



# Landslide Susceptibility Evaluation and Analysis: A Review on Articles Published During 2000 to 2020

# 14

Jonmenjoy Barman, David Durjoy  
Lal Soren, and Brototi Biswas

## Abstract

Landslides are man-induced or natural triggering natural hazards with large-scale environmental and socioeconomic impact. From the last decade, landslide susceptibility zonation, using quantitative and qualitative techniques, is an interesting area of interest among scholars. The purpose of the present study was to analyze and review the trend of the published articles, methodologies adopted, and the area of study of the published articles during 2000 to 2020. The result of the review revealed that among the various methodologies adopted, machine learning and logistic regression were the maximum implemented, and south and southeast Asian countries are the most landslide-prone areas. The development of remote sensing and GIS has played a significant role in data gathering, analysis, visualization, and identification of landslide susceptible zones for proper monitoring. Knowledge-based study like the geographically weighted overlay method is much applicable in the northeastern states of India. Researchers emphasize on slope angle, topographic wetness index, and land use/land

cover as important conditioning factors in landslide occurrence. The study would be helpful for the researchers to choose study areas, methodologies, and preferable journals for publishing their research.

## Keywords

Landslide · Susceptibility · Machine learning · RS · GIS

## 14.1 Introduction

Landslide or landslip is a geological hazard that commonly happens in mountainous areas due to high energy and instability of mass (Roy and Saha 2019). The landslide has a complex mechanism, mainly driven by geomorphology, topography, geology, and seismic events (Pourghasemi et al. 2018). These factors are broadly divided into two groups such as causative factors and triggering factors. Factors like lithology, slope angle, altitude, aspect, faults, land use, drainage density, and soil are known as causative factors, while human interventions, earthquakes, precipitations are known as triggering factors (Pourghasemi et al. 2018). Hundreds of billions of properties have been damaged by landslides as well affecting about 1.5 million people in the world (Sterlacchini 2011; Chen and Chen 2021). Susceptibility, hazard,

J. Barman · D. D. L. Soren (✉) · B. Biswas  
Department of Geography and RM, Mizoram  
University, Aizawl 796004, India  
e-mail: [devid.dls.king@gmail.com](mailto:devid.dls.king@gmail.com)

**Table 14.1** Approaches of landslides study

Models	Features	Details
Physical based	Quantitative	Emphasis on landslide failure mechanism
Knowledge based	Qualitative	Emphasis on landslide conditioning factors and their weights
Data based	Qualitative	Emphasis on geoenvironmental characteristics of landslide

and risk mapping are the three steps for landslide analysis. Terminologies such as landslide susceptibility mapping, landslide susceptibility assessment had newly arrived in the literature regarding landslide. Landslide susceptibility mapping is the potentiality of spatial landslide occurrence of known slope slide, a set of given geoenvironmental conditions including historical landslide sites mapping (Guzzetti et al. 2006; Merghadi et al. 2020), while landslide susceptibility assessment is temporal and spatial perdiction of landslide and landslide susceptibility map preparation (Chen and Chen 2021). Analysis of landslides is a hierarchical process consisting of susceptibility, possibility, and risk as expressed in formulas (14.1–14.3) (Lee and Min 2001).

$$\text{Susceptibility} = f(\text{Landslide-related factors, Landslide}) \quad (14.1)$$

$$\text{Possibility} = f(\text{impact factors, susceptibility}) \quad (14.2)$$

$$\text{Risk} = f(\text{Damageable objects, possibility}) \quad (14.3)$$

Although natural hazard like landslide cannot be fully mitigated, a suitable understanding of scientific methodologies could be an important tool for reducing vulnerability (Pourghasemi et al. 2018). Methods for working landslide susceptibility mainly can be divided into three types: physical-based, knowledge-based, and data-based methods (Table 14.1) (Huang and Zhao 2018). Identification of susceptible zones is the first step to mitigate any hazard. During the past decade, satellite data-based landslide susceptibility modeling has increased due to development in the field of remote sensing & GIS (Huang and Zhao 2018). To analysis landslide susceptibility, a total of 201 relevant

published articles during the last 20 years (2000–2020) were categorized according to publishing year, models and methodologies used, study area, etc. Although a number of literature reviews on landslide susceptibility were attempted by Segoni et al. (2018), Budimir et al. (2015), Aleotti and Chowdhury (1999) and Kanungo et al. (2012), however the present study is different from the previous since the previous studies focused on a specific model or region, while the present study is an overall study on landslide susceptibility evolution and analysis.

