remote sensing

Review

Insights Gained from the Review of Landslide Susceptibility Assessment Studies in Italy

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Abstract: We conducted a systematic literature review of 105 landslide susceptibility studies in Italy from 1980 to 2023, retrieved from the Scopus database. We discovered that Italian researchers primarily focus on rainfall-induced landslides (86.67% of the articles), especially shallow and fast movements (60%), with 72% of studies conducted at the local scale, while regional and national-level studies are rare. The most common data sources include remote sensing images validated by field surveys and official data portals at the national or regional level. Data splitting usually follows a 70:30 ratio and 24 modelling techniques were identified, with logistic regression being historically prevalent, although machine learning methods have rapidly gained popularity. Italian studies used 97 predisposing factors, with slope angle (98.09%), lithology (89.52%), land use/land cover (78.09%), and aspect (77.14%) being the most employed. This review also identifies and discusses a few less-used factors, like soil sealing, rainfall, NDVI, and proximity to faults, which showed promising results in experimental studies. Predisposing factors are generally selected by expert judgment, but methods for forward factors selection and collinearity tests are becoming more common. This review synthesizes current knowledge, pinpointing gaps, highlighting emerging methodologies, and suggesting future research directions for better integration of susceptibility studies with landslide risk management.

Keywords: Italy; landslides; Scopus; susceptibility; systematic review

Citation: Segoni, S.; Ajin, R.S.; Nocentini, N.; Fanti, R. Insights Gained from the Review of Landslide Susceptibility Assessment Studies in Italy. *Remote Sens.* **2024**, *16*, 4491. https://doi.org/10.3390/rs16234491

Academic Editors: Zhong Lu, Magaly Koch, Xiaokang Zhang, Adel Asadi and Weiwei Zhan

Received: 12 September 2024
Revised: 13 November 2024
Accepted: 25 November 2024
Published: 29 November 2024

1. Introduction

In mountainous regions worldwide, landslides are the most prevalent geohazards, which have dire consequences in terms of casualties and property damage [1–4]. The factors that trigger these events encompass excessive rainfall, earthquakes, and human interventions [3,5] like haphazard development activities (construction of buildings and roads, road widening, and modification of streams) [6–9], mining or blasting operations [3,10], and deforestation on the mountain slopes [11,12]. Landslides have the potential to cause both direct and indirect socio-economic impacts [13–16], as well as casualties [17–19]. Moreover, landslides can cause the destruction of critical infrastructure [20], disruption of transportation and communication networks [21], deterioration of water quality in rivers and streams [22], depletion of natural resources and wildlife habitats [22], and negative mental health consequences such as post-traumatic stress disorder [23,24]. According to Froude and Petley [3], between 2004 and 2016, a total of 4862 landslides occurred worldwide, resulting in the tragic loss of 55,997 lives. In addition, Gómez et al. [25] documented 37,946 landslide events recorded between 1903 and 2020, which tragically resulted in 185,753 fatalities. The annual total financial losses from landslides were estimated at 20 billion USD (~18.5 billion Euros) [26]. Recent research conducted by Wang et al. [27] indicates that the average annual frequency of landslides triggered by extreme rainfall is estimated to rise by 7% and 10% in the upcoming 30-year periods of 2031–2060 and 2066–2095, respectively, compared to the period from 1971 to 2000.

The European region is no exception, with a total of 1370 deaths and 784 injuries reported in Europe due to 476 deadly landslides between 1995 and 2014 [19]. The annual economic loss in Europe averages around 4.7 billion Euros [19]. Italy ranks second, following Turkey, in terms of European countries with the highest number of fatalities, and ranks first in highest annual economic loss at 3.9 billion Euros per year [19].

The relevance of Italy as a case study for landslide hazard and risk is well underscored by an overwhelming number of nationwide assessments. IFFI, the official national landslide database, maps more than 630,000 landslides among active, quiescent, and inactive phenomena [28]. Regarding recent landslides, Calvello and Pecoraro [29] surveyed 8931 landslides that occurred between 2010 and 2017, while Peruccacci et al. [30] reported 6312 rainfall-induced landslides between 1996 and 2021, confined to the Alps and the Apennines mountain ranges (Figure 1). The social impact of landslides in Italy is stressed by the echo received in the media space: Franceschini et al. [31] stated that from 2010 to 2019, 184,000 online news articles were published on the internet referring to 32,000 small and severe distinct landslide events, affecting 42% of Italian municipalities. Indeed, Rossi et al. [32] report 5571 fatalities due to landslides in Italy in the period 1861–2015. Calvello and Pecoraro [29] reported that from 1967 to 2016, landslide disasters in Italy led to the fatalities of 1205 people, with 12 individuals going missing, and 1509 injured. Lastly, Gatto et al. [33] noted that from 2013 to 2022, the Italian Civil Protection declared 123 national-level emergencies to face the same number of disasters, mainly consisting of heavy rainstorms, each triggering floods and hundreds of widespread landslides. The Alpine areas are highly prone to rapid landslides, including rockslides, rockfalls, and rock avalanches, and these events are frequently observed across the entire Alpine region [29]. The Eastern Alps experience debris flows due to loose debris present on steep slopes within mountain basins [29]. In the Apennines region, most landslides are classified as earth flows (in clay shales), slides (in sandstones), and complex landslides with both flow and sliding elements [34,35]. These landslides typically move periodically at controlled velocities, although some may experience sudden acceleration during certain rainfall events [35]. Given this framework, it is no surprise that the Italian scientific community has been traditionally engaged in landslide studies [36].

Landslide susceptibility maps (LSMs) are static instruments designed to assess the potential for future landslide occurrence, based on the spatial distribution of past landslides and predisposing factors [37]. Susceptibility studies are vital for proactive risk management [38,39] since they enable the identification of prone areas, assessment of potential risks, and facilitate the implementation of mitigation strategies such as drainage control, slope stabilization, and land-use planning; consequently, they aid in minimizing the impact of landslides and protecting communities [39–42].

This study endeavors to systematically assess the literature pertaining to 'landslide susceptibility assessment in Italy' from 1980 to 2023. A total of 426 publications retrieved from the Scopus database were collated and analyzed. The aim was to synthesize current knowledge, identify gaps, and outline future research priorities to enhance the effectiveness of landslide risk management.

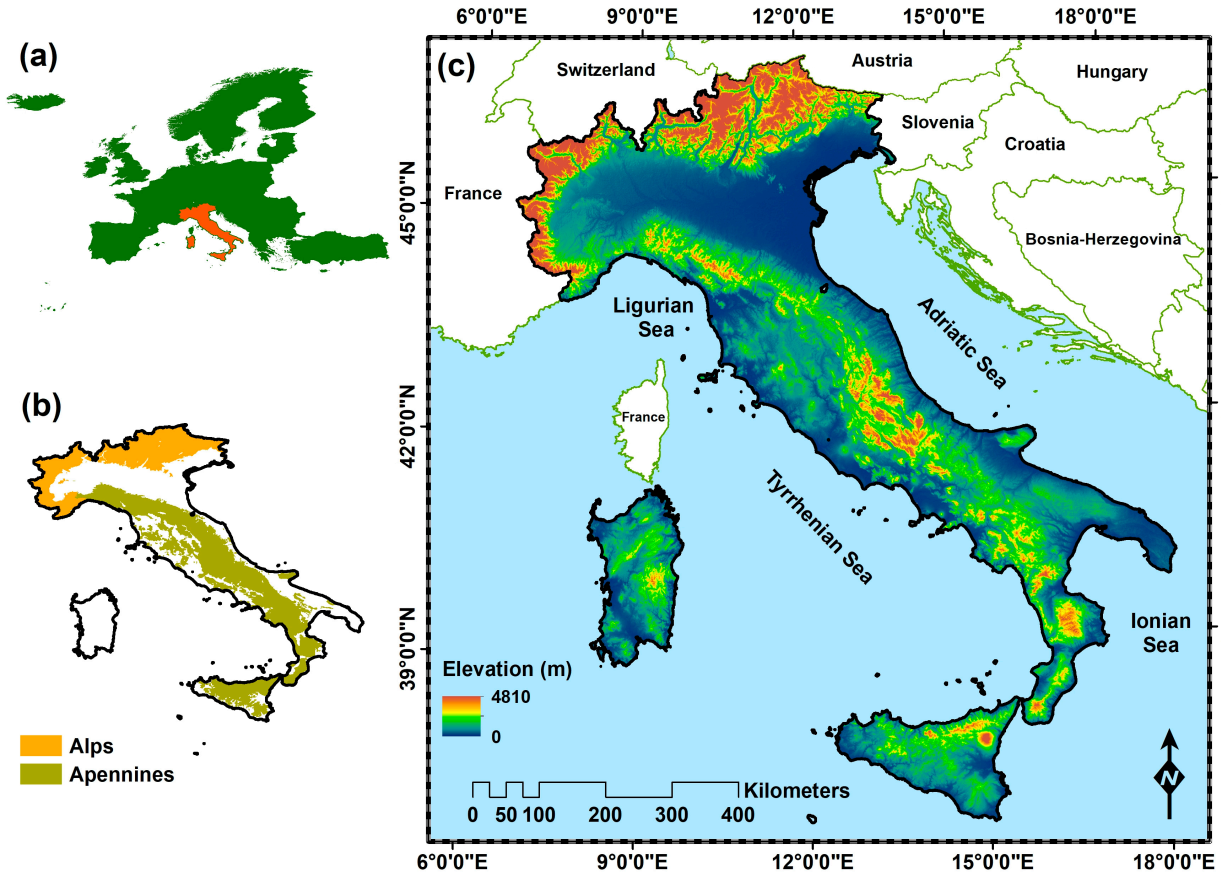

Figure 1. (**a**) Location of Italy in Europe, (**b**) The Alps and Apennines mountains in Italy, and (**c**) elevation range of Italy.

