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Review

Current and Future Status of GIS-based Landslide Susceptibility Mapping: A Literature Review

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Abstract: Landslides are one of the most damaging geological hazards worldwide, threating both humans and property. Hence, there have been many efforts to prevent landslides and mitigate the damage that they cause. Among such efforts, there have been many studies on mapping landslide susceptibility. Geographic information system (GIS)-based techniques have been developed and applied widely, and are now the main tools used to map landslide susceptibility. We reviewed the status of landslide susceptibility mapping using GIS by number of papers, year, study area, number of landslides, cause, and models applied, based on 776 articles over the last 20 years (1999–2018). The number of studies published annually increased rapidly over time. The total study area spanned 65 countries, and 47.7% of study areas were in China, India, South Korea, and Iran, where more than 500 landslides, 27.3% of all landslides, have occurred. Slope (97.6% of total articles) and geology (82.7% of total articles) were most often implicated as causes, and logistic regression (26.9% of total articles) and frequency ratio (24.7% of total article) models were the most widely used models. We analyzed trends in the causes of and models used to simulate landslides. The main causes were similar each year, but machine learning models have increased in popularity over time. In the future, more study areas should be investigated to improve the generalizability and accuracy of the results. Furthermore, more causes, especially those related to topography and soil, should be considered and more machine learning models should be applied. Finally, landslide hazard and risk maps should be studied in addition to landslide susceptibility maps.

Key Words: Landslide susceptibility, GIS, trend, literature review

1. Introduction

Landslides are one of the most frequent natural and geological hazards worldwide. Hence, there is widespread concern over landslides, not only among scientists, engineers, and policy-makers, but also the general public. Many studies have investigated landslides. For instance, application of probabilistic,

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statistical, and machine learning-based technologies to the study of landslides has increased substantially over time, and geographic information system (GIS) technology is now used widely. In particular, GIS-based landslide susceptibility mapping has increased rapidly in recent years.

There are three assessment steps in landslide analysis: susceptibility, hazard (or possibility), and risk, as defined in Equations (1), (2), and (3) (Einstein, 1988):

$$\text{Susceptibility} = \text{f(landslide, landslide-related factors)} \quad (1)$$

$$\text{Hazard} = \text{f(susceptibility, impact factors)} \quad (2)$$

$$\text{Risk} = \text{f(hazard, damageable objects)} \quad (3)$$

The susceptibility term is a function of the probability of potential landslide occurrence and landslide-related factors. It does not depend on influencing factors, such as rainfall, earthquakes, and human activity. The hazard term depends on both influencing factors and susceptibility. The risk term depends on the presence of vulnerable target, such as people and property, and the hazard term. Influencing factors, such as precipitation and seismic activity, are very important.

Among these steps, susceptibility has been studied most frequently. To evaluate the status and trends of GIS-based landslide susceptibility mapping, we analyzed 776 relevant articles published over the last 20 years (1999–2018) in terms of study area, number of articles, number of landslides, causes, and models used. Furthermore, we analyzed the causes and models used in three periods to identify temporal trends. The purpose of this study was to analyze the status and trends in GIS-based landslide susceptibility mapping studies and propose avenues for future study.

There have been several reviews of GIS-based landslide susceptibility mapping (Sudhakar *et al*., 2013; Wu *et al*., 2015; Pourghasemi *et al*., 2018). The differences between these studies and our study is that we analyzed more articles, including newly published articles, so that we could better identify trends. Moreover, we suggest avenues for future study based on our analysis.

2. Methodology

To clarify the status of GIS-based landslide susceptibility mapping, we analyzed 776 articles published over the last 20 years (1999–2018). The articles were retrieved from Scopus (www.scopus.com) using the keywords “landslide” and “GIS.” We selected all articles from the retrieved data, omitting conference and review papers. After excluding several references that appeared in the search but could not be downloaded, we retrieved 768 articles. We also retrieved all relevant articles from the website of the Korean Society of Remote Sensing (http://ksrs.or.kr/), of which there were eight in total.

The articles were classified by year to determine the number of articles published per year. This information was used to identify yearly trends in GIS-based landslide susceptibility mapping studies. The study areas and number of landslides were extracted from the articles to evaluate the status of global landslide occurrence. Moreover, the study area and number of landslides can be used by researchers in the future to identify new causes, apply new models, and generalize and standardize results. We also extracted the causes of and models used to simulate landslides from the articles. To more clearly identify temporal trends, the articles were divided into three periods of 5 or 10 years based on the publication year and considering the number of articles: 1999–2008 (10 years), which included 146 articles; 2009–2013 (5 years), which included 250 articles; and 2014–2018 (5 years), which included 380 articles. We used information from each period to determine which landslide cause and model were most common and identify trends.

