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Assessment of Landslide Hazards Using GIS-Based different Techniques: An Overview 2000-2020

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ABSTRACT

Landslides considers one among the most popular dangerous natural calamities in environment, causing widespread social, economic, and environmental damage. Landslide result from rock's movement, soil, or debris on the ground a sloped area of terrain. According to geologists, who study the physical formations of the Earth the landslides are one sort of mass wasting. Moreover, zoning for landslide susceptibility, that has become popular in recent decades for the prediction landslide areas and manage land usage. The most important goal of this research is to introduce the main techniques that was used to evaluate landslides between the years 2000 and 2020. The findings revealed that the published researches have been discuss different techniques in statistical and analytical ways depending on the different variables and impacts. Moreover, the majority of prevalent procedure for determining vulnerability to landslides are: the Logistic regression with 20.49 % from total publication, Frequency ratio with 13.66%, Artificial neural network and Weights-of-evidence were about 9 % from the total articles publications with direct or indirect integration with geographical information system (GIS). The finding also revealed that the statistical methods were employed in 69.56 % of studies on the susceptibility to landslides, and Heuristic models were 24.45 %, and the articles based on models predetermined were 10.70 % of published articles of landslide applications.

1. Introduction

The movement of rock, soil, or debris down a sloped area of terrain is known as a landslide. Rain, earthquakes, volcanoes, and other elements that make the slope unstable produce landslides [1]. On the other hand, new approaches are necessary to acquire a superior knowledge of landslide danger and assess the reasonable judgments based on distribution of funding and then the management to effectively reduce the risk of a landslide [2]. Recent advancements in hazard assessment are allowing the evolution of more systematic rigorous slope management processes. The process of analyzing and assessing risks has evolved a popular approach for dealing with the uncertainty that comes with landslide hazards in recent years. Landslides are one sort of mass wasting, according to geologists, who study the physical formations of the Earth. Precipitation, shakings, as well as human intervention are referred to as triggering variables, whereas slope degree, aspect, altitude, fault, lithology, drainage density, land use, and soil are known as influencing factors [3]. The assessment of vulnerability to landslides one of the most significant subjects in foreign publications, given the challenge of predicting the occurrence of a landslides. As a result, several methodologies and strategies for modeling and assessing landslide vulnerability have been presented. The goal of the landslide susceptibility analysis is to use the statistics, data mining, and soft computing methodologies, as well as geographic information systems, to build a relationship between the landslide site and different variables to spatially locate locations [4].

The landslides threaten 3.8 million square kilometers of land surface and 300 million people which represent about 6% in the population of the world. The soil thematic strategy of the European Union (EU) has recognized landslides are one of the eight types of soil erosion concerns in addition encourages the recognition of landslide-disposed to locations. Although natural hazards such as landslides cannot be prevented, a thorough grasp of trend and scientific findings approach designed for anticipating similar occurrences' pattern of conduct can be useful tackles in reducing usual susceptibility. The advancement of techniques in remote sensing and modeling tools, in addition to the geographic information systems (GIS) has resulted an increasing in landslide susceptibility research during the last decade. the goals of this study are to review articles that published on the topics of landslide susceptibility around the world during the period of 2000 to 2020. For this purpose, we have investigated, reviewed, and analyzed 732 published articles in different databases including the Science Direct and Springer.

2. Methodology

With 732 publications in Science Direct and Springer databases were used to investigate the scientific background and to reviewed landslide susceptibility for the period from 2000 to 2020 because of the importance of studding landslide in many researchers. The database was created that included the year of publication, name of the author, nation, name of the journal, and the applicable impact factor (IF), kind used as a model assess landslide vulnerability, and influencing factors as part of the model. Finally, models used for assessing landslide susceptibility and criteria for assessing landslide sensitivity[5]. The database's structure allows us to find the history of landslide susceptibility from 2000 until 2020. Also create the landslide inventory map were created and transformed to a pixel unit size that everyone could understand. Hence creation two landslide-prediction maps using modeling and pair-wise comparisons of the terminal nodes and as a result from the reviewed article, we developed a trend of these articles.

3. Results And Discussion

Time trend of published articles. The majority of the 732 landslide susceptibility publications published between 2000 and 2020 were largely related to landslide susceptibility assessment in different journals (Fig. 1), Table)2(shows part of the research, models and factors used in the published papers. Statistics found that the number of papers published in foreign journals increased from 2010 to 2020.