## 14.2 Materials and Methods

At the onset, a total of 201 articles published during 2000 to 2020 were collected from Google Scholar using searching keyword landslide susceptibility. Articles were then categorized according to their publication year, i.e., from 2000 to 2020. A quantitative and qualitative literature review has been done to understand the temporal and spatial changes. A database was then created for all the review papers categorizing them into years of publication, methodologies, name of journals, and study area.

## 14.3 Results and Discussion

### 14.3.1 Temporal Trend of Published Articles

Out of the total of 201 review papers from 2000 to 2020, highest number of articles were published in 2019 (14%) followed by 2020 (11%), 2018 and 2010 (7%), 2012 (7%), and 2016 (6%) details in Fig. 14.1.

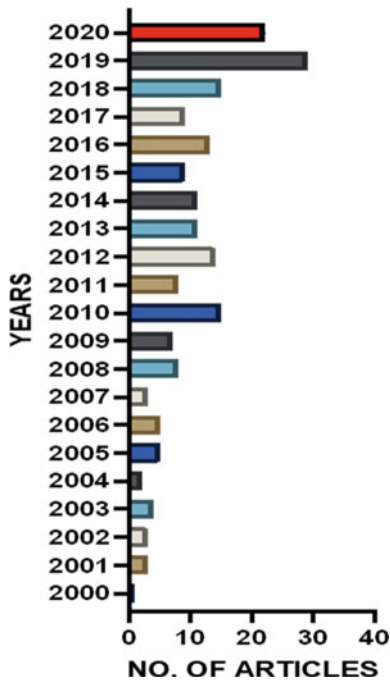


Fig. 14.1 Temporal trend of journals publication

### 14.3.2 Spatial Trend of Published Articles

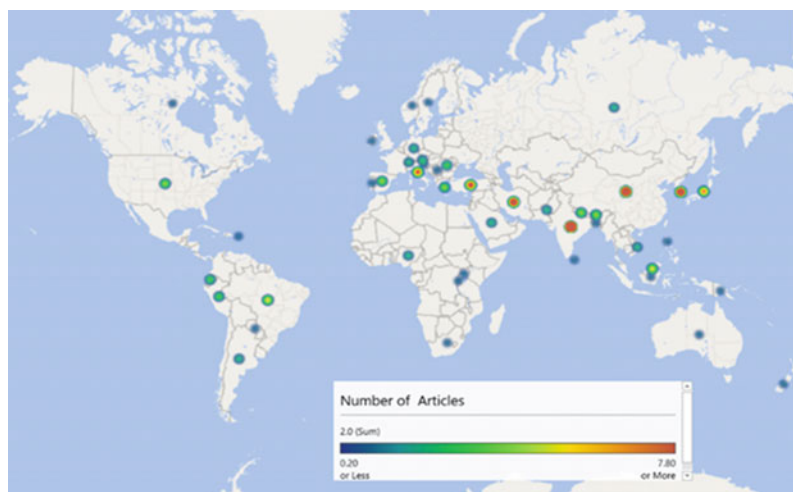
The 201 research articles taken into consideration encompassed 46 countries. Almost 55% of the articles represents works from 8 countries, with

India ranking first (19%) followed by China (10%), South Korea (6%), and Iran (5%), respectively. Furthermore, it was found that most of the authors had taken their study area from the southeast and south Asian monsoonal climatic region (India, China, and South Korea); revealing rainfall is an important triggering factor for landslides details in Fig. 14.2.

### 14.3.3 The Trend of Publishing Journals

From 2000 to 2020, a total of 79 journals have published articles on landslide susceptibility. *Geomorphology*, *Natural hazard*, *Engineering geology*, *Environmental earth science*, and *Landslide* have published more than 10 articles each and account for 38% of the total published articles. *Computer and geoscience*, *Journal of the Geological Society of India*, *Environmental geology*, *Natural hazard and earth system science*, *Catena*, *Environmental modeling and software*, *Geocarto international*, *Bulletin of engineering geology*, and *The Environment* were the most trending journals giving priorities about publishing articles on landslide susceptibility (Table 14.2).