2. Materials and Methods

A systematic review of the literature on the topic 'landslide susceptibility in Italy' was conducted for the period 1 January 1980–31 December 2023 (Figure 2). The Scopus database was utilized to retrieve the articles. Scopus, one of the two principal bibliographic citation databases alongside Web of Science, has attained equal standing to Web of Science [43,44] and is frequently employed in systematic literature reviews and analyses [45–47]. By selecting three keywords, "landslides", "susceptibility", AND "Italy", from the Title, Keywords, and Abstract, a total of 426 publications were retrieved. Afterward, exclusion criteria were set: 'book chapters', 'conference papers', 'review articles', and 'articles written in the Italian language' were excluded. This approach is common in review papers as it allows the filtering out of articles with a weak scientific background, or minor works that duplicate prior works with only minor changes. Thus, 24 book chapters, 66 conference papers, 11 review articles, and 18 articles in Italian (i.e., a total of 119 publications) were excluded. The abstract of the resulting 307 articles were read and 202 false positive articles (i.e., the keywords were present, but the article was not about performing a landslide susceptibility assessment or defining a landslide susceptibility map) were discarded.

We acknowledge that the selection criterion outlined here does not encompass all studies related to landslide susceptibility in Italy. A considerable number of additional studies may also exist within the realm of "grey literature" [48]. These studies might have been executed outside the academic sector, potentially by public authorities or technical firms. Additionally, some of these works may not have been formally published, such as theses or susceptibility maps presented at congresses but not featured in Scopus-indexed academic journals. This could be a potential weakness in our analysis, but we decided to use only works published in peer-reviewed indexed international journals to focus the analysis on works for which there is a strong basis to trust the robustness, quality, and significance of the results.

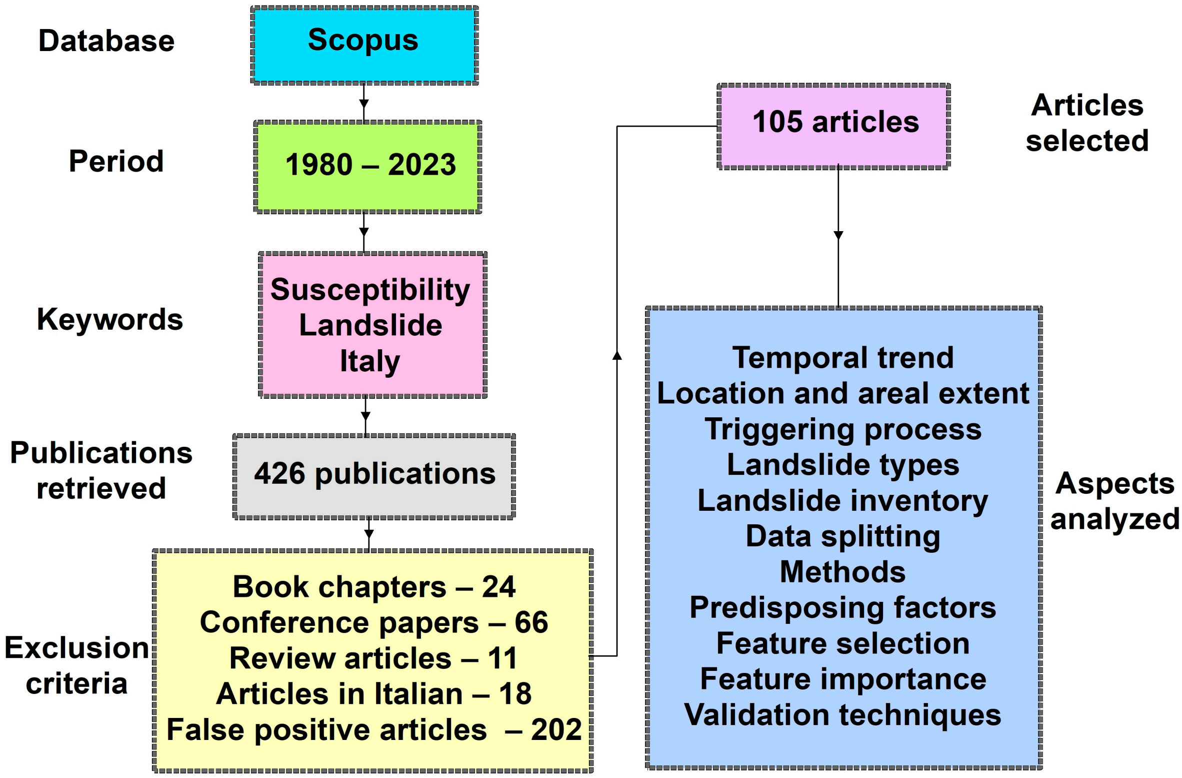

Figure 2. The framework adopted for this systematic review.

With these criteria, 105 articles were selected for analysis. The articles were read and analyzed to extract information on key topics and aspects in landslide susceptibility studies, such as (1) temporal trend, (2) location and areal extent, (3) triggering process, (4) landslide types, (5) landslide inventory used, (6) data splitting, (7) methods used, (8) predisposing factors, (9) feature selection, (10) feature importance and ranking, and (11) validation techniques.

3. Results and Discussion

3.1. Temporal Trend

Though the period chosen for the study was 1980–2023, no articles meeting the study criteria were found between 1980 and 1997. This is because a relevant number of articles in the earlier years pertain to the so-called “grey literature”, including also conference proceedings, technical reports, and articles in Italian; thus, they were filtered out. Additionally, this timeframe has been incorporated into Figure 3 to provide a historical lens, showcasing the early developments in research within this domain. We aimed to convey that it was primarily after 1997 that landslide susceptibility modelling studies gained significant attention from the scientific community, with a rise in the number of researchers publishing their studies in peer-reviewed scientific journals. Indeed, an upward trend was observed in the number of articles starting from 2005. The number of articles published during 2006–2010, 2011–2015, and 2016–2020 was 17, 31, and 31, respectively. A total of 20 articles were published from 2021 to 2023, indicating a similar pattern. Since 2011, an average of 5 articles per year have been published, with exceptions in 2019 and 2020. The slight decrease in articles during these years could be attributed to the disruptions caused by the COVID-19 pandemic on academic and research activities [49].

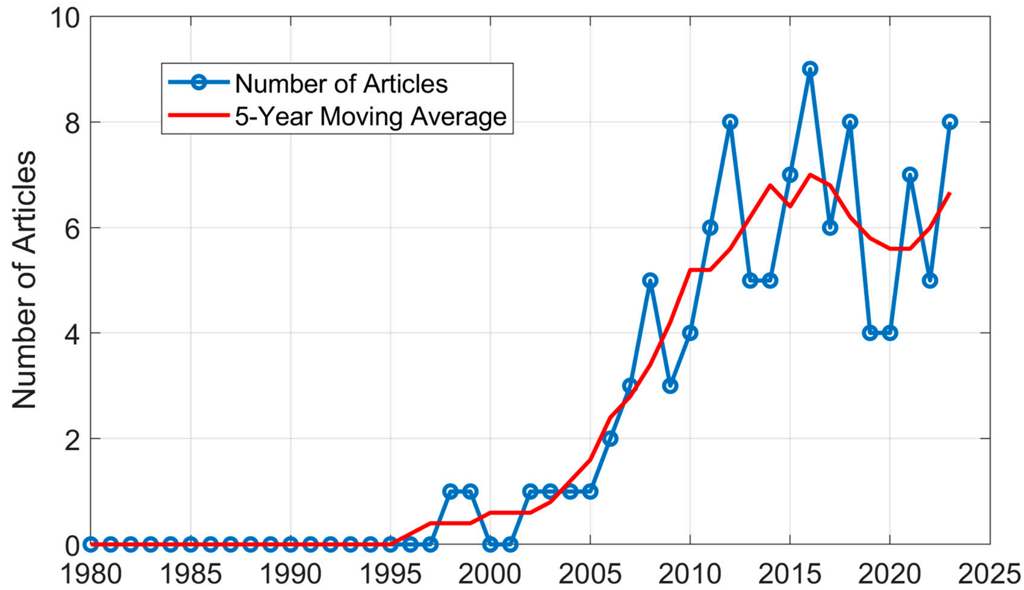

Figure 3. Number of articles published from 1980 to 2023.

3.2. Location and Areal Extent of Test Sites

The region with the highest number of articles is Sicily (20 articles), followed by Calabria (16), Tuscany (10), and Lombardy (9) (Figure 4). Amato et al. [50] conducted an assessment of susceptibility on a national scale (entire Italy), whereas Atkinson and Massari [51], Bordoni et al. [52], Magliulo et al. [53], and Massari and Atkinson [54] carried out studies in test sites situated in two different regions. The boxplots in Figure 5 provide an overview of the distribution of the study areas' extent (in km^2) in the articles selected. Notably, only 1 study assessed susceptibility for the whole of Italy [50], and 11 studies presented a map for an entire administrative region, namely Abruzzo [55], Aosta Valley [56], Calabria [57–59], Emilia–Romagna [60], Marche [61,62], Molise [63,64], and Sicily [65]. Most of these works are identified as outliers in Figure 5a. In contrast, ~81% of the articles were focused on test sites with areas smaller than 1750 km^2, and ~74% of the articles focused on test sites smaller than 750 km^2 (Figure 5b). Corominas et al. [66] classified map scales into three categories: site-specific (up to 10 km^2), local (10 to 1000 km^2), and regional (greater than 1000 km^2). It was found that roughly 72% (76) of the articles reviewed focused on local-scale zoning (Figure 5c), which is the standard scale utilized for the planning and execution of developments, early warning systems, and disaster management plans at the local level [66].

3.3. Triggering Process and Landslide Types

Rainfall is the predominant triggering process leading to landslides in Italy [30,67,68]. From January 1996 to December 2021, the ITALICA (ITAlian rainfall-induced LandslIdes CAtalogue) database documented a total of 6312 landslides triggered by rainfall in Italy, as reported by Peruccacci et al. [30]. This is reflected in the landslide susceptibility studies: 91 (86.67%) articles considered exclusively rainfall-induced landslides, followed by 9 (8.57%) articles that addressed both rainfall- and earthquake-induced landslides, while only the remaining 5 (4.76%) articles focused on landslides triggered by earthquakes (Figure 6a).