The majority of publication were in Environmental Earth Sciences (EES), Geomorphology, Natural Hazards, Arabian Journal of Geosciences, Landslides, Science and Practice, Computers and Geosciences, Engineering Geology, Catena Landslide and Bulletin of Engineering Geology and the Environment journals[6].

Geomorphology, Natural Hazards, Environmental Earth Sciences, in addition other subjects were also revealed, and Landslides was the sole subject of this publication. Between 2000 and 2020, In China, Iran, Italy, India, Japan, Greece, and Austria, the number of publications increased, China then Turkey was awarded the first and the second place, respectively, in this category as shown in Figure 2.

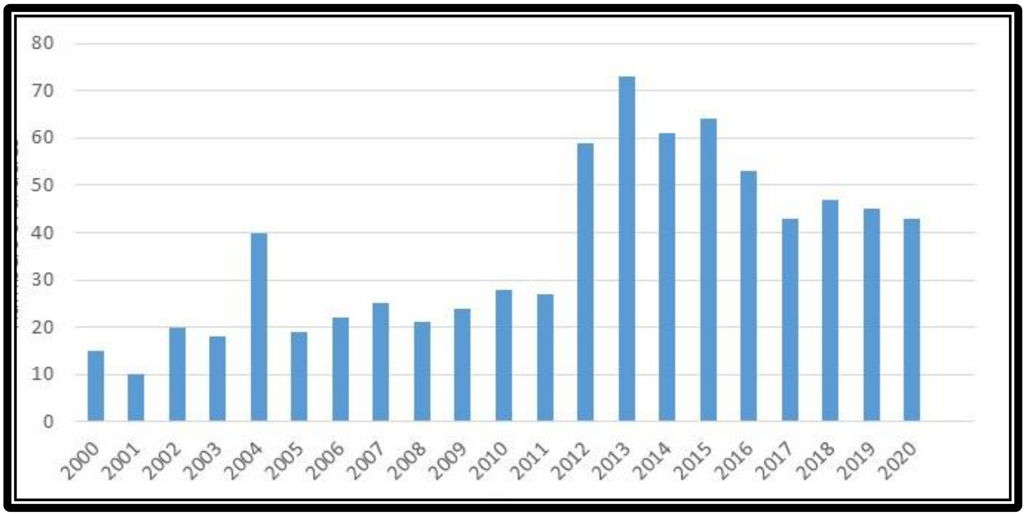

Figure 1: The relationship between published papers and year of publications

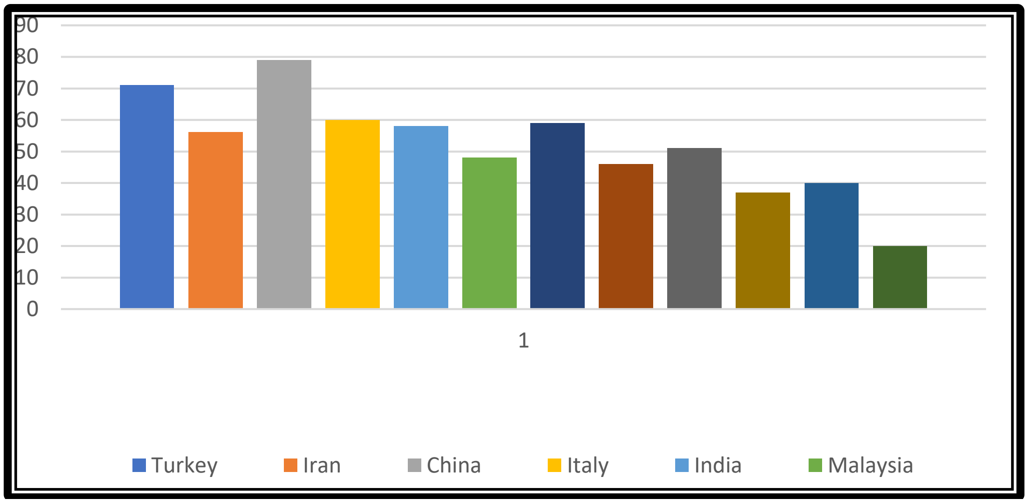

Figure 2: Published articles according to country.