Fig. 14.2 Spatial distribution of study areas



**Table 14.2** Published articles in different journals

Journal	Number	Journal	Number
Geomorphology	16	International journal of digital earth	1
Environmental geology	4	Civil Engineering and environmental system	1
Natural hazard	19	Forest	1
Engineering geology	12	Journal of Zhejiang university	1
Earth surface processes and landforms: the journal of the British geomorphological research group	1	International journal of sediment research	1
International Journal of remote sensing	1	Journal of the society of remote sensing	2
Science of total environment	1	International journal of geology, earth and environmental sciences	1
Engineering with computers	1	International journal of engineering sciences and research technology	2
Journal of the geological society of India	3	Environment, development and sustainability	4
Environmental disasters	1	International journal of engineering and technical research	1
Entropy	1	Nature, environment and pollution technology	1
Palynology	1	Thematic journal of geography	1
Geoscience journal	1	Geotechnical and geological engineering	2
Journal of soils and sediments	1	Journal of applied geophysics	1
Natural hazard and earth system sciences	4	Sustainability	1
Canadian geotechnical journal	1	Theoretical and applied climatology	1
Geojournal	1	Innovative infrastructure solution	1
Annals of GIS	1	Remote sensing of environment	1
Science China earth sciences	1	Spatial information research	1
Environmental monitoring and assessment	1	International journal of geographical information science	1
Mathematical problem in engineering	1	Indian journal of science and technology	1
Geoscience letters	1	Quarterly journal of engineering geology and hydrology	1
Computers and geosciences	8	Modeling earth system and environment	2
Earth science reviews	1	International journal of computer application and engineering	1
Catena	5	Geoenvironmental disasters	1
Environmental modeling & software	5	Spatial information research	1
Environmental earth sciences	15	Applied geomatics	1
Landslide	13	International journal of disaster risk science	1
Mathematical geosciences	1	Advance civil engineering	1

(continued)

**Table 14.2** (continued)

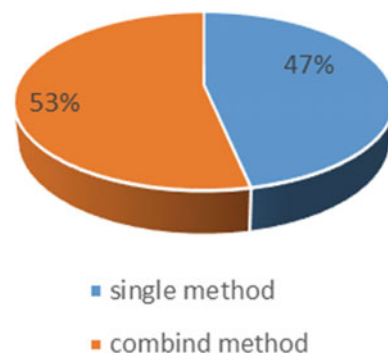
Journal	Number	Journal	Number
Hamburger Beitragezur Physischen Geographie Und Landschaftsokologie	1	Water	1
Big earth data	1	Geoscience	2
Geocarto international	6	In landslide science for a safer geoenvironment	2
Bulletin of engineering geology and the environment	5	Arabian journal of geoscience	3
International journal of applied earth observation and geoinformation	1	The Egyptian journal of remote sensing and space science	1
Procedia engineering	2	In transportation soil engineering in cold region	1
Remote sensing	2	Journal of maps	1
Journal of mountain science	2	Expert system with application	1
Remote sensing and multi-criteria decision analysis: in-publication for urban planning and development	1	In 2020 seventh international conference on edemocracy and government	1
In spatial modeling in GIS and R for earth and environmental sciences	1		

### 14.3.4 Trending of Methodology

A total of 77 types of methodologies have been used by the authors; among them, logistic regression ranked first (31) (Kincal et al. 2009; Samia et al. 2018) followed by the frequency ratio (28) (Mind'je et al. 2019; Silalahi et al. 2019), support vector machine (21) (Marjanović et al. 2011), artificial neural networks (20) (Bragagnolo et al. 2020), GIS weighted overlay (18) (Pachau 2019), and analytical hierarchy processes (17) (Ahmed 2015; Basu and Pal 2017), respectively. Of the various articles, authors used single methodology in 92 research works, while the rest of the works were comparative analysis among various methodologies (Fig. 14.3). Some of the works focused on validation checking, chorology of landslide susceptibility, correlation between topography and geological structure for landslide susceptibility, etc. Among single methodology used, maximum authors have chosen GIS weighted overlay (15). Intergrade methodologies like neuro-fuzzy and fuzzy-AHP have taken a footprint on recent trending methodologies as well as machine

learning methodologies. Support vector machine is the highest trending machine learning method followed by artificial neural networks (20) and random forest, which covered 72% of the total articles as represented in Table 14.3.

Except the traditional methodologies, some researchers have discussed about the correlation between geological structure and topography with landslide susceptibility, geomorphological and structural features extraction of landslide susceptibility.