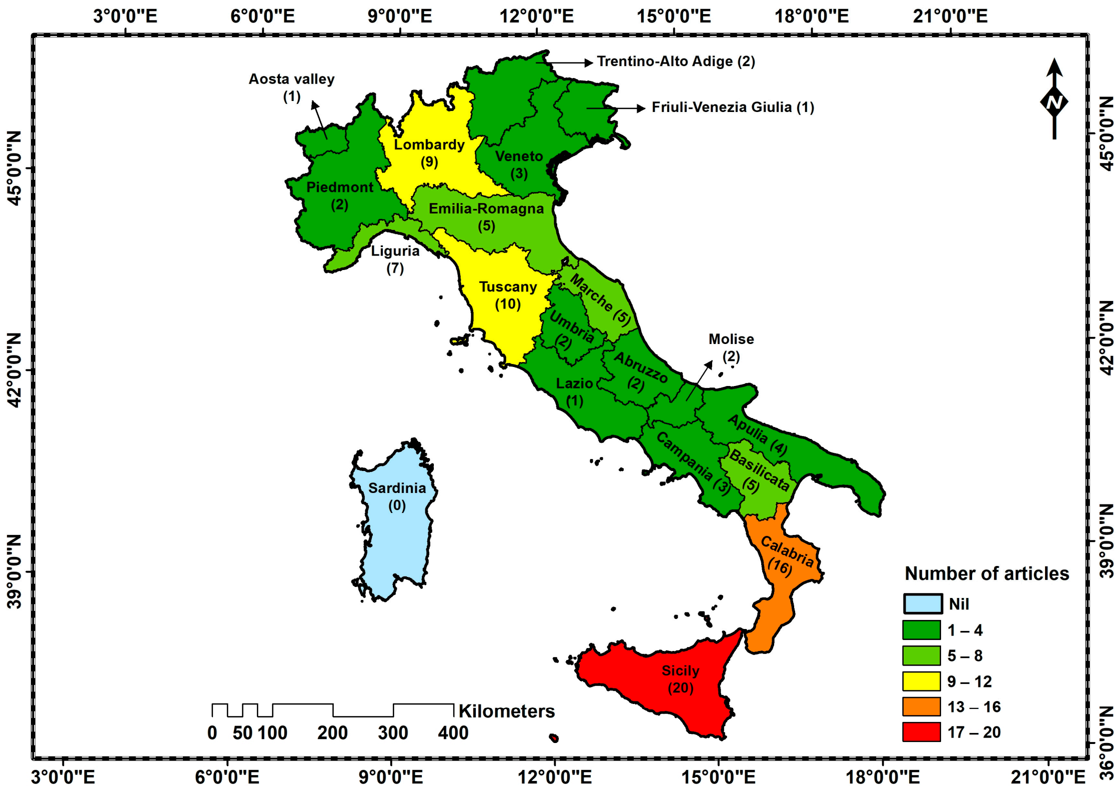

Figure 4. Region-wise number of landslide susceptibility assessment studies.

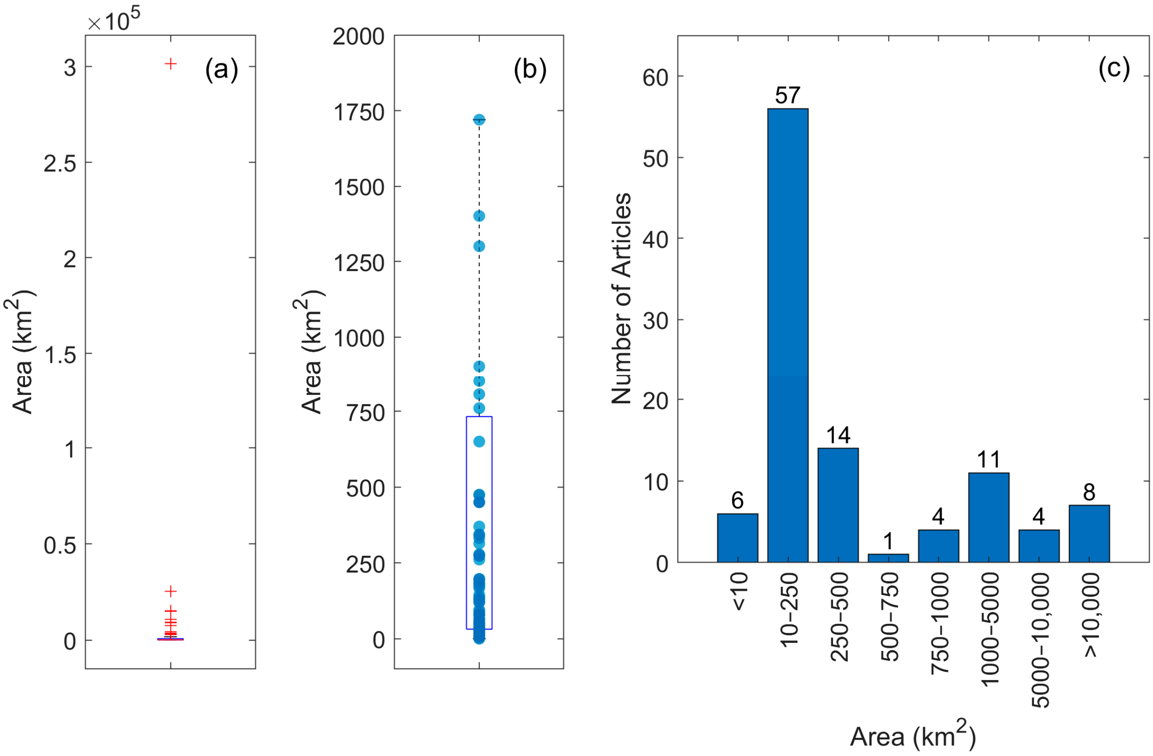

Figure 5. (**a**) Boxplot illustrating the distribution of study area extents (in km^2) (red plus signs indicate outliers); (**b**) boxplot of the same data with outliers removed (blue circles represent individual data points); and (**c**) bar plot showing the number of articles across different area classes.

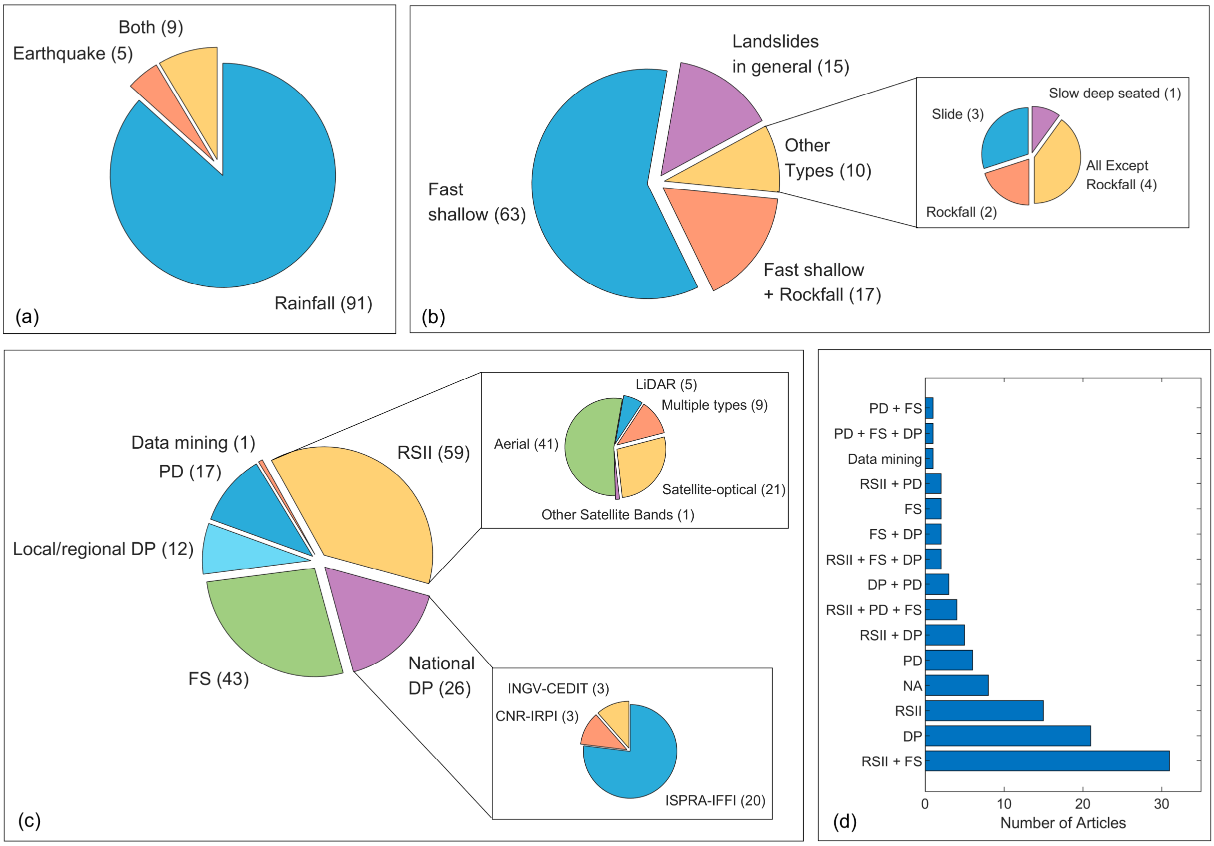

Figure 6. (**a**) Triggering processes; (**b**) landslide types; (**c**) sources of landslide inventory (RSII = remote sensing image interpretation; FS = field survey; DP = data portal; PD = published documents); (**d**) number of articles and their respective inventory sources (NA = not available).