3. Results

1) Temporal trends in published articles

During 1999–2018, 776 articles on GIS-based landslide susceptibility mapping were published. Hence, an average of 39 articles were published each year. Generally, the number of articles published per year increased over time (Fig. 1). Whereas only 40 articles were published in the first 5 years (1999–2013), 9.5 times as many papers (380 articles) were published in the final 5 years (2013–2018). Of these, 87 articles were published in each of 2016 and 2017. During the whole study period, the gradient of the trendline of number of publications per year was 4.60 and the coefficient of determination (R^2) was 0.92, indicative of a rapid increase with a reliable fit.

2) Study area and number of landslides

The study areas of the investigated articles spanned many regions from 65 countries (Fig. 2); however, 83.1% of articles originated from 15 countries. The most common study areas were China (143 articles, 18.5%), India (89 articles, 11.5%), South Korea (70 articles, 9.1%), Iran (67 articles, 8.7%), Malaysia (53 articles, 6.9%), Turkey (46 articles, 6.0%), Italy (39 articles, 5.0%), Nepal (23 articles, 3.0%), United States (22 articles, 2.8%), Greece (19 articles, 2.5%), Vietnam (19 articles, 2.5%), Romania (15 articles, 1.9%), Japan (14 articles, 1.8%), Hong Kong (13 articles, 1.7%), and Taiwan (13 articles, 1.7%), respectively (Fig. 2). Although Hong Kong is a Chinese territory, it was separated for the purpose of this analysis because of the large number of landslide studies in Hong Kong. Examples of these studies included GIS-based landslide susceptibility mapping in China (Chen *et al*., 2018) and India (Singh and Kumar, 2017), as well as landslide susceptibility modeling in South Korea (Park *et al*., 2018a), Iran (Kalantar *et al*., 2018), Malaysia (Tien Bui *et al*., 2018), Turkey (Arca *et al*., 2016), and Italy (Borrelli *et al*., 2018), respectively.

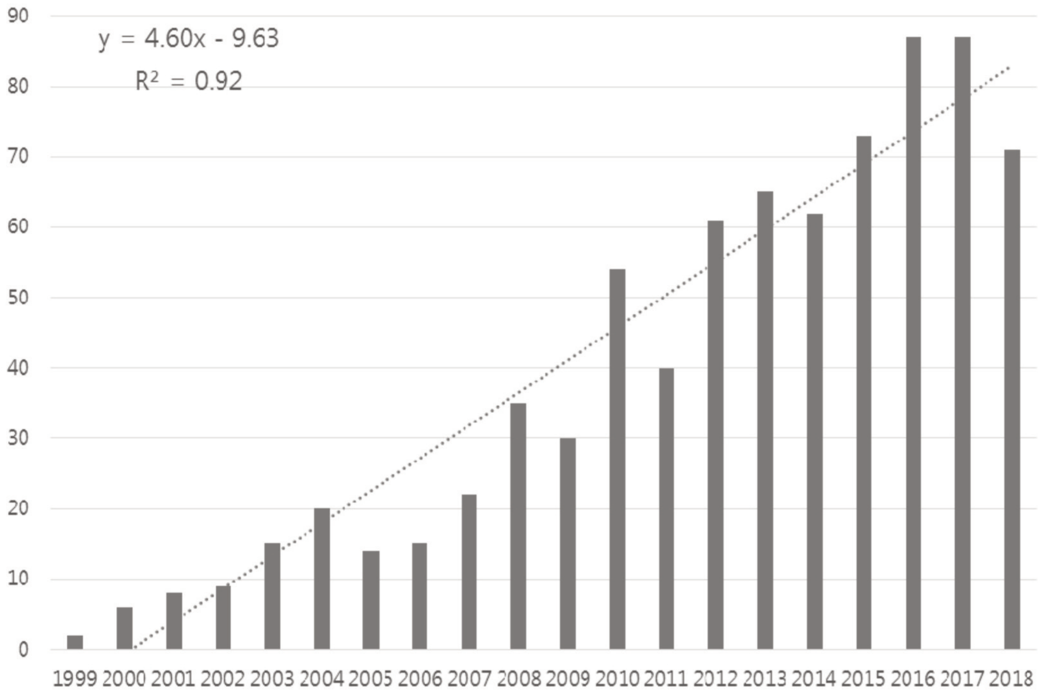

Fig. 1. Number of published articles in the research field of landslide from 1999 to 2018.