**Fig. 14.3** Methodology involved for analysis

**Table 14.3** Methodologies emphasized by the researchers

Name of method	Number of articles	Name of method	Number of articles
Frequency ratio	28	Temporal probability	1
Keefer method	1	Convolutional neural network	2
Harp and Noble method	1	Recurrent neural network	1
Analytical hierarchy method	17	TRIGRS	1
GIS Weighted overlay	18	Neuro-fuzzy	1
Weight of evidence	16	AdaBoost	2
Information value	10	Satellite sar interferometry	1
Index of entropy	9	Fuzzy-Gama	2
Yule index	1	Factor analysis	1
Distance distribution analysis	1	Landslide rupture hypothesis	1
Probability of landslide occurrence	1	Stability index mapping	1
Binary logistic regression	3	Support vector machine	21
Bayesian theory	7	Decision tree	11
SINMAP model	3	Multi-layer perception neural network	1
Adaptive neuro-fuzzy interface system	2	Kernel logistic regression	1
Random forest	15	Artificial neural network	20
Fuzzy membership	9	Reduced error pruning trees	1
Relative effect	1	Bagging	5
Logistic regression	31	Multi-boost	4
Evidential belief function	3	Rotation forest	6
Classification and regression tree	1	Random subspace	3
GPS and GRP	1	Dempster-Shafer	4
RSAGA package	1	Stability index mapping	1
Quantitative heuristic method	1	Certainty factor	6
Landslide density	1	Statistical index	6
Like hood ratio	4	Fuzzy-AHP	2
Discriminant analysis	5	Kernel logistic regression	1
Slope model	1	Classification and regression tree	1
Alternative decision tree	2	Logistic model tree	1
Weighted linear combination	1	Empirical conditional probability	3
Ordered weighted averaging	1	Newmark's method	1
Landslide relative frequency	1	Naïve Bayes	1
Forest canopy density model	1	MLP neural networks	1
Landslide susceptibility index	1	Functional tree	1
General linear model	2	Structural and geomorphological feature extraction	1
Multi-layer perception	1	Shallow landslide stability (SHALSTAB)	2

(continued)

**Table 14.3** (continued)

Name of method	Number of articles	Name of method	Number of articles
Geographically weighted regression	2	Rainfall I-D threshold	1
Interactive back analysis and sensitivity	1	Root cohesion	1
Spatial regression	1	–	–

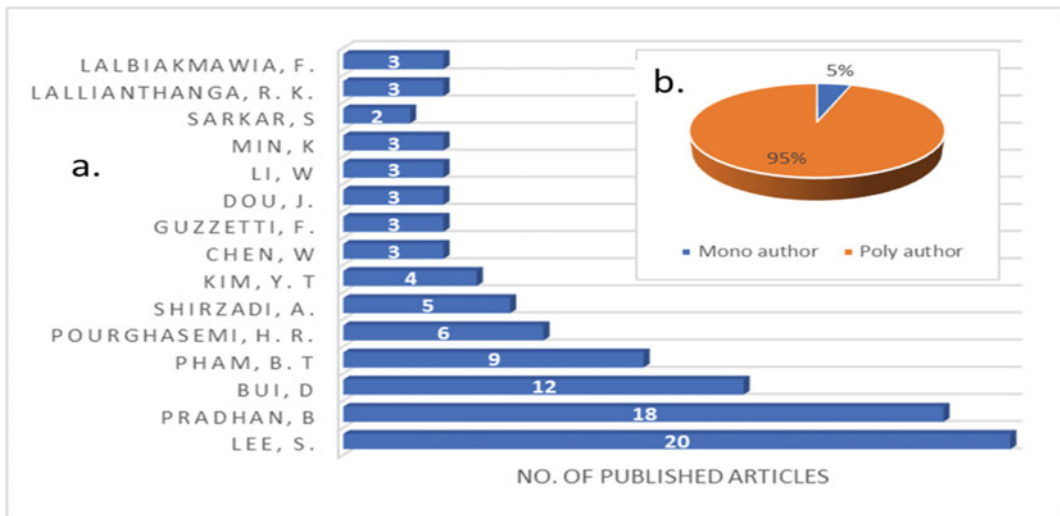
**14.3.5 Authors**

Of the 201 articles considered for review, 10 papers were mono-authored, and the rest have poly authorship. Most of the authors published one paper, while only 6 authors published above 5 papers, as viewed in Fig. 14.4b. Lee S has the highest number of published papers (20) with co-authors.