Moreover, it is found that Asia has the largest percentage of articles published on avalanches compared to other continents as shown in Figure (2)

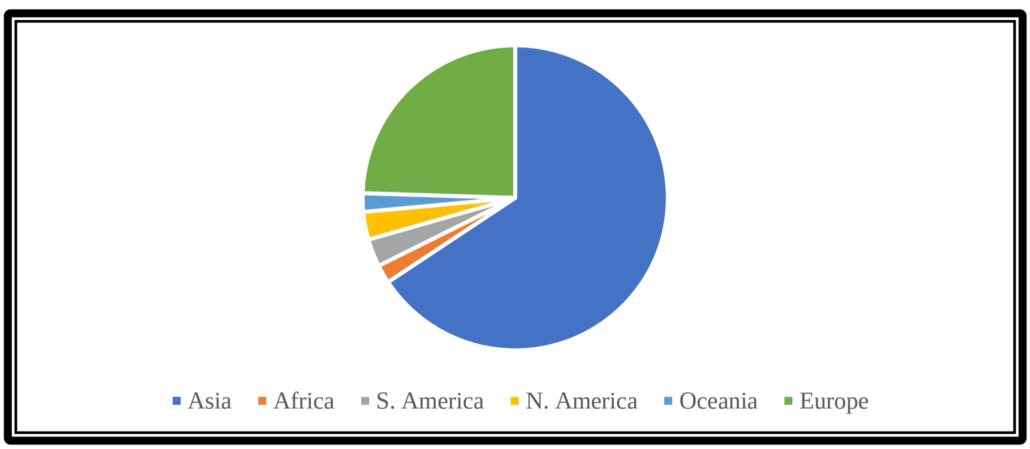

Figure 3: Landslide susceptibility papers in the world for the period 2000 to 2020

The Logistic regression is the most common techniques used in research with 20.49 % from total publication and Frequency ratio was 13.66% artificial neural network and Weights-of-evidence were about 9 % from the total publications. The term "logistic regression" refers to a method of ideal technique since this method has lowest mistake rate among the statistical techniques [4]. When the reliant on variable is definite (e.g., presence or absence) and the descriptive (independent) variables are definite, arithmetical, or together, logistic regression is a valuable tool for assessing landslide incidence. Frequency ratio, weights-of-evidence, artificial neural network (ANN), analytic hierarchy process (AHP), fuzzy models, statistical index, and index of entropy are some of the various models in 100, 71, 70, 60, 56, 50, 30, and 28 examples available as shown in (Table 1).

Statistical methods were employed in 69.56 percent of on susceptibility to landslides studies, Heuristic models, on the other hand, were in usage 24.45 percent of papers, and models that are predetermined were in usage only 10.70 percent of papers.

According to the results, the logistic regression analysis ranked in the first stage as terms of the total applications. Where there were 65 cases between 2000 and 2012, while between 2013 and 2020, there were 86 cases.

Other models, such as statistical indexes, entropy indexes, support vector machines, integrated replicas, factors of certainty, Indexes of Stability, choice trees, and haphazard forests, are becoming more popular. Combination-based models saw the greatest substantial increase, from one publication throughout the first period articles published between 2013 and 2020. Though, when compared to the first era, Dempster–Shafer, fuzzy logic, ANN, AHP, weights-of-evidence, and frequency ratio are all used declined between 2013 and 2020.

Table 1: Techniques used with GIS to assess landslide sensitivity

No	ID models	Description	Number of research papers	Percentage of the publication %
1	LR	Logistic regression	150	20.49
2	FR	Frequency	100	13.66
3	WOE	Weights-of-evidence	71	9.70
4	ANN	Artificial neural network	70	9.56
5	AHP	Analytic hierarchy process	60	8.20
6	Fuzzy or Fuzzy AHP	Fuzzy or Fuzzy Analytic hierarchy process	56	7.65
7	SI, VI	Statistical index, information value	50	6.83
8	IOE	Index of entropy	30	4.10
9	SVM	Support vector regression Combined models	28	3.83
10	CF	Certainty factor	15	2.05
11	DS	Dempster–Shafer	11	1.50
12	SINMAP	Stability index mapping	10	1.37
13	DT	Decision tree	9	1.23
14	RF	Random forest	8	1.09
15	EBE	Evidential belief function	8	1.09
16	SMCE	Spatial multi-criteria evaluation	7	0.96
17	WLC	Weighted linear combination	8	1.09
18	DS	Discriminant analysis	6	0.82
19	GAM	Generalized additive model	6	0.82
20	MARS	Splines Multi-variate adaptive regression splines model	6	0.82
21	MCE	Multi-criteria evaluation	5	0.68
22	Matrix method		5	0.68
23	RS	Rough sets	5	0.68
24	CA	Cluster analysis	4	0.55
25	NB	Naïve Bayes	4	0.55

