 2005; Paulin et al., 2010; Palamakumbure et al., 2015), and others have evaluated and tested different landslide sampling strategies in a grid-based statistical susceptibility model (Nefeslioglu et al., 2008; Yilmaz, 2010; Hussin et al., 2015). Despite their popularity and operational advantages, grid-cells have clear drawbacks for susceptibility modelling (Guzzetti et al., 1999).

First, there is no physical relationship between a grid-cell, or a group of grid-cells, and landslides. Landslides are the result of slope processes acting at different spatial and temporal scales that result in geomorphological forms of very different shapes and sizes (Malamud et al., 2004; Guzzetti et al., 2012) that are difficult to capture by grid-cells accurately. The geometry of a landslide is better represented by a polygon or a set of polygons in vector format; unless the size of the grid-cell is very small compared to the size of the landslide.

Second, analysis of the literature database revealed that the majority of the models that adopted grid-cells as the mapping unit (79.5%) used cells of the same size (resolution) of the DEM, and that only 20.5% used different resolutions for the mapping unit and the DEM. Use of the same resolution for the landslide and the geo-environmental information (including the DEM) has clear practical advantages, but may introduce biases or lead to potentially misleading results. As an example, small grid-cells (5 m × 5 m, or less) allows to capture in great detail the morphometric signature (Pike, 1988) of small, shallow landslides (Tarolli and Tarboton, 2006; Passalacqua et al., 2010), but may have little, or no physical, geological or geomorphological significance for large, deep-seated landslides whose morphology is better captured by a coarser resolution DEM (Pike, 1988). When assessing the susceptibility to large and very large landslides, investigators should consider resampling a VHR DEM to a coarser resolution that may better capture the morphologic signature of the large landslides.

Third, use of grid-cells poses potential problems for statistical modelling. Typically, landslides cover a minor portion of a landscape, and where landslides are very abundant and cover the major part of a landscape there is little scope for a susceptibility zonation. As a result, in susceptibility modelling the number of non-landslide ("stable") cells is typically larger, or much larger, than the number of landslide ("unstable") cells. This may result in a sampling bias that can affect the classification models. The problem is exacerbated if the size of the grid-cells is small, or very small. Investigators have attempted to address the problem performing a random selection of sets with a (nearly) equal number of landslide and non-landslide cells (Petschko et al., 2014). The strategy may prove acceptable if multiple random selections are performed to evaluate the effects of the sampling, and to investigate the natural variability and the uncertainty introduced by the sampling. However, this is seldom performed in the literature (Hussin et al., 2015). Typically, when using grid-cells the spatial auto-correlation (or the lack of auto-correlation) of the single variables (e.g., slope), or of multiple geo-environmental variables, is not considered. This also may introduce errors in the susceptibility modelling.

Investigators have proposed to use a single "representative" grid-cell to characterise an entire landslide, with the "representative" cell located typically in the landslide crown area (Qi et al., 2010; Gorum et al., 2011; Xu et al., 2014). The approach has a number of limitations, including the fact that the geo-environmental conditions in the landslide source area, or in the immediately surrounding areas, may not be indicative of the real conditions that have caused the slope failure. The drawback is particularly significant for large and complex mass movements for which the source area typically exhibits terrain conditions different from the deposit.

Fourth, and lastly, use of grid-cells invariably results in susceptibility zonations that are difficult to use operationally. A single grid-cell predicted stable by a model might be surrounded by grid-cells predicted as unstable, or vice-versa. These results are difficult to interpret and may jeopardize the practical use of the zonation. Authors have addressed the problem performing a "post-processing" of the modelling results, detecting and where necessary changing results that are unrealistic, or difficult to interpret. These attempts are based on a set of rules defined heuristically. Once clear rules are defined to modify the original zonation, the approach is simple to implement in a GIS. However, the approach introduces subjectivity in the final modelling zonation (which may not be desirable), and makes the model more difficult to verify, objectively.

Where grid-cells are selected as the mapping unit for susceptibility modelling, we recommend that: (i) the size of the grid-cell – which may differ from the resolution of the DEM, depending on the landslide type, the resolution of the DEM and of the other geo-environmental information – is selected considering the characteristics and prevalent size of the landslides, and the scale and the cartographic and thematic accuracy of the geo-environmental information, including the DEM, (ii) a proper sampling strategy is adopted (e.g., jackknife bootstrap, Efron, 1979; Efron and Stein, 1981) to limit problems related to the use of a single random draw, and to measure the associated model variability and uncertainty, and (iii) rules for the post-processing, where required, are clear and unambiguous, and defined adopting objective criteria.

Unique condition units (Bonham-Carter, 1994; Chung et al., 1995; van Westen et al., 1997; Chung and Fabbri, 1999) are obtained by intersecting all the geo-environmental layers considered important for susceptibility modelling; an operation simple to perform in a GIS on both vector (Carrara et al., 1995) and raster (Chung et al., 1995) data. In the literature, unique condition units were introduced in 1993 (Maharaj, 1993), and were used primarily by investigators that adopted Bayesian approaches for landslide susceptibility modelling (Chung et al., 1995; van Westen et al., 1997; Chung and Fabbri, 1999). The main advantage of unique condition units lays in the simplicity with which they are obtained in a GIS, and in the fact that they reduce (partially) some of the conceptual and operational problems of grid-cells. However, unique condition units have at least three main, potentially severe problems.

First, geo-environmental factors represented by continuous variables (e.g., elevation, terrain slope, aspect, curvature) must be classified using a small number of classes, as the use of a large number of classes results in many units of very small size; an undesirable condition (Carrara et al., 1995; Guzzetti, 2006). However, selection of the classes is problematic, heuristic, and seldom based on local knowledge of the physical processes controlling the landslides. Fabbri et al. (2003) investigated the problem and found that the selection of the number of classes used to categorize continuous geo-environmental information was not particularly significant for their data sets. Despite this result, a heuristic selection of the number and the limits of the thematic classes conditions the size and number of the terrain units. This affects the statistical analysis and introduces uncertainty in the model.

Second, when dealing with vector data, the geometric overlay in a GIS of multiple thematic layers, or of layers containing many small polygons (e.g., a land use map), easily results in a very large number (hundreds of thousands) of terrain units, making it difficult to analyse the results (Carrara et al., 1995). A large number of terrain units reduces the size of the units, and their representativeness for landslide susceptibility. As for single grid-cells or a few grid-cells, a unique condition unit represented by a very small polygon, may have little (or no) significance for large, deep-seated landslides.

Third, intersection of geo-environmental layers affected by even minor digitization errors results in small terrain units whose significance is difficult to interpret, for example, a mismatch between a landslide boundary and the river network (a common problem in landslide mapping). A very small polygon, or a single grid-cell may reflect unique (exclusive) geo-environmental conditions important to determine landslide susceptibility, or it may be the result of a cartographic or mapping error, and therefore irrelevant to landslide susceptibility (Guzzetti, 2006).

An alternative to grid-cells and unique condition units are slope units, which are hydrological terrain units bounded by drainage and divide lines (Carrara, 1983; Carrara et al., 1991, 1995; Guzzetti et al., 1999), and corresponds to what a geomorphologist would recognize as a slope. Since landslides occur primarily on slopes, slope units are – at least in principle – particularly well suited for landslide susceptibility modelling (Carrara et al., 1991, 1995; Guzzetti, 2006). Depending on the landslide type (e.g., deep-seated vs. shallow, slides vs. debris flows), a slope unit may correspond to an individual slope, an ensemble of adjacent slopes, or a small catchment.