Concerning the landslide type, 63 (60%) articles exclusively focused on fast-moving shallow landslides, followed by 17 (16.19%) articles examining shallow landslides and rockfall, 15 (14.28%) articles focusing on landslides in general, while the remaining 10 (9.52%) focused on other types (Figure 6b). The emphasis on assessing the susceptibility of shallow landslides may be attributed to the thousands of incidences and subsequent damages caused by them each year due to short yet intense rainfall [69–71]. Indeed, several studies have demonstrated that this landslide typology has become increasingly frequent in Italy, due to climate change [59,61,72–77]. The limited size of shallow landslides does not diminish their destructive potential, as they can rapidly propagate with devastating consequences [78]. Moreover, shallow rapid movements (e.g., soil slips, debris flows, and mudflows) are ubiquitous phenomena that often occur with limited precursory signals. For similar landslide types, widespread instrumental monitoring is generally not applicable (for economic and technical reasons); thus, susceptibility mapping is a fundamental prerequisite for prevention measures.

3.4. Source of Landslide Inventory and Data Splitting

A landslide inventory is a comprehensive record of the location and characteristics of past occurrences [79,80], which is crucial for conducting susceptibility assessments as its completeness and quality reflect the reliability of the final susceptibility map [81,82].

The IFFI (Inventario dei Fenomeni Franosi in Italia) project, managed by the Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA), serves as the primary, official national landslide inventory in Italy, providing extensive information on landslides throughout the country with a high degree of completeness and reliability [28,83,84]. Furthermore, the Consiglio Nazionale delle Ricerche (CNR) also maintains detailed records of landslides and associated geo-hydrological events in Italy [30,85,86]. The CEDIT (Catalogo degli Effetti Deformativi Indotti da Terremoti in Italia) portal, managed by the Centro di Ricerca Previsione, Prevenzione e Controllo dei Rischi Geologici (CERI), is a national inventory specifically documenting landslides triggered by seismic events [87–89].

However, our analysis revealed that these national-level data portals, although extensively covering the whole national territory, were used only in 24.76% (26 articles) of the reviewed works: 20 studies gathered data from IFFI, 3 from the CEDIT portal, and 3 from CNR datasets (Figure 6c).

In most cases, the authors integrated diverse sources to compile their landslide inventory. The literature review revealed that 59 (56.19%) studies extracted data through the interpretation of remote sensing images, 43 (40.95%) studies carried out field surveys, 38 (36.19%) studies made use of data portals (with 26 studies using the three aforementioned national portals and 12 studies using local or regional portals), 17 (16.19%) studies gathered data from published documents, and 1 study extracted landslide locations through a social media data mining technique.

More precisely, some typical associations of two or more of the aforementioned techniques emerge as the most recurrent methods to establish a trustworthy landslide inventory for susceptibility studies: 31 (29.52%) articles purposely created an inventory by interpreting remote sensing images and validating it through field survey; 22 (20.95%) articles homogenized data retrieved from different data portals at different scales (e.g., national portals and portals from local or regional public administration), and 15 (14.28%) articles were based solely on interpreting remote sensing images (Figure 6d). The preference of researchers lies in interpreting remote sensing images and verifying them with field surveys to compile landslide inventories, rather than solely relying on data available in data portals. Remote sensing offers the advantage of near-real-time data collection, enabling the identification of new landslides, while field surveys guarantee verification. This combined approach guarantees the accuracy and comprehensiveness of landslide inventories, as data portals may not always offer the most up-to-date information or comprehensive coverage [90], especially in less explored regions. In addition, nationwide datasets (e.g., the IFFI inventory) are not regularly updated and the updates are not homogeneous among the various regions. Therefore, such datasets are used mainly in studies covering very large areas, while local-scale studies (which are the majority in the surveyed literature) integrate diverse sources to guarantee the incorporation of recent events, thereby augmenting the accuracy of predictions.

Among the articles that used remote sensing images, only nine utilized more than one type of imagery, such as LiDAR, aerial photos, and optical satellite data. Aerial photos were the most commonly used source of data (41 articles), followed by optical satellite imagery (21 articles) and LiDAR (5 articles) (Figure 6c). Only one study used different satellite bands rather than the optical ones: Spinetti et al. [91] employed InSAR C-band from Envisat-ASAR and X-band from COSMO-SkyMed. The image resolutions ranged from a few centimeters for LiDAR acquisitions [92,93] to 1–10 m for satellite and aerial images [91,94]. Notably, 36 articles did not specify the image resolution, which poses a significant limitation for reproducibility. Among the 59 articles, 58 performed manual detection of landslides, while only 1 implemented an automated methodology, then validated through aerial interpretation and field survey. Namely, Spinetti et al. [91] applied the Small Baseline Subset (SBAS) technique to detect slow deformations.

The process of data splitting consists of creating two independent training and testing subsets, and it is widely utilized in statistical and machine learning models [95]. The training dataset is used to construct the model with multiple parameter settings, whereas the testing dataset is employed to evaluate the accuracy of the model [96,97]. Moreover, by utilizing distinct datasets for model development and validation, we can ensure an unbiased evaluation of the model's performance and avoid overfitting problems [95,98,99]. The process of data splitting is not applicable for qualitative and semi-quantitative approaches in landslide susceptibility evaluations, as these methods depend on expert judgment and heuristic analysis [100,101] instead of data-driven (statistical or machine learning) models, which necessitate validation through training and testing datasets [102]. Despite some authors suggesting that improper data splitting can lead to unreliable and highly fluctuating model performance [103], there is no agreement on the best data splitting ratio to use in landslide susceptibility studies.

Consequently, it is not surprising that in the reviewed works seven different splitting ratios have been used, namely 90:10, 80:20, 75:25, 70:30, 65:35, 60:40, and 50:50 (Figure 7a). Among these, the researchers preferred the 70:30 ratio (16 articles), followed by the 75:25 ratio (10 articles). The 70:30 data splitting ratio is widely adopted for its ability to strike a balance between ensuring sufficient data for training and a robust sample for testing, ultimately aiding in the development of reliable and generalizable models. Several studies [42,103,104] have determined that the 70:30 data splitting ratio is the most efficient when comparing different splitting ratios. It is surprising to observe that 51 articles, which constitute 49.04%, did not include information on the data splitting ratio. Conversely, 15 articles utilized either qualitative or semi-quantitative methods, rendering data splitting inapplicable. The absence of clearly defined data splitting ratios in landslide susceptibility assessments may impede the reproducibility and clear evaluation of the research, thereby complicating the efforts of future researchers to assess or enhance existing models.

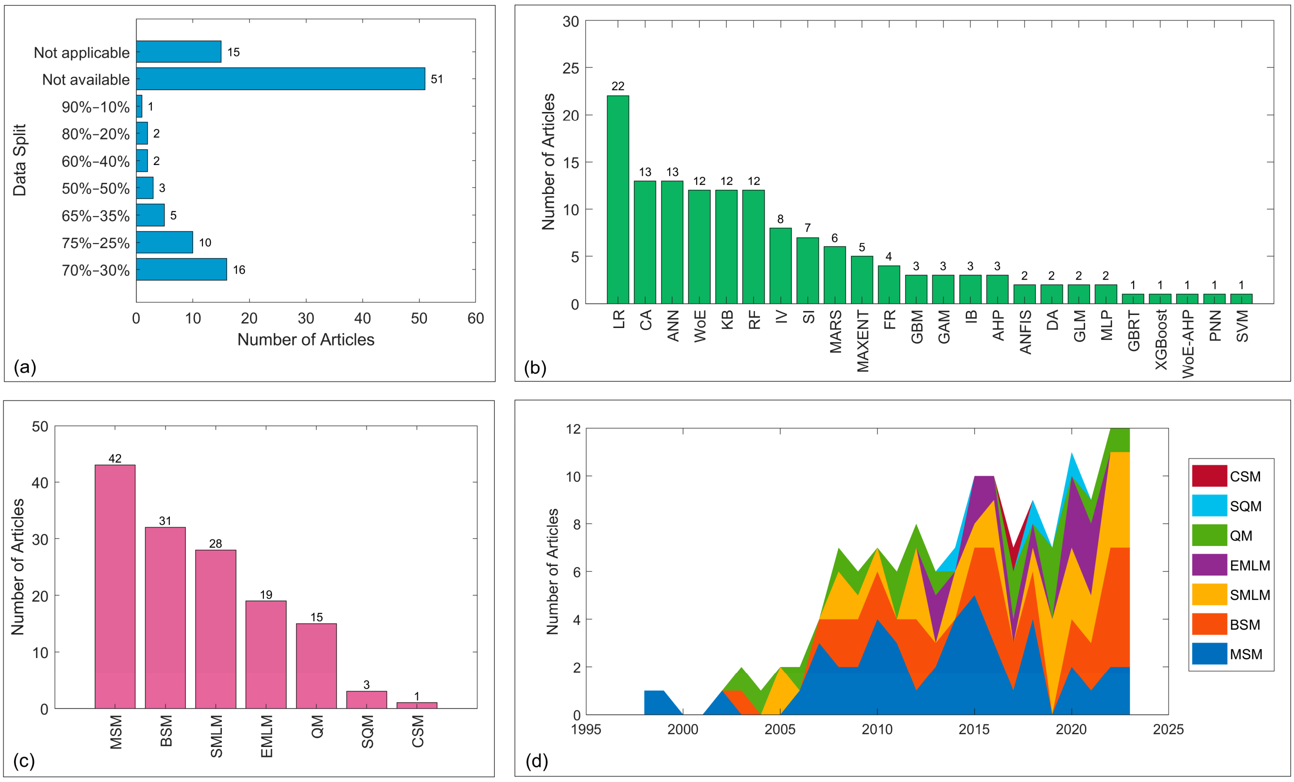

Figure 7. (**a**) Data splitting ratio; (**b**) methods utilized (refer to Table A1 for acronyms); (**c**) categories of methods; and (**d**) temporal distribution of each method category in terms of the number of article published.