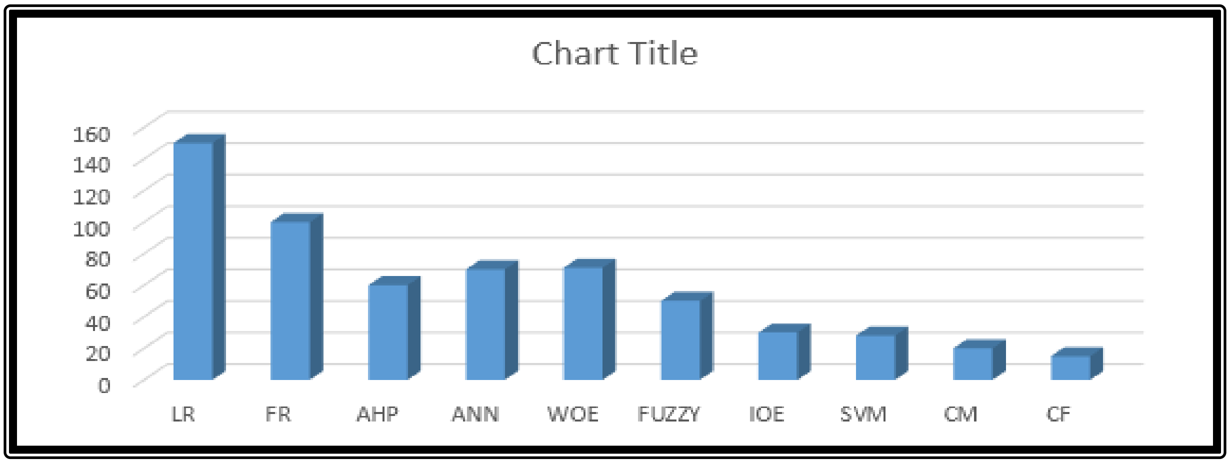

Figure 4: Landslide vulnerability assessment models used in articles for the period 2000–2020

Figure 4 also shows the most used and most important models in the papers published from 2000 to 2020.

Table 2: The models and fabrications used in the studies

No	Author & Country	Model type	Slope Degree	Altitude	Faul t	Litholo gy	Lan d use	Precipitation	Earthquake s
1	Dou, et al., 2015 (Japan)	Statistical index (SI) Logistic regression (LR)	√	√	√	√		√	√
2	Murat et al., .٢٠0٧ (Turkey)	Fuzzy approach	√	√		√			√
3	Ali Yalcin, 2008 (Turkey)	Analytical hierarchy process (AHP)	√	√		√			√
4	Ercanoglu, et. al. 2011 (Turkey)	logistic regression Fuzzy	√	√	√	√	√	√	√
5	Alireza, et. al. 2020 (Iran)	random forest (RF), Alternative decision tree (AD Tree) Fisher's Linear Discriminant Function (FLDA)	√	√	√	√	√		√
6	Pourghasemi, et. al., 2014 (Iran)	Analytical hierarchy process (AHP)	√	√	√	√	√	√	
7	Shahabi, et. al., 2014 (Iran)	Logistic regression, Analytical hierarchy process (AHP) Frequency ratio	√		√	√	√		√
8	Samaneh, et.al., 2016 (Iran)	Frequency ratio Statistical index Weights of evidence models	√	√	√	√	√		√
9	Aiding, et. al., 2016 (Iran)	Frandom forest Frequency ratio	√	√	√	√	√		√
١0	Hamid, et. al., 2016 (Iran)	Random forest (RF) Evidential belief function (EBF)	√	√	√	√	√		√
١1	Dieu, et. al., (2018)	Support Vector Machine Index of Entropy Models	√	√	√	√	√	√	
١2	Biswajeet. 2010 Malaysia	Frequency ratio Logistic regression Artificial neural network	√			√		√	
١3	Norbazlan, et. al., 2015	Logistic regression (LR)	√	√				√	