The size of the slope units can be tailored to the type and size of the landslides, allowing for using the geo-environmental information best suited for the specific landslide type. This is particularly relevant for the morphometric variables. Descriptive statistics (e.g., mean, range, standard deviation) of elevation and slope in a slope unit are better predictors of the presence (or absence) of landslides than the same indices computed for the single DEM cells (Carrara et al., 1991; Alvioli et al., 2016). Variables describing the overall geometry of a slope (represented by a slope unit) are also good predictors of the presence (or absence) of landslides, for example, a straight, concave, convex, complex slope. Lastly, slope units allow for using very detailed DEM and their derivatives, which can provide important statistics to describe the finer morphometric signature of large, deep-seated landslides. Novel approaches propose to consider and integrate in landslide susceptibility evaluation the spatial dependence and influence of variables exploiting probabilistic frameworks based on Poisson point processes (Lombardo et al., 2018).

Despite their conceptual and operational advantage over grid-cells and unique condition units, and the fact that they are simple to recognize in the field and in topographic maps making them easy to use for practical applications, only a few authors have used slope units for susceptibility modelling (Carrara et al., 1991, 1995; Guzzetti et al., 1999, 2004, 2005; Anbalagan, 1992; Saito et al., 2009; Yu et al., 2016). The reason is that slope units are difficult to obtain manually, particularly for large areas. The process is time consuming and error prone, and specific software is required for their effective automatic delineation from DEMs (e.g., Carrara, 1983; Fairfield and Laymarie, 1991; Alvioli et al., 2016).

Until recently, software for the automatic delineation of slope units specifically designed for landslide susceptibility modelling was not available freely. Alvioli et al. (2016) have recently developed specific, open-source software for the GRASS GIS (Neteler and Mitasova, 2007) for the automatic delineation of slope units, given a DEM and a set of user-defined input parameters. They have also proposed an approach to determine an optimal slope-unit-based terrain subdivision best suited for landslide susceptibility modelling. The approach first calculates a number of different terrain subdivisions using slope units of different sizes, based on a reduced set of user-defined input parameters. Second, the quality of the terrain subdivision is assessed using terrain aspect and a specific objective function. Third, landslide susceptibility zonations are prepared using any standard statistically-based modelling approach (e.g., logistic regression) for each of the different terrain subdivisions, and the quality of the resulting models is evaluated using standard metrics. Fourth, the objective functions of terrain aspect and susceptibility modelling are optimized jointly to obtain an "optimal" set of parameters for the delineation of a set of slope-units best suited for susceptibility modelling in the specific study area. The approach is computer intensive but addresses two major limitations inherent to the use of slope units: (i) their automatic production from a DEM, and (ii) the conceptual difficulty in tailoring the size of the slope units to the known distribution of landslides (Alvioli et al., 2016). We expect this and similar software to foster the exploitation of slope units for landslide susceptibility modelling at different scales.

An additional limitation of slope units is that in specific areas or conditions, drainage and divide lines may not correspond to geomorphological or geological subdivisions important for landslide susceptibility. This problem is (partially) solved by further partitioning the slope units using the main lithological types considered important to separate dissimilar susceptibility conditions within the same slope (Ardizzone et al., 2007; Cardinali et al., 2002). This can be easily obtained in a GIS by intersecting a slope unit subdivision with a simplified lithological map, obtaining a geo-hydrological subdivision that maintains all the information typical of a division based solely on drainage and divides lines (i.e., the morphological and hydrological factors), and limits the problem of having in the same slope two or more rock types of different landslide propensity.

In conclusion, we recommend that great care is taken in the selection of the most appropriate mapping unit, considering: (i) the scale, type, and quality of the landslide and the geo-environmental information, including the DEM, (ii) the type, size, and characteristics of the landslides in the study area, (iii) the statistical modelling approach selected to ascertain landslide susceptibility, and (iv) the scope of the susceptibility assessment (Guzzetti, 2006). When selecting a mapping unit, an investigator should have clear all the consequences (i.e., the advantages and the limitations) of the selection.

4.6. Model types

Statistically-based landslide susceptibility models are constructed to describe the functional (statistical) relationship between instability factors, described by sets of geo-environmental (independent) variables, and the known distribution of landslides, taken as the dependent model variable. The functional relationship is then used to ascertain the propensity of the terrain to generate landslides, and to predict susceptibility (Carrara, 1983; Chung and Fabbri, 1999, Chung and Fabbri, 2003; Guzzetti et al., 2006a,b; Rossi et al., 2010).

In the literature, the majority of the models employs one of several possible classification methods that can be clustered into six main groups, namely: (i) classical statistics (e.g., logistic regression, discriminant analysis, linear regression), (ii) index-based (e.g., weight-of-evidence, heuristic analysis), (iii) machine learning (e.g., fuzzy logic systems, support vector machines, forest trees), (iv) neural networks, (v) multi criteria decision analysis, and (vi) other statistics. A description of the mathematical/statistical properties and the peculiarities of the different classification methods, and of their advantages and limitations for the specific task of landslide susceptibility modelling, is beyond the scope of this work. Details can be found in other sources, including Michie et al. (1994), Chung and Fabbri (1999), Aleotti and Chowdhury (1999), Wang et al. (2005), Chacón et al. (2006), Guzzetti et al. (2006a), Guzzetti (2006), Melchiorre et al. (2008), van Westen et al. (2008), and Kanungo et al. (2009). Here, we focus on general considerations based on previous literature review papers, the information collected in our literature database, and our own experience in preparing landslide susceptibility models in different physiographical and environmental settings.

Analysis of the literature revealed that investigators have used 163 different classification methods. This very large, and probably disproportionate number of methods compared to the number of susceptibility articles (565), highlights a largely unjustified and excessive interest in experimenting different statistical methods, rather than focusing on the relevant task of obtaining reliable susceptibility assessments and zonations for the scope of the investigation (e.g., land planning, early warning). The excessive number of methods also complicates the comparison of the susceptibility models and of the associated zonations.

Despite uncertainty in deciding precisely the type of models described in some of the articles, primarily due to the lack of sufficient