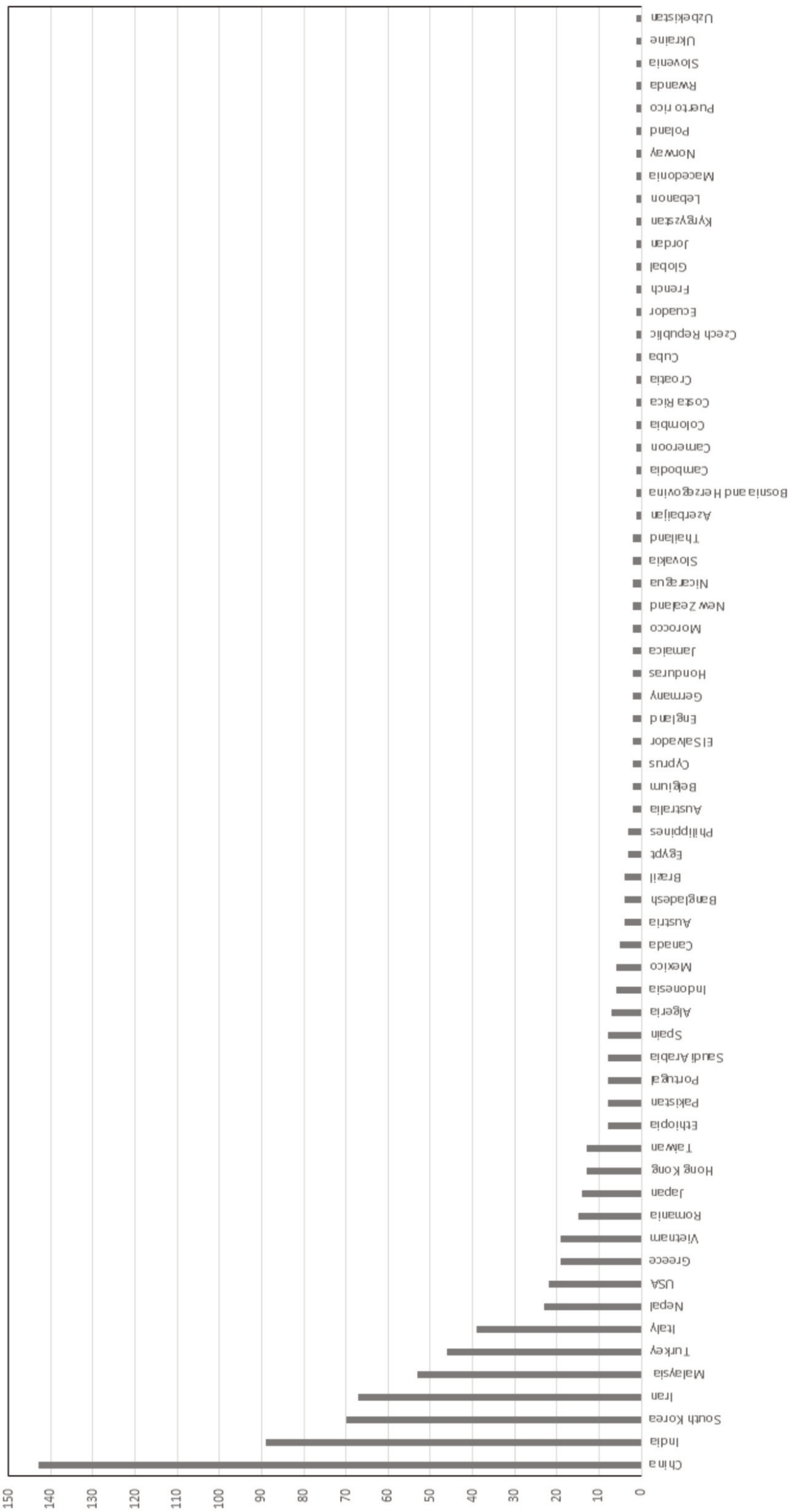

Fig. 2. Number of landslide study areas used for the published articles with respect to countries.

More than 700,000 landslides were used for GIS-based landslide susceptibility mapping, with an average of 1072 landslides studied per paper. Of note, it was not possible to count the number of landslides considered in some articles, because they used pixel numbers or contained no data. According to the number of landslides (Fig. 3), 182 articles (27.1%) studied less than 100 landslides (Oh *et al*., 2018), 143 articles (21.3%) studied 101–200 landslides (Lee *et al*., 2018a), 73 articles (10.9%) studied 201–300 landsides (Truong *et al*., 2018), 45 articles (6.7%) studied 301–400 landsides (Shirani *et al*., 2018), 45 articles (6.7%) studied 401–500 landslides (Hadji, 2017), 91 articles (13.6%) studied 501–1000 landslides (Kadavi *et al*., 2018), 47 articles (7.0%) studied 1001–2000 landslides (Aghdam *et al*., 2016), and 45 articles (6.7%) studied more than 2000 landslides (Lee *et al*., 2017; Pellicani *et al*., 2017).

3) Causes of landslides and trends

Many researchers have considered a variety of causes of landslides when performing GIS-based landslide susceptibility mapping and have found many causes of landslides. Each of the 776 investigated articles considered multiple causes for GIS-based landslide susceptibility mapping, for a total of 7030 causes. In terms of the trends in the number of causes studied, 1079, 2190, and 3761 causes were considered during the first (1999–2008), second (2009–2013), and third (2014–2018) periods, respectively. On average, 7.4, 8.8 and 9.9, causes were considered in the first, second and third periods, respectively.