3.5. Methods Used

The evaluation of landslide susceptibility can be conducted using both qualitative and quantitative methods [66]. Qualitative techniques such as inventory analysis, geomorphological mapping, and heuristic evaluation rely on field observations and expert knowledge [55,62,85,100,101]. The utilization of quantitative methods, which leverage numerical data and mathematical models, provides a more reliable framework for evaluating landslide susceptibility [41]. The quantitative methods encompass diverse approaches, such as statistical analysis (bivariate and multivariate statistics), probabilistic methods, and machine learning or deep learning methods [105]. Bivariate statistics like "frequency ratio" focus on understanding the relationship between two factors (e.g., landslide density and an environmental variable) [57,106], while multivariate statistics, such as logistic regression, investigate the simultaneous effect of multiple factors [107,108]. Probabilistic methods assess the probability of landslide events by taking into account the uncertainty and variability associated with predisposing factors (e.g., Monte Carlo simulation and Bayesian networks) [109–111]. Furthermore, semi-quantitative approaches involving multi-criteria decision analysis (e.g., analytic hierarchy process and fuzzy set-based analysis) have also been applied for landslide susceptibility analysis [112–114]. Data-driven models like machine learning involve self-learning algorithms that extract insights from data [115], which generally include supervised, unsupervised, and reinforcement learning [116,117]. Ensemble machine learning methods are currently in vogue as they involve combining predictions from multiple models to enhance performance [106,118–120]. The suitability of a method depends on the particular context, data availability, and scale of the study [121]. Each method possesses its unique strengths and applications, making it crucial to carefully consider these aspects before making a choice.

Our literature review revealed that 82 (78.09%) articles applied a single method, while the remaining 23 (21.91%) articles applied multiple methods to assess susceptibility. Applying multiple methods can facilitate the comparison of outcomes, which can emphasize the strengths and weaknesses of each method, thus promoting advancements and innovations in methodology.

During 1980–2023, researchers employed a total of 24 methods for landslide susceptibility assessment in Italy, with the most used methods being logistic regression (LR, 22 articles), conditional analysis (CA, 13 articles), artificial neural network (ANN, 13 articles), weight of evidence (WoE, 12 articles), knowledge-based or heuristic (KB, 12 articles), and Random Forest (RF, 12 articles) (Figure 7b). Similar trends can also be found outside Italy. The global-scale review articles by Pourghasemi et al. [122] and Reichenbach et al. [123] also identified LR as the most used method in landslide susceptibility assessments.

Different reasons stand behind the popularity of each of the aforementioned methods. LR can perform well when the independent variables are categorical, numerical, or both, and it is preferred over other statistical methods because of the lowest error rates [107,122,124–126]. Indeed, the review conducted by Lima et al. [127] observed that LR remains a popular method despite the rising trend of machine learning methods. The application of CA along with KB methods was prevalent in the earlier years, largely owing to the unavailability of advanced computational tools and reliable datasets. Additionally, Pourghasemi et al. [122] ranked the Analytic Hierarchy Process (AHP) as the fifth most utilized model. Nevertheless, the findings of this study indicate that AHP is not favored among researchers in Italy. This may be attributed to a stronger inclination among Italian researchers towards data-driven models. AHP is a semi-quantitative (knowledge-based) model that relies on the insights and judgments of experts [56,128], which can introduce potential biases into the decision-making framework [129]. Unlike traditional regression techniques, ANN is proficient in capturing intricate nonlinear relationships, and exhibits remarkable fault tolerance, enabling it to cope with incomplete datasets and noise efficiently [130,131]. Additionally, ANNs are known for their rapid processing speed and scalability through parallel computing, as well as their ability to generalize effectively [50,132,133]. The RF algorithm (proposed by Breiman [134]) is an ensemble of Decision Tree classifiers that produces predictions by amalgamating the output of each tree, thus yielding enhanced predictive accuracy [103,135]. Researchers favour this algorithm for its simple design, ease of comprehension, fast computational performance, proficiency in feature prioritization, and the ability to allocate distinct weight coefficients to various classes [102,136,137]. WoE is a data-driven approach that fundamentally adopts the Bayesian framework in a log-linear structure, integrating prior and posterior probabilities, and boasts various advantages relative to other statistical approaches [138]. WoE facilitates the handling of both continuous and categorical factors by discretizing them and assigning unique WoE values, while assuming conditional independence among factors and mandating normally distributed data, necessitating the exclusion of factors if these criteria are not fulfilled [112,139,140]. The global review by Pourghasemi et al. [122] ranked WoE as the third most commonly used model, with ANN in fourth place. In a different assessment, Reichenbach et al. [123] ranked ANN third and WoE sixth. This demonstrates the significant preference for these models among researchers on a global scale.

More generally, the 24 methods can be broadly subdivided into seven categories (Table A1), including multivariate statistical methods (MSMs, 42 articles), bivariate statistical methods (BSMs, 31 articles), standalone machine learning models (SMLMs, 28 articles), ensemble machine learning methods (EMLMs, 19 articles), qualitative methods (QMs, 15 articles), semi-quantitative methods (SQMs, 3 articles), and combined statistical methods (CSMs, one article) (Figure 7c). The first article utilizing a standalone machine learning method (namely, ANN) appeared in 2005 [116], whereas the first article on an ensemble machine learning method (namely, RF) was published in 2013 [103]. The number of articles published in the last five years indicates that machine learning methods are showing an increasing trend (Figure 7d). Furthermore, the last five-year data confirmed machine learning (standalone + ensemble) methods appeared in 25 articles, statistical (bivariate + multivariate) methods in 14 articles, qualitative methods in 5 articles, and semi-quantitative methods in 2 articles.

3.6. Predisposing Factors

The choice of appropriate predisposing factors is contingent upon the characteristics of the terrain, type of landslides considered, study scale, chosen methodology, data quality and availability, as well as expert knowledge and experience [122,123,127,141]. Describing the most frequently utilized predisposing factors is useful for researchers and future studies. While there are no precise guidelines for choosing predisposing factors, employing a common set of such factors, particularly in regions with similar geo-environmental characteristics, enables method standardization and facilitates meta-analysis [142]. Moreover, researchers can prioritize gathering high-quality data for deriving these factors when they are knowledgeable about the commonly utilized ones.

Upon analyzing the 105 articles, 107 predisposing factors were identified (a complete list can be found in Table A2). These factors can be grouped into morphological (35 factors), hydrological (22 factors), geological (33 factors), environmental (12 factors), and climatic (5 factors) groups (Table A2). The top 10 most utilized predisposing factors are slope angle (103 or 96.3% of all articles), lithology (94 or 87.9%), land use/land cover (LULC, 82 or 76.6%), aspect (81 or 75.7%), plan curvature (49 or 45.8%), elevation (49 or 45.8%), topographic wetness index (TWI, 42 or 39.3%), profile curvature (39 or 36.4%), distance from the streams (32 or 29.9%), and general curvature (29 or 27.1%) (Figure 8a).

Pourghasemi et al. [122] conducted a review of susceptibility studies and also identified slope as the most frequently used predisposing factor. The authors ranked the top ten most used factors as slope > lithology > aspect > LULC > elevation > distance from the stream/river > distance from the fault > plan curvature > distance from the road > profile curvature. We can conclude that the most used factors are largely the same in Italy and all over the world, with some exceptions worth noting. Distance from roads is used less frequently in Italy than elsewhere. As demonstrated by recent studies [143–145], the road network is also a hotspot for landslides in Italy. However, global-scale statistics are typically influenced by developing countries, where road networks are less engineered and thus more exposed to landslides compared to the average roadways in Italy. Indeed, distance from the road network is used in 21 studies. Moreover, Italian case studies use TWI more frequently than reported in global-scale surveys. This could be explained by the fact that most studies in Italy focus on rainfall-induced landslides, thus taking advantage of significant hydrological indexes like TWI.

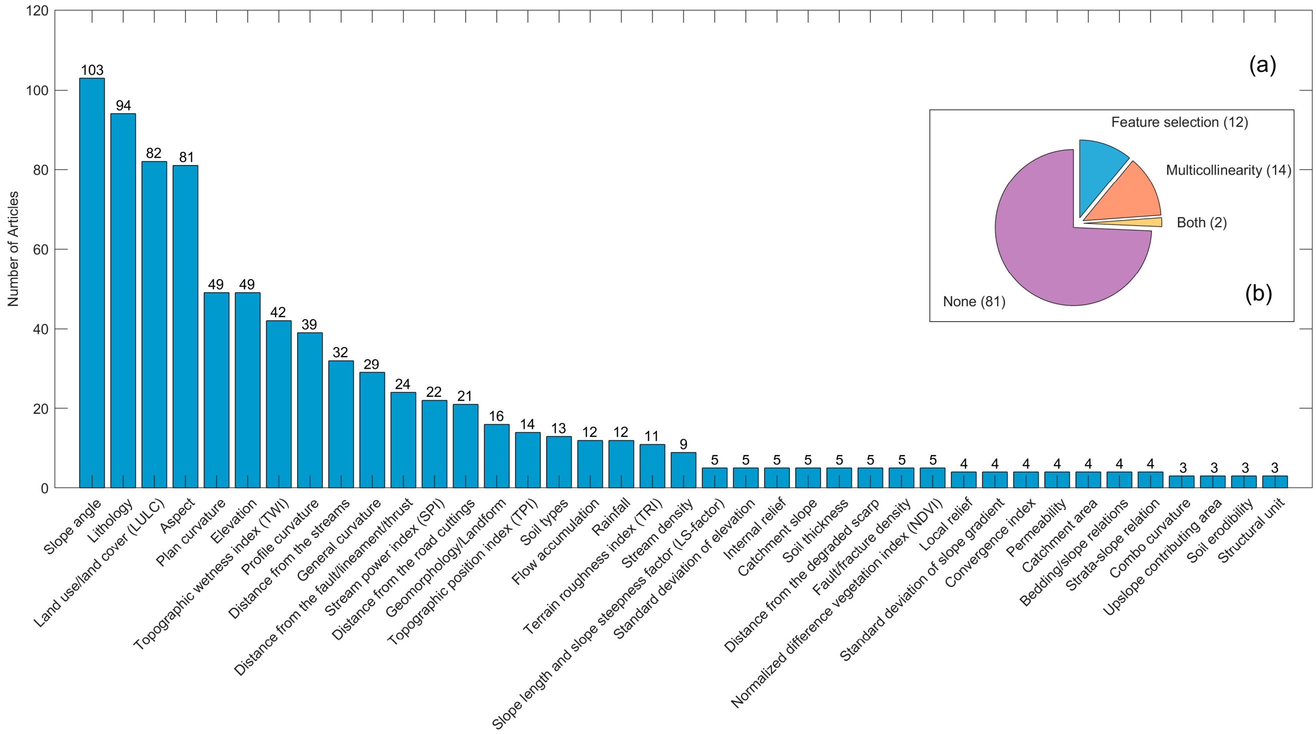

Figure 8. (**a**) Predisposing factors associated with more than two articles; and (**b**) articles that applied feature selection techniques, performed multicollinearity analysis, or both.