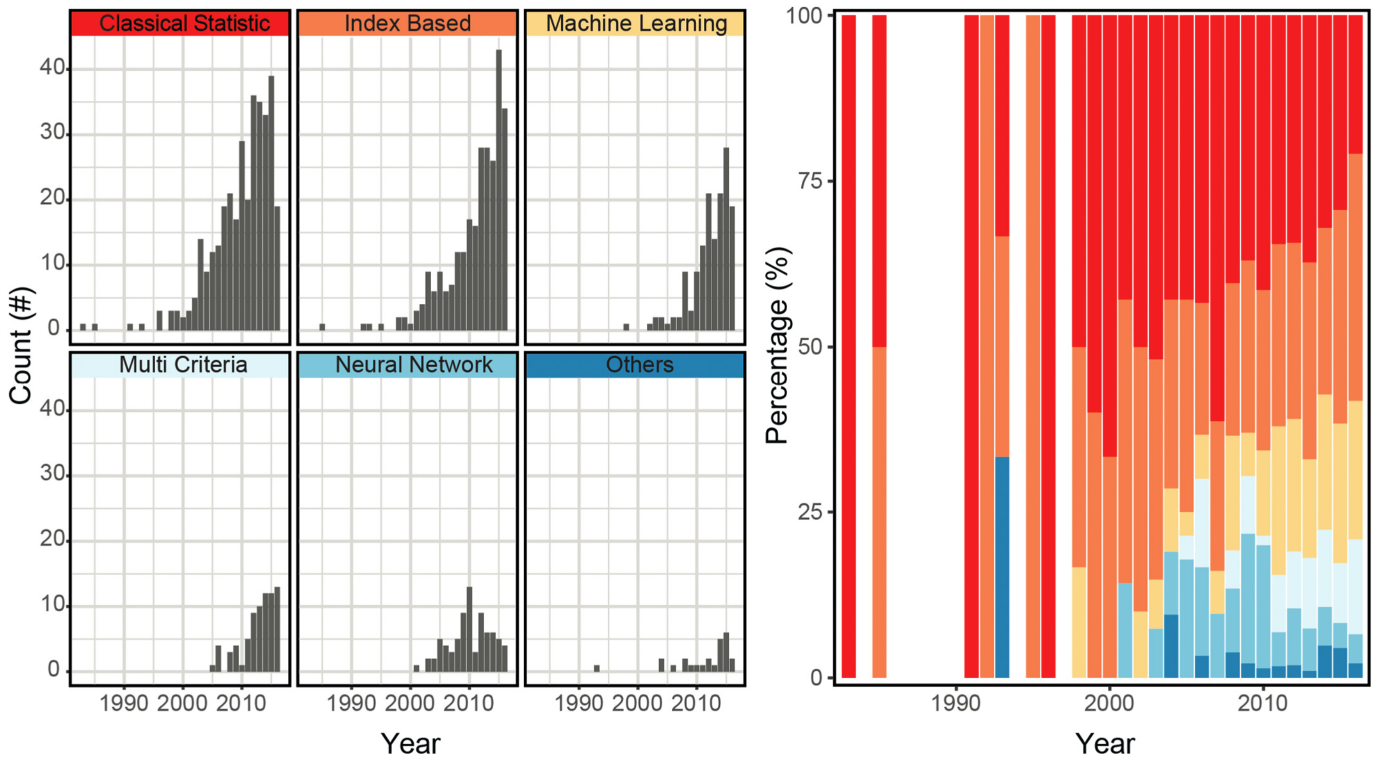

Fig. 13. Susceptibility model types. Grey histograms show number of articles in the literature database per cluster of model type, per year. Stacked bar chart shows percentage of the six cluster of model types, per year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

information, the 163 classification methods (model type names as given by the authors) can be broadly grouped into 19 model classes, pertaining to the six main groups of classification techniques listed above (Fig. 13). Classical statistics methods (36.5%) were preferred over other approaches, as index-based (28.9%), machine learning (15.8%), neural networks (8.3%), multi-criteria decision analysis (7.9%), and other statistical analyses (2.7%). Considering the model types, logistic regression (18.5%) was the preferred one, followed by data overlay (10.7%), neural networks (8.3%), index-based approaches (8.2%), and multi-criteria decision analysis (7.9%). These five model types account for > 50% of all the examined susceptibility assessments.

Analysis of the literature database revealed an increase with time of the number of model types that were used in each study. Before 1995, only five model types had been tested, whereas in the recent period 2009–2016 investigators have used the 19 model types shown in Fig. 14. Besides the clear interest in experimenting with new classification methods mentioned before, this is largely a result of the increased availability of a wide range of classification tools in open source (e.g., R, R Core Team 2016) and commercial (e.g., SPSS©, MATLAB©, SAS©) data analysis software packages, combined with the ability of the data analysis packages to interoperate with modern open source (e.g., GRASS, SAGA) and commercial (e.g., ESRI© ARC-GIS©) GIS software (Goodchild, 2010).

Interoperability of GIS and data analysis packages produced a positive effect, giving to non-experts (e.g., non-statisticians) the possibility to elaborate complex, spatially-distributed, geo-environmental information, facilitating the preparation of statistically-based landslide susceptibility models and zonations. However, we note that the ease of use of the modern software packages has decreased the user awareness on the general and specific requirements of the selected classification methods, and the perception of the significance of the results, which may be statistically erroneous or geomorphologically unrealistic. We stress that the use of more complex classification methods – a trend observed in the literature in the recent years (Fig. 13) – does not guarantee better susceptibility models and sound terrain zonations, necessarily. Rather, the opposite is true; the use of complex modelling techniques requires a full understanding of the model constrains, not all of which may be obvious to a non-expert user.

We recommend that great care is taken in selecting and using appropriate classification model types for landslide susceptibility assessment.

Analysis of the literature database further revealed geographical and team biases in the selection of the most appropriate model type for susceptibility assessments. As an example, investigators have preferred index-based analysis in India (16 times, 19.7% of all susceptibility models in India), and logistic regression in Turkey (23, 24.7%), in the Republic of Korea (20, 23.8%), in China (22, 19.5%), and in Italy (20, 21.3%) (Fig. 14). There is no statistical, geomorphological or operational justification for these biases, except that single teams of investigators favour modelling tools that they have already used and/or they know how to operate. There is nothing wrong with this, and we encourage investigators to use the modelling tools they are familiar with. However, the geographical and team biases complicate further the possibility to compare susceptibility models prepared by different investigators in different areas.

Of all the considered susceptibility assessments presented in the 565 examined articles, the majority (339, 60.0%) presented a single model type, and the others (226, 40.0%) considered two (134, 23.7%) or more (92, 16.3%) model types. Of the later, the vast majority compared the different models, and only a small fraction of the works proposed combined (i.e., "optimal", Rossi et al., 2010) susceptibility assessments. This is surprising, for at least two reasons. First, where different models for the same area differ in their local or general assessment of landslide susceptibility (a very probable condition, based on our experience), the differences measure the uncertainty inherent to the susceptibility assessment (Rossi et al., 2010), combining aleatory and epistemic uncertainties; an issue worth investigating. Second, where susceptibility zonations are prepared for land planning, early warning or other practical applications, availability of two or more models with local or general differences limits their possible application (Huabin et al.,

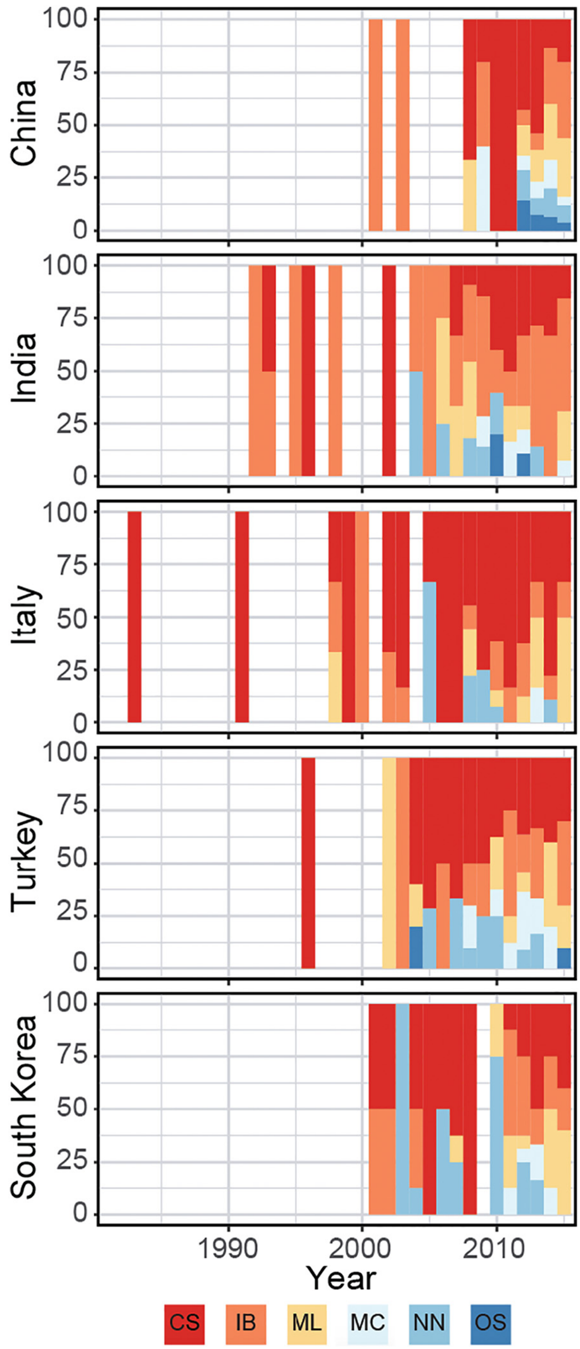

Fig. 14. Susceptibility model types. For China, India, Italy Turkey and South Korea, five countries with close to, or > 50 study areas per country in the literature database, the stacked bar charts show the percentage of clusters of model types, per year. Legend: CS, classical statistics; IB, index-based; ML, machine learning; MC, multi-criteria; NN, neural network; OS, other statistics. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2005; Chacón et al., 2006). In these cases, and for practical applications, a single "optimal" model is preferred by the end-users.