The causes could be divided into six major groups: topographic, hydrologic, transportation, geologic, soil, forest, and land use. Topographic factors included elevation, slope, aspect, curvature, relief, and geomorphology. Many types of curvature (e.g., planar, plan, and profile curvature) have been implicated as causes. Generally, many factors can be extracted using digital elevation models (DEMs). Among topographic factors, slope was considered very frequently (Nguyen *et al*., 2017), and other topographic factors such as

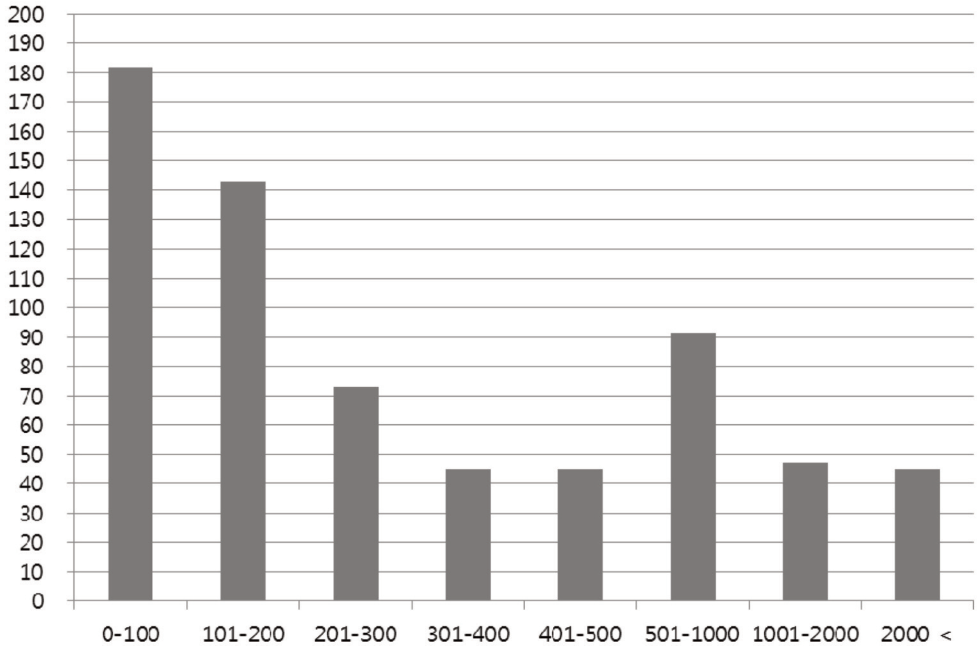

Fig. 3. Number of published articles with respect to number of landslides occurred in the study area of each published article.

aspect (Cui *et al*., 2017), curvature (Ge *et al*., 2018), elevation (Pourghasemi and Rahmati, 2018), and geomorphology (Ahmed and Dewan, 2017) were considered frequently. Common hydrological factors included distance from and density of river, stream, and drainage (Lyu *et al*., 2018); topographic wetness index (TWI) (Abdulwahid and Pradhan, 2017); and stream power index (SPI) (Lee *et al*., 2018b). Transportation-related factors included distance from roads and railways, and density of roads and railways (Kornejady *et al*., 2017). Common geological factors included lithology, distance from fault and lineament, density of faults and lineaments, bedding, and foliation (Achour *et al*., 2017), among which distance from faults (Park *et al*., 2018b) and lineaments (Singh and Kumar, 2018) have been implicated frequently as causative factors. Soil-related causes included soil type, material, thickness, drainage, and strength (Pham *et al*., 2017). Commonly investigated forest-related factors included forest type, age, diameter, density, vegetation, and normalized difference vegetation index (NDVI) (Kim *et al*., 2018). Finally, within land use, researchers have considered both land use (Tien Bui *et al*., 2017) and land cover. Other notable influencing factors included precipitation and earthquakes (Jeong *et al*., 2018).

As shown in Fig. 4, slopes were considered in 757 times of total factors (10.8%). The other most commonly considered factors were geology (642 times; 9.1%), aspect (592 times; 8.5%), river or stream (580 times; 8.3%), curvature (567 times; 8.1%), land use (461 times; 6.6%), elevation (450 times; 6.4%), soil (433 times; 6.2%) and fault (5.2%).