In contrast, some of the prevailing factors in the international literature, such as NDVI, distance from the faults, and rainfall [122], are rarely used in Italian studies. NDVI is commonly used as a proxy to identify bare areas or to account for vegetation density [146], which in turn exerts a stabilizing effect on slopes. Only five articles have utilized NDVI in Italy, generally because direct information on land cover and vegetation type/density is available with good thematic and spatial accuracy [59,102,147,148]. Indeed, LULC derived from Corine Land Cover is widely used [53,93,107,149], but sometimes regions also provide accurate thematic maps [118,150]. The relatively infrequent incorporation of distance from the fault/lineament/thrust among the input parameters (24 articles—22.4%), can be attributed to the fact that the use of this factor is more acknowledged for earthquake-triggered landslides, which are a minority in our analysis [151–153]. Concerning rainfall-related parameters, only 12 articles (11.2%) took it into account. The use of rainfall parameters in landslide susceptibility studies is still debated. Traditionally, rainfall is considered a triggering factor to be thoroughly analyzed when passing from susceptibility to the hazard (intended as the spatiotemporal probability of landslide occurrence [154]). Thus, in susceptibility assessments, rainfall-related parameters are usually neglected to avoid duplication in the final analysis of hazard or risk. However, recently, the use of rainfall-derived parameters has increased to also integrate elements accounting for climatic characteristics in the susceptibility assessment. For instance, Taalab et al. [155] used mean annual precipitation and Meena et al. [106] used the mean monthly rainfall; Ganga et al. [156] used the maximum rainfall observed in one day. Moreover, another series of studies use different rainfall-derived parameters to quantify climatic anomalies [65], the exceptionality of the registered rainfall events [157], or the attitude of the territory (expressed in terms of return time) to be affected by prolonged rainfalls or by exceptionally intense rainfalls [103,136]. These climate-related parameters are not popular (they are used in only 15 articles), but are usually very impactful in model performance [103,106,136].

It is also worth mentioning some variables that have been used only in a few studies: the rare usage does not mean that they are not good predictors; on the contrary, they often represent a novel attempt by researchers to tackle scientific issues for which a solution has not been generally established yet. For instance, the detrimental effect of abandonment of mountain cultivation is well acknowledged, but its implementation in a susceptibility map is not straightforward. Consequently, Di Napoli et al. [147] included a thematic map representing the degree of abandonment of agricultural terraces in their susceptibility model. Similarly, Trigila et al. [108] and Di Napoli et al. [118] integrated the perimeter of burnt areas to explicitly account for the effect of wildfires on landslide susceptibility. Another highly debated topic is the impact of urbanization on landslide hazards. Most studies worldwide indirectly account for it using LULC maps [158,159]. However, given the growing importance and attention devoted to this topic [9,160], some authors recently started to investigate the possibility of using other environmental variables better targeted to this peculiar process. For instance, Luti et al. [102] proposed an indicator derived from the national soil sealing monitoring program, and Roccati et al. [161] directly used a map of the anthropic elements.

The factor “distance from the earthquake epicentre” has been employed in only two studies. The first, conducted by Carabella et al. [55], analyzes the susceptibility to earthquake-induced landslides across the entire Abruzzo region, one of the most seismically active areas in Italy. The second study, by Ganga et al. [156], focuses on a mountainous area in northern Puglia. Another parameter used exclusively for the assessment of earthquake-induced landslides is Peak Ground Acceleration (PGA), employed only by Ganga et al. [156]. The relationship between these earthquake-related parameters and landslide occurrences during and after seismic shocks is well-documented in the literature, thus representing a promising factor to be included in susceptibility studies of seismically induced landslides [50,142,162].

Parameters such as degree of rock fracturing and fracture density have been primarily utilized for rockfall susceptibility mapping, particularly in an area of the Basilicata region characterized by frequent sliding rock blocks [163], and in the Abruzzo region for assessing susceptibility to earthquake-induced landslides [55]. Despite the strong correlation with landslide activity documented by the authors, these parameters have not been widely used because assessing their spatial distribution is time-consuming and is typically feasible only for studies conducted at detailed scales. The only study on deep-seated landslides identified in this review, conducted by Pecoraro et al. [140], focuses on susceptibility assessment along specific strategic road sections in the Basilicata region. In fact, the presence of inappropriate and steep slope cuts made for road construction is typically the main cause of deep-seated landslides that can trigger movement in such anthropogenic slopes [164].

3.7. Feature Selection

Identification of highly correlated or multicollinear factors is a crucial and preliminary analysis that should be performed prior to the susceptibility analysis and can be used to refine the selection of the optimal set of parameters [103,117,137,165]. Multicollinearity is defined as the situation where two or more independent factors are highly correlated within a regression model [126]. This poses a challenge as it diminishes the statistical significance of an independent factor and may result in biased or erroneous estimates [166,167]. One way to address this issue is by excluding highly correlated or multicollinear factors from the analysis [168]. Researchers often compute the correlation coefficient, variance inflation factor, or tolerance scores to identify the highly correlated or multicollinear factors [169,170]. The study by Davino et al. [171] revealed that standard errors rise with increasing multicollinearity.

Datasets containing irrelevant and redundant features may cause machine learning algorithms to perform less efficiently [102,137,172–174]. Feature selection is a technique that efficiently decreases the dimensionality of data and processing time by removing redundant and irrelevant features, ultimately improving the accuracy of models [65,106,119]. Several studies [103,136,172,175] have demonstrated that implementing feature selection techniques boost the accuracy of the models. However, the systematic review affirmed that only 14 (13.33%) articles assessed the correlation or multicollinearity, only 12 articles (11.43%) applied feature selection techniques, and only 2 articles (1.90%) applied both (Figure 8b). Notably, 81 articles (77.14%) did not apply any of these feature selection techniques. Among the retrieved papers, researchers used methods like Gini coefficient [149], Recursive Feature Elimination [117], Out-of-Bag Error [102,103,119,136,137], and Bivariate Success Index and Bivariate Standard Deviation Index of the normalized weights [176].

3.8. Feature Importance

Many studies also perform additional analyses aimed at assessing how much each of the input parameters influences the computed susceptibility values [103,106,177–179]. In other words, the weight, or explanatory power, of each parameter is assessed in absolute or relative terms and the input parameters may also be ranked by importance [180]. This additional analysis is very important to gain a deeper understanding of the study case and could be used as an objective basis for the aforementioned process of feature selection [181,182]. Nocentini et al. [154] noted that a similar assessment is particularly important in data-driven approaches, to demonstrate the consistency of the outcomes with the physics of the triggering mechanism of landslides. Among the 105 articles analyzed, only 22 (20.95%) articles utilized a feature importance technique to determine the importance of predisposing factors. As depicted in Figure 9a, the techniques most commonly used to assess feature importance are based on the Out-of-Bag permuted predictor (7 articles), followed by other permutation-based techniques (5 articles). However, five articles [92,93,183–185] used other techniques without specifying the technique applied. The heat map (Figure 9b) created utilizing the top three factors from the 22 articles revealed that slope, elevation, lithology, distance from the streams, TWI, plan, and profile curvatures are the most influential predisposing factors.

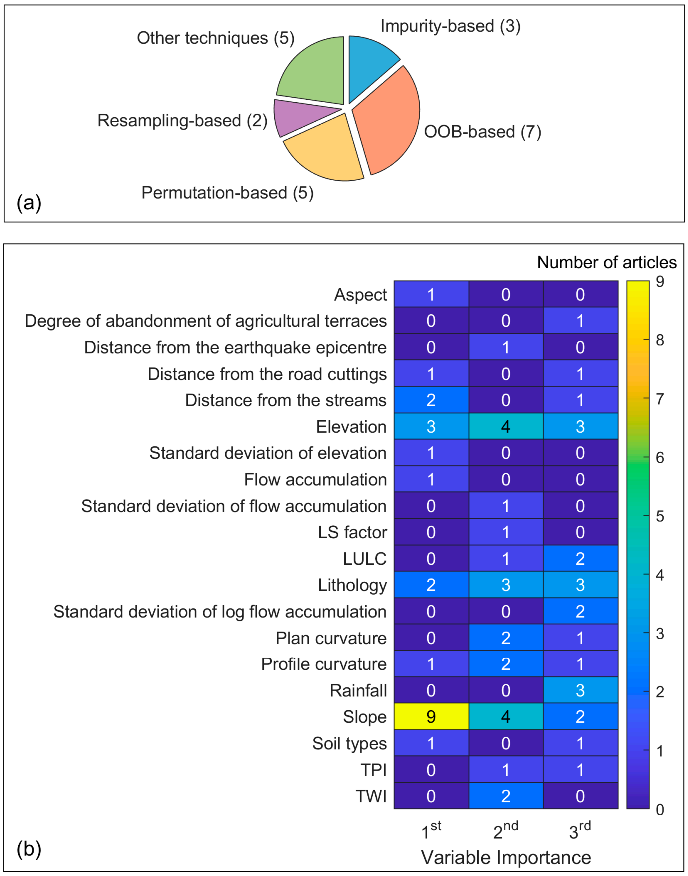

Figure 9. (**a**) Feature importance techniques; (**b**) heat map depicting the top three most important factors identified in the 22 articles that assessed variable importance.