We recommend using multiple model types to ascertain landslide susceptibility, and to combine the different model outcomes into "optimal" susceptibility zonations (Rossi et al., 2010). We expect that this will reduce the model errors and will foster the reliability (and credibility) of the resulting terrain zonations.

Parametric (e.g., cluster analysis, principal component analysis) and non-parametric statistical techniques, and associated tests, can also be used to analyse the information content of large sets of geo-environmental variables. These techniques and associated tests help to recognize collinearity among the variables, and to identify those variables most relevant for susceptibility modelling, contributing to reduce the number of the explanatory variables used in a susceptibility assessment (Neuland 1976; Carrara, 1983; Carrara et al., 1999; Son et al., 2016; Torizin, 2016; Yu et al., 2016).

We recommend performing parametric and non-parametric statistical tests systematically prior to, and as part of any sound statistically-based susceptibility modelling effort. We expect that this will contribute to the overall quality of the susceptibility assessment.

Statistically-based approaches can also be used to zone a territory for further physically-based susceptibility modelling. As an example, Frattini et al. (2008), working in the Fassa Valley (Trentino, northern Italy), used a stepwise discriminant analysis applied to 23 morphometric, lithological, structural, and land-cover variables, to classify the source areas of rock falls as active or inactive. The group membership probability of the active and inactive rock fall source areas was then used as the probability of rock fall triggering occurrence in their HY-STONE, physically-based rock fall numerical simulation model (Agliardi and Crosta, 2003).

4.7. Model performance evaluation

Different metrics and indices can be used to evaluate the performance of a susceptibility model and associated zonation (Guzzetti et al., 2006a,b; Melchiorre et al., 2006; Frattini et al., 2010; Rossi et al., 2010). Regardless of the metrics or indices used, an important difference exists between the evaluation of the model fit and of the model prediction performance. The former (evaluation of model fit) measures the ability of the classification model to describe ("match") the known distribution of landslides, and it is obtained comparing the model outcomes against the same landslide information used to train (calibrate) the model. The latter (evaluation of the model prediction performance) measures the ability of the susceptibility model to predict other landslides and is obtained comparing the model outcomes against independent landslide information not used to construct the model. Evaluation of the model prediction performance is a measure of the predictive power of a susceptibility model (Chung and Fabbri, 1999, 2006; Guzzetti et al., 2006a,b; Frattini et al., 2010; Rossi et al., 2010), and it is more difficult to obtain than the evaluation of the model fit. Ideally, the independent landslide information should not be available to the investigators when a susceptibility model is calibrated. To the best of our knowledge, this is never the case, hampering the evaluation of the long-term prediction performance of the susceptibility models, and the associated terrain zonations. Evaluation of the model prediction performance is entirely equivalent to model validation. However, in the literature the term "validation" is also (erroneously) used to refer to the model skill evaluation. To avoid any confusion, we do not use the term validation here.

Analysis of the literature database reveals that 68.0% of the articles (384 out of 565) used one or more metrics to evaluate the model fit, with 29.7% (168) using more than one metrics, and that 61.1% of the articles (345) used one or more metrics for the evaluation of the model prediction performance, with 18.6% (105) using more than one metrics. Conversely, 32.0% of the articles (181) did not measure the model fit, and 38.9% (220) did not measure the prediction performance of the model, including 16.3% of the articles (92) that did not measure the model fit, and 23.0% of the articles (130) did not measure the model prediction performance in the recent period 2010–2016.

We note that the number of susceptibility models without any measure of their performances (model fit and prediction performance) remains high, and we recommend not publishing susceptibility assessments without any evaluation of the model performances.

Early investigators favoured simple measures of the model performances, including contingency tables ("confusion matrices") (Neuland, 1976; Carrara, 1983) and density/frequency measures (Carrara et al., 1991; Maharaj, 1993; Atkinson and Massari, 1998; Binaghi et al., 1998). Only after the year 2000, success/prediction rate (Chung and Fabbri, 1999, 2006) curves, and Receiver Operating Characteristic (ROC) curves, Ayalew and Yamagishi, 2005) have become popular, together with related indexes (Van Den Eeckhaut et al., 2006; Frattini et al., 2010; Rossi et al., 2010). Analysis of the literature database further revealed an increase in the number and in the complexity of the metrics used to measure the model performances (model skill and prediction performance). Overall, our review identified at least 92 different (unique) metrics, with the number of different metrics per year increasing significantly, particularly after the year 2000. Investigators have also increased the number of individual metrics used to evaluate a susceptibility model (Chen et al., 2016).

We consider it a positive outcome that the different metric types per year for model performance evaluation has increased with time, and we recommend using multiple metrics to evaluate the performances of any susceptibility model and zonation.

A discussion of the different model evaluation metrics and indices, and of their specific advantages and limitations, is not within the scope of this work. Detailed descriptions of the indexes, and discussions of their use and misuse can be found in a number of sources, including Chung and Fabbri (1999, 2003, 2006), Remondo et al. (2003), Jollifee and Stephenson (2003), Fawcett (2006), Guzzetti et al. (2006a,b), Rossi et al. (2010), Frattini et al. (2010) and Steger et al. (2016). As for the susceptibility model types, we base the discussion on the previous literature reviews, the information collected in the database, and our own experience in preparing landslide susceptibility models.

Measuring the performance of a landslide susceptibility model, and of the associated terrain zonation, remains a difficult task. Single metrics provide only a limited insight on the full model performances, since each metric (or group of metrics) has its own advantages and limitations. As an example, success/prediction rate curves have the advantage of making it straightforward the identification on a graph of the proportion of the study area considered most (least) susceptible. Thus, they can be used to answer the question "where is located the (for example) 5% most (least) susceptible part of a study area?" This may prove a particularly useful information for land-planners and decision makers. Conversely, success/prediction rate curves do not provide information on the accuracy of the spatial distribution of the areas predicted as stable or unstable predicted zones, a fundamental information for land-planners and decision makers.

We stress that single model performance metrics, group of metrics, as for example the success/prediction rate and ROC curves, measure the overall performance of a landslide susceptibility model, but cannot capture local conditions or relevant geomorphological characteristics. A model with a large AUC has a better (statistical) performance than a different model with a lower AUC. However, the second model may be more meaningful (reliable, useful) from a geomorphological perspective than the first model. For instance, the errors of the first model can be more severe (e.g., geomorphologically) than those of the second model, or the geographical distribution of the terrain units classified correctly/incorrectly as stable/unstable makes more sense from a landslide and/or a planning perspective. As pointed out by Carrara et al. (1991), the meanings of the model classification errors (type A vs. type B errors) are different for landslide susceptibility zonation, and their practical use.

We recommend that the meaning of the model classification errors is considered when evaluating the performance of a landslide susceptibility model.

Some performance metrics (e.g., ROC curve, contingency tables) do not consider the spatial extent of the mapping units used to prepare a landslide susceptibility model. Where the mapping units are of different sizes (e.g., where unique-condition units, slope-units, administrative subdivisions are used as mapping units), a better value of one or more of the metrics does not guarantee that the percentage of the terrain classified correctly (or incorrectly) is larger than in a different model characterized by a poorer performance. A few large terrain units classified erroneously by the better performing model may cover a larger area than all the miss-classified mapping units of the least performing model.

We recommend, that to evaluate the performance of a landslide susceptibility model the following are considered: (i) to use a broad set of metrics, considering their specific advantages and limitations (Rossi et al., 2010), (ii) to consider the geographical distribution of the model outcomes (e.g., the landslide susceptibility terrain zonation), and particularly the distribution of the model errors (Guzzetti et al., 2006a,b), and (iii) to consider the uncertainty associated to the model results, and particularly the uncertainty associated to the single mapping units (Guzzetti et al., 2006a,b; Rossi et al., 2010). The latter is particularly important for land planning, as "rules" may be different for mapping units characterized by low uncertainty, and for others characterized by a high uncertainty.