The most commonly included influencing factors during the first period (1999–2008) were slope (141 times; 13.1%), geology (112 times; 10.4%), soil (109 times; 10.1%), aspect (101 times; 9.4%), land use (83 times; 7.7%), forest (78 times; 7.2%), and curvature (73 times; 6.8) were used most widely (Fig. 5). The most commonly included influencing factors during the second period (2009–2013) were slope (241 times; 11.0%), geology (217 times; 86.8%), river or stream (201 times; 9.2%), aspect (191 times; 8.7%), land use (168 times; 7.7%), curvature (154 times; 7.0%) and fault (129 times; 5.9%) (Fig. 6). The most commonly

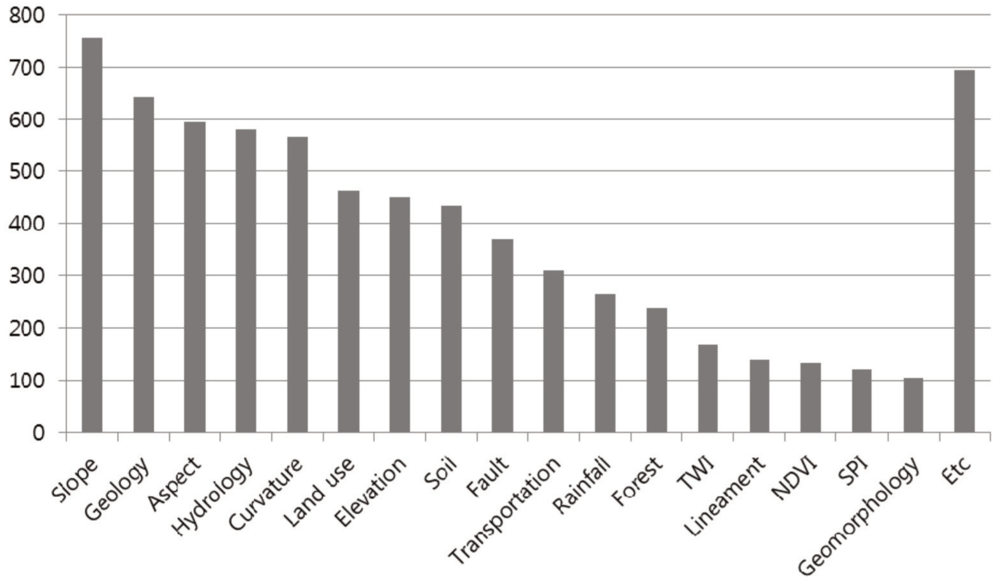

Fig. 4. Number of published articles with respect to the factor used as landslide causes in all of the published articles used for this study.

included influencing factors during the third period (2014–2018) were slope (375 times; 10.0%), curvature (340 times; 9.0%), geology (313 times; 8.3%), river or stream (307 times; 8.2%), aspect (303 times; 8.1%), elevation (264 times; 7.0%) and land use (210 times; 5.6%) (Fig. 7).

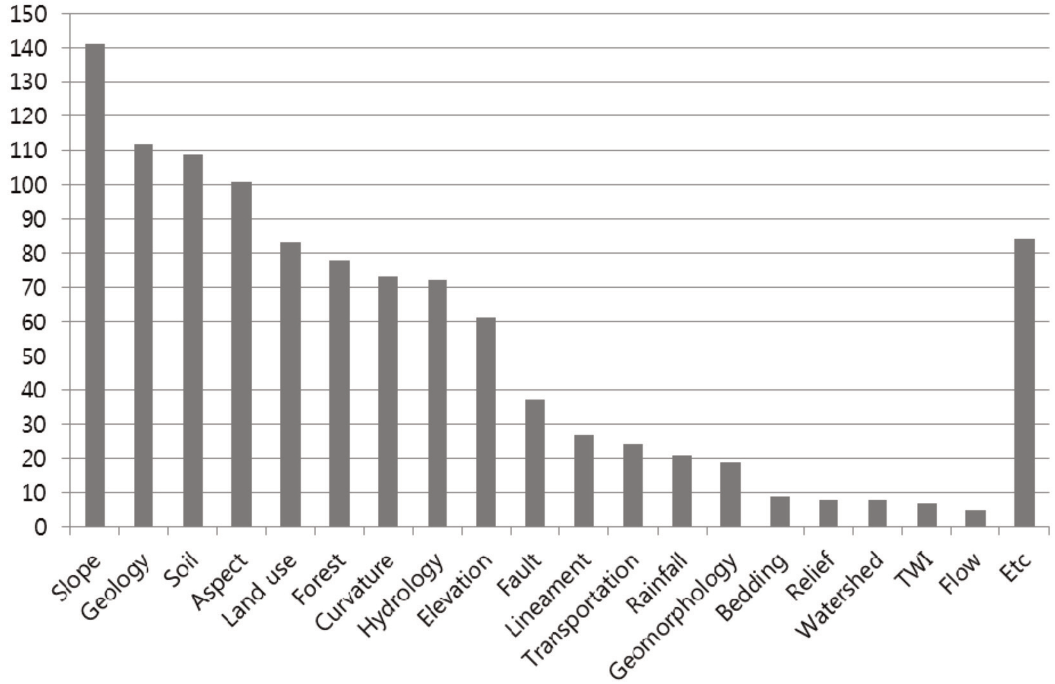

Fig. 5. Number of published articles with respect to the factor used as landslide causes in the articles published in the first period (1999–2008).