3.9. Validation of Susceptibility Maps

The final objective of a susceptibility study is the definition of a susceptibility map, which is the representation of the proneness of each spatial unit to being involved in landslides. The output of all models reviewed in this work is a susceptibility index, which is a continuous numerical value. However, to ease the visualization and interpretation of the map, the continuous susceptibility values are aggregated into susceptibility classes (e.g., low, moderate, high, and very high susceptibility). This reclassification process involves defining threshold values to delineate each class, which ideally should be calibrated using the landslide inventory [103,116,186]. However, in some cases, authors opt for natural breaks (Jenks) method [187], which provides a straightforward yet robust and acknowledged method to maximize variability between classes while minimizing variability within each class. In some works, the reclassification approach is not specified, as it is presented merely as a matter of visualization.

It is crucial to validate the results of the landslide susceptibility map to assess the accuracy, reliability, and real-world applicability of the models and resulting maps, and many different methods can be employed for this purpose [188]. According to our review, 14 different validation techniques were employed in Italy (Figure 10a). The most commonly used methods are the Receiver–Operating Characteristic Curve and the relative Area Under the Curve (ROC curve/AUC, 61 articles), inventory comparison (IC, 22 articles), prediction rate curve and success rate curve (PRC_SRC, 16 articles), skill scores (12 articles), and Cohen's Kappa index (KI, 8 articles) (Figure 10a). The review article by Lima et al. [127] also identified the ROC curve/AUC as the most used validation technique. The ROC curve, along with the AUC, is instrumental in visualizing performance variations and effectively addresses the issue of class imbalance often present in accuracy and consistency metrics, facilitating a more nuanced evaluation of classification outcomes [188].

The practice of validation through inventory comparison was primarily employed in earlier years, likely due to the limited computational tools available at that time. A notable disadvantage of utilizing inventory comparison for validating landslide susceptibility is its tendency to lack the quantitative rigor and nuanced evaluation offered by statistical techniques. Statistical approaches provide insights into model performance across different thresholds. Moreover, inventory comparison may not fully represent a model's predictive accuracy, especially in areas with incomplete or skewed historical data.

The SRC serves as a tool for assessing how effectively the model aligns with the training data, while the PRC is applied to testing data to evaluate the model's ability to predict outcomes on new data [117]. Utilizing both curves ensures a robust validation process. Compared to ROC curve/AUC, their use is more limited because their computation and interpretation are not as straightforward as for ROC curve/AUC. The PRC and SRC depict the percentage of landslide areas within a susceptibility class, with a steeper curve signifying a higher concentration of events [101,189]. Additionally, PRC and SRC may be influenced by class imbalance, particularly when one class dominates, potentially distorting the assessment of model performance. Furthermore, while PRC and SRC curves generally highlight the model's efficacy in accurately identifying areas susceptible to landslides, they may not sufficiently account for the occurrence of false positives, which are non-prone areas erroneously identified as prone.

The skill scores denote one or more metrics, including Accuracy, Sensitivity, Specificity, Precision, and Recall. By offering a greater level of objectivity and standardization, these scores establish a quantitative basis for evaluating and contrasting the performance of different models [93]. The KI, much like the ROC curve/AUC, quantifies the accuracy of models by providing a singular numerical representation that encapsulates model performance [190–192]. The KI accounts for agreement that may occur by chance, while the ROC curve/AUC reflects the balance between sensitivity and specificity [193].

Our analysis affirmed that the first use of the ROC curve/AUC in an article dates back to 2009 [133], prior to which validation through inventory comparison was widely used. Since then, the popularity of the use of ROC curve/AUC gradually emerged over other methods (Figure 10b). The application of the KI for validation purposes has shown a slight increase over the past few years.

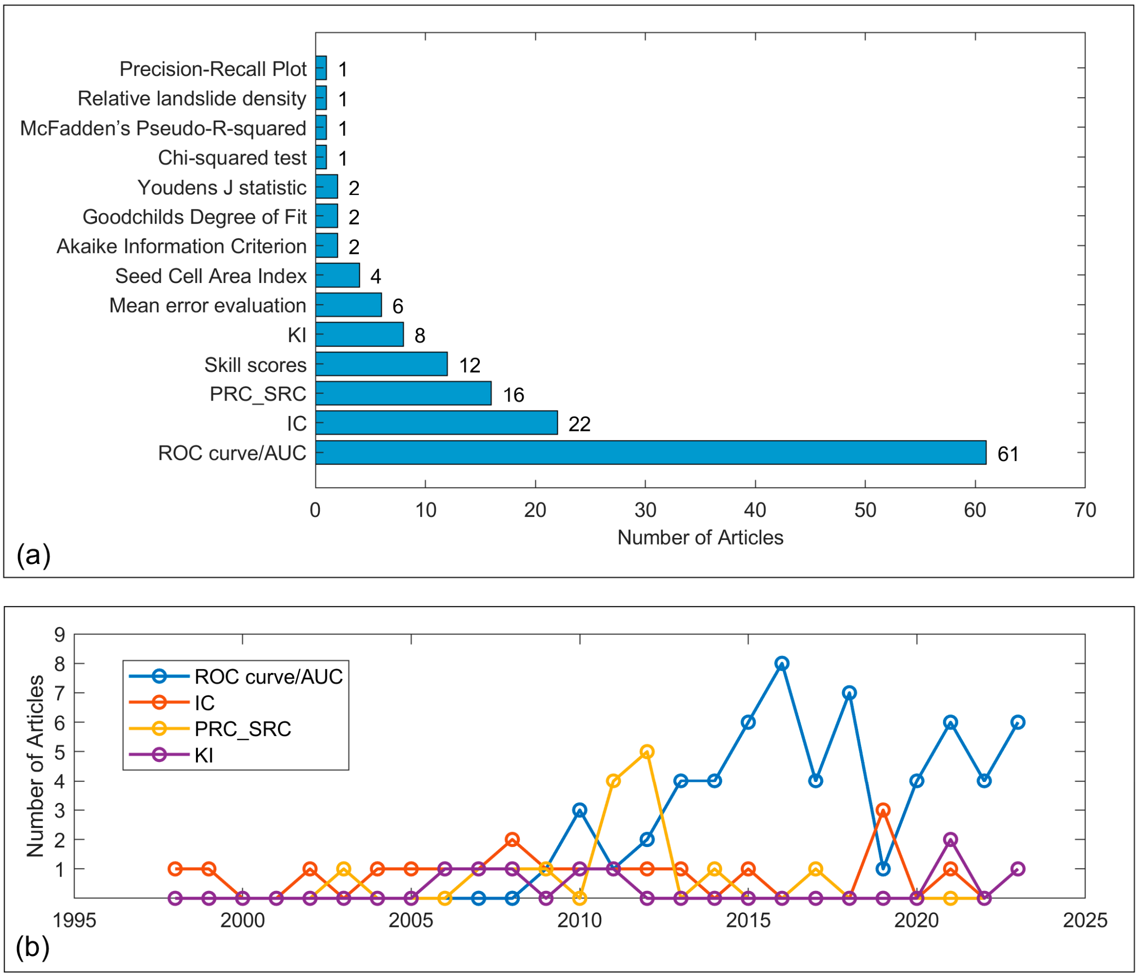

Figure 10. (**a**) Validation techniques employed; and (**b**) temporal distribution of the most frequently used validation techniques.

3.10. Model Comparison

The 23 reviewed articles report a quantitative comparison between two or three different methods. These comparisons are based on quantitative validation to assess which method provides the most reliable results. In Table 1, we have summarized all the comparisons found in the reviewed literature and counted how many times each model outperformed others in the Italian case studies. The summary statistics reveal that machine learning methods generally outperform simpler, traditional methods. Despite methods like LR and FR historically being among the most popular because of their simplicity and ease of use, they were consistently outperformed by ANN, RF, XGBoost, and other advanced methods. Considering all comparisons, XGBoost, RF, PNN, and MAXENT were found to be the most reliable models. Defining a model as "the best" in absolute terms is beyond the scope of this work and may be trivial. Indeed, our review highlighted that performance differences between two advanced models are generally smaller than those resulting from applying the same model with different configurations (e.g., different predisposing factors, sampling strategies, or spatial resolutions). For example, Meena et al. [106] found small differences between the models such as RF and XGBoost applied with the same number of input features (AUC 0.902 and 0.910, respectively), while larger differences were found by Catani et al. [103] applying the same model (namely, RF) with different pixel sizes (AUC ranging from 0.54 to 0.88 with 10m and 50m pixel size, respectively) or training sample size (AUC ranging from 0.97 to 0.74 when the model, based on the "best" pixel size, was trained with 50% or 5% of the sample).

Table 1. Comparison matrix showing the number of times the model in each row outperformed the model in each column based on the specified performance metric (For example, ANN outperformed DA one time and LR two times).

Models	ANFIS	ANN	CA	DA	FR	GBM	GBRT	GLM	IB	IV	KB	LR	MARS	MAXENT	MLP	PNN	RF	SI	WoE	WoE-AHP	XGBoost
ANFIS					**1**																
ANN				**1**								**2**									
CA																					
DA																					
FR										**1**		**1**									
GBM		**1**												**1**							
GBRT												**1**									
GLM			**1**																		
IB																					
IV																					
KB																					
LR				**2**	**1**					**1**								**1**	**1**		
MARS												**1**									
MAXENT		**1**			**1**					**1**		**1**									
MLP																**1**					
PNN	**1**				**1**																
RF					**1**							**2**						**1**			
SI									**1**	**1**	**1**										
WoE					**1**					**1**											
WoE-AHP																			**1**		
XGBoost					**1**												**1**				

4. Conclusions and Recommendations

We reviewed the scientific articles concerning landslide susceptibility mapping in Italian test sites published in the last 43 years in peer-reviewed Scopus-indexed journals. The analysis of 105 relevant articles revealed notable heterogeneity in the methods, predisposing factors, landslide inventories, data partitioning, and validation techniques utilized for assessing the reliability of maps. In part, this can be explained by the heterogeneity of the Italian territory (from a geological and geomorphological point of view), the long time span covered by the analysis (thus reflecting the technical and scientific improvements that occurred over the last decades), and the different aspects of the studies analyzed.