We stress that statistically-based susceptibility models are functional i.e., they depend entirely on the type, abundance, quality and relevance of the available landslide and the geo-environmental information. A consequence is that susceptibility models and the associated terrain zonations do not have a predefined or fixed validity period, provided the landslide and the geo-environmental conditions do not change significantly. However, where the distribution and abundance of landslides change e.g., as a result of a major triggering event, or where the geo-environmental conditions are altered e.g., as a result of land cover, meteorological or climate modifications, we recommend that existing susceptibility models are revaluated, and eventually updated, as the functional relationships between the slope instability factors and the distribution of landslides may have changed.

4.8. Susceptibility Quality Level

Guzzetti et al. (2006a,b) proposed a set of criteria for ranking the quality of a landslide susceptibility assessment, which we call here the Susceptibility Quality Level (SQL). The SQL criteria consider the type of tests performed to evaluate the susceptibility assessments (Table 2). The ranking scheme establishes different levels of quality of a susceptibility assessment, on a scale from SQL = 0 (lowest quality) to SQL = 7 (highest quality).

Based on the established criteria, where no information is available on the quality of a landslide susceptibility model, the resulting susceptibility assessment has the lowest level of quality (SQL = 0 in Table 2), which Guzzetti et al. (2006a,b) considered unacceptable for modern susceptibility assessments. Where estimates of the degree of model fit are available, the assessment has the least acceptable quality (SQL = 1). Where the error associated with the predicted susceptibility estimate for each mapping unit is known, the assessment has SQL = 2. Where the prediction performance of the model is known exploiting external landslide information, the susceptibility assessment has SQL = 4. The quality ranking scheme allows summing the individual levels, and hence a susceptibility assessment for which the fitting (SQL = 1) and the prediction performances (SQL = 4) are known, has SQL = 5 (1 + 4). For the same assessment, if the error associated to the predicted susceptibility for each mapping unit is also known (SQL = 2), the SQL = 7 (1 + 2 + 4).

We applied the SQL criteria proposed by Guzzetti et al. (2006a,b) and listed in Table 2, and the corresponding susceptibility quality-ranking scheme, to the 565 articles considered in our review. Results are summarized in Fig. 15, which shows that 45 (8.0%) of all the papers in the literature database have the lowest quality level (SQL = 0). These articles did not provide sufficient information to evaluate and to determine the quality of the landslide susceptibility assessment. We note that the percentage of the lowest quality assessments was highest in the early period covered by our review (50% between 1983 and 1994), and has decreased constantly in time. In the most recent period 2010–2016, the information required to evaluate the quality of the susceptibility

Table 2
Criteria and Susceptibility Quality Level (SQL) for landslide susceptibility models and associated terrain zonations (modified after Guzzetti et al., 2006a,b). The categories "a", "b", "c", "e" are unique. The categories "d", "f", "g", "h" are composed of a combination of the unique categories.

Category	Sum of previous categories	Criteria	SQL
a		No information available or no test performed to determine the quality and prediction performance of the landslide susceptibility assessment.	0
b		Estimates of degree of model fit available, obtained exploiting the same landslide information used to prepare the susceptibility model.	1
c		Estimates of the error associated with the predicted susceptibility in each mapping unit available, obtained exploiting the same landslide information used to prepare the susceptibility model.	2
d	[b & c]	[b] Estimates of degree of model fit available & [c] error associated with the predicted susceptibility in each terrain unit available.	3
e		Estimates of model prediction performance available, obtained exploiting independent landslide information not used to prepare the susceptibility model.	4
f	[b & e]	[b] Estimates of degree of model fit available & [e] estimates of model prediction performance available.	5
g	[c & e]	[c] Estimates of the error associated with the predicted susceptibility in each terrain unit available & [e] Estimates of model prediction performance available.	6
h	[b & c & e]	[b] Estimates of degree of model fit available & [c] estimates of the error associated with the predicted susceptibility in each mapping unit available & [e] estimates of model prediction performance available.	7

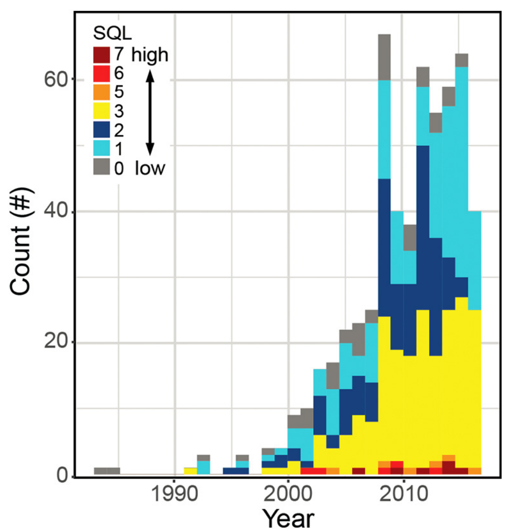

Fig. 15. Quality of landslide susceptibility models. Histogram shows the temporal distribution of the Susceptibility Quality Level (SQL) index, in seven classes, computed as proposed by Guzzetti et al. (2006a,b) for the 565 articles in the literature database. Zero is the lowest and 7 is the highest SQL (see Table 2). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

assessments is not given only in a few (4.0%) articles.

We recommend not to prepare (and publish) susceptibility assessments of quality level SQL = 0.

On the highest side of the quality scale, only six articles (1.1%) have reached the highest quality level (SQL = 7), with the first article published in 2006 (Guzzetti et al., 2006a,b), and the number of high quality assessments increasing in the most recent period of our review, with five articles published between 2010 and 2015 (Gorsevski and Jankowski, 2010; Bui et al., 2012; Peng et al., 2014; Petschko et al., 2014; Murillo-García and Alcántara-Ayala, 2015) (Fig. 15).

Despite the recent increase, we consider the number of high quality assessments very low, and we recommend increasing the number of susceptibility assessments that reach the highest rank in the scale, particularly by consideration of uncertainties.

Analysis of the literature database revealed that a significant number of susceptibility assessments have ascertained the degree of model fit (384, 169 at SQL = 1; 6 at SQL = 3; 203 at SQL = 5; 6 at SQL = 7), comparing the classification model to the distribution of landslides used to calibrate the model. Similarly, a significant number of assessments have estimated the predictive performance of the susceptibility classification (345, including 131 at SQL = 4; 203 at SQL = 5; 5 at SQL = 6; 6 at SQL = 7), comparing the susceptibility zonation to landslides not used to calibrate the model. The number of assessments for which the predictive performance was tested against independent landslide information (SQL = 4, 6 and 7) has increased with time.

We consider that the increase in time of the number of assessments for which the predictive performance was tested against independent landslide information is a good result, and we recommend continuing the trend. We note that only a few articles considered the errors associated to the predicted susceptibility for each mapping unit, including six articles at SQL = 3, and 11 articles at SQL = 6 or 7. This is surprising, as estimating the errors of a prediction should be a standard practice for statistically-based, spatially-distributed models. We encourage investigators to evaluate the susceptibility errors for each mapping unit.

4.9. Non-susceptibility modelling

It is worth noting that a few authors have attempted “non-susceptibility” terrain zonation, which consists in identifying areas where susceptibility to landslides is expected to be “negligible”, or nil (Marchesini et al., 2014). These works are statistically-based, but are conceptually different from the works that determine landslide susceptibility using the statistical classification modelling approaches discussed before. Godt et al. (2012) were the first to exploit the concept of “non-susceptible” terrain zonation in their synoptic landslide hazard map for the conterminous United States, showing areas with negligible landslide susceptibility i.e., areas where landslides are not expected. Building on this work, Marchesini et al. (2014) exploited landslide information from 13 inventories in Italy, and morphometric information obtained from the 3-arc-second Shuttle Radar Topography Mission (SRTM) DEM, to determine areas where landslide susceptibility is expected to be negligible in Italy, and in the landmasses surrounding the Mediterranean Sea. Tested with independent landslide information in three study areas in Spain, the non-susceptibility zonation proved capable of determining areas where landslides were not expected in the three validation areas.