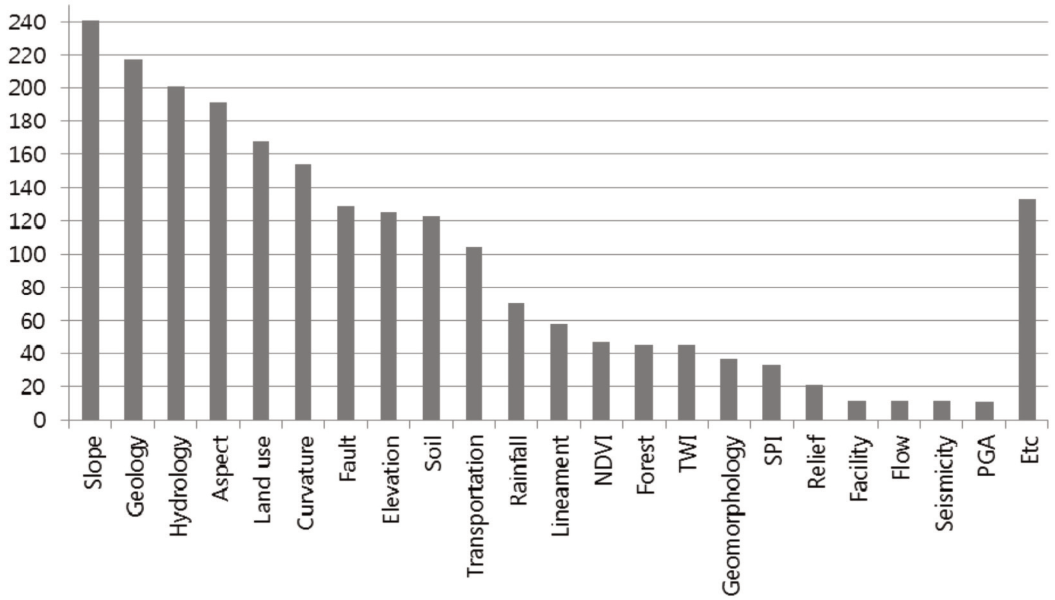

Fig. 6. Number of published articles with respect to the factor used as landslide causes in the articles published in the second period (2009–2013).

4) Models used to analyze landslide susceptibility and their trends

A wide range of models, algorithms, and techniques are used for GIS-based landslide susceptibility mapping. Models can be divided into data- and knowledge-driven categories. Data-driven models can be further divided into three categories: probabilistic, statistical, and machine learning models. Among knowledge-driven models, the analytic hierarchy process (AHP) and weight overlay are used widely. Among probabilistic models, frequency ratio, weight of evidence, evidential belief function, information value, and certainty factor models are used frequently. Among statistical models, logistic regression and statistical index models are used widely. Finally, popular machine learning models include artificial neural networks support vector machines, decision trees, adaptive neuro-fuzzy inference systems, and random forests.

Based on the literature review, there were 1498 instances of model use for GIS-based landslide susceptibility mapping in the 776 articles published during 1999–2018, with an average of 1.9 models used per article. Logistic regression models, used in 209 times (14.0%), were used most frequently (e.g., Lee and Lee, 2017; Zhu *et al*., 2018) (Table 1). Other most frequently used models were frequency ratio model (192 times; 12.8%) (e.g., Son *et al*., 2016; Aditian *et al*., 2018), artificial neural networks (121 times; 8.1%) (e.g., Chen *et al*., 2017; Gorsevski *et al*., 2016), fuzzy logic (114 times; 7.6%) (e.g., Mallick *et al*., 2018; Rostami *et al*., 2016), support vector machine (98 times; 6.5%) (e.g., Tien Bui *et al*., 2016; Hong *et al*., 2018), AHP (90 times; 6.0%) (e.g., Demir, 2018; Nicu, 2018), and weight of evidence (86 times; 11.1%) (Rahman *et al*., 2017; Jaafari, 2018). In addition to these frequently used models, index of entropy, naïve Bayes, boosted trees, functional trees, bagging, adaptive boosting, relevance vector machines, and logistic model trees have also been used.