	(Malaysia)	Evidential belief function (EBF							
١4	Kayastha, et. al., 2013 (Nepal)	Analytical hierarchy process (AHP)	√				√	√	√
١5	Chandra, et. al., 2010 (Nepal)	Frequency ratio Artificial neural networks	√			√	√		√
١6	Prabin, et. al., 2012 (Nepal)	Weight of evidence	√		√		√	√	√
١7	Amar, et. al., 2014 (Nepal)	Frequency ratio Statistical index weights-of-evidence	√	√		√	√		√
١8	Saro, et. al., 2007 (Korea)	The likelihood ratio logistic regression Artificial Neural Networks	√	√			√	√	
19	Soo-Min, et. al., 2017 (Korea)	Support Vector Machine (SVM)	√		√		√	√	√
20	Sunmin, et. al., 2017 (Korea)	Support Vector Machine (SVM) Artificial neural network (ANN)	√					√	√
21	Ronda, et. al., 2019 (USA)	Frequency ratio (FR)	√	√		√	√	√	√

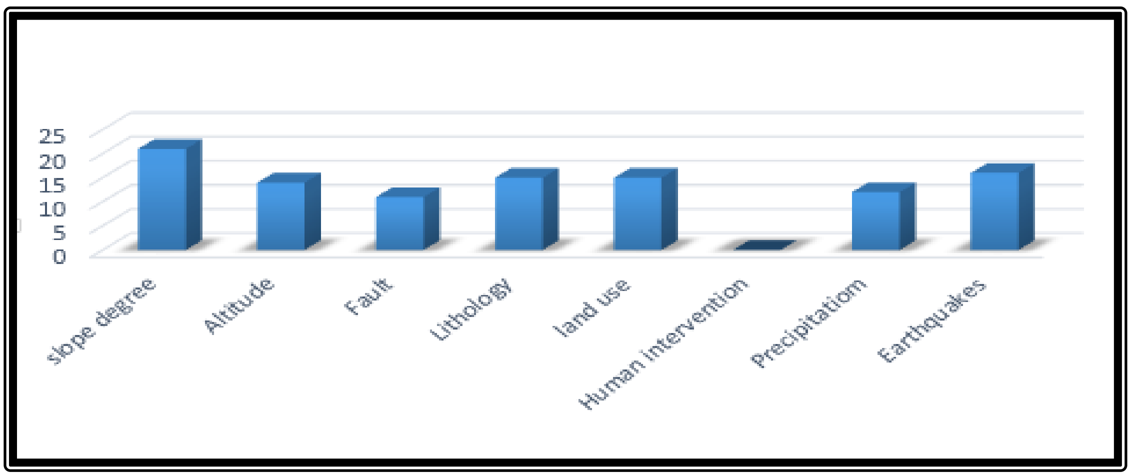

Figure 5: Triggering and Conditioning Factors

Figure 5 shows the factors that have been used the most in research, It also explains the causative factors such as earthquakes or the human factor.

4. Conditioning Factors And Their Trends

The great diversity of methods that have been used to assess vulnerability to landslides necessitated a large number of data inputs, although this does not necessarily mean that they have a high predictive power. The optimal factor selection is determined by the landslide mechanism and kind, the physiognomies of the examined zone, the scope of the investigation, data accessibility, in addition the technique that was used [7]. Landslide susceptibility evaluation parameters are classified into four categories: geological, topographical, geotechnical, and ecological aspects. Regrettably, there isn't a single instruction or recommendation for selecting the beneficial elements in the event of a landslide, and the variables chosen vary from one study to the next, according to the findings. As a result, providing a collection of criteria utilized in landslide susceptibility evaluation can assist future studies better pick the input variables [8]. Factors were utilized to evaluate landslide susceptibility in 732 studies reviewed. In more than 95.3 percent of the studies, the grade of the slope was identified as the most significant element in vulnerability to landslides analyses. Also consider lithology, aspect, land use/cover, and elevation. Another set of variables to consider (plan curvature, distance from road, profile curvature, precipitation, topographic wetness index,

Table 3 Landslide sensitivity assessment articles' factors

NO	Factors	No of articles
1	Slope	500
2	Lithology	415
3	Aspect	390
4	Land use/land cover	340
5	Elevation	300
6	Distance from river	290
7	Distance from faults	275
8	Plan curvature	200
9	Distance from road	190
10	Profile curvature	175
11	Precipitation	157
12	Topographic wetness index	138
13	Soil type	100
14	Stream power index	90
15	Normalized difference vegetation index	90
16	Slope length	85
17	Curvature	75
18	Drainage density	67
19	Geomorphology unit	45
20	Fault density	38
21	Soil depth	40
22	Relative relief	33
23	Forest type	26
24	Seismic intensity	24
25	Peak ground acceleration	21
26	Tangential curvature	19
27	Roughness index	19
28	Soil drainage	17
29	Solar radiation	15
30	Topographic position index	15