We recommend exploiting the concept of “non-susceptible” terrain zonation, and further testing of the non-susceptibility zonation proposed by Marchesini et al. (2014). This will serve two purposes: (i) testing the extent to which a non-susceptibility zonation prepared using landslide information in a region (e.g., Italy) can be extended in other geographical and physiographical regions, and (ii) obtaining non-susceptibility zonations to confront with global landslide susceptibility or hazard maps (Nadim et al., 2006, 2013).

4.10. Use of landslide susceptibility and non-susceptibility assessments

Early investigators in the mid-1970s to the mid-1980s (Humbert, 1976; Nilsen and Brabb, 1977; Brabb, 1984, 1991, 1995, 1996; Hansen, 1984; Varnes, and IAEG Commission on Landslides and other Mass-Movements, 1984) considered landslide susceptibility zonation obtained using different approaches, including statistically-based methods, a potentially valuable tool for land planning and to reduce the costs of landslides (Bernknopf et al., 1988; Fell et al., 2008a, 2008b). In the view of these early investigators, a landslide susceptibility map served the purpose of showing users and stakeholders where landslides are expected, contributing to adopt policies and to take proactive actions to avoid landslides and their negative consequences (Brabb, 1991). Users and stakeholders might include decision makers, administrators, urban planners, real estate agents, environmental agencies, road, transport and utility companies, agriculture and forest managers, the insurance industry, communities and individual citizens. Reality proved different, and landslide susceptibility maps have not become popular or widespread as expected for planning purposes and landscape decision-making (Guzzetti et al., 2000; Chacón et al., 2006). Reasons for this discontinuity between intent of those producing the landslide susceptibility maps and the users are manifold.

First, Huabin et al., 2005 have argued that susceptibility maps are difficult to understand by non-specialists, including planners and policymakers. Indeed, the typical legend of a susceptibility map does not help. Susceptibility levels are commonly given in relative and descriptive terms (e.g., very high, high, intermediate, low, very low) without any quantitative measure of the differences. This makes it difficult to compare the classes, for practical applications. The streetlight colour scheme most-commonly adopted to show susceptibility is also potentially misleading. High susceptibility zones are shown in red and low susceptibility zones in green. However, in the “green” areas, landslides are possible – albeit with a smaller probability – and this may be difficult to understand.

Second, the outcome of a typical, statistically-based classification model is not trivial to understand. A common misconception is that a probability value close to 0.5 (in the range from 0 to 1) represents an “intermediate” level of susceptibility. This is incorrect, as values around 0.5 represent the inability of the classification model to decide if a specific mapping unit is stable or unstable. This is different from an “intermediate” level of susceptibility. Investigators have also shown that mapping units with probability values close to 0.5 have a higher uncertainty than mapping units with probability close to 0 or 1 (Guzzetti et al., 2006a,b; Van Den Eeckhaut et al., 2009; Rossi et al., 2010).

Third, where new landslide or geo-environmental information becomes available, or where the geo-environmental conditions change, even a good quality susceptibly zonation obtained through statistical modelling may change locally, hampering its effective practical use. To be effective for urban and land planning, the adopted zonation should be kept the same for sufficiently long periods, typically several years to a few decades. Alternatively, rules to change land policies where the susceptibility assessment changes must be defined beforehand; and this may be difficult to do.

Fourth, statistically-based models depend on the data used, and implicitly on the extent of the study area. A slope considered stable where a small area is investigated, it may be considered moderately or highly unstable if a larger area is studied, or vice versa. These difficulties, which have remained largely unresolved, have hampered the widespread applicability and use of landslide susceptibility models and terrain zonations.

As discussed previously, determining the quality and the predicting performances of a landslide susceptibility model is not trivial, and different models (e.g., prepared by the same or by different investigators, using similar of different techniques) may provide different results. We recommend (i) the use of multiple metrics to evaluate a susceptibility model, and we encourage the production of “optimal” susceptibility models obtained combining multiple models (Rossi et al., 2010), and (ii) the importance of establishing common standards and recommended practices to construct, validate, and evaluate the susceptibility models, and the associated zonations (Chacón et al., 2006).

As pointed out by Guzzetti et al. (2012), in the modern Earth Sciences, lack of standards limits the credibility and usefulness of the landslide maps, including susceptibility maps. We expect that the increasing availability and widespread adoption of open source software (Rossi et al., 2010; Jebur et al., 2015; Rossi and Reichenbach, 2016) will contribute to establish “de facto” standards for landslide susceptibility modelling and terrain zonation.

In recent years, applications of landslide susceptibility models other than for land planning have emerged, of which the most important consists in the use of susceptibility zonations in landslide early warning systems, at different geographical scales. Hong and Adler (2007) and Hong et al. (2007) used a global-scale susceptibility model obtained through weighted linear combination of six explanatory variables (slope, soil type, soil texture, elevation, land cover type, drainage density), in combination with the NASA–JAXA satellite Tropical Rainfall Measuring Mission (TRMM) global data and the USGS Prompt Assessment of Global Earthquakes for Response (PAGER) near-real-time earthquake information. They used this model to prototype a global early warning system for rainfall and seismically triggered landslides. Liao et al. (2010) described an experimental early warning system for rainfall-induced landslides in Indonesia, which exploited the TRMM rainfall data set and a susceptibility zonation based on a modified version of the SLIDE physically-based slope stability model (Fredlund et al., 1996; Montrasio and Valentino, 2008).

Rossi et al. (2012) used hourly rainfall measurements obtained by a network of 1950 rain gauges in Italy, two-day quantitative rainfall forecasts generated twice a day by the Local Area Model for Italy (LAMI), and an empirical rainfall intensity–duration / cumulated rainfall–duration threshold (Brunetti et al., 2010; Peruccacci et al., 2012, 2017), to forecast the possible occurrence of rainfall-induced landslides, in Italy. Every hour, the landslide forecast prepared using rainfall measured in the previous 96 h and rainfall forecasted for the next 24 h is combined with a national-scale, statistically-based landslide susceptibility model. Berenguer et al. (2015) combined debris flow susceptibility assessment obtained through a weight-of-evidence modelling with 1 km × 1 km, 30-minute cumulated rainfall obtained from radar Quantitative Precipitation Estimates (QPE), to forecast rainfall-induced debris flows in the Spanish Pyrenees. Segoni et al. (2015) used a susceptibility model constructed using a non-parametric random forest approach (Breiman, 2001), and rainfall measurements and empirical rainfall thresholds for possible landslide occurrence, to predict where rainfall-induced landslides are expected during rainfall events in the Emilia-Romagna region, northern Italy.

Due to the increasing availability of frequent and reliable QPE (Alfieri et al., 2012), and precipitation measurements obtained by network of rain gauges and ground-based meteorological radars (Germann et al., 2006; Marra et al., 2014), and by the NASA–JAXA Global Precipitation Mission (GPM) (Hou et al., 2008) and other satellite-based precipitation data sets (Kucera et al., 2013), we expect that efforts to establish landslide early warning systems that exploit susceptibility zonations will grow in the future, and that the performances of the systems will increase.

We recommend that investigators are more explicit in describing how the susceptibility models are combined – heuristically, statistically or in a probabilistic framework – with rainfall measurements, estimates, and forecasts in operational landslide early warning systems. We note here that the schemes used to classify and portray landslide susceptibility for early warning purposes may be different from land planning. Where this is the case, we recommend that the differences are outlined and explained.