Next, we analyzed the trends in model usage in the three periods. In the first period (1999–2008), the most

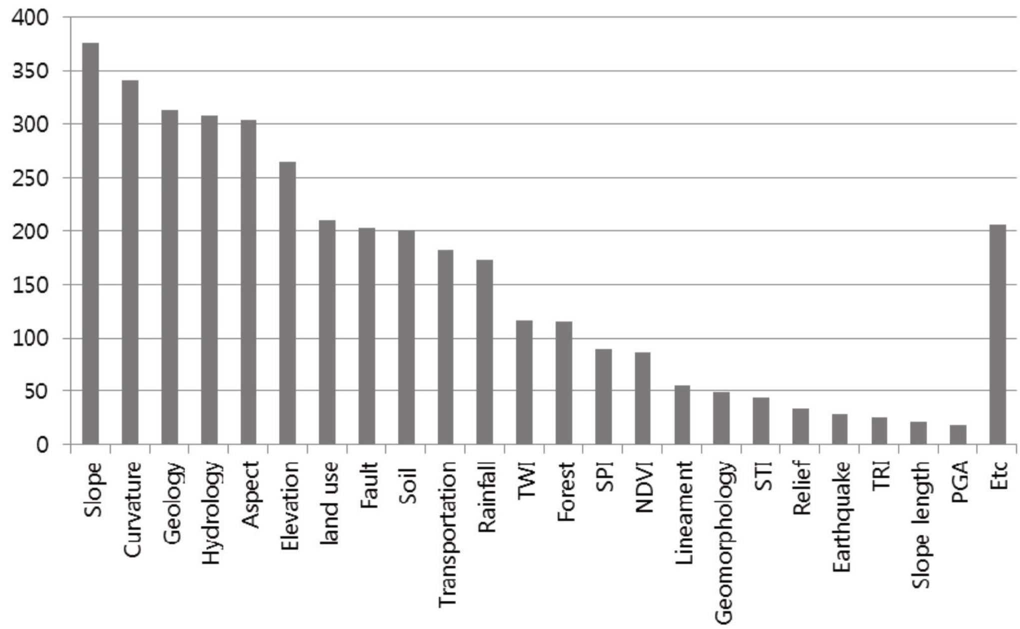

Fig. 7. Number of published articles with respect to the factor used as landslide causes in the articles published in the third period (2014–2018).

Table 1. Models used in the published articles

Model	No. of Model Used	% of Model Used
Logistic Regression	209	14.0%
Frequency Ratio	192	12.8%
Artificial Neural Network	121	8.1%
Fuzzy Logic	114	7.6%
Support Vector Machine	98	6.5%
Analytic Hierarchy Process	90	6.0%
Weight of Evidence	86	5.7%
Weighted Overlay	35	2.3%
Decision Tree	35	2.3%
Evidential Belief Function	34	2.3%
Information value	34	2.3%
Multi-Criteria Analysis	27	1.8%
Adaptive Neuro-Fuzzy Inference System	24	1.6%
Random Forest	24	1.6%
Statistical Index	22	1.5%
Weighted Linear Combination	17	1.1%
Certainty Factor	16	1.1%
Etc	320	21.4%

Table 2. Models used in the articles published in the first period (1999–2008)

Model	No. of Model Used	% of Model Used
Logistic Regression	48	25.0%
Frequency Ratio	33	17.2%
Weight of Evidence	15	7.8%
Artificial Neural Network	14	7.3%
Fuzzy logic	13	6.8%
Analytic Hierarchy Process (AHP)	6	3.1%
Weighted overlay	6	3.1%
Information Value	3	1.6%
Statistical index	3	1.6%
Weighted Linear Combination (WLC)	3	1.6%
Conditional Probability (CP)	2	1.0%
Multi criteria evaluation	2	1.0%
Newmark displacement	2	1.0%
Statistical analysis	2	1.0%
Etc.	40	20.8%

frequently used models were logistic regression (48 times; 25.0%), frequency ratio (33 times; 17.2%), weight of evidence (15 times; 7.8%), artificial neural network (14 articles; 7.3%), and fuzzy logic (13 times; 6.89%) (Table 2). In the second period (2009–2013), the most widely used models were logistic regression (69 times; 14.4%), frequency ratio (65 times; 13.5%), artificial neural network (65 times; 13.5%), fuzzy logic (62 times; 12.9%), and weight of evidence (31 times; 6.5%) (Table 3). During the third period (2014–2018), the most frequently used models were logistic regression (96 times; 11.6%), frequency ratio (90 times;

Table 3. Models used in the articles published in the second period (2009–2013)

Model	No. of Model Used	% of Model Used
Frequency Ratio	69	14.4%
Logistic Regression	65	13.5%
Artificial Neural Network	65	13.5%
Fuzzy logic	62	12.9%
Weight of Evidence	31	6.5%
Analytic Hierarchy Process (AHP)	30	6.3%
Support Vector Machine (SVM)	26	5.4%
Adaptive Neuro-Fuzzy Inference System (ANFIS)	12	2.5%
Information value (IV)	12	2.5%
Weighted overlay	10	2.1%
Evidential Belief Function (EBF)	8	1.7%
Weighted Linear Combination (WLC)	7	1.5%
Certainty Factor (CF)	4	0.8%
Conditional Probability (CP)	3	0.6%
Heuristic method	3	0.6%
Statistical Index	3	0.6%
Etc.	70	14.6%

Table 4. Models used in the articles published in the third period (2014–2018)