Broeckx et al. (2019), Ayalew and Yamagishi (2005) used logistic regression. The result was very satisfactory occupied with 0.94% accuracy level. Frequency ratio method also widely used with attending accuracy level of 0.73% (Jana et al. 2019), to assess the landslide slope is argued as most influencing factor then other (Mind’je et al. 2019). Singh et al. (2020) conducted one study in Indian sub-continent; there investigation shows that less vegetated and barren land is most influencing indicator than TWI, lineament density, geomorphology, and slope, respectively. Artificial neural network (ANN) also widely used method to landslide assessment with commendable accuracy level (AUC= 0.84%) (Chauhan et al. 2010). Landslide study also conducted with one single method

**14.4 Summary of Reviews**

The work Landslide Susceptibility Evaluation and Analysis conducted from 2000 to 2020 around the world. Various methods applied to evaluate landslide susceptibility evaluation,



**Fig. 14.4** a Top 15 authors and their published articles on landslide susceptibility. b Number of authors for collaboration

(Cárdenas and Mera 2016; Neuhäuser and Terhorst 2007; Ayalew and Yamagishi 2005) as well as used combined methodologies (Chen et al. 2017; Shirzadi et al. 2018; Pham et al. 2016). The detailed of the study area, methodology with findings referred in Table 14.4.

### 14.5 Conclusion

Landslide susceptibility is an emerging study in literacy number of methodologies also increased day by day. These growths happen due to the development of remote sensing and GIS.

**Table 14.4** Brief summary of review

Author	Study area	Methods	Findings
Broeckx et al. (2019)	Uganda	Logistic regression	1. AUC= 0.94 2. Landslide susceptibility is a significant indicator of LMR 3. Landslide is a major sediment source in Africa
Mind'je et al. (2019)	Rwanda	Frequency ratio	1. AUC= 84.6% 2. Slope is the most influencing factor (17.23%) followed by land use land cover
Singh et al. (2020)	India	Information value, index of entropy	1. LULC (sparse vegetation and barren land) rank first for a landslide in this region followed by TWI, lineament density, geomorphology, and slope respectively
Cárdenas and Mera (2016)	Ecuador	Yule coefficient	1. Result found that slope facing north and northeast was the highest chance of landslide occurrence
Neuhäuser and Terhorst (2007)	Germany	Weight of evidence	1. Result indicated that the slope between 11° to 26° with colluvial soil layer was an indicator of slope instability
Mondal and Mandal (2019)	India	Index of entropy	1.ROC= 78.2% 2. Method resulted that soil types were the highest causative factor whereas NDVI was the least factor
Ayalew and Yamagishi (2005)	Japan	Logistic regression	1. Road network found the major causative factor of landslide in this study area
Chauhan et al. (2010)	India	Artificial neural network	1.AUC= 0.84%
Chen et al. (2017)	China	Evidential belief function, certainty factor, frequency ratio	1. The success rates of the EBF, CF, and FR models are 0.8038, 0.7924, and 0.8088, respectively
Dias and Gunathilake (2014)	Sri Lanka	WAA, SINMAP	1. The factor of safety ranging from 0 to >1.5
Dunning et al. (2009)	Bhutan	Structural and geomorphological feature extraction	1. Nam Ling Landslide is indicative of deeper-seated deformation and is not purely a function of road construction

(continued)



**Table 14.4** (continued)

Author	Study area	Methods	Findings
Shirzadi et al. (2018)	Iran	Alternating decision tree, bagging, multiboot, random subspace, rotation forest	1. Study resulted TWI and slope angle was most triggering factors of landslide
Pham et al. (2016)	India	Support vector machine, linear regression, Fisher's linear discriminant analysis, Bayesian network, Naïve Bayes	1. Among five models, SVM model played the best performance
Jana et al. (2019)	Papua New Guinea	Frequency ratio	AUC= 0.73%
Roy and Saha (2019)	India	Fuzzy- LNRF, Fuzzy- AHP	AUC= 91% and 90%, respectively

Landslide susceptibility zonation is the first step to landslide hazard mitigation, management, and measures. In the present study, we reviewed 201 published articles to understand the spatial and temporal changes. The number of publishing articles increase 7.19 times per year during the period 2000–2020; it is increased quite less by about 4.1 times per year during the period 2000–2009. The overall increase has happened due to the availability of digital information and the development of machine learning methodologies. Logistic regression, frequency ratio, analytical hierarchy method, GIS overlay weighted, information value, the weight of evidence, and recent methodologies like support vector machine, artificial neural networks, random forest, and decision tree were widely used methodologies that reflect their high accuracy. Review articles were covered across 46 countries over the world among them most of the countries fall in the southeast and East Asian countries that also indicated the high landslide-prone area. A lot of journals have given priority to publishing articles on landslide susceptibility and associates works; most of the articles are published under science direct, Elsevier, and Springer base journals like *Geomorphology*, *Natural Hazard*, *Engineering geology*, *Environmental earth science*, and *landslide* published more than 10 papers. Although landslide is an unprotectable natural hazard, we can reduce risk magnitude by proper management and awareness.

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