soil type, stream power index, normalized difference vegetation index, slope length, curvature, and drainage density) has a medium use in more than 15% of the situations in comparison to the aforementioned elements as shown in Table 3. Obviously, the application of components when it comes to landslide susceptibility modeling is dependent on a variety of parameters, including data availability, scale, and research region. Using the information provided components for landslide resiliency throughout the dual eras does not differ significantly, as expected (2000-2020). In both periods, there was a trend of employing factors in landslide susceptibility analysis as shown in table (3)It has observed that there is a rising trend of conditioning elements such as slope gradient, lithology, slope direction, elevation, distance from river, distance from fault, distance from road, slope length, and drainage density.

This rise is proportional to the second period's the quantity of articles has increased. In compared to the period 2000–2012, Precipitation, topographic wetness index, and slope shape have all increased by 74% and 23%, respectively, and 69 percent, respectively, in the year 2013–2020. This particular It is possible to observe a pattern attributed to the increased accessibility of precipitation data collection and remote sensing - derivative goods over the last eight years (topographic wetness index, slope shape, drainage density) [9]. Soil type, stream power index, normalized difference vegetation index (NDVI), geomorphological units, and soil depth are all factors to consider, on the other hand, were less commonly referenced in the second period's publications. The most significant decline is due to the soil type parameter, which has been reduced by a factor of one hundred percent.

5. Conclusion

The number of publications in landslide evaluations has increased considerably within the last period, with an average of 32 articles every year between 2000 and 2012, and 67 articles every year between the years 2013 and 2020, with 135 % increase. This increase because of the contributions and developments of remote sensing techniques, modeling tools, data availability, as well as an increased awareness among managers of the value of scientific research in identifying high-risk locations for better land use planning and preventing or minimizing landslide damage. In this study, China, Turkey, Iran, Italy, India, Malaysia, Korea, Japan, and Nepal are among the authors, as well as the United States, Greece and Austria undertook landslide susceptibility assessment research. According to studies, the majority of these countries are located in landslide-prone zones, with the highest number of casualties and occurrences. There were 65 models employed in the 732 publications that were reviewed . The logistic regression model, was the most extensively used for determining landslide risk utilized in 20.49 %of the studies published between 2000 and 2020. This because of the fact that the logistic regression models have lower error rates compared to other statistical methods and necessitates fewer environmental data. The factor for slope gradient was regarded a significant influence in 94.2 % of papers between 2000 and 2020 for landslide susceptibility study and then the lithology, aspect, and land use.

Findings revealed that the parameters including slope gradient, lithology, elevation from sea level, and land use are commonly used in the different studies, but the application of other factors is still up for debate. It has been concluded from all of the studies that the employed techniques are working to identify sites and areas that are prone to collapse and pinpoint their location using methodologies, as well as to prevent future collapses to minimize damages. Review of these researches it has been concluded that recent developments in the technological fields of remote sensing, computer systems and geographic information systems have all contributed to an increase in landslide sensitivity assessment research.

References

[1] Highland, L., & Bobrowsky, P. T. (2008). The landslide handbook: a guide to understanding landslides (p. 129). Reston: US Geological Survey.

[2] K. M. Scott, Catastrophic debris flows transformed from landslides in volcanic terrains: mobility, hazard assessment, and mitigation strategies, 2001.

[3] N. R. Council, Partnerships for reducing landslide risk: assessment of the national landslide hazards mitigation strategy, 2004.

[4] G. J. Dick, "Development of an early-warning time-of-failure analysis methodology for open-pit mine slopes utilizing ground-based slope stability radar monitoring data.", 2015.

[5] E. a. J. Henrique, "Control and prevention of infectious diseases from a One Health perspective.", 2021.

[6] A. AS, "Postglacial extreme events and human action in the transformation of Estonian topography and landscapes.", 2003.

[7] T. J. Boves, "Emulating natural disturbances for declining late-successional species: A case study of the consequences for Cerulean Warblers, 2013.

[8] F. Dierickx, "Socio-economic consequences of landslides in Mount Elgon region (Uganda).", (2014).

[9] A. M. S. a. Y.-T. K. Pradhan, "Relative effect method of landslide susceptibility zonation in weathered granite soil: a case study in Deokjeok-ri Creek, South Korea.", 2014.