Model	No. of Model Used	% of Model Used
Logistic Regression	96	11.6%
Frequency Ratio	90	10.9%
Support Vector Machine	72	8.7%
Analytic Hierarchy Process	54	6.5%
Artificial Neural Network	42	5.1%
Weight of Evidence	40	4.8%
Fuzzy logic	39	4.7%
Decision Tree	35	4.2%
Evidential Belief Function	26	3.1%
Random Forest	24	2.9%
Weighted Overlay	19	2.3%
Multi-Criteria Analysis	25	3.0%
Information Value	18	2.2%
Statistical Index	16	1.9%
Adaptive Neuro-Fuzzy Inference System	12	1.5%
Certainty factor	11	1.3%
Naïve Bayes	9	1.1%
Index of Entropy	8	1.0%
Etc.	190	23.0%

10.9%), support vector machine (72 times; 8.7%), AHP (54 times; 6.5%), and artificial neural network (42 times; 5.1%) (Table 4).

5. Conclusion and Discussion

In this study, we reviewed 776 articles on GIS-based landslide susceptibility mapping from the last 20 years

(1999–2018) and analyzed them by year, country, number of landslides, causes, and model. In addition, we divided the articles into three periods to identify temporal trends.

The number of articles published annually increased rapidly over the 20-year study period, with more than 9.5 times the number of articles in the first 5 years (1999–2003) published in the last 5 years (2014–2018). This increase may have been driven by the availability of digital data, including remote sensing data, and development of new models such as machine learning models. This increase indicates that many researchers are interested in landslides, likely due to their global ubiquity and ability to inflict serious damage to both people and property, and have carried out GIS-based landslide susceptibility mapping studies. Furthermore, GIS technology has become a popular tool for analyzing landslide susceptibility, further driving the increase in the number of articles published on this subject.

The investigated articles covered many study areas in 65 countries; however, China (18.5% of studies), India (11.5%), and South Korea (9.1%) were particular targets of study. The results mirrored the global occurrence of landslides. The incidence of landslides is related to country-specific characteristics. For instance, countries with more mountainous areas and impact events (e.g., rainfall and earthquakes) are more likely to experience landslides, resulting in greater data availability and supporting more studies. In addition to collecting more landslide data, there should be concerted academic effort towards understanding landslides. Therefore, further case studies are required to improve the generalizability and accuracy of landslide information and modeling.

Among the 776 investigated papers, more than 700,000 landslides were considered; however, some of these may have been duplicates. Regardless, numerous landslides have been studied in individual studies, indicating that landslides occur very frequently. In particular, 94 articles considered more than 1000 landslides. These landslide data can be used for further analysis based on new and more accurate models, and the data can be merged for more reliable analysis. Hence, we recommend that researchers partake in international collaborations in which new models are applied to merged data on landslide locations and causes.

Causes, including DEM-based information, drainage, road, geology, fault, soil, forest, land use and others, were considered more than 7000 times in the GIS-based landslide susceptibility mapping studies. Among these causes, slopes were included in 97.6% of the articles and geology (82.7%), aspect (76.7%), hydrology (74.7%), and curvature (73.1%) were considered very frequently in the total articles. Furthermore, land use, elevation, soil, fault, transportation, rainfall, forest, TWI, lineament, NDVI, SPI, and geomorphology were considered frequently. These causes were considered frequently, suggestive of their close association with landslide occurrence. Over the three investigated periods, the average number of causes considered per article increased (first period: 7.4; second period: 8.8; third period: 9.9). However, the causes implicated in landslides did not vary significantly over the study period. To more clearly understand the relationships between causes and landslide occurrence and to improve the accuracy of mapping results, more causes should be identified and analyzed using existing data, such as DEM with SAGA GIS (Conrad *et al*., 2015). Furthermore, the importance or weights of causes can be analyzed using sensitivity analysis, artificial neural networks, or other models. Finally, the most predictive causes should be selected and standardized.

In terms of the models used, more than 100 types of models were used for GIS-based landslide susceptibility mapping, with a total of 1498 applications of models among all studies, corresponding to 1.9 model applications per article. Logistic regression models were applied most frequently (26.9% of all articles) to GIS-based landslide susceptibility mapping. Frequency ratio, artificial neural network, fuzzy logic, support vector machine, AHP, and weight of evidence models were applied in more than 10% of the articles. Logistic regression, frequency ratio, artificial neural network, fuzzy logic, and AHP models were used frequently during all three periods. Machine learning models, such as support vector machine, random forest, decision tree, and naïve Bayes models, have been applied more recently.

Landslide analysis involves three steps: susceptibility, hazard, and risk mapping. Many studies have analyzed susceptibility, including the present literature review. However, there are fewer articles on the hazard and risk steps. Hence, more studies should be carried out on the hazard and risk steps to decrease the damage caused by landslides, save lives, and protect property.

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