For instance, most of the articles focused on local scale zoning (areas smaller than 750 km^2), with more than half focusing on site-specific applications (areas smaller than 250 km^2). A total of 60% of the articles exclusively assessed fast, shallow-type landslides, and rainfall is the predominant triggering process modelled in Italy. Only about 20% of the articles applied two or more methods to validate the results and to select the most effective one, with the ROC curve/AUC being the most used.

Remote sensing image interpretation is the most common approach for landslide mapping, yet only one article utilized automated landslide detection techniques alongside manual mapping methods. The use of automated techniques and machine learning approaches for extracting landslides from optical and SAR images for landslide susceptibility assessments in Italy remains limited, despite their growing popularity worldwide [194–196]. This can partly be attributed to the smaller areas analyzed in most studies that employ remote sensing images. For small areas, identifying landslides manually is often more practical [197,198]. Given that the primary uncertainties in LSMs stem from the completeness of landslide inventories, automated techniques not only have the potential to save the time required for manual interpretation but can also enhance the accuracy of the results, making them highly recommended.

Regarding the ratios used to split the training and testing datasets, the 70:30 ratio is by far the most used; however, about half of the reviewed articles did not explicitly provide such information. We recommend specifying the data splitting ratio in future articles to ensure the reproducibility and validation of the research outcomes.

LR is the most used method, but machine learning (especially RF) has been on the rise in recent years, largely due to the necessity to handle predisposing factors with increasingly complex, high-resolution, and large datasets. On the other hand, deep learning techniques have not yet been tested in Italy for landslide susceptibility assessment. However, recent pioneering studies on the application of such approaches in other countries can be found in the literature [40,199,200] and can serve as the basis for future attempts in Italy.

Despite finding that advanced machine learning methods like XGBoost, RF, PNN, and MAXENT regularly outperformed other models, we do not believe we have found evidence to consider a model as "the best" in absolute terms. On the contrary, we discovered that sometimes switching from one advanced ML method to another results in limited improvement in terms of AUC. In contrast, using the same model can lead to significant improvements by optimizing other aspects of the modelling procedure, such as identifying appropriate and balanced sampling techniques or defining the optimal parameter set, including predisposing factors specific to the case study.

Among the 105 articles reviewed, researchers have incorporated 97 predisposing factors, with slope angle being predominant, followed by lithology and LULC. In addition to the most common factors, our review also highlighted some recently proposed environmental variables that, despite their relatively limited use, could offer promising approaches to better integrate emerging topics such as climate change, urbanization, and other human-driven environmental dynamics into landslide susceptibility assessments.

Concerning the selection of the predisposing factors, Italian scholars appear confident in their expert judgment, as ~77% of the articles have not incorporated any objective methods to verify the effectiveness and appropriateness of the input parameters selected. For future research, it is recommended to use feature selection techniques instead of relying solely on traditional factors. Given the distinct geo-environmental contexts of each study area, identifying the most suitable factors is crucial for improving the efficacy of the modelling and ensuring reproducibility.

Additionally, about 80% of articles have not determined the importance of predisposing factors through feature importance analysis. Especially with the rise of ML techniques, it will be crucial for future articles to perform a feature importance analysis for an objective interpretation of the results. Such analysis allows us to verify if the model outcomes align with the physical mechanism of landslide triggering [154] and will help other researchers to recognize the key factors that are applicable to similar geo-environmental and climatic contexts, even in different countries.

To improve the robustness of the models, reproducibility, and objective interpretation of the results, we advise addressing the recommendations derived from the proposed systematic review, which can serve as objective bases for future landslide susceptibility assessment in Italy and abroad.

Author Contributions: Conceptualization, S.S. and R.F.; methodology, R.S.A., N.N. and S.S.; software, N.N. and R.S.A.; formal analysis, R.S.A., N.N. and S.S.; investigation, R.S.A., S.S. and N.N.; resources, S.S. and R.S.A.; data curation, N.N. and R.S.A.; writing—original draft preparation, S.S., R.S.A. and N.N.; writing—review and editing, S.S. and R.F.; visualization, N.N. and R.S.A.; supervision, S.S. and R.F.; project administration, R.F.; funding acquisition, R.F. All authors have read and agreed to the published version of the manuscript.

Funding: This study was carried out within the RETURN Extended Partnership and received funding from the European Union Next-GenerationEU (National Recovery and Resilience Plan—NRRP, Mission 4, Component 2, Investment 1.3—D.D. 1243 2/8/2022, PE0000005).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Various methods, their corresponding categories, and bibliographic references.

Category of Method	Method Name	No. of Articles	References
Bivariate statistical methods (BSMs)	Weight of Evidence (WoE)	12	[61,63,86,112,140,157,191,201–205]
	Information value (IV)	8	[57,64,140,176,206–209]
	Statistical index (SI)	7	[42,53,64,150,210–212]
	Frequency ratio (FR)	4	[57,106,213,214]
Combined statistical methods (CSMs)	WoE-AHP	1	[86]
Ensemble machine learning methods (EMLMs)	Random Fsorest (RF)	12	[42,60,102,103,106,108,118,119,136,137,155,215]
	Generalized boosting model (GBM)	3	[118,147,184]
	Adaptive neuro-fuzzy inference system (ANFIS)	2	[163,214]
	Gradient boosted regression trees (GBRTs)	1	[183]
	Extreme Gradient Boosting (XGBoost)	1	[106]
Multivariate statistical methods (MSMs)	Logistic regression (LR)	22	[42,51,57,63,65,77,94,104,107,108,133,152,156,183,213, 216–222]
	Conditional analysis (CA)	13	[58,133,139,149,189,223–230]
	Generalized additive model (GAM)	3	[52,145,231]
	Discriminant analysis (DA)	2	[221,222]
	Generalized linear model (GLM)	2	[54,139]
Qualitative methods (QMs)	Knowledge (heuristic or index) based (KB)	12	[55,62,64,85,91,100,101,151,161,221,232,233]
	Inventory based (IB)	3	[192,211,234]
Semi-quantitative methods (SQMs)	Analytic hierarchy process (AHP)	3	[56,128,235]
Standalone machine learning methods (SMLMs)	Artificial neural network (ANN)	13	[50,59,118,132,133,147,148,153,184,190,222,236,237]
	Multiple adaptive regression spline (MARS)	6	[92,93,165,185,218,238]
	Maximum entropy (MAXENT)	5	[57,118,147,184,239]
	Multilayer perceptron (MLP)	2	[116,214]
	Probabilistic neural network (PNN)	1	[116]
	Support vector machine (SVM)	1	[117]

Table A2. Predisposing factors used for landslide susceptibility assessments in Italy.

Group	Predisposing Factors	No. of Articles
Morphology	Slope angle	103
	Aspect	81
	Plan curvature	49
	Elevation	49
	Profile curvature	39
	General curvature	29
	Geomorphology/Landform	16
	Topographic position index (TPI)	14
	Terrain roughness index (TRI)	11
	Slope length and slope steepness factor (LS-factor)	5
	Standard deviation of elevation	5
	Internal relief	5
	Local relief	4
	Standard deviation of slope gradient	4
	Combo curvature	3
	Relative relief	2
	Relative slope position	2
	Slope roughness	2
	Standard deviation of curvature	2
	Standard deviation of plan curvature	2
	Standard deviation of profile curvature	2
	Amplitude of relief	2
	Slope maximum	1
	Curvature maximum	1
	Plan curvature maximum	1
	Profile curvature maximum	1
	Downslope distance gradient	1
	Log of the slope angle	1
	Log of the slope angle squared	1
	Mass balance index (MBI)	1
	Morphological protection index (MPI)	1
	Relief energy	1
	Slope height	1
	Vector Ruggedness Measure (VRM)	1
	Terrace state of activity	1
Hydrology	Topographic wetness index (TWI)	42
	Distance from the streams	32
	Stream power index (SPI)	22
	Flow accumulation	12
	Stream density	9
	Catchment slope	5

Table A2. *Cont.*

Group	Predisposing Factors	No. of Articles
Hydrology	Convergence index	4
	Permeability	4
	Catchment area	4
	Upslope contributing area	3
	Log flow accumulation	2
	Slope-SPI	2
	Slope-TWI	2
	Standard deviation of flow accumulation	2
	Standard deviation of log flow accumulation	2
	Standard deviation of TWI	2
	Channel base level	1
	Curve number (CN)	1
	CN derived index	1
	Hydrogeological complex	1
	Index of sediment connectivity	1
	Sediment transport index (STI)	1
Geology	Lithology	94
	Distance from the fault/lineament/thrust	24
	Soil types	13
	Soil thickness	5
	Distance from the degraded scarp	5
	Bedding/slope relations	4
	Strata-slope relation	4
	Fault/fracture density	5
	Soil erodibility	3
	Structural unit	3
	Chronological unit	2
	Dip	2
	Distance from the earthquake epicentre	2
	Genetic units	2
	Paleogeographic unit	2
	Soil bulk density	2
	Soil sand percentage	2
	Weathering	2
	Karst incidences (Karstification degree)	2
	Outcropping lithofacies	2
	Degree of rock fracturing	1
	Deposit thickness	1
	Distance from the landslide source area	1
	Geomechanical classification of rock types	1
	Kinematic hazard index of planar sliding	1

Table A2. *Cont.*

Group	Predisposing Factors	No. of Articles
Geology	Kinematic hazard index of toppling	1
	Kinematic hazard index of wedge sliding	1
	Near-surface deposit	1
	Peak ground acceleration (PGA)	1
	Potential erodibility	1
	Soil clay percentage	1
	Soil silt percentage	1
	Strike	1
Environment	Land use/land cover (LULC)	82
	Distance from the road cuttings	21
	Normalized difference vegetation index (NDVI)	5
	Soil sealing aggregation	2
	Wildfire (burned) area	2
	Anthropogenic elements	1
	Degree of abandonment of agricultural terraces	1
	Distance from the anthropogenic sinkholes	1
	Soil sealing	1
	Terraced soil	1
	Urban density	1
	Vegetation density	1
Climate	Rainfall	12
	Extreme events	1
	Pluviometric anomaly index (PAI)	1
	Temperature range	1
	Insolation	1

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