5. Future challenges

The general problem of determining landslide susceptibility through the statistical modelling of landslide and geo-environmental information has been largely addressed in the literature, both conceptually and operationally, at most geographical scales. However, relevant challenges remain for the future.

First, the production of landslide susceptibility/non-susceptibility models and zonations for very large regions, including entire continents and the globe (Nadim et al., 2006; Hong et al., 2007; Günther et al., 2013, 2014), remains difficult, particularly due to the lack of sufficient and adequate landslide information. Guzzetti et al. (2012) have estimated that landslide maps cover < 1% of the slopes in the landmasses. This evidence limits greatly the possibility to prepare reliable susceptibility models and zonations. In addition to the production of landslide inventory maps for the vast areas for which they are not available, we recommend developing and testing methods and strategies for exploiting the results of susceptibility models constructed in an area to neighbouring and distant areas. This will require standardization of the landslide information and of the explanatory thematic variables.

Second, the evaluation of the predictive performances of the susceptibility models, at all scales, remains a difficult and uncertain task. This is because of intrinsic difficulties in testing spatially-distributed predictions of landslide susceptibility (Chung and Fabbri, 2003; Guzzetti et al., 2006b; Lobo et al., 2008; Frattini et al., 2010; Rossi et al., 2010; Steger et al., 2016), due to the lack of proper information to test the models reliably, and particularly of multi-temporal landslide inventory maps (Guzzetti et al., 2012). In addition to using multiple metrics to evaluate the quality and performance of a susceptibility model (Rossi et al., 2010; Steger et al., 2016), we recommend concentrating on the design of new and more reliable methods and indices for the evaluation of model quality, thus increasing their credibility and usefulness. We expect that this will favour their adoption and use by different stakeholders.

Third, standards for ranking and portraying susceptibility levels are lacking, and it is unclear if a susceptibility map should (or should not) include information on the known landslides in the same area (i.e., the landslide inventory). The adoption of common standards for ranking and portraying landslide susceptibility (including the number of classes and the colours used) may facilitate the comparison of different models for the same area. The combined use of landslide inventories and susceptibility zonations is more problematic, with the effectiveness of the overlay dependent on the application. For large or medium-scale land planning, information on known (past) landslides may be as relevant as the susceptibility zonation i.e., an estimate of where the (future) landslides may occur. Thus, showing the maps together maximizes the information content of the landslide inventory and the susceptibility model (Galli et al., 2008; Van Den Eeckhaut et al., 2009). Conversely, for small-scale planning and for regional/national landslide early warning, the susceptibility zonation may be preferable, as the information shown in a good quality landslide inventory may be too detailed and difficult to use.

Fourth, work is required to design and test strategies and methods for the effective combination of susceptibility terrain zonations prepared for different landslide types. The process is not trivial, conceptually and operationally, and the problem is aggravated where the zonations are prepared using different modelling methods, including e.g., statistically-based and physically-based methods. Yet, the condition is common, as it arises wherever different landslide types coexist in the same area, including e.g., slow-moving slides, flows and complex or compound landslides – whose susceptibility is best ascertained using statistically-based models – and rock falls, debris flows and rock slides/avalanches that can travel long distances at a range of velocities – and whose susceptibility is best determined using physically-based models (Guzzetti, 2006).

Fifth, further efforts are required to facilitate the adoption of landslide susceptibility (and hazard) zonations for land planning and decision-making (Fell et al., 2008a, 2008b). Brabb (1996) argued that "the preparation of hazard maps does not guarantee that they will be used", and Guzzetti et al. (2000) maintained that landslide maps in general, and susceptibility (and hazard) maps in particular, could not satisfy totally the needs of decision-makers, planners and other stakeholders. To facilitate the use of susceptibility maps, sets of regulations or instructions are necessary to link the terrain domains outlined in the terrain zonations to specific actions (Rossi et al., 1982; Olshansky and Rogers, 1987). This was called a "landslide protocol" by Guzzetti et al. (2000) and Van Den Eeckhaut et al. (2009). Designing, testing and enforcing a landslide protocol is proving the most difficult part of landslide susceptibility or hazard assessment and exploitation. For this purpose, we recommend involving relevant stakeholders in the preparation of the susceptibility zonations and in the design of the landslide protocol (Wang et al., 2005). We expect that this will foster the adoption and widespread use of the terrain zonations.

Sixth, recent studies have challenged the concept that susceptibility is stationary ("time invariant"), at least in the period of validity of a typical susceptibility assessment i.e., a few to several decades (Guzzetti et al., 2005). Reichenbach et al. (2014), working in NE Sicily, Italy, showed that landslide susceptibility changed in the period 1954–2009 in response to land use changes driven by human actions. Samia et al. (2017a,b) studied an accurate multi-temporal inventory map extending for multiple decades in a study area in central Umbria, Italy, and identified a short-term legacy (hereditary) effect of existing landslides on new landslides, with exiting landslides causing a greater susceptibility for follow-up landslides over a period of about ten years. It remains to be understood if this legacy effect exists in other areas, and if the length of the hereditary period is the same, or similar in other areas, or it changes depending on climate, lithology, or other factors. We recommend that similar longitudinal studies in time are conducted in other areas to determine the short-term rate of change of landslide susceptibility. Should the investigations reveal that susceptibility changes at a faster rate than expected, the existing models to determine landslide hazard that assume independence of susceptibility from other hazard components, and specifically the temporal frequency of landslides (Guzzetti et al., 2005), will have to be revised. Where susceptibility changes, this should be considered by the landslide protocols linked to the terrain zonations.

Seventh, in the time frame of modern climate projections (i.e., from a few decades to a few centuries), landslide susceptibility may change due to meteorological and environmental changes driven or conditioned by the predicted climate changes. In recent years, a few investigators have attempted to consider future climate scenarios in regional landslide susceptibility (Fan et al., 2013; Kim et al., 2015; Gassner et al., 2015; Shou and Yang, 2015) and hazard (Baills et al., 2013; Lee et al., 2014; Winter and Shearer, 2015) assessments. However, the effects of climate and environmental changes on landslide susceptibility at different spatial and temporal scales remain uncertain, and largely undermined. The topic is central to understand the effects of climate changes on landslides, and to predict their increasing or decreasing impact (Gariano and Guzzetti, 2016). We recommend that studies should include climate-related variables in landslide susceptibility models.

Eighth, with the exception of a few study areas (e.g., Hampton et al., 1996; Locat and Lee, 2002; Masson et al., 2002; Schwab et al., 2002; Lee, 2009; Twichell et al., 2009; Camerlenghi et al., 2010; Mosher et al., 2010; Katz et al., 2015), little is known on the susceptibility to subaqueous landslides. Given the increasing exploitation of the sea and ocean floors (Ramirez-Llodra et al., 2011; Mengerink et al., 2014), much work is needed to determine the susceptibility to subaqueous landslides.

Table 3
Nine inter-related steps for the preparation of landslide susceptibility assessments and for the proper use of the associated terrain zonations.

#	Step	Description
1	Obtain relevant landslide information	Check existing landslide maps, or prepare new maps. Verify the landslide spatial, temporal and size distributions. Consider the type and scale of the inventory, the mapping technique, the landslide type(s), and the type of the triggering event(s).
2	Obtain relevant thematic information	Check and select appropriate and relevant geo-environmental information. Consider the original scale of the information. Digital terrain/elevation models are mandatory, and their resolution condition the scale and resolution of the analysis. Consider the quality, accuracy and relevance of the landslide and the geo-environmental information, with respect to the scale and the scope of the analysis.
3	Select appropriate mapping unit	Select an appropriate mapping unit (e.g., pixel, terrain unit, administrative) considering (a) the geometry of the landslide information (i.e., polygons, points, grid cells); (b) the scope(s) of the analysis (e.g., understanding of the processes and their controlling factors, land planning, early warning); (c) the scale of the analysis (basin, regional, national, etc.); and (d) the type of data (categorical, numeric, etc.).
4	Select appropriate statistical model	Select appropriate statistical model(s), guided by (a) the type of landslide and geo-environmental information (e.g., categorical, numeric); (b) the available knowledge and resources; and (c) the scope(s) and expected results of the modelling. Prefer combined ("optimal") models.
5	Evaluate the model fitting performance	Choose and apply proper techniques and multiple metrics to evaluate the model fitting performance. Consider the geographical distribution and the geomorphological significance of the model errors.
6	Evaluate the model predictive performance	Choose and apply proper techniques and multiple metrics to evaluate the model prediction performance. Use landslide information not used to construct the model(s). Consider the geographical distribution and the significance relevance of the model errors.
7	Estimate the model uncertainty	Choose and apply proper techniques to estimate quantitatively the uncertainty associated to the model prediction(s).
8	Rank the model quality	Use the Susceptibility Quality Level (SQL) index to measure and rank the quality of the landslide susceptibility model(s). Do not prepare susceptibility assessments with SQL = 0
9	Design a landslide protocol	Design an appropriate landslide protocol involving relevant stakeholders, and considering the consequences of the susceptibility terrain zonation.

6. Conclusions

Since early attempts in the mid-1970s to the mid-1980s to ascertaining landslide susceptibility in Germany (Neuland, 1976), California (Nilsen and Brabb, 1977), and Italy (Carrara et al., 1977, 1978, 1982; Carrara, 1983), hundreds of papers have been published describing attempts to assess the susceptibility to landslides in different geological, climatic, and physiographical settings. Investigators have used many direct or indirect approaches, producing qualitative and/or quantitative assessments (Aleotti and Chowdhury, 1999; Guzzetti et al., 1999; Chacón et al., 2006; van Westen et al., 2008). In this work, we have focused on statistically-based susceptibility modelling methods, a class of indirect, quantitative approaches (Guzzetti, 2006). For our review, we systematically searched the international literature in the 33.5-year period between January 1983 and June 2016, and selected 565 articles in peer-reviewed journals, where the articles discussed methods and tools for statistically-based landslide susceptibility assessment and associated terrain zonation.

The critical literature review using the extensive literature database as evidence, revealed a considerable heterogeneity of the landslide and thematic data types and scales, the modelling approaches, and the criteria used to evaluate the model performance. The most common statistical classification methods for susceptibility assessment were logistic regression, neural network analysis, data-overlay, index-based and weight of evidence analyses, with a preference towards machine learning methods in recent years. Although some methods performed better than others, no single method proved to be superior in all conditions. We conclude that the experience and skill of the investigators in using a specific classification method is more important than the method itself, and we argue in favour of using multiple methods to obtain different susceptibility assessments exploiting the same landslide and thematic data, and to combine them into "optimal" models, which typically perform better than single models (Rossi et al., 2010).

Adopting the Susceptibility Quality Level index (Guzzetti et al., 2006a,b), we measured the quality of most of the susceptibility models we have analysed, and found that this has improved over the years, but top quality assessments remain rare. To improve the quality of the models, we recommend that besides assessing the model fit and prediction performances, both becoming common in the literature, the uncertainty of models and zonations should be measured quantitatively.

Our review revealed a distinct geographical bias of the susceptibility studies (Fig. 3), with many of the study areas in a few countries (China, India, Italy, Turkey), and only a few studies in the continents of Africa, South America and Oceania. With a few exceptions, very little is known on the susceptibility to submarine landslides. We also observed that the majority of the studies covered relatively small areas ($< 1000\,km^2$, Fig. 3), and only very few studies covered a continent (Günther et al., 2013, 2014) or the entire world (Nadim et al., 2006, 2013; Hong et al., 2007). There is a need for landslide susceptibility assessments that cover large regions, entire continents, and the entire world, including the seas and the oceans.

The review outlined a clear lack of recognized standards and accepted practices for statistically-based landslide susceptibility modelling. The lack of standards hampers the possibility to confront different methods and models, and limits the credibility and usefulness of the susceptibility models and maps (Guzzetti, 2006). The later has unfavourable consequences on the derivative products and analyses, including hazard assessments and risk evaluations (Guzzetti et al., 2012). We expect that the availability of open software for statistically-based susceptibility modelling will contribute to solve this problem (Jebur et al., 2015; Rossi and Reichenbach, 2016). We note that in the related field of physically-based susceptibility modelling, availability of open software is increasing (Baum et al., 2002, 2008; Mergili et al., 2012a, 2012b, 2013, 2014; Alvioli and Baum, 2016).

Early investigators considered landslide susceptibility zonation a valuable tool for land planning, and for reducing costs of landslide impact (Bernknopf et al., 1988). Our review revealed that landslide susceptibility maps have not become popular for planning purposes and landscape decision-making as anticipated by the early investigators (Brabb, 1996; Guzzetti et al., 2000; Chacón et al., 2006). Reasons for this are manifold, but we argue that common standards and the increasing availability of landslide and thematic data will contribute to the future expansion of the susceptibility assessments. We also expect that statistically-based landslide susceptibility models will be used for other applications, such as for part of landslide early warning systems at different geographical scales. However, we think that scopes and characteristics of susceptibility assessments may change for different applications (for example use in early warning systems is different from use in land planning and environmental management).

Our review also revealed good practices and strengths in landslide susceptibility analysis and in the evaluation of specific aspects of the modelling, particularly in recent years. Even not numerous, significant and relevant studies have been done to (i) compare and combine different modelling approaches, (ii) test the thematic variables significance and the relative model sensitivity, (iii) analyse the influence of mapping unit types on susceptibility models and zonations, (iv) test different performance evaluation metrics, (v) select appropriate mapping unit sampling schema for the training/validation dataset, (vi) develop software to partition the territory and (vi) provide tools for the susceptibility modelling and zonation also to non-experienced user.

Complementing the results of the literature review analysis with our experience, we have identified nine main steps that we consider important to prepare a reliable landslide susceptibility zonation (Table 3), with some steps inter-related. We maintain this Table could become a starting point for the discussion and definition of a standard for statistically-based landslide susceptibility modelling and zonation.

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Appendix A. List of acronyms

Acronyms and abbreviations used in text.

Acronym	Description
3DEP	USGS 3D Elevation Program
ALOS	Advanced Land Observing Satellite (Daichi)
ATLAS	Advanced Topographic Laser Altimeter System
AUC	Area Under the ROC Curve
DEM	digital elevation model
ESA	European Space Agency
ESRI	Environmental Systems Research Institute
FN	false negative
FP	false positive
GIS	Geographical Information System
GPM	Global Precipitation Mission
GRASS	Geographic Resources Analysis Support System
HR	high resolution
JAXA	Japan Aerospace eXploration Agency
LAMI	Local Area Model for Italy
LiDAR	Light Detection And Ranging
MPA	Multi-satellite Precipitation Analysis
NASA	National Aeronautics and Space Administration
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
PAGER	Prompt Assessment of Global Earthquakes for Response
QPE	Quantitative Precipitation Estimate
ROC	Receiver Operating Characteristic
SAGA	Geographic Resources Analysis Support System
SPSS	Statistical Package for Social Science
SQL	Susceptibility Quality Level
SRTM	Shuttle Radar Topography Mission
TN	true negative
TP	true positive
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
VHR	very high resolution

Appendix B. Supplementary data

Ancillary materials — list of articles in the literature database

The list of articles in the literature database is available as Zotero web page (https://www.zotero.org/groups/1873771/esr_statistical_landslide_susceptibility) and as ancillary material in the following format:

1) ESR_statistical_landslide_susceptibility.bib
2) ESR_statistical_landslide_susceptibility.csv. Supplementary data associated with this article can be found in the online version, at doi: https://doi.org/10.1016/j.earscirev.2018.03.